Natural science models in management: Opportunities and challenges

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Duncan A. Robertson, Duncan Robertson, adrian.caldart Caldart

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Abstract

This paper sets out how models from natural science can be used within the management domain. We contend that this transformation between domains is best served by agent-based models, where the agent behavior is important, not the specifics of the agent type. We also note that these models are useful for exploring complexity and extending the research that has been performed within management to date. We demonstrate this with two models: the NK model, a theoretical biology model that has had 10 years of development within the strategy field, and the Forest Fire model, a model from physics that is at an early stage within its application within the management domain. In doing so, we also focus on the specific issues that need to be addressed when applying and extending these models to management studies due to the ontological differences between the realms of natural science and social science.

Introduction

Interest in complexity and, particularly, on understanding the distinctive features that characterize complex systems, has increased dramatically during the last two decades across many scientific disciplines. The reason for this is that the study of complex systems focuses on understanding how parts of a system give rise to its collective behavior, how such collective behavior affects such parts, and how systems interact with their environment (Bar-Yam, 2003). This focus on questions about parts, wholes, and relationships explains the relevance of the study of complex systems in the lives of biologists, physicists, economists, physicians, meteorologists, financial traders, and organizational theorists.

The increasing adoption of the complexity paradigm within the study of organizations has led to the adoption of computational agent based modeling as a method that enables us to address formally central features of complex systems such as nonlinear dynamics, interdependencies between subsystems, and emergent behavior. In this paper we analyze how models originally developed in the context of other sciences were "imported" to the realm of management studies with the purpose of dealing with research questions that require viewing firms as complex systems. We focus on two of these models: Kauffman's *NK* model, originally developed in biology, and the Forest Fire model, developed in physics. Despite their attractiveness in addressing questions related to the study of organizations, issues can be raised regarding the limitations of such models "imported" from the natural sciences when dealing with social science issues. We analyze these limitations in the context of the above-mentioned models and discuss possible resolutions. We focus first on the NK model, a model used extensively in the last decade in work focused on the impact of organizational trade-offs on performance. We then explore the Forest Fire model as a relatively new model and discuss the challenges related to its migration to the realm of organization studies. The purpose of this paper is twofold. First, we want to remark that these models offer significant potential in providing answers to questions related to organizations that other research methods cannot address effectively. Second, we wish to highlight the fact that work based on these models can only be suitable in the realm of social science if the researcher develops extensions to the model that bridge the important qualitative differences between the behavior of natural and social systems.

The use of models within management science

The use of models is commonplace within management science. We distinguish here between 'models' and 'frameworks'. We use the sense of modeling "to devise a (usually mathematical) model or simplified description of (a phenomenon, system, etc.)" (Suppes, 1974) in contrast to a framework such as Porter's Five Forces: Porter (1980:47) describes this as a "*framework* for competitor analysis" (emphasis added), not describing it as a model. However, models (in our sense) generally have limitations: they are, by virtue of their simplified nature, *designed to be soluble*. Therein lies their limitation: generally, there is little scope for out-of-equilibrium behavior: the solution of these models generally ignores the *path* to equilibrium.

The use of existing linear models may not be appropriate when we are observing complicated (and normally out of equilibrium) phenomena such as those that may be confronted within management.

Agent-based modeling can alter this: we design these interactions within these models at the level of the agent: individual actors who, as an aggregate, define the system. Much of the research into agent-based modeling (also referred to as individual-based modeling or ‘bottom-up’ modeling) has been based in the trans-disciplinary work of complexity, leading to several ‘centers of excellence’ being formed. For example, the Santa Fe Institute in New Mexico, founded in 1984, concentrates on collaborative multi-disciplinary research to ‘break down the barriers between traditional disciplines, to spread its ideas and methodologies to other institutions, and to encourage the practical application of its results’ (Santa Fe Institute, 1998).

