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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 seven methods based on citation counts. The results show a strong correlation with the opinion-based ranking.

Keywords: Academic journal ranking, invariant method, LP-method, impact factor, PageRank method, export scores model

Various databases offer access to thousands of academic journals. This is the case of the Thomson Reuters' Web of Science (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 average number of times articles have been cited to the number of citable articles published in the two preceding years, is still extensively used despite its numerous and well-known weaknesses, in particular, a high susceptibility to manipulations, a significant correlation with self-citations, and a weak correlation with the article rejection rates [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: this is the case for the *Audience Factor* proposed by Zitt and Small [3] to control for the fields propensity to cite, or for the *SNIP indicator* proposed by Moed [4] and made available in the Elsevier Scopus database. The *Export Scores Model* introduced by Stigler et al. [5] is an original approach based on the pairwise comparisons between journals which uses the log odds that a citation involving two journals i and j has j citing i rather than the opposite. The *H-index*, a metric proposed by Hirsch [6] and Braun et al. [7, 8], is defined as the largest number h for which a journal has h articles cited at least h times in other journals. The *Author Affiliation Index* introduced by Gorman and Kanet [9] is another approach built on the idea that the quality of a journal is highly correlated with the reputation of the authors publishing in it and, consequently, with the reputation of their respective universities or research institutions. Other indicators, belonging to the group of eigenvector centrality methods, are based on iterative procedures which 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 *Invariant method* introduced by Pinski and Narin [10] and Palacios-Huerta and Volij [11], for the *LP-method* proposed by Liebowitz and Palmer [12] and, more recently, the *PageRank*-inspired methods proposed by Ma et al. [13] and Xu et al. [14] which derives from the work of Page et al. [15]. The same eigenvector centrality approach is used in the *Eigenfactor* published in the Journal Citation Reports and the *SJR indicator* introduced by González--Pereira et al. [16] and made available in the Elsevier Scopus database.

This article introduces an iterative ranking algorithm based on the direct influence between each pair of a list of journals. In the same manner as the Export Scores Model introduced by Stigler et al. [5], it is based on pairwise comparisons, however, while the Export Scores Model only measures the direct mutual influences, the proposed approach also measures their indirect influences by integrating an iterative procedure similar to what is found in the eigenvector centrality methods. As such, it recognizes that citations can be more valuable than others by assigning them a weight proportional to the attractiveness of the citing journals.

The remainder of this paper is organized as follows. In Section 1, we provide a definition of the direct influence exerted by a journal on another, and we introduce a measure of the relative direct influences in a pair of journals. In Section 2, we describe the *direct influence aggregation model*, the

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iterative method used to aggregate the pairwise comparisons and to establish a ranking based on the direct and the indirect influences. In Section 3, a synthesis of the main properties of the method is given. A numerical application is presented in Section 4 for a list of 25 OR/MS journals, including a comparison with an opinion-based ranking published in 2005, and with seven other ranking methods based on citation counts. Conclusions are provided in Section 5.

1. Pairwise comparisons and direct mutual influences

To compare two journals, the Export Scores Model proposed by Stigler et al. [5] uses the ratio c_{ji}/c_{ij}, where c_{ij} denotes the number of citations from journal i to journal j. This measure, unbounded at both ends, is used in a model based on a logit formulation of quasi-symmetry [17] to aggregate all pairwise comparisons and generate the ranking. However, as outlined by Palacios-Huerta and Volij [11], Stigler et al. [5] "are not clear as whether or not [the varying average number of references in articles published by each journal] calls for correction". In this section, we propose to compare two journals with a bounded ratio based on the mutual numbers of citations c_{ij} and c_{ji}, and adjusted for any difference in reference intensities, denoted by u_i and u_j, and corresponding to the average number of emitted references per article in journals i and j, respectively.

Denote by A_i the set of articles published in journal i, and by R_j the set of emitted citations by journal j. We define the direct influence d_{ij} of journal i on journal j as the proportion $c_{ji}/|A_i||R_j|$, i.e. the proportion of *observed* citations from journal j to journal i among all *potential* citations from j to i. Since $|R_i| = u_i|A_i|$ and $|R_j| = u_j|A_j|$, we have $d_{ij} = c_{ji}/u_j|A_i||A_j|$ and $d_{ji} = c_{ij}/u_i|A_i||A_j|$, and we define the relative direct influence h_{ij} of journal i on journal j as:

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

which can be rewritten as:

$$h_{ij} = \begin{cases} \frac{u_i c_{ji}}{u_j c_{ij}+u_i c_{ji}} & \text{if } i \neq j \text{ and } u_j c_{ij}+u_i c_{ji} > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

This measure lies in the closed interval $[0,1]$ and is defined for any pair of journals. Like the ratio used by Stigler et al. [5], it is invariant to the relative sizes of the journals, but contrary to the Export Scores Model, this measure controls for reference intensity. We have $h_{ij} + h_{ji} = 1$ when citations exist between the two journals, otherwise the sum takes the value 0. When the direct influence is unidirectional from i to j, h_{ij} takes the value 1, and h_{ji} the value 0, and we have $h_{ij} = h_{ji} = 1/2$ when the same direct mutual influence is observed.

