Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 22 (2013) 633 – 642

Procedia Computer Science

Automatic Paper-to-reviewer Assignment, Based on the Matching Degree of the Reviewers

Xinlian Li [a] and Toyohide Watanabe [a, b]

a Graduate School of Information Science, Nagoya University, Nagoya 464-8603, Japan
b Nagoya Industrial Science research Institute, Nagoya 464-0819, Japan

Abstract

There are a number of issues which are involved with organizing a conference. Among these issues, assigning conference-papers to reviewers is one of the most difficult tasks. Assigning conference-papers to reviewers is automatically the most crucial part. In this paper, we address this issue of paper-to-reviewer assignment, and we propose a method to model the reviewers, based on the matching degree between the reviewers and the papers by combining a preference-based approach and a topic-based approach. We explain the assignment algorithm and show the evaluation results in comparison with the Hungarian algorithm.

Keywords: paper-to-reviewer assignment, Hungarian algorithm, matching degree, expertise degree, relevance degree

1. Introduction

Peer review is an evaluation process for the competence, significance and originality of researches by qualified experts [1]. The process is to comment on the validity of research by identifying scientific errors, judge the significance of research by evaluating the importance of findings, determine the originality of work, based on how much it advances the field, and recommend the paper to be published or rejected. One of the most important and time-consuming tasks is to assign each paper to appropriate reviewers [2]. The major concern is to take both suitability and efficiency into consideration simultaneously. It is laborious to decide which reviewer has enough knowledge of the research areas related to papers. Due to the great amount of reviewers and papers, it is huge for the program committee to carry out the assignment task.

Our objective is to reduce the loads of both program committee and reviewers and make the conference-paper assignment task effectual. In order to achieve this objective, the following issues must be solved:

- How to find out proper reviewers? : In the peer review process, the opinions of reviewers play a significant role in determining whether a paper should be accepted or not. At present, the process of evaluating and selecting reviewers is mainly semi-manual. However, the semi-manual selection method adopted currently is not only random but also subjective; and this leads to end up with unfair and inappropriate results. Hereby, selecting the suitable reviewer is the key step to ensure the quality of peer review process.
- How to assign papers to reviewers? : Assigning papers to reviewers is another critical part of peer review process. The ideal assignment, which takes factors such as assigning efficiency and research area similarity

doi:10.1016/j.procs.2013.09.144

in consideration, is possible if every member reads every paper. However, this is impossible since there are usually several hundred submissions. Moreover, papers are submitted from a wide variety of topics; it is unlikely that every person would have the same ability and interests to review every paper. Therefore, it is necessary to balance the load as well as to assign papers to reviewers.

2. Related Work

Generally, the paper-to-reviewer assignment method can be classified into two categories: preference-based approach and topic-based approach.

Preference-based approach:
Several approaches in the paper-to-reviewer assignment problem make use of preference or bidding data from reviewers. In most preference-based approaches, the systems require the reviewers to bid papers to see whether they have their interest for the papers or not. A weakness in this approach is the inadequacy of bidding information. Rigaux [3] suggested the use of collaborative filtering techniques to grow the preference by asking users to bid on most of papers in a given topic. The basic assumption of collaborative filtering techniques is that reviewers who bid similarly on a number of the same papers have likely the similar preference for other papers.

Topic-based approach:
One view of paper-to-reviewer assignments is that papers should be assigned to reviewers with a certain degree of familiarity in the topic of paper. This view leads to topic-based approaches that use additional information. By using this information, reviewer assignments can be made so as to ensure a degree of similarity between paper's topic and reviewer's research area. The resultant ranking of each reviewer, based on topical knowledge with respect to a given paper, was called expert-finding or expertise modeling. One problem aroused with this approach is to identify what topics are covered in papers. Early efforts in this field focused mainly on paper abstracts, and topical similarity was determined through common information retrieval means involving keywords. Dumais and Nielsen [4] matched papers to reviewers by Latent Semantic Indexing trained on reviewer-supplied abstracts. In Basu et al. [5], abstracts from papers written by potential reviewers were extracted from the web via search engine, and then a Vector Space Model was constructed for the matching. Yarowsky and Florian [6] extended this idea by a similar Vector Space Model with a Naïve Bayes Classifier. Wei and Croft [7] proposed a topic-based means by a language model with Dirichlet smoothing.

