4 The small worlds of creativity and innovation

This chapter deals with the 'small-world' phenomenon. It starts by presenting the first experiments conducted by social psychologist Stanley Milgram on the transmission of information through chains of acquaintances, and then moves on to small-world and scale-free networks. The second part discusses the application of these models to the themes of innovation, analysing certain examples of empirical research regarding: affiliation networks in scientific collaboration and company boards of directors; the 'small worlds' of creativity and innovation in Broadway musicals and businesses partnerships; and the Silicon Valley hub.

4.1 Six degrees of separation

The expression 'six degrees of separation' has become popular both in everyday language and in scientific literature to indicate that each person can be reached through a limited chain of acquaintances. It is a good representation of the concept that 'the world is shrinking' – in the sense that it requires just a handful of intermediaries for us to get in touch with all the people we are interested in, no matter how geographically or socially distant they may be. This image, so familiar nowadays in the age of globalisation, is not of particularly recent origin. In fact, it appeared for the first time in 1929 in a short story, not coincidentally entitled *Chains*, by the Hungarian writer Frigyes Karinthy (2006). The story describes a little experiment carried out by a group of friends in order to demonstrate that the population of the planet is more accessible and closer than it had ever been in the past. Each of the participants had to select a random person in the world and show that it was possible to reach them through their network of personal acquaintances. Two of the friends immediately demonstrated that they could easily contact a Swedish Nobel Prize winner for literature and an ordinary American worker employed in a Ford factory – two complete strangers who could be reached via short 'acquaintance chains'. The game went on to try to demonstrate the plausibility of the assumption that 'nobody from the group needed more than five links in the chain to reach, just by using the method of acquaintance, any inhabitant of our Planet' (ibid., 23). Through this story Karinthy gives credence to the idea that *anyone*, *anywhere* in the world, can reach any other person through five intermediaries, only the first of whom is a person they know directly.[1]

Why should this literary idea be of interest here? First, because it influenced initial thinking about social networks; and second, because it received empirical confirmation from the small-world experiments, which then gave rise to less evocative and more scientifically rigorous theoretical formulations in the field of network studies. Third, because the phenomena described – the 'small worlds' and the ties that bind them – have important implications for Innovation Studies.

To start with the first point: towards the end of the fifties, two American scientists at the Massachusetts Institute of Technology in Boston (MIT) circulated a manuscript that marks the origin of scientific research into the 'small-world' phenomenon. The manuscript was published only 20 years later as, appropriately, the opening article of the first issue of a new journal – *Social Networks* – dedicated to the theoretical and empirical analysis of social networks. This text, devised by political scientist Ithiel de Sola Pool and mathematician Manfred Kochen, contains some of the basic questions that have guided subsequent research (Pool and Kochen 1978). The two scholars were interested in developing the first steps of a theory of (social and political) influence as a function of social relationships – the ability, in other words, to reach the 'right' people through the appropriate channels. With this in mind, they considered the morphology of social structure: the volume and distribution of social acquaintance present within a given population. The questions they asked are apparently simple: what is the probability that a pair of randomly selected individuals know each other? What is the chance that they have a friend in common? What is the probability that the shortest acquaintance chain to put them in contact is made up of two intermediaries – the friend of a friend, in other words? Or, perhaps, 3, 4, 5, 6 … *n* intermediaries? The answer to these questions does not involve a simple calculation of probabilities, but rather a profound understanding of the society in question.

Acquaintance networks are not in fact randomly distributed amongst people: they are *socially structured*. This significantly lessens the distance between *certain*, apparently far-flung, individuals, while extending the distance between *certain others*. People and acquaintance networks tend, in varying degrees, to accumulate around certain dimensions of social structure: territory, with relationships of geographical proximity; occupations, through professional relationships; the family, within kinship relations; and leisure time, through elective relationships. Companies and organisations, in other words, can be thought of as social groups or clusters, within which the individuals collected together know each other well.[2] The problem is to understand to what extent these relationship clusters are self-contained, and to what extent they are connected to – or disconnected from – one another. The likelihood of reciprocal acquaintance between two people, therefore, is highly dependent on the relationship structure that links the various social clusters.

The two MIT academics address these issues by developing a *mathematical model* of acquaintance networks: a model that depends essentially on three parameters: the total number of persons (N) that make up the population studied; the average number of acquaintances (n) of each individual; the level of structuration

(k) of social relationships (what others would, subsequently, call the *clustering coefficient*).

If the level of social structuration was equal to zero (i.e. if no relationship clusters existed) the likelihood of reciprocal acquaintance between two people would be known. It would be determined solely by the first two parameters (N, n). Taking the UK population as the total number of persons studied (amounting to about 64 million people), and assuming that on average each citizen has 1,000 acquaintances, the probability that two people know each other is equal to n / N, or 1 / 64,000.[3] To this very low probability, however, must be added an extremely low level of social distance. In this hypothetical society, with no structure, where each one of a person's acquaintances do not know each other, and where there are no isolated individuals, the relationship chain that makes it possible for one person to reach another is very short. Each of our acquaintances is, in turn, in contact with 1,000 people. Through our primary acquaintance network alone, then, we can easily reach a million people ($1{,}000^2$). Through two intermediaries, we can contact a billion people ($1{,}000^3$). With three intermediaries the scale of potential acquaintances widens to a trillion contacts: a million billion people ($1{,}000^4$). In theory, therefore, one or two intermediaries are sufficient to establish contact with any other UK citizen. And if we want to contact another person on the planet, the chain does not have to be unduly lengthened: all we have to do is activate an acquaintance of an acquaintance of an *acquaintance of ours*.[4]

This case, however, is purely hypothetical. Real societies are different. Friends often live in the same city, have similar jobs, similar leisure tastes and habits, etc. They move within the same circuits of social relationships, so it is an easy matter for them to know one another. This means that the number of new acquaintances with whom a friend can put us in touch is more limited and this tends to extend – and complicate – the social 'chains'. In other words, it is the parameter k – the level of social structuration – that determines how many intermediaries are required to connect two people. And it is the distribution of relational capital (social capital) between the various groups and individuals that conditions their social opportunities.

Therefore, to understand how many steps are required to contact a specific person, probability calculation is of no help. We do need to know, however, the *relational structure present in the population studied*. Aware of this fact, and to estimate the unknown parameters of their equation, Pool and Kochen took advantage of research carried out on a limited sample of US citizens from a range of social backgrounds: blue and white collar workers, professionals and housewives.[5] Starting from the *contacts* registered by 27 'real individuals' in a time period of 100 days, they calculated the average number of acquaintances (n) of a typical citizen. Furthermore, based on the percentage of people who in turn knew one another amongst those included on the lists of sample contacts, they produced an estimate of the level of structuration (k) of social relations (Pool and Kochen 1978, 29). Finally, they defined a stylised model of the empirical situation, which they then applied to the US: from this, it appeared that the modal number of intermediaries required to connect any two people was equal to 2.

The two MIT scholars ended the article by conjecturing the following: if American society *was not structured* and the average number of acquaintances for each individual was equivalent to 1,000, then it would take fewer than two intermediaries to connect any two people chosen at random.

'In a structured population', said the article, this result 'is less likely, but still seems probable. And perhaps for the whole world's population probably only one more bridging individual should be needed' (ibid., 42).

To sum up, although the chance of direct acquaintance between two US citizens was – then – just 1/200,000, the addition of one or two intermediaries dramatically increased the likelihood of *indirect acquaintance*.

4.2 It's a small world

But the mathematical model developed by the MIT group, however interesting from a theoretical viewpoint, rested on rather fragile empirical grounds. The problem of structure and social connectivity was not resolved in a satisfactory manner. This stimulated a variety of different paths. In 1967, in *Psychology Today*, social psychologist Stanley Milgram published the results obtained using an experimental method: the so-called 'Harvard approach' to the small-world phenomenon. Milgram and his associates addressed the study of social structure and acquaintance networks via two ingenious empirical experiments. Certain 'randomly chosen' people (*starting-persons*) were equipped with basic information regarding a resident of another state (the *target-person*): they were then asked to send a letter provided by the researchers to this target-person. The only constraint was that if they did not know the person directly, exclusive use had to be made of chains of acquaintance: the letter had to be forwarded to a relative, friend or mere acquaintance (someone personally known, however).

In the first study, the starting-persons were chosen from among the residents of Wichita, Kansas. The target-person was Alice, the wife of a student who lived in Cambridge, Massachusetts. In the second study, the chains stretched out from Nebraska (for a detailed account of this experiment see section 4.2.1 below). Initially, the Harvard researchers were sceptical about the experiment's chances of success: they entertained serious doubts that any of the messages would ever reach their destination. The results were surprising. The first message reached Alice after only four days. At the end of the two experiments the 'transmission chain' count ranged from a minimum of two to a maximum of ten intermediaries, with a median value of 5 and a modal value equal to 6.[6] The number of messages that reached the goal, however, was limited. This induced the researchers to speculate that the length of the chains was slightly underestimated, assuming that the interrupted chains were also the longest. However, the experiment provided some interesting insights. First, that it was social rather than physical distance that limited the transmission of information. Second, that there existed relational hubs:[7] many different chains, in fact, converged towards a limited number of people who then delivered messages to the recipient.

Third, that these hubs are highly specialised: some were the terminals of *professional chains* (those who, to deliver the message, followed the professional tracks of the target-person), and others of *territorial chains* (those who followed the residential tracks).

