On logic and probability synthesis in AGI

(Task-driven approach as a logical-probabilistic AGI)

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Deep learning problems

1. Neural networks is a "black box" and does not provide an explanation for making this or that decision. This makes it impossible to use neural networks in such areas as medicine, finance, military applications, where the cost of error is too high, or an explanation of the solution is necessary for legal reasons. For example, a refusal by a neural network to issue a loan or to perform a dangerous surgical operation should be legally argued.
2. Secondly, they have a poor ability for generalization. For example, a neural network trained to recognize elephants and whales, in case of presentation of a whale, washed ashore, will see an elephant in it, and an elephant swimming in the surf will be recognized as a whale.
3. Neural networks memorize individual, often random details presented during training samples and make further decisions based on these details, and not on the basis of a full-fledged generalized subject. For example, replacing an image with noise can lead to recognition of a non-existent object, and replacing one pixel in the image to recognition of an object other than that presented.
4. Neural networks are not invariant with respect to permissible scale transformations — they can make different decisions after converting units of measure in data.

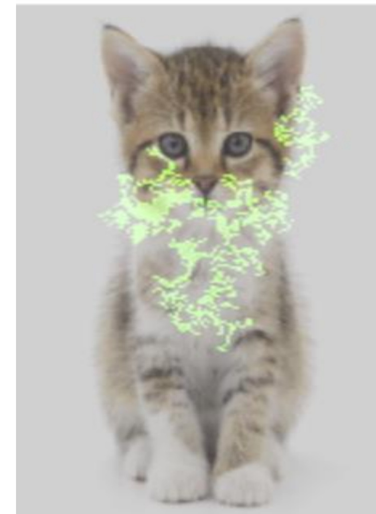
Alternative approaches to AI:
Explained AI (eXplainable XAI),
Agent approach,
AGI - Artificial General Intelligence,
Task-driven approach.

Approaches to Artificial Intelligence

eXplainable AI, XAI

A system of methods that explain how and why AI makes certain decisions.

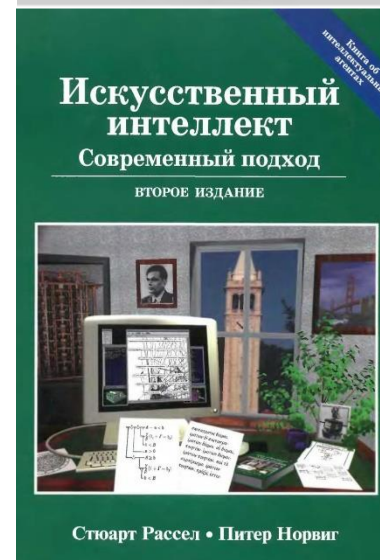
1. A method showing the contribution of each feature to the forecast obtained. In the explanation, the predicted class is shown along with the pixels that have the greatest impact on the forecast result.



2. The method of checking the influence of individual characteristics on the forecast. Verification of characteristics can provide an understanding of the forecast, but it cannot be generalized to the entire class. To get more generalized information, you can combine characteristics by subsets of the data or throughout the data set.

Agent approach:

Stuart Russell, Peter Norwig. Artificial Intelligence: A Modern Approach, 2003 by Pearson Education, 1409 pp.



Various tasks of artificial intelligence are considered as tasks of interaction of a “rational agent” with the environment.

The following agents are considered in this approach:

Simple reflective agents, world-based agents, goal-based agents, utility-based agents, learning agents.

Artificial General Intelligence

AGI - Artificial General Intelligence:

Deep learning has shown that human nature is not necessarily a condition for solving cognitive tasks of varying degrees of complexity.

According to the concept of "general artificial intelligence", it can potentially be possessed by either a person or a living organism with a highly developed central nervous system or an abstract robotic system.

> Ben Goertzel - "General intelligence is the ability to achieve complex goals in complex environments";
>
> Shane Legg and Marcus Hutter - "Intelligence is measured by the agent's ability to successfully operate in a wide range of environments";
>
> Pei Wang - "Intelligence is the ability of a system to adapt to its environment, working with insufficient knowledge and resources".

AGI: "the ability to solve cognitive tasks as a whole, acting purposefully, adapting to environmental conditions through training, minimizing risks and optimizing losses to achieve their goals."