Under such approaches, systems with automatic paper-to-review assignment features are developed. Myreview proposed by Rigaux is designed to solve the problem of reviewer assignments. This is based on the preference-based approach: it asks each user to rate a sample of papers. A collaborative filtering algorithm is then performed to generate predicted preferences of reviewers. MyReview web-based system was used in the ACM/GIS2003 conference. Another web-based conference management system is GRAPE, based on Di Mauro et al. [8]. GRAPE is notable for considering both reviewers' biddings and topical similarity. The paper's topics from its title, abstract and references, and the reviewers' topics by analyzing their previously written papers and web pages are respectively extracted. The system was evaluated on real-world datasets built by data from a previous European conference.

3. Approach

Although many studies have been published concerning the problem of conference-paper assignment, these studies mainly focused on biddings and did not provide much attention to other input sources. For example, the collaborative filtering approach of MyReview considers only reviewers' preferences. GAPRE considers both reviewers' biddings and topical similarity, but the secondary source is only used when the reviewers fails to provide any preference. Therefore, the current preference-based systems render the following problems:

- Consume additional hand-work and time;
- Place too much emphasis on reviewers' interests;
- Require huge amount of calculation for meaning the similarity of research topics.

Our approach combines both preference-based approach and topic-based approach in a way that does not require the bidding process of reviewers. We set out to present our approach in solving two viewpoints.

Evaluation criteria and method:
We propose a method to model reviewers, based on the matching degree between reviewers and papers by combining preference-based approach and topic-based approach. The traditional preference-based approaches assume that a person who has high interest for a paper is the suitable reviewer. However, these approaches suffer from several weaknesses. To solve this problem, we transform the reviewer preference into paper preference. As for the topic-based approach whose objective is to measure the similarity between reviewer's and paper's research area, we employ a new method by the reference information. Our matching degree is divided into two parts:

- Preference of papers: reviewer's expertise;
- Similarity of topics: relevance of references.

Assignment criteria and method:
After the matching degree is measured, a matrix is constructed for assignment. Several constraints should be fulfilled to balance each load, and each paper is examined by adequate amount of reviewers. Since the existing algorithms are not applied to this assignment problem directly, we propose a flexible method.

Figure 1 illustrates our system structure with calculation of matching degree and assignment algorithm.

4. Framework of Reviewer Modeling

The essential part of paper-to-reviewer matching task is to model the appropriateness for an expert. Until now, many researchers have carried out on the expertise modeling. An excellent example of expertise modeling is Author Persona Topic (APT), proposed by Mimno and McCallum [9]. APT model contains a number of features to capture the better association between a paper and a reviewer. The basic idea of APT model is that even if an author might study and write about several distinct topics, the author's ranking for a given topic would not be decreased by his/her writings on different topics since papers are clustered from these topics into separate author persona. Although APT model is excellent in taking both author's ranking and topic into consideration, it is very complicated for reviewer modeling.

4.1. Reviewer Modeling

We present our model for assessing the matching degree. We divide the matching degree between reviewer and paper into two aspects: expertise degree of reviewer, and relevance degree between reviewer and paper.

Expertise degree of reviewer:
Publications provide an effective way to evaluate the expertise of reviewer. Jauch and Glueck [10] stated that simple count of publications, modified by the quality index of journals, is the best way to assess the academic contributions of a researcher. Sun et al. [11] proposed a method to evaluate experts for R&D projects by

measuring each expert's performance as publications, projects, historical performance in project selection and other experts' opinions. Although these methods provide us with some illumination, they only offer simple solutions in limited domains.

