Eigenfactor: ranking and mapping scientific knowledge

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This is to certify that I have examined this copy of a doctoral dissertation by

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and have found that it is complete and satisfactory in all respects,
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Abstract

Eigenfactor: ranking and mapping the scholarly literature

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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, these citations form a vast network linking up the collective research output of the scholarly community. These well-defined and well-preserved networks are model systems well suited for studying communication networks and the flow of information on these networks. In this dissertation, I explain how I used citation networks to develop an algorithm that I call 'Eigenfactor.' The goal of Eigenfactor is to mine the wealth of information contained within the full *structure* of the scholarly web, in order to identify the important nodes in these networks. This is different from the conventional approach to scholarly evaluation. Metrics like impact factor ignore the network when ranking scholarly journals and only count incoming links. Eigenfactor not only counts citations but takes into account the source of those citations. By considering the whole network, I claim that Eigenfactor is a more information rich statistic. Librarians, publishers, editors and scholars around the world are now using Eigenfactor

alongside impact factor to evaluate their journal collections. This dissertation consists of a collection of papers that provide an overview of Eigenfactor — what it is, what it measures and how it can be used to better evaluate and navigate the ever-expanding scholarly literature.

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Dedication

- To My Family and Friends -

Chapter 1

Introduction

1.1 The 'network' matters

When I started graduate school, I was given the following advice...

"work on interesting problems, problems that are messy and problems that get you excited; don't consider disciplinary boundaries; teach; write a few papers; and most importantly, surround yourself with good people."

My graduate experience was all that and more. I came to the University of Washington five years ago interested in complex systems, networks, information theory and evolutionary ecology. I had the opportunity to work on each one of those things, but the project that really got me excited and the project I contributed most to is something that I call 'Eigenfactor.'

Carl Bergstrom and I came up with the word 'Eigenfactor' back in 2005 over conversations on how to better evaluate scholarly work. Carl was interested in the economics of scholarly publishing and had written several papers with his father, Ted Bergstrom, about the subject [8, 11, 7]. Among the thousands of journals that are published each year, which journals contribute most to the moving frontier of science? Which journals are the best value to have in a librarian collection? Which are the best journals to read? And which journals are the best to publish in? For most of the last century, citation counts and impact factor have been the tools used to answer these questions [30, 28].

I was interested in networks and had done some work studying distributed computation on stomatal networks [44, 63]. The scholarly literature seemed an enticing next system to work on. It formed a vast network, where the links represent citations and the nodes represent journals[1] [19]. Can we use this kind of network to better evaluate scholarly journals, to build maps of science and to better navigate the scholarly web? And, if so, what additional information do we gain by taking into account the source of citations (the topic of Chapter 3)?

Through our conversations about citation networks and scholarly evaluation, we realized something very odd. We knew the scholarly literature formed a massive network that is well-definied and well-preserved. We knew that the 'network' matters — that how a system is connected affects the individuals in that system and how that system functions. So, why had this network property of the scholarly literature largely been ignored throughout the first century of scholarly evaluation?

The aim of Eigenfactor was to do exactly this — to take into account the *source* of citations when ranking the influential nodes in these massive communication networks. More generally, Eigenfactor extracts the structural information of networks in order to measure information flow.

[1]The nodes can also represent authors, papers or institutions. Chapter 4 explains how the Eigenfactor approach can be extended to author citation networks.

This dissertation is about Eigenfactor and how it does this for journal citation networks[2]. In this collection of papers, I hope to convey why I think this is exciting and where I see it going.

1.2 Eigenfactor

As far as we know, the word 'Eigenfactor' did not exist pre-2005. Back in 2005, we tried to find any consistent use of the word using various kinds of search engines. We found nothing, so this is the word we have used and it has stuck.

Eigenfactor, the word, is an amalgamation of two terms: eigenvector centrality and impact factor (see Chapter 2 for more details). It is both an algorithm and a project. At the core of the Eigenfactor algorithm is eigenvector centrality [16], and the impetus for developing the algorithm was impact factor [27]. Together, these two terms began what I call Eigenfactor, the project.

Today, Google now finds over 7 million pages on the web that mention the word[3]. Carl and I have been invited to talk about Eigenfactor at places around the world[4]. It is mentioned in over seventy scholarly publications. It

[2]The title of the dissertation, *Eigenfactor: ranking and mapping scientific knowledge*, is also the title at `Eigenfactor.org` — the website we built to disseminate the results of this project. This website and this form of scholarly communication has been central to the work that I will describe in this dissertation.

[3]This search was conducted on August 1, 2010. These kinds of blanketed searches can be misleading; however, it is not the absolute number that I care about. I just want to show that the number is far great than zero — zero being the number of results we found using Google just five years ago when we first came up with word and wanted to see if anyone else had used it before.

[4]Some of these invited talks can be found at `http://octavia.zoology.washington.edu/people/jevin/Presentations.html`

is used by librarians, publishers, editors, administrators and scholars around the world to evaluate scholarly journals. And, the metric is now included in Thomson-Reuters' annual Journal Citation Reports. So, why this response? Chapter 5 addresses this question.

The Eigenfactor algorithm and the Eigenfactor project focus in on two questions. The algorithm aims to answer the following question:

How does one evaluate the scholarly literature using the *entire* citation network, but *only* the citation network?

This has become an important question for librarians, publishers, editors, administrators and scholars. Limited time and limited budgets require tools that can help evaluators determine which journals, papers or researchers are contributing most to science.

The overarching question of the Eigenfactor project is more general.

How does network structure affect function?

The project therefore encompasses the algorithm, the philosophy and approach to network science and information aesthetics, the mapping of science, the economics of scholarly publishing and a whole new series of projects and data that share the common theme of being big, and highly connected. This relationship between structure and function is a central question for those who study networks, but it is also a fundamental question for my field of biology.

This question is far from being answered, but fortunately there now exists a great model system — citation networks — for testing these ideas and stimulating further theory. The links and nodes are well-defined, the networks are readily available and there exists a treasure trove of interesting stories in the data. The Eigenfactor project takes advantage of this massive network (of thousands of nodes and millions of links that have been perfectly preserved over hundreds of years) and develops statistics and visualizations to extract those stories and track how the flow of information on these networks is changing over time.

The obvious application of the Eigenfactor algorithm is easy to see and tends to overshadow these fundamental questions. In this dissertation, I will spend most of my time talking about the algorithm — how it works, what it measures (Chapter 2), how it differs from existing metrics (Chapter 3) and how it can be extended to other types of citation networks (Chapter 4) — but it is the fundamental questions involving structure and function that I am most excited about and the types of questions that will keep science busy for decades to come.

1.3 Chapter Explanations

Chapter two is an introduction to the Eigenfactor Metrics. My co-authors and I explain what the Eigenfactor Score and Article Influence Score measure and briefly explain how these metrics differ from Impact Factor. The paper was originally written for librarians and published in one of their top journals (*College and Research Libraries*) [62]. However, I often recommend this paper to publishers, administrators and scholars who want a non-mathematical introduction to the algorithm.

Chapter three is a paper that was published in the *Journal of the American Society for Information Science and Technology* (JASIST) [59]. It was a response to a previously published paper in JASIST that questioned whether eigenvector centrality measures like Eigenfactor provide additional information beyond just counting citations or calculating Impact Factor scores [18]. We show the statistical fallacy in the author's argument, we point out the spurious correlation that he found, and we conduct a much more thorough investigation into the relationship between degree centrality measures and eigenvector centrality measures.

Chapter four extends the Eigenfactor approach to author-level citation networks and explains some of the challenges when working with author-level data that is temporally directed. Author-level Eigenfactor scores are calculated on data extracted from the Social Science Research Network (SSRN) at Harvard[5]. Economists, lawyers and social scientists post their pre-prints and post-prints at this archive. The goal of this type of archive is to decrease the time for disseminating ideas and for connecting the community for search reasons.

Chapter five is a reflections chapter. The Eigenfactor project has received a fair amount of attention over a short time period. What explains this? I provide a list of possible explanations and reflect on the importance of each.

The Appendix includes code and pseudo-code that I have written over the last several years that won't be published in any journal but probably is used more than any of my published papers. The dissertation seemed to be the perfect place to put this work. I have also included a couple of the

[5]More information can be found at `http://www.ssrn.com/`

commentaries I have written about Eigenfactor.

This dissertation, of course, is far from complete. There are missing articles that I should have included. And, tomorrow there will something new we think about that I should have put in the dissertation. Fortunately, there are two places that are better for finding out about the current and new stuff we are up to and all the other stuff I should have included.

1. My website: `http://octavia.zoology.washington.edu/people/jevin/`

2. The Eigenfactor website: `www.eigenfactor.org`

Chapter 2

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

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*This chapter was published in 2010 in the *College of Research Libraries* **71**(3): 236-244. The formatted article can be found at `http://octavia.zoology.washington.edu/people/jevin/Publications.html`

**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.

Keywords: Eigenfactor^{TM} Score, Article Influence^{TM} Score, Impact Factor, Bibliometrics, Citation Networks

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.

2.1 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 [27], but its use has expanded enormously: impact factor scores now affect hiring decisions, ad placement, promotion and tenure, university rankings and academic funding [41]. 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 [47], 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 [21]. 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.

2.2 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[19], 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 2.1). 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 [16]. 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 com-

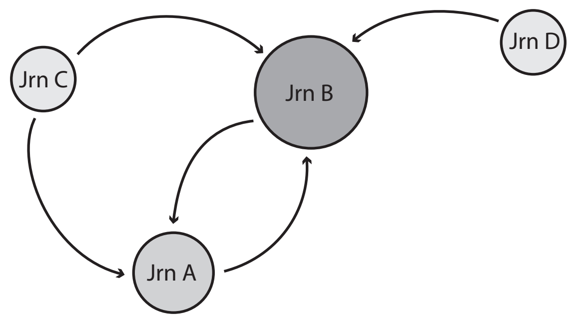

Figure 2.1: A small journal citation network. Arrows indicate citations from each of four journals, A, B, C, and D, to one another. The size of the nodes represent the centrality of each node in the network, determined by the Eigenfactor Algorithm. Larger, darker nodes are more highly connected to other highly connected nodes.

pute in a recursive manner. The most prominent commercial application of eigenvector centrality is Google's PageRank algorithm, which ranks the importance of websites by looking at the hyperlink structure of the world wide web [42]. Researchers have likewise applied this approach to a number of other network types, including citation networks [46, 37, 32, 43, 34, 12].

The concept of eigenvector centrality is at the core of the Eigenfactor Metrics as well[6]. The idea is to take a network like the one shown in Figure 2.1 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 2.1 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 2.1 the most central node is Journal B. It receives more incoming links than any other node. The size of this node

[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.

in Figure 2.1 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 2.1. 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$^{\text{TM}}$ Score and Article Influence$^{\text{TM}}$ 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-effectiness of a journal, it is therefore useful to compare subscription price with Eigenfactor score. Table 2.2 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 2.2 have an Eigenfactor sum of 8.909. This means that a researcher spends approxi-

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

mately 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 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 2.2 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

	Journal	EF	AI	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 2.1: Top 20 Journals by Eigenfactor Score (EF). The Article Influence Score (AI) are also shown. 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.

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	EF	AI	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 2.2: Top 20 Journals by Article Influence Score (AI). The Eigenfactor Score (EF) is also shown. 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.

2.3 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 2.2 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

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

in the figure illustrate that there are marked differences as well[5].

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 [2]. 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 2.2). 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

[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.

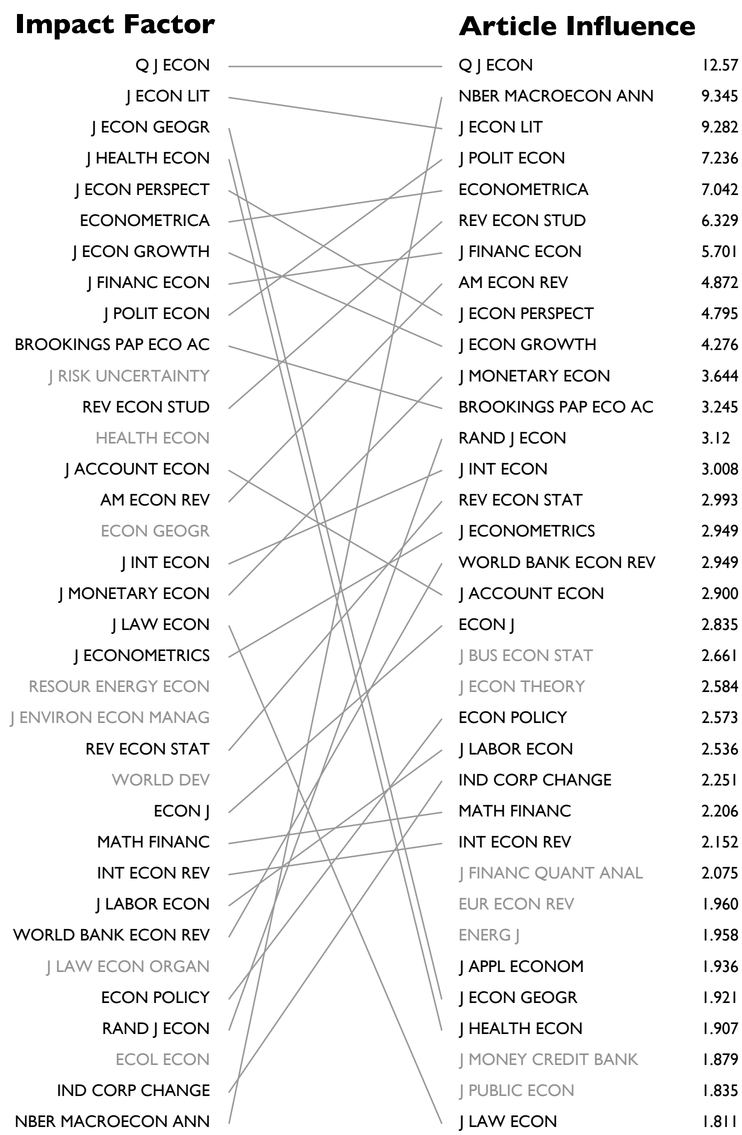

Figure 2.2: Relative ranking differences under impact factor and Article Influence. The left column are the top 35 Economics journals in the JCR by impact factor. The right column lists the top 35 Economics journals by Article Influence and their respective Article Influence Scores. The journals in grey 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.

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.

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 2.3 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

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

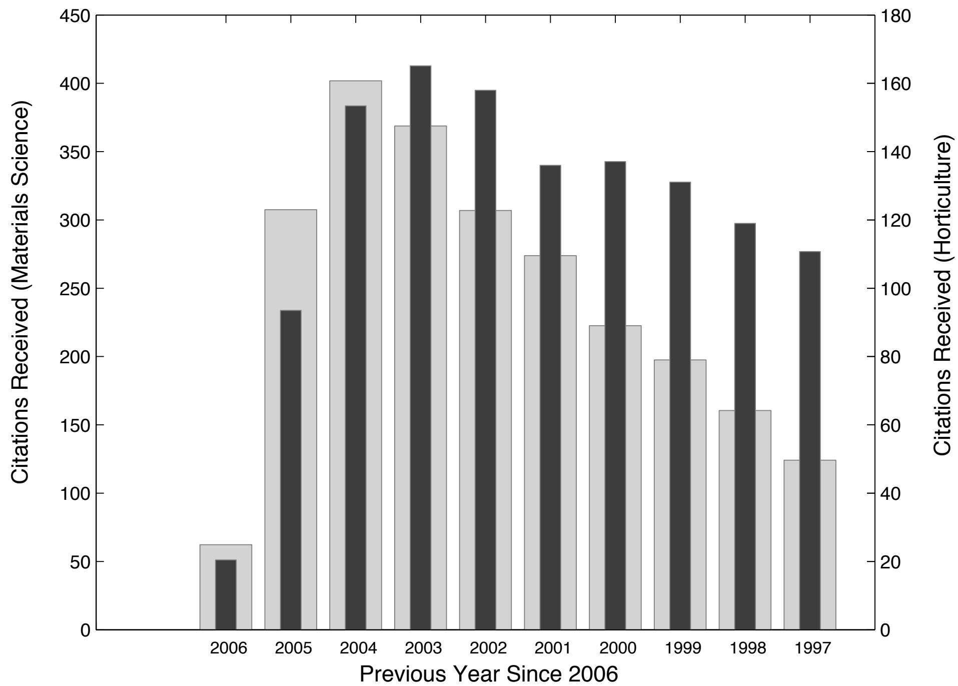

Figure 2.3: Differences in citation timing between Materials Science and Horticulture. Grey bars: citations from papers published in 2006 to Materials Science journals published in the indicated year. Black bars: citation from papers publishing in 2006 to Horticulture journals published in the indicated year.

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 [4].[8]

2.4 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.

[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.

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

Chapter 3

Big Macs and Eigenfactor Scores: Don't Let Correlation Coefficients Fool You

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Keywords: Eigenfactor™ Metrics, Eigenfactor™ Score, Article Influence™ Score, Impact Factor, Correlation Coefficient

Abstract

The Eigenfactor$^{\mathrm{TM}}$ Metrics provide an alternative way of evaluating scholarly journals based on an iterative ranking procedure analogous to Google's PageRank algorithm. These metrics have recently been adopted by Thomson-Reuters and are listed alongside the Impact Factor in the Journal Citation Reports. But do these metrics differ sufficiently so as to be a useful addition to the bibliometric toolbox? Davis (2008) has argued otherwise, based on his finding of a 0.95 correlation coefficient between Eigenfactor score and Total Citations for a sample of journals in the field of medicine [18]. This conclusion is mistaken; here we illustrate the basic statistical fallacy to which Davis succumbed. We provide a complete analysis of the 2006 Journal Citation Reports and demonstrate that there are statistically and economically significant differences between the information provided by the Eigenfactor Metrics and that provided by Impact Factor and Total Citations.

3.1 Big Macs and Correlation Coefficients

One might think that if the correlation coefficient between two variables is high, those variables convey the same information, and thus can be used interchangably — but this line of reasoning is erroneous. A simple example helps to illustrate. In Table 3.1, we provide two statistics for each of 22 countries: the cost of a Big Mac in local currency, and the mean hourly wage in local currency. The Pearson product-moment correlation coefficient, ρ, between these two statistics is 0.99. Since ρ is nearly 1, one might conclude that we can use hourly wages to predict burger prices with high accuracy and one might question why anyone should waste his or her time collecting burger price information if the hourly wage rates are already known. But take a look at the column "Real Wage". The real wage — the ratio of burger prices to hourly wages — is the variable of economic interest, since it measures a worker's purchasing power. We see that real wages differ dramatically across countries. In Denmark, a worker making the mean hourly wage need only work for seven minutes to earn a Big Mac, whereas in China, a worker making the mean hourly wage must work for nearly two hours to afford a burger.

In our hamburger example, it is pretty clear what is going on. The denominations of currencies vary immensely and arbitrarily. It is indeed true that differences in real wages are small relative to differences in currency denominations. But it is not true that after correcting for differences in denominations, differences in real wages are negligible. One way to think of this is that the greatest part of the variation in hourly wage comes from the

Country	Burger Price	Hourly Wage	Real Wage
Denmark	24.75	211.13	8.53
Australia	3.00	19.86	6.62
New Zealand	3.60	21.94	6.09
Switzerland	6.30	37.85	6.01
United States	2.54	14.32	5.64
Britain/UK	1.99	11.15	5.60
Germany	2.61	14.32	5.49
Canada	3.33	16.78	5.04
Singapore	3.30	15.65	4.74
Sweden	24.00	110.90	4.62
Hong Kong	10.70	44.26	4.14
Spain	2.37	8.59	3.62
South Africa	9.70	30.86	3.18
France	2.82	8.50	3.01
Poland	5.90	11.80	2.00
Hungary	399.00	704.34	1.77
Czech Rep.	56.00	85.34	1.52
Brazil	3.60	4.58	1.27
South Korea	3000.00	3134.00	1.04
Mexico	21.90	17.61	0.80
Thailand	55.00	31.69	0.58
China	9.90	5.56	0.56
mean	166.01	207.32	3.72
std. dev.	638.49	670.63	2.29
std. dev./mean	3.85	3.23	0.62

Table 3.1: Hourly Wage versus Real Wage. Burger price and hourly wage are in the local currency. Burger price is the average cost of a Big Mac. The units for Real Wage are burgers per hour. Data comes from Behar's "Who earns the most hamburgers per hour?" [5]. The correlation coefficient between burger price and hourly wage is $\rho = 0.99$.

relatively unimportant fact that currency is denominated differently in different countries. The standard deviation of hourly wages in nominal terms is about 300 times as large as that in real terms. Although the standard deviation of real wages across countries is tiny compared to that of nominal exchange rates, this variation is far more important for the quality of life of workers. Thus, one would be wrong to conclude from the high correlation coefficient that the real wage is constant across countries. Quite the contrary; the standard deviation of this ratio is 62% of the mean.

3.2 Davis's analysis

Davis (2008) fell into a similar trap in his recent comparison of journal rankings by Eigenfactor score and by Impact Factor or Total Citations [18]. In that paper, Davis aimed to determine whether measures of "popularity" such as Impact Factor and total citation differ substantially from measures of "prestige" such as the journal PageRank [12] and the Eigenfactor metrics [6][1]. To do so, Davis conducted a regression analysis of Eigenfactor scores

[1]The same issue was the subject of a more comprehensive analysis by Bollen and colleagues in 2006 [12]. In that paper, Bollen and colleagues compare weighted PageRank with Impact Factor and with Total Citations to explore differences between popularity and prestige. Weighted PageRank and Eigenfactor are both variants of the PageRank algorithm. See also Pinski and Narin (1976) for an early attempt at constructing prestige-based measures using citation data, and Vigna (2009) for a discussion of how Pinski and Narin's measure differs from current approaches [46, 53].

on Total Citations[2] for a set of 165 medical journals[3]. Davis reports that the correlation coefficient between 2006 Eigenfactor scores and Total Citations[4] is $\rho = 0.9493$. Based on this result, Davis concluded that:

> "At least for medical journals, it does not appear that iterative weighting of journals based on citation counts results in rankings that are significantly different from raw citation counts. Or, stated another way, the concepts of popularity (as measured by total citation counts) and prestige (as measured by a weighting mechanism) appear to provide very similar information."

