A Decentralized Review System for Data Marketplaces

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***Abstract*—Data Marketplaces allow a wide range of public and private data providers on the one hand, and data-consuming applications on the other, to interact. They can be used to exchange valuable data relevant to a community, such as data relevant to traffic, road conditions, parking, air quality and other urban internet of things (IoT) applications, in a scalable manner. Traditionally, online marketplaces use ratings by buyers to help potential consumers identify good quality products; however such rating systems are often easy for sellers to game by paying for flattering ratings and reviews. These problems are even more challenging in data marketplaces due to the possibility of sellers launching Sybil attacks (taking on multiple fake identities) to rate their own products. We propose a novel decentralized crypto-economic system to ensure the credibility of reviews. The key idea of our proposed system, which can be implemented using decentralized smart contracts, is to have sellers apply for their products to be reviewed, followed by an allocation of products to a select subset of reviewers with credibility. The reviewer allocation process is randomized and double-blinded to minimize the possibility of collusion with the seller. The reviewers are incentivized through a mechanism that not only provides a reward for reviewing products posted by sellers but also an additional reward for reviewing test products posted by the marketplace. We analyze the incentive mechanism through game theoretical modeling and show conditions under which the Nash equilibrium policy is for all reviewers to perform the work needed for the review (without guessing at the answer). We also show how the staking mechanism in conjunction with high quality reviews incentivizes sellers to post higher-quality products. A marketplace with higher-quality products, in turn, is likely to have a stronger reputation and attract more customers, helping the entire ecosystem.**

I. Introduction

There has been a growing interest in developing IoT and data-driven machine learning based applications for smart cities for a number of applications ranging from parking to traffic monitoring to air quality monitoring. Building each such IoT data-driven application as a separate vertically integrated silo is very challenging to scale. Therefore several groups of researchers and practitioners have recently proposed the development of online data marketplaces that decouple data sources and data providers from data consuming application developers. Examples of such recent data marketplaces and data management platforms for smart cities include Terbine [1], Snowflake [2], Cisco Kinetic, Fiware [3] and the I3 data marketplace [4].

Ratings and reviews play a significant role in helping to inform and guide buyers about the relevance and quality of products on a marketplace platform. Maintaining the integrity and reliability of ratings and reviews for online marketplace has been a continuing challenge. Many of the concerns have had to do with sellers manipulating platforms by injecting fake ratings. Another unaddressed challenge for centralized marketplaces is that buyers must implicitly trust the single platform owner to not censor or manipulate reviews and ratings in such a way as to maximize their own profits.

In this paper, we propose a novel decentralized rating and review system for a high-quality, curated data marketplace. Unlike a traditional marketplace where sellers can proceed to post products directly and then an open-ended review process is followed, the proposed system is aimed at a more curated system, which requires sellers to first apply to have their data products reviewed along with an application fee and a staked security deposit. The product is then allocated for a double-blind review process (to prevent collusion) to a subset of qualified reviewers, who assess the quality of the product and provide their ratings. Reviewer assessment mechanisms are proposed and analyzed to ensure a good-quality review process, with reviewers compensated using funds from the application fees as well as any forfeited deposits. The posting of the product on the marketplace will be conditioned on sufficient positive reviews, and the seller may also lose their deposit in case of sufficiently negative reviews, driving the marketplace towards high-quality products. By running the process transparently in a decentralized manner using smart contracts on an immutable Blockchain, the system guards against the possibility of manipulation by a single marketplace administrator.

The following are the key contributions of this work:

- A novel incentive-based decentralized review system for data marketplaces.
- Game theoretic modeling of the incentivized review process, identifying conditions under which the combination of rewards from reviewing legitimate products and test products yields all reviewers behaving honestly as the sole equilibrium.

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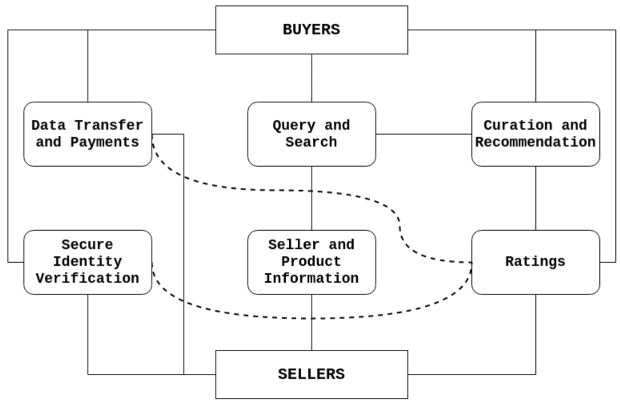


Fig. 1. Key Elements of a Decentralized Data Marketplace [5]

- Analysis of seller-incentives showing how the mechanism would contribute to a marketplace with high quality goods.
- Code and data from our results are made publicly available for use by other researchers at https://github.com/ANRGUSC/DecentralizedReviewSystem.

