Chapter 2
Emergent Organizations

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Abstract This chapter overviews existing applications of agent-based modeling (ABMg) in organization science, pointing to possible cross-contaminations of these research fields. The reviewed applications include the garbage can model of organizational choice, the usage of cellular automata and of the NK model in order to investigate various problems of organizational interdependencies, and realistic agent-based models of agile productive plants. Possible future applications may include employing unsupervised neural networks in applied research on organizational routines, as well as employing sophisticated models of organizational evolution in order to understand such neglected features as punctuated equilibria and exaptation. Given the scope of the research agendas that ABMg can provide, it is quite surprising that this tool has been largely ignored by organization science hitherto. One possible explanation is that ABMg, which presents itself as a computational technique, inadvertently conceives its very nature of a tool for the exploration of novel research hypotheses. It is eventually perceived by non-practitioners as one more statistical technique for the validation of given hypotheses, and possibly a needlessly complex one.

Keywords Garbage can model • Organizational interdependencies • Agile manufacturing • Organizational routines • Organizational ecologies

2.1 Introduction

Once upon a time, computers used to make computations. As pieces of hard wares, computers are machines that carry out logical operations specified by the sequences of instructions they are fed with. These input sequences are *computer programs*, or *computer code*. For instance, the left side of Fig. 2.1 illustrates a sequence of instructions taking the absolute value of a number.

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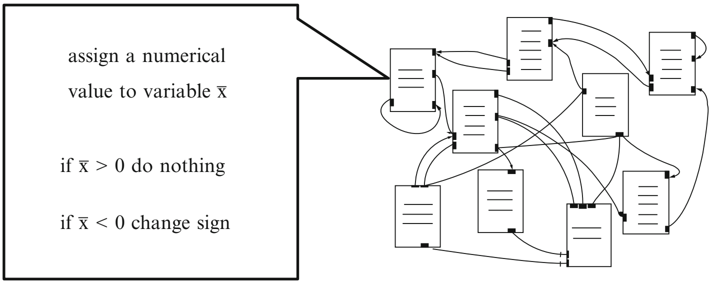

Fig. 2.1 *Left*, a sequence of instructions taking the absolute value of a number. *Right*, objects entailing sequences of instructions and interacting with one another

However, with growing computing power and growing user needs, computer programs grew larger and larger. Programmers started to split long sequences of computer code into small chunks that would be linked to one another, called "objects." This technology for writing computer code has been called *object-oriented* programming. It is illustrated on the right side of Fig. 2.1. The previous technology, consisting of writing one single, possibly long piece of code, has come to be known as *procedural programming*.

Obviously, by splitting a huge program into semi-independent components, its tasks could be handled more easily. However, another implication proved even more important, i.e., that these "objects" must communicate with one another in order to make the whole system work. Some objects would ask other objects for information, which they would deliver (or not) depending on the programs that each object was running. A network of relations would emerge from the behavior of single objects. A huge number of possibilities would arise out of this combinatorial explosion. The set of interacting objects would constitute an *artificial environment*, or *artificial world*, so complex that even its author would be surprised by its outcomes. In the end, object-oriented programming suggested new ways of conceiving computer simulations.

In applications of object-oriented programming, "objects" may represent actors in the real world. Objects can reproduce the behavior of single decision makers, social groups, or institutions, and these artificial actors may interact with one another in their virtual reality pretty much as real actors do. It is out of this mapping between software "objects" and real-life actors that the concept of "autonomous agent" has been conceived (Drogoul, Vanbergue, & Meurisse, 2003), as well as the expression "agent-based models" (ABMs). Agent-based modeling (ABMg) gave rise to new fields of research, such as artificial life and artificial chemistry, as well as to the burgeoning industry of videogames (settlers in a virgin land, astronauts in space, or monsters in fairy tales are autonomous agents who interact in a virtual reality). Essentially, ABMs construct a virtual reality where artificial actors interact, eventually repeating certain interactions along recurring patterns that constitute a sort of collective decision making.

It is fair to remark that the relationship between ABMg and object-oriented programming is not strictly one to one. It is in principle conceivable, though practically difficult, to encode autonomous agents by means of procedural programming, and some early models actually did (Allen & McGlade, 1987). Furthermore, ABMs in a sense generalized a family of models where independent entities would interact with one another, such as the cellular automata (CA), the artificial neural networks (ANNs), and the NK model that will be mentioned later in this chapter. These models may be called connectionist models (Farmer, 1990), and may be understood as ABMs whose agents are particularly simple. These models existed well before object-oriented programming was developed and today's complex ABMs could be conceived. Their existence favored the acceptance and understanding of ABMs by researchers who had already developed a similar modeling philosophy. In some cases, object-oriented code was eventually written for some of these models (Vidgen & Padget, 2009).

Today, ABMg has reached a level of awareness where nearly any scientific discipline has at least a few practicing specialists, and a healthy curiosity surrounds this tool. Moreover, even non-practicing scientists are acquainted with videogames, and this makes it relatively easy for agent-based modelers to explain what they do. "Figure out a videogame where you have consumers, voters, banks, firms and politicians interacting in social space instead of settlers creating a civilization on virgin land," a social scientist may say. One would expect that, in most disciplines, scientists have a clear idea of what ABMs are and what they can do, as well as what they cannot do.

Unfortunately, reality is simply opposite. In particular, misunderstandings among social scientists call for serious concern. Typically, social scientists who do not make use of ABMg associate the word "model" to the sets of equations employed by statistical estimation techniques. Thus, they eventually understand ABMg as one more quantitative technique. Consequently, those social scientists who are skeptical about quantitative techniques stay away from ABMg simply because it is computational. Conversely, those social scientists who employ quantitative techniques may be perplexed at the lack of ready-made rules for building and employing ABMs.