But is Davis right? Is it really the case that if you know the number of citations, you would be wasting your time by finding the Eigenfactor score? Not at all.

First, Davis made a classic statistical error — cautioned against by Karl Pearson in 1897 — in comparing two measures with a common factor [45]. Second, Davis suggests that a high correlation coefficient implies that there

[2] In his paper Davis also looked at the correlation coefficient between Eigenfactor and Impact Factor scores. This ρ value is lower ($\rho = 0.86$), but the point is not so much what this value is, but rather that the comparison makes little sense. Eigenfactor is a measure of total citation impact, and should (all else equal) scale with the size of the journal. Impact factor is a measure of citation impact per paper, and all else equal should be independent of journal size. If one wants to compare an Eigenfactor metric with the Impact Factor, one should use the Article Influence Score, which is a per-article measure like Impact Factor. We explore this comparison later in the paper.

[3] Contrary to what is specified in that paper, Davis appears to have sampled from both the "Medicine General and Internal" and "Medicine Research and Experimental" fields, not merely the former category. In our analysis of the same subfields of medicine, we included 168 journals (of the 171 journals in this field); we eliminated 3 journals because they had an Impact Factor and/or Article Influence score of zero

[4] Davis appears to have used citations (from year 2006) to all articles published in the journals he selected. A cleaner comparison, which would have resulted in a higher correlation, would have been to extract citations (from year 2006) to articles published in the past five years, since the Eigenfactor score takes into account only the past 5 years' citations.

is no significant difference between two alternative measures; this is simply false. We address these issues in turn.

3.3 Journal Sizes and Spurious Correlations

There are enormous differences in the size of academic journals, and these differences swamp the patterns that Davis was seeking in his analysis. The JCR indexes journals that range in size from tiny (*Astronomy and Astrophysics Review* has published 13 articles over the previous five years) to huge (*The Journal of Biological Chemistry* has published 31,045 articles over the same period) with a coefficient of variation, c_v, equal to 1.910. Per-article citation intensity varies less, whether measured by Article Influence or by Impact Factor (AI: range 0–27.5, coefficient of variation= 1.785; IF: range 0–63.3, coefficient of variation= 1.548).

We can formalize these observations by decomposing Davis' regression of Eigenfactor on Total Citations. Davis regresses

$$\text{Log}(EF_i) \quad \text{vs} \quad \text{Log}(CT_i),$$

where EF_i is the Eigenfactor score for journal i and CT_i is the Total Citations received by journal i. We let AI_i be the Article Influence for journal i, and $N_{i,5}$ is the total number of articles published over the last five years for journal i. Then by definition

$$\begin{aligned} \log(EF_i) &= \log(c_1 \times AI_i \times N_{i,5}) \\ &= \log c_1 + \log AI_i + \log N_{i,5}, \end{aligned}$$

where c_1 is a scaling constant that normalizes the Article Influence scores so that the mean article in the JCR has an Article Influence score of 1.00. Similarly, letting IF_i be the Impact Factor for journal i,

$$\begin{aligned}\log(CT_i) &\approx \log(c_2 \times IF_i \times N_{i,2}) \\ &\approx \log(c_2\, c_3 \times IF_i \times N_{i,5}) \\ &= \log c_2\, c_3 + \log IF_i + \log N_{i,5}\end{aligned}$$

where c_2 and c_3 are additional scaling constants. The scaling constant, c_2, accounts for the fact that Davis compared citations for *all* years and not just citations for 2 years. The scaling constant c_3 relates the number of articles published in two years to the number of articles published in five years (and thus is approximately 5/2). As a result, Davis is effectively calculating a regression between

$$\log(\text{Article Influence}) + \mathbf{log(Total\ Articles)}$$

and

$$\log(\text{Impact Factor}) + \mathbf{log(Total\ Articles)}.$$

Having the "log(Total Articles)" term on both sides of the regression — especially given that it varies more than the other two terms — obscures the relation between the variables that one would actually wish to observe when trying to evaluate the difference between "popularity" and "prestige".

This pitfall is famous in the history in mathematical statistics. In 1897, two years after pioneering statistician Karl Pearson developed the product-moment correlation coefficient, he presented a paper to the Royal Society in which he noted that fellow biometrician W. F. R. Weldon had made precisely this mistake in the analysis of body dimensions of crustaceans [45, 58]. Explaining this error, Pearson wrote

> "If the ratio of two absolute measurements on the same or different organs be taken it is convenient to term this ratio an index. If $u = f_1(x, y)$ and $v = f_2(z, y)$ be two functions of the three variables x, y, z, and these variables be selected at random so that there exists no correlation between x,y, y,z, or z,x, there will still be found to exist correlation between u and v. Thus a real danger arises when a statistical biologist attributes the correlation between two functions, like u and v to organic relationship."

It was to describe this danger that Pearson coined the term *spurious correlation* [45, 1]. He imagined a set of bones assembled at random. Based on correlations between measurements that share a common factor, a biologist could easily make the mistake of concluding that the bones were properly assembled into their original skeletons:

> "For example, a quantity of bones are taken from an ossuarium, and are put together in groups, which are asserted to be those of individual skeletons. To test this a biologist takes the triplet femur, tibia, humerus, and seeks the correlation between the in-

> dices femur/humerus and tibia/humerus. He might reasonably conclude that this correlation marked organic relationship, and believe that the bones had really been put together substantially in their individual grouping. As a matter of fact, since the coefficients of variation for femur, tibia, and humerus are approximately equal, there would be, as we shall see later, a correlation of about 0.4 to 0.5 between these indices had the bones been sorted absolutely at random. I term this a spurious organic correlation, or simply a spurious correlation. I understand by this phrase the amount of correlation which would still exist between the indices, were the absolute lengths on which they depend distributed at random."

The reason for this correlation will be that some of the random femur and tibia pairs will be combined with a large humerus; in this case both the femur/humerus and tibia/humerus ratio will tend to be smaller than average. Other femur and tibia pairs will be combined with a small humerus; in this case both the femur/humerus and tibia/humerus ratio will tend to be larger than average. Correlation coefficients of the two ratios give the illusion that tibia and femur length covary, even when they in fact do not. For his part, Weldon was forced to concede that nearly 50% of the correlation he had observed in body measurements was actually due to this effect.

Just over a decade later, another important figure in the development of mathematical statics, G. U. Yule, noted that when absolute values share a common factor, they are just as susceptible to this problem as are "indices" or ratios [65]:

> "Suppose we combine at random two indices z_1 and z_2, e.g. two death-rates, and also combine at random with each pair a denominator or population x_3. The correlations between z_1, z_2, and x_3 will then be zero within the limits of sampling. But now suppose we work out the total deaths $x_1 = z_1x_3$ and $x_2 = z_2x_3$; the correlation r_{12} between x_1 and x_2 will not be zero, but positive."

This is precisely the form of spurious correlation that arises in Davis's analysis. Per-article popularity as measured by Impact Factor takes the role of z_1 in Yule's example, and per-article prestige as measured by Article Influence score takes the role of z_2. Total Articles takes the role of Yule's x_3. Even if Impact Factor and Article Influence were entirely uncorrelated, Davis still would have observed a high correlation coefficient in his regression of Eigenfactor and Total Citations ($\sim \rho = 0.6$ for all journals), because both share number of articles as a common factor. What Davis discovered is not that popularity and prestige are the same thing; he discovered that big journals are big and small journals are small. Because of this wide variation in journal size, one would also observe a high correlation coefficient between pages and total cites, though very few would argue that the former is an adequate surrogate for the latter[5].

To avoid this problem, we might want to look at the correlation between popularity *per article* and prestige *per article*. That is, we need to look at

[5] We collected page and citation information for 149 Economics journals in 2006. The correlation coefficient between total pages and total citations is $\rho = 0.615$.

the comparison

$$\text{Log(Article Influence)} \quad \text{vs.} \quad \text{Log(Impact Factor)}.$$

Since its inception in January 2007, Eigenfactor.org has provided exactly this information at `http://www.eigenfactor.org/correlation/`, for the entire JCR dataset and also for each individual field of scholarship as defined by the JCR[6]. Figure 3.1 is a histogram of the correlation coefficients between Impact Factor and Article Influence scores for all 231 categories in the 2006 JCR. The mean for all fields was 0.853 with a standard deviation of 0.099. The field with the lowest correlation coefficient is Communication ($\rho = 0.478$). Marine Engineering has the highest correlation ($\rho = 0.986$). The sample of medical journals that Davis selected, with $\rho = 0.954$, ranks in the 90th percentile when compared to all 231 fields. Correlation coefficients within fields typically exceed the correlation coefficient for all journals together. For all $7,611$ journals considered together, $\rho = 0.818$. This value is lower than the mean of individual-field correlation coefficients, which is $\rho = 0.853$.

3.4 Correlation and significant differences

To evaluate Davis's claim that Eigenfactor score and Total Citations are telling us the same thing, we can focus on the *ratio* of Eigenfactor score to Total Citations (EF/TC). (When we look at the ratio, the common factor

[6]Falagas et. al (2008) presented a similar comparison of Impact Factor and the SJR indicator (a per-article measure of prestige) [25]. Waltman and van Eck look at a correlations among a number of bibliometric measures; their discussion of differences between Impact Factor and Article Influence is noteworthy [56].

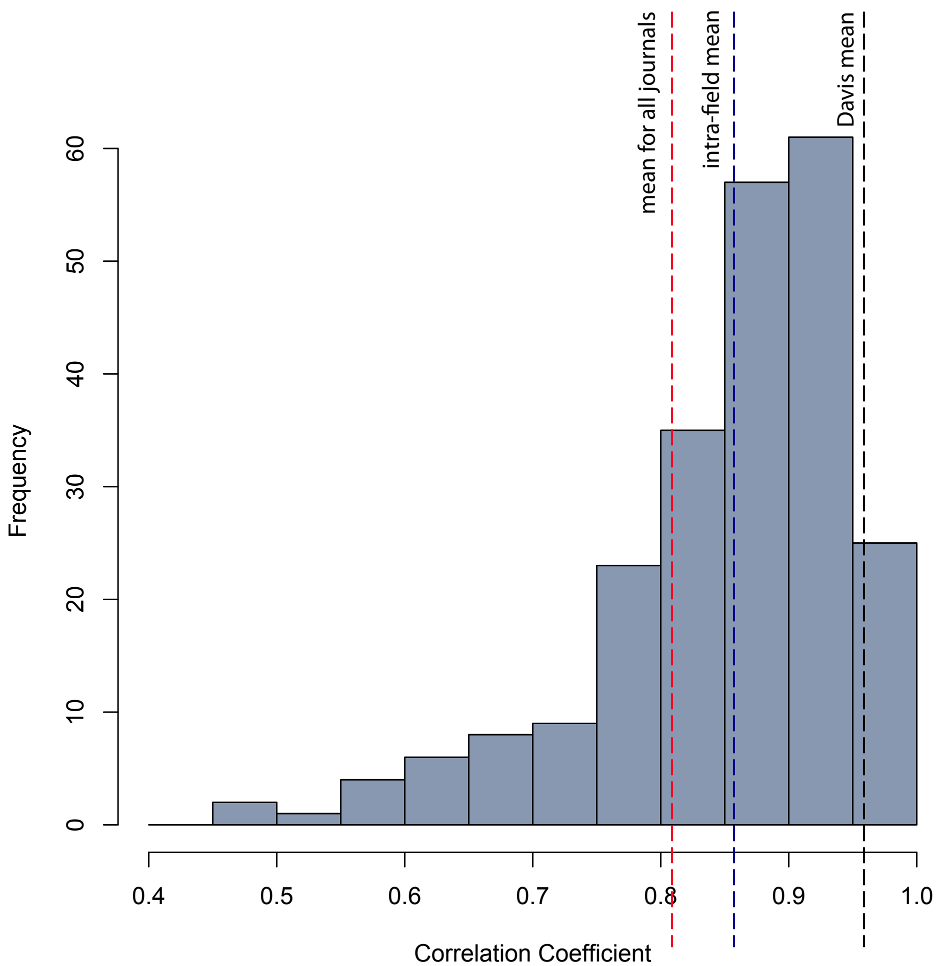

Figure 3.1: Histogram of correlation coefficients between Impact Factor and Article Influence scores. This includes all 231 categories in the 2006 Science and Social Science JCR. The mean of all fields is 0.853 (intra-field mean) and the standard deviation is 0.099. The correlation for all journals considered together is 0.818. The correlation for the field of Medicine as studied by Davis is 0.954. The correlation coefficients for all fields can be found at `http:/www.eigenfactor.org/correlation/`.

"Total Articles" divides out.) Notice that a journal's EF/TC ratio is a measure of "bang per cite received" – that is, how much Eigenfactor boost does this journal receive, on average, when it is cited. In the hamburger example, the corresponding notion is "burgers per hour," the real wage or purchasing power of an hour's work. Does a high correlation between Total Citations and Eigenfactor score mean that the bang per cite received is about constant? If it is, there really would be no point to looking at Eigenfactor scores instead of Total Citations. So let's see what happens.

Figure 3.2 shows the ratio of Eigenfactor score to Total Citations for every journal in the JCR, and the insert shows just the medical journals. The standard deviation of this ratio is 1.1×10^{-5} and the mean is 1.56×10^{-5}. The standard deviation, in this case, is 71% of the mean. This is even more variable than the Big Mac case! Moreover, there are nearly 1000 journals with twice the mean "bang per cite".

The thing to notice in both the Big Mac and the journal example is that if you are interested in the ratio of A to B and if $A = ax$ and $B = bx$ for some x with a very high variance relative to that of a and of b, you will get a very high ρ value when you regress B on A. However, if what really interests you is the ratio A/B, you will note that the x's cancel and $A/B = ax/bx = a/b$. Thus, the variance of x has literally nothing to tell you about the variance of the ratio a/b. You don't learn about whether a/b is nearly constant or highly variable from looking at the correlation of B on A.

If, as Davis claims, Eigenfactor scores do not differ significantly from Total Citation counts, the ratio EF/TC should be constant across different

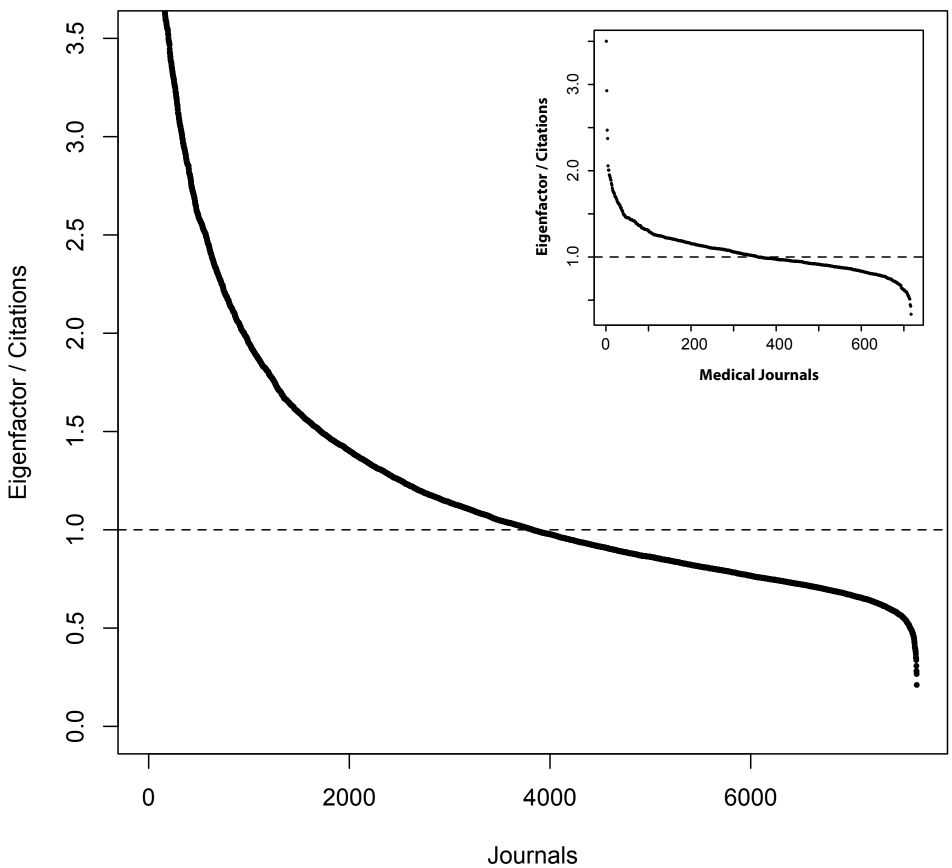

Figure 3.2: Ratio of Eigenfactor score to Total Citations. Data are normalized by the median ratio of the data set. The dashed line indicates a ratio of one. The journals are ordered from those with the highest ratio to the lowest. The inset shows only the 168 medical journals from Davis's analysis.

groups of journals. To evaluate this claim, we look at the EF/TC ratios of social journals with those of science journals, with groupings determined by whether a journal is listed in the Social Science JCR or the Science JCR. (Journals listed in both are omitted from the analysis). The mean EF/TC ratio for science journals is 1.42×10^{-5}, whereas the mean for social science journals is 2.12×10^{-5}. A Mann-Whitney U test shows that this difference is highly significant, at the $p < 10^{-167}$ level.

These differences are not only statistically significant, but also economically relevant. The 49% difference in mean EF/TC ratios indicates that a librarian who uses Total Citations to measure journal value will underestimate the value of social science journals by 49% relative to a librarian who uses Eigenfactor scores to measure value.

There are also significant differences within the sample of journals that Davis considered. Based on the difference between science and social science ratios described above, one might expect medical journals more closely associated with the social sciences, such as those in public health, to have higher-than-average EF/TC ratios. Seven of the publications in Davis's sample of medical journals are cross-listed in the JCR category of public, environmental, and occupational health. Indeed, this group of journals has a 29% higher EF/TC ratio than do the rest of the journals in Davis's sample, again statistically significant (Mann-Whitney U test, $p < .01$).

Note that there is nothing special about this particular comparison between sciences and social sciences; one could test any number of alternative hypotheses and would find significant differences between EF/TC ratios for many other comparisons as well.

3.5 The value of visualization

So, if correlation coefficients are misleading, what is the alternative? First, we argue for a deeper examination of the data. Figure 3.3 is an example of this strategy[7]. Listing the journals in this way, one is able to quickly see the ordinal differences that exist between this highly correlated data. This type of graphical display illustrates the interesting stories that can be lost behind a summary statistic such as the Spearman correlation.

Figure 3.3 illustrates the ordinal ranks of the top 50% of the medical journals used in Davis's study. In the left column, the journals in this subfield of medicine are ranked by the total number of citations. In the right column, the journals are ordered by Eigenfactor score. The lines connecting the journals indicate whether the journal moved up (green), down (red) or stayed the same (black) relative to their ranking by Total Citations. The figure highlights the differences between the metrics. For example, *Aviation Space and Environmental Medicine* drops 30 places while *PLoS Medicine* raises 31 places. Davis claims in his paper that the ordering of journals does not change drastically. Figure 3.3 suggests otherwise.

Figure 3.4 compares the ordinal ranking by Impact Factor and Article Influence for 84 journals — the top-ranked half — from Davis's study[8].

[7] **Figure 3.3 caption:** Journal ranking comparisons by Total Citations and Eigenfactor score. The journals listed are the top 50% from the field of Medicine that Davis analyzed. Journals in the left column are ranked by Total Citations for all years. Journals in the right column are ranked by Eigenfactor score. The lines connecting the journals indicate whether the journal moved up (green), down (red) or stayed the same (black) relative to their ranking by Total Citations. Journal names in black can also be journals that do not exist in both columns.

[8] **Figure 3.4 caption:** Comparing Impact Factor and Article Influence. The journals shown are from the same field that Davis analyzed (because of limited space, only the top 84 journals are shown). For these 84 journals, the correlation coefficient between IF and

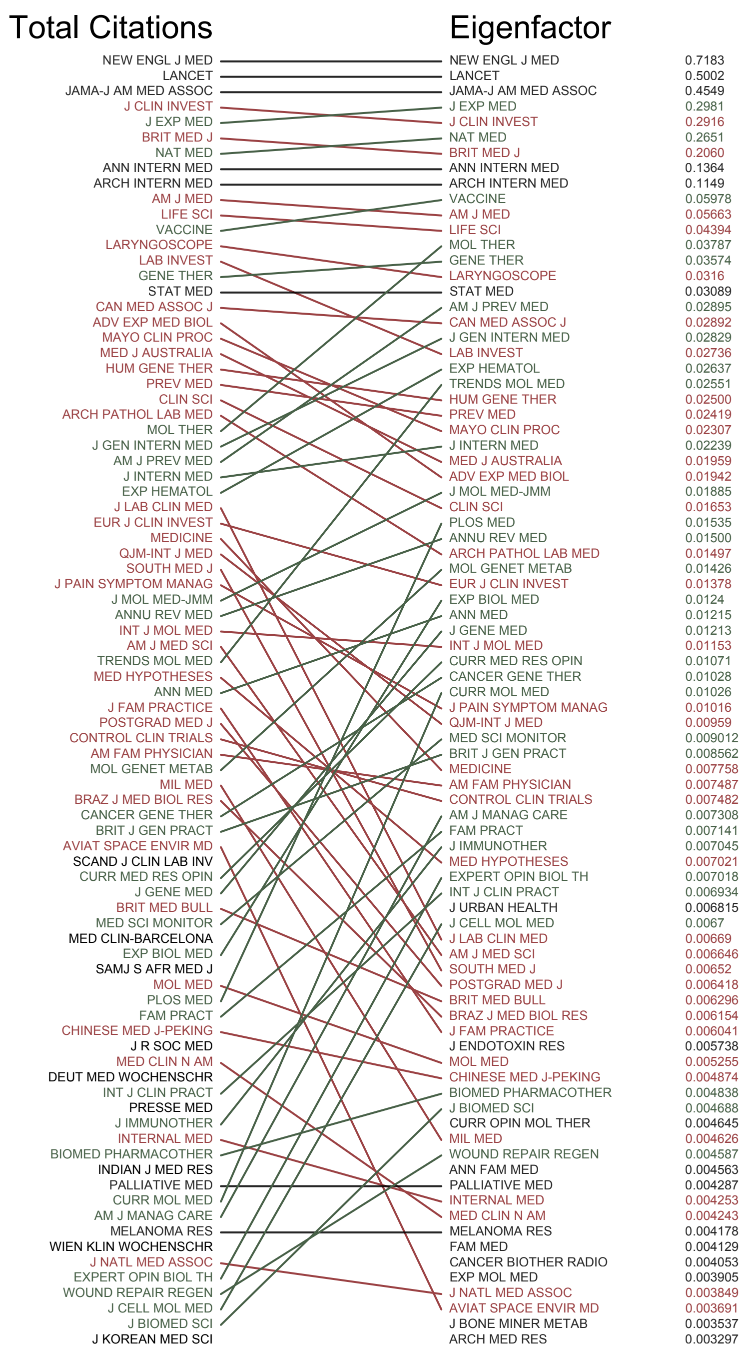

Figure 3.3: See footnote in text for caption.

