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RelRank: A relevance-based author ranking algorithm for individual publication venues

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ABSTRACT

Hiring appropriate editors, chairs and committee members for academic journals and conferences is challenging. It requires a targeted search for high profile scholars who are active in the field as well as in the publication venue. Many author-level metrics have been employed for this task, such as the *h*-index, PageRank and their variants. However, these metrics are global measures which evaluate authors' productivity and impact without differentiating the publication venues. From the perspective of a venue, it is also important to have a localised metric which can specifically indicate the significance of academic authors for the particular venue. In this paper, we propose a relevance-based author ranking algorithm to measure the significance of authors to individual venues. Specifically, we develop a co-authorship network considering the author-venue relationship which integrates the statistical relevance of authors to individual venues. The RelRank, an improved PageRank algorithm embedding author relevance, is then proposed to rank authors for each venue. Extensive experiments are carried out to analyse the proposed RelRank in comparison with classic author-level metrics on three datasets of different research domains. We also evaluate the effectiveness of the RelRank and comparison metrics in recommending editorial boards of three venues using test data. Results demonstrate that the RelRank is able to identify not only the high profile scholars but also those who are particularly significant for individual venues.

1. Introduction

Identifying appropriate scholars is an important task for academic journals and conferences since these scholars can be hired to take editorial roles such as conference chairs or committees, journal editors, paper reviewers, etc. Current approaches for this task can be broadly divided into three categories, namely peer recommendation, language modelling-based methods and bibliometrics-based methods.

Peer recommendation relies on subjective judgement and human expertise, which can be expensive, time demanding and effort consuming especially when the quantity of required scholars becomes too large (Bornmann & Daniel, 2009). The language modelling-based methods consider scholar recommendation as information retrieval problems and employ language models to identify or establish matching relationship between the scholars' expertise and the required jobs (e.g., papers to be reviewed or conference sessions to be chaired) (Mirzaei, Sander, & Stroulia, 2019). These methods focus on semantic matching but tend to overlook the academic and social impact of the scholars, which may lead to unsuitable recommendation (Amjad, Daud, & Aljohani, 2018).

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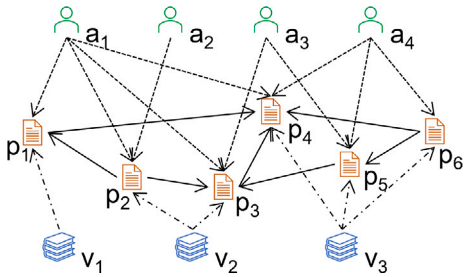


Fig. 1. Classic bibliometric network.

In comparison, the bibliometrics-based methods evaluate the impact, prestige and popularity of academic authors based on their bibliometric information. Some author-level indicators, such as h-index (Hirsch, 2005) and its variants, have been widely used in practical services such as the Google Scholar and Web of Science. However, these methods are not designed to serve individual publication venues (journals or conferences). They provide a global evaluation of academic authors without taking into account the authors' relevance to specific venues.

From the perspective of a venue, being able to specifically indicate the significance of authors to this particular venue is important. The "significance" here involves three aspects: citation impact, collaboration impact, and relevance. An author is considered significant to a venue if he/she is a highly cited author, develops broad collaborations within the venue, and importantly has a larger number of papers published in this venue compared to that in other venues. Fig. 1 shows an example to illustrate the importance of the last point. Assume four authors ($a_i, i \in \{1, \ldots, 4\}$) have collaboratively or individually published six papers ($p_j, j \in \{1, \ldots, 6\}$) discussing similar topics in three venues ($v_q, q \in \{1, 2, 3\}$) that are in the same research field, hence these bibliometric entities are interacted in a heterogeneous graph as shown. Which author should be considered more significant for venue v_3? By counting citations and h-index, author a_1 will be ranked in the first place since it receives 6 citations and h-index at 2, followed by a_4 then a_3 and a_2. If the collaboration factor is considered, a_1 has the largest number of co-authors, suggesting that a_1 will outrank the others. Since the authors are assumed to be researchers from the same field, using the language modelling-based models will give the same recommendation result for the three venues. However, locally speaking for v_3, author a_4 may be a better choice because all of this author's papers have been published in v_3, while a_1 only distributes one out of four papers to this venue.

The above example reflects the motivation of this study, that is, to design an author ranking algorithm which can identify high impact authors who are also active and devoted to specific publication venues. In this paper, we propose the RelRank to measure the significance of authors to individual publication venues. To this end, a relevance-based co-authorship network is designed to incorporate information about the authors' collaborations and their devotion to the venues. We refer to an author a's devotion to a venue v as author relevance $r_{a,v}$, and formulate $r_{a,v}$ based on the concept of term frequency–inverse document frequency (TF–IDF) (Jones, 1972) — a numerical statistic originally used in information retrieval to reflect how important a word is to a document in a collection or corpus. The proposed RelRank is then built on top of the relevance-based co-authorship network and further incorporates the author citations in the iteration procedure.

The contributions of this study are: (1) we define and formulate the author relevance $r_{a,v}$ which measures the statistical relevance of an author to individual venues; (2) by integrating the author relevance, a relevance-based co-authorship network is designed to serve individual venues; and (3) a novel author ranking algorithm, RelRank, is proposed to assist in seeking significant authors for individual venues.

The remainder of the paper is organised as follows. Section 2 categorises the pathways of academic author evaluation methods and reviews important author indexes and author evaluation algorithms. Section 3 explains the methodology of the proposed RelRank. Datasets, baseline metrics and settings are listed in Section 4. Section 5 demonstrates the results of our analysis and evaluation on the RelRank. Section 6 discusses the advantages and limitations of the RelRank, followed by Section 7 concluding this study.

2. Related work

2.1. Pathways of evaluating academic authors

Existing approaches for evaluating academic authors can be divided into three categories, namely, peer recommendation, language modelling-based methods, and bibliometric analysis-based methods. In peer recommendation, candidate authors are reviewed and evaluated manually by domain experts or peers based on their knowledge and experience (August & Muraskin, 1999). This subjective method is effective in recommending small number of authors, however it is extremely time demanding and effort consuming when the quantity of required authors becomes too large (Bornmann & Daniel, 2009). In addition, subjective recommendation may be influenced by human factors during the evaluation process, such as cognitive distortions (Protasiewicz et al., 2016). To address these, many approaches have been proposed to recommend authors automatically and objectively based on language modelling and bibliometrics (Amjad et al., 2018). The language modelling-based methods consider author recommendation as information retrieval problems in the literature (Gao, Dai, Gao, & Jin, 2019). A range of language models have been employed, including Latent Semantic Indexing (LSI), Latent Dirichlet Allocation (LDA), TF–IDF, Author-Topic (AT) models, etc., in order to identify or establish the matching relationship between candidates' expertise and documents of the required tasks (e.g., papers to be reviewed and topic lists of conference sessions to be chaired) (Kou, U, Mamoulis, & Gong, 2015; Mirzaei et al., 2019). These methods have achieved promising matching results and can recommend authors for specific venues, however the language models do not consider the academic and social impact of the authors, which may lead to unsuitable recommendation (Amjad et al., 2018). For instance, an editorial role of a journal may be matched to too many potential candidates of the same field, but those who are more qualified cannot be found, not to mention identifying those who are likely to commit to the role.

