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Feature-enriched author ranking in incomplete networks

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Abstract

Evaluating scientists based on their scientific production is a controversial topic. Nevertheless, bibliometrics and algorithmic approaches can assist traditional peer review in numerous tasks, such as attributing research grants, deciding scientific committees, or choosing faculty promotions. Traditional bibliometrics rank individual entities (e.g., researchers, journals, faculties) without looking at the whole data (i.e., the whole network). Network algorithms, such as PageRank, have been used to measure node importance in a network, and have been applied to author ranking. However, traditional PageRank only uses network topology and ignores relevant features of scientific collaborations. Multiple extensions of PageRank have been proposed, more suited for author ranking. These methods enrich the network with information about the author's productivity or the venue and year of the publication/citation. Most state-of-the-art (STOA) feature-enriched methods either ignore or do not combine effectively this information. Furthermore, STOA algorithms typically disregard that the full network is not known for most real-world cases.

Here we describe OTARIOS, an author ranking method recently developed by us, which combines multiple publication/citation criteria (i.e., features) to evaluate authors. OTARIOS divides the original network into two subnetworks, *insiders* and *outsiders*, which is an adequate representation of citation networks with missing information. We evaluate OTARIOS on a set of five real networks, each with publications in distinct areas of Computer Science, and compare it against STOA methods. When matching OTARIOS' produced ranking with a ground-truth ranking (comprised of best paper award nominations), we observe that OTARIOS is > 30% more accurate than traditional PageRank (i.e., topology based method) and > 20% more accurate than STOA (i.e., competing feature enriched methods). We obtain the best results when OTARIOS considers (i) the author's publication volume and publication recency, (ii) how recently the author's work is being cited by outsiders, and (iii) how recently the author's work is being cited by insiders and how individual he is. Our results showcase (a) the importance of efficiently combining relevant features and (b) how to adequately perform author ranking in incomplete networks.

Keywords: Node ranking, Citation networks, Incomplete networks

Introduction

The scientific impact of a researcher measures how much a person has contributed to a scientific field. Due to the nature of scientific development, more impactful researchers tend to have access to more funding which supports the creation of more quality work. As a result estimating the scientific impact of researchers has a direct impact on science. For

more important decisions such as allocating scientific committees, attributing research grants, or choosing faculty promotions, the process is mostly done via peer review. More recently, bibliometrics (i.e., measures to determine scientific impact without human intervention) have been proposed to assist the peer review process (Vieira et al. 2014). Bibliometrics typically take into account the author's productivity (i.e., statistics of author's papers) and the author's impact (i.e., statistics of author's citations) (BV 2018). The h-index (Hirsch 2005) is one of the most widely used bibliometrics; it measures the impact of an author as the number of citations of his most cited papers (e.g., an author has h-index = 3 if he has 3 papers with at least 3 citations).

Traditional bibliometrics have, however, the drawback of assigning impact to direct citations only, thus ignoring indirect citations. For example, if *A* cites *B*, and *B* cites *C*, traditional bibliometrics give no additional credit to *C* from *A*'s indirect citation. To address this limitation, graph algorithms have been developed for citation networks (Ding 2009; Radicchi et al. 2009; Dunaiski and Visser 2012; West et al. 2013; Sidiropoulos and Manolopoulos 2006). These algorithms are modifications of PageRank applied to citation networks (Page et al. 1998). One of PageRank's major algorithmic ideas is that not all nodes are equal, i.e., in the context of hyperlinks, it is good to be referenced by any webpage but it is better to be referenced by important webpages. This idea extends naturally to citation networks, i.e., it is good to be cited by any author but is better to be cited by important authors. State-of-the-art (STOA) author ranking algorithms (discussed in "State-of-the-art author ranking methods" section) adapt PageRank and introduce modifications to favour different types of authors (e.g., authors cited in important venues, or authors cited more recently). Since these methods introduce *features* outside of the topology of the network, we call them *featured enriched methods*, in contrast with traditional PageRank, which is a *topology-based method*.

We found that STOA methods were lacking in two aspects. First, they do not adequately combine publication features (e.g., author's productivity, the venues prestige of where he usually publishes, and how recent his papers are) with citation features (e.g., the prestige of the venue he is being cited from, how recent his citations are). Second, these methods assume that the full network is known, thus the algorithm does not distinguish between *fully explored nodes* and *partially explored nodes*. Therefore, these methods are not capable of adequately dealing with *incomplete networks* (Kim and Leskovec 2011).

We recently proposed a new feature enriched author ranking algorithm for incomplete networks named OTARIOS (**O**p**T**imizing **A**uthor **R**anking with **I**nside**R**s/**O**utside**R**s **S**ubnetworks) (Silva et al. 2018), and showed that OTARIOS outperformed traditional PageRank (a topology-based method) and simple bibliometrics. Here we compare OTARIOS against other feature-enriched author ranking methods.

OTARIOS efficiently combines different publication/citation features in a multi-edge weighted network (instead of a simple unweighted network used by STOA methods). OTARIOS is also a flexible algorithm in the sense that publication/citation features can be personalised to fit what the user wants to rank the researchers by (e.g., take in consideration venue's prestige and citation's age for the rankings). OTARIOS handles incomplete networks by dividing the citation network in two subnetworks, *insiders* and *outsiders*. Then, only insiders are ranked (since we have their full information) while outsiders contribute to the ranks of insiders, not being themselves ranked. Our results on five networks belonging to different areas of Computer Science show that OTARIOS is > 20% more

accurate than STOA methods. OTARIOS obtains the best results when considering (i) the author’s publication volume and recency, (ii) how recently his work is being cited by outsiders, and (iii) how recently his work is being cited by insiders and how individual he is (i.e., publishing a paper with few co-authors).

The paper is organised as follows. “Preliminaries” section describes terminology that is used throughout the work, as well as an overview of STOA methods. “Methodology” section describes OTARIOS and our methodology. “Results” section presents the performance of OTARIOS against STOA methods on a set of five networks. Finally, “Conclusions” section presents our main conclusions and gives some directions for future work.

