Diversity measures and network centralities as indicators of interdisciplinarity: case studies in bionanoscience

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Abstract
Mapping and evaluating interdisciplinarity poses major challenges, due to its multidimensional character and its inherent conflict with categorisation methods. Here we develop indicators of interdisciplinarity as cognitive diversity that are not dependent on categorisation. To do so, we integrate in a conceptual framework measures of diversity used in ecology and economics, the measures of similarity predominant in bibliometrics and recently proposed indicators of interdisciplinarity based on social network analysis. We carry out two case studies in bionanoscience which illustrate how these indicators do capture the diversity of research topics engaged by an author or a publication, in contrast to category-based indicators that fail to do so. We suggest that these simple and ready-to-use indicators of cognitive diversity may be of potential importance in comparative studies of emergent scientific and technological fields, where claims of novelty and interdisciplinarity are rife but not always justified.

Keywords
Interdisciplinary research; nanotechnology; nanoscience; diversity; indicators; social network analysis.

Introduction
In the policy discourse interdisciplinarity is often perceived as a mark of ‘good’ research: interdisciplinary research is seen as more successful at making breakthroughs and generating more relevant outcomes, be it in terms of innovation for economic growth or for social needs. This belief has led to the design of policies aimed at fostering interdisciplinarity, particularly in those fields, such as biotechnologies or nanotechnologies that are regarded as emerging through technological convergence.

However, the concept of interdisciplinarity and its variants (multi-, trans- and cross-) is problematic in many respects, if not plainly controversial (Weingart and Stehr, 2000). In the first place, because, given its polysemous and multidimensional nature (Sanz-Menéndez et al., 2001), there has been no agreement so far concerning its most pertinent indicators, or the appropriateness of categorisation methods based on disciplines (van Raan, 2000; Bordons, 2004, Rafols and Meyer, 2007). Second, although the etymology of inter-, multi-, trans- and cross-disciplinarity suggests that this is a property of research lying between, beyond or across various disciplines, interdisciplinarity is currently widely (and ambiguously) used to mean research spanning over a variety of areas, whether the areas are academic disciplines, technological fields and/or even industrial sectors. Given this use beyond the disciplinary boundaries, Glaser (2006) suggested that ‘interdisciplinarity’ as employed in science policy is a misnomer: cognitive diversity (in relation to either disciplines, specialties, technologies, industries, stakeholders, research fronts or specialties, etc.) would be a more appropriate label.

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As a result of the problems highlighted above, policies fostering interdisciplinarity appear to be based more on conventional wisdom rather than on an empirical analysis of research practices. The aim of this investigation is to inform policy-making on the dynamics of emerging fields by providing simple measures that can help capture the intensity of interdisciplinarity in the wider sense of cognitive diversity.

Diversity is a concept used across a range of scientific fields, from ecology to economics and cultural studies, to refer to three different attributes of a system composed of different elements and/or categories (Stirling, 1998, 2007; Purvis and Hector, 2000):

- **Variety**: number of distinctive categories.
- **Balance**: evenness of the distribution of categories.
- **Disparity**: degree to which the categories examined are different from each other.

<table>
<thead>
<tr>
<th>Table 1. Measures of diversity.</th>
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<tr>
<td><strong>Notation:</strong></td>
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<tr>
<td>Proportion of elements in category $i$: $p_i$</td>
</tr>
<tr>
<td>Distance between categories $i$ and $j$: $d_{ij}$</td>
</tr>
<tr>
<td>Similarity between categories $i$ and $j$: $s_{ij}$</td>
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</table>

<table>
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<tr>
<th><strong>Indices:</strong></th>
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<tbody>
<tr>
<td>Shannon-Wiener</td>
</tr>
<tr>
<td>Herfindahl-Hirschmann$^2$</td>
</tr>
<tr>
<td>Disparity (or similarity)</td>
</tr>
<tr>
<td>Stirling</td>
</tr>
</tbody>
</table>

