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Author ranking based on personalized PageRank

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ABSTRACT

In this paper we evaluate citation networks of authors, publications and journals, constructed from the *ISI Web of Science* database (Computer Science categories). Our aim was to find a method with which to rank authors of scientific papers so that the most important occupy the top positions. We utilized a hand-made list of authors, each of whom have received an *ACM Fellowship* or have been awarded by an ACM SIG (*Artificial Intelligence* or *Hardware* categories). The developed method also included the adoption of the PageRank algorithm, which can be considered a measure of prestige, as well as other measures of significance (h-index, publication count, citation count, publication's author count), with these measures analyzed regarding their influence on the final rankings.

Our main objective, to determine whether a better author ranking can be obtained using journal values, was achieved. The best of our author ranking systems was obtained by using journal impact values in PageRank, which was applied to a citation network of publications. The effectiveness of the ranking system was confirmed after calculations were carried out involving authors who were awarded after the final year used in our dataset or who were awarded in selected categories.

1. Introduction and related work

In this paper we explore the possibility of evaluating authors of scientific publications, based on a citation network. Such author rankings could be utilized in searching or comparing authors in a given research area, processing tenders, assigning awards, etc. Our main method employed for the evaluation of citation networks was PageRank, an algorithm developed by Brin and Page (1998) which uses the impact of citing network nodes (websites, articles, authors and so on) to determine the importance of the cited nodes. In bibliometry, PageRank is used to evaluate networks built from bibliographic data – usually the records of scientific publications. The nodes of these networks can represent publications, authors, journals, research groups, institutions or countries, although all nodes are usually of the same type. As described by Ding (2011a), the characteristics of PageRank are such that it can be used as a good indicator of author prestige (a prestigious author is usually defined as one cited by many often-cited authors). Ding also considers citation count to be a good indicator of author popularity (a popular author is one often cited by normal authors). The idea of popularity and prestige is depicted in Fig. 1, in which author A can be labeled as prestigious and author C as popular. Although author C is often cited in non-cited papers, his work is built upon the work of author A. Author A is also more prestigious than author B. Fig. 1 further illustrates that PageRank has a higher resolution than citation count. A positive feature of PageRank is its ability to discover papers which contain groundbreaking results, but are not often cited (Chen, Xie, Maslov, & Redner, 2007; Maslov & Redner, 2008).

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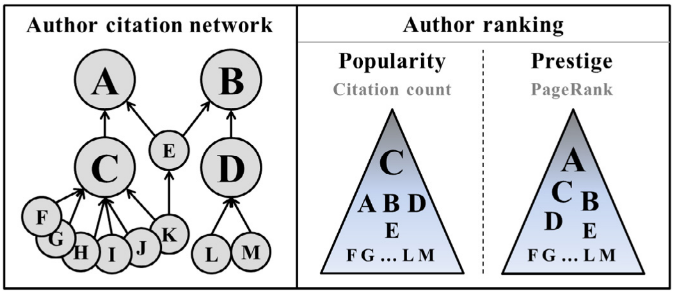

Fig. 1. Difference between popularity (citation count) and prestige (PageRank).

In the past, bibliographic evaluation was performed based on co-authorship networks (in which edges are between nodes with a common publication), citation networks (edges oriented from a node which is citing the other node) or co-citation networks (edges between nodes which cited the same publication). Liu, Bollen, Nelson, and Van De Sompel (2005) proposed the AuthorRank algorithm for determining author importance by evaluating co-authorship networks. Yan and Ding (2011), on the other hand, evaluated such networks via the PageRank algorithm enhanced with personalization[1] in terms of the number of individual author citations. Fiala, Rousselot, and Ježek (2008) created an author citation network, determined edge weights with regard to number of citations and co-authorship, and in (Fiala, 2012) introduced Time-aware PageRank. Other variants of bibliographic network evaluation (comprising e.g., co-citation networks) were compared by Yan and Ding (2012). The evaluation of heterogeneous scholarly networks combining authorship, journal-ship and publication citation networks, using PageRank, was tested by Yan, Ding, and Sugimoto (2011), while the evaluation of a network connecting citation networks of papers, authors, affiliations and publishing venues by authorship, affiliation, publishing and co-authorship relations, was conducted by Yang, Hong, and Davison (2010).

It should be noted that a bibliometrical concept similar to PageRank was first proposed by Pinski and Narin (1976), but its full potential was realized only some years later by Brin and Page (1998) in the design of PageRank itself. The latter has been used in bibliometry for evaluating journals (Bollen, Rodriquez, & Van De Sompel, 2006; González-Pereira, Guerrero-Bote, & Moya-Anegón, 2010; West, Bergstrom, & Bergstrom, 2010), publications (Chen et al., 2007; Li & Willett, 2009; Ma, Guan, & Zhao, 2008; Maslov & Redner, 2008; Sayyadi & Getoor, 2009), authors (Ding, Yan, Frazho, & Caverlee, 2009; Ding, 2011a; Fiala et al., 2008; Fiala, 2012; Nykl, Ježek, Fiala, & Dostal, 2014; Radicchi, Fortunato, Markines, & Vespignani, 2009; West, Jensen, Dandrea, Gordon, & Bergstrom, 2013), institutions or departments (Fiala, 2013; West et al., 2013), and countries (Ma et al., 2008). Modified variants of PageRank are also being employed to evaluate journals in the ISI Web of Science and Scopus databases, specifically Eigenfactor™ Metrics (West et al., 2010) in the former and SCImago Journal Rank (González-Pereira et al., 2010) in the latter.

The rest of this section is devoted to the previous research in the field of author evaluation, our previous research conclusions, and also to the motivation behind the new work presented here. The following Section 2 describes the ISI Web of Science (WoS) data and lists of prestigious awards used. The *Author ranking methodologies* Section 3 provides information regarding the PageRank algorithm, how to add weights to edges in the author citation network, and how to distribute publication scores among authors. Next, we describe the different evaluations of citation networks, variations of personalizations, as well as the possibility of obtaining the values of journals and their utilization in publication citation networks. The analyses and their results are summarized and discussed in the *Results and discussion* Section 4. The conclusion and recommendations are presented in the final Section 5.

1.1. Differences between the present work and previous studies

Many methods have already been proposed for evaluating authors and many of them are, like our methods, based on PageRank. Especially, the possibility of changing its personalization provides many variants. Ding et al. (2009) use personalization with the number of citations and the number of publications for the evaluation of co-citation networks, which allow evaluating the frequency the author being cited, along with highly cited authors. They then compare these obtained rankings with rankings evaluated by PageRank without personalization, h-index (Hirsch, 2005), citation count and centrality measures (Freeman, 1979). Their results show that the correlations of rankings, computed by citation counts, are close to PageRank, but both methods significantly differ from centrality measures. Centrality measures and h-index show different perspectives of measures when compared with citation counts and various PageRank algorithms. In (Ding, 2011a), the author again compares the rankings obtained by applying PageRank with personalization by the number of citations and the number of publications. She uses a citation network of authors, which is then evaluated by PageRank with personalization, PageRank without personalization, h-index and the number of citations. From the comparison of results with lists of holders

[1] PageRank personalization – a static part of a given node's PageRank value, which is usually determined before the computation and does not change. See more about personalization in the section entitled *Author ranking methodologies* (3).

of prestigious awards comes PageRank, with personalization by citation count, as the best method. In (Ding, 2011b), for ranking authors in the topics from Information Retrieval, the author uses a co-citation network and PageRank, at first multiplied, and then personalized by a measure of author's productivity in the given topic. She compares these methods with the same methods as mentioned in the previous paper, and argues that methods which use a productivity measure provide better results at the topic level than other tested methods. This is why they are usable for searching authors based on a user query. PageRank with personalization by the number of citations is also applied by Yan and Ding (2011) on co-authorship networks and they also argue, that this PageRank provides reliable results in measuring author impact. The personalization of PageRank by publication count was also tested by Radicchi et al. (2009) and West et al. (2013), who concluded, that this personalization provides better author rankings then other tested approaches. An interesting combination of PageRank with other methods is proposed by Bollen et al. (2006), who presented a comparison between PageRank, the Journal Impact Factor, and a product of their multiplication called the Y-factor, for journal impact evaluation (the Y-factor produced the best results). Another possible combination of PageRank with other metrics included the values of these metrics into the weights of edges in the network. This was utilized, for example, by Fiala et al. (2008), who set the weights of edges of a citation network of authors according to the measure of their cooperation and citations. On top of that, Fiala (2012) added into these weights the time of publication.

Utilizing the personalization of PageRank for evaluating authors provides many other possibilities, which have not yet been explored. The research presented in this paper is a direct continuation of (Nykl et al., 2014), where in order to conduct our analysis on data which would be as consistent as possible, we purchased the ISI Web of Science bibliographic data collection (Computer Science categories). Although many other authors use data collected personally (Ding et al., 2009; Fiala, Šubelj, Žitnik, & Bajec, 2015; Fiala, 2012), these collections may be inconsistent or, for example, derived from only one particular source paper (Li & Willett, 2009). In Nykl et al. (2014) we rated authors based on the evaluation of author and publication citation networks via the use of PageRank and weighted in-degree, because citation networks enabled us to determine the prestige of nodes therein. In this case, we were mainly interested as to whether it was possible to achieve a better author ranking by evaluating the publication citation network or the author citation network, the latter of which omits certain information, e.g., the chronological order of citations. To this day, the evaluation of authors was computed on author citation networks more often than on publication citation networks, e.g. (Ding, 2011a; Fiala et al., 2008; Radicchi et al., 2009) and others. We also tried to enhance the evaluation by emphasizing a certain degree of author or publication quality. The easiest values to acquire in this regard were each author's number of publications and the number of authors of a publication. We used these values as a PageRank personalization, with the number of publications increasing the advantage of more productive authors, and the number of authors favoring those publications whose creation required more effort or resources. A paper with more authors should therefore have a higher quality of content.

Our analyses in Nykl et al. (2014) showed that using PageRank to rank authors is more effective than in-degree, and that using a proper personalization enhances the results even further, which confirmed conclusions made by (Ding et al., 2009; Ding, 2011a, 2011b; Radicchi et al., 2009; West et al., 2013). The main conclusion reached was that it is better to evaluate authors using a citation network of publications, rather than a network of authors. Furthermore, we also confirmed that including self-citations in the evaluation has a negative effect on the result, and so it is convenient to remove them at the publication level. Overall, the best of our author rankings was obtained via the use of PageRank, with personalization based on the number of authors of a publication, while evaluating publication citation networks. It also proved to be better to evenly distribute partial publication values between authors, rather than summing them whole for each author.

