Chapter 15
Exaptive Processes: An Agent Based Model

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15.1 Introduction

This chapter introduces an agent-based model designed to investigate the dynamics of some aspects of exaptation that have been discussed previously in this volume. It is strongly related to the model introduced in the previous chapter. Indeed, in the model described here, cognitive categories represent the main tools that the producers and users of artifacts employ in order to interpret their environment, as in the case discussed in Chapter 14. The main addition provided by the current model, however, is the explicit introduction of artifacts.

As stressed in Chapter 1, artifacts are a key component of human organizations and activities. Artifacts are entities constructed by an organization to enhance its or other organizations' functionalities functionality. One of their main properties of interest to us is their capability to convey information, although they may not be explicitly designed for this purpose. In addition, there are artifacts specifically designed to store and carry information, like e.g. books, radios, televisions, including the very special kind of artifact represented by computers, which are able to process information at a very high level of abstraction.

Since artifacts convey information, their explicit representation eases the understanding of the exaptation phenomenon, seen in this context as a shift in terms of "leading attributions." Actually, their introduction is important in order to characterize the ontology necessary to identify exaptation events. Here we focus on phenomena occurring at the micro-level (how individuals collect information about the external world, categorize it, and combine existing categories in order to create new ones) and meso-level (the exchange of information among individuals). However, we do not explicitly include the details concerning the macro-level events (the shared system of beliefs and the common physical and technological resources); which are left for further research.

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D. Lane et al. (eds.), *Complexity Perspectives in Innovation and Social Change*,
Methodos Series 7, DOI 10.1007/978-1-4020-9663-1_16,

In the first two sections, we introduce the notion of exaptation. The third and fourth sections describe the model that we developed in order to explore some aspects of exaptation and its dynamics. Finally, we discuss the results of our first simulations and identify some elements able to favor the emergence of exaptation phenomena.

15.2 Exaptation

Recently, the concept of exaptation has been introduced to explain the changes resulting from innovation processes and the rise of new technologies. Exaptation originates from the domain of biology, where it appeared in Gould and Verba (1982) who referred to species evolution as the mechanism complementary to Darwinian adaptation. The following definition (Ceruti, 1995) gives insight into the main idea of exaptation: "...the processes whereby an organ, a part, a characteristic (behavioral, morphologic, biochemical) of an organism, which was originally developed for a certain task, is employed for carrying out tasks that are completely different from the original one." The typical example provided by Gould (2002) is represented by a line of feathered dinosaurs, arboreal or runners who developed the capability to take advantage of feathers for flying, when originally they were adapted for thermoregulation.

Furthermore, exaptation can provide a key to interpret the serendipity that characterizes the generation of new products. Exaptation emphasizes that the functionalities for which a technology has been developed are only a subset of the consequences generated by its introduction. In many cases, there can be several different consequences generated by a new technology, a product, or a process and thus its exaptive potential can be very large. Hence, exaptation is to be interpreted as a central idea connecting technological progress and emergence of recurrent patterns of interaction.

Mokyr (1998) states that exaptation "refers to cases in which an entity was selected for one trait, but eventually ended up carrying out a related but different function." Such a definition captures the idea that exaptations are those characteristics of a certain technology that are recruited for a purpose different from the original one (a process that may lead in turn to a cascade of further changes). Different from *adaptations*, which present functions for which they are selected, exaptations generate effects that are not subject to pressures from the current selections, but potentially relevant later on.

A classical example of technical innovation illustrating both adaptation and exaptation is the Compact Disk (CD). The CD was originally developed in 1960 in the Pacific Northwest National Laboratory in Richland, WA and it was designed for a specific task: to solve the problem of the sound quality deterioration of the classical vinyl records. Its inventor, J.T. Russell, developed a system based on the idea of using light to carry information, avoiding the usual contact with mechanical parts of the recording device. The CD-ROM was patented in 1970 as a digital-optic system for recording and reproducing sound. Later, researchers exapted the technology of the CD-ROM for a different purpose: storage media for computer data. Although the latter represented a function not originally intended for the CD-ROM, it became clear that it was indeed effective. As a result, during the 1970's, the Laboratory refined the CD-ROM technology, selling a product that could be usefully employed for different purposes and improving some of its characteristics (increase of memory capacity, recording speed, sound quality).

Another important aspect of such a phenomenon is represented by what Gould defines as the "exaptive pool." The exaptive pool represents the potential allowed for future selection episodes (at all levels). There are two categories of potential: (i) intrinsic potential and (ii) real instantiations.

To understand intrinsic potential, let us recall that the smallest and lightest among the US coins, the dime, despite its small purchasing value, is still in use. An unforeseen consequence of its technical characteristics is that the dime can be employed as an occasional screwdriver. Hence, the dime is an adaptation if considered as money and exaptation if considered as a screwdriver. Note that the potential for the additional functionality as a screwdriver is an intrinsic characteristic of the dimensions and the shape of the coin and, thus, cannot be considered as disjoint or separated from it.

The second category of the exaptive pool includes real entities, material things that become part of the item under consideration, due to various reasons. They are not currently associated with a particular use and at the same time do not generate substantial damages, thus avoiding elimination by selection. The members of this category can be generated in various ways as structures that previously were considered useful, or as neutral characteristics introduced "incognito" with respect to the selection process.

