EXAMINING THE IMPACT OF POSITIVE AND NEGATIVE CONSTANT LEARNING ON THE EVOLUTION RATE

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Abstract: The paper discusses the influence of learning on evolutionary processes. In biological sciences it is a well-known fact that the rate of evolution can be effected by learning and the same phenomena can also be observed in artificial evolutionary systems, however, their nature is still not sufficiently well understood. In the paper the influence of constant learning on the rate of evolution is examined. The constant learning is a kind of learning during which the genotype of the individual being taught is moved toward the global optimum over a constant value. If the fitness function is monotonic, it can be concluded from the mathematical theory that such kind of learning should decelerate evolution. However, this fact is highly counterintuitive and for this reason it should be proved by numerical experiments. In the article the results of numerical simulations are presented. They prove that evolution is indeed decelerated by learning in case of the sigmoid fitness function. Moreover, two cases of constant learning were examined in the paper. These are the positive and negative constant learning. It was demonstrated that in the case of the negative constant learning the evolution was decelerated to a larger extent than in the case of the positive constant learning. The obtained results can help explain certain phenomena concerning the impact of learning on the evolution both in natural and artificial evolutionary systems.

Keywords: evolutionary systems, learning process, constant learning

1. Introduction

Evolution and learning are two main processes that are commonly encountered in the biologically inspired artificial intelligence systems [1]. It is a well-known fact that learning can influence the rate of evolution, and such a phenomenon in biological sciences is called the Baldwin effect. Interactions between the processes of evolution and learning can be observed both in artificial and natural systems, yet their nature is still not well understood [2].

What is especially interesting is that learning can both accelerate and decelerate evolution. A number of numerical experiments have proved that learning can induce the acceleration of the rate of evolutionary changes. The first computational experiment demonstrating that learning can accelerate evolution was performed by Hinton and Nowlan [3]. That experiment proved that under the conditions of an extremely flat fitness function with only one global optimum, learning could lead the population toward that global optimum, in contrast to the non-learning population which was not able to find the evolutionary goal within the Hinton and Nowlan computational model framework [2]. Contrary to Hinton and Nowlan's results, the fact that learning can also decelerate evolution is rather counterintuitive. The computational model of Papaj [4] can be taken as an example of a system in which learning decelerates evolution. In Papaj's simulation model the interactions between evolution and learning were studied in insects that adapt to new environmental conditions. The numerical experiments demonstrated that learning decelerated evolution because it weakened the selection pressure on the population [2]. The effect of decelerating evolution which is induced by learning was also observed during the experiments with some biological systems. Such experiments were conducted by Mery and Kawecki on fruit flies (*Drosophila melanogaster*) [5]. In these experiments fruit flies were taught to choose the right kind of resources for laying their eggs. It was observed that learning decelerated the evolution of resource preferences [2].

Despite certain results concerning the influence of learning on evolution that have been obtained so far, there is still no solid theory that could explain these phenomena in a general case. Theoretical results have been obtained only in a case of a monotonic fitness function, and they are based on the so-called gain function $g(x)$, which is a ratio of a fitness function with learning $f(l(x))$ and a fitness function without learning $f(x)$, thus $g(x)=f(l(x))/f(x)$. Here $l(x)$ denotes the genotype which was modified during the learning process. In [2] it has been proved that the fact whether the evolution is accelerated or decelerated as a result of learning depends only on the sign of the first derivative of the gain function $g'(x)$ in the case of a monotonic fitness function. If the sign of the first derivative of the gain function is positive, the evolution is accelerated by learning. However, if the sign of the first derivative of the gain function is negative, the process of learning decelerates the evolution. Moreover, if the first derivative of the gain function equals zero, learning has no impact on the rate of the evolution. In [2] the case of a sigmoid fitness function with a constant learning was examined. It was theoretically proved, and confirmed with numerical simulations that in the case of a constant learning the evolution is always decelerated.

2. The sigmoid fitness function case

Let there be given an artificial evolutionary system, such as that described in [2], in which a sigmoid function $f(x)=(1+\exp(-x))^{-1}$ is the fitness function.

In [2] the population was initialized uniformly in the interval $[-3.1, -2.9]$, and it was composed of 100 individuals. Moreover, the operation of mutation was introduced which was realized by adding a random number to the genotypic value x. In the first scenario, the evolution was examined without learning, and it was demonstrated by a numerical simulation that the population drifted systematically toward higher values of the fitness function. Then, the learning process was defined as $l(x) = x + 0.25$. Such kind of learning is called constant learning because it moves an individual over a constant distance of the value of 0.25 toward the global optimum [2].

