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Interdisciplinarity of scientific fields and its evolution based on graph of project collaboration and co-authoring

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Abstract The paper investigates interdisciplinarity of scientific fields based on graph of collaboration between the researchers. A new measure for interdisciplinarity is proposed that takes into account graph content and structure. Similarity between science categories is estimated based on text similarity between their descriptions. The proposed new measure is applied in exploratory analysis of research community in Slovenia. We found that Biotechnology and Natural sciences are the most interdisciplinary in their publications and collaborations on research projects. In addition evolution of interdisciplinarity of scientific fields in Slovenia is observed, showing that over the last decade interdisciplinarity increases the fastest in Medical sciences mainly due to collaborations with Natural and Technical sciences.

Keywords Interdisciplinarity · Diversity · Network analysis · Scientific collaboration · Topical analysis · Bibliometric analysis

Introduction

Many believe that the great advances take place at the interstices between disciplines, making the interdisciplinary research almost universally acclaimed as "the way to go" (Porter and Rafols 2009). Interdisciplinary research is seen as more successful at making breakthroughs and generating more relevant outcomes, be in terms of innovation for economic growth or for social needs (Rafols and Meyer 2010). It is a complex issue as modern society increasingly demands application-oriented knowledge and the usability of scientific knowledge generally requires combination and integration of knowledge from

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various scientific disciplines (van den Besselaar and Heimeriks 2001). An analysis of 17.9 million papers spanning all scientific fields shows the importance of interdisciplinarity for scientific impact (Uzzi et al. 2013).

In this study we propose a new measure for interdisciplinarity and a methodology for constructing subject categories similarity matrix based on text similarities between descriptions of categories. The methods are applied on research community in Slovenia, a smaller European country in need for innovations that could stimulate the growth of the economy, strongly affected by the economic crisis. Below is the summary of key scientific contributions on methods and exploratory findings of this study.

Key contributions on methods:

- Extending Stirling's diversity index for graphs, by adding a component that captures connectivity between subject categories.
- Using text similarity approach for constructing science categories similarity matrix used for interdisciplinarity calculation.

Key exploratory findings:

- The interdisciplinarity based on research collaboration of medical science increases fastest with time. The main reasons are intensive collaborations with Technical, Natural and Social sciences in the period from 2004 to 2006 and with Natural and especially Technical science from 2011 to 2013.
- Biotechnology and natural sciences are the most interdisciplinary, whether we look at project collaboration or co-authorship of publications.
- In co-authoring publications Social and Humanistic sciences are more interdisciplinary than Technical and Medical sciences, while in collaborations on research projects we can see the opposite.
- The collaboration and interdisciplinarity based on projects increases more intensively with time than collaboration and interdisciplinarity based on publications.
- The annual linear growth rate of interdisciplinarity based on projects is approximately double of the rate of growth of collaboration on projects, while the interdisciplinarity based on publications is approximately half of the rate of the growth of collaboration on publications.
- Some diverse research topics are less interdisciplinary than some other less diverse topics, and vice versa.
- Interdisciplinarity based on co-authoring versus project collaboration varies across topics.

Background

Since there are many different definitions of interdisciplinarity, we begin with the review of the basic terms: scientific discipline, unidisciplinary, multidisciplinary, interdisciplinary and trans-disciplinary science. Next, we introduce some of the most related work on measuring interdisciplinarity. Finally, background on using collaboration as the basis for interdisciplinarity is given.

Basic concepts

Scientific disciplines are organized around the study of particular substantive phenomena (e.g., psychological, social, environmental, biological facts). It is useful in that it highlights the distinctive substantive concerns (e.g., biological, psychological, social, geographical phenomena), analytic levels (e.g., cellular, cognitive, emotional, interpersonal, organizational, social), concepts, measures, and methods associated with particular fields of study (Stokols Daniel 2003). The concept of a scientific discipline comprises both a body of knowledge and a social body that generates, evaluates, communicates, and teaches the corresponding knowledge, i.e. discipline is a combined cognitive and social category (Schummer 2004). In rest of this paper we will use the terms science field and science subfield as a type of scientific discipline used in this research.

Unidisciplinary research relies solely on the methods, concepts, and theories associated with a single discipline, such as psychology, sociology, geography, or medicine. Multidisciplinarity refers to a process whereby researchers in different disciplines work independently or sequentially, each from his or her own discipline-specific perspective, to address a common problem. (Stokols Daniel 2003)

Interdisciplinarity has a vast number of different definitions and there is no common established meaning of the term. In Stokols Daniel (2003) interdisciplinarity is defined as a process in which researchers work jointly, but from each of their respective disciplinary perspective, to address a common problem. This definition differs from others in that it does not include the integrative effect of the process, which is included in the definition of the next step—transdisciplinary. Interdisciplinary approaches integrate separate disciplinary data, methods, tools, concepts, and theories in order to create holistic view or common understanding of a complex issue, question, or problem. The critical indicators of interdisciplinarity in research include evidence that the integrative synthesis is different from, and greater than, the sum of its parts (Stokols Daniel 2003; Wagner et al. 2010). Interdisciplinary research requires an integration of concepts, techniques, and/or data from different fields of established research (The National Academies 2005; Porter et al. 2007). Interdisciplinarity is a process of integrating different bodies of knowledge rather than transgression of disciplinary boundaries per se. The integration is the key aspect of so-called interdisciplinary research (The National Academies 2005; Rafols and Meyer 2010).

Transdisciplinarity is a term related to interdisciplinarity. The existing definitions emphasize existence of frameworks and taking into account sustainability and all the possible disciplines and stakeholders. In contrast to unidisciplinary research, transdisciplinary science involves collaboration among scholars representing two or more disciplines in which the collaborative products reflect an integration of conceptual and/or methodological perspective drawn from two or more fields (Stokols Daniel 2003). Transdisciplinary approaches are comprehensive frameworks that transcend the narrow scope of disciplinary worldviews. For instance, transdisciplinary science in cancer research is a form of transcendent interdisciplinary research that fosters systematic theoretical framework for defining and analyzing social, economic, political, environmental, and institutional factors in human health well-being. It is a new mode of knowledge production that draws on expertise from wider range of organizations, and collaborative partnerships for sustainability that integrate research from different disciplines with the knowledge stakeholders in society. The transdisciplinary product is greater than the sum of its parts, though the scope of the overall effort is more comprehensive and the parts may be more diverse (Stokols Daniel 2003). Transdisciplinary science involves the integration of theoretical and methodological perspectives drawn from different disciplines, for the purpose of generating novel conceptual and empirical analysis of a particular research topic (Rosenfield 1992; Klein 1996). Transdisciplinarity concerns that which is at once between the disciplines, across different disciplines, and beyond all disciplines. Its goal is (a) the understanding of the present world, of which one of the imperatives is the unity of knowledge, and (b) the solution of mega and complex problems by drawing on and seeking to integrate disciplinary and stakeholder views on the basis of some overarching theory (Klein, 1996). According to the definitions, the transdiciplinarity is a transcendent form of interdisciplinary research, relaying on the same key concept as the interdisciplinarity—integration of knowledge.

