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Network analysis of co-participation in thesis examination committees in an academic field in Spain

Garrido-Labrador JL, Ramírez-Sanz JM, Ahedo V, Arnaiz-Rodríguez A,
García-Osorio C, Santos JI, Galán JM

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Abstract

This paper applies complex network analysis to unveil the informal structure of the knowledge area of business organization —Organización de empresas— in Spain. To do so, we use the TESEO database. We retrieve and statically analyze all the theses referred to the UNESCO academic field of Organization and management of enterprises. Our results reveal a degree distribution of the participation in thesis examining committees and thesis supervision compatible with a truncated power law. Community analysis of the projected network of co-participation in thesis committees presents modular structure. When we focus on the backbone of such network, we find that the patterns detected can be partially explained by homophily of scholars that interact in the same academic association.

Keywords

Complex networks, community detection, doctoral thesis, business organization, pattern recognition

José Luis Garrido-Labrador (1)
jlgarrido@ubu.es
https://orcid.org/0000-0002-3441-4223

José Miguel Ramírez-Sanz (1)
jmrsanz@ubu.es
https://orcid.org/0000-0003-0189-8046

Virginia Ahedo (2)
vahedo@ubu.es
https://orcid.org/0000-0002-9812-388X

Adrián Arnaiz-Rodríguez (1)
adrianar@ubu.es
https://orcid.org/0000-0001-5567-801X

César García-Osorio (1)
cgosorio@ubu.es
https://orcid.org/0000-0002-1206-1084

José Ignacio Santos (2)
jisantos@ubu.es
https://orcid.org/0000-0002-6653-043X

José Manuel Galán (3)
jmgalan@ubu.es
https://orcid.org/0000-0003-3360-7602

(1) Dpto. de Ingeniería Informática. Escuela Politécnica Superior. Universidad de Burgos. Avda. Cantabria S/N, 09006 Burgos (Spain).
(2) Dpto. de Ingeniería de Organización. Escuela Politécnica Superior. Universidad de Burgos. Avda. Cantabria S/N, 09006 Burgos (Spain).
(3) INSISOC. Dpto. de Ingeniería de Organización. Escuela Politécnica Superior. Universidad de Burgos. Avda. Cantabria S/N, 09006 Burgos (Spain).

1. Introduction

Some of the key elements of the structure of the Spanish university system are or-ganized around the concept of knowledge area. The different academic fields and disciplines are grouped into a closed classification of areas. A scholar can only be assigned to a particular one, and all the academic positions in the Spanish university system are necessarily associated with a given active knowledge area. Currently, there are 190 different knowledge areas (in some cases with some potential overlapping) divided into five branches of knowledge: Sciences, Health Sciences, Social Sciences, Arts and Humanities, and Engineering and Architecture.

One of the most eclectic and numerous knowledge areas in Spain is the field of business organization –Organización de empresas–. This area includes subjects as varied as finance, operations research, economics, business and management, mathematics, statistics, quantitative methods and production, among others. It is included in the branch of Social Sciences, although some elements of its foundations are also rooted in engineering fields.

In Spain, as in many other countries, Ph.D. studies culminate with a public thesis defense in which the candidate must explain her original research in front of a thesis committee, which usually consists of three to five members, depending on the requirements of each university. Each member must fulfill several academic requisites to be able to participate in the committee, and there are also restrictions on how many members can be from the same university and department as the Ph.D. candidate. Although thesis supervisors cannot be part of the assessment board, they usually propose the pool of possible candidate members and have a strong influence (Villarroya, Barrios, Borrego & Frías 2008) in the formation of the thesis examination committee (as well as in the choice of the possible substitutes) that the responsible department or the doctorate program will have to approve before the defense. This mechanism suggests some kind of relation or link between the members of the committee and supervisors, either some previous interaction, interest, or expertise in the same topics and approaches, etc.

