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TUTORIAL ON NK MODEL

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Abstract

NK model, proposed by Kauffman (1993), is a strong simulation framework to study competing dynamics. It has been applied in some social science fields, for instance, organization science. However, like many other simulation methods, NK model has not received much attention from Management Information Systems (MIS) discipline. This tutorial, thus, is trying to introduce NK model in a simple way and encourage related studies. To demonstrate how NK model works, this tutorial reproduces several Levinthal's (1997) experiments. Besides, this tutorial attempts to make clear the relevance between NK model and agent-based modeling (ABM). The relevance can be a theoretical basis to further develop NK model framework for other research scenarios. For example, this tutorial provides an NK model solution to study IT value cocreation process by extending network structure and agent interactions.

Keywords: NK model, Agent-based modeling, IT value cocreation, Tutorial

1 INTRODUCTION

Simulation, also called computer modeling or computer experimentation, refers to the efforts in which real cases are represented by simple abstract models. Unlike formal mathematical modeling, simulation process cannot be described only by mathematic deductions. Usually, only basic rules are defined and simulation objects may behave totally differently. Simulation is often used in complex contexts that formal mathematical modeling cannot handle with. It stands at the cross-section of qualitative and quantitative methodology. It can set the computational context into the qualitative domain, such as using surveys to define characteristics and rules of context, as well as using mathematical methods (like algebra, calculus, or probability theory) to represent, transform and analyze the simulation objects in a quantitative way. In natural science, simulation is widely applied. However, it is still a novel idea in social science. Many social sciences disciplines, like management information systems (MIS), still have not fully accepted this new method.

Simulation models are quite similar in research design but are different in technical details (Zacharias et al. 2008). Popular simulation methods contain (multi) agent-based models (ABM), system dynamic modes, cellular automata, event-based models and statistical forecasting (Carley 2009). In MIS field, almost all simulation-related literature uses ABM (e.g. Nan 2011; Zhang 2014). Discussions of ABM can trace back to early literature of complexity theory. Complexity theory generally deems society as a system made up of a large number of parts with interactions (Simon 1996). Complex adaptive systems (CAS), as a branch of complexity theory, are defined as "systems composed of interacting agents described in terms of rules. Agents adapt by changing their rules as experience accumulates"(Holland 1995). ABM is a computational simulation tool that has been widely adopted by CAS researchers (Epstein 2006; Epstein and Axtell 1996). It is a practical instrument of CAS (Nan 2011). In ABM, agents are allowed to interact with each other under several basic rules. Macroscopic structures then emerge from these interactions (Amaral and Uzzi 2007).

NK model is one of the popular simulation methods in social science studies. It is proposed by Kauffman (1993) to simulate the organisms' adaptation and self-evolvement processes in competing environment. Later, the method is applied to organization science and many excellent works come out (e.g. Levinthal 1997; McKelvey 1999; Gavetti and Levinthal 2000). With a simple structure and strong analytic power, NK model can easily depict firm structure, behavior dynamics, and complex social context when compared to other research methods. Although original NK model framework has been largely applied in organization science, few literatures have tried to further extend the framework for other research contexts. One of the possible reasons is that it is hard to justify any revisions on a mature framework without any strong theoretical support.

One possibility using NK model in MIS discipline is IT value cocreation. Traditional IT value literatures study within one firm boundary, which is limited (Kohli & Grover 2008; Zhang 2014). Thus, a new trend starts to emerge, which studies multi-firm IT value cocreation. Related works in special issues of *Information Systems Research (2010)* and *MIS Quarterly (2012)* have clarified the concepts of IT value cocreation and its generation process (e.g. Gnyawali et al. 2010; Rai & Tang 2010; Rai et al. 2012; Han et al. 2012). However, knowledge of firm dynamics in IT value cocreation is still uncovered (Grover & Kohli 2012). To address the issue, simulation is a suitable research method, especially NK model. The organization competition scenario has been examined many times using NK model in organization science. Using NK model for IT value cocreation can enable answering questions like "How an alliance relationship is formed and evolved in competing environment?" "How different cocreation structures affect the value cocreation process?" "What conditions cause a firm to terminate a relationship?" "How different processes interact with each other to generate cocreated values?"

This tutorial aims to provide a simple tutorial on NK model, expecting to encourage researches using simulation and NK model. To show how NK model works, this tutorial also provides a replication of Levinthal's (1997) research. Besides, the link between ABM and NK model is also discussed. It can be the basis for further developing NK model framework. For example, the concepts of network structure and interaction extensions are borrowed from ABM.

In the later sections, this paper is structured as follows. First concepts of NK model are introduced. Then the relationship between NK model and ABM is discussed. Next several replicated NK model experiments from Levinthal (1997) are given. Finally, to study IT value cocreation, an example of NK model framework extensions are offered.