The proposed approach carefully synthesizes and builds on a number of complementary ideas from different domains in a fundamentally new construction, including double-blind allocation from the traditional academic peer-review process as well as the use and analysis of incentives using game theory. To our knowledge no prior works have proposed such a comprehensive, incentive-based decentralized review system for such data marketplaces.

The rest of the paper is structured as follows: Section II introduces data marketplaces and discusses the related work. The proposed mechanism for our decentralized review system is presented in Section III. The game theory analysis of the proposed review system is presented in Section IV. Section V presents the simulation results of the proposed review system. The sellers' strategy is analyzed in Section VI. Section VII discusses open challenges. Section VIII concludes the paper.

II. Background and Related Work

A. Marketplaces

Online Marketplaces: Online e-commerce services have been active for almost two decades now to help consumers buy physical goods without visiting multiple shops. Amazon, e-Bay, and Alibaba are examples of digital marketplaces, attracting thousands of sellers and buyers. Empirical studies on marketplaces discuss the importance of ratings and show how it influences the consumers' buying behavior [6], [7]. Hu *et al.* highlights that the buyers tend to focus not only on the reviews but also on the credibility of the reviewers before buying a product in online data marketplaces [7]. From the seller's point of view, it is important to receive high ratings from the customers. Some firms even devise strategies to manipulate ratings on online marketplaces [8]. Even online ratings and recommendation platforms such as Yelp allow malicious sellers to tamper with the ratings of products or services [9].

Decentralized Marketplaces: The marketplaces such as Amazon, eBay, and Alibaba follow a centralized architecture with a single administrative domain. Centralized architectures are susceptible to a single point of failure since the administrative organization can manipulate the marketplace operations or incorporate malicious policies to increase profits while deceiving the sellers and/or buyers. OpenBazaar [10] presents a decentralized marketplace using the blockchain technology. Following a decentralized, peer-to-peer architecture, OpenBazaar allows the seller to list products for free without any platform fee. Besides, all the marketplace operations are executed on top of a blockchain platform, providing high transparency for the sellers and buyers.

Data marketplaces: Like marketplaces for physical goods such as books and electronic items, the data marketplaces [4], [1], [2], [11] are being created to help the IoT device owners and data providers to sell their data with application developers. I3 [4] is an open-source IoT data marketplace [12] for smart communities. A city-wide parking application is currently being developed using the I3 data marketplace in Los Angeles, USA [13]. Another active data marketplace is Terbine [1], which sells traffic and environment related data such as temperature, humidity, and air quality for multiple countries. Data from various sources, including financial and governmental organizations, are available on the Snowflake data marketplace [2]. QueXopa [11] is an emerging data marketplace in Latin America, providing data about the transportation industry and environment for application developers. These efforts show that the data marketplaces are starting to gain traction, and many application developers are leveraging such platforms to build data-driven applications.

Decentralized data marketplaces: The data marketplaces such as I3, Terbine, and SnowFlake are centralized marketplaces administered by a single organization. Such an operational model allows the administrator to control the operations and policies with little to no transparency. DDM [5], Ocean [14], and Streamr [15] are examples of decentralized data marketplaces, which leverage blockchain technology and smart contracts to involve multiple organizations in the administration process, enhancing trust and transparency. Figure 1 shows the elements of a decentralized data marketplace.

B. Ratings for Online Marketplaces

In its early days, Amazon hired review writers to create product reviews for books to provide a signal for buyers [16]. In this case, reviewers may not offer honest and negative thoughts since it may discourage buyers, impacting product sales. Such practices are harder to identify when the marketplace is administrated by a single organization, which sets the reviewing processes' policies.

Malbon [17] also present examples of sellers and marketers, leaving fake reviews in the online marketplace to increase sales. The majority of the marketplaces suffer from Sybil attacks, wherein a set of malicious individuals create multiple fake identities on the digital platform to leave fake reviews. In the literature, to mitigate such Sybil attacks, approaches based on social networks [18], [19] have been presented. Such techniques look at the social connections between identities to check for human-established trust in relationships. Unfortunately, these approaches do not entirely reduce the Sybil attacks, since some users may act honestly for sufficient duration to gain credibility on the platform and then use it to let malicious users enter the platform. These attackers are referred to as "traitors" since they turn against the platform after acting honestly for a sufficient period [20].

Some marketplaces provide more credibility to the ratings provided by the product purchasers. For example, the Amazon marketplace adds a label "verified purchaser" next to ratings added by people who bought it. Lately, malicious sellers have started creating accounts in the name of random people, shipped products to their address, and then added fake reviews on the marketplace [21]. This scam, a more sophisticated form of Sybil attack, is known as "brushing". Such incidents show that malicious sellers are willing to try various approaches to gain a reputation in the marketplace maliciously.

