Knowledge diffusion and complex networks: a model of high-tech geographical industrial clusters

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Abstract

Knowledge diffusion takes place over network structures and is also a mechanism of network creation. The use of network analysis techniques and of the ideas coming from recent developments of the theory of complex networks may be of utility to study knowledge diffusion processes among organizational populations. In this work, the network approach is used to analyze the results obtained by an agent-based model used to simulate two cases of high-tech geographical industrial clusters: Silicon Valley and Boston's Route 128. The results obtained point to interesting ideas for the improvement of the simulation model and for possible empirical research.

Keywords: Knowledge management, social networks, complexity, agent-based modeling

Suggested track: F - Communities of practice, knowledge networks and networking

1. Introduction

The diffusion of knowledge is a fundamental aspect of the economic activity. Innovation requires that knowledge is diffused in the economic system between organizations (Zander and Kogut, 1995; Appleyard, 2002). This fact was already noticed by Alfred Marshall when he identified the facility in sharing knowledge between firms as one of the fundamental reasons for the spatial agglomeration of industries (Marshall, 1920).

Processes of knowledge diffusion involve interactions between agents in the form of knowledge assets transfer. Those interactions are mediated by physical distances, but also by social, cultural and political gaps. The use of the idea of networks as the turf on which interactions happen may be very useful. But knowledge diffusion is also a mechanism of network building. Studying the structure of the networks formed may be a way to know more in depth the knowledge transfer processes.

Social systems where knowledge diffusion takes place are complex social systems. One methodology for the study of this kind of systems is agent-based simulation modeling. Using complex networks analysis tools to explore the ideas mentioned above may be a powerful complement for this technique. A modest first step in this direction will be the aim of this work.

The results of an agent-based model of a population of knowledge-intensive industries used to simulate two cases of high-tech geographical industrial clusters will be analyzed in terms of the knowledge networks formed after knowledge transfer. Social network analysis techniques and recent ideas coming from the study of complex networks will be applied to this endeavor.

Which kind of networks are formed? Which are their main features? Do they follow a general law? Which are the main differences between the two cases modeled? Does the simulation model represent the real world well enough? These are the kind of questions addressed.

The paper begins with a short introduction of the issues to be studied and their implications. After that, the general problematic of knowledge diffusion is presented. It follows a brief review of the state of the art of the study of social networks and the main developments in the complex networks field, and its application to organization sciences and specifically to knowledge diffusion. Then, after a brief presentation of the simulation model used, the results obtained on the networks of knowledge diffusion are presented. The discussion of the results leads to the final conclusions.

Specific social network analysis calculations are made with the software Ucinet (Borgatti et al., 2002) and the program Pajek (Batagelj and Mrvar, 1996) has been used for the graphical representation of networks.

2. Diffusion of knowledge

Several mechanisms can contribute to the diffusion of knowledge between organizations. A convenient distinction may be made between those knowledge transfer processes embedded in the normal activity of firms as a mean to fulfill its objectives, and those which are facilitated by the unavoidable social interaction of their members, but do not respond to any business goal—and sometimes are even in conflict with them.

The first kind of processes usually take place in a formal way through the use of documents and databases or through interaction in face-to-face meetings or by using technological means as e-mail or videoconference. In this case, it may be considered that knowledge assets are traded as one part of the regular transactions between organizations. Knowledge diffusion is, therefore, intended by the organization.

The second kind of knowledge diffusion processes are not formalized and do not involve commercial transaction between organizations. These processes often take advantage of the social relationships of individual employees of the firms, be it of a professional type through communities—or networks—of practice or more of a personal nature (Wenger, 1998; Brown and Duguid, 2000; Amin and Cohendet, 2004). From an organizational point of view, this is seen as unintended diffusion of knowledge assets and economists place it under the category of knowledge spillovers.

Any attempt at modeling the diffusion of knowledge among a group of organizations should take into account both kinds of mechanisms. It would be as dangerous to rely only on intended knowledge diffusion mechanisms, leaving aside knowledge spillovers, as seeing the process only as a consequence of unintended spreading of knowledge among the members of different organizations. Knowledge diffusion is not, in that sense, equivalent to other diffusion processes modeled in natural sciences as epidemics or in social sciences like the spread of rumors.

In any of the two kinds of mechanisms pointed out, several factors influence the facility in the transfer of knowledge and, therefore, contribute to the probability of the success of the knowledge transfer. On the one hand, there is a group of factors which relate to the nature of the knowledge that is being transferred. Structured—codified and abstract—knowledge is much easier to transfer than its more unstructured—uncodified and concrete—counterpart (Boisot, 2002). On the other hand, there is another group of factors not related to knowledge itself that also influence knowledge transfer. To be successful, any communication process must overcome a series of barriers of many sorts, i.e., physical, technological, legal, cultural, linguistic. Knowledge diffusion will only be possible getting over these barriers. I will term the first kind *intrinsic* factors and the second kind *extrinsic* factors.

