Preprint submitted to Scientometrics
October 28, 2015

My interdisciplinarity *à moi*. An analysis of Neuroscience research in French universities, 2008-2012

Lorenzo Cassi · Wilfriedo Mescheba ·
Élisabeth de Turckheim

Abstract Interdisciplinary research is recognised as a powerful factor in the renewal of science and its societal effectiveness, and many research institutions are now promoting it. Their management teams need new tools to follow-up interdisciplinary dynamics in the research fields of the institution and to support their understanding of these practises. The Rao-Stirling indicator serves not only to measure the overall level of interdisciplinarity in a research field but also to characterise the environment and actual interdisciplinary practices of researchers. This follows from two decompositions of the indicator: the first decomposition is analogous to the decomposition of the inertia of a set of weighted points as developed in a earlier paper (Cassi et al., 2014), the second one breaks the indicator down into contributions from disciplinary categories. The case study makes it possible to show how this indicator can be used to highlight different institution strategies. Beyond serving as an empirical application, the present study is also a result of a participatory project involving indicator designers and intended users.

Keywords Interdisciplinarity indicators · Rao-Stirling index · Research institution management · Participatory design of indicators · Neuroscience

L. Cassi · W. Mescheba · E. de Turckheim
HCERES-Observatoire des Sciences et des Techniques, 75002 Paris, France
E-mail: (lorenzo.cassi, wilfriedo.mescheba, elisabeth.deturckheim)@obs-ost.fr

L. Cassi
Paris School Economics, Université Paris 1, Paris, France
Address for correspondence: lorenzo.cassi@univ-paris1.fr

É. de Turckheim
INRA, Délégation à l'évaluation, 75007 Paris, France
E-mail: elisabeth.deturckheim@paris.inra.fr

Introduction

Interdisciplinary research is a powerful driving force for the development of science. Cognitive dynamics naturally explore the frontiers of knowledge and transgress the perimeters of the established scientific disciplines. In this way, interdisciplinary research contributes to the emergence of new disciplinary spaces. Besides this endogenous process, the demand of the society towards a science that is able to solve complex and global problems is another strong driving force for opening up research practices, boosting collaborations between scientific communities and involving stakeholders in the knowledge production process (Gibbons et al., 1994). Integrative practices are required in order to go beyond simply coordinating results achieved by researchers in different disciplines, usually identified as multidisciplinarity. Governments and international organisations have pushed towards interdisciplinary research programmes as did, among others, the US National Academies since 2004 (National Academy of Sciences, National Academy of Engineering, Institute of Medicine, 2004; National Research Council, 2014) or recently the European Commission in the H2020 call for projects for *Future and Emerging Technologies* (European Commission, 2014). Research performing organisations such as the Center for Interdisciplinary Research (ZIF) in Bielefeld University or the Centre de Recherches Interdisciplinaires at Paris Descartes University include interdisciplinarity as a main feature of their research and education policy.

In France, a process of consolidating and merging universities has been underway for ten years, strongly encouraged by the government. This process aims to improve the international visibility of universities, to strengthen synergies between local institutions and, more generally, to improve the effectiveness of the research system. A new institutional closeness between research teams is often seen as an opportunity to develop new interdisciplinary research programmes. Universities management teams are therefore looking for new indicators to identify the potential of interdisciplinarity and to follow-up their strategies and the impact of incentive measures they have implemented.

This work is based on a previous methodological work on the Rao-Stirling indicator which exploited its ability to measure interdisciplinarity at different scales (Cassi et al., 2014) and on a collaborative project between HCERES-OST and members of the management teams of some French universities. The objective of this collaboration was to ensure that these indicators are understandable and to explore how useful they could be in managing the scientific strategy of universities. This collaboration directed the choice of the data as well as further methodological developments.

The rest of the paper is organized as follows: the Decompositions of the Rao-Stirling index for multi-level analyses section reviews the definition of the Rao-Stirling index and the issues around choosing a disciplinary classification for scientific papers. It then develops how the indicator can be broken down through two additive decompositions and shows the supplementary information they could provide. It also briefly summaries how statistical properties of the indicators are useful for characterising the significance of the indicator values on different corpora. The Neuroscience study section applies these methodological results. Comparison of the neuroscience interdisciplinarity indicators for eight French universities suggests that different strategies are adopted by universities and that the indicators can help to start evaluate these strategies. A short Material and methods section follows the Discussion.

