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Research Paper

The Scientometric Measurement of Interdisciplinarity and Diversity in the Research Portfolios of Chinese Universities

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Citation: Zhang, L., & Leydesdorff, L. (2021). The scientometric measurement of interdisciplinarity and diversity in the research portfolios of Chinese Universities. *Journal of Data and Information Science*, 6(4), 13–35. https://doi.org/10.2478/jdis-2021-0027

Received: Jan. 17, 2021
Revised: Feb. 25, 2021; May 10, 2021
Accepted: Jun. 1, 2021

Abstract

Purpose: Interdisciplinarity is a hot topic in science and technology policy. However, the concept of interdisciplinarity is both abstract and complex, and therefore difficult to measure using a single indicator. A variety of metrics for measuring the diversity and interdisciplinarity of articles, journals, and fields have been proposed in the literature. In this article, we ask whether institutions can be ranked in terms of their (inter-)disciplinary diversity.

Design/methodology/approach: We developed a software application (interd_vb.exe) that outputs the values of relevant diversity indicators for any document set or network structure. The software is made available, free to the public, online. The indicators it considers include the advanced diversity indicators Rao-Stirling (*RS*) diversity and *DIV**, as well as standard measures of diversity, such as the Gini coefficient, Shannon entropy, and the Simpson Index. As an empirical demonstration of how the application works, we compared the research portfolios of 42 "Double First-Class" Chinese universities across Web of Science Subject Categories (WCs).

Findings: The empirical results suggest that *DIV** provides results that are more in line with one's intuitive impressions than *RS*, particularly when the results are based on sample-dependent disparity measures. Furthermore, the scores for diversity are more consistent when based on a global disparity matrix than on a local map.

Research limitations: "Interdisciplinarity" can be operationalized as bibliographic coupling among (sets of) documents with references to disciplines. At the institutional level, however, diversity may also indicate comprehensiveness. Unlike impact (e.g. citation), diversity and interdisciplinarity are context-specific and therefore provide a second dimension to the evaluation.

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Policy or practical implications: Operationalization and quantification make it necessary for analysts to make their choices and options clear. Although the equations used to calculate diversity are often mathematically transparent, the specification in terms of computer code helps the analyst to further precision in decisions. Although diversity is not necessarily a goal of universities, a high diversity score may inform potential policies concerning interdisciplinarity at the university level.

Originality/value: This article introduces a non-commercial online application to the public domain that allows researchers and policy analysts to measure "diversity" and "interdisciplinarity" using the various indicators as encompassing as possible for any document set or network structure (e.g. a network of co-authors). Insofar as we know, such a professional computing tool for evaluating data sets using diversity indicators has not yet been made available online.

Keywords Diversity; Balance; Disparity; Variety; Measurement; Interdisciplinarity; Comprehensiveness; Portfolio

1 Introduction

On July 29, 2020, the Academic Degrees Committee of the State Council—an advisory council of the Chinese government—announced that the category "inter-discipline" had been added to the list of national disciplines accessible for academic degrees. This initiative will not only result in a structural change to China's classification of academic degrees, it was also designed to promote the future development of interdisciplinarity in China. As a case in point, three months after its release in late October 2020, the National Natural Sciences Foundations of China (NSFC) announced the launch of a new department for "interdisciplinary studies". This will be the ninth department of the NSFC, and will focus on funding interdisciplinary projects. As the first change to the NSFC funding scheme in 11 years, the decision has drawn much attention.

Interdisciplinarity is a hot topic in science and technology policy. However, the concept of interdisciplinarity is both abstract and complex, which makes it difficult to fully represent or measure interdisciplinarity in terms of indicators, which can be compared among them. A variety of measures for diversity, as a proxy of interdisciplinarity, has been proposed in the literature. Further, one can find such indicators to measure the interdisciplinarity of a set of articles, patents, or journals. In this study, we ask: Can one rank institutions in terms of their disciplinary diversity? And, if so, what does this tell us about interdisciplinarity?—noting that diversity is not necessarily a goal universities strive for; some aspire to be the best in a particular discipline.

During the last few years, we, the authors of this paper, have explored the scientometric measurement of interdisciplinarity and diversity in scholarly communications in collaboration with a number of colleagues. Contributions to this program of studies were made (in alphabetic order) by Lutz Bornmann, Wolfgang Glänzel, Inga Ivanova, Ronald Rousseau, Caroline S. Wagner, and Ping Zhou (Leydesdorff & Ivanova, 2020; Leydesdorff, Wagner, & Bornmann, 2018 and 2019; Zhang, Rousseau, & Glänzel, 2016; Zhang, Sun, Chinchilla-Rodríguez, Chen, & Huang, 2018; Zhang, Sun, Jiang, & Huang, 2021). One of our objectives has been to develop a non-commercial, public-domain application that allows researchers and policy analysts to measure the diversity of any document set or network structure using a range of indicators. To our best knowledge, no such tool has ever been developed, at least not for public consumption.

A large number of indicators of "diversity" have been proposed in the literature (e.g. Rao-Stirling diversity; Stirling (2007), the Gini-coefficient, Simpson (1949) indicator, Hirschman-Herfindahl (Herfindahl, 1950; Hirschman, 1945), etc. In this communication, we report on the facilities which we created during the last two years. Particularly, we introduce the freely available program interd_vb.exe (available at http://www.leydesdorff.net/software/interdisc.2020/) for this purpose. We document the various options and provide instructions for practitioners interested in measuring diversity and interdisciplinarity. By elaborating on the measurement of the disciplinary diversity of the research portfolios of the 42 top universities listed as the "Double First-Class" universities (Liu et al., 2018), we are able to show the options and choices to be made given the current state of the art.