On account of the fact that including personalization improves the results of author evaluation, we attempt here to use various PageRank personalizations. Our goal is to compare various types of personalizations and determine which of them provides the best rankings, when compared to lists of awarded authors. The most promising possibility of personalization we considered the use of impact of journals (1), h-index (2), and citation count (3). Other results, presented in this paper, were computed by previously used methods and intended for comparison. Furthermore, we also tested alternative means of publication values distribution among authors (4), as inspired by Assimakis and Adam (2010). These distributions should tell us, whether it makes sense to favor authors, who are mentioned on the front positions below the title. The most interesting variants of our evaluations are:

(1) Using the impact of the journal in which the publication was printed in the personalization of publications. Our assumption here was that if a paper passed the reviewing process of a renowned journal, this process should reflect the former's quality. We thus expected PageRank with journal impact personalization to provide the best results among all our methods.
(2) Using the h-index (Hirsch, 2005) in the personalization of authors, because h-index is one of the most known non-iterative methods for evaluating authors. The main aim of this approach was to determine whether using author maturity improves the results more than the use of author productivity (number of publications).
(3) Using of the number of citations in the personalization of publications, which indicates a publication's popularity. This approach is similar to (Ding, 2011a), where only the first authors were taken into account. This experiment also interests us, because of using other variants of distributing publication values among authors, see the next point (4).
(4) Exploring other means of publication value distributions, which favor authors who are mentioned on the front positions below the title. We want to test this, because our previous research revealed that distributing publication values evenly between authors improves ranking results (Nykl et al., 2014).

Analyses using all the data collected will provide us with rankings of authors from the entire field of Computer Science (hereafter referred to as "global computer science author ranking"), which we can then compare with the list of awarded authors from the same field (*ACM Fellows*). In order to test our findings on more specific categories of research, we additionally experimented with rankings of authors from the *Artificial Intelligence* and *Hardware* categories. Also, where possible, we employed larger reference lists of important authors, as using a small number of authors (Ding, 2011a; Fiala et al., 2015; Fiala, 2012; Sidiropoulos & Manolopoulos, 2006) may lead to distorted results. Other option is to use the program committees of scientific conferences (e.g., Liu et al., 2005) or the editorial boards of scientific journals (e.g., Fiala et al., 2015). We chose the *Artificial Intelligence* and *Hardware* categories because of their clear boundaries and the good correspondence between the Computer Science categories in the *ISI Web of Science* database and the *Special Interest Groups* (SIGs) of the *Association for Computing Machinery* (ACM), which provided sufficiently extensive lists of awarded persons. Assigning categories to journals was done based on the JCR, as well as Fiala et al. (2015). Although it is also possible to search for publications based on a query (Ding, 2011b; Haveliwala, 2003), such an approach is more complex. The ranking of authors in specific categories can be convenient when searching for experts with a particular specialization.

2. Used data

Although all of our experiments can be conducted via arbitrary bibliographic data collection, we used the already purchased Thomson Reuters collection employed in our previous studies (Fiala, 2012; Nykl et al., 2014). Section 2.1 provides further details regarding our collection methods and chosen categories; this information can be used for comparison with other collections and experimental results. The quality of our author rankings was determined on the basis of human-made lists of award holders, as described in Section 2.2.

2.1. ISI Web of Science collection and citation networks

The ISI Web of Science (WoS) bibliographic collection employed here consisted of all publications issued between 1996 and 2005 and classified as an "article" in Journal Citation Reports (JCR) 2009 in the Computer Science categories. We used the complete collection of 386 journals containing 149 347 publications from 157 440 different authors for analyses based on global computer science author ranking. The computer sciences have a unique scholarly communication pattern in that a certain amount of papers are published at leading conference venues but not in journals. However, due to their irregular placement into WoS, we did not use these papers.

While determining the specific categories with which to experiment with author rankings, we focused only on those WoS categories corresponding to categories of ACM SIGs, because we largely determined the quality of author rankings based on ACM awards. The category distribution is stated in the following list (comparable categories are in italics):

- **ACM SIG categories**: *Artificial Intelligence*, *Applications*, Digital Content, Education, *Hardware Design*, Interaction, Networking, *Software*, Ops & Management, Performance, and *Theory*.
- **WoS Computer Science categories**: *Artificial Intelligence*, Cybernetics, *Hardware & Architecture*, Information Systems, *Interdisciplinary Applications*, *Software Engineering*, and *Theory & Methods*.

In our experiments we used only the *Artificial Intelligence (AI)* and *Hardware (HW)* categories because *Applications*, *Software* and *Theory* all represent very broad areas of interest, which often extend into other categories.

Journal Citation Report 2013 on the WoS website[2] contains 121 journals in the category of *Artificial Intelligence*. This is in contrast to the 84 journals in our WoS collection, which means that JCR 2013 contains 37 more journals (from the area of *Artificial Intelligence*) than JCR 2009 (including some journals removed from the index and others added). The selected 84 *AI* journals contain 31 749 publications with 39 891 different authors. In the *Hardware & Architecture* category, there are 50 journals on the WoS website and 40 in our collection, representing 18 917 publications with 29 243 authors. The only journal found in both categories is *IEEE Transactions on Neural Networks and Learning Systems*. The percentage of publications published each year between 1996 and 2005 in our WoS collection is shown in Fig. 2, the analysis of which reveals that the productivity of scientists and/or its indexation has increased by over one third in the last decade.

Using the above bibliographic data we created publication, author and journal citation networks with various types of self-citation:

- The *ALL* variant takes into account all citations.
- The *PART* variant applies only to author networks in which all self-loops are removed. The same approach was used, for example, by West et al. (2013).
- The *NOT* variant removes citations between publications with at least one common author. The same approach was used, for example, by Fiala et al. (2008).

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[2] The Web of Science website – http://www.webofknowledge.com (note: Web of Science is now known as Web of Knowledge).

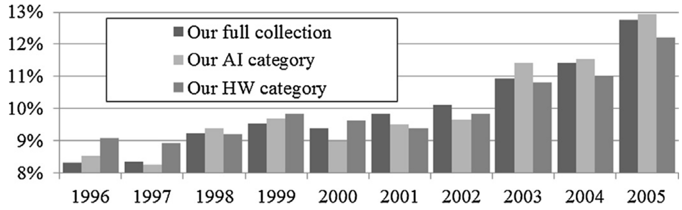

Fig. 2. Percentage of publications from years 1996–2005 in our WoS collection.

Eventually, self-citations can be assigned with lower weights, as explored by Yang et al. (2010) for instance, but this is beyond the scope of our analyses. We also did not create *AI* and *HW* category networks for journals.

In the further described networks, edges represent distinct citations (without parallel edges) and nodes represent publications, authors or journals. The specific types of nodes are:

- *dangling* nodes, which lack an outgoing edge,
- *uncited* nodes, which lack an incoming edge,
- *isolated* nodes, which lack both outgoing and incoming edges.

For the comparison of categories, we employed quantitative indicators which we considered to represent the characteristics of networks (see Table 1), including the number of nodes, edges and dangling, uncited and isolated nodes. It is worth noting that networks derived from the *Hardware* category contain few citations and roughly half of all isolated nodes. However, networks derived from *Artificial Intelligence* and the complete collection contain "only" a third of isolated nodes. This leads us to believe that the results obtained from the *Hardware* category will be slightly distorted and will not correspond to those from other networks. The larger amount of isolated nodes in the *Hardware* category is possibly caused by a reduced citing trend in this category.

On average, each journal in our collection has published 387 papers in 10 years from 727 different authors. *AI* journals have on average published 378 publications (473 in *HW*) from 722 different authors (948 in *HW*). It is apparent that whereas journals in the *HW* category are associated with a higher than average number of publications and authors, the *AI* category is only average in this aspect. Publications have a similar average number of authors (2.5 in full collection and *AI* category, and 2.7 in *HW*) in the two categories, but the *HW* category has a lower than average number of all citations (1.3 in full collection, 1.5 in *AI*, but only 0.6 in *HW*). This discrepancy may be caused by a reduced citation trend or by fewer publications in the *HW* category. For the sake of completeness, an average author in our collection has written 2.4 publications (2 in *AI* and 1.8 in *HW*) and has 6.8 citations (5.6 in *AI* and 3.2 in *HW*).

Because we wanted to test the influence of different personalization settings (number of author's publications, h-index, number of authors of a publication, and number of citations of a publication) on the final results, we examined how authors or publications are distributed according to these metrics (see Fig. A1 in the appendix). According to this analysis, only the number of authors of a publication setting provided a slightly different result in terms of assigning authors into groups, because most publications were written by two authors. Author's number of publications and number of citations of a

Table 1
Numbers of elements in the citation networks created from our WoS collection.

Category	Type of network	Nodes	Self-cit.	Edges	Dangling	Uncited	Isolated
Our full WoS Computer Science collection	Publication	149 347	ALL	191 447	79 571	90 901	49 774
			NOT	145 372	92 694	103 312	64 517
	Author	157 440	ALL	1 062 886	71 354	83 146	48 333
			PART	1 039 339	71 843	83 662	48 482
			NOT	852 356	82 170	94 094	56 907
	Journal	386	ALL	20 488	3	21	2
			NOT	20 135	3	26	2
Our WoS Artificial Intelligence category	Publication	31 749	ALL	46 203	15 946	18 866	9767
			NOT	36 381	18 428	21 252	12 394
	Author	39 891	ALL	226 898	18 648	22 278	12 882
			PART	221 713	18 738	22 386	12 912
			NOT	188 461	20 961	24 669	14 748
Our WoS Hardware & Architecture category	Publication	18 917	ALL	10 765	13 200	14 159	10 064
			NOT	7967	14 460	15 350	11 834
	Author	29 243	ALL	94 663	18 384	19 955	14 330
			PART	92 278	18 439	20 011	14 350
			NOT	68 958	20 094	21 793	16 008

publication provided very similar author and publication distributions. The h-index offers only a low resolution, because authors were divided into a maximum of 13 groups. More details regarding the groups can be found in the following list:

- Authors can be divided in terms of their number of publications into 101 groups (*AI* 47, *HW* 41), with a maximum of 181 (*AI* 76, *HW* 60).
- H-index with all citations divided authors into 13 groups (*AI* 12, *HW* 8), with the highest value being 16 (*AI* 15, *HW* 7). H-index without self-citations also divided authors into 13 groups (*AI* 11, *HW* 7) with the highest value again 16 (*AI* 14, *HW* 6).
- Publications were divided in terms of the number of authors into 31 groups (*AI* 21, *HW* 27), with a maximum of 64 (*AI* 64, *HW* 28).
- Publications were divided in terms of the number of citations into 99 groups (*AI* 75, *HW* 29), with a maximum of 262 (*AI* 189, *HW* 44). When author self-citations were omitted, publications were divided into 98 groups (*AI* 69, *HW* 27) with a maximum of 258 (*AI* 185, *HW* 43).

2.2. Used lists of award-winning authors

We used several human-made lists of scientists, each of whom are holders of prestigious awards in computer science, in order to evaluate the machine-made author rankings. Although a similar approach was proposed by Sidiropoulos and Manolopoulos (2006), we preferred to employ awards given to a larger number of people. Authors were represented by their surname and initials of their first and possibly other names, as in the WoS collection. From our lists we removed incomplete names, but name disambiguation and unification was not performed. The same method of searching for awarded authors in WoS was used previously in Fiala et al. (2015), Fiala (2012), and Nykl et al. (2014).

