Empirical Bayes approaches to PageRank type algorithms for rating scientific journals

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Abstract

Following criticisms against the journal Impact Factor, new journal influence scores have been developed such as the Eigenfactor or the Prestige Scimago Journal Rank. They are based on PageRank type algorithms on the cross-citations transition matrix of the citing-cited network. The PageRank algorithm performs a smoothing of the transition matrix combining a random walk on the data network and a teleportation to all possible nodes with fixed probabilities (the damping factor being $\alpha = 0.85$). We reinterpret this smoothing matrix as the mean of a posterior distribution of a Dirichlet-multinomial model in an empirical Bayes perspective. We suggest a simple yet efficient way to make a clear distinction between structural and sampling zeroes. This allows us to contrast cases with self-citations are included or excluded to avoid overvalued journal bias. We estimate the model parameters by maximizing the marginal likelihood with a Majorize-Minimize algorithm. The procedure ends up with a score similar to the PageRank ones but with a damping factor depending on the journal at hand. The procedures are illustrated with an example about cross-citations among 47 statistical journals studied by Varin et al. (2016).

keywords: Empirical Bayes, PageRank, Networks, Ranking, Bibliometrics, Structural zeros

1 Introduction

Assessing and ranking journals using influence indicators is an old practice (Gross and Gross, 1927) which has grown with the introduction of the impact factor (IF) (Archambault and Larivière, 2009). The

IF measures the reputation of a journal by the average number of annual citations it receives per published article in the last two years (Garfield, 1972). The systematic publication of IF by Clarivate Analytics (ex Thomson-Reuters, ex Institute of Science Information) in journal of citation reports (JCR) greatly impacts all sectors of scientific life and policies. The hierarchy created between journals generates intense competition among them and among researchers and institutions. However, the IF is widely criticized: it does not take into account the critical (positive, neutral or negative) assessment of citations; it strongly depends on the disciplinary field; the citation window is too narrow (2 years); the asymmetric distribution of the number of citations of an article is poorly taken into account by the average; the self-citations may have a negative influence as well as the equal weight attributed to each quotation whatever its origin. Various alternatives have been proposed to deal with these issues: lengthening of the citation window, standardization by disciplinary field, etc. (Zitt and Small, 2008).

Recent approaches taken into account the importance of citing sources to improve upon the IF have been suggested such as methods based on group lasso (Varin et al., 2016), stochastic bloc models, clustering with modularity classes (Stigler, 1994; Arbel and Robert, 2016) or methods using symmetric row-column (RC) models (Goodman, 1985; Grah, 2016).

Other solutions include scores derived from the Google PageRank (PR) algorithm (Waltman and van Eck, 2010) such as prestige scimago journal rank (PSJR) from Scimago Lab (Gonzalez-Pereira and Moya-Anegon, 2010) which is released by Elsevier and the Eigenfactor (EIFA) from Eigenfactor$^{\text{TM}}$ Metrics (Bergstrom, 2007; West and Bergstrom, 2010) which is released by Clarivate Analytics. They are widely use due to their simplicity and ease of computation. However, such scoring procedures lack a probabilistic model framework which can be helpful to make the underlying assumptions explicit and their derivation mathematically rigorously. One aim of this article is thus to suggest underlying models for these scores to better understand what is the rationale of the different operations applied. We focus on EIFA which has the particularity of excluding self-citations in order to compensate for the biases in the incentive policies of certain journals and the harmful effects of a form of intellectual consanguinity.

The outline of the paper is as follows. In Section 2, we detail the different steps to obtain the EIFA score. In Section 3, we show how this construction can be reinterpreted using a more formal empirical Bayesian perspective with a specific Dirichlet-multinomial model. We derive an Majorize-Minimize algorithm for the inference. We highlight the potential of the new method to appropriately handle structural zeros and distinguish them from sampling zeros which is always a key issue in statistical inference.

This ensures dealing with self-citations (inclusion or exclusion) and we show that our method results in a more flexible PageRank score. In Section 4, we compare and contrast our proposition with PR and EIFA methods on an exemple to rank statistical journals. A discussion section ends the paper.

2 PageRank influence scores

Let $C \in \mathbb{N}^{N\times N}$ be a square matrix of the cross-quotations between N journals of the same disciplinary field with citing (issuing references) in rows and cited (receiving citations) in columns. More precisely, c_{ij} corresponds to the number of times journal i, in a given year, quotes articles published by the journal j over a previous period of time (usually 2, 3 or 5 years). From this matrix, it is possible to define a weighted oriented network citing→cited with the transition probability matrix P, with elements $p_{ij} = (\frac{c_{ij}}{c_{i+}})_{(i=1,\dots,N),(j=1,\dots,N)}$ where $c_{i+} = C\mathbf{1}_N$ with $\mathbf{1}_N$ a vector of 1 of size N. PageRank produces a smoothing of P by a linear combination of P and a so-called "teleportation" matrix denoted $\mathbf{1}_N\pi^\top$ as follows:

$$G = \alpha P + (1-\alpha)\mathbf{1}_N\pi^\top, \tag{1}$$

with $\pi = \frac{1}{N}\mathbf{1}_N$.

The teleportation allows to avoid absorbing states and in particular disconnected components. Then, formula (1) guarantees the graph to be strongly connected and thus the existence of a discrete-time, irreducible and aperiodic Markov chain between the N nodes (namely the journals). Note that in the case of zero rows in P, corresponding to dangling nodes, *i.e.* nodes without any outgoing citations, there are replaced by the vector π to make P a stochastic matrix (Langville and Meyer, 2006). Formula (1) can be illustrated with the famous "random surfer" of Google which starting from i moves, with probability α, in the data network according to a random walk with transition probability p_{ij} and is randomly teleported, with a probability $(1-\alpha)$, to any other node with a transition probability π_j independent of the node i. The parameter α is called the damping factor and is usually set to 0.85. We will discuss this choice in the Section 3.1.

The algorithm PR, as defined in the original article (Brin and Page, 1998), is a recursive algorithm which ranks the nodes according to the following expression for an iteration ℓ:

$$r_j^{\ell+1} = \sum_{i=1}^{N} g_{ij} r_i^{\ell}\ , \ j = 1,\dots,N. \tag{2}$$

This means that, in the calculation of the score for the journal j, the contribution of the citing journal i is equal to its frequency g_{ij}, but this frequency is weighted by the proper influence r_i of i. Then, a quotation from a leading journal such as JRRS-B or JASA does not have the same weight than a quotation from another journal. Since the influence scores are unknown, they are iteratively estimated according to the so-called power method. As a matter of fact, the limit value of (2) corresponds to the stationary distribution of the Markov chain with transition matrix given in (1) and this stationary distribution is independent of the initial state. The solution is given by the eigenvector r with unit norm $(r^\top \mathbf{1}_N = 1)$ of G, $r^\top = r^\top G$ associated to the greatest eigenvalue. Since the chain is irreducible and aperiodic, this eigenvalue is unique and equal to one (Fouss and Shimbo, 2016). In practice, this means that knowing G, the smoothed matrix of transition of C, it is possible to establish a ranking among the journals based on their importance. Using the Google's random surfing representation, the importance of nodes corresponds to the limit visit frequency of these nodes during a very long walk on the network for a large number of surfers whatever their initial position.