Technical instructions are additionally available at http://www.leydesdorff.net/software/interdisc.2020/index.htm. The inputs and outputs are in .csv format. The same output is also stored in interdis.bdf. The subsequent analysis demonstrates the options and choices that can be made as route to a final comparison. As a disclaimer, note that we are in no way professional programmers. We cannot guarantee that our routines are error-free, and we acknowledge that the user interface could be improved. However, as a test, one of us programmed the application in two different computer languages, and the results were virtually the same. Additionally, we do believe the functionality is unique and, therefore, state of the art for what it is.

One of the advantages of the application is its ability to handle large volumes of data. For example, the need to analyze an entire database, such as Web-of-Science (WoS), Scopus, or Google Scholar, is becoming increasingly common. Analyses of this magnitude can generate baselines for evaluating the disciplinary diversity of articles, journals, topics, etc. The Interdisc program can relieve the computational overhead of processing massive amounts of data. That said, although the equations used to calculate diversity indicators are often mathematically transparent, specifying the terms as computer code can help analysts to further precision in decisions that would not otherwise be involved in a manual calculation.

2 The relation of the indicators to bibliometrics

Interdisciplinarity can be operationalized as references to different literatures. Such co-citing is known in scientometrics as bibliographic coupling (Kessler, 1963). When a document, for example, cites both articles in physics journals and in sociology journals, this can be expected to indicate interdisciplinarity more than citing chemical physics and solid-state physics in the same document or in the same set. In other words, one couples literature from different disciplines in the references. This coupling can be at the level of articles, journals, or Web-of-Science Subject Categories (WCs).

Bibliographic coupling is an indicator on the citing side and thus the operation opposite to co-citation: co-citations across disciplinary borders indicate interdisciplinary diffusion, whereas the measurement of interdisciplinarity by bibliographic coupling focuses on aggregated citing behaviour.

Whereas "interdisciplinarity" by citing papers refers to documents, documents are often not the units of analysis in the case of research evaluation at the institutional level. The interdisciplinary operator of bibliographic coupling is defined in terms of disciplines and not in terms of institutions. Does the diversity of a university in terms of departments indicate interdisciplinarity or only comprehensiveness of a research portfolio? Since there is no coupling in terms of different fields, one may measure only comprehensiveness, and not interdisciplinarity.

Institutional units are primarily administratively and not disciplinarily organized. The diversity indicators apply to disciplinary differentiations; social differentiation in terms of departments, etc., may have a different meaning. For example, diversity may also indicate comprehensiveness. How does this work out empirically?

3 Indicators of diversity

In this section, we first discuss the following indicators of diversity and interdisciplinarity in terms of the basic equations:

3.1 Shannon's entropy

Using Shannon's (1948) information theory, one can measure diversity as the uncertainty in a distribution. The equation of the Shannon entropy can be stated as follows:

$$H = -\sum p_i \log(p_i) \qquad (1)$$

Where $p_i = x_i / X$, and $\sum p_i = 1$. x_i denotes the number of cells belonging to subject category i. Based on information theory, the maximum capacity ($H_{\max}$) of a system is composed of two parts which are (1) the number of realized states and (2) the not-yet-realized but possible states ($H_{\max} - H_{system}$); that is, the redundancy. Leydesdorff and Ivanova (2021t) proposed to use redundancy as a measure of synergy.

3.2 The Simpson index

The Simpson index was originally developed to measure "concentration" (Rousseau, 2018; Simpson, 1949). Stirling (2007) introduced the concept into the field of scientometrics as a way to evaluate the variety of subject categories and the unevenness in the distribution of these categories. For this reason, Simpson diversity is often called a "dual concept" indicator of diversity. It combines variety with balance in a single number. The equation for Simpson's diversity index is

$$SI = 1 - \sum p_i^2 \tag{2}$$

where $p_i = x_i / X$, $X = \sum x_i$, and x_i denotes the number of elements belonging to the subject category i.

3.3 Rao-Stirling index

Stirling (2007) proposed Rao-Stirling (RS) diversity to measure interdisciplinarity, distinguishing variety, balance, and disparity as the three components of interdisciplinarity. Formally, the indicator is calculated as

$$RS = \sum_{i,j} \left(p_i p_j\right)^{\alpha} d_{ij}^{\ \beta} \tag{3}$$

where d_{ij} (or equivalently 1-S_{ij}) denotes the distance between subject i and subject j, and S_{ij} is the similarity between the subjects i and j. $p_i = x_i / X$, $X = \sum x_i$, and x_i denotes the number of cells belonging to subject i. The exponents α and β are two parameters for adjusting the relative weights of distance d_{ij} and variety or balance $p_i p_j$.

The novelty of *RS* lies in the disparity term (d_{ij}). The other part of Eq. 3 is the same as the Simpson index, which measures both variety and balance.

In most scientometric applications, α and β are set to 1 (Rafols & Meyer, 2010), which simplifies Eq. (3) to:

$$D = \sum_{i \neq j} d_{ij} p_i p_j \tag{4}$$

3.4 True RS diversity

True RS diversity has its origins in a variant of the Hill indicator proposed by Leinster and Cobbold (2012) which adds disparity into the Hill equation traditionally used in ecology. This indicator was subsequently modified by Zhang et al. (2016) as follows:

$$^{2}D^{S}=\left(\sum_{i=1}^{n}p_{i}\left(\sum_{j=1}^{n}s_{ij}p_{j}\right)\right)^{-1}=\frac{1}{\sum_{i,j=1}^{n}s_{ij}p_{i}p_{j}} \tag{5}$$

where S_{ij} denotes the similarity between subjects i and j. $p_i = x_i/X$, $X=\sum x_i$, and x_i is the number of cells belonging to subject i. Note that True RS is no longer bounded between zero and one, and it allows the parameters to be scaled such that one unit of study is, say, twice as interdisciplinary as another.

