MATCHING PAPERS AND REVIEWERS AT LARGE CONFERENCES

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ABSTRACT

Peer-reviewed conferences, the main publication venues in CS, rely critically on matching highly qualified reviewers for each paper. Because of the growing scale of these conferences, the tight timelines on which they operate, and a recent surge in explicitly dishonest behavior, there is now no alternative to performing this matching in an automated way. This paper studies a novel reviewer–paper matching approach that was recently deployed in the 35th AAAI Conference on Artificial Intelligence (AAAI 2021), and has since been adopted by other conferences including AAAI 2022 and ICML 2022. This approach has three main elements: (1) collecting and processing input data to identify problematic matches and generate reviewer–paper scores; (2) formulating and solving an optimization problem to find good reviewer–paper matchings; and (3) the introduction of a novel, two-phase reviewing process that shifted reviewing resources away from papers likely to be rejected and towards papers closer to the decision boundary. This paper also describes an evaluation of these innovations based on an extensive post-hoc analysis on real data—including a comparison with the matching algorithm used in AAAI's previous (2020) iteration—and supplements this with additional numerical experimentation.²

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²Writing this paper and conducting the experimental analysis described herein took almost a full year beyond the conclusion of AAAI 2021. Nevertheless, this paper is grounded in our experiences as Program Chairs (Mausam, Kevin), Workflow Chairs (Hedayat, Yatin, Dinesh) and Associate Workflow Chairs (Chris, Neil) at AAAI 2021. Many other people contributed to the the conference's design and operation. Notably, Qiang Yang was Conference Chair; Gabriele Röger and Yan Liu were Associate Program Chairs, and Guangneng Hu was a Workflow Chair; all contributed to the design and planning process throughout the year preceding the conference. Even more concretely impacting the content of this paper, Gabi provided draft text on filtering manipulative bids that we adapted into Section 2.2, and Yan made contributions to the MIP formulation described in Section 3. The CMT support team provided invaluable real-time service and development during the conference which made our introduction of two-phase reviewing process feasible. Carol Hamilton and the AAAI Office provided innumerable forms of behind-the-scenes support. Finally, an organization as large as AAAI operates only through the efforts of literally thousands of volunteers in myriad roles; we thank all of them for their continued service to the community.

Keywords Reviewer-paper matching · Two-phase reviewing process · Conference organization

1 Introduction

Submissions to prominent AI conferences have grown steadily in recent years. The AAAI Conference on Artificial Intelligence (AAAI) received fewer than 1,000 submissions in its first 33 years (1980–2012); fewer than 2,000 submissions until 2015; and fewer than 4,000 submissions until 2018. AAAI 2021 received over 9,000 submissions! Program committees have grown to keep pace with submissions; nearly 10,000 reviewers were involved in the 2021 conference. Given the scale and the tight timeline on which such large conferences operate, it is becoming an increasingly challenging problem to assign reviewers³ to papers about which they can provide high-quality reviews. Some key subproblems are estimating how qualified a given reviewer is to review a particular paper; tractably determining good matchings; determining which papers can be rejected without full review; and identifying reviewers who have bid, reviewed, or scored papers in an attempt to manipulate outcomes.

We addressed these challenges with a novel automated pipeline for reviewer–paper matching at AAAI 2021. Our pipeline consists of three main elements: (1) collecting and processing input data to identify problematic matches and generating reviewer–paper scores; (2) formulating and solving a constrained matching problem; and (3) splitting the reviewing process into two phases to better allocate reviewing resources towards borderline papers. We briefly describe each of these in turn (and then devote a full section to each in what follows). Code for our pipeline is available at https://github.com/ChrisCameron1/LargeConferenceMatching.

Data collection and processing: Program chairs need to transform a reviewer's profile into an estimate of how qualified that reviewer is to review each paper. Profiles can be as detailed as program chairs are creative, containing features such as: reviewers' identities, past email addresses, DBLP/Semantic Scholar profiles, self-reported reviewing proficiency via a bidding phase, self-declared conflicts of interest (COIs), and text of previously written papers. A key question that conference organizers need to answer is how to process this data and transform it into a numerical score assessing the quality of every plausible reviewer—paper pair. Two notable examples of such numerical scores are TPMS [Charlin and Zemel, 2013] and ACL scores [Neubig et al., 2020]. These scores are both computed based on textual similarity between a submitted paper and reviewer's prior publications. However, they are not always available; TPMS scores can only be computed for reviewers whose prior publications are known and ACL scores can only be computed for reviewers whose past publication abstracts are accessible, e.g., via a known Semantic Scholar profile. In AAAI 2021, we computed TPMS and ACL scores for all applicable reviewer—paper pairs. We also knew reviewers' and papers' primary and secondary subject areas and received explicit bids from reviewers. We aggregated all of our data to obtain final reviewer—paper scores which were between 0 and 1 and were unbiased to missing data. We refer to the resulting scoring function as aggscore.

The input data is only as useful as it is trustworthy: a rising concern for large scale conferences is that participants may self-report information to direct their submission to a specific reviewer or to ensure they review a specific paper [Jecmen et al., 2020]. To that end, we constructed relationship graphs based on each user's publication history to identify unreported conflicts (which, of course, also arose via mistakes or oversights from non-malicious users). We also developed a set of heuristics to identify suspicious patterns of self-reported conflicts and of bidding for papers to review; we prevented such suspicious assignments.

Formulating a Constrained Matching Problem: Once scores have been assigned, the next key problem is to come up with an actual assignment. We formulated this problem as a Mixed-Integer Programming (MIP) problem. We are far from the first to use a MIP formulation for the reviewer—paper matching [Flach et al., 2010, Garg et al., 2010, Tang et al., 2010, Lian et al., 2018, Taylor, 2008, Kobren et al., 2019, Charlin and Zemel, 2013, Charlin et al., 2011]. However, we differed from the vanilla "find a score maximizing assignment" formulation by including additional (soft) desiderata. We penalized assigning coauthors to review the same paper, rewarded geographic diversity in assignments, and penalized assignments where reviewers each bid positively on each other's papers. These soft constraints served both to ensure that each paper was reviewed by an intellectually diverse set of reviewers and to make collusion rings (reviewers conspiring to review each other's papers) [Littman, 2021] harder to sustain. Separately, we introduced a seniority constraint to encourage our matching algorithm to distribute experienced reviewers across papers. We show in our experimental analysis that despite the mentioned advantages, these soft constraints only marginally impacted the mean aggregate score, and hence did not significantly degrade average match quality.

³Modern conference reviewing is often divided into four hierarchical roles: at the bottom, program committee members (PCs) review submissions; senior program committee members (SPCs) facilitate discussions and write meta-reviews; area chairs (ACs) oversee the review process, communicate with SPCs about final decisions, and recommend the final decisions to the Program chairs, who make the final decisions. In this paper, we overload the term reviewer to sometimes mean only PCs and sometimes include SPCs and ACs. This should be clear from the context.

To ensure that the resulting MIP formulation could be solved within a reasonable amount of time, we sparsified our space of possible assignments by not creating variables representing assignments of papers to reviewers with insufficiently high scores; we used column generation as necessary to identify further candidate reviewers for hard-to-match papers. Our coauthorship constraints, being too large to specify in memory, similarly leveraged row generation (i.e., we identified an initial solution without coauthorship constraints and then iteratively added individual violated constraints and reran the optimization).

Two-Phase Reviewer Assignment: The quality of papers submitted to conferences like AAAI 2021 varies vastly. Reviews are signals of quality, but can be very noisy. This was perhaps most convincingly demonstrated via an influential NeurIPS experiment [Lawrence and Cortes, 2014], which split reviewing between two independent program committees. The experiment found that while the strongest and weakest papers could be reliably identified, many papers close to the decision boundary were accepted by one program committee and rejected by the other. This finding invites the idea of obtaining additional reviews for papers close to the decision boundary to reduce variance, and points out that one way to obtain this additional reviewing capacity is to reduce the reviewing load allocated to papers far below threshold.

One widely used approach summarily rejects some fraction of papers without full reviews (based, e.g., on quick perusal of each paper by one or more area chairs); however, this approach can be difficult to implement fairly (area chairs may not have strong opinions after a quick perusal; some papers will be missed; and such an approach would still impose a huge workload across 9,000 submissions). Even when it works well, the approach still leads to poorly explained decisions that many authors find frustrating (a quick perusal does not result in a detailed justification for the decision or suggestions about how work can be improved).

We introduced a novel alternative to summary rejection, called two-phase reviewing. This approach was maintained by AAAI 2022 and has also been adopted by IJCAI 2022 and ICML 2022. Roughly, the key idea is that instead of assigning, say, three reviews to each paper, we initially only assign two. If the two reviews are in agreement that a paper should be rejected, it does not receive further reviews. A second phase of review assignments allocate two additional reviews to the papers that remain. This approach: (a) redirects reviews to borderline papers while also giving meaningful feedback (two full reviews) to authors of rejected Phase 1 papers; (b) avoids the overhead of a separate summary rejection phase treating all papers in the same way; and (c) as a bonus, gives program chairs a second opportunity to assign additional reviewers for papers identified as problematic or for which Phase 1 reviewers went missing.

At AAAI 2021, 2,615 papers (37%)⁴ received two high-confidence reviews recommending rejection and so were rejected in Phase 1, which gave us a surplus of 2,615 reviews (relative to an approach that would hypothetically have assigned 3 reviews to each paper indiscriminately) to spread amongst borderline papers in Phase 2. Of course, a key question is whether the rejected papers in Phase 1 would ultimately have been accepted if they received four full reviews? Luckily, we had a control group of papers that were not subject to two-phase reviewing: those that did not receive two full reviews in Phase 1. By subsampling pairs of reviews from the larger set of reviews that these papers eventually received, we estimated that there was only a 2.9% probability that a Phase 1 rejected paper would eventually have been accepted to AAAI 2021.

The remainder of this paper is organized as follows. We begin by describing the details of our approach for data collection and processing in Section 2. Then, we present our mixed-integer programming formulation of the reviewer–paper matching problem in Section 3. We describe our two-phase reviewing scheme in Section 4. Section 5 consists of an exhaustive experimental analysis of data from AAAI 2021 in which we deployed these methods. Finally, we summarize our contributions in Section 6. We note that much related work has studied different aspects of the reviewer–paper matching problem. To streamline exposition, we discuss related work in each corresponding section.