2 NK MODEL DESCRIPTION

In NK model an entity is a conceptualized organism, which is shaped into a fixed length array with N attributes. Fitness of an entity refers to its competitive ability (or adaptive ability to environment), which is affected by all attributes. Some attributes may have interactions. The degree of interaction is designated by a parameter *K*. It means each attribute have interactions with other *K* attributes. The mechanism how attributes influence overall fitness is shaped by *K*. In specific, an attribute's contribution to fitness is determined by its and *K* interacted attributes' values. If $K = 0$, the contribution of each attribute is entirely independent. With *K* increasing, the contribution pattern of each attribute becomes more complex. When $K = N-1$, which is the max value *K* can reach, one attribute's contribution depends on all other attributes' values. Let us assume each attribute can take *D* kinds of values[1]. Then there are in total D^N kinds of entity type and each attribute has possible D^{K+1} patterns of contribution to overall fitness.

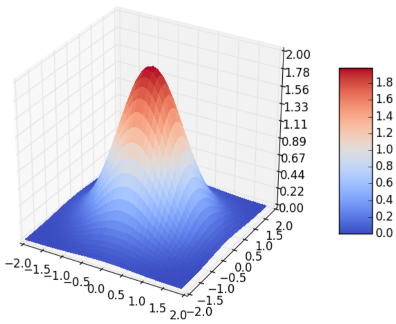
NK model is a repetition of competing and evolving processes. It begins with initializing simulation environment, including simulation population (a group of entities) and a fitness landscape (collection of all possible entity's fitness). After initialization, the population goes through a natural selection phase at the beginning of each simulation period. In natural selection phase, entities with higher fitness survive in the environment while the others die. After natural selection, a surviving entity adapts to environment to gain a higher fitness, fearing to lose competitive ability and thus failing to survive in the next simulation period. Such phase is called adaptation. Unlike surviving entities, dead entities go to birth phase. This phase models the birth process of surviving entities. Specifically, each dead entity is replaced by a new entity. That means the population number always remains constant over time. This is a rule from mathematical genetics literature (Smith 1989). The rationality is easy to capture. Assuming the total resources environment possess is fixed, the number of entities that it can hold is certain. When actual population number is bigger or smaller than the fixed threshold, population growing or competition, respectively, forces the population number back to the threshold. These three phrases comprise an independent simulation period. Running NK model means running the simulation period one by one until equilibrium is achieved.

2.1 Fitness Landscape

A fitness landscape is a collection of fitness values for all possible entities. If NK model entity has *N* attributes and each attribute can take *D* kinds of values, there are D^N kinds of entities and the fitness landscape should include D^N fitness values. A fitness landscape can be seen as a surface, where entity attributes determine location and the corresponding fitness is height. In the adaptation process, some entities may successfully adopt new forms with higher fitness. Reflecting in the fitness landscape, these entities "walks" from lower positions to higher ones, like "climbing" a mountain.

The shape of a fitness landscape varies due to several factors. Among them, the value of *K* is essential. With *K* increasing, the contribution patterns of one attribute become more complex. When *K* is relatively big, even the value of an attribute changes a little (new location on the fitness landscape is not far away), the overall fitness value can experience a huge variation. Under a big *K* configuration, the fitness landscape is "rugged" and multi-peaked. A peak is defined as a fitness landscape location, at where the entity has higher fitness than its neighbors. Neighbors refer to those entities that have one different attribute from the original entity. On the contrary, the fitness landscape has fewer peaks and tends to be "smooth" when *K* is small. Figure 1 and 2 give a glance on how different *K* can influence the shape of fitness landscape.

[1] Usually it is set to 2 and each attribute can only take value from 0 or 1 for research convenience.



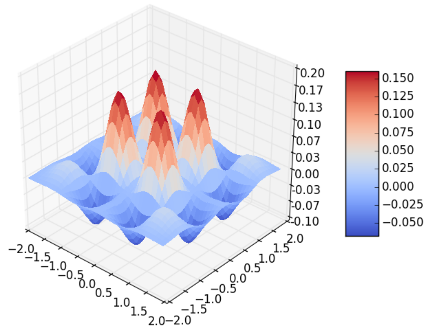
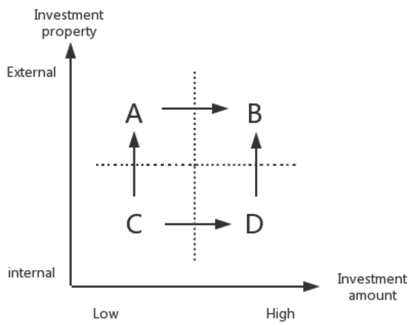


Figure 1. Shape of fitness landscape (k=0) *Figure 2. Shape of fitness landscape (k=1)*

The shape of fitness landscape influences the adaptation process greatly. For instance, assuming a firm only has two strategies to decide its IT investment: internal or external investment, low or high investment. Assume external investment has higher outcome than internal investment and higher investment leads to higher returns. Also firm can change one strategy to get higher fitness once a time. When $K=0$, two strategies are independent and there is only one peak in the fitness landscape. If one firm has internal investment strategy, it will adopt the external investment strategy in the end. For the other strategy, it is the same. The result of adaptation is that all firms adopt external investment and high IT investment strategies. The dynamics are illustrated in Figure 3. Firms in the area A and D will find firms in area B have higher fitness, then they "walk" to area B. Firms in area C will walk to area A and D at first, then to area B. In the final equilibrium, all firms should in area B.

