Ranking dynamics and volatility

Carlos Garcia-Zorita[a,b], Ronald Rousseau[c,d], Sergio Marugan-Lazaro[a] and Elias Sanz-Casado[a,b]

czorita@bib.uc3m.es
[a]Laboratory of Metric Studies on Information (LEMI). Department of Library and Information Science. Carlos III University of Madrid. C/Madrid 126, Getafe, 28903 Madrid, Spain.
[b]Research Institute for Higher Education and Science (INAECU). Carlos III University of Madrid-Autonomous University of Madrid. C/Madrid 126, Getafe, 28903 Madrid, Spain.

ronald.rousseau@uantwerpen.be ; *ronald.rousseau@kuleuven.be*
[c]University of Antwerp, Faculty of Social Sciences, B-2020 Antwerpen, Belgium.
[d]KU Leuven, Facultair Onderzoekscentrum ECOOM, Naamsestraat 61, Leuven B-3000, Belgium.

smarugan@pa.uc3m.es
[a]Laboratory of Metric Studies on Information (LEMI). Department of Library and Information Science. Carlos III University of Madrid. C/Madrid 126, Getafe, 28903 Madrid, Spain.

elias.sanz@uc3m.es
[a]Laboratory of Metric Studies on Information (LEMI). Department of Library and Information Science. Carlos III University of Madrid. C/Madrid 126, Getafe, 28903 Madrid, Spain.
[b]Research Institute for Higher Education and Science (INAECU). Carlos III University of Madrid-Autonomous University of Madrid. C/Madrid 126, Getafe, 28903 Madrid, Spain.

ABSTRACT

Scientific journals are ordered by their impact factor while countries, institutions or researchers can be ranked by their scientific production, impact or by other simple or composite indicators as in the case of university rankings. In this paper, the theoretical framework proposed by Criado et al. (2013) for football competitions is used as a starting point to define a general index describing the dynamics or its opposite, stability, of rankings. Some characteristics to study rankings are presented, ranking dynamics measures are presented and some axioms for such indices are presented. Furthermore, the notion of volatility of elements in rankings is introduced. Finally, some worked out examples are shown.

KEYWORDS

Ranking dynamics, ranking volatility, stability, competitiveness

1. Introduction

Nowadays many colleagues complain about the ubiquity of rankings and the resulting increased competition in science. Besides competition between scientists to get a tenured job at a well-known university – something that has existed since such positions became available– we have nowadays competition among departments in the same university, among universities, spurred by university rankings, and even between continents or parts thereof, typically: America, China and Europe (Shelton & Holdridge, 2004; Bonaccorsi et al., 2017).

Recently Criado, Garcia, Pedroche and Romance (2013) studied rankings in European football competitions, trying to answer the question "Which competition is the most exciting", in the sense that there are many position switches in the rankings. They answered this question using competitivity graphs and derived *measures of competitiveness*. As we will apply their idea to any ranking, not just football competitions, and as the term *competitiveness* has a specific meaning in economics (Ambec et al., 2013; Buser et al., 2014; World Economic Forum, 2016), we will not use their term *competitiveness* but replace it by the term ranking dynamics, referring to the phenomenon of changes in rankings, mainly over time.

In this contribution we will discuss the notion of ranking dynamics, consider how to measure it, look in more detail to the approach proposed by Criado et al. (2013), introduce a generalization and apply it to rankings in academia. Our work is a generalization of work presented during the S&T Indicators Conference in Paris (García-Zorita et al., 2017).

2. The Criado et al. (2013) framework

Before introducing a generalization of the Criado et al. (2013) work we first describe here and in Section 4 how these authors defined competitiveness. Consider a set E of n elements or nodes (when described in a network context), denoted as $\{e_1, e_2, \ldots, e_n\}$. Next we consider an ordered set **R** of rankings of these n elements. Rankings denoted as $c_1, \ldots, c_r$ are ordered (usually in time, referred to as instances), where each c_j is a complete ranking (no ties) of the n elements at instance j.

We say that element e_i changes position with element e_j if they exchange their relative positions between two consecutive rankings. Roughly speaking the more position shifts the more dynamic a ranking system, e.g., a football competition.

