On the orthogonality of indicators of journal performance

Gangan Prathap*, P. Nishy and S. Savithri

CSIR National Institute for Interdisciplinary Science and Technology, Thiruvananthapuram 695 019, India

We identify two orthogonal journal performance indicators from the points of view of size-dependence and principal component analysis using graph-theoretic constructs from social network analysis. One, the power–weakness ratio is a size-independent recursive proxy for the quality of the journal's performance in the network. The second, the number of references (out-links) that the journal makes to all journals in the network is the size-dependent proxy for the size of the journal (a quantity metric). In an input–output sense, the number of references becomes the measure of the input and the number of citations received by the journal from all journals in the network becomes the size-dependent measure of the output. The power–weakness ratio of citations to references before recursive iteration becomes the non-network measure of popularity and the power–weakness ratio of weighted citations and weighted references after recursive iteration becomes the network measure of prestige of the journal. It is also possible to propose first-order and second-order measures of influence which are products of the quality and quantity parameter space. We also show that the influence weight that emerges from a Pinski–Narin or Google PageRank formulation is a size-dependent measure of prestige that is orthogonal to the power–weakness ratio. We illustrate the concepts using two simple artificial two- and three-journal networks and a real-life example of a sub-graph of 10 well-known statistical journals with network data collected from the *Web of Science*.

Keywords: Bibliometrics, journal performance, power–weakness ratio, social network analysis.

CITATION analysis as a tool, first for journal evaluation, and later for more broad-based research evaluation of individuals, groups, institutions and scientists is now nearly 50 years old[1,2]. The simplest way to summarize the original concept is to interpret it in terms of two Aristotelian categories – quality and quantity. In the case of journal evaluation, when it belongs to a network (say that in the Web of Science Core Collection), the size of the journal is measured by the count of all articles P published in it during a chosen window (called the publications window). This can be viewed as a size-dependent input term for evaluating journal performance. The size-dependent output term is the number of citations C received by these P articles from all articles published in all journals in the network during a specified period called the citations window. From these it is possible to derive a size-independent quality proxy called impact $i = C/P$. Indeed, this is the provenance for the journal impact factor (IF), the numerator C being the number of cites in the current year (citations window) to the articles published in the previous two years (publications window), while the numerator is the number of articles P published during the same publications window. Note that this factor is now a size-independent ratio of two size-dependent values.

A half century since its introduction, and thousands of articles on IF itself, new and more mathematically rigorous indicators for journal performance evaluation have been introduced[3–5]. Pinski and Narin[6] proposed an iterative algorithm that proceeded from the raw count of citations C to a weighted count that took cognizance of the 'prestige' of the citing journal. These are problems that arise frequently in social network analysis and there are well-established graph theoretic tools that allow computation of the recursive indicators. In this communication we shall particularly exploit an idea that was introduced by Ramanujacharyulu[7] for defining a new size-independent network property. The raw count of citations is a non-recursive non-network measure. Taking into account the 'prestige' of the journal from which a citation arises is a network measure that needs a recursive iterative computation[6,8,9]. Thus, while counting total citations is a non-recursive measure, taking into account the 'prestige' of the journal from which the citation arises needs a recursive iterative computation. It has even become fashionable to relate the 'raw' counts of citations to 'popularity' and 'weighted' recursively computed counts of citations to measure 'prestige'[6,10].

At this stage we discuss the distinction between size-dependent metrics and size-independent metrics[6,11–13]. As a journal performance metric, the IF has been around for more than half a century[1]. It is computed from two size-dependent indicators: the total number of articles P published in the journal during a two-year publications window and the total citations C to these articles from all articles published during the one-year citation window immediately following the publications window. For example, the two-year IF for any journal in a database (say, the contemporary Web of Science Core Collection of Thomson Reuters) for the year 2013 is based on a two-year publications window (in this case, 2011 and 2012). Then the impact i is computed as citations per paper, C/P, which is a size-independent measure. While C is a size-dependent total impact, i is a size-independent specific impact. Very quickly, i began to be used as a proxy for quality not only for journal evaluation but also by extension (mis)used for evaluation of authors and institutions. Fortunately, without much controversy, P is a candidate proxy for quantity or size.

