Evaluating Journals Performance Over Time Using Functional Instruments

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Abstract. In recent years, scientific research has become a business for many actors involved, particularly for journals' publishers. Therefore, there is a great increase in those studies looking for advanced methods for evaluating the impact of scientific journals in various scientific communities. Most of the indicators used in the literature for this purpose are very simple indexes, such as the number of citations, number of articles, SCImago Journal Rank, and h-index. In this research, we suggest the use of functional data analysis to obtain new advanced statistical indicators starting from the classical bibliometric indexes. Specifically, we will show through an application to real data how to use functional data analysis to add interesting insights via the analysis of classical bibliometric indexes.

Introduction

Recently, scientific research has become a business for many enterprises, particularly for journals' publishers. Indeed, many journals require publications charges, and the career of many researchers depends essentially on the ranking of the magazines where they publish. Hence, it can be said that sometimes researchers need to pay for publishing, especially in a particular field of research such as the medical one. Therefore, the interest about journals' ranking regards both firms (publishers), which gain from publishing and researcher (authors), who are available to spend their money only if making a "good investment" for their future.

For this reason, the importance of indicators able to classify scientific journals based on their actual value within the scientific community plays a fundamental role both from a methodological perspective and from business concerns. Effectively, there is a great increase in those studies looking for advanced methods for evaluating the impact of scientific journals in various scientific communities. Indeed, to date, there are many databases that collect biometric data to rank scientific journals, e.g. SCOPUS (https://www.scopus.com/), Web of Science (WOS - https://webofknowledge.com/), and Google Scholar (https://scholar.google.it/). Most of the indicators used in the literature are simple indexes, such as the number of citations or total articles published by a journal, and its impact factor (IF). Other more interesting indices are the SCImago Journal Rank (SJR), the source normalized impact per paper (SNIP), and the h-index.

The IF is a simple yearly average number of citations to recent articles published in a journal. It can be easily manipulated by pushing the authors who publish in a journal to cite the articles of the same. Instead, the H-index is considered one the best indicators [e.g. see 1, 2] because it is more objective and difficult to manipulate. Exactly, we can say that a journal with an index of h has published h papers each of which has been cited at least h times. More sophisticated indices are the SJR or the SNIP that normalizes the score according to the specific area. Particularly, the former is very interesting because it is a size-independent prestige indicator that ranks journals by their "average prestige per article". It is based on the idea that all citations are not created equal. SJR is a measure of scientific influence of journals that accounts for both the number of citations received by a journal and the importance or prestige of the journals where such citations come from. It measures the scientific influence of the average article in a journal, it expresses how central to the global scientific discussion an average article of the journal is (http://www.scimagojr.com/).

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It is clear that the first group of indicators does not provide sufficient information to judge the value of a journal. It is also evident that the second group of indicators, being composite indicators, has a greater power to identify journals with high potential. However, it should be noted that all these indices for measuring the value of a journal have a common flaw, that is, they take into consideration only the instantaneous situation of a journal and seem to neglect their history and trend. This is a strong limit for two reasons: the first is that the reputation of a journal must be evaluated in a sufficiently long period of time, and the second is that new journals entering the market, and which are highly promising, certainly can not be compared, from a point of view of bibliometric indicators, with those ones that have been on the market for several years collecting citations and therefore increasing their H-index.

Therefore, in this research, we propose an approach for classifying different journals considering their scores' evolution over time. Specifically, we suggest the use of the functional data analysis (FDA) approach to obtain new advanced statistical indicators starting from the classical bibliometric indexes. We will show through an application to real data how the use of FDA can add interesting insights to the classical assessment measures [e.g. see 3, 4, 5, 6, 7, 8, 9, 10, 11, 12].

The remainder of this paper is structured as follows. Section 2 presents our material and methods. Section 3 displays a real application of FDA to the problem of clustering scientific journals. The paper ends with our discussion and conclusions.