Intrinsic factors may be affected by the knowledge management strategies adopted by firms in terms of working with a higher or lower degree of structuring—codification and abstraction—in the knowledge they use. Extrinsic factors may equally depend on some knowledge management strategic options when barriers to diffusion are placed—or removed—on purpose as a consequence of strategic decisions. Some other strategic decisions of the organization—i.e., deciding locations—may directly influence extrinsic factors, but the influence of strategies will be more difficult to predict due to the complexity of the systems, and in some cases strategic moves will have no influence at all. For extrinsic factors a lot of influence will come also from the cultural values and practices of the organizations—i.e., in the sharing of knowledge—, and also on the characteristics of the environment as, for instance, the degree of development of information and communication technologies (ICTs).

All the factors above contribute to the generation of knowledge transfer patterns among firms and institutions. The aim of this work is double. Firstly, finding a model that, taking into account the factors described above, is able to reproduce some of those knowledge transfer patterns. And, secondly, proposing a way to analyze the mentioned patterns.

Assuming that economic systems are instances of complex adaptive systems (Arthur et al., 1997), the structure of those patterns cannot be directly deduced from the low-level rules applied by each organization and their individual behavior. Therefore, we will make use of a simulation model that makes it possible that some of those patterns appear. But, before presenting that model, let us see how network analysis may be a way to progress in the second goal of the paper.

3. Networks and knowledge diffusion

Knowledge diffusion processes have as a consequence that a very large number of knowledge assets may be shared by a different number of members of an organizational population. A detailed description of the final situation might be—apart from a titanic endeavor—too complex to be useful. Is it possible to find a way to get a general picture? The use of the concept of networks in social systems and the recent advances in the knowledge about the structure of complex networks may open a path to advance in that direction. Indeed, we can think of a population of organizations as the nodes of a network. Two nodes will be linked when they share one or more knowledge assets. The application of network analysis techniques to this network will make it possible a comprehensible analysis of the situation resulting from knowledge diffusion processes.

Social network analysis developed mainly in the second half of the 20th century putting together three different research strands in sociology: sociometric analysis, the study of interpersonal relationships and the formation of “cliques” and the study of the structure of “community” relations in tribal and village societies (Scott, 1991: 7). The initial works of Harvard sociologists in the 1960s and 70s gave rise to the relevant studies of different researchers as Granovetter (1973; 1985) or Blau (Blau, 1977), which contributed to the development of a corpus of social network analysis (Scott, 1991; Wasserman and Faust, 1994). In the last decades, the increasing use of computing tools has signified a thrust in this kind of research.

Lately, social network analysis has received the strong influence of another line of research devoted to the study of general networks. Based on early works on graph theory (Erdös and Rényi, 1959), complexity scientists have shed light on the different possible topological structures of networks—such as the so-called small worlds (Watts, 1999) and the scale-free networks (Barabási, 2002)—and on its dynamics (Dorogovtsev and Mendes, 2003). The general study of complex networks has direct application to social networks, although they seem to present characteristics that distinguish them from other types of networks (Newman and Park, 2003).

The use of the concept of social network is increasing in organization science (Thompson, 2003). The relationship between knowledge or information diffusion and network structure have been studied in organization theory and management (Hansen, 2002; Reagans and McEvily, 2003; Borgatti and Foster, 2003) and also in the complex networks field (Watts and Strogatz, 1998). However, specially in the latter the most common approaches have considered only one part of the picture. The application of traditional diffusion models—similar to those used in classical problems such as disease diffusion in epidemic—has had as a consequence that often only unintended, informal diffusion of knowledge has been taken into account. But, as we stated above, an important part of knowledge diffusion corresponds to intended knowledge transfer through transactions.

Another characteristic of the bulk of research about knowledge or information diffusion through complex social networks is that often the structure of networks is taken as a given and not as a consequence of the knowledge transfer processes. This point of view is adequate in order to understand diffusion mechanisms when networks are already in place. But knowledge transfer is in itself a powerful way of building links between organizations. Networks are formed and evolve through knowledge diffusion processes.

The work proposed here introduces a simulation model that incorporates the two stated elements—i.e., considering at the same time unintended and intended diffusion of knowledge and looking at network formation through this process. With the help of agent-based simulation techniques, different knowledge networks are obtained for different ideal cases of organizational populations. Concretely, it allows to compare the types of networks formed in the ideal cases representing two high-tech geographic industrial clusters: Silicon Valley and Boston's Route 128.

4. A model of high-tech geographic industrial clusters

The cases of the two high-tech geographical industrial districts are modeled taking advantage of an agent-based simulation model presented in previous works (Canals et al., 2004a). In this model, agents represent a population of organizations which have the capacity of holding knowledge assets. Agents may have different knowledge management strategies. Underpinning the model is the consideration of populations of economic agents as complex adaptive systems. The model incorporates as assumptions the theoretical tenets of the I-Space framework (Boisot, 1995; 1998) relative to the creation and diffusion of knowledge.

Knowledge assets in the model may be created within the organizations through investment of funds and may be transferred between agents. Two different processes exist that have as a consequence the transfer of knowledge assets: unintended knowledge diffusion and intended trade of knowledge assets. The model features also a knowledge creation process in which agents may create new knowledge. Both kinds of processes are paid for with the funds acquired by agents from the exploitation of their knowledge assets.

