Applying the Publication Power Approach to Artificial Intelligence Journals

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Abstract

This study evaluates the utility of a Publication Power Approach (PPA) for assessing the quality of journals in the field of artificial intelligence. PPA is compared with the Thomson-Reuters Institute for Scientific Information (TR) five-year and two-year impact factors and with expert opinion. The ranking produced by the method under study is only partially correlated with citation-based measures (TR), but exhibits close agreement with expert survey rankings. A simple average of TR and power rankings results in a new ranking that is highly correlated with the expert survey rankings. This evidence suggests that power ranking can contribute to evaluating AI journals.

Introduction and Related Work

Because journals serve as the main outlets for publishing scientific research, it is not surprising that one of the most widely studied problems in scientometrics is determining the merit of academic journals and ranking them accordingly. Although journal ranking helps academic libraries to select journals, it is often and more importantly used as a measure of research quality. For example, the Israel Higher Education Planning and Budgeting Committee (VATAT) financially rewards universities for publishing in top-tier journals, and many university administrators around the world evaluate their scholars according to their publications as part of the tenure, promotion, and reward process. Given a journal’s ranking, researchers can target their papers to top-ranked journals and improve their chances for promotion.

The four common approaches for generating journal rankings are based on opinion surveys, citations, authors' affiliation, and behavioral approaches. In expert opinion surveys, a number of scholars rank each journal according to a predefined set of criteria. The results reflect the cumulative peer opinion of a representative group of experts within a particular discipline or field. However, expert surveys have also been criticized for their subjectivity, the lack of clarity of their rating criteria (Holsapple, 2008), and various biases (such as preferring outlets that publish more articles per year; Serenko & Dohan, 2011). Finally, establishing a valid expert survey that includes a sufficiently large number of qualitative responders can be time-consuming.

Many citation-based measures have been suggested for ranking journals, including impact factors (Garfield, 2006), the eigenfactor (Bergstrom, 2007), and the h-index and its variants (Harzing et al., 2007). The main advantage of these measures is their objectivity; however, they have also been criticized, with some claiming that a few highly cited papers skew the citation distribution (Calver & Bradley, 2009) or that not all citations have the same significance (Holsapple, 2008). Moreover, because citation patterns vary across disciplines, it is very difficult to evaluate multidisciplinary journals. Research shows that using citation-based measures tends to generate journal rankings that are only weakly correlated with expert surveys (see, for instance, Schloegl & Stock, 2004 and Serenko & Dohan, 2011 for a complete list). Even when a strong correlation can be found, there are still considerable differences in the ranking of certain journals (Serenko & Dohan, 2011).

A relatively new approach to ranking is based on the author's university affiliation. The underlying premise is that tenured faculty members of prominent research universities tend to publish their work in premier journals. The Author Affiliation Index (AAI) of a journal (or set of journals) is defined as the percentage of authors who publish in that journal (or set of journals) and are affiliated with a predetermined group of top-rated universities (or university departments) in the domain under study (Harless & Reilly, 1998; Cronin & Meho, 2008; Agrawal, 2011). However, author-based methods have drawbacks. The first limitation is the need to select a set of leading affiliations. If the set is too narrowly defined, then it might not be sufficient to rank journals reliably (because of the small sample size). On the other hand, if the set is defined too broadly, it might include universities that are not at the required research level and thereby distort the rankings. Therefore, author-based measures can be used to identify premier journals, but not for ranking non-premier journals.

Behavior-based approaches examine the actual publishing behaviors of tenured researchers at an independently determined set of prominent research universities. This approach assumes that these particular faculty members tend to publish their works in outlets which they regard as of high quality in the field under study. The behavior of these researchers can be trusted because they have demonstrated a level of research excellence which is recognized by their peers (who have participated in their tenure and promotion committees). Holsapple (2008) has developed the publication power approach (PPA) for identifying the premier journals in a specific domain. The PPA of a journal is determined by how many prominent researchers decide to publish their research results in that journal and at what frequency.