Many bibliometric studies of interdisciplinarity have examined the **variety** and **balance** of disciplines as indicators of degree of diversity using pre-existing categories (see review by Bordons et al., 2004). Many other studies have used **similarity** measures between in order to visualise the relative ‘position’ of different scientific disciplines and fields (see review by Noyons, 2004; Boyack et al. 2005). Thus, different bibliometric studies on interdisciplinarity have indeed already looked into the three different aspects of diversity listed above. Other attempts to measure interdisciplinarity include: (i) van den Besselaar and Heimeriks (2001), who used factor analysis on similarity measures to discriminate the interdisciplinary elements within a set (journals in their case) as those elements that do not fit into the latent classes represented by eigenvectors; (ii) very recently Leydesdorff (2007) who incorporated measures of centrality in social network analysis. The current investigation builds on previous research on mapping using similarity distances defined by co-occurrence (Noyons 2004) and Leydesdorff’s introduction of social network analysis.

Here, we use Stirling’s measure of diversity (see Error! Reference source not found.) (Stirling, 1998, 2007) but later simplify it to disparity to avoid imposing categorisation. This measure is a sum over the **distances** between each pair of categories of a set with a weight proportional to the product of their **shares**. This form incorporates the various properties inherent in the concept of diversity: variety, balance and disparity. In order to apply this diversity measure, we need two previous requirements which will determine the final measure: (i) a categorisation method for partitioning the set; (ii) a definition of distance between categories.

Since our aim is to find a measure of cognitive diversity for a given set of publications, we would need in the first place to assign each publication to a cognitive category (e.g. a discipline or research specialty). However, as outlined above, there are several reasons for avoiding categorisation. In the

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$^2$ Herfindahl-Hirschman’s index is equivalent to Simpson’s index, used in biodiversity.
first place, the only multidisciplinary and most widely used categorisation system is the one provided by ISI, which assigns each journal to one or more disciplines. This assignment may work at the journal level, but is very problematic at the paper level given the heterogeneous contents of many journals. In consequence, our first intention was to conduct cluster analysis in order to create self-organised categories for each bibliometric set, following the approach pursued by Schmidt and collaborators’ (2006). However, clustering exercises result in extremely skewed size distributions (few large clusters, many smalls ones, see Schmidt, 2006, p.9), as one might expect from the power-law distributions of citation networks (Price, 1965). Due to these skewed distributions, the clustering approach is only feasible for large data sets and even then it is very sensitive on the cutting threshold set. The alternative we pursue here is to take each paper as its own category, with all the categories having the same weight $p_i$. This approach simplifies the measure of diversity to a measure of disparity or dissimilarity, i.e. of how different the various elements are: $\sum_{i \neq j}^\infty d_{ij}$, with $i, j$ now being the indices for all the elements of the set. Although this description is mathematically more straightforward, we should like to emphasize that it is not a simplification. On the contrary, we may argue that it is a more complete description as it adds to the diversity measure between clusters we had, a measure of the diversity within clusters --which was assumed to be zero, but is not negligible in skewed distributions that include macro-clusters.

As it has been explained in many clustering exercises (e.g. Boyack et al., 2005, p.354) in order to measure the distances or the similarities between a given set of elements we need to make some choices. First, we must select a context (the e.g. a wider set of papers), that will provide the properties or attributes used to measure the distances. Second, we must choose which attributes will be used to compare the units and third we have to adopt a functional form for the similarity or dissimilarity matrix.

**Network centralities as measures of diversity**

Since in this study we are interested in mapping the breadth of knowledge sources a set of papers (e.g. publications by an author during a period), we select the co-occurrences of references as the attribute for comparison (bibliographic coupling). This choice implies that we select the references included in our initial set as the context of comparison. Then, we compute the similarity among all the papers of the context using as functional form the Salton’s cosine of the bibliographic coupling ($s_{ij} = \text{number of references shared by papers } i \text{ and } j \text{ divided by the geometric mean of references in } i \text{ and } j$). Finally, the distance between two papers is estimated using centrality measures of social network analysis. For an explanation of centrality measures in terms of bibliometrics, we refer to the recent article by Leydesdorff (2007).