Rating the Raters: There is existing work on managing trust and reputation to check fraudulent and discriminatory ratings and inflated reviews in wiki-like collaborative information platforms, social networks, and centralized digital marketplaces to draw upon [22], [23], [24]. Some notable examples are game-theoretic analysis to find strategies in reputation-based systems [22], algorithms to filter out unfair ratings e.g., Bayesian methods [23] and simulations to find the proportion of good raters required by the algorithm to reduce the effects of inflated or malicious rating [24]. Such efforts highlight the importance of assessing the credibility of the raters.

C. Blockchain and Decentralized Systems

The blockchain technology introduced techniques to create decentralized systems involving multiple organizations. A new class of solutions [25], [26], [27], [28], [29], [30] involving Blockchain and distributed ledger technology, smart contracts, and incentive mechanisms are starting to address Sybil attacks and other trust issues in marketplaces. Siddarth *et al.* [25] discuss the pros and cons of Sybil-resistant mechanisms based on voting and consensus algorithms. Teutsch *et al.* [27] introduce TrueBit, a scalability solution for blockchain involving public nodes, where the execution of blockchain smart contracts are off-loaded onto "prover" nodes whose job is to execute the computation and return the result. However, the prover may cheat and produce incorrect computation results. To address this, [27] presents a verification mechanism involving a set of "verifier" nodes, whose job is to verify the computation's correctness using the proofs submitted by the prover nodes. There is a possibility that even the verifier may cheat by not checking the correctness. TrueBit incentivizes the verifier nodes by randomly injecting forced errors into the verification process to overcome this problem. The nodes that successfully verify and detect the forced error win a big reward (denoted as "jackpot" in [27]). Through this innovative incentive mechanism, TrueBit can ensure that the verifier nodes are correctly doing their job. This example shows that incentive-based schemes can enhance trust in online platforms.

The Token Curated Registry (TCR) is another crypto-economic mechanism that we have analyzed in prior work [30]. It allows the community members to curate lists or registries. For an item to be placed on a list, the owner of the item has to stake money prior to the curation process. The community members, who are also token holders then assess the item and accept or reject the item based on their collective knowledge. This approach allows application developers to create quality lists and the vetting process is carried out by the community members. Kosmarski *et al.* [29] have applied the idea of a token curated registry to academic review process, wherein the papers are reviewed by a selected set of reviewers from the review pool. Our proposed idea borrows concepts from TCR and the academic review process. However, as shown in prior work [30] TCR suffers from the problem of equilibrium selection – reviewers can either all vote to accept or reject good products – both are equilibria. We address this problem in this paper by proposing and analyzing a mechanism that guarantees a unique desirable equilibrium.

D. Shortcomings in the State of the Art Review Systems

A large body of literature addresses rating and reputation schemes for marketplaces that sell physical goods. Unfortunately, the rating and reputation schemes developed for marketplaces such as Amazon and e-Bay do not directly apply to data marketplaces since the items exchanged between sellers and buyers are no longer physical goods but intangible data. Moreover, the digital data quality is very subjective, and it largely depends on how the buyer is using the data to make business decisions in their use case. Existing data marketplaces such as I3 do not currently offer robust rating mechanisms to weed out malicious sellers and corrupt raters, and many of them involve central marketplace operators who can themselves censor or promote biased reviews.

Besides, the current rating and reputation systems allow the sellers to list products in the marketplace without any scrutiny. The products are rated mostly by the buyers after the products are listed on the marketplace. Such an approach may harm the marketplace's reputation since many malicious sellers may register bad quality products on the platform. The buyers who find or purchase such low-quality products would start to form negative opinions about the entire marketplace. Therefore, it is essential to filter in good quality products into the marketplace and increase the marketplace's reputation and utility. Considering this issue, we investigate a novel and decentralized rating scheme that scrutinizes the products at the time of registration and enables credible and trustworthy reviews to incentivize and support the listing of high quality products on the marketplace.