3.5 DIV

Stirling (1998) stated that "any integration of variety and balance into dual concept diversity must necessarily involve the implicit or explicit prioritization of the subordinate properties". From this, Leydesdorff et al. (2019) proposed a new diversity indicator, called *DIV,* that divides interdisciplinarity into its three components (variety, balance, and disparity) and recombines them by multiplication. An empirical experiment proves the advantages of this new indicator over RS diversity. Formally, *DIV* is expressed as follows:

$$DIV_{c}=\left[\frac{n_{c}}{N}\right]*\left[1-G(c)\right]*\left[\sum_{\substack{i=1,\\ j=1,\\ i\neq j}}^{\substack{j=n_c\\ i=n_c}}\frac{d_{ij}}{\left\{n_{c}*\left(n_{c}-1\right)\right\}}\right] \tag{6}$$

where *n(c)* is the number of elements in the case under study; *N* is the total number of elements in the set; *c* is the sequence number of the column vector in the set; *G(c)* is the Gini coefficient of *c*; and d_{ij} is the level of disparity between elements *i* and *j*.

Rousseau (2019) suggested some improvements to *DIV.* He showed that *DIV* can be turned into a measure of True Diversity by removing the term *N* (variety) in the denominator of Eq. 6. Rousseau argued that a better framework for diversity measurement would account for several requirements, not all of which are met by existing frameworks. Responding to the improvements made by Rousseau (2019), Leydesdorff, Wagner, and Bornmann (2019) provided an updated version of the improved *DIV** as a True Diversity measure:

$$DIV_{c}^{*}=n_{c}*\left[1-G(c)\right]*\left[\sum_{\substack{i=1,\\ j=1,\\ i\neq j}}^{\substack{j=n_c\\ i=n_c}}\frac{d_{ij}}{\left\{n_{c}*\left(n_{c}-1\right)\right\}}\right] \tag{7}$$

where *n*(c) is the number of elements in subject c; *G*(c) is the Gini coefficient of *c*; and d_{ij} is the level of disparity between elements *i* and *j*.

3.6 Gini coefficient

The Gini coefficient is a well-known indicator for representing income inequality among people and wealth inequality among nations (Lorenz, 1905). Hence, when measuring the diversity of interdisciplinary research with the Gini coefficient, the research is treated as a system comprised of three elements—variety, balance, and disparity (Porter & Rafols, 2009; Rafols & Meyer, 2010) where (1 – Gini) is used as the indicator of balance (Nijssen et al., 1998).

The theory of relative mean differences defines the Gini coefficient as (e.g. Buchan, 2002):

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2n^2\bar{x}} \tag{8}$$

where x is an observed value, n is the number of values observed, and x bar is the mean value.

Note, however, that there are several alternative definitions of the Gini coefficient. See, for example, that provided at https://en.wikipedia.org/wiki/Gini_coefficient (cf. Rousseau (1992)).

If the x values are first placed in ascending order such that each x has rank i, some of the comparisons above can be avoided and computation is therefore more efficient, i.e.:

$$G = \frac{2}{n^2\bar{x}}\sum_{i=1}^{n} i\left(x_i - \bar{x}\right) \tag{9}$$

$$G = \frac{\sum_{i=1}^{n}\left(2i - n - 1\right)x_i}{n\sum_{i=1}^{n}x_i} \tag{10}$$

where x is an observed value, n is the number of values observed, and i is the rank of values in ascending order.

For G to be an unbiased estimate of the true population value, it should be multiplied by $n/(n\text{-}1)$ (Dixon, 1987; Mills & Zandvakili, 1997). In the bibliometric literature, this index is also known as the Pratt index (Pratt, 1977). The value of both the Gini and the normalized G are provided by interd_vb.exe.

3.7 Other indicators

The concept of coherence based on network analysis has attracted attention from researchers in scientometrics (e.g. Rafols, 2014). While the diversity indicators rely on a pre-defined category system, coherence can be generated via a bottom-up approach that describes the intensity of the relations between any elements in a network. From this perspective, comprehensive frameworks composed of diversity and coherence have been proposed to improve the depiction of interdisciplinary systems (Rafols & Meyer, 2010).

4 The computation of diversity and interdisciplinarity indicators

The program interd_vb.exe (http://www.leydesdorff.net/software/interdisc.2020/interd_vb.exe) was rewritten based on the routine Mode2Div.exe previously programmed in the so-called xBase language. Unfortunately, computing cosine values for large matrices can be time-consuming with xBase, which imposes a soft limit on the size of the datasets that can be processed. Hence, we rewrote Mode2Div.exe in Visual Basic 6 to become interd_vb.exe, i.e. the online Interdisc application. Visual Basic 6 runs on Win10 (32/64 bits) and does not require the predetermined amount of memory to be allocated to processing. Therefore, the only limitation to the size of the dataset that can be processed is hardware. The two programs, interd_vb.exe and Mode2Div.exe, have similar objectives but a different organization and architecture, and the results they produce are exactly the same. Both programs are documented in Leydesdorff et al. (2018, 2019) and the software is available for download from https://www.leydesdorff.net/software/interdisc.2020/ and Figshare (https://figshare.com/account/articles/12871529).

One key difference between the two versions of the program is their input requirements. In the case of mode2div.exe, the input is stored listwise using the Pajek format, each line describing the row and column of a cell in a matrix of values. Thus, the input can be read as three fields without any system limitations. The data is assumed to be 2-mode so that an asymmetrical (citation) matrix can be processed. The program then computes the diversity measures along the column vectors of a data matrix saved in .csv format. As an example, to measure the interdisciplinarity of a set of documents, one could use jcitnetw.exe[①] to easily generate a co-occurrence matrix of cited journals in the Pajek format, using plain text downloaded from the Web of Science. More details on this can be found at https://www.leydesdorff.net/software/mode2div/.

