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Authors
West, Jevin D.
Bergstrom, Carl T.
Bergstrom, Ted C

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The Eigenfactor Metrics^{TM}: A network approach to assessing scholarly journals

Jevin D. West[1] Theodore C. Bergstrom[2]
Carl T. Bergstrom[1]

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[1]Department of Biology, University of Washington, Seattle, WA

[2]Department of Economics, University of California, Santa Barbara, CA

*The authors are the founders of the Eigenfactor Project. All of the rankings, algorithms, visual tools and maps of science described here are freely available at `http://www.eigenfactor.org/`. Correspondence can be sent to Jevin D. West at jevinw@u.washington.edu.

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Abstract

Limited time and budgets have created a legitimate need for quantitative measures of scholarly work. The well-known journal impact factor is the leading measure of this sort; here we describe an alternative approach based on the full structure of the scholarly citation network. The Eigenfactor Metrics — Eigenfactor Score and Article Influence Score — use an iterative ranking scheme similar to Google's PageRank algorithm. By this approach, citations from top journals are weighted more heavily than citations from lower-tier publications. Here we describe these metrics and the rankings that they provide.

1 The Need for Alternative Metrics

There is only one adequate approach to evaluating the quality of an individual paper: read it carefully, or talk to others who have done so. The same is largely true when it comes to evaluating any small collection of papers, such as the publications of an individual scholar. But as one moves toward assessment challenges that involve larger bodies of work across broader segments of scholarship, reading individual papers becomes infeasible and a legitimate need arises for quantitative metrics for research evaluation.

The impact factor measure is perhaps the best known tool for this purpose. Impact factor was originally conceived by Eugene Garfield as way of selecting which journals to include in his Science Citation Index (Garfield 2006), but its use has expanded enormously: impact factor scores now affect hiring decisions, ad placement, promotion and tenure, university rankings and academic funding (Menastosky 2005). With so much at stake, we should be careful how aggregate, journal-level metrics like impact factor are used[1].

Impact factor has certain advantages as a citation measure: it is widely used and well understood. Moreover it is simple to calculate, and simple to explain. But this simplicity comes at a cost. Impact factor tallies the number of citations received, but ignores any information about the sources of those citations. A citation from top tier journal such as *The American Economic Review* is weighted the same as a citation from a journal that is

[1]Because of the large skew in the distribution of citations to papers in any given journal (Redner 1998), the quality or influence of a single paper is poorly estimated by the impact factor of the journal in which it has been published. For example, in 2005 the journal *Nature* reported that 89 percent of its impact factor came from 25 percent of its papers (Editor 2005). As a result, most papers from this journal are over-inflated by this method and some are greatly under-inflated.

rarely cited by anyone. Accounting for the source of each citation requires a more complicated computation, but the reward is a richer measure of quality. The Eigenfactor Metrics take this approach.

2 The Eigenfactor Metrics

Each year, tens of thousands of scholarly journals publish hundreds of thousands of scholarly papers, collectively containing tens of millions of citations. As De Solla Price recognized in 1965(de Solla Price 1965), these citations form a vast network linking up the collective research output of the scholarly community. If we think of this network at the journal level, each node in the network represents an individual journal. Each link in the network represents citations from one journal to another. The links are weighted and directed: strong weights represent large numbers of citations, and the direction of the link indicates the direction of the citations (see Figure 1). By viewing citation data as a network, we can use powerful algorithmic tools to mine valuable information from these data.

