Eliciting Honest Information From Authors Using Sequential Review

July 11, 2023

Abstract

In the setting of conference peer review, the conference aims to accept high-quality papers and reject low-quality papers based on noisy review scores. A recent work proposes the isotonic mechanism, which can elicit the ranking of paper qualities from an author with multiple submissions to help improve the conference's decisions. However, the isotonic mechanism relies on the assumption that the author's utility is both an increasing and a convex function with respect to the review score, which might be violated in realistic settings (e.g. when authors aim to maximize the number of accepted papers). In this paper, we propose a sequential review mechanism that can elicit the ranking information from authors while only assuming the agent's utility is increasing with respect to the true quality of her accepted papers. The idea is to review the papers of an author in sequence based on the provided ranking and condition the review of the next paper on the review scores of the previous papers. Advantages of the sequential mechanism include: 1) eliciting truthful ranking information under a weaker assumption while achieving competitive conference utility as the isotonic mechanism; 2) reducing the reviewing workload and increasing the average quality of papers being reviewed; 3) incentivizing authors to write fewer papers of higher quality.

1 Introduction

Peer review, the process of evaluating scientific research by volunteered experts, undergirds the success of a conference by ensuring the accepted papers are of a high-quality. However, the reliability of peer review (especially for large computer science conferences) has raised significant concerns. In a NeurIPS experiment conducted in 2014, the review scores were found to be surprisingly noisy. Even worse, the rapid growth of the reviewing workload and the shortage of qualified reviewers, has posed unprecedented challenges to our review system [15]. While the number of papers grows as the community grows, so does the number of authors. Unfortunately, the number of papers is growing faster: between 2017 and 2020, the average number of papers published by the most prolific authors has doubled, indicating a growing trend of authors producing more papers in recent years [9].

This leads to the dilemma of conference peer review: the conference's objective of accepting only high-quality papers (from a large set of submissions) clashes with the shortage of reliable peer reviews upon which the conference must base its decisions. To mitigate this issue, we introduce a novel review mechanism called the *sequential mechanism* that can 1) solicit high-quality information from authors to assist the acceptance/rejection decisions, 2) reduce the reviewing workload and 3) incentivize authors to write high-quality papers.

The main challenge is how to elicit useful information from the authors who have conflicting interests with the conference. For instance, authors may sometimes prioritize having more publications, regardless of the quality of their work. In this case, although authors may possess the best signals of their own papers' quality compared with any reviewer, they may prefer not disclosing this information truthfully to the conference. For example, while being asked to report the true quality of their papers, authors may be inclined to inflate scores in order to increase the chance of acceptance.

Fortunately, positive results exist. Su [21] shows that it is possible to elicit truthful rankings of paper quality from an author with multiple submissions. The main idea of the proposed *isotonic mechanism* is to round the noisy review scores by running an isotonic regression based on the author's reported ranking. It is shown that reporting the ranking of papers truthfully is the best response for an author if her utility function is increasing and convex in terms of the review score. However, the assumption of convex utility might be strong in the setting of conference peer review. For example, suppose an author who aims to maximize the number of accepted papers has several borderline papers and one outstanding paper to submit. Under the isotonic mechanism, her best response is nonetheless to rank the outstanding paper at the bottom such that the review scores of all borderline papers will be shifted up after the isotonic regression, which can almost certainly lead to the acceptance of all papers.

To address this issue, we propose the sequential mechanism which can elicit the true ranking information as long as the author's utility of an accepted paper is, what we call, increasing. In particular, we assume the author's utility is additive in terms of the reward of all accepted papers and the reward is increasing in the quality of the paper. The sequential mechanism works by reviewing an author's submissions in sequence. In particular, papers with higher reported rankings are reviewed with priority, while papers with lower reported rankings will be conditionally reviewed depending on the review scores received by previous papers. If the review process terminates, e.g. due to a notably low review score of a paper, any remaining unreviewed papers will be rejected without further assessment. Intuitively, under the sequential mechanism, any misreporting of the true ranking of the papers will result in an earlier termination of the review process, which penalizes dishonest behaviors.[1]

We highlight two additional compelling properties of the sequential mechanism. First, it utilizes the self-selection of authors to prioritize the reviewing of high-quality papers. Therefore, not only can the reviewing workload be reduced, but also the average quality of the reviewed papers can be increased, both of which benefit the reviewers' utility. Second, the sequential mechanism decreases the marginal return of producing lower-quality papers. This is because the probability of a bottom-ranked paper being reviewed is exponentially discounted in terms of the number of papers. Thus, if the authors have a fixed budget of effort for paper writing, the sequential mechanism encourages them to write fewer but higher-quality papers. Both properties are particularly valuable in light of the explosion in the number of papers in recent years.

1.1 Our Results

Truthful sequential mechanisms. We first present a framework for designing sequential mechanisms and identify a sufficient constraint that ensures a sequential mechanism to be truthful (i.e. reporting the true ranking of the paper quality is the best response for authors with increasing utility functions). While not necessary, this constraint provides a large space of truthful sequential mechanisms. To show the effectiveness of our framework, we introduce two practical mechanisms as examples: the *memoryless coin-flip mechanism* that reviews the $k + 1$th ranked paper with a probability determined by the review score of the kth ranked paper; and the *credit pool mechanism*, which counts the cumulative review scores (positive or negative) of the reviewed papers and terminates the review process when the "credit pool" is empty.

Conference utility and review burden. We empirically evaluate the performance of a sequential mechanism using conference utility, which we define as the sum of the accepted papers' quality in expectation. We use the *parallel mechanism* as the baseline. The parallel mechanism reviews all papers unconditionally and independently, and is a special case of the sequential mechanism. We further use the isotonic mechanism with oracle access to the true ranking information as an unachievable upper bound.[2] Our simulations imply that even a simple threshold sequential mechanism (a special case of the memoryless coin-flip mechanism) can not only beat the baseline but also improve the conference utility by over 40% of the gap between the upper bound and the baseline.

Moreover, we empirically investigate the number of reviews that a sequential mechanism can save while achieving the same conference utility as the parallel mechanism. We show that, in reasonable parameter settings, the threshold sequential mechanism can reduce the review burden by up to 40%. This reduction is even greater when the author submits more papers and the quality of her papers is lower.

[1] One may be concerned that the sequential mechanism will result in a significant delay in the review process. However, note that the mechanism works exactly the same if all submissions are simultaneously reviewed or reviewed in batches, as long as the acceptance/rejection decisions are made in sequence.

[2] Note that the isotonic mechanism is not truthful in our setting where the utility function is not convex. Nonetheless, we additionally provide oracle access of the underlying true ranking to the isotonic mechanism and use it as a benchmark of an upper bound.

Endogenous paper quality. In the scenario where authors can choose the effort they exert on each of their papers, we show that compared with the parallel mechanism, the sequential mechanism always provides a stronger incentive for writing fewer papers of higher-quality. Specifically, we prove that the sequential mechanism exhibits a higher *marginal return of substitution* between a high-quality paper and a low-quality paper. This implies that under the sequential mechanism, authors are willing to giving up more lower-quality papers for writing a single higher-quality paper.

2 Related Works

Other than the isotonic mechanism [21], several attempts exist with the goal of improving the peer review system with the focus on dealing with strategic interactions between conferences and authors. In a setting where authors can strategically decide the venues to submit their papers, Zhang et al. [24] model the paper (re)submission process as a Stackelberg game between the author and the conference. They focus on how to design the review mechanism to achieve the Pareto optimal tradeoff between the conference quality and the review burden. In a recent work, Srinivasan and Morgenstern [20] propose the idea of using the VCG mechanism to elicit bids from authors and using peer prediction mechanisms to evaluate reviews and reward the reviewers (with virtual money). Thus, agents are motivated to provide high-quality reviews so as to raise enough funding to bid for reviewing slots. In dealing with the malicious bidding problem, a stream of literature focuses on designing and optimizing the paper-reviewer assignment mechanism [1, 10, 7, 23]. The goal here is to achieve strategyproofness such that the outcomes of any reviewer's own submissions are (approximately) independent of the reviews they provide for other submissions.

Our work is also related to the impartial peer selection problem, where self-interested agents assess one another in such a way that none of them has an incentive to misrepresent their evaluation. A notable application of this problem is the US National Science Foundation (NSF) experiment, each PI was asked to rank 7 proposals from other PIs Naghizadeh and Liu [13]. To incentivize careful reviews, the chance for a PI to be funded is tied to the quality of their reviews. The primary goal of the literature on the peer selection problem is to improve the accuracy of assessments while guaranteeing strategyproofness [13, 1, 6, 14]. However, these investigations differ from our problem in that our focus is on eliciting evaluations of multiple items held by a single agent directly from the agent itself, rather than relying on evaluations from other agents.

The above work is closely tied to analyze strategic interaction between conferences and authors, while there exists a considerable body of literature that aims to improve peer review more from the reviewer's perspective. This includes investigations into single versus double blind reviewing [3, 18, 2], assignment versus bidding [4, 12], review scale and miscalibration [17, 22, 19], and dishonest behaviors [5, 8, 11]. A recent survey by Shah [16] provides additional contexts and perspectives on the problems of peer review.

3 Model

Throughout the paper, we will use $[n]$ to denote the set $\{1, 2, \dots, n\}$ and use $[n]_0$ to denote $\{0, 1, \dots, n\}$. Suppose an author has n submissions indexed by $i \in [n]$, each with a quality of $q_i \in \mathbb{R}$. Suppose without loss of generality that $q_1 \geq q_2 \geq \cdots q_n$. We name each paper by its true ranking, e.g. paper 1 is the paper with the highest quality. We assume that the author knows the true qualities of all her papers.

The conference decides whether to accept or to reject each of the n submissions based on its review score. Given the true quality q_i, the paper's review score is observed by adding an error term, i.e. $r_i = q_i + \epsilon_i$, where ϵ_i are i.i.d. sampled from some distribution. The conference commits to an acceptance policy such that a paper with review score r (if it is reviewed) is accepted with probability $P_{\text{acc}}(r)$. For example, for a threshold acceptance policy, $P_{\text{acc}}(r) = 1$ if $r \geq \tau_{acc}$ and 0 otherwise. We assume the utility of the conference is the sum of the accepted papers' quality, i.e. $U_c(\mathcal{M}) = \sum_{i\in[n]} q_i \cdot \mathbb{1}[\text{paper } i \text{ is accepted under mechanism } \mathcal{M}]$.

In addition to soliciting review scores, the conference can solicit a ranking of the author's submissions. That is, the author reports a permutation π on the indexes $1, 2, \dots, n$ of her papers, where $\pi(i)$ is the rank of paper i after the permutation. The truthful report is the original ranking, i.e. $\pi^*(i) = i$. We assume the author's utility is the sum of the rewards of her accepted papers: each paper's reward is zero if rejected and $u_a(q_i)$ if accepted where u_a is a non-negative and increasing reward function. For example, if $u_a(q) = 1$ for any q, the author's goal is to maximize the expected number of accepted papers. The author can strategically report a ranking π so as to maximize its expected utility. We use $U_a(\pi)$ to denote the expected author utility under the permutation π, where the randomness is respect to the review noise.

