Measuring the attractiveness of academic journals: A direct influence aggregation model

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Abstract

Various journal-ranking algorithms have been proposed, most of them based on citation counts. This article introduces a new approach based on the reciprocal direct influence of all pairs of a list of journals. The proposed method is assessed against an opinion-based ranking published in 2005 for 25 operations research and management science (OR/MS) journals, and five existing approaches based on citation counts. The results show a strong correlation with the opinion-based ranking.

Keywords: Journal ranking, citations, invariant method, LP-method, impact factor, PageRank method

Various databases offer access to thousands of academic journals. This is the case of the Thomson Reuters Master Journal List (which included 17,590 peer-reviewed journals in 2013) and of the Scopus database (with more than 20,000 registered journals). This huge quantity of journals presents a heterogeneous picture with respect to quality, scientific influence, and prestige. To respond to the need to assess the quality of the increasing quantity of journals several metrics have been proposed. Most are based on citation counts, though they sometimes combine with other indicators such as the number of citable documents or the average number of citations per article. The Journal Impact Factor was a first metric proposed by Garfield [1]. This indicator, which consists of the ratio of the mean number of cited articles to the number of citable articles published in the two preceding years, is still extensively used despite its numerous and well-known weaknesses [see 2]. Several variants use different ways to compute the numerator and the denominator of the Impact Factor in an attempt to correct some of these weaknesses. One major improvement consists in ignoring self-citations in the numerator. Stigler et al. [3] proposed the *export score* which consists of the log odds that a citation involving two journals i and j has j citing i rather than the contrary. The H-index, another metric proposed by Hirsch [4] and Braun et al. [5, 6], is the largest number h for which a journal has h articles cited at least h times in other journals. Other metrics based on an iterative approach use a citation matrix with the idea that citations from prestigious journals should be valued more than citations from less prestigious journals. This is the case for the LP-method proposed by Liebowitz and Palmer [7], the invariant method proposed by Pinski and Narin [8] and Palacios-Huerta and Volij [9] and, more recently, the PageRank-inspired method proposed by Xu et al. [10] which derives from the work of Page et al. [11].

In this article, an iterative ranking algorithm based on the direct influence between each pair of a list of journals is proposed. It only uses a citation matrix and, contrary to other iterative approaches, presents the particularity of not requiring any adjustment with respect to the size of the journals. However, in the same manner as all other iterative methods, it recognizes that citations can be more valuable than others by assigning them a weight proportional to the attractiveness of the citing journals.

1. Comparing the attractiveness of two journals

Denote by L a list of journals, and by (i, j) a pair of journals in L. Randomly select an article u from journal i, an article v from journal j, and a reference r from any article of any journal in L. We say that journal i is more attractive than journal j if and only if the probability p_i that citation r refers to article u is greater than the probability p_j that it refers to article v. As such, these probabilities are a measure of the attractiveness defined as the influence per article, not the total influence on the scientific community which depends on the number of publications. Below, the terms "influence" and "direct influence" refer to the influence per article.

2. Direct influences between two journals with homogeneous reference intensity

In this section, we assume a constant average number of references per article for all journals. This corresponds to the *homogeneous reference intensity* assumption introduced by Palacios--Huerta and Volij [9]. Denote by c_{ij} the number of citations from journal i to journal j, by $E[c_{ij}]$ the expected value of c_{ij}, and by h_{ij} the direct influence of journal i on journal j.