Global computer science author rankings were evaluated based on the prestigious *ACM Fellowship*[3] (1994–2011) award, already described and utilized in Nykl et al. (2014). Here we did not use the most recently awarded authors, but instead selected 576 well-distinguishable names on the *ACM Fellows* list. The results are therefore comparable with our previous research. In order for us to be able to test the ranking of authors for different categories, we chose authors awarded by ACM SIGs in the given categories of *Artificial Intelligence* and *Hardware Design.* These categories include the following SIGs:

- **ACM Artificial Intelligence SIGs**: Artificial Intelligence (SIGAI), Electronic Commerce (SIGecom), Genetic and Evolutionary Computation (SIGEVO), Information Retrieval (SIGIR), Knowledge Discovery in Data (SIGKDD), and Hypertext and the Web (SIGWEB).
- **ACM Hardware Design SIGs**: Computer Architecture (SIGARCH), Embedded Systems (SIGBED), Design Automation (SIGDA), Mobility of Systems, Users, Data and Computing (SIGMOBILE), and Microarchitecture (SIGMICRO).

Various awards granted by these groups are listed in Table 2. These awards are given for long-term or outstanding contribution in the area of the SIG, for current research, for the best paper, and for the "test-of-time paper" (given 10 or more years retrospectively). We did not include student awards. The "Awarded authors" column in Table 2 shows how many different authors were found for each given award. The "In our full coll." column shows how many of these authors are in our WoS collection, and the final column shows their representation in the given WoS category.

Overall, we found 354 different authors awarded by *Artificial Intelligence* SIGs, 224 of whom were recognized in our WoS collection and 133 in their corresponding category. 158 unique names were found in the list of awards given by *Hardware Design* SIGs, 85 of which were in our WoS collection and 76 in the corresponding category. To evaluate our methods we used data regarding authors who were found in their corresponding WoS categories. The number of similar names in each list of awarded authors is shown in Table 3; as expected, these lists contain only a small number of identical names.

The distribution of years in which the selected authors were awarded is depicted in Fig. 3 (cf. Fig. 2). As is evident from Fig. 3, we also included many authors awarded after the year 2005 (the last year covered by our WoS collection) in our evaluation, with the aim of attempting to determine whether our methods were capable of selecting authors who were awarded in the following years (2006–2014). This corresponds to the need to search for the best present-day authors/scientists, as well as those who will likely be among the best in the near future.

To conclude this section, it should be noted that even though ACM is the largest computing organization in the world, its focus is restricted mainly to the U.S. (unlike the Nobel prize, which has a global appeal) and as such may have led to U.S. scientists being favored in the presented analysis. Furthermore, as WoS publication data are gathered from around the globe, a potential mismatch between the two data sets is more likely.

3. Author ranking methodologies

We evaluated the citation networks mainly by using the PageRank algorithm (Brin & Page, 1998), one of the first and most important components of the Google search engine. The PageRank algorithm can be described by formula (1), where:

[3] The *ACM Fellows* website – http://fellows.acm.org/

Table 2
Awards given by ACM SIGs in the *Artificial Intelligence* and *Hardware Design* categories.

Category	SIG name	Award	Awarded authors	In our full coll.	In our categ.
Artificial intelligence (354 persons)	SIGAI	Allen Newell Award (1994–2012)	21	15	11
		The ACM/SIGAI Autonomous Agents Research Award (2001–2014)	14	12	12
		A.M. Turing Award (AI, 2010–2011)	2	2	2
	SIGecom	The SIGecom Best Paper Awards (2006–2014)	37	14	9
	SIGEVO	SIGEVO Impact Award (2011–2013)	8	2	2
	SIGIR	Gerard Salton Award (1983–2012)	10	8	0
		Best paper award (1996–2014)	51	36	15
		Test of Time Award 2014 (2002–2003)	13	9	6
	SIGKDD	SIGKDD Innovation Award (2000–2014)	14	13	13
		SIGKDD Service Award (2000–2014)	12	10	7
		SIGKDD Best Research Paper Awards (1997–2007)	48	37	22
		SIGKDD Best Application Paper Award (1997–2007)	52	37	29
	SIGWEB	Hypertext Douglas Engelbart Best Paper Award (1996–2013)	46	22	9
		SIGWEB/SIGIR Vannevar Bush Award (1998–2013)	47	27	11
Hardware design (158 persons)	SIGARCH	ACM/IEEE Eckert-Mauchly Award (1979–2014)	36	0	0
		ACM SIGARCH Maurice Wilkes Award (1998–2014)	17	16	14
		ACM SIGARCH Distinguished Service Award (2008–2014)	6	4	3
		ACM SIGARCH/IEEE-CS TCCA Influential ISCA Paper Award (2003–2014)	46	31	30
	SIGBED	SIGBED EMSOFT Best Paper Award (2008–2013)	18	8	7
	SIGDA	SIGDA Outstanding New Faculty Award (2004–2014)	13	11	10
	SIGMOBILE	The SIGMOBILE Distinguished Service Award (2001–2003)	3	3	0
		The SIGMOBILE Outstanding Contribution Award (1996–2014)	15	14	12
		The SIGMOBILE RockStar Award (2013–2014)	2	2	2
	SIGMICRO	–			

Table 3
Number of the same names in the prestigious award lists.

List of prestigious authors	ACM fellows	ACM AI	ACM HW
ACM fellows	576	13	21
ACM artificial intelligence SIGs	13	133	1
ACM hardware SIGs	21	1	76

- $PR_x(A)$ is the PageRank score of node A in iteration x,
- d is the damping factor,
- P is a set or vector of personalization and P_A its value at node A,
- U_A is the set of nodes which have an edge incoming to node A,
- w_{utoA} is the weight of the edge from node u to node A,
- w_{uout} is the sum of weights of all outgoing edges from node u,
- $|V|$ is the cardinality of the all-nodes set V,
- and D is the set of all dangling nodes in the network.

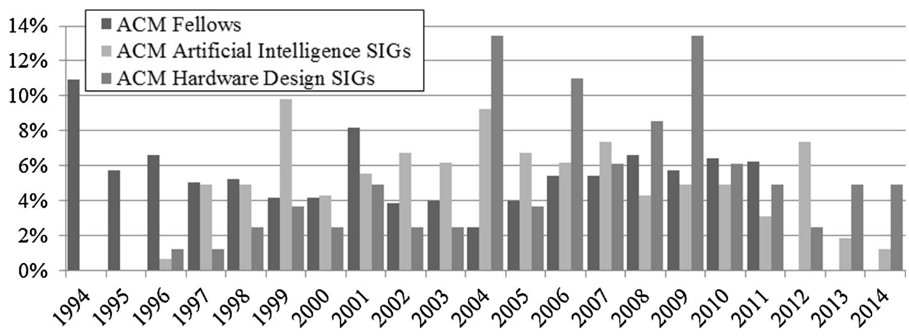

Fig. 3. Proportion of award holders in each of the tested award years.

Each node can be assigned with a different value of the static part of PageRank by using personalization P_A. The term "personalization" was introduced by Brin and Page (1998) when they wanted to include various preferences of the users of their internet search engine. The extent to which PageRank values include personalization is given by the damping factor d, with $0 < d < 1$ (note: if $d = 1$, PageRank might not converge; if $d = 0$, the node values consist only of personalization). Whereas Brin and Page (1998) proposed the value $d = 0.85$ for the evaluation of a website citation network, Chen et al. (2007) subsequently argued that a value of $d = 0.5$ is better for evaluating scholarly citation networks. Yan and Ding (2011) also arrived at the value $d = 0.55$ when they applied PageRank with citation count personalization to co-authorship networks. We tested values of $d \in <0.85; 0.15>$ with step 0.1.

The computation of PageRank values in which personalization is not included and therefore each node has personalization set to 1, is known as *PageRank without personalization*. In this case, the value of the damping factor has only a minimal influence on the results (rounding errors might be present) and so we used its standard value of 0.85. The number of iterations of the PageRank algorithm is always set to 50, which is, according to our previous experience, sufficient for stabilization of node values. The sensitivity to changes in PageRank parameters has been discussed, for example, by Langville and Meyer (2006a, chapter 6).

Note: generally, formula (1) can contain multiple dynamic parts, connected by damping factors, which add up to 1 (Sayyadi & Getoor, 2009). Another possibility is to replace personalization with a dynamic part (Sidiropoulos & Manolopoulos, 2006), but this method is beyond the scope of the present paper.

$$PR_x(A) = \frac{(1-d) \cdot P_A}{\sum_{p \in P} p} + d \cdot \left(\sum_{u \in U_A} \frac{PR_x(u) \cdot w_{u\ toA}}{w_{u\,out}} + \frac{1}{|V|} \sum_{s \in D} PR_x(S) \right) \tag{1}$$

As mentioned in Section 1.1, our analyses also included the h-index and the number of citations of a publication, defined as follows:

- An author has h-index value equal to h if h of his/her papers have at least h citations each, and the other papers have no more than h citations each (Hirsch, 2005). An author's h-index should increase with each year of his/her activity in a given area of research, and as such can be perceived as a measure of author maturity.
- Citation count is defined as the sum of all incoming citations and thus reflects the popularity of a node (Bollen et al., 2006; Ding, 2011a).

The following lists detail each of the methods used here for ranking authors, as well as the reasons why. The first group (1a–5a) contains methods with which to acquire different author values. Method (5a) requires the computation of publication values based on options (1p–8p). Methods (5a5p–5a8p) exploit journal values, computed according to (1j–3j).

Methods for computing the significance of authors:

(1a) *H-index*, which represents the maturity of authors.
(2a) *PageRank without personalization*, which represents the prestige of authors and serves as a baseline for the evaluation of author networks.
(3a) *PageRank with h-index personalization*, which includes author maturity in the computation of his/her prestige.
(4a) *PageRank with personalization in terms of each author's number of publications*, which includes his/her productivity in the prestige computation.
(5a) *Sum of values of publications*, written by the author (see below).