Both attitudes are misplaced, for ABMg is not a tool for hypotheses testing. It is rather a tool for exploring the consequences of hypotheses by means of complex conceptual experiments, which may eventually suggest novel research hypotheses in their turn, and so forth. Model building turns into an opportunity for generalizing empirical observations or conceiving new theories, and the very process of constructing a model is in general just as important as the outputs that the model yields (Epstein, 1999; Gross & Strand, 2000). Thus, to scientists who focus on testing hypotheses that have been formulated by their peers, ABMg is simply useless. By contrast, ABMg is extremely useful for epistemologically sophisticated social scientists who creatively engage in hypotheses formulation. However, insofar these scientists are allergic to techniques of any sort, ABMg has little future.

Paradoxically, ABMg is rejected or ignored precisely by those social scientists who would most benefit from it. In particular organization science (OS), a discipline where ABMg is still unknown to most practitioners, would greatly benefit from ABMg. OS is concerned, among else, about structures of interactions between human beings, stable patterns in human relations, routines, social networks, and, more in general, the relationship between organizational behavior and individual behavior. In its turn, ABMg is concerned with complex behavior emerging out of the interaction of simple components, evolution of networks of relations between agents, and, more in general, generating aggregate behavior out of interactions. OS and ABMg have, in principle, a large area of overlap.

In particular, I envisage a role for ABMg in OS for all those situations where organizations emerge out of tentative interactions between human beings. Think, for instance, of the huge field of organizations emerging in emergency situations, such as fires or earthquakes. Science may well proceed "from funeral to funeral,"[1] but sooner or later the potentialities of ABMg will be certainly picked up by young scholars looking for distinctiveness.

This chapter offers a twofold contribution to the acceptance of ABMg within OS. First, it reviews a few applications that have been developed hitherto. Secondly, it points to concepts that might be useful for further applications.

Both in reviewing models and pointing to applications, ABMg is understood as encompassing any sort of model where relatively autonomous units interact with one another, including CA, ANNs, the NK model, the tangled nature (TN) model or other models of evolution, as well as models that are not cited in this chapter such as classifier systems. All of these models belong to the wider family of connectionist models (Farmer, 1990) and, from one particular but acceptable perspective, they can be viewed as ABMs whose agents are particularly simple.

2.2 A Few ABMs in Organization Science

In this section I shall review three models, or classes of models, where OS already met ABMg:

1. The Garbage Can Model (GCM) of organizational choice
2. Cellular automata and the NK as models of organizational interdependencies
3. ABMs of agile productive plants

These models will not be reviewed in any detail, nor their design and purpose will be discussed. Rather, I shall illustrate why specific organizational problems have been framed by means of ABMs.

[1]Max Planck is credited for the sentence "Science proceeds from funeral to funeral." It conveys the idea that novel theories are not accepted until the previous generation of scientists disappears.

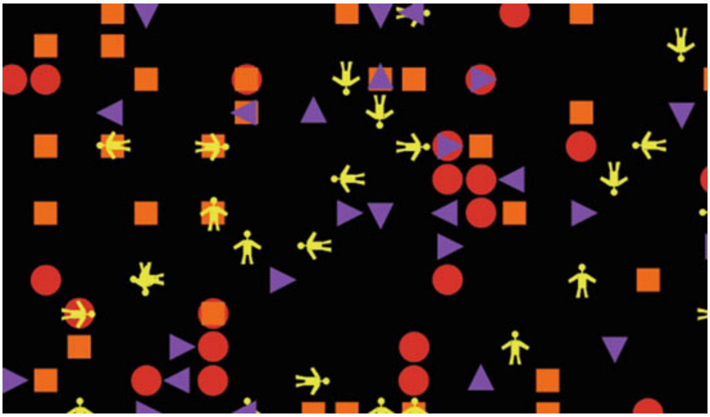

Fig. 2.2 A snapshot of the GCM (Fioretti & Lomi, 2010): *Yellow* men represents organization members, *orange squares* represent choice opportunities, *red circles* represent solutions, and *violet triangles* represent problems

2.2.1 The GCM of Organizational Choice

The GCM of organizational choice by Cohen, March, and Olsen (1972) is among the most widely cited works in OS. Its amazing ability to generate unexpected and profound insights out of simple assumptions makes it a common reference to cite as well as a never-ending source of discussions.

The GCM can be thought as a sort of chemical reactor where “molecules” for organizational decision making have been dumped: organization members, choice opportunities, solutions, and problems jump around, meet, and interact according to rules specified by the model. Organization members make decisions depending on these encounters rather than according to individual utility functions, a circumstance that marks a difference between the GCM and many other models of decision making. Figure 2.2 illustrates a snapshot of the GCM.

The GCM is also a rare case of a piece of organizational theory that was constructed also *by means* of a computer simulation. While many models and theories may be supported and enhanced by computer simulation, the GCM was *defined* in terms of a computer simulation.

The GCM was designed in 1972. At that time, object-oriented programming did not exist. Thus, it is not surprising that the original code entailed a number of limitations as well as real mistakes (Bendor, Moe, & Shotts, 2001).

However, the very structure of the GCM calls for ABMg. The “chemical reactor” where organization members, choice opportunities, solutions and problems meet and interact reminds of a virtual space where agents operate. Somehow, it appears that the GCM was conceived ahead of its time. Indeed, a more recent agent-based version overcomes the main shortcomings of the GCM while its main results stay intact (Fioretti & Lomi, 2008a, 2008b, 2010).

2.2.2 Cellular Automata and the NK as Models of Organizational Interdependencies

Organizations are connected to one another, depending on one another for social legitimacy, strategy formulation, and implementation of decisions. On this issue, at least two streams of research can be identified that make use of specific ABMs.

On the one hand, Lomi and Larsen (1996, 1998) remarked that the local vs. global character of interactions between organizations is crucial in order to explain their diffusion over time. In their model, local competition couples with population-wide legitimation to explain the empirically observed pattern of organization diffusion—the number of novel organizations grows first slowly, and then rapidly, up to a peak. Previous theory had already pointed out that organization density increases legitimation at a decreasing rate while it increases competition at an increasing rate (Hannan, 1992; Hannan & Freeman, 1989), but building an ABM helped realizing that competition and legitimation work at different levels—competition mainly works at the local level, whereas legitimation mainly works at the population level.

