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Extremal Search on a Technology Landscape

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Extremal Search on a Technology Landscape

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“If it Ain’t Broken, Don’t Fix it:”
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Abstract

We use an NK technology landscape to create a toy world with which to “test” the performance of a common managerial search rule – identify what is broken, try to fix it and leave the rest well enough alone, a search rule we term “extremal search.” Our results indicate that such a search rule, when applied rigidly, performs badly on combinatorially complex technology search spaces characterized by high levels of “intranalities.” We find a tension between selecting which of technological components to “fix” and the criteria applied for evaluating whether the change should be accepted. As the interdependency between operations within an organization increases, achieving a balance between what to change and determining if the new state of the organization’s technology is actually better, becomes more difficult.
1. Innovation Through Search

Successful organizations, including firms, are capable of steady, and occasionally dramatic, improvements in performance in a wide variety of dimensions. Learning and innovating are a quest into the unknown, involving a probing search of technological, organizational and market opportunities. This *search process* takes place within a *space of possibilities* whose elements are all possible variations for the technologies, production processes, operational routines, engineering designs, organizational forms, inventory methods, scheduling systems, supply chains or managerial practices utilized by the firm. Technological innovation takes the form of finding technologies that improve the firm’s performance. The various means by which a firm moves in its space of possibilities, which is to say, management’s choice of search strategies, greatly influence the direction, rate and overall success of learning and innovating.

The computational (or simulation) model presented here explores the performance of a specific search procedure assumed to be a good approximation of how many firms search. We do not make the simplistic claim that all salient aspects of technological or organizational search can be reduced to an algorithmic representation in a “toy world.” We do make the claim, however, that useful insights into technological search can be gained by simulating search in a computer – provided that the search procedure and the search space capture relevant and important aspects of firms’ realities. By specifying a search space plausibly representing some of the salient features of firms’ actual search spaces, one can investigate the effectiveness of different search procedures assumed to model how firms actually search for performance improvements. (For a discussion of how business use simulations to explore major policy changes through “what-if?” scenarios see Bertsche, Crawford and Macadam (1996).)

“If it isn’t broken, do not fix it,” is a useful dictum not only for individuals and their everyday circumstances, but also for firms, and constitutes, in effect, a search procedure. For many firms this dictum is implemented by the attempt to identify those components of the firm’s operations which are failing or under performing, trying to fix them, and leaving the rest of the firm’s operations alone. Far from being a myopic search procedure, this approach acknowledges the complexity and uncertainty characterizing most firms’ operational environments (Arrow, 1974). In such circumstances, fixing what is wrong constitutes a very smart managerial search approach. “The theory of constraints,” advocated and popularized by Goldratt, answers the managerial question “what to change?” with the advice “identify what is broken, fix it and leave the rest alone.” (Goldratt, 1990; Goldratt and Cox, 1992).

The starting point for our discussion is the representation of technology first presented in Auerswald, Kauffman, Lobo and Shell (2000) and Kauffman, Lobo and Macready (2000). A technology is comprised of $N$ distinct *operations*, each of which can occupy one of $S$ discrete states. A *configuration* denotes a specific assignment of states for every operation in the technology. The productivity of labor employed by a firm is a summation over the labor efficiency associated with each of the $N$ technology operations. The labor efficiency of any given operation is dependent on the state that it occupies, as well as the states of $K$ other operations. The parameter $K$ represents the magnitude of production externalities among the $N$ operations comprising a technology, what we refer to as “intranalities.” In the course of production during
any given time period, the state of one or more operations is changed as a result either of spontaneous experimentation or strategic behavior. This change in the state of one or more operations of the firm's technology alters the firm's labor efficiency. The firm improves its labor efficiency -- that is to say, the firm finds technological improvements -- by searching over the space of possible configurations for its technology.

In order to consider explicitly the ways in which the firm's technological search is constrained by the firm's location in the search space, as well as the features of the space, we go beyond the standard search model and specify a technology landscape. The distance metric on the technology landscape is defined by the number of operations whose states need to be changed in order to turn one configuration into another. The firm's search for more efficient technologies is represented here as a “walk” on a technology landscape. In the present discussion we explore how a search rule based on the principle of “fix what is broken,” and which we call “extremal search,” performs in a complex combinatorial search space. Our virtual search space is specified so as to capture a salient feature of firms’ search spaces, namely the extent to which the various components of a firm’s technology affect each other’s performance. The performance of the constituent components, and thus the performance of the technology as a whole, critically depends upon the web of interactions linking the various components. This web of interactions also affects, crucially, the speed and ease with which experimentation, learning and adaptation occur within an organization. As in Lobo and Macready (1999), Auerswald, Kauffman, Lobo and Shell (2000), and Kauffman, Lobo and Macready (2000), we utilize a landscape modeling framework to represent the firm’s technological search space. (Our exploration is in the same vein as that of Carley and Svoboda (1996), who modeled organizational adaptation as a process of simulated annealing in a virtual organizational space.)