In a first instance, we use directly the Salton’s cosine value of bibliographic coupling as the similarity between two papers, which a number of studies have claimed to be preferable to others (e.g. see a detailed comparison in Boyack et al. 2005). The similarity measure over the whole network is then the sum of the similarity matrix, which is also the sum of the valued degree centrality for all vertices ($S_{\text{degree}}$):

$$S_{\text{degree}} = (N^*(N-1))^{-1} \sum_{i \neq j}^\infty s_{ij}$$

with $s_{ij} = \text{Salton’s cosine of reference vectors}$

This measure has a notable downside: if two papers do not share any reference, their similarity is set to zero, irrespectively of their location in the wider context provided. In other words: if they don’t share a reference, the distance between a paper in biophysics and one in biochemistry is assumed to be the same as between one in biophysics and one in sociology.

In order to take a wider context into account, we propose a second measure based on the length of the geodesic (the shortest path). Here the length of the geodesic $d_{ij}$ is the minimum number of links or

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3 The measure gives us the network similarity instead of the diversity, because we sum over element-to-element similarities instead of distances.
edges that are needed to connect papers $i$ and $j$ within the network of papers. Two papers are considered to be connected when their similarity value $s_{ij}$ exceed a chosen threshold $s_{\text{min}}^4$. The diversity-dissimilarity measure is then the sum over all the length of geodesics for the connected papers. After normalisation this yields the average distance between vertices (papers) in the network. Given that this is approximately the inverse of the mean over all the vertices of the \textbf{closeness centrality}, we will choose this well-established index of social network analysis as the second indicator of similarity ($S_{\text{close}}$)$^5$:

$$S_{\text{close}} = (N^*(N-1))^{-1} \sum_{(i\neq j)} 1/d_{ij}$$

with $d_{ij} = \text{Number of edges crossed to connect } i \text{ and } j$

Here we set $s_{\text{min}} = 0.05 = 1/20$, so that the measure can retain the connection between two short research papers with only 20 references each that share one (a typical case in\textit{ Nature, Science} letters), but at the same time dismiss as irrelevant a small number of shared references between review papers (typically with long reference lists). The normalisation of these indices of similarity/diversity to account for size effects is a complex issue that we aim to address in a future investigation (see discussion). For the purposes of this study, we have normalised the indices so that they take a value in the $[0,1]$ interval and size does not have an effect on the minimum and maximum values.

<table>
<thead>
<tr>
<th>Research tradition:</th>
<th>Ecology $\rightarrow$</th>
<th>Bibliometrics $\rightarrow$</th>
<th>Social Network Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main concept:</td>
<td>Diversity $\rightarrow$</td>
<td>Similarity $\rightarrow$</td>
<td>Centrality measures</td>
</tr>
<tr>
<td>Main formulations:</td>
<td>$\sum_{(i\neq j)} d_{ij} p_i p_j$</td>
<td>$\sum_{(i\neq j)} s_{ij}$ where $s_{ij}=1/d_{ij}$ is \textit{Salton's cosine}</td>
<td>Valued Degree Centrality $\sum s_{ij}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Closeness Centrality $\sum (N-1)/d_{ij}$</td>
</tr>
</tbody>
</table>

Here we present two case studies to test these measures against other measures of diversity used in previous studies. In particular we compare $S_{\text{degree}}$ and $S_{\text{close}}$, with measures of diversity based on the number of categories, first using the journals that appear in the references ($N_{\text{jou}}=$number of journals) and second the widely used ISI subject categories ($N_{\text{cat}}=$number of categories). For these two categorisation methods, we compute the numerical richness ($N_{\text{cat}}/N$), a normalised Shannon-Wiener index$^6$ and the Herfindahl-Hirschmann index. When feasible, we also compute the betweenness centrality, which was proposed on empirical grounds by Leydesdorff (2007).

These two studies within the emerging field of bionanotechnology take two different units of analysis: first we compare single papers; second, the publication record of a researcher over various periods. We downloaded sets of papers from searches of ISI Web of Knowledge, computed the Salton’s cosine of similarities with our own software, then visualised results and computed centrality measures using Pajek (Batagelj and Mvar, 2006), Bibexcel (Persson, 2006) and the statistical packet R (2006) (all freeware). Since the two cases presented are pilot studies based on previous interviews to the authors, they are made of very small publications sets (between 21 and 44 for case 1, and between 8 and 28 for case 2) –results need to be interpreted accordingly as indicative or exploratory. For detailed narratives of the case studies we refer to our previous publication (Rafols and Meyer, 2007).