Preliminaries

Terminology

Recency of a paper

$$\delta(P_j) = \left(\max_{P_{j'} \in \mathcal{P}} y(P_{j'}) \right) - y(P_j) \tag{1}$$

Recency of an author

$$\delta(A_i) = \min_{P_j \in \mathcal{P}_{A_i}} \delta(P_j) \tag{2}$$

Venue prestige

$$\lambda(V_k, y) = \frac{c(V_k, y)}{\sum_{x=1}^3 p(V_k, y - x)} \tag{3}$$

Cited individuality

$$w(A_{i'} \rightarrow A_i, P_j) = \frac{1}{|\mathcal{A}_{P_j}|}, A_i \in \mathcal{A}_{P_j} \tag{4}$$

Citation recency

$$a(A_{i'} \rightarrow A_i, P_j) = e^{\frac{-\delta(P_j)}{\tau}}, A_{i'} \in \mathcal{A}_{P_j} \tag{5}$$

Citation prestige

$$v(A_{i'} \rightarrow A_i, P_j) = v(P_j), A_{i'} \in \mathcal{A}_{P_j} \tag{6}$$

For consistency, we denote sets by calligraphic letters (e.g., \mathcal{S}), elements of those sets (i.e., entities) by capital letters with an index (e.g., $S_i \in \mathcal{S}$), features of entities (e.g., year, impact factor) as functions named in lower-case alphabetic or Greek letters (e.g., $a(S_i)$ or $\alpha(S_i)$), and constants as sole Greek letters (e.g., τ). The cardinality of a given set \mathcal{S} is denoted by $|\mathcal{S}|$. We address the following problem.

Problem 1 *Given a set of papers \mathcal{P} published in a set of venues \mathcal{V} by a set of authors \mathcal{A} , who are the top- n ranked authors?*

A paper $P_j \in \mathcal{P}$ is co-authored by authors $\mathcal{A}_{P_j} \subseteq \mathcal{A}$. Likewise, an author $A_i \in \mathcal{A}$ is (one of) the author(s) of papers $\mathcal{P}_{A_i} \subseteq \mathcal{P}$. In *paper-level networks*, graph $G = \{\mathcal{N}, \mathcal{E}\}$ comprises a set \mathcal{N} of nodes that represent papers and a set \mathcal{E} of edges that represent paper citations, written as $P_{j'} \rightarrow P_j$. In *author-level networks*, nodes represent authors and edges represent citations between authors, written as $A_{i'} \rightarrow A_i$.

Regarding node features, papers have publication metadata which we use as features, namely the year, venue prestige, and the number of references, represented by $y(P_j)$, $v(P_j)$ and $r_{out}(P_j)$, respectively. The *recency* of a paper (Eq. 1), represented by $\delta(P_j)$, is the difference in years between the year of the paper and the most recent paper in the dataset (e.g., a paper from 2015 in a dataset where the most recent paper is from 2017 has a recency of 2). Similarly, the *recency* of an author (Eq. 2), represented by $\delta(A_i)$, is simply the recency of his most recent paper (i.e. the number of years that have passed since his last publication). The venue prestige of a paper P_j (Eq. 3) depends on the venue $V_k \in \mathcal{V}$ where it was published and the year when it was published, represented by $v(P_j) = \lambda(V_k, y(P_j))$. We estimate venue prestige with *CiteScore*, a widely used metric (BV 2018) (Eq. 3), where $p(V_k, y)$ is the number of papers published in V_k in year y and $c(V_k, y)$ is the number of citations that all papers published in V_k in year y received. Thus, we are assuming that venues with many citations per paper have higher prestige.

Regarding edges, in paper-level networks edges are traditionally unweighted and simple, i.e., two papers are connected by a single edge with weight equal to 1 (Hwang et al. 2010; Dunaïski and Visser 2012). In author-level networks, edges are weighted and multiple, i.e., two authors are connected by multiple edges with different weights. These multiple edges concern different edge features that depend on the publication P_j where author $A_{i'}$ cites author A_i . The recency of an edge (Eq. 5), represented by $a(A_{i'} \rightarrow A_i, P_j)$, gives more importance to recent citations. As discussed in the YetRank paper which originally proposes this concept for author ranking algorithms (Dunaïski and Visser 2012), we set the decay factor $\tau = 4$. This value highly favours received citations in the last 4 years (e.g., a citation with recency 0 has a maximum link weight of 1.0, while citations with recency 4 and 8 have links with weights 0.37 and 0.13 respectively). The venue prestige of an edge (Eq. 6), represented by $v(A_{i'} \rightarrow A_i, P_j)$, gives more importance to citations in important venues (e.g. citations coming from the most prestigious venue in the dataset have a maximum link weight of 1.0, while citations coming from the least prestigious venues have a value close to 0.0). Finally, the individuality of an edge (Eq. 4), represented by $w(A_{i'} \rightarrow A_i, P_j)$, gives more importance to citations received in papers that author A_i has few (or no) co-authors (e.g. if an author has a publication P_1 with 2 authors and a publication P_2 with 4 authors, the importance of citations coming to P_1 is double of the ones coming to P_2 for that author). Thus, $w(A_{i'} \rightarrow A_i, P_j)$, unlike $a(A_{i'} \rightarrow A_i, P_j)$ and $v(A_{i'} \rightarrow A_i, P_j)$, depends on the cited author A_i and not on the citing author $A_{i'}$. The author's feature total out-edge weight is obtained by summing all of its out-edges (e.g., for citation recency, $a_{out}(A_i) = \sum_{(A_i \rightarrow A_{i'}, P_j)} a(A_i \rightarrow A_{i'}, P_j)$). w_{out} and v_{out} are obtained in the same way).

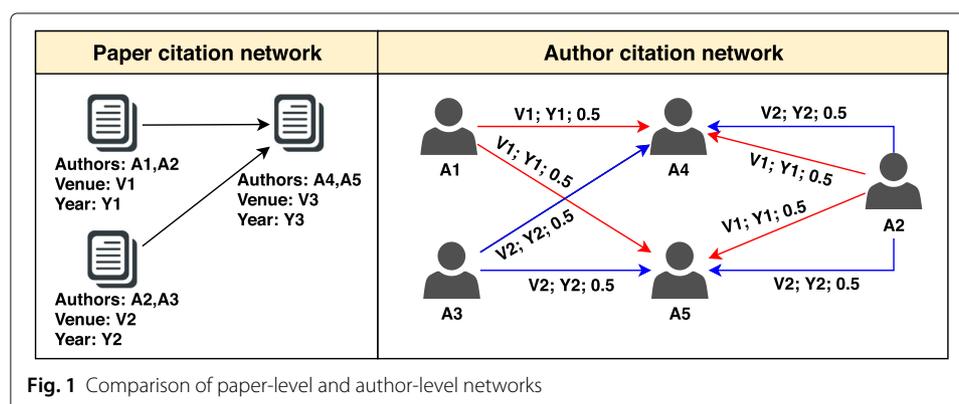
State-of-the-art author ranking methods

Measuring the scientific impact of institutions, journals, or authors is an important task in the peer review process. Here we focus on measuring the scientific impact of authors, i.e., author ranking. Paper citations are often used by traditional bibliometrics; for instance, the widely adopted h-index (Hirsch 2005) measures an author's impact by the number of citations of his most cited papers. However, h-index and similar bibliometrics fail to capture the nature of scientific development since they disregard the fact that a new discovery is not solely due to previous work directly referenced. Graph-based metrics, on the other hand, spread the credit to previous works that paved the way (Wang et al. 2016).