To unveil and better understand the informal structure of the business organization area, we have applied complex network analysis (Newman 2003a; Amaral & Ottino 2004) to the co-participation networks in thesis examination committees from the field of business and management. Such networks were obtained using the information available in the TESEO database. This approach has been recently proposed as a bibliometric tool to detect scientific communities (Duarte-Martínez, López-Herrera & Cobo 2018; Arnaiz-Rodríguez, Ramírez-Sanz, Garrido-Labrador & Olivares-Gil 2021; Olivares-Gil et al. 2022) or to identify the most relevant actors in a specific academic field (Castelló i Cogollos, Bueno Cañigral & Valderrama Zurián 2019). In addition, for some time now, the use of doctoral theses for the characterization of research in a scientific field is considered a particularly insightful approximation (Ardanuy, Urbano & Quintana 2009). More specifically, given the effort in human and temporal resources required to complete a doctoral thesis, the fact is that Ph.D. theses reflect the scientific lines, their priorities and trends in a more robust way than scientific articles. In this vein, the use of doctoral theses as a proxy is even of greater significance if our interest is on the social structure of scientific research, as they allow to identify the protagonists of scientific generation, academic genealogies and different schools or sensibilities within scientific areas (Delgado López-Cózar, Torres-Salinas, Jiménez-Contreras & Ruiz-Pérez 2006).

2. Methodological Approach: Network analysis

In this work, a network approach was selected. Notably, in the last few years, the development of Network Science (with its different nuances and approaches under the names of Complex Networks, Network Analysis, Graph Theory, etc.) has been outstanding in many and diverse scientific fields (Barabási, A.-L. 2016; Newman 2018), being particularly remarkable its growth within the framework of Complex Systems analysis and Computational Social Science (Lazer et al. 2009; Conte et al. 2012; Edelmann, Wolff, Montagne & Bail 2020).

Basically, Network Science is an interdisciplinary field whose most defining trait is that it enables the formalization and subsequent consideration of the relational dimension of systems. From a very general perspective, a network can be defined as a finite set of entities –whether people, companies, groups, animals, computers, etc.– that exhibit a pattern of relationship or interaction between them. To abstract and model these relationships, systems are formalized as networks or graphs in which nodes represent the entities and links represent the interactions between them. Depending on the type of interaction, these links can be directed or undirected, weighted or unweighted, signed or unsigned, etc. Modelling a system as a network is very convenient, since, once the network is defined, the use of graph theory as a formal framework enables to extract useful information from the network itself and to identify the possible implications that the results may have at different levels –and/or in relation to the real system. Recall that such an approach is very general and applicable in very diverse contexts. According to Newman (2003a), real networks can be categorized into four major categories: information networks, technological networks, biological networks and social networks. As regards the present contribution, the network obtained is a formalization of the social interactions that take place within the knowledge area of business organization in the context of thesis evaluation committees, thus being it attributable to the subfield known as Social Network Analysis (Tabassum, Pereira, Fernandes & Gama 2018).

The analysis of a network can be either static or dynamic. In the present work, we focused solely on the static analysis of our network of interest; however, it should be noted that its dynamic analysis would be a worthwhile future line of research, as it may serve to shed light into the temporal evolution of the different research lines and interests.

Typically, the static analysis of a network includes –but is not limited to–: the application of different tools aimed at determining the importance of nodes under different prisms or measures of centrality (Landherr, Friedl & Heidemann 2010); the identification of the general patterns of the network as a whole – how the network links are distributed, how easy it is to navigate from one point to another, how dense the network is, what is the probability of closed triangles, etc. – which, in many cases, determine its functioning (Newman 2003a); and/or the analysis of the mesoscale behavior of the network, that is, of the intermediate levels between the node and the network as a whole, which can provide relevant information about the network; remarkably, community detection algorithms are among the most important mesoscale analysis tools (Bedi & Sharma 2016; Fortunato & Hric 2016; Fortunato & Newman 2022).

