Eliciting Honest Information From Authors Using Sequential Review

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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 heavily relies on the assumption that the author's utility is both an increasing and a convex function with respect to the review score, which is often 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 truthfully 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 key idea is to review the papers of an author in a sequence based on the provided ranking and conditioning the review of the next paper on the review scores of the previous papers. Advantages of the sequential review mechanism include 1) eliciting truthful ranking information in a more realistic setting than prior work; 2) improving the quality of accepted papers, 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 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 [13], it was shown that within the set of papers recommended for acceptance by two independent committees, the disagreement rate was as high as 50%. This result was further confirmed in the repeated experiment conducted in 2021 [6]. Even worse, the rapid growth of the reviewing workload and the shortage of qualified reviewers, has posed unprecedented challenges to our review system [19, 20].

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 review 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 desire to have more publications and thus desire to have their papers accepted for publication, regardless of their quality. In this case, although authors possess the best signals of their own papers' quality compared with any reviewer, they may prefer not to disclose 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 [27] 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

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shown that reporting the ranking of papers truthfully is the best response for an author. Unfortunately, this result only holds when the agent's utility for each paper is an **increasing and convex** function of the review score and additive across papers. However, the assumption of convex utility is strong and likely violated in the setting of conference peer review. For example, this assumption is violated in the reasonable case that an author aims to maximize the number of her accepted papers. Moreover, in this case, the isotonic mechanism can be gamed in a rather straightforward manner. Suppose such an author 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 will almost certainly lead to the acceptance of all papers.[1]

In this work, we build on the idea of eliciting the author's ranking information from the previous work and primarily focus on addressing the incentive issue discussed above. We propose the sequential review mechanism in a natural conference review model. Our method can elicit the true ranking information as long as the author's utility is additive in terms of the rewards of all **accepted** papers, where the reward is a **non-decreasing** function of the accepted papers' qualities. The sequential review 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 review mechanism, any misreporting of the true ranking of the papers will result in an earlier termination of the review process, which penalizes dishonest behaviors.[2]

1.1 Contributions and Results

Our main contribution is a framework for designing theoretically robust mechanisms in realistic settings and that has the potential to improve peer review and guide decisions. In particular, the proposed sequential review mechanism not only addresses a key practical incentive issue that plagues prior work but also exhibits many appealing properties for practical use.

Truthful sequential review mechanisms. Under the sequential review mechanism framework, we first identify a sufficient constraint that ensures a sequential review mechanism to be truthful (i.e. reporting the true ranking of the paper quality is the best response for any author). While not necessary, this constraint provides a large space of truthful sequential review 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. The sequential review mechanism utilizes the authors' information to prioritize the review of high-quality papers. Therefore, it can improve the conference's utility (as low-quality papers are less likely to be accepted), while reducing the review burden by reallocating more review resources to papers deemed likely to be of higher quality. To evaluate the performance of the sequential review mechanism, we use the *parallel review mechanism* as the baseline which unconditionally reviews all papers. We further use the isotonic mechanism with Oracle access to the true ranking information as an unachievable upper bound.[3]

Our simulation results suggest that compared with the baseline, the sequential review mechanism can improve the conference utility towards the upper bound by over 40% when the author submits more than three items. This effect is even more significant when 1) each author has more papers, 2) papers are more likely to be of low quality and 3) reviewers are more noisy. Moreover, we empirically investigate the number of reviews that a sequential review mechanism can save while achieving the same conference utility as the

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[1]For an introduction of the isotonic mechanism and a careful illustration of this example, please refer Appendix A.

[2]One may be concerned that the sequential review mechanism will result in a significant delay in the review process. However, note that the mechanism works exactly the same if all papers are simultaneously reviewed or reviewed in batches, as long as the acceptance/rejection decisions are made in sequence. See more in Section 7.

[3]The isotonic mechanism is not truthful in our setting but we nonetheless provide oracle access of the true ranking to it.

parallel review mechanism. We employ the ICLR OpenReview datasets spanning recent years and develop a more realistic review model. Our results indicate that about 20% of the review burden can be saved when utilizing the sequential review mechanism. Furthermore, this number will increase over time if the trend of a growing number of submissions per author continues.

Endogenous paper quality. In the setting where authors can choose the effort they exert on each of their papers, we show that compared with the parallel review mechanism, the sequential review mechanism always provides a stronger incentive for writing (fewer) papers of higher quality instead of (more) papers of low-quality. This is because the sequential review mechanism decreases the marginal return of producing lower-quality papers by penalizing bottom-ranked papers with lower probabilities of being reviewed. We view this property particularly valuable, especially in light of the prevailing trend where authors submit an increasingly large number of papers to conferences, often disregarding their inherent quality. This also aligns with the policies adopted by many conferences (e.g. AAAI) in recent years, which limit the maximum number of papers that an author can submit.

2   Related Works

Other than the isotonic mechanism [27, 29], several attempts exist with the goal of improving the peer review system with a 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. [31] 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 recent work, Srinivasan and Morgenstern [26] 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 review slots. In dealing with the malicious bidding problem, a stream of literature focuses on designing and optimizing the paper-reviewer assignment mechanism [1, 11, 8, 30]. 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 [17]. 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 [17, 1, 7, 18]. 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.

Additionally, there exists a considerable body of literature that aims to improve peer review from the reviewer's perspective. This includes investigations into single versus double blind reviewing [3, 23, 2], assignment versus bidding [4, 16], review scale and miscalibration [22, 28, 25], reviewer bias [14, 10, 12], and dishonest behaviors [5, 9, 15]. A recent survey by Shah [21] provides additional contexts and perspectives on the problems of peer review.

3   Model

We view the peer review mechanism as an individual contract. That is, each paper is reviewed and evaluated independently based on its review scores.[4] Therefore, while reasoning about an agent's best response (Section 4 and 6), it is sufficient to assume that there is only one agent with n papers. We eventually investigate

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[4]An example of a review policy that is not an individual contract is when the conference maintains a fixed acceptance rate, which results in a contest setting where authors have to compete with each other for acceptance. However, in such a case, as the number of authors and papers becomes large, the importance of interactions between individual authors will decrease and therefore limit our model.

the optimization of a review mechanism, and here we assume authors are drawn from a distribution (see Section 5.3).

Throughout the paper, we will use $[n]$ to denote the set $\{1, 2, \ldots, n\}$. Suppose an author has n submissions indexed by $i \in [n]$, each with a quality of $q_i \in \mathbb{R}$. The author observes a noisy signal $s_i = q_i + \xi_i$ for each of her papers where ξ_i are i.i.d. sampled from some distribution. This information is private to the author.

For each paper i the conference decides whether to accept or reject based on its review score $r_i = q_i + \epsilon_i$, 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 that 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. The author first ranks her papers based on her review scores s_i such that, without loss of generality, $s_1 \geq s_2 \geq \cdots \geq s_n$. We name each paper by the author's true ranking, i.e. paper i is the paper that the author's signal is s_i. The author reports a permutation π on the indexes $1, 2, \ldots, n$ 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 that 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 non-decreasing reward function for the true quality of the paper. For example, if $u_a(q) = 1$ for any q, the author's goal is to maximize the expected number of accepted papers. Note that the reward is a function of the true quality rather than the author's signal because the value of an accepted paper (e.g. its citations) largely depends on how other people evaluate it. The author strategically reports a ranking π to maximize its expected utility. We use $U_a(\pi)$ to denote the expected author utility under the permutation π, where the randomness is with respect to the review noise and the mechanism.

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 variant of the general model by additionally considering that the author can choose the quality of the papers that she writes.

4   Truthful Sequential Review Mechanisms

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

4.1   The Sequential Review Mechanism Framework

We first introduce the *naive sequential mechanism* as an illustrative example of the more general sequential review mechanism framework.

Definition 1. *Given an author with n papers and a ranking of these papers, the naive sequential mechanism reviews one paper at a time based on the order of the reported ranking. The first paper is always reviewed. However, for i ranging from 2 to n the paper ranked in the ith place is reviewed if and only if the paper ranked in i − 1st place is accepted.*

The idea of the sequential review mechanism is to condition the review of lower-ranked papers on the acceptance (and thus the review score) of the higher-ranked papers. If the mechanism decides not to review the paper in round i, any paper in round $j > i$ will be rejected without review. We then say that the mechanism terminates in round i. Intuitively, any manipulation of the true ranking will result in the more likely early termination of the review process which harms the utility of the author.

However, the naive sequential mechanism can be too stringent in reality, especially when authors are likely to produce good papers. To address this, we generalize this idea and present the sequential review mechanism framework. This framework offers a diverse range of mechanisms that can be fine-tuned to optimize performance in various circumstances.

