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# A new journal power-weakness ratio to measure journal impact

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## Abstract

Journal impact indicators are useful measures to determine the relative importance of journals within a given discipline. By recasting the journal cross-citation matrix as a directed network, journals can be represented by nodes and journal-journal citations correspond to weighted directed links between nodes. In this form, it is possible to use graph-theoretic approaches to determine a ranking of nodes based on the structure of the links they are embedded in. Based on the Power-Weakness paradigm originally introduced by Ramanajucharyulu for ranking players in a tournament, we show how this idea can be modified under a bibliometric setting to find journals that contribute proportionate inbound and outbound citation flows within a homogeneous citation network to the extent that the power to influence and the weakness to be influenced by other journals are in near equal measure. We study two journal systems based on the Library and Information Sciences field based on a citation window in 2012 and another in 2018.

**Keywords** Journal impact analysis · Citation network · Power-weakness ratio

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## Introduction

Journal indicators measure the confluence of research publications based on some scoring of journal-to-journal citation flows for a given field or subfield of knowledge (Zhang et al. 2009). Typically, each indicator requires the construction of a journal cross-citation matrix based on a given corpus, sometimes referred to as the journal cited-citing matrix or simply the journal citation matrix (Todorov and Glänzel 1988).

A well-designed indicator can be used to determine a ranking of journals within a corpus whereby the highest ranks signify the core repositories for the exchange of academic discourse (Garfield 1972). Such highly ranked journals typically cover the broadest range of topics while journals assigned to intermediate ranks may correspond to journals focused on more specialized topics (Moore 1972). By extension, journals occupying the lowest ranks form the periphery of that corpus (Dong et al. 2005).

Pinski and Narin (1976) have traced the development of a type of journal indicator, specifically, journal impact measurements to several seminal publications. In one of the earliest works, Gross and Gross (1927) used citations to determine the importance of chemistry journals while Cason and Lubotsky (1936) provided one of the earliest formulations of journal impact based on cross-citations between journals. Daniel and Louttit (1953) studied the similarity of journals based on citation patterns for the purpose of clustering. Kessler (1965) explored the probability that a journal carries a specific type of information based on the journal cross-citation matrix from a case study of physics journals.

The application of network theoretic concepts to study the relationships between journals and their similarities in terms of referencing patterns was investigated in Xhignesse and Osgood (1967). Subsequently, Narin et al. (1972) analysed citations to map connections between journals and between fields while Garfield (1972) studied the policy implications in journal evaluations. The latter paper signifies a landmark in journal citation analysis as it introduced the concept of the journal "impact factor". For a given journal $X$, its impact factor at year $t$ is expressed as the fraction $A/B$ where $A$ is the number of times articles published in $X$ during the previous two years $t-1$ and $t-2$ are cited in year $t$, and $B$ is the total number of citable items published by $X$ in that same two year citing period.

Since the advent of the impact factor (Garfield 1972), newer journal impact indicators have emerged, many of which are applications of network (graph) theoretic principles. This is made possible by structuring journal to journal citation linkages into a cross-citation matrix and this, in turn, into a directed network (Leydesdorff 2009). By convention, the impact factor uses simple citation counts that do not factor the relative importance of the citing document and the reference cited (i.e. all citations are valued equally) (Zhu et al. 2015).

The use of network theory in this setting allows for a more accurate representation of interrelated entities (documents, journals, etc.) by taking into account the influence it exudes on others via direct and indirect relationships. Some recent and prominent examples are EigenFactor™Bergstrom (2007); Bergstrom and West (2008); West et al. (2010) which is now included in the Journal Citation Reports, as well as the SCImago Journal Rank (SJR) (Falagas et al. 2008). Both indicators are based on the concept of eigenvector centrality in networks and are essentially variants of the PageRank algorithm used in web search (Brin and Page 1998).

It is interesting to explore if other network or eigen-analysis based measures can be constructed for measuring journal impact. Prathap and Nishy (2016) explored one such alternative to measure impact for "science on the periphery" which is characterised by derivative science done at the periphery in contrast to ground-breaking research carried out at the core of a given field of study (Arunachalam and Manorama 1989). This typically applies to journals that are published in developing or less developed countries (Velho 1986) including national journals that may feature languages other than English (Van Leeuwen et al. 2001; Bordons et al. 2002).

Arunachalam and Manorama (1989) point out that such peripheral journals tend to publish a smaller number of papers that are also cited a smaller number of times. As a result, such journals tend to be omitted from the Web of Science which effectively reduces the impact factor of other peripheral journals that somehow do make the cut. If researchers tend to publish their best work in peripheral journals, an overemphasis on impact factor in the scientific community at large would tend to underrepresent or overlook the value of such work.

This line of thinking forms the basis of the indicator proposed in Prathap and Nishy (2016). In that work, the authors repurposed a size-independent recursive indicator originally proposed by Ramanajucharyulu (henceforth, Ram) for finding the most "talented" player in a tournament (Ramanujacharyulu 1964). This involves computing two scores, a *power* score that recursively measures one's "*power to influence*" and a *weakness* score that recursively measures one's "*weakness to be influenced by*". The most talented player is then determined by the one that possesses the largest power-to-weakness ratio, or Power-Weakness Ratio (PWR).

One of the appealing features of PWR is its applicability on nearly complete directed graphs with self-loops which tend to describe the connectivity of peripheral journal networks. Prathap and Nishy (2016) used PWR to measure the impact of two sets of highly localized journal ecosystems at the periphery in chemistry (the first corresponds to journals from India and the second to journals from China). The authors conclude that the power score represents recursive citation counts while the weakness score can be considered as a recursive proxy for journal size. This suggests that PWR is a dimensionless size-independent recursive indicator for specific impact.

Subsequently, Leydesdorff et al. (2017) also studied the use of PWR as a journal indicator using a set of 83 Web of Science indexed journals in the Library and Information Sciences (LIS). A set of two smaller sub-graphs were also constructed from this dataset to represent two sets of strongly connected journals. These comprise seven journals that cite the *Journal of the Association for Information Science and Technology* (*JASIST*) more than 100 times in 2012 and *MIS Quarterly* with nine other journals citing this journal to the same extent.

