

The complexity of transitions

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Eindhoven Centre for Innovation Studies

The complexity of transitions

Paolo Zeppini, Koen Frenken and Roland Kupers

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The complexity of transitions

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1. Introduction

Models that belong to the realm of complexity studies turn very insightful when addressing societal and technological transitions. The very idea of transition finds direct counterparts in a number of phenomena in natural sciences, the most notable one being phase transitions.

A complexity approach recognizes in socio economic systems many dynamic patterns that are similar to patterns already observed in natural systems. Pushing the approach further, the economy and the whole society may be seen as a system to study with a natural science approach, by defining a physics of society.

Without entering the debate on how or whether social and economic systems will ever become another - the biggest ever - physical system to study, it is surely true that tools and perspectives from natural sciences such as complexity theories may offer useful insights. The most notable example is probably the series of studies entitled "*The economy as an evolving complex system*".

Complexity approaches to socio-economic systems have mostly involved financial markets (see for instance Hens and Schenk-Hoppe', 2009). Here we claim that technological change is another promising field for complexity theories, and that technological transitions in particular have a large potential of new insights that complexity thinking can offer.

In this paper we review a number of concepts and modelling approaches that we believe are particularly interesting in attacking technological transitions. It is not our aim to be exhaustive in this review, but only to propose the approaches that we believe were most significant and that we think are most promising for future research. In a number of cases, we explicitly indicate direction for further research.

The article is organized as follows. Section 2 addresses multiple equilibria, network externalities and positive feedback. Section 3 shows how game theory and evolutionary game theory are insightful for transitions in a strategic context. Section 4 presents diffusion on networks, with an accent on phase transitions. Section 5 reviews models of cascades and herding behavior. Section 6 is totally dedicated to a model of network formation based on the concept of catalytic processes. Section 7 is about the complexity of modular technologies, and Section 8 considers the case of niche technologies. Finally, Section 9 concludes.

The sections of this paper are self-contained, and can also be read separately. Some complexity concepts are transversal to the sections, and may guide in a selective reading of the article: multiple equilibria are addressed in Sections 2, 3 and 5. Positive feedback and path-dependence are in Sections 2 and 5. The coordination problem is studied in Sections 3, 6 and 7. Diffusion is both in Sections 4 and 5, and the concept of modularity is in Section 7 and Section 8.

2. Non-linear social dynamics

A central belief in economics has been for a long time that returns to an agent's action are decreasing, meaning that when some quantity accumulates, the effect of adding a given unit of the same quantity decreases with accumulation. A meaningful example is the *law of demand*: as Marshall puts it, the marginal price of a given good diminishes with an increase in the demanded quantity. Another example is the marginal impact of money, which diminishes as one becomes wealthier. Nevertheless, there are important situations in economic and social systems where returns are increasing. The importance of increasing returns was recognized only in the 80's, mainly thanks to the work of Paul David, Katz and Shapiro and Brian Arthur on network technologies and technology competition. As it happens, increasing returns are a key factor of many processes of scaling.

There are a number of different and alternative expressions for increasing returns: positive feedback, self-reinforcement, cumulative causation, rich-get-richer, etc. This type of process is well described by *urn models*. Consider an urn which contains an equal number of black and white balls. The probability of extracting white or black is equal. Now, let's implement the following scheme of action: whenever one extracts a white ball, this is put back in the urn together with another ball of the same colour. The same holds true for the black ball. This procedure introduces a positive feedback in the process, because the probability of extracting one colour increases with the event itself. This conceptual example was turned into a model by Arthur et al. (1987). The stochastic process of this model is a type of Markov process called *Polya processes*. There are two major insights from Polya processes: first, in the scheme just described we always converge to a given fraction x of white balls, which is not known *a priori*. This means, the proportion does not fluctuate but it is stable in the long run. Second, whenever the probability of extracting a colour is a given function $f(x)$, the fraction of balls converge to a proportion which is exactly given by the fixed points $x=f(x)$ of that function. This means that one knows *a priori* which will be the final long run values of the fraction of colour. An example of this generalization is the following: let's add more than one ball after extracting a given colour. This gives an acceleration of increasing returns. The new scenario is represented by an S-shaped probability function $f(x)$ (Figure 1, left panel). If we run this modified urn scheme the outcome will be a convergence to either $x=0$ or $x=1$ which means that either black or white balls will tend to a share of 100%. Put differently, one out of two possible stable equilibria are selected by chance. The right panel of Figure 1 shows seven simulation runs: four times white balls became dominant ($x=1$), while three times black balls were dominant ($x=0$).

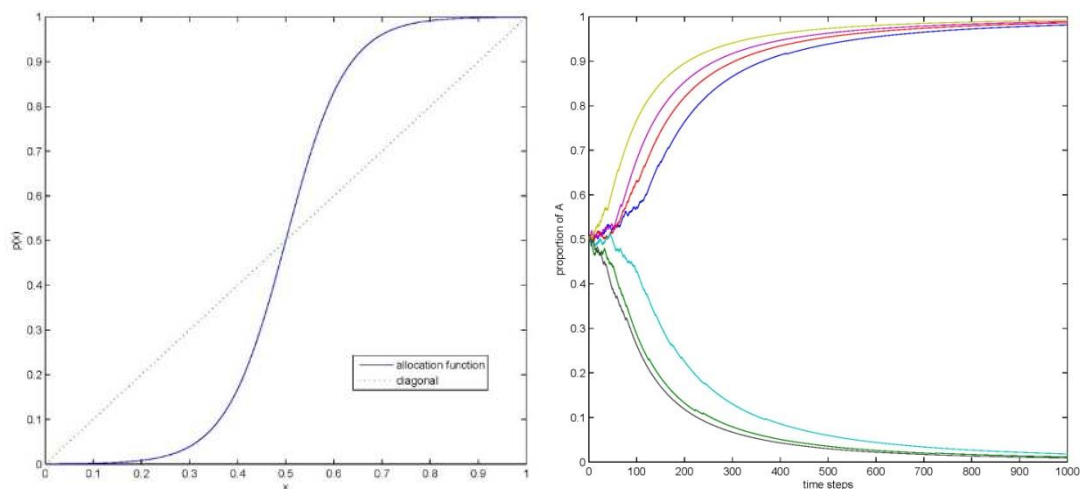


Figure 1: Polya processes. Example of probability function (left). Simulations of the model (right).

The self-reinforcing mechanism just described is characterized by an evolution law that changes endogenously. This leads to *non-autonomous* equations, where the independent variable, time, appears explicitly. The mutual interplay between the state variable and the environment is what makes these systems “complex”. For such processes local minima do not exist *a priori* but are created by the evolution of the system itself. This is what makes lock-in a much stronger scenario than a simple stable equilibrium.

There are several economic systems that can be described by this model. One example is the location of industries. It has been shown that spin-offs process are important and often the dominant mechanism of firms’ birth. Assuming for the spin-off firm the same location as the parent firm, and thinking of the different regions as the different colours, the location of new firms is described by the model above, since the probability of locating in one region for an industry is increasing in the concentration of that industry in the region.

Increasing returns is at the core of *path dependence* where the trajectory of a process depends on the realizations of the process itself. Early realizations are most important, because they affect successive realization irreversibly. One consequence is that starting with the same initial conditions, two different runs of the model can lead to opposed outcomes due to the values randomly occurred in the first few time periods. The extreme case of path dependence is *lock-in*, where a process is stuck in a state and the state reinforces itself in successive realization of the process, due to increasing returns.

2.1 Network externalities

Arthur (1989) is a famous model that explains how increasing returns to technology adoption lead to path dependence and lock-in of technology competition. In the model there are two technologies *A* and *B* competing for adoption in a market. Such technologies are “equally good”, in the sense that no one presents any intrinsic superiority. The market is formed by heterogeneous agents, being of type *R* or *S*. Type *R* have a natural preference for technology *A*, while type *S* prefer technology *B*. Returns from adoption of technologies *A* and *B* are a_R and b_R respectively, for type *R*, while a_S and b_S are the returns for type *S*. Preferences are such that $a_R > b_R$, and $a_S < b_S$. Beside preferences, a feedback mechanism makes the return to depend also on previous adoptions. If n_A and n_B are the market shares of the two technologies, the overall returns are the following:

	Technology A	Technology B
R-agent	$a_R + rn_A$	$b_R + rn_B$
S-agent	$a_S + sn_A$	$b_S + sn_B$

When coefficients r and s are positive, the more one technology is adopted, the higher its return to any agent. This is a mechanism of positive feedback. Examples are network technologies which value strongly depends on the installed base, as for instance telephones, fax machines, and generally all types of telecommunication services. If coefficients r and s were negative, there would be a negative feedback. In this model *R* agents switch technology when $a_R + rn_A < b_R + rn_B$, while *S* agents switch whenever $b_S + sn_B < a_S + sn_A$. If we define the relative frequency $d_n = n_A - n_B$, the conditions for switching are represented by two “absorbing” barriers $\frac{b_R - a_R}{r} \equiv \Delta_R^{ir}$ and $\frac{b_S - a_S}{s} \equiv \Delta_S^{ir}$. Agents switch technology abandoning their preferred one whenever these barriers are reached.

Positive feedback does not only characterize network technologies, and stems from other sources of positive externalities. Arthur lists four different sources of positive externalities in technology competition:

- large set up or fixed costs,
- learning effects,
- coordination effects and imitation,
- self-reinforcing expectations.

The model above is relevant to all cases of the competition of alternative options such as products, norms, behaviours. It is also relevant to technological transitions, when there is an incumbent technology (or product, customary behavior, widely accepted norm, etc.) that faces the threat of an innovative technology.

