



A rational indicator of scientific creativity

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Abstract

A model is proposed for the creation and transmission of scientific knowledge, based on the network of citations among research articles. The model allows to assign to each article a non-negative value for its creativity, *i.e.* its creation of new knowledge. If the entire publication network is truncated to the first neighbors of an article (the n references that it makes and the m citations that it receives), its creativity value becomes a simple function of n and m . After splitting the creativity of each article among its authors, the cumulative creativity of an author is then proposed as an indicator of her or his merit of research. In contrast with other merit indicators, this creativity index yields similar values for the top scientists in two very different areas (life sciences and physics), thus offering good promise for interdisciplinary analyses.

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1. Introduction

Evaluating the scientific merit and potential, of tenure and professorship candidates, is perhaps the most critical single activity in the academic profession. In countries and institutions with a long scientific tradition, selection committees are generally well trained and trusted to balance wisely the vast variety of factors that may influence the decision, in the sense of optimizing the long-term scientific output. In less established environments, decisions are frequently perceived as arbitrary, and the use of objective indicators and procedures may be necessary to obtain a wide consensus (Moed, 2005).

The most traditional indicator of research output, the number of published papers, has been progressively substituted by the number of citations received by those papers, when this impact indicator has become widely available and easy to obtain (Garfield, 1964; ISI-Thomson, 2006). Different combinations of both magnitudes have been proposed (Rinia, van Leeuwen, van Vuren, & van Raan, 1998) like those in the SPIRES database (SPIRES, 2006). The field has been recently revitalized by the proposal by Hirsch (2005) of yet another combination, the so-called h index, which has gained a rapid popularity, partly because the ISI-Thomson Web of Knowledge database (ISI-Thomson, 2006) provides a handy tool to sort articles by their number of citations. Apart from that comparative handiness, there is little objective evidence for the relative advantages of different indexes, which are generally motivated in terms of “impact” or “influence”. However, it must not be forgotten that the task of a scientist is to create useful knowledge (in its broadest sense), not merely to produce an impact. It is therefore desirable to derive some rational measure of the magnitude and quality

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of research output, rooted in a plausible model of the creation and transmission of scientific knowledge (Rinia, van Leeuwen, Bruins, van Vuren, & van Raan, 2002).

2. Creativity model

Basic scientific knowledge, as opposed to technological or industrial knowledge, is created by the minds of scientists and expressed almost exclusively as research articles. The knowledge is transmitted to other scientists, who read previous articles and acknowledge this transmission in the form of references (in what follows, I will call *references* of an article those made to previous papers, and *citations* those received from posterior papers). Thus, the output knowledge of an article comes partly from previous work, which is simply transmitted, and partly from the creation of new knowledge by the authors. However, there are many possible reasons why references are made (Cozzens, 1989; Garfield, 1964; Gilbert, 1977; Merton, 1968). Furthermore, some of the references of an article may be more important than others. Thus, it is rather uncertain to what extent a given reference reflects the use of previous knowledge. Therefore, in the present model, I will simply assume that each reference reflects the transmission of a different non-negative value x_{ij} of knowledge, with probability $P(x_{ij})$, from the cited article i to the citing article j . The maximum entropy principle (Tribus, 1969) dictates that, in the absence of any *a priori* information, other than the average value $\langle x \rangle = 1/\alpha$, the probability is given by $P(x) = \alpha e^{-\alpha x}$.

Consider the network formed by all published papers connected by their citations. The growth, connectivity, and statistical properties of this and similar networks have been the subject of much recent work (Albert & Barabasi, 2002; Redner, 2005). To model the flow of knowledge on this supporting network (Rinia et al., 2002), we may assign random flow numbers x_{ij} to all citations, with probability $P(x_{ij})$. Flow conservation implies that the articles' knowledge-creation values c_i (that I will simply call *creativities*) obey

$$c_i = \sum_j x_{ij} - \sum_k x_{ki} \quad (1)$$

I will discard negative knowledge as meaningless.¹ Thus, I will require that $c_i \geq 0 \forall i$, and reject the sets $\{x_{ij}\}$ that violate this condition.^{2,3,4} The final values c_i will then be averages over all valid sets $\{x_{ij}\}$, with a relative weight $P(\{x_{ij}\}) \propto \exp(-\alpha \sum_{ij} x_{ij})$.

