Ten good reasons to use the Eigenfactor$^{\mathrm{TM}}$ metrics[☆]

Massimo Franceschet

Department of Mathematics and Computer Science, University of Udine
Via delle Scienze 206 – 33100 Udine, Italy
`massimo.franceschet@dimi.uniud.it`

Abstract

The Eigenfactor score is a journal influence metric developed at the Department of Biology of the University of Washington and recently introduced in the Science and Social Science Journal Citation Reports maintained by Thomson Reuters. It provides a compelling measure of journal status with solid mathematical background, sound axiomatic foundation, intriguing stochastic interpretation, and many interesting relationships to other ranking measures. In this short contribution, we give ten reasons to motivate the use of the Eigenfactor method.

Key words: Journal influence measures; Eigenfactor metrics; Impact Factor.

1. Introduction

The *Eigenfactor* metric is a measure of journal influence (Bergstrom, 2007; Bergstrom et al., 2008; West et al., 2010). Unlike traditional metrics, like the popular Impact Factor, the Eigenfactor method weights journal citations by the influence of the citing journals. As a result, a journal is influential if it is cited by other influential journals. The definition is clearly *recursive* in terms of influence and the computation of the Eigenfactor scores involves the search of a *stationary* distribution, which corresponds to the leading eigenvector of a perturbed citation matrix.

The Eigenfactor method was initially developed by Jevin West, Ben Althouse, Martin Rosvall, and Carl Bergstrom at the University of Washington

[☆]Accepted for publication in Information Processing & Management. DOI: `10.1016/j.ipm.2010.01.001`

and Ted Bergstrom at the University of California Santa Barbara. Eigenfactor scores are freely accessible at the Eigenfactor web site (West et al., 2010) and, since 2007, they have been incorporated into Thomson Reuters Journal Citation Reports (JCR) for both science and social science journals.

The idea underlying the Eigenfactor method originates from the work of Pinski and Narin (1976) in the field of bibliometrics and from the contribution of Hubbell (1965) in the context of sociometry, which, in turn, generalizes Leontief's input-output model for the economic system (Leontief, 1941). Notably, Brin and Page use a similar intuition to design the popular PageRank algorithm that is part of their Google search engine: the importance of a web page is determined by the number of hyperlinks it receives from other pages as well as by the importance of the linking pages (Brin and Page, 1998; Brin et al., 1999).

In this short contribution, we suggest and motivate ten reasons to use the Eigenfactor journal ranking method.

2. The Eigenfactor metrics

We illustrate the Eigenfactor method to measure journal influence. Let us fix a *census year* and let $C = (c_{i,j})$ be a journal-journal citation matrix such that $c_{i,j}$ is the number of citations from articles published in journal i in the census year to articles published in journal j during a *target window* consisting of the five previous years. Hence, the ith row represents the citations given by journal i to other journals, and the jth column contains the citations received by journal j from other journals. Journal self-citations are ignored, hence $c_{i,i} = 0$ for all i. The citation matrix corresponds to a weighted directed *citation network* in which nodes represent journals and there exists an edge from node i to node j weighted $c_{i,j}$ if and only if $c_{i,j} > 0$. Moreover, let a be an article vector such that $a_i > 0$ is the number of articles published by journal i over the five-year target window divided by the total number of articles published by all journals over the same period. Notice that a is positive and sum to 1.

A dangling node in the citation network corresponds to a journal i that does not cite any other journals; hence, if i is a dangling node, then i has no outgoing edges and the ith row of the citation matrix has all 0 entries. The citation matrix C is transformed into a normalized matrix $H = (h_{i,j})$ such that all rows that are not dangling nodes are normalized by the row sum, that is,

$$h_{i,j} = \frac{c_{i,j}}{\sum_j c_{i,j}}$$

for all non-dangling i and all j. Furthermore, H is mapped to a matrix $\hat{H}$ in which all rows corresponding to dangling nodes are replaced with the article vector a. Notice that $\hat{H}$ is row-stochastic, that is all rows are non-negative and sum to 1.

A new row-stochastic matrix P is defined as follows:

$$P = \alpha\hat{H} + (1-\alpha)A$$

where A, known as the *teleportation matrix*, is composed of identical rows each equal to the article vector a, and α is a parameter set to 0.85. Let π be the left eigenvector of P associated with the unity eigenvalue, that is, the vector π such that $\pi = \pi P$. It is possible to prove that this vector exists and is unique. The vector π, called the *influence vector*, contains the scores used to weight citations allocated in matrix H. The Eigenfactor vector r is computed as $r = \pi H$, that is, the Eigenfactor score of journal j is:

$$r_j = \sum_i \pi_i h_{i,j}$$

In words, the Eigenfactor score of a journal is the sum of normalized citations received from other journals weighted by the influence of the citing journals. The Eigenfactor scores are normalized such that they sum to 100.