2.2 Critical mass

There are simpler systems where the environment is not coupled with the state variable, but still the state variable presents multiple equilibria. These are deterministic system with a self-reinforcing mechanism, where the initial condition determines which equilibrium will be selected. Examples are poverty traps due to learning-by-doing, search externalities, human capital externalities, etc. (Azariadis and Stachurski, 2005). The state of these systems may be represented by a flow map F through the difference equation $x_t = F(x_{t-1})$. The map F does not depend on time. Assume that a high value of x means a “better” condition of the system, as per capita income or wages, while a low x refers to a worse state. If function F has only one stable equilibrium (Figure 2, left panel), there is no positive feedback. When a self-reinforcing mechanism is at work, there may be two alternative equilibria (Figure 2, right panel), and one is a “poverty trap”. If the initial condition x_0 is below the unstable equilibrium x_c (say an underdeveloped country) the system converges to the poverty trap. Stable and unstable equilibria can be seen as minima and maxima of a potential function, as in Figure 3.

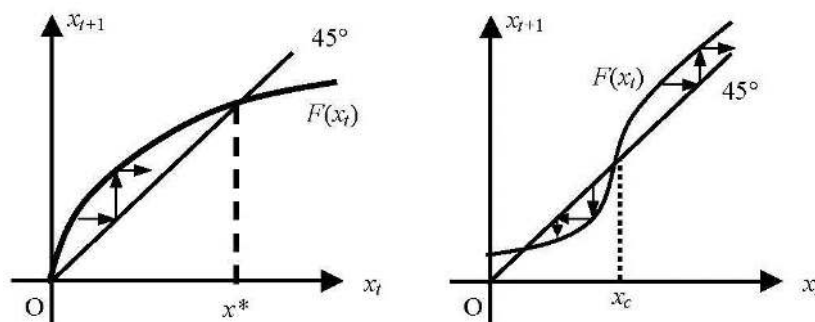


Figure 2: examples of flow map

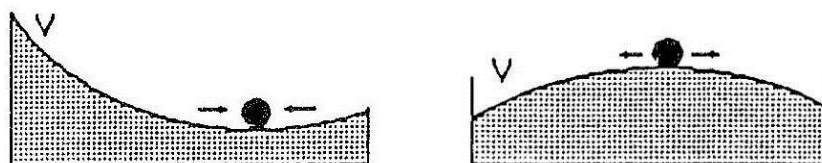


Figure 3: potential function V

An instructive representation of critical mass is the hyperselection model of technological transition of Brickner et al. (1996). Here competing technologies are species competing for survival. The time evolution of shares is described by a differential equation that includes a positive term (birth), and a negative term (death). The positive term is quadratic, which accounts for increasing returns, while the negative term is linear. The solution has two stable equilibria and an unstable equilibrium. The unstable equilibrium works as a barrier. Being below or above this barrier deterministically sets the surviving species, that is to say the winning technology. There are a number of differences with Arthur's model: first, this model is deterministic, while Arthur's model is stochastic. Second, here the barrier is unique, while Arthur's model allows for a mid range of values where it is not possible to know which option will prevail. Finally, in this case the dominance of one option is absolute, and one technology completely disappears (extinction).

Because of multiple equilibria, even incremental technological progress may cause abrupt and sudden changes in technology patterns. This is explained by Krugman in *The self-organizing economy* (1996). Suppose that consumers can choose between an established technology, say traditional cars with internal combustion engine, and an innovative technology, for instance electrical cars. Assume that a critical mass characterizes the innovative technology, both for consumers, who decide whether to buy an electrical car, and for producers, who decide to install recharging slots: the two affect each other, and give two instances of critical mass. This is represented by the two curves in Figure 4 (left panel).

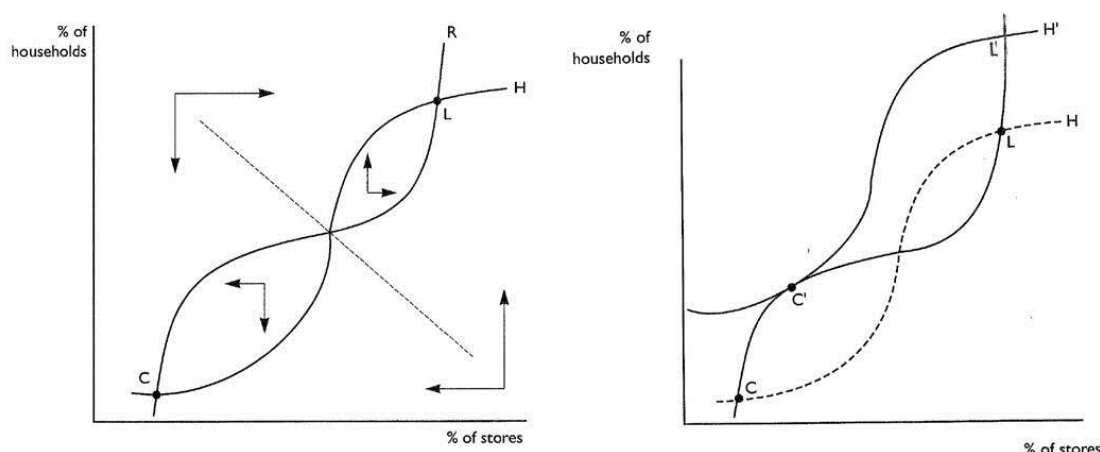


Figure 4: critical mass in the demand and supply sides.

Curve H represents the share of consumer adopting the electrical car, given the share of recharge slots available ($\% \text{ of stores}$ on the horizontal axis), while curve R is the share of recharge slots installed, given the number of electrical cars around ($\% \text{ of households}$ on the vertical axis). There are two stable equilibria in this system: the equilibrium C represents a scenario where diffusion of electrical cars is scarce, and the incumbent technology is dominant. Equilibrium L is the alternative one, where electrical cars are dominant. Because of the self-reinforcing mechanism of a critical mass, there is little hope that we can have a transition in the market from the old to the new technology. This is an example of *chicken-egg* dilemma, and more generally of coordination problem. Consider now the following phenomenon: thanks to technological progress electrical cars become more attractive, say due to improving performances and decreasing prices. This has the effect of shifting upward curve H . Initially the effect of the shift on the equilibrium shares is little and gradual. But at some point the equilibrium C' where traditional cars are dominant disappears, and only an equilibrium L' with electrical cars remains (Figure 4, right panel). The market flips towards

electrical cars with a sudden jump. Summarizing, a system with a critical mass presents multiple equilibria, and gradual changes such as incremental technological progress may eliminate an equilibrium and un-lock the market with the transition from an incumbent to an innovative technology.

Un-locking events did occur in history, mostly due to technological progress (examples are the airplane propeller replaced by the jet engine, videotape cassettes and laser discs, electromechanical valves and semiconductors). Mostly in the post-industrial revolution era the human society went through several different equilibria, following a pattern of *punctuated growth*. Mainstream economics has missed so far to explain such a complex pattern, simply accounting for gradual changes in the technology production frontier. For a recent modeling attempt to explain technological transitions with endogenous mechanisms see *Frenken et al (2012)*. The explanation of the complex interplay between market forces, human incentives and technological change is still a research challenge.

3. A game theory approach to transitions

In some cases technological and societal transitions present a strategic character, and occur as the solution to a coordination problem. An example is renewable energy in transportation systems. The incumbent technology is the internal combustion engine, while innovations are the electrical engine and fuel cells. The model by Krugman considered in Section 2 can be re-stated in a strategic setting: no consumer will adopt a fuel cell car if expecting that only few refueling stations are available. On the other hand, no energy company will build refueling stations, facing such a slim demand. This is a chicken-and-egg problem, which Game Theory addresses to as a coordination problem.

Technological change is primarily important for any analysis of environmental problems, not excluded all situations that are characterized by strategic behavior. Touza and Perrings (2011) show how different games stem from different technological settings, and address the challenges for environmental agreements in enforcing efficient equilibria.

3.1 The Coordination Game

The most relevant game for understanding transitions in socio-economic systems is the coordination game. This game describes how multiple equilibria result in a strategic setting, and it is relevant to all situations where there are multiple competing technologies. A coordination game is the strategic counterpart of technology competition models presented in Section 2. An example of coordination game in normal form is given by the following payoff matrix:

	Cooperate	Defect
Cooperate	(3, 3)	(0, 2)
Defect	(2, 0)	(2, 2)

Table 1: coordination game with asymmetric strategies.

There are two Nash equilibria (NE henceforth): (Cooperate, Cooperate) and (Defect, Defect). The cooperative equilibrium is socially optimal. Nevertheless, also in the defection equilibrium players do not have incentives to change strategy. This is a coordination problem.

Beside NE and social efficiency, there is a third way to evaluate strategies, risk dominance, proposed by Harsanyi and Selten (1988). Notice how the defective action is less risky here. With no clue about the opponent's action one places probability 50% on both Cooperate and Defect. This gives an expected payoff from cooperation equal to 1.5, lower than the expected payoff from defection.

The two equilibria above are not the only ones for that game. There is also a mixed strategy NE. This is one where each player plays Cooperate with probability q , and Defect with probability $1-q$. In the example above the mixed strategy equilibrium is $(2/3, 1/3)$. A possible interpretation is that two out of three times players play Cooperate, and one time they play Defect. Another interpretation of mixed strategies is from the population approach of Evolutionary Game Theory.

The emergence of cooperation is a key factor whenever an innovation has to face an incumbent technology. Think of traditional cars and fuel cells cars. Beside the resistance by established industrial sectors and by whatever economic activities that are connected with the existing technological infrastructure, the demand side has to coordinate in order to escape the lock-in equilibrium and make the innovation viable. This is due to the chicken-and egg problem of coordination. A critical mass of adopting consumers is necessary to install capacity that would drive down costs and prices, making the innovation more and more attractive. Every consumer knows that, and every consumer is also aware of the superior quality of the innovation (higher environmental performance in the case of cars), but no one wants to be the only guy going around in search of a hydrogen refueling station.

3.2 Setting Standards

A business case where coordination is important is coalitions' formation in standards-setting alliances. The issue of technological standards is central to Brian Arthur's models of competing technologies (Section 2). Axelrod et al. (1995) addressed the strategic aspects of the problem by using a model that he initially conceived for wartime alignments, and was successful in explaining the empirical evidence of competing UNIX operating systems standards for technical workstations in 1988.