Changes in ranking are even more dramatic when we look at the lower-ranked 84 journals. The correlation coefficient between Impact Factor and Article Influence for these 84 journals is $\rho = 0.955$. Despite this high correlation, the figure highlights the fact that the two metrics yield substantially different ordinal rankings.

Figure 3.4 reveals that the top few journals change in rank less than those further down the hierarchy. For example, going from Impact Factor to Article Influence, the journals in the top ten change in rank by only 1 or 2 positions. By contrast, there are many larger changes further on in the rankings[9]. For example, as we go from Impact Factor to Article Influence, the Journal of General Inernal Medicine rises 18 spots to number 19 while *Pain Medicine* drops 35 spots to end up at number 80. These are just two of the many major shifts (in a field with a correlation of 0.955!). These changes in relative ranking would certainly not go unnoticed by editors or publishers.

Furthermore, while ordinal changes are interesting, cardinal changes are often more important. Figure 3.5 shows the top ten journals from Figure 3.3 — those with the least ordinal change from one metric to another — now in their cardinal positions. Even those journals that do not change ordinal rank

AI is $\rho = 0.955$. The relative rankings by Impact Factor and Article Influence are listed in the left and right column, respectively. The third column lists the Article Influence scores. The journal names in green indicate those that fare better when ranked by Article Influence; the journal names in red fare better when ranked by Impact Factor. The names in black are journals that exhibit no change or exist outside the range of the journals shown.

[9] Bollen (2006) observed a similar pattern in a series of scatterplots contrasting PageRank and Impact Factor values for all journals [12]. In these scatterplots the rankings of top-tier journals differ relatively little whereas more variation is found in the middle and bottom portions of the hierarchy.

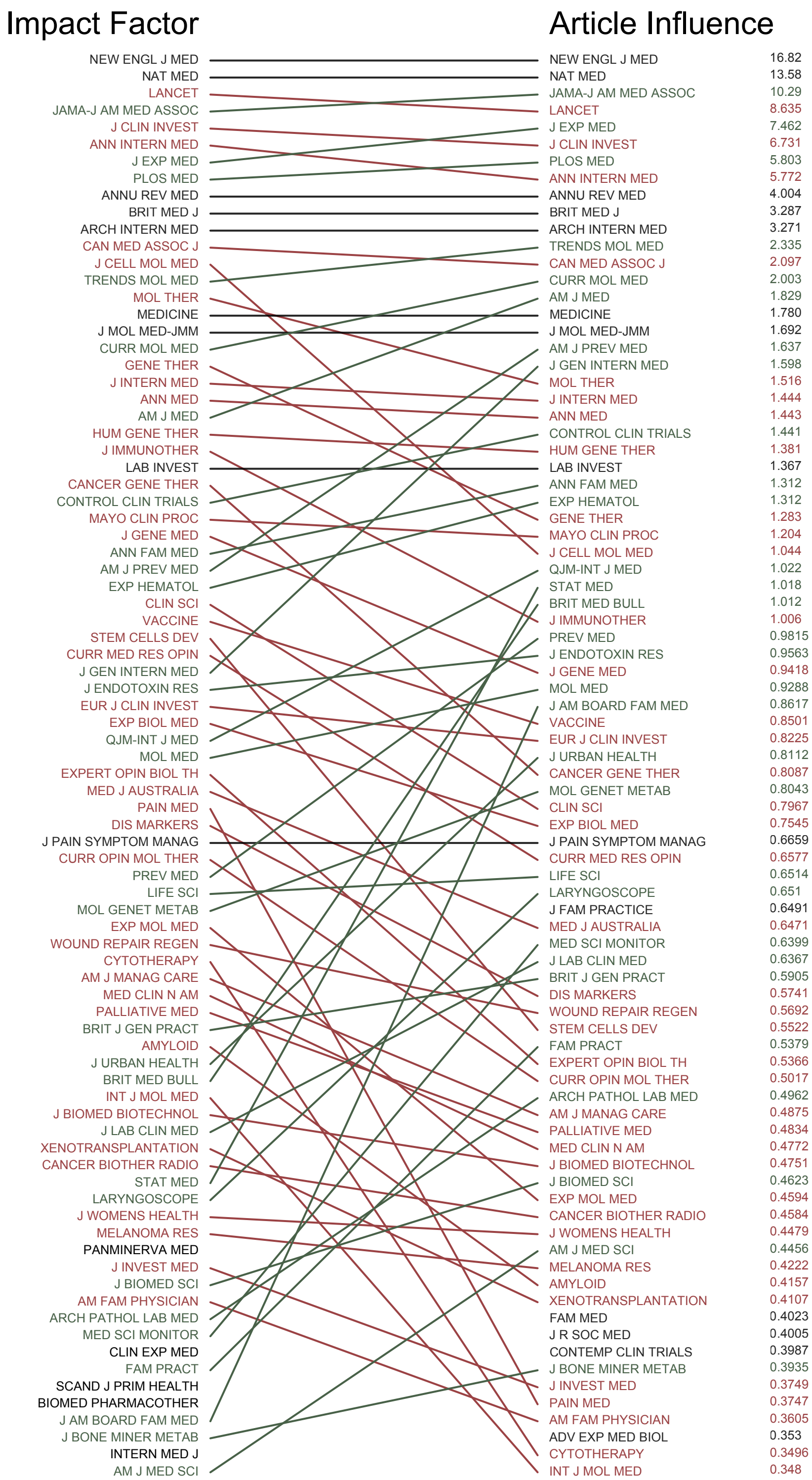

Figure 3.4: See footnote in text for caption.

from one metric to another may be valued very differently under the two different metrics. For example, *Nature Medicine* is the #2 journal regardless of whether one uses Impact Factor or Article Influence. But under Impact Factor, it has barely half the prestige of the first-place *New England Journal of Medicine*, whereas by Article Influence it makes up a good deal of that ground.

3.6 Conclusion

Correlation coefficients can be useful statistical tools. They can help us identify some kinds of statistically significant relationships between pairs of variables, and they can tell us about the sign (positive or negative) of these relationships. One must use considerably greater caution, however, when drawing conclusions from the magnitude of correlation coefficients — all the more so in the presence of spurious correlates and in the absence of a formal hypothesis-testing framework. In particular, we have illustrated that just because two metrics have a high correlation — 0.8 or 0.9 or even higher —- we cannot safely conclude that they convey the same information, or that one has little additional information to tell us beyond what we learn from the other.

Comparative studies of alternative measures can be very useful in choosing an appropriate bibliometric toolkit. We close with a few suggestions for how one might better conduct these sorts of analyses. First, be wary of what correlation coefficients say about the relationship of two metrics [52, 3]. High correlation does *not* necessarily mean that two variables provide the

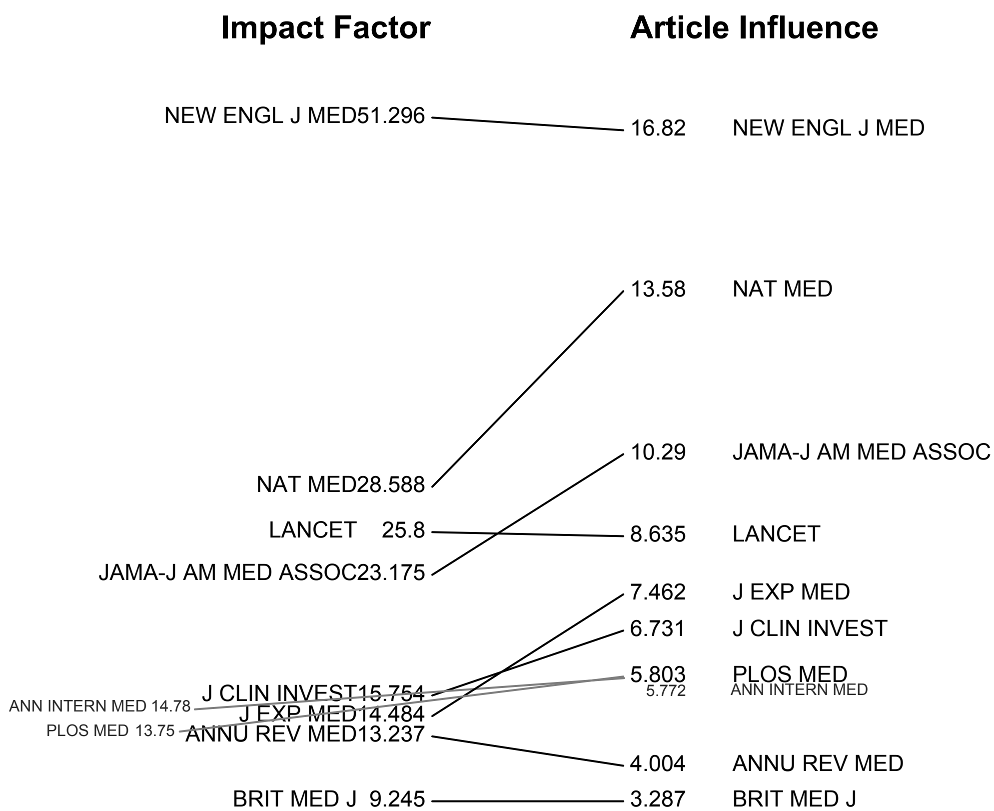

Figure 3.5: Cardinal differences between Impact Factor and Article Influence score. The top ten journals by Impact Factor are shown in the left column. The scores are scaled vertically, reflecting their cardinal positions. The smallest Impact Factor score is on the bottom, and the highest Impact Factor score is on the top. The right column shows the same journals scaled by Article Influence.

same information any more than a low correlation means that two variables are unrelated. Purchasing power varies wildly despite the high correlation between wage and hamburger price in our Big Mac example. At the other end of the spectrum, in the chaotic region of the logistic map, successive iterates have an immediate algebraic relationship yet a correlation of zero.

Second, appropriate data visualization can bring out facets of the data that are obscured by summary statistics. Different forms of data graphics can be better suited for certain tasks; for example the comparison plots such as those in Figure 3.4 better highlight the differences between bibliometric measures than do standard scatter plots.

Finally, simple observations can be at least as powerful as rote statistical calculations in understanding the nature of our data. For example, the median of the burgers/hour in the top third of the countries is about five times the median of the burgers/hour in the bottom third. This says a great deal about the differences in purchasing power across countries. The median "bang per cite received" in the top third of journals is almost 2.4 times of the median in the bottom third. This says a great deal about the difference in how journals are valued under the Eigenfactor metrics, and helps us understand why the Eigenfactor metrics offer a substantially different view of journal prestige than that which we get from straight citation counts.

3.7 Acknowledgements

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Chapter 4

Author-Level Eigenfactor* Metrics: Evaluating the influence of authors, institutions and countries within the SSRN** community

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*The Eigenfactor™ Project is sponsored by the Bergstrom Lab in the Department of Biology at the University of Washington in Seattle, WA, USA. All the algorithms, visual tools and maps of science are freely available at http://www.eigenfactor.org/.

**The Social Science Research Network is a pre- and post-print archive devoted to the rapid dissemination of scholarly research in the social sciences, business, law and humanities. More information can be found at http://www.ssrn.com/.

Note: SSRN provides rankings for authors and institutions based on citations and downloads. A complete list of the rankings can be found at http://hq.ssrn.com/Rankings/Ranking_Display.cfm?TRN_gID=7. *These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader[1] has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

[1]A description of CiteReader is available at http://ssrn.com/abstract=996660 [17].

Abstract

The Social Science Research Network (SSRN) is a pre- and post-print archive devoted to the rapid dissemination of scholarly research in the social sciences and humanities. Here we describe the application of the Eigenfactor Metrics to author-level citation data[2] from more than 237,382 papers in the SSRN collection[3], to generate author, institution, and country rankings for the contributors to the SSRN[4].

Keywords: Eigenfactor Metrics, Author-Level Eigenfactor Score, SSRN, Author Rankings, Institutional Rankings, Citation Networks

[2]Care was taken in this study to protect all authors' personal information. Only citation, article, institutional and download information were extracted from papers by SSRN authors.

[3]Citation data for this paper is based on SSRN CiteReader statistics as of May 27, 2010.

[4]There are over 50,000 papers — primarily law papers — in the SSRN that have no formal bibliography. We did not include these in the analysis for this version of the paper, but as the citations from the footnotes in these papers are extracted by CiteReader, they will be included in the rankings and in future versions of this paper. We *acknowledge* that omitting these papers creates a substantial bias in the statistics that we report.

4.1 Introduction

Since 1927, when two chemistry professors proposed using citation counts to make subscription decisions for university libraries [30], citation tallies have been used to estimate the academic influence and prestige of articles [55], authors [31], journals [26], departments [33], universities [38], and even nations [40]. But citations are not independent and isolated events. Rather, they form a network of interrelations among scholarly articles. The structure of this network reflects millions of individual decisions by academic researchers about which papers are most important and relevant to their own work. In our efforts to extract the wealth of information from this network of citations, we can do better than simply tallying the raw number of citations: we can explicitly use information about the network structure in order to reveal the importance of each node (paper, author, journal or institution) within the citation network as a whole.

In this paper, we develop an Author-Level Eigenfactor™ Score as a network-based measure of an author's influence within the Social Science Research Network (SSRN). At the time the data for this paper was extracted from SSRN, this scholarly community consisted of 86,170 authors who either cited or received citations from other SSRN authors. We then use Author-Level Eigenfactor Scores to rank institutions and countries associated with this set of scholars.

4.2 Methods

4.2.1 The Citation Network

There are 237,382 papers that have been submitted to the SSRN archive, representing 136,348 unique authors (as of 05/27/10). For each paper, we extract the authors and their primary institutional affiliations, and the works cited in the article's references and footnotes. This includes over 5.9 million citations. These references in each paper in the SSRN database can then be used to create large networks where the links represent citations to other SSRN papers or from other SSRN papers; the nodes can represent either papers, authors or institutions. For this paper, the nodes are authors and the links are citations between authors.

The SSRN network that we examined for the analysis in this paper was a subset of the total number of authors. For an author to be included in the network, it had to either be cited by another SSRN author and/or cite another SSRN author. This network consisted of 5,946 institutions, 86,170 authors, 171,904 papers and over 2.4 million citations (05/11/10). Note the hierarchical structure of the data: authors are affiliated with one or more institutions; papers are affiliated with one or more authors; citations are directed among papers. To illustrate this basic structure, Figure 4.1 shows a hypothetical example for a much smaller citation network with 10 authors, 8 papers and 3 institutions. The colored ellipses represent institutions, the numbers are individual authors and the rectangles labeled with letters are papers. The paper, author and institution relationships are combined in this figure, but they can be disaggregated to show only the papers (Figure 4.2), authors (Figure 4.3) or institutions. In this paper, we compute rankings based on the author-level network.

4.2.2 Eigenfactor Scores

The Eigenfactor$^{\text{TM}}$ Algorithm provides a methodology for determining which nodes in a citation network are the most important or influential. The algorithm does this by computing a modified form of the eigenvector centrality of each node in the network [16]. The intuition behind eigenvector centrality is that important nodes are those which have links to other important nodes; while this may sound circular, importance scores can be calculated recursively according to this principle. While we apply this approach to citation networks, there are many other applications. For example, this basic concept is at the heart of Google's PageRank algorithm [42].

The Eigenfactor scores can be seen as the outcome of either of two conceptually different but mathematically equivalent stochastic processes[5]. The first process is a simple model of research in which a hypothetical reader follows chains of citations as she moves from node to node. Imagine that a researcher goes to the SSRN and selects an article at random. After (optionally) reading the article, the researcher selects at random one of the citations from the article. She then proceeds to that citation, and now downloads it from the SSRN. The researcher repeats this process ad infinitum. Eventually, her download patterns reach a steady state[6]. An author's Eigenfactor

[5] See "rate view" at http://www.mapequation.org/mapdemo/index.html for a demo of this process

[6] So long as the citation matrix is irreducible and aperiodic; we ensure these via the "teleportation" procedure discussed below.

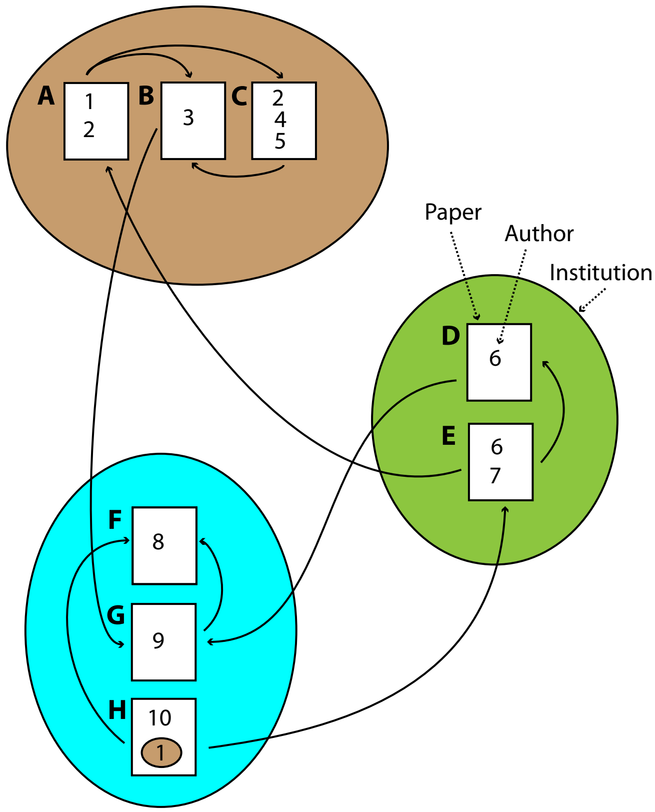

Figure 4.1: An example citation network among authors, papers and institutions. The large colored ellipses represent institutions. The white rectangles (labeled with letters) within each ellipse represent papers. The numbers within the rectangles represent individual authors. Many of the papers are multi-authored. For example, paper C has three authors (*2,4,5*). Authors are affiliated with the institution in which a given paper is located, unless indicated otherwise by coloration. For example, Author *1* is associated with the brown institution even though paper H appears in the blue ellipse. The arrows represent citations. There are 10 citations, 8 papers, 10 authors and 3 institutions in this citation network.

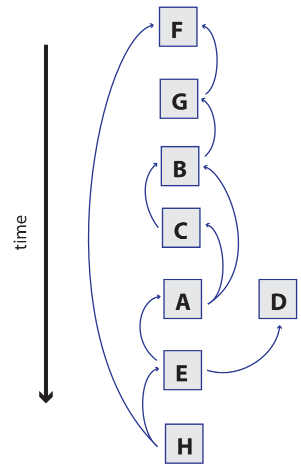

Figure 4.2: Paper citation network corresponding to Figure 4.1. Just as in that figure, the rectangles represent papers and the arrows represent citations among those papers. Paper F is the oldest paper in the example and paper H is the most recent paper written. Many of the papers cite multiple other papers but only cite backwards in time. Because of this time constraint, paper F cites no papers in this network and paper H receives no citations. Therefore, older papers in this type of network typically receive larger number of citations than newer papers.

score is the percentage of the time that she spends with this author's work in her random walk through the literature.

The second, equivalent, process is an iterated voting procedure. Each author begins with a single vote and passes it on, dividing the vote equally among those authors whom she cites. After one round of this procedure, some authors will receive more votes than others. In the second round, each author passes on her current vote total, as received in the previous round, again dividing this quantity equally among those authors whom she cites. This process is iterated indefinitely. Eventually, we reach a steady state in which each author receives an unchanging number of votes in each round[7]. An author's Eigenfactor score is the percentage of the total votes that she receives at this steady state.

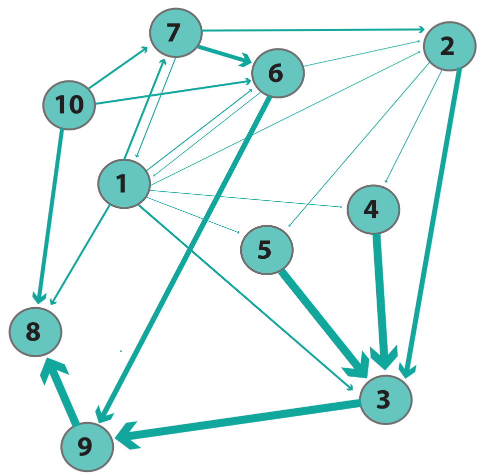

Figure 4.3: Author citation network corresponding to Figure 4.1. The circles represent authors and the arrows represent citations among the authors. The weight of each directed arrow indicates the relative fraction of citations from the source author to the recipient author. For example, the citation weight from author *9* to author *8* is twice the weight of that from author *10* to author *8*. This is because author *9* cites *only* author *8* whereas author *10* cites multiple authors.