Related work

Porter and Rafols (2009) have performed interdisciplinarity study of six research fields corresponding to the Web of Science subject categories, in the period from 1975 to 2005. They use the Stirling's (1998) diversity index as the integration score, which was based on citations and subject categories associated with journal that published the cited articles. The similarity matrix between subject categories was constructed by calculating integration score on a subset of the data. The results showed that the integration score of all six fields increases over time, but significantly less than the mean number of authors per paper and the mean number of disciplines per paper. Rafols and Meyer (2010) used Stirling's measure of diversity simplified to disparity (to avoid imposing categorization), network centrality measures and the normalized Shannon-Wiener and Herfindahl-Hirschmann (Simpson's index used in biodiversity) index to perform interdisciplinarity study on authors and publication in two case studies from bionanoscience. Morillo et al. (2003) examined variety and balance of scientific disciplines using pre-existing categories. Research areas and categories are described according to the quantity of their links (number of related categories) and their quality (with close or distant categories, diversity, and strength of links). Schummer (2004) investigates interdisciplinary research collaboration in nanoscience and nanotechnology in 2003 and 2004. The applied interdisciplinarity measure was based on co-authorship of authors from different scientific disciplines. Similar as work of Porter et al. (2008), this work uses co-authors' affiliation as an in interdisciplinarity indicator, which is the same method used in our work. Adams et al. (2007) have analyzed bibliometric indicators of interdisciplinary research, with hypothesis that since it is marginal to core subjects, it would be systematically cited less often. Using the Shannon diversity index, they found no tendency for the most interdisciplinary articles to be less frequently cited on any consistent basis within or across categories, and a weak tendency for the articles with highest citation impact to be neither very monodisciplinary nor very multidisciplinary in terms of their cited references. Work of Leydesdorff (2007a) focuses on applying social network analysis measure of betweeness centrality (Freeman 1977) as an indicator of interdisciplinarity. Betweeness centrality is shown to be an indicator of the interdisciplinarity of journals, but only in local citation environments. The same method is used in Leydesdorff (2007b) for measuring the interdisciplinarity of journals that are parts of the overlap between the Science Citation Index and the Social Science Citation Index.

Other related work includes (van den Besselaar and Heimeriks 2001) where factor analysis of the journal—journal citations matrix of the core journal of a specialty is applied to describe research fields in terms of their position within scientific communication networks. The work of Zitt et al. (2005) is a study of impact of level of aggregation (journal, specialties (ISI subject categories), sub-disciplines and disciplines) on the interdisciplinarity measure.

Interdisciplinarity and collaboration

It is widely-held view that the publication is an essential part of scientific research process (Wagner et al. 2010). It provides the function within science of correction, evaluation, and acceptance by a community (Price 1978). Even though research is mostly measured by publication output; there are other activities important for the research process (Porter et al. 2007). These include research projects, patents, lectures and discussions. Wagner et al. (2010) state that co-authorship of scholarly output is "a convenient, but weak indicator of interdisciplinarity". However, the only given argument is the difficulty of obtaining data about discipline/field of authors. The inconvenience of obtaining data is not convincing argument of weakness of a method. Moreover, in some cases (as shown in the rest of the paper) the discipline and affiliation data is accurate and available. Research publications are recognized as the most clear-cut entities on which to gauge interdisciplinarity of the underlying research by Porter et al. (2007). The authors suggest the co-authoring of publication is the primary information for investigating collaboration aspect of interdisciplinary research, but secondary for integration aspect—the essence of definition of interdisciplinarity. The argument is that the integration can be accomplished by a single author as well as by a team. At the same time the conducted interdisciplinarity investigation performed on publication co-referencing information was based on a premise that integration can be measured by examining the spread of a paper's references, which is not a stronger premise than the one relying on a spread of paper's authors. We argue that for investigating interdisciplinarity of research at some scope, all the information of research activity has to be considered. The availability and quality of different types of information varies in different datasets, which has to be taken into account in every investigation. We perform investigation of interdisciplinarity of research collaboration based on co-authoring publications and cooperation on research projects and, show results of both static and dynamic analysis on the case of the national research community of Slovenia. We investigate collaboration of researchers from different science fields on publications and projects, as we believe that research collaboration stimulates sharing and integration of knowledge, resulting with the interdisciplinary of research.

Dataset description

The information on research activity in Slovenia was obtained from SICRIS national database containing information about researchers, research projects and organizations and COBISS national bibliographic database containing information on publications. Time period of 18 years from 1996 to 2013 was covered in the analysis. The researchers are classified by Slovenian National Research Agency classification into sciences fields and science subfields. The classification of researchers into seven science fields: (1) natural, (2) technical, (3) medical, (4) biotechnical, (5) social, (6) humanistic and (7) interdisciplinary, and 72 subfields was the basic information used for measuring interdisciplinarity. Each researcher selects the classification that best matches her research interest. The largest of the fields is technical science with 6,041 researcher, followed by natural science with 2,975, social science with 2,460, medical science with 2,050, biotechnical with 1,234, humanistic 1209 and finally interdisciplinary science with 282 researchers. The researchers have assigned keywords in their profiles that describe their research interest.[1] In average a researcher contains five keywords.

[1] The list of keywords is available at: http://scienceatlas.ijs.si/interdisciplinarity/keywords.pdf.

Approach

Here we introduce measures used for measuring interdisciplinarity and the extension of Stirling's index with connectivity attribute, what makes it suitable for measuring interdisciplinarity of graphs.

Interdisciplinarity measure

In order to quantify interdisciplinarity, we apply a general framework for analyzing diversity proposed by Stirling (2007),

$$\Delta = \sum_{ij(i \neq j)} (d_{ij})^{\alpha} \cdot (p_i . p_j)^{\beta}, \tag{1}$$

where p_i and p_j are proportional representations of elements of disciplines i and j in the system (balance) and d_{ij} is the degree of difference (disparity) attributed to elements i and j. Combinations of the values 0 and 1 of parameters α and β, yield four properties of interest: variety, balance, disparity and diversity. As shown in Fig. 1, diversity increases with variety, balance and disparity. We apply the diversity variant of the generalized diversity framework (Eq. 1) with values of exponents $\alpha = 1$ and $\beta = 1$, as the main measure for interdisciplinarity. By changing the parameters α and β, diversity indices can be explored for different variations of the properties of diversity—variety, balance and disparity (Table 1). Note that the variant where $\alpha = 1$ and $\beta = 1$ was initially introduced by (Rao 1982).

Shannon's diversity is a more traditional measure based on Entropy. It does not take into account differences among categories,

$$S = -\sum_{i} p_i \log p_i \tag{2}$$

Entropy is a concept used to measure the randomness or uncertainty of a given set of elements. This formula was used by Grupp (1990) conjunction with literature statistics (bibliometrics) and patent statistics for studies of disorder of institutions engaged in certain R&D fields.

Extension of Stirling's diversity for graphs

Here we introduce the extension of the Stirling's diversity index that enables measuring diversity of networks or graphs. This is accomplished with addition of the degree of connectedness between elements i and j in the system e_{ij}.

$$\Delta g = \sum_{ij(i \neq j)} (d_{ij})^{\alpha} \cdot (p_i . p_j)^{\beta} \cdot (e_{ij})^{\gamma} \tag{3}$$

The parameter γ enables control of the general framework and different variations of diversity. e_{ij} is the proportions of edges connecting elements in the network i and j to all edges in the network. In the case of some elements i and j being completely disconnected $e_{ij} = 0$. In the case elements i and j are connected with all edges in the network $e_{ij} = 1$. The measure works on weighted graph, in which case e_{ij} is the proportion of sum of the weights of all the edges connecting elements i and j, to sum of weight of all the edges.