On the other hand, Levinthal and others remarked that the fitness of an organization depends on component units that may be either tightly or loosely coupled to one another—for instance, an organization with lots of coordination roles is likely to be a tightly coupled one. Organizations whose units are tightly coupled to one another are subject to failure in rapidly changing environments unless they are capable of fundamental restructurings. By contrast, organizations whose component units are loosely coupled to one another can easily adapt to a changing environment by changing a few of their components (Levinthal, 1997; Levinthal & Warglien, 1999). This observation suggested several implications. One is that the strategies of tightly coupled organizations are difficult to imitate, precisely because imitation involves thorough reorganization (Rivkin, 2000). Another one is that organizations embedded in unpredictable environments cannot be managed by means of rational deduction, whereas analogical reasoning that allows to transfer useful wisdom from similar settings may work (Gavetti, Levinthal, & Rivkin, 2005). Still another one is that tightly coupled organization may not be selected in the short run, even if they would be perfectly fit at a later stage (Levinthal & Posen, 2007).

Lomi and Larsen employed cellular automata (CA), whereas Levinthal and his followers employed the NK model. None of their results could have been obtained without CA and NK reconstructing structures of relations between organizations. And both CA and the NK model can be seen as instances of ABMs.

The first of these tools, CA, originated with John Conway's *Game of Life* (Berlekamp, Conway, & Guy, 1982). In essence, CA can be seen as ABMs where agents are squares placed on a grid and whose state may change with time depending on the states taken by neighboring squares. In spite of their simplicity, CA are able to exhibit a huge variety of graphical patterns evolving and diffusing along the grid where they are placed. With proper mapping, they can constitute simple and yet powerful models of influence and diffusion.

In its turn, the NK model was conceived by Kauffman (1993) as a stylized model of interactions between living organisms and species in an ecosystem. It may be seen as an ABM where agents are strings of N characters which can either be zero or one: each zero/one has a fitness which depends on K neighboring characters as well as—in a more advanced version, called the NKC model—on some characters of other strings (the fitness value of each $(K + 1)$-ple of characters is generated randomly before the actual simulation begins). The fitness of an agent, i.e., of a string, is the sum of the fitness values of its characters.

Suppose that an agent tries to improve its fitness and, therefore, mutates one of its characters. This mutation causes the fitness of the characters to change that are at a distance less or equal than K on the right. Thus, the greater the K—i.e., the greater the interdependencies between the units of an organization—the more difficult it is for an agent to improve its overall fitness unless several of its components are changed at a time. In spite of its simplicity, the NK model reproduces a crucial feature of ecologies, namely the fact that the fitness of organisms and species depends on their ability to change single features without impairing overall fitness and, in the more advanced NKC model, that the fitness of species depends on the relations they entertain with one another.

Figure 2.3 is designed to illustrate the similarities between cellular automata and the NK model. Left, CA A, B, and C are placed on a grid: each of them can be thought as an agent. Each agent contacts only neighboring agents. For instance, agent A contacts agent B because it lies within its neighboring positions (white pixels), but not agent C (which is on the brown pixels). Right, one of the strings of zeros and ones that make up an NK model: [0110]. The fitness of each character in the string depends on the two ensuing characters (black). For instance, the fitness of the first character on the left, i.e., 0, depends on the two 1 s in the middle.

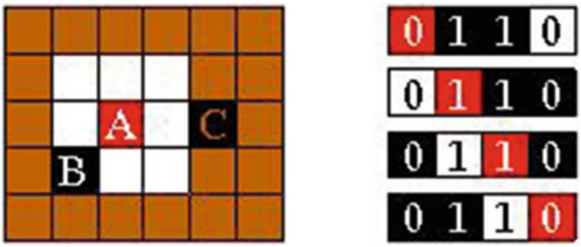

Fig. 2.3 Both CA and the NK model are ABMs that constrain the interactions between agents. *Left*, the agents are CA on a grid. *Right*, the agents are strings of zeros and ones in the NK model. In both models, elements on *red background* depend on elements on *black background* but not on elements on *white background*. CA can only see other automata that lie within their vision, delimited by the *brown area* for automaton A. On the *right*, an NK model with $N = 4$ and $K = 2$. The fitness of the element highlighted in *red* depends on the two elements on the right of it which, since the string is arranged in a *circle*, may find themselves at the other end of the string

Note that in both models each element (for instance, the one highlighted in red) depends on several but not all other elements (not on those highlighted in black, not included in the brown area). Indeed, both CA and the NK model can be seen as ABMs designed to constrain the interactions between agents along specific patterns.

2.2.3 ABMs of Agile Productive Plants

Since the 1980s, an increasing number of productive plants are being organized along *lean/agile manufacturing* principles rather than the more traditional Fordism focused on scale economies. One feature of the lean/agile manufacturing paradigm is that smaller, more flexible machines are typically employed. Workers and machines are eventually organized in "work teams" around "production islands" that can make independent decisions concerning work pace and routing of their semi-manufactured products (which can be processed by several flexible machines) while experimenting with workers' operations (with an incentive to keep production time as low as possible). Thus, many decisions are decentralized to production islands and their work teams, which eventually learn to interact along stable patterns and routines.

Several engineers have built ABMs of specific productive plants where agents are the "islands" where decisions are made (Nilsson & Darley, 2006; Pěchouček & Mařík, 2008). However, the problems of different lean manufacturing plants are similar to one another and, moreover, they are akin to those of many other organizations where decision making is decentralized, such as hospitals or public administrations.