Table 1 summarizes the various approaches to ranking journals and specifies the advantages and limitations of each approach. As can be seen from Table 1, and as has been indicated by Holsapple and Lee-Post (2010), the recently developed PPA sidesteps the limitations of the other three approaches. For example, various AI researchers have noted that according to the TR two-year impact factor for 2010, the *Journal of Machine Learning Research* was ranked much higher than *Machine Learning* (rank 9 vs. rank 31), while according to the expert survey, the order should be reversed (Serenko & Dohan, 2011). This discrepancy can be explained by the limitations of citation-based approaches that tend to prefer open-access journals over other journals. As will be seen later, PPA does not suffer from this limitation and obtains the correct order. Thus, PPA can potentially provide rankings from a different perspective. In particular, PPA provides secondary evidence for highly accepted approaches (expert surveys and citations) and indirect indications for objectively measuring journal quality.

Several rankings of AI journals are available in the literature (Cheng et al., 1996). Serenko (2010) compared different citation-based methods for ranking AI journals, while Serenko and Dohan (2011) reported on expert surveys in this field. However, there have been no reports to date on author-based rankings in AI. Therefore, the goal of this paper is to apply PPA to the AI field and to compare its results to existing rankings based on citations and expert surveys.

Methods

1. 108 peer-reviewed AI journals were identified based on the sub-category "Computer Sciences – Artificial Intelligence" as indexed by the Thomson-Reuters Web of Knowledge (WoK). The bibliographic data used in this paper were extracted from the WoK. These data refer to all journal publications of the benchmark scholar.
2. 199 active AI scholars were selected in the manner described as follows. Instead of selecting tenured AI faculty members as defined by a set of benchmark institutions, as proposed by Holsapple (2008), the recipients of the Association for the Advancement of Artificial Intelligence (AAAI) Fellowship Award were selected as benchmark scholars. This provided a degree of flexibility because the list contains researchers with various affiliations. The AAAI Fellowship Award recognizes a small percentage of AAAI researchers who have made significant, sustained contributions to the field of artificial intelligence[1]. This award has become very selective since 1995. Between 1990 and 1994, 147 researchers won the award; from 1995 to 2011, only 106 researchers gained this coveted prize. The list of ***current*** AAAI fellows contains 199 active scholars (http://www.aaai.org/Awards/fellows-current.php).
3. TR records were used to extract the bibliographic data from all papers (6,738 papers in total) that were written by recipients of the AAAI Fellowship Award from 1995 to 2010 inclusive. Note that when the PPA was originally applied to the field of information systems, a slightly longer period of time, a quarter century, was used. However, because the benchmark list used here contains more scholars and because of the rapidly evolving nature of the AI domain, a shorter period of time was chosen for this research.
4. To address the issue of name ambiguity, the "Author Finder" feature in the WoK was used to select authors according to their affiliations and publication

[1] http://www.aaai.org/Awards/fellows.php

category. Note that because certain benchmark researchers changed their affiliation over time, their resumes had to be used to identify this situation and to include all their affiliations.

5. Each journal was analyzed in terms of both the number of prominent researchers who publish manuscripts in this journal (publishing breadth) and the frequency with which they publish (publishing intensity). A journal's publishing breadth is the number of prominent researchers who have authored at least one article in this journal. A journal's publishing intensity is the sum of the number of times that this particular journal has acted as a publication outlet for prominent researchers.
6. Finally, the publication power of a journal is defined as the product of its publishing intensity and its publishing breadth (Holsapple & O'Leary, 2009; Holsapple & Lee-Post, 2010).

Results and Discussion

Table 2 shows the ranking of a number of AI journals. Note that the PPA was capable of ranking only 78 out of 108 journals in the KoW category of AI. This can be explained by the fact that top-rated researchers seldom publish in non-prestige journals. Therefore, some journals had a power of zero and were not included in the analysis. Four of the journals had a publication power of 10,000 or higher. This power level is equivalent to 100 benchmark researchers collectively having authored 100 articles in the journal. Table 1 also specifies the TR impact factor for 2010 and the expert survey score that was reported by Serenko and Dohan (2011) based on 873 experts.

A natural way to test the validity of the proposed method is to compare it with peer review. Several researchers argue that a bibliometric-based journal ranking procedure that correlates positively with expert surveys of journal quality should be preferred (see, for example, McAllister et al., 1989; Hodge & Lacasse, 2011; Harnad, 2008); others do not agree with this claim. In either case, highly correlated measures have a better chance of being accepted by the community.

