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Bibliometric author evaluation through linear regression on the coauthor network

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ABSTRACT

The rising trend of coauthored academic works obscures the credit assignment that is the basis for decisions of funding and career advancements. In this paper, a simple model based on the assumption of an unvarying "author ability" is introduced. With this assumption, the weight of author contributions to a body of coauthored work can be statistically estimated. The method is tested on a set of some more than five-hundred authors in a coauthor network from the CiteSeerX database. The ranking obtained agrees fairly well with that given by total fractional citation counts for an author, but noticeable differences exist.

1. Introduction

Typical quantitative indicators of scientific productivity and quality that have been proposed—be it on the level of individuals, institutions or even whole geographic regions—are, in some form or another, ultimately based on the citation distribution to previous (and available) scientific works (in this paper referred to as "papers" for short for all types [books, regular articles, rapid communications, commentaries, proceedings, *etc.*]). A fairly extensive scientific literature exists on the subject of discriminating between individuals or scientific institutions, motivated to a large extent by the perceived need of the merit-based distribution of funding which is scarce in relation to the number of active scientists. Such indicators range from the simple (counting the number of papers and/or citations) to the more elaborate, such as the *h*-index (Bornmann & Daniel, 2005, 2007b; Bornmann, Mutz, & Daniel, 2008; Hirsch, 2005, 2007; Jin, 2006) and its many variants (Ausloos, 2015; Bras-Amorós, Domingo-Ferrer, & Torra, 2011; Egghe, 2006; Egghe & Rousseau, 2008; Jin, 2007; Jin, Liang, Rousseau, & Egghe, 2007; Kosmulski, 2006). For a recent and in-depth review of the fundamentals this topic (citation counting), see the paper by Waltman (2016). This comparison is in some schools of bibliometrics developed further in that the incoming citations to a paper are weighted by the importance of the citing source. This importance can be defined, for instance, from the number of citations the citing paper has itself received, or the number of citations of the citing author. For a review of this topic and an empirical investigation of its robustness, see the paper by Wang, Shen, and Cheng (2016).

In this paper, we are motivated by the confounding factor that coauthorship poses to any such analysis. Different options for dealing with this problem have been proposed. The simplest is to divide the credit equally among all contributing authors (Batista, Campiteli, Kinouchi, & Martinez, 2006; Schreiber, 2008) (known both as "fractional counting" or "normalized counting"); after that comes weighting author credit by a simple function of the author's position in the author list (Hagen, 2009; Sekercioglu, 2008; Zhang, 2009), or even more intricate schemes based on this notion (Aziz & Rozing, 2013). However, these alternatives cannot be motivated by more than "hunches" about how a particular "authorship culture" assigns credit.

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Clearly, a quantitative approach is more scientific than a qualitative, or worse, arbitrary one. Special mention is here given to the papers by Tol (2011) and by Shen and Barabási (2014), in which intuitive statistical models are used to disentangle the coauthorship contributions.

Tol's (2011) idea may be summarized as follows. Whenever two authors write a joint paper and it is highly cited, the senior author of the pair[1] should receive a disproportionally large share of the citation credit. The rationale for this is that it is more typical of the senior author, judging from past experience, to write highly cited papers, and it is therefore reasonable to assume that her contribution is more responsible for the ultimate quality. With his method and a limited sample set comprising some fifty authors, Tol (2011) finds small deviations of up to 25% between his "Pareto weights" and what he terms "egalitarian weights" in which coauthorship credit is equally distributed.

Shen and Barabási (2014) agree with Tol (2011) on the principle of assigning more credit to the "senior author", but the algorithm to determine the actual credit assignment is different. To determine the "relative seniority" of each coauthor, their algorithm weighs both the number of papers by the author and the degree to which these papers share citations from papers citing the one under consideration. In this way, papers that are more "similar" to the one under consideration contribute more to the "seniority" of that coauthor when assigning the authorship credit.

The idea behind the present paper is basically the same, but the execution is different. Rather than assume a fixed form of a distribution like Tol (2011), we assume a fixed form for the underlying "ability" to produce said distribution in the first place. We then solve for this "author ability" statistically to find those authors who consistently manage to contribute to "high-quality" papers. Another difference, which also distinguishes the method from that by Shen and Barabási (2014), is that a junior author is not necessarily "punished" for publishing with a senior coauthor. If a paper is very successful compared to previous papers on the topic, it is not altogether unreasonable to assume that this atypical performance should be disproportionately credited to any authors not participating in the earlier work. However, in both Shen and Barabási (2014) and in Tol (2011), credit is instead disproportionately allocated to the senior author. Much like Tol (2011), the rigorous application of our method requires knowledge of complete coauthor networks, and can only be approximately applied otherwise. This is, however, more of a formal problem than a practical one.

