

## Mapping the Scientific Structure of Organization and Management of Enterprises Using Complex Networks

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### Abstract:

Understanding the scientific and social structure of a discipline is a fundamental aspect for scientific evaluation processes, identifying trends and niches, and balancing the trade-off between exploitation and exploration in research. In the present contribution, the production of doctoral theses is used as a proxy to analyze the scientific structure of the knowledge area of business organization in Spain. To that end, a complex networks approach is selected, and two different networks are built: (i) the social network of co-participation in thesis examining committees and thesis supervision, and (ii) a bipartite network of theses and thesis descriptors. The former has a modular structure that is partially explained by thematic specialization in different subdisciplines. The latter serves to assess the interdisciplinary structure of the discipline, as it enables the characterization of affinity levels between fields, research poles and thematic clusters. Our results have implications for the scientific evaluation and formal definition of related fields.

### Key words:

Complex networks, community detection, doctoral theses, pattern recognition, interdisciplinarity, Organization and management of enterprises.

## 1. Introduction

Science mapping is an essential tool for understanding the structure of science and determining both the scientific strategy and the evaluation criteria of scientific production (Sedighi, 2016). This process is often conducted through the formal analysis of

networks such as journal citation networks or citation networks, among others (Newman, 2003). One of the ways in which the mapping process can be carried out is through the study of the doctoral theses produced within a given field. Such an approach, that uses theses as interaction entities, presents some interesting particularities. The most notable of all of them is probably that the effort

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and commitment required to undertake a doctoral dissertation—often greater than in other scientific enterprises, where collaborations may be more punctual and opportunistic—has the potential to indicate more robust trends and research lines.

Doctoral theses are a crucial source of information to understand the scientific structure of disciplines and identify the social dimension of science, its main actors and protagonists, and how they are related to each other (Repiso, Torres, & Delgado, 2011). In the case of Spain, the influence of supervisors on the composition of the thesis evaluation committee is a well-known phenomenon (Villarroya, Barrios, Borrego, & Frías, 2008). Thereupon, the co-occurrence of members and supervisors combined with the thesis descriptors can provide relevant information on both the academic and social structure of the scientific field(s) under consideration.

Scientific areas are the central element in the evaluation and development of the scientific career. In Spain, the knowledge area of business organization—*Organización de empresas*—is one of the most varied in terms of subjects and one of the most numerous in the number of academics. Previous theses-based analyses of the scientific structure of this area have shown: (i) an unequal distribution of participation in thesis evaluation committees (compatible with a truncated power-law); (ii) a modular structure; and (iii) a positive assortativity among network members belonging to the same scientific association (Garrido-Labrador et al., 2022).

The present work continues this line of research and further uses complex networks analysis tools (Newman, 2003) to extend and deepen previous findings and intuitions on the TESEO database. More specifically, we combine the co-participation networks in thesis examination committees in Organization and management of enterprises with the UNESCO descriptors (UNESCO, 1988) that define the topics and areas of each doctoral thesis. Notably, by expanding the information on the theses at the subdiscipline level, we find a more detailed scientific map of the field and can relate it to the levels and areas of scientific specialization. Eventually, we complete our analysis by identifying the interdisciplinary relations of Organization and management of enterprises with the rest of existing domains.

## 2. Methods and data sources

### 2.1. Methodological framework: Network science

The methodological framework used in this work to formalize the problem is network science (also called complex networks or network analysis). This approach has received much attention within the academia, and its development and applications have grown significantly in recent years (Latora, Nicosia, & Russo, 2017). Modeling a system as a network is a very general abstraction, as networks allow describing the interactions between elements of systems of a very diverse nature—from social and biological to technological and information phenomena (Newman, 2003). The advantages of modeling a system as a network lie not only in the intuitiveness of the description but also in the fact that, once a system has been described in network terms, it can be analyzed using the powerful mathematical apparatus of graph theory. Such apparatus makes it possible to extract, analyze and summarize information on the functioning of the system in a powerful and tractable way, both in static and dynamic terms.

In a network approach, the elements that constitute a given system are modeled as nodes, and the interactions between them as links. According to the characteristics of these links and/or nodes, networks are divided into different types: weighted/unweighted, unimodal/bimodal, bipartite, etc. Once the network is built, the resulting topology allows to formally infer many relevant properties and patterns of the system as a whole (Mata, 2020), the relative importance of the nodes (Rodrigues, 2019), and/or whether it presents structure in the mesoscale (Fortunato & Hric, 2016), among others. In specific applications, it is also possible to determine how the interaction structure—network structure—conditions the processes under study and vice versa.