Agent-based models

The identification of the advantages of the agent-based approach has been highlighted within the social sciences literature. Gilbert and Terna (2000) describe the use of agent-based models as the ‘third way’ of carrying out social science (over and above argumentation and formalization). McKelvey (1997, 1999) explores the phenomenon of complexity research applied to management and includes agent-based modeling as a promising research methodology. Axelrod (1997) explains agent-based modeling as being a ‘third way of doing science’ differing from induction and deduction: induction being the discovery of patterns within empirical data; deduction being the proof of consequences that can be derived from a set of specified axioms. Epstein and Axtell (1996: 177) describe this as ‘generative’ social science. Davis *et al*. (2007) state that these models are particularly effective for research questions involving fundamental organizational tensions or trade-offs. Tensions often result in nonlinear relationships that are difficult to discover through inductive cases and difficult to explore using traditional statistical techniques. Finally, Chang and Harrington (2006) remark that while neoclassical economics describes “what is best”, agent based models describe “what is better”.

Agent-based models grew out of the burgeoning research into complexity, with the use of agent-based models increasing in the last few years (Epstein & Axtell, 1996, Gilbert & Troitzch, 1999). Most of the models are used in management research are rational, linear, and non-dynamic and by definition have not contributed to our understanding of complex interactions. Such models restrict their analysis to a few key variables, and do not fully investigate complicated interactions between multiple variables. Agent-based modeling provides us with a way of overcoming this restriction.

One of the earliest tools that was a forerunner to agent-based modeling is *Swarm* (Minar *et al*., 1996). The rationale behind *Swarm* is to provide a framework for modeling a collection of independent agents interacting via discrete events. More recently, tools such as *RePast* (Collier, 2001) and *NetLogo* (Wilensky, 1999) have been developed, each with their own idiosyncratic advantages. An extensive review of software for agent-based modeling can be found in Mangina (2002), while specific toolkits are reviewed in Robertson (2005).

The language of agent-based modeling is rather specialized. We set out some of the key concepts below.

The agent

Agents are at the heart of an agent-based model. While there is no universally accepted definition of an agent (Gilbert & Troitzsch, 1999), Ferber (1989: 249, cited in Bura *et al*., 1995) provides an appropriate conceptualization: “a real or abstract entity that is able to act on itself and its environment; which has a partial representation of its environment; which can, in a multi-agent universe, communicate with other agents; and whose behavior is a result of its observations, its knowledge and its interactions with the other agents.” Importantly, agents can be heterogeneous in that they all have individual characteristics, unlike other models that may assume all entities are homogeneous.

Agents are assigned behaviors, rules that enable them to interact in their environment. For example, an agent may have a set of rules that indicate how it may respond to stimuli from its environment. It should be noted that the response need not be deterministic: a level of randomness or stochastic behavior can be included in the agent. In addition, a cognitive element can be built into the agent – it may have a perception of the world that is different to another agent. In this way, the actions of the agent need not be restricted to behavior that is rational.

The agents within an agent-based model interact via a series of discrete events. An agent is an actor in a system that is capable of generating events that affect both itself and other agents. Agents can be created or destroyed as the model is run, such creation and destruction being controlled by rules within the model. While the model is being run, it is possible to interrogate or ‘probe’ the properties of each agent. In this way, one can extract details of each *individual agent* rather than being restricted to investigating the macro-parameters of the model itself.

The environment

Agents are populated within an environment. In the simplest form, this can be a two-dimensional square lattice (the topology familiar to cellular automata, although cellular automata models are usually restricted to homogeneous agents). However, agent-based models in *Swarm* and *RePast* are not restricted to such topologies. Topologies can be discrete (for example a lattice) or continuous (for example a plane). The user can define the topology, or choose from pre-defined grids and networks available within the modeling package. Abstract spaces (useful for example those used in network analysis) can also be defined. The space, as well as the agents that are situated within this space, comprise the model ‘world’. Agents can interact with the environment thereby altering their world. This in turn changes the agent's perception of the world and offers a notion of feedback to the system. Thus, agent-based models can incorporate the feedback effects found in game theoretical models.

