Detecting key actors in interorganizational networks

Detectando actores clave en redes inter-organizativas

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Abstract:

Interorganizational network structure can be modified by the actions of key actors. This paper presents a set of strategies for detecting those actors through Social Network Analysis. To that end the potential of centrality measures, the Key Player Problem and the power of graphic visualization for identifying such actors and determining their ability to generate changes in network structures are introduced. To test the hypothesis under study five interorganizational networks made up of 32 cultural organizations are analyzed. Four types of key player are identified: (a) central actors; (b) intermediary actors; (c) disseminators; and (d) brokers. Each type has a distinct ability to influence network structures. The Structural Social Capital (SSC) in networks is examined in order to identify the elements that characterize each type of key actor. To that end, structural hole measures are evaluated. Two multiple regression models are developed to learn what factors influence SSC. Results show centrality and brokerage have positive impacts on SSC while density and constraint have negative effects. Finally the potential of each group of key actors for implementing strategies focused on optimizing inter-organizational networks is discussed.

Keywords:

Broker, interorganizational networks, key player, structural holes, structural social capital, social network analysis.

Resumen:

La estructura de las redes inter-organizativas puede modificarse por la acción de actores clave. En este artículo se presentan un conjunto de estrategias para detectar a estos actores a través del Análisis de Redes Sociales. Para alcanzar este objetivo introducimos el potencial de las medidas de centralidad, el problema del actor clave y el poder de la visualización de grafos para identificar a los actores clave y determinar su capacidad para generar cambios en las redes. Para testar las hipótesis de trabajo son analizadas cinco redes inter-organizativas conformadas por 32 organizaciones culturales. Identificamos cuatro tipos de actores clave que hemos llamado: (a) centrales; (b) intermediarios, (c) difusores y (d) brókeres. Cada tipo tiene una capacidad diferencial para

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incidir en la estructura de las redes. Con el objetivo de identificar los elementos que caracterizan a cada tipo, analizamos el Capital Social Estructural (CSE) presente en las redes examinadas. Para ello se evaluaron las medidas que analizan la existencia de agujeros estructurales. Para conocer los factores que influyen en la creación de CSE desarrollamos dos modelos de regresión múltiple. Los resultados muestran que la centralidad y la intermediación inciden positivamente en la generación de CSE, mientras que la densidad y la constricción afectan de forma negativa. Finalmente se discute el potencial de cada grupo de actores clave para implementar estrategias centradas en optimizar redes inter-organizativas.

Palabras clave:

Actor clave, Agujeros estructurales, Análisis de redes sociales, Bróker, Capital social estructural, Redes inter-organizativas.

1. INTRODUCTION

Social Network Analysis (SNA) is expanding in a broad range of disciplines, and can now be said to have spread to the academic community. Its adoption has been especially productive in Social Sciences (Borgatti et al. 2009). The core elements of SNA include the following: (a) it is focused on the structure of relationships between a set of actors; (b) it uses empirical data; (c) it is supported by mathematical algorithms; (d) it employs diagrams to represent network structures; (e) it generates specific indicators; and (f) it creates its own terms to explain network features (Wasserman and Faust 1994).

Despite the increasing development of SNA, there is still some confusion as to how to interpret network measures and graph visualizations. It must be taken into account that the proper interpretation of diagrams requires knowledge of qualitative data and accurate information as to context. The most common critique received by SNA studies is perhaps that they are excessively descriptive in nature, although the paradigm has great explanatory potential which is often not thoroughly exploited (Provan et al. 2009, p. 890). This phenomenon is observed in SNA studies designed to assess inter-organizational networks and partnerships. In this particular context, the main problem is to answer the following questions: *What is the minimum density needed to ensure effective communication between network members? What degree of centralization should be given to ensure that coordination occurs successfully? How many actors should be located at the core and the periphery to foster the equilibrium of the structure?* By analyzing relational data it is possible to obtain a plethora of whole network measures and information about nodes. Nevertheless it is important to know how to interpret network indicators in order to evaluate and optimize the social systems under study. At the same time access to information on context is needed. It is also important to know details of previous paths of collaboration between organizations.

To date there are few studies that systematize the interpretation of structural measures to analyze specific contexts. Provan et al. (2007) provides a systematic review to identify the main measures applied to evaluate whole networks[2]. Other publications summarize some structural analysis techniques which may be helpful in increasing the effectiveness of intervention programs (Gest et al. 2011; Valente et al. 2015). In another study Feinberg et al. (2005) implement an SNA study to evaluate a partnership created to deliver health services. Earlier studies have presented methods for detecting subgroups and whole network indicators related to community coalition functioning (Ramos-Vidal 2015a) and public-sector policy assessment (Ramos-Vidal 2015b).

