On Strategyproof Conference Peer Review

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Abstract

We consider peer review in a conference setting where there is typically an overlap between the set of reviewers and the set of authors. This overlap can incentivize strategic reviews to influence the final ranking of one's own papers. In this work, we address this problem through the lens of social choice, and present a theoretical framework for strategyproof and efficient peer review. We first present and analyze an algorithm for reviewer-assignment and aggregation that guarantees strategyproofness and a natural efficiency property called unanimity, when the authorship graph satisfies a simple property. Our algorithm is based on the so-called partitioning method, and can be thought as a generalization of this method to conference peer review settings. We then empirically show that the requisite property on the authorship graph is indeed satisfied in the ICLR-17 submission data, and further demonstrate a simple trick to make the partitioning method more practically appealing for conference peer review. Finally, we complement our positive results with negative theoretical results where we prove that under various ways of strengthening the requirements, it is impossible for any algorithm to be strategyproof and efficient.

1 Introduction

Peer review serves as an effective solution for quality evaluation in reviewing processes, especially in academic paper review (Dörfler et al., 2017; Shah et al., 2017) and massive open online courses (MOOCs) (Díez Peláez et al., 2013; Piech et al., 2013; Shah et al., 2013). However, despite its scalability, competitive peer review faces the serious challenge of being vulnerable to strategic manipulations (Anderson et al., 2007; Thurner and Hanel, 2011; Alon et al., 2011; Kurokawa et al., 2015; Kahng et al., 2017). By giving lower scores to competitive submissions, reviewers may be able to increase the chance that their own submissions get accepted. For instance, a recent experimental study (Balietti et al., 2016) on peer review of art, published in the Proceedings of the National Academy of Sciences (USA), concludes

"...competition incentivizes reviewers to behave strategically, which reduces the fairness of evaluations and the consensus among referees."

As noted by Thurner and Hanel (2011), even a small number of selfish, strategic reviewers can drastically reduce the quality of scientific standard. In the context of conference peer review, Langford (2008) calls academia inherently adversarial:

"It explains why your paper was rejected based on poor logic. The reviewer wasn't concerned with research quality, but rather with rejecting a competitor."

Langford states that a number of people agree with this viewpoint. Thus the importance of peer review in academia and its considerable influence over the careers of researchers significantly underscores the need to design peer review systems that are insulated from strategic manipulations.

In this work, we present a higher-level framework to address the problem of strategic behavior in conference peer review. We present an informal description of the framework here and formalize it later in

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the paper. The problem setting comprises a number of submitted papers and a number of reviewers. We are given a graph which we term as the "conflict graph". The conflict graph is a bipartite graph with the reviewers and papers as the two partitions of vertices, and an edge between any reviewer and paper if that reviewer has a conflict with that paper. Conflicts may arise due to authorship (the reviewer is an author of the paper) or other reasons such as institutional conflicts etc. Given this conflict graph, there are two design steps in the peer review procedure: (i) assigning each paper to a subset of reviewers for review, and (ii) aggregating the reviews provided by the reviewers to give a final evaluation of each paper. Under our framework, the goal is to design these two steps of the peer-review procedure that satisfies two properties – strategyproofness and efficiency.

The first goal is to design peer-review procedures that are strategyproof with respect to the given conflict graph. A peer-review procedure is said to be strategyproof if no reviewer can change the outcome for any papers with which she/he has a conflict. This definition is formalized later in the paper. Strategyproofness not only reassures the authors that the review process is fair, but also ensures that the authors receive proper feedback for their work. We note that a strategyproof peer-review procedure alone is inadequate with respect to any practical requirements – simply giving out a fixed, arbitrary evaluation makes the peer-review procedure strategyproof.

Consequently, in addition to requiring strategyproofness, our framework measures the peer-review procedure with another yardstick – that of efficiency. Informally, the efficiency of a peer-review procedure is a measurement of how well the final outcome reflects reviewers' assessments of the quality of the submissions, or a measurement of the accuracy in terms of the final acceptance decisions. There are several ways to define efficiency – from a social choice perspective or a statistical perspective. In this paper, we consider efficiency in terms of the notion of unanimity in social choice theory: an agreement among all reviewers must be reflected in the final aggregation.

In addition to the conceptual contribution based on this framework, we make several technical contributions towards this important problem. We first design a peer review algorithm which theoretically guarantees strategyproofness along with a notion of efficiency that we term "group unanimity". Our result requires only a mild assumption on the conflict graph of the peer-review design task. We show this assumption indeed holds true in practice via an empirical analysis of the submissions made to the 2017 International Conference on Learning Representations (ICLR-17) conference¹. Our algorithm is based on the popular partitioning method, and our positive results can be regarded as generalizing it to the setting of conference peer review. We further demonstrate a simple trick to make the partitioning method more practically appealing for conference peer review and validate it on the ICLR-17 data.

We then complement our positive results with negative results showing that one cannot expect to meet requirements that are much stronger than that provided by our algorithm. In particular, we show that under mild assumptions on the authorships, there is no algorithm that can be both strategyproof and "pairwise unanimous". Pairwise unanimity is a stronger notion of efficiency than group unanimity, and is also known as Pareto efficiency in the literature of social choice (Brandt et al., 2016). We show that our negative result continues to hold even when the notion of strategyproofness is made extremely weak. We then provide a conjecture and insightful results on the impossibility when the assignment satisfies a simple "connectivity" condition. Finally, we connect back to the traditional settings in social choice theory, and show an impossibility when every reviewer reviews every paper. These negative results highlight the intrinsic hardness in designing strategyproof conference review systems.

2 Related Work

As early as in the 1970s, Gibbard and Satterthwaite had already been aware of the importance of a healthy voting rule that is strategyproof in the setting of social choice (Gibbard, 1973; Satterthwaite, 1975). Nowadays, the fact that prominent peer review mechanisms such as the one used by the National Science Foundation (Hazelrigg, 2013) and the one for time allocation on telescope (Merrifield and Saari, 2009) are manipu-

¹https://openreview.net/group?id=ICLR.cc/2017/conference

lable has further called for strategyproof peer review mechanisms.

Our work is most closely related to a series of works on strategyproof peer selection (De Clippel et al., 2008; Alon et al., 2011; Holzman and Moulin, 2013; Fischer and Klimm, 2015; Kurokawa et al., 2015; Aziz et al., 2016; Kahng et al., 2017), where agents cannot benefit from misreporting their preferences over other agents.² De Clippel et al. (2008) consider strategyproof decision making under the setting where a divisible resource is shared among a set of agents. Later, Alon et al. (2011); Holzman and Moulin (2013) consider strategyproof peer approval voting where each agent nominates a subset of agents and the goal is to select one agent with large approvals. Alon et al. (2011) propose a randomized strategyproof mechanism using partitioning that achieves provable approximate guarantee to the deterministic but non-strategyproof mechanism that simply selects the agent with maximum approvals. Bousquet et al. (2014) and Fischer and Klimm (2015) further extended and analyzed this mechanism to provide an optimal approximate ratio in expectation. Although the first partitioning-based mechanism partitions all the voters into two disjoint subsets, this has been recently extended to k-partition by Kahng et al. (2017). In all these works, each agent is essentially required to evaluate all the other agents except herself. This is impractical for conference peer review, where each reviewer only has limited time and energy to review a small subset of submissions. In light of such constraints, Kurokawa et al. (2015) propose an impartial mechanism (Credible Subset) and provide associated approximation guarantees for a setting in which each agent is only required to review a few other agents. Credible Subset is a randomized mechanism that outputs a subset of k agents, but it has non-zero probability returns an empty set. Based on the work of De Clippel et al. (2008); Aziz et al. (2016) propose a mechanism for peer selection, termed as Dollar Partition, which is strategyproof and satisfies a natural monotonicity property. Empirically the authors showed that Dollar Partition outperforms Credible Subset consistently and in the worst case is better than partition-based approach. However, even if the target output size is k, Dollar Partition may return a subset of size strictly larger than k. Our positive results, specifically our Divide-and-Rank algorithm presented subsequently, borrows heavily from this line of literature. That said, our work addresses the application of conference peer review which is significantly more general and challenging as compared to the settings considered in past works.

Our setting of conference peer review is more challenging as compared to these past works as each reviewer may author multiple papers and moreover each paper may have multiple authors as reviewers. Specifically, the conflict graph under conference peer review is a general bipartite graph, where conflicts between reviewers and papers can arise not only because of authorships, but also advisor-advisee relationships, institutional conflicts, etc. In contrast, past works focus on applications of peer-grading and grant proposal review, and hence consider only one-to-one conflict graphs (that is, where every reviewer is conflicted with exactly one paper).

Apart from the most important difference mentioned above, there are a couple of other differences of this work as compared to some past works. In this paper we focus on ordinal preferences where each reviewer is asked to give a total ranking of the assigned papers, as opposed to providing numeric ratings. We do so inspired by past literature (Barnett, 2003; Stewart et al., 2005; Douceur, 2009; Tsukida and Gupta, 2011; Shah et al., 2013, 2016) which highlights the benefits of ordinal data in terms of avoiding biases and miscalibrations as well as allowing for a more direct comparison between papers. Secondly, while most previous mechanisms either output a single paper or a subset of papers, we require our mechanism to output a total ranking over all papers. We consider this requirement since this automated output in practice will be used by the program chairs as a guideline to make their decisions, and this more nuanced data comprising the ranking of the papers can be more useful towards this goal.