The authors argue that the rank-ordering in LIS journals by PWR did not yield readily interpretable results in the sense that the most influential LIS journals are not assigned top ranks according to this indicator. To support this claim, a weak negative correlation was found between PWR and the SCImago Journal Rank (SJR) indicator, whereby the latter indicator is considered to provide an intuitive journal impact ranking that agrees with expert opinion. This suggests that PWR measures a different type of journal impact or not at all. Furthermore, it is pointed out that the application of PWR is necessarily limited to strongly connected components to avoid the generation of spuriously large scores. Finally, Leydesdorff and co-workers question the applicability of the tournament metaphor in the evaluation of journal impact in the sense that one journal's gain in citations is not necessarily another journal's loss.

On a more recent note, Prathap (2019) considered the Pinski-Narin influence weight (IW) and PWR as proxies for the journal impact based on each journal's location within a structure journal citation network links. The Pinski-Narin procedure computes a matrix of ratios first and evaluates the IW after recursive iteration of the matrix of ratios (Pinski and Narin 1976). On the other hand, Ram's PWR is computed as a ratio of terms in the weighted citations vector and weighted references vector after the power and weakness matrices are separately recursively instead. Hence, IW and PWR are analogues of ratio of averages (RoA) and average of ratios (AoR) methods for computing relative citation indicators.

The present work is mainly focused on reconciling the findings presented in Prathap and Nishy (2016) and Leydesdorff et al. (2017). The current formulation of the Power-Weakness Ratio purports that the most impactful journal is the one with the strongest power to influence and lowest weakness to be influenced. Here, we propose an alternative size-independent ratio computed from power and weakness scores that reproduces established notions of journal ranking in LIS. We develop the work in the sections that follow.

## The Ramanujacharyulu power-weakness ratio

Ramanujacharyulu (1964) was among the first works to explore the use of eigenvector algorithms for ranking nodes on networks, with a specific focus on ranking players in a tournament. Consider a network $G = (V, E)$ that is defined by a set of $N$ nodes (vertices), $V = \{v_1, v_2, \dots, v_N\}$, and $M$ links (edges), $E = \{e_1, e_2, \dots, e_M\}$ connecting pairs of nodes.

Alternatively, the link structure of $G$ can be represented in matrix form by the adjacency matrix $\mathbf{A}$ in which an element $A_{ij} = 1$ if node $i$ has an outbound link pointing into node $j$ and is zero otherwise. For directed graphs, the adjacency matrix is assymetric thus a link from node $i$ to $j$ is not necessarily reciprocated in the opposite direction. This matrix can be generalized to elements $A_{ij} \geq 0$ to encode link weights to indicate the strength of connections.

Given that an adjacency matrix $\mathbf{A}$ can be raised indefinitely to the $k$-th power, i.e. $\mathbf{A}^k$, each element $(\mathbf{A}^k)_{ij}$ gives the number of paths of length $k$ connecting node $i$ to node $j$. Then, the iterated weakness of order $k$ for a node "to be influenced" can be expressed by the matrix product:

$$\mathbf{w}^{(k)} = \mathbf{A}^k \mathbf{e}^T \tag{1}$$

where $\mathbf{e}$ is a row vector of ones with dimensions $1 \times n$. This can be rewritten as the following recursion relation:

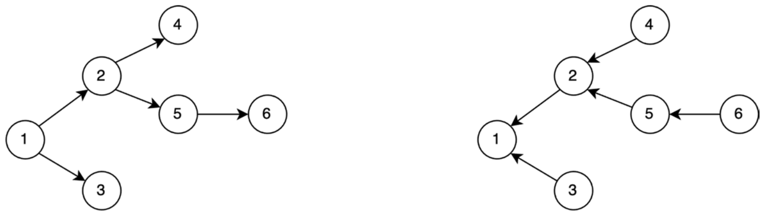
$$\mathbf{w}^{(k)} = \mathbf{A}\mathbf{A}^{k-1}\mathbf{e}^T = \mathbf{A}\mathbf{w}^{(k-1)} \tag{2}$$

Since $\mathbf{w}^{(k)}$ is a column vector, then the entry at row-$i$, $w_i^{(k)}$, is the resulting weakness score:

$$w_i^{(k)} = \sum_j [\mathbf{A}^k]_{ij} \tag{3}$$

Entries of the vector $\mathbf{w}$ are normalized by setting $w_i^{(k)} \leftarrow w_i^{(k)} / \sum_i w_i^{(k)}$ to ensure that $0 \leq w_i^{(k)} \leq 1$ at every $k$-th iteration of the power method. Hence, a recursive iteration can raise $\mathbf{A}$ to an order where convergence is obtained for what is effectively the weighted value of the total outbound links.

It was Ram's insight that it is possible to carry out the same operations column-wise by using the transpose of the matrix $\mathbf{A}^T$ and then proceeding row-wise on these transposed elements in the same recursive and iterative manner indicated above. A transposition of the adjacency matrix effectively reverses the directionality of links in its associated graph $G$ as




$$A = \begin{array}{c} \begin{array}{cccccc} 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array} \qquad B = A^T = \begin{array}{c} \begin{array}{cccccc} 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{array} \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array}$$

**Fig. 1** An example of a directed graph, its adjacency matrix **A** and its transpose **B**

shown in Fig. 1. If we write $\mathbf{B} = \mathbf{A}^T$ , then the iterated power of order $k$ for a node "to influence" is expressed as:

$$\mathbf{p}^{(k)} = \mathbf{B}^k \mathbf{e}^T \tag{4}$$

This can be rewritten as the following recursion relation:

$$\mathbf{p}^{(k)} = \mathbf{B}\mathbf{B}^{(k-1)}\mathbf{e}^T = \mathbf{B}\mathbf{p}^{(k-1)} \tag{5}$$

Since $\mathbf{p}$ is also a column vector, then the entry at row-$i$, $p_i^{(k)}$, is the resulting power score:

$$p_i^{(k)} = \sum_j [\mathbf{B}^k]_{ij} = \sum_j [\mathbf{A}^k]_{ji} \tag{6}$$

Entries of the vector $\mathbf{p}$ are normalized by setting $p_i^{(k)} \leftarrow p_i^{(k)} / \sum_i p_i^{(k)}$ to ensure that $0 \leq p_i^{(k)} \leq 1$ at every $k$-th iteration. In other words, a recursive iteration can raise $\mathbf{A}^T$ to an order where convergence is obtained for what is effectively the weighted value of the total inbound links. The recursion relations defined in Equation 2 and Equation 5 ensures that we take into account indirect influence of up to the $k$-th order when comparing nodes.