5 The distance metric and the disparity measure

Stirling (2007) added a new element to diversity measurement: disparity. Disparity indicates the distance between two subjects in the sample(s) under study. For example, if the distances in a subset are small, this space can be considered a niche of related variety (Frenken et al., 2007). However, disparity as a factor in both RS

[①] https://www.leydesdorff.net/software/interdisc/jcitnetw.exe and the *DIV* requires the choice of a distance metric. Following Salton and McGill (1983), Ahlgren, Jarneving, and Rousseau (2003) proposed cosine as a non-parametric measure of similarity for bibliometrics. From a comparison of a number of similarity/distance measures, Egghe and Leydesdorff (2009) concluded that the cosine fulfills a number of requirements.

Like Pearson correlations, cosine values are defined in a vector space and are therefore positional, whereas the very similar Jaccard index is relational. Unlike the Pearson correlation, however, cosines do not normalize to a mean and, since bibliometric distributions are highly skewed, normalizations using the mean are to be avoided. Our routines use (1 – cosine), which can be considered a distance measure. Pragmatically, the terms of a cosine can be written as co-occurrence in the numerator and the sum of squares along the two column vectors x and y multiplied in the denominator. Note that, here, the matrix rows contain the disciplines and the columns contain the universities, so the cosine values are computed between the row vectors.

One disadvantage of Mode2Div.exe is that data is often not readily available in Pajek format and converting the data into this format may generate other problems (Pfeffer, Mrvar, & Batagelj, 2013). The most generic format for data, however, is a matrix as a comma or tab-separated plain ASCII file. There are no size limitations for this data, although Excel (depending on the Office version) may not allow for more than 255 variables. This data, however, can also be written using a text editor (e.g. the freeware *Note*++) or any other program. The size of the matrix is only limited by external factors such as free diskspace.

The routine begins with asking for the name of the .csv file containing the variables and the number of vectors to be compared for the purposes of error correction. The file is then rewritten into output which is reported in the files interdis.dbf and equivalently interdis.csv. The specific differences in terms of inputs, outputs, and other related items about these programs are summarized in Appendix Table S1.[2]

6 Data

As empirical data, we used the portfolio of research articles from the 42 Chinese universities listed as "Double First-Class universities" between 2017 (when the list was first released) and 2019. The Chinese government offers substantial support to this select group of universities through a series of special programs. Additionally, although this particular list has only been published since 2017, similar initiatives

[2] See for further details at http://www.leydesdorff.net/software/interdisc.2020/

under different names have existed periodically since the 1990s, with the majority of universities considered to be elite remaining much the same this whole time. Thus, these 42 institutions were selected because this group is both clearly delineated and large enough to provide a large-scale sample. In addition, we also included the portfolios of two well-known American universities, Harvard and Stanford, to provide a standard those in the West might find easier to benchmark. In a subsequent article, Leydesdorff, Wagner, and Zhang (2021), we further compare these results with 205 Chinese universities.

Each of the universities in the sample promotes itself as a comprehensive university. However, some note specific missions or strengths; for instance, the agricultural universities. The publications associated with each university were retrieved using the organization's name and/or its variants from the Preferred Organization Index in WoS.

The domains searched include the Science Citation Index Expanded (SCI-E), the Social Sciences Citation Index (SSCI), and the Arts & Humanities Citation Index (A&HCI) in the Web of Science (WoS) Core Collection. We limited the document type to articles and reviews. The number of articles retrieved per university are listed in Table 1 in decreasing order.

Table 1. Number of publications associated with the 44 universities in our sample (2017–2019); in decreasing order.

No.	University name	Papers	No.	University name	Papers
1	Harvard Univ	76,144	23	Northeastern Univ	14,893
2	Shanghai Jiao Tong Univ	37,016	24	Beihang Univ	14,484
3	Zhejiang Univ	35,204	25	Dalian Univ of Technology	13,861
4	Tsinghua Univ	32,681	26	Zhengzhou Univ	12,993
5	Stanford Univ	32,428	27	Northwestern Polytechnical Univ	12,497
6	Peking Univ	30,160	28	Chongqing Univ	12,451
7	Sun Yat-Sen Univ	26,823	29	Univ of Electronic S & T of China	12,334
8	Huazhong Univ of S & T	24,822	30	Xiamen Univ	11,607
9	Fudan Univ	24,475	31	Beijing Institute of Technology	11,206
10	Sichuan Univ	23,259	32	Beijing Normal Univ	10,043
11	Central South Univ	22,870	33	Nankai Univ	9970
12	Xi'an Jiaotong Univ	22,698	34	Hunan Univ	9811
13	Shandong Univ	21,601	35	Lanzhou Univ	9156
14	Jilin Univ	21,068	36	China Agricultural Univ	8762
15	Harbin Institute of Technology	20,750	37	Northwest A & F Univ	7817
16	Univ of S & T of China	20,747	38	East China Normal Univ	7610
17	Wuhan Univ	19,748	39	National Univ of Defense Technology	6601
18	Nanjing Univ	19,246	40	Ocean Univ of China	6390
19	Tianjin Univ	17,778	41	Renmin Univ of China	2946
20	Tongji Univ	17,226	42	Yunnan Univ	2835
21	Southeast Univ	16,959	43	Xinjiang Univ	1979
22	South China Univ of Technology	15,595	44	Minzu Univ of China	760

We first organized the data into an asymmetrical occurrence matrix of the 44 universities against 254 WoS categories. We then computed the six diversity measures using Interd_vb.exe.

7 Results

7.1 Ranking of universities in terms of interdisciplinarity

The interdisciplinarity scores for each indicator and university are listed in Table 2. Additionally, we have provided a ranking against each indicator. For example, for the *DIV** indicator, Stanford University is ranked No. 1, whereas, according to the True RS indicator, it is ranked No. 15. Tsinghua University, which is widely considered to be the top university in China, sits in 21st place on the list of *DIV**. Keep in mind, however, that this is a ranking of comprehensiveness as measured by disciplinary diversity, not of impact. As mentioned in Section 2.6, the Gini coefficient is a measure of unbalance, and therefore (1 – Gini) is used in the computation of *DIV** (Eq. 7; Table 2).