Table 3 shows Spearman rank correlations for the ranks obtained using all scores presented in Table 2. It was found that the PPA was only weakly correlated with the TR impact factors (rho=0.192 in the case of a five-year impact factor). PPA, TR two-year, and TR five-year impact factors all have high levels of correlation with expert survey rankings (rho=0.498, 0.514, and 0.564 respectively). Note that the level of correlation found between the TR two-year impact factor and the expert survey ranking is consistent with previous findings (rho=0.508 as reported by Serenko and Dohan, 2011).

Table 1: Various approaches for ranking journals.

Approach	Advantages	Limitations
Citation Based (including impact factor).	• Objective • Highly accepted (Lowry et al., 2007) • Can compare journals across different disciplines (Lowry et al., 2007)	• Highly disputed if impact factor endorses the quality of all articles (Seglen, 1997, Lowry et al., 2007). • Long tail: A fortuitous publication of one seminal work can skew the entire results for a given journal (Calver & Bradley, 2009). • Ignores semantics of references (Holsapple, 2008) by simply assuming that every citation in an article's reference list is equally important. • Self-citations (Rousseau, 1999). • Not useful for ranking small fields in which only a few of these journals appear in journal ranking indexes (Seglen, 2006). • Not useful for ranking niche journals which are read and cited by a small community of researchers (Serenko and Dohan, 2011). • Biased towards open and online journals which are not constrained by physical print limitations (Antelman, 2004). • Biased towards journals that have been longer in-print (Serenko and Dohan, 2011). • Citation habits can vary greatly by discipline and country, with non-English speaking academics being cited far less often (Seglen, 2006). • Citations can be manipulated through editorial practices such as requiring accepted authors to cite more articles previously published in their specific journals (Sevinc, 2004) • Review articles can inflate citation numbers (Seglen, 2006). • Journal databases may contain errors resulting in incorrectly reported journal impact indices (Elkins et al. 2010). • Journal rankings can differ depending on how the citation counts are analyzed (total, age-adjustment, etc.) which can lead to confusion (Holsapple and Lee-Post, 2010). • Cannot be used for ranking new outlets.
Expert Survey	• Highly accepted (Lowry et al., 2007) • "Journal's ranking position reflects a cumulative opinion of a representative group of its readers and contributors." (Serenko and Dohan, 2011, page 630) • Allows rankings to be produced for under-represented niche research areas (Seglen, 2006). • Allows rankings by various demographics (Lowry et al., 2007).	• Subjective • Difficulties in obtaining sufficiently large and representative sample (Gorman and Kanet, 2005; Saha et al., 2003). • Sensitive to various factors including different time periods, respondents' research fields, different sets and numbers of anchor journals, and ranking criteria. (Olson 2005). • Less effective when large, predefined lists are used (Lowry et al., 2007) • Vague about rating criteria that may not be interpreted uniformly by all respondents (Holsapple, 2008). • Biased in various ways(Holsapple, 2008). • It takes long time for most respondents to change their opinion about the journal's quality (Tahai and Meyer, 1999), which produces inflexible ranking lists. • Affected by intra-institutional politics (Adler & Harzing, 2009) because some scholars may prefer the outlets appearing in their internal ranking lists. • Exposure effect: participants of journal ranking surveys may prefer certain journals merely because they are more familiar to them (Serenko and Bontis, 2011). Therefore newer and more specialized journals are ignored (Gallivan and Benbunan-Fich, 2007). • Path Dependency ; many expert surveys are based on previous rankings. Therefore making it relatively more difficult for newer or niche journals to break into the rankings (Truex, et al., 2009).
AAI (Author Affiliation	• Objective • Robust with respect to	• The precise size of a university set is unclear. If it is too small the results will be biased. If it is too large it will be difficult to differentiate among the journals

