Multilevel cognitive processes

Vladimir G. Red’ko, Zarema B. Sokhova

Scientific Research Institute for System Analysis,

Russian Academy of Sciences

vgredko@gmail.com, zarema.sokhova@gmail.com

Plan

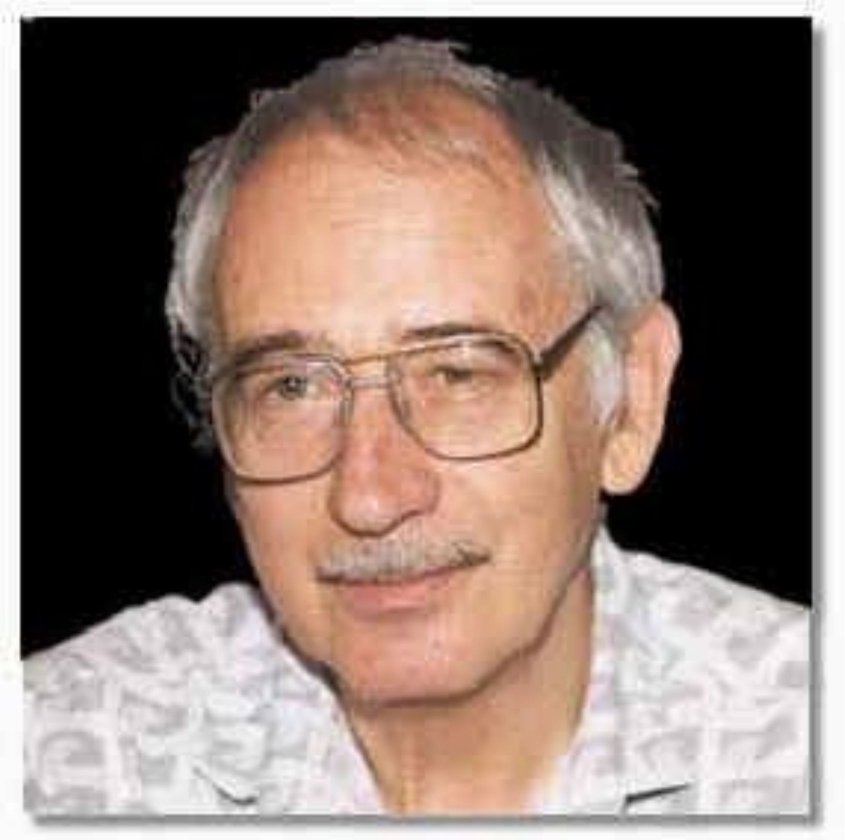
1. Conceptual theory of metasystem transitions by Valentin Turchin
2. Examples of two-level models:

    2.1. Models of interaction between learning and evolution

    2.2. Model of autonomous agents with basic needs: the needs of eating, reproduction, security, searching. Method of selection of the leading need.