15.3 The Origin and Peculiar Features of Exaptation

To complete a picture of exaptation as a phenomenon, we consider two questions:

1. What are the factors that give rise to exaptation?
2. What are the traits that distinguish it from other processes?

In order to answer the first question, we refer to the idea of decomposability introduced by Simon (1969) to study the architecture of complex systems. An artifact is seen as a hierarchical structure composed of subparts that are approximately independent in the short term, but connected by a global behavior in the long term. Therefore, the subparts are selected, and they proliferate as a consequence of being only one among many aspects of the whole artifact. While some such subparts can have an important role with respect to the current functionality of the whole artifact, others remain latent awaiting future activation.

Based on the above observations, we can divide the possible origins of an exaptation into three groups: (1) the case where a subpart is already providing a positive contribution to the functionality for which the technology was designed. Only in a later moment and after changing the context, the subpart becomes the main component. (2) The case where the subpart has no role in the overall performance of the system. (3) Finally, the case where the subpart provides a negative contribution to the overall performance of the system.

An example of case (1) is represented by the phonograph invented by Edison in 1877. The innovative technology for amplifying and reproducing sound suggested the commercialization of the invention as an office dictaphone. Only a dramatic change of the context led to the exaptation of the phonograph, later re-named a gramophone, and nowadays considered one of the most popular inventions made during the 19th century. Case (2) is well identifiable in the process of waste vitrification, originally developed to reduce environmental pollution (safe waste disposition and limited radioactive waste), which is now mainly for biological hazards, e.g. the elimination of biochemical weapons. Finally, case, (3) can be exemplified by the innovation in plastic production during the Second World War, based on subproducts (formerly not used) deriving from oil refineries (Dew, Sarasvathy, & Venkataraman, 2004).

Let us now address the question of which traits distinguish exaptation from other processes. An exaptation is usually identifiable with respect to a change of context, which generates a change in the utility of the technology, and not simply to a new mixture of existing elements, as for example in Schumpeter's processes (Schumpeter, 1934, 1976). One could think that an exaptation is simply an unintended consequence of technology. However, this statement ignores the fact that the act of exapting requires the intentional activation of a technology that otherwise would remain latent.

15.4 A Model of Exaptation

The idea that exaptation plays a key role in innovations is convincing and appealing, and can be supported by case studies, like those briefly mentioned in the previous sections. Yet the concept has some subtleties, and in order to explore the behavior of a system which can undergo exaptation it is interesting to take a modeling approach. Key questions to be addressed include the very possibility to develop a model that shows exaptation, the growth dynamics of artifact space generated in this way, and its possible unbounded expansion.

The aim of the EMIS system (*Exaptation Model in Innovation Studies*) is to highlight the factors that contribute to the occurrences of exaptation. EMIS is an agent-based model characterized by the presence of two kinds of social agents (A), producers and users. The agents have only partial knowledge of the world and each agent owns: (i) a set of categories (C), utilized to interpret a certain set of artifacts and (ii) a set of weights representing the importance that the agent assigns to each cognitive characteristic of an artifact (represented by means of the correspondent categories). The model postulates a continuous interaction between producers and users: the artifacts are transferred from the producers to the users and subsequent feedback messages are sent from the users to the producers. In this section, we introduce the general architecture of the model, while later we will introduce some simplifications that make the model more manageable (and which could be relaxed in future research).

15.4.1 Agents

The agents A_i ($i \in \{1, \ldots g\},\ g \in N^0$) are the model's main active units. They have limited system knowledge and are distinguishable by means of their identifier ID. Their total number g does not change in time, and they are grouped in two different classes:

- producers (represented by means of the symbol A_p, where $p \in \{1, \ldots l\}$)
- users (represented by means of the symbol A_u, where $u \in \{1, \ldots h\}$)

Thus, the total number of agents is $g = l + h$.

Each agent owns a given number of categories, which can be different for agents belonging to the two different classes. We denote the categories belonging to producers and users by C_p and C_u, respectively[1]. The number of categories belonging to a given agent is constant through time. Moreover, each agent is characterized by a weight vector (different for agents belonging to different classes, respectively W_p and W_u).

Note that in our representation, only the producers are able to build and modify the artifacts (one artifact for each category owned by the producer). Conversely, only the users can evaluate the artifacts.

15.4.2 Artifacts

The artifacts are "goods," built by producers and utilized by users. Each artifact $art^s{}_p$ is identified by an identification variable, IDs, and corresponds to only one category (each category belonging to a particular producer IDp). The artifacts $art^s{}_p$ are characterized by an extremely simple representation: they are D-dimensional vectors, whose elements (indicated by the words "characteristic", or "feature") take values in $\{0,1\}$, where 1 indicates the presence of a given characteristic (feature) and 0 its absence.

Despite this simple representation, the artifacts are suitably defined for conveying information, and can be successfully "interpreted" by users; this fact allows the system to produce interesting behaviors.

[1] A more correct notation would be $C_{k,p}$ and $C_{k,u}$, with $k \in [1, \ldots s]$, s being different for producers and users. Nevertheless, for reason of clarity, in the following we omit such an index: simply, the reader should remember that both users and producers possess more than one category (the producers owning one category for each artifact).

15.4.3 Categories

Categories are the tools the agents use in order to interpret their environment; in particular, the users have to evaluate the artifacts and the producers have to assemble them. In this context, each category is a D-dimensional vector, whose elements $C^{(j)}{}_x$ (again indicated by the words "characteristic", or "feature") are discrete random variables taking values "1" and "0", respectively with probability τ and $(1-\tau)$, $\tau \in [0, 1]$. Further, we assume that the number of relevant characteristics (that is, the characteristics corresponding to symbols "1") is only a fraction η of the total number of features. A category composed only of relevant characteristics would entail the unrealistic assumption that agents attribute relevance to every single perceptible detail.

