January 17th 2005

The use of Social Network Analysis in Innovation Research: A literature review

Fabrice Coulon, PhD Candidate[1]
Division of Innovation - LTH
Lund University, Sweden

Table of Contents

Abstract

The purpose of this paper is to review the innovation research literature which has made an explicit use of social network analysis methodology in order to provide empirical support to innovation theories or conceptual frameworks. The review introduces social network analysis then discusses why and how it has been used in innovation research so far. This paper argues that studies using social network analysis tend to focus too much on change in the relationships between interacting units or nodes of the network to the detriment of change within units/nodes. Therefore, a combination of case study and social network analysis can offer a solution to that problem by providing the best of both methodologies.

1 Introduction

Social network analysis (SNA) is an interdisciplinary methodology developed mainly by sociologists and researchers in social psychology in the 1960s and 1970s, further developed in collaboration with mathematics, statistics, and computing that led to a rapid development of formal analyzing techniques which made it an attractive tool for other disciplines like economics, marketing or industrial engineering (Scott, 2000). SNA is based on an assumption of the importance of relationships among interacting units or *nodes*. These relations defined by linkages among units/nodes are a fundamental component of SNA (Scott, 2000).

[1] Fabrice.coulon@innovation.lth.se, Phone: +46 462220248

Borgatti and Foster (2003) have shown that the exponential growth of the literature in social network research is part of a general shift, beginning in the second half of the 20th century, away from individualist, essentialist and atomistic explanations toward more relational, contextual and systemic understandings. This rapid increase of network research in several disciplines, and in innovation research in particular, has created the need for a review and a classification of studies done in this area.

The purpose of this paper is to review the innovation research literature which has made an explicit use of social network analysis methodology in order to provide empirical support to innovation theories or conceptual frameworks. The review introduces social network analysis then discusses why and how it has been used in innovation research so far. This paper argues that studies using network analysis tend to focus too much on change in the relationships between interacting units or nodes of the network to the detriment of change within units/nodes. Therefore, a combination of case study and social network analysis can offer a solution to that problem by providing the best of both methodologies.

The document is structured as followed: section 2 provides a very short introduction to network analysis which describes what it is, where it came from, the terminology used, and defines the concepts of structure and dynamics or evolution, and finally this section ends with the definition of the various measures offered by network analysis and their corresponding advantages and disadvantages. Section 3 presents the methodology used for searching, collecting and selecting the documents read for this literature review. Section 4 is the review itself, followed by Section 5, the conclusion and suggestions for further research.

2 Network analysis

2.1 Terminology

For those not familiar with network analysis, I start by introducing a bit of terminology.

A *network* is a set of *nodes* connected by a set of *ties*. The *nodes* can be anything persons/individuals, teams, organisations, concepts, patents, etc. In the case of social networks the nodes are individuals.[2] Networks which are only made of one type of nodes are *homogeneous*, they are *heterogeneous* otherwise. Whereas *ties* connect pairs of nodes and can be directed (i.e., potentially one-directional, as in giving advice to someone) or undirected (as in being physically proximate) and can be dichotomous (present or absent, as in whether two people are friends or not) or weighted (measured on a scale, as in strength of friendship). It is important to note that as a matter of fact, all ties are weighted or have values, even dichotomous relations have binary values (either the tie exist and is assigned a value of 1 or it doesn't and is assigned a value of 0). However, in this

[2] Traditionally, Social Network Analysis (SNA) has focused on networks of individuals, the literature reviewed here includes studies which make use of measures developed in SNA but applied to networks of firms, other organisations, patents, and even whole sectors in some cases. Basically, the methodology is the same and the measures are the same but they should be called "network analysis" studies instead of SNA.

document we will treat dichotomous ties as unweighted ties. When we focus our attention on a single node, we call that node the *ego* and call the set of nodes that ego has ties with *alters*. When network analysts collect data on ties from a set of nodes, they call it *relational data*. Relational data can be visualised in matrix form or in graphic form.

Table 1, below, summarises this terminology.

Table 1. Important terms and definitions

Network Analysis Terms	***Definitions***
Node	The basic element of a network
Tie / Edge	A set of two nodes. Ties can be dichotomous (unweighted) or weighted/valued, directed or not (undirected)
Directed Tie	An ordered set of two nodes, i.e., with an initial/source and a terminal/destination node
Network	A set of nodes connected by a set of ties
Valued Network	A network whose ties/edges are associated with a measure of magnitude or strength
Ego	A node which receives particular focus
Alters	The set of nodes that has ties with the ego but not including the ego itself
Network Size	The total number of nodes of a network
Relational data	The set of ties of a network

Following this terminology, Table 2 below summarizes the four types of networks that will be considered in this review, depending whether ties are weighted or not, and directed or not.

Table 2. Four network types

Types of networks	***Weighted***	***Unweighted***
Directed	(a) Directed & Weighted ties	(b) Directed & Unweighted ties
Undirected	(c) Undirected & Weighted ties	(d) Undirected & Unweighted ties

Network analysis is very different from other methodologies, in that, several levels/units of analysis are embedded in the network analysis itself. Measures are available at the node-level, the group or local-level and at the network-level. The choice of the appropriate measure depends on what the network analyst wants to show.

2.2 Structure

For social network analysts, there is a sharp distinction between information about the social actors and information concerning the social structures within which these actors are located. Wellman (1988) clearly emphasize this paradigm: “behavior is interpreted in terms of structural constraints on activity rather than in terms of inner forces within [actors].” (Wellman, 1988: 20). For some social network analysts (Doreian, 2001: 83), the “rather than” can be replaced by “in addition to.” Therefore social network analysts have developed two strands of thought in one, they focus only on structure to interpret behaviour, but in the other, they focus on both structure and actor-diversity to interpret behaviour. The nodes of the networks in their studies are often *individuals* or *members of a social group*.