3. Towards modeling of cognitive evolution

Conceptual theory of metasystem transition by Valentin Turchin



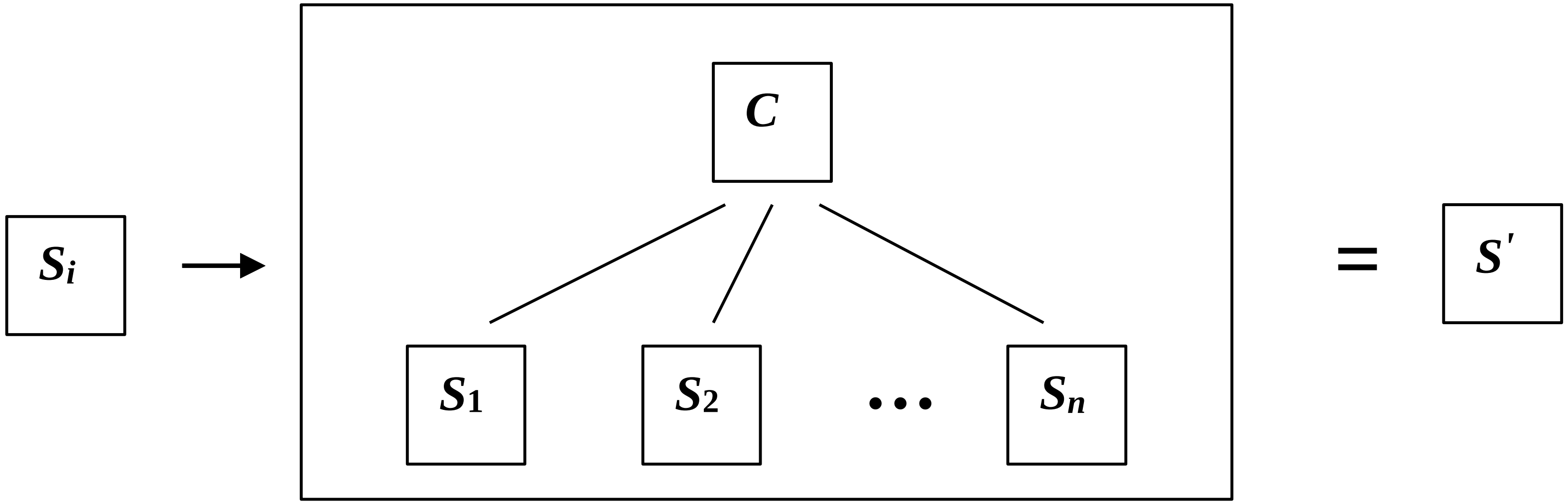
Valentin Turchin
1931-2010

Turchin V.F. The Phenomenon of Science: A Cybernetic Approach to Human Evolution. New York: Columbia University Press, 1977.

This book is in the web site:
http://pespmc1.vub.ac.be/POS/TurPOS.pdf

Turchin outlined the evolution of cybernetic properties of biological organisms and considered the evolution of scientific cognition as a continuation of biocybernetic evolution. To interpret the increase of complexity of cybernetic systems during evolution, Turchin proposed the metasystem transition theory.

The metasystem transition



A transition from a lower level of system hierarchy to a next higher level is a symbiosis of a number of systems S_i of the lower level into the combined set $\Sigma_i S_i$; the symbiosis is supplemented by an emergence of the additional system C, which controls the behavior of the combined set. This metasystem transition results in the creation of the system S' of the new level ($S' = C + \Sigma_i S_i$). The system S' can be included as a subsystem into the next metasystem transition.

The metasystem transition

Turchin characterizes the biological evolution by the following main metasystem transitions:

control of *position* = *movement*

control of *movement* = *irritability* (simple reflex)

control of *irritability* = *complex reflex*

control of *reflexes* = *associating*

control of *associating* = *thinking*

control of *thinking* = *culture*

The metasystem transition

Turchin describes the metasystem transition as a certain cybernetic analog of the physical phase transition.

He pays a special attention to the following features of such transition:

1) **the quantitative accumulation of progressive traits in subsystems S_i just before a metasystem transition**
2) **reduplication and development of subsystems of the penultimate level of the hierarchy after the metasystem transition.**

Plan

1. **Conceptual theory of metasystem transitions by Valentin Turchin**
2. **Examples of two-level models**

    2.1. Models of interaction between learning and evolution

    2.2. Model of autonomous agents with basic needs: the needs of eating, reproduction, security, searching. Method of selection of the leading need.

3. **Towards modeling of cognitive evolution**

Models of interaction between learning and evolution
Backgrounds

Hinton, G. E., & Nowlan, S. J. (1987). How learning can guide evolution. Complex Systems, 1(3), 495–502.

Mayley, G. (1997). Guiding or hiding: Explorations into the effects of learning on the rate of evolution. In: P. Husbands & I. Harvey (Eds.). Proceedings of the fourth European conference on artificial life (ECAL 97). (pp. 135–144). Cambridge, Massachusetts: The MIT Press.

Models of interaction between learning and evolution
General scheme of modeling

The evolution of the population of learning agents is analyzed.
Each agent has a genotype and a phenotype.

Genotypes are optimized in the course of evolution, as a result of selection and mutations. During one generation, the genotypes of agents do not change.

Phenotypes of agents are optimized in the process of generation through learning by trial and error. At the end of a generation, agents are selected into the next generation according to their fitness. Fitness is determined by the final phenotypes obtained as a result of learning.

Genotypes and phenotypes have the same structure. At the beginning of the generation, the phenotype of each agent is equal to its genotype.

The agent of the next generation inherits the genotype (slightly mutated) of its parent. Therefore, the evolution has Darwinian character.

Model of interaction between learning and evolution
Single optimum

Genotypes G and phenotypes P are encoded by long chains of binary (equal to 0 or 1) symbols. There is a single optimum S_0 .

The fitness of the agent *f* is determined by Hamming distance *ρ* between final phenotype P_F of the agent and this optimum:

$$f = \exp[-\beta\rho(P_F , S_0)], \quad \beta > 0 .$$

The model was analyzed by means of computer simulation.

Red'ko V.G. Mechanisms of interaction between learning and evolution // Biologically Inspired Cognitive Architectures. 2017. Vol. 22. PP. 95–103.
DOI: 10.1016/j.bica.2017.10.002

Model of interaction between learning and evolution
Spin glass case

Genotypes G and phenotypes P are encoded by long chains of bipolar symbols (equal to -1 or 1) symbols. There are very large numbers of local optima.