If $K=1$, the final situation possibly is different. Since contribution of one strategy is related to the other one, it could be possible that the strategy set (low, internal) has a higher fitness than (low, external) and (high, internal). In such case, firms in area B still have the highest fitness value. However, firms in area C have a little higher fitness value than area A and D. Under this circumstance, firms in area A and D will "walk" to area C as well. As a result, there will be two kinds of form existing at the end (B & C), which are both local peaks in the fitness landscape. This kind of process is shown in Figure 4.



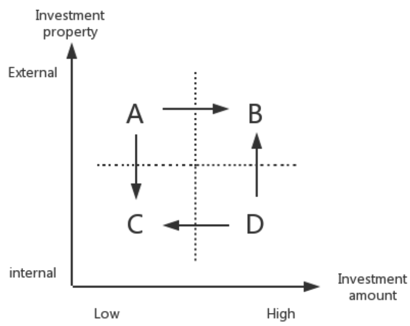


Figure 3. Firm adaptation dynamics (k=0) *Figure 4. Firm adaptation dynamics (k=1)*

2.2 Modeling Adaptation

NK model is a modeling approach for competing environment. An environment is supposed to have limited "resources". Entities must compete for these limited "resources" to survive. The higher fitness they have, the more surviving ability they possess. In order to survive, entities have to adapt themselves to a form with higher fitness. Such process is called adaptation.

In general, there are two approaches for adaptation. One is local adaptation, also called "local climbing". Taking this approach, an entity searches for a higher location nearby in the fitness landscape, at where an entity is its neighbor, and "walk" to it (replicate the entity form there). If an entity cannot find a "higher" neighbor, it should stand at one of the local peaks. In such case, this entity can take the other approach to adapt, which is called "long jump". "Long jump" means an entity randomly choose a location far away and evaluate it by "height". If that location is "higher" than the current location, this entity will "jump" to the new location.

An entity will always try "local climbing" at first. It only adopts "long jump" when the first approach is unsuccessful. That makes sense as "local search" costs much less effort than "long jump". Changing fewer attribute values means requiring fewer effort. At the same time, it seems to be less risky as an entity is more familiar with the current local landscape.

2.3 Modeling Birth

At the beginning of each simulation period, some entities die due to failing natural selection. New entities then are added to the simulation environment to make population number stable. Such process is called birth process.

There are two ways to determine attributes of new entities. One is replicating current existing forms, called replication. The other one is choosing a random form, defined as random birth. These two ways can be understood by comparing to the biological birth process. Babies are supposed to inherit parents' genes. This is similar to replication process. However, genetic mutation sometimes happens. Then babies will have different genes with their parents. The extreme case is the random birth.

Taking which birth approach is according to the average fitness of the whole simulation population. When the average fitness is relatively high, the majority of entities are quite close to the global peak on the fitness landscape. Just replicating the existing forms can gain high fitness immediately. Thus, new birth will choose replication process. Otherwise, they will choose the random birth process. The degree of average fitness is detected by genetic load, which is calculated by one minus average fitness by max fitness in the population (equation in 3.2.4).

3 ABM REPRESENTATIONS OF NK MODEL

Complexity theory is the theoretical basis for simulation methodology. Complex adaptive systems (CAS) theory, as a branch of complexity theory, is an instrument that "allows researchers to capture interactions among basic entities of actions and relationships between these entities and an environment, and analyze their contributions to macroscopic observations" (Nan 2011). Agent-based modeling (ABM), deriving from CAS perspective, describes a paradigm to investigate real complex systems by simulation. Recent literatures highlight two elements in ABM: agent, environment (e.g. Zhang 2013; Nan 2011). According to the definition of complexity theory, the biological environment that NK model simulates is a complex adaptive system. Although no previous literature has indicated, NK model actually is one kind of agent-based modeling approach. The competing environment can be deemed as the ABM environment and competing entities can be seen as ABM agents. This section aims to represent NK model in a ABM form. It provides a basis for future NK model extensions.

3.1 Operationalize Theoretical Constructs

To align NK model and ABM, firstly NK model constructs need to be mapped into ABM constructs. The mapping is illustrated in Table 1.