2 Data collection and processing

In this section, we describe the techniques we designed for collecting and processing raw data about reviewers and papers into an aggregated score for reviewer–paper matching.

2.1 Calculating Conflicts of Interests

A conflict of interest (COI) exists between a reviewer and a paper if the reviewer may not be able to provide an impartial review of the paper due to their relationships with one or more of the paper's authors—such reviewers may have an interest in a paper's acceptance or rejection that goes beyond a desire to see high-quality papers get published. For

⁴Out of 9071 abstract submissions in Phase 1, only 7133 were accompanied with a full paper, out of which 37% were rejected in Phase 1.

example, most of us would struggle to provide a fully unbiased opinion about a paper authored by a former supervisor. Clearly, a reviewer should not be matched to a paper with which they have a COI.

2.1.1 Filtering Manipulative Conflicts

Existing reviewer–paper matching systems detect COIs by asking authors and reviewers to disclose all of their current and past affiliations as well as to declare any additional explicit conflicts. This creates the possibility for a malicious author to provide very long lists of potential conflicts, either in an attempt to lead the system to choose a desired reviewer or simply to avoid expert assessment of their work. We identified COI declarations as suspicious if they satisfied any of the following criteria: (1) a user listed an unusually large number of email domains as affiliations (8 or more); (2) a user listed an unusually large number of non co-authors as COIs (15 or more); (3) a user self-reported an unusually large number of COIs for which the corresponding reported users did not self-report a reciprocal COI (10 or more). We manually examined all such cases and removed all self-declared COIs that did not appear justified on inspecting the user's publicly available profile. The exact parameters listed above were chosen empirically to capture only extreme behavior: the three conditions respectively captured only (1) 1.1% of users who reported more than a one conflict domain; (2) 0.14% of users who self-reported at least one conflict; and (3) 0.44% of users with at least one asymmetric conflict. In some cases, we observed evidence of quite egregious behavior: one user reported 35 conflict domains; another reported 57 asymmetric conflicts.

2.1.2 Automatic Detection of Conflicts of Interest

In many conference management systems, a user provides information such as email domain names for any organizations they are currently or have been associated with. Unfortunately, such user-provided information is often incomplete. Users can purposefully withhold information; they can forget to include a past affiliation; and even if they remember every one, they can mistype a domain or fail to report all of their organization's aliases (*e.g.*, *iitd.ac.in* vs *cse.iitd.ac.in*). Domain normalization and data cleaning can help (*e.g.*, identifying common domain prefixes and suffixes, like *.cse*, *.edu*, and *.ac*, and unifying different aliases of the same organization), but obviously cannot detect unreported or incorrect information.

We thus augmented user-reported conflicts with additional conflicts based on coauthorship information. We required authors and reviewers to supply DBLP profiles and downloaded the full DBLP database from http://dblp.uni-trier.de/xml/dblp.xml.gz. This allowed us to identify coauthorship relations without worrying about disambiguating similar names. We augmented this database with the current conference submissions and built a weighted coauthorship graph, with nodes corresponding to authors and edges existing between couathors with a weight representing the number of couathored publications.

One way to prevent COIs would be to prohibit a reviewer from reviewing a paper submitted by a previous coauthor. However, we consider this treatment too strict as it disallows cross reviewing between authors that may not have interacted in years⁵. Instead, we considered a reviewer i to have a COI with paper p if any of the following conditions were satisfied for some author j of p:

- 1. i coauthored a current conference submission with j;
- 2. i coauthored a published paper with j over the previous 5 years; or
- 3. i and j coauthored more than 6 published papers over any time period.

We further added conflicts between reviewer i and papers by an author j when we inferred that j supervised i or that both i and j were students of the same supervisor. We note that advisor-advisee relationships between users are unknown; hence we need to extract them from the coauthorship graph. We inferred that j was one of i's supervisors if all of the following conditions hold:

- 1. j began publishing considerably earlier than i (at least 5 years);
- 2. j published at least 10 more papers than i; and
- 3. *j* coauthored many of *i*'s early papers (at least 3 out of the first 10).

These inferences did not need to be perfect: each COI simply prevented a particular reviewer–paper matching, and a few false positive COIs were unlikely to be harmful. Indeed, as we show later in Figure 3 (Section 5.1), most papers had a large number of highly qualified reviewers, indicating that occasionally forbidding one of them was unlikely to materially affect the quality of the matching.

⁵In Section 3.1, we describe softer penalties for such cases.

We observe that we are not the first to use DBLP to infer COIs; Long et al. [2013] describe methods for inferring coauthor, colleague, advisor–advisee, and competitor relationships. Like us, they used DBLP data to identify coauthor relationships; however, they relied on users' homepages to identify colleague and advisor–advisee relationships. We did not consider the latter approach feasible given the large scale of AAAI 2021.

2.2 Filtering Manipulative Bids

Bids carry important information about reviewers' preferences. We believe, taking them into account significantly contributes to reviewers' satisfaction with an assignment. Unfortunately, reviewers can maliciously misreport bids with the aim of ensuring a paper's acceptance or rejection [Noothigattu et al., 2021]. Most past conferences have tried to detect such misbehavior via area chair (AC) oversight, spot-checking of discussions, and whistleblower reports. However, such approaches are labor-intensive and not scalable.

A recent paper [Jecmen et al., 2020] proposed alleviating this issue by using a randomized algorithm for the reviewer assignment problem, decreasing the impact of malicious behavior by controlling the probability that certain (suspicious) reviewers or pairs of reviewers are matched to a paper. However, such randomization can impose significant costs in terms of match quality. We nevertheless strongly agree with Jecmen et al. that malicious behavior is better prevented at the matching phase than detected afterwards. We found that the vast majority of papers at AAAI 2021 received a large number of bids by qualified reviewers. As was the case for COIs, the abundance of qualified reviewers allowed us to relatively harmlessly suppress a few potentially suspicious matches even in the unlikely event that many of them were false positives. At AAAI 2021, bidders could express their level of enthusiasm as *not willing*, in a pinch, willing, and eager. To reduce the risk of making problematic assignments, we downgraded or suppressed a reviewer's bids when they appeared suspicious, which could happen in a number of ways.

First, a reviewer might place only a few bids to manipulate the likelihood that they would be assigned particular papers (in the most extreme example, bidding positively on only a single paper). To mitigate this risk, we discarded *all* of a program committee (PC) member's bidding information if they placed fewer than 9 positive bids overall (counting *in-a-pinch* bids as half).

We did something similar at other levels of enthusiasm: if a bidder placed fewer than $4\ eager$ bids, we transformed them into willing bids; then we transformed fewer than $4\ willing\ bids$ into in-a-pinch. We performed a similar procedure for senior program committee (SPC) members, setting a higher threshold of 10 to reflect the higher number of required positive bids.

Second, a reviewer could increase their chances of being assigned a particular paper by bidding negatively on many other papers for which they were qualified. We therefore discarded all *not willing* bids of PCs and SPCs if the number of *not willing* bids exceeded six times the number of *willing* and *eager* bids.

Third, and most complex, *collusion rings* are arrangements under which two or more reviewers agree to positively review each other's papers, a dismaying phenomenon that is reportedly on the rise [Littman, 2021]. We define two criteria to judge whether a bid by a reviewer r on a paper p indicates participation in a collusion ring: (1) at least 40% of r's positive bids are on papers coauthored by a specific coauthor of p; (2) there exists some coauthor r^* of p such that both r and r^* bid positively on each other's papers. Specifically, the sum of the number of r's positive bids on papers coauthored by r^* and the number of r^* 's positive bids on papers coauthored by r is at least 60% of the total number of positive bids by r and r^* . For both (1) and (2) above, we considered *eager* and *willing* bids as positive. These criteria are not perfect; e.g., (1) can occur in small subcommunities where a few researchers focus on a given topic, and (2) can wrongly flag reviewers with a few submissions (e.g., two authors with one paper each bid on each other's paper). We were willing to tolerate some false positives (for the same reasons outlined above), but aimed to reduce their number by requiring a substantial pattern of suspicious bidding across all of a reviewer's bids. In the assignment process we discarded *all* of a reviewer's bids when either (1) or (2) indicate the reviewer's participation in a collusion ring.

We conducted an extensive manual examination of bids, using various heuristic criteria. In all cases that we judged problematic, our method had already eliminated the appropriate bids.

2.3 Scoring Matches

A key question in automated reviewer–paper matching is quantifying the value of matching a reviewer j with a submitted paper i, which we denote as s_{ij} . It is critical to get this right.⁶ In brief, we considered a match to be good if the reviewer both had expertise in the paper's subject matter and was interested in the paper. We assessed expertise by aggregating

⁶Indeed, a few readers may remember that our initial matching at AAAI 2021 had to be changed, and the reason was that we accidentally miscalibrated our scoring function. Based on the emails we received, reviewers definitely noticed!

three complementary signals: Toronto Paper Matching System (TPMS) scores; ACL matching scores; and degree of match between the paper's primary and secondary subject area keywords and those of the reviewers. We assessed degree of interest via bids, assuming a baseline level of interest for papers about which a reviewer was predicted to have expertise and for which the reviewer did not submit any explicit (positive or negative) bid.

Much existing work uses similar signals. There is a body of work on automatically discovering latent topics of a submission and comparing it with latent topics of a set of papers authored by a given reviewer [Mimno and McCallum, 2007, Long et al., 2013, Anjum et al., 2019, Kobren et al., 2019, Wieting et al., 2019].

We describe three further scoring approaches in detail, since we either extended them (the first) or leveraged them directly (the second and third). First, Conry et al. [2009] proposed a score based on the primary and secondary subject areas of the paper and that of the reviewer. The fundamental idea was to embed both reviewers and papers into a discrete vector space with each discrete dimension quantifying the affinity of either the reviewer or the paper to the corresponding topic.

Second, the TPMS score [Charlin and Zemel, 2013] is computed based on the similarity between the text of a submitted paper and a reviewer's prior publications. The similarity is quantified by the dot product between a paper vector and a reviewer vector. The paper vector is constructed using the topic proportions in the text of the submitted paper identified by Latent Dirichlet Allocation (LDA) [Blei et al., 2003]. The reviewer vector is computed by taking an average of the topic proportions in each of the reviewer's prior publications. TPMS scores can only be computed for reviewers whose prior publications are known.