We propose a model for measuring the expertise degree of reviewer in two main aspects in Figure 2:

- authority: quality and quantity of publications
- freshness: when was the paper published?

Calculating expertise degree:

In order to calculate the expertise degree of reviewer, we first measure the quantity, quality and time interval independently. Quantity is calculated by the sum amount of the publications. Quality consists of two factors: number of citations to the paper and the ranking of journal. Here, we denote the ranking of journal to be the ratio of the impact factor of journal for the maximum impact factor within its field. Freshness is measured by using time interval with respect to the ratio for five years as the basis unit. For example, if a paper was published in 2005, then the time interval from 2013 is 8 years; and the freshness can be derived as 8/5 = 1.6. Since quality and time contributes independently to the expertise degree, they can be calculated by multiplicative algorithm. The quality and quantity are the benefit attributes. They positively relate to the reviewer's authority. The greater the values of quality and quantity are, the greater the reviewer's expertise degree is. The time is a cost attribute; it negatively reflects the freshness of a publication.

The quality can be represented as: $Quality = (c_j+1) \times if_j \,/\, if_{max}$. (1)

The freshness can be described as time by e-index: $Freshness = \mathbf{exp}(-t_j/5)$. (2)

Here, c_j is number of citations for paper j; t_j is time interval between published year of paper j and current year; if_j is impact factor of journal in which paper j published; and if_{max} is maximum impact factor of journal within research discipline. Then, the expertise degree (*Expertise*) of each reviewer can be calculated as:

$$Expertise = \Sigma_{Quantity}\, Quality \times Freshness = \Sigma_{j=1,n} (c_j+1) \times (if_j \,/\, if_{max}) \times \mathbf{exp}(-t_j/5). \quad (3)$$

Finally, the normalized expertise degree for each reviewer is calculated, so that the maximum of each reviewer's expertise degree is 1.

Relevance degree between reviewer and paper:

The traditional approach for measuring the relevance is to estimate the similarity between reviewer's publication and submitted paper. Methods including Vector Space Model [12] and Latent Semantic Indexing techniques [13] have been devised for estimating the similarity of text documents. The weakness of the similarity-based methods is obvious: in most case, these methods involve the processes of extracting features from documents and calculating the similarity based on the extracted features. The process is of low efficiency because it is too complex and consumes a lot of time.

Our approach is based on the assumption that two papers which refer to the same reference share similar research areas strongly. Therefore, the more the number of common references two papers have, the more similar research field they are in. In order to compute the similarity of reference between reviewers and papers, we gather all references cited by a reviewer from his/her previous publications, and extract paper's references from its bibliography. Bibliography contains a lot of information, including paper title, author, source and published year. Not only title but also author information should be taken into consideration when computing the similarity of reference. We classify the types of common referring into three categories: direct referring, same paper referring and same author referring, as shown in Figure 3:

- Direct referring: paper *P* quotes one of reviewer *R*'s publication directly;
- Same paper referring: both paper *P* and reviewer *R* refer to the same reference;
- Same author referring: both paper *P* and reviewer *R* cite the same author *A*'s publication.

The relevance degree between reviewer and paper is calculated by combining these three referring information. We assign different weights to different kinds of referring. The method for determining the relative weight for three kinds of common referring is stressed.

The relevance between paper and reviewer is computed: $Relevance = \Sigma_{i=1,3} (w_i \times r_i)$ (4)

Where *Relevance* is the relevance degree between reviewer and paper, w is the weight of common referring type, and r is the number of common referring type. The relevance degree is normalized so that the range of relevance degree is from 0 to 1.