The most famous of these tools, known as eigenvector centrality, was first introduced by sociologist Phillip Bonacich in 1972 as a way of quantifying an individual's status or popularity in communication networks (Bonacich 1972). Bonacich's aim was to use a network structure's to figure out who were the important people in the network. How do we tell who are the important people? They are the ones with important friends, of course. While this answer may sound circular, it turns out to be well-defined mathematically, and moreover the "importances" of individuals in a network are easy to compute in a recursive manner. The most prominent commercial application of eigenvector centrality is Google's PageRank algorithm, which

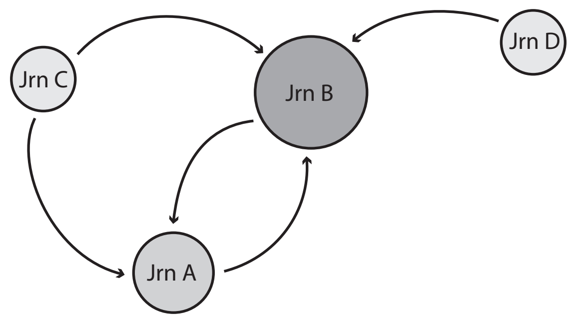

Figure 1: A small journal citation network. Arrows indicate citations from each of four journals, A, B, C, and D, to one another. The size of the nodes represent the centrality of each node in the network, determined by the Eigenfactor Algorithm. Larger, darker nodes are more highly connected to other highly connected nodes.

ranks the importance of websites by looking at the hyperlink structure of the world wide web (Page et al. 1998). Researchers have likewise applied this approach to a number of other network types, including citation networks (Pinski and Narin 1976; Liebowitz and Palmer 1984; Kalaitzidakis, Mamuneas, and Stengos 2003; Palacios-Huerta and Volij 2004; Kodrzycki and Yu 2006; Bollen, Rodriquez, and Van de Sompel 2006).

The concept of eigenvector centrality is at the core of the Eigenfactor Metrics as well(Bergstrom 2007). The idea is to take a network like the one shown in Figure 1 and determine which journals are the important journals. The importance depends on where a journal resides in this mesh of citation links. The more citations a journal receives—especially from other well connected journals—the more central the journal is in the network.

There are a number of ways to think about the recursive calculations by which importance scores are determined. For our purposes, it is particularly useful to think about the importance scores as coming from the result of a simple random process:

Imagine that a researcher is to spend all eternity in the library randomly following citations within scientific periodicals. The researcher begins by picking a random journal in the library. From this volume she selects a random citation. She then walks over to the journal referenced by this citation. From this new volume she now selects another random citation and proceeds to that journal. This process is repeated ad infinitum.

How often does the researcher visit each journal? The researcher will frequently visit journals that are highly cited by journals that are also highly cited. The Eigenfactor score of a journal is the percentage of the time that the model researcher visits that journal in her walk through the library[2]. So when we report that *Nature* had an Eigenfactor score of 2.0 in 2006, that means that two percent of the time, the model researcher would have been directed to *Nature*.

Figure 1 provides an example network where this idea of centrality can be explored further. Because of the simplicity of the network, it is not difficult to see that in Figure 1 the most central node is Journal B. It receives more

[2]The Eigenfactor Algorithm expands somewhat upon the basic eigenvector centrality approach to better estimate the influence of journals from citation data. Further details are provided at http://www.eigenfactor.org/methods.htm. The full mathematical description of the Eigenfactor Algorithm is available at http://www.eigenfactor.org/methods.pdf. In addition, a pseudocode description that provides the recipe for the calculation is available at http://www.eigenfactor.org/methods.htm.

incoming links than any other node. The size of this node in Figure 1 reflects this centrality. If citations are a proxy for scientific importance, this journal would likely be a key component of a library's collection.

Real citation networks are much more complicated than the one in Figure 1. At Eigenfactor.org, we present metrics based on a network of 7,600 journals and over 8,500,000 citations, using data from the Thomson-Reuters Journal Citation Reports (JCR)[3]. With networks of this size, we need a fast computational approach to assess the importance of each journal. Fortunately, the Eigenfactor Algorithm computes the importance values for a network of this size in a matter of seconds on a standard desktop computer.

We use the Eigenfactor Algorithm to calculate two principal metrics that address two different questions: Eigenfactor™ Score and Article Influence™ Score. If one is interested in asking what the *total value* of a journal is—in other words, how often our model researcher is directed to any article within the journal by following citation chains—one would use the *Eigenfactor* score. When looking at the cost-effectiveness of a journal, it is therefore useful to compare subscription price with Eigenfactor score. Table 2 lists the top twenty journals by Eigenfactor Score in 2006.

