Decelerating the rate of evolution with constant learning

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Abstract: Evolution and learning are two main processes that are considered in the case of artificial intelligence and artificial life systems. These two processes can interact with each other, which is called the Baldwin effect. Especially, the introduction of learning process into an evolutionary system can cause acceleration or deceleration of the rate of evolution both in the case of artificial and natural evolutionary systems. However, there is still a lack of a solid mathematical theory that could thoroughly explain the phenomena concerned with the impact of learning on the rate of evolution. In the case of constant learning, that is a process during which individuals are moved a constant value toward the optimum, it was proved that if the second derivative of the logarithm of the fitness function is negative, the rate of the evolution should be slowed down as a result of the introduction of constant learning. In the paper we assume an evolutionary system with the asymptotic fitness function for which the theory states that the introduction of constant learning should lead to deceleration of the rate of evolution. The results of numerous computer simulations confirmed the theory and demonstrated that the deceleration of the rate of the evolution is significant. Moreover, the impact of the intensity of mutation on the degree of deceleration of the rate of evolution could also be observed.

Keywords: evolutionary systems, learning process, constant learning, the Baldwin effect

1. Introduction

The rate of evolution can be accelerated or decelerated as the effect of the introduction of a learning process [3]. For the first time this phenomenon was observed long ago in biological sciences. Now, this phenomenon is referred to as the Baldwin effect [2]. The related work [6] presents the results of experiments conducted on the population of fruit flies (*Drosophila melanogaster*) during which a significant deceleration of the rate of evolution could be observed as the result of learning [10].

The impact of learning on the rate of evolution can also be observed in the case of artificial evolutionary systems [1, 5, 8]. In the literature there are numerous examples of the systems in the case of which the rate of evolution was accelerated after the introduction of learning [4]. There is also evidence of counterexamples of the applications of the artificial evolutionary systems in the case of which the rate of evolution was decelerated by learning [9].

Up till now there is no general theory that could explain these phenomena even in a qualitative manner, i.e. to state under what conditions the rate of evolution would be accelerated or decelerated by learning. Some results were obtained for the case of the class of positive and monotonic fitness functions. The related work [7] presents the proof of the mathematical theorem according to which the fact that evolution is accelerated or decelerated by learning depends on the case of constant learning only on the sign of the second derivative of the logarithm of the fitness function.

The article is organized as follows: Section 1 is the introduction. In Section 2 the principles of constant learning are explained and the framework for numerical experiments is outlined. In Section 3 the results of computer simulation are presented, which demonstrate that constant learning really decelerates the rate of the evolution to a significant extent. Finally, Section 4 concludes the paper.

2. The impact of constant learning on evolution

Constant learning is a process during which individuals are moved in each step a constant value ($\delta > 0$) toward the global optimum. According to the related work [7], the rate of the evolution is accelerated by constant learning if the sign of the second derivative of the logarithm of the fitness function is positive

$$\left(\ln\left(f(x)\right)\right)'' > 0 . \tag{1}$$

On the contrary, if the sign of the second derivative of the logarithm of the fitness function is negative

$$\left(\ln\left(f(x)\right)\right)'' < 0 \tag{2}$$

then the introduction of constant learning to the evolutionary system will cause deceleration of the rate of evolution. On the other hand, if the second derivative of the logarithm of the fitness function is equal to zero

$$\left(\ln\left(f(x)\right)\right)'' = 0 \tag{3}$$

learning has no impact on the rate of evolution.

An example of the fitness function for which the condition (3) is fulfilled is the fitness function given by the following formula

$$f(x) = e^{x} \tag{4}$$

Indeed, the logarithm of the fitness function given by (4) is equal to x and thus its second derivative is equal to zero, which implicates that the process of constant learning should have no impact on the rate of evolution. Evolution could be accelerated only in the case of the fitness function which grows faster than the exponential function (4). For example, in the case of the fitness function given by the following formula

$$f(x) = e^{x^2} \tag{4}$$

the second derivative of the logarithm of the fitness function equals to 2, so the rate of evolution should be accelerated by constant learning.

For any asymptotic function, which naturally grows slower than the exponential function, the sign of the second derivative of the logarithm of the fitness function is negative, so according to the theory presented in the literature [7] the introduction of constant learning to the evolutionary system should lead to the deceleration of the rate of evolution.