Before we come to possible measures of ranking dynamics we shortly discuss different aspects of this framework.

3. Aspects when studying the dynamics of rankings

1) The underlying scoring method leading to a ranking.
For football it makes a difference if a winner receives 3 points or 2 (as it used to be); it would make no difference if the winner receives 6 points, the loser zero and both teams 2 points in case of a drawn. In qualitative comparisons the underlying scoring method may be based on two-by-two

preference relations. In bibliometrics one can imagine journal rankings based on the 2-year IF, the 5-year IF, total cites, immediacy index etc.., perhaps using different databases. For university rankings one can use the ARWU, THE, etc., rankings. For a group of scientists one could study each scientist's h-index (each year, but also per half-year, 2-year) and the resulting rankings.

2) Whether the ranking is complete or if ties are allowed.
Criado et al. (2013) studied rankings without ties, but we will show that ties form an essential aspect of real-world rankings.

3) The 'timing' of the r rankings.
For the football case the timing is each 'calendar week'. For the bibliometric rankings (journals, universities) it would be consecutive years (but other time intervals are feasible). Note that rankings must have a natural order, say time. Studying different preference rankings – drawn by different referees in a beauty contest – does not fit into the framework we study here.

4) One may study rankings of different entities as by Criado et al. (2013) who studied four football competitions; or rankings based on different criteria for the same entity (journals ranked by IF, immediacy index, total number of received citations, etc...).

5) Possible dynamics
We mention three aspects:
a) In the football case changes between consecutive rankings (weeks) are small as the maximum change in the underlying score is 3, but if one considers final rankings at the end of the season then anything is (theoretically) possible. A similar remark applies to JIFs, especially if one would study the 2-year IF with a time gap of two or more years.
Rankings based on h-indices are probably more stable than those based on JIFs, as h-indices are cumulative, while JIFs refer to articles published in different journals and the number of possible citations has a very high upper limit.
b) Another aspect is whether numbers on which rankings are based are completely independent between events (as for yearly final rankings in a national football competition) or are cumulative (as in the football competition data based on weekly data or h-indices for researchers). Yearly rankings of journals based on their impact factor is a case in-between as half of the articles that determine the JIF are replaced, admitting that citations that determine the JIF are received during different years.
c) Finally, another dynamic aspect is the fact that one must take into account that some teams/journals enter or leave the rankings. This will be studied later (see Section 7).

4. Representing competitiveness in the sense of (Criado et al., 2013)

Criado et al. (2013) only studied the case of a fixed number of elements (football teams in their case study) without ties in the ranking. We first describe their framework. They represent a set of rankings **R,** as introduced in Section 2**,** as a weighted network, with nodes $(e_j)_{j=1,\ \ldots,\ n}$. Two nodes are linked with weight k if these nodes perform k position shifts. If there are r instances, then there are at most r-1 position shifts between two given elements (recall that position shifts are always considered between consecutive instances). We present a simple example: let n = 6 and let E = {e_1, e_2, …, e_6 }. Assume that we consider 4 instances (r = 4):

$$c_1 = (e_1, e_2, e_3, e_4, e_5, e_6)$$
$$c_2 = (e_1, e_4, e_6, e_5, e_2, e_3)$$
$$c_3 = (e_1, e_2, e_5, e_3, e_4, e_6)$$
$$c_4 = (e_4, e_2, e_3, e_1, e_5, e_6)$$

The number of position shifts between two elements can be expressed in a (symmetric) matrix M or, equivalently, in a network.

$$M = \begin{matrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6 \end{matrix} \begin{pmatrix} - & 1 & 1 & 1 & 0 & 0 \\ & - & 0 & 3 & 2 & 2 \\ & & - & 3 & 2 & 2 \\ & & & - & 2 & 0 \\ & & & & - & 2 \\ & & & & & - \end{pmatrix}$$

We see that the four possible cases: no shifts, 1, 2 and 3 shifts occur in this example. As a weighted network, called the ranking dynamics graph (referred to as competitivity graph in Criado et al., 2013), this example becomes:

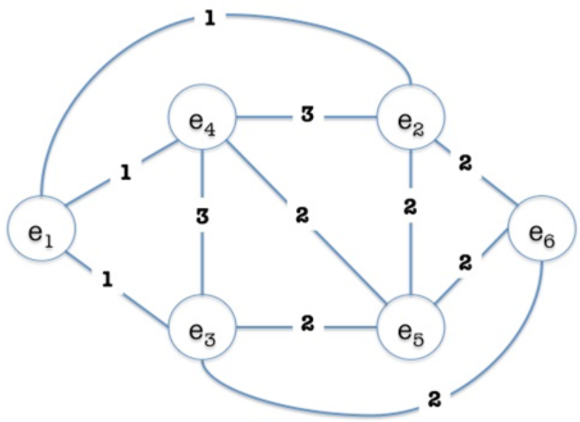

Fig. 1. A ranking dynamics graph

We note that sets of rankings with a different number of instances can lead to the same matrix and the same weighted network. It suffices to repeat one instance so that r becomes r+1, but as this operation has no influence on the number of position shifts the corresponding matrix and graph stay invariant.
Ranking dynamics or competitiveness in the sense of (Criado et al., 2013) is a property of a set of rankings. The sum of all position shifts of an element is called its volatility. Using the matrix representation $M = (m_{ij})_{ij}$, the (absolute) volatility of element e_j is defined as: $\mathrm{vol}(e_j) = \sum_{i=1}^{n} m_{ij}$.
The relative volatility is then: $\mathrm{relvol}(e_j) = \frac{\mathrm{vol}(e_j)}{(n-1)(r-1)}$. Note that we divided by (n-1) as there are at most n-1 position shifts between two instances; we, moreover, divided by (r-1) as r-1 comparisons are performed.

5. Measuring ranking dynamics

In this section we consider some candidate measures for ranking dynamics. We restrict ourselves to basic measures, admitting that other ones are feasible.

First measure: absolute form

This measure is just the total sum of the node degrees of all nodes in the ranking dynamics graph.

$$\sum_{j=1}^{n} \deg(e_j)$$

Equivalently, this is the sum of all degree centralities of the ranking dynamics graph (Otte & Rousseau, 2002).

First measure: normalized form

The normalized degree of a set of rankings **R,** denoted as ND(**R**), is defined as:

$$\mathrm{ND}(\mathbf{R}) = \frac{\left(\sum_{j=1}^{n} \deg(e_j)\right)/2}{n(n-1)/2}$$

This is the number of links divided by the maximum number of links, namely n(n-1)/2. This indicator can be described as the normalized sum of all node degrees (= degree centrality) in the (unweighted) ranking dynamics graph. Clearly, this is a weak indicator as it does not taken into account how often elements have shifted positions.
Before defining the second measure we recall the definition of the node strength in a weighted undirected network.

Node strength
The node strength of a node in an undirected weighted network is defined as the sum of the strengths (or weights) of all its links (Barrat et al., 2004). This is denoted as $d_S(e_j)$. When all weights are equal to 1 (corresponding to the unweighted case) the node strength becomes the degree centrality of the node.

Second measure: absolute form
This measure is defined as the sum of the node strengths of all nodes in the ranking dynamics graph.

$$\sum_{j=1}^{n} d_S(e_j)$$

This is twice the sum of all weights, or the sum of all elements in the matrix M. It is also equal to the sum of the volatilities of all elements.

Second measure: relative, i.e. normalized, form
The normalized mean strength, denoted as NS is the normalized sum of all node strengths in the ranking dynamics graph:

$$\mathrm{NS}(\mathbf{R}) = \frac{\sum_{j=1}^{n} d_S(e_j)}{n(n-1)(r-1)} = \frac{1}{n}\sum_{j=1}^{n}\frac{d_S(e_j)}{(n-1)(r-1)}$$

Note that (r-1) is the highest possible link weight. The formula shows that NS(**R**) is also equal to the average relative volatility of all elements. Clearly, 0 ≤ NS(**R**) ≤ 1.

