Pre-print of: Journal of Informetrics, 2014, vol. 8(2), p. 369-383.
http://dx.doi.org/10.1016/j.joi.2014.01.011

Optimising SCImago Journal & Country Rank classification by community detection

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Abstract

Subject classification arises as an important topic for bibliometrics and scientometrics as to develop reliable and consistent tools and outputs. For this matter, a well delimited underlying subject classification scheme reflecting science fields becomes essential. Within the broad ensemble of classification techniques clustering analysis is one of the most successful.

Two clustering algorithms based on modularity, namely, VOS and Louvain methods, are presented in order to update and optimise journal classification of SCImago Journal & Country Rank (SJR) platform. We used network analysis and visualization software *Pajek* to run both algorithms on a network of more than 18,000 SJR journals combining three citation-based measures, that is, direct citation, co-citation and bibliographic coupling. The set of clusters obtained was termed through category labels assigned to SJR journals and significant words from journal titles.

Despite of both algorithms exhibiting slight performance differences, the results showed a similar behaviour in grouping journals and, consequently, they seem to be appropriate solutions for classification purposes. The two new generated algorithm-based classifications were compared to other bibliometric classification systems such as the original SJR one and WoS Subject Categories in order to validate their consistency, adequacy and accuracy. Although there are notable differences among the four classification systems analysed, we found a certain coherence and homogeneity among them.

Keywords: Community detection; Clustering; SCImago Journal & Country Rank; Journal classification; Citation-based network.

1.- Introduction

Classification is a broadly covered topic in *Bibliometrics* and *Scientometrics* because of its significance in developing of final bibliometric and scientometric outputs, mainly based on scientific literature included in databases and repositories. Thus, the literature collected by these information and reference sources need to be organized through an appropriate and consistent classification scheme not only for information retrieval purposes, but also for designing reliable and solid tools as rankings, domain analysis or scientograms, which are of an outstanding value, for instance, in science policy design and science evaluation processes.

Normally, database subject classification schemes are constructed on the basis of a disciplinary structure which pretends to replicate the main fields and subfields of research and scientific knowledge recorded in the literature stored in databases. Then, classification of scientific literature can be made at journal or paper level. The most highly reputed scientific databases at present, namely, Web of Science (Thomson Reuters, 2009) and Scopus (Elsevier, 2004), have a very similar two-level hierarchical subject classification schemes consisting of subject areas at a high and wider level and subject categories at low and more specific level. In both databases, journals are assigned to one or more categories and their papers are inheriting subject categories of journals which they belong to. In Web of Science (WoS) case, journal assignment is executed by ISI (currently, Thomson Reuters) staff taking into account several criteria as journal titles or citation patterns (Pudovkin & Garfield, 2002).

Delimitation of scientific fields required in developing disciplinary subject classification schemes can be done through many different approaches varying from empirical and pragmatic techniques to automated procedures based on statistics and computerized methods. Within the latter ones, clustering analysis is one of the most valuable and usual methods used for classification tasks in several and distinct scientific fields as *Library and Information Science*, *Psychology*, *Medicine* or *Biology* among others.

2.- Related Works

Many clustering algorithms and techniques have been developed in order to get optimal solutions for the classification problems befallen in scientific fields above mentioned. However, clustering methods have been widely used by researchers dealing with information visualization techniques in order to map the structure of scientific knowledge and research. For this reason, they needed a good underlying classification of fields and subfields to be mapped. A total of 20 representative approaches in mapping science fields and their relations working from Web of Knowledge and Scopus database literature were compared and condensed by Klavans and Boyack (2009).

Clustering and mapping procedures have been conducted on different levels of aggregation, or in other words, using different units of analyses. Thus, at journal level a large number of researchers have applied different cluster algorithms to journal-journal relation matrices or networks based on citations, co-citations or bibliographic coupling. Chang and Chen (2011) applied the *minimum span clustering (MSC)* method to a citation square matrix of roughly 1,600 SSCI journals. Leydesdorff, Hammarfelt and Salah (2011) tried to merge a map of humanities based on Thomson Reuters' A&HCI database in a global map of science previously developed (Rafols, Porter, & Leydesdorff, 2010) and used the k-core algorithm for mapping 25 specific A&HCI subject categories. Archambault, Beauchesne and Caruso (2011) designed a scientific journal ontology aimed to simplify the output of bibliometric data and analysis. The new journal ontology was built on feedback from previous existing journal classification whose categories were considered as "seeds" for the initial journal assignment. Three automatic classification procedures using either text or citation data from papers published in around 34,000 journals and conference proceedings from Scopus and WoS were executed. However, the final solution was generated according to the iterative analysis of citation and references patterns between subject fields and journals. Leydesdorff and Rafols (2012) collaborative work produced a study where a 9,162 journal-journal citation matrix extracted from the 2009 volume of the SCI-Expanded was used to map interactive global journal maps. They compared several methods and, among them, different clustering algorithms to group journals into clusters. More recently, Börner et al. (2012) introduced a methodology to design and subsequently update a map of science and classification system solicited by the University of California, San Diego (UCSD). To build the map a combination of text and link journal-journal similarity matrices based on Scopus and WoS data were used. Then, journal clustering was executed on a filtered matrix derived from modified cosine similarities. Finally, the calculation of similarities among clusters as well as their positions and relationships enabled depicting the UCSD map.

Lately, there has existed a research trend working with clustering algorithms for analysis, validation, and improvement of classification schemes based on journals from various perspectives. ECOOM research group of KU Leuven has addressed this topic throughout several publications where different clustering algorithms as Ward clustering or Multi-level Aggregation Method (also known as Louvain method) were applied on journal cross-citation and hybrid (text/citation) matrices (Janssens, Zhang, Moor, & Glänzel, 2009; Zhang, Glänzel, & Liang, 2009; Zhang, Janssens, Liang, & Glänzel, 2010).

On the other side, by taking documents as unit of analysis Small (1999) developed a methodology to visualize and to obtain a hierarchical multidisciplinary map of science through a method combining fractional citation counting of cited papers, co-citation single-linkage clustering with limits on cluster size, and two-dimensional ordination according to a geometric triangulation process. Ahlgren and Colliander (2009) studied different document-document similarity approaches based on text, coupling and a combination of both as well as several methods to map and classify a set of 43 documents from the journal *Information Retrieval*. Complete-linkage clustering was applied to group articles and the final result of assignment was compared with an expert-based classification using adjusted Rand Index. Similarly, Boyack et al. (2011) employed a combination of graph layout and average-link clustering to different text-based similarity-measure matrices constructed through relevant information from titles, abstracts, and MeSH subject headings of 2.15 million of papers extracted from the Medline database. They compared and assessed nine similarity approaches through Jensen-Chanon divergence and concentration measures. Later on, Waltman and Van Eck (2012) faced an even more complex challenge by designing a detailed methodology to create a publication-level classification system using a multilevel clustering algorithm on a direct citation (disregarding the direction) network constituted of almost 10 million publications. In their opinion, the methodology strength is sustained on transparency and simplicity as well as modest computing and memory requirements. Klavans, Small and Boyack (2013) introduced the reference pair proximities as a new variable to improve accuracy of co-citation clustering. To do so, they used a corpus of 270,521 Scopus full text documents from 2007 and compared the results of traditional co-citation clustering approach to their new co-citation clustering, which evidenced a significant accuracy improvement.

Generally, clustering procedures on networks and matrices involves complex and hard calculations. This fact is more relevant when large datasets are being manipulated since hardware and software requirements are generally high. Another important issue is related to visualization of clustered data which should be clear and comprehensible. Both software VOSViewer (Van Eck & Waltman, 2010) and Pajek (Batagelj & Mrvar, 1997; Nooy, Mrvar, & Batagelj, 2012) arise as good tools for network analysis and information visualization, especially when large networks have to be manipulated. Additionally, VOSViewer includes its own classification algorithm whereas Pajek integrates different clustering algorithms that can be run easily once dataset is adapted to appropriated format required by the software.

3.- Objectives

The main goal of this study is to optimise and update journal classification of SCImago Journal & Country Rank (SJR) platform (SCImago, 2007) via clustering techniques. Using the software Pajek, we ran two automatic classification algorithms as to detect and extract communities (subject clusters) from a SJR journal network combining three citation-based measures. The set of automatic-extracted communities is representing the subject disciplinary structure of science and research recorded in SJR journals. Finally, the new resulted cluster-based systems will be compared to other classification systems such as WoS Subject Categories and the original SJR Classification to validate their consistency and accuracy by analysing and discussing the strengths and weakness of the results.