2. Direct influence aggregation model

In a universe of two journals i and j the comparison could be made on the sole basis of their direct mutual influences h_{ij} and h_{ji} as there would be no possible indirect influence across other journals. However, with more than two journals, indirect influences could have a significant impact. Indeed, it seems reasonable to state that the relative direct influence exerted on a prestigious journal is more valuable than the same direct influence on a less prestigious journal. As outlined by Palacios-Huerta and Volij [11], "in building a desirable ranking method one would like to take into account not only the direct influence of the journals on each other, but also their indirect influence. Thus, though conveying important information, [the ratios c_{ij}/c_{ji} and c_{ji}/c_{ij} used by Stigler et al. [5]] are not, per se, a perfect index of the journals total impact. In a two-journal problem, however, the value c_{ij} is a measure of the total impact of journal i on journal j". In the next paragraph, we provide a recursive model, named as direct influence aggregation (DIA) model, to aggregate the relative direct influences of all pairs of journals and to measure their attractiveness defined as the sum of their direct and indirect influences.

Let us define the attractiveness w_i of a journal i as the weighted average of its relative direct influence on all other journals, to each of which is accorded a weight indicative of its own attractiveness w_j. By using this measure of attractiveness we recognize that the relative direct influence on prestigious journals is more valuable than the same relative direct influence on less prestigious journals. Formally, the attractiveness of journal i in a list L of journals is recursively defined as:

$$w_i = \frac{\sum_{j\in L\setminus\{i\}} w_j h_{ij}}{\sum_{j\in L\setminus\{i\}} w_j}, \tag{3}$$

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

$$\mathbf{w} = \text{diag}[(\mathbf{J}-\mathbf{I})\mathbf{w}]^{-1}\mathbf{H}\mathbf{w}, |\mathbf{w}|_1 = 1, \tag{4}$$

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 associated with the matrix of citations $\mathbf{C} = (c_{ij})$ and the vector of reference intensities $\mathbf{u} = \langle u_i \rangle$ such that:

$$\mathbf{C} = \begin{bmatrix} 9 & 3 & 3 \\ 2 & 4 & 2 \\ 1 & 0 & 1 \end{bmatrix}, \tag{5}$$

and

$$\mathbf{u} = \langle 3,2,1 \rangle. \tag{6}$$

We obtain the matrix $\mathbf{H}$ of relative direct influences as defined by Equation (2):

$$\mathbf{H} = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 0 \\ 1/2 & 1 & 0 \end{bmatrix}. \tag{7}$$

Equation (3) is solved iteratively with an arbitrary initial attractiveness vector $\mathbf{w}^{(0)}$. Here:

$$\mathbf{w}^{(0)} = \langle 1/3, 1/3, 1/3 \rangle. \tag{8}$$

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

$$\hat{\mathbf{w}}^{(1)} = \langle 1/2, 1/4, 3/4\rangle, \tag{9}$$

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

$$\mathbf{w}^{(1)} = \langle 1/3, 1/6, 1/2\rangle. \tag{10}$$

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

$$\mathbf{w} = \langle 0.365, 0.159, 0.476\rangle. \tag{11}$$

3. 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:

Strong homogeneity. *Weak homogeneity* and *homogeneity* properties were introduced by Palacios-Huerta and Volij [11]. 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. It satisfies *homogeneity* if this condition holds for any two-journal ranking problem with different publication intensities.

Property. *A ranking method satisfies strong homogeneity if, for any two-journal ranking problem with different reference intensities and different numbers of publications, we have:*

$$\frac{w_i}{w_j} = \frac{u_i c_{ji}}{u_j c_{ij}}. \tag{12}$$

Proposition. *The DIA model satisfies homogeneity and strong homogeneity properties.*

Proof. Consider a ranking problem with only two journals i and j with different publication intensities and different reference intensities u_i and u_j. By definition, we have $h_{ij} = w_i = u_i c_{ji}/(u_j c_{ij} + u_i c_{ji})$ and $h_{ji} = w_j = u_j c_{ij}/(u_j c_{ij} + u_i c_{ji})$, then $w_i/w_j = u_i c_{ji}/u_j c_{ij}$ (*strong homogeneity*). It readily follows that $w_i/w_j = c_{ji}/c_{ij}$ whenever $u_i = u_j$ (*homogeneity*). □

By satisfying *strong homogeneity* property, the DIA model is invariant to publication intensity and controls for reference intensity.