Eigenfactor Scores have previously been used to rank scholarly journals [6, 62], and the scores are freely available at `http://www.eigenfactor.org`. Here we extend the Eigenfactor Algorithm to the author level, and apply it to the SSRN database. The SSRN data tallies the number of times that each paper in the SSRN database has been cited by each other paper in

[7]Again we require irreducibility and aperiodicity.

the SSRN database since the inception of the database. From this data we can construct an *author citation network*—a directed network in which each author is a node and a weighted, directed edge connects author 1 to author 2 if any paper by author 1 cites any paper by author 2.

4.2.3 Creating the weighted cross-citation matrix

From the citation database developed by SSRN, we begin by extracting those citations from SSRN papers that reference other SSRN papers[8]. At the time of the analysis, this set of papers features 86,170 unique authors. From these authors and citations, we create a 86,170 by 86,170 square *cross-citation matrix* $\mathbf{R}$ that tallies the raw number of times that the SSRN papers of each author cite the SSRN papers of each other author, where

$$R_{ij} = \text{citations from author } j \text{ to author } i. \tag{4.1}$$

When constructing $\mathbf{R}$, we omit all self-citations by setting the values along the diagonal of this matrix to zero. We ignore self-citations in order to minimize the incentive for opportunistic self-citation. In the data used for this analysis, there were 21,564 authors who cited at least one of their own SSRN papers (25% of all authors)[9]. Those citations consisted of 5.4% of all the weighted citations before their removal.

[8]At present, SSRN records only those citations listed in the references. Thus, we have missed citations from legal scholars, who often include citations in footnotes. SSRN is in the process of tallying these footnote citations. These citations will increase the number of citations by approximately 75% and will disproportionately affect law authors.

[9]There were (94) authors that (1) only cited themselves and no other authors in the SSRN and (2) only received citations from themselves. This indicates that they did not co-author any of their self-cited papers with any other SSRN authors.

Before we calculate Eigenfactor Scores, the citation matrix **R** must be normalized to divide credit among authors of multiple-authored papers and to scale by the number of outgoing citations from each paper. We treat these steps in turn.

Dividing credit by the number of authors. The number of authors on a scholarly paper varies widely both within and between fields. As de Solla Price notes [20], if every author on a paper were to receive full credit for each citation that the paper received, this would cause some papers (namely those with many authors) to be counted multiple times in the bibliometric tally, whereas others (solo-authored papers) would be counted only once. Similarly, authors who tend to work as parts of large teams would be correspondingly overvalued. Such factors can have a major influence on both cardinal and ordinal rankings [22, 29].

We follow de Solla Price's proposed solution: the credit for a paper "must be divided among all the authors listed on the byline, and in the absence of evidence to the contrary it must be divided equally among them. Thus, each author of a three-author paper gets credit for one-third of a publication and one-third of the ensuing citations." [20].

Dividing credit by the number of outgoing citations. Papers also vary widely in the number of outgoing citations that they confer upon other articles. In order to correct for these differences, in our choice of weights we divide each citation by the number of outgoing citations that each paper confers, such that each paper contributes a total citation weight of 1.0 that is shared among all of the papers that it cites.

Assigning credit across multiple versions of a paper. Pre-print archives such as SSRN tend to house multiple versions of the same paper. It is not unusual for each one of these versions to receive unique citations and the final published paper may receive only a modest fraction of the total citations received by all versions. Thus instead of counting citations only to the final version of a paper, and also to avoid having to assign a unique paper identifier to every new version of the same paper, SSRN groups all variants of the same paper together into a "version group," and tallies the total number of citations to all versions of the version group. We do this for the *citing* paper and the *cited* paper.

Computing the weighted citation matrix. Assume that authors have unique identifiers $\{1, 2, \ldots ..n_{\text{authors}}\}$. From the raw citation matrix $\mathbf{R}$, we construct a *weighted* cross-citation matrix $\mathbf{Z}$ such that Z_{ij} gives us the weighted number of times that author j has cited author i.

Per the discussion above, the weights are determined as follows. Take a paper X with m authors $x_1, x_2, \ldots, x_m$ that cites a paper Y with n authors $y_1, y_2, \ldots, y_n$. Let $c(X)$ be the number of citations in the bibliography of paper X. Then this citation from paper X to paper Y contributes weights

$$\omega = \frac{1}{c(X)} \frac{1}{m} \frac{1}{n} \tag{4.2}$$

for each author j of paper X to each author i in paper Y. The entry Z_{ij} is the sum of all weights as calculated above for all citations from author j to author i. And if the paper has multiple versions, the above refers to the version group, not any individual paper in the group.

4.2.4 Calculating Eigenfactor Scores for Authors

The Eigenfactor Algorithm models a random walk on the author citation network. This random walk is described by the column-stochastic form of the weighted citation matrix $\mathbf{Z}$. Thus to calculate Eigenfactor Scores, we first normalize $\mathbf{Z}$ by the column sums (i.e., by the total number of outgoing citations from each author) to create a column-stochastic matrix $\mathbf{M}$, which can be written as

$$M_{ij} = \frac{Z_{ij}}{\sum_k Z_{kj}} \tag{4.3}$$

Following Google's PageRank approach [42, 36], we define a new stochastic matrix $\mathbf{P}$ as follows:

$$\mathbf{P} = \alpha\mathbf{M} + (1 - \alpha)\mathbf{A}, \tag{4.4}$$

where

$$\mathbf{A} = \mathbf{a}.\mathbf{e}^T, \tag{4.5}$$

where $\mathbf{a}$ is a column vector such that a_i = (number of articles by author i) / (number of total articles written by all authors in the database) and $\mathbf{e}^T$ is a row vector of 1's.

Under our stochastic process interpretation, the matrix $\mathbf{M}$ corresponds to a random walk on the citation network, and the matrix $\mathbf{P}$ corresponds to a Markov process, which with probability α follows a random walk on the author citation network and with probability $(1-\alpha)$ "teleports" to a random author, proportional to the number of articles published by each author. We teleport to an author with probability proportional to the number of articles (version groups) written by that author in order to avoid over-inflating the influence of authors with small numbers of articles and under-inflating the influence of authors with large number of articles (version groups). We define the weight of each author as the leading eigenvector of $\mathbf{P}$. We compute the leading eigenvector of the matrix $\mathbf{P}$ (with teleportation) rather than using the leading eigenvector of $\mathbf{M}$ (without teleportation) for two reasons:

1. The stochastic matrix $\mathbf{M}$ may be non-irreducible or periodic. Adding the teleport probability $1 - \alpha$ ensures that $\mathbf{P}$ is both irreducible and aperiodic, and therefore has a unique leading eigenvector by the Perron-Frobenius Theorem [39].

2. Even if the network is irreducible without teleporting, rankings can be unreliable and highly volatile when some components are extremely sparsely connected. Teleporting keeps the system from getting trapped in small nearly-dangling clusters by reducing the expected duration of a stay in these small cliques.

However, the teleportation procedure introduces a small but systematic bias in favor of rarely-cited authors, because these authors are visited occasionally by teleportation. The Eigenfactor Algorithm corrects for this directly. Our final author rankings will not be given by the author eigenvector $\mathbf{f}$ but rather by the product of $\mathbf{M}.\mathbf{f}$. Note that as the teleportation frequency α vanishes, $\mathbf{M}.\mathbf{f}$ converges to $\mathbf{f}$. We define the *Author-Level Eigenfactor Score* w_i of author i as the percentage of the total weighted citations that author i receives from our 86,170 source authors. We can write the vector of Author-level Eigenfactor scores as

$$\mathbf{w} = \frac{100\,\mathbf{M}\,\mathbf{f}}{\mathbf{e}^T\mathbf{M}\,\mathbf{f}}. \tag{4.6}$$

4.2.5 Institutional Rankings

The Eigenfactor score $\mathbf{w}$ is an additive metric. To find the Eigenfactor of a group of authors, simply sum the Eigenfactor scores of the authors in the group. Thus, it is straightforward to use the author-level Eigenfactor scores to rank various departments, universities, or other institutions. By this approach, the Eigenfactor score assigned to an institution I_j is simply the sum $I_j = \sum_k w_k$, where w_k is the author-level Eigenfactor score of author k associated with institution I_j.

Notice that the Eigenfactor score computed in this way is not the same as what one would get by operating directly on the institution-level cross-citation matrix. Aggregating up to the institution level, and computing Eigenfactor scores based on an institution-by-institution cross citation matrix imputes uniform weights to the authors within the institution. If, for example, the most highly regarded authors are more likely to cite within the institution, the institution-level aggregation will make it appear as though in-citations are less common than is the actually case under the author-level model.

4.3 Results

4.3.1 Author Rankings

The Eigenfactor Algorithm was independently coded by the Eigenfactor team and the SSRN team in two different programming languages in order to insure accuracy of the results.

There were 86,170 authors ranked by Eigenfactor Scores. The top twenty authors and their institution affiliations are shown in Table 4.1. When summed together, the top twenty authors accounted for 6.8% of the total Eigenfactor Score for all authors. The mean Eigenfactor Score for all 86,170 authors is 0.0012 with a standard deviation of 0.0088. The author-level Eigenfactor scores can be interpreted in the following way: if one were to randomly follow citations in the SSRN database for a very long time, 0.752% of the time would be spent at literature contributed by Andrei Shleifer and his co-authors (see Methods for alternate explanations). That is a significant proportion, given the 86,170 authors in this citation network.

Columns four, five and six indicate the total citation weight given to other SSRN authors, the total citation weight received from other SSRN authors and the number of papers authored or co-authored by each author, respectively (CT_o = Out Citations, CT_i = In Citations, Art = Articles Written). The numbers in these three columns are not integer-valued because of

Table 4.1: The top 20 authors of 86,170 authors ranked by their Author-Level Eigenfactor Scores in the SSRN. A complete list for the top 10,000 authors on SSRN can be found at SSRN.com. EF = Eigenfactor, CT_o = Out Citations, CT_i = In Citations, Art = Articles Written. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

	Author	**EF**	**$\mathbf{CT_o}$**	**$\mathbf{CT_i}$**	**Art.**	**Institution**
1	Shleifer, Andrei	0.752	16.2	298.5	74.6	Harvard University
2	Jensen, Michael C.	0.513	5.7	210.9	77.8	Harvard University
3	Campbell, John Y.	0.440	12.9	165.4	58.3	Harvard University
4	Vishny, Robert W.	0.404	1.7	167.0	17.6	University of Chicago
5	Acemoglu, Daron	0.340	17.1	127.0	87.2	MIT
6	Shavell, Steven	0.336	7.4	127.8	86.7	Harvard University
7	Rajan, Raghuram G.	0.328	14.3	137.9	47.0	University of Chicago
8	La Porta, Rafael	0.327	4.2	139.7	17.7	Dartmouth College
9	Glaeser, Edward L.	0.325	22.6	94.7	94.1	Harvard University
10	Zingales, Luigi	0.310	15.2	144.0	59.0	University of Chicago
11	Heckman, James J.	0.309	8.0	81.6	83.8	University of Chicago
12	Lopez de Silanes, F.	0.300	5.1	124.6	22.4	EDHEC Business School
13	Stein, Jeremy C.	0.274	8.4	104.6	40.1	Harvard University
14	Levine, Ross	0.271	20.8	134.1	47.8	Brown University
15	Harvey, Campbell R.	0.263	19.3	132.5	55.4	Duke University
16	Cochrane, John H.	0.259	8.0	95.7	47.2	University of Chicago
17	Hall, Robert E.	0.258	8.2	72.0	48.9	Stanford University
18	Krueger, Alan B.	0.257	2.7	67.4	55.0	Princeton University
19	Svensson, Lars E.O.	0.246	12.4	107.7	80.8	Sveriges Riksbank
20	Fama, Eugene F.	0.245	8.3	90.5	22.7	University of Chicago

the way citation and article credit are divided among multi-authored papers (see Methods, Equation 4.2).

The cumulative distribution of Eigenfactor Scores for the top 10,000 authors is shown in Figure 4.4. The authors are ordered on the x-axis from highest ranked to lowest ranked (i.e., author 100 was the author that ranked 100th by Eigenfactor Score). The dashed lines indicate the authors at which 50% and 80% of the total Eigenfactor Score is attained. The top 736 authors account for 50% of the Eigenfactor Score, and the top 3,897 authors account for 80% of the Eigenfactor Score. The top 25 authors account for 7.9% of the Eigenfactor Score (not shown in figure).

The Eigenfactor Score can be viewed as a form of weighted citation count where the weights reflect the prestige of the citing documents. Therefore, one would expect the Eigenfactor Scores to correlate with other weighted citation counts. Figure 4.5 shows a log-log plot of Eigenfactor Scores versus the total citation weight Ω for each author. We calculate total citation weight by simply tallying citations, and weighing each author's fractional share as we have done for the Eigenfactor scores, as given in Equation 4.2. Each author i receives citation weight ω from author j. Therefore, the total citation weight for author i is

$$\Omega_i = \sum_j w_j \tag{4.7}$$

Table 4.2 lists the top 20 authors by this criteria:

The red line in Figure 4.5 is a best fit linear regression line on the log data. Despite the correlation ($\rho = 0.89$), an Eigenfactor score near the middle portion of the distribution could be associated with a three-order of magnitude range of citation weights. The converse is even more extreme. These differences result in very different ordinal rankings based on the two different criteria of either ranking by citations or ranking by Eigenfactor.

4.3.2 Network Sparseness

Author citation networks are typically very sparsely connected (i.e., the cross-citation network has many zero entries). However, there are well-

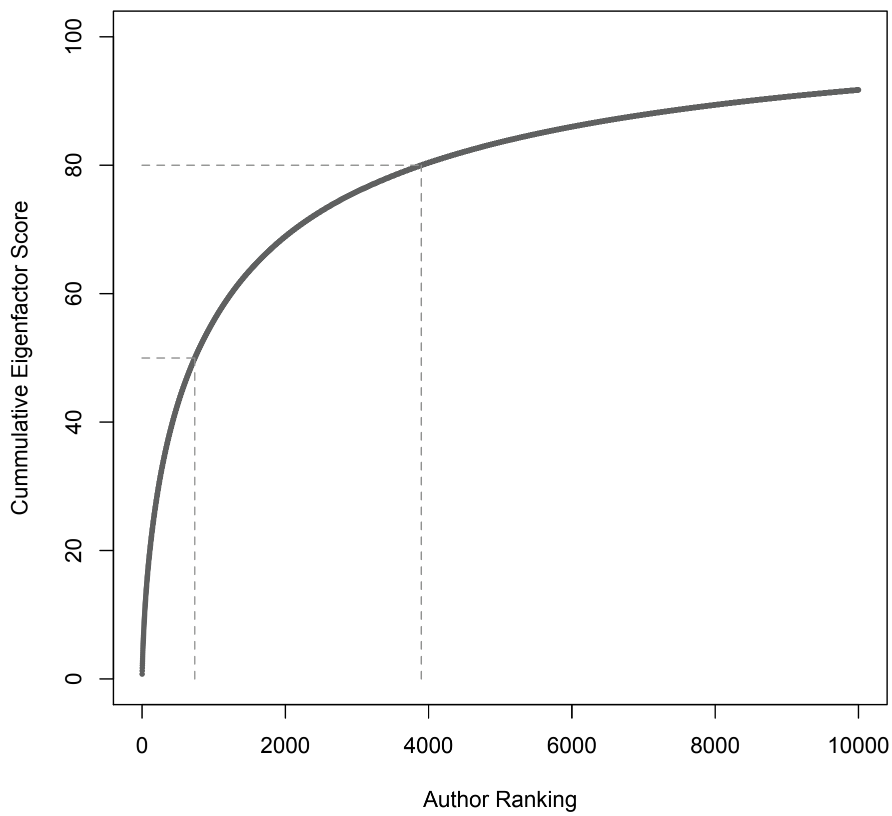

Figure 4.4: Cumulative Distribution of Eigenfactor Score. The figure shows the fraction of the total Eigenfactor accounted for by the first 10,000 authors out of 86,170 total authors. The x-axis lists the author rankings (i.e., author 500 is the 500th highest-ranked author ranked by Eigenfactor). The y-axis is the cummulative Eigenfactor Score. The dashed vertical lines indicate how many authors account for 50% of the total Eigenfactor Score and 80% of the Eigenfactor Score. The 50% line crosses the x-axis at the author ranked 736 and the 80% line crosses the x-axis at the author ranked 3,897. The top 20 authors account for nearly 7.9% of the total Eigenfactor Score (not shown).

Table 4.2: The top 20 authors of 86,170 authors ranked by their total incoming citation weight. CT_i = In Citations. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

	Author	$\mathbf{CT_i}$	**Institution**
1	Shleifer, Andrei	298.5	Harvard University
2	Jensen, Michael C.	210.9	Harvard University
3	Vishny, Robert W.	167.0	University of Chicago
4	Campbell, John Y.	165.4	Harvard University
5	Zingales, Luigi	144.0	University of Chicago
6	La Porta, Rafael	139.7	Dartmouth College
7	Rajan, Raghuram G.	137.9	University of Chicago
8	Levine, Ross	134.1	Brown University
9	Harvey, Campbell R.	132.5	Duke University
10	Shavell, Steven	127.8	Harvard University
11	Acemoglu, Daron	127.0	MIT
12	Lopez de Silanes, Florencio	124.6	EDHEC Business School
13	Svensson, Lars E.O.	107.7	Sveriges Riksbank
14	Stein, Jeremy C.	104.6	Harvard University
15	Cochrane, John H.	95.7	University of Chicago
16	Stulz, Rene M.	95.4	Ohio State University (OSU)
17	Glaeser, Edward L.	94.7	Harvard University
18	Helpman, Elhanan	93.4	Harvard University
19	Fama, Eugene F.	90.5	University of Chicago
20	Gali, Jordi	90.1	Universitat Pompeu Fabra

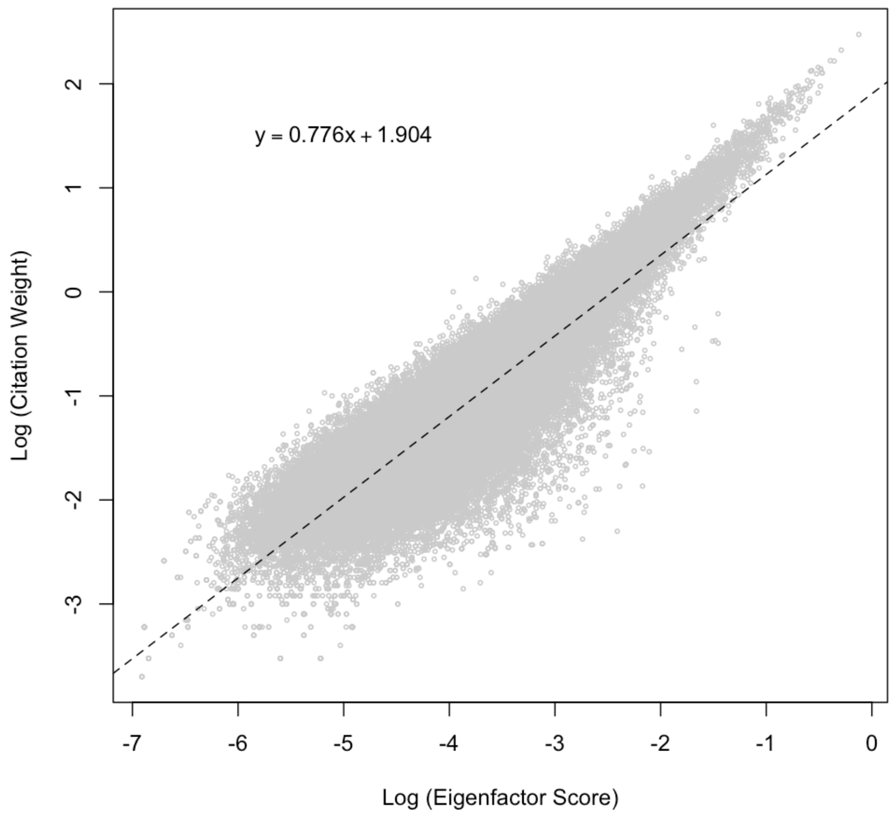

Figure 4.5: Relationship between Eigenfactor Score and total citation weight. The x-axis is the Eigenfactor Score. The y-axis is the total citation weight Ω for each author. The linear regression (dashed line) of log citation weight a on log Eigenfactor score b is given by the following equation: $a = 0.776b + 1.904$. ($\rho = 0.89$)

connected authors that cite a relatively large portion of all the other authors in the database[10]. One contributor, Iftekhar Hasan, cited 1,066 unique SSRN authors. Figure 4.6 illustrates this network sparseness. For the 70,582 authors that cited at least one author in the SSRN (not counting self citations), we counted the number of unique authors cited. The log distribution of this tally is shown in Figure 4.6. There are 79,342 authors (92.1% of all authors) that cite fewer than 100 other different SSRN authors.

Figure 4.7 illustrates the converse; it shows the number of unique SSRN authors citing each author in the database. It addresses the question of which authors receive citations from the largest audience? For example, Andrei Schleifer has received citations from 9,298 different authors. The mean number is 38.3, slightly higher[11] than in Figure 4.7. The distribution is shifted to the left, and the standard deviation is much higher (150.9). Most authors receive citations from relatively few other authors. However, there are authors that receive citations from a significantly large portion of the SSRN author base. Another way to think about it is that 10.8% of all authors in the SSRN community have cited Schleifer. This speaks to the centrality of Schleifer in this particular community. Table 4.3 lists the top twenty authors by this metric.

Many authors either received no citations or gave out no citations —

[10]It should be noted here that this is not total citations given out by an author but the unique number of authors cited. Therefore, these tallies are independent of the number of papers and citations, although an author with a large number of papers and citations would more likely cite a large number of unique authors.

[11]Because of the conservation of total citations, the means in Figure 4.6 and Figure 4.7 are the same (31.3). They are reported differently in the text because for these figures authors that give out zero citations and received zero citations are removed, respectively. This is also why the means for these figures are both higher than 31.3.