This paper focuses on the third category, i.e., bibliometrics-based methods, where academic authors are evaluated by analysing bibliometric information, and then the top ranked ones are recommended. Two pathways are found in existing literature of this area: One path is to evaluate academic authors using their own bibliometric information, such as the classic h-index. We refer to the approaches in this pathway as *author indexes*; The other path is to calculate scores for a collection of authors based on the relationships amongst the bibliometric entities associated to the authors such as the authors' affiliations, collaborations, publications, citations, venues, etc. The PageRank algorithm is a classic representative of this pathway, and we refer to these approaches as *author evaluation algorithms*.

2.2. Author indexes

In the first pathway, the h-index has gained well recognition in assessing individual scientific achievement (Bornmann, 2014), however it tends to overlook the highly cited papers of authors (Schreiber, 2018; Waltman & Van Eck, 2012). Many variants of h-index were proposed to improve their predecessors. For instance, g-index was proposed to generate a maximised number g for an author, such that g of his/her papers altogether have at least g^2 citations (Egghe, 2006). This alleviated the issue of the h-index being insensitive to highly cited papers by taking into account the citations of these papers. π-index (Vinkler, 2009) also contributed to addressing this issue by considering highly cited researchers. An Eigenfactor method was proposed to favour the highly cited authors by giving them higher weight (West, Jensen, Dandrea, Gordon, & Bergstrom, 2013).

In addition, some indexes were introduced to distinguish the contribution of co-authors from their collaborations. For instance, h_m-index (Schreiber, 2008) and h_α index (Hirsch, 2019) were proposed to differentiate authors who shared authorship yet had different collaboration patterns by considering fractional citation count and α-authors of academic papers. Moreover, the publication time factor was involved to measure the trend and evolution of the scholarly impact of academic authors. Jin, Liang, Rousseau, and Egghe (2007) proposed AR-index which integrated h-index and publication time into the AR-index calculation where only the recent publications of an author with exactly h citations are considered. Pan and Fortunato (2014) proposed Author Impact Factor (AIF) which computed the impact factor of an author in year t based on the average number of citations from the papers published in year t to the papers published by the author in a certain period of time before t. This method was designed to not only assess the impact of academic authors but also capture the trend of their scientific output in time.

These author indexes are easy to use when evaluating individual authors and flexible to modify for different indexing purposes, however they tend to overlook important information, such as the relationships between bibliometric entities, that may lead to biased results.

2.3. Author evaluation algorithms

PageRank is a classic algorithm in the second pathway. It was initially designed to measure the importance of web pages by propagating node in-links based on the underlying assumption that a website is likely to be more important if it receives more links from other important websites (Page, Brin, Motwani, & Winograd, 1999). The algorithm was later employed on bibliometric networks where nodes represents academic authors. The PageRank of author a_i is given as:

$$PR(a_i) = \frac{1-d}{N} + d \sum_{j=1}^{k} \frac{PR(a_j)}{C(a_j)} \tag{1}$$

where N refers to the total number of authors in the network; d is damping factor; a_j denotes the author that links to a_i; k is the number of a_i's links; and $C(a_j)$ is the count of out-links from a_j. The network can be either author citation network or co-authorship network, depending on how the network is constructed and the purposes of ranking.

In author citation networks, the links denote the citations between authors, and the authors are usually ranked by calculating scores for authors based on the citations of their papers. For instance, Sidiropoulos and Manolopoulos (2006) proposed an improved PageRank which computed scores for all the papers in the citation network, and then ranked the authors based on the average score of their papers. Radicchi, Fortunato, Markines, and Vespignani (2009) proposed to distinguish citations by offering higher weight to those coming from prominent authors compared to the less prominent ones, and then assessed the authors using a modified PageRank method. Gao, Wang, Li, Zhang, and Zeng (2016) introduced PR-index which integrated the PageRank scores of an author's papers into the h-index calculation for this author, i.e., the citation component of an author's h-index is replaced by the normalised PageRank scores of this author's papers. Zhao, Zhang, Lu, and Shai (2019) proposed Author-PageRank (APR) approach which added new links between the old and new papers of an author so that the random walk can directly move from the author's old papers to the new ones. To incorporate more bibliometric information to the citation networks, many studies integrated weight to the edges of the networks, and the weight was calculated based on semantics similarity between papers (Zhang, Wang, Gottwalt, Saberi, &

Chang, 2019), time of publication (Yu, Wang, Zhang, Zhang, & Liu, 2017), and domain topics (Amjad, Ding, Daud, Xu, & Malic, 2015).

As for co-authorship networks, the edges reflect the collaborations between authors, and the authors are commonly ranked based on the roles that they play in their collaborations (Ebadi & Schiffauerova, 2015). Specifically, Liu, Bollen, Nelson, and Van de Sompel (2005) introduced AuthorRank, based on PageRank, which offered more weight to the authors who had fewer collaborators and less weight to those with more co-authors. The collaboration frequency between co-authors was also discussed by Fiala, Rousselot, and Ježek (2008), and they granted less credit to the cited author if he or she had more frequent collaborations with the citing author. In other words, the credit that an author received from another author was inversely proportional to the number of their collaborative publications. A time aware PageRank was proposed by Fiala (2012), which combined time of publications, citations and collaborations of authors. The algorithm leveraged the collaboration information from co-authorship networks to give different weight to the citations from different authors with publication time considered. In addition, the mutual influence was considered for author evaluation, where the citation exclusivity was defined based on the weight of citations normalised by the authors' positions in the author lists of their papers, and then integrated into author score calculation (Amjad, Daud, Akram, & Muhammed, 2016; Amjad, Daud, Che, & Akram, 2016). Furthermore, researchers integrated different author credit allocation model into the co-authorship network to assist author evaluation. For instance, leaders and followers were distinguished; important contributors and ordinary contributors were categorised; and "influencers" were identified based on their significance scores (Yoshikane, Nozawa, & Tsuji, 2006), collaboration strength (Li & You, 2013), level of co-author contribution (Zhou, Zeng, Fan, & Di, 2018), author bylines (Kim & Diesner, 2015; Lü, Zhang, Yeung, & Zhou, 2011), and geographic information (He, Wu, & Zhang, 2021).