Decompositions of the Rao-Stirling index for multi-level analyses

Defining the index, choosing the classification and the distance

Interdisciplinarity is usually defined as the integration of knowledge, theories and methods from different disciplines, which are at varying epistemological distances. A natural way to capture this integration is to measure the disciplinary diversity of the documents cited in scientific papers. A diversity index is based on a classification and usually accounts for the number of classes in which items are present - the variety - and for the balance of the distribution of items into classes. When measuring interdisciplinarity, the choice of a classification of publications into discipline categories is related to the type of interdisciplinarity under study, and whether close interdisciplinarity should be accounted for as well as remote interdisciplinarity. Some authors such as Prudhomme et al. (2012) calculate indicators and analyse interdisciplinarity for two levels of a hierarchical classification of science. Another way to cope with this issue is to integrate a distance in the definition of the diversity index. The Rao-Stirling index, which is now widely used in interdisciplinarity studies (Porter et al., 2007; Porter and Rafols, 2009; Campbell et al., 2015), takes into account variety and balance but also a distance between categories in such a way as to give a greater weight to pairs of references in more distant categories as follows:

$$ST = \sum_{i,j} q_i q_j d_{ij}$$

where q_i and q_j are the proportions of references in categories i and j and d_{ij} is the distance between the two categories. This index integrates close and remote interdisciplinarity by weighting them in a single formula. It is interesting to notice that this index is robust to an over specification of categories[1] so taking distance into account in the definition of the index makes the choice of the classification less problematic. In a way, this partly defers the issue of carefully choosing the classification to that of choosing the distance. Different distances designed to achieve graphical maps of science may be used in a diversity index. We use the cosine distance as in Leydesdorff and Rafols (2009) which is derived from the cosine similarity between the profiles of references of the two categories in the whole database (i.e. the inter-category aggregated citing dimension).

[1] This is because the value of the index does not change when two categories with a zero distance are merged.

In this paper, we use a classification of scientific papers derived from the classification of journals into the WoS categories. If a larger base of publications is desired, for instance to capture more references in social sciences and humanities, the UCSD classification of journals could be chosen (Börner et al., 2012). Based on a journal/journal similarity matrix, their clustering of journals into 554 sub-disciplines would be a relevant classification. It is also possible to use a classification of articles that does not take journals into account but only citation links between publications. The classification of Waltman and van Eck (2012) provides an alternative choice for categories and their 672 middle level clusters could be used as a classification of references.

Benchmarking the indicator

This basic index is used to design indicators for different analyses. As the citation practices of scientific communities are different and as the databases do not cover the various scientific fields - or disciplines or subject categories - homogeneously, the index has different ranges for different fields. This introduces uncertainty into the interpretation of the comparison between institutions. An institution could have a high indicator value because it is specialised in scientific fields with a propensity for interdisciplinary collaboration but its researchers may not exhibit behaviour that differs from the standard in their field. Campbell et al. (2015) overcome this problem by normalizing the index at the level of each sub-field[2]. Our approach is more basic in the sense that we recommend performing separate analyses for the different research fields or departments of an institution.

Though the indicator ranges between 0 - for a paper or a corpus showing no interdisciplinarity - and 1, a benchmark value is required for understanding what is a low or a high value. When the scientific work in a field or domain under study is identified by the publications in a set of selected journals, a natural benchmark is the world publications in the same journals and for the same period. The difference between the institution indicator and the world indicator - the centred indicator - is therefore used in this work. It ranges between 1 and -1, with a symmetrical scale on both sides of 0.

Breaking down the indicator

Many authors such as Porter et al. (2007) or Campbell et al. (2015) calculate the interdisciplinarity index of an institution as the average of interdisciplinarity index of publications. This index reflects the disciplinary diversity observable in publications considered separately. It measures the interdisciplinarity within publications and is referred to as the *within* interdisciplinarity indicator in Cassi et al. (2014), and denoted ST^W. However, interdisciplinarity is

[2] They count the publications of each institution in the top 1% of the most interdisciplinary papers in each subfield before aggregating these counts at the institution level.

a social process and the cultural and management environment in a department plays a role in the effective or potential interdisciplinary behaviour of the researchers (Stokols et al., 2008). An indication of an environment that is favourable for interdisciplinarity is partially captured by the diversity of the whole set of references in the department publications. As Garner et al. (2013) we think that the “integration score for a set of papers (e.g. by ‘project’) provides an additional perspective” (p 137). It is also the choice that Rafols et al. (2012) consider relevant for comparing different departments in Business and Management schools and Innovation studies units in the UK. This approach leads to calculate an overall interdisciplinarity indicator based on the whole list of references in the department publications.

But the overall index ST of a corpus is higher than the *within* index ST^W: the difference captures the variation of the sources between publications. Because of the similarity of the overall index with the inertia of a set of weighted points in an Euclidean space, it is possible to interpret the difference between ST and ST^W as a diversity between the centres of gravity of the reference categories of each publication[3]. This difference between the overall interdisciplinarity index and the *within* index is therefore called the *between* interdisciplinarity indicator and denoted ST^B. This provides a first decomposition of the overall index

$$ST = ST^W + ST^B.$$

Table 1 Four types of interdisciplinarity

	Within index	
Between index	*lower than world benchmark*	*higher than world benchmark*
higher than world benchmark	4. **Thematic diversity** with **specialised articles**	1. **Thematic diversity** with **integrative articles**
lower than world benchmark	3. **Niche research** with **specialised articles**	2. **Niche research** with **integrative articles**