Fourth, the chains revealed strong gender segregation (often men and women forwarded messages to friends of the same sex), and the tendency to use chains of acquaintances and friends rather than relatives. As the researchers observed, these social traits were specific to the US at that time and might vary from society to society. In brief, the experiment provided interesting indications regarding the modality of social integration and, more importantly, the social mechanisms that 'govern' the circulation of information.

4.2.1 How small is the world? The small-world experiments in greater detail

4.2.1.1 The sixties' experiment with traditional mail

At the end of the sixties, Stanley Milgram and Jeffrey Travers at Harvard University (Boston) carried out experimental research into the small-world problem (Milgram 1967; Travers and Milgram 1969). The question they asked was very similar to the one that had inspired Pool and Kochen: what was the probability that any two people, arbitrarily chosen from a large population such as that of the US, would know each other? And assuming that they did not know each other, how many intermediaries would be required to put them in touch? To answer these questions, the two scholars organised an experiment that was quite simple, yet at the same time ingenious. They randomly selected a target-person and a group of starting-persons with the aim of bringing them into contact through 'acquaintances chains' (Figure 4.1).

Each starter received a document containing the description and purpose of the study and the rules to follow to help it reach its objective. The document contained some basic information about the target-person: name and address, profession, the city in which he worked and the town he came from, age, his wife's name, etc. The rules regarding sending the document were as follows: if the starter was personally acquainted with the target (*on a first name basis*) then they must send the document directly to the person. Otherwise, it must be sent to an intermediary (a friend, relative or other personal acquaintance) who the starter believed capable of reaching – whether directly or indirectly – the target. At each step of the chain, a system of postcards sent to the research group made it possible to track the path of the document. This could end in two ways: by interrupting the chain of transmission, or with the attainment of the objective. In addition, on the postcard, each new intermediary had to write down some biographical information about themselves and about the person to whom they were forwarding the document. In this way the research team could, through comparison,

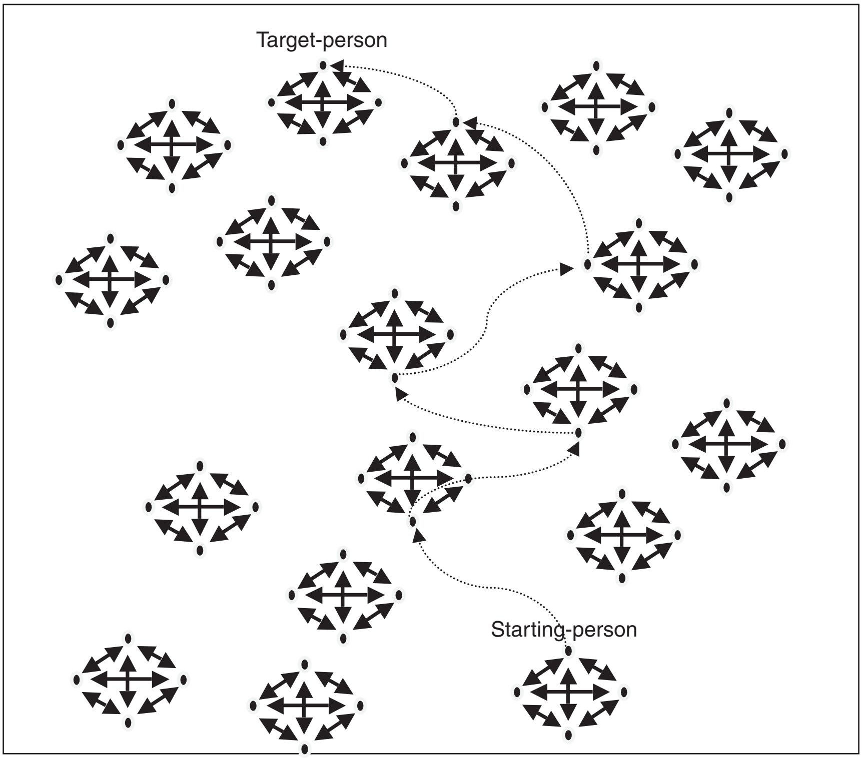

Figure 4.1 The Travers and Milgram small-world experiment.

accurately determine the characteristics of both the interrupted and the successful chains and, in the case of the former, even identify the 'breaking point'.

The person chosen as the target was a financial broker who lived and worked in Boston. The other participants in the experiment – the starters – were divided into groups: 196 residing in Nebraska (a state considered to be sufficiently distant from the target) and 100 in the Boston area. The first group included 100 share-holders in large companies listed on the stock exchange (*Nebraska stockholders*), with the rest randomly selected from the state population (*Nebraska random*). The Boston group was selected from people who replied to an advertisement placed in a newspaper (*Boston random*). The aim was to see how the different social and geographical distances to the objective influenced the success rate and the length of the chains of transmission. Of the 296 people selected for the study, 217 agreed to participate in the experiment. Some 64 chains reached the Boston broker, 29 per cent of those initiated. As regards the broken chains, no particularly significant social characteristic came to the fore. As the researchers expected, geographical and social distance influenced the results of the experiment. The Boston random group registered the highest success rate in terms of the chains (35 per cent), with an average number of intermediaries of 4.4. The Nebraska stockholders reached the goal in 31 per cent of cases, through an average of 5.4 intermediaries. The Nebraska random group reached the broker in only 24 per cent of cases, with an average of 5.7 intermediaries. The results of the experiment gave rise to the 'six degrees of separation' formula made famous by John Guare. The experiment was subsequently repeated by Milgram, and it recorded similar results, despite changes being made to certain social and statistical characteristics with regard to starters and targets (race, for example) (Korte and Milgram 1970).

4.2.1.2 The millennium email experiment

Nearly 40 years later, a team of researchers at Columbia University (New York) repeated the test on a larger scale using the internet. Peter Sheridan Dodds, Roby Muhamad, and Duncan J. Watts (2003) organised a social search experiment with several thousand participants of different nationalities. The targets to be reached were 18 people of different social backgrounds living in 13 different countries. These target-persons included, for instance, an Ivy League university professor in the US, an archival inspector in Estonia, a technology consultant in India, a police officer in Australia and an army veterinarian in Norway. In this case, too, participants had to deliver the message via acquaintances whom they believed were closer to their final destination. In addition to providing the research team with the name and email address of the intermediary, participants had to explain why they had chosen that person, how they had come to know each other, the type of relationship that linked them (parental, friendship, professional) and the intensity of their relationship. In short, the intention was to replicate the small-world experiment on a global scale, monitoring the transmission chains and their social characteristics. The experiment, conducted between 2001–03, involved more than 61,000 people from 166 different nations and triggered 24,163 'message chains'. About two-thirds of the starting-persons initiated the chain by using friends: 41 per cent described the relationship as 'very close' and another 33 per cent as 'quite close'. The success rate was higher in the case of those chains that made use of relations originating in the professional workplace, or from a period of higher education. Although strong ties were predominantly used, networks employing less close acquaintances actually reached the target-persons in greater numbers: giving rise to the observation – in line with Granovetter's thesis – that 'weak' ties are disproportionately responsible for social connectivity' (Dodds *et al*. 2003, 827).

This was a rather imperfect connectivity, however, judging by the limited number of chains that reached their destination: only 384, each using an average of 4.05 intermediaries. The success rate, therefore, was extremely low – only about 1.6 per cent of the chains originally initiated. Another, later, experiment, involving 85,000 participants and 56,000 message chains, proved even more disappointing (Goel *et al*. 2009, 703–4). This was mainly attributed – in addition to its greater geographic scope than the Milgram and Travers test – to the lack of incentives or interest in the experiment. The results, therefore, suggested that in the absence of 'sufficient incentives to proceed, the small-world hypothesis will not appear to hold' (Dodds *et al*. 2003, 828). The researchers did add, however, that it would only take a modest increase in incentives (not necessarily financial) to raise the success rate of this type of *social search*. This seemingly trivial conclusion has theoretical relevance. It tells us that the structure of relationship networks does not exercise social influence in itself, but assumes meaning and significance only in the light of the strategies and motivations of the actors that are placed within it.

Figure 4.1, however, makes the exact meaning of the Harvard experiment immediately clear. Separation by five intermediaries does not mean that the person who initiates the search is socially close to the target person. As Milgram observed (1967, 67), any citizen was theoretically separated by only five intermediaries from the president of the United States or Nelson Rockefeller. This did not mean, however, that their lives were effectively integrated with those of the White House incumbent or the US billionaire. The separation was not only a matter of five people, but of five *circles of acquaintance*; and that is a huge social distance. And the meaning of the experiment, especially with regard to innovation, is precisely this: it lies in the idea that social distance can be reduced and that, through social networks, people can access information and knowledge which is different from that which they – and their inner circle of relatives, friends, acquaintances and colleagues – already possess. To use the terminology of the previous chapters, it is possible, through these networks, to acquire *non-redundant information*.

But as we shall see, two other important things also came out of the experiment. The first is that the small-world phenomenon must be conjugated in the plural. Society, the fields of scientific research, the sectors of technological innovation, all constitute a series of *small worlds*, highly integrated internally. It is precisely because of the strongly *clustered* aspect of societies that the number of steps required to reach an individual increases, when compared to how many would be needed if acquaintance networks were randomly distributed. The fact that Stephen knows John and John knows Mike greatly increases the likelihood that Stephen and Mike will, sooner or later, get to know one another. The 'closure' of acquaintance networks therefore tends to reduce and complicate the ability to acquire new information. The second thing is that close acquaintance *cliques* (family, relatives, friends, work colleagues, etc.) – who communicate via direct links – are also connected to the outside by a series of indirect links. This is what creates communication between their *small social worlds*, leading to the small-world phenomenon.

