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Do PageRank-based author rankings outperform simple citation counts?

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ABSTRACT

The basic indicators of a researcher's productivity and impact are still the number of publications and their citation counts. These metrics are clear, straightforward, and easy to obtain. When a ranking of scholars is needed, for instance in grant, award, or promotion procedures, their use is the fastest and cheapest way of prioritizing some scientists over others. However, due to their nature, there is a danger of oversimplifying scientific achievements. Therefore, many other indicators have been proposed including the usage of the PageRank algorithm known for the ranking of webpages and its modifications suited to citation networks. Nevertheless, this recursive method is computationally expensive and even if it has the advantage of favouring prestige over popularity, its application should be well justified, particularly when compared to the standard citation counts. In this study, we analyze three large datasets of computer science papers in the categories of artificial intelligence, software engineering, and theory and methods and apply 12 different ranking methods to the citation networks of authors. We compare the resulting rankings with self-compiled lists of outstanding researchers selected as frequent editorial board members of prestigious journals in the field and conclude that there is no evidence of PageRank-based methods outperforming simple citation counts.

1. Introduction and related work

Ranking researchers has become very popular due to the possible applications in various hiring, promotion, grant, or award procedures, in which manual assessment can be efficiently supplemented with automated techniques. Apart from counting the research money granted, the easiest way to evaluate a researcher's performance is to estimate the quantity and quality of scholarly publications he/she has produced. The former concentrates on production (or productivity) and the latter on impact (or influence). In its basic form, production is the number of research papers a scientist has published and impact is the number of citations from other research publications these papers have attracted. These two simple indicators may already form a basis for an easy ranking of researchers (or authors as all of these evaluations are based on the authorship of research publications). One of the drawbacks of this simplistic approach is that it does not differentiate between popularity and prestige, i.e. it considers all citations as equivalent. In the practice, however, a citation by a Nobel Prize laureate is certainly more valuable than that by a doctoral student, a citation by a scientist with a high number of citations has probably more weight than that by a scholar with only a few citations, and many citations from the same researcher are apparently less

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worth than the same number of citations from many different scientists. All this motivated the application of "higher-order" evaluation methods (citations being a "first-order" method) such as PageRank to citation networks of authors.

The recursive PageRank algorithm by Brin and Page (1998), the founders of Google, was originally meant to evaluate the importance of webpages on the basis of the link structure of the web. The principal idea is that an important webpage is itself linked to from other important webpages. Thus, a webpage can have a high rank if it has inlinks from many webpages with low ranks but also if it has inlinks from few webpages with high ranks. The rank of a webpage depends on the ranks of the webpages linking to it. In practice, the costly calculation of PageRank in a directed graph is done in an iterative fashion and more on this will be said in the following section. Even though a similar bibliometric concept was introduced by Pinski and Narin (1976) long before Google, the PageRank's property of being applicable to any directed graph was soon utilized in the analysis of citation networks to rank journals (Bergstrom, 2007; Bollen, Rodriguez, & Van De Sompel, 2006; González-Pereira, Guerrero-Bote, & Moya-Anegón, 2010), papers (Chen, Xie, Maslov, & Redner, 2007; Ma, Guan, & Zhao, 2008; Walker, Xie, Yan, & Maslov, 2007; Yan & Ding, 2010), authors (Ding, Yan, Frazho, & Caverlee, 2009; Ding, 2011; Fiala, Rousselot, & Ježek, 2008; Fiala, 2011, 2012b, 2013a; Nykl, Ježek, Fiala, & Dostal, 2014; Radicchi, Fortunato, Markines, & Vespignani, 2009; Yan & Ding, 2011), a combination of the three (Yan, Ding, & Sugimoto, 2011), institutions (Yan, 2014), departments (Fiala, 2013b, 2014), countries (Fiala, 2012a; Ma et al., 2008), or a mixture of the above entities (West, Jensen, Dandrea, Gordon, & Bergstrom, 2013). In the many previous studies of ours we investigated various PageRank modifications with respect to the standard (baseline) PageRank and concluded that some of the variants performed better than the baseline in that they generated rankings closer to the human perception of a good ranking. In the present study, however, we consider simple citations as the baseline and the main research question is whether author rankings based on PageRank (and its variants) outperform citations in terms of better ranks assigned to outstanding researchers. If the answer was yes, the high computational cost of PageRank needed to overcome some deficiencies of citations would be well justified.

Let us remark in this place that PageRank-based (or, in general, recursive) ranking methods are only one branch of research performance evaluation techniques (in addition to standard publication and citation counts) with the other notable one being the family of h- and g-indices (Egghe, 2006; Hirsch, 2005) that combine both production and impact in a single number. These indices may obviously be used to rank authors as well, but they are not the concern of the present paper which is further organized as follows: In Section 2 we briefly recall the substance of PageRank, its modifications used in our analysis, and other related methods and refer to the relevant literature for more details. In Section 3 we describe the dataset we examined, which consists of papers from three large computer science categories (artificial intelligence, software engineering, and theory and methods). In Section 4 we present and discuss the main results of our analysis and give a negative answer to the main research question asked in the title of this article. And finally, in the last section, we summarize the most important contributions and results of this study and propose some research lines for our future work.

2. Methods

Let us define the directed author citation graph as $G=(V, E)$, where V is the set of vertices (authors) and E is the set of edges (unique citations between authors). If author v cites author u (once or more times), there is an edge $(v, u) \in E$. Then, by the recursive definition, the PageRank score $\mathrm{PR}(u)$ of author u depends on the scores of all citing authors in the following way:

$$PR(u) = \frac{1-d}{|V|} + d \sum_{(v,u)\in E} PR(v)\Omega \tag{1}$$

where d is the damping factor, which was set to 0.85 in the original web experiments by Brin and Page (1998), and Ω is either the multiplicative inverse of the out-degree of v like in the standard PageRank or $\sigma_{v,u}/\sum_{(v,k)\in E}\sigma_{v,k}$ like in the bibliographic PageRank by Fiala et al. (2008), where

$$\sigma_{v,k} = \frac{w_{v,k}}{[(c_{v,k}+1)/(b_{v,k}+1)]\sum_{(v,j)\in E} w_{v,j}} \tag{2}$$

with w, b, and c being various coefficients determined from both the citation and the collaboration networks of authors which will be explained below. Note that as follows from (1), an author with no citations (incoming edges) will still have a non-zero PageRank, which will be close to the multiplicative inverse of the total number of authors in the dataset. Of course, this will be influenced by the damping factor d, which was intitially determined empirically after the observation that a typical web user usually followed five links to other webpages and then chose a random webpage, e.g. by starting a new keyword search, thus resulting in about one sixth (≈ 0.15) of all transactions between webpages to be random. Indeed, the total PageRank in the system (or network) should be 1 and the individual PageRanks of vertices are then the fractions of time a random surfer spends there. We refer to the paper by Diligenti, Gori, and Maggini (2004) for an explanation of PageRank within a random walk framework. Other approaches to the PageRank problem include solving a linear system (Bianchini, Gori, & Scarselli, 2005; Langville & Meyer, 2004), but for practical reasons it is mostly computed dynamically in an iterative manner until convergence of subsequently generated rankings, which may be measured with Spearman's rank correlation coefficients. This is also the way we applied in our analysis with the maximum number of iterations set to 50, which was enough even with stricter convergence criteria and millions of nodes in the experiment by Brin and Page, and the damping factor set to 0.9 for the calculations to be consistent with our previous studies. (But we also experimented with other damping factors as will be said later in the paper.)