Index)	changes in input, such as number of top universities taken into account (Gorman and Kanet, 2005). • Easy-to-use (Cronin and Meho, 2008). • Stable over time (Gorman and Kanet, 2005). • Can provide peer groups of journals of equivalent quality (Gorman and Kanet, 2005).	(Holsapple and Lee-Post, 2010). • Working only with prominent universities can be misleading; some outstanding researchers may choose to work at an institution of modest ranking (Cronin and Meho, 2008). • While journal's decisions should be made indifferent to author affiliation, practically institutional affiliation can sometimes influence publication decisions (Cronin and Meho, 2008). • Not useful for ranking "loosely structured and less clearly delineated fields such Library and Information Science" (Cronin and Meho, 2008, page 1864). • The resultant journal rankings are limited to the particular journals for which AAI is calculated. A journal can be partially relevant to the examined field but it is still highly ranked because many of those who publish in it are faculty members at prominent universities (Holsapple and Lee-Post, 2010). • Defining the set of prominent universities is partially based on the publications their faculties have in a preselected set of high-quality journals. Thus it creates a circular effect which biases the results (Holsapple and Lee-Post, 2010).
PAA (Publication Power Approach)	• Objective • Provides a multi-dimensional metric of journal importance (Holsapple and Lee-Post, 2010) • Allows establishing of national or regional journal rankings (Serenko and Jiao, 2011)	• Sensitive to size and composition of the benchmark set. Thus the benchmark set should be carefully selected (Holsapple, 2008) . • Regardless of the benchmarks used, certain outstanding journals from reference disciplines or specialty niches can be excluded (Holsapple, 2008). • Does not addresses cases of multi-authored articles by the benchmark scholar set (Holsapple, 2008). • In its original form, it does not consider the number of papers (or pages or words) published annually in the various journals (Holsapple and O'Leary, 2009). • Journal characteristics may unduly influence researchers' behavior (such as acceptance rate or review time (Holsapple and Lee-Post, 2010). • Existing journal ranking may unduly influence researchers' behavior (Holsapple, 2008). • It is sensitive to the time window used (Holsapple and Lee-Post, 2010). • As changes happen over time (new researchers become tenured while other retired), the benchmark set is not stable over time and thus we should expect that the ranking will also vary over time (Holsapple and Lee-Post, 2010).

Table 2: AI journals ranked according to the publication power.