Application examples of network science are bountiful and diverse, ranging from epidemic models (Pastor-Satorras, Castellano, Van Mieghem, & Vespignani, 2015), interaction between species and the evolution of social groups in ecology (Bascompte, 2007), to the management of communications in nuclear emergency plans (Ruiz-Martín, Ramírez-Ferrero, Gonzalez-Alvarez, & López-Paredes, 2015), the identification of efficacious combination therapies in drug development (Cheng, Kovács, & Barabási, 2019) and many other applications in many different

contexts (Havlin et al., 2012; Newman, 2018; Schweitzer et al., 2009).

Remarkably, since the Erdős number became famous (Grossman, 1997), the use of networks to analyze scientific interconnectedness and productivity has developed an important tradition. In fact, scientometrics and bibliometrics have made intensive use of network analysis to identify academic patterns. Typically, the networks built to that end are based on article citations, being co-citation networks and bibliographic coupling common approximations (Newman, 2018). The reason behind using article citations is that they are a good proxy for scholarly activity as, in general, when one article cites another, it indicates that the cited article is relevant in some way to the citing article. The first analyses in this line date back to the 1960s with the pioneering work of Price (1965). In these studies, the articles constituted the nodes of the citation network, and directed links were used to indicate which articles cited or were cited by others. As regards co-citation networks, their links represent the number of other articles that simultaneously cite both, being hence undirected and weighted. Eventually, in bibliographic coupling studies, the weight of the links represents the number of articles cited by both papers. Thanks to these complementary approaches, it is possible not only to map different scientific areas, but also to shed light onto the relative influence of different scientific ideas, their evolution, the similarity or difference between papers, etc.

Furthermore, it is worth noting that the analysis of scientific networks is not restricted to article networks. As a matter of fact, co-authorship and social relations within the academia have also been explored using network approaches. Notably, some of these works have served to better understand the social dimension of science and the formation processes behind the patterns found. See, for instance, the high clustering and small distance between researchers, compatible with the small-world property (Watts, 1999), and/or the heavy-tailed collaborative distributions identified in scientific networks (Newman, 2001a, 2001b, 2001c). Even models have been developed to characterize the evolution of co-authorship networks (Barabási et al., 2002).

## 2.2. Data

The data used in this work was collected using the TESEO database compiled by the Spanish Ministry of Education, Culture and Sports

(<https://www.educacion.gob.es/teseo>). This repository contains a unified database with all the doctoral theses from Spanish universities since 1976. The database provides information on the title of the thesis, the university, the author, the date, the supervisors, the examining committee, and the thesis classification according to the UNESCO nomenclature for the fields of science and technology. This terminology was an international effort that began in 1966 and was successfully completed in 1988 to create a global standard system for classifying science and technology. Although, initially, its objective was to classify research articles and doctoral theses, today, the classification standard is used for broader purposes — classification of research projects, academic positions, research lines, etc. (Martínez-Frías & Hochberg, 2007).

Basically, the nomenclature is organized into three hierarchical levels of aggregation. The first level (2-digit code) is the level corresponding to the scientific field (e.g., Chemistry, Physics, Medical Science); the second level (4-digit code) establishes the level of scientific discipline (e.g., within Chemistry: Analytical Chemistry, Biochemistry, Inorganic Chemistry, etc.); and, finally, the third level (6-digit code) determines the level of the subdiscipline, thus corresponding to individual specializations in science and technology.

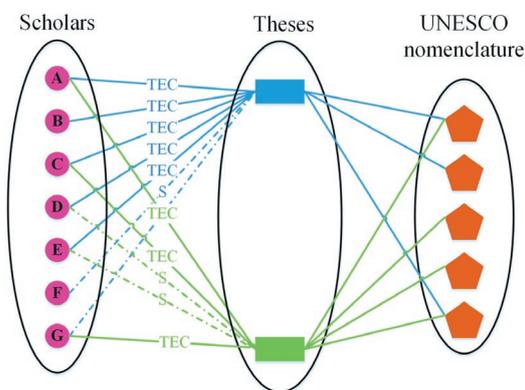
In our contribution, we have filtered the complete database to the theses that contain the UNESCO code 5311XX —*Organization and management of enterprises*. Unlike previous studies, in this work, we have selected not only those theses that include the four-digit code but also those that include the six-digit code, i.e., the other nine subdisciplines that comprise the discipline: Sales Management, Industry Studies, Manpower Management, Financial Management, Operations Research, Marketing, Optimum Production Levels, Organization of Production and Advertising.