Now, let us consider an evolutionary system with the fitness function given by the following formula

$$f(x) = 1 - \sin\left(\frac{1}{x}\right) \tag{5}$$

The fitness function given by (5) is a monotonic function for any $x \in (2/\Pi, \infty)$, which asymptotically approaches 1 for x going to infinity. The second derivative of the logarithm of the fitness function (5) is given by the following formula

$$\left(\ln\left(f(x)\right)\right)'' = \frac{\sin\left(\frac{1}{x}\right)\ln\left(1-\sin\left(\frac{1}{x}\right)\right) - \cos\left(\frac{1}{x}\right)\left(2x\ln\left(1-\sin\left(\frac{1}{x}\right)\right) + \frac{\cos\left(\frac{1}{x}\right)}{\ln\left(1-\sin\left(\frac{1}{x}\right)\right)}\right)}{\left(x^2\ln\left(1-\sin\left(\frac{1}{x}\right)\right)\right)^2} \tag{6}$$

It can be demonstrated that the second derivative of the logarithm of the fitness function is negative for any $x \in (2/\Pi, \infty)$, which implies that for such a fitness function the introduction of constant learning should lead to deceleration of the rate of evolution.

In order to confirm the theoretical result presented above and to assess the strength of the impact of constant learning on the rate of evolution, some series of numerical experiments were conducted.

We assumed a population consisting of 100 individuals. The genetic material of each individual was composed of only one real number x. The population was initialized in the vicinity of the point $x_0 = 1$, in such a manner that $x \in (0.9, 1.1)$. The step of constant learning was set at $\delta = 0.25$. Moreover, some of the individuals underwent the operation of mutation, which was realised by the addition of a real number from the interval (–0.01, 0.01) to the value coded in the individual's genetic material. The operation of selection was performed as a tournament selection during which the individuals were grouped into pairs and only this individual that had a greater value of its fitness function passed from each pair to the next generation.

3. The results of numerical experiments

For the sake of computer simulations, a uniform population of 100 individuals was assumed. Moreover, the size of the population was the same during all the generations of the evolutionary algorithm. The main goal of the numerical experiments was to determine the impact of constant learning on the rate of evolution. According to the theory, the rate of evolution should be decelerated, however, the mathematical theory presented in the work [7] specifies nothing about the degree of this deceleration. We do not even know whether the effect of deceleration of the rate of evolution is significant and thus whether it can be observed at all.

We conducted five series of numerical experiments during which a different number of individuals in each generation underwent the process of constant learning. The results of numerical simulations are presented by plots, which can be seen in fig. 1–5. In each instance of a numerical simulation 100 000 generations of the evolutionary algorithm were performed. Moreover, each fig. 1–5 presents six different plots that were obtained for the case of the evolutionary algorithm without learning (no learning) and respectively for five different values of intensity of the constant learning process, which are numbered in fig. 1–5 as (10), (20), (30), (40), and (50).

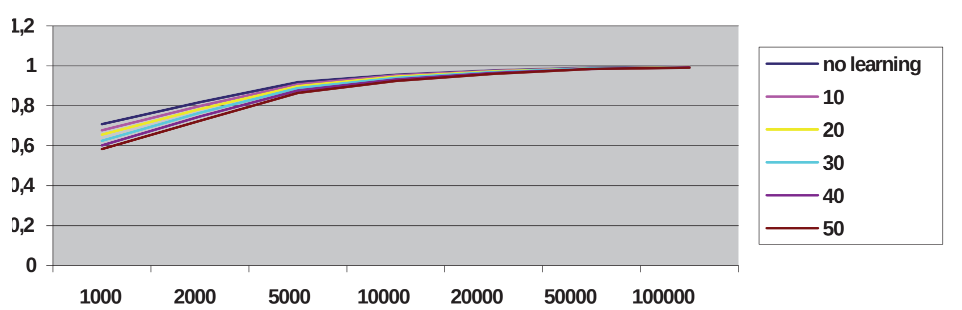

Fig. 1. The plots illustrate the effect of decelerating the rate of evolution for different numbers of the individuals that underwent the process of learning (mutation intensity was set at 10 % of the population)

Rys. 1 Wykresy ilustrujące efekt spowolnienia tempa ewolucji dla różnej liczby osobników, które podlegały procesowi uczenia (mutacji podlegało 10 % populacji osobników)

The simulations were run for the case in which 10 individuals in each generation underwent the process of constant learning, and further 20, 30, 40, and 50 individuals respectively underwent constant learning.

Moreover, during the computer simulations we examined the impact of mutation intensity on the behaviour of the evolving population. In fig. 1 we present the results of numerical simulations which were obtained for the case in which 10 % of the population was mutated.

Further, in fig. 2 we present the results of numerical simulations which were obtained for the case in which 20 % of the population was mutated.

The results of numerical simulations for the mutation intensity such that 30 % of the population was mutated are presented in fig. 3.

In fig. 4 we present the results of numerical experiments for the case of mutation intensity such that 40 % of the population was mutated.