Let us analyse the gain function for the case of constant learning. In general, constant learning can be defined as $l(x) = x + \delta$, where δ is a positive constant ($\delta > 0$). Thus, the fitness function with constant learning is given by the formula $f(l(x)) = (1 + \exp(-(x+\delta)))^{-1}$. By definition, the gain function is given as $g(x) = f(l(x))/f(x)$. In the case of constant learning the gain function is given by the formula $g(x) = (1+\exp(-x))/(1+\exp(-(x+\delta)))$. Then. we can calculate the first derivative of the gain function $g'(x)$. The denominator of the first derivative of the gain function equals $(1+\exp(-(x+\delta)))^2$, and is positive for all x and δ. Thus, the sign of the first derivative of the gain function depends only on the sign of its numerator which is given as $-\exp(-x) \cdot (1+\exp(-(x+\delta))) + (1+\exp(-x)) \cdot \exp(-(x+\delta))$. After some simple calculations, we obtain that the numerator equals $\exp(-x) \cdot (\exp(-\delta) - 1)$ and is negative for all x and any positive value of δ. Based on it, we can conclude that the first derivative of the gain function is negative for any kind of constant learning, *i.e.* for any $\delta > 0$. The conclusion is that constant learning decelerates evolution.

This counterintuitive conclusion (we would rather expect that any kind of learning would lead to an acceleration of evolution) can be easily explained, if we realise that constant learning ameliorates the genetic material also for individuals that are poorly adapted to the environment, *i.e.* for individuals that have lower fitness function values. This fact is the reason why such individuals with lower fitness function values can pass their genes to the next generations, which weakens the selection pressure, because lower value genomes are not quickly eliminated form the population.

In [2] it was also proved that for a monotonic and differentiable fitness function with constant learning the sign of the first derivative of the gain function depended on the sign of the second derivative of the logarithm of the fitness function, thus $\mathrm{sign}(g'(x)) = \mathrm{sign}((\ln(f(x))'')$. The second derivative of the logarithm of sigmoid function equals $-\exp(-x) \cdot (1+\exp(-x))^{-2}$, and is negative for all x [2].

Now, let us once again have a closer look at the numerator of the first derivative of the gain function $\exp(-x) \cdot (\exp(-\delta) - 1)$. If we take any positive value of δ ($\delta > 0$), we call such kind of learning positive constant learning and we conclude that the first derivative of the gain function is negative which implies that the process of evolution is decelerated according to the theory of the gain function mathematical framework [2]. However, the gain function mathematical framework does not say anything about the case in which the value of δ is negative ($\delta < 0$). Here, we call the learning process with a negative value of δ negative constant learning, because during it individuals are moved over a constant distance away from the optimum value. Whether the negative constant learning accelerates or decelerates the evolution is difficult to predict and numerical experiments are necessary here. One may expect that negative constant learning increases the selection pressure on the evolving population and thus some acceleration of the evolutionary process may be noticed. In order to demonstrate this, a series of numerical simulations were performed.

3. Results of numerical simulations

The numerical experiments were conducted for a population composed of 100 individuals. The population was initialized randomly as in the experiments described in [2]. Based on this, the individuals were initialized uniformly in the interval $[-3.1, -2.9]$. The only genetic operation used was mutation. In order to simulate mutation, a random number from the interval $[-0.01, 0.01]$ was added to the genotype value of an individual. The intensity of mutation was regulated and its influence on the convergence of the evolutionary process was examined. For the purpose of performing a selection operation, a tournament selection method was implemented. In this type of selection two individuals are chosen randomly and the values of their fitness functions are compared. The individual with a higher value of the fitness function passes to the next generation, whereas the other does not. Moreover, it was assumed that the number of individuals in the population was constant and was equal to 100 during all the generations. The sigmoid function $f(x) = (1+\exp(-x))^{-1}$ was assumed as the fitness function.

The process of evolution was examined with and without introduction of additional learning. In the numerical experiments both positive and negative constant learning was implemented. The negative constant learning was introduced by adding a constant negative value, equal to -0.25, to the genomes of all the individuals being taught. In the first series of numerical simulations the case without learning was examined for different mutation intensity values. During the numerical experiments the mean value of the fitness function calculated for the population was examined.

