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Balancing exploration and exploitation in complex environments

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Abstract

Purpose – The objective of this study is to model and analyze the exploration-exploitation dynamics of March's model of mutual learning in a complex environment. By enhancing the above mentioned model, the paper seeks to propose a new agent-based model of mutual learning within an organization.

Design/methodology/approach – The paper replicates March's model of simulating learning within an organization using an agent-based simulation approach, and extends it by modelling the problem space as a fitness landscape using Kauffman's NK model technique.

Findings – It was found that it is impossible to find a right balance between exploration and exploitation using the communication structure of March's model.

Practical implications – The proposed model could help create a virtual laboratory for experimenting organizations' behavior in a complex co-evolving environment. This virtual laboratory may be used in the future to support the decision-making process of managers and policy makers.

Originality/value – Designing the external environment as a fitness landscape helps in discovering what effect the environmental complexity has on the emerging balance between exploration and exploitation. It is the first study to design the environment of a model which analyzes the mutual learning between an organization and its members as a complex non-linear space.

Keywords Exploration-exploitation trade-off, Learning rates, Complexity theory, Learning, Organizations

Paper type Research paper

1. Introduction

This study is based on the assumption that organizational learning is a purposive quest to retain and to improve competitiveness, productivity and innovativeness in uncertain technological, market and environmental circumstances (Dharmadasa, 2009). Within the organizational learning research, finding a trade-off between exploration and exploitation has been proposed as a way to survive in a complex, competitive environment. March's (1991) seminal paper, “Exploration and exploitation in organizational learning” is a go-to citation for anybody talking about exploration and exploitation. Although much work has been done to expand these dual themes, little work has been done to extend the model on which the exploration-exploitation themes have been built. The few extensions of March's original model are mostly introducing organizational structures (Bray and Prietula, 2007; Fang et al., 2007; Kane and Prietula, 2006; Miller et al., 2006), considering internal variety (Rodan, 2005; Kim and Rhee, 2009) and environmental dynamism (Kim and Rhee, 2009).

One key element to be considered when analyzing the exploration-exploitation dynamics within the organizations is their connection with the complexity of the
external environment. In March’s model, the external environment, named “reality” is represented as a system in a steady position, where its states are unalterable and taken as a benchmark. To create a realistic conceptualization of a complex environment, one should represent it as a dynamic process involving the interrelationships of its subparts. The higher the number of factors and the extent of difference among them, the higher the environmental complexity. The aspect of how the external complexity influences the balance between exploration and exploitation remains still to be analyzed as the existing literature does not provide specific models to deal with this issue. Consequently there is the need to better understand the interplay between the knowledge components that form the environment created by the organization and its members in their attempt to learn.

Considering the above research gap, the overall objective of this paper is to model and to analyze the balance between exploration and exploitation learning modes on a complex space. This purpose is being summarized in the following research question:

RQ1. What effect has the environmental complexity on the emerging balance between exploration and exploitation within organizations?

This paper replicates and extends March’s (1991) model of simulating learning within an organization, using an agent-based simulation. First, it extends the model by developing a complex problem space on which an organization and its members mutually learn. And second, it enlarges the original model by considering direct interpersonal learning in addition to learning from an organizational code. The study intends to contribute to the theoretical interest of scholars on what effect has the environmental complexity on the emerging balance between exploration and exploitation by modelling this co-evolution as a fitness landscape. Our approach to overcome this gap is by constructing the environment as a fitness landscape, where small changes can have nonlinear effects on the outcomes. We use Kauffman’s (1993) NK model to develop a complex environment, with intertwined knowledge components.

Kauffman’s (1993) NK model has been widely employed in the study of organizations (Ethiraj and Levinthal, 2004; Gavetti and Levinthal, 2000; Levinthal, 1997; McKelvey, 1999; Rivkin and Siggelkow, 2003; Sorenson, 2002). The NK model has been extremely used in the last decade in works focused on the impact of organizational trade-offs on performance. In the NK model (Kauffman, 1993), the parameter N is the number of genes randomly assigned fitness contribution drawing from a uniform distribution; in our model, N represents the number of organizational and individual opinions about an external environment. The parameter K stands for the interdependence degree between the opinions. Our work contributes to the existent research on computational modeling the exploration-exploitation balance in organizations by modeling the complexity of the external environment through the use of parameters N and K.