Material and Methods

The theory of statistical methods in circumstances in which the data are considered as functions is often referred to as FDA [13, 14]. Hence, FDA [15, 16, 17] addresses problems in which the observations are described by functions rather than finite dimensional vectors. This approach has many advantages highlighted by scholars. First of all, in the FDA framework, unlike time series analyses, no assumptions of stationarity are made, and data can not be sampled at equally spaced time points [18]. Moreover, the objective of an analysis can be functional in nature and sometimes relevant information is included in the derivatives rather than in the data themselves [17]. The latter motivation is what leads us to extend this approach to the context of the journals' evaluation over time.

In real applications, functional data are often observed as a sequence of point data, and thus the function denoted by $y = f(x)$ reduces to record of discrete observations that are denoted by the T pairs $(x_j; y_j)$ where $x \in \Re$ and y_j are the values of the function computed at the points x_j, $j = 1, 2, ..., T$ [19]. The first step in FDA is to convert the values $y_{i1}, y_{i2}, ..., y_{iT}$ for each unit $i = 1, 2, ..., N$ to a functional form computable at any desired point $x \in \Re$. A functional variable X is just a random variable taking values in a functional space ξ. Thus, a functional data set is just a sample X_1 ,...,X_N (also denoted $X_1(t)$,...,$X_N(t)$) drawn from a functional variable X. Usually, ξ is assumed to be a normed or seminormed metric space [17]. Because, in this context, the data are functions, the observed random variables are stochastic processes, i.e., random elements taking values in a function space. Hence, many essential notions and theorems of classical statistics should be extended and adapted to the infinite-dimensional framework of FDA [18].

In the literature, many methods have been used to recover the functional datum but the most adopted is the b-spline approximation via a finite representation in a fixed basis [15]. Let $X(t) \in \mathcal{L}_2$. A basis function system is a set of K known functions $\phi_j(t)$, that are linearly independent of each other and can be extended to include any number K in the system. There are many different types of basis functions but, in this study, we focus on b-splines that are sets of polynomials (of order m) defined in subintervals constructed in such a way that in the border of the subintervals the polynomials coincide (up to $m - 2$ derivative). Thus, a function $X(t)$ can be constructed as a linear combination of these basis functions:

$$X(t) = \sum_{j \in \mathbb{N}} c_j \phi_j(t) \approx \sum_{j=1}^{K} c_j \phi_j(t) \tag{1}$$

where c_j is the vector of coefficient defining the linear combination and $\phi_j(t)$ is the vector of basis functions. Once we have the approximation, we obtain $X(t) = \widehat{X}(t) + \varepsilon(t)$, and the observed residual series $\varepsilon_i(t) = X_i(t) - \widehat{X}_i(t)$.

Focusing on the case of an Hilbert space with a metric $d(\cdot, \cdot)$ associated with a norm so that $d(X_1(t), X_2(t)) = \|X_1(t) - X_2(t)\|$, and where the norm $\|\cdot\|$ is associated with an inner product $\langle \cdot, \cdot \rangle$ so that $\|X(t)\| = \langle X(t), X(t) \rangle^{1/2}$, we can obtain as specific case the space $L_2[a, b]$ of real square-integrable functions defined on $[a, b]$ by $\langle X_1(t), X_2(t) \rangle = \int_a^b X_1(t) X_2(t) dt$ [20]. Hence, focusing on the L_2-norm, a commonly used distance between functional elements is given by

$$\|X_1(t) - X_2(t)\|_2 = \left\{ \frac{1}{\int_a^b w(t)dt} \int_a^b |X_1(t) - X_2(t)|^2 \, w(t)dt \right\}^{1/2} \tag{2}$$

where w are the weight and the observed points on each curve are equally spaced [20].

