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Modifying the rate of evolution using the learning process

***Abstract**. The paper discusses the issues concerned with the impact of learning process on the rate of evolution in evolutionary systems. In the paper we tried to answer the question whether it is possible to speed up the evolution by introduction of learning process of individuals. We also consider some practical consequences of the obtained results.*

***Streszczenie.** Artykuł dotyczy zagadnień wpływu procesu uczenia na tempo zachodzenia przemian w systemach ewolucyjnych. W szczególności w artykule starano się odpowiedzieć na pytanie, czy możliwe jest przyspieszenie ewolucji poprzez wprowadzenie procesu uczenia osobników. Rozważono także praktyczne konsekwencje uzyskanych wyników. (**Wpływanie na tempo ewolucji z wykorzystaniem procesu uczenia**).*

Keywords: evolutionary systems, learning process, the Baldwin effect.
Słowa kluczowe: systemy ewolucyjne, proces uczenia, efekt Baldwina.

Introduction

Evolution and learning are two main processes that are most often examined within the Artificial Life (AL) domain [6]. The evolution and learning processes are considered both in the context of artificial [1] and natural systems, the behavior of which is simulated with the use of computers [4]. The processes of evolution and learning operate in different time scales, which are respectively the time of existence of a species that evolves on the span of consequent generations, and the time of life of an individual that is taught during a certain period. Moreover, evolution operates on the entire population while learning is applied only to some selected individuals [5]. Despite this it is a well-known fact that evolution and learning can interact with each other [3]. In particular, evolution can be accelerated or slowed down by learning, and this phenomenon is called the Baldwin effect [2].

The phenomena considered with the impact of learning on the rate of evolution are still not understood well enough. Moreover, there is no general theory that would be able to account for the effect of learning on the evolution rate, i.e. explain under which conditions evolution should be accelerated or decelerated by learning. Some results were obtained only for the case of a monotonic and positive fitness function and they were presented in the work of Paenke, Kawecki, and Sendhoff [5]. Their work presents a mathematical framework based on the gain function with the help of which one can determine for the case of a monotonic and positive fitness function, whether the evolution will be accelerated or decelerated by learning. Moreover, in [5] the special case of constant learning is examined in more detail. In the literature constant learning is defined as a learning process which moves an individual a constant distance toward the optimal fitness function value. Importantly, this distance does not depend on the genotype of the individual being taught. Further the obtained results [5] demonstrate that in the case of constant learning the sign of the first derivative of the gain function is the same as the sign of the second derivative of the logarithm of fitness function.

The final conclusion in [5] is that in the case of a monotonic and positive fitness function and constant learning, the evolution is accelerated by learning if the sign of the second derivative of the logarithm of the fitness function is positive ($\mathrm{sign}(d^2(\ln f(x))/dx^2) > 0$), where f(x) is the monotonic and positive fitness function). Here, we define *x* as the genotype that undergoes the genetic operation of mutation. On the other hand, if the sign of the second derivative of the logarithm of the fitness function is negative ($\mathrm{sign}(d^2(\ln f(x))/dx^2) < 0$), the evolution is decelerated by learning. Moreover, if the second derivative of the logarithm of the fitness function is equal zero, learning has no impact on the rate of evolution. In [5] the original experiment of Papaj is repeated and analyzed theoretically within the gain function mathematical framework. The theoretical analysis demonstrates that in the case of Papaj's evolutionary system with a sigmoid fitness function evolution should be decelerated by learning, which was also proved by numerical experiments, as described in [5]. The author of this paper also conducted a series of similar experiments for different types of fitness functions. The fitness functions, for which numerical simulations were performed, were asymptotic fitness functions such as:

$$f(x) = 1 - e^{-x} \tag{1}$$

$$f(x) = 1 + \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

$$f(x) = \frac{\pi}{2} + arcth(x) \tag{3}$$

The domain for function (1) is for x Є (0, ∞) and for functions (2) and (3) x Є (-∞, ∞).

