

Is science becoming more interdisciplinary? Measuring and mapping six research fields over time

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In the last two decades there have been studies claiming that science is becoming ever more interdisciplinary. However, the evidence has been anecdotal or partial. Here we investigate how the degree of interdisciplinarity has changed between 1975 and 2005 over six research domains. To do so, we compute well-established bibliometric indicators alongside a new index of interdisciplinarity (Integration score, aka Rao-Stirling diversity) and a science mapping visualization method. The results attest to notable changes in research practices over this 30 year period, namely major increases in number of cited disciplines and references per article (both show about 50% growth), and co-authors per article (about 75% growth). However, the new index of interdisciplinarity only shows a modest increase (mostly around 5% growth). Science maps hint that this is because the distribution of citations of an article remains mainly within neighboring disciplinary areas. These findings suggest that science is indeed becoming more interdisciplinary, but in small steps – drawing mainly from neighboring fields and only modestly increasing the connections to distant cognitive areas. The combination of metrics and overlay science maps provides general benchmarks for future studies of interdisciplinary research characteristics.

1. Introduction

Interdisciplinary research seems almost universally acclaimed as “the way to go.” Many believe that the great advances disproportionately take place at the interstices between disciplines, and that today’s research knowledge “knows no disciplinary boundaries.” Or does it? This paper both measures and maps cross-disciplinary research interchanges over time. We measure how integrative particular research articles are based on the association of the journals they cite to corresponding Subject Categories (“SCs”) of the Web of Science (“WoS”). And, we present a practical way to map scientific outputs, again based on dispersion across SCs. We apply these measures and visualizations together to depict how six substantial research fields have changed from 1975 to 2005. Collectively, these results help address our guiding questions: How interdisciplinary are different areas of science? Are they becoming more interdisciplinary?

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In 2003, the US National Academy of Sciences, National Academy of Engineering, and Institute of Medicine launched the *National Academies Keck Futures Initiative* (“NAKFI”) to bolster interdisciplinary research in the US. This \$40 million, 15-year program needed to be able to measure interdisciplinarity in order to track its status and changes thereto. A National Academies study of *Facilitating Interdisciplinary Research* [NATIONAL ACADEMIES, 2005] generally echoed the conventional wisdom that academia, with its staunch disciplinary roots, was not highly conducive to interdisciplinary research flourishing. This report operationally defined interdisciplinary research as:

- a mode of research by teams or individuals that *integrates*
- perspectives/concepts/theories and/or
- tools/techniques and/or
- information/data
- from two or more bodies of knowledge or research practice.

The purpose of interdisciplinary research is to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single field of research practice. Examples of bodies of specialized knowledge or research practice include: low temperature physics, molecular biology, developmental psychology, toxicology, operations research, and fluid mechanics. Understood as knowledge integration, interdisciplinarity is not the opposite of specialization. research can be specialized (i.e. focused on a narrow topic) either within a disciplinary framework or drawing on various disciplines [RAFOLS & MEYER, FORTHCOMING]. Our investigation here does not concern the degree of topic specialization of research but the degree that it relies on distinct disciplinary traditions.

A key charge to the NAKFI evaluation team was to measure the degree of research interdisciplinarity, both at the macro (e.g., national) and micro level (e.g., NAKFI participants in its seed grant programs on topics such as genomics or complexity). The evaluators compared perspectives to ascertain essential dimensions of interdisciplinary research [PORTER & AL., 2006]. They concurred with the summation by MORILLO & AL. [2001; 2003] that “we do not have appropriate indicators to measure interdisciplinarity.”

Our approach here is to investigate changes of degree of interdisciplinarity over time using various established indicators (e.g. number of disciplines cited, percentage of citations within-field), together with a new indicator developed the NAKFI evaluation team [PORTER & AL., 2007]:¹

Integration – reflecting the diversity of knowledge sources, as shown by the breadth of references cited by a paper.

¹ A second indicator we presented in PORTER & AL. [2007] reflects the diversity of disciplinary areas of publication, but that does not pertain to these analyses. The concept originally derives from LEAHEY [2006].

Integration draws directly upon the above definition of interdisciplinary research. In addition to specifying integration of different knowledge sources, it allows for this to be accomplished by research teams *or by individuals*. It addresses “bodies of specialized knowledge or research practice,” operationalized in the form of WoS Subject Categories, as the essential knowledge bases to be combined.² As per the preceding illustrations, these do not correspond closely to the nominal disciplines (e.g., chemistry, psychology). However, we later determined that Integration is a particular case of the Rao-Stirling index of diversity [RAO, 1982], which was presented as a general heuristic of diversity by STIRLING [2007]. Following Stirling’s heuristic, we have previously argued that in order to explore interdisciplinarity, one needs to investigate multiple aspects, namely: the number of disciplines cited (variety), the distribution of citations among disciplines (balance), and, crucially, how similar or dissimilar these categories are (disparity) [RAFOLS & MEYER, FORTHCOMING].

The key novelty of this Integration score (aka Rao-Stirling diversity index) is that it captures not only the number of disciplines cited by a paper or their degree of concentration (as Herfindahl or Shannon indices do), but also how disparate (i.e. how different) these disciplines are. In order to do so, it relies on a specific metric of distances (or similarities) between pairs of disciplines, as explained in previous papers [PORTER & AL., 2007; RAFOLS & MEYER, FORTHCOMING].

Given that a measure of interdisciplinarity for a case is only meaningful in comparison to other fields or cases, the initial aim of this article is to provide benchmarks across different areas of science and at different times. To this purpose, we selected six Web of Science Subject Categories and examined their Integration indices, as well as other indicators pertaining to interdisciplinarity, over a 30-year period, namely from 1975 to 2005. The second and main aim of the paper is to use these benchmarks to investigate whether science is becoming more interdisciplinary – as has been suggested by various studies, on different empirical bases [GIBBONS & AL., 1994; HICKS & KATZ, 1996; BRAUN & SCHUBERT, 2003].

Although metrics provide a helpful perspective on the nature of research endeavors, they can be tremendously enriched through suitable visualizations. Therefore, we also present a visualization method that aims to convey the degree of Integration (i.e. the diversity of knowledge sources) via overlays on a map of science.

Our findings suggest that although science is becoming more interdisciplinary, there are two sides to this growth. On the one hand, simple indicators of number of authors per paper and number of cited disciplines show a sustained and important increase (above 50%). On the other hand, in most fields, the new Integration score, in agreement with other sophisticated measures of diversity such as Shannon or Herfindahl index, show a more modest growth (mostly around 5%). The reason is that, although the total

² Our measures are based on the attribution of journals to ISI SCs in 2007 – hence they are not affected by previous changes in ISI categorization.

number of cited disciplines has increased, the distribution of citations occurs within neighboring areas and is only becoming a bit broader.

This article is organized as follows. Section 2 explains the methods used in some details. Section 3 presents the main results of the interdisciplinarity measures and the mapping. Section 4 summarizes and discusses the findings.

2. Methods

The computation and visualization of the interdisciplinarity measure has taken five steps, presented consecutively in this section:

1. Operationalization of an interdisciplinary measure (the Integration index or disciplinary diversity)
2. Construction of a similarity matrix among Subject Categories that is used to compute the Integration index
3. Grouping via factor analysis of the SCs into macro-disciplines using the similarity matrix as a base to facilitate visualization
4. Generating science maps
5. Selection of a bibliometric sample of 6 SCs, to serve as benchmarks here and in future explorations.