A two dimensional graphical representation of institutions as in Figure 2 provides more information than the overall index alone. The four quadrants in this representation correspond to four types of interdisciplinarity, combining specialisation *versus* integration at the publication level (on the ST^W axis) with thematic diversification *versus* thematic concentration of the institution policy (on the ST^B axis). This decomposition of the overall interdisciplinarity

[3] As shown in Cassi et al. (2014), this decomposition of the overall index holds if the distance d_{ij} is the square of a Euclidean distance as are the distances associated with the cosine similarity by $d_{ij} = 1 - s_{ij}$, or the Jensen-Shannon divergence.

indicator could thus provide some differentiation between institutions with similar overall indexes.

Another useful differentiation is related to specific reference profiles. When the overall index of a corpus is higher than the world index, a natural question is to ask which categories are cited more by the institution than the standard world behaviour, and which are cited less. To answer this question, a second way to break down the overall indicator is to decompose it into category contributions. The contribution C_i of category i is defined as the product of the proportion q_i of references in category i and the average distance of this category to the other categories of references $\sum_j q_j d_{ij}$ so that

$$C_i = q_i \sum_j q_j d_{ij}.$$

The overall index is just the sum of the category contributions

$$ST = \sum_i C_i.$$

Comparing the category contributions for the institution and the world provides information on the specificity of the institution references profile and a better understanding of the overall indicator.

Ancillary statistics

In order to derive relevant results from the comparison of indicator values and prevent abusive interpretation when these values could be overly affected by errors or exceptional data, some statistical properties of the indicators are helpful. Using a multinomial probabilistic model for the reference counts in categories and the delta-method[4] for calculating the variance of the indicators as in Cassi et al. (2014, 2015), it is possible to calculate p-values for each indicator - overall, *within* and *between* - as well as for the contribution of each category. These p-values make it straightforward to know, for any chosen threshold of error - or significance level - , if an observed difference between an indicator and the corresponding benchmark value is significant or not and to produce the corresponding confidence intervals or areas. This provides a relevant statistical criterion to avoid interpreting indicators calculated on samples that are too small or on samples with too much variability.

Neuroscience study

Involving users in the development of interdisciplinarity indicators

The motivation of this work is to design and provide indicators that are appropriated by end users. For this particular project, the Observatory of Science

[4] The delta method is simply a first order approximation of the indicator considered as a function of averages of independent, identically distributed variables.

and Technologies of the French High Council for Evaluation of Research and Higher Education (HCERES-OST) is working particularly with universities. Much effort is being put in to supporting the delivery of research indicators with training sessions. This process is carefully implemented when new indicators are developed. As soon as the methodological aspects are mastered and before providing such indicators to all institutions on a national scale, interactive groups with targeted users are launched to test usefulness and improve the ergonomics of the new indicators. This kind of group was set up in 2014 with representatives of about twelve university management teams concerned with measuring and managing interdisciplinary research processes. The first step consisted in screening the research fields of each university and mapping the interdisciplinarity of these fields. Universities were then compared for selected fields. This collaboration aimed to understand what facts these indicators could reveal, and the questions they would raise. The work presented here is an example of a research field selected with the group that was involved over the whole project duration.

Neuroscience: a multidisciplinary research field

Neuroscience - also referred to in the plural as neurosciences - is the study of the structure, functions, development, abnormalities of the nervous system and its impact on behaviour and cognitive functions both in the normal functioning and in the case of neurological, psychiatric and neurodevelopmental disorders. Neuroscience has traditionally been classed as a subdivision of biology and the term neurobiology also used for the field refers to the biology of the nervous system (Medical News Today, 2014). However, the scientific study of the nervous system has significantly increased since the 1950s due to advances in molecular biology, electrophysiology and computational neuroscience. Neuroscience is currently a multidisciplinary field involving biomedical sciences - such as clinical neurology, psychiatry, cognitive and behavioural science -, fundamental biology - such as genetics and molecular biology -, as well as other disciplines as psychology, linguistics and philosophy, together with engineering, chemistry, physics, mathematics and computer science (Wikipedia, 2015). Due to the large range of disciplines in the field, it is interesting to measure the diversity of an institution research projects in neuroscience and the level of integration by neuroscientists of theories or methods from different disciplines.

For the bibliometric approach, a corpus representing the domain has to be defined. WoS has a category and Scimago has a subject area with the title Neurosciences whereas the Science-Metrix classification does not provide such a field or subfield[5]. The WoS Neurosciences category is defined by a set of

[5] We checked in two subfields that should contain neuroscience journals namely: Neurology & Neurosurgery (subfield of Clinical Medicine), and General Psychology & Cognitive Sciences (subfield of Psychology & Cognitive Sciences). Of these 619 journals, 137 are common with the Neurosciences WoS category, but journals publishing neuroscience research classified in the subfield Psychiatry (in Clinical Medicine) and other subfields of Psychology & Cognitive Sciences are missing.