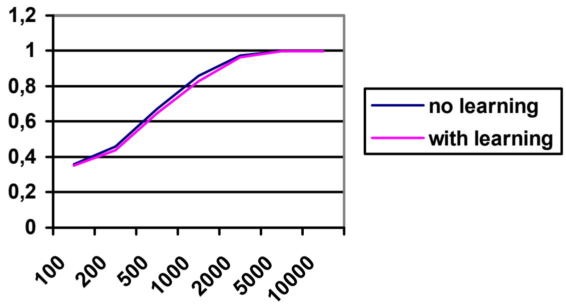

Fig. 1. The plots of the fitness functions values obtained for the case of learning and without learning (5% of the individuals were mutated)

For all the functions (1 – 3) the second derivatives of their logarithm are negative for any *x* values. According to the theory presented in [5], in the case of such fitness functions learning should decelerate evolution, and the results of numerical simulations proved the theory very well.

In the case of the fitness function which is given by the formula (1) we obtained the results that are presented in Fig. 1 – 5. The plots were obtained for different intensity of mutation operation.

As can be observed basing on the plots depicted in Fig. 1 – 5 for all examined cases the introduction of learning slowed down the rate of evolution. We can conclude that the numerical experiments confirmed totally the former theoretical results.

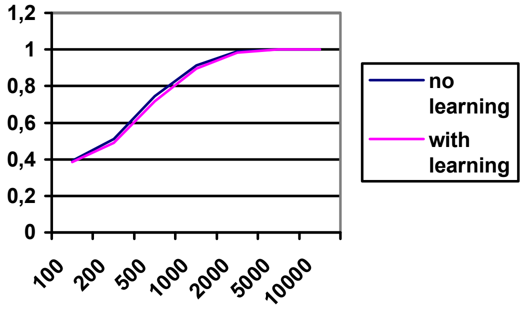

Fig. 2. The plots of the fitness functions values obtained for the case of learning and without learning (10% of the individuals were mutated)

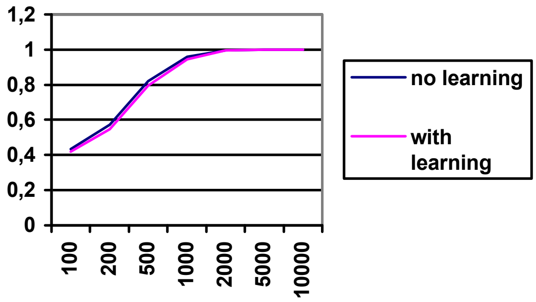

Fig. 3. The plots of the fitness functions values obtained for the case of learning and without learning (20% of the individuals were mutated)

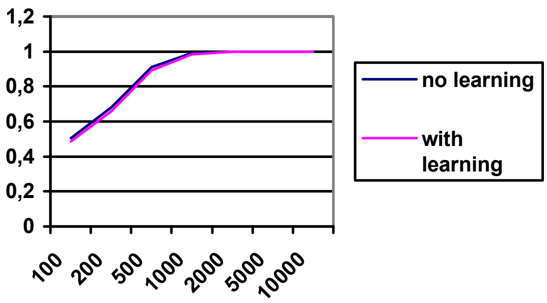

Fig. 4. The plots of the fitness functions values obtained for the case of learning and without learning (50% of the individuals were mutated)

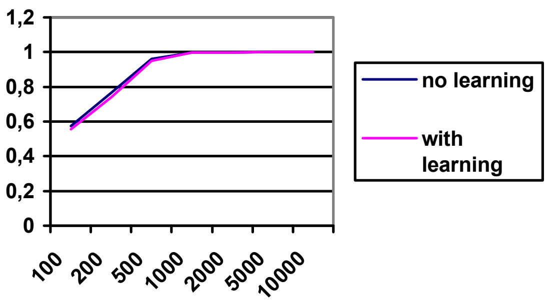

Fig. 5. The plots of the fitness functions values obtained for the case of learning and without learning (100% of the individuals were mutated)

The question we will now try to answer in this paper is whether there exists such a fitness function for which evolution would be accelerated by constant learning.