The fitness of the agent *f* is determined by the spin glass energy corresponding to final phenotype P_F of the agent ($E(S_{PF})$):

$$f = \exp[-\beta E(S_{PF})] \,,$$

Red'ko V.G. Spin glass energy minimization through learning and evolution // Optical Memory and Neural Networks. 2020. Vol. 29. No. 3. PP. 187–197.
DOI: 10.3103/S1060992X20030054

Model of interaction between learning and evolution. Effects of interaction for simple chains of symbols

In outlined two cases, when genotypes and phenotypes are encoded by simple chains of symbols, the following effects of the interaction between learning and evolution are observed:

1) Genetic assimilation of acquired skills over a number of generations of Darwinian evolution. During genetic assimilation, skills individually acquired through individual learning are "reinvented" by evolution and are written directly into the genotype of agents.

2) The hiding effect, in which strong learning slows down the evolutionary search for optimal genotypes.

3) The effect of the influence of the load on learning, this load leads to a significant acceleration of the evolutionary search.

Model of interaction between learning and evolution. The case of Stuart Kauffman's NK networks

In this case, the evolution of the population of learning agents was also considered, but the genotype and phenotype are encoded by Kaufman's NK networks. Each such network consists of *N* Boolean logic elements. Each logic element has *K* inputs and one output. The signals at the inputs and outputs of the elements take on the values 0 or 1. The outputs of some elements go to the inputs of others, these connections are random, but the number of inputs *K* of each element is fixed. The logic elements themselves are also chosen randomly.

The number of attractors of NK networks of agents is maximized during learning and evolution.

The fitness of the agent is: $f = \exp[\beta M]$, *M* is the number of attractors of the phenotype of the agent at the end of the generation.

Model of interaction between learning and evolution
The case of Stuart Kauffman's NK networks

We tried to detect 3 mentioned effects of interaction between learning and evolution in this case. However, only the hiding effect was found, and no genetic assimilation and learning load effects were observed. Thus, the effects of the interaction between learning and evolution strongly depend on the degree of correlation between genotypes and phenotypes. For simple chains of symbols, there is a fairly strong correlation between genotypes and phenotypes, but for Kauffman's NK networks there is no such strong correlation between genotypes and phenotypes, so only a hiding effect was observed, which does not depend on such a correlation.

Red'ko V.G. Model of evolution and learning of Kauffman's NK networks. Features of the interaction between learning and evolution // Russian Advances in Fuzzy Systems and Soft Computing: Selected Contributions to the 10th International Conference on "Integrated Models and Soft Computing in Artificial Intelligence (IMSC-2021)". CEUR Workshop Proceedings, Vol. 2965. Aachen, Germany, 2021. PP. 238–243.

Models of interaction between learning and evolution. Conclusion

1. **Learning and evolution in the considered models have different rates of optimization: high rate during learning, small rate during evolution.**

2. **Effects of the interaction between learning and evolution depend on correlation between genotypes and phenotypes. If correlation is strong (for genotypes and phenotypes coded by rather simple chains of symbols), then three effects (the genetic assimilation, the hiding effect, the effect of influence of loading load) of the interaction between learning and evolution are observed in our models. If there is no such strong correlation (for genotypes and phenotypes coded by NK Kaffman's networks) only the hiding effect is observed.**

Plan

1. **Conceptual theory of metasystem transitions by Valentin Turchin**
2. **Examples of two-level models**

    2.1. Models of interaction between learning and evolution

    2.2. Model of autonomous agents with basic needs: the needs of eating, reproduction, security, searching. Method of selection of the leading need.

