

The effect of database dirty data on h -index calculation

Franceschini Fiorenzo · Maisano Domenico · Mastrogiacomo Luca

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Abstract As all databases, the bibliometric ones (e.g. Scopus, Web of Knowledge and Google Scholar) are not exempt from errors, such as missing or wrong records, which may obviously affect publication/citation statistics and—more in general—the resulting bibliometric indicators. This paper tries to answer to the question “What is the effect of database uncertainty on the evaluation of the h -index?”, breaking the paradigm of deterministic database analysis and treating responses to database queries as random variables. Precisely an informetric model of the h -index is used to quantify the variability of this indicator with respect to the variability stemming from errors in database records. Some preliminary results are presented and discussed.

Keywords Citations · h -index · h -index robustness · Uncertain data · Dirty database

Introduction

In recent years, the proposal of merit-based methods for the evaluation of scientific research has generated a growing interest towards bibliometric indicators. A crucial turning point in the history of bibliometrics was marked by the Hirsch’s h -index (Hirsch 2005). Although originally proposed for assessing the research output of individual scientists, this indicator has been actually used for the evaluation of group of papers, such as those of teams of scientists, or entire scientific journals (Braun et al. 2006; Van Raan 2006). By definition, a scientist (or any group of papers) has index h if h of his/her papers have at least h citations each and the other papers have $\leq h$ citations each (Hirsch 2005). Of course, h depends both on the quantity and the impact—in terms of received citations—of the papers of interest. For more on the (dis)advantages, properties, variants and improvements of h , please refer to the vast literature and extensive reviews (Bornmann and Daniel 2005; Braun et al. 2006; Van Raan 2006; Alonso et al. 2009; Franceschini and Maisano 2010a, b).

F. Fiorenzo (✉) · M. Domenico · M. Luca
Dipartimento di Ingegneria Gestionale e della Produzione (DIGEP), Politecnico di Torino,
Corso Duca degli Abruzzi 24, 10129 Turin, Italy
e-mail: fiorenzo.franceschini@polito.it

The popularity of the h -index has to be ascribed to its simplicity, immediacy and robustness, i.e. its insensitivity to small changes in publication/citation data.

As for all bibliometric indicators, the evaluation of h is based on data retrieved from bibliometric databases, which can differ significantly as regards their coverage and contents (Bar-Ilan et al. 2007; Jacsó 2008, 2011a, b).

The purpose of this paper is to investigate and quantify the robustness of the h -index to dirty input data (Hernández and Stolfo 1998; Kim et al. 2003). As a conceptual reference framework, we consider Egghe and Rousseau (2006) informetric model, which asymptotically describes the behaviour of the h -index, assuming that publications and citations are distributed according to Lotka's law.

The remaining of the paper is organized as follows. After an introductory example in Sect. 2, Sect. 3 provides a review of the literature concerning the robustness of the h -index. Section 4 recalls the main elements of Egghe et al.'s informetric model. Section 5 focuses on the estimation of the h -index's variability with respect to the parameters of Lotka's law. Section 6 presents and discusses some preliminary results. Finally, the conclusions are given, summarizing the original contributions of the paper.

Introductory example

This section aims at giving an initial idea of the robustness of h to changes in the input data. Although bibliometric databases often contain missing or wrong citation records, it will be shown that their distorting effect on the calculation of h is rather small.

As an example, let us consider a subset of eight publications of the authors of this paper, as presented in Table 1. For each article, it is reported the number of citing papers according to two bibliometric databases (i.e., Web of Knowledge and Scopus), considering only those papers from journals indexed by both databases (Scopus-Elsevier 2012; Thomson-Reuters 2012). This “redundancy of information” can be exploited for helping

Table 1 Example of citation data for some of the authors' papers extracted from the two main bibliometric databases (Web of knowledge and Scopus)

Article's DOI	“True” no. of citations	No. of citations returned by Web of knowledge	No. of citations returned by Scopus
10.1080/09511920601182217	15	11	13
10.1080/00207540701881852	8	5	8
10.1016/j.precisioneng.2008.11.003	3	3	3
10.1007/s00170-008-1677-0	2	2	2
10.1007/s00170-009-2331-1	1	1	1
10.1080/09511921003642147	2	2	2
10.1080/00207540902896220	1	1	0
10.1109/TIM.2009.2022106	1	1	1
<i>P</i>	8	8	7
<i>C</i>	33	26	30
<i>h</i> -index	3	3	3

Results are related to journals explicitly indexed by both databases. Despite database errors, h does not change. The same does not apply to P (i.e., the number of publications with at least one citation) and C (i.e., the total number of citations)

the detection of errors in the citation statistics provided by the two databases. The second column of Table 1 reports the “true” number of citations of each publication, obtained after manually checking the citing papers so as to identify “phantom” and omitted citations (Jacso 2006). On the other hand, the third and fourth columns reports the citation count respectively obtained from Web of Knowledge and Scopus.