Axelrod's model is based on two assumptions regarding the incentives of companies in forming alliances in a situation of technological standards setting. The first incentive is that firms prefer to join large standard-setting alliances, because a larger alliance has higher probability of being the winning horse. A second incentive is that firms prefer to avoid allying with rivals, especially with those rivals that are close in the technology space and seemingly compete in the same market. This second incentive is partially conflicting with the first one. The incentive for large alliances comes from the positive feedback mechanism of a coordination game. The competition incentive is absent in a coordination game, and the trade-off between the two makes the standard-setting problem a more complicated game.

The technology standard competition considered by Axelrod is perfectly symmetric, because no standard is superior. There are not an efficient or a risk-dominant equilibrium. The coordination part of the standards game could be expressed by the following payoff matrix:

	Cooperate	Defect
Cooperate	(3, 3)	(1, 1)
Defect	(1, 1)	(3, 3)

Table 2: coordination game with symmetric strategies.

But beside coordination there is a competition issue. In Axelrod's model the two incentives for forming alliances are formalized in a function that measures the firms' utility: positive terms refer to coordination incentives, and negative terms refer to competition.

The NE alliances are found through an energy metric function. A firm joins an alliance if doing so it minimizes the energy of the system, and doing so the firm improves its utility. NE are local minima of the energy function.

The prisoner's dilemma is an extreme case of coordination problem, where only the socially undesirable NE exists. Coordination games and prisoner's dilemma are particularly useful in describing a class of social coordination problems that goes under the name of tragedy of the commons. Keeping clean a common space, or a green park, or implementing measures for the abatement of pollution, are all situations where common rewards are surely high, but expenses are also high, if not everybody agree and coordinate on the cooperative action. Without additional incentives, such as reciprocity, or reputation, cooperation cannot be enforced.

The study of the emergence of cooperation requires a setting where the game is played repeatedly. Robert Axelrod organized a prisoner's dilemma championship, asking to prominent game theorists to design strategies to play the repeated prisoner's dilemma. The winning strategy, submitted by Anatol Rapoport, was tit-for-tat. This strategy starts with playing Cooperate, and in any following period it plays whatever strategy was played by the opponent in the previous period. Playing against tit-for-tat is like playing against one's own image shifted one period. Results from the tournament are reported in Axelrod (1984). In following years evolutionary game theory has addressed extensively the emergence of cooperation in different settings, including networks (see Nowak, 2006).

3.3 Evolutionary Game Theory

In many cases of strategic choice players are many, and interactions are better described with a population approach. Mathematical biologists have applied concepts of game theory to the study of life forms population dynamics. This field of studies started with Maynard Smith and Price (1973). In Evolutionary Game Theory there is a population of many players, with a round-robin setup of interaction: players are matched randomly, and play a bilateral stage game of traditional Game Theory. Payoffs for each player are the sum of all payoffs accruing during repeated interactions.

Players do not need to be rational in models of Evolutionary Game Theory. Here each player is identified by a strategy and such strategy is genetically inherited. The idea is that better strategies reproduce faster, the key factor being the fitness of strategies. The fitness depends on the relative abundance of other strategies. Beside reproduction and selection, another evolutionary factor at work is mutation. Sometimes a new type/strategy appears, which may be characterized by lower or higher fitness. In the latter case, such invasion leads to the extinction of all other strategies.

In Evolutionary Game Theory the basic founding concept that parallels the NE of Game Theory is Evolutionary Stable Strategy: an ESS is robust to invasion. If an entire population adopts a ESS, no other strategy can invade.

The concept of mixed strategy equilibrium turns useful in Evolutionary Game Theory. Let consider the coordination game with asymmetric strategies of

Table 1. The pure strategy NE are (Cooperate, Cooperate) and (Defect, Defect), while the mixed strategy equilibrium is $(2/3, 1/3)$. The cooperation equilibrium is the efficient one, while the defection equilibrium is the risk dominant: the first gives the higher total payoff, but the second gives the higher expected individual payoff. The mixed strategy equilibrium indicates which pure strategy equilibrium is risk dominant: it is the one that is played by the majority of the population in an evolutionary game context, in this case, $2/3$ of the population. This counterintuitive result can be understood in terms of critical mass. Figure 5 reports a phase diagram of the game with an axis representing the fraction of players playing Cooperate.



Figure 5: phase diagram of a coordination game.

As we can see, the fraction $x=2/3$ defining the mixed strategy equilibrium is the threshold that divides the basin of attraction of the two pure strategy Nash equilibria, $x=0$ and $x=1$. The two thirds of the population represent the critical mass of cooperating agents that need to be reached in order to flip the population from defection to cooperation. In this case the basin of attraction of cooperation is smaller, and the threshold for switching from cooperation to defection ($1/3$) is lower than the threshold for the opposite switch. As it happens, the equilibrium with the larger basin of attraction is the risk dominant equilibrium.

3.4 Social Learning and Equilibrium Selection

Evolutionary Game Theory offers one way out of the coordination problem, which is based on mutation and learning. This idea is proposed by Kandori et al. (1993) with the model of stochastic stability and equilibrium selection. This model studies how an equilibrium is attained and how it is robust to stochastic perturbations. Implicitly, it addresses the question of equilibrium switching. This question is maximally relevant to transitions.

Assume that players can adjust their behavior according to some learning mechanism, and also assume that such learning is in turn subject to (rare) perturbations. Two possible learning mechanisms proposed in the literature are learning by imitation and best-response adjustment. In the first case one player looks at the set of strategies that give a higher payoff than the strategy he is using. In the second case, one player looks at the strategies that are best response to the strategies that other players are playing. A further revision mechanism is proposed by Binmore et al. (1995) with their Aspiration and imitation model. Here agents compare their payoffs with an aspiration level, and strategies that fall short of such aspiration level are rejected in favour of better strategies. This aspiration-imitation mechanism pushes agents towards best replies.

Kandori et al. (1993) give a useful illustration of the mutation and learning mechanism, that here we adapt to the example of coordination game considered above. Consider a small community of graduate students, for instance ten students forming one cohort of a PhD university program in mathematical economics. They have to do assignments, for a number of computer packages must be used, say for quantitative analysis of empirical data. Students can do assignments in pairs, but they are randomly matched in order to maximize exchange of knowledge. The problem is that working in

pairs is fruitful only if the two students have the same type of computer operating system, say Apple or Microsoft. In this case, assume that coordinating on Apple gives the efficient equilibrium, while coordinating on Microsoft gives the risk dominant equilibrium. We have seen that a mixed strategy equilibrium exists, which places probability $2/3$ on students playing Apple. Only if at least two third of the population (7 students) use an Apple, the best response in the random matching game is to have an Apple. If 6 or less have an Apple, it is better to have a Microsoft. Assume that students have occasionally the possibility to change computer, which corresponds to the learning process of our evolutionary game. Assume that in buying a new computer they consider a random matching of future assignments. Students face a process of “Darwinian” adjustments of the type of the equilibrium selection models presented above. The final outcome depends on the initial conditions: if initially there are at least 7 students with an Apple, all students will have an Apple in the end. Otherwise, all students will end up with Microsoft. Positive feedback in a stochastic process is a cause of path-dependence. Models of stochastic stability and equilibrium selection show that sometimes is possible to solve this coordination problem and switch equilibrium. Assume that students randomly leave the program with probability p , and are replaced with new students using Apple with probability m , and Microsoft with probability $1-m$. This is the mutation probability of the evolutionary game. Kandori et al. (1993) show that if p and m are positive, students switch computer and coordinate soon or later. The system perpetually fluctuates between all using Microsoft and all using Apple. Overall more time is spent with in the Microsoft than in the Apple equilibrium. In order for the Microsoft-to-Apple switch to occur seven students must mutate in a row, while only 4 mutations to Microsoft are needed for the opposite transition. This is due to the risk dominance of the Microsoft over the Apple equilibrium, which translates in different sizes for the basins of attraction.

The founding idea of stochastic stability and equilibrium selection is that behavioural adjustments such as learning-by-imitation, learning-by-best-response, or aspiration-and-imitation, can take players from one to the other set of strategies, and then the entire population systems from one equilibrium to the alternative one. First of all we allow that players mutate, which means that each single player can play a new strategy with some positive probability. There may be a number of different and not necessarily exclusive interpretations for mutation. One is that players sometimes perform experimentations, and when they do that they are kind of innovators. An alternative interpretation is that players can make mistakes, which do not necessarily end up with being a bad thing.¹ Furthermore, mutation can be the entry of new players which substitute old ones, a kind of renewal.

Thanks to mutations, some players may be ending up with making higher payoffs from the game. Moreover, due to other players’ mutations, the payoffs of non-mutating agents may change, and possibly change for worse. Now, thanks to learning, players may revise strategy and follow mutating agents by imitating their strategy. In the setting of learning-by-best-response, for instance, players may coordinate in a unique best response strategy. Due to mutations and due to the consequent strategies revision mechanisms, the equilibria of the population game change. There will again be two alternative equilibria, but the barrier that separates them will change. Possibly such barrier may become less difficult to overcome.

The model just presented is relevant for all socio-economic systems where a population of agents with forward looking behaviour finds itself in an undesirable equilibrium (less efficient), and where an alternative equilibrium exists, it is possibly risk-dominated, and usually is not occupied yet. Most sustainability challenges ore of this kind. An example is fossil fuels and renewable energy. There are plenty of such situations in the history of technology: for instance technology standards as the QWERTY keyboard (David, 1985) or computer operating systems.

¹ In latin the word “*errare*” means “to change path”.

4. Diffusion

A fundamental process of technological change is the diffusion of innovations, which is maximally important in a case of technological transition. Diffusion is relevant to societal transitions in many respects, from the diffusion of new products and innovative technologies to the diffusion of information, social behaviours, fads and fashion. The theme of diffusion is quite interdisciplinary, involving fields as physics, epidemiology, sociology and economics. Recently the research on diffusion has focused on networks (Vega-Redondo, 2007, Jackson 2008).