The schedule

The organization of these discrete events takes place through a 'schedule', an ordered list of events that take place as the model is run. The simulation system orders these events by assigning each time step a 'tick' count.

The model

The collection of all agents, the schedule that instructs these agents, and the rules of the simulation, together comprise the model. The model is parameterized, in that one can change the initial conditions of the simulation without having to re-write the simulation. In this way, parameter spaces can be 'swept', allowing an analysis of how the interactions of parameters change the results of the model.

Emergent behavior

The concept of emergence (Holland, 1998) within agent-based models explains how global properties of the system can come from simple rules of agent behavior. One of the most useful facets of using agent-based models is that, from the simple behavior of locally interacting agents, complex global behavior can be exhibited by the system. This is one of the greatest values of the use of agent-based models: the results may reveal global behavior that is not immediately obvious given the simple interaction rules of the agents.

Adapting agent-based models to managerial problems

In this section we discuss two agent-based models originally developed in the realm of the natural sciences. We describe the features of such models that offer potential to deal with questions from the realm of strategic management and organization theory. First we discuss Kauffman's *NK* model, arguably the most frequently used in recent work on organizations based on agent-based modeling. Later we describe and analyze the Forest Fire model. This model is still in the infancy of development within organization studies but, as we will show, it offers a high potential to address complex dynamic organizational issues.

Kauffman's NK model

Work based on the NK model has been developed by organizational theorists to provide insights on important management issues such as understanding the interplay between adaptive and selective forces (Levinthal, 1997), why successful strategies are so difficult to imitate (Rivkin, 2000), why and to what extent can analogical reasoning inform strategy development in novel industries (Gavetti *et al*., 2005), why firms need to engage in periodical organizational restructurings in order to improve performance (Siggelkow & Levinthal, 2005), how different ways of managing the headquarters-business unit relationship affects performance (Caldart & Ricart, 2007), and how managers' dominant logics affect organizational strategic development processes including the development of capabilities (Gavetti, 2005).

In this section, we first review the theoretical roots and main characteristics of the *NK* model. Second, we discuss the reason that justifies its increasing adoption by researchers working in organization studies under the perspective of evolutionary theory. Finally, we discuss which assumptions of the model are incompatible with the realm of organizations.

Foundations of the NK model

For most of the twentieth century, biologists have assumed that "order" was due to the effects of selection, as developed under the general label of Darwinian "selectionist" theory. The intuitions behind this idea derived from statistical mechanics, particularly the idea of entropy. Entropy measures the amount of order in a system, with increasing disorder corresponding to increasing entropy. Left to themselves, systems tend to disorder and lack of structure. Therefore "selective" work is necessary to achieve and maintain order1. Kauffman challenged this notion suggesting that while natural selection is a prominent force in evolution, order can also emerge spontaneously due to the self-organizing properties of complex systems. As the complexity of the system under selection increases, selection is progressively less able to alter the properties of such a system2. In these cases we can say that selection is unable to avoid the *spontaneous* or self-organized order derived from the properties of the system. Kauffman examined the relationship between selection and self-organization and tried to find out under what conditions an adaptive evolution is optimized. The variability in behavior as the structure of a system is altered can be pictured as characterizing the ruggedness of a *fitness landscape*. This fitness or performance landscape consists of a multidimensional space in which each attribute of the entity is represented by a dimension of the space and a final dimension indicates the performance level of the firm. While trying to improve their fitness, many parts and processes of the agent must become coordinated to achieve some measure of overall success, but conflicting “design constraints” limit the results achieved (Kauffman, 1993)3. Kauffman demonstrates that the degree of conflicting constraints affecting the evolving entity affects the topography of the performance landscape. Increasing the density of the interdependencies between policies affects the complexity of the landscape and, consequently, increases the number of possible emergent patterns of behavior that the agent can follow. In order to model such webs of complex interdependencies, Kauffman developed the NK model. In Kauffman’s NK model fitness landscapes are characterized with, essentially, two structural variables. The parameter N, represents the number of attributes that characterize the agent. The second parameter is K, representing the number of elements of N with which a given policy decision interacts. The higher K, the more interdependent the parts of the firm and, therefore, the higher is the number of conflicting design constraints.