We note that a value of 1 for NS(**R**) is possible by alternating a ranking and its opposite as in:

$$c_1 = \left(e_1, e_2, e_3, e_{4,} e_5, e_6\right)$$
$$c_2 = \left(e_6, e_5, e_4, e_{3,} e_2, e_1\right)$$
$$c_3 = \left(e_1, e_2, e_3, e_{4,} e_5, e_6\right)$$
$$c_4 = \left(e_6, e_5, e_4, e_{3,} e_2, e_1\right)$$

6. Properties of measures of ranking dynamics
We define some basic operations and consider the resulting requirements for changes in measures for ranking dynamics. This leads to some basic axioms for measures of ranking dynamics.

Axiom 1: Relabelling
Relabelling the elements (technicality: applying a permutation) must not change the resulting measure for dynamics. Dynamics is only determined

by a change in overall configuration. This relabelling or anonymity axiom must always be satisfied by a bona fide measure of ranking dynamics.

Axiom 2: No change
If R = (c, c, c, c, …c) then there are no changes in rankings for consecutive instances, hence there is no dynamics. We require that a measure of ranking dynamics must take the value zero for this case. The "no-change" operation happens if one always applies alphabetical order.

Axiom 3: Replication
If the ordered set of r rankings, R = (c_1, c_2, … , c_r) is replaced by the ordered set of r+1 rankings R'= (c_1, c_1, c_2, … , c_r), where one of the c_j's (not necessarily the first) is duplicated, then this has no influence on absolute ranking dynamics. Of course, if more than one duplication occurs this has no influence either. A replication operation has no influence on the network and its weights. Note that duplication must occur between consecutive rankings.
Replication must decrease relative ranking dynamics, yet *ND(**R**)* stays invariant under duplication. For this reason, we do not consider this to be an acceptable measure of ranking dynamics.

Axiom 4: Adding an element which is always ranked first or last
When this operation is applied there must be no influence on absolute measures but a decrease on relative measures of ranking dynamics.

Axiom 5. Instance reversion
If the order of the instances is reversed then this has no influence on ranking dynamics.

Clearly, NS is an acceptable relative measure for ranking dynamics.

7. New entrants, leavers and ties

In real-world rankings it often happens that new entrants join the set of elements or that some leave. Moreover, it may easily happen that ties occur. Hence, we will adapt the previous framework so that one can take new entrants, leavers and ties into account. In this new framework measures must still satisfy all requirements discussed in section 6.

As in the Criado et al. (2013) framework we consider a strictly ordered column of r instances. Each instance is a ranked set of elements, where ties are allowed. By definition, tied elements have the same rank. The symbol S denotes the set of all (different) elements occurring in the r instances; let #S = n. We add to each instance those elements in S which are absent in this particular instance, ranking them as ties on the last position. The original elements in a given instance are called the active elements, the added ones are called the inactive elements. Being active or inactive is referred to as the state of an element in a given instance. Active and inactive elements are separated by the symbol ";" . Denoting a tie between elements e and f as $\ldots,\underbrace{e,f},\ldots$and assuming that elements x, y and z are missing in instance c, this means that c = (s_1, s_2, …, s_{n-3}) is rewritten as c = $\left(s_1, s_2, \ldots, s_{n-3}; \underbrace{x, y, z}\right)$. The rank of an element s in instance c is denoted as $r_c(s)$.

We will explain how to calculate the value of a new relative ranking dynamics indicator NS. In the framework studied by Criado et al. (2013) this new NS will be equal to the old one. As before NS is the average of the relative volatility scores of all elements in S. Besides position shifts, also leaving or entering, i.e. becoming active or becoming inactive are signs of dynamics and are taken into account when determining a volatility score. Most of the time our notation implies that becoming active or inactive implies a position shift, but this is not always the case (see further). At any instance c and for any two elements e and f: we either have $r_c(e) < r_c(f)$, or $r_c(e) = r_c(f)$ or $r_c(e) > r_c(f)$.