The paper is organized as follows. The next section summarizes a vast literature on how firms actually search on their technology spaces. Section three presents our representation of technology while section 4 introduces a technology landscape. Section 5 describes a specific technology landscape, namely one based on the NK model of fitness landscapes. Section 6 discusses what we considered to be one of the salient characteristics of technology: the way in which the components of a technology or production process are connected to each other and how this web of connectivity affects the performance of the technology as a whole. Section 7 describes “extremal search,” the search rule that our toy firm implements in its toy search space. Section 8 discusses our simulation results while section 9 concludes.

2. How Firms Search

We assume that there is a space of technological possibilities (which we denote by $\Omega$) and that the elements of this space are all the possible variants of the firm's technology (these variants correspond to small modifications, large scale alterations and everything in between). At any time the firm can sample from $\Omega$ in an attempt to find an improved variant of its technology (i.e., one associated with lower costs or higher efficiency or increased profits). Sampling from $\Omega$ corresponds to trials or experiments conducted by the firm in the expectation that they will lead to technological improvements. If a sampled technological variant is found to be associated with improved performance, the firm adopts this variant and makes it the current technology; if, on the contrary, the sampled variant is not associated with a higher payoff, the firm keeps the “old”
technology. (Much of modern macroeconomics and the management science literature on technological and organizational innovation is couched in the framework of search theory: see, for example, Bikhchandani and Sharma, 1996; Evenson and Kislev, 1976; Kohn & Shavell, 1974; Lippman and McCall, 1976; March, 1991; Muth, 1986; Nelson and Winter, 1982, Sargent, 1987; Telser, 1982; Weitzman, 1979.)

We actually know quite a bit about how firms carry out search within their space of technological possibilities. The empirical literature on technology management and firm-level technological change emphasizes that although firms employ a wide range of search strategies, firms tend to engage in local search -- that is, search that enables firms to build upon their established technology and expertise (see, i.e., Barney, 1991; Boeker, 1989; Christensen, 1998; Freeman, 1982; Hannan and Freeman, 1984; Helfat, 1994; Henderson and Clark, 1990; Lee and Allen, 1982; Sahal, 1981, 1985; Shan, 1990; and Tushman and Anderson, 1986). The prevalence of local search stems from the significant effort required for firms to achieve a certain level of technological competence, as well as from the greater risks and uncertainty faced by firms when they search for innovations far away from their current knowledge base (see the discussion in Abernathy and Clark, 1985; Cohen and Levinthal, 1989; Levinthal and March, 1981; March, 1991; and Stuart and Podolny, 1996).

There is also evidence that firms are sporadic innovators. Although most large companies frequently invest money in research, few make a habit of developing innovations. Typically, firms innovate every so often, then go a long time before doing so again --- preferring, instead, to tinker and perfect. The design skills, technical know-how, organizational knowledge and managerial styles resident in a company today result from the cumulative choices made by the firm's engineers, scientists and managers, choices which tend to reinforce successful practices and steer the firm away from “disruptive” changes (Christensen, 1997, 1998).

Note that local and undirected search is not necessarily antithetical to innovation. In a recent examination of successful business organizations, Collins and Porras (1997: 141) observe: “In examining the history of the visionary companies, we were struck by how often they made some of their best moves not by detailed strategic planning, but rather by experimentation, trial and error, opportunism and -- quite literally -- accident. What looks in hindsight like a brilliant strategy was often the residual result of opportunistic experimentation and ‘purposeful accidents.’ ” Empirical evidence, engineering practice and historical record all strongly suggest that firms’ current technological, managerial and organizational practices greatly constraint the firm's technological search to remain close to what the firm already does and knows (Anderson and Tushman, 1990; Ashmos, Duchon and McDaniel, 1998; Basalla, 1988; Caselli, 1999; and Freeman, 1994).
3. Technology

A firm using technology $\omega$ and labor input $l_i$ produces $q_i$ units of output during time period $t$:

$$q_i = F[\theta, l_i]. \quad (1)$$

The parameter $\theta$ represents a cardinal measure of the level of organizational capital associated with technology $\omega$. The firm’s level of organizational capital determines the firm’s labor productivity (i.e., how much output is produced by a fixed amount of labor). Firm-level output is thus an increasing function of organizational capital. A firm's level of organizational capital is in turn a function of the technology utilized by the firm. The firm's technology encompasses all of the deliberate organizational, managerial and technical practices which, when performed together, result in the production of a specific good, delivery of a service, or performance of a task. (Our concept of organizational capital is very similar to that found in Prescott and Visscher (1980) and Hall (1991).)

We assume, however, that technologies as we define them are not fully known even to the firms which use them, much less to outsiders looking in. In order to allow for a possibly high-level of heterogeneity among technologies utilized by different firms, we posit the existence of a space of all possible technologies, $\Omega$. We will refer to a single element $\omega_i \in \Omega$ as a technology. The efficiency mapping:

$$\theta : \omega_i \in \Omega \rightarrow \mathbb{R}^{+}, \quad (2)$$

associates each technology with a unique labor efficiency.

