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N-mode network approach for socio-semantic analysis of scientific publications

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ABSTRACT

The sciences develop as conglomerates of ideas, texts, and agents. In this study, we propose a n-mode network approach to integrate the network matrices containing social, semantic, and epistemic attributes analytically into a single network and visualization. For example, authors, words (e.g., title words and keywords), and knowledge claims can be attributed to publications as units of analysis. This results in a 2-mode document/attributes matrix which stores both the dimensionality in the data and the interaction terms. Multiplication of this matrix by its transposed provides an affiliations matrix which can be decomposed in specific combinations such as socio-semantic networks. The methodology is illustrated by using the Brugada Syndrome as a specialty in the medical sciences. The proposed n-mode network approach can be extended beyond scientific data; a dynamic extension would allow us to model co-evolutions in more than two dimensions. The proposed approach can be applied to a wide array of studies, such as socio-semantic network analysis or heterogenous networks in actor-network theory.

1. Introduction

Recently, social network analysis (SNA) has been complemented with semantic network analysis in order to better encounter the dynamics of communication networks. Whereas social network analysis focuses on measuring the relations among agents (e.g. Wasserman & Faust, 1994), semantic network analysis aims at analyzing the content of the communications, for example by mapping co-occurring words (e.g., Callon et al., 1986 and 2002; Landauer, Foltz, & Laham, 2018). Diesner and Carley (2005) have developed an approach for mapping both the content entities in semantic networks and social network relations using a meta-matrix (see also Diesner, 2013). Others have followed Breiger's (1974) proposal to work with bipartite networks that combine actors and their group affiliations, or (multiple) correspondence analysis for mapping categorical variables in two dimensions (Breiger, 2000), and the analysis of social networks and culture as interrelated (Breiger & Puetz, 2016). Co-addressing the social and the semantic networks has urgently been advocated as a means to provide comprehensive insights into the dynamics of communication in scientific groups (Roth & Cointet, 2010) or, more generally, in small groups (Basov, 2020; Basov, Lee, & Antoniuk, 2017; Saint-Charles & Mongeau, 2018, in this issue). In a similar vein, Fuhse, Stuhler, Riebling, and Levi Martin, 2020, in this issue) develop further socio-semantic analysis of cultural relations (networks of symbols), socio-symbolic combinations (relations between actors and their symbols), and social relations (interaction between actors).

Scholars in the quantitative branch of Science & Technology Studies (STS), have developed a toolbox of bibliometric methods to

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study the developments of the sciences as bodies of texts (e.g. Leydesdorff, 1987, 1989; Wyatt, Milojević, Park, & Leydesdorff, 2017). However, "scientometric" research has hitherto mainly focused on mapping each type of the various relations, such as co-authorships, and co-occurring keywords, among documents separately. We build upon calls for hybrid methods for the study of heterogeneous networks (Glänzel & Thijs, 2017; Janssens, Glänzel, & de Moor, 2008), dating back from the origins of Actor Network Theory (ANT) (Callon, Courtial, Turner, & Bauin, 1983; Latour, 1996; Law, 1986), and combine the three (or more) types of nodes (authors' institutes, journals and keywords into a single analysis of heterogeneous document/attribute matrices and the related networks in order to provide a more comprehensive view of a research field under study (see Hellsten & Leydesdorff, 2019 for a more detailed discussion of ANT).

The combination of perspectives is relatively novel in scientometrics. Bornmann and Leydesdorff (2015), for example, have recently combined the analyses of institutional co-authorships and (co-)citation analyses while Hellsten and Leydesdorff (2016) analyzed separately the semantics of editorials as programmatic focus, and the development of the knowledge base in the journal *Climatic Change*. On the basis of these previous studies, we concluded that there is a need for developing an instrument that would consider homogenous and heterogenous relations as *ex ante* equivalent, so that the similarities and differences among them can be tested for statistical significance. In this paper, we focus on presenting the instrument, and will further test it in a follow-up paper.

This contribution to the special issue is methodological: we aim at providing a broadly applicable approach to socio-semantic network analysis. In our example, we focus on the social relations between authors of academic publications at the level of their university affiliations (social networks), the keywords attached to their publications (semantic networks), and the journals where the authors publish (epistemic networks). Our aim is to analyze academic publications in these three dimensions without losing the connections between the different types of nodes and links: Departmental addresses, journals, and Medical Subject Heading (MeSH), for example, are related to each other in sets of publications. We therefore use publications as the units of analysis and operationalize these aspects into a single analysis and related visualization. Our research question is methodological: How can academic publications be mapped in social, semantic and epistemic dimensions without losing the connections? We discuss the implications of this *n*-mode network approach for socio-semantic network analysis in more detail in the Discussion section.

2. Network approaches and objectives

Our approach can be positioned in the recent developments of co-addressing social relations and semantic networks. For example, Roth and Cointet (2010), see also Roth, 2013) introduced a theoretical approach that combines joint influence and co-evolutions of social and semantic features in epistemic communities. The resulting socio-semantic networks can be visualized as two-mode networks, i.e. networks consisting of individual actors and words, in a single network visualization. In social network analysis (SNA), bipartiate (2-mode) graphs of individual actors, and their group affiliations, have been studied since the 1970s (Borgatti & Halgin, 2011; Breiger, 1974). A disadvantage of bipartiate graphs (actors and their group affiliations, or actors and the content of their communications) is that the various categories are not intermediated, but assorted in either partition.

Social and semantic network analysis has been applied to the research on scientific knowledge in the field of science and technology studies (STS). For example, co-authorship networks have been mapped at different levels of aggregation: individual author names, their institutional affiliations, and countries of origin can be used as measures of scientific collaboration at the respective levels of aggregation (Melin & Persson, 1996), Furthermore, tools have been developed to automate this analysis for each level of co-authorship relations, such as VOSViewer (Van Eck & Waltman, 2010; Waltman, Van Eck & Noyons, 2010). Focusing on only the departments where the authors are based in, the journals in which they publish, or the Medical Subject Headings (MeSH) under which their work is categorized, provides only partial views on scientific developments. The quality of these partial views has been compared and evaluated in a large number of studies (e.g., Braam, Moed, & van Raan, 1991). Our aim is to combine the different networks.

Furthermore, Breiger (2000) proposed practice theory to encounter the inter-penetration of the material and the cultural worlds using either Galois lattices, for example among organizations, projects and events, or correspondence analysis to map several types of nodes in two dimensions. Multiple correspondence analysis can be used for mapping several types of variables in a single visualization, using two dimensions. In contrast, the *n*-mode network approach compiles several document/attribute matrices into a single network visualization without losing co-occurrences as the ties in the network. The *n*-mode approach advances the previous 2-mode analyses by focusing on actual co-occurrences of journals, institutes and keywords in publications, instead of constructing ties between nodes of one type by their joined ties to nodes of another type.

