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An annual JCR impact factor calculation based on Bayesian credibility formulas

Patricia Pérez-Hornero[a], José Pablo Arias-Nicolás[b], Antonio A. Pulgarín[b,*], Antonio Pulgarín[c]

[a] University of Extremadura, 10071 Cáceres, Spain
[b] Department of Mathematics, University of Extremadura, 10071 Cáceres, Spain
[c] Department of Information and Communication, University of Extremadura, 06071 Badajoz, Spain

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ABSTRACT

Our aim deals with appraising the annual impact calculation of journals belonging to the JCR, in terms of the expected citation (with or without selfcitations) by published paper in a range of k-years. A Bayesian approach to the problem, should reflect not only the current prestige of a journal, but also taking into account its recent trajectory. In this wide context, credibility theory becomes an adequate mechanism deciding whether journal's impact factor calculation to be more or less plausible. Under prior belief that journal quality is determined by its impact factor, we model the citation-quality process by choosing a conjugated family of the exponential class in order to obtain a net impact credibility formula. Proposed weighting schema produces the effect of smoothing out any sudden increases or decreases in the year-by-year impact factor.

1. Introduction

The use of citation analysis has been advocated to provide a quantitative mean to measure the impact of the published scientific journals (this topic has been widely treated by authors like King (1987), Porter, Chubin, and Jin (1988) or Van Leeuwen (2012)). Garfield (1955) proposed the concept of journal impact factor (IF) for journal evaluation reported annually by Thomson Reuters, and which is currently one of the most frequently used scientometric index (Thomson Scientific, 2011).

The IF of a journal reflects the frequency with which journal papers are cited in scientific literature, being a quotient the numerator of which is the number of citations in the current year to items published in the previous two (or five) years; the denominator is the number of substantive articles published within the same two (or five) years.

However, serious problems arise in using these indices (Cronin, 1984; Garfield, 1979; Gilbert, 1978; Macroberts & Macroberts, 1989). One is the variability of these rankings of journals in the same subject category, reflecting the variability of the number of the annual citations received by the scientific works published in the journals. Often such a fluctuation is due to sudden changes in editorial policies of the journals toward getting a higher IF, for instance by deciding not to publish specialized papers devoted to small audiences and unlikely to be cited. Amin and Mabe (2000) list all the important features and practical problems concerning the IF.

* Corresponding author at: Departamento de Matemáticas, Escuela Politécnica, Universidad de Extremadura, Avda. Universidad s/n, 10071 Cáceres, Spain. Tel.: +34 927 257446; fax: +34 927 257203.

E-mail addresses: pperezho@alumnos.unex.es (P. Pérez-Hornero), jparias@unex.es (J.P. Arias-Nicolás), aapulgar@unex.es (A.A. Pulgarín), pulgarin@unex.es (A. Pulgarín).

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Vanclay (2012) criticizes Thomson Reuters for the errors and limitations which may be attributed to IF. According to Vanclay the necessary statistical measures (mean, median, standard deviation, etc.) referring to the IF of journals fail from JCR, Thomson Reuters, and there is given no distribution of the citations among the publications of journals.

For Mutz and Daniel (2012), the IF may profit from its comprehensibility, robustness, methodological reproducibility, simplicity, and rapid availability, but it is at the expense of serious technical and methodological flaws.

Habibzadeh and Yadollahie (2008) propose the "weighted impact factor" instead of IF. For the calculation of the impact factor, they not only take into account the number of citations, but also incorporate a factor reflecting the prestige of the citing journals relative to the cited journal.

We do not disagree at all with the fact that the average citation per published paper should be the main indicator to decide the impact of a journal (in fact, we emphasize that this mechanism should be an adequate indicator), but we strongly support the idea that some prior information (e.g. previous IF) should have a weight in its calculation, and it would be desirable measuring "how credible" is this indicator. Credibility theory was originally developed in actuarial sciences (starting by Whitney, 1918) to determine risk premiums, as a convex linear combination of the the individual experience and a prior belief on the collective. Bailey (1945) showed that credibility formulas may be derived from Bayes theorem, and further Bayesian techniques were introduced in a big way in the late 1960s when Bühlmann (1967, 1969) laid down the foundation to the empirical Bayes credibility approach, which is still being used extensively.

Roughly speaking, we claim for a simply computed credibility formula of the impact of a journal combining both the IF and a "prior belief" I_0, betting by the IF whether we would have a lot of information on the citation behavior of a journal. Otherwise, if the information not to be enough, we should support I_0 as a more credible impact of the journal. Let us formulate the problem rigorously.

