

## Coevolution of learning and niche construction

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### Abstract

Roles of ecological processes in evolution are attracting much attention in evolutionary studies. Especially, learning and niche construction are regarded as ecological processes that can affect the course of evolution directly or indirectly. However, the effects of mutual interactions between them on evolution are still poorly understood. Our purpose is to give a valuable insight into the coevolutionary dynamics of learning and niche construction. As a first approach, we constructed a simple individual-based model in which individuals can perform both a niche construction of their shared environmental factor and an acquisition of the adaptive phenotype through their lifetime learning. We report that a cyclic coevolution of genes for learning and niche construction occurred in preliminary experiments.

**Keywords:** learning, niche construction, coevolution, Baldwin effect, artificial life.

### 1 Introduction

In the standard view of the modern evolutionary synthesis, organisms are basically regarded as passively evolving entities based on selection and mutations. However, they can modify the selection pressure on themselves through their two different ecological activities. One is to change their own phenotype called learning, and the other is to change their environmental condition called niche construction[1]. Recently, roles of these ecological processes in evolution are attracting much attention in evolutionary studies called Evo-devo [2] or Eco-devo[3].

A wide variety of species have abilities to modify their own traits to make themselves more adaptive in their existing environments. It has been controversial how this ecological process called individual learning or ontogenetic adaptation based on phenotypic plasticity can affect evolution indirectly. Since Hinton and Nowlan's pioneering work [4], ALife researchers have focused on the Baldwin effect [5, 6], which is typically interpreted as a two-step evolution of the genetic acquisition of a learned trait without the Lamarckian mechanism [7]. An important finding is that the balances between the benefit and

cost of learning can modify the shape of the fitness landscape, and can either accelerate or decelerate the adaptive evolution [8]. The recent studies also discussed effects of the ruggedness of the fitness landscape [9]. It was clarified that if the shape of the fitness landscape is rugged, the drastic changes in roles of learning bring about the complex three-step evolution through the Baldwin effect.

On the other hand, a niche construction is another ecological process, performed by organisms, that modify their own or the others' niches (selection pressures) through their ecological activities by changing their external environments[1]. The niche-constructing processes are observed in various taxonomic groups such as bacteria (decomposition of vegetative and animal matter), plants (production of oxygen), non-human animals (nest building) and humans (cultural process).

Recently, conditions for niche-constructing traits to evolve have been analyzed using theoretical or constructive approaches, which have discussed the maintenance of polymorphism [10], the co-evolutionary dynamics of multiple species induced by their niche constructions [11], and the effects of the spatial locality of niche constructions [12, 13], and so on.

So far, the effects of individual learning and niche construction on evolution have been mainly analyzed separately as described above, because these have independent intellectual origins and also could be interpreted as different processes in that the former is a change in the phenotype of the learning individual itself and the latter is the change in the surrounding environment of the niche-constructing individual[14]. However, it is clear that both processes can interact indirectly with each other through the changes in the relationship between the environmental conditions and individual phenotypes, which implies that both processes can co-evolve in complex ways. That is, a niche construction can change an environmental factor, which can modify the selection pressures on individuals that share the modified environment. Such an environmental change can further affect their learning process. A gene-culture coevolution or a language evolution seem such situations in which their mutual interactions were implicitly incorporated (discussed later). However, as far as we

know, there are still few constructive approaches that focused on interactions between learning and niche construction in the above sense explicitly.

Our purpose is to give a valuable insight into the coevolutionary dynamics of learning and niche construction. As a first approach, we constructed a simple individual-based model in which the individuals can perform both a niche construction of their shared environmental factor and an acquisition of the adaptive phenotype through their lifetime learning. We report that a cyclic coevolution of genes for niche construction and learning occurred in preliminary experiments.