ABM concepts	NK model concepts	Definition	Components	Description
Agent	Entity	NK model entity is an agent of agent-based model. An agent is also called the basic "intelligent creature". All agents have the same structure and adopt some strategies to behave in the simulation environment.	Attribute 1	Agent subpart 1, taking D kinds of value.
			…	…
			Attribute N	Agent subpart N, taking D kinds of value.
			Behaviour 1 (Natural selection)	Before each time period, each agent

				survives or dies according to its fitness.
			Behaviour 2 (Local climbing)	Firstly surviving agents try to "climb local hill" to get a higher location on fitness landscape.
			Behaviour 3 (Long jump)	Surviving agents who find themselves at the local peaks tries to find a higher location far away.
			Behaviour 4 (Replication)	Dead agents are replaced by new agents. The new agent's form is a replication from extant forms.
			Behaviour 5 (Random birth)	Dead agents are replaced by new agents. The new agent's form is a random form.
			Behavioural rule	Agent is always seeking forms with higher fitness.
Environment	Environment	Environment is the place in where all entities interact with each other and adapt to environment. In most times, it is an abstract and virtual space.	Attribute	The number of agents in the environment (population size).
			Rules	Environment's attributes are fixed.
			Networking structures	No physical distance. Agents' interactions are manifested by attribute observation.
			Fitness Landscape	A collection of all possible agents' fitness

Table 1. Mapping NK model constructs into ABM

3.2 Build Computational Algorithms Mirroring Theoretical Logic

3.2.1 Calculating the Fitness Level of Agent

In the main NK model literatures, an agent's overall fitness is determined by all attributes. Besides, their contribution weights are deemed as the same, unless some attributes have a salient influence on competing ability in specific contexts. For instance, when taking teamwork, the contribution weight of all members is supposed to be the same while for a leader it might be higher. This is because a leader may have more power in the final decision-making process. Kauffman (1993) calculates fitness by average contributions of all attributes. If an agent is represented by $d = (d_1, d_2, \dots, d_N)$, its fitness $F(d)$ is:

$$F(d) = \frac{1}{N}\sum_{i} F_i\ (d_i; d_{i1}, d_{i2}, \dots, d_{ik})$$

Where the attribute *i*'s contribution F_i depends on its value d_i and other related *K* attributes' values. For each attribute, its contribution F_i is assigned a number from uniform distribution ranging from 0 to 1. This calculation method is also adopted in later NK model researches.

3.2.2 Natural selection

At the beginning of each simulation period, there is a population-level natural selection process. Through such process, agents with high fitness survive. The others die because of losing surviving competition. The probability of agent *i*'s survival is defined as

$$P_i = {}^{F_i}/_{F_{max}}$$

Where F_i is fitness of agent *i* and F_{max} donates the max fitness values in the whole population.

3.2.3 Adaptation: local climbing and long jump

In adaptation phase, surviving agent adopts the local climbing strategy at first, wishing to replicate a neighbor's form with higher fitness. If this attempt fails, it tries to find a superior form, which is quite different from the current form. Representing the two strategies in fitness landscape, firstly an agent is heading to a higher local location in each adaptation process (local climbing). If this agent is already at one of peaks in fitness landscape, it attempts to jump to a higher location far away (long jump).

3.2.4 Birth: replication and random birth

New birth agents have two strategies to decide their initial attributes – replication and random birth. When average population fitness is relatively high, they tend to replicate the existing agent forms. On the contrary, they choose forms with random attribute values. The degree of average population fitness is shown by genetic load. The genetic load is defined as following:

$$GL = 1 - {F_{average}}/{F_{max}}$$

Where $F_{average}$ donates the average population fitness and F_{max} represents the max agent fitness in the population. The probability ratio to choose replication and random birth is $(1 - GL): GL$.

If a new agent chooses replication strategy, which form to replicate depends on its fitness level. The probability to replicate the existing agent *i* is:

$$P_i = {F_i}/{F_{sum}}$$

Where F_i is the fitness of agent *i* and F_{sum} is the sum fitness of all agents.

4 EXAMPLES OF NK MODEL

One of the most famous studies using NK model is Levinthal (1997). He borrows the NK model framework to explore how organizations adapt and evolve themselves within a competing social environment. This section is a simplified replication of his work. The purpose is to illustrate how NK model is applied in social research[2]. In Levinthal's (1997) research, original NK model framework is applied without changes. What he does is giving NK model concepts practical meaning for competing organization scenario. In his work, agent refers to an individual organization. Environment represents competing social context. Fitness stands for organization performance. Agent behavior and simulation process are both consistent with original NK model framework. The novelty and contribution of his research are efforts to bring NK model into social science research. Later parts briefly discuss how he explains NK model experiments from an organizational perspective.

4.1 Parameter Initialization

From the initialization process, the general parameter settings and research purpose can be easily spotted. The work of NK model initialization contains creating simulation environment and generating agent population. The parameter configurations of Levinthal's (1997) various experiments are almost the same. The initialization details of this paper are shown in Table 2.