255 journals of which 25% of the articles are in journals assigned only to this category, and 27% are simultaneously assigned to Neurosciences and to Clinical Neurology[6]. The other journals share less than 10% of articles with one or more other categories such as, in decreasing order, Psychiatry (9.4%), Pharmacology & Pharmacy (6.1%), Behavioral sciences (5.4%), Physiology (5.1%), Biochemistry & Molecular Biology (4.3%), Psychology Experimental (3.5%), Psychology (3.3%), Neuroimaging (3.1%) etc. The Scimago Neurosciences subject area contains 509 journals, distributed in 9 subject categories. The two sets have 206 journals in common. Selecting these 206 journals could be a relevant choice but, for the sake of convenience, we simply selected the publications in the WoS Neurosciences category as the corpus for this study.

Positioning universities on three interdisciplinarity scales

Twenty seven universities produced more than 100 WoS indexed publications in the period 2008-2012. Six of them whose representatives were involved in the working group were included in the study as well as two other universities that were considered references for French neuroscience. The overall, *between* and *within* interdisciplinarity centred indexes were calculated. Figures 1 and 2 show the results for the eight universities of the study[7]. We arbitrarily chose a probability level and decided not to display a difference which p-value is larger than 0.1 and to replace non significant values by 0.

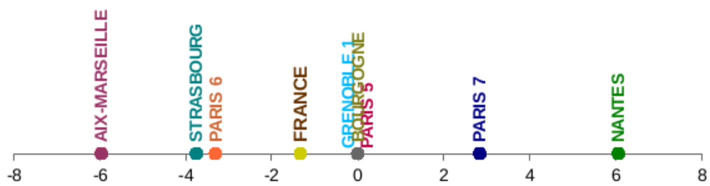

Fig. 1 Overall interdisciplinarity index for 8 universities. Indexes shown are the differences between the institution and world values. Non-significant differences at a level of 1% have been replaced by zero for three universities: Paris 5, Bourgogne and Grenoble 1.

Among the universities in the study, two of them have an overall index greater than the world index: Paris 7 which has a medium production (526 publications) and Nantes with a small production (134 publications) compared to Paris 6, the French university that published the most in Neurosciences (1391 publications). Two universities with a high production have an overall index that is lower than the benchmark: Aix-Marseille (993 publications) and Paris 6, but this is not the case for Paris 5, which also has a large production (1030 documents). Two universities with medium production have indexes

[6] Data for 2012.

[7] For simpler axes coordinates, we multiplied indexes and contributions by 100.

on opposite sides of zero: Strasbourg (416 publications) and Paris 7. Two universities with a small production such as Bourgogne (158 publications) and Grenoble 1 (280 publications) have, unlike the University of Nantes, standard values for the overall indicator. This first observation shows that the overall index does not correlate with the size of the corpus.

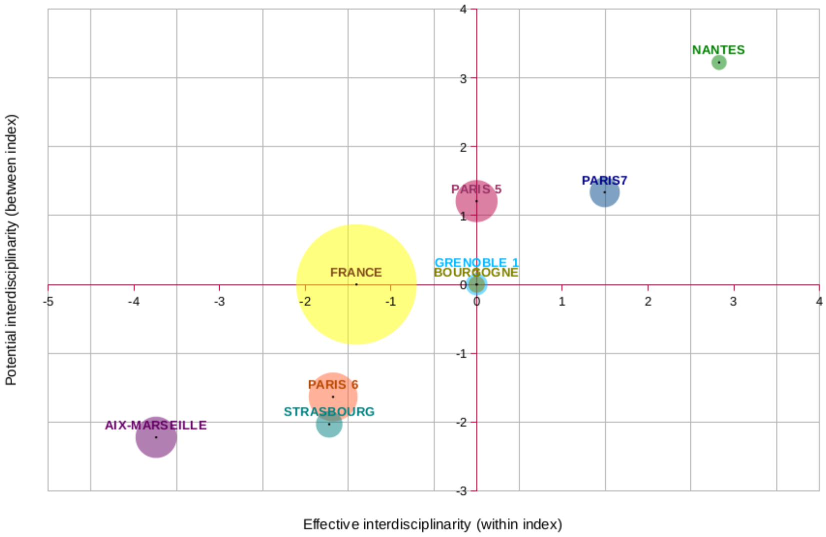

Fig. 2 Within and between interdisciplinarity indexes for 8 universities. Indexes are centred on the world indexes. Non-significant values at a level of 1% have been replaced by zero. Bubble surface areas are proportional to the number of publications.