2. Regression model for coauthorship contribution

We assume that the arbitrary author i has an unchanging ability a_i for contributing to scientific papers.[2] A paper α, once produced, possesses a "scientific quality" that we non-committally denote by q_α for now. This variable could be, for instance, the total number of citations or the rate of citation accumulation, to name a few. For notational simplicity, we define the elements, $f_{\alpha i}$, of a dimensionless "authorship tensor" $\mathbf{F}$, to be unity if author i contributes to paper α, and zero otherwise:

$$f_{\alpha i} = \begin{cases} 1, & \text{if } i \text{ is author of } \alpha \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

With these definitions, we now define a_i through,

$$\ln q_\alpha = \sum_{i=1}^{M_\mathrm{a}} f_{\alpha i} \ln a_i \tag{2}$$

where M_a is the total number of authors in the statistical sample, formally the number of individuals who have ever produced a work of science. In practical calculations, we limit ourselves to much smaller subsets of authors in a citation database. With modern computers, solving the complete system of equations is possible if one has access to the entire database. Typically, for individuals, the database is only partially accessible through search keywords of an online interface and the database in its entirety is not allowed (because of commercial contracts between the library and the database provider, for instance) to be downloaded and mined for its data. Such a limitation does not pose a greater problem than the reduction of the underlying statistical data.

Before we continue, we note that the choice of the logarithm function in Eq. (2) is judicious. First, it implies that "the whole is not equal to the sum of its parts" and is meant to capture at least some of the synergistic effects of a collaboration (as suggested, for instance, by Figg et al. (2006)): in other words, the relation between the number of authors and the resulting quality of the paper is taken to be non-linear rather than linear. Here, we follow Ke (2013) closely, but replace his "paper fitness" by our "author ability". Ke's model is more general, but we do not want to proliferate the number of fitting parameters needlessly. Second, since the value of q may vary over several orders of magnitude in typical cases (*vide infra*), the logarithm ensures a more modest range for the regression. This said, Eq. (2) is obviously an *Ansatz* chosen merely for its simple mathematical form rather than being based on some underlying physical understanding of research production within collaborations.

[1] Defined in terms of "Pareto weights" which are directly related to the average citations per article of an author.

[2] This assumption does not contradict the statement in Section 1 that "a senior author, judging from past experience," is more typically able to write highly cited papers. The senior author may always have been good at producing highly cited scientific output, but contrary to the case of the junior author, she has the credentials to back it up.

If among themselves, M_a authors have published exactly M_a papers, Eq. (2) forms a system of M_a linear equations that can be solved, in principle, for the unique set $\{a_i\}_{i=1}^{M_a}$ of author abilities if the determinant of the square matrix

$$\mathbf{F} = \begin{bmatrix} f_{11} & \cdots & f_{1M_a} \\ \vdots & \ddots & \vdots \\ f_{M_a1} & \cdots & f_{M_aM_a} \end{bmatrix} \tag{3}$$

is non-zero. Such a situation is *a priori* atypical, and the more common case is where the number of papers, M_p, does not equal M_a. However, the methods of statistical fitting (*e.g.*, least-squares) can still produce a set $\{a_i\}_{i=1}^{M_a}$, which may be unique or not depending on the circumstances. Hence, the proposed method may be seen as the regression analysis for the unknown "author ability" underlying quality scientific paper production. The method of least squares is the one which we will employ in this work. It has two desirable properties: first, it is sensitive to outliers, and thus to very productive or skilled researchers—a concern raised principally by Egghe in his *g*-index (Egghe, 2006); second, it is numerically easier to handle than, say, the least-absolute error. For clarity, we note that the error function which we seek to minimize is the sum of the squared residuals:

$$R(\{a_i\}) \equiv \sum_\alpha \left(\ln q_\alpha - \sum_i f_{\alpha i} \ln a_i \right)^2 \tag{4}$$

In a set of scientific papers, the quality—however defined—will exhibit a distribution over the papers. The least-squares fitting of the set $\{\ln a_i\}$ to the set $\{\ln q_\alpha\}$ may, if no further constraints are present, lead to negative values in the former set. While this is reasonable from a statistical point of view, it seems self-contradictory from a physical point of view that the addition of an extra author to a paper may lead to a decline in the quality of the resulting product. Therefore, in this paper we always impose the extra condition $\ln a_i \geq 0$ for all i in the author set. The least-square solution of Eq. (2) may then be found by, for instance, iterative gradient minimization techniques.