The Spearman rank-order correlations are provided in Table 3. The *DIV** indicator correlates much more closely to the VARIETY and GINI indicator, as is to be expected since (1-GINI) is actually used to calculate *DIV**. However, there is only a moderate correlation between the two true diversity indicators, True RS and *DIV** at (ρ = 0.50; $p < 0.01$). Further, the rankings of the top five universities according to these two indicators are inconsistent. These unexpected results raise further questions.

The new element added to the Striling (2007) to the measurement of diversity and interdisciplinarity was disparity. In Table 3, disparity indeed is not significantly correlated with any of the other diversity indicators. Factor analysis of this data (Table 4) shows disparity (and variety) as a second component. Unlike True RS, *DIV** captures both dimensions, as was Stirling's theoretical intention.

As stated above, when applying interd_vb.exe, the terms of the *cosine* are pragmatically computed using co-occurrences in the sample in the numerator and the square roots of the products of sum of squares along the thus affiliated vectors x and y in the denominator. Disparity is then defined as the sum of local values of (1-*cosine*) over the set. This matrix is a "sample-dependent" *local matrix* since it reflects the disparity within the data samples. Consequently, these values vary with the data-sample used as input. It may often be convenient for analysts and developers to calculate the diversity values in this way (locally), particularly, when one has no access to a global disparity matrix. However, the systems of reference for the cosine-normalization are then different among samples.

Table 2. The Indicator scores generated by interd_vb.exe routine.

University	DIV*	Rank	True RS	Rank	Simpson	Rank	Shannon	Rank	Variety	Rank	Disparity	Rank	(1-Gini)	Rank
Stanford Univ	40.260	1	1.503	15	0.986	1	6.831	1	0.988	1	0.472	23	0.340	1
Sun Yat-Sen Univ	35.754	2	1.549	6	0.983	5	6.663	2	0.945	5	0.474	12	0.314	2
Peking Univ	33.352	3	1.516	13	0.982	7	6.568	4	0.953	3	0.474	15	0.291	4
Zhejiang Univ	33.237	4	1.549	7	0.983	3	6.594	3	0.949	4	0.473	18	0.292	3
Harvard Univ	32.328	5	1.288	39	0.983	6	6.512	7	0.988	1	0.471	25	0.274	7
Shanghai Jiao Tong Univ	31.151	6	1.553	5	0.984	2	6.565	5	0.921	9	0.471	26	0.283	5
Sichuan Univ	30.092	7	1.527	12	0.983	4	6.517	6	0.913	11	0.473	19	0.274	6
Wuhan Univ	29.117	8	1.548	8	0.982	9	6.465	8	0.917	10	0.473	16	0.264	8
Northeastern Univ	28.892	9	1.485	18	0.975	24	6.335	15	0.945	5	0.466	37	0.258	10
Fudan Univ	28.102	10	1.457	22	0.979	17	6.361	12	0.929	7	0.468	35	0.254	12
Shandong Univ	27.683	11	1.492	17	0.981	11	6.416	9	0.898	13	0.472	24	0.257	11
East China Normal Univ	27.471	12	1.495	16	0.980	12	6.415	10	0.886	18	0.470	28	0.260	9
Nanjing Univ	26.735	13	1.444	24	0.977	20	6.256	21	0.929	7	0.475	9	0.238	19
Beijing Normal Univ	26.427	14	1.575	4	0.976	22	6.328	16	0.890	16	0.467	36	0.250	13
Xiamen Univ	26.392	15	1.439	25	0.977	18	6.301	19	0.894	14	0.474	13	0.245	16
Tongji Univ	26.286	16	1.538	11	0.979	13	6.341	13	0.894	14	0.471	27	0.246	15
Huazhong Univ of S&T	25.700	17	1.452	23	0.979	15	6.308	18	0.886	18	0.475	10	0.241	18
Central South Univ	25.298	18	1.545	9	0.979	16	6.336	14	0.843	23	0.479	2	0.247	14
Lanzhou Univ	23.959	19	1.513	14	0.981	10	6.362	11	0.815	26	0.472	22	0.245	17
Jilin Univ	23.323	20	1.431	26	0.975	26	6.177	22	0.866	21	0.474	14	0.224	22
Tsinghua Univ	23.253	21	1.371	29	0.975	27	6.120	25	0.913	11	0.470	29	0.213	25
Xi’an Jiaotong Univ	22.879	22	1.409	27	0.975	25	6.128	24	0.890	16	0.472	21	0.214	24
Zhengzhou Univ	21.553	23	1.463	20	0.976	23	6.152	23	0.811	27	0.475	7	0.220	23
Southeast Univ	20.325	24	1.385	28	0.970	33	5.971	29	0.870	20	0.470	30	0.196	28
Renmin Univ	20.323	25	1.458	21	0.979	14	6.277	20	0.748	35	0.457	41	0.234	20
Yunnan Univ	18.896	26	1.540	10	0.982	8	6.314	17	0.681	39	0.469	31	0.233	21
Nankai Univ	18.091	27	1.334	32	0.969	40	5.894	32	0.827	24	0.462	40	0.187	30
Univ of S&T – China	17.782	28	1.303	37	0.968	41	5.797	38	0.850	22	0.477	5	0.172	38
Tianjin Univ	17.466	29	1.296	38	0.970	35	5.852	37	0.819	25	0.475	11	0.177	35
South China Univ of Technol	17.286	30	1.349	31	0.970	36	5.882	33	0.795	28	0.473	20	0.181	31
Chongqing Univ	17.029	31	1.313	34	0.970	34	5.856	36	0.795	28	0.478	3	0.176	36
Hunan Univ	16.958	32	1.307	36	0.973	30	5.913	31	0.772	32	0.480	1	0.180	32
Ocean Univ of China	16.824	33	1.734	1	0.977	21	6.102	26	0.677	40	0.473	17	0.207	26