A special weighted PageRank proposed by Yan and Ding (2011) inspired our research. It provided influential authors with a higher probability to be randomly surfed in a co-authorship network, and updated the traditional weighted PageRank for author a_i as:

$$wPR(a_i) = (1-d)\frac{CC(a_i)}{\sum_{n=1}^{N} CC(a_n)} + d\sum_{j=1}^{k}\frac{wPR(a_j)}{C(a_j)} \tag{2}$$

where $CC(a_i)$ refers to the citation count of author a_i, and $\sum_{n=1}^{N} CC(a_n)$ denotes the sum of the citation count of all the N number of authors. a_j denotes the author that links to author a_i; k is the number of a_i's links; and $C(p_j)$ is the number of outlinks from author a_j. This method added weight to the static $(1-d)$ part of the traditional PageRank so that it is able to score authors from the aspects of collaborations and citations of academic authors in a simple and efficient way.

Different approaches have been proposed for author evaluation based on author citations, collaborations and associated information. However, none of these methods was designed to serve specific venues. They provided a global evaluation of academic authors without taking into account their significance in specific venues. This study aims to fill this gap by integrating the core idea of TF–IDF into co-authorship networks. The original TF–IDF was designed to measure the relevance of a keyword to a document, suggesting that a keyword is more relevant to a document if it appears more frequently in that document but less in others (Jones, 1972). This concept inspired us to improve the PageRank by taking into account the relevance of an academic author to individual publication venues, so that the improved PageRank can assist the venues in seeking significant authors.

3. Methodology

The overall framework of the proposed method is illustrated in Fig. 2. Information about the authors, papers, venues, and co-authorship relationships are extracted from the bibliometric information collection (e.g., a domain dataset). The co-authorship network is then constructed, and the author-venue relevance is calculated. Integrating the author relevance into the co-authorship network, a relevance-based co-authorship network is established, based on which the RelRank algorithm outputs the final author scores. Details of these components are elaborated in the following sub-sections.

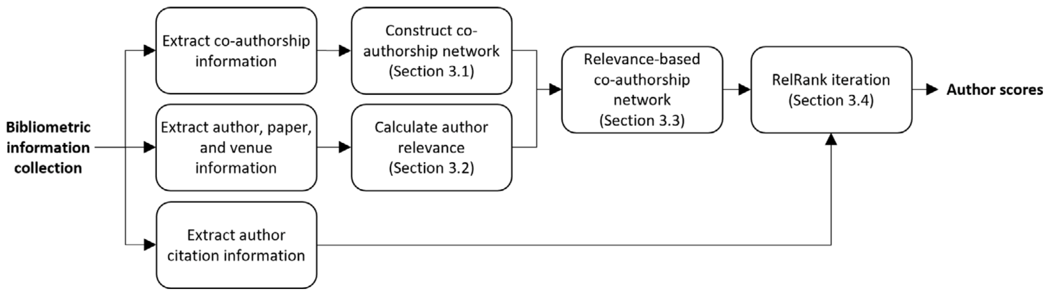
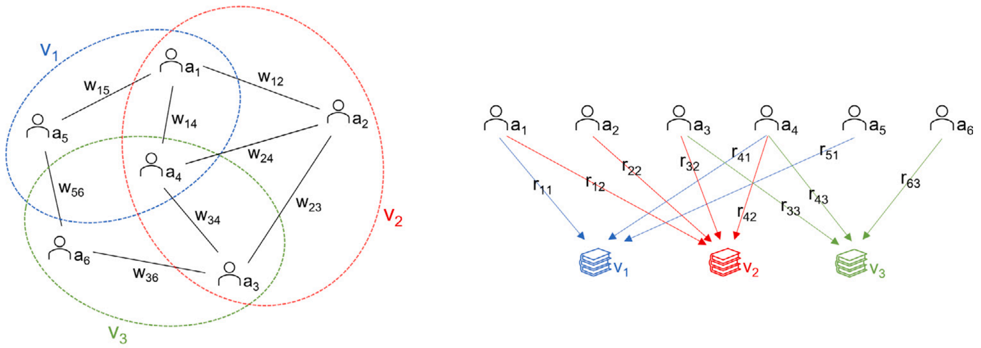


Fig. 2. Framework of the proposed method.

3.1. Co-authorship network sectioned by venues

Co-authorship network can demonstrate academic authors' social impact through their collaborations, hence it has been widely used for author evaluation (Amjad et al., 2018; Dino et al., 2020; Fiala et al., 2008). A co-authorship network can be presented as an adjacency matrix A with element A_{ij} equal to 1 if node a_i and node a_j are linked and 0 otherwise. Here, nodes refer to individual authors; edges represent the collaborating relationship between authors; and weight of an edge denotes the collaboration frequency between the authors linked by this edge. For example, if author a_i and a_j have collaborated three times, then weight of the edge, w_{ij}, connecting a_i and a_j is 3. For undirected co-authorship network, $w_{ij} = w_{ji} = 3$, and the diagonal elements of matrix A is set to zero (Yan & Ding, 2011).



(a) Co-authorship network. (b) Author-venue relationship.

Fig. 3. Co-authorship network sectioned by publication venues.

Fig. 3(a) demonstrates a such co-authorship network constructed by six authors ($a_i, i \in \{1, \ldots, 6\}$). Assume these authors have collaborated to publish in three venues ($v_j, j \in \{1, 2, 3\}$), and the relationship between a_i and v_j can be constructed by a bipartite author-venue graph as shown in Fig. 3(b). In this bipartite graph, we define weight of the edges, r_{ij}, to indicate the relevance of author a_i to venue v_j, and edge direction to represent if an author has published in a venue. This author-venue relationship helps section the co-authorship network by publication venues as shown in Fig. 3(a), where authors are enclosed by their corresponding venues in which they have published papers. In addition, it is arguably useful to feature the co-authorship network with direction and to update the weight on its edges. This will be illustrated in the following section.

3.2. Relevance of authors to venues

This section defines and formulates the statistical relevance of an author to individual venues based on the author's publications. This measure is used to reflect the devotion or focus of an author to a venue given his or her publications in this particular venue relevant to the other venues. For instance, if an author a_i has published 20 papers in which 10 are in journal v, we can say that a_i is devoted to v to a certain level, and v can consider a_i relevant to an extent. In contrast, another author a_j publishing only one out of 20 papers in v would be regarded less relevant to v compared to a_i.

Formally, given a group of authors $a \in A$ who have published papers $p \in P$ in a collection of venues $v \in V$, the author relevance $r_{a,v}$ is defined based on the concept of TF–IDF as:

$$r_{a,v} = AF_{a,v} \cdot IVF_a \quad , \tag{3}$$

where $AF_{a,v}$ and IVF_a refer to author frequency (AF) and inverse venue frequency (IVF) terms, respectively. The value of $r_{a,v}$ increases proportionally to the number of papers an author published in the venue and is offset by the number of venues in the collection that the author published, which helps to adjust for the fact that some authors publish frequently in many venues. Here, the AF term is defined as:

$$AF_{a,v} = \frac{f_{a,v}}{\sum f_{a',v}} \quad , \quad \text{where} \quad f_{a,v} = \sum_{p \in P_{a,v}} 1 \quad . \tag{4}$$

The $P_{a,v}$ refers to the collection of papers that a has published in v; a' denotes all the authors that have ever published in v, thus $f_{a,v}$ delivers the number of papers author a has published in venue v; and $\sum f_{a',v}$ produces the overall number of papers that are published in v.

