

# Models of Autonomous Cognitive Agents

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**Abstract** The lecture describes current models of autonomous cognitive agents. The study of these models can be considered as the method of investigations of biologically inspired cognitive architectures (BICA). The main attention is paid to the models that are used at studying of cognitive evolution. Several examples of such models are outlined. Schemes of new models are proposed.

**Keywords** Models of autonomous cognitive agents • Modeling animal behavior • Evolutionary origin of human cognition

## 1 Introduction

One of the main methods of BICA investigations is the study of models of autonomous cognitive agents. We consider an autonomous agent as a modeled organism. The review [1] characterizes early researches of cognitive agents. Our approach is in close relation with investigations of cognitive evolution [2, 3]. The current lecture describes shortly the following models:

- the computer model of adaptive behavior of autonomous agents that have natural needs: food, safety, and reproduction [4];
- the model of formation of heuristics and generalized notions by the self-learning agent [5];

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- the models of agent movement in mazes, accumulation of knowledge, and formation of predictions [6];
- the model of plan formation of rather complex behavior [7].

In addition, we propose schemes of new models of autonomous cognitive agents that could do scientific discoveries [8].

## 2 Examples of Models of Cognitive Agents

### 2.1 *Model of Autonomous Agents with Several Natural Needs*

We believe that an agent has the needs of food, safety, and reproduction. We consider the population of agents. Each agent has the internal resource  $R(t)$ . The time  $t$  is discrete. Each agent is placed in a certain cell; there is a predator in the same cell. The predator activity varies periodically: after every  $T_p$  time moments, the active predator becomes inactive; the inactive predator becomes active. The active predator can reduce essentially the resource  $R$  of the agent that is in the predator cell.

There is the hierarchy of needs: the need of food has highest priority, the need of reproduction has the lowest priority.

Satisfaction of agent needs is regulated by means of three factors  $F_F$ ,  $F_S$ ,  $F_R$ , related to needs of food ( $F_F$ ), safety ( $F_S$ ), and reproduction ( $F_R$ ). We believe that there is a threshold for each factor ( $T_F$ ,  $T_S$ ,  $T_R$ ). If a certain factor is greater than the corresponding threshold, then the related need is satisfied. The agent has the leading need, which has the highest priority among unsatisfied needs.

The agent control system is a set of rules:  $S_k \rightarrow A_k$ , where  $S_k$  is the situation,  $A_k$  is the action,  $k$  is the rule index. Each rule has its own weight  $W_k$ . The agent rule weights  $W_k$  are adjusted by means of the reinforcement learning [9]. The change of the factor of the leading need is the reward of the agent. The agent prefers the actions that correspond to large rule weights  $W_k$ . The situation vector  $S_k$  characterizes (1) the predator activity in the agent cell, (2) the previous agent action, (3) the leading need of the agent. The agent can execute the following actions: (1) searching for food, (2) to eat the food, (3) preparation for reproduction, (4) reproduction, (5) to do defense action, (6) to do nothing (to rest).

At eating food, the agent increases its resource  $R$ . At reproduction, the agent transmits an essential part of its resource  $R$  to its descendant. The agent-child inherits the rule weights  $W_k$  of the parent with small variations. If the agent executes the action “defense”, it is protected from the active predator that is in the agent cell, whereas, the active predator reduces essentially the resource of the non-defensive agent.

The computer simulation demonstrates the cyclical behavior of agents. During the cycle, the agent firstly accumulates the internal resource (by eating the food),

then the agent's actions are aimed at maximizing the safety and maintaining the level of internal resource, and when both needs (food and safety needs) are satisfied, the agent replicates (the need of reproduction is satisfied too).

Thus, the behavior of autonomous agents that have several natural needs has been analyzed. The model demonstrates the formation of cycles of behavior; the needs of food, safety, and reproduction are consecutively satisfied in these cycles.