The first strand deals with the relationship between *network structure*, i.e., the observed set of ties linking the members of a population like a firm, a school, or a political organization, and the corresponding *social structure*, according to which individuals can be differentiated by their membership in socially distinct groups or roles. The combination of network structure and social structure is the *social network*. A substantial array of definitions and techniques have been introduced over the years, like *blockmodels* (e.g., DiMaggio, 1986), *hierarchical clustering* (e.g., Lorrain and White, 1977) and *multidimensional scaling* (Bailey, 1976). But in short, they are essentially designed to extract information about socially distinct groups from purely relational data, either in terms of some direct measure of social “distance” between nodes or by grouping nodes in the network.[3] According to this view, networks are the signature of social identity/role – the pattern of relations between individuals reflects the underlying preferences and characteristics of the individuals themselves (Watts, 2003: 48).

The second strand of techniques bears a more mechanistic flavour. In this strand, the network is viewed as a conduit for the propagation of information or the exertion of influence, and an individual’s place or position in the overall pattern of relations determines what information that person has access to or, correspondingly, whom he or she is in a position to influence. A person’s social identity/role therefore depends not only on the groups to which the individual belongs but also on the individual’s position within these groups. Similarly to the first strand, a number of metrics, i.e., measures of social “distance”, have been developed to quantify individuals’ network positions relatively to others and to explain observable differences in individual performance in terms of difference in these metrics (Watts, 2003: 48-49).

An exception to these strands is Granovetter (1973), which introduced the distinction between strong and weak ties, e.g., contractual/formal and informal ties, or friend and acquaintance. Grannoveter shows that effective social coordination does not arise from densely and strongly interconnected networks but from the presence of occasional weak ties between individuals who frequently didn’t know each other that well or have much in common. According to Granovetter’s “strength of weak ties” theory, in order for an individual to get a job, it is not its close friends who are important and who will inform about that job but casual acquaintances who can give access to information that would never have been received otherwise (Scott, 2000: 34-35).

[3] Social “distance” or “proximity” is a metric (a mathematical formula) that allows social network analysts to measure a distance between individuals. This distance can be dependent on the number of nodes or ties that has to be traversed in order to go from one individual (or ego) to another (or alter). The average of all these distances calculated for the whole network gives an estimate of the efficiency of a network.

After this important finding the question that Granovetter put on the research agenda was how to distinguish strong and weak ties. He claimed that by observing the structure (i.e., the social network) in which the individuals are embedded it would be possible to make this distinction. Granovetter's study distinguishes itself from previous works, because Granovetter suggested that in order to define relations at the individual level as strong or weak, it is necessary to observe the group or the whole network (Watts, 2003: 49). So far, not so much work has been done on weak, indirect, ties probably because of their empirical intractability. Most of the studies reviewed here are focused on strong and direct ties.

The critique that has emerged in parallel with these two strands of literature is that they are static descriptions of structure – they do not consider change but apply their techniques to "frozen" networks, in other words, there is no dynamics. Instead of thinking of social networks as entities that evolve under the influence of social forces, network analysts have tended to treat them effectively as the static embodiment of those forces (Watts, 2003: 50). Purely structural and static measures of network structure cannot account for whatever action is taking place in the network – social network analysis offer no systematic way to translate the output of various metrics into meaningful statements about outcomes (Watts, 2003: 51). This is why it is only an analytical tool and not theory (Scott, 2000: 37). Without a corresponding theory of agency or behaviour, i.e., including the dynamics, the metrics remain essentially un-interpretable and of little practical use.

In the rest of this text, when not dealing with individuals but, for example, with organizations, we will talk about "network analysis" and not SNA. However, all measures developed by social network analysts can be adapted to networks of firms or other organizations, since the network nodes can represent anything from humans and organizations to technologies.

2.3 Network Dynamics or Evolution

According to the definition of network structure introduced previously, there are two types of dynamics that can be defined, i.e., first, dynamics *of the network* and second, dynamics *on the network* (Watts, 2003: 54-55).

In the first type, dynamics refer to the evolving or changing structure of the network itself, i.e., the making and breaking of ties. The network structure of network analysts explained previously are snapshots taken during this ongoing process of evolution. However, a dynamic view of networks claims that existing network structure can only be properly understood in terms of the nature of the process that led to it.

In the second type, the individuals (or firms, etc.) represented by the nodes of the network are doing something. They can search for information, learn, spread a rumour, make decisions, etc., the outcome of their actions is influenced by what their neighbours are also doing and therefore, to some extent by the network structure either locally from the nearest neighbours or globally from distant neighbours.

In reality, both dynamics are taking place concurrently. For example, an individual can meet new friends and lose contact with old ones and simultaneously learn or make decisions. If you do not like the behaviour of a friend you can either decide to alter his or her behaviour or choose to spend time with another friend instead, both examples illustrate the two types of dynamics taking place in a personal network of friends.

In the rest of this text, examples and explanations will be given for networks of individuals but similar examples can be found for a network of firms or other organisations since the measures developed by SNA apply to these other networks. However, one must be careful on terminological issues. Two problems emerge when applying SNA to other type of nodes than individuals which are important for describing the change or evolution of any network.

The first problem is that, since firms, or more generally, organisations, are already made of individuals involved in social networks (in the social network analyst sense), is there a need to talk about "network organizations"? One can just call them "networks" and claim that in the 21st century, firms must transform themselves from organizations into networks (Palmer and Richards, 1999), confusing those who think, like social network analysts, already in terms of social networks of individuals. To be terminologically correct, they should be called "network analysis" of organisations.