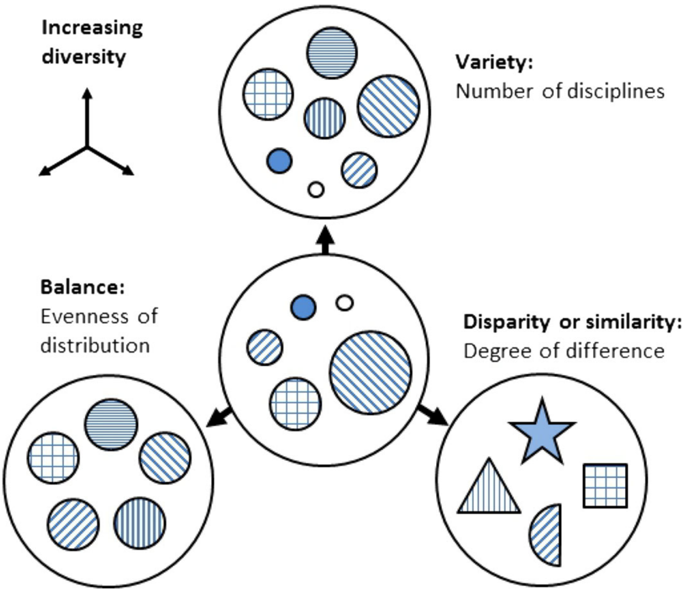

Fig. 1 Schematic representation of the attributes of diversity, based on Stirling (1998)

Table 1 Measures of interdisciplinarity used in this research

Property	Parameters	Equation
Diversity (balance/disparity-weighted variety)	$\alpha = 1, \beta = 1$	$\sum_{ij(i \neq j)}(d_{ij})^{\alpha} \cdot (p_i \cdot p_j)^{\beta} = \sum_{ij(i \neq j)} d_{ij} \cdot p_i \cdot p_j$
Variety (scaled variety)	$\alpha = 0, \beta = 0$	$\sum_{ij(i \neq j)}(d_{ij})^{\alpha} \cdot (p_i \cdot p_j)^{\beta} = \sum_{ij(i \neq j)}(d_{ij})^{0}$
Balance (balance-weighted variety)	$\alpha = 0, \beta = 1$	$\sum_{ij(i \neq j)}(d_{ij})^{\alpha} \cdot (p_i \cdot p_j)^{\beta} = \sum_{ij(i \neq j)} p_i \cdot p_j$
Disparity (disparity-weighted variety)	$\alpha = 1, \beta = 0$	$\sum_{ij(i \neq j)}(d_{ij})^{\alpha} \cdot (p_i \cdot p_j)^{\beta} = \sum_{ij(i \neq j)} d_{ij}$
Shannon's diversity		$-\sum_i p_i \log p_i$
Stirling's diversity for graphs	$\alpha = 1, \beta = 1, \gamma = 1$	$\sum_{ij(i \neq j)}(d_{ij})^{\alpha} \cdot (p_i \cdot p_j)^{\beta} \cdot (e_{ij})^{\gamma} = \sum_{ij(i \neq j)} d_{ij} \cdot p_i \cdot p_j \cdot e_{ij}$

Figure 2 shows an example of eight graphs with the same set of nodes and different set of edges. Table 2 contains the values of interdisciplinarity measured by Stirling's diversity and our extension of Stirling's measure for graphs. The dissimilarity between each pair of the four categories used in this example is 0.25. Notice that the absolute values of Stirling's diversity and the proposed Stirling's diversity for graphs cannot be compared, thus we are observing relative change of values for each measure separately. The original Stirling's measure is the same for all graphs from 2a to 2h, because the set of nodes does not change for any graph. Graphs 2a and 2b have extended diversity 0, because there are no edges connecting nodes from different categories. In graphs 2c through 2h nodes from 4 different categories become increasingly connected, which increases the interdisciplinarity measured according to our extension of Stirling's diversity for graphs.

The example illustrates how the extension enables measuring interdisciplinarity where in addition to variety (number of disciplines), balance (evenness of distribution) and disparity (degree of difference), the elements have different connectivity. The measure is

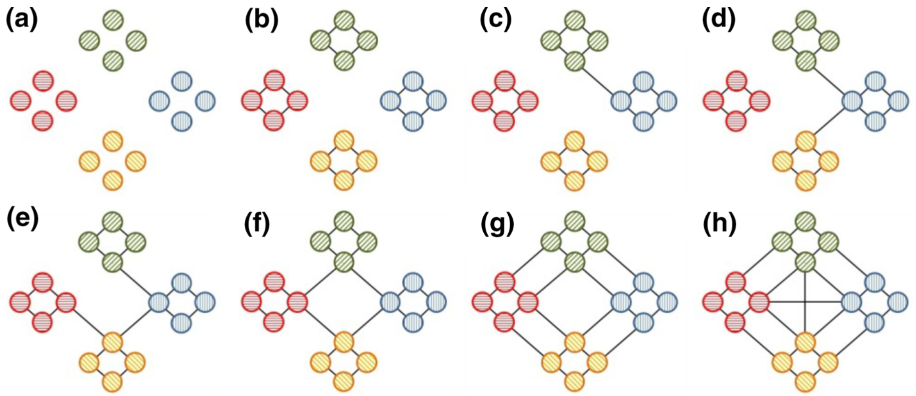

Fig. 2 Graph with the same sate of nodes from 4 groups and different set of edges. From **a**–**h** the groups in the graph are increasingly more connected

further tested on real networks defined by research topics in chapter 5.2 interdisciplinarity of topic subgraphs.

Subject categories similarity matrix

In order to include disparity component into interdisciplinarity, the information on similarity between subject categories is needed. Subject categories similarity matrix enables distinction of influences that different pairs of subject categories have on interdisciplinarity. For instance, physics and mathematics are known to be related scientific fields, thus, scientific collaboration and integration of knowledge between those two fields is less interdisciplinary than between some two less related fields like physics and literature. In the related work most of the authors constructed the similarity matrix by using a subset of the original dataset to calculate Salton's cosine similarity (Salton and McGill 1983) between categories, which were described with the same information (Porter and Rafols 2009) as used for interdisciplinarity.

We avoid this circularity and apply method of measuring similarity between textual descriptions of categories, which is to our best knowledge a novel approach for constructing similarity matrix between subject categories. This approach is feasible, because researchers belonging to subject categories have manually entered keywords describing their research interest. Although interdisciplinary collaboration between two fields certainly influences the research interests of the fields, we believe that relatedness of fields causes collaboration more than collaboration causes assimilation of research interests. Also, keywords are in most cases entered when entering the base and rarely changed in the later stages. For those reasons we believe this is a valid method of constructing subject categories similarity matrix. Below is the detailed approach of subject categories similarity matrix construction:

1. Extracting keywords from researchers and constructing documents for each subject category, in the way that each document contains only the keywords of researchers belonging to the category.
2. Generate bag-of-words representation of each document with removing stop-words, applying stemming and identifying n-grams ($n \leq 5$).

Table 2 Stirling's diversity versus the extension for networks, measured on illustrative graphs from

Interdisciplinarity	a	b	c	d	e	f	g	h
Stirling's diversity	0.093750	0.093750	0.093750	0.093750	0.093750	0.093750	0.093750	0.093750
Stirling's diversity for graphs	0	0	0.000919	0.001736	0.002467	0.003125	0.005208	0.006010

Table 3 Subject categories similarity matrix for 7 scientific fields

	1—Nat	2—Tec	3—Med	4—Bio	5—Soc	6—Hum	7—Int
1—Natural	1.000	**0.323**	**0.193**	**0.239**	0.046	0.016	0.103
2—Technical	**0.323**	1.000	0.053	0.060	0.127	0.021	**0.180**
3—Medical	**0.193**	0.053	1.000	0.175	0.054	0.007	0.029
4—Biotechnical	**0.239**	0.060	0.175	1.000	0.028	0.009	0.048
5—Social	0.046	0.127	0.054	0.028	1.000	**0.291**	0.122
6—Humanities	0.016	0.021	0.007	0.009	**0.291**	1.000	0.169
7—Interdisciplinary	0.103	**0.180**	0.029	0.048	0.122	0.169	1.000

