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Balancing Inertia, Innovation, and Imitation in Complex Environments

Geoffrey M. Hodgson
and
Thorbjørn Knudsen

Since Thorstein Veblen, perennial themes in institutionalist writings have included the role of imitation (or emulation) and the tension between inertia (or conservatism) and innovation in individual and organizational behavior. Prior models of organizational behavior have examined two search processes that represent this tension. One is local search, in which an organization restricts experimentation to a single attribute at a time. In contrast, distant search is associated with changing all of the organization's attributes, in other words, extreme innovativeness. In both cases, the organization adopts the new form if its fitness is thereby improved.

Previous research has established that high levels of complexity favor extreme innovativeness (distant search) over a modest level of inertia (local search). However, it is unclear if organizations balancing inertia and innovativeness at intermediate levels may have an advantage over these extremes (Sorenson 2002). In order to address this gap in our knowledge, we are here concerned with balancing inertia and innovativeness in task environments of intermediate complexity, in other words, when organizational attributes are more or less interdependent. The present work is related to literature which has developed agent-based models of interacting innovators and imitators. Peter Allen and J. M. McGlade (1986) described two distinct search strategies among fishing vessels: "stochasts" who randomly seek out new areas, and "cartesians" who watch where stochasts go and then fish in the most promising areas. The fisheries model is a topical variation on the well-known exploitation-exploration problem (March 1991), with

Geoffrey Hodgson is a Research Professor in Business Studies in The Business School, University of Hertfordshire, De Havilland Campus, Hatfield, U.K. Thorbjørn Knudsen is Professor in the Department of Marketing and Management, University of Southern Denmark, Odense Campus. *This paper was presented at the annual meeting of the Association for Evolutionary Economics in Boston January 6–8, 2006.*

stochasts representing the exploration pole and cartesians representing the exploitation pole.[1] In social organizations, innovation and imitation is usually a mixture, however, rather than distinct modes of behavior in different kinds of organization. Also, the complexity of the task environment may influence the viable proportion of innovation and imitation in a social organization. To address these issues, we characterize organizations with mixtures of innovation and imitation and examine how the viable mixture is influenced by the complexity of the task environment.

The next section develops a modeling structure on the basis of Stuart Kauffman's (1993) *NK* model. This is followed by sections providing results and a conclusion.

The Model

Organizational Forms and Fitness

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). We use a variant of this model and specify a set of possible organizational forms as consisting of N attributes. Each attribute can take on two states, so there are 2^N different organizational forms. The fitness landscape created by the *NK* model is a mapping of the set of attributes onto fitness values. The fitness values of each of the N attributes are determined by random draws from a uniform distribution over the unit interval. The fitness of the organizational form is the average of the values assigned to each of its N attributes.

Organizational attributes can be more or less interdependent; the value of each of the N individual attributes is affected by both the state of that attribute itself and the states of K other attributes. If $K = 0$, there are no interdependencies among the attributes of an organization's form. As K increases, more and more attributes become interdependent. With $K = N - 1$, all attributes of an organization's form are interdependent. The number of interdependencies given by K determines the surface of the fitness landscape. With $K = 0$, the fitness surface is smooth. As K increases, the fitness surface becomes more rugged. That is, higher K leads to a loss of order in the correspondence between organizational forms and fitness values.

With higher values of K, there are larger fitness differences among neighboring organizational forms (a neighbor differs only on a single attribute) and there are more local peaks (organizational forms whose neighbors all have lower fitness). In consequence, local search where experimentation is constrained to changing a single attribute at a time becomes problematic while even (radical) distant search becomes viable (Levinthal 1997). As K increases, there are fewer paths leading to the configuration with max fitness through single bit mutations, in other words, organizations engaging in local search become victims of their randomly assigned initial configurations. An increasing number of organizations can then escape being trapped on inferior points in the fitness landscape only if they risk changing more attributes at a time. With $K = N - 1$, even distant search, where all N attributes are changed at a time, can be advantageous.

