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Modeling of Cognitive Evolution

Vladimir G. Red'ko
Scientific Research Institute for System Analysis, Russian Academy of Sciences,
Nakhimovskiy Prospect, 36, bld.1. Moscow,117218, Russia,
vgredko@gmail.com, https://www.niisi.ru/iont/staff/rvg/index_eng.php

***Abstract*— The report describes a new scientific area of investigation, namely, modeling of cognitive evolution. Cognitive evolution is the evolution of cognitive abilities of biological organisms. The important result of cognitive evolution is human thinking, which is used in the scientific cognition of nature. Modeling of cognitive evolution is the study of cognitive evolution by means of the mathematical and computer models of cognitive abilities of living organisms of different evolutionary levels.**

Underlying problems, backgrounds, and the sketch program for modeling of cognitive evolution are characterized. The initial models, which were developed in accordance with the sketch program, are briefly described.

Possible applications of models of autonomous agents are discussed.

Keywords—modeling of cognitive evolution, autonomous cognitive agents; biologically inspired models

I. INTRODUCTION

The current work describes approaches to modeling of cognitive evolution [1].

Why is the modeling of cognitive evolution interesting and important?

Firstly, because this direction of investigation is directly connected with the following fundamental scientific problems:

– How did human thinking emerge in the process of biological evolution?

– Why is human formal thinking applicable to the cognition of nature? Why are the human formal logical inferences (which are used in mathematical proofs) applicable to the cognition of the natural phenomena?

Secondly, there are serious backgrounds for modeling of cognitive evolution: 1) models of autonomous cognitive agents and 2) biological studies of the cognitive abilities of animals.

Thirdly, modeling of cognitive evolution in the future should have many interdisciplinary connections:

– with the foundations of science, foundations of mathematics,

– with the epistemology,

– with cognitive science,

– with biological studies,

– with the scientific foundations of artificial intelligence.

Finally, modeling of cognitive evolution is aimed at the serious development of the scientific worldview. Using the evolutionary approach, it is possible to investigate the cognitive abilities of biological organisms of different evolutionary levels, to analyze how and why these abilities arose, to seek to uncover the reasons for their emergence. The general approaches to modeling of cognitive evolution are described in the book [1].

II. RELATED WORKS

There are two directions of investigations that are related to modeling of cognitive evolution.

The first direction is biological investigations of cognitive abilities of animals of different evolutionary levels. This direction of investigations includes: 1) studies of simple forms of animal mental inferences [2, 3], 2) analysis of planning of future behavior on the basis of previous learning [4] (see also a model of plan formation in Section IV B below), 3) comparison of cognitive abilities of birds and babies [5], 4) analysis of the evolutionary origins of the human mind [6]. Certain intelligent features of animals were analyzed, see, for example [7].

The second direction of related investigations contains several areas of research of biologically inspired cognitive systems that can be used in artificial intelligence. These areas are 1) Artificial Life, 2) Adaptive Behavior, 3) Cognitive Architectures, in particular, Biologically Inspired Cognitive Architectures, Autonomous Agents. There are international societies, journals, conferences corresponding to these areas. Note that models of autonomous cognitive agents can be directly used during modeling of cognitive evolution. We present here only several examples of these investigations.

Cognitive architectures characterize structures and principles of functioning of cognitive systems that can be used in artificial intelligence [8]. An example of cognitive architectures is SOAR (from State, Operator, And Result) [9]. SOAR is based on symbolic representations of rather general cognitive architecture. The SOAR system was created by specialists in the field of artificial intelligence after the attempt to construct unified theories of cognition

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[10]. Biologically inspired cognitive architectures are intensively investigated in recent years [11].

The good review of investigations on autonomous cognitive agents is presented in the paper [12]. The work [13] analyzed different approaches to the development of autonomous cognitive agents and biologically inspired cognitive architectures.

III. Sketch Program for Modeling of Cognitive Evolution

Basing on related works on autonomous agents and biological experiments on animal cognitive abilities, it is possible to propose the sketch program for modeling of cognitive evolution. Future investigations of cognitive evolution can include the following steps.

A) Modeling of adaptive behavior of autonomous agents that have several natural needs: food, reproduction, safety. Such modeling can be simulations of the natural behavior of simple modeled organisms.