4.1 Phase transitions

Diffusion in networks is characterized by a phase transition. In physics a phase transition characterizes a system undergoing a transformation from a state to an alternative one. An example is water when it freezes, passing from the liquid to the solid state. Phase transitions are very peculiar types of change where there is a threshold value in some parameter of the system that can be exactly identified and measured. This gives place to a sharp change from one state to the other. Critical or second order phase transitions are characterized by a discontinuity in the first derivative of the state variable with respect to the changing parameter, but the state variable is continuous. The large scale diffusion in a network is subject to the existence of a giant network component, which is a portion of the network whose nodes are connected between them by at least one pattern. The component is “giant” whenever it is macroscopic, that is whenever its number of nodes is of the same order of magnitude as the total number of nodes (say half of them, for instance). Increasing the average connectivity of the network z (that is the average number of links per node), the size of the largest connected component $\chi(z)$ presents a sharp transition at a certain threshold value, as Figure 6 shows.

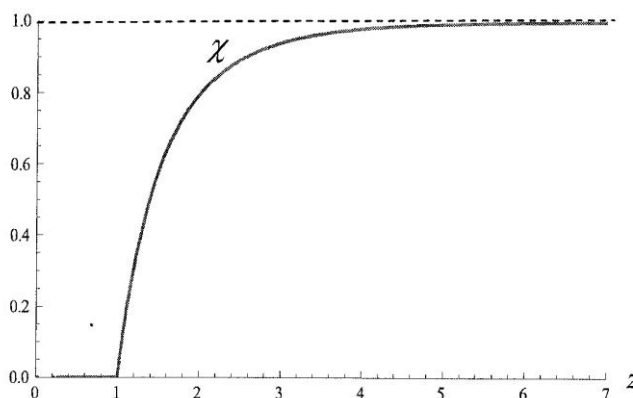


Figure 6: relative size of the giant connected component in a random network.

The value of the threshold depends on the type of network, and it is $z=1$ for a Poisson random network. Below the threshold connected components are relatively small (orders of magnitude below the total number of agents), while above the threshold a giant component shows up. Diffusion on random network reflects this phase transition, and presents a sharp separation of two regimes: one where diffusion is scarce and one where it is large.

Phase transitions are more “fundamental” changes than critical mass phenomena. In a critical phase transition the system undergoes a structural change, where an organized state builds up, while in systems with multiple equilibria the change is just a “selection” of two alternative but equivalent states.

Beside average connectivity and connectivity variance, an important factor of diffusion in a random network is connectivity spreading. A network “spreads” if the number of second order neighbours (the friends of your friends) is larger than the number of direct neighbours, and so on for all successive order. This property in a network boosts diffusion, and the intuition is straightforward: if diffusion occurs by direct contact, starting from an “infected” node it gets multiplied at every contact step, in a spreading network. This topological spreading in a random network is present whenever the connectivity variance is sufficiently large. In particular, the variance must be larger than twice the average connectivity (Vega-Redondo, 2007, pag.46).

Another way to think of connectivity spreading is the connectivity distribution of neighbours. This is a subtle concept, but the connectivity distribution of neighbours (your friends) is not the same thing as the connectivity distribution of a given node. In particular, the average connectivity of the neighbor of one node is larger than the average connectivity of this node. This point can be understood thinking that if one draw a node at random, this node may be unconnected with some probability. If instead one draws one node at random and in case it has one or more neighbours, considers one of them, this latter node will have at least connectivity one, by assumption. This theoretical fact is the first of a number of reason that suggest the following marketing trick for launching a new product: sample a population at random, ask the sampled people who are their friends, and then give the product to their friends. A refinement of this trick is to find the friends that are cited more often and then give the product to them: with high probability they have many friends also outside the sample.

The last paragraph introduces an important issue of diffusion in a network, which are the seeds of diffusion, that is the initial nodes starting the diffusion process. In a marketing perspective, these are the people who are given the new product at the beginning. It is intuitive that seeding is primarily important: if a seller is able to spot the “right” people to start its launching campaign, the diffusion may go through much more easily. Following the consideration above, diffusion is larger is the seeds are hubs, that is they have many links. This is surely so, but connectivity is not the only important factor. Another key factor is the centrality of seeds. The centrality of a node in a network is measured in a number of different ways: there are the closeness centrality, the betweenness centrality, the eigenvector centrality (PageRank, Google’s algorithm to rank webpages, is based on the latter). Basically all these measures indicate the following: how likely it is that a node is positioned on the shortest path between any other two nodes.

A further relevant network characteristic is clustering. The role of clustering in diffusion is controversial, and likely depends on the nature of the diffusing entity, whether it is information, behaviours, new products, and so on. The whole point is to understand if the redundant links of a network with high clustering favour diffusion. If one consider the diffusion of information, clustering is useless, because news is transmitted by only one links. Regarding products diffusion the point is whether adoption decisions only depend on personal preferences or also on social pressure. Based on the latter, a consumer adopts with a probability that increases with the number of neighbours adopting. There is mixed empirical evidence on this (Banerjee et al 2012). Recent studies suggest that clustering is useful for the diffusion of behaviours (Centola, 2010), while technology diffusion works better in networks with low clustering, as individualist societies, than in networks with high clustering, as in collectivist societies Fogli and Veldkamp, 2012). A suggestive hypothesis is that clustering may be helpful in helping a niche or laggard technology to be adopted, when a leading technology has already established a larger basis, if consumers are influenced by their acquaintances. (Lee et al, 2006)

4.2 Percolation

A meaningful description of diffusion on networks is the percolation model. Percolation is the diffusion of a liquid through a porous material layer. The density of the material regulates porosity, and this regulates diffusion. If one increases the density, porosity decreases, and eventually percolation stops. This process shows a phase transition, with a sudden passage from diffusion to a no-diffusion regime. A typical percolation process occurs in making coffee. But several other natural phenomena can be described as percolation, like the spread of fire in a wood.

Percolation is a very “economic” model, and can be used for studying the diffusion of innovations in a market, as soon as the density is turned into say a product price. Solomon et al (2000) is a seminal paper where the social percolation model is proposed.

Assume that agents form a network of social relationships. An agent adopts the product when she is informed about its existence. Information is local, and a consumer is informed when a neighbor adopts. Once the agent is informed, she adopts if the product price p is below her reservation price, $p_r > p$. Reservation prices are randomly distributed.

In a standard percolation model consumers are the nodes of a regular lattice. Drawing reservation prices amounts to “remove” nodes randomly, in that consumers with a too low reservation price are unwilling to buy, do not convey information (Figure 7).

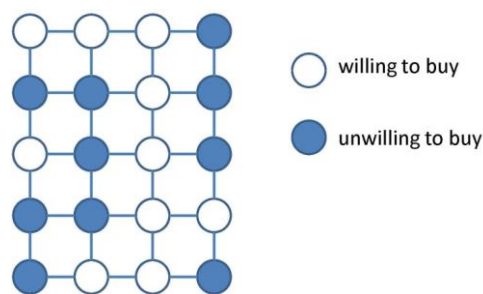


Figure 7: only willing to buy consumers convey information.

If a giant connected component remains after nodes removal, percolation occurs. Figure 8 shows the critical transition of percolation. A threshold price separates the diffusion from the no-diffusion phases. For a regular 2-dimensional lattice the threshold is $p_t \approx 0.407$.

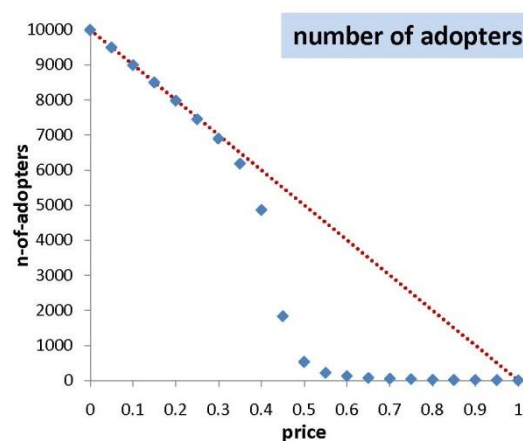


Figure 8: percolation shows a critical transition.

5. Cascades

Informational cascades are at the basis of phenomena of herding behavior, when people act simply following what others do. It is evident how herding in general and informational cascades in particular present a positive feedback mechanism. Although herding sounds like myopic or even irrational behaviour, it is surprising to see how it may well result out of the aggregation of perfectly rational individual actions. The point is that it may be perfectly rational for an individual to make a decision (adoption of a technology or choice of an investment option) following the actions of other agents, disregarding one's own information. This intuition is developed into two different but equivalently insightful models, which not surprisingly appeared in the same year: Banerjee (1992) and Bikhchandani et al (1992).

The basic idea of herding models is that agents are fully rational but imperfectly informed. It is exactly because of imperfect information that herding occurs. Choices are perfectly rational and made by maximizing an expected payoff based on the available information, which is limited. The main difference between the two models is in their scope: Banerjee aims at explaining the occurrence of cascades and their acceleration dynamics, as in financial bubbles, for instance. Bikhchandani et al (1992) are interested in the up and down dynamics of fads and fashion, instead. They consequently aim at explaining also the fragility of cascades, that is to explain not only how and why an informational cascade occurs but also how it suddenly vanishes.

Both models are based on a dynamic sequential decisions mechanism. Agents are called one at a time to make a choice out of a set of available options. This choice can be a financial asset for investment, as in Banerjee or the adoption of a behavior, as in Bikhchandani et al. Information enters the picture in that agents know something about the value of the payoff resulting from their action. Herding arises when an agent makes a choice based on the actions of predecessors and disregards her own information. When this happens, an informational cascade occurs and all other agents in the queue will take the same action.