Third, the ACL matching score [Neubig et al., 2020] compares abstracts of a submitted paper and the abstracts of a reviewer's prior publications in a dense vector space. The abstract representation is computed by averaging the embeddings of subwords generated by SentencePiece tokenizer [Kudo and Richardson, 2018]. A score is then computed for each of the reviewer's prior publications with respect to the paper. The top three scores are aggregated to compute the ACL score. Note that ACL scores can only be computed for reviewers whose past publication abstracts are accessible, e.g., via a known Semantic Scholar profile.

The rest of this section is organized as follows: we first describe how we computed Subject Area Matching Scores (SAMS) which is an extension of discrete affinity scores to continuous ones in a way that captures more information. Then, we describe how we normalized raw TPMS, ACL and SAMS scores to make sure that they have the same scale. We then explain how we merged these scores to make them robust to missing data. This was a real concern because we needed to rely on reviewers to manually provide the information required to compute these scores, and thus many reviewers had at least once missing entry. Next, we explain how we leveraged bids by reviewers. Finally, we describe an approach for pruning low-scoring matches, which we used to avoid the possibility of wildly inappropriate matches.

2.3.1 Subject Area Matching Score (SAMS)

To score the keyword match between papers and reviewers, we extended the affinity scoring idea described earlier [Conry et al., 2009], which embeds each reviewer and paper in a vector space. Our new idea is to go beyond the subject areas specified explicitly by learning correlations between different keywords. This is important because the approach of [Conry et al., 2009] assigns a weight of 0 to keywords that are not specified explicitly, even when these have a strong degree of semantic similarity with a keyword that *is* specified. For example, keywords "Humans and AI -> Human-Agent Negotiation" and "Game Theory and Economic Paradigms -> Negotiation and Contract-Based Systems" were considered highly correlated in AAAI 21. We call the result Subject Area Matching Score (SAMS).

Some intuitive properties of SAMS are that it takes into account the fact that the primary keyword is more important than all the secondary keywords; gives each individual keyword less weight when more keywords are listed; and imputes additional keywords (with lower weights) for reviewers based on keyword co-occurence patterns across the whole conference. The details of the SAMS calculation are presented in Appendix A.

2.3.2 Normalizing Scores

We wanted all final scores to lie in the range [0,1] so that we could use consistent units to set the parameters that penalize violations of soft constraints (e.g., we might penalize violation of a soft constraint by 0.1 units, meaning that we would accept a match that scored 0.09 units worse in order to preserve the constraint, but not a match that scored 0.11 units worse). Since we computed the three component scores (TPMS, ACL and SAMS) independently, and since we observed a huge discrepancy between the numerical range of the three raw scores, we first normalized them each individually before taking their weighted average as the final matching score.

To do so, for each score, we independently and randomly selected many (paper, reviewer) pairs. A Program Chair manually examined each pair (reading the paper's abstract and the reviewer's profiles) and annotated each pair (i, p) as

 $y_{ip} \in \{1, 0.75, 0.5, 0\}$, corresponding to *excellent*, *good*, *in-a-pinch*, and *bad* matches respectively. We then performed a linear regression mapping the raw score component to y_{ip} and clipped the resulting function to the range [0, 1].

2.3.3 Aggregating Scores

Our next task was to aggregate scores into a single number between 0 and 1, in a way that was robust to missing TPMS and ACL scores. We decided to give more weight to keyword-based scores than either of the automatically inferred scores (TPMS and ACL) as keyword scores were computed directly using information provided by the paper's authors and potential reviewers and hence were more reliable. When both TPMS and ACL were present, we summed TPMS + ACL + 2 * SAMS and then renormalized; when only one of TPMS and ACL were present, we summed the available score and SAMS and renormalized; when only SAMS was present we used it as the base aggregated score.

2.3.4 Accounting for bids

Given this score capturing reviewer *expertise*, we must now account for reviewer *interest* as expressed through bidding: we call the final result *aggscore*. We create aggscore by raising the expertise score to a power encoding the reviewer's bid: 20, 1, 0.67, 0.4, 0.25 corresponding to *not-willing*, *not-entered*, *in-a-pinch*, *willing*, *and eager* bids respectively. Observe that this procedure maintained scores in the range between 0 and 1; exponents greater than 1 (for *not-willing*) reduced scores while exponents less than 1 (for *in-a-pinch*, *willing*, and *eager*) increased scores. Our use of an exponent of 1 for papers that received no explicit bid left those scores unchanged. Observe also that our use of exponentiation (as compared e.g., to adding a constant and renormalizing) meant that reviewers could not influence the system to give them papers for which they were manifestly unqualified, whereas the presence or absence of a bid could make a significant difference to the scores of sufficiently qualified reviewers.

2.3.5 Cleaning up low scoring matches

Finally, we observed that while high ACL or TPMS scores indicated good matches, their assignment of low values carried much less signal than low SAMS scores. Hence, when aggscore was less than 0.15, we used the minimum of 0.15 and the SAMS score exponentiated by the reviewer's bid. This transformation ensured that whenever a low-scoring match was selected, it was at least from the same subject area. This avoided the possibility of wildly inappropriate matches and helped reviewers see some rationale for our decisions to assign poorly matching papers.

3 Formulating the Review Assignment problem

We formulated the problem of maximizing our scoring function subject to our set of both hard and soft constraints as a Mixed-Integer Programming (MIP) problem. Of course, it is quite natural to formulate the reviewer–paper matching problem as one of maximizing an aggregate weighted matching score subject to reviewer and paper capacity constraints and avoiding COIs, and much past work has done so [Flach et al., 2010, Garg et al., 2010, Tang et al., 2010, Lian et al., 2018, Taylor, 2008, Kobren et al., 2019, Charlin and Zemel, 2013, Charlin et al., 2011]. Indeed, with only COI and capacity constraints, this formulation corresponds to a network flow problem and is thus solvable in polynomial time [Taylor, 2008]. Unfortunately, that formulation can yield an inequitable distribution of work across reviewers and of score across papers. To address this, Stelmakh et al. [2019] and Kobren et al. [2019] focused on finding more balanced matchings. Specifically, instead of the common objective of maximizing the aggregate weighted matching score, Stelmakh et al. [2019] look into finding matches that maximize the minimum matching score across all papers. Because the resulting optimization problem is NP-hard, they design an approximation algorithm, which finds a suboptimal solution by solving a series of network flow problems. Kobren et al. – like us – aim to maximize an aggregate weighted matching score. However, they took a somewhat different approach. Specifically, they augmented an Integer Linear Program with lower and upper bounds on the assignments per reviewer and also added local fairness constraints to ensure that the total matching score for each paper would exceed a threshold; they propose an approximation algorithm that relaxes integrality constraints to solve their assignment problem. Our own approach uses slack variables to soften hard constraints instead of relaxing the integer constraints, resulting in a mixed-integer program. We also introduce a wide range of additional constraints.

We now describe our approach in more detail.

3.1 Constraining Matches

It would not suffice simply to identify a score-maximizing matching: the best reviewers could be given hundreds of papers; different papers could receive very different treatment; and the matching would be wide open to manipulation via malicious behavior. We thus imposed various *constraints* on reviewer–paper matchings.

Constraint 1 (COI). *No reviewer should be assigned to a paper with which they are in conflict.*

Constraint 2 (Number of Reviewers). Each paper must receive a specified number of reviews. Historically, this has been 3 at AAAI and many other AI conferences. In our novel two-phase reviewing system (see Section 4) we solved the reviewer–paper matching problem separately in each of our phases, assigning 2 reviewers for each paper in phase 1, and additional reviewers in phase 2 such that each paper not rejected in phase 1 gets at least 4 reviews in the two phases.

Constraint 3 (Reviewer Load). The number of papers assigned to any reviewer should not exceed some maximum. At AAAI 2021 we had a hard limit of 3 papers per reviewer per phase, and (as we will discuss later) penalized matchings that assigned more than 2 papers per reviewer in a given phase.

Constraint 4 (Seniority). Each paper is assigned at least one experienced reviewer. Our goals were: (1) to ensure that experienced reviewers were distributed fairly across papers, (2) to reduce variance in reviews, and (3) to ensure that each discussion had at least one experienced participant, and thereby aid in the training of novice reviewers.

A second set of constraints served both to ensure that each paper is reviewed by an intellectually diverse set of reviewers and to make collusion rings harder to sustain. Collusion is only possible amongst reviewers who can somehow communicate with one another. By preventing pairs of co-authors from reviewing the same papers, preventing arbitrary pairs of reviewers from bidding to review each other's papers, and by choosing reviewers from as diverse a set of geographic regions as possible, we limited opportunities for gaming the system.

Constraint 5 (Coauthorship Distance). *No two reviewers assigned to the same paper have small distance in the coauthorship graph.*

Constraint 6 (Geographic Diversity). *No two reviewers assigned to the same paper belong to the same geographic region. We inferred regions based on academic affiliations and email addresses.*

Constraint 7 (No 2-Cycles). *No pair of reviewers who both bid positively on each other's papers may review each other's submissions.*

For many papers, it was easy to find qualified reviewers satisfying all of these constraints; however, for others imposing all of these constraints could dramatically degrade reviewer quality or even make it impossible to find the required number of reviewers. It would not have been desirable to satisfy these constraints at all costs. For example, reviewers bidding on each other's papers is natural when they work in similar areas and is not always an indicator of malicious intent. We preferred to avoid such cases out of caution when reasonable alternatives were present, but only up to a point. We therefore expressed all but *COI* and *Number of Reviewers* as soft constraints. More specifically, for each constraint we identified a constant expressing its importance and penalized the objective function by this constant each time the constraint was violated for a reviewer–paper pair. Observe that the task of identifying these constants was dramatically simplified by our decision to normalize our scoring function between 0 (worst possible reviewer–paper matching) and 1 (best possible matching). For example, expressing a coauthorship distance penalty of 0.1 would mean that we would prefer to accept a reviewer–paper matching scoring up to 0.1 points lower in exchange for satisfying the constraint.