Proposition 1. *In a two-journal ranking problem with homogeneous reference intensity,* $h_{ij} > h_{ji}$ *if and only if* $E[c_{ij}] <$

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$E[c_{ji}]$*, whatever the number of published articles in both journals.*

Proof. Assume, without loss of generality, that all articles contain only one reference, and denote by p_{ij} the probability that a random article of journal i refers to journal j, and by n_i and n_j the non-negative numbers of articles published in journals i and j. In a two-journal ranking problem, we have $h_{ij} > h_{ji}$ if and only if $p_i > p_j$. Multiplying both terms of the inequality by $n_i n_j$, we get $n_i n_j p_i > n_i n_j p_j$. As each article contains only one reference, we have $p_{ij} = n_j p_j$ and $p_{ji} = n_i p_i$, then $n_j p_{ji} > n_i p_{ij}$ which can be rewritten as $E[c_{ji}] > E[c_{ij}]$. □

Therefore, in a two-journal ranking problem with homogeneous reference intensity the direct influence of journal i on journal j only depends on c_{ij} and c_{ji}, without any consideration of the publication intensity. Thus, it is possible to define a measure h_{ij} of direct influence of journal i on journal j as follows:

$$h_{ij} = \begin{cases} \frac{c_{ji}}{c_{ij}+c_{ji}} & \text{if } i \neq j \text{ and } c_{ij} + c_{ji} > 0\,, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The value of h_{ij} is a bounded measure lying in the closed interval $[0, 1]$. One can think of the denominator $c_{ij} + c_{ji}$ as the communication's bandwidth between journals i and j, and the numerator c_{ji} as the fraction of the bandwidth used by journal i to influence journal j. When communication exists between two journals i and j, we have $h_{ij}+h_{ji} = 1$, and the same reciprocal direct influence is observed when $h_{ij} = h_{ji} = 1/2$. When no communication exists between two journals i and j, h_{ij} and h_{ji} are equal to 0.

3. Direct influence aggregation model

In the direct influence aggregation (DIA) model, the attractiveness w_i of a journal i is the weighted average of its direct influence on all other journals, to each of which is accorded a weight indicative of its own attractiveness w_j. Thus, the model recognizes that the direct influence on prestigious journals is more valuable than the same direct influence on less prestigious journals, and the attractiveness of journal i is recursively defined as:

$$w_i = \frac{\sum_{j\in L\setminus\{i\}} w_j h_{ij}}{\sum_{j\in L\setminus\{i\}} w_j}\,, \tag{2}$$

such that $\sum_{i\in L} w_i = 1$, or in matrix notation:

$$\mathbf{w} = \operatorname{diag}[(\mathbf{J} - \mathbf{I})\mathbf{w}]^{-1}\mathbf{H}\mathbf{w}\,, |\mathbf{w}|_1 = 1, \tag{3}$$

where $\mathbf{H} = (h_{ij})$ is an $|L| \times |L|$ direct influence matrix, $\mathbf{J}$ is the all-ones matrix, $\mathbf{I}$ the identity matrix, and $|\mathbf{w}|_1$ the L^1-norm of vector $\mathbf{w}$.

Illustration

Consider a list of three journals and the corresponding matrix $\mathbf{C} = (c_{ij})$ of citations:

$$\mathbf{C} = \begin{bmatrix} 3 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 0 & 1 \end{bmatrix}. \tag{4}$$

By definition (1), we obtain the matrix $\mathbf{H}$ of direct influences:

$$\mathbf{H} = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 0 \\ 1/2 & 1 & 0 \end{bmatrix}. \tag{5}$$

Equation (2) is solved iteratively with an arbitrary initial attractiveness vector $\mathbf{w^{(0)}}$. Here:

$$\mathbf{w^{(0)}} = (1/3, 1/3, 1/3)\,. \tag{6}$$

A new attractiveness vector $\hat{\mathbf{w}}^{(1)}$ is obtained after the first iteration:

$$\hat{\mathbf{w}}^{(1)} = (1/2, 1/4, 3/4)\,, \tag{7}$$

which is normalized by dividing it by $|\hat{\mathbf{w}}^{(1)}|_1 = \sum_{i\in J} \hat{w}_i^{(1)} = 3/2$ to obtain:

$$\mathbf{w^{(1)}} = (1/3, 1/6, 1/2)\,. \tag{8}$$

After some iterations, the algorithm converges to the following normalized solution:

$$\mathbf{w} = (0.365, 0.159, 0.476). \tag{9}$$

4. Direct influence aggregation with heterogeneous reference intensity

In this section, we consider the case where the number of references per article u_i differ for each journal i. This corresponds to the *heterogeneous reference intensity* assumption defined by Palacios-Huerta and Volij [9].