Bold values indicate largest similarities of science field from the row with the science field from the column

Table 4 Pairs with extreme high values of similarity from the constructed scientific subfields similarity matrix

Pairs with highest similarity (top 10) Similarity		
Biotechnology	Biochemistry and molecular biology	0.58917
Urbanism	Architecture and design	0.580269
Mechanical design	Mechanical Engineering	0.56665
Computer science and informatics	Telecommunications	0.547943
Ethnology	Anthropology	0.53212
Theology	Philosophy	0.515005
Urbanism	Landscape design	0.511337
Systems and cybernetics	Manufacturing technologies and systems	0.509537
Educational studies	Sport	0.506045
Cultorology	Sociology	0.495131

Bold values indicate the largest values of mean diversity, variety, balance, disparity and Shannon's diversity

3. Compute term frequency–inverse document frequency (TF–IDF) weights.
4. Calculate cosine similarity between each pair of documents—the cosine of the angle between the vectors representing the documents. $cos\theta = \frac{\vec{a}\cdot\vec{b}}{\vec{a}\vec{b}}$
5. Calculate disparity between fields as $1 - \quad Cos\theta$

Table 3 shows similarity matrix constructed for 7 science fields of national ARRS classification. According to the matrix the most similar pairs of science fields are: (1) natural—technical, (2) social—humanities, and (3) natural—humanities. On the other hand, the most unrelated pairs of science fields according to the matrix in Table 3 are: (1) medical—humanities, (2) biotechnical—humanities, and (3) natural—humanities.

Besides similarity matrix for 7 science fields we have constructed a matrix for 72 science subfields of the national ARRS classification. Since the whole matrix would not fit in the form of a table, in Table 4 we are highlighting ten pairs of subfields with the highest similarity.

Results

Community of researchers can be defined based on different properties. Scientific fields and subfields are one possible way of defining research communities. Another possibility is to consider research topic. First, we report results of interdisciplinarity investigation on the defined scientific fields and subfields. In the second part, we generate collaboration subgraphs based on different research topics and apply the extended Stirling's diversity index to calculate interdisciplinarity.

Interdisciplinarity of science fields and subfields based on project collaboration and co-authoring publications (1996–2013)

In order to investigate evolution of interdisciplinarity, ego-networks of researchers were constructed. Ego network is a network containing a central node and all the nodes that collaborated with the central node in a defined time (notice that collaborations between the other nodes are not considered in the ego-network). Ego networks were constructed for each researcher and for every year from 1996 to 2013, with addition of a network that included the complete time span. Since interdisciplinarity was calculated both based on collaboration on research projects and co-authoring scientific publications, two variations of each ego network were constructed. Stirling's diversity index, together with the three components of the diversity (variety, balance and disparity) and the more traditional Shannon's measure were calculated for each ego network. In order to calculate the diversity of the scientific fields, the values of the individuals (belonging to the field) were averaged with arithmetic mean, with reported standard deviation. Notice that in this way we estimate interdisciplinary of the field based on collaborations without considering the content of research work.

Another way would be to construct a network for each field and determining interdisciplinarity based on set of nodes. The set of nodes would consist of the researcher belonging to the field and the researcher connected to them. We use the ego-networks approach because it is more robust. For example, consider a scientific field a with n researchers where only one researcher collaborates with n researchers from another field, while the rest $n - 1$ researchers from a do not collaborate. Using the second approach, the interdisciplinarity of the field would be greater than interdisciplinarity of the most interdisciplinary researcher. Using the ego-networks approach, the interdisciplinarity of the field would be influenced by the most interdisciplinary researcher, but it would be lowered by other non-interdisciplinary researchers. The downside of ego-centric approach is that the collaborators in different ego-networks can be set of the same researchers and the interdisciplinarity of the field would be the same as if this set would be different in every ego-network. However, we consider a field to be as interdisciplinary as are the researchers who belong to the field and find the ego-networks approach the most suitable.

Interdisciplinarity based on project collaboration

The results of interdisciplinarity of the 7 scientific fields based on project collaboration are reported in Table 5. Probability density functions for the diversity are plotted in Fig. 3. The diagrams show that frequency of ego-networks with very low interdisciplinarity (from 0, to 0.02) is very high for all diagrams except for interdisciplinarity. This shows that most of the researchers for every field have un-interdisciplinary collaboration. Exception is the Interdisciplinary field which was established especially with the reason to foster interdisciplinarity, but we must bear in mind that this field is much smaller than the rest of the fields. Note that the Interdisciplinary science field is a field designed especially for the researchers who are performing highly interdisciplinary research work. It is thus expected that this research field is the most interdisciplinary. Another thing that makes this science field special is the small number of researchers belonging to the filed—282, in opposition to 2,975 (Natural), 6,041 (Technical), 2,050 (Medical), 1,234 (Biotechnical), 2,460 (Social) and 1,209 (Humanities). As expected, the interdisciplinary science field has the highest value of diversity, measured by project collaboration. From the other six fields, the highest Stirling's diversity index is for the biotechnical sciences, followed by the natural, medical, technical, social and finally humanities. Looking at the dimensions of diversity, we can see that the technical sciences have higher variety and disparity than medical sciences, but since the balance of the medical sciences is higher, the overall diversity of the medical sciences exceeds that of the technical sciences. Comparing the Shannon's and Stirling's indexes reveals the high correlation between the two, with Pearson correlation coefficient 0.99652.

The dynamics of interdisciplinarity over scientific fields is shown in Fig. 4. We see that over time, interdisciplinarity has increasing trend for all science fields. The fastest growing interdisciplinarity has medical science with linear trend function $y = 0.0043x + 0.0626$ and $R^2 = 0.8449$. The biggest increases of interdisciplinarity of medical science are in year intervals 2004–2007 and 2011–2013.

In order to further analyze the interdisciplinarity of the medical science field, we have plotted the percentage of collaboration of researchers from medical sciences with researchers from other sciences (Fig. 5). This shows that the collaboration is strongest with natural and technical sciences, with some collaboration with biotechnical and social sciences and almost no collaboration with humanities. The intervals when medical sciences recorded the fastest growth (wider lines in Fig. 5) are caused by strong increases of collaboration with natural, technical and biotechnical sciences in the interval 2004–2007 and with natural and especially technical sciences in the interval 2011–2013. In the last interval the collaboration with technical science raised from 8.62 % in 2011 to 14.33 % in 2013, which almost equals with the collaboration with natural science (14.34 %)—the most collaborative throughout the whole measured period.

We have examined in detail the percentage of research collaboration of each scientific field, results are reported in Table 6 and plotted in Fig. 6. The results show that the Humanistic science has the highest percentage of within field collaboration (75.14 %), which then results with the lowest interdisciplinarity of this science. From other fields, Humanities collaborate mostly with Social (11.31 %), Technical (6.07 %) and Natural sciences (5.06 %), while the collaboration with Biotechnology (1.58 %) and Medical (0.42 %) sciences is negligibly small. The strongest collaboration with Social sciences is expected, because these two sciences are related, which is confirmed with our similarity matrix constructed on the basis of keywords similarity. The similarity of humanities and social sciences is 29.1 % according to our similarity matrix. This means the collaboration of Humanities with Social sciences does not contribute much to the interdisciplinarity, but the collaboration with Technical and Natural sciences even if almost twice less intense will have stronger impact on interdisciplinarity measure because of low similarities with these fields—2.1 and 1.6 % respectively.