EIFA belongs to the family of PageRank indicators in which self-citations are excluded ($c_{ii} = 0, p_{ii} = 0$, for all $i = 1, \ldots, N$) and the vector π does not give equiprobability to all the nodes but is taken as $\pi = \left(\frac{a_i}{a_+}\right)_{(i=1,\ldots,N)}$, a_i being the number of references published by i in the time window considered (5 years) and $a_+ = \sum_{k=1}^N a_k$. In addition, EIFA is not exactly equal to the eigenvector r associated with G but Bergstrom (2007) defines it as follows: starting with $r = G^\top r$, he computes $\tilde{r} = P^\top r$ and $r^\star = \frac{\tilde{r}}{\mathbf{1}_N^\top \tilde{r}}$. This is equivalent to

$$r^\star = \frac{r - (1-\alpha)\pi}{\alpha}. \tag{3}$$

This new formulation (3) shows that, in a somewhat *ad hoc* way, the EIFA algorithm consists of introducing the "teleportation" part to facilitate the computation and then attenuate its effect.

Note that the article influence (AI) score also produced by Eigenfactor™ Metrics is defined for a journal i as $\mathrm{AI}_i = \mathrm{EIFA}_i/\pi_i$ so that it is a size free score (influence *per* article) in the same vein as the IF score. Instead of normalizing by the proportion of published articles for a journal, it is possible to normalize by the proportion of references emitted by this journal. This latter normalization was actually introduced by Pinski and Narin (1976) when deriving the first recursive citation weighting system for ranking physics journals.

Even if the EIFA method is easy and straightforward to implement, it could be useful to study to what extent it could be embedded into a model framework while retaining the constraints of excluding self-citations and the simplicity of its expression. We tackle this problem by suggesting an empirical Bayes approach of a modified Dirichlet-multinomial model. We do not revisit the case where self-citations are kept since it can be easily handle with a standard Dirichlet-multinomial model (see, for example, Wang et al. (2008)).

3 A Bayesian Dirichlet-multinomial model without diagonal

Let $\underline{C}_i^\top = (c_{ij})$ for $j \neq i, i = 1, \ldots, N$ be the row i of C without its diagonal elements so that $\underline{C}$ is of dimension $(N \times N - 1)$ and can be written $\underline{C}^\top = [\underline{C}_1, \ldots, \underline{C}_N]$. We consider the following hierarchical probabilistic model.

1. Multinomial sampling of the elements of $\underline{C}_i^\top$

$$\underline{C}_i^\top | \underline{\theta}_i^\top \sim \mathscr{M}(n_i, \underline{\theta}_i^\top) \tag{4}$$

   of parameters $n_i = \sum_{j \neq i} c_{ij}$ and probability vector elements $\underline{\theta}_i = (\theta_{i1}, \ldots, \theta_{i,i-1}, \theta_{i,i+1}, \ldots, \theta_{i,N})^\top$. The random vectors $\underline{C}_i$ are assumed independent.

2. Dirichlet prior distributions for the parameters of the distributions (4). The prior distributions are also assumed independent:

$$\underline{\theta}_i^\top | \gamma_{\setminus i} \sim \mathscr{D}(\gamma_{\setminus i}^\top) \tag{5}$$

   where $\gamma_{\setminus i}^\top = (\gamma_1, \gamma_2, \ldots, \gamma_{i-1}, \gamma_{i+1}, \ldots, \gamma_N)$.

Due to the conjugacy property of these distributions, the posterior distributions are Dirichlet distributions:

$$\underline{\theta}_i^\top | \gamma_{\setminus i}, \underline{C}_i^\top \sim \mathscr{D}(\underline{C}_i^\top + \gamma_{\setminus i}^\top),\ i = 1, \ldots, N. \tag{6}$$

We easily get the expression of the posterior expectations:

$$\mathbb{E}_{\text{post}}(\underline{\theta_{ij}}) = \frac{c_{ij} + \gamma_j}{\sum_{j \neq i} c_{ij} + \sum_{j \neq i} \gamma_j},\ \text{for } j \neq i, i = 1, \ldots, N. \tag{7}$$

Denoting

$$\alpha_i = \frac{n_i}{n_i + K_{\setminus i}}, \tag{8}$$

with $K_{\setminus i} = K - \gamma_i$ and $K = \sum_{i=1}^{N} \gamma_i$, formulae (7) can be written as $\mathbb{E}_{\text{post}}(\underline{\theta_{ij}}) = \frac{c_{ij}+\gamma_j}{n_i+K_{\setminus i}}$. Using a reparametrization of the prior distribution with $\gamma_{\setminus i}^{\top} = (K_{\setminus i}(\pi_i^{\star}))^{\top}$ so that the prior expectation can be written as $\mathbb{E}(\underline{\theta}_i^{\top}) = (\pi_i^{\star})^{\top}$, the posterior expectation (7) of the row i can also be written as:

$$G_i^{\star\top} = \alpha_i p_i^{\top} + (1-\alpha_i)(\pi_i^{\star})^{\top} \tag{9}$$

with $\pi_i^{\star} = (\pi_{ij}^{\star})_{j\neq i, j=1,\ldots,N}$, $\pi_{ij}^{\star} = \frac{\gamma_j}{K_{\setminus i}}$ and $\pi_{ii}^{\star} = 0$.

Equation (9) is a classical linear combination of the data P and the prior expectation $\pi_i^{\star}$, which is the prior probability that i cites any other journals. It has the same form as (1) so that the modified multinomial-Dirichet model can be considered as an underlying modelisation for EIFA. However, the damping factor α is no longer fixed, but depends both on the number of references n_i produced by each journal i and on a parameter $K_{\setminus i}$ depending on i and on the parameters γ_j. The concentration parameter $K_{\setminus i}$, also known as the flattering constant, can be regarded as the total number of ”fictive” citations given by i. The shrinkage coefficient $(1-\alpha_i)$ given by (8) varies between 0 and 1. It is large when n_i is small and $K_{\setminus i}$ is large. When the data is not self-sufficient, when $K_{\setminus i}$ is large in comparison to n_i, there is a need to borrow information from other journals. The limiting case of $n_i = 0$ and $\alpha_i = 0$ corresponds to a dangling node. In such a situation, the corresponding row $G_i^{\star\top}$ will be equal to the prior probabilities $(\pi_i^{\star})^{\top}$. This adjustment is automatic contrary to what happens with PageRank as described in the introduction.