4.- Material

Our data set, covering a total number of 18,891 journals for a two-year time window (2009-2010), was gathered from SCImago Journal & Country Rank (SJR) database. In this set, only cited references going back from 2010 to 2000 were contemplated. All references were counted at paper level and later aggregated to journal level.

5.- Methods

In order to clarify and favour a better understanding of the distinct procedures developed in performing our study we have divided this section in 7 stages covering and detailing the required steps to follow.

5.1.- SJR Journal Classification: The Starting Point

Scopus classification system, and by extension, SJR original classification, is an a-priori two-level hierarchical classification system originally designed according to an up-bottom approach. Hence, at first level, the classification covers a total of 27 broad *subject areas* which, at once, comprise a set of 308 specific subject categories at second level. Then, journals recorded at database are ascribed to one or several subject categories. Areas and categories tags were determined on the basis of All Science Journal Classification (ASJC). Generally, each subject area includes a subject category taking the same tag followed by '*miscellaneous*' addition. Journal assignment to categories was made on the basis of items adscription. Then, SCImago Research Group conducted some improvements on classification based on journal scope analysis and a constant feedback from journal editors. From the point of view of improving journal classification, feedback from editors may be an interesting argument to take into account. Thus, Archambault et al. (2011) even claim to be interested in feedback from researchers and practitioners using their journal ontology as to persist in refining journal assignment. However, in spite of various attempts, a wider improvement of SJR journal classification is needed in order to remove inconsistencies inherited from Scopus by allowing to final users to customise the journal-sets of SJR subject categories as to generate tailored rankings (Jacsó, 2013). A previous work based on SJR journal reference analysis (Gómez-Núñez, Vargas-Quesada, Moya-Anegón, & Glänzel, 2011) was oriented to this end.

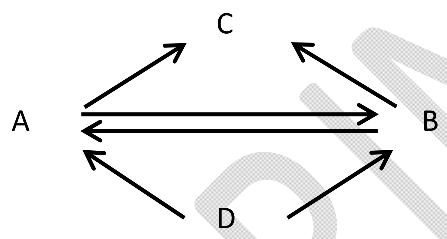
5.2.- Journal Citation-based Relatedness Measures: Calculation and Formatting

A plenty of publications dealing with classification and mapping of science and research have adopted text-based networks (Cantos-Mateos, Vargas-Quesada, Chinchilla-Rodríguez, & Zulueta, 2012; Liu, Hu, & Wang, 2011), citation-based networks (Leydesdorff & Rafols, 2012; Rafols & Leydesdorff, 2009) or combination of both (Glänzel, 2012; Janssens et al., 2009). Boyack y Klavans (2010) applied *Jensen-Shannon divergence* and *concentration* metrics as to prove the accuracy of clustering solutions emerging from different citation-based mapping methods. The results revealed the best performance in bibliographic coupling approach, followed closely by co-citation and direct citation further. Also, Waltman and Van Eck (2012) analysed advantages and disadvantages of three citation-based approaches. After that, they chose direct citation as relatedness measure in constructing a publication-level classification. Primarily, they based their decision on saving computer resources for processing the large data set of almost 10 million of publications that they copied with. However, they argued that direct citation are expected to provide strongest relatedness links between publication, contrary to co-citation and bibliographic coupling, which could be considered more indirect mechanisms. On the other hand, they noted that the use of direct citations can lead up to a loss of information because of citations to earlier publications and, similarly, citations from later publications are not being contemplated.

In this work, we are exploiting citation-based approaches on journal networks. This allows us to cover the three main types of citation links expressing a degree of relatedness between journals. In this way, we will be adding both strengths and weakness from each measure. Thereby, our approach could be considered a 'fair' and balanced one by offsetting all weakness coming from *direct citation*, *co-citation* and *bibliographic coupling* separately. When these important points were reflected, we constructed three journal networks, one for each citation-based measure. The three networks were calculated at the document level and then aggregated to journals. For co-citation and bibliographic coupling calculation, references co-occurring were counted only once per paper by following the binary counting described by Rousseau and Zuccala (2004) and avoiding what Vargas-Quesada and Moya-Anegón (2007) named latent co-citation.

5.3.- Citation-based Measures Combination

Once the three citation-based networks were generated we combined them into a new one collecting pairwise journals and their relatedness strength expressed by the sum of direct citation, co-citation and bibliographic coupling links. By doing so, we got a final network based on raw data and containing what Persson (Persson, 2010) named *Weighted Direct Citation (WDC)* links. Below, we can display the diagram used by Persson in order to integrate these three citation-based measures and calculate the WDC. Nevertheless, we have introduced a small shift referring to both senses of the direct citation links.



Thus, we have used the next formula in citation based-measures combination:

$$c_{ij} = cu_{ij} + cc_{ij} + \max(ci_{ij}, ci_{ji})$$

Where cu_{ij} = coupling, cc_{ij}= co-citation, ci_{ij} = direct citacion from i to j and ci_{ji} = direct citation from j to i.

Also, by knowing that A, B, C and D are journals we can adapt this formula according to Person's diagram in this way:

$$c_{ij} = ABC + DAB + \max(AB, BA)$$

5.4.- Network Normalization

At the following stage of out method, the final network resulted from aggregation of raw data links was normalized using *Geo similarity* formula as follows:

$$s_{ij} = c_{ij} / \mathrm{sqrt}(c_i * c_j),\ c_i = \mathrm{sum}\{ j: j!=i: c_{ij} \}$$

This similarity measure is close to Cosine one and performs dividing elements of the matrix by geometric mean of both diagonal elements (Batagelj & Mrvar, 2003). Thereby, raw data were corrected and relatedness values between pairwise journals were transformed to values ranging from 0 to 1. This avoids problems related to misleading representations and overestimation of some science fields characterized by strong citation habits or covering large-size journals with a high power of attraction.

5.5.- Clustering Procedures

The next step in our methodology was to run clustering algorithms included in Pajek software on the normalized network. Pajek integrates several clustering methods in order to decompose networks by extracting different partitions such as islands, k-neighbours or block modelling. However, after several initial tests, we targeted on communities detection algorithms, namely, *VOS Clustering* (Waltman, Van Eck, & Noyons, 2010) and *Louvain Method* (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Both methods are grounded in modularity clustering proposed by Newman and Girvan (2004). However, while Louvain method optimizes modularity, VOS Clustering focused on optimizing a quality function (Batagelj & Mrvar, 2011). For this experiment, we chose Louvain and VOS methods based on Multilevel Coarsening + Single Refinement. Moreover, we had to set up several options regarding *resolution parameter*, *random restarts*, *maximum number of levels in each iteration*, and *maximum number of repetitions in each level*. Here, we fixed just the same options for VOS and Louvain algorithms. Firstly, we introduced distinct values in *resolution parameter*, moving them from 10 to 20 in order to get different Pajek partitions depicting diverse solutions in decomposing network and producing different set of clusters or communities. Then, the remaining parameters were configured with default values.

By analysing certain relevant indicators for each parameterized clustering algorithm solution, basically, the *number of clusters generated* and the *number of journal per clusters*, we estimated that network decompositions providing between 250 and 300 groups would be interesting for our final journal classification objective. Here, some important issues were considered. Firstly, we took into account the 250 subject categories currently included in WoS database since this scientific information source is not only an international referent within bibliometric and scientometric fields but also for scientists and researchers in general. Presently, SJR is including 308 subject categories and, therefore, we thought that a final set ranging from 250-300 categories will provide a balanced and refined subject structure. This point was reinforced with the experience acquired in a previous work (Gómez-Núñez et al., 2011). There, we noticed a regular behaviour in grouping journals which reveals a strong concentration of them in a few leading categories from a final set of 198 SJR categories. These leading categories are characterized by a high attractiveness, especially, when iterative reference analysis method was used. As commented earlier, this behaviour may be derived from citation habits of some scientific fields with an intense and well-defined citation practice such as the *Medicine* and allied sciences or some social science subfields as *Economics* or *Education*.