Definition 2. *A sequential review mechanism $\mathcal{M}_s = (P_{acc}, P_{rev}, \boldsymbol{\mu})$ has three 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, for $i \in [n]$.*

- *A state transition mapping μ_i that maps from a review state and a review score of the paper in round i to a distribution of states in round $i + 1$, for $i \in [n-1]$.*

In the above definition, a *review state* in round i, denoted as $\phi_i \in \Phi_i$, is sufficient to determine the probability that the paper in round i will be reviewed, where Φ_i is the space of review states in round i. 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 $i \in [n]$. We use $\phi'_i \succ \phi_i$ to represent the strict ordering. Furthermore, if the author is indifferent between two states, we say $\phi'_i \sim \phi_i$. When comparing two vectors of states, we use the same notations to indicate term-wise preference. For example, if $\boldsymbol{\phi}, \boldsymbol{\phi}' \in \Phi^m$, $\boldsymbol{\phi}' \succeq \boldsymbol{\phi}$ implies that $\phi'_j \succeq \phi_j$ for any $1 \le j \le m$.

Specially, we use ω to denote the termination state such that $P_{rev}(\omega) = 0$ and $\mu(\omega, \cdot) = \omega$ with probability of 1. Note that for any round i and any review state $\phi \in \Phi_i \backslash \{\omega\}$, we have $\phi \succ \omega$.

Taking the naive sequential mechanism as an example, the review state is $\phi_i = \psi$ if the paper in round i is accepted and ω otherwise. In round 1, $\phi_1 = \psi$. Then, the review policy is $P_{rev}^{std}(\psi) = 1$ and $P_{rev}^{std}(\omega) = 0$ for any round. The state transition mapping of the standard naive mechanism is that $\mu^{std}(\psi, r) = \psi$ with probability $P_{acc}(r)$, $\mu^{std}(\psi, r) = \omega$ with probability $1 - P_{acc}(r)$, and $\mu^{std}(\omega, \cdot) = \omega$ with probability 1.

Furthermore, note that by our definition, the acceptance policy is assumed to be memoryless, where the acceptance of a paper only depends on its own review score. In other words, conditioned on a paper being reviewed, the same acceptance policy is applied. However, the review policy can have memory such that review scores from previous rounds may affect the distribution of the review state in the current round through a Markov chain.

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 review mechanism to be truthful. First of all, we need both policies to be monotone which reward higher review scores and punishes lower review scores.

Definition 3. *We say an acceptance policy is monotone if P_{acc} is (weakly) increasing, i.e. $P_{acc}(r') \ge P_{acc}(r)$ for any $r' \ge r$.*

Definition 4. *We say a review policy is monotone if $P_{rev}(\phi'_i) \ge P_{rev}(\phi_i)$ for any $\phi'_i, \phi_i \in \Phi_i$ such that $\phi'_i \succeq \phi_i$ in any 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 5. *Let $\boldsymbol{X}$ and $\boldsymbol{Y}$ be two m-dimension random vectors of review states $\boldsymbol{X}, \boldsymbol{Y} \in \Phi^m$ for some review state space Φ. We say $\boldsymbol{X}$ first-order stochastic dominates $\boldsymbol{Y}$ if $\Pr(\boldsymbol{X} \succeq \boldsymbol{\phi}) \ge \Pr(\boldsymbol{Y} \succeq \boldsymbol{\phi})$ for any $\boldsymbol{\phi} \in \Phi^m$.*

For simplicity, let $\tilde{\mu}(r_1, r_2 | \phi_i) = \mu_{i+1}(\mu_i(\phi_i, r_1), r_2)$ be the state distribution in round $i + 1$ conditioned on having review state ϕ_i in round $i - 1$, and having review scores r_1 and r_2 in round i and round $i + 1$ respectively.

Definition 6. *We say the state transition mapping $\boldsymbol{\mu}$ is monotone if for any review round $i \in [n-1]$*

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 in ordering: For any state $\phi_i \in \Phi_i$ and review scores $r' \geq r$, $\tilde{\mu}(r', r|\phi_i)$ first-order stochastic dominates $\tilde{\mu}(r, r'|\phi_i)$. Furthermore, for any $r_1 \leq r_2 \leq r_3 \leq r_4$ such that $r_1 + r_4 = r_2 + r_3$, let $X \sim \tilde{\mu}(r_4, r_1|\phi_i)$, $Y \sim \tilde{\mu}(r_2, r_3|\phi_i)$, $X' \sim \tilde{\mu}(r_1, r_4|\phi_i)$ and $Y' \sim \tilde{\mu}(r_3, r_2|\phi_i)$. Let $\bar{Z} = \max(X, Y)$, $\underline{Z} = \min(X, Y)$, $\bar{Z}' = \max(X', Y')$, $\underline{Z}' = \min(X', Y')$.[5] Then, $(\bar{Z}, \underline{Z})$ first-order stochastic dominates $(\bar{Z}', \underline{Z}')$.*

The monotonicities of $\boldsymbol{\mu}$ in score and state are intuitive which suggests that the state transition mapping results in a better state when the review score is higher and the review state is higher-ordered, respectively. The monotonicity in ordering deals with the cases where the review scores in two rounds are swapped. First, it requires the review state distribution to be better if the higher review score is put earlier. Furthermore, when there are four ordered review scores and a pair of review states, the monotonicity in ordering suggests that putting the largest score r_4 earlier in round i with the lowest score r_1 in round $i + 1$ and putting r_2 in round i with r_3 in round $i + 1$ leads to better state distributions than swapping the review scores in round i and $i + 1$ in this ordering.

We are ready to present the main theorem.

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.*

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

Proof. We first show that the proof can be reduced to reasoning about the setting which the author possesses perfect information regarding the true quality of her papers. Intuitively, this is because the author's noise affects her reasoning about the ranking of papers in the same way as the review noise. The argument is as follows. Suppose the author observes the true quality of her papers, and her best response is to truthfully rank her papers based on q_i for any i.i.d. review noise ϵ_i. Then, we can always construct a new review noise $\tilde{\epsilon}_i = \epsilon_i - \xi_i$ such that the review score of paper i is $r_i = s_i + \hat{\epsilon}_i$. By assumption, $\hat{\epsilon}_i$ is i.i.d. for all papers. Consequently, it straightforwardly follows that the author's best response is to rank her papers based on the true order of s_i in this case. Therefore, in the following proof, it is sufficient to focus on the setting where the author knows the true qualities.

Consider an arbitrary untruthful ranking π. Without loss of generality, suppose under π, there exists a pair of papers such that the lower-quality one is ranked higher than the higher-quality one. Otherwise, π only permutes papers with the same quality and is trivially (weakly) dominated by the truthful ranking. Suppose paper j and k are ranked in adjacent places under π, however $\pi(j) > \pi(k)$ but $q_j > q_k$—that is, paper j is better than paper k but ranked slightly worse. Let $\pi(k) = t$, so $\pi(j) = t + 1$. The existence of such two papers is guaranteed by the design of π. Then, consider a ranking π' which switches the ordering of paper j and k such that $\pi'(j) = t$ and $\pi'(k) = t + 1$. We will show that the author always weakly prefers to report π' instead of π. Note that this is sufficient to guarantee truthfulness because this shows the author always prefers to rank a higher-quality paper ahead of an adjacent lower-quality paper.

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.

To accomplish this, we will present a coupling where in any realization of outcomes, every paper accepted in π corresponds to a paper accepted in π' with the same or higher quality.
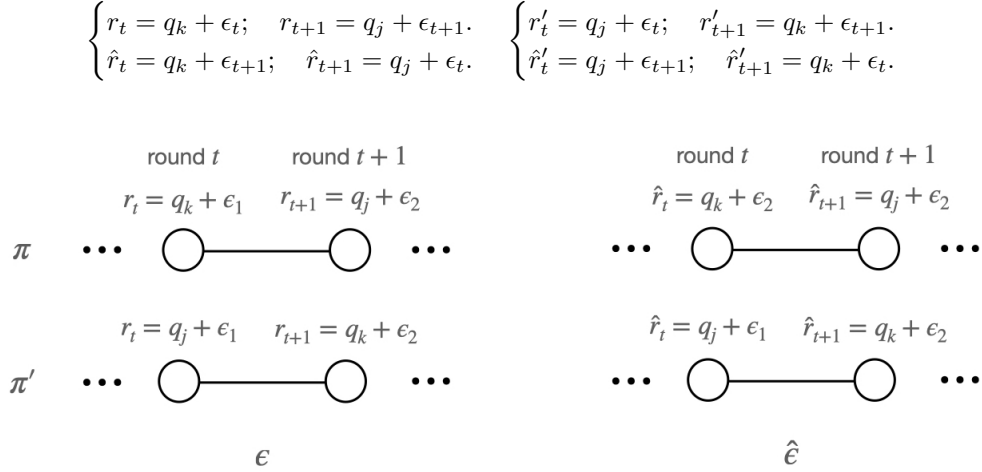
We now construct such a coupling.