Parameter	**Name of Parameter**	**Definition**	**Initializing Process**	**Memo**
$C_{d_i;d_{i1},d_{i2},\ldots,d_{ik}}$	Contribution	Attribute d_i's contribution to fitness. Its K interacting attributes are $d_{i1}, d_{i2}, \ldots, d_{ik}$.	Generating a random number from uniform distribution ranging 0 to 1.	They are basic parts of fitness landscape. Once initialized, it is fixed. Only when environment changes, the two kinds of parameter will be initialized again.
F_i	Fitness	Fitness value of agent *i*.	Averaging of all attribute contributions of this agent.	
Context	Environment	Simulation environment containing agent population.	Create object with mathematical representations of environment attributes and fitness landscape.	Most time it is fixed once initialized.
Agent	Agent	Simulation agent with random attribute values and pre-defined	Creating a child object of context object containing 10-attribute array	The population number is set to be 100.

[2] Java repast programming environment is employed here.

		behavior rules.	and mathematical representations of behavioral rules. The array attributes are set to 0 or 1 randomly.	
Observer	Observer	An object used to observe simulation process.	Creating an object of context object with recording functions.	This object is called before each simulation period to renew experiment records.

Table 2. Experiment initialization details

4.2 Computational Experiments

This part illustrates the replications of Levinthal's (1997) work. It includes seven independent experiments. Each experiment has a little difference in research design. Their research designs are compared in Table 3. Each experiment will be discussed separately. Every experiment result is an average of 100 repetitions.

Experiment	Initial agent attributes	Fitness landscape	Natural selection	Adaptation		Birth	Noise search
				Local climbing	Long jumps		
Emergence of order	Random	Fixed	✖	✔	✖	✖	✖
Distribution of organization forms	Random	Fixed	✖	✔	✖	✖	✖
Radiation of forms under adaptation	Identical	Fixed	✖	✔	✔	✖	✖
Emergence of order under selection	Random	Fixed	✔	✖	✖	✔	✖
Survival in changing environment	Random	Change in one dimension	✔	✔	✔	✖	✖
Variation in changing Landscape	A comparison of properties in different landscapes						
Survival in changing environment (Noise = 0.025)	Random	Change in one dimension	✔	✔	✔	✖	✔

Table 3. Research designs of different experiments

4.2.1 Experiment 1: Emergence of order (local adaptation)

Research purpose of this experiment is exploring implications from local adaptation alone. That is to say, no natural selection and birth process are involved. Besides, agents can only take local adaptation strategy in adaptation phase. Organization "order" emerges from the reduction of organizational forms in the local adaptation process. Different parameter *K* configurations are examined and compared. The experiment output is illustrated in Figure 5.

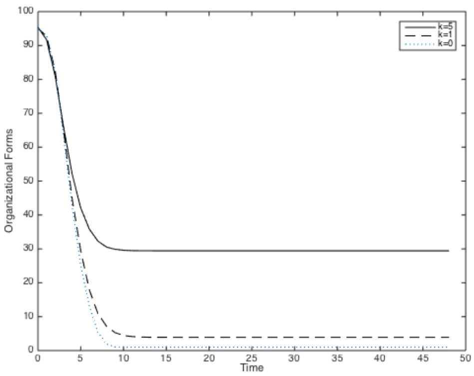


Figure 5. Emergence of order (local adaptation)

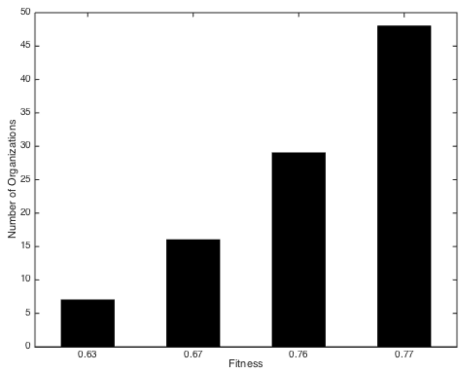


Figure 6. Distribution of organization forms (local adaptation, K=1)

Initial organization forms are 95, 95.35, and 95.09 for, respectively, $K = 0$, $K = 1$, and $K = 5$. Then they sharply go down, indicating that numerous forms have diminished. This is because organizations are adapting and adopting better forms. After simulation period 10, all three experiments reach balance and curves become horizontal. In the beginning, local adapting is easy. This is because initial agents are randomly located on the fitness landscape and there are many chances for local climbing. After a short time, each agent has reached its nearest local peak. Local adaptation stops and organizational forms never change again. Most times the number of final organizational forms represents number of local peaks in fitness landscape. The difference for different *K* configurations is consistent with the former discussion in fitness landscape section. When *K* becomes bigger, the fitness landscape is more "rugged". In other words, there are more local peaks on fitness landscape. Final organizational forms are 1, 3.9, and 29.4 when $K = 0$, $K = 1$, and $K = 5$. It clearly shows how quickly a fitness landscape becomes "rugged" with *K* increasing.

