Twenty Years of Network Science: A Bibliographic and Co-Authorship Network Analysis

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Abstract. Two decades ago three pioneering papers turned the attention to complex networks and initiated a new era of research, establishing an interdisciplinary field called network science. Namely, these highly-cited seminal papers were written by Watts & Strogatz, Barabási & Albert and Girvan & Newman on small-world networks, on scale-free networks and on the community structure of complex networks, respectively. In the past 20 years – due to the multidisciplinary nature of the field – a diverse but not divided network science community has emerged. In this paper, we investigate how this community has evolved over time with respect to speed, diversity and interdisciplinary nature as seen through the growing co-authorship network of network scientists (here the notion refers to a scholar with at least one paper citing at least one of the three aforementioned milestone papers). After providing a bibliographic analysis of 31,763 network science papers, we construct the co-authorship network of 56,646 network scientists and we analyze its topology and dynamics. We shed light on the collaboration patterns of the last 20 years of network science by investigating numerous structural properties of the co-authorship network and by using enhanced data visualization techniques. We also identify the most central authors, the largest communities, investigate the spatiotemporal changes, and compare the properties of the network to scientometric indicators.

Keywords: Science of science · Network science · Bibliometrics · Scholarly data · Scholarly network analysis · Co-authorship network

1 Introduction

Complex networks have been studied extensively since they efficiently describe a wide range of systems, spanning many different disciplines, such as Biology (e.g., protein interaction networks), Information Technology (e.g., WWW, Internet), Social Sciences (e.g., collaboration, communication, economic, and political networks), etc. Moreover, not only the networks originate from different domains,
but the methodologies of network science as well, for instance, it heavily relies on
the theories and methods of graph theory, statistical physics, computer science,
statistics, and sociology.

In the last two decades, network science has become a new discipline of great
importance. It can be regarded as a new academic field since 2005 when the
U.S. National Research Council defined network science as a new field of basic
research [11]. The most distinguished academic publishing companies announce
the launch of new journals devoted to complex networks, one after another (e.g.
Journal of Complex Networks by Oxford University Press, Network Science by
Cambridge University Press, Applied Network Science and Social Network Anal-
ysis and Mining by Springer). Network science also has its own prestigious con-
ferences attended by thousands of scientists. Leading universities continuously
establish research centers and new departments for network science, furthermore,
launched Master and PhD programs in this field (such as Yale University, Duke
University, Northeastern University or Central European University).

The significance of network theory is also reflected in the large number of
publications on complex networks and in the enormous number of citations of
the pioneering papers by Barabási & Albert [5], Watts & Strogatz [33] and
Girvan & Newman [13]. Some researchers interpret network science as a new
paradigm shift [14]. However, complex networks are not only acknowledged by
the research community, but innovative textbooks aimed for a wider audience
have also been published [7,21], moreover, the concepts of network science have
appeared in the popular literature [4,32] and mass media [28] as well.

In the last two decades, complex networks became in the center of research
interest thanks to – among many others – the aforementioned three pioneering
papers and due to the fact that the prompt evolution of information technology
has opened up new approaches to the investigation of large networks. This pe-
riod of 20 years can be regarded as the golden age of network science. The first
challenge was to understand network topology, to this end, structural properties
were put under the microscope one after the other (small-worldness, scale-free
property, modularity, fractality, etc.) and various network models were proposed
to understand and to mathematically describe the architecture and evolution
of real-world networks [31]. In recent years, there has been a shift from
the structural analysis to studying the control principles of complex networks [3].
Remarkable computing power, massive datasets, and novel computational tech-
niques keep great potential for network scientists for yet another 20 years [31].

This work is a tribute to the achievements of the network science community
in the past 20 years. We provide a bibliographic analysis of 31,763 network
science papers and we also construct and investigate the co-authorship network
of network scientists to identify how the network science community has been
evolving over time.