Technologies are assumed to involve a number of distinct and well-defined operations. Denote by $N$ the number of operations in the firm's technology, which is determined by engineering and organizational considerations. The $i$th technology, $\omega_i$, can be represented in vector form by

$$\omega_i = \{ \omega_{i1}, \ldots, \omega_{iN} \}, \quad (3)$$

where $\omega_{ij}$ is the description of the $j$th operation (for $j=1,\ldots,N$). We assume that the operations comprising a technology can be characterized by a set of discrete choices. These discrete choices may represent either qualitative choices (e.g., whether to use a conveyor belt or a forklift for internal transport), quantitative choices (e.g., the setting of a knob on a machine), or a mixture of both. In particular we assume that

$$\omega_{ij} \in \{1,\ldots,S\} \quad (4)$$
for each \( i \in \{1, \ldots, N\} \) and where \( S \) is a positive integer. Each operation \( \omega_i^j \) of the technology \( \omega_i \) can thus occupy one of \( S \) states.

We denote a specific assignment of states to each operation in a technology as a \textit{technological configuration} (or \textit{configuration} for short). Making the simplifying assumption that the number of possible states is the same for all operations that comprise a given technology, the number of all possible and distinct configurations for a given technology associated with a specific good or service is equal to:

\[
|\Omega| = S^N. \tag{5}
\]

New technologies are created by altering the states of the operations which comprise a production recipe. Technological change in this framework takes the form of finding technologies which maximize labor efficiency per unit of output (\textit{i.e.}, technological progress is Harrod-neutral).

We assume that there are significant external economies and diseconomies among the \( N \) operations comprising a technology – that is to say, significant externalities exist within the firm. These “intranalities” can be thought of as connections among the operations constituting a technology (Reiter and Sherman, 1962, 1965). To say that a connection exists between any two operations is simply to say that the performance of the two operations affect each, either bilaterally or unilaterally, positively or negatively. The contribution to overall labor efficiency made by the \( j \)th operation depends on the setting or state chosen for that operation, \( \omega_i^j \), and possibly on the settings chosen for all other operations, \( \omega_i^{-j} \equiv \{\omega_i^1, \ldots, \omega_i^{j-1}, \omega_i^{j+1}, \ldots, \omega_i^N\} \). Hence the labor efficiency of the \( j \)th operation is in general a function \( \phi_i^j \) of \( \omega_i^j \) and \( \omega_i^{-j} \), so that we can write

\[
\phi_i^j = \phi_i^j(\omega_i^j, \omega_i^{-j}). \tag{6}
\]

We assume that the \( N \) distinct operations that comprise the technology contribute additively to the firm’s labor efficiency:

\[
\theta(\omega_i) = \frac{1}{N} \sum_{j=1}^{N} \phi_i^j = \frac{1}{N} \sum_{j=1}^{N} \phi^j(\omega_i^j, \omega_i^{-j}). \tag{7}
\]

We can think of \( \phi^j(\omega_i^j, \omega_i^{-j}) \) as the payoff to the \( j \)th operating unit when it is in state \( \omega_i^j \) and the other operations are in the states encoded by the vector \( \omega_i^{-j} \). In our cooperative setting, operations act not to maximize their own labor efficiency, but rather the aggregate productivity of the firm. (The use of the \( 1/N \) term is simply for normalizing purposes.)
4. Search on a Technology Landscape

Once the intuitively appealing premise of “innovating through search” is adopted, the following related questions immediately press themselves upon us.

- How is the relevant search space to be represented?
- What is the structure of the firm's search space?
- How do the features of the search space affect the firm's search?

One way to impose structure on a search space is to define it as a *landscape*. If we assign a numerical value (*fitness, performance* or *payoff*) to each variant in the space of possibilities (search space), then the “peaks” in the landscape correspond to good variants, while “valleys” correspond to possible variations that are undesirable (more costly, less efficient, *etc.*). The function that assigns these values is often called a *fitness function* (or objective function, cost function, energy function). Formally, a *landscape* consists of two components:

1. a mapping \( f : \omega \in \Omega \rightarrow \mathbb{R} \),
2. a metric structure over \( \Omega \),

where \( \Omega \) is the solution space, and \( \omega \) is a solution. The metric structure serves to define a measure of distance between any two solutions and the “neighborhood” around any given solution. Similar solutions are adjacent in the landscape, while dissimilar solutions are distant. More generally, a landscape consists of a mapping from any domain \( X \) into the reals and a metric structure on \( X \). Landscapes arise in many settings and have been used in research areas as diverse as evolutionary genetics, molecular biology, combinatorial optimization, chemistry, and statistical mechanics. (For a comprehensive discussion of landscape models see Macken, Hagan and Perelson, 1991; Macken and Stadler, 1995; and Stadler, 1995.)