These simulations are proving useful in at least two respects:

- *Identification and elimination of bottlenecks*. While no simulation may be necessary in order to observe bottlenecks in a real plant, ABMg can be very useful in order to evaluate the consequences of policies designed to eliminate bottlenecks. Eliminating bottlenecks is a tricky issue, because productive systems are typically characterized by nonlinearities such that, by increasing the productive capacity of a production island that has a long waiting queue, longer queues may arise at other points in the system. It is quite likely that productive capacity should be increased at different places; yet in practice it is very difficult to understand which are the relevant ones. Thus, a simulator may prove useful in order to experiment with organizational configurations searching for one where bottlenecks are actually eliminated.
- *Prediction and management of the organizational learning curve*. Production time decreases with cumulative production along a (negative) exponential curve whose slope is crucial in order to foresee production costs. Since learning curves are more pronounced in assembling rather than in machining operations, it is widely believed that they arise because workers learn to coordinate their efforts, developing routines that nearly optimize their interactions (Hirsch, 1952, 1956).

> The problem with learning curves is, however, that their slope is difficult to predict. In practice, engineers have collected empirical tables for the slope of learning curves in extremely narrowly defined industrial sectors, yet with no guarantee that a learning curve with the predicted slope will actually set in when new production starts. ABMs can prove useful in order to predict which routines may eventually emerge and how long it takes to approach minimum production time.

A simulation platform is under construction, which will be able to handle all sorts of organizations characterized by distributed decision making (AESOP, 2014). AESOP is based on the observation that albeit technologies may differ widely from one another, all agile production plants can be represented as bakery shops applying a set of recipes to a set of ingredients to yield a set of products. While the possible relations between work teams or production islands are in principle as many as their number and technical specifications allow, recipes constrain the set of feasible paths to a subset of meaningful ones. Just like cherries cannot be put on top of a cake before the cake is done, recipes set apart meaningful sequences from meaningless ones. However, recipes do much more. Recipes can specify batch processes—just like a bakery may wait that a tray is filled up with cakes before letting it enter the oven—as well as concurrent processes, bifurcations along different sequences that obtain the same result—inside a cake, it may make no difference whether cream or candies come first—and calls for shipments of ingredients. According to the AESOP framework, customers eventually place orders, which imply that some recipe must be applied—just like one may place an order for a chocolate cake, which requires the recipe for chocolate cakes to be applied.

Within AESOP, both orders and compounds of workers and machines (work teams, production islands, etc.) are agents. Agents representing compounds of workers and machines may be endowed with complex decision-making capabilities, ranging from heuristics to neural networks. Together, these agents generate possible stories of interactions within an organization—hence the name. AESOP can be applied to any organization where decision making is to some extent distributed, ranging from agile production plants to hospitals and administrative bodies.

Figure 2.4 illustrates a snapshot of a typical AESOP run. Nodes represent machines in a productive plant, whereas edges represent exchanges of semi-manufactured goods of various intensities. The simulator constructs possible developments of this graph, with stable patterns of interaction eventually emerging while organizational learning is taking place.

2.3 Concepts and Theories for New Applications

In the three above examples, ABMs were used in order to investigate the emergence of organizational arrangements out of interactions of some constitutive elements, or agents. In the GCM, interaction between the constitutive elements of decisions

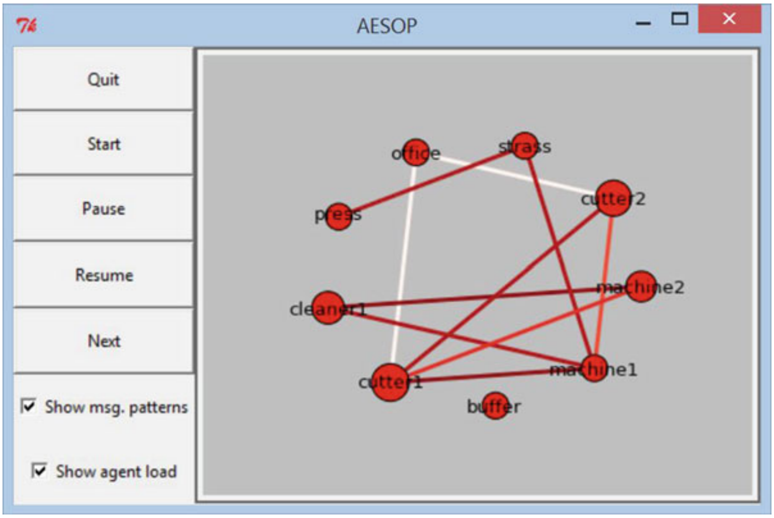

Fig. 2.4 The network of interactions between production islands as they are reconstructed by the AESOP simulator: edges of increasing thickness and darkness denote larger exchanges of semi-manufactured goods

would eventually yield organizational decision making. In CA- and NK-based models of organizational interdependencies, neighboring organizations would affect each organization's fitness and ability to survive. Finally, in ABMs of productive plants the production islands eventually settle down on stable patterns of shipments of semi-manufactured goods whose emergence corresponds to production time decreasing along the organizational learning curve.

Emergence of organizational arrangements is, indeed, a domain where ABMg and OS may meet. Potential unexploited applications may include the emergence of organizations in emergencies such as earthquakes, gaining insights into criminal and therefore fluid and unobservable organizations, exploring the possible outcomes of restructurings that require substantial horizontal communication—as it is currently happening in healthcare—or understanding network organizations in free software development and elsewhere. This list is certainly not exhaustive and, indeed, it could easily grow too long and too detailed to be useful. Rather, an indication of conceptual tools that may be relevant in several domains may be more appropriate to this stage of development.

Henceforth, I shall report on two pieces of knowledge that are quite well developed as ABMs and yet did not find corresponding applications in OS hitherto. It is neither obvious that they will, nor that these will be the leading ABMs in OS. Simply, I selected them because their current state of development is quite advanced, so applications to OS might be around the corner. These pieces of knowledge are relevant for the formation of organizational routines and for the evolutionary dynamics of organizational populations, respectively.