2.1. Definition of the integration score (Disciplinary Diversity Index)

Although interdisciplinarity has been explored using various research attributes (e.g., research formulation, team processes, collaborations, research outputs, dispersion, and impact), the National Academies definition given above suggests that the key aspect to check whether interdisciplinarity has been achieved is whether the research outputs reflect knowledge integration. In other words, since knowledge integration is an epistemic category, indicators of interdisciplinarity should be based on the content of the research outcomes rather than on team membership, departmental affiliations, or collaborations (see illustrations in case studies in RAFOLS & MEYER, 2007).

Here, we focus on research publications, in particular, journal articles. After investigation of the options available, we settled upon Web of Science as our essential data resource. While recognizing limitations of that source, we appreciate its substantial coverage of science, engineering, and medicine; its provision of citation information; and its categorization of research areas into SCs that correspond to disciplines. These offer a granular view – quite consistent with the National Academies Committee definition of interdisciplinary research. Thomson Scientific's Institute for Scientific Information (ISI) convenes editors who compose the SCs based on a combination of subject matter expert judgments and inter-journal citation patterns that, together, serve to cluster journals into topical groupings (the SCs). The bibliometric community has

noted that the SCs have some problems. In journal clustering exercises, only about 50% of clusters were found to be closely aligned with SCs [BOYACK & AL., 2005; (BOYACK, personal communication, 14 September 2008)]. Poor matching between SCs and classifications derived from citation networks has also been reported [LEYDESDORFF, 2006, p. 611], but surprisingly the mismatch only has limited effect on the corresponding science maps [RAFOLS & LEYDESDORFF, UNDER REVIEW]. Nonetheless, the SCs offer the most widely available categorization resource that we could ascertain for the purpose of providing an accessible measure of Integration. Note also that our categorization of articles is not based on individual article content analysis; rather we associate the journal in which an article appears to the SC (or SCs) into which ISI places the journal.

Over the past several years, we have been refining the NAKFI interdisciplinary metrics. The formulations have evolved somewhat, as detailed elsewhere [PORTER & AL., 2008]. This paper addresses samples of journal articles, for which Integration is the salient metric. As derived in RAFOLS & MEYER [forthcoming], the formula for the Integration index can be expressed as:

$$I = 1 - \sum_{i,j} s_{ij} p_i p_j$$

where p_i is the proportion of references citing the SC i in a given paper. The summation is taken over the cells of the SC x SC matrix. s_{ij} is the cosine measure of similarity between SCs i and j (the cosine measure may be understood as a variation of correlation). Here this matrix s_{ij} is based on a US national co-citation sample of 30,261 papers from Web of Science as explained below in detail.

This Integration measure (aka, Rao-Stirling's diversity³) can be compared with Shannon diversity:

$$S = - \sum_i p_i \log p_i$$

or with Herfindhal's diversity (the complement of Herfindahl's concentration):

$$H = \sum_{i,j(i \neq j)} p_i p_j = 1 - \sum_i p_i^2$$

³ STIRLING [2007] proposed as a general diversity heuristic, where diversity indices can be explored for different valuations of the properties of diversity – variety, balance and disparity in Stirling's framework – by changing the parameters α and β :

$$\Delta_{\alpha,\beta} = \sum_{i,j} (1 - s_{ij})^\alpha (p_i p_j)^\beta$$

Here we call Rao-Stirling diversity index the variant where $\alpha=1$ and $\beta=1$, initially introduced by RAO [1982]. Notice that the Herfindhal index is a particular case for $\alpha=0$ and $\beta=1$ (the summation then is restricted to i,j for $i \neq j$, since $s_{ii}=1$ by definition). For the particular case $\alpha=0$ and $\beta=0$, the index returns the total number of categories -another basic measure of diversity.

The power of the Integration index is that it characterizes interdisciplinarity in terms of the diversity of knowledge sources of papers, using a general formulation of diversity [STIRLING, 2007] rather than an ad hoc indicator. A number of researchers have used these traditional measures of diversity, such as Shannon or Herfindhal, to measure interdisciplinarity [E.G. GRUPP, 1990; HAMILTON & AL., 2005, or ADAMS & AL., 2007].⁴ These measures do not take into account how different the categories are, whereas our Integration measure reveals increased diversity only when added categories are significantly different. For instance, in agreement with Shannon and Herfindhal, an article that cites other articles that all appear in a single SC would have an Integration score of 0. However only in our Integration score would an article that cites articles appearing in two SCs that were extremely similar also have a score close to zero.

2.2. Construction of the similarity matrix among subject categories

Over the past five years, we have been developing the interdisciplinary metrics. The empirical base on which the calculations are based has been growing. In particular, a broad national sample of articles from WoS is used to create the s_{ij} matrix that underlies the metrics used for computing Integration. First we describe the sample used as a basis for the similarity matrix; second, the construction of the matrix.

We combine six separate weeks of all papers in WoS, with one or more authors having a USA address, sampled during 2005–2007, to obtain 30261 articles.⁵ This provides a broadly based, yet manageable base sample. We processed the “Cited References” of these abstract records to identify the “Cited SCs.” This poses challenges. These data come from WoS in somewhat varying formats. We use *VantagePoint* text mining software⁶ to process the cited reference information as follows:

- Extract the source (journal) information from each Cited Reference text string
- Apply a Find-and-Replace thesaurus to consolidate alternative term forms within the journal titles (e.g., “American” and “Amer” and “Am”)

⁴ ADAMS & AL. [2007] examine interdisciplinarity for a sizable set of articles from two research universities, looking backward (at cited references) and forward (to articles citing these). They employ three indices – proportion of citations outside source category, # of cited categories, and Shannon diversity index. They use a different set of 106 subject categories from Thomson’s Current Contents; these compare to those we use from WoS as somewhat less granular. They report strong correlation between subject category diversity (Shannon index) based on cited vs. citing articles.

⁵ We excluded the other 22 document types included in the sample of 44239 records (e.g., meeting abstracts, book reviews, editorials, reviews, letters). In particular, inclusion of reviews that may reference huge numbers of journal articles could alter co-citation-based relationships.

⁶ See www.theVantagePoint.com

- Apply a thesaurus that associates journals to SCs.⁷ [About 39% of journals are associated with more than one SC.]
- Check results and iteratively improve the matching thesauri. [This has been done at least 6 times on portions of these data.]

The process captures a high percentage of the oft-cited journals. Our sample of 30261 WoS articles contains 1,020,528 cited references (an average of 33.7 per article). Of those, our thesauri link 768,440 to a particular Subject Category. Another 28,000 have been checked and assigned to “not being in an SC.” So, in terms of cited reference frequency, we are properly addressing almost 80% of them.

Our sample addresses all the SCs covered in WoS – i.e., Science Citation Index, Social Science Citation Index, and Arts & Humanities Citation Index. That set evolves, so the number of SCs changes over time. For our purposes in addressing *cited SCs*, the list includes a few more than the current set, for a total of 244 SCs. The sample contains 1,114,930 instances of cited SCs. The range for individual SCs stretches from only 4 cites of articles published in journals associated with “Dance” to 78,148 cites associated with “Biochemistry and Molecular Biology.” Our sample has at least 500 cites to 190 of the SCs (77%); it has at least 100 cites for 226 of the SCs (93%). Generally, citation of each SC is substantial, except for many arts and humanities SCs that are infrequently cited.

The 30261 articles, by 244 SCs, described allow for construction of a co-citation similarity matrix, s_{ij} , using Salton cosine [SALTON & MCGILL, 1983; AHLGREN & AL., 2003]. To test the results obtained with this matrix, we have used a second similarity matrix, based on Salton’s cosine similarities between SCs using all the ISI data for 2007, as detailed in LEYDESDORFF & RAFOLS [2008]. This procedure resembles that of the co-citation of SCs used by Moya & al. to generate a map of science [MOYA & AL., 2004; 2007]. We considered adjusting for expectancies, but chose the widely used cosine measure for these large sample analyses [KLAVANS & BOYACK, 2006]. The values of s_{ij} are high (i.e. closer to one) when SCs i and j are co-cited by a high proportion of articles that cite one or the other. The cosine value approaches zero when two SCs are rarely cited together. That is, if articles often reference two SCs, say, “materials science, multidisciplinary” and “nanoscience & nanotechnology,” there is a presumptive degree of association.