Social science has second strongest within field collaboration (72.51 %). From collaboration with other fields, the strongest is with Technical science (10.02 %), although it is more similar to Humanities science with second largest share of collaboration (7 %). Humanistic science collaborates to a lesser extent with Natural and Medical science and even less with Biotechnical and Interdisciplinary science field. Technical science has the next highest percentage of within field collaboration (69.36 %) and some collaboration with Natural (13.68 %), Medical (6.57 %), Social (4.36 %), Biotechnical (3.93 %) and Humanistic (1.60 %) science. Interesting is the fairly high percentage of collaboration with

Table 5 Interdisciplinary of science fields measured by research project collaboration

	Diversity		Variety[2]	Balance	Disparity	Shannon
	Mean	SD				
Natural	0.1446	0.0914	0.4744	0.1854	2.7925	0.6378
Technical	0.1131	0.0980	0.3725	0.1403	2.2080	0.4907
Medical	0.1279	0.0987	0.3560	0.1486	2.1141	0.5147
Biotechnical	**0.1581**	0.0795	**0.6610**	**0.1935**	**3.9392**	**0.6976**
Social	0.1051	0.0964	0.3098	0.1240	1.8866	0.4308
Humanities	0.0893	0.0930	0.2574	0.1079	1.5381	0.3716
Interdisciplinary	0.2324	0.0582	0.9755	0.2756	5.9546	1.0086

Values for variety are 0–1 normalized by the number of disciplines (in this case 7)

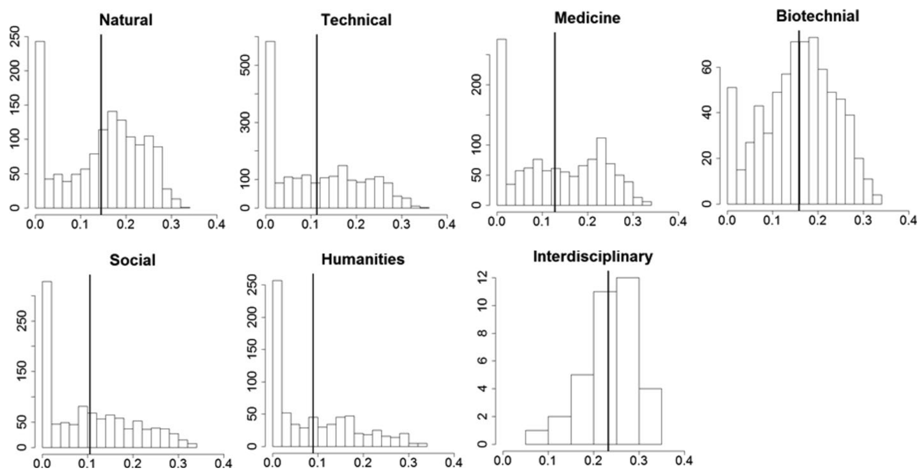

Fig. 3 Probability density functions of ego networks diversity index based on project collaboration for science fields from Table 5. Diversity is on x-axis and frequency on y-axis. Intervals for x-axis are equal for each histogram (0–0.4), while intervals for y-axis differ depending on the size of the field. There are 20 classes of width 0.02 for each diagram except for Interdisciplinarity, which has 8 classes of size 0.05. *Vertical lines* indicate mean values

Medical science. Since the similarity score between Technical and Medical sciences is low in our similarity matrix (0.053), this type of collaboration is important contribution to interdisciplinarity of Technical science. Medical science has within field collaboration 68.3 %, expectedly (similarity score 0.193) strongest collaboration with Natural science (12.31 %) and surprisingly (similarity score 0.053) high collaboration with Technical science (10.63 %). Biotechnical science has 67.85 % of within field collaboration and a high percentage of collaboration with Natural science (18.40 %), which is the strongest between fields collaboration (without taking into account the Interdisciplinary field). The percentage of within field collaboration of Natural science is by far the lowest (56.05 %) (except Interdisciplinary field), the collaboration is divided mostly on Technical (16.08 %), Biotechnical (14.60 %) and Medical (8.95 %) sciences. Interdisciplinary field is the only one with the percentage of within field collaboration (5.96 %) lower than collaboration

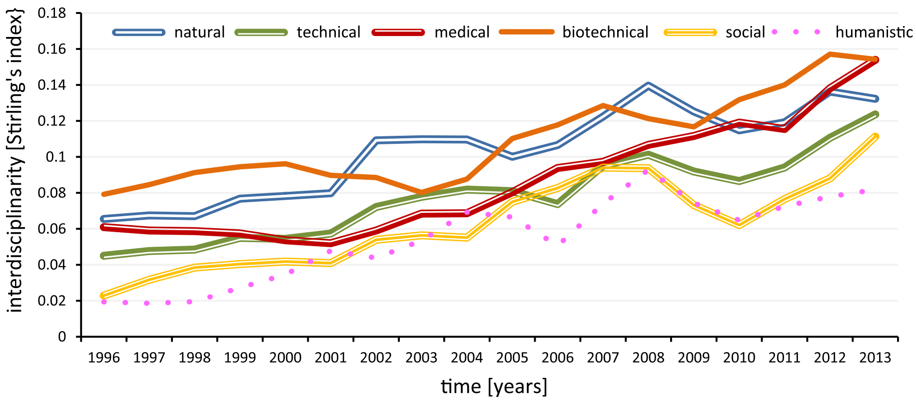

Fig. 4 Interdisciplinarity of research fields from 1996 to 2013, based on collaboration on research projects

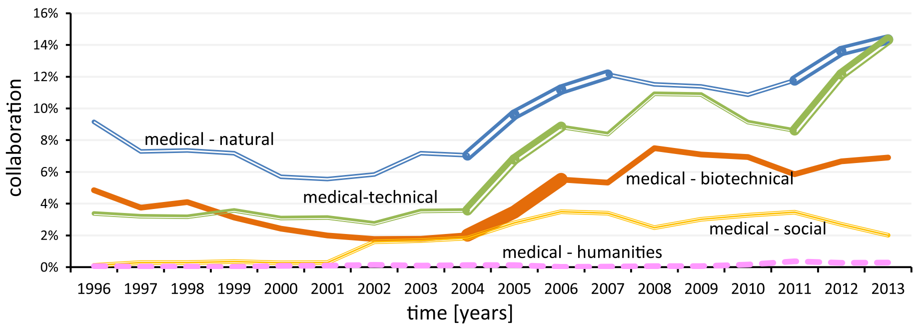

Fig. 5 Collaboration of researchers from Medical science with researchers from other sciences over time (%)

with some other fields. Since the field involves very small number of researchers, its percentage in other fields' collaboration is very low (under 1 %). The researchers from Interdisciplinary science mostly collaborate with Natural (25.90 %), Technical (23.02 %), Biotechnical (21.69 %) and Social sciences (11.31 %) and somewhat less with Humanistic (5.55 %) and Medical sciences (2.26 %).