The striking aspect of the story is that in cases where there is a "right" option and a "wrong" option, it may happen that an agent with the right information decides to jump on a newly formed wrong bandwagon and act wrongly. This is the case in Banerjee (1992). Here there is a continuous set of assets, among which only one gives a positive final payoff. Agents make a choice and pick an asset out of the set. They are ordered and choices are sequential. Agents may have private information about the right asset and observe choices made by predecessors. Their choice does not influence the payoff of subsequent agents but it does influence their information set. An informed agent knows her own private signal about the right asset as well as what she can infer from the actions of her predecessors. Trivially, whenever some agent has a signal matching the action made by someone before, she always makes the same choice. What is more interesting, when an agent sees the same choice made by more than one agent before her, she will follow suit irrespective of her own information.

In Bikhchandani et al. (1992) all agents are informed, since they have a clue about whether the final payoff from adopting one behaviour is high or low. They may be wrong with some positive probability as in the previous model. Agents also face a cost from adoption, and must evaluate the expected final payoff net of this cost. Here agents face a binary choice: adopt or not to adopt. As a consequence, herding takes the form of an up cascade or a down cascade. In a refined version of the model the final payoff assume many different values, but the main idea is the same: whenever an agent sees more than one predecessor making the same choice, she will imitate disregarding her signal. From this point onwards a cascade occurs and everybody jump on the bandwagon.

Both models address the issue of finding the probability that a wrong cascade occurs. This is not just a technical question, in that an answer to it has strong welfare implications: it would be socially more efficient if agents could not observe actions by others. This result is rather unintuitive, and its message quite striking: less information may be preferable to more information, since a cascade prevent the aggregation of information detained by all agents.

The sequential decision problem considered here may be described by an urn model. If we restrict to the case of a binary choice as in Bikhchandani et al. (1992) the translation into the probabilistic setting of the urn model is rather simple, Consider the the number of times that an option i is selected (say the time series of product sales) as given by $b_{n+1}^i = b_n^i + \beta^i(x_n)$, with $i=A,B$, where x_n is the share of i at time n . The incremental term is $\beta^i = 1$ with probability $p(x)$ and $\beta^i = -1$ with probability $1-p(x)$. If we use a S-shaped function for $p(x)$ we can generate cascades. The idea is to have a self-reinforcing probability $p(x)$. With positive probability up or down cascades occur at some stage n . This means a lock-in into option A or option B, depending on chance. Figure 9 reports two simulations of the model with an up cascade (left) and a down cascade (right).

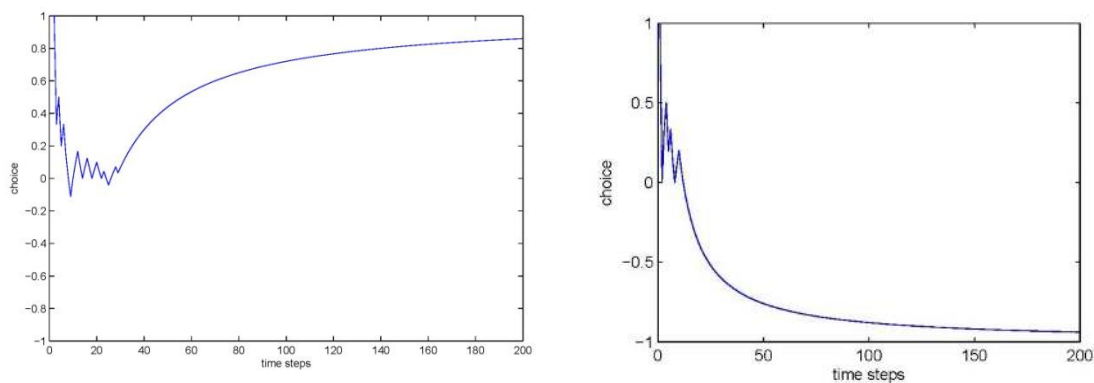


Figure 9: time series of the share of binary decisions. Right: up cascade. Left: down cascade.

In its basic form the model by Bikhchandani et al. (1992) is as follows. Adoption of a certain behaviour leads to a future gain V . This may be either 0 or 1 with posterior probability γ . Adoption bears a cost C , with $0 < C < 1$. The expected net gain is $E[V] - C = \gamma - C$ and can be either negative or positive. Agents chose sequentially and are privately informed about the future value of the payoff from adoption. Agents do not have an exact information but only a signal telling with some positive probability whether this value will be 1 (signal H) or 0 (signal L). After receiving signal H the probability that the final value will be $V=1$ is $p > 1/2$. On top of their private information agents also observe choices of previous agents and use the information they extract when making their decision on adoption.

A typical story can be the one of this example. Say the first agent of the sequence gets a H signal. Then she adopts, since $p > 1/2$. The second agent gets again a H signal. Without hesitating she will adopt either, since the probability that the signal is right is even larger than p . The third agent gets a L signal, instead. Based on her information she would refuse adoption. But the action (adoption) by the first and the second agent speaks very loud: they must have got two H signals or maybe the first got a H signal and the second a L signal. But in this last case the second agent was adopting with only $1/2$ probability. This means that the third agent correctly assigns more likelihood to the occurrence of a signal sequence (H,H,L) than to the signal sequence (H,L,L) and she rationally adopts. This adoption by the third agent arises based on a herd externality, since she disregards her private information. In this way an *up* cascade takes place, and all subsequent agents will adopt irrespective of their signals. A *down* cascade occurs in the same way with just H and L signals exchanged.

Moreover, it is not necessary that only the third agent initiate the cascade: if an even number of agents initially receive alternatively H and L signals, a neutral situation perpetuates and the agent coming after this homogeneous sequence find herself exactly in the same situation as the third agent of the example above.

Bikhchandani et al. also show how informational cascades may be fragile and eventually vanish. The idea is that in a herding mechanism positive feedback vanishes as further adoptions are less and less informative. The authors here show how the release of a small amount of public information is enough to end an informational cascade and leave place for a new one to start. This model also explains the occurrence of regime shifts in collective behaviour.

The issue of cascade fragility and regime shifts means a departure from pure positive feedback, and it is addressed with some more detail for instance by Alan Kirman in his famous article *Ants, rationality and recruitment*. (Kirman 1993). In this model the occurrence of a wave of collective behavior is explained as a phenomenon of contagion. The model is based on a probabilistic description of agents' behaviour that is close to the family of non-linear Polya processes of the urn model does studied in the chapter on increasing returns. In Kirman's model herding is not explained by rational decision making (although with limited information) as in Banerjee (1992) and in Bikhchandani et al. (1992), but with a behavioural rule which resembles an act of recruitment. This approach is close to the principal-agent model proposed by Sharfstein and Stein (1990), where agents get a reward for convincing a principal that they are right. Nevertheless Kirman's approach is based on a mechanistic rule, which in economics is referred to as agents following simple heuristics or rules of thumb, and then it departs from neo-classical mainstream economics.

The model by Kirman (1993) is based on a metaphor: while addressing herding in economic and social systems, Kirman recognizes a striking resemblance with the behaviour of ants during a foraging process. Kirman then builds a model that explains the behaviour of ants and eventually resolves the metaphor claiming that collective human action in cases of herding follows the same pattern.

Experimental studies in life sciences have shown that ants distribute unevenly in a perfectly symmetric foraging environment, with four out of five insects eating at one source and only one at the other. This system perfectly adapts to social systems with binary adoption decisions, for instance two different technologies A and B , or a building with multiple exits in an emergency: it is empirically documented that congestion forms at one exit and other exits are almost not used.

The asymmetric exploitation of symmetric sources is explained in Kirman's model by a stochastic mechanism of recruitment, where contagion takes place because ants "recruit" other ants to their source. Kirman also addresses another equally important empirical fact, which is the regime shift of ants' concentrations that flip from one source to the other. As it happens, after some time ants collectively abandon one food source and start exploiting the other, which was largely neglected before. Regime shifts are present in numerous human social systems, where behaviours do not last forever, but extinguish and are possibly replaced by new ones. Examples are fashion, opinion dynamic, and political voting.

The model of ants' behavior is as follows. There are N identical ants and two identical sources of food, A and B . Only one state variable describe the system, say the number of ants using source A , $k=0,1,2,\dots,N$. Ants meet randomly. A probability of *recruitment* is defined, $1 - \delta$: this is the probability that, following an encounter, one ant recruits the other to its source of food. Such probability is the parameter describing the intensity of recruitment. There is a probability of *self-conversion* ϵ which accounts for the event of an ant changing source of food autonomously. The probability ϵ prevents the system to get stuck in one of the two extreme states $k=0$ and $k=N$ (lock-in).

The system dynamics is governed by the transitions probabilities $P(k,k+1)$ and $P(k,k-1)$, describing the transition from the state where k ants eat at source A to the $k+1$ state and to the $k-1$ state, respectively. Assuming an uniform distribution of states, $P(k,k+1) = P(k+1,k)$, Kirman obtains a threshold value $(1 - \delta)/(N - 1)$ for the probability of self-conversion ϵ : if this is below such threshold, the equilibrium distribution is larger towards the extremes $k=0$ and $k=N$. Such bi-modal distribution says that *lock-in* into one of the two food sources is very likely to occur. In other words, this distribution expresses probabilistically the asymmetric scenario where ants largely select one of two identical sources of food. The key factor is the relative magnitude of probabilities ϵ and δ : given the total population size N , the asymmetric condition is met for ϵ small enough (self-conversion is relatively rare) or δ small enough (recruitment is relatively likely).

The same conditions for the asymmetric scenario of a bi-modal distribution also give the regime switching of the system, which is the second main focus of the model. Simulations of the model show that when ϵ is large compared to $1 - \delta$, the state variable k moves around $N/2$ uniformly and with relatively little oscillations. When ϵ is below the threshold value, the system stays away from $N/2$ for most of the time, and rapidly switches to and from $k=0$ and $k=N$. Notice that none of the states here is an equilibrium. There are not multiple equilibria here, but an equilibrium distribution of the state of the system.