Both power and weakness scores can be considered as a form of node centrality that is rooted in weighted path counting. A node's power or weakness is proportional to the number of paths branching outwards or inwards into it. This can be contrasted with closeness centrality (reciprocal of the sum of shortest paths between a given node and all other nodes) and betweenness centrality (the proportion of shortest paths that pass through a given node) (Bavelas 1950; Freeman 1977).

The power score vector $\mathbf{p}^{(k)}$ and the weakness score vector $\mathbf{w}^{(k)}$ are size-dependent measures. To obtain a size-independent measure, Ram introduced the power-weakness ratio (PWR):

$$\mathrm{PWR}_i^{(k)} = \frac{p_i^{(k)}}{w_i^{(k)}} \tag{7}$$

As $k \to \infty$, we get the converged power-weakness ratio. To avoid elements in PWR from taking on infinite values (as weakness approaches zero), Ram added loops to the graph $G$ at each node which is equivalent to setting the diagonal elements $A_{ii} = 1$.

There are two alternate formulations of PWR that can be used to circumvent this scenario. The first option is to introduce a small correction factor $\alpha$ as proposed in Todeschini et al. (2019) and Valsecchi et al. (2020):

$$\mathrm{PWR}_i^{(k)} = \frac{\alpha + p_i^{(k)}}{\alpha + w_i^{(k)}} \tag{8}$$

where $\alpha = 1/N$ is an empirically defined parameter and $N$ is the number of nodes on the graph. Another possible choice is to set $\alpha = 1/(N + N\log_2 N)$ as described in Todeschini et al. (2015). Both choices mitigate the case of a near-zero or zero denominator when weakness takes on extremely small or zero values. Equation 8 rescales PWR over a more reasonable range which can then be rescaled to unit interval if required.

The second alternate formulation of PWR is the normalized power-weakness difference (nPWD) (Prathap 2020):

$$\mathrm{nPWD}_i^{(k)} = \frac{p_i^{(k)} - w_i^{(k)}}{p_i^{(k)} + w_i^{(k)}} \tag{9}$$

$$= \frac{\left(p_i^{(k)} - w_i^{(k)}\right)\frac{1}{w_i^{(k)}}}{\left(p_i^{(k)} + w_i^{(k)}\right)\frac{1}{w_i^{(k)}}} \tag{10}$$

$$= \frac{\mathrm{PWR}_i^{(k)} - 1}{\mathrm{PWR}_i^{(k)} + 1} \tag{11}$$

This formulation rescales the original PWR scores to be bounded within the $[-1, 1]$ interval. In particular, nPWD approaches the value of $+1$ as $\mathrm{PWR}_i^{(k)} \to +\infty$ and a value of $-1$ as $\mathrm{PWR}_i^{(k)} \to 0$. Additionally, nPWD is zero when $\mathrm{PWR}_i^{(k)} = 1$.

## Construction of the journal citation matrix from paper-to-paper citations

Consider a network of $N$ journals that contribute a total of $n$ papers that cross-cite each other. Let us encode the one-to-one mapping of each paper to each journal as the source-paper (membership) matrix, $\mathbf{V}$:

$$\mathbf{V} = \begin{array}{c} \\ s_1 \\ s_2 \\ \vdots \\ s_N \end{array} \begin{array}{c} \begin{array}{cccc} p_1 & p_2 & \cdots & p_n \end{array} \\ \begin{pmatrix} V_{11} & V_{12} & \cdots & V_{1n} \\ V_{21} & V_{22} & \cdots & V_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ V_{N1} & V_{N2} & \cdots & V_{Nn} \end{pmatrix} \end{array} \tag{12}$$

where each entry $V_{sp}$ equals 1 if journal $s$ publishes paper $p$ and zero otherwise. Consider also the paper citation matrix, $C$:

$$\mathbf{C} = \begin{array}{c c} & \begin{array}{cccc} p_1 & p_2 & \cdots & p_n \end{array} \\ \begin{array}{c} p_1 \\ p_2 \\ \vdots \\ p_n \end{array} & \begin{pmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} \end{pmatrix} \end{array} \tag{13}$$

The $n \times n$ citation matrix $\mathbf{C}$ describes the adjacency of a citation network consisting of $n$ papers represented as nodes on this network. Accordingly, citation links on the network are encoded in the columns of $\mathbf{C}$, while reference links are encoded in the rows of $\mathbf{C}$.

To convert the paper citation network, $\mathbf{C}$, to a journal citation network, $\mathbf{A}$, we compute the following matrix product:

$$\mathbf{A} = \mathbf{V}\mathbf{C}\mathbf{V}^T \tag{14}$$

Also useful is its transpose, $\mathbf{A}^T$:

$$\mathbf{A}^T = \mathbf{V}\mathbf{C}^T\mathbf{V}^T \tag{15}$$

Note that this cross-citation matrix is a citing-cited matrix, that is, each element $A_{ij}$ encodes a citation from journal $i$ in row-$i$ to a cited journal $j$ in column-$j$. Hence, Equation 14 is the transpose to the cited-citing matrix convention used in Prathap (2019) and Leydesdorff et al. (2017). Although the matrix $\mathbf{C}$ tends to be sparse for large paper citation networks, the matrix $\mathbf{A}$ will tend to be dense in comparison since inter-journal links can only be drawn from far fewer alternatives (the number of journals $N$ is significantly smaller than the number of papers $n$).