From a theoretical perspective, this study approaches a cross-disciplinary perspective, connecting knowledge management theories, organizational learning and complexity theory applied to business. The human organization is seen as a complex adaptive system (Holland, 1975), formed by groups of interdependent, autonomous agents, with shared goals, and which operates in accordance with individually and collectively held rules.
2. Theoretical background
First, this section briefly reviews the literature on exploration and exploitation concepts, which allows us to get a sharpened understanding of the issue. Then, we introduce the notion of fitness landscape as a way to represent an organization’s problem space which is a method to describe more accurately the balance between exploration and exploitation. Third, we portray March’s (1991) model of exploration-exploitation in organizational learning, the most representative computational approach on this dilemma.

2.1 The concepts of exploration and exploitation
The concepts of exploration and exploitation have been engaged in various contexts such as technology and product innovation (e.g. Danneels, 2002; Greve, 2007; He and Wong, 2004; Tushman et al., 2004), strategic alliances (e.g. Beckman et al., 2004; Koza and Lewin, 1998; Lavie and Rosenkopf, 2006; Rothenberg, 2001; Rothenberg and Deeds, 2004), and senior-management teams (e.g. Beckman, 2006; McGrath, 2001). Furthermore, the notions of exploration and exploitation have been investigated at various levels of analysis, generating research at the individual (e.g. Mom et al., 2007), group (e.g. Beckman, 2006; McGrath, 2001), organizational (e.g. Benner and Tushman, 2002; Greve, 2007; Harreld et al., 2007; Jansen et al., 2006), inter-organizational (e.g. Lavie and Rosenkopf, 2006; Lin et al., 2007; Rothenberg, 2001; Vassolo et al., 2004), and industry levels (e.g. Gilsing and Nooteboom, 2006).

There is a general ambiguity in how exploration and exploitation can be defined and which are their implications and effects. Gupta et al. (2006) implies that this haziness lies in whether the two are distinguished by differences in the types of learning or by the presence versus absence of learning. Depending on the research area, most of the studies refer at exploration and exploitation as learning mechanisms (Argyris and Schon, 1978; March, 1991; Senge, 1990; Nooteboom, 2000, Chen and Van de Ven, 1996), innovation strategies (Benner and Tushman, 2003; Brown and Eisenhardt, 1997; Christensen and Bower, 1996; He and Wong, 2004; Jansen, 2005, Lee et al., 2003), strategic activities (Burgelman, 1983; Danneels, 2002; Gibson and Birkinshaw, 2004; Luo, 2002; Miles and Snow, 1978; Volberda, 1998; Winter and Szulanski, 2001), knowledge development and utilization (McNamara and Baden-Fuller, 1999; Liu, 2006; Sheremata, 2000; Van Den Bosch et al., 1999), search processes (Garcia et al., 2003; Katila and Ahuja, 2002; Levinthal, 1997; Rivkin and Siggelkow, 2003) or technologies (Ashby, 1960; Boynton and Victor, 1991; Hannan and Freeman, 1987; Juran and Gryna, 1988; Lee and Ryu, 2002; Sitkin et al., 1994).

Organizations able to continuously search and identify new opportunities and, at the same time, capable to develop its existent resources, are going to succeed in today’s complex environment. March (1991) was the first to introduce the relation between the exploration of new possibilities and the exploitation of old certainties in organizational learning theories. His study states that “exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation” whereas “exploitation includes such things as refinement, choice, production, efficiency, selection, implementation, execution” (March, 1991, p. 71). March argues that there is always a tension between exploitation and exploration where firms have to decide how to allocate resources between exploiting existing knowledge and exploring new knowledge. Compared to exploitation, returns from
exploration are less certain, more remote and more risky. As firms learn from their experiences, the advantages of exploitation cumulate. An exclusive focus on either exploration or exploitation may cause a threat to a firm’s competitive advantage over time; Levinthal and March (1993, p. 105) for instance argue that “an organization that engages exclusively in exploration will ordinarily suffer from the fact that it never gains the returns of its knowledge. An organization that engages exclusively in exploitation will ordinarily suffer from obsolescence”. Recent empirical studies (Gibson and Birkinshaw, 2004; He and Wong, 2004) seem to confirm that there is a relationship between exploration and exploitation and a firm’s success. They show that firms or business units having high levels of both exploration and exploitation outperform those firms or units having low levels.