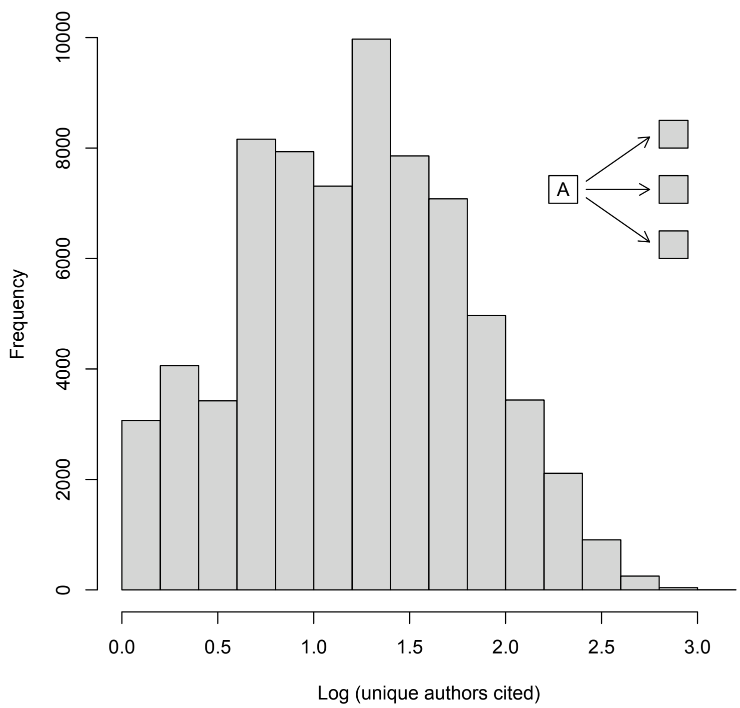

Figure 4.6: Unique Authors Cited. The histogram shows the number of different authors cited by each individual author in the SSRN. The 15,588 authors that cited zero authors (but received citations) are not shown. Most authors cite fewer than 100 different authors. The mean number of authors cited is 38.3 with a standard deviation of 62.0. The network schematic shows the direction of citations being tallied in this figure.

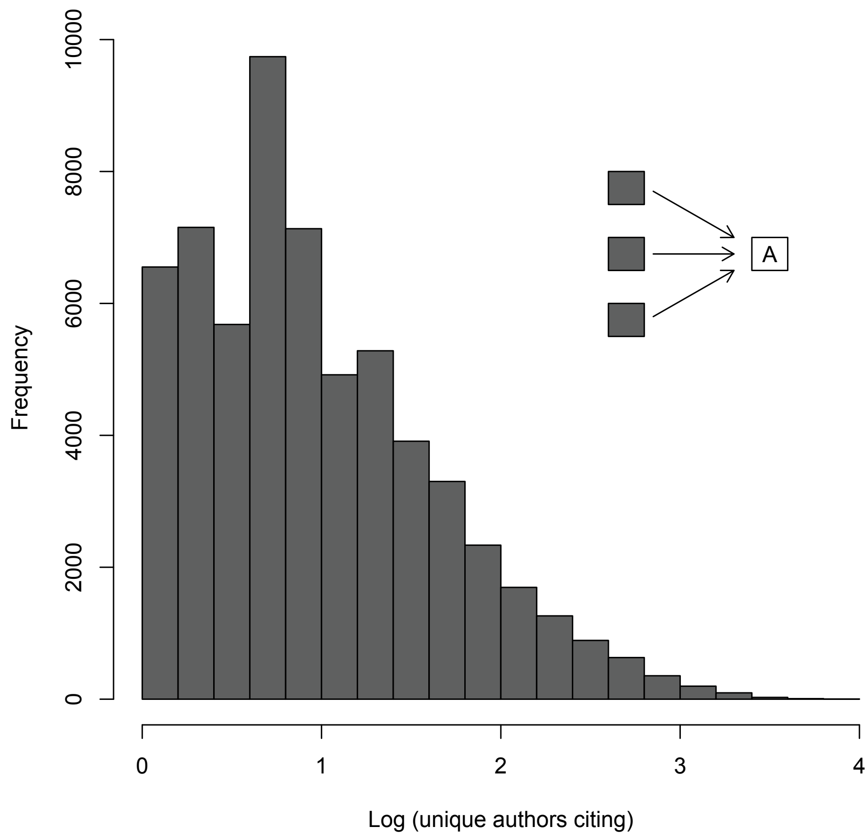

Figure 4.7: Unique Citing Authors. The histogram above is the converse of Figure 4.6. It shows the frequency of different authors citing one individual author (see the network schematic in the figure which shows the direction of citations tallied). Only the 61,173 authors receiving at least one citation are shown. The mean number of unique citing authors is 44.1 and the standard deviation is 170.2.

Table 4.3: The top 20 authors cited by the largest number of unique authors. This table enumerates the members of the right-hand tail in Figure 4.7. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

	Author	**Unique Authors**	**Institution**
1	Shleifer, Andrei	9,298	Harvard University
2	Jensen, Michael C.	7,524	Harvard University
3	Vishny, Robert W.	7,395	University of Chicago
4	La Porta, Rafael	5,196	Dartmouth College
5	Fama, Eugene F.	5,084	University of Chicago
6	Lopez de Silanes, Florencio	5,002	EDHEC Bus. School
7	Zingales, Luigi	4,396	University of Chicago
8	Rajan, Raghuram G.	4,375	University of Chicago
9	Meckling, William H.	4,357	University of Rochester
10	Campbell, John Y.	4,354	Harvard University
11	Stulz, Rene M.	3,999	Ohio State University
12	Barro, Robert J.	3,951	Harvard University
13	Stein, Jeremy C.	3,839	Harvard University
14	Harvey, Campbell R.	3,697	Duke University
15	Stock, James H.	3,524	Harvard University
16	Blanchard, Olivier J.	3,519	MIT
17	Poterba, James M.	3,491	MIT
18	Levine, Ross	3,474	Brown University
19	Acemoglu, Daron	3,440	MIT
20	French, Kenneth R.	3,399	Dartmouth College

or both. There were 15,588 authors that received citations but gave out no citations. These authors in a citation network are known as dangling nodes. Conversely, there were 24,997 authors that gave out citations but received no citations. There were no authors that both gave out zero citations and received zero citations; these authors were eliminated before the 86,170 x 86,170 matrix was created. Also, authors with zero articles were eliminated before the construction of the adjacency matrix or authors that have abstracts but no full text documents in the SSRN eLibrary.

4.3.3 Ranking Institutions

Thousands of institutions from around the world are represented in the SSRN database. Most of these institutions are universities or university departments, but there are other types of institutions such as aggregators (e.g., NBER, CEPR, ECGI, IZA, and CESifo)[12]. Using the author-level Eigenfactor Scores, these universities and departments can be ranked. This analysis was performed on 5,946 different institutions. Table 4.4 lists the top twenty institutions by Eigenfactor Score.

Just as universities can be ranked with this method, so can countries. There are 127 countries represented in the SSRN. The top twenty can be found in Table 4.5. The United States carries 77% of the total Eigenfactor for all countries. As with author rankings, it is important to understand this is a measure of centrality to the SSRN rather than a measure of the relative overall productivity of researchers in various countries.

4.3.4 Usage vs citations

Citation counts are not the only way to assess the quality or impact of scholarly work, and indeed they may systematically undervalue certain papers that are widely read by authors, students or practitioners but less often cited in the subsequent research literature[14]. In addition to tracking citations, SSRN has collected usage data as well, tracking every single download of every single paper in the archive since the archive's inception. We can use

[12]Because these organizations do not employ the authors whose papers they aggregate, we do not compare them directly to institutions like universities and other research institutions that do employ the authors that are affiliated with these aggregator research institutions.

Table 4.4: The top 20 research universities and other academic institutions ranked by SSRN authors. There were 5,946 institutions ranked. A complete list can be found at SSRN.com. $\sum EF$ = Sum of SSRN Author-Level Eigenfactor Scores associated with that institution. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

Rank	**Institution**	$\sum$ **EF**
1	Harvard University	8.73
2	University of Chicago	5.01
3	Massachusetts Institute of Technology (MIT)	3.60
4	New York University	3.44
5	University of California, Berkeley	3.10
6	Stanford University	2.83
7	Columbia University	2.62
8	University of Pennsylvania	2.38
9	Princeton University	2.29
10	Yale University	2.12
11	Northwestern University	1.77
12	Federal Reserve Banks	1.77
13	International Monetary Fund (IMF)	1.58
14	Dartmouth College	1.57
15	World Bank	1.54
16	Government of the United States of America	1.52
17	Duke University	1.29
18	University of Michigan at Ann Arbor	1.25
19	University of California, Los Angeles (UCLA)	1.23
20	London School of Economics & Political Science (LSE)	1.02

Table 4.5: The top 20 countries represented in the SSRN database, ranked by Author-Level Eigenfactor Scores. There were 113 countries represented in the database. A complete list can be found at SSRN.com. $\sum EF$ = Sum of SSRN Author-Level Eigenfactor Scores associated with that country. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

Rank	**Country**	$\sum$ **EF**
1	United States	77.24
2	United Kingdom	4.16
3	Germany	1.78
4	Canada	1.46
5	France	1.41
6	Italy	1.14
7	Switzerland	1.09
8	Netherlands	1.01
9	Israel	0.97
10	Spain	0.95
11	Sweden	0.85
12	Albania	0.67
13	Australia	0.63
14	China	0.49
15	Belgium	.41
16	Denmark	.023
17	Korea	0.20
18	Bulgaria	0.20
19	Japan	0.19
20	Norway	0.18

these data to rank authors by downloads. Table 4.6 lists the top 20 authors by this metric. Each time a paper is downloaded, the authors of that paper receive credit for that download. The credit is divided evenly among the authors, similar to how citation credit is distributed (see Methods). The download weight is simply the sum of this weight for each author in the SSRN[13].

Comparing Table 4.2 to Table 4.6, the top 20 lists change dramatically, indicating that downloads and citations provide different information. Researchers in bibliometrics have explored the relationships between citations and usage for several data sets; in general, citation measures and usage measures are positively correlated but provide complementary information about the influence of scholarly papers [35, 15, 13, 57]. Figure 4.8 is a log-log plot that shows author-level Eigenfactor Scores plotted against the "download weight" for each author. Download weight is a weighted form of total downloads, with weights dividing credit equally among authors so that a paper with 3 authors and 300 downloads contributes a score of 100 to each author.

We collected download information for the same 86,170 authors included in the citation network. The average number of downloads for these authors is 705.6, with a standard deviation of 3428.2. When the credit is divided among the authors (as explained in previous paragraph), the average is 384.7 and the standard deviation is 2184.2. The maximum download weight attained up to this point is 300,322 (accomplished by one of the authors of

[13]SSRN goest to great lengths to ensure that reported downloads are free of biases caused by bots, search engines, or gaming.

Table 4.6: The top 20 authors by downloads per author. The weight for each downloaded paper is distributed evenly among the authors (i.e., an author will receive half a download if they co-author a paper with one other author). The downloads shown in the table is the sum of this weight for each author. A complete list can be found at SSRN.com. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

	Author	**Downloads**	**Institution**
1	Jensen, Michael C.	300,322.12	Harvard University
2	Fernandez, Pablo	200,550.08	University of Navarra
3	Fama, Eugene F.	176,373.45	University of Chicago
4	Velez-Pareja, Ignacio	124,042.96	Univ Tecnologica de Bolivar
5	Solove, Daniel J.	119,976.50	George Washington University
6	Bruner, Robert F.	110,471.78	University of Virginia (UVA)
7	French, Kenneth R.	85,399.17	Dartmouth College
8	Bebchuk, Lucian A.	85,086.42	Harvard University
9	Goetzmann, William N.	68,465.07	Yale University
10	Castronova, Edward	67,984.33	Indiana Univ. Bloomington
11	Lott, John R.	66,524.67	University of Maryland
12	Bainbridge, Stephen Mark	63,295.83	UCLA
13	Sunstein, Cass R.	63,154.87	Harvard University
14	Meckling, William H.	59,753.17	University of Rochester
15	McGee, Robert W.	57,461.33	Florida International Univ.
16	Black, Bernard S.	56,655.45	Northwestern University
17	Faber, Mebane T.	56,231.00	Unaffiliated Authors
18	Lemley, Mark A.	53,060.62	Stanford University
19	Penman, Stephen H.	52,890.04	Columbia University
20	Lo, Andrew W.	52,752.20	MIT

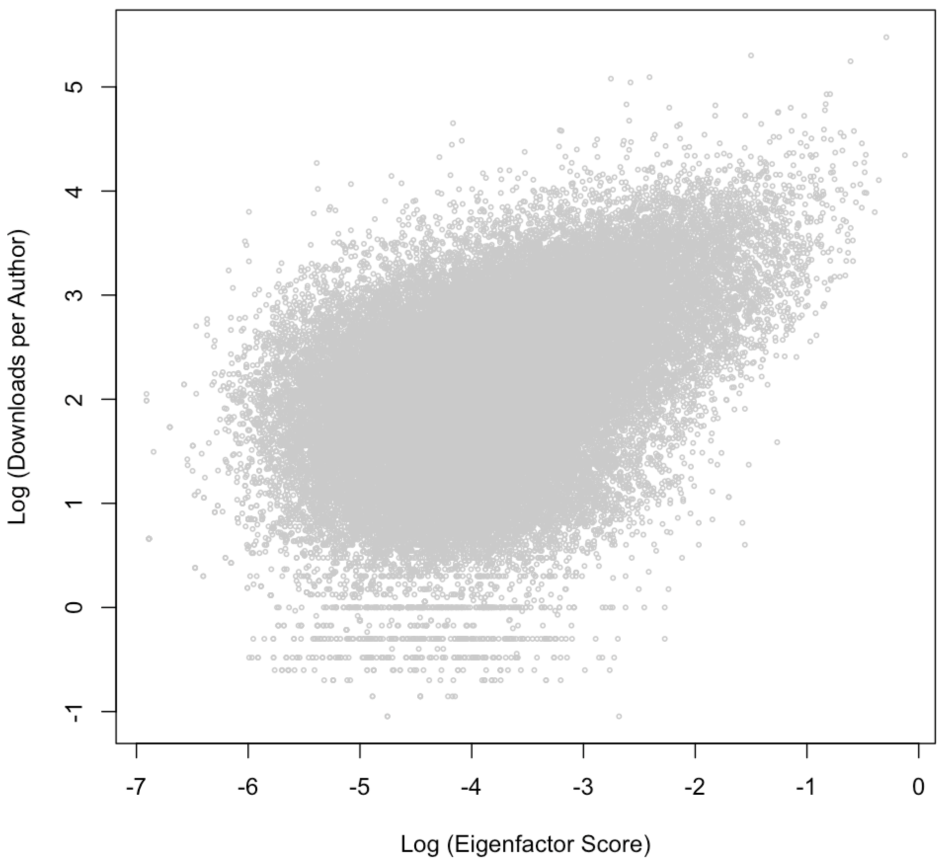

Figure 4.8: Downloads vs Eigenfactor Scores for SSRN authors. In this log-log plot, each data point represents an author and their corresponding Eigenfactor Score and number of downloads per Author. There are 50,233 authors represented in this figure. Authors that have an Eigenfactor Score of zero or have zero downloads are not shown.

this paper).

The Pearson's linear correlation coefficient between Eigenfactor and downloads is 0.466. The correlation between Eigenfactor and download weight is $\rho = 0.461$. Thus, we see that Eigenfactor scores provide considerable information above and beyond that available from download scores and vice versa. There are scholars that have a relatively high Eigenfactor Scores but few downloads; in many cases this occurs because the paper is available from other sources such as the NBER or CEPR servers and because NBER and CFPR charge non-members $5 for downloading NBER and CEPR papers on SSRN, while most of the rest of the papers on SSRN can be downloaded at no cost. There are also authors (such as Fairmain with his classic treatise "Fuck" [23]; see also [24] for the impact of that oft-downloaded article on institutional rankings) who have written papers that are downloaded a large number of times for various reasons but receive relatively few citations.

There are 20,759 authors that have an Eigenfactor Score of zero but have a nonzero number of downloads per author. This means that there are many papers in the SSRN that are downloaded and viewed but are not cited. There are no authors that had zero downloads but a nonzero Eigenfactor Score. This occurs because no citations are counted in SSRN unless the full text paper is available on SSRN.

Usage data can also be used to rank institutions. Table 4.7 shows the top 20 institutions ordered by download weight. The $\sum \mathbf{D}$ was calculated by summing the download weight for every author associated with each institution. As with author rankings, institutional citational ranks differ substantially from institutional download ranks.

Table 4.7: The top 20 research universities and other academic institutions ranked by author downloads. There were 5,946 institutions ranked. A complete list can be found at SSRN.com. $\sum D$ = Sum of SSRN Author-Level Download Weight associated with that institution. *Note: These rankings are preliminary and incomplete (05/27/10). Citations to and from legal scholars are substantially undercounted until CiteReader has completed the extraction of references in footnotes in legal papers in the SSRN eLibrary. These rankings will change as the task is completed.*

Rank	**Institution**	$\sum$**D**
1	Harvard University	1,395,085.95
2	University of Chicago	825,794.72
3	New York University	680,270.35
4	Yale University	653,609.49
5	Columbia University	552,881.43
6	World Bank	484,480.50
7	University of Pennsylvania	479,531.53
8	Massachusetts Institute of Technology (MIT)	446,829.69
9	Stanford University	439,257.11
10	University of Virginia (UVA)	413,694.73
11	International Monetary Fund (IMF)	389,620.21
12	Duke University	377,830.67
13	University of California, Berkeley	354,032.59
14	University of California, Los Angeles (UCLA)	327,435.03
15	George Washington University	326,110.12
16	University of Michigan at Ann Arbor	306,579.04
17	Government of the United States of America	304,925.15
18	Federal Reserve Banks	296,349.09
19	University of Navarra	267,593.82
20	University of Illinois at Urbana-Champaign	258,415.56

4.3.5 The arrow of time

One particular challenge with iterative ranking algorithms at the paper level is the time-directionality of citation networks: any given paper cites only papers published earlier than it. Therefore, a random walker following citations will progressively move backwards in time. One way to counter this effect is to bias the teleport process toward more recent publications [54]. In principle, the same problem could arise for author-level networks if they extend over sufficiently long time intervals; Alfred Marshall never cited Paul Samuelson. Random walks on the author network will tend to move backward in time and thus earlier authors may receive a disproportionate number of visits and thus a disproportionately high score.

In practice, this does not turn out to be a major problem for the SSRN corpus, given its relatively narrow time window (1998 to present[14]) and the fact that most authors with early papers in the database remain active in the community at present. Thus we do not need to employ any sort of time-biased teleport mechanism in the article-level Eigenfactor rankings that we compute for the SSRN. To check this we looked at the distribution of papers dates[15] immediately after teleport, one step after teleport, etc. If

[14] Authors can and do submit papers with dates earlier than 1998. As time goes on, more early papers will be uploaded to SSRN; however, if those earlier papers are from authors still active in the SSRN community, we don't expect our random walker to progressively move backwards in time.

[15] The 'paper date' is the first available date that we could find for each paper. The date would be the earliest of the following: (1) paper date, (2) date the paper was entered into the SSRN system, or (3) date shown on any citation that is matched to the paper. If a paper was entered in 2000 but has a paper date of 1975, then 1975 is the date used for the paper. If a paper was entered in 2000, has an unrecognizable paper date, but has a citation that indicates that is was written in 1975, then 1975 is used. The earliest date of these three scenarios is always used. This is especially useful when dealing with multiple versions of a paper.

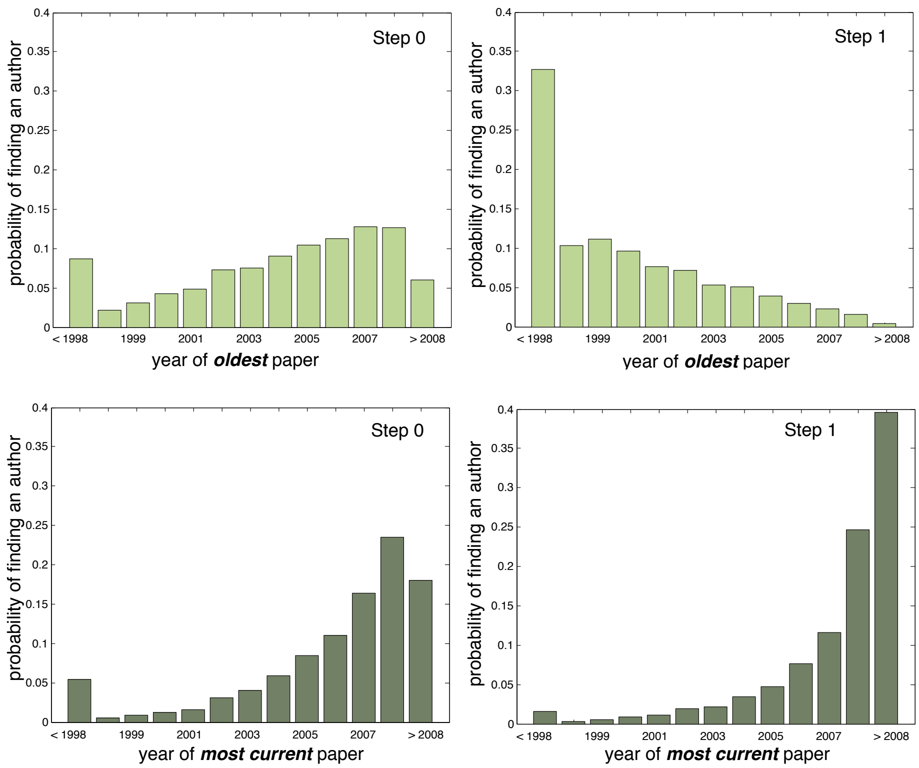

Figure 4.9: The probability distribution of finding an author with their oldest paper (top panels) and most current paper (bottom panels) in each of the last ten years, after teleportation and one step after teleportation. After one step on the network, their is a higher probability of finding an author with a paper before 1998, but the probability is higher still of finding an author —possibly the same author — with a paper subsequent to 2008.

the random walk tended to drift back in time, we would see that, as we take more random walk steps, the distribution of paper dates would shift to earlier years. Figure 4.9 shows the distribution of authors' earliest papers (top panel), and most recent papers (bottom panel) after teleport (0 steps) and after a single step on the network[16]. After one step, the distribution of the oldest paper is shifted back in time, but this does not in and of itself indicate strong overall backward movement. In fact, the distribution of the most recent paper actually shifts forward in time after a step on the network. This means that the random walk process moves us toward authors with older papers in the database–but these same authors also have more recent papers as well. This is less counterintuitive than it seems; the random walk process moves toward authors with more papers overall and thus we should not be so surprised to see a broader range of dates for these authors.