2.3.1 Unsupervised Neural Networks and Organizational Routines

Organizations are characterized by modes of behavior that are specific to each single organization, ways to react to contingencies, and ways to approach problems that exhibit some invariance with time and that are so intimately tied to organizational culture to persist in spite of organization members turning over with time. These modes of behavior are eventually known as *organizational routines*. One way to conceptualize organizational routines is that of conceiving them as sequences of actions that single organization members may undertake out of managerial directions, personal deliberation, or even unconscious responses (Becker, 2004; Pentland, Feldman, Becker, & Liu, 2012). Such sequences of actions can be activated by specific stimuli, but they can also repeat themselves indefinitely if they close in a loop (Hutchins, 1991). Either such loops may unfold within one single organization or they may involve several organizations if they include external actors such as long-standing customers and suppliers.

Closure in a loop is essential for a routine to be repeated over and over even without explicit directions while at the same time being open to change. The stability of routines is ensured by socialization of new organization members into groups where certain routines are practiced, which amounts for them to learn to perform a certain subset of actions along the loop. In its turn, the flexibility of routines arises both from top-down intervention and bottom-up fine-tuning. On the one hand, organizational routines can be influenced by leading personalities by means of personal example, involvement and socialization of other members in groups where different activity routines are used, or official regulations. On the other hand, the decision makers involved in a routine may change it by modifying their own actions, by adding new members to the loop, or by shortcutting it.

This view of organizational routines may suggest that there is some similarity between the behavior of human beings in an organization and the behavior of neurons in a brain. Just like individual behavior is the outcome of billions of neurons firing signals according to relatively simple principles, organizational behavior can be seen, to some extent, as the unintended outcome of the actions of many organization members pursuing a variety of goals. This understanding is actually at the core of the very concept of “organizational behavior” which—as an instance of the dictum that the whole is more than the sum of its parts—should capture the idea that organizations make decisions that cannot be fully explained by rational composition of the interests of their most powerful members.

All analogies are imperfect, and the analogy between human beings in an organization and neurons in a brain has limitations that organization scientists should not overlook. Its shortcomings are indeed evident to the extent a few members are able to steer the decisions and strategies of a whole organization. In more theoretical terms one may observe that this analogy is imperfect to the extent organization members optimize long-term strategies that they are able to put in practice, whereas it fits very well with an idea of organization members as boundedly rational, myopic, satisfycing decision makers (March & Simon, 1958). Since this last tradition is well established in OS, I deem that the analogy between neurons in a brain and human beings within an organization deserves careful attention. In particular, this analogy is likely to be fruitful with respect to:

- *Persistence of organizational routines independently of personnel turnover*
- *Organizational learning as formation of routines in response to environmental stimuli*
- *Enactment of routines when situations present themselves that remind of similar situations experienced in the past*

The connectionist revolution that swept across cognitive sciences in the 1980s provided a view of the brain which is absolutely relevant for the above aspects of organizational routines (McClelland, 2010; McClelland & Rumelhart, 1986; Smolensky, 1988). According to connectionism brain memory, just like organizational routines, consists of information circulating in loops. Cognitive scientists talk about *distributed memory*, as opposed to the *localized memory* of a computer (whose memory is localized on its hard disk) or a library (whose memory is localized on shelves). This explains the fact that patients who lost a substantial portion of their cortex as a consequence of accidents still retain their memories intact albeit their ability to learn new concepts is substantially reduced. Since memory does not reside in any particular place, circulating information may easily take on other paths if a subset of neurons is removed. However, a brain with less neurons may be too congested to allow the formation of new information loops, hence the difficulty of such patients to learn.

Compare the insight about information taking on other paths if a subset of neurons is removed with the observation that organizational routines persist in spite of personnel turnover (Stein, 1995): It is fair to recognize that opportunities for cross-fertilizations exist. Conversely, the insight about neuron removal causing inability to learn should be taken with some care. In organizations, inability to learn does not originate from removing employees but rather from stifling hierarchical relations into patterns where managers are happy to control whereas subordinates are happy to delegate responsibility (Argyris, 1994). In a sense, unempowered organization members are like "removed" from the organization. However, it would be much better that connectionist visions develop to the point of including control of low-level brain functions by high-level functions (including conscious activities) if a good matching with organizational problems is sought.

Organizational learning has a lot to do with connectionism, however. One important instance of organizational learning is the organizational learning curve, also known as progress ratio or learning by doing, which is the observation that throughput time decreases with cumulative production. At least a couple of models ascribe this fact to the formation of stable patterns of interaction (routines) among workers (Fioretti, 2007, 2010; Huberman, 2001; Schrager, Hogg, & Huberman, 1988). Connectionism, in its turn, understands the formation of stable connections among neurons as due to exposure to stable stimuli that deepen the "grooves" where information flows (Hebb, 1949). These statements may seem unrelated to one another, but consider that a few cases where the learning curve did not set in were due to continuous change of product specification (the Lockheed Tri-Star, cited in Huberman, 2001). Unless this happens, successful interactions among workers stabilize pretty much as connections between neurons do. Another hint on the conceptual linkage between organizational learning and connectionism is provided by the observation that the organizational learning curve is strongest in industries where assembling operations are paramount, such as the airframe industry or ship building (Hirsch, 1952, 1956). Similarly to the above issue, organizational learning is best understood by connectionist frameworks if all organization members are actively involved in creating novel routines, as it is the case of industries where assembling operations are paramount; by contrast, connectionism provides limited insight into organizational learning occurring under strong constraints on individual freedom.

Finally, connectionism is very relevant for the process of recalling and enacting organizational routines when proper situations appear (March, 1994). This is due to the fact that distributed memories are also *associative memories* (Clark, 1993; Kohonen, 1988), in the sense that their content is not retrieved by pointing to memory location (e.g., the position of a book on the shelves of a library) but rather by association with a neighboring concept (e.g., as students do when they make use of mnemonic rules). Likewise, we may understand an organization's reactions to environmental conditions as due to the fact that some features of those conditions trigger a routine that had been previously developed for other purposes. A trivial example may be the activation of bureaucratic rules in inappropriate contexts; a more complex one might be the construction of organizational narratives out of past experiences and occasional encounters (Lane & Maxfield, 2009).