In recent studies, combining the social network of actors and the semantic similarity (of dissimilarity) of their discourses has led to the hypothesis that the denser the social networks, the more similar the semantic, discourse networks are among the actors. Saint-Charles and Mongeau (2018) also found a threshold after which the discourse similarity decreases when social influence increases (see also Basov & Brennecke, 2017). In social media settings, where the social relations between the actors remain less clear, this result provides a theoretical and methodological challenge since less is known about the social actors, and their ties. We argue that this challenge can, potentially, be overcome by providing a systematic approach and methodological focus for the analysis of *n*-mode communication networks which can be applied beyond scientific publications also to small group communications and social media data, and the results can be compared across the different types of data.

We provide a broadly applicable methodology to compile different document/attribute matrices into a single n-mode matrix of documents / authors; institutions; keywords, based on actual co-occurrences. This methodology can also be applied at the level of journals, or universities for academic publications, or to social media data, for example, using authors, addressed actors and hashtags as the attributes to the documents (for instance tweets) (Hellsten, Jacobs, & Wonneberger, 2019).

3. Method, case study, and data

3.1. Method

We focus first, on co-authorships at the level of the authors' institutional affiliations. Second, we focus on the co-occurrences of journal titles. We map the co-occurrences of journals in which authors from specific universities publish their articles. Instead of mapping the bibliographic coupling among journals, i.e., citations to similar sources at the journal level, using the list of references provided in the academic articles (e.g., Price, 1965), in this paper we use journal names in order not to overburden the complexity of the analysis. Third, we map the semantic networks as represented by the Medical Subject Headings provided in the PubMed database. Co-occurrences of title words, keywords, or subject headings have been used to study semantic developments in the sciences (Callon, 1986b).

We use documents (publications) as the units of analysis to which institutional affiliations, journals and MeSHs are attributed. For example, documents are authored, worded, published in journals, indexed, and contain different types of meta-data. The various attributes can be assigned to single publications. Each document will be represented as a row of a matrix. The rows can be aggregated into different sets. We use sets of documents in our illustration.

The result is an asymmetrical (2-mode) document/attributes matrix with the units of analysis in the rows and the authors' institutional affiliations, the publishing journals, and MeSH as attributes to the documents in the column vectors (Fig. 1). This 2-mode matrix can contain as many dimensions as an analyst wishes, including, for example, qualitative scores of content analysis. In other words, this is a parsimonious representation of complex data. The result is an attribution matrix which can be used for various forms of multi-variate analysis such as MDS and factor analysis (using, e.g., SPSS). Note that the statistics of attributes and the networks are related: a network can be written in terms of its attributes, and the attributes can be connected based on co-occurrences.

Multiplication of the 2-mode matrix (in Fig. 1) with its transposed provides sub-matrices of a grand matrix which can be studied as co-author, co-word, etc., networks (Fig. 2). Off-diagonal sub-matrices provide combinations among classes of variables such as sets of words which are unequally distributed across different attributes.[1]

In summary, the aggregate of the three matrices in Fig. 1 can be multiplied by its transposed leading to the matrix in Fig. 2. This procedure can be done for any dimensionality of the data. Social network analysis programs such as UCInet or Pajek provide routines for this manipulation of the matrix. This *n*-mode approach provides us off-diagonally with the relevant co-occurrence matrices such as matrices of co-words and co-authors, and also with all the heterogeneous combinations. Furthermore, the information contained in each cell of Fig. 2 can be decomposed in terms of the cell-values of the matrix in Fig. 1 for enriching the micro-details underlying the aggregated effects (cf. Mika, 2007).

We describe the automation of this routine in more detail in the Appendix. For the layout and visualization of the networks, we used the open software program VOSViewer that visualizes similarities between the nodes, and uses a distance-based mapping where the nodes are closer to each other when they co-occur more often in the text documents (Van Eck & Waltman, 2010). We used the non-normalized co-occurrence data, and used the Newman community algorithm (Newman, 2004) for the clustering.

In the network visualization, the size of the nodes represents the frequency of use, and the line thickness the number of co-occurrences between the nodes. The choices of the parameters for the visualization in VOSViewer, however, are not central to our argument. One can show the same n-mode networks using other tools such as Gephi, or other algorithms, such as Kamada and Kawai's (1989) spring-embedding.

3.2. The case study of "Brugada Syndrome"

As a substantive example, we focus on the Brugada Syndrome (BrS) as a well-defined medical specialty studying a cardiac aberration, to map the social, semantic, and epistemic attributes to the publications into a single analysis and visualization. Using an interface between the Web of Science and PubMed databases (developed by Leydesdorff & Opthof, 2013), we combine Medical Subject Headings (MeSH) of the Index Medicus with rich citation data at the article level in the Science Citation Index in order to show the flexibility of our multimode approach. Specifically, we construct a grand matrix that allows for adding *n* different types of nodes into the analysis as partitions, thus providing opportunities to decompose and recombine heterogeneous networks.

BrS is a rare cardiac disease which may lead to sudden cardiac death caused by fatal arrhythmias. Originally, it was described by the Brugada brothers (Brugada & Brugada, 1992). It is well known that the disease develops at adult age, has a higher preponderance in males and is more common in South-East Asia. The disease leads to aberrations in the electrocardiogram (ECG) that may become manifest after fever, or a heavy meal. This temporal variability has fueled debate on the significance of genetic aspects and also on the electrophysiological background of the disease (Wilde et al., 2010).