3. **Towards modeling of cognitive evolution**

Model of autonomous agents with basic needs

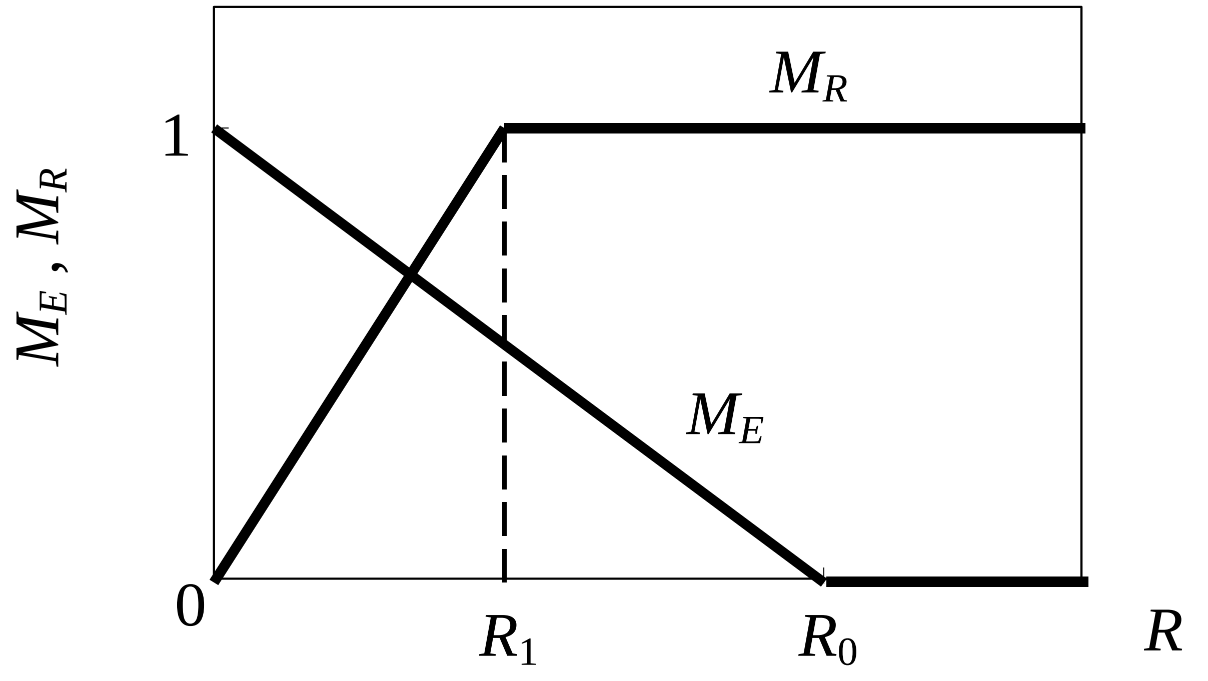
We studied the model of population of autonomous agents that have the natural needs: the need for eating, the need for reproduction, the need for security, and the exploratory need. For any need there is a motivation corresponding to this need.

Agents are in a two-dimensional cellular world. The agent sees the situation in its cell and in four adjacent cells. Each cell can contain only one agent. A cell can also contain a portion of food and a predator. The agent has the resource R, which is replenished when the agent is eating and lost when the agent is performing actions. The time is discrete. The number of cells in the world is 900.

The number of predators N_P is fixed. Initially, predators are randomly distributed over the cells of the world. Each time moment, each predator moves one cell in a random direction.

Initially, N_F portions of food are randomly distributed among the cells of the world. When a portion is eaten in a cell, a new portion of food is added to a random cell.

Model of autonomous agents with basic needs. Motivations



Dependence of the motivation to eat M_E and the motivation to reproduce M_R on the agent resource R.

Model of autonomous agents with basic needs. Motivations

The exploratory motivation is M_I .

The safety motivation is M_S . We assume that when a predator is in the same cell as an agent, this predator eats the agent. The values M_I and M_S are constant for a given agent.

Each time moment the need corresponding to the maximum value of motivation is determined, and an action corresponding to this leading need is performed.

The parameters R_0 , R_1 , M_I , M_S constitute the genotype of the agent:

$$G = \{R_0 , R_1 , M_I , M_S \}$$

Model of autonomous agents with basic needs. Agent actions

Escaping a predator. When an agent sees a predator in a neighboring cell and M_S is large, then the security need becomes its leading one. Further the agent runs away from the predator to one of the nearest free cells.

Eating. If the agent is in a cell with a portion of food, then if it has a leading need for eating, the agent completely eat this portion. Its resource increases by ΔR.

Reproduction. If the need for reproduction the agent becomes leading, then the agent reproduces: it divides in half. In this case, a part of the agent's resource is transferred to the descendant. The offspring's genotype G = $\{R_0 , R_1 , M_I , M_S \}$ is equal to the parent's genotype (slightly mutated) The child agent is placed in a random free nearest cell.