The *k-years impact factor* ($k \geq 2$) of a given journal belonging to the JCR (is widely assumed either $k = 2$ or $k = 5$) in the year $z \in \mathbb{Z}$ is defined by

$$\mathrm{IF}_z^k = \frac{m_z}{n_z},$$

where n_z denotes the total number of papers published by the journal in the previous range of k-years $\{z-k, \ldots, z-1\}$, and m_z is the total number of citations received by such n_z papers during the year z by papers belonging to the JCR (with or without considering selfcitations).

Definition 1. A credibility formula is a convex linear combination

$$I_1 = C\mathrm{IF}_z^k + (1-C)I_0, \tag{1}$$

being C an increasing function on n_z called *credibility factor*, bounded from below by 0 and from above by 1, and I_0 is a prior belief elicited from assuming propensity of a paper belonging to the journal to be cited follows a certain distribution of probability.

In accordance with the general estimation principle of "the larger the sample the better", the approach that more accurately should reflect the impact of a journal would be the one based on the larger number of contributing articles. In this sense, a naive approach could argue that the assigned weight should have

$$C \propto n_z, \quad (1-C) \propto n_{z-1} \tag{2}$$

where n_{z-1} is the total number of papers published by the journal in the range $\{z-k-1, \ldots, z-2\}$.

In order to enhance the readability of the manuscript we are outlining briefly the transition among the different sections of the research by highlighting the following:

1.1. Core-ideas

In Section 2 we model the citation process by means of a class of distributions of probability conditioned by a "quality parameter" which determines the propensity of a journal to be cited. We shall pay special attention to the Poisson distribution, an adequate candidate to describe citation phenomena under the assumption that the quality parameter follows a Gamma distribution (a Bayesian perspective to the problem consists on assuming that the quality parameter takes values of a random variable which follows some prior distribution).

Given an observed sample consisting of received citations in a year by papers published in a range of some previous years, we may obtain a posterior distribution of probability of the quality parameter conditioned to such a sample. We are claiming for citation-quality conjugated families, that is, pairs of parametric families such that both the prior and posterior distribution belong to the same family. A highlighting that the pair Poisson–Gamma becomes a conjugated family, i.e., whenever the citation process follows a Poisson distribution with quality parameter following a Gamma distribution, then the posterior distribution follows a Gamma as well.

We conclude this section by setting principles for the impact calculation, i.e., different forms of calculating the impact of a journal by means of a loss function (attributes the error assumed having a prestige indicator and meeting with an amount of citation). Once fixed a principle of impact, we obtain the main magnitudes of this study. The prior impact is the value I_0

minimizing the expected loss under prior distribution, and the posterior impact (PI) is the value I_1 minimizing the expected loss under posterior distribution from a given sample.

In Section 3 we study the standard squared-error loss function, deriving the so called net impact principle and which it coincides with the values of the quality parameter. This loss function is very useful and intuitive, since we obtain for both the prior and posterior impact their respective means. Thus, we may set a credibility formula valid for any conjugated family belonging to the exponential class, by obtaining a formulation of the credibility factor in function of certain constants depending of the chosen model.

We argue along Section 4 the approach of the compound model Poisson–Gamma, since its marginal distribution of probability follows a Negative-Binomial, an adequate model for discrete overdispersed data. By using the maximum likelihood method we may estimate that prior impact coincides with the IF in the previous year, and we obtain a very natural credibility formula

$$I_1 = C\mathrm{IF}_z^k + (1 - C)\mathrm{IF}_{z-1}^k$$

with a credibility factor being not only a function of the size of the sample, but also a function of a hyperparameter proportional to n_{z-1}, and which can be understood as a measure of uncertainty in the knowledge about the mean of previous IF. Hence, estimating the variance of the quality parameter as the deviation of the last k-years IF with respect to the previous one, seems to be the most plausible procedure to estimate such a hyperparameter.

In Section 5 we illustrate our approach by using the Subject Category Listing "Information Science & Library Science" of 2009–2010 JRC Social Science Edition (ISI Web of Knowledge).

2. Model

2.1. The citation process as a conditioned random variable

By fixing a year z, we may consider the sample space Ω consisting of papers published in journals belonging to the JCR during the range $\{z-k, \ldots, z-1\}$ of k-previous years.

Our object of study is the random variable $X : \Omega \to \mathbb{Z}_+, \omega \mapsto X(\omega) = x$ determining the total amount x of received citations by a given paper ω during the year z.

