Fair Reviewer Assignment Considering Academic Social Network

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Abstract. An important task in peer review is assigning papers to appropriate reviewers, which is known as Reviewer Assignment (RA) problem. Most of existing works mainly focus on the similarity between paper topics and reviewer expertise, few works consider multiple relationships between authors and reviewers on academic social network. However, these relationships could influence reviewer assessments on fairness. In this paper, we address RA problem considering academic social network to find a confident, fair and balanced assignment. We model papers and reviewers based on matching degree by combining collaboration distance and topic similarity, and propose Maximum Sum of Matching degree RA (MSMRA) problem. Two algorithms are designed for MSMRA problem: Simulated Annealing-based Stochastic Approximation, and Maximum Matching and Minimum Deviation. Experiments show that our methods achieved good performance both on overall effectiveness and fairness distribution within reasonable running time.

Keywords: Reviewer Assignment, Academic Social Network, Fair

1 Introduction

One of the most challenging tasks in peer review is assigning papers to appropriate reviewers within a reasonable time, which is known as Reviewer Assignment (RA) problem. The opinions of reviewers determine whether papers should be accepted or not, so assigning papers to reviewers in a way that would maximize the quality of assessments, is the focus of RA problem. At present, most of conferences handle this task semi-automatically, which requires reviewers to bid on papers by providing preferences. Due to the large number of paper submissions, each reviewer would go through a great deal of papers (at least abstracts) to provide preferences. In some cases, reviewers choose preferences semi-randomly, which may lead to an inappropriate assignment. What is an appropriate reviewer assignment? We measure it by three important factors:

- **Confidence**: In order to ensure the quality of the assessment, reviewer should have adequate expertise on the topic of assigned paper.
- **Fairness**: For fairness, each reviewer should deal each paper in same manner, and each paper should be reviewed by a certain number of distinct reviewers.

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– **Balance**: As the number of submitted papers is huge, making a balance workload for each reviewer is also a factor need to be considered.

To complete the reviewer assignment in the given assignment time window, which is usually a couple of days, **reasonable running time** is also an important criterion.

Automatic RA problem has already been studied in community like Dumais et al. [1]. They modeled a paper as a query, attempted to retrieve reviewers with most relevant expertise based on content-reviewer expertise similarity, and expressed colleague relationship conflict-of-interest (COI) and reviewer workload as linear inequalities constraints. Long et al. [2] studied RA problem both on goodness and fairness. For goodness, they proposed to maximize the topic coverage between papers and reviewers. For fairness, they discussed COI as constraints. Most of the previous works mainly focus on the similarity between paper topics and reviewer expertise, and just add some constraints as linear inequalities for fairness. Few studies conduct an in-depth exploration of relationships between authors and reviewers on academic social network. The tendency of effects to spread from person to person, beyond an individual's direct social ties [3]. If we ignore these connections when assigning papers, these direct and indirect social ties are likely to affect reviewers' judgments, leading to partial review results.

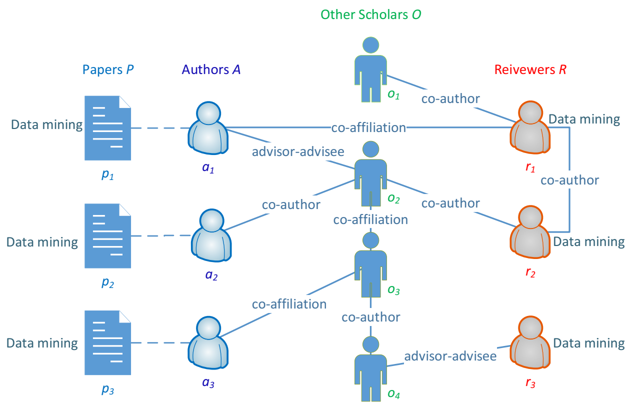


Fig. 1. An example of academic social network

For example, in Fig. 1, there are 3 papers about data mining, 4 scholars, and 3 reviewers. Each paper has one author. Every reviewer has expertise on data mining. Just according to the topic similarity, any paper in P can be assigned to any reviewer in R. However, paper p_1 cannot be assigned to reviewer r_1, because author a_1 has co-affiliation relationship with reviewer r_1. It is still not a fair assignment if we assign paper p_1 to reviewer r_2, since author a_1 is very likely to communicate with reviewer r_2 through scholar o_2. It does not mean that paper p_1 cannot be assigned to any reviewer in R. Our influence gradually dissipates and ceases to have a noticeable effect on people beyond the social frontier that lies at three degrees of separation [3]. As distance increase, influence decrease. The shortest path distance between author a_1 and reviewer r_3 is 4, the probability that author a_1 influences reviewer r_3 is much lower than reviewer r_1 and r_2. Comparing against reviewers r_1 and r_2, it is better to assign paper p_1 to reviewer r_3.