B) Investigation of the transition from information processing in the nervous system of animals to the level of generalized "notions". Such a transition can be considered as the emergence of "notions" in animal minds. Generalized notions can be considered as the mental analogs of our words. Animals do not say such "words", but actually use them. Usage of notions leads to the essential reduction of both the needed memory and the time of information processing, therefore this usage should be evolutionarily advantageous.

C) Investigations of processes of generating the causal relations in animal memory. Memorizing of relationships between the cause and the effect and the adequate use of these relationships is one of the key properties of active cognition of regularities of the external world by animals. This ability allows to predict events in the external world and to use adequately these predictions.

D) Investigations of "logic conclusions" in animal minds. Actually, at the classical conditioning, animals do the "logical conclusion": "If the conditioned stimulus takes place and the conditioned stimulus leads to the unconditioned one, then the appearance of unconditioned stimulus is expected". Such conclusion is similar to simple logical conclusions at mathematical deductions "If there is the statement A and the statement B is the consequence of A, then there is the statement B". It is important to understand, how do systems of these conclusions operate, to what extent this animal "logic" is similar to human logic.

E) Study of communications, analysis of the emergence of language. Our thinking is closely connected with language. Therefore, it is reasonable to analyze the evolutionary emergence of "language" of animals and the development of communications and language during the evolutionary origin of logic, thinking, and intelligence.

These steps outline the range of research, from the modeling of the simplest forms of behavior to logical rules of deductive inferences that are used in mathematics.

IV. Initial Models of Cognitive Evolution

We began to create and investigate models of cognitive evolution. This section outlines briefly these models. Initially, we only mention several models and then we will characterize the model of plan formation by New Caledonian crows and the model of the feeling of causality. Some of these models are described in details in the book [1].

A. Several Initial Models

The following models have been developed and analyzed.

Model of autonomous agents that have several natural needs. This model corresponds to step A of the sketch program.

Model of formation of generalized notions by autonomous agents. This model corresponds to step B of the sketch program.

Models of fish exploratory behavior in mazes.

B. Model of Plan Formation by New Caledonian Crows

The current section outlines the model of a process of plan formation by New Caledonian (NC) crows. Our model is based on the biological experiment on NC crows [4]. In that work, NC crows were preliminarily trained to execute particular elements of rather complex behavior. After the preliminary training, the crows had to solve a problem, the solution is the behavior that includes these particular elements. After solving the problem, the crow obtained the food.

We assume that each crow memorizes results of the preliminary training in the form of the prediction of the next situation (S_{next}) for the current situation and action ($S_{current}$ and $A_{current}$):

$$\{S_{current}, A_{current}\} \rightarrow S_{next} \,. \tag{1}$$

The main situations (S_i) and actions (A_i) are [4]:

S_1: the short stick is tied to the end of the string; the long stick is in the barred toolbox; the food is in the deep hole

S_2: the short stick is free; the long stick is in the barred toolbox; the food is in the deep hole

S_3: the long stick is free; the food is in the deep hole

S_4: the food is free

A_1: to pull up the string and to release the short stick tied to the end of the string

A_2: to extract the long stick from the barred toolbox by means of the short stick

A_3: to extract the food from the deep hole by means of the long stick

S_1 is the starting situation; S_4 is the goal situation.

Thus, the goal of crows was to reach the food. It was impossible (a) to extract the food from the deep hole by means of the short stick or by means of a beak and (b) to extract the long stick from the barred toolbox by means of a beak. Therefore, in order to reach the food, the crow had to execute the ordered chain of sequential actions $A_1 \rightarrow A_2 \rightarrow A_3$.

We developed two variants of the model of planning by NC crows:

1) Backward mental analysis of situations and actions from the goal situation S_4 to the starting situation S_1 [14].

2) Forward mental consideration from the starting situation S_1 to the goal situation S_4 [1].

In both variants of the model, we took into account that some predictions (see the expression (1)), which are needed to solve completely the problem of reaching the goal, were obtained during preliminary training and other predictions should be guessed by crows during planning.

Additionally, in the second variant of the model, we supposed that after finding the solution of the problem, the crow checks (via a testing backward mental consideration) the sequence of actions leading to the goal. Note that this process of the testing backward consideration is analogous to the reverse replay of behavioral sequences in hippocampal place cells [15, 16].