Another type of confusion appears in innovation research with for example "networks of innovators" (Powell, 2004) and "networks of innovation" (Tuomi, 2002). The former sees innovators as firms or other organisations, therefore talks about *homogeneous* networks in which nodes are organisations and the ties between them are contractual or informal relations. Whereas the latter is about *heterogeneous* networks in which nodes can be programmers or technologies and ties are relationship of use, e.g, a programmer using a text editor. This distinction is important since social network analysts have been mainly interested in homogenous networks, whereas actor-network theorists, e.g., Callon (2001), have particularly been interested in heterogeneous networks. As we will see later in this review, the metrics defined in SNA are not directly applicable to studies of heterogeneous networks (one need to transform them into multiple-mode networks[4]), and often these studies are limited to visualization of the network only.

2.4 Descriptive Measures

This section starts by briefly describing the different measures that have been encountered during the review of the literature. Some or all of these measures are often present in any network analysis and their understanding is fundamental for the comprehension of the empirical work reviewed here. I also include a short discussion of the methodological problems associated with each of these measures. I do not present the mathematical formulas behind them the reader should consult Scott (2000) for further details.

[4] See Scott (2000) for more details about multiple-mode networks

The four most important concepts used in network analysis are network *density*, *centrality*, *betweenness* and *centralization*. Under these concepts are grouped several measures (or mathematical formulas) with various corresponding advantages and disadvantages regarding their use. Additionally, there are four measures of network performance: *robustness*, *efficiency, effectiveness* and *diversity*. Whereas the first set of measures concerns structure, the second set concerns the dynamics and thus depends on a theory explaining why certain agents do certain things (e.g., access to information). Most of the definitions are adapted (so that they use the terminology previously defined) from Scott (2000) and Burt (1992).

Network Density

Intuitively density is a measure of the connectedness in a network. *Density* is defined as the actual number of ties in a network, expressed as a proportion of the maximum possible number of ties. It is a number that varies between 0 and 1.0. When density is close to 1.0, the network is said to be dense, otherwise it is sparse. When dealing with directed ties, the maximum possible number of pairs is used instead. The problem with the measure of density is that it is sensible to the number of network nodes, therefore, it cannot be used for comparisons across networks that vary significantly in size (Scott, 2000: 76).

Centrality: local and global

The concept of centrality encompasses two levels: local and global. Intuitively, a node is central (locally) when it has the higher number of ties with other nodes. *Local centrality* only considers direct ties (the ties directly connected to that node) whereas global centrality also considers indirect ties (which are not directly connected to that node). For example, in a network with a "star" structure, in which, all nodes have ties with one central node, local centrality of the central node is equal to 1.0.

Whereas local centrality measures are expressed in terms of the number of nodes to which a node is connected, *global centrality* is expressed in terms of the *distances* among the various nodes. Two nodes are connected by a *path* if there is a sequence of distinct ties connecting them, and the length of the path is simply the number of ties that make it up (Scott, 2000: 86). The shortest distance between two points on the surface of the earth lies along the geodesic that connects them, and, by analogy, the shortest path between any particular pair of nodes in a network is termed a *geodesic*. A node is globally central if it lies at short distance from many other nodes. Such node is said to be "close" to many of the other nodes in the network, sometimes global centrality is also called *closeness*.

Local and global centrality depends on, among other things, the size of the network, and therefore they cannot be compared when networks differ significantly in size. A *relative* measure of centrality has been developed, to solve this problem, in which, the actual number of ties is related to the maximum number that the node can support.

Betweenness

Betweenness explores further the concept of centrality. Betweenness measures the extent to which a particular node lies “between” the various other nodes in the network: a node with few ties may play an important intermediary role and so be very central to the network. The betweenness of a node measures the extent to which an agent (represented by a node) can play the part of a broker or gatekeeper with a potential for control over others. Burt (1992) has described the same concept in term of “structural holes”. A structural hole exists where two nodes are connected at distance 2 but not at distance 1. Methodologically, betweenness is the most complex of the measures of centrality to calculate and also suffers from the same disadvantages as local and global centrality, however, it is intuitively meaningful.

Centralization

Centralization provides a measure on the extent to which a whole network has a centralized structure. Whereas density describes the general level of connectedness in a network; centralization describes the extent to which this connectedness is organized around particular focal nodes. Centralization and density, therefore, are important complementary measures. The general procedure involved in any measure of network centralization is to look at the differences between centrality scores of the most central node and those of all other nodes. Centralization is them the ratio of the actual sum of differences to the maximum possible sum of differences (Scott, 2000: 90). There are three types of graph centralization – one for each of the 3 centrality measures: local, global and betweenness. All 3 centralization measures vary from 0 to 1.0. A value of 1.0 is achieved on all 3 measures for “star” networks. 0 corresponds to a network in which all the nodes are connected to all other nodes. Between these two extremes lie the majority of the real networks. Methodologically, the choices of one of these 3 centralization measures depend on which specific structural features the researcher wants to illuminate. For example, a local centrality based measure of network centralization seems to be particularly sensitive to the local dominance of nodes, while a betweenness-based measure is rather more sensitive to the chaining of nodes.

Network performance

Once a theory of agency which predicts the two dynamics explained previously is chosen, network’s performance can be evaluated as a combination of (1) its robustness to the removal of ties and/or nodes. (2) Its efficiency in terms of the distance to traverse from one node to another and its non-redundant size. (3) Its effectiveness in terms of information benefits allocated to central nodes and (4) its diversity in terms of the history of each of the nodes.

Robustness

Social network analysts have highlighted the importance of network structure in discussion of network’s *robustness*. The robustness can be evaluated by studying how it becomes fragmented as an increasing fraction of nodes is removed. Robustness is measured by an estimate of the tendency of individuals in networks to form local groups or *clusters* of individuals with whom they share similar characteristics, i.e., *clustering*. E.g., if individuals A, B, and C are all bioinformatics experts and if A knows B and B knows C, then it is highly likely that A knows C. When the measure of the clustering of individuals is high for a given network, the robustness of that network increase – within a cluster/group where everyone knows everybody it is unlikely that a given person will serve as a lynchpin in the network, potentially destroying connectivity within the network by leaving.