Some attention must be paid to the definition of knowledge that is being used. It might seem that all the knowledge created by an article must be present already when it is published. However, this would make it difficult to judge the relative importance of the knowledge created by different papers. Therefore, I rather consider the amount of “used knowledge” (and therefore useful). The situation is very similar in commercial software development: the economic value of a computer library does not materialize when it is written, but when licenses of it are sold, presum-

¹ An ironic observer might object to this assumption, arguing that many articles contribute only to confusion, and that some citations are in fact critical. I find this questionable, since most readers will filter efficiently this “negative” knowledge, simply ignoring it. Also, even wrong ideas can stimulate new valid ones. In any case, critical references cannot be easily distinguished from positive ones, but their average effect might be taken into account by renormalizing the mean flow value $\langle x \rangle$.

² Since new, non-negative knowledge is created in every article and transmitted to the future, the total flow of knowledge must increase with time. Such an increase may be absorbed in three ways: by an increase in the number of articles published per year, by an increase in the number of references per article, and by an increase in the average flow per citation $\langle x \rangle$. The increase of the rate of publications is indeed a large effect, while that of citations per paper is much weaker, if positive at all. In any case, it is not clear whether those two effects combined can fully account for the transmission of the new knowledge predicted by the model. Thus, it may be necessary to adjust self-consistently a function $\alpha(t)$, of time t . In this work, I have taken $\alpha = \text{constant} = 1$.

³ Some of the basic scientific knowledge “leaks” out of the academic research literature in various forms: as knowledge absorbed by scientists who read the articles but do not cite them; as established knowledge transmitted to textbooks and no longer cited in research articles (oblivion by incorporation); as technological knowledge translated to patents, that may cite the literature but that are not included in databases of basic research (Narin, Hamilton, & Olivastro, 1997); and as industrial knowledge translated to unpublished manufacture methods and products. It seems reasonable to assume that this “hidden” flow of knowledge is proportional on average to the “visible” flow shown by citations. Therefore, in order to account for the hidden flow, we may multiply the visible output flow of each article (first term of Eq. (1)) by a factor $(1 + \gamma)$, where γ is a phenomenological adjustable parameter. In the simplified model of this work I have taken $\gamma = 0$.

⁴ The boundary problem posed by recent papers, that have had no time to transmit their knowledge, may be addressed by not imposing flow conservation on them, or by assigning to them an average number of additional expected citations, that will be a decreasing function of their age. In any case, it is clear that any figure of merit based on citations will not be as reliable for very recent papers as for old ones.

ably to create new software. Similarly, I am counting every “copy” of the knowledge, used in every new paper that cites it.

This economic analogy can be pursued further. Thus, I will argue that, to a large extent, the citation network acts as a market in which citing and cited articles act, respectively, as buyers and sellers of scientific knowledge. At first sight, it might seem that the price of existing knowledge is zero, since it costs nothing to read and cite a published article. However, there are practical limits to the number of references that can be made. These limits are dictated by journal conditions, by the community citation practices, and, most importantly, by the authors limited time to read new articles, and memory to remember them. Therefore, authors are forced in practice to select a limited number of references, that are most relevant to their works. As in any market, the limited resources determine the “prices”, in this case the flows of knowledge assigned to each citation.

Some of the general qualitative features of the model, as an indicator of research merit, may be expected *a priori*: articles with less citations than references will have a positive but small creativity value; articles with a large output (very cited) and a small input (not many references) will have the largest creativities; in contrast, the merit of review articles will be much more moderate than that shown by their raw impact factor (citation count); the differences between the creativities of authors in very large and active fields (with large publication and citation rates), and those in smaller and less active fields, will be largely attenuated, as compared to other merit indicators, since the basic measure is the difference between citations and references, which should be roughly zero in all fields; self-citations will be largely discounted, since they will count both as a negative contribution (to the citing paper) and a positive one (to the cited paper); citations received from a successful article (*i.e.* a very cited one itself) will be more valuable than those made by a poorly cited one (Chen, Xie, Maslov, & Redner, 2006; Pinski & Narin, 1976). In particular, citations by uncited papers will add no value at all, since no knowledge can flow through them; more generally, articles that generate a divergent citation tree (*e.g.* the DNA paper of Watson and Crick) will have a large creativity, while those leading ultimately to a dead end (*e.g.* the cold fusion paper of Fleischmann and Pons) will have a small one, even if they had the same number of direct citations.