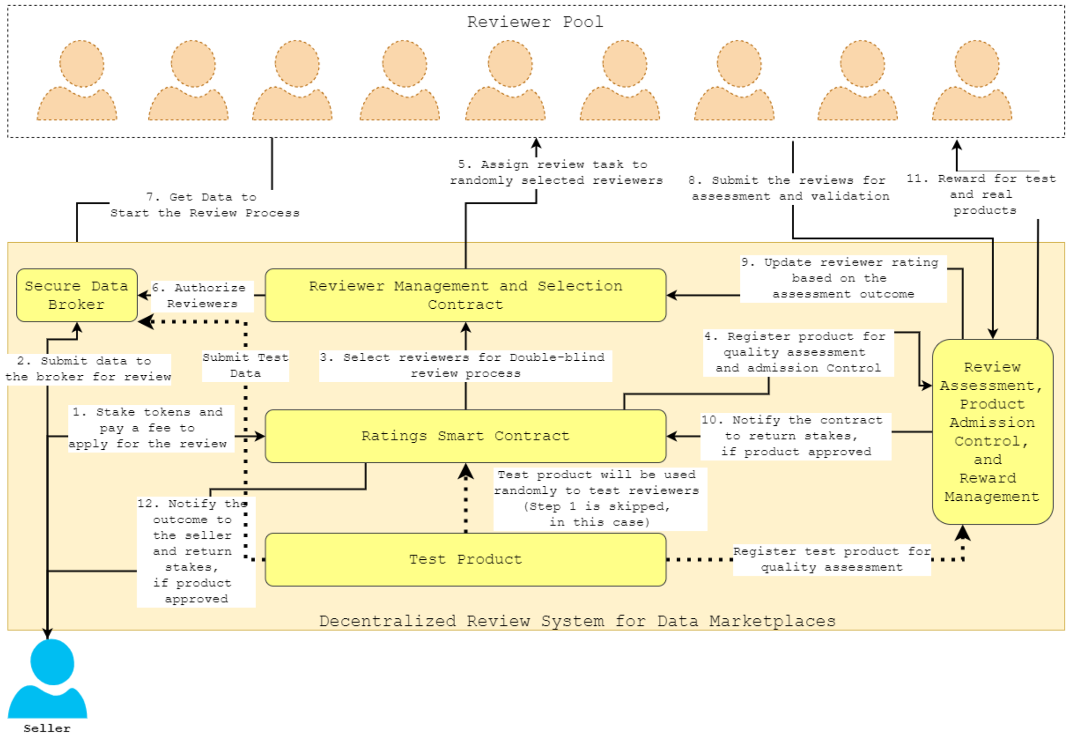


Fig. 2. A High-Level Overview of the Proposed Approach.

III. Proposed Mechanism

Consider a seller about to post a data product on the marketplace. The platform has a pool of reviewers who are registered in the system. There may be some á priori process of selecting reviewers, e.g. screening by a committee appointed by the governance body, which would improve the quality of reviews, but this is not required.

Figure 2 shows our proposed mechanism, which proceeds as follows:

- Seller must first apply for the product to be reviewed by providing a fee F and a stake amount S.
- K reviewers are selected in a double-blind and random manner (e.g. using a distributed random beacon).
- Reviewers are allocated a product to review with a given deadline and must provide a numerical rating for the product. For simplicity, we assume a binary (accept / reject) decision.
- If the majority of reviewers agree to accept, the product will be accepted; the fee will be retained but the stake will be returned to seller; a reward R will be given to reviewers who agreed to accept. The reviewers in the minority will not get anything.
- If the majority of reviewers agree to reject, the product will be rejected; the stake and fees will be retained. A reward R will be given to reviewers who agreed to reject. (The reward for each review is drawn from a pool that increases over time due to the combination of fees and stake collected from the applying sellers).
- To incentivize the reviewers to do a thorough review, occasionally, randomly, test products (for which the correct decision is known *a priori*) are injected to the system and are allocated for review. Reviewers that vote correctly with regards to the test product are given an incentive, W.

We next analyze the proposed mechanism from two perspectives. In section IV and section V, we first consider the decision made by reviewers – whether or not to perform reviews or simply guess a decision. We analyze this using game theory and identify conditions under which a desirable unique equilibrium is obtained. We then, in section VI analyze the decision made by sellers – whether or not to apply for review of a product depending on whether it is of high or low quality.

IV. Game Theoretic Analysis of Reviewer Strategy

A. Model Assumptions

We build a mathematical model to analyze whether reviewers will be honest in doing the work needed for the review process or simply "guess" whether a product should be accepted or not. For simplicity, we consider a simple binary rating in this model - each reviewer either recommends the product to be approved or recommends that it be rejected. The model proceeds as follows. We assume that each reviewer has probability p_Q of being able to review a given product correctly. A product under review is a test product (one for which the correct outcome is known *a priori*) with probability

	Guess	Review
Guess	$[\alpha = \frac{(1-p_T)R}{2} + \frac{p_T W}{2}, \quad \alpha]$	$[\alpha, \quad \beta = \frac{(1-p_T)R}{2} + p_T p_Q W + \frac{p_T(1-p_Q)W}{2} - p_L C]$
Review	$[\beta, \quad \alpha]$	$[\gamma = (1-p_T)(p_Q^2 R + p_Q(1-p_Q)R + \frac{(1-p_Q)^2 R}{2}) + p_T p_Q W + \frac{p_T(1-p_Q)W}{2} - p_L C, \gamma]$

TABLE I
PAYOFF MATRIX FOR REVIEWER GAME

p_T, and a regular product to be reviewed with probability $1 - p_T$. The reviewer is given a reward W if they review a test product correctly, and a reward R if they review a regular product correctly. If they guess, they expend no effort and thus incur no cost for doing the review. Reviewers are "lazy" with probability p_L and lazy reviewers incur a cost C if they do the review (or, to put it differently, in expectation, the cost of doing a review for any reviewer is the product $p_L C$).