$^4$ Notice that this procedure converts the $s_{ij}$ matrix into a binary matrix, thus losing information about element-to-element distances. 

$^5$ Closeness centrality for each vertex is defined as $C_i = (N-1)/\sum d_{ij}$, with $d_{ij}$ being the length of the geodesic between $i$ and $j$. By summing over $i$ and dividing by $N$, we obtain the mean of closeness centrality, $S_{\text{close}}$.

$^6$ The Shannon index presented here is normalised with the logarithm of the number of papers in a set. This normalized index reflects the evenness or balance of the distribution.
Table 2. Measures of diversity in the reference set of publications.

<table>
<thead>
<tr>
<th>Paper</th>
<th>N</th>
<th>1/\text{S}_{\text{degree}}</th>
<th>1/\text{S}_{\text{close}}</th>
<th>Betw</th>
<th>\text{N}_{\text{jou}}/\text{N}</th>
<th>\text{Shan}</th>
<th>1/\text{Herf}</th>
<th>\text{N}_{\text{cat}}/\text{N}</th>
<th>\text{Shan}</th>
<th>1/\text{Herf}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Funatsu 1995</td>
<td>23</td>
<td>17.6</td>
<td>1.7</td>
<td>0.14</td>
<td>0.57</td>
<td>0.66</td>
<td>4.60</td>
<td>0.26</td>
<td>0.43</td>
<td>3.05</td>
</tr>
<tr>
<td>Kojima 1997</td>
<td>24</td>
<td>13.0</td>
<td>1.4</td>
<td>0.07</td>
<td>0.50</td>
<td>0.68</td>
<td>6.40</td>
<td>0.17</td>
<td>0.41</td>
<td>3.43</td>
</tr>
<tr>
<td>Ishijima 1998</td>
<td>51</td>
<td>23.5</td>
<td>1.8</td>
<td>0.04</td>
<td>0.37</td>
<td>0.61</td>
<td>6.19</td>
<td>0.12</td>
<td>0.36</td>
<td>3.43</td>
</tr>
<tr>
<td>Noji 1997</td>
<td>21</td>
<td>39.1</td>
<td>2.3</td>
<td>0.35</td>
<td>0.52</td>
<td>0.72</td>
<td>7.41</td>
<td>0.24</td>
<td>0.45</td>
<td>3.60</td>
</tr>
<tr>
<td>Yasuda 1998</td>
<td>31</td>
<td>24.8</td>
<td>1.8</td>
<td>0.07</td>
<td>0.45</td>
<td>0.69</td>
<td>8.66</td>
<td>0.13</td>
<td>0.38</td>
<td>3.33</td>
</tr>
<tr>
<td>Okada 1999</td>
<td>29</td>
<td>9.1</td>
<td>1.3</td>
<td>0.01</td>
<td>0.34</td>
<td>0.60</td>
<td>6.23</td>
<td>0.14</td>
<td>0.36</td>
<td>3.06</td>
</tr>
<tr>
<td>kawa 2001</td>
<td>45</td>
<td>13.6</td>
<td>1.5</td>
<td>0.01</td>
<td>0.36</td>
<td>0.63</td>
<td>8.13</td>
<td>0.18</td>
<td>0.41</td>
<td>3.94</td>
</tr>
<tr>
<td>Sakakibara 1999</td>
<td>26</td>
<td>32.7</td>
<td>2.1</td>
<td>0.11</td>
<td>0.46</td>
<td>0.67</td>
<td>6.58</td>
<td>0.23</td>
<td>0.46</td>
<td>4.02</td>
</tr>
<tr>
<td>Burgess 2003</td>
<td>35</td>
<td>19.5</td>
<td>1.6</td>
<td>0.04</td>
<td>0.57</td>
<td>0.78</td>
<td>13.46</td>
<td>0.26</td>
<td>0.46</td>
<td>3.94</td>
</tr>
<tr>
<td>Tomishige 2000</td>
<td>44</td>
<td>9.4</td>
<td>1.4</td>
<td>0.01</td>
<td>0.36</td>
<td>0.65</td>
<td>9.20</td>
<td>0.14</td>
<td>0.39</td>
<td>3.82</td>
</tr>
<tr>
<td>Tomishige 2001</td>
<td>17</td>
<td>8.3</td>
<td>1.2</td>
<td>0.00</td>
<td>0.71</td>
<td>0.83</td>
<td>8.76</td>
<td>0.29</td>
<td>0.49</td>
<td>3.50</td>
</tr>
<tr>
<td>Yildiz 2004</td>
<td>19</td>
<td>14.6</td>
<td>1.6</td>
<td>0.02</td>
<td>0.63</td>
<td>0.79</td>
<td>8.80</td>
<td>0.53</td>
<td>0.67</td>
<td>5.88</td>
</tr>
</tbody>
</table>