Proposition 2. *In a two-journal ranking problem with heterogeneous reference intensity,* $h_{ij} > h_{ji}$ *if and only if* $u_j E[c_{ij}] < u_i E[c_{ji}]$*, whatever the number of published articles in both journals.*

Proof. Assume, without loss of generality, that all articles of journals i and j contain u_i and u_j references, respectively. Denote by p_{ij} the probability that a random article of journal i refers to journal j, and by n_i and n_j the non-negative numbers of articles published in journals i and j. In a two-journal ranking problem, we have $h_{ij} > h_{ji}$ if and only if $p_i > p_j$. Multiplying both terms of the inequality by $n_i n_j$, we get $n_i n_j p_i > n_i n_j p_j$. As $p_{ij} = u_i n_j p_j$ and $p_{ji} = u_j n_i p_i$, we have $u_i n_j p_{ji} > u_j n_i p_{ij}$ which can be rewritten as $u_i E[c_{ji}] > u_j E[c_{ij}]$. □

Therefore, when citation patterns differ for each journal, it is possible to control for reference intensity by dividing c_{ij} by the reference intensity u_i of journal i for each pair (i, j) of journals or, in matrix notation, to replace matrix $\mathbf{C}$ of citations by matrix $\hat{\mathbf{C}} = \operatorname{diag}(\mathbf{u})^{-1}\mathbf{C}$, where $\mathbf{u}$ is the vector of reference intensities. With this simple adjustment, the direct influence aggregation model satisfies invariance to reference intensity.

Illustration

Consider a two-journal ranking problem associated with the matrix $\mathbf{C}$ of citations:

$$\mathbf{C} = \begin{bmatrix} 9 & 3 \\ 4 & 6 \end{bmatrix}, \tag{10}$$

and the vector $\mathbf{u} = (3, 2)$ of reference intensities. We obtain:

$$\hat{\mathbf{C}} = \begin{bmatrix} 1/3 & 0 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} 9 & 3 \\ 4 & 6 \end{bmatrix} = \begin{bmatrix} 3 & 1 \\ 2 & 3 \end{bmatrix}, \tag{11}$$

then:

$$\mathbf{H} = \begin{bmatrix} 0 & 2/3 \\ 1/3 & 0 \end{bmatrix}, \tag{12}$$

which gives the solution $\mathbf{w} = (2/3, 1/3)$.

5. Properties of the direct influence aggregation model

The direct influence aggregation model exhibits desirable characteristics and properties that can be expected from a journal ranking method. These properties include the following:

Invariance to publication intensity. Proposition 2 shows that the direct influence between two journals does not depend on their respective number of published articles and only depends on their mutual citations in the homogeneous case, or on their mutual citations and their reference intensities in the heterogeneous case.

Weighted citations. Each direct influence is weighted by the attractiveness of journal on which it is exerted: the direct influence exerted on a prestigious journal is recognized as more valuable than the same direct influence on a less prestigious journal.

Invariance to reference intensity. By Proposition 2, the direct influence aggregation model controls for reference intensity by dividing the number of citations made by all journals by their reference intensities.

Invariance to self-citations. By definition, the attractiveness of a journal is a weighted average of its direct influence on all other journals. As such, self-citations are ignored and do not have any influence on the ranking.

Homogeneity. *Weak homogeneity* and *homogeneity* properties were introduced by Palacios-Huerta and Volij [9]. A ranking method satisfies *weak homogeneity* if for any two-journal ranking problem with the same reference intensity and the same number of publications the ratio of their relative valuations is equal to the ratio of their mutual numbers of received citations. The DIA model satisfies *homogeneity* as this condition holds for any two-journal ranking problem with different publication intensities.