The Eigenfactor score is a size-dependent measure: with all else equal, bigger journals will have larger Eigenfactor scores, since they have more articles and hence we expect them to be cited more often. The *Article Influence* measure is the size-independent counterpart of the Eigenfactor metric (Bergstrom et al., 2008). The Article Influence score for a journal is simply the journal Eigenfactor score divided by the number of articles published by the journal over the five-year target period; hence, it corresponds to the journal Eigenfactor score per published article.

Finally, we recall the definition of the Impact Factor, which is, undoubtedly, the most popular and controversial bibliometric indicator available at the moment. It is defined, for a given journal, as the mean number of citations in a given census year to papers published in the journal during a target window consisting of the two previous years (Garfield, 2006).

3. Ten good reasons to use the Eigenfactor metrics

In our opinion, there are enough good reasons to use the Eigenfactor method to evaluate journal influence:

1. *It weights citations with the importance of the citing journals.* Citations from highly-ranked journals, like Nature, Science, and Proceedings of the National Academy of Sciences of USA, are considered more important than citations from lower-tier journals. By contrast, the Impact Factor simply counts citations without weighting them. As a result, the Impact Factor has been classified as a bibliometric measure of *popularity*, while the Eigenfactor score captures the bibliometric notions of *prestige* and *trustworthiness* (Bollen et al., 2006; Franceschet, 2010a). A journal that is endorsed by prestigious and trustworthy sources is more likely to be prestigious and trustworthy.

2. *It considers the reference intensity of the citing journals.* The reference intensity of a journal is the length of reference lists of papers published in the journal. Citations from journals with short bibliographies are considered more important than citations from journals with high citation intensity. This is also an attempt to adjust the metric for differences inside and across fields and over time due to variations in the average number of cited references per paper (Althouse et al., 2008). Such an intuition is successful only if the size-independent Article Influence version of the measure is considered, whose cross-field variability has been found to be much lower than that of both Eigenfactor and Impact Factor measures (Franceschet, 2010b).

3. *It uses a target window of five years.* This period is larger than the two-year target window exploited in the commonly used Impact Factor. This allows, in general, a broader evaluation of journal citations, in particular for disciplines with longer cited lives. Indeed, the latest results tell us that the Impact Factor scores computed on a five-year target window are higher than those computed on a two-year target period for the majority of disciplines and journals (76% of science journals and 84% of social science journals) (Franceschet, 2010b).

4. *It exploits the entire citation network.* The algorithm underlying the Eigenfactor metric uses the structure of the entire citation network for science and social science journals: the Eigenfactor score of a journal is recursively defined in terms of the scores of the citing journals and its computation involves the propagation of the journal scores over the entire citation graph.

By contrast, the computation of the Impact Factor of a journal exploits only the citation information of the local part of the network consisting of the journal predecessors in the citation graph.

5. *It ignores journal self-citations.* This avoids over inflating journals that engage in the practice of opportunistic self-citations.

6. *It has a solid mathematical background and an intuitive stochastic interpretation.* The modified citation matrix P is a primitive stochastic matrix. By virtue of Perron theorem for primitive matrices, there exists a unique vector π, the influence vector, such that (i) $\pi > 0$, (ii) $\sum_i \pi_i = 1$, and (iii) $\pi = \pi P$ (Pillai et al., 2005). The influence vector corresponds to the leading left eigenvector of P, that is, the left eigenvector associated with the largest eigenvalue of P, which equals 1 since P is a stochastic matrix. Furthermore, the influence vector also corresponds to the fixpoint of the linear transformation associated with matrix P.

Alternatively, the row-stochastic matrix P can be interpreted as the transition matrix of a Markov chain on a finite set of states (journals). Since P is primitive, the Markov theorem applies, and the influence vector π corresponds to the unique stationary distribution of the Markov chain. The stochastic Markov process has the following intuitive interpretation in terms of random walks on the citation network (Bergstrom et al., 2008). Imagine a researcher that moves from journal to journal by following chains of citations. The researcher selects a journal article at random and reads it. Then, he retrieves at random one of the citations in the article and proceeds to the cited journal. Hence, the researcher chooses at random an article from the reached journal and goes on like this. Eventually, the researcher gets bored of following citations, and selects a random journal in proportion to the number of article published by each journal. With this model of research, by virtue of the Ergodic theorem for Markov chains, the influence weight of a journal corresponds to the relative frequency with which the random researcher visits the journal.