Interdisciplinarity based on co-authoring publications

Table 7 shows the results of interdisciplinarity, measured with Stirlings and Shannons diversity index, on the basis of co-authoring scientific publications. Probability density functions for the diversity are plotted in Fig. 7. Like in the case of project collaboration ego-networks, we can notice that all the diagrams except the one for interdisciplinary field have class with lowest interdisciplinarity index (from 0 to 0.02) of much higher frequency than the rest of the classes. The most interdisciplinary science is Biotechnology, followed by Natural, Social, Humanistic, Medical and Technical sciences. The Interdisciplinary science field has to be considered separately, because it is a special field designed for Interdisciplinary research with significantly smaller number of researchers. Similarly as in the case of projects, the Stirling's and Shannon's diversity indexes are highly correlated,

Table 6 The table shows how much percentage of research collaboration a field from row has with each field from the columns

	Natural	Technical	Medical	Biotechnical	Social	Humanistic	Interdisciplinary
Natural	56.05	**16.08**	8.95	14.60	2.11	1.60	0.61
Technical	**13.68**	69.36	6.57	3.93	4.36	1.63	0.46
Medical	**12.31**	10.63	68.33	5.89	2.58	0.18	0.07
Biotechnical	**18.40**	5.82	5.40	67.85	1.26	0.63	0.65
Social	4.12	**10.02**	3.67	1.95	72.51	7.00	0.72
Humanistic	5.06	6.07	0.42	1.58	**11.31**	75.14	0.41
Interdisciplinary	**25.90**	23.02	2.26	21.69	15.62	5.55	5.96

E.g. in average 18.4 % of collaborators of Medical science are from Natural science and 10.63 % are from Technical science. The value on the diagonal shows the collaboration within a science, e.g., 75.14 % for Humanistic

Bold values show the largest percentages of collaboration of science fields from rows with other science fields

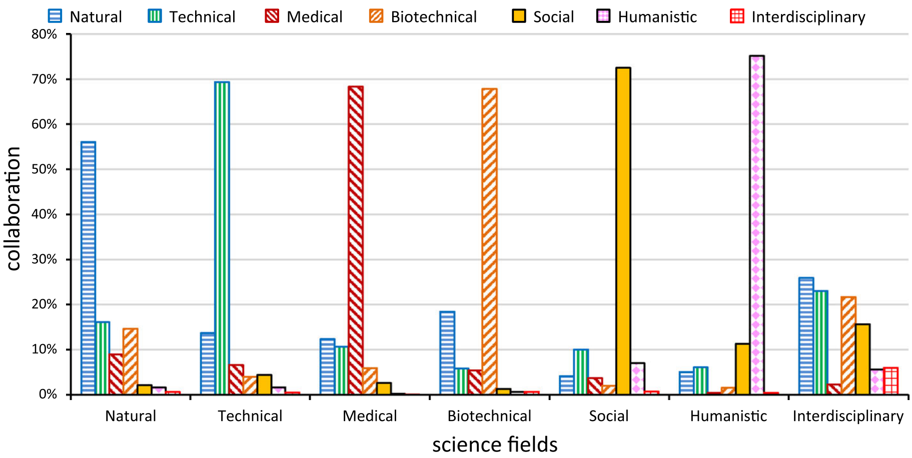

Fig. 6 Share of research collaboration of each science with the other sciences based on research projects collaboration

with Pearson coefficient 0.99788. This is in accordance with (Porter and Rafols 2009) the finding that Stirling's diversity is very closely associated with traditional diversity indicators (Shannon and Herfindahl). At this point we can notice that the two most interdisciplinary sciences are the same as with the project collaboration and the interdisciplinarity of all sciences is growing with time (Fig. 8). Detailed comparison of results obtained on the basis of project and publication collaboration is given in the next chapter.

Table 8 shows the percentages of collaboration each science from a row has with the science from a column (plotted in Fig. 9). The Medical science has the highest percent of within field collaboration (79.31 %) and low collaboration with other fields, from which the most with Natural science (8.08 %). Technical science has 73.02 % of within collaboration, 12.72 % of collaboration with the most related Natural science and some collaboration with Social (5.63 %), Medical (4.06 %), Biotechnical (2.42 %) and Humanistic (1.66 %) sciences. Humanistic science collaborates 71.32 % within the field with noticeable collaboration with Social science (16.50 %). Social science has slightly

Table 7 Interdisciplinarity of science fields measured on the basis of co-authoring publications

	Diversity		Variety	Balance	Disparity	Shannon
	Mean	SD				
Natural	0.1404	0.0906	0.5369	0.1791	3.2059	0.6284
Technical	0.0973	0.0914	0.3558	0.1207	2.1295	0.4230
Medical	0.1100	0.0915	0.4822	0.1265	2.9243	0.4682
Biotechnical	**0.1516**	0.0864	**0.6024**	**0.1851**	**3.6063**	**0.6624**
Social	0.1327	0.0918	0.5130	0.1569	3.1536	0.5575
Humanities	0.1142	0.0920	0.4463	0.1395	2.7215	0.4961
Interdisciplinary	0.2357	0.0739	0.8707	0.2741	5.3290	0.9978

Bold values indicate the largest values of mean diversity, variety, balance, disparity and Shannon's diversity

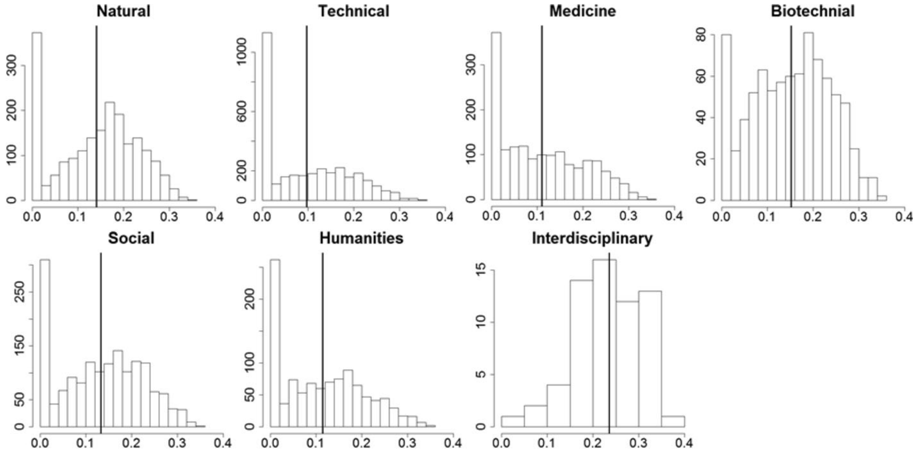

Fig. 7 Probability density functions of ego networks diversity index based on co-authoring for science fields from Table 7. Diversity is on x-axis and frequency on y-axis. Intervals for x-axis are equal for each histogram (0–0.4), while intervals for y-axis differ depending on the size of the field. There are 20 classes of width 0.02 for each diagram except for Interdisciplinarity, which has 8 classes of size 0.05. *Vertical lines* indicate mean values

lower within field collaboration (69.21 %) and has more balanced collaboration with other science fields: Humanistic (10.78 %), Technical (8.86 %), Medical (4.68 %), Natural (4.71 %) and Biotechnical (1.45 %). Biotechnical science is the most interdisciplinary, but has second lowest within field collaboration (65.47 %), with strongest collaboration with Natural science (19.51 %).

Comparison of results based on project and publication collaboration

The most interdisciplinary science fields based on co-authoring publications are Biotechnologies and Natural sciences, which is the same as in the case of research collaboration on projects. However the collaboration of Social and Humanistic scientists is more interdisciplinary than the collaboration of Medical and Technical scientists, which is a different result than the one based on research projects. The Biotechnical science is the most and the

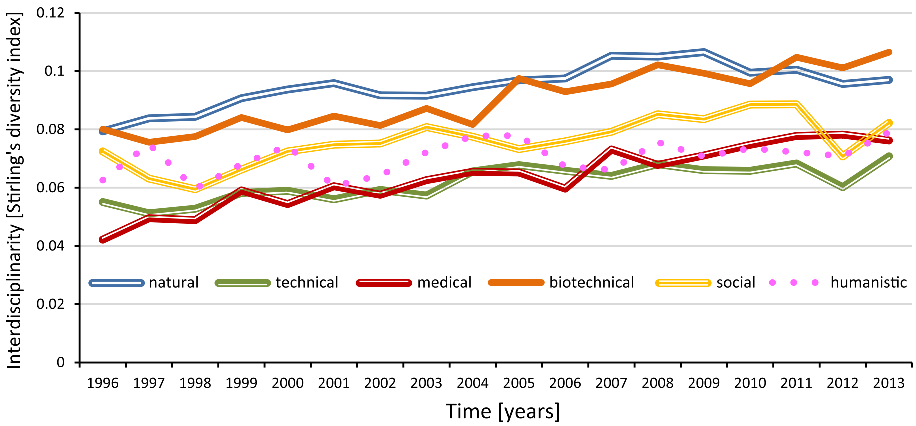

Fig. 8 Interdisciplinarity of research fields from 1996 to 2013, based on co-authoring publications