4.2.2 Experiment 2: Distribution of organization forms (local adaptation)

Research design of experiment 2 is the same as experiment 1. This experiment shows how final fitness distributes, shown in Figure 6. The result here is from a single arbitrary simulation experiment when $K = 1$. Kauffman (1993) gives the term of "basin of attraction" to describe the set of locations, which adopt one same local peak through local adaptation process. An interesting phenomenon is that the breadth of a basin is highly correlated with its height. In other words, in the final equilibrium, the number of organizations with higher fitness is bigger that the lower ones, as indicated by Figure 6. Besides, the result implies that the adaptive evolution in NK model is path-independent. For heterogeneous firms with different initial forms, they are still likely to achieve the same location with same high performance in totally disparate adaptation routes.

4.2.3 Experiment 3: Radiation of forms under adaptation

An alternative way to investigate "order" of organization adaptation process is to examine radiation of organizational forms. The term of radiation is used to refer periods of dramatic growth in the diversity of a population. Research design is quite similar to experiment 1. No natural selection and birth phase are involved. However, long jumps are included here. Besides, all agents are initialized with identical agent attributes. How organizational forms change over time with different parameter *K* configurations is illustrated in Figure 7.

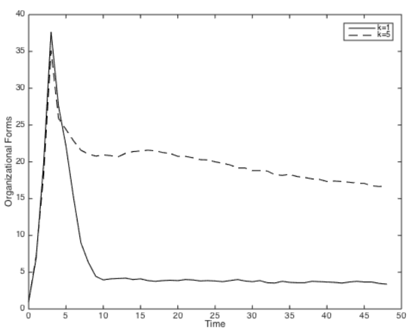


Figure 7. Radiation of forms under adaptation

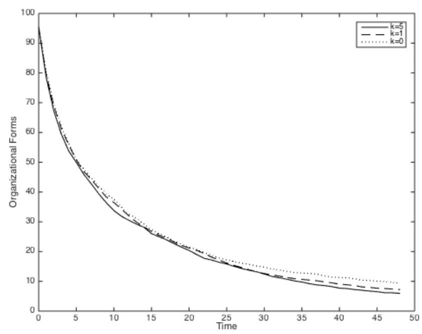


Figure 8. Emergence of order under selection

In the beginning periods of simulation, nearly half of organizations have identified attractive forms largely based on long jumps. When the number of organization forms reaches a peak, it experiences a rapid decline in a short time due to the effect of local adaptation. Also, final equilibrium illustrates "ruggedness" of fitness landscape. As Figure 7 shows, in the *K=5* situation, there are more organization forms than the *K=1* situation. Levinthal (1997) also mentions a practical implication of this experiment: the route of industry evolution (Utterback and Abernathy 1975; Anderson and TushMan 1990). When a new industry is born, organization forms are quite similar at the beginning. Then, with an explosion of numerous innovative ideas, diversity of organization form increases sharply. Over time, this variation reduces because only several kinds of product are accepted and producing process is becoming standardized.

4.2.4 Experiment 4: Emergence of order under selection

Another kind of "order" comes from the process of pure natural selection. This experiment examines how natural selection process influences the organizational form reduction without any adaptation. In this experiment, only natural selection and the responsive birth process happen in each simulation period. The experiment result is shown in Figure 8. Selection process enables organizations with higher fitness to stay and leaves out bad ones. Thus, it drives the population to a single form, which has the highest fitness value. As indicated in Figure 8, selection doesn't show much difference under various *K* settings. The speed of death is relatively faster in the beginning. When the average population fitness becomes higher, the death speed is correspondingly slowing down. Compared to "order" emerging from adaptation processes, the reduction rate is considerably slower. One reason why parameter *K* does not make a difference here is that, natural selection is independent with fitness landscape. In other words, natural selection only cares the fitness value or "height" on the fitness landscape. In comparison, adaptation depends on the shape of fitness landscape. It relies on an accessible "path" on fitness landscape to achieve higher location.

4.2.5 Experiment 5: Survival in changing environment

The real organizational environment is not always fixed. Many cases have witnessed how social, political, and cultural changes lead to performance pattern's mutation. To explore this issue within the context of NK model, the simulation experiment was re-run half way (e.g. period 25). A new fitness landscape was formed to replace the old one, by changing contribution of one attribute. In this experiment, complete natural selection and adaptation phases are involved. Figure 9 shows the percentage of surviving organizations over time.