3.2 MIP Problem Formulation

We now formally specify our mixed-integer program. Let us denote the set of N papers by \mathcal{P} , the set of program committee members (PCs) by \mathcal{PC} , the set of SPCs (senior program committee members) by \mathcal{SPC} , and the set of area chairs (ACs) by \mathcal{AC} . We define the set of reviewers to be $\mathcal{R} = \mathcal{PC} \cup \mathcal{SPC} \cup \mathcal{AC}$ and use the term *reviewer* to refer to any of a PC, SPC or AC.

Our goal is to assign $\gamma_{\rm pc}$ PCs, $\gamma_{\rm spc}$ SPCs, and $\gamma_{\rm ac}$ ACs to each paper p_i , for $1 \le i \le N$, such that the total reviewer–paper matching score is maximized subject to a set of constraints denoted by $\mathcal C$. Our overall objective function not only includes the total matching score, but also various penalties via the slack variables, due to violation of corresponding hard constraints. We initialize the overall objective function O as the total matching score and then keep on adding terms to it as we relax the various constraints in the next section. We create binary variables x_{ij} that denote whether paper i is assigned to reviewer j^7 . We can write:

Initial Objective:
$$O^{\text{match}} = \sum_{i \in \mathcal{P}, j \in \mathcal{R}} s_{ij} x_{ij}$$
. (1)

Recall that $s_{ij} \in [0, 1]$ is the match score between reviewer j and paper i as discussed in section 2.3. Next, we formulate all the (soft) constraints in C as described earlier.

⁷In Phase 2, we set $x_{ij} = 1$ if j was already assigned to i in Phase 1 to ensure that the matching from Phase 2 is a superset of Phase 1 matching. The capacity limits on reviewers were increased accordingly.

3.3 Formulation of Constraints in C

• Constraint 1 (COI): Let $coi_{ij} = 1$, if there exists a conflict of interest between reviewer j and any of the authors of the paper i, and 0 otherwise. reviewer j cannot review paper i if $coi_{ij} = 1$:

$$x_{ij} = 0$$
, for each $i \in \mathcal{P}, j \in \mathcal{R}$, such that $coi_{ij} = 1$ (2)

• Constraint 2 (Number of reviewers): For each paper p_i , we need to ensure that it gets the desired number of reviewers:

$$\sum_{j \in \mathcal{PC}} x_{ij} \le \gamma_{\text{pc}} \; ; \; \sum_{j \in \mathcal{SPC}} x_{ij} \le \gamma_{\text{spc}} \; ; \; \sum_{j \in \mathcal{AC}} x_{ij} \le \gamma_{\text{ac}}$$
 (3)

Usually these constraints will be tight because the scoring function is non-negative. However, it is possible to have a case in which conditional on the rest of the assignment, the only remaining matches do not contribute to the objective function. In such a case, the optimizer will not assign those papers their full capacity of reviewers since such assignments would be of poor quality. Such papers can be flagged for manual review.

Constraint 3 (Reviewer Load): The total number of papers assigned to a reviewer j should not exceed their capacity c_i ∈ Z⁺:

$$\sum_{i \in \mathcal{P}} x_{ij} \le c_j, \forall j \in \mathcal{R}.$$

Just ensuring the above upper bound may lead to an inequitable assignment of papers to reviewers, especially ACs and SPCs, many of whom may end up with no assignment at all. To resolve this, one option is to add a lower bound l_i on the number of papers assigned to ACs and SPCs, as suggested by Kobren et al. [2019]:

$$\sum_{i \in \mathcal{P}} x_{ij} \ge l_j, \forall j \in \mathcal{SPC} \cup \mathcal{AC}.$$

However, the lower bound constraint only ensures that no SPC or AC is unassigned, rather than preventing skewed matchings. To promote an equitable distribution of papers amongst reviewers, we introduce W intermediate capacity levels. For each $w \in \{1, 2, \ldots, W\}$, we define c_{jw} to be the intermediate capacity for reviewer j and set $c_{j1} = l_j$ and $c_{jW} = c_j$. For ACs and SPCs, we replace the hard capacity constraints with a sequence of soft capacity constraints, one for each capacity level w. These constraints promote equitable distribution of papers as additional penalties are incurred each time an assignment crosses a new capacity level, making it very expensive to overload an individual.

To do so, we introduce new slack variables, $s_{jw}^{\text{cap}} \geq 0, \forall j \in \mathcal{SPC} \cup \mathcal{AC}, \forall w \in \{1 \dots W\}$ and penalize the objective by $p_w^{\text{cap}}(\mathsf{type}_j)$ for each additional assignment above c_{jw} , where type_j denotes the reviewer category (SPC or AC). Then, for each $w \in \{1 \dots W\}$:

$$\sum_{i \in \mathcal{P}} x_{ij} - s_{jw}^{\text{cap}} \le c_{jw}, \forall j \in \mathcal{SPC} \cup \mathcal{AC} \text{ and } \forall w \in \{1 \dots W\}$$
 (4)

$$O^{\text{cap}} = \sum_{w \in W} \sum_{j \in \mathcal{SPC} \cup \mathcal{AC}} p_w^{\text{cap}}(\text{type}_j) s_{jw}^{\text{cap}}$$
 (5)

• Constraint 4 (Seniority): We first assign seniority $j \in \{0, 1, 2, 3\}$ to each reviewer j, such that 3 is the senior-most category and 0 is the junior-most category. In AAAI 2021, we chose to assign seniority levels as follows: Reviewers who had previously reviewed for at least 3 relevant conferences or published 10 or more papers in AAAI or a sister conference were assigned seniority level 3. Remaining reviewers with between 4 and 9 published papers were assigned seniority level 2. Remaining reviewers with 2 to 4 papers or that had reviewed one or two previous conferences were assigned seniority level 1. All other reviewers were assigned a seniority level of 0.

⁸Reviewers were asked: "How many times have you been part of the program committee (as PC/SPC/AC, etc) of AAAI, IJCAI, NeurIPS, ACL, SIGIR, WWW, RSS, NAACL, KDD, IROS, ICRA, ICML, ICCV, EMNLP, EC, CVPR, AAMAS, HCOMP, HRI, ICAPS, ICDM, ICLR, ICWSM, IUI, KR, SAT, WSDM, UAI, AISTATS, COLT, CORL, CP, CPAIOR, ECAI, or ECML in the past?"

We then reward each paper for maximizing its seniority level, up to some maximum reward. We introduce slack variables, $s_i^{\text{sen}} \ge 0 \ \forall i \in \mathcal{P}$.

$$s_i^{\text{sen}} \le \sum_{j \in \mathcal{PC}} \text{seniority}_j x_{ij}, \forall i \in \mathcal{P}$$
 (6)

$$s_i^{\text{sen}} \leq \text{TargetSeniority}, \forall i \in \mathcal{P}$$
 (7)

$$s_i^{\text{sen}} \ge \text{MinSeniority}, \forall i \in \mathcal{P}$$
 (8)

$$O^{\text{sen}} = \sum_{i \in \mathcal{P}} \text{Reward}^{\text{sen}} s_i^{\text{sen}} \tag{9}$$

Note that setting MinSeniority greater than 0 can result in possible infeasibility (i.e., it may not be possible to assign a minimum level of seniority simultaneously to every paper). Setting MinSeniority = 0 keeps the constraint soft. Papers are rewarded for seniority up to a maximum seniority level given by TargetSeniority. Setting this target allows us to express a preference for spreading seniority out over many papers rather than concentrating it on a few papers, as the objective only gets a bonus for the first TargetSeniority units of seniority per paper.

• Constraint 5 (Coauthorship Distance): This set of constraints penalizes the assignment of pairs of reviewers who have ever coauthored a paper together to the same paper. This reduces the chances of papers' reviewers knowing each other, promoting review diversity. To do so, for each pair of reviewers in $V = \{(j, j')|j < j', j, j' \in \mathcal{PC} \cup \mathcal{SPC}\}$, we define a new variable $\operatorname{cad}_{jj'} \geq 0$ such that it takes the value of 1 if there exists a common paper assigned to both j and j', and 0 otherwise.

The following constraints define $cad_{ij'}$:

$$\operatorname{cad}_{jj'} \ge 0, \forall j, j' \in V \tag{10}$$

$$\operatorname{cad}_{jj'} \ge x_{ij} + x_{ij'} - 1, \ \forall i \in \mathcal{P} \text{ and } \forall j, j' \in V$$
 (11)

Next, let $d_{jj'}$ denote the edge distance between two reviewers j and j' in a coauthorship graph with reviewers as nodes. An edge exists between j and j' iff they have ever published a paper together (based on DBLP data, as described in Section 2.1.2). To discourage coauthors being reviewers of the same paper, we add a penalty that is bigger when coauthorship distance is small:

$$O^{\operatorname{co}} = \sum_{(j,j')\in V} p^{\operatorname{co}}(d_{jj'})\operatorname{cad}_{jj'} \tag{12}$$

 $p^{co}(d)$ is the penalty coefficient, which depends on coauthorship edge distance d. We set $|p^{co}(1)| > |p^{co}(2)| > 0$ and $p^{co}(d) = 0, \forall d > 3$.