The model has been applied to two paradigmatic examples of high-tech geographical industrial clusters such as Silicon Valley and Boston's Route 128 (Canals et al., 2004b). The initial parameter settings of the two cases are based in observations of some physical and cultural characteristics in the real systems (Saxenian, 1994; Castells and Hall, 1994). Those features may be summarized as follows:

1. A larger number of firms are located in Silicon Valley than in Route 128.
2. Along Route 128, firms tend to be larger than in Silicon Valley, and to each use a greater number of technologies.
3. Interaction between firms, of both the informal and the formal kind, is much more frequent in Silicon Valley than along Boston's Route 128.
4. The Silicon Valley culture is more prone to collaboration.

A relevant characteristic of the model is that it is possible to model, for each case, different scenarios corresponding to different ICT regimes, that is, different degrees of development of information and communication technologies represented by different bandwidths.

Agents in the simulation may present different preferences in terms of two knowledge management strategic options. Some of them may show a preference for working with highly structured knowledge assets while the others prefer to work with less structured knowledge. Also, they may adopt a strategy aimed at blocking diffusion of knowledge in order to extract as much value as possible from it or they may prefer to permit diffusion in order to engage in a process of creative destruction that benefits the whole population of agents included them. At the beginning of the simulation, these strategies are equally distributed

Agents are assigned a location in a flat two-dimensional representation of the physical space (see Figure 1) . Introducing a dependence on physical distance of the probability of interaction between two agents it is possible to incorporate the spatial dimension into the simulation.

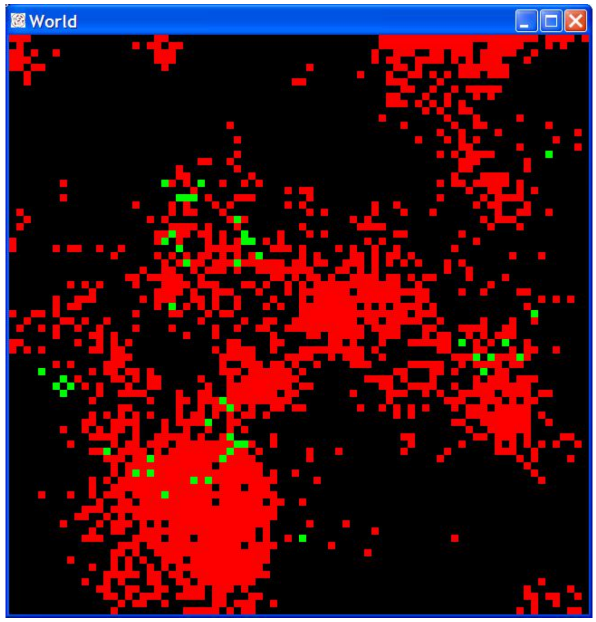


Figure 1 Image of the simulation graphic representation

During the run of the simulation neither knowledge management strategic options nor physical location do change for a given agent and they are in some way “inherited” by new agents formed as subsidiaries, joint ventures or mergers of previous ones. Strategic options are inherited through a mechanism similar to genetic algorithms and location by making more probable for the new agents to be located in the neighborhood of “parent” agents. This makes it possible an evolutionary process where physical locations and knowledge management strategies coevolve in the organizational population while new agents are created and old agents die or leave the simulation. As a consequence, for different cases modeled the final picture of the simulation may be quite different. Figure 2 and Figure 3 show respectively the final spatial distribution of agents and knowledge assets of a selected run of the simulation for each of the two cases modeled and for three different ICT regimes. The analysis of the results obtained with the model has proved its validity to reproduce general patterns observed in the real world. These results and their interpretation are described in a previous work (Canals et al., 2004b).

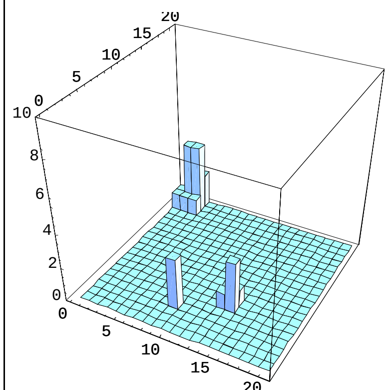
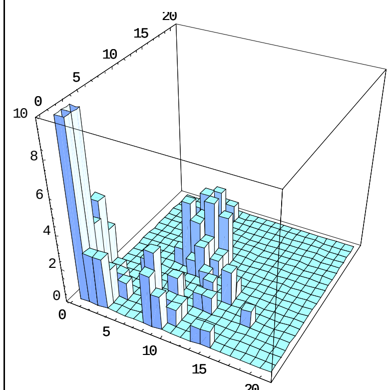
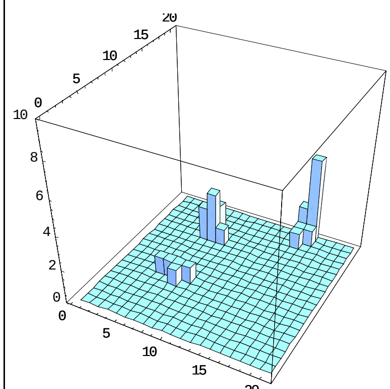
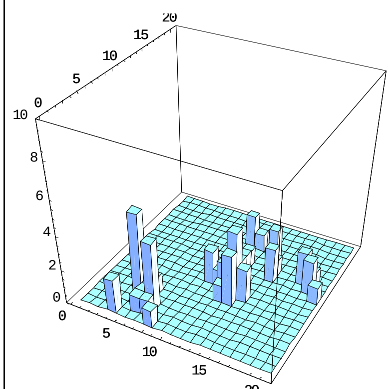
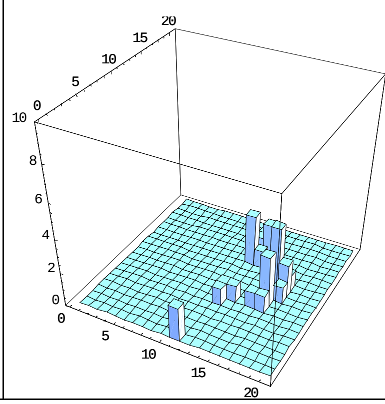
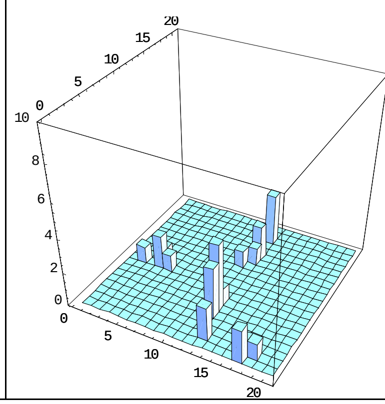
Band-width	Case R128	Case SV
Narrow		
Medium		
Broad		