Motivated by above observation, we build an academic social network $G(V, E)$, which is used to mine multiple relationships between authors and reviewers, for fair assignment. We propose collaboration distance on academic social network for fairness, combining with topic similarity for confidence and some constraints for balance to find an appropriate reviewer assignment solution.

The main contributions in our work are summarized as follows:

1. To the best of our knowledge, this is the first work to address RA problem considering academic social network for fair assignment. We model papers and reviewers based on matching degree by combining collaboration distance on fairness with topic similarity on confidence, then we define Maximum Sum of Matching degree RA (MSMRA) problem subject to four constraints on balance: group size, relationship indicator, distinct assignment and balanced workload.

2. Two algorithms are proposed to solve MSMRA problem. One is Simulated Annealing-based Stochastic Approximation (SASA) algorithm, the other is Maximum Matching and Minimum Deviation (MMMD) algorithm.

3. Experimental evaluations on real datasets demonstrate that the proposed algorithms outperform baseline approach in terms of overall effectiveness, more balance distribution on fairness, and run within reasonable time.

The remaining of this paper is organized as follows: Section 2 summarizes relate work of reviewer assignment. Section 3 describes formal specification and formal definitions about MSMRA problem. Section 4 and Section 5 present two algorithms to solve the problem, and Section 6 evaluates our experiments on real data. We conclude this paper in Section 7.

2 Related Work

A bulk of related works have studied the RA problem, we discuss these works from two aspects: how to compute confidence between papers and reviewers, and how to enhance fairness for each pair of paper and reviewer.

For **confidence** aspect, relevant studies can be divided into two methods. One is information retrieval method [1, 4–7]. Geller et al. [4] implemented an intelligent knowledge-based reviewer selection program for IJCAI 1999. Basu et al. [5] mined reviewer abstracts from web and then use a TF-IDF weighted vector space model to rank reviewers for a given submitted paper. Hettich et al. [6] measured the association of reviewers with applications by a TF-IDF weighted vector space model. Rodriguez et al. [7] identified related reviewers in a co-authorship network by using an energy distribution in a manner similar to the spreading activation techniques used for information retrieval. Mimno et al. [8] proposed an author-persona-topic model for reviewer retrieving. The other is topic similarity method [2, 9–17]. Ferilli et al. [9] adopted latent semantic indexing to identify paper topics and reviewer expertise. Xue et al. [10] introduced interval fuzzy ontology to compute the similarity of research subjects. Hartvigsen et al. [11] proposed that every paper should be sent to at least one reviewer whose expertise is greater than or equal to the threshold. Kou et al. [12] proposed a weighted-coverage group-based reviewer assignment problem. Li et al. [13] assigned papers to reviewers by combining preference-based approach and topic-based approach. Kolasa et al. [14] defined the quality degree based on the number of paper keywords covered by assigned reviewer keywords. Karimzadehgan et al. [15] studied matching of multiple aspects of expertise so that the assigned reviewers can cover all the aspects of a paper in a complementary manner. Kou et al. [16] demonstrated reviewer assignment system, which maximizes the topics coverage of each paper by the profiles of assigned reviewers. Charlin et al. [17] explored language model and collaborative filtering to learn confidence scores between papers and reviewers.

For **fairness** aspect, we mainly discuss avoiding conflict-of-interest (COI) methods. Karimzadehgan et al. [18] studied constrained multi-aspect expertise matching problem and modeled COI as one of inequality linear constraints. Kolasa et al. [19] used a Boolean variable bar to indicate COI. Benferhat et al. [20] expressed geographical distribution as a relaxed constraint. Wang et al. [21] suggested that paper cannot be reviewed by friends or enemies of the authors, or by colleagues from the same institution. Conry et al. [22] modeled COI by hardwiring the desired entries of assignment matrix and took them out of play. Tang et al. [23] explored various domain-specific constraints in a constraint-based optimization framework. Garg et al. [24] modeled an edge-labelled bipartite graph of papers and reviewers, and connected an edge if two nodes have no COI. Dell et al. [25] represented problem as a weighted bipartite graph, and computing f-matching of the graph. Taylor et al. [26] solved a variant of the bipartite matching problem to find an assignment between papers and reviewers that maximizes the total affinity subject to constraints on the number of reviewers that can be assigned to a paper and the load that can be assigned to any individual reviewer.

3 Problem Statements

3.1 Notation Specification

In this paper, the **data** of reviewer assignment problem consist of:

- A set of n reviewers, which is denoted as $R = \{r_1, r_2, ..., r_n\}$. Each reviewer $r \in R$ has four attributes: id, $name$, $topics$, and $affiliations$.
- A set of m papers, which is denoted as $P = \{p_1, p_2, ..., p_m\}$. Each paper $p \in P$ has three attributes: id, $topics$, and authors set $A(p)$. All authors of papers form a set of m subsets, which is denoted as $A = A(p_1), A(p_2), ..., A(p_m)$. Each author a has three attributes: id, $name$, and $affiliations$.