Efficiency

Efficient networks are those in which nodes (individuals or firms) can access instantly a large number of different nodes – sources of knowledge, status, etc., through a relatively small number of ties, Burt (1992) call these nodes *non-redundant contacts*. Given two networks of equal size, the one with more non-redundant contacts provides more benefits. There is little gain from a new contact redundant with existing contacts. Time and energy would be better spent cultivating a new contact to un-reached people (Burt, 1992: 20). Social network analysts measure efficiency by the number of non-redundant contacts and the average number of ties an ego has to traverse to reach any alter, this number is referred to as the *average path length*. The shorter the average path length relative to the size of the network and the lower the number of redundant contacts and the more efficient is the network.

Effectiveness

While efficiency targets the reduction of the time and energy spent on redundant contacts by, e.g., decreasing the number of ties with redundant contacts, *effectiveness* targets the cluster of nodes that can be reached through non-redundant contacts. Each cluster of contacts is an independent source of information. According to Burt (1992), one cluster around this non-redundant node, no matter how numerous its members are, is only one source of information, because people connected to one another tend to know about the same things at about the same time. For example, a network is more effective when the information benefit provided by multiple clusters of contacts is broader, providing better assurance that the central node will be informed. Moreover, because non-redundant contacts are only connected through the central node, the central node is assured of being the first to see new opportunities created by needs in one group that could be served by skills in another group (Burt, 1992: 23).

Diversity

While efficiency is about reaching a large number of (non-redundant) nodes, node's diversity, not to be confused with network heterogeneity introduced previously, suggests that it is critical from a performance point of view that those nodes are diverse in nature, i.e., the history of each individual node within the network is important. It is particularly this aspect that can be explored through case studies (Yin, 2003), which is a matter of intense discussion among social network analysts (Doreian, 2001: 83). The starting point of this debate is Wellman (1988), who wrote: "structural methods supplement and supplant individualistic methods" (Wellman 1988: 38). It seems to suggest that social scientists should prefer and use network analysis according to the first strand of thought developed by social network analysts like Wellman instead of actor-attribute-oriented accounts based on the diversity of each the nodes.

3 Methodology

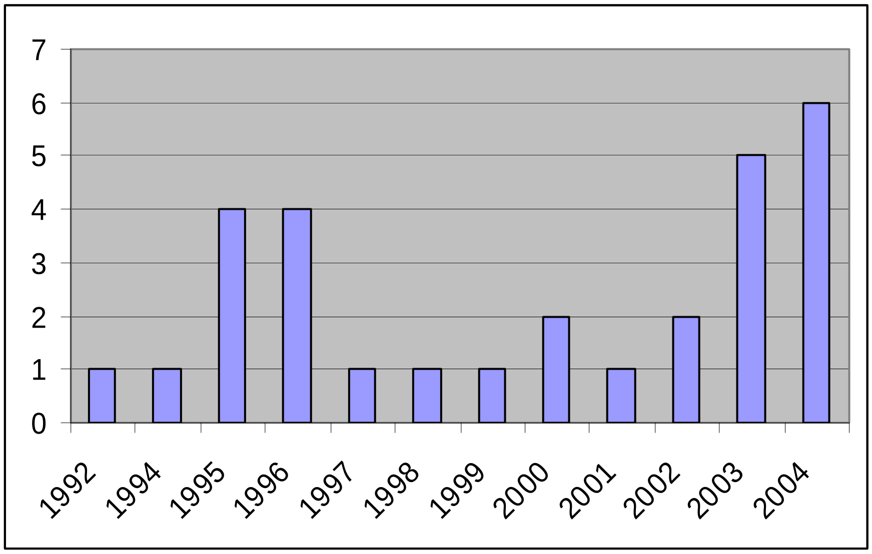
Table 3, located at the end of this document, gives the list of studies that have been reviewed in this document. The selection of the literature is based on two criteria. First, the literature must empirically analyse a phenomenon related to innovation research/studies. Second, it must use network analysis measures or visualization techniques such as those described previously. The literature was classified chronologically according to the date of publication from 1992 to 2004. We do not utilise statistical techniques as a means of analysing the contributions we have identified. Rather we adopt a broadly interpretive approach and simple descriptive statistics. Because a gap in terms of the analysis of the consequences or outcomes of networking was identified in previous literature reviews, we concentrate the review on books, working papers, journal articles or conferences articles on which the emphasis is explicitly on the consequence of networking on innovation (Oliver and Ebers, 1998).

4 Network analysis in innovation research

There has been an impressive accumulation of studies focusing on organizational relations and networks over the last decades (Oliver and Ebers, 1998: 549). At the same time, Oliver and Ebers suggest that this work has not resulted in an accumulation of knowledge nor of conceptual consolidation. By examining several articles from leading journals, the authors have shown that there are three core theoretical approaches: resource dependency (Pfeffer and Salancik, 1978), political power (Zald, 1970) and network approaches (Powell, 1990; Burt, 1992). These studies demonstrate a central paradigm which "has tended to view inter-organizational networking as a response to dependencies among organizations in order to foster their success" (Oliver and Ebers, 1998: 565). Moreover, they have shown that methodological approaches are dominated by cross-sectional, quantitative empirical studies carried out at the organisational level. In addition to that there seem to be a focus on the driving forces behind inter-organizational networking, rather than on the possible consequences or outcomes of networking (such as network performance), and there has been little attention devoted to analysing the detailed structuring of the relationships between organisations (Sobrero and Schrader, 1998).

However, Figure 1, below, shows that since 1999 there seems to be a rapid increase in the number of empirical studies employing network analysis, thus looking at the detailed structuring of the relationships between organisations/individuals and at the impact of network structure on performance, particularly in innovation studies. For example, Owen-Smith, Riccaboni, Pammolli, and Powell (2002) compare the organization and structure of scientific research in the United States and Europe by building networks of R&D cooperation. Breschi and Lissoni (2003) as well as Singh (2003) expand the study of Jaffe, Trajtenberg, and Henderson (1993) and find that social proximity has a stronger relevance for the degree of knowledge spillovers than geographical proximity. Therefore, if the statements made by Oliver and Ebers (1998) or Sobrero and Schrader (1998) were true in 1998 they are certainly not true today, because since 1999, we know more about inter-organizational networking and the possible consequences or outcomes of networking.