There are two groups of author ranking methods: paper-level and author-level (Wang et al. 2016) (Fig. 1). On one hand, paper-level ranking uses the papers' citation network to diffuse scientific credit to cited papers, and then authors credit is derived from the credit of their papers (Hwang et al. 2010; Dunaiski and Visser 2012). On the other hand, author-level ranking uses the authors' citation network to diffuse scientific credit to cited authors, thus the authors' credit is directly obtained (Radicchi et al. 2009; Ding 2009; West et al. 2013). Numerous graph centrality measures exist and can be used to measure node importance (Valente et al. 2008). PageRank (Page et al. 1998) is one of the most widely used measures and its rationale is intuitive in author-ranking, i.e., authors cited by important authors are (themselves) more important than authors cited by less important authors.

PageRank consists of two main steps: score initialisation and score diffusion. The score initialisation step creates a vector R that defines an initial score for every node using a priori information. In the simplest case, every node (i.e., paper or author) is considered equally important, thus an uniform distribution is used (i.e., $R[A_i] = \frac{1}{|A_i|}$) (Page et al. 1998; Ding 2009; Sidiropoulos and Manolopoulos 2006). Approaches based on paper citation networks typically assign higher initial scores to more recent papers (Dunaiski and Visser 2012) or favour a combination of recent papers and papers published in venues with higher impact factor (Hwang et al. 2010). Approaches based on author citation networks typically assign higher initial scores to authors that publish many papers (West et al. 2013) or favour authors that publish many papers but with few co-authors (Radicchi et al. 2009).

The score diffusion step updates the node scores taking into consideration network dynamics. Score diffusion is an iterative process which computes three addends: random restart, dangling nodes, and score term. Random restart (RR) evaluates how likely it is to reach a certain node by moving randomly in the network. PageRank defines a value q as the random restart probability, and q is multiplied by the node's initial score R (thus, nodes with higher initialisation receive higher random restart score). Dangling nodes (DN) is a process where the score of nodes that do not have any out-links is split by all other nodes. This is performed to avoid having nodes that do not disseminate their credit. Like random restart, this division takes into consideration the initialisation vector R (thus, nodes initialised with higher values receive higher dangling nodes score). Score term (ST) updates the score of a node A_i , according to the score of his in-links (i.e., nodes citing A_i). In the simplest case, scores are evenly split by co-authors of the cited publication, e.g., if the paper has two authors, the score is divided by the two authors, if it has three authors,



the score is divided by the three authors, thus, in the case of three authors, each author receives less credit than in the case with just two authors (Radicchi et al. 2009; Ding 2009; West et al. 2013). SCEAS (Sidiropoulos and Manolopoulos 2006) adds a constant value b to the every score received by nodes and divides the total score received by another constant a in order to make the algorithm converge faster. YetRank (Hwang et al. 2010) and NewRank (Dunaiski and Visser 2012) take into consideration the vector R in the score distribution (i.e., if a paper cites a paper P_j from 2015 and another paper P'_j from 2010, P_j receives a bigger chunk of the score). In case of the YetRank, the distribution of score also takes into consideration the impact factor of the venues where P_j and P'_j where published, favouring papers published in venues with higher prestige. Table 1 summarises STOA methods and their differences.

These approaches have two drawbacks. One is that none combines all possible features of the publications and citations. Another drawback is that they assume that the complete citation network is known. However, in real-world cases, it is not possible to obtain a complete network. Let's assume that we want to rank a set of authors \mathcal{A} . First, we need to expand the network by obtaining all authors $B_i \in \mathcal{B}$ that cite any $A_i \in \mathcal{A}$ such that $B_i \notin \mathcal{A}$. Then, we need to also extract all authors $C_i \in \mathcal{C}$ that cite any $B_i \in \mathcal{B}$ such that $C_i \notin \{\mathcal{A} \cup \mathcal{B}\}$, to correctly determine the scores of all $A_i \in \mathcal{A}$, i.e., C_i does not cite A_i directly but C_i cites some B_i which cites A_i , thus C_i cites A_i indirectly. Ideally, this should be performed recursively until the complete set authors (and their citations) with seed \mathcal{A} is obtained. Due to memory and time constraints, only a sample of the citation network can be obtained. As a result, current STOA author ranking algorithms estimate scientific rankings based on incorrect information, i.e., authors in the periphery are not being adequately taken into account since their citations are not in the network. Although there is no ideal solution for this problem, one can be more careful in estimating the rank of nodes in the periphery.

Table 2 summarises current STOA methods and contrasts them with OTARIOS, our proposed method (Silva et al. 2018). OTARIOS is the only method that efficiently combines multiple features (of the publications and citations) and deals with incomplete networks.

Table 1 Comparison of state of the art methods

	Method	Initialisation: $R(N_i)$	Score term: $ST(N_i)$
Author-level	RLPR (Ding 2009)	$\frac{1}{ \mathcal{A} }$	
	SARA (Radicchi et al. 2009)	$\frac{\sum_{(P_j \in \mathcal{P}_{A_i})} \frac{1}{ A_{P_j} }}{\sum_{(A_f \in \mathcal{A})} \sum_{(P_j \in \mathcal{P}_{A_f})} \frac{1}{ A_{P_j} }}$	$(1 - q) \sum_{(A_f \rightarrow A_i, P_j)} \frac{S(A_f) \times w(A_f \rightarrow A_i, P_j)}{w_{out}(A_f)}$
	ALEF (West et al. 2013)	$\frac{ P_{A_i} }{ P }$	
	SCEAS (Sidiropoulos and Manolopoulos 2006)	$\frac{1}{ \mathcal{A} }$	$\frac{(1-q)}{a} \sum_{(A_f \rightarrow A_i, P_j)} \frac{(S(A_f) + b) \times w(A_f \rightarrow A_i, P_j)}{w_{out}(A_f)}$
Paper-level	YetRank (Hwang et al. 2010)	$v(P_j) \times \frac{e^{-\delta(P_j)}}{\tau}$	$(1 - q) \sum_{(P_f \rightarrow P_i)} \frac{S(P_f) \times R(P_i)}{I_{out}(P_f)}$
	NewRank (Dunaiski and Visser 2012)	$e^{-\frac{\delta(P_i)}{\tau}}$	