Using the decomposition of the overall index into *within* and *between* indexes, Figure 2 shows that, in general, the universities of this study are distributed around the first bisector[8]. The two universities of Nantes and Paris 7 stand out because they report higher values than the world for both indices. Though its overall index has a standard value, Paris 5 university has a high *between* interdisciplinarity index which suggests high diversification of research themes. Below we explain what makes the research portfolio of this university so unusual. Finally, the research in neuroscience at the universities of Paris 6, Strasbourg and Aix-Marseille has a lower *between* index and a lower *within* index than the world. This suggests that their neuroscience research is focused on specific topics and that they probably favour advanced specialised approaches over interdisciplinary ones.

[8] This configuration along the first bisector is not necessary. For other fields, quite often, there are universities positioned in the second quadrant, with positive ST^W and negative ST^B.

Specific university profiles of references

The second decomposition of the overall index provides a deeper understanding of interdisciplinarity. Figure 3 shows for two universities the relative contributions of cited WoS categories - i.e. the differences between the institution and the world contribution - on the y axis.

For the University of Strasbourg, only 4 categories have a relative contribution higher than 0.2, and 14 categories have a relative contribution lower than -0.2. This negative balance is already known since the overall index is lower than the world index, but here we see that the neuroscientists in Strasbourg have much less interaction with clinical research than neuroscientists across the world. Moreover, neuroscience research at Strasbourg University is strongly linked with fundamental biology and pharmacology which explains the specialisation of neuroscience research in this university.

In a contrasting way, the contributions for Paris 7 University highlight a positive balance in the relative contributions that show a strong interaction between neuroscience research and clinical neurology and three other medical research disciplines as well as genetics and developmental biology. The indicators provide quantitative evidence of the unusual positioning of hospital research such as that of the recently created University Hospital Department for Cerebrovascular Diseases (DHU NeuroVasc).

Such results could be displayed in a more summary way with a heatmap, making it easier to compare universities. In Figure 4, the values of contributions are represented on a colour scale from dark blue for the lowest contribution to dark red for the highest. This figure shows that Paris 5 boasts significant specific collaborations with psychiatry, psychology and ophthalmology and this gives Paris 5 a very different profile from that of Paris 7, despite the fact that the two universities have a number of joint publications. As in Strasbourg, at Aix-Marseille University, neuroscientists do not get involved with clinical research. They interact specifically with experimental psychology, physiology and sport science.

The three universities of Grenoble 1, Bourgogne and Nantes which have a smaller production in neuroscience, focus their research efforts on motor skills, physical performance and rehabilitation and mainly cite publications in sport science, physiology, and experimental psychology journals. To this specific common strategy, Grenoble 1 adds the use of imaging techniques. Research in neuroscience at the University of Bourgogne has a strong interaction with food science and technology which is related to a long term regional strategy to develop innovation through interaction of research with food industries as with *The Taste, Nutrition, and Health Innovation Centre*. Finally, the high interdisciplinarity indexes of Nantes University correspond to an exceptional diversity in the collaborations of the various research teams involved in neuroscience.