We conclude comparing Kirman' model to the urn scheme of Polya processes studied in the chapter on increasing returns. Both models are characterized by a stochastic approach, and are based on *Markov chains*. In both cases memory turns into path-dependence. Nevertheless, the two models are different in three main points: the first is the probability of self-conversion in Kirman's model, which gives regime shifts. Second, urn models are based on Markov chains that are not time-homogeneous, in that transition probabilities depend explicitly on time, and not just on the value of the state variable. Finally, Kirman's model considers a finite number of agents N , which is not the case with generalized urn models where the number of agent is never an issue.

6. Emergence

One of the most meaningful characters defining a complex system is that it cannot be reduced to the sum of its parts. Quoting Philip Anderson, "more is different" (Anderson 1972). The study of complex systems has represented an important conceptual revolution of twentieth century, which has earned Anderson the Nobel prize in Physics in 1977.

Before addressing socio-economic systems, examples from physics can be instructive. An atom is undoubtedly a complex system, but it is so in loose terms, because it is made of several parts of different nature, the electrons and the nucleus, and the nucleus itself is made of protons and neutrons. True examples of physical systems that are complex in strict sense are a bunch of atoms showing superfluidity or electrons in a superconductive state. In superfluid and superconductive states atoms and electrons do not undergo any structural change. The point is that when they are many, under a certain temperature, atoms have virtually no viscosity, and electrons form a current with no resistance. This magic is a kind of physical cooperation.

Social networks have raised huge interest in complexity studies. Examples are firms' R&D collaborations, financial credit relationships and the trade network. Physical networks of social relevance are transportation networks, the electrical power grid and the internet. (Albert and Barabasi, 2002). More recently, the class of complex social networks has been enriched with online social networks such as Facebook, LinkedIn and Twitter.

Jain and Krishna (2001, 2002) proposed a theoretical framework to describe the emergence and the evolution of a network, with the purpose to show how a network can build as a self-organizing system, and also how it can collapse without exogenous events. Their model is an evolutionary framework based on catalytic interactions between species, which can be chemical substances in a pre-biotic pond, living organisms in a food web, industrial sectors, technologies or even financial institutions. Species are grouped together and form a weighted directed graph, where a link from node j to node i represents the catalytic effect of species j on the production of species i . In other words, without species j there would not be species i , and the larger the weight of the link (j,i) the stronger the catalytic effect. Self-organization of this system leads to an autocatalytic set.

The main idea of the model is to have two dynamics on two different time scales: a fast dynamics, where each single species evolves because of catalytic interactions, and a slow dynamics, where both mutation and selection occur. The slow dynamic process consists of the addition of new species that replace the less performing species (or a set of less performing species). The fast dynamics is assumed to quickly end in an equilibrium state, where the relative abundance of species remains stationary. The fast dynamics is governed by a differential equation that expresses the rate of production of population of a species i as the linear combination of catalytic effects from all species $j=1, \dots, S$ that have a link with i , where S is the total number of species.

The slow dynamics is made of rare selection events occurring at times much longer than the fast dynamics. Such events modify the stationary state by reshuffling the system. A set of less fit species are eliminated with some probability p , and their links are destroyed. This is a structural transformation that modifies the performance of all remaining species that are directly or indirectly connected to the species eliminated. New species are added with new links randomly distributed.

The purpose of the authors with this model is to show how the emergence of cooperation (Jain and Krishna, 2001) and extinctions (Jain and Krishna, 2002) can be described as an emergent phenomenon, where the cooperation network builds and extinguishes endogenously, based on a self-organization. Autocatalytic sets are the key element of the model. These are defined as sets of nodes that have at least one positive (catalytic) incoming link. Such a set grows through time and the complexity of the network increases, as peripheral nodes are removed. The emergence of cooperation and interdependence is sudden and leads to a state where the whole network is an autocatalytic set (**Error! Reference source not found.**). This is a critical state, because the least fit node is a member of the set, a keystone species that plays an important role in the organizational structure of the network. Its removal causes a dramatic reorganization of the whole network, possibly leading to the complete destruction of the autocatalytic set.

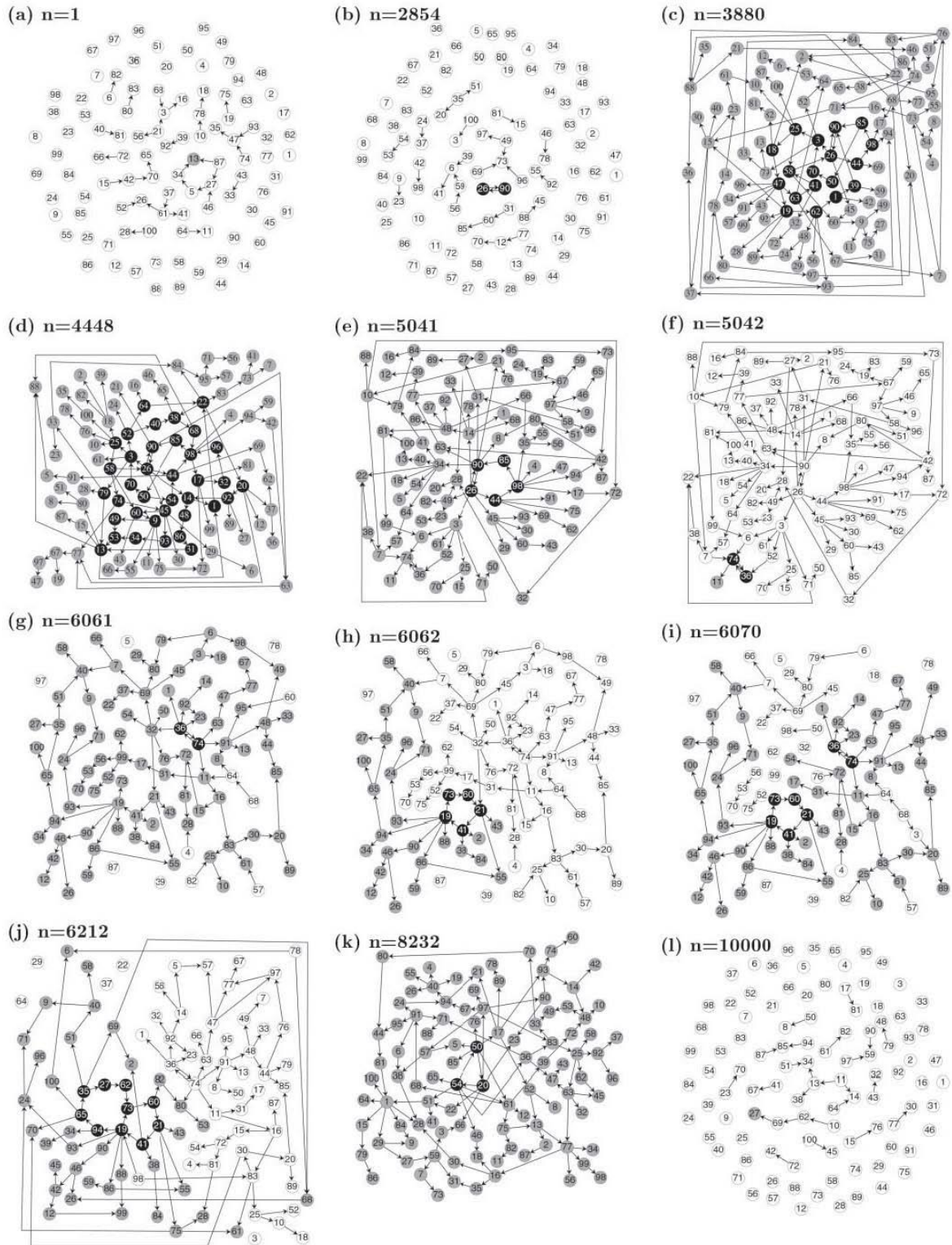


Figure 10: emergence and extinction of an autocatalytic set (example with 100 species).

The dynamics of emergence and fall of cooperation described by autocatalytic networks is represented by plotting the time series of the number of species s_1 that belong to the autocatalytic set (Figure 11). The left panel shows the realization of a large autocatalytic set.

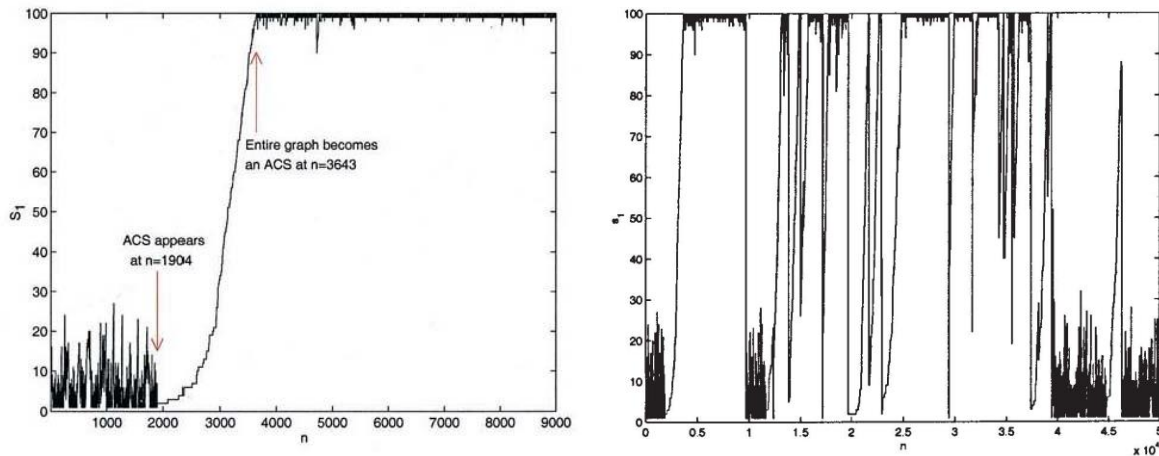


Figure 11: Time series of the number of species in the autocatalytic set (simulation with 100 species).

On the right panel of Figure 11, the same simulation of the model is reported for a longer time horizon. After some time cooperation fails and the autocatalytic set is destroyed. Following this fall, a new phase begins with a stochastically fluctuating set with negligible size. Periods of emergence and extinction alternate then, which represent the self-organizing dynamics of emergence and fall of cooperation.