This is an aspect, however, that requires correct interpretation. The experiments discussed so far – both the original version using traditional mail and the subsequent experiment using email –tell a different story from the one that is often highlighted: and that is *the difficulty in terms of the search for, and transmission of, reliable information*. In the small-world experiments, in fact, only a very small percentage of chains reached the established target, and even those that were successful were of very different lengths. This highlights the transaction problems and costs inherent in the use of networks.

The most obvious factor is motivational. While it is true that it does not cost a great deal to connect two acquaintances, it is also true that sufficient motivation must exist in order for them to be brought together. The ties that convey non-redundant information, therefore, must be weak – but *not so weak* as to interrupt the flow. Another problematic aspect is linked to the fact that the longer the chains, the greater the risk of their breaking or not conveying the expected advantages. As Ronald Burt has pointed out, networks generate two types of benefit, involving *information* and *control*. These advantages are mainly related to *accessing new information* that creates favourable opportunities and the *timeliness* with which this can be obtained with respect to possible competitors. It is evident that each additional step in the chain tends to diffuse (and disperse) new information amongst multiple subjects and, above all, it delays access – thus reducing the benefits related to *timing*. There is also another important aspect that concerns a third type of advantage indicated by Burt: one connected to *referrals*. The acquaintances that pass on information, in fact, perform a filtering function that legitimises both the information and the person from whom it comes, in the sense that this renders them credible and reliable. It is evident that the more this *function of accreditation* is dependent on a long chain of 'acquaintances of acquaintances', the more it tends to lose power. As we shall see, these are aspects of importance in the study of research teams and the transmission of complex and tacit knowledge in situations of high uncertainty.

4.3 Small-world networks

The small-world experiment was replicated several times in order to test the influence of certain variables: sex (Lin *et al*. 1977); ethnicity (Korte and Milgram 1970; Weimann 1983); organisational context (Lundberg 1975); the media employed, e.g. the telephone (Guiot 1976) and email (Dodds *et al*. 2003; Goel *et al*. 2009).[8] This type of experiment – based on the sending of messages (*letter referral studies*) – was, however, subjected to severe criticism. Several empirical and methodological flaws were discovered that cast more than one doubt over the adequacy of such methods to detect the structure of social relations and measure the distances between subjects. Several of the reported problems were already evident in the investigations of Milgram and Travers: the limited size and arbitrariness of selection criteria undermined the randomness and representativeness of the samples used (Erickson 1979); the low rates of response and chain completion made them unreliable for detecting social networks and estimating the length of the paths (White 1970; Kleinfeld 2002); the inappropriate strategies in the selection of intermediaries – in other words, the errors of choice made by the subjects – tended to elongate the chains, compared to shorter paths theoretically available to reach the target (Killworth *et al.* 2006).

Although many of these problems can be solved, and certain best practices have been identified to render experiments more robust (Schnettler 2009a), the fact remains that these types of study are becoming less frequently employed for the analysis of the structure of 'real networks'. In addition, the increasing availability of empirical data regarding large-scale networks (often digital) makes it possible to study the small-world phenomenon using others methods. A resurgence of interest has taken place through the creation of mathematical models for the small-world networks present in social, biological and technological systems. At the end of the nineties, two Cornell University researchers – Duncan J. Watts and Steven Strogatz (1998) – published an article that echoed throughout a wide variety of disciplines. The article showed that, starting from an ordered model of local clusters – i.e. short-range relationships between contiguous points – and with the random addition of a few long-distance relationships, it is possible to significantly reduce the average distance between the points present in the model. In short, it creates the small-world effect: from small (local) worlds to a small (global) world.

The model, in fact, describes a scenario composed of many small local worlds – made up of close relationships, dense networks, redundant information – connected to each other by certain random links that make them all accessible through just a few intermediaries. To prove their case the two scholars built two polar models: a regular network and a random one. The first represents an ordered interaction, a condition of strong social *clusterisation* where the probability that the friends of a social actor know one other is very high. In the second model, however, there is no order at all to the interaction: personal relationships follow a completely random logic, so that there is just as much likelihood of a person knowing any other person, whether a stranger or a 'friend of a friend'. The hypothesis put forward by the two researchers is that many situations present in the real world are collocated in an intermediate position between these two extremes.

These models should be interpreted against the background of graph theory inaugurated in the first half of the eighteenth century by the Swiss mathematician Leonhard Euler. A graph is a set of points (also called vertices or nodes) joined together by a series of lines (also called arcs, edges, links, etc.).[9] This branch of mathematics shows that graphs possess structural properties that depend on the number of nodes and the way they are linked. With this reasoning transposed to social relations, the configuration of a network provides social actors with both opportunities and constraints of a 'structural' kind.

Watts and Strogatz take as their starting point the ordered situation, represented through the properties of a *regular graph* (Figure 4.2), composed of nodes that have the same degree – that is, the same number of links.[10]

In particular, beginning from a *regular lattice*[11] and connecting the opposite vertices (so as to form a ring), a *periodic lattice* is formed. Each point of the regular network shown in Figure 4.2 presents the same number of links. For example, point A has 4 *adjacent nodes* (connected to it by a link: a1, a2, a3, a4) that constitute its 'neighbourhood' (Scott 1991). These are in turn joined together by three links: nodes a1 and a2 are adjacent, as are nodes a1 and a3, and nodes a3 and a4. Moving to the opposite side of the network – in correspondence to

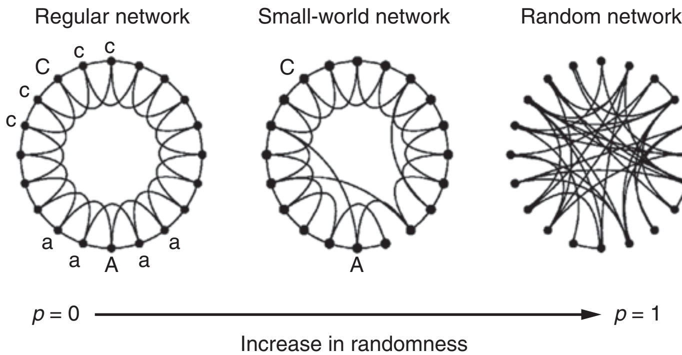

Figure 4.2 Small-world networks.

point C – the same arrangement of nodes is found. These are in fact the properties of the periodic network: that with any selected node, the relational structure is identical. And this is the reason why it is used to represent a situation of 'orderly interaction' (Watts 2004a, 84).

At the opposite extreme, however, we find the *random graph*, which represents the situation of interactions that lack any order. The two academics built this through a process of random reorientation of all the links between the nodes. In the first graph on the left (the regular example), each link has a zero probability ($p=0$) to be reoriented; while in the graph on the right (the random example), each link is randomly reoriented ($p=1$).

Before following Watts and Strogatz in their reasoning, it is useful to introduce some basic information regarding the *theory of random graphs*. The foundations of this theory were laid in 1959 by Hungarian mathematicians Paul Erdős and Alfred Renyi as part of their reflections on the formation of social networks. They proposed a model based on random connections, and decided that the simplest formation model for a network was to establish links between nodes using the throw of a dice. Connecting a set of isolated nodes in this manner initially results in the formation of dyads (pairs of nodes), and then, subsequently, some isolated clusters (groups of nodes separated from other groups of nodes).[12] When a certain threshold is reached there occurs what physicists call a 'phase transition' (a classic example is the freezing of water): the formation of a single complete cluster. All nodes will be part of a single network and will be accessible through direct links or paths of indirect links.[13]

Erdős and Renyi show that the minimum threshold for this change to be realised is for each node to have at least one tie. Once this critical threshold is reached, all the nodes become part of what mathematicians define as a 'giant component'. As links are gradually added, the theory of random networks shows that, with the critical threshold exceeded, the number of nodes excluded from the giant component decreases exponentially. As a pupil of Erdős will later demonstrate, for fairly extended networks all nodes also end up having on average the same number of links. In other words, randomly assigned links follow a 'Poisson distribution', gathering around a mean value, while decreasing rapidly in terms of both lower and higher than average values (Barabási 2002).

A random graph presents two main features. The first is that it has low levels of *clustering*: the nodes do not tend to agglomerate locally, according to highly integrated neighbourly relations. There is, in other words, a low local density: our friends do not know each other and the same goes for the friends of our friends. This means that the giant component – or society as a whole – is easily navigated through indirect links. The second characteristic of random graphs is that the distances between nodes are very short. As seen above, if each person has 100 or 1,000 acquaintances who do not know each other, any individual on earth can be reached through only three or four intermediaries.

Conversely, an ordered graph has properties of an opposite kind: there is a high level of local clustering in terms of links (friends of friends know each other), and limited explorability of the giant component. If we draw a graph loop consisting of 6.8 billion nodes (equal to the number of inhabitants of the earth), and imagine having to reach a point located exactly on the opposite side, using only the closest points – for example, in Figure 4.2, the two points a1 and a3 at the side of A – the chain becomes very long indeed.