⁷ Thomson Scientific’s Institute for Scientific Information (ISI) kindly provided the base thesaurus that listed 16036 journal entries (for 10550 journals), showing full journal name, a 29-character abbreviation, an 11-character version, and the corresponding SC. WoS Cited References approximate the 29-character version, but are not fully standardized. Over time as we run various analyses, we check for unmatched journals against name variations and in the Web of Knowledge Journal Citation Reports to enhance the J-SC thesaurus (currently up to 27144 entries).

2.3. Aggregation of SCs into macro-disciplines

For various purposes and in particular for visualization, it helps to consolidate the narrow research areas of the ISI SCs into larger categories, which we call “macro-disciplines.” Since there is no established, widely accepted “best grouping,” we determined to derive our own from observed relationships among the SCs based upon the s_{ij} similarity matrix (i.e. their co-citation in articles).

We base our grouping of SCs on a type of factor analysis – Principal Components Analysis (PCA) – following a similar methodology to that developed by LEYDESDORFF & RAFOLS [2008] to cluster SCs into macro-disciplines. Within *VantagePoint*, we constructed the matrix of cosine similarities for the 244 cited SCs by 244 cited SCs described in the previous section. That was exported to MS Excel and thence into SPSS. We explored various factor analysis solutions, eventually adopting a 20-factor solution (Varimax rotation).

We located each SC on a single factor, that on which the SC loaded highest. In earlier explorations, we were tempted to fine-tune these assignments. However, in comparing factor solutions, we have come to believe the statistical assignments are at least as good as any refinements we might attempt. We compiled a 21st “factor” of the SCs without substantial loading on any factor. These consisted of 8 “Literature” SCs and 8 additional “Arts” SCs (e.g., Theater, Medieval & Renaissance Studies, Poetry, Dance). The 21 macro-disciplines reflect this factor solution.⁸

Appendix A gives the resulting assignment of Subject Categories to macro-disciplines. By and large, these are reasonably intuitive. That said, many individual SC assignments lead one to wonder about alternatives – might the SC load heavily as well upon another macro-discipline? We examined the high and low loading SCs for each macro-discipline (the Appendix lists SCs within macro-discipline in descending degree to which they relate to that factor). Indeed, some SCs do relate to more than one macro-discipline – e.g., “Industrial Relations & Labor” loads 0.27 on “Industrial Engineering & Management Science,” versus 0.24 on “Policy Sciences.” Very few SCs show secondary loadings that would lead us to seriously consider reassignment. Given that, we retain the statistically based assignments of SCs to macro-disciplines. However, the readers should keep in mind these science maps contain areas of ambiguous attribution – and some of the macro-disciplines (e.g. Reproductive Sciences) are less robust groupings than are others. In naming, we placed emphasis on those SCs that load more highly on the given factor to best characterize that macro-discipline. Naming criteria were brevity (to not unduly clutter the science maps) and clarity, so that all would

⁸ To see whether additional structure was warranted for the arts and humanities, and to check the location of the social science SCs, we ran a supplemental sample of 4590 articles from the Arts and Humanities Citation Index (AHCI). Various factoring solutions did not ascertain finer arts and humanities structuring or suggest significant relocation of particular SCs among the macro-disciplines (factors). So, we retain a 21st “Literature & Arts” factor in our science map.

understand their thrust. Behavior of the SCs that include a traditional discipline in their name (e.g., “Chemistry, Analytical”) is interesting. We were curious as to whether the seven such Chemistry SCs would form distinct factors (i.e., our macro-disciplines). They do generally coalesce, but not completely. For instance, 5 of the 7 Chemistry SCs consolidate in the macro-discipline which we name “Chemistry.” Likewise, 5 of 8 Physics SCs load on the “Physics” factor; and 6 of 11 Psychology SCs fall in “Cognitive Sciences.” However, only 5 of 17 Engineering SCs group with “Engineering Sciences”; the others divide among 6 other macro-disciplines. (See Appendix A for details.)

So, to a considerable degree, named sub-disciplines do not fully coalesce within a single macro-discipline. This warns that the evolving research enterprise does not neatly conform to the traditional scholarly disciplines. So, as we measure degree of interdisciplinarity, reliance on traditional disciplinary labels is not necessarily the most valid approach.

2.4. Science mapping approach

Our science maps help one perceive the diversity of SCs on which a given set of publications draw. These maps present the SCs, their relative importance in size, and how related they are to each other over all science. The main aim of these science maps is to locate particular bodies of research among the macro-disciplines. Building on the overall science interrelationship representation (as already developed by CHEN [2003] or BOYACK & AL. [2005]) among others, here we mainly seek a base upon which to situate particular research cases. That can help identify changes in degree of interrelationship over time, and key cross-“disciplinary” relationships that might benefit from nurturing.⁹ It should also be informative to see whether knowledge sources of a set of publications are coming from research domains that are closely related (little interdisciplinarity) or that span very disparate domains (high interdisciplinarity).

These maps are constructed using the cosine similarity matrix s_{ij} among SCs, then running factor analyses to find the macro-disciplines (following, until this stage, the method used by LEYDESDORFF & RAFOLS [2008]). We then construct a new Salton cosine similarity matrix among SCs using the loadings of each SC on the 21 factors (as discussed in the previous subsection). This matrix is then uploaded into the network analysis software Pajek [BATAGELJ & MVAR, 2008]. In Pajek, the minimum similarity threshold was arbitrarily set to 0.6 (this choice was found to provide a good readability-to-accuracy trade-off) and the SCs were distributed in a 2-D plane according to their similarities, to obtain a base science map. Finally, for each particular case, the proportions of citations of each SC, p_i , are uploaded as a vector to represent the

⁹ For other analytical purposes it may be vital to examine relationships at the finer level of particular SCs. On our websites, we will provide individual SC labeling to aid in recovering such specifics from these maps.

distribution of cited SCs for that case (see RAFOLS & MEYER, forthcoming, for more details). Using only 21 factors [see Footnote 10], which explain 40% of the variance, is a major simplification, but it was found to be the most effective way of achieving good readability in the 2-D projections. As is always the case in 2-D or 3-D representations of highly multidimensional spaces, there is a trade-off between readability and accuracy. We are making the essential elements available on our websites to enable others to map their own cases over this base “science map.”

2.5. Sample characterization

We selected 6 of the 244 Subject Categories to benchmark research behavior. We sought to compare both across research fields (the 6 SCs) and over time (sampling in 1975, 1985, 1995, and 2005). For each SC and year we gathered on average about 1000 articles (the smallest and largest samples have 294 and 1910 articles respectively). The process of selecting this sample of 6 SCs involved many tradeoffs, but keyed on spanning US National Academies’ interests in science, engineering, and medicine. We initially studied 3 SCs, then expanded by another 3 to broaden coverage. The six selected SCs are:

- Biotechnology & Applied Microbiology [Biotech]
- Engineering, Electrical & Electronic [EE]
- Mathematics [Math]
- Medicine – Research & Experimental [Medicine-R&E]
- Neurosciences [Neurosciences]
- Physics – Atomic, Molecular & Chemical [Physics-AMC]

We sought variety in terms of traditional vs. emergent, and basic vs. applied, research domains. Previously we have profiled 22 SCs [PORTER & AL., 2008]. There, we had analyzed samples of about 100 papers published in 2005, associated with the particular SC. We initially sought to replicate those analyses for other years, but decided that we wanted larger (more robust) article sample sets. In the process of choosing SCs for presumed diversity in research approach, we picked one that was not included in the set of 22 SCs – namely, Math.