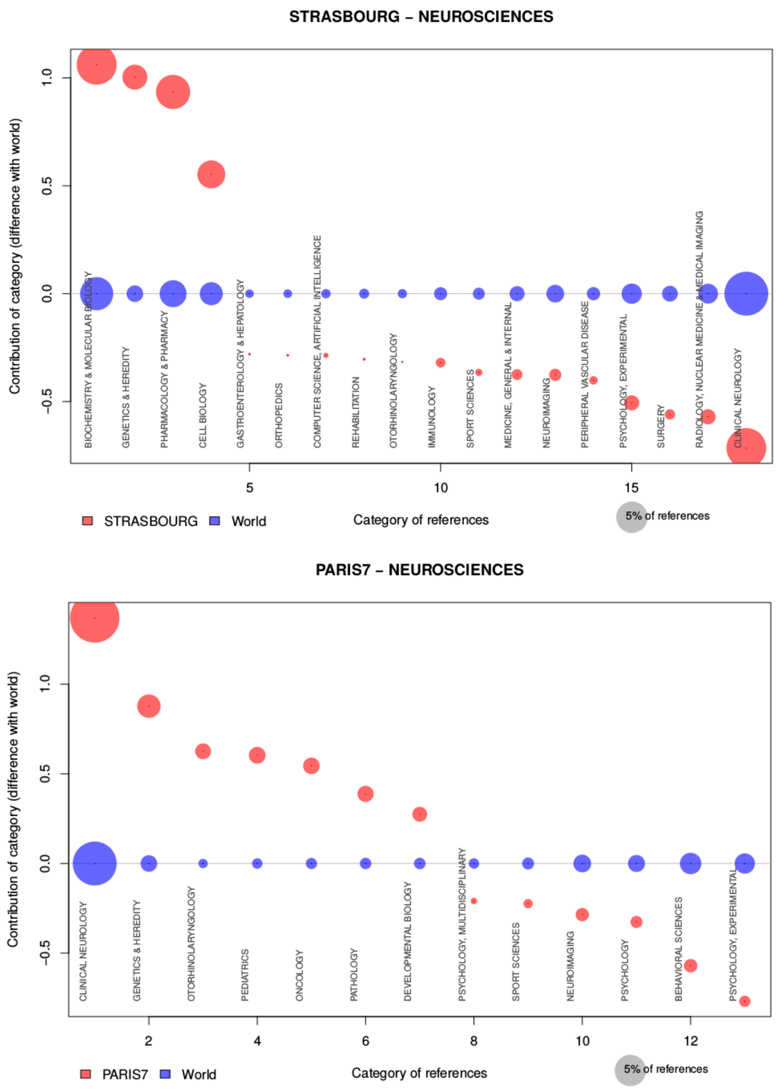

Fig. 3 Contributions of the categories to the overall index for Strasbourg and Paris 7 Universities. Centred contributions - i.e. difference of university contribution with world contribution - displayed in this figure are significant at a level of 1% and have an absolute value greater than 0.2. The surface area of the bubbles show the proportion q_i of references for the institutions and for the world publications.

Different strategies suggested by the indicators

This study reveals a diversity of strategy and practice in terms of interdisciplinarity. It makes it possible to identify universities that develop a wide

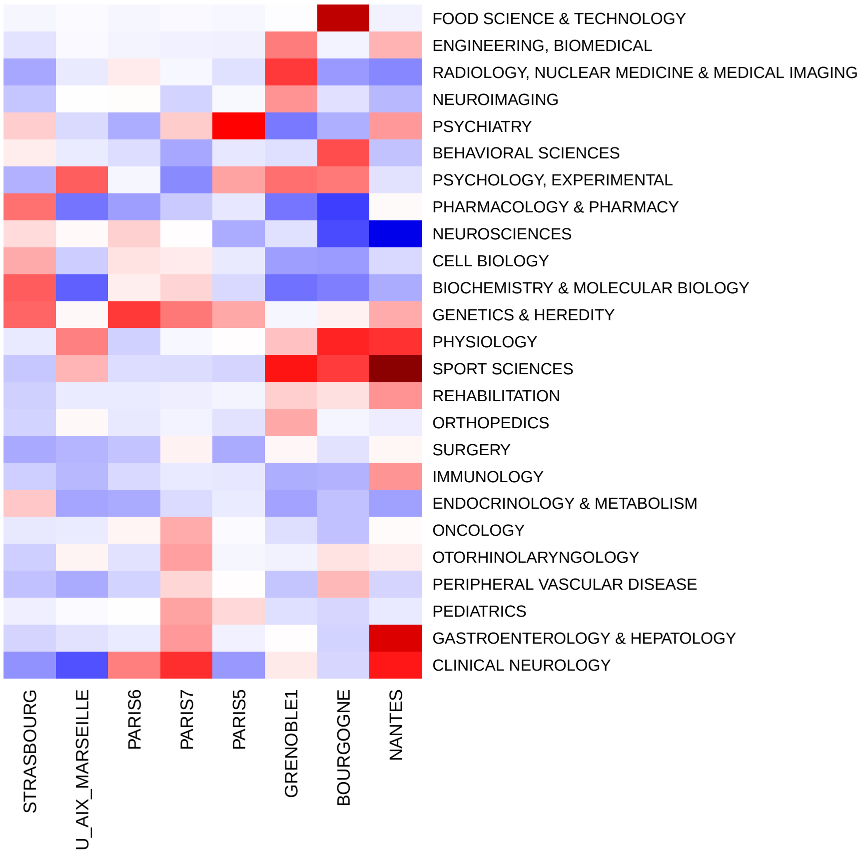

Fig. 4 Comparison of category contributions for 8 universities. Red cells correspond to positive values of the centred contributions, while blue cells correspond to negative values. White cells correspond to contributions with p-values larger than 0.1. Categories are displayed only if the centred contribution is greater than 0.5 or smaller than -0.5 for at least one of the eight universities.

variety of themes in various institutes or teams, leading them to cover the discipline in a richer way than the world standard. Such a university may have an article level interdisciplinarity equivalent to the world average - as does Paris 5 University - or higher than this average, such as Nantes and Paris 7. It would be interesting to understand how these two universities provide a favourable environment for effective interdisciplinarity by analysing the institution at a smaller organisational level - e.g. research unit. Universities which have a modest investment in the discipline can target their research effort on collaboration with other fields, as in Nantes. Another strategic option for these universities is to develop a specialised component round its areas of excellence as the University of Grenoble 1 does with imaging technology and computer analysis. Finally, universities that have heavily invested in this domain such as Aix-Marseille may have a strategy focusing on advanced research on specific topics where it has leading research teams.

Discussion

This study shows how interdisciplinarity indexes could be useful to discover varying strategies through the comparison of institutions in a research domain and how they could lead more detailed analysis of an institution positioning in this domain. The analysis can be applied to any corpus of publication provided a relevant benchmark corpus is available. The indicators can also be used to quickly screen a large set of domains. The only constraint is that there is a corpus - generally a set of journals - that is relevant to describe the research of each domain. Moreover, the systematic use of statistical tests before displaying indicator values ensures that datasets which are too small will not lead to statistically irrelevant conclusions.