First, we couple the realizations of the review noise under both permutations. In particular, consider two noise vectors $\boldsymbol{\epsilon}$ and $\hat{\boldsymbol{\epsilon}}$ which are identical everywhere except that the noises in round t and $t + 1$ are swapped. Let $\boldsymbol{\epsilon}_t = \hat{\boldsymbol{\epsilon}}_{t+1} = \epsilon_t$ and $\boldsymbol{\epsilon}_{t+1} = \hat{\boldsymbol{\epsilon}}_t = \epsilon_{t+1}$. We couple the review noise under two permutations such that

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[5]Here, the max and min function select the higher-ordered state and the lower-ordered state respectively.

whenever the review noise is $\boldsymbol{\epsilon}$ under π, the review noise is $\hat{\boldsymbol{\epsilon}}$ under π'; while whenever the review noise is $\hat{\boldsymbol{\epsilon}}$ under π, the review noise is $\boldsymbol{\epsilon}$ under π'. This is possible because all the review noise terms are i.i.d.. Then, we will show that conditioned on the review noise, $\mathbb{E}[U_a(\pi')|\boldsymbol{\epsilon}]+\mathbb{E}[U_a(\pi')|\hat{\boldsymbol{\epsilon}}] \geq \mathbb{E}[U_a(\pi)|\boldsymbol{\epsilon}]+\mathbb{E}[U_a(\pi)|\hat{\boldsymbol{\epsilon}}]$, where the expectation is taken over the randomness of the sequential review mechanism.

Fixing the review noise fixes the review score. Let $\boldsymbol{r}$ and $\hat{\boldsymbol{r}}$ be the review score vectors under π with review noise $\boldsymbol{\epsilon}$ and $\hat{\boldsymbol{\epsilon}}$ respectively, and let $\boldsymbol{r}'$ and $\hat{\boldsymbol{r}}'$ be the corresponding terms under π'. Therefore, $\boldsymbol{r}$, $\hat{\boldsymbol{r}}$, $\boldsymbol{r}'$ and $\hat{\boldsymbol{r}}'$ are identical except on the following entries.

$$\begin{cases} r_t = q_k + \epsilon_t; & r_{t+1} = q_j + \epsilon_{t+1}. \\ \hat{r}_t = q_k + \epsilon_{t+1}; & \hat{r}_{t+1} = q_j + \epsilon_t. \end{cases} \qquad \begin{cases} r'_t = q_j + \epsilon_t; & r'_{t+1} = q_k + \epsilon_{t+1}. \\ \hat{r}'_t = q_j + \epsilon_{t+1}; & \hat{r}'_{t+1} = q_k + \epsilon_t. \end{cases}$$

We want to show that the sum of the expected utility of having review scores $\boldsymbol{r}'$ and $\hat{\boldsymbol{r}}'$ (review scores under π') is larger than that of having $\boldsymbol{r}$ and $\hat{\boldsymbol{r}}$ (review scores under π). We prove this by discussing two cases depending on the relationship between the review scores.

Case 1. In the first case, permutation π' has a larger review score in round t for both noise vectors, i.e. $\max(q_k + \epsilon_t, q_k + \epsilon_{t+1}) \leq \min(q_j + \epsilon_t, q_j + \epsilon_{t+1})$. We show that $\mathbb{E}[U_a|\boldsymbol{r}'] \geq \mathbb{E}[U_a|\hat{\boldsymbol{r}}]$ and $\mathbb{E}[U_a|\hat{\boldsymbol{r}}'] \geq \mathbb{E}[U_a|\boldsymbol{r}]$. This is sufficient to prove case 1 because permutation π' always leads to a higher expected utility under every realization of review noise.

We present the proof of $\mathbb{E}[U_a|\boldsymbol{r}'] \geq \mathbb{E}[U_a|\hat{\boldsymbol{r}}]$ while the proof of $\mathbb{E}[U_a|\hat{\boldsymbol{r}}'] \geq \mathbb{E}[U_a|\boldsymbol{r}]$ is analogous. Let $\boldsymbol{\phi}'$ and $\hat{\boldsymbol{\phi}}$ be the vectors of review states under $\boldsymbol{r}'$ (corresponds to π') and $\hat{\boldsymbol{r}}$ (corresponds to π) receptively, where each entry is the review state in round i. We first show that in any round i, the distribution of ϕ'_i first-order stochastic dominates that of $\hat{\phi}_i$.

Depending on where is i, the argument follows by discussing the following four cases.

1. If $i \leq t$, the statement holds because the review scores are identical. Then, the review state distribution must be identical for any round before t.

2. If $i = t+1$, the statement holds because $\boldsymbol{\mu}$ is monotone in score. Since $r'_t \geq r_t$, permutation π' has a larger score than π in round i.

3. If $i = t+2$, the statement holds because $\boldsymbol{\mu}$ is monotone in ordering. In particular, because conditioned on the same review state ϕ_t, $\tilde{\mu}(r', r|\phi_t)$ first-order stochastic dominates $\tilde{\mu}(r, r'|\phi_t)$ for every $r' \geq r$. Furthermore, ϕ_t has the same distribution under both permutations.

4. If $i > t+2$, the statement holds because $\boldsymbol{\mu}$ is monotone in state. This can be shown by induction. First, if $i = t+3$, we know that ϕ'_{t+2} first-order stochastic dominates ϕ_{t+2} and $r'_{t+2} = r_{t+2}$. Therefore, because $\boldsymbol{\mu}$ is monotone in state, we can couple the realizations of states in round $t+3$ such that whenever the review state under π is ϕ_{t+3}, the review state under π' is at least as good as ϕ_{t+3}. The above argument holds for any $i > t+2$ which completes the proof.

Now, we couple the review states such that $\phi'_i \succeq \hat{\phi}_i$ for any round i. Then, we further couple the randomness of P_{rev}. Because P_{rev} is monotone, in any realization of outcomes, whenever the review process

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terminates under π', it also terminates under π. This guarantees that π' always results in the reviewing of a set of papers that have weakly better qualities. In other words, whenever a paper is reviewed under π, a paper with the same or better quality is reviewed under π'.

Finally, we couple the randomness of P_{acc} so that whenever a paper is reviewed and accepted under π, a paper with a higher review score and a higher quality is reviewed and accepted under π'. This is possible because in this case, a higher quality paper corresponds to a higher review score. Therefore, because P_{acc} is monotone, whenever a paper is reviewed and accepted under π, a paper with a higher review score and a higher quality is reviewed and accepted under π'. This completes the proof of case 1.

Case 2. The second case corresponds to the review noise vectors such that $q_j - q_k < |\epsilon_t - \epsilon_{t+1}|$. In this case, we cannot isolate a pair of expectations as what we have done in case 1 but have to prove the theorem by directly showing that $\mathbb{E}[U_a|\boldsymbol{r}'] + \mathbb{E}[U_a|\hat{\boldsymbol{r}}'] \geq \mathbb{E}[U_a|\boldsymbol{r}] + \mathbb{E}[U_a|\hat{\boldsymbol{r}}]$.

Again, the key is to show that the states under π' first order stochastic dominate the states under π. However, we have to prove this for a pair of states. Let $\boldsymbol{\phi}'$, $\hat{\boldsymbol{\phi}}'$, $\boldsymbol{\phi}$ and $\hat{\boldsymbol{\phi}}$ be the vector of review states conditioned on $\boldsymbol{r}'$, $\hat{\boldsymbol{r}}'$, $\boldsymbol{r}$ and $\hat{\boldsymbol{r}}$ respectively. Let $\tilde{\phi}_i = (\max(\phi_i, \hat{\phi}_i), \min(\phi_i, \hat{\phi}_i))$ be a pair of review states in round i under permutation π such that the first entry is always the better state between ϕ_i and $\hat{\phi}_i$ while the second entry is the worse one. Let $\tilde{\phi}'_i$ be the analogous notation for π'. We will show that the distribution of $\tilde{\phi}'_i$ first order stochastic dominates the distribution of $\tilde{\phi}_i$.

Again, we discuss four cases:

1. If $i \leq t$, the statement holds because the review scores are identical.

2. If $i = t+1$, the statement holds because $r'_t > r_t$ and $\boldsymbol{\mu}$ is monotone in score. Therefore, the distribution of ϕ'_{t+1} must first-order stochastic dominate that of ϕ_{t+1}. Analogously, the distribution of $\hat{\phi}'_{t+1}$ first-order stochastic dominates that of $\hat{\phi}_{t+1}$. Therefore, by definition, $\tilde{\phi}'_{t+1}$ must dominate $\tilde{\phi}_{t+1}$.

3. If $i = t+2$, the statement holds because $\boldsymbol{\mu}$ is monotone in ordering. Suppose without loss of generality that $\epsilon_t \leq \epsilon_{t+1}$ while the proof of the other case is analogous. For simplicity, let $\rho_1 = r_t = \hat{r}'_{t+1}$, $\rho_2 = r'_t = \hat{r}_{t+1}$, $\rho_3 = \hat{r}_t = r'_{t+1}$ and $\rho_4 = \hat{r}'_t = r_{t+1}$. In this case, $\rho_1 \leq \rho_2 < \rho_3 \leq \rho_4$. Then, by definition, $\phi'_{t+2} \sim \tilde{\mu}(\rho_2, \rho_3)$, $\hat{\phi}'_{t+2} \sim \tilde{\mu}(\rho_4, \rho_1)$, $\phi_{t+2} \sim \tilde{\mu}(\rho_1, \rho_4)$, $\hat{\phi}_{t+2} \sim \tilde{\mu}(\rho_3, \rho_2)$. Therefore, conditioned on the same review state ϕ_t, we have that the distribution of $\tilde{\phi}'_{t+2}$ first-order stochastic dominates that of $\tilde{\phi}_{t+2}$. This is why we need the definition of the monotonicity of ordering (Definition 6).