Proof. Consider a ranking problem with only two journals i and j such that $n_i \neq n_j$ and $u_i = u_j$. By definition, we have $h_{ij} = w_i = \frac{c_{ji}}{c_{ij}+c_{ji}}$ and $h_{ji} = w_j = \frac{c_{ij}}{c_{ij}+c_{ji}}$, then $\frac{w_i}{w_j} = \frac{c_{ji}}{c_{ij}}$. □

6. Illustration from operations research and management science (OR/MS) journals

In this section, we explore the correlation between the results of the DIA model and the results of existing ranking methods. As a ranking should ideally correlate the perception of experts and academicians, the DIA model is assessed on a set of 25 out of 39 OR/MS journals ranked by Olson [12] through two surveys of faculty members from the top-25 US business schools in 2000 and 2002.

Table 1 shows the titles and the abbreviations of the 25 journals under consideration. This list comprises all journals ranked by Olson and included in the Journal Citation Report [13] (JCR 2003). Five journals not specifically related to OR/MS, and two dangling journal nodes of the citation network that do not cite any other journals of the list are discarded. The data used to conduct the numerical experiment were collected from the JCR 2003 database with a home-made software, and all the citations in articles published in 2003 to articles published between 1994 and 2003 were considered.

The two versions of the DIA model, with and without control for reference intensity (DIA2 and DIA1, respectively), are compared to five methods based on citation counts: the LP-method (LP), the invariant method (INV) as defined in Palacios-Huerta and Volij [9], the 2-year Impact Factor (IF1), the 2-year Impact Factor without self-citations (IF2) and the PageRank method (PR) proposed by Xu et al. [10].

The scores obtained through all the methods are shown in Table 2 and resulting rankings are shown in Table 3. Except for the Olson's survey, all methods rank the journals in decreasing order of scores. Impact Factors IF1 and IF2 are those of the JCR 2003, and PageRank scores are those published in Xu et al. [10].

Table 4 exhibits the Kendall rank-order correlation coefficient and the corresponding p-value for each pair of rankings. Compared to Olson [12], the rankings derived from the DIA scores, the PageRank scores and, to a lesser extent, scores obtained through the invariant method, have positive correlations at very strong significance levels (with p-value $\leq$ .00142). If DIA2 and PR give the best correlations with the Olson's ranking, it is worth noting that the ranking from PR corresponds to the maximum Kendall's correlation found by Xu et al. [10] among 121 combinations of the parameters β and γ, respectively the proportion of self-citations and external citations to consider, with β and γ in $\{0.0, 0.1, \ldots, 1.0\}$. From these 121 combinations, only the highest correlation of 0.5843 was retained with $\beta = 0$ and $\gamma = 0.3$. Xu et al. [10] reported the lowest correlation of 0.5017 with $\beta = 0$ and $\gamma = 0$, and a correlation of 0.5339 with $\beta = 1$ and $\gamma = 1$. A major drawback of the PageRank method is the sensitivity to the parameters. Xu et al. [10] recognized that the need for a calibration could introduce some subjectivities, and that setting the parameters is not easy. Moreover, to calibrate the PageRank method one needs a reference such as an opinion-based ranking that is not always available. The DIA model is nonparametric and overcomes these drawbacks.

In Table 4, we also observe a weak correlation between

Table 1: List of journals under consideration

Full Journal Title	Abbreviation	Citable articles (2003)	Relative reference Intensity (2003) (base: Operations Research Letters)
Annals of Operations Research	AOR	81	2.19
Computer & Operations Research	COR	134	1.73
Decision Support Systems	DSS	63	2.57
European Journal of Operational Research	EJOR	364	2.14
IIE Transactions	IIE	92	2.04
INFORMS Journal on Computing	IJC	23	2.92
Interfaces	INTF	93	2.27
International Journal of Production Economics	IJPE	219	2.22
International Journal of Production Research	IJPR	42	1.32
Journal of Combinatorial Optimization	JCO	18	1.65
Journal of Global Optimization	JGO	72	1.99
Journal of Heuristics	JH	22	2.60
Journal of Manufacturing Systems	JMS	11	2.16
Journal of Operations Management	JOM	25	5.39
Journal of the Operational Research Society	JORS	132	1.97
Management Science	MS	104	3.53
Mathematical Programming	MP	43	2.18
Mathematics of Operations Research	MOR	107	2.83
Naval Research Logistics	NRL	48	1.87
Networks	NET	43	1.45
Omega	OMG	45	2.85
Operations Research	OR	74	2.16
Operations Research Letters	ORL	73	1.00
Production and Operations Management	POM	14	3.46
Transportation Science	TS	25	2.17