Let us now return to the coefficients w, b, and c appearing in the bibliographic version of (1) and thus in (2). Their combination will produce a weight of each citation between two authors. The key ideas are the following: a citation between two authors is more intense if it occurrs repeatedly ($w_{u,v}$ is the number of all citations from u to v); a citation from a colleague (who has coauthored some publications with the cited author) is considered less valuable than a citation from a foreign scientist who has no common papers with the cited author ($c_{u,v}$ is the number of collaborations of u and v), and the "collaboration penalty" is mitigated proportionally to some other factors, for instance to the number of coauthors in the joint publications by u and v ($b_{u,v}$ is then the number of common publications by u and v). If all the coefficients b and c are set to 0 and w to 1, the bibliographic PageRank becomes the standard PageRank (*PR*) by Brin and Page (1998). If only b's and c's are set to 0, the resulting method is a weighted PageRank (*PR weighted*) similar to that by Xing and Ghorbani (2004). If only b's are set to 0, the variant is called *PR collaboration*. If $b_{u,v}$ is generally non-zero, it can represent one of the following numbers: the number of publications by u plus the number of publications by v (*PR publications*), the number of all coauthors of u plus the number of all coauthors of v (*PR allCoauthors*), the number of all distinct coauthors of u plus the number of all distinct coauthors of v (*PR allDistCoauthors*), the number of publications by u where u is not the only author plus the number of publications by v where v is not the only author (*PR allCollaborations*), the number of coauthors in the common publications by u and v (*PR coauthors*), or the number of distinct coauthors in the common publications by u and v (*PR distCoauthors*). Because it was not the aim of this paper to redefine the bibliographic PageRank and its variants, for its formal definitions we refer to Fiala et al. (2008) and particularly to Fiala (2012b).

There is another recursive method related to PageRank which was invented independently of Brin and Page (1998) by Kleinberg (1999). This technique is called HITS and proposes two scores for a webpage, authority and hubness, suggesting that a good authority will be linked to from good hubs and a good hub will link to good authorities. This mutually reinforcing relationship is expressed by the indirect recursion in the following formula:

$$A(u) = \sum_{(v,u)\in E} H(v), \quad H(u) = \sum_{(u,v)\in E} A(v) \tag{3}$$

where $A(u)$ is the authority score of u and $H(u)$ its hubness. A close relationship of HITS to PageRank was shown by Ding, He, Husbands, Zha, and Simon (2002). We included HITS in our experiments with author rankings and computed iteratively (similarly to PageRank) the authority scores of authors, which were then used to rank them in descending order. In makes no sense to use the hubness score for the ranking because an author with a high hubness means a highly referencing author, whose prestige, however, may be low.

In addition to the computationally intensive "higher-order" methods PageRank and HITS, we also wanted to rank authors using simple, non-recursive techniques, which are sometimes called "first-order" methods. A prominent representative of this category is the simple citation counting (*Citations*), which is a well established metric of scientific impact and which we will consider as the baseline ranking method. Compared to PageRank, citations are not only cheap in terms of calculation and data collection, but they are also more transparent and easier to understand, which is a big advantage in research assessment. Citations between authors can be easily extracted from the citation networks of papers we had at our disposal. But unlike paper citations that are distinct by nature, there are usually many duplicate citations between authors because researchers often refer to publications on a specific topic covered by a limited set of scholars. So it may well happen that a large number of citations come from a single author. Therefore, it may be useful to count the number of distinct citing authors rather than citations. In the author citation graph (without parallel edges), this number is the in-degree of nodes and we call this method *In-degree* consistently in this study as well as in our earlier articles although alternative names like "CitingAuthors" would also be thinkable.

Thus, in total, we have these 12 author ranking methods: *Citations* (our baseline), *In-degree* (distinct citing authors), *HITS* (authority score), *PR* (standard PageRank), *PR weighted* (weighted PageRank), and bibliographic PageRank variations *PR collaboration, PR publications*, *PR allCoauthors*, *PR allDistCoauthors*, *PR allCollaborations*, *PR coauthors*, and *PR allCoauthors* whose rationale is explained above. We will apply these techniques to three large citation networks of computer science authors, generate author rankings, and try to answer the question raised in the title of this article.

3. Data

In middle 2013 we got access to programmatically download XML records with metadata on journal articles and conference papers from the well-known Web of Science (WoS) database. These metadata typically included paper titles, author names, author emails, source titles (journal or conference names), publication years, links to citing papers as well as some other information. We were interested in three subcategories of computer science, namely Artificial Intelligence (AI), Software Engineering (SE), and Theory and Methods (TM), which we wanted to inspect more closely. The choice of these three subcategories was determined by the research interests of the authors of this paper as well as by the necessity to balance the sufficient amount of data for analysis and the time (and costs) needed to acquire these data. Finally, we managed to obtain 179,510 publication records in AI, along with 215,745 records in SE, and 159,107 records in TM. However, these document sets are not disjoint as we can see in Fig. 1. This is due to the fact that in the Web of Science papers belong to one or more

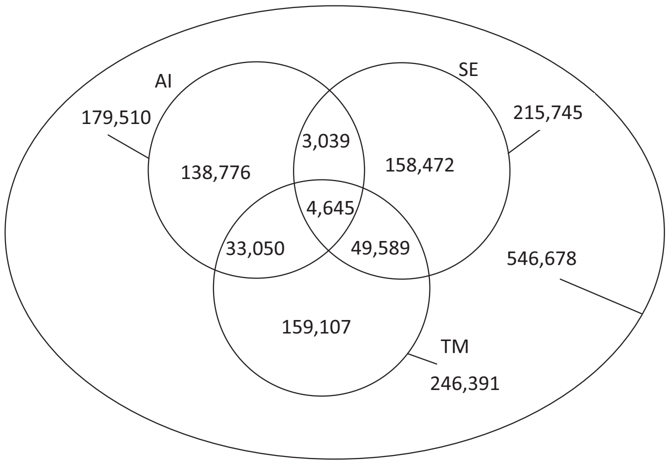

Fig. 1. Venn diagram showing the numbers of documents in artificial intelligence (AI), software engineering (SE), and theory and methods (TM) categories.

subject categories or subcategories. Thus, there is an overlap of almost five thousand papers that are classified in each of the three subcategories with a slightly smaller overlap between AI and SE but substantially bigger intersections (by an order of magnitude) between AI and TM on the one hand and SE and TM on the other. In the latter case about a third of the documents are shared by both subcategories. This indicates well that software engineering and theory and methods are two closely related disciplines of computer science. All in all, we analyzed 546,678 publication records in this study.

The publications under investigation span a time period from 1964 to 2013 for AI and from 1954 to 2013 for SE and TM. AI is, therefore, a "younger" discipline than both SE and TM and, of course, year 2013 is incomplete in each case. We can observe in Fig. 2 that all disciplines evolved similarly in the course of time and their production gradually increased from a few dozens of papers in the first years to almost 17,000 AI papers in 2006, 9000 SE papers in 2004, and more than 24,000 TM papers in 2005. (Again, let us recall that the document sets are not disjoint so the total numbers of papers published in the above disciplines are smaller.) We may notice a few remarkable things in Fig. 2 and those are the sudden production rise of software engineering publications in the 1980s, the explosion of publication activity in all three areas after 2000 and a rather dramatic general decrease after 2006. This spectacular decline may be partly caused by decreasing governmental budgets due to the approaching global economic and financial crisis but in particular by a change in the indexing strategy of the Web of Science database. This change included, among others, discontinuing the indexation of the well-known "Lecture Notes" book series in the Science Citation Index Expanded.