Interdependence is one of the classical principles of SNA. This implies that the actions of a single actor may influence the behavior of other network members and vice-versa. At the same time, the whole system structure affects ties between individuals in a network (Mitchell 1969). This basic premise assumes that actors have some power to influence the overall network structure. This research focuses specifically on this topic. The objectives of this paper are: (1) to analyze the influence of a set of nodes to modify inter-organizational networks structure; (2) to provide helpful procedures for identifying key actors; and (3) to

[2] Within SNA two main levels of analysis are usually considered: Whole networks and Egocentric networks. Whole networks evaluate relationships between a defined set of actors. Egocentric networks are focused on direct ties established by a single actor (ego) with other network members (alter).

introduce measures and concepts linked to Structural Social Capital (SSC) that enable the potential of key nodes to determine inter-organizational network structures to be assessed. We use data from our previous research to evaluate different types of relationship between organizations that form an inter-organizational network in the performing arts sector in Andalusia (*Spain*). The next section shows the influence of individual actors on the whole network configuration.

1.1. **Individual impact on social structure**

Social network configuration is the product of interactions between nodes integrated into a social system. Therefore the deletion –or addition- of new ties or new nodes can transform the structure of entire networks (Knoke and Yang 2008). This means that each network member has some power to modify network structure. However, not all actors have the same ability to influence structural properties and social network evolution.

The analysis of the traffic of information is a key element for detecting potentially powerful actors (Pettigrew 1972). Individuals situated in betweenness positions are considered as natural brokers, introducing new information into the subgroups to which they connect. Brokers can also act as opinion leaders and triggers for changes and innovations (Burt 1999). Access to diverse flows of information could improve the decision making process at individual and collective levels. For example, within an organization individuals who are the nexus between subunits and departments are usually powerful (Brass and Burkhardt 1993). Other classic studies have evidenced the importance of having access to heterogeneous groups through weak ties to achieve better positions in labor markets (Granovetter 1973).

Most studies focused on the inter-organizational level analyze factors that explain (a) the rise of strategic alliances (Uzzi 1997); (b) the genesis of trust between members (Zaheer and Venkatraman 1995); and (c) the acquisition of competitive advantages (Dyer and Singh 1998). But there is little research that empirically evaluates the influence of a small set of organizations on the evolution of interorganizational networks. This, along with the increase in the number of such structures now operating in a globalized environment, justifies developing strategies to identify the role assumed by each organization within partnerships.

Some research shows that changes in networks are often orchestrated by a small number of actors whose actions promote changes at network level (Owen-Smith and Powell 2004; Danaraj and Parkhe 2006). Provan et al. (2007) describe the mechanisms that explain why a set comprising a small number of organizations has a greater capacity for influencing the structure and evolution of socio-centric networks:

> “A key group of nodes (organizations) within the network and their leaders often play a central role as the main carriers of those rules and practices, often reflecting the environment in which they are situated […]. The practices and commitments of those key nodes may result in the development of dominant logics at the network and community levels […]. In other words, a dominant core within the network may drive how the network develops and/or evolves” (p. 502).

The next section explains the connections between SNA and the genesis of Structural Social Capital (SSC). This kind of social capital is a helpful concept in understanding what factors determine the success of individuals and organizations depending on their abilities to access innovations and non-redundant information (Granovetter 1973; Burt 1992; Ramos-Vidal 2015c).

1.2. **Competitive advantages and SSC**

SSC is a construct which has captured the attention of many researchers for its potential to explain the importance of relationships by generating added value. The conceptual framework of SSC may explain why some organizations get better results than others. At individual level, SSC describes how single organizations leverage the knowledge and skills of their members to climb to higher positions within markets. At collective level, SSC enables us to describe roles played by whole structures for generating ideas and new knowledge. Nahapiet and Ghoshal (1998) claim that SSC is an important source of intellectual capital in organizational settings. This process explains why corporate clusters generate innovations, making it possible to secure competitive advantages.

Ronald Burt is perhaps the author who has contributed most to the operationalization of SSC. A key concept of his theory is the notion of *structural holes*. According to Burt (1992, p. 18) a structural hole is the separation between nonredundant contacts: Assuming that non redundant contacts are connected by a structural hole, a structural hole is a relationship of non redundancy between two contacts. This concept is outstanding because the lack of links between actors –*a structural hole*- may result in aditional profits for the entire network. The presence of structural holes implies relationships within networks that are non redundant, so the information flowing through the network is not repeated. There are several measures for evaluating structural holes, including the indicators presented in Table 1. These indicators are used to evaluate the SSC of each actor, on the basis that it is possible to isolate the ties of an actor within networks.

Table 1

Description of measures and formulas for calculating variables under study

Indicators	Description	Formula
Centrality	Number of links established by an actor. This measure it is positively related to the capacity of action deployed by organizations. However redundant ties have the opposite effect by offering repeated information.	$d(n_i)$= Number of nodes to which ego is connected. g= Number of nodes in the network (network size). $C_D(n_i)=\mathrm{d}(n_i)=\sum_j x_{ij}=\sum_j x_{ji}$ Standardized formula: $C_D(n_i)=\frac{\mathrm{d}(n_i)}{g-1}$