Finally, in fig. 5 we present the results of numerical experiments for the mutation intensity such that 50 % of the population was mutated.

4. Conclusions

The results of numerical simulations which were presented in the form of plots in fig. 1–5 confirmed very well the previous theoretical results. The final conclusion is that the introduction of constant learning into the evolutionary system slows down the rate of evolution. The deceleration of the rate of evolution is especially visible for lower numbers of generations (below 5000) of the evolutionary algorithm. For higher numbers of generations the plots obtained for the cases of the evolutionary algorithm with and without constant learning are almost the same.

Moreover, a certain regularity can be observed concerning the impact of the number of individuals which undergo the process of constant learning on the degree of deceleration of the rate of evolution. If the number of individuals which undergo the constant learning is greater, the impact on the rate of evolution is more visible. Especially, it is even more visible for the lower values of intensity of mutation.

Concerning the impact of intensity of mutation on the behaviour of the population of the evolutionary system, we can state that the greater the intensity of mutation, the quicker the population converges to the optimal value.

The last problem that should be discussed are the practical implications of the obtained results. Evolutionary systems and evolutionary computations are nowadays commonly

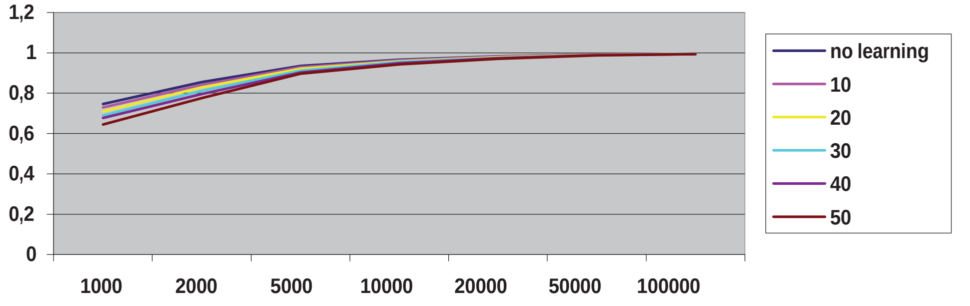

Fig. 2. The plots illustrate the effect of decelerating the rate of evolution for different numbers of the individuals that underwent the process of learning (mutation intensity was set at 20 % of the population)

Rys. 2. Wykresy ilustrujące efekt spowolnienia tempa ewolucji dla różnej liczby osobników, które podlegały procesowi uczenia (mutacji podlegało 20 % populacji osobników)

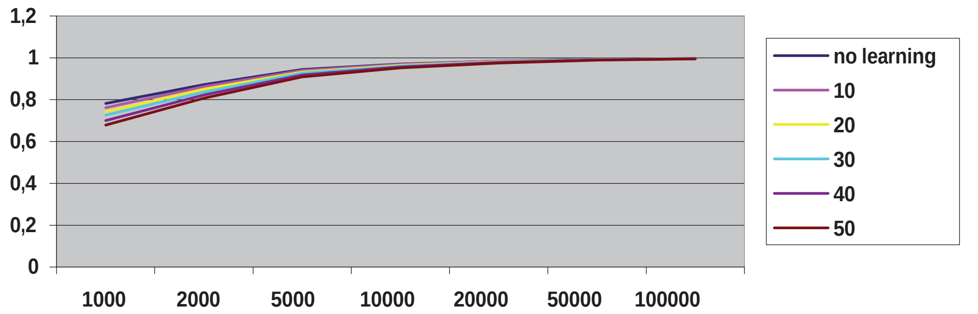

Fig. 3. The plots illustrate the effect of decelerating the rate of evolution for different numbers of the individuals that underwent the process of learning (mutation intensity was set at 30 % of the population)

Rys. 3. Wykresy ilustrujące efekt spowolnienia tempa ewolucji dla różnej liczby osobników, które podlegały procesowi uczenia (mutacji podlegało 30 % populacji osobników)

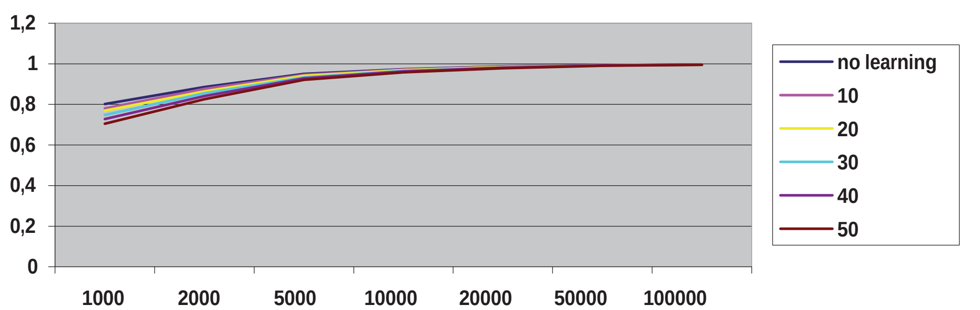

Fig. 4. The plots illustrate the effect of decelerating the rate of evolution for different numbers of the individuals that underwent the process of learning (mutation intensity was set at 40 % of the population)