## 2 Model

### 2.1 Environment and genetic description of individuals

In our model, an environmental state shared by all  $N$  individuals is represented as a single real value  $e$  ( $\in [0, 1]$ ). Each agent has a real-valued phenotype  $p$  ( $\in [0, 1]$ ) whose initial value is determined by its genotype  $g_p$  ( $\in [0, 1]$ ). The fitness contribution of  $p$  depends on  $e$ , and is determined by the following hut shaped function  $f(p, e)$ :

$$f(p, e) = \begin{cases} 1 - |p - e|/L & \text{if } |p - e| \leq L, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Fig. 1 shows an example situation of the model. This function has a peak value 1 at  $e$ . Its value linearly decreases from the peak, and reaches 0 when the distance between  $p$  and  $e$  becomes  $L$ . Thus, the closer each agent's  $p$  is to  $e$ , the more adaptive it is.

### 2.2 Learning and niche construction

Each agent also has real-valued genes for learning  $g_l$  ( $\in [0, 1]$ ) and niche construction  $g_n$  ( $\in [-1, 1]$ ).

A learning process of each individual moves its phenotypic value  $p$  closer to  $e$  by (at most)  $g_l$  so as to increase its fitness contribution. The actual phenotypic value of an agent after its learning process  $p'$  is calculated from the equations as follows:

$$p' = \begin{cases} e & \text{if } |e - p| < g_l, \\ p - \text{sgn}(p - e) g_l & \text{otherwise.} \end{cases} \quad (2)$$

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 0, \\ 0 & \text{if } x = 0, \\ -1 & \text{if } x < 0. \end{cases} \quad (3)$$

This means that if the distance between the phenotype  $p$  of the focal individual and the environmental value  $e$  is smaller than its  $g_l$ , it can make its own  $p$  the same value as  $e$  completely. Otherwise, it can move its own  $p$  closer to  $e$  by  $g_l$ .

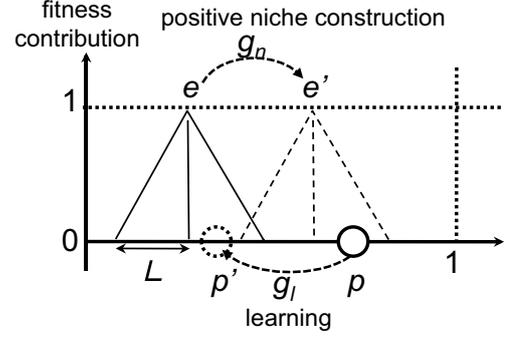


Figure 1: A learning and a niche construction in the proposed model.

Also, each individual can perform either positive or negative niche construction, which means that a niche construction can increase or decrease the fitness of the performing individual. If  $g_n$  of an individual is positive (or 0), its niche construction is positive and the actual environmental value  $e'$  after its niche-constructing process is calculated from the equation as follows:

$$e' = \begin{cases} p & \text{if } |e - p| < g_n, \\ e - \text{sgn}(e - p) g_n & \text{otherwise.} \end{cases} \quad (4)$$

On the other hand, if its  $g_n$  is negative, its niche construction is negative, and  $e'$  is calculated as follows:

$$e_{temp} = e - \text{sgn}(e - p) g_n, \quad (5)$$

$$e' = \begin{cases} 0 & \text{if } e_{temp} < 0, \\ e_{temp} & \text{if } 0 \leq e_{temp} \leq 1, \\ 1 & \text{if } e_{temp} > 1. \end{cases} \quad (6)$$

When  $g_n$  is positive, a niche construction moves  $e$  to closer to its  $p$  (at most) by  $g_n$ . That is, a positive niche-constructing process is basically similar to a learning process except that it shifts the environmental value  $e$  rather than its own phenotype  $p$ . On the other hand, if  $g_n$  is negative, it makes  $e$  more distant from its  $p$  by  $|g_n|$  within the range of the domain of  $e \in [0, 1]$ . Note that if  $g_n$  is negative and  $p$  is exactly the same as  $e$ , we randomly add  $g_n$  or  $-g_n$  to  $e$ .

### 2.3 Ecological interactions and evolution

In each generation, there are  $T$  sets of ecological interactions among individuals. Each set is composed of  $N$  steps, each in which an individual who have not done its ecological process yet is randomly selected and it randomly performs either a learning or a niche-constructing process. The fitness of each individual is defined as the average fitness contribution of its phenotype  $p$  measured over all steps, and

the evolutionary process is based on a “roulette wheel selection” according to the fitness. For each gene, a mutation occurs with a small probability  $p_m$ , which randomly determines its genotypic value.