In general, the agents use the categories with several objectives; in this work, we wish to highlight two of these:

- the agents use the categories to evaluate artifacts, or
- the agents use the categories to produce new artifacts (which could be new kinds of artifacts, or simply copies of already existing ones).

In general, the categories that the agents use in order to interpret the artifacts could be similar, but not identical, to the categories used to produce the same artifacts. This is an interesting interplay, but it is out of the scope of this work: as previously noticed, in the following we make the simplifying hypothesis that a typical agent uses different categories to interpret artifacts or to produce them. The other assumption we make is that we are dealing with two specialized class of agents, the users (who use the categories in order to evaluate the artifacts' functionality) and the producers (who use the categories in order to process the artifacts).

15.4.3.1 Artifact Evaluation Phase

The evaluation phase is a complex process that could be decomposed into the following simpler steps:

- identification of the artifact's relevant characteristics
- definition of their positive or negative impact on the artifact evaluation
- quantitative computation of their influence on the global evaluation

With the word "identification," we mean the process that individuates the features of the artifact the agent suppose interesting; these features correspond to the "1" tags on the category, and in such a way considers the category acts as a "filter."

Once the interesting features are identified, the agent has to make a first evaluation defining the features' positive or negative impact. Moreover, for each characteristic the agent could or could not use the information coming from the "context:" for example, an agent could like a sport car such as a Ferrari, regardless of its color, or it could like only a red Ferrari. In the first case it is enough that the feature "Ferrari" is present, whereas for a positive evaluation the second case needs also the "red" tag present. Another possibility is that the agent likes Ferrari cars, whatever their color, unless the color is yellow: it hates yellow Ferraris (like, for example, one of the authors): in this case, the simultaneous presence of a "1" tag in the "Ferrari" and "Yellow" fields determines a negative contribution. Eventually, for this agent, the fact that a Ferrari has no wings never enters into consideration: not all the possible features are relevant, and in such a way the only feasible "context" is determined by relevant characteristics. The process we described takes into consideration only relevant characteristics, and requires just three levels: "1" for positive contributions, "−1" for negative contributions, and "0" for contributions neither positive nor negative. In order to summarize, for each features the final process takes the shape of an input-output table, where the Boolean inputs coming from the features composing the context determine the three-level outcome (see Fig. 15.1).

In this paper, we use the term "*functional attribution*," or simply "*attribution*," referring to: "the functionality carried out by the corresponding feature of the artifact I'm evaluating – given the context I'm considering – is useful/indifferent/damaging."

This is a very complex step, and, in general, it is very hard to insert realistic details. However, a first approximation, we suppose here that the context of each feature is random (the other features involved in the evaluation are randomly chosen), and that the outcome of the evaluation is random (for each "input" combination there is a given probability that the outcome be "1", "0" or "−1"). This approach is by now a standard one and, for example, was successfully used in classical work in

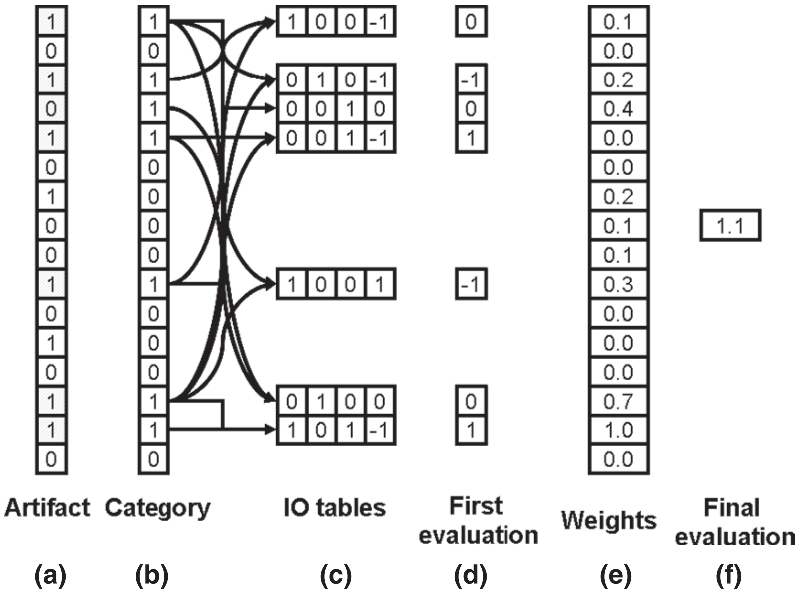

Fig. 15.1 The artifact evaluation process. The category identifies the artifact's relevant features (in colored background in -**a**-); the values of these characteristics are filtered through the category (**b**) and passed to the IO tables (**c**); the outcomes of this table constitutes the first feature evaluations (**d**); the scalar product of the outcomes of the IO tables and the weight vector (**e**) constitutes the artifact evaluation (**f**)

theoretical biology by Stuart Kauffman (1993). In this work and its descendants, a common practice is that of identifying a unique value, common to all the relationships, for the number of the inputs constituting the context. In this chapter we are following the same procedure, identifying therefore with the variable k the number of inputs of the input-output tables (IO table in the following part of this chapter).

During the last step, the agent provides a quantitative evaluation by multiplying the result of this first evaluation by a weighting factor that depends upon the particular agents' propensities. For this purpose, each agent owns a D-dimensional vector of weights, whose elements, ${W^{(i)}}_p$ and ${W^{(j)}}_u$ take values in the interval [0,1]. Each element represents the importance that the agent assigns to the corresponding cognitive feature of one of its categories. For example, we could appreciate a car for several reasons: power, style, size, price, color, maintenance costs, practicality, and so on; nevertheless, not all these characteristics have the same influence on our judgment. ${W^{(i)}}_x (x \in \{u, p\})$ represents the weight that the agent assigns to the i-th cognitive feature of the D-dimensional cognitive space (color is more important than maintenance costs, or class more than price, etc.). In the present version of the model, these vectors are built during the initialization phase at $t = 0$ and are constant in time.