We use a technology landscape to make visible the structure of a firm's multidimensional and combinatorial search space. If we assign a numerical value (performance or cost) to each variant in the space of technological possibilities, then “peaks” in the landscape correspond to good variants, while “valleys” correspond to undesirable variations. The dimensions of the landscape correspond to those traits, or characteristics, amenable to alteration by the firm, which contribute to the performance of a technological variant. Traits for a product, for example, might include such factors as reliability, ease of use, size, weight, and compatibility with competing products. For a firm, traits might consist of market share, investments in personnel training, ratio of managers to employees, marketing budget, etc. Any particular combination of traits, together with a cost assignment, represents a different location on the landscape.

We use the term *technology landscape* to emphasize that the locations on the landscape we are interested in correspond to the elements of the firm's technological search space. Similar technological variants are adjacent in the landscape, while variants with dissimilar performance are distant from one another. The “distance” between any two technological variants depends on the ease with which one technology can be transformed or modified into the other. The \( d \)-neighborhood of any given technology consists of all the technology's variants located at a
distance $d$ away on the landscape. Whether the landscape is smooth with few peaks or very rugged and multi-peaked affects the ease with which the firm can move in its search space.

One of the most important properties of a technology landscape is its level of correlation, denoted by $\rho$ (Stadler, 1992). The correlation of a technology landscape measures the extent to which nearby technological variants have similar levels of performance. Landscape correlation depends on the characteristics of the firm's technology -- correlation is low if slight changes to a technology drastically alter performance, and correlation is high if profitability is relatively insensitive to changes in the technological configuration. (The correlation of a landscape is equivalent to the familiar concept of statistical correlation.) A given production method, for example, might admit alterations which produce very similar efficiency gains; in this case the resulting technology landscape would be fairly smooth, with only a few local peaks, and highly correlated -- meaning that nearby locations in the landscape (corresponding to variants of the firm's technology) have very similar attributes. A firm seeking to improve the communication network linking its various managers, however, might find that there are many possible variations for the network, and that each variation (altering the lines of communication among managers, for example) results in widely differing performance. In this case the landscape corresponding to the firm's search space would be very rugged and uncorrelated, since nearby locations on the landscape are characterized by very different levels of performance (or costs). Whether a technology landscape is smooth with few peaks or very rugged and multi-peaked greatly affects the ease with which the firm can move in its relevant search space.

Another important feature of a technology landscape, one with significant implications for firms' search, is the number of local optima. A technological variant is a local optima if its associated performance or cost is better than that of neighboring variants. Landscapes with multiple local optima are considered rugged landscapes. Ruggedness results from a lack of correlation between neighboring configurations. The most rugged landscapes are called random landscapes since the cost at each location is completely uncorrelated with all other costs. There is a close and inverse relationship between the correlation of a technology landscape and the number of local optima found in the landscape: as landscape correlation decreases, the number of local optima increases. And as the correlation of a technology landscape decreases, so does the likelihood that a randomly chosen technological variant is a local optimum.

The firm seeks technological improvements by sampling variants of its technology found a distance $d$ away from its currently utilized technology. We can reformulate the firm's technological search as moving, or “walking,” on a technology landscape. The steps constituting such a walk represent the adoption, by the firm, of the sampled variants for its technology.

5. An NK Technology Landscape

Since the work by Sewell Wright in the 1920s, biologists often characterize evolution as uphill movement on a fitness landscape -- in which peaks represent successful organisms, high fitness, and valleys represent relatively unsuccessful organisms, low fitness (Provine, 1986). As evolution proceeds, a population of organisms in effect engages in an “adaptive walk” across such a landscape. There are many landscape models as well as families of landscape models, but
one of the most widely studied and used landscape models is the NK model, originally devised to study genetic evolution (Kauffman, 1993).

In the NK model, a combinatorial system consists of \( N \) components (for the search space of proteins, a component would be an amino acid, but the components can as well represent the parts of an artifact or the operations of a production process or divisions within a firm or agents in an organization). Each component contributes to the overall fitness (or performance or payoff) of the system, with each component characterized by one of \( S \) possible states. A specific assignment of states to each component is labeled a configuration. Thus the total number of possible configurational variants for the system in question is \( S^N \). Each given component makes a fitness contribution that depends not only on its own state, but also on the relationship between itself and the state of \( K \) other components (\( K \leq N - 1 \)). The parameter \( K \) thus reflects the extent to which the components of a system are interconnected. The effective payoff of any given component is determined by \( K + 1 \) states. When \( K = 0 \), each component is totally independent of all other components; when \( K = N - 1 \), the performance of each component depends upon itself as well as all other components taken together. It can be shown that the correlation of an NK landscape is related to the parameter \( K \) via the following equation:

\[
\rho = \left(1 - \frac{1}{N}\right)\left(1 - \frac{K}{N - 1}\right).
\]

(For a derivation see Fontana et al., 1993; and Kauffman, Lobo and Macready, 2000.)