Note that, although the number of citations is significantly different in some cases, the values of h do not differ. Although this is just an example, the goal of the rest of the paper is to provide theoretical evidence of this feature of h .

Literature review

Many bibliometricians have been recently debating about the robustness of h -index (Egghe 2006; Glänzel 2006b; Alonso et al. 2009; Franceschini and Maisano 2010a, b), which is twofold:

- it regards publications, since small variations in the amount of publications do not necessarily affect h .
- it regards citations, since h is relatively insensitive to small variations in the amount of citations of (i) uncited or lowly cited papers and (ii) outstandingly highly cited papers (Glänzel 2006b).

As a consequence, the h -index is generally robust to database dirty data, such as missing or wrong publication/citation records. Although this opinion is widely accepted in the literature, it is not often supported by a sound empirical or theoretical basis. Only few recent papers address this issue. Founding it hard to establish an error-free reference standard for the verification of bibliometric database records, Vanclay (2007) focuses his study on his personal publication output. Since it empirically emerges that the great majority of errors in databases tend to affect the low cited portion of a researcher’s scientific production, Vanclay argues that their influence on the h -index is relatively limited.

Henzinger et al. (2010) investigate whether rankings based on h are stable in the case of (i) use of different databases, (ii) citation count normalization by the number of authors, (iii) exclusion of self-citations, and (iv) introduction of artificial “noise”, by randomly removing citations or publications. They conduct an experiment for 5,283 computer scientists and 1,354 physicists showing that, although the ranking of the h -index is stable under most of the aforementioned changes, it may vary significantly when different databases are used.

Courtault and Hayek (2008) show that “in order to increase the h -index of a set of papers it is necessary to add a significant number of papers significantly cited”.

Even if these (and other) contributions from the existing literature conclude that the h -index is robust with respect to small amounts of noise in database records, none of them quantifies this robustness. This paper attempts to “plug this gap”, by estimating how much the h -index is sensitive to dirty data in databases. The approach herein proposed breaks the paradigm of deterministic database analysis, treating the h -index as a random variable, i.e. a variable whose value is subject to variations due to random chances (in this case the noise of bibliometric databases) (Kim et al. 2003). Consequently, each evaluation of h is seen as a realization of the random variable, which depends on the bibliometric database in use.

A reference informetric model of the h -index

The reference framework of our analysis is given by the informetric model of the h -index proposed by Egghe and Rousseau (2006). This model is based on Lotka's law:

$$f(j) = \frac{K}{j^a}, \quad (1)$$

where $K > 0$, $a > 1$ (Lotka 1926). Lotka function is used as a size-frequency density function $f(j)$ expressing the number of articles with exactly j citations. Even if many other informetric laws have been proposed in the literature, Lotka's law is the simplest and probably the most used one (Egghe 2009). In Eq. 1, K represents the number of articles with exactly one citation. In other terms,

$$f(1) = \frac{K}{1^a} = K. \quad (2)$$

To simplify, a common choice is to replace the discrete Lotka function with a continuous variant of Eq. 1. The continuous Lotka function φ is given by a power function of a continuous variable $j \geq 1$:

$$\varphi(j) = \frac{k}{j^\alpha}, \quad (3)$$

where $k > 0$, $\alpha > 1$. The use of a continuous function allows an easy evaluation of derivatives and integrals (Egghe 2005b). While recognizing the benefits of this approximation, Egghe (2005b) warns about its implications.

Under the assumption of Lotka's distribution and conforming to the continuous notation, Egghe (2006) shows that the h -index of a certain set of publications can be modelled as:

$$h = h(P, \alpha) = P^{1/\alpha}, \quad (4)$$

where P is the number of publications with at least one citation. Alternatively, the h -index can be modelled as a function of the total number of citations (C):

$$h = h(C, \alpha) = \left(\frac{\alpha - 2}{\alpha - 1} C \right)^{1/\alpha}. \quad (5)$$

It is worth remarking that this model is valid if and only if $\alpha > 2$ (Egghe and Rousseau 2006; Franceschini et al. 2012a, b).