Task-driven approach. The concept of task in the foundations of mathematics

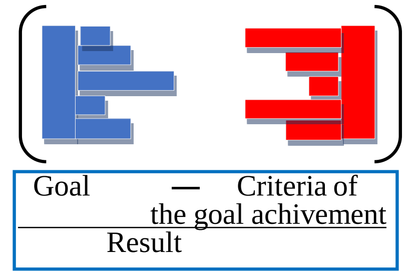
K.F. Samokhvalov: "I am thirsty" - what does it mean? Of course, there is no mistake in believing that the words "I am thirsty" simply mean this, where it is a certain state of consciousness that I am experiencing now and which I call thirst. But then a new question arises: how is the feeling of thirst (desire) related to actual drinking (satisfaction of desire)? How do I know that thirst can be satisfied with a drink? Does the thirst experience itself contain a consciousness of how this thirst can be satisfied? ... ***To know desire does not mean to know what is desired.***

A ***TASK*** is defined (comprehended) if and only if we have a criterion for solving the task – a criterion for checking whether the presented solution is really a solution to the task. In mathematical theories, such a criterion is usually considered to be a prof of the task solution. But this criterion is applied only when, within the framework of the formal system itself, we have both prof of the task solution and the ability to verify by means of the system itself that this proof is indeed a solution to the task. It was proved that only in "weak" formal systems (for which Gödel's theorem does not hold) can we determine by means of the formal system itself whether a text is a proof of task or not.

Yu.L.Ershov, K.F.Samokhvalov. Modern Philosophy of Mathematics, 2007.

As a result, Hilbert's program for substantiating mathematics is formulated differently: it is not necessary for all mathematics to prove its consistency — this is impossible and unnecessary. It is necessary to formulate and solve problems within the framework of weak formal systems.

The concept of “Task" in cognitive sciences



A generalization of the task concept is the concept of a **Goal**. A goal cannot be achieved without a criterion for its achievement, otherwise one can always assume that it has already been achieved. Therefore, the formulation of the goal should always be accompanied by a definition of the ***criteria of the goal achievement***. Reaching the goal gives a certain ***Result***.

The only physiological theory in which the Goal achievement and the Result obtaining is considered as the solution by the brain of the TASK to satisfy some need is the Theory of Functional Systems by P.K. Anokhin. This theory also reveals the physiological mechanisms for achieving the goal and solving the task by the brain.

“Perhaps one of the most dramatic moments in the history of the brain study as an integrative formation is the fixation of attention on the action itself, and not on its results ... we can assume that the result of the “grasping reflex” will not be grabbing as an action, but that ***totality afferent stimuli***, which corresponds to the signs of the "captured" subject” P.K. Anokhin. “***The totality of afferent stimuli***” is the criterion for achieving the goal in TFS.

Therefore, a prerequisite for the purposeful behavior of an intelligent agent is goal-setting, including a criterion for achieving the goal.

Evgenii E. Vityaev Purposefulness as a Principle of Brain Activity // Anticipation: Learning from the Past, (ed.) M. Nadin. Cognitive Systems Monographs, V.25, Chapter No.: 13. Springer, 2015, pp. 231-254.

The definition of the goal is paradoxical, since the criterion of the goal achievement does not contain any knowledge on how to achieve it. You can define a goal without determining how to achieve it. This paradox of the Goal is called the ***goal paradox***. As it follows from TFS, the brain, with purposeful behavior, constantly resolves the goal paradox, determining what, how and when to achieve the goal.

What are the goals in TFS? “Every need, even with a slight deviation of the vital function from the optimal level for metabolism (in which the need manifests itself), is immediately perceived by special receptor apparatuses” (forming the criterion for the goal achievement). Thus, the ***need is the goal*** that is set before the body.

Interaction of results and goals in the TFS is carried out in several ways: according to the “dominant principle”, “hierarchy of results” and “result models”.

Leading excitation ... determining a focused activity is motivational excitation, which is formed on the basis of the dominant need.

In relation to the dominant functional system, the remaining functional systems are arranged in a hierarchy according to the principle of “hierarchy of results”.

“So, a hungry rabbit is dominated by a functional system whose activity is aimed at finding food. At this time, other functional systems that determine … blood pressure, respiration, excretion, are aimed at better providing the dominant food-producing functional system“.

According to P.K. Anokhin, the central mechanisms of functional systems that provide purposeful behavior have the same architecture.

Afferent synthesis. The initial stage of a behavioral act of any complexity is afferent synthesis, which includes the synthesis of motivational excitation, memory, situational and triggering afferentation.

Motivational excitation. The goal setting is carried out by the arising need, which is transformed into motivational excitation.