3. Simplified model

The quantitative analysis of the model presented above is an interesting challenge that will be addressed in the future. In this work, I am rather interested in simplifying the model to allow the easy generation of a practical indicator of merit of research. The simplified model will keep many of the general features discussed above, though not all (in particular, it will loose the last two properties mentioned above). Thus, I propose to truncate the citation network beyond the first neighbors of any given paper, *i.e.* to consider only its n references and m citations, and to impose the conservation of flow, Eq. (1), only in the central node i . The average value $\langle x \rangle$ can be used as a convenient unit of knowledge, so that $\alpha = 1$ and $P(x) = e^{-x}$. The probability that an article, with n references and m citations, has a creativity c is then, for $n, m > 0$:

$$P(c|n, m) = N^{-1} \int \cdots \int_0^\infty dx_1 \cdots dx_n dy_1 \cdots dy_m \delta(c + x - y) e^{-x-y} \quad (2)$$

with $x = \sum_{i=1}^n x_i$ and $y = \sum_{j=1}^m y_j$, where x_i are the input flows (references) and y_j are the outputs (citations). $\delta(x)$ is Dirac's delta function and N is a normalization factor given by

$$N = \int \cdots \int_0^\infty dx_1 \cdots dx_n dy_1 \cdots dy_m \theta(y - x) e^{-x-y} \quad (3)$$

where $\theta(x)$ is the step function. Using a convenient change of variables, the integrals can be evaluated as

$$N = \int_0^\infty \int_0^\infty \frac{dx dy x^{n-1} y^{m-1}}{(n-1)!(m-1)!} \theta(y - x) e^{-x-y} \quad (4)$$

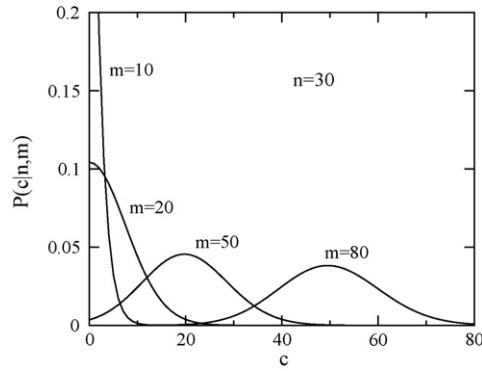


Fig. 1. Probability that an article, that has made $n = 30$ references and has received m citations, has created a value c of scientific knowledge. It was obtained from Eq. (6).

$$P(c|n, m) = N^{-1} \int_0^\infty \int_0^\infty \frac{dx dy x^{n-1} y^{m-1}}{(n-1)!(m-1)!} \delta(c+x-y) e^{-x-y} \quad (5)$$

The result is

$$P(c|n, m) = \frac{n e^{-c}}{n+m-1} \frac{{}_1F_1(1-m, 2-n-m; 2c)}{{}_2F_1(1, 1-m; 1+n; -1)} \quad (6)$$

where ${}_1F_1$ and ${}_2F_1$ are hypergeometric functions, which can be expanded as a finite series (Gradshteyn & Rydhik, 1980). Fig. 1 shows some typical probability distributions.

The average value of c ,

$$c(n, m) = \int_0^\infty dc c P(c|n, m), \quad (7)$$

is, for $n, m > 0$:

$$c(n, m) = \frac{\sum_{k=0}^{m-1} ((n+m-2-k)!/(m-1-k)!)(k+1)2^k}{\sum_{k=0}^{m-1} ((n-1)!(n+m-1)!)/((n+k)!(m-1-k)!)} \quad (8)$$

It is represented in Fig. 2 for some typical values of n and m . As expected, $c(n, m)$ increases with m and it decreases with n . It obeys $c(0, m) = m$, $c(n, 0) = 0$, $c(n, 1) = 1$, and $c(n, m) \geq \max(1, m-n) \forall m > 0$. For the present purposes, a

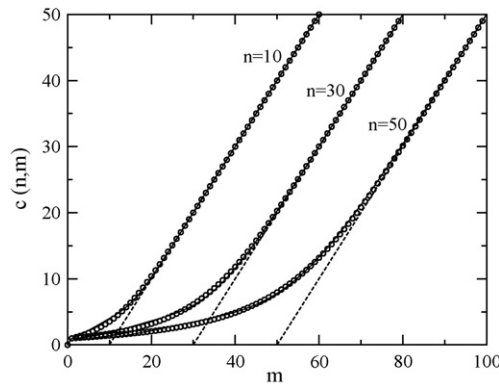


Fig. 2. Circles: mean creation of knowledge (creativity) of an article with n references and m citations, calculated from Eq. (8) (in units of the mean transmission of knowledge reflected by one reference). Solid lines: fits given by Eq. (9). Dashed lines: $m - n$.

reasonably accurate fit is, for $m > 0$:

$$c(n, m) \simeq m - n + \frac{n}{A e^{az} + B e^{bz}} \quad (9)$$

where $z = (m - 1)/(n + 5)$, $A = 0.986$, $B = 0.014$, $a = 1.08$, and $b = 6.3$. The accumulated creativity of an author with N_p published papers is then defined as

$$C_a = \sum_{i=1}^{N_p} \frac{c(n_i, m_i)}{a_i} \quad (10)$$

where a_i is the number of authors of paper i . Notice that, being positive and cumulative, C_a can only increase with time and with the number of published papers.