Rank	Journal	Intensity	Breadth	Power	Two Years Impact Factor (2010)	Five Years Impact Factor (2010)	Expert Survey Score
1	ARTIFICIAL INTELLIGENCE	707	138	97566	2.511	3.106	2.119
2	AI MAGAZINE	389	121	47069	0.525	0.866	1.494
3	JOURNAL OF ARTIFICIAL INTELLIGENCE RESEARCH	208	72	14976	1.691	1.975	2.044
4	MACHINE LEARNING	197	55	10835	1.956	2.655	2.23
5	IEEE INTELLIGENT SYSTEMS	155	54	8370	2.57	2.632	1.536
6	IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE	108	29	3132	5.027	7.228	2.716
7	AUTONOMOUS AGENTS AND MULTI-AGENT SYSTEMS	80	29	2320	2.103	2.163	0.929
8	ANNALS OF MATHEMATICS AND ARTIFICIAL INTELLIGENCE	73	27	1971	0.418	0.589	0.892
9	IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING	61	26	1586	1.847	2.893	1.856
10	COMPUTATIONAL INTELLIGENCE	50	31	1550	0.704	0.854	0.896
11	JOURNAL OF MACHINE LEARNING RESEARCH	56	24	1344	2.949	4.939	1.767
12	ROBOTICS AND AUTONOMOUS SYSTEMS	51	21	1071	1.313	1.801	0.896
13	APPLIED ARTIFICIAL INTELLIGENCE	41	23	943	0.563	0.616	1.086
14	AUTONOMOUS ROBOTS	43	21	903	2.011	2.277	0.826
15	KNOWLEDGE ENGINEERING REVIEW	40	18	720	1.229	1.82	0.708
16	NEURAL COMPUTATION	39	17	663	2.29	2.943	1.334
17	INTERNATIONAL JOURNAL OF COMPUTER VISION	50	11	550	4.93	6.697	1.277
18	AI EDAM-ARTIFICIAL INTELLIGENCE FOR ENGINEERING DESIGN ANALYSIS AND MANUFACTURING	32	13	416	0.64	1.035	0.47
19	JOURNAL OF AUTOMATED REASONING	25	14	350	2.26	2.06	0.78
20	JOURNAL OF EXPERIMENTAL & THEORETICAL ARTIFICIAL INTELLIGENCE	22	15	330	0.655	0.581	0.691
21	DECISION SUPPORT SYSTEMS	23	14	322	2.135	2.568	
22	ARTIFICIAL INTELLIGENCE REVIEW	21	15	315	0.429	0.565	0.943
23	COMPUTATIONAL LINGUISTICS	26	10	260	2.971	3.7	0.802
24	CONSTRAINTS	22	11	242	1.41	1.438	0.481
25	COMPUTER VISION AND IMAGE UNDERSTANDING	21	11	231	2.404	2.73	0.945
26	KNOWLEDGE-BASED SYSTEMS	20	11	220	1.574	1.454	0.979
27	INTERNATIONAL JOURNAL OF APPROXIMATE REASONING	18	9	162	1.679	1.717	0.816
28	COGNITIVE SYSTEMS RESEARCH	15	9	135	1	1.073	0.655
28	DATA MINING AND KNOWLEDGE DISCOVERY	15	9	135	1.238	2.894	1.195
30	EXPERT SYSTEMS WITH APPLICATIONS	12	11	132	1.924	2.193	1.107
31	INTERNATIONAL JOURNAL OF INTELLIGENT SYSTEMS	13	9	117	1.314	1.249	1.016
32	PATTERN RECOGNITION	12	9	108	2.607	3.402	1.338
33	NEURAL NETWORKS	12	7	84	1.955	2.652	1.431
34	IMAGE AND VISION COMPUTING	13	6	78	1.525	1.84	0.779
35	IEEE TRANSACTIONS ON NEURAL NETWORKS	12	6	72	2.624	3.417	2.171
36	IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS PART B-CYBERNETICS	10	7	70	2.674	3.255	2.558
37	JOURNAL OF WEB SEMANTICS	13	5	65	2.789	3.593	
38	JOURNAL OF INTELLIGENT MANUFACTURING	8	8	64	1.081	1.384	0.473
39	MACHINE VISION AND APPLICATIONS	9	7	63	1.479	1.655	0.688
40	IEEE TRANSACTIONS ON IMAGE PROCESSING	10	6	60	2.606	3.908	1.632
41	AI COMMUNICATIONS	8	7	56	0.837	0.824	0.809
41	MEDICAL IMAGE ANALYSIS	8	7	56	4.248	4.521	0.464
43	IEEE TRANSACTIONS ON SYSTEMS MAN	9	6	54	2.089	2.112	2.558