Assuming that most of the networks in the real world fall in an intermediate position between these two poles, Watts and Strogatz show that just a few links added randomly (with probability $0<p<1$) will give rise to a situation that combines some properties of the regular network (the high clustering of local relations) with those of the random network (high reachability of all nodes). These are the so-called *small-world networks*. To make the kind of situation described by these networks more immediately comprehensible, it is worthwhile focusing your mind on the fact that most of us do not only have acquaintances who live in the same city but also, directly or indirectly (through our friends), ones located in other countries. There are, in other words, 'shortcuts' that drastically reduce the distance that – theoretically – separates us from any other person placed at the other end of the world. This plunges us back into the small-world phenomenon. The structural properties of each of the three types of graph are described by two parameters: *the path length* L (p) and the *clustering coefficient* C (p). The former is a global property of the graph and measures the average separation between any two nodes. The latter is a local property and measures the density level of a typical 'neighbourhood' of nodes.[14] The *regular network* ($p=0$) is strongly clustered locally for which the value of C is close to 1 (the maximum possible density). The value of L, however, is also high: the average distance between nodes is very long. With the *random network* ($p=1$), on the other hand, both the values are very low. The *small-world network* ($0<p<1$) combines some features of the two previous types. Duncan and Strogatz show that in these networks the value of C remains very high, as in regular networks (the networks are highly *clustered*); but the value of L is very low, as in random networks. With the addition of just a few shortcuts – long-distance links – the world shrinks dramatically. The two academics also show that this type of network describes properties actually present in reality. To test their hypothesis they calculated the values of L and C for different kinds of real-world networks: the network of collaborations between Hollywood actors (an example of a social network); the network of electricity distribution in the western part of the US (an example of a technological network); the connection system of the 302 neurons that make up the *Caenorhabditis elegans* (better known as *C. elegans*, a small multicellular organism only 1 mm long, widely studied in developmental biology (an example of a neural network).

All three of these 'real networks' turned out to be small-world networks. Compared to a random network, with the same number of nodes (*n*) and average links (*k*), the three real networks demonstrate geodetic distances that are slightly higher than those present in the random simulation, but also far higher values in terms of clustering (Table 4.1). Two surprising elements came out of this experiment. The first is that the small-world phenomenon is not confined only to social networks. The second is that just a minimum number of local variations (a few long-range relationships) are required to generate highly consistent global effects (an exponential reduction in the average distance). The first randomly added five long-distance links reduce the average geodesic distance between all nodes by half, regardless of the size of the network. A logic of diminishing marginal returns is apparent, however: to reduce the average distances by another 50 per cent, another 50 long-distance links are required. And successive reductions require even more links to achieve a far smaller effect (Watt 2004a, 89–90).

This class of networks 'discovered' by the two academics meets the four conditions listed by Watts (1999, 495–6) to define the small-world phenomenon. In order for this label to be applied, in fact, it is necessary for the networks to be:

- numerically large;
- globally sparse (the number of links that connect the individual nodes to each other is on average much smaller in comparison to the total number of nodes);
- decentralised (there is no central node to which all others are directly connected);
- locally highly clustered (the links between adjacent nodes are very dense).

4.4 Scale-invariant networks

Subsequently, other studies have enriched the mathematical modelling of networks, providing a significant contribution to the understanding of their dynamic evolution. Almost at the same time as the analysis of small-world networks, Albert-László Barabási, a physicist at the University of Notre Dame, Indiana, together with two of his collaborators, Réka Albert and Hawoong Jeong, published two very influential articles in *Science* and *Nature* (Barabási and Albert 1999; Albert *et al*. 1999) highlighting the existence of other types of network – ones governed by different rules than those explored by Watts and Strogatz.[15]

Table. 4.1 Empirical examples of small-world networks

	n	k	*Distance*		*Clustering*	
			L (real network)	*L (random network)*	*C (real network)*	*C (random network)*
Actors	225,226	61	3.65	2.99	0.79	0.00027
Electricity network	4,941	2.67	18.7	12.4	0.08	0.005
C. elegans	282	14	2.65	2.25	0.28	0.05

Source: adapted from Watts and Strogatz (1998).

These researchers show that many real networks do not follow a normal distribution of links but rather a *power law*. With this type of distribution, cases peak at very low values and then tend to decline very slowly. The configuration then is a curve with a constant decrease, where *many small events* (nodes with few links) co-exist with *a few large events* (nodes with many links) (Barabási 2002). Applied to real-world networks, this means that a large number of nodes have a restricted number of links. As links increase, cases tend to rarefy. However, there are still nodes which possess extremely high numbers of links: these are the so-called *connector*s, or *hubs*. Power laws have a precise exponent, which is given by the ratio between the rarest and most frequent events. In random networks, all the nodes have, on average, the same number of links. In terms of connectivity, then, they have a *typical scale*, represented by the average node. For distributions that follow a power law, however, it does not make sense to indicate a mean value, since no 'representative' node exists that can summarise the characteristics. This type of network, not possessing a typical scale, is referred to as a *scale-invariant network* (ibid.).

Barabási and his collaborators used the world wide web as a starting point for their observations. Employing a specific software, they explored the pages (nodes) and the links that unite them.[16] Given the impossibility of exploring the network completely, they arrived at an inductive estimate of its diameter. Analysing increasingly large portions of the web, they showed the average distance between pairs of documents, and calculated the increment of the number of pages analysed. They thus derived a mathematical formula which was then applied to calculate the average distance between two documents chosen at random from the (then) estimated 800 million web pages.[17] The surprising result of this exploration was that the *vast world web* had a relatively limited diameter (equal to 18.6 links) – with all of its documents, in fact, lying at an average distance of just 19 clicks away from each other (Albert *et al.* 1999, 130). Furthermore, increasing the number of nodes had little influence on the extension of the diameter: the two authors estimated that even in the case of a 1,000 per cent increase, the average distance between nodes would increase only slightly, from 19 to 21.

In brief, as Barabási himself noted a general property of networks is that they are 'small worlds' (Barabási 2002). It is another aspect of the contribution from this group of physicists, however, which is the most significant and innovative. They show that global connectivity is not uniformly guaranteed by all the nodes – as is assumed in both random and 'small world' models – but above all by the hub. For example, by examining the 325,000 pages of the Notre Dame University domain, they discovered that 82 per cent of them had at most three links, while 42 (just 0.013 per cent) had more than 1,000. Expanding the exploration to 203 million web pages, the same phenomenon was observed: about 90 per cent of the nodes had a maximum of ten links, while two or three had about a million. Hence the conclusion that the web was based on a handful of highly connected nodes.

And, according to the group of physicists, the same goes for many other real-world networks. *The hubs are responsible for the small-world phenomenon*, their great connectivity holding together many nodes and ensuring reachability through fairly short paths. At base, there lay two generative mechanisms ignored by previous theories. Models based on random networks, for example, are static and egalitarian: the number of nodes is kept constant and each of them is considered equivalent. The scale-invariant model proposed by Barabási and Albert is based on two opposite hypotheses, explaining the generation of power laws on the basis of two simple mechanisms present in many complex systems, both social and otherwise:

1 *growth*, since networks tend to be in constant expansion, continually adding
2 *preferential connections*, since new nodes tend to enter into relationships by favouring nodes that are already well connected (Barabási and Albert 1999, 511; Barabási 2002).

Real-world networks are, in other words, often *dynamic systems*: the number of nodes grows and newcomer nodes, connecting to the existing network, tend to favour the hub.

From these initial reflections, and subsequent contributions from other physicists, mathematicians, sociologists, biologists and computer and information scientists, a field of study has taken shape regarding the evolution of networks, in which the scale-invariant model has become a special case. The topology of the networks and their different modes of transformation introduce greater variety into these models than Barabási originally imagined. For example, the different modes of ageing, disappearance and replacement of the nodes, the criteria for the generation of new links, and whether they are onerous (i.e. time-consuming) or not, considerably modify the number and size of hubs present in the real world. These developments led Barabási to admit that in the theory of network evolution the scale-invariant model is a particular case (ibid.). He also stated, however, that in complex networks, when growth and preferential connections are present, power laws and hubs will in any case emerge 'most of the time'.

While taking these clarifications on board, it should be added that the study of complex networks – especially social ones – would derive considerable benefit from empirical research into operating modes in different socio-institutional contexts: in other words, from a specifically sociological approach to the study. The resources required to foster social links, in fact, are very different from those needed to keep alive or generate web page links, and most importantly they vary with interactional context. Such elements make it quite clear that, in social worlds, the presence and role of the hub, as well as the degree of connectivity of the network, do not depend on the invariant properties of complex networks in their abstract sense. They are highly variable and contingent,[18] dependent as they are on the social and institutional contexts in which the links are deployed. And that is in a logic of complex, biunivocal interdependence, so networks both *condition* and are *conditioned by* the socio-institutional structure within which they develop interpersonal and inter-organisational relations.

To sum up, whereas Barabási characterises the new science of networks in a nomothetic sense, stating that certain 'simple and far-reaching *natural laws* govern the structure and evolution of all the complex networks that surround us' (2002, 6, my italics), a sociological approach tends instead to introduce more elements of variability and contingency. The effort to emancipate the study of complex networks from the *random* logic that had dominated the early stages – on the basis of the work of Erdős and Renyi – induced Barabási to focus on the transition from disorder to order, analysing the self-organisational mechanisms and laws that governed the phase transitions. This attempt to discover elements of uniformity should not, however, overlook the differences present in various scientific and phenomenal fields. It is not, in other words, possible to push forward to the formulation of universally valid natural laws. As Raymond Boudon taught (1984), when reflecting on the nomothetic and deterministic flaw present in many theories of social transformation, the new science of networks had to take into account the *place of disorder* in social phenomena.