In order to avoid the issue brought by the fact that different venues publish papers in different pace or quantity, we employ the term frequency maximum normalisation (Salton & Buckley, 1988). Specifically, $f_{a,v}$ is normalised by the maximum value in venue v to compute a normalised version as follows:

$$nf_{a,v} = \beta + (1 - \beta) \frac{f_{a,v}}{f_{max}(v)} \quad , \tag{5}$$

where β is a smoothing factor between 0 to 1 and is generally set to 0.4 (Christopher D. Manning & Schütze, 2008). With this normalisation, the final $AF_{a,v}$ is computed as:

$$AF_{a,v} = \frac{nf_{a,v}}{\sum nf_{a',v}} \quad , \quad \text{where} \quad nf_{a,v} = \beta + (1-\beta)\frac{f_{a,v}}{f_{max}(v)} \quad . \tag{6}$$

Meanwhile, the IVF part of the author relevance is defined as:

$$IVF_a = log\frac{N}{\sum_{i=1}^{N} I(a, v_i)} \quad , \tag{7}$$

where N is the number of overall venues in the collection V, and $\sum_{i=1}^{N} f'_{a,v_i}$ denotes the number of venues in which the author a has published papers. The 1 in the denominator of the original TF–IDF equation is removed because in the case of publication there does not exist an author who is not associated with any publication venues.

In addition, time of collaboration is important. Authors who have recently published or collaborated in a venue are generally more active and more likely to accept to serve as editors and reviewers. Hence, we further incorporate the time factor and propose the time-aware author relevance, $r^t_{a,v}$. It takes into account the publication time (i.e., collaboration time) to promote newly published papers (i.e., collaborations). The impact of time is formulated using an exponential function:

$$w_p = e^{-\rho(t_0 - t_p)} \quad , \tag{8}$$

where ρ is a constant and assigned as 0.62 in this paper based on empirical analysis in previous study (Zhang et al., 2019), t_0 is the time point of evaluation, and t_p denotes the publication year of paper p. Only the papers published before the evaluation time are considered, i.e., $t_p \le t_0$. Consequently, the $f_{a,v}$ can be updated to $f^t_{a,v}$ as:

$$f^t_{a,v} = \sum_{p \in P_{a,v}} w_p \quad . \tag{9}$$

Hence the time-aware author relevance $r^t_{a,v}$ can be obtained by replacing the $f_{a,v}$ and $nf_{a,v}$ in Eq. (6) with $f^t_{a,v}$ and $nf^t_{a,v}$ respectively.

3.3. Relevance-based co-authorship network

By considering the relevance of authors to individual venues, a weighted directed co-authorship network can be constructed for each publication venue as shown in Fig. 4. Here we use a snapshot of the co-authorship network in Fig. 3(a) where only author a_1, a_3 and a_4 are involved, as well as the three associated venues. Author a_1 has published in both venue v_1 and v_2; a_3 published in v_2 and v_3; and a_4 in all three venues.

Within each sub-network sectioned for a venue, the author relevance is used to define direction of the edges and calculate weight of the edges. Specifically, in sub-network for venue v_m, a node represents an author, and the edge between two authors (a_i and a_j) denotes the co-authorship between them. The weight that directs to both ends of an edge is different, that is, the weight for target author a_j is computed by multiplying the number of papers co-authored by a_i and a_j in the venue v_m and a_j's relevance to the venue v_m (i.e., $w_{ij} \times r_{jm}$). For instance, in the sub-network developed for venue v_1, weight of the edge between author a_1 and a_4 is $w_{14} \times r_{11}$ for author a_1 and $w_{14} \times r_{41}$ for author a_4. In the sub-network of v_2, weight of the same edge becomes $w_{14} \times r_{12}$ for a_1 and $w_{14} \times r_{42}$ for author a_4.

By integrating the author relevance to co-authorship network, two advantages are achieved: (1) within the same venue sub-network, collaborating co-authors can be differentiated based on each co-author's relevance to the venue; and (2) in different venue sub-networks, the same author can be viewed from different aspects based on the author's publications in and relevance to this venue.

3.4. RelRank: Relevance-based author ranking method

This section proposes the RelRank algorithm on the relevance-based co-authorship network developed in Section 3.3 to identify significant authors for individual venues.

To calculate scores of authors for individual venues, multiple bibliometric information including author collaboration, citations and relevance is considered. Here, we extend the weighted PageRank as shown in Eq. (2) by integrating the author relevance factor into the algorithm. Concretely, the RelRank score of author a_i to venue v_m is defined as:

$$Rel(a_i, v_m) = (1-d)\frac{CC_{a_i}}{CC_A} + d \sum_{a_j \in In(a_i)} \frac{w_{ij} \cdot r_{im} \cdot Rel(a_j, v_m)}{Out(a_j)}, \tag{10}$$

where $In(a_i)$ denotes the all the links pointing to author a_i while $Out(a_j)$ denotes the links pointing out from a_j; w_{ij} refers to the collaboration frequency between author a_i and a_j; r_{im} is the relevance of author a_i to venue v_m which can be calculated using Eq. (3). The part $w_{ij} \cdot r_{im}$ is the weight of edges in the relevance-based co-authorship network as shown in Fig. 4. CC_{a_i} refers to the citation count of author a_i, and CC_A is the total citations of all the authors.

The RelRank algorithm measures the significance of authors for individual venues under the assumption that a publication venue considers an author more significant if this author brings more collaborations and citations for the venue, and the author will be favoured if the author has focused more on publishing in this venue. It is able to recommend scholars who have shown not only higher publication performance but also active publishing profile in a journal or conference.