	AND CYBERNETICS PART C-APPLICATIONS AND REVIEWS						
44	INTERNATIONAL JOURNAL OF SOFTWARE ENGINEERING AND KNOWLEDGE ENGINEERING	9	5	45	0.248	0.313	0.534
45	APPLIED INTELLIGENCE	9	4	36	0.881	1.238	0.859
45	COMPUTER SPEECH AND LANGUAGE	9	4	36	1.353	1.489	0.616
45	JOURNAL OF HEURISTICS	6	6	36	1.623	1.683	0.523
48	MINDS AND MACHINES	7	5	35	0.618	0.641	0.604
49	JOURNAL OF INTELLIGENT & ROBOTIC SYSTEMS	8	4	32	0.757	0.877	0.616
50	IEEE TRANSACTIONS ON FUZZY SYSTEMS	7	4	28	2.683	3.752	1.691
51	DATA & KNOWLEDGE ENGINEERING	5	5	25	1.717	1.852	1.199
52	ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	6	4	24	1.344	1.598	0.612
52	JOURNAL OF INTELLIGENT INFORMATION SYSTEMS	6	4	24	0.875	0.927	0.604
54	NEUROCOMPUTING	5	4	20	1.429	1.434	1.19
55	CONNECTION SCIENCE	6	3	18	1.057	1.34	0.535
56	INTEGRATED COMPUTER-AIDED ENGINEERING	4	4	16	1.551	1.376	0.361
57	ADAPTIVE BEHAVIOR	4	3	12	1.136	1.809	0.607
57	CHEMOMETRICS AND INTELLIGENT LABORATORY SYSTEMS	4	3	12	2.222	2.415	0.271
57	INTERNATIONAL JOURNAL ON ARTIFICIAL INTELLIGENCE TOOLS	4	3	12	0.32	0.553	0.766
60	INTERNATIONAL JOURNAL OF COMPUTATIONAL INTELLIGENCE SYSTEMS	3	3	9	1.471	1.471	
60	INTERNATIONAL JOURNAL ON SEMANTIC WEB AND INFORMATION SYSTEMS	3	3	9	1.679		
62	IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE	3	2	6	2.833	4.094	1.233
62	INTERNATIONAL JOURNAL ON DOCUMENT ANALYSIS AND RECOGNITION	3	2	6	1.03		0.442
64	APPLIED SOFT COMPUTING	2	2	4	2.084	2.1	0.762
64	INTERNATIONAL JOURNAL OF NEURAL SYSTEMS	2	2	4	4.237	2.581	0.757
64	JOURNAL OF INTELLIGENT & FUZZY SYSTEMS	2	2	4	0.648	0.69	0.635
64	JOURNAL OF MATHEMATICAL IMAGING AND VISION	2	2	4	1.244	1.664	0.562
64	MECHATRONICS	2	2	4	0.944	1.343	0.341
64	PATTERN RECOGNITION LETTERS	2	2	4	1.213	1.864	1.396
70	IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION	2	1	2	4.371	5.409	1.71
71	ADVANCED ENGINEERING INFORMATICS	1	1	1	1.4	1.909	0.444
71	EVOLUTIONARY COMPUTATION	1	1	1	2.63	4.305	1.196
71	FUZZY OPTIMIZATION AND DECISION MAKING	1	1	1	0.702		0.64
71	INTELLIGENT AUTOMATION AND SOFT COMPUTING	1	1	1	0.187	0.233	0.439
71	INTERNATIONAL JOURNAL OF UNCERTAINTY FUZZINESS AND KNOWLEDGE-BASED SYSTEMS	1	1	1	0.85	0.918	0.704
71	JOURNAL OF COMPUTER AND SYSTEMS SCIENCES INTERNATIONAL	1	1	1	0.191	0.182	0.494
71	NETWORK-COMPUTATION IN NEURAL SYSTEMS	1	1	1	0.957	1.667	0.62
71	SOFT COMPUTING	1	1	1	1.512	1.348	0.629

Table 3: Two-tailed Spearman Rank Correlations for Journal Indices (the p-values are indicated in parenthesis, the abbreviation N.S. refers to cases for which the correlation is not significant, i.e. p>0.1).

	Expert Survey Score	**Intensity**	**Breadth**	**Power**	**Two Years Impact Factor (2010)**
Expert Survey Score	1.000				
Intensity	0.510 (p<0.001)	1.000			
Breadth	0.477 (p<0.001)	0.976 (p<0.001)	1.000		
Power	0.498 (p<0.001)	0.995 (p<0.001)	0.991 (p<0.001)	1.000	
Two-Year Impact Factor (2010)	0.514 (p<0.001)	0.203 (p=0.074)	0.167 (p=0.145) N.S.	0.191 (p=0.094)	1.000
Five-Year Impact Factor (2010)	0.564 (p<0.001)	0.207 (p=0.074)	0.155 (p=0.185) N.S.	0.192 (p=0.099)	0.939 (p<0.001)

Combining PPA and TR Impact Factor

Combining journal rankings from multiple lists into a single list is not a novel idea (see, for example, Cook et al., 2010). Because each approach is based on a different assumption, the resulted rankings are correspondingly different. Therefore, journal rankings are usually combined in an attempt to achieve consensus among experts

However, in other types of systems, such as recommender systems (Burke, 2002), multiple rankings are combined to improve the results. Each approach has its strengths and weaknesses, and by combining two or more approaches, better performance can be achieved with fewer drawbacks than any individual approach. This is a well-known practice in machine learning called *committee machines* (sometime associated with a more specific term such as ensemble learning or a mixture of experts) in which the outputs from several experts are combined. Each of the experts addresses the same task (i.e., trying to obtain a good journal ranking). Combining these various rankings usually results in better composite global rankings. This idea imitates a common human characteristic, the desire to obtain several opinions before making a crucial decision. People tend to weigh a number of individual opinions and then combine them to reach a final decision. In a previous study (Rokach et al., 2011), it was shown that combining various methods can improve the ranking of AI researchers.