## Power-weakness ratio in journal citation analysis

By substituting Equation 15 into 5, the iterated power of order $k$ for a journal citation network, is thus:

$$\mathbf{p}^{(k)} = \left(\mathbf{V}\mathbf{C}^T\mathbf{V}^T\right)^k\mathbf{e}^T = (\mathbf{A}^T)^k\mathbf{e}^T = \mathbf{A}^T\mathbf{p}^{(k-1)} \tag{16}$$

Accordingly, the iterated weakness of order k for a journal citation network, is:

$$\mathbf{w}^{(k)} = \left(\mathbf{V}\mathbf{C}\mathbf{V}^T\right)^k\mathbf{e}^T = \mathbf{A}^k\mathbf{e}^T = \mathbf{A}\mathbf{w}^{(k-1)} \tag{17}$$

The column-sum corresponding to column-$i$ of $\mathbf{A}$ is therefore the nonrecursive 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 $i$ (Pinski and Narin 1976). If we also have an article vector $\mathbf{a}$, where $a_i$ is the number of articles published by journal $i$ over the publication window, then this is the value $P$ for journal $i$ and the ratio $C/P$ is the nonrecursive impact of the journal.

With the power and weakness score vectors, we can then compute Ram's Power-Weakness Ratio for the given journal system using Equation 7. Prathap et al. (2016) proposed that if $w_i^{(k)}$ is taken as the recursive surrogate of the size of a journal $i$, then PWR and nPWD becomes a candidate for a dimensionless size-independent recursive network measure of impact or quality of that journal.

Most journal impact indicators are concerned with measuring the extent to which a journal influences others and generally ignores how it is influenced by others. The application of indicators such as PWR and nPWD in journal citation analysis points to an interesting extension because it pairs two pieces of information – how influential a journal is, and how easily it is influenced.

## Journal power-weakness ratio (jPWR)

The current formulation of the Power-Weakness Ratio purports that the journal with the strongest power and lowest weakness is the most impactful journal. Initially, Ram assigns the power score as a measure of each node's "power to influence" while the weakness score as its "weakness to be influenced". Under a tournament setting, a player with high power and low weakness is indeed the most talented or "balanced" player.

However, for a journal system, a journal with high power and low weakness (consequently high Power-Weakness Ratio) is one that has many paths pointing inward into it while having the least paths pointing outward from it. This may not be the ideal definition for "balance" in a bibliometric setting given that the core of academic discourse is centered on the exchange of ideas. A case with high power and low weakness would then point to the presence of a lop-sided flow of communication.

In this way, it is perhaps more appropriate to think of the "balanced" journal as one with "proportionate inbound and outbound citation flows", i.e., journals with power and weakness with near equal measure. Following this interpretation, a Journal Power-Weakness Ratio can then be defined as follows:

$$\mathrm{jPWR}_i^{(k)} = \frac{p_i^{(k)}}{1 - w_i^{(k)}} \tag{18}$$

This equation takes advantage of the empirical tendency for power scores to exhibit a strong positive correlation with weakness scores. This assumption should hold because journal citation networks tend to form loops which correspond to journal self-citations. That is, a sizable fraction of references made by a typical article in a given journal is frequently made to other articles published within that same journal. To wit, journal self-citations are also journal self-references and vice versa. As a consequence, the strength of journal references $R$ (weighted out-degree) will tend to have a strong positive correlation with the strength of journal citations $C$ (weighted in-degree).

Following this logic, it is reasonable to expect that power scores should also exhibit a strong positive correlation with weakness scores since on first iteration, power and weakness scores are directly proportional to the number and strength of its outbound and inbound links, respectively. Hence, it is unlikely to find large values of $\mathbf{p}^{(k)}$ paired with small values of $\mathbf{w}^{(k)}$, and vice versa. Since jPWR $\approx 1$ for cases where $p_i^{(k)} \approx 1 - w_i^{(k)}$, this value is attained when $p_i^{(k)} \approx 0.5$ and $w_i^{(k)} \approx 0.5$, that is, when journals have power and weakness with near equal measure.

This modification of the PWR score allows us to score journals by how they influence and are influenced by others (a measure of two-way impact). Since node centrality measures that hinge on counting paths into and out from a node are proxy measures for flow, jPWR can be considered as a measure of proportionate inbound and outbound citation flows. In effect, it allows us to find the journals that are highly integrated within knowledge flows in a given journal ecosystem. Network flow approaches in journal analysis can be traced back to the work of Pinski and Narin (1976) on "influence weights", Salancik (1986) on an application of Leontief's input-output theorem called the "importance index" (Hubbell 1965; Leontief 1941), and more recently to work by Lathabai et al. (2017) on a network metric called "flow vergence".

It is important to note that jPWR is zero when $p_i^{(k)} = 0$ and approaches $+\infty$ when $w_i^{(k)} \to 1$ (resulting in a near-zero denominator). A journal can only have a power score of zero when it does not receive any inbound links. On the other hand, a weakness score of one is only possible when all journals cite one single dominant journal and no other. We are unlikely to encounter the latter case in real-world data, hence, the value of jPWR is not likely to take on extremely large values. Since both the power and weakness scores are unit-normalized quantities, the jPWR score is a size-independent dimensionless ratio.

To rescale the jPWR score over the unit interval, we can normalize it by dividing over the sum of all jPWR scores:

$$\mathrm{njPWR}_i^{(k)} = \frac{\mathrm{jPWR}_i^{(k)}}{\sum_{j=1}^{N} \mathrm{jPWR}_j^{(k)}} \tag{19}$$

This formulation yields values that can be compared over the same range as other network-based scores such as PageRank (Brin and Page 1998). A clear advantage of rescaling in this way is that each normalized score then signifies its size percentage relative to all other journals.