In order to find in practice the creativity of an author (among many other merit indicators), one can follow these steps: (1) download the programs *filter* and *merit* from this author's web page (Soler, 2006), and compile them if necessary. (2) Perform a "General search" in the ISI-Thomson Web of Science database (ISI-Thomson, 2006) for the author's name, using the appropriate filters. (3) Select the required records. Usually the easiest way is to check "Records from 1 to last_one" and click on "ADD TO MARKED LIST" (if you find too many articles, you may have to mark and save them by parts, say (1–500) → file1, (501–last_one) → file2); (4) click on "MARKED LIST". (5) Check the boxes "Author(s)", "Title", "Source", "keywords", "addresses", "cited reference count", "times cited", "source abbrev.", "page count", and "subject category". Do not check "Abstract" nor "cited references", since this would slow down considerably the next step. (6) Click on "SAVE TO FILE" and save it in your computer. (7) Click on "BACK", then on "DELETE THIS LIST" and "RETURN", and go to step 2 to make another search, if desired. (8) If you suspect that there are two or more authors with the same name, use the *filter* program to help in selecting the papers of the desired author. (9) Run the *merit* program to find the merit indicators. Mind for hidden file extensions, possibly added by your navigator, when giving file names in this and previous step.

4. Results and discussion

Table 1 shows several indexes of merit of top scientists in life sciences and physics, taken from Hirsch's selection (Hirsch, 2005). It may be seen that the h index of all biologists is larger than that of all physicists, and their average number of publications and citations is 1.5–2.5 times larger. In contrast, the two creativity distributions are remarkably similar, with averages that differ only ~15%, well below the standard deviation of both distributions. This offers the promise of direct interdisciplinary comparisons, without any field normalization, a highly desirable characteristic of any index of merit.

Although it is a natural consequence of the idea of knowledge flow, the fact that the references of an article will result in lowering the merit assigned to it, is admittedly striking. It is thus appropriate to recognize that this is partly due to a deliberate intent of measuring creativity rather than productivity (or, in economic terms, added value rather than sales). To illustrate the point, imagine that two scientists, Alice and Bob, address independently an important and difficult problem in their field. Bob takes an interdisciplinary approach and discovers that a method developed in a different field just fits their need. Simultaneously, Alice faces the problem directly and re-invents the same method by herself (thus making less references in her publication and achieving a higher creativity index).⁵ All other factors being equal, both papers will receive roughly the same number of citations, since they transmit the same knowledge to their field. But, while it may be argued that Alice's work was more creative in some sense, it might also be argued that Bob's approach is better, since it additionally shows the relationship with a different field. Thus, although I believe that C_a genuinely correlates with scientific creativity, I would not argue that this is necessarily the most valuable research ability in general.

Eventually, the usefulness of different merit indicators will depend on how well they correlate with real human-made selections (Cole & Cole, 1971; Rinia et al., 1998). Thus, Table 1 shows also a "productivity index" P_a (not a probability), given by the author's share of the citations received by her/his papers. Notice that, in the model proposed,

⁵ This is somewhat hypothetical since good citation practice (frequently enforced by the referees) requires that previous relevant work is cited, independently of whether it was actually used.

Table 1

Several merit indicators of the 10 most cited scientists in life sciences and physics (Hirsch, 2005)

Name	N_p	N_c (10^3)	h	P_a (10^3)	C_a (10^3)
B. Vogelstein	447	144.4	154	34.1	32.0
S.H. Snyder	1144	138.3	194	48.2	38.9
S. Moncada	693	106.2	145	32.5	27.8
P. Chambon	987	98.1	153	23.0	17.7
R.C. Gallo	1247	95.9	154	17.9	13.8
D. Baltimore	657	95.3	162	33.0	28.2
R.M. Evans	428	78.8	130	21.2	18.3
T. Kishimoto	1621	77.5	134	14.6	10.2
C.A. Dinarello	992	74.3	138	26.3	19.2
A. Ullrich	615	73.0	122	13.6	10.9
Average	883	98.2	149	26.4	21.7
Standard deviation	364	24.1	19	10.1	9.1
P.W. Anderson	342	56.7	96	39.1	36.9
A.J. Heeger	999	53.5	109	14.2	10.3
E. Witten	254	53.1	111	39.9	35.9
S. Weinberg	444	38.8	88	32.7	29.3
M.L. Cohen	625	37.4	94	14.3	10.6
M. Cardona	1096	37.0	88	12.8	7.8
A.C. Gossard	918	34.3	92	7.4	5.8
P.G. deGennes	358	32.6	80	26.7	23.9
M.E. Fisher	446	29.8	88	19.0	14.3
G. Parisi	469	24.9	75	12.2	9.9
Average	595	39.8	92	21.8	18.5
Standard deviation	286	10.4	11	11.3	11.3