3. Data

Data acquisition has been performed using the TESEO database (https://www.educacion.gob.es/teseo) compiled by the Spanish Ministry of Education, Culture and Sports. This source is a repository that includes all the theses successfully defended at Spanish Universities since the ’70s. The information retrieved consists of the title of the thesis, the university where the thesis was done, the author, the date, the supervisors, the examining committee and the classification of the thesis according to the UNESCO nomenclature for fields of science and technology (UNESCO 1988).

We have recovered more than 200.000 records. Subsequently, we filtered all the records to keep only those that include in the UNESCO classification the code 531100 –Organization and management of enterprises–. Please note that we are only sampling theses that have explicitly included the general four code description in this initial study, leaving the six-code specification and their possible implications and analysis for future research.

As other authors have previously pointed out (Castelló i Cogollos, Bueno Cañigral & Valderrama Zurián 2019), the TESEO database has several limitations related to the lack of consistency in several database fields. In the particular case of our study, we have initially applied some string similarity algorithms (Jaccard, weighted Levenshtein, etc.) to match names that have been misspelled or written in different but valid ways (for instance, in some cases, including or not the middle name).

In a later step, we have formalized the information gathered as a bipartite and bimodal network –that is, there are two types of nodes, with links running only between nodes of unlike types– (see Fig. 1). In this graph, we have included two types of nodes: scholars and theses. There is a link between a thesis and a scholar if the scholar has been a doctoral supervisor (S) or a member of the thesis examination committee (TEC) of the given dissertation. The network includes 6443 scholar nodes and 2799 theses from 14th October 1991 to 27th July 2018.

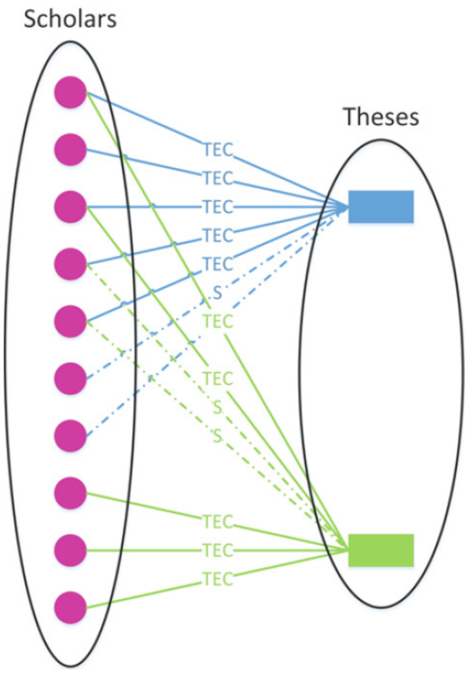

Figure 1 The database is formalized as a bipartite network between scholars and doctoral thesis. A scholar is linked to a particular thesis if he/she has been doctoral supervisor (S) or a member of the thesis examination committee (TEC).

4. Analysis

One of the first and more insightful analyses of a network consists in obtaining its degree distribution. The degree of a node in a given graph is the number of links that the node has with other nodes, and the degree distribution is the probability distribution of the degrees on the complete network –i.e., it provides the probability that a randomly selected node in the network has degree k.

Many real networks are heavy-tailed in the degree distribution (Clauset, Shalizi & Newman 2009), i.e., the distribution is not exponentially bounded. In other words, it means that the tail (usually the right one) contains a relevant portion of the probability and that extreme cases are possible. Several distributions are known to be heavy-tailed; however, fitting these distributions to empirical data is not an easy undertaking. We have used the powerlaw Python package (Alstott, Bullmore & Plenz 2014) to compare the goodness of fit among several distributions. The top picture in Fig. 2 shows the degree distribution of the bipartite network for the scholar nodes (excluding the theses). Results suggest a heavy tail in which extreme events occur –see, for example, that some scholars participate in almost one hundred thesis examining committees. To better understand the behavior of our distribution, analyses with log-log plots have also been performed. We have represented the probability density function (PDF) using logarithmic binning and the complementary cumulative distribution function or survival function (CCDF), which does not require binning and is usually preferred to estimate distributions