• Constraint 6 (Geographic Diversity): For each paper i, let variable reg_i count the number of distinct geographic regions of its assigned reviewers. To encourage assignment of reviewers from different geographic regions, we add a reward proportional to reg_i in the overall objective function so that reg_i is maximized. To count reg_i , we need to introduce auxiliary indicator variables, $v_{ir} \leq 1$, that take the value of 1 only if paper i is assigned at least 1 reviewer from region i0 Regions. Let i1 i2 indicate if reviewer i3 belongs to region i3 or not. The following expressions define the overall regional constraint for each paper:

$$\operatorname{reg}_{i} \leq \sum_{r \in \operatorname{Regions}} v_{ir}, \ \forall i \in \mathcal{P}$$
 (13)

$$v_{ir} \le \sum_{j \in \mathcal{PC} \cup \mathcal{SPC}} t_{jr} x_{ij}, \forall r \in \text{Regions and } \forall i \in \mathcal{P}$$
 (14)

$$v_{ir} \le 1, \forall r \in \text{Regions and } \forall i \in \mathcal{P}$$
 (15)

$$O^{\text{reg}} = \sum_{i \in \mathcal{P}} \text{Reward}^{\text{reg}} \text{reg}_i$$
 (16)

• Constraint 7 (No 2-Cycles): These constraints aim to avoid scenarios where two reviewers both bid positively on each other's papers and are assigned these papers to review. We first identify all such bidding cycles, where reviewer j bids positively on paper i authored by reviewer j' and j' bids positively on paper i' authored by reviewer j, with $j, j' \in \mathcal{PC} \cup \mathcal{SPC}$. Denote such a bidding cycle by a 4-tuple (j, j', i, i'), and the set of all such cycles as CY. We then aim to avoid any of the assignments in the bidding cycle (j, j', i, i'). We introduce

slack variables, $s_{jj'ii'}^{cy} \ge 0$, for each bidding cycle, and add a penalty p^{cy} in Equation (18) for every assignment that belongs to a bidding cycle⁹.

$$x_{ij} \le s_{jj'ii'}^{\text{cy}}, \forall j, j', i, i' \in CY \tag{17}$$

$$O^{\text{cy}} = \sum_{j,j',i,i' \in CY} p^{\text{cy}} s_{jj'ii'}^{\text{cy}}$$
(18)

Finally, our overall assignment problem can be stated as:

$$\max O = O^{\text{match}} + O^{\text{cap}} + O^{\text{sen}} + O^{\text{co}} + O^{\text{reg}} + O^{\text{cy}}$$
 subject to \mathcal{C} .

3.4 Solving the Review Assignment problem

Given our formulation, instantiating a variable x_{ij} for each possible (reviewer j, paper i) combination, along with all of the associated slack variables and constraints, would lead to a MIP too large to store in memory, let alone to solve. We therefore applied column (variable) generation, only creating variables for a subset of all possible assignments and employed row (constraint) generation.

3.4.1 Generation of Assignment Variables

We only created x_{ij} variables that were likely to be relevant (thereby restricting the space of possible assignments; implicitly, non-generated variables are set to 0). There was little point in considering variables that correspond to (i,j) pairs with low matching scores, as these would represent poor matches. In rare cases, this may result in papers receiving fewer than the desired number of reviews. When the MIP is infeasible in this way, one can iterate (perform column generation) by generating more matching variables for the corresponding papers. However, at AAAI we assigned matches to such papers manually, as the algorithm is unlikely to do much better than a random assignment when given only low-scoring alternatives. We did not create variables for any reviewer–paper pair (i,j) with $s_{ij} < 0.15$.

We created variables as follows: for each paper, we created a variable for the k highest scoring PC, SPC, and AC reviewers. Similarly, for each PC/SPC/AC member, we created a variable (if it did not exist already) for their highest scoring k/5k/10k papers. k can be iteratively expanded as time allows (perhaps in a targeted way, such as increasing k for underutilized reviewers) until the dense matrix is recovered. However, our MIP was computationally feasible at high enough k that further increases to k offered only negligible improvements, so we did not iteratively perform column generation.

3.4.2 Generation of Coauthor Constraints

Even given our reduced k, there were too many coauthor constraints to include (the number scales with the product of the number of x_{ij} variables and the number of reviewers). Instead, we started solving the problem with no coauthor constraints. After reaching an initial solution, we identified violated coauthor constraints and added them explicitly to the MIP. We repeated this process until we were satisfied with the number of violated constraints; in practice the number of violations plateaued after eight iterations. Pseudocode is given as Algorithm 1 in the following:

⁹In the conference and this paper's experiments, we used an alternate formulation of the constraint which only penalized bidding cycles that led to assignment cycles. In this formulation, slack variables $s_{jj'}^{cy}$ were created for each pair of reviewers (j,j') involved in a bidding cycle, and the constraint was enforced with $x_{ij} + x_{i'j'} \le (1 + s_{jj'}^{cy})$. We prefer the above formulation because we now feel that it is more correct to penalize both halves of a cycle separately.

¹⁰We note that this suggests a refinement to the bidding procedure: it is only necessary to show reviewers papers for which a sufficiently positive bid could bring their score above the threshold. This could result in large time savings for reviewers in the bidding phase, as it can be hard to sift through an entire conference worth of papers.

Algorithm 1: Assignment Variable Sparsification and Constraint Generation

```
1: Let V_{\mathrm{master}} contain all coauthor constraints
2: Let \mathbf{X}_k be the set of x_{ij} variables obtained by sampling a constant multiple of the top k papers for every reviewer and top k reviewers for every paper
3: i \leftarrow 0
4: V_i \leftarrow \{\} {Store of violated coauthor constraints up to iteration i, initially empty}
5: while True do
6: Solve the MIP defined by \mathbf{X}_k and V_i. Store the solution in \mathbf{X}^*
1: Identify all new coauthor violations V_{\mathrm{new}} in \mathbf{X}^* using V_{\mathrm{master}}
8: if V_{\mathrm{new}} is empty or time has run out then
9: Return \mathbf{X}^*
10: end if
11: V_{i+1} \leftarrow V_i \cup V_{\mathrm{new}}
12: i \leftarrow i + 1
13: end while
```

Lastly, to reduce computation time, we did not attempt to find an optimal solution to the MIP. Instead, we set an absolute MIP-gap tolerance of 20. Since aggscore is on a scale between 0 and 1 and we make on the order of tens of thousands of assignments, being sub optimal by at most 20 objective function units is relatively benign. The result was that we found a very nearly optimal solution much more quickly.

4 Two-Phase Reviewer Assignment

The quality of papers submitted to large conferences such as AAAI 2021 varies vastly. An influential experiment by organizers of the 2014 NeurIPS conference [Lawrence and Cortes, 2014] split reviewing between two independent program committees and had them both review 10% of submissions. It found that the strongest papers (a small set) and the weakest papers (a much larger set) could be reliably identified, but that many papers close to the decision boundary were accepted by one program committee and rejected by the other. In the years since, conference organizers have sought to reallocate reviewing resources from papers that are nearly certain to be rejected to papers that have a realistic chance of acceptance, to improve review quality for the latter group. A popular approach is to employ simple heuristics designed to detect low-quality papers, a process known as "summary rejection" or "desk rejection". For example, in IJCAI 2020, area chairs were asked to spend a short amount of time skimming each paper to decide whether it deserved a more careful review [Bessiere, 2020]. Neurips 2020 employed a similar system: over three weeks, area chairs skimmed over 9,000 papers to identify obvious rejects and senior area chairs cross-checked these choices; 11% of submissions received summary rejects [Yuan, 2020]. Given the size of AI conferences, such summary rejection procedures are time consuming for area chairs. Furthermore, they are likely to be noisy and also may reflect unconscious biases against superficial properties of a paper, meaning that they may not be reliable enough to eliminate more than a relatively small fraction of papers. Finally, they tend to be unpopular with authors, who dislike having their paper rejected via an opaque process that produces no reviews. For these reasons, NeurIPS decided not to employ such an approach in 2021 on the basis of negative feedback received in 2020.

We propose an alternative early-rejection approach that simultaneously concentrates the conference's reviewing budget on papers close to the decision boundary; provides meaningful feedback to authors of early-rejected papers; and early-rejects few papers that could ultimately have been accepted (see our evaluation below). The key idea is to break reviewing into two phases. In Phase 1 each paper is assigned 2 reviewers. Papers that receive two sufficiently-high-confidence reviews recommending rejection are rejected at this stage, with the authors immediately receiving these full reviews and being offered no opportunity for rebuttal. The process then proceeds to Phase 2, where two or more additional reviewers are assigned to each of the papers that remain. After the second round of reviews, rebuttals are solicited from authors and reviewers from both phases are asked to read rebuttals and each other's reviews, to engage in a discussion mediated by SPCs and ACs, and ultimately to revise their reviews accordingly. Program Chairs then make decisions based on recommendations from ACs.

The key rationale for this system is that, given the low acceptance rates at AI conferences, papers for which the first two reviews are both confident and negative have a very low chance of eventual acceptance. Because reviews are much more careful than quick perusals by ACs, this system is also able to reject a larger fraction of papers than the summary rejection approaches employed by IJCAI, NeurIPS, and other conferences. The resulting reviewing resources can be devoted to papers with a larger chance of acceptance, reducing variance in these recommendations. In the experimental section below, we offer evidence both that papers rejected in Phase 1 were indeed likely to be rejected if given more reviews, and that additional reviews performed in Phase 2 indeed reduced variance in confidence-weighted average scores.

It is also worth mentioning three additional benefits of the Two-Phase approach. First, inevitably some reviewers fail to complete their assignments, others report low confidence, and still others point out a need for additional reviews by

specialists in particular topics. When this occurs in Phase 1, new reviewers can be found without needing to resort to ad hoc, manual approaches that scale badly to large conferences. Second, the existence of a second reviewer–paper matching period at the beginning of Phase 2 makes it possible to fast-track high-quality rejected submissions from another conference, using their previous reviews and some numerical constraint on their average scores to take the place of the reviews that would have been obtained in Phase 1. We deployed such a "fast-track" in AAAI 2021 for papers that received NeurIPS and EMNLP reviews that scored them roughly in the top half of submissions. Third, many authors appreciate receiving rejection notifications quickly so that they can resubmit their work to another venue without waiting for the whole review process to conclude.

Finally, we note two key drawbacks of Two-Phase reviewing: reviewers have to be chased twice, increasing workload for program chairs, ACs, and SPCs; and authors rejected in Phase 1 have no opportunity to rebut reviews that they consider erroneous.

5 Evaluations

5.1 Analysis of Match Quality

We deployed the reviewer–paper matching approach described above for the AAAI 2021 conference. In this section, we analyze a dataset of 6,729 submissions and their reviews from 8,072 reviewers in the main conference's PC. Unfortunately, we are unable to release the data used for any analyses because data about a conference review process is inherently sensitive, but we summarize our findings in what follows. We used the following parameters (see Section 3.2 for definitions): Reward^{reg} = 0.1, |Regions| = 5, $p^{cy} = -0.05$, $p^{co}(1) = -0.3$, $p^{co}(2) = -0.2$, $Reward^{sen} = 4$, Regions = 4, Regions =

We begin by evaluating the quality of the matches we made in the real conference. Evaluating whether high quality matches were made is tricky. Of course, the gold standard is to ask area chairs to manually ensure that matchings make sense; it is also possible to monitor social media for outrage [Lawrence, 2014]. Our focus here was to go beyond such subjective measures, performing a data-driven and quantitative evaluation along as many dimensions as possible. What follows is, to our knowledge, the most comprehensive post-hoc evaluation of a Computer Science conference's match quality. (We note that such analyses are typically limited only to figures that appear in program chairs' presentations at conference business meetings. Of course, the confidentiality of reviewing data typically prevents others from conducting further, in-depth analyses.)