Memory. Motivational excitation, on the basis of existing experience, “extracts from memory” the various sequences of actions that can lead to the goal.

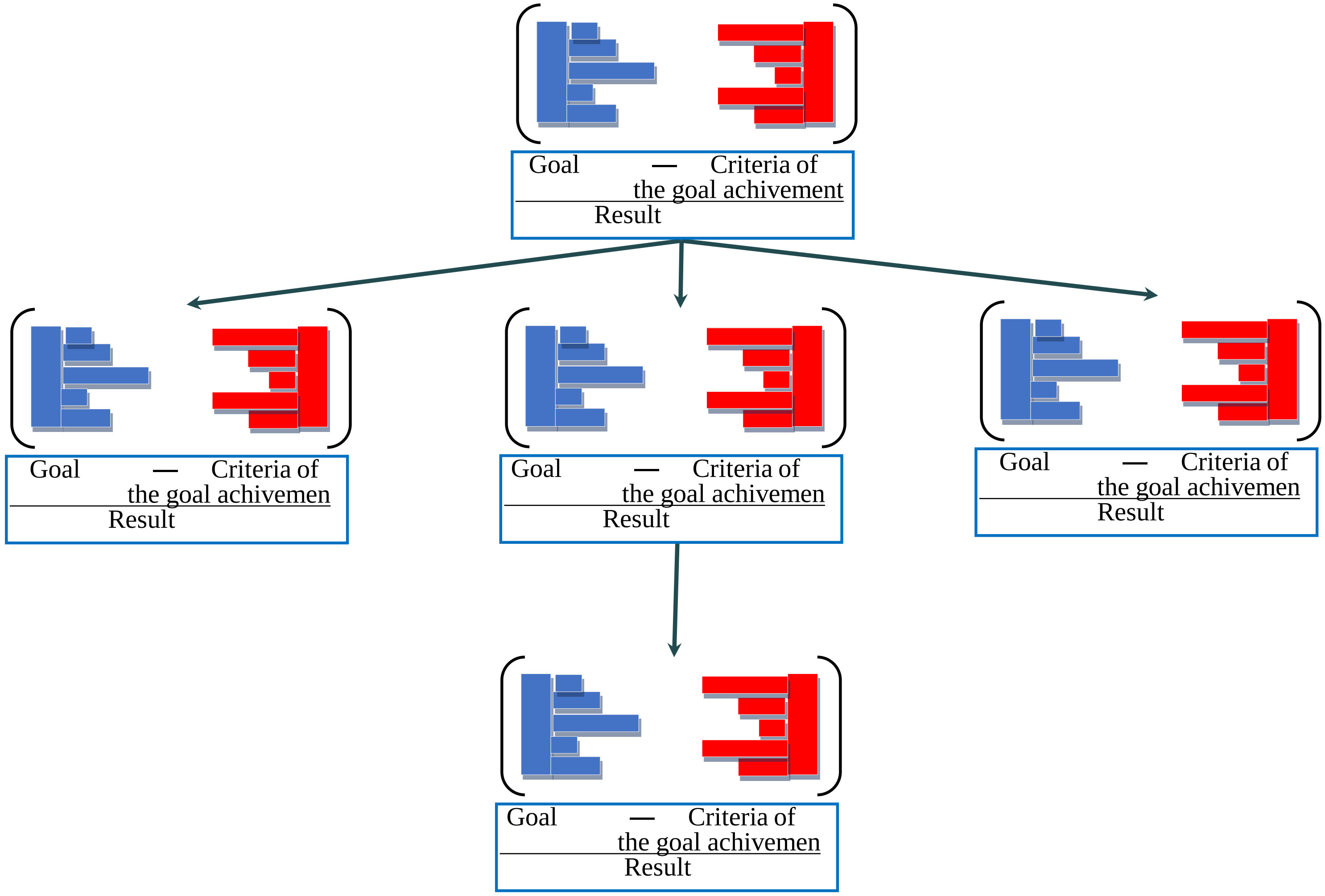
Furnishing afferentation. Only those methods of the goal achievement are extract from the memory that are applicable to the given situation.

Starting afferentation. Starting afferentation is also a situational afferentation, only related to the time and place of achieving the result. Starting afferentation answers the question of where and when the result can be achieved.

Thus, at the stage of afferent synthesis, the goal paradox is largely resolved and it is determine what, how and when to do to achieve the goal.

Decisions Making. At the afferent synthesis stage, several ways to achieve the goal can be extracted from the memory by motivational excitation. At the decision-making stage, one is selected that forms a ***particular action plan***.