Options for determining the significance of publications, as used in method (5a):

(1p) *All publication values are set to 1*, thus serving, after their transfer to authors, as a measure of author productivity.
(2p) *PageRank without personalization*, which computes the prestige of publications and thus also the prestige of authors. This method provides a baseline for evaluating the publication networks.
(3p) *PageRank with personalization based on a publication's number of citations*, which includes popularity in the computation of their prestige.
(4p) *PageRank with personalization based on a publication's number of authors*, which includes its laboriousness in the prestige computation (i.e., the more authors, the greater effort and work put into the publication).
(5p) *All publication values are set to the value of the journal* in which they were printed. This, after transfer to authors, provides a measure of their productivity based on journal significance.
(6p) *PageRank with personalization and weights of input edges, based on the values of journals*, which includes the significance of journals in the computation of publication prestige.
(7p) *PageRank with personalization based on journal values*. This and the following option identify whether it is better to use the significance of journals as personalization or as weights of edges.
(8p) *PageRank without personalization, but with weights of input edges based on journal values* (e.g., if a publication was printed in a journal with Impact Factor 12, the input edges of the given publication have their weight set to 12). This

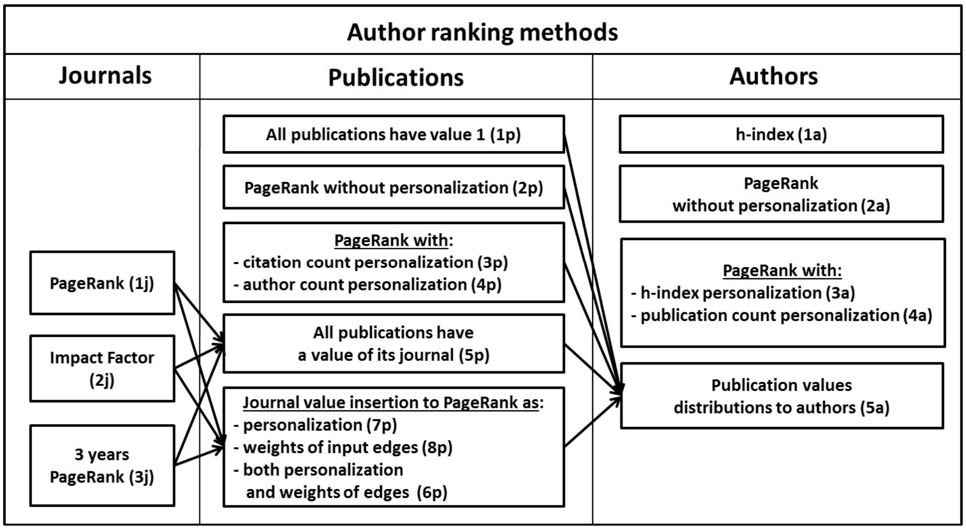

Fig. 4. The author ranking methods.

method, when compared to the baseline, can also illustrate whether it is beneficial to change the weights of edges in the publication citation network.

Options for determining the significance of journals, as used in methods (5a5p–5a8p):

(1j) *PageRank without personalization*, which computes the prestige of journals.
(2j) *Impact Factor*, which computes the popularity of journals during their period of publication.
(3j) *3-year PageRank*, which computes the prestige of journals during their period of publication.

All the examined methods of author ranking are recapitulated in Fig. 4, in which the arrows depict the use of journal or publication values in author ranking, and the rectangles depict the algorithms. For example, method (5a7p1j) of author evaluation uses the PageRank values of journals (1j) as a personalization in the publication citation network (7p). The resulting values are then distributed among the authors (5a).

For the evaluations, we used averages of awarded author positions in the obtained rankings. In this system the author with the best rank occupies the first position in the ranking; therefore, the lower the position average the better. Baselines (2a) and (5a2p) determine the minimum average positions the authors can acquire based on the computation of prestige via PageRank.

All of the proposed methods were then tested via global computer science network evaluations. In order to utilize our chosen categories of *Artificial Intelligence* and *Hardware*, we also tested two methods of their evaluation, here entitled category-independent and category-dependent, respectively. This terminology is based on using PageRank to sort the relevant results of a website search engine, in which the PageRank value is usually computed before a query is given (query-independent). However, algorithms such as HITS (Kleinberg, 1999) are computed after a query is given (query-dependent). Further details are available in (Langville & Meyer, 2006b, chapter 3.3).

The employed evaluation of categories can be described in more detail as follows:

- **Category-independent** author ranking utilizes the results of a global computer science author ranking system, from which authors are chosen who have published at least one paper in the given category. Authors are selected along with their computed values, which are used in their ordering. The advantage of this approach is that it utilizes information from our whole WoS collection, i.e., from all areas of the computer sciences.
- **Category-dependent** author ranking evaluates publication or author networks which are based on the articles published in any journal within a given WoS category. The advantage here is that author evaluation is based only on their publication activity in the chosen category.

3.1. Author network analyses

In experimenting with author citation networks, we used three variants (Nykl et al., 2014) to determine the weights of edges, based on the number of citations and authors of a given publication:

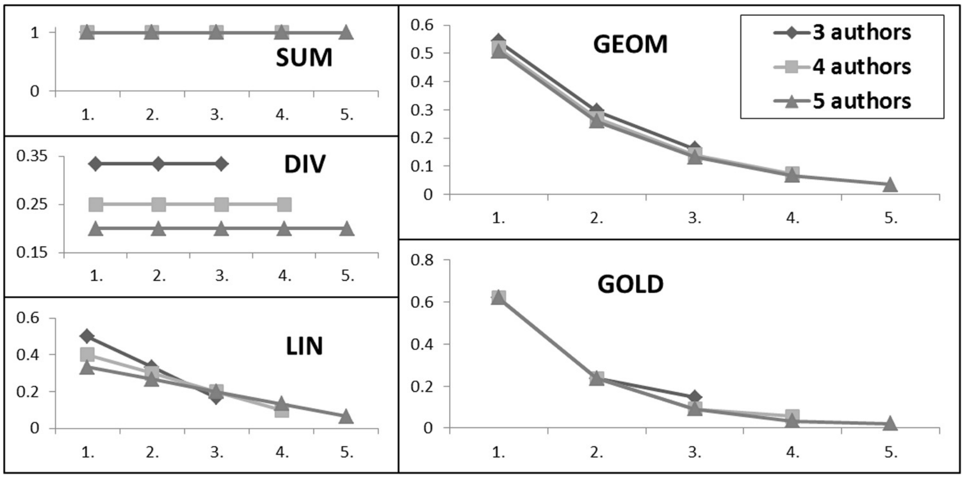

Fig. 5. Distribution of publication values between authors (The graphs show distributions for a publication by 3, 4 or 5 authors).

- The *N* variant assigns weights to edges based on authors' number of citations in the publication network. For example, if author B has two publications citing a publication by author C, then, in the author network, there exists an edge from B to C with weight 2.
- In the 1/*N* variant, publications' values are uniformly distributed according to outgoing citations. This means that if a publication by author A cites a publication by two authors B and C as well as a publication by author E, then in the author network, there are edges from A to B and A to C, both with weight ½, and an edge from A to E with weight 1.
- The 1 variant assigns a weight of 1 to all edges. The sum of the weights of an author's incoming edges is thus the number of his/her citing authors.

PageRank without personalization (2a) served as a first baseline for evaluating the author networks, as we assumed that it would provide better results than the h-index (1a). The method utilizing PageRank with personalization based on the significance of authors in terms of their number of publications (4a) proved to be the best of our methods for evaluating author citation networks (Nykl et al., 2014). The present paper further assumed that PageRank using the maturity of authors (h-index personalization, 3a) would provide even better results.

Author citation networks with edge weights, here denoted as 1/*N*, were previously evaluated using a similar method (4a) by Radicchi et al. (2009), who examined authors found in a collection of Physical Review journals. The latter method (4a) was also employed by West et al. (2013) to evaluate similar networks. As mentioned in both of these works, the proposed methods provide a better ordering of authors than other tested approaches.

3.2. *Distributions of publication values to their authors*

If one intends to determine the relative importance of authors based on publication values (5a), there are several options available as to how to distribute the publication values among the authors. In the literature these distributions are also known as *Counting methods* (Gauffriau & Larsen, 2005). We can add up either full or partial publication values, based on the number and order of authors stated below the title of the publication. Here we used formulas (2)–(5) and (8) to distribute publication values among authors, all of which were inspired by Assimakis and Adam (2010). Fig. 5 shows how to divide publication values among 3, 4 and 5 authors using these formulas, with the horizontal axes representing the author's position in the publication and the vertical axes his/her share of the publication value, which he/she will obtain. In formulas (2)–(8), ψ_A is the set of publications of author *A*, *VAL(Q)* is the value of publication *Q*, Q_N is the number of authors of *Q*, and Q_{Aj} is the position of author *A* as provided below the title of publication *Q*. *SUM(A)*, *DIV(A)*, *LIN(A)*, *GEOM(A)* and *GOLD(A)* are various methods with which to compute the distribution of publication values for author *A*.

The *SUM* distribution (formula (2)) assigns to each author the sum of whole values of his/her publications, and the uniform *division* (*DIV*) the sum of shares of these values (formula (3)). In the literature the *SUM* distribution is also known as *Normal*, *Total*, *Full* or *Whole counting* and the *DIV* distribution as *Fractional* or *Adjusted counting* (Egghe, Rousseau, & Van Hooydonk, 2000; Gauffriau & Larsen, 2005; Lindsey, 1980).

$$SUM(A) = \sum_{Q \in \Psi_A} VAL(Q) \tag{2}$$

$$DIV(A) = \sum_{Q \in \Psi_A} \left[\frac{1}{Q_N} \cdot VAL(Q) \right] \tag{3}$$

The *linear* distribution (*LIN*), also known as *Arithmetic* or *Proportional counting* (Van Hooydonk, 1997), uses a linear function (formula (4)) which includes publication author order.

$$LIN(A) = \sum_{Q \in \Psi_A} \left[\left(\frac{2}{Q_N} \cdot \left(1 - \frac{Q_{Aj}}{Q_N + 1} \right) \right) \cdot VAL(Q) \right] \tag{4}$$

The *geometric* distribution (*GEOM*) of publication values, according to Assimakis and Adam (2010), utilizes formula (5), where λ is a constant, computed based on the number of authors calculated via formula (6) or (7), which provide identical results. Although formulas (6) and (7) have several real roots, here we are only interested in those that satisfy the criterion $0 < \lambda < 1$, and as Assimakis and Adam (2010) mentioned, there is always exactly one such root. Egghe et al. (2000) called a similar approach to publication value distribution the *Pure geometric count*. Comparisons of the *DIV*, *LIN* and *Pure geometric count* methods are provided in (Egghe et al., 2000; Hagen, 2010) and elsewhere.

$$GEOM(A) \sum_{Q \in \Psi_A} [\lambda^{QAj} \cdot VAL(Q)] \tag{5}$$

$$\lambda^{Q_N} + \lambda^{Q_{N-1}} + \cdots + \lambda^1 = 1 \tag{6}$$

$$\lambda^{Q_{N+1}} - 2 \cdot \lambda + 1 = 0 \tag{7}$$

The *gold* distribution (*GOLD*), again introduced by Assimakis and Adam (2010), assigns values to authors using formula (8), where φ is a constant computed as $\varphi^2 + \varphi = 1$, which has only one positive real solution: 0.618. Whereas the *geometric* distribution, with an increasing number of authors, changes the ratios of publication values for all authors, the *gold* distribution changes only the last one. For example, if a publication has three or more authors, the second will always gain 23.6% and the first 61.8% of its value.

$$GOLD(A) = \sum_{Q \in \Psi_A} [VAL(Q) \cdot \Gamma(A)]$$
$$\Gamma(A) = \begin{cases} 1 & Q_N = 1 \\ \varphi^{2 \cdot Q_{Aj} - 1} & Q_{Aj} = 1, \ldots, (Q_N - 1); \quad Q_N > 1 \\ \varphi^{2 \cdot Q_{Aj} - 2} & Q_{Aj} = Q_N \end{cases} \tag{8}$$

We previously used the uniform distributions *SUM* and *DIV* in (Nykl et al., 2014), with the uniform division of values *(DIV)* usually providing better results than did summing whole values *(SUM)*. This is the reason why we here tested other non-uniform distributions *LIN*, *GEOM* and *GOLD*. Another option would be, for example, to employ only first-author counting (Ding, 2011a; Zhao, 2005), but we believe that it is fair to assign even a small part of the publication value to each author. An approach involving the use of only the first-named author would, in our case, be closest to the *GOLD* distribution.