Moreover, we assume X depending on the "*quality*" of the journal in which a paper is published. We are denoting $P\left[X = x|\theta\right]$ the probability that a paper published in a journal of quality θ (at prior unknown), to have x citations during the year z.

Our first task will consist in modeling such a phenomenon. A class covering a wide spectrum of the most popular families used in the study of quantitative aspects of information (namely; Binomial, Negative-Binomial, Poisson, Gamma, Beta, Normal, among others) is the exponential class (Morris, 1982), defined by means of probability measures of X over an interval $(\theta_0, \theta_1) \subset \{\theta \in \mathbb{R} : a\theta^2 + b\theta + c \text{ and } g(\theta) > 0\}$ having a density of the form:

$$f_X(x|\theta) = g(\theta)\exp(h(\theta)x) \tag{3}$$

where g and h are real-valued continuously differentiable functions satisfying:

$$\frac{\partial h(\theta)}{\partial \theta} = \frac{1}{a\theta^2 + b\theta + c}, \quad \frac{\partial(\log g(\theta))}{\partial \theta} = \frac{-\theta}{a\theta^2 + b\theta + c}.$$

Example 2. In the case

$$X \sim \mathrm{Poisson}(\theta), \text{ i.e. } P\left[X = x|\theta\right] = \frac{\exp(-\theta)\theta^x}{x!},$$

formula (3) holds for $g(\theta) = \exp(-\theta)$, $h(\theta) = \log\theta$, $b = 1$ and $a = c = 0$.

2.2. The conjugated family citation-quality

Bayes approach relies on the knowledge of a prior distribution for the quality parameter. Such an assertion suggests us to consider a random variable $Q : \mathrm{JCR} \to \mathbb{R}_+$, where $Q(j) = \theta$ indicates that journal j is provided with a quality index θ (at prior unknown), characterizing the propensity of a paper to be cited. We raise the problem having a prior belief $Q \sim f_Q(\theta)$.

Given a certain journal $j \in \mathrm{JCR}$ we shall have the observed sample $X_j = \{x_1, \ldots, x_{n_z}\}$ consisting of received citations during the year z by the n_z papers published in the range $\{z-k, \ldots, z-1\}$ of k-previous years. If $m_z = \sum_{i=1}^{n_z} x_i$, then the likelihood function based on the sample X_j is given by,

$$l(X_j|\theta) = \prod_{i=1}^{n_z} P[X = x_i|\theta] = g^{n_z}(\theta)\exp(h(\theta)m_z). \tag{4}$$

Bayes theorem, allows to obtain a *posterior distribution* of probability by means of the likelihood function and the prior distribution:

$$f_{Q|j}(\theta|X_j) = \frac{l(X_j|\theta) f_Q(\theta)}{E_Q[l(X_j|\theta)]}. \tag{5}$$

We claim for a parametric family of distributions *conjugated* with the likelihood $l(X_j|\theta)$, i.e. such that both $f_Q(\theta)$ and $f_{Q|j}(\theta|X_j)$ belong to the same family. Further information on conjugated families can be found in Jewell (1974).

We consider conjugate prior distributions over the parameter θ

$$Q \sim \Gamma_{(\alpha,\beta)}, \text{ i.e. } f_Q(\theta) = k g^{\alpha}(\theta)\exp(h(\theta)\beta), \tag{6}$$

where $\alpha > 3a$ and $\theta_0(\alpha - 2a) < \beta + b < \theta_1(\alpha - 2a)$. Thus,

$$\begin{aligned} f_{Q|j}(\theta|X_j) &\propto l(X_j|\theta) f_Q(\theta) \\ &\propto g^{\alpha+n_z}(\theta)\exp(h(\theta)(\beta + m_z)), \end{aligned}$$

and therefore $Q|j \sim \Gamma_{(\alpha+n_z,\beta+m_z)}$. Recall that (Chen, Eichenauer-Hermann, Hofmann, & Kindler, 1991)

$$E_Q[\theta] = \frac{\beta + b}{\alpha - 2a}, \quad E_{Q|j}[\theta] = \frac{\beta + b + m_z}{\alpha - 2a + n_z}. \tag{7}$$

2.3. Principles for the impact calculation

Now we define principles for the calculation of the impact of a journal. Recall that a *loss function* is a mapping $L : \mathbb{R}^2 \to \mathbb{R}$ which attributes to each pair (x, F) the error assumed in the year z for a journal with "prestige indicator" F meeting with a citation x.