- A set of s topics, which is denoted as $T = \{t_1, t_2, ..., t_s\}$. Each reviewer r is associated with a set of topics, which is denoted as $T(r)$, and $T(r) \subset T$. $t \in T(r)$ means reviewer r possess expertise t. Each paper p is associated with a set of topics, which is denoted as $T(p)$, and $T(p) \subset T$. $t \in T(p)$ means paper p covers subject t. Topics can be given by organizing committee as a topic keyword list, or learned from the abstract of papers by statistical topic models such as latent dirichlet allocation.
- A $s \times s$ similarity degree matrix S, which records the similarity degree of every pair of topics in T, and the value ranges in [0, 1]. Due to the cross-integration of knowledge domain, there are similarities between different topics, so a reviewer can also have other similar expertise. Topic similarity can be given or calculated by similarity measure such as cosine similarity.
- An integer k, which is the group size of required reviewers per paper.
- An undirected graph $G(V, E)$ of academic social network, which is used to represent multiple relationships between authors and reviewers. Node set V contains three types of nodes: reviewers in R, authors in A, and other scholars in an academic digital library, and $R \subset V$, $A \subset V$. Edge set E represents the relationship (co-author, co-affiliation, and advisor-advisee) between two nodes, and the weight of an edge is 1. Advisor-advisee relationship can be submitted by the authors, or extracted from personal homepage of reviewers. Co-affiliation relationship can be get from the attributes of authors and reviewers, and co-author relationship can be get from co-author dataset. $d(v_1, v_2)$ denotes the **distance** between two nodes v_1 and v_2, and the value is the shortest path between them in G. The value of $d(v_1, v_1)$ is 0.

The **output** is an assignment, which is a set with m two-tuple groups and is denoted as $\mathbb{R} = \{\langle p_1, R_{p_1}\rangle, \langle p_2, R_{p_2}\rangle, ..., \langle p_m, R_{p_m}\rangle\}$. R_p is a set with distinct reviewers being assigned for paper p, recorded as $\{r_p^1, r_p^2, ..., r_p^k\}$.

In remainder sections, R denotes a reviewer set, P denotes a papers set, T denotes a topic set, S denotes the similarity degree matrix of T, k denotes the group size, and G denotes the graph of academic social network.

3.2 Problem Definitions

In this section, we formally define the MSMRA problem. The goal of MSMRA is to find a reviewer assignment $\mathbb{R}$ such that the Sum of matching Degree (SM) of $\mathbb{R}$ is maximum subject to four constraints: group size, relationship indicator, distinct assignment and balance workload.

DEFINITION 1. (**Collaboration Distance**) Given G, P and R, the collaboration distance between paper p and reviewer r is defined as:

$$D(p, r) = \min \left(d\left(a, r\right) \middle| \, \forall a \in A(p)\right) \tag{1}$$

$MaxD$ denotes maximum collaboration distance between papers and reviewers. $MaxD$ can be set to 1 plus the maximum distance between all pairs of reviewers and authors, or a larger integer. If two nodes are not connected in G, the collaboration distance of them is set to $MaxD$.

DEFINITION 2. (**Topic Similarity**) Given P, R, T and S, the topic similarity between paper p and reviewer r is defined as:

$$S(p,r) = \max \left(S\left[t_p\right]\left[t_r\right] \middle| \forall t_p \in T(p), \forall t_r \in T(r) \right) \tag{2}$$

DEFINITION 3. (**Matching Degree**) Given $MaxD$, α, collaboration distance and topic similarity, the matching degree between paper p and reviewer r is defined as:

$$M(p,r) = \alpha \times \frac{D\left(p,r\right)}{MaxD} + (1-\alpha) \times S(p,r) \tag{3}$$

According to formula (3), with longer collaboration distance and higher topic similarity, matching degree is higher. α is a weighting coefficient.