Table 8 The percentage of publication co-authoring collaboration a field from a row has with each field from the columns

	Natural	Technical	Medical	Biotechnical	Social	Humanistic	Interdisciplinary
Natural	60.02	**15.03**	7.85	10.74	3.54	2.54	0.28
Technical	**12.72**	73.02	4.06	2.42	5.63	1.66	0.50
Medical	**8.08**	4.94	79.31	3.42	3.62	0.54	0.08
Biotechnical	**19.51**	5.18	6.03	65.47	1.97	1.43	0.40
Social	4.71	8.86	4.68	1.45	69.21	**10.78**	0.31
Humanistic	5.19	3.99	1.08	1.61	**16.50**	71.32	0.31
Interdisciplinary	16.25	**34.49**	4.40	12.79	13.52	8.70	9.85

The value on the diagonal shows the collaboration within a science

Bold values show the largest percentages of collaboration of science fields from rows with other science fields

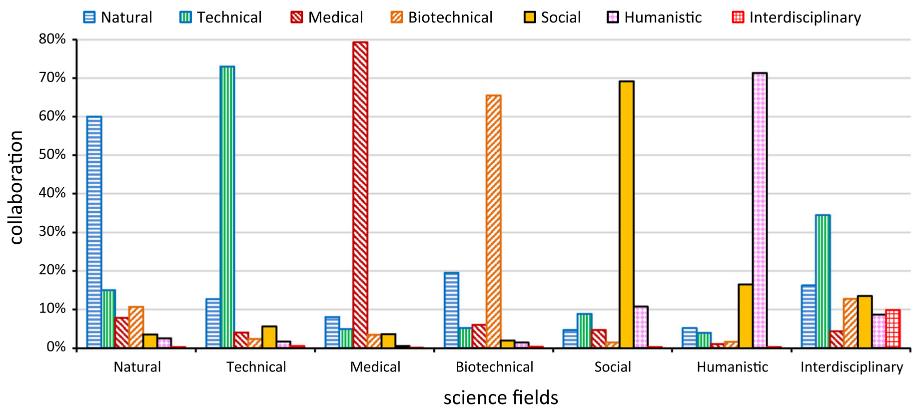

Fig. 9 Share of research collaboration of each science with the other sciences based on co-authoring publications

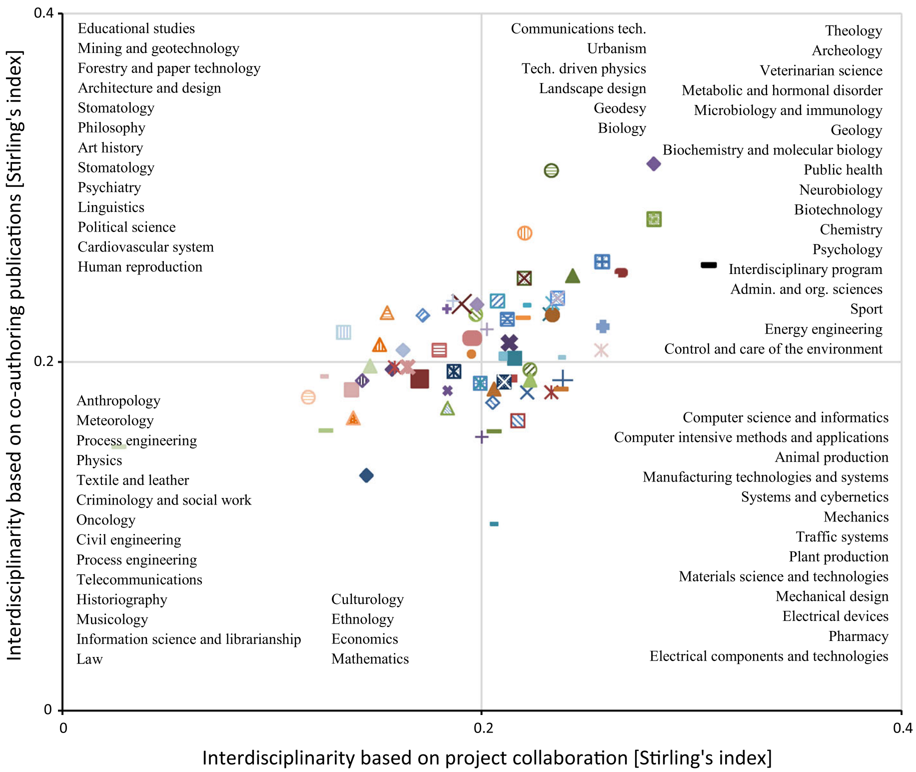

Fig. 10 Interdisciplinarity of science subfields based on projects and publication collaboration. *Symbols* in each quadrant represent the subfields in the corresponding quadrant. The subfields are ordered from more to less interdisciplinary. For example, Communication technologies represented with a *rhombus* in the *upper right corner* have high interdisciplinarity according to both projects and publications. On the other hand *rhombus* on the *lower left corner* represents Mathematics with low interdisciplinarity

Natural science is the second most interdisciplinary field in both cases—measured by projects collaboration and co-authoring. The results indicate that researchers behave differently regarding the interdisciplinarity of collaboration in the two research activities—projects and publications. However, there is some correlation between interdisciplinarity based on projects and publications. Measured on the 7 science fields the Pearson's correlation coefficient is 0.91, while measured on the 72 science subfields the Pearson's correlation coefficient is 0.49. According to interdisciplinarity based on projects and publications, we can cluster the 72 science subfields into four categories: (1) high projects ($\geq$0.2) and publications ($\geq$0.2) based interdisciplinarity, (2) high project ($\geq$0.2) and low publications (<0.2) interdisciplinarity, (3) low projects (<0.2) and high publications ($\geq$0.2) based interdisciplinarity and (4) low projects (<0.2) and publications (<0.2) based interdisciplinarity. Figure 10 depicts placing of the subfields on a two dimensional plane, where one dimension is interdisciplinarity based on projects collaboration and the other one is interdisciplinarity based on co-authoring publications. We can see that if the border between high and low is set to 0.2, the clustering into four groups is quite balanced. Also, there is no obvious pattern for belonging to a group related to soft/hard, lab/office (Kronegger et al. 2012), or natural/technical science subfields types.

Evolution of interdisciplinarity Evolution of interdisciplinarity observed by Mali et al. (2010) showed that the amount of coauthored publications in the field of sociology increased over the last two decades (1986–2005). We measured the mean number of authors peer publication for all scientific disciplines and obtained the same result—increasing number of authors. Similarly, increasing trend is found with research projects. Both results are plotted in Fig. 11. The mean number of authors peer publications increase in linear trend function $y = 0.0204x + 1.4356$ and $R^2 = 0.8494$, which gives an average annual linear grow rate of 1.4 %. The number of researchers in projects grows with liner trend function $y = 0.2134x + 5.8041$, with $R^2 = 0.2544$ and has an annual linear growth rate of 3.5 %. Measures of co-authorship were examined in Porter and Rafols (2009) with findings of average growth in the period of 30 years about 75 % (annual linear grow rate 2.59 %), which ranged from 48 % in Math, 54 % in Physics to 90 % in Neurosciences. We did not find any other work that measured collaboration of research projects over time, but our results indicate these main differences compared to co-authoring: the average and the variance of number of researchers in projects is larger than on publications, which makes the growth much less stable than on publications. Furthermore the projects have faster growth of number of participants in time.