Another important idea crucial to the development of the arguments here is that of dimensionality. The new

*For correspondence. (e-mail: gp@niist.res.in)

generation of bibliometric indicators that come from social network considerations may measure different dimensions of the citation networks, or may be highly correlated among themselves[4]. It is possible to distinguish two main dimensions – size and impact – and Leydesdorff[4] argues that together they shape a property called 'influence'[14]. The primary non-recursive non-network indicators like P, C and i have dimensions like size/quantity assigned to P and quality assigned to i, while C being a product of quality and size has both dimensions and can be identified with total impact or total 'influence' of a journal. It is not so easy to assign dimensionality to the recursive network indicators that emerge from a graph-theoretical and social network methodology. This is clear from the evaluation of bibliometric indicators arising from the social network analysis performed on journal citation data[4,15]. Bollen *et al.*[15] have shown through a rigorous principal component analysis study of 39 scientific impact measures that the notion of scientific impact is a multi-dimensional construct that cannot be adequately measured by any single indicator, although some measures are more suitable than others. In their scheme also, the citation impact is just one measure at the periphery.

Here we propose a size-independent metric for journal evaluation using an idea developed from Ramanujacharyulu[7]. To illustrate the effectiveness of this indicator we choose two artificially generated journal ecosystems and one real-life journal ecosystem.

Around the same time that the journal citation networks were being set up, Ramanujacharyulu[7] worked with the associated matrices that arise in graph theory, and proposed to balance the 'power to influence' with the 'weakness to be influenced' through a measure called the power-weakness ratio. Consider the 'cited-citing' matrix that arises in a bibliometric formulation. We shall follow the terminology used to compute the Eigenfactor Score and the Article Influence Score indicators to explain the principal features[9,16]. Let $\mathbf{Z}$ be the cited–citing matrix. When entries are read row-wise, then for a journal in row i, an entry such as $\mathbf{Z_{ij}}$ are the citations from journal j in the citation window (say 2013) to articles published in journal i during the publications window (say 2011–12); in social network analysis these are the in-coming links. The matrix can also be read column-wise; now for the journal in column j, the entry $\mathbf{Z_{ij}}$ are the references from journal j in the citation window (2013) to articles published in journal i during the publications window (2011–12). In social network analysis, these are the out-going links. Thus, row-wise, we see the journal i's 'power to influence' and 'column-wise' we see the journal j's 'weakness to be influenced.' The row-sum corresponding to row i is therefore the non-recursive indicator C, i.e. the total citations to journal i from all the journals in the ecosystem, including itself. This is taken as a measure of the 'popularity' of journal i. If we also have an article vector a, where a_i is the number of articles published by journal i over the publications window, then this is the value P for journal i, and the ratio C/P is the non-recursive impact of the journal. A note of caution to be introduced is that the subscript i is used here as an indicial notation and elsewhere in this communication, from the compulsions of historical legacy, as the notation for journal impact.

In the graph theoretic sense, $\mathbf{Z} = [\mathbf{Z_{ij}}]$ is the matrix associated with the graph[7]. Many properties of such matrices are known and it can be raised indefinitely to the kth power, i.e. $\mathbf{Z}^k$. This is the matrix used to define the 'power of the journal to influence'[7]. The eigenfactor approach is thus a recursive iteration that raises $\mathbf{Z}$ to an order were convergence is obtained for what is effectively the weighted value of the total citations. So far the matrix calculations have all proceeded row-wise. For each journal we can find a value $p_i(k)$, which can be called the iterated power of order k of the journal i 'to influence'.

Next, the same operations are performed on the transpose of the matrix $\mathbf{Z}^{\mathrm{T}}$ and then proceeding row-wise on these transposed elements in the same recursive and iterative manner indicated above[7]. This now defines the 'weakness of the journal to be influenced by.' Again, for each journal we can find a value $w_i(k)$, which can be called the iterated weakness of order k of the journal i 'to be influenced by'.