2.1. On the interpretation of the meaning behind the author ability variable

From the purely mathematical perspective of author ranking, the condition that $\ln a_i \geq 0$ is not strictly necessary and there would be some numerical benefits for the solution of Eq. (2), were it to be relaxed. For one thing, the residuals in the regression would be decreased. However, we stick to this condition in this paper because we want to maintain at least some "physical" connotation for the a-values. If we allow negative values for $\ln a$ in the fitting, we basically say that adding an author to a collaborative work may lead to a decrease in the resulting quality. However—*assuming the scientific field in which the paper is produced is sufficiently rigorous to permit a general consensus of the importance of results*—it should be clear that such a situation is only possible if the coauthors allow the quality to decline. What would motivate the other authors to allow such a decline? In this paper, we work with the basic theoretical assumption that all authors are rational agents that seek to maximize the quality of their work. This is why the unreasonableness of allowing negative values of $\ln a$ in the fitting becomes even greater in the "hard sciences" in which the consensus on the methods and results (for instance, theorems and proofs in computer science and mathematics; quantitative measurements and models in the natural sciences) that constitute a paper is clear.

Nevertheless (anticipating our choice for measuring q in the next section), we note that while there is general support for the notion that the "quality" of a paper—when measured as the number of citations that it accrues—benefits from the work of additional authors (Bornmann & Daniel, 2007a; Figg et al., 2006; Lokker, McKibbon, McKinlay, Wilczynski, & Haynes, 2008), Waltman and van Eck (2015) find a very slight detrimental effect on the citation counts of papers with three, four or five authors with respect to papers authored by two authors (they are still cited substantially more than papers by a single author). For six and more authors, an unequivocal benefit is seen. Their analysis is based on an average of field-normalized citation scores across all the disciplines in the Web of Science database and seems to indicate, at first glance, that contrary to our assumption additional authors may have a detrimental effect on the quality of a joint paper.

While the results of Waltman and van Eck (2015) merit more careful scrutiny and an analysis broken down by scientific fields, one possible reason for this apparent average decline in quality with additional authors could be that larger collaborations tend to split work over several different papers, a strategy with a known benefit (Bornmann & Daniel, 2007a), to a greater extent than the author pair. In this case, the total citation count of that group of coauthors should be the sum over their joint papers. We shall correct for this eventuality in our analysis (*vide infra*) by multiplying the author abilities by the number of coauthored papers. However, if the motive were simply to minimize the residuals in the fitting, a more malleable model with more fitting parameters would be appropriate. Using such a strategy, the residuals can be made to disappear completely but at the same time, the validity of the extracted parameters is decreased. Nevertheless, at the express insistence of one of the reviewers, the analogous results of those given in the next section will be provided in Appendix A.