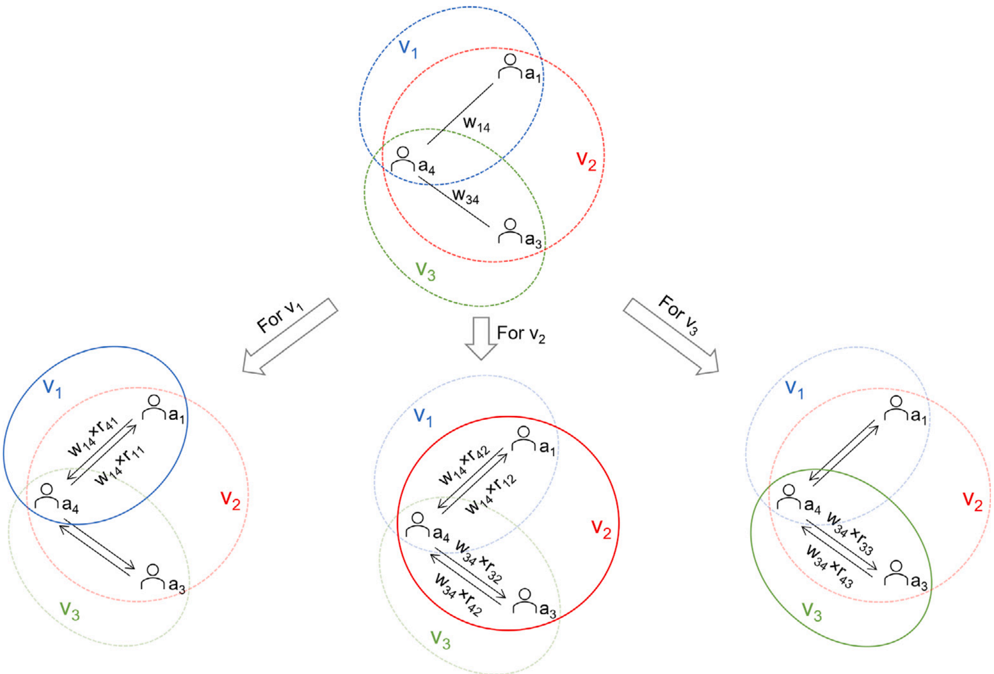


Fig. 4. Relevance-based co-authorship network.

Table 1
Information of the three domain datasets collected from the MAG.

Dataset	ML	CV	DM
# of Paper	576,003	488,272	553,230
# of Venues	641	458	685
# of Authors	17,692	17,317	13,388
# of Citations	10,467,219	7,093,807	9,027,310
# of A-V links	83,694	77,628	59,334

4. Datasets and baselines

The Microsoft Academic Graph (MAG) database is used for analysis and evaluation in this study due to its easy access, high reliability, and rich resources in terms of research domains and time span (Sinha et al., 2015). It provides over 126 million papers and associated metadata in a wide range of disciplines and time span (from early 1990s to 2018), which has been commonly used to evaluate author and paper ranking algorithms (Dunaiski, 2019; Zhang et al., 2019). Importantly, the MAG contains huge size bibliometric data in most fields of research, which offers flexibility in choosing domains for evaluation. We collected three domain datasets from the MAG in machine learning (ML), computer vision (CV), and data mining (DM), and then extracted metadata of the papers published from 2003 to 2018 including author affiliation, venue, publication year and references. We further implemented author name disambiguation using a well-established rule-based heuristic method (Strotmann, Zhao, & Bubela, 2009) which has been proved effective in pre-processing author names in bibliometric analysis (Sanyal, Bhowmick, & Das, 2021). Detailed information about the three datasets is summarised in Table 1, where the “# of A-V links” shows the number of links between authors and venues in each domain datasets.

To evaluate the proposed RelRank, five classic author indexes and author evaluation algorithms in the literature are selected as baseline metrics for comparison.

- Citation count (CC): It counts the total citations that an author’s publications have received. For author a, $CC_a = \sum_{p\in P(a)} Cite(p)$ where $P(a)$ refers to the collection of papers that author a has published, and $Cite(p)$ delivers the number of papers which cite paper p.
- h-index: It measures the h score of an author, such that at most h number of his/her papers have received at least h citations.
- g-index: It generates a maximised number g for an author, such that g number of his/her papers altogether have received at least g^2 citations.
- PageRank: It estimates the collaboration impact of academic authors in an undirected unweighted co-authorship network. The PageRank score of an author can be calculated by Eq. (1).

- Weighted PageRank (wPageRank): It computes the collaboration impact of authors meanwhile considering the author's citation impact. The wPageRank score of an author can be calculated by Eq. (2).

The above author-level metrics are usually performed to evaluate authors of a domain globally, without differentiating the publication venues. In order to fairly compare the proposed RelRank with the baseline metrics, two settings of these metrics are used in the following experiments, namely global setting and venue-specific setting. Specifically, to generate an author ranking result for a specific venue, under global setting all the authors of a dataset are scored by these metrics using all the information associated with them, and then the authors corresponding to the venue are selected and ranked based on their received scores. This setting is to simulate how the global author-level metrics work for author evaluation. In comparison, under venue-specific setting, only the information associated with an author's publications in a specific venue is used to evaluate the author. This setting is to simulate the scenarios when the baseline metrics and RelRank are used to serve individual venues. Take the co-authorship network in Fig. 3(a) for example, to assess the author a_1 for venue v_1, the metrics under global setting will use all the information associated with author a_1, such as a_1's publications in v_1 and v_2, and collaborations with a_2, a_4 and a_5. However, under venue-specific setting, the metrics use only the information within venue v_1 to evaluate a_1, such as a_1's publications in v_1 and collaborations with a_4 and a_5.

5. Analysis and results

To explore the characteristics and validate the effectiveness of the proposed RelRank, two experiments are conducted, namely correlation analysis and effectiveness evaluation. In addition, a case study is carried out to analyse the scoring behaviour of the RelRank.

5.1. Correlation analysis

In bibliometric analysis, the Spearman's correlation coefficient has been commonly used to analyse and obtain insights into new ranking methods (Dunaiski, Geldenhuys, & Visser, 2018a; Nykl, Campr, & Ježek, 2015). It is used in this analysis to assess the monotonic relationships between author ranking results of RelRank and the baseline metrics. The coefficient ρ is defined by the following equation (Myers, Well, & Lorch Jr, 2013):

$$\rho = \frac{\sum_i (R_1(A_i) - \overline{R_1})(R_2(A_i) - \overline{R_2})}{\sqrt{\sum_i (R_1(A_i) - \overline{R_1})^2 (R_2(A_i) - \overline{R_2})^2}} \tag{11}$$

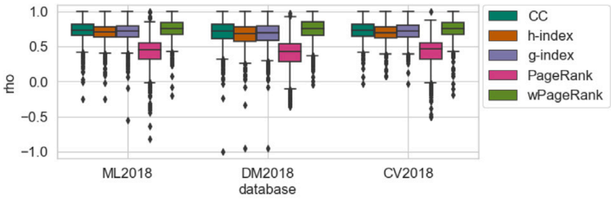
where $R_1(A_i)$ and $R_2(A_i)$ refer to the position of author A_i in the rank lists generated by two metrics, $\overline{R_1}$ and $\overline{R_2}$ are the average rank positions of all authors in the two rank lists respectively. The ρ ranges from -1 to 1. Intuitively, a larger ρ suggests that the relative positions of the authors (1st, 2nd, 3rd, etc.) in two author rank lists are similar (or identical if $\rho = 1$), and a lower ρ indicates that the authors are ranked in dissimilar positions by the two rank lists. Analysing ρ between the ranking results of RelRank and those of the baseline metrics helps observe whether the author scoring behaviour of the RelRank is similar to that of the baselines.