At this stage we have two vectors of power k – the power vector $p(k)$ and the weakness vector $w(k)$. The elements of the former are the recursive counts of citations. The eigenfactor methodology divides $p_i(k)$ by a_i, the number of articles published by journal i over the publications window, to get the Article Influence, which is the surrogate for the recursive impact of the journal. In this communication, we propose that instead of a_i, take $w_i(k)$ as the recursive surrogate of the size of the journal. Then Ramanujacharyulu's power–weakness ratio of order k, $r_i(k) = p_i(k)/w_i(k)$ becomes a size-independent recursive network measure of impact or quality of the journal. As $k \to \infty$, we get the converged power–weakness ratio.

We shall carry out a few studies to illustrate this idea below and to establish that the power–weakness ratio is a size-independent measure that is orthogonal to the number of references, which is a size-dependent measure.

We artificially create a two-journal network so that size and citation density effects can be clearly identified[17]. Garfield's[17] definition of citation density was based on the ratio of citations to articles and belonged to the pre-network analysis era. We now see from Ramanujacharyulu's approach that a better definition of citation density from the network connection point of view is to take the ratio of citations to references. Figure 1 shows the relevant cells of an Excel spreadsheet that has two elements, A and B. B is seven times bigger than A in the sense that reading the data column-wise, it has seven times as many references. What this means is that assuming that A and B belong to the same field (or sub-field), Two-journal network; Size ratio=1:7; Citation Ratio=1:8

Power iteration			p(0)		p(1)		p(2)
	A	B	x	X	x	X	x
A	1	8	0.500	4.500	0.125	7.125	0.125
B	7	56	0.500	31.500	0.875	49.875	0.875
	8	64	1	36	1	57	1

Reference Ratio		
A	1/8	0.125
B	7/8	0.875

Weakness iteration			w(0)		w(1)		w(2)
	A	B	x	X	x	X	x
A	1	7	0.500	4.000	0.111	6.333	0.111
B	8	56	0.500	32.000	0.889	50.667	0.889
	9	63	1	36	1	57	1

Citation Ratio		
A	1/9	0.111
B	8/9	0.889

Power-Weakness ratio r(k)					r(1)		r(k)
A					1.125		1.125
B					0.984		0.984

Citation Density		
A	9/8	1.125
B	63/64	0.984

Size-dep Indicators			
Order	0th	1st	2nd
Indicator	W	P=Wi	iP=iWi
A	6.33	7.13	8.02
B	50.67	49.88	49.10

PageRank iteration							
	A	B	x	X	x	X	x
A	0.125	0.125	0.500	0.125	0.125	0.125	0.125
B	0.875	0.875	0.500	0.875	0.875	0.875	0.875
	1	1	1	1	1	1	1

Reference Ratio		
A	1/8	0.125
B	7/8	0.875

Figure 1. Two-element journal network to illustrate size and citation density influence on power–weakness ratio.

the references to itself and to the other journals are in the same size ratio. However, the citation ratio is slightly different from the size ratio at 1 : 8, so that the effect on power–weakness ratio can be seen. (If the citation ratio had been taken as 1 : 7 so that the citation density is unity, then the power–weakness ratio vector would have comprised unit values.) The spreadsheet shows how the power and weakness iteration proceeds. We see that the power vector maintains the reference ratio and the weakness vector maintains the citation ratio. That is, A is eight times more powerful than B, and at the same time is seven times weaker than B from the two criteria, maintaining a citation density of 9/8. This is ultimately reflected in the power–weakness ratio vector $r(k)$. This is a dimensionless ratio and is size-independent. The same spreadsheet shows how the Pinski–Narin or Google PageRank iteration proceeds (in the latter case, as the network is irreducible and there are no dangling nodes, no intervention in any form is needed) – it is driven towards a size-dependent measure. This has been noticed and commented on when the principal component analysis was done in Leydesdorff[4]. In Figure 2, we capture how the iterative recursion operations work for a three-element journal network. Once again, the reference and citation ratios have been chosen to illustrate that the power–weakness ratio vector is size-independent, while the influence weight vector is actually size-dependent. In both Figures 1 and 2, we have also interpolated how zeroth-, first- and second-order performance indicators can be constructed from the size-independent power–weakness ratio vector and the various size vectors. Note that all these definitions are free of the conventional size vector used to calculate IF, namely the number of articles published in the journal.