As for the names of the supervisors and members of the thesis examination committees, they have been pre-processed to reduce the lack of consistency presented by TESEO in some fields of the database (Castelló i Cogollos, Bueno Cañigral, & Valderrama Zurián, 2019), and/or to identify possible academics who have been registered under different names.

The filtered database has been formalized into a tripartite network (Figure 1), that is latter transformed into two different bimodal and bipartite networks —

recall that bimodal means that there are two different groups of nodes, and bipartite implies that edges run only between nodes of unlike group.

In the first bipartite network, the node groups are the theses and the scholars, while in the second network, the groups are the theses and their descriptors. As regards the theses-scholars network, there is a link between a scholar and a thesis if the academic has been a supervisor or a member of the examination committee of that thesis. Note that the set of the UNESCO codes of each thesis has been kept as an attribute of the corresponding thesis node. The resulting network is constituted by 7911 scholar nodes and 3572 theses that were defended from 14<sup>th</sup> October 1991 to 27<sup>th</sup> February 2020.



**Figure 1.** The data structure of the analysis of this work corresponds to a tripartite network with three types of nodes, i) academics who have been part of an evaluation committee (TEC) or supervised a thesis (S); ii) theses defended in the scientific field; and iii) UNESCO scientific field descriptors of each thesis.

As for the second bipartite and bimodal network, there is a link between each thesis and each of its descriptors —i.e., the UNESCO codes used to describe it in TESEO. Recall that since the set of descriptors of each thesis is determined by its author, some inconsistencies might be found in relation to the categorization of topics.

### 3. Analysis and results

#### 3.1. Communities of scholars and their specialization

The first step of our analyses consisted in performing a simple weighting projection of the scholars-theses bipartite network onto the scholars' space.

One-mode projections are commonly used when dealing with bimodal/bipartite networks, as the set of mathematical tools available for their analysis is much more developed. However, since one-mode projections inevitably lead to the loss of information, it is important to choose a projection procedure with a suitable type of weighting, i.e., one that allows preserving as much information as possible. Among the different projection possibilities, simple weighting is probably the most frequent of all of them. It consists in assigning a weight to the links that is equal to the number of times the common association is repeated (Zhou, Ren, Medo, & Zhang, 2007).

In our case, the result of the one-mode projection onto the scholars was an undirected monomodal network in which the scholars constitute the nodes, and there exists a link between two of them if they have coincided in the same thesis (either as supervisors or as members of the examination committee).

Interestingly, the scholar monomodal network thus obtained reveals a giant component that contains more than 90% of the nodes —i.e., 90% of its nodes are connected to each other and belong to the same component. In addition, recall that each of the nodes in this network is endowed with two attributes: the first is the number of theses in which the researcher has participated; the second is her profile of specialization in Organization and management of enterprises. To calculate this latter attribute, we propagated the UNESCO thesis descriptors to each scholar at the 6-digit (subdiscipline) level. More specifically, we considered the number of thesis descriptors so that they summed up to one for each thesis. For example, in a thesis with two descriptors, Organization of Production and Industry Studies, each subdiscipline counted 0.5. On its part, if the thesis had only the Organization of Production descriptor, it counted 1.0. Once all the theses related to each researcher had been recorded in accordance with this procedure, we calculated the relative frequency of each UNESCO code for each person, hence obtaining the different research specialization profiles.

To interpret this network, we filtered it to include only the scholars who had been in at least 10 doctoral theses —i.e., the scholars with a degree equal to or greater than 10. This threshold reduced the network from 7911 nodes and 41433 links to 305 nodes and 3088 links respectively, thus serving to eliminate noise, avoid considering spurious structure and helping to

identify the core patterns. The resulting network is typically referred to as backbone. Afterwards, we explored the backbone with the Louvain algorithm for community detection (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Such algorithm allows determining if a network presents a modular structure, i.e., if it has nodes densely connected to each other but weakly connected to the rest of the network. To that end, the Louvain algorithm uses a modularity maximization heuristic, i.e., it seeks to maximize the difference between the number of actual links between each pair of nodes, and the expected number of links if they had been established at random while preserving the degree of each node. In the modularity Formula (1)  $m$  is the number of links in the network;  $k_i$  is the degree of node  $i$ ; and  $c_i$  is an integer representing the community of node  $i$ ;  $\delta(c_i, c_j)$  denotes the Kronecker delta, which equals 1 if both nodes belong to the same community and 0 otherwise.