Table 2. *Continued*

University	DIV*	Rank	True RS	Rank	Simpson	Rank	Shannon	Rank	Variety	Rank	Disparity	Rank	(1-Gini)	Rank
Dalian Univ of Technol	16.509	34	1.315	33	0.974	29	5.922	30	0.756	34	0.478	4	0.180	33
Harbin Inst of Technology	15.412	35	1.286	40	0.969	38	5.769	39	0.776	31	0.475	8	0.165	39
Beihang Univ	15.007	36	1.311	35	0.970	37	5.762	40	0.780	30	0.465	38	0.163	40
China Agricultural Univ	14.671	37	1.670	3	0.973	31	5.873	35	0.701	37	0.469	34	0.176	37
Northwest A&F Univ	14.040	38	1.681	2	0.972	32	5.881	34	0.665	41	0.469	33	0.177	34
Beijing Inst of Technol	13.944	39	1.269	44	0.969	39	5.728	41	0.724	36	0.475	6	0.159	41
Xinjiang Univ	12.921	40	1.369	30	0.975	28	5.997	28	0.571	42	0.463	39	0.193	29
Univ of Electronic S&T of China	12.847	41	1.281	42	0.950	44	5.428	43	0.768	33	0.448	43	0.147	42
Minzu Univ of China	12.104	42	1.464	19	0.977	19	6.049	27	0.535	44	0.448	42	0.199	27
Northwestern Polytechnical Univ	12.062	43	1.275	43	0.962	42	5.571	42	0.693	38	0.469	32	0.146	43
National Univ of Defense Technol	7.783	44	1.285	41	0.951	43	5.274	44	0.563	43	0.446	44	0.122	44

Table 3. Spearman's correlations for ranking order generated by Interd_vb.exe (N = 42).

	DIV*	TRUE RS	VARIETY	DISPARITY	(1 -GINI)	SIMPSON	SHANNON
DIV*							
TRUE RS	.563**						
VARIETY	.926**	.323*					
DISPARITY	.215	-.092	.230				
(1 – GINI)	.936	.717**	.772**	.074			
SIMPSON	.789**	.766**	.551**	.085	.917**		
SHANNON	.911**	.734**	.725**	087	.990**	.950**	

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4. Factor analysis of the interdisciplinarity and diversity indicators (N = 42).

Rotated Component Matrix[a]

	Component	
	1	2
True RS	.881	-.133
Shannon	.877	.455
(1-Gini)	.862	.456
Simpson	.830	.390
Div*	.703	.657
Variety	.329	.853
Disparity		.792

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 3 iterations; 85.1% of the variance explained.

7.2 Local versus global disparity

In contrast to local disparity, using a global matrix solves (almost by definition) the problem of comparability across samples. To demonstrate the difference between "local" and "global" matrices, we recalculated the diversity scores using a global cosine matrix based on the full set of JCR data for 2019. These data include 236 subject categories in the Science and Social Sciences Citation Indexes (but not the 25 in the *Arts & Humanities Citation Index*).

The results for both *DIV** and True RS are shown in Table 5, and Table 6 shows the Spearman's correlations for the ranking order of the two indicators.[3] As expected, the correlation between *DIV** and True RS (or RS) increased (from 0.502 to 0.695), demonstrating that the consistency between different diversity indicator values can be improved by using a global matrix instead of a local matrix.

[3] The local cosine matrix was generated with interdisc_vb.exe; the global one was retrieved from http://www.leydesdorff.net/software/wc19. The cosine similarity matrix for the WoS categories based on JCR 2019 data is also provided at http://www.leydesdorff.net/wc15/wc19.

Table 5. Local vs. global disparity using JCR data for 2019.

University	DIV*	Rank	TRUE RS	Rank
Stanford Univ	72.956	1	5.488	2
Sun Yat-Sen Univ	68.429	2	4.741	5
Zhejiang Univ	63.343	3	4.300	12
Peking Univ	62.654	4	4.632	8
Shanghai Jiao Tong Univ	60.907	5	4.643	7
Sichuan Univ	58.367	6	4.033	19
Harvard Univ	58.301	7	4.461	9
Wuhan Univ	56.903	8	4.702	6
Northeastern Univ	54.887	9	4.161	15
Fudan Univ	54.196	10	3.897	22
Shandong Univ	53.921	11	4.162	14
East China Normal Univ	51.757	12	4.309	11
Xiamen Univ	51.354	13	3.705	24
Tongji Univ	51.348	14	4.823	4
Beijing Normal Univ	50.815	15	5.082	3
Huazhong Univ of S&T	50.632	16	3.963	20
Central South Univ	50.535	17	4.107	17
Nanjing Univ	50.285	18	3.851	23
Lanzhou Univ	47.622	19	4.087	18
Jilin Univ	46.049	20	3.292	34
Xi’an Jiaotong Univ	45.655	21	3.664	25
Tsinghua Univ	45.121	22	3.601	26
Zhengzhou Univ	43.389	23	3.442	29
Southeast Univ	39.662	24	3.902	21
Renmin Univ	37.896	25	5.563	1
Nankai Univ	36.427	26	2.950	43
Yunnan Univ	36.236	27	4.382	10
Univ of S & T – China	35.002	28	2.876	44
Tianjin Univ	34.613	29	2.995	41
South China Univ of Technol	34.388	30	2.978	42
Ocean Univ of China	32.747	31	4.202	13
Chongqing Univ	32.519	32	3.260	35
Hunan Univ	32.394	33	3.379	32
Dalian Univ of Technol	31.933	34	3.355	33
Harbin Inst of Technol	30.166	35	3.191	36
Beihang Univ	30.029	36	3.508	28
China Agricultural Univ	29.258	37	3.396	31
Northwest A & F Univ	27.904	38	3.402	30
Beijing Inst of Technol	27.102	39	3.184	37
Univ of Electronic S&T of China	26.892	40	3.073	39
Xinjiang Univ	25.828	41	3.531	27
Northwestern Polytechnical Univ	23.873	42	3.031	40
Minzu Univ of China	22.645	43	4.132	16
National Univ of Defense Technol	16.236	44	3.118	38

Table 6. Spearman's correlations for consistency of rank order – local vs. global disparity.