In both variants of the model, the crows form the knowledge base that characterizes situations, actions, and results of actions (Table 1).

TABLE I. KNOWLEDGE BASE

Current situation, $S_{current}$	Current action, $A_{current}$	Next situation, S_{next}	$\rho(S_{current},S_4)$	$\rho(S_{next},S_4)$
S_1	A_1	S_2	3	2
S_2	A_2	S_3	2	1
S_3	A_3	S_4	1	0

$\rho(S_{current},S_4)/\rho(S_{next},S_4)$ in this table is the distance between the situation $S_{current}/S_{next}$ and the goal situation S_4. This distance is equal to the number of actions that are needed to reach the goal from the considered situation.

Three first columns of this table represent the plan of the behavior that is aimed at reaching the goal situation S_4.

The described schemes of plan formation were implemented into the computer program. The results of computer simulation were in qualitative agreement with the biological experiment.

Note that, according to Table 1, for any situation, there is only one action leading to a decrease of the distance ρ. However, in the general case, there can be several possible actions, any of which can reduce the distance ρ. The knowledge base should include all these actions. Such knowledge base with several possible useful actions for the example of the searching behavior of fishes was considered in the work [1]. In such a case, the useful action can be selected probabilistically.

Thus, the biologically inspired models of plan formation have been created and analyzed [1, 14]. The plan formation is based on predictions that are obtained during preliminary learning or during guessing some predictions. These models correspond to step *C* of the sketch program.

C. Model of Feeling of Causality

The important ability that is used at scientific cognition is feeling of causality. The current section analyzes a formal model of the internal feeling of causality in autonomous agents. The model has the most general form to characterize the main properties of the concept of causality. The model is analyzed for the example of goal-directed behavior by means of computer simulation.

We assume that there is an agent that interacts with the external environment. There are N_S possible situations. One of these situations is the goal situation S_G, we believe that the agent receives a reward in this situation. Time is discrete: t = 1, 2, ... There are N_A possible actions of the agent. Each time moment, the agent executes one action. The relationships between the current situations, the actions of the agent, and the result of the actions are clearly determined and fixed. These relationships between the current situation $S_{current}$, the current action $A_{current}$, and the next situation S_{next} are characterized by the expression (1) that determines the causal relationship of the interaction of the agent with the external environment.

There are two types of agents: 1) an agent with the internal feeling of causality, 2) an agent without such a feeling.

The agent with the feeling of causality is self-learning in advance. Before the learning, the agent is in some starting situation S_S. During learning, the agent cognizes and uses causal relationships (1). It considers various situations, performs randomly various actions until finding the goal situation S_G. After this, the agent tries different situations and actions until it finds a pre-goal situation, from which it can move into the goal situation via one action. At this analysis, the agent memorizes causal relationships (1) and actions that lead to the goal situation. Then the agent continues the searching for situations and actions leading to the pre-goal situation. At the same time, it memorizes new causal relations of the form (1). The agent memorizes the number of actions that lead to the goal situation from the considered situation. A similar analysis and memorization of relationships occur until the agent reaches the starting situation S_S. As a result of this learning, the knowledge base of the agent is formed. The form of the knowledge base is shown in Table 1. Each row of the knowledge base characterizes a situation, an action, a result of the action, and the distance ρ between the considered situation and the goal situation. The distance ρ is equal to the number of actions that are needed to reach the goal.

After learning, the agent with the feeling of causality uses the knowledge base, that is, the agent performs actions that lead to a decrease of the distance between the considered situation and the goal situation. Thus, using the knowledge base, this agent reaches the goal situation S_G rather quickly.

An agent that does not have a feeling of causality can also find the goal situation by performing various actions, randomly selecting them from the possible ones. In this case, situations are changed in accordance with the rules (1). However, the agent without a feeling of causality does not know and does not memorize these rules. The agent simply conducts a random search.