3.1 Choosing the prior hyperparameters

Non informative priors Various options exist at this stage to pursue the analysis. The first one corresponds to the situation where the Dirichlet distribution (6) is completely specified: the parameters are assumed to be known. This corresponds to a non informative prior distribution such as

- Bayes-Laplace: $K = N$ and $\gamma = \mathbf{1}_N$,
- Jeffreys: $K = N/2$ and $\gamma = 1/2 \times \mathbf{1}_N$,
- Perks: $K = 1$ and $\gamma = 1/N \times \mathbf{1}_N$.

Opinions are divided on the merits of these different priors (Berger, 1985; Tuyl, 2016), especially in the presence of a large number of zero cells, which is precisely the main objective of a PageRank type of smoothing. In all cases, it gives an equiprobability solution to the teleportation $(\pi_i = (1/N, \ldots, 1/N))$ used by PR at the origin. But it was not considered acceptable in bibliometry.

Empirical Bayes priors Another option consists of using a standard empirical Bayesian framework, also known as the ML-II approach (Berger, 1985), where the hyperparameters γ are replaced by the maximum likelihood estimates of the marginal distribution $\mathscr{L}(\underline{C}|\gamma)$ obtained after integrating out the parameters of the multinomial distribution θ. The density of this marginal distribution is the product of compound Dirichlet multinomial (or Polya distribution):

$$
\begin{aligned}
\mathscr{L}(\underline{C}|\gamma) &= \Pi_{i=1}^{N} \mathscr{L}(\underline{C}_i^\top|\gamma_{\setminus i}) \\
\mathscr{L}(\underline{C}_i^\top|\gamma_{\setminus i}) &= \int p(\underline{C}_i^\top|\underline{\theta}_i^\top) p(\underline{\theta}_i^\top|\gamma_{\setminus i}) d\underline{\theta}_i^\top
\end{aligned}
$$

where $p(\underline{C}_i^\top|\underline{\theta}_i^\top)$ is the multinomial component:

$$p(\underline{C}_i^\top|\underline{\theta}_i^\top) = \frac{n_i!}{\Pi_{j\neq i} c_{ij}!} \Pi_{j\neq i} \theta_{ij}^{c_{ij}}$$

and $p(\underline{\theta}_i^\top|\gamma_{\setminus i})$, the Dirichlet component:

$$p(\underline{\theta}_i^\top|\gamma_{\setminus i}) = \frac{\Gamma\left(\sum_{j\neq i} \gamma_j\right)}{\Pi_{j\neq i} \Gamma(\gamma_j)} \Pi_{j\neq i} \theta_{ij}^{\gamma_j - 1}.$$

Then, $\Pi_{j\neq i} \theta_{ij}^{c_{ij}+\gamma_j-1}$ is the kernel of a Dirichlet distribution so that $\int \Pi_{j\neq i} \theta_{ij}^{c_{ij}+\gamma_j-1} d\underline{\theta}_i = \frac{\Pi_{j\neq i}\Gamma(c_{ij}+\gamma_j)}{\Gamma\left(\sum_{j\neq i}(c_{ij}+\gamma_j)\right)}$ which leads to

$$\mathscr{L}_i(\underline{C}_i^\top|\gamma_{\setminus i}) = \frac{n_i!\Gamma\left(\sum_{j\neq i} \gamma_j\right)}{\Pi_{j\neq i} c_{ij}!\Gamma\left(\sum_{j\neq i}(c_{ij}+\gamma_j)\right)} \Pi_{j\neq i} \frac{\Gamma(c_{ij}+\gamma_j)}{\Gamma(\gamma_j)}. \tag{10}$$

Note that a zero, whereas sampling or structural, is not important in the multinomial part, since it multiplies the likelihood by 1 even if we do not exclude the index i. However, for the Dirichlet part, it has an impact since we explicitly remove a parameter in each θ_i so that $\underline{\theta}_i$ has a size of $(N-1)$ instead of N. The impact of such a strategy will be illustrated in Section 4.

3.2 Estimating the hyperparameters in an empirical Bayes framework

The log-likelihood can be written as:

$$L_i(\gamma_{\setminus i}) = \log\Gamma(\mathrm{K}_{\setminus \mathrm{i}}) - \log\Gamma(\mathrm{n_i} + \mathrm{K}_{\setminus \mathrm{i}}) + \sum_{\mathrm{j}\neq \mathrm{i}} \left[\log\Gamma(\mathrm{c_{ij}} + \gamma_{\mathrm{j}}) - \log\Gamma(\gamma_{\mathrm{j}})\right], \quad (11)$$

and its gradient can be written as:

$$\frac{d\mathscr{L}_i(\underline{C}_i^\top|\gamma_{\setminus i})}{d\gamma_j} = \psi(\sum_{j\neq i}\gamma_j) + \psi(n_i + \sum_{j\neq i}\gamma_j) + \psi(c_{ij}+\gamma_j) - \psi(\gamma_j), \text{ for all } i \neq j \quad (12)$$

$$\frac{d\mathscr{L}_i(\underline{C}_i^\top|\gamma_{\setminus i})}{d\gamma_i} = 0. \quad (13)$$

We then sum to get:

$$[\nabla L(\gamma)]_j = \frac{d\mathscr{L}(\underline{C}|\gamma)}{d\gamma_j} = \sum_{i\neq j}\frac{d\mathscr{L}(\underline{C}_i|\gamma_{\setminus i})}{d\gamma_j} = \sum_{i\neq j}\psi(K_{\setminus i}) - (N-1)\psi(\gamma_j) + \sum_{i\neq j}\left(\psi(c_{ij}+\gamma_j) - \psi(n_i + K_{\setminus i})\right), \quad (14)$$

where $\psi(x) = d\log\Gamma(\mathrm{x})/\mathrm{dx}$, is the digamma function.

Different algorithms can be used to maximize the log-likelihood (11) such as Minorization-Maximization algorithms. Indeed, using results from Minka (2012), we get a lower bound for the likelihood that can be iteratively maximized. It leads to a fixed point iteration algorithm defined defined for $j = 1,\dots,N$, by iterating:

$$\gamma_j^{\ell+1} = \gamma_j^{\ell}\frac{\sum_{i\neq j}\psi(c_{ij}+\gamma_j^{\ell}) - (N-1)\psi(\gamma_j^{\ell})}{\sum_{i\neq j}\psi(n_i + K_{\setminus i}^{\ell}) - \psi(K_{\setminus i}^{\ell})}. \quad (15)$$

Other options include a first order algorithm with inversion, second order algorithms such as Levenberg-Marquardt which require computing the Hessian matrix, or an expectation-maximization (EM) variant of this latter algorithm. Of course, second order algorithms have the great advantage of giving as an output the asymptotic sampling variance-covariance matrix but this comes at the price of supplement burden from the computational point of view. In the Appendix, we detail the other algorithms and give a small comparison study highlighting the merits of the first order fixed point method.