To summarize this important process, in EMIS we define the "functionality of an artifact with respect to a particular category," as an index measuring the level of user satisfaction with the artifact. The index appraises the satisfaction received from the artifact, when the user evaluates the artifact by filtering it by means of the corresponding category. In order to evaluate an artifact, the agent must "interpret" it by means of its IO tables. We can define the artifact functionality (with respect to a given category) simply as the scalar product between the vector resulting from the IO tables and the agent's weight vector W_u.

15.4.3.2 Artifact Building Phase

In this section, we introduce the production of artifacts. Typically, an agent tries to build an artifact as much similar as possible to the prototype memorized in one of its categories, by processing already existing artifacts. It tries to add some desirable characteristics to the artifact, but despite its efforts it has to deal with errors and physical/technical constraints.

The artifact building phase is a process that may be decomposed in a series of steps very similar to the evaluation phase:

- identification of the artifact's relevant characteristics
- definition of their positive or negative impact on the artifact's evaluation
- artifact processing

Typically, the agent already used the category in order to build an artifact; therefore, the agent takes into consideration the same artifact in order to ameliorate it. As during the evaluation phase, the agent identifies the relevant features by means of the "1" tags of the category it uses to process the artifact, and defines their positive or negative impact by means of input-output tables. We remember that in general these latter tables are not identical to the first ones: the evaluations of a user could be different from the needs and the considerations of an artifact producer.

However, at this point, we can introduce a suitable simplification. The aim of the producer is to build an artifact useful to the users: but to do that, it does not need to reproduce exactly the details of the set of (category + IO tables) present on the users' minds. As we will see below, the users communicate to the producers the position of the features of the artifacts they like/dislike. In this case, for the producers it is enough to integrate in their categories the users' information, and subsequently to try to introduce on the artifact this same information, without further modifications. In other words, if we assume that the particular producer's desires (or idiosyncrasies) have only second-order effects, we can assume that the producer's IO tables have the simple form of an identity (only one entry, with the outcome identical to the entry value) for a desired characteristic, and of a negation (only one entry, with the outcome reverse with respect to the entry value) for an undesired characteristic.

As a last step, the producer attaches the tag "1" to the artifact in correspondence to the outcome "1" of the IO tables, and a "0" tag in correspondence to a "-1". Their relevant features, or the "0" outcomes of the IO tables, mean that in this positions the producer is not interested in changes, and that therefore the already present values will not altered (see Table 15.1).

The feature correspondence represented in Table 15.1 can be summarized as follows:

- if the values are identical, there is no change in $art^s{}_p$
- if $C^{(j)}{}_p = 1$, then $art^s{}_p = 1$
- if $C^{(j)}{}_p = 0$, then $art^s{}_p$ is unchanged
- if $C^{(j)}{}_p = -1$, then $art^s{}_p = 0$

If some additional restrictions were not imposed, this process would lead to the "perfect" artifact, where all the desired characteristics are present at the maximum level (e.g., think of a car that can fly, navigate, interact with human beings, produce and translate documents, and make excellent coffees!). In order to take into account these constraints, we decided simply to limit the number of characteristics present simultaneously in the same artifact. If, after producer processing, an artifact has a number of 1's exceeding the given threshold σ, a stochastic removal process eliminates a subset of the current characteristics.

Finally, we remark that since the final goal is to simulate exaptation phenomena, we can disregard an overly detailed description of production processes and costs.

Table 15.1 Example: artifact production/innovation

Considered vector	Features value					
Artifact – A_p	1	0	1	0	1	0
Outcome from the IO tables	1	1	0	0	-1	-1
New artifact	1	1	1	0	0	0

15.4.4 Model Dynamics

The most critical interactions for the outcome of the model take place between producers and users. Two distinct parts compose the interaction process: (i) when the user receives and evaluates an artifact built by a producer; and (ii) when the user provides feedback evaluation to the producer about the satisfaction level reached by the artifact (the artifact functionality).

First, we focus attention on the delivery and subsequent evaluation of an artifact. In order to evaluate the artifact the user: filters the artifact with respect to all its categories; computes its functionality (already described in the previous paragraphs); and finally communicates the best result to the producer. Moreover, the user can deliver to the producer some additional information, which can be useful for future artifact innovations. Specifically, the user can transmit to the producer particular subsets of the two categories that give the highest functionality values. These subset are composed of

- I_{jq} (q = 1), A*ctual Information (AI)*. Groups of features of the selected artifact that correspond to the inputs of the characteristics that contributed highly to the determination of the functionality value; at the same time, the user communicates their positive or negative contribution to the global evaluation;
- I_{jq} (q = 2), D*esired Information (DI)*. Groups of features of the selected category that potentially have the highest positive contribution power (that is, among the interesting features, the input combinations that have as outcome a "1" and that correspond to the highest values of the weights W_u).

These two different kinds of information allow the user to make explicit its requests. In particular,

- AI represents the features of the current artifact that make a positive or negative contribution to the functionality; and
- DI expresses what the agent likes or dislikes about the artifact.

Sometimes, it is possible that the two subsets have a non-empty intersection: for example, it is possible that an artifact feature (or a combination of features) is important for a category, and, at the same time, it gives a negative contribution to the functionality of another category. In such a case, we impose that either AI or DI is randomly left out in the transmission.

