Chapter 9
Propagation of Innovations in Complex Patterns of Interaction

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9.1 Introduction

In recent times the possibility of using the tools of statistical physics to analyze the rich dynamical behaviors observed in social, technological, and economical systems has attracted a lot of attention from the physics community (Arthur et al. 1997, Mantegna and Stanley 1999, Bouchaud and Potters 2000). So far, one of the main contributions to these fields has been the analysis of simple models that capture the basic features of the investigated phenomena. The goal is to identify the relevant parameters as well as the essential mechanisms governing their dynamics with the hope that this information will help us to understand the physical behavior of real complex systems. A real part of this effort has been devoted to the characterization of real networks, identifying their main features, and understanding how they arise (Watts and Strogatz 1998, Barabasi and Albert 1999, Strogatz 2001, Dorogovtsev and Mendes 2002, Albert and Barabasi 2002).

In particular, we tackle the problem of diffusion of innovations in a social network, and we try to understand how the stimulus for change spreads by gradual local interaction between the individual nodes (agents) forming the network. Most of the times these 'waves' of change come in terms of intermittent bursts separating relatively long periods of quiescence (Krugman 1996, Arenas et al. 2000).

There are two mechanisms involved in the diffusion of innovations that a mathematical model should take into account. On the one hand, there is a pressure for adopting a new technology coming from marketing campaigns and mass media (Guardiola 2001). These external processes are essentially independent of the social network structure and one can view their effects as a random independent process on the agents. On the other hand, one should take into account the effect of the surrounding agents who define the social network. Once an agent has decided to adopt a new technology, those who are in contact with him can evaluate the new payoff the agent has got by acquiring the new technology and compare it with the

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current benefits. This propagating mechanism stands for inter-agent communication processes. By balancing the payoff increment with the associated upgrading cost, they may decide to adopt, or not, the new technology.

In the first part of this contribution, we review some of the results obtained by our group in the last years concerning models of propagation of innovations within different frameworks. Most of this work was initiated in regular lattices, but the last attempts have taken into account that social environments are not well modeled by regular patterns of interactions but by heterogeneous ones. This has led us to investigate a practical case reported in the social sciences literature (Saxenian 1994), where not only the resistance of the agents to innovate is important, but also the structure of the social network plays a crucial role in the development of a more or less innovative society. To the description of this analysis, we devote the final part of the contribution.

9.2 The Model

Our starting point is a model of diffusion of innovations by imitation proposed in Guardiola et al. (2002) and also studied in Llas et al. (2003a). Although it is simple it displays a very rich collective behavior that can be related to well-known theories of self-organized criticality and its avalanche dynamics (Jensen 1998).

The dynamics of the model are implemented such that each site in the network (agent) is characterized by a real and continuous variable a_i. In a general way, we can consider this quantity as a characteristic of an agent that other agents might want to imitate. When an agent has adopted a new characteristic, her neighbors become aware of the change and balance their interest (quantified as a_i–a_j) with their resistance to change C to decide if they would like to imitate this change. In this way, C controls the mechanism of imitation and it is constant in time and the same for all the agents in the current scenario.

The dynamics can be summarized as follows:

- The system is asynchronously updated. At each time step a randomly selected agent updates her state a_i

$$a_i \rightarrow a_i + \Delta_i, \tag{9.1}$$

  where Δ_i is a random variable with mean λ.
- All agents $j \in \Gamma(i)$, where $\Gamma(i)$ is the set of neighbors of agent i, decide whether they want to upgrade or not, according to the following rule:

$$a_i - a_j > C \Rightarrow a_j = a_i. \tag{9.2}$$

- If any $j \in \Gamma(i)$ has decided to imitate, we also let her neighbors decide whether they want to imitate this behavior or not. In this way, the information of an update may spread beyond the first neighbors of the originally perturbed site.

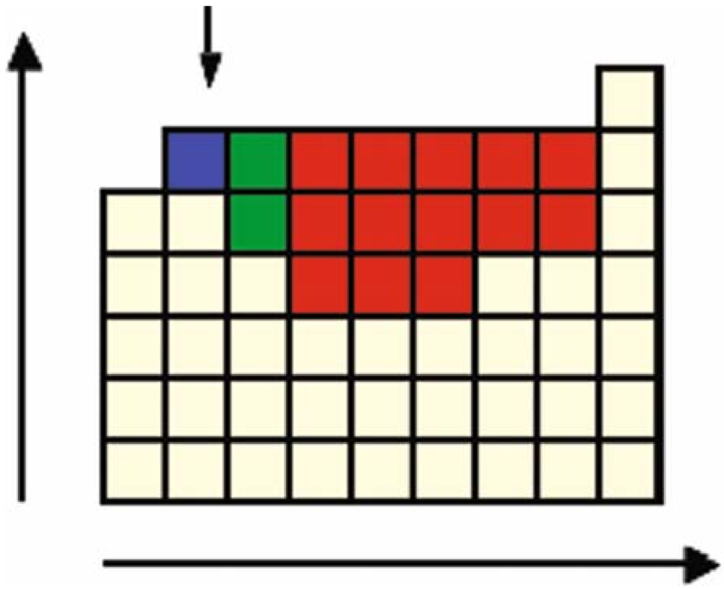

Fig. 9.1 Schematic representation of the dynamical rules in a one-dimensional system with a cost $C = 1$. Initially, the state of the system corresponds to the *white area*. The agent where the *vertical arrow points* receives an external update. The agent at its right now is two units below it and decides to imitate. This generates an avalanche that involves most of the neighbors at the right, since any agent has at its given time a level that is below its left neighbor, corresponding to the *darker area*

This procedure is repeated until no more agents want to change, concluding an *avalanche* of imitation events. In this way, we have assumed that the time scale of the imitation process is much shorter than that corresponding to the external updates. In Fig. 9.1 we present schematically these dynamical rules.