A useful starting point to analyze adaptation processes of exploration-exploitation is to consider a mapping representation of the population. The concept of “fitness landscape” developed by Wright (1931) is defined as a representation of the space of all different possible configurations of the population according to their fitness. Each individual of the population is represented by a dimension of the space associated to a fitness value, which depends on how well that individual solves the problem at hand. However, as the economic rationality of agents is bounded and because they cannot observe all the possible positions over the landscape, an accurate representation has to consider a limited space within which components can move. Thus, the search process has to be local, as suggested by Wright (1931). Among several types of analytical models available, “NK model” (Kauffman, 1993) is a simple formal model of rugged fitness landscape which demonstrates that the fitness landscape topology is determined by the interdependence degree of the fitness contribution of the various attributes of the organism. These interactions refer to the epistatic effects (Smith, 1989). N represents the number of parts of the system, i.e. the number of individuals in a population, whereas K is the number of other attributes with which each individual interacts. Thus, the contribution of each element to the fitness landscape depends on its own fitness level and on the K other elements among N. Interdependency models like NK facilitate understanding the exploration/exploitation behaviors.

Previous research on organizational learning and innovation has consistently argued that exploration and exploitation draw on different structures, processes, and resources (He and Wong, 2004), and they differ significantly in their performance outcomes over time. By reducing variety, increasing efficiency and improving adaptation to current environments, exploitation activities can produce positive performance effects in the short run. However, these short-term performance improvements might come at the expense of long term performance, since the reduced variety and the adaptation to an existing environment become liabilities as environments change over time. Firms emphasizing exploitation in their activities might lack the capability to adapt to significant environment changes and thus the recipe that makes these firms successful in the short run might endanger their success in the long run. Exploration-oriented activities help the firm to develop new knowledge and create those capabilities necessary to survive and prosper in the long run. However, by their nature exploration activities are uncertain in their pay-offs and their performance effects occur in the long run. Without a balancing orientation towards exploitation, exploration can be similarly detrimental for the firm locking it into a cycle
in which “failure leads to search and change which leads to failure which leads to more
search, and so on” (Levinthal and March, 1993, p. 105).

2.2 March’s (1991) model of exploration-exploitation in the organizational learning
The seminal paper of March (1991) presents two simple models about development and
the use of knowledge in organizations, and considers two distinctive features of the
social context. One is the mutual learning of an organization and its individuals, and
the second future of organizational learning is the context of competition for primacy.
This study refers to the model of mutual learning between an organization and its
members.

The mutual learning model can be described as the development and storage of
knowledge through an organizational code that is simultaneously learning from its
members. It is a useful starting-point for further theorizing about organizational
learning because it presents a method of learning collectively in circumstances where
individuals cannot learn independently. The most prominent consequence of this
mutual learning is represented by the conflicts between short-run and long-run
concerns and between gains to individual and collective knowledge.

March believes that organizational learning is important to the manner in which
firms divide their resources. “Each increase in competence at an activity increases the
likelihood of rewards for engaging in that activity, thereby further increasing the
competence and the likelihood.” (March, 1991, p. 73) Success at exploration will lead to
exploitation of those experiences, just as success with exploitation will lead to more
exploitation. March indicates that the likelihood of firm exploration increases as:

• turnover and heterogeneous employment patterns will postpone the homogenous
socialization patterns that breed self-reinforcing exploitation; and
• the competitive nature of an industry is such that market position has significant
effects on returns.

2.3 Model description
There are four key features of the model:

(1) The organization’s environment, called external reality is independent of
organization’s members’ beliefs. The reality is modelled as an m-dimensional
vector, each of which takes a value of 1 or −1 with equal probability.

(2) N individuals holding beliefs about each of the m dimensions of the
organization’s environment. The individuals’ beliefs can take the values of −1,
0, or 1, where 0 represents the absence of a belief about a particular dimension of
the reality. We will refer to the individuals having the beliefs with the value “0”
as the “I don’t know” individuals.

(3) There is an organization code, or the storage of all the knowledge that the
organization has accumulated over time in its process of learning from its
members. Organization’s members change their beliefs through the process of
learning from this code as a consequence of socialization and education. In each
period, if the code differs on a particular dimension from the beliefs of an
individual, the later will change his belief with the one of the code with the
probability of p1. This is the probability that reveals how successful is the
learning from the code (socialization process).
The organization’s code adjusts its beliefs to the ones of those individuals whose beliefs correspond to the ones of reality on more dimensions than does the code with the probability of $p_2$. How? First, it is being allocated a score to each individual and to the code. The score is given by the number of dimensions having the same beliefs with the code. The individuals with a lowers score than the one of the code will be ignored. The individuals left are grouped and called superior group, and they are the ones with the dominant beliefs. Within the superior group, it is selected the majority belief on each dimension. The organizational code remains unchanged if it has the same beliefs like the dominant belief of the superior group. But if the code differs from the majority belief of the superior group, it will change to the later with the probability $1-(1-p_2)^k$, where $k$ is the number of individuals within the superior group that share the majority belief minus the number of individuals who do not.