## Data and methods

There are two Library and Information Sciences datasets used in this study which we shall refer to as LIS-7 and LIS-73. LIS-7 is a reproduction of the citation matrix for seven LIS journals studied in Leydesdorff et al. (2017). These journals form an induced subgraph extracted from a larger set of 83 journals indexed under the Web of Science (WoS) assigned to the "Information and Library Science" category. The induced subgraph was selected based on the seven journals that cite the *Journal of American Society for Information Science and Technology* (*JASIST*) at least 100 times. This dataset uses the year 2013 as the citation window and assigns the publication window to all previous years.

A second dataset consisting of 244 WoS-indexed journals under the "Information Science & Library Science" category between the years 2008 to 2018 inclusive was also sourced to construct a larger journal citation network. This dataset comprises of a total of 109,341 publication records (from all publication types) with full cited references. The cited references for each record were parsed to extract journal-to-journal citations within this dataset.

To avoid vanishingly small weakness scores that result in extremely large PWR scores, we retain only those journals that contribute at least one reference link above a minimum threshold $R_{min} > 0$ such that the removal of other journals (and their links) yields a journal citation network with density $D \geq 0.5$[1]. This constraint ensures that the resulting induced subgraph is sufficiently dense (i.e. not sparse) and contains outbound link weights that are

[1] For a directed graph with $N$ nodes the maximum number of links is $N(N-1)$. Hence, the network density for a directed graph with $M$ links is $D = M/[N(N-1)] \in [0, 1]$. Sparse networks have a value of $D$ closer to zero while dense networks will have $D$ tending to 1.

not too small. In other words, the extracted subgraph should correspond to a strongly connected component as suggested in Leydesdorff et al. (2017).

The value of $R_{min}$ can be determined by looping over values ranging from 1 to the maximum total number of references and finding the first instance where the removal of each node $i$ that does not satisfy $\max(A_{ij}) \geq R_{min} > 0$ yields a network density of at least 0.5. Based on the original set of 244 journals, a threshold of $R_{min} = 102$ is required to produce a 73-node induced subgraph with the minimum required density. The resulting $73 \times 73$ cited-citing matrix will be referred to as LIS-73.

Based on LIS-7 and LIS-73, we calculate multiple iterations of the power and weakness score vectors (Equation 2 and Equation 5) until convergence is obtained relative to a given tolerance, $\epsilon = 0.5 \times 10^{-6}$ (i.e. up to 6 decimal places). Once the $\mathbf{p}$ and $\mathbf{w}$ scores vectors are obtained, we then compute the corresponding PWR and jPWR scores based on Equation 7 and Equation 18, respectively. The top 10 ranks by PWR and jPWR score are then determined. To validate the findings, we compare the PWR and jPWR scores with Impact Factor scores from the 2018 Journal Citation Reports (JCR) in addition to the SCImago Journal Rank scores for the same year.

The data processing and iterative calculations are carried out using standard Python libraries, i.e. Numpy for general purpose calculations (Harris et al. 2020), Scipy for sparse matrices (Virtanen et al. 2020), Scikit-Learn for matrix normalization (Pedregosa et al. 2011), and Networkx for network analysis (Hagberg et al. 2008). The Python notebooks for the calculations associated to each dataset are made available at https://gitlab.com/ephrance/power-weakness-ratio.

## Real-world application

The results for the LIS-7 and LIS-73 datasets are as shown in Tables 1 and 2, respectively. For LIS-7, the calculation takes 14 iterations to converge to 6 decimal places. We are able to replicate the PWR rank ordering and scores obtained in Leydesdorff et al. (2017) with some slight variation in the second decimal place. For LIS-73, 15 iterations are needed to converge to the same accuracy level for a larger set of 73 journals.

A comparison of the top ten journals ranked by jPWR and PWR score is as shown in Table 3. For jPWR, the top ten listing appears consistent with journals that are commonly regarded as influential within LIS. This is supported by the confluence of Q1 journals that correspond to some of the highest SJR and Journal Impact Factor scores in LIS. Interestingly, the top ten ranks by jPWR score for LIS-73 also shares good agreement with that previously obtained in LIS-7 as reported in Leydesdorff et al. (2017). In both datasets, Scientometrics occupies the top rank due to its higher fraction of journal self-citations among the top 10 journals listed (0.61 and 0.53 in LIS-7 and LIS-73, respectively).

Journal self-citations correspond to loops on the network that allow for a node's power and weakness score to propagate back into itself during each iteration in proportion to the weight of the self-loop link. This implies that the jPWR score assigns higher scores to journals that exhibit a larger fraction of self-citations. According to Gazni and Didegah (2020), papers that self-cite the journal they are published in are likely to receive more citations and form more tightly knit connections within the journal's scope of influence (i.e. between its authors, editors, and readers in addition to the various subject matter it covers). Following this line of thought, high power and low

**Table 1** The LIS-7 dataset and its power ($p$), weakness ($w$), PWR and jPWR scores. The columns J1 thru J7 are the cross-citation matrix reproduced from Leydesdorff et al. (2017). The rows follow the original ordering used in that paper. The columns $R$, $C$, $S$, $C_{-S}$, and $\phi$ signify the total number of references, citations, self-citations, citations with self-citations removed, and fraction of self-citations on the journal level