Under both global and venue-specific settings, for each venue there is one set of correlation coefficients between the ranking results of the proposed RelRank and those of the baseline metrics, hence a total of n sets of coefficients will be obtained, where n equals to the number of venues in a dataset. Fig. 5 summarises the statistic information of the correlation coefficients between RelRank and baseline metrics in all the venues across the three datasets.

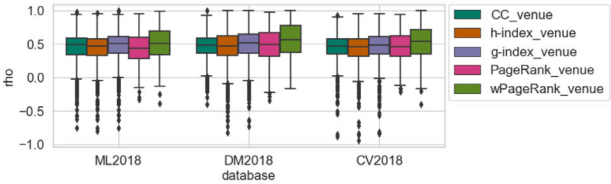
The correlation coefficients are mostly above zero across three datasets under both settings, and especially those obtained by comparing the RelRank against CC, h-index, g-index and wPageRank under global setting are rather high (interquartile of ρ ranges from 0.6 to 0.8). This indicates that the proposed RelRank is able to generate author rank lists that are positively correlated to those generated by the well-recognised author-level metrics. In comparison, the range of ρ between the RelRank and PageRank under global setting is lower, and the dispersion is much wider. This suggests that RelRank tends to show a scoring behaviour that is similar to the citation-based methods on the global setting, because the CC, h-index, g-index and wPageRank takes into account author citations while the PageRank (performed on co-authorship networks) does not.

Under the venue-specific setting, the dispersion of the correlation between RelRank and baseline metrics becomes wider compared to that using global setting, and the interquartile range drops considerably, with median values falling down for most metrics. This reveals the difference in the scoring behaviour of these metrics when serving globally and locally (i.e., under global setting and venue-specific setting). The ranking results of RelRank are less similar to these metrics under venue-specific setting, which highlights the impact of considering author relevance on ranking authors within individual venues.

To sum up, the correlation analysis has shown that the proposed RelRank can rank authors for individual venues, and the ranking results are in general positively correlated to those generated by the classic author-level metrics. However, the difference between RelRank and the baseline metrics does exist, and the degree to which depends on the venue of interest. This suggests that considering the relevance of authors to individual venues makes a difference to the RelRank in ranking the authors, and the effect of considering the author relevance is more obvious in some venues but less in others. This may have highlighted the unique capability of RelRank in identifying the authors who have not shown high academic profile but worth considering as significant for some venues. We will discuss this point at length using a case study later. Note that the RelRank is not proposed as another global author ranking approach, rather it is designed to assist individual venues in seeking significant authors for themselves, hence the large variety of the correlation coefficients calculated for different venues.



(a) Comparison with baseline metrics under the global setting



(b) Comparison with baseline metrics under the venue-specific setting

Fig. 5. Statistic information of the Spearman's ranking correlation between the ranking results of the proposed RelRank and baseline metrics using two types of settings. All the results are statistically significant at the level of 0.05.

Table 2
Information of the test datasets collected from three venues in 2019.

Research field	Venue	#Authors	#Editors/Chairs
DM	ICDM 2019	1459	51
ML	Neural Networks	533	81
CV	Pattern Recognition	941	132

5.2. Effectiveness evaluation

One of the important tasks that the proposed RelRank is designed for is to assist individual venues (journals or conferences) in seeking significant authors who may be suitable for journal editorial board members, conference committee members, area chairs, and paper reviewers. Ideally, these authors are expected to be familiar with the tracks and history of the journals or conferences so that they can provide corresponding services based on their expertise and experience. This cannot be reflected by their h-index or PageRank scores, however we believe that the RelRank is better suited for this task. As far as we understand, the task of seeking these authors is manually performed by viewing the publication performance and reputation of the candidates to make a decision, which is time consuming and may not be able to find all the suitable authors. In this experiment, we evaluate the effectiveness of the RelRank in searching those authors for individual venues and compare the results with those obtained by the baseline methods.

This evaluation is recognised difficult since there does not exist ground truth in academic ranking or evaluation, thus the list of authors who are truly significant for specific venues is not accessible (Dunaiski, Geldenhuys, & Visser, 2018b). The common practice in bibliometric analysis is to employ test data for metrics evaluation (Dunaiski, Visser, & Geldenhuys, 2016; Mariani, Medo, & Zhang, 2016). The test data contains generally agreed true data such as awarded papers or award laureates, which can be used to assess the effectiveness of the metrics in discovering these preferred papers or authors.

Assuming that journals and conferences consider their editors and area chairs significant to themselves, we created test datasets by manually collecting the editors and chairs from two journals and one conference, namely the Neural Networks, Pattern Recognition and The IEEE International Conference on Data Mining (ICDM). These venues are all well recognised in their own fields of research, respectively in machine learning, computer vision and data mining which correspond to the three domain datasets (Table 1) that we collected from the MAG. Since the time span of the collected datasets is from 2003 to 2018, we collected editors and chairs of these venues at the snapshot of 2019 to test whether the algorithms based on historical data can help identify significant authors for the next year. The information of the collected test datasets is shown in Table 2 where the '# of Authors' refers to the total number of authors in each venue, and '# of Editors/Chairs' denotes the number of editors or chairs manually collected from the official websites of the venues in 2019.

The Discounted Cumulative Gain (DCG) is commonly used to evaluate ranking quality in the field of information retrieval (Järvelin & Kekäläinen, 2002). It measures the gain of an author based on its position in the resulting rank list using a graded relevance scale of authors in the list. The DCG at a certain position (i.e., cut-off value), denoted as $DCG@p$, is accumulated from the top of the result list to the position p with the gain of each result discounted at lower ranks, as follows:

$$DCG@p = \sum_{i=1}^{p} \frac{rel_i}{log_2(i+1)} \tag{12}$$

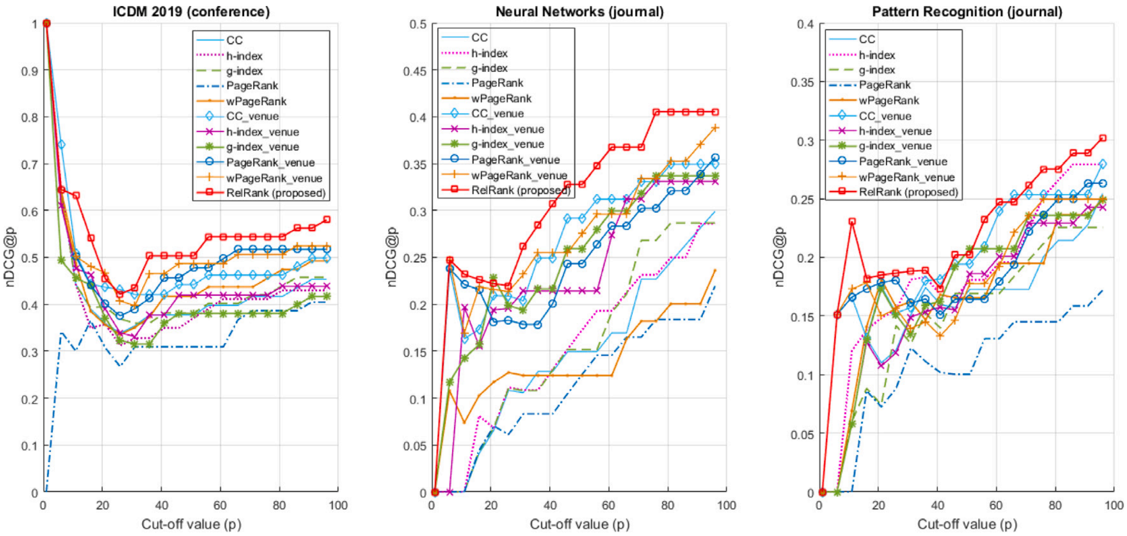


Fig. 6. nDCG curves of the RelRank and baseline metrics on three test datasets using both global and venue-specific settings. To differentiate the curves, each metric uses one unique colour. The metrics evaluated under venue-specific setting are marked with different shapes, while those under global setting use solid or dashed lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where rel_i refers to the graded relevance of the result at position i. We set the relevance of the chair authors to 1 and 0 otherwise. The normalised DCG is computed as:

$$nDCG@p = \frac{DCG@p}{IDCG@p} \tag{13}$$

where $IDCG@p$ denotes the ideal DCG at position p that is calculated as follows:

$$IDCG@p = \sum_{i=1}^{|REL_p|} \frac{rel_i}{log_2(i+1)} \tag{14}$$

where REL_p represents the list of the relevant authors (ordered by their relevance) in the rank list up to position p. The $nDCG@p$ is an effective measure when using test datasets for evaluation. In this experiment, we calculate the $nDCG$ at different cut-off values moving from 1 to 100 to evaluate the methods in searching for different number of significant authors. Top ranked authors will contribute greater to the $nDCG$ compared to those behind, and the decrease in the gain of authors is proportional to the logarithm of their position. A greater $nDCG@p$ indicates better performance of a metric in terms of identifying more significant authors in the top p authors ranked by the metric. The nDCG results of the RelRank and baseline metrics under both settings are demonstrated in Fig. 6 .

Fig. 6 shows that the RelRank outperforms the other methods in terms of finding more editors and chairs at most of the cut-off values ($p \in (0, 100]$) on the three test datasets. This indicates that the relevance of authors to individual venues does make a contribution to identifying the significant authors who can be hired for tasks such as chairing conference tracks or reviewing manuscripts. This is also reflected by comparing the curve of RelRank against that of the PageRank_venue and wPageRank_venue. Although the latter two metrics achieved promising $nDCG$ at certain cut-off values compared to the other metrics, the RelRank prevailed them (to a large extent in Neural Networks test dataset) by integrating the author relevance into calculation.

In addition, comparing between the metrics using venue-specific setting and global setting, the former group tends to achieve better performance in general compared to the latter. This makes sense since the editors and chairs were most likely selected based on the number of papers that the authors had published in the corresponding venues and the citation performance of these papers, rather than the papers that these authors published in other venues. This also confirms that global author ranking methods cannot provide satisfying performance in helping individual venues find significant authors.

Furthermore, comparing across different test datasets, the curves of methods using venue-specific setting and global setting are intertwined with each other on some test datasets (e.g., ICDM 2019 and Pattern Recognition) and scattered on others (e.g., Neural Networks). Two possible explanations for this result are that: (1) the authors who perform well (more publications, citations, collocations and more focused) in one particular venue may or may not have outstanding global impact in a field; and (2) venues may have employed different principles in selecting their editors or chairs, i.e., some venues tend to hire the authors who have been continuously focusing on publishing papers in these venues regardless of their global publication impact, while other venues prefer to hire authors with greater scholarly impact in the field. These two points deserve further study, although beyond the scope of this research, and we would like to collect more test datasets in the future for extended validation and discussion. Note that the result does not imply a better way of recruiting editors or chairs, rather, the publication impact and relevance of authors should be considered collectively for such tasks.

Table 3
Positions of the top 10 true authors ranked by RelRank and their positions ranked by the baseline metrics using global and venue-specific settings on the test datasets ICDM 2019, Neural Networks and Pattern Recognition.

Venues	Authors	Venue-specific setting				Global setting				
		RelRank	*h*-index	*g*-index	PR	Citations	*h*-index	*g*-index	PR	w_PR
ICDM 2019	P.S. Yu	1	1	2	1	2	2	2	2	2
	J.W. Han	2	1	1	2	1	1	1	3	1
	F. Wang	3	58	43	3	165	124	184	27	87
	X.D. Wu	7	13	16	12	52	83	50	15	55
	J.X. Yu	9	33	43	21	32	20	43	8	10
	H. Xiong	11	13	12	10	69	53	85	28	31
	J. Pei	14	8	16	24	3	3	3	12	4
	E.H. Chen	24	110	105	93	181	145	175	121	80
	J.Y. Wang	29	33	37	27	29	43	26	225	41
	W. Ding	32	58	105	86	374	496	319	253	300
Neural Networks	J.D. Cao	4	9	5	4	34	24	38	30	62
	M. Sugiyama	5	9	15	5	26	40	26	12	12
	N. Kasabov	9	15	21	16	15	17	13	17	26
	B. Hammer	13	5	10	26	24	24	26	49	21
	Z.D. Wang	19	96	54	37	86	79	70	126	140
	Z.G. Zeng	22	27	21	44	80	46	70	96	92
	K. Chen	30	255	346	101	294	232	287	255	181
	A. Sperduti	31	96	87	97	57	96	57	120	66
	K. Doya	33	27	15	11	67	96	57	110	120
	R. Sun	37	96	87	71	227	232	214	197	284
Pattern Recognition	E.R. Hancock	3	17	13	3	94	106	142	93	80
	D.C. Tao	7	49	13	9	12	9	16	12	12
	S.W. Lee	11	10	19	14	173	161	209	225	184
	U. Pal	19	49	36	17	271	256	311	216	241
	L. Wang	25	96	108	71	29	33	23	65	37
	J.B. Luo	28	17	19	26	36	29	35	29	30
	X.L. Li	36	49	36	35	15	12	25	26	14
	J. Kittler	45	205	108	44	31	33	45	14	19
	A. Leonardis	46	205	168	79	72	78	63	176	78
	R. Schettini	53	49	75	79	133	140	142	226	125

Note: Authors are ranked in the same position if they receive the same score from the ranking methods.

5.3. Case study

To better demonstrate the value brought by the proposed RelRank, we further conduct a case study to discuss the differences between the RelRank and the comparison methods in selecting significant authors, and explore the potential factors that may contribute to these differences. To this end, we list the top 10 editors/chairs (ground truth in test data) ranked by the RelRank and the positions of these authors in the ranks generated by the baseline metrics as shown in Table 3.