The present study also extends the earlier conference version of this paper [19]
in several important directions. Namely, here we provide a more detailed litera-
ture review; we examine a longer time period; and we answer the question of
how the network science community has evolved over time with respect to speed,
diversity and interdisciplinary nature by implementing novel analyses. Here we
also provide an analysis of the co-occurrence network of the keywords. More-
over, we supplement our previous work with several other new methods and
data visualizations that help to make insightful observations regarding the last
two decades of network science.

The main contributions of this work can be summarized as follows:

– We collect 31,763 network science papers and provide a bibliographic anal-
ysis investigating various characteristics of the papers and showing how the
discipline has developed over time.
– We construct the co-authorship network of 56,646 network scientists and
undertake a scholarly network analysis study by analyzing its topology and
dynamics.
– We answer the following major research questions:
  • What are the most important venues of network science and how have
    they changed over time?
  • How the publication patterns vary over research areas and time?
  • What are the most important topics of network science and how have
    they evolved through time? What relationships can we explore among
    the most frequent keywords of network science?
  • How the network science community has evolved over time with respect
    to speed, diversity and interdisciplinary nature?
  • What are the most typical patterns in terms of international and inter-
    disciplinary collaborations?
  • Who are the most central authors and how do the largest communities
    look like? How do these network properties compare to other sciento-
    metric indicators?

2 Scholarly networks analysis

The present paper joins the line of research focused on scholarly network analysis
that is based on big scholarly data [26]. Big scholarly data refers to the rapidly
growing data accessible in digital libraries containing information on millions of
scientific publications and authors [34]. The easily available data sources (Web of
Science, Scopus, PubMed, Google Scholar, Microsoft Academic, the U.S. Patent
and Trademark Office, etc.) together with novel powerful data analysis technolo-
gies have led to the emergence of science of science [12] that gives us a better
understanding of the self-organizing rules and patterns of science, e.g. how a
discipline has emerged and evolved over time [17]. Various scholarly networks
at many levels can be formed based on scholarly data; Pawar et al. identify the
following forms of scholarly networks of great interest [24]:

1. co-authorship networks (a link is formed between scientists by their co-
   authorship of at least one scientific paper),
2. citation networks (a directed link is formed between documents referencing
   one another),
3. co-citation networks (a link is formed between documents if they are cited together),
4. bibliographic coupling (documents are linked if they share common references),
5. co-occurrence networks (keywords/topics are linked if they occur in the same document), and
6. heterogeneous networks (two or more coupled scholarly networks).

Among the aforementioned scholarly networks perhaps co-authorship networks have attracted the greatest deal of research interest, owing to the fact that co-authorship is one of the most important reflections of research collaboration, which is an essential mechanism that joins together distributed knowledge and expertise into novel discoveries. Furthermore, building the map of sciences is not only important for sociologists and other scholars to understand researchers’ interaction but for policymakers as well to address sharing resources [34]. Co-authorship networks have been studied extensively in various ways and from various perspectives: e.g. the collaboration network determined by the articles of a certain journal, a specific country or a research community that cites a particular influential paper or author [1,2,6,15,22,23]. In this paper, we investigate the co-authorship network of network scientists as defined in the following section.

Keywords co-occurrence networks have also been investigated thoroughly [18,27,29]. Keywords of academic articles can provide a concise overview of the content and the core idea of the body of the papers. In contrast to word clouds, co-occurrence networks do not only show the frequency of the keywords but also allow us to discover the relationship between them. Li et al. investigated 6,900 articles published between 1982 and 2013 which had been indexed using the keyword ‘complex network(s)’ and provided a co-keyword network and a keyword co-occurrence network analysis [18].

3 Preliminaries and data

In this section, we describe how the co-authorship network of network scientists was constructed, how the examined set of academic publications was chosen and collected, what data preparation steps were conducted. Moreover, we also present some useful notions and preliminaries.

3.1 Co-authorship network of network scientists

To the best of our knowledge, the co-authorship network of network scientists has been analyzed only by Newman et al. [24,25]. However, their network consists of 1,589 authors, while this study investigates a much larger network (56,646 vertices and 357,585 edges) spanning a longer time horizon (1998-2019).