The model was analyzed by means of computer simulation. Agents with the feeling of causality were preliminary self-learning; they formed knowledge bases (similar to the knowledge base shown in Table 1). Then these agents used the knowledge bases in the goal-directed behavior; they sought to reach the goal situation S_G at this behavior. The number of situations N_S and the number of possible actions N_A were varied. For definiteness, it was supposed that $N_A = N_S$. The time (the number of time moments) T_G, which is needed to reach the goal situation S_G, was determined. The number of time moments T_{LS} , which are used by agents during learning and searching for S_G, was 100000: T_{LS} = 100000. To obtain reliable data, the results were averaged over 10000 independent simulations. The error of the simulation results was about 1%. The dependence of the time T_G needed to find the goal situation S_G on the number of situations N_S for both types of agents is shown in Fig. 1.

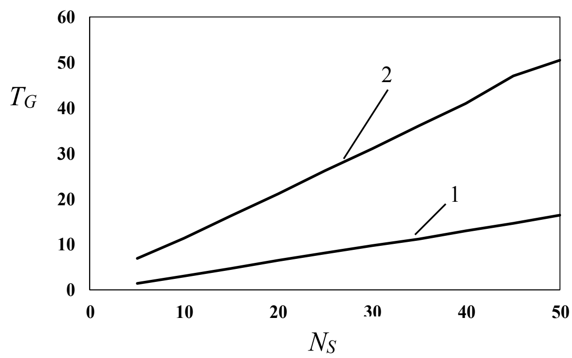

Figure 1. Dependence of the time T_G needed to find the goal situation S_G on the number of situations N_S. The curve 1 corresponds to agents with the feeling of causality. The curve 2 corresponds to agents without a feeling of causality. Results are averaged over 10000 independent calculations

Fig. 1 demonstrates that agents with the feeling of causality, which memorize the causal relations and use their knowledge, find the goal situation much faster than agents without a feeling of causality.

The described model also corresponds to step *C* of the sketch program.

V. Further Steps for Modeling of Cognitive Evolution

It should be noted that the considered models are based on autonomous agents (modeled animals). How can we move from these rather simple models of autonomous agents to more powerful models? How can we analyze the evolutionary roots of the human thinking that is used in the scientific cognition?

First, we can consider a hierarchical structure of predictions. The knowledge bases described above are simple. A hierarchical structure of predictions would be more profound.

Another important possibility that can be used is the introduction of the self-assessment of agent activity by the agent itself (see, for example, a discussion of this approach in the work [17]). Self-assessing their behavior, the agents can be trained without a teacher.

We can also consider approaches to modeling of an autonomous cognitive agent with certain scientific abilities [1]. The autonomous agent can try to cognize elementary laws of mechanics in the following manner. The agent observes movements and collisions of rigid bodies. Basing on these observations, the agent can cognize regularities of mechanical interactions. Using computer simulation, we can analyze, how the autonomous cognitive agent can discover the laws of mechanics.

VI. Elimination of Genes of Aggressiveness in the Evolving Population of Conflicting Agents and the Idea of the Project for the Nobel Peace Prize

Using models of autonomous agents, we can also consider some areas of applied researches. We will consider here the possibility of elimination of genes of aggressiveness in the evolving population of conflicting agents.

The computer model of the evolving population of autonomous agents, which can fight with each other, was proposed and investigated by Mikhail Burtsev [18]. The model considers the two-dimensional cellular world. The cells of the world contain agents and their food (Fig. 2). The portions of food are placed randomly in a part of the cells of the world. Time is discrete: t = 1,2,... In each time moment, the agent executes one of the following actions: 1) resting, 2) eating, 3) reduplicating itself, 4) moving forward, 5) turning to the left, 6) turning to the right, 7) hitting of the other agent in the forward cell (fighting with the other agent), 8) defending from the other agent.

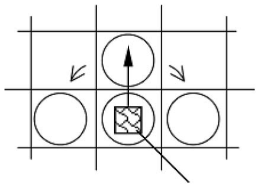

Figure 2. The agent in the two-dimensional cellular world. The agent has the direction "forward" (shown by the upward arrow). Agents can rest, eat food, divide themselves, move forward, turn to the left or right, and fight with other agents. Cells of the field of vision of the agent are shown by circles. The agent control system is the neural network that is evolutionarily optimizing

Each agent has the energy resource *R*, which is increased when the agent executes the action "eating" and there is the portion of food in the agent cell. The agent spends its resource at executing the other actions. The fighting between agents takes place as follows. If the first agent hits the second agent and the second agent does not execute the action "defending", then the first agent takes away some portion of the resource from the second agent. But if the second agent is defending itself, then the first agent only spends a significant portion of its resource.