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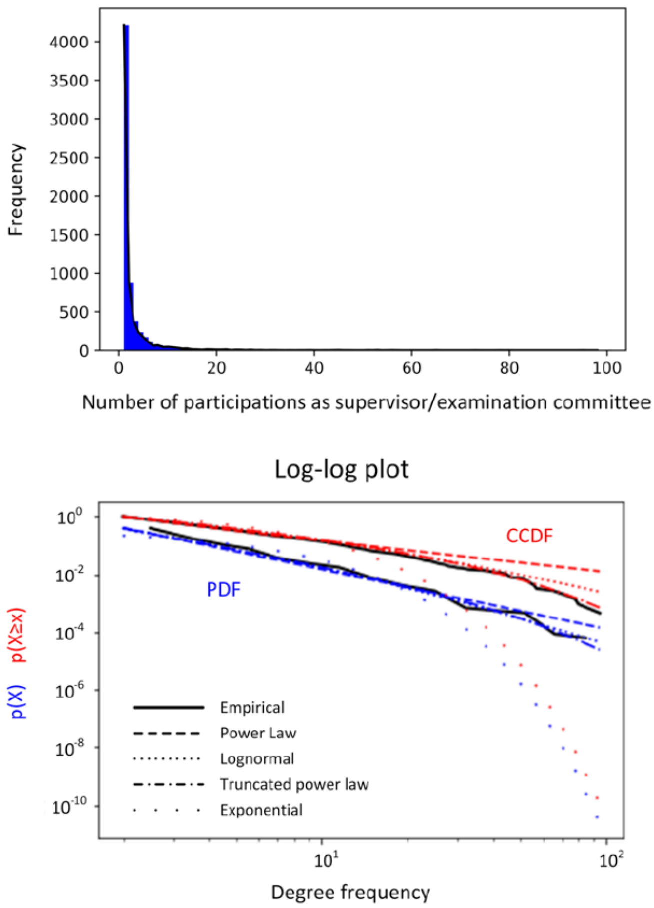
Table 1 Comparison of candidate distributions. Goodness of fit is compared using the loglikehood ratio (normalized by its standard deviation) between pairs of distributions (R). If this ratio is positive, it means that data is more likely adjusted by the row distribution. The significance value is provided by the p-value.

R (p-value)	Exponential	Power Law	Lognormal
Exponential			
Power Law	7.51 (6.1e-14)		
Lognormal	9.39 (6.0e-21)	6.16 (7.1e-10)	
Truncated power law	9.51 (1.9e-21)	7.21 (0.0)	2.14 (0.032)

Table 1 provides the comparison of different distributions using the loglikehood ratio and providing the statistical significance of the tests (p-value). All the candidate distributions are significantly more likely than the exponential distribution and hence, the empirical data distribution can be considered heavy-tailed.

An interesting mechanism known to produce power-law distributions –a particular case of heavy-tailed distribution– is preferential attachment (Barabási, A. L. & Albert 1999). This process, in which "the rich get richer", can be interpreted in the context of our contribution as follows: having previously been a thesis supervisor or a member of an examining thesis committee, increases your probability of being again supervisor or member of a committee, which could well be a possible explanation of why we obtain a heavy-tailed distribution. Although Table 1 shows that power law is a better candidate distribution than the exponential, there are better alternatives. We obtained the best fit with an exponentially truncated power law. Such fitting suggests that there may be an upper bounding effect in the distribution, and that as a consequence of a limited resource (maybe the finite time of the academic career of an individual) or due to some cost in the establishment of links (Amaral, Scala, Barthelemy & Stanley 2000), the preferential attachment mechanism cannot act in the whole range, limiting the power law.

Figure 2 The empirical degree distribution of the bipartite network (excluded the degree of theses nodes) is represented on the top figure. Although an important fraction of the nodes has only a few links, the tail of the distribution is heavy. On the bottom figure, the empirical degree distri-bution (PDF) and survival function (CCDF) together with some fitting distributions are repre-sented in a log-log plot.