4 Ranking statistical journals

The application concerns the matrix C of cross-references between 47 statistical journals, studied by Varin et al. (2016). It concerns citations published in 2010 related to articles published from 2001 to

2010. A subset of the matrix is given in Table 1 and the complete list with abbrevations is given in Table 6 of Appendix 6.2 . We apply our method described in Section 3 called EBEF for Empirical

		AmS	AISM	AoS	ANZS	Bern
1	AmS	43	1	2	0	0
2	AISM	0	18	3	3	5
3	AoS	9	24	291	4	53
4	ANZS	0	5	2	5	0
5	Bern	1	7	27	0	22

Table 1: Extract of the 47×47 cross-citation matrix between statistics journals.

Bayes Eigen Factor. The maximum likelihood estimate and the associated variance of the parameter K of concentration is established at K = 58.10 +/- 2.82 with a significant variation between the γ_j values ranging from 6.61 +/- 0.54 for JASA to 0.06 +/- 0.03 for STATAJ. Note that ignoring self-citations by considering these data as sampling zeros (using a standard Dirichlet-multinomial scheme without specific modification for the Dirichlet parameters as in equation (5)) leads to a substantially different estimation for K (K = 49.00).

Looking at the parameters α_i shows that journals such as CSDA or STMED has values close to 0.95 whereas it is equal to 0.39 for STATAJ (the mean is 0.77). Teleportation is decreasing with the number of references emitted by a journal. It makes sense since it is less relevant to use teleportation in the case of many outgoing links. The scores obtained by EBEF are given in Table 2 column 4 and associated rank are given in Table 7 in Appendix 6.2.

We compare EBEF to EIFA (column 3) since it can be regarded as its Bayesian counterpart. Note that here EIFA is applied on a dataset where 10 years are considered whereas the official time window is 5 years. We also add two scores that include self-citations namely EBPR (Empirical Bayes Page Rank) and the Prestige Scimago Journal Rank (PSJR). EBPR consists of using the Multinomial-Dirichlet scheme but without excluding the diagonal. The implementation is straightforward from EBEF. The PSJR score is produced by Scimago Lab and released by Scopus, the citation database of Elsevier. It is defined as

$$G_2 = \alpha_2 P + (1-\alpha_2-\beta)\mathbf{1}\pi^\top + \beta\frac{\mathbf{11}^\top}{N}, \tag{16}$$

with $\pi = (\tilde{a}_i)_{1,\dots,N}$ where $\tilde{a}_i = a_i/a_+$, $\alpha_2 = 0.90$ and $\beta = 10^{-4}$. (Recall that a_i is the number of articles published by i in the considered time window.) Then, the first eigenvector is computed: $G_2^\top r_2 = r_2$. PSJR uses a teleportation which depends on the number of papers published and adds a small term of uniform teleportation. In addition, self-citations are restricted to 33% of references emitted by each journal. We apply (16) on the same cross-references matrix between the 47 journals for fair comparisons.

However, PSJR uses the information contained in the Scopus data base of Elsevier on a 3-year window while EIFA is based on journals indexed by Clarivate Analytics (ex Thomson-Reuters) on a 5-year window. This makes the comparison of both scores EIFA and PSJR, released by two concurents, more difficult.

To get rid of the strong effect of the number of papers published, we favor the scores normalized with the number of published papers, exactly as the article influence (AI) discussed in the introduction. It gives sensitive different results as illustrated in Table 3 for the scores and in Table 8 (see Appendix 6.2) for the ranks. Indeed, with EBEF, journals such as CSDA decreases from rank 8 to rank 28. On the contrary TEST increases from rank 23 to 11, etc. The top quintet, JRSS-B, STSCI, AOS, JASA, BKA is stable across the article influence scores.

In addition, we compute in Table 4 both Spearman rank correlation and Kendall tau correlation to assess the similarities between ranking given by the different scores. EBEF is highly correlated with EIFA which was expected thus giving credit to EIFA for its efficiency. The same applies to PSJR with respect to EBPR. Although highly correlated (kendal-tau of 0.90), EBPR and EBEF do not rate and rank journals in the same way, making clear the importance of self-citations in defining journal influence rating systems.

5 Discussion

The suggested method EBEF is an extension of the PR-type algorithm used for the establishment of the Eigenfactor according to a well-established probabilistic model (Dirichlet-multinomial model) which allows to rigorously take into account the exclusion constraint of self-citations. The smoothing of the adjacent matrix corresponding to the citing to cited network is obtained as in PR by a convex combination of the corresponding vector of the observed transition probabilities and of a teleportation vector according to respective probabilities which vary from one journal to another as a function of the total number of references n_i and of a concentration coefficient $K_{\setminus i}$. In addition to its conceptual and computational simplicity, the Bayesian PR developed here has the merit of taking into account and distinguishing the zeros of structure from those of sampling. The way we deal with structural zeroes can be extended to non diagonal terms to take into account other constraints such as restriction or exclusion on links between subgroups of journals belonging to a specific field.

The maximum likelihood estimate of the parameters, derived with a Majorize-Minimize algorithm, could also be obtained as a by-product of hierarchical Bayes strategy with an additional step of specifying non informative prior distributions on the parameters γs and computing the posterior modes of the corresponding marginal distributions. A simpler alternative should be to fix π either as $\pi = (\tilde{a}_i)_{i=1,\dots,N}$ or $\pi = (c_{+i}/c_{++})_{i=1,\dots,N}$ and to replace K with its maximum likelihood estimation. An even simpler solution would be to fix π as before and setting $K = N$. This would make EBEF and EIFA closer to each other and EBEF could be easier to compute.

Finally, one potential concern with the empirical Bayes approach is that it uses twice the data, both to estimate the parameters γs and to give the final scores and ranking. To tackle this issue, one can resort to a Monte Carlo half sampling procedure as follows. A training matrix $\tilde{C} = (\tilde{c}_{ij})$ is generated with $\tilde{c}_{ij} \sim \text{Binomial}(c_{ij}, (1-\delta))$, with $\delta = 0.5$. Parameters γs are estimated with the training matrix and these estimates are used to calculate PSJR, EBPR, EIFA and EBEF scores on the complementary matrix $C - \tilde{C}$. This process is repeated $m = 200$ times and final scores are obtained as means of elementary scores over the m replications. We give the results of a slightly different approach in Appendix 6.3.

Dealing with self-citations is a critical topic since including or excluding it may appear too radical. The *ad hoc* solution used by PSJR which consists of bounding the self-citations to 33% could be a solution. We suggest an alternative solution allowing to underweight self-citations in a data-driven way. It is as follows. Let us consider the simple score defined for journal i as the ratio of the total number of citations received ($c_{i+} = \sum_{j=1}^{N} c_{ij}$) by i from other journals including itself divided by the total number of references made by this to other journals: $S_i = \frac{c_{+i}}{c_{i+}}$. This ratio provides a natural starting approximation to the iterative algorithm for computing the "influence weight" of journal i introduced by Pinski and Narin (1976). The numerator of S_i can be decomposed into self (c_{ii}) and external ($R_{\setminus i}$) citations received and the denominator likewise into self (c_{ii}) and external ($M_{\setminus i}$) references made so that:

$$S_i = \frac{c_{+i}}{c_{i+}} = \frac{c_{ii} + R_{\setminus i}}{c_{ii} + M_{\setminus i}}.$$

Let $\kappa \in [0,1]$ be a tuning parameter devoted to attenuate the effect of self-citations. Define

$$S_i(\kappa) = \frac{\kappa c_{ii} + R_{\setminus i}}{\kappa c_{ii} + M_{\setminus i}}.$$

It can easily be shown that

- if $S_i(0) < 1$, $S_i(\kappa)$ is an increasing function of κ which remains upper bounded by 1.