TABLE II
NOTATION FOR PARAMETERS

		For Reviewer's Game (Section IV)
p_T	:	Probability that a test product is given to review
W	:	Reward for reviewing the test product correctly
R	:	Reward for a matching (majority) decision
p_L	:	Probability that reviewer is lazy
C	:	Cost of doing the review when lazy
p_Q	:	Probability that quality of review is high
		For Sellers Game (Section VI)
K	:	Number of reviewers
p_Q	:	Probability that quality of review is high
$P_{A,H}$	:	Probability of accepting a high quality product
$P_{R,L}$	:	Probability of rejecting a low quality product
M_H	:	Profit expected when a high quality product is posted on the marketplace
M_L	:	Profit expected when a low quality product is posted on the marketplace
F_{apply}	:	Application fee for getting a product reviewed
F_{stake}	:	Staking fee risked by the Seller
$U^{seller}_{\text{apply,H}}$	:	Seller's utility for a high quality product
$U^{seller}_{\text{apply,L}}$	:	Seller's utility for a low quality product

B. Game Payoffs

Under the above model, we illustrate the payoffs for a simple 2-reviewer system in table I. As can be seen, the terms in the payoff matrix can be summarized by the expressions denoted by variables α, β, and γ.

Desired Equilibrium: The necessary and sufficient condition under which (Review, Review) is the only Nash equilibrium is as follows:

$$\beta > \alpha \quad \text{and} \quad \gamma > \alpha \tag{1}$$

This is because with $\beta > \alpha$, a player would prefer reviewing to guessing even if the other player is guessing; and with $\gamma > \beta$ as well as $\gamma > \alpha$ neither player would deviate from reviewing if the other player is reviewing; equivalently if one player is guessing while the other is reviewing, they would prefer to switch to reviewing as well.

To gain some insight, we consider the case when both reviewers are always capable of doing correct reviews, i.e. $p_Q = 1$. In this case $\beta > \alpha$ is equivalent to:

$$W > \frac{2p_L C}{p_T} \tag{2}$$

And $\gamma > \beta > \alpha$ so long as:

$$R > 0 \tag{3}$$

Thus, so long as both conditions (2) and (3) hold, the Nash equilibrium strategy profile is for both players to do the work of reviewing (without guessing). The outcome may be somewhat surprising at first glance - it suggests that the incentive for reviewing, R, is less important for ensuring the honesty of reviewers than the introduction of tests (with probability p_T) and a high reward for reviewing those tests (W) correctly. Further, the reward W has to be sufficiently high compared to the effort incurred in reviewing i.e. $p_L C$ and inversely proportional to frequency with which test reviews are provided to the reviewers.

While we have presented the payoff matrix for just 2 players for ease of exposition, in fact, the above analysis is quite general and applicable to any number of reviewers. The sufficient conditions for ensuring honest reviews from all reviewers is the equilibrium that for any individual reviewer, they should get sufficient incentive from honestly reviewing the test products. Though we do not provide the full proof here due to space limitations, in fact, conditions (2) and (3) are necessary and sufficient for any number of reviewers to have a unique equilibrium as the outcome that they all behave honestly.

Undesirable Equilibrium We can also analyze the condition under which the game is guaranteed to have the unique undesirable equilibrium of both reviewers choosing to guess. This undesired equilibrium is obtained when the following inequalities hold:

$$\alpha > \beta \quad \text{and} \quad \alpha > \gamma \tag{4}$$

Assuming $p_Q = 1$, the condition in (4) is equivalent to the following:

$$\frac{p_T W}{2} + \frac{(1-p_T)R}{2} < p_L C \tag{5}$$

V. SIMULATION RESULTS

We present some numerical simulations to illustrate and validate the analysis in the previous section. We generate

100,000 random 2-reviewer games, with the following parameters being varied uniformly at random in each instance as described: C from 0 to 50, p_L from 0 to 1, $R = W$ varied from 0 to 100, and the following parameters are fixed in most of our experiments as follows: $p_Q = 1$, $p_T = 0.5$. These values were chosen to illustrate the combinations when the dominant unique Nash equilibrium strategy is to review. In one of the results we present, we also vary p_T from 0.1 to 0.4, showing that W needs to be chosen accordingly to ensure that reviewing remains the dominant unique Nash equilibrium strategy.