Legend: N: Number of references in paper. Betw: Betweenness centrality. Shan: Shannon diversity. Herf: Herfindahl-Hirschmann diversity measure. \text{N}_{\text{jou}}: Number of journals in references. \text{N}_{\text{cat}}: Number of ISI categories in references. \text{S}_{\text{degree}} and \text{S}_{\text{close}} are the similarity measures as defined above. The form of the indices in the table is presented so that it increases its value with increasing diversity. The two papers highlighted are those presenting a higher diversity according to the centrality measures. Papers within the same box belong to the same project.

Figure 1. Relation between the various diversity indices and $1/\text{S}_{\text{degree}}$ (based on data shown in Table 1). We observe that there is a linear relation between $1/\text{S}_{\text{close}}$ and $1/\text{S}_{\text{degree}}$ and a positive but irregular correlation for Betweenness Centrality and $1/\text{S}_{\text{degree}}$. However, the more widely used Shannon (entropy) and Herfindahl diversity measures do not show a correlation with $1/\text{S}_{\text{degree}}$—neither if computed from ISI subject categories, or using each journal as a category.
Case study 1: Diversity of single articles on molecular motors

In this case, we are interested in tracking the interdisciplinarity of single contributions in molecular motors research. We build on a previous paper investigation that carried out detailed cases studies on interdisciplinary practices in five research projects (Rafols and Meyer, 2007). It emerged from interviews that while all the cases used techniques and concepts from a variety of disciplines (they were similarly interdisciplinary in this respect), in some cases the project was the continuation of a well-established research tradition, while in others the project brought together different research traditions (the later are more interdisciplinary in terms of knowledge integration). The analysis here shows that while the new measures of diversity $S_{\text{degree}}$ and $S_{\text{close}}$ can track this difference in knowledge integration, category-based measures Shannon and Herfindahl fail to do so.

We assess the diversity of knowledge sources of one article by using its reference as the set of papers for comparison. This implies making two steps back: take an article, look the references, compute the similarities using the references of the references. The threshold for the computation of $S_{\text{close}}$ was set at $s_{\text{min}}=0.05$ for all cases except Noji 1997, where in order to avoid the network splitting into two, it was lowered to 0.025. The results are presented in 2 and in Figure 1. While we see an agreement between those measures of diversity based on reference similarity, there is no correlation between these measures and those based on journal and subject categorisation.

![References in Noji 1997](image)

Figure 2. Bibliographic coupling of the reference set in Noji 1997 (threshold=0.025). The graph illustrates that this seminal paper was based on contribution from two research communities. On the right hand side, the researchers working on linear molecular motors (myosin and kinesin). On the left, those working on bio-energetics of rotary motors ($F_1$-ATPase). The black circles in the figures at the bottom show the papers classified in different disciplines according to ISI subject classification. Both the left and the right clusters have papers from different disciplines.
In order to investigate this disagreement, we have first plotted the network of references (see Figure 2 through Figure 5). The measures of diversity $S_{\text{degree}}$ and $S_{\text{close}}$ can be understood by looking at the number and structure of the clusters formed through similarity links: the two clusters in Noji 1997’s mean higher diversity than the only cluster in Ishijima 1998’s. However, disciplinary categories are not correlated with the clustering: biochemistry and biophysics are equally found in the two clusters in Noji 1997 or in the one cluster in Ishijima 1998. As a result, diversity measures based on ISI subject category do not correlate with number of clusters.