A particular action plan also “draws” from memory the entire sequence of actions related to the Goal achievement, transforming the Goal into a ***particular goal*** that determines the way its achievement. It is called in the TFS “***supreme motivation***”



A particular action plan also “extracts from memory” the entire sequence and hierarchy of results that must be obtained when implementing an action plan. In TFS, this sequence and hierarchy is called the ***action result acceptor***, which is the ***criterion for achieving a particular goal.***

The acceptor of the action results represents the dominant need (Goal) of the body, transformed in the form of advancing brain excitation, into a kind of ***complex receptor*** of the future reinforcement.

Thus the acceptor of the action results is a ***criterion for achieving a particular goal***.

Reinforcement. **Sanctioning stage**. A purposeful behavioral act ... ends with the last authorizing stage. “At this stage, under the action of a stimulus that satisfies the leading need (reinforcement), the parameters of the achieved result cause reverse afferentation flows, which in all its properties correspond to the previously programmed properties of a reinforcing stimulus in the acceptor of the action results”.

Implemented particular action plan is reinforced and recorded in the memory.

Effector mechanisms of functional systems. “Evaluation of the achieved result of an action occurs with the help of an active ***orientation-research activity***, which occurs in all cases when the result of a perfect action does not correspond to the properties of the acceptor of the action results, that is, when a “mismatch ”occurs in behavioral activity. Thanks to the inclusion of such a reaction, afferent synthesis is immediately rebuilt, a new decision is made, a new particular action plan is being built. ”

In these way the brain solves TASKS to satisfy its needs.

What is TASK in general case

The task is defined only if there are:

- an indication of the subject domain to which the task belongs, knowledge about the subject domain, recorded in the form of its model, including a description of the signature and structure of the domain description language, a set of terms and concepts (ontology), initial data, facts and knowledge written in terms of ontology ;
- to which request, formulated in the task, to the subject domain should we get an answer;
- the criterion for satisfying the request is defined – it is determined in which case it can be considered that a response to the request has been received;
- in what context should we look for the answer to the request – what do we expect from the result and what are its consequences and what to do if the answer is negative.

In the task approach the purpose of AI is ***automation of task solving***, understanding the "automation" as formulation of the requests/solutions in terms of ***executable specifications***.

The ∑-definability of computations was chosen as the basic model of computations and verifying the truth of ∑-formulas on a constructive model M and its list superstructure HW(M).

Yu.L. Ershov, S.S. Goncharov & D.I. Sviridenko, "Semantic programming" // Information Processing 86: Proceedings of the IFIP 10th World Computer Congress, IFIP* Congress Series, vol. 10, Elsevier Science, Dublin, 1986, pp. 1093–1100.

Goncharov S.S., Sviridenko D.I. Theoretical aspects of Σ-programming. Lecture Notes in Computer Science, 1986, vol. 215, p. 169–179. (in Russian)

Goncharov S.S., Sviridenko D.I. Σ-programming / Transl., II. Ser., Am. Math. Soc., 1989, v.142, p.101–121.