## 2.2 *Model of Formation of Heuristics and Generalized Notions by Self-learning Agent*

One of the most important cognitive properties of living organisms is the formation of generalized notions. Using notions leads to a reduction in the required memory and the processing time. However, how do the notions emerge? Can we imagine the processes of formation of notions by means of computer simulation? We outline a computer model in which the autonomous agent alone produces generalizations and forms notions.

The model describes behavior of the autonomous agent in the two-dimensional cellular world. The control system of the agent is a set of rules:  $S_k \rightarrow A_k$ , where  $S_k$  is the situation,  $A_k$  is the action,  $k$  is the index of the rule. Each rule has its own weight  $W_k$ . The vector  $S_k$  characterizes presence or absence of food in cells in the "field of vision" of the agent. The field of vision includes four cells: the cell, in which the agent is, the cell ahead of the agent and the two cells to right and left from the agent. The agent executes one of the following five actions: eating food, moving forward, turning to right or left, to rest. Portions of food are randomly placed into a half of the cells of the cellular world. The agent resource  $R$  increases at eating food.

Rule weights  $W_k$  are modified by means of the reinforcement learning [9]. Changes of the agent resource  $R$  are rewards at this learning. The reinforcement learning increases the weights of the rules, the use of which leads to an increase of the agent resource. The agent prefers the actions corresponding to large rule weights  $W_k$ .

The computer simulation demonstrates that the self-learning agent itself generates the following heuristics. The agent executes the action *eating food*, if there is food in the cell containing the agent (irrespective of presence of food in the other cells of the field of vision of the agent). The agent executes the action *moving forward*, if there is no food in the agent cell, and there is food in the ahead cell. The agent executes the action *turning to right or left*, if there is no food in the agent cell and in the forward cell, but there is food in the right or left cell from the agent. The frequency of the action *to rest* is negligible small.

In addition, the computer program included the averaging procedure. Namely, the average number of executions of certain actions for a given situation  $S$  was calculated. The averaging procedure results in creation of the following agent notions: *there is food in my cell*, *there is food in the forward cell*, and *there is food*

*in the right or left cell.* Therefore, the agent itself is able to generate autonomously the notions, characterizing the sensory information.

### 2.3 Models of Fish Exploratory Behavior in Mazes

We designed and analyzed models of cognitive behavior of fish in the course of maze exploration. The models are inspired by the biological experiment on zebrafish, *Danio rerio*, in mazes [6]. Three types of models are designed and investigated. The model 1 describes how the fish acquires knowledge about arms of the maze. The model 2 characterizes fish's predictions of the next situation for the current situation and action. The model 3 is the hypothetical model of plan formation in a rather complex maze.

The model 1 assumes that the agent (modeled fish) has a certain knowledge  $K_i$  about each arm. When the agent visits  $i$ -th arm, the value  $K_i$  becomes equal to certain maximal value. Additionally, all values  $K_i$  slightly decrease with time.

The model 2 characterizes assurance of agent predictions. Namely, for the given initial situation  $S_i$  (each situation corresponds to a particular arm) and the action  $A_i$  (moving forward, turning to left or right) the assurance of the prediction of the next situation  $S_{i+1}$  is characterized by the value  $A_S$ . The values of assurances  $A_S$  are adjusted as follows. At the time step  $t + 1$ , the agent checks the prediction that it has made at the time step  $t$ . If the prediction of the next situation is correct, then the assurance of this prediction increases; if the prediction is wrong, then the assurance of this prediction decreases.

The model 3 assumes that after certain period of maze exploration, the fish is able to form some generalized notions that characterize the essential places (situations) in rather complex maze. The agent has knowledges about situations and reliable predictions of results of possible actions. The model 3 describes the process of forming the plan of movement to the goal situation, which was not visited for a long time (such situation has the minimal value of knowledge  $K_i$ ). The agent creates a plan of movement from some starting situation to the goal situation.

The agent creates this plan as follows. Using the table of reliable predictions, the agent begins to analyze such situations and actions that result in the goal situation. Then the agent analyzes situations and actions that result in the pre-goal situations, and so on. Thus, *the agent begins from the goal situation* and analyzes consecutively possible ways to reach this situation. The agent also takes into account the distance from the considered situation  $S_i$  to the goal situation; this distance is the number of actions needed to reach the goal situation from the situation  $S_i$ .