| Journal | J1 | J2 | J3 | J4 | J5 | J6 | J7 | $R$ | $C$ | $S$ | $C_{-S}$ | $\phi$ | $p$ | $w$ | PWR | jPWR | Rank PWR | Rank jPWR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| J1: *Inform Process Manag* | 132 | 165 | 49 | 86 | 68 | 46 | 23 | 381 | 569 | 132 | 437 | 0.23 | 0.054 | 0.031 | 1.747 | 0.056 | 1 | 4 |
| J2: *J Assoc Inf Sci Tech* | 120 | 756 | 107 | 495 | 189 | 139 | 219 | 1537 | 2025 | 756 | 1269 | 0.37 | 0.264 | 0.177 | 1.488 | 0.321 | 3 | 2 |
| J3: *J Inf Sci* | 12 | 66 | 89 | 72 | 26 | 26 | 30 | 354 | 321 | 89 | 232 | 0.28 | 0.033 | 0.023 | 1.452 | 0.034 | 4 | 6 |
| J4: *Scientometrics* | 48 | 320 | 34 | 1542 | 13 | 25 | 552 | 2541 | 2534 | 1542 | 992 | 0.61 | 0.495 | 0.509 | 0.974 | 1.008 | 5 | 1 |
| J5: *Inform Res* | 14 | 43 | 29 | 8 | 93 | 39 | 4 | 521 | 230 | 93 | 137 | 0.40 | 0.011 | 0.027 | 0.406 | 0.011 | 7 | 7 |
| J6: *J Doc* | 26 | 96 | 44 | 69 | 128 | 108 | 29 | 386 | 500 | 108 | 392 | 0.22 | 0.039 | 0.024 | 1.626 | 0.040 | 2 | 5 |
| J7: *J Informetr* | 29 | 91 | 2 | 269 | 4 | 3 | 302 | 1159 | 700 | 302 | 398 | 0.43 | 0.104 | 0.210 | 0.494 | 0.131 | 6 | 3 |

**Table 2** The top ten journals ranked by jPWR score in the LIS-73 dataset with its corresponding power ($p$), weakness ($w$), and PWR scores (the complete dataset is provided online). The columns J1 thru J10 depict the partial cross-citation matrix. The columns $R$, $C$, $S$, $C_{-S}$, and $\phi$ signify the total number of references, citations, self-citations, citations with self-citations removed, and fraction of self-citations on the journal level. The rows are ordered alphabetically by journal name

| Journal | J1 | J2 | J3 | J4 | J5 | J6 | J7 | J8 | J9 | J10 | $R$ | $C$ | $S$ | $C_{-S}$ | $\phi$ | $p$ | $w$ | PWR | jPWR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| J1: *Inform Process Manag* | 673 | 416 | 116 | 151 | 115 | 4 | 54 | 44 | 9 | 220 | 1576 | 2537 | 673 | 1864 | 0.27 | 0.022 | 0.012 | 1.8942 | 0.0224 |
| J2: *J Assoc Inf Sci Tech* | 338 | 3,655 | 455 | 379 | 1,811 | 135 | 272 | 345 | 223 | 3,117 | 9078 | 14735 | 3655 | 11080 | 0.25 | 0.240 | 0.120 | 2.0057 | 0.2726 |
| J3: *J Doc* | 27 | 335 | 585 | 82 | 89 | 11 | 121 | 46 | 11 | 167 | 2446 | 2611 | 585 | 2026 | 0.22 | 0.017 | 0.011 | 1.4925 | 0.0173 |
| J4: *J Inf Sci* | 39 | 238 | 107 | 464 | 69 | 8 | 46 | 41 | 4 | 162 | 1665 | 2005 | 464 | 1541 | 0.23 | 0.014 | 0.009 | 1.5277 | 0.0142 |
| J5: *J Informetr* | 70 | 846 | 38 | 30 | 2,443 | 41 | 18 | 100 | 189 | 2,570 | 7468 | 7328 | 2443 | 4885 | 0.33 | 0.161 | 0.172 | 0.9312 | 0.1941 |
| J6: *Learn Publ* | 2 | 88 | 24 | 6 | 45 | 325 | 9 | 17 | 12 | 119 | 794 | 1019 | 325 | 694 | 0.32 | 0.008 | 0.007 | 1.1439 | 0.0079 |
| J7: *Libr Inform Sci Res* | 13 | 181 | 136 | 37 | 9 | 19 | 334 | 19 | 2 | 54 | 1739 | 2225 | 334 | 1891 | 0.15 | 0.007 | 0.006 | 1.1742 | 0.0072 |
| J8: *Online Inform Rev* | 18 | 139 | 33 | 30 | 62 | 8 | 14 | 719 | 12 | 169 | 2459 | 2103 | 719 | 1384 | 0.34 | 0.012 | 0.015 | 0.7793 | 0.0122 |
| J9: *Res Evaluat* | 0 | 113 | 6 | 5 | 162 | 2 | 2 | 7 | 477 | 419 | 1438 | 1396 | 477 | 919 | 0.34 | 0.023 | 0.027 | 0.8528 | 0.0236 |
| J10: *Scientometrics* | 125 | 1,339 | 97 | 77 | 2,393 | 94 | 45 | 182 | 431 | 8,713 | 16946 | 16406 | 8713 | 7693 | 0.53 | 0.418 | 0.483 | 0.8652 | 0.8079 |

**Table 3** Top ten LIS-73 journals **a** by jPWR score and **b** by PWR score. The corresponding Impact Factor (IF) and SCImago Journal Rank (SJR) indicators in 2018 are listed for comparison