We construct the co-authorship network of network scientists as follows. We consider three ground-breaking papers around the millennium that can be regarded as the roots of the rise of network science: the paper of Watts & Strogatz [33] on small-world networks, the work of Barabási & Albert [5] about
scale-free networks and the paper of Girvan & Newman [13] that reveals the community structure of complex networks.

In this work, we consider a paper as a network science paper if it cites at least one of the three aforementioned pivotal articles (in addition, the three originating papers are also regarded as network science papers, obviously). Similarly, we call someone a network scientist if (s)he has at least one network science paper. The previous definitions of network science paper and network scientist are of course quite arbitrary. It is important to note that the papers that refer to one of the three seminal papers are not necessarily about network science and there certainly exist network science articles that do not refer to any of the aforementioned pioneering papers. On the other hand, we believe that this concept is a good proxy for our purposes and it is worth studying. We construct the co-authorship network of the network scientists where two of them are connected if they have at least one joint network science paper (see Fig. 1). In other words, this network is a one-mode projection onto scientists, from the bipartite network of scientists and the network science papers they authored. The anonymized data of the constructed network is available in the supplementary material [20].

![Fig. 1: The co-authorship network of network scientists colored by communities.](image)

![Fig. 2: Distribution of the citations among the three pioneering papers.](image)

### 3.2 Glossary

**Definition 1 (Average path length).** A path is a sequence of edges which connect a sequence of vertices. The distance $d(u, v)$ between the vertices $u$ and $v$ is the length (number of edges) of the shortest path connecting them. The $l_G$
average path length of a graph $G$ of size $n$ is defined as:

$$l_G = \frac{1}{n(n-1)} \sum_{i \neq j} d(v_i, v_j).$$

**Definition 2 (Degree distribution).** The degree $\deg(v)$ of a vertex $v$ in a simple, undirected graph is its number of incident edges. The degree distribution $P$ is the probability distribution of the degrees over the whole network, i.e. $P(k)$ is the probability that the degree of a randomly chosen vertex is equal to $k$.

**Definition 3 (Assortativity coefficient).** The assortativity coefficient is the Pearson correlation coefficient of degree between pairs of linked nodes. The assortativity coefficient is given by

$$r = \frac{\sum_{j,k} j \cdot k (e_{j,k} - q_j q_k)}{\sigma_q^2},$$

where the term $q_k$ is the mass function of the distribution of the remaining degrees (degree of the nodes minus one) and $j$ and $k$ indicates the remaining degrees. Furthermore, $e_{j,k}$ refers to the mass function of the joint probability distribution of the remaining degrees of the two vertices. Finally, $\sigma_q^2$ denotes the variance of the remaining degree distribution with mass function $q_k$ i.e. $\sigma_q^2 = \sum_k k^2 q_k - (\sum_k k q_k)^2$.

**Definition 4 (Local clustering coefficient).** The local clustering coefficient of vertex $v$ is the fraction of pairs of neighbors of $v$ that are connected over all pairs of neighbors of $v$. Formally:

$$C_{loc}(v) = \frac{|\{(s,t) \text{ edges} : s,t \in N_v \text{ and } (s,t) \in E\}|}{\deg(v)(\deg(v) - 1)},$$

where $N_v$ is the neighborhood of the node $v$ i.e. the vertices adjacent to $v$.

The average (local) clustering coefficient of a $G$ graph is defined as:

$$\bar{C}(G) = \frac{1}{n} \sum_{v \in V(G)} C_{loc}(v),$$

where $n$ is the size of the graph.

**Definition 5 (Global clustering coefficient).** The global clustering coefficient $C$ of the graph $G$ is the fraction of closed triplets (paths of length two in $G$ that are closed) over all of the triplets (paths of length two) in $G$.