Definition 3. A *principle for the calculation of the impact* of a journal from a loss function $L : \mathbb{R}^2 \to \mathbb{R}$, is the functional $F(\theta)$ minimizing the expected loss

$$E_X[L(x, F)]. \tag{8}$$

From a principle of impact $F(\theta)$ we define the *prior impact* as the value I_0 minimizing the expected loss

$$E_Q\left[L\left(F(\theta), I_0\right)\right]. \tag{9}$$

Given a journal $j \in$ JCR and being X_j the observed vector consisting of received citations during the year z by papers published in the range $\{z - k, \ldots, z - 1\}$ of k-previous years, we define the *posterior impact* (PI) of the journal j as the value I_1 minimizing the expected mean

$$E_{Q|j}\left[L\left(F(\theta), I_1\right)\right]. \tag{10}$$

3. A credibility formula of net impact

If we consider the standard squared-error loss function

$$L(x, F) = (x - F)^2,$$

by deriving (8) over F we have

$$\frac{dE_X\left[(x - F)^2\right]}{dF} = -2E_X[x] + 2F,$$

(the second derivation is $2 > 0$, thus a minimum), therefore $F(\theta) = E_X[x]$ which is known as the *net impact principle*.

If we are considering exponential families as defined in (3):

$$f_X(x|\theta) = g(\theta)\exp(h(\theta)x),$$

net impact principle is

$$F(\theta) = E_X[x] = \int x g(\theta)\exp(h(\theta)x)\mathrm{d}x = -\frac{g'(\theta)}{g(\theta)h'(\theta)} = \theta. \tag{11}$$

Following analogous procedures of derivation in (9) and (10), we may estimate both the prior and posterior impact

$$I_0 = E_Q\left[E_X[x]\right] = E_Q[\theta], \quad I_1 = E_{Q|j}\left[E_X[x]\right] = E_{Q|j}[\theta].$$

Since we are assuming conjugated exponential families,

$$Q \sim \Gamma_{(\alpha,\beta)}, \quad Q|j \sim \Gamma_{(\alpha+n_z,\beta+m_z)},$$

we derive from (7) that

$$I_0 = \frac{\beta + b}{\alpha - 2a}, \quad I_1 = \frac{\beta + b + m_z}{\alpha - 2a + n_z}, \tag{12}$$

and therefore

$$I_1 = \frac{\beta + b + m_z}{\alpha - 2a + n_z} = \left(\frac{n_z}{\alpha - 2a + n_z}\right)\left(\frac{m_z}{n_z}\right) + \left(\frac{\alpha - 2a}{\alpha - 2a + n_z}\right)\left(\frac{\beta + b}{\alpha - 2a}\right),$$

which establishes a credibility formula

$$I_1 = C\mathrm{IF}_z^k + (1 - C)I_0$$

with credibility factor

$$C = \frac{n_z}{\alpha - 2a + n_z}. \tag{13}$$

4. The Poisson–Gamma choice

Given a journal $j \in \mathrm{JCR}$ consider the sample subspace $\Omega_j = \{\omega \in \Omega$ published in the journal $j\}$, and define the random variable $X^j : \Omega_j \to \mathbb{Z}_+$, determining the total number of citations received by a paper belonging to Ω_j during the year z.

In our instance, we are assuming that

$$X^j \sim \mathrm{Bin}(N, p), \text{ i.e. } P\left[X^j = x | p\right] = \binom{N}{x} p^x (1 - p)^{N-x},$$

a Binomial distribution of probability, where $N \in \mathbb{N}$ is the total number of published papers in journals belonging to the JCR during the year z, and $p \in [0, 1]$ is the probability that a given paper of the JCR cites a paper belonging to Ω_j during z.

It is well-known, that Bin(N, p) can be approximated by a Poisson distribution of probability with parameter $\theta = Np$ whether N is sufficiently large and p sufficiently small (as a rule of thumb, this approximation works for $N \geq 20$ and $p \leq 0.05$, or $N \geq 100$ and $\theta \leq 10$).

Thus, we consider

$$X^j \sim \mathrm{Poisson}(\theta), \text{ i.e. } P\left[X^j = x | \theta\right] = \frac{\exp(-\theta)\theta^x}{x!}.$$

Recall that $E_{X^j}[x] = \theta$.