| (a) Top 10 Journals by jPWR | Rank jPWR | Rank PWR | jPWR | PWR | IF (2018) | SJR (2018) |
|---|---|---|---|---|---|---|
| *Scientometrics* | 1 | 38 | 0.8079 | 0.865 | 2.173 | 1.113 |
| *J Assoc Inf Sci Tech* | 2 | 16 | 0.2726 | 2.006 | 2.835 | 1.443 |
| *J Informetr* | 3 | 37 | 0.1941 | 0.931 | 3.484 | 1.952 |
| *Res Evaluat* | 4 | 39 | 0.0236 | 0.853 | 2.449 | 1.589 |
| *Inform Process Manag* | 5 | 17 | 0.0224 | 1.894 | 3.444 | 1.043 |
| *J Doc* | 6 | 26 | 0.0173 | 1.493 | 1.157 | 0.789 |
| *J Inf Sci* | 7 | 23 | 0.0142 | 1.528 | 1.939 | 0.636 |
| *Online Inform Rev* | 8 | 41 | 0.0122 | 0.779 | 1.675 | 0.656 |
| *Learn Publ* | 9 | 32 | 0.0079 | 1.144 | 1.632 | 1.078 |
| *Libr Inform Sci Res* | 10 | 31 | 0.0072 | 1.174 | 1.372 | 0.790 |
| *(b) Top 10 Journals by PWR* | | | | | | |
| *MIS Q Exec* | 57 | 1 | 0.0003 | 15.215 | 1.862 | 1.366 |
| *MIS Quart* | 11 | 2 | 0.0060 | 8.361 | 5.430 | 4.212 |
| *J Am Med Inform Assn* | 13 | 3 | 0.0041 | 6.145 | 4.270 | 1.711 |
| *J Comput-Mediat Comm* | 20 | 4 | 0.0029 | 5.757 | 4.000 | 3.311 |
| *Int J Comp-Supp Coll* | 54 | 5 | 0.0003 | 4.613 | 3.273 | 1.853 |
| *Inform Syst Res* | 24 | 6 | 0.0024 | 4.170 | 2.301 | 3.476 |
| *Libr Quar* | 33 | 7 | 0.0013 | 4.167 | 0.913 | 0.717 |
| *Inform Organ-UK* | 49 | 8 | 0.0004 | 3.955 | 1.857 | 1.105 |
| *J Health Commun* | 42 | 9 | 0.0006 | 3.676 | 1.648 | 1.007 |
| *Qual Health Res* | 52 | 10 | 0.0004 | 3.236 | 2.413 | 1.437 |

weakness journals with a high level of journal self-citations play an important role in shaping knowledge flows within its respective community.

On the other hand, the top ten journals by PWR appear to be a mixture of journals within the subfield of management information systems (*MIS Q Exec*, *MIS Quart*), information retrieval (*J Comput-Mediat Comm*, *Int J Comp-Supp Coll*, *Inform Syst Res*, *Inform Organ-UK*), medical information systems (*J Am Med Inform Assn*, *J Health Commun*, *Qual Health Res*) and library science (*Libr Quart*). This listing features journals with a combination of high inbound citation flow with low outbound reference flow. The top ten listing also coincides with Q1 journals in the aforementioned subfields that correspond to high impact factor and SJR scores.

Two main observations can be drawn between the results obtained by PWR and jPWR score. First, consider the case where the power and weakness scores are nearly equal thus resulting in an approximate PWR score of 1. This is the reason why *Scientometrics* and other highly influential LIS journals end up in the lower ranks by PWR score as shown in Table 3a. Such journals are "well integrated" within the structure of journal citations whereby a significant outward influence on other journals is reciprocated by a significant dependency on works published in other journals. This signifies a symbiotic relationship within the LIS journal ecosystem. By tweaking the denominator of the PWR score we can introduce a bias towards journals that pair a high power to influence with a high weakness to be influenced. This mechanism explains the observed inversion of PWR and jPWR ranks.

Second, recall that the conventional PWR score is equal to the converged power score divided over the converged weakness score (Equation 7). By implication, journals with (or approaching) zero weakness have an indeterminate (or extremely large) PWR score. The sensible approach to avoid such cases is to extract a dense induced subgraph that satisfies some minimum outbound link weight threshold such that for a given node $i$, the constraint $\max(A_{ij}) > R_{min} > 0$ ensures the removal of dangling or weakly outbound connected nodes (which correspond to zero weakness).

From a bibliometric perspective, journals that correspond to dangling nodes do not appear to extend the citation trail, and hence, do not indicate (signal) a transfer of knowledge "forward" to other journals. For jPWR, the presence of dangling nodes does not cause indeterminate scores and therefore a clear advantage of this indicator is that it can be applied on both sparsely or densely connected journal citation networks. This is consistent with Leydesdorff et al. (2017) which concluded that PWR could be evaluated on homogeneous subgraphs but not across different communities on the journal citation network.

Naturally, dangling nodes may appear in real-world analyses as artefacts from a partial reconstruction of the global citation network (Yan and Ding 2011). For LIS-73, it could be the case that the top-ranked journals by PWR score shown in Table 3b are actually under-represented in LIS and perhaps have better reference coverage in other WoS categories such as "Operations Research & Management Science" or "Medical Informatics", for example.

While this can be solved by ensuring the study data covers as much relevant information as possible, in some instances such as in the case of peripheral journals, the data may not be available under widely used indices such as Web of Science (Garfield 1972; Arunachalam and Manorama 1989). In this sense, the PWR score could provide a useful measure to identify journal egonets (egocentric networks) that potentially suffer from missing reference data since such journals will tend to feature low weakness (Prathap and Nishy 2016). This is an interesting direction to explore in future work.

In general, the power score is a recursive measure of direct and indirect citations received by each journal, and can therefore be considered as a proxy for how influential a journal is relative to others within the same system. On the other hand, the weakness score is a recursive measure of direct and indirect references made by each journal and could be considered as a proxy for how receptive a journal is relative to others in the same system.

The accounting of such indirect network effects is rooted in the inner workings of the power method when applied on the adjacency matrix $\mathbf{A}$ of a network $G$. Raising the adjacency matrix to power $k$ yields the number of paths of walk length $k$ on $G$ that connect any of its two nodes $i$ and $j$. If a node $j$ is unreachable from $i$ via a walk length of $k$, then $(\mathbf{A}^k)_{ij} = 0$. For an interconnected system of journals, a direct effect between journals corresponds to a walk of length $k = 1$ (either inbound or outbound) while indirect effects correspond to paths of walk length $k > 1$.

A rank correlation analysis of the various node scores constructed in this study can be carried out to determine how one score scales against another. The results are as shown in Table 4. Indeed, we find that: (1) the total number of references (weighted out-degree) has a strong positive correlation ($r = 0.87$) with the total number of citations (weighted in-degree); and (2) the power and weakness scores exhibit a strong positive correlation ($r = 0.83$) with each other ( In Section "Power-weakness ratio in journal citation analysis"). Hence, the jPWR score should yield a value approaching 1 for journals that possess power and weakness scores in near equal measure such as that found for *Scientometrics*.