**Definition 6 (Betweenness centrality).** Betweenness centrality of a node $v$ is given by the expression:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}},$$

where $\sigma_{st}$ is the total number of shortest paths from node $s$ to node $t$ and $\sigma_{st}(v)$ is the number of those paths that pass through $v$. 
Definition 7 (h-index). The h-index is an author-level metric defined as the maximum value of h such that the given author has published h papers that have each been cited at least h times.

Definition 8 (Harmonic centrality). Harmonic centrality of a node $v$ is the sum of the reciprocal of the shortest path distances from all other nodes to $v$:

$$H(v) = \sum_{u \neq v} \frac{1}{d(u,v)}.$$

3.3 Data collection and preparation

We build our analysis on data collected from the Web of Science bibliographic database, retrieved on January 2, 2020. The collected data consist of 41,245 rows with multiplicity corresponding to the citing works of the three seminal articles [5,13,33]. For each citing paper we have information on the document title, publication name, publication type, publisher, publication year, authors full name, author address, research area, keywords, cited reference count, total times cited count, page count, abstract, etc.

After the data were collected, various data preparation steps were conducted, including merging the files, handling missing fields, deleting duplicates and indicating which of the three seminal papers were cited by the given article. These preparation steps reduced the dataset to 31,763 unique rows and the citation pattern of the corresponding articles is shown in Fig. 2.

The authors are represented by the full name field of Web of Science, however, this field is unfortunately not consistent, the author called John Michael Doe may appear as Doe, John; John Doe; Doe, J.; Doe, J. M.; Doe, John Michael, and other variants. To overcome this issue, we created a dictionary that defines the name variants that correspond to the same author. Furthermore, we cannot distinguish between different scientists with the same name, this issue is mainly relevant for Asian authors. However, the error introduced by this problem is negligible, as also pointed out by Newman [22] and by Barabási et al. [6].

4 Analysis of network science papers

First, we analyze the enormous number of citing works, i.e. the network science papers. Fig. 3 shows the top 10 research areas where the citing works belong to, illustrating the interdisciplinary nature of network science. We can see that the first decade was dominated by physics while later computer science took over. It is also clear from the figure that neuroscience has started to use network science tools in the last decade. The journals that publish the most network science papers are also shown in Fig. 3. Considering the number of publications, Physical Review E was the leading scientific forum of network science in the first half of the examined period, while PLOS One and Scientific Reports emerged in the last decade. Currently, Physica A can be regarded as the leading journal of network science in terms of the number of published network science articles.
Fig. 3: Top 10 research areas and journals of network science papers

Fig. 4 shows the number of collaborating authors per citing works, the most typical numbers of co-authors in a network science paper are 2 and 3. Almost one-tenth of the network science papers are sole-authored. M. E. J. Newman has the highest number of sole-authored network science papers, namely 27. While the figure shows only up to 15 number of authors, there are a few papers with a high number of collaborating authors e.g. the paper with the highest number of authors (387) is a paper of the Alzheimers Disease Neuroimaging Initiative \cite{16}. The authors of this article emerge as a maximal clique of the co-authorship network of network scientists as it can be seen in Fig. \ref{fig:1}.

We also investigate the distribution of network science papers written by network scientists. The authors with the highest number of network science papers together with the citation count of their network science papers are shown in Table \ref{tab:1}. Guanrong Chen has the highest number of network science papers, his research areas are nonlinear systems and complex network dynamics and control.
To gain some insights on how the publication patterns vary in network science depending on the research area, we show how the distribution of the number of cited references and the length of the papers differ across research areas (see Fig. 5). We can observe that in neuroscience and neurology authors typically cite a high number of articles while in computer science or engineering the typical number of cited references is much smaller. Engineering together with telecommunications and physics are also the areas with the shortest articles, while it can also be due to the fact that in those disciplines double-column publication formats are quite typical. It is important to emphasize that these observations are not necessarily representative of the disciplines in general, only for those papers that were defined as network science papers.