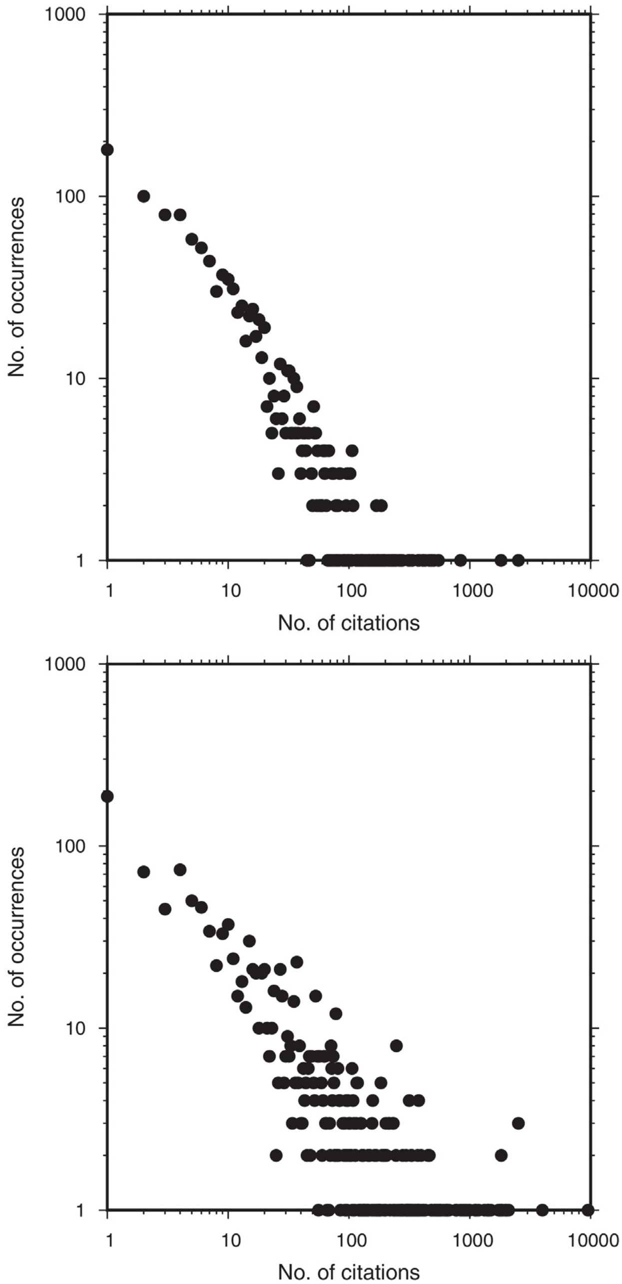

Fig. 1. (Top panel) Frequency distribution of paper citation counts in the dataset. (Bottom panel) Frequency distribution of author citation counts in the dataset.

3. Illustrative real-world example

For purposes of illustration, we take the variable q_α to correspond to the number of citations of paper α. We will then rank authors, not by a_i directly however, because that will give undue weight to the average performance of an author, but rather by n_ia_i, where n_i is the number of papers to which author i has contributed in the statistical sample. Like this, we hope to cover both the "breadth" and "depth" of an author's output. As the starting point for the iterative solution of Eq. (2), we take the fractional number of citations per paper for each author i. All numerical calculations were performed using the GNU Octave (Eaton, Bateman, & Hauberg, 2009) software, version 3.8.1.

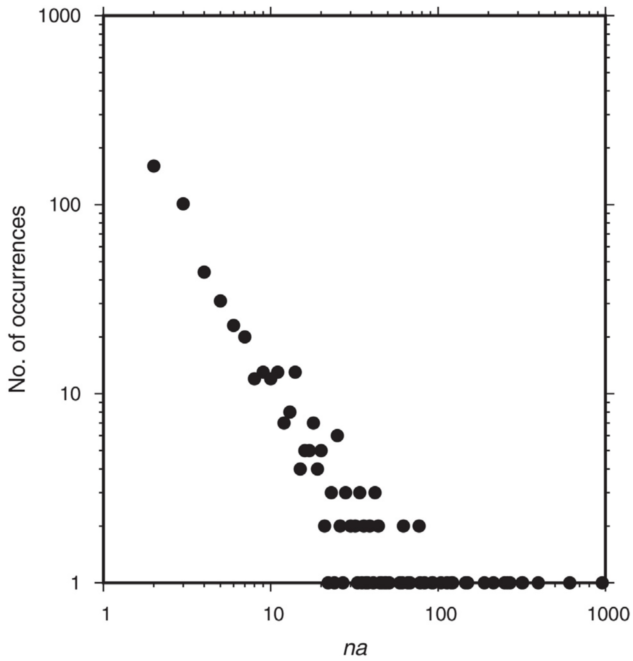

Fig. 2. The distribution of *na* (rounded to integer values) obtained from the regression analysis.