N_i represents a node in the network, i.e., $N_i = A_i$ in author-level networks, and $N_i = P_i$ in paper-level networks. Score diffusion $S(N_i)$ is equal to $ST(N_i) + RR(N_i) + DN(N_i)$. For all methods, $RR(N_i) = q \times R(N_i)$ and $DN(N_i) = (1 - q) \times R(N_i)$, thus we omit them from the table

Table 2 Comparison of state of the art methods with OTARIOS

Method	Publications			Citations			Incomplete Networks
	Volume	Recency	Venues	Individuality	Recency	Venues	
RLPR				✓			
SARA	✓			✓			
ALEF	✓*			✓			
SCEAS				✓			
YetRank		✓	✓	✓			
NewRank		✓		✓			
OTARIOS	✓	✓	✓	✓	✓	✓	✓

OTARIOS tries to combine all features efficiently and is also the only method that adequately deals with incomplete networks by using insiders/outside subnetworks

*ALEF gives higher score to authors with many publications but ignores the number of authors in the publications

Methodology

Problem description

We formalize the problem of author ranking as the task of receiving a set of authors \mathcal{I} and ranking them according to their scientific impact based on a set of user-defined criteria. First, we obtain all citations between all authors $I_i, I_j \in \mathcal{I}$ (i.e., a complete citation network for \mathcal{I}). Second, for each author I_i , we obtain all of his received citations coming from authors $O_i \notin \mathcal{I}$. The process stops here, i.e., we do not obtain all received citations for authors $O_i \in \mathcal{O}$. Doing so iteratively is unfeasible in practice because the number of authors added at each step grows very rapidly. Thus, we divide the citation network into two groups of nodes: *insiders* (\mathcal{I}) and *outsiders* (\mathcal{O}), i.e., $\mathcal{A} = \{\mathcal{I}, \mathcal{O}\}$ (Fig. 2). Note that no outsider can also be an insider, and vice-versa. Edges connect insiders ($\mathcal{E}_{\mathcal{I}}$) or outsiders to insiders ($\mathcal{E}_{\mathcal{O}}$), but no edges exist from insiders to outsiders nor between outsiders, i.e., $\mathcal{E} = \{\mathcal{E}_{\mathcal{I}}, \mathcal{E}_{\mathcal{O}}\}$.

The outsiders are authors that were not in the initial set of authors \mathcal{I} , thus they are not ranked. Instead they are used to mitigate the problem of incomplete networks and improve the insiders' ranks. Before calculating the ranks of the insiders we estimate outsiders' prestige (λ). We use the outsider's history of publications and give higher prestige to authors with more citations ($c(A_i)$) in fewer publications ($p(A_i)$) (Eq. 7). The outsiders'

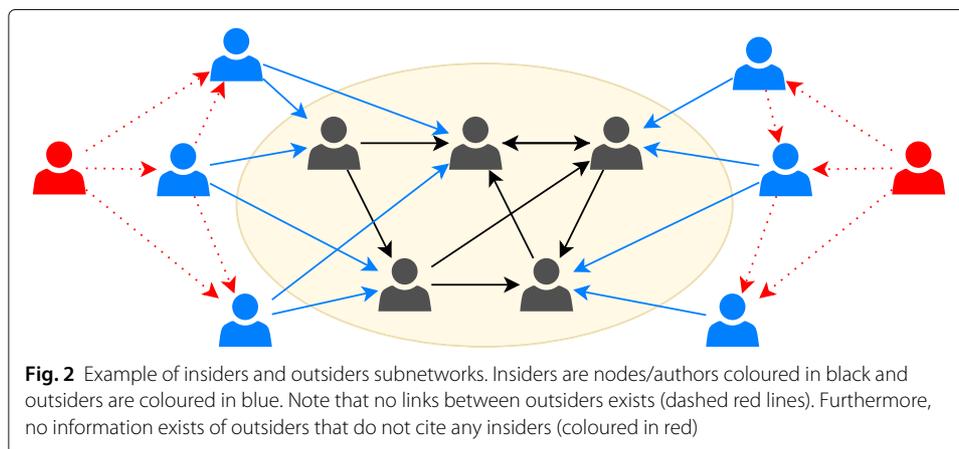


Fig. 2 Example of insiders and outsiders subnetworks. Insiders are nodes/authors coloured in black and outsiders are coloured in blue. Note that no links between outsiders exists (dashed red lines). Furthermore, no information exists of outsiders that do not cite any insiders (coloured in red)

prestige is then used along the links between outsiders and insiders to improve the initial rankings of the insiders.

Outsider prestige
$$\lambda(A_i) = \frac{c(A_i)}{p(A_i)} \tag{7}$$

OTARIOS

OTARIOS is a graph-based algorithm for author-level citation networks. Its aim is to rank authors based on their publication and citation history. OTARIOS uses the notion of insider/outsider subnetworks to adequately estimate authors scores in a network with limited information. Furthermore, OTARIOS is a flexible algorithm that analyses which set of publication/citation attributes lead to better rankings.

As a first step, OTARIOS computes an initial score for each author, represented by $R(A_i)$. OTARIOS calculates $R(A_i)$ by taking into account multiple features that favour different author characteristics (Table 3). We divide the features into two categories: productivity and outsiders influence. Productivity measures the value of the author’s publications, while outsider influence measures the value of the author’s citations coming from outsiders. Regarding productivity, OTARIOS takes three factors into account: volume, recency and venues. Regarding outsiders influence, OTARIOS takes another three factors into account: individuality, recency and venues. We compute the author’s initial score $R(A_i)$ as the sum of the two products of the factors in each group (i.e., productivity ($volume \times recency \times venues$) + outsiders influence ($individuality \times recency \times venues$)).