Before applying ranking methods to authors, we needed to create citation networks of authors from the citation networks of papers. Between the papers in AI there were 639,126 citations, in SE there were 323,444 citations, and in TM there were 483,603 citations. We extracted publications' authors and linked together the authors of each citing and cited paper removing self-citations. In this way, we obtained 119,430 authors linked by 4,349,759 citations in AI, 108,079 authors with 2,118,037 citations in SE, and 123,656 authors with 3,248,792 citations in TM. Let us note in this place that no name unification or

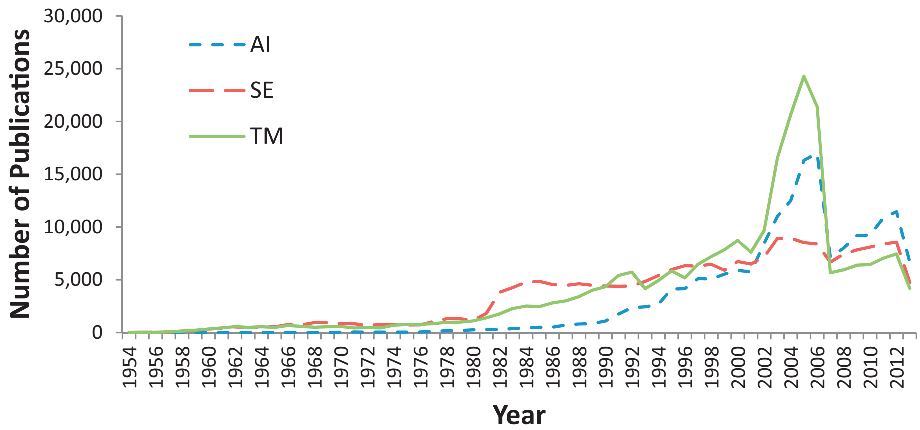

Fig. 2. Numbers of publications in artificial intelligence (AI), software engineering (SE), and theory and methods (TM) categories in individual years.

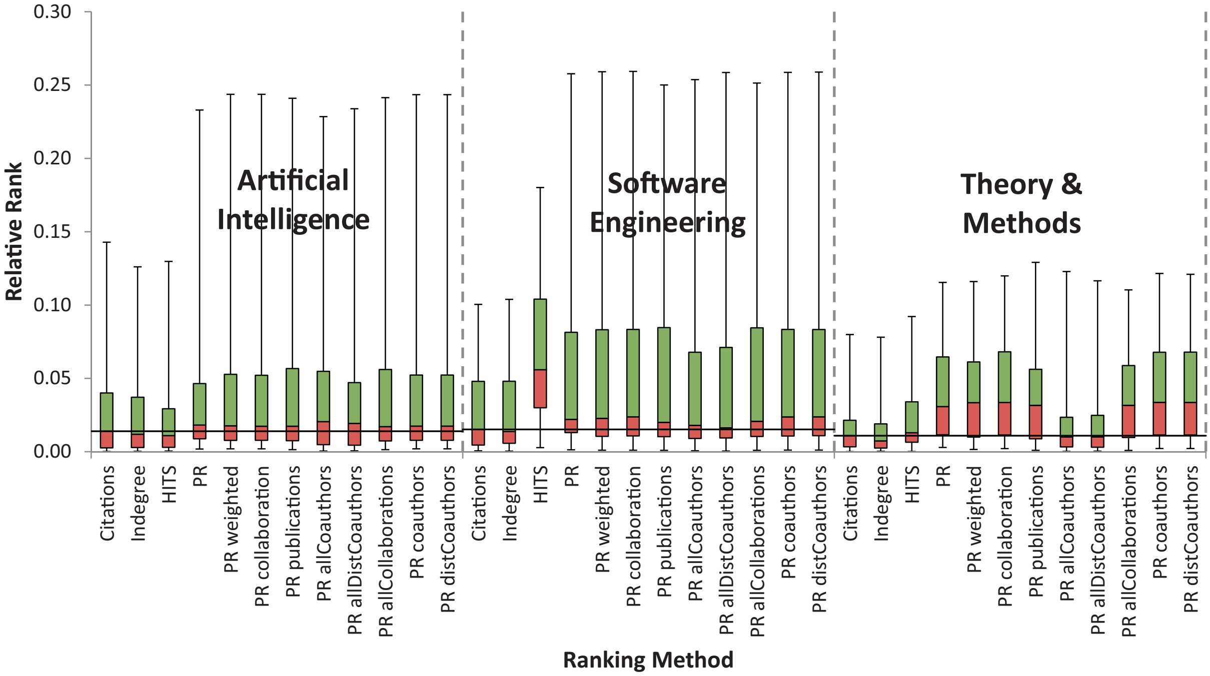

Fig. 3. Boxplots depicting relative ranks achieved by various ranking methods for artificial intelligence (left), software engineering (centre), and theory and methods (right) editorial board members, with the horizontal lines marking the median rank yielded by the "baseline" method (simple citation counts) in each category.

disambiguation was performed, which would have been extremely time-consuming regarding the big volume of data we analyzed. The authors were only identified by their full surnames and first name and middle name initials, which was the usual way they were supplied in our WoS data. All in all, our primary goal was to present general ranking features rather than individual ranks although these are also provided for the reader's reference in the appendix.

Comparing author rankings is always tricky as there are no "ground truth values" for the ranks that would tell us whether a ranking method works well or not. The only viable option if such a standard (or reference) ranking does not exist is to have a reference set of "good" authors about whom we know that they should be ranked high by a good ranking and low by a "bad" ranking. We may compile a list of outstanding authors based on the winners of some prestigious computer science awards (Fiala et al., 2008; Fiala, 2011, 2012b; Sidiropoulos & Manolopoulos, 2005) or on the editorial board members of some prestigious computer science journals (a similar concept employed by Liu, Bollen, Nelson, & Van De Sompel, 2005), which we have done in this study because there are no compatible awards in artificial intelligence, software engineering, and theory and methods. To this end, we manually inspected the editorial boards of the top ten journals by impact factor in the 2012 edition of Journal Citation Reports® in the three aforementioned categories. After some minimum data cleaning we included in our reference set of significant authors in each area those who appeared on more than one editorial board and checked these names for ambiguities. At the end of this process, we obtained 32, 12, and 17 authors whose names can be seen in Tables A.4–A.6 in the appendix.

4. Results and discussion

We applied all of the twelve ranking methods mentioned in Section 3 to the author citation networks in AI, SE, and TM and obtained 12 different author rankings. The ranking methods are *Citations*, *In-degree*, *HITS*, (standard) PageRank (*PR*), weighted PageRank (*PR weighted*) and seven other PageRank variants described earlier. Fig. 3 depicts boxplots of author rankings in each category showing the relative ranks (to be able to compare networks of different sizes) achieved by the best, worst, and median editorial board member from the reference set of outstanding researchers in a discipline. Relative ranks are calculated by dividing the original ranks by the number of authors in each network (AI, SE, and TM) to always fall between 0 and 1. This is a very simple way how rankings with different numbers of authors may be compared. Alternatively, a ranking function might be used for the comparison of these rankings such as the normalized discounted cumulative gain (Järvelin & Kekäläinen, 2002), but its more costly computation would likely not result in a better visualization than the boxplots in Fig. 3. As is usual with boxplots, the top edge of each bar marks the 75th percentile of the ranks assigned to the outstanding scholars by a particular ranking method and the bottom edge of each bar represents the 25th percentile. The short line dividing each box into two sections is the median rank. Please note that the lower the rank the better the