Sensitivity analysis of h

Although being approximated, the model in Eqs. 4 and 5 may be useful to study the response of the h -index to variations of the independent variables, C , P and α .

This section proposes a sensitivity analysis of h , based on a classic approach borrowed from metrology: the *delta method* (also referred as *law of propagation of uncertainty* or *error transmission formula*) (Casella 2001; JCGM100:2008 2008; Montgomery 2009). By means of a linearization, this approach allows the calculation of the expected value and variance of a random variable, obtained as dependent nonlinear function of other random variables.

According to Eqs. 4 and 5, the h -index can be seen as a non-linear function of the random variables P , α and C , α respectively. Since the model of Eq. 5 is continuous,

differentiable and relatively smooth with respect to C and α , it can be expanded into a first order Taylor series about their expected values (μ_C, μ_α) as:

$$h = h(\mu_C, \mu_\alpha) + \left. \frac{\partial h}{\partial C} \right|_{\mu_\alpha, \mu_C} \cdot (C - \mu_C) + \left. \frac{\partial h}{\partial \alpha} \right|_{\mu_\alpha, \mu_C} \cdot (\alpha - \mu_\alpha) + R, \tag{6}$$

where R represents the higher order terms of h with respect to independent variables.

Partial derivatives are:

$$\frac{\partial h}{\partial \alpha} = \left(\frac{\alpha - 2}{\alpha - 1} C \right)^{1/\alpha} \left[-\frac{1}{\alpha^2} \ln \left(\frac{\alpha - 2}{\alpha - 1} C \right) + \frac{1}{\alpha(\alpha - 1)(\alpha - 2)} \right] \tag{7}$$

and

$$\frac{\partial h}{\partial C} = \left(\frac{\alpha - 2}{\alpha - 1} \right)^{1/\alpha} \frac{1}{\alpha} C^{\frac{1}{\alpha} - 1}. \tag{8}$$

Neglecting the terms of higher order, and applying the expected value and the variance operators to Eq. 6, one obtains:

$$\mu_h \approx \left(\frac{\mu_\alpha - 2}{\mu_\alpha - 1} \mu_C \right)^{1/\mu_\alpha}, \tag{9}$$

and

$$\sigma_h^2 \approx t_1^2 \sigma_\alpha^2 + t_2^2 \sigma_C^2 + 2t_1 t_2 \sigma_{\alpha, C} \tag{10}$$

being $\sigma_C, \sigma_\alpha, \sigma_{C,\alpha}$ respectively the standard deviations and the covariance of C and α , and t_1, t_2 the uncertainty propagation coefficients:

$$t_1 = \left. \frac{\partial h}{\partial \alpha} \right|_{\mu_\alpha, \mu_C} = \left[\left(\frac{\mu_\alpha - 2}{\mu_\alpha - 1} \mu_C \right)^{1/\mu_\alpha} \left(-\frac{1}{\mu_\alpha^2} \ln \left(\frac{\mu_\alpha - 2}{\mu_\alpha - 1} \mu_C \right) + \frac{1}{\mu_\alpha(\mu_\alpha - 1)(\mu_\alpha - 2)} \right) \right], \tag{11}$$

$$t_2 = \left. \frac{\partial h}{\partial C} \right|_{\mu_\alpha, \mu_C} = \left[\left(\frac{\mu_\alpha - 2}{\mu_\alpha - 1} \right)^{1/\mu_\alpha} \frac{1}{\mu_\alpha} \mu_C^{\frac{1}{\mu_\alpha} - 1} \right].$$

Similarly, *delta method* can be applied to Eq. 4 providing that

$$\mu_h \approx (\mu_P)^{1/\mu_\alpha} \tag{12}$$

and

$$\sigma_h^2 \approx t_3^2 \sigma_\alpha^2 + t_4^2 \sigma_P^2 + 2t_3 t_4 \sigma_{\alpha, P} \tag{13}$$

being $\sigma_\alpha, \sigma_P, \sigma_{\alpha, P}$ the standard deviations and the covariance of α and P , and t_3, t_4 the uncertainty propagation coefficients:

$$t_3 = \left. \frac{\partial h}{\partial \alpha} \right|_{\mu_\alpha, \mu_P} = \left[-\frac{\mu_P^{1/\mu_\alpha}}{\mu_\alpha^2} \ln \mu_P \right]. \tag{14}$$

$$t_4 = \left. \frac{\partial h}{\partial C} \right|_{\mu_\alpha, \mu_P} \left[\frac{1}{\mu_\alpha} \mu_P^{\frac{1-\mu_\alpha}{\mu_\alpha}} \right]$$