A number of other papers study various other aspects of conference peer review. The works Hartvigsen et al (1999); Charlin and Zemel (2013); Garg et al. (2010); Stelmakh et al. (2018) design algorithms for assigning reviewers to papers under various objectives, and these objectives and algorithms may in fact be used as alternative definitions of the objective of "efficiency" studied in the present paper. The papers Roos et al. (2011); Ge et al. (2013); Wang and Shah (2018) consider review settings where reviewers provide scores to

²Some past literature refers to this requirement as ensuring that agents are "impartial". However, the term "impartial" also has connotations on (possibly implicit) biases due to extraneous factors such as some features about the agents (Hojat et al., 2003). In this paper, we deliberately use the term "strategyproof" in order to make the scope of our contribution clear in that we do not address implicit biases.

each paper, with the aim of addressing the problems of biases and miscalibrations in these scores. Finally, experiments and empirical evaluations of conference peer reviews can be found in Lawrence and Cortes (2014); Mathieus (2008); Connolly et al. (2014); Shah et al. (2017); Tomkins et al. (2017).

3 Problem setting

In this section, we first give a brief introduction to the setting of our problem, and then introduce the notation used in the paper. At last, we formally define various concepts and properties to be discussed in the subsequent sections.

Modern review process is governed by four key steps: (i) a number of papers are submitted for review; (ii) each paper is assigned to a number of reviewers; (iii) reviewers provide their feedback on the papers they are reviewing; and (iv) the feedback from all reviewers is aggregated to make final decisions on the papers. Let m be the number of reviewers and n be the number of submitted papers. Define $\mathcal{R} := \{r_1, \ldots, r_m\}$ to be the set of m reviewers and $\mathcal{P} := \{p_1, \ldots, p_n\}$ to be the set of n submitted papers.

The review process must deal with a number of conflicts of interest. The most common form of conflict is the authorship conflict: a large number of reviewers are also authors of submitted papers. Additional sources of conflicts may include advisor-advisee relationships between reviewers and authors of papers, institutional conflicts, etc. To characterize conflicts of interest, we use a bipartite graph \mathcal{C} with vertices $(\mathcal{R}, \mathcal{P})$, where an edge is connected between a reviewer r and a paper p if there exists some conflict of interests between reviewer r and paper p. In this graph we omit the authors of papers who are not reviewers. Reviewers who do not have conflicts of interest with any paper are nodes with no edges. Given the set of submitted papers and reviewers, this graph is fixed and cannot be controlled. Note that the conflict graph \mathcal{C} defined above can be viewed as a generalization of the authorship graph in the previously-studied settings (Merrifield and Saari, 2009; Alon et al., 2011; Holzman and Moulin, 2013; Fischer and Klimm, 2015; Kurokawa et al., 2015; Aziz et al., 2016; Kahng et al., 2017) of peer grading and grant proposal review, where each reviewer (paper) is connected to at most one paper (reviewer).

The review process is modeled by a second bipartite graph \mathcal{G} , termed as review graph, that also has the reviewers and papers $(\mathcal{R}, \mathcal{P})$ as its vertices. This review graph has an edge between a reviewer and a paper if that reviewer reviews that paper. For every reviewer r_i $(i \in [m])$, we let $\mathcal{P}_i \subseteq \mathcal{P}$ denote the set of papers assigned to this reviewer for review, or in other words, the neighborhood of node r_i in the bipartite graph \mathcal{G} . The program chairs of the conference are free to choose this graph, but subject to certain constraints and preferences. To ensure balanced workloads across reviewers, we require that every reviewer is assigned at most μ papers for some integers $1 \leq \mu \leq n$. In other words, every node in \mathcal{R} has at most μ neighbors (in \mathcal{P}) in graph \mathcal{G} . Additionally, each paper must be reviewed by a certain minimum number of reviewers, and we denote this minimum number as λ . Thus every node in the set \mathcal{P} must have at least λ neighbors (in \mathcal{R}) in the graph \mathcal{G} . For any (directed or undirected) graph \mathcal{H} , we let the notation $E_{\mathcal{H}}$ denote the set of (directed or undirected, respectively) edges in graph \mathcal{H} .

At the end of the reviewing period, each reviewer provides a total ranking of the papers that she/he reviewed. For any set of papers $\mathcal{P}' \subseteq \mathcal{P}$, we let $\Pi(\mathcal{P}')$ denote the set of all permutations of papers in \mathcal{P}' . Furthermore, for any paper $p_j \in \mathcal{P}'$ and any permutation $\pi(\mathcal{P}') \in \Pi(\mathcal{P}')$, we let $\pi_j(\mathcal{P}')$ denote the position of paper p_j in the permutation $\pi(\mathcal{P}')$. At the end of the reviewing period, each reviewer r_i ($i \in [m]$) submits a total ranking $\pi^{(i)}(\mathcal{P}_i) \in \Pi(\mathcal{P}_i)$ of the papers in \mathcal{P}_i . We define a (partial) ranking profile $\pi := (\pi^{(1)}(\mathcal{P}_1), \ldots, \pi^{(m)}(\mathcal{P}_m))$ as the collection of rankings from all the reviewers. When the assignment $\mathcal{P}_1, \ldots, \mathcal{P}_m$ of papers to reviewers is fixed, we use the shorthand $(\pi^{(1)}, \ldots, \pi^{(m)})$ for profile π . For any subset of papers $\mathcal{P}' \subseteq \mathcal{P}$, we let $\pi_{\mathcal{P}'}$ denote the restriction of π to only the induced rankings on \mathcal{P}' . Finally, when the ranking under consideration is clear from context, we use the notation p > p' to say that paper p is ranked higher than paper p' in the ranking.

Under this framework, the goal is to jointly design: (a) a paper-reviewer assignment scheme, that is, edges of the graph \mathcal{G} , and (b) an associated review aggregation rule $f:\prod_{i=1}^m \Pi(\mathcal{P}_i) \to \Pi(\mathcal{P})$ which maps

³We use the standard notation $[\kappa]$ to represent the set $\{1,\ldots,\kappa\}$ for any positive integer κ .

from the ranking profile to an aggregate total ranking of all papers.⁴ For any aggregation function f, we let $f_j(\pi)$ be the position of paper p_j when the input to f is the profile π .

We consider two factors for designing the review process (\mathcal{G}, f) . The first factor is efficiency: the output ranking should reflect opinions of most reviewers. We capture this notion of efficiency by a function Φ takes a review graph and an aggregation rule as inputs and outputs a measure of efficiency (with higher values indicating a higher efficiency). This function may be chosen by the program chairs of the conference; we discuss some choices below which we use in this paper. The second factor we consider is strategyproofness: we want to make sure that no reviewer can benefit from mis-reporting her preferences. Then the goal is to solve the following optimization problem:

$$\begin{array}{ll} \underset{\mathcal{G},f}{\text{maximize}} & \Phi(\mathcal{G},f) \\ \text{subject to} & (\mathcal{G},f) \text{ is strategyproof with respect to } \mathcal{C}. \end{array}$$
 (1)

We denote the optimal value of (1) by $\operatorname{Opt}(\Phi, \mathcal{C})$. In what follows we define strategyproofness and efficiency that any conference review mechanism f should satisfy under our paper-review setting. Inspired by the theory of social choice, in this paper we define the notion of efficiency via two variants of "unanimity", and we also discuss two natural notions of strategyproofness. That said, we emphasize that the formulation in (1) is a general framework that can additionally incorporate other notions of efficiency such as statistical efficiency. For any choice of Φ under our framework, the goal is to maximize the efficiency of the review mechanism under the constraint that it should also be strategyproof.

3.1 Efficiency (unanimity)

In this paper, we consider efficiency of a peer-review process in terms of the notion of unanimity. Unanimity is one of the most prevalent and classic properties to measure the efficiency of a voting system in the theory of social choice (Fishburn, 2015).

At a colloquial level, unanimity states that when there is a common agreement among all reviewers, then the aggregation of their opinions must also respect this agreement. In this paper we discuss two kinds of unanimity, termed group unanimity (GU) and pairwise unanimity (PU). Both kinds of unanimity impose requirements on the aggregation function for any given reviewer assignment. Specifically, both notions of unanimity are represented by efficiency functions which are binary and set as 1 if the respective notion of unanimity is satisfied and 0 otherwise; we denote the efficiency function as Φ^{PU} when considering pairwise unanimity and as Φ^{GU} when considering group unanimity.

We first define group unanimity:

Definition 3.1 (Group Unanimity, GU). We define (\mathcal{G}, f) to be group unanimous (GU) if the following condition holds for every possible profile π . If there is a non-empty set of papers $\mathcal{P}' \subset \mathcal{P}$ such that every reviewer ranks the papers she reviewed from \mathcal{P}' higher than those she reviewed from $\mathcal{P} \setminus \mathcal{P}'$, then $f(\pi)$ must have $p_x > p_y$ for every pair of papers $p_x \in \mathcal{P}'$ and $p_y \in \mathcal{P} \setminus \mathcal{P}'$ such that at least one reviewer has reviewed both p_x and p_y . The efficiency objective $\Phi^{\mathrm{GU}}(\mathcal{G}, f) = 1$ if (\mathcal{G}, f) is group unanimous, and $\Phi^{\mathrm{GU}}(\mathcal{G}, f) = 0$ otherwise.

Intuitively, group unanimity says that if papers can be partitioned into two sets such that every reviewer who has reviewed papers from both sets agrees that the papers she has reviewed from the first set are better than what she reviewed from the second set, then the final output ranking should respect this agreement.

Our second notion of unanimity, termed pairwise unanimity, is a local refinement of group unanimity. This notion is identical to the classical notion of unanimity stated in Arrow's impossibility theorem (Arrow, 1950) – the classical unanimity considers every reviewer to review all papers (that is, $\mathcal{P}_i = \mathcal{P}, \forall i \in [m]$), whereas our notion is also defined for settings where reviewers may review only subsets of papers.