The NK model in the organizational literature

As discussed above, the NK model allows many central concerns of analysts of organizational decision making to be addressed, especially for those rooting their work within evolutionary perspectives. Behavioral theory and evolutionary theory (March & Simon, 1958; Cyert & March, 1963; Nelson & Winter, 1982) conceive firms as entities that engage in problem-solving through processes of search and discovery. Behavioral theory assumes that, while searching for solutions to their problems, firms adopt some form of adaptive behavior in response to feedback about their previous performance.

In order to formalize the analysis of the concept of adaptive search developed by evolutionary theorists, we need a defined search space, a set of rules that agents use for moving across such space, and a criteria to determine the quality of a proposed solution. Kauffman’s *NK* model provides such elements and so has become the mainstream formal modeling strategy for recent work rooted in the evolutionary tradition.

While adapting, under bounded rationality (Simon, 1997), agents can identify the positive and negative gradients around and close to their current position, but are not capable of making similar judgments for more distant ones. In the context of the*NK* model, we can observe that in a rugged landscape, such incremental search procedure will lead only to the local maximum or *peak* closest to the starting point of the search process, regardless of its height relative to other peaks in the landscape. As a result of this locking in to the first available solution, a strong form of path dependence is observed and, on average, only modest performance, sometimes referred to as *competency traps*, is achieved (Levitt & March, 1988). In these situations firms achieve the best possible configuration of an unattractive strategy. One mechanism to overcome such “traps” is to engage in “long-jumps”, random explorations of more distant portions of the landscape. However, despite these distant explorations help to prevent falling into “competency traps”, they may result in a deterioration of performance by not exploiting wisdom gained by past experience. So, the problem of adaptation strategies in rugged landscapes can be reframed as a familiar dilemma faced by managers and organization theorists: how to get the benefits of exploring new areas of the landscape, escaping from low

Table 1

Organizational Features in the NK Model

Topic	**Operationalization in the NK model**
Emergent nature of organization behavior	Performance derives from parallel search by multiple agents
Path dependence in decision-making	Path dependent local search. Risk of ‘long jumps’
Interdependence in decision-making	Parameter K
Bounded rationality	Firm only aware of neighboring strategies
Exploitation and exploration	Local search v. long jumps
Differentiation and integration	Parameter K
Difficulty to imitate firms	Low correlation of strategies in highly rugged landscapes

local maxima, without losing the advantages of exploiting acquired knowledge (March, 1991).
Table 1 summarizes some central concepts associated to organizational theory that can be operationalized effectively through the *NK* model.

As it can be seen from the list above, the organizational features that can be studied with the help of the NK model can involve organizational phenomena taking place at different levels of analysis, such as the team (Solow *et al*., 2002, 2003), the business (Rivkin, 2000; Gavetti *et al*., 2005) or the corporation (Gavetti, 2005; Caldart & Ricart, 2007).

Key organizational features neglected by the assumptions of the NK model

The features described in Table 1 show the potential of the NK model to represent formally organizational phenomena. However, the model has several strong assumptions that work adequately in the realm of natural science but fail to capture central features of social phenomena. In this section we review the model's limitations and discuss how many of these can be overcome by extending the model.