The initial conditions of the model consist of a fixed $m$-dimensional reality, each taking with equal probability the values of 1 and $-1$, an organizational code initialized with neutral beliefs on all dimensions, and $n$ individuals represented as well as an $m$-dimensional vector of beliefs, each with the values of 0, 1, or $-1$. “Within this closed system, the model yields time paths of organizational and individual beliefs, thus knowledge levels depending stochastically on the initial conditions and the parameters affecting learning” (March, 1991).

The state of knowledge is measured for every period as the proportion of reality correctly represented in the organizational code and on average in individuals’ beliefs. Thus, knowledge depends on the extent to which beliefs match the external reality. But neither the individuals, nor the organization contain any information about “reality”. The organizational code knows just which individuals are closer to reality than himself, but not on which dimensions. In this context, both organization and the members can reproduce false beliefs in their processes of exploration and exploitation. The changes in beliefs help in eliminating the differences between the code and the individuals. Consequently, the beliefs of individuals and the code converge over time. As individuals in the organization become more knowledgeable, they also become more homogeneous with respect to knowledge. Equilibrium is reached when all individuals and the code share the same (not necessarily accurate) belief with respect to each dimension (March, 1991, p. 75). From this point, nothing in the system can be changed.

The study presents four approaches to control the learning in this system and to stimulate the relations between exploration and exploitation. The first stage shows the effects of the learning rates that depend on the socialization rate ($p_1$) and on the average equilibrium knowledge ($p_2$). The results illustrate that a slower socialization leads to a faster learning of the code. “The gains to individuals from adapting rapidly to the code (which is consistently closer to reality than the average individual) are offset by second-order losses stemming from the fact that code can learn only from individuals who deviate from it. Slow learning on the art of the individuals maintains diversity longer, thereby providing the exploration that allows the knowledge found in the organizational code to improve.” (March, 1991, p. 76) Until now, individuals learn from the code at the same rate ($p_1$). The second stage of the simulations considers also the heterogeneity of the individuals. There are considered fast learners ($p_1 = 0.9$) and slow
learners ($p_1 = 0.1$). Given an average socialization level, heterogeneous individuals are better than homogeneous, as the code learns more from the slow learners.

In the third and fourth stages, March expands his formative model to consider an open system, and adds a personnel turnover rate and an environmental turbulence rate. For each iteration, every individual has the potential to leave an organization with a probability $p_3$. In this way, new individuals with randomly distributed beliefs are being introduced in the organization. In addition, any dimension of external reality can have the possibility to flip, with a probability $p_4$. This new probability reflects the external environmental turbulence.

In March’s (1991) model, the organizational members (initially endowed with diverse set of beliefs), interact with an organizational code. The organizational code learns from these individuals, and they learn in turn from the code. As a consequence, the organization’s knowledge improves over time. Exploitation is achieved by the “fast learners” who quickly adopt higher performing ideas or routines. In this way it is increased the organizational learning efficiency. However, such fast learners also tend to converge prematurely to homogeneous sets of ideas or routines, thwarting long-run learning and leading the organization to a suboptimal equilibrium. By contrast, “slow learners” allow the organization to preserve more diversity of individual beliefs, and thus play an important role in enabling the firm to explore a wider range of possible combinations of beliefs. As a result, the presence of slow learners increases the chance of improving the quality of organizational knowledge in the long run.

In short, March’s model demonstrated in an organizational context that although exploitation yields more certain and immediate returns, exploration creates and preserves the requisite variety of knowledge necessary for the organization to sustain its learning in the long term (Levitt and March, 1988; Levinthal and March, 1981, 1993).

3. Methodology
The methodological section aims to extend March’s (1991) exploration-exploitation model by modeling the external environment as an NK Landscape (Kauffman, 1993) and understanding in this way the influence of increasing complexity of the background in which organizations perform. The March-NK model represents the core of this paper, incorporates the logic of March (1991) on the dynamics between exploration and exploitation learning modes, and the NK model as a method to represent complexity of the environment. By representing the complexity of the external environment as a fitness landscape, by varying the parameter $K$, which stands for the degree of interdependencies between actors’ beliefs, we manage to create a more realistic organizational context. Complexity increases with the degree of interdependencies between agents, and in this way we can “tune” the landscape just by modifying one parameter, $K$.