However, several metric and semi-metric distances have been proposed in the literature because data are not necessarily better described by their simple original function [e.g. 17, 20]. Particularly, the distance between the r-order derivatives of two curves $X_1(t)$ and $X_2(t)$ can be given by

$$d_2^{(r)}(X_1(t), X_2(t)) = \left[\frac{1}{T} \int_T \left(X_1^{(r)}(t) - X_2^{(r)}(t) \right)^2 dt \right]^{\frac{1}{2}} \tag{3}$$

where $X_1^{(r)}(t)$ and $X_2^{(r)}(t)$ are the r-derivatives of $X_1(t)$ and $X_2(t)$, respectively. In the following, we will refer to the L_2 distance and the semi-metric of the first two derivatives for clustering journal according to their scores over time. However, after the representation of the functional data, many classical statistical concepts can be adapted to FDA [e.g. see 15, 17, 21]. In this context, we concentrate only on the clustering problem [e.g. see 20] but we highlight that many other interesting applications could be considered in this framework.

A common way for analyzing functional data is the clustering, in which the considered distance plays a fundamental role. The basic idea is to find a partition for which the variability within clusters is minimized. In this context, we focus on the functional k-means approach [20]. Starting from n functional observations, it looks for grouping units into $G \leq n$ groups, $C_1, C_2, ..., C_G$ so as to minimize the within-cluster sum of squares. In particular, for each m-th iteration ($m = 1, ..., M$), a functional observation, $X_i(t)$, is assigned to the cluster C_g such that:

$$d_2\Big(X_i(t), \psi_g^{m-1}(t)\Big) < d_2\Big(X_i(t), \psi_h^{m-1}(t)\Big) \;\; \forall\, h \neq g; \;\; g, h = 1, ..., G \tag{4}$$

where $\psi_1^{(0)}(t), ..., \psi_G^{(0)}(t)$ are the initial centroids. If the distance to the centroids of two clusters is the same, the function is assigned to the cluster with the less index (for example to C_g with $g < h$). Once all the functions have been assigned to a cluster, the cluster means are updated. Further details about this method can be found in Ferraty and Vieu [17], Febrero-Bande and de la Fuente [20], Fortuna, Maturo, and Di Battista [22], Fortuna and Maturo [23].

Application and Results

In this section, we apply the FDA approach to the context of journals' bibliometric data. In particular, we start from the basic idea that international journals can not be classified only on the basis of indicators calculated on the last available date but must also take into account the history of the journal. Secondly, we insist that younger journals can not be compared to journals that have been in databases for a long time because the bibliometric indicators of these magazines are not comparable with each other. Instead, it is very important to consider the speed and acceleration of the change of these indicators rather than the original functions. This information is contained for example in the derivatives of the functions. In fact, this information can reveal much more interesting results than the functions themselves because they can highlight the existence of very promising journal that are climbing the rankings. Instead, we believe that a static analysis is of little interest (even less interesting if based on scalar values instead of functions).

For these reasons, we perform a functional k-means using the semi-metric distance among derivatives and compare the results with a clustering approach based on the classical L_2 distance. In this context, we focus on the analysis of the SJR indicator collected from 2009 to 2017.

Our sample is composed of 31 scientific journals respecting the following criteria: they belong to the area "*applied mathematics*"; only open access journal are considered; they must be indexed in Web of Science; and they must be indexed in SCOPUS (data available on SCIMAGO) during the last three years. Therefore, the journals that do not respect these criteria over the whole period are not included in the sample. The journals indexed in SCOPUS during the period, i.e. after 2009, have zeros as starting values. Table 1 shows the data of the index SJR over 9 years for the 31 scientific journals. Figures 1, 2 and 3 illustrate the SJR, its smoothed version (see Equation 2), and the centered smoothed version of the SJR functions over time.

TABLE 1. Scimago Journals Ranking Scores from 2009 to 2017.