However, the case for a cross-fertilization between connectionism and OS is not based on loose analogies only. Indeed the main issue at stake is that connectionism developed computational tools and mathematical formalizations that may be relevant for OS. The main tool is ANNs, particularly unsupervised neural networks.

Formally, ANNs are constituted by nodes, called neurons, connected to one another by edges according to a given architecture. Neurons produce an output y by summing inputs $x_1,\ x_2, \cdots x_N$ by means of coefficients $a_1,\ a_2, \cdots a_N$:

$$y = \sum_{i=1}^{N} a_i\, x_i \tag{2.1}$$

As previously hinted, ANNs can also be seen as ABMs whose agents simply weigh and sum up the inputs that they receive in order to yield an output that they pass on to other neurons.

The sort of neural networks I would suggest organization scientists to pay attention to are *unsupervised* neural networks. There exist substantial differences between unsupervised neural networks and the more common, more widely known supervised ones:

- In supervised neural networks, the weights of the neurons are settled during a training phase prior to the normal operation of the network. In unsupervised neural networks, no training phase takes place. Instead, each neuron adjusts its own weights by means of a positive feedback from its own inputs and output—it is more a sort of an agent. Expressions may take different forms, but the rationale is that the weights of a neuron grow when they receive inputs that already generated a high output, an effect that may be obtained by multiplying inputs x_i by output y (which amounts to deepening the groove of established paths between neurons), whereas they decrease if output grows too high. Here is an example, where **x** denotes the vector of neuron inputs, **a** denotes the vector of the coefficients of a neuron whereas μ and ν are constants:

$$\dot{\mathbf{a}} = \mu y \mathbf{x} - \nu \mathbf{y} \mathbf{a} \tag{2.2}$$

  The first term on the right makes each neuron specialize into reacting to stimuli to which its random initialization made it slightly more sensible than other neurons. This ensures the formation of stable linkages between neurons depending on the input patterns they have been exposed to. The second term on the right side of Eq. (2.2) is a forgetting term. It is simply there in order to ensure that the behavior of the network does not explode in the long run.
- While supervised ANNs are generally arranged in three layers, no a priori architecture exists for unsupervised ANNs. In general, each neuron of an unsupervised ANN is connected to all other neurons in the network. Eventually, special care is taken in order to ensure that loops can arise. Thus, only unsupervised neural networks are able to reproduce routine formation and routine retrieval.
- While most supervised ANNs are digital systems operating with zeroes and ones, unsupervised ANNs generally operate with continuous signals. Albeit biological neurons fire spikes, receiving neurons react to the frequency of spikes. Thus, employing continuous variables makes unsupervised ANNs somewhat closer to biological networks.

Suppose that an unsupervised ANN is endowed with linkages feeding the outputs of the neurons back into their inputs so that information loops are possible. Figure 2.5 illustrates one example taken from Kohonen (1988). Note that, for the sake of simplicity, neurons' coefficients weigh only the signals feeding back from neurons' outputs.

Let us focus on short-term dynamics, so the forgetting term (the second term on the right) of Eq. (2.2) can be neglected. Let us make the further simplification that coefficients μ and **A** can be subsumed by one single coefficient α when describing the variations of **A**. Then, the neural network of Fig. 2.5 can be described by

$$\mathbf{y} = \mathbf{x} + \mathbf{A}\mathbf{y} \tag{2.3}$$

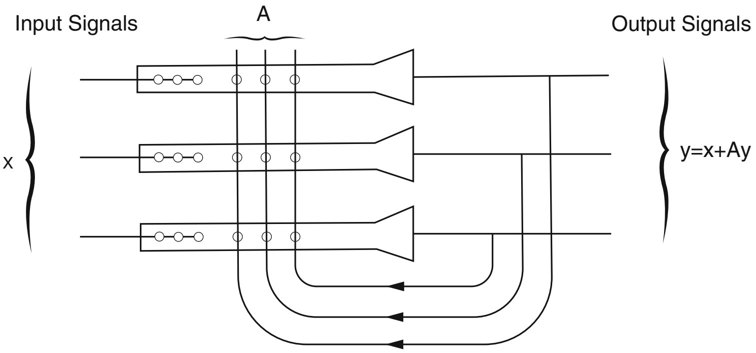

Fig. 2.5 An unsupervised ANN with feedbacks that enable the formation of information loops where, for simplicity, the coefficients entailed in matrix **A** weigh only the outputs that are fed back (from Kohonen, 1988)

$$\dot{\mathbf{A}} = \alpha \mathbf{y}\mathbf{y}^{\mathrm{T}} \tag{2.4}$$

From Eq. (2.3) we can write the transfer function $\mathbf{y} = \boldsymbol{\Omega}\mathbf{x}$ where $\boldsymbol{\Omega} = (\mathbf{I} - \mathbf{A})^{-1}$ provided that $(\mathbf{I} - \mathbf{A})$ exists, which is normally true. Kohonen (1988, Ch.IV) has the passages to obtain from Eq. (2.4):

$$\dot{\boldsymbol{\Omega}} = \alpha \boldsymbol{\Omega}^2 \mathbf{x}\mathbf{x}^{\mathrm{T}} \boldsymbol{\Omega}^{\mathrm{T}} \boldsymbol{\Omega} \tag{2.5}$$

Equation (2.5) has been obtained by neglecting the forgetting term. Thus, it makes sense to approximate it further in order to observe the short-term dynamics. By assuming $\boldsymbol{\Omega} \approx \mathbf{I}$ Eq. (2.5) becomes $\dot{\boldsymbol{\Omega}} \cong \alpha \mathbf{x}\mathbf{x}^{\mathrm{T}}$ which means that the first-order solution for the transfer operator is

$$\boldsymbol{\Omega}(t) \cong \mathbf{I} + \alpha \int_0^t \mathbf{x}(t')\, \mathbf{x}(t')^{\mathrm{T}} dt' \tag{2.6}$$