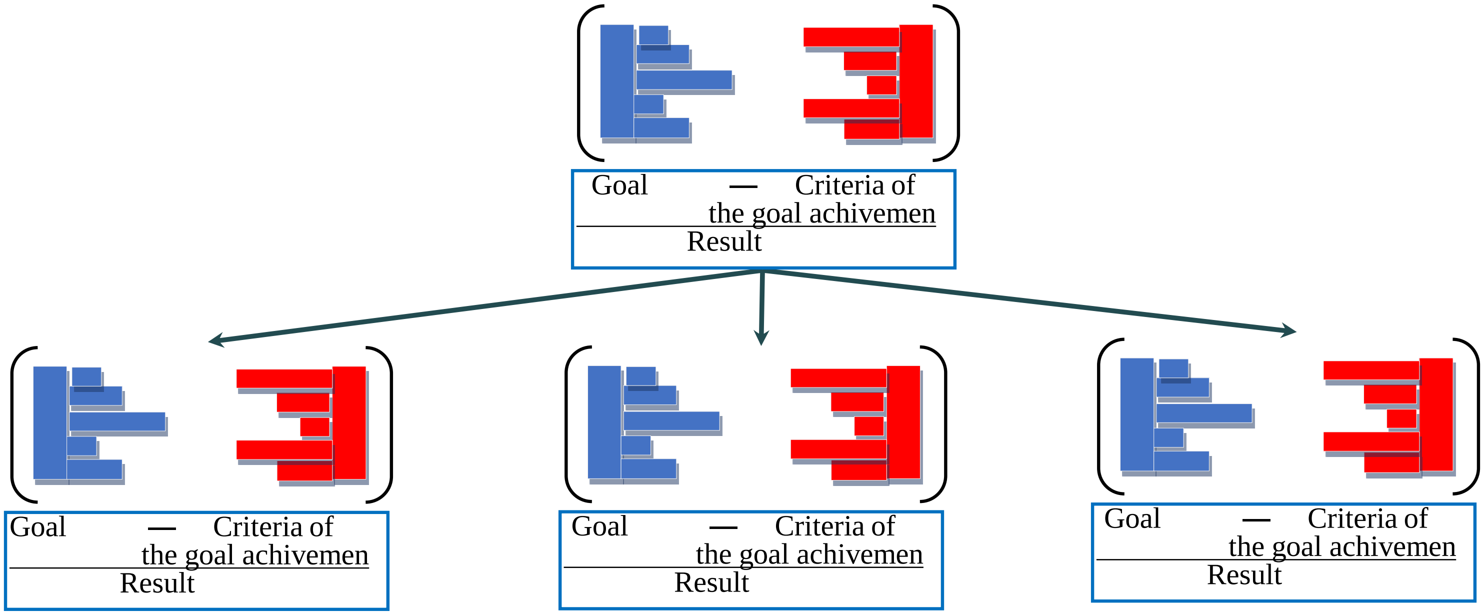
Goncharov S.S., Sviridenko D.I., Vityaev E.E. On the task approach in artificial intelligence // Siberian Journal of Philosophy. 2019.V. 17, No. 4. (in Russian)

Automation of tasks solving – semantic modeling

Tasks definition in semantic modeling.

- It is assumed that we have a multi-sorted constructive model M, together with its list superstructure HW (M), which is a kind of basic computer. The task ***Domain Model*** **(DM)** under consideration is formulated in the signature of the predicate calculus language of this basic constructive model M together with its list superstructure HW (M) as a set of ∑-definitions, i.e. ∑-formulas and ∑-terms of this language. Moreover, recursive schemes of ∑-definitions are allowed with some restrictions on the occurrence of definable predicates and terms in them.
- A ***query*** to a domain model is also defined as a ∑-formula, in which both signature constructions of the constructive model M and defined predicates and terms of the domain can be used.
- By the ***solution of the task*** is meant a set of constants that makes the ∑-query formula when its variables are designated by constants true on the domain model. This ***truth*** of the ∑-query formula is the ***criterion for the task solution***.
- There may be several solutions (sets of constants that make the ∑-query formula true) and then it is possible to choose the best solution, taking into account the context of the problem.

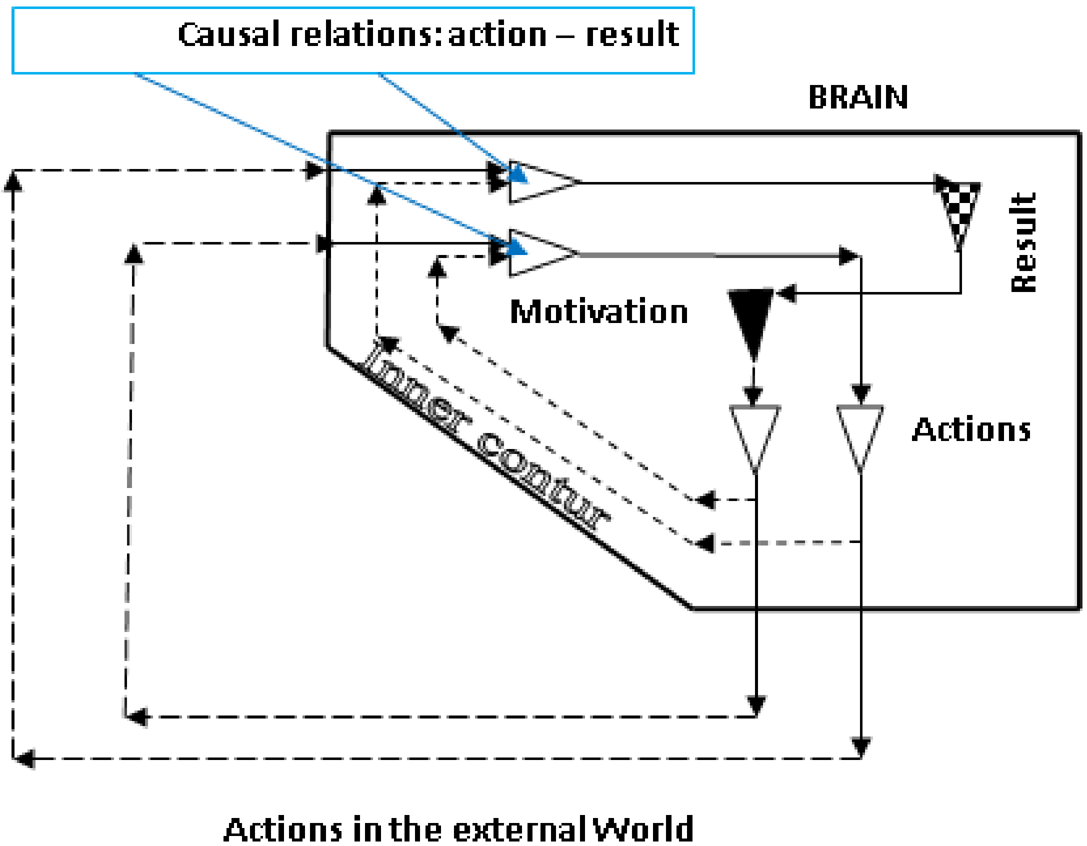
Further, we show that the formalization of TFS can be defined as a special case of this definition of a task, so the brain, with its physiological mechanisms, provides a solution of its task of the needs satisfaction in purposeful behavior in this sense.