This model captures the principles of self-organization that underlie the emergence of a complex system, and at the same time shows how the same principles determine its fragility. There are models in the literature that have described further characters of complex systems, as for instance the phenomenon of hysteresis. This is another concept imported from physics where a system is characterized by two different critical transitions when an external force is applied and then replaced by an equal but opposite force. Hysteresis dynamics can also characterize social systems, and is explained by models of complex networks formation. (Marsili et al, 2004, Ehrhardt et al, 2006)

7. Modular technologies

The challenge for designers in designing new technologies is to put together components in a system such that the components “fit” together, meaning that the components work in complementary, instead of conflicting ways. The set of optimal choices for individual components regarding component-specific criteria may prove sub-optimal when these components are combined in a system, because of technological interdependencies. For example, a type of suspension which is found optimal according to suspension tests, and a type of engine which is found optimal in engine tests, may prove to be sub-optimal when put together in a car system. The engine may generate negative effects on the working of suspension, for example, caused by high vibration. Or, vice versa, the suspension may generate negative effects on the working of the engine, for example, caused by high resistance. The existence of interdependencies renders technologies complex systems (Frenken, 2006).

To find out what is the best combination of components put together in a system, one should generally try out all possible combinations of components. Hence, the difficulty in finding a good design is of a higher magnitude than finding a good component design. Simon (1969, p. 194) explains this instance of “combinatorial complexity” using the example of a working and a defective lock: “Suppose the task is to open a safe whose lock has 10 dials, each with 100 possible settings, numbered from 0 to 99. How long will it take to open the safe by a blind trial-and-error search for the correct setting? Since there are 10010 possible settings, we may expect to examine about half of these, on the average, before finding the correct one – that is, 50 billion billion settings”

The strategy of evaluating all possible combinations between components is called exhaustive search. Contrary to complex systems, as Simon (1969, p. 194) goes on explaining, modular systems are characterised by independence between its components, and can hence be optimised by local search: “Suppose, however, that the safe is defective, so that a click can be heard when any one dial is turned to the correct setting. Now each dial can be adjusted independently and does not need to be touched again while the others are being set. The total number of settings that have to be tried is only 10 x 50, or 500. The task of opening the safe has been altered, by the cues the clicks provide, from a practically impossible one to a trivial one”

The metaphorical description of technological complexity by Simon can be modelled analytically by Kauffman’s NK-model (Kauffman 1993; Frenken 2006). NK refers to systems with N components ($n=1,\dots,N$). For each component n, there exist a number of possible component designs called “alleles” that refer to the possible states of this component. The different alleles of a component are labelled by integers “0”, “1”, “2”, “3”, etc. Each string s is described by alleles $s_1s_2\dots s_N$ and is part of possibility set S, for which holds that the size of the design space S is given. The number of possible design that make up the design space, is the product of the number of design possible for each component. In the example of Simon’s working lock, with have 100 possible designs for all 10 components and, hence, a design space of 10010 possible strings. Another example, which we elaborate below, is a system with 3 elements with each 2 possible designs, which has $2^3=8$ possible designs for the system.

In the NK-model, K is the parameter that denotes the complexity of a system, that is, the extent to which the functioning of each component is dependent on other components. The possible K-value of a system ranges from $K=0$ to $K=N-1$. When interdependencies are absent, one deals with systems of minimum complexity ($K=0$), and when all components are interdependent one deals with systems with maximum complexity ($K=N-1$). (In between the two limit cases of minimum and maximum complexity, there is the class of systems with “intermediate” complexity, which we will not go into here). Consider the example of a system consisting of three dimensions, $N=3$, each of which has two alleles, so we have a binary design space.

Following Kauffman (1993), the functional properties of this system for each design s is simulated by drawing randomly from a uniform distribution [0,1] a “fitness” value w_n for each allele of a component s_n . The fitness of the system as a whole $W(s)$ is calculated as the mean value of the fitness values of the alleles of components, so:

$$W(s) = \frac{1}{N} \cdot \sum_{n=1}^N w_n (s_n) \tag{1}$$

The design space of this system contains 2^3 possible strings, which can be represented as coordinates in the three dimensions of a cube as in Figure 12. Each string represents a different design with a fitness value $W(s)$, which is derived from the mean of the fitness values $w_n(s_n)$ of individual components.

In the case of maximum complexity ($K=N-1$), the functioning of an allele of a component depends upon the choice of the alleles of all other components (see Figure 12). This implies that the fitness value of a particular allele of a component w_n (s_n) is different for different configurations of alleles of other components. To simulate the fitness landscape of this system, the fitness value of an allele of a component is randomly drawn for each possible configuration of alleles of other components. An example of fitness landscape for a system with $N=K-1$ is given in Figure 12.

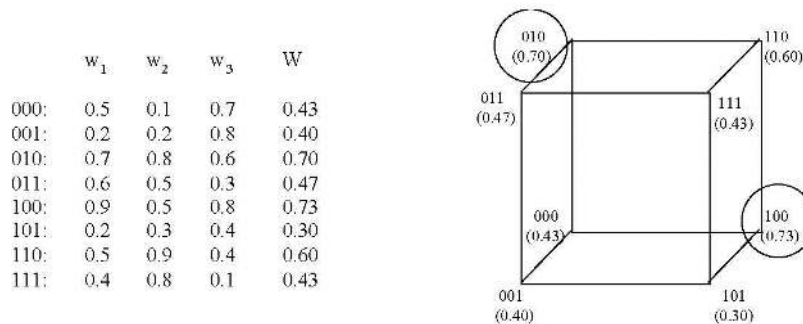


Figure 12: Simulation of a fitness landscape of a $N=3$ system with $K=2$.

A fitness landscape of systems containing interdependencies can contain several fitness peaks. In a landscape containing several peaks, one also speaks of several local optima and one global optimum. Local optima have sub-optimal fitness values compared to the optimal fitness of the global optimum. In the example of Figure 12, string 100 is a global optimum since its fitness is the highest of all strings, while string 010 is a local optimum since its fitness is higher than the fitness of its neighbouring strings, but lower than the fitness of the global optimum. For both global and local optima it holds that they cannot be improved by mutating a single component.

This means that local trial-and-error search on rugged landscapes can end up in several optima. Local trial-and-error here means that a designer mutates one component (from 0 to 1 or vice versa) and accepts this mutation if total fitness W increases. Then, a designer will not always find the optimal solution as one runs the risk of ending up in a local optimum instead of the global optimum. Once a search leads to a local optimum, a designer is “locked-in”. Leaving a local optimum is not possible since any mutation in one component leads to lower fitness and is thus rejected.

Since several local optima exist in complex systems, a designer can end up in different local optima depending on the starting point in the landscape and the particular sequence of mutations that follow. Search is “path-dependent” on the initial starting point of search and the sequence of searches that follow. An example of path-dependence in the simulation example is when search starts from string 001 and the first mutation leads to string 000, and the second mutation to string 100. The resulting solution 100 would be optimal. However, when search starts again in 001, but the first mutation leads to 011, the next successful mutation will inevitably lead to the sub-optimal solution 010.

So far, we considered a single firm hill-climbing the fitness landscape. This reasoning only holds if a single firm controls all parts of the technology. In today’s economy, different firms typically control different components in a complex technological system. Then, a problem of coordination emerges. Since a mutation in one part may make parties responsible for other parts worse off, compensation for losses may be required. For example, in Figure 1, the global optimum 100 is now unstable, because once it is reached, the firm controlling the second component will mutate the component from 0 to 1 thus moving the system from 100 to 110, since by doing so it can increase its own fitness w_2 from 0.5 to 0.9. This means that for good system solutions to work, some firms have to be willing

to give up fitness, which is likely to occur only if such losing firms are compensated by the winning firms.

Adner (2012) calls this a ‘ecosystem perspective’ to innovation strategy, where the innovating firm does not only look at the performance of its own part in the whole technological ecosystem, but also anticipates the effects on other parts of the technology that fall outside their control. Anticipation generally means that the innovating firm builds a strategic alliance with all other parties in the ecosystem who need to change their respective parts as to make the new system fully working. Adner (2012) provides many case studies of companies that failed to view their own innovation as being part of an ecosystem. One telling example of the need for coordination in an ecosystem of non-modular technology is Michelin’s radical innovation in tires, which was completely re-designed to make it possible to continue to drive for over 125 miles on a flat tire. Though this innovation greatly improved the safety of driving and the convenience for drivers of not having to pull over in case of a flat tire, the company did not invest in training repair men. Repair service stations themselves, being small, also had little incentive to train their personnel since the new product only gradually diffused. The first costumers, therefore, were forced to buy new ones instead of having it repaired at a low price. A second example is Nokia’s that was first to market with a 3G handset, but failed to profit from their first-mover advantage since content providers did not come up with the necessary complementary innovations such as video streaming, location based services, and automated payment systems.

7.1 Modularity

In the absence of complexity ($K=0$) the functionality of a component is solely dependent upon its own allele (here, “0” or “1”) and independent of alleles of other components. The important feature of fitness landscapes of $K=0$ systems holds that the fitness value of an allele of a component w_n (s_n) is the same for all configurations of alleles of other components. The optimal design is therefore the design in which all components have the allele s_n with the highest fitness value w_n (s_n). Optimisation is therefore easy since a mutation in one component does not affect the functioning of other components. Put another way, systems without complexity do not have trade-offs between the functioning of components. Therefore, the individual components can be optimised independently through local trial-and-error, that is, by randomly mutating from one allele to the other allele, and accepting this mutation if fitness W is increased. In the example of Figure 13, any series of mutations in one component at the time will always lead the designer to find the optimum system design 110. Note here that the case of $K=0$ corresponds to the earlier example of Simon’s defective lock.