Apart from indicators above mentioned we applied some others (see Results section) to VOS and Louvain partitions matching with different 10-20 resolution parameters and we proceed to compare the results of both of them. Every partition was executed in Pajek and, later, saved to files as to be processed using spreadsheets and statistical software. Concretely, we selected VOS partition referring to resolution parameter 15, while a resolution parameter 18 was appointed in the Louvain case. In this decision, we basically looked for similar partitions in terms of the final number of clusters generated by VOS and Louvain methods under the premise of making comparable the results and the classification solutions in both clustering algorithms evaluated. Besides, we established a threshold to define the minimum cluster size to 10 journals, discarding all those clusters which were not complying with this requirement.

5.6.- Labelling

After executing automatic clustering techniques we had to label the different subject groups or communities depicted by both algorithms and recorded in the selected partitions. To this end, we designed a multi-phase approach to solve the various instances occurred. At this moment, it is well to explain that in this work we are proposing a journal multi-assignment. Nevertheless, journal multi-assignment was due to labelling process and not to clustering methods used which have conducted a journal single assignment per cluster.

5.6.1. Labelling through SJR category tags

In a first approach, we took into consideration the citation frequencies from journals to former SJR categories. Thus, we counted how many times journals forming part of a cluster were citing original categories from SJR. After that, frequencies were transformed into percentages and into weighted scores using tf-idf formula by Salton and Buckley (1988) which we adapted to our particular case so:

$w_{i,j} = catf_{i,j} \times \text{Log}\ (N / cluf_i)$

Where $w_{i,j}$ = total weighted score; $catf_{i,j}$ = raw frequency of category 'i' into cluster 'j'; N = total number of clusters; and $cluf_i$ = number of clusters containing category 'i'

After that, all the categories were ranked by tf-idf scores and only those categories amounting at least a 33% over the total set of references cited by journals forming distinct clusters were selected as to delineate the cluster subjects. By means of this procedure journals were allocated to one up to four categories. Although many research works have defended a single and exclusive assignment of journals to clusters or categories (Archambault et al., 2011; Thijs, Zhang, & Glänzel, 2013; Waltman & Van Eck, 2012), there are strong reasons to think in journal multi-assignment. Generally, most of scientific journals are not covering a unique topic. This can be checked, for instance, by having a look at journal scopes. In some cases, authors have interest for publishing in journals out of their expertise field in order to get a higher prestigious, visibility or even impact. Moreover, current science often follows an interdisciplinary and collaborative model with several fields involved in solving different problems, copying with new challenges or looking for a continuous advance and development of science and research. Finally, we are aware of journal multi-assignment carried out in original SJR journal classification and we have pretended to keep taking this approach but with the aim of improving it.

5.6.2. Labelling through significant words of journal titles

This labelling approach was adopted in two particular cases:

1) When using category tags we found two clusters with exactly the same categories assigned, and, then, representing two identical subject groups.
2) In the whole labelling procedure, *Miscellaneous* and *Multidisciplinary* categories were rejected. After removing these categories, percentages and tf-idf scores were re-calculated. However, in some clusters the number of journals was lower than the number or links

pointing to SJR categories. This was not satisfying the condition of at least one link to category per journal.

In the two instances above noted, we reconsidered the labelling approach for clusters by using a textual component, such as significant words extracted from journal titles. After counting them, frequencies of most repeated words were taken as to delineate the subject topic of clusters. To support the text-based labelling stage and to fine-tune in denoting clusters we used some *Voyeur Tools* platform, which provides a set of online text analysis tools forming part of *Hermeneuti.ca* collaborative project (Sinclair & Rockwell, 2009).

5.7.- Validating Classification Proposals.

In closing our method, a validation of classifications generated by algorithms was desirable. There are different approaches aimed to this end. Expert assessment could be the best one, but, generally, it is very time- and cost-consuming. We thought that a suitable and less resource-consuming method is a comparison with some other classification systems. Especially useful would be a comparison versus the original SJR classification since the journal data set is just the same which facilitates the process. Nevertheless, we also included a comparison with ISI Subject Categories which is the subject classification system of the referent database in bibliometric scope, namely, WoS (and consequently, JCR + Arts & Humanities). To make possible this comparison we prepared a combined list consisting of SCI+SSCI journals collected from JCR 2010 release. JCR do not include journals of Arts & Humanities areas so an extra list of A&HCI journals of 2012 release downloaded from Thomson Reuter's website was added. The final list of journals was integrated by 11,715 journals, pertaining 8,005 to SCI, 2,678 to SSCI and 1,758 to A&HCI respectively. Therefore, there is a certain level of overlapping because a total of 726 journals were covered by distinct indexes together. Finally, we used ISSN field as to generate matching between journals of SJR, WoS, VOS and Louvain classifications which rise to 9694 journals, that is, an 82.75% from the total set.

6.- Results

6.1. Analysis of results derived from algorithm solutions

In an attempt to optimise and update SJR journal classification we analysed and compared the results derived from VOS and Louvain clustering methods according to distinct indicators related to the proper performance of both algorithms, such as (1) *number of given clusters*, (2) *number of journals classified* after applying the threshold of 10 journals as the minimum cluster size, and (3) *mean number of journals per cluster*. Besides, we developed two indicators coming from cluster labelling process, just as the (4) *journal multi-assignment*, and the (5) *weighted average of categories assigned to journals*. Again, we would like to remark that journal multi-assignment was a consequence of our labelling procedure and not due to VOS and Louvain performance which carries out a journal single assignment as they are hard clustering techniques.

Table 1 captures the values of the indicators (1), (2) and (3). As we pointed in the previous section, we projected around 250-300 journal subject groups to trace a basic and cohesive disciplinary structure in order to classify scientific journals. Therefore, we retained this premise during the parameterization of VOS and Louvain algorithms as well as in choosing final partitions giving suitable results and better adapting to our final classification aim.

	(1) number of given clusters				(2) number of journals classified				(3) mean number of journals per cluster			
Resolution Parameter	*VOS*	*Louvain*	*VOS Threshold 10*	*Louvain Threshold 10*	*VOS*	*Louvain*	*VOS Threshold 10*	*Louvain Threshold 10*	*VOS*	*Louvain*	*VOS Threshold 10*	*Louvain Threshold 10*
10	531	550	174	153	18,891	18,891	18,271	18,170	35.6	34.3	105.0	118.8
11	593	601	200	173	18,891	18,891	18,212	18,085	31.9	31.4	91.1	104.5
12	662	666	225	186	18,891	18,891	18,080	17,966	28.5	28.4	80.4	96.6
13	723	727	234	201	18,891	18,891	18,018	17,890	26.1	26.0	77.0	89.0
14	787	794	261	216	18,891	18,891	17,896	17,739	24.0	23.8	68.6	82.1
15	848	862	270	234	18,891	18,891	17,729	17,652	22.3	21.9	65.7	75.4
16	904	932	297	245	18,891	18,891	17,665	17,488	20.9	20.3	59.5	71.4
17	973	999	308	266	18,891	18,891	17,504	17,412	19.4	18.9	56.8	65.5
18	1,043	1,064	337	280	18,891	18,891	17,422	17,287	18.1	17.8	51.7	61.7
19	1,120	1,126	348	301	18,891	18,891	17,266	17,235	16.9	16.8	49.6	57.3
20	1,170	1,195	367	319	18,891	18,891	17,135	17,086	16.1	15.8	46.7	53.6

Table 1: Number of clusters, number of journals classified and mean number of journals per cluster according to the diverse resolution parameters of VOS and Louvain

A simple glance to the distinct figures exposed in this work denotes a considerable parallelism in the distributions depicted over the alternative resolution parameters of VOS and Louvain indicators. In a certain way, this might be expected as a normal event since both algorithms are grounded in modularity clustering method proposed by Newman and Girvan (2004). If we focus on the (1) *number of clusters* offered by two clustering methods it can be noticed that VOS algorithm needed a resolution parameter lower than Louvain to get a similar number of groups. Moreover, when a threshold of 10 journals as minimum cluster size was set, VOS algorithm presented a more balanced ratio between the clusters upholding this threshold and the clusters without doing it as compared to Louvain one. Thus, VOS partition with resolution parameter 15 returned just 270 clusters collecting ten or more journals from the total set of 848 clusters, what is equivalent to a ratio of 0.3184 or almost 32% of clusters satisfying the threshold. On the other hand, Louvain partition with resolution parameter 18 produced a total set of 1064 clusters with only 280 clusters reaching ten or more journals, what involves a ratio amounting to 0.2632, meaning a little bit more of 26% of clusters with more than ten journals. Figures 1 and 2 show the whole distribution of clusters according to the resolution parameter defined in VOS and Louvain algorithms.