Rys. 4. Wykresy ilustrujące efekt spowolnienia tempa ewolucji dla różnej liczby osobników, które podlegały procesowi uczenia (mutacji podlegało 40 % populacji osobników)

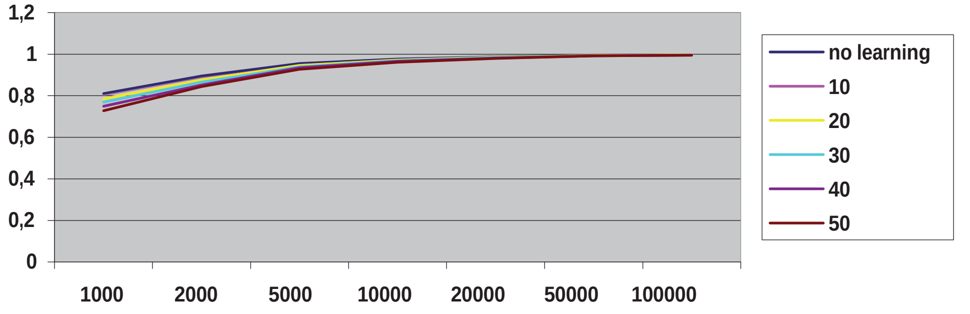

Fig. 5. The plots illustrate the effect of decelerating the rate of evolution for different numbers of the individuals that underwent the process of learning (mutation intensity was set at 50 % of the population)

Rys. 5. Wykresy ilustrujące efekt spowolnienia tempa ewolucji dla różnej liczby osobników, które podlegały procesowi uczenia (mutacji podlegało 50% populacji osobników)

used in many domains of science and engineering, e.g. optimizing of the work of energetic systems, optimizing the power flow in high-voltage transmission lines, minimizing the thermal losses in transmission lines and transformers etc. It often happens that for the sake of effective realization of evolutionary computations a great computational power is necessary and in most cases it takes a lot of time to obtain the valuable results. In such a case introducing a learning process into the evolutionary system should be advantageous if this learning process could lead to speeding up the rate of evolution and thus shortening the time of computations. As we can see basing on the obtained results such speeding up the rate of evolution in most cases is not easy and it requires the special form of the fitness function.

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Spowalnianie tempa ewolucji z wykorzystaniem uczenia stałego

Streszczenie: Ewolucja i uczenie się są dwoma głównymi procesami rozpatrywanymi w kontekście systemów sztucznej inteligencji i systemów sztucznego życia. Oba wymienione procesy mogą wchodzić we wzajemną interakcję, co bywa określane mianem efektu Baldwina. W szczególności wprowadzenie procesu uczenia do systemu ewolucyjnego może powodować przyspieszenie bądź spowolnienie tempa ewolucji zarówno w przypadku sztucznych, jak i naturalnych systemów ewolucyjnych. Obecnie wciąż odczuwany jest brak solidnej teorii matematycznej, która byłaby w stanie wyjaśnić w pełni zjawiska związane z wpływem procesu uczenia na tempo przebiegu ewolucji. W przypadku tzw. uczenia stałego, które polega na systematycznym przesuwaniu o stałą wartość genotypu osobnika w kierunku poszukiwanego optimum, udowodniono, że jeżeli druga pochodna logarytmu funkcji dopasowania jest ujemna, wówczas tempo przebiegu ewolucji powinno ulec spowolnieniu w wyniku wprowadzenia do systemu ewolucyjnego uczenia stałego. W artykule rozważono system ewolucyjny z asymptotyczną funkcją dopasowania, w przypadku którego zgodnie z teorią wprowadzenie uczenia stałego powinno wywołać spowolnienie tempa przebiegu ewolucji. Liczne wyniki symulacji komputerowych potwierdzają przewidywania teorii i pokazują, że spowolnienie tempa ewolucji jest istotne. Ponadto można zaobserwować dodatkowy wpływ częstotliwości mutacji na spowolnienie tempa ewolucji.

Słowa kluczowe: systemy ewolucyjne, proces uczenia się, uczenie stałe, efekt Baldwina

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