In the following section we discuss a list of major issues that the NK model does not contemplate in its original form that require changes in order to make the model suitable for management-related applications.

a) Non-Full Decomposability of Problems. First, we need to address the fact that organizations are not fully decomposable systems, as implicitly assumed in the pure form of the NK model. Organizational problems tend to have a nearly decomposable structure (Simon, 1996). Tasks tend to cluster into subsystems, with interaction within such subsystems, on average, being stronger than interactions across subsystems. For instance, on average, we will always see more interaction within marketing than between marketing and operations. Recent contributions based on the *NK* model, such as Gavetti *et al*. (2005) address this issue by clustering decision variables in subgroups or units, and by splitting the parameter K in two sub-parameters that track separately interdependence within and between subunits.

b) Hierarchy of Decisions. Not only do Kauffman's vectors assume full decomposability of problems but also they neglect another central feature of decisions in organizations: decisions in social groups beyond a minimum level of complexity are also integrated vertically through decision levels. Gavetti *et al*. (2005) address this issue by defining a hierarchy of decisions in which upper level decisions limit the discretion of lower level decisions. Further work should focus on the fact that influence between decision levels is not entirely hierarchical, as modeled in these contributions, but also lower levels can develop ideas that eventually influence top level decisions (Burgelman, 1994).

c) Purposeful Behavior. In social systems we cannot neglect the issue of deliberateness of individual and organizational behavior. Managers may freely choose how to formulate or change the firm's strategy, an ability that the genotypes referred in biology models do not have. Therefore, models may include decision rules followed by managers at the time of, for instance, adopting a strategy and deciding whether to maintain it or to modify it. This feature also requires an acknowledgement of the limits of human rationality. Gavetti and Levinthal (2000) used an adaptation of the NK model to study the role and interrelationships between search processes based on cognitive representations that are articulated in strategic plans (which they label "forward-looking") and search processes based on the lessons learnt in previous experience ("backward-looking"). Following the notion of bounded rationality, the authors simulated cognition as a representation of the performance landscape that, being grounded on the actual landscape, has a lower dimensionality. In this way, as firms know the expected performance values associated with certain strategies that the firm may follow, they are able to identify more or less attractive sub-areas of the problem space. However, as their representation has a lower dimensionality than the real problem, they cannot foresee the most attractive peaks within each of those sub-areas, therefore suffering the risk of falling in a competency trap. Gavetti *et al*. (2005) further developed the study of the relationship between managerial cognition and strategic decision making through the development of a highly sophisticated model of how managers reason by analogy. They show how the depth and the breadth of managers' "portfolio" of experiences can help them to make sense of novel situations and develop superior strategies reasoning by analogy.

d) Learning Through Experience. Social systems also have the ability of learning through experience. *NK* vectors only evolve according to their rules of behavior and do not increase their understanding of the landscape through experience. *NK* simulations developed in the realm of social science should address this fact by, for instance, by progressively refining the quality of the firm's cognitive representation of the landscape as it evolves.

e) Weight of Decisions on Performance. Each X_i refers to a particular policy decision within the firm, such as advertising, product development, research on product line extensions or production planning. In the *NK* model it is assumed that all policies have an equal weight on performance. This contradicts the reality marked by the existence of "core" and "peripheral" areas of the firm and the dynamism of such relative importance due to the environmental change.

f) The Social Agent's Environment is Dynamic. In the *NK* model, the organization's adaptive search processes are developed in a fixed performance landscape, i.e., the firm is deemed as a complex but closed system that evolves facing only the constraints derived from its own complexity captured by the interaction parameter *K*. Siggelkow and Rivkin (2005) addressed this limitation of *NK* models by introducing exogenous "shocks" that alter the topography of a focal organization's performance landscape. However, these shocks do not capture the impact on the shape of the performance landscape resulting from specific decisions made by other firms whose actions are interdependent with those of the focal firm. Kauffman's *NK(C)* model addresses this issue by modeling the coevolution of many agents and capturing the interdependence of their decisions through the parameter *C*. This model therefore introduces dynamism in the fitness landscapes of the interacting agents. However it also has two important limitations. First, the model only captures interactions, not being able to distinguish between competitive and collaborative ones. Second, all the agents have the same structure in terms of the value of *N*, *K* and *C*. This assumes that firms only interact with similar peers and in the same critical decisions. This contradicts the reality of markets characterized by the existence of competitors, suppliers, regulators, customers, complementors, etc., whose sizes and types of interactions vary dramatically.