⁴To be clear, the function f is tied to the assignment graph \mathcal{G} . The graph \mathcal{G} specifies the sets $(\mathcal{P}_1, \ldots, \mathcal{P}_m)$, and then the function f takes permutations of these sets of papers as its inputs. We omit this from the notation for brevity.

Definition 3.2 (Pairwise Unanimity, PU). We define (\mathcal{G}, f) to be pairwise unanimous (PU) if the following condition holds for every possible profile π and every pair of papers $p_{j_1}, p_{j_2} \in \mathcal{P}$: If at least one reviewer has reviewed both p_{j_1} and p_{j_2} and all the reviewers that have reviewed p_{j_1} and p_{j_2} agree on $p_{j_1} > p_{j_2}$, then $f_{j_1}(\pi) > f_{j_2}(\pi)$. The efficiency objective $\Phi^{\text{PU}}(\mathcal{G}, f) = 1$ if (\mathcal{G}, f) is pairwise unanimous, and $\Phi^{\text{PU}}(\mathcal{G}, f) = 0$ otherwise.

An important property is that pairwise unanimity is stronger than group unanimity:

Proposition 3.1. $\Phi^{\text{GU}}(\mathcal{G}, f) \geqslant \Phi^{\text{PU}}(\mathcal{G}, f)$, that is, if (\mathcal{G}, f) is pairwise unanimous, then (\mathcal{G}, f) is also group unanimous.

We now move on to our other requirement in peer review, that of strategyproofness.

3.2 Strategyproofness

Intuitively, strategyproofness means that a reviewer cannot benefit from being dishonest; in the context of conference review, this means that a reviewer cannot change the position of her conflicting papers, by changing her own ranking. Strategyproofness is defined with respect to a given conflict graph which we denote by C; we recall the notation E_C as the set of edges of graph C.

Definition 3.3 (Strategyproofness, SP). A review process (\mathcal{G}, f) is called strategyproof with respect to a conflict graph \mathcal{C} if for every reviewer $r_i \in \mathcal{R}$ and paper $p_j \in \mathcal{P}$ such that $(r_i, p_j) \in E_{\mathcal{C}}$ the following condition holds: for every pair of profiles (under assignment \mathcal{G}) that differ only in the ranking given by reviewer r_i , the position of p_j is unchanged. Formally, $\forall \boldsymbol{\pi} = (\pi^{(1)}, \dots, \pi^{(i-1)}, \pi^{(i)}, \pi^{(i+1)}, \dots, \pi^{(m)})$ and $\boldsymbol{\pi}' = (\pi^{(1)}, \dots, \pi^{(i-1)}, \pi^{(i)'}, \pi^{(i+1)}, \dots, \pi^{(m)})$, it must be that $f_j(\boldsymbol{\pi}) = f_j(\boldsymbol{\pi}')$.

Having established these preliminaries, we now move on to the main results of this paper.

4 Positive results: Group unanimity and strategyproofness

In this section we consider the design of reviewer assignments and aggregation rules for strategyproofness and group unanimity (efficiency). It is not hard to see that strategyproofness and group unanimity cannot be simultaneously guaranteed for arbitrary conflict graphs \mathcal{C} , for instance, when \mathcal{C} is a fully-connected bipartite graph. Prior works on this topic consider a specific class of conflict graphs — those with one-to-one relations between papers and reviewers — which do not capture conference peer review settings. We consider a more general class of conflict graphs and present an algorithm based on the partitioning-based method (Alon et al., 2011), which we show can achieve $\mathrm{Opt}(\Phi^{\mathrm{GU}},\mathcal{C})=1$. We then empirically demonstrate, using submission data from the ICLR-17 conference, that this class of conflict graphs is indeed representative of peer review settings. In addition to the feasibility, we present a simple trick to significantly improve the practical appeal of our algorithm (and more generally the partitioning method) to conference peer review.

4.1 The Divide-and-Rank Algorithm

We now present our algorithm "Divide-and-Rank" for reviewer assignment and rank aggregation. At a higher level, our algorithm performs a partition of the reviewers and papers for assignment, and aggregates the reviews by computing a ranking which is consistent with any group agreements. The Divide-and-Rank algorithm works for a general conflict graph $\mathcal C$ as long as the conflict graph can be divided into two reasonably-sized disconnected components (we verify this assumption in the next section). The algorithm is simple yet flexible in that the assignment within each partition and the aggregation among certain groups of papers can be done using any existing algorithm for assignment and aggregation respectively. This flexibility is useful as it allows to further optimize various other metrics in addition to strategyproofness and unanimity.

The Divide-and-Rank assignment algorithm and Divide-and-Rank aggregation algorithm are formally presented as Algorithm 1 and Algorithm 2 respectively, and we discuss the details in the next two paragraphs.

Algorithm 1 Divide-and-Rank assignment

```
Input: conflict graph C, parameters \lambda, \mu, assignment algorithm \mathfrak{A}
Output: an assignment of reviewers to papers
  1: (\mathcal{R}_C, \mathcal{P}_C), (\mathcal{R}_{\bar{C}}, \mathcal{P}_{\bar{C}}) \leftarrow \mathsf{Partition}(\mathcal{C}, \lambda, \mu)
  2: use algorithm \mathfrak A to assign papers \mathcal P_{\bar C} to reviewers \mathcal R_C
  3: use algorithm \mathfrak A to assign papers \mathcal P_C to reviewers \mathcal R_{\bar C}
     return the union of assignments from step 2 and 3
      procedure Partition(conflict graph C, parameters \lambda, \mu)
  6:
            run a BFS on \mathcal{C} to get connected K components \{(\mathcal{R}_k, \mathcal{P}_k)\}_{k=1}^K
  7:
            let r_k = |\mathcal{R}_k|, p_k = |\mathcal{P}_k|, \forall k \in [K]
initialize a table T[\cdot, \cdot, \cdot] \in \{0, 1\}^{K \times (m+1) \times (n+1)} so that T[1, r_1, p_1] = T[1, 0, 0] = 1, otherwise 0
  8:
  9:
            for k = 2 to K do
10:
                  T[k, r, p] = T[k-1, r, p] \vee T[k-1, r-r_k, p-p_k], \ \forall 0 \le r \le m, 0 \le p \le n
11:
12:
            for 0 \le r \le m, 0 \le p \le n, if there is no T[K, r, p] = 1 such that \max\{\frac{p}{m-r}, \frac{n-p}{r}\} \le \frac{\mu}{\lambda}, return ERROR use the standard backtracking in the table T[\cdot, \cdot, \cdot] to return (\mathcal{R}_C, \mathcal{P}_C) and (\mathcal{R}_{\bar{C}}, \mathcal{P}_{\bar{C}})
13:
14:
      end procedure
15:
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The Divide-and-Rank assignment algorithm begins by partitioning the conflict graph into two disconnected components that meet the requirements specified by μ and λ . This is achieved using the subroutine Partition. Partition first runs a breadth-first-search (BFS) algorithm to partition the original conflict graph into K connected components, where the kth connected component contains $r_k \geq 0$ reviewers and $p_k \geq 0$ papers. Next, the algorithm performs a dynamic programming to compute all the possible subset sums achievable by the K connected components. Here T[k,r,p]=1 means that there exists a partition of the first k components such that one side of the partition has r reviewers and p papers, and p otherwise. The last step is to check whether there exists a subset p0 satisfying the requirement, and if so, runs a standard backtracking algorithm along the table to find the actual subset p1. Clearly the Partition runs in p2.

Then the algorithm assigns papers to reviewers in a fashion that guarantees each paper is going to be reviewed by at least λ reviewers and each reviewer reviews at most μ papers. The assignment of papers in any individual component (to reviewers in the other component) can be done using any assignment algorithm (taken as an input \mathfrak{A}) as long as the algorithm can satisfy the (μ, λ) -requirements. Possible choices for the algorithm \mathfrak{A} include the popular Toronto paper matching system (Charlin and Zemel, 2013) or others Hartvigsen et al. (1999); Garg et al. (2010); Stelmakh et al. (2018).

We now move to the aggregation procedure in Algorithm 2. At a high level, the papers in each component are aggregated separately using the subroutine Contract-and-Sort. This aggregation in Contract-and-Sort is performed by identifying sets of papers that dominate one another, ensuring that any set of papers is necessarily ranked higher than any set which it dominates, and finally ranking the papers within each set using any arbitrary aggregation algorithm (taken as an input \mathfrak{B}). Possible choices for the algorithm \mathfrak{B} include the modified Borda count (Emerson, 2013), Plackett-Luce aggregation (Hajek et al., 2014), or others (Caragiannis et al., 2017). Moving back to the main algorithm, the two rankings returned by Contract-and-Sort respectively for the two components are simply interlaced to obtain a total ranking over all the papers.

The following theorem now shows that Divide-and-Rank satisfies group unanimity and is strategyproof.

Theorem 4.1. Suppose the vertices of \mathcal{C} can be partitioned into two groups $(\mathcal{R}_C, \mathcal{P}_C)$ and $(\mathcal{R}_{\bar{C}}, \mathcal{P}_{\bar{C}})$ such that there are no edges in \mathcal{C} across the groups and that $\max\left\{\frac{|\mathcal{P}_C|}{|\mathcal{R}_{\bar{C}}|}, \frac{|\mathcal{P}_{\bar{C}}|}{|\mathcal{R}_{\bar{C}}|}\right\} \leqslant \frac{\mu}{\lambda}$. Then $\operatorname{Opt}(\Phi^{\mathrm{GU}}, \mathcal{C}) = 1$, that is, Divide-and-Rank is group unanimous and strategyproof.

Recall that $Opt(\Phi^{GU})$ is the optimal value of (1) under strategyproof and group unanimity. The assignment (Algorithm 1) in Divide-and-Rank ensures strategyproofness while the aggregation (Algorithm 2) yields

Algorithm 2 Divide-and-Rank aggregation

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Input: profile \pi = (\pi^{(1)}(\mathcal{P}_1), \dots, \pi^{(m)}(\mathcal{P}_m)), groups (\mathcal{R}_C, \mathcal{P}_C), (\mathcal{R}_{\bar{C}}, \mathcal{P}_{\bar{C}}) with |\mathcal{P}_C| \ge |\mathcal{P}_{\bar{C}}|, aggregation
     algorithm B
Output: total ranking of all papers
  1: compute \pi_C as the restriction of profile \pi to only papers in \mathcal{P}_C, and \pi_{\bar{C}} as the restriction of profile \pi
     to only papers in \mathcal{P}_{\bar{C}}
  2: \pi_C \leftarrow \mathsf{Contract}\text{-and-Sort}(\boldsymbol{\pi}_C, \mathfrak{B})
 3: \pi_{\overline{C}} \leftarrow \text{Contract-and-Sort}(\pi_{\overline{C}}, \mathfrak{B})
4: define I = \left(\left\lfloor \frac{n}{|\mathcal{P}_C|} \right\rfloor, \left\lfloor \frac{2n}{|\mathcal{P}_C|} \right\rfloor, ..., n\right)
5: return total ranking obtained by filling papers in \mathcal{P}_C into positions in I in order given by \pi_C, and
     papers in \mathcal{P}_{\bar{C}} into positions in [n]\backslash I in order given by \pi_{\bar{C}}
  6:
     procedure Contract-and-Sort(profile \widetilde{\pi}, aggregation algorithm \mathfrak{B})
           build a directed graph G_{\tilde{\pi}} with the papers in \tilde{\pi} as its vertices and no edges
 9:
           for each i \in [m'] do
                denoting \pi^{(i)} = (p_{i_1} > \ldots > p_{i_{t_i}}), add a directed edge from p_{i_j} to p_{i_{j+1}} in G_{\widetilde{\pi}}, \forall j \in [t_i - 1]
10:
           end for
11:
           for every ordered pair (p_{j_1}, p_{j_2}) \in E_{G_{\tilde{\pi}}}, replace multiple edges from p_{j_1} to p_{j_2} with a single edge
12:
           compute a topological ordering of the strongly connected components (SCCs) in G_{\tilde{\pi}}
13:
           for every SCC in G_{\tilde{\pi}}, compute a permutation of the papers in the component using algorithm \mathfrak{B}
14:
           return the permutation of all papers that is consistent with the topological ordering of the SCCs
15:
     and the permutations within the SCCs
16: end procedure
```