An extension of the March-NK model (let’s call it March-NK-i) is then developed to include learning between organizational members, and local search and long-jump search as ways of structuring the learning process at different levels of organization. Specifically, there are two different search mechanisms, or, in other words, socialization processes which are possible. One is local search in which an individual learns from its neighbor with a probability of $p_1$. The other mechanism is the “long jump search” in which an individual learns from the organizational code with a probability of $p_2$. In case of confliction, it is chosen the one with a better fitness to
update itself. On the other hand, the organizational code updates only via long jump search mechanism. In each period, code updates each of its dimensions with probability $p_3$ if the score of individual is higher than the score of the organizational code.

### 3.1 March-NK model

We aim to extend March’s (1991) exploration-exploitation model by modelling the external environment as an NK Landscape (Kauffman, 1993) and understanding in this way the impact of increasing complexity of the background in which organizations perform on the balance between exploration and exploitation. The present paper represents the early stage of this research path. Our model extends March’s model by representing the complexity of the external environment through the logic of the NK model. By varying the degree of interdependencies between actors’ beliefs, we aim to create a more realistic organizational context. The complexity of the organizations’ environment increases with the degree of interdependencies between agents’ beliefs.

The “reality” from March’s model is being replaced with a rugged landscape formed by individuals and organizational code in their attempt to search the environment. The scores of the individuals and of the organizational code represent the payoffs calculated according to the NK model rules. As a first step of research, we have successfully replicated March’s simulation experiments in order to verify the robustness of the original model, and then we generated the NK landscape in order to analyze the influence of the environmental complexity on an organization and its members. The paper presents the replication of the first experiment of March’s (1991) mutual learning model, and a modified model where we create the environment as an NK landscape.

### 3.2 The reality (environment) modeled as a fitness landscape

Kauffman’s (1993) NK landscape is our approach to model the degree to which the beliefs about the external environment are correlated with one another. Reality in March’s model is represented as a system in a steady representation, where its state is characterized by dynamics which are not themselves changing across time. But a more realistic conceptualization of the external environment would be represented as a dynamic process involving the interrelationships of many actors who possess limited information about the intentions and objectives of others. The beliefs about the external environment are not independent; they interact and depend on different levels on each other. Consequently, there is the need to better understand the interplay between the components that form the external environment.

The notion of “fitness landscape” was first introduced as a conceptual tool by Wright (1931) for studying the evolution of organisms. He considered the mapping of genes to the fitness level of the overall organism. A fitness landscape is a representation of the space of the all different possible configurations of the population according to its fitness. A fitness function serves to record a set of attributes into a single, most advantageous value of a particular combination of beliefs. However as the economic rationality of agents is bounded and because they cannot observe all the possible positions on the landscape, there must be an accurate representation to consider a limited space within which components can move. Thus, the search process has to be local, as suggested by Wright (1931).
Kauffman (1993) increased the usefulness of this heuristic tool by formulating the NK-model as a method to link the interdependence variable to the topology of these landscapes (Sorenson, 2002, p. 5). In the domain of organizations, the set of elements that influences fitness may be interpreted in a variety of ways. For instance, the attributes that determine fitness for an organization may comprise the elements of its business strategy, its human resource policy, manufacturing system, and so on. Fitness can be represented by profit, or by a mix of variables related to the organization’s goals. Alternatively, the fitness landscape can be applied as a mapping of the actions of a set of individuals and their collective performance. The same structure can also be viewed from an individual’s perspective. In this case, one is modeling the payoff to a focal individual conditional on the actions of the other members of the group of actors under consideration.

In this study, the variable N refers to the number of distinct “beliefs” about an external environment. The variable K refers to the extent to which the fitness associated with one belief depends on the other beliefs.

A lack of interdependence generates a single peaked landscape, as the contribution of each value to the global fitness is independent from that of others, and implies a situation of universal best-practices. The interdependence among a set of beliefs results in a multiple peaks, or rugged landscape. With a high degree of interdependence, a change in a single action may appear dysfunctional (i.e. diminishing performance or fitness) despite the fact that a simultaneous change in a large set of actions may enhance performance. (Levinthal and Warglien, 1999, p. 345)

Our “reality” is a mapping from the set \{0,1\}^m that randomly assigns a fitness to each combination of beliefs. This mapping depends on the parameter K which reflects the interdependence of each belief 0, or 1. A change in the fitness contribution of the \(i^{th}\) value is influenced by the change in the \(i^{th}\) decision, and by the change in K other components of the entire set of beliefs. When K = 0, there is no interdependency between beliefs, each one contributes to fitness independently, leading in this way to a fully decomposable landscape. The decomposability of a fitness function defines the degree to which the impact of each individual attribute on fitness is independent of the values of the other attributes (Gill, 2008). But what if we cannot determine the contribution of one attribute to fitness without knowing the contribution of the others? We can have the case that a given belief can only be determined by considering the value of every other belief. This is the case of a complete interdependency and a chaotic landscape will be formed.