4. If $i > t+2$, the statement holds because $\boldsymbol{\mu}$ is monotone in state. This analysis is analogous to the analysis in case 1.

Now, we further couple the randomness of $\boldsymbol{\mu}$, P_{rev}, and P_{acc} and simultaneously reason about the outcomes under two review processes corresponding to noise vectors $\boldsymbol{\epsilon}$ and $\hat{\boldsymbol{\epsilon}}$ respectively. First, we can couple a pair of review states such that $\tilde{\phi}'_i \succeq \tilde{\phi}_i$ for any round.

Then, because P_{rev} is monotone, we can further couple the review outcomes such that whenever the review process(es) correspond to review scores $\boldsymbol{r}'$ and $\hat{\boldsymbol{r}}'$ terminate, a weakly larger number of the review process(es) must have terminated under π. This means that if we consider the reviewed papers under two processes altogether, every paper that is reviewed under π can be paired with a reviewed paper under π' that has a weakly higher quality and review score. Finally, because P_{acc} is monotone, we can couple the outcome of the acceptance such that whenever a paper is accepted under π a paper with a weakly higher quality is accepted under π'. This completes the proof.

$\square$

4.3 The memoryless Coin-Flip Mechanism

Here, we provide an 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 probability $\rho(r_i)$ determined by the review score of the paper in round i. Furthermore, the mechanism always reviews the first paper. We call this mechanism the *memoryless coin-flip mechanism*.

To map this mechanism into the sequential review mechanism framework, we first define the review states. Consider $\phi_i = (\alpha, \gamma) \in \{0,1\}^2$ for any round $i > 1$, where the first entry indicates whether the paper in round $i-1$ 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. That is $(0,0) = \omega$. Note that the distribution of the review state in round i only depends on the review score of round $i - 1$, which implies that the review policy is "memoryless". Furthermore, because the first paper is always reviewed, let $\phi_1 = (1, \gamma)$. In this example, the ordering of the review states is $(1,1) \sim (1,0) \sim (0,1) \succ \omega$.

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.

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

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

where $\rho : \mathbb{R} \to [0,1]$ maps from a review score to a probability of reviewing the next paper. Note that the memoryless coin-flip mechanism reduces to the parallel review mechanism when $\rho(r) = 1$ for any review score r, and reduces to the naive sequential mechanism when $\rho(r) = 0$ for any r. 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. We defer the proof to Appendix B.1.

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

4.4 The Credit Pool Mechanism

Another example of the sequential reviewing framework implements the idea of a reputation system. Suppose the conference keeps a record of a credit pool, which is initialized at $B_1 \geq 0$. For every reviewed paper, the mechanism will increase (or decrease) the credit pool by a credit score which is determined by the review of that paper. Let $\beta : \mathbb{R} \to \mathbb{R}$ be a credit function that maps from a review score to a review credit. Note that β can be negative, indicating a punishment of papers with low review scores. The credit pool mechanism reviews the paper in round i if and only if $B_i \geq 0$. Details of the credit pool mechanism are presented in 1.

Speaking in the language of the sequential review mechanism framework, we first define the review state as the credit in the pool, i.e. $\phi_i = B_i$ for round i. States are ordered in terms of their credit, however, and any negative credit will correspond to the termination state ω. More formally, the ordering of the states is $B' \succeq B \succ \omega$ for any $B' \geq B \geq 0$. We define the review policy as

$$P_{\mathrm{rev}}^{cp}(B) = \begin{cases} 1 & \text{if } B \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

Furthermore, the state transition mapping $\boldsymbol{\mu}^{cp}$ is deterministic such that $\boldsymbol{\mu}^{cp}(\omega, r) = \omega$ with probability of 1 and conditioned on $B_i \geq 0$,

$$\mu^{cp}(B_i, r_i) = B_i + \beta(r_i) \quad \text{with probability of 1.}$$

Again, we can omit the subscript i since μ^{cp} does not depend on the review round. The following theorem indicates sufficient conditions for a credit pool mechanism to be truthful.

Proposition 4.3. *The credit pool mechanism $(P_{acc}, P_{rev}^{cf}, \boldsymbol{\mu}^{cf})$ is truthful if P_{acc} is monotone and β is increasing and convex.*

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MECHANISM 1: The credit pool mechanism.

Input: The ordered review scores $\boldsymbol{r}$ with r_t being the score of the paper ranked by the author in round t, the acceptance policy P_{acc}, the initial credit B_1 and the credit function β.

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

---

1 Initialize the credit pool as $B = B_1 \geq 0$ and $t = 1$;

2 while $B \geq 0$ **do**

3   Flip a biased coin with a probability of heads equal to $P_{\mathrm{acc}}(r_t)$, and the outcome is γ_t (with 1 being heads and 0 being tails);

4   **if** $\gamma_t = 1$ **then**

5 $\alpha_t = 1$;

6   **else**

7 $\alpha_t = 0$;

8   **end**

9 $B \mathrel{+}= \beta(r_t)$;

10 $t \mathrel{+}= 1$;

11 end

12 $\alpha_j = 0$ **for** $j \in \{t, \ldots, n\}$.

We defer the proof to Appendix B.2. 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 illustrates what can go wrong.

Ranking bundles of papers. A plausible generalization of the sequential review mechanism is to require the author 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).

However, such an idea is not truthful in general. 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, and two of them are outstanding and basically guaranteed acceptance while the remaining four papers are of borderline quality. Suppose the author knows the true qualities. 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 reports the true ranking, it is more likely that only the top four papers will be reviewed, while the bottom two papers will be rejected without review.

The limited credit pool mechanism. We present a non-truthful variant of the credit pool mechanism with a credit pool of a limited size. 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.

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 ranking 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 Threshold Sequential Review Mechanism

The previous section identifies a space of truthful mechanisms, while this section focuses on empirically evaluating the performance of the threshold sequential review mechanism. We evaluate a mechanism from two dimensions: conference utility and review burden. The former is measured by the sum of accepted papers' quality, and the latter quantifies the number of reviewed papers, while both are normalized by the total number of submitted papers. For both computational and practical considerations, we focus on the threshold sequential review mechanism, a special case of the memoryless coin-flip mechanism discussed in Section 4.3. In comparison, we use the threshold parallel review mechanism as a baseline and the threshold isotonic mechanism with the underlying ranking information as an unreachable upper bound. Therefore, when we refer to a mechanism in this section, unless otherwise specified, we simply mean the threshold implementation of it.

We conduct experiments on both a simple 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 show that the sequential review mechanism can achieve conference utility that is competitive compared to the upper bound and can significantly reduce the review burden. Moreover, in the real-data estimated model, we show that the sequential review mechanism can save more than 20% review burden compared with the baseline conditioned on a weakly better conference utility. For better illustrations of our main results and because of a lack of ground truth data, in this section, we simply assume that authors observe the perfect information about the true quality of their papers.

5.1   Mechanisms of Comparison

Here, we introduce how we implement and optimize the threshold sequential review mechanism, the parallel review 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.

The threshold sequential review mechanism. We restrict our attention to a special case of the sequential review mechanism with two special parameters τ_{acc}^s and τ_{rev}^s where $\tau_{acc}^s \geq \tau_{rev}^s$. The threshold sequential review mechanism is a memoryless coin-flip mechanism with P_{acc} and ρ being threshold functions: $P_{\mathrm{acc}}(r) = 1$ if $r \geq \tau_{acc}^s$ and 0 otherwise; $\rho(r) = 1$ if $r \geq \tau_{rev}^s$ and 0 otherwise. In words, the threshold sequential review mechanism accepts a paper, conditioned on it being reviewed, if its review score is larger than a threshold τ_{acc}^s; and it reviews the next paper if the review score is larger than a lower threshold τ_{rev}^s. We study the threshold sequential review mechanism mainly because of its simplicity, making it easy to optimize and implement in practice. This illustrates the power of the sequential review mechanism even in a simplified form.

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

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 uses the isotonic mechanism with this information as the upper bound. In particular, given the original review scores, the isotonic mechanism modifies them by solving the isotonic

regression conditioned on the author's ranking (details are presented in Appendix A). Then, a threshold acceptance policy is applied to the modified review scores such that the paper with score r is accepted if and only if $r \geq \tau_{acc}^i$.

To emphasize the importance of truthfulness, we note that in the absence of truthful ranking information, the isotonic mechanism can yield a conference utility that is even worse than the baseline. We illustrate this with an example presented in Appendix A. However, assuming truthfulness gives us a (likely unachievable) benchmark.

5.2 Gaussian Review Noise

We first introduce a simple yet intuitive model where each paper is associated with a single review score, which is the true quality plus an additive Gaussian review noise. The simplicity of this model offers computational convenience, enabling us to efficiently explore the influence of various model parameters on the performance of the sequential review mechanism. Note that under this simple model, we again assume that there is only one author so as to present our results in a clear manner.