Then, on the second step, OTARIOS improves author scores in an iterative process. Outsiders are removed from the network since their presence degrades the score diffusion step. In each iteration, OTARIOS updates an author’s score $S(A_i)$ as $ST(A_i) + RR(A_i) + DN(A_i)$. We compute $RR(A_i)$ and $DN(A_i)$ as a function of the initial rank of each author (discussed in Table 3), and compute $ST(A_i)$ as a function of the author’s citations coming from other insiders. OTARIOS considers three different features to assess score term $ST(A_i)$: individuality, recency and venues (Table 4). The $ST(A_i)$ at each iteration is the

Table 3 List of features used for OTARIOS’ author rank initialisation: $R(A_i)$

	Feature	Initialisation: $R(A_i)$	Description
Productivity	Volume (P)	$\frac{\sum_{(P_j \in \mathcal{P}_{A_i})} \frac{1}{ A_{P_j} }}{\sum_{(A_{P'} \in \mathcal{A})} \sum_{(P_j \in \mathcal{P}_{A_{P'}})} \frac{1}{ A_{P_j} }}$	Favours publishing many papers with few co-authors.
	Recency (A)	$e^{\frac{-\delta(A_i)}{\tau}}$	Favours publishing recently.
	Venues (V)	$\left(\sum_{(P_j \in \mathcal{P}_{A_i})} v(P_j) \right) \times \mathcal{P}_{A_i} ^{-1}$	Favours publishing in prestigious venues.
Outsiders Influence	Individuality (W)	$\sum_{(A_{P'} \rightarrow A_i, P_j)} \frac{\lambda(A_{P'}) \times w(A_{P'} \rightarrow A_i, P_j)}{w_{out}(A_{P'})}, A_{P'} \in \mathcal{O}$	Favours being cited by outsiders that cite few authors.
	Recency (A)	$\sum_{(A_{P'} \rightarrow A_i, P_j)} \frac{\lambda(A_{P'}) \times \alpha(A_{P'} \rightarrow A_i, P_j)}{\alpha_{out}(A_{P'})}, A_{P'} \in \mathcal{O}$	Favours being cited by outsiders more recently.
	Venues (V)	$\sum_{(A_{P'} \rightarrow A_i, P_j)} \frac{\lambda(A_{P'}) \times v(A_{P'} \rightarrow A_i, P_j)}{v_{out}(A_{P'})}, A_{P'} \in \mathcal{O}$	Favours being cited by outsiders in prestigious venues.

OTARIOS considers both the authors’ productivity and the direct influence of outsiders on the authors. We create different variants of these criteria, e.g., $PV + V$ uses volume (P) and venue prestige (V) to measure author productivity, and uses venue prestige (V) to measure the direct influence of outsiders

Table 4 List of features used for OTARIOS' author score term calculation: $ST(A_i)$

Feature	Score term: $ST(A_i)$	Description
Individuality (W)	$\sum_{(A_i \rightarrow A_j, P_j)} \frac{S(A_i) \times w(A_i \rightarrow A_j, P_j)}{w_{out}(A_i)}, A_i \in \mathcal{I}$	Favours being cited by insiders that cite few authors.
Recency (A)	$\sum_{(A_i \rightarrow A_j, P_j)} \frac{S(A_i) \times a(A_i \rightarrow A_j, P_j)}{a_{out}(A_i)}, A_i \in \mathcal{I}$	Favours being cited by insiders more recently.
Venues (V)	$\sum_{(A_i \rightarrow A_j, P_j)} \frac{S(A_i) \times v(A_i \rightarrow A_j, P_j)}{v_{out}(A_i)}, A_i \in \mathcal{I}$	Favours being cited by insiders in prestigious venues.

Combined with author initialisation (Table 3), we create different variants, e.g., PV+V+A combines initialisation PV+V with score term A, i.e., using citation recency. All variants use $RR(N_i) = q \times R(N_i)$ and $DN(N_i) = (1 - q) \times R(N_i)$, thus we omit them from the table

product of every feature (i.e., score term (*individuality* \times *recency* \times *venues*)). Like PageRank, OTARIOS stops when it reaches low variation in the node scores. Figure 3 illustrates the three feature categories used in the OTARIOS algorithm.

Here we do not assume that every feature should be used for author ranking. The features' importance depends greatly on the dataset. For instance, venue prestige might be very important to rank some communities (i.e., top authors publish in top conferences of that scientific area, e.g., machine learning) but irrelevant in some other community because we are studying a specific conference (i.e., all authors publish in the same venue, e.g., KDD). OTARIOS is parameterisable, i.e., users can define by which features authors are ranked. For example, for a certain application, we may want to rank authors taking into account recent publications and the venue prestige of citations coming from both insiders and outsiders¹.

Results

In this section we compare OTARIOS against STOA methods. We create a test scenario using a snapshot from December of 2017 of the DBLP dataset (a bibliographic database for computer science). This dataset contains over 3 million publications and for each one we have: title, authors, abstract, venue, year, number of citations and references. Using the publications' references we obtain the author-citation network of 26 top-tier computer science venues. In order to prevent the impact of citation manipulation in the rankings we do not consider self-citations in the networks (Ioannidis 2015). Furthermore, for each conference we create a ground. We counted each paper award as a unit of prestige which is equally divided by its authors. Thus, we are assuming that authors that have won more awards with fewer co-authors should be ranked higher. We use the ACM taxonomy² in order to group the conferences into five networks (see Table 5), each representing a different computer science area.

In truth ranking using the best paper award information³ our experiments, we evaluate a predicted rank (i.e., one produced by OTARIOS or any STOA method) against a ground truth rank (i.e., the ranking based on conferences best paper awards). Methods that produce rankings more similar to the ground truth (obtained by human judgement)

¹Note that we define variants using notation APV+AVW+AVW, where the addends define the features used at each group. The first for productivity, the second for outsiders influence and the last for score term. For the example in the text, the variant nomenclature is A+V+V.

²<https://www.acm.org/about-acm/class>

³Awards information obtained from: https://jeffhuang.com/best_paper_awards.html

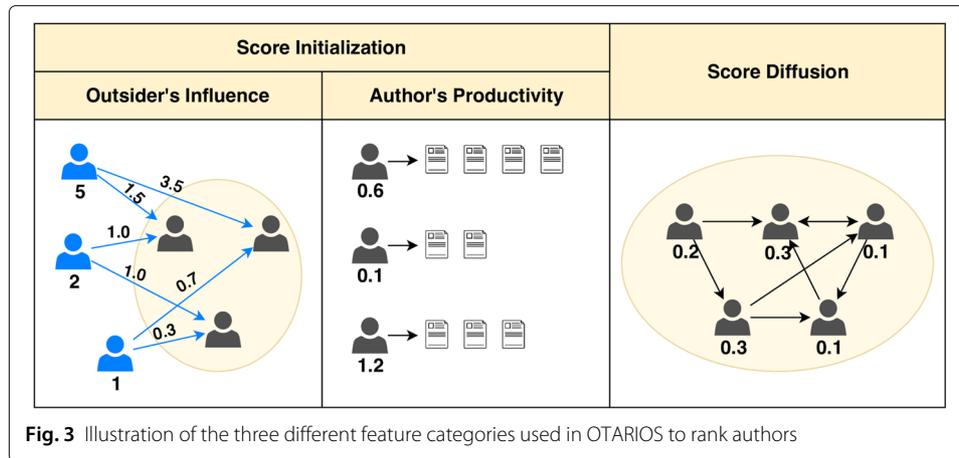


Fig. 3 Illustration of the three different feature categories used in OTARIOS to rank authors