3. Results:

Evolution of interdisciplinarity in 6 research fields (1975–2005)

How interdisciplinary is science? In order to investigate this issue we analyze sets of articles representative of those published in journals associated with 6 WoS SCs, at 10-year intervals. For each set we compute multiple measures, each of them providing a perspective on interdisciplinarity. We key on the Integration score (aka Rao-Stirling

diversity), but want to examine it together with other basic indicators. Since interdisciplinarity is inherently multidimensional, examining a variety of perspectives (indicators) can both enrich and validate the new metric, Integration.

In this section we first present the quantitative measures of interdisciplinarity and then explore how science mapping can help to illustrate these results. Further results of the analysis are available at Appendix B, posted on our websites.

3.1 Indicators of interdisciplinarity

Citations within subject category. Table 1 and Figure 1 present the percentage of Citations within SC for each of the six SCs under study. This indicator partially captures one of the aspects of diversity – namely the balance in the distribution of citations. Note that the size of SCs varies greatly. Physics-AMC contains only 32 journals as of the 2007 Journal Citation Reports, whereas EE contains 227.¹⁰ Interestingly, the percentage of citations to journals within the article's own SC is not a simple function of SC size. For instance, note that the tiny SC, Physics-AMC, is quite inclined to reference articles published in Physics-AMC journals. Its concentration in 2005 is quite similar to that for two huge SCs – EE and Neurosciences. Two of these six SCs might be deemed “undisciplines” – i.e., those drawing relatively little on prior work published in their own SC. Those two, Biotech and Medicine-R&E, are of moderate size. Math provides another point of contrast. It behaves the most like one might have anticipated a strong “discipline” to do, primarily citing research published in Math journals. The Math SC contains a lot of journals, but so do EE and Neurosciences (Table 1).

Table 2 presents essential empirical results concerning research published in journals associated with the six SCs from 1975 through 2005. In the following paragraphs and figures we will focus on each of the measures.

Indicators of collaboration. Since research collaboration is often (and sometimes mistakenly) associated with interdisciplinarity, we examine measures of co-authorship. Figure 2 shows the number of authors per paper. This varies notably by field, with Math the stingiest and Medicine-R&E the most generous. The ordering by fields remains quite steady across these three decades. However, within research domain, the number of authors per paper has escalated remarkably, with about 75% average growth. This increase ranges from 48% in Math and 54% in Physics-AMC to 90% in Neurosciences.

¹⁰ This recent value is the pertinent size to consider here as we used a currently derived thesaurus to associate journals to Subject Categories.

Table 1. Percentage of citations within subject category

	Biotech	EE	Math	Medicine R&E	Neurosci	Physics – AMC
# Journals SC, 2007	138	227	207	81	211	32
Cited SC instances within SC, 1975	14.0%	25.9%	79.1%	15.0%	24.8%	44.2%
Cited SC instances within SC, 2005	11.0%	29.1%	69.1%	9.3%	30.3%	28.0%

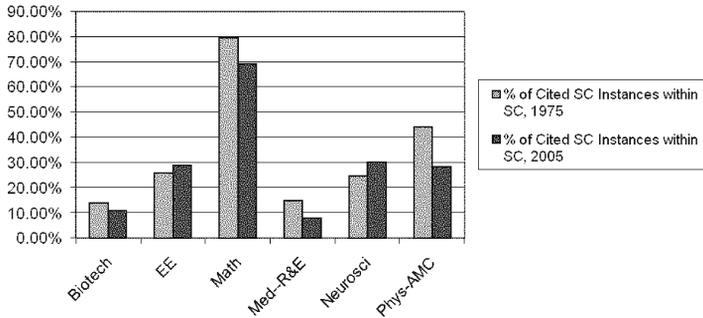


Figure 1. Percentage of citations within field

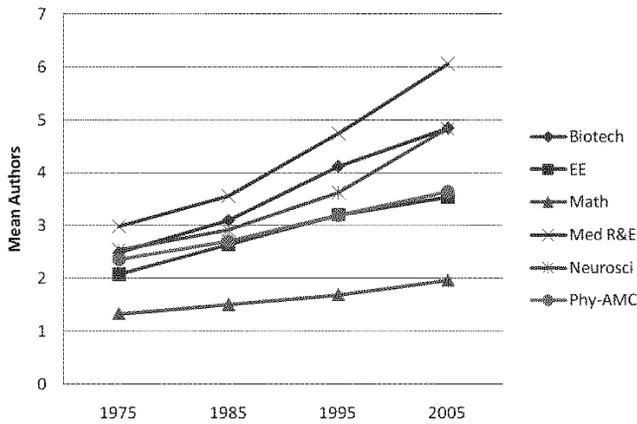


Figure 2. Number of authors per paper over time

ABT [2007A] notes that many have observed the increase in number of authors per paper over time. He gathers data from 64 leading journals in 16 *Journal Citation Reports* categories (these don't map directly to the WoS SCs) for 2004. He finds an average of 5.5 authors per paper, ranging from 2.8 in Math to 9.4 in Physics. He also finds the percentage of single-authored papers to average 6.6%, with Math, Physics, and Astronomy the only categories averaging over 10%. In another paper ABT [2007B] compiled data on single-authored papers in four fields over the period, 1975–2005. For astronomy, the drop over this period (averaged for four important journals) was

from 44% to 10%; in physics and in biology, from about 40% to just under 20%. Chemistry drops from about 12% to 4%. Our results reinforce his with somewhat more encompassing datasets. The message is clear – norms vary by field, but all show a tendency toward increased collaboration.

Table 2. Interdisciplinary facets of articles published in 6 subject categories over time

SC	Year	Sample Size	Authors /Paper			%Single-Authored	Cited References			# of Cited Subject Categories			Integration Score		
			Mean	SD	Mdn		Mean	SD	Mdn	Mean	SD	Mdn	Mean	SD	Mdn
Biotech	1975	294	2.49	1.17	2	14.6%	20.75	11.97	18	7.29	3.30	7	0.613	0.124	0.632
	1985	382	3.10	1.61	3	8.1%	24.93	14.01	22	8.27	3.52	8	0.620	0.123	0.637
	1995	840	4.12	2.70	3	7.5%	31.23	16.86	28	9.42	3.84	9	0.594	0.119	0.614
	2005	990	4.84	3.31	4	4.5%	36.29	18.57	33	12.74	5.04	12	0.654	0.101	0.665
EE	1975	963	2.08	1.33	2	38.7%	15.86	15.82	12	4.53	2.56	4	0.513	0.175	0.537
	1985	1382	2.64	1.93	2	26.5%	17.44	14.55	14	4.83	2.63	4	0.514	0.166	0.534
	1995	1719	3.21	1.99	3	11.8%	18.39	12.55	16	4.96	2.91	4	0.501	0.168	0.508
	2005	1797	3.55	2.34	3	6.5%	21.42	13.62	18	5.95	3.94	5	0.533	0.175	0.546
Math	1975	1081	1.33	0.56	1	70.9%	12.77	8.66	11	2.16	1.25	2	0.211	0.192	0.194
	1985	767	1.51	0.71	1	59.8%	15.16	9.93	13	2.73	1.84	2	0.276	0.229	0.261
	1995	658	1.70	0.76	2	46.5%	17.90	11.42	15	3.04	2.10	2	0.283	0.225	0.261
	2005	684	1.97	1.09	2	36.5%	20.19	11.30	17	3.21	2.23	2	0.293	0.223	0.279
Med-R&E	1975	1067	2.99	1.43	3	12.5%	23.14	12.56	21	8.81	3.52	9	0.631	0.109	0.652
	1985	730	3.57	1.88	3	10.5%	27.66	15.26	24	9.54	3.88	9	0.636	0.106	0.655
	1995	664	4.75	2.95	4	9.6%	33.65	16.49	32	11.19	4.37	11	0.639	0.103	0.655
	2005	775	6.06	4.38	5	8.3%	37.60	19.75	35	12.90	5.06	13	0.664	0.097	0.675
Neurosciences	1975	822	2.54	1.19	2	16.4%	28.66	16.22	25	8.94	3.27	9	0.620	0.109	0.635
	1985	1377	2.91	1.45	3	13.0%	32.65	17.61	30	9.42	3.55	9	0.611	0.100	0.621
	1995	1910	3.63	2.11	3	7.9%	42.53	21.00	40	10.86	4.07	10	0.608	0.105	0.613
	2005	1768	4.84	2.68	4	3.7%	46.76	20.50	44	13.43	4.95	13	0.637	0.097	0.651
Physics-AMC	1975	1407	2.36	1.08	2	19.3%	24.16	14.80	21	6.04	2.65	6	0.525	0.151	0.553
	1985	1054	2.71	1.47	2	15.9%	26.53	17.45	23	6.57	2.86	6	0.544	0.162	0.569
	1995	1017	3.20	1.94	3	10.0%	33.40	18.74	30	7.55	3.10	7	0.557	0.139	0.568
	2005	804	3.64	2.38	3	7.1%	35.40	17.43	31	8.70	3.57	8	0.601	0.120	0.612