We obtain a volatility score for each element, e, by comparing with each other element. This score is obtained by a comparison of the positions and states of e and the other element in consecutive instances, leading to partial volatility scores. The sum of all these volatility scores is the (global) volatility score of element e. Partial volatility scores are symmetric: the partial volatility score between elements e and f is the same as the one between f and e. In each comparison between instances the score either stays unchanged or increases by one. The initial score is zero. When the state of (at least) one of the two elements changes from active (A) to inactive (I) then the score increases; if both elements do not change state, then we compare the relative position of e and the other element between two consecutive instances. If the relation < (between $r_c(e)$ and $r_c(f)$) changes to > or vice versa, then the volatility score increases; if there is no change in the relative ranking of e and the other element the score stays the same. If the two elements become tied then the score does not change, but the previous relative position is kept in memory. If the two elements were tied and are still tied, then nothing changes; if they were tied and are not tied anymore then the last time they were not tied determines if there is a position change and hence if the volatility score increases or not. Finally, if the two elements have always been tied since the first instance and they are not tied anymore then this counts as a position shift and the volatility score increases. Note that it is impossible that the two elements were inactive and tied, and are not tied anymore, since then at least one of them has become active and we have already dealt with this case (leading to an increase in the volatility score). In the very special case that two elements are inactive, then become both active and tied, and then at a later instance one is ranked before the other the volatility score is increased, similar to the case where they have been tied since the beginning.

To describe formally what happens step by step we use the following 8-tuple, referred to as a dynamic ranking tuple:

> (element1, state of element 1, element2, state of element2, instance, relational symbol, counter, additional information symbol).

We want to determine the volatility score of element1 and compare with element2; these elements are either active (A) or not (inactive, indicated by I); the fifth position of the tuple denotes the second instance used in the comparison between two instances, the sixth shows the relation between element1 and element2 in that order: the relational symbol is either <, > or =; the seventh position is the partial volatility score up to that instance and the eighth position is a memory symbol that helps to deal with equalities: it is either * (meaning that element1 and element2 are not tied); < (meaning that element1 and element2 are tied and the last time they were not tied we had element1 < element2; or > referring to the opposite relation; finally # means that element1 and element2 have always (since c_1) been tied.

The value of the score at the last instance is the partial volatility score for the pair element1-element2.

We will illustrate the method by the following example:

Consider the four instances

$$c_1 = (s,t,u,v)$$

$$c_2 = (s,u,w,x)$$

$$c_3 = (\underbrace{s,u},w,y)$$

$$c_4 = (z,y,u,s)$$

The set S is here {s,t,u,v,w,x,y,z}, with #S=8. Consequently the four instances are rewritten as:

$$c_1 = (s,t,u,v;\underbrace{w,x,y,z})$$

$$c_2 = (s,u,w,x;\underbrace{t,v,y,z})$$

$$c_3 = (\underbrace{s,u},w,y;\underbrace{t,v,x,z})$$

$$c_4 = (z,y,u,s;\underbrace{t,v,w,x})$$

Now we illustrate, step by step, how we count the partial volatility score for {t,x}. We start with showing the initial position. Here, this initial position is: (t,A,x,I,c_1,<,0,*). A first comparison yields:

$(t,I,x,A,c_2,>,1,*)$: the score becomes 1 because t becomes inactive (and moreover x becomes active, but this has no influence on the score anymore). Next we have:

$(t,I,x,I,c_3,=,2,>)$: t becomes inactive (leading to an increase in the score); we note that moreover t and x are tied and the last time they were not tied x was ranked before t;

$(t,I,x,I,c_4,=,2,>)$: this is the end result: the partial volatility score for the pair {t,x} is 2.

As a second example we consider the pair {s,u}:

The initial position is: $(s,A,u,A,c_1,<,0,*)$.

The next dynamic ranking tuple becomes: (s,u,c2,<,0,*), followed by (s,A,u,A,c3,=,0,<); finally we reach (s,A,u,A,c4,>,1,*): there is one position shift between s and u; if the fourth position had been: (s,A,u,A,c4,<, 0, *), then this would not have counted as a position shift and hence the partial volatility score would have been zero.

Finally we illustrate the case {y,z}. The consecutive dynamic ranking tuples are:

$(y,I,z,I,c_1,=,0,\#)$
$(y,I,z,I,c_2,=,0,\#)$
$(y,A,z,I,c_3,<,1,*)$: because y becomes active
$(y,A,z,A,c_4,>,2,*)$: because z becomes active

Table 1 shows all partial results.