4.2. Matching Degree

Determining weights of expertise degree and relevance degree:

We can acquire two kinds of criteria for evaluating the matching degree between reviewer and paper. Here, we employ Analytic Hierarchy Process (AHP) [14] to determine the relative importance of expertise degree and relevance degree. As listed in Table 1, the scale "[1, 9]" is used for making the pair-wise comparison judgment in AHP. Since relevance degree is computed by combining three kinds of common referring, we need to determine the weight of different types of common referring at first. Figure 4 illustrates AHP hierarchy structure model for determining matching degree for 3 users. w_e stands for the relative weight of expertise degree, while w_r stands for the weight of relevance degree.

Calculating matching degree by example:

We asked 3 users to give pair-wise comparison matrices for the relevance degree and matching degree as shown in Tables 2 and 3. The pair-wise comparison matrices on three types of referring are presented:

$$U_1 = \begin{pmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 5/3 \\ 1/5 & 3/5 & 1 \end{pmatrix}, \quad U_2 = \begin{pmatrix} 1 & 4 & 4 \\ 1/4 & 1 & 1 \\ 1/4 & 1 & 1 \end{pmatrix}, \quad U_3 = \begin{pmatrix} 1 & 2 & 3 \\ 1/2 & 1 & 3/2 \\ 1/3 & 2/3 & 1 \end{pmatrix}$$

And, the pair-wise comparison matrices on expertise degree and relevance degree are:

$$U_1 = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}, \quad U_2 = \begin{pmatrix} 1 & 2 \\ 1/2 & 1 \end{pmatrix}, \quad U_3 = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

According to AHP algorithm, the weights for different kinds of common referring are derived as w_1=0.62, w_2=0.22 and w_3=0.16, respectively. The important criterion on expertise degree and relevance degree are w_e=0,56 and w_r=0.44. Then, the matching degree *Matching* is given by:

$Matching = w_e \times Expertise + w_r \times Relevance$ (5)

5. Assignment Problem

How to find out the appropriate and sufficient experts for each paper is a combinatorial optimization problem to find a maximum weight matching in a weighted bipartite graph. A weighted bipartite graph is a graph whose vertices are divided into two disjoint sets U and V such that every edge connects a vertex in U to one in V with a weight W. Hungarian algorithm [15] is one of many algorithms which were devised to solve the linear assignment problem. Hungarian algorithm is based on the viewpoint that an optimal assignment for the resulting cost matrix is also an optimal assignment for the original cost matrix if a number is added to or subtracted from all entries in any one row or column of a cost matrix. Unfortunately, the complex process in Hungarian algorithm cannot be fully adapted to our problem for the following reasons:

- to solve the minimum weight matching problem; it cannot be applied to our problem directly;
- to be a linear assignment problem, in which the numbers of reviewers and papers have to be equal. Each paper is only examined by one person and each reviewer inspects only one paper;
- to become extremely complex and time-consuming when the numbers of reviewers and papers are too huge.

5.1. Problem Formulation

In order to present this problem in all of its complexities, we must consider matching degree as well as load balance. First of all, the assignments of papers to reviewers should be made so that the total matching degree is maximized. Given R for reviewers and P for papers together with a weight function M, the problem is expressed as: $\mathbf{max}\ \Sigma_{i \in R}\ \Sigma_{j \in P} M(i, j) \times a_{ij}$ (6)

Where a_{ij} = 1, if reviewer i is assigned to paper j;

0, if reviewer i is not assigned to paper j.

a_{ij} stands for the assignment of reviewer i to paper j. When m is the number of reviewers, the number of papers (n) reviewed by each reviewer is defined as: $n = \mathbf{ceil}(m \times |R| / |P|)$ (7)

Additionally, since the amount of papers and reviewers is huge, it is necessry to ensure that no single reviewer is overworked. Thus, the following constraints must be fulfilled:

- Each reviewer should be assigned without more than n papers: $\Sigma_{j \in P}\, a_{ij} \leqq n$ for $i \in R$; (8)
- Each paper should be reviewed by m reviewers: $\Sigma_{i \in R}\, a_{ij} = m$ for $j \in P$. (9)

5.2. Assignment Algorithm

Solving assignment problem:

Without the above constraints, the best way to obtain the assignment with the maximum weight is to assign papers to the reviewer who has the largest matching degree. However, given the above objective function and constraints, we should find out a way to rearrange the assignment when conflicts occur. The fundamental idea is that when the conflict assignments occur it is proper to keep the assignment with larger deviation and remove the assignment with smaller deviation. This idea is based on the theory that if a value's deviation is bigger in average it should be likely that the rest of data are smaller. Consider an example. Although the maximum values of data-sets **a** and **b** are both the same (100) as shown in Table 4, the rest data of **a** is smaller than that of **b** since the maximum value of **a** is more numerically distant from the rest of the data than that of **b**. If the assignment **b3** is eliminated, it is still more possible to find a large value in the rest data of **b** than that of **a**. Thus, the maximum assignment in Table 4 should be **a3** and **b1** where the sum of the assignment is 100+70=170.

In order to decide which value is distant from the average of the data, we first need to construct a matrix of matching and calculate the average matching degree of each row and column. Table 5 is an example of a matching degree matrix, and Table 6 is an example of assignment matrix.

After calculating the average value of each row and column, the deviation is defined as follows:

$$D_{ij} = M_{ij} - ra_i \quad (10)$$

$$Q_{ij} = M_{ij} - ca_j \quad (11)$$

D denotes the row deviation, which is the difference between the matching degrees of reviewer j and paper i, and the average matching degree of paper i. Q denotes the column deviation, which is the difference between the matching degree of reviewer j and paper i, and the average matching degree of reviewer j. Figure 5 gives the pseudo-code for the proposed deviation-based algorithm.

Example:

We give an example to illustrate the process of our proposed algorithm. Consider the nonlinear assignment problem in Table 7, where the numbers of reviewers and papers are no equal. In this example, every reviewer is assigned to no more than two papers (*n*=2) and every paper is reviewer by exactly one reviewer (*m*=1). Find out the maximum matching degree in each row.

(1) Round 1: A_{13}, A_{22}, A_{33}, A_{43}

Totally 3 assignments exist in column R_3. The row deviation of M_{33} (0.17) is the smallest among three assignments. The assignment A_{33} should be removed. Continue the maximum value in row that does not yet have an assignment.

(2) Round 2: A_{31}

Stop when all papers are assigned to one reviewer. The final assignment is shown in Table 8(c) via their temporary assignment s in Table 8(a) and Table 8(b).

6. Experiments and Evaluation

We conduct experiments and evaluate our approach based on the experimental results. The available data sets for reviewer modeling were collected from the existing public data. The impact factor is acquired from the Journal Citation reports (JCR) [16], the cited time of a paper and its references can be obtained from CiteSeerX [17]. Moreover, the quantity of reviewer's publications and their published year can be gathered from DBLP [18]. Totally 313,620 papers with 2,084,019 references were stored in the constructed database. All papers are published in the field of Computer Science from 1980 to 2011.

The experiment is to evaluate the efficiency and effectiveness of our algorithm. All experiments were carried out on PC, running Windows 7 with AMD Athlon 64 Processor 3200+ (2.0GHz), 2G RAM. The experimental data sets are random data that range from 0 to 1.

(1) Efficiency: time consumption

We evaluated the efficiency performance of our algorithm. As shown in Table 9, our algorithm can significantly reduce the time consumption in comparison with Hungarian (bipartite graph matching) algorithm.

(2) Effectiveness: assignments under constraints

We conducted an experiment to demonstrate the effectiveness of our algorithm. The results demonstrate the rate of assignments which succeed in achieving maximum matching degree, as shown in Table 10. Our algorithm is successful in satisfying maximum weight assignment in most cases though it fails in small-scale matrixes.