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

Remarkably, in the backbone of our scholars' network, the algorithm found a modularity value of 0.584 and identified nine different communities (see Figure 2), hence revealing the social structure of the network of researchers in the field of Organization and management of enterprises in Spain. In this regard, an interesting research question is whether such network can be explained according to the scientific sub-specialization of each community and/or in accordance with the social relations between its members. To try to answer it, we conducted various complementary analyses.

First, we analyzed the general specialization profile of each community from the profiles of the researchers who belong to it. The community profile was calculated in two ways: (i) through a consensus distribution obtained by averaging the profile of all the researchers in the community, and (ii) through a weighted average using the number of theses —i.e., the degree of the scholar— as weight; we found that the results are robust to both approximations. The subdiscipline distributions obtained for each community are represented in the lower part of Figure 2. To determine whether the clusters are specialized or generalist, we calculated the normalized entropy of each subdiscipline distribution according to Equation (2), where  $x_i$  represents each subdiscipline and  $n$  the total number

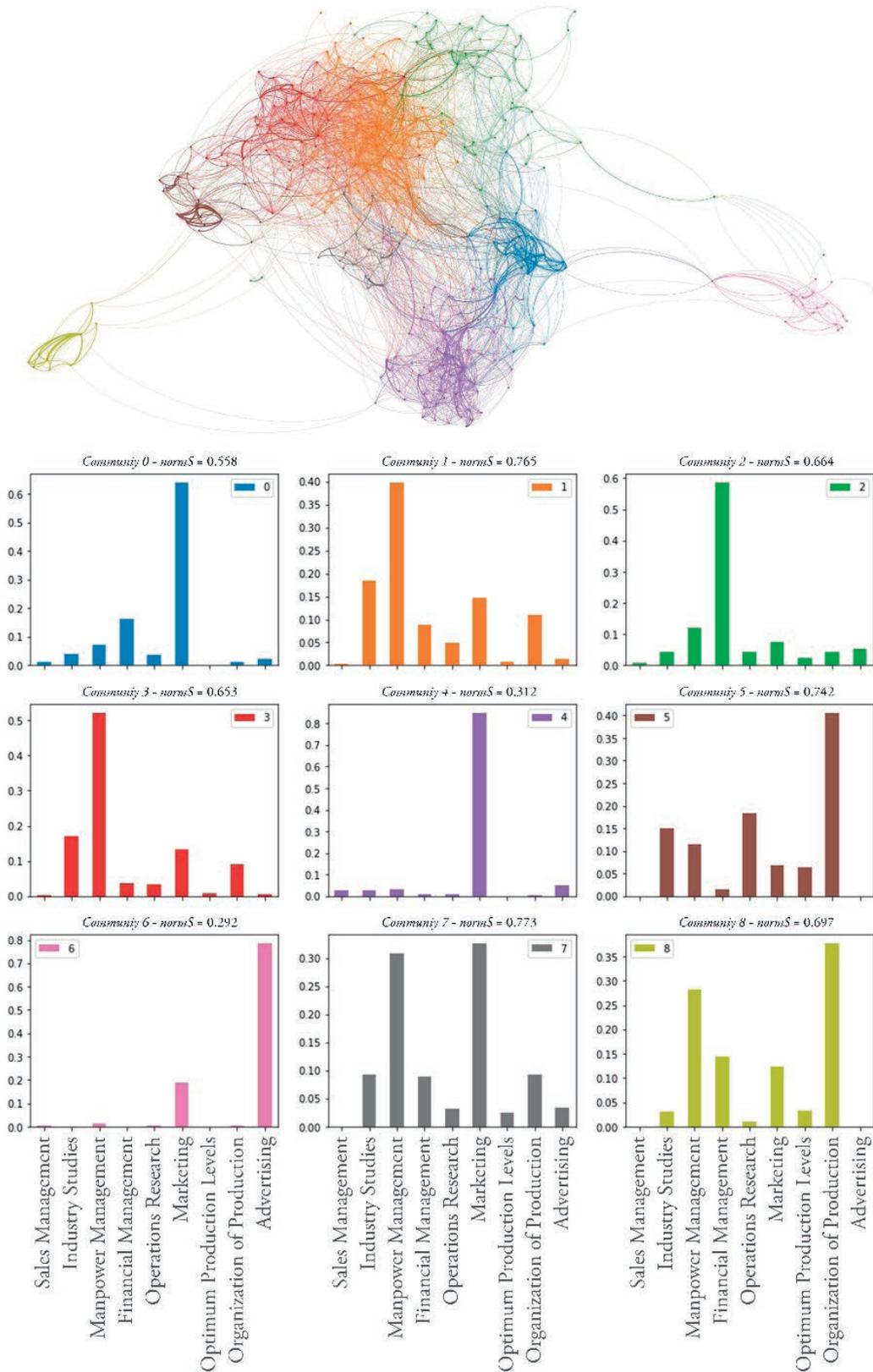
of subdisciplines —recall that the higher the entropy, the more generalist the specialization profile of the community and vice versa.