Our results reported below reflect the average of 100 organizations searching on each of a 100 distinct landscapes, in other words, a simulation of 10,000 organizations.[2] Each of these landscapes has the same structure in terms of K, the degree of interdependence among attributes in contributing to performance, but represents a distinct realization of random draws. We set $N = 10$, and to facilitate comparison of results across values of K, we normalized the maximum performance level on each surface so that average performance equals 0.5 and maximum performance equals 1.

Inertia and Innovativeness

If an organization resists changing any of its attributes, it is completely inert. As the probability of changing an organization's attributes increases, it becomes less inert. At the opposite pole stands innovativeness, the tendency to change all of the organization's attributes.

In any time step, the organization changes each of the N attributes with probability P_i.[3] For each simulation, the probability P_i does not change. The expected number of attributes to be changed in a time step is P_iN. All N attributes are changed if $P_i = 1$, and no attributes are changed if $P_i = 0$. For intermediate values of P_i ($0 < P_i < 1$), on average P_iN attributes are changed. For example, if $P_i = 0.5$ and $N = 10$, the organization *on average* changes five attributes. Thus, innovativeness is the probability P_i, and inertia is the probability $1 - P_i$.

As a special case, this specification includes (radical) distant search ($P_i = 1$) where the organization, in each time-step, changes all of its attributes—unless no improvement in fitness is achieved. We examine distant search as well as intermediate cases where some level of innovativeness is balanced with some level of inertia. We set $P_i = \{0, 0.1, 0.2, ..., 1.0\}$, including extreme inertia ($P_i = 0$) and extreme innovativeness ($P_i = 1$).

We do not consider the traditional specification of local search (changing a single attribute at a time) since its properties are well known. The specification examined here that comes closest to local search is $P_i = 0.1$. The difference is that we examine the effect of changing one (P_iN) attribute *on average* whereas local search is constrained to literally changing a single attribute in each time step.[4]

Imitation

An organization must avoid the danger of being prematurely trapped on inferior peaks in the fitness landscape, a danger augmented by high levels of inertia. It must also avoid spending too long time "in transit" on inferior peaks while searching for the global peak, a danger augmented by low levels of inertia. Rather than trying to solve this problem itself, the organization may imitate the promising activities of other exploring organizations.[5]

We define a weight W_i determining the extent to which an organization relies on the experience of others as a basis for organizational change. At one pole ($W_i = 1$) organizations completely rely on the experience of others (imitation), and on the other pole ($W_i = 0$) organizations solely rely on their own experience.

Observable behavior is the basis for imitation. We realistically assume that the fitness of other organizations is unobservable. In our model, organizations may follow the population frequencies of observable organizational attributes, rather than selectively imitating prestige groups. In technical terms, we consider conformist rather than prestige-based transmission (Boyd and Richerson 1985; Henrich 2004).

Each organization observes the current organizational attributes of the entire population of organizations. Based on this observation, an organization computes a probability $F_{(t-1, i)}$ of changing each attribute, if it were a pure imitator. $F_{(t-1, i)}$ is computed as the population average of changed attributes to total number of attributes. Rather than using P_i, imitators use these probabilities $F_{(t-1, i)}$ (computed at the end of the previous time-step) as a basis for changing organizational attributes. We consider pure imitating organizations ($W_i = 1$), pure self-relying organizations ($W_i = 0$), as well as intermediate cases. The complete set of weights explored here is $W_i = \{0, 0.1, 0.2, ..., 1.0\}$. These determine the weight that an organization puts on imitation (as opposed to relying on own experience) in changing each of the N attributes:

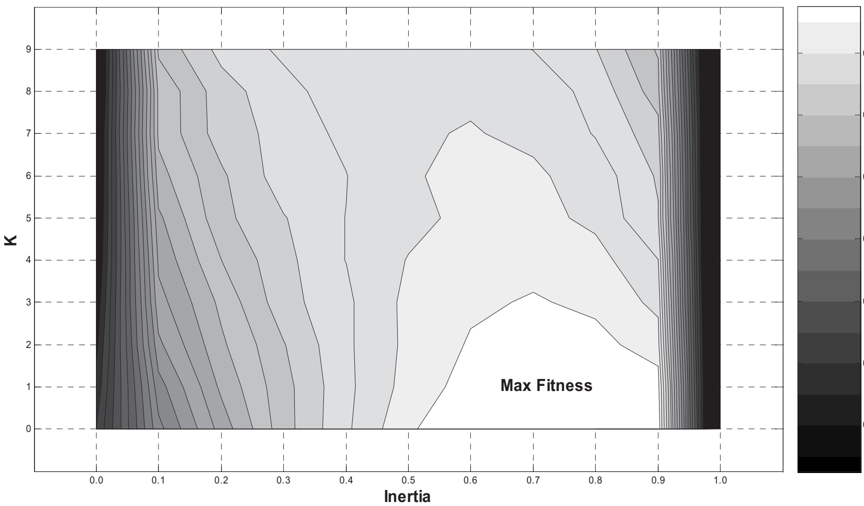
$$P_{(t, i)} = (1 - W_i)\, P_i + W_i\, F_{(t-1, i)}$$

where $P_{(t, i)}$ is the probability of updating attribute i in time-step t, P_i is a hard-coded propensity to innovate ($1 - P_i$ is inertia), W_i is the weight that an organization puts on imitation, and $F_{(t-1, i)}$ is the population average of the attributes that were actually changed during the previous period. Initial conditions are defined by setting $F_{(0, i)} = P_i$.

Results

With no imitation, both extreme inertia and extreme innovativeness are unpromising search strategies. Extreme inertia is the search strategy where randomly assigned initial configurations are never changed. This is dysfunctional because most organizations become trapped on inferior peaks in the fitness landscape. Extreme innovativeness is also dysfunctional because the organization spends most of the time in "transit," cruising from one inferior peak to the next. No matter what the level of complexity, organizations that apply some mixture of inertia and innovativeness have markedly higher fitness than organizations characterized by extreme inertia and innovativeness. As shown in figure 1, organizations that put a relatively higher weight on inertia (>0.5) generally have higher fitness.

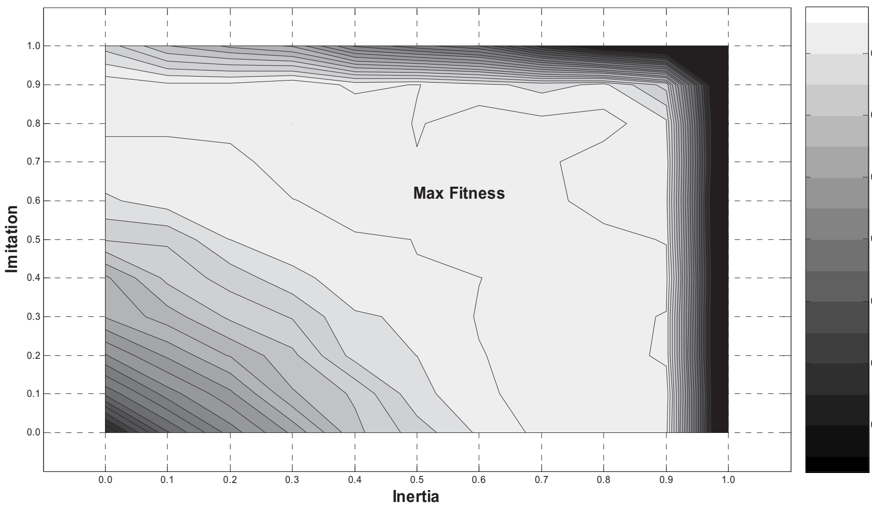
Figure 1. Inertia by Levels of *K* (Contours Capture Different Levels of Fitness)