A failed example is given to explain the limitation of our algorithm. Consider the case of 3-order matrix assignments, shown in Table 11. The result of assignments is displayed in Table 12. The sum of the assignment is sum(1) = 0.20+0.99+0.99 = 2.18. However, the sum of the maximum matching degree is sum(2) = 0.99+0.99+0.40 = 2.38 > sum(1). It can be seen from this example that our algorithm may fail to satisfy maximum matching degree assignment in small-scale matrix. The failure is caused by insufficient amount of data for measuring the average value and deviation. When the scale of the matrix becomes larger, our algorithm is able to conform to the maximum assignment requirements.

7. Conclusion

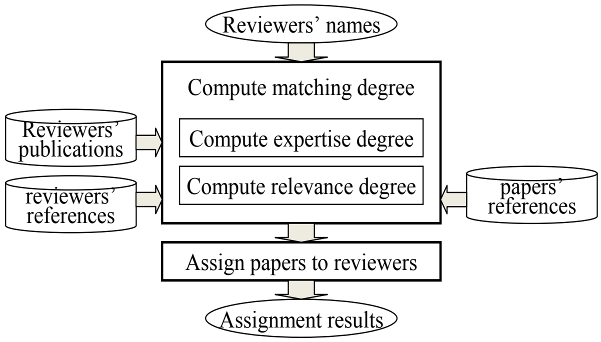
We investigated the problem of automatic paper-to-reviewer assignment. Our paper analyzed the problem of paper-to-reviewer assignment and proposed a framework of reviewer modeling, based on matching degree by using their previous publications. More importantly, we showed an assignment algorithm that could lead to efficiency improvements in large size assignments. The main contributions of our paper are:

- In the theoretical aspect, our assignment algorithm throws light on the solution of other kinds of assignment problems;
- In the applicant aspect, the paper-to-reviewer assignment method can be fielded to provide support for academic conference management.

A key question for future work is to rearrange the assignments dynamically by allowing reviewers to send feedback to the assignment results. Additional analysis and observation of user's feedback in future could significantly help to improve the satisfaction of users.

References

[1] B.T.Sense: "Peer Review and the Acceptance of New Scientific Ideas", Sense about Scienece, 2004.
[2] J.Goldsmith, R.H.Aloan: "The AI Conference Paper Assignment Problem", Preference Handling for Artificial Intelligence, 2007.
[3] P.Rigaux: "An Interactive Rating Method: Application to Web-based Conference Management", in Proc.of ACM Symposium on Applied Computing, pp.1682-1687, 2004.
[4] S.T.Dumais and J.Nielsen: "Automating the Assignment of Submitted Manuscripts to Reviewers", in Proc.of 15th ACM International Conference on Research and Development in Information Retrieval, pp.233-244, 1992.
[5] C.Basu, H.Hirsh, W.Cohen and C.N.Manning: "Technical Paper Recommendation: A Study in Combining Multiple Information Sources", Journal of Artificial Intelligence Research, pp.231-252, 2001.
[6] D.Yarowsky and R.Florian: "Taking the Load off the Conference Chairs: towards a Digital Paper-routing Assistant", in Proc.of Joint SIGDAT Conference on Empirical Methods in NLP and very-Large Corpora, pp.220-230, 1999.
[7] X.Wei and W.B.Croft: "LDA-based Document Models for Ad-hoc Retrieval", in Proc.of 29th ACM International Conference on Research and Development in Information Retrieval, pp.178-185, 2006.
[8] N.Di Mauro, T.M.Basile and S.Ferilli: "GRAPE: an Expert Review Assignment Component for Scientific Conference Management Systems", in Proc.of 18th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Experet Systems", pp.789-798, 2005.
[9] D.Mimno and A.Mccallum: "Expertise Modeling for Matching Papers with Reviewers", in Proc.of 13th ACM/SIGKDD, pp.500-509, 2007.
[10] L.R.Jauch and W.F.Glueck: "Business Policy and Strategic Management", 5th edition, McGraw-hill, 1988.
[11] Y.H.Sun, Ma, Z.P.Fan and J.Wang: "A Group Decision Support Approach to Evaluate Experts for R&D Project Selection", IEEE Trans.on Engineering Management, pp.158-170, 2008.
[12] G.Salton, A.Wong and C.S.Yang: "A Vector Space Model for Automatic Indexing", Comm.of ACM, pp.613-620, 1975.
[13] T.Hofmann: "Probabilistic Latent Semantic Indexing", in Proc.of 22nd Annual International ACM/SGIR, pp.50-57, 1999.
[14] T.L.Saaty: "A Scaling Method for Priorities in Hierarchical Structures", Journal of Mathematical Psychology, pp.248-281, 1977.
[15] H.W.Kuhn and B.Yaw: "The Hungarian Method for the Assignment Problems", Naval Research Logistics Quart, pp.83-97, 1955.
[16] Thomson Reuters: "Journal Citation Reports", http://thomsonreuters.com/products_services/science/science_products/a-z/journal_citation_reports//.
[17] C.L.Giles, K.D.Bollacker and S.Lawrence: "CiteSeer: An Automatic Citation Indexing System", in Proc.of 3rd ACM Conference on Digital Libraries, pp.89-98, 1998.
[18] M.ley: "The DBLP Computer Science Bibliography: Evolution, Research Issues Perspectives", in Proc.of 9th International Symposium on String Processing and Information Retrieval, pp.1-10, 2002.