This question seems to be very important from the point of view of practical applications of evolutionary systems. Nowadays evolutionary systems are commonly used in many domains of engineering.

Especially, evolutionary computations are used for optimization of many technical systems. For example evolutionary computations can be used in the domain of electrical engineering. They can be applied for the purpose of reduction of transmission losses in high voltage power transmission lines. They are also used for finding the optimal power flow distribution in transmission lines. The technique of evolutionary computations can be even used to solving the non-linear electrical circuits and finding the points of work of semiconductor devices [7 – 16].

Moreover, evolutionary systems are used for the aim of simulation of many natural processes, especially in the domain of artificial chemistry and artificial life [17 – 21].

It is a commonly acknowledge fact that evolutionary computations require the great computational power. In most cases realization of evolutionary computations requires also a great amount of time, which very often constitutes a barrier for their practical implementations. If it were possible to speed up the rate of evolutionary processes and thus to obtain the necessary results quicker, it would be a step ahead to more common implementation of the technique of evolutionary computations in further domains of science and engineering.

This is why in the next paragraph we will try to answer the question whether accelerating the speed of evolution is possible and under what conditions.

Searching for the appropriate fitness function formula

If constant learning should accelerate evolution, there must be fulfilled the condition that the second derivative of the logarithm of the fitness function ought to be positive

$$(\ln(f(x)))'' > 0 \tag{4}$$

Let us consider the fitness function which is given by the following formula

$$f(x) = e^{ax+b} \tag{5}$$

In the case in which the fitness function is given by the formula (5), the second derivative of the logarithm of the fitness function is equal zero. according to the theory in that case learning should have no impact on the rate of evolution.

If we consider that the fitness function is a positive function (f(x) > 0)for any possible *x* values of its domain, we can also assume that the function f(x) could be given by the following formula

$$f(x) = e^{g(x)} \tag{6}$$

In the formula (6) the function g(x) is a real function that could have positive or negative values. The condition (4) is fulfilled only when g”(x) > 0. So the conclusion is that the function g(x) could be any convex function. For example the function g(x) could be the function which is given by the formula $g(x) = x^2$ or in general $g(x) = x^{2m}$, where m = 1, 2, 3, ... , N. The function g(x) can also be given by the formula $g(x) = e^x$.

Moreover, if we consider that any convex function grows faster to infinity than the linear function g(x) = ax +b (for which learning has no impact on the rate of evolution), we can conclude that the fitness function must also grow faster to infinity than the function $f(x) = e^{ax+b}$ and only under that condition the process of learning can accelerate the rate of evolution.

Final conclusions

In the above section it was demonstrated that only in the case in which the fitness function grows faster than any exponential function the evolution would be accelerated by learning [22].

Although there exist theoretically some class of fitness functions for which the evolution is accelerated by learning (according to the theory presented in [5]), these functions do not belong to the class of asymptotic functions. On the contrary, they grow very fast. In fact, they grow even faster than any exponential function. Due to this fact, it is impossible to use such fitness functions in any realistic computational system without overflowing the processor registers just after a few iterations of learning process (the computed numbers would be soon too great for any further processing). The fitness functions that would grow faster than any exponential function are obviously not encountered in any natural evolutionary system. In the case of biological evolutionary systems, the fitness functions are mostly asymptotic functions, and for all natural processes the effect of saturation is observed. Under such conditions, the scenario in which natural evolution is accelerated by constant learning is impossible. This observation also holds for any artificial evolutionary system in the case of which the fitness function can not grow faster than any exponential function just for the computational reasons [23].

According to the analysis, which was presented above, one must acknowledge that the answer to the question posed in the title of this paper is negative, because in the case of real computational systems constant learning can by no means accelerate evolution in any real computational system.

Also from the practical point of view we can say that it is not possible to accelerate the evolutionary processes in any practically used artificial evolutionary system so as to obtain the results of evolutionary computations faster.

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