- if $S_i(0) = 1$, $S_i(\kappa) = 1$ for any κ.

- if $S_i(0) > 1$, $S_i(\kappa)$ is a decreasing function of κ which remains lower bounded by 1.

This scores implies that powerful journals have no interest in favoring self-citations contrary to lower in status journals. However, the impact of self-citations remains bounded. Based on this comment, we would suggest selecting κ for journal i, with

$$\kappa_i = \min\left(\frac{\min(R_i, M_i)}{c_{ii}}, 1\right),$$

which penalises lower status journals trying to take advantage of self-citations.

Applying this rule to the 47 statistical journals at hand in this paper leads to choose $\kappa_i = 1$ for all the journals except for STATATJ which receives the weight $\kappa = 0.442$ (self-citation rate= 67%) and JSS which receives the weight $\kappa = 0.887$ (self-citation rate= 32%). These journals have by their very nature a lot of self-citations since they are related to softwares. In particular, STATAJ is exclusively the journal of the software STATA. There are two other journals having a self-citation rate greater than the PSJR threshold of 33%: Annals of Statistics (36%) and Statistics in Medecine (37%) but still with κ values of 1. This choice of weights seems quite sensible. Actually, most of the statistical journals do not use much self-citations (the mean of self-citation rate is 20%).

6 Appendix

6.1 Algorithms comparison

In this section, we describe and compare other algorithms that can be used to maximize the marginal likelihood (11). From (14), we can write

$$\psi(\gamma_j) = \frac{1}{(N-1)}\left[\sum_{i\neq j}\psi(K_{\backslash i}) + \sum_{i\neq j}\left(\psi(c_{ij}+\gamma_j) - \psi(n_i + K_{\backslash i})\right)\right]. \tag{17}$$

Formula (17) serves as a basis for an inversion method (INV) i.e. $\psi(\gamma_j) = a$ that can be solved via Newton Raphson by iterating:

$$\gamma_j^{\ell+1} = \gamma_j^{\ell} - \frac{\psi(\gamma_j^{\ell}) - a^{\ell}}{\psi'(\gamma_j^{\ell})}, \tag{18}$$

with $a^\ell = (N-1)^{-1}\left[\sum_{i\neq j}\left(\psi(K^\ell_{\backslash i}) - \psi(n_i + K^\ell_{\backslash i})\right) + \sum_{i\neq j}\psi(c_{ij}+\gamma^\ell_j)\right]$.

Second order algorithms can also be considered. The second derivatives can be written as:

$$\frac{d^2\mathscr{L}(\underline{C}|\gamma)}{d\gamma_j^2} = \sum_{j\neq i}\frac{d^2\mathscr{L}(\underline{C}_i|\gamma_{\backslash i})}{d\gamma_j^2} = \sum_{i\neq j}\psi^{'}(K_{\backslash i}) - (N-1)\psi^{'}(\gamma_j) + \sum_{i\neq j}\left(\psi^{'}(c_{ij}+\gamma_j) - \psi^{'}(n_i + K_{\backslash i})\right), \quad (19)$$

with $\psi^{'}$ the trigamma function and

$$\frac{d^2\mathscr{L}(\underline{C}|\gamma)}{d\gamma_j d\gamma_k} = \sum_{j\neq i\neq k}\frac{d^2\mathscr{L}(\underline{C}_i|\gamma_{\backslash i})}{d\gamma_j d\gamma_k} = \sum_{i\neq j\neq k}\psi^{'}(K_{\backslash i}) - \psi^{'}(n_i + K_{\backslash i}). \quad (20)$$

Denoting the Hessian matrix as $H(\gamma) = \frac{d^2L(\gamma)}{d\gamma d\gamma^\top}$, a Levenberg-Marquardt algorithm consists of iterating:

$$\left[H(\gamma^\ell) + \lambda^\ell \mathrm{diag}\left(\mathrm{H}(\gamma^\ell)\right)\right]\left(\gamma^{\ell+1} - \gamma^\ell\right) = \nabla L(\gamma^\ell), \quad (21)$$

where λ^ℓ is a damping factor adjusted at each iteration with decreasing values if $L(\gamma)$ increases and of increasing values if $L(\gamma)$ decreases. When $\lambda^\ell = 0$, the algorithm boils down to Newton-Raphson. The adaptive sequence $(\lambda_1, \ldots, \lambda_L)$, with L the number of iterations, can be chosen as suggested by Nielsen (1999) and Giordan et al. (2017) with:

$$\lambda^{\ell+1} = \lambda^\ell \max\left(1/3, 1-(2\rho^\ell - 1)^3\right) \text{ if } \rho^{\ell+1} > 0, \quad (22)$$

$$\lambda^{\ell+1} = 2\lambda^\ell \text{ otherwise} \quad (23)$$

with, $\lambda^0 = 0$ and $\rho^{\ell+1} = \frac{L(\gamma^{\ell+1}) - L(\gamma^\ell))}{1/2(\gamma^{\ell+1}-\gamma^\ell)^\top H(\gamma^\ell)((\gamma^{\ell+1}-\gamma^\ell))}$. The stopping rule can be defined as $\frac{||\gamma^{\ell+1}-\gamma^\ell||}{||\gamma^\ell||+\varepsilon_1} < \varepsilon_2$.

It is also possible to derive an EM algorithm to maximize the likelihood with θ being regarded as the missing latent variables. However, the EM is not relevant since a first order algorithm to achieve the M step leads to equation (12).

As shown in Table 5, there is a striking contrast between the performance of the algorithms in terms of number of iterations *versus* computing time to convergence. The Levenberg-Marquardt (LM) algorithm (21) is by far the algorithm needing the lowest number of iterations whatever are the stopping rule and the starting point. Fixed point iteration (FP) (15) and inversion (INV) (18) require 7 to 8 times more runs for convergence. But, as far as computing time is concerned, the most efficient algorithm is FP (5 to 7 seconds for $\varepsilon_2 = 10^{-6}$) while INV and LM require twice as much time but within reasonable figures. Moreover, LM produces an estimate of the asymptotic sampling variance-covariance matrix whereas FP and INV do not. In conclusion, one may suggest using FP to get a quick estimation of parameters and then checking it with LM. Incidentally, the EM-based LM algorithm does not display any advantage as compared to the standard LM. In all cases, a start with the empirical value $\gamma_j^0 = Nc_{+j}/c_{++}$ provides the most effective performance both in time and number of iterations, but using the other ones is not worthless to check insensitivity of the solutions to initial conditions.