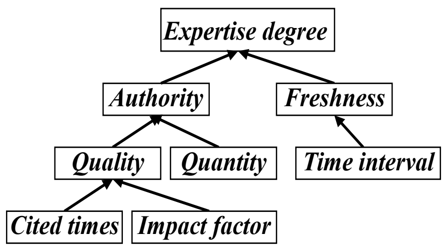


Figure 1: Processing flow in our approach

Figure 2: Expertise defree of reviewer

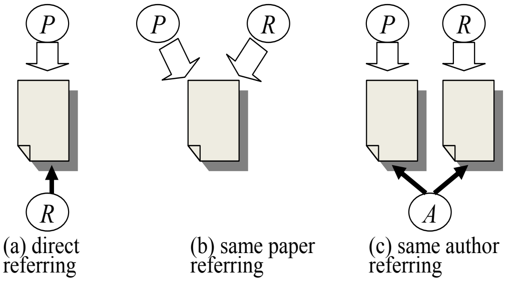


Figure 3: Common referring types

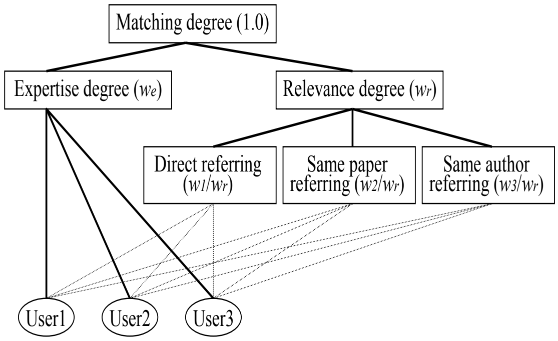


Figure 4: Matching degree in AHP hierarchy

Algorithm: Assigning papers to reviewers
==================================
Input: *M*: A matrix of matching degree;
m: The number of reviewers assigned to each paper;
n: The number of papers reviewed by each reviewer.
Output: *A*: A matrix of assignments.
Methods:
1) SET *assignnum* to 0
2) WHILE *assignnum* $\neq n \times$ number of columns of *M*
3) FOR each row r_i
4) WHILE number of assignments in $r_i < m$ DO
5) SET maximum matching degree's *columnID* into list *maxClumnIDs*
6) IF size of *maxColumnIDs* > 1 THEN
7) SET *j* to *columnID* which maximizes *Q* in *maxColumnIDs*
8) ELSE IF size of *maxColumnIDs* =1 THEN
9) SET *j* to first ID in *maxColumnIDs*
10) ENDIF
11) SET A_{ij} ro 1
12) SET M_{ij} to 0
13) ADD 1 to *assignnum*
14) ENDWHILE
15) ENDFOR
16) FOR each column c_j
17) SET *assignRowIDs* to list of *rowID* which be assigned paper in c_j
18) WHILE number of assignments in $c_j > n$ DO
19) SET *i* to *rowID* which minimizes *D* in *assignRowIDs*
20) SET A_{ij} to 0
21) ADD -1 to *assignenum*
22) ENDWHILE
23) ENDFOR
24) ENDWHILE