Table 1. Details of the volatility calculations for the example.

elements	c_1-c_2	c_2-c_3	c_3-c_4	total		elements	c_1-c_2	c_2-c_3	c_3-c_4	total
s-t	1	0	0	1		u-w	1	0	1	2
s-u	0	0	1	1		u-x	1	1	0	2
s-v	1	0	0	1		u-y	0	1	1	2
s-w	1	0	1	2		u-z	0	0	1	1
s-x	1	1	0	2		v-w	1	0	1	2
s-y	0	1	1	2		v-x	1	1	0	2
s-z	0	0	1	1		v-y	1	1	0	2
t-u	1	0	0	1		v-z	1	0	1	2
t-v	1	0	0	1		w-x	1	1	1	3
t-w	1	0	1	2		w-y	1	1	1	3
t-x	1	1	0	2		w-z	1	0	1	2
t-y	1	1	0	2		x-y	1	1	0	2
t-z	1	0	1	2		x-z	1	1	1	3
u-v	1	0	0	1		y-z	0	1	1	2

In matrix form this becomes:

$$
M = \begin{pmatrix}
 & s & t & u & v & w & x & y & z \\
s & - & 1 & 1 & 1 & 2 & 2 & 2 & 1 \\
t & 1 & - & 1 & 1 & 2 & 2 & 2 & 2 \\
u & 1 & 1 & - & 1 & 2 & 2 & 2 & 1 \\
v & 1 & 1 & 1 & - & 2 & 2 & 2 & 2 \\
w & 2 & 2 & 2 & 2 & - & 3 & 3 & 2 \\
x & 2 & 2 & 2 & 2 & 3 & - & 2 & 3 \\
y & 2 & 2 & 2 & 2 & 3 & 2 & - & 2 \\
z & 1 & 2 & 1 & 2 & 2 & 3 & 2 & -
\end{pmatrix}
$$

The global and relative volatility of the elements in S are shown in Table 2.

Table 2: global and relative volatility of the elements in S

Elements	s	t	u	v	w	x	y	z
Volatility	10	11	10	11	16	16	15	13
Relative volatility	10/21	10/21	10/21	11/21	16/21	16/21	15/21	13/21

Clearly leavers and entrants have the highest volatility and hence contribute most to the overall ranking dynamics (also because in this simple example there are relatively many of them!).
Finally, the absolute volatility (total strength) is 100 and NS, the normalized mean strength, is $102/(8 \times 7 \times 3) = 0.607$ which is the average of the relative volatilities. In the example, the value of ND is 100% (all elements have at least one position-shift with the rest).

(NOTE: A python script to calculate volatility and position shifts is available in https://github.com/smarugan/uc3m_dynamics)

8. An application

As an illustrative real-world example, we calculated the ranking dynamics of the WOS-JIF (Web of Science journal impact factor) for three JCR (Journal Citation Reports) classes, namely *Economics*, *Information Sciences & Library Sciences*, two categories from the social sciences and *Biology*, a category in the SCI (Science Citation Index), and this over the period 1997-2015. The results are shown in Table 3.

Table 3. Ranking dynamics measures for some JCR categories

JCR category	# Journals	r	NS(R) in %	ND(R) in %
Information Science & Library Science (LIS)	113	19	15.18	97.63
Economics	392	19	12.70	95.23
Biology	138	19	12.95	98.90

Clearly ranking dynamics is higher in the category *Information Science & Library Science* than in the other two categories, which differ only marginally.
We further calculated the relative volatility of some selected LIS journals. Results are shown in Table 4. The journals *Serials Review* and *Journal of the Medical Library Association* have the highest volatility, while *MIS Quarterly* has the lowest.

Table 4. Relative volatility of some selected LIS journals

Journal	NS RelVol (%)
ASLIB PROC	13.79
INFORM PROCESS MANAG	11.76
INVESTIG BIBLIOTECOL	12.25
J.DOC	9.92
J. INFORMETR	11.76
J MED LIBR ASSOC	16.67
MIS QUART	6.40
PROF INFORM	14.73
SCIENTOMETRICS	10.62
SERIALS REV	16.37