3.3. Experiments with author ranking methods based on publication network evaluation

In order to determine author values based on their publications (5a), we used the publication value distributions described in the previous section, with the publication values themselves calculated in eight different ways. The method in which each publication has a value of 1 (5a1p) should enable the identification of whether it is meaningful to use non-uniform distributions of publication values among authors. Furthermore, the *SUM* distribution, in this case, represents author ranking based on publication count. The PageRank without personalization method should identify the extent of any improvement in the results achieved when using the citation network of publications (5a2p) rather than evaluating the network of authors (2a) or the addition of publication values (5a1p). This method was also used as a secondary baseline. As both citation count (representing author popularity) and PageRank (author prestige) best reflect an author's influence on the scientific community, we further tested PageRank with personalization based on publication citations (5a3p).

The method which provided the best author rankings in (Nykl et al., 2014) – PageRank with personalization in terms of the number of authors of a publication applied to a citation network of publications (5a4p) – was determined by comparing the obtained results with lists of holders of prestigious awards. This is why we can describe author ranking in terms of the PageRank of his/her publications as reflecting the "*author's prestige based on the prestige of his/her publications*...". Personalization based on the number of authors primarily took into account the laboriousness of the publication, which we defined as the amount of resources spent on its creation, and in the present paper was used to indicate the improvement in results achieved by our newly tested methods.

The final indicator of publication quality tested was the value of the journal in which the publication was printed. The best publications are generally accepted by the most important journals in any given scientific area. Our assumption was that the developed method of author evaluation, using publications ranked by journal value, would provide the best author

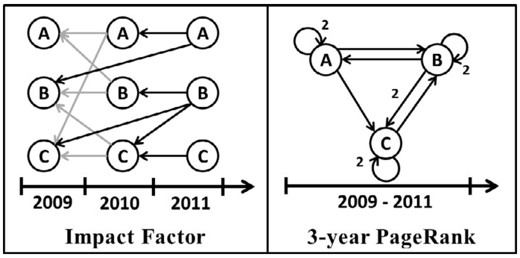

Fig. 6. Difference in the impact factor and 3-year PageRank for a journal network (The gray citations were not used in the Impact Factor computation).

ranking. As we decided to compute and utilize journal values in several different ways, the whole of the following section is devoted to the description of these methods (5a5p–5a8p).

3.4. Journal citation network evaluations

We obtained journal values directly from our data collection, more specifically in terms of two metrics: Impact Factor (Garfield, 1972) and PageRank. We evaluated both journal citation networks, i.e., with all citations (*ALL*) and with author self-citations omitted (NOT). The edge weights represented the number of citations (the *N* variant) in both cases. Another option would have been to use the Impact Factor provided in the JCR of the given year, but this approach was not considered feasible since historical records of the JCR were not available.

The Journal Impact Factor[4] of journal *J* in a given year (e.g., 2011) is here defined as the number of citations in this year (2011) of all items published in journal *J* in the preceding two years (2010 and 2009) divided by the total number of journal *J*'s citable items (i.e., excluding notes, editorials, etc.) published in those two years (2010 and 2009). Note that in the evaluation, the Impact Factor of the citing journals is not taken into account. Evidently, whereas the Impact Factor uses only citations from the year for which it is computed of publications issued in the two preceding years, PageRank utilizes the whole citation network. For at least a partial comparison of PageRank and Impact Factor, we also decided to evaluate (via PageRank) citation sub-networks created by three-year windows, e.g., 1996–1998, 1997–1999, etc. We call this type of evaluation a *3-year PageRank*. The difference between networks in terms of the Impact Factor and 3-year PageRank is shown in Fig. 6. Gray citations are not included into the Impact Factor computation, because they do not come from the year for which the Impact Factor is computed.

We then used these journal values in four different methods of publication evaluation. The first of these methods assigns to each publication the value of the journal in which it was published (5a5p). This method, compared to that assigning a value of 1 to every publication (5a1p), should indicate whether it is beneficial to use specific journal values. The other three methods modify PageRank applied to publication citation networks: (5a7p) uses the journal values for publication personalization, (5a8p) uses them as the weights of publication input edges, and (5a6p) uses both.

4. Results and discussion

We used all the described methods of citation network evaluation, and compared the resulting author orders (sorted by rank) with the lists of awarded scientists. Table 4 summarizes the results of the tested methods and shows their rank (*r.*) from best (1) to worst (12). Note that the lower the value, the better the results provided by the given method. The lowest average rank of awarded authors, obtained by the method with *r.* = 1, is shown in the last (m_{best}) row of the table for each list of awarded authors. As each method has multiple variants (different edge weights; distributions of publication values; self-citations; etc.), here we present only those variants which provided the best awarded author ranks (a more detailed evaluation is described in the following sections). The deterioration in ranking provided by any given method from the best one is depicted in the percentage ($m_{\%}$) column. The value of the average position of awarded authors *avg(m)* in the ranking obtained by the best variant of a given method *m*, can be reconstructed via formula (9), which utilizes the average position of awarded authors in the ranking obtained by the best of our methods (line m_{best}) and the percentage deterioration of method *m* from m_{best}.

$$avg(m) = m_{best} \cdot \left(1 + \frac{m_{\%}}{100}\right) \tag{9}$$

The results of both the global computer science and category-independent evaluations were also compared using the boxplots depicted in Fig. A2 in the appendix. These boxplots show the relative positions of awarded authors, computed by dividing the obtained rankings of awarded authors by the number of authors evaluated. The first and the last quarters are not shown because the tested methods were generally able to rank at least one awarded author among the best authors

[4] Computation of Journal Impact Factor in the WoS database – http://admin-apps.webofknowledge.com/JCR/help/h_impfact.htm

Table 4
Comparison of the developed author ranking methods (the *r.* columns represent the rank of a given method and the $m_{\%}$ columns the percentage deterioration from the method providing the best author ranking m_{best}).

Authors awarded between 1994 and 2014												
Network	Method		Global		Category-independent				Category-dependent			
			Fellows 576/157440		AI 133/39891		HW 76/29243		AI 133/39891		HW 76/29243	
			r.	$m_{\%}$	*r.*	$m_{\%}$	*r.*	$m_{\%}$	*r.*	$m_{\%}$	*r.*	$m_{\%}$
Author	1a	H-index	12	35%	12	31%	11	24%	12	38%	11	29%
	2a	PageRank	11	23%	11	29%	10	17%	11	29%	10	25%
	3a	H-index personalization	10	21%	10	26%	8	10%	10	29%	8	21%
	4a	Publication count personalization	**6**	**7%**	**7**	**13%**	**5**	**8%**	**5**	**11%**	**5**	**14%**
Publication	5a1p	Values 1	9	20%	9	22%	12	29%	9	25%	12	54%
	5a2p	PageRank	5	5%	4	12%	6	9%	4	11%	7	19%
	5a3p	In-degree personalization	7	8%	6	13%	7	10%	7	13%	**4**	**9%**
	5a4p	Author count personalization	**3**	**4%**	**3**	**8%**	**3**	**5%**	**3**	**7%**	9	21%
	5a5p	Values based on the journal values	8	10%	8	15%	9	12%	8	19%	3	6%
	5a6p	Journal values in person. and edges	2	0.4%	2	2%	2	0.1%	2	1.5%	**1**	**0%**
	5a7p	Journal values personalization	**1**	**0%**	**1**	**0%**	**1**	**0%**	**1**	**0%**	2	1.0%
	5a8p	Journal values in incoming edges	4	4%	5	12%	4	7%	6	12%	6	17%
Minimum average authors position ($\boldsymbol{m_{best}}$)			24315		7892		4949		9515		4715	

(e.g., among the first fifteen positions, see Section 4.3). Also, in *ACM Fellows*, at least one author was always placed among the worst authors.

Analysis of the results revealed that:

- The h-index (1a) was often the worst method for evaluating authors, worse even than a simple count of publications (5a1p). This fact is evidently caused by the low resolution of the h-index. As shown in Fig. A1 in the appendix and mentioned earlier in Section 2.1, whereas the h-index was able to distribute authors in our whole WoS collection into only 16 groups, the number of publications method was able to distinguish 101 such groups. Taking a more specific example, whereas the best 105 authors were split into only 6 groups based on the h-index, the same authors were split into 51 groups based on publication count.
- Using author maturity as a PageRank personalization (h-index, 3a) provided worse results than using his/her productivity (publication count, 4a). However, method (3a) proved to be better than the baseline (2a).

Methods based on the relative importance of publications (5a) showed that:

- Evaluating a publication citation network provided a better author ranking than did the evaluation of author citation networks (PageRank without personalization, applied to a publication citation network (5a2p), proved more effective than our best author network evaluation method (4a)).
- The method based on publication popularity (citation count, 5a3p) was the only one to provide worse results than its respective baseline (5a2p). The addition of popularity into the prestige computation therefore likely has a negative effect, and thus it is better to include other measures of publication quality.
- Using any measure of journal importance improved the final ranking of all methods based on author productivity (5a1p compared with 5a5p).
- Using journal importance for PageRank personalization when evaluating a publication network (5a7p) provided the best author ranking results of any method, thus confirming our main assumption that the best results would be obtained by utilizing journal values in a publication citation network.
- Although changing the weights of edges between publications based on journal values (5a8p) often resulted in a slight improvement in comparison with the baseline (5a2p), using journal importance as a personalization method in combination with weights of input edges (5a6p) provided slightly worse results for the best of our methods (5a7p). In both cases the changes were at max. 2%.
- For completeness: although in-degree of publications provided better results than in-degree of authors, these results differed by 24% from those obtained via the very best method (5a7p1j). The performance of the h-index was worse by an average of 34%.