Effective size	Number of alters –weighted by tie strength- to which ego is connected and has the potential to minimize the redundancy of relationships. An increase in access to new sources of information takes place because the actor may affect the number of subgroups to which ego is connected.	Effective size[3] is the number of alters minus the average degree of alters within the ego network, not counting ties to ego. $\sum_j [1 - \sum_q p_{iq} m_{jq}]\ q \neq ij$ (Eq.1) $p_{iq} = \frac{(z_{iq}+z_{qi})}{\sum_j (z_{ij}+z_{ji})}, i \neq j$ (Eq.2) $m_{jq} = \frac{(z_{jq}+z_{qj})}{max_k(z_{jk}+z_{kj})}, j \neq k$ (Eq.3)
Constraint	Burt's constraint measure (equation 2.4, p. 55 of Burt, 1992). Essentially this is a measure of the extent to which ego is invested in people who are invested in other ego's alters.	Degree in which the network of "i" invests directly or indirectly in the network of actor "j, where P_{ij} is the proportion of time and resources invested by actor "i" in actor "j". $C_{ij} = \left(P_{ij} + \sum_q \mathrm{P_{iq}}\ \mathrm{P_{qj}} \right)^2$
Betweenness	This shows the times when an actor is located on the shortest path (geodesic distance) between two pairs of nodes. Organizations with high betweenness are able to influence an actor's behavior because they can control the communication flows between different clusters and hence they have the potential to access more resources.	G_{jk}= Number of geodesic paths that link "j" to "k". $G_{jk}(n_i)$ = Number of geodesic paths between "j" and "k" that pass through "i". $C_B(ni) = \sum_{j<k} g_{jk(ni)}/g_{jk}$ Standardized formula: $C_B^{'}(n_i) = \frac{C_B(n_i)}{[(\mathrm{g}-1)(\mathrm{g}-2)/2]}$
Density	This shows the total number of ties divided by the total number of possible ties. This indicator is negatively related to SSC. The higher the density, the more likely ties between organizations are to be redundant[4].	Density is calculated by dividing the number of connections "L" by the number of possible arcs g (g-1). $\Delta = \frac{L}{\mathrm{g}(\mathrm{g}-1)}$

Source: Own work based on Ron Burt's (1992) seminal research.

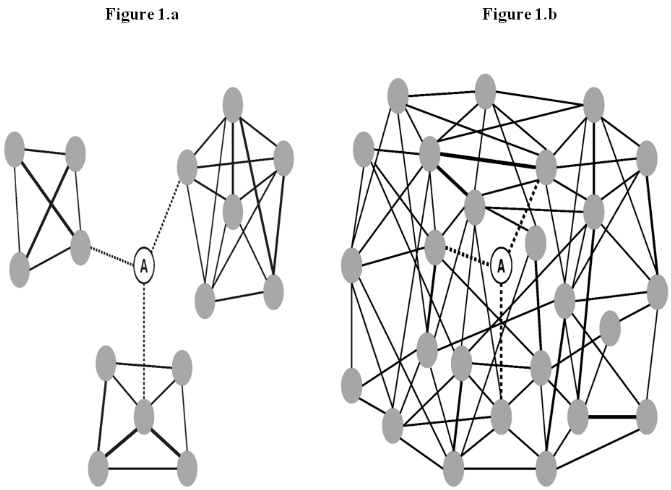
Figure 1 explains Burt's (1992) Structural Holes Theory visually. Two examples of networks are presented to show how the position of an actor within social networks is related to SSC.

[3] Borgatti (1997) provides a critical review of the redundancy measures developed in Ron Burt's (1992) Structural Holes Theory.

[4] There is another form of SSC named Bonding Social Capital. This kind of SSC often gains profits from high relationship densities, tie strength and transitivity. For example, in certain sectors it is positive to show local structures with high levels of cohesion. This phenomenon is common in traditional sectors (e.g. small craft firms). In such environments, which are usually characterized by a local business projection, management practices often require high levels of trust and commitment (Crowe 2007). This clarification is made in answer to a relevant comment by an anonymous reviewer.

Figure 1

Illustration of Burt's (1992) Structural Holes Theory



Source: Own elaboration.

In Figure 1.a node A maintains three connections which in turn connect node A to three non-overlapping subgroups. Nevertheless, node A in Figure 1.b maintains three links within a single cohesive network. Burt's theory shows that actors who have access to different subgroups (which are not connected to each other) have more options to acquire better information and innovations than actors embedded in cohesive networks.

Ahuja (2000) studies this topic in regard to chemical industry firms. His conclusions underline the prominent role of structural holes in explaining the adoption of innovations. The results show that organizations which occupy bridging positions act as early adopters of innovative processses. Zaheer and Bell (2005) reach similar conclusions in regard to Canadian financial companies. Other studies highlight that network structures have to combine structural holes (to facilitate the creation of innovations) with a minimum level of internal cohesion to ease and smooth coordination within networks (Burt 2000; Sytch et al. 2012). A set of strategies for identifying key actors is shown in the next section.

2. **TECHNIQUES FOR DETECTING KEY ACTORS**

One of the main distinctive features of SNA is its ability to generate indicators to assess whole network structural properties (cohesion measures) and individual actors (centrality measures). Cohesion measures are indicators of the entire network while centrality measures assess the positioning of individual actors. This article focuses on analyzing the changes induced by individual actors in whole network parameters. To that end, centrality measures of individual actors are analyzed first. Then the changes in cohesion measures that result from deleting different sets of key actors are examined. The next section describes indicators of centrality designed to evaluate the prominence of actors, then a complementary technique for detecting influential actors is presented (Borgatti 2006).