N_p , number of papers published; N_c , number of citations received by those papers; h , number of papers with h or more citations (Hirsch index) (Hirsch, 2005); P_a , author's knowledge-productivity index, $P_a = \sum_{i=1}^{N_p} m_i/a_i$, where a_i and m_i are the number of authors and of citations received by paper i ; C_a , author's creativity index, Eq. (10). The data were obtained in April 2006.

Table 2

Several indicators of some of the main multidisciplinary, review and non-review physics journals

Journal	N_p	N_r/N_p	N_c/N_p	C/N_p	IF
<i>Nature</i>	3676	10	67	59	28.8
<i>Science</i>	2449	14	74	63	24.4
<i>PNAS</i>	2133	31	112	84	9.8
<i>Rev. Mod. Phys.</i>	20	284	327	160	13.4
<i>Adv. Phys.</i>	8	391	149	18	12.7
<i>Surf. Sci. Rep.</i>	5	159	61	3	10.3
<i>Rep. Prog. Phys.</i>	29	198	90	32	6.2
<i>Phys. Rep.</i>	81	166	90	22	5.6
<i>Phys. Rev. Lett.</i>	1904	18	59	44	6.0
<i>Phys. Rev. D</i>	1049	27	23	11	3.9
<i>Nucl. Phys. B</i>	620	37	42	24	3.3
<i>Appl. Phys. Lett.</i>	1819	13	34	26	3.3
<i>J. Chem. Phys.</i>	2040	37	37	16	3.1
<i>Phys. Rev. B</i>	3488	27	35	18	2.8

N_p , number of “papers” (documents) published in year 1990, in all the sections included in the Science Citation Index database; N_r , number of references made by those papers; N_c , number of citations received by those papers until May 2006 (August 2006 for *PNAS*); C , sum of the creativities, Eq. (8), of those papers, $C = \sum_{i=1}^{N_p} c(n_i, m_i)$; IF, impact factor in 1998 (center of the period 1990–2006), as defined by the Journal of Citation Reports (ISI-Thomson, 2006). For the non-review physics journals (last group), the indicators (other than N_p and IF) have been obtained from a random sample of their N_p papers, rather than from the whole set.

N_c is the total output flow of knowledge from the author's papers, while P_a is her/his share of it. It may be seen that P_a also allows reliable interdisciplinary comparisons. It may be concluded that the main difference between the two communities is the larger average number of authors per article in the life sciences, which is taken into account in both P_a and C_a , but not in the other indexes.

Knowledge-productivity and creativity indicators can be used also for groups, institutions, or journals. Thus, Table 2 shows them for some leading journals. As expected, most review journals have considerably smaller creativities than productivities (dramatically smaller in some cases). Still, *Reviews of Modern Physics* has the largest creativity index of all the journals studied, showing that collecting, processing, and presenting knowledge in a coherent way can by itself create much *new* useful knowledge.

Finally, in a world of strong competition for positions and funds, a negative merit assignment to references might result in a tendency to reduce them below what would be scientifically desirable and professionally fair. A possible solution is to use, in Eq. (8), a fixed value of n (equal to the journal reference intensity, *i.e.* the average number of references per article in that journal), to calculate the creativities for competitive-evaluation purposes. This would spoil a few desirable properties of the model (like the discount of self-citations), but most of its effects would probably be rather mild, since the number of references per paper has a much smaller variance than the number of citations. Thus, the root mean squared difference between the creativities of Table 1, calculated using the average references of the journals, rather than the actual references of each article, is only $\sim 4\%$.

5. Conclusion

In conclusion, I have proposed an index of research merit based on creativity, defined as the creation of new scientific knowledge, in a plausible model of knowledge generation and transmission. It is calculated easily from the citations and references of the author's articles, and it is well suited for interdisciplinary comparisons. An advantage of such an index is that its meaning may be more easily perceived, by policy makers and the general public, as a measure of a scientist's social and economic service to the community.

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