The software was written using the NashPy library in Python. The code and data used for the simulation is available at the following link: https://github.com/ANRGUSC/DecentralizedReviewSystem.

In Figure 3, we show the results from our experiments. These results show the fraction of cases when there was a single equilibrium with both players choosing to review, the cases of when there was single equilibrium with both players choosing to guess, and cases when there is no unique equilibrium. Each plot shows how these three cases vary as the corresponding parameters are varied. We can see in particular that:

1) The number of cases where the only equilibrium is for both players to review decreases with p_L and C. This is consistent with the fact that the condition (2) becomes harder to satisfy as these quantities increase.
2) The number of cases where the equilibrium is for both players to review increases with R and W. This is consistent with the fact that the condition (2) becomes easier to satisfy as these quantities increase.

The condition in (2) is also directly validated in Figure 4 (a) and 4 (c). If $p_T = 0.5$, the condition for the only equilibrium to correspond to both players reviewing honestly reduces to the following:

$$W > 4p_L C \tag{6}$$

And if $p_L \cdot C = 10$, then that condition reduces to

$$W > \frac{20}{p_T} \tag{7}$$

These are precisely the regions in which we observe the games having the desired unique equilibrium of review in Figure 4 (a) and 4 (c).

If we let $p_T = 0.5$ and set $R = W$, the condition in (5) reduces to the following, which is exactly the region shown in Figure 4 (b):

$$R = W < 2p_L C \tag{8}$$

VI. Analysis of Seller Strategy and Market Quality

From the analysis in the previous section we have learned that so long as there are sufficient incentives (in particular, so long as the product of frequency of tests and the reward for completing the test reviews correctly $p_T W$ is sufficiently high compared to the expected effort involved in doing the work of reviewing $p_L C$), the reviewers will have an incentive to always do a full review.

We assume that each reviewer that does a full review has an independent probability $p_Q > 0.5$ that their decision is correct (i.e. that they vote to accept a high quality product or to reject a low quality product with this probability p_Q). For a high-quality product (respectively, low-quality product), if the threshold for acceptance (rejection) is that more than 50% of K reviewers vote to accept (reject) it, then the probability it will be accepted (rejected) is given by the expression $1 - F_X(K/2)$, where X is a Binomial random variable with parameters (K, p_Q). Assume $p_Q >= 0.5$. A bound on the probability of accepting a high quality product $P_{A,H}$ can be given using the Chernoff bound (even tighter bounds are possible [31]):

$$\begin{aligned} P_{A,H} &> 1 - (2p_Q(1-p_Q))^K \\ \implies P_{A,H} &> 1 - \left(\frac{1}{2}\right)^K \end{aligned} \tag{9}$$

The same bound also holds for $P_{R,L}$, the probability of rejecting a low-quality product. We can see that the likelihood of making correct accept decisions for high-quality products and the probability of making correct reject decisions for low-quality products both rapidly approach 1, exponentially fast with the size of the review committee K. Specifically, a committee of size $K > \frac{log(\epsilon)}{log(0.5)}$ will ensure that correct decisions are made with probability at least $1 - \epsilon$. Concretely, this implies that just 4 reviewers could ensure more than 90% correct decisions, and $K = 7$ reviewers could ensure more than 99% correct decisions.

From a seller's perspective, consider their utility with respect to applying to post a high-quality or low-quality product. Let M_H be the units of profit a high quality product is expected to make if posted on the marketplace, and let M_L be the units of profit a low quality product is expected to make if posted on the marketplace. Let the application fee be F_{apply} and the staking fee is F_{stake}. The seller's utility in applying for review for the two types of products will be as follows:

$$U^{seller}_{apply,H} = P_{A,H} M_H - (1 - P_{A,H}) F_{stake} - F_{apply} \tag{10}$$
$$U^{seller}_{apply,L} = (1 - P_{R,L}) M_L - P_{R,L} F_{stake} - F_{apply} \tag{11}$$

The seller will apply for a product whenever its corresponding utility is positive. It is clear from the above expressions that the seller's utility for applying for a high quality product increases as $P_{A,H}$ increases and their utility for applying with a low-quality product likewise decreases as $P_{R,L}$ increases. Higher staking fees will particularly discourage posting low-quality products, though higher application fees would generally discourage posting any product that will not have significant expected profit.