The producer uses the transmitted features to modify the features $C^{(i)}{}_p$ of the category employed to build the artifact. The producers have to integrate the new information coming from the users with the information already present on their categories. In order to do this action, the producer

- Copies, in its category, the feature (or the combination of features) giving a positive contribution to the functionality and sets to identity the corresponding IO tables; and

- Copies, in its category, the feature (or the combination of features) giving a negative contribution to the functionality, and sets to negation the corresponding IO tables.

The goal of the above calculation is to transform the features communicated to the producer by the user. All the remaining features are left unchanged, except some random "noise" (with a given probability, some "1" becomes "0" or some "0" becomes "1", and similarly some identity becomes a negation or some negation becomes identity). Finally, in order to limit the number of relevant features, the new vector is filtered by the removal process described in the previous section, according to the given threshold σ. The final vector represents the new category that the producer employs with the final IO tables to build the subsequent artifacts' generation.

15.4.5 EMIS and the Study of Exaptation

In the initial paragraph, we have defined exaptation as an emergent phenomenon in evolution dynamics. Where does exaptation appear in our model? Recall that EMIS simulates exchanges of products (artifacts) between producers and users, the users evaluating the artifacts by means of their tables and categories. In this context, an exaptation is a category change in interpreting the artifact. For example, after hundreds of steps the category that systematically was returning the best functionality might no longer be the best one: the last innovation(s) has (have) increased the functionality of another category, which in such a way becomes the new reference category for the selected artifact.

Recall that the producer supplies the user only with the best functionality value among all the values computed using all the categories it owns. The category that furnishes such a best value during one interaction is likely to have a large value also in the next interaction, and so forth. In a sense, the best category is, for the user, the "leading" category for this particular artifact. Sometimes, but quite rarely, another category reaches a functionality value larger than that of the leading category. In a sense, this can be interpreted as a variation of the utilization context of the artifact under consideration; in this case, we are observing an exaptation event.

15.4.5.1 The $k = 1$ Model

As we previously stated, in order to perform a first analysis of the model behaviors, we introduce some simplications. The IO tables represent a flexible but complex feature of the model, and sometime this machinery is over-dimensioned with respect to the evaluation task. A straightforward simplification is that of setting to 1 the number of entries of IO tables: in such a way, we are neglecting the complex internal relations some categories can have, in order to focus our attention on the information exchange among agents. A very interesting result is that in this context exaptation can be present.

The $k = 1$ simplification allows an easier realization of several model steps. In particular:

Table 15.2 Example of semantic distance calculation between artifact and category

Considered vector	Features value					
Artifact – A_p	1	0	1	0	1	0
Category – A_u	1	1	0	0	−1	−1
Distance	0	1	0	0	1	0

- the categories can include directly the first artifact evaluation, composed of elements $\{1, 0, -1\}$ and eliminating in such a way the IO tables
- the information provided by the user to the producer is composed only of features and not of a group of features
- in order to incorporate the users' information, the producer simply computes feature by feature the average among its values and the incoming ones
- the production of the artifact is straightforward

It is easy to find the largest functionality value F_{max} of an artifact with respect to a particular category: it is simply given by the scalar product of the weight vector and the category itself, where all the "-1"s are set to "0". Eventually, it is possible to define in an intuitive manner a semantic distance between 2 categories: in this context, the distance describes the discrepancy between the artifact and the category referred to that particular artifact. Table 15.2 is based on the two following principles:

- a distance between artifact and category occurs when the agent's "desires" a feature that is not currently present
- a distance between artifact and category occurs when the agent "does not desire" the present feature

A detailed description of this realization can be found in Villani, Bonacini, Ferrari, Serra, and Lane (2007); in the following part of this chapter we comment on the results obtained using this $k = 1$ model and compare them with its full version with $k > 1$.

15.5 Model Dynamics

15.5.1 k = 1 *Model: the Initialization*

In order to test the model, simple simulations for which we reduce the number of the actors, maintaining only one producer and one user:

$$l = 1 \quad h = 1 \quad g = 2$$

The knowledge space of the categories involved is $D = 1,000$ features. The user utilizes five categories, which guarantee sufficient diversity, while the producer owns only one category, corresponding to the artifact that it is building. The other parameters we have to fix in order to create the initial categories are:

1. the threshold η, limiting the number of $|1|$'s in $C^{(j)}{}_i$, is set to 100
2. the initial fraction of 1s in $C^{(j)}{}_i$, is set to 0.05
3. the initial fraction of -1s in $C^{(j)}{}_i$, is set to 0.05

The value of η is relatively low with respect to the D value and indicates that the space of all the possible characteristics of a category is very large with respect to the really imagined ones. Each feature of the initial artifact (at time $t = 0$) takes the value 1 with probability

$$P_{art} = \frac{\sigma}{D} \tag{15.1}$$

where σ is the threshold defining the maximum number of 1s that can be present on an artifact, and D is the total number of features composing the knowledge space. Thus, initially we have a "raw" artifact that is able to contain a large number of details. This raw artifact is processed a first time by the producer, to correctly link each artifact to its referring category. Because of the fact that $\sigma > \eta$, the artifact carries out a number of functions larger than the number of functionalities for which it has been selected (exaptive pool of possibilities).

15.5.2 A Typical Run

Figure 15.2 shows some of the main variables simulated by EMIS. Figure 15.2a shows the best functionality value of the artifact at a given time step, and its F_{max} value. Note that at step 207, the user changes the leading category (exaptation) and F_{max}. In this case, the upper limit for the achievable satisfaction decreases, despite that an increase of the actual functionality. Figure 15.2b shows the distance among user's categories and the artifact actually built by the producer.