it the unanimity property.

The Divide-and-Rank algorithm aptly handles the various nuances of real-world conferences peer review, which render other algorithms inapplicable. This includes the features that each reviewer can write multiple papers and each paper can have multiple authors, and furthermore that each reviewer may review only a subset of papers. Even under this challenging setting, our algorithm guarantees that no reviewer can influence the ranking of her own paper via strategic behavior, and it is efficient from a social choice perspective.

In the remainder of this subsection, we delve a little deeper into the interleaving step (Step 5) of the aggregation algorithm. At first glance, this interleaving – performed independent of the reviewers' reports – may be a cause of concern. Indeed, assuming there is some ground truth ranking of all papers and even under the assumption that the outputs of the Contract-and-Sort procedure are consistent with this ranking, the worst case scenario is where the interleaving causes papers to be placed at a positions that are $\Theta(n)$ away from their respective positions in the true ranking. We show that, however, such a worst case scenario is unlikely to arise, when the ground truth ranking is independent of the conflict graph.

Proposition 4.2. Suppose \mathcal{C} satisfies the conditions given in Theorem 4.1 and there exists constant $c \geq 2$ such that $\max\{\frac{|\mathcal{P}|}{|\mathcal{P}_{\mathcal{C}}|}, \frac{|\mathcal{P}|}{|\mathcal{P}_{\mathcal{C}}|}\} \leq c$. Assume the ground-truth ranking π^* is chosen uniformly at random from all permutations in $\Pi(\mathcal{P})$ independent of \mathcal{C} , and that the two partial outputs of Contract-and-Sort in Algorithm 2 respect π^* . Let the output ranking of Divide-and-Rank be $\hat{\pi}$. Then for every $n \geq 4c/\log 2$, for any $\delta \in (0,1)$, with probability at least $1-\delta$, we have:

$$\max_{1 \le i \le n} |\pi_i^* - \widehat{\pi}_i| \le 2\sqrt{nc \cdot \log(2n/\delta)}.$$

Proposition 4.2 shows that the maximum deviation between the aggregated ranking and the ground truth ranking is $O(\sqrt{n \log(n/\delta)})$ with high probability. Hence for n large enough, such deviation is negligible when program chairs of conferences need to make accept/reject decisions, where the number of accepted papers usually scales linearly with n.

4.2 Analysis of ICLR-17 submissions

Our Divide-and-Rank algorithm is based on the partitioning method which relies on a partition of the set of authors and papers such that there is no conflict across the partition. The most prominent type of conflicts is authorships, and here we restrict attention to the authorship conflict graph. In this section, we empirically verify that the partitioning conditions indeed hold in a conference peer-review setting using data from the ICLR-17 conference. We then empirically demonstrate how to make the partitioning method more appealing for conference peer review. In particular, we show that removing only a small number of reviewers can result in a dramatic reduction in the size of the largest component in the conflict graph thereby providing great flexibility towards partitioning the papers and authors.

We analyzed all papers submitted to the ICLR-17 conference with the given authorship relationship as the conflict g. ICLR-17 received 489 submissions by 1,417 authors; we believe this dataset is a good representative of a medium-sized modern conference. In the analysis of this dataset, we instantiate the conflict graph as the authorship graph. It is important to note that we consider only the set of authors as the entire reviewer pool (since we do not have access to the actual reviewer identities). Adding reviewers from outside the set of authors would only improve the results since these additional reviewers will have no edges in the (authorship) conflict graph.

We first investigate the existence of (moderately sized) components in the conflict graph. Our analysis shows that the authorship graph is not only disconnected, but also has more than 250 components. The largest connected component contains 133 (that is, about 27%) of all papers, and the second largest CC is much smaller. We tabulate the results from our analysis in Table 1. These statistics indeed verify our assumption in Theorem 4.1 that the conflict graph is disconnected and can be divided into two disconnected parts of similar size.

The partitioning method has previously been considered for the problem of peer grading (Kahng et al., 2017). The peer grading setting is quite homogeneous in that each reviewer (student) goes through the same course and hence any paper (homework) can be assigned to any reviewer. In peer review, however, different reviewers typically have different areas of expertise and hence their abilities to review any paper varies by the area of the paper. In order to accommodate this diversity in area of expertise in peer review, one must have a greater flexibility in terms of assigning papers to reviewers. In our analysis in Table 1 we saw that the largest connected component comprises 372 authors and 133 papers. It is reasonable to expect that a large number of reviewers with expertise required to review these 133 papers would also fall in the same connected component, meaning that a naïve application of Divide-and-Rank to this data would assign these 133 papers to reviewers who may have a significantly lower expertise for these papers. This is indeed a concern, and in what follows, we discuss a simple yet effective way to ameliorate this problem.

We show empirically using the ICLR-17 data that by removing only a small number of authors from the reviewer pool, we can make the conflict graph much more sparse, allowing for a significantly more flexible application of our algorithm Divide-and-Rank (or more generally, any partition-based algorithm). In more detail, we remove a small fraction of authors from the reviewer pool. We use the simple heuristic of choosing to remove the authors with the maximum degree in the (authorship) conflict graph. We then study the statistics of the resulting conflict graph (with all papers but only the remaining reviewers) in terms of the

Description	Number
Number of submitted papers	489
Number of distinct authors	1417
Average $\#$ papers written per author	1.27
Maximum $\#$ papers written by an author	14
Number of connected components	253
#authors, #papers in largest connected component	371, 133
#authors, #papers in second largest connected component	65, 20

Table 1: Statistics of ICLR-17 submissions.

numbers and sizes of the connected components. We present the results in Table 2. We see that on removing only a small fraction of authors -50 authors which is only about 3.5% of all others - the number of papers in the largest connected component reduces by 86% to just 18. Likewise, the number of authors in the largest connected component reduces to as small as 55 from 371 originally. These numbers thus demonstrate that despite all the idiosyncrasies of conference peer review, the Divide-and-Rank and the partitioning method can be made practically applicable for peer review.

Table 2: Statistics of the conflict graph on removing a small number (<7%) of authors from the reviewer pool comprising the 1,417 authors.

	#Authors removed from reviewer pool						
	0	5	10	15	20	50	100
#Components	253	268	278	292	302	334	389
1st $\#$ Authors	371	313	304	228	205	55	28
1st #Papers	133	114	110	82	74	18	8

5 Negative Results

The positive results in the previous section focus on group unanimity, which is weaker than the conventional notion of unanimity (which we refer to as pairwise unanimity). Moreover, the algorithm had a disconnected review graph whereas the review graphs of (not strategyproof) conferences today are typically connected (Shah et al., 2017). It is thus natural to wonder about the extent to which these results can be strengthened. Can a peer-review system with a connected reviewer graph satisfy these properties? Can a strategyproof peer-review system be pairwise unanimous? In this section we present some negative results toward these questions, thereby highlighting the critical impediments towards (much) stronger results.