The results obtained for the mutation intensity such that 5, 10, 20, 50, and 100 individuals of the population were mutated on average are presented in Figure 1. The results are presented for 100, 200, 500, 1000, 2000, 5000, and 10 000 generations of the evolutionary algorithm. Figure 1 presents the average results obtained for 10 runs of the evolution process for each number of generations and for each intensity of mutation.

It can be observed from the results presented in Figure 1 that the mutation intensity has a serious impact on the convergence of the evolutionary process. A regularity can be notices that the more intensive the mutations, the higher the

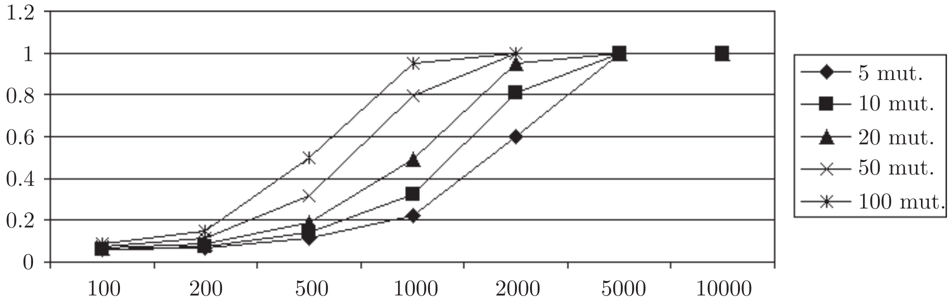

Figure 1. Average fitness values obtained for different numbers of generations (100, 200, 500, 1000, 2000, 5000, and 10 000 generations of the evolutionary system) and for different mutation intensities (5, 10, 20, 50, and 100 of mutated individuals); the case of no learning of individuals

values of the fitness function noted for any number of generations. In the case of the experiments during which every individual was mutated on average, the evolutionary goal (the value of the fitness function equal to 1.0000) was achieved after a few thousands of generations.

In the second series of numerical experiments the learning process was implemented. The positive constant learning was introduced by adding a constant positive value equal to 0.25 to the fitness function of an individual. Algorithm 10 individuals were selected at random for the learning process in each generation of the evolutionary. The obtained results for different numbers of generations (100, 200, 500, 1000, 2000, 5000, and 10 000 generations of the evolutionary system) and different intensity of mutation (5, 10, 20, 50, and 100 individuals were mutated, respectively) are presented in Figure 2.

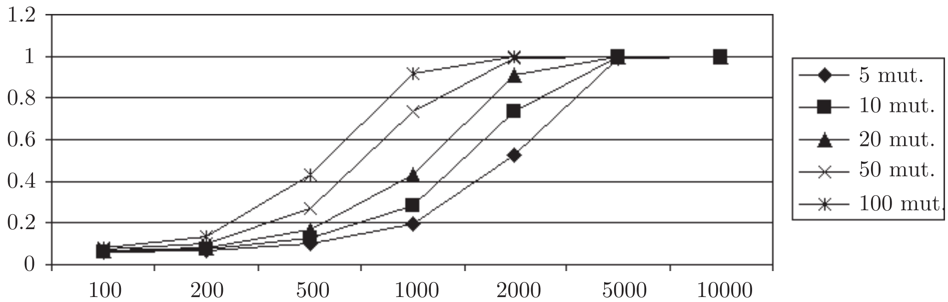

Figure 2. Average fitness values obtained for different numbers of generations (100, 200, 500, 1000, 2000, 5000, and 10 000 generations of the evolutionary system) and for different mutation intensities (5, 10, 20, 50, and 100 of mutated individuals); the case of positive constant learning of individuals

Based on the results of the numerical experiments which were presented in Figure 2, it can be observed that the positive constant learning decelerates the evolution for any intensity of mutation. The values of the fitness function obtained with the positive constant learning were lower than in the case without learning.

This is especially visible for lower numbers of generations where the evolutionary process without learning significantly outperforms the results obtained with the use of the positive constant learning.

The third series of numerical experiments was conducted for the case of negative constant learning. The results that were obtained during the simulations are presented in Figure 3. The numerical experiments were conducted for different numbers of generations of the evolutionary system (100, 200, 500, 1000, 2000, 5000, and 10 000 generations) and for different intensities of mutations (5, 10, 20, 50, and 100 of mutated individuals).