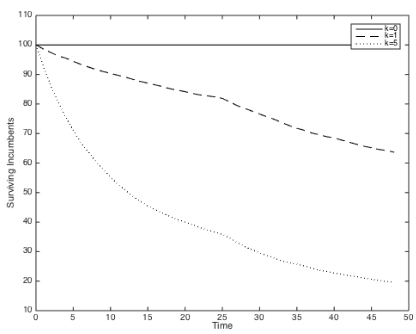


Figure 9. Survival in changing environment

(Change in fitness landscape in one dimension)

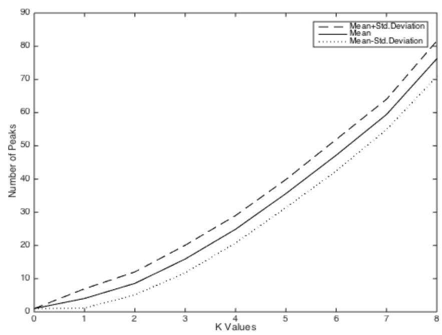


Figure 10. Variation in landscape

As indicated in Figure 9, fitness is highly correlated with locations on fitness landscape when *K* is small. That means organizations can rapidly re-adjust themselves when confronting fierce environment turbulence. That is why survivals always remain 100 when $K = 0$. In a bigger *K* situation, the contribution of one attribute is relative to many other attributes. An organization is hard to re-gain high fitness by adaptation in a short time. Besides, it is obvious that the speed of organization reduction is faster when *K* is bigger.

4.2.6 Experiment 6: Variation in Landscape (Number of local peaks)

As fitness landscape is initialized arbitrarily, its representativeness is doubtful. To test robustness, Levinthal (1997) designs experiment 6. This experiment tests fitness landscape initialization process by generating 100 heterogeneous fitness landscapes with parameter *K* ranging from 0 to 8. Figure 10 demonstrates the variance of peak number. The result shows that whatever *K* is, the deviation of peak number always remains small. It proves that the fitness landscape generation method is stable. Besides, the peak number increasing speed is gentle. This is quite interesting when compared to the great difference for different *K* configurations in adaptation process.

4.2.7 *Experiment 7: Survival in Changing Environment (Search noise =0.025)*

The research settings here are consistent with experiment 5. However, a concept of search noise is introduced. Search noise is taken to mean that one entity may identify a wrong fitness (real fitness plus an observation error) in adaptation process. Error is modeled by a uniform distribution from $-E$ to E, where $E = \Delta\epsilon$. Δ is the number of attribute that target agent is different from the original agent. ϵ is the intension of noise. Here $\epsilon = 0.025$.[3] In previous experiments, the existence of noise can also be considered. However, ϵ is set to be 0.

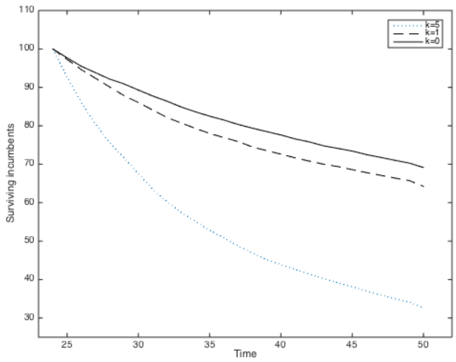


Figure 11. Survivals in changing environment (noise=0.025)

Compared to Figure 9, Figure 11 shows that even K is small; population still suffers death due to search error. However, high K settings seem to endure less impact. It makes sense. When parameter K is big, locations nearby on the fitness landscape can have great fitness difference. On that, search noise has little disturbance to the fitness identification process.

5 EXTENSIONS TO IT VALUE COCREATION CONTEXT

Applying into IT value cocreation research, firstly NK model framework needs extensions on network structure and interaction settings. These two concepts are cores of agent-based modeling (ABM). However, in original NK model design, network structure and interaction mechanisms are not mentioned. To further develop the NK model through an ABM perspective, one solution is provided as following.

5.1 Network Structure

Network structure refers to the structures by which agents are interconnected in simulation experiments. In IT value cocreation scenario, to define simulation network structure, the typology of cocreation structure must be given at first. Zhang (2014) offers a typology of relational network. Based on firm number and scenario of competition and/or cooperation relationships within one industry, five types of IT co-creation are summarized. This topology is shown in Figure 12 (reproduced from figure 3 in Zhang 2014, pp. 6).

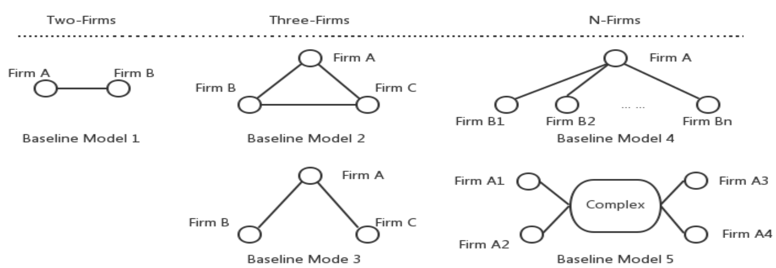


Figure 12. The typology of the IT value cocreation structures

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[3] Referring to (Levinthal 1997, pp. 947) for justification.