However, for a combined ranking to bring about improvement, its constituent members should perform better than random while at the same time being sufficiently diverse to avoid making common mistakes (Rokach, 2009). In the present case, the PPA and TR impact factors are weakly correlated (and therefore diverse) while being moderately correlated with the results of the expert survey approach (and hence better than random). Therefore, one can expect that their combination can generate a useful result.

This raises the question of how to combine the two rankings. In fact, most of the combination methods developed in recommender systems (Burke, 2002) can be used. One approach is to use a cascade method in which one list is used as the primary indicator and the other list is used to rank the journals within a primary cluster. A much simpler option is to combine the rankings with equal weight. In this paper, the latter combination approach was used because it can be considered to be the default method. The examination of other combination methods remains as a topic for future research.

A combined ranking which weights the TR five-year ranking equally with PPA was generated. For example, the journal *Artificial Intelligence* has a PPA score of 97,566 and is ranked number 1 according to PPA (PPA=1). The same journal has a TR five-year impact factor of 3.106 and is ranked number 15 according to the TR five-year factor (TR=15). Therefore, the combined score of the journal *Artificial Intelligence* is 1+15=8. This simple rank averaging is equivalent to the following transformation: instead of using the actual value, the value is normalized and converted to the corresponding percentile. This normalization helps to combine two different measures (TR and PPA) that have different scaling and distribution functions.

The results obtained are interesting in that the combined ranking has a high correlation with the expert survey rankings (rho=0.689, p<0.001). Furthermore, it is much higher than the correlations of the PPA and TR impact factors separately. This result may indicate that the experts who answered the survey tried to balance various considerations when providing their rankings.

Conclusions

This paper has examined how the publication power approach can be used to rank AI journals. This approach was found to be only weakly correlated with citation-based indices such as the TR impact factor. Although at first glance this appears to be a disadvantage, actually it is not. If the PPA were highly correlated with the TR impact factor, then its use could be considered as redundant. The fact that the PPA is not highly correlated with the TR impact factor indicates that it brings a different perspective to ranking the journals. Evidently, the PPA seems to be complementary to the TR impact-factor approach because the combination of the two creates a much higher correlation with the expert survey results than either index alone. In particular, the TR impact factor ranked the *Journal of Machine Learning Research* much higher than *Machine Learning*, mainly because the former is an open-access journal. On the other hand, expert survey rankings indicated the reverse order. It is interesting to note that the PPA ranked these two journals similarly to the expert survey rankings. Counterexamples can of course be found as well. The PPA ranked the journal *Annals of Mathematics* and *Artificial Intelligence* highly, while both the TR impact factor and the expert survey ranked them relatively low. It can be hypothesized that *Annals of Mathematics* and *Artificial Intelligence* achieved high scores on the PPA because these journals are considered to be general AI journals which will naturally attract more papers from prominent researchers than more subject-specific journals .

The question arises as to why the PPA correlates better with the expert survey than with the TR impact factor. One possible explanation is that prominent AI researchers have a concept of journal ranking that is similar to that of other AI researchers. In fact, it is not inconceivable that prominent researchers, who by their nature are usually active and involved in their field, took part in the expert survey rankings. In addition, prominent researchers who are no longer influenced by promotion processes can insist in publishing only in journals that they regard as having the highest stature and not necessarily the highest impact factor (because they do not need to please a promotion committee). For this reason, the publication behavior of prominent researchers might be better aligned with their concept of ranking than that of other researchers .

Another possible reason for the better correlation might be that when survey respondents assess the quality of journals, the main factor they consider is the reputations of the editor and the review board, while the citation impact factor is considered only as the fifth factor (Serenko & Bontis, 2009). This shows that when key researchers select what they believe to be the most prestigious outlets for their work, journal impact factor is not the main factor that they consider.

As indicated in Table 1, the PPA, along with its benefits, has many limitations. In particular, it is clear that although the PPA can be used to identify premier AI journals, it cannot be used to discriminate between less prestigious journals (because the power of 30 of the 108 journals is virtually zero). Therefore, it is not suggested here that the PPA should replace expert surveys or TR impact factors as the sole method for ranking journals. The PPA ranks journals from a different perspective. Thus, it provides secondary evidence and indirect indications for objectively measuring the quality of journals.

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