9.3 Dynamical Regimes

According to the cost value C it is possible to distinguish several regimes. In Fig. 9.2, we can see the technology profile (the interface defined by technology of all the agents) of two extreme cases. For $C < 1$, once there is an external update, a system size avalanche is immediately triggered and all agents end up in a very close technological level, and the profile is hence very planar. For $C >> 1$, upgrading is so expensive that agents never care about their neighbors technology, and most avalanches are of size just 1. In this regime the profile, as seen in Fig. 9.2 (right), is quite rough.

In between these two regimes (see Fig. 9.3, left), there is a region showing a rich dynamics where one finds technological avalanches of all possible sizes. Actually, for some values of C the probability density of having an avalanche of size s shows a power-law behavior

$$P(s) \approx s^{-\tau}. \tag{9.3}$$

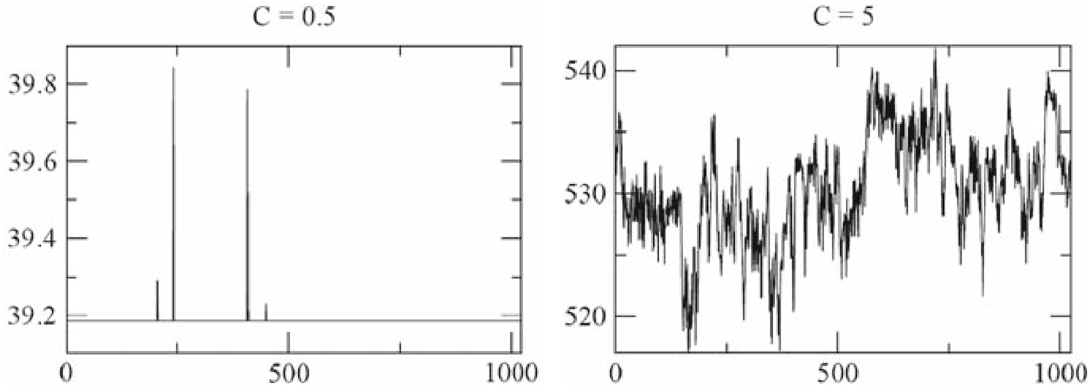

Fig. 9.2 Technological profile of a one-dimensional system in two extreme cases. *Left*: supercritical that corresponds to a dynamical state where avalanches are always very large. *Right*: subcritical, which corresponds to avalanches of unit size

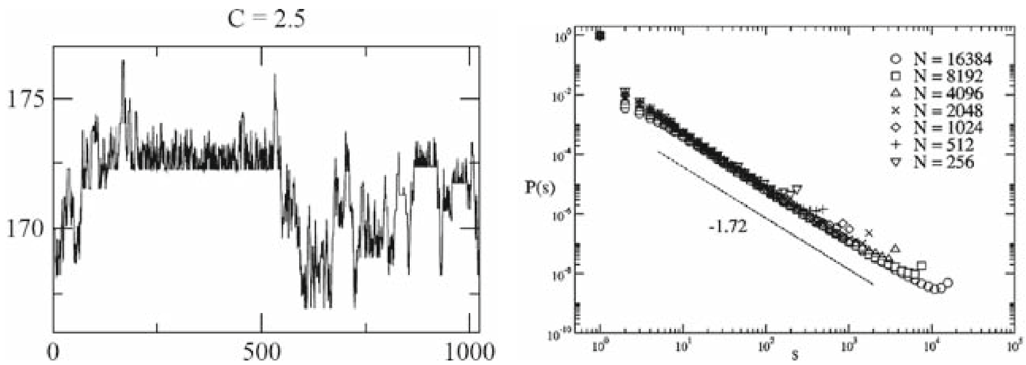

Fig. 9.3 *Left*: technological profile for the critical region. *Right*: probability density of having a technological avalanche of size s for $C = 3$ in a log–log scale

Figure 9.3 right shows $P(s)$ for several system sizes and $C = 3$ in a log–log scale. We can observe there a power-law distribution over four decades for the largest system size.

9.4 The Observables

9.4.1 Mean Rate of Progress

In the model introduced so far, we have considered that each individual adjustment elicits a certain cost. This cost is fixed and does not depend on the advanced technological level. In economic terms, an optimal situation would be one in which the system reaches a certain average global technological level with the minimum cost, that is, the minimum number of adjustments. According to such social perspective, the problem is to find the most advantageous regime of advance, leading to the largest global advance given a fixed cost.

For these reasons, it is convenient to define a macroscopic observable measuring the advance rate of the system. A useful magnitude for such purposes is the following:

$$\rho \equiv \lim_{T\to\infty} \rho(T) = \lim_{T\to\infty} \frac{\sum_{t=1}^{T} H(t)}{\sum_{t=1}^{T} s(t)}, \tag{9.4}$$

where $s(t)$ is the size of the avalanche occurring at time t, i.e., the number of agents whose technological level has been updated, and $H(t)$

$$H(t) = \sum_{i=1}^{N} [a_i(t) - a_i(t-1)] \tag{9.5}$$

is the total advance achieved during the same event (the interface area increment caused by an avalanche). According to the definition of the mean rate of progress, it is easy to see that for the two extreme cases its value is very small. For low cost C, any external update is followed by a large avalanche in which all agents advance the same amount, since the profile is extremely smooth, and hence ρ is equal to the mean value of the external update λ. On the other hand, for large C, all the avalanches are very small (most of them of size one) and hence the advance of the avalanche is equal to the mean value of the external update again. It is interesting to realize that for intermediate values of the cost, the system is optimal since it reaches a maximum for the mean rate of progress. In Fig. 9.4, we show several plots of ρ versus the cost, for several system sizes (Guardiola et al. 2002).