7. *It has a sound axiomatic foundation.* Palacios-Huerta and Volij (2004) follow an axiomatic approach to show a uniqueness result for the *Invariant method*, which ranks journals using the leading eigenvector of the normalized citation matrix H as defined in Section 2, but including journal self-citations. They show that the Invariant method is the *unique* ranking method that satisfies the following logically independent desirable properties:

1. *invariance to reference intensity*: the rank of a journal is not affected by an homogeneous change in the number of citations that the journal gives to other journals;
2. *homogeneity*: in two-journal ranking problems where both journals have the same reference intensity, the relative valuation of a journal is proportional to the ratio of their mutual citations;
3. *weak consistency*: the ranking method of few journals can be extended to a ranking method of more journals in a consistent way;
4. *invariance to splitting of journals*: the relative valuation of the journals is not affected by the split of a journal into sub-journals with the same profile of references and citations.

It is worth pointing out that Serrano (2004) proves an impossibility result by identifying an additional axiom – limited influence of boundary journals – that is violated by the Invariant method. Informally, the axiom claims that, when moving from a system of journals with a heavy flow of mutual citations to an expanded one in which the influence of a new journal on the system and that of the system on the new journal are negligible (hence the citations involving the new journal are mostly self-citations), the weight assigned to the new journal should be not too large.

8. *It is strongly related to other ranking metrics.* Journal PageRank is a journal ranking technique proposed by Bollen et al. (2006) with two minor differences with respect to the Eigenfactor metric: journal PageRank includes journal self-citations, while the Eigenfactor metric does not. Moreover, in the journal PageRank approach teleporting transitions are uniformly distributed over all journals, while in the Eigenfactor metric the weight of each teleporting transition is proportional to the number of article published by the target journal.

A number of interesting connections have been established between journal PageRank metric and other ranking measures. Journal PageRank is highly related to centrality measures used in social network analysis, in particular to betweeness centrality (Bollen et al., 2009; Leydesdorff, 2009). Moreover, usage-based measures are statistically more correlated with journal PageRank than they are with Impact Factor, a result that corroborates the interpretation of the journal PageRank score as the journal visiting frequency (usage) in the random researcher model (Bollen et al., 2009). Furthermore, there are important connections of the journal PageRank procedure with the log-multiplicative model used by Nerur et al. (2005) to estimate the relative influence of a journal both as a receiver (or a knowledge source) and as a sender (or a knowledge storer) of citations, and with techniques to separate web pages into authorities and hubs (Kleinberg, 1999). There a more than few chances that the mentioned relationships hold for the Eigenfactor metric as well.

9. *It is a flexible method that can be applied to a variety of contexts.* In principle, the algorithmic schema underlying the Eigenfactor method can be applied to estimate the centrality of nodes in any (weighted) network. Examples include scientific papers linked by citations (Chen et al., 2007; Ma et al., 2008), authors related by co-authorship (Liu et al., 2005), web pages connected by hyperlinks (Kleinberg, 1999; Brin et al., 1999), patents and corresponding citations (Narin, 1994), published opinions of judges and their citations within and across opinion circuits (Landes et al., 1998), and even sections of the Bible and the biblical citations they receive in religious texts (Murai and Tokosumi, 2005).

10. *It is freely available for a significant share of journal publication sources.* The Eigenfactor website is a free resource that provides scores for over 8,000 JCR-listed journals since year 1995 as well as scores for over 100,000 non-JCR-listed titles only for year 2005. Thomson Reuters has also included the Eigenfactor metrics in both Science and Social Science JCR starting from year 2007. The Eigenfactor website is currently updated six months after Thomson Reuters releases their scores. The free availability of the Eigenfactor scores is good news for developing countries who might not have the resources to procure access to commercial data sources.

4. Conclusion

Despite the statistically significant correlation between the journal rankings provided by the Impact Factor and the Eigenfactor metrics – Franceschet (2010b) measured a Spearman correlation coefficient of 0.77 with respect to the Eigenfactor score and of 0.84 with respect to the Article Influence score – a close analysis reveals that the journal compilations according to the three metrics contain more than a few marked discrepancies (Bollen et al., 2006; Franceschet, 2010a; West et al., 2009). In the latest (2008) edition of Science JCR, the Eigenfactor compilation is dominated by Nature, Proceedings of the National Academy of Sciences of USA, and Science. The Article Influence ranking is leaded by Reviews of Modern Physics, Annual Review of

Immunology, and Annual Review of Biochemistry. The Eigenfactor leader, Nature, ranks 9th. The top-3 journals according to Impact Factor are CA: A Cancer Journal for Clinicians, The New England Journal of Medicine, and Annual Review of Immunology. Nature, the Eigenfactor head, ranks 8th, while the Article Influence skipper, Reviews of Modern Physics, ranks 6th. Finally, the Impact Factor dominator, CA: A Cancer Journal for Clinicians, ranks 8th in the Article Influence listing, and even 521st in the Eigenfactor compilation.