The main question studied in this paper (Section 4) is how to design a *truthful* review mechanism such that reporting π^* is the author's best response, i.e. $U_a(\pi^*) \geq U_a(\pi)$ for any π. Then, in Section 5, we study how to (empirically) optimize the conference utility conditioned on truthfulness. Finally, in Section 6, we consider a variance of the general model by additionally considering that the author can choose the quality of the papers that she writes.

4 Truthful Sequential Mechanisms

This section focuses on a framework of designing truthful review mechanisms. In particular, we introduce the sequential mechanism framework and show a sufficient condition for a sequential mechanism to be truthful. We further provide two concrete and practical truthful sequential mechanisms under this framework as examples.

4.1 The Sequential Mechanism Framework

We first introduce the sequential mechanism. By its name, the mechanism reviews an author's papers in sequence based on the reported ranking of the papers' quality. That is, there are n rounds of review in total where the paper ranked in the ith place is reviewed in round i. A sequential mechanism $\mathcal{M}_s = (P_{\text{acc}}, P_{\text{rev}}, \boldsymbol{\mu})$ has three key components:

- An *acceptance policy* P_{acc} that maps from a review score to a probability of accepting the corresponding paper.
- A *review policy* P_{rev} that maps from a review state in round i to a probability of reviewing the paper in round $i+1$, for $i \in [n-1]_0$.
- A *state transition mapping* μ_i that maps from a review state in round i and the review score of the paper in round $i+1$ to a distribution of states in in round $i+1$, for $i \in [n-1]_0$.[3]

A key characteristic of the sequential mechanism is that if the mechanism decides not to review the paper in round i (due to a bad review state), any paper in round $j > i$ will be rejected without review. We then say that the mechanism terminates in round i. Note that by our definition, we assume the acceptance policy to be memoryless, where the acceptance of a paper only depends on its own review score. However, the review policy can have memory such that previous review scores may affect the distribution of the review state in round i which affects the probability of the paper in round $i+1$ being reviewed.

Now, we formally define the review states which are essential for guaranteeing the sequqntial mechanism to be truthful. In round i, we assume that the review state, denoted as $\phi_i \in \Phi_i$, is sufficient to determine the probability that the paper in round $i+1$ will be reviewed, where Φ_i is the space of review states in round i. Specially, Φ_0 is the space of initial states before the review of the first paper. The review states are weakly ordered such that the author always prefers to be in a higher-ordered state. That is, for each pair of states in round i, one of which must have a (weakly) higher order than the other, denoted as $\phi_i' \succeq \phi_i$ for every $\phi_i', \phi_i \in \Phi_i$ and every $i \in [n-1]_0$. We use $\phi_i' \succ \phi_i$ to represent the strict ordering. Furthermore, if the author is indifferent between two states, we say $\phi_i' \sim \phi_i$. For example, if $\hat{\phi}$ is a state indicating that the sequential mechanism has terminated, any other state will be at least weakly preferred over $\hat{\phi}$.

4.2 A Sufficient Condition For Truthfulness

Now, we investigate what properties of the acceptance policy, the review policy and the state transition mapping are sufficient for a sequential mechanism to be truthful. At a high level, we need both policies to be monotone which reward higher review scores and punishes lower review scores.

[3]Here, we assume $i < n$ because there is no need to discuss the review policy in round n.

Definition 1. *We say an acceptance policy is monotone if P_{acc} is (weakly) increasing, i.e. $P_{acc}(r') \geq P_{acc}(r)$ for any $r' \geq r$.*

Definition 2. *We say a review policy is monotone if $P_{rev}(\phi_i') \geq P_{rev}(\phi_i)$ for every $\phi_i' \succeq \phi_i$ and every round i.*

A monotone acceptance policy rewards a paper with a higher review score by accepting it with a higher probability; a monotone review policy rewards a higher-ordered review state with an increased probability of reviewing the paper in the next round. However, the requirements on the state transition mapping is a little more complicated. In particular, we utilize the concept of stochastic dominance.

Definition 3. *Let X and Y be two random variables of the review state $\phi \in \Phi$. We say X first-order stochastic dominates Y if $\Pr(X \succeq \phi) \geq \Pr(Y \succeq \phi)$ for any $\phi \in \Phi$.*

Definition 4. *We say the state transition mapping $\boldsymbol{\mu}$ is* monotone *if for any review round $i \in [n-1]_0$*

1. *it is monotone in state: for any state $\phi_i \in \Phi_i$, $\mu_i(\phi, r')$ first-order stochastic dominates $\mu_i(\phi, r)$ for any $r' \geq r$;*
2. *it is monotone in score: for any review score r, $\mu_i(\phi', r)$ first-order stochastic dominates $\mu_i(\phi, r)$ for any state $\phi' \succeq \phi$;*
3. *it is monotone of paper quality: for any state $\phi_i \in \Phi_i$ and review scores $r' \geq r$, $\mu_{i+1}(\mu_i(\phi_i, r'), r)$ first-order stochastic dominates $\mu_{i+1}(\mu_i(\phi_i, r), r')$.*

In words, a state transition mapping is monotone if it leads to a better distribution over states when 1) the review score is higher, and 2) the review state has a higher order, and 3) a higher review score is ranked earlier. Now, we are able to introduce our main result.

Theorem 4.1. *The sequential review mechanism $\mathcal{M}^s = (P_{acc}, P_{rev}, \boldsymbol{\mu})$ is truthful if P_{acc}, P_{rev} and $\boldsymbol{\mu}$ are monotone.*

Proof. Without loss of generality, suppose there exist no two papers that have identical quality. Consider an arbitrary ranking π that is untruthful, i.e. there exists at least one paper i such that $\pi(i) \neq i$. Suppose paper j and k are ranked in adjacent places under π where $\pi(j) = \pi(k) + 1$ but $j < k$. The existence of such two papers is guaranteed when π is untruthful. Then, consider a ranking π' which switches the ordering of paper j and k such that $\pi'(k) = \pi'(j) + 1 = \pi(j)$. We will show that the author always weakly prefers to report π' instead of π. Note that this is sufficient to guarantee truthfulness because the author always prefers to rank a higher-quality paper ahead if there exists any missequencing.

We apply the idea of coupling to show $\mathbb{E}[U_a(\pi')] \geq \mathbb{E}[U_a(\pi)]$, where the expectation is taken over the randomness of the review noise and the sequential review mechanism. First, we couple the realization of the review scores. Let ϵ_i and ϵ_i' be realization of the review noise in round i under π and π' respectively. Because all the review noise terms are i.i.d., we can couple the error terms such that $\epsilon_i = \epsilon_i'$ for any i. By this coupling, the review score that we observe in round $\pi(k)$ under permutation π is $r_{\pi(k)} = q_k + \epsilon_{\pi(k)}$, which is smaller than the review score in the same round under permutation π', $r'_{\pi(k)} = q_j + \epsilon'_{\pi(k)}$. Note that $q_j > q_k$. Similarly, the review score that we observe in round $\pi(j) = \pi(k) + 1$ is larger for π than π'. In words, if we look at the realizations of all the review scores, π' always puts a larger score in an earlier round than π while leaving a smaller review score in a later round.

Next, under this coupling of review noise, we will show that we can further couple the review states such that the author is always in a weakly better review state under π' than π. This completes the proof because in any realization of outcomes, reporting π' always results in 1) a weakly larger set of papers being reviewed, and a weakly larger set of papers being accepted (due to the monotonicity of the acceptance policy).

Now, we present this coupling of states. Let $\boldsymbol{r}$ and $\boldsymbol{r}'$ be the vector of review scores under π and π' respectively, where each entry is the review score for the paper in round i. By coupling, $r'_{\pi(k)} > r_{\pi(k)}$ and $r'_{\pi(j)} < r_{\pi(j)}$ where $\pi(j) = \pi(k) + 1$. Now, the state distribution under π' first order stochastic dominates the state distribution under π' in any round i due to the following reasons.

1. If $i < \pi(k)$, the above statement holds because the review scores are identical;

2. if $i = \pi(k)$, the above statement holds because $\boldsymbol{\mu}$ is monotone in score.
3. If $i = \pi(k) + 1$, the above statement holds because $\boldsymbol{\mu}$ is monotone of paper quality.
4. If $i > \pi(k) + 1$, the above statement holds because $\boldsymbol{\mu}$ is monotone in state.

Because the review state distribution under π' always first order stochastic dominates the state distribution under π', we can couple the realizations of states such that whenever the author is in state ϕ_i by reporting π, she will be in state $\phi_i' \succeq \phi_i$ in round i by reporting π'. This completes the proof.

□

The proof follows by coupling the realizations of the review noise. Then, due to the monotonicity of all three components of the sequential mechanism, flipping the true order of any two papers will result in a review state that is always dominated by truthful reporting.

4.3 The memoryless Coin-Flip Mechanism

Here, we provide a concrete example of how to use our framework to design a truthful sequential review mechanism. In this example, the acceptance of a paper in round i will guarantee the review of the paper in the next round; while if a paper is rejected, the mechanism will review the paper in round $i+1$ with some probability determined by the review score. We call this mechanism the *memoryless coin-flip mechanism.*

To map this mechanism into the sequential mechanism framework, we first define the review states. Consider $\phi_i = (\alpha, \gamma) \in \{0,1\}^2$ for any round $i > 0$, where the first entry indicates whether the paper has been accepted (with 1 being accepted and 0 being rejected), and the second entry indicates whether a (biased) coin flip has an outcome of heads (with 1 being heads and 0 being tails). If at least one of α and γ is 1, the next paper will be reviewed; otherwise the review process terminates. Note that the distribution of the review state in round i only depends on the review score of that round, which implies that the review policy is "memoryless". Furthermore, we assume the mechanism always reviews the first paper, i.e. $\phi_0 = (1, \gamma)$. In this example, the ordering of the review states are $(1,1) \sim (1,0) \sim (0,1) \succ (0,0)$.