The agent control system is the neural network, the inputs of the neural network are the sensory signals from the external and internal environment of the agent, the outputs of the network determine the actions of the agent. The inputs of the neural network are the sensors of the agent; the outputs of the neural network are the effectors of the agent.

The genotype of an agent determines the structure of the neural network and the weights of synaptic connections in the network. The agent-child inherits the neural network (modified by mutations) of the agent-parent. Synaptic weights of the neural network are modified at mutations. Additionally, sensors and effectors can be removed and restored via mutations.

The interesting phenomenon was observed in the model. At some computer simulations of evolutionary processes, surprising peaks in time dependences of population size *N* were observed (Fig. 3, the lower curve).

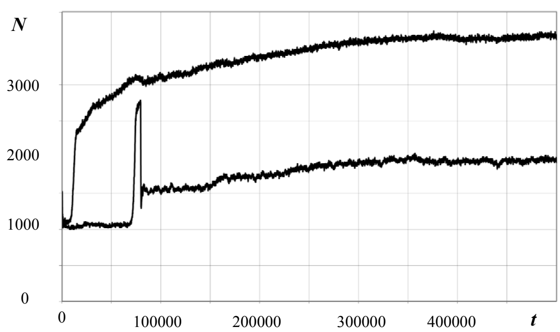

Figure 3. The time dependence of the population size *N*(*t*) in the full model (the lower curve) and after removing the fighting effectors from agent control systems (the upper curve)

In order to analyze this phenomenon, the fighting effectors were externally removed (in the computer program) from the agent control systems. In this case, the population size *N*(*t*) had significantly increased (Fig. 3, the upper curve). Thus, the observed peaks in the full model are due to the disappearance of the fighting effectors from agent control systems. This disappearance is a result of mutations during the evolutionary process. If the fighting effectors are removed from control systems of all agents of the population, then the "global pacifism" in the population takes place (the upper curve). Fig. 3 shows that in the case of such "global pacifism", the population size is approximately 2 times greater than for fighting agents. So, such agents do not fight each with others, instead, they use their energy resource for other useful actions. The fighting effectors can be considered as "genes of aggressiveness" of agents. The considered model demonstrates that genes of aggressiveness can be removed automatically in the process of evolutionary self-organization.

Thus, the genes of aggressiveness of modeled organisms can disappear during evolutionary processes. However, the considered processes are not too simple. The duration of peaks of the population size is small: the fighting effectors are restored via mutations and the population size is decreased (Fig. 3, the lower curve). The short duration of peaks is due to reverse mutations that restore the genes of aggressiveness, after this, the aggressive agents kill the peaceful agents.

We can apply this approach to socio-economic systems. In this case, we consider the evolution of countries analogously to the evolution of agents. Using such an approach, we can propose the idea of the project for the Nobel peace prize "Development of the scientific basis for global disarmament". Of course, the outlined simulation results characterize a very small step, which should be complemented by serious investigations. But this step is based on the concrete computer simulation that demonstrates the possibility of the development of the proposed project.

It should be noted that there was a very interesting development of the outlined model. The model of the evolutionary emergence of cooperation between agents was investigated in the work [19]. The results of the work [19] can be also used in the analysis of social systems in the human community.

Thus, based on models of the evolution of multi-agent systems, we can propose a project for developing of the scientific basis for the global disarmament.

VII. Conclusion

Thus, the approaches to modeling of cognitive evolution have been characterized. Modeling of cognitive evolution is directed to study the evolutionary roots of our human thinking, which is used at scientific cognition. The program of future investigations of cognitive evolution has been characterized. These investigations can use models of autonomous cognitive agents. The initial models that were developed in accordance with the considered program have been outlined. These models include: 1) the model of autonomous agents that form and use the generalized notions characterizing the external environment, 2) the biologically inspired models of plan formation of agent behavior, which is based on the predictions obtained at preliminary learning, 3) the model of the feeling of causality that is used by the autonomous agent.

The application possibility of models of autonomous agents has been considered. In particular, the model of evolutionary elimination of genes of aggressiveness has been described. The idea of the project "Development of the scientific basis for global disarmament" has been discussed.