Fig. 6 depicts separate word clouds of the most frequently used keywords of network science papers written in the four 5-year-long periods of the last two decades of network science. We can observe that in the first half of the examined period structure related (e.g., scale-free, small-world, topology) and modeling related keywords (e.g., preferential attachment, evolution, growing network, small-world model) dominated the study of complex networks, while in the last decade topics such as community detection, social network analysis, data-driven
research (big data, data mining, link prediction, machine learning) have become more popular keywords. In the first decade of the examined period, the most studied real-world networks were Internet, peer-to-peer and protein interaction networks, however, since 2010 the research has tended to focus on online social networks and brain networks.

To gain a more comprehensive understanding of the keywords of network science papers, we also construct their co-occurrence network. Fig. 7 and Fig. 8 together with Fig. 6 clearly shows that 'complex network' is the most important keyword of the examined set of papers that supports our hypothesis that our definition of network science paper was indeed a good proxy of our purposes. We can observe that the keyword 'random graph' often goes together with 'network' but less often with 'complex network' that suggests the term 'complex network' is not that widespread among mathematicians. Another observation is that community detection is rather popular in the social network domain, the bottom left side of the figures is dominated by terms associated with social network analysis and community detection. We can also observe that the keywords 'scale-free' and 'small-world' are frequently used together. The complete keyword co-occurrence network can be found in the supplementary material [20].

Based on the address of the first author, we identify the network science hot-spots and investigate the spatiotemporal changes. Fig. 9 demonstrates that China and the USA are the two leading countries of network science with a fast increase in Chinese network science papers in the last few years.
Fig. 6: Word cloud of the most frequent keywords of network science papers before 2006 (top right), between 2006 and 2010 (top left), between 2011 and 2015 (bottom left) and since 2016 (bottom right).

Fig. 7: Visualization of two-dimensional knowledge map of keywords. Keywords that have co-occurred more frequently are placed closer to each other on the map. The font size indicates the number and strength of the connections of a keyword. A more intense color implies a larger number of keywords and higher connectivity in the neighborhood of the point. The figure was created with VOSviewer.
Fig. 8: Co-occurrence network of keywords. The size of the node indicates the frequency of keywords in network science papers, the edge width indicates their relative co-occurrence. Only keywords with frequency at least 100 and edges with weight at least 10 are shown in the figure.

Fig. 10 illustrates how the ratio of multidisciplinary and international papers varied over the years. We can observe that network science research gets both increasingly international and multidisciplinary. Here we consider a paper international if it has at least two co-authors who do not share an affiliation within the same country. The ratio of international papers in an important indicator, since it was also shown that scientific impact increases if researchers publish in international collaboration [8]. The multidisciplinary nature of papers is defined by the fact that more than one research area is attached to the document in Web of Science.

5 Analysis of the co-authorship network

The nodes of the co-authorship network of network scientists correspond to the authors who have at least one network science paper (i.e., a paper that cites at least one of the three seminal papers [5, 13, 33]), two of them are connected if they co-authored at least one network science paper. The network is simple, undirected and unweighted meaning that here we ignore the strength of the connection between two scientists, i.e. the number of their joint papers. The network has 56,646 nodes and 357,585 edges with an average degree of 12.63, however, the median degree is just 4. The largest connected component consists of 35,716 nodes and it is depicted in Fig. 14.

The degree distribution of the network is illustrated in Fig. 11. There are 897 isolated nodes in the graph (nodes with zero degrees), i.e. scholars who have a single-authored network science paper but have not co-authored any network
science papers. The most typical number of co-authors are between 2 and 4 and the tail of the distribution decays much slower than the number of authors per paper does (c.f. Fig. 4) since here the degree reflects all the number of co-authors who do not necessarily author the same paper. The highest degree is 546 corresponding to Roberto Bellotti medical physicist, who is also an author of the paper with the highest number of collaborating authors [16] and another many-authored paper [9]. While our network is unweighted by definition, a possible weight could be assigned to the edges corresponding to the number of joint papers written by the two authors at the endpoints of the edge. Table 2 shows the most 'active links', i.e. the edges with the highest weights in the edge-weighted version of the co-authorship network.