However, a sociological approach to the study of complex networks does not appear to be in contradiction with the research agenda of the *new science of networks*. In what can be considered a sort of manifesto, Mark E. J. Newman, Albert-László Barabási and Duncan J. Watts (2006, 4) indicated the three characteristics that distinguished the new science of networks:

1 focus is on the properties of networks present in the real world and there is interest therefore in both theoretical and empirical issues;
2 networks are not assumed to be static: they evolve over time according to *various* dynamic rules;
3 the aim is to understand networks not as simple 'topological objects' but as structures on which dynamic distributed systems are built.

The authors of this 'new agenda' at the same time criticised both the *excessively abstract* nature of early graph theory – developed in the context of mathematics – and the *over-descriptive and empirical* nature of *social network analysis*, practised in the social science field.

This second criticism, however, seems less than appropriate, especially with regard to new economic sociology – a branch in which the use of network analysis has been accompanied by substantial theoretical elaboration, albeit in ways suitable to the social sciences (Boudon 1984). Its use, in fact, has allowed the development of *partial and local laws* – such as the law regarding the 'strength of weak ties' – which apply to specific historical and social situations: that is, within defined space-time coordinates. It has also developed *formal theories* with analytical purposes – specially constructed logico-formal models that are used to describe and explain certain empirical phenomena. This second category includes the 'theory' of small-world and complex networks.

The rehabilitation of the networks' 'social dimension', meanwhile, arose from the observations of the above-mentioned Duncan Watts, who, not coincidentally, taught sociology for several years at Columbia University. The sociological question was once again foregrounded in relation to the networks' 'issue of searchability', connected to the small-world experiments. The problem concerned the ability of individuals to identify the 'right tracks' through their relationships in order to reach to the individuals selected as their target. This question emerged as a result of certain of the writings published by Jon Kleinberg (2000a, 2000b), a computer scientist who analysed the phenomena of *direct research* such as those found in Milgram's small-world experiments. Kleinberg partially altered the procedure used in the experiments by Watts and Strogatz, introducing a provision regarding distance – randomly adding links to the nodes of an ordered graph, but with the condition that the probability that a link unites two nodes decreases according to their distance in the network. In brief, new connections are added at random *but are not, however, randomly distributed*, as they tend to favour the nodes adjacent to one other (a 'realistic' assumption). The question that Kleinberg wanted to answer was whether it was possible 'that individuals using local information are collectively very effective at actually *constructing* short paths between two points in a social network' (Kleinberg 2000b, 163). He showed that using *decentralised algorithms* – computer programs that operate exclusively through local information – it is not possible to find these paths (except under very restrictive conditions). As Watts points out, if the real world actually worked as the small-world network model did, as Strogatz and he described in the journal *Nature*, the *direct searches* observed in Milgram's experiments would be impossible.

Kleinberg showed that forcing the program to use only local information,[19] the short paths between two points in the network were difficult to find. The general conclusions that Kleinberg drew from his experiment are quite clear: the tracks present in the local structure, regarding the existence of long-distance connections, are those that provide crucial information for finding the right paths within the network (ibid., 167 and 170).

Should these tracks disappear, searching would be impossible: the actors would find themselves immersed in a huge throng of social relations, too homogeneous with one another to be distinguishable. This would lead to disorientation and the inability to identify which local acquaintances could point them in the right direction. The key factor in the whole argument was that the *various identities of the actors defined both the map and the compass required to* *navigate social networks*. They provided, for example, essential information about the distances present in interpersonal relationships, and the ability of some links to overcome the barriers that keep other social worlds separate. Two points should be emphasised:

1 The distances that separate these worlds – though very different from each other (it may be a matter of geography, income, professionalism, religion, education, race, etc.) – are however all intrinsically social: they are connected to relationships between individuals and the morphology of the social structure.
2 The identities of the nodes make social networks explorable, so that *searchability* is a specific property of these networks (Watts *et al*. 2002).

Banal as it may seem, the 'discovery' prompted by Kleinberg's observations is that *social networks* are composed of nodes equipped with *social identities*. The latter also structure their networks according to the sociological principle of homophily (Lazarsfeld and Merton 1954), which leads individuals to associate mainly with other people who share similar characteristics. As has been said, 'similarity generates connection', with the result that social networks tend to be homogeneous with respect to different characteristics (McPherson *et al*. 2001).[20] This principle of homophily restricts the individual's social world, limiting their interactions to a circle of 'similars', thus reducing the amount of information they can receive and the experiences they can encounter. That said, these small worlds of 'similars' are also layered and interconnected, allowing windows to open on different worlds. Identities and social interactions are indeed multi-dimensional and this makes it possible to navigate through a variety of contexts, exceeding even large distances. This dual profile of social identities, therefore, moulds the networks according to two principles which act in opposite directions: (1) *homophily* renders local worlds small, following a criterion of homogeneity; (2) *multi-dimensionality*, however, renders the global world small, making it possible to cross the boundaries of local worlds. In conclusion, *the distinctive feature of social networks is that they are composed of actors who deliberately use and manipulate their relationships and this feature conditions the properties that the social networks deploy*.

As Watts himself noted, in a scientific field increasingly dominated by physicists, mathematical simulations and computer algorithms, it is a significant step forward:

> [W]hile there's nothing wrong with simple models, for any complex reality there are many such models, and only by thinking deeply about the way the world works – only by thinking like sociologists *as well as* like mathematicians – can we pick the right one.
>
> (Watts, 2004a, 156)

It is precisely this return to sociological detail that gives these models – the small-world and scale-invariant networks – their interest for the social sciences.

Following the 'sociological track', it may be observed how studies based on the small-world approach are prevalently directed towards two main aspects: the phenomena of *diffusion* and *search* (Schnettler 2009b). The former relates to the events of infection (e.g. viruses and diseases) or the spread of phenomena of various kinds (e.g. innovation) through the relations between social actors. The second concerns the exploration of social networks through the use of intermediaries and research aimed at the transmission or retrieval of useful resources for those involved. In both cases these are matters of extreme importance for Innovation Studies. Many of Watts' observations on affiliation networks (applied to *interlock directorates* and scientific collaborations), on models of threshold decisions and cascade phenomena (applied to the phenomena of social contagion and diffusion of innovation), and the robustness of multi-scale organisational networks (applied to information exchange and problem-solving processes in situations of radical uncertainty requiring distributed innovative capacity),[21] indicate some of the possible applications to innovative processes. I will look at some of these in the following sections.

4.5 Affiliation networks

Affiliation networks – often referred to as bimodal or bipartite networks – consist of a set of nodes/actors and the events associated with them.[22] Applied to social phenomena, this means that they describe events associated with groups of actors, rather than simple links between pairs of individuals, and this makes it possible to analyse them from a dual perspective: that of the actors, and that of groups. Two social actors define themselves as affiliates when they belong to the same group. Two technicians working on an innovative project on behalf of a company; two inventors who patent a discovery together; two university researchers who publish an article as co-authors – these are all good examples of affiliation networks relevant for innovation processes.

These types of partnership, as suggested by research conducted by Mark Newman – a physicist at the University of Michigan – are often structured as small-world networks. Newman examined the collaborations between scientists, using co-authorships of articles and scientific papers as his basis. For the analysis he made use of a plurality of databases containing information about millions of articles and authors: an electronic archive of research contributions in the field of physics (LANL e-Print Archive); an archive on research in the field of biology and medicine (MEDLINE) and two minor archives relating to physics (SPIRES) and computer science (NCSTRL). The analysis of this huge amount of data confirmed the importance of small-world networks in scientific collaborations (Newman 2001a, 2001b, 2001c).

Despite the strong sectoral specialisation that characterises these particular professional areas – which might suggest the existence of researchers isolated from each other or otherwise segregated in small groups – the scientific communities show a high level of connectivity. Differences in the various scientific sectors do emerge from the study – with regard to the average number of collaborations, the clustering coefficient, and average distance – and yet the variations in the end are far from extensive. In all areas the vast majority of scientists are gathered into one 'giant component', within which distances are relatively limited. With regard to the two major archives (LANL and MEDLINE), it takes on average only four or five intermediaries to get in touch with any other component of the scientific community. In other words, each researcher can be reached by means of fairly short *chains of scientific collaboration*. Similar results were also achieved in the fields of mathematics and economics. In the former case, articles published jointly by more than 71,000 researchers between 1991–98 were analysed (Barabási 2002); while the latter involved articles co-published by more than 160,000 economists between 1970–2000 (Goyal *et al*. 2006). In all cases the various scientific communities present themselves as one small-world.

The same reasoning applies to a different type of affiliation network, one often studied in the field of economic sociology: *interlocking directorates*. The intersecting presence of managers on the boards of directors of different firms – something that has characterised American capitalism since the beginning of the twentieth century (Mizruchi 1982) – has been studied to analyse the coordinating modalities of economic activities in both manufacturing companies and financial and credit bodies. Cross-shareholding and positions, and mechanisms of co-optation and interpersonal relationships between corporate executives (managers or other representatives), constitute modes of regulation of company relationships – which go far beyond the rules of the market (Chiesi 1978, 1982; Burt 1979, 1983; Mintz and Schwartz 1985; Scott 1986; Mizruchi 1996).

Co-presence on the same board, for example, is a circulation channel of the changes introduced in organisational structures, managerial practices and business strategies – thus fostering innovation based both on contamination between different ideas and organisational isomorphism: the diffusion-imitation of the same innovations. In this respect, it represents a powerful coordination and transformation mechanism for large American companies. But how does this mechanism work? Is it an intentionally planned or spontaneous kind of phenomenon? Which actors and which institutions play a central role?