As complexity increases, it becomes more difficult to balance the risk of being trapped on inferior peaks with the risk of spending too much time "in transit" while searching for better peaks. In consequence, fitness generally decreases with higher levels of complexity. It is remarkable, however, that an appropriate mixture of inertia and innovativeness will only lead to a very slight decrease in max fitness even when all attributes are interdependent (K = 9). Even with the highest level of complexity (K = 9), organizations with inertia between 0.4 and 0.7 will have a (normalized) fitness of approximately 0.95. This is quite remarkable in comparison to local and distant search, the strategies examined in prior studies (Gavetti and Levinthal 2000; Levinthal 1997). While local and distant search represent stylized opposites, the more realistic intermediate mixtures of inertia and innovativeness are much more viable. Prior research has established that high levels of complexity favor extreme innovativeness (distant search) over a modest level of inertia (local search). The present examination of intermediate mixtures of inertia and innovativeness, however, adds to this result. Organizations applying such mixtures will generally obtain higher fitness if they put more weight on inertia than they do on innovativeness, no matter what the level of complexity. Max fitness is generally obtained for inertia > 0.5. As complexity increases, however, achieving max fitness requires slightly more weight is put on innovativeness (most contour lines in figure 1 bend toward the northwest).

Considering imitation in a task environment with minimal complexity (K = 0), figure 2 reveals a range of equally viable search strategies. Very inert organizations obtain higher fitness if they put limited weight on imitation of other organizations (W_i < 0.5).

Figure 2. Inertia by Imitation for K = 0 (Contours Capture Different Levels of Fitness)



In contrast, very innovative organizations are better off if they put a high weight on imitation (W_i > 0.5). As more weight is put on imitation, behavior converges to the population average (in terms of observed changes in attributes of an organizational form). As most new organizational forms have rather low fitness, the population average will tend to relatively modest frequencies of changed attributes. In this way, the population average, to some extent, becomes a substitute for inertia at the individual level.

As can be seen from figures 2–4, an increase in complexity has a number of effects: the set of viable strategies shrinks (i.e., the area with high fitness values) and high levels of fitness are obtained at lower levels of inertia and imitation. For high levels of complexity (K = 9), very innovative organizations (inertia < 0.2) can obtain high fitness only if they to some extent rely on imitation (the max fitness area to the west in figure 4). An alternative strategy of being less innovative (0.25 < inertia < 0.5) is also viable for lower levels of imitation. However, a rather inert organization (inertia about 0.6) can obtain approximately the same high level of fitness if it does not imitate other organizations.

Conclusion

Our results establish that organizations balancing inertia and innovativeness at intermediate levels always have en advantage over the extremes. We thus add to prior studies in the literature on organizations that have primarily examined the stylized opposites of local and distant search (see review in Sorenson 2002). Much higher fitness is

Figure 3. Inertia by Imitation for *K* = 3 (Contours Capture Different Levels of Fitness