Now, fixing an acceptance policy P_{acc}, we design the review policy P_{rev}^{cf} and the state transition mapping μ_i^{cf} for each round i as follows.

$$P_{\text{rev}}^{cf}((\alpha,\gamma)) = \begin{cases} 0 & \text{if } \alpha = \gamma = 0, \\ 1 & \text{otherwise.} \end{cases}$$

$$\mu_i^{cf}((\alpha_i,\gamma_i), r_{i+1}) = \begin{cases} (1, \gamma_{i+1}) & \text{with probability } P_{\text{acc}}(r_{i+1}), \\ (0,1) & \text{with probability } (1 - P_{\text{acc}}(r_{i+1})) \cdot \rho(r_{i+1}), \\ (0,0) & \text{with probability } (1 - P_{\text{acc}}(r_{i+1})) \cdot (1 - \rho(r_{i+1})), \end{cases}$$

where $\rho : \mathbb{R} \to [0,1]$ maps from a review score to a probability of reviewing the next paper. Specially, if the review process has terminated in round i, we define the state in the next round to be $(0,0)$ with a probability of 1. Note that if $\rho(r) = 1$ for any review score r, the memoryless coin-flip mechanism reduces to the parallel mechanism. Because the transition mapping does not depend on the index of round, we thus omit the subscript of μ while discussing the memoryless coin-flip mechanism.

Now, we show that the memoryless coin-flip mechanism is truthful by mapping it to the sufficient conditions of truthfulness as shown in Theorem 4.1.

Theorem 4.2. *The memoryless coin-flip mechanism $(P_{acc}, P_{rev}^{cf}, \boldsymbol{\mu}^{cf})$ is truthful if P_{acc} and ρ are increasing.*

Proof. By Theorem 4.1, it is sufficient to show that if P_{acc} and ρ are increasing, P_{rev}^{cf} and $\boldsymbol{\mu}^{cf}$ are monotone. It is easy to see that P_{rev}^{cf} is monotone based on the construction. Specifically, $P_{\text{rev}}^{cf}((\alpha,\gamma)) = 1 > P_{\text{rev}}^{cf}((0,0)) = 0$ for any (α,γ) such that at least one of the entries is 1.

Next, we show that $\boldsymbol{\mu}^{cf}$ is monotone. This includes three steps. First, to show that $\boldsymbol{\mu}^{cf}$ is monotone in state, fix a review score r and consider any pair of states $(\alpha',\gamma') \succeq (\alpha,\gamma)$ where $\alpha, \alpha', \gamma, \gamma' \in \{0,1\}$. If $(\alpha,\gamma) = (0,0)$, then $\mu((\alpha,\gamma), r) = (0,0)$ with a probability of 1, which is always (weakly) dominated by $\mu((\alpha',\gamma'), r)$. If $(\alpha,\gamma) \neq (0,0)$, it is straightforward to show that $\mu((\alpha',\gamma'), r) = \mu((\alpha,\gamma), r)$ because the review process is memoryless. This, again, implies weakly first-order stochastic dominance.

Second, to show that $\boldsymbol{\mu}^{cf}$ is monotone in score, consider any review state (α_i, γ_i) and any pair of review scores $r' \geq r$. Note that if $(\alpha_i, \gamma_i) = (0, 0)$, the review state in round $i + 1$ will be $(0, 0)$ for sure and the statement trivially holds. For any $(\alpha_i, \gamma_i) \neq (0, 0)$, we want to show that $\mu^{cf}((\alpha_i, \gamma_i), r')$ first-order stochastic dominates $\mu^{cf}((\alpha_i, \gamma_i), r)$. Because $(0, 0)$ is the only state that has a lower order than any other state, it is sufficient to show that $\mu^{cf}((0, 0)|(\alpha_i, \gamma_i), r') \leq \mu^{cf}((0, 0)|(\alpha_i, \gamma_i), r)$. This holds because if ρ and P_{acc} are increasing, $\mu^{cf}((0, 0)|(\alpha_i, \gamma_i), r') = (1 - P_{\text{acc}}(r'))(1 - \rho(r')) \leq (1 - P_{\text{acc}}(r))((1 - \rho(r)) = \mu^{cf}((0, 0)|(\alpha_i, \gamma_i), r)$.

Finally, we show that $\boldsymbol{\mu}^{cf}$ is monotone of paper quality. Consider any review state $(\alpha, \gamma) \neq (0, 0)$ and any pair of review scores $r' \geq r$. Again, it is sufficient to show that $\mu^{cf}((0, 0)|\mu^{cf}((\alpha, \gamma), r'), r) \leq \mu^{cf}((0, 0)|\mu^{cf}((\alpha, \gamma), r), r')$. Let $A(r) = (1 - P_{\text{acc}}(r))(1 - \rho(r))$ be the probability of termination in the round where the paper has a review score r. The above statement holds because

$$\begin{aligned}
\mu^{cf}((0, 0)|\mu^{cf}((\alpha, \gamma), r'), r) &= A(r') + (1 - A(r'))A(r) \\
&= A(r') + A(r) - A(r')A(r) \\
&= A(r) + (1 - A(r))A(r') \\
&= \mu^{cf}((0, 0)|\mu^{cf}((\alpha, \gamma), r), r').
\end{aligned}$$

Therefore, the state distribution after flipping the ordering of two adjacent review scores remains the same under the momeryless coin-flip mechanism, which completes the proof. □

4.4 The Credit Pool Mechanism

Another example of the sequential reviewing framework implements the idea of a reputation system. The main idea is that conditioned on a good submission history, e.g. an authors' first i papers are all accepted with high review scores, we can have a higher tolerance over some rejections of the authors' papers. More formally, suppose the conference keeps record of a credit pool denoted by B, which is initialized at B_0. For every reviewed paper, the mechanism will increase (or decrease) the credit pool by a credit score determined by the review of that paper. Let $\beta : \mathbb{R} \to \mathbb{R}$ be a credit function which maps from a review score to a review credit added to the credit pool. Note that β can be negative which indicates a punishment of papers with low review scores. The next paper will be reviewed if and only if the credit pool is non-negative. This idea is summarized in 1. Note that $\pi^{-1}(i)$ is the index of the paper that is ranked in the ith place under the permutation π.

MECHANISM 1: The credit pool mechanism.

Input: The review scores of n papers $\boldsymbol{r}$, the author's ranking of n papers π, the acceptance policy P_{acc}, the initial credit B_0 and the credit function β.

Output: The acceptance decision of each of the n papers $\boldsymbol{\alpha}$.

```
Initialize the credit pool as B = B_0 and i = 1;
while B ≥ 0 do
    Flip a biased coin with a probability of heads equal to P_acc(r_{π^{-1}(i)}), and the outcome is γ_i (with
      1 being heads and 0 being tails);
    if γ_i = 1 then
        α_{π(i)} = 1;
    else
        α_{π(i)} = 0;
    end
    B += β(r_{π^{-1}(i)});
    i += 1;
end
α_{π(j)} = 0 for j ∈ {i + 1, ..., n}.
```

Speaking in the language of the sequential mechanism framework, we first define the review state as the credit in the pool, i.e. $\phi_i = B_i$ for round i. Then, the ordering of the states is $\bar{B}' \succeq \bar{B} \succ \hat{B}' \sim \hat{B}$ for any

$\bar{B}' \geq \bar{B} \geq 0 > \hat{B}' \geq \hat{B}$. We define the review policy as

$$P^{cp}_{\text{rev}}(B) = \begin{cases} 0 & \text{if } B < 0, \\ 1 & \text{otherwise.} \end{cases}$$

Furthermore, the state transition mapping $\boldsymbol{\mu}^{cp}$ is deterministic such that conditioned on $B_i \geq 0$,

$$\mu_i^{cp}(B_i, r_{i+1}) = B_i + \beta(r_{r+i}) \qquad \text{with a probability of 1.}$$

If $B_i < 0$, we simply let $B_{i+1} = B_i$. Again, we can omit the subscript i since μ^{cp} does not depend on the review round. The following theorem indicates the sufficient conditions for a credit pool mechanism to be truthful.

Theorem 4.3. *The credit pool mechanism $(P_{acc}, P^{cf}_{rev}, \boldsymbol{\mu}^{cf})$ is truthful if P_{acc} and β are increasing.*

Proof. By Theorem 4.1, it is sufficient to show that if P_{acc} and β are increasing, P^{cp}_{rev} and $\boldsymbol{\mu}^{cp}$ are monotone. Under the definition of the ordering of states, it is clear that the review policy is monotone. Because for any $B' \geq B$, it follows that whenever $P^{cp}_{\text{rev}}(B) = 1$, $P^{cp}_{\text{rev}}(B') = 1$.

Now, we show that the transition probability mapping is monotone. First, to show that $\boldsymbol{\mu}^{cp}$ is monotone in state, fix a review score r. Then, a better review state in round i indicates a better review state in round $i+1$ because 1) if $B'_i \geq B_i \geq 0$, we have $B'_{i+1} = B'_i + \beta(r) \geq B_i + \beta(r) = B_{i+1}$; 2) if $B_i < 0$, it follows that $B'_{i+1} \succeq B_{i+1} = B_i$ for any B'_{i+1}.

Second, $\boldsymbol{\mu}^{cp}$ is monotone in score because for any $r' \geq r$, $B'_{i+1} = B_i + \beta(r') \geq B_i + \beta(r) = B_{i+1}$ for any $B_i \geq 0$. Furthermore, if $B_i < 0$, $B'_{i+1} = B_{i+1}$. In both cases, a better review score leads to a weakly preferred state.

Finally, it is also straightforward to show that $\boldsymbol{\mu}^{cp}$ is monotone of paper quality. Consider any state B and any pair of review scores $r' \geq r$. For any state $\mu(\mu(B, r), r') \geq 0$ (note that the state transition mapping is deterministic), it must be the case that $\mu(\mu(B, r'), r) = \mu(\mu(B, r), r') = B + \beta(r') + \beta(r)$. For any state $\mu(\mu(B, r), r') < 0$, then any state is weakly preferred than $\mu(\mu(B, r), r')$. This completes the proof.

□

Intuitively, the credit pool mechanism is truthful because a higher-quality paper has both a larger acceptance probability and a larger chance of increasing the review credit. Therefore, any untruthful permutation will, more likely, result in an earlier termination of the review process which always leads to a smaller utility in expectation.

4.5 Non-truthful Examples

We further provide a discussion on several heuristic mechanisms that are not truthful, which serves as a cautionary exploration of the correct application of our tools.

Review multiple papers at a time. A plausible generalization of the sequential mechanism is to review more than one papers at a time. That is, the author is required to divide her papers into several bundles and provide an order of bundles. For example, an author with four papers can be asked to report two papers as the (equally) best papers and two as the (equally) bottom papers. Then, the mechanism will review the papers in the next bundle if and only if certain conditions are satisfied based on the review scores of the papers in the previous bundle (e.g., the acceptance of at least one paper). In practice, this method is particularly useful when papers are evaluated across multiple dimensions, such as writing quality, novelty, and influence, where a strict ordering between any two papers may not be feasible.