We now turn to a real-life example to illustrate the effectiveness of the power–weakness ratio as a recursive size-independent measure of journal-specific impact. The journal ecosystem we choose comprises 10 statistical journals from the Web of Science Core Collection. For this ecosystem, we take the citation window to be the year 2013 and the publications window to be all years preceding that year. The matrix **Z** could be set up easily and two approaches could be followed, the first with self-citations included, as is done in the *Web of Science*, and a second cycle of analysis carried out without self-citations (by setting all the diagonal elements Z_{ii} to zero), as is done in the eigenfactor approach. Table 1 shows the **Z** matrix of the 10 statistics journals as a subgraph of the main graph of all the journals in the *Web of Science* Core Collection. The weakness matrix is obtained as the

Three-journal network; Size ratio=1:7; Citation Ratio=1:8

Power iteration				p(0)		p(1)		p(2)
	A	B	C	x	X	x	X	x
A	1	8	64	0.333	24.33	0.018	56.02	0.018
B	7	56	448	0.333	170.33	0.123	392.12	0.123
C	49	392	3136	0.333	1192.33	0.860	2744.86	0.860
	57	456	3648	1	1387	1	3193	1

Reference Ratio		
A	1/57	0.018
B	7/57	0.123
C	49/57	0.860

Weakness iteration				w(0)		w(1)		w(2)
	A	B	C	x	X	x	X	x
A	1	7	49	0.333	19.00	0.014	43.74	0.014
B	8	56	392	0.333	152.00	0.110	349.92	0.110
C	64	448	3136	0.333	1216.00	0.877	2799.34	0.877
	73	511	3577	1	1387	1	3193	1

Citation Ratio		
A	1/73	0.014
B	8/73	0.110
C	64/73	0.877

Power-Weakness ratio r(k)	r1	rk
A	1.281	1.281
B	1.121	1.121
C	0.981	0.981

Citation Density		
A	(1/57)/(1/73)	1.281
B	(7/57)/(8/73)	1.121
C	(49/57)/(64/73)	0.981

Size-dep Indicators			
Order	0th	1st	2nd
Indicator	W	P=Wi	iP=iWi
A	43.74	56.02	71.74
B	349.92	392.12	439.42
C	2799.34	2744.86	2691.44

PageRank iteration								
	A	B	C	x	X	x	X	x
A	0.018	0.018	0.018	0.333	0.018	0.018	0.018	0.018
B	0.123	0.123	0.123	0.333	0.123	0.123	0.123	0.123
C	0.860	0.860	0.860	0.333	0.860	0.860	0.860	0.860
	1	1	1	1	1	1	1	1

Reference Ratio		
A	1/57	0.018
B	7/57	0.123
C	49/57	0.860

Figure 2. Three-element journal network to illustrate size and citation density influence on power–weakness ratio.

Table 1. ***Z*** matrix of the 10 statistics journals as a subgraph of the main graph of all the journals in the Web of Science Core Collection

Statistics journals in JCR (power matrix)	AM STAT	ANN STAT	ECONOMET THEOR	ECONO-METRICA	J AM STAT ASSOC	J COMPUT GRAPH STAT	J ROY STAT SOC A STAT	J ROY STAT SOC B	SCAND J STAT	TECHNO-METRICS	Cita-tions
AM STAT	**42**	3	1	2	11	23	5		1	4	92
ANN STAT	8	**621**	105	34	302	94	7	113	144	21	1449
ECONOMET THEOR	1	25	**140**	20	15	1	4	12	24		242
ECONOMETRICA	4	58	135	**431**	92	5	19	25	18	1	788
J AM STAT ASSOC	48	228	59	18	**460**	139	35	108	70	63	1228
J COMPUT GRAPH STAT	8	20			33	**66**		8	10	18	163
J ROY STAT SOC A STAT	5	7	1	1	14	3	**57**	5	6	2	101
J ROY STAT SOC B	12	118	18	4	195	68	9	**81**	56	39	600
SCAND J STAT	2	24	5	1	31	13		11	**48**	3	138
TECHNOMETRICS	15	11	1		27	21	2	5	6	**108**	196
References	145	1115	465	511	1180	433	138	368	383	259	4997

transpose and the cases without self-citation are obtained by discarding the entries in the diagonal and replacing them with zeroes. These matrices are simple, irreducible and well-connected, and there is no need for the PageRank kind of modifications in order to carry out the recursive iterations. Ramanujacharyulu power and weakness iterations can be carried out using standard excel spreadsheets.