Olsen's ranking and both the Impact Factor and the LP-method. In particular, rankings from IF1 and IF2 are the least consistent with the perception of academicians and present some remarkable discrepancies. For instance, *Decisions Support Systems* is ranked third and second by IF1 and IF2, and not less than 20th by other methods. *Management Science* is ranked second and third by IF1 and IF2, and ranked first by all other methods. DIA shows a clear improvement over IF1, IF2, and LP.

7. Conclusions

Ranking academic journals is a difficult exercise. Whether one agrees with ranking methods based on citation counts or not, they are an attempt to give an objective evaluation of the academic journals which are nowadays part of the academic landscape and will not disappear in the near future. Considering the importance of journal rankings in the academic life, it is essential to propose consistent and comprehensible ranking methods. This study confirms that Impact Factor, despite its prominence, fails to demonstrate favorable consistency. It also shows that rankings derived from the direct influence aggregation model and the PageRank index [10] are the most consistent with the opinion-based ranking done by Olson [12]. However, and contrary to the PageRank method, the direct influence aggregation model does not need any calibration and, as such, it ignores any subjective influence. It offers a very intuitive and easy-to-implement way to rank academic journals. It is also quicker to compute than the invariant and the PageRank methods and exhibits various properties that a journal ranking method is expected to satisfy: invariance to publication intensity, invariance to reference intensity, invariance to self-citations, homogeneity, and distinction between citations from the most and least prestigious journals. The direct influence aggregation model offers a consistent alternative in the academic journal ranking toolbox.

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Rankings based on the direct influence aggregation model are freely available for about 11,000 academic journals at:

http://www.diamscience.com

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Table 2: Scores

	Olson	DIA1	DIA2	INV	LP	IF1	IF2	PR
Management Science	1.10	0.081	0.090	0.147	0.109	1.468	1.241	7.17
Operations Research	1.12	0.073	0.074	0.095	0.094	0.672	0.563	6.53
Mathematics of Operations Research	1.41	0.063	0.062	0.039	0.024	1.146	1.010	5.04
Mathematical Programming	1.62	0.039	0.044	0.029	0.017	1.290	1.046	4.30
Naval Research Logistics	2.38	0.043	0.040	0.031	0.039	0.368	0.347	2.12
Transportation Science	2.42	0.052	0.053	0.076	0.068	0.491	0.316	5.01
IIE Transactions	2.44	0.035	0.033	0.029	0.042	0.541	0.454	2.10
Interfaces	2.53	0.062	0.055	0.086	0.079	0.712	0.692	2.39
INFORMS Journal on Computing	2.63	0.047	0.053	0.060	0.063	0.761	0.696	3.42
Operations Research Letters	2.65	0.068	0.052	0.025	0.027	0.449	0.390	2.22
Networks	2.78	0.041	0.036	0.020	0.016	0.649	0.553	1.45
European Journal of Operational Research	2.83	0.052	0.053	0.030	0.029	0.605	0.559	2.01
Annals of Operations Research	2.97	0.050	0.052	0.022	0.027	0.331	0.311	2.25
Production and Operations Management	2.99	0.005	0.007	0.024	0.042	0.393	0.295	2.44
Journal of Operations Management	3.02	0.041	0.045	0.085	0.079	1.795	1.411	2.44
Journal of Combinatorial Optimization	3.08	0.013	0.011	0.009	0.011	0.667	0.667	0.74
Journal of the Operational Research Society	3.27	0.038	0.037	0.024	0.024	0.416	0.305	1.86
Journal of Global Optimization	3.67	0.018	0.018	0.009	0.006	0.559	0.488	1.64
International Journal of Production Research	3.88	0.017	0.017	0.015	0.017	0.557	0.344	0.92
Journal of Heuristics	4.00	0.031	0.034	0.037	0.042	0.633	0.633	2.54
Computer & Operations Research	4.05	0.043	0.039	0.017	0.021	0.486	0.443	1.31
International Journal of Production Economics	4.06	0.022	0.023	0.019	0.027	0.410	0.367	1.18
Decision Support Systems	4.18	0.019	0.020	0.011	0.009	1.316	1.265	0.96
Journal of Manufacturing Systems	4.36	0.015	0.015	0.039	0.056	0.253	0.213	0.88
Omega	4.37	0.031	0.033	0.022	0.032	0.558	0.488	1.65