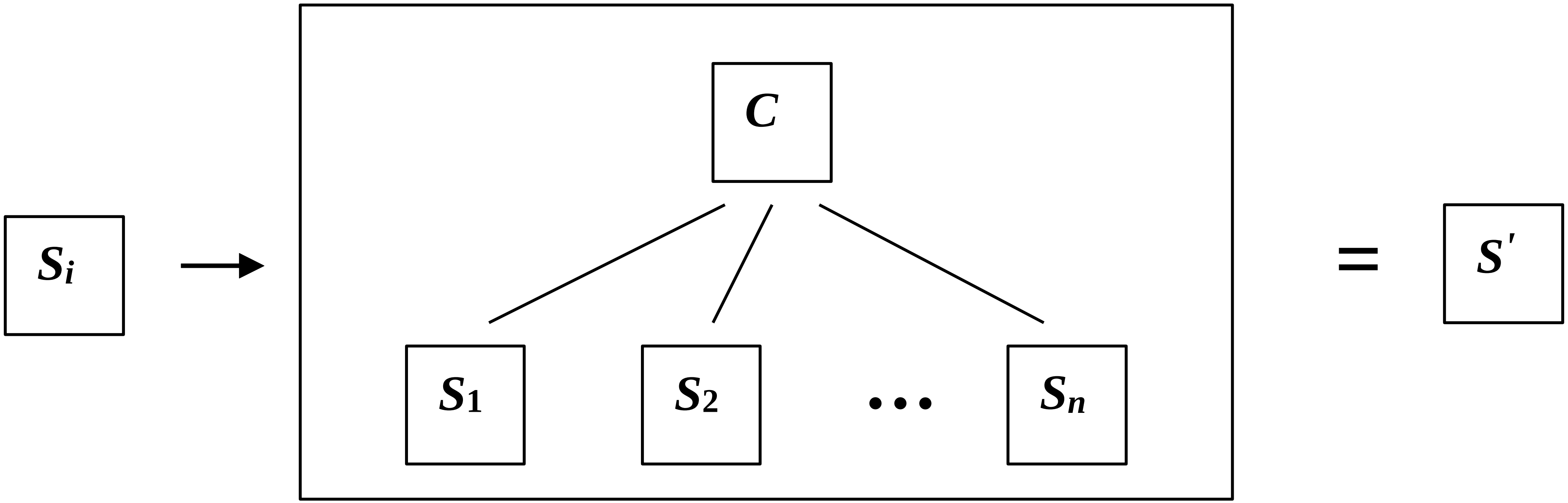
Model of autonomous agents with basic needs. Agent actions

Exploration of the world. If the exploration need of the agent becomes the leading one, then the agent moves to one of the nearest 4 free cells in a random direction.

Resource consumption per action. After performing any action, the agent's resource decreases by ΔL.

The death of an agent. The agent dies if it is eaten by a predator or if its resource is less than 0.

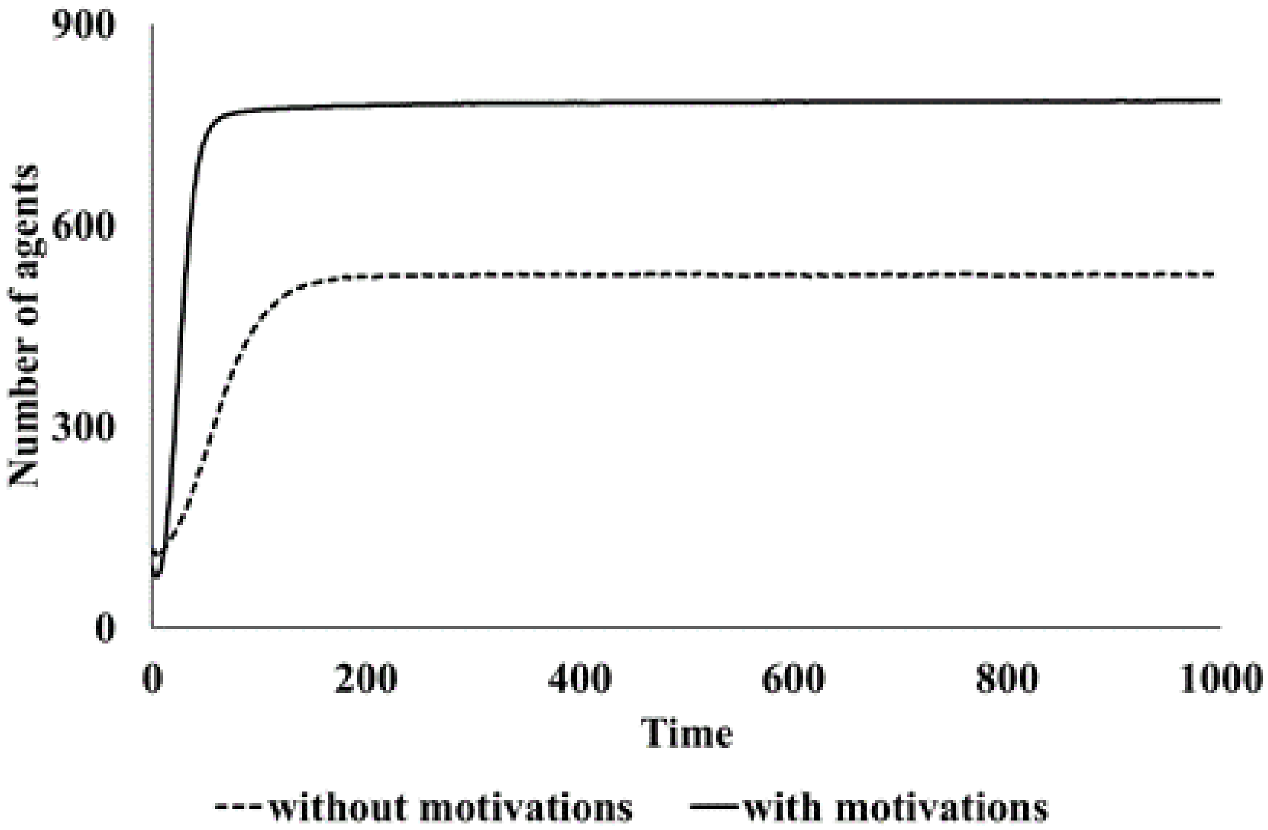
Model of autonomous agents with basic needs. The metasystem transition