Table 2: The most active links between authors.

| Authors                        | Number of joint papers |
|--------------------------------|------------------------|
| Shlomo Havlin & Eugene H. Stanley | 52                     |
| Bing-Hong Wang & Tao Zhou      | 51                     |
| Jihong Guan & Shuigeng Zhou    | 50                     |
| Zhongzhi Zhang & Shuigeng Zhou | 48                     |
| Jihong Guan & Zhongzhi Zhang   | 40                     |
| Zeng-Ru Di & Ying Fan          | 34                     |
| Sergey Dorogovtsev & José F.F. Mendes | 32            |

The network has a high assortativity coefficient of 0.53 that suggests that nodes tend to be connected to other nodes with similar degrees. The co-authorship network is highly clustered with a global clustering coefficient of 0.97 and an average local clustering coefficient of 0.8. The fact that the average shortest path...
length in the largest connected component is 6.6 also supports the small-world
nature of co-authorship networks.

Table 3: The top 12 authors with the highest betweenness centrality. Their ranks
with respect to each metric are shown in brackets.

| Name                | Betweenness | Harmonic Degree | Number of citations | h-index |
|---------------------|-------------|------------------|---------------------|---------|
| Jrgen Kurths        | 0.025 (1)   | 0.169 (1)        | 216 (1,017)         | 9,249 (30) 96 (2) |
| H. Eugene Stanley   | 0.024 (2)   | 0.168 (2)        | 220 (1,013)         | 10,479 (18) 57 (7) |
| Guanrong Chen       | 0.019 (3)   | 0.165 (4)        | 215 (1,018)         | 12,859 (15) 27 (30) |
| Albert-László Barabási | 0.017 (4)   | 0.160 (12)       | 202 (1,023)         | 73,937 (2) 83 (3) |
| Yong He             | 0.014 (5)   | 0.163 (6)        | 242 (1,012)         | 9,104 (32) 61 (6) |
| Zhen Wang           | 0.014 (6)   | 0.163 (5)        | 155 (1,117)         | 3,306 (365) 39 (16) |
| Santo Fortunato     | 0.013 (7)   | 0.160 (13)       | 208 (1,021)         | 13,923 (12) 40 (14) |
| Shlomo Havlin       | 0.013 (8)   | 0.163 (7)        | 165 (1,042)         | 13,377 (13) 110 (1) |
| Tao Zhou            | 0.013 (9)   | 0.167 (3)        | 220 (1,013)         | 9,911 (20) 40 (14) |
| Edward T. Bullmore  | 0.012 (10)  | 0.151 (49)       | 210 (1,020)         | 17,915 (7) 50 (10) |
| Wei Wang            | 0.012 (11)  | 0.161 (10)       | 145 (1,178)         | 467 (1511) 14 (188) |
| Stefano Boccaletti  | 0.112 (12)  | 0.162 (9)        | 130 (1,179)         | 9,609 (21) 22 (58) |

Fig. 11: The degree distribution of the network (truncated at 30).

Fig. 12: Spearman correlation heatmap between various centrality measures
and scientometric indicators.

To identify the most central authors of the network science community as
seen through the co-authorship network, we calculate centrality measures such
as betweenness, harmonic and degree centralities of the nodes. The most central
authors are shown in Table 3. We also compare the centrality measures of the
authors with the citation count of their network science papers and with their h-

\[ h \text{-index} \]

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\[ h \text{-index} \]
indices (restricted only to their network science papers). Common characteristics of the most central authors that they are famous, well-established researchers, moreover, they are typically active in more research areas forming bridges between subdisciplines. The highest betweenness and harmonic centralities correspond to Jürgen Kurths, German physicist and mathematician whose research is mainly concerned with nonlinear physics and complex systems sciences. As we mentioned before, the highest degree corresponds to Roberto Bellotti medical physicist. Mark Newman English-American physicist has the highest number of citations on his network science papers (77,418), while Shlomo Havlin, Israeli physicist is ranked first with respect to $h$-index.