Table 3: Rankings

Rank	Olson	DIA1	DIA2	INV	LP	IF1	IF2	PR
1	MS	MS	MS	MS	MS	JOM	JOM	MS
2	OR	OR	OR	OR	OR	MS	DSS	OR
3	MOR	ORL	MOR	INTF	INTF	DSS	MS	MOR
4	MP	MOR	INTF	JOM	JOM	MP	MP	TS
5	NRL	INTF	IJC	TS	TS	MOR	MOR	MP
6	TS	TS	TS	IJC	IJC	IJC	IJC	IJC
7	IIE	EJOR	EJOR	JMS	JMS	INTF	INTF	JH
8	INTF	AOR	ORL	MOR	IIE	OR	JCO	JOM
9	IJC	IJC	AOR	JH	POM	JCO	JH	POM
10	ORL	NRL	JOM	NRL	JH	NET	OR	INTF
11	NET	COR	MP	EJOR	NRL	JH	EJOR	AOR
12	EJOR	JOM	NRL	MP	OMG	EJOR	NET	ORL
13	AOR	NET	COR	IIE	EJOR	JGO	JGO	NRL
14	POM	MP	JORS	ORL	IJPE	OMG	OMG	IIE
15	JOM	JORS	NET	JORS	AOR	IJPR	IIE	EJOR
16	JCO	IIE	JH	POM	ORL	IIE	COR	JORS
17	JORS	JH	OMG	OMG	MOR	TS	ORL	OMG
18	JGO	OMG	IIE	AOR	JORS	COR	IJPE	JGO
19	IJPR	IJPE	IJPE	NET	COR	ORL	NRL	NET
20	JH	DSS	DSS	IJPE	MP	JORS	IJPR	COR
21	COR	JGO	JGO	COR	IJPR	IJPE	TS	IJPE
22	IJPE	IJPR	IJPR	IJPR	NET	POM	AOR	DSS
23	DSS	JMS	JMS	DSS	JCO	NRL	JORS	IJPR
24	JMS	JCO	JCO	JCO	DSS	AOR	POM	JMS
25	OMG	POM	POM	JGO	JGO	JMS	JMS	JCO

Table 4: Kendall rank-order correlation coefficients and p-values (N = 25)

	DIA1	DIA2	INV	LP	IF1	IF2	PR
Olson							
	0.5200	**0.5467**	**0.4467**	**0.2800**	**0.2400**	**0.2170**	**0.5843**
	0.00016	0.00006	0.00142	0.05186	0.09755	0.12890	0.00004
DIA1							
		0.8933	0.5000	0.3467	0.1867	0.2104	0.5643
		0.00000	0.00030	0.01502	0.20120	0.14110	0.00008
DIA2							
			0.5667	0.3733	0.2800	0.2905	0.6311
			0.00003	0.00852	0.05186	0.04211	0.00001
INV							
				0.7533	0.1800	0.1770	0.6110
				0.00000	0.21820	0.21570	0.00002
LP							
					0.0000	0.0100	0.4574
					1.00000	0.94410	0.00137
IF1							
						0.8715	0.2437
						0.00000	0.08812
IF2							
							0.2408
							0.09248