5.1.1 Did our scoring function capture reviewer expertise?

First, we investigated whether reviewers actually bid on papers for which we assigned them high "expertise" scores; presumably reviewers bid positively on papers that they were capable of reviewing. Considering the set of reviewers who submitted at least one bid, we looked at all reviewer–paper pairs that participated in our matching and that we assigned base scores (i.e., aggscores before exponentiation to take bids into account) greater than 0.75. We found that 29% of these pairs were accompanied by *eager* bids, 38% *willing*, and 3% *in a pinch* (the remainder no bids). This constitutes strong evidence that high base scores indeed correlated with high match quality.¹⁴

Second, we observed that the distribution of paper scores (reviewers could score papers between 1 and 10) noticeably changed as a function of self-reported confidence.¹⁵ Figure 1 shows that more confident reviewers tended to give more

¹¹For this analysis we removed papers that were withdrawn, desk rejected, or were rejected as dual submissions. We also excluded all papers from the AI for Social Impact track as these papers conducted matching via a somewhat different process. We included papers that were only submitted in the second phase.

¹²The values of these parameters express tradeoffs between violating a constraint and match quality, and hence induce the reviewer–paper matching problem's objective function. There is no "right" way to set them: they reflect program chairs' subjective answers to questions like the value of having senior reviewers allocated to each paper and the risk of authors forming bidding cycles. This paper does not experimentally investigate these parameter settings, but we note that other conference organizers could conceivably want to set them differently.

¹³SPCs and ACs were only assigned in Phase 1. We set reviewer capacities to 24 and 60 for SPCs and ACs respectively. We set W=5 with $c_j.=[8,12,16,20,24] \forall j\in\mathcal{SPC}$ and $c_j.=[20,30,40,50,60]$ for $j\in\mathcal{AC}$, with $p_w^{\text{cap}}(\cdot)=-0.05,1\leq w\leq (W-1)$ and a very high penalty of -0.5 for $p_w^{\text{cap}}(\cdot)$ for both SPCs and ACs, so that the system never assigned beyond $c_{jW}=c_j$.

¹⁴We acknowledge that the bidding interface is a possible confounding factor here—users could sort through papers ordered by their TPMS scores (one of the inputs to aggscore) and it is extremely unlikely that any user looked at a large fraction of the submissions.

¹⁵Confidence levels could be reported as "Reviewer made an educated guess", "Reviewer is broadly knowledgeable, but not an expert in the area", "Reviewer is knowledgeable in the area of the paper", or "Reviewer is an expert in the specific topic of the paper".

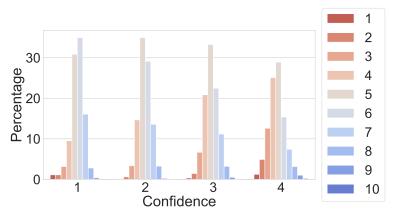


Figure 1: Paper score distribution by confidence of reviewer. More confident reviewers gave fewer 5s and 6s.

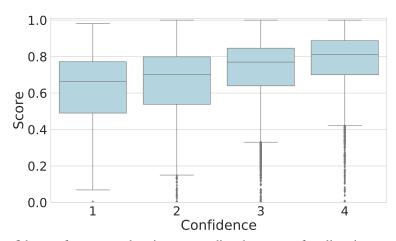


Figure 2: Reported confidence of an eventual review vs. predicted aggscore for all reviewer–paper pairs matched at AAAI 2021.

informative paper scores (fewer borderline 5 and 6 scores). Given that higher confidence reviews were more informative, we examined the relationship between our scoring function and reported reviewer confidence. Figure 2 shows that our scoring function was positively correlated with confidence: as confidence increased, so did the 25th, 50th, and 75th percentile of scores.

5.1.2 Assuming that our scoring function predicted review quality, how close did we come on average to assigning the best possible reviewer to each paper?

We considered the ordinal ranking of reviewers assigned to each paper in terms of aggscore, where rank 1 corresponds to the reviewer with the highest aggscore for that paper. We then looked at the mean reviewer ranking for each paper with respect to the ranks of all of the paper's reviewers. The first/second/third quartiles of papers in terms of mean reviewer ranking were 7/13.5/38, which implies that papers were often assigned to their top reviewers. (Note that the median of number of reviews per paper was 4.)

5.1.3 Was our scoring function stable under missing data?

Recall that our paper-reviewer matching score, aggscore, is a combination of three constituent scores: ACL, TPMS, and SAMS (see section 2.3.3). The overall coverage of constituent scores at AAAI 2021 was 96.64%, and 60.25% for ACL and TPMS score respectively. We excluded the SAMS component from the analysis since there were no papers with this score missing. We considered only "qualified" (paper, reviewer) pairs ($s_{ij} \ge 0.15$) for which all of the three scores were available. We then computed two proxy aggregate scores, simulating scenarios where TPMS and ACL scores were missing, respectively.

The standard deviation of the changes in aggscores caused by missing data were 0.049 and 0.048 respectively, whereas the mean standard deviation of the complete-data score for a given paper was 0.127. Since the variance of the differences between the hidden data aggscores and the full-data aggscores was much smaller than the average variance in aggscores across reviewers for a paper, the aggscore was still likely to have made a similar assessment of reviewer–paper pairings even when some data was withheld.

5.1.4 How important were positive bids for matching?

Over all matches, reviewers were assigned papers for which they bid positively (willing or eager) 77.4% of the time. A back-of-the-envelope calculation leads us to estimate that 79.3% of these matches may not have happened had the reviewer not bid positively. To calculate this, we first extracted the minimum aggscore amongst the papers' matches and considered this the lowest threshold for a match to happen on that paper, comparing to the aggscore without the reviewer's bid. This analysis ignored soft constraints, since it did not re-run the optimization to evaluate each counterfactual scenario where a bid was not submitted.

5.1.5 How effective was our COI detection?

We considered self-reported conflict domains, explicitly given conflicts, and a conflict between coauthors of papers submitted to AAAI 2021 as 'trivial conflicts'. Out of the total 2,674,372 conflicts we found, 96.4% were trivial. Of the remaining 3.6% conflicts, 2.8% were due to unreported coauthorship relationships we verified via DBLP. The remaining 0.8% of conflicts were between predicted student-supervisor pairs or predicted students of the same supervisor. Overall, our system added at least one nontrivial conflict to a large majority (78.8%) of submissions.

5.2 Analysis of MIP Solving

We now evaluate our matching algorithm described in Section 3, including a comparison to the previous year's matching algorithm. For our experiments, we created a full conference dataset containing all submitted AAAI 2021 papers and reviewers analyzed above, including additional reviewers that were not ultimately assigned any reviews in practice, bringing the total number of reviewers up to 8,964. Except where otherwise noted, we evaluated our algorithm in terms of the single-phase matching problem, as this is more representative of traditional conferences. To facilitate comparison with prior work, we required each paper to be assigned four reviews ($\gamma_{pc} = 4$) and set a limit of five reviews per reviewer ($c_j = 5$). We ran row generation (as described in Section 3.4.2) for 10 iterations. We ran all of our experiments on a 16-core machine with Intel Silver 4216 Cascade Lake 2.1GHz processors and 96 GB RAM. For MIP solving, we used CPLEX version 12.9.0.0 with default parameters.

We note a subtlety that arises when comparing different assignments. Recall that we used an inequality instead of a hard constraint on the number of matches each paper receives, allowing the MIP to assign fewer than γ_{pc} reviewers to a paper. This can occur for papers for which there are no qualified reviewers or only very poor matches conditional on the rest of the assignment. A consequence is that we can find ourselves needing to make comparisons across assignments in which different numbers of reviewer–paper matches exist. In these cases, we pad all matchings with reviewer–paper matches that contributed nothing to the objective function, as though we had matched the paper to a reviewer having an aggscore of 0 who imposed neither rewards or penalties via soft constraints. Such zero-contribution matches accounted for at most 1% of the total reviews in any of our matchings reported below. While in reality we addressed all such cases at AAAI 2021 manually, we note that many AAAI 2021 reviewers were ultimately assigned zero papers, meaning that a large pool of available and unused reviewers did exist.

5.2.1 How did our algorithm compare to the algorithm used by the previous iteration of the conference?

We compared our matching algorithm to the method used in the conference's previous iteration (AAAI 2020), a flow-based matching algorithm. Rather than simple capacity constraints, each paper and reviewer had a number of weighted *slots* that linearly scaled the contribution of each assignment to prioritize each paper getting some good reviewers and each reviewer getting some good papers. Based on advice from the previous program chairs, we set the paper slot weights to be 8/4/1/1 and reviewer slot weights to be 8/2/1/1/1. Their reviewer—paper scoring function differed from ours in two main ways: (1) it did not use ACL scores, and (2) bids scaled scores multiplicatively rather than exponentially. Beyond the scoring function, their matching algorithm did not attempt to satisfy any soft constraints.

Nevertheless, we investigated how effective last year's approach was at limiting soft constraint violations despite not optimizing for them (i.e., we tested how frequently these violations occur organically at the optimum of a simpler matching problem). We ran both algorithms and evaluated the number of soft constraint violations compared to our approach. For reference, we also performed a similar experiment that compared our AAAI 2021 algorithm to a version of the same algorithm that omitted all soft constraints. We summarize the results in Table 1, reporting the percent

Soft constraint	Baseline (no soft constraints)	AAAI 2020
Constraint 4 (Seniority)	56.1	9.5
Constraint 5 (Coauthorship Distance)	88.1	76.8
Constraint 6 (Geographic Diversity)	24.1	23.3
Constraint 7 (No 2-Cycles)	84.6	-90.9

Table 1: Percent reduction of soft constraint violations using our approach relative to (1) our approach without soft constraints and (2) last year's matching algorithm for a simulation of a single-phase version of AAAI 2021.