VII. Discussion

The model of seller decisions in the previous section, in conjunction with our analysis of the reviewer decisions,

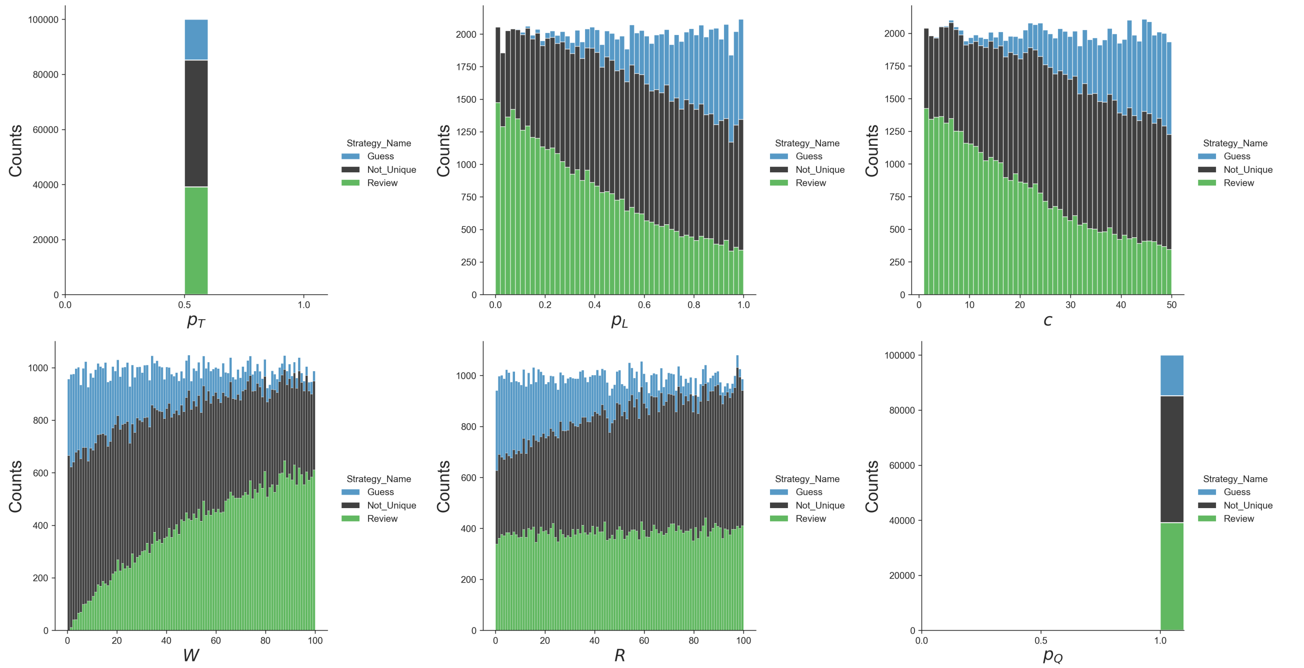
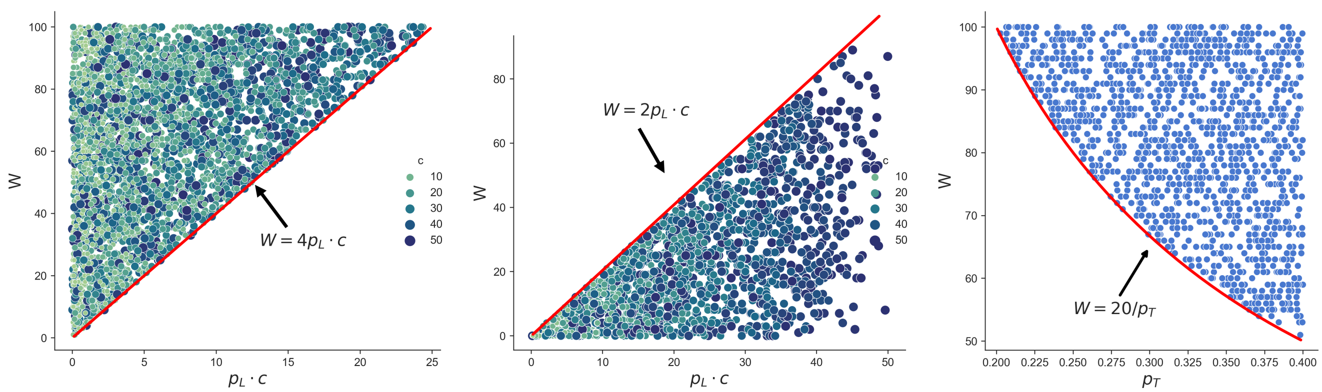


Fig. 3. Distribution of Strategies for Different Values of p_T (top-left), p_L (top-center), C (top-right), W (bottom-left), and R (bottom-center), and p_Q (bottom-right).