Both, collaboration and interdisciplinarity grow in time. The annual linear growth rate of number of collaborators in projects is 3.5 %, while the annual liner growth rate of interdisciplinarity based on projects is 8.5 %. The annual linear growth rate of number of authors peer publication is 1.4 %, while the interdisciplinarity based on publications grows with rate of 0.7 %. This shows that interdisciplinarity of projects grows faster than the collaboration, while the interdisciplinarity of publications grows slower than the collaboration. Increase of collaboration does not influence the measure of interdisciplinarity (Eq. 1), because only the proportional representations of elements of disciplines in the system are taken into account. With fixed distribution of field sizes, the expected value of the proportional representations of elements stays the same and does not depend on the sizes of observed ego networks.

Interdisciplinarity of topic subgraphs

Topic subgraphs are constructed by selecting researchers whose research work is related to a selected topic. This is done by matching the selected topic with keywords that describe research interest, descriptions of projects and descriptions of publications. The researchers

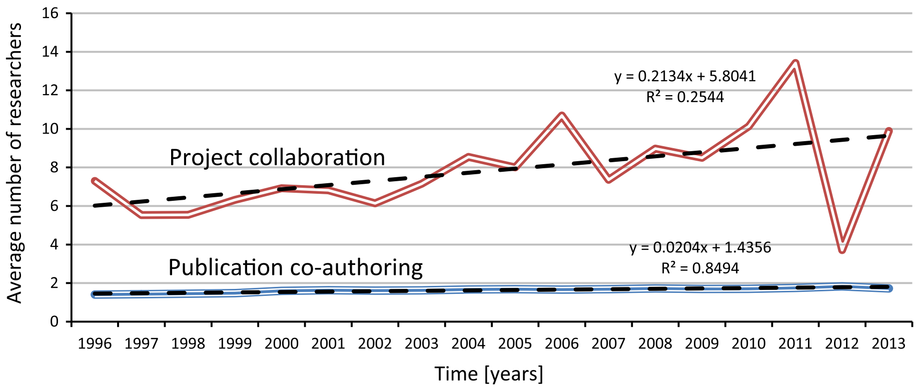

Fig. 11 Average (mean) number of researchers peer project and publications from 1996 to 2013

are the nodes of a topic subgraph, while the edges represent collaborations between the set of nodes. Since our approach is based on project collaboration and co-authoring publications, two variations of each topic subgraph was constructed, one with edges representing project collaboration and the other with edges representing co-authoring, while the set of nodes is the same in both cases. Using the Stirling's diversity index that combines variety, balance and disparity, we can measure the diversity of the selected set of nodes. However, since this measure ignores the connections between the nodes, it misses the key concept of interdisciplinarity—the knowledge integration. In the scope of our problem domain, we are interested not only in diversity of researchers related to a research topic, but also in the degree of collaborative work between them. To capture the attribute of connectivity in addition to variety, balance and disparity we are using the extension of Stirling's diversity for graphs. It is well known fact that some research topics are more interdisciplinary than others. In our research work we examined how interdisciplinary are the topics when knowledge integration is done by project collaboration and co-authoring publications. We set two main hypotheses:

H1 Some diverse research topics are less interdisciplinary than some other less diverse topics, and vice versa. This occurs in cases when knowledge integration is weak in a topic with potential for interdisciplinary collaboration, and/or the integration is stronger in a less diverse topic.

H2 Interdisciplinarity based on co-authoring versus project collaboration varies across topics. Causes for this could be different preferences of the involved researchers to write publications or to work on projects, suitability of a topic for publishing, overlapping with project financing programs.

We constructed ten different topics subgraph and calculated Stirling's diversity index and the extended version of the index suitable for graphs. The results are given in Table 9. The values of Stirling's diversity and the extended version are not mutually comparable, but the topics are sorted by Interdisciplinarity for easier comparison of rankings.

The results confirm the hypothesis H1. For instance, Anthropology is related to more diverse researchers than Pharmacy, but more knowledge integration based on co-authoring is present in the Pharmacy topic graph. Another example is Machine learning, a topic which is more interdisciplinary than some other topics (Economy, Artificial intelligence, Nanotechnology) which are more diverse if the integration is ignored. We also observe that some topics are more integrative on project, while others are more integrative on publications, which confirms the hypothesis H2. In our sample of 10 topic graphs, exactly half of them are more interdisciplinary on projects versus publications. Although the topics with more integration of knowledge based on projects instead on publications seem more technical, more detailed analysis would have to be performed to understand the causes of this phenomenon.

Conclusion and future work

In this paper we have presented a new measure of interdisciplinarity based on Stirling's diversity index. The measure extends the Stirling's index by adding the component of connectivity, what makes it suitable for measuring interdisciplinarity of graphs. Since one of the components of the Stirling's index is disparity which takes into account similarities between subject categories, construction of subject categories similarity matrix is one of

Table 9 Interdisciplinarity of subject topics graphs

Extended Stirling's diversity	Stirling's diversity	
Based on projects	Based on publications	
Pharmacy (0.044661)	Pharmacy (0.280000)	Anthropology (0.439999)
Anthropology (0.033762)	**Anthropology (0.094626)**	Pharmacy (0.280000)
Political sciences (0.020816)	**Political sciences (0.027454)**	Political sciences (0.267939)
Machine learning (0.020781)	Machine learning (0.018986)	Economy (0.240534)
Economy (0.016346)	**Economy (0.018405)**	Artificial intelligence (0.167873)
Artificial intelligence (0.016186)	**Artificial intelligence (0.017829)**	Nanotechnology (0.159772)
Linear algebra (0.014265)	Nanotechnology (0.012470)	Machine learning (0.131334)
Nanotechnology (0.013030)	Linear algebra (0.011513)	Graph theory (0.121634)
Graph theory (0.006412)	**Nutrition (0.009090)**	Linear algebra (0.119849)
Nutrition (0.007467)	Graph theory (0.006234)	Nutrition (0.120185)

Bold values indicate the science subjects with different orderings with the two measures

the key steps in measuring interdisciplinarity. Rather than using a circular approach with a subset of data to construct the matrix using the same information that is used for measuring interdisciplinarity, we applied a methodology based on calculating similarities of the textual descriptions of the categories. This methodology seems natural and applicable in many cases, but we did not find any other work applying it for construction of subject categories similarity matrix.

The methods were applied on Slovenian research community. Unlike most of the related work, we based measuring of interdisciplinarity on collaboration. Research work is performed with number of different activities (Porter et al. 2007). We argue that research projects and scientific publications are two typical kinds of work which support knowledge integration. The analysis was performed taking into account the temporal component in order to be able to observe the evolution of interdisciplinarity. The results of the exploratory analysis give several interesting findings related to interdisciplinarity and evolution of interdisciplinarity of particular science fields, comparison of interdisciplinarity based on projects and publications, growth of interdisciplinarity compared to growth of collaboration and comparison of interdisciplinarity of different topic graphs.

Results of the exploratory analysis open a big space for future work. The most interesting direction seems investigation of the causes why some subject topics are more interdisciplinary based on projects, while other are more interdisciplinary on publications. Another interesting phenomenon is the difference in knowledge integration across topics. Understanding and ability to direct interdisciplinarity of particular topics would of a great value in the context of interdisciplinarity as an environment for exceptional scientific achievements and innovation.

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