Before we go to our results, we give another notion of strategyproofness, which is significantly weaker than the notion of strategyproofness (Definition 3.3), and is hence termed as weak strategyproofness. As compared to strategyproofness which is defined with respect to a given conflict graph, weak strategyproofness only requires the existence of a conflict graph (with non-zero reviewer-degrees) for which the review process is strategyproof.

Definition 5.1 (Weak Strategyproofness, WSP). A review process (\mathcal{G}, f) is called weakly strategyproof, if for every reviewer r_i , there exists some paper $p_j \in \mathcal{P}$ such that for every pair of distinct profiles (under assignment \mathcal{G}) $\boldsymbol{\pi} = (\pi^{(1)}, \dots, \pi^{(i-1)}, \pi^{(i)}, \pi^{(i+1)}, \dots, \pi^{(m)})$ and $\boldsymbol{\pi}' = (\pi^{(1)}, \dots, \pi^{(i-1)}, \pi^{(i)'}, \pi^{(i+1)}, \dots, \pi^{(m)})$, it is guaranteed that $f_j(\boldsymbol{\pi}) = f_j(\boldsymbol{\pi}')$.

In other words, weak strategyproofness requires that for each reviewer there is at least one paper (not necessarily authored by this reviewer) whose ranking cannot be influenced by the reviewer. As the name suggests, strategyproofness is strictly stronger than weak strategyproofness, when each reviewer has at least one paper of conflict.

We define the notion of weak strategyproofness mainly for theoretical purposes; obviously WSP is too weak to be useful for practical applications. However we show that even this extremely weak requirement is impossible to satisfy in situations of practical interest.

We summarize our results in Table 3. Recall that we show the property of group unanimity and strategyproof for Divide-and-Rank; as the first direction of possible extension, we show in Theorem 5.1 that the slightly stronger notion of pairwise unanimity is impossible to satisfy under mild assumptions, even without strategyproof constraints. Then in Section 5.2 we explore the second direction of extension, by requiring a connected \mathcal{G} ; we give conjectures and insights that group unanimity and weak strategyproofness is impossible under this setting. At last in Theorem 5.4 we revert to the traditional setting of social choice, where every reviewer gives a total ranking of the set of all papers \mathcal{P} ; we show that in this setting it is impossible for any review process to be pairwise unanimous and weakly strategyproof.

Table 3: Summary of our negative results (first three rows of the table), and a comparison to our positive result (fourth row).

	Unanimity	Strategyproof	Requirement on \mathcal{G}	Possible?	Reference
Ī	Pairwise	None	Mild (see Corollary 5.2)	No	Theorem 5.1
	Group	Weak	Mild (Connected \mathcal{G})	Conjecture: No	Proposition 5.3
	Pairwise	Weak	Complete \mathcal{G}	No	Theorem 5.4
ĺ	Group	Yes	None	Yes	Theorem 4.1

5.1 Impossibility of Pairwise Unanimity

We show in this section that pairwise unanimity is too strong to satisfy under mild assumptions. These assumptions are mild in the sense that a violation of the assumptions leads to severely limited and somewhat impractical choices of \mathcal{G} .

In order to precisely state our result, we first introduce the notion of a review-relation graph \mathcal{H} . Given a paper-review assignment $\{\mathcal{P}_i\}_{i=1}^m$, the review-relation graph \mathcal{H} is an undirected graph with [n] as its vertices and where any two papers p_{j_1} and p_{j_2} are connected iff there exists at least one reviewer who reviews both the papers. With this preliminary in place, we are now ready to state the main result of this section:

Theorem 5.1. There is no review process (\mathcal{G}, f) that is pairwise unanimous (that is, $\Phi^{PU}(\mathcal{G}, f) = 0$ for every \mathcal{G}, f), when the following condition holds: \mathcal{H} contains a cycle of length 3 or more such that no single reviewer reviews all the papers in the cycle.

In the corollary below we give some direct implications of the condition in Theorem 5.1 when $|\mathcal{P}_1| = \cdots = |\mathcal{P}_m| = \mu$, that is, when every reviewer ranks a same number of papers.

Corollary 5.2. Suppose $|\mathcal{P}_1| = \cdots = |\mathcal{P}_m| = \mu \ge 2$. If (\mathcal{G}, f) is pairwise unanimous, the following conditions hold:

- (i) \mathcal{H} does not contain any cycles of length $\mu + 1$ or more.
- (ii) The set of papers reviewed by any pair of reviewers r_{i_1} and r_{i_2} must satisfy the condition $|\mathcal{P}_{i_1} \cap \mathcal{P}_{i_2}| \in \{0, 1, \mu\}$. In words, if a pair of reviewers review more than one papers in common then they must review exactly the same set of papers.
- (iii) The number of distinct sets in $\mathcal{P}_1, \ldots, \mathcal{P}_m$ is at most $\frac{n-1}{\mu-1}$.

Remarks. In modern conferences like NIPS (Shah et al., 2017), each reviewer usually reviews around 3 to 6 papers. If we make the review process pairwise unanimous, by point (iii) of Corollary 5.2 the number of distinct review sets is much smaller than the number of reviewers; this severely limits the design of review sets, since many reviewers would be necessitated to review identical sets of papers. Point (ii) is a related, strong requirement, since the specialization of reviewers might not allow for such limiting of the intersection of review sets. For instance, there are a large number of pairs of reviewers who review more than one common paper but none with exactly the same set of papers in NIPS 2016 (Shah et al., 2017). In general, Theorem 5.1 and Corollary 5.2 show that it is difficult to satisfy pairwise unanimity, even without considering strategyproofness. This justifies our choice of group unanimity in the positive results.

5.2 Group Unanimity and Strategyproof for a Connected Review Graph

Having shown that pairwise unanimity is too strong a requirement to satisfy, we now consider another direction for extension – conditions on the review graph \mathcal{G} . A natural question follows: Under what condition on the review graph \mathcal{G} are both group unanimity and strategyproofness possible? Although we will leave the question of finding the exact condition open, we conjecture that if we require \mathcal{G} to be connected, then group unanimity and strategyproofness cannot be simultaneously satisfied.

To show our insights, we analyze an extremely simplified review setting. We show that even in this very simple case, $\Phi^{\text{GU}}(\mathcal{G}, f) = 0$ for every weakly strategyproof (\mathcal{G}, f) .

Proposition 5.3. Consider any $n \ge 4$ and suppose $\mathcal{P} = P_1 \cup P_2 \cup P_3 \cup P_4$, where P_1, P_2, P_3, P_4 are disjoint nonempty sets of papers. Consider a review graph \mathcal{G} with m = 3 reviewers, where reviewer r_1 reviews $\{P_1, P_2\}$, r_2 reviews $\{P_2, P_3\}$, and r_3 reviews $\{P_3, P_4\}$. Then $\Phi^{\mathrm{GU}}(\mathcal{G}, f) = 0$ for every f such that (\mathcal{G}, f) is weakly strategyproof.

Proposition 5.3 thus shows that for the simple review graph considered in the statement, group unanimity and weak strategyproofness cannot hold at the same time. We conjecture that such a negative result may hold for more general connected review graphs, and such a negative result may be proved by identifying a component of the general review graph that meets the condition of Proposition 5.3. This shows that our design process of the review graph in Section 4 is quite essential for ensuring those important properties.

5.3 Pairwise Unanimity and Strategyproof under Total Ranking

Throughout the paper so far, motivated by the application of conference peer review, we considered a setting where every reviewer reviews a (small) subset of the papers. In contrast, a bulk of the classical literature in social choice theory considers a setting where each reviewer ranks *all* candidates or papers (Arrow, 1950; Satterthwaite, 1975). Given this long line of literature, intellectual curiosity drives us to study the case of all reviewers reviewing all papers for our conference peer-review setting.

We now consider our notion of pairwise unanimous and weakly strategyproof in this section under this total-ranking setting, where $\mathcal{P}_1 = \cdots = \mathcal{P}_m = \mathcal{P}$. In this case, the review graph \mathcal{G} is always a complete bipartite graph, and it only remains to design the aggregation function f. Although total rankings might not be practical for large-scale conferences, it is still helpful for smaller-sized conferences and workshops.

Under this total ranking setting, we prove a negative result showing that pairwise unanimity and strategyproofness cannot be satisfied together, and furthermore, even the notion of weak strategyproofness (together with PU) is impossible to achieve.

Theorem 5.4. Suppose $n \ge 2$. If $\mathcal{P}_1 = \cdots = \mathcal{P}_m = \mathcal{P}$, then $\operatorname{Opt}^{\operatorname{PU}}(\Phi, \mathcal{C}) = 0$ for any weakly strategyproof (\mathcal{G}, f) .

To prove Theorem 5.4, we use Cantor's diagonalization argument to generate a contradiction by assuming there exists f that is both PU and WSP. (Note that the conditions required for Theorem 5.1 are not met in the total ranking case.)

It is interesting to note that pairwise unanimity can be easily satisfied in this setting of total rankings, by using a simple aggregation scheme such as the Borda count. However, Theorem 5.4 shows that surprisingly, even under the extremely mild notion of strategyproofness given by WSP, it is impossible to achieve pairwise unanimity and strategyproofness simultaneously.

6 Proofs

In this section, we provide the proofs of all the results from previous sections.