Most importantly, the hearts of BrS patients appear to have structural abnormalities (fibrosis) at autopsy that remain clinically unnoticed (Hoogendijk et al., 2010). The implantation of ICDs (internal cardiac defibrillators) is a therapeutic possibility, but this critically depends on the precision of diagnosis. True positives (the ICD gives a shock when the arrhythmia is present) are the goal, but false positives (a shock despite the absence of the arrhythmia) are the price of the (expensive) treatment. Without treatment the

[1] A limitation of the method is its use, for example, in Internet research when one is able to retrieve the co-occurrences online, but one does not easily have access to single occurrences without downloading and local analysis (Morris, 2005). In this case, Fig. 2 does not have to be generated from Fig. 1.

$$
\begin{array}{c|cccc}
 & jo_1 & jo_2 & \ldots & jo_m \\ \hline
doc_1 & a_{11} & a_{21} & \ldots & a_{m1} \\
doc_2 & a_{12} & \ldots & \ldots & a_{m2} \\
doc_3 & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
doc_n & a_{1n} & \ldots & \ldots & a_{mn}
\end{array}
\quad + \quad
\begin{array}{c|cccc}
 & w_1 & w_2 & \ldots & w_k \\ \hline
doc_1 & b_{11} & b_{21} & \ldots & b_{k1} \\
doc_2 & b_{12} & \ldots & \ldots & b_{k2} \\
doc_3 & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
doc_n & b_{1n} & \ldots & \ldots & b_{kn}
\end{array}
\quad + \quad
\begin{array}{c|cccc}
 & inst_1 & nst_2 & \ldots & inst_{(m+k+l)} \\ \hline
doc_1 & c_{11} & c_{21} & \ldots & c_{(m+k+l)1} \\
doc_2 & c_{12} & \ldots & \ldots & c_{(m+k+l)2} \\
doc_3 & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
doc_n & c_{1n} & \ldots & \ldots & c_{(m+k+l)n}
\end{array}
$$

Fig. 1. Three matrices of n documents with m journal co-occurrences, k MeSH classes, and l institutional addresses, respectively, can be combined into a single matrix of n documents with $(m + k + l)$ variables.

	jo_1 jo_2 … $jo_{(m)}$	w_1 w_2 … $w_{(k)}$	$inst_1$ $inst_2$ … $inst_{(i)}$
jo_1 jo_2 … $jo_{(m)}$	Journal occurrence matrix *(epistemic network)*	MeSH/Journal Matrix	Inst/Journal matrix
w_1 w_2 … $w_{(k)}$	Journal/ MeSH matrix	MeSH matrix *(semantic network)*	Inst/MeSH Matrix
$inst_1$ $inst_2$ … $inst_{(i)}$	Journal/Inst Matrix	MeSH/Inst Matrix	Institutional matrix *(social network)*

Fig. 2. Affiliations matrix of journals, MeSH classes, and institutional addresses, generated by multiplying the matrix depicted in Fig. 1 with its transposed.

syndrome can be lethal.

3.3. Data

We collected the author addresses from the Web-of-Science (WoS) database and the MeSH from the PubMed database using the search term "Brugada Syndrome" in both databases for publications that were published between 2006 and 2016. We retrieved 1493 documents in the Medline database and 1335 documents in the Web-of-Science database. We used the larger dataset of 1493 publications to combine the three types of attributes: Medical Subject Headings are solely used in the PubMed/Medline database whereas the institutional addresses can be found in the Web-of-Science database. These 1493 publications comprised 1614 unique institutional addresses, 1672 unique MeSH, and 303 journal titles in which these articles were published (see Table 1 below).

We analyze this set of publications as the units of analysis, and the three types of attributes to these documents following the

Table 1
Descriptive statistics of the institutional addresses (set 1), MeSH classes (set 2), and journal names (set 3) as well as the combinations of institutional addresses and journals (1 + 3), MeSH classes and journals (2 + 3), and all three attributes (1 + 2 + 3); *Q* denotes the modularity; *N of Clusters* is based on using Blondel et al. (2008).

Sets	N of Variables (a)	Modularity Q (b)	N of Clusters (c)	Largest component (d)
1 + 2 + 3	3592	0.20	18	3592
1 + 3	1920	0.60	127	1733
2 + 3	1975	0.17	16	1975
1	1614	0.67	325	
2	1672	0.16	11	
3	303	Not networked		

Table 2
Fourteen journals that published 15 or more articles on Brugada syndrome during the period.2006–2016.

Journal Title	N
Heart rhythm	165
Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular elec	93
International journal of cardiology	87
Journal of cardiovascular electrophysiology	65
Pacing and clinical electrophysiology : PACE	53
Circulation journal : official journal of the Japanese Circulation Society	52
Journal of electrocardiology	45
Circulation. Arrhythmia and electrophysiology	43
Journal of the American College of Cardiology	42
Annals of noninvasive electrocardiology : the official journal of the International Society for Holter and Noninvasive Electrocardiology, Inc	41
Circulation	32
European heart journal	21
The American journal of cardiology	20
The American journal of emergency medicine	17
…	….
Sum	1493

procedure specified in the Appendix (see also at: https://www.leydesdorff.net/software/nmode/).

4. Results

We show first the results of each separate analysis of co-occurring institution affiliations, co-occurring Medical Subject Headings, and the 303 unique journals in which the papers were published, and thereafter the combined 3-mode networks showing all three in a single visualization, applying the combinations as presented in Table 1.

Since we focus on actual co-occurrences in the publications, a modest degree of modularity can be expected – for example when authors from different institutes co-author an article that uses specific keywords, the journal, the institutes and the keywords form a fully connected clique.

4.1. Journals

Table 2 shows the journals in which 15 or more publications were published in our data set. These fourteen journals can be considered as the main outlet for publishing research into Brugada syndrome, out of the total of 303 journals in our data set. Only a minority of the papers were published in the three journals with the highest impact factors from a total of 128 journals in the category *Cardiac & Cardiovascular Systems* in the 2017 version of Journal Citation Reports of *Clarivate Analytics*. These journals are the *Eur Heart J*, *Circulation* and *J Am Coll Cardiol*. Most papers were published in *Heart Rhythm*, *Europace* and *Int J Cardiol*, ranking at positions 29, 25 and 41 in the above mentioned category.

4.2. Institutional addresses network

Fig. 3 shows the clustering between the 1614 addresses of the 1493 papers. The colours of the clusters and the sizes of the nodes correspond to the decomposition in VOSviewer (Van Eck & Waltman, 2010). The thin lines that interconnect the circles point to less frequent co-occurrences. Whether a department appears at the center or at the periphery is determined by the number of occurrences, and the similarity to other nodes. The main clusters are around national research institutes and universities, such as a number of Japanese groups (yellow in the upper center corner), but also into more regional clusters, such as the Netherlands and France (blue in the center). The University of Amsterdam is located in the center of the institutional affiliation network. Some of the clusters show international, academic collaborations, such as between the University of Groningen (the Netherlands), University of Tampere (Finland) and University of Washington (USA) (brown on slightly right-hand lower side).

Furthermore, collaborations between universities and medical institutes are common, such as the Mayo Clinic and University of Pavia (purple, in the middle), or National Cardiovascular Center, University of Copenhagen, University Paris and National Cerebral and Cardiovascular Center (green, slightly on the right-hand side, in the center). The Spanish universities and academic medical centers form a more separated cluster (light pink, in the bottom).

The institutional network shows that scientific collaboration centers around national level co-authorships, but by itself it does not tell us anything about the content of the publications.

