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RESEARCH ARTICLE

# Optimization of autonomous agents by means of learning and evolution

Vladimir Red'ko

*Scientific Research Institute for System Analysis, Russian Academy of Sciences, Moscow, Russia*

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**Abstract**
Interaction between learning and evolution in populations of autonomous agents is investigated. Any agent of the population has both the genotype (the genome) and the phenotype. The genotype and the phenotype are chains of binary symbols. The initial phenotype (at the moment of the agent birth) is equal to the agent genotype. There is a certain optimum; namely, there is the optimal chain that is searched for by means of learning and evolution. Genotypes are optimized by evolution; phenotypes are optimized by learning. The final phenotype (at the moment of the end of the agent life) determines the agent fitness. Three mechanisms of interaction between learning and evolution are investigated. (1) The mechanism of the genetic assimilation of the acquired features during a number of generations of Darwinian evolution is analyzed. It is shown that the genetic assimilation takes place as follows: the phenotype distribution moves towards the optimum at learning and further selection; subsequently the genomes of selected organisms also move towards the optimum. (2) The mechanism of the hiding effect is studied; this effect means that strong learning can ensure finding the optimal phenotype independently on the agent genotype in some situations; consequently, strong learning can inhibit the genotype optimization. (3) The mechanism of influence of the learning load on investigated processes is also analyzed. It is shown that the learning load leads to a significant acceleration of the genetic assimilation.


## Introduction

After the appearance of the Darwinian theory of evolution, many researchers asked the following question. The evolutionary process is a result of mutations and further selection. So, are random mutations able to ensure finding very non-trivial useful features of living organisms? In the XIX century, the concepts, suggesting that interaction between learning (or other processes of the acquisition of organism features during the life of the organism) and the evolutionary process is possible, appeared (Baldwin, 1896; Morgan, 1896; Osborn, 1896). Moreover, according to these concepts, learning can contribute significantly to the evolutionary process. This type of influence of learning on the

*E-mail address:* vgredko@gmail.com

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evolutionary process is often called the Baldwin effect. According to this effect, initially acquired features can become inherited during a number of generations. The evolutionary ''re-invention'' of useful features, initially obtained by means of learning, is often called the genetic assimilation (Waddington, 1942).

A number of works attempted to model and analyze interactions between learning and evolution by means of computer simulations (Belew & Mitchell, 1996; Turney, Whitley, & Anderson, 1996; Ackley & Littman, 1992; Hinton & Nowlan, 1987; Mayley, 1997; Red'ko, Mosalov, & Prokhorov, 2005). In particular, Hinton and Nowlan (1987) demonstrated that learning can guide the evolutionary process to find the optimum. Mayley (1997) investigated different aspects of interaction between learning and evolution and demonstrated that the hiding effect can take place if learning is sufficiently strong. The essence of the hiding effect is as follows: if learning is strong enough to optimize the phenotype of the organism, and the organism is selected at the evolution in accordance with the phenotype, then the selection can be independent on the genotype. The hiding effect significantly reduced the role of genotypes at the evolutionary selection, and the genetic assimilation becomes less pronounced. In addition, Mayley (1997) took the learning load into account. The learning load means that the process of learning has an additional load for the organism and the fitness of the organism is reduced under influence of the load.

Red'ko et al. (2005) modeled interaction between learning and evolution for the case of neural network control systems of autonomous agents. The genetic assimilation of acquired features of agents was observed during several generations of evolution. In addition, it was demonstrated that learning could significantly accelerate the evolutionary optimization. However, it was difficult to analyze detailed mechanisms of interaction between learning and evolution in that models, as these mechanisms were ''hidden'' in the dynamics of numerous synapse weights of neural networks of agents.

The current work develops above-mentioned works. It uses works (Hinton & Nowlan, 1987; Mayley, 1997) as background. However, rather complex forms of the genetic algorithm (with crossovers) were used in that works, so it was difficult to analyze mechanisms of influence of learning on evolution. In contrast to works (Hinton & Nowlan, 1987; Mayley, 1997), the current work uses the clear evolution model, namely, the quasispecies model, proposed by Eigen (Eigen, 1971; Eigen & Schuster, 1979) and the quantitative estimation of the evolutionary rate and the effectiveness of evolutionary algorithms, obtained by Red'ko and Tsoy (2005). The quasispecies model considers the process of evolution that is based on the selection and mutations of genomes of organisms (without crossovers) and describes main properties of evolutionary processes. This model allows getting a better understanding of mechanisms of interaction between learning and evolution.