Figure 1. Number of network analysis study per year in innovation research



The increasing interest in the use of network analysis can be explained by the availability of standard texts (Wasserman and Faust, 1994; Scott, 2000), the emergence of robust software package needed for the complex calculations involved in the measures previously introduced, such as UCINET[5], and packages for the visualisation of large networks, such as NetDraw[6] or Pajek[7]. Moreover, the diffusion of this methodology to a large audience of researchers in various areas of social science is accelerated through international conferences (the Sunbelt Social Network Conferences) since 1997, sponsored by the International Network for Social Network Analysis (INSNA[8]), which exists since 1978 and has its own electronic Journal of Social Structure since 2000 (JoSS[9]).

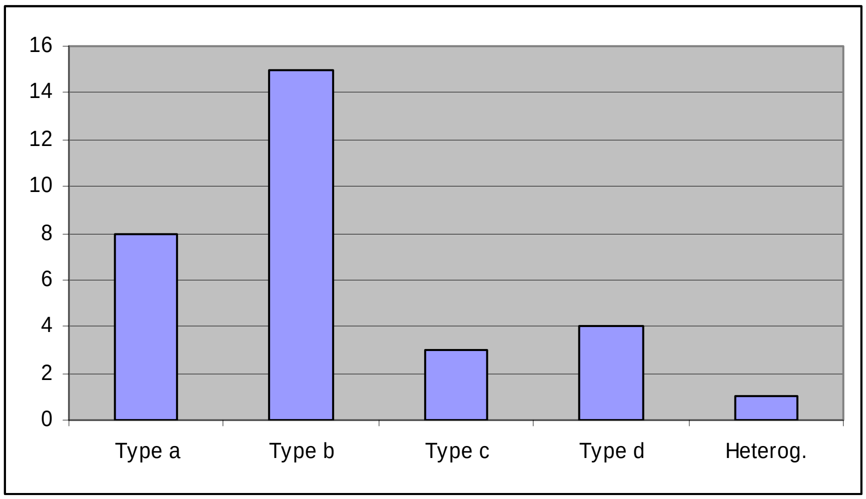
How was the methodology used?

Figure 2, below, shows that in terms of the type of network analysed, there seems to be a large number of type b (directed and unweighted ties) and type a (undirected and unweighted ties), few type c (undirected and weighted ties) and few type d (undirected and unweighted ties). And only one study was about heterogeneous network. This is not

[5] http://www.analytictech.com/ucinet.htm
[6] http://www.analytictech.com/netdraw.htm
[7] http://vlado.fmf.uni-lj.si/pub/networks/pajek/
[8] http://www.insna.org
[9] http://www.cmu.edu/joss/

surprising since measures involving unweighted ties are easier to calculate and it is simpler to encode or visualize dichotomous ties, whereas weighted ties need more complex formulas. Moreover, directed ties are required if one wants to talk about "flows" of something, such as flows of knowledge, it implies that the knowledge in question has a source and a destination and thus has a direction of flow. Also, most of the measures presented previously are not easily applicable to heterogeneous networks, there is only one study of a heterogeneous network and it only uses a visualization tool. In these 29 studies, 2 studies analyse type a, and type b networks.

Figure 2. Type of networks analysed



Additionally, it is not surprising that there are few studies on networks with weighted ties since they not only need more complex formulas but need a process of quantification when quantitative empirical data is not directly available. For example, if one wants to value or weight a knowledge flow, you can grade these flow yourself according to some arbitrary criteria. For instance, if a knowledge flow between two nodes is non-existing you assign a value of 0 to that tie, if it is minor you assign it a value of 1. If it is somewhat larger, such as patent transfers, then you can assign it a value of 2. There are two serious problems with this quantification procedure. First, the used criteria for quantifying or putting a weight on the ties must have a good theoretical underpinning as it is on these criteria that the whole analysis of the relational data relies on. Therefore, there is a higher risk that the conclusions from the study will be erroneous when the criteria are badly chosen. Second, this grading procedure can be extremely time-consuming. If we are talking about 500 nodes (e.g. firms) you need to repeat this quantification process for 250,000 ties. Fortunately, there are other software packages than the one introduced previously (called software parsers) that can help you in this process, especially if the raw data is available electronically like for example electronic mailboxes, newsgroups, newspaper archives, or patents databases.

In terms of the type of nodes of the network that have been analysed, 46% of the networks use organisations or firms as nodes, 30% use patents or scientific articles, 13% use individuals or inventors, and 11% use sectors or markets. Some studies use multiple types of nodes, e.g., inventors, patents and firms. Therefore, the two most studied types of nodes are organisations and publications such as patents and scientific articles. Moreover, regarding the economic sector from which relational data has been collected, biotechnology and semiconductors represents 67% of the studies. This is not surprising since patenting is one of the most common available measures of innovative activity in these two sectors and they are often used in order to measure the flow of knowledge between organisations or firms, within and across sectors, and test theories relative to, for example, the importance of geographical location of the inventors on the diffusion of knowledge.

Concerning the size of the network analysed according to the type of nodes: organisations, and patents since they are the most common types of network nodes encountered. The network size for patent-based studies varies from about 2000 in the early and mid-1990s to 500000 patents in the last five years, this can be explained by the fact that only recent advances in the software packages introduced previously have enabled the treatment of large scale networks, and access to patent databases is much easier than doing interviews. The network size for organisations-based studies not using patent data is much smaller due probably to the time consuming characteristic of collecting the data and varies between about 10 and 250 organisations. This is important to know if one is to use network analysis methodology and want to have an idea of how big the network should be, it is usually a good practice to look at what has been done in previous studies.