4.3. MeSH network

Fig. 4 shows the clustering between the 1672 MeSHs of the 1493 papers. The colours are generated by VOSViewer clustering algorithm (Van Eck & Waltman, 2010). Compared with Fig. 3 we see many more distinct colours, pointing to a larger number of clusters. The diameter of the circles indicates the number of occurrences of the MeSHs. Whether a MeSH appears at the center or at

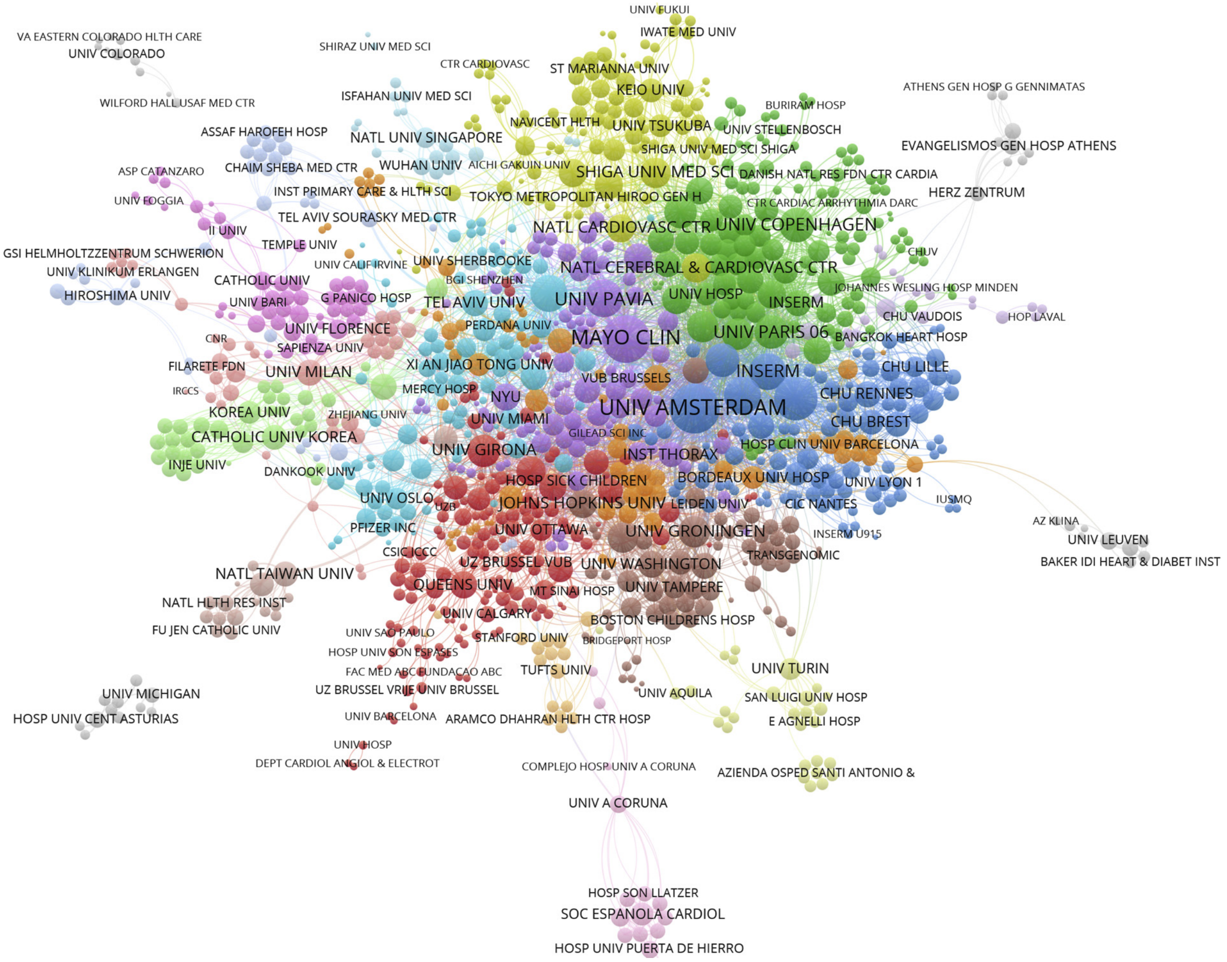

Fig. 3. Institutional affiliations network of the 1614 addresses in the set of 1493 papers on Brugada Syndrome published between 2006 and 2016. Note: Affiliations are based on how the authors stated their affiliations; hence some of the nodes are labeled as Universities and others as Departments at the Universities.

the periphery is determined by the number of occurrences and connections to other nodes as well as the similarity between the nodes.

The Medical Subject Headings are clustered around specific academic and medical-practice related clusters: research into the causes of the disease, in particular genetic, DNA-related reasons as well as cell line and protein transport are clustered in red whereas mutational analysis and odds-ratio are clustered in blue, both on the left-hand side. General MeSHs, such as 'humans' are positioned in the center of Fig. 4 as they are the most often used MeSHs in the set of documents, and are also most often used in connection to more specific MeSHs.

Whereas the map of MeSH is very rich in content, it is not anchored in systems of reference such as authors, institutions, and not even theoretical structures. The map remains a "bag of words." These 1-mode analyses cannot inform us about the relative connections and disconnections between the different types of nodes: Are the social actors, or the semantics driving the temporary ordering of the research field? In the next steps, we combine the separate networks into heterogeneous networks as called for in ANT (Law, 1992).

4.4. Institutional affiliations and journals

Fig. 5 shows the combination of 1614 institutional addresses and the 303 publishing journals with the former in red and the latter in blue. In the 2-mode network representing the journals and the authors" institutional affiliations, the journal *Heart Rhythm* is positioned centrally close to the *Journal of Cardiovascular Electrophysiology* whereas *Circulation* is positioned more in the periphery (on the left-hand side). This represents that authors affiliated to the same institutes published their work in these three journals. Overall the number of institutions overshadows the lower number of journals publishing papers about the Brugada Syndrome.