2.1. **Centrality measures**

Centrality parameters serve to compare the individual positions of actors within social networks (Freeman 1979). Each actor has a different power to affect network structures depending on the role assumed in the whole structure. As a result, all nodes are interdependent on each other. To learn the internal dynamics of interaction the characteristics of actors with the greatest potential to define network structure is evaluated. The measures used to explain structural influences processes are Degree and Betweenness centrality (Freeman 1979; Wasserman and Faust 1994).

Degree is a measure that comprises two independent parameters: Indegree (received nominations) and Outdegree (sent nominations). Degree is the measure that best explains the power of actors in social networks. Central actors are directly connected with many actors, so they are able to reach several nodes via direct paths. Occupying central positions has different effects depending on the kind of relationship analyzed. Being a central node in networks in which actors exchange confidential information could have positive effects on business strategy, whereas being a central node in a network of organizations characterized by unethical business practices could result in negative effects on reputation.

Betweenness represents the extent to which an actor occupies strategic positions. Betweenness refers to the times when an actor is situated on the shortest path (*geodesic distance*) between pairs of actors. Nodes with high betweenness have many options for connecting subgroups. Such nodes may be influential actors because they may control the information and resources that flow across linkages. The next subsection presents alternative procedures for detecting key actors in social networks.

2.2. **The Key Player Problem**

Centrality measures offer valuable clues for identifying influential actors, but there are other measures that add effective solutions adapted to meet specific needs for detecting key players. Borgatti and other colleagues developed the Keyplayer software to close this gap (Borgatti and Dreyfus 2003; Borgatti 2006). They recognized certain limitations of centrality parameters in identifying key actors, and developed a technique for solving a two-fold dilemma[5]:

(1) *Which actors are best able to disseminate information, resources, and ideas through the network?*

(2) *Which are the actors whose removal has the greatest power to fragment the structure?*

[5] Borgatti (2006) refers to both questions jointly as the Key Player Problem (KPP). He defines the Key Player Problem Positive (KPP+) to identify the set of actors that can act as disseminators, and the Key Player Problem Negative (KPP-) to detect actors whose removal has the most power to fragment social structures.

The answers to both these questions have multiples applications in social science, e.g. learning which actors are able to disseminate messages and good practices has notable advantages in fields such as public health (e.g. in reducing response time on implementing new protocols) and in management science (e.g. in increasing the speed at which production innovations are adopted). Being able to identify actors whose removal fragments the structure may serve to reduce the power of organizations that exert control over local markets. The mathematical foundations of each procedure are not explained in this paper, but it may be desirable to look in more depth at the practical solutions to both questions.

2.2.1. *Looking for disseminators (KPP+)*

KPP+ alludes to identifying the smallest set of key players (*Kp set*+) that is maximally connected to the rest of the nodes in a network (Borgatti 2006, p. 22). It is possible to consider that this small set will comprise actors with a high degree of centrality[6]. These measures could guide selection in the early stages, but they are not always effective in detecting actors with high dissemination power because cohesion measures do not take into account the structural equivalence of the actors who make up the *Kp set*. This means that if only the subgroup of *n* actors with highest centrality is identified they actors are likely to share the same contacts with third parties. Thus, actors are structurally equivalent and many contacts are redundant. If the set of key actors is chosen solely on the basis of centrality measures, other actors are not selected, even if they do not maintain many links but are connected to other actors who are not accessible through central nodes. To identify the members of the *KP set,* the Keyplayer program considers graph theory and the principles of centrality of groups and classes. This last concept expresses the idea that the centrality of a subset may be greater than the aggregate centrality of actors (Everett and Borgatti 1999).

2.2.2. *Identifying brokers (KPP-)*

The second dilemma for detecting key actors involves choosing a subset of actors (*Kp set*) whose removal results in a residual graph with the lowest possible cohesion. By detecting -and subsequently deleting- these actors from the network, the aim is to disconnect the graph removing the smallest possible number of nodes. As indicated previously, it might make sense to select actors with high betweenness. However, as also noted above, centrality parameters are not designed for this purpose so the detection of both types of *KP set* and the identification of the actors with the greatest centrality and betweenness may be a suitable option for implementing structural intervention strategies.

3. **METHOD**

The concepts and techniques presented are illustrated by studying data from a case study covering six kinds of relationship between 32 cultural organizations (Ramos-Vidal

[6] The measure used to calculate the Kp set of potential disseminators is Closeness Centrality.

and Maya-Jariego 2013). The relationships assessed in this research represent different types of link, from relationships that require no commitment to ones that require some degree of formalization (e.g. joint participation in projects)[7]. According to Barringer and Harrison (2000), to learn what constellation of interactions is shaping inter-organizational networks, different types of link should be analyzed. A member of each organization provides information about the relationships that his/her organization maintains with other organizations registered on the same public census. Six types of relationship are analyzed, each of which gives rise to a different network. Participants assess tie strength from 0 (no relationship) to 3 (highly intense contacts). The network of recognition between members is excluded because it shows a high level of density. The design of the research is described below.

The first step is to calculate cohesion measures. Density reflects the total number of ties divided by the total number of possible ties. Centralization analyzes the degree to which relationships are concentrated on a few actors. Reciprocity shows the degree to which ties are returned to the sender. A clique is a subgroup comprising at least three actors who are maximally connected (full triad).