According to the general formulation, Example 2 showed that $g(\theta) = \exp(-\theta)$, $h(\theta) = \log\theta$, $b = 1$ and $a = c = 0$. Thus, from (12) we have that

$$I_0 = \frac{\beta + 1}{\alpha}, \tag{14}$$

and on the other side we derive a conjugate family (6) of the form

$$f_Q(\theta) \propto \exp(-\alpha\theta)\theta^\beta.$$

Therefore, we may assume

$$Q \sim \mathrm{Gamma}(\alpha, \beta + 1), \text{ i.e. } f_Q(\theta) = \frac{\alpha^{\beta+1}\exp(-\alpha\theta)\theta^\beta}{\Gamma(\beta + 1)}.$$

Prior distribution Gamma is one of the most useful no compound collective models. The main empirical support for the Gamma distribution is that it provides a better fit to the aggregate citation frequency distribution than that given by the assumption that all individuals have the same Poisson distribution (the adequacy of the Poisson–Gamma assumption can be read from (Venter, 1991)). The adequacy of prior distribution Gamma becomes evident once realized that its marginal distribution

$$\begin{aligned} P[X^j = x] &= \int_0^{+\infty} \left(\frac{\exp(-\theta)\theta^x}{x!}\right)\left(\frac{\alpha^{\beta+1}\exp(-\alpha\theta)\theta^\beta}{\Gamma(\beta + 1)}\right) d\theta \\ &= \frac{\alpha^{\beta+1}\Gamma(\beta + 1 + x)}{x!\,\Gamma(\beta + 1)(\alpha + 1)^{\beta+1+x}} \\ &= \binom{\beta + x}{x}\left(\frac{\alpha}{\alpha + 1}\right)^{\beta+1}\left(\frac{1}{\alpha + 1}\right)^x, \end{aligned}$$

follows a Negative-Binomial distribution NBin($\beta+1, \alpha/\alpha+1$). This distribution of probability is widely used as an alternative for the Poisson distribution modeling discrete overdispersed data (variance bigger than mean).

In Bayesian statistics, a hyperparameter is a parameter of a prior distribution (this term is used to distinguish the parameters of the model for the underlying system under analysis). From the Bayesian point of view, using data establishing the prior might seem inappropriate, however several authors support this approach as a useful approximation to the preferred method of hierarchical modeling.

By means of the maximum likelihood method, is not difficult to obtain a natural relationship between the hyperparameters. Let $\{x_1, \ldots, x_{n_{z-1}}\}$ be now the sample consisting of received citations during the year $z-1$ by the n_{z-1} published papers in the previous range $\{z-k-1, \ldots, z-2\}$ of k-years, and $m_{z-1} = \sum_{i=1}^{n_{z-1}} x_i$. By passing to the log-likelihood function

$$\begin{aligned}\ell(\alpha,\beta) = & \log\left(\prod_{i=1}^{n_{z-1}} P[X^j = x_i]\right)\\ = & \sum_{i=1}^{n_{z-1}} \log\begin{pmatrix}\beta+x_i\\ x_i\end{pmatrix} + n_{z-1}(\beta+1)\log\left(\frac{\alpha}{\alpha+1}\right) - m_{z-1}\log(\alpha+1)\\ = & \sum_{i=1}^{n_{z-1}}\left[\sum_{j=1}^{x_i-1}\log(\beta+x_i-j) - \log(x_i!)\right] + n_{z-1}(\beta+1)\log\left(\frac{\alpha}{\alpha+1}\right)\\ & -m_{z-1}\log(\alpha+1),\end{aligned}$$

if we derive partially on α and equaling 0, we obtain that:

$$\frac{\partial \ell}{\partial \alpha} = 0 \Leftrightarrow \frac{\beta+1}{\alpha} = \frac{m_{z-1}}{n_{z-1}}, \tag{15}$$

i.e. from (14) we have $I_0 = \mathrm{IF}_{z-1}^k$, which establishes a credibility formula

$$I_1 = C\mathrm{IF}_z^k + (1-C)\mathrm{IF}_{z-1}^k$$

with credibility factor (see (13) by taking $a=0$)

$$C = \frac{n_z}{\alpha+n_z} \propto n_z. \tag{16}$$

Above equality (15) ensures the existence of some constant $d \in \mathbb{R}$ such that $\beta+1 = dm_{z-1}$, $\alpha = dn_{z-1}$, and therefore

$$(1-C) = \frac{dn_{z-1}}{dn_{z-1}+n_z} \propto n_{z-1}, \tag{17}$$

as the naive approach (2) suggested.

Determining the maximum likelihood estimate of α (or d) becomes an arduous analytic calculus. However, since $Q \sim \mathrm{Gamma}(\alpha, \beta+1)$, relationship (15) ensures that $E_Q[\theta] = \mathrm{IF}_{z-1}^k$, and furthermore

$$\alpha = \frac{\mathrm{IF}_{z-1}^k}{\mathrm{Var}_Q[\theta]}. \tag{18}$$

According to the above (18), the variance of θ decreases when α increases. Thus, α can be understood as a measure of the certainty in the knowledge about the mean of the Gamma distribution, and therefore, on the previous impact factor IF_{z-1}^k.