The Eigenfactor Score is additive: to find the Eigenfactor of a group of journals, simply sum the Eigenfactors of each journal in the group. (One cannot do this with a measure such as impact factor or Article Influence, discussed below.) For example, the top five journals in Table 2 have an Eigenfactor sum of 8.909. This means that a researcher spends approximately 8.909 percent of her time at this five journals (and thus these five are an important backbone of a science library collection). This additive

[3] As of February 2009, the Thomson-Reuters Journal Citation Reports also includes the Eigenfactor Metrics

property can be very useful for collection managers that deal with journal bundles such as Elsevier's Big Deal, because the Eigenfactor Score of a bundle is just the sum of the Eigenfactor scores of its constituent journals.

With all else equal, bigger journals will have larger Eigenfactor Scores: they have more articles and so we expect them to be visited more often. But in scholarly publishing, the most prestigious journals are not necessarily the biggest. They are ones that receive the most citations *per article*. These are the journals that (in the good old days of paper) would be tattered and worn from being pulled off the shelf so many times. The *Article Influence* Score measures the influence, per article, of a given journal and such is directly comparable to Thomson-Reuters' impact factor metric. The Article Influence Score is calculated as a journal's Eigenfactor Score divided by the number of articles in that journal, normalized so that the average article in the Journal Citation Reports has an Article Influence Score of 1. Table 2 lists the top 20 journals by Article Influence. As is the case with impact factor scores, review journals will score higher because of the large number of citations that individual articles in these journals receive. Thus, it can be important for some applications to compare non-review journals with non-review journals and review journals with review journals.

The difference between the two measures is best illustrated with an example. The journal *PLOS Biology* has an Eigenfactor Score of 0.089. This means that the random walker in the library spent a non-trivial 0.089% of her time at this journal — not bad, given that there are 7611 journals in the JCR. As a result, *PLoS Biology* is ranked as the 179th most influential journal by Eigenfactor Score, putting it in the top 3% of all journals in the JCR. But *PLoS Biology* is a small journal; it achieves this high Eigenfactor Score even with relatively few articles. Therefore, when we assess this journal by its Article Influence Score, it does even better. The Article Influence Score of *PLoS Biology* is 9.63, ranking it 33rd for 2006 and placing it in the top 0.5% in the JCR.

	Journal	Eigenfactor	Article Influence	Field
1	NATURE	1.992	17.563	MCB
2	SCIENCE	1.905	18.287	MCB
3	PNAS	1.830	5.153	MCB
4	J BIOL CHEM	1.821	2.395	MCB
5	PHYS REV LETT	1.361	3.433	Physics
6	J AM CHEM SOC	0.959	2.689	Chemistry
7	PHYS REV B	0.856	1.345	Physics
8	APPLY PHYS LETT	0.749	1.768	Physics
9	NEW ENGL J MED	0.718	16.825	Medicine
10	ASTROPHYS J	0.689	2.264	Astrophysics
11	CELL	0.659	17.037	MCB
12	CIRCULATION	0.548	4.273	Medicine
13	J IMMUNOL	0.527	2.446	MCB
14	J NEUROSCI	0.508	3.443	Neurosciece
15	LANCET	0.500	8.635	Medicine
16	BLOOD	0.474	3.190	MCB
17	JAMA	0.455	10.290	Medicine
18	ANGEW CHEM	0.453	3.254	Chemistry
19	J PHYS CHEM B	0.441	1.658	Physics
20	CANCER RES	0.430	2.721	MCB

Table 1: Top 20 Journals by Eigenfactor Score. The journals and citation data are from the Journal Citation Reports (2006) produced by Thomson-Reuters. MCB is molecular and cellular biology. These rankings, as well as those for all of the other journals in the JCR, can be found at www.eigenfactor.org.