Studies conducted on the largest companies in the US across different historical periods – from the beginning of the twentieth century until the seventies – show a strong concentration and interconnection of business structures. Corporate board interlock networks rendered each component of the American managerial élite reachable in just a few steps: between four and five, depending on the study (Davis *et al*. 2003, 302ff.). Moreover, at least until the beginning of the eighties, the country's major commercial banks (such as J. P. Morgan and Chase Manhattan, which then merged in 2000) played a central role in the connectivity of this *corporate élite* (Mintz and Schwartz 1985). Given the need to monitor the companies they were financing, banks packed their own boards of directors with managers from the major companies dotted around the country. This tended to create reciprocal synergies: the banks obtained crucial knowledge about the strength and strategies of the companies (their clients), thus guaranteeing their investments; while managers were assured privileged access to the credit system and could influence decision-making. For several decades, therefore, commercial banks represented the 'stable core of the interlock network' (Davis *et al*. 2003, 309).

After the eighties, however, this world of stability began to crumble: banks progressively lost their central role as the panorama of the major American companies went through changes. With the growth of internationalisation, the criteria for recruitment and management practices of the élite were also modified: mechanisms of corporate governance were increasingly directed towards shareholders. With the emergence of so-called *shareholder capitalism*, the boards of directors grew smaller in size (on average), thus becoming less interconnected with each other and comprising a smaller number of internal managers. Managers were paid in company shares and subjected to greater demands (including monitoring by institutional investors): the increased responsibilities associated with these tasks made it less possible for them to serve contemporaneously on an array of boards.

How, then, following these developments, did the integration of the American business élite, and the connectivity ensured by interlocking directorates, change? To answer these questions, three University of Michigan sociologists studied the composition of the boards of major American companies in the industrial, financial, services and communications sectors, across three distinct phases: 1982, 1990 and 1999 (Davis *et al*. 2003). The hypothesis they intended to test – using the Watts and Strogatz method – was the presence of small-world networks: in other words, the presence of (1) small worlds highly integrated at a local level, but also (2) well-interconnected to each other. The results of the analysis showed that despite all the changes that had occurred in corporate governance, both at the beginning and at the end of the three periods analysed, the American business élite (which ranged from between 5,300 to 6,500 people) was in effect a small-world, combining high levels of local integration and low mutual distance.[23]

This was the case despite the great demographic change recorded during the three periods. In fact, less than one-third of the companies present in 1999 were also present in 1982. For managers, this presence fell to 5 per cent, and for relationships between companies to 2 per cent. Even the ten central companies in the network were different.[24] In 1982, nine were commercial banks, but in the nineties their presence was reduced to three.

This data shows that the overall morphology of the network and its properties do not depend on specific managers or companies, or on the continuity of inter-organisational ties or the type of institutions that are at the centre (as, for instance, commercial banks). The high level of integration of the American business élite is an emergent property of the (small-world) network, which does not require any particular intentional design, or any centralised planning authority or group that facilitates coordination among the actors (ibid., 313). Network connectivity is especially stable over time, surviving even if certain principal nodes are lost. The authors, in fact, show that even by removing the central actors, the overall connectivity of the network is not weakened and the average distances do not grow to any great extent.

The same results also emerge in the analysis carried out by Bruce Kogut and Gordon Walker (2001) into shareholding and acquisitions by major German companies between 1993–97. The research highlights the particular stability (and German nationality) of the ownership structure, despite the ongoing processes of globalisation. Small-world networks, therefore, are particularly robust and resistant to change, and this attribute does not depend on the existence of specific hubs – as indicated in the scale-invariant networks highlighted by Barabási – but rather on the overall properties of the network. In this case, moreover, what is worth emphasising is that given the frequency of relations between the components of the business élite – many of whom meet at board meetings every month – interlocking directorates represent a particularly relevant mechanism of diffusion of innovation (Davis *et al*. 2003, 322).

4.6 The musicals industry

What is the relationship between small-world networks and innovative capacity? This is an issue addressed by Brian Uzzi and Jarrett Spiro (2005) in their study of the world of artistic creativity. The idea they take as their point of departure is that creativity and innovation are stimulated by a combination of different ideas, or by contamination between various artistic fields. Creative tension, moreover, derives not from the solitary efforts of lone individuals but from a system of social relations. The question that the two authors ask is whether the dual characteristic of small-world networks – that is, the fact of being highly clustered at a local level, but also strongly connected globally – does or does not influence creative performance. As they rightly point out, reflection on this kind of network is mostly limited to the classification of events, or to verify if it is traceable in the real world. Few studies correlate the structural properties of these networks with their performance.

Networks affect the behaviour of actors, influencing the connection and cohesion of their 'relational world'. In this respect, the high level of connectivity of small-world networks makes it possible to establish contact between a larger number of subjects, allowing information to circulate through the various clusters of relationships. Cohesion, however, creates a basis for trust and reputation, so that material coming from a particular cluster acquires credibility and value in different environments. Uzzi and Spiro tested these hypotheses starting with the Broadway musical industry. The data examined included information on more than 2,000 people who worked on 474 original musicals produced between 1945–89. The core team of a musical is made up of six figures: composer, lyricist, librettist (who writes the plot of the story), choreographer, director (who facilitates collaboration between the team members) and producer (who guarantees financial backing). Their collaboration begins when one or more of the artists create new material and involve others in the team. Intense group work is thus initiated – fusional in nature – which requires the sharing of ideas and the resolution of common problems. This teamwork generates great emotional and creative tension, which tends to cement strong collective ties (and here it is worth recalling Durkheim's remarks on 'collective effervescence', mentioned in Chapter 1). Once completed, if the musical manages to pass the test of the preview shows, then it is launched to market as a 'Broadway musical'. Commercial success is defined by takings at the box office, while artistic worth is determined by the judgement of the critics. Success is due in large measure to the originality of the new product, which, in turn, depends on two factors: the accessibility and diversity of the artistic material available to the team, and the perception that the new experimentations do not carry excessive risk. Both of these factors increase the creativity of artists and the chance of producing a 'hit' musical.

The creative material is rooted in conventions that provide the rules around which artists can fruitfully collaborate, while also allowing them to predict the reactions of the public and the critics. Original artists are able to tailor such conventions to their own requirements – creating a personal style and introducing innovations which, once they have become popular and imitated, themselves become part of the conventional artistic fabric. Innovation depends on the availability of the 'uncommon' creative materials that arise from collaborations with other artists. This new material expands the range of creative opportunities: it generates a reservoir of possible variations from which the team can draw to develop their own original product. A successful show is based on a combination of convention and innovative material. Without the first – shared standards – the product would be incomprehensible; while without the latter it would be boring and repetitive.

Groups of artists who collaborate closely and repeatedly with one another over time (local clusters) share the same artistic repertoire. In contrast, the bridge-links that are established between different clusters – by virtue of the relationships between certain artists – produce a double positive effect: on the one hand making it possible for a variety of conventions to come into contact, and on the other facilitating the validation of new material. The reputation of the new artists – made familiar through previous collaborations or through third parties – mitigates any risk associated with the testing of unfamiliar artistic material. Small-world networks constitute an ideal environment for this particularly felicitous union to be achieved: i.e. high levels of local cluster integration and low reciprocal distance. To illustrate the conformation of the Broadway musical network at different times, Uzzi and Spiro developed a *small-world quotient* (Q) whose values increased with the network's increasing connectivity and cohesion.[25] In bipartite affiliation networks – such as the musical team – the small-world effect influences actors through two distinct mechanisms: (1) *structurally*, through the relationships between the various clusters that facilitate the circulation of non-redundant information; and (2) *relationally*, through the cohesion-increasing links between actors. The effect induced by small-world networks, in fact, is not only to create bridge-links in order to overcome structural holes, but also to generate the necessary confidence so that innovators will take on the risks posed by new experimentations.

What Uzzi and Spiro succeeded in demonstrating empirically was that, as the mix of local cohesion and global connectivity changed, so creative performance changed as well. The relationship identified was not, however, a linear one: instead, it followed an inverted U function. Low values of Q (*small-world quotient*) were associated with poor performance, since weak network connectivity was not able to foster the circulation and validation of creative material. With higher Q values, the performance of the creative team and the success of the show improved, but only up to a certain threshold: above this, the performance tended to deteriorate again. Too high a level of global network connectivity and cohesion, in fact, tended to result in an excessive reduction of differences, thereby standardising conventions. In other words, Q values that were either too low or too high generated opposite problems: on the one hand an *excess of variety* in artistic products on the network (which did not circulate or were unusable); on the other, an *excess of homogeneity* (which reduced the range of variations available).

The best results, therefore, were at intermediate levels of the small-world quotient. A similar argument had already been made by Uzzi while analysing embeddedness effects on the performance of companies in the clothing and credit industries. Uzzi (1999, 500) placed particular emphasis on the importance of *network complementarity*: i.e. the need to mix socially rooted economic relations (*embedded ties*), with market relations (*arm's length ties*). This allowed companies to balance two types of benefit. The first type of tie prevented opportunistic behaviour and facilitated complex and reliable knowledge. The second type favoured the acquisition of new information and adaptation to stimuli coming from the market and the environment. For these reasons, companies that use a mix of both ties (*integrated networks*) perform better than those who only use market relationships (*under-embedded networks*) or economic relations that are overly influenced by personal ties (*over-embedded networks*) (Uzzi 1997, 59–60).