$$normS = \frac{-\sum_{i=1}^n p(x_i) \log_2 p(x_i)}{\log_2 n} \quad (2)$$

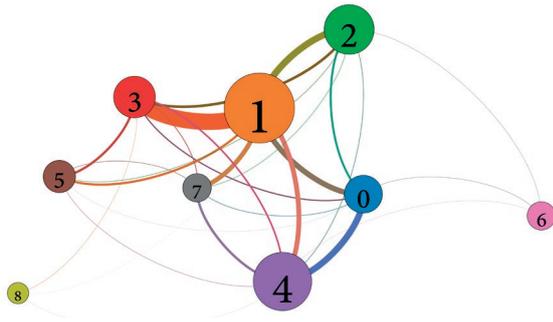
The results show two highly specialized communities: community 4 (purple) in Marketing, and community 6 (pink) in Marketing and Advertising; interestingly, these two communities are weakly connected between them. Community 0 (blue) is also specialized in Marketing, but with a certain level of Financial Management; it acts as a bridge between the purple and pink communities. The rest of the communities show an intermediate degree of specialization: the green community is focused on Financial Management; the communities 1 (orange) and 3 (red) present a relevant relative focus on Manpower Management; the 7 (gray) and 8 (yellow) combine Manpower Management with Marketing and Financial Management in the former case and Organization of Production in the latter; community 5 (brown), which is strongly associated with the Association for the Development of Management Engineering (*Asociación para el Desarrollo de la Ingeniería de Organización*, Adingor) —see Garrido-Labrador et al. (2022)— also presents an intermediate level of specialization in which Organization of Production, Operations Research, and Industry Studies are overrepresented. It is noteworthy that the most specialized communities are more peripheral in the network, as might be expected. However, some peripheral communities are rather generalist, hence challenging the explanation of the patterns observed exclusively on the grounds of scientific specialization, at least for the scale of analysis selected.

To better understand this latter issue, we decided to address the problem as follows. We built an additional network in which the nodes represented each of the nine communities, and the weight of the links represented the number of shared links (edges between them) in the original projected network (Figure 3).

Once such a network of communities was built, we used as proxy for the social component of the problem the weight of the links. Under this approach, if two nodes have a high weight between them, they are assumed to be closely socially related and vice versa. As regards the second component of the problem —i.e., the similarity/dissimilarity in the thematic



**Figure 2.** At the top of the figure, the backbone of the network projected onto the scholars is shown. The colors indicate the different communities obtained using the Louvain algorithm. At the bottom of the figure, the specialization profile of each community is represented by its distribution and normalized entropy.



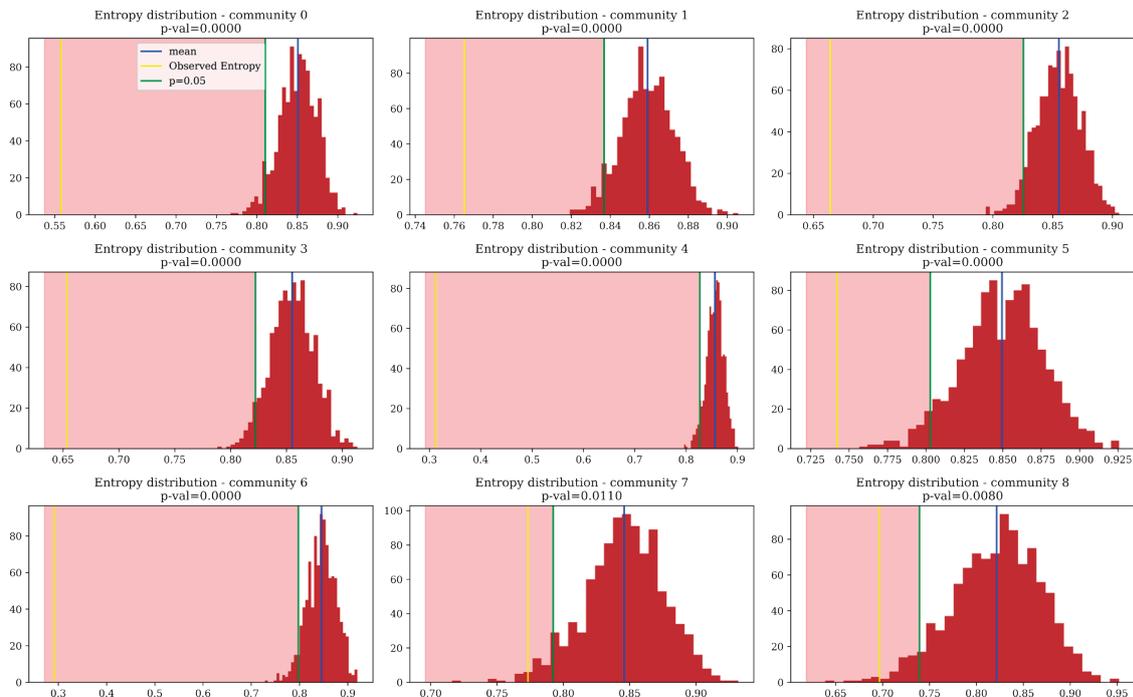
**Figure 3.** Collapsed community network of academics. In this network the nodes are the different communities previously identified in Figure 2 and the weight of the links represent the number of shared links between them. The size of the node is proportional to the number of scholars in each community.