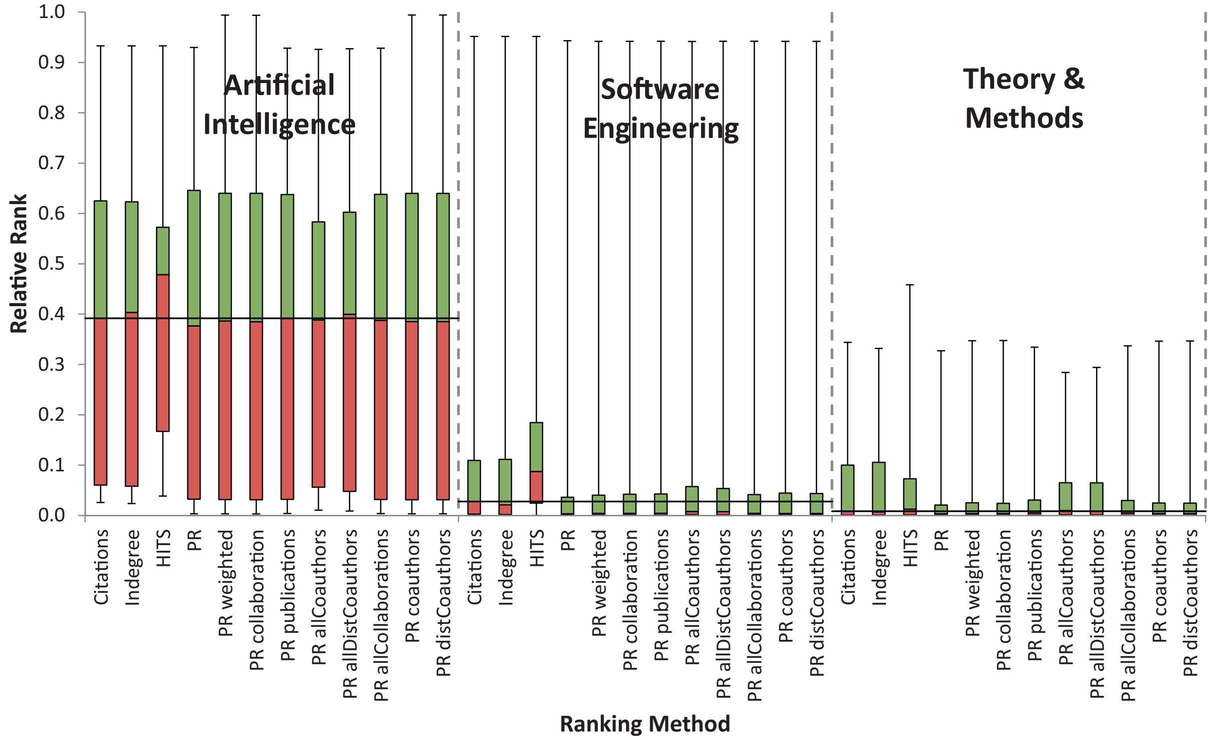

Fig. 4. Boxplots depicting relative ranks achieved by various ranking methods for artificial intelligence (left), software engineering (centre), and theory and methods (right) ACM A.M. Turing Award winners, with the horizontal lines marking the median rank yielded by the "baseline" method (simple citation counts) in each category.

position of a researcher because, obviously, rank 1 is better than rank 100 when speaking in absolute terms. (An optimum ranking, if there is one, would place all the authors from the reference set to top positions, e.g. 1–32 in AI, and the box in its boxplot would be virtually invisible in Fig. 3.) There is also a straight line in each section of the chart denoting the median rank yielded by the simple citation counting, which we consider a baseline. As we may notice, PageRank-based variants always have a worse median rank than citations except for *PR allCoauthors* and *PR allDistCoauthors* in TM, where, however, they still have much worse maximum ranks. These two variants take into account the number of all (distinct) coauthors in the common publications of the citing and cited author and perform comparably well (but not better than) citations in SE. However, their reputation as the best PageRank variants does not hold in AI in which they perform worse than the other PageRank-like methods. Thus, it is inconclusive and we cannot say which PageRank-based methods are the best, but we can almost certainly claim that, on the basis of our experiment, there is no evidence that author ranking methods similar to PageRank outperform simple (and much cheaper) citation counts.

What is somewhat striking is the poor performance of HITS in SE but actually quite good scores in AI and TM. So, again, it is unclear whether HITS is better or worse than citations based on this experiment, similarly to our previous studies (Fiala et al., 2008; Fiala, 2011, 2012b). On the other hand, the good performance of *In-degree* seems to be quite stable in Fig. 3 where it slightly outperforms *Citations* in all three citation networks. (Let us recall that in *In-degree* citations from one author are counted only once so a high rank in *In-degree* may better indicate how well-known an author is in the community than simple citations. This feature of *In-degree* seems to be crucial for editorial board members.) To get some additional support for these conclusions, we ran another set of experiments the main results of which may be seen in Fig. 4. Despite the lack of compatible awards in the three disciplines under study and a different evaluation methodology of choice for the present analysis we mentioned earlier, this time the reference set of researchers, whose ranks yielded by various ranking methods we compared, consisted of 28 ACM A.M. Turing Award winners from 1991 to 2010 as described in Fiala (2012b). As we may note, the median ranks achieved in AI are quite high and very low in SE and particularly in TM, which indicates that the Turing Award is more relevant for the latter two categories. Indeed, even the worst positions of the awardees based on TM data are still in the better half of the rankings, in contrast to AI and SE. And in addition, while there is no award winner missing in the TM rankings, there is one omission in SE and even 15 laureates missing in AI. Thus, although the PageRank-related methods perform roughly the same as simple citations in AI and TM and somewhat better in SE, due to the missing data and unequal relevance of the three computer science categories for the selected assessment methodology, we may probably conclude again that there is no evidence that PageRank-based rankings would outperform citation counts.

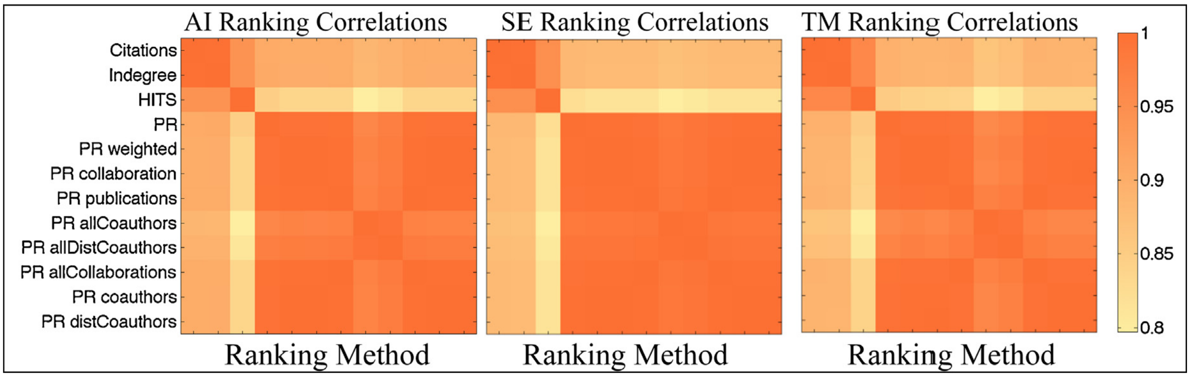

Fig. 5. Heatmaps of pairwise Spearman correlations of all rankings in artificial intelligence (AI), software engineering (SE), and theory and methods (TM) categories.