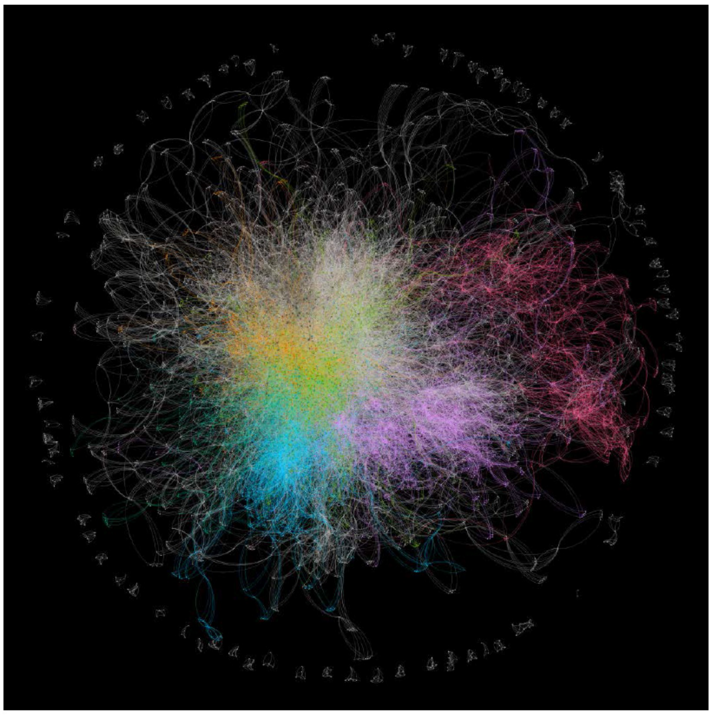
Even though in bipartite networks the bimodal representation may be the most complete, it is often convenient to work with only one type of nodes and the direct connections between them. Accordingly, the subsequent step of our analyses consisted in obtaining the simple weighting projection of the bipartite network onto the scholars. In this projection, the result is a weighted undirected network in which the weight corresponds to the number of theses in which two scholars have been members of a TEC and/or to a co-supervising relationship. Interestingly, this network presents a giant component with almost 90% of the nodes –i.e., 90% of the nodes (scholars) are part of a single connected component, which means that there exists a path between every pair of them– (see Fig. 3). For a summary of the general characteristics of the projected network, please refer to Table 2, which provides a general overview of the structure of the network and its basic properties:

Table 2 Overall description of the complete projected network

Statistics	Value
Nodes	6443
Links	34517
Average Degree	10.715
Average Weighted Degree	13.179
Graph Density	0.002
Average Clustering Coefficient	0.794
Connected Components	80
Percentage of nodes in the larger component	92.5%
Modularity (obtained with Louvain algorithm)	0.662
Number of communities	103

Afterwards, the community structure of the projection onto the scholars was assessed by means of the Louvain community detection algorithm (Blondel, Guillaume, Lambiotte & Lefebvre 2008), and several communities were found, i.e., nodes densely connected internally and loosely connected with the rest of the network. Remarkably, the Louvain algorithm implements a hierarchical clustering approach aimed at the maximization of modularity –which, in the context of community detection, quantifies the quality of an assignment of nodes to communities by comparing the actual number of intracommunity links with the expected number of intracommunity links if they were established at random while keeping the degree of each node. This algorithm is one of the most popular communities partitioning methods. It is highly accurate in estimating the maximum modularity, generally better than greedy techniques, presents low computational complexity, and can consequently be used efficiently and with good results in networks of a wide range of sizes (Lancichinetti & Fortunato 2009).

Figure 3 Simple weighting projection of the bipartite network over the scholars. Louvain algorithm has been applied to identify and color possible communities.



