Bibliometric author evaluation through linear regression on the coauthor network

Rasmus Persson

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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 (Hirsch, 2005; Jin, 2006; Hirsch, 2007; Bornmann and Daniel, 2005, 2007; Bornmann et al., 2008) and its many variants (Egghe, 2006; Kosmulski, 2006; Jin, 2007; Jin et al., 2007; Egghe and Rousseau, 2008; Bras-Amorós et al., 2011; Ausloos, 2015).

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 et al., 2006; Schreiber, 2008); after that comes weighting author credit by a simple function of their position in the author list (Hagen, 2009; Sekercioglu, 2008; Zhang, 2009), or even more intricate schemes based on this notion (Aziz and Rozing, 2013). However, these alternatives cannot be motivated by more than “hunches” about how a particular “authorship culture” assigns credit. Clearly, a quantitative approach is more scientific than a qualitative, or worse, arbitrary one. Special mention is here given to the paper by R. S. J. Tol (2011), in which an intuitive statistical model is 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 should receive a disproportionately 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.

The idea behind this paper is basically the same, but the execution is different. Rather than assume a fixed form of a distribution, 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. 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. A paper $\alpha$, once produced, possesses a “scientific quality” that we non-commitally denote by $q_\alpha$ 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” $F$, to be unity if author $i$ contributes to paper $\alpha$, and zero otherwise. With these definitions, we now define $q_\alpha$ through,

$$\ln q_\alpha = \sum_{i=1}^{M_a} f_{\alpha i} \ln a_i$$  \hspace{1cm} (1)$$

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.

If among themselves, $M_a$ authors have published exactly $M_a$ papers, Eq. (1) 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

$$F = \begin{bmatrix} f_{11} & \cdots & f_{1M_a} \\ \vdots & \ddots & \vdots \\ f_{M_a1} & \cdots & f_{M_aM_a} \end{bmatrix}$$  \hspace{1cm} (2)$$

\footnote{Defined in terms of “Pareto weights” which are directly related to the average citations per article of an author}

\footnote{This assumption does not contradict the statement in the Introduction 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.}
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.

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. (1) may then be found by, for instance, iterative gradient minimization techniques.

From the perspective of author ranking, the condition that \( \ln a_i \geq 0, \forall i \) is not strictly necessary and there would be some numerical benefits for the solution of Eq. (1), were it to be relaxed. However, we stick to this condition in this paper because we want to maintain at least some “physical” connotation for the \( a \)-values.\(^3\) Future work may see it removed. Finally, we note that the exact form of the relation between the set \( \{q_\alpha\} \) and \( \{a_i\} \) is arbitrary to a great extent, due to the latitude we have in interpreting the \( a \)-variable once the \( q \)-variable is defined. The non-linear relation that we have chosen is meant to capture a synergistic effect in every collaboration. As the prediction of the \( a \)-value of an author is not envisioned to serve any other purpose than ranking among other authors, the question need not concern us further.

3 Illustrative real-world example

For purposes of illustration, we take the variable \( q_\alpha \) to correspond to the number of citations of paper \( \alpha \). 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 \( n_i a_i \), 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. (1), we take the fractional number of citations per paper for each author \( i \). All numerical calculations were performed using the GNU OCTAVE (Eaton et al., 2009) software, version 3.8.1.

The statistical basis for this non-exhaustive study was obtained from the CiteSeerX online database\(^4\) by compiling the cited papers\(^5\) of renowned computer scientists.

\(^3\)This view is not universally shared, as an anonymous correspondent contests that “there are many examples of people who actually can make a paper worse [by being involved]”. However, it is nonetheless clear that such a situation is only possible if the coauthors allow the quality to decline (which they may have reason to do if they are junior to the author causing the decline). In such situations, we are looking at the problem from a psychological rather than strictly physical point of view.

\(^4\)http://citeseerx.ist.psu.edu, accessed February, 2015.

\(^5\)We limit our study to cited papers, not out of theoretical necessity, but out of practical convenience.
Figure 1: (Top panel) Frequency distribution of paper citation counts in the dataset. (Bottom panel) Frequency distribution of author citation counts in the dataset. In both cases, the complete tail of the distributions is not shown for clarity.
Figure 2: The distribution of $na$ obtained from the regression analysis. The complete tail is not shown for clarity.

Thomas H. Cormen$^6$ and Charles E. Leiserson$^7$ and their immediate coauthors.$^8$ This search yielded data for 1228 publications by a total of 1452 authors, after some manual pruning for author name variations where ambiguity was not an issue 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, 891 only appear on one paper each in the dataset and were excluded from the regression analysis.$^9$ The frequency distributions for the number of times a document or an author is cited is given in Figure 1 and are shown 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 $n_ia_i$ range from 2 to almost 1000; the lower end of the distribution is visualized in Figure 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. 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 three notable exceptions: Silvan Toledo, David M. Nicol and Benny

$^6$Search query: author:"thomas+h+cormen"
$^7$Search query: author:"charles+e+leiserson"
$^8$Search queries generated automatically by a script on the same model as used for Cormen and Leiserson.
$^9$This increases the robustness of the results.
Table 1: Number of publications (n), na-value and total (not fractional) number of citations for the ten top-ranked authors in the dataset according to na-value. The value of na is rounded to the nearest integer.

| Author             | n  | na  | Citations |
|--------------------|----|-----|-----------|
| Ronald L. Rivest   | 101| 939 | 9504      |
| David Kotz         | 145| 609 | 3987      |
| Guy E. Blelloch    | 71 | 401 | 2006      |
| Robert D. Blumofe  | 13 | 323 | 1780      |
| Michael A. Bender  | 59 | 312 | 1409      |
| Silvan Toledo      | 60 | 271 | 994       |
| David M. Nicol     | 68 | 269 | 856       |
| Satish Rao         | 51 | 260 | 1964      |
| Benny Chor         | 41 | 216 | 1824      |
| C. Greg Plaxton    | 45 | 194 | 1857      |

Chor all obtain a higher ranking under the na-system than they would by just counting total citations.

The rank correlation between the integer citation count and the na-values apparent from Table 1 is slightly stronger when the fractional citation count is substituted for the integer one. A frequency plot of the natural logarithm of the normalized author na-rank divided by the corresponding rank by the fractional citation count is seen in Figure 3. About 77% of the authors fall in the narrow range between ±0.5 natural log units from the origin.

4 Conclusion and outlook

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.

It is important to stress that the strong rank correlation between citations (fractional or otherwise) notwithstanding, the idea is not to introduce a more “expensive” method to calculate the citation ranks. It is 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, his

10The 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.
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 ($a$).

Finally, it should be pointed out 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.

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