(a) (b) (c)

Fig. 4. Comparison of the Relationship between the Effort ($p_L \cdot c$) and the Reward for Review of Test Products (W) for Review Strategy in (a) and Guess Strategy in (b) with p_T fixed at 0.5. Variation between Probability of Test Product p_T and W for Review Strategy in (c) when p_T varies from 0.1 to 0.4 and $p_L \cdot c = 10$ is kept constant.

indicates that having carefully and sufficiently incentivized reviews has a cascading effect on the quality and reputation of the market. If sufficient numbers of reviewers are incentivized to put in the effort, the resulting increase in correct decisions causes sellers to self-select and be more likely to apply with higher quality products. A marketplace with more high quality products in turn will attract more customers resulting in a thriving ecosystem. At the same time, one must bear in mind that all of this is predicated on providing sufficient incentives, which in turn requires higher application fees. Such a review system will be best suited to high quality products with sufficient profit margins for the sellers to be able to afford the high application fees.

We note that our problem formulation is motivated by the need to ensure honesty in reviews in a decentralized system where the reviewers may not be personally known to or hired by a centralized organization. The use of a blockchain-based smart contract would provide an enforcement mechanism for the the payoffs indicated in the game-matrix that is credible because it is transparent and tamper-proof. The implementation of our system on a blockchain platform would also facilitate making the payments in an automated fashion using cryptocurrencies.

The following are some of the open questions that we believe merit further research:

- **Formation of Review Committee:** How to identify potential reviewers, especially when the platform is still new?
- **Selection of Reviewers:** Our proposed scheme relies on external reviewers for quality assessment. It is important to select the right number of reviewers since a small number of reviewers may reduce the safety of the marketplaces, while a large number of reviewers may lead to high cost of incentives. What is the optimal number?
- **Test generation:** Our proposed mechanism relies on the use of test reviews to incentive reviewers to do the work. Generating test reviews in a decentralized manner is an open problem.
- **Review Frequency:** When a product gets reviewed only once at the initial registration time, there is a possibility that the seller may provide quality data at the registration phase just to convince the reviewers. To ensure consistently high data quality, the review process has to be carried out frequently. How regularly or frequently should a streaming data product be reviewed?
- **Preserving confidentiality:** How to preserve confidentiality of the seller and rater to ensure true double blind review? Also, it is important that the reviewer not know if the product being reviewed is a test product or not. This will require keeping this information from being transparently visible to all on-chain participants. What cryptographic primitives would this need?
- **Scalability challenges:** When the marketplace becomes large with high number of data products, there may not be enough number of qualified reviewers to carry out the review process; a problem also faced by academic conferences that receive a large number of submissions. What is relationship between the number of products, number of reviewers, and the quality of the products? How can the review process be scaled to keep up with the growing marketplace?
- **Counterfeiting:** The problem of counterfeiting is more problematic for data products compared to physical goods because fake data is very low cost to generate. Will the review and rating mechanism we are proposing help combat the problem of dumping or flooding of the market with fake data products?
- **Penalty for Incorrect Reviews:** In this work we have focused on a reward-mechanism for correct reviews and analyzed it as a single shot game. It would be of interest to analyze repeated interactions involving the same reviewers as a repeated game setting and consider reputation mechanisms as well as penalties for incorrect reviews.
- **Malicious Users:** The game theoretic modeling here doesn't explicitly model a user whose payoff is outside the given values, such as a malicious reviewer who derives value from purposely injecting bad/incorrect reviews into the system. How can we protect the system from malicious users/reviewers?

What is presented in this paper is a general framework and theoretical analysis that is platform-agnostic. The model and simulations therefore do not depend on particular blockchain platform characteristics such as the underlying consensus mechanism for the platform itself, other than that it be tamper proof and support decentralized smart contracts. The implementation details and performance may differ from platform to platform, and will need to take into account the security needs of the system. For example, since the selection of test/real reviews must be kept hidden from the reviewers, this part will have to be implemented either off-chain or with some privacy mechanism.

As part of further work, it will be of interest to implement the system presented in this work as a smart contract and evaluate it empirically with real users.

VIII. Conclusions

Data marketplaces are being deployed to connect the data sellers with application developers. The success of such data marketplaces depends on the reputation and quality of the data products. We have presented a decentralized review system based on blockchain technology and smart contracts to increase sellers' and buyers' trust for such platforms. The game-theoretic analysis and the simulation of the proposed review mechanism show conditions under which a unique equilibrium strategy in our game encourages the reviewers to do an honest review to assess data product quality instead of guessing. We have also shown that the quality of the marketplace would increase when the reviewers are accurate and accept high-quality products into the marketplace, which, in turn, would encourage sellers to submit high-quality products. To the best of our knowledge, no prior works have proposed and analyzed a comprehensive incentive-based decentralized review system for such data marketplaces.

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