4.7 Strategic alliances and patent partnerships

In recent years, research on small-world networks has been extended to a number of economic phenomena. The presence of these networks has been reported in various areas of activity: agreements between investment banks (Baum *et al.* 2003); collaborations between companies in the fields of research and technology transfer (Verspagen and Duysters 2004; Schilling and Phelps 2007); and partnerships between inventors (Fleming *et al.* 2007). Several studies have emphasised their efficiency in terms of information flow, as well as the transfer and increase in level of knowledge (Cowan and Jonard 2003, 516 and 525; Verspagen and Duysters 2004, 570). In particular, small-world networks appear to positively influence the innovative capacity of companies through mechanisms similar to those identified for the artists of the Broadway musical. This is what emerges from a study conducted by Melissa Schilling and Corey Phelps (2007) on strategic alliances formed in the period 1990–2000 by more than 1,000 US firms operating in 11 high-tech sectors. Strategic alliances are widely regarded as an effective mechanism for knowledge-sharing between different organisations, and for facilitatating the production of innovative solutions (Freeman 1991; Gulati 1998; Powell, Koput and Smith-Doerr 1996). Schilling and Phelps conceptualise innovation as a recombinatory problem-solving process: the search for new solutions is often based on a creative combination of elements that are already partially known. In this respect, small-world networks delineate a favourable structure of innovative opportunity. High levels of local clustering do, in fact, improve the *capacity for information transmission* between companies, as well as generating the conditions of trust for knowledge-sharing and joint research into solutions. The presence, however, of *bridging ties* (which combine several local clusters), facilitates the circulation of non-redundant information between the various clusters, thus expanding the range of recombination possibilities available to the companies.

Research data confirms the hypothesis. First, strategic alliances are strongly clustered: companies tend to ally themselves with other companies which are in turn united by cooperation agreements. Moreover, in industrial areas where low distances exist between clusters – that is, where there is a small-world effect– the innovative capacity of the companies increases (when measured by the production of new patents in the years following the alliance).[26] In other words, Schilling and Phelps highlight the influence of the overall structure of the network present in various industrial sectors on the performance of individual companies.

The same effects are identified (by other scholars) in partnerships between inventors. Research work carried out in small teams fosters trust, as well as the sharing of ideas and a collective approach to problem-solving that enhances researcher creativity – especially in the development and diffusion phases of inventions. Excessive cohesion in such teams, on the other hand, hinders the circulation of non-redundant knowledge and the production of original ideas, and instead favours group conformity (*groupthink*).[27] Bridging ties avoid the problem, however – improving the inventors' *generative creativity* (Fleming *et al*. 2007, 458). At an individual level, therefore, small-world networks induce a 'virtuous and self-reinforcing cycle of creativity' (Fleming and Marx 2006, 11).

At a more aggregated, meso-style, level of analysis, the relationship is rather less evident. Lee Fleming, Charles King and Adam Juda (2007) find weak empirical support for the hypothesis of the positive influence of small-world networks on patent innovation at a regional level. The three academics analysed the collaborations between more than two million US inventors in the period 1975–2002, and from this data reconstructed the patent partnerships in 337 metropolitan areas.[28] The results of the analysis revealed a progressive 'narrowing' of the networks: a growing trend towards the aggregation of regional networks of inventors which increasingly took on a small-world configuration. As already mentioned, the inventors work in small, highly integrated research teams and this does not significantly change during the periods analysed in the study – the average level of local cluster cohesion remains fairly unaltered. Instead, what *does* change is global network connectivity: the average distances, in fact, decrease over time, and a growing percentage of inventors is included in the 'main component' of the regional network.[29] This is due to the growth of professional mobility and inter-organisational alliances, as well as the continuity of relationships between inventors who have worked together on the same patents. In particular, diachronic analysis shows the full development of a small-world network – first in Silicon Valley, and then in the Boston area (ibid.; Fleming *et al.* 2004). The analysis conducted in the 300 metropolitan areas, however, shows no statistically significant relationship between the small-world structure of collaborations between inventors and patent productivity at a regional level. What does tend to influence innovative activity is the network's degree of connectivity and the size of its main component: in other words, the reduction of the distances between the inventors, and their increasing integration into a fully connected regional network (Fleming *et al*. 2007, 949–51).

4.8 The Silicon Valley hubs

The new science of networks – often referred to as *complex network theory* – was also used by Michel Ferrary and Mark Granovetter (2009) to analyse a particularly well-known innovative cluster: Silicon Valley. The two scholars make a distinction between this type of cluster and the industrial type, characterised mainly by an incremental form of innovation within the prevalent specialisation. Innovative clusters, in contrast, are notable for their ability to radically reconfigure their value chain through *breakthrough innovation* that creates new industrial sectors (ibid., 328). In particular, the competitive advantage of these clusters lies in the continuous generation of cutting-edge start-ups. Innovation, however, is not produced by individual companies but by the entire local system: it derives from the interaction of a variety of actors rooted in a complex network of social relations. For these reasons, Ferrary and Granovetter believe that the new science of networks can make a significant contribution to the analysis of innovative clusters.

Complex networks possess certain distinctive features. First, they are composed of a plurality of nodes that interact without any form of hierarchical coordination. Second, the relational structure and the emerging modalities of coordination influence the efficiency of the actors. Their performance does not depend solely on individually possessed resources and skills but also on their modes of interaction with their surrounding environment. There exists, in other words, a systemic interdependence between the nodes and the network, and the survival capacity of both depends on the variety of the first and the connectivity of the second. Another distinctive feature of complex networks is their robustness – their resistance to external perturbations. Robustness does not mean the stability of the network, but rather its ability to reconfigure itself in the face of radical challenges that threaten its survival. This resistance comes from the *completeness* of the network, within which, in a decentralised manner, a plurality of heterogeneous actors interact: this makes it possible to integrate different modes of learning, stimulating the creativity and innovation of the system.

Ferrary and Granovetter present Silicon Valley as a paradigmatic case of an innovative cluster based on a complex network. It is a territory, in fact, where a wide range of socio-economic actors interact: not just businesses, universities and research laboratories, but also law and consultancy firms, investment and commercial banks, finance companies, service and recruitment agencies, and so forth. A dense network of relationships is formed, in which organisational and economic links are mixed with personal and social relations (*multiplex ties*). The innovative dynamism of this area also depends on the *completeness* of its network, which includes heterogeneous but complementary actors.

According to Ferrary and Granovetter, other areas with significant innovative resources under-perform due to the inferior completeness of their networks. Silicon Valley itself was formed historically through successive layers, with the addition of a variety of actors who have strengthened the relationship system. The presence of a prestigious university such as Stanford, the emergence of companies like Hewlett Packard, and the arrival of large external companies such as General Electric, IBM and Lockheed during the thirties, were not sufficient in themselves to render this area highly innovative. Only later, in fact, were other essential pieces of the puzzle added: private research laboratories (Stanford Research Institute in 1946 and Xerox PARC in 1970); the first investment banks in the late sixties; the birth of the large venture capital companies in the seventies; and the development of firms specialising in legal assistance to high-tech companies in the eighties. Only in the late fifties and early sixties, with the birth of the semiconductor industry, did Silicon Valley become an innovative cluster – something that would continue to evolve and grow with the completion of its network. The complexity of the network gives the system its special ability to alter organisational architecture and areas of specialisation through major innovation. The area, in fact, was given its initial boost through semiconductors (with companies such as Fairchild Semi-conductor, Intel etc.) but subsequently went on to specialise in personal computers (Apple), software (Oracle, Sun Microsystems, Symantec, etc.), telecommunication systems (Cisco System, Jupiter Networks, 3Com), and the internet (Netscape, Excite, eBay, Yahoo!, Google).

As we have seen, certain actors in complex networks can play the role of a hub (Barabási 2002). In Silicon Valley, venture capital firms (VCs) fulfil this function, investing venture capital in the most promising local start-ups. This strong VC presence distinguishes this area from many other technological districts. In 2006, 180 of the USA's 650 VCs had their headquarters in Silicon Valley. Between 1995–2005, investments directed towards the Californian VC cluster amounted to about one-third of the total of those made in the US and Europe.

The presence of these investment companies improves the innovative capacity and the overall robustness of Silicon Valley, and carries out five specific functions. The first, and most famous, is the *financing* of technological start-ups. The second is *selecting* them. The VCs fund a small part of the Valley's start-ups – about 9 per cent of the more than 2,000 new companies that are created every year. However, almost all of those that have been successful have received support from the VC: in 2006 as many as 28 of the 30 largest high-tech companies in the area fell within this category. The VCs' high level of competence in the leading sectors of the Californian cluster allows them to identify the most promising entrepreneurial projects, fostering their survival before market mechanisms come into operation. This links to the third function, which is that of *signalling* the best start-up: the fact of being funded by a VC, especially one of the more established ones, produces a ripple effect of accreditation in relation to other actors in the system – which in turn facilitates the subsequent development of new businesses. The fourth function is the *embedding* of new companies – the activation of the VCs' own relationships in order to facilitate the entry of start-ups into the network as a whole. From this point of view, the VCs – by performing activities of integration and coordination in the regional network – are one of the main hubs of Silicon Valley. The fifth function, finally, concerns *collective learning* – the accumulation of entrepreneurial knowledge and experience that is made available to new businesses.