Accordingly, estimating the variance as the deviation of the last k-years IF with respect to the impact factor IF_{z-1}^k seems to be the most plausible procedure, i.e. if $\{\mathrm{IF}_{z-k-1}^k, \ldots, \mathrm{IF}_{z-2}^k\}$ denote the previous k-years impact factors of the journal, an estimation of the variance by means of the expression holding as follows:

$$\widetilde{\mathrm{Var}}_Q[\theta] = \frac{\sum_{i=1}^k (\mathrm{IF}_{z-i-1}^k - \mathrm{IF}_{z-1}^k)^2}{k}. \tag{19}$$

Remark. Credibility factor does not only depend on the number of published papers n_z, but also on the variability of the last k-years IF with respect to the previous one. Thus, if previous IF_{z-1}^k is relatively far from their k-previous ones $\{\mathrm{IF}_{z-k-1}^k, \ldots, \mathrm{IF}_{z-2}^k\}$, then there will be a lot of uncertainty on IF_{z-1}^k and much more credibility on the current IF_z^k. Conversely, IF_{z-1}^k to be close from their k-previous ones would imply to be more credible.

5. An application to a scientific field

Our next task will consist of providing an empirical illustration to compute the credibility factor in a concrete instance. We have used data from the available Thomson Reuters Journal Citation Reports (JCR) Editions 2007-2010 (by removing

Table 1
Subject category: information science & library science.

Journal name	n_{2010}	IF^2_{2009}	IF^2_{2010}	α	C	I_1
ANNU REV INFORM SCI	23	2.929	2.000	7.87	0.75	2.24
ASLIB PROC	75	0.595	0.600	41.2	0.65	0.6
COLL RES LIBR	60	0.855	0.683	385.19	0.13	0.83
ECONTENT	88	0.079	0.068	4.65	0.95	0.07
ELECTRON LIBR	131	0.544	0.488	13.31	0.91	0.49
GOV INFORM Q	98	2.098	1.163	3.71	0.96	1.2
HEALTH INFO LIBR J	67	1.521	0.761	3.8	0.95	0.8
INFORM MANAGE-AMSTER	118	2.282	2.627	15.94	0.88	2.59
INFORM PROCESS MANAG	165	1.783	1.673	63.04	0.72	1.7
INFORM RES	90	0.490	0.822	2.68	0.97	0.81
INFORM SOC	50	1.111	1.240	21.04	0.7	1.2
INFORM SYST J	49	1.419	2.184	4.59	0.91	2.12
INFORM SYST RES	53	1.792	3.358	5.31	0.91	3.22
INFORM TECHNOL LIBR	36	0.618	0.528	20.07	0.64	0.56
INT J GEOGR INF SCI	131	1.533	1.489	52.57	0.71	1.5
INT J INFORM MANAGE	101	0.723	1.564	12.29	0.89	1.47
INTERLEND DOC SUPPLY	65	0.403	0.308	51.74	0.56	0.35
J ACAD LIBR	108	1.000	0.870	9.6	0.92	0.88
J AM MED INFORM ASSN	205	3.974	3.088	11.12	0.95	3.13
J AM SOC INF SCI TEC	387	2.300	2.137	7.97	0.98	2.14
J ASSOC INF SYST	60	2.246	2.217	26.72	0.69	2.23
J COMPUT-MEDIAT COMM	96	3.639	1.958	1.24	0.99	1.98
J DOC	85	1.405	1.447	40.74	0.68	1.43
J GLOB INF MANAG	36	0.706	1.222	2.82	0.93	1.18
J HEALTH COMMUN	106	1.344	1.500	5.37	0.95	1.49
J INF SCI	101	1.706	1.406	12.95	0.89	1.44
J INF TECHNOL	54	2.049	2.907	30.13	0.64	2.6
J INFORMETR	67	3.379	3.119	9.4	0.88	3.15
J LIBR INF SCI	33	0.581	0.636	55.86	0.37	0.6
J MANAGE INFORM SYST	80	2.098	2.663	52.03	0.61	2.44
J MED LIBR ASSOC	90	0.889	0.844	3.09	0.97	0.85
J SCHOLARLY PUBL	48	0.237	0.521	14.58	0.77	0.45
LAW LIBR J	54	0.385	0.898	6.73	0.88	0.84
LEARN PUBL	34	0.722	1.037	80.59	0.4	0.85
LIBR COLLECT ACQUIS	92	0.429	0.529	35.65	0.49	0.48
LIBR HI TECH	22	0.272	0.413	103.95	0.47	0.34
LIBR INFORM SC	58	0.125	0.045	16.26	0.57	0.08
LIBR INFORM SCI RES	173	1.236	1.362	27.66	0.68	1.32
LIBR J	43	0.343	0.191	237.58	0.42	0.28
LIBR QUART	46	0.857	0.651	7.7	0.85	0.68
LIBR RESOUR TECH SER	69	0.444	0.239	13.6	0.77	0.29
LIBR TRENDS	52	0.392	0.667	43.45	0.61	0.56
LIBRI	34	0.160	0.365	30.2	0.63	0.29
MIS QUART	74	4.485	5.041	5.89	0.93	5
ONLINE	67	0.300	0.522	122.82	0.35	0.38
ONLINE INFORM REV	114	1.423	0.991	6.39	0.95	1.01
PORTAL-LIBR ACAD	54	0.896	0.870	42.85	0.56	0.88
PROF INFORM	144	0.478	0.375	157.5	0.48	0.43
PROGRAM-ELECTRON LIB	52	0.385	0.596	13.64	0.79	0.55
REF USER SERV Q	65	0.533	0.338	9.63	0.87	0.36
RES EVALUAT	66	0.963	0.939	9.51	0.87	0.94
RESTAURATOR	32	0.400	0.375	17.75	0.64	0.38
SCIENTIST	119	0.310	0.252	474.88	0.2	0.3
SCIENTOMETRICS	317	2.167	1.905	12.77	0.96	1.92
SERIALS REV	41	0.952	0.707	7.92	0.84	0.75
SOC SCI COMPUT REV	69	0.635	0.913	32.22	0.68	0.82
SOC SCI INFORM	60	0.604	0.550	23.96	0.71	0.57
TELECOMMUN POLICY	107	0.969	0.962	13.4	0.89	0.96
Z BIBL BIBL	43	0.040	0.023	58.79	0.42	0.03