Second, we have also compared $S_{\text{degree}}$ and $S_{\text{close}}$ with betweenness centrality. Here we measured the betweenness centrality by placing the examined paper among the network formed by its own references. Figure 1 shows that these measures are only roughly correlated. Figure 5 compares two cases with high diversity in terms of $1/S_{\text{degree}}$ and $1/S_{\text{close}}$ but different betweenness. The comparison shows that betweenness is very sensitive to the overall structure of the network. If, as in the case of Sakakibara 1999 (right), the reference set is diverse but there are already other links between groups, then betweenness centrality has a much lower value.

Figure 3. Bibliographic coupling of the reference set in Ishijima 1997 (threshold = 0.05). This is a case of research related to various disciplines but belonging to a well-established line of research. Therefore, the vast majority of its references are related to each other, but they form a cluster where the incumbent disciplines are mixed. Black circles in the figures at the bottom show the papers classified in different disciplines according to ISI subject classification. Most of those not marked in any category fall into the ISI category of ‘Multidisciplinary’ journals.
Figure 4. Bibliographic coupling of the reference set in Sakakibara 1999 (threshold = 0.05). This set integrates literature from the single molecule detection and manipulation based on kinesin and myosin (left cluster), with studies on dynein (right) and dynein role in the axoneme (top). Rather than clear-cut clusters, the network has three or four fuzzy groups, what explains its diversity. The figures at the bottom, show, again, that these groups do not coincide with established categories. The black circles show the papers classified in different disciplines according to ISI subject classification.

Figure 5. Betweenness centrality (size of nodes) of each of references in Noji 1997 (left) and Sakakibara 1999 (right), with the lines representing the bibliographic coupling (threshold = 0.05). To the reference set, we have added a black circle in each figure representing the position of the article studied within their own reference set. We can see that this betweenness centrality (of the article) takes a very high value when the article is the only link between clusters (see left: Betw=0.35), but it quickly decreases if there are other links that were already making a brokerage role (see right: Betw=0.11).
Case study 2: Diversity in the publication set of an author

In a second case studied, we aim to trace how diverse is the career of a given researcher. Here we traced the publications of TQP Uyeda, a researcher in molecular motors, from 1983 to 2006 and computed $S_{\text{degree}}$, $S_{\text{close}}$ and Shannon and Herfindahl’s diversities at different periods of his career\(^7\) (see 2 and Figure 6). In each of the first three periods, Uyeda’s research was linked through a common topic, which changed as he moved to new labs. However since 2000, he kept the focus he had since the mid-90’s (on the role of myosin, a molecular motor, in cytokinesis), while combining in with papers in a related topic (conformational changes in myosin) and started a new line of research in the bioengineering side (applications of molecular protein on nanofabricated devices).

The indices $S_{\text{degree}}$ and $S_{\text{close}}$ are able to track this increase in diversity in the last period, whereas Shannon and Herfindahl’s can not do it, because the categories used (journals and subject category) cannot make the distinction between distinct clusters that have similar journal or disciplinary mix. The relatively high values of $1/S_{\text{degree}}$ and $1/S_{\text{close}}$ are attributable to the fact that 3 out of 12 publications were completely unrelated to the others. Comparison of Figure 6 and Figure 7 shows that there is a correlation between research topics and disciplinary categories: in two clusters cell biology is predominant, while in other two we observe a combination of biophysics and biochemistry.

Discussion and conclusions

In this paper we have presented a conceptual development which we think helps to understand the relation between measures of diversity used in ecology and economics (Shannon, Herfindahl and Stirling’s; see Stirling, 1998, 2007), the measures of similarity predominant in bibliometrics (van Raan, 2000; Boyack et al., 2005) and recently proposed measures of interdisciplinarity based on social network analysis (Leydesdorff, 2007).

Building on these previous contributions, we have used network centrality measures $S_{\text{degree}}$ and $S_{\text{close}}$ as indicators of cognitive diversity for two case studies in bionanoscience. The case studies illustrate that the proposed $S_{\text{degree}}$ and $S_{\text{close}}$ do capture the variety of research topics in the references of a publication or pursued by an author, whereas category-based indicators fail to do so. This result is consistent with the conceptual insights on the dynamics of science in the 1970’s (Mulkay, 1974; Small, 1977) which showed that science develops more in terms of ever-changing research fronts and specialties than as a structure of well established disciplines. As a consequence indicators based on categories cannot adequately map emergent fields.