are considered better. In order to compare two ranks we use two ranking quality measures: Normalized Discounted Cumulative Gain (NDCG) (Järvelin and Kekäläinen 2002) and Mean Reciprocal Rank (MRR) (Voorhees and et al. 1999). NDCG is a Discounted Cumulative Gain(DCG) based metric which divides the DCG of the predicted rank by the DCG of the ground truth (i.e., the perfect ranking). The idea of DCG is that highly relevant authors (from the ground truth) appearing lower in the predicted rank should be penalized using a logarithmic function (base 2) proportional to the position of the result. For example, placing an author with 0 relevance at the 2nd position presents an higher penalty than placing him in the 10th position. The NDCG value ranges from 0 to 1, where 1 represents the perfect ranking (i.e., the predicted rank is the same as the ground truth one). MRR is the mean ground truth ranking position of a set of the top authors of a predicted rank. Thus, lower MRRs indicate better rankings since the top authors of the ground truth are, on average, ranked more highly by the method. For example, a method that places the 1st, 5th and 6th highest ranked authors from the ground truth in its top-3 authors is better than one that places the 2nd, 6th and 7th highest ranked authors from the ground-truth in its top-3 authors. Usually, both measures are calculated considering only the top- n authors. For a detailed analysis, we calculate NDCG and MRR for the top-5, 10, 20, 50, 100 authors.

Finding the best oTARIOS variants

OTARIOS does not define a strict set of rules to rank authors, since the criteria (i.e., features) used depends on many factors (e.g., scientific area, preferences of the entity ranking

Table 5 Set of networks used for experimental evaluation

Network	Conferences	# AA	Nodes		Edges	
			$ \mathcal{I} $	$ \mathcal{O} $	$ \mathcal{E}_{\mathcal{I}} $	$ \mathcal{E}_{\mathcal{O}} $
CM	AAAI, IJCAI, ICML, ACL, ICCV, CVPR	380	35.6k	224.9k	4.6M	4.9M
TC	FOCS, SODA, STOC	440	5.0k	82.4k	0.5M	0.8M
NET	INFOCOM, NSDI, SIGCOMM, MOBICOM, SIGMETRICS	95	15.2k	138.8k	2.1M	3.7M
IS	KDD, CIKM, PODS, SIGMOD, VLDB, WWW, SIGIR	752	282.7k	190.9k	4.0M	5.1M
SE	PLDI, FSE, ICSE, OSDI, SOSP	349	10.8k	99.9k	1.0M	2.1M

Data was taken from (Tang et al. 2017; 2008). The full DBLP dataset contains over 3M publications from 1936 to 2018. Each network contains publications from only a set of conferences, e.g., networks TC contains publications from FOCS, SODA and STOC. For each network we show the number of: awarded authors (AA), insider and outsider nodes ($|\mathcal{I}|$ and $|\mathcal{O}|$ respectively), and insider and outsider edges ($|\mathcal{E}_{\mathcal{I}}|$ and $|\mathcal{E}_{\mathcal{O}}|$ respectively)

authors). Instead, OTARIOS gives the freedom to personalise the features used to rank authors. In the particular case of our test scenario, we did not know a priori which features would be the most important, so we did an exploratory analysis to find the best OTARIOS variants. However, there are more than 500 variants that we can create by combining different features. In order to estimate the best variant without testing a large number of variants, we performed a greedy search for each network.

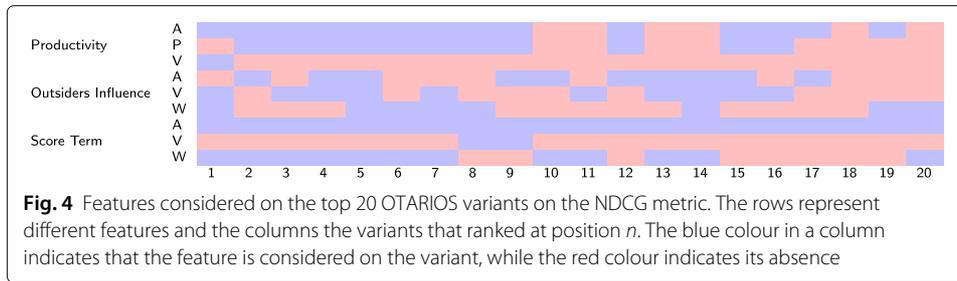
We start with simple variants (with a single feature) and progressively add more features to the more promising variants. We illustrate this process for the network NET on Table 6. We begin by comparing OTARIOS variants that only contain outsiders influence (e.g., $\emptyset + A + \emptyset$). For the best ones, we added the productivity (e.g., $AP + A + \emptyset$). In general, we see that results improve when merging outsiders influence with productivity. Finally, we add the score term calculation to the best variants (e.g., $AP + A + A$). Again, we see that overall the results improve when we add this feature to the score term. For the NET network, we see that $AP + A + AW$ is the best variant with a mean NDCG of 0.330 and a mean MRR of 606. This variant uses recency and volume to measure author productivity, uses recency to calculate outsiders influence, and uses recency and individuality on the score diffusion step.

Figure 4 presents the features used by the 20 best OTARIOS variants according to the average NDCG across the five networks created. We observe that the top-9 variants always use a mix of productivity, outsiders influence and score term, thus revealing the importance of considering multiple aspects of publications and citations information. Of the top 20 variants, only 6 do not use productivity features and only 1 does not use the outsiders influence; score term features are present in all top-20 variants. Regarding specific features, we observe that recency (A) seems to be the most important feature for all three categories: productivity, outsider influence and score term. In fact, recency is used in the score term of all top-20 variants. This indicates that most of awarded authors are still actively publishing and/or being cited. Individuality (W) and volume (P) seem to be more important to measure productivity and score term than to measure outsiders influence. This indicates that awarded authors publish more papers and also that publish with fewer co-authors. Venue prestige (V) seems to be more relevant when measuring outsiders influence than productivity and insiders score term. This is expected because, due to the nature of the two subnetworks, insiders tend to publish in the same venues, while outsiders cite insiders in any venues, thus the venue prestige of outsiders citations varies greatly.