However, such an idea is not truthful in general. It is important to review one paper at a time. Consider a simple example where the mechanism reviews two papers at a time and will review the next two papers if and only if at least one of the two papers is accepted. Suppose an author has six papers to submit where two of them are outstanding and basically guaranteed acceptance, while the remaining four papers are of borderline quality. Now, the author has the incentive to put one of the two outstanding papers in the third place and rank one borderline paper in the second place. This strategy almost certainly ensures that all six papers can be reviewed. However, if the author report the true ranking, if it likely that only the top four papers will be reviewed, while the bottom two papers are rejected without being reviewed.

The limited credit pool mechanism We present a non-truthful variant of the credit pool mechanism, specifically designed to mitigate the problem of unnecessarily reviewing a surplus of low-quality papers by an author. This variant introduces a credit pool with a limited size, whereby the growth of the pool is halted once the accumulated credit reaches a predefined threshold. When the threshold is reached, even if subsequent papers receive high review scores, they will no longer contribute more credit to the pool.

However, the limited credit pool mechanism is not truthful, because authors are better-off to have their high-quality papers reviewed only when the credit pool is not full. For example, suppose an author has a lot of borderline papers with negative quality and two outstanding papers that are basically guaranteed acceptance and any one of them can fill the credit pool. Now, compared with truth-telling, the author is better-off to rank one outstanding paper in the first place followed by one or two borderline papers and then the other outstanding paper. This untruthful ranking ensures that the author secures more reviews for her borderline papers than the truthful ranking.

5 Evaluating The Sequential Mechanism

The previous section identifies a space of truthful mechanisms, while this section focuses on empirically evaluating the performance of the sequential mechanism. We use the conference utility — the sum of the accepted papers' quality normalized by the total number of submitted papers — to measure the performance of a mechanism. For both computational and practical considerations, we focus on the simply threshold sequential mechanism, a special case of the memoryless coin-flip mechanism discussed in Section 4.3. In comparison, we use the parallel mechanism as a baseline and the isotonic mechanism with the underlying ranking information as an unreachable upper bound[4].

For robustness, we conduct experiments on both a simply model with Gaussian review noise, and a more complicated real-data estimated model where each paper has multiple integer-valued review scores. Through Monte-Carlo simulations, we observe that the sequential mechanism can achieve conference utility that is competitive even compared to the upper bound and always outperforms the baseline. Furthermore, in real-data estimated model, we show that the sequential mechanism can save more than 20% review burden compared with the baseline conditioned on the same or better conference utility.

5.1 Mechanisms of Comparison

Here, we introduce how we implement and optimize the sequential mechanism, the parallel mechanism and the isotonic mechanism in our experiments. For all three types of mechanisms, we focus on the threshold acceptance policy, i.e. a paper is accepted if and only if its (modified) review score is no less than a threshold. We note that due to the monotonicity of our model (a higher review score always induces a higher expected quality of the paper), the threshold acceptance policy is optimal if the same policy is applied independently for each paper.[5] To be a little more formal, if the conference is restricted to use the same acceptance policy P_{acc} for every paper (e.g. for fairness considerations), the threshold acceptance policy maximizes the conference utility.

The threshold sequential mechanism. We restrict our attention to a special case of the sequential mechanism. Specifically, the threshold sequential mechanism is a memoryless coin-flip mechanism with P_{acc} and ρ being threshold functions: $P_{\text{acc}}(r) = 1$ if $r \geq \tau^s_{acc}$ and 0 otherwise; $\rho(r) = 1$ if $r \geq \tau^s_{rev}$ and 0 otherwise. Furthermore, $\tau^s_{rev} \leq \tau^s_{acc}$. In words, the threshold sequential mechanism accepts a paper, conditioned on it being reviewed, if its review score is larger than a threshold τ^s_{acc}; and it reviews the next paper if the review score is larger than a lower threshold τ^s_{rev}. We study the threshold sequential mechanism mainly because of its simplicity, making it easy to optimize and implement in practice.

[4]The istonic mechanism cannot truthfully elicit the ranking information in our setting where the utility is not a convex of the review score.

[5]As a natural set of acceptance policies, more discussions about the threshold acceptance policy exist. For example, the threshold policy is also shown to be optimal (under some constraints) in a setting where authors are choose where to submit their papers [24].

The threshold parallel mechanism. We consider the parallel mechanism as a baseline for comparison. Under a parallel mechanism, all papers are guaranteed to be independently reviewed. The parallel mechanism operates without soliciting the ranking information from authors. The threshold parallel mechanism is characterized by the acceptance threshold τ^p_{acc} where papers are accepted if and only if their review scores are no less than τ^p_{acc}. Note that the threshold parallel mechanism is a special case of the threshold sequential mechanism by setting $\tau^s_{rev} = -\infty$.

The threshold isotonic mechanism with true ranking information. In general, the isotonic mechanism cannot truthfully elicit the ranking information from authors in our setting where the author's utility is not convex with respect to the review score. However, we assume the author still reports the ranking of their papers' quality truthfully and use the isotonic mechanism with this information as the upper bound. In particular, given the vector $\boldsymbol{r}$ where each entry r_i is the review score of the paper ranked in the ith place (note that $q_i \geq q_j$ for any $i \leq j$), the conference will modify the review score by solving the isotonic regression: $\min_{\boldsymbol{r}'} ||\boldsymbol{r}' - \boldsymbol{r}||_2$ s.t. $r'_i \geq r'_j$ for any $i \leq j$. Then, a threshold acceptance policy is applied on the modified review scores such that the paper with score r' is accepted if and only if $r' \geq \tau^i_{acc}$.

To emphasize the importance of truthfulness, note that in the absence of truthful ranking information, the isotonic mechanism can experience a performance that is even worse than the baseline. For example, suppose an author submits many borderline papers of negative quality and one paper of extremely high quality. The author can strategically rank the outstanding paper at the bottom so that all of her papers can be accepted. Consequently, even the parallel mechanism is a better choice for the conference.

5.2 Gaussian Review Noise

We first introduce a simple but intuitive model where where each paper has one review score that is a noisy observation of the true quality of the paper with additive Gaussian review noise. The biggest advantage of this model is that it is computationally convenient to scale, which allows us to efficiently investigate the impact of different model parameters on the mechanisms' performance.

5.2.1 Model and Experiment Setup

Suppose the conference has a Gaussian prior of the quality of the author's papers. In particular, the author draws n i.i.d. samples from the Gaussian distribution $\mathcal{N}(\mu_q, \sigma_q)$ as the qualities of her papers. Then, the conference observes the true ranking of the quality of the papers. Let $\boldsymbol{q}$ be the ordered vector of paper qualities such that $q_i \geq q_j$ for any $1 \leq i \leq j \leq n$. Next, the conference draws an i.i.d. review noise term from a zero-mean Gaussian distribution $\epsilon_i \sim \mathcal{N}(0, \sigma_r)$ for each $i \in [n]$. Finally, the conference observes one review score for each paper, $r_i = q_i + \epsilon_i$. Note that the parameters $(n, \mu_q, \sigma_q, \sigma_r)$ defines a *Gaussian review setting* φ^G.

Given a setting φ^G and a mechanism $\mathcal{M}$ (which is determined by the threshold(s)), we use the Monte-Carlo method to estimate the expected conference utility. In particular, we draw $10,000$ samples of $\boldsymbol{q}$ where each $\boldsymbol{q}$ is obtained by first drawing n i.i.d. samples from $\mathcal{N}(\mu_q, \sigma_q)$ and then reordering based on the qualities from high to low. For each sample of qualities, we are able to analytically compute the expected probability that each paper is accepted (and thus the expected conference utility) for the threshold sequential mechanism and the threshold parallel mechanism:

- For the threshold parallel mechanism, Pr(paper i is accepted) $= 1 - G_{\sigma_r}(\tau^p_{acc} - r_i)$, where G_{σ_r} is the c.d.f. of the zero-mean Gaussian distribution with standard deviation σ_r.
- For the threshold sequential mechanism, Pr(paper i is accepted) $= \prod_{j=1}^{i-1} (1 - G_{\sigma_r}(\tau^s_{rev} - r_j)) \cdot (1 - G_{\sigma_r}(\tau^s_{acc} - r_i))$.

For the isotonic mechanism, due to the non-linear isotonic regression, we don't have a closed-form expected conference utility as shown above. Thus, we first draw 100 review noise terms $\boldsymbol{\epsilon}$ and numerically estimate the conference utility by taking the average. Finally, for all implemented mechanisms, the estimated conference utility is the average over $10,000$ samples of $\boldsymbol{q}$.

For each Gaussian setting, we further optimize the threshold(s) of the three types of mechanisms using stochastic gradient decent. Again, the gradient function can be estimated using a Monte-Carlo method.

5.2.2 Results

Conference utility. We first see how different parameters affect the conference utility achieved by the sequential mechanism. Let U_c^p, U_c^s and U_c^i be the expected conference utility under the parallel mechanism, sequential mechanism and the isotonic mechanism with the optimized thresholds, respectively. We are interested in the relative conference utility of the sequential mechanism, $\hat{U}_c^s = \frac{U_c^s - U_c^p}{U_c^i - U_c^p}$. That is, the conference utility of the sequential mechanism while normalizing the baseline to 0 and the upper bound to 1. As shown in 1, the sequential mechanism exhibits a significant improvement over the baseline, with at least a 40% improvement towards the upper bound across a broad range of parameter settings. Furthermore, we observe that the sequential mechanism is particularly more effective in the following three cases.

1. Papers have lower qualities. In this case, due to the review noise, reviewing more papers will increase the probability of accepting more low-quality papers and thus harms the conference quality. Therefore, the sequential mechanism that rejects lower-quality papers without reviewing becomes more beneficial compared with the parallel mechanism.

2. The author has more papers. Intuitively, as the number of papers increases, more low-quality papers that are mistakenly accepted by the parallel mechanism are rejected by the sequential mechanism, which enlarges the gap.

3. Reviews are noisier. In this case, the sequential mechanism benefits the conference utility by utilizing the author's ranking information. At a high-level, the noisier the reviews are, the more the conference's decisions rely on the author's ranking information which the parallel mechanism does not utilize.