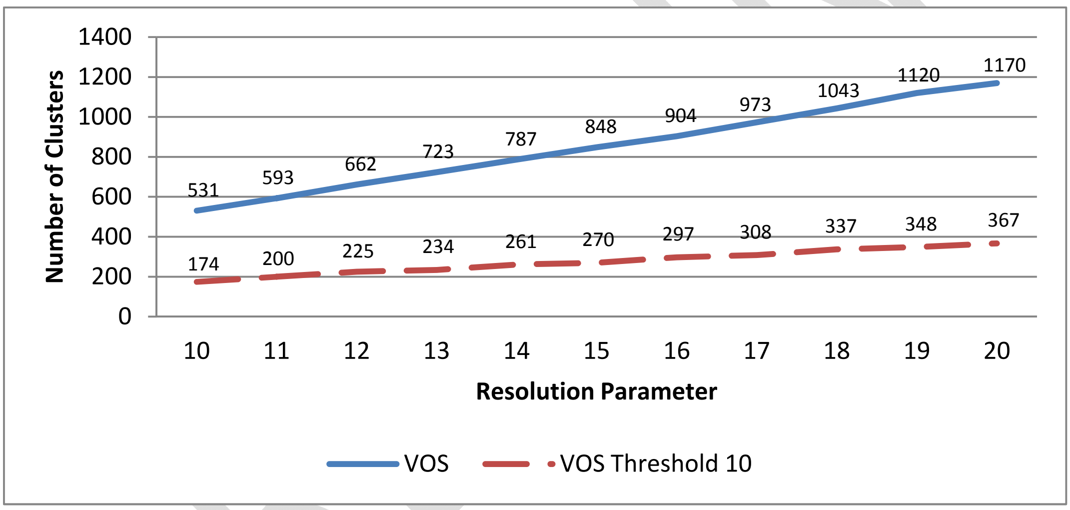


Figure 1: VOS cluster distribution over the different resolution parameters tuned

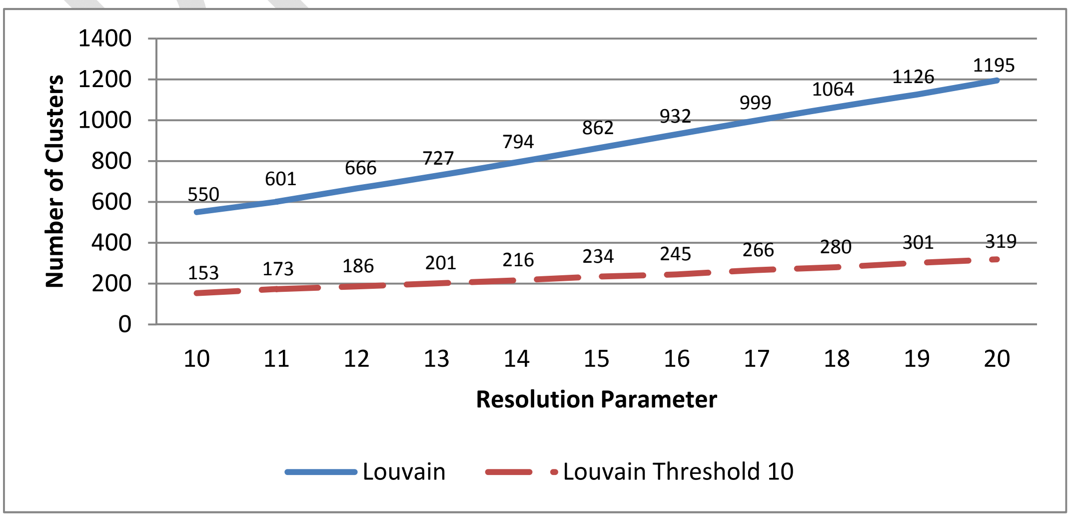


Figure 2: Louvain cluster distribution over the different resolution parameters tuned

In the own words of the authors of VOS clustering algorithm the resolution parameter included in their algorithm "helps to deal with the resolution limit problem of modularity-based clustering". They also claim that by introducing a sufficiently large value for the resolution parameter of their clustering technique all small clusters can always be determined, being the number of clusters generated larger when the value of resolution parameter is higher (Waltman et al., 2010). Then, the final number of clusters is directly proportional to the value of resolution parameter. Indeed, VOS and Louvain methods permitted to classify the 18,891 journals forming part of the initial network explored through the set of clusters provided. Nevertheless, a wide amount of this clusters were too small and were not able to form reliable and solid groups of journals. We have pointed out that only 31.84% of the total number of VOS clusters had a size higher than 10, while a mere 26.32% of clusters reached this threshold in Louvain method. This phenomenon could be due to the use of citation and their derivatives as measure units. Earlier on, we mentioned that some scientific fields portray a strong concentration and an outstanding attraction power of citations linking to publications including in them, normally, because of the own marked citation habits occurring inside these fields. So, the subject categories defining these fields are characterized by a great variance aggregation derived from the high quantity of citation received.

By observing indicators related to the (2) *number of journals classified* and the (3) *mean number of journals per cluster*, we detected a general behaviour which describes a better performance of VOS algorithm in classifying journals, that is, including journals in a particular cluster. In general, the mean of journals per cluster over the different resolution parameters returned by Louvain algorithm was higher. However, by examining the two partitions selected for our classification purpose, the mean number of journals per cluster was also a bit higher in favour of VOS resolution parameter 15. Figure 3 shows the whole distribution of journals classified in VOS and Louvain clusters over the distinct resolution parameters executed. In the same way, Figure 4 exposes the mean number of journals per cluster in two selected VOS and Louvain partitions.

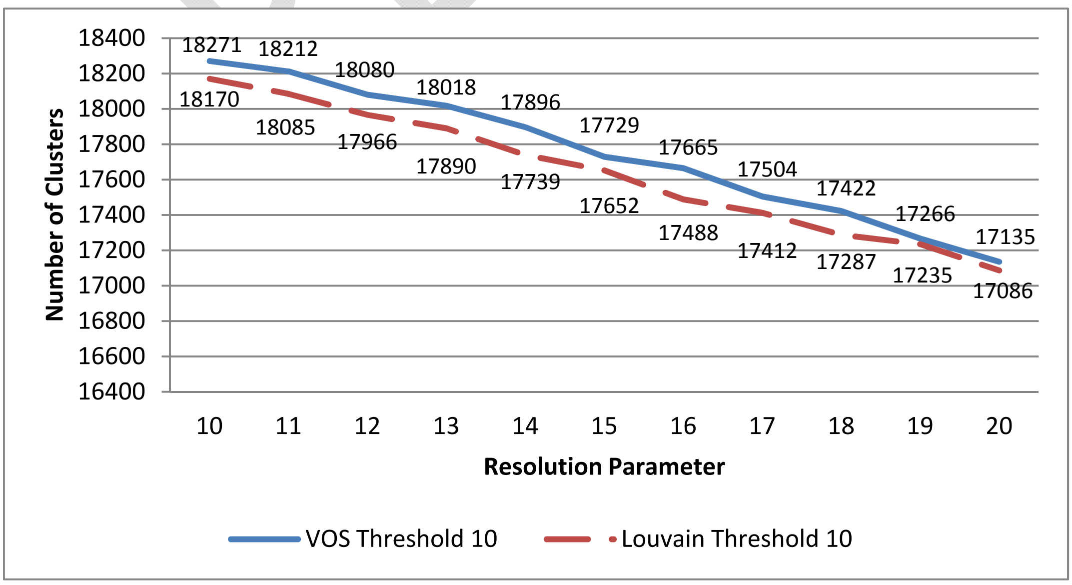


Figure 3: Distribution of classified journals over the different resolution parameters tuned in VOS & Louvain clustering algorithms