Let us note at this place that we carried out the whole analysis with the damping factor set to 0.9 for the study to be compatible with our earlier research, but we also tested a damping factor set to 0.5 as proposed by Chen et al. (2007), Walker et al. (2007), Ma et al. (2008) or Ding et al. (2009) to find out that even if performing slightly better, PageRank variants are still far from outperforming simple citations. The exact ranks along with aggregate values underlying Fig. 3 are shown in Tables A.1–A.3 in the appendix. The values of the baseline method (*Citations*) are typeset in italics and the aggregate values that are better than baseline are highlighted in bold. In the other tables in the appendix (Tables A.4–A.6), we show the top 30 researchers in AI, SE, and TM as calculated by *Citations*, *In-degree*, *HITS*, (standard) PageRank (*PR*), and the most different PageRank variant (*PR allCoauthors*). HITS and PageRank scores are also presented (although they depend on many factors like the convergence criterion, damping factor, etc.) for the reader to get a clue how wide or narrow the gaps between the ranks are. But we will not discuss the standings of the individual authors in detail because the aim of this analysis was to evaluate various ranking methods as a whole rather than to assess individuals. As for the PageRank variant whose ranks differ most from the standard PageRank (*PR allCoauthors*), we found it by comparing pairwise Spearman correlations of the 12 rankings in each of the three computer science categories. From the heatmaps in Fig. 5 it is quite obvious that there are three groups of rankings: *Citations* and *In-degree* are, as expected, very closely related as are PageRank and its modifications while HITS is a stand-alone category. However, even though all the correlations are very high (more than 0.8), we must be aware that this is true for rankings with well over 100,000 authors. Rankings with far fewer authors (e.g. 100, 500, or 1000), which are much more common in reality, would very probably have considerably lower correlations.

Let us now return to the evaluation methodology again. Besides editorial board members (or conference programme committee members, which is the same in essence but less appropriate with WoS data where conference papers are known to be absent or scarcely present) as the reference set of outstanding researchers, an alternative approach are lists of various computer science award winners. As we have said, we used this methodology successfully in the past (Fiala et al., 2008; Fiala, 2011, 2012b) and although the research goals set in those studies were different, it is easy to check that even then the PageRank-based methods mostly did not perform better than simple citations. In this analysis, we intentionally avoid prize awardees in order to test the viability of the current approach with editorial board members. Regarding author name disambiguation, even though no merging and/or unmerging of author names was performed prior to the analysis and the WoS data were treated "as is", we believe that the results of our study are still valid. We have shown in our earlier work (Fiala, 2011) that analyzing even much more inconsistent CiteSeer data may lead to relevant conclusions. And while we recognize that some of the names presented in the tables in the appendix may need disambiguation or merging (as may also some others in lower positions not shown there), their individual ranks are actually not so important as the aggregate values displayed in Fig. 3. As none of the ranking methods applied disambiguates author names, we expect the overall trend not to change even if all of them did.

Finally, let us speculate a little bit about the reasons of the disappointing performance of the PageRank-based methods as compared to simple citations. The most straightforward explanation seems to be that the evaluation methodology (editorial board membership) itself relies on pure citations. This appears to be a valid point since members of journal editorial boards are usually persons of high repute, well known in their scientific community, who publish frequently and are often cited by other researchers. The same is certainly true also for conference programme committee chairs or members or for computer science award winners. On the other hand, PageRank and related techniques are concerned with the quantity of citations as well as with their quality. They reflect prestige rather than popularity. In this context, it would seem that the editorial board members of the journals we selected for our analysis were chosen on the basis of popularity rather than prestige. Thus, they were not necessarily of high repute but certainly of high visibility with their work being cited a lot. Interestingly, a similar observation may be made for the award winners in our previous studies (e.g. Fiala et al., 2008), where, however, the baseline method was the standard PageRank and not citations. Even in studies where author credit was distributed in a slightly different (West et al., 2013) or a more different (Radicchi et al., 2009) way, a high correlation with simple citations was reported. We can see no reason why this bias of the assessment methodology towards simple citations should be absent when conference programme committee members are used as a reference set. In fact, all thinkable evaluation approaches (including peer judgement) are based on citations to some extent and we are not aware of any exception. If such an exceptional approach existed, it would be interesting to run our experiments again and see if the outcome is different.

5. Conclusions and future work

The quality of researchers is often assessed using basic scientometric indicators like the number of publications and citations and even though many other more advanced metrics have been proposed, in principle they always rely on the publication output and impact of a scholar. One of these more advanced techniques is the PageRank algorithm which was originally conceived to rank webpages but has been successfully used to evaluate authors of research papers as well. This algorithm is recursive in nature and requires dozens of iterations over the whole citation network to generate a stable ranking of authors. Thus, it is quite costly compared to simply counting citations and the key question is whether it is worth of it. Does PageRank benefit author rankings compared to citation counts? In this study we tried to address this problem and our response to the question is negative. In particular, we made the following contributions:

- We created large citation networks of authors from 179,510 papers in artificial intelligence, 215,745 papers in software engineering, and 246,391 papers in theory and methods – subfields of computer science – by programmatically querying the Web of Science database.
- We compiled lists of editorial board members of prestigious journals in each category to have three reference sets of outstanding researchers and generated 12 rankings of authors using various methods including citation counts, PageRank, and its modifications.
- We compared the rankings with each other by visualizing their basic statistics on boxplot charts and depicting their correlations on heatmaps.

The main findings of our study are the following:

- There is no evidence of PageRank-based author rankings outperforming simple citation counts in terms of better mean or median ranks assigned to the authors in a reference set of prestigious scholars in a computer science category.
- From the PageRank modifications, the variant with considering all coauthors in common publications of the citing and cited authors seems to work best. The performance of HITS is unstable and the ranking that takes into account citations only from distinct authors (*In-degree*) appears to yield better results than standard citation counts.
- All PageRank-based rankings are very highly correlated with each other, while HITS and citations-based rankings are the other two distinct ranking groups. Still, all the 12 rankings under study are rather strongly correlated with Spearman's rho being 0.8 at least.

In our future work, we would like to concentrate also on other categories of computer science or on other scientific fields. We intend to extend our experiments and further investigate some phenomena we observed in this analysis such as the circumstances in which *In-degree* performs better or worse than citations or HITS performs better or worse than PageRank. Moreover, the bad performance of PageRank-based methods in this study should be further verified by applying also other PageRank-related techniques such as those by Radicchi et al. (2009) or West et al. (2013). In addition to editorial board members, who may themselves be selected based on their citation counts, another set of experiments should be run with different reference sets of outstanding authors, e.g. with researchers receiving a prestigious award in a particular domain of computer science or another research area. Another line of research may include investigations whether simple citations outperform also some other well established evaluation metrics such as the h-index.

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Appendix A.

Table A.1
Top artificial intelligence editorial board members and their ranks achieved by various ranking methods.