Note to Table 1: Sample sizes vary as a function of the total available articles published in a given year in that SC as a maximum, with the aim of obtaining ~300 or more as a minimum. Within that range, the size reflects convenience in data downloading from WoS. For extremely large article sets, we developed a sampling frame; for moderate article sets, we downloaded them all. We then processed the downloaded set using a special macro (programmed routine) to calculate Integration for each article semi-automatically using *VantagePoint*.

A closely related statistic tells a similar story – Figure 3 shows the decline in single-authorship. Even as long ago as 1975 in most of these fields, single-authored papers were relatively rare.¹¹ Math was a strong exception and EE also evidenced a lot of individual research. In all of these SCs, except Math, single-authored articles now constitute fewer than 10% of the WoS publications.

¹¹ These figures can be compared with the time series of single authorship over all fields from 1900 to 1960 by PRICE [1986] and more recently by HICKS & KATZ [1996, p. 392].

The results support the view that publishing in teams (co-authoring) is now the dominant form of research. However, as we will see, this increase in working in teams should not be equated with interdisciplinarity.¹²

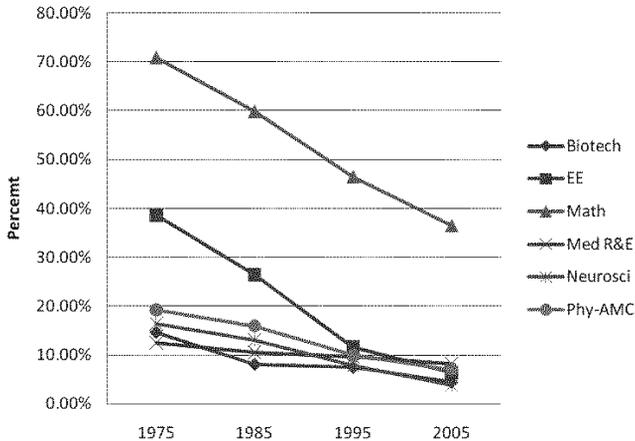


Figure 3. Single-authored papers over time

Number of cited subject categories. Before turning to Integration scores, we consider the number of distinct SCs that one article cites. This is a relatively raw measure, but one that should correlate somewhat with Integration. Table 2 and Figure 4 show a sturdy increase in the breadth of citing in all six of these research domains (about a 50% growth on average).

As indicated in Table 1, care should be taken in directly comparing such citation behavior across SCs because they differ in size of their journal pool. Nevertheless, journal pool size alone does not account for the wide variation in researcher outreach to knowledge from other SCs. EE, Math, and Neurosciences are similar in journal set size (all very large). But, the average Math article published in 2005 cites only 3 SCs (presumably often including itself); the EE article, 6; and the Neurosciences article, 13 SCs.

Since the linking of a publication (journal) to an SC is based on a recently constructed thesaurus, temporal comparison is not inherently clouded by changes in SC inclusivity over time. Nonetheless, a number of potentially confounding factors caution against easy conclusion of increasing interdisciplinarity. For instance, publication norms encouraging more referencing (see Table 2) are strongly evidenced from 1975–2005 for all six fields.

¹² Moreover, we have to keep in mind that co-authorships are the result of very different types of collaboration practices (agreements between labs, recruitment, materials or facilities support, etc.) leading to publication co-authorship, and that not all forms collaboration not captured by co-authorship [CRONIN, 2001; GLÄNZEL, 2002; LAUDEL, 2002; RAFOLS, 2007].

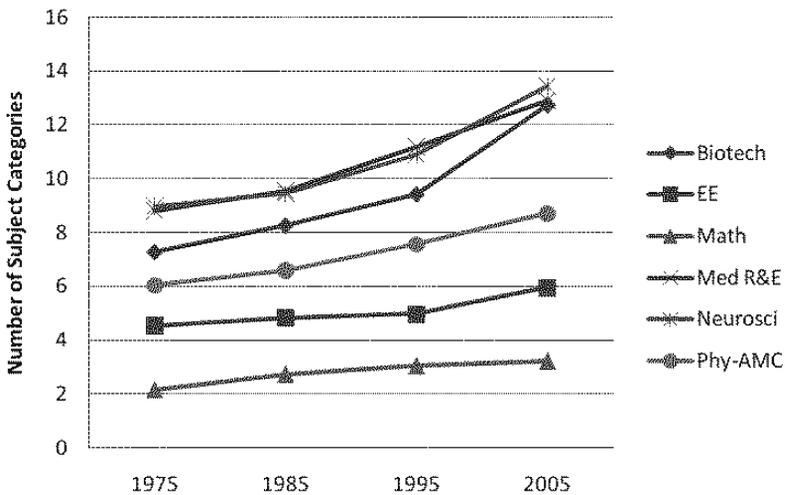


Figure 4. Change in number of subject categories cited, over time

Integration Score. Integration scores are tabulated in Table 2 and shown in Figure 5. We see that over time, there is a modest increase in Integration scores and that math researchers are notably less integrative in their citing patterns. However, math has the highest relative growth (39%) whereas other SCs' growth ranges from 3% to 14% (5% on average). t-tests between the 1975 and 2005 samples show these differences to be highly significant ($<.005$ for EE, assuming either equal or unequal variances; all others even more highly significant). One-way analyses of variance for the two series for which differences among the four samples appear more questionable (EE and Neurosciences) yield F statistics significant at $<.001$.

In order to better understand the Integration score, we compared it with the more traditional Shannon and Herfindhal indicators of diversity (see the methods section for the equations). Pearson's correlation between Integration and Herfindhal takes a mean value of 0.91 (standard deviation = 0.07) and between Integration and Shannon, a mean value of 0.88 (standard deviation = 0.07).¹³ These high correlations confirm that Integration is very closely associated with traditional diversity indicators – as could be expected by construction.¹⁴

¹³ The correlation between Herfindahl and Shannon is 0.94 with standard deviation = 0.02.