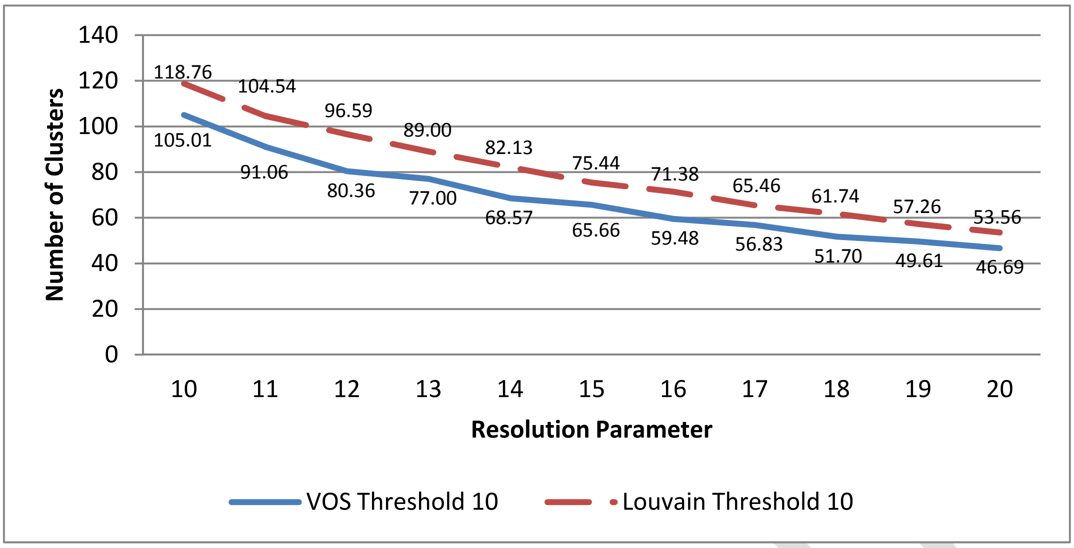


Figure 4: Distribution of mean of journals per cluster over the different resolution parameters tuned in VOS & Louvain clustering algorithms

Another example of the similitude of the results yielded by two clustering algorithms concerns to the (4) *journal multi-assignment indicator* which reflects the number of journals assigned to one or multiple categories at once. Figure 5 traces a very similar distribution of journals assigned by VOS and Louvain with more than 50% of them being ascribed to only one category and slight differences in journal multi-assignment. Admittedly, Louvain method had a worse result in assigning journals to four categories but, on the whole, Louvain assignment was a little bit better by concentrating more journals in only one category and fewer journals than VOS in two and three categories respectively. Also, this point can be supplemented and inferred by comparing the (5) *weighted average of categories assigned to journals* of VOS, which amounts to 1.50 categories per journal, and Louvain, which rises only to 1.48. Even so, the differences in VOS and Louvain algorithms multi-assignment are not very significant.

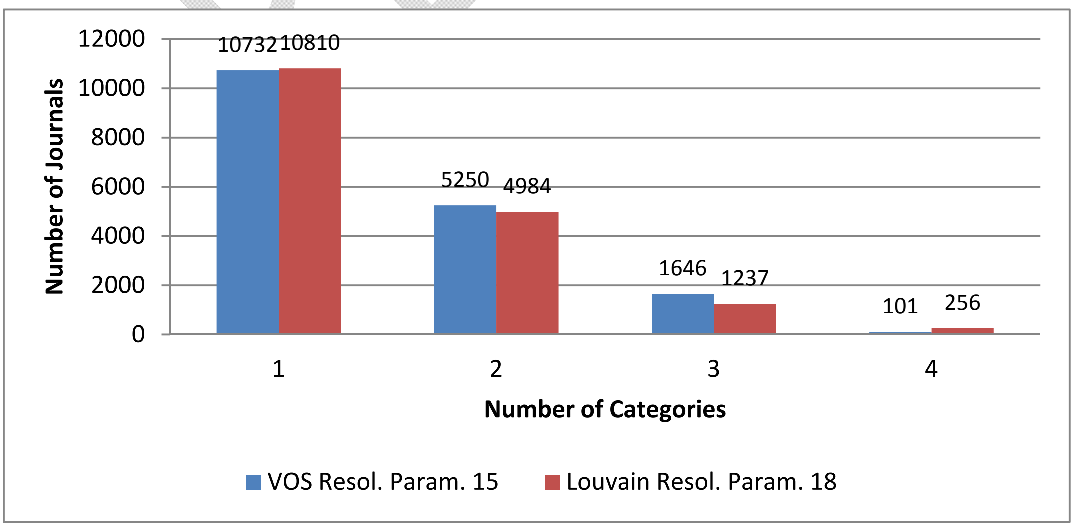


Figure 5: VOS & Louvain journal multi-assignment

6.1. Overall analysis and comparison among four different classification systems

Hitherto, we have highlighted only the analysis of VOS and Louvain clustering algorithms on the basis of statistical data and indicators. At this moment, we are detailing results related to differences and resemblances in journal final classification obtained after applying both algorithms. To do so, we are going to analyse and compare classifications originated by both clustering techniques together with original SJR classification and WoS (ISI Subject Categories).

	WoS					SJR					Louvain 18					VOS 15				
Total Set of Journals	11,715					18,891					18,891					18,891				
Number of Classified Journals	11,715					18,891					17,287					17,729				
Number of Categories	251					308					272					267				
Mean Number of Journals per Category	46.67					61.33					63.56					66.40				
Mean Number of Categories per Journal	1.54					1.61					1.48					1.50				
Overlapping Percentage	54.48%					60.73%					47.58%					49.89%				
Journals changing their Classification	-					-					7,159					7,606				
Journal Multi-Assignment	**Number of Categories**					**Number of Categories**					**Number of Categories**					**Number of Categories**				
	1	**2**	**3**	**4**	**+**	**1**	**2**	**3**	**4**	**+**	**1**	**2**	**3**	**4**	**+**	**1**	**2**	**3**	**4**	**+**
	6,990	3,432	986	261	46	12,025	3,893	1,863	751	359	10,806	4,986	1,237	256	0	10,730	5,251	1,646	101	0
	59.7%	29.3%	8.4%	2.2%	0.4%	63.7%	20.6%	9.9%	4.0%	1.9%	62.5%	28.8%	7.2%	1.5%	0%	60.5%	29.6%	9.3%	0.6%	0%

Table 2: Overall comparison among four classifications systems analysed. The Number of Classified Journals in Louvain and VOS systems results from application of minimum cluster size threshold (t ≥ 10)

Table 2 captures overall data about four classifications compared. A detailed analysis of it enables to note some important observations. Regarding the *total set of journals* included, it is worth to mention that the number of journals covered by SJR overcomes the WoS set more than 1/3. Related to the *number of classified journals* we can see that after fixing threshold 10 in Louvain and VOS algorithms, the number of journals being classified descended to 17287 and 17729 respectively. This is not a result of performance of algorithms which were able to classify the whole set of 18891 original SJR journals. Journals left out the final set will have to be classified separately by a different solution. Reference analysis applied in a previous work (Gómez-Núñez et al., 2011) or 'sibling journals' which can be defined as those journals originally sharing former SJR categories and then extending their new cluster-based classification to journals under the threshold could be used.

The next point to address is the final *number of categories* forming part of the classification system. Here is convenient to clarify why the number of clusters expressed in Table 1 for VOS and Louvain methods are not in consensus with the number of categories (subject clusters) displayed in Table 2. Table 1 collects the number of clusters generated by algorithms without labelling. On its side, Table 2 is reflecting the number of clusters after our labelling process.

Our approach made possible to have some clusters with different number and tags of categories assigned. For instance, cluster #82 in Louvain solution was labelled as 'Artificial Intelligence' + 'Information Systems' + 'Software' category tags, while cluster #90 was assigned to 'Artificial Intelligence' + 'Theoretical Computer Science' categories. The potential combinations of different number and tags of categories among the set of clusters is, therefore, the main reason to explain the difference in the number of categories included in Table 2. The final number of categories in VOS and Louvain decreased meaningfully in comparison to original SJR subject classification system and being closer to WoS system. This can be understood as a broad improvement, especially when data referring to overlap (Table 2) and distribution of journals over categories (Table 3) are observed. After indicating the *number of classified journals* and the final *number of categories* we can calculate the *mean number of journals per category*. VOS, Louvain and SJR systems overcome the value of 60 journals per category, being the highest value for VOS one with a total of 66.4. On his side, WoS system mean number only amounts to 46.67 journals per category although it is true that WoS journal coverage is much more reduced in comparison to the other three systems.