Author	Citations	In-degree	HITS	*PR*	PR weighted	PR collaboration	PR publications	PR allCoauthors	PR allDistCoauthors	PR allCollaborations	PR coauthors	PR distCoauthors
Abbass, H	*2511*	2791	3130	8424	8337	8603	8022	2256	2664	8199	8505	8503
Bach, F	*1248*	1083	944	1311	1395	1349	1465	3627	3380	1447	1361	1361
Bregler, C	*5621*	6430	4523	7333	6474	6321	6826	15,633	13,735	6747	6255	6265
Brown, M	*2238*	1847	1827	2986	3110	3041	3260	4356	4261	3235	3041	3038
Collins, R	*1021*	836	516	1562	1807	1777	1632	2742	2459	1631	1789	1792
Cordon, O	*519*	732	1115	3487	2816	2887	2905	1921	2041	2892	2866	2863
Herrera, F	*20*	64	221	840	518	564	543	115	192	535	567	567
Ishibuchi, H	*196*	311	470	1130	931	947	919	440	548	931	948	947
Ishikawa, H	*2612*	3006	2133	1900	1306	1280	1438	2645	2310	1415	1288	1286
Kim, JH	*240*	202	182	601	707	721	480	220	203	484	726	727
Learned-Miller, E	*10,287*	8965	7059	7650	8709	8622	8606	14,287	12,928	8535	8607	8604
Li, X	*108*	237	156	1464	1116	1219	735	106	109	723	1221	1220
Liu, D	*968*	995	1144	3106	3236	3197	3322	1987	2177	3313	3227	3211
Lu, J	*283*	463	192	935	770	731	855	383	395	853	760	757
Matsushita, Y	*9374*	8723	4015	10,601	11,167	11,337	11,636	6494	6188	11,519	11,389	11,359
Mori, G	*3402*	2991	1817	5669	6775	7002	7282	3005	3738	7246	7007	7005
Navab, N	*4639*	4310	4746	5511	6252	6200	6760	7563	7071	6685	6242	6238
Ong, YS	*257*	341	591	2040	1596	1767	1618	95	88	1639	1776	1776
Pal, NR	*47*	36	54	221	239	238	171	56	70	168	240	241
Panella, M	*13,653*	12,638	9662	27,826	29,104	29,103	28,780	27,286	27,932	28,835	29,075	29,074
Pedrycz, W	*122*	110	208	619	622	651	327	169	174	405	661	660
Pennec, X	*1369*	1183	1401	1724	1723	1739	1864	1485	1452	1835	1742	1741
Ramanan, D	*1972*	1675	1224	3012	2854	2859	2286	2320	2297	2252	2850	2853
Roth, S	*3161*	2528	3333	2298	2715	2660	2792	5153	4542	2768	2656	2658
Sato, Y	*2668*	2025	2126	1062	1126	1105	1167	2584	2239	1171	1114	1110
Skrjanc, I	*7506*	7767	15,498	13,279	13,090	13,299	12,829	7857	9121	12,901	13,294	13,298
Sutton, C	*17,064*	15,058	12,722	5237	5803	5871	5643	7369	6747	5645	5736	5768
Torralba, A	*453*	448	383	1038	896	874	914	2127	1866	894	880	878
Vemuri, BC	*329*	283	244	310	287	280	336	631	563	328	283	283
Welling, M	*5245*	4816	2901	2826	2420	2374	2551	6710	5441	2520	2380	2373
Williams, C	*363*	343	269	234	247	249	278	621	493	270	248	249
Zhao, D	*7181*	6665	4885	13,043	11,287	11,214	11,546	16,970	16,078	11,470	11,243	11,233
Mean rank	*3334*	3122	2803	4352	4357	4378	4368	4663	4484	4359	4374	4373
Median rank	*1671*	1429	1313	2169	2114	2076	2075	2452	2304	2044	2085	2083
Min. rank	*20*	36	54	221	239	238	171	56	70	168	240	241
Max. rank	*17,064*	15,058	15,498	27,826	29,104	29,103	28,780	27,286	27,932	28,835	29,075	29,074
Std. deviation	*4188*	3821	3666	5523	5692	5709	5685	6023	5879	5689	5702	5701

Table A.2
Top software engineering editorial board members and their ranks achieved by various ranking methods (bold values are better than baseline in italics).

Author	Citations	In-degree	HITS	*PR*	PR weighted	PR collaboration	PR publications	PR allCoauthors	PR allDistCoauthors	PR allCollaborations	PR coauthors	PR distCoauthors
Bertino, E	*839*	652	3463	2941	3033	3161	2707	1631	1703	2848	3147	3144
Blake, MB	*8130*	9806	19,472	26,215	26,903	26,841	26,756	27,425	27,949	26,833	26,836	26,843
Boneh, D	*10,861*	11,226	16,476	27,857	28,005	28,024	27,032	23,581	24,605	27,173	27,959	27,979
Clarke, S	*2707*	2928	8537	7008	6478	6909	4265	1681	1679	4864	6899	6920
Dustdar, S	*2390*	2028	5830	6552	7117	7172	7372	3911	4373	7344	7181	7176
Forsyth, D	*387*	532	303	1446	1028	1012	1092	2211	1817	1104	1041	1030
Ghezzi, C	*413*	246	2566	822	989	1020	651	447	508	654	984	999
Gottlob, G	*896*	944	6262	1817	1883	1975	1614	1004	1067	1642	1978	2006
Jouppi, N	*9322*	8419	18,865	14,183	14,603	14,554	14,462	17,584	17,641	14,494	14,519	14,505
Morrisett, G	*511*	663	4462	1557	1170	1209	1117	900	866	1136	1200	1228
Wing, J	*68*	38	2096	140	116	116	106	70	49	101	117	118
Wright, MH	*4209*	4122	9503	1285	1463	1429	1600	3116	2632	1535	1419	1406
Mean rank	*3394*	3467	8153	7652	7732	7785	7398	6963	7074	7477	7773	7780
Median rank	*1643*	1486	6046	2379	2458	2568	2161	1946	1760	2245	2563	2575
Min. rank	*68*	38	303	140	116	116	106	70	**49**	101	117	118
Max. rank	*10,861*	11,226	19,472	27,857	28,005	28,024	27,032	27,425	27,949	27,173	27,959	27,979
Std. deviation	*3714*	3879	6379	9454	9638	9613	9517	9456	9723	9536	9601	9602

Table A.3
Top theory and methods editorial board members and their ranks achieved by various ranking methods (bold values are better than baseline in italics).

Author	Citations	In-degree	HITS	*PR*	PR weighted	PR collaboration	PR publications	PR allCoauthors	PR allDistCoauthors	PR allCollaborations	PR coauthors	PR distCoauthors
Liu, Y	*417*	309	964	1778	1747	1806	1453	333	321	1478	1795	1794
Wing, J	*453*	340	528	699	573	564	679	603	571	613	579	572
Gottlob, G	*233*	230	309	990	1024	1079	653	405	381	681	1099	1099
Morrisett, G	*9879*	9659	11,399	14,279	14,353	14,829	15,970	15,195	14,413	13,646	15,033	14,964
Boneh, D	*14*	37	21	366	189	259	118	59	49	114	273	272
Crowcroft, J	*5990*	4926	3878	12,312	13,402	13,355	15,719	6507	7118	13,382	13,566	13,503
Beyer, HG	*145*	155	872	1432	838	1229	1086	29	57	1195	1239	1244
Dorigo, M	*524*	496	1606	2434	2127	2302	2123	775	727	2122	2292	2301
Lozano, JA	*1920*	1641	4696	7560	7031	8423	6850	1247	1251	7267	8389	8398
Miller, J	*192*	143	722	1454	1230	1417	988	177	253	1196	1418	1417
Suganthan, PN	*2777*	2735	6428	9520	8861	9204	7388	2905	3065	7555	9102	9119
Tan, KC	*2657*	2352	4412	5019	5525	5455	5706	3166	3841	5776	5482	5478
Zhang, M	*7037*	5734	2612	12,081	12,999	12,887	12,308	7953	8277	12,383	12,814	12,819
Zhang, J	*1354*	908	2521	3804	4137	4149	3916	1427	1481	3913	4166	4157
Li, X	*1950*	1531	1150	5128	5880	5870	5557	2299	2676	5627	5949	5926
Ong, YS	*1561*	1395	4212	7993	7569	7754	6954	1979	1910	7083	7684	7704
Wu, J	*572*	421	802	1385	1546	1528	1382	652	608	1390	1548	1546
Mean rank	*2216*	1942	2772	5190	5237	5418	5226	2689	2765	5025	5437	5430
Median rank	*1354*	908	1606	3804	4137	4149	3916	**1247**	**1251**	3913	4166	4157
Min. rank	*14*	37	21	366	189	259	118	29	49	114	273	272
Max. rank	*9879*	9659	11,399	14,279	14,353	14,829	15,970	15,195	14,413	13,646	15,033	14,964
Std. deviation	*2735*	2519	2820	4458	4661	4718	5026	3808	3736	4486	4745	4733

Table A.4
Top 30 artificial intelligence researchers by citations, in-degree, HITS, PageRank and the most different PageRank variant.