The statistical basis for this non-exhaustive study was obtained from the CiteSeerX online database[3] by compiling the cited papers[4] of renowned computer scientists Thomas H. Cormen[5] and Charles E. Leiserson[6] and their immediate coauthors.[7] This search yielded data for 1228 publications by a total of 1416 authors, after some manual pruning for author name variations where ambiguity was not an issue (*e.g.* "James" or "Jim") and also for some transcription errors in the database (*e.g.* part of the title of the paper or author information [affiliation, *etc.*] contaminating an author name). However, of these authors, 856 only appear on one paper each in the dataset and were excluded from the regression analysis. This increases the robustness of the results, as any statistical method is only reliable if there are repeated occurrences in the dataset. No correction for "inseparable coauthors" (authors who invariably publish together) was made in the analysis, as such groups are indistinguishable from a single author in output and citation data and so cannot be mathematically disentangled. The frequency distributions for the number of times a document or an author is cited are given in Fig. 1 and are seen to exhibit the heavy tail typical of citation distributions (Egghe, 1998). The statistical basis should be sufficient for our purposes.

A least-squares regression analysis was performed on the data to yield a set of unique author abilities $\{a_i\}$. The values for $n_i a_i$ range from 2 to almost 1000; the distribution is visualized in Fig. 2. Evidently, the shape of the distribution of the *na*-values is reminiscent of those of the paper and author citations: most authors are of "ordinary" ability and not easily distinguishable. The author with the highest *na*-value (and, incidentally, also the highest *a*-value) in the dataset turns out to be renowned cryptologist Ronald L. Rivest (known for the RSA cryptosystem). He is, however, not the most productive author in the dataset, having fewer papers than David Kotz; he does, on the other hand, have more citations than Kotz and so would rank higher also in most classical rankings. The top-ten ranked authors are given in Table 1 with some bibliometric data from the dataset. The *na*-ranking of the top ten follows that of the total number of citations closely, but with some notable exceptions: Sivan Toledo, David M. Nicol, Michael A. Bender and Robert D. Blumofe all obtain a higher ranking under the *na*-system than they would by just counting total citations. Conversely, Satish Rao, Benny Chor and C. Greg Plaxton obtain lower rankings under the *na*-system than they would by total citations.

The correlation between the integer citation count and the *na*-values apparent from Table 1 is slightly stronger when the fractional citation count *including all authors* is substituted for the integer one. This is actually a surprising result since the *na* values are calculated from a sample from which authors who only appear once have been removed. The strong correlations are, nevertheless, somewhat attenuated when the whole data sample is considered instead of only the most outstanding authors: the Pearson correlation coefficient between *na* and the total citation counts for the whole dataset is $r = 0.89$; and between *na* and the fractional citation counts, it is either $r = 0.89$ (excluding authors who only appear once) or

[3] http://citeseerx.ist.psu.edu, accessed February 2015.
[4] We limit our study to *cited* papers, not out of theoretical necessity, but out of practical convenience.
[5] Search query: `author:"thomas+h+cormen"`.
[6] Search query: `author:"charles+e+leiserson"`.
[7] Search queries generated automatically by a script on the same model as used for Cormen and Leiserson.

Table 1
Number of publications (n), na-value, total and fractional number of citations (with or without authors included that only appear once) as well as the h-index (h) for the ten top-ranked authors in the dataset according to na-value. The value of na, as well as that of the fractional citation count, is rounded to the nearest integer. The Pearson correlation coefficient between na and the total citation count in this table is $r = 0.95$; between na and the fractional citation count in this table, it is $r = 0.94$ if authors who only appear once are excluded and $r = 0.97$ if they are included.

Author	n	na	Citations	Frac. cit.[a]	Frac. cit.[b]	h
Ronald L. Rivest	102	957	9524	6531	3766	31
David Kotz	145	613	3987	1900	1769	32
Guy E. Blelloch	71	398	2006	997	929	23
Robert D. Blumofe	13	321	1780	963	600	11
Michael A. Bender	59	317	1409	583	496	19
David M. Nicol	68	270	856	384	319	17
Satish Rao	51	260	1964	834	664	22
Sivan Toledo	60	251	994	638	557	17
Benny Chor	41	215	1824	793	590	18
C. Greg Plaxton	46	189	1857	771	595	17

[a] Authors who only appear once not counted.
[b] Authors who only appear once counted.

$r = 0.92$ (including authors who only appear once). However, perhaps more interesting for the purposes of author ranking is the rank correlation. The Spearman rank correlation between the fractional citation count and the na values is $\rho = 0.79$ (when rounded to two decimal places, the result is the same whether or not authors who only appear once in the dataset are excluded or not from the denominator), which is slightly stronger than the corresponding rank correlation of $\rho = 0.70$ with the total citation count.