9. A detailed investigation of this example

Our measure deals with given rankings. If the underlying ranking methodology or philosophy changes, then obviously the measure will change. Concretely, with respect to the examples shown in Tables 3 and 4, we observed that values were influenced by entrants and leavers, where these include name changes. In our calculations we followed the JCR definition of a journal. Although for most colleagues the *Journal of the American Society for Information*, the *Journal of the American Society for Information and Technology* and the *Journal of the Association for Information Science and Technology* are probably the same, these are considered three different journals in the JCR, as shown by their abbreviations, namely: J AM SOC INFORM SCI, J AM SOC INF SCI TEC and J ASSOC INF SCI TECH (in this order), the calculation of the impact factor and other indicators, although the last two have the same ISSN and informal abbreviation (JASIST).
Table 5 shows the number of entrants or leavers for each pair of consecutive years. We were really surprised by these relatively high number of changes. If a journal enters or leaves this results in an increase of its volatility score by n-1.

Table 5. Numbers of entrants and leavers for each pair of consecutive years in the category *Information Sciences & Library Sciences*.

Period	# entrants	# leavers	sum
1997-1998	0	2	2
1998-1999	6	3	9

1999-2000	4	6	10
2000-2001	5	5	10
2001-2002	3	3	6
2002-2003	0	0	0
2003-2004	4	5	9
2004-2005	2	1	3
2005-2006	0	2	2
2006-2007	5	2	7
2007-2008	5	0	5
2008-2009	5	0	5
2009-2010	12	1	13
2010-2011	8	2	10
2011-2012	3	1	4
2012-2013	3	4	7
2013-2014	5	4	9
2014-2015	3	1	3
Total	72	42	114

We note that it follows from the total number of leavers and entrants that 114 is the minimum possible absolute volatility for a journal that appears in all rankings.
Next we discuss some journals with high volatility scores.
Case A. INF TARSAD (ISSN: 2063-4552. "Informacios Tarsadalom", Hungary). Its states and partial volatility scores are shown in Table 6.

Table 6. States and scores of INF TARSAD

<table>
<tr><th>Year</th><th>State</th><th colspan="2">Volatility</th></tr>
<tr><td>1997</td><td>I</td><td></td><td>sum</td></tr>
<tr><td>1998</td><td>I</td><td>2</td><td rowspan="12">68</td></tr>
<tr><td>1999</td><td>I</td><td>9</td></tr>
<tr><td>2000</td><td>I</td><td>10</td></tr>
<tr><td>2001</td><td>I</td><td>10</td></tr>
<tr><td>2002</td><td>I</td><td>6</td></tr>
<tr><td>2003</td><td>I</td><td>0</td></tr>
<tr><td>2004</td><td>I</td><td>9</td></tr>
<tr><td>2005</td><td>I</td><td>3</td></tr>
<tr><td>2006</td><td>I</td><td>2</td></tr>
<tr><td>2007</td><td>I</td><td>7</td></tr>
<tr><td>2008</td><td>I</td><td>5</td></tr>
<tr><td>2009</td><td>I</td><td>5</td></tr>
<tr><td>2010</td><td>A</td><td>112</td><td rowspan="4">672</td></tr>
<tr><td>2011</td><td>I</td><td>112</td></tr>
<tr><td>2012</td><td>A</td><td>112</td></tr>
<tr><td>2013</td><td>I</td><td>112</td></tr>
</table>

2014	A	112	
2015	I	112	
	Total	740	740

The journal INF TARSAD appears only in three rankings: 2010, 2012 and 2014 (probably due to a change of criteria in the journal's classification or due of inconsistencies of JCR). Despite being only active in these three years, it is the journal with highest volatility (740/2016 = 36.7%) of the area. As it enters and leaves in three alternative years, it reaches the maximum number of possible changes (n-1 = 112) in six events (112*6= 672). In addition, it accumulates 68 more changes, due to all the journals that have entered and left from the beginning until the event 2008-2009.
Case B. J EDUC LIBR INF SCI (ISSN: 0748-5786, "Journal of Education for Library and Information Science", USA). The states and partial volatility scores of this journal are shown in Table 7.