	Citations		In-degree		HITS [$\times 10^{-2}$]		PR [$\times 10^{-4}$]		PR allCoauthors [$\times 10^{-3}$]	
1	Jain, AK	15,021	Jain, AK	6810	Jain, AK	13.1856	Horn, BKP	26.7431	Jain, AK	18.9662
2	Malik, J	8607	Malik, J	4417	Malik, J	10.2278	Ballard, DH	26.6847	Kittler, J	12.9174
3	Kittler, J	8238	Kittler, J	4344	Kittler, J	9.8324	Geman, S	25.9486	Wang, L	8.3717
4	Kriegman, DJ	7541	Scholkopf, B	3600	Kriegman, DJ	9.1965	Hornik, K	23.4745	Wang, J	8.1870
5	Scholkopf, B	7332	Vapnik, V	3593	Scholkopf, B	8.9430	Geman, D	22.9776	Kanade, T	7.1650
6	Kanade, T	7032	Kanade, T	3586	Belhumeur, PN	8.7021	Jain, AK	21.5837	Oja, E	6.2053
7	Duin, RPW	6670	Lowe, DG	3520	Duin, RPW	8.5493	White, H	20.6053	Huang, TS	6.1994
8	Belhumeur, PN	6471	Duin, RPW	3330	Kanade, T	8.5259	Fikes, RE	20.5439	Scholkopf, B	5.8157
9	Vapnik, V	6075	Breiman, L	3147	Lowe, DG	8.0279	Nilsson, NJ	19.8517	Zhang, D	5.0933
10	Breiman, L	6006	Jordan, MI	3069	Muller, KR	7.9694	Kanade, T	19.6396	Duin, RPW	4.6992
11	Muller, Kr	5729	Kriegman, DJ	3046	Vapnik, V	7.6957	Funahashi, K	19.1373	Jain, A	3.9943
12	Lowe, DG	5725	Hornik, K	3043	Poggio, T	7.3748	Haralick, RM	18.5182	Poggio, T	3.7520
13	Geman, D	5028	Geman, S	2978	Matas, J	7.1384	Stinchcombe, M	18.4966	Nayar, SK	3.6473
14	Lin, CJ	5019	Muller, KR	2932	Hespanha, JP	7.0629	Brooks, RA	16.7612	Rosenfeld, A	3.2826
15	Jordan, MI	4987	Lin, CJ	2918	Meer, P	6.8320	Pearl, J	16.4261	Bigun, J	3.0795
16	Sejnowski, TJ	4921	Geman, D	2863	Huang, TS	6.7858	Pentland, AP	15.7140	Bischof, H	3.0754
17	Bezdek, JC	4914	Belhumeur, PN	2723	Jordan, MI	6.7426	Terzopoulos, D	14.7983	Hornik, K	2.9340
18	Hornik, K	4749	Wang, L	2679	Breiman, L	6.3566	Rosenfeld, A	14.0835	Plaza, E	2.5533
19	Zhang, D	4732	Sejnowski, TJ	2651	Taylor, CJ	6.3527	Vapnik, V	13.4566	Weickert, J	2.4774
20	Herrera, F	4724	Poggio, T	2604	Lin, CJ	6.3022	Schunck, BG	13.4545	Leonardis, A	2.4613
21	Geman, S	4711	Ballard, DH	2579	Geman, D	6.2773	Canny, J	13.4450	Sycara, K	2.3444
22	Grossberg, S	4630	Rosenfeld, A	2562	Geman, S	6.2021	Newell, A	13.3067	Rangarajan, A	2.1807
23	Poggio, T	4626	Meer, P	2539	Zhang, D	6.1346	Malik, J	13.1673	Amari, S	2.1802
24	Schmid, C	4585	Huang, TS	2533	Wang, L	6.0553	Grossberg, S	13.1471	Matas, J	2.1711
25	Taylor, Cj	4475	Canny, J	2498	Cootes, TF	5.9839	Davis, R	13.0938	Kimmel, R	2.1366
26	Rosenfeld, A	4427	Cortes, C	2494	Canny, J	5.9161	Lowe, DG	13.0680	Muller, KR	2.0960
27	Oja, E	4332	Matas, J	2479	Pentland, AP	5.8954	Sejnowski, TJ	13.0536	Dorigo, M	2.0939
28	Huang, TS	4312	Haralick, RM	2472	Ballard, DH	5.8614	Hinton, GE	13.0220	Liu, J	2.0708
29	Jennings, NR	4199	Pentland, AP	2415	Cortes, C	5.8490	Huang, TS	12.6856	Zisserman, A	2.0354
30	Horn, BKP	4181	Oja, E	2381	Sejnowski, TJ	5.8004	Davis, LS	12.5888	Bro, R	2.0325

Table A.5
Top 30 software engineering researchers by citations, in-degree, HITS, PageRank and the most different PageRank variant.