The peaks or local optima on the NK landscape are defined as a configuration of elements of the decision vector such that it is not possible to improve the decision’s overall payoff by performing a given type of search. (Ganco and Hoetker, 2008). The \(N\)-dimensional landscape is typically depicted either as a cube (Kauffman, 1993, 1995 for \(N = 3\)) or only illustratively in two dimensions where the payoffs are shown as a rugged surface over this space (with many peaks and valleys if K is high and smooth one if K is low). Figure 1 displays an \(N\)-dimensional binary space in two dimensions.

A unique feature of Kauffman’s model is its “rugged landscape.” As N and K increase:

- The number of fitness optima available to an agent increases geometrically.
- The level of fitness at any given optima diminishes so peaks are less valuable if attained.
3.3 Implementation of the NK reality

In March’s (1991) model, the organization is modelled as a number of individuals and an organizational code, both holding beliefs about a fixed external reality. The effects of the environment are indirect, neither the individuals nor the organization experience reality.

Our model integrates March’s simulation model with Kauffman’s (1993) NK search algorithm. The idea is to replace the “reality” from March’s model with a rugged landscape formed by individuals and organizational code in their attempt to search the environment. The scores of the individuals and of the organizational code represent the payoffs calculated according to the NK model. The generation of the NK Landscape is the most challenging step within the entire development process. The NK space is generated at the beginning of each simulation run. It is conceptualized as a matrix of all possible positions in the $N$-dimensional binary space and their corresponding fitness. The overall landscape is created by randomly generating $2^{(k+1)\times N}$ fitness values. The landscape is generated by randomly assigning a number between 0 and 1 (the payoff) to each belief and to each instance where the payoff value changes. The mapping for a belief $x$ is given by:

$$f(x, N, K) = \frac{\sum_{i=1}^{N} f_i(x_{i; j(i)}, x_{j(i)}^{1}, ..., x_{j(i)}^{K})}{N}, i \notin j(i)$$

For any $i$ we obtain a vector of indexes $j(i)$ mapping from $N$ to $N^k$ and where $x_{j(i)}^{K}$ means that the index of $x$ is the $k^{th}$ element of the vector $j(i)$.

- The predictability of finding a better than average fitness peak diminishes rapidly.
- Agents more likely will be trapped on suboptimal fitness (McKelvey and Yuan, 2004).
We have first created a matrix of all possible positions in the landscape (the $N$-dimension binary space) and their corresponding fitness. The global fitness (the “score” from March’s model) is calculated by selecting the maximum fitness and placing the appropriate entry in the corresponding position.

### 3.4 Extending March-NK model

In this extension we are introducing the possibility of mutual learning between the organizational members. Whereas March-NK model portrayed learning in an organization as mediated by an organizational code, with this extension we add a direct interpersonal learning level. By allowing for interpersonal learning, we recognize that face-to-face interaction can be critical to knowledge transfer (Orlikowski, 2002). Interpersonal learning is a decentralized process that takes place without the mediation of an organizational code. This spatial dimension allows one to consider both local and distant search as distinct aspects of the process of interpersonal learning.

Because the March-NK model does not allow for the interpersonal learning, the way individuals are distribution is not important, but once we allow for direct person-to-person learning, the network between agents becomes essential from many points of view. One reason is the fact that people tend to learn from those nearby, and to look for alternatives that are most readily at hand. Because of the low cost of the interaction and the easy access to one each other, individuals tend to form social networks with their neighbors, and thus to be influence by their beliefs and knowledge. A face-to-face interaction facilitates information exchange and thus the overall learning process. In 2006, Miller et al. proposed an extension of March’s (1991) model where they portrayed the interpersonal learning as a “decentralized exploitation of others’ knowledge” taking place without the intervention of an organizational code.