	Journal	Eigenfactor	Article Influence	Field
1	ANNU REV IMMUNOL	0.090	27.454	MCB
2	REV MOD PHYS	0.098	24.744	Physics
3	ANNU REV BIOCHEM	0.077	23.194	MCB
4	NAT REV MOL CELL BIO	0.189	20.252	MCB
5	SCIENCE	1.905	18.287	MCB
6	NATURE	1.992	17.563	MCB
7	ANNU REV CELL DEV BI	0.057	17.497	MCB
8	ANNU REV NEUROSCI	0.055	17.449	Neuroscience
9	NAT REV CANCER	0.136	17.272	MCB
10	CELL	0.660	17.037	MCB
11	NEW ENGL J MED	0.718	16.825	Medicine
12	NAT REV IMMUNOL	0.131	16.766	MCB
13	PHYSIOL REV	0.068	16.037	MCB
14	NAT IMMUNOL	0.242	14.830	MCB
15	Q J ECON	0.073	14.671	Economics
16	CA-CANCER J CLIN	0.031	13.944	Medicine
17	NAT REV NEUROSCI	0.122	13.912	Neuroscience
18	ANNU REV ASTR	0.027	13.848	Astrophysics
19	NAT MED	0.265	13.579	MCB
20	NAT GENET	0.323	13.337	MCB

Table 2: Top 20 Journals by Article Influence Score. The journals and citation data are from the Journal Citation Reports (2006) produced by Thomson-Reuters. MCB is molecular and cellular biology. These rankings, as well as those for all of the other journals in the JCR, can be found at www.eigenfactor.org.

3 Article Influence and Impact Factor Differences

Any time a new metric is introduced, the first question that arises is how the new one differs from the previous standard. We have already discussed the theoretical considerations in favor of the Eigenfactor approach; here we turn to the empirical differences between rankings based on the Eigenfactor Metrics and those based on Thomson-Reuters' journal impact factor. Because impact factor is a per-article measure, we compare it to our per-article measure, the Article Influence score.

Impact factors and Article Influence Scores are derived from the same underlying journal citation data, and as a result we see considerable correlation between these measures[4]. Despite the correlations, there are many individual journal rankings that change considerably from one measure to the next. The left column in Figure 2 lists the top 35 Economics journals by impact factor. The right column lists the top 35 Economics journals by Article Influence and their respective Article Influence Scores. The lines connecting the two columns indicate the changes in relative ranking between the two different measures. Journals indicated in grey are journals that do not exist in both columns. For example, *Health Economics*—the 13th best journal by impact factor—is not even in the top 35 journals when ranked by Article Influence Score. Although similarities exist between the relative rankings ranked by impact factor and Article Influence, the connecting lines in the figure illustrate that there are marked differences as well[5].

[4]You can view these relationships at `http://www.eigenfactor.org/correlation/`.

[5]The large jump in rank for *NBER Macroeconomics Annual* is largely due to the difference in citation windows. This small but influential journal had a particularly good year in 2001, which shows up in the 2005 Article Influence scores with their five year window, but not in the 2005 impact factors with their two year window.