DEFINITION 4. (**Relationship Indicator**) Given G, P and R, the relationship indicator between paper p and reviewer r is defined as:

$$B\left(p,r\right) = \begin{cases} 0 & \forall a \in A(p), d(a,r) > 1 \\ 1 & \text{others} \end{cases} \tag{4}$$

PROBLEM DEFINITION (**MSMRA problem**) Given G, P, R, T, S and k, Maximum Sum of Matching degree Reviewer Assignment (MSMRA) problem is to find a reviewer assignment $\mathbb{R} = \{\langle p_1, R_{p_1}\rangle, \langle p_2, R_{p_2}\rangle, ..., \langle p_m, R_{p_m}\rangle\}$, such that:

$$\begin{array}{ll} \max\ (\displaystyle\sum_{p \in P} \sum_{r_p \in R_p} M(p, r_p)\ )\ ) & \\ st.\ |R_p| = k & \text{(group size)} \\ \quad B(p, r_p) = 0 & \forall p \in P, \forall r_p \in R_p \text{(relationship indicator)} \\ \quad r_p^i \neq r_p^j & \forall r_p^i, r_p^j \in R_p, i \neq j \text{(distinct assignment)} \\ \quad r.count \leq \mu & \forall r \in R \text{(balance workload)} \end{array} \tag{5}$$

In formula (5), $r.count$ denotes the number of papers being assigned to reviewer r. μ denotes an upper bound of the number of average assigned papers per reviewer for balance workload, and can be calculated by formula (6):

$$\mu = \lceil k \times |P| / |R| \rceil \tag{6}$$

According to formula (5), $\mathbb{R}$ satisfies that authors of paper p and reviewer r_p have no co-author, no co-affiliation, and no advisor-advisee relationship. Each paper is reviewed by k distinct reviewers, and the workload of reviewers is balanced. The Sum of collaboration Degree (SD), and the Sum of topic Similarity (SS) of $\mathbb{R}$ can also be maximized simultaneously.

In remainder sections, SM denotes sum of matching degree, SD denotes the sum of collaboration distance, SS denotes the sum of topic similarity, and $SM(\mathbb{R})$, $SD(\mathbb{R})$, and $SS(\mathbb{R})$ denote the SM, SD, and SS of $\mathbb{R}$ respectively.

4 SASA: Simulated Annealing-based Stochastic Approximation algorithm

We propose a stochastic approximation algorithm based on simulated annealing, which is denoted as SASA. Simulated Annealing algorithm was first used for combinatorial optimization problem by Kirkpatricket et al. [27], and has been proved to converge to an optimal solution in theory. The process of SASA consists of three steps:

Algorithm 1 Simulated Annealing-based Stochastic Approximation

input: G, P, R, T, S, k, $TEMP$, $MinT$, $RATE$
output: $\mathbb{R}$, SM, SD,and SS of $\mathbb{R}$
$temp \leftarrow TEMP$
$\mathbb{R} \leftarrow$ RandomAssignment(G, P, R, k)
while $temp > MinT$ **do**
  $p_1 \leftarrow$ math.random$(1, |P|)$
  $p_2 \leftarrow$ math.random$(1, |P|)$
  if $p_1 \neq p_2$ **then**
    $r_1 \leftarrow$ get minmum matching reviewer$(\mathbb{R}, p_1)$
    $r_2 \leftarrow$ get minmum matching reviewer$(\mathbb{R}, p_2)$
    if $r_1 \neq r_2$ **and** $B(p_1, r_2) = 0$ **and** $B(p_2, r_1) = 0$ **then**
      $\Delta \leftarrow M(p_1, r_2) + M(p_2, r_1) - M(p_1, r_1) - M(p_2, r_2)$
      if $\Delta > 0$ **or** math.exp$(\Delta/temp) >$ math.random$(0, 1)$ **then**
        $\mathbb{R} \leftarrow$ exchange reviewers (p_1, r_1, p_2, r_2)
  $temp \leftarrow temp \times RATE$
return $\mathbb{R}$, $SD(\mathbb{R})$, $SS(\mathbb{R})$, $SM(\mathbb{R})$

Step 1. **Initialization**. Generate a random assignment subject to four constraints of MSMRA, and $temp$ is set to initial temperature $TEMP$.

Step 2. **Simulated Annealing**. We use f_t to denote the solution at time t, and f_{t-1} denote the solution at time $t-1$. Then loop following steps until $temp$ dropping to minimum temperature $MinT$:

Step 2.1 At time t, we randomly select two distinct papers p_1 and p_2, and get assigned reviewers with minimum matching degree of p_1 and p_2 respectively, which are denoted as r_1 and r_2. If $r_1 \neq r_2$ and relationship indicators of (p_1, r_2) and (p_2, r_1) are equal to 0, exchange r_1 and r_2, then a new solution f_t is obtained by formula (7):

$$f_t = f_{t-1} - \langle p_1, r_1 \rangle - \langle p_2, r_2 \rangle + \langle p_1, r_2 \rangle + \langle p_2, r_1 \rangle \tag{7}$$

Step 2.2 The deviation Δ of f_t and f_{t-1} is calculated by formula (8):

$$\begin{aligned} \Delta &= SM(f_t) - SM(f_{t-1}) \\ &= M(p_1, r_2) + M(p_2, r_1) - M(p_1, r_1) - M(p_2, r_2) \end{aligned} \tag{8}$$

If $\varDelta > 0$, f_t is accepted; if $\varDelta \leq 0$, f_t is accepted with a certain probability, and the probability decreases over time gradually. Accepted principle is defined as:

$$\mathbb{R} = \begin{cases} f_t & \varDelta > 0 \textbf{ or } \text{math.exp}(\varDelta/temp) > \text{math.random}(0,1) \\ f_{t-1} & \text{others} \end{cases} \tag{9}$$

Step 2.3. Decrease $temp$ by multiplying a cooling rate $RATE$, which is a decimal number between 0 and 1. Then set $t = t + 1$.