Other two interesting points of Table 2 are concerning *the mean number of categories per journal* and *overlapping percentage*. Both indicators are totally correlated and show the level of overlapping existing in four classifications compared. The main difference holds that mean number of categories per journal is expressed as per unit. The lowest level of overlapping was reached by Louvain system, followed closely by VOS. In both cases, overlapping levels are not going over the 50%. WoS and SJR systems surpass this level, being the worst overlapping figure the SJR one with a 60.73%. In this sense, again VOS and Louvain methods evidenced better solutions than SJR and WoS. Overlapping percentage was calculated by subtracting the number of records corresponding to (A) journals covered by the system (or in other words, the set of journals under consideration) from the number of records referring to final (B) journal multi-assignment (set of classified journals including multi-assigned journals), then multiplying by 100 and dividing the total by the (A) journals covered by the system [B-A/A*100].

The next row displayed in the table 2 is dealing with the number of journals *changing their classification* from SJR to Louvain and VOS system. Again VOS system get the highest figures by allocating a total of 7606 journals in new subject categories either by changing or by adding a new subject category to journals. This is equal to a 42.0% of the total set of journals classified. On the other hand, Louvain rise a 41.4% of journals changing their old classification. Such as the whole comparison process, both algorithm solutions yielded very similar results.

Finally, Table 2 is displaying the figures related to *journal multi-assignment* in four classification systems compared. Here, the best assignment of journals to one category was for SJR system with a 63.7% of the total set. The last place in the ranking was for WoS with a 59.7%. However, the four classification systems offered close percentages of journals assigned to one category. By taking into account our desire of allowing journal multi-assignment, the results obtained by Louvain and VOS can be judged as convenient because they concentrated the most of the journals in one and two categories. Louvain and VOS relative figures representing journal assignment executed on three and four categories are outperforming SJR and WoS systems by far. In addition, SJR and WoS systems made possible a journal assignment to more than four categories. Louvain and VOS solutions did not enable this kind of multi-assignment and, therefore, they provided a more balanced classification system.

A last important issue to analyse among the four classification systems is the proper *distribution of journals over the set of subject clusters or categories* generated. Table 3 is covering the top-20 categories regarding the number of journals included and expressed in raw data and percentage. Finally, we added a cumulative percentage in order to calculate the continuing aggregation of journals spread over categories. Now, the slightest distribution of journals over categories becomes WoS one. However, when classified journal set of WoS is compared with Louvain or VOS ones, then, these distributions are very similar among them. This is underscored through the percentage values of journals calculated in three classification systems. Admittedly SJR system has the largest set of classified journals it achieved the worst distribution of journals over categories as well. Furthermore, 'Medicine (miscellaneous)' category resulted especially remarkable by showing a high concentration of journals in it. More concretely, a 5.2% of the total set of SJR journals was included in this category. Of course, all indicators and calculations relating journals and categories were made considering journal overlap in four classification systems. A last thing to mind in Table 3 is related to the number of the same or really close categories which appear in 20-top ranking. A detailed analysis allowed uncovering that 7 of 20-top categories covered by the four classification systems were appearing in four systems together. This leads to think that despite the fact of having four different classification systems, there are certain coherence and homogeneity among them. Thus, while changes in number and position of categories may imply, in the case of algorithm systems a refinement of original SJR classification, a matching of a considerable number of categories may be a symptom of stability and consistency. The seven categories matching in WoS are: (1) 'HISTORY'; (2) 'ECONOMICS'; (3) 'MATHEMATICS'; (4) 'ENGINEERING, ELECTRICAL & ELECTRONIC'; (5) 'PSYCHIATRY'; (6) 'LANGUAGE & LINGUISTICS'; (7) 'EDUCATION & EDUCATIONAL RESEARCH'. The correspondence of these categories in SJR is: (1) 'History'; (2) 'Economics and Econometrics'; (3) 'Mathematics (miscellaneous)'; (4) 'Electrical and Electronic Engineering'; (5) 'Psychiatry and Mental Health'; (6) 'Language and Linguistics'; (7) 'Education'. Finally, the set of categories in Louvain and VOS system was identical to SJR one, except for the category (3) 'Mathematics (miscellaneous)' which were labelled as 'Mathematics (general)'.

The final master tables covering the new classification of SJR journals proceeding from VOS and Louvain clustering methods can be accessed through the following links:

- VOS Classification: http://www.ugr.es/local/benjamin/vos15_classification.pdf
- Louvain Classification: http://www.ugr.es/local/benjamin/louvain18_classification.pdf

WoS				SJR				LOUVAIN RES. PAR. 18				VOS RES. PAR. 15			
Category	**Num. of Journals**	**% Journals**	**Cumul. %**	**Category**	**Num. of Journals**	**% Journals**	**Cumul. %**	**Category**	**Num. of Journals**	**% Journals**	**Cumul. %**	**Category**	**Num. of Journals**	**% Journals**	**Cumul. %**
HISTORY	331	1.829	1.829	Medicine (miscellaneous)	1,579	5.200	5.200	Sociology and Political Science	496	1.944	1.944	Electrical and Electronic Engineering	534	2.009	2.009
ECONOMICS	302	1.669	3.498	Education	524	1.726	6.926	Geology	417	1.634	3.579	Sociology and Political Science	480	1.806	3.816
BIOCHEMISTRY & MOLECULAR BIOLOGY	284	1.569	5.067	Sociology and Political Science	460	1.515	8.441	Literature and Literary Theory	415	1.627	5.205	Literature and Literary Theory	427	1.607	5.423
MATHEMATICS	276	1.525	6.592	Geography, Planning and Development	450	1.482	9.923	Geography, Planning and Development	393	1.540	6.746	Plant Science	393	1.479	6.901
PUBLIC, ENVIRONMENTAL & OCCUPATIONAL HEALTH	254	1.404	7.996	History	444	1.462	11.386	Electrical and Electronic Engineering	393	1.540	8.286	Geology	380	1.430	8.331
PHARMACOLOGY & PHARMACY	249	1.376	9.372	Electrical and Electronic Engineering	406	1.337	12.723	Psychiatry and Mental Health	372	1.458	9.744	Artificial Intelligence	371	1.396	9.728
ENGINEERING, ELECTRICAL & ELECTRONIC	247	1.365	10.737	Cultural Studies	375	1.235	13.958	Software	331	1.297	11.041	Education	369	1.389	11.116
NEUROSCIENCES	235	1.299	12.035	Social Sciences (miscellaneous)	374	1.232	15.190	Education	331	1.297	12.339	Software	352	1.325	12.441
MATHEMATICS, APPLIED	235	1.299	13.334	Economics and Econometrics	368	1.212	16.402	Hardware and Architecture	297	1.164	13.503	Psychiatry and Mental Health	341	1.283	13.724
PSYCHIATRY	233	1.288	14.621	Literature and Literary Theory	366	1.205	17.607	Religious Studies	297	1.164	14.667	Water Science and Technology	338	1.272	14.996
MATERIALS SCIENCE, MULTIDISCIPLINARY	219	1.210	15.831	Engineering (miscellaneous)	356	1.172	18.779	Applied Mathematics	283	1.109	15.776	Mathematics (general)	334	1.257	16.253
ENVIRONMENTAL SCIENCES	192	1.061	16.892	Psychology (miscellaneous)	351	1.156	19.935	Geochemistry and Petrology	282	1.105	16.882	Economics and Econometrics	318	1.197	17.449