There is a strong correlation (0.967) between the ML estimations of the parameters and the numbers or proportions of cites received by the different journals with the highest values for JASA, AOS, JRSS-B, BKA, BCS and the lowest for STATJ, EES, JBS, STPAP, JABES confirming that it is a good starting value γ_j^0. However, the concentration parameter K remains a key issue in the estimation process. For the starting values we took $K = N = 47$ whereas the estimation turns out to be 58 +-2.82.

6.2 Ranking statistical journals

The Table 6 displays the list of the 47 statistical journals.

6.3 Half sampling procedure

We generate training matrices according to a Beta-Bernoulli process such that $\tilde{c}_{ij} = \sum_{k=1}^{c_{ij}} X_k$, with $X_k \in \{0,1\}$, $P(X_k = 0) = q$ and $q \sim \text{Beta}(a,b)$. Then $\mathbb{E}(X_k) = q = \frac{a}{a+b}$, $\text{Var}(X_k) = q(1-q)$ and $\text{Cor}(X_k, X_\ell) = \rho = (a+b+1)^{-1}$. The marginal distribution of $\tilde{c}_{ij}$ is a Beta-Binomial distribution with parameters (a, b, c_{ij}) and has expectation $\mathbb{E}(\tilde{c}_{ij}) = c_{ij}q$ and $\text{Var}(\tilde{c}_{ij}) = c_{ij}q(1-q)[1+(c-1)\rho]$. This sampling procedure is similar to the Binomial sampling described in the Discussion but it takes into account the overdispersion due to an intra-class correlation ρ among binary draws intra cells. For the Monte Carlo half sampling we take: $a = b = 10$ resulting in $q = 0.5$ and $\rho \approx 0.05$. Other values would have been envisioned, but this one corresponds to the estimation of an average intra-class correlation $\text{Cor}(X_{ijk}, X_{ij\ell}$ within citing journals i for each category of response j (journal cited) as defined by (Landis and Koch, 1977) and estimated via MANOVA procedures.

The two sampling procedures ($\rho = 0$ and $\rho = 0.05$) gave almost the same results either for parameter ML estimation and for influence scores given in Table 9. Moreover, the results obtained with MC half samples are similar to the results obtained on the complete data set. The coefficients γ are stable. Nevertheless, we observe that the coefficients α_i are smaller (0.90 for CSDA instead of 0.95 and 0.23 for STATAJ nstead of 0.39) which implies a more aggressive shrinkage. This behavior is expected as there are less data available to rely on.

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	Journal	PSJR	EBPR	EIFA	EBEF
1	JASA	119.51	132.49	126.84	127.28
2	AOS	105.35	116.95	97.62	97.17
3	JRSS-B	71.12	79.67	78.24	79.91
4	BKA	62.43	68.48	71.92	72.97
5	BCS	63.11	66.57	64.23	63.81
6	STMED	67.01	62.17	53.63	51.27
7	JSPI	45.88	40.46	43.76	42.39
8	CSDA	45.71	42.24	38.16	38.44
9	STSIN	28.09	29.63	33.69	34.45
10	JMA	29.96	29.26	30.74	30.27
11	BIOST	23.65	25.01	26.77	26.65
12	JCGS	21.69	23.33	24.28	25.10
13	SPL	31.90	23.89	24.78	23.75
14	SJS	18.34	19.66	22.73	23.47
15	STSCI	18.70	20.93	22.81	23.26
16	BERN	14.77	14.65	16.70	16.31
17	CJS	11.09	11.80	13.16	13.79
18	STCMP	11.19	11.89	12.87	13.42
19	BIOJ	11.98	11.04	12.14	12.14
20	TECH	11.76	11.60	11.65	11.80
21	CSTM	17.59	10.74	13.50	11.61
22	JRSS-C	9.30	9.55	10.51	11.08
23	TEST	7.94	8.51	9.87	10.27
24	JRSS-A	10.93	10.44	9.66	9.81
25	AISM	9.73	8.66	10.28	9.79
26	AMS	10.28	9.82	9.17	9.62
27	JNS	7.82	7.25	8.59	8.54
28	LTA	7.67	7.61	8.60	8.52
29	JSCS	8.03	6.43	7.18	7.31
30	ENVR	7.90	6.88	6.91	7.26
31	SMMR	6.15	5.86	6.67	6.54
32	MTKA	6.35	5.11	6.21	5.77
33	CSSC	7.32	4.77	6.08	5.63
34	JSS	6.52	6.13	5.17	5.43
35	JTSA	6.81	5.28	5.88	5.43
36	ANZS	4.84	4.38	5.02	5.28
37	JBS	7.22	5.45	5.35	5.12
38	STATS	4.92	4.13	5.21	5.04
39	ISR	5.35	4.91	4.86	5.03
40	JAS	6.58	4.09	4.83	4.72
41	CMPST	4.18	3.71	4.12	4.49
42	JABES	4.46	4.01	4.26	4.44
43	STMOD	3.56	3.60	3.95	4.28
44	STNEE	3.41	3.16	3.45	3.83
45	EES	4.41	3.75	3.41	3.55
46	STPAP	3.45	2.09	2.70	2.45
47	STATAJ	4.27	2.18	2.07	1.73

Table 2: Total influence scores. PSJR: Prestige Scimago Journal Rank (self-citations restricted to 33% of references); EBPR: Empirical Bayes PageRank (self-citations included); EIFA*: Eigenfactor; EBEF*: Empirical Bayes Eigen Factor * without self-citations. Journals are ordered according to EBEF scores.