Soft constraint	% Aggscore reduction
Constraint 4 (Seniority)	0.05
Constraint 5 (Coauthorship Distance)	1.17
Constraint 6 (Geographic Diversity)	0.85
Constraint 7 (No 2-Cycles)	0.01
All constraints	2.04

Table 2: Percent reduction in aggscore when each soft constraint was turned on individually relative to a base MIP having no soft constraints. The final row displays the reduction when all soft constraints were present.

reduction of: (a.) papers without a senior reviewer (Constraint 4), (b.) coauthor violations (Constraint 5), (c.) papers with reviewers from the same region (Constraint 6), and (d.) cycle violations (Constraint 7). We observed that AAAI 2020's approach led to substantially more violations of three of the four soft constraints. Most notably, our algorithm assigned to the same paper 76.8% fewer pairs of reviewers who were previous coauthors. Conversely, our approach led to 90% *more* violations of our no-2-cycles constraint, prohibiting pairs of reviewers who bid positively on each other's submissions from being assigned to each other's papers. However, such matchings were quite rare overall (22 for AAAI 2020 and 42 for our approach out of total 26,916 reviewer—paper matchings). We believe that the AAAI 2020 method led to fewer 2-cycles because their scoring function weighs positive bids less heavily than ours does and therefore is less likely to match reviewers to papers where a reviewer bid positively. When using our scoring function, we were able to reduce 2-cycle violations by 84% using our soft constraint over the baseline version with no soft constraints.

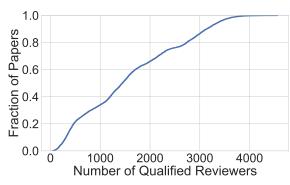
Our algorithm had approximately the same memory footprint as the flow-based approach (96 GB vs 95 GB) despite the additional soft constraints that our method represented: the flow-based method creates an edge for every reviewer–paper pair whereas we only created variables for a subset of qualified reviewers. In terms of runtime, running our algorithm with 10 iterations of row generation required 52.0 walltime hours compared to 0.8 needed for the AAAI 2020 approach. Note that our approach is anytime: it can terminate after any number of iterations of row generation. One iteration of our algorithm took 0.9 walltime hours and five iterations took 7.3 walltime hours. We were willing to devote a few days to computation, so we find these numbers reasonable. Nevertheless, in what follows we identify some ways to reduce runtimes without sacrificing much in performance (e.g., $5 \times$ speedup via decomposing the matching into two stages; $1.7 \times$ speedup via reducing k to further sparsify the constraint matrix).

5.2.2 What did introducing soft constraints cost us in matching aggscore?

Table 2 shows that for the most part, with our specific settings of the soft constraint parameters, we were able to have our cake and eat it too. With all of our soft constraints turned on, we only lost 2.04% mean aggscore. With each soft constraint turned on individually, the Coauthorship Distance and Geographic Diversity constraints reduced mean aggscore the most (1.17% and 0.85% respectively) while the Seniority and No 2-Cycles constraints reduced mean aggscore the least (0.05% and 0.01% respectively). The sum of the aggscore reductions across matchings where each soft constraint was turned on individually was 2.08% (sum of first four rows in Table 2), very similar to the 2.04% reduction in mean aggscore when all constraints were turned on simultaneously. This suggests that there was very little complementarity across different constraints (e.g., when we reduced Coauthorship Distance violations, we rarely also increased Geographic Diversity as a side effect).

5.2.3 How well did the row generation of coauthorship distance constraints perform?

Ideally we would evaluate the performance of the row generation of coauthorship distance constraints by comparison after a fixed number of iterations to an optimal approach that held all rows of the constraint matrix in memory. Unfortunately, we were unable to compute the optimal objective value (OPT) for our dataset. Nevertheless, we can



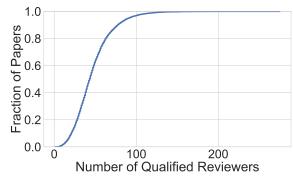


Figure 3: ECDF of the number of "qualified" reviewers for each paper (i.e., reviewers with $s_{ij} \ge 0.15$), considering both all reviewers (Left) and only reviewers who also made a positive bid for the paper (Right). The median paper had 1446 qualified reviewers and 43 qualified reviewers who also placed a positive bid.

compare to an upper bound on OPT. Since each additional coauthorship constraint can only penalize the objective function, the optimal value of the objective function (without coauthorship penalty from ungenerated constraints) can only weakly decrease as these soft constraints are added. Therefore, the objective value we observe after the last iteration of row generation is an upper bound on OPT. After 10 iterations, we closed the gap between the initial solution before row generation (obtained with V_0 in Algorithm 1) and the upper bound on OPT by 77.5%.

5.2.4 How did the choice of our column generation parameter k impact the objective?

Recall that to reduce the size of our MIP, we created variables only for the most-promising paper—reviewer pairs: for each reviewer, we sampled the k best-scoring papers, and for every paper, we sampled the k best-scoring reviewers. We then filtered out any paper—reviewer pairs with score below a threshold, keeping only qualified reviewers. We set k=50 when creating the match for AAAI 2021. Figure 3 shows that after this filtering, the median paper had $\approx 1,500$ qualified reviewers. Expanding to include variables for all possible qualified assignments (unbounded k) would have required much more memory than was available via our computing resources.

We investigated the impact of k on the quality of the resulting matching. Running our algorithm with a much smaller k value (k = 10), we observed only a 1.8% loss in the objective but a 1.7 times speedup in performing 10 iterations of row generation, as compared to k = 50. Increasing k to 100 had a negligible impact on the objective (0.04%). We consider it unlikely that significant additional gains would be achieved by even further increases to k.

5.2.5 What were the tradeoffs between objective value and computational savings with multiple phases?

In a two-phase conference, about half of the total reviews are assigned in each phase, so the Phase 1 and Phase 2 MIPs have half as many free variables as the MIP for a corresponding single-phase conference. We should expect solving the two smaller problems to be much faster than solving the larger one, since the running time of MIP solvers tends to scale superlinearly with problem size. However, of course, the solution obtained by solving two phases optimally in succession is likely to achieve lower objective value than the optimal solution to the single-phase problem. For example, imagine that each stage assigns two reviews per paper and that for some paper, there are only four qualified reviewers. The two-phase algorithm will not consider that it may need to save two qualified reviewers for the second phase, and may assign these highly specialized reviewers elsewhere, consuming their capacity. We thus empirically evaluated loss in objective value due to running a two-phase version of our conference. In these experiments, we assigned two reviewers per paper in Phase 1, fixed those assignments, and then assigned two more reviewers per paper in Phase 2. We found that the resulting matching had objective value only 0.02% lower, as compared to the single-phase conference. On the other hand, decomposing the problem in this way led to a $5\times$ speedup.

It occurred to us that this approach of incrementally building up a MIP solution reviewer by reviewer did not require that the conference actually did perform two-phase reviewing. For example, a single-phase conference could use this same two-phase strategy simply to speedup MIP solving, which could be very important for conferences significantly larger than AAAI 2021. To investigate this idea, we evaluated a four-phase approach that assigned one reviewer per paper, fixed those assignments, and repeated four times until each paper had four reviewers. As before, we observed very encouraging results: the objective value decreased by only 0.33% relative to a single-phase conference, whereas MIP solving was accelerated by 28× (see Table 3)!

Number of phases	Objective reduction	Speed up
2	0.02%	5.4×
4	0.33%	$28.1 \times$

Table 3: Sacrifice in objective function vs. computational savings of multi-phase conferences relative to single-phase conference.

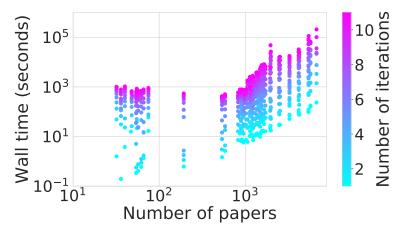


Figure 4: Running time vs. conference size (number of papers); points represent (conference, iteration) pairs.

5.2.6 How did our algorithm scale?

To understand how our algorithm's performance depends on the size of the conference, we generated 77 synthetic conferences of different sizes by subsampling papers and reviewers (without replacement) from our dataset. In an attempt to make the structure of our simulated conferences more realistic, we constructed them based on related keywords. At AAAI 2021, keywords were divided into top-level (e.g., Machine Learning) and bottom-level (e.g., Learning Theory) categories; papers and reviewers could select one top-level and multiple bottom-level keywords.

Our generator works as follows. We begin with an initial bottom-level keyword and then initialize our conference to contain all papers associated with that keyword and a set of reviewers associated with the corresponding top-level keyword proportional to the fraction of papers belonging to the bottom-level keyword within that top-level area. We store a set of keywords associated with our conference as the generator runs. In each iteration, we add to our set of keywords the keyword belonging to most papers in our current set of papers that is not yet part of our tracked set of keywords. Papers corresponding to this keyword and additional reviewers are then added accordingly. Every time the number of papers grew by a constant factor, we created a new synthetic conference containing the current set of papers and reviewers and added it to our set of samples. For diversity, we ran our generator on three trajectories, each seeded with a different keyword: one from game theory, one from computer vision, and one from constraint satisfaction, because each of these areas are quite distinct and have their own dedicated conferences. The conference dataset used above is also included as one of the 78 datapoints.

We then turned to studying how our row generation approach scaled. Figure 4 shows cumulative wall-clock time for each (conference, iteration) point. Points are coloured by iteration. For conferences with fewer than 1,000 papers, we could always complete 10 iterations in less than an hour. Interestingly, the smallest conferences were harder to optimize than medium-sized conferences. We speculate that this occurred because some soft constraints (e.g., coauthor / cycle constraints) were harder to satisfy when the set of papers and reviewers were more densely connected. Running time appeared to scale exponentially with the number of papers beyond 1,000, with the biggest size taking a few hours per iteration.