	*DIV**_local	TRUE RS_local	*DIV**_global	TRUE RS_global
*DIV**_local				
TRUE RS_local	.502**			
*DIV**_global	.996**	.516**		
TRUE RS_global	.697**	.707**	.695**	

**Correlation is significant at the 0.01 level (2-tailed).

With a correlation between the local and global values of *DIV** at .996, *DIV** is obviously not sensitive to the scaling. As Rousseau (2019) noted, the disparity in *DIV** "is just a relative (normalized) sum." With hindsight, this seems an advantage of *DIV** when compared with True RS.

7.3 Differences among specific universities

There are some interesting observations to be made in terms of the results of specific universities. Comparing Stanford University and Tsinghua University as examples, Stanford University ranks significantly higher than Tsinghua according to both *DIV** and True RS, as shown in Table 4. The science overlay maps in Figures 1 and 2 illustrate this vividly (Carley et al., 2017; Leydesdorff et al., 2016;

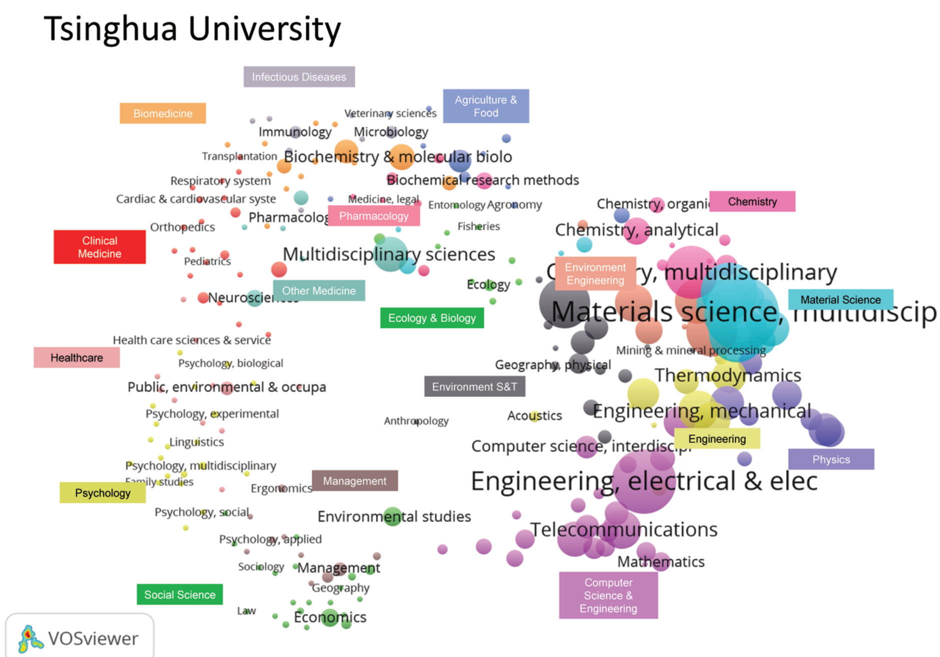

Figure 1. Science overlay map of the publications with an address at Tsinghua University. [Note: The base map of disciplines was developed from the matrix of 227 × 227 cells of WoS categories. This was generated on the basis of direct citation counting and normalized with the cosine function (Carley et al. 2017).

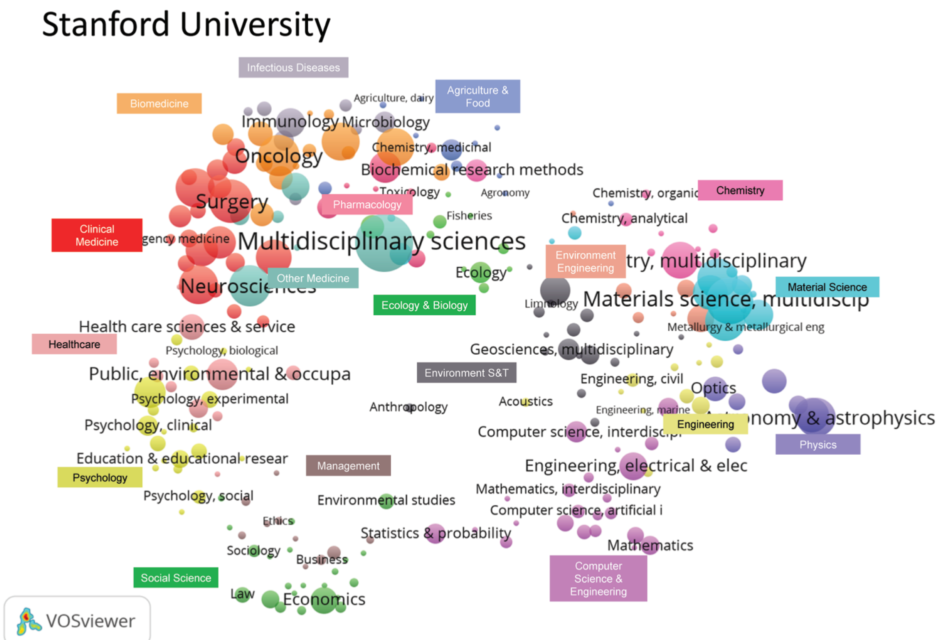

Figure 2. The science overlay map of the publications associated with Stanford University. [Note: The base map of disciplines was developed from the matrix of 227 × 227 cells of WoS categories. This was generated on the basis of direct citation counting and normalized with the cosine function (Carley et al. 2017).

Rafols et al., 2010). Using VOS Viewer for the visualization (Waltman et al., 2010), each node represents a WoS category, and the size of the node indicates the number of publications.