A participatory approach was essential for the work presented in this paper. After some methodological development on the Rao-Stirling indicator reported in a preceding paper, this was the second step of the project which aims to produce indicators of interdisciplinarity that are useful for supporting strategic decisions of stakeholders and which could "contribute to the autonomous coordination of the research system" as recommended by Lepori et al. (2008). The process had a number of outputs: it required and enabled a finer interpretation of the *within* and *between* components of the overall indicator. The decomposition into category contributions emerged as a necessary information for refining the interpretation of indicator values. Extensive discussions took place about the relevant scale of the domains which can be analysed with these indicators. These reflections are not reported here because the case of neurosciences posed few problems, but they will feed in to future work. Finally, the participants in the working group had high demands concerning the presentation of the method and the results, with a deep concern about how easily these results could be appropriated by others. Time will tell if this process is successful on a larger scale and if more interactions with end users are needed to achieve the objective.

Material and methods

Data consist of documents of the four types *article, letter, note* and *review* published over the period 2008-2014 in journals classified in the *Neurosciences* category in the Thomson Reuters database at OST, updated in 2013 with TR updates and with the affiliation validation process carried out by OST with French universities. Documents with less than three references are not taken into account.

For the overall index which is based on the references of the whole corpus, the references of each document are weighted by the inverse of the number of references of the document, so that the set of references for each document has the same weight. This option, called EWA (Equal weight by article) in Cassi et al. (2014) is recommended because it makes it possible to consider both review papers and articles.

For a reference in a journal assigned to many categories, a reference was counted in each category (whole counting option). The fractional counting option was also tested but no important difference with the whole counts occurred in the results. We do not use the "Multidisciplinary" WoS category and articles in these journals are classified in another category on the basis of their references.

Statistical p-values are calculated with a central limit theorem for a function of averages of identically distributed random variables (Cassi et al., 2014, 2015).

R-scripts for computing the values of the indicators and their statistics are available in Champeimont et al. (2015) as well as a self-consistent document on the underlying statistical theory and some data used for this study.

Acknowledgements This work relied on the involvement of seven universities management team members: Françoise Curtit (Université de Strasbourg), Christiane Grillier (Université de Franche-Comté, Besançon), Denis Leroux (Université Joseph Fourier, Grenoble 1), Nathalie Reymonet (Université Paris Diderot, Paris 7), Valérie Ricoux, Arnaud Sillet (Université Paris Descartes, Paris 5), Guillaume Tatti (Université Blaise Pascal, Clermont 1). Françoise Rojouan is responsible for the ongoing relationship of OST with universities. Raphaël Champeimont developed the definitive version of the programs with R, including clever tricks in graphical outputs. Agénor Lahatte and Hélène Méchoulam helped with specific contributions. The authors are indebted to the programme committee of the STI 2015 Conference (Lugano, 2-4 October 2015) for relevant advice and constructive comments on improving this paper before submission for publication.

References

Börner, K., Klavans, R., Patek, M., Zoss, A. M., Biberstine, J. R., Light, R. P., Larivière, V., and W., B. K. (2012). Design and update of a classification system: The UCSD map of science. *PLoS ONE*, 7(7):e39464.

Campbell, D., Deschamps, P., Côté, G., Roberge, G., Lefebvre, C., and Archambault, É. (2015). Application of an "interdisciplinarity" metric at the paper level and its use in a comparative analysis of the most publishing ERA and non-ERA universities. In *STI 2015. Research organizations under scrutiny. New indicators and analytical results.* Universitá della Svizzera italiana, Lugano, ENID.

Cassi, L., Mescheba, W., and de Turckheim, É. (2014). How to evaluate the degree of interdisciplinarity of an institution? *Scientometrics*, 101(3):1871–1895.

Cassi, L., Mescheba, W., and de Turckheim, É. (2015). Statistical properties of the Rao-Stirling indicators of interdisciplinarity. http://github/turckheim/interdisciplinarity/blob/master/

Papers/Statistical_properties_of_Rao_Stirling_indicators.pdf. Accessed: 2015-10-01.

Champeimont, R., Mescheba, W., Cassi, L., and de Turckheim, É. (2015). Interdisciplinarity indicators for research institutions. http://github/turckheim/interdisciplinarity. Accessed: 2015-10-01.

European Commission (2014). Future and emerging technologies: Living interdisciplinarity. https://ec.europa.eu/programmes/horizon2020/en/news/fet-living-interdisciplinarity. Accessed: 2015-10-05.

Garner, J., Porter, A. L., Borrego, M., Tran, E., and Teutonico, R. (2013). Facilitating social and natural science cross-disciplinarity: Assessing the human and social dynamics program. *Research Evaluation*, 22(2):134–144.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., and Trow, M. (1994). *The new production of knowledge: the dynamics of science and research in contemporary societies*. Sage, London.