In terms of ANT, the institutional affiliations and the journals form a densely connected network of social and organizational actants, instead of the journals ordering the institutions or vice versa. As a further step, one can zoom into a specific journal, for example, to construct a network of institutional addresses co-publishing in the specific journals. This provides more information

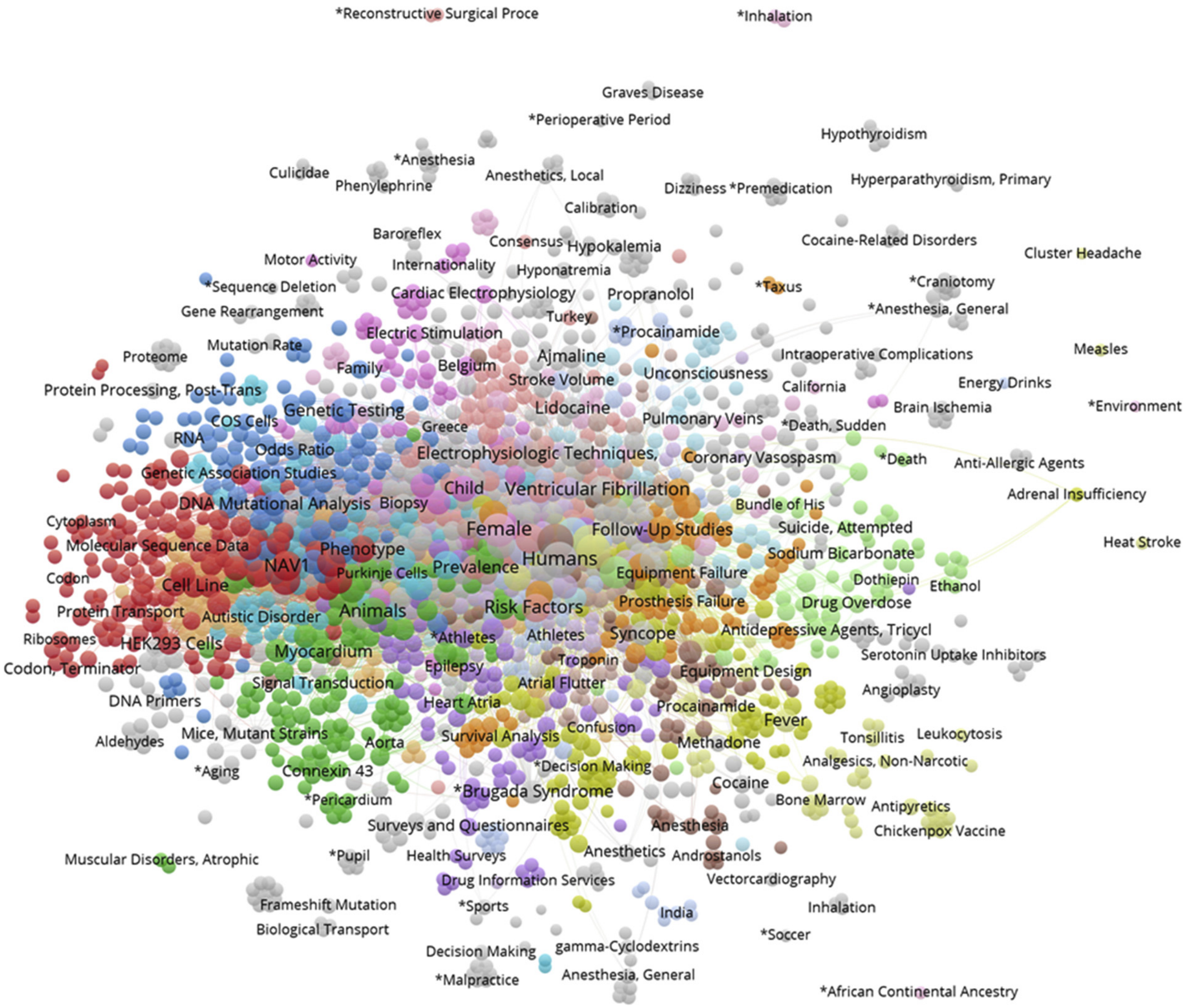

Fig. 4. The network of the 1672 unique MeSH classes attributed to papers in the set of 1493 papers on Brugada Syndrome published between 2006 and 2016.

about the academic research field than the 1-mode networks of institutional co-occurrences, presented above in Fig. 3.

4.5. *Medical subject headings and journals*

Fig. 6 shows the combination of 303 journals (blue) with 1672 MeSHs (green). As with the previous combination, the number of MeSHs is higher than the number of journals. However, the general MeSHs: human, male, female, adult, middle-aged, electrocardiography are positioned centrally together with the journals *Heart Rhythm* and *PloSONE*. This means that the general, most frequently used MeSHs have been used in more general journals. In terms of ANT, the keywords attributed to the publications integrates the field, whereas the journals and institutional affiliations add competition to the research field. More specialized journals co-occur with more specific MeSHs, such as *The Journal of Physiology* (lower center) that is close to the MeSHs related to animal and mice. The journal *Eur Heart J*, which is at present the number 1 journal in the cardiovascular sciences, in turn, holds a central position in the network of journals. In comparison to the addresses and journal network, the MeSHs have more organizing power than the institutional affiliations in relation to the journals.

4.6. *Institutional affiliations, journals, and MeSHs*

Fig. 7 shows the relations among the three types of attributes to the publications. The network is driven by the MeSHs, and in particular those related to humans, male, female, and different age categories: adult, young adults, adolescents, and middle-aged indicating that the specialty is focused on clinical research into the syndrome affecting different age and gender groups. This may be obvious for scientists specialized in these analyses, but not for a general cardiologist interested in this work. (Some journal titles have