those journals for which the obtained results were non a number, e.g. having not previous impact factor, or variance equals 0).

We have analyzed the Subject Category Listing: Information Science & Library Science, whose data summary is reported in Table 1.

Credibility formulas should fulfill the condition which the bigger the information (i.e. number of publications), the more the current IF should be favored against the prior information. In this sense, for classical journals publishing big amount of papers, e.g. J AM SOC INF SCI TEC ($n_{2010} = 387$, $C = 0.98$) or SCIENTOMETRICS ($n_{2010} = 317$, $C = 0.96$), the method works fine.

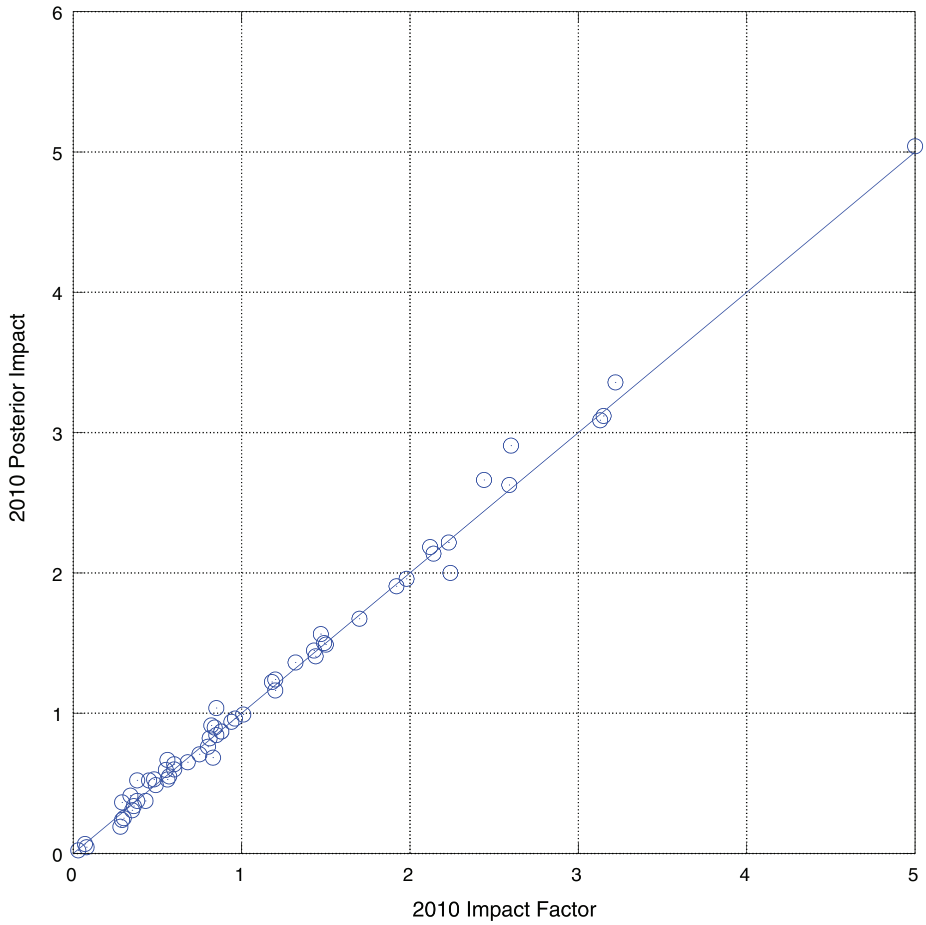

Fig. 1. 2010 PI versus IF.

However, there are journals with a low credibility factor despite having enough published papers, e.g. SCIENTIST ($n_{2010} = 119$, $C = 0.2$). The reason of this behavior is due to having a very small variance from the prior impact during the previous two years. It seems plausible to assume the prior impact as a correct impact index since the journal had almost the same IF during three consecutive years (0.322, 0.353 and 0.310).

Surprisedly, there are more punished journals (understanding it as bigger changes in the positions of the ranking) than favored. For instance, LEARN PUBL ($C = 0.4$) lost six positions (from the 24th to the 30th) and LIBR HI TECH ($C = 0.47$) lost four positions (from the 48th to the 52th). The most favored journal was ANNU REV INFORM SCI ($C = 0.75$) which climbed three positions (from the 11th to the 8th). This journal presents the pathology of having a relatively high IF (1.963, 2.500 and 2.929) during previous years, but going down to 2 in 2010. Credibility theory have smoothed this sudden fall.

Among the top journals there are no significative change since credibility factors are close to 1, and therefore IF calculation for these journals seems a plausible mechanism for determining the quality of a journal from the Bayesian point of view. Fig. 1 displays a scatter diagram showing the PI behavior versus IF:

6. Concluding remarks