Journal	2009	2010	2011	2012	2013	2014	2015	2016	2017
Advances in Difference Equations	0.56	0.47	0.73	0.68	0.61	0.61	0.69	0.55	0.54
Advances in Mathematical Physics	0.00	0.21	0.39	0.22	0.24	0.29	0.35	0.28	0.22
Algorithms for Molecular Biology	0.73	1.42	0.98	1.00	1.38	1.98	1.01	1.57	1.33
Anal. St. ale Univ. Ovidius Const.	0.00	0.12	0.22	0.23	0.27	0.32	0.38	0.35	0.32
Analysis and Geom. in Metric Sp.	0.00	0.00	0.00	0.00	0.00	0.91	1.13	1.60	1.06
Applicable Analysis and Disc. Math.	0.48	0.43	0.54	0.83	0.79	0.77	0.81	0.44	0.45
Applied Math. E - Notes	0.22	0.38	0.26	0.25	0.28	0.27	0.17	0.34	0.22
Austrian J. of Statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.11	0.23
Bioinformatics and Biology Ins.	0.00	0.17	0.57	0.64	0.45	0.70	0.69	0.85	1.14
Biology Direct	2.77	2.45	2.27	2.15	2.65	2.94	3.27	1.96	1.69
BMC Bioinformatics	1.89	1.77	1.66	1.90	2.00	1.92	1.74	1.58	1.48
Bulletin of the Amer. Math. Soc.	2.44	2.56	2.25	2.58	1.80	4.01	2.89	1.54	1.69
Com. in Applied and Ind. Math.	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.42	0.32
Dolomites Res. Notes on Approx.	0.00	0.00	0.00	0.00	0.00	0.24	0.34	0.16	0.71
Dynamics of Partial Differential Eq.	0.97	2.29	1.10	1.30	0.94	0.68	0.87	1.22	0.65
Elec. J. of Qual. Theory of Diff. Eq.	0.47	0.49	0.84	0.72	0.67	0.56	0.60	0.73	0.49
Eurasian J. of Math. and Comp. App.	0.00	0.00	0.00	0.00	0.00	0.31	0.38	0.40	0.36
European J. of Remote Sensing	0.11	0.14	0.18	0.18	0.44	0.51	0.56	0.57	0.58
Formalized Math.	0.11	0.10	0.10	0.10	0.13	0.12	0.18	0.20	0.12
Informatica	0.38	0.47	0.48	0.50	0.35	0.49	0.41	0.32	0.46
Int.l J. of App. Math. and Comp. S.	0.34	0.38	0.30	0.44	0.71	0.63	0.71	0.47	0.73
International J. of Diff. Eq.	0.00	0.00	0.47	0.40	0.51	0.35	0.38	0.36	0.19
J. of Algorithms and Comp. Tech.	0.00	0.00	0.00	0.12	0.15	0.24	0.21	0.15	0.13
J. of Math. in Industry	0.00	0.00	0.00	0.24	1.02	0.84	0.22	0.23	0.24
Kyungpook Mathematical J.	0.19	0.26	0.26	0.33	0.31	0.21	0.17	0.27	0.27
Math. and Computational Fore....	0.00	0.16	0.23	0.38	0.31	0.29	0.30	0.30	0.39
Math. Com.	0.27	0.17	0.31	0.32	0.38	0.29	0.39	0.30	0.38
Molecular Systems Biology	6.97	6.59	7.62	8.16	9.99	10.19	8.69	8.77	8.50
Revista Int.de Metodos Num....	0.00	0.13	0.15	0.17	0.22	0.29	0.19	0.26	0.26
Scient. Annals of Computer Sc.	0.00	0.22	0.99	0.65	0.32	0.26	0.37	0.28	0.20
Tamkang J. of Math.	0.17	0.20	0.18	0.19	0.25	0.29	0.33	0.29	0.33

Figures 4 and 5 display the first and second derivative of SJR over time (centered functions). Figure 6 shows the k-means clustering results according to different types of distances, i.e. the L_2 distance (Equation 2), the semi-metric of first derivatives (Equation 3 with $r = 1$), and the semi-metric on second derivative (Equation 3 with $r = 2$), respectively.

Discussion and Conclusions

Recently FDA has received great attention in diverse areas of application, this is because it makes it possible to analyze the data by adding numerous functional tools to classical analyzes with considerable interpretations of the results as well. This research has proposed to study the classical bibliometric indexes using the functional data analysis approach and suggesting an original application of FDA to cluster journals according to some suitable distance measures based on the SJR indicator. The main reason for our research is that a static view of the classical journal's performance indicators does not provide an interesting insight to understand which journal are increasing or decreasing their reputation. Moreover, when "young" new journals are indexed in a database, it has no sense to compare them with the "older" journals (according to H-index, impact factor, number of citation). Effectively, there is a period of time necessary for the results to become comparable.