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A fundamental aspect in network analysis is the identification of the role that each of its components has within the network, and the configuration of these different roles in the network itself. This structure determines and partially explains the general behavior and dynamics of the network as a whole. Guimerà and Amaral (2005a, 2005b) proposed an interesting classification to map the different universal roles in all kinds of networks based only on the topological structure. This approach has been applied across various disciplines, such as the analysis of the role of several species in ecological networks (Delmas et al. 2019), the examination of different roles of institutions and universities in multidisciplinary research (Díaz-de la Fuente et al. 2021) or the investigation of brain structure and its relationship with cognition (Cohen & D'Esposito 2016), among many other applications.

Specifically, their proposal consists of, as a starting point, identifying the communities of the network. In the original method, the proposed algorithm is based on a simulated annealing approach to obtain the communities by optimizing modularity. In our case, and to be consistent with the different community analyses done in this work, the partitioning into communities is done based on Louvain's algorithm (Blondel et al. 2008), which also tries to maximize modularity, but using a different heuristic. The second step of the method consists in classifying the nodes into roles according to two dimensions: their pattern of within- and between-community connections.

Within-module degree is defined as a z-score that measures how well connected each node is within its own community. On the other hand, the participation coefficient determines how well connected each node is in relation to its own community and the communities outside it. These two dimensions allow dividing the roles of the nodes into seven different categories: four for non-hub nodes and three for hub nodes. Non-hub nodes can be categorized into role R1 (Ultraperipheral nodes), R2 (Peripheral nodes), R3 (Non-hub connectors), and R4 (Non-hub kinless nodes) depending on whether their participation in terms of links within their own community is higher or lower. On the other hand, and similarly, hub nodes can be divided into three roles R5 (Provincial hubs), R6 (Connector hubs), and R7 (Kinless hubs), again depending on their intensity of participation in their community and on their interaction with other modules.

Based on this analysis, the role structure found in the complete network is as follows (Table 3):

Table 3 Proportion of roles in the complete projected network

Code	Role	Proportion
R1	Ultra-peripheral nodes	0.4720
R2	Peripheral nodes	0.4085
R3	Non-hub connectors	0.0854
R4	Non-hub kinless nodes	0.0047
R5	Provincial hubs	0.0074
R6	Connector hubs	0.0208
R7	Kinless hubs	0.0012

To try to interpret the modular structure identified in Fig. 3, we filtered the network to the backbone of the graph, that is, we have kept the giant component constituted by those scholars with a degree (number of links) in the projected network within the range 70-509 (see Fig. 4). This filter reduces the graph to 151 nodes and 1712 links. Notably, when we applied the Louvain community detection algorithm to the backbone, six communities were obtained. The visual inspection of the nodes belonging to each community reveals that two communities (pink and black) are constituted by academics in many cases related to engineering; that another two communities (purple and blue) are both quite overlapped and related to economic faculties; and that the two additional communities (green and orange) are constituted by scholars that do not belong to the knowledge area of business organization, but to marketing in the case of the green community (Gutiérrez-Salcedo, Duarte-Martínez, López-Herrera, Torres-Ruiz & Cobo 2017) and to finance in the case of the orange one.

To formally verify our intuitions that the community structure found may be partially explained by scholar membership to the same academic association, we analyzed the homophily (sometimes also called assortative mixing) of the network in relation to the membership to the most relevant academic association in organization engineering in Spain (Asociación para el Desarrollo de la Ingeniería de Organización - Adingor). Recall that homophily is defined as the preference of nodes to link to other nodes that are similar in some way, and that it is measured by means of the assortativity coefficient (Newman 2002, 2003b), which quantifies the fraction of links in the network that run between nodes of the same type (See Eq.[1]):