## Description of the Model

An evolving population of agents (or individuals) is considered. Similar to the work (Hinton & Nowlan, 1987) we assume that there is a strong correlation between the genotype and the phenotype of agents. We assume that the genotype (or the genome) and the phenotype of the agent have the same form, namely, they are chains (sequences of symbols); symbols of both chains are equal to 0 or 1. For example, we can assume that the genome is a modeled DNA chain, ''letters'' of which are equal to 0 or 1, and the phenotype is determined by the neural network of organisms, synaptic weights of the neural network are equal to 0 or 1 too. Initial synaptic weights, received at the agent birth, are determined by the genome (more precisely, synaptic weights are equal to genome symbols). These weights are changed by means of learning during the agent life.

We assume that each agent has its own genome $\mathbf{S_0}$. A population consists of $n$ agents, agent genomes are $\mathbf{S}_{0k}$, $k = 1, \ldots, n$. The agent genome $\mathbf{S}_{0k}$ is the chain of symbols, $S_{0ki}$, $i = 1, \ldots, N$. Symbols $S_{0ki}$ are equal to 0 or 1. We also assume that the length of chains $N$ and the number of agents in the population $n$ are large: $N, n \gg 1$. Values $N$ and $n$ do not change in the course of evolution. We assume that $N$ is so large that only a small part of possible $2^N$ genomes can be present in a particular population: $2^N \gg n$. Typical values of $N$ and $n$ in our computer simulations are as follows: $N \sim n \sim 100$.

The evolutionary process consists of a sequence of generations. The new generation is obtained from the old one by the selection and mutations of agents. Genomes of agents of the initial generation are random.

In order to consider learning processes, we introduce two types of sequences: (1) the genome or the initial sequence $\mathbf{S}_{0k}$ that is received by the agent at its birth, and (2) the current sequence of the agent $\mathbf{S}_{\mathrm{T}k}$. The sequence $\mathbf{S}_{\mathrm{T}k}$ is the phenotype of the agent.

Agents inherit genomes $\mathbf{S}_{0k}$ from their parents, these genomes do not change during the agent life and are transmitted (with small mutations) to their descendants. Mutations are random changes of symbols $S_{0ki}$. The agent receives the genome at its birth, the current sequence $\mathbf{S}_{\mathrm{T}k}$ at the birth of the agent is equal to the genome: $\mathbf{S}_{\mathrm{T}k}$ $(t = 1)$=$\mathbf{S}_{0k}$. The life time of any agent is equal to $T$. The time is discrete: $t = 1, \ldots, T$. Duration of the generation is equal to $T$. The sequence of $\mathbf{S}_{\mathrm{T}k}$ is modified during the agent life by means of learning.

As descendants of agents obtain the genomes $\mathbf{S}_{0k}$ that are received by agents from their parents but not sequences $\mathbf{S}_{\mathrm{T}k}$ that are optimized by learning, the evolutionary process has a Darwinian character.

It is assumed that there is an optimal sequence $\mathbf{S}_m$ (components of which are also equal to 0 or 1), which is searched for in processes of evolution and learning. At computer simulation, the sequence $\mathbf{S}_m$ is set to be random.

Learning is performed by the following method of trial and error. Every time moment $t$ each symbol of the sequence $\mathbf{S}_{\mathrm{T}k}$ is randomly changed to 0 or 1, and if this new symbol coincides with the corresponding symbol of the optimal sequence $\mathbf{S}_m$, then this symbol is fixed in the $\mathbf{S}_{\mathrm{T}k}$; otherwise, the old symbol of the sequence $\mathbf{S}_{\mathrm{T}k}$ is restored. So, during learning, the current sequence $\mathbf{S}_{\mathrm{T}k}$ moves towards the optimal sequence $\mathbf{S}_m$.

At the end of the generation, the selection of individuals in accordance with their fitness takes place. The fitness is determined by the sequence $\mathbf{S}_{\mathrm{T}k}$ at the time moment