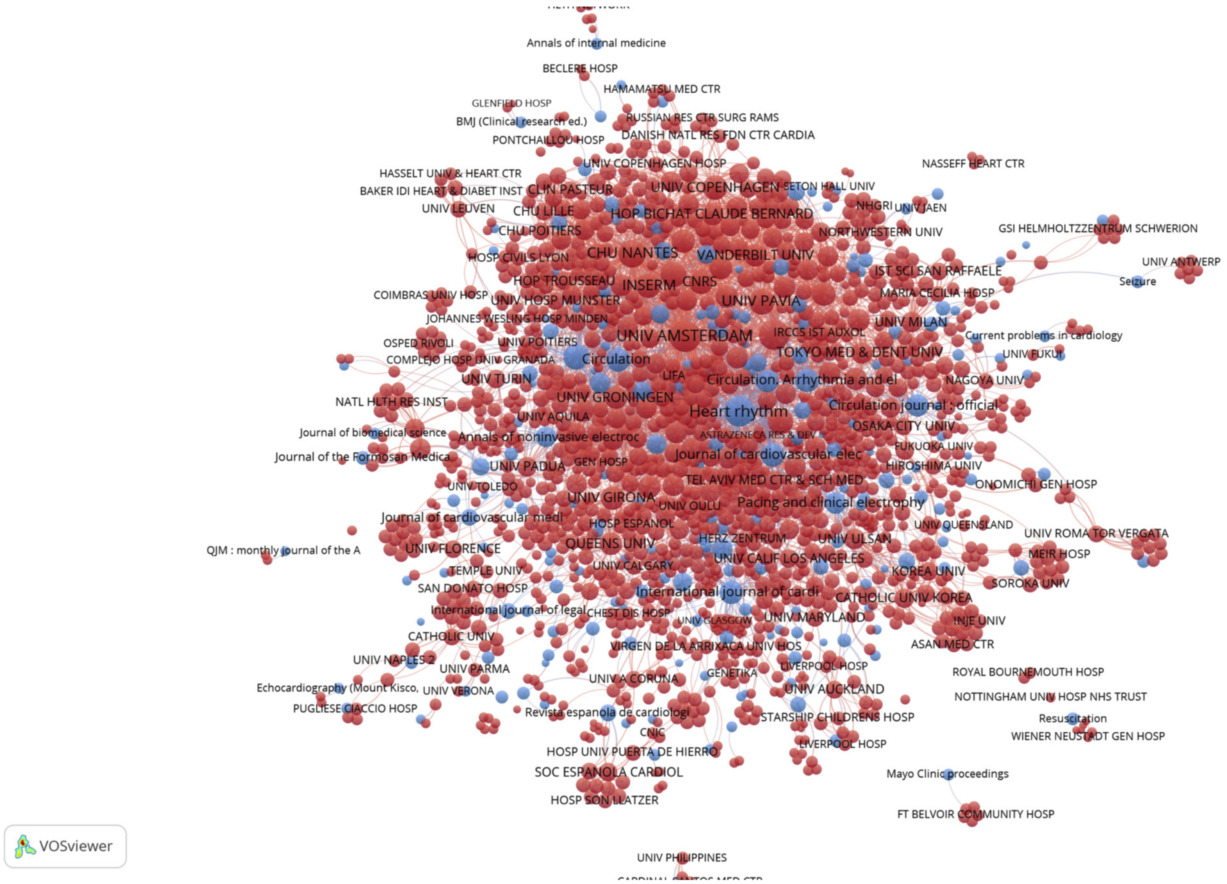

Fig. 5. The 2-mode network of 1614 unique institutional addresses and 303 journals in the set of 1493 publications on Brugada Syndrome published between 2006 and 2016; modularity $Q = 0.20$ (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008); VOSviewer was used for the visualization. Institutional addresses are colored red and journal names blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

been spelled in two ways in the data set, such as the journal *Electrocardiography*, and therefore appear twice in the network.)

The institutes and journals are located in the periphery. The relative power of the MeSHs in ordering the field as compared to the journals and the institutional affiliations is more prominent in the 3-mode network (Fig. 7) than in the 2-mode network (Fig. 6 above). Note also that the modularity of the network increases slightly in the 3-mode network (from Q = 0.16 in Fig. 6 to Q = 0.20 in Fig. 7). Additional attributes seem to add variation to the analysis. This remains an empirical question for a follow-up study. In terms of ANT, the heterogeneous network shows the relative positions of the nodes, and their potential ordering power for the research field. In the Brugada case the dominance in ordering of the MeSHs is larger than that of the relation between scientists and journals.

Fig. 7 shows that in scientific publications, BrS is constructed as a human disease with a predominance in male adults which is diagnosed by electrocardiography. This is established knowledge among cardiologists with a specialization in electrophysiology. The fact that the proposed *n*-mode method results in the prominent position of these vital key-words in the absence of such knowledge in the analysis underscores the usefulness of this approach in research fields where such specialized a priori knowledge is lacking.

Furthermore, we measured the eigenvector centralities for the three attributes of journals, institutes and MeSH keywords. Eigenvector centrality assumes that a node is more central when it is connected to other central nodes (Bonacich, 1972; Ruhnau, 2000). We chose eigenvector centrality since our data set consists of several types of nodes. Degree-centrality, for example, is expected to perform less well for semantics where the most common words tend to have the most ties to other, less common words, but they nevertheless carry the least meaning. The MeSH keywords have the highest eigenvector centralities, and in this sense drive the research field (see Fig. 8).

In summary, whereas the networks representing co-occurrences with one type of attribute—epistemic networks indicated by journal citations, semantic networks of subject headings, or social networks of authors institutional affiliations—show partial views into the specialty, the combined network of three types of attributes is able to show the relative dominance of the subject headings in structuring the research field as well as detailed information about in which journals the authors affiliated to specific institutions, publish their work. This finding calls for future research into the relations between different types of "drivers" in scientometrics, and in socio-semantic network analysis, in general.