¹⁴ These integration scores were generated using the similarity matrix between SCs introduced in the methods (based on samples of 30000). We have checked that very similar results were obtained with a different similarity matrix based on all the ISI database, computed for 2007 following the LEYDESORFF & RAFOLS [2008] methodology. Using this other matrix, which has higher s_{ij} values, most integration scores take values between 0.35 and 0.45. Notably, the correlation with Herfindahl and Shannon indices drop to a 0.5-0.8 range – particularly for the most integrative SCs, such as Neurosciences. This empirical result supports the

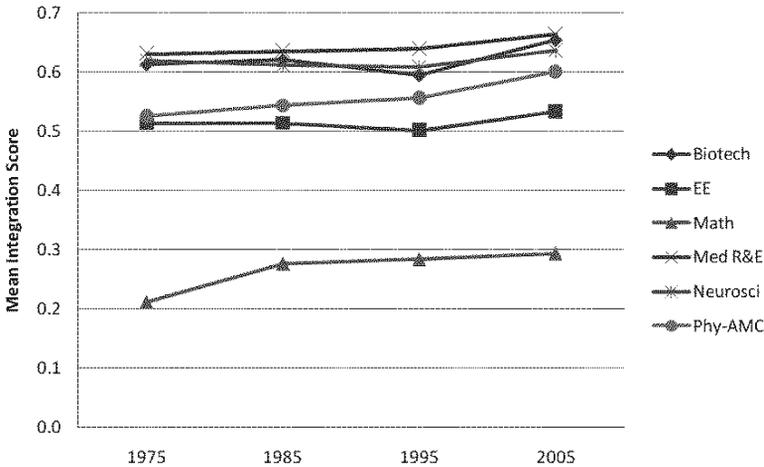


Figure 5. Change in integration scores over time

The main finding is that Integration scores increase over time, but significantly less so than other indicators, such as percentage of singleauthored papers, mean authors per paper, and mean number of disciplines per paper. Why is this? We believe there are three compounded reasons:

- First, although the number of cited SCs increases significantly, since the average number of references in a paper also shows a quicker increase (see central columns in Table 2), the actual change in the proportions of citation to different SCs is not as important as could be expected. In other words, although there are more SCs cited in 2005 than in 1975, the proportions contributed by the newly cited SCs are rather small.¹⁵ We believe that this is the reason for the slight decrease in Integration scores in 1995 for Neurosciences, EE and Biotech.
- Second, as we will show in Figures 7 through 10, the citation patterns of a given SC tend to be with SCs in its vicinity. Since these neighboring SCs have high similarity values with the one investigated, their contribution to Integration (to diversity) is smaller than in other indicators.

theoretical expectation that corrections to traditional diversity indicators will be most important in research areas where there are major overlaps among SCs (e.g., more important in biomedical sciences than in math).

¹⁵ This observation is corroborated by the fact that the Shannon index (which gives higher weight to smaller proportions than the Integration score or Herfindahl), shows a slightly more pronounced increase of diversity over time (data not presented).

This means that the Integration score “deflates” the diversity recorded by Shannon or Herfindahl because most of the cited SCs are not very different from the SC doing the citing.¹⁶

- Finally, but possibly less important, diversity indicators such as Shannon and Herfindahl (i.e. including our Integration score) have a saturation effect: an increase from 8.9 to 13.4 cited SCs (as in Neurosciences) has much less weight than an increase from 2.2 to 3.2 SCs (as in Math). Diversity is viewed as increasing proportionately more in the second case. This may explain why the increase of Integration score for Math is more prominent than for the other SCs analyzed.

Hence, the main conclusion of the reading of the trend in Integration scores, as presented in Figure 5, is that we should be cautious regarding the increase of interdisciplinarity. Yes, there is an increase in the number of disciplines cited, but their relative increase, the proportion of the newly cited disciplines, and their degree of disparity are not as large as suggested by previous indicators.

3.2. Mapping of disciplinary diversity

Indicators of interdisciplinarity provide us a guide regarding the trend in interdisciplinarity of a given SC, but they do not provide details regarding the areas on which this SC draws. This is much easier to convey using science maps that directly show the three aspects of disciplinary diversity, namely:

1. the variety of “disciplines” (i.e., discrete research areas, the SCs, shown by the number of nodes in the map)
2. the balance, or distribution, of disciplines (relative size of nodes)
3. the disparity, or degree of difference, between the disciplines (distance between the nodes)

As explained in the methodology, the cosine similarity matrix among SCs allows us to construct a map of science, as shown in Figure 6, which aims to represent in a 2-dimensional space how similar the SCs are. For example, it conveys in an intuitive

¹⁶ An examination of the matrix, s_{ij} (to be posted on our website) shows that most of the values are close to 0 – which explains why the correction of Shannon or Herfindahl values has been smaller than initially expected. In the current formulation this matrix does not seem to make enough difference between SCs which are slightly related (e.g. Astronomy vs mathematical physics $s_{ij}= 0.012$) and SCs which are unrelated (e.g. Astronomy and Physiology $s_{ij}= 0.003$). For example, consider the changes seen between 1975 (Figure 7) and 2005 (Figure 8) of the distributions of the least cited SCs by Biotech in the map of science (e.g., the appearance in 2005 of a small but significant contribution from Materials Sciences and Mathematics not present in 1975). The fact that the Integration score cannot fully capture these differences points to the need for re-framing our understanding the exploration of these indices as “heuristics” to make manifest different aspects of diversity, rather than aiming at self-contained, black-box indicators. See STIRLING, 2007, and RAFOLS and MEYER [forthcoming], for a discussion of the “heuristics” approach.

way that Materials Sciences are closely associated with Physics; indirectly connected to Ecological Science via Chemistry, and to Environmental Sciences; but very distant from Clinical Medicine. However, since this is 2-dimensional representation (a reduction of 242 dimensions for the set of SCs!), it fails to show that there is one SC, namely Biomaterials, that lies in the Clinical Medicine area (as shown from the factor analysis), but has a strong connection with Materials Sciences.

These maps were created followed the techniques developed in LEYDESDORFF & RAFOLS [2008], in the context of the current interest in science mapping [MOYA-ANEGON & AL., 2004; BOYACK & AL., 2005; MOYA-ANEGON & AL., 2007]. We have recently verified that for a given methodology of visualization, the maps are surprisingly robust to very different categorizations [RAFOLS & LEYDESDORFF, under review]. In the figures presented in this article, we only label groups of SCs on the basis of macro-disciplines found by factor analysis, as explained in the methodology. However, the same maps with detailed labeling of each SC will be found on our websites (which will also include an open KIT for the construction of maps with other data).¹⁷

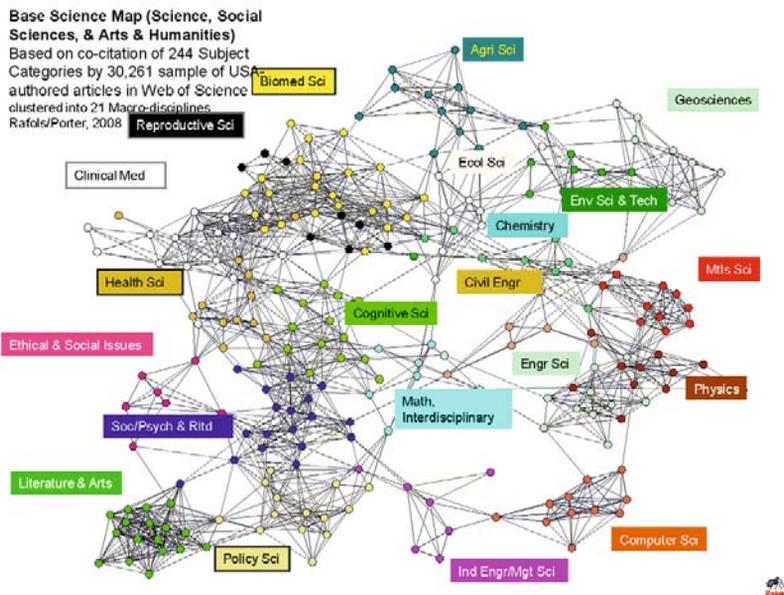


Figure 6. Base map of science

¹⁷ See www.sussex.ac.uk/spru/irafols and <http://tpac.gatech.edu/>

Figures 7 and 8 overlay Biotech Cited SCs over the base map in 1975 and 2005. The size (area) of nodes is proportional to the number of citations to a given SC by articles in the Biotech SC. The maps illustrate how Biotech research has changed over three decades:

- The Biotech SC is located in the Biomedical Sciences macro-discipline (see Appendix A for the full macro-discipline names in case the shorthand names need explanation). The heavy concentration of citations by Biotech papers is on Biomedical Science SCs in 1975 and in 2005.
- Several nearby macro-disciplines are cited to a considerable degree, as well, in both years.
- Macro-disciplines increasingly cited in 2005 include: Ecol Sci; Math, Interdisciplinary; Clinical Med, Reproductive Sci – perhaps suggesting that Biotech is becoming increasingly useful in clinical applications.
- Materials Science areas show up in 2005 – it could prove interesting to explore what is taking place at the intersection of Biotech and Materials Sciences.
- The Computer Sciences appearing in 2005 may reflect the advent of bioinformatics, which did not exist in 1975.

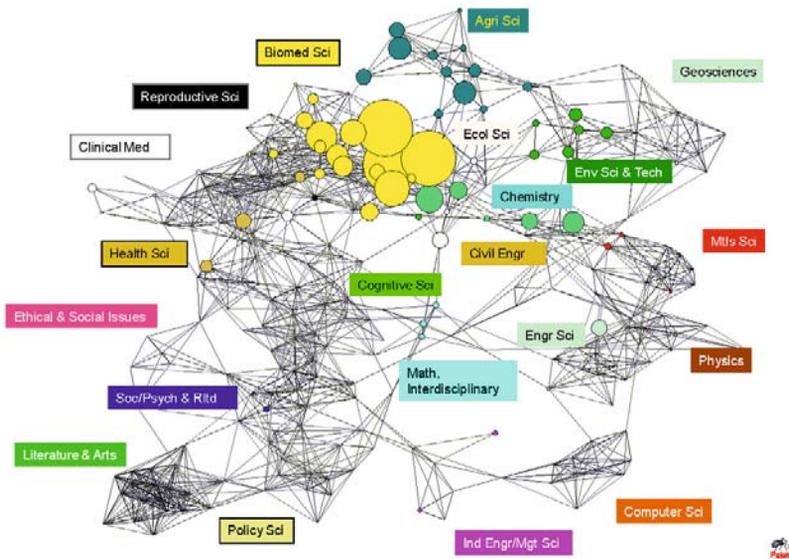


Figure 7. Biotech-1975 citation pattern (overlaid on the map of science)

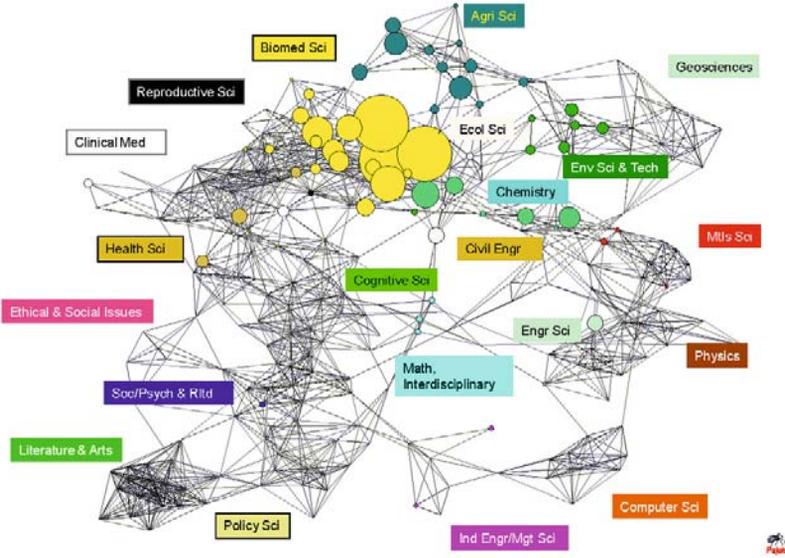


Figure 8. Biotech-2005 citation pattern

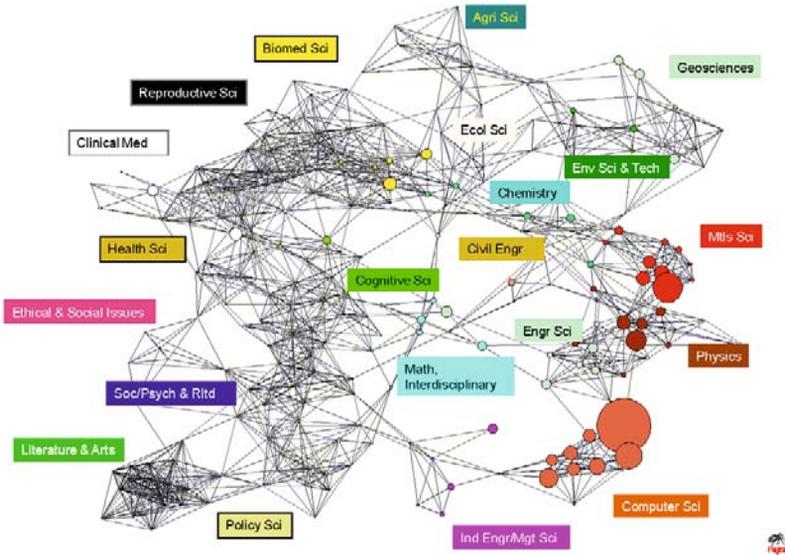


Figure 9. EE-2005 citation pattern

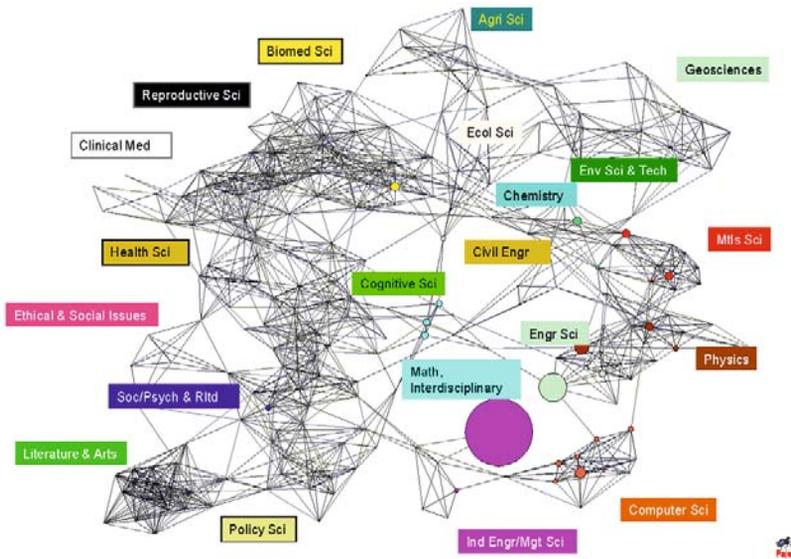


Figure 10. Math-2005 citation pattern

Figures 9 and 10 show how science maps allow the visualization of comparison between two different SCs, in this case EE and Math – confirming visually the results obtained with the indicators of interdisciplinarity (e.g. in Figures 4 and 5) – the degree of interdisciplinarity of EE falls between that of Biotech and Math.