Step 3. **Result**. Return the assignment $\mathbb{R}$, and the SD, SS, and SM of $\mathbb{R}$.

The pseudo code of SASA is presented in algorithm 1.

The time complexity of RandomAssignment(G, P, R, k) is $O(k \times |P|)$. The outer loop of algorithm 1 is $O(N)$. N depends on initial temperature $TEMP$, minimum temperature $MinT$, and cooling rate $RATE$. When $TEMP$ and $MinT$ are fixed, as $RATE$ is higher, N is larger. The time complexity of algorithm 1 is $O(N \times k \times |P|)$. In order to achieve a good result, N is usually a large number, so the running time is mainly affected by N while parameters k and $|P|$ have little effect.

5 MMMD: Maximum Matching and Minimum Deviation algorithm

Since the running time of SASA is easily influenced by the input parameters, we propose an exact polynomial algorithm for MSMRA problem, named Maximum Matching and Minimum Deviation algorithm, which is denoted as MMMD. A state matrix Q is used to record the assignment state, and Q could be adjusted according to minimum deviation principle. After initializing μ and state matrix Q, the process of MMMD mainly contains two steps:

Step 1. **Maximum matching degree assignment**. For each paper p, we compute Q of every reviewer and p by relationship indicator. If $B(p, r) = 0$, $Q[p][r] = 0$ means reviewer r is **assignable** for p; else $Q[p][r] = -1$ means reviewer r cannot be assigned to p.

We assign p to the assignable reviewer r with maximum matching degree, and set $Q[p][r] = 1$ for distinct assignment. $Q[p][r] = 1$ means reviewer r has been assigned to p. Then set $r.count = r.count + 1$.

If $r.count > \mu$, balanced workload is broken and needs to be adjusted, then jump to step 2; else perform step 1 until the number of reviewers assigned to paper p is equal to group size k.

Step 2. **Minimum deviation adjust**. Reviewers with less number of assigned papers than μ are **adjustable**, and can be adjusted in step 2.

For each paper $i \in [1, p]$ with $Q[i][r] = 1$, we first get reviewer t which is assignable, adjustable and with maximum matching degree for p. Then we calculate the deviation of $M(i, r)$ and $M(i, t)$, and use p_a and r_a to denote the paper and the reviewer with minimum deviation $MinDev$. Finally, we set $Q[p_a][r] = -1$, $Q[p_a][r_a] = 1$, then return to step 1.

Algorithm 2 Maximum Matching and Minimum Deviation algorithm

input: G, P, R, T, S, k
output: $\mathbb{R}$, SM, SD,and SS of $\mathbb{R}$

$\mu \leftarrow \lceil k \times |P|/|R| \rceil$
$Q[|P|][|R|] \leftarrow \{0\}$
for each $p \in P$ **do**
    $queue \leftarrow$ ReverseSortReviewers($M(p, R)$)
    for $i = 1 \rightarrow k$ **do**
        $r \leftarrow queue$.poll()
        if $B(p, r) = 1$ **then**
            $Q[p][r] \leftarrow -1$
        else
            $Q[p][r] \leftarrow 1$
            $r.count \leftarrow r.count + 1$
            if $r.count > \mu$ **then**
                $Q \leftarrow$ MinimumDeviationAdjustment(Q, r, p, μ)
            $i \leftarrow i + 1$
$\mathbb{R} \leftarrow$ get assignment (Q)
return $\mathbb{R}$, $SD(\mathbb{R})$, $SS(\mathbb{R})$, $SM(\mathbb{R})$

The pseudo code of MMMD is shown in algorithm 2, and the pseudo code of MinimumDeviationAdjustment(Q, r, p, μ) is shown in algorithm 3.