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i c_j) \quad [1]$$

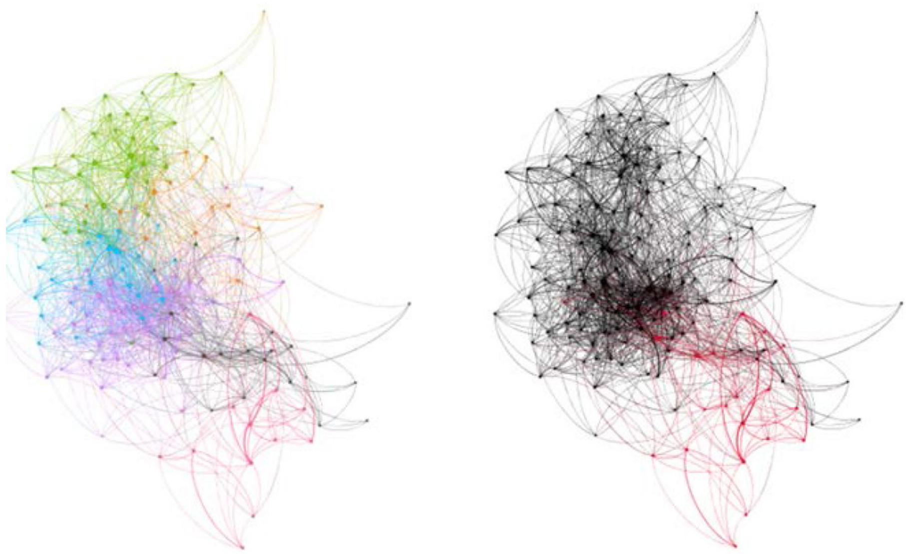
Where m is the number of links in the network; k_i, is the degree of vertex i; and c_i is an integer representing the type or class of node i; On its part, $\delta(c_i\, c_j)$ denotes the Kronecker delta, which equals 1 if both nodes belong to the same class, and 0 otherwise.

This metric takes positive values when there are more links between nodes of the same type than would be expected at random, and negative if there are fewer. (Note that in order to provide the fraction of links instead of their number, equation [1] is the normalized version).

In our particular case study, the assortativity attribute considered was the node membership to the Adingor association, or that at least they attend the annual association conference –currently named The International Conference on Industrial Engineering and Industrial Management (ICIEIM). Such information was obtained from http://adingor.es/, by means of their author search engine: https://adingores.sserver.es/congresos/web/buscar/autor and/or by manual inspection of the conference proceedings of the last years (from 2012 to 2020). Notably, for the backbone, we obtained a value of the assortative coefficient of r=0.39, which implies assortativity by association affiliation, in particular, assortativity by membership to Adingor and/or attendance to its conferences.

In Fig. 4, the left side shows the backbone of the projection onto scholars colored according to the different communities found. The right side shows in red the scholars who have coauthored a minimum of one communication in the International Conference of Industrial Engineering and Industrial Management conference organized by Adingor.

Figure 4 Backbone of the projected network. The left figure shows the community structure of the network using Louvain algorithm. The right picture presents the same network but representing the scholars that have attended the Adingor conferences in red.



5. Conclusions and future work

We have used network analysis to capture the patterns underlying the formation of thesis examination committees in the knowledge area of business organization in Spain. Since the TESEO database does not include the knowledge area but the UNESCO nomenclature of academic fields, we have filtered the theses in the domain of organization and management of enterprises, which has been considered as a proxy of the knowledge area. The thesis-scholars bipartite network formalized allows us to analyze the degree distribution of the graph. Our results show that a truncated power law is a plausible fitting curve for the distribution. This may suggest a rich-get-richer phenomenon with a bounding effect.

In addition, we have projected the network to analyze the scholars' unimodal network. Our results reveal the presence of a giant component and the existence of a modular structure in the graph, with almost 90% of the scholars classified as ultra-peripheral nodes and peripheral nodes. We then filtered the unimodal network to the nodes with a higher degree (the most relevant ones) for the sake of interpretation. The backbone network obtained presents again modular structure, which in this case can be partially explained by the membership to scientific associations. There are also relations, overlapping, and mutual interest between different knowledge areas, but further research is needed to fully understand those phenomena.

Our contribution constitutes a first step towards scientifically defining and understanding discipline organization in Spain; future studies in this line that may bring additional insights include the dynamic analysis of the network formation, the assessment of the communities found to check if they are a mirror of the informal relationships or simply rooted in the same research approaches or interests, and the effect of sampling by the field codes, among others.

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