Assessing the impact of journals according to scalar measures, e.g. the value of SJR in 2017, strongly limits the information about the trend and its variability over time. In fact, in this framework, the functional analysis of

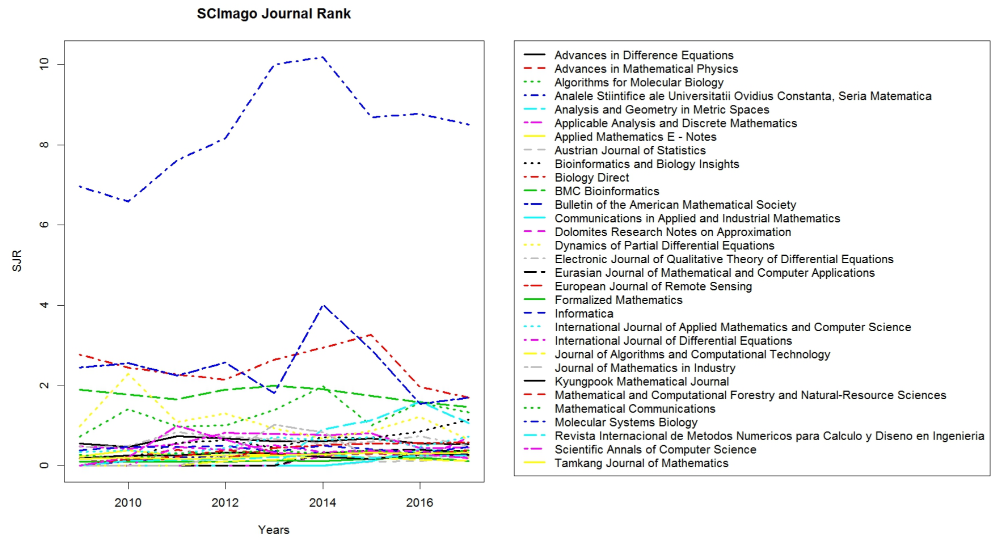

FIGURE 1. SJR over 9 years for the 31 scientific journals.

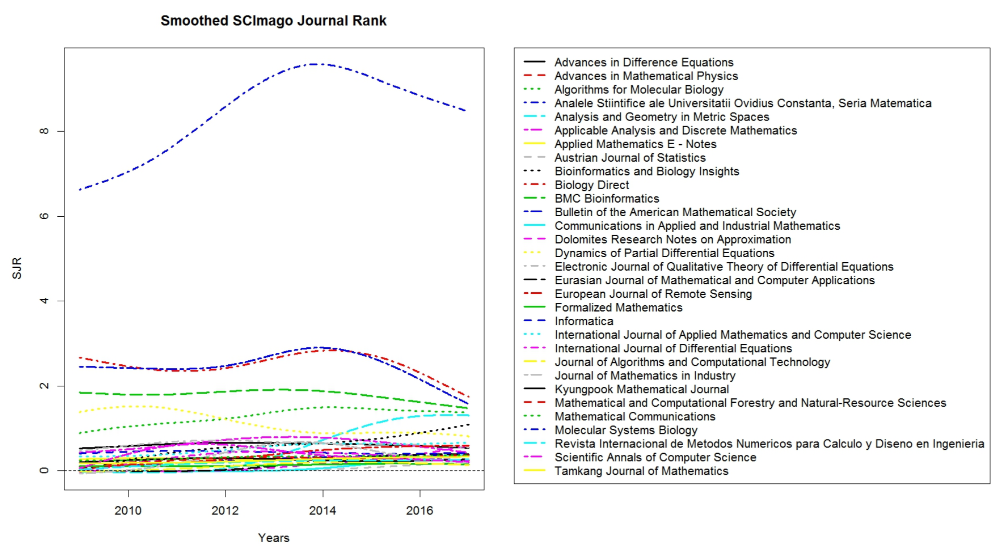

FIGURE 2. Smoothed SJR over 9 years for the 31 scientific journals.