Centrality measures are calculated to identify a subset formed by the four actors with the greatest centrality and a subset of four actors with the highest betweenness. The Keyplayer program (version 1.45) is used to detect *KP sets* of potential disseminators and brokers[8]. Afterwards all four subgroups of actors with the greatest centrality, betweenness and the subgroups of disseminators (*Kp set+*) and brokers (*Kp set-*) are independently deleted in each network. Next, cohesion parameters are calculated again after removing each subgroup. This procedure enables us to test for different effects of such subset on the whole network structure (Borgatti and Everett 2006).

Next we estimate several measures aimed at checking for structural holes (Burt 1992)[9]. This step is carried out on all five networks evaluated. For each indicator a new variable is created built up from the aggregation of values in each network. Next, two regression models are drawn up to test two hypotheses. The study hypotheses are designed to assess the impact exerted by key actors on network structure in terms of opportunities to create SSC:

H1: Centrality and Betweenness will exert a positive influence on SSC.

H2: Density and constriction will exert a negative influence on SSC.

Finally, the core-periphery structure is calculated for all the networks assessed (Borgatti and Everett 1999). This analysis is performed to identify actors located in the core and the periphery. This step enables us to detect whether the four subsets of key actors tend to occupy core or peripheral positions. Empirical evidence suggests that actors who determine network structures are usually located at the core while peripheral actors usually play a secondary role in the evolution of the system (Provan et al. 2007; Ramos-Vidal and Maya-Jariego 2013; Ramos-Vidal 2015c). Visone software is utilized for graph visualiza-

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7 The socio-centric assessment questionnaire applied in this research is available in Appendix I of Ramos-Vidal (2015b).

8 The selection of subsets of four actors is justified because some studies suggest that structural changes are usually conducted by no more than 20% of network members (Valente et al. 2008).

9 Structural hole measures are individually calculated for each actor using Ucinet (Borgatti et al. 2002). See Burt (1992), Borgatti et al. (1998) and Ramos-Vidal (2015c) for a more precise description of indicators and the relationships maintained with inter-organizational network evolution and SSC at individual and collective levels.

tion (Baur et al. 2001). To learn more about the individual positioning of each key player subset, the core and periphery are differentiated. The final step (Figures 3 and 4) shows ego-networks of a single organization representing each subset so that qualitative comparisons can be made.

4. RESULTS

Following the sequence presented in the previous section, Table 2 shows the cohesion measures found. Whole network indicators are presented first, then the successive rows show structural parameters again after each subgroup of key actors is deleted.

Table 2 shows the power of a subset of central actors to modify network structural properties. Significant decreases in density and in the number of cliques are observed when the subgroup of central actors is removed. This may be due to the fact that central actors base their power on the number of direct ties that they maintain. If this subgroup is deleted the whole network structure tends to be fragmented. The group with the second greatest power to alter structural parameters comprises intermediaries. The influence of intermediaries is less than that of central actors, but density and centralization levels are reduced if this subset is deleted.

The subgroups of brokers and disseminators are quite different. If both subgroups are removed from the graph there are no major changes in the parameters assessed, except that the subset of brokers shows a slight potential for modifying the number of cliques. Nonetheless this subgroup shares some members with the subgroup of centrals. Table 3 identifies organizations that belong to each subset of key actors. Subgroups of centrals and brokers share members in all networks. This is logical if the (small) size of the network and the (high) level of Outdegree centralization are considered.

We also select a small proportion of actors to explain the potential influence exerted by such subset. If the number of members of each group is increased the level of overlapping and the composition of each subgroup becomes more heterogeneous. Table 4 shows descriptive statistics of aggregated measures checking for structural holes. Bivariate correlations between variables are shown in Table 5.

Table 2

Comparison of averages and changes in structural measures after deleting each subgroup of key actors

Indicator	Parameters	Formal contacts	Informal contacts	Perception of affinity	Collaboration on projects[10]	Options for future contacts	T Test[11]
Density	Total	14%	28.59%	16.23%	20.16%	14.37%	
	Without central actors	0.9%	23.41%	0.8%	13.49%	0.7%	t=5,153 p<.001
	Without intermediaries	11.64%	30.03%	11.11%	17.20%	0.8%	t=1,762 NS
	Without Kp set+	13%	27.38%	14.55%	21.16%	20.16%	t=-4,70 NS
	Without Kp set-	0.9%	25.79%	0.09%	14.95%	17.85%	t=1,888 NS
Reciprocity	Total	16.67%	28.05%	29.84%	24.22%	16.82%	
	Without central actors	19.05%	25.53%	19.64%	25.93%	0.8%	t=1,383 NS
	Without intermediaries	17.33%	27.53%	27.27%	23.81%	0.1%	t=1,206 NS
	Without Kp set+	18.18%	31.85%	27.91%	25.98%	20.69%	t=-1,707 NS
	Without Kp set-	20%	34.48%	19.67%	25.56%	18.37%	t=-0,176 NS
Cliques (n=5)	Total	36	78	25	49	13	
	Without central actors	0	29	1	6	0	t=5,754 p<.001
	Without intermediaries	0	60	10	42	3	t=3,390 p<.05
	Without Kp set+	15	37	15	46	11	t=2,126 NS
	Without Kp set-	11	25	2	28	12	t=2,92 p<.05
Indegree Centralization[12]	Total	11.72%	27.50%	25.52%	29.13%	19.59%	
	Without central actors	8.39%	26.39%	19.28%	16.73%	14.18%	t=3,04 p<.05
	Without intermediaries	11.48%	23.37%	22.44%	20.57%	17.10%	t=2,84 p<.05
	Without Kp set+	20.30%	28.16%	20.84%	29.96%	17.48%	t=-2,95 NS
	Without Kp set-	16.64%	28.33%	19.80%	18.21%	20.04%	t=0,75 NS