In previous works in similar models, it was shown that the system reaches its maximum mean rate of progress in a self-organized way (Arenas et al. 2000, 2000a). It is the result of the aggregated dynamics that the system reaches by itself its optimal outcome, for a constant and uniform value of the cost. In any case, we can say that there exists a certain value of the cost which, following the usual terminology in statistical physics (Stanley 1971), we will call the critical value, for which the technology profile grows more efficiently. This leads to the following paradoxical result: upgrading costs should be neither cheap nor expensive in order to have an optimal technological growth (Arenas et al. 2002). Obviously, our concept of efficiency is related to the number of times cost is paid, that is, from the point of view of the population, but not of the companies who sell the product. Sellers will always look for a scenario where agents acquire as many new products as often as possible (Guardiola 2001).

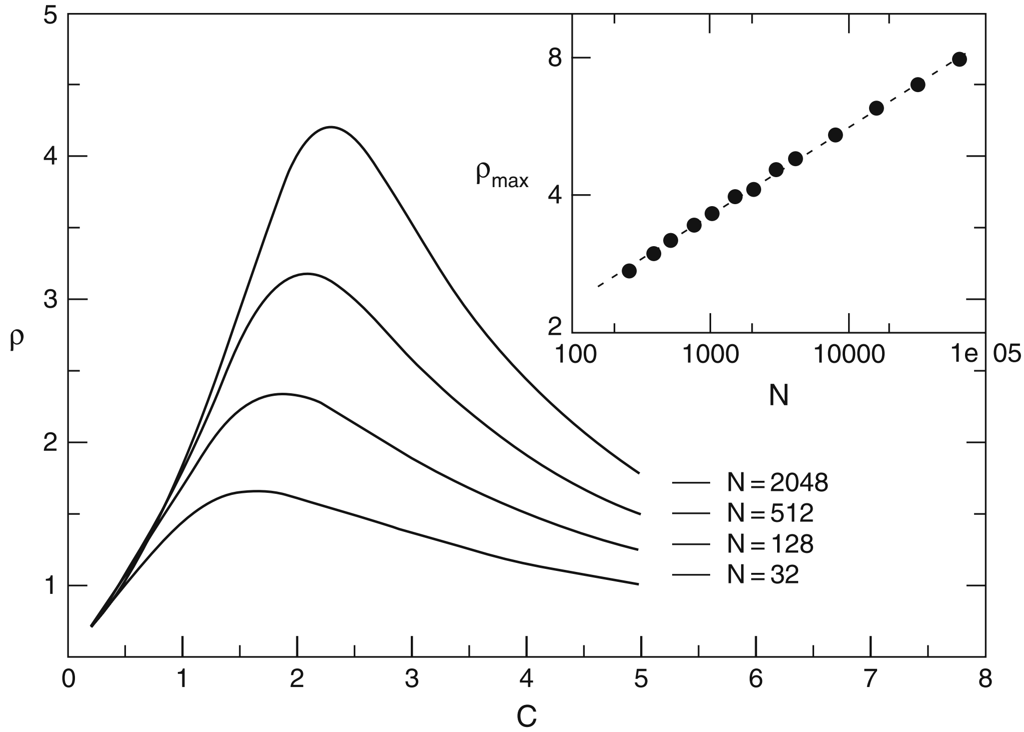

Fig. 9.4 Mean rate of progress as a function of the cost C for several system sizes. At the extremes, the value of ρ goes to the mean value of the update. There is a peak, $\rho_{\max}$, that diverges in the large system size limit. In the inset, we plot $\rho_{\max}$ against system size N. Dashed line shows $\rho_{\max} \approx N^{0.20}$

9.4.2 Profile Roughness

In the previous section, we showed several snapshots of the population technological profile. This profile corresponds to the continuous interface defined by the technological level a_i of all agents. We have also analyzed the technological profile from the point of view of the statistical mechanics of non-equilibrium growing interfaces (Barabasi and Stanley 1995).

The most straightforward way of giving a quantitative measure of the roughening of the interface is to look at the interface height fluctuations around its mean value. The interface width is defined by the variance of the technological profile

$$w(N,t) \equiv \sqrt{\frac{1}{N}\sum_{i=1}^{N}[a_i(t) - \overline{a(t)}]^2}, \tag{9.6}$$

where $\overline{a(t)}$ is the spatially averaged technological profile. From this definition one can define many different properties, as for instance how this interface width scales with time and with the system size, showing different scaling properties (Guardiola 2001). In terms of this scaling some anomalous properties have been found (Llas et al. 2003b, Llas et al. 2007).