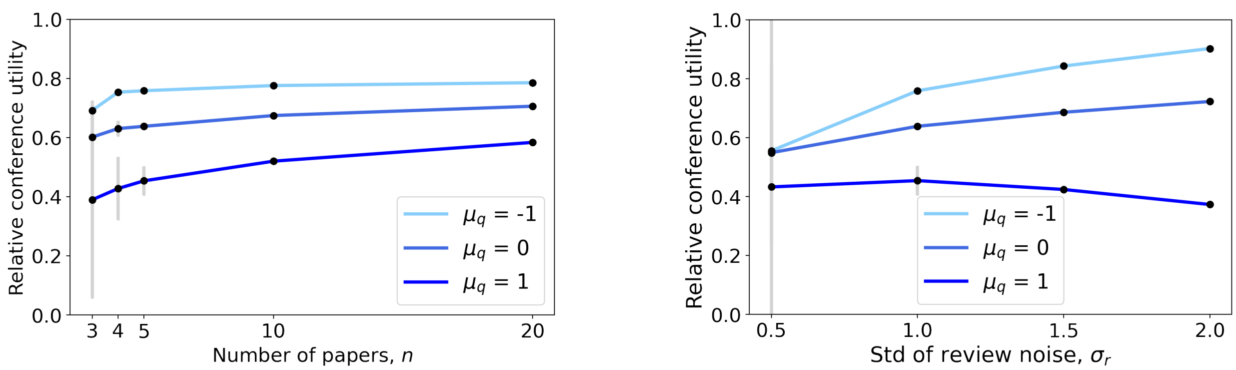


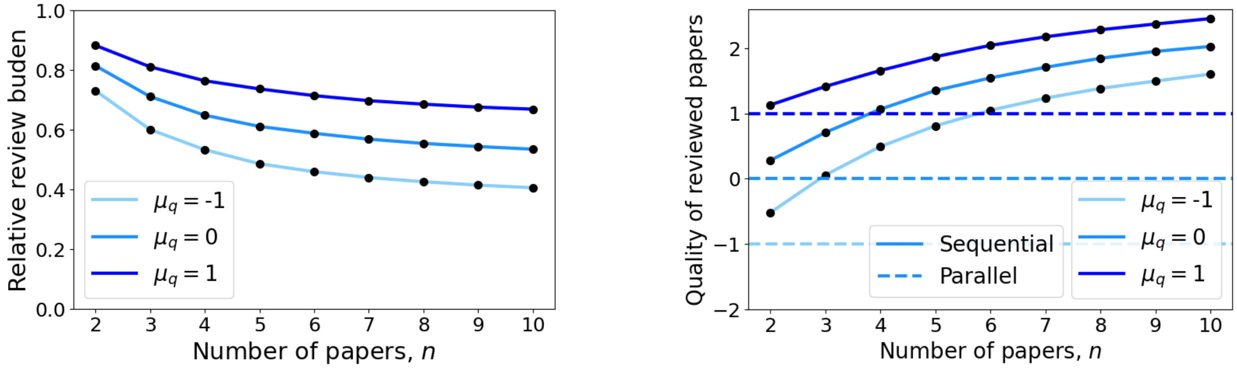
Figure 1: The relative conference utility under different parameter settings. Unless otherwise specified, the default parameter setting is $\varphi^G = (n = 5, \mu_q = -1, \sigma_q = 2, \sigma_r = 1)$. Note that the error bars are particularly large for small n, large μ_q and small σ_r because in these cases the difference between the performances of three mechanisms is small.

Review burden. Here, we study how many reviews can be saved using a sequential mechanism. Meanwhile, we study how much improvement can be made in the average quality of the reviewed paper as the review burden decreases.

Suppose an author has n papers for review, we define the *review burden* of a mechanism as the expected number of papers that are reviewed. The review burden of a parallel mechanism is thus $B^p = n$, while the review burden of a sequential mechanism B^s is weakly smaller than n depending on the thresholds. We are interested in the relative review burden $\hat{B}^s = \frac{B^s}{B^p}$ conditioned on achieving the same conference utility. By definition, $0 < \hat{B}^s \leq 1$ and a smaller relative review burden implies that the sequential mechanism can save more reviews compared with the parallel mechanism without harming the conference utility.

Figure 2 (a) shows the effectiveness of the sequential mechanism in reducing the review burden while Fig. 2 (b) presents the ability of the sequential mechanism in improving the average quality of the reviewed papers. Specifically, we find that the sequential mechanism is relatively more effective when 1) the author is more likely to write low-quality papers (indicated by smaller μ_q), 2) the author has more papers (indicated by larger n) and 3) reviews are noisier (indicated by larger σ_r).[6] The intuition is line with our discussions on the conference utility. Notably, even when the author has only two papers, the sequential mechanism can still reduce the review burden by 10-30% depending on the prior.

The reduction in the review burden and improvement in the quality of reviewed papers may potentially improve the review quality, creating a virtuous circle that ultimately benefits the conference more.



(a) Relative review burden v.s. n.

(b) Average quality of the reviewed paper v.s. n.

Figure 2: The relative conference utility and the relative review burden under different parameter settings. Unless otherwise specified, the default parameter setting is $\varphi^G = (n = 5, \mu_q = -1, \sigma_q = 2, \sigma_r = 1)$.

5.3 Softmax Review Noise With Real Data

The real review data has two features that are not carefully captured by the previously discussed Gaussian noise model. First, the review scores are integers, not real values. Second, each paper has multiple independent review scores, not just one score. To incorporate these differences, we focus on fitting the real data with a slightly more complicated model where review noise is modeled by a softmax function.

5.3.1 Model and Experiment Setup

Suppose authors are ex-ante homogeneous, where each author has the same paper quality distribution which is Gaussian, i.e. $\mathcal{N}(\mu_q, \sigma_q)$. That is, the author, no matter how many papers she has, will draw n_i i.i.d. samples from this distribution. The distribution of the number of papers an author has is denoted as $\pi_n(n_i) : \mathbb{N}_+ \to [0, 1]$. Then, conditioned on the quality q of a paper, the conference draws k i.i.d. review scores from softmax distribution. Formally,

$$\Pr(r = s|q) = \frac{e^{-t_r \cdot (s-q)^2}}{\sum_{s' \in \mathcal{S}} e^{-t_r \cdot (s'-q)^2}},$$

where t_r is the temperature parameter which models the noisiness of the reviews, and $\mathcal{S}$ is a finite set of integers that is the set of all possible review scores. The parameters $(\pi_n, k, \mu_q, \sigma_q, t_r)$ defines a *softmax review setting*.

The Monte-Carlo estimation process of this softmax review model is essentially the same as the Gaussian review model. The key difference lies in the thresholds of the review mechanism. Instead of setting thresholds on the review scores directly, the thresholds are set in the posterior world. In particular, conditioned on k i.i.d. review scores of a paper and the prior of paper quality, the conference can compute an expected quality of the paper. Then, a paper will be accepted (or the review process will continue) if and only if the expected quality surpasses the acceptance (review) threshold. Because of this complexity, we will not include the discussions of the isotonic mechanism, where a reasonably accurate estimate of the performance can be computationally difficult.

[6]Figures that investigating the review noise are deferred to appendix due to space limitation.

We use real review datasets to fit the model. Details are shown as follows.

- To learn π_n, we first assign every paper to one of its authors. We do this by selecting the author with the most papers. In particular, the following procedure is iterated until all papers are assigned: 1) from the set of papers that haven't been assigned with an author, find the author with the most papers; 2) assign those papers to that author; 3) remove the papers and the corresponding authors from the set. This gives us a one-to-one mapping between authors and papers, and π_n is set to be the empirical distribution of the number of papers each author has.
- While the prevailing choice is soliciting four reviews per paper, we set $k = 3$ (the second common choice) due to computational considerations.
- We use average review scores as the true qualities of papers so that μ_q and σ_q can be straightforwardly estimated.
- Finally, t_r can learned using an MAP method.

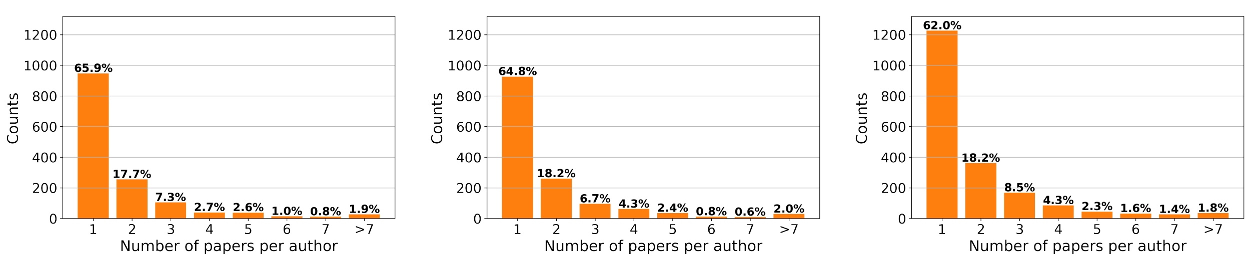
5.3.2 Datasets

We use the public ICLR openreview datasets from 2021 to 2023. The datasets are reasonably large and include both the accepted and the rejected papers, which are suitable to fit our model. Some key features of the datasets and the learned parameters are summarized in Table 1, where desk-rejected papers are excluded.

Year	# of papers	# of papers per author	μ_q	σ_q	t_r
2021	2595	1.806	5.511	1.009	0.513
2022	2612	1.834	5.519	1.286	0.363
2023	3812	1.926	5.468	1.295	0.342

Table 1: Key features and learned model parameters of the recent ICLR datasets.

Perhaps not surprisingly, both the total number of submitted papers and the average number of papers per author (where papers with coauthors are attributed to the author with the highest paper count) have been steadily increasing over the years. This trend indicates a rise in researchers entering the field and an inclination for authors to produce an larger number of papers. Figure 3 presents the empirical distribution of the number of papers per author for each year. Notably, the fraction of authors with only one submission decreases over year and the fraction of authors with more than 5 papers significantly increases in the year of 2023.



(a) 2021 (b) 2022 (c) 2023

Figure 3: Empirical distributions of the number of papers each author has for ICLR 2021-2023. Papers with multiple authors are attributed to the author with the largest number of papers.

5.3.3 Results

Figure 4 illustrates the relative review burden (as defined in Section 5.2.2) of the sequential mechanism. Recall that the smaller the relative review burden is, the more reviews burden can be saved by implementing the sequential mechanism, while ensuring an equivalent conference utility to that of the parallel mechanism. Our results indicate that over 20% of review burden can be saved under this real-data estimated model. The relative review burden decreases from 2021 to 2023 as more and more authors have more than one papers which enlarges the effect of the sequential mechanism.

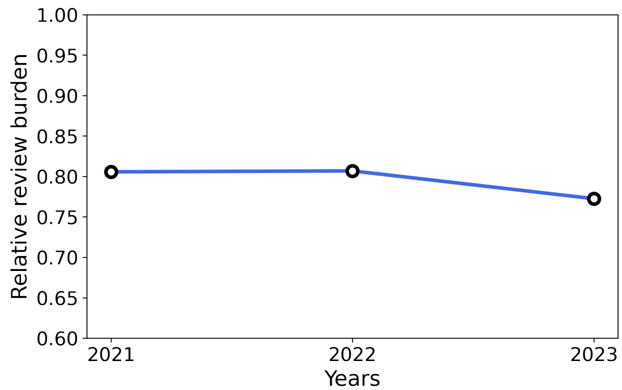


Figure 4: Relative review burden of the threshold sequential mechanism for ICLR 2021-2023.