Several aspects of the proposed indicators need further exploration. First, the scalability and field dependence of the diversity measures need to be investigated in order to make meaningful comparisons between sets of different size or field. Trial comparisons between similar sets of different sizes (not shown here) suggest that size dependence is very strong and needs to be taken into account. Moreover, we need extend the measure to other fields in order to have values of reference for what it is a high or low level of diversity. Second, the current method to construct the indicators captures the difference between publication of related research, but cannot make the distinction between: (i) elements that are relatively close but not directly related (e.g. two papers in different research specialties within the big area of biochemistry) and (ii) elements that very far apart (e.g. papers on protein conformational changes and Adorno’s social thought). In order to measure this long-range distances, it would be necessary to extend the context for their computation to science-wide maps of the type devised by Boyack et al. (2005).

We suggest that the simple and ready-to-use indicators of cognitive diversity presented here may be of special use in comparative studies for evaluation and mapping of emergent fields, where claims of

\(^7\) Since in this instance the object of study (the set of publications) is also the context, we could not think of a simple and meaningful procedure to compute, for a set, betweenness centrality.
novelty and interdisciplinarity are rife and not always justified. In the policy making process of emerging fields, which by definition are out-of-discipline/field and attract special funding, indicators of interdisciplinarity such as the ones we have developed will be potentially important in order to make the distinction between established developments, conceivable future visions, and the politics and/or rhetoric of technological promise.

References


Table 3. Measures of diversity in the publications of an author (TQP Uyeda).

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<thead>
<tr>
<th>Diversity</th>
<th>Centrality measures</th>
<th>Journal category</th>
<th>ISI subject category</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>1/S&lt;sub&gt;degree&lt;/sub&gt;</td>
<td>1/S&lt;sub&gt;close&lt;/sub&gt;</td>
</tr>
<tr>
<td>2001-2006</td>
<td>28</td>
<td>23.4</td>
<td>2.9</td>
</tr>
<tr>
<td>1996-2000</td>
<td>12</td>
<td>7.1</td>
<td>1.2</td>
</tr>
<tr>
<td>1991-1995</td>
<td>8</td>
<td>6.8</td>
<td>1.3</td>
</tr>
<tr>
<td>1983-1990</td>
<td>12</td>
<td>11.6</td>
<td>2.0</td>
</tr>
<tr>
<td>1983-2006</td>
<td>60</td>
<td>24.4</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Legend: N: Number of references in paper. Betw: Betweenness centrality. Shan: Shannon diversity. Herf: Herfindahl-Hirschmann diversity measure. N<sub>Jou</sub>: Number or journals in references. N<sub>cat</sub>: Number of ISI categories in references. S<sub>degree</sub> and S<sub>close</sub> are the similarity measures as defined above. The form of the indices in the table is presented so that it increases its value with increasing diversity. The two papers highlighted are those presenting a higher diversity according to the centrality measures. Papers within the same box belong to the same project.

Figure 6. Bibliographic coupling of the publications of TQP Uyeda (1983-2006) (threshold = 0.05). Islands were created using the island partition algorithm in Pajek (min-size =5, max-size= 10). In the periods 83-90, 91-95 and 96-00 the researcher focused mainly on one topic. However, since the late 1990s he starts branching into two topics of molecular motors (C: role of Myosin II in cytokinesis; D: conformational change in myosin) and later in 2000’s into investigations of bioengineering applications of molecular motors (E).
Figure 7. Disciplinary ascription of all TQP Uyeda publications according to ISI subject categories. The links between nodes represent bibliographic coupling. Black circles correspond to publications in journals of a specific ISI subject category. Whereas the initial publications of Uyeda focused on cell biology and plant biology (bottom cluster), his latest contributions (left) and his work in the last 15 years (centre) can not be distinguished in terms of their disciplinary mix: both comprise some cell biology, and well as biophysics and biochemistry related papers. But the existence of two clearly differentiated clusters indicates that they are different cognitive territories –a result that was confirmed by an interview.