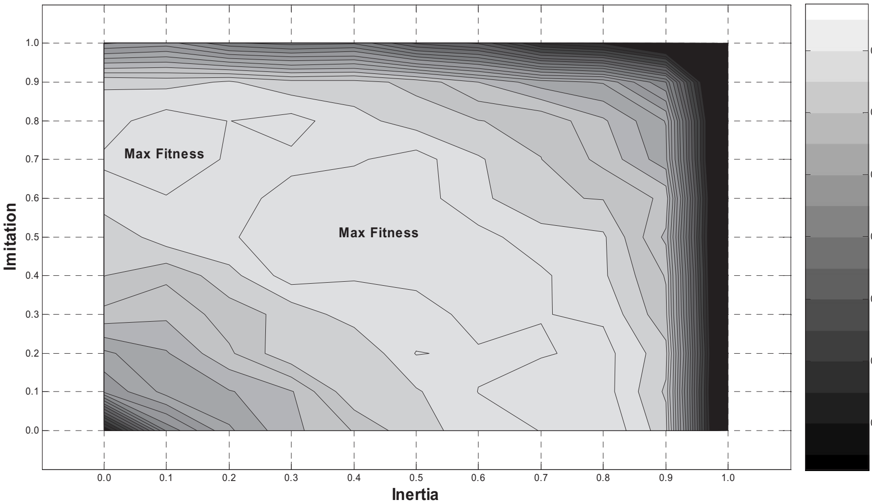
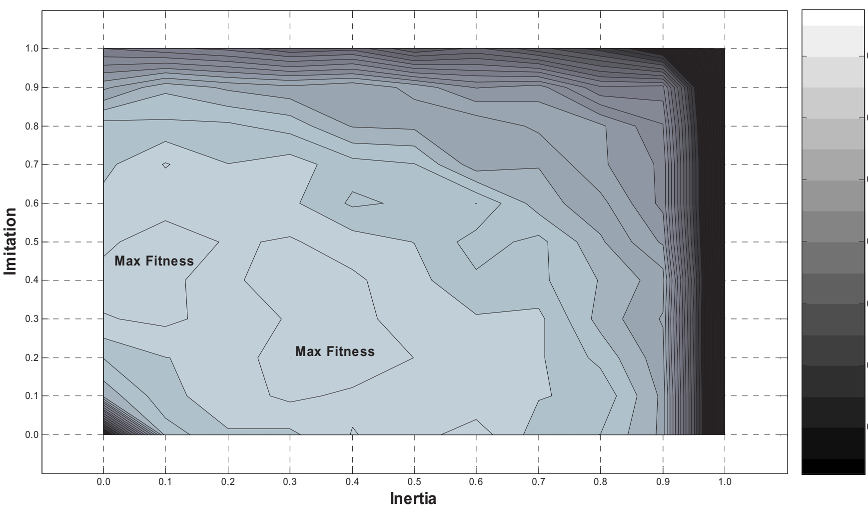


Figure 4. Inertia by Imitation for *K* = 9 (Contours Capture Different Levels Of Fitness)



obtained by balancing an intermediate mixture of inertia and innovativeness, no matter what the level of complexity. Considering imitation, we have further shown that a range of equally viable search strategies are available (with imitation and inertia as substitutes). As complexity increases, however, the set of viable strategies shrinks and high levels of fitness are obtained at lower levels of inertia and imitation.

The results obtained here may have broader implications. It is commonly thought that the socio-economic world is becoming more complex (Pryor 1996; Hodgson 1999). According to our results, such development would favor the emergence of more innovative (less inert) and self-reliant organizations. Both egalitarian cultures that favor imitation and traditional cultures that favor inertia would be challenged by innovating organizations emerging in response to increasing complexity. Moreover, organizations that reflect highly traditional cultures will be at a distinct disadvantage, as complexity increases, in particular if they are extremely self-reliant. These are obviously rather loose speculations warranting more systematic examination. The model developed here offers a simple, useful basis for such an effort.

Notes

1. Peter Allen and J. M. McGlade's (1986) fisheries model has recently been used to account for changes in stock of biomass as a consequence of vessel fishing behavior (Little et al. 2004).
2. These values as well as the value of $N = 10$ are commonly used (Levinthal 1997; Rivkin and Siggelkow 2003).
3. Changing an attribute refers to a random draw determining the state of an attribute. An attribute has two states. So, changing an attribute in this sense will result in the attribute taking a new state with probability 0.5.
4. There is no compelling reason why local search has traditionally been modeled as literally changing a single attribute at a time rather than changing a single attribute in an expected sense.
5. Knudsen and Levinthal (2005) consider how imperfect evaluation and organizational structures (with members that are imperfect evaluators) can achieve an advantage in balancing inertia and innovativeness. Neither does the present work consider imperfect evaluation nor the role of organization structures. In contrast, we focus on the role of imitation with mixed levels of inertia and innovativeness.

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