These descriptive statistics inform us on how network analysis has been used in innovation research. The main type of networks studied has been networks with directed and dichotomous/unweighted ties. This was explain by the fact that dichotomous ties are easier to deal with and directed ties are needed in order to study any kind of flow taking place between the nodes, e.g., knowledge flows. The main types of network nodes are organisations and patents. This is not surprising since they are the most common units of analysis in innovation research. In terms on how the data was collected, the most studied sectors are biotechnology and semiconductors and the size of the networks are quite different when comparing organisations-based studies with patents-based studies. This was explained by the time consuming characteristic of network analysis when the relational data is not readily available in an electronic form such as patents databases.

Why was this methodology used and for which purpose (useful for what)?

After this short overview of the literature briefly answering the question of how network analysis has been used so far in innovation studies, it is also important to understand why it was used instead of other available methodologies, for example, statistical analysis or case study (Yin, 2003).

The use of (social) network analysis in innovation research has been mainly motivated by the need to explain or simply describe *causal (social) mechanisms* related to innovation. It is not the objective of this paper to discuss what innovation is, according to Schumpeter (1934), *innovation* occurs when: (1) a new product is developed, (2) a new method of production (process) is used, (3) a new market is created, (4) a new source of input is used, and (5) new combinations are created (Schumpeter, 1934). Without discussing all the different possible definitions of causal mechanisms, let us define a causal mechanism as the process by which a cause brings about an effect. A *mechanism* is a theory or an explanation, and what it explains is how one event causes another (Kosowski, 1996: 6). Thus, a causal mechanisms related to innovation is the study of the process by which “social proximity” has an effect on “knowledge spillovers” or, another example, the process by which “network structure” shape or affect “innovative output.” What is meant by the words between quotes depends on the theory chosen to formulate the research question relative to the causal mechanism under study.

In many of the studies reviewed here, the causal mechanisms are the process by which interaction(s) or relation(s) between agents, products, or pieces of knowledge (patents, individuals, firms, organisations, or sectors) causes another event such as the creation of something new, e.g., new knowledge, new organisations, new sectors, and new combinations. From this point of view, statistical analysis cannot help for studying these interactions or relations between agents because it is an analysis based on the inputs and outputs of the causal mechanism under study but not the causal mechanism itself – statistics tend to consider the causal mechanism under study as a *black box*. A black box according to Elster (1983) is the antonym of a mechanism, an emphasis on mechanisms takes us inside the black box and helps explain the phenomena (and not variables or, rather, covariances of variables) (Doreian, 2001: 98). Arguing against statistics and statistical causality, Freedman (1997) wrote, “I see no cases in which regression equations, let alone the more complex methods, have succeeded as engines for discovering causal relations.” (Freedman, 1997: 114)

However, most of the studies reviewed here, construct measures of centrality, betweenness, status, etc., from network data for use as variables to help characterize actors. These studies go into statements such as “the greater the centrality of an actor, the greater (or lesser)…”, and use statistical analysis to test their statements. All of the reasons that have been cited previously for not being able to determine statistical causality (of the causal mechanisms under study) unambiguously extend to the use of variables constructed from network data (Doreian, 2001: 101). Thus, we encounter again the problem of using aggregates to refer to individual behaviour and the debate related to the first strand of network analysts – that structure and inner forces within actors or node-diversity should be considered together.

Among this literature, few studies have made use of case studies for exploring node-diversity in addition to network analytical constructs. With the exception of Cambrosio et al. (2004), in which, the authors map collaborative work and innovation in biomedicine. In short, they claim that the study of collaborative networks, such as techno-scientific networks, with traditional quantitative or qualitative methodologies, cannot adequately capture their degree of complexity. They introduce a network visualization tool designed to analyse heterogeneous networks, which considers research laboratories and molecules in the same network. They show how network visualization can be successfully blended with and used as an input for more traditional ethnographic research which, in turn, can be recursively used to interpret network patterns. The use of network analytical constructs without making statements about causal mechanisms avoid the pitfall described previously. Those combined with case studies provide a socio-historical context and an understanding of why, e.g., research laboratories in the US and France are different.

5 Conclusion

In this document I have tried to answer three questions about (social) network analysis: What it is? How it has been used in innovation research? For which purpose? Social network analysis is a methodology not a theory and to some extend it is close to statistical analysis (descriptive statistics) when one looks at the set of aggregated measures developed from data collected at the node-level. These measures enable the researcher to uncover some properties for the whole network such as, density and centralization.

The main type of networks studied has been networks with directed and dichotomous/unweighted ties. This was explain by the fact that dichotomous ties are easier to deal with and directed ties are needed in order to study any kind of flow taking place between the nodes, e.g., knowledge flows. The main types of network nodes are organisations and patents. In terms of how the data was collected, the most studied sectors are biotechnology and semiconductors and the size of the networks studied are larger in patents-based studies than in organisations-based studies.

Network analysis was used to explore causal mechanisms related to innovation research. When case studies alone are not able to capture the degree of complexity of the causal mechanisms under investigation because of the large number and diversity of the actors involved, as it is the case for the study of innovation in biotechnology or semiconductors, it is preferable to use a combination of case study and network analysis. It is possible that in the narrative giving a deep socio-historical understanding of the inner forces within the actors or nodes under study the researcher misses some important relations/ties between actors. In combination with network analysis and other sources of data, it is possible that these ties could be detected much more easily, especially in large-scale network.

Additionally, regarding causal mechanisms, since network analysis suffers from the same problem as statistical analysis such as the impossibility to use aggregates to refer to individual behaviour. Network analysis should be used to describe networks and attempt to link these descriptions to network outcomes but not to outcomes for specific actors located in networks (Doreian, 2001: 110). Only case studies of some of the actors (depending on geographical, time and budget constraints) will enable the researcher to make the bridge between the network level explanations to the node level explanations of causal mechanisms.