The extended model, let’s call it March-NK-i model respects the principles presented in March-NK model, but adds the possibility that an individual can learn from another individual in the organization with a probability of $p_1$. This experiment takes three levels of probability of mutual learning: low ($p_1 = 0.1$), medium ($p_1 = 0.5$) and high ($p_1 = 0.9$). The probabilities that individuals can learn from the organizational code ($p_2$ in this case), and the one that also the organizational code can learn from the individuals ($p_3$) remain the same. We also considered three different levels of complexity, low ($K = 1$), medium ($K = 5$) and high ($K = 10$), and we performed 80 runs for each parameter combination.

### 4. Data generation and analysis

Based on the assumption that “the equilibrium level of knowledge attained by an organization depends interactively on the two learning parameters” (March, 1991, p. 75), we explore the effects of learning rates on the equilibrium knowledge. This experiment analyzes the effect of complexity on learning performances of an organization in a dynamic system. In particular, the aim of this experiment is to understand the impact of a rugged problem space on the dynamics of the learning rates $p_1$ and $p_2$ when exists also the possibility of mutual learning between individuals.

Table I illustrates the experimental settings for March-NK model and also for its extension (March-NKi) where it is included a probability of individual mutual learning.

The default values for the simulations are set up as follows: $n = 50$ individuals, $m = 10$ dimensions of beliefs, the interaction parameter, $K$ is varied over five levels: 1,
3, 5, 10 and 15. The organizational learning rate, $p_2$ is kept stabled over three levels (0.1, 0.5, and 0.9), we varied the value of individuals’ learning, $p_1$ over nine levels (0.1:0.9), and for each combination of $p_1$ and $p_2$ we run 80 iterations. For each individual has been randomly assigned a value for each belief from the normal distribution $0:1$. The interaction parameter, $K$ is varied in order to notify the effects of interaction between dimensions composing the reality. There are $2^K$ possible values to define the fitness landscape, or the so-called ‘reality’ from March’s (1991) model. Each belief can take $2^{(k+1)}$ values as each belief is interdependent of other $K$ beliefs. The score of every resulted entity is defined as the average of values for its every dimension.

5. Simulation results
The first result is that complexity (high level of interaction among dimensions, $K$) brings a downward effect on organizational learning independently of the balance of exploration and exploitation.

The topology of fitness landscape depends on the degree to which the payoff (score) to a given belief is dependent on other beliefs. Increasing the density of interdependencies affects the complexity of the landscape, and consequently the emergent patterns of behavior. As peaks multiply, they become less differentiated from the general landscape (see Figure 2). In steep rugged landscapes, adaptive progression is trapped on many sub-optimal (local) peaks. This means that even in the face of

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Table 1.

Figure 2.
The effect of different levels of complexity on the average equilibrium knowledge

$$m = 30, N = 50, p_2 = 0.9$$
strong selection forces, the fittest members of the population exhibit characteristics little different from the entire population (McKelvey, 1997).

In a single-peak world, local, incremental adaptation is a satisfactory solution to this dilemma. But in a rugged landscape, such an incremental search procedure will lead only to the local 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, we observe a strong form of path dependence and, on average, a modest performance (Levinthal and Warglien, 1999).

The second important result is that, as K increases, the average of the randomly assigned contributions falls back toward the mean of 0.5 – “complexity catastrophe”. Kauffman (1993, pp. 52-54) makes a special point of noting that as K increases the average of the randomly assigned contributions recedes toward the mean of 0.5. This effect is reflecting how he modelled the complexity catastrophe. That is, as the web of interdependencies (complexity) grows in size, the likelihood that a particular agent will achieve higher than average fitness tends towards zero. Thus, the basic Kauffman argument that under some conditions complexity effects dominate selection effects is represented by a simple averaging process and the effect of the Central Limit Theorem.

For high levels of complexity (K > 3), system’s performances are strongly affected by randomness. Figure 3 points up the findings in the case of learning dynamics in a very complex environment. It seems that we cannot detect the right balance between exploration and exploitation, and the learning process in a complex environment is a sort of random walk (March, 1991). As the degree of interdependences increases, the learning rates’ trends are guided by chance. For high levels of complexity, the learning dynamics between organizational code of rules and procedures have a casual direction.

Regarding the March-NK extension, we found that the mutual learning between organization learning brings a positive impact on the learning performances of the overall organization (see Figure 4). Setting a fixed level of mutual individual learning, the maximum performance is increasing until 0.7 for all levels of complexity (K = 1, 5, or 10). In March-NK model we saw that the learning performances stagnate at level 0.5.

Figure 3. Effects of the learning rates in a complex environment
Thus we can say that the mutual learning between organization learning brings a positive impact on the learning performances of the overall organization.