We can firstly observe that there are at least 10 ground truth authors contained in the top 50 authors ranked by the RelRank on the three datasets (except R. Schettini being ranked 53 on the Pattern Recognition test data), which verifies its efficiency in finding editors and chairs for the selected journals and conference. These authors recognised by RelRank also present higher impact measured by the baseline metrics in general, meaning that the RelRank is able to identify high-profile authors while demonstrating its difference when serving individual venues.

Secondly, a few authors in each venue are ranked higher by the RelRank but lower by the other metrics. This is not surprising as the RelRank is designed to discover the authors who are significant to individual venues rather than selecting those with exceptional publication performance. Taking the three authors, E. H. Chen in ICDM 2019, K. Chen in Neural Networks and J. Kittler in Pattern Recognition, as examples, they are identified as significant to the respective venues by RelRank but ranked lower by the other methods. A closer exploration of their public profiles reveals that these authors had continuously published papers in the three venues, which shows their publication devotion to these venues. Another finding from the exploration is that the roles of these authors in their collaborations are different, e.g., E. H. Chen and J. Kittler are mostly listed at the last position of their publication bylines in ICDM and Pattern Recognition respectively, while K. Chen has been acting at first authors for most of his co-authored publications in Neural Networks. This observation highlights another advantage of the proposed RelRank that it detects authors' devotion to a venue regardless the positions of their names in their publication bylines. Although some authors may have not built prestige publication impact compared to the top authors in the fields, their continuous focus on publishing in these venues deserves to be recognised particularly by these venues. Similar situation is also found on many other authors in the raking lists, which is not displayed in this table.

In addition, we find that some authors who are much higher ranked based on citation count, *h*-index, *g*-index and PageRank using the global setting, however these authors are not ranked top by RelRank. Although these authors have achieved higher publication impact overall, they may not fit the roles that are required by these three venues. Therefore, it is important for the RelRank to identify the authors who not only has higher academic profile (citation and collaboration impact) but also shows devotion (author relevance) to particular venues, and these authors deserve recognition especially from these venues.

6. Discussion

Based on the results of the evaluation experiments and case study, the proposed RelRank is proved to have the following advantages:

- The proposed RelRank method is able to identify high profile authors as the classic author-level metrics do, meanwhile it can serve individual venues by considering authors' devotion in publishing in those particular venues. This is achieved by integrating the statistical relevance of authors to individual venues, r_{ij}, into a weighted PageRank algorithm working on co-authorship networks. The r_{ij} essentially measures the devotion of author a_i to venue v_j based on author a_i's papers distributed into venue v_j and other venues. With this author relevance r_{ij}, the RelRank can assist a specific venue in identifying those authors who not only have higher citation and collaboration performance but also are more devoted to the venue. This enriches the existing literature by extending the author ranking approaches to helping individual venues find significant and suitable authors for important tasks such as chairing conference sessions, acting journal editors, and seeking paper reviewers.
- The above point was proved by the results of the correlation analysis and effectiveness evaluation experiments. The correlation results demonstrated that the ranking results of RelRank were positively correlated with those of five classic author-level metrics in general, however difference in-between did exist especially when they were compared for serving specific venues. This means that RelRank assesses authors in a different manner from the five comparison metrics when serving individual venues. In addition, we evaluated how effective the RelRank was in identifying editors and committee members for three well-known publication venues using nDCG at different cut-off values (i.e., $nDCG@p,\ p \in (0, 100]$). The results showed the advantage of the RelRank in recognising more editors and committee members for these venues at most of the cut-off values compared to the five metrics.
- Another advantage of the RelRank is that co-authors who collaborate on a collection of papers published in a venue can be distinguished by considering the co-authors' relevance to this venue rather than their contribution in their collaborations (usually reflected by the bylines of papers). This is helpful for identifying significant authors for the venue since these authors are devoted to this venue more frequently than the others, which in turn suggests that these authors are more likely to accept the jobs called for by the venue and can better serve and promote the venue.
- The authors who have not yet built high publication profile due to specific reasons (e.g., early career researchers and special research fields) can be identified for the venues to which the authors have been devoted. This is important for both individual authors and venues. For instance, the rising authors in their early career need engagement more than the senior researchers in order to further develop their profile, hence these authors are highly valuable and deserve to be recognised by their frequently targeted venues. This point was revealed in the case study where we found that some authors were prone to keep contributing frequently, if not more, to a venue after they were hired as committee members or editors.

The RelRank also has its limitations. Although it can identify high profile authors, the RelRank is designed to seek significant authors for individual publication venues, hence it may not suit for other author ranking purposes. In addition, RelRank faces cold start issue, that is, the algorithm cannot work well for new established journals or conferences which have none or small number of authors involved. Therefore, our future study aims to integrate the semantic relationship between authors and venues into the proposed definition of author relevance, so that the extended RelRank will be able to rank authors based on both bibliometrics and semantics.

7. Conclusion

This research proposed a novel author ranking method, namely RelRank, aiming to evaluate the significance of academic authors to individual venues (journals and conferences). We defined and formulated a new author-venue relationship, i.e., relevance of authors to venues (author relevance), based on the concept of TF–IDF. Integrating this information together with author collaborations and citations, a weighted and directed co-authorship network was constructed, based on which the RelRank algorithm was proposed. Different from the existing author-level indexes and algorithms which are mostly designed as global measures to assess author impact, the proposed RelRank serves individual venues to identify the authors who are particularly significant for them. This is valuable for individual venues in carrying out tasks such as recruiting and hiring editors, general chairs, area chairs, committee members or manuscript reviewers.

Extensive experiments were conducted to analyse and evaluate the proposed RelRank in terms of its author ranking behaviour and effectiveness in identifying significant authors for individual venues. Three datasets were collected from three research fields, including machine learning, computer vision and data mining. Spearman's ranking correlation and Discounted Cumulative Gain (DCG) were employed to compare the author ranking results of the RelRank and five selected baseline metrics. The results indicated that the RelRank is able to identify high profile authors as the baseline metrics do, meanwhile it can serve individual venues by favouring those authors who have shown devotion in publishing their papers to particular venues. Considering the relevance of authors to individual venues does make a difference to the RelRank in ranking the authors, making it more effective in identifying the editors and chairs in the effectiveness evaluation. In addition, we conducted a case study at individual author level, which further confirmed the special characteristic of the RelRank in picking up the devoted authors.

CRediT authorship contribution statement

Yu Zhang: Conceptualization, Methodology, Data curation and analysis, Writing – original draft, Writing – review & editing. **Min Wang:** Data curation and analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Michael Zipperle:** Data curation and analysis, Software. **Alireza Abbasi:** Conceptualization, Methodology, Writing – review & editing. **Massimiliano Tani:** Methodology, Writing – review & editing.

Data availability

Data will be made available on request.

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