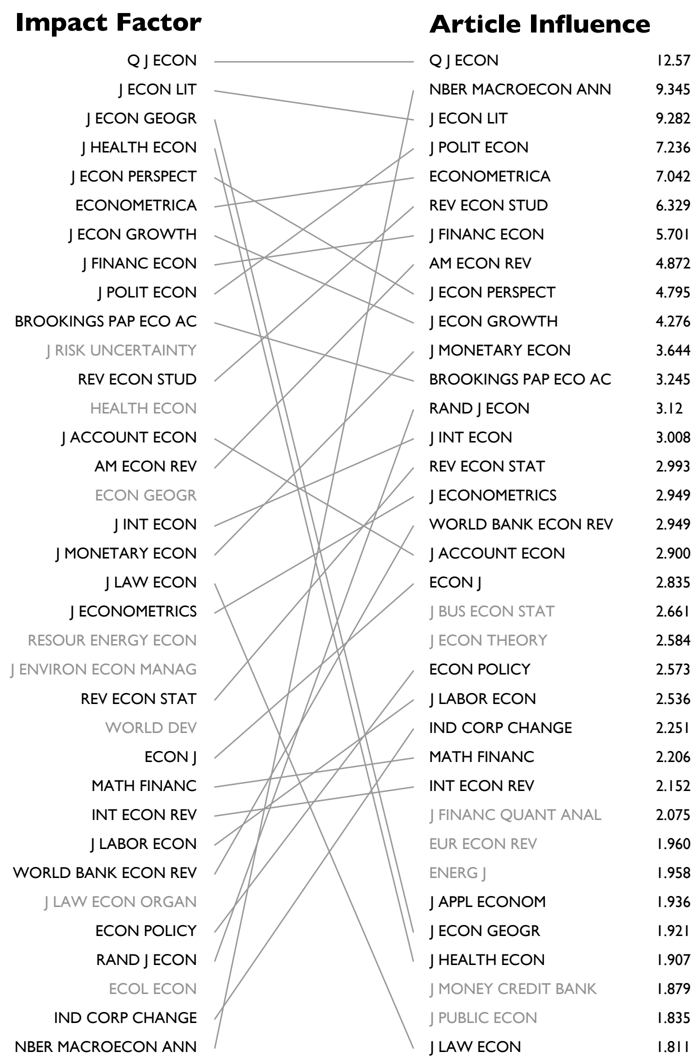

Figure 2: Relative ranking differences under impact factor and Article Influence. The left column are the top 35 Economics journals in the JCR by impact factor. The right column lists the top 35 Economics journals by Article Influence and their respective Article Influence Scores. The journals in grey are journals that do not exist in both lists. The lines between the two lists indicate changes in relative ranking. The data come from the 2005 JCR.

There are several reasons for these differences. We have already discussed the way that the Eigenfactor Metrics account for differences in the prestige of the citing journal. They also adjust for differences in citation patterns. Impact factors vary widely across disciplines due to differences in the number of citations in a typical paper, in the prevalence of citations to preprints, in the average age of cited papers, and other considerations (Althouse et al. 2009). The random-walker model used to derive the Eigenfactor Metrics is relatively insensitive to these differences, because with the Eigenfactor Metrics, we look at the proportion of citations going to any given source rather than at the absolute number going to that source. In a field that cites 80 articles per paper, each citation is worth only 1/80th of a vote, so to speak, whereas in a field that cites 10 articles per paper, each citation is worth 1/10 of a vote. For example, health economics journals and economic geography journals tend to have longer reference lists, cite fewer preprints, and have shorter intervals between citations than do journals in other areas of Economics; as a result, their impact factor scores are inflated relative to other areas of Economics. This bias is reduced when we look at the Article Influence Scores (Figure 2). We see a similar pattern when looking at Article Influence and impact factor scores between disciplines. The differences between fields—although not fully eliminated—fall way when looking at Article Influence instead of impact factor. For example, Economics is a field with relatively short reference lists, long time lags between citations, and a large fraction of preprints. As a result, there are no Economics journals in the top 400 journals ranked by impact factor. By contrast, when ranked by Article Influence Score, there are thirty one Economics journals in the top 400 journals, with the leader, *Quarterly Journal of Economics*, checking in at number 15 overall.