At this point, Kohonen (1988) asks to figure out that $\boldsymbol{\Omega}$ has been formed during some period $0 \le t' \le t$. Thus, $\boldsymbol{\Omega}$ represents what the network has learned up to time t as a consequence of stimuli $\mathbf{x}(t)$—it describes a configuration of neuron weights that make information circulate along certain loops. Assume that $\boldsymbol{\Omega}(0) = \mathbf{I}$. If at some later time $t_0 > t$ the network is excited by a stimulus $\mathbf{x}_0$, its response is

$$\mathbf{y} = \boldsymbol{\Omega}\mathbf{x}_0 = \mathbf{x}_0 + \alpha \int_0^t \left[\mathbf{x}^{\mathrm{T}}(t')\ \mathbf{x}_0\right] \mathbf{x}(t')\, dt' \tag{2.7}$$

The second term on the right side of Eq. (2.7) represents the recollection of information from the network's associative memory. That is, stimulus $\mathbf{x}_0$ generates a response that depends on its ability to reach the information that the network received in the $[0, t]$ interval, which is now circulating within the network. Its ability to recall the information stored in an associative memory depends on its similarity with stored information.

Kohonen's formulas could be usefully applied to organizations reacting to environmental stimuli by activating stored routines. It is true that quantitative data on organizational routines is hard to collect, but there are exceptions. Think, for instance, of Jazz ensembles learning "standards"[2] and activating them whenever a musician starts a phrase. Jazz ensembles are organizations; they are organizations whose members are encouraged to express themselves, so the analogy with neurons in a brain makes sense and, finally, for these organizations huge amounts of data could be obtained by analyzing recordings.

2.3.2 Organizational Ecologies and Evolutionary Theory

It is quite common for the popular management press to stress the qualities of prominent, successful CEOs with the aim to distill from their experiences some magical rule—often expressed in expressions like "the 5 A of management," "the 7 B of marketing," and the like—which would inevitably lead previously bankrupt organizations to success. Implicit in these statements is the view that organizations can easily change, and that they do so as a consequence of the involvement, passion, and power of their boss. The popular management press is echoed by substantial streams of scholarly research on "change management," i.e., what managers should do in order to change organizations.

The opposite view is that sunk investments, available competencies, established power structures, and organizational routines make it extremely difficult for organizations to change. Organizational populations do change, of course, but rather in the sense that new organizations are born which supersede the less efficient ones, pushing them to extinction. This view has a clear ecological flavor, with organizational competences and routines taking the role of a sort of DNA that cannot be changed by any single organism although random mutations may produce novel organisms with a different genome—i.e., new organizations with novel competences and routines (Hannan & Freeman, 1977, 1984).

Accepting the existence of this organizational ecology does not amount to claim that organizations are not capable of innovation. However, organizational ecologists would submit that organizations are only able to innovate within their established routines and competences. They would point to the fact that no producer of vacuum

[2]In Jazz jargon, "standards" are certain tunes that have been repeatedly used by Jazz musicians with infinite variations.

tubes was able to switch to transistors, no producer of chemical films was able to switch to digital cameras, and so on.[3] They would claim that organizations die rather than change.

Organizational ecology is absent from the popular management press, and it is relatively rare among academics. Casual search on Google Scholar yields 439,000 results for "organizational ecology" and 4,450,000 results for "change management." By restricting search to title words only, the figures were even more apart from one another: only 369 entries for "organizational ecology," but 27,200 entries for "change management" (Access: November 17th, 2014).

Whatever the merits of each point of view, as a matter of fact ABMg has little to say to a lonely enterprise as change management is. By contrast, ABMg actively concurred to our understanding of evolution (Gould, 2002), so it is a relevant tool for organizational ecology.

Organizational ecology is an approach that is still in its infancy. Arousal and diffusion of organizational populations is the only aspect that has been investigated hitherto. But many more issues are awaiting for proper research, for evolutionary theory is extremely insightful and complex.

A superficial understanding of evolution would equate it with the combination of mutation and selection in order to ensure "survival of the fittest." In particular, this expression is frequently misinterpreted as implying that whatever is empirically observed must have been "the fittest," or "the best" available option. This is particularly dangerous in the social sciences, where "social Darwinism" served as *ex post* justification of whatever organizations and institutions were eventually in place, including racist regimes. In reality, "survival of the fittest" can only be employed *ex ante*. It simply means that a specific organism is fittest with respect to the demands of other organisms in a particular niche at a specific point in time, for the fitness of an organism is constructed by all organisms that share its ecological niche. It is not, in any sense, an evaluation of how good an organism is with respect to "objectively" defined criteria (Lewontin, 1979).

Here are a few nontrivial aspects of evolutionary theory, which may convey how many interesting implications it has for organizational ecology:

- A substantial fraction of mutations are simply neutral with respect to fitness. Genetic drift makes organisms change quite independently of their fitness (Kimura, 1968).

  In organizational ecologies, neutral evolution has a counterpart in management fads. Some fads may be beneficial for some organizations or disruptive for

[3] Olivetti provides an apparently contrary example, since it used to be a producer of typing machines that did attempt to produce personal computers. However, this could only happen because its visionary leader, Adriano Olivetti, being aware of the opposition that computers would face by the typing machines people, set out a separate division. His early death marked the beginning of internal warfare against this division, which ultimately caused Olivetti to lose its leading position. Olivetti did switch to computers finally, but it was too late. It later stopped making computers altogether and, today, it no longer exists as a brand.

others, but for most organizations fads come and go with little or no effect on performance. Quite often management fads leave catchphrases and labels behind them, which persist insofar they are not terribly harmful. One simple example is organization charts where accounting, production, or marketing functions are called "divisions."

- Quite many features appear as necessary consequences of the features that are actually selected (Gould & Lewontin, 1979). These additional features do not arise because they are immediately useful, although they might be employed once they are available. By analogy with triangular spaces that arose out of the need to place a circular dome on a square basement of churches, which eventually provided unplanned opportunities for paintings, this sort of additional features is called *spandrels*.