LANGUAGE & LINGUISTICS	192	1.061	17.953	Public Health, Environmental and Occupational Health	335	1.103	21.039	Cultural Studies	264	1.035	17.916	Agronomy and Crop Science	312	1.174	18.623
SURGERY	186	1.028	18.981	Plant Science	327	1.077	22.116	Economics and Econometrics	252	0.988	18.904	Paleontology	309	1.163	19.786
CLINICAL NEUROLOGY	185	1.022	20.003	Language and Linguistics	327	1.077	23.193	History	250	0.980	19.884	History	300	1.129	20.915
PLANT SCIENCES	185	1.022	21.026	Psychiatry and Mental Health	325	1.070	24.263	Mechanical Engineering	245	0.960	20.844	Geography, Planning and Development	283	1.065	21.980
ONCOLOGY	181	1.000	22.026	Animal Science and Zoology	315	1.037	25.301	Civil and Structural Engineering	242	0.949	21.793	Mechanical Engineering	279	1.050	23.030
PHILOSOPHY	178	0.984	23.009	Mathematics (miscellaneous)	306	1.008	26.308	Rehabilitation	240	0.941	22.734	Developmental and Educational Psychology	278	1.046	24.076
EDUCATION & EDUCATIONAL RESEARCH	177	0.978	23.987	Cardiology and Cardiovascular Medicine	273	0.899	27.207	Mathematics (general)	235	0.921	23.655	Language and Linguistics	274	1.031	25.107
CELL BIOLOGY	174	0.961	24.949	Agricultural and Biological Sciences (miscellaneous)	269	0.886	28.093	Language and Linguistics	222	0.870	24.525	Cultural Studies	269	1.012	26.120

Table 3: Top-20 categories of the four classifications systems analysed

7.- Discussion and conclusions

A wide variety of research works have approached the problem of science classification for mapping, knowledge organisation, information retrieval or bibliometric and scientometric purposes. Up to date, some authors have commented the non-existence of a classification system which is considered an international standard in bibliometric fields (Gomez & Bordons, 1996; Archambault et al., 2011; Waltman & Van Eck, 2012) Different levels of aggregation, the distinct systems adopted for organising information as well as the degrees of specialisation or multidisciplinary of several scientific databases, are reasons enough to make difficult the construction of an international classification system for bibliometric ends. At this work, however, we have proposed a methodology to update and refine SJR journal classification system which can be applied to others through clustering and bibliometric techniques.

Another topic commonly addressed over the scientific literature on classification is the adequacy and possibility of developing automatic classification systems which avoids as far as possible the human intervention. First works on it were developed by authors as Luhn (Luhn, 1957) in Information Retrieval scope at the end of 1950s, but the interest kept holding over the 1960s (Garland, 1982) and further, especially, with the advance and development of scientific databases, bibliometric indicators, science mapping, etc., and spanning up to the present. Some of research works reviewed here have tried to avoid human intervention and they conclude it was not possible to do it completely. Waltman and Van Eck (2012) ensured that human involvement was minimized to the choice of certain values in parameters. Archambault et al. (2011) asserted that human intelligence and expertise originates more useful and flexible classification schemes as the same time as they can be considered inadequate and biased systems. They continue claiming that "From the outset, we decided that it would also be necessary to use expert judgment to finalize the work. In the end, it took substantially more work than initially expected, with alternating iterations using an algorithmic approach followed by manual fine-tuning".

In accordance with above cited works and the own experience gained from our previous studies we thought that a classification system based on a fully automatic approach has been not possible to be conducted up to date. Furthermore, there are many choices which can be enriched by expertise and human learning. Some relevant stages emanating from automatic classification implementations such as labelling in clustering approaches are very complicated to conduct without human involvement. Decisions as labelling based on significant words or citation links, single or multiple assignments, definition of thresholds, etc., are really difficult to do. Moreover, human expertise and guidance can become very helpful during these tasks. In this work, we have avoided human intervention as much as possible, but now, we think that a mixed approach could be very realistic and convenient, particularly, after examining the final results. There is no doubt that clustering algorithms used here work fine in classifying journals. This is clearly evident when results of our tests are checked. However, once our algorithms have been run and the set of clusters have been labelled, we have found that some of them have been termed through adjacent and close categories. In some cases, these categories were coming from original tags of SJR system, and others, resulting from our text-based approach. For instance, in VOS system we obtained categories as 'Anatomy' or 'Anatomy and Morphology' covering 18 and 15 journals respectively. Also, in Louvain system we got

‘Women's Reproductive Health’ and ‘Women's and Children's Health’ categories including 10 and 28 journals respectively. Following our expertise and insight of SJR database we have considered that we can group categories covering very close knowledge domains, above all, after checking journals inside them. Then, we could obtain a VOS final category named ‘Anatomy and Morphology’ and consisting of 33 journals and a Louvain final category termed ‘Women's and Children's Health’ and embracing a total of 38 journals. These examples can be extended to approximately two tens of categories in both algorithm classifications.

After analysing and comparing clustering methods introduced in this work it should be emphasized the similitude in final results of VOS and Louvain clustering solutions in relation to facets studied, as evidence figures and tables shown throughout the text. However, the same value for resolution parameter produces a higher number of clusters in Louvain method which reveals a finer granularity than VOS one. According to the initial objectives pursued, this could be an important criterion to consider in selecting one or other algorithm. Anyway, by taking into consideration the several points analysed it is hard to decide which one of clustering algorithms analysed is suiting better to our journal classification aim. In our particular case, we consider that both VOS and Louvain clustering solutions provide a good performance in classifying SJR journals deriving from the extensive journal citation-based measures network. A particular analysis of journals assigned to clusters of specific and well-known knowledge field for authors (such as Library and Information Science) and, additionally, one or some cluster validation techniques based on expert opinions or statistical methods to validate the number and the goodness of clusters generated (Rand Index, Silhouette, Entropy, etc.) might be useful in selecting a final clustering solution.

In comparison with the original SJR journal classification, we have found an especially marked improvement regarding the distribution of journals over categories and the final number of categories available in the new solutions based on VOS and Louvain methods. The original SJR classification scheme includes 304 categories where a number of 29 have less than 10 journals assigned and the remaining categories are covering more than 10. This means that almost the totality of 18,891 journals is included in only 275 categories. Besides, journal multi-assignment is reduced and ‘Miscellaneous’ categories are removed so that, by extension, overlapping is minimized for both algorithm solutions provided. In addition, we have compared our algorithm classifications with WoS Subject Categories and we have found a certain consistency and consensus among the several classification systems both in the number of journals distributed over categories and in the number of categories appearing in top-20 categories together.

A final but not less important issue arises with regards to large and leading Multidisciplinary journals such as Science, Nature or PNAS which are not included in any cluster of size higher than 10. This might be due to their special features, with a citation pattern characterized by a vast quantity of citations emitted and received which differentiate them from the remaining journals. By looking at the whole set of clusters, including those below the threshold 10, we uncovered Science, Nature and PNAS are allocated in different singletons. Thus, it seems necessary to look for an alternative method in classifying Multidisciplinary journals. A good and reasonable choice may be to classify these journals on the basis of the papers published in them. Multidisciplinary label could be ascribed to analysed journals with papers covering a broad spectrum of topics and overcoming a limit in journal multi-assignment previously defined.

This work corresponds to a succession of several studies (Gómez-Núñez, Vargas-Quesada, & Moya-Anegón, ('unpublished results'); Gómez-Núñez et al., 2011) concerned with optimising and boosting of SJR journal classification system and the related subsequent journal assignment. We can articulate the future research by testing new clustering algorithms and automatic techniques (factor analysis) as well as different units of analysis (papers) and measures (text-approaches). However, we do not pretend to proclaim none of these classification proposals as definitive or exclusive among them. For sure, we think it is necessary to keep working in combining several techniques and processing units of analysis in order to get a consensus from scientific community aimed to develop a new final SJR classification.

8.- Acknowledgments

The authors thank María Montserrat Posse Moure for editing the text and the reviewers for their helpful and relevant comments.

9.- Bibliographic References

Ahlgren, P., & Colliander, C. (2009). Document–document similarity approaches and science mapping: Experimental comparison of five approaches. *Journal of Informetrics*, *3*(1), 49–63. doi:10.1016/j.joi.2008.11.003

Archambault, É., Beauchesne, O. H., & Caruso, J. (2011). Towards a Multilingual , Comprehensive and Open Scientific Journal Ontology. In *E.C.M. Noyons, P. Ngulube, & J. Leta (Eds.), Proceedings of the 13th International Conference of the International Society for Scientometrics and Informetrics* (pp. 66–77).