Figure 2 Spatial distribution of the number of agents

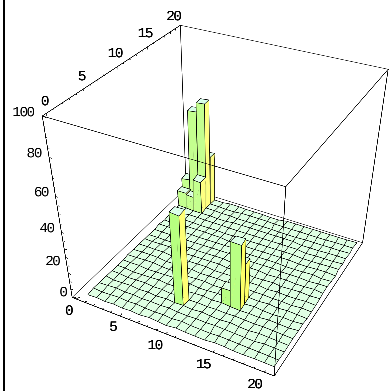
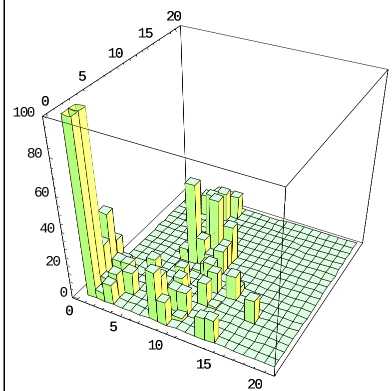
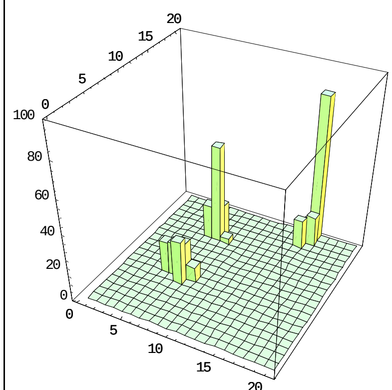
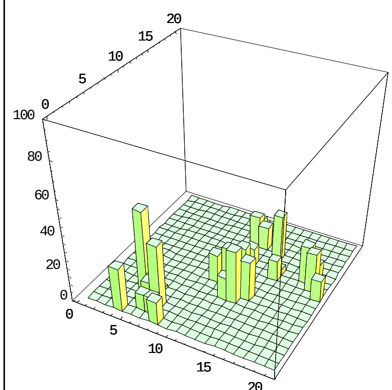
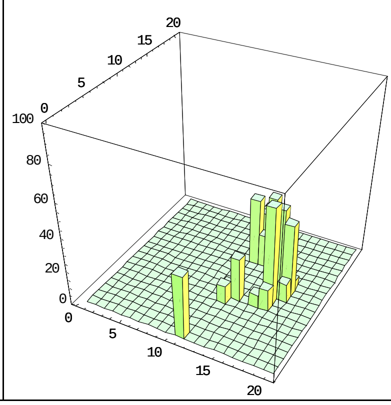
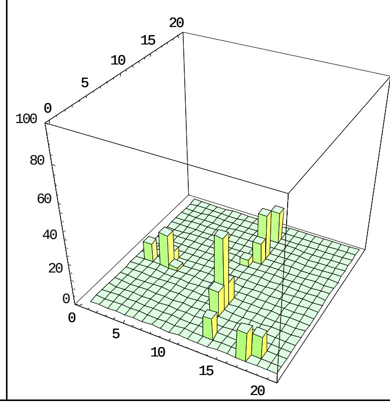
Band-width	Case R128	Case SV
Narrow		
Medium		
Broad		

Figure 3 Spatial distribution of the number of knowledge assets

However, although interesting patterns have been obtained, the internal mechanisms which give rise to those patterns need to be understood. This presents some difficulties due to the great number of agents and knowledge assets present along the runs of the simulation and their complicated interaction dynamics. It is not possible—and probably useless—to analyze the individual trajectory of each agent and asset, but still it is necessary to distinguish the differences in behavior among the different cases modeled, specially in terms of interaction. Network analysis provides a whole set of tools which will be of help for this purpose.