In addition, we adopted a situation called ecological inheritance, which means that an environmental state can be succeeded to the next generation. Actually, we determined the initial value of  $e$  in each generation as its value at the last step in the previous generation.

### 3 Preliminary results

#### 4 Cyclic coevolution of learning and niche construction

We conducted evolutionary experiments for 2000 generations using the following parameters:  $N=250$ ,  $T=300$ ,  $L=0.1$ ,  $p_m=0.05$ . In the initial population, the values of genotypes  $g_p$ ,  $g_l$  and  $g_n$  were randomly decided within their domains, and the environmental state  $e$  was set to the intermediate value 0.5.

So as to clarify a possible dynamics of interactions between learning and niche-constructing processes, we focus on the evolutionary trajectory of  $g_l$  and  $g_n$  shown in Fig. 2. The horizontal axis is the average  $g_n$  and the vertical axis is the average  $g_l$  among all individuals at each generation respectively. Although there were a large amount of fluctuations, we can see cyclic evolutionary processes of both indices, and there were typical four states from (i) to (iv) in a clockwise cycle. This means that the evolutionary trend of learning behaviors is strongly affected by existing niche-constructing behaviors and vice versa. Note that this evolutionary scenario was observed and continued throughout experiments when  $N$  and  $T$  were sufficiently large and  $L$  was sufficiently small.

The detailed analyses, shown later, clarified that the transitions between these typical states could be briefly summarized as follows: (i) - (ii) the nearly neutral evolution of niche-constructing behavior, which brings about large fluctuations of the environmental state, (ii) - (iii) the adaptive evolution of learning behavior in dynamically changing environment, (iii) - (iv) the adaptive evolution of positively niche-constructing behavior, which makes the environment stable, and (iv) - (i) the adaptive evolution of non-learnable individuals due to the implicit cost of learning in the stable environment. This implies that the change in the stability of the environmental state arising from positive and negative niche constructions dynamically changes the balances between benefit and cost of learning behaviors. Because effects of the environmental changes on evolution, and the benefit and cost of learning are focused on in the context of niche construction and the Baldwin effect respectively, we believe that this scenario reflect, at

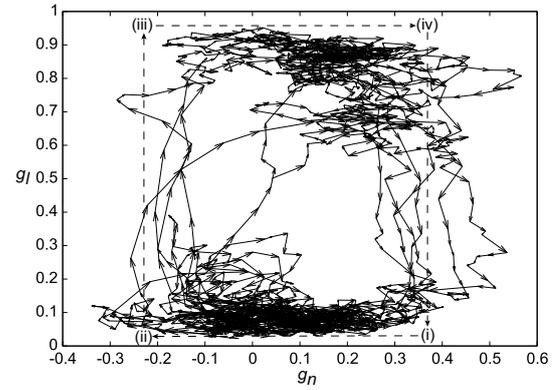


Figure 2: An example evolution of the average  $g_l$  and  $g_n$  through 2000 generations.

least in part, an essential relationship between these ecological behaviors. Thus, we explain the causal relationship that brought about this scenario in detail.

#### 4.1 The detailed analyses of evolutionary dynamics

Fig. 3 shows the evolution of the average and standard deviation of  $g_n$ ,  $g_l$ ,  $g_p$  and  $e$  through initial 1000 generations in the same experiment as that shown in Fig. 2. As for  $g_n$ ,  $g_l$  and  $g_p$ , each value is derived from the values of all individuals in each generation. As for  $e$ , each value is derived from the values in all steps in each generation. Note that the standard deviation represents spacial variation and temporal variation in the former and the latter, respectively.

Let us start from a situation around the state (i) at around the 500th generation in Fig. 2 in which positively niche-constructing but non-learnable individuals dominated the population. As shown in Fig. 3, the standard deviation of  $g_p$  was relatively small (less than 0.2), which means that the most individuals had basically the similar and intermediate phenotypic value  $g_p$ . In this situation, there was basically almost no selection pressure on the niche-constructing gene  $g_n$  because it can increase or decrease the fitness contribution of all individuals' phenotypes equally. Thus, the average  $g_n$  tended to fluctuate between the state (i) and (ii) due to the effect of random drift.