6 Endogenous Paper Quality

This section considers the setting where authors have the choice of the quality of papers they write. Papers of higher quality have higher probabilities to be accepted and bring higher rewards to the author if accepted. However, producing a high-quality paper usually requires greater effort and time from the author. The question of interest is: can we incentivize authors to exert more effort on improving the quality of a smaller set of papers instead of producing more papers but each with a lower quality?

We examine the power of sequential mechanism in addressing this problem. Using an economic concept called the *marginal rate of substitution* (MRS), we show that authors always have a stronger willing to write more high-quality papers and less low-quality papers under the sequential mechanism compared with the parallel mechanism.

6.1 Binary Effort

As a toy example, we first consider a binary effort setting. Suppose the author can either exert a high effort to write a high-quality paper with an acceptance probability p_h or exert a low effort to write a lower-quality paper with an acceptance probability $p_l < p_h$. Furthermore, the acceptance of a low quality paper gives the author a reward u_l while the acceptance of a high quality paper brings a reward $u_h \geq u_l$. Let $U_a^{\mathcal{M}}(n_h, n_l)$ be the expected reward of writing n_h high-quality papers and n_l low-quality papers under the true ranking π^* and mechanism $\mathcal{M}$. We first introduce a key concept in this section.

Definition 5. *Given a review mechanism, the marginal rate of substitution between a high-quality paper and a low-quality paper ($MRS_{h,l}$) is defined as the ratio between the expected reward gain of writing one more high-quality paper and the expected reward gain of writing one more low-quality paper. Mathematically,* $MRS_{h,l}(n_h, n_l) = \frac{U_a(n_h+1,n_l)-U_a(n_h,n_l)}{U_a(n_h,n_l+1)-U_a(n_h,n_l)}$ *where U_a is the expected reward of the author.*

$MRS_{h,l}$ measures the number of low-quality papers that an author is willing to give up for an additional high-quality paper. A higher MRS implies that an additional high-quality paper values more than an additional low-quality paper under the corresponding mechanism. In this section, we focus on the simplest sequential mechanism, called the *naive sequential mechanism*, which reviews the paper in round $k+1$ if and only if the paper in round k is accepted. The following lemma this the key to prove our main result.

Lemma 6.1. *The naive sequential review mechanism has a weakly higher $MRS_{h,l}$ than the parallel review mechanism, i.e. $MRS^s_{h,l} \geq MRS^p_{h,l} > 1$ for any $n_h, n_l \in \mathbb{N}_0$. Moreover, the statement is strict if $n_l \geq 1$.*

Proof. We first write down the expected utility and derive the MRS of the parallel review mechanism.

$$U_a^p(n_h, n_l) = u_h \sum_{k \in [n_h]} k \cdot \binom{n_h}{k} p_h^k (1-p_h)^{n_h-k} + u_l \sum_{k \in [n_l]} k \cdot \binom{n_l}{k} p_l^k (1-p_l)^{n_l-k}.$$

Because under the parallel mechanism, every paper is independently reviewed, the utility gain of generating one more paper it exactly equal to the expected utility of having that paper reviewed, i.e. the product of acceptance probability and the reward of acceptance. Therefore,

$$MRS^p(n_h, n_l) = \frac{U_a^p(n_h+1, n_l) - U_a^p(n_h, n_l)}{U_a^p(n_h, n_l+1) - U_a^p(n_h, n_l)} = \frac{p_h u_h}{p_l u_l} > 1.$$

For the standard sequential mechanism, note that the author will always rank high-quality papers before low-quality papers under π^*. Therefore,

$$U_a^s(n_h, n_l) = u_h \sum_{k_h \in [n_h]} p_h^{k_h} + u_l \cdot p_h^{n_h} \sum_{k_l \in [n_l]} p_l^{k_l}$$

The marginal return of writing a high-quality paper and a low-quality, respectively, can be written as

$$U_a^s(n_h+1, n_l) - U_a^s(n_h, n_l) = p_h^{n_h} u_h - p_h^{n_h}(1-p_h) u_l \sum_{k_l \in [n_l]} p_l^{k_l} = p_h^{n_h}\left(p_h u_h - \frac{1-p_h}{1-p_l} p_l (1-p_l^{n_l}) u_l\right) \quad (1)$$

$$U_a^s(n_h, n_l+1) - U_a^s(n_h, n_l) = p_h^{n_h} p_l^{n_l+1} u_l. \quad (2)$$

Therefore,

$$\begin{aligned} MRS^s(n_h, n_l) &= \frac{p_h u_h - \frac{1-p_h}{1-p_l} p_l (1-p_l^{n_l}) u_l}{p_l^{n_l+1} u_l} \\ &= \frac{p_h u_h}{p_l u_l} \cdot \frac{1 - \frac{(1-p_h)p_l}{(1-p_l)p_h} \cdot \frac{u_l}{u_h} \cdot (1-p_l^{n_l})}{p_l^{n_l}} \\ &= MRS^p(n_h, n_l) \cdot \frac{1 - \frac{(1-p_h)p_l}{(1-p_l)p_h} \frac{u_l}{u_h} \cdot (1-p_l^{n_l})}{p_l^{n_l}} := MRS^p(n_h, n_l) \cdot \eta(n_l). \end{aligned}$$

We want to show $\eta(n_l) \geq 1$ for any $n_l \geq 0$. First note that because $0 \leq p_l < p_h \leq 1$, $\frac{(1-p_h)p_l}{(1-p_l)p_h} < 1$. Furthermore, by assumption, $\frac{u_l}{u_h} \leq 1$. Therefore, $\eta(n_l) \geq \frac{1-(1-p_l^{n_l})}{p_l^{n_l}} = 1$, and the inequality is strict when $n_l \geq 1$. This completes the proof. $\square$

Lemma 6.1 suggests that no matter how many high-quality papers and low-quality papers the author has, the benefit of writing one more high-quality paper compared with writing one more low-quality paper is always larger under the standard sequential mechanism. We further note that this intuition can be straightforwardly generalized to any truthful sequential mechanism as long as the probability of reviewing the next paper is higher for a high-quality paper than a low-quality paper.

Now, we show that a higher $MRS_{h,l}$ implies a stronger preference of writing more high-quality papers over low-quality papers.

Proposition 6.2. *For any $n_h, n_l, n'_h, n'_l \in \mathbb{N}_0$ such that $n'_h > n_h$ and $n'_l > n_l$, if $U_a^p(n'_h, n_l) \geq U_a^p(n_h, n'_l)$, $U_a^s(n'_h, n_l) \geq U_a^s(n_h, n'_l)$.*

Proof. The proof follows by rewriting the expected reward $U_a^p(n'_h, n_l)$ using $U_a^p(n_h, n_l)$ and $U_a^p(n_h+1, n_l)$, and rewriting $U_a^p(n_h, n'_l)$ using $U_a^p(n_h, n_l)$ and $U_a^p(n_h, n_l+1)$. First note that for the parallel mechanism, the marginal reward of writing one paper depends only on the quality of that paper. In particular, $U_a^p(\hat{n}+1, n_l) - U_a^p(\hat{n}, n_l) = p_h u_h$ for any $\hat{n}, n_l$. This property allows us to rewrite the reward

$$\begin{aligned} U_a^p(n'_h, n_l) &= U_a^p(n'_h, n_l) - U_a^p(n'_h - 1, n_l) + \cdots + U_a^p(n_h+1, n_l) - U_a^p(n_h, n_l) + U_a^p(n_h, n_l) \\ &= (n'_h - n_h) \cdot (U_a^p(n_h+1, n_l) - U_a^p(n_h, n_l)) + U_a^p(n_h, n_l). \end{aligned}$$

Similarly, we have

$$U_a^p(n_h, n_l') = (n_l' - n_l) \cdot (U_a^p(n_h, n_l + 1) - U_a^p(n_h, n_l)) + U_a^p(n_h, n_l).$$

Therefore, the author's preference $U_a^p(n_h', n_l) \geq U_a^p(n_h, n_l')$ implies that

$$\begin{aligned}
& U_a^p(n_h', n_l) - U_a^p(n_h, n_l') \geq 0 \\
\Leftrightarrow \quad & (n_h' - n_h) \cdot (U_a^p(n_h + 1, n_l) - U_a^p(n_h, n_l)) - (n_l' - n_l) \cdot (U_a^p(n_h, n_l + 1) - U_a^p(n_h, n_l)) \geq 0 \\
\Leftrightarrow \quad & MRS_{h,l}^p(n_h, n_l) \geq \frac{n_l' - n_l}{n_h' - n_h} \qquad (3)
\end{aligned}$$

Next, we focus on the sequential mechanism.

$$U_a^s(n_h', n_l) = U_a^s(n_h', n_l) - U_a^s(n_h' - 1, n_l) + \cdots + U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l) + U_a^s(n_h, n_l)$$

To relate the marginal utilities, let $U_a^s(n_h + k, n_l) - U_a^s(n_h + k - 1, n_l) = \lambda_h(k)(U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l))$ for any $k \geq 1$. Intuitively, $\lambda_h(k) > 0$ for any k.

$$U_a^s(n_h', n_l) = (1 + \lambda_h(2) + \cdots + \lambda_h(n_h' - n_h)) \cdot (U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l)) + U_a^s(n_h, n_l).$$

Similarly, let $U_a^s(n_h, n_l + k) - U_a^s(n_h, n_l + k - 1) = \lambda_l(k)(U_a^s(n_h, n_l + 1) - U_a^s(n_h, n_l))$. We have

$$U_a^s(n_h, n_l') = (1 + \lambda_l(2) + \cdots + \lambda_l(n_l' - n_l)) \cdot (U_a^s(n_h, n_l + 1) - U_a^s(n_h, n_l)) + U_a^s(n_h, n_l).$$

Given Eq. (3), we want to show

$$\begin{aligned}
& U_a^s(n_h', n_l) - U_a^s(n_h, n_l') \geq 0 \\
\Leftrightarrow \quad & \sum_{k=1}^{n_h' - n_h} \lambda_h(k) \cdot (U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l)) - \sum_{k=1}^{n_l' - n_l} \lambda_l(k) \cdot (U_a^s(n_h, n_l + 1) - U_a^s(n_h, n_l)) \geq 0 \\
\Leftrightarrow \quad & MRS_{h,l}^s(n_h, n_l) \geq \frac{\sum_{k=1}^{n_l' - n_l} \lambda_l(k)}{\sum_{k=1}^{n_h' - n_h} \lambda_h(k)}. \qquad (4)
\end{aligned}$$

The following two lemmas are important for the proof.