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

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

4. 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 [18] 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 JCR [19] (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 from 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.

Two versions of the DIA model, with and without control for reference intensity (DIA2 and DIA1, respectively), are compared to the ranking published by Olson (OL) and seven methods based on citation counts: the LP-method (LP), the invariant method (INV) as defined in Palacios-Huerta and Volij [11], the 2-year Impact Factor (IF1) and the 2-year Impact Factor without self-citations (IF2) published in the JCR 2003, a 10-year Impact Factor (IF3), the PageRank method (PR) proposed by Xu et al. [14], and the Export Scores Model (ES) proposed by Stigler et al. [5] with the journal *Operations Research* set as the baseline journal.

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 a decreasing order of scores. Impact Factors IF1 and IF2 are those published in the JCR 2003 and PageRank scores are those published in Xu et al. [14].

Table 4 exhibits the Kendall rank-order correlation coefficient and the corresponding p-value for each pair of rankings. Compared to Olson [18], the rankings derived from the DIA scores, the PageRank scores and, to a lesser extent, the INV scores, the IF3 scores and the ES scores, have positive correlations at very strong significance levels (with p-value ≤ .0034). 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. [14] 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. [14] 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. [14] 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

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

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 Olsen's scores and IF1, IF2 and LP scores. In particular, rankings from IF1 and IF2, published by the JCR 2003, 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 17th 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.

5. 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 provide consistent and comprehensible ranking methods. This study confirms that the 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 of Xu et al. [14] are the most consistent with the opinion-based ranking done by Olson [18]. However, and contrary to the PageRank method, the direct influence aggregation model does not need any calibration and, as such, it is less sensitive to subjective influences. 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, control for reference intensity, invariance to self-citations, and distinction between citations from the most and least prestigious journals. As with all other methods, the direct influence aggregation model is not a panacea, it offers, however, a consistent alternative in the academic journal ranking toolbox.

Table 2: Scores

	OL	DIA1	DIA2	INV	LP	IF1	IF2	IF3	PR	ES
MS	1.10	0.0807	0.0905	0.1470	0.1086	1.468	1.241	0.562	7.17	0.559
OR	1.12	0.0728	0.0742	0.0949	0.0942	0.672	0.563	0.668	6.53	0.000
MOR	1.41	0.0632	0.0624	0.0393	0.0243	1.146	1.010	0.953	5.04	−0.143
MP	1.62	0.0394	0.0444	0.0291	0.0174	1.290	1.046	0.352	4.30	−1.080
NRL	2.38	0.0427	0.0403	0.0310	0.0385	0.368	0.347	0.187	2.12	−0.941
TS	2.42	0.0524	0.0532	0.0761	0.0682	0.491	0.316	0.512	5.01	−0.379
IIE	2.44	0.0347	0.0334	0.0287	0.0422	0.541	0.454	0.437	2.10	−1.135
INTF	2.53	0.0618	0.0550	0.0859	0.0795	0.712	0.692	0.387	2.39	0.175
IJC	2.63	0.0474	0.0534	0.0600	0.0630	0.761	0.696	0.535	3.42	−0.380
ORL	2.65	0.0675	0.0525	0.0250	0.0265	0.449	0.390	0.293	2.22	−0.108
NET	2.78	0.0411	0.0356	0.0197	0.0160	0.649	0.553	0.360	1.45	−0.809
EJOR	2.83	0.0521	0.0526	0.0305	0.0288	0.605	0.559	0.359	2.01	−0.841
AOR	2.97	0.0505	0.0518	0.0218	0.0269	0.331	0.311	0.159	2.25	−0.819
POM	2.99	0.0055	0.0075	0.0241	0.0420	0.393	0.295	0.170	2.44	−2.822
JOM	3.02	0.0414	0.0454	0.0846	0.0786	1.795	1.411	0.978	2.44	−0.549
JCO	3.08	0.0130	0.0114	0.0094	0.0105	0.667	0.667	0.078	0.74	−1.796
JORS	3.27	0.0376	0.0366	0.0241	0.0240	0.416	0.305	0.301	1.86	−1.280
JGO	3.67	0.0184	0.0182	0.0088	0.0063	0.559	0.488	0.172	1.64	−1.735
IJPR	3.88	0.0165	0.0169	0.0145	0.0173	0.557	0.344	0.346	0.92	−2.004
JH	4.00	0.0314	0.0339	0.0368	0.0418	0.633	0.633	0.283	2.54	−0.505
COR	4.05	0.0426	0.0394	0.0175	0.0209	0.486	0.443	0.297	1.31	−1.269
IJPE	4.06	0.0222	0.0228	0.0189	0.0274	0.410	0.367	0.180	1.18	−1.440
DSS	4.18	0.0190	0.0203	0.0110	0.0093	1.316	1.265	0.171	0.96	−1.193
JMS	4.36	0.0151	0.0151	0.0394	0.0557	0.253	0.213	0.307	0.88	−1.561
OMG	4.37	0.0310	0.0335	0.0219	0.0321	0.558	0.488	0.337	1.65	−1.105