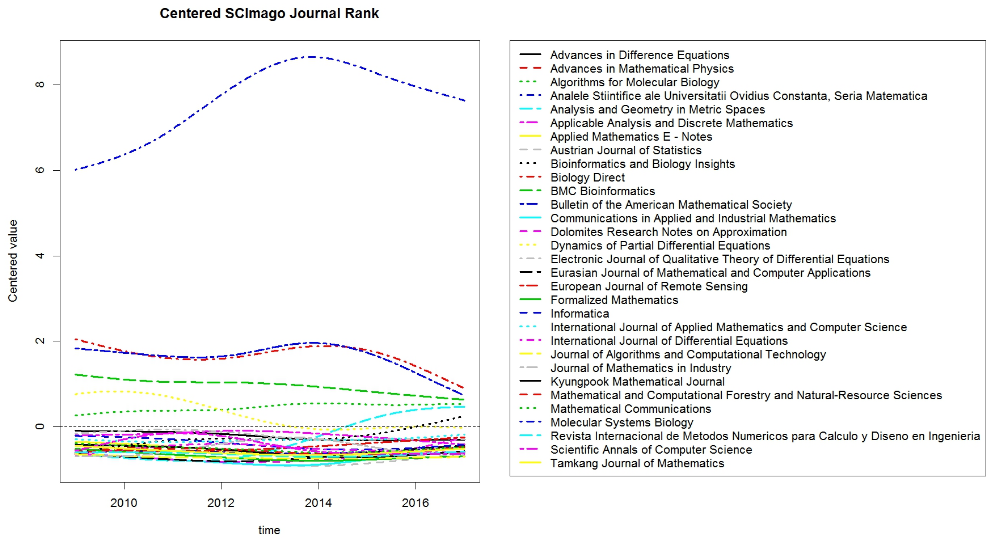

FIGURE 3. Smoothed SJR over 9 years for the 31 scientific journals.

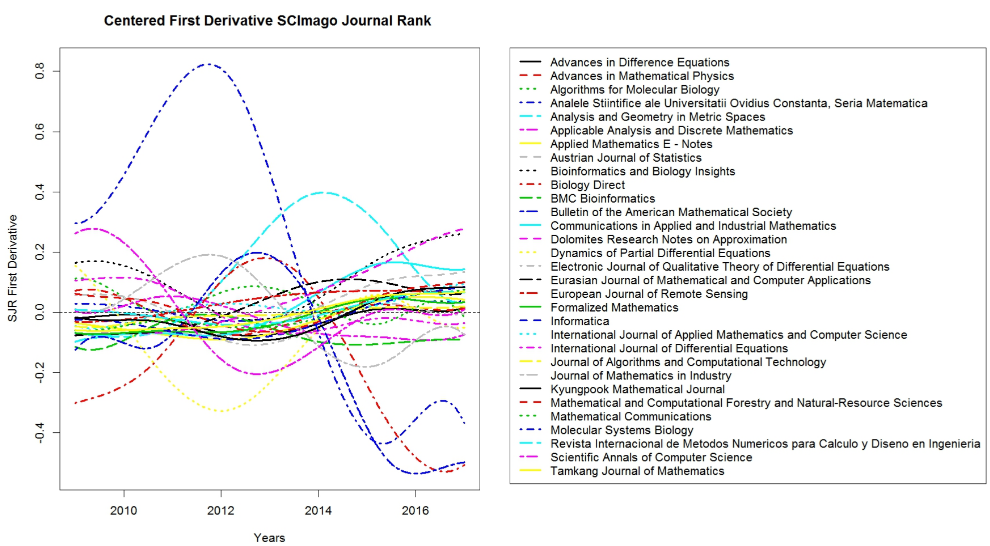

FIGURE 4. SJR Centered First Derivative over 9 years for the 31 scientific journals.