Figure 5: Assignment algorithm

Table 1: Comparison scales in AHP

Value	Definition
1	equal importance
3	moderate importance of one over another
5	strong or essential importance of one over another
7	very strong or demonstrated importance of one over another
9	extreme importance of one over another
2,4,6,8	intermediate values
reciprocals	reciprocals for inverse comparison

Table 2: Comparison matrix of relevance degree

	w_1	w_2	w_3
w_1	w_{11}	w_{12}	w_{13}
w_2	w_{21}	w_{22}	w_{23}
w_3	w_{31}	w_{32}	w_{33}

Table 3: Comparison matrix of matching degree

	w_e	w_r
w_e	w_{ee}	w_{er}
w_r	w_{re}	w_{rr}

Table 4: Example in conflict assignment

	1	2	3	average	deviation
a	30	50	**100**	60 (=180/3)	40 (=100-60)
b	70	40	**100**	70 (=210/3)	30 (=100-70)

Table 5: Matching degree matrix

	R_1	R_2	R_3	Row average
P_1	M_{11}	M_{12}	M_{13}	ra_1
P_2	M_{21}	M_{22}	M_{23}	ra_2
P_3	M_{31}	M_{32}	M_{33}	ra_3
P_4	M_{41}	M_{42}	M_{43}	ra_4
Column average	ca_1	ca_2	ca_3	

Table 6: Assignment matrix

	R_1	R_2	R_3
P_1	A_{11}	A_{12}	A_{13}
P_2	A_{21}	A_{22}	A_{23}
P_3	A_{31}	A_{32}	A_{33}
P_4	A_{41}	A_{42}	A_{43}

Table 7: Example of matching degree matrix

	R_1	R_2	R_3	Row average
P_1	0.75	0.37	0.92	0.69
P_2	0.61	0.87	0.37	0.62
P_3	0.57	0.42	0.75	0.58
P_4	0.18	0.57	0.87	0.54
Column average	0.53	0.56	0.73	

Table 8: Example of nonlinear assignment

	R_1	R_2	R_3
P_1	0	0	1
P_2	0	1	0
P_3	0	0	0
P_4	0	0	1

(a)

	R_1	R_2	R_3
P_1	0	0	1
P_2	0	1	0
P_3	1	0	0
P_4	0	0	1

(b)

	R_1	R_2	R_3
P_1	0	0	1
P_2	0	1	0
P_3	1	0	0
P_4	0	0	1

(c)

Table 9: Comparison in time-comsumption

	3×3 matrix	5×5 matrix	10×10 matrix	20×20 matrix
Our algorithm	0.005 sec.	0.037 sec.	0.087 sec.	0.174 sec.
Hungarian algorithm	0.01 sec.	0.079 sec.	0.179 sec.	0.313 sec.

Table 10: Successful rate of matrix weight assignment

	3×3 matrix	5×5 matrix	10×10 matrix	20×20 matrix
Successful rate(%)	80	100	100	100

Table 11: Failed example in our approach

	A	B	C	Row average
I	0.99	0.90	0.20	0.70
II	0.20	0.99	0.15	0.45
III	0.99	0.50	0.40	0.63
Column average	0.73	0.80	0.25	

Table 12: Example of assignment

	A	B	C
I	0	0	1
II	0	1	0
III	1	0	0

(a)

	A	B	C
I	1	0	0
II	0	1	0
III	0	0	1

(b)