Lemma 6.3. *For $i \in \{h, l\}$, $\lambda_i(1) = 1$ and $0 < \lambda_i(k + 1) \leq \lambda_i(k)$ for any $k \geq 1$.*

Lemma 6.4. *$\lambda_h(k) \geq \lambda_l(k)$ for any $k \geq 1$.*

We defer the proof of the above two lemmas while focusing on finishing the proof of Proposition 6.2. First note that Eq. (4) trivially holds when $n_h' - n_h \geq n_l' - n_l$. This is because by Lemma 6.1, the left-hand-side of Eq. (4) is greater than 1, while by Lemma 6.4, the right-hand-side of Eq. (4) is smaller than 1. Therefore, we focus on the case where $n_h' - n_h < n_l' - n_l$.

By Lemma 6.1 and Eq. (3), in order to prove Eq. (4), it is sufficient to show that

$$\begin{aligned}
& \frac{n_l' - n_l}{n_h' - n_h} \geq \frac{\sum_{k=1}^{n_l' - n_l} \lambda_l(k)}{\sum_{k=1}^{n_h' - n_h} \lambda_h(k)} \\
\Leftrightarrow \quad & \frac{\sum_{k=1}^{n_h' - n_h} \lambda_h(k)}{n_h' - n_h} \geq \frac{\sum_{k=1}^{n_l' - n_l} \lambda_l(k)}{n_l' - n_l}. \qquad (5)
\end{aligned}$$

This is straightforward because

$$\begin{aligned}
\frac{\sum_{k=1}^{n_h' - n_h} \lambda_h(k)}{n_h' - n_h} & \geq \frac{\sum_{k=1}^{n_h' - n_h} \lambda_l(k)}{n_h' - n_h} && \text{(by Lemma 6.4)} \\
& \geq \frac{\sum_{k=1}^{n_l' - n_l} \lambda_l(k)}{n_l' - n_l}. && \text{(because } n_h' - n_h < n_l' - n_l \text{ and by Lemma 6.3)}
\end{aligned}$$

This completes the proof. □

Proof of Lemma 6.3. We want to show that $\lambda_i(k)$ is decreasing in k.

$$\begin{aligned}\lambda_h(k) &= \frac{U_a^s(n_h+k, n_l) - U_a^s(n_h+k-1, n_l)}{U_a^s(n_h+1, n_l) - U_a^s(n_h, n_l)} \\ &= \frac{p_h^{n_h+k-1}\left(p_h u_h - \frac{1-p_h}{1-p_l} p_l (1-p_l^{n_l}) u_l\right)}{p_h^{n_h}\left(p_h u_h - \frac{1-p_h}{1-p_l} p_l (1-p_l^{n_l}) u_l\right)} && \text{(by Eq. (1))} \\ &= p_h^{k-1}. && (6)\end{aligned}$$

Similarly, by Eq. (2), $\lambda_l(k) = p_l^{k-1}$. Therefore, both $\lambda_h(k)$ and $\lambda_l(k)$ are decreasing in k and $\lambda_h(1) = \lambda_l(1) = 1$. □

Proof of Lemma 6.4. Note that $\lambda_h(k) = p_h^{k-1}$ and $\lambda_l(k) = p_l^{k-1}$. The lemma straightforwardly follows because $p_h > p_l$. □

In words, Proposition 6.2 shows that whenever the author wants to write $k_h = n'_h - n_h$ more high-quality papers compared with writing $k_l = n'_l - n_l$ more low-quality papers under the parallel mechanism, she is always willing to do so under the sequential mechanism. Furthermore, based on the proof, it is easy to see that the condition is not necessary. That is, there exist some cases where the author wants to write k_l more low-quality papers rather than writing k_h more high-quality papers under the parallel mechanism, but she is willing to choose writing more high-quality papers under the sequential mechanism.

6.2 Finite Effort

The intuitions and results from the binary effort setting can be straightforwardly generalized to a finite effort setting. Now, suppose the author has m distinct effort levels to choose from. Suppose without loss of generality that these choices of effort result in m distinct acceptance probabilities such that $p_1 > p_2 > \cdots > p_m$. Let $U_a(\boldsymbol{n})$ be the expected reward of writing n_i papers with acceptance probability p_i for every $i \in [m]$ where $\boldsymbol{n} = (n_1, n_2, \ldots, n_m)$. We first generalize the definition of the marginal rate of substitution.

Definition 6. *Given a review mechanism, the marginal rate of substitution (MRS) between a paper with acceptance probability p_i and a paper with acceptance probability p_j in the finite setting is defined as $MRS_{i,j}(\boldsymbol{n}) = \frac{U_a(\boldsymbol{n}') - U_a(\boldsymbol{n})}{U_a(\boldsymbol{n}'') - U_a(\boldsymbol{n})}$ where $\boldsymbol{n}' = (n_1, \ldots, n_{i-1}, n_i + 1, \ldots, n_m)$ and $\boldsymbol{n}'' = (n_1, \ldots, n_{j-1}, n_j + 1, \ldots, n_m)$.*

Intuitively, $MSR_{i,j}$ is the ratio between the gain of reward of writing one more paper with acceptance probability p_i and the gain of reward of writing one more paper with acceptance probability p_j. Again, a higher $MSR_{i,j}$ implies that the author is willing to give up more papers with acceptance probability p_j to write one more paper with probability p_i. The following lemma generalizes Lemma 6.1 to the finite effort setting. The proof is left in Appendix A.

Lemma 6.5. *The standard sequential review mechanism has a weakly higher $MRS_{i,j}(\boldsymbol{n})$ than the parallel review mechanism for any $\boldsymbol{n} \in \mathbb{N}_0^{|\boldsymbol{n}|}$ and $i < j$. Moreover, the statement is strict if $\sum_{k=i+1}^m n_k > 0$.*

With the help of Lemma 6.5, we generalize the main result, i.e. Proposition 6.2, from the binary effort setting to the finite effort setting.

Proposition 6.6. *For any $1 \le i < j \le m$, let $n_i, n_j, n'_i, n'_j \in \mathbb{N}_0$ such that $n'_i > n_i$ and $n'_j > n_j$. Then, if $U_a^p(n'_i, n_j) \ge U_a^p(n_i, n'_j)$, $U_a^s(n'_i, n_j) \ge U_a^s(n_i, n'_j)$.*

To proof the above proposition, it is sufficient to generalize Lemma 6.3 and 6.4 to the finite effort setting. The details of these generalizations are provided in Appendix A.

7 Conclusion, Limitations and Future Work

In the setting of peer review, we study the problem of how to elicit honest information from authors, who themselves belong to the party of interests in this game between the conference and authors. Our main contribution is a framework of designing mechanisms that can elicit the quality ranking from an author with multiple submissions. Compared with the previous isotonic mechanism, the proposed sequential mechanism requires a weaker assumption on author's utility function. We further investigate the advantages of our mechanism from the aspects of reducing reviewing workload, improving the average quality of the reviewed papers, and incentivizing authors to focus more on the quality of papers rather than the quantity.

We believe that the design of truthful mechanisms beyond the convex utility assumption is an important step before the implementation of the idea of eliciting author information. However, more work should be done. First, one challenge lies in eliciting honest information and aggregating it when multiple authors collaborate on the same set of papers. Second, can we generalize our results to settings where authors can only observe noisy signals about the true quality of their papers, and what if the noise (of both the authors and the reviewers) are correlated with paper qualities? Finally, while we primarily focus on assuming there is a single review score, an open question remains in optimally aggregating review scores from heterogeneous reviewers, while guaranteeing the truthfulness of the review mechanism.

References

[1] Haris Aziz, Omer Lev, Nicholas Mattei, Jeffrey S Rosenschein, and Toby Walsh. Strategyproof peer selection using randomization, partitioning, and apportionment. *Artificial Intelligence*, 275:295–309, 2019.

[2] Tony Bazi. Peer review: single-blind, double-blind, or all the way-blind? *International Urogynecology Journal*, 31(3):481–483, 2020.

[3] Rebecca M Blank. The effects of double-blind versus single-blind reviewing: Experimental evidence from the american economic review. *The American Economic Review*, pages 1041–1067, 1991.

[4] Guillaume Cabanac and Thomas Preuss. Capitalizing on order effects in the bids of peer-reviewed conferences to secure reviews by expert referees. *Journal of the American Society for Information Science and Technology*, 64(2):405–415, 2013. doi: https://doi.org/10.1002/asi.22747. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/asi.22747`.

[5] Adam Cohen, Smita Pattanaik, Praveen Kumar, Robert R Bies, Anthonius De Boer, Albert Ferro, Annette Gilchrist, Geoffrey K Isbister, Sarah Ross, and Andrew J Webb. Organised crime against the academic peer review system. *British Journal of Clinical Pharmacology*, 81(6):1012, 2016.

[6] Geoffroy De Clippel, Herve Moulin, and Nicolaus Tideman. Impartial division of a dollar. *Journal of Economic Theory*, 139(1):176–191, 2008.

[7] Komal Dhull, Steven Jecmen, Pravesh Kothari, and Nihar B Shah. Strategyproofing peer assessment via partitioning: The price in terms of evaluators' expertise. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 10, pages 53–63, 2022.

[8] Daniele Fanelli. How many scientists fabricate and falsify research? a systematic review and meta-analysis of survey data. *PloS one*, 4(5):e5738, 2009.

[9] Sergei Ivanov. Neurips 2020. comprehensive analysis of authors, organizations, and countries., Oct 2020. URL `https://medium.com/criteo-engineering/neurips-2020-comprehensive-analysis-of-authors-organizations-and-countries-a1b55a08132e`.

[10] Steven Jecmen, Hanrui Zhang, Ryan Liu, Nihar Shah, Vincent Conitzer, and Fei Fang. Mitigating manipulation in peer review via randomized reviewer assignments. *Advances in Neural Information Processing Systems*, 33:12533–12545, 2020.

[11] Michael L Littman. Collusion rings threaten the integrity of computer science research. *Communications of the ACM*, 64(6):43–44, 2021.

[12] Reshef Meir, Jérôme Lang, Julien Lesca, Nicholas Mattei, and Natan Kaminsky. A market-inspired bidding scheme for peer review paper assignment. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 4776–4784, 2021.

[13] Parinaz Naghizadeh and Mingyan Liu. Incentives, quality, and risks: A look into the nsf proposal review pilot, 2013.

[14] Parinaz Naghizadeh and Mingyan Liu. Perceptions and truth: A mechanism design approach to crowd-sourcing reputation. *IEEE/ACM Transactions on Networking*, 24(1):163–176, 2016. doi: 10.1109/TNET.2014.2359767.

[15] D Sculley, Jasper Snoek, and Alex Wiltschko. Avoiding a tragedy of the commons in the peer review process, 2018.

[16] Nihar B Shah. Challenges, experiments, and computational solutions in peer review. *Communications of the ACM*, 65(6):76–87, 2022.

[17] S S Siegelman. Assassins and zealots: variations in peer review. special report. *Radiology*, 178(3): 637–642, 1991. doi: 10.1148/radiology.178.3.1994394. URL `https://doi.org/10.1148/radiology.178.3.1994394`. PMID: 1994394.