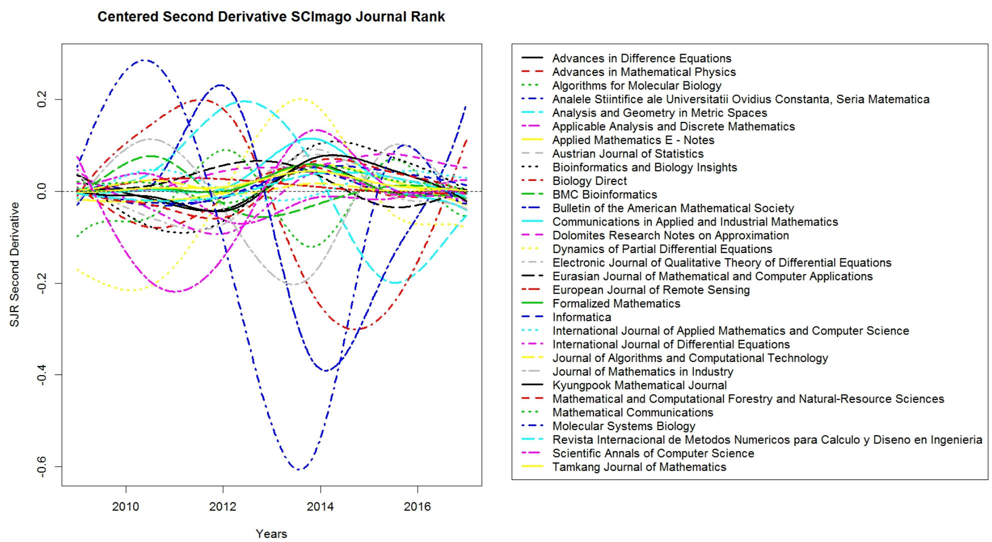

FIGURE 5. SJR Centered Second Derivative over 9 years for the 31 scientific journals.

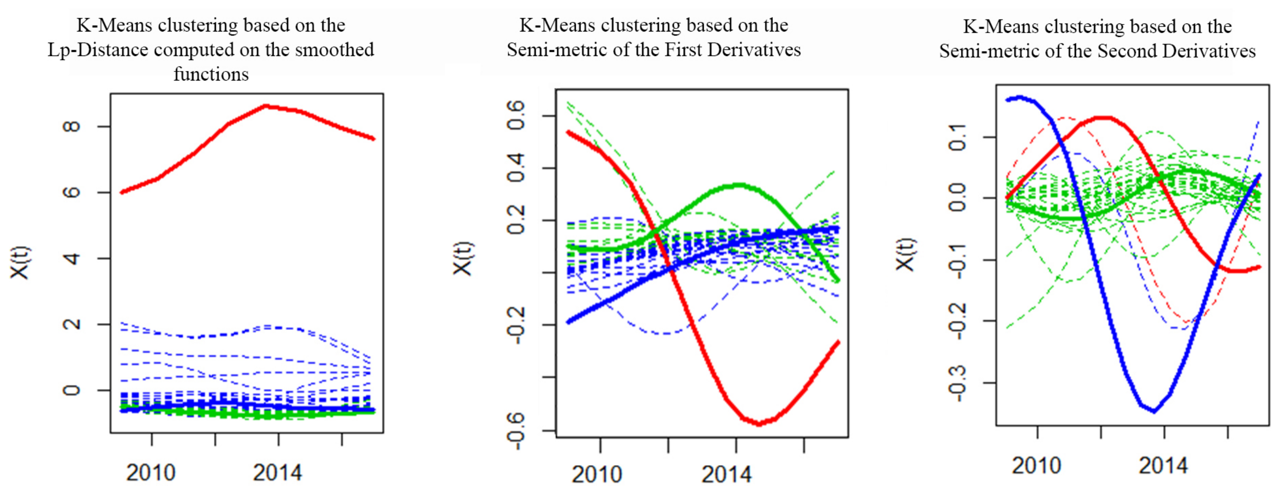

FIGURE 6. Different approaches to the functional k-means.