Subsystems S_i correspond to needs.

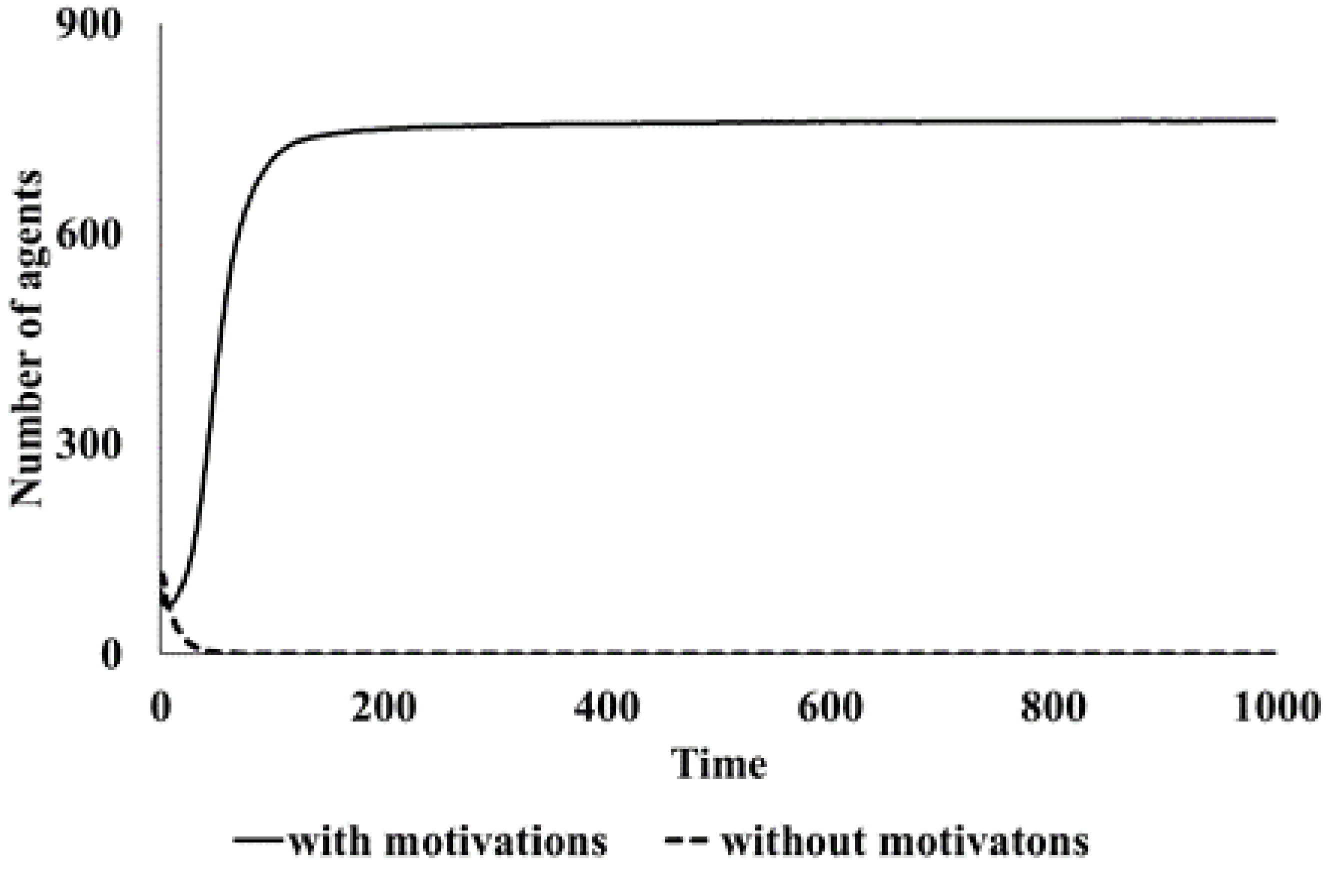
Control system C corresponds to mechanism of switching of leading motivations.