specialization of the different communities— it was formalized by means of the cosine similarity (3) of their specialization profiles (obtained from the descriptors of the different theses that each community is linked to in the bipartite network). Cosine similarity is the cosine of the angle between two  $n$ -dimensional vectors, and it is calculated as the dot product of the two vectors divided by the product of their magnitudes —Equation (3).

$$\cos\theta = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (3)$$

In order to determine if the social proximity between communities (weights of the links in the community network) and their thematic proximity (cosine similarity) were correlated, we used the Spearman coefficient. In this regard, to ascertain whether the correlation value thus obtained was significant or not, a reference correlation value (baseline) was required. To establish it, we assumed a null model according to which the network of scholars would have formed exclusively on the basis of the social relations between its members —i.e., regardless of their thematic specialization. Thereupon, we maintained the empirically found social network by keeping the thesis evaluation committees untouched and randomized only the theses assigned to each scholar.

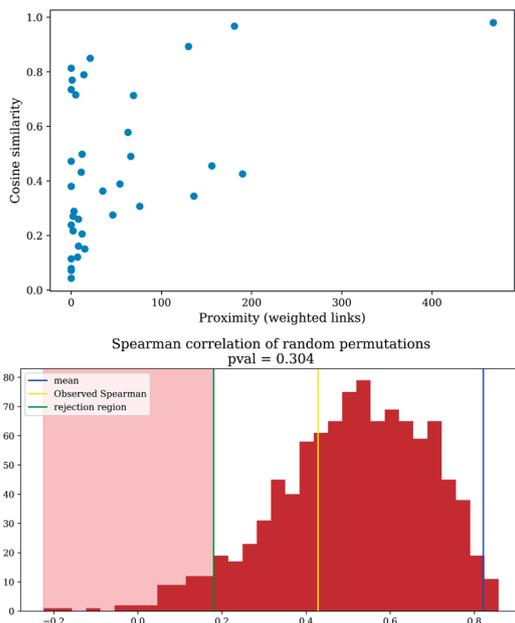
Comparison of the empirical results and the simulation results of the null model suggest that the formation of the different communities is partially driven by thematic specialization. Figure 4 shows the  $p$ -value of the normalized entropy in each of the communities found. In all cases, the null hypothesis



**Figure 4.** The figure shows the expected distribution of normalized entropy under the null hypothesis that thesis committees are randomly assigned. The empirically observed value is shown in yellow. In all cases, the null hypothesis is rejected at 0.05 significance level.

is rejected, i.e., the empirical communities are significantly more specialized than what would be expected according to the null model.

Subsequently, we studied the nature of the relationships between the 9 communities. Our results show a positive Spearman correlation of 0.428 between the social proximity between communities (number of shared links) and their thematic similarity (measured by the cosine similarity between the thematic specialization vectors of each community). Although these results indicate a more intense interaction with the more thematically similar communities, the empirical correlation value is within what would be expected according to the distribution of the null model —i.e., that obtained by randomizing the theses assigned to each scholar through the permutation test (see Figure 5). Thus, with these results, it is not possible to conclude that the relationships found between communities are driven by thematic similarity rather than by the structure of the co-participation network.