5.2.7 How did our results on optimality and aggscore reduction translate to our generated conferences?

Figure 5 shows ECDFs of how much of the gap we close between the initial solution before row generation and the upper bound on OPT described earlier in Section 5.2.3. After just one iteration of row generation, we closed at least 25% of the gap for 80% of the generated conferences. After 10 iterations, we closed 75% of the gap for over 90% of conferences. The trend in which these ECDFs become closer and closer together after successive iterations led us to

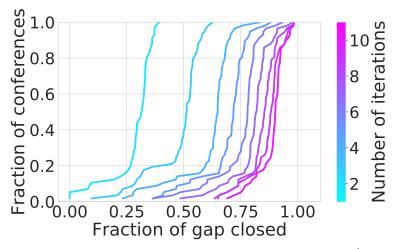


Figure 5: ECDF of % of gap closed (relative to our upper bound) between the first and k^{th} iteration of row generation.

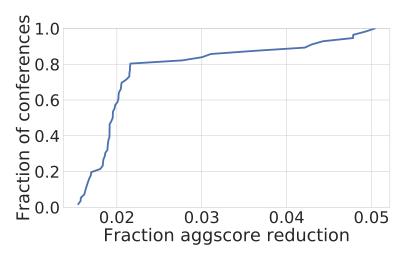


Figure 6: ECDF of the fractional reduction in mean aggscore upon adding soft constraints.

believe that we were approaching optimality, and that much of the remaining 25% of the gap after 10 iterations was due to looseness in our upper bound on OPT.

Similar to the results previously reported about our full conference in Section 5.2.2, we observed that introducing soft constraints led to only small reductions in aggscore across our 77 variable-sized conferences. For 60% of these conferences, we lost less than 2% in aggscore; at worst, we lost 5%. Figure 6 shows an ECDF of the reduction in aggscore across all the generated conferences.

5.3 Evaluation of Two-Phase Reviewing

5.3.1 How prevalent were false negatives?

We considered the most significant risk incurred by rejecting papers in Phase 1 to be the possibility that they might have been accepted with another review, opportunity for rebuttal, and discussion ("false negatives"). The cleanest way to estimate the probability of such eventual acceptance would have been to randomly promote some fraction of papers that would otherwise have been rejected in Phase 1 and observing the result. We did not perform this experiment, but the real data provides a very similar natural experiment. Specifically, we can consider all papers that were promoted to Phase 2 because one or more reviews were missing or reviewers had low confidence, and examine the subset of these papers that were eventually accepted. In total, 231 papers were promoted in this manner, 16 of which were eventually accepted. Each of these papers eventually received four or more high-confidence reviews, allowing us to calculate the probability that two randomly selected reviews would both be negative, meaning that the paper would have been rejected in Phase 1 given those reviews. This allowed us to estimate what fraction of Phase 1 rejections might eventually

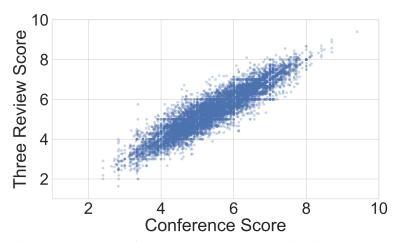


Figure 7: Confidence-weighted average scores for Phase 2 papers based on all reviews vs. all combinations of 3 reviews.

have been accepted. In our data this probability was about 2.9%, suggesting that Phase 1 rejections included very few false negatives.

5.3.2 Did Phase 1 reviewers participate in discussion after Phase 2?

There was a relatively long delay between the end of Phase 1 and the start of the discussion period (in our case, almost a month), leading to some public speculation that Phase 1 reviewers might have tended to be less active in the discussion phase [Kambhampati, 2021]. We found little evidence of such a trend: Phase 2 papers received a discussion post from 55% of Phase 1 reviewers and likewise 55% of Phase 2 reviewers. We did find that reviewers who reviewed only in Phase 1 (who were responsible for a relatively small fraction of reviews overall) had a slightly smaller (52%) rate of participation in the discussion. We further note that two-phase reviewing is not the only possible explanation for this small discrepancy: e.g., this group may also have contained a smaller fraction of highly qualified reviewers.

5.3.3 How many additional reviews were gained?

AAAI 2021 received 7,133 full paper submissions to the first phase. We were able to reject 2,615 (about 37%) of the submitted papers in Phase 1, leaving us with a surplus of 2,615 reviews (relative to an approach that assigns 3 reviews to each paper indiscriminately) to spread amongst the remaining papers. This made it possible for us to assign at least four reviewers to every main track paper in Phase 2 and at least 3 reviews to the 737 fast track submissions. Additionally, 721 submissions received more than 4 reviews.

5.3.4 How important was it to have additional reviews?

For every Phase 2 paper, we sampled every subset of 3 reviews that it might have received if a subset of the same reviewers had been assigned in a single-phase conference and calculated the confidence-weighted average score that the paper would have received in this scenario. (Confidence ranged between 1 (low) and 4 (high); corresponding weights were 0.25, 0.5, 0.75, and 1.) We plot the result in Figure 7. Each point corresponds to a 3-review scenario for a single paper. The x axis gives the paper's score in the AAAI 2021 conference (where it received more than 3 reviews); the y axis gives the spectrum of 3-review scores. The decision boundary for acceptance fell around 6.4, though many papers below this threshold were accepted and many above this threshold were rejected. Nevertheless, variance in the score is a good proxy for variance in reviewer support for the paper and increasing the number of reviews for a paper can only decrease the variance in the estimate of its true score.

6 Conclusion

This paper has presented a novel method for reviewer–paper matching that is scalable to large conferences and more robust to malicious behavior. Our formulation is based on a mixed-integer program that combines a scoring function (which itself combines three match scores and reviewer bids) with various soft constraints encouraging the optimizer to pick, for each paper, a set of reviewers that is geographically diverse, includes at least one senior reviewer, and does not include co-authors. Several preprocessing steps predict new conflicts of interest alongside known ones, and reviewer

bids are also processed to undermine malicious bids. A novel two-phase reviewing scheme uses available reviewing resources more efficiently by allocating fewer reviews to papers that have low acceptance probability. We performed extensive evaluation and post-hoc analysis to demonstrate the value of our methods. We have publicly released our reviewer–paper matching software for further use by other conferences, and indeed it is already in use at ICML 2022. Furthermore, the two-phase reviewing methodology and various other novel elements of the design described here have been adopted by AAAI 2022 and IJCAI 2022.

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A The formal definition of SAMS

In AAAI 2021, authors described their submissions via one primary keyword and a variable number of secondary keywords; likewise reviewers characterized their area(s) of expertise. Let $\Psi = \{\psi_1, \cdots \psi_{N_\psi}\}$ be the set of subject areas. We represent each paper i using two vectors based on their associated subject areas: a primary vector $\mathbf{i}_p \in \{0,1\}^{N_\psi}$ and secondary vector $\mathbf{i}_s \in \{0,1\}^{N_\psi}$. \mathbf{i}_p is a one hot vector that represents the primary subject area and \mathbf{i}_p is a multi hot vector that represents the secondary subject areas. We represent each reviewer j using a vector $\mathbf{j} \in [0,1]^{N_\psi}$. We set the dimensions corresponding to the reviewer's primary subject area to 1 and the reviewer's secondary subject areas to 0.5. Constructing a sparse vector representation using just the primary and secondary areas will fail to capture reviewer's expertise in semantically similar areas that were not explicitly mentioned. To alleviate this problem, we convert the sparse \mathbf{j} vector to a dense vector by inferring the reviewer's expertise in subject areas other than primary and secondary.

Let $\psi' \in \Psi$ be a subject area which is neither in reviewer's primary or secondary areas. We first identify multiple sources that can help us infer the expertise value $j_{\psi'} \in [0,1]$ for ψ' . We then infer an expertise value using each source one at a time and aggregate them. We now discuss each source and how we infer the expertise value using them.

Co-occurrence: Given that a reviewer is an expert in ψ , we compute conditional expertise in ψ' as $P_e(\psi'|\psi) = n(\psi,\psi')/n(\psi)$, where $n(\psi,\psi')$ is the number of reviewers and papers with both ψ and ψ' in their subject areas and $n(\psi)$ is the number of reviewers and papers with ψ in their subject area. The intuition behind this approximation is two fold: (1) P_e uses the current trend to capture correlation among the subject areas and (2) the asymmetry in P_e ensures expertise in a specialized area can indicate expertise in that generic areas but not vice-versa. Given a reviewer's subject area ψ , the expertise value of ψ' is $\rho * P_e(\psi'|\psi)$. ρ is set to 1 when ψ is a primary area and 0.5 when ψ is a secondary area. We consider the primary and the secondary areas as different sources and compute a expertise value for each source separately.

Paper Subject Areas: The subject areas of papers submitted by j (if any) that are not already in the reviewer's subject areas are set to a value (0.2) lower than the one used for secondary areas. This helps capture expertise of reviewers in areas they just started exploring.

Common Parent: Each subject area ψ can be expressed as $parent(\psi) \to child(\psi)$. For example, in $NLP \to Dialog$ Systems, NLP is the parent and Dialog Systems is the child. Each parent can have multiple children. Given a reviewer's subject area ψ , we assign a score of $\rho * 0.4$ to ψ' if $parent(\psi')$ is same as $parent(\psi)$ and 0 otherwise. ρ is same as the one used for co-occurrence computation.

For each subject area ψ' , we compute the expertise value from different sources, aggregate them using the max operator and assign it to $j_{\psi'}$. The max operator helps pick the source that best models ψ' . Finally, we compute SAMS using sparse paper vectors and dense reviewer vector as $SAMS(i,j) = \frac{\mathbf{i}_p \cdot \mathbf{j} + \boldsymbol{\lambda} \cdot Sorted(\mathbf{i}_s \circ \mathbf{j})}{Z}$, where the operator \circ indicates Hadamard product, the function $Sorted(\mathbf{x})$ sorts the elements in \mathbf{x} in decreasing order and $\boldsymbol{\lambda} = [0.5, 0.5^2, \cdots, 0.5^{N_{\psi}}]$.

The normalizer $Z=1+\sum_{m=1}^{M}0.5^m$, where M is the number of non-zero values in \mathbf{i}_s . The scoring function ensures (1) paper's primary area contributes more than all the secondary areas, (2) the more the number of secondary areas match, the higher the score, and (3) papers do not get penalized for providing fewer (or zero) secondary areas.