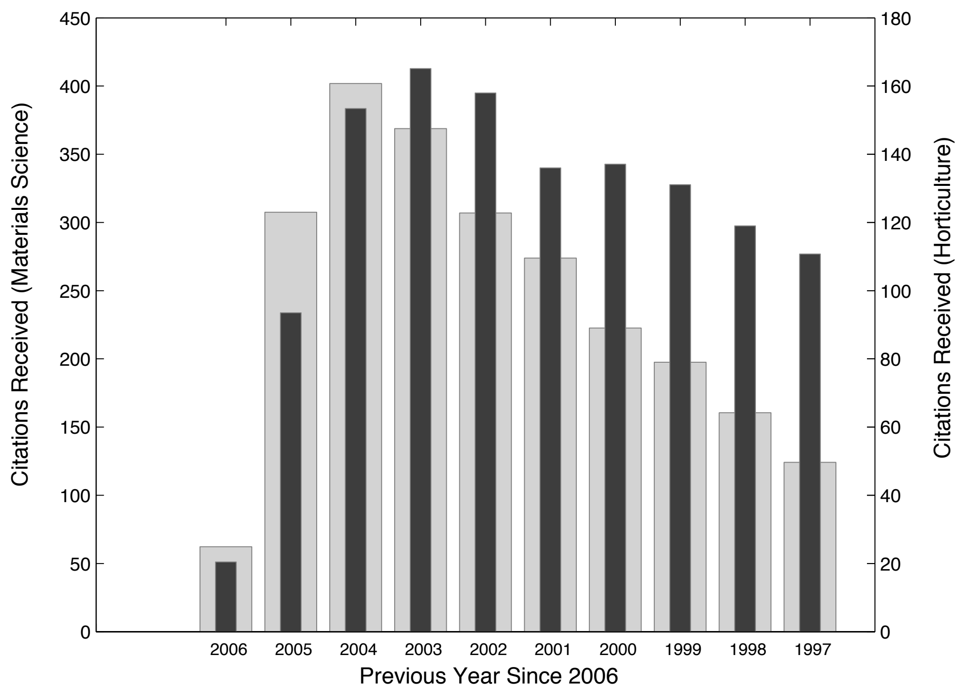

Figure 3: Differences in citation timing between Materials Science and Horticulture. Grey bars: citations from papers published in 2006 to Materials Science journals published in the indicated year. Black bars: citation from papers publishing in 2006 to Horticulture journals published in the indicated year.

Another difference between impact factor and the Eigenfactor Metrics is that the former counts citations over a two-year census window, whereas the latter counts citations across a five year window[6]. This difference can lift fields such as Mathematics and Ecology, in which it can take longer for an article to begin to receive citations. Figure 3 provides an example, with the bars illustrating the number of times that articles published in 2006 cite articles published in the indicated years. The grey bars show the total number of 2006 citations received by journals in the field of Materials Science in the years prior. The black bars show the total number of 2006 citations received by journals in field of Horticulture. The bar chart illustrates the lag time differences between fields. For Materials Science the peak number of citations was two years previous. After 2004 citation totals drop significantly. By contrast, horticulture citations peak in papers published in 2003, and the drop off is less sharp. Thus compared to a two-year window, a five-year window favors Horticulture relative to Materials Science. Differences in timing have a considerable effect on the relative scores of journals in different fields, and this is why the time-window used for any citation-based measure should be chosen carefully.

Another major difference between the standard impact factor measure and the Eigenfactor Metrics is that the Eigenfactor Metrics do not include self-citations[7]. This is done to minimize the opportunity and incentive for journal editors and others to game the system by artfully placed self-citations

[6]As of February 2009, the Thomson-Reuters Journal Citation Reports introduced a new impact factor based on a five-year window.

[7]Because we work with citations at the level of journals and not individual papers, "self-citations" are between journals, not individual authors. In other words, a citation from an author from Journal A to another author also from Journal A would be considered a self-citation in our journal citation matrix.

(Begley 2006).[8]

4 Conclusion

Accounting for the origin of citations takes advantage the wealth of information available in networks like the scholarly literature and the web. The objective behind the Eigenfactor Metrics is to extract as much of this information as possible in order to better evaluate an ever-expanding scholarly library. The continued advances in network mathematics, the availability of computational resources, the improvement in citation data collation and the rising demand for scholarly evaluation has made it an exciting time to be working in this field.

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[8]As of February 2009, the Thomson-Reuters Journal Citation Reports introduced a new impact factor that omits self-citations.

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