TABLE 2. Groups membership according to the chosen distance. Cluster Codes: Blue (G=1) Red (G=2) Green (G=3).

	L2	D1	D2
Advances in Difference Equations	1	2	3
Advances in Mathematical Physics	1	2	3
Algorithms for Molecular Biology	1	2	3
Analele Stiintifice ale Universitatii Ovidius Constanta, Seria Matematica	1	2	3
Analysis and Geometry in Metric Spaces	1	2	3
Applicable Analysis and Discrete Mathematics	1	1	3
Applied Mathematics E - Notes	1	2	3
Austrian Journal of Statistics	3	2	3
Bioinformatics and Biology Insights	1	2	3
Biology Direct	1	1	1
BMC Bioinformatics	1	1	3
Bulletin of the American Mathematical Society	1	1	1
Communications in Applied and Industrial Mathematics	3	2	3
Dolomites Research Notes on Approximation	1	2	3
Dynamics of Partial Differential Equations	1	1	2
Electronic Journal of Qualitative Theory of Differential Equations	1	2	3
Eurasian Journal of Mathematical and Computer Applications	1	2	3
European Journal of Remote Sensing	1	2	3
Formalized Mathematics	1	2	3
Informatica	1	2	3
International Journal of Applied Mathematics and Computer Science	1	2	3
International Journal of Differential Equations	1	1	3
Journal of Algorithms and Computational Technology	1	2	3
Journal of Mathematics in Industry	1	1	3
Kyungpook Mathematical Journal	1	2	3
Mathematical and Computational Forestry and Natural-Resource Sciences	1	2	3
Mathematical Communications	1	2	3
Molecular Systems Biology	2	3	1
Revista Internacional de Metodos Numericos para Calculo y Diseno en Ingenieria	1	2	3
Scientific Annals of Computer Science	1	1	2
Tamkang Journal of Mathematics	1	2	3

the derivatives provides more interesting insights on the journals' performance. Indeed, the first derivative indicates the velocity of the SJR in increasing or decreasing, whereas its second derivative is a measure of the acceleration in increasing or decreasing. These simple tools can help to detect early signals of declining or increasing of scientific journals' conditions better than the simple scalar measures.

A suitable distance measure based on these tools can help insiders to group journals according to their real condition better than the original smoothed functions. Effectively, our results underline that the clusters, and also their number, change according to the adopted distance measure.

According to Figure 2 and 3, we detect the presence of a journal, namely *Molecular Systems Biology*, that is an outlier with respect to the others. It presents very high values of SRJ, and as a consequence, in the first cluster analysis (see Figure 6 and Table 2), it is the only unit composing the red group. To detect the trend of the other journal, Figures 4 and 5 are more detailed because they detect small variations in the original curve. As a consequence, the results of the second and third cluster analysis have a different meaning because they group journals with similar behaviour of velocity and acceleration of the SJR. Effectively, Table 2 demonstrates that the groups' membership greatly change if considering these different distances. For example, *Bulletin of the American Mathematical Society* and *Biology Direct* are in the same group of *Molecular Systems Biology* because they had similar trends of acceleration over time. Similarly, the clustering results based on the first derivative give conflicting results with respect to the clustering based on the the L_2 distance between the original functions.

From a methodological perspective, this study presents the original idea to improve the existing metrics for research analytics via the use of the semi-metric of the first two derivatives; however, many other statistical techniques based on FDA could be adopted in this framework. Hence, starting from this study, other instruments may be extended to this context to improve the existing techniques adopted by institutions and enterprises to rank and classify journals according to their reputation and performances. Further studies can also extend this approach to the analysis of economic concerns such as regional competitiveness [see e.g. 24, 25] or financial mathematics and decision making problems such as those in Maturo, Squillante, and Ventre [26], Olivieri, Squillante, and Ventre [27], Lygeros and Vougiouklis [28], Rambaud, Maturo, and Pérez [29], Maturo [30], Nath and Singh [31], Rambaud and Pérez [32], Maturo [33].

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