[18] Richard Snodgrass. Single-versus double-blind reviewing: An analysis of the literature. *ACM Sigmod Record*, 35(3):8–21, 2006.

[19] Arnaldo Spalvieri, Silvio Mandelli, Maurizio Magarini, and Giuseppe Bianchi. Weighting peer reviewers. In *2014 Twelfth Annual International Conference on Privacy, Security and Trust*, pages 414–419. IEEE, 2014.

[20] Siddarth Srinivasan and Jamie Morgenstern. Auctions and prediction markets for scientific peer review. *arXiv preprint arXiv:2109.00923*, 2021.

[21] Weijie J Su. You are the best reviewer of your own papers: An owner-assisted scoring mechanism. In A. Beygelzimer, Y. Dauphin, P. Liang, and J. Wortman Vaughan, editors, *Advances in Neural Information Processing Systems*, 2021. URL `https://openreview.net/forum?id=xmx5rE9QP7R`.

[22] Jingyan Wang and Nihar B. Shah. Your 2 is my 1, your 3 is my 9: Handling arbitrary miscalibrations in ratings, 2018.

[23] Yichong Xu, Han Zhao, Xiaofei Shi, Jeremy Zhang, and Nihar B Shah. On strategyproof conference peer review. *arXiv preprint arXiv:1806.06266*, 2018.

[24] Yichi Zhang, Fang-Yi Yu, Grant Schoenebeck, and David Kempe. A system-level analysis of conference peer review. In *Proceedings of the 23rd ACM Conference on Economics and Computation*, EC '22, page 1041–1080, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 9781450391504. doi: 10.1145/3490486.3538235. URL `https://doi.org/10.1145/3490486.3538235`.

A Proofs of Generalizations to the Finite Effort Setting

We first prove the key property of marginal rate of substitution.

Proof of Lemma 6.5. The proof of this proposition is analogue to the proof of Lemma 6.1. For simplicity, let

$$\Gamma_i = \prod_{k\in[i]} p_k^{n_k}, \qquad S_i = \sum_{k\in[n_i]} p_i^k = \frac{p_i(1-p_i^{n_i})}{1-p_i}.$$

Again, because each paper is independently reviewed under the parallel mechanism, it is easy to show

$$MRS^p_{i,j}(\boldsymbol{n}) = \frac{p_i u_i}{p_j u_j}.$$

The MRS of the sequential mechanism is more complicated. We first write down the author's expected reward of writing $\boldsymbol{n}$ papers and rank them truthfully.

$$\begin{aligned} U_a^s(\boldsymbol{n}) &= \sum_{l\in[|\boldsymbol{n}|]} \Pr(\text{paper } 1,\dots,l \text{ are accepted}) \cdot <\text{the reward of paper } l> \\ &= S_1u_1 + \Gamma_1 S_2 u_2 + \cdots + \Gamma_{m-1} S_m u_m \end{aligned}$$

For simplicity, let $Z_i = \sum_{l=i}^m \Gamma_{l-1} S_l u_l$ for any $2 \le i \le m$ and let $Z_1 = S_1u_1 + \sum_{l=2}^m \Gamma_{l-1}S_lu_l$. Thus, $U_a^s(\boldsymbol{n}) = Z_1$. Now, suppose the author writes one more paper with acceptance probability p_i. Recall that we use $\boldsymbol{n}' = (n_1, \dots, n_{i-1}, n_i+1, \dots, n_m)$ to denote the new vector of number of papers.

$$\begin{aligned} U_a^s(\boldsymbol{n}') &= S_1u_1 + \Gamma_1S_2u_2 + \cdots + \Gamma_{i-1}S_iu_i + \Gamma_i p_i u_i + p_i\left(\Gamma_i S_{i+1}u_{i+1} + \cdots + \Gamma_{m-1}S_m u_m\right) \\ &= Z_1 - Z_{i+1} + \Gamma_i p_i u_i + p_i Z_{i+1} \\ &= Z_1 - (1-p_i)Z_{i+1} + \Gamma_i p_i u_i. \end{aligned}$$

Therefore,

$$U_a^s(\boldsymbol{n}') - U_a^s(\boldsymbol{n}) = \Gamma_i p_i u_i - (1-p_i)Z_{i+1}. \tag{7}$$

Similarly, if the author writes one more paper with acceptance probability p_j where $j > i$, we have

$$U_a^s(\boldsymbol{n}'') - U_a^s(\boldsymbol{n}) = \Gamma_j p_j u_j - (1-p_j)Z_{j+1}.$$

Therefore,

$$\begin{aligned} MRS^s_{i,j}(\boldsymbol{n}) &= \frac{U_a^s(\boldsymbol{n}') - U_a^s(\boldsymbol{n})}{U_a^s(\boldsymbol{n}'') - U_a^s(\boldsymbol{n})} \\ &= \frac{\Gamma_i p_i u_i - (1-p_i)Z_{i+1}}{\Gamma_j p_j u_j - (1-p_j)Z_{j+1}} \\ &= \frac{p_i u_i}{p_j u_j} \cdot \frac{\Gamma_i - \frac{1-p_i}{p_i u_i} Z_{i+1}}{\Gamma_j - \frac{1-p_j}{p_j u_j} Z_{j+1}} := MRS^p_{i,j}(\boldsymbol{n}) \cdot \eta(\boldsymbol{n}). \end{aligned}$$

We want to show $\eta(\boldsymbol{n}) - 1 \ge 0$. Because $U_a^s(\boldsymbol{n}'') - U_a^s(\boldsymbol{n}) > 0$, it is sufficient to show

$$h(\boldsymbol{n}) = \Gamma_i - \Gamma_j + \frac{1-p_j}{p_j u_j} Z_{j+1} - \frac{1-p_i}{p_i u_i} Z_{i+1} \ge 0.$$

This inequality holds because

$$h(\boldsymbol{n}) = \Gamma_i - \Gamma_j + \frac{1-p_j}{p_j u_j} Z_{j+1} - \frac{1-p_i}{p_i u_i}(Z_{i+1} - Z_{j+1}) - \frac{1-p_i}{p_i u_i} Z_{j+1}$$

Because $p_i > p_j$ and $u_i \ge u_j$, $\frac{1-p_i}{p_i u_i} < \frac{1-p_j}{p_j u_j}$.

$$\ge \Gamma_i - \Gamma_j - \frac{1-p_i}{p_i u_i}(Z_{i+1} - Z_{j+1}). \qquad \text{(The inequality is strict if } Z_{j+1} > 0\text{, i.e. } \textstyle\sum_{k=j+1}^m n_k > 0.\text{)}$$

Note that

$$\frac{1-p_i}{p_i u_i} Z_k = \frac{1-p_i}{p_i u_i} \cdot \sum_{l=k}^{m} \Gamma_{l-1} S_l u_l = \sum_{l=k}^{m} \frac{1-p_i}{p_i} \cdot \frac{p_l(1-p_l^{n_l})}{1-p_l} \cdot \frac{u_l}{u_i} \cdot \Gamma_{l-1}.$$

Therefore, for any $k > i$, we have

$$\frac{1-p_i}{p_i u_i} Z_k \le \sum_{l=k}^{m} (1-p_l^{n_l})\Gamma_{l-1} = \sum_{l=k}^{m} (\Gamma_{l-1} - \Gamma_l) = \Gamma_{k-1} - \Gamma_m.$$

Furthermore, the above inequality is strict if $\sum_{l=k}^m n_k > 0$. Now, we complete the proof by showing $h(\boldsymbol{n})$ is non-negative.

$$\begin{aligned} h(\boldsymbol{n}) &\ge \Gamma_i - \Gamma_j - \frac{1-p_i}{p_i u_i}(Z_{i+1} - Z_{j+1}) \\ &\ge \Gamma_i - \Gamma_j - (\Gamma_i - \Gamma_m - \Gamma_j + \Gamma_m) \\ &= 0. \end{aligned}$$

If $\sum_{k=i+1}^m n_k > 0$, at least one of the above two inequality is strict, and thus $MSR^s_{i,j}(\boldsymbol{n}) > MSR^p_{i,j}(\boldsymbol{n})$ for any $\boldsymbol{n}$ and $i < j$. ∎

Then, we generalize Lemma 6.3 and 6.4 to the finite effort setting respectively. Then, the proof of Proposition 6.2 straightforwardly generalizes if we treat every high-quality paper in the binary setting as a paper with acceptance probability p_i, and every low-quality paper as a paper with acceptance probability p_j for any $i < j$. Let $\lambda_i(k) = \frac{U^s_a(\boldsymbol{n}_i^{(k)}) - U^s_a(\boldsymbol{n}_i^{(k-1)})}{U^s_a(\boldsymbol{n}_i^{(1)}) - U^s_a(\boldsymbol{n}_i^{(0)})}$, where $\boldsymbol{n}_i^{(k)} = (n_1, \ldots, n_{i-1}, n_i + k, \ldots, n_m)$.

Lemma A.1. *For any $i \in [m]$, $\lambda_i(1) = 1$ and $0 < \lambda_i(k+1) \le \lambda_i(k)$ for any $k \ge 1$.*

Proof. For simplicity, let

$$\Gamma_i = \prod_{k \in [i]} p_k^{n_k}, \qquad S_i = \sum_{k \in [n_i]} p_i^k = \frac{p_i(1-p_i^{n_i})}{1-p_i}, \qquad Z_i = \sum_{l=i}^{m} \Gamma_{l-1} S_l u_l.$$

By Eq. (7), we know that if there is one more paper with acceptance probability p_i, the gain of expected reward is $U^s_a(\boldsymbol{n}_i^{(1)}) - U^s_a(\boldsymbol{n}_i^{(0)}) = \Gamma_i p_i u_i - (1-p_i)Z_{i+1}$. Intuitively, if there are k more papers of acceptance probability p_i, while reasoning about the expected reward, it is equivalent to say that there is a new category of papers that have the same acceptance probability p_i and are ranked lower than the n_{i-1} papers with p_{i-1} but higher than the n_i papers with p_i. Therefore, every term of the gain of expected reward is exponentially discounted, i.e. $U^s_a(\boldsymbol{n}_i^{(k)}) - U^s_a(\boldsymbol{n}_i^{(k-1)}) = p_i^{k-1} \cdot \left(U^s_a(\boldsymbol{n}_i^{(1)}) - U^s_a(\boldsymbol{n}_i^{(0)})\right)$. This implies that $\lambda_i(k) = p_i^{k-1}$, which is decreasing in k. ∎

Lemma A.2. *For any $1 \le i < j \le m$, $\lambda_i(k) \ge \lambda_j(k)$ for any $k \ge 1$.*

The proof is straightforward given that $\lambda_i(k) = p_i^{k-1}$, and $p_i > p_j$ for any $1 \le i < j \le m$.