Data necessary for the calculation of PI are already available in the data base Thomson Reuters Journal Citation Reports (JCR), and therefore it can be easily calculated. Although we cannot determine its efficacy (there is no universally accepted procedure measuring journal quality), we may ensure it provides a more credible yardstick for assessing the quality of journals as compared to the traditional IF. Furthermore, weighting schema used in PI is taking into account previous IF for each specific journal, having an impact on smoothness, i.e. the strong impact of a high number of manuscripts is, actually, compensated by a high variability of previous IF.

However, the approach is restricted by requirements of bibliometric data bases, as Web of Science that the number of publications should not strongly differ from year to year. Strictly speaking, we should have absolute frequencies of citation of the published papers instead of using previous IF to estimate the mean, but JCR data strives to take as broad a view as possible of the citation impact of the journal, collecting all citations to the journal title, whether or not the specific item can be identified: a journal should be publishing according to its stated frequency to be considered for inclusion in Web of Science.

Proposed PI depends on the choice of a distribution of probability for the citation process and a prior distribution over the parameter. In our specific model, we have chosen a conjugated family Poisson–Gamma whose mean is the IF in the previous year. This model can be considered as a generalization of the Negative-Binomial distribution, seeming adequate for studying overdispersed citation. Elicitation of prior distribution is rather difficult and it can be uncertain. To this aim, Bayesian sensitivity analysis uses a class of prior instead of an unique prior distribution to model uncertainty of prior information (Berger, 1994; Ríos Insua & Ruggeri, 2000). Future researches could focus on finding robust solutions in the context of the annual impact calculation (e.g. conditional Γ-minimax (Eichenauer, Lehn, & Rettig, 1988), posterior regret Γ-minimax (Rios Insua, Ruggeri, & Vidakovic, 1995), least sensitive actions (Arias-Nicolás, Martín, Ruggeri, & Suárez-Llorens, 2009), etc.).

On the other hand, and despite which many obtained credibility formulas refer to net principle (based on quadratic loss function), an approach to posterior index factor calculation based on different loss functions (exponential principle, Esscher principle, percentile principle) could work (Heilmann, 1989).

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