References

Althouse, B. M., West, J. D., Bergstrom, C. T., Bergstrom, T., 2008. Differences in impact factor across fields and over time. Journal of the American Society for Information Science and Technology 60 (1), 27–34.

Bergstrom, C. T., 2007. Eigenfactor: Measuring the value and prestige of scholarly journals. C&RL News 68 (5), 314–316.

Bergstrom, C. T., West, J. D., Wiseman, M. A., 2008. The Eigenfactor metrics. Journal of Neuroscience 28 (45), 11433–11434.

Bollen, J., de Sompel, H. V., Hagberg, A., Chute, R., 2009. A principal component analysis of 39 scientific impact measures. PLoS ONE 4, e6022.

Bollen, J., Rodriguez, M. A., de Sompel, H. V., 2006. Journal status. Scientometrics 69 (3), 669–687.

Brin, S., Page, L., 1998. The anatomy of a large-scale hypertextual web search engine. Computer networks and ISDN systems 30 (1-7), 107–117.

Brin, S., Page, L., Motwani, R., Winograd, T., November 1999. The PageRank citation ranking: Bringing order to the Web. Technical Report 1999-66, Stanford InfoLab, retrieved January 1, 2010, from `http://ilpubs.stanford.edu:8090/422/`.

Chen, P., Xie, H., Maslov, S., Redner, S., 2007. Finding scientific gems with Google's PageRank algorithm. Journal of Informetrics 1 (1), 8 – 15.

Franceschet, M., 2010a. The difference between popularity and prestige in the sciences and in the social sciences: a bibliometric analysis. Journal of Informetrics 4 (1), 55–63.

Franceschet, M., 2010b. Journal influence factors. Journal of Informetrics. In Press.

Garfield, E., 2006. The history and meaning of the journal impact factor. Journal of the American Medical Association 295 (1), 90–93.

Hubbell, C. H., 1965. An input-output approach to clique identification. Sociometry 28, 377–399.

Kleinberg, J. M., 1999. Authoritative sources in a hyperlinked environment. Journal of the ACM 46 (5), 604–632.

Landes, W. M., Lessig, L., Solimine, M. E., 1998. Judicial influence: A citation analysis of federal courts of appeal judges. Journal of Legal Studies 27, 271–332.

Leontief, W. W., 1941. The Structure of American Economy, 1919-1929. Harvard University Press.

Leydesdorff, L., 2009. How are new citation-based journal indicators adding to the bibliometric toolbox? Journal of the American Society for Information Science and Technology 60 (7), 1327–1336.

Liu, X., Bollen, J., Nelson, M. L., de Sompel, H. V., 2005. Co-authorship networks in the digital library research community. Information Processing and Management 41 (6), 1462–1480.

Ma, N., Guan, J., Zhao, Y., 2008. Bringing PageRank to the citation analysis. Information Processing & Management 44 (2), 800 – 810.

Murai, H., Tokosumi, A., 2005. A network analysis of hermeneutic documents based on Bible citations. In: Annual Conference of the Cognitive Science Society. pp. 1565–1570.

Narin, F., 1994. Patent bibliometrics. Scientometrics 30 (1), 147–155.

Nerur, S. P., Sikora, R., Mangalaraj, G., Balijepally, V., 2005. Assessing the relative influence of journals in a citation network. Communications of the ACM 48 (11), 71–74.

Palacios-Huerta, I., Volij, O., 2004. The measurement of intellectual influence. Econometrica 72, 963–977.

Pillai, S. U., Suel, T., Cha, S., 2005. The Perron-Frobenius theorem: some of its applications. IEEE Signal Processing Magazine 22 (2), 62–75.

Pinski, G., Narin, F., 1976. Citation influence for journal aggregates of scientific publications: Theory, with application to the literature of physics. Information Processing & Management 12 (5), 297 – 312.

Serrano, R., 2004. The measurement of intellectual influence: the views of a sceptic. Economics Bulletin 1 (3), 1–6.

West, J., Althouse, B., Bergstrom, C., Rosvall, M., Bergstrom, T., 2010. Eigenfactor.org – Ranking and mapping scientific knowledge. Accessed January 1, 2010, at `http://www.eigenfactor.org`.

West, J., Bergstrom, T., Bergstrom, C., 2009. Big macs and Eigenfactor scores: Don't let correlation coefficients fool you. Tech. Rep. arXiv:0911.1807v1 [cs.DL], retrieved January 1, 2010, from `http://arxiv.org/abs/0911.1807`.