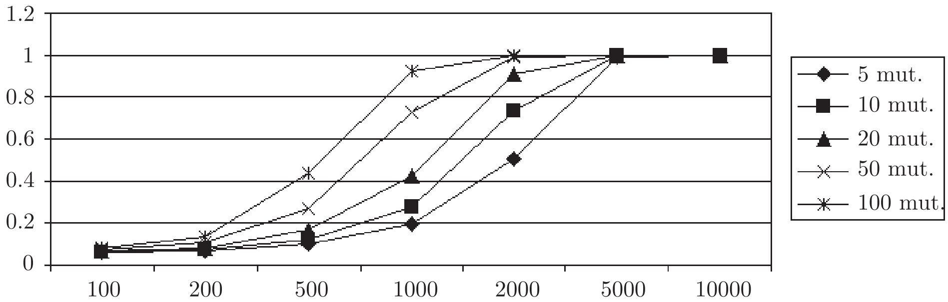

Figure 3. Average fitness values obtained for different numbers of generations (100, 200, 500, 1000, 2000, 5000, and 10 000 generations of the evolutionary system) and for different mutation intensities (5, 10, 20, 50, and 100 of mutated individuals); the case of negative constant learning of individuals

As can be seen from Figure 3, the application of the negative constant learning leads to a deceleration of the evolutionary process. If we compare the results from Figure 3 with the results from Figure 2, we can see that this deceleration is even somewhat stronger than in the case of the positive constant learning.

4. Conclusions

The interactions between learning and the process of evolution are still weakly understood. Especially, the lack of a solid theory that could explain the phenomena concerning the impact of learning of individuals on the rate of the evolution of their population can be noticed. A mathematical framework within which the impact of learning on the rate of evolution can be described in a quantitative manner was developed only for the case of the monotonic fitness function. This mathematical framework is based on the gain function and it was proved in [2] that the fact whether the evolution was accelerated or decelerated by learning for the monotonic fitness function depended only on the sign of the first derivative of the gain function. Moreover, it was proved in [2] that for the case of constant learning, where individuals were moved over a constant value toward the global optimum, the acceleration or deceleration of the evolution depended on the sign of the second derivative of the logarithmic fitness function.

In the paper the case of a sigmoid fitness function was examined. The sigmoid function is a monotonic function for which it has been proved that the value of the first derivative of the gain function in the case of a constant learning is negative for any genotypic value. From the theory presented in [2] it can be concluded that in the case of the sigmoid fitness function, learning should decelerate the evolution. In order to prove this a few series of numerical experiments were conducted. Constant learning was divided into two categories. The first type was positive constant learning in which the learning step was a positive constant, and the second type was negative constant learning in which the learning step was a negative constant.

The numerical simulations have demonstrated that in cases of both positive and negative constant learning, the evolution is decelerated. For the same absolute value of the learning step ($|\delta| = 0.25$) in the case of negative and positive constant learning the evolution is decelerated somewhat more in the case of the negative constant learning than in the case of the positive constant learning.

The fact that the negative constant learning decelerates the evolution can be well understood if we realize that such kind of learning is *de facto* an anti-learning process because the genome of individuals is artificially worsened. Moreover, it happens very often during the tournament selection that a worse individual outperforms the one that was superior before the negative constant learning was implemented. All this leads to the degeneration of the population and makes the evolutionary processes run slower, however the evolutionary goal is always attained.

The situation with the positive constant learning is different and the results obtained during the numerical experiments are rather counterintuitive. However, we can explain this phenomenon if we realize that ameliorating the genotype of well-fit individuals can lead to the domination of such individuals in the entire population, thus reducing the selection pressure which certainly causes the deceleration of the evolution.

The obtained results can be important from the perspective of research in both natural and artificial evolutionary systems [6]. It is especially important in the Artificial Life (AL) research domain where evolutionary processes in artificial populations are examined [7]. In such systems lifetime learning of individuals is often a very important factor that has a significant impact on the evolution of the whole population [8]. Basing on the mathematical framework of the gain function, many phenomena that are observed in natural and artificial populations can be explained. What is especially important, is that learning not always leads to an acceleration of the evolution. Thus, in certain cases it is better not to introduce any kind of additional learning into the population, if we want the evolution to run faster. However, there is no symmetry in the case of negative constant learning. Unfortunately, the negative constant learning does not just do the opposite to the positive constant learning and thus it does not accelerate evolution. What is even worse, it decelerates the evolution to a larger extent because in fact such anti-learning only degenerates a population.

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