This result is in the same line with Miller et al. (2006) study which also includes the learning between individuals and which also finds positive outcomes. By allowing for interpersonal learning, we recognize that face-to-face interaction can be critical to knowledge transfer (Orlikowski, 2002). Because of the low cost of the interaction and the easy access to one another, individuals tend to form social networks with their neighbors, and thus to be influenced by their beliefs and knowledge. A face-to-face interaction facilitates information exchange and indubitable the learning process.

6. Conclusion and future steps

This study models the “space of possibilities” in which organizational learning takes place as a fitness landscape where organizational and individual opinions are interrelated and depend on the states of an external reality. The omnisciente external environment from March’s (1991) model is now represented more realistically and can be manipulated by varying a parameter of complexity.

In general, organizations are part of a larger system; this system has influence on their structure, behavior and resources. Open systems refer to entities that interact with the outside environment, whereas closed systems refer to systems having relatively little interaction with the outside environment (Nadler and Tushman, 1980). In March’s (1991) model and in most of the works proposing agent-based models to deal with internal dynamics, the system is a closed one, rigid to any interaction and omniscient. But organizations in an open system have to deal with their business environment in order to survive. This is due to the fact that the environment makes demands on the organization (e.g. requiring low price products or services, low margins per unit), it may place constraints on organizational action (quality of the infrastructure, lack of governmental regulations) and the environment provides opportunities that an organization can explore (large untapped market).

The research objective and approaches of the mutual learning model of March (1991) we are analyzing are heavily influenced by the ruggedness of the fitness landscape we have created. The complexity of the organizations’ environment increases with the degree of interdependencies between agents’ beliefs. The presence of the

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Figure 4. March-NK vs March-NKi model

Notes: $K = 5$ (complexity parameter); $p1 = 0.1, 0.2, ..., 0.9$; $p2 = 0.5$ (organizational learning); $p4 = 0.9$ (mutual learning between organizational members)
ruggedness (high level of interaction between dimensions) in a fixed environment represents a negative impact on the performance of the overall system analyzed. If in March’s model what drives mutual learning is sustained diversity in beliefs, in complex landscapes diversity seems to not matter. The role of individuals’ diversity is actually decreasing in moderate to high rugged landscapes. The trade-off where exploration and exploitation compete for resources requires a cooperation strategy to make balancing exploration and exploitation work dynamically. When there is high level of complexity the learning dynamics between organizational code of rules and procedures have a casual direction.

We found that it is impossible to find a right balance between exploration and exploitation using the communication structure of March’s (1991) model where the members of an organization can learn from each other only through an organizational code. Here, the exploration-exploitation trade-off is able just to cope with the complexity by maintaining the learning performance at the level of randomness (0.5). It is desirable that the organization surpasses this level of survival and is able to govern the internal and external complexity. By allowing the free communication between organizational members we see how the learning performances are increasing from the random value of 0.5 until 0.7. In our experimental model it was the only modality to overcome the “complexity catastrophe”. The operations, market presence, strategy and performance of each company cannot be understood solely as the sum of the characteristics and decisions of the individual employees (Jackson, 2005). In this way, the “chemistry” developed between the employees of the company, namely the good relationships and the friendly environment that exists becomes a valuable dynamic capability of the organization.

Actors attempting to climb a given landscape may find that the landscape shifts and deforms, as the result of two factors: the adaptive efforts of other actors with whom they are linked, and their own actions, like the creation of new knowledge. The management of the organization can develop various activities in order to control the landscape’s continuous shift and deformation. One of these is giving “injections” of knowledge to specific employees or departments, following two main ways:

1. continuous training in all aspects and procedures of the company; and
2. hiring “outsiders”, namely employees who either were working in another company, or have just graduated, thus offering new, innovative ways of thinking and solving problems.

In this way, they can avoid the bias created in the company and enrich the obsolete knowledge that exists. Another method to deal with a constantly changing complex environment is by facilitating communication at all levels of the system. Because of the low cost of the interaction and the easy access to one another, individuals tend to form social networks with their neighbors, and thus to be influenced by their beliefs and knowledge. A face-to-face interaction facilitates information exchange and indubitable the learning process.

One of the possible future developments of this experimental study is the introduction of different types the organizational structure to test its influence on the overall learning process and on the exploration-exploitation balance. Another future step is to apply the present model at the level of a network of organizations and see how exploration and exploitation dynamics can be condivided in the way to provide
the best learning outcomes. Finally, all the aforementioned models would have to be calibrated with empirical data and applied in real organizations.

References


Further reading


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