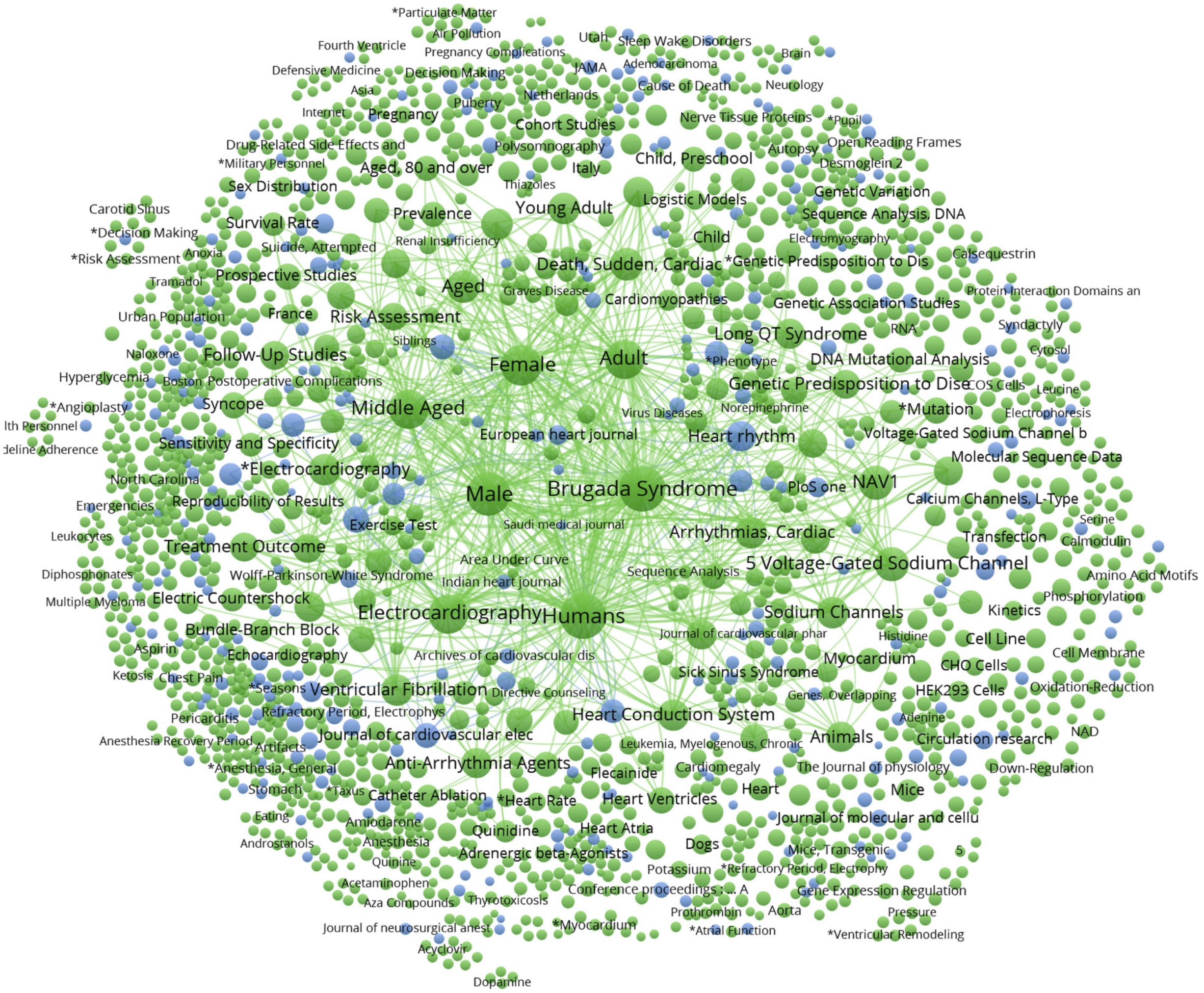

Fig. 6. The 2-mode network of 1672 unique MeSHs and the 303 journals in the set of 1493 publications on Brugada Syndrome published between 2006 and 2016; modularity $Q = 0.16$ (Blondel et al., 2008); VOSviewer used for the visualization.

5. Discussion

We proposed a new method for studying *n*-mode heterogeneous networks that allows for combining hitherto separate document/attribute matrices (e.g. document/institutional affiliation; document/keywords, and document/journal) into one comprehensive document/institute; keyword; journal matrix. In particular, we constructed 2-mode and 3-mode networks of the social, semantic, and epistemic networks among scientific publications about the Brugada Syndrome. An advantage of our approach is that it allows for any combination of attributes to publications. In comparison to previous methods (e.g., correspondence analysis), our approach allows for the unlimited combination of attributes attached to the documents as the units of analysis.

As an illustration, we focused on the journals, the institutional affiliations of authors, and Medical Subject Headings in the case of studies about Brugada Syndrome (BrS). Although BrS can be replaced by any other disease, the choice of a medical topic is not coincidental in this study. The relatively high degree of codification in the medical sciences enables us to validate the outcome of our analysis. One of us is an electrophysiologist, but his knowledge was not a prerequisite for the application of our method. The fact that this pre-existing knowledge can be recapitulated by the technique suggests its application in scientific arenas with less codification of knowledge in protocols.

Our methodology is also relevant for combining heterogeneous nodes into networks of "actants." The comprehensive analysis of *n*-mode networks can take into account the relations among the different types of nodes. In terms of actor-networks, our results show the relative positions of the different types of nodes as juxtaposed to each other. The results provide an empirical way to answer the call of ANT for treating both humans and non-humans, social and semantic aspects as *ex ante* equal in the creation of a research field (Callon, 1986a, 1996b; Callon & Latour, 1981; Law, 1992). Our results suggest that the semantics determines the field more than the epistemic and social dimensions; the semantics diffuse into the latter dimensions. This result is interesting for the field of socio-semantic networks. The dominant role of semantics is in line with earlier results that semantic and social networks are the most