In future experiments, every baseline model should be studied separately. Adding network structure means agents are permitted to form groups to coevolve in competing environment. The group structure is consistent with one particular baseline model. Introduction of higher architecture definitely changes the way to calculate an agent's fitness. Engaged in a cocreation relationship, an agent's fitness depends on not only its own attribute values, but also its partners' (other agents engaged in the same relationship) attributes. In other words, attribute i's contribution is related to k_1 internal attributes (attributes of its own) and k_2 external attributes (attributes from partners). Taking firm A in baseline model 3 as an example, the fitness-influencing pattern is illustrated in Figure 13. The arrows indicate that fitness contribution of attribute *A2* in agent A depends on attribute value of itself, *A1* and *A3* in agent A ($k_1 = 2$), attribute value of *B2* in agent *B* and *C2* in agent *C* ($k_2 = 2$). As there is no relationship between agent *B* and agent *C*, when calculating attribute's contributions in agent *B* (or *C*), related external attributes are only from agent A.

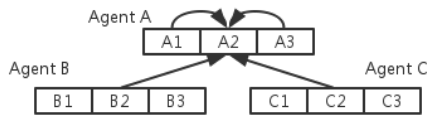

Figure 13. Contribution mechanism in network structure (baseline model 3 in Figure 12)

5.2 Interaction

Interaction refers to mutually adaptive behaviors of agents (Nan 2011). There are no interactions in original NK model. However, interactions among firms in real IT value cocreation are not rare. These interactions include co-investment and cocreating values (e.g. Rai 2012), value appropriation (Durand et al. 2008), and partner finding (Zhang 2014). Reflecting in NK model, the basis of theses interactions are heterogeneous attribute dynamics. To fit IT value cocreation context, three basic attribute dynamics are designed: attribute identification, attribute distribution, and attribute changing. Attribute identification means understanding of other agents' attributes status. This can be modeled by an identification noise, which works the same way as search noise in experiment 7. For alliances, noise is 0. For other firms, identification noise is a reflection of protection behaviors to firm resource configurations. Attribute distribution refers to the percentage of particular attributes allocated to cocreation process. Out of protecting purpose, a firm may only invest part of its resources into cocreation process. The contribution effect from external attributes on contribution thus should base on real investment of other firms. In other words, in the figure 13 example let attribute value of *B2* is *M* and attribute value of *C2* is *N*. The attribute distribution for agent *B* is $\theta_B\%$ and for agent *C* is $\theta_C\%$. In the end, actual attribute values affecting *A2*'s fitness contribution is $\theta_B\% \cdot M$ and $\theta_C\% \cdot N$. Attribute changing simply stands for changes in attribute value. Two reasons lead to attribute changing. One is adaptation behavior in original NK model. Agent is adapting to peers with higher fitness. Successful adaptations in each simulation period definitely change some attributes. The other one is "learning and stealing" behaviors in value cocreation process. A firm may change its attribute by learning even stealing knowledge or techniques in cooperation (Zhang 2014). This can be modeled by learning rate. Also using Figure 13 as an example, assume learning rate for firm A is ρ. The value of ρ varies from 0 to 1. All attributes that agent A is different from agent *B* and agent *C* take ρ probability to change to attributes of agent *B* or agent *C*.

6 CONCLUSIONS

This tutorial briefly introduces NK model framework and aligns it with agent-based modeling (ABM). At the same time, a simple extension example is given for IT value cocreation scenario. Future studies may try further developing the framework and its extensions.

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APPENDIX

Pseudo-Code of NK model experiments in chapter 4

Create 100 agents (organizations)
Ask each agent {
    If experiment is experiment 3
        Set the identical 10-array from other agents. The array is a random array with each attribute takes a value of 0 or 1 with equal probabilities.
    Else
        Set the random 10-array, with each attribute takes a value of 0 or 1 with equal probabilities.
    Set K
    Set this agent alive
}
Create fitness landscape
Run one tick of the model clock {
    If experiment is experiment 4, 5, or 7
        Ask each agent goes through natural selection
    Ask each agent if it is alive
        If so and experiment name is not experiment 4
            Do local adaptation (search noise = 0.025 if experiment is experiment 7)
        If local adaptation failed and experiment is 3, 5, or 7
            Do long jump (search noise = 0.025 if experiment is experiment 7)
    Else if this agent is dead and experiment is 4
        If average fitness is high
            Replace with a new agent, which takes an existing form from population
        Else
            Replace with a new agent, which takes a random form
        Set new agent alive
}
Repeat the “Run one tick of the model clock” procedure 50 times
Collect experiment data

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