9.5 Interplay Between Dynamics and Structure

Let us now put some attention to the influence of the connectivity pattern on the collective properties of the system and, in particular, in macroscopic observables such as ρ. There are two simple cases that have been systematically analyzed: a fully connected network and a regular lattice. In the globally coupled case, the information referent to any change elicited in an arbitrary position of the network is immediately available to every other agent. As a consequence, the state of all agents a_i is bound in gaps of width C. This limits the advance of any agent to a maximum of C. On the other hand, when the system is defined on a 1D ring this limitation only applies to the nearest neighbors. If the information spreads beyond these neighbors, the advance achieved can exceed C. In this extreme cases different qualitative behaviors are observed, which can be quantified by the exponent by which the maximum value of the mean advance rate scales with the system size

$$\rho_{\max} \approx N^{\alpha}. \tag{9.7}$$

When one considers the dynamics of the model on a ring $\alpha = 0.20$, while mean-field calculations and numerical simulations of the dynamics of the model on a fully connected network show that $\alpha = 0.50$ (Guardiola et al. 2002).

The two particular cases considered so far are usually chosen either for their numerical simplicity, as in the ring, or because they allow for simple mean-field calculations as in the fully connected network. Clearly, the structure of both cases is far from the much more complex pattern of interactions observed in realistic systems (Strogatz 2001). However, they appear as paradigms of two opposite generic situations either a scenario where the propagation of information can be constrained to a local neighborhood, or one where it may reach the whole population in just one step. One wonders which will be the dominant features in a more general situation. In this section, we will consider this issue. In particular, we will study the relation between the salient features present in a more general structure and the dynamical properties of the system.

It is well known that, starting from a ring, the random addition of a few links produces changes in the properties of the network, such as a rapid drop in the average distance between nodes, maintaining the local structure (Watts and Strogatz 1998). It has been shown that this feature can be related to significant changes in the dynamical properties in some systems. In order to study what effects may be present in our model, we will consider the dynamics on a ring lattice with N vertices and $k = 2$ edges per vertex, adding a new link at random with probability p per edge. In general, when one modifies the underlying structure, a quantitative variation of the numerical values of the dynamical magnitudes that characterize the system is observed. However, we will focus our attention on whether the scaling properties are modified, since they are an indication of qualitative changes in these properties. In order to quantify the changes in the scaling behavior of the system, we have computed the exponent for different values of p, as shown in Fig. 9.5.

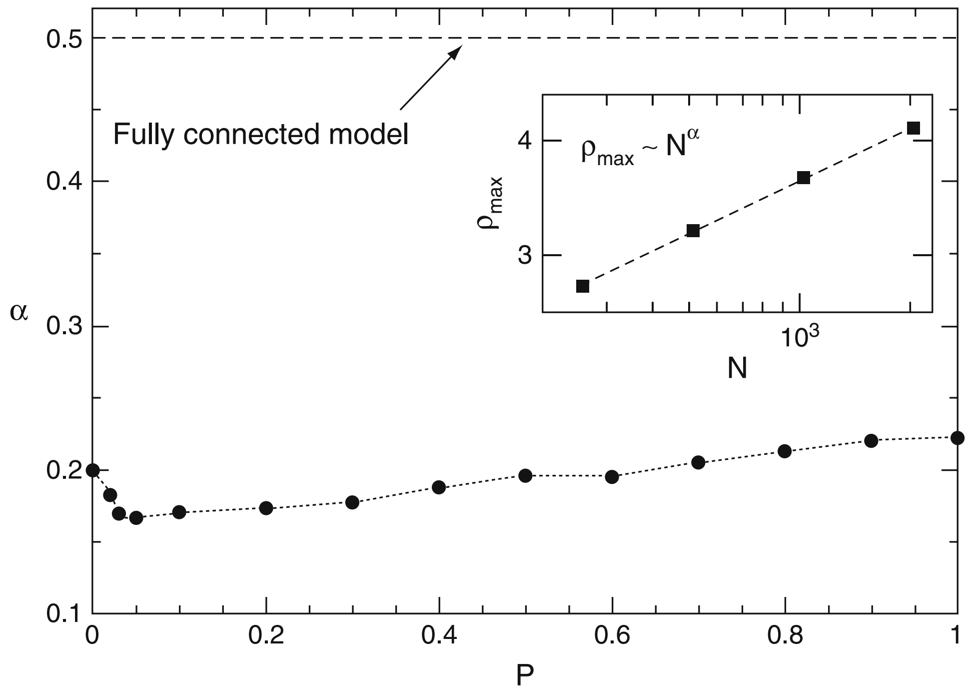

Fig. 9.5 The exponent α characterizes the power-law divergence. The figure displays α vs. p. The *inset* shows the fit used to obtain α when $p = 0.5$

The main conclusion that can be extracted from the figure is that the addition of new links does not modify substantially the scaling properties of the system. For small p we observe a small decrease in the value of α, an effect that seems to be correlated with the rapid drop in the average distance between agents. As p increases to $p = 1$ a slight growth of α is reported. It is important to understand why the qualitative behavior of the system is similar to the one characteristic of the ring. In this case, an avalanche propagates through steps in which the information reaches the nearest neighbors of a modified site. To generate a large event or simply to reach agents far away from the initial updated unit, a large number of steps are required. In this sense, the information propagates by a local process. The addition of new links allows the information to reach agents through shortcuts, but it does not change the mean mechanism of diffusion, i.e., in order to proceed further, an avalanche still requires a large number of steps, which is still dominated by a local process. One cannot under-stress the fact that for the imitation strategy described in this contribution, in contrast to what is observed in other models, the characteristic behavior of the ring is dominant even when a more general structure, such as a small world network, is considered (Llas et al. 2003a).