Based on the presented results, we cannot conclusively determine whether we obtained a better author ranking via category-independent or category-dependent evaluation (see Table 4). Nevertheless, as category-dependent evaluation in the *Hardware* category exhibited larger deviations, likely caused by the larger number of isolated nodes and smaller number of citations in the respective networks (and also eventually by a smaller number of awarded authors), we suggest using category-independent evaluation. This approach uses data from the whole network to determine author values (similar to how Google orders search results), and therefore these values more closely correspond to an author's overall publication/scientific effort. On the other hand, an author who has written only one publication, e.g., in the Hardware area, but who is much renowned within the whole collection, will be ranked very positively in the HW category (a discrepancy which would not happen in category-dependent evaluation). This behavior can be removed by employing one of the following options, none of which were tested here:

- Publication values are computed from the whole publication citation network, but author values are determined only from publications in the given category.
- Author values, computed based on all publications, are multiplied by a ratio of the number of his/her publications published in the given category, to his/her total number of publications. This should take into account the author's productivity in the given category.

Our methods have several degrees of freedom (different edge weights, distributions of publication values, self-citations, damping factors, etc.), with the results compared in Table 4 the best achievable using these methods, i.e., they were obtained based on a specific set of parameters. Although this technique can lead to a phenomenon known in the areas of statistics and machine learning as overfitting[5] (Hawkins, 2004), such a problem can be considered unlikely here because we assessed the quality of author rankings using three different lists of awarded authors, and the results did not vary by a large amount

[5] A statistical or machine learning model that has been overfit will generally makes accurate predictions for examples in the training set (a model memorizes the training data), but does not generalize well enough to make accurate predictions regarding new, previously unseen examples.

(see Tables 4 and 6). The sensitivity of PageRank to different parameters has been discussed in more detail by, for example, Langville and Meyer (2006a, chapter 6).

4.1. Discussion of the results of author network experiments

Although the methods developed for evaluating the author citation network did not provide the best ranking of authors, for the sake of completeness we will now discuss how to achieve optimal results with each of these methods:

(1a) H-index – remove self-citations at the publication level (h-index without self-citations),
(2a) PageRank without personalization – $d = 0.85$,
(3a) H-index personalization – $d = 0.45$, h-index without self-citations,
(4a) Personalization based on number of publications – $d = 0.55$, self-citations removed at the publication level.

As the list of method parameters does not include those which cannot be clearly identified by the given method (self-citation type or edge weights), the following section describes how sensitive the applied computations are to those parameters. Differences in author rankings obtained via evaluations using various parameters can be demonstrated based on either Spearman rank correlation coefficients (see Fig. A3 in the appendix), the number of the same people in the best positions, or the number of awarded people in the best positions in the final author order.

Author ranks obtained using the h-index with all citations and the h-index without self-citations were found to have a correlation coefficient of 0.95; the ranks produced via these two methods contained the same authors in the top 10 positions, and shared 95 of the top 100 authors. The similarity of both variants can be attributed to the rather low resolution of the h-index.

Analysis of Spearman rank correlation coefficients also revealed author network evaluation to be more affected by the type of self-citation used than the weights of edges. This roughly corresponds to similar numbers of awarded authors in the best positions in the final rankings. An interesting (although not strictly important) fact is that if we focus on the same authors found at the best positions, more similar values are gained by using variants with the same type of weight, than by using the same type of self-citation. According to the obtained correlation coefficient values, the largest difference was found using networks with removed self-citations at the publication level. Based on the difference between min. and max. coefficients, it can be stated that the most stable author ranking was provided by personalization based on the number of publications (4a), where the lowest correlation value obtained was 0.96. In contrast, the largest differences were associated with PageRank without personalization (2a), with the lowest value being 0.88.

When comparing method parameters in terms of the number of awarded authors in the top 10 and 100 positions, the best evaluations were those carried out on a network with self-citations removed at the publication level. When using the top 1000 positions, those variants using self-citations removed at the author level were slightly better. Based on these results, one can conclude that self-citations should not be taken into account when evaluating author citation networks.

4.2. Discussion of author ranking methods based on publication network evaluation

The results of our experiments involving distributing publication values among authors (5a) revealed that whereas the *DIV* distribution usually performed better in global computer science author ranking, the *SUM* distribution was always the best performer in category-based evaluation. Because of the similarity between the *GEOM* distribution and the variant in which only the first few authors of a publication are used for author evaluation (see Assimakis and Adam, 2010), one can argue that it is always better to consider all authors of a publication, and that each of them should be assigned the same value (*SUM* or *DIV*). This approach also does not handicap authors who have been placed in "worse" positions (for instance due to alphabetic reasons), despite the fact that their contribution to the publication may have been significant (Waltman, 2012).

Fig. A4 in the appendix presents a comparison of the various distributions of publication values to authors used in the methods computing author productivity (5a1p and 5a5p). These comparisons are based on Spearman correlation coefficients. For the method employing journal values (5a5p), the publication values are substituted by PageRank journal values (1j) obtained from the journal citation network including all citations. Evidently, using the journal values improves author ranking, with the *SUM* and *DIV* distributions achieving better results than non-uniform distributions; however, the *DIV* distribution was itself more strongly correlated with non-uniform distributions than with *SUM*.

As already mentioned, journal values were best used solely for the personalization of publications, with their simultaneous application as weights of input edges worsening the produced author rankings (see Table 4). For the *AI* category, it was slightly better to use journal Impact Factor values (2j), but for the rest of the list of awarded authors, journal PageRank proved more effective (1j). Although the difference in author rankings obtained using different journal values was very small, we recommend using journal PageRank values. PageRank based on the whole journal network (1j) usually provided better results than 3-year PageRank (3j), a discrepancy probably caused by the application of a larger amount of data.

A comparison of the Impact Factor and 3-year PageRank methods is provided in Fig. A5 in the appendix. The smallest correlation between the different metrics was recorded between Impact Factor *NOT* and PageRank *ALL* (average correlation value 0.55), and the largest correlation between Impact Factor *NOT* and PageRank *NOT* (average correlation value 0.70).

The type of self-citations used in the journal network had only a small influence on the final author rankings. This is probably due to the fact that the journal network includes only a small number of nodes (386), with a large number of citations distributed among them (either 191447 for all citations, or 145372 if self-citations at the publication level are removed). Removing self-citations generally influenced only edge weight (only 356 out of 20 488 edges removed from the journal network). As the awarded authors almost certainly published their works in important journals, their positions in the final rankings should not significantly change. This is why it probably does not matter which type of self-citations are used in the journal network. Even so, variants including all citations provided slightly better results in global computer science author rankings.

For the sake of completeness, we here provide comparisons of the *SUM* and *DIV* distributions and some of the methods employed for author evaluation, using the publication citation network without author self-citations. The remaining method parameters were assigned according to the best of our variants:

- 5a2p, 5a8p; $d = 0.85$
- 5a3p, 5a4p; $d = 0.75$
- 5a6p, 5a7p; d = 0.55
- and 5a6p, 5a7p, 5a8p, with journal PageRank values obtained from the journal citation network including all citations.

The developed methods of author evaluation were also compared with Spearman correlation coefficients (Fig. A6 in the appendix) and the number of awarded authors occupying the best positions in the final rankings. Analysis of the correlation coefficients clearly reveals that those methods using personalization based on journal values (5a6p a 5a7p) differ the most from the other methods. Interestingly, these methods exhibit a higher correlation with the method combining journal values as input edge weights and no personalization, rather than those using other personalizations (5a3p, 5a4p). Furthermore, methods (5a6p) and (5a7p) provided almost identical author rankings (correlation 0.9985). These findings are confirmed by comparisons based on the number of the same authors in the best ranking positions. Finally, it should be noted that in this case even *SUM* and *DIV* are not highly correlated (the highest value being 0.92).

4.3. The best authors from the best of our evaluation methods

Many papers dealing with author evaluation depict their results in terms of the best positions achieved by authors in the rankings obtained via the tested method. For demonstration, we here chose five methods, whose parameters were set according to those variants providing the best rankings of authors awarded with an *ACM Fellowship* (highest number of awarded authors). Table 5 shows the authors ranked in the 15 top positions in the rankings obtained using these parameters:

- All cases below have self-citations removed at the publication level. Journal networks always contain all citations.
- (5a7p1j) Publication citation network; $d = 0.55$; personalization based on journal PageRank values; *SUM* distribution.
- (5a6p1j) Publication citation network; $d = 0.55$; personalization and input edge weights set according to journal PageRank values; *SUM* distribution.
- (5a8p1j) Publication citation network; $d = 0.85$; input edge weights set according to journal PageRank values; *DIV* distribution.
- (5a4p) Publication citation network; $d = 0.75$; personalization based on the number of authors of a publication; *DIV* distribution.
- (4a) Author citation network; $d = 0.55$; personalization based on author's number of publications; edge weights $1/N$.

From Table 5 it is apparent that the methods including personalization based on journal values (5a7p1j and 5a6p1j) vary considerably from each other. For example, *HOLZMANN*, who is ranked in position 6 using method (4a), is ranked only in position 1145 using method (5a7p1j). On the other hand, column (5a8p1j) seems to unify the surrounding columns – authors ranked among the 15 best in other columns being ranked among the 63 best in this column. A search for awarded authors (marked with *) reveals that most of them are ranked among the top 15, particularly in the method based on author network evaluation (4a). Although these findings are not necessarily significant, it would be interesting to identify their causes and as such could be a topic for further research.

4.4. Prediction of awarded authors

Because our ranking lists contained authors awarded after the year 2005 (the last year in our WoS collection), we also used the developed methods to determine how they ranked these particular individuals. The aim of this task was to establish whether our methods could be used for the prediction of future awarded authors. In our entire WoS collection (1996–2005), we found 206 holders of *ACM Fellowships* awarded after the year 2005. In the *Artificial Intelligence* category we identified 62

Table 5
Authors occupying the top 15 positions in the rankings obtained via the selected methods (those authors not among the top 15 in the relevant column but who are among the top 15 in any of the other columns are mentioned in the lower half of the table. Authors who appear at least once in the top 3 positions are shown in bold, and awarded authors are marked with *).