It is clear (on the basis of visual inspection of these two maps) that the category distributions of the two universities are very different. Stanford University obviously prioritizes research in Clinical Medicine, Biomedicine, and other medical disciplines, while Tsinghua University has a clear focus on Computer Science & Engineering, Material Science, and other Engineering fields. However, although each university has strengths in particular disciplines, the distribution of disciplines across Stanford's portfolio is more balanced than that across Tsinghua's.

8 Discussion and conclusion

*DIV** values were more in line with our intuition about the diversity of these universities than the RS or True RS values. The latter, particularly worsen when the results are based on local disparity matrices. Using this local matrix, however, some field-specific universities like Ocean University of China and the Northwest Agriculture & Forestry University are found to have high diversity values with the True RS (and RS) indicators. These results raise further questions.

The results for RS/True RS are more sensitive than *DIV** to the choice of similarity measures (Rafols & Leydesdorff, 2010). As Rousseau (2019) notes: "DIV, taking disparity into account as just a relative (normalized) sum" is not sensitive to scaling. In Eq. (8), disparity is only defined at the level of the sample; the interaction between category i and category j (p_i and p_j, respectively) with d_{ij} is not taken into account at the cell level, only the total sum of all disparity values is.

Table 2 (above) showed that the Ocean University has the highest True RS diversity of all universities. However, when checking the specific distribution of Web of Science categories, we found that more papers are published within *Oceanography* (14.01%) than any other category. Yet, *Oceanography* is a relatively marginal category in our sample, with much lower cosine similarities than other categories. As a result, the disparity (1-*cosine*) between *Oceanography* and other categories is much higher than on average, at a value of 0.73 vs 0.47, respectively. The extraordinarily high proportion of publications in *Oceanography* and the category's high disparity from other categories leads to an unexpectedly high diversity value when measured with RS/True RS. However, when using a global similarity matrix (Table 4), the scores of RS/True RS in most field-specialized universities decreased. As noted, these rankings were not affected by this effect when using *DIV**.

The portfolio of papers with a Harvard address covers a wide range of categories and the distribution is relatively balanced. However, the cosine similarities of the categories with most publications are relatively high, i.e. they tend to have low disparity values, which results in a lower valus of RS/True RS when using a local similarity matrix. These empirical results suggest that RS diversity values based on a global disparity matrix provide results that are more in line with expectations. Therefore, insofar as a user has access to a global matrix one is advised to use this instead of the values generated endogenously by our software.

When universities operate in similar markets with the same institutional imperatives, such as tasks specified in national legislation, one might expect them to develop isomorphism (Halffman & Leydesdorff, 2010; Powell & DiMaggio, 1991; Wagner, Bornmann, Cai, & Leydesdorff, in preparation). However, our results indicate that universities do not tend toward isomorphism when it comes to comprehensiveness, as they do with impact. We reason that this is because impact is measured and prioritized in the bureaucratic frameworks of the state, whereas comprehensiveness is influenced by local opportunities, such as emerging technologies in the companies geographically or intellectually nearby. Hence, developing a deeper understanding of institutional comprehensiveness demands consideration of a broader context and more aspects of society, such as missions of specific universities.

Our analysis clarifies further differences between impact and comprehensiveness. Competition for impact pertains to quality, while competition for diversity/specialty pertains to differentiation. For example, shielding intellectual property rights is specific to a university's relations with industry. When it comes to comprehensiveness, the specificity of the knowledge content matters more than the formal criteria of measuring and comparing output and impact. In our opinion, interdisciplinarity, diversity, or comprehensiveness should not be considered another type of impact. While impact can be formalized across units of operation, e.g. faculties, departments, etc., after proper normalization, diversity or comprehensiveness remains content-based.

In other words, the analytical distinction between intellectual and social organization does not mean that the two dimensions can be traded off at the level of a university. On the contrary, one can expect a correlation, whether positive or negative, between the different types of research efforts. However, the differences between the two make it urgent that we develop a set of indicators for measuring diversity comparable to those of impact. By making an application available that allows users to generate the various measures of diversity for any data matrix, we hope to have contributed to this objective of quantifying and measuring diversity.

Finally, we note that although diversity is often used as a proxy for measuring interdisciplinarity, one should not expect any simplistic index to produce an informative outcome on its own (Abramo et al., 2018). The interpretations of the values of indicators should always be addressed according to the context, the purpose, and the specific object under study. The empirical analysis of the 42+ Chinese universities in terms of diversity measures not only relates to interdisciplinarity at the intellectual level, but also reflects comprehensiveness at the institutional level. Although comprehensiveness is not necessarily a goal of universities, it may reflect the status quo of disciplinary diversity within a university (or at least the structural feature of a disciplinary distribution). The measurement results of this study provide a knowledge base for understanding portfolios. A better understanding may provide new windows on potential policies and thus facilitate the development of interdisciplinarity within a university.

Acknowledgements

We are grateful to Caroline S. Wagner for her comments on a previous draft of this article; to ISI/Clarivate for providing us with the JCR data for 2019; and to Ronald Rousseau for his insightful suggestions. Lin Zhang is grateful for support from the National Natural Science Foundation of China (Grant No. 71573085; 71974150).

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Appendix

Table S1. The differences among provided programs.

Routine	Name of program required	Input	Output	Other output	Website
Interd_vb.exe	Interdis.exe	*.txt file containing comma-separated variables	Interdis.csv Interdis.dbf		https://www.leydesdorff.net/software/interdisc.2020/
Syn3_vb.exe	Syn3.exe	*.txt file containing comma-separated variables	synergy.csv synergy.dbf	Minus.net; minus.txt; t_edges.dbf, t_nodes.dbf, t123.dbf	https://www.leydesdorff.net/software/synergy.triads/
Mode2div.exe		.net file (Pajek) format	Div_col.dbf		https://www.leydesdorff.net/software/mode2div/
jcitnetw.exe		WoS downloads	CR as input for mode2div		https://www.leydesdorff.net/software/interdisc/index.htm