4.4 Discussion

The SSRN community, like other on-line archives, performs an important function for the scholarly community. By facilitating the distribution of working papers and by making author-submitted manuscripts at all stages easily available and at zero cost, SSRN reduces the time that it takes for an idea, first conceived in one scholar's mind, to become a part of the conversations among many scholars around the world. With the work described in this paper, we aim to provide a similar service to the academic community. The infrastructure at SSRN aids the *delivery* process: it makes it easy to

[16]The distributions change very little for higher numbers of steps and thus are not shown.

find a paper once you know that you want to read it.

Using bibliometric analyses of the sort developed here, we can also aid the *discovery* process, helping people discover papers that they would like to have read. As Eugene Garfield recognized in 1955 [28], the latticework of citations in scholarly publications offer a valuable reference tool in their own right; users can follow citations backward in time to pursue the origins of the ideas presented in a paper, and forward in time to see the subsequent development of those ideas. Indeed, SSRN makes this very easy now. Each abstract page has on it a tab that allows readers to look backward in the literature by presenting the references of the current paper (with links where available) and allows readers to look forward in the literature by providing a tab that presents links to the citing papers. In effect these tabs provide a very useful search technology.

Just as Google's PageRank algorithm helps with the discovery process on the world wide web by filtering search results, the Eigenfactor metrics described here can help with the discovery process within this citation network. Properly integrated with other search tools and algorithms, the Eigenfactor metrics can help users to find important papers that may have been overlooked by other ranking methods based on downloads or reputation. Such applications in discovery provide a major motivation for the present work. We have ongoing research in this area.

Rather than running the Eigenfactor Algorithm on the full network, we can apply the algorithm to any subset of the citation network, such as those authors affiliated with one particular institution or country, to get rankings specific to the interests of that group. Librarians and other collection agencies could analyze their own specific subscriptions. Departments and colleges could look at intra-college citations among their faculty to look at how closely their faculty are working together and who is most central to the collaborative work being done. Journal societies and associations could use these algorithms to find the active members—who is citing and who is being cited by their members. Other online archives like SSRN could find who is being read in their collections and what groups are contributing to their particular field. There are many ways that reference networks can be analyzed using the Eigenfactor metrics and related approaches.

Finally, it is important to recognize what these statistics do and do not represent. Eigenfactor is not a direct measure of quality. Rather, Eigenfactor is (as discussed above) one of a family of network centrality measures. The Author-Level Eigenfactor Scores presented here measure the *centrality* of authors within the particular network (SSRN) that we study. For example, notice that of the top 10 authors in Table 4.1, half of them are associated with Harvard University. While all of these individuals are influential academics by any measure, the preponderance of Harvard faculty at the top of the list probably reflects the origins of SSRN at Harvard and thus the centrality of this group of researchers in the broader network they have formed around themselves. The same caution should also be applied to the institutional rankings derived here.

For our purposes, these rankings are simply one of many filters that can be applied to a large, seemingly unmanageable data set. We believe that pre-print and post-print archives such as SSRN are extremely useful for the scholarly community and for the quick dissemination of new ideas and papers. Ultimately, we would like to use filters like these to build better search algorithms that help researchers mine the vast, and ever-expanding scholarly literature.

4.5 Conclusion

We would like to conclude with a more general note about the act of ranking. Ranking papers, authors, journals, departments, or institutions does not necessary make the world a better place. Indeed, where ranking systems provide narrow-minded administrators and faculty with an excuse to avoid hard work and deep thought, they may even be harmful to the functioning of academia. Then why rank at all? While ranking for its own sake may or may not offer net benefits to the community, ranking in the service of search will unquestionably improve our ability to do science. Search engines such as Google have fundamentally changed scholarship by improving our ability to find the information that we value, rapidly and efficiently. Ranking algorithms such as PageRank lie at the heart of these search engines — effective search requires that we account for not only the match of search terms to target document, but also for the importance of the target document within a larger collection. It is our hope and belief that advances in ranking will serve our quest for more efficient search, helping academics sift through ever-growing volumes of information to find the hidden gems and lost papers that are valuable for their research endeavors.

Chapter 5

Eigenfactor.ORG

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Keywords: Eigenfactor^{TM} Metrics, Eigenfactor^{TM} Score, Article Influence^{TM} Score, Scholarly Communication

Abstract

To date, there is no definitive paper on the Eigenfactor Metrics yet the work has received considerable recognition by the academic community in a relatively short amount of time. Does this mean that traditional forms of scholarly communication are outdated? Not necessarily, but I do contend in this short paper that a key ingredient of Eigenfactor.org has been the ".ORG" part. Instead of writing a scientific paper describing how one could use the entire citation network to rank journals, we simply did it and then put the results on the web for the world to see. My experience has been that by doing this, the idea has been recognized far more than it would have been sitting in some low or even high impact journal.

5.1 Introduction

In the previous four chapters, I have talked about what the Eigenfactor Algorithm is (Chapter 1), what it measures (Chapter 2), how it differs from Impact Factor (Chapter 3) and how it can be extended to author-level citation networks (Chapter 4). This chapter will focus on a slightly different aspect of the Eigenfator Project. It will focus on the implementation and presentation of the Eigenfactor project. This has been critical to the success of the project, and I think the lessons learned from this component reflect the changing landscape of scholarly communication[1].

If the idea of Eigenfactor would have been born just one decade earlier, it would likely have been published in a conventional academic journal . A few scholars may have come across the paper, but the chances of Eigenfactor being used by librarians, administrators, publishers, editors and scholars around the world would have been very low. What did the extra decade provide for this idea? The World Wide Web. Instead of talking about this idea of using a pagerank approach to evaluate scholarly journals, we did it and then used existing web technologies to display our results (`www.eigenfactor.org`). This aspect of the Eigenfactor story has been critical to its success and encourages me to reflect on these alternative forms of scholarly communication for my future work in science.

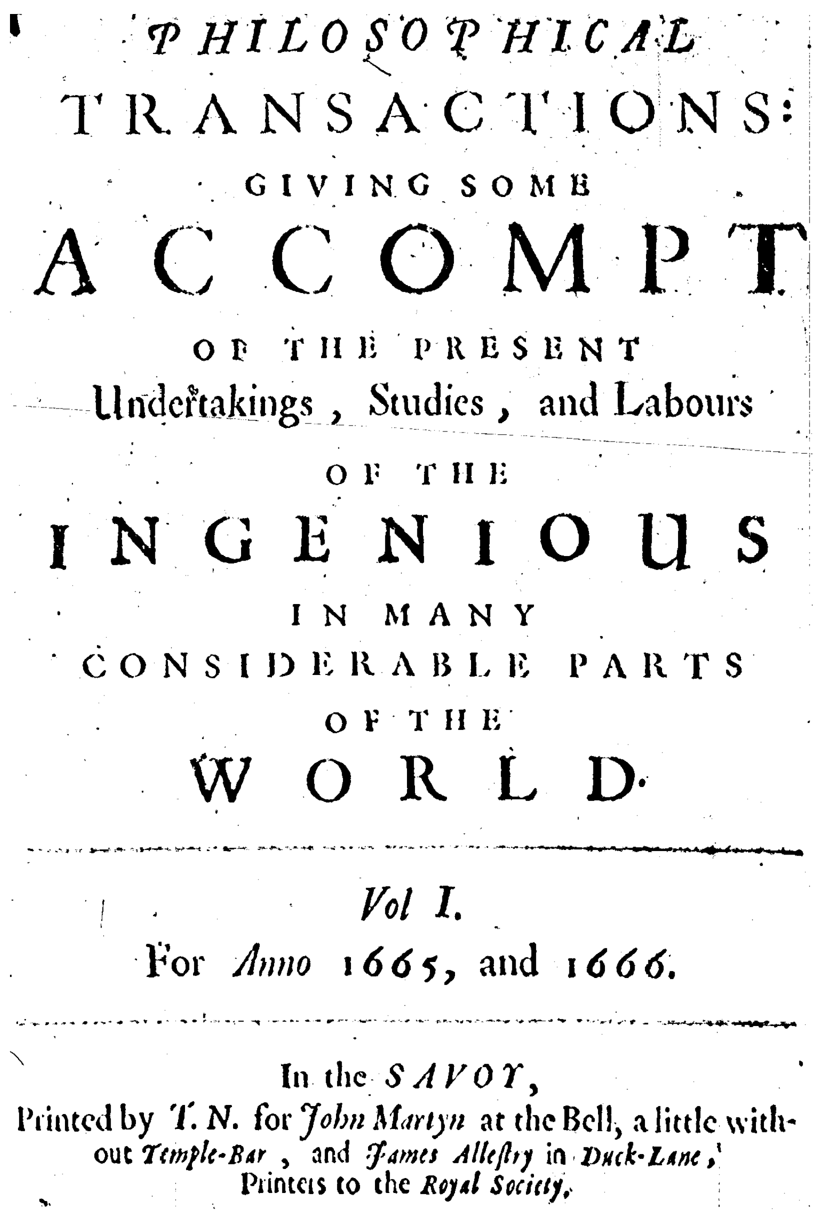
[1] I am writing this chapter in first person because this chapter is a chapter of reflections. It is not a chapter of data or hypotheses. I see my dissertation as a medium for telling the parts of the Eigenfactor story that otherwise would not be told in any journal article or book chapter. And, it is the story of this chapter that has been so critical to the success of this project.

5.2 The changing landscape of scholarly publication

Scientific scholarship depends on a system of communication. Ever since the first issue in 1665 of the *Philosophical Transactions of the Royal Society*, the scientific periodical has been one of the pillars of this system of communication (Figure 5.1). Other forms have existed (e.g., conference proceedings, books, etc); however, publishing in a high impact journals has carried the most prestige in most fields of science for the most part of the last three centuries.

The high impact journals reward authors with three things: a large audience, peer review and peer recognition[2]. The currency of scholarship is recognition; therefore, scientists are willing to work very hard to publish their ideas in these journals. How does one receive recognition? People first have to read what is to be recognized. Maximizing readership is a goal of most scholars. But it is not just a large audience that drives scientists to *Nature* and *Science*. These journals also attract some of the best reviewers in their respective fields. This has two consequences. One, it offers opportunities to greatly improve an author's paper. And, two, it creates a general attitude that good journals are more difficult to publish in. A paper published in a high ranking journal is recognized by peers, especially those peers making tenure and promotion decisions.

[2]Some may claim that journals not only provided a means of disseminating ideas but also provide a reliable repository. In that case, journals also reward authors with a place to dependably archive their ideas for future generations. I will focus on the transmittance rewards for this paper.



PHILOSOPHICAL

TRANSACTIONS:

GIVING SOME

ACCOMPT

OF THE PRESENT

Undertakings, Studies, and Labours

OF THE

INGENIOUS

IN MANY

CONSIDERABLE PARTS

OF THE

WORLD.

Vol I.

For *Anno* 1665, and 1666.

In the *SAVOY*,

Printed by *T. N.* for *John Martyn* at the Bell, a little without *Temple-Bar*, and *James Allestry* in *Duck-Lane*, Printers to the *Royal Society*.

Figure 5.1: The cover of the first issue of the *Philosophical Transactions of the Royal Society.* This is considered one of the first issues of a scholarly journal ever published. The copyright has expired on this image and is in the public domain.

In my graduate student lifetime, the digital revolution has offered more options for maximizing the readership reward. The open access movement has produced journals like *PLoS One*, which aim to maximize readership by removing the cost for readers. The World Wide Web has offered a medium where scientists can report findings and discuss new ideas on blogs and personal websites. Neither of this modes of communication have achieved the peer recognition status of *Nature* and *Science*. But will increased exposure over time eventually lead to open access journals and web technologies as viable forms of scientific communication? The Eigenfactor example is one case study.

5.3 Publish or Perish?

When Carl Bergstrom, Ted Bergstrom and I came up with the idea of using the entire network to rank scholarly journals back in 2005, we first thought (as any good academic would) "we need to write this up." That was in 2005; it is now 2010 and we still have not written the definitive paper on Eigenfactor. So, what explains the widespread success[3] of the project? Both Carl and I have been invited to speak about Eigenfactor at conferences and meetings around the world[4]. Thomson-Reuters has adopted the metric and placed it alongside Impact Factor in the Journal Citation Reports (see

[3]'Success' is a sticky term. It can mean many different things to different people. Some could easily argue that Eigenfactor was not a success. In this chapter, I equate 'success' with the number of articles and places using or mentioning Eigenfactor. I understand that this is not the best proxy of success, but I want to stress that this chapter is not about the success of Eigenfactor. This chapter is really about alternative forms of scholarly communication, and I am using the Eigenfactor story as a way of supporting this claim.

[4]A list of some of the invited talks can be found here `http://octavia.zoology.washington.edu/people/jevin/Presentations.html`

Figure 5.2). The Scholarly Publishing and Academic Resources Coalition (SPARC) awarded Carl and Ted Bergstrom the annual SPARC Innovator Award[5] based on the work at `journalprices.com` and `eigenfactor.org`. One of PNAS's most downloaded articles of all time is about Eigenfactor[6]. A radial diagram displaying Eigenfactor data has been on the cover of one of the largest academic journals in the world[7]. Google has located over 7 million instances of "Eigenfactor" – a word that didn't exist just 5 years ago[8].

"Publish or perish." If this is true, does this advice apply only to researchers or does it also apply to the research itself? In the digital age, is it necessary to communicate one's findings in a high impact journal in order to get noticed by the rest of the academic community? Or, are there better ways to get one's ideas noticed? In a climate of limited research funding, how important is the training of graduate students in all forms of scholarly communication? Based on my experience working on the Eigenfactor Project, I will address these questions and specifically aim to answer the following: given that no definitive paper has been written on Eigenfactor, what is the source of its recognition?

I see four, possible (non-mutually exclusive) explanations that I will address in turn:

- Eigenfactor as a tool
- Eigenfactor.org

[5]http://www.arl.org/sparc/innovator/bergstroms.shtml
[6]http://www.pnas.org/content/106/17/6883.full
[7]http://www.jbc.org/content/284/19.toc
[8]Search was conducted on August 2, 2010

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Journals 1 - 20 (of 161)

[1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9]

Page 1 of 9

MARK ALL UPDATE MARKED LIST

Ranking is based on your journal and sort selections.

Mark	Rank	Abbreviated Journal Title (linked to journal information)	ISSN	JCR Data						Eigenfactor™ Metrics	
				Total Cites	Impact Factor	5-Year Impact Factor	Immediacy Index	Articles	Cited Half-life	Eigenfactor™ Score	Article Influence™ Score
	1	ACTA CYTOL	0001-5547	2657	0.690	0.800	0.293	123	>10	[illegible]	[illegible]
	2	ACTA HISTOCHEM	0065-1281	795	1.234	1.211	0.357	56	7.3	0.00198	0.356
	3	ACTA HISTOCHEM CYTOC	0044-5991	242	1.675	0.792	0.111	27	5.4	0.00067	0.208
	4	ADV ANAT EMBRYOL CEL	0301-5556	382	2.211	2.677	0.455	11	>10.0	0.00059	0.910
	5	AGEING RES REV	1568-1637	1170	5.622	6.328	1.500	32	4.5	0.00504	1.933
	6	AGING CELL	1474-9718	2564	7.554	7.207	0.871	70	3.0	0.01819	2.906
	7	AM J PHYSIOL-CELL PH	0363-6143	16835	4.013	4.128	0.788	288	7.0	0.05379	1.502
	8	AM J RESP CELL MOL	1044-1549	9930	4.319	4.389	1.308	156	7.2	0.02843	1.561
	9	ANIM CELLS SYST	1976-8354	18	0.415	0.415	0.018	57		0.00002	0.025
	10	ANNU REV CELL DEV BI	1081-0706	8328	19.571	25.533	0.704	27	7.0	0.04390	15.587
	11	APOPTOSIS	1360-8185	3862	4.066	3.802	0.960	124	3.7	0.01816	1.206
	12	ARCH HISTOL CYTOL	0914-9465	959	0.875	1.613	0.000	12	>10.0	0.00193	0.550
	13	AUTOPHAGY	1554-8627	3197	6.829	6.917	1.376	149	2.2	0.02453	2.722
	14	BBA-MOL CELL BIOL L	1388-1981	4858	4.357	4.092	1.021	141	5.2	0.01918	1.503
	15	BBA-MOL CELL RES	0167-4889	7018	4.374	5.275	1.508	195	4.6	0.04008	2.273
	16	BIOCHEM CELL BIOL	0829-8211	2678	2.605	3.126	0.550	80	6.8	0.01022	1.263
	17	BIOL CELL	0248-4900	2396	3.974	3.789	1.135	52	5.6	0.01148	1.657
	18	BIOL MEMBRANY	0233-4755	143	0.175	0.210	0.040	50	8.3	0.00017	0.030
	19	BIOSCIENCE REP	0144-8463	1213	3.061	2.689	0.692	39	8.5	0.00260	0.841
	20	BIOTECH HISTOCHEM	1052-0295	396	0.667	0.983	0.079	38	9.6	0.00076	0.303

MARK ALL UPDATE MARKED LIST

Journals 1 - 20 (of 161)

[1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9]

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Figure 5.2: A snapshot of Thomson-Reuters Journal Citation Reports. The Eigenfactor Metrics are now included in the annual report alongside Impact Factor.

- Need for alternative metrics
- Information visualization

5.3.1 Eigenfactor as a tool

Eigenfactor is something that people use. Librarians use it to make collections decisions. Publishers use it to compare their journals to their competitors. Scholars use it to make decisions on which journals give them the biggest bang for the article. Eigenfactor is *not* a discovery about the world. It is a statistical tool for identifying important nodes in citation networks. Those nodes can be journals, authors, institutions or papers.

This distinction between a tool and a discovery explains part of the response Eigenfactor has received. When Eugene Garfield introduced Impact Factor [28, 26, 27], it wasn't that he discovered some deep, important law of the universe; he developed a statistic that has become very popular for identifying important journals (that publish those deep, important laws of the universe).

The same goes for Eigenfactor. It is another way of ranking the relative influence that each scholarly journal is having on the moving frontier of science. These rankings can be very useful for academia and industries associated with academia. This is one of the big reasons for the attention Eigenfactor has received.

This is very similar to the Impact Factor response; however, there are differences between the two. In addition to the algorithmic variations (see Chapter 2), Eigenfactor and Impact Factor differ in their approach to the problem itself. Impact Factor is a degree centrality measure, whereas Eigenfactor is an eigenvector centrality measure. This has important philosophical differences. Impact Factor does not care about the network; for the Eigenfactor algorithm, it is the network that matters (and, more specifically, the *whole* network). This 'whole-network' approach to citation data has lead to other developments, most notably the map equation and mapequation.org[9] [49, 50, 48, 51]. Combining these network measures and mapping techniques, the next application of this Eigenfactor 'tool' will be to build better ways of navigating large networks like the scholarly literature.

In sum, Eigenfactor is a tool that people use. This partly explains the high traffic to Eigenfactor.org. But it is not popular *just* because it's just a tool. It's a tool that has been used to rank journals, inspire maps of science and better navigate the scholarly literature.

5.3.2 Eigenfactor.org

Using citation data from Thomson-Reuters' Journal Citation Reports, we calculated Eigenfactor Scores and Article Influence Scores for over 8,000 journals. We then built a website with the help of Ben Althouse, an undergrad in our lab at the time, registered the website and put the scores up for the world to see (Figure 5.3). We have been tracking our visitors since the inception of Eigenfactor.org. When the site first went up in January of 2006 (check date), users trickled in mainly by word of mouth. We now receive thousands of visitors a day[10]. According to Google Scholar, the *College*

[9] Details can be found at `www.mapequation.org`

[10] On average, the site receives about 1.5 million hits per month and more than 80,000 visits per month

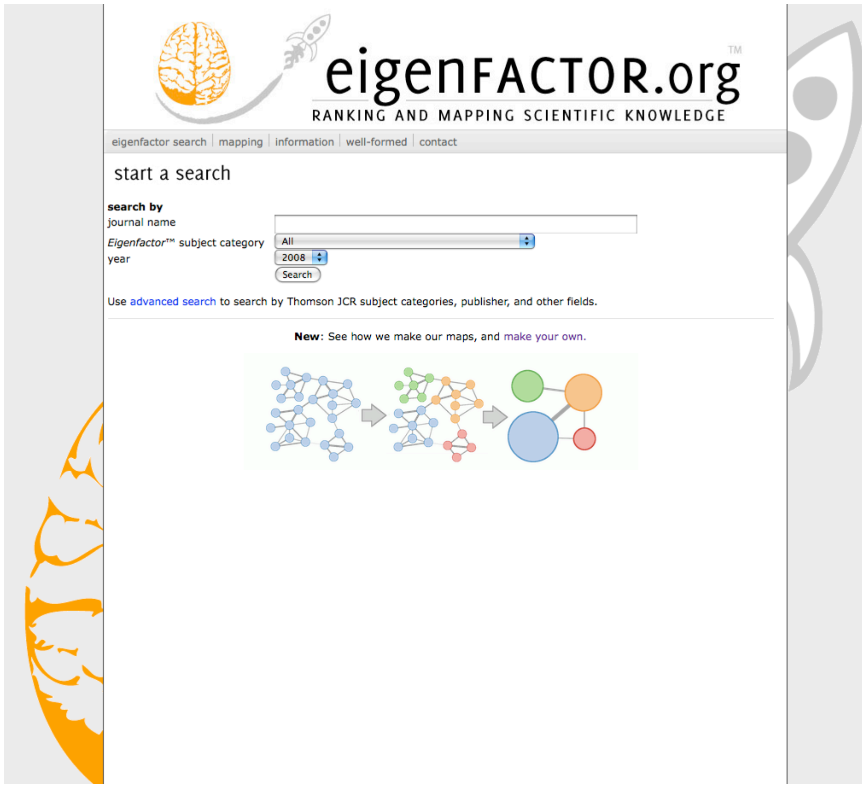

Figure 5.3: A snapshot of the website built for the Eigenfactor Project.

and Research Libraries article on Eigenfactor [6] has been cited 74 times[11], Eigenfactor is mentioned in hundreds of blogs and websites, it is recognized by almost any librarian around the world involved with journal collections and included in conference programs around the world.