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REFERENCES

[1] V. G. Red'ko, *Modeling of Cognitive Evolution. Toward the Theory of Evolutionary Origin of Human Thinking*. Moscow: KRASAND/URSS, 2018.

[2] R. Gruber, M. Schiestl, M. Boeckle, A. Frohnwieser, R. Miller, R. D. Gray, N. S. Clayton, and A. H. Taylor, "New Caledonian crows use mental representations to solve metatool problems," *Current Biology*, vol. 29, no. 4, pp. 686–692, 2019.

[3] S. A. Jelbert, R. Miller, M. Schiestl, M. Boeckle, L. G. Cheke, R. D. Gray, A. H. Taylor, and N. S. Clayton, "New Caledonian crows infer the weight of objects from observing their movements in a breeze," *Proceedings of the Royal Society B*, vol. B286, no. 1894, 20182332, 2019.

[4] A. H. Taylor, D. Elliffe, G. R. Hunt, and R. D. Gray, "Complex cognition and behavioural innovation in New Caledonian crows," *Proceedings of the Royal Society B*, vol. B277, no. 1694, pp. 2637–2643, 2010.

[5] A. H. Taylor, L. G. Cheke, A. Waismeyer, A. N. Meltzoff, R. Miller, A. Gopnik, N. S. Clayton, and R. D. Gray, "Of babies and birds: complex tool behaviours are not sufficient for the evolution of the ability to create a novel causal intervention," *Proceedings of the Royal Society B*, vol. B281, no. 1787, 20140837, 2014.

[6] A. G. Rosati, "Chimpanzee cognition and the roots of the human mind," in: *Chimpanzees and Human Evolution*, M. Muller, R. Wrangham, and D. Pilbeam, Eds. Cambridge: The Belknap Press of Harvard University Press, 2017, pp. 703–745.

[7] Zh. Reznikova. *Animal Intelligence: From Individual to Social Cognition*. Cambridge: Cambridge University Press, 2007.

[8] P. Langley, J. E. Laird, and S. Rogers, "Cognitive architectures: Research issues and challenges," *Cognitive Systems Research*, vol. 10, no. 2, pp. 141–160, 2009.

[9] L. E. Laird, *The Soar Cognitive Architecture*. Cambridge et al.: The MIT Press, 2012.

[10] A. Newel, *Unified Theories of Cognition*. Cambridge, MA: Harvard University Press, 1990.

[11] A. V. Samsonovich, "On a roadmap for the BICA Challenge," *Biologically Inspired Cognitive Architectures*, vol. 1, pp. 100–107, 2012.

[12] D. Vernon, G. Metta, and G. Sandini, "A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents," *IEEE Transactions on Evolutionary Computation (special issue on Autonomous Mental Development)*, vol. 11, no. 2, pp. 151–180, 2007.

[13] D. Vernon, C. von Hofsten, and L. Fadiga, "Desiderata for developmental cognitive architectures," *Biologically Inspired Cognitive Architectures*, vol. 18, pp. 116–127, 2016.

[14] V. G. Red'ko and V. A. Nepomnyashchikh, "Model of plan formation by New Caledonian crows," *Procedia Computer Science*, vol. 71, pp. 248–253, 2015. See also: https://www.sciencedirect.com/science/article/pii/S1877050915036820

[15] D. J. Foster, A. Matthew, and M. A. Wilson, "Reverse replay of behavioural sequences in hippocampal place cells during the awake state," *Nature*, vol. 440, no. 7084, pp. 680–683, 2006.

[16] K. Diba and G. Buzsaki, "Forward and reverse hippocampal place-cell sequences during ripples," *Nature Neuroscience*, vol. 10, no. 10, pp. 1241–1242, 2007.

[17] C. Finn and S. Levine, "Deep visual foresight for planning robot motion," arXiv:1610.00696: https://arxiv.org/abs/1610.00696

[18] M. S. Burtsev, "Model of evolutionary emergence of goal-directed adaptive behavior. 2. Investigation of development of hierarchy of goals," *Preprint of M.V. Keldysh Institute of Applied Mathematics*, Moscow, no. 69, 2002 (in Russian).

[19] M. Burtsev and P. Turchin, "Evolution of cooperative strategies from first principles," *Nature*, vol. 440, no. 7087, pp. 1041–1044, 2006.