Table 2. Size-independent and size-dependent indicators for the 10 statistics journals from JCR

	Size-independent indicators			Size-dependent indicators			
Statistics journals in JCR	IF 2012	PWR w sc	PWR wo sc	References wo sc	Citations wo sc	Influence vector-PageRank	Eigen factor-PageRank
AM STAT	0.976	0.0300	0.0283	0.0350	0.0170	0.0125	0.0125
ANN STAT	2.528	0.1451	0.1422	0.1679	0.2813	0.2740	0.2741
ECONOMET THEOR	1.477	0.0369	0.0393	0.1104	0.0347	0.0577	0.0579
ECONOMETRICA	3.823	0.3477	0.3670	0.0272	0.1213	0.1115	0.1117
J AM STAT ASSOC	1.834	0.1057	0.1015	0.2446	0.2610	0.2679	0.2678
J COMPUT GRAPH STAT	1.269	0.0268	0.0252	0.1247	0.0330	0.0330	0.0330
J ROY STAT SOC A STAT	1.361	0.0605	0.0573	0.0275	0.0150	0.0154	0.0154
J ROY STAT SOC B	4.810	0.1679	0.1651	0.0975	0.1764	0.1683	0.1682
SCAND J STAT	1.169	0.0306	0.0305	0.1138	0.0306	0.0354	0.0355
TECHNOMETRICS	1.424	0.0489	0.0435	0.0513	0.0299	0.0241	0.0240
Correlation	IF	r_w_sc	r_wo_sc	R	C	IV	Ef
IF 2012	1.00	0.81	0.79	–0.03	0.54	0.50	0.50
PWR w sc	0.81	1.00	1.00	–0.12	0.49	0.45	0.45
PWR wo sc	0.79	1.00	1.00	–0.14	0.46	0.42	0.42
R	–0.03	–0.12	–0.14	1.00	0.70	0.74	0.74
C	0.54	0.49	0.46	0.70	1.00	1.00	1.00
IV-PR	0.50	0.45	0.42	0.74	1.00	1.00	1.00
EF-PR	0.50	0.45	0.42	0.74	1.00	1.00	1.00

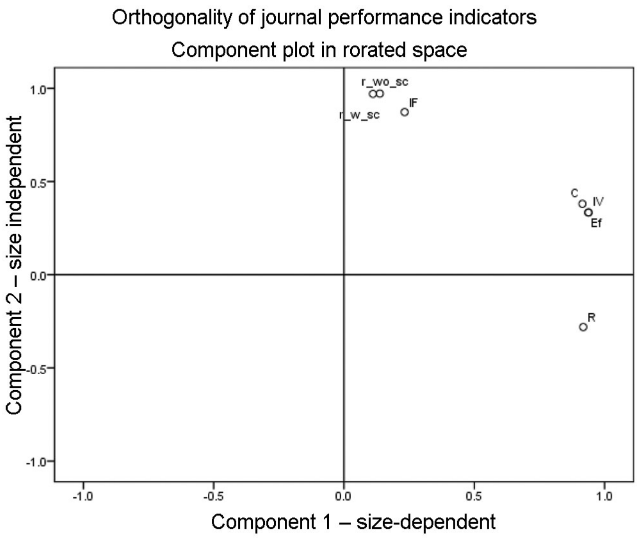

Figure 3. Scatterplot of the four size-dependent and three size-independent indicators on the two main components; $N = 10$.

At the very first stage of the iteration, when $k = 1$, we get the raw or non-recursive or non-network value of impact and when the iteration is continued to higher orders of k, as $k \to \infty$ we find rapid convergence of the recursive or network power–weakness ratio.