Model of autonomous agents with basic needs. Results of simulation



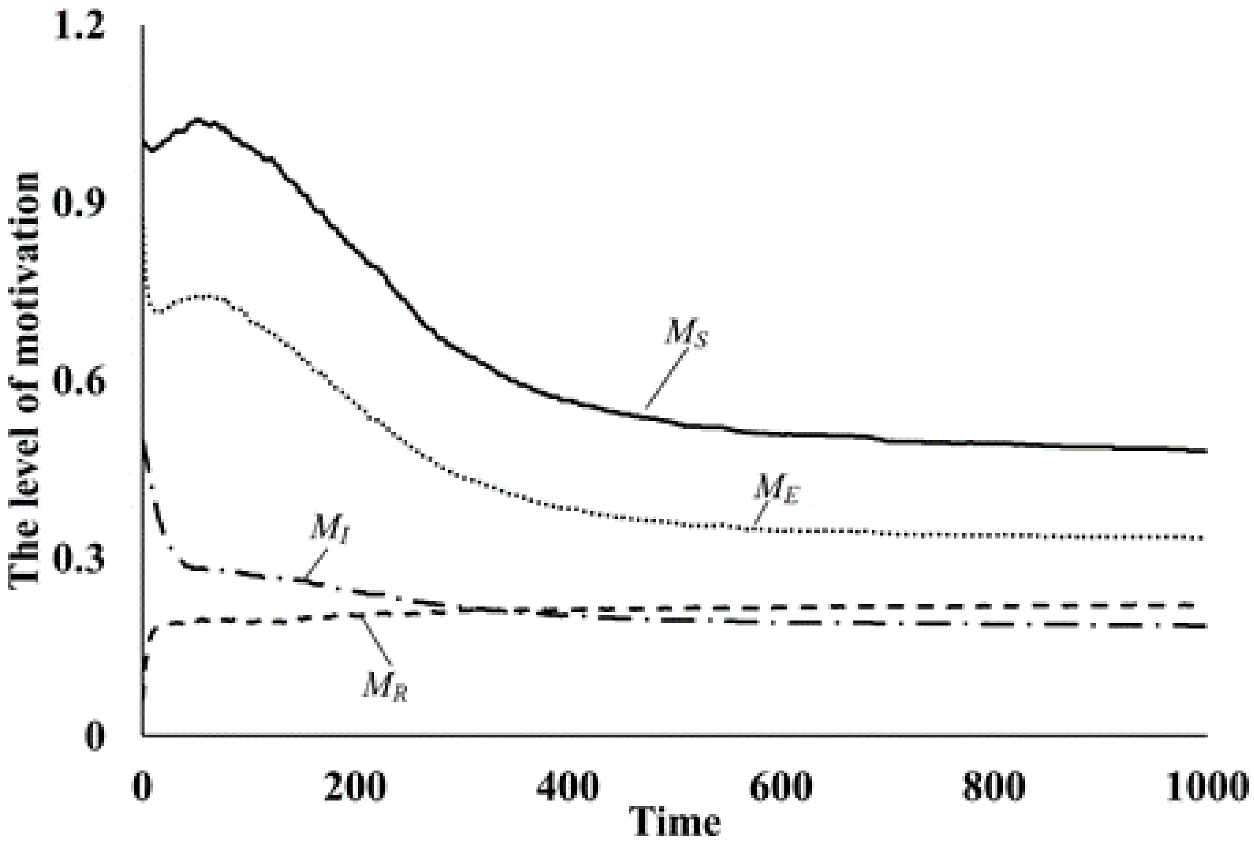
Time dependence of number of agents in the world at sufficiently large amount of food. Number of cells with food is N_F = 800. Without motivation means that a leading motivation is chosen randomly.