When the average  $g_n$  became negative as in the state (ii) at around the 600th generation, the environmental state  $e$  began to fluctuate by taking either extreme value 0.0 or 1.0 and its standard deviation increased to higher values (around 0.4). Note that collective behaviors with positive and negative niche construction tend to make the environment state stable and unstable, respectively. In this case, the learnable individuals became adaptive because they can catch up with such environmental changes through

their learning processes. Thus, the average  $g_l$  increased quickly, and the population reached to the state (iii) at around the 650th generation.

If individuals had the enough amount of learning ability, the learning process drastically reduced the selection pressure on the initial phenotypic values  $g_p$  and brought about their variations. This effect of learning on evolution is sometimes called hiding effect [15]. Instead, the positively niche-constructing individuals slowly occupied the population because they can keep the environmental values close to their own phenotypes dynamically changed by learning. Thus, the population reached the state (iv) at around the 840th generation.

Finally, when the number of such individuals increased enough, the standard deviation of the environmental value began to decrease and the environmental value come to fluctuate around the intermediate values (around 0.5). In such a relatively stable environment, the average  $g_l$  began to decrease. In this situation, the small fluctuation in the environmental value is still maintained. Thus, the learning sometimes makes the individual's phenotype largely deviate from the standard and intermediate environmental value, if the current environmental value is distant from the standard one. Such an implicit cost of learning is expected to have caused the gradual decrease in  $g_l$ , which also have made the initial phenotypes  $g_p$  tend to converge to the same value of the stable environmental state by unmasking the selection pressure on the initial phenotypic values. As a result, the population got back to the state (i).

## 5 Conclusion

We have discussed the universal nature of coevolution of learning and niche construction by using a simple evolutionary model of learning and niche-constructing genes. We found that a cyclic coevolution of genes for learning and niche construction occurred, and the changes in the stability of the environmental state arising from positive and negative niche constructions is a key factor that dynamically determines the benefit and cost of learning behaviors.

One of the controversial topics that closely relates to this discussion will be interactions between evolution and learning in the context of language evolution in that the fitness of each individual is determined by its linguistic niche composed of the other individuals' linguistic abilities based on learning. Yamauchi showed that the accumulated linguistic information through an ecological inheritance masks the selection pressure on the innate linguistic traits acquired through the Baldwin effect [16]. Suzuki and Arita also showed that the Baldwin effect can occur repeatedly on dynamically changing fitness landscapes (linguistic niches) which arise from communicative

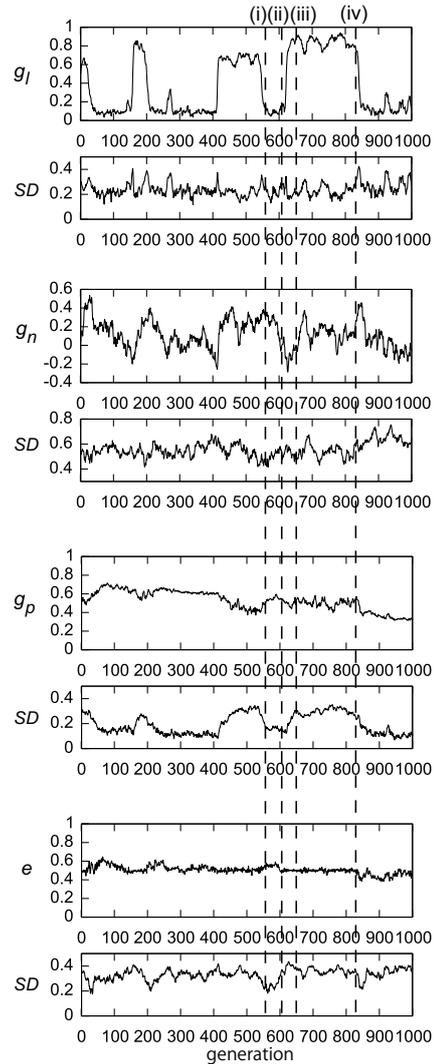


Figure 3: The evolution of the average and standard deviation of  $g_l$ ,  $g_n$ ,  $g_p$  and  $e$  through the initial 1000 generations.

interactions among individuals, and facilitate the genetic evolution as a whole [17].