The local character of the diffusion process typical of low connectivity networks is lost when considering densely connected networks. In this situation, the information about the state of a given agent is available to any other agent in just a few steps. The small world construction is far away from this limit, even when $p = 1$ the mean number of links per site, i.e., the connectivity of the system, has increased very slightly. In order to reach a highly connected state, we added links randomly to the ring up to a fraction f of the total possible links in the system. This means adding $f[N(N-1)/2]-N$ connections to the ring. This recipe allows us to interpolate between the ring ($f = 0$) and the fully connected model ($f = 1$). For finite values of f, the system corresponds to a ring with a superimposed random graph. For this construction the connectivity of the system will be fN, and thus, for a fixed value of f, the connectivity will increase as N grows. If this plays a significant role in the dynamical behavior of the system, we expect that it will be reflected in an important quantitative change in α. In Fig. 9.6, we present the behavior of the peak of the mean rate of advance ρ_{max} as a function of system size N when $f = 0.005$. For low values of N, the behavior resembles the one observed in the small world case. As N grows there is a crossover to the fully connected behavior and $\rho_{max} \approxeq N^{0.5}$ (Llas et al. 2003a).

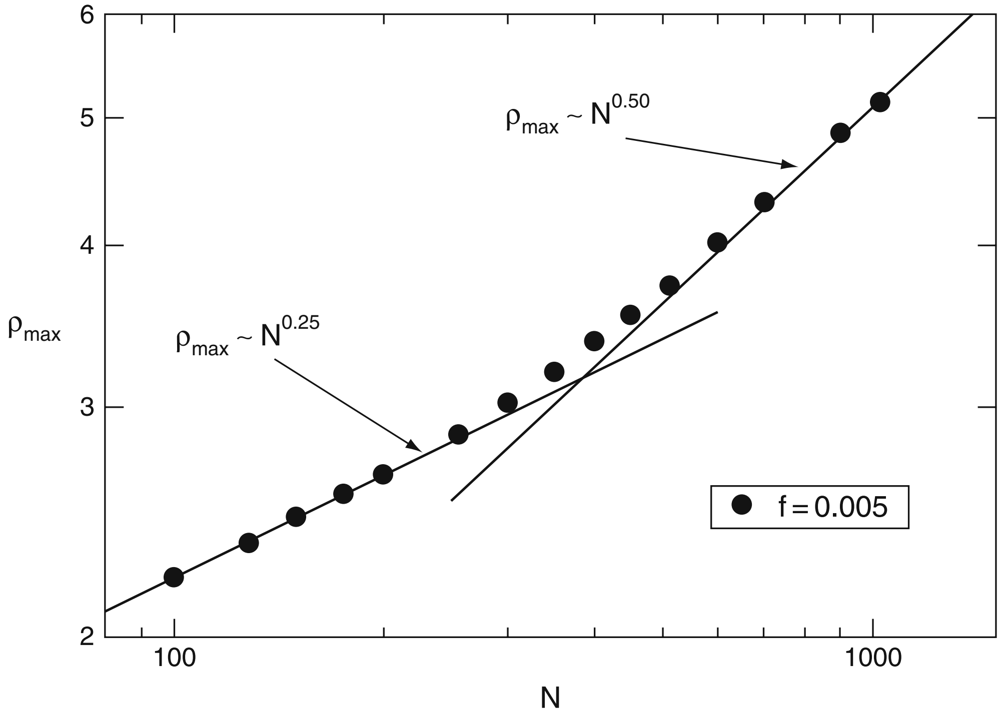

Fig. 9.6 The peak of the mean rate of advance in terms of the system size for a fixed value of the fraction of added links. A clear crossover is observed for a sufficiently large system size

9.5.1 Identification of an Optimal Behavior

Up to now, we have analyzed different mechanisms for the spreading of the information. On one hand, C appears as a parameter that can be tuned in order to reach an optimal regime for a fixed underlying network. On the other hand, we have also seen that diverse structures lead to different ways in which the information spreads. This line of reasoning naturally leads to the question of which is the structure that gives the optimal regime for a fixed value of C. For small C there is almost no resistance to change and the information easily spreads. In fact, we expect that if $C \to 0$ then ρ will also decrease independently of the underlying network. On the other extreme, for $C \to \infty$ the behavior of the system will resemble a random deposition process, and again the behavior of ρ is expected to decrease when considering any general structure. To analyze what happens for intermediate values of C, we should proceed with care, as we will see immediately.

In order to do this, we consider a system with a certain distribution of couplings between agents and a fixed C. In general, the value of ρ will be smaller than $\rho_{\max}$. Now, supposing that we can modify the connectivity pattern, it is natural to ask which structure leads to the optimal behavior. The question cannot be answered properly without looking at the parameter that control the dynamics, i.e., the strategy to follow depends precisely on C. To optimize the behavior of the system, one cannot split the problem into two independent parts; dynamics and the underlying structure must be considered as a whole (Llas et al. 2003a).

Let us analyze some features associated to the mechanism of imitation and consider the difference between the highest ($a_{\max}$) and the lowest ($a_{\min}$) characteristic values in the system. For sufficiently high connectivity C will bound this gap and, as a consequence, for these systems, the value of ρ cannot exceed this value. On the other hand, when the propagation of the information is constrained to advance through local processes, a more heterogeneous profile of characteristic values can be formed, allowing for a larger gap between $a_{\max}$ and $a_{\min}$. In this case, avalanche events consisting of a large number of steps will produce a large advance, allowing the value of ρ to exceed C. In fact, by using the probability distribution of avalanches $P(s)$ and advances $P(H)$ obtained using numerical simulations in Guardiola et al. (2002) this can be easily verified analytically. In this situation, a sparsely connected network will necessarily have a greater ρ than a highly connected one. For increasing values of C, avalanche events will easily get blocked in a few steps. In this context, large advances in a sparsely connected network will become very rare. More frequent advances will be observed in a highly connected network since many agents are permitted to find out about an update in any step. This situation offers the possibility for a higher ρ to be observed in highly connected structures.