Fig. 13 illustrates the relationship between centrality measures of network scientists and the scientometric indicators of their network science papers. On the left it shows the number of citations against the vertex betweenness centrality, colored by the harmonic centrality; on the right one can see the $h$-index against the vertex betweenness centrality, colored by the degree. We can conclude that there is a positive correlation between the authors’ central role in the co-authorship network and their scientometric indicators. Fig. 12 shows the Spearman’s rank correlation heatmap of the aforementioned measures indicating positive correlations, with the highest positive correlation between citation count and $h$-index. Considering centrality measures against scientometric indicators, betweenness centrality and $h$-index has the highest correlation.

![Fig. 13: Relationship between centrality measures of network scientists and the scientometric indicators of their network science papers.](image)

Network scientists have become more connected as time has gone by, as it is illustrated in Fig. 15, since not only the size of the largest component has increased over the years but also the ratio of the size of the giant component to the size of the entire network, indicating the emergence of a diverse but not divided network science community. The giant component consists of 35,716 nodes that is 63% of the entire network size and it is illustrated in Fig. 14.

Using Clauset-Newman-Moore greedy modularity maximization community detection algorithm [10], we identify the dense subgraphs of the network. To
retrieve some important discipline and location-related characteristics of the largest communities, we assigned a research area and a country for each author as the majority of the research areas corresponding to their papers and the most frequent country of their affiliations respectively. The compositions of the ten largest communities are shown in Table 4. The largest community consists of 15,693 authors dominated by Chinese physicists and computer scientists. We can observe that the smaller the communities are, the more homogeneous they are. For example, the vast majority of the third largest community are North American neuroscientists, moreover, there is a community with 53% EU scientists and 44% environmental scientists.

Network scientists come from 118 different countries which shows the international significance of network science. To illustrate the typical patterns of international collaborations, we created an edge-weighted network of countries where edge weights correspond to the number of network science papers that were written in the collaboration of at least one author from both countries (see Fig. 16). We can observe that while China has the highest number of network science papers (see also Fig. 9), US scientists wrote the most articles in international collaboration. It is also apparent that EU countries collaborate with each other a lot.

Similarly to the network of international collaborations, we also created a network of multidisciplinary collaborations illustrating the importance of multidisciplinary research in network science. Fig. 17 shows an edge-weighted network of research areas where the edge weights correspond to the number of network science papers that were written in the collaboration of authors whose main research areas are the ones at the endpoints of the edge. The main research area of the authors is not given in Web of Science, so for each author we assigned the most frequent research area associated with their papers. We can observe
that computer scientists and physicists dominate network science. It is also clear that the collaboration of physicists and network scientists made huge progress in network science. We can conclude that – as far as network science papers are concerned – mathematicians collaborate the most with physicists, while engineers collaborate more with computer scientists. It is not surprising that telecommunication experts usually collaborate with engineers and computer scientists, while mathematical & computational biologists work a lot with biochemists & molecular biologists and computer scientists on network science papers.

6 Conclusion

Two decades ago a new multidisciplinary scientific field was born: network science. In this paper, we paid tribute to the network science community by investigating the past 20 years of complex network research as seen through the co-authorship network of network scientists. We studied 31,763 network science papers by extracting the distributions of research areas, journals, and keywords. We identified the most important publication venues and topics in network science and shed light on how they changed over time, we also explored the co-occurrence network of the keywords. Moreover, we constructed and extensively analyzed the co-authorship network of 56,646 network scientists, for example investigating its topological properties, namely its community structure, degree and centrality distributions. We identified the most central authors of network science as seen through the co-authorship network. We also studied the spatiotemporal changes to provide insights on collaboration patterns. We can conclude that both inter-
national and interdisciplinary collaborations are on the increase. Furthermore, we compared the centrality measures of authors with well-known scientometric indicators (e.g. citation count and $h$-index) and found a high correlation.

After investigating the publication and collaboration patterns of network science and observing an increasing impact of complex networks, we are convinced that the next 20 years will produce at least as many fruitful scientific collaborations and outstanding discoveries in network science as the last two decades.

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