Table 3. List of network analysis studies reviewed in this document

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Burt (1992)	Social capital and the strength of weak ties theory (Granovetter, 1973)	* Provides a definition of structural holes. Entrepreneurs bridging structural holes have economic benefits even if the bridge is weak	* Product markets * Dollar flows between product markets	* (a) Directed and weighted ties	* Data on American markets from the US Dept. of Commerce (1963-77) * 77 product markets
Shan, Walker & Kogut (1994)	Embeddedness as structural equivalence (Kogut, Shan & Walker, 1992)	* Provides support to the hypothesis that number of cooperative relations has a positive effect on innovative output * Provides contradictory support to the hypothesis that innovative output explains the number of cooperative relations	* Firms * Cooperative agreements between firms * Innovative output in terms of patents	* (b) Directed and unweighted ties	* Data on 114 US Biotechnology start-ups (1980-88)
Podolny & Stuart (1995)	Technological niche as a role or relationally defined position (White 1981; Burt 1992; Podolny 1993)	* Provides a systematic understanding of competition among individual inventions * Provides a measure of status based on previous contributions to the advancement of knowledge	* Focal innovation * Patents * Patent citations * Patent citation rate	* (b) Directed and unweighted ties	* All US patents in the Semiconductor industry (1976-91). 4048 patents.
Lundgren (1995) **(book)**	Industrial networks and technological systems (Håkansson, 1987)	* Provides a deeper understanding of how industrial networks emerge and evolve through three phases: genesis, coalescence and dissemination	* Organisations pursuing R&D in image processing in Sweden * R&D collaborations	* (b) Directed and unweighted ties	* Digital image processing in Sweden (1975;1983;1989), 82 actors.

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Kogut, Walker & Kim (1995)	Network externalities (Farell & Shapiro, 1988)	* Provides support for the influence of network structure and suggest a new perspective on start-ups entry induced by the rivalry of incumbents for technological dominance	* Start-up semiconductors companies * Strategic alliances	* (b) Directed and unweighted ties * Ties are differentiated according to types: R&D agreements, marketing, etc.	* Semiconductor industry (1977-89) * 205 firms * Data on inter-firm agreements
Valente (1995)	Diffusion of innovations (Rogers, 1983)	* Provides a deeper understanding of the process of adoption of innovations under four network characteristics: structural equivalence, cohesion, threshold and critical mass	* Network * Relations between individuals * Time of adoption	* (b) Directed and unweighted ties	* Medical innovation 125 respondents * Family planning 1047 respondents * Farmers 692 respondents
Podolny, Stuart & Hannan (1996)	Organization-specific niche in a technological network (Podolny and Stuart, 1995)	* Provides an additional dimension for a niche: crowding in terms of niche overlap between two organisations * Organisations occupy niches in multiple domains	* Firms * Patents * Patent citations	* (a) Directed and weighted ties * and (b) Directed and unweighted ties	* Semiconductor industry (1985-91) * 113 firms in US, EU & JP * 19000 patents * 60000 citations
Stuart & Podolny (1996)	Evolutionary economics (Nelson & Winter, 1982)	* Provides a systematic definition of local search in technological landscape and the trajectories of firms within it	* Firms * Patents * Patent citations	* (a) Directed and weighted ties	Japanese semiconductor industry (1982-92) * 10 firms in JP. 2400 patents

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Powell, Koput & Smith-Doerr (1996)	Networks of Learning (Powell & Brantley, 1992; Brown & Duguid, 1991)	* Provides empirical support to the concept of network as the locus of innovation in industries where the knowledge is complex, dispersed and changing rapidly	* Network of firms * Firms	* (a) Directed and weighted ties	* 225 biotechnology firms * Data on strategic alliances 1990-94
Leoncini, Maggioni & Montresor (1996)	Technological system (Antonelli and De Liso, 1993)	* Compares two technological systems: Italy and Germany	* Sectors * Products * R&D investments	* (a) Directed and weighted ties	* 13 sectors * Inter-sectoral innovation flow matrix based on products and R&D investments
Walker, Kogut & Shan (1997)	Social capital (Bourdieu, 1980; Coleman, 1990) and Structural Holes (Burt, 1992)	* Provides support to social capital for explaining the formation of network among biotechnology firms. Social capital reproduces the network over time	* Network of firms * New relations by startups	* (b) Directed and unweighted ties	* 114 biotech startups * Proprietary database 1988-89
Stuart (1998)	Sociology of markets (White, 1981; Burt, 1992; Podolny, 1993)	* Demonstrates that the location of firms along dimensions of a market's structure affects the firm's propensity to enter strategic alliances	* Firms * Dyadic relationships * Patents * Patent citations	* (b) Directed and unweighted ties	* Alliance database (1986-92) in the semiconductor industry * 150 firms. 50000 patents

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Park & Kim (1999)	Patterns of inter-sectoral knowledge flows (Pavitt, 1984)	* Provides an inductive taxonomy of industries based on user-supplier relations in terms of knowledge diffusion	* Sectors * Disembodied Knowledge in number of researchers * Embodied knowledge in number of goods	* (b) Directed and unweighted ties	* 34 Manufacturing sectors in Korea during 1984-90
Ahuja (2000)	Structural holes and social capital (Burt, 1992; Coleman, 1988)	* Provides empirical support to Coleman (1988). Increasing structural holes decrease innovative output but this is not universally true	* Firms * Yearly patenting rate * Collaborative agreements	* (a) Directed and weighted ties	* Chemicals industry in EU, US, JP (1981-91) * 97 firms * 268 joint ventures * 152 tech agreements
Leoncini & Montresor (2000)	Technological systems (Carlsson and Stankiewicz, 1991)	* Compares 8 technological systems in 8 OECD countries. Structure affects cluster emergence and technological system convergence	* Sectors * Inter-sectoral innovation flows	* (a) Directed and unweighted ties	* Data on 15 sectors in 8 OECD countries during 1980-90
Owen-Smith et al (2001)	Collaborative capacity (Koput and Powell, 2001)	* Compares linkages between research universities, public research institutes and the private sector in life sciences. Early-stage research collaborations explain national differences	* National * Cross-National R&D agreements * Organizations	* (c) Undirected and weighted ties	* Upstream life science research in US and EU during 1988-99. 1026 linkages. 482 firms. 89 universities. 8031 patents.