Algorithm 3 Minimum Deviation Adjustment

function MinimumDeviationAdjustment(Q, r, p, μ)
    $p_a, r_a \leftarrow 0$
    $MinDev \leftarrow \infty$
    for $i = 1 \rightarrow p$ **do**
        if $Q[i][r] = 1$ **then**
            $t \leftarrow$ get maximum, adjustable, and assignable reviewer (i)
            $\Delta \leftarrow M(i, s) - M(i, t)$
            if $\Delta < MinDev$ **then**
                $p_a \leftarrow i$
                $r_a \leftarrow t$
                $MinDev \leftarrow \Delta$
    $Q[p_a][r] \leftarrow -1$
    $Q[p_a][r_a] \leftarrow 1$
    return Q

The time complexity of algorithm 3 is $O(|P|(|P| + 1)/2)$. The running time of ReverseSortReviewers($M(p, R)$) in algorithm 2 is $O(|R| \times log|R|)$, so the time complexity of algorithm 2 is $O(|P| \times (|R| \times log|R| + k \times (|P|(|P| + 1)/2)))$. Generally, $|R|$ is smaller than $|P|$, so the time complexity of algorithm 2 is approximately equal to $O(k \times |P|^2)$. But not each assignment needs to be adjusted in practice, so the time complexity is much lower than the theoretical value, we will see it later in our experiments on real data sets.

6 EMPIRICAL EVALUATION

In this section, we evaluate proposed algorithms for MSMRA problem. We implement all the algorithms in Java. The experiments are conducted on a computer with Intel (R) Core (TM) i5-2400 CPU (3. 10 GHZ) of 8G RAM, and Windows 10 64 bit.

6.1 Experimental Setup

Datasets: We collect accepted papers of SIGMOD 2014[1], 2015[2] and 2016[3] as the paper set P, and use the program committee of SIGMOD 2016 as the reviewer set R. The topic set T is collected from the topics of SIGMOD 2016. We randomly assign 1 to 3 topics as expertise of each reviewer. For each pair of topics, we manually assign a similarity degree range from 0 to 1 based on the similarity between research fields. Finally, there are 305 papers, 851 authors, 190 reviewers, 21 topics and a 21×21 similarity degree matrix S.

We use a snapshot of the DBLP dataset[4] taken on November 25, 2016. We get more than 1.81 million scholars, and collect co-author relationships between them in the DBLP dataset.

The academic social network G in our experiments contains more than 1,816,262 nodes and 8,021,719 edges. The running time of constructing G is 74 seconds.

Baseline algorithms: We take two reasonable algorithms as baseline. One is Similarity-based Greedy (SimGreedy) algorithm subject to constraints of MSMRA, which is used in most academic conferences. Another is Random algorithm (Ran) subject to constraints of MSMRA.

BBFS for Shortest Path: We use Bidirectional Breadth First Search (BBFS) to compute the shortest path distance between authors and reviewers in G. The running time of BBFS for 851 authors and 190 reviewers is 63 seconds.

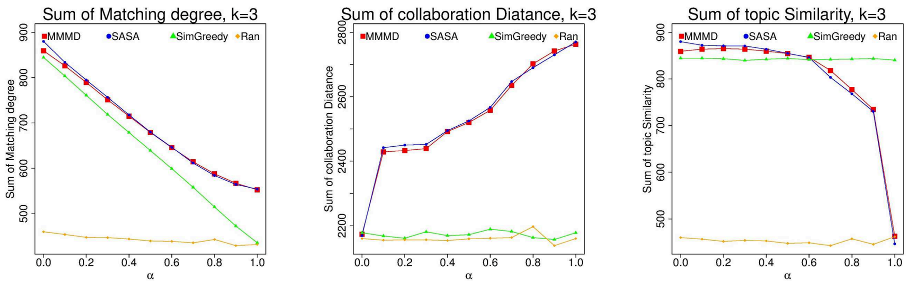
Parameters Setting: We vary $|P|$, $|R|$, k, and α and evaluate different results. In SASA algorithm, temperature $TEMP = 10^8$, minimum temperature $MinT = 10^{-8}$, and cooling rate $RATE = 0.9999$.

Optimality Ratio: A reasonable approach to evaluate the quality of assignment $\mathbb{R}$ is to compute its approximation ratio $SM(\mathbb{R})/SM(\mathbb{O})$ to the optimal assignment $\mathbb{O}$ [12]. But computing $\mathbb{O}$ will be very time consuming. We use an ideal assignment $\mathbb{I}$ to compute the optimality ratio $SM(\mathbb{R})/SM(\mathbb{I})$. To generate ideal assignment $\mathbb{I}$, we greedily select k maximum matching degree reviewers for each paper, and disregard other constraints in MSMRA. Therefore $SM(\mathbb{I}) > SM(\mathbb{O})$. So $SM(\mathbb{R})/SM(\mathbb{I})$ is a lower bound $SM(\mathbb{R})/SM(\mathbb{O})$.