6.1 Proof of Proposition 3.1

Suppose (\mathcal{G}, f) is PU, and $\mathcal{P}' \subset \mathcal{P}$ satisfies that every reviewer ranks the papers she reviewed from \mathcal{P}' higher than those she reviewed from $\mathcal{P} \setminus \mathcal{P}'$. Now for every $p_x \in \mathcal{P}'$ and $p_y \in \mathcal{P} \setminus \mathcal{P}'$ and reviewer r_i such that r_i reviews both p_x and p_y , r_i must rank $p_x > p_y$ since otherwise the assumption of \mathcal{P}' is violated. Since f is PU, we know that $f(\pi)$ must respect $p_x > p_y$ as well. This argument holds for every $p_x \in \mathcal{P}'$ and $p_y \in \mathcal{P} \setminus \mathcal{P}'$ that have been reviewed by at least one reviewer, and hence (\mathcal{G}, f) is also GU.

6.2 Proof of Theorem 4.1

We assume that the condition on the partitioning of the conflict graph, as stated in the statement of this theorem, is met. We begin with a lemma which shows that for any aggregation algorithm \mathfrak{B} , Contract-and-Sort is group unanimous.

Lemma 6.1. For any assignment and aggregation algorithms $\mathfrak A$ and $\mathfrak B$, the aggregation procedure Contractand-Sort is group unanimous.

We prove this lemma in Section 6.2.1. Under the assumptions on μ , λ and sizes of \mathcal{R}_C , $\mathcal{R}_{\bar{C}}$, \mathcal{P}_C , $\mathcal{P}_{\bar{C}}$, it is easy to verify that there is a paper allocation satisfies $|\mathcal{P}_i| \leq \mu$, $\forall i \in [m]$ and each paper gets at least λ reviews. The strategyproofness of Divide-and-Rank follows from the standard ideas in the past literature on partitioning-based methods (Alon et al., 2011): Algorithm 1 guarantees that reviewers in \mathcal{R}_C do not review papers in \mathcal{P}_C , and reviewers in $\mathcal{R}_{\bar{C}}$ do not review papers in \mathcal{P}_C . Hence the fact that Divide-and-Rank is strategyproof trivially follows from the assignment procedure where each reviewer does not review the papers that are in conflict with her, as specified by the conflict graph \mathcal{C} . Given that all the other reviews are fixed, the ranking of the papers in conflict with her will only be determined by the other group of reviewers and so fixed no matter how she changes her own ranking. On the other hand, from Lemma 6.1, since Contract-and-Sort is group unanimous, we know that π_C and $\pi_{\bar{C}}$ respect group unanimity w.r.t. π_C and $\pi_{\bar{C}}$, respectively. Since $\pi = (\pi_C, \pi_{\bar{C}})$, it follows that π_C and $\pi_{\bar{C}}$ also respect group unanimity w.r.t. π . Finally, note that there is no reviewer who has reviewed both papers from \mathcal{P}_C and $\mathcal{P}_{\bar{C}}$, the interlacing step preserves the group unanimity, which completes our proof.

6.2.1 Proof of Lemma 6.1

Let $f(\tilde{\pi}) := \text{Contract-and-Sort}(\tilde{\pi}, \mathfrak{B})$, where $\tilde{\pi}$ is a preference profile. Define $\pi = f(\tilde{\pi})$. Let k denote the number of SCCs in $G_{\tilde{\pi}}$. Construct a directed graph $\tilde{G}_{\tilde{\pi}}$ such that each of its vertices represents a SCC in $G_{\tilde{\pi}}$, and there is an edge from one vertex to another in $\tilde{G}_{\tilde{\pi}}$ iff there exists an edge going from one SCC to the other in the original graph $G_{\tilde{\pi}}$. Let $\tilde{v}_1, \ldots, \tilde{v}_k$ be a topological ordering of the vertices in $\tilde{G}_{\tilde{\pi}}$. Since $\tilde{v}_1, \ldots, \tilde{v}_k$ is a topological ordering, then edges can only go from \tilde{v}_{j_1} to \tilde{v}_{j_2} where $j_1 < j_2$. Now consider any cut $(\mathcal{P}_X, \mathcal{P}_Y)$ in $G_{\tilde{\pi}}$ that satisfies the requirement of group unanimity, i.e., all edges in the cut direct from \mathcal{P}_X to \mathcal{P}_Y . Then there is no pair of papers $p_x \in \mathcal{P}_X$ and $p_y \in \mathcal{P}_Y$ such that p_x and p_y are in the same connected component, otherwise there will be both paths from p_x to p_y and p_y to p_x , contradicting that $(\mathcal{P}_X, \mathcal{P}_Y)$ forms a cut where all the edges go in one direction. This shows that \mathcal{P}_X and \mathcal{P}_Y also form a partition of all the vertices $\tilde{v}_1, \ldots, \tilde{v}_k$. Now consider any edge (p_x, p_y) from \mathcal{P}_X to \mathcal{P}_Y . Suppose p_x is in component \tilde{v}_{j_x} and p_y in component \tilde{v}_{j_y} . We have $p_x \neq p_y$, since $p_x \neq p_y$ forms a partition of all SCCs; also it cannot happen that $p_x > p_y$, otherwise $\tilde{v}_1, \ldots, \tilde{v}_k$ is not a topological ordering returned by $p_x \neq p_y$. So it must be $p_x < p_y$, and the edge $p_x > p_y$ is respected in the final ordering.

6.3 Proof of Proposition 4.2

We would first need a lemma for the location of papers:

Lemma 6.2. Let $I_1 = \left\{ \left\lfloor \frac{n}{|\mathcal{P}_C|} \right\rfloor, \left\lfloor \frac{2n}{|\mathcal{P}_C|} \right\rfloor, ..., n \right\}, I_2 = \left\{ g \left(\frac{n}{|\mathcal{P}_{\overline{C}}|} \right), g \left(\frac{2n}{|\mathcal{P}_{\overline{C}}|} \right), ..., n - 1 \right\}, \text{ where } g(x) = \lceil x \rceil - 1 \text{ is the largest integer that is } strictly \text{ smaller than } x. \text{ Then } I_1 \cap I_2 = \emptyset \text{ and } I_1 \cup I_2 = [n].$

We prove this lemma in Section 6.3.1.

Consider any paper p_i , and suppose its position in π^* is ℓ . Define $n_1 = |\mathcal{P}_C|$ and $n_2 = |\mathcal{P}_{\bar{C}}|$. Without loss of generality assume $n_1 \ge n_2$ (the other case is symmetric) and let $n \ge 4c/\log 2$. We discuss the following two cases depending on whether $p_i \in \mathcal{P}_C$ or $p_i \in \mathcal{P}_{\bar{C}}$.

Case I: If $p_i \in \mathcal{P}_C$. Let k be the number of papers in \mathcal{P}_C ranked strictly higher (better) than ℓ according to π^* . Since the permutation π^* is uniformly random, conditioned on this value of ℓ , the other papers' positions in the true ranking are uniformly at random in positions $[n]\setminus\{\ell\}$. Now for any paper $p_i, j \neq i$,

let X_j be an indicator random variable set as 1 if position of p_j is higher than ℓ in π^* , and 0 otherwise. So $k = \sum_{p_j \in \mathcal{P}_C \setminus \{p_i\}} X_j$, and $\Pr(X_j = 1) = \frac{\ell - 1}{n - 1}$ when $j \neq i$. Then using Hoeffding's inequality without replacement, we have

$$\Pr\left(\left|\frac{k}{n_1-1} - \frac{\ell-1}{n-1}\right| \geqslant \varepsilon\right) \leqslant 2\exp(-2(n_1-1)\varepsilon^2) \leqslant 2\exp(-n_1\varepsilon^2)$$

for any $\varepsilon > 0$. The last inequality is due to $n_1 \ge 2$, which holds because $n/n_1 \le c$ with a constant c. Now setting $\varepsilon = \sqrt{\frac{\log(2/\delta)}{n_1}}$ we have the bound

$$\Pr\left(\left|\frac{k}{n_1-1} - \frac{\ell-1}{n-1}\right| \leqslant \sqrt{\frac{\log(2/\delta)}{n_1}}\right) \geqslant 1-\delta.$$

Now note that by Algorithm 2, the position of paper p_i in the ranking $\hat{\pi}$ is $\hat{\pi}_i = \left\lfloor (k+1) \cdot \frac{n}{n_1} \right\rfloor$. Use this relationship to substitute k in the above inequality, and notice that by assumption $\max\{n/n_1, n/n_2\} \leq c$, we have

$$(k+1) \cdot \frac{n}{n_1} \le \left((n_1 - 1) \left(\varepsilon + \frac{\ell - 1}{n - 1} \right) + 1 \right) \frac{n}{n_1}$$

$$= \frac{n_1 - 1}{n_1} \cdot \frac{n}{n - 1} (\ell - 1) + \frac{n_1 - 1}{n_1} \cdot n\varepsilon + \frac{n}{n_1}$$

$$\le \frac{n}{n_1} + n\varepsilon + \ell - 1.$$

On the other hand,

$$(k+1) \cdot \frac{n}{n_1} \geqslant \left((n_1 - 1) \left(\frac{\ell - 1}{n - 1} - \varepsilon \right) + 1 \right) \frac{n}{n_1}$$

$$= \frac{n_1 - 1}{n_1} \cdot \frac{n}{n - 1} (\ell - 1) - \frac{n_1 - 1}{n_1} \cdot n\varepsilon + \frac{n}{n_1}$$

$$\geqslant \frac{n}{n_1} - n\varepsilon + \frac{n_1 - 1}{n_1} \cdot \frac{n}{n - 1} (\ell - 1).$$

So

$$(k+1) \cdot \frac{n}{n_1} - \ell \geqslant \frac{n}{n_1} - n\varepsilon + \frac{n_1 - 1}{n_1} \cdot \frac{n}{n-1} (\ell - 1) - \ell$$

$$\geqslant \frac{n}{n_1} - n\varepsilon + \frac{n_1 - 1}{n_1} \cdot \frac{n}{n-1} (n-1) - n$$

$$\geqslant -n\varepsilon.$$

$$(2)$$

Here (3) is because $\frac{n_1-1}{n_1}\cdot\frac{n}{n-1}<1$, and thus RHS of (2) is minimized (as a function of ℓ) when $\ell=n$. Combining the two inequalities above we have

$$|\widehat{\pi}_i - \ell| \le n\varepsilon + \frac{n}{n_1} = n\sqrt{\frac{\log(2/\delta)}{n_1}} + \frac{n}{n_1} \le 2\sqrt{nc \cdot \log(2/\delta)},$$

where the last inequality is by the assumption that n is large enough so that $2c \leq \sqrt{nc \cdot \log(2/\delta)}$.