Table 6 Comparison of OTARIOS variants on network NET (from Table 5)

OTARIOS variant	NDCG					Mean	MRR					
	5	10	20	50	100		5	10	20	50	100	Mean
$\emptyset + A + \emptyset$	0.269	0.233	0.207	0.186	0.174	0.214	443	1125	903	1526	2066	1213
$\emptyset + V + \emptyset$	0.269	0.233	0.207	0.186	0.185	0.216	412	1108	916	1522	2096	1211
$\emptyset + AV + \emptyset$	0.269	0.233	0.207	0.186	0.177	0.215	419	1109	902	1511	2074	1203
$AP + A + \emptyset$	0.288	0.246	0.259	0.218	0.241	0.250	350	500	440	1121	1502	783
$AP + V + \emptyset$	0.288	0.246	0.258	0.218	0.239	0.250	344	489	439	1134	1527	787
$AP + AV + \emptyset$	0.288	0.246	0.259	0.218	0.240	0.250	345	494	439	1143	1523	789
$AP + A + A$	0.380	0.297	0.283	0.282	0.280	0.304	385	647	472	1111	1416	806
$AP + A + V$	0.350	0.261	0.217	0.203	0.203	0.247	255	726	617	1251	1615	893
$AP + A + AV$	0.407	0.345	0.291	0.291	0.274	0.322	242	614	473	1116	1455	780
$AP + A + AW$	0.381	0.369	0.313	0.302	0.288	0.330	219	386	328	879	1219	606

For each OTARIOS variant, we measure its ranking's NDCG and MRR for the top-5, top-10, top-20, top-50 and top-100 authors, as well as the metric's mean value. In bold we highlight the highest score for each metric. The best OTARIOS variant is coloured in blue



Comparison against sTOA

We compare OTARIOS against STOA methods discussed in “State-of-the-art author ranking methods” section and a baseline method named CountRank (CR) which counts the citations received by each author. We create three CR variants: uniform, individuality, and position. For each citation received, uniform assigns the same merit to all of the authors in publication (i.e., merit = 1), individuality equally divides the merit for all the authors (i.e., merit = $\frac{1}{|A|}$), and position gives more credit to authors whose name appears first in the publication (first author: merit = 1, second author: merit = $\frac{1}{2}$, third author: merit = $\frac{1}{3}$, ...). Table 7 shows the results obtained for all STOA methods and 5 OTARIOS variants over all networks. For each network, we calculate NDCG and MRR for the top-5, 10, 20, 50 and 100 authors, and compute their mean values. Furthermore, we compute the mean NDCG and MRR across all networks.

In our experiments, *SCEAS* is the best STOA method, obtaining the highest mean NDCG (0.208) and the lowest mean MRR (691). The $CR_{position}$ method obtained the lowest NDCG mean (0.154), while *NewRank* obtained the highest mean MRR by a considerable margin (4091). An important aspect to highlight is that $CR_{individuality}$, despite being a baseline strategy, obtained the second highest NDCG and MRR across the five networks, among the STOA methods.

With respect to OTARIOS variants, we tested 53 variants and 21 of them obtained higher mean MRR and mean NDCG than the best STOA method, *SCEAS*. The best mean NDCG and mean MRR that OTARIOS variants obtained were 0.246 and 567, respectively. Assuming that both NDCG and MRR measures have the same weight (i.e., are equally important), the best OTARIOS variant is (AP+A+AW), which uses (a) recency and volume to measure productivity, (b) recency to measure outsiders influence, and (c) recency

Table 7 Comparison of state of the art (STOA) methods against OTARIOS over all networks

Method	NDCG						MRR					
	CM	TC	NET	IS	SE	Mean	CM	TC	NET	IS	SE	Mean
State of the art												
$CR_{position}$	0.097	0.049	0.189	0.176	0.261	0.154	1427	463	1009	892	324	823
YetRank	0.128	0.028	0.206	0.157	0.271	0.158	2083	673	1047	846	491	1028
ALEF	0.152	0.020	0.182	0.129	0.323	0.161	1260	561	670	803	310	721
$CR_{uniform}$	0.138	0.045	0.278	0.189	0.222	0.174	1659	516	1066	1067	387	939
RLPR	0.180	0.032	0.231	0.176	0.338	0.191	1203	508	817	720	356	721
SARA	0.193	0.035	0.232	0.156	0.354	0.194	1122	461	738	668	303	658
NewRank	0.115	0.004	0.297	0.319	0.266	0.200	5057	3112	3597	6637	2050	4091
$CR_{individuality}$	0.129	0.043	0.247	0.211	0.372	0.200	1171	438	878	744	289	704
<i>SCEAS</i>	0.143	0.035	0.275	0.255	0.335	0.208	1154	493	776	752	279	691
OTARIOS												
$\emptyset + AVW + AW$	0.143	0.081	0.323	0.213	0.315	0.215	1161	324	664	707	289	629
$\emptyset + V + AW$	0.148	0.080	0.321	0.214	0.314	0.215	1169	325	671	709	294	634
AP + VW + AW	0.150	0.087	0.330	0.268	0.383	0.244	1070	273	604	680	207	567
AV + VW + AW	0.143	0.085	0.356	0.264	0.383	0.246	1333	285	618	676	215	626
AP + A + AW	0.152	0.087	0.330	0.273	0.383	0.245 (+18%)	1079	272	606	688	207	570 (+21%)

The value of each cell is the metric’s mean value for that network (e.g., the mean NDCG and MRR of AP+A+AW for network NET is highlighted in Table 6). In bold we highlight the highest score for each metric. The best STOA method (i.e., *SCEAS*) is colored in red and the best OTARIOS variant is colored in blue. Inside parentheses we show the gain of OTARIOS versus *SCEAS*, i.e., G_{NDCG} and G_{MRR} , respectively

and individuality to measure the score term. This variant obtained a mean NDCG of 0.245 and a mean MRR of 570. We compared the gain of this variant with respect to STOA methods, using Eqs. 8 and 9. Compared to *RLPR*, a topology-based author ranking algorithm, we achieved a gain of 28% in terms of NDCG and 27% in terms of MRR. With respect to the best feature-enriched author ranking method (*SCEAS*), we achieved a gain of 18% in terms of NDCG and 21% in terms of MRR.

$$G_{NDCG} = \frac{OTARIOS_{\langle NDCG \rangle} - STOA_{\langle NDCG \rangle}}{\min(OTARIOS_{\langle NDCG \rangle}, STOA_{\langle NDCG \rangle})} \quad (8)$$

$$G_{MRR} = \frac{STOA_{\langle MRR \rangle} - OTARIOS_{\langle MRR \rangle}}{\min(OTARIOS_{\langle MRR \rangle}, STOA_{\langle MRR \rangle})} \quad (9)$$