Following this analysis, we have considered a general system of fixed size N. The evolution of the mean rate of advance ρ versus C has been studied for two different situations: the ring and another structure where the number of links (measured in terms of f) is large enough to observe fully connected behavior. The results are illustrated in Fig. 9.7. Note that as f is varied the qualitative shape of the ρ curve is similar. However, the position of the peak corresponds to different values of C. For increasing values of f the peak corresponds to larger values of C, eventually reaching the curve corresponding to the globally coupled case. It is important to stress that, as C is varied, the optimal network may change from a highly connected to a sparsely connected one. This behavior is clearly reflected in the inset, where we present the behavior of ρ versus f for two different values of C. For $C = 2$ a decrease in ρ is observed as f grows. The addition of links is harmful to the system. On the other

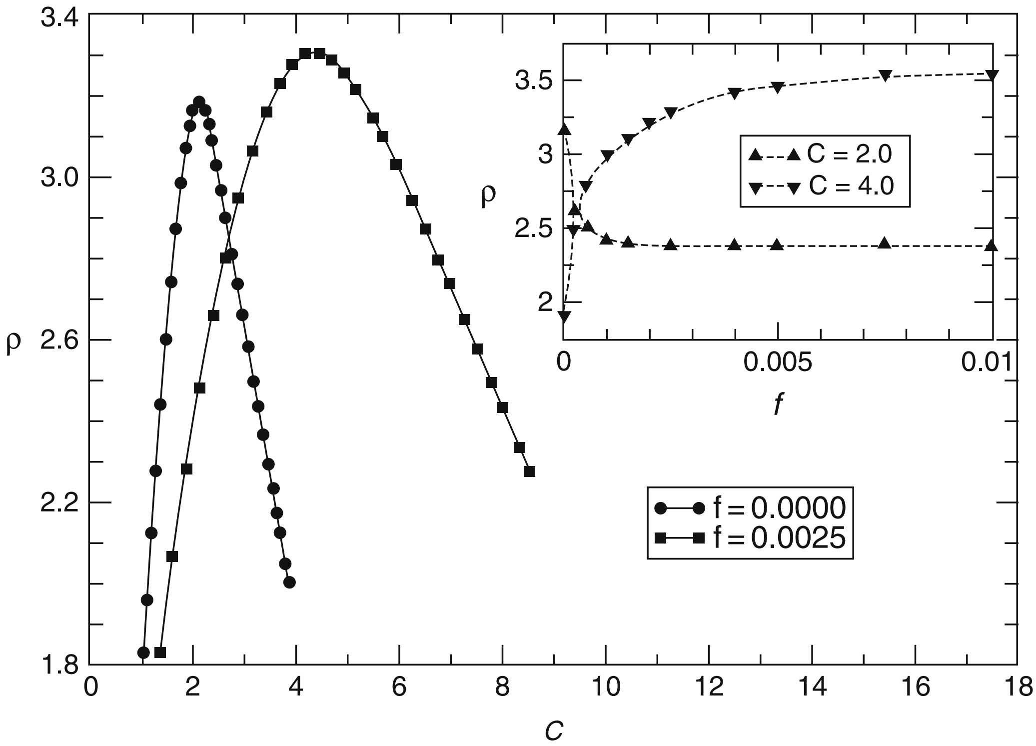

Fig. 9.7 Mean rate of advance as a function of the cost for a fixed system size $N = 512$ and for two different values of the fraction of added links. The *inset* represents the behavior of the mean rate of advance as a function of the fraction of added links for two values of the cost

hand, for $C = 4.0$ the opposite behavior is observed, and ρ increases its value as f grows. Clearly, in this case, the addition of links is beneficial.

These results show that in order to optimize the behavior of the system a non-trivial combination of dynamical rules and underlying structure should be considered. When the interplay between both allows for $\rho C > 1$, a sparsely connected structure performs better than a highly connected one. On the other hand, when $\rho C < 1$ the opposite is true. Note that when $\rho/C \sim 1$ the behavior should be independent of the underlying network. In fact, Fig. 9.7 shows that when $\rho/C \sim 1$ both curves intersect. Numerical simulations for different N and f also show these qualitative behaviors.

9.6 Practical Case

It is a common claim of scholars from social disciplines that computational models, like the one we have presented above, are too simple to represent the richness of real scenarios. In order to deepen on this matter, the aim of the second part of this contribution is to present an example of how this sort of models can be used as a quantitative tool to support a previous research made by social scientists.

9.6.1 Anna Lee Saxenian's Network Perspective

About a decade ago, Anna Lee Saxenian authored a book which pointed out the key role of relational aspects as success factors of regional economic development (Saxenian 1994). Her theories were supported by historical data from two North American hi-tech industrial poles (Silicon Valley and Boston's Route 128), which had presented significantly divergent behaviors during the late 1980s. In her opinion, certain cultural features could perfectly justify that divergent evolution.