	5a7p1j	5a6p1j	5a8p1j	5a4p	4a
1.	**JAIN, AK***	**JAIN, AK***	**SIMON, DR**	**BREIMAN, L***	**BREIMAN, L***
2.	**OSHER, S**	**OSHER, S**	**BREIMAN, L***	**JAIN, AK***	**JAIN, AK***
3.	**PEDRYCZ, W**	**PEDRYCZ, W**	**JAIN, AK***	**MOLTENBREY, K**	**ZADEH, LA***
4.	WANG, J	AMARI, S	**MOLTENBREY, K**	YAGER, RR*	HYVARINEN, A
5.	KIM, J	WANG, J	YAGER, RR*	**SIMON, DR**	BURGES, CJC
6.	AMARI, S	KIM, J	VAZIRANI, U	ROBERTSON, B	HOLZMANN, GJ*
7.	YAGER, RR*	YAGER, RR*	BERNSTEIN, E	**ZADEH, LA***	YAGER, RR*
8.	TANAKA, K	TANAKA, K	**ZADEH, LA***	**PEDRYCZ, W**	AMARI, S
9.	KIM, JH	KITTLER, J	ROBERTSON, B	CHANG, CC	PAXSON, V*
10.	YAN, H	LI, J	**PEDRYCZ, W**	WANG, J	OJA, E
11.	LI, J	ZHU, SC	AMARI, S	HYVARINEN, A	CIMINO, JJ
12.	SAPIRO, G	KIM, JH	DIETTERICH, TG*	LEE, J	TANAKA, K
13.	WANG, Y	YAN, H	HYVARINEN, A	AMARI, S	PENTLAND, A
14.	LEE, J	KANADE, T*	TANAKA, K	LEE, S	HARTLEY, RI
15.	KITTLER, J	LEE, J	CHANG, CC	KIM, J	**PEDRYCZ, W**
	(19) CHANG, CC	(16) SAPIRO, G	(16) WANG, J	(16) OJA, E	(16) DIETTERICH, TG*
	(22) KANADE, T*	(17) WANG, Y	(17) LEE, J	(17) TANAKA, K	**(21) SIMON, DR**
	(23) ZHU, SC	(24) CHANG, CC	(19) OJA, E	(18) BURGES, CJC	(23) KIM, J
	(25) LEE, S	(27) PENTLAND, A	(21) KIM, J	(20) KIM, JH	(27) LEE, J
	(26) BREIMAN, L*	(29) LEE, S	(22) LEE, S	(21) VAZIRANI, U	(29) KANADE, T*
	(29) OJA, E	**(34) BREIMAN, L***	(24) HARTLEY, RI	(22) YAN, H	(30) WANG, J
	(31) PENTLAND, A	(35) OJA, E	(25) HOLZMANN, GJ*	(23) CIMINO, JJ	(33) SAPIRO, G
	(55) HYVARINEN, A	(52) HYVARINEN, A	(28) YAN, H	(24) WANG, Y	(35) CHANG, CC
	(114) HARTLEY, RI	(88) HARTLEY, RI	(29) KIM, JH	(26) BERNSTEIN, E	(37) ZHU, SC
	(124) ZADEH, LA*	**(118) ZADEH, LA***	(31) PAXSON, V*	(27) DIETTERICH, TG*	(38) LEE, S
	(140) MOLTENBREY, K	(138) VAZIRANI, U	(34) LI, J	(29) LI, J	(46) YAN, H
	(150) VAZIRANI, U	**(153) MOLTENBREY, K**	(39) PENTLAND, A	(30) HOLZMANN, GJ*	(49) KIM, JH
	(235) BERNSTEIN, E	(223) BERNSTEIN, E	(43) WANG, Y	(40) PENTLAND, A	(52) KITTLER, J
	(239) BURGES, CJC	(347) ROBERTSON, B	(48) CIMINO, JJ	(41) PAXSON, V*	(53) LI, J
	(311) ROBERTSON, B	(426) CIMINO, JJ	(49) BURGES, CJC	(46) HARTLEY, RI	(57) WANG, Y
	(362) CIMINO, JJ	(494) PAXSON, V*	(51) ZHU, SC	(51) SAPIRO, G	**(59) OSHER, S**
	(611) PAXSON, V*	(540) BURGES, CJC	**(55) OSHER, S**	(54) KITTLER, J	**(77) MOLTENBREY, K**
	(616) DIETTERICH, TG*	(556) DIETTERICH, TG*	(57) KANADE, T*	**(59) OSHER, S**	(87) VAZIRANI, U
	(642) SIMON, DR	**(590) SIMON, DR**	(59) KITTLER, J	(76) KANADE, T*	(111) BERNSTEIN, E
	(1145) HOLZMANN, GJ*	(997) HOLZMANN, GJ*	(63) SAPIRO, G	(91) ZHU, SC	(164) ROBERTSON, B

holders, with 49 found in the *Hardware* category. The results obtained using each of the methods are compared in Table 6, which is similar in structure to Table 4.

Because one can draw almost the same conclusions from Table 6 as from Table 4, one can assume that the developed author ranking methods could also be used for the prediction of future awardees. Indeed, the results only differ for the method involving personalization based on popularity (number of publication's citations, 5a3p), which in this case performed better than PageRank without personalization (5a2p). This did not apply, however, when using all entries from the lists of awarded authors.

4.5. Can our PageRank methods outperform the citation count?

In a recently published paper (Fiala et al., 2015), the authors claim that there is "*no evidence that author ranking methods similar to PageRank outperform simple citation count*". In reaction to this statement, we would like to discuss why, at least according to our results, we cannot agree with this argument. The main problem is that there is no unified author ranking method, and thus any individual wishing to evaluate these methods must develop his/her own technique. For this purpose, Sidiropoulos and Manolopoulos (2006) utilized lists of the holders of the *ACM Codd Award*, with later studies also often employing similar lists for different prestigious awards, which is the case here. Other analyses have been undertaken based on data regarding the program committees of scientific conferences (e.g., Liu et al., 2005) or the editorial boards of scientific journals (e.g., Fiala et al., 2015).

One could also argue that the main conclusion reached by Fiala et al. (2015) is "only" that chosen members of editorial boards are better ranked by measures of popularity (citation count), rather than by measures of prestige (PageRank-based methods). Besides, as the authors themselves admit, the holders of the important *ACM Turing Award* are better ranked by measures of prestige. This means that the holders of important awards are rightfully regarded as prestigious and thus lists of these authors are better employed for evaluating methods which measure prestige. On the other hand, members of editorial boards can be considered as popular. The correctness of using awarded authors for evaluating measures of prestige is demonstrated by our analyses (along with those of Ding (2011a), Fiala (2012), Sidiropoulos and Manolopoulos

Table 6
Comparison of author ranking methods for authors awarded between 2006 and 2014 (The *r*. columns represent the rank of the given method, and the $m_{\%}$ columns the percentage deterioration from the method providing the best author ranking m_{best}).

Only authors awarded between 2006 and 2014												
Network		Method	Global		Category-independent				Category-dependent			
			Fellows 206/157440		AI 62/39891		HW 49/29243		AI 62/39891		HW 49/29243	
			r.	$m_{\%}$	*r*.	$m_{\%}$	*r*.	$m_{\%}$	*r*.	$m_{\%}$	*r*.	$m_{\%}$
Author	1a	H-index	12	40%	11	23%	11	26%	12	57%	8	15%
	2a	PageRank	11	25%	12	25%	10	23%	11	45%	9	16%
	3a	H-index personalization	9	24%	10	19%	8	15%	10	45%	6	10%
	4a	Publication count personalization	**4**	**3%**	**7**	**9%**	**7**	**13%**	**7**	**21%**	**5**	**9%**
Publication	5a1p	Values 1	8	20%	8	15%	12	29%	9	35%	12	56%
	5a2p	PageRank	7	4%	5	7%	6	12%	5	17%	10	17%
	5a3p	In-degree personalization	5	3%	4	6%	5	11%	4	14%	**1**	**0%**
	5a4p	Author count personalization	**3**	**0.6%**	**3**	**5%**	**3**	**3%**	**3**	**13%**	11	19%
	5a5p	Values based on the journal values	10	25%	9	17%	9	18%	8	22%	4	7%
	5a6p	Journal values in person. and edges	**1**	**0%**	2	3%	**1**	**0%**	2	2%	**2**	**3%**
	5a7p	Journal values personalization	2	0.04%	**1**	**0%**	2	0.6%	**1**	**0%**	3	5%
	5a8p	Journal values in incoming edges	6	4%	6	7%	4	10%	6	18%	7	15%
Minimum average authors position ($\boldsymbol{m_{best}}$)			17 973		7404		5466		7623		5579	

(2006) and others). One of the conclusions made here is that methods involving counting publication citations provide better author rankings (measured using awarded authors) than methods counting author citations. Indeed, the latter methods were approximately 24% less effective than our best method based on PageRank (5a7p1j). Fiala et al.'s evaluations may also have been influenced by the small number of authors on each of their reference lists (32 in *Artificial Intelligence*, 12 in *Software Engineering*, and 17 in *Theory & Methods*).

5. Conclusion

The present paper describes our research involving the ranking of authors of scientific publications, based on citation analysis. Based on data obtained from the ISI Web of Science (Computer Science categories, 1996–2005), we created citation networks of publications, authors and journals. We then conducted tests aimed at identifying which network evaluation method produced results closest to human-made author ranks – a network of authors, network of publications or network of publications enriched by journal values.

We also worked with other measures of author or publication quality (h-index, publication count, citation count, and author count). The final author rankings were then compared using the average position of awarded authors, with the list of awardees constructed on the basis of the *ACM Fellow* award, which was used for the evaluation of author-ranking methods in combination with the global computer science citation networks. In order to test how our methods ranked authors in specialist categories we chose the *Artificial Intelligence* and *Hardware* categories, with the final author rankings then compared to the holders of awards from ACM SIGs in the respective category.

Furthermore, we also experimented with two forms of evaluation:

- category-independent – authors (who belong to a given category) were chosen from the global computer science author rankings, with awarded authors searched for from among this group.
- category-dependent – author rankings were obtained from the evaluation of a network for the given category.

The results revealed that the best overall method for author evaluation (5a7p1j) possesses the following characteristics:

- uses PageRank, rather than non-iterative approaches (in-degree, publication count, h-index),
- evaluates a publication network with author self-citations removed, rather than an author network. It is also better to distribute publication values among authors using a uniform division or by summing whole publication values.
- uses publication personalization based on PageRank journal values, rather than any other personalization type.

Interestingly, these findings were also confirmed by an evaluation in which we used only authors awarded after 2005 (the final year covered by our WoS collection). Based on the obtained results, we can say that the best of our author-ranking methods might also be useful for identifying authors who will likely be awarded in the near future.

Category-independent evaluation provided the best results among the tested category-based author evaluation methods (data from the whole citation network were used to compute the values of publications/authors). However, we recommend that further experiments be undertaken in which author values are obtained from evaluations which take into account author productivity in the given category, as opposed to all categories in which he/she published.

Analyses also revealed that the use of personalization based on publication popularity (citation count) or author maturity (h-index) did not provide better results than the personalization methods tested earlier. Although h-index personalization proved more effective than no personalization, the results were still worse than those achieved via personalization based on author productivity (publication count). Personalization based on citation count performed worse than PageRank without such personalization, and so one can state that adding popularity into the computation of prestige is undesirable.

Besides experimenting with category-independent evaluation or with quality criteria for the computed rankings, further work should include the utilization of a domain classification system (e.g., ACM Computing Classification System[6]) or ontology (e.g., DBpedia[7]) as a more advanced author search method. Another interesting area for future study could involve analyses aimed at determining the prestige of groups, departments or institutions.

Acknowledgement

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[6] ACM Computing Classification System – http://www.acm.org/about/class/ and the 2012 example – http://delivery.acm.org/10.1145/2380000/2371137/ACMCCSTaxonomy.html

[7] DBpedia – http://www.dbpedia.org and the *Data mining* example – http://dbpedia.org/page/Category:Data_mining

Appendix.