**Table 4** The Spearman rank correlation matrix for various node scores on the journal citation network constructed from the LIS-73 dataset. The symbols $R$, $C$, $S$, $p$ and $w$ signify the total number of references (weighted out-degree), citations (weighted in-degree), self-citations (weighted loops), power score and weakness score, respectively

| | $R$ | $C$ | $S$ | $p$ | $w$ | PWR | jPWR | IF | SJR |
|---|---|---|---|---|---|---|---|---|---|
| $R$ | 1.00 | 0.87 | 0.82 | 0.61 | 0.58 | 0.01 | 0.61 | 0.52 | 0.51 |
| $C$ | 0.87 | 1.00 | 0.86 | 0.70 | 0.47 | 0.35 | 0.70 | 0.63 | 0.69 |
| $S$ | 0.82 | 0.86 | 1.00 | 0.47 | 0.34 | 0.24 | 0.47 | 0.57 | 0.52 |
| $p$ | 0.61 | 0.70 | 0.47 | 1.00 | 0.83 | 0.12 | 1.00 | 0.31 | 0.37 |
| $w$ | 0.58 | 0.47 | 0.34 | 0.83 | 1.00 | −0.39 | 0.83 | 0.10 | 0.10 |
| PWR | 0.01 | 0.35 | 0.24 | 0.12 | −0.39 | 1.00 | 0.11 | 0.47 | 0.55 |
| jPWR | 0.61 | 0.70 | 0.47 | 1.00 | 0.83 | 0.11 | 1.00 | 0.31 | 0.37 |
| IF | 0.52 | 0.63 | 0.57 | 0.31 | 0.10 | 0.47 | 0.31 | 1.00 | 0.85 |
| SJR | 0.51 | 0.69 | 0.52 | 0.37 | 0.10 | 0.55 | 0.37 | 0.85 | 1.00 |

While we find that both Impact Factor (IF) and SJR share a strong positive correlation ($r = 0.85$), this is not the case when either score is paired up with PWR or even jPWR. The reason for this is that both PWR and jPWR do not measure journal impact in a conventional sense such as IF or SJR which are designed to score journals according to how they impact other journals based on the extent to which they are embedded within the structure of inter-journal citations.

In contrast, both PWR and jPWR are designed to measure how each journal impacts and is impacted by other journals based on the same citation network information. This form of journal impact is rooted in the channeling or propagation of information through direct and indirect paths along the journal citation network while considering both inbound and outbound flows. A journal with a high power score is reachable (and therefore influential) from many inbound paths of varying breadth and depth. Conversely, a journal with high weakness score (signifying a high propensity to be influenced by others) propagates the influence of each of its references within the journal system across multiple outbound paths.

For PWR, a high score is assigned to journals that have the highest power to influence with the lowest weakness to be influenced. Meanwhile, jPWR assigns high scores to journals that have a near equal power to influence and weakness to be influenced. Since high power coupled with high weakness results in a higher jPWR score, this indicator can be used as a recursive measure of proportionate inbound and outbound citation flow. The Spearman rank correlation of $r = 0.11$ between PWR and jPWR shows that both scores indeed measure two different network properties.

## Concluding remarks

In this paper, we re-examined the application of the Power-Weakness Ratio (PWR) score introduced by Ramanujacharyulu (1964) for the evaluation of journal impact as first suggested by Prathap and Nishy (2016). The PWR score was first described as a recursive method to find the most "talented" or "balanced" player in a tournament. Such a player is defined as one who simultaneously has the highest "power" to influence and the lowest "weakness" to be influenced by others. Both power and weakness scores are computed recursively via the power method based on the adjacency matrix that connects players in the tournament. A ratio between the power and weakness scores results in the PWR score.

Under a bibliometric setting, the tournament matrix can be replaced with the underlying adjacency matrix for a journal citation network. Accordingly, the power score gives a recursive count of journal citations while the weakness score is a recursive proxy for the size of each journal. The PWR score then provides a size-independent recursive measure of the impact of each journal which is inclined towards journals that have the highest power to influence and the lowest weakness to influence.

Leydesdorff et al. (2017) put this notion to the test and found that the PWR score does not yield an interpretable ranking for a system of seven prominent Library and Information Science (LIS) journals. Leydesdorff and co-workers attribute this limitation to the fact that PWR was originally constructed to evaluate players in a tournament setting whereby one player's win is another player's loss. This constraint however may not apply under a bibliometric setting since one journal's gain is not necessarily another journal's loss.

In this paper, we propose that a slight modification is required to create an alternate PWR score dubbed the Journal Power-Weakness Ratio or jPWR. Specifically, we propose that journal impact can be measured as a recursive measure of proportionate inbound and outbound citation flow. In this sense, a high impact journal is one that has a high power to influence coupled with a high weakness to be influenced. This is made possible by modifying the denominator for the PWR score to equal one minus the weakness score. This ensures that high weakness values result in a smaller denominator thus amplifying the contribution from the power score numerator.

We tested the jPWR score on the same dataset used in Leydesdorff et al. (2017) and introduced an additional LIS dataset consisting of 73 journals. We found that the resulting jPWR ranking is in close agreement with Impact Factor scores from the 2018 edition of the Journal Citation Reports as well as the SCImago Journal Rank indicator for 2018. This strengthens the case for using Ramanajucharyulu's Power-Weakness paradigm in journal citation analysis.

An important limitation of the present work is the omission of journals that result in rather large or indeterminate PWR values. Effectively, the removal of such journals leaves behind a strongly connected component consistent with the methodology outlined in Leydesdorff et al. (2017). However, it is worthwhile in future work to explore empirical corrections of PWR, and by extension, jPWR, that retain all data points such as that proposed in Todeschini et al. (2015) or Todeschini et al. (2019). The incorporation of such corrections may provide a more robust approach to handling the full range of real-world bibliometric data.

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