The Forest Fire model

We introduce a model from physical science that is less developed compared with the NK model, but is one that has significant potential for transfer to the domain of management science.

The Forest Fire model (Bak *et al*., 1990) is a model where trees exist on a square lattice, with $L \times L = L^2$ cells (we can also model an *N*-dimensional hypercube, with L^N sites, but in this example, we shall restrict the lattice to being a square with two dimensions and L^2 sites). Each site can be in one of three states:

- The site may be empty;
- The site may be occupied by a tree that is not on fire, or;
- The site may be occupied by a tree that is on fire.

The transition between these states is defined by the simple rules that govern the model (Bak *et al*. ,1990: 297):

- “Trees grow with a small probability *p* from empty sites at each time step;
- Trees on fire will burn down at the next time step;
- The fire on a site will spread to trees at its nearest neighbor sites at the next time step.”

The model is thus specified. We are interested in the behavior of the system over time, a system that evolves as a result of these rules being applied over many iterations. However, several variations of the ‘Forest Fire’ model exist, so it is important to specify the exact model that is being used. Even the simple rules of the forest fire model are ambiguous: what do we mean by ‘nearest neighbors’? And what happens at the edges of the lattice? We assume that a von Neumann neighborhood is used (where the four cardinal—north, south, east, west—neighbors are included), rather than a Moore neighborhood (where, in addition to the cardinal points, ordinal points, e.g., north-east, are included in the neighborhood). We also assume that the lattice is bounded rather than being toroidal (where there is no boundary). Is the behavior of the system similar when we substitute a triangular lattice for the square lattice? These may seem trivial specifications, however specifying these attributes is important.

Later models (Drossel & Schwabl 1992: 47) have included a further rule:

- “a tree becomes a burning tree during one time step with probability *f* if no neighbor is burning.”

This corresponds to ‘lightning strikes’, which start a fire in a particular location, that, if appropriate conditions exist, will spread to other trees.

We can summarize these rules in a stochastic transition matrix (Table 2), the parameters being the probability of a state transition for any point in the lattice during an iteration of the model:

The model, as specified within the physics domain, was seen as an example of ‘self-organized criticality’ (self-similar fractal structures that exhibit ‘1/*f*’ noise (power laws), see Bak *et al*., 1987: 381), although this has been debated (for a review see for example Clar *et al*., 1994).

For the purposes of our initial exploration of this model and its transfer to the management domain, we can investigate a system that has evolved over time, but for which there has been no fire (whether caused by lightning strike or otherwise). We can then initiate a fire and investigate how the tree density has an effect on how the fire propagates. Consider the system in Figure 1 where, at the initialization of the system, the trees on the extreme left-hand side of the forest are lit (lit trees are shown in red).

After a number of iterations, following the rules of the model, the fire starts to propagate from left to right, with the cells following the transition rules (in this case, we set *p*=*f*=0, and allow the fire to transit without new tree growth). The figure shows the state of the system, with the fire front dissipating, and a fire shadow of burnt cells[4].

We can investigate the proportion of trees burned as a function of the number of trees in the lattice (the tree density). In this particular (Wilensky, 1998) operationalization of the model, we see the following behavior (statistics generated from several runs of the model[5]) in Figure 2.

As can be seen, there is a rapid transition from a very low percentage of trees burned to a very high percentage of trees burned. There is a critical point with a tree density of *ca*. 58%. The macro-level behavior of the system, that is the proportion of trees burnt as a function of tree density, changes abruptly. What differs from other models of propagation, is that we are modeling the individual agents (trees) that comprise the system, we are *not* explicitly modeling the system as a whole.