If we regard the x axis in Fig. 1 as a space of possible language and each agent has a specific language determined by its  $p$ , the value of the environmental state  $e$  can be regarded as the most adaptive language due to the accumulation of its linguistic resources which can contribute to its fitness increase, for example. In this case, a learning behavior corresponds to the process in which each agent changes its own language to more adaptive one in its current linguistic environment, and a positive / negative niche construction corresponds to making its own language more / less adaptive by producing linguistic resources. Our results imply that the intrinsic dynamics of coevolution of the abilities of learning language and constructing linguistic niche can bring about the dynamic and diverse aspects of

language evolution without any external effects on environments.

## References

- [1] Odling-Smee, F. J., Laland, K. N. and Feldman, M. W., *Niche Construction -The Neglected Process in Evolution-*, Princeton University Press (2003).
- [2] West-Eberhard, M. J.: *Developmental Plasticity and Evolution*, Oxford University Press (2003).
- [3] Gilbert, S. F. and Epel, D.: *Ecological Developmental Biology: Integrating Epigenetics, Medicine, and Evolution*, Sinauer Associates (2009).
- [4] Hinton, G. E. and Nowlan, S. J.: How learning can guide evolution, *Complex Systems*, 1: 495–502 (1987).
- [5] Baldwin, J. M.: A new factor in evolution, *American Naturalist*, 30: 441–451 (1896).
- [6] Weber, B. H. and Depew, D. J. (Eds.): *Evolution and learning -The Baldwin effect reconsidered -*, MIT Press (2003).
- [7] Turney, P., Whitley, D. and Anderson, R. W.: Evolution, learning, and instinct: 100 years of the Baldwin effect, *Evolutionary Computation*, 4(3): 4–8 (1996).
- [8] Paenke, I., Kawecki, T. J. and Sendhoff, B.: The influence of learning on evolution: A mathematical framework, *Artificial Life*, 15(2): 228–245 (2009).
- [9] Suzuki, R. and Arita, T.: The dynamic changes in roles of learning through the Baldwin effect, *Artificial Life*, 13(1): 31–43 (2007).
- [10] Laland, K. N., Odling-Smee, F. J. and Feldman, M. W., Evolutionary consequences of niche construction: A theoretical investigation using two-locus theory, *Journal of Evolutionary Biology*, 9: 293–316 (1996).
- [11] Suzuki, R. and Arita, T.: How niche construction can guide coevolution, *LNAI 3630 (Proceedings of the Eighth European Conference on Artificial Life (ECAL2005))*, pp. 373–382 (2005).
- [12] Suzuki, R. and Arita, T.: How spatial locality affects the evolution of niche construction, *Proceedings of Artificial Life X*, pp. 452–458 (2006).
- [13] Silver, M. and Di Paolo, E.: Spatial effects favour the evolution of niche construction, *Theoretical Population Biology*, 70: 387–400 (2006).
- [14] Laland, K. N., Odling-Smee, J. N. and Gilbert, S. F.: EvoDevo and niche construction: building bridges, *Journal of Experimental Zoology Part B: Molecular and Developmental Evolution*, 310B(7): 549–566 (2008).
- [15] Mayley, G.: Guiding or hiding: explorations into the effects of learning on the rate of evolution, *Proceedings of the Fourth European Conference on Artificial Life*, pp. 135–144 (1997).
- [16] Yamauchi, H.: How does niche construction reverse the Baldwin effect?, *Proceedings of the Ninth European Conference on Artificial Life*, pp. 315–324 (2007).
- [17] Suzuki, R. and Arita, T.: How learning can guide evolution of communication, *Proceedings of Artificial Life XI*, pp. 608–615 (2008).