Outdegree Centralization	Total	45.02%	45.26%	32.18%	59.10%	31.80%	
	Without central actors	25.04%	43.04%	15.95%	28.25%	28.61%	t=2,69 p<.05
	Without inter-mediaries	21.47%	38.91%	27.99%	43.62%	28.20%	t=2,27 p<.05
	Without Kp set+	43.34%	42.59%	29.72%	39.95%	26.36%	t=1,91 NS
	Without Kp set-	43.28%	39.43%	26.46%	28.20%	32.25%	t=1,54 NS

Note: NS= No Significance
Source: Own elaboration.

Table 3

Identification of organizations that form each subgroup of key actors

Types of key actors	**Kind of relationship (networks)**				
	Formal contacts	**Informal contacts**	**Perception of affinity**	**Collaboration on projects**	**Options for future contacts**
Central actors	7, 11, 16, 27	3, 11, 26, 28	9, 11, 16, 20	6, 7, 27, 28	4, 11, 16, 20
Intermediaries	1, 11, 14, 22	11, 14, 22, 28	9, 10, 11, 20	7, 10, 27, 28	4, 11, 16, 20
Disseminators	10, 11, 25, 27	2, 14, 20, 28	4, 16, 27, 28	10, 12,28, 29	1, 2, 3, 4
Brokers	10, 11, 22, 26	11, 14, 22, 28	9, 11, 16, 30	7, 10, 27,28	1, 10, 12, 24

Source: Own elaboration.

[10] Networks of collaboration on projects are binary while the rest are valued from zero (no relationship) to three (highly intense contacts).

[11] We perform a T test for related samples. In all cases, there are 4 degrees of freedom.

[12] Centralization parameters are calculated using a weighted matrix to capture internal diversity and intensity of relationships.

Table 4

Descriptive statistics of the indicators assessed

Indicators	Min.	Max.	M	SD
Degree	4	93	50.03	26.75
Effective size	5	62	33.41	16.06
Constriction	.87	5.68	2.18	1.1
Betweenness	0	283.60	74.36	71.24
Density	.152 (15.2%)	.300 (30%)	220.8 (22.08%)	36.86

Source: Own elaboration.

There are interesting associations between study variables. Degree of centrality and Betweenness are correlated because the more links an actor maintains the more likely it is that one or more of those links is connected to several subgroups.

Table 5

Correlations between variables included in the analysis

Indicators	1	2	3	4	5
1. Degree	--				
2. Effective size	.91**	--			
3. Constriction	-.81**	-.80**	--		
4. Betweenness	.78**	.77**	-.55**	--	
5. Density	-.36*	-.44*	.55**	-.41*	--

***p<.001; *p<.05*
Source: Own elaboration.

Effective size is negatively related to density and constriction. A high level of density and transitivity may be hindering the emergence of structural holes. Regression analysis coefficients are shown in Table 6.

The first regression model confirms the first hypothesis. The model summary shows how the positions of brokerage and centrality influence effective size, which is the most telltale sign of SSC. This suggests that central and intermediary actors are crucial for developing structural intervention strategies. On the other hand, the intense relationship may reflect that both (a) the number of ties; and (b) the power to connect subgroups are major elements for creating structural holes.

The second regression model is designed to test the effects of density and constriction on effective size. We find that density and the extent to which the links that provide access to information sources are concentrated in a few actors have a negative influence on effective size. This finding is relevant because effective size is the optimal configuration for maximizing the harnessing of links. A highly cohesive network increases the chances of links being transitive and redundant. This type of structure decreases the chance of there being structural holes which could be exploited by different organizations to gain access to new resources. The same applies in the case of constriction. Organizations that concentrate their relationships on a small number of actors increase their dependence on those actors, which may diminish their capacity for action. The positions occupied by each subset of key actors are analyzed through graph visualizations.

Table 6

Summary and coefficients of regression models

Model	Independent variables	Dependent variables Effective size				
		R^2	ΔR^2	DF*	B	F
1	- Degree - Betweenness	.839***	.828***	31	.790***	75.596
2	- Density - Constriction	.701**	.681**	31	-.553**	34.044

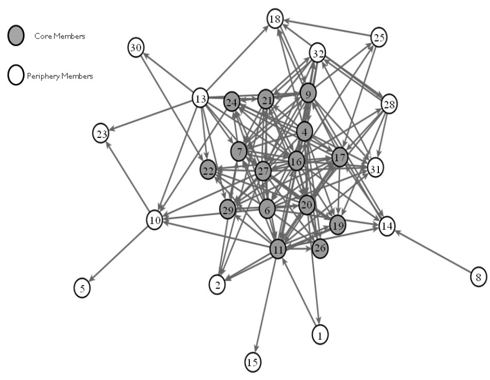
*** p < .001; *** p < .0001; *DF: Degrees of Freedom*
Source: Own elaboration.