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Johnson and Mareva (2002)	Inter-firm knowledge transfers or spillovers (Feldman, 1999)	* Examines knowledge flows in biotechnology. Shows that inter-firm knowledge transfers decrease with distance but with a diminishing effect over time	* Patent citations * Geographical location of patents (by states)	* (b) Directed and unweighted ties	* US Patents in biotechnology during 1975-94 divided into 4 periods. 51095 patents.
Valentin & Jensen (2002)	Technological Systems (Carlsson and Stankiewicz, 1991)	* Shows that system with best performance in the emergence of science-based technologies are those combining internal and external connections	* Patents * Inventors * Organisations * System	* (c) Undirected and weighted ties	* Patents in Food biotechnology during 1976-2000. 128 patents. 275 inventors. 87 organisations.
Assimapkopoulos et al (2003)	Critical mass in the diffusion of innovation (Rogers, 1983; Valente, 1995)	* Demonstrates how a new democratic community culture was diffused through successive generations of spin-offs * Provides an objective way for visualising networks	* Firms' founder	* (d) Undirected and unweighted ties	* US Semiconductor firms in six periods during 1960-86 from genealogy charts. 102 firms.
Breschi & Lissoni (2003)	Localised knowledge spillovers (Jaffe, Trajtenberg and Hendersson, 1993)	* Localisation effects tend to vanish where citing and cited patents are not linked to each other by any network relationship	* Patents * Patent citations * Geographical location of inventors	* (b) Directed and unweighted ties	* 3 periods of patent applications 1987; 1988; 1989. 2200 patents by Italian firms

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Paci & Batteta (2003)	Localised knowledge spillovers (Jaffe, Trajtenberg and Hendersson, 1993)	* Examine the technological networks represented by the flows of patent citations in 3 sectors. Drug and computer industries depend from other sectors while for shoe, intra industry citations are prevalent	* Patents * Patent citations * Geographical location of inventors	* (b) Directed and unweighted ties	* US patents granted to European firms during 1963-99. 350000 patents, 2 million citations. 3 sectors: shoes, drugs and computers
Singh (2003)	Diffusion of information through social links (Granovetter, 1973; Burt, 1992)	* Examines whether social networks of inventors are a significant mechanism for diffusion of knowledge. Considers indirect ties.	* Inventors * Patents * Patent citations	* (b) Directed and unweighted ties	* US patents from 1975-95. 3000 firms in manufacturing sectors. 500000 patents.
Spencer (2003)	Knowledge-diffusion networks (Jaffe, Trajtenberg and Hendersson, 1993)	* Structural features of networks contribute to the emergence of dominant designs and national competitiveness	* Scientific articles * Article citations * Firm-level aggregation	* (a) Directed and weighted ties * and (b) Directed and unweighted ties	* Global flat panel display industry. Citations from 3448 Scientific journal articles in US, Japan and Europe.
Breschi & Cusmano (2004)	Network "theories" (Watts and Strogatz, 1998; Barabasi et al. 1999)	* Describes structural properties and dynamics of the emerging network stemming from the R&D consortia promoted under the 3rd and 4th Framework Programmes	* R&D joint ventures	* (d) Undirected and unweighted ties	* R&D joint ventures (RJVs) funded by the EC during 1992-96. 3874 projects and 9816 organisations

Author(s)	Theory	Theoretical Contribution(s)	Unit(s) of analysis	Type of network	Dataset
Cambrosio et al (2004)	Actor-Network theory (Callon, 2001)	* Describes the hybrid, heterogeneous nature of collaborative networks in the biomedical field without reducing the data to a few indicators	* Research organisations * Cluster designations: groups of antibodies (molecules)	* Heterogeneous networks combining research labs and molecules in the same network	* Six biomedical workshops, 6000 antibodies (molecules) during 1982-96
Cantner & Graf (2004)	Local Innovation Systems (Allen, 1983)	* Describes the evolution of the innovator network of Jena. Innovators on the periphery of the network exit and new entrants position themselves closer to the core of the network	* R&D cooperative agreements * Patents	* (c) Undirected and weighted ties	* Patent data from Jena during 1995- 2001. 1181 patents.
Giulliani & Bell (2004)	Absorptive capacity (Cohen & Levinthal, 1990)	* Examines the influence of individual firms' absorptive capacities on intra- and extra-cluster knowledge system	* Firms	* (b) Directed and unweighted ties	* Chilean wine cluster of wine producers, 32 firms.
Muller and Penin (2004)	Open knowledge disclosure (Hicks, 1995)	* Provides a theoretical framework describing the emergence and dynamics of innovation networks. Firm's open knowledge disclosure affects its propensity to form R&D collaborations	* Firms (high disclosing and low disclosing)	* (d) Undirected and unweighted ties	* Data is generated through computer (numerical) simulations based on a parametrical mathematical model

Author(s)	**Theory**	**Theoretical Contribution(s)**	**Unit(s) of analysis**	**Type of network**	**Dataset**
Ouimet et al (2004)	* Structural holes (Burt, 1992) and strength of weak ties (Granovetter, 1973)	* Explores the relation between the network positions of firms within an industrial cluster and radical innovation	* Organisations: firms, research institutes, universities, government organisations, financial institutions, local development organisations	* (d) Undirected and unweighted ties	* Quebec optics and photonics cluster with 58 organisations.

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