At each step, the user analyses the producer's artifacts, which are interpreted using its own categories and furnishes to the producer the corresponding (more elevated) value of functionality. At step 207, the functionality value of category 2 outperforms the functionality value of category 4. During the rest of the simulations, category 2 maintains its superiority and we do not observe other exaptation events.

The exaptations occur mostly during the first steps of the simulations, whereas they are rarely observed during the long stabilization period (that is – by definition – after 50 steps). Actually, during the first interactions the producer can easily modify its artifacts and simultaneously increase the functionality values with respect to several different categories. However, when the artifact is highly specialized the simultaneous satisfaction of several requirements is a challenging task. Conversely, symmetric information and large bandwidth values can support best performances of the model in terms of attainment of F_{max}, allowing the producer to satisfy the user's requests.

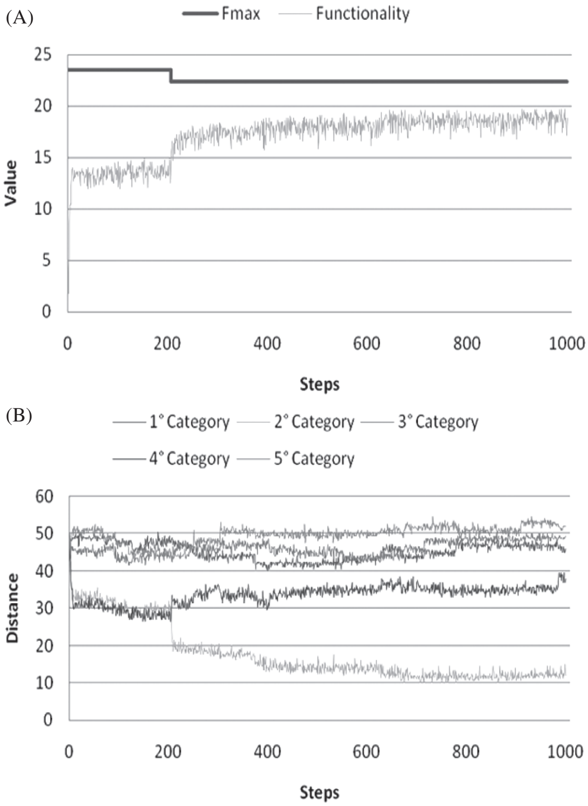

Fig. 15.2 (**A**) The best functionality value of an artifact in time, and its F_{max} value. At step 207, the user changes the referring category (exaptation); similarly the F_{max} value changes. In this case, the maximum reachable satisfaction decreases despite the actual functionality value increases. (**B**) The distance among the user categories and the artifact built by the producer

15.6 Experiments

We individuate three main factors that are able to favor the emergence of exaptation phenomena:

1. communication among different agents,
2. communication and production noise, and
3. evolution of the users' categories.

In all the situations, the user can utilize two different modalities of communication:

1. symmetrical: both communicated categories provide the same amount of information, "actual" and "desired" or
2. asymmetrical: the category that better interprets the artifact provides "actual" information, while the second one provides "desired" information

This specification has been introduced to verify whether the presence of communication of symmetry/asymmetry can favor the occurrence of exaptation phenomena. Recall that the "actual" information represents the objective user's evaluation, whereas the "desired" information expresses what the user wants. Therefore, symmetric communication means that the user treats the categories without any bias, whereas asymmetric communication means that the user transmits an objective report about its first category, and then communicates some desires corresponding to a second one.

15.6.1 Communication

Typically, the user transmits to the producer a (small) subset of the features extracted from the two categories that are returning the best functionality values. In this paragraph, we analyze the behavior of the $k = 1$ model by varying the number of transmitted features, or bandwidth (B). In particular, in this set of experiments the total number of transmitted characteristics is set to be $B = \{20,\ 40,\ 60,\ 80, 100,\ 200\}$.

The data are noisy, but we can propose two considerations:

- exaptation phenomena have a weak link with the bandwidth; nevertheless, it seems that larger values of the bandwidth correspond to more numerous late exaptation events
- the number of exaptations found by using the asymmetric modality is larger than the number of exaptation found by using the symmetric modality

These facts suggest that an unbiased communication modality is not able to favor a context change, whereas a qualitatively asymmetric communication modality could effectively support the success of categories that are not favored initially. Furthermore, to favor exaptation phenomena, it seems to be helpful to transmit a large amount of information, creating the potential for the discovery of new and previously disregarded solutions.

15.6.2 Noise

A second study concerns the analysis of two types of noise that could be specified in the model:

- *Communication noise*. The value of the features communicated by the user agents is changed with probability α, (1 or -1 from a 0 tag, 0 or -1 from a 1 tag, and 1 or 0 from a -1 tag).
- *Production noise*. The value of the characteristics of the artifact built by the producer is changed with probability β (0 from 1, and 1 from 0).

The communication noise does not affect the main behavior of the model, although its presence requires more time to reach higher functionality values. The production noise worsens such a tendency, but at the same time increases the frequency of exaptation occurrences, both in the long period and in presence of low bandwidth communications. Some innovations, obtained because of this type of error, are able to foster a change of context for the whole artifact.