5.2.1 Model and Experiment Setup

The *Gaussian review setting* $\varphi^G = (n, \mu_q, \sigma_q, \sigma_r)$ is defined by four parameters. The conference has a Gaussian prior of the quality of the author's papers with parameters μ_q and σ_q. Thus, 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 author sends the conference a ranked list of her papers in terms of their quality (hence the conference observes the true ranking of the quality of the papers). Let 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, $r_i = q_i + \epsilon_i$.

Given a setting φ^G and a mechanism $\mathcal{M}$ (which is determined by the threshold(s) τ_{acc}^s and τ_{acc}^s), we use the Monte-Carlo method to estimate the expected conference utility. In particular, we draw 10,000 samples of q where each 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 review mechanism and the threshold parallel review mechanism:

- For the threshold parallel review mechanism, $\Pr(\text{paper } i \text{ is accepted}) = 1 - G_{\sigma_r}(\tau_{acc}^P - r_i)$, where G_{σ_r} is the c.d.f. of the zero-mean Gaussian distribution with standard deviation σ_r.

- For the threshold sequential review mechanism, $\Pr(\text{paper } i \text{ is accepted}) = \prod_{j=1}^{i-1} \left(1 - G_{\sigma_r}(\tau_{rev}^s - r_j)\right) \cdot \left(1 - G_{\sigma_r}(\tau_{acc}^s - r_i)\right)$.

For the isotonic mechanism, due to the non-linear isotonic regression, we do not have a closed-form expected conference utility. Thus, we first draw 100 review noise terms ϵ and numerically estimate the expected conference utility by taking the average. Finally, for all implemented mechanisms, the estimated conference utility is the average over 10,000 samples of q.

For each Gaussian review setting, we further optimize the threshold(s) of the three types of mechanisms using stochastic gradient descent. To estimate the gradient, we simply vary the threshold by a small step and draw 10,000 samples of q to estimate the change of conference utility.

5.2.2 Results

Conference utility.   We first see how different parameters affect the conference utility achieved by the sequential review mechanism. Let U_c^p, U_c^s, and U_c^i be the expected conference utility under the parallel review mechanism, sequential review mechanism, and isotonic mechanism with the optimized thresholds, respectively. We are interested in the relative conference utility of the sequential review 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 review mechanism while normalizing the baseline U_c^p to 0 and the upper bound U_c^i to 1. As shown in Figure 2, the sequential review 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. 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. Furthermore, we observe that the sequential review 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 harm the conference quality. Therefore, the sequential review mechanism that rejects lower-quality papers without reviewing them becomes more beneficial compared with the parallel review 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 review mechanism are rejected by the sequential review mechanism, which enlarges the gap.

3. Reviews are noisier. In this case, the sequential review mechanism benefits the conference's 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 review mechanism does not utilize.
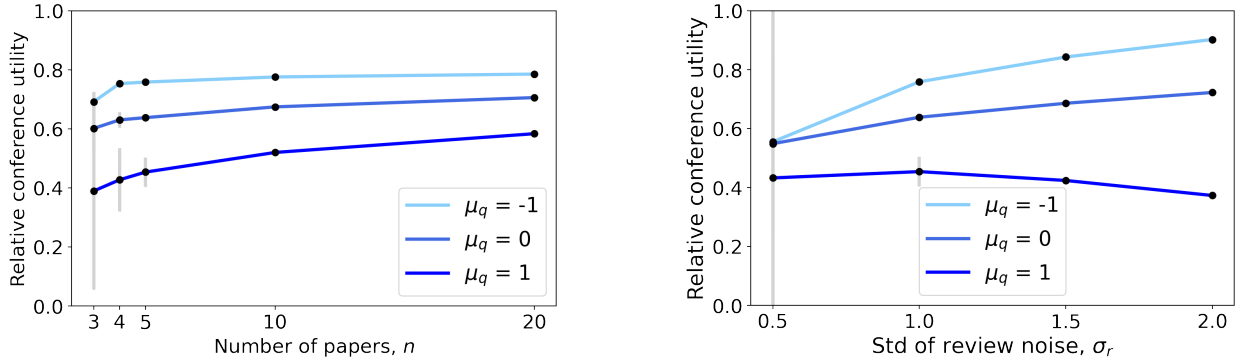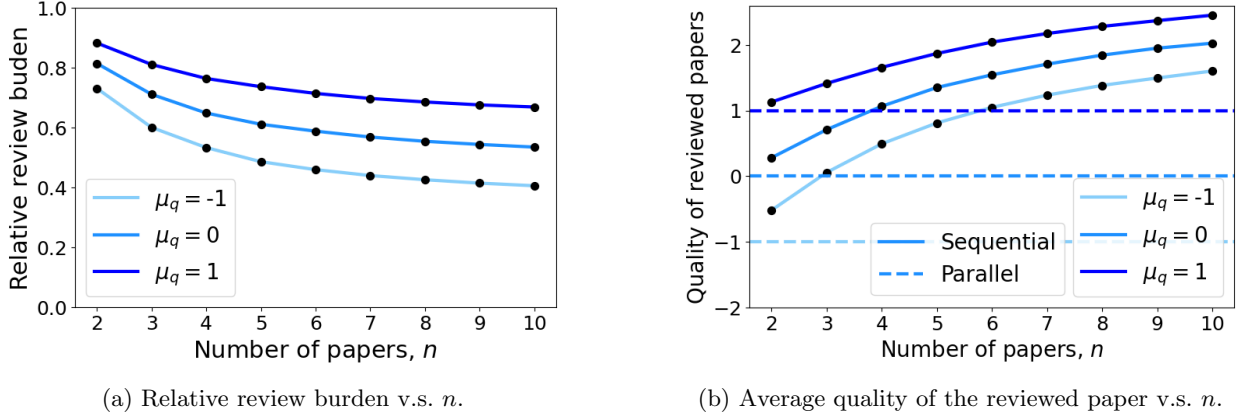

Figure 2: The relative conference utility under different parameter settings. Unless otherwise specified, the default parameter setting is $\varphi^G = (n = 5, \mu_q = -1, \sigma_q = 2, \sigma_r = 1)$.

Review burden. Here, we study how many reviews can be saved using a sequential review 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 review mechanism is thus $B^p = n$, while the review burden of a sequential review 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 imply that the sequential review mechanism can save more reviews compared with the parallel review mechanism without harming the conference utility.

Figure 3 (a) shows the effectiveness of the sequential review mechanism in reducing the review burden while Fig. 3 (b) presents the ability of the sequential review mechanism to improve the average quality of the reviewed papers. Specifically, we find that the sequential review 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 in line with our discussions on the conference utility. Notably, even when the author has only two papers, the sequential review mechanism can still reduce the review burden by 10-30% depending on the prior.

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

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Figure 3 (b), we observe that the sequential review mechanism can significantly improve the average quality of the reviewed papers, as low-quality papers that are ranked at the bottom are more likely to be rejected without review. In reality, 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. However, this is not explicitly captured by our model, which thus likely underestimates the improvement using a sequential review mechanism.

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

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

Figure 3: 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 adequately modeled by the previously discussed Gaussian noise model. First, review scores are integers, not continuous real values. Second, each paper has multiple independent review scores, rather than a single score. To incorporate these distinctions, we present a more fine-grained model, wherein the review score is characterized by a softmax function. Furthermore, in this section, we optimize the mechanisms for the entire population, rather than an individual agent, based on the empirical quality distribution estimated from real data.

5.3.1 Model and Experiment Setup

The parameters $(\pi_n, k, \mu_q, \sigma_q, t_r)$ defines a *softmax review setting*. Authors are ex-ante homogeneous. The pdf of the distribution of the number of papers an author has is denoted as $\pi_n(\cdot) : \mathbb{N}_+ \to [0, 1]$. No matter how many papers n_i author i has, the qualities of the papers are generated by n_i i.i.d. samples from the same Gaussian paper quality distribution $\mathcal{N}(\mu_q, \sigma_q)$. Then, conditioned on the quality q of a paper, the conference draws k i.i.d. review scores from softmax distribution:

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

where t_r is a temperature parameter which models the noisiness of the reviews, and $\mathcal{S}$, a finite set of integers, is the set of all possible review scores.

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 is computationally difficult.

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We use real review datasets to fit the model, where a key challenge is how to deal with the coauthorship problem. Our solution is to assign every paper to one of its authors and only simulate and use the ranking information from that author. This reduces the multi-author problem to the single-author problem which can be solved by our method. Details of the model-fitting procedure are shown as follows.

- First, we want to estimate π_n. We construct an author-paper mapping from the dataset that maps each author to the set of papers he/she submits. Then, the following procedure is iterated until all papers are assigned with one author:

  1) Greedily select the author with the largest number of papers from the current author-paper mapping, employing random tie-breaking if necessary.
  2) Assign those papers to the selected author in the previous step.
  3) Remove the author and his/her papers from the author-paper mapping.

  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 now often soliciting four reviews per paper, we set $k = 3$ (the second most common choice) due to computational considerations.

- We use the average review scores as the true qualities of papers so that μ_q and σ_q can be straightforwardly estimated.

- Finally, t_r can be learned using an MAP algorithm [24].