Table 7. States and scores of J EDUC LIBR INF SCI

Year	State	Volatility	
1997	A		sum
1998	I	112	336
1999	A	112	
2000	I	112	
2001	I	10	93
2002	I	6	
2003	I	0	
2004	I	9	
2005	I	3	
2006	I	2	
2007	I	7	
2008	I	5	
2009	I	5	
2010	I	13	
2011	I	10	
2012	I	4	
2013	I	7	
2014	I	9	
2015	I	3	
	Total	429	429

J EDUC LIBR INF SCI is a journal that is active in two alternative years at the beginning of the list. This behaviour leads to three times the maximum number of shifts (3*112=336). In addition, we add a total of 93

shifts (equal to the accumulated number of entrants and leavers since 2001).
In a next step, we recalculated the results shown in Tables 3 and 4 in the case of 5 ranks, namely four quartiles plus the inactive ones and in the case of 11 ranks (10 deciles, plus the inactive ones). This leads to large numbers of ties of active journals, but the total number of journals in LIS, namely n = 113, stays the same. It is expected that these ties reduce the volatility and hence the ranking dynamics. This expectation turns out to hold, see Tables 8 and 9.

Table 8. Ranking dynamics scores by different kinds of ranks for some JCR categories

Category	Total journals	NS (2-year IF)	NS (decile)	NS (quartile)
Information Science & Library Science (LIS)	113	15.18%	14.28%	13.40%
Economics	392	12.70%	11.63%	10.83%
Biology	138	12.95%	12.44%	12.14%

Table 9. Volatility of some selected LIS journals by different types of ranks.

		Volatility with JCR position		Volatility with decile position		Volatility with quartile position	
Journal	Max. Shifts	Shifts (2-year IF)	NS (2-year IF)	Shifts (decile)	NS (decile)	Shifts (quartile)	NS (quartile)
ASLIB PROC	2016	278	13.79%	249	12.35%	237	10.07%
INFORM PROCESS MANAG	2016	237	11.76%	215	10.66%	170	8.43%
INVESTIG BIBLIOTECOL	2016	247	12.25%	238	11.81%	237	11.76%
J DOC	2016	200	9.92%	179	8.88%	166	8.23%
J INFORMETR	2016	237	11.76%	236	11.71%	229	11.36%
J MED LIBR ASSOC	2016	336	16.67%	314	15.58%	303	15.03%
MIS QUART	2016	129	6.40%	124	6.15%	129	6.40%
PROF INFORM	2016	297	14.73%	288	14.29%	267	13.24%
SCIENTOMETRICS	2016	214	10.62%	180	8.93%	150	7.44%
SERIALS REV	2016	330	16.37%	303	15.03%	282	13.99%

We note that the decile shifts (absolute volatility) for MIS QUART happen to be smaller than the quartile one. Although generally the more ties – induced by using deciles or quantiles - the less the number of shifts, we remark that journals that belong to the same decile do not have to belong to the same quartile, explaining the occasional exception.

10. Note on a previous approach

In the article presented during the 2017 S&T Indicator Conference (García-Zorita et al., 2017) we calculated a measure with respect to the maximum number of position shifts that occurred, providing in this way a solution for the case of entrants and leavers. Yet this approach does not take one-time entrants or leavers into account. Concretely, if s_k is in c_1 but not in any other instance, s_l is in c_2 but not in any other instance, s_m occurs only in c_3 etc. then any measure that makes use of position shifts between consecutive instances ignores the occurrence of s_k, s_l, s_m etc., while these elements clearly contribute to the overall dynamics. The new approach which adds these unique elements as ties on the last place of an instance, does take their contribution to the overall dynamics into account, see example in section 7.

11. Conclusion

In many application not the dynamics but the stability of rankings is of importance. Clearly, 1 – NS yields a relative measure of stability. The stability measure of the example in section 7 is 0.393.
Ranking dynamics is an aspect of any ordered set of rankings. Its study can be performed in many fields, including markets, sports and informetrics. In this contribution, we proposed minimal requirements for measures of ranking dynamics and studied some proposals for its measurement. Moreover, we introduced the notion of volatility of elements included in such rankings. As measuring the dynamics of rankings is, as far as we know, not been done before there is ample opportunity for further research. One aspect we would like to investigate is the following question: if a long list, say of 500 elements, is subdivided in the first 100, the first 200 and so on, what can be said about the dynamics. Does the total (500 element) list have a higher dynamics than the sublist consisting of the first 100?

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