Model of autonomous agents with basic needs. Results of simulation



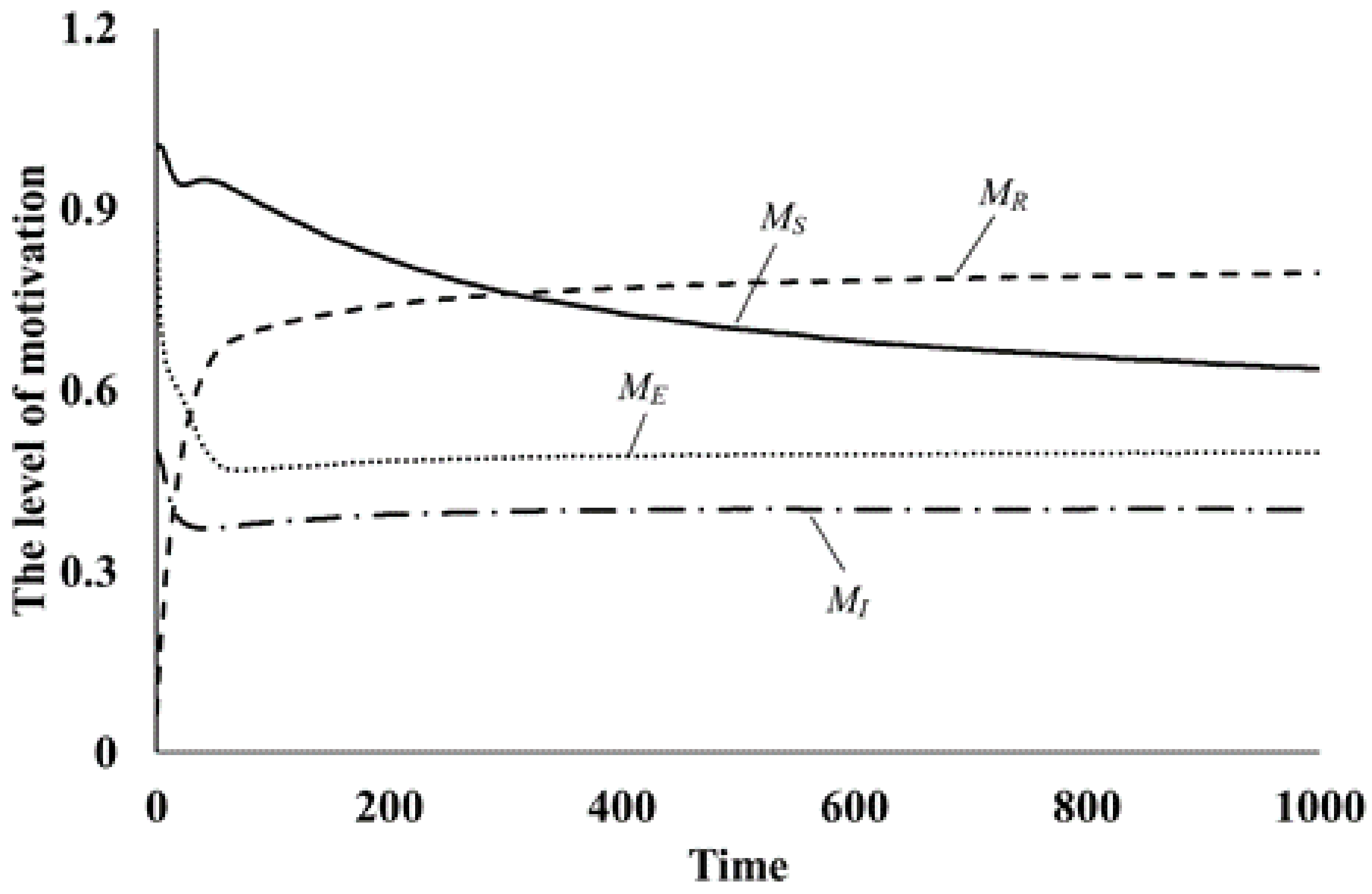
Time dependence of number of agents in the world at small amount of food, Number of cells with food is N_F = 400. The population without motivation dies.

Model of autonomous agents with basic needs. Results of simulation



Time dependence of average motivation values in the world at sufficiently large amount of food. Number of cells with food is N_F = 800. Security is important.

Model of autonomous agents with basic needs. Results of simulation



Time dependence of average motivation values in the world at small amount of food. Number of cells with food is N_F = 300. Reproduction is important.

Model of autonomous agents with basic needs. Summary

The considered model characterizes behavior of population of agents that have natural needs and motivations. Of course, the model is rather simple. In future, it is interesting to analyze cognitive agents that have internal models of the world.

Towards modeling of cognitive evolution

We can underline the important role of internal models of biological organism. Using these models, organisms can learn the regularities of the external environment. These models can be considered as precursors of the models of nature formed in scientific cognition.

Approaches to modeling of cognitive evolution are characterized in the book:

Red’ko V.G. Modeling of Cognitive Evolution. Toward the Theory of Evolutionary Origin of Human Thinking. Moscow: KRASAND/URSS, 2018.