15.6.3 Learning

For the $k = 1$ model, it is possible to propose a simple and interesting learning modality. Agents can modify their categories by learning from the environment: at each time step there is the probability f of selecting a category for a modification; in this case, a fraction P_{ch} of the category's features change their value (in all our trials $P_{ch} = 0.02$). The general schema of this learning is that the differences between artifact and category tend to decrease and that the category is plastic. Therefore: (a) if the artifact feature is "1", the corresponding feature of the new category becomes "1", unless the involved characteristic be "not desired" (in this case, it reduces the distance and becomes "0"); (b) if the artifact feature is "0", the corresponding feature of the new category becomes "0", unless the involved characteristic be "not desired" (in this case, it maintains the old value).

With these settings, we find that the exaptation frequency increases almost linearly with the growth of the adjournment rate f (see also Fig. 15.4a) and that the F_{max} level of satisfaction increases with the adjournment rate (Fig. 15.4b). A real example of "learned" exaptation could be that of the SMS (the Short Message Service), initially introduced to send brief official messages from the telephone company, which subsequently became a new means for social communication (especially among the young!). In this case the users succeeded in understanding the communicative potentiality of this system, overcoming limits of space by means of the creation of a particular language, more "assembled" and intuitive. As a result, the phone companies initiated a market strategy based upon this new functionality.

15.6.4 $k = 1$ First Conclusion

From these first simulations, we can conclude that some of the most important elements favoring the emergence of exaptation events are:

1. an asymmetrical communication, where evaluations and desires are differently expressed for different categories;
2. a high number of cognitive features (characteristics) communicated among the agents;
3. a high level of production noise; and
4. the plasticity of the users' categories.

15.6.5 Higher k

Now we can insert in the system the relationships among the different features belonging to the same category, following the same stages as in the previous analysis.

The only exception concerns the learning experiments, because the presence of the feature contexts deepens the problem and increases considerably the cognitive dimensions involved; these aspects will be analyzed in future work.

We performed simulations with $k = 2$, $k = 3$, and $k = 4$, generally similar to the ones depicted in Figs. 15.2 and 15.3. During this first session of trials, we assumed a uniform distribution of "1", "-1" and "0" inside the IO tables of the users' categories; of course, in the near future, we are planning a huge simulation campaign in order to deepen the first conclusions presented in this chapter. The performed simulations confirm that the exaptation phenomena have a weak link with the bandwidth, and do not reveal important differences between symmetric and asymmetric modalities.

The influence of noise is similar in both systems, that is, the communication noise has no effects whereas the growth of the production noise increases the exaptation occurrences (Fig. 15.5a); Fig. 15.5b confirms that the differences between the symmetric and asymmetric modalities are not so great. Figure 15.5c shows that as production noise increases, this also augments in a significant manner the long term exaptations (the exaptations that happen after the threshold of 50 steps); this phenomenon is not so evident in the case of the $k = 1$ model. Last, but not least, the increase of the number of inputs of the IO tables does not have significant consequences (Fig. 15.5d).

To summarize the previous paragraphs, as we supposed, the simple case of $k = 1$ is able to capture the main exaptation phenomenon traits, and it could be used profitably to scout for new behaviors, which can be confirmed successively by the

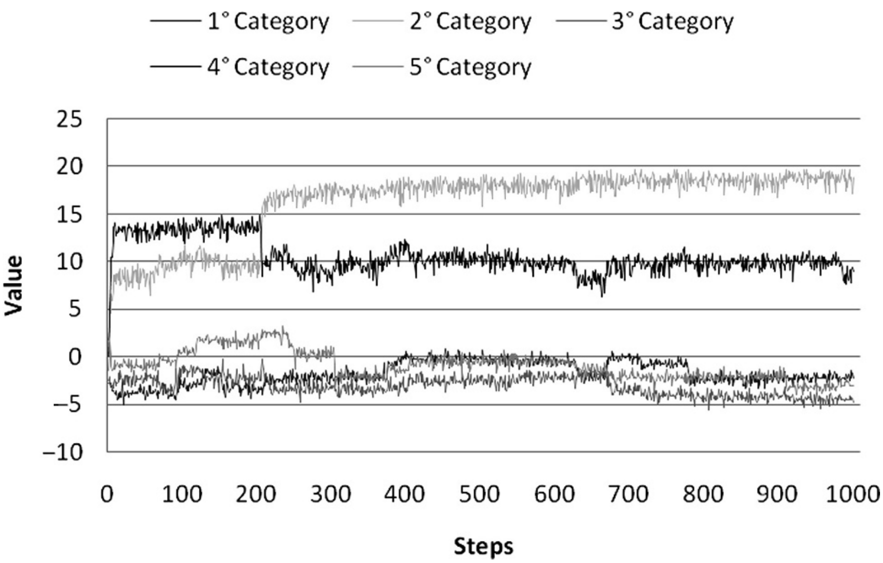

Fig. 15.3 The figure shows the evaluation of the artifact received from the agent's categories, during the same simulation of Fig. 15.2. Please note that, at step 207, the second category suddenly increases its value and becomes the referring category