Although the development of the NK model was originally motivated by questions of biological evolution, the model has appealed to researchers interested in organizational and technological search (see, for example, Auerswald, Kauffman, Lobo and Shell, 2000; Beinhocker, 1999; Kauffman, 1995; Levinthal, 1997; Lobo and Macready, 1999; Kauffman, Lobo and Macready, 2000; McKevel, 1999; Rivkin, 2000, 2001). This appeal is due mostly to the NK model's explicit representation of interactions among the components of combinatorial systems and how these interactions affect each component's performance, and therefore systemic performance as a whole. The \( K \) parameter has an appealing significance when the NK model is applied to the study of organizations, namely, the extent to which organizational or technical components affect each other.

To define an NK technology landscape we require a measure of distance between two different technologies, \( \omega_i \) and \( \omega_j \) each drawn from \( \Omega \). The distance metric used here is not based on the relative efficiencies of technologies, but rather on the similarity between the operations constituting the technologies. More precisely, the distance \( d(\omega_i, \omega_j) \) between the technologies \( \omega_i \) and \( \omega_j \) is the minimum number of operations which must be changed in order to convert \( \omega_i \) into \( \omega_j \). Given this distance metric, we can define the set of “neighbors” for any technology:

\[
N_d(\omega_i) = \{\omega_j \in \Omega - \omega_i : d(\omega_i, \omega_j) = d\},
\]

where \( N_d(\omega_i) \) denotes the set of \( d \)-neighbors of technology \( \omega_i \) and \( d \in \{0, \ldots, N\} \).
With this definition of distance between technologies, it is straightforward to specify the technological graph, \( \Gamma(V,E) \). The set of nodes, or vertices, \( V \), are the technologies and the set of edges of the technology graph, \( E \), connect any given technology to its \( d = 1 \) neighbors (i.e., the elements of \( N_i(\omega_i) \)). For any technology, the number of one operation variant neighbors is given by:

\[
|N_i(\omega_i)| = (S - 1)N \quad \text{for all } \omega_i \in \Omega. \tag{9}
\]

Thus each node of \( \Gamma \) is connected to \((S-1)N\) other nodes. The technology graph, together with the efficiency mapping in equation 7 (efficiencies can be associated with each node of the graph) constitute an NK technology landscape.

Search on an NK technology landscape proceeds via an “adaptive walk”: starting from any location on the landscape, the firm performs a series of “trials,” sampling from among any of its neighboring configurations differing in the state of at least one operation. The greater the number of operations whose state differs from that of the starting location, the greater the distance between the two locations. The success of the firm's walk (the ease with which the firm finds technological improvements) depends on the landscape's correlation, which in turn depends on the connectivity characterizing the firm's technology.

Consider a firm that at period \( t \) is utilizing a given technology. The firm can take either of two actions: (1) continue using the same technology, or (2) sample a technological variant from its neighbors at distance \( d \). Whether or not to accept the change of state and its associated performance depends on the evaluation criteria used by managers: is the change accepted as long as the performance of the changed component is better? Or is the change of state in one component accepted only if the performance of the aggregate (that is, the technology as a whole) improves? (As we will see later on, which acceptance criteria is used is a crucial ingredient in the firm’s search process.) This sampling process is then iterated from the potentially new technological starting point. We call the adoption of a new technology at \( d = 1 \) an uphill step since the firm has changed its technology and increased its profitability (by achieving a cost reduction). The firm can continue making uphill steps until it reaches a technological configuration that is a local optimum. At this point no further improvements are available through variations found at distance \( d \) and further improvement by the firm is impossible. We refer to this search process as an adaptive walk. Local search -- the most common type of technological search that firms engage in -- corresponds to an adaptive walk performed at a distance equal or close to 1.

The fact that improvement terminates on a local optimum doesn't mean that further improvement is impossible but rather that further technological change requires more substantial alterations (i.e., \( d > 1 \)) to the technology. Indeed, on a rugged technology landscape it is very likely that the firm's search will get stuck on a local optimum. An important implication of technological landscapes having a multiplicity of local optima is that adaptive walks starting at different locations on the same technology landscape may end at different local optima. A model of technological search as a walk on a technology landscape can thus easily accommodate the related observations that firms can become trapped in technological dead ends and that firms with different technologies occupy different local optima with different profitabilities (see
Audretsch, 1991, 1994; Bower and Christensen, 1995; Christensen, 1997; Dwyer, 1995; Rosenbloom and Christensen, 1994; and Tushman and Anderson, 1986).

6. Connectivity and Conflicting Constraints

Typically the components constituting a technology are “connected,” meaning that the performance of any given component affects, or is affected by, other components. This is clearly seen in the case of sequential production processes, in which an interruption in one operation along the assembly line can paralyze the whole manufacturing procedure. If a software engineer in a consulting company shifts to using JAVA instead of C++, this will have effects on the performance of other programmers within the firm and the delivery of the final product. (An economist would be inclined to say that there are externalities -- both positive and negative -- among the components of a technology.)