The networks that will be analyzed here are formed by agents which will be considered linked if they happen to have at least a knowledge asset in common. This will be as a consequence of trade, unintended diffusion or inheritance. Thus, a link between two agents will be a signal that there has been some sort of interaction between them that has resulted in knowledge diffusion. Examining the structural characteristics of those networks in the light of the different topologies thoroughly studied in the literature of complex networks it will be possible to grasp the patterns of knowledge diffusion in the models. This will provide interesting cues on how the structure of networks is affected by the knowledge management strategies and cultural features of the organizations in the population and which is the effect of that in the diffusion of knowledge.

In the following section six different networks will be analyzed, which correspond to the final period of simulation of selected runs. For each of the two cases modeled, Silicon Valley and Route 128, three different ICT regimes—i.e., different degrees of development of information and communication technologies—are considered. This will allow not only compare the different knowledge diffusion patterns between the two cases, but also the different evolutionary patterns they may experience with the future increase of information processing power and, as a consequence, communication bandwidth.

The six networks studied are depicted in Figure 4. Green circles represent agents—that is, nodes of the network—and dark lines represent links—meaning that the two agents at each side of the line share one or more knowledge assets. Agents are distributed according to their spatial location.

At first sight, the networks appear quite different, specially for narrow and medium bandwidths. The fact that in the SV case there are more agents, more interaction and more creation of knowledge results in a much denser network. However, this continuous “creative destruction” could make that perhaps the links are not so strong. Indeed, if we consider that a link between two nodes exists only if they share 5 or more knowledge assets, the picture is quite another (see Figure 5). The resulting networks are more similar, or even denser in the R128 case.

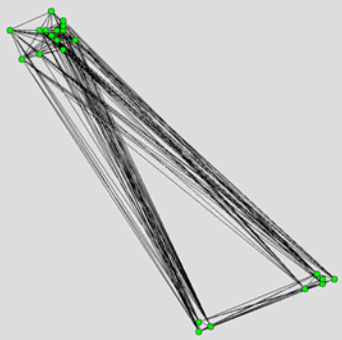
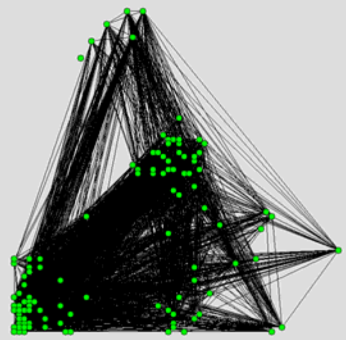
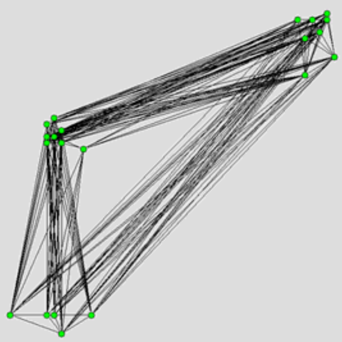
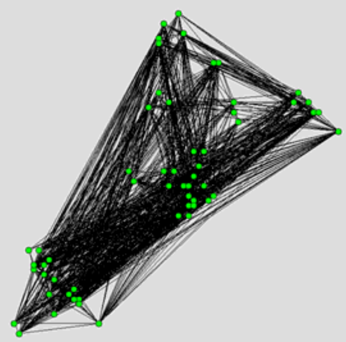
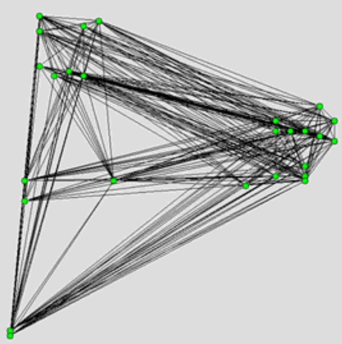
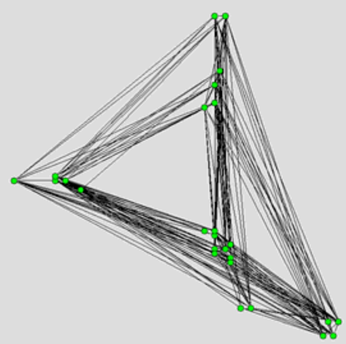
Band-width	Case R128	Case SV
Narrow		
Medium		
Broad		