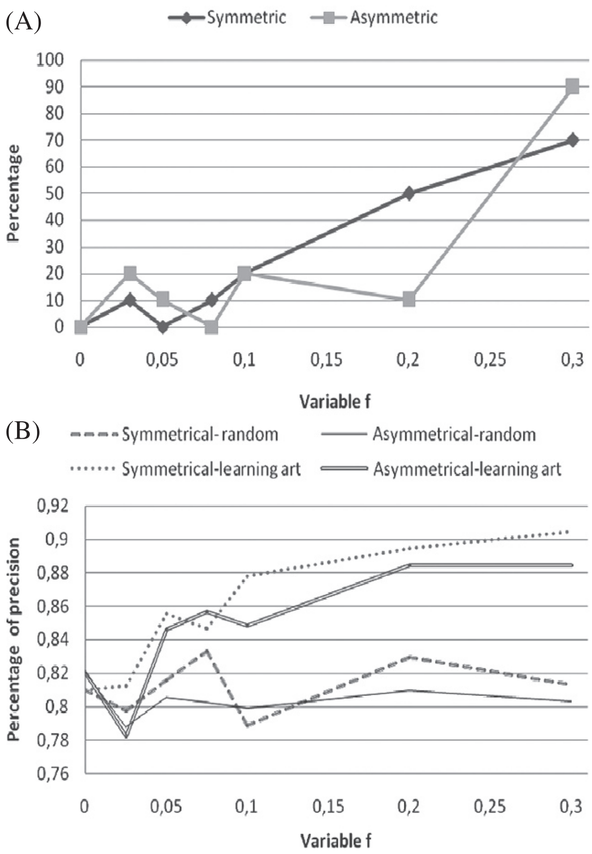

Fig. 15.4 (**A**) Learning modality: the percentage of simulations (over 10 runs) with at least one exaptation, by varying the adjournment rate f. (**B**) The fraction of F_{max} reached by the artifact functionality, by varying the adjournment rate f for both random and learning modality

general model with $k > 1$. The presence of IO tables allows a higher probability of exaptation occurrences in long term sequences, and we have some indications that it is enough to use a limited context in order to have complex situations.

15.7 Conclusion

In this chapter, we have introduced an agent-based model designed to investigate the dynamics of some aspects of exaptation in a world populated by agents, whose activity is organized around production and utilization of artifacts. The model, EMIS (*Exaptation Model in Innovation Studies*), not only explicitly includes agents and artifacts, but also encompasses the agents' subjective representation of the artifacts by means of cognitive categories. In our model, the agents build (as producers) and interpret (as users) the artifacts using cognitive categories.

One of the main features of EMIS is the description of the information exchange dynamics among agents. Two main processes characterize these dynamics: (i) interpretation and storage of information by each agent, and (ii) circulation of

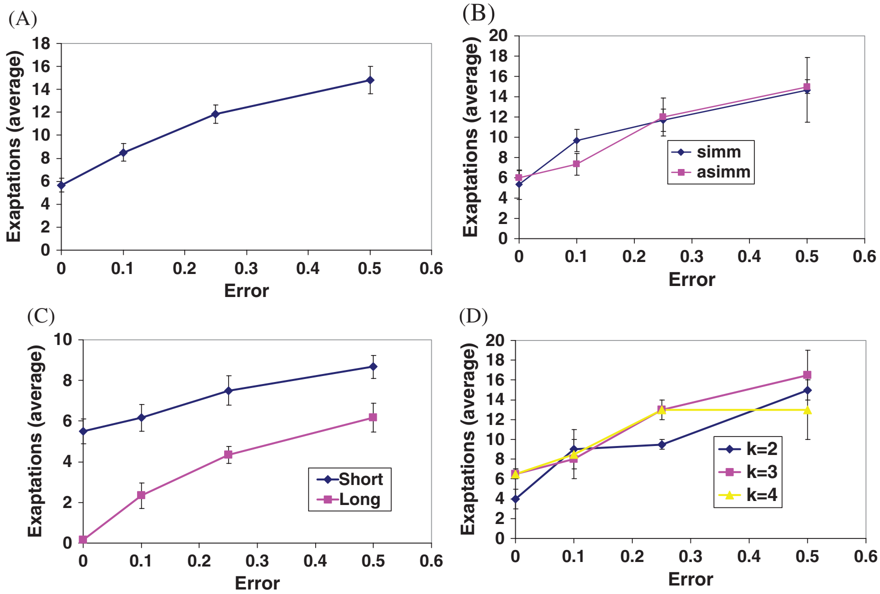

Fig. 15.5 The effect of production noise. (**A**) The average of exaptation occurrences as function of the production error; (**B**) the average of exaptation occurrences for symmetrical and asymmetrical communication modalities; (**C**) the average of exaptation occurrences in short and long runs; (**D**) the average of exaptation occurrences for systems with different k values

information through the exchange of artifacts. The first process takes place in the cognitive domain of each agent. In particular, at any given time, each agent owns a cognitive representation of a number of real objects (artifacts) in terms of a set of cognitive features (categories). The second process involves the communication among agents of a fraction of the information stored in categories. As a last step, the producers employ their sets of cognitive categories to make artifacts that are in turn submitted to the users. The users evaluate the functionality of such artifacts by means of their cognitive categories and next send signals to producers about their "satisfaction" with such artifacts.

The agents in the model are able to attribute "functionalities" to the artifacts in terms of categories and IO tables; a given attribution can generate a certain reward associated with the artifact of reference. Thus, the type of representation proposed is suitable to take into account exaptation events, which are understood as shifts in terms of the "leading attributions" (attributions corresponding to highest reward) that the agents assign to the artifacts.

The model has been implemented in a computer environment. The main goal of the computer simulations is to determine which factors play a central role in the information exchange processes, with particular attention to the study of exaptation. From our first simulations, we can conclude that some of the most important elements favoring the emergence of exaptation events are

1. a high level of production noise and
2. the plasticity of the users' categories.

There are also indications that an asymmetrical communication (where evaluations and desires are differently expressed for different categories, and a high number of cognitive features, or characteristics, are communicated among the agents) could be helpful to increase the exaptation occurrences.

While the present version represents a highly simplified model, the results obtained so far appear to encourage the further development of EMIS. Future research improvements to the model should be aimed at expanding the exploration of the synergistic effects among the different features belonging to the same category, and simulating more complex interactions among categories and artifacts.

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