The link to analytical models of innovation

This sigmoidal result obtained above is reminiscent of the s-shaped curves that represent the effect of advertising, or the diffusion of innovation. The corresponding models in marketing science are however generally closed-form models, which are analytically tractable. For instance, diffusion models may take the form of analytical models, such as the logistic equation:

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Fig. 1: Table 2

Transition Matrix for the Forest Fire Model

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Fig. 2: Figure 1

Forest Fire Model with Fire Propagation (NetLogo)

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where *r* is the rate of maximum population growth, and *K* is the carrying capacity (the maximum sustainable population). The solution to this equation gives the following sigmoidal curve, similar to the results from our agent-based forest-fire model. While the spread of innovation, and the diffusion of ideas are well modeled using analytical methods such as the Bass diffusion model (Bass, 1969) and other s-curve population growth models based on Verhulst (1845, 1847), these models ignore individual actors within the population, and report only the population statistic.

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Fig. 3: Figure 2

Forest Fire Model Results

A derived social network

Although the Forest Fire model is one of trees that are arranged in a lattice, we have to change our perception of this model and apply it to the management situation that we are interested in. As we shall see below, we are in fact generalizing a system that has already been simplified by turning a physical phenomenon into a ‘toy model’.

When we investigate the Forest lattice in Figure 3, we can see that, rather than modeling trees on a square lattice, we can reconfigure the lattice to be a social network construction.

If we look at the *links* between the trees within the lattice, we reconfigure this problem as one of a *network*. We can provide an alternative representation of the system in the form of a network, as shown in Figure 4.

The network derived above may appear restricted, in that a social actor may have a maximum degree, or number of links to other actors, of four. This however need not be a constraint: we can either change the definition of a neighborhood, or change the dimensionality of the lattice: in a two-dimensional lattice, we have a maximum number of neighbors of 4, whereas in an N-dimensional lattice, we have a maximum degree of $2N$.

While the forest fire may be described in terms of trees in a square lattice forest, we have to realize that this is in fact a metaphor for the actual system that we are considering. As can be seen above, the agents we consider can change from trees to people forming a social network, and the lattice changes to an unstructured linkage of people within that network.

Towards an organizational model

We can see that the model has now been re-formulated in terms of a social network construction. However, we can use the lattice construction to obtain the same results. We can see the propagation of an idea throughout the population, and can trace the route of this propagation, by investigating the state of the system at each point in time. The model as it exists places agents randomly on the lattice. We can change this initial setup to specify the links between people, if these are known. The main result from the model is that the density

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Fig. 4: Figure 3

Random tree network in lattice form (probability of tree being ? = 0.57)

of population is important, as this forces links to be made between different people. For instance, we may decide, on the basis of this model, that best propagation of ideas takes place when many people are in the same domain. It is the *spatial* element that is important.

There exist a number of potential avenues for such a model: we can investigate how ideas or product adoption diffuses through a population by means of inter-personal contact, modeled by proximity on the lattice (and hence proximity in a social network). By taking this approach, use of this model allows us to investigate the *micro-level* behavior which can be lost when investigating a macro-level property such as percentage of a population to which the idea or product has spread.

The challenges of applying models from natural science to management

While models from natural science may be developed with specific applications in mind, the systematic reduction of a system to its elemental parts and interactions is a skill that is useful in itself. We see two distinct methods for applying natural science models to social science. We can change the agents of the model but keep the fundamental model unchanged (for example interpreting the Forest Fire model as a model of propagation of ideas through a social network). An alternative to this is, as discussed above for the NK model, to amend the interactions of the agents from interactions that are over-simplified for a social science to incorporate behavioral assumptions and extend and develop a natural science model.

Toy models

Many of the models of natural science are termed ‘toy models’ (Bak *et al.*, 1988). Toy

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Fig. 5: Figure 4

Social Network Representation of the ‘Tree’ Lattice Structure.

models are designed so that the mechanisms of the interactions can be examined, not by modeling the exact system that we are interested in, but by changing the unit of analysis to something more easily understood. An example of this occurs in the forest fire model: we are not actually interested in modeling trees, rather a physical system that exhibits this behavior. We are therefore able, with some degree of ease, to apply the model to another domain, specifically management, where we understand similar behavior exists.