Lepori, B., Barré, R., and Filliatreau, G. (2008). New perspectives and challenges for the design and production of S&T indicators. *Research Evaluation*, 17(1):33–44.

Leydesdorff, L. and Rafols, I. (2009). A Global Map of Science Based on the ISI Subject Categories. *Journal of the American Society for Information Science and Technology*, 60(2):348–362.

Medical News Today (2014). What is neuroscience? http://www.medicalnewstoday.com/articles/248680.php. Accessed: 2015-10-03.

National Academy of Sciences, National Academy of Engineering, Institute of Medicine (2004). *Facilitating interdisciplinary research*. The National Academies Press, Washington, D.C. http://www.nap.edu/read/11153/chapter/1.

National Research Council (2014). *Convergence: Facilitating transdisciplinary integration of life sciences, physical sciences, engineering, and beyond*. The National Academies Press, Washington, D.C. http://www.nap.edu/read/18722/chapter/1.

Porter, A. and Rafols, I. (2009). Is science becoming more interdisciplinary? measuring and mapping six research fields over time. *Scientometrics*, 81(3):719–745.

Porter, A. L., Cohen, A. S., Roessner, D. J., and Perreault, M. (2007). Measuring researcher interdisciplinarity. *Scientometrics*, 72(1):117–147.

Prudhomme, J., Gingras, Y., Couillard, A., and Terrasson, D. (2012). Les mesures de l'interdisciplinarité. Pratiques et attitudes dans un centre de recherche français : l'IRSTEA. Technical report, CIRST, UQAM, Montréal. http://www.cirst.uqam.ca/Portals/0/docs/note_rech/2012-01.pdf Accessed: 2015-10-5.

Rafols, I., Leydesdorff, L., O'Hare, A., Nightingale, P., and Stirling, A. (2012). How journal rankings can suppress interdisciplinary research: A comparison between Innovation Studies and Business & Management. *Research Policy*, 41(7):1262 – 1282.

Stokols, D., Misra, S., Moser, R. P., Hall, K. L., and Taylor, B. K. (2008). The ecology of team science. *American Journal of Preventive Medicine*, 35(2):S96–S115.

Templin, J. (2011). Multivariate normal distribution, Lecture 4, ICPSR Summer Session 2. http://jonathantemplin.com/files/multivariate/mv11icpsr/mv11icpsr_lecture04.pdf. Accessed: 2015-09-30.

Waltman, L. and van Eck, N. J. (2012). A new methodology for constructing a publication-level classification system of science. *Journal of the American Society for Information Science and Technology*, 63(12):2378–2392.

Wikipedia (2015). Neuroscience. https://en.wikipedia.org/wiki/Neuroscience. Accessed: 2015-10-03.

Appendix: confidence areas for (ST^W, ST^B)

In the figures of this paper, we replaced the non significant values of the indicators by zero. Another relevant representation would be to show the calculated values together with their confidence intervals. As the two components ST^W and ST^B of ST are not independent random variables, a confidence area with a given probability is an ellipsis, which axis orientation depends on the correlation of the two components (Templin, 2011). In Figure 5, we show the confidence areas of probability 0.98 for the two-dimensional indicator (ST^W, ST^B).

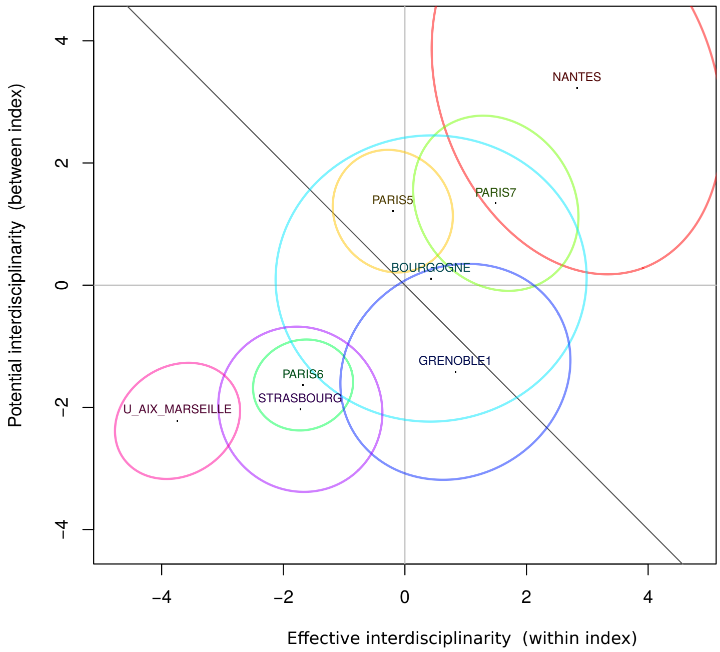

Fig. 5 Within and between indicators for the eight universities of the study and their joint confidence areas of probability 0.98