Connectivity among the components of a technology often manifests itself as a tradeoff between competing or conflicting criteria: the management decision to buy in bulk can lead to decreasing per unit production costs but also to higher warehousing costs; using gas turbines (which are relatively easy to turn on and off) can make a power grid more flexible but at the same time more expensive to run; giving greater autonomy to design teams within a company can accelerate the rate at which new ideas are generated but can make product design integration much more difficult. Suppose a firm is designing a supersonic airliner. The fuel tanks must be placed somewhere; the wings must be strong but flexible to carry the load; the engines must be powerful, fuel efficient and sufficiently quiet to meet Federal regulations; the plane must carry enough passengers to make each flight commercially viable; the electric wiring for the flight controls must be located where they are least likely to get damaged, and so on. Unfortunately, the best solution to one part of the design problem conflicts with optimal solutions to other parts of the overall design. Thus a solution must be found that satisfies the conflicting constraints of the various, and different, local problems.

In general, conflicting requirements must somehow be reconciled if a firm is to make near-optimal technological choices, but frequently, conflicting constraints are just that, conflicting and without resolution. A similar theme is found in the work of Dörner (1996), Kennedy (1994), Langewiesche (1998), Perrow (1999) and Sagan (1993) who draw a sharp distinction between the behavior of “linear” organizations and those characterized by interactive complexity and close coupling, where the constituent parts are linked to one another in multiple, and often unpredictable, ways. Conflicting constraints and connectivity between a technology's constituent parts contribute to landscape ruggedness thereby making learning more difficult.

The NK technology landscape explicitly captures the effects of connectivity and conflicting constraints on a firm's technological search. The “effective” state of any given operation depends on its own state and that state of \( K \) other operations. New technologies are created by altering the states of the operations comprising a technology (note than when the state of one operation is changed, thereby affecting its efficiency or payoff, the efficiencies of \( K \) other operations are also affected). Our view of technological innovation is similar to that of Romer (1990, 1996), who notes that that over the past few hundred years the raw materials used in production have not changed much but as a result of trial and error, experimentation, refinement
and scientific investigation, the “instructions” or “recipes” followed when combining raw materials have become more sophisticated. Our “technologies” are directly analogous to Romer’s “instructions” and “recipes.”

Each given operation makes a contribution to the cost associated with a technology that depends not only on its own state, but also on the relationship between itself and the state of \( K \) other operations \( (K \leq N-1) \). When \( K = 0 \) (no connectivity), each operation is totally independent of all other operations; at the other extreme, when \( K = N-1 \) (maximal connectivity), the performance of each operation depends upon itself as well as all other components taken together. The parameter \( K \) represents the connections among the operations constituting a technology and therefore determines the level of conflicting constraints saddling a firm’s technology. The \( K \) parameter also determines the correlation of an \( NK \) technology landscape. When \( K \) equals zero, the landscape will have a single, smooth-sided, peak; as \( K \) increases, the landscape becomes more rugged as nearby technologies have very different performances values. When \( K = N-I \) the technology landscape becomes completely rugged. As the connectivity characterizing an \( NK \)-type technology increases, so does the number of local optima found on the technology landscape.

7. Extremal Search

We proceed to implement, on an \( NK \) technology landscape, a search procedure inspired by the business rule “if it isn’t broken, don’t fix it.” Specifically, we use a search algorithm known in the optimization literature as “extremal optimization.” Extremal optimization was originally inspired by a model of biological evolution (Bak and Sneppen, 1993). Evolution progresses by selecting against poorly adapted organisms, rather than by expressly selecting or breeding those organisms well adapted to their environment. In a similar way, extremal optimization is not guided by a notion of what an optimal or near-optimal solution is or where such a solution may be found in a search space. In the basic version of extremal optimization the performance of the individual components of a combinatorial system is rank-ordered from best to worst performing with the worst performing component assigned a new state, and therefore a new fitness or performance value. The other components to which the worst performing component is connected also get new states assigned to them and thus new performance values as well. This procedure is iterated without a natural stopping point (for a discussion of extremal optimization see Boettcher and Percus (2001)).

We note a strong resemblance between extremal optimization and the business search rule “if it isn’t broken, don’t fix it,” which we term “extremal search.” Managers are very often unable to discern what is the correct managerial path to follow but can, with reasonable proficiency, identify what is not working with their firms. Goldratt’s notion of “continual improvement” advises managers to identify the bottlenecks and malfunctioning processes in a firm, then to try to change them, not always knowing what the “correct” method or optimal technology will be. The identification process implies that management has some way of discerning a rank ordering of the performance of the firm’s various operations. Once ranked, the manager can alter the worst performing operation in an attempt to improve its performance, hence the firm’s overall performance. Further, Goldratt warns his readers that altering one operation will result in the creation of new bottlenecks in other production processes so that the
identification process begins anew. It is important to recognize that the rank ordering, subject as it is to errors of perception or analysis, makes the selection of an operation to be “improved” in effect a probabilistic process.