Then the agent creates a simple *knowledge database* that is a table. Each row of this table includes the following information: (1) the given situation, (2) the action that reduces the distance between the given situation and the goal situation, (3) the next situation that is the result of the action and (4) distances between the given/next situations and the goal situation.

Finally, using this knowledge database, the agent forms a plan of movement from *the starting situation to the goal situation*. In this process of plan formation, the agent consecutively selects actions, which reduce the distance between the considered situation and the goal situation.

Thus, the models of accumulation of knowledge, prediction of results of actions, and planning of movement towards the goal situation have been developed and investigated.

The similar model of planning by New Caledonian crows is outlined below.

## 2.4 Model of Plan Formation by New Caledonian Crows

The model is based on the biological experiment on New Caledonian (NC) crows [10]. In that work, NC crows were preliminary trained to execute particular elements of a rather complex behavior. After the preliminary training, the crows should solve the three-stage problem that includes the following particular elements:

1. to pull up a short stick tied to the end of a string and to release this stick,
2. to extract a long stick from a barred toolbox by means of the short stick, and
3. to extract the food from a deep hole by means of the long stick.

It was impossible (a) to extract the food from the deep hole by means of the short stick and the bill, and (b) to extract the long stick from the barred toolbox by means of the bill. Therefore, in order to reach the food, the crow had to execute the ordered chain of sequential actions  $1 \rightarrow 2 \rightarrow 3$ .

Similar to the model of plan formation by fish, the agents (modeled crows) use the predictions of results of particular actions to create a *knowledge database*. The predictions were obtained during the preliminary training. The agent knowledge database characterizes situations, actions, results of actions, and distances between considered situations and the goal situation. The agent uses this knowledge database at forming the plan of solving the three-stage problem.

The process of plan formation was observed at computer simulation. See [7] for details.

The next section describes the scheme for future modeling of the autonomous agent-physicist (artificial scientist).

## 3 Proposal for Modeling of Autonomous Agent-Physicist

The proposal is based on the fact that *the most serious cognitive processes are processes of scientific cognition*. The background of this proposal is the report by Modest Vaintsvaig at the Russian conference “Neuroinformatics-2011” [11]; that report considers the models of an autonomous agent that tries to cognize elementary

laws of mechanics. The agent observes movements and collisions of rigid bodies. Basing on these observations, the agent can generalize its knowledge and cognize regularities of mechanical interactions. Therefore, modeling of such autonomous agents, we can try to analyze, how agents could discover (by themselves, without any human help) elementary laws of mechanics. Ultimately, such agents could discover three Newton's laws of mechanics. Thus, we can investigate autonomous agents that could come to the discovery of the laws of the nature.

Using our knowledge about scientific activity of Isaac Newton, we can represent intelligence of such investigating agent in some details. The agent should have an aspiration for the acquisition of the new knowledge and for the transforming of its knowledge into compact form. The agent should have the curiosity that directs the agent to ask the questions about the external world and to resolve these questions by executing the real physical experiments. The agent should take into account the interrelations between different kinds of the scientific knowledge. It is natural to assume that a certain society of cognizing agents exists; the agent of the society informs other agents about its scientific results. For example, considering Isaac Newton as a prototype of the main agent, we can consider also agents that are analogous to Galileo Galilei, Rene Descartes, Johannes Kepler, Gottfried Wilhelm Leibniz, Robert Hooke. The agent should have the self-consciousness, the emotional estimation of the results of its cognition activity and the desire to reach the highest results within the scientific society. Agents should have the tendency to get the clear, strong and compact knowledge, such as Newton's laws or Euclidean axioms.

## 4 Conclusion

Thus, simple models of autonomous cognitive agents have been described. These models characterize initial steps of modeling of cognitive evolution [3]. The scheme of new models of the autonomous agent-scientists, which could cognize the nature, has been proposed.

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