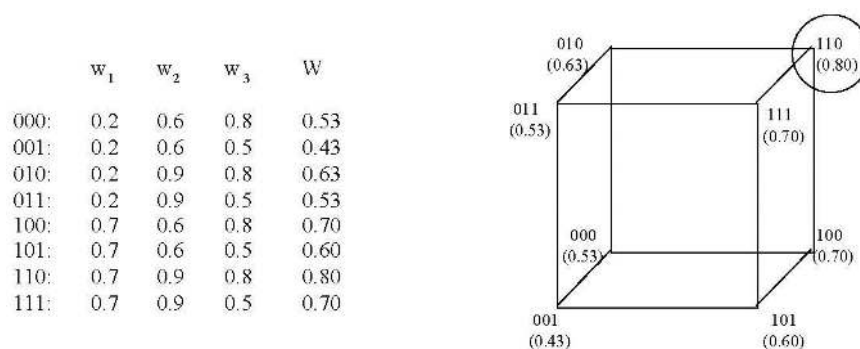


Figure 13: Simulation of a fitness landscape of a $N=3$ system with $K=0$.

What is important to note is that although systems without interdependencies ($K=0$) are modular, not all modular systems are without interdependencies. One can construct systems with interdependencies that are nevertheless modular (Frenken 2006). The modularity only depends on the specific architecture of the system. In a modular system search can proceed in a decentralized and parallel manner. Since the two modules can be search in parallel (in contrast to non-modular systems), search time can be reduced to 22 parallel trials. As exhaustive search requires 24 sequential tests, hence 16 time units, the modular system can be searched 75% more efficient. This means that different modules can be improved by different departments in an organization or even different organizations, without the need for coordination. In the latter case, a firm producing a technology can outsource not just the production process of modules to suppliers, but also the innovation process within modules.

7.2 Mass-individualization

Modularity has important search advantages because fewer mutations are required to find the global optimum and even less time is required as search can proceed in parallel. However, modularity is a concept with even broader implications. If users of a technology are heterogeneous, a modular system allows offering different components for different types of users. And, for some users some components can be left out all together (typically against lower price). This model is followed now by many companies as to provide a large variety of products while using the same production technology.

An even more powerful business model is to have the users themselves assemble the product by mixing and matching the modules they like. For firms this solves the problem of knowing about the needs of each single customer. And for the users, this allows for perfect individual customisation of a product. A typical example is the self-service regime that has become dominant in many service companies allowing customers to organise the service in their own way (e.g., combining your own meal). If one elaborates this mass-individualisation model even further to include innovation activities, modularity also allows users to come with their own solutions. Hence, modularity can be a model of “user innovation”.

All these advantages of modular systems, however, come at one important cost. The type of innovations that can introduced in modules are constrained by the requirements that the modular system. Modules can only work together if interfaces between the modules are well-specified and standardised. Hence, a new module that does not adhere to the interface standards will, in fact, create unwanted interdependencies between modules. Then, a system is no longer modular. For example, if a new engine type for aircraft is being developed that cannot be attached to the wings in the same way as current jet engines are attached to the wings, that the introduction of such a new engine type would render the system no longer to be modular. Only if a new aircraft engine type can be attached to the wings in the same way as current jet engines, the advantages of modularity remain.

8. Niches, exaptation and the evolutionary dynamics of technical change

A niche can be defined as “The particular area within a habitat occupied by an organism” (Free dictionary). This definition also applied to whole species. The size of a niche, then, is conditioned by availability of resources on which a species depends for its survival and reproduction (such as food, light, etc.) and the level of competition of other species for the same resources. If these resources are in abundance, a species will grow in size and the more such resources are scarce, the more a species will shrink (and even may become extinct).

In technology, the concept of niche also applies (Schot and Geels 2007). Here, a niche is an area in consumer space with high willing to pay because of specific (combination of) characteristics of the technology that provide particular benefits for consumers. If a technology satisfies a consumer need that cannot be well met by other technologies, competition is low, and it has found a viable market niche. And the more resources available to these consumers, the more the technology will grow.

To understand competition between technologies, one needs a representation of the functionalities they provide. In most cases, the functionality of a technology is multi-dimensional. For example, a plane’s basic functionality is transport through air, but the quality of a plane can be further detailed by specific “service characteristics” such as speed, fuel efficiency, size, range, etc. For higher levels of these characteristics, higher prices need to be paid. Competition, then, can be mapped by looking at the multi-dimensional distance of an aircraft design to other aircraft design. The larger this distance, the less competition is will experience from other designs (Saviotti 1996). In Figure 14 technology 0 occupies a niche vis-à-vis all the instances of technology x. For example, technology 0 can be a small and fast aircraft using for fighter operations that is distinct from the typical larger and slower aircraft used for bombing, cargo and passenger transportation.

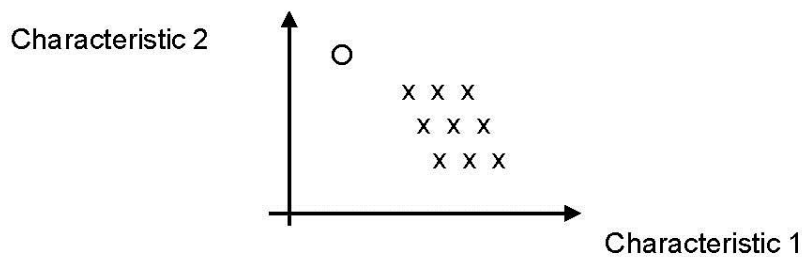


Figure 14: a technology with two dimensions.

From detailed empirical studies of several technologies (Frenken 2006; Schot and Geels 2007), a typical pattern has emerged, where most successful technologies initially started out as niches. For example, the laptop that has come to replace the PC in many households started out as a device for business men travelling to their clients. And, the jet engine that is now powering almost all types of aircraft having replaced propeller type aircraft, was first used only in fighter aircraft where speed is the key service characteristic. Or, think of solar panels first used in aerospace.

Once a new technology is successful in a niche more resources become available for further improvements. More importantly, new functionalities are added to the technologies expanding its range of applications often to completely different markets. These functionalities are initially unforeseen, but once the technology is introduced in a niche market, producers and users start to learn how to use it and experiment with new uses.

In evolutionary theory, this phenomenon has become known as exaptation. For Lane (2011, p. 69), “exaptation is the taking on of new functionality by existing structure”. The classic example of exaptation in nature is that of bird feathers, which were initially evolved for temperature regulation, but later for flying. In the context of technological artifacts, Lane (2011, p. 69) argued that: “artifacts gain their meaning through use, and not all the possible meanings that can arise when agents begin to incorporate new artifacts in patterns of use could have been anticipated by the designers and producers of those artifacts”. One of the main reasons, why all relevant functionalities are not known ex ante but to be discovered over time, holds that the functionalities of a new technology are generally defined by the user context of the older technologies that they initially substitute. New functionalities are being discovered only gradually, and then further improved, leading to a progressive differentiation between the old and the new technology.

A well-known example of exaptation is the phonograph (Dew et al. 2004). When Edison invented the phonograph in 1877, his marketing plan was to sell it as a dictating machine, which failed. The

successful function of the phonograph came from other entrepreneurs who exapted the phonograph into jukeboxes. This successful function was unpredicted by Edison and, later on, he refused to enter into this application area of his phonograph. Jukebox technology then started its own trajectory, based on optimization of functions relevant to playing recorded music: transition from cylinders to discs, improvement of the reproducibility of recorded music, longevity of discs and the like. These improvements have eventually provided the foundations of the music industry.

A more recent example is SMS. From its beginning in the early 1990s, the GSM norm included the technological basis of the SMS, but only as a means for the mobile service providers to send text messages to the end users. The exaptation event was thus to adapt the existing technologies in order to allow users to communicate directly via text messages. The user-to-user SMS function was unpredicted by most of the industrial actors, who considered that texting with a telephone keypad was cumbersome, but once SMS became popular, it subsequently guided new technological improvements (e.g., predictive text-entry), new services (e.g., billing), and new user practices (e.g., the rise of SMS jargon).

Thus, often, a niche technology becomes a mass product only after exaptation events have broadened the scope of applications and users. Querbes and Frenken (2012) use an NK-model (see also chapter 1) to show that the first firm initially discovering the niche is likely to fail in transforming the niche technology into a mass product. Exaptation provides a window of opportunity for new entrants, when incumbents find it difficult to incorporate the new functionality within their existent product design. This difficulty stems from the fact that their technology was previously optimized without reference to the newly discovered functionality. By contrast, newcomers can start 'from scratch' in optimizing their new design with reference to both the existing and the new functionalities. Hence, exaptation may be one of the mechanisms underlying a change in industry leadership; that is, exaptation can be an important source of late comer advantage.

As Querbes and Frenken (2012) argue, exaptation will not always create difficulties for incumbents firms. The extent to which the competitive advantage of incumbent firms is threatened by the discovery of new functionalities will depend on at least two factors. First, the lower the willingness-to-pay for the new functionality, the less the competitive advantage of incumbent firms is weakened in case they stick to their old designs. This follows directly from the additional surplus that entrants can extract compared to incumbents. And, second, the more modular a technology is, the easier incumbents can incorporate the new functionality by adapting their existing designs. That is, for products with few interdependencies, particular components can be readily substituted as to optimize the new functionality without too much negative repercussions for the functionalities that were already optimized in the past.

9. Conclusion

We have presented a number of models and theoretical frameworks that we believe are meaningful approaches to the complexity of technological and societal transitions. The main idea underlying this presentation is to think of transitions as events showing a "big change" with respect to the "regular" dynamics before and after the transition. Such big change may have different connotations, as phase transitions or critical mass, for instance. Different mechanisms underlie different cases of transitions, and call for different modeling frameworks. In some cases the transition is the result of a coordination dynamics, as in critical mass phenomena. In other cases it stems from a structural change in the system, as in phase transitions. But in all cases, the intimate nature of the process is "complex", because the transition dynamics shows characteristics that are unknown to the system without transition. The diffusion regime of a percolation process is more than just a larger diffusion size, in the same way as superconductivity is more than a higher electrical current.

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