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 (withdrawn papers are excluded from our analysis), 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 a larger number of papers. Figure 4 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 time and the fraction of authors with more than 5 papers significantly increases in 2023.

5.3.3 Results

Figure 5 illustrates the relative review burden (as defined in Section 5.2.2) of the sequential review mechanism. Recall that the smaller the relative review burden is, the more reviews can be saved by implementing the sequential review mechanism while ensuring an equivalent conference utility to that of the parallel review mechanism. Our results indicate that over 20% of the review burden can be saved under this real-data estimated model. Moreover, the relative review burden decreases from 2021 to 2023 as more and more authors have more than one paper which enlarges the effect of the sequential review mechanism.
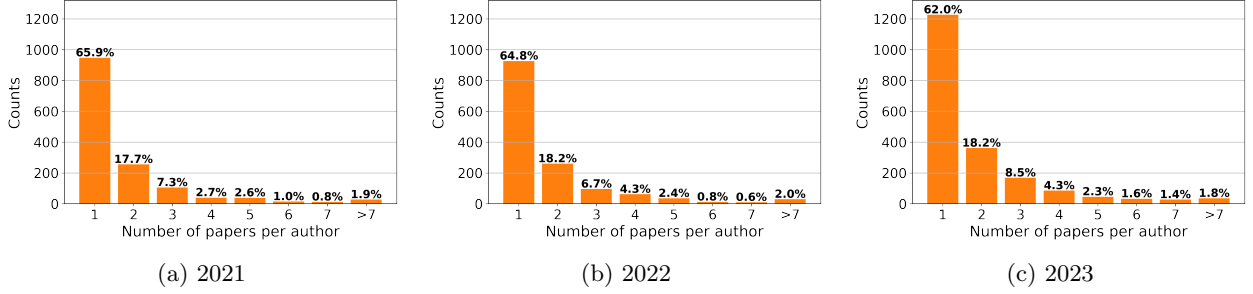
Figure 4: Empirical distributions of the number of papers each author has for ICLR 2021-2023. Papers with multiple authors are attributed to the author with the largest number of papers.
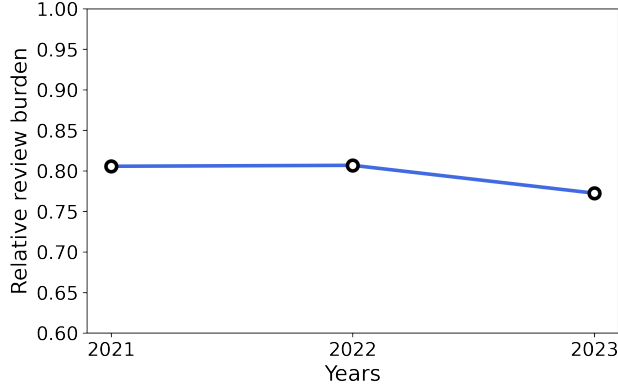

Figure 5: Relative review burden of the threshold sequential review mechanism for ICLR 2021-2023.

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 a higher probability of being 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 each with a lower quality?

We examine the power of the sequential review mechanism in addressing this problem. Using an economic concept called the *marginal rate of substitution* (MRS), we show that authors always have a stronger willingness to write more high-quality papers and less low-quality papers under the sequential review mechanism compared with the parallel review 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 7. *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.*

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$MRS_{h,l}$ 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.

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

The proof is deferred to Appendix C.1. Intuitively, the lemma follows because the sequential review mechanism applies an exponential discount on the utilities contributed by the bottom-ranked, low-quality papers. As a result, the ratio between the marginal utility of writing a high-quality paper compared to a low-quality paper is greater under the sequential review mechanism than under the parallel review mechanism. We further note (without formal proof) that this intuition can be straightforwardly generalized to any truthful sequential review mechanism, as long as the review policy P_{rev} is monotone in paper quality.

Now, we show that a higher $MRS_{h,l}$ implies a stronger preference of writing more high-quality papers over low-quality papers. Let $U_a^s(n_h, n_l)$ and $U_a^p(n_h, n_l)$ be the expected utility of writing n_h high-quality papers and n_l low-quality papers under the standard sequential review mechanism and the parallel review mechanism respectively.

Theorem 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 $U_a^p(n_h', n_l) \geq U_a^p(n_h, n_l')$, $U_a^s(n_h', n_l) \geq U_a^s(n_h, n_l')$. Furthermore, there exist settings where $U_a^s(n_h', n_l) \geq U_a^s(n_h, n_l')$, but $U_a^p(n_h', n_l) < U_a^p(n_h, n_l')$.*

In words, Theorem 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 review mechanism, she is always willing to do so under the sequential review 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 review mechanism, but she is willing to choose writing more high-quality papers under the sequential review 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 8. *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 the reward of writing one more paper with acceptance probability p_i and the gain of the 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 C.3.

Lemma 6.3. *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 6.3, we generalize the main result, i.e. Theorem 6.2, from the binary effort setting to the finite effort setting. We defer the proof to Appendix C.3.

Theorem 6.4. *For any $1 \leq i < j \leq m$, 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 $U_a^p(n_i', n_j) \geq U_a^p(n_i, n_j')$, $U_a^s(n_i', n_j) \geq U_a^s(n_i, n_j')$. Furthermore, there exist settings where $U_a^s(n_i', n_j) \geq U_a^s(n_i, n_j')$, but $U_a^p(n_i', n_j) < U_a^p(n_i, n_j')$.*

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7   Limitations, Discussions, and Future Work

Here, we discuss the limitations of our analysis and how to use our insights to implement the proposed method in practice.

Coauthorship   The first limitation of our model is the assumption that every paper has only one author. However, in practice, coauthorship is an inevitable issue for the implementation of our method. A straightforward solution is to assign each paper to one of its authors and only solicit the ranking information from that author.

Various strategies can be employed for the paper-to-author assignment. For example, we can assign each paper only to its first author, driven by the notion that the first author may possess the most accurate insight into the paper's quality. However, this assignment weakens the power of the sequential review mechanism, as many first authors have fewer than three submissions to their name. Another approach is to assign each paper to the author with the largest number of submissions, as discussed in Section 5.3.1. In a recent work [29] that generalizes the isotonic mechanism to the multi-author setting, it is shown that this greedy assignment is truthful and has appealing robust approximation guarantees for the isotonic mechanism.

The trade-off between review burden and delay   Another practical concern is the delay in the review process. As presented, the mechanism requires n phases where n is the maximum number of papers owned by any single author. Within phase i, the i'th ranked paper of every author (if any) is simultaneously reviewed and an acceptance/rejection decision is promptly reached. Then, phase $i+1$ can only start after the reviews of phase i are in. Intuitively, this implementation significantly delays the review process but minimizes the review burden. At the other extreme, the conference could only have one review phase, where all the papers are simultaneously reviewed. Then, for each author, the acceptance/rejection decision is made in sequence based on the sequential review mechanism. Note that any paper that should not have been reviewed according to the mechanism could be rejected, its reviews simply ignored. Here the review burden is not decreased at all (though, as we saw, the conference quality may still be increased).

Intuitively, varying the number of review phases can trade off the review burden and the delay in the review process. In reality, perhaps a two-phase implementation of the sequential review mechanism can achieve a desirable trade-off. For example, some conferences such as AAAI and EC are already implementing a two-phase review mechanism: all papers are assigned with two reviews in the first phase and only papers with at least one good review will enter the second phase where two more reviews are assigned. We can integrate the sequential review mechanism with this framework. In the first phase, the top $\max(3, \lfloor n_i/2 \rfloor)$ ranked papers of each author with n_i papers are assigned with two reviews, and the remaining papers are assigned with one review (so that no paper is rejected without reviewing). Then, any paper with two negative reviews and those papers that are ranked lower than them by authors are rejected with no further review. The surviving papers enter the second phase, wherein they are assigned additional reviews to reach a total of four reviews each, and a sequential review mechanism is implemented. The advantage of using the sequential review mechanism to assist peer review is that the author's information can be leveraged to prioritize the reviewing of high-quality papers.

Broader Applications   Although our paper primarily focuses on the conference peer review problem, our insights can be potentially applied to address general principal-agent problems with decisions rely on noisy evaluations. For example, consider content-recommendation platforms where content producers are entrusted with the ability to highlight their videos or products for priority recommendations. While the original intent is to leverage producer signals to promote high-quality content, strategic producers may game this mechanism by prioritizing utility-maximizing content, such as advertisements, which may not necessarily align with user preferences. Our proposed sequential review mechanism offers a solution to this incentive issue by soliciting content rankings from producers and penalizing lower-ranked items with reduced user recommendations, particularly if the top-ranked items receive unfavorable user feedback. Additional applications suitable for our method include employee recruitment and second-hand product trading markets, where principals can benefit from agents' ranking information.

8   Conclusion and Future Work

In the setting of (conference) peer review, we study the problem of how to elicit honest information from authors, who themselves are interested in the outcome. Our main contribution is a framework for designing mechanisms capable of eliciting quality rankings from authors with multiple submissions. Compared with the previous isotonic mechanism, our mechanism works within a more realistic utility model for peer review and addresses a key incentive issue that plagued the previous method. 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.