STOA performance on outsider and insiders network

In our previous experiments, STOA methods only used the author citation network of the insider authors (i.e., outsiders were not part of the network). However, for the OTARIOS variants, since we require outsiders to calculate outsider influence features, we used a network consisting of insiders and outsiders. In order to demonstrate that we were not unfairly comparing our variants with other methods with less information, we tested STOA algorithms using the complete network (i.e., outsiders + insiders) and compared those results with the ones obtained using only the insiders network. Table 8 shows the results of this comparison⁴. The results indicate that, on average, the STOA methods obtained a negative gain of -17% for NDCG and -25% for MRR when using the full network. The *NewRank* and *SCEAS* methods were the ones that presented the highest losses (-54% and -30% on NDCG, and -63% and -37% on MRR). These methods were among the top STOA methods when considering only the insiders network, as a result the complete network had a higher negative impact when compared to other methods that obtained worse results when considering only the insiders (e.g., *NewRank*). The only method that presented an overall positive gain was *YetRank* in terms of NDCG. This test demonstrated that adding more authors to the citation network decreases the overall performance of STOA methods when there is incomplete information about the new authors (i.e., their received citations are unknown) and they are treated equally as those authors whose full citation network is known. Thus, this further corroborates our hypothesis that incomplete networks should be carefully divided into fully known nodes and partially known nodes.

Conclusions

In this paper, we described OTARIOS, a new feature-enriched author ranking algorithm, and compared it against (a) bibliometrics, (b) topology-based author ranking algorithms, and (c) feature enriched author ranking algorithms. Previous author ranking methods did not combine relevant information effectively, such as the author's productivity and the citations' relevance. Furthermore, previous methods assume that the full network is known, which is not true for most real cases. We thus divided the network into insiders (i.e., the authors that we want to rank) and outsiders (i.e., the authors that cite insiders but we do not rank). In our experiments, we analysed which publication/citation information is more relevant and how it can be efficiently combined.

⁴Gains estimated using Eqs. 8 and 9

Table 8 Gain of using outsiders as part of the network in the score diffusion step

Method	NDCG						MRR					
	CM	TC	NET	IS	SE	Mean	CM	TC	NET	IS	SE	Mean
SCEAS	0.144	0.036	0.275	0.255	0.335	0.209	1154	493	776	753	279	691
Fullnet SCEAS	0.106	0.024	0.224	0.198	0.250	0.160	1517	845	929	999	433	945
Gain	-36%	-51%	-23%	-29%	-34%	-30%	-31%	-71%	-20%	-33%	-55%	-37%
SARA	0.194	0.036	0.232	0.157	0.355	0.195	1123	461	739	668	303	659
Fullnet SARA	0.181	0.030	0.227	0.177	0.300	0.183	1146	602	885	719	408	752
Gain	-7%	-20%	-2%	+13%	-18%	-6%	-2%	-31%	-20%	-8%	-35%	-14%
RLPR	0.181	0.032	0.231	0.177	0.338	0.192	1203	508	817	721	357	721
Fullnet RLPR	0.174	0.027	0.227	0.162	0.276	0.173	1274	728	864	757	436	812
Gain	-4%	-18%	-2%	-9%	-22%	-11%	-6%	-43%	-6%	-5%	-22%	-13%
ALEF	0.152	0.021	0.183	0.130	0.323	0.162	1261	561	670	804	310	721
Fullnet ALEF	0.125	0.024	0.203	0.151	0.299	0.160	1373	608	930	735	432	816
Gain	-22%	+13%	+11%	+16%	-8%	-1%	-9%	-8%	-39%	+9%	-39%	-13%
NewRank	0.116	0.004	0.297	0.320	0.267	0.201	5057	3113	3598	6638	2050	4091
Fullnet NewRank	0.089	0.020	0.180	0.191	0.170	0.130	11277	6951	6877	6541	1651	6659
Gain	-29%	+381%	-66%	-68%	-57%	-54%	-123%	-123%	-91%	+1%	+24%	-63%
YetRank	0.128	0.028	0.206	0.158	0.272	0.158	2084	673	1048	846	492	1029
Fullnet YetRank	0.157	0.029	0.224	0.149	0.259	0.163	2031	874	1200	836	561	1101
Gain	+22%	+1%	+9%	-6%	-5%	+3%	+3%	-30%	-15%	+1%	-14%	-7%

The *fullnet* versions incorporate outsiders in the network, i.e., they convert outsiders in insiders. Note that OTARIOS does not use outsiders as part of the network in the score diffusion step, only in the initialisation step. The mean of both NDCG and MRR is highlighted, showing that, overall, STOA methods' performance degrades when they use outsiders as insiders

We obtained the best results when OTARIOS considers (i) the author's publication volume and publication recency, (ii) how recently his work is being cited by outsiders, and (iii) how recently his work is being cited by insiders and how individual his work is (i.e., publishing with few authors is better). This evaluation was performed on a set of five networks where the ground-truth was the number of best awards in the conferences belonging to the specific network. Our tests showed that OTARIOS is > 30% more efficient than topology-based author ranking methods, namely PageRank, and is > 20% more efficient than other feature-enriched author ranking methods. We demonstrated that OTARIOS efficiently uses outsiders (i.e., authors whose received citations are not fully known) on the score initialisation process. Furthermore, we showed that adding outsiders to the score diffusion process decreases the performance of STOA algorithms. These results indicate that current methods have poor results on networks where some nodes have missing information (which is true for most real cases), while OTARIOS is able to use nodes with limited information adequately.

Finally, regarding future work, we plan to test OTARIOS on paper-level citations and verify that we are also capable of improving that approach from the STOA. We also plan to develop a method to automatically identify outsiders (e.g., insiders with low density in the citation network, or insiders with low co-authorship ratio to other insiders) and analyse if this strategy improves author-ranking. Furthermore we intend to tackle the problem of the impact of citation manipulation on the rankings (Ioannidis 2015) not only by removing self-citations (our current strategy) but also by decreasing the credit given by citations between colleagues and collaborators. For the purpose we plan to use a multi-layered network that augments the author citation network with the co-authorship network.

Abbreviations

DCG: Discounted cumulative gain; DN: Dangling nodes; MRR: Mean reciprocal rank; NDCG: Normalized discounted cumulative gain; OTARIOS: OpTmizing author ranking with insiders/outside subnetworks; RR: Random restart; ST: Score term; STOA: State-of-the-art

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Authors' contributions

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Availability of data and materials

The datasets generated and/or analysed during the current study are available in the AMiner and Jeff Huang repositories, <https://aminer.org/citation> and https://jeffhuang.com/best_paper_awards.html.

Competing interests

The authors declare that they have no competing interests.

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