Positioning analysis reveals that all four groups share members. This explains why influence processes conducted by disseminators and brokers need to have the support of actors who have established a large number of links with cohesive subsets located in the core. At the same time, it may be positive to involve other actors who maintain weak connections with multiple peripheral subgroups.

Figure 2 illustrates the network of formal contacts between cultural organizations. Black nodes represent central actors and white nodes represent peripheral actors. A categorical core-periphery model (Borgatti and Everett, 1999) is computed to differentiate between the two structures using Ucinet software (Borgatti et al. 2002).

Figure 2

Inter-organizational network of formal contacts distinguishing between core and peripheral actors



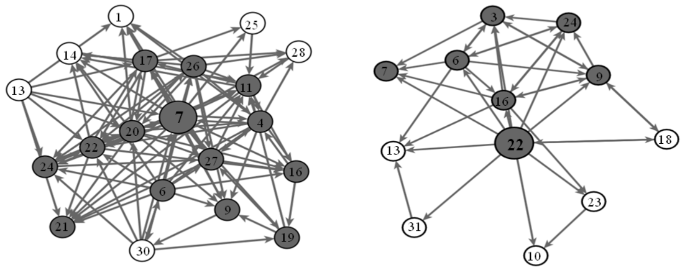
Note: Isolated nodes have been deleted
Source: Own elaboration.

Figure 2 represents how central actors deploy multiples links with other actors situated in the core, and at the same time maintain links with peripheral nodes. To accurately learn what links are established by each subgroup, the relationships of an organization which is representative of each subset of key actors are isolated in Figures 3 and 4. By extracting the relationship of a single organization the ego-centric network structure is represented. Larger nodes represent Ego.

Figure 3

Egocentric networks representing the subgroups of centrals and intermediaries

Figure 3.a	**Figure 3.b**
Egocentric network of organization 7 (subgroup of centrals)	Egocentric network of organization 22 (subgroup of intermediaries)



Source: Own elaboration.

There are obvious differences between the egocentric networks representing each subgroup of key actors. Organization 7 (which belongs to the central subset) maintains several formal contacts with multiple nodes. It is connected to nineteen organizations (thirteen centrals and six peripherals), so its power of influence is greater in the core structure, where there are highly intense links. The situation is different in the case of Organization 22 (subset of intermediaries), which has eleven links, i.e. half as many as Organization 7. Furthermore, relationships are equally distributed between core and peripheral members. This enables Organization 22 to obtain balanced access to organizations belonging to both structures.

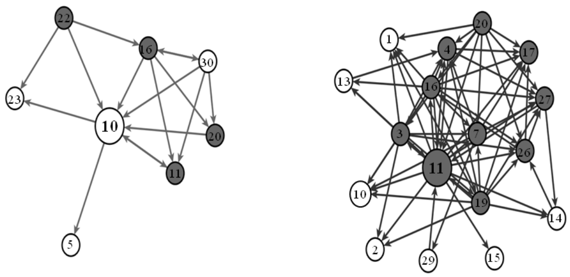
The egocentric network of Organization 10 (subset of disseminators) has a more limited relational environment than the other organizations selected. Altogether it has seven links, four with central organizations and three with peripheral nodes. The distribution of relationships between the two structures is balanced, and there is evidence of a phenomenon characteristic of this type of key actor: their links are concentrated on organizations which in turn have few connections to each other. Organization 10 has relationships with loosely connected nodes, in contrast to the organizations mentioned previously, which have links with actors who in turn maintain multiple connections to each other. Indeed it is the only node that has ties to Organization 5 (a pendant node). Finally, Organization 11 represents the subgroup of brokers. This node maintains sixteen links, nine of them with central organizations and seven with peripheral actors. The zone of influence of Organization 7 spreads across both structures. A distinctive feature of disseminators is their ability to access cohesive subgroups formed by adjacent entities and organizations that have few contacts (such as Organizations 29 and 14). The next section explains our main findings.

Figure 4

Egocentric networks representing the subgroups of disseminators and brokers

Figure 4.a
Egocentric network of organization 10
(subgroup of disseminators)

Figure 4.b
Egocentric network of organization 11
(subgroup of brokers)



Source: Own elaboration.

5. **CONCLUSIONS**

This paper seeks to (a) highlight the impacts of subsets of key actors on network structure; (b) present different procedures for identifying those actors; and (c) show the role of centrality measures in creating SSC. Some elements that help understand the implications of this research should be emphasized: Central actors are able to exert influence on the subset in which they are embedded, but intermediaries, brokers, and disseminators extend their connections between the core and the periphery, and between the groups that make up the network. This finding suggests that degree of centrality is an appropriate measure for learning about the predominant roles of some actors within cohesive subgroups, while intermediaries, brokers, and disseminators are particularly influential when the objective is to assess inter-group relationships.