Model simplification

An important requirement for the practical application of previous models is the possibility of estimating α in terms of average value and standard deviation. The most used approach for the statistical estimation of α is the one proposed by Egghe (1990, 2005a):

$$\alpha \approx \frac{2C - P}{C - P}. \tag{15}$$

Equation 15 relates α with C and P . Using this approximation, Eq. 4 can reformulated as:

$$h = P^{\frac{C-P}{2C-P}}. \tag{16}$$

Given a set of P papers with at least one citation, the calculation of the h -index is affected by the uncertainty related to the estimation of C and P . Let us apply the *delta method* to Eq. 16. As seen before, it can be developed into a Taylor series:

$$h = h(\mu_C, \mu_P) + \frac{\partial h}{\partial C} \Big|_{\mu_C, \mu_P} (C - \mu_C) + \frac{\partial h}{\partial P} \Big|_{\mu_C, \mu_P} (P - \mu_P) + R, \tag{17}$$

where C and P are the independent variables with expected values μ_C and μ_P and R represents the higher order terms.

The partial derivatives of h with respect to C and P are:

$$\begin{aligned} \frac{\partial h}{\partial C} &= P^{\frac{C-P}{2C-P}} \left(\frac{P}{(2C - P)^2} \ln P \right), \\ \frac{\partial h}{\partial P} &= P^{\frac{C-P}{2C-P}} \left(\frac{-C}{(2C - P)^2} \ln P + \left(\frac{C - P}{2C - P} \right) \frac{1}{P} \right). \end{aligned} \tag{18}$$

Neglecting the terms of higher order and applying the expected value and the variance operators to Eq. 17, it is obtained:

$$\mu_h \approx \mu_P^{\frac{\mu_C - \mu_P}{2\mu_C - \mu_P}}, \tag{19}$$

and

$$\sigma_h^2 \approx t_5^2 \sigma_C^2 + t_6^2 \sigma_P^2 + 2t_5 t_6 \sigma_{C,P} \tag{20}$$

being σ_C the standard deviation of C and t_5, t_6 the uncertainty propagation coefficients:

$$\begin{aligned} t_5 &= \mu_P^{\frac{\mu_C - \mu_P}{2\mu_C - \mu_P}} \left(\frac{\mu_P}{(2\mu_C - \mu_P)^2} \ln \mu_P \right), \\ t_6 &= \mu_P^{\frac{\mu_C - \mu_P}{2\mu_C - \mu_P}} \left(\frac{-\mu_C}{(2\mu_C - \mu_P)^2} \ln \mu_P + \left(\frac{\mu_C - \mu_P}{2\mu_C - \mu_P} \right) \frac{1}{\mu_P} \right). \end{aligned} \tag{21}$$

Compared to the models proposed before, this one is based on the simplifying hypothesis that α is estimated by Eq. 15. The model can be further simplified by assuming the independence between P and C ($\sigma_{C,P} = 0$) and ignoring the contribution relating to the variability of P (i.e., $\sigma_P = 0$):

$$\sigma_h^2 \approx t_5^2 \sigma_C^2. \tag{22}$$

Equation 22 means that the uncertainty in the calculation of the h -index by the bibliometric model proposed by Egghe depends on the uncertainty in evaluating C . In practice, C is strictly influenced by the inaccuracy level of the database in use.

Application example

Without introducing any assumption about the distribution of C , this section exemplifies the use of the simplified model in Eq. 22.

Since Lotka’s law applies well for high values of P and C , this model is herein used to estimate the σ_h relating to relatively large publication portfolios. Specifically, it was considered the publication output of the authors’ institution (i.e. Politecnico di Torino) and those of the top three world universities according to the Times Higher Education World University Rankings 2011–2012 (Times Higher Education 2012). As an example, the analysis is limited to the articles published in the year 2008. For this case study, Scopus was queried in July 2012. The results of the queries are synthetically shown in Table 2.