4. Concluding discussion

While the na-ranks agree rather well with traditional measures of high-level scientific productivity, contrary to the traditional approach which is purely *ad hoc*, the proposed model of this paper is based on the assumption that the underlying scientific productivity is governed by a factor that can be estimated from regression analysis. Arguably, the age-old adage: "practice makes perfect" is likely to hold true to some extent also when performing scientific research and writing scientific papers, but in the interest of keeping the unknown parameters to a minimum, we have not considered this effect in our model. Nevertheless, the results support the view that fractional citation counting is a fair way to distribute credit, at least within the computer science field. In line with this finding, it is important to stress that the strong rank correlation between citations (fractional or otherwise) notwithstanding, the idea in this paper is not to introduce a more "expensive" method to calculate the citation ranks. It is only the differences with respect to the traditional ranking that are interesting, because they show precisely the extent to which there is a need to step away from the simplified author ranking for purposes of promotion and funding.

It is interesting to compare the proposed method with that of Tol (2011), seeing as it is the one with which it shares the most of the undergirding philosophy. Contrary to Tol (2011), there is no need to assume any form for the citation distribution. Since Tol (2011), implicitly at least, assumes an unvarying distribution for each author,[8] his model is also based on the concept of an unchanging, inherent "author ability" that is used to produce cited papers. The proposed method is hence seen to be more general in its assumptions. For instance, the "ability" to publish pages of scientific output could just as well be the underlying variable that we wish to extract statistically; *i.e.*, the bibliometric indicator could be the number of pages per paper instead of citations. The idea is that one first identifies a measure of quality (q) for the individual paper, and then proceeds to analyze the underlying distribution of the authors' abilities (a).

Note that one of the basic ideas in the Shen–Barabási (Shen & Barabási, 2014) approach—to distinguish coauthor disciplines through their degree of "cocitedness" with other papers (essentially distinguishing scientific disciplines by the sets of papers that cite a particular paper)—is easily adapted to the current algorithm. One needs simply to redefine the quantity q accordingly by, for instance, defining q_α to be a weighted sum of citations, in which the weight of a citation to paper α from paper β is determined by the "cocitation strength" (Shen & Barabási, 2014) between papers α and β: *i.e.*, the number of papers citing both α and β. This is an interesting avenue for further development.

Finally, I stress once more that in some extreme cases, individual author abilities cannot be distinguished even in principle. This occurs, for instance, when two authors are "inseparable coauthors", and the one never publishes a paper without the other. This problem is, however, endemic to the whole domain of citation analysis and becomes less of an issue in practice as the seniority of an author increases.

[8] The distributions that Tol (2011) considers change through the iterations used to solve the model, but the converged result is a function, like the a-value, only of the bibliographic record and does not change for one and the same author from one paper to the next.

Table A.2
Number of publications (n), na-value and total number of citations for the ten top-ranked authors in the dataset according to na-value *when authors are allowed to have a-values less than unity in the statistical fitting*. The value of na is rounded to the nearest integer.

Author	n	na	Citations
Ronald L. Rivest	102	1272	9524
David Kotz	145	957	3987
Guy E. Blelloch	71	776	2006
James Demmel	7	725	631
Marc Moreno Maza	45	618	514
Michael A. Bender	59	428	1409
Sivan Toledo	60	374	994
David M. Nicol	68	339	856
Anastassia Ailamaki	4	337	116
Robert D. Blumofe	13	333	1780

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Appendix A. Regression with “destructive authors” in the dataset

If we relax the requirement that $\ln a_i \geq 0$ for any author i, we assume that said author i is a “destructive force” which unbeknownst to his coauthors and herself/himself sabotages the paper they produce. For completeness, we provide the resulting “top ten” authors using this assumption in Table A.2. This provides an indirect measure of the robustness of the method.

Like before the top two spots are still claimed by Rivest and Kotz (while now their na-values are higher for obvious reasons). With the exception of Demmel, Maza and Ailamaki, all of the top ten names appear also in Table 1, indicating only a slight reordering. The rank correlations between the na-values and the number of citations are $\rho = 0.67$ (total), $\rho = 0.73$ (fractional with all authors) and $\rho = 0.74$ (fractional excluding one-time authors) in the whole dataset. The corresponding Pearson correlation coefficients are $r = 0.78$, $r = 0.81$ and $r = 0.78$, respectively. Thus, even with this “unphysical” assumption, we see a stronger correlation with fractional citation counts than with the integer one.

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