On the one side, she observed that Silicon Valley presented a densely networked and flexible organization; within this community information was shared quite freely between companies (even competitors) and with research institutes and local government institutions. Moreover, the extremal high values of job mobility and business creation rates, was interpreted by Saxenian as an indicator of individual initiative and independence.

On the other hand, she found that Boston Route 128 was dominated by large and autarkic corporations with a very rigid hierarchy, where people involved in research and development were expected to be strictly loyal to the company and behave synchronized as a block.

After publication of Saxenian's book, many scholars have positioned either close to her position or clearly opposite to it, following a viewpoint presented in Florida and Kenney (1990), which minimizes those cultural traits compared with technological ones. This situation has grown up a debate that is still alive.

Here, we would like to contribute to this discussion from a completely different point of view. Using a variation of the model presented before, we simulate characteristics of both technological sites and obtain numerical results that agree with Saxenian's hypothesis.

9.6.2 The Experiment

More concretely, we have modified some characteristics of the model of diffusion of innovations presented in order to make it realistic enough to capture two concrete cultural features, that summarize the differences pointed out by Saxenian to be determinant. These characteristics are the topology of the social substrate of each pole and the diversity of individual behavior.

About the social topology, our model should reflect that people in Silicon Valley used their formal and informal links to share information with other people beyond their organizational boundaries, while in Boston, because of the autarky and secrecy imposed, information exchange was mainly restricted to the same group (company, division, department, or team).

In relation to individual behavior of actors in our model, individual initiative and independence observed in Silicon Valley should be represented as a wide diversity of individual behaviors (to highlight the idea that each actor had its own perspective). On the contrary, rigid hierarchy and employee obedience in Boston would correspond to a configuration with low diversity, where decisions are taken centrally and actors act as synchronized as possible.

After 'translating' observations made by Saxenian into concrete constraints, the next step consists on adapting the original model to them.

In order to obtain social topologies that agree with the first constraint, we have used an algorithm proposed in Boguñá et al. (2004) that is able to build up social-like network topologies from the homophile characteristic, which is everyone's preference to establish and maintain relations with people that have any common characteristic with (profession, hobbies, age, or political feelings, for example). In our study case, network of Boston 128 is considered to have a large homophile, because actors tend to exchange information only with people in closed homogeneous groups. On the contrary, Silicon Valley is supposed to have a small one, due to people's inter-organizational interactions.

Since, as it was explained above, in our model the resistance to change value of an actor defines its role as innovation adopter, the incorporation of the other feature to be treated (diversity on individual behavior) has been solved by introducing differences on the resistance value of actors. To explain this second adaptation more detailed, we need to introduce a new concept called 'resistance profile.'

The resistance profile of a system is the representation as a histogram of the frequency of occurrence in the system of each possible value of resistance to change. In the original model, where all agents had the same resistance to change value C, the resistance profile would be 0 for all values except C. This particular performance of the resistance profile is far from reality. If we calculated the resistance profile of a real scenario, we would find some kind of distribution of resistance values around a central or average one. Consequently, if we want to reproduce artificially a real resistance profile we can assign resistance values to actors following a statistical distribution. Moreover, if we want to reproduce a situation with a wide diversity of behaviors (a wide resistance profile) we need a distribution with a high standard deviation. On the contrary, a low standard deviation leads us to a narrow resistance profile simulating a homogeneous scenario.

In our particular case, we have used a Gaussian distribution to generate actor's resistance with a high deviation to simulate Silicon Valley heterogeneity and a low one for Boston Route 128.

Figure 9.8 shows, graphically, particularities introduced to the original model in order to simulate Silicon Valley and Boston Route 128 scenarios, respectively.

9.6.3 Results

Once both technological poles have been simulated as two configurations of the original model, we can obtain some results and analyze them. Before this, however, we have to define the variables we will play with. Our intention is to have a quantitative measure of the fitness of each technological pole to different values of economic dynamism.

First, we need an observable that indicates how well an innovation system (an industrial district) works in a certain situation. In this case, we have chosen the mean rate of progress (ρ), an observable defined and explained in the first part of this contribution.