We remark that, in this specific case, the model derived from Lotka’s Law systematically underestimates the empirical value of the h -index. Table 3 shows the values of σ_h calculated by Eq. 22 for different possible values of σ_C , in order to reproduce several database inaccuracy levels.

Note that the results obtained are obviously influenced by P and C . However, this dependence is not so marked, and rather similar values of σ_h are associated with completely different universities. Although quite expectable, these results are remarkable. A practical consequence of the model in Eq. 22 is that the resulting h -indices are robust even to significant changes in C : a $\sigma_C = 10\% \cdot C$ would produce a σ_h smaller than one! Also, we remark that the proposed method does not require any assumption about the distribution of C or h .

As a verification of the proposed method, a Monte Carlo simulation was performed. The portfolio of ($P = 664$) publications of Politecnico di Torino (see Table 2) was simulated introducing a Gaussian noise on the total number of citations (i.e. $C \sim N(\mu_C = 5564, \sigma_C^2)$). The standard deviation σ_C was increased from 1 % of C up to the 20 % of C . For each value of σ_C , 10,000 values of C were generated. Then, σ_h values were calculated for simulated data, as well as through the model proposed in Eq. 22. Results are shown in Fig. 1.

The comparison shows a good correspondence between simulated and calculated values of σ_h . As expected, differences are more pronounced for high values of σ_C , due to the linearization introduced by the *delta method*.

Table 2 Publication/citation statistics concerning the publication output of four universities, in the year 2008

Parameter	Politecnico di Torino	California Institute of Technology	Harvard University	Stanford University
P	664	2631	2419	3224
C	5564	45740	64895	71619
$h = P^{\frac{C-P}{2C-P}}$	21	46	46	52

Data were retrieved from Scopus, in July 2012

Table 3 Estimation of the σ_h values relating to the publication/citation statistics in Table 2 and different values of σ_C

	Politecnico di Torino	California Institute of Technology	Harvard University	Stanford University
σ_h				
$\sigma_C = 1 \%C$	0.05	0.03	0.03	0.05
$\sigma_C = 5 \%C$	0.23	0.27	0.17	0.25
$\sigma_C = 10 \%C$	0.45	0.55	0.34	0.49

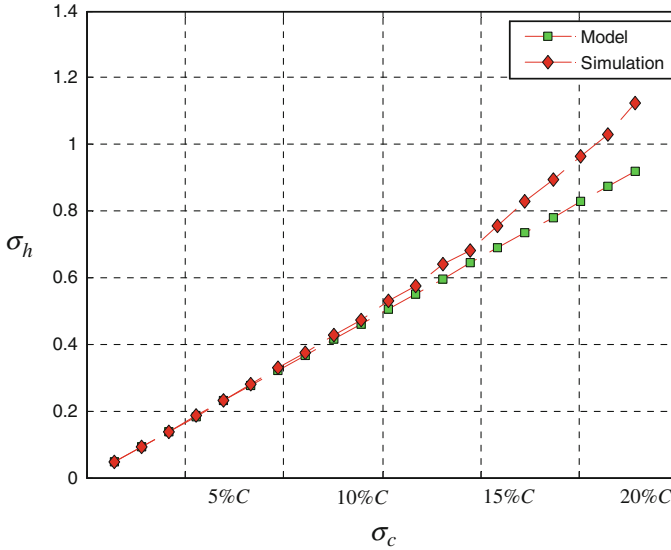


Fig. 1 Comparison between simulated and modelled results of σ_h

Although this is only a simplified example referring to a specific situation (i.e., when $P = 664$ and $C = 5564$), the relatively low values of σ_h are a consequence of the h -index’s robustness to changes in C and P .

Conclusions

This paper proposed a model for estimating the variability of the h -index by means of the informetric model by Egghe and Rousseau (2006), which relates the variability of h with that of C and P .

The proposed approach breaks the paradigm of deterministic database analysis, treating database records as random variables characterized by intrinsic variability, due to the noise (dirty data) contained into each database. A remarkable result is that the h -index is weakly sensitive even to significant changes in the C values of the papers of interest.

The proposed methodology could be applied to other informetric models of the h -index, such as that of Glänzel (2006a) based on Zipf’s distribution, in order to confirm the results of this analysis.

Further research will define a practical procedure for the quantification of dirty data contained into bibliometric databases.

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