**Figure 5.** The top part of the figure represents the relationship between the interaction proximity between the communities, measured by the number of shared theses (as evaluation committee or supervision) among their members, versus the scientific proximity measured by the cosine similarity of the thematic distributions of each community. The Spearman coefficient found is 0.428. Although the value is positive and relatively high, the significance analysis under the null hypothesis (bottom of the figure) shows that the value is compatible with the null hypothesis and cannot be rejected.

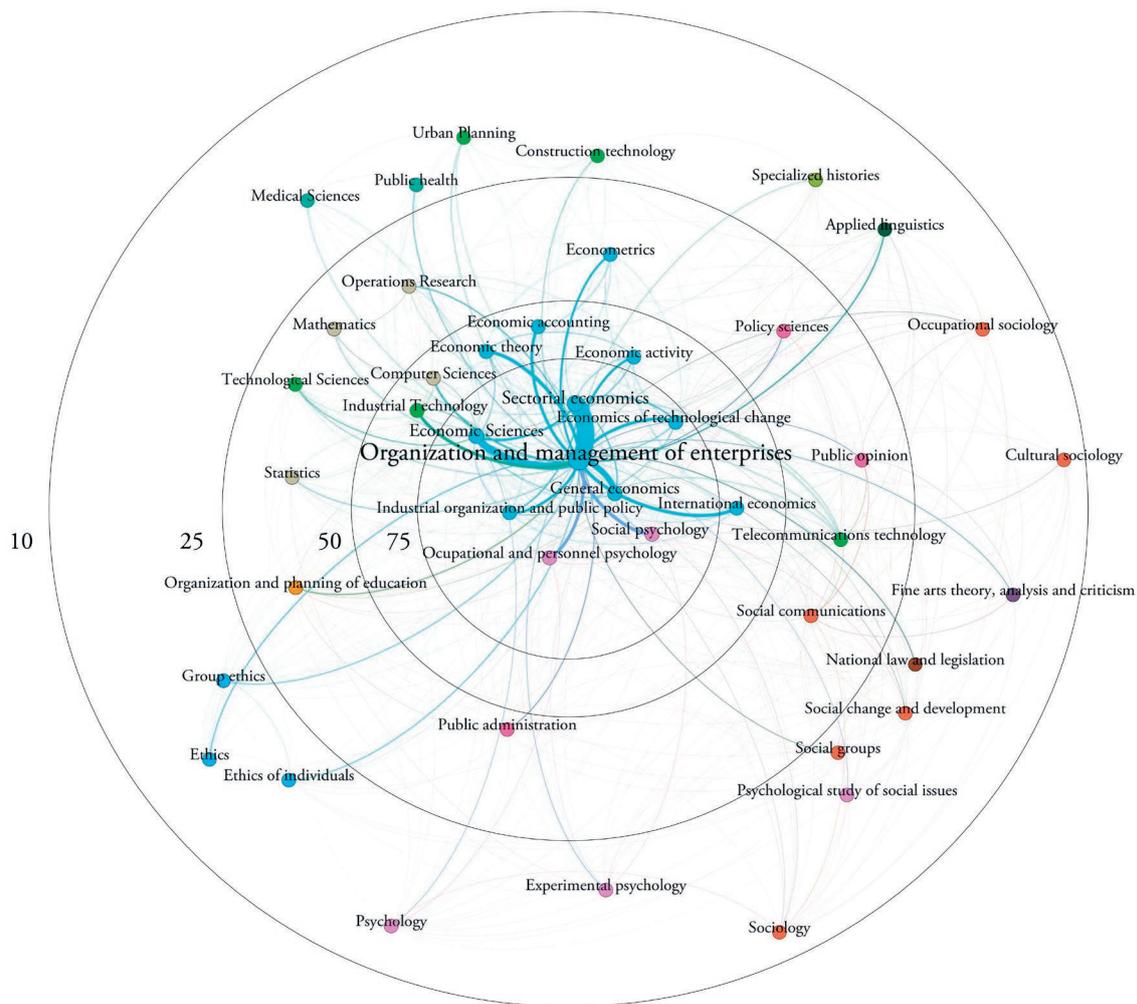
### 3.2. Organization and management of enterprises Ego-network

In the previous section, we identified the social structure of the field of Organization and management of enterprises in Spain and shed light onto the relationship of such structure with its own subdisciplines. Here, we complete our study by assessing its interdisciplinary nature, i.e., how the discipline of Organization and management of enterprises relates to other fields.