Unit of analysis

The unit of analysis is important when considering the behavior of the system, as shown in Table 3.

Micro—macro scales

Analytical models tend to look at the behavior of the system as a whole, modeling the percentage of the system that is affected by the innovation. What is not modeled, explicitly, is the micro-level actors and interactions that comprise the system. The emergent properties of this micro-macro level interaction can be seen by the agent-based model: the macro-level system variable of interest is replicated, yet we can see the behavior of every actor who makes up the system.

In analytical models, we may not model the connections between actors, seeing these as being trivial. However, by using an agent-based model, we can control these connections. While replicating the analytical result is possible, we can go beyond these results and alter the initial system: what is the initial state of the actors? Who is connected to whom? All these assumptions of analytical models can be made explicit by altering the initial setup (which could be chosen randomly or may be imposed) of the simulation.

Analytical models can be ‘solved’ by finding an equilibrium solution. Agent-based models such as those introduced in this note are not hampered by this restriction: we can track agent movement *out of equilibrium*. This feature permits, in the case of the *NK* model, to deal with questions on dynamic issues characterized by non-linear behavior, such as the impact of organizational forms and/or cognitive representations of the environment on the ability of the firm to adapt (Gavetti & Levinthal, 2000). In a social network context, the spread of the ‘fire’ actually shows the places where agent to agent, social, communication is taking

Table 3

Units of Analysis

NK Model	Biology	Strategic Management
	Gene	Decision
	Genotype	Organization/Team/Department
Forest Fire Model	Physics	Strategic Management
	Tree	Social Actor
	Fire	Transmission of Idea/ Propagation through the Social Network
	Forest	Social Network

place: the fire envelope actually shows where the interaction is taking place at any moment in time. We can therefore track the propagation through the network (the fire front being the envelope of propagation at a certain time).

Future research

While the *NK* model has nurtured academic work related to organizations for a decade, it still offers potential being used by researchers interested in organizational phenomena characterized by the preeminence of trade-offs and situations where it is important to understand short versus long term implications. Further research could benefit, for instance, the field of strategic change by representing the risk/return profile of different approaches for different time horizons. Another extension of the model that could lead to valuable insights for the decision making literature would be the introduction of bounded rationality in the assessment of the performance associated to each “move” of the firm.

The Forest Fire is at an early stage of development within the management field. The Forest Fire model results presented here show the state of the system (the percentage of trees burned) at the end of the simulation run. While we can see the spread of the fire from tree to tree, we are not using the full model: if we introduce the p and f probabilities (where $f < p < 1$ (Grassberger, 1993)), we see that the system evolves to self-organized criticality. We leave this to the reader to consider how this dynamical system can be applied to the spread of ideas through a population. Winter *et al*. (2007:415-416) note the potential for fractal dimensionality to be of interest to organizational research, a property that is exhibited in the Forest Fire model. We hope that further investigation of the dynamics of the Forest Fire model can add to this contemporary line of research.

There exists a vast, largely untapped, repertoire of natural science models. While some models may not be appropriate to transfer to management science, there is tremendous scope for further transfer of the work of the natural sciences to management applications.

Notes

1. In the context of strategic management, selection is translated as competition, the force that makes firms keep “fit” in their quest to survive and develop.
2. This would be the case, for instance, of a firm stalled as a consequence of excessive bureaucracy or by strong power struggles.
3. For instance, major decisions on the location of production systems cannot be made without considering how these decisions might impact other activities of the firm such as as sourcing, logistics, or finance.
4. For more details of the software toolkit used to generate this model, and the relative strengths and weaknesses of such toolkits, see Robertson (2005).
5. Simulation results are for a 101×101 unit grid.

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