Batagelj, V., & Mrvar, A. (1997). Pajek – Program for Large Network Analysis. Retrieved from http://pajek.imfm.si/doku.php

Batagelj, V., & Mrvar, A. (2003). Density based approaches to network analysis Analysis of Reuters terror news network, 1–20. Retrieved from http://www.cs.cmu.edu/~dunja/LinkKDD2003/papers/Batagelj.pdf

Batagelj, V., & Mrvar, A. (2011). Pajek: Program for Analysis and Visualization of Large Networks: Reference Manual. *version 3.13*. Retrieved September 02, 2013, from http://pajek.imfm.si/lib/exe/fetch.php?media=dl:pajekman.pdf

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *October*(10), P10008. doi:10.1088/1742-5468/2008/10/P10008

Börner, K., Klavans, R., Patek, M., Zoss, A. M., Biberstine, J. R., Light, R. P., … Boyack, K. W. (2012). Design and update of a classification system: the UCSD map of science. *PloS one*, *7*(7), e39464. doi:10.1371/journal.pone.0039464

Boyack, K. W., & Klavans, R. (2010). Co-Citation Analysis , Bibliographic Coupling , and Direct Citation: Which Citation Approach Represents the Research Front Most Accurately?, *61*(12), 2389–2404. doi:10.1002/asi

Boyack, K. W., Newman, D., Duhon, R. J., Klavans, R., Patek, M., Biberstine, J. R., … Börner, K. (2011). Clustering more than two million biomedical publications: comparing the accuracies of nine text-based similarity approaches. *PloS one*, *6*(3), e18029. doi:10.1371/journal.pone.0018029

Boyack, K. W., Small, H., & Klavans, R. (2013). Improving the accuracy of co-citation clustering using full text. *Journal of the American Society for Information Science and Technology*, *64*(9), 1759–1767. doi:10.1002/asi.22896

Cantos-Mateos, G., Vargas-Quesada, B., Chinchilla-Rodríguez, Z., & Zulueta, M. A. (2012). Stem cell research: bibliometric analysis of main research areas through KeyWords Plus. *Aslib Proceedings*, *64*(6), 561–590. doi:10.1108/00012531211281698

Chang, Y. F., & Chen, C. (2011). Classification and Visualization of the Social Science Network by the Minimum Span Clustering Method, *62*(12), 2404–2413. doi:10.1002/asi

Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. doi:10.1007/s11192-009-0146-3

Elsevier. (2004). Scopus. Retrieved May 30, 2013, from http://www.scopus.com/home.url

Garland, K. (1982). An experiment in automatic hierarchical document classification. *Information Processing & Management*, *19*(3), 113–120.

Glänzel, W. (2012). Bibliometric methods for detecting and analysing emerging research topics. *El Profesional de la Informacion*, *21*(2), 194–201. doi:10.3145/epi.2012.mar.11

Gomez, I., & Bordons, M. (1996). Coping with the problem of subject classification diversity, *35*(2), 223–235.

Gómez-Núñez, A. J., Vargas-Quesada, B., & Moya-Anegón, F. ('unpublished results'). A new SJR journal classification through a combination of citation measures.

Gómez-Núñez, A. J., Vargas-Quesada, B., Moya-Anegón, F., & Glänzel, W. (2011). Improving SCImago Journal & Country Rank (SJR) subject classification through reference analysis. *Scientometrics*, *89*(3), 741–758. doi:10.1007/s11192-011-0485-8

Jacsó, P. (2013). The need for end-user customization of the journal-sets of the subject categories in the SCImago Journal Ranking database for more appropriate league lists. A case study for the Library & Information Science field. *El Profesional de la Informacion*, *22*(5), 459–473. Retrieved from http://dx.doi.org/10.3145/epi.2013.sep.12

Janssens, F., Zhang, L., Moor, B. De, & Glänzel, W. (2009). Hybrid clustering for validation and improvement of subject-classification schemes. *Information Processing & Management*, *45*(6), 683–702. doi:10.1016/j.ipm.2009.06.003

Klavans, R., & Boyack, K. W. (2009). Toward a consensus map of science. *Journal of the American Society for Information Science and Technology*, *60*(3), 455–476. doi:10.1002/asi.20991

Leydesdorff, L., Hammarfelt, B., & Salah, A. (2011). The Structure of the Arts & Humanities Citation Index : A Mapping on the Basis of Aggregated Citations Among 1 , 157 Journals, *62*(12), 2414–2426. doi:10.1002/asi

Leydesdorff, L., & Rafols, I. (2012). Interactive overlays: A new method for generating global journal maps from Web-of-Science data. *Journal of Informetrics*, *6*(2), 318–332. doi:10.1016/j.joi.2011.11.003

Liu, G.-Y., Hu, J.-M., & Wang, H.-L. (2011). A co-word analysis of digital library field in China. *Scientometrics*, *91*(1), 203–217. doi:10.1007/s11192-011-0586-4

Luhn, H. P. (1957). A Statistical Approach to Mechanized Encoding and Searching of Literary Information. *IBM Journal of Research and Development*, *1*(4), 309–317. doi:10.1147/rd.14.0309

Newman, M., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 026113. doi:10.1103/PhysRevE.69.026113

Nooy, W. de, Mrvar, A., & Batagelj, V. (2012). *Exploratory Social Network Analysis with Pajek, Revised and Expanded 2nd Edition. Cambridge University Press.* (Revised an.). Cambridge [etc.]: Cambridge University Press.

Persson, O. (2010). Identifying research themes with weighted direct citation links. *Journal of Informetrics*, *4*(3), 415–422. doi:10.1016/j.joi.2010.03.006

Pudovkin, A. I., & Garfield, E. (2002). Algorithmic procedure for finding semantically related journals, *53*(13), 1113–1119.

Rafols, I., & Leydesdorff, L. (2009). Content-based and algorithmic classifications of journals: Perspectives on the dynamics of scientific communication and indexer effects. *Journal of the American Society for Information Science and Technology*, *60*(9), 1823–1835. doi:10.1002/asi.21086

Rafols, I., Porter, A. L., & Leydesdorff, L. (2010). Science Overlay Maps : A New Tool for Research Policy and Library Management. *Journal of the American Society for Information Science and Technology*, *61*(9), 1871–1887. doi:10.1002/asi

Rousseau, R., & Zuccala, A. (2004). A classification of author co-citations: Definitions and search strategies. *Journal of the American Society for Information Science and Technology*, *55*(6), 513–529. doi:10.1002/asi.10401

Salton, G., & Buckley, C. (1988). Term-weighting approaches in automatic text retrieval. *Information Processing & Management*, *24*(5), 513–523.

Scimago. (2007). Scimago Journal & Country Rank (SJR). Retrieved April 15, 2011, from http://www.scimagojr.com/

Sinclair, S., & Rockwell, G. (2009). Voyeur Tools: See Through Your Texts. *Hermeneuti.ca – The Rhetoric of Text Analysis*. Retrieved September 01, 2013, from http://hermeneuti.ca/

Small, H. (1999). Visualizing Science by Citation Mapping, *50*(1973), 799–813.

Thijs, B., Zhang, L., & Glänzel, W. (2013). Bibliographic Coupling and Hierarchical Clustering for the validation and improvement of subject-classification schemes. In *14th International Conference on Scientometrics and Informetrics (15–19 July, 2013), Vienna (Austria)* (pp. 237–250). Viena: International Society of Scientometrics and Informetrics. Retrieved from http://www.mtakszi.hu/kszi_aktak/

Thomson Reuters. (2009). ISI Web of Knowledge. Retrieved September 01, 2013, from http://thomsonreuters.com/web-of-science/

Vargas-Quesada, B., & Moya-Anegón, F. (2007). *Visualizing the structure of science*. New York: Springer.

Waltman, L., Van Eck, N. J., & Noyons, E. C. M. (2010). A unified approach to mapping and clustering of bibliometric networks. *Journal of Informetrics*, *4*(4), 629–635. doi:10.1016/j.joi.2010.07.002

Waltman, L., & Van Eck, N. J. (2012). A New Methodology for Constructing a Publication-Level Classification System of Science, *63*(12), 2378–2392. doi:10.1002/asi

Zhang, L., Glänzel, W., & Liang, L. (2009). Tracing the role of individual journals in a cross-citation network based on different indicators. *Scientometrics*, *81*(3), 821–838. doi:10.1007/s11192-008-2245-y

Zhang, L., Janssens, F., Liang, L., & Glänzel, W. (2010). Journal cross-citation analysis for validation and improvement of journal-based subject classification in bibliometric research. *Scientometrics*, *82*(3), 687–706. doi:10.1007/s11192-010-0180-1