Certainly having a website has catapulted the idea and the adoption of the metric. Publishers can go to the website and check what their journal's Eigenfactor score is. If the Eigenfactor idea had only been described in a published paper, that publisher would likely never see an Eigenfactor score

[11] As of August 1, 2010

or even know what an Eigenfactor score is.

The website is also a repository for other aspects of the project, such as cost-effectiveness[12], commentaries (see Appendix) [60, 6, 10, 9, 64, 61], and visualizations (`www.eigenfactor.org`). There likely exists a feedback among explanations – the website lead to more commentaries and the commentaries lead more people to the website – but it is website that I see as having the most influence at least in the beginning of the project.

I want to emphasize one important thing. I do not claim that publishing on the web and writing commentaries is the best strategy for every graduate student. In fact, the project may have been even more successful with that defnititve, highly cited, highly read paper that we never wrote (but still may write). But I think there is a lesson to be learned for other graduate students and for me. Writing papers is still the currency of success in academia, but it would be foolish nowadays to ignore the power of the web for getting your idea out. The Eigenfactor Project was ideal because it is a tool people use and the results can easily be displayed and understood on a webpage. Not everyone's research is as conducive to this kind of presentation.

5.3.3 Need for alternative journal metrics

Since Gross and Gross's proposal in 1927, scholars have used citation counts as the primary statistic for evaluating scientific journals [30]. There have been small modifications on this proposal since then. The most famous modification is Impact Factor [28]. Administrators use this number to make tenure and promotion decisions. Librarians use it to determine which jour-

[12] More info at `http://www.eigenfactor.org/pricesearch.php`

nals to keep in their collections. Publishers use it for making purchasing decisions of new journals. Researchers use it to determine the best journals to publish their work in. University rankings systems use it to assess the best schools. Advertisers use this as a way of determining which journals to place their ads in.

But, as anyone knows who has written about Impact Factor, it has its limitations, and many are concerned with its overuse and misuse [41]. The community has been asking for alternative metrics. Simply publishing an idea about a new metric is not enough. Over the last ten years, there have been hundreds of papers proposing a new scholarly metric[13]. Only a few have stuck. Eigenfactor is one example. Other examples include the h-index [31], other pagerank variants [25] and metrics that use download data versus citations [15, 14].

Why is it that Eigenfactor took off while many of these others have not? The Eigenfactor Metrics had to capture the mindshare of the community. To do this, the idea had to be good (and was the result of many contributors before this project, such as Bonacich, De Solla Price, Garfield, Page and Brin), and the idea had to be accessible. The accessibility came in the form of a website (`www.eigenfactor.org`), commentaries (see Appendix) [60, 6, 10, 9, 64, 61] and presentation (`http://octavia.zoology.washington.edu/people/jevin/Presentations.html`). After it had captured the mindshare of the community, the Eigenfactor Metrics were included in the JCR, which also speaks to the need for alternative metrics.

[13]Using Web of Science and Google Scholar and then limiting the search to just two journals, *JASIST* and *Scientometrics*, one can find well over a hundred articles that deal with these kinds of metrics.

Over the last decade, the need for good alternative metrics has been strong, and the timing has been good for Eigenfactor. Nonetheless, I do think the idea would have survived 10 years earlier given the same technologies of communication.

5.3.4 Good information visualization

Having good visualizations at `eigenfactor.org` has definitely helped in promoting the Eigenfactor project. Good visualizations can tell stories one knows exists in the data, and they can reveal stories one didn't even know existed. The interactive browser (Figure 5.4) and the radial diagram[14], the motion charts (Figure 5.5) and the maps of science are all examples of this story telling. And, even if they didn't tell stories, people like pretty pictures. Packaging and branding matters[15], even in science.

Good visualizations have brought visitors to Eigenfactor, but I found through server logs that the majority of visitors to eigenfactor.org are there to look at Eigenfactor scores and Article Influence scores. Still, if I have learned anything over the last several years working on big data sets and big networks, good visualizations matter and I look to improve my skills in information visualization in the years to come.

The following quote from Hal Varian[16], Google's chief economist, echos this perfectly:

[14] These and other visualizations at `well-formed.eigenfactor.org` were built by Moritz Stefaner. Other work by Moritz can be found at `http://moritz.stefaner.eu/`

[15] See `http://128.95.253.42/motion/`

[16] Source of quote can be found at `http://flowingdata.com/2009/06/04/rise-of-the-data-scientist/`

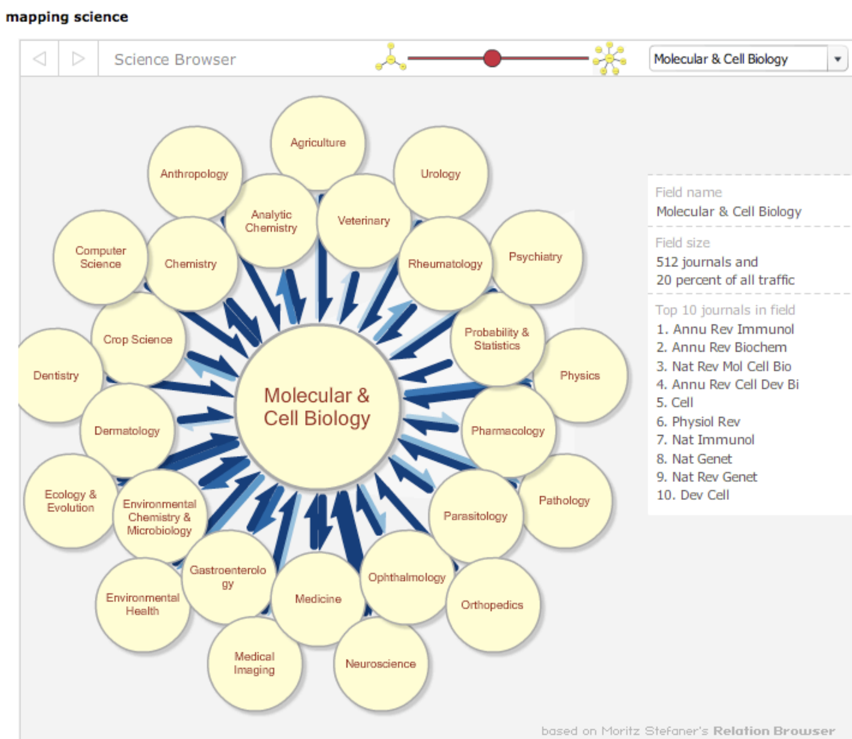

Figure 5.4: A snapshot of the interactive browser that moves a user through the map of science. This is an example of the power of information visualization.

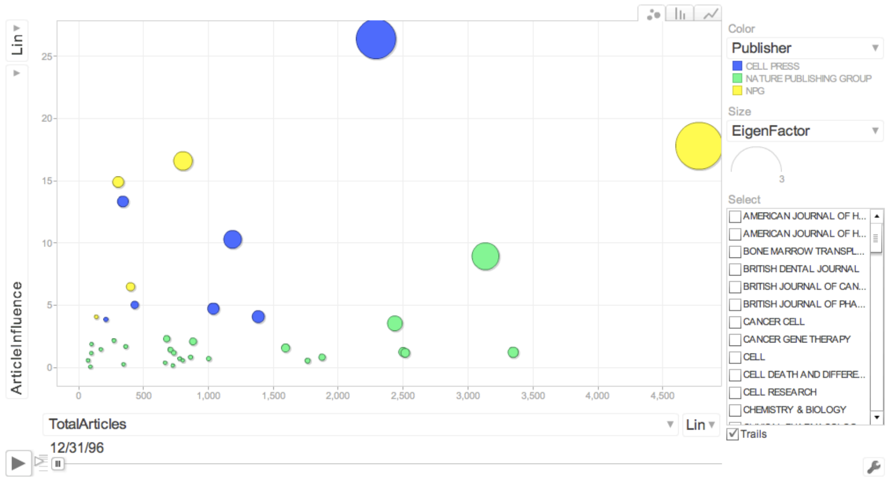

Figure 5.5: A snapshot of the motion graphs included at Eigenfactor.org that show in an interactive way how the scores of journals change over time. Stories can be revealed through visualizations like this that one would not otherwise find.

” The sexy job in the next ten years will be statisticians The ability to take datato be able to understand it, to process it, to extract value from it, to visualize it, to communicate itthats going to be a hugely important skill.”

5.4 Conclusion

Aside from the idea itself, the four explanations all contributed to the response the Eigenfactor project has received. There was and is a need for alternative metrics, and Eigenfactor is one tool to meet that need. The biggest lessons for me, though, have been the lessons in web presentation and information visualization that I will take to any new project I work on. The old mantra in academics — publish or perish — may be changing with these other forms of communication. The challenge for the tenure committees will be to figure out how to assess the value of a researcher's work when the work is presented using these alternative forms of communication.

One of the biggest changes in academia that I have seen during my lifetime as a graduate student has been the changes in how science is communicated and evaluated. Eigenfactor has been a product of this change and a possible contributor of further changes down the road.

5.5 Acknowledgements

The real reason for the success of Eigenfactor has been the people involved. I would like to thank Carl Bergstrom and Ted Bergstrom – two people that the project required and would not exist without them. I would also like to thank Ben Althouse for designing the Eigenfactor website and Martin Rosvall for his valuable input.

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Appendix

Appendix A

Calculating Journal-Level Eigenfactors (Pseudocode)

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A.1 Overview

There are seven steps for calculating Journal-Level Eigenfactors:

1. Data Input
2. Creating an Adjacency Matrix
3. Modifying the Adjacency Matrix
4. Identifying the Dangling Nodes
5. Calculating the Stationary Vector
6. Calculationg EigenFactor (EF) and ArticleInfluence (AI)
7. Outputting the Results

Like Thomson's Impact Factor metric, Eigenfactor measures the number of times that articles published during a *census period* provide citations to papers published during an earlier *target window.* The Impact Factor as reported by Thomson Scientific has a one year census period and uses the two previous years for the target window. In its current form, Eigenfactor has a one year census period and uses the five previous years for the target window.

A.1.1 Data Input

Four inputs — two files and two constants — are needed:

- Journal File: using the JCR database, create a list of unique journals included in the Science and Social Science JCR.[2] This list should contain journals from the Sciences and the Social Sciences. For Eigenfactor we combine these two lists instead of treating them as two separate lists. Then list how often each journal cites each other journal, where we count citations that are given during census period (e.g. 2006) to papers published during the target window (e.g. 2001–2005).

- Article File: this is the file that contains the number of articles that each journal produces in the five previous years.[3]

- Alpha constant ($\alpha = 0.85$)

- Epsilon constant ($\epsilon = 0.00001$)

A.1.2 Creating an Adjacency Matrix

The journal citation network can be conveniently represented as an adjacency matrix $\mathbf{Z}$, where the $\mathbf{Z_{ij}}$-th entry indicates the number of times that articles published in journal j during the census period cite articles in journal i published during the target window. The dimension of this square matrix is n x n where n is the number of unique ISI journals. For example, suppose there are journals A, B, and C.

[2]For 2006, there were 7611 unique ISI journals for the combined Science and Social Science combined list in the JCR (Journal Citation Reports).

[3]Note: In checking to be sure that you are able to replicate our results, we should compare our article counts for five years since there are some changes in the article numbers reported for each journal from year to year.

	A	B	C
A	2	0	3
B	4	1	1
C	0	2	7

In the adjacency matrix above, journal A cites itself 2 times, it cites journal B 4 times, and it doesn't cite journal C at all. Journal B receives 4 citations from journal A, 1 citation from itself, and 1 citation from journal C.

A.1.3 Modifying the Adjacency Matrix

There are some modifications that need to be done to $\mathbf{Z}$ before the eigenvectors can be calculated.

- First, we set the diagonal of $\mathbf{Z}$ to zero (i.e., we set all of the entries $Z_{ii} = 0$). This is done so that journals do not receive credit for self-citations.

- Second, we normalize the columns of the matrix $\mathbf{Z}$ (i.e., divide each entry in a column by the sum of that column). To do this, compute the column sums for each column j as $Z_j = \sum_i \mathbf{Z_{ij}}$. Then divide the entries from each column by the corresponding column sum to get the entries of the $\mathbf{H}$ matrix: $\mathbf{H_{ij}} = \mathbf{Z_{ij}}/Z_j$. There may be columns that sum up to zero (i.e., journals that cite no other journals). These are danlging nodes, and we will deal with them in the next section.

In the example below, we take an adjacency matrix through these two modifications. The matrix you get after these two modifications is $\mathbf{H}$. This example matrix will be used throughout the pseudocode as an example of how to calculate the EF of a journal. The numbers in parentheses next to each journal letter represent the number of papers that each journal has published.

Example raw adjacency matrix (Z)

	A	B	C	D	E	F
$A(3)$	1	0	2	0	4	3
$B(2)$	3	0	1	1	0	0
$C(5)$	2	0	4	0	1	0
$D(1)$	0	0	1	0	0	1
$E(2)$	8	0	3	0	5	2
$F(1)$	0	0	0	0	0	0

1. Set the diagonal to zero

$\downarrow$

	A	B	C	D	E	F
$A(3)$	0	0	2	0	4	3
$B(2)$	3	0	1	1	0	0
$C(5)$	2	0	0	0	1	0
$D(1)$	0	0	1	0	0	1
$E(2)$	8	0	3	0	0	2
$F(1)$	0	0	0	0	0	0

2. Normalize the columns. This matrix is H.

$\downarrow$

	A	B	C	D	E	F
$A(3)$	0	0	2/7	0	4/5	3/6
$B(2)$	3/13	0	1/7	1	0	0
$C(5)$	2/13	0	0	0	1/5	0
$D(1)$	0	0	1/7	0	0	1/6
$E(2)$	8/13	0	3/7	0	0	2/6
$F(1)$	0	0	0	0	0	0

A.1.4 Identifying the Dangling Nodes

As mentioned in the previous section, there will be journals that don't cite any other journals. These journals are called dangling nodes and can be identified by looking for columns that contain all zeros. These columns need to be identified with a row vector of 1's and 0's. Call this vector d. The 1's indicate that a journal is a dangling node; the 0's indicate a non-dangling node. For the example above, d would be the following row vector:

	A	B	C	D	E	F
d_i	0	1	0	0	0	0

A.1.5 Calculating the Influence Vector

The next step is to construct a transition matrix $\mathbf{P}$ and compute its leading eigenvector. This eigenvector, normalized so that its components sum to 1, will be called the influence vector π^*. This vector gives us the journal weights that we will use in assigning eigenfactor scores.

To calculate the influence vector π^*, we need six inputs: the matrix $\mathbf{H}$ that we just created, an initial start vector $\pi^{(\mathbf{0})}$, the constants α and ϵ, the dangling node vector d and the article vector a.

Article Vector. Let A_{tot} be the total number of articles published by all of the journals. The article vector a is a column vector of the number of articles published in each journal over the (five-year) target window, normalized so that its entries sum to 1. (To do this normalization, divide the number of articles that each journal publishes by A_{tot}). Using the example from above, $A_{\text{tot}} = 3 + 5 + 2 + 1 + 2 + 1 = 14$ and the article vector would be

Article Vector

	a_i
A	3/14
B	2/14
C	5/14
D	1/14
E	2/14
F	1/14

Initial start vector $\pi^{(\mathbf{0})}$. This vector is used in iterating the influence vector. Set each entry of this column vector to $1/n$. For our example, this vector would look like

	$\pi_{\mathbf{i}}^{(\mathbf{0})}$
A	1/6
B	1/6
C	1/6
D	1/6
E	1/6
F	1/6

Calculating the influence vector π^*. The influence vector π^* is the leading eigenvector (normalized so that its terms sum to one) of the matrix $\mathbf{P}$, defined as follows:[4]

$$\mathbf{P} = \alpha \mathbf{H}' + (1-\alpha) a.e^T,$$

Here e^T is a row vector of all 1's and $a.e^T$ is thus a matrix with identical columns a. The matrix $\mathbf{H}'$ is the matrix $\mathbf{H}$, with all columns corresponding to dangling nodes replaced with the article vector a. In the example, $\mathbf{H}'$ would be the following matrix (notice the replacement of the B column):

	A	B	C	D	E	F
$A(3)$	0	3/14	2/7	0	4/5	3/6
$B(2)$	3/13	2/14	1/7	1	0	0
$C(5)$	2/13	5/14	0	0	1/5	0
$D(1)$	0	1/14	1/7	0	0	1/6
$E(2)$	8/13	2/14	3/7	0	0	2/6
$F(1)$	0	1/14	0	0	0	0

Because $\mathbf{P}$ will be an irreducible aperiodic Markov chain by construction, it will have a unique leading eigenvector by the Perron-Frobenius theorem. We could compute the normalized leading eigenvector of the matrix

[4]This matrix describes a stochastic process in which a random walker moves through the scientific literature; it is analogous to the "google matrix" that Google uses to compute the PageRank scores of websites. The stochastic process can be interpreted as follows: a fraction α of the time the random walker follows citations and a fraction $1-\alpha$ of the time the random walker "teleports" to a random journal chosen at a frequency proportional to the number of articles published.

P directly using the power method, but this involves repeated matrix multiplication operations on the dense matrix $\mathbf{P}$ and thus is computationally intensive. Instead, we can use an alternative approach that involves only operations on the sparse matrix $\mathbf{H}$ and thus is far faster[5]. To compute the influence vector rapidly, we will iterate the following equation

$$\pi^{(k+1)} = \alpha\,\mathbf{H}\,\pi^{(k)} + [\alpha\, d.\pi^{(k)} + (1-\alpha)]a$$

This iteration will converge uniquely to the leading eigenvector of $\mathbf{P}$, normalized so that its terms sum to 1. To find this eigenvector, iterate repeatedly. After each iteration, check to see if the residual ($\tau = \pi^{(k+1)} - \pi^{(k)}$) is less than ϵ. If it is, then $\pi^* \approx \pi^{(k+1)}$ is the influence vector. Typically, this does not take more than 100 iterations with $\epsilon = 0.00001$. Using the raw adjacency matrx example above and the corresponding article vector, the stationary vector converges after 16 iterations to the following vector with $\alpha = 0.85$ and $\epsilon = 0.00001$:

	$\pi^*_{\mathbf{i}}$
A	0.3040
B	0.1636
C	0.1898
D	0.0466
E	0.2753
F	0.0206

[5]Notice that the equation below uses the matrix $\mathbf{H}$, without the dangling node columns replaced, not the matrix $\mathbf{H}'$. In fact, one does not need to ever construct the matrix $\mathbf{H}'$ in the process of doing these calculations.

A.1.6 Calculationg Eigenfactor ($\mathbf{EF_i}$) and Article Influence ($\mathbf{AI_i}$)

The vector of eigenfactor values for each journal is given by the dot product of the H matrix and the influence vector π^*, normalized to sum to 1 and then multiplied by 100 to convert the values from fractions to percentages:

$$\text{EF} = 100 \frac{\mathbf{H}.\pi^*}{\sum_i [\mathbf{H}.\pi^*]_i}$$

The Eigenfactor values for our example are thus

	EF_i
A	34.0510
B	17.2037
C	12.1755
D	3.6532
E	32.9166
F	0.0000

The ArticleInfluence $\mathbf{AI_i}$ for each journal (i) is calculated using the following equation:

$$\mathbf{AI_i} = 0.01 \frac{\mathbf{EF}_i}{a_i}$$

where $\mathbf{EF_i}$ is the Eigenfactor for journal i and a_i is the normalized article vector. In words, the Article Influence is essentially the Eigenfactor/100, divided by the fraction of all articles that each journal has published. The Article Influence values for our example are

	AI_i
A	1.5890
B	1.2043
C	0.3409
D	0.5114
E	2.3042
F	0.0000

A.1.7 Calculating $(\mathbf{EF_i})$ and $(\mathbf{AI_i})$ for non-ISI journals

Because the JCR lists citations from listed journals to many non-listed journals (and other reference items such as the *New York Times*), EFs can be calculated for these non-ISI journals. AIs can also be calculated for non-ISI journals if article information is available. Article information for these journals are not found in the JCR database, so this information would have to come from other sources.

To calculate non-ISI EFs, first retrieve the matrix $\mathbf{Z}$. Zero the diagonals and then find the sum of each column. Second, construct a matrix $\mathbf{N}$ that contains the number of citations from the ISI journals. The matrix below illustrates what it would look like when these two matrices are sewed together. The journal R, S and T are non-ISI journals of the matrix $\mathbf{N}$. As you can see, the non-ISI jouranals receive citations from ISI journals, but since they are not listed in the JCR, we do not have a tally of the citations that they give to ISI journals A–F.

	A	B	C	D	E	F
$A(3)$	0	0	2	0	4	3
$B(2)$	3	0	1	1	0	0
$C(5)$	2	0	0	0	1	0
$D(1)$	0	0	1	0	0	1
$E(2)$	8	0	3	0	0	2
$F(1)$	0	0	0	0	0	0
R(n/a)	3	0	0	0	0	2
$S(2)$	0	0	1	0	0	0
T(n/a)	0	0	1	0	1	0

In the example above, the ISI journal, A, cites the non-ISI journal, R, 3 times. The ISI journal, E, cites the non-ISI journal, T, 1 time. The numbers in parentheses again indicate the number of articles that each non-ISI journal produced in the five year target window. In this example, we have data only for journal S; we do not know how many articles were published by R or T.