	Journal	PSJR	EBPR	EIFA (AI)	EBEF
1	JRSS-B	5.31	5.95	5.84	5.97
2	STSCI	3.46	3.87	4.22	4.30
3	AOS	4.12	4.58	3.82	3.80
4	JASA	3.44	3.81	3.65	3.66
5	BKA	2.66	2.92	3.07	3.12
6	BIOST	1.71	1.81	1.93	1.92
7	SJS	1.40	1.50	1.74	1.80
8	JCGS	1.52	1.63	1.70	1.76
9	BCS	1.70	1.80	1.73	1.72
10	STSIN	1.28	1.35	1.53	1.56
11	TEST	1.15	1.24	1.44	1.49
12	CJS	1.15	1.22	1.36	1.43
13	STCMP	1.11	1.18	1.28	1.33
14	BERN	1.05	1.04	1.19	1.16
15	TECH	1.05	1.04	1.04	1.06
16	LTA	0.94	0.93	1.05	1.04
17	JRSS-C	0.79	0.82	0.90	0.95
18	JRSS-A	1.03	0.98	0.91	0.93
19	JMA	0.89	0.87	0.91	0.90
20	STMOD	0.64	0.65	0.71	0.78
21	SMMR	0.70	0.66	0.76	0.74
22	AMS	0.76	0.72	0.68	0.71
23	ISR	0.74	0.68	0.68	0.70
24	AISM	0.65	0.58	0.69	0.65
25	JNS	0.59	0.54	0.64	0.64
26	STMED	0.82	0.76	0.66	0.63
27	BIOJ	0.58	0.54	0.59	0.59
28	CSDA	0.66	0.61	0.55	0.55
29	JSS	0.66	0.62	0.52	0.55
30	JSPI	0.58	0.51	0.56	0.54
31	JABES	0.50	0.45	0.48	0.50
32	ANZS	0.46	0.41	0.47	0.50
33	STNEE	0.41	0.38	0.41	0.46
34	STATS	0.44	0.37	0.46	0.45
35	EES	0.55	0.47	0.42	0.44
36	MTKA	0.48	0.38	0.47	0.44
37	JTSA	0.54	0.42	0.47	0.43
38	ENVR	0.46	0.40	0.41	0.43
39	CMPST	0.37	0.33	0.37	0.40
40	JSCS	0.36	0.29	0.32	0.33
41	SPL	0.39	0.30	0.31	0.29
42	JBS	0.40	0.31	0.30	0.29
43	CSSC	0.28	0.18	0.23	0.21
44	CSTM	0.30	0.18	0.23	0.20
45	STATAJ	0.46	0.24	0.22	0.19
46	STPAP	0.26	0.16	0.20	0.18
47	JAS	0.25	0.15	0.18	0.18

Table 3: Article influence scores. PSJR: Prestige Scimago Journal Rank (self-citations restricted to 33% of references); EBPR: Empirical Bayes PageRank (self-citations included); EIFA*: Eigenfactor; EBEF*: Empirical Bayes Eigen Factor * without self-citations. Journals are ordered according to EBEF scores.

	PSJR	EBPR	EIFA	EBEF
PSJR	1	0.994	0.978	0.9753
EBPR	0.964	1	0.987	0.987
EIFA	0.893	0.92 1	1	0.996
EBEF	0.886	0.918	0.965	1

Table 4: Correlations among article based journal scores. Below diagonal: Kendall tau. Above diagonal: Spearman rank correlation.

	FP			INV			LM			LMem		
	a	b	c	a	b	c	a	b	c	a	b	c
Nb iterations	86	75	54	88	99	66	15	11	8	61	45	44
Times (s)	6	4	3	9	11	8	37	26	25			
	FP			INV			LM			LMem		
	a	b	c	a	b	c	a	b	c	a	b	c
Nb iterations	107	96	75	111	127	84	16	12	9	87	70	69
Times (s)	7	6	5	12	13	9	17	12	9	43	41	40

Table 5: Comparison of algorithms used to compute maximum-likelihood estimations of the Compound Dirichlet Multinomial parameters. FP: Fixed Point Iteration; INV: Inversion Method; LM: Levenberg-Marquardt; LMem: LM for EM. Top table with stopping threshold equals to $\varepsilon_2 = 10^{-5}$ and bottom table $\varepsilon_2 = 10^{-6}$.

	Journal.Name	Abbreviation
1	American Statistician	AmS
2	Annals of the Institute of Statistical Mathematics	AISM
3	Annals of Statistics	AoS
4	Australian and Neww Zealand Journal of Statistics	ANZS
5	Bernoulli	Bern
6	Biometrical Journal	BioJ
7	Biometrics	Bcs
8	Biometrika	Bka
9	Biostatistics	Biost
10	Canadian Journal of Statistics	CJS
11	Communication in Statistics-Simulation and Computation	CSSC
12	Communication in Statistics-Theory and Methods	CSTM
13	Computational Statistics	CmpSt
14	Computational Statistics and Data Analysis	CSDA
15	Environmental and Ecological Statistics	EES
16	Environmetrics	Envr
17	International Statistical Review	ISR
18	Journal of Agricultural Biological and Environmental Statistics	JABES
19	Journal of the American Statistical Association	JASA
20	Journal of Applied Statistics	JAS
21	Journal of Biopharmaceutical Statistics	JBS
22	Journal of Computational and Graphical Statistics	JCGS
23	Journal of Multivariate Analysis	JMA
24	Journal of Nonparametric Statistics	JNS
25	Journal of the Royal Statistical Society, Series A	JRSS-A
26	Journal of the Royal Statistical Society, Series B	JRSS-B
27	Journal of the Royal Statistical Society, Series C	JRSS-C
28	Journal of Statistical Computation and Simulation	JSCS
29	Journal of Statistical Planning and Inference	JSPI
30	Journal of Statistical Software	JSS
31	Journal of Time Series Analysis	JTSA
32	Life Data Analysis	LDA
33	Metrika	Mtka
34	Scandinavian Journal of Statistics	SJS
35	Stata Journal	StataJ
36	Statistics and Computing	StCmp
37	Statistics	Stats
38	Statistics in Medicine	StMed
39	Statistical Methods in Medical Research	SMMR
40	Statistical Modelling	StMod
41	Statistica Neerlandica	StNee
42	Statistical Papers	StPap
43	Statistics and Probability Letters	SPL
44	Statistical Science	StSci
45	Statistica Sinica	StSin
46	Technometrics	Tech
47	Test	Test

Table 6: List and abbreviations of the 47 statistical Journals

	PSJR	EBPR	EIFA	EBEF
1	JASA	JASA	JASA	JASA
2	AOS	AOS	AOS	AOS
3	JRSS-B	JRSS-B	JRSS-B	JRSS-B
4	STMED	BKA	BKA	BKA
5	BCS	BCS	BCS	BCS
6	BKA	STMED	STMED	STMED
7	JSPI	CSDA	JSPI	JSPI
8	CSDA	JSPI	CSDA	CSDA
9	SPL	STSIN	STSIN	STSIN
10	JMA	JMA	JMA	JMA
11	STSIN	BIOST	BIOST	BIOST
12	BIOST	SPL	SPL	JCGS
13	JCGS	JCGS	JCGS	SPL
14	STSCI	STSCI	STSCI	SJS
15	SJS	SJS	SJS	STSCI
16	CSTM	BERN	BERN	BERN
17	BERN	STCMP	CSTM	CJS
18	BIOJ	CJS	CJS	STCMP
19	TECH	TECH	STCMP	BIOJ
20	STCMP	BIOJ	BIOJ	TECH
21	CJS	CSTM	TECH	CSTM
22	JRSS-A	JRSS-A	JRSS-C	JRSS-C
23	AMS	AMS	AISM	TEST
24	AISM	JRSS-C	TEST	JRSS-A
25	JRSS-C	AISM	JRSS-A	AISM
26	JSCS	TEST	AMS	AMS
27	TEST	LTA	LTA	JNS
28	ENVR	JNS	JNS	LTA
29	JNS	ENVR	JSCS	JSCS
30	LTA	JSCS	ENVR	ENVR
31	CSSC	JSS	SMMR	SMMR
32	JBS	SMMR	MTKA	MTKA
33	JTSA	JBS	CSSC	CSSC
34	JAS	JTSA	JTSA	JSS
35	JSS	MTKA	JBS	JTSA
36	MTKA	ISR	STATS	ANZS
37	SMMR	CSSC	JSS	JBS
38	ISR	ANZS	ANZS	STATS
39	STATS	STATS	ISR	ISR
40	ANZS	JAS	JAS	JAS
41	JABES	JABES	JABES	CMPST
42	EES	EES	CMPST	JABES
43	STATAJ	CMPST	STMOD	STMOD
44	CMPST	STMOD	STNEE	STNEE
45	STMOD	STNEE	EES	EES
46	STPAP	STATAJ	STPAP	STPAP
47	STNEE	STPAP	STATAJ	STATAJ