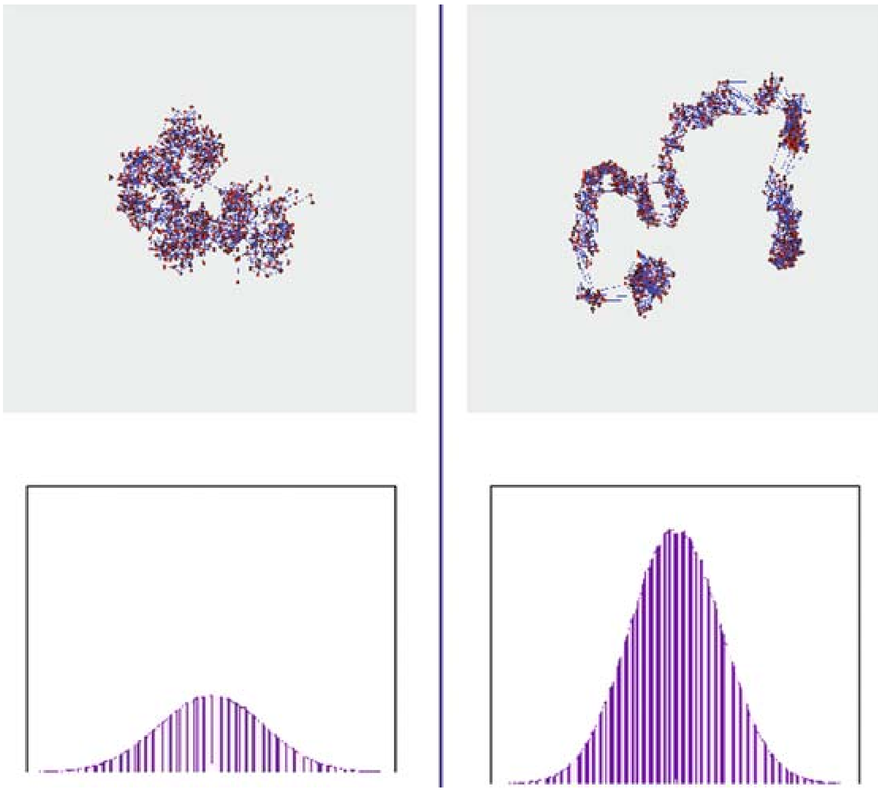

Fig. 9.8 Modifications made to the original model to introduce Silicon Valley (*left*) and Boston Route 128 (*right*) particularities. For each configuration, the topology (*top*) and the resistance to change profile (*bottom*) are shown

We also have to define an independent variable to quantify economical dynamism. The idea of using resistance to change to represent the behavior of actors is also useful here. In a dynamic situation, people tend to adopt novelties easily (their resistance to change is low) and, on the contrary, become more conservative in a more quiet situation (their resistance to change increases). Taking this into account, we can express the dynamism of the environment as the inverse of the average of the resistance to change values of all actors in the system.

The evolution of ρ as a function of the economical dynamism for both configurations is shown in Fig. 9.9. We can see that the maximum value of each model's ρ corresponds to different values of dynamism. This means that each configuration works better with a particular economical environment. Route 128 model gains its peak for a medium value and, if environment conditions change to a more dynamic scenario, its ρ value drops down. This agrees strictly with Saxenian (1994): '. . .Route 128 system flourishes in an environment of market stability and slowly-changing technologies.'

On the other hand, plot for Silicon Valley's model presents a stronger peak at a dynamism value a half upper. Once again, this behavior has its correspondence in Saxenian (1994): 'The region, if not all the firms in the region, is organized to innovate continuously. . ..'

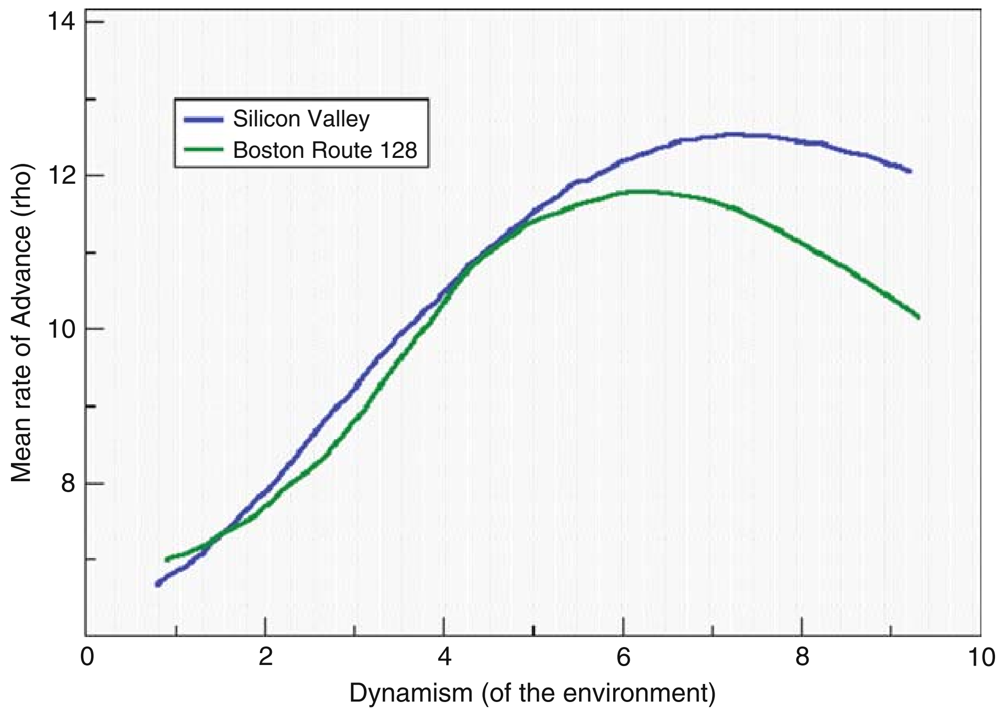

Fig. 9.9 Evolution of the fitness of each innovation system as a function of the dynamism of the situation

Finally, if environment moves to an extremely quiet economical situation, both values fall down. This should be read as a consequence of the loss of dynamism of regional economy, that affects in a similar way all industrial complexes independently from their particular characteristics.

9.7 Conclusions

We have presented results obtained in different scenarios about propagation of innovations, in regular as well as in heterogeneous patterns of connectivity. On the one hand, we have defined relevant observables and reviewed some aspects. On the other hand, we have shown that, in a particular case of study in the social science literature, structural features play a fundamental role in explaining the success of innovation systems. In order to tackle this second topic, we have adapted a computational model and obtained quantitative results that supports the conclusions of the previous qualitative analysis of the real raw data. We feel that this sort of two-step approach (from raw data to qualitative conclusions and from these conclusions to simple modeling) could be very useful in the study of different social and economical issues, not only innovation diffusion but also other kind of phenomena with a dependence on the underlying social structure.

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