Table 3: Rankings

Rank	OL	DIA1	DIA2	INV	LP	IF1	IF2	IF3	PR	ES
1	MS	MS	MS	MS	MS	JOM	JOM	JOM	MS	MS
2	OR	OR	OR	OR	OR	MS	DSS	MOR	OR	INTF
3	MOR	ORL	MOR	INTF	INTF	DSS	MS	OR	MOR	OR
4	MP	MOR	INTF	JOM	JOM	MP	MP	MS	TS	ORL
5	NRL	INTF	IJC	TS	TS	MOR	MOR	IJC	MP	MOR
6	TS	TS	TS	IJC	IJC	IJC	IJC	TS	IJC	TS
7	IIE	EJOR	EJOR	JMS	JMS	INTF	INTF	IIE	JH	IJC
8	INTF	AOR	ORL	MOR	IIE	OR	JCO	INTF	JOM	JH
9	IJC	IJC	AOR	JH	POM	JCO	JH	NET	POM	JOM
10	ORL	NRL	JOM	NRL	JH	NET	OR	EJOR	INTF	NET
11	NET	COR	MP	EJOR	NRL	JH	EJOR	MP	AOR	AOR
12	EJOR	JOM	NRL	MP	OMG	EJOR	NET	IJPR	ORL	EJOR
13	AOR	NET	COR	IIE	EJOR	JGO	JGO	OMG	NRL	NRL
14	POM	MP	JORS	ORL	IJPE	OMG	OMG	JMS	IIE	MP
15	JOM	JORS	NET	JORS	AOR	IJPR	IIE	JORS	EJOR	OMG
16	JCO	IIE	JH	POM	ORL	IIE	COR	COR	JORS	IIE
17	JORS	JH	OMG	OMG	MOR	TS	ORL	ORL	OMG	DSS
18	JGO	OMG	IIE	AOR	JORS	COR	IJPE	JH	JGO	COR
19	IJPR	IJPE	IJPE	NET	COR	ORL	NRL	NRL	NET	JORS
20	JH	DSS	DSS	IJPE	MP	JORS	IJPR	IJPE	COR	IJPE
21	COR	JGO	JGO	COR	IJPR	IJPE	TS	JGO	IJPE	JMS
22	IJPE	IJPR	IJPR	IJPR	NET	POM	AOR	DSS	DSS	JGO
23	DSS	JMS	JMS	DSS	JCO	NRL	JORS	POM	IJPR	JCO
24	JMS	JCO	JCO	JCO	DSS	AOR	POM	AOR	JMS	IJPR
25	OMG	POM	POM	JGO	JGO	JMS	JMS	JCO	JCO	POM

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

	DIA1	DIA2	INV	LP	IF1	IF2	IF3	PR	ES
Olson									
	0.5200	**0.5467**	**0.4467**	**0.2800**	**0.2400**	**0.2170**	**0.4133**	**0.5843**	**0.4467**
	0.0002	0.0001	0.0014	0.0519	0.0975	0.1289	0.0034	0.0000	0.0014
DIA1									
		0.8933	0.5000	0.3467	0.1867	0.2104	0.4133	0.5643	0.7667
		0.0000	0.0003	0.0150	0.2012	0.1411	0.0034	0.0001	0.0000
DIA2									
			0.5667	0.3733	0.2800	0.2905	0.4933	0.6311	0.7667
			0.0000	0.0085	0.0518	0.0421	0.0004	0.0000	0.0000
INV									
				0.7533	0.1800	0.1770	0.5933	0.6110	0.5733
				0.0000	0.2182	0.2157	0.0000	0.0000	0.0000
LP									
					0.0000	0.0100	0.4933	0.4574	0.3933
					1.0000	0.9441	0.0004	0.0014	0.0054
IF1									
						0.8715	0.3200	0.2437	0.3267
						0.0000	0.0254	0.0881	0.0223
IF2									
							0.2771	0.2408	0.3506
							0.0525	0.0925	0.0142
IF3									
								0.4574	0.4067
								0.0014	0.0039
PR									
									0.6110
									0.0000

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