Figure 4 Graphical representation of the networks in the physical space

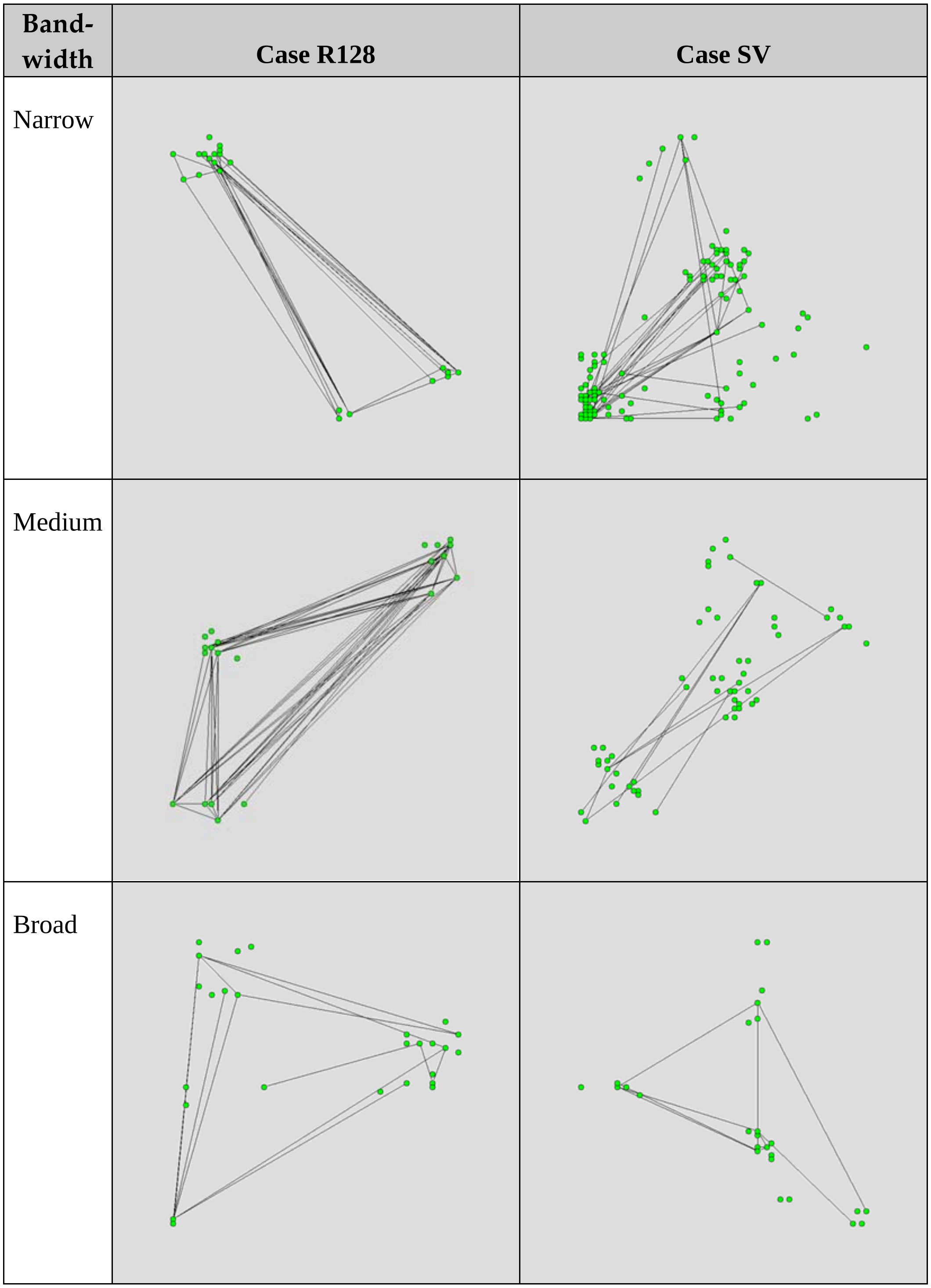


Figure 5 Graphical representation of the networks formed only by strong ties in the physical space

5. Results

For each network, different characteristics will be compared. The number of nodes and links will give an idea of the size of the network. The average physical distance of links will relate the network structure with physical space. Six properties used in network analysis are examined: degree, density, shortest path length, diameter, betweenness and clustering coefficient (see the formal definitions of those properties in (Scott, 1991; Hanneman, 2001; Newman, 2003; Dorogovtsev and Mendes, 2003)). The values obtained are shown in Table 1.

Table 1 Characteristics of networks formed in the last period of selected simulations.

Model	**Route 128**			**Silicon Valley**		
Bandwidth	**Narrow**	**Medium**	**Broad**	**Narrow**	**Medium**	**Broad**
Number of nodes	23	24	26	124	58	27
Number of links	163	232	240	3018	892	187
Average physical distance	38.6	31.6	24.0	32.0	31.5	31.9
Average degree	14.2	19.3	18.4	48.7	30.8	13.8
Average density	0.644	0.841	0.738	0.396	0.540	0.533
Avg. Shortest path length	1.36	1.16	1.26	1.54	1.40	1.45
Diameter	2	2	2	3	3	3
Avg. Betweenness	3.91	1.83	3.27	27.53	10.29	5.41
Avg. Normalized Betweenness	1.69	0.72	1.09	0.37	0.64	1.66
Avg. Clustering Coefficient	0.796	0.899	0.821	0.719	0.777	0.832

1.1. Number of nodes and links

For the R128 case the number of nodes and links is comparable for the different ICT regimes modeled, with around 25 agents and between 150 and 250 links. For the SV case, the increase in bandwidth produces a severe reduction in the number of agents and links. This is relevant because the initial endowment of agents is in this case much higher than in the R128 case, reflecting the real situation. For the broad bandwidth regime, the SV case is comparable to R128 in terms of the number of nodes and links.