To that end, we analyzed our second bipartite network, the one of theses and descriptors. Please note that, as previously stated, this network was built by filtering the whole Teseo database to include only those theses that have at least one UNESCO descriptor related to the discipline of Organization and management of enterprises at the 4- and/or 6-digit level. In this case, the bimodal network was transformed into a unimodal one by projecting it onto the descriptors using hyperbolic weighting (Newman, 2001b). The reason behind the choice of hyperbolic weighting is as follows. In simple weighting, each node from the mode that we do not project onto—the theses in this case—contributes the same—a unit—to the weight of the respective link. However, in the problem at hand, it seems reasonable to think that two descriptors will be more closely related if they typically appear together but in the absence of any other descriptors—or accompanied by just a few of them—than if they appear together but in conjunction with plenty of other descriptors. This phenomenon—known as saturation effect—is accounted and compensated for in hyperbolic weighting. Specifically, in hyperbolic weighting, the marginal contribution of each node decreases with the number of nodes to which it is connected to in the initial bipartite network. Thereupon, in our particular case, it gives a weight to the link that is inversely proportional to the number of UNESCO codes present in the thesis.

Once the monomodal projection onto the descriptors was obtained, for the sake of interpretation it was analyzed at the 4-digit level. Accordingly, in the projection process the descriptors of the different subdisciplines were assimilated to the discipline to which they belong—i.e., to the immediately higher 4-digit level. Self-loops between fields were not considered in the analysis.

The outcome obtained is an ego-network with 176 different nodes and Organization and management of enterprises as the central node. In



**Figure 6.** Ego-network of the Organization and management of enterprises descriptor and its relationship with other descriptors in the TESEO database. The circles represent the weighted degree ranges after the projection. Colors represent the field of each discipline according to UNESCO classification.

Figura 6, however, the network shown has only 44 nodes, as it is the core obtained after removing the nodes that in the projection had a weighted degree of less than 10.

Figure 6 provides an accurate picture of the relationships between the discipline of Organization and management of enterprises and the rest of the scientific disciplines in Spain. In its immediate circle of proximity, there is an important association with other disciplines in the field of Economic Sciences (field 53), as could be expected. Such connection is particularly intense with Economic Sciences and Sectorial Economics. More surprising is the relationship of the discipline with others in the field of Psychology, such as Social Psychology and Occupational and Personal Psychology, which form a

cluster with other domains that are not so intensely related, such as different disciplines of Sociology and Psychology. Apart from this, there is another cluster of theses that connects Organization and management of enterprises with more instrumental disciplines, such as Mathematics, Statistics and Operations Research, being Computer Science the closest to the field of Organization and management of enterprises. This latter cluster is also closer to applied and technological disciplines, especially in the industrial field.

#### 4. Conclusions and implications

The conclusions and implications of the present study can be divided in accordance with the two perspectives adopted in our analyses.

The analysis of the backbone of the projection of the theses-scholars network onto the scholars demonstrates that specialization plays an important role in the discipline and shapes and determines the evaluation relationships. This structure is markedly modular, so it may be necessary to take it into account in general assessment processes so as to capture the nuances and differences of evaluation specific to each subdiscipline. Secondly, our graph reveals the social patterns and research topics addressed in Spain, allowing the identification of possible niches and research opportunities still to be developed within the discipline.

The ego-network obtained after projecting the theses-descriptors network onto the descriptors also provides relevant insights. It confirms the eclectic nature of business organization, as it shows how it interacts with a wide range of disciplines. The map obtained shows that these relationships have various degrees of intensity, defining different circles of interaction. Furthermore, the proposed approach also evinces the role of the discipline as a crossroads between a formal, technological pole and another pole focused on human relations and its scientific disciplines.

Besides, this latter analysis provides a formal tool to clarify the concept of related field (*área afín*), relevant in the Spanish academic system. The accreditation committees and the areas of knowledge assigned to each of them are based on this idea. In addition, commissions for the selection of university faculty are usually composed of researchers from the same area as the required position and, in case of difficulty, by members of related areas. When there are problems in the assignment of teaching duties in universities caused by a deficit of human resources in a given field, sometimes it is considered that academics can teach specific courses from related areas. Nevertheless, the definitions of the similarity and affinity between scientific fields and disciplines

are not precise; they can evolve and are not exempt from possible subjectivities. Such is so that the lists of related areas are generally approved by each university's Governing board and may differ from one to another. Although the results obtained in our descriptors network do not show the relationship of the areas of knowledge, but rather the relationship between the disciplines according to the UNESCO international standard system, a mapping between the areas, the disciplines and the subdisciplines could serve to identify similarities and to establish the associations of affinity both appropriately and dynamically.

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