Now, divide each number in $\mathbf{N}$ by the corresponding column sum in the $\mathbf{Z}$ matrix.[6] . This new matrix $\mathbf{N}'$ would look like

	A	B	C	D	E	F
R(n/a)	3/13	0	0	0	0	2/6
S(2)	0	0	1/7	0	0	0
T(n/a)	0	0	1/7	0	1/5	0

The Eigenfactor score for each non-ISI journal in this $\mathbf{N}'$ matrix is the product of that row vector times the influence vector π^* for the ISI journals times 100. In vector notation, the vector of eigenfactors is simply $100\,\mathbf{N}'.\pi^*$. For example, the row vector for journal R is $\{3/13, 0, 0, 0, 0, 2/6\}$ and the influence vector is the column vector that we calculated before, $\pi^* = \{0.3040, 0.1636, 0.1898, 0.0466, 0.02753, 0.0206\}$. Thus the extended eigenfactor for journal B is the product of these vectors: $EF_{(R)} = 100\,(\frac{3}{13} \times 0.3040 + \frac{2}{6} \times 0.0206)$

Thus calculated, the eigenfactors for the non-ISI journals are

[6]Recall that the j-th column sum of this $\mathbf{Z}$ matrix indicates how many citations are given out by that journal to all ISI-listed journals excluding itself. We use this — rather than the column sum of the extended matrix formed by appending $\mathbf{N}$ to $\mathbf{Z}$ — because this was the denominator we used in computing Eigenfactors for ISI-listed journals in Section 1.5. We want to make the eigenfactor scores of for the non-ISI journals directly comparable, so we use the same denominator here.

	EF_i
R	7.7041
S	2.7114
T	8.2176

ArticleInfluence scores can be calculated for the non-ISI journals so long as we have article counts. If we don't have the article count for a non-ISI journal, its AI is listed as *NA*. To calculate AI for non-ISI journals, use the same equation used for the ISI journals

$$\mathbf{AI_i} = 0.01\,\frac{\mathbf{EF}_i}{a_i}$$

Here a_i represents the entries in an extended version of the article vector computed in step 1.5. The denominator for the a_i's should be the total number of articles A_{tot} published by ISI-listed journals, not the total number of articles published by all journals, ISI-listed or otherwise.[7] Thus in our example the a_i value for journal S should be 2/14, not 2/16. Thus calculated, the AIs for the non-ISI journals are

	AI_i
R	NA
S	0.1898
T	NA

[7]Again, we want our AI values for non-ISI journals to be directly comparable to those for ISI journals, so we have to use the same denominator in our calculations.

A.1.8 Outputting the Results

To get the journal rankings, just sort in descending order the **EF** and **AI** vectors. Output the results in whatever format is easiest to compare rankings. Right now, we are using Excel. The following is what we include in our data output:

- Year
- Short Name
- Long Name
- Group (Science or Social Science)
- Field (e.g., Physics)
- Eigenfactor
- ArticleInfluence
- Impact Factor
- Total Articles (5 yrs)
- Total Citations Received (5 yrs)

Computing the *Eigenfactor* ™ Score and the *Article Influence* ™ Score

Carl Bergstrom and Jevin West
University of Washington

Below is the complete source code for the *Eigenfactor* (TM) Algorthm used to compute the *Eigenfactor* (TM) Score and *Article Influence (TM)* Score, using Wolfram Research's *Mathematica* programming language. The three import files are the cross-citation matrix in .mtx sparse matrix format, a list of article counts, and a list of journal names.

```
rawData = Import@"Zmatrix2007E.mtx", "MTX" D
articleCount = Import@"Article5yr_2007.csv", "CSV"D;
journalList = Import@"ISIuniqueJrns2007.csv", "CSV"D;

zeroDiagonal = rawData - DiagonalMatrix@Diagonal@rawDataDD;
columnSums = Normal@Apply@Plus, zeroDiagonalDD;
danglingNodes = Position@columnSums, 0D;
d = ReplacePart@Table@0, 8Length@columnSumsD<D,
   danglingNodes Ø 1D;
cs = ReplacePart@columnSums, danglingNodes Ø 1D;
h = Table@zeroDiagonal@@i, jDDê cs@@jDD, 8i, 1, Length@csD<,
   8j, 1, Length@zeroDiagonal@@1DDD<D;
a = articleCount ê Apply@Plus, articleCountD@@1DD;
update@pi_D := .85 h.pi + H.85 Hd.piL@@1DD + .15L a
iter@pi_, k_D := Nest@update, pi, kD
piStar = iter@Table@81 ê Length@articleCountD<,
   8Length@articleCountD<D, 30D
ef = Module@8prod<,
  prod = h.piStar; 100 * prod ê Apply@Plus, Flatten@prodDDD
ai = 0.01 * ef ê a
resultsTable = Transpose@8Flatten@journalListD, Flatten@efD,
   Flatten@aiD, Flatten@articleCountD<D

Export@"MathematicaEFScores_compressed_2007.csv",
 resultsTableD
```

Appendix B

Eigenfactor — The Google Approach to Bibliometrics

Jevin West, University of Washington, Seattle, WA

*This article was published in 2008 in Allen Press's *Front Matter* **4**:7. The formatted article can be found at `http://octavia.zoology.washington.edu/people/jevin/Publications.html`

B.1 Not all citations are created equal

Not all citations are created equal. This is one of the core ideas behind Eigenfactor[1]. Citations from more prestigious journals (like *Science* and *Nature*) are worth more than citations from less important journals (like the *Journal of Obscurity*). This meritocratic approach to Bibliometrics is very similar to the philosophy behind Google's PageRank algorithm, which is at "the heart of [its] software"[2]. Receiving a hyperlink from a highly reputable website means more than a hyperlink from a neighborhood blog. Both Google and Eigenfactor utilize the wealth of information inherent in the structure of their respective networks. For Google, that information can be found in the topology of the web, and for Eigenfactor, the information can be found in the citation structure of the scholarly literature. The success of Google's search engine illustrates the power of this approach to ranking. Part of the success behind PageRank can actually be traced back to prior work that had been done in the field of Bibliometrics[3]. With the advent of scholarly measures like Eigenfactor, this relationship has come full circle.

The idea that important journals are cited by other important journals may at first sound hopelessly circular, but the idea can be formalized in a beautiful mathematical formula. We find the following heuristic helpful in explaining what the Eigenfactor number represents. Imagine that a

[1]All the methods and data are freely available at www.eigenfactor.org. Feel free to send comments or questions to Jevin West at jevinw@u.washington.edu

[2]2http://www.google.com/technology/index.html

[3]3Langville AN, Meyer CD. Google's PageRank and Beyond, The Science of Search Engine Rankings (2006) Princenton University Press

researcher decides to spend all of eternity in the library randomly following citations. In other words, the researcher first picks some random journal in the library and, in that journal, points to some random citation. The researcher then walks over to the journal of that citation and finds another random citation. The researcher does this ad infinitum. Eigenfactor measures how much time the researcher spends at each journal during that infinite walk in the library. For example, the Eigenfactor for the *Journal of Biological Chemistry* in 2006 is 1.82. This means that the researcher spent 1.82 percent of her time at the Journal of Biological Chemistry.

Eigenfactor therefore measures total value within the scientific literature. Librarians are typically more interested in this sort of measure. However, if a publisher or author wanted to know the value per article of a journal, they would use the complimentary metric that we call Article Influence. This particular measure is more comparable to the well-known Impact Factor. Article Influence is simply the Eigenfactor of a journal divided by the number of articles that the journal produced over a given time period. Article Influence measures the prestige of a journal, rather than the total value.

The Eigenfactor approach to measuring journal influence has some notable nuances. For example, citations from non-review journals are worth more than citations from review journals that typically have longer reference lists. When the infinite researcher ends up at this type of journal in the library, she can only choose one of those many references. The more citations means the less likely any one of them will be followed in the next step. This also means that citations from frugal fields are also worth more. All these nuances are hopefully in service of a metric that is less gameable.

No metric will ever replace reading papers as the best form of evaluation. Nonetheless, with increasingly limited time and limited budgets, there will continue to be a legitimate need for quantitative measures of the scholarly literature. We would like to think that Eigenfactor is at least a step in the right direction.

Appendix C

The Eigenfactor^{TM} Metrics: How does the Journal of Biological Chemistry stack up?

Jevin D. West[1] and Moritz Stefaner[2] and Carl T. Bergstrom[1]

*This article was published in 2009 in the *The American Society for Biochemistry and Molecular Biology, Today* April 2009: 20-21 . The formatted article can be found at `http://octavia.zoology.washington.edu/people/jevin/Publications.html`

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

[2]Interaction Design Lab, University of Applied Sciences Potsdam, Germany

C.1 The Eigenfactor Metrics

The scientific literature comprises a vast network of research papers, linked to one another by scholarly citations; this network traces out the spread of ideas through the scientific community [19]. At the Eigenfactor Project, we use the structure of this network to assess the influence of scholarly journals and to map out relations among scientific fields [6].

The main idea behind the Eigenfactor Metrics is that a journals influence is determined by a weighted sum of the citations that it receives. Citations from influential journals such as *Nature*, *PLoS Biology*, or *Cell* carry more weight than citations from second- and third-tier journals. Which journals are influential is determined by an iterative procedure analogous to Googles PageRank algorithm [42]. Although iterative rankings require more complicated computations than measures like impact factor, the reward of accounting for the variable influence of citation sources is a much richer measure of journal quality.

We use two primary measures to rank scholarly journals. The Eigenfactor Score measures a journals total influence; with all else being equal, larger journals have higher Eigenfactor scores. The Article Influence^{TM} Score measures the influence per article of a journal. As a per-article measure of prestige, the Article Influence is comparable to Impact Factor. At the Eigenfactor website, `http://www.eigenfactor.org`, we provide the Eigenfactor scores and Article Influence scores for more than 8000 scholarly journals over the past decade, based on citation data from the

Thomson-Reuters Journal Citation Reports (JCR)[1].

C.2 How does *JBC* stack up?

So what do the Eigenfactor metrics tell us about the *Journal of Biological Chemistry* (*JBC*)? In 2006[2], *JBC* had an Eigenfactor Score of 1.82. Basically, this score tells us that the journal is both large and influential. The Eigenfactor algorithm estimates that the *JBC* constitutes 1.82 percent of the total citation traffic in all of the scientific literature. In fact, *JBC* has the fourth-highest Eigenfactor score out of the 7,611 journals indexed, after only *Science*, *Nature*, and *Proc. Nat. Acad. Sci. USA*.

The 2006 Article Influence Score of *JBC* is 2.4. This means that an article in this journal is on average 2.4 times more influential than the average article in the JCR, placing it in the top 5% of all journals in all fields.

C.3 Cost Effectiveness

Another important consideration is the price of a journal. In studying the economics of scientific publishing, we have been struck by the enormous discrepancies in journal prices [7]. In most disciplines, the library subscription prices for journals produced by for-profit publishers are 3 to 5 times as much per page as those charged for journals produced by societies

[1] As of February 2009, Eigenfactor scores and Article Influence scores are also provided as part of Thomson-Reuters Journal Citation Reports database.

[2] At the time of publication, the 2006 scores were the latest available on the Eigenfactor.org website. These scores will be updated periodically.

and university presses. The high prices of many for-profit journals do not reflect higher quality as measured by citation rates — but they have contributed to the current serials crisis that leaves even large research libraries unable to afford all of the journals that their users demand.

Quantitative measures of cost effectiveness are therefore useful as libraries struggle to make difficult subscription decisions, and as authors endeavor to steer their best work toward journals that provide good value to the scholarly community. Our Cost Effectiveness[3] tool provides a way of quantifying the value per dollar that a journal provides; the basic assessment metric is the subscription cost per Eigenfactor score. By this measure, the *JBC* is an exceptionally good deal — the tenth best deal in all of science, placing it in the 99.9% percentile in terms of the value per dollar that it offers.

C.4 Mapping citation flow

The Eigenfactor Project is not, however, only about ranking and assessing cost effectiveness. It is also about understanding the structure of the sciences and mapping the way that citations flow among the disciplines. The radial diagram in Figure C.1 illustrates one of the interactive tools we have developed for exploring these patterns. In this figure, we see the flow of citations between the *JBC* and 399 other leading journals in the natural and social sciences. The most striking aspect of this diagram is the breadth of reach that the *JBC* has across the sciences. We see strong

[3]Cost Effectiveness rankings can be found at `http://www.eigenfactor.org/pricesearch.php`

Figure C.1: Citation flow for the *Journal of Biological Chemistry*, from well-formed.eigenfactor.org/radial.html. The figure highlights the citation relationships between the *JBC* and the rest of science. The colors depict major groups within science. For example, the greenish color represents physics and chemistry. The thickness and opacity of the lines connecting the different journals indicate connection strength.

connections not only to chemistry, biochemistry and molecular biology but also to neuroscience, medicine, evolutionary biology, ecology, geosciences, and physics. We also see the major gaps in citation influence: there is little connection between *JBC* and the area of astronomy and astrophysics, for obvious reasons. The interactive on-line version of this diagram allows one to select any field or journal and see its citation flow patterns; this application can be found at
`http://well-formed.eigenfactor.org/radial.html`.

The Eigenfactor Project began as an attempt to better evaluate the scholarly literature, using citation data and powerful tools from network and information theory. In the process, we have found that citation networks tell us not just about relative ranks among journals, but also about the connections between them. We hope to use this information to better understand the nature and structure of the scientific enterprise.

Curriculum Vitae

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Education

2005 – 2010	PhD, Biology, University of Washington, Seattle, WA Advisors: Carl Bergstrom and Ben Kerr
2000 – 2004	M.S., Biology (theoretical emphasis), Utah State University, Logan, UT Advisors: Keith Mott and David Peak
1996 – 2000	B.S., Biology, Chemistry m., Utah State University, Logan, UT

Research Areas

Complex Systems, Networks, Self-Organization, Information Theory
Evolutionary Ecology, Physiology, Mathematical Biology
Bibliometrics, Economics of Publishing, History and Philosophy of Science

Honors and Awards

+ WRF-Hall Fellowship (2010), Sargent Award (2008), ARCS Fellowship (2005 – 2008)
+ Huckabay Fellowship (2006 – 2007), UW Top Scholar Award (2005 – 2006)
+ Vice President for Research Fellowship (2000 – 2001), URCO Undergraduate Research Award (2000)
+ Presidential Scholarship ('96 – 2000), Outstanding Student of Year Award, College of Engineering ('98)
+ Columbia/HCA Foundation Scholarship ('96 – 2000), Student Athlete Award ('98 – 2000)
+ Valedictorian, Hillcrest High School ('96), National Exchange Club Youth of Year Scholarship ('96)

Publications

Response to "Big Macs and Eigenfactors: The Correlation Conundrum"
J.D. West, T.C. Bergstrom, C.T. Bergstrom, *J. Am. Soc. for Info. Sci. & Tech.* (in press)
How to improve the use of metrics: Learn from Game Theory – Opinion (2010)
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J.D. West, D. Peak, K.A. Mott, S.M. Messinger, *Proc. of the Int. Conf. on Complex Systems*, ICCS2004
Investigations into the spatial and temporal dynamics of stomatal networks… (2004)
J.D. West, *Masters Thesis.* Utah State University, Logan, UT

Invited Talks

+ Society for Scholarly Publishing 32nd Annual Meeting, San Francisco, CA (June 4, 2010)
+ American Chemistry Society National Meeting, San Francisco, CA (March 24, 2010)
+ NSF Workshop: "Scholarly Evaluation Metrics: Opportunities & Challenges" Washington, DC (Dec. 16, 2009)
+ International Workshop on "What is Evolution?" Kyoto University, Japan (Oct. 17, 2009)
+ Department of Physics, Umea University, Sweden (Oct. 2, 2009)
+ ALPSP International Conference, Oxford, UK (Sept. 10, 2009)
+ Council of Science Editors Annual Meeting, Pittsburgh, PA (May 3, 2009)
+ Digital Research Symposium, Portland State University (April 29, 2009)
+ BioOne, Washington, DC (April 17, 2009)
+ University of California, Los Angeles (Feb. 11, 2009)
+ National Inst. of Informatics & National Inst. for Materials Science, Tokyo, Japan (Nov. 25, 2008)
+ Yale Library and Faculty, Yale University (Nov. 3, 2008)
+ Center for Digital Research and Scholarship, Columbia University (Oct. 30, 2008)
+ Inst. of Economic Research & Yukawa Inst. of Theoretical Physics, Kyoto, Japan (Oct. 21, 2008)
+ Library Assessment, University of Washington, Seattle, WA
+ American Library Association Annual Conference, Anaheim, CA (June 29, 2008)
+ SLA International Conference, Seattle, WA (June 16, 2008)
+ Council of Science Editors Annual Meeting, Vancouver, B.C. (May 19, 2008)
+ HighWire Press, Stanford University (May 6, 2008)
+ University of California, Los Angeles (May 5, 2008)
+ Emerging Trends in Scholarly Publishing, National Press Club, Washington, D.C. (April 17, 2008)
+ National Academy of Sciences, Washington, D.C. (March 18, 2008)
+ European Science Foundation, University of Granada, Spain (November 19, 2007)
+ 29th Annual ARCS Luncheon, Westin Hotel, Seattle, WA (Nov. 13, 2007)
+ ARCS Auction Dinner, Conibear Shellhouse, University of Washington, Seattle, WA
+ Berkman Center for Internet & Society, Harvard University, Cambridge, MA (May 4, 2006)
+ Long Lab, Department of Plant Biology, University of Illinois, Champaign-Urbana, IL (March 2005)

Other Talks

+ UW Department of Biology (July 27, 2010)
+ USU Department of Biology (Nov. 9, 2004)
+ International Conference on Complex Systems, Boston MA (May 17, 2004)

Poster presentations

+ Gordon Research Conference (Microbial Population Biology), Proctor Academy, NH
  (1) J. Nahum, B.M Althouse, J.D. West, C. Ofria, B. Kerr, *Best Poster Award* (July 20 – 24, 2009)
  (2) J.D. West, J. Nahum, C. Levy, B. Kerr (July 22-27, 2007)
+ Scholarship of Teaching and Learning, University of Washington, Seattle, WA
  J.D. West, C.T. Bergstrom, B. Kerr (April 2007)
+ Evolutionary Biology in the Northwest (EVO-WIBO), Port Townsend, WA
  J.D. West, A. Dean, C. Neuhauser, B. Bohannan, B. Kerr (April 2006)
+ Symposium on Plant Neurobiology, Universitatbonn, Florence, Italy
  J.D. West, D. Peak, K.A. Mott (May 17-20, 2005)
+ American Association for the Advancement of Science, Pacific Division
  J.D. West, S.M. Messinger, D. Peak, K.A. Mott (June 2004)
+ Int. Conf. on Complex Systems, New England Complex Systems Institute, Boston, MA
  J.D. West, S.M. Messinger, D. Peak, K.A. Mott, *Best Poster Award – USU Dept. of Biology* (May 2004)
+ Center for Nonlinear Studies, Los Alamos National Laboratory, Santa Fe, NM
  J.D. West, D. Peak, K.A. Mott, S.M. Messinger (May 2003)

+ Utah State University Student Research Symposium, Logan, UT
  J.D. West, D. Peak, K.A. Mott (April 2001)

Other conferences & meetings

+ PLoS Forum, San Francisco, CA (March 25, 2010)
+ Lenski/Ofria Lab Visit, Michigan State University, East Lansing, MI (June 24-28, 2008)
+ Mathematical Modeling of Infectious Diseases, Fred Hutchinson Cancer Res. Ctr, Seattle, WA (Feb. 13, 2008)
+ Models of Emergent Behavior in Complex Adaptive Systems, Santa Fe Institute, NM (Dec. 6-9, 2007)
+ Evoluion of Coooperation in Microbes, Princeton University, Park City, UT (Aug. 23-28, 2006)
+ Identity Mash-UP, Berkman Ctr. for Internet & Society, Harvard Law School, Boston, MA (June 19-21, 2006)

Acknowledgements

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+ C.T. Bergstrom, M. Lipsitch (2006) Evolution lessons from infectious diseases. *Geotimes* March 2006
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Teaching

Teaching Assistant

BIOL 354	Foundations in Evolution and Systematics, UW (Spring 2009)
BIOL 462	Advanced Animal Physiology, UW (Fall 2009 & Fall 2009)
BIOL 481	Experimental Evolutionary Ecology, UW (Fall 2006)
BIOL 4400	Plant Physiology, USU (Fall 2004 & Fall 2003)
BIOL 2010	Human Anatomy, USU (Spring 2004 & Spring 2003)

Guest Lectures

BIOL 180	Biodiversity Field Trips (Fall 2005 – Summer 2009)
BIS 232	Visualizing Quantitative Data, UW Bothell (Feb. 25, 2009)
BIOL 113	Diversity in Learning (May 22, 2008)
BIOL 492	The Teaching of Biology, UW (Spring 2007)
BIOL 429	Models in Biology, UW (Dec. 6, '06)
BIOL 510	Seminar in Mathematical Biology, UW (May 11, '06)
HS AP Cal	Elizabeth Mott's Honors Calculus, Logan High School (May 5, '04)

Curriculum Development

Summer Teaching Institute, Seattle School District (Summer 2009)
Howard Hughes RA for developing Experimental Evolutionary Ecology (Summer 2006)

Academic Outreach and Service

Reviewer: *PLoS Comp. Biology, Harvard Rev. of Psych, Information Proc. & Manag, Faculty 1000*
Greenhouse Tour Guide (W. '06 – present), Medicinal Herb Garden Docent (F. '06 – present)
Mammal Day Volunteer, Burke Museum (Aug. 5, 2006), Huckabay Panel Member (Winter 2007)
CIDR Conference (F. '06, F. '07), UW Center for Learning & Undergrad Enrichment (W. '08)
Guest speaker for Seattle book club, "The Beak of the Finch" (Oct. 20, '05)
FOSEP (Forum on Science, Ethics and Policy) ('05 – '07), GPSS Senator ('05 – '06)
Graduate Student Symposium, UW Department of Biology (Nov. 17, '06)

Collaborations

Ted Bergstrom, University of California, Santa Barbara, Martin Rosvall, Umea University, Sweden
Johan Bollen, Indiana University, Michael Jensen, Harvard University, Charles Ofria, Michigan State University