Case II: If $p_i \in \mathcal{P}_{\bar{C}}$. Again, let k be the number of papers in $\mathcal{P}_{\bar{C}}$ ranked strictly higher (better) than ℓ according to π^* . As the analysis in Case I, similarly, we have $k = \sum_{p_j \in \mathcal{P}_{\bar{C}} \setminus \{p_i\}} X_j$, and $\Pr(X_j = 1) = \frac{\ell - 1}{n - 1}$. With the same analysis using Hoeffding's inequality without replacement, with probability at least $1 - \delta$ we have

$$\left| \frac{k}{n_2 - 1} - \frac{\ell - 1}{n - 1} \right| \leqslant \sqrt{\frac{\log(2/\delta)}{n_2}}.$$

Now using Lemma 6.2, the position of paper p_i in $\hat{\pi}$ in this case is $\hat{\pi}_i = g\left((k+1) \cdot \frac{n}{n_2}\right)$. Using exactly the same analysis as Case I we have

$$-n\varepsilon \leqslant (k+1) \cdot \frac{n}{n_2} - \ell \leqslant \frac{n}{n_2} + n\varepsilon - 1,$$

and thus

$$|\hat{\pi}_i - \ell| \le n\varepsilon + \frac{n}{n_2} = n\sqrt{\frac{\log(2/\delta)}{n_2}} + \frac{n}{n_2} \le 2\sqrt{nc \cdot \log(2/\delta)}.$$

Combine both Case I and Case II, and notice that π_i^* is uniformly distributed in [n]. Using a union bound over i = 1, 2, ..., n, with probability $1 - \delta$ we have:

$$\max_{1 \le i \le n} |\widehat{\pi}_i - \pi_i^*| \le 2\sqrt{nc \cdot \log(2n/\delta)}.$$

6.3.1 Proof of Lemma 6.2

We show that for every slot q that there is no p such that $\left[p \cdot \frac{n}{n_1}\right] = q$, there exists one slot p' for $\mathcal{P}_{\bar{C}}$ such that $g\left(p' \cdot \frac{n}{n_2}\right) = q$, i.e., all slots that are left empty by \mathcal{P}_C are taken by slots of $\mathcal{P}_{\bar{C}}$. Since that the two kinds of slots have a total number of n, we show that there are no overlap between the two kinds of slots, thus proving the lemma.

Let $t = n/n_1$. Suppose if there is no p such that $\left[p \cdot \frac{n}{n_1}\right] = q$, then there must exist some \hat{p} such that

$$q + 1 \leqslant \hat{p}t < q + t. \tag{4}$$

This is because there must be a multiple of t in the range [q, q + t), but our assumption makes that there is no such multiply in [q, q + 1).

Now let $u = n/n_2$. By $n_1 + n_2 = n$ we have 1/u + 1/t = 1; substituting t = u/(u - 1) in (4) we have

$$q < (q - \hat{p} + 1)u \leqslant q + 1.$$

Thus there exists $p' = g((q - \hat{p} + 1)u) \in \mathcal{P}_{\bar{C}}$. Thus we prove the lemma.

6.4 Proof of Theorem 5.1

The proof of Theorem 5.1 is a direct formulation of our intuition in Section 5.1. Without loss of generality let (p_1, \ldots, p_l) be the cycle not reviewed by a single reviewer, for $l \ge 3$. Hence there exists a partial profile π such that for all the reviewers who have reviewed both p_j and p_{j+1} , $p_j > p_{j+1}$, $\forall j \in [l]$ (define $p_{l+1} = p_1$). On the other hand, since for each reviewer, at least one pair (p_j, p_{j+1}) is not reviewed by her, the constructed partial profile is valid. Now assume f is PU, then we must have $p_1 > \cdots > p_l$ and $p_l > p_1$, which contradicts the transitivity of the ranking.

6.5 Proof of Corollary 5.2

We prove each of the conditions in order.

Proof of part (i): If there is a cycle of size $\mu + 1$, then no reviewer can review all the papers in it since it exceeds the size of review sets. So there is no such cycle.

Proof of part (ii): The statement trivially holds for $\mu = 2$. For $\mu \geq 3$, Suppose there are two reviewers r_{i_1} and r_{i_2} such that $2 \leq |\mathcal{P}_{i_1} \cap \mathcal{P}_{i_2}| \leq \mu - 1$. Since $\mathcal{P}_{i_1} \neq \mathcal{P}_{i_2}$, there exist papers p_{j_1} and p_{j_2} such that $p_{j_1} \in \mathcal{P}_{i_1} \setminus \mathcal{P}_{i_2}$ and $p_{j_2} \in \mathcal{P}_{i_2} \setminus \mathcal{P}_{i_1}$. Also $|\mathcal{P}_{i_1} \cap \mathcal{P}_{i_2}| \geq 2$, and let $p_{j_3}, p_{j_4} \in \mathcal{P}_{i_1} \cap \mathcal{P}_{i_2}$. By definition it is easy

to verify that $(p_{j_1}, p_{j_3}, p_{j_2}, p_{j_4})$ forms a cycle that satisfies the condition in Theorem 5.1, and hence (\mathcal{G}, f) is not pairwise unanimous.

Proof of part (iii): Define a "paper-relation graph" \mathcal{G}_p as follows: Given a paper-review assignment $\{\mathcal{P}_i\}_{i=1}^m$, the paper-relation graph \mathcal{G}_p is an undirected graph, whose nodes are the distinct sets in $\{\mathcal{P}_i\}_{i=1}^m$; we connect two review sets iff they have one paper in common. Note that by (ii), each pair of distinct sets has at most one paper in common.

We first show that (\mathcal{G}, f) is pairwise unanimous, then \mathcal{G}_p must necessarily be a forest. If there is a cycle in \mathcal{G}_p , then there is a corresponding cycle in the review relation graph \mathcal{H} . To see this, not losing generality suppose the shortest cycle in \mathcal{G}_p is $(\mathcal{P}_1, ..., \mathcal{P}_l)$. Also, suppose $\mathcal{P}_1 \cap \mathcal{P}_2 = \{p_1\}, \mathcal{P}_2 \cap \mathcal{P}_3 = \{p_2\}, ..., \mathcal{P}_l \cap \mathcal{P}_1 = \{p_l\}$ not losing generality. Then $(p_1, ..., p_l)$ forms a cycle in \mathcal{G}_p by its definition. Since each reviewer reviews exactly one set in \mathcal{G}_p , there is no reviewer reviewing all papers in this cycle of papers in \mathcal{G}_p . Thus the condition in Theorem 5.1 is satisfied, and (\mathcal{G}, f) is not pairwise unanimous.

We now use this result to complete our proof. Consider the union of all sets of papers that form vertices of \mathcal{G}_p . We know that this union contains exactly n papers since each paper is reviewed at least once. Now let k_p denote the number of distinct review sets (that is, number of vertices of \mathcal{G}_p), and let $\mathcal{P}_{i_i}, ..., \mathcal{P}_{i_{k_p}}$ denote the vertices of \mathcal{G}_p . The union of three or more sets in $\{\mathcal{P}_{i_k}\}_{k=1}^{k_p}$ is empty, since otherwise there will be a cycle in \mathcal{G}_p . Using this fact, we apply the inclusion-exclusion principle to obtain

$$n = \sum_{k=1}^{k_p} |\mathcal{P}_{i_k}| - \sum_{1 \leq k_1 < k_2 \leq k_p} |\mathcal{P}_{i_{k_1}} \cap \mathcal{P}_{i_{k_2}}| = k_p \mu - |E_{\mathcal{G}_p}|.$$

Now use the inequality $|E_{\mathcal{G}_p}| \leq k_p - 1$ which arises since \mathcal{G}_p is a forest, to obtain the claimed bound $k_p \leq \frac{n-1}{\mu-1}$.

6.6 Proof of Proposition 5.3

Fix some ranking of papers within each individual set P_1 , P_2 , P_3 and P_4 (e.g., according to the natural order of their indices). In the remainder of the proof, any ranking of all papers always considers these fixed rankings within these individual sets. With this in place, in what follows, we refer to any ranking in terms of the rankings of the four sets of papers.