Concluding, the use of the new science of networks allows Ferrary and Granovetter to focus on the interdependence between the performance of individual actors, and that of the overall network. As they point out, the theoretical contribution provided by their study is to highlight the relevance of the actors in the system. To explain the emergent properties of networks, complex network theory tends to focus on the structure of the links rather than on the nature of the nodes. As we have already observed, however, in social networks the identity of the actors is important. In Silicon Valley, for example, the specific characteristics of the VC determine their centrality in the network and condition the performance of the entire system. This, by implication, also draws attention to the role of the institutional and regulatory systems within which the actors operate. The modalities of the regulation of the financial market and of the contractual relations present in the US, together with the specific cultural climate of Silicon

Box 4 Self-study prompts

1. What is meant by the small-world phenomenon?
2. How were Stanley Milgram's experiments conducted and what did they show?
3. What are the essential characteristics of the small-world networks analysed by Watts and Strogatz?
4. What are scale-invariant networks and what role do the hubs play?
5. Is it possible to apply a sociological approach to the study of complex networks?
6. What is shown by empirical research on affiliation networks?
7. Do small worlds of creativity and innovation exist? What examples can be found in scientific research?
8. What role is played by venture capital firms in Silicon Valley?

Valley, are essential ingredients for an understanding not only of the identity of the actors but also of the modes in which they interact. This consideration therefore paves the way for the empirical and comparative analysis of complex networks, taking into greater account not only the actors and their ability to intentionally manipulate the networks, but also the role of institutions in shaping the context of interaction. While this research perspective inevitably introduces greater elements of contingency into the theory of complex networks, it also opens up more space to the contribution of the new economic sociology and comparative political economy.

Notes

1 This same idea – slightly modified – was divulged to a far larger audience by John Guare's play *Six Degrees of Separation*, which was then made into the eponymous film directed by Fred Schepisi. One of the play's characters comes out with the statement that has popularised the phenomenon: 'I read somewhere that everybody on this planet is separated by only six other people. Six degrees of separation. Between us and everybody else on this planet. The president of the United States. A gondolier in Venice. Fill in the names.… It's not just big names. It's anyone. A native in a rain forest. A Tierra del Fuegan. An Eskimo.… How every person is a new door, opening up into other worlds. Six degrees of separation between me and everyone else on this planet' (Guare 1994).

2 For a definition of the cluster concept in terms of graph theory, see note 11 below.

3 According to the classical definition of probability, the chance of an event, X, occurring (e.g. that two UK citizens chosen at random will know each other) is given by the ratio between the number of favourable cases (the average number of acquaintances, which we have arbitrarily set as 1,000) and the number of possible cases (64 million inhabitants) – provided that all the latter are equiprobable. With the number of favourable cases defined as n, and N the number of possible cases, the probability of X is the following: $P(X) = n/N = 1{,}000/64{,}000{,}000 = 1/64{,}000$.

4 Even drastically reducing the average number of acquaintances – to 100 units, for example – does not change the result much: three intermediaries are required to reach any UK citizen, rising to four to reach any inhabitant of the earth.

5 The data was collected by Michael Gurevitch as part of his PhD thesis (1961).

6 In statistics, the median represents the value that occupies the middle position in the orderly distribution of the values of a variable. In other words, it is the value that divides the frequency distribution in half. The mode, on the other hand, is the value with the maximum frequency of occurrence.

7 In computer networks, a hub is a device that operates as the sorting node of a data communication network. Think of the airport structure of a country or continent, where many small airports are linked to a few large airports (hubs) from which aircraft fly all over the world. Through simple local flights, from a small airport to a large regional hub, the inhabitants of any provincial city can move around on a global scale, with one or more simple changes.

8 Outside the experimental context, the small-world hypothesis has also recently been tested using Messenger, the instant messaging system from Microsoft. The dataset realised (30 billion conversations between 240 million people) made it possible to analyse a massive social network made up of 180 million nodes and 1.3 billion links. One of the results of the analysis was that the average length of paths between individual Messenger users was 6.6 (Leskovec and Horvitz 2007).

9 For an introduction to the concepts and terminology of graph theory and its applications to social networks, see Chiesi (1999) and Wasserman and Faust (1994).

10 In graph theory, the degree of node A is given by A's number of links with other nodes. In a graph composed, say, of a number of nodes (n) equal to 10, its value can fluctuate between 0, in the case of an isolated node – and 9 ($n-1$), in the case of a node connected to all the others.

11 This term is used as it is in physics (Watts 2004b, 244, note 1) – in other words, as a crystalline lattice whose constitutive components (atoms, etc.) possess a geometrically regular arrangement in all three spatial dimensions.

12 A cluster can be defined as an area of the graph with a relatively high density (Scott 1991). The density, in turn, is given by the proportion of effective links (k) with respect to the maximum number of links possible, given the numerosity (n) of the nodes. The number of possible links is calculated as follows: $n*(n-1)/2$. The formula for the calculation of density, therefore, is as follows: $k/(n*(n-1)/2)$. The values range between 0 (all nodes are isolated) and 1 (all nodes are linked).

13 A *walk* 'is a sequence of nodes and lines, starting and ending with nodes, in which each node is incident with the lines following and preceding it in the sequence'. Its length is given by the number of lines of which it is composed. A *path* 'is a walk in which all nodes and all lines are distinct'; that is, where the same nodes and lines can appear only once within a sequence. The geodesic distance is the shortest path between two nodes (Wasserman and Faust 1994, pos. 2976 ff.; Chiesi 1999, 87–8).

14 In formal terms, L (p) represents the average geodesic distance between all nodes, while the coefficient C (p) represents the average density of relationships between neighbouring nodes at each point of the graph.

15 According to Thomson Reuters' *Essential Science Indicators*, Barabási and Albert's article in *Science* was, in 2008, the fifth most cited in the field of physics. Between the year of its publication and 2009, the item received 4,363 citations (source: ISI Web of Science). The article in *Nature*, however, peaked at 1,076. By comparison, and in the same period, the article by Watts and Strogatz received 4,082 citations.

16 This is what computer scientists call a crawler (or 'spider' or robot/'bot'): a program that is able to perform automatic and recursive searches on the contents of a network. The software is similar to that used by search engines (Google, Yahoo!, Live Search, Ask.com, etc.) to explore the web.

17 The formula used is as follows: $d=0.35+2.06 \log (N)$.

18 I use the term 'contingent' with reference to events whose occurrence does not depend on a fixed and necessary causal connection, but rather is related to certain situations and circumstances.

19 If the program could draw on the 'global knowledge' of all the connections present in the network, the shortest chain would very easily be discovered.

20 Duncan J. Watts recently carried out a survey on the principle of homophily from data collected on more than 30,000 students at a large American university and their email exchanges (Kossinets and Watts 2009). The study focuses on the formation of ties between students, with two factors kept distinct: the effects arising from 'choice homophily' – connected to individual preference – and those arising from 'induced homophily', which derives from the structural opportunity for interaction – connected simply to living in the same neighbourhood, working in the same organisation, attending the same school, etc. Regarding this distinction, see also McPherson and Smith-Lovin (1987, 371).

21 On this theme, from an organisational perspective, see the study carried out by Peter Sheridan Dodds, Duncan J. Watts and Charles F. Sabel (2003).

22 For an introduction to affiliation networks, see Wasserman and Faust (1994, Chapter 8).

23 The average geodesic distance remains stable across all three periods and is fairly limited: for companies, it is around 3.4, and for managers, 4.3.

24 These are the ten companies that in over the three periods demonstrate the highest values of 'betweenness centrality' – defined as the number of times a node appears in

the shortest geodesic distance between all possible pairs of network nodes (Wasserman and Faust 1997; Davis *et al*. 2003, 318).

25 Simplifying slightly, it can be said that the lower the geodesic distances between the actors, and the greater the density of the network, the more the small-world quotient increases. The latter takes the form of a ratio of ratios: CC_{ratio}/PL_{ratio}. The denominator shows the average length of the path (PL) or the average number of intermediaries between all the pairs of actors in the network. The numerator shows the clustering coefficient (CC), which measures the average fraction of the collaborators of an actor who in turn collaborate with one another. Following the model suggested by Watts (1999) – and as modified by Newman, Strogatz and Watts (2001) to adapt it to bipartite affiliation networks – the values of these two network parameters are compared to those of a random graph of the same size. PL_{ratio} values close to 1 indicate low levels of separation between the global network actors. CC_{ratio} values greater than 1 indicate two things: (1) that an increasing number of links connect the various teams to one another (*between-team clustering*); (2) that these cross-team links are increasingly composed of artists who have collaborated in the past or who have mutual acquaintances.

26 Patents are considered a strong indicator – albeit proxy in nature – of the generation of inventions and new knowledge (Basberg 1987; Trajtenberg 1987).

27 The term *groupthink* was used by social psychologist Irving Janis (1972, 9) with reference to the making of wrong collective decisions due to the presence of group dynamics that reduce individual capacity for reasoning and problem analysis. The term refers to the way of thinking prevalent within a strongly cohesive *ingroup*: a closed and homogeneous collective composed of subjects with the same background and isolated from outside opinions. In such a context the tendency to maintain consensus and avoid conflict with the other members of the group leads to the ignoring of differences of opinion and a lack of evaluation of alternative courses of action.

28 A unit of statistical measurement used in the US, which refers to metropolitan labour markets. The *metropolitan statistical areas* include high levels of population, distributed throughout several urban centres that revolve around a big city and have high levels of social and economic integration.

29 The main component of a disconnected graph indicates the largest sub-graph: the part of the overall graph that includes the greatest number of nodes connected to one another.