Table 7: Total influence ranking. PSJR: Prestige Scimago Journal Rank (self-citations restricted to 33% of references); EBPR: Empirical Bayes PageRank (self-citations included); EIFA*: Eigenfactor; EBEF*: Empirical Bayes Eigen Factor * without self-citations. Journals are ordered according to EBEF scores.

	EBPR	PSJR	EIFA	EBEF
1	JRSS-B	JRSS-B	JRSS-B	JRSS-B
2	AOS	AOS	STSCI	STSCI
3	STSCI	STSCI	AOS	AOS
4	JASA	JASA	JASA	JASA
5	BKA	BKA	BKA	BKA
6	BIOST	BIOST	BIOST	BIOST
7	BCS	BCS	SJS	SJS
8	JCGS	JCGS	BCS	JCGS
9	SJS	SJS	JCGS	BCS
10	STSIN	STSIN	STSIN	STSIN
11	TEST	TEST	TEST	TEST
12	CJS	CJS	CJS	CJS
13	STCMP	STCMP	STCMP	STCMP
14	TECH	BERN	BERN	BERN
15	BERN	TECH	LTA	TECH
16	JRSS-A	JRSS-A	TECH	LTA
17	LTA	LTA	JRSS-A	JRSS-C
18	JMA	JMA	JMA	JRSS-A
19	STMED	JRSS-C	JRSS-C	JMA
20	JRSS-C	STMED	SMMR	STMOD
21	AMS	AMS	STMOD	SMMR
22	ISR	ISR	AISM	AMS
23	SMMR	SMMR	AMS	ISR
24	JSS	STMOD	ISR	AISM
25	CSDA	JSS	STMED	JNS
26	AISM	CSDA	JNS	STMED
27	STMOD	AISM	BIOJ	BIOJ
28	JNS	JNS	JSPI	CSDA
29	BIOJ	BIOJ	CSDA	JSS
30	JSPI	JSPI	JSS	JSPI
31	EES	EES	JABES	JABES
32	JTSA	JABES	ANZS	ANZS
33	JABES	JTSA	MTKA	STNEE
34	MTKA	ANZS	JTSA	STATS
35	ENVR	ENVR	STATS	EES
36	STATAJ	MTKA	EES	MTKA
37	ANZS	STNEE	STNEE	JTSA
38	STATS	STATS	ENVR	ENVR
39	STNEE	CMPST	CMPST	CMPST
40	JBS	JBS	JSCS	JSCS
41	SPL	SPL	SPL	SPL
42	CMPST	JSCS	JBS	JBS
43	JSCS	STATAJ	CSSC	CSSC
44	CSTM	CSTM	CSTM	CSTM
45	CSSC	CSSC	STATAJ	STATAJ
46	STPAP	STPAP	STPAP	STPAP
47	JAS	JAS	JAS	JAS

Table 8: Articles-level influence ranking. PSJR: Prestige Scimago Journal Rank (self-citations restricted to 33% of references); EBPR: Empirical Bayes PageRank (self-citations included); EIFA*: Eigenfactor; EBEF*: Empirical Bayes Eigen Factor * without self-citations. Journals are ordered according to EBEF scores.

	Journal	EBPR	PSJR	EIFA	EBEF
1	JRSS-B	5.29	5.77	5.84	5.82
2	STSCI	3.45	3.83	4.22	4.22
3	AOS	4.11	4.40	3.82	3.67
4	JASA	3.43	3.73	3.65	3.57
5	BKA	2.66	2.88	3.07	3.05
6	BIOST	1.70	1.79	1.94	1.90
7	SJS	1.40	1.51	1.74	1.79
8	JCGS	1.51	1.61	1.70	1.73
9	BCS	1.70	1.78	1.73	1.72
10	STSIN	1.27	1.35	1.53	1.55
11	TEST	1.15	1.25	1.43	1.48
12	CJS	1.15	1.25	1.36	1.46
13	STCMP	1.11	1.17	1.28	1.29
14	BERN	1.05	1.03	1.19	1.14
15	TECH	1.05	1.06	1.04	1.11
16	LTA	0.94	0.95	1.05	1.06
17	JRSS-C	0.79	0.83	0.90	0.95
18	JRSS-A	1.03	0.95	0.91	0.92
19	JMA	0.89	0.87	0.91	0.90
20	STMOD	0.64	0.71	0.71	0.85
21	SMMR	0.70	0.69	0.76	0.77
22	AMS	0.76	0.72	0.68	0.73
23	ISR	0.75	0.69	0.68	0.72
24	AISM	0.65	0.60	0.69	0.68
25	JNS	0.59	0.56	0.65	0.66
26	STMED	0.85	0.80	0.66	0.63
27	BIOJ	0.58	0.56	0.59	0.61
28	CSDA	0.66	0.62	0.55	0.57
29	JSS	0.66	0.62	0.52	0.56
30	JSPI	0.58	0.52	0.56	0.55
31	ANZS	0.46	0.44	0.47	0.52
32	JABES	0.50	0.47	0.48	0.52
33	STATS	0.44	0.40	0.46	0.48
34	STNEE	0.41	0.40	0.41	0.48
35	MTKA	0.48	0.41	0.47	0.47
36	JTSA	0.54	0.43	0.47	0.46
37	EES	0.55	0.47	0.42	0.45
38	ENVR	0.46	0.41	0.41	0.44
39	CMPST	0.37	0.34	0.37	0.41
40	JSCS	0.36	0.31	0.33	0.35
41	SPL	0.39	0.30	0.31	0.30
42	JBS	0.40	0.31	0.30	0.29
43	CSSC	0.28	0.20	0.23	0.24
44	STPAP	0.26	0.18	0.20	0.22
45	CSTM	0.30	0.20	0.23	0.21
46	JAS	0.25	0.17	0.18	0.20
47	STATAJ	0.47	0.22	0.23	0.19

Table 9: Articles-level influence score with half sampling procedure. PSJR: Prestige Scimago Journal Rank (self-citations restricted to 33% of references); EBPR: Empirical Bayes PageRank (self-citations included); EIFA*: Eigenfactor; EBEF*: Empirical Bayes Eigen Factor * without self-citations. Journals are ordered according to EBEF scores.