Table 2 gives the size-dependent and size-independent recursive indicators for the 10 statistics journals. We show the power–weakness ratio vector for the cases with and without self-citations (*r_w_sc* and *r_wo_sc* respectively). Also shown are the influence vectors (IV) and eigenfactors (Ef) from PageRank type operations performed without self-citations. The Eigenfactors have been normalized so that the sum becomes unity. The IF for these journals for 2012 are taken from the Journal Citations Report. *R* is the total number of references and *C* is the total number of citations, without taking self-citations into account. We see that the size-independent indicators, namely *r_w_sc*, *r_wo_sc* and IF are all well correlated with each other. Similarly, the size-dependent indicators, *R*, *C*, IV and Ef are well correlated with each other. As is to be expected, the size-dependent and size-independent indicators are less strongly correlated with each other. This becomes clear when an extraction using principle component analysis is carried out. A Varimax rotation with Kaiser normalization was adopted and the rotation converged in three iterations. Two components accounted for 94.53% of the common variance (64.13% and 30.40% respectively). Component one represents the size-dependent or quantity factor, while component two represents the size-independent and arguably the quality factor. Figure 3 shows that the four size-dependent indicators are orthogonal to the three size-independent indicators. The influence vector and eigenfactor that emerge from a Pinski–Narin or Google PageRank formulation are greatly influenced by the size term.

Ramanujacharyulu's approach is interesting and historically significant in that it incorporated the eigenvector centrality methods even prior to the Pinksi–Narin paper[6]. The latter used only a one-dimensional evaluation (the power iteration alone). Ramunjacharyulu recognized that a two-dimensional approach using both row-wise information (power iteration) and column-wise information (weakness iteration) is now possible in the analysis of all preferential experiments. From such graph-theoretic considerations which are now found in social network analysis, we identify in this communication, two orthogonal indicators from the points of view of size-dependence and principal component analysis to identify the components. One, the power–weakness ratio, is a size-independent recursive proxy for specific impact or specific influence (quality) of the journal's performance in the network. The second, the number of references (out-links) that the journal makes to all journals in the network is the size-dependent proxy for the size of the journal (a quantity metric). The power indicator, $p(k)$, where a sufficiently large value of k will ensure convergence, becomes the size-dependent recursive value of the citations, or recursive total impact or total influence, taking the prestige of all journals in the ecosystem. This is the numerator of the formula for size-independent recursive specific impact or influence. The recursive weakness indicator, $w(k)$, is the size-dependent term for the denominator. Thus, the power–weakness ratio, $r(k) = p(k)/w(k)$ becomes the size-independent recursive indicator for specific impact. Unlike the conventional approach for calculating IF, or even the Article Influence Score, the number of articles is not taken as the size-dependent term in the denominator for the calculation of the size-independent specific impact. In an input–output sense, the number of references becomes the measure of the input and the number of citations received by the journal from all journals in the network becomes the size-dependent measure of the output. A similar idea, but without recursive iteration, was proposed by Nicolaisen and Frandsen[18]. The power–weakness ratio of citations to references before recursive iteration becomes the non-network measure of popularity, and the power–weakness ratio of weighted citations and weighted references after recursive iteration becomes the network measure of prestige of the journal. It is also possible to propose first- and second-order measures of influence which are products of the quality and quantity parameter space. We also show that the influence weight that emerges from a Pinski–Narin or Google PageRank formulation is a size-dependent measure of prestige that is orthogonal to the power–weakness ratio. We have illustrated the concepts using two simple, artificial, two- and three-journal networks and a real-life example of a subgraph of 10 well-known statistics journals with network data collected from the *Web of Science*.

To sum up, IF counts only the number of incoming links (citations in bibliometric usage) and ignores the role of the outgoing links (references). While the number of incoming links is a size-dependent property of the network, IF is normalized into a size-independent measure by diving the citation count by the number of articles attributed to a node (in this case, the journal in a citation network). In Ramanujacharyulu's approach, the non-recursive power–weakness ratio is obtained as a size-independent measure by taking the ratio of citations (incoming links) to the references (outgoing links).

Another way in which IF is deficient is that it does not take into account the 'prestige' or 'power' of the source of the incoming citation[5]. The Pinski–Narin and Google PageRank procedures were meant to correct this recursively, but only using information from the incoming links (the power iteration in Ramanujacharyulu's terminology). By also taking into account information in the outgoing links through a recursive weakness iteration, the picture is made complete. The power–weakness ratio becomes arguably the best quantifiable size-independent network measure of quality of any journal which is a node in a citation network, taking into account the full information in the network.

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