Figure 9 helps us to “see” why the factor analysis locates EE with Computer Science instead of Engineering Sciences (as one might have expected): most of its citations fall in the former rather than the latter. The strong secondary concentration in Materials Science stands forth boldly as well. Some of the SCs that EE-2005 cites highly from this macro-discipline are: Physics, Applied; Materials Science, Multidisciplinary; Physics, Condensed Matter; and Nanoscience & Nanotechnology. In addition we see heavy citing of the Physics macro-discipline.

Math is by far the most monodisciplinary of these six SCs. It is clear that Math research draws primarily upon prior Math research. Most intriguing is to see the macro-disciplines to which the highly cited SCs have been assigned. Math itself is located in the macro-discipline (PCA factor) that we named Industrial Engineering/Management Science. “Mathematics, Applied” is located in the Engineering Sciences macro-discipline,¹⁸ while “Physics, Mathematical” lies in Physics. Other SCs on which Math draws heavily are quite dispersed.

¹⁸ Checking the factor solution, we see that “Mathematics, Applied” is strongly related to four of the Macro-disciplines: Engineering Sciences (loading 0.52), Computer Science (0.32), Physics (0.18) and Math, Interdisciplinary (0.16).

Here, we are using the science overlay maps mainly to enrich understanding of the interdisciplinarity metrics. We believe that these visualization tools can be used for a variety of purposes, including research profiling, identification of new methods and findings (“science intelligence”), and research evaluation. Further details and analyses of the other SCs investigated here are provided in Appendix B, to be posted on our websites.

4. Discussion and conclusions

In this article we have investigated how the degree of interdisciplinarity has changed between 1975 and 2005 for six research domains, including both long-established (e.g., Math) and relatively newly formed ones (e.g., Neurosciences). In so doing, we compute both widely used indicators of interdisciplinarity and a new index of diversity (Rao-Stirling index or Integration score) that we have developed recently [PORTER & AL., 2007; RAFOLS & MEYER, forthcoming], and provide a visualization method based on overlay science maps [LEYDESDORFF & RAFOLS, 2008]. We believe that the combination of interdisciplinarity metrics with science mapping enables us to characterize and track research interdisciplinarity with a detail not previously available.

The Integration score proposed not only takes into account the number of disciplines and their distribution, but it incorporates a measure of how distant the knowledge sources are (in this instance in terms of WoS SCs). To “deflate” the counting of disciplines including distance is very important because most classifications of science (and particularly the most widely used, i.e., the SCs from the WoS) have many categories strongly intersecting with each other [RAFOLS & LEYDESDORFF, under review] – which leads to an overstatement of the degree of interdisciplinarity. This is apparent in the maps of science, when different categories “pile up” in the same region.

The results on profiles of research articles in six SCs over the period, 1975–2005, attest to notable changes in how research is conducted. Particularly striking is the extent to which research is now a team effort. In all of these SCs, except Math, single-authored articles now constitute fewer than 10% of the WoS publications in 2005. Research papers in 2005 cite many more references (more than 50% growth, on average), and these draw upon about 50% more SCs than did counterpart papers in 1975. The average number of cited SCs per article is very dependent on the SC doing the citing – from averages of only 2 or 3 in Math to 13 in Neurosciences. From this perspective, the measures of interdisciplinarity indicate considerably greater interchange of research knowledge than many of us anticipated. Except for certain disciplines, such as Math, by no means is modern research knowledge exchange restricted within narrow silos.¹⁹

¹⁹ This result should not be interpreted as meaning that researchers are not specialized. It suggests that most publications cite various and increasingly more disciplines, although they are possibly specialized in terms of topic (an issue we have not covered here –see PORTER et al. [2007] and RAFOLS and MEYER [forthcoming] on indicators of specialization).

However, the perspective provided by the Integration score and the science maps suggests that the practice of interdisciplinarity in citations occurs mainly between neighboring SCs and has undergone a much more modest increase (on average only 5%, excluding math). This is mainly for two reasons: first, although the number of cited SCs has increased, the growth of citations means that the increase in the proportion of citations to new SCs is small; second, the newly cited SCs tend to be in the vicinity of the previous ones – hence they don't add as much interdisciplinarity as they would if they were very disparate/distant disciplines. Moreover, for already very interdisciplinary SCs, such as Neuroscience, the indicator may have a certain “saturation” effect.

In summary, science is indeed becoming more interdisciplinary, but in small steps. Research knowledge transfer, as evidenced by citation, draws mainly on neighboring fields. Only slowly do we see increase in the small proportion of sources from more disparate disciplines.

The study of the six research domains examined here is not only interesting on its own right to track the evolution of interdisciplinarity over time, but it also provides essential *benchmarks* for future investigations. By giving these profiles of cited SCs, Integration scores, and other indicators for six SCs representing quite diverse scientific areas, we (and hopefully other researchers) can build upon these results to investigate interdisciplinary practices for specific research topics, scientific communities, or organizations. For instance, NAKFI can compare the research of attendees at its conferences to these benchmark SCs. These benchmarks and the maps will serve both the aims of research intelligence (e.g., “surmising” possible cognitive complementarities) and evaluation (e.g., to monitor whether their research practices change as a result of a policy initiative such as NAKFI).

*

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Appendix A:
Assignment of subject categories to macro-disciplines

Full macro-discipline names (in the order they appear on these pages)

Biomedical Sciences
Reproductive Sciences
Clinical Medicine
Materials Sciences
Engineering Sciences
Civil Engineering
Computer Science
Mathematics, Interdisciplinary
Health Sciences
Ecological Sciences
Environmental Science & Technology
Agricultural Sciences
Geosciences
Industrial Engineering and Management Science
Cognitive Sciences
Social/Psychological & Related
Policy Sciences
Chemistry
Physics
Ethical and Social Issues
Literature and Arts

The macro-disciplines have been generated by Principal Components Analysis (PCA) applied to co-citation data for a large sample of articles from Web of Science. The process is described in Section 2.3. A listing of the Web of Science (WoS) Subject Categories (SCs) associated with each of the 21 Macro-disciplines is given in the Supplementary Materials (see below). The SCs are ordered within macro-discipline in this listing according to the strength of their loading on that PCA factor.

Supplementary Materials

Supplementary Materials provided on our websites: www.sussex.ac.uk/spru/irafols and <http://tpac.gatech.edu/> include:

- MS Word file [“Supplement to Is Science Becoming More Interdisciplinary paper”]
 - Tables showing the “Top 10” cited SCs by articles in each of our six SCs in 1975 and 2005, with discussion
 - Figure B1 plotting Integration score vs. SC # of journals for 23 SCs, reporting a modest negative correlation
 - Plots showing the distribution of Integration scores for each of the six SCs over time (1975, 1985, 1995, and 2005) – Figure B2-B7.
 - Science mapping: consideration of producing and using the science overlay maps for purposes beyond consideration of interdisciplinarity
- MS PowerPoint file [“Maps supplement to Is Science Becoming More Interdisciplinary paper”]
 - Overlay Science Maps for the six SCs for 1975 and also for 2005
 - Various map templates with each SC named, different node size base maps, etc.
- MS Excel file [“21 Macro-disciplines – 244 SCs”]
 - 244x244 SC Cosine matrix (essential to the Integration score calculations)
 - PCA 21-factor solution matrix that yields the macro-disciplines
- As we develop these, we will provide SCIENCE MAPPING KITS to enable others to perform desired calculations and to generate overlay science maps for topics of interest.