[1] http://www.sigmod2014.org/
[2] http://www.sigmod2015.org/
[3] http://www.sigmod2016.org/
[4] http://dblp.uni-trier.de/xml/

6.2 Overall Effectiveness

In this section, we use 305 papers and 100 reviewers, and $k = 3$ to measure SM, SD, and SS of $\mathbb{R}$. It means that every paper needs 3 reviewers, and every reviewer needs to review no more than 10 papers. In order to obtain good experimental results, we vary α from 0 to 1, plus 0.1 per step. For showing optimality ratio in different cases, the values of k are 1, 3, 5, the values of α are 0.4, 0.5, 0.6. We use these measures to evaluate how well each algorithm maximize value of assignment in comparison to others.



(a) SM, k=3 (b) SD, k=3 (c) SS, k=3

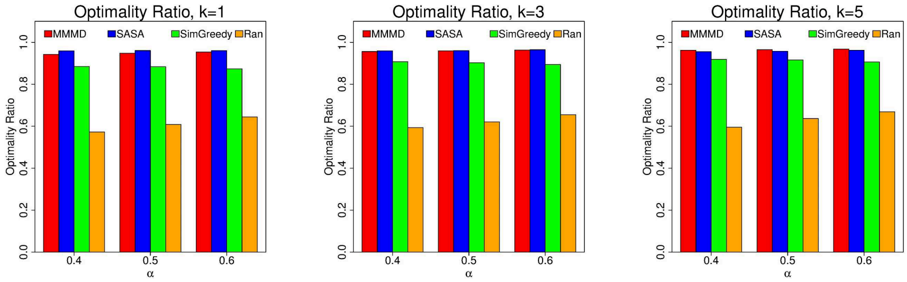
Fig. 2. Overall Effectiveness: SM, SD, and SS

Sum of Matching degree: In Fig. 2(a), when α is larger, SM is smaller On MMMD, SASA, and SimGreedy. This is because α is a weighting coefficient of collaboration distance, and normalized collaboration distance is smaller than topic similarity. MMMD and SASA are always outperform SimGreedy and Ran. While α is 0.4, 0.5 and 0.6, MMMD and SASA even have similar values, this phenomenon also appears in Fig. 2(b) and 2(c).

Sum of collaboration Distance: In Fig. 2(b), MMMD and SASA are obviously superior to others. When α is larger, SD is smaller On MMMD, SASA. The reason is same as above. SimGreedy and Ran have no change when varying α, because they ignore the collaboration distance, which is an important factor when assigning reviewers.

Sum of topic Similarity: In Fig. 2(c), when $\alpha \leq 0.6$, MMMD and SASA outperform SimGreedy and Ran. When $\alpha > 0.6$, the SS of MMMD and SASA decline rapidly, since the weight of topic similarity is $1-\alpha$. Considering similarity priority, SimGreedy always has a large value when varying α. The values of Ran are always low in Fig. 2(a), 2(b) and 2(c).

Optimality ratio: In Fig. 3, the optimality ratios of MMMD and SASA are consistently greater than 0.9, and very close to 1. The optimality ratio of SimGreedy is also not less than 0.9. However, as shown in Fig.2(b) and 2(c), although SS of SimGreedy is large, SD of SimGreedy is small. Ran is lower than 0.6 in most cases.



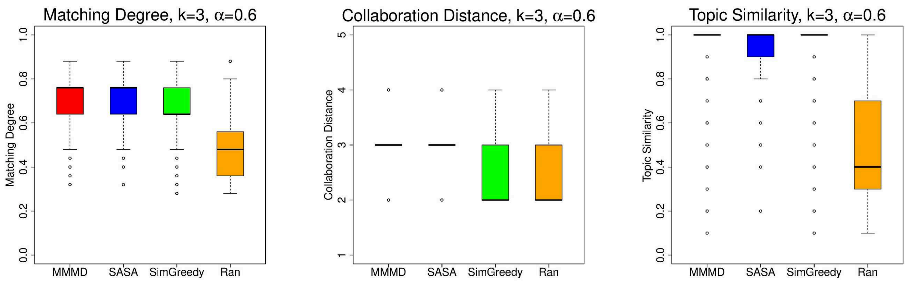
(a) O. R., k=1 (b) O. R., k=3 (c) O. R., k=5

Fig. 3. Overall Effectiveness: Optimality Ratio

Given the superior performance in practice, both MMMD and SASA achieve much better Overall Effectiveness than SimGreedy and Ran.

6.3 Fairness Distribution Analysis

In this section, we use 305 papers and 100 reviewers totally with k=3. We vary α to evaluate assignment quality on individuals by distribution state. Subject to space restrictions, we only show the result of $\alpha = 0.6$.