Suppose there is one such f that satisfies group unanimity and weak strategyproofness for \mathcal{G} , and consider the following 4 profiles:

$$(1) \ r_1: P_1 > P_2, r_2: P_2 > P_3, r_3: P_3 > P_4 \quad \ (2) \ r_1: P_2 > P_1, r_2: P_3 > P_2, r_3: P_4 > P_3$$

(3)
$$r_1: P_2 > P_1, r_2: P_2 > P_3, r_3: P_3 > P_4$$
 (4) $r_1: P_2 > P_1, r_2: P_3 > P_2, r_3: P_3 > P_4$

By the property of GU, profile (1) leads to output $P_1 > P_2 > P_3 > P_4$, whereas (2) leads to output $P_4 > P_3 > P_2 > P_1$. Now compare (1) and (3): The output of (3) must have P_2 at the top and satisfy $P_3 > P_4$, by the property of GU. So the output of profile (3) must be one of i) $P_2 > P_1 > P_3 > P_4$, ii) $P_2 > P_3 > P_1 > P_4$, or iii) $P_2 > P_3 > P_4 > P_1$. Now note that only reviewer $P_3 > P_4 > P_3$ must be the same as in that of profile (1). This makes iii) infeasible, so the output of (3) must be either i) or ii). Similarly, the output of (4) is either $P_3 > P_4 > P_2 > P_3$ or $P_3 > P_4 > P_4 > P_3$. Now comparing (3) and (4): only $P_3 > P_4 > P_3$ and the same position no matter how we choose the outputs of (3) and (4). This yields a contradiction.

6.7 Proof of Theorem 5.4

We begin with a definition of an "influence graph" \mathcal{G}_f induced by any given aggregation rule f.

Definition 6.1 (Influence graph). For any review aggregation rule f, the influence graph \mathcal{G}_f induced by f is a bipartite graph with two groups of vertices \mathcal{R} and \mathcal{P} , and edges as follows. A vertex r_i is connected to

vertex p_j iff there exists a certain profile $\boldsymbol{\pi}$ such that r_i is able to change the output ranking of p_j by changing her own preference. Formally, there exists an edge between any pair $(r_i, p_j) \in E_{\mathcal{G}_f}$ iff there exist profiles $\boldsymbol{\pi} = \{\pi^{(1)}, \dots, \pi^{(i-1)}, \pi^{(i)}, \pi^{(i+1)}, \dots, \pi^{(m)}\}$ and $\boldsymbol{\pi}' = \{\pi^{(1)}, \dots, \pi^{(i-1)}, \tilde{\pi}^{(i)}, \pi^{(i+1)}, \dots, \pi^{(m)}\}$ and $j \in [n]$ such that $f(\boldsymbol{\pi})(j) \neq f(\boldsymbol{\pi}')(j)$.

From this definition, it is thus not hard to see that f is WSP if and only if the degree of every reviewer node in \mathcal{G}_f is strictly smaller than n.

We prove the claim via a contradiction argument. Assume that f is both PU and WSP. Let \mathcal{G}_f be the corresponding influence graph. Firstly we show that $\deg(p)>0$ for every paper p, where the degree is for the influence graph \mathcal{G}_f . Suppose otherwise that $\deg(p_j)=0$ for some paper p_j . This means no reviewer can affect the ranking of p_j ; in other words, the position of paper p_j is fixed regardless of the profile. This contradicts with our assumption of pairwise unanimity; to see this, pick another paper $p_{j'}$ where $j' \neq j$ (this is possible since $n \geq 2$). Not losing generality suppose j < j'. Consider a profile π where every reviewer ranks $p_j > p_{j'} > P_{-(j,j')}$, and another profile π' where everyone ranks $p_{j'} > p_j > P_{-(j,j')}$; here $P_{-(j,j')}$ means the ordinal ranking of papers other than $p_j, p_{j'}$, i.e., $p_1 > \cdots > p_{j-1} > p_{j+1} > \cdots > p_{j'-1} > p_{j'+1} > \cdots > p_n$. By the property of PU, when everyone ranks the same the final result must be the same as everyone; however this means the position of p_j is different in the two profiles, and thus the position of p_j is not fixed. This makes contradiction and we prove that $\deg(p) > 0$ for every paper p.

Now for any reviewer $r_i \in \mathcal{R}$, let $e(r_i) \in \mathcal{P}$ be the paper with the lowest index in \mathcal{P} such that $(r_i, e(r_i)) \notin E_{\mathcal{G}_f}$. Since f is WSP, $e(r_i)$ must exist for all $i \in [m]$. Define the set of such papers as $\mathcal{P}' := \{e_1, \ldots, e_{m'}\} = \{e(r_i) : r_i \in \mathcal{R}\}$. Note that we must have $m' \leq m$ and in fact m' can be strictly smaller than m because of the possible overlap between $e(r_i), \forall i \in [m]$. From the definition of m' and property of WSP, it is clear that $m' \geq 1$. If m' = 1, we have $(r_i, e_1) \notin E_{\mathcal{G}_f}$ for every reviewer r_i ; this contradicts with the fact that $\deg(p) \geq 0$ for every paper p. So m' > 1.

In this proof, we slightly overload the notation of $f_{e_k}(\pi)$ to mean the position of paper e_k in $f(\pi)$. Based on the inverse mapping from \mathcal{P}' to \mathcal{R} , we partition all the reviewers \mathcal{R} into m' groups $\{\mathcal{R}'_1, \ldots, \mathcal{R}'_{m'}\}$ such that all reviewers in any set \mathcal{R}'_k contributed paper e_k when defining set \mathcal{P}' . In particular, we have that no reviewer in \mathcal{R}'_j is connected to paper e_j in the influence graph \mathcal{G}_f .

In the description that follows, we restrict attention to the papers in \mathcal{P}' , and assume that in any ranking all remaining (n-n') papers are positioned at the end of the preference list of any reviewer. Now consider the following two preferences over \mathcal{P}' :

$$\pi = e_1 > e_2 > \dots > e_{m'}, \quad \pi' = e_2 > e_3 > \dots > e_{m'} > e_1.$$

Using π and π' , define the following m' + 1 different profiles:

$$\boldsymbol{\pi}_0 = (\pi, \dots, \pi), \ \boldsymbol{\pi}_k = (\underbrace{\pi', \dots, \pi'}_{k}, \underbrace{\pi, \dots, \pi}_{m'-k}) \ \forall k \in [m'].$$

where in π_k the first k preferences are π' and the last (m'-k) preferences are π . In what follows, we will use a diagonalization argument to generate a contradiction using the condition that f is WSP. We first present a lemma, which we prove in Section 6.7.1.

Lemma 6.3. If f is pairwise unanimous and weakly strategyproof, $f_{e_k}(\pi_k) = k$ for every $k \in [m']$, that is, under profile π_k , the k-th position in the output ranking must be taken by paper e_k .

Applying Lemma 6.3 with k=m', we obtain that $f_{e_{m'}}(\pi_{m'})=m'$. However, on the other side, since $\pi_{m'}=(\pi',\ldots,\pi')$ and $\pi'=e_2>e_3>\cdots>e_{m'}>e_1$, again by the PU property we have $f_{e_{m'}}(\pi_{m'})=1$. This leads to a contradiction, hence f cannot be both WSP and PU.

6.7.1 Proof of Lemma 6.3

We prove by induction on k.

Base case. Since f is PU, the output ranking $f(\pi_0)$ must be:

$$f(\pi_0) = e_1 > e_2 > \cdots > e_{m'}$$

Consider k = 1. Note that π and π' differ only at the position of e_1 , and in π_1 , only \mathcal{P}'_1 changes their preference and all the other preferences are kept fixed. Then by the WSP of f, the output ranking of e_1 will not be changed because \mathcal{P}'_1 are not connected to e_1 in the influence graph, so we must have:

$$f(\pi_1) = e_1 > e_2 > \dots > e_{m'},$$

Induction step. Suppose the claim of this lemma holds for $\{1, \ldots, k\}$. Consider the case of k+1. Observe that $f(\pi_k)(e_k) = k$, and in both π and π' we have:

$$e_k > e_{k+1} > \cdots > e_{m'}$$
.

Then since f is PU, we know that the last m' - k + 1 positions in the output ranking of $f(\pi_k)$ must be given by $e_k > e_{k+1} > \cdots > e_{m'}$, i.e., $f_{e_{k+1}}(\pi_k) = k + 1$. The profiles π_k and π_{k+1} differ only in the preference given by \mathcal{P}'_{k+1} , and no reviewer in set \mathcal{P}'_{k+1} can influence the position of paper e_{k+1} . It follows that $f_{e_{k+1}}(\pi_{k+1}) = k + 1$, which completes our proof.

7 Discussion

In this paper we address the important problem of designing strategyproof and efficient peer-review mechanism. The setting of peer review is challenging due to the various idiosyncrasies of the peer-review process: reviewers review only a subset of papers, each paper has multiple authors who may be reviewers, and each reviewer may author multiple submissions. We design an algorithm that is indeed strategyproof and satisfies group unanimity, and show that in contrast, it is impossible for any algorithm to remain strategyproof and satisfy the stronger notion of pairwise unanimity.

The framework established here leads to a number of useful open problems:

- Consider the following weaker notion of strategy proofness defined for authorship conflicts: No author should be able to *improve* the rank of her/his own paper. Can this weaker notion of strategy proofness allow for more efficiency?
- Can recruitment of a small number of reviewers with no conflicts (e.g., in case of authorship conflicts, reviewers who have not submitted any papers) lead to significant improvements in efficiency? Can better ways to eliminate some authors from the reviewer pool increase applicability of partition-based algorithms?
- The results in this paper considered the social choice property of unanimity as a measure of efficiency. While this can be regarded as a first-order notion of efficiency, it is of interest to consider complex notions of efficiency. One useful notion is a statistical notion, in which case the function Φ would represent the statistical utility of estimation (Stelmakh et al., 2018) of the (partial or full) ranking of papers under a statistical model for reviewer reports. An alternative notion of efficiency combines an assignment quality based on the similarities of assigned reviewers and papers with group unanimity, or formally, as $\Phi(\mathcal{G}, f) = (\sum_{ij} [\mathcal{G}]_{ij} S_{ij}) \cdot \Phi^{\mathrm{GU}}(\mathcal{G}, f)$, where S_{ij} denotes the similarity between reviewer i and paper j.

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