The noisy conference peer review has been the source of frequent complains and concerns for authors over the years. We believe that properly utilizing author information has the potential to improve conference decision-making and mitigate the dilemma of peer review. Nonetheless, our work leaves room for further exploration. The largest space of this is in optimally integrating the sequential review mechanism with a practical multi-phase review mechanism. In particular, in order to optimally trade off the conference utility, review burden and some definition of fairness, how many review phases should the conference have? Furthermore, within each review phase, how many papers from each author should be reviewed and how many reviews should be solicited for each paper?

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A The Isotonic Mechanism

For self-containedness, we briefly introduce the isotonic mechanism and why it is not truthful when authors' utility is not convex of the review score.

Consider the model in Section 3. The isotonic mechanism takes the input of a sequence of review scores $\boldsymbol{r}$ and a ranking π reported by the author, and outputs the modified review scores $\hat{\boldsymbol{r}}$ by solving the following convex program:

$$\min_{\hat{\boldsymbol{r}}} \quad \frac{1}{2}||\hat{\boldsymbol{r}} - \boldsymbol{r}||^2$$
$$s.t. \quad \hat{r}_{\pi(1)} \geq \hat{r}_{\pi(2)} \geq \cdots \geq \hat{r}_{\pi(n)}.$$

That is, the isotonic mechanism projects the raw review scores onto the feasible region $\{\boldsymbol{r} : \hat{r}_{\pi(1)} \geq \hat{r}_{\pi(2)} \geq \cdots \geq \hat{r}_{\pi(n)}\}$ and forms the new review scores $\hat{\boldsymbol{r}}$.

Now, we provide an example of why the isotonic mechanism experiences incentive issues when the convex utility assumption is violated.

Example A.1. *Suppose an author has three papers a, b and c, whose qualities are $q_a = 2, q_b = -1, q_c = -1$. The author aims to maximize the expected number of accepted papers. Suppose the review score is rather accurate such that $r_i = q_i$ for $i \in [a, b, c]$, and the conference has an acceptance threshold at 0. Therefore, if the author reports truthfully, the modified review score $\hat{r}_i$ agrees with the true quality, resulting in the rejection of both paper b and paper c. However, if the author ranks paper a in third place, resulting in scores $\hat{r}_a = \hat{r}_b = \hat{r}_c = 0$, which means all three papers will be accepted. This is part of a more general phenomenon where a high paper can push up the ratings of lower papers that are ranked ahead of it, and extends to the case where review scores are noisy. Furthermore, note that in this example the conference is even better utilizing the parallel review mechanism, resulting a utility of 2.*

B Proofs in Section 4

B.1 Ttuthfulness of the Memoryless Coin-flip Mechanism

Proof of Proposition 4.2. By Theorem 4.1, it is sufficient to show that 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, $P_{\text{rev}}^{cf}((\alpha, \gamma)) = 1 > P_{\text{rev}}^{cf}(\omega) = 0$ for any $(\alpha, \gamma) \neq \omega$.

Next, we show that $\boldsymbol{\mu}^{cf}$ is monotone. This includes three steps. For simplicity, we omit the superscript within this proof.

1. We first show that $\boldsymbol{\mu}$ is monotone in score. Consider any review state $(\alpha_i, \gamma_i) \neq \omega$ and any pair of review scores $r' \geq r$. Because any state other than ω has the same order, it is sufficient to show that $\mu(\omega|(\alpha_i, \gamma_i), r') \leq \mu(\omega|(\alpha_i, \gamma_i), r)$. This holds because when P_{acc} is monotone and ρ is increasing, $\mu(\omega|(\alpha_i, \gamma_i), r') = (1 - P_{\text{acc}}(r'))(1 - \rho(r')) \leq (1 - P_{\text{acc}}(r))((1 - \rho(r)) = \mu(\omega|(\alpha_i, \gamma_i), r)$.

2. Then, we show that $\boldsymbol{\mu}$ is monotone in state. Fix a review score r and consider any pair of states $(\alpha', \gamma') \succeq (\alpha, \gamma)$. We want to show that $\mu(\omega|(\alpha', \gamma'), r) \leq \mu(\omega|(\alpha, \gamma), r)$. There are two cases. First, if $(\alpha, \gamma) = \omega$, the statement trivially holds. Second, if $(\alpha', \gamma') \sim (\alpha, \gamma) \succ \omega$, $\mu((\alpha', \gamma'), r) = \mu((\alpha, \gamma), r)$ because the review process is memoryless. In any case, conditioned on the same score, a better state leads to a dominating state distribution in the next round.

3. Finally, we show that $\boldsymbol{\mu}$ is monotone of ordering. Let $\tilde{\mu}_\omega(r_1, r_2|\phi)$ be the probability of reaching the termination state ω in round $i + 2$, given the review state to be ϕ in round i and review scores to be r_1 and r_2 in round i and $i + 1$ respectively. Now, consider any review state $\phi \neq \omega$. The following property of the memoryless coin-flip mechanism is the key to the proof.

   Lemma B.1. *For any ϕ and $r' \geq r$, $\tilde{\mu}_\omega^{cf}(r', r|\phi) = \tilde{\mu}_\omega^{cf}(r, r'|\phi)$.*

The lemma suggests that the state distribution after flipping the ordering of two adjacent review scores remains the same under the momeryless coin-flip mechanism We defer the proof of the lemma and present the proof of the theorem first, which has two parts.

(a) By Lemma B.1, $\tilde{\mu}_\omega(r', r|\phi) = \tilde{\mu}_\omega(r, r'|\phi)$.

(b) Consider four review scores $r_1 \leq r_2 \leq r_3 \leq r_4$. Let $X \sim \tilde{\mu}(r_4, r_1|\phi)$, $Y \sim \tilde{\mu}(r_2, r_3|\phi)$, $X' \sim \tilde{\mu}(r_1, r_4|\phi)$ and $Y' \sim \tilde{\mu}(r_3, r_2|\phi)$. Let $\bar{Z} = \max(X, Y)$, $\underline{Z} = \min(X, Y)$, $\bar{Z}' = \max(X', Y')$, $\underline{Z}' = \min(X', Y')$. By Lemma B.1, $\bar{Z}$ and $\bar{Z}'$ have the same distribution, as do $\underline{Z}$ and $\underline{Z}'$. Therefore, $(\bar{Z}, \underline{Z})$ has the same distribution as $(\bar{Z}', \underline{Z}')$.

$\square$

Now, we prove the Lemma.

Proof of Lemma B.1. First note that if $\phi = \omega$, the lemma trivially holds. Let $A(r) = (1 - P_{\mathrm{acc}}(r))(1 - \rho(r))$ be the probability of termination in the round where the state is not ω and the paper has a review score r.

$$\begin{aligned}
\tilde{\mu}_\omega^{cf}(r', r|\phi) &= A(r') + (1 - A(r'))A(r) \\
&= A(r) + (1 - A(r))A(r') \\
&= \tilde{\mu}_\omega^{cf}(r, r'|\phi).
\end{aligned}$$

$\square$

B.2 Ttuthfulness of the Credit Pool Mechanism

Proof of Proposition 4.3. By Theorem 4.1, it is sufficient to show that P_{rev}^{cp} 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 $P_{\mathrm{rev}}^{cp}(B) = 1$, $P_{\mathrm{rev}}^{cp}(B') = 1$.

Now, we show that the transition probability mapping is monotone. For simplicity, we omit the superscript.

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

2. Then, we show that $\boldsymbol{\mu}$ is monotone in state. Fixing a review score r, 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}.

3. Finally, we show that $\boldsymbol{\mu}$ is monotone in ordering, which has the following two steps.

   (a) First, we show that if two review scores in adjacent rounds are swapped, it is always better to put the higher score ahead. Consider any state $B \geq$ and any pair of review scores $r' \geq r$. Because the transition mapping is deterministic, if $B + \beta(r) < 0$, we have $\tilde{\mu}(r, r'|B) = \omega$ with probability 1, and thus is trivially dominated by $\tilde{\mu}(r', r|B)$. If $B + \beta(r) > 0$, $\tilde{\mu}(r', r|B) = \tilde{\mu}(r, r'|B) = B + \beta(r') + \beta(r)$ with probability 1. In any case, ranking the higher review score ahead results in a better review state.

   (b) Suppose $r_1 \leq r_2 \leq r_3 \leq r_4$ and $r_1 + r_4 = r_2 + r_3$. For any review state B_i in round i, we want to reason about the review states after two rounds under different pairs of review scores. Let $\bar{Z} = \max(\tilde{\mu}(r_3, r_2|B), \tilde{\mu}(r_1, r_4|B))$, $\underline{Z} = \min(\tilde{\mu}(r_3, r_2|B), \tilde{\mu}(r_1, r_4|B))$, $\bar{Z}' = \max(\tilde{\mu}(r_4, r_1|B), \tilde{\mu}(r_2, r_3|B))$ and $\underline{Z}' = \min(\tilde{\mu}(r_4, r_1|B), \tilde{\mu}(r_2, r_3|B))$. We want to show that $\bar{Z}' \geq \bar{Z}$ and $\underline{Z}' \geq \underline{Z}$. There are four cases.

      i. $B + \beta(r_1) < 0$ and $B + \beta(r_2) \geq 0$. In this case, because β is convex, $\bar{Z}' = B + \beta(r_1) + \beta(r_4) \geq B + \beta(r_2) + \beta(r_3) = \bar{Z}$ and $\underline{Z}' = B + \beta(r_2) + \beta(r_3) > \omega = \underline{Z}$.

      ii. $B + \beta(r_2) < 0$ and $B + \beta(r_3) \geq 0$. In this case, because β is convex, $\bar{Z}' = B + \beta(r_1) + \beta(r_4) \geq B + \beta(r_2) + \beta(r_3) = \bar{Z}$ and $\underline{Z}' = \omega = \underline{Z}$.