(a) M. D., k=3, α=0.6 (b) C. D., k=3, α=0.6 (c) T. S., k=3, α=0.6

Fig. 4. Fairness Distribution Analysis

Matching degree: In Fig. 4(a). The medians of MMMD and SASA are larger than SimGreedy and Ran, which means most of papers are assigned to reviewers with matching degree greater than 0.7 by MMMD and SASA. The assignments of MMMD, SASA and SimGreedy are more convergent than Ran In Fig. 4(a), Fig. 4(b) and Fig. 4(c), which are fairer than Ran.

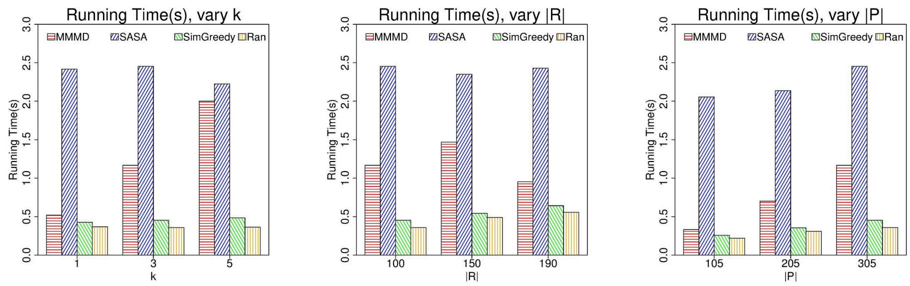
Collaboration distance: In Fig. 4(b), there are more papers assigned to reviewers with collaboration distance 3 by MMMD and SASA. The medians of SimGreedy and Ran is only 2.

Topic similarity: In Fig. 4(c), the medians of MMMD, SASA and SimGreedy are equal to 1, which are far greater than Ran. $Q1$ of SASA is 0.9, lower than MMMD and SimGreedy. As the similarity between different areas of expertise, the reviewer is also qualified to review papers with 0.9 topic similarity.

Since the results of MMMD and SASA have better balanced distribution and greater median, MMMD and SASA are superior to SimGreedy and Ran.

6.4 Running Time Evaluation

In this section, we use $\alpha = 0.6$, fix two parameters and vary one parameter. Since constructing graph G and computing distances between authors and reviewers have been preprocessed, the running time of them is not presented in Fig. 5, which is 137 seconds regarded as a reasonable and acceptable cost time. As shown in Fig. 5, all the algorithms can be completed in 2.5 seconds. The total running time of each algorithm is no more than 140 seconds.



(a) $|P|$=305, $|R|$=100, vary k, α=0.6

(b) $|P|$=305, vary $|R|$, k=3, α=0.6

(c) vary $|P|$, $|R|$=100, k=3, α=0.6

Fig. 5. Running Time (s)

Varying k: We fix $|P| = 305$, $|R| = 100$, and set the values of k as 1, 3, 5 in Fig. 5(a). The running time of MMMD grows linearly when k is lager. As k is normally a small number, the running time of MMMD will always in a reasonable range. The running time of SASA is not affected by k, and is mainly affected by the random initial solution and related parameters. SimGreedy and Ran have lower running time in Fig. 5(a), 5(b) and 5(c).

Varying $|R|$: We fix $|P| = 305$, $k = 3$, and set the values of $|R|$ as 100, 150, 190 in Fig. 5(b). When $|R|$ grows, the running time of MMMD firstly increase and then decrease. When $|R|$ is larger, the number of assignable reviewers for each paper is larger. There may be less adjustment, so the running time of MMMD will be lower. Therefore $|R|$ is not a major factor for the running time of MMMD. The running time of other algorithms are not obviously affected by $|R|$.

Varying $|P|$: We fix $|R| = 100$, $k = 3$, and set the values of $|P|$ as 105, 205, 305 in Fig. 5(c). The running time of MMMD is longer when $|P|$ is lager, but do not grow exponentially with $|P|$. This is much lower than the worst time complexity. The running times of other algorithms are not affected by $|P|$.

Based on above analyses, even in large conferences with thousands of papers, hundreds of reviewers, MMMD and SASA can also work within a reasonable time. Futher more, MMMD always take less time to achieve a better result than SASA.

7 Conclusions

In this paper, we formulate reviewer assignment as a Maximum Sum of Matching degree Reviewer Assignment (MSMRA) problem subject to four constraints: group size, relationship indicator, distinct assignment and balanced workload. We introduce collaboration distance on academic social network to utilize multiple relationships between authors and reviewers for fair assignment. Combining collaboration distance and topic similarity, we model matching degree of papers and reviewers, aimed to find a confident, fair and balanced assignment. Two algorithms are proposed to solve this problem: Simulated Annealing-based Stochastic Approximation (SASA), and Maximum Matching and Minimum Deviation (MMMD). Our experimental evaluations show that, comparing against reasonable baseline approaches, our algorithms produced assignment with greater values on overall effectiveness and more balanced distribution on fairness, and also run within reasonable time.

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