In our toy world, a firm is initially randomly assigned a technological configuration on the NK technology landscape. Extremal search proceeds by rank ordering the components of the firm’s technology according to each component’s payoff from \( n = 1 \) for the lowest payoff to \( n = N \) for the component with the highest payoff. The probability that any given component is selected for a change of state is governed by the probability:

\[
P(n) \propto n^{-\tau}, \quad 1 \leq n \leq N.
\]  

For finite values of the parameter \( \tau \) the probability in equation (10) ensures that no rank gets excluded from further evolution while maintaining a clear bias towards components with low performance. This probability process reflects the uncertainty in a decision maker’s ability to identify and select the lowest performing individual operation in the firm’s production process. The critical variable in this equation is \( \tau \), which controls, or tunes, the level of uncertainty in selecting the worst performing component. When \( \tau = 0 \) each component is equally likely to be selected for a change of state, selection is essentially random. For finite and increasing values of \( \tau \) the probability that the worst performing component is selected for a change of state strictly increases toward 1, but no component is ever completely excluded from selection.

There are two possible “business” interpretations of equation (10). Under one interpretation, the parameter reflects an explicit choice on the part of the firm. In one extreme a firm can experiment by randomly selecting components of its technology to change in anticipation that these changes will, on average, improve the firm’s profitability. This process is arbitrary and frequently to the detriment of the best performing operations. At the other end of the spectrum, a firm strictly focus on attempting to improve only the worst performers. In reality a firm’s choice lies between these two extremes, but is nonetheless assumed in this case to be an explicit policy decision. The second interpretation is that \( \tau \) is a measure of a firm’s ability to discern which components are the poor performers. In this case \( \tau \) does not represent an explicit policy choice on the part of the firm, reflecting instead an unintended consequence of the firm’s behavior. Identifying bad performers is not, however, always an easy or obvious task. Indeed, the more removed the decision makers responsible for the changes are from the operations they must evaluate, the more difficult it may become to determine precisely what needs to be fixed or who needs to be replaced. In this case, \( \tau \) is a measure of the firm’s competency to identify and target poorly performing areas. From the perspective of someone outside the firm these two interpretations are indistinguishable. In a firm with a low \( \tau \), the outside evaluator observes a sequence of swiftly changing payoffs occurring throughout the firm, which is to say, they keep missing the target, and it does not matter whether they miss on purpose or miss in error, the point is they keep missing.

Extremal search, however, is not only about how to select an operation for a change of state, but also what criteria a firm uses to decide if the change made to an operation is accepted or not. Once an individual production process is changed the manager must apply some rule to
determine if the change has been for the better or to the detriment of production. There are several possible rules a manager may apply to reach this determination. The manager could apply no rule at all, and simply change a low performing production process and move on to the rank ordering process all over again. It may be that the same production process once again is the worst performer and subject to further alteration. A manager could measure the performance of the individually altered operation, and if its performance alone is improved, accept this new state as part of the firm’s new technology recipe. A third alternative is for the manager to apply a firm-wide criteria, and only accept the new state of the altered component if the firm’s overall performance has improved. We test each of these three acceptance rules in our simulations and refer to them as the \textit{random rule}, the \textit{individual rule} and the \textit{group rule} respectively.

Accordingly, in extremal search once a component has been selected according to equation 10 above, and its state has been changed, its new payoff, the payoff to its $K$ interdependent components, and the system-wide payoff is recalculated. Under the \textit{random acceptance rule} these changes are accepted with no further consideration and the algorithm proceeds to the next iteration. Under the \textit{individual acceptance rule} the change of state of the component is accepted whenever the individual component’s payoff has increased, regardless on the effect to system-wide performance. Under the \textit{group acceptance rule} the change of a component’s state is accepted only when system-wide performance has strictly increased.

8. Numerical Results

Each set of parameter values for the three variants of extremal search were tried on 1,000 landscapes. Across a thousand walks on a landscape, the minimum, maximum and average payoff per time step were recorded. For all simulations the number of components was $N = 100$ while the number of states a component can occupy was simulated for $S = 2, 3$ and $5$. Only the results for $S = 5$ are discussed here although the results were consistent across $S$ values. Each simulation was run for 5,000 time steps, although asymptotic results were achieved well before the 5,000 iterations limit was reached. Payoff or performance is normalized so as to range from 0 to 1.

Figures 1 to 3 plot the “average final” payoff – meaning the technology’s payoff at the end of the 5,000 iteration run averaged over 1,000 landscapes – for different magnitudes of tau and varying levels of landscape correlation. A salient feature is that even for moderately rugged technology landscapes the performance of extremal search drops significantly. These results suggest that for technologies with even moderate levels of “intranalities” extremal search might not be a smart choice of search strategy. There is, however, a striking difference between the performance of extremal search using the group acceptance rule and the performance of extremal search with the two other acceptance rules: the decrease in performance as ruggedness increases (\textit{i.e.}, correlation decreases) is much more gradual. And while the final payoff for extremal search with either the random or individual acceptance rule is approximately 0.5, with the group acceptance rule the final payoff value is greater than 0.6 even for very rugged technology landscapes.