Central actors have the power to affect the immediate structure, and thus to influence the actors with whom they are directly connected. But networks are formed by different components. Social networks tend to show a core-periphery structure in which the processes and the dynamics of relationships are substantially different. This means that central actors can exert their power over those subgroups which are connected in a direct way, but their influence may be lower in other subsets. The subgroup of disseminators is made up of actors who belong to different network components. They are located in the periphery and to a lesser extent in the core, enabling them to be connected to powerful actors within cohesive subgroups and to peripheral actors. The role of brokers between the core and the periphery gives them access to information that flows between the two areas. The optimal network configuration may be to strike a balance between being immersed in highly cohesive local relationships and linked to multiple groups via weak ties. Empirical evidence on SSC addresses this issue and indicates that at individual level it is positive for there to be structural holes across which new information may flow (Burt 1992). From another perspective, Granovetter (1973) claims that SSC comes when there are low levels of transitivity. Few studies combine the two approaches to explain the generation of SSC at individual and collective levels (Borgatti et al. 1998; Ramos-Vidal 2015c). Both trends show that the influential actors are those capable of efficiently combining the two connectivity strategies.

But being immersed in different subgroups does not always involve competitive advantages. Engaging with different subgroups at the same time often means accepting the rules that shape the behavior of group members. Belonging to multiple components means accepting codes of conduct which may limit the independence and autonomy of actors, constraining their power to promote network interventions (Krackhardt 1999, p. 207). Beyond this view, bridging ties are important to connect several subsets and generate a structure that maximizes business opportunities, contributing to the stratification of the whole system (Watts 1999). This stresses the catalytic effect of micro-social processes in shaping macro-social systems (Burt 2000; Buskens and Van de Rijt 2008).

By using different networks to test our approaches we have been able to identify various groups of actors that are crucial in different types of relationship (Barringer and Harrison 2000). An organization may be highly active in establishing informal contacts and therefore be a key player articulating a particular kind of relationship. Nevertheless, an organization that is key in multiple relationships is more prominent because it can define network structures from different perspectives.

A further element affecting the selection of key actors is the level of activity in establishing contacts. Relationships reflect complex phenomena. Creating links means investing time and resources, often in response to a planned strategy. Highly active nodes in developing informal relationships are actors who are perhaps not able to spend the time required to mature links. Social influence processes require direct and continuous interactions that call for time and resources (Marsden and Friedkin 1993; Hansen et al. 2001). To exert influence on a specific subset, it may be better to select nodes that have only a few links with actors belonging to different subgroups instead of choosing highly connected actors. The fact that they have fewer contacts means that they can invest more in developing trust and may this be able to adopt the role of influencers more effectively.

Distinguishing between the four types of key actors leads us to the issue of whether all social influence processes could be implemented by the same actors. The choice of one subgroup or another depends on the purpose of the intervention (or influence process) to be performed. When the goal is to spread generic announcements or public events as quickly as possible, implicating the subgroup of centrals and intermediaries could be enough. However when the goal is to produce deeper modifications (e.g. to make changes in market strategy or introduce new production methods) there is a need to develop strategies focused on dissuasion through continuous, close interactions. For this second objective it may be more effective to enlist the support of disseminators and brokers, because they have fewer contacts and therefore have more time to develop their influence. The links of these actors are diversified, which gives them access to subunits. When the intervention is hybrid, i.e. when it pursues both large-scale dissemination and behavior changes in certain actors, it may be more suitable to choose different subsets of key actors.

Before designing strategies and selecting actors, it is helpful to have some knowledge of some of the elements related to network dynamics that could affect intervention outcomes. It is necessary to have information related to background and previous collaboration paths. The presence of lobbies or actors with high formal and informal power may require alternative strategies to be developed to trigger structural changes. It is common for lobbyists to lead resistance movements that hamper intervention. To spread an intervention to the rest of the network it is essential to have the support of actors with a positive reputation and actors who have previously led other processes of change (Gulati 1995; Burt 1999; Watts and Dodds 2007; Provan et al. 2009). Early adoption of innovation by key actors could facilitate the success of interventions and their dissemination to other network members (Chesbrough and Crowther 2006).

Analyzing the interaction between centrality measures and the generating of structural holes provides relevant insights for determining the influence of specific types of link in generating SSC. This finding makes it possible to understand from a structural viewpoint why some organizations achieve better results than others. Organizations that build relationships with diverse groups are able to access heterogeneous sources of information which may affect innovations positively (Obstfeld 2005; Uzzi and Spiro 2005). Organizations should carefully select the actors with whom they build alliances and design networking strategies to reach different subgroups. By implementing such strategies it is possible to take advantage simultaneously of the opportunities provided by bonding and bridging ties (Hansen et al. 2001).

The main contributions of this research are as follows: (a) it shows different strategies for identifying key actors; (b) it compares their properties; and (c) it describes the potential advantages of using each type of key actor for implementing different types of structural intervention. Through SNA, organizations are identified that may disseminate information, introduce new methods or promote the adoption of good managerial practices. The procedures set out here could accelerate the processes mentioned above by amplifying intervention effects and optimizing the resources allocated to them. Nevertheless, for structural intervention strategies based on detection key actors to be successful it is vital to gather information about the context in which interactions occur, and about the political and economic factors that determine the configuration of social networks.

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