1.2. Physical distance of links

At each extreme of the links that form the network there is an agent. The physical distance between those two agents can be associated to the link. The measure of the average of that distance for all the links in the network is presented in Table 1. The differences observed among the different networks examined are not very important and do not seem to be attributable to other factors than random evolution of location patterns.

1.3. Degree and density

The degree of a node in the network is the number of links connected to that node. Looking at Figure 4, the number of dark lines ending at each green circle is the degree of the node represented by that circle. The average degree of the nodes of each network is presented in Table 1. As one can expect taking into account the number of nodes and looking at the figures of Figure 4, the average degree of the SV case for narrow and medium bandwidth is much higher than in the other SV network and in the R128 case.

The data mentioned above could hint towards a higher density of links in the cases SV-Narrow Bandwidth and SV-Medium Bandwidth, but this is not the case, as can be seen looking at the density, also depicted in Table 1. The density measures the ratio of the actual degree of a node in the network and the maximum possible degree, which corresponds obviously to the number of nodes in the network minus one. The average density is higher in the R128 case than in the SV case.

Often, more important than the average degree is, for network analysis, the degree distribution. Figure 6 shows the different degree distributions for the networks studied. The form of these distributions suggests a structure more similar to a random network—featuring a Poisson distribution—than to a scale-free network—featuring a power law distribution.

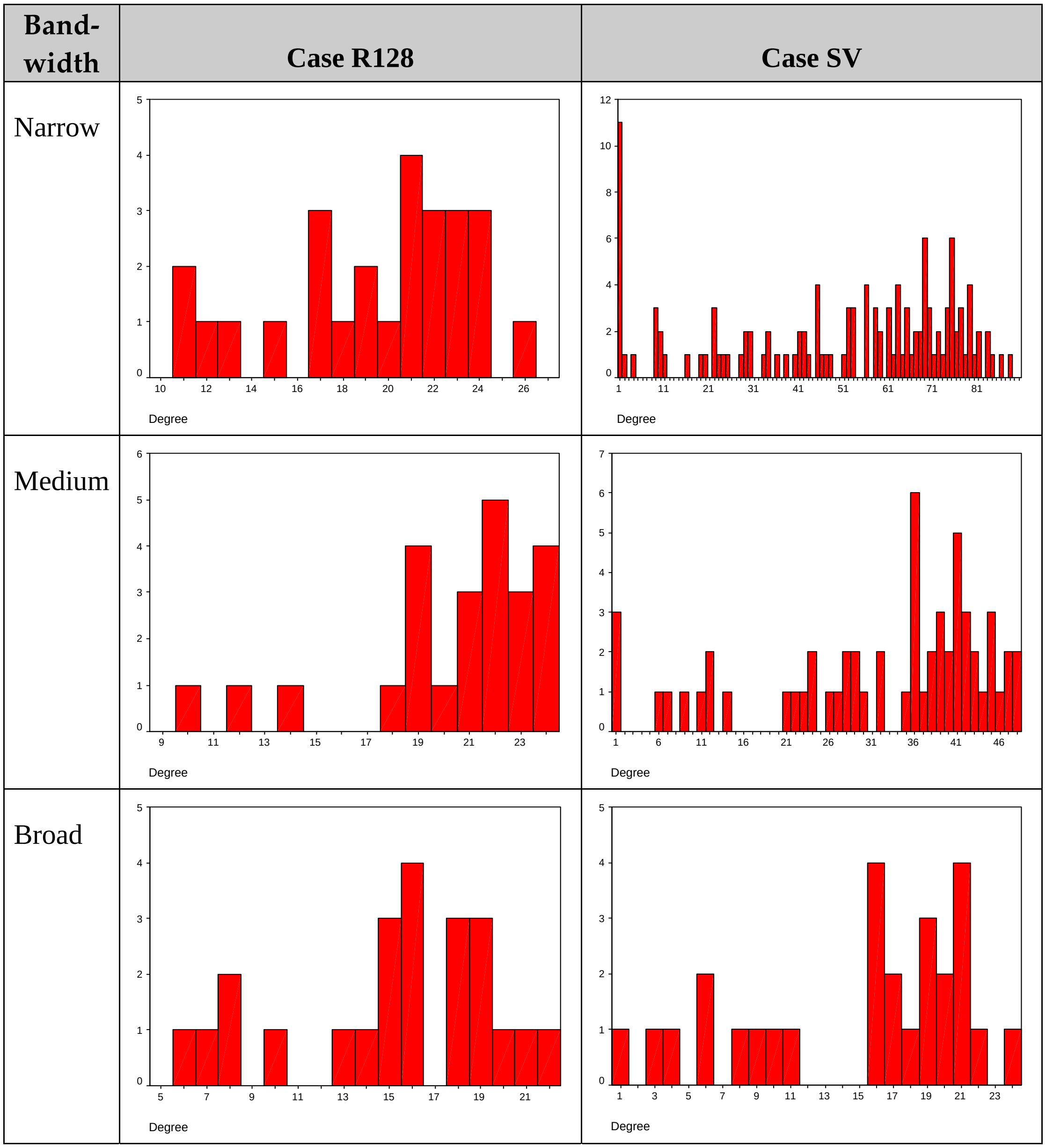


Figure 6 Degree distributions of the networks studied

1.4. Shortest path length and diameter

The path length between two nodes of a network is defined as the number of links one has to follow to go from one to the other. Of course, there are a lot of possible paths between two nodes, but shortest among them receives the name of *geodesic*. The average length of all shortest paths or geodesics is a relevant characteristic of a network, since it gives an idea of how far away is any given node of the rest.