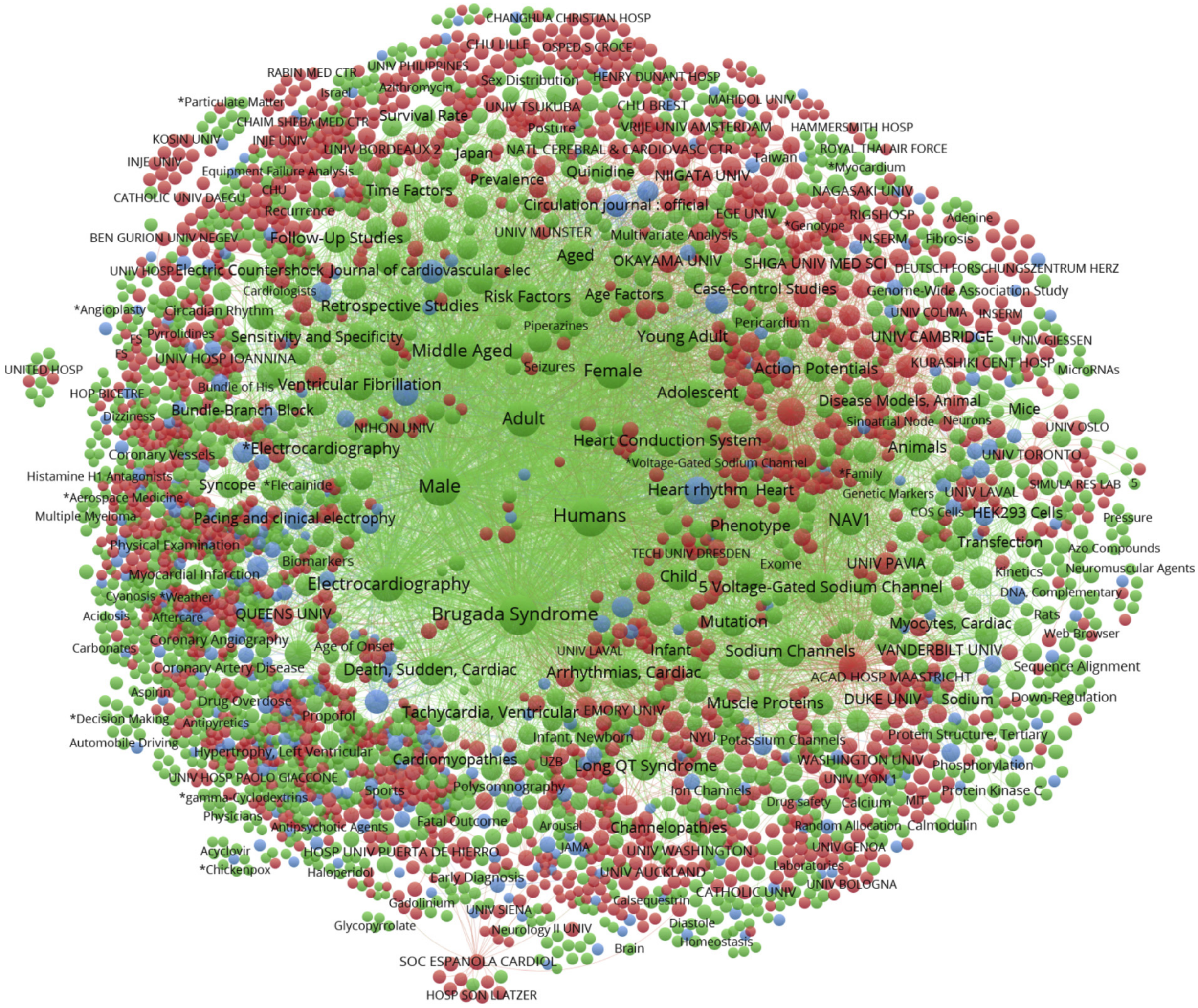

Fig. 7. The 3-mode network of the institutional addresses, journal titles, and the MeSH classess in the set of 1493 publications on "Brugada Syndrome" published between 2006 and 2016; modularity $Q = 0.20$ (Blondel et al., 2008); VOSViewer used for the visualization.

different from each other (Yan & Ding, 2012). A future research could apply the n-mode method to the analysis of small group communications: Does discourse similarity "drive" the social networks between actors (Saint-Charles & Mongeau, 2018, see also Karell & Freedman, 2020 and Basov, 2020 in this issue)?

Our approach combines the networks using attributes to the scientific publications instead of measuring their structural similarities. The result that semantic networks are driving the research field, calls for further research on *n*-mode networks in other research fields. For example, the position in the sociology of scientific knowledge (SSK) was that the socio-cognitive interactions can be explained in terms of (social) interests (Barnes & Edge, 1982; Bloor, 1976; cf. Slezak, 1989). Such programmatic statements can be tested as hypotheses using our approach that is based on attributes to the documents.

While the co-occurrences of one type of node, for instance author-author relations, or MeSH-MeSH relations show a unilateral network, combining several types of nodes adds to a three-dimensional network that shows the similarities between, for example, the institutes and the Medical Subject Headings attributed to the publications authored by scientists at that institute. Without the combined networks, it would not be possible to say which MeSHs were shared by which institutes. Combining the names of authors, institutes, and journals, the approach allows for the analysis and visualization in which journals, authors from which institutes published. Combining the various types of networks of "actants" adds to the understanding of the relative similarities and differences across the journals, the institutes, and the MeSHs. Future research could focus on such *n*-mode socio-semantic networks in other scientific research fields, and map the development of the field over time.

In conclusion, we applied this *n*-mode approach to scientific publications in this paper. However, the same approach can be applied to a wide variety of case studies and other types of communication networks as well. For example, one can combine newspaper titles with news headline words and mentioned actors, using news items as the units of analysis. Analogously, one can map Twitter network using Twitter message authors, hashtags as indication of topics of discussion, and addressed @usernames as

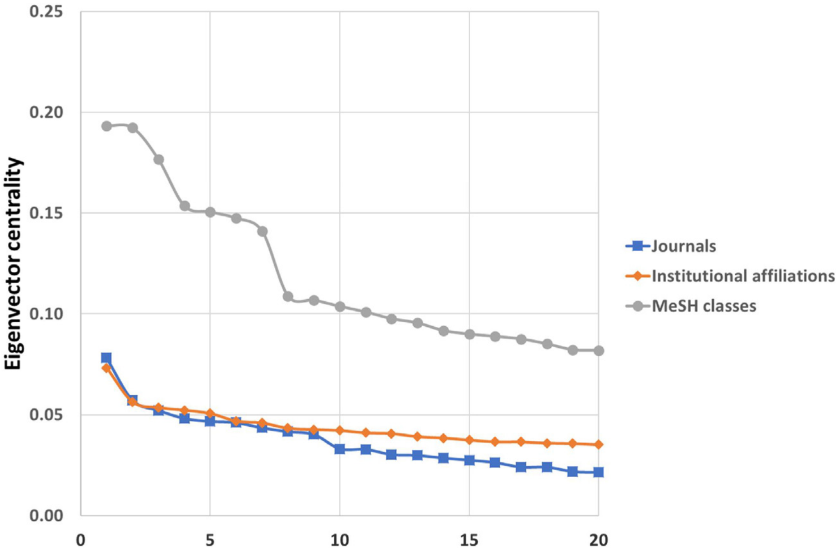

Fig. 8. Eigenvector centralities of the 20 highest-ranked nodes for the journals, the institutional affiliations, and the MeSH classes in the set of 1493 publications on Brugada syndrome published between 2006 and 2016.

representation of mentioned actors to construct more comprehensive socio-semantic network analysis (Hellsten et al., 2019), and ask which of these three drives online public debates? One can also repeat the analysis for different years and thus model co-evolutions among more than two types of nodes (e.g., epistemic, social, or textual ones) using time-series analysis (e.g., Leydesdorff, 2010).

Appendix A. An automated routine for generating maps of Medical Subject Headings, institutional addresses, and journal names. See also: https://www.leydesdorff.net/software/nmode/

1 Collect a set of documents from *PubMed* < at http://www.ncbi.nlm.nih.gov/pubmed/advanced > or from *MedLine* in the Web-of-Science (WoS); combine the retrieval if necessary into a single file to be named “data.txt”;
2 Download the files pubmed.exe and pubmed.dbf from http://www.leydesdorff.net/software/pubmed. Copy these files and “data.txt” into a single folder;
3 Run pubmed.exe; choose the appropriate option when prompted depending on the choice made ad 1;
4 Use the resulting file “string.wos” as a combined search string in the advanced search of the core collection of WoS; save the retrieval as “plain text” in the tagged format via the “marked list;”

```
FN Clarivate Analytics Web of Science

VR 1.0

PT J

AU Rogozhina, Y

   Mironovich, S

   Shestak, A

AF Rogozhina, Y.

   Mironovich, S.
```

5 Rename the retrieval from WoS “data.txt” and run part3.exe;
6 The resulting file cs_mh_jj.net can be read into Pajek, UCInet, etc. The file origin.clu contains the partition information in the Pajek format.
7 Read cs_mh_jj.net into Pajek and choose *Network* > *2-Mode Network* > *2-Mode to 1-Mode Network* > *Columns*. Save the resulting network as a Pajek. net file. This file can be read with the partition information in “origin.clu” into VOSviewer. Choose “Create a map from network data”.

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