	Citations		In-degree		HITS [$\times 10^{-2}$]		PR [$\times 10^{-4}$]		PR allCoauthors [$\times 10^{-3}$]	
1	Basili, VR	4155	Lamport, L	2372	Cohen-Or, D	14.4513	Hoare, CAR	49.7986	Hoare, CAR	14.0238
2	Lamport, L	4022	Hoare, CAR	2213	Seidel, HP	13.1369	McCarthy, J	34.9504	Wirth, N	11.5275
3	Cohen-Or, D	3903	Basili, VR	2002	Shum, HY	12.8951	Kammerer, HC	31.8550	Seidel, HP	9.4998
4	Hoare, CAR	3385	Harel, D	1814	Guo, BN	11.1822	Oktay, S	31.8550	Cohen-Or, D	4.3613
5	Seidel, HP	3075	Shamir, A	1730	Turk, G	10.9546	Dennis, JB	29.6339	Shum, HY	4.0523
6	Shamir, A	3025	Seidel, HP	1663	Desbrun, M	10.5037	Codd, EF	27.8712	Basili, VR	3.8873
7	Shum, HY	2942	Cohen-Or, D	1653	Zhou, K	9.4780	Dijkstra, EW	27.5035	Harel, D	3.8712
8	Harel, D	2749	Parnas, DL	1543	Hoppe, H	9.3236	Wirth, N	24.9930	Parnas, DL	3.3924
9	Briand, LC	2559	Shum, HY	1375	Gross, M	9.3158	Denning, PJ	24.7114	Denning, PJ	3.2165
10	Guo, BN	2333	Tarjan, RE	1354	Alexa, M	9.2896	Parnas, DL	23.3554	McCarthy, J	3.1794
11	Kemerer, CF	2285	Kemerer, CF	1274	Rusinkiewicz, S	9.2514	Floyd, RW	23.2359	Vardi, MY	3.1321
12	Parnas, DL	2233	Turk, G	1192	Durand, F	9.1238	Perlis, AJ	21.8722	Dennis, JB	3.0947
13	Weyuker, EJ	2229	Weiser, M	1108	Sheffer, A	8.6284	Chu, RC	21.4381	Dijkstra, EW	3.0317
14	Tarjan, RE	2183	Weyuker, EJ	1104	Bao, HJ	8.4892	Hwang, UP	21.4381	Emerson, EA	2.7773
15	Desbrun, M	2097	Dijkstra, EW	1103	Sorkine, O	8.4684	Simons, RE	21.4381	Shamir, A	2.5844
16	Turk, G	2036	Briand, LC	1101	Kobbelt, L	8.4185	Lamport, L	20.1893	Flanagan, C	2.4894
17	Gross, M	1928	Guo, BN	1087	Hu, SM	8.3370	Knuth, DE	17.0970	Clarke, EM	2.4707
18	Fedkiw, R	1814	Desbrun, M	1083	Pauly, M	8.2149	Horst, R	16.7542	Ball, T	2.3321
19	Cignoni, P	1776	Cignoni, P	1055	Shamir, A	8.2064	Hoffman, KL	16.6144	Tarjan, RE	2.3015
20	Reps, T	1756	Reps, T	1051	Cignoni, P	8.1103	Mizell, AM	15.6718	Alur, R	2.2184
21	Levoy, M	1747	Levoy, M	1049	Lischinski, D	7.9935	Tarjan, RE	15.6258	Guo, BN	2.1979
22	Zhou, K	1728	Clarke, EM	1006	Curless, B	7.9242	Weiss, RA	15.5402	Gross, M	2.1701
23	Durand, F	1695	Gross, M	999	Gotsman, C	7.6949	Phong, BT	15.4064	Durand, F	2.1210
24	Weiser, M	1665	Durand, F	979	Levy, B	7.4184	Shamir, A	14.4281	Lamport, L	2.1072
25	Alexa, M	1646	Scopigno, R	979	Alliez, P	7.3908	Gries, D	14.3008	Montanari, U	2.0659
26	Kobbelt, L	1621	Lee, J	971	Ju, T	7.3030	Harel, D	13.0491	Floyd, RW	2.0252
27	Rusinkiewicz, S	1577	Ferrante, J	918	Yu, YZ	7.3017	Landin, PJ	12.3079	Todd, SJP	1.9993
28	Scopigno, R	1569	Kramer, J	894	Popovic, J	7.2730	Metcalfe, RM	12.0450	Chamberlin, DD	1.8682
29	Clarke, EM	1564	Alexa, M	890	Warren, J	7.2027	Robinson, JA	11.8506	Codd, EF	1.8481
30	Hoppe, H	1541	Hoppe, H	881	Scopigno, R	7.1808	Boggs, DR	11.5930	Lee, J	1.7246

Table A.6
Top 30 theory and methods researchers by citations, in-degree, HITS, PageRank and the most different PageRank variant.

	Citations		In-degree		HITS [$\times 10^{-2}$]		PR [$\times 10^{-4}$]		PR allCoauthors [$\times 10^{-3}$]	
1	Tarjan, RE	9586	Tarjan, RE	3587	Tarjan, RE	10.9182	Hoare, CAR	37.8686	Yung, M	14.5603
2	Shamir, A	8108	Lamport, L	3315	Shamir, A	10.8676	Perlis, AJ	32.1774	Alur, R	7.4745
3	Lamport, L	7324	Shamir, A	3035	Rivest, RL	10.4166	Codd, EF	30.4506	Vardi, MY	6.2202
4	Micali, S	6653	Zadeh, LA	2810	Yannakakis, M	9.6018	Dennis, JB	30.1616	Dongarra, J	6.0710
5	Alur, R	6389	Rivest, RL	2513	Yung, M	9.3902	Tarjan, RE	29.2852	Shamir, A	6.0548
6	Yannakakis, M	5429	Papadimitriou, CH	2375	Papadimitriou, CH	9.2467	Dijkstra, EW	27.6138	Hoare, CAR	6.0394
7	Rivest, RL	5354	Valiant, LG	2357	Lamport, L	8.9736	McCarthy, J	24.0778	Preneel, B	5.7847
8	Goldwasser, S	5270	Hoare, CAR	2351	Micali, S	8.7176	Shamir, A	22.4969	Deb, K	5.6748
9	Valiant, LG	5265	Yannakakis, M	2351	Goldwasser, S	8.5713	Knuth, DE	21.9525	Pnueli, A	5.2145
10	Papadimitriou, CH	5104	Foster, I	2138	Goldreich, O	8.4746	Zadeh, LA	21.7615	Dongarra, JJ	4.9583
11	Bellare, M	4981	Alur, R	1926	Bellare, M	8.2476	Denning, PJ	21.3309	Tarjan, RE	4.7165
12	Yung, M	4943	Yung, M	1900	Valiant, LG	7.9701	Lamport, L	21.1109	Nielsen, M	4.5767
13	Milner, R	4905	Fischer, MJ	1899	Naor, M	7.4863	Walden, DC	20.6401	Micali, S	3.7363
14	Boneh, D	4585	Milner, R	1855	Stern, J	7.3887	Wirth, N	20.6227	Rozenberg, G	3.5906
15	Zadeh, LA	4371	Floyd, S	1704	Luby, M	7.3704	Rivest, RL	20.5698	Rivest, RL	3.5245
16	Goldreich, O	4339	Vardi, MY	1692	Fischer, MJ	7.0054	Floyd, RW	19.3385	Zadeh, LA	3.2584
17	Stern, J	4286	Parrow, J	1660	Parrow, J	6.9366	Valiant, LG	17.2807	Naor, M	3.1258
18	Henzinger, TA	4280	Kesselman, C	1657	Alur, R	6.6362	Adleman, L	15.5315	Bellare, M	3.0279
19	Hoare, CAR	4167	Dongarra, JJ	1602	Preneel, B	6.6117	Vanhorn, EC	15.3883	Kumar, V	2.8850
20	Vardi, MY	4099	Micali, S	1557	Krawczyk, H	6.5033	Robinson, JA	15.3753	Henzinger, TA	2.8087
21	Deb, K	4024	Dongarra, J	1553	Boneh, D	6.5033	Parnas, DL	13.9488	Grumberg, O	2.7709
22	Foster, I	3833	Bellare, M	1539	Fiat, A	6.3567	Milner, R	13.6916	Hennessy, M	2.7249
23	Krawczyk, H	3725	Tuecke, S	1531	Adleman, L	6.3541	Fischer, MJ	13.1500	Bergstra, JA	2.6503
24	Camenisch, J	3556	Adleman, L	1530	Johnson, DS	6.3340	Ullman, JD	12.9868	Krawczyk, H	2.6414
25	Parrow, J	3533	Goldreich, O	1506	Okamoto, T	6.2513	Gries, D	12.7681	Goldreich, O	2.5898
26	Fischer, MJ	3532	Goldwasser, S	1502	Abadi, M	6.2247	Papadimitriou, CH	12.3012	Stern, J	2.5846
27	Kaliski, BS	3455	Johnson, DS	1492	Wigderson, A	6.2152	Blum, M	12.0470	Colchester, A	2.5771
28	Preneel, B	3376	Pnueli, A	1481	Franklin, M	6.1176	Yannakakis, M	11.8855	Dubois, D	2.4958
29	Dill, DL	3368	Jain, AK	1473	Maurer, U	6.1106	Gustafson, RN	11.7996	Beyer, HG	2.4750
30	Okamoto, T	3224	Ullman, JD	1463	Vardi, MY	6.0960	Sparacio, FJ	11.7996	Yager, RR	2.4538

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