The shortest path length is used to assess “how big” is the world represented by the network. In the R128 case, the shortest path length remains between 1.16 and 1.36, while for SV it is over 1.40 and below 1.55. We can consider that both cases and for all ICT regimes are “small worlds”.

The longest geodesic length—or the longest shortest path length—in a given network is often called the *diameter* of that network. This is another measure of the size of the network. In our cases, the diameter of the networks of the SV case for all regimes (3) is bigger that for the R128 case (2). This fact confirms that, although both sets of networks can be considered “small worlds”, in the R128 case they are slightly smaller.

1.5. Betweenness

The betweenness of a node is the number of geodesics between all possible pair of nodes that pass through that node. If there are more than one geodesic between two nodes and not all of them pass through the considered node, those that do contribute with the corresponding reduced weight. It indicates to what extent a node is important in the *traffic* of the network.

In the networks studied, the average betweenness is much higher for the SV case, but if we look at the normalized betweenness—which modulates the number according to the total number of nodes and links of the network—it turns out to be higher for the R128 case.

1.6. Clustering Coefficient

The clustering coefficient of a node in the network is a measure of how connected are the adjacent nodes. It gives an idea of how compact is the network, but also of how necessary is a given node to go from one of its neighbors to the other. The higher the clustering coefficient, the fewer necessary is the node. The maximum clustering coefficient for a node is one, and it happens when all its neighbors are connected in all possible ways. In all of the networks studied, the clustering coefficient is quite high, above 0.750 except for the narrow bandwidth ICT regime for the SV case, in which it is of 0.719.

6. Conclusions

The results described above do not come from real data, but from a simulation model. Therefore, their function is to provide insights on which could possibly be the mechanisms at play in the real world systems modeled. The simulation model has been used before and has shown some capacity to reproduce real world patterns (Canals et al., 2004b). Here an attempt is made to get more in depth into the structure of the interaction that gives rise to those patterns by analysing the networks of agents formed by knowledge transfer. The objective here will be to develop some insights that could be used to develop hypotheses suitable to be tested with empirical data or to improve the simulation model.

One first thing to note is that, as one would expect from the initial parameter setting, the networks for the SV case are larger, at least for the two lower ICT regimes. However, a closer examination leads to discover that ties are not so strong as in the R128 case, probably due to the high rate of change imposed by the “creative destruction” of Schumpeterian economic environments. This fact could be contrasted with empirical data on knowledge diffusion in geographical industrial clusters.

In the SV case, the increase in ICT bandwidth causes a reduction of agents, as seen in the previous work mentioned, what is translated into a network more similar to the R128 case. The advantage of the Silicon Valley cultural model in terms of the structure of knowledge diffusion over the Route 128 model could be in the future eroded by the development of information and communication technologies.

An important result obtained is that the networks formed are not scale-free, that is, their degree distribution does not follow a power law. Instead, they are more similar to a dense random network. This contrasts with the fact that a lot of the real world networks studied—although certainly not all of them—seem to be scale-free.

One of the more popular mechanisms of network growth that ends up with scale-free networks is the *preferential attachment* (Barabási and Albert, 2002), what suggests the need of a capacity by agents to choose their interactions a priory according to the expected benefits. For this mechanism to be in place, agents should be endowed with memory, which is not the case in the actual simulation model. Further development of the model could take that direction if the real knowledge diffusion networks are found to be scale-free.

Density is quite high in the networks studied, specially in the R128 case. This suggests a tight relationship among agents. Each agent is linked to a large part of their counterparts. This is probably related to the fact that the networks studied are really “small worlds”, with very low shortest path lengths and low diameters. This characteristic is also more acute in the R128 case, with a diameter of 2, but it is still noticeable in the SV case, with a diameter of 3. Perhaps these are the distinctive features of geographic industrial clusters and are in the basis of their success.

Although the average betweenness is quite high, probably there are not much nodes in the networks studied that are specially important in terms of the traffic they may facilitate because the clustering coefficient is high too. This is in consonance with the fact that the degree distributions are not scale-free—there are not a few nodes with many links and a lot of them with a few.

Of course, the conclusions of this research present limitations. Most of them come from the use of a simulation model and have been described elsewhere (Canals et al., 2004b). Another source of limitations is the fact that the study has been made with one network as a representative of each case and ICT regime. Although they have been chosen avoiding outliers and picking what seemed to be sound representatives of their class, there is a slight possibility that their specific features could lead to some bias. The way to avoid this would be working with a set of results for each case and ICT regime, but this was beyond the scope of this first exploratory work. A final limitation comes from the difficulty of relating the knowledge networks described here to knowledge networks in the real world when it comes to contrast the results obtained here with empirical facts. Further research may be directed to overcome some of these limitations. This work has been an initial attempt to assess the validity of the network analysis approach to better understand the dynamics of agent-based simulation models applied to knowledge-intensive economic systems.

7. References

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