See Figs. A1–A6

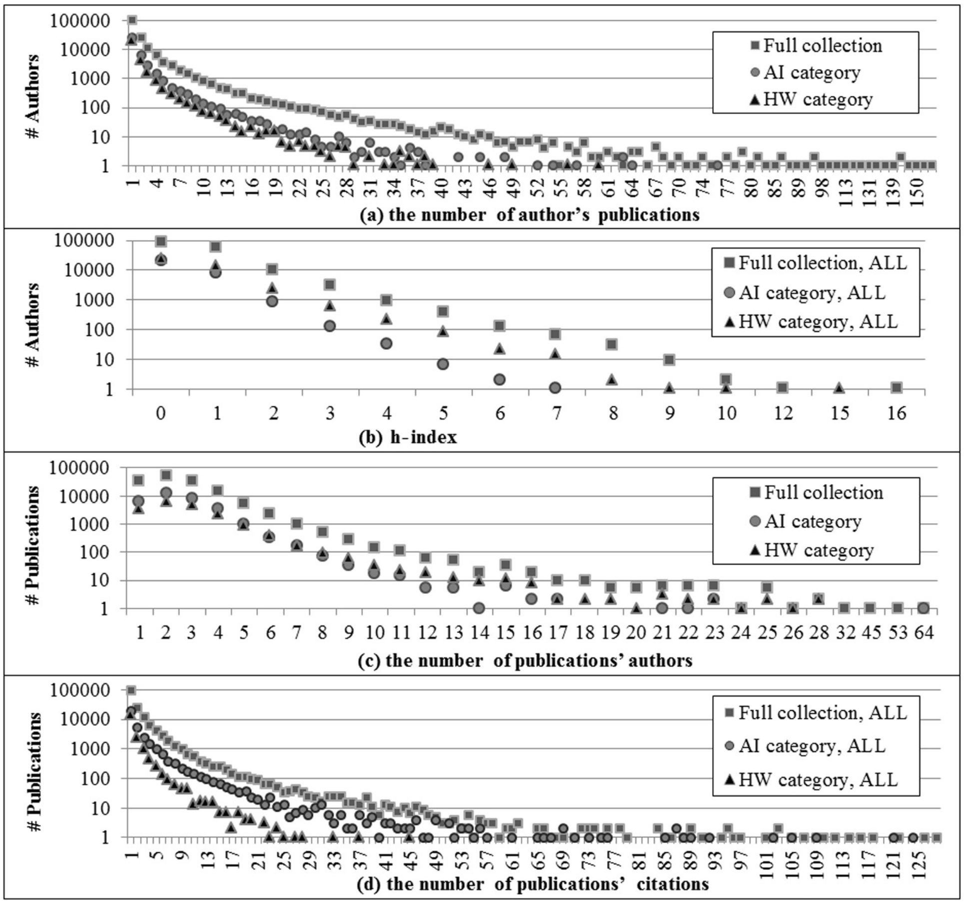

Fig. A1. Features of the WoS collection used in our experiments (the horizontal axes depict the different metrics and the vertical axes the number of authors/publications for the given value; empty sets are not included and all graphs have a logarithmic scale).

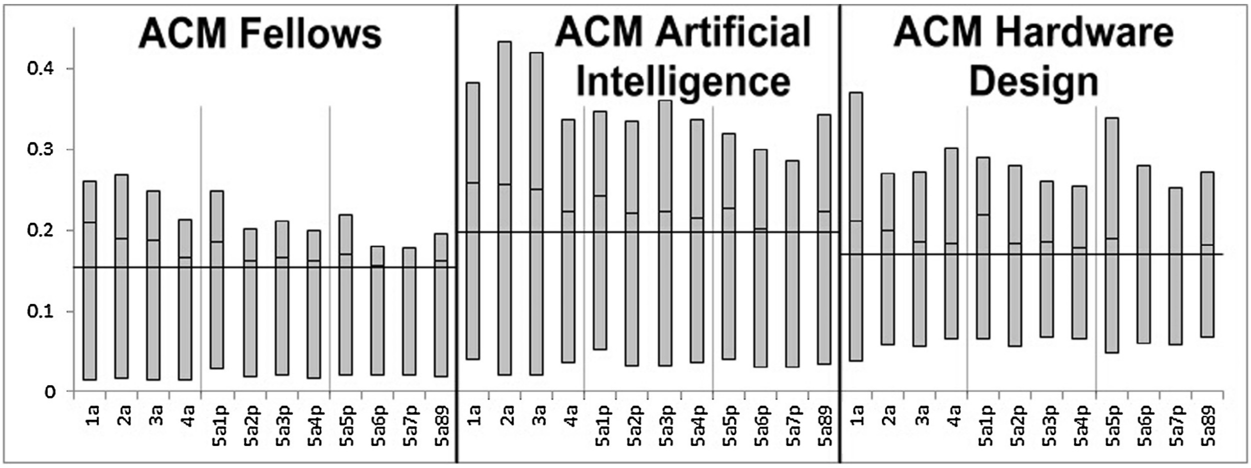

Fig. A2. Boxplots comparing our methods based on the relative awarded author ranks (the top edge of each bar marks the 75th percentile and the bottom edge the 25th percentile of the ranks assigned to the authors on the awarded author lists; the short line dividing each box into two sections is the average rank and the straight line in each section of the chart denotes the average rank yielded by the best of our methods in this section).

(2a) PageRank

		ALL			PART			NOT		
		N	1/N	1	N	1/N	1	N	1/N	1
ALL	N	x	99	100	99	98	98	89	88	89
	1/N	99	x	98	97	99	97	89	90	89
	1	100	98	x	99	98	99	90	88	90
PART	N	99	97	99	x	99	100	91	89	90
	1/N	98	99	98	99	x	98	90	91	90
	1	98	97	99	100	98	x	91	89	91
NOT	N	89	89	90	91	90	91	x	99	100
	1/N	88	90	88	89	91	89	99	x	99
	1	89	89	90	90	90	91	100	99	x

(3a) H-index personalization

		ALL			PART			NOT		
		N	1/N	1	N	1/N	1	N	1/N	1
ALL	N	x	99	100	100	99	99	94	93	94
	1/N	99	x	99	99	100	98	94	94	93
	1	100	99	x	99	99	100	94	93	94
PART	N	100	99	99	x	99	100	94	93	94
	1/N	99	100	99	99	x	99	94	95	94
	1	99	98	100	100	99	x	94	94	95
NOT	N	94	94	94	94	94	94	x	99	100
	1/N	93	94	93	93	95	94	99	x	99
	1	94	93	94	94	94	95	100	99	x

(4a) Publication count personalization

		ALL			PART			NOT		
		N	1/N	1	N	1/N	1	N	1/N	1
ALL	N	x	99	100	100	99	99	96	96	96
	1/N	99	x	99	99	100	98	96	97	96
	1	100	99	x	100	99	100	96	96	96
PART	N	100	99	100	x	99	100	97	96	96
	1/N	99	100	99	99	x	99	96	97	96
	1	99	98	100	100	99	x	97	96	97
NOT	N	96	96	96	97	96	97	x	99	100
	1/N	96	97	96	96	97	96	99	x	99
	1	96	96	96	96	96	97	100	99	x

Fig. A3. Comparison of the parameters used in author network evaluation based on Spearman rank correlation coefficients (other parameters set according to the list in Section 4.1; coefficients are multiplied by 100, and better values are depicted with a lighter gray background).

		Publications with 1 values (5a1p)					Publications wits the Journal PageRank values (5a5p1j)				
		SUM	DIV	LIN	GEOM	GOLD	SUM	DIV	LIN	GEOM	GOLD
1 values (5a1p)	SUM	x	81	70	73	76	58	54	51	50	51
	DIV	81	x	95	96	95	67	73	70	70	71
	LIN	70	95	x	98	96	64	73	76	77	77
	GEOM	73	96	98	x	99	65	71	73	74	75
	GOLD	76	95	96	99	x	64	69	71	72	74
Journal PageRank (5a5p1j)	SUM	58	67	64	65	64	x	95	91	89	87
	DIV	54	73	73	71	69	95	x	97	96	94
	LIN	51	70	76	73	71	91	97	x	99	98
	GEOM	50	70	77	74	72	89	96	99	x	100
	GOLD	51	71	77	75	74	87	94	98	100	x

Fig. A4. Comparison of publication value distributions based on Spearman rank correlation coefficients (coefficients are multiplied by 100, and better values are depicted with a lighter gray background).

year	1998				1999				2000				2001			
M.	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N
PR_A	x	87	71	59	x	88	66	53	x	85	68	55	x	86	60	48
PR_N	87	x	73	75	88	x	69	69	85	x	64	68	86	x	62	65
IF_A	71	73	x	88	66	69	x	87	68	64	x	86	60	62	x	87
IF_N	59	75	88	x	53	69	87	x	55	68	86	x	48	65	87	x

year	2002				2003				2004				2005			
M.	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N	PR_A	PR_N	IF_A	IF_N
PR_A	x	86	63	53	x	89	66	57	x	88	66	55	x	88	65	56
PR_N	86	x	68	70	89	x	67	71	88	x	66	69	88	x	66	71
IF_A	63	68	x	87	66	67	x	88	66	66	x	86	65	66	x	87
IF_N	53	70	87	x	57	71	88	x	55	69	86	x	56	71	87	x

Fig. A5. Correlations between Impact Factor and 3-year PageRank in the evaluation of journal networks; PR_A – 3-year PageRank *ALL*; PR_N – 3-year PageRank *NOT*; IF_A – Impact Factor *ALL*; IF_N – Impact Factor *NOT*; (period 1998–1995 is marked 1998, etc.; coefficients are multiplied by 100, and better values are depicted with a lighter gray background).

.

		SUM						DIV					
		5a2p	5a8p	5a3p	5a4p	5a6p	5a7p	5a2p	5a8p	5a3p	5a4p	5a6p	5a7p
SUM	5a2p	x	97	97	97	87	88	91	89	90	94	80	81
	5a8p	97	x	94	97	91	91	91	91	89	94	83	84
	5a3p	97	94	x	94	86	87	87	85	92	90	78	79
	5a4p	97	97	94	x	87	88	85	83	84	89	75	76
	5a6p	87	91	86	87	x	100	82	83	83	85	92	91
	5a7p	88	91	87	88	100	x	82	83	83	86	91	91
DIV	5a2p	91	91	87	85	82	82	x	99	97	99	90	90
	5a8p	89	91	85	83	83	83	99	x	96	99	92	92
	5a3p	90	89	92	84	83	83	97	96	x	97	89	89
	5a4p	94	94	90	89	85	86	99	99	97	x	90	90
	5a6p	80	83	78	75	92	91	90	92	89	90	x	100
	5a7p	81	84	79	76	91	91	90	92	89	90	100	x

Fig. A6. Comparison of publication network evaluation methods based on Spearman rank correlation coefficients (coefficients are multiplied by 100, and better values are depicted with a lighter gray background).

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