  In organizational ecologies, new organizations are often created in order to put some invention into practice. And quite many of them originated from opportunities provided by other technical processes (Nooteboom, 2000). One example is the discovery of petrol as a by-product of the production of lubricants from crude oil. The whole automotive industry is a spandrel.
- Adaptation to current environmental requirements is not the only reason why certain mutations may be accepted. It happens quite often that mutations that had been selected for a specific purpose acquire a different function once they become available (e.g., small wings would have never been useful to fly, but devices that were originally selected for temperature regulation would be later used as wings). This is called *exaptation* in order to mark the difference with the more obvious "adaptation" (Gould & Vrba, 1982).

  Several examples of exaptation exist in organizational ecologies, mainly due to finding of a novel usage for a technology that had been developed for an entirely different purpose (Andriani & Cohen, 2013). One example is the microwave oven, which applies a radar technology into an entirely different domain. Just like exaptation of devices for temperature regulation into wings gave rise to qualitatively different organisms, the exaptation of technologies gives rise to different firms.
- Ecological niches may provide locally favorable environments to highly specialized organisms (Freeman & Hannan, 1983), who themselves concur to create the niche they exploit (Odling-Smee, Laland, & Feldman, 1996). Besides the curiosity of "living fossils" in remote places, niches may be important to allow organisms and species to grow before entering global competition.

  An example is provided by the pros and cons of closed vs. open economies. Closed economies shield domestic firms from international competition, allowing them to grow. However, protection from international competition may induce domestic firms not to innovate. Conversely, open economies prompt domestic firms to innovate in order to stand international competition but, if international competition is orders of magnitude stronger than domestic firms, domestic firms will not survive. Closed economies constitute niches for domestic firms.
- Dependencies between species are very intricate, with preys generally having many predators, predators chasing many preys, and symbiosis involving several

species at a time (e.g., insects favor pollination of very many vegetal species). This has the consequence that, while most mutations have no consequences, a few may trigger avalanches of extinctions and formation of new species. Evolution is said to proceed by *punctuated equilibria*, meaning that long intervals where little happens are interrupted by comparatively short times where dramatic events—such as dinosaurs' extinction—take place (Gould, 2002).

The consequences of the existence of firms producing smartphones on producers of simpler and smaller cellular phones, digital cameras, and music listening devices are one punctuation of an otherwise relatively stable equilibrium. And it is not an isolated instance, for punctuated equilibria are the rule in organizational ecologies. The empirical observation that innovations come in bursts (Silverberg & Verspagen, 2003, 2005) originates precisely from the tight linkages between firms in productive systems.

- Natural selection acts on different levels of aggregation at the same time: organisms, species, taxa, etc. (Gould, 2002; Lewontin, 1970). This may have the consequence, for instance, that single organisms are to be selected because their species is selected, independently of their individual performance.

  In the ecology of organizations, organizational forms such as the machine bureaucracy, the professional bureaucracy, and many others (Mintzberg, 1983) correspond to species whereas the single organizations correspond to the single organisms. Consider the neo-institutional stream in OS. It has emphasized that organizations may make substantial efforts to comply with expected behavior in order to gain social legitimacy (Meyer & Rowan, 1977; Powell & DiMaggio, 1991)—think, for instance, of a firm that restructures to comply with a fashionable organizational form in order to be positively valued by banks and rating agencies. This would be a case where selection, i.e., bank loans, accrues to the organizational form (the species) rather than the single organization.

Understanding the nuances and the implications of evolutionary theory is an ongoing enterprise that spans over biology, paleontology, philosophy, and, remarkably, ABMg. In particular, the NK model (Kauffman, 1993) has been useful in order to reproduce punctuated equilibria (Gould, 2002).

Today, the NK model may still make sense for very simple settings, but evolutionary modelers may want more realism and more detail. Consider, for instance, that the NK models handle the case of a multi-species ecology with one representative organism for each species. It is clear that punctuated equilibria are really the most that the NK model can do.

Other ABMs, such as the tangled nature model (Christensen, Di Collobiano, Hall, & Jensen, 2002), could be a better starting point to transfer evolutionary concepts to the world of organizational ecologies. This is a model where organisms reproduce themselves, species arise endogenously, and fitness depends on relations between organisms. Experimentations are at the very beginning, yet it seems safe to maintain that organizational ecologists have still a lot to learn from combinations of evolutionary dynamics and ABMg.

2.4 Conclusions

One interesting feature of ABMg is its ability to bridge the gap between the microscopic level of interactions between individuals and the macroscopic level of aggregate behavior of organizations. By including structures in quantitative analysis, it can give a precise meaning to the dictum “the whole is more than the sum of its parts.” With these premises, one would expect ABMg to be a main tool in OS.

Reality is opposite, with ABMg still ignored or unknown to most organization scientists. My personal interpretation for this puzzling state of affairs is that, given the current mental frames and schemes among social scientists, ABMg deceives its true nature. Because it is computational, ABMg is perceived as one more quantitative technique. Thus, it is scrutinized by evaluating its ability to test given hypotheses. With this criterion, ABMg is rejected and finally ignored.

This sort of judgment is a misunderstanding, simply because ABMg is actually a tool to help researchers carry out sophisticated conceptual experiments. By allowing researchers to explore the implications of their hypotheses, it easily leads them to formulate new ones. It is a tool for creative researchers who do not content themselves with looking for databases by which the research hypotheses that are most popular in their discipline can be tested.

The contributors to this book constitute an exception. This book gathers organization scientists who know how relevant ABMg is to their discipline, and for what reasons. The question is how should this community proceed in order for ABMg to obtain the recognition that it deserves.

While several strategies can be conceived and should possibly be pursued at the same time, I would suggest that by enriching the cultural and conceptual content of ABMg, this tool may become more appealing to sophisticated scientists who are interested in formulating novel research questions. Connectionism has revolutionized cognitive sciences since the 1980s. Punctuated equilibria and other issues have deeply changed our understanding of evolution since the late 1970s. Hopefully, creative researchers will be attracted by the possibility to exploit these intellectual streams in order to gain a better understanding of organizing processes.

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