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iii. $B + \beta(r_3) < 0$ and $B + \beta(r_4) \geq 0$. In this case, $\bar{Z}' = B + \beta(r_1) + \beta(r_4) \geq \omega = \bar{Z}$ and $\underline{Z}' = \omega = \underline{Z}$.

iv. $B + \beta(r_4) < 0$. In this case, all the review processes terminates in round i, satisfying the monotonicity in ordering.

$\square$

C   Proofs in Section 6

C.1   Marginal Rate of Substitution in the Binary Effort Setting

Proofs in Lemma 6.1. 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 review 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 review 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. $\square$

C.2   Proof of Proposition 6.2

Proof. The proof follows by rewriting the expected reward $U_a(n_h', n_l)$ using $U_a(n_h, n_l)$ and $U_a(n_h + 1, n_l)$, and rewriting $U_a(n_h, n_l')$ using $U_a(n_h, n_l)$ and $U_a(n_h, n_l + 1)$. Then, we can prove the theorem using the property of the marginal rate of substitution shown in Lemma 6.1.

Parallel review mechanism. We first rewrite the expected reward for the parallel review mechanism. Note that under the parallel review mechanism, the marginal reward of writing one paper depends only on the quality of that paper. That is, $U_a^p(n_h + 1, n_l) - U_a^p(n_h, n_l) = p_h u_h$ for any n_h, n_l. Therefore

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

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

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

Sequential review mechanism. The analysis for the sequential review mechanism is a little more complicated. For simplicity, let $\lambda_h(k) = \frac{U_a^s(n_h + k, n_l) - U_a^s(n_h + k - 1, n_l)}{U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l)}$ for any $k \geq 1$. Analogously, let $\lambda_l(k) = \frac{U_a^s(n_h, n_l + k) - U_a^s(n_h, n_l + k - 1)}{U_a^s(n_h, n_l + 1) - U_a^s(n_h, n_l)}$. Note that both $\lambda_h(k)$ and $\lambda_l(k)$ are positive for any k. Using the same recipe as the analysis of the parallel review mechanism,

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

Similarly,

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

The following lemma simplifies λ_h and λ_l.

Lemma C.1. $\lambda_h(k) = p_h^{k-1}$ and $\lambda_l(k) = p_l^{k-1}$.

We want to show that whenever Eq. (3) holds, the following inequality holds.

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

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 because $p_h > p_l$, the right-hand-side of Eq. (4) is smaller than 1. Therefore, we can focus on the case where $n_h' - n_h < n_l' - n_l$.

By Lemma 6.1, we know that $MRS_{h,l}^s(n_h, n_l) \geq MRS_{h,l}^p(n_h, n_l)$. Therefore, to show that Eq. (4) holds whenever Eq. (3) holds, it is sufficient to show that

$$\frac{n_l' - n_l}{n_h' - n_h} \geq \frac{\sum_{k=1}^{n_l' - n_l} p_l^{k-1}}{\sum_{k=1}^{n_h' - n_h} p_h^{k-1}}$$
$$\Leftrightarrow \quad \frac{\sum_{k=1}^{n_h' - n_h} p_h^{k-1}}{n_h' - n_h} \geq \frac{\sum_{k=1}^{n_l' - n_l} p_l^{k-1}}{n_l' - n_l}. \tag{5}$$

Equation (5) holds because

$$\frac{\sum_{k=1}^{n'_h - n_h} p_h^{k-1}}{n'_h - n_h} \geq \frac{\sum_{k=1}^{n'_h - n_h} p_l^{k-1}}{n'_h - n_h} \qquad \text{(because } p_h > p_l\text{)}$$

$$\geq \frac{\sum_{k=1}^{n'_l - n_l} p_l^{k-1}}{n'_l - n_l}. \qquad \text{(because } n'_h - n_h < n'_l - n_l\text{)}$$

This completes the proof of the first part of the theorem.

To prove the second part of the theorem, we only have to find a counter example. Suppose $p_h = 1$, $p_l = 0.5$, and let $n_h = n_l = 0$, $n'_h = 1$ and $n'_l = 3$. In this example, $U_a^s(n'_h, n_l) = 1$ and $U_a^s(n_h, n'_l) = 0.5 + 0.5^2 + 0.5^3 = 0.875$, implying that $U_a^s(n'_h, n_l) > U_a^s(n_h, n'_l)$. However, $U_a^p(n'_h, n_l) = 1$ and $U_a^p(n_h, n'_l) = 1.5$, implying that $U_a^p(n'_h, n_l) < U_a^s(n_h, n'_l)$. This completes the proof of Theorem 6.2. □

Now, we prove Lemma C.1.

Proof of Lemma C.1. We present the proof for λ_h while the proof for λ_l is analogous. By definition

$$\lambda_h(k) = \frac{U_a^s(n_h + k, n_l) - U_a^s(n_h + k - 1, n_l)}{U_a^s(n_h + 1, n_l) - U_a^s(n_h, n_l)}$$

$$= \frac{p_h^{n_h + k - 1}\left(p_h u_h - \frac{1-p_h}{1-p_l} p_l(1 - p_l^{n_l})u_l\right)}{p_h^{n_h}\left(p_h u_h - \frac{1-p_h}{1-p_l} p_l(1 - p_l^{n_l})u_l\right)} \qquad \text{(by Eq. (1))}$$

$$= p_h^{k-1}. \tag{6}$$

□

C.3 Generalizations to the Finite Effort Setting

We first generalize the key property of marginal rate of substitution to the finite effort setting

Proof of Lemma 6.3. 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 review mechanism, it is easy to show

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

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

$$U_a^s(\boldsymbol{n}) = \sum_{l \in [|\boldsymbol{n}|]} \Pr(\text{paper } 1, \ldots, l \text{ are accepted}) \cdot <\text{the reward of paper } l >$$

$$= S_1 u_1 + \Gamma_1 S_2 u_2 + \cdots + \Gamma_{m-1} S_m u_m$$

For simplicity, let $Z_i = \sum_{l=i}^m \Gamma_{l-1} S_l u_l$ for any $2 \leq i \leq m$ and let $Z_1 = S_1 u_1 + \sum_{l=2}^m \Gamma_{l-1} S_l u_l$. 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 $\boldsymbol{n}' = (n_1, \ldots, n_{i-1}, n_i + 1, \ldots, n_m)$ to denote the new vector of number of papers.

$$U_a^s(\boldsymbol{n}') = S_1 u_1 + \Gamma_1 S_2 u_2 + \cdots + \Gamma_{i-1} S_i u_i + \Gamma_i p_i u_i + p_i\left(\Gamma_i S_{i+1} u_{i+1} + \cdots + \Gamma_{m-1} S_m u_m\right)$$

$$= Z_1 - Z_{i+1} + \Gamma_i p_i u_i + p_i Z_{i+1}$$

$$= Z_1 - (1 - p_i)Z_{i+1} + \Gamma_i p_i u_i.$$

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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,

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

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

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

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 $u_i \geq u_j$, $\frac{1-p_i}{p_i u_i} < \frac{1-p_j}{p_j u_j}$.

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

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

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

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.

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

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

Then, we generalize Lemma C.1 to the finite effort setting respectively. If Lemma C.1 can be generalized, the proof of Theorem 6.2 straightforwardly generalizes because we can 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 $\lambda_i(k) = \frac{U_a^s(\boldsymbol{n}_i^{(k)}) - U_a^s(\boldsymbol{n}_i^{(k-1)})}{U_a^s(\boldsymbol{n}_i^{(1)}) - U_a^s(\boldsymbol{n}_i^{(0)})}$, where $\boldsymbol{n}_i^{(k)} = (n_1, \ldots, n_{i-1}, n_i + k, \ldots, n_m)$.

Lemma C.2. $\lambda_i(k) = p_i^{k-1}$.

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 $U_a^s(\boldsymbol{n}_i^{(1)}) - U_a^s(\boldsymbol{n}_i^{(0)}) = \Gamma_i p_i u_i - (1 - p_i) Z_{i+1}$. 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. $U_a^s(\boldsymbol{n}_i^{(k)}) - U_a^s(\boldsymbol{n}_i^{(k-1)}) = p_i^{k-1} \cdot \left(U_a^s(\boldsymbol{n}_i^{(1)}) - U_a^s(\boldsymbol{n}_i^{(0)}) \right)$. This implies that $\lambda_i(k) = p_i^{k-1}$. $\square$