The random acceptance rule and the individual acceptance rule allow the technology’s performance to rise and fall as the search process takes place. Only the group acceptance rule
preserves improvements, hence system-wide performance increases monotonically when extremal search is implemented with the group acceptance rule. Under the random acceptance rule, \( \tau \) is the sole factor driving system improvement, so that when search is carried out even on smooth (i.e., highly correlated) landscapes, low values of \( \tau \) do not generate improvements in system performance there being no selection bias toward the under performers.

In Figure 4 we do not plot final payoff, instead in every landscape that is searched, with all three acceptance rules, we track the payoff of the best technological configuration the search process was able to identify (the vertical bars indicate the standard deviation). These values are averaged for each time step across the 1,000 landscapes sampled. For each level of landscape correlation and each acceptance rule, the value of \( \tau \) that resulted in the best performance is selected as the optimal value of \( \tau \). These are the results that are depicted in figure 4. Clearly the Group acceptance rule dominates across almost all correlation values. However, for extremely rugged landscapes \( 0.0 \leq \rho \leq 0.2 \) the group acceptance rule does not perform as well as the other 2 acceptance rules. Under such extremely rugged topologies attempts to preserve system wide gains result in the search process getting stuck on a local optima very quickly, whereas the other two rules allows the search process to move beyond local optima even if its occurs in a rather aimless manner. Figure 5 graphs the actual \( \tau \) values that were found to be optimal in figure 4. While there does not appear to be any easily discernible pattern in the values of \( \tau \), there is a distinct difference in the regimes between the individual and random acceptance rules and the group acceptance rule. The group acceptance rule relies on a lower selection bias to move the search process beyond local optima.

The firm’s goal is to continually move forward in its technological search process, but to do so without sacrificing many hard won performance gains and without disrupting proven top performers. As a result there is a tension between the acceptance rules and the values of \( \tau \). A search process can rely on the acceptance rule to move the search process beyond local optima or a search process can rely on \( \tau \) to select with a lower bias toward the poorest performer to move the search process forward. When \( \tau \) is low and the acceptance rule is either the random or individual rule, then there is no selection bias or performance criteria being applied to the search process and therefore no lasting improvement takes place. When \( \tau \) is high and the acceptance rule is the group rule, the search process is excessively rigid and gets stuck prematurely on local optima. Interesting phenomena occur when there exists tension between the selection bias and the acceptance criteria. This balance between performance and selection.
allows the search process to move forward, yet retain performance gains forward through the firm’s technological evolution.

There are two ways, at least, to successfully balance the tension between tau and the acceptance rule. One way is to narrowly select from among the worst performing operations in repeated attempt to improve their performance. In this case tau is held high and the appropriate acceptance rule is the individual or random rule. Another way to navigate this tension is to select more broadly among the technology’s operations but maintaining a rigid acceptance criteria, namely, the group acceptance rule with a low tau value.

9. Conclusion

We have used an \( NK \) technology landscape to create a toy world with which to “test” the performance of a common managerial search rule – identify what is broken and leave the rest well enough alone, a search rule we term “extremal search.” Our results indicate that such a search rule, when applied rigidly, performs badly on combinatorially complex technology search spaces characterized by high levels of “intranalities.” The performance of extremal search is strongly mediated by the acceptance rule used to accept or reject a new technological configuration. Our most interesting finding is the tension and interplay between the selection bias of extremal search and the acceptance rule. A firm’s goal is to continually move forward in its technological search process, but to do so without sacrificing many hard won performance gains and without disrupting proven top performers. As a result there is a tension between the acceptance rules and the level of “noise” allowed in the selection process. As the interdependency between operations within an organization increases achieving a balance between what or whom to change and determining if the new state of the organization’s technology is actually better becomes more difficult.

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References


Freeman, C. 1982 *The Economics of Industrial Innovation*. Cambridge, The MIT Press.


FIGURE 1

Average Final Payoff for Varying Landscape Correlation and Tau, Random Acceptance Rule, $S = 5$. 
FIGURE 2
Average Final Payoff for Varying Landscape Correlation and Tau, Individual Acceptance Rule, $S = 5$. 

![Graph showing average final payoff for varying landscape correlation and tau with individual acceptance rule, S = 5.](image)
FIGURE 3
Average Final Payoff for Varying Landscape Correlation and Tau, Group Acceptance Rule, \( S = 5 \).
FIGURE 4

Average Best Final Payoff For All Landscape Correlation Values Given Optimal Tau, S = 5.
FIGURE 5

Optimal Value of Tau for Each Landscape Correlation Values, S = 5.