In semantic modeling, the task solved by the brain is formulated as follows:

- The ***domain model*** is an experience that is obtained as a result of training and in which purposeful behavior is carried out;
- The ***request*** (the Goal, marked in blue) to the subject domain – is a need that must be satisfied. Denote it by the predicate P_0;
- ***Decision making*** is carried out by choosing a ***particular action plan***, based on the experience and model of the external world, leading to an object a such that $P_0(a)$.
- A ***particular action plan*** converts the goal request into a ***particular request***, giving a way to find the desired object and together with the totality of the goal sub-requests and the hierarchy of the corresponding results (the ***action results acceptor***).
- The ***result of the task solution*** – is the object, the situation, perceived by the "set of afferent stimuli" a (red block), on which the predicate P_0 is true $P_0(a)$ (satisfies the need) – this is the ***criterion for the task solution***.

Causation and Theory of Functional Systems



“We are talking about collateral branches of the pyramidal tract, leading to many neurons “copies” of those efferent premises that go to the pyramidal tract ...” P.K. Anokhin.

The ***principle of advancing reflection of reality***: “There was one universal regularity in the adaptation of organisms to external conditions, which subsequently developed rapidly throughout the evolution of the living world: a highly rapid reflection of slowly unfolding events in the external world” P.K. Anokhin.

From this point of view, we not only make a decision and choose an action plan, but also predict the achievement of the goal in acceptor of actions result.

ANTICIPATORY REFLECTION OF REALITY IS PREDICTION

Covering Law Model: The task of prediction (explanation) is to demonstrate that the predicted fact is a special case of the law.

There are two cases of prediction (explanation):

Deductive-Nomological (D-N), facts and laws based explanation;

Inductive-Statistical (I - S) explanation based on facts and probabilistic laws.

DEDUCTIVE-NOMOLOGICAL MODEL

$$\frac{L_1,\ldots,L_m \quad C_1,\ldots,C_n}{G}$$

INDUCTIVE-STATISTICAL MODEL

$$\frac{L_1,\ldots,L_m \quad C_1,\ldots,C_n}{G}\,[r]$$

$L_1,\ldots, L_m$ – set of laws; $C_1,\ldots,C_n$ – set of facts;

G – explained/predicted statement; $L_1,\ldots,L_m,C_1,\ldots,C_n \vdash G$.

The set $\{L_1,\ldots, L_m,C_1,\ldots,C_n\}$ is consistent; $L_1,\ldots, L_m \nvdash G$, $C_1,\ldots,C_n \nvdash G$;

$L_1,\ldots, L_m$ – laws have only universal quantifiers; $C_1,\ldots,C_n,G$ – are quantifier-free.

The search for the result and solutions in semantic modeling can be carried out both by D-N inference if we use the laws $L_1, \ldots,L_m$, and through I-S inference if we use probabilistic laws.

In this case, we simultaneously obtain a ***forecast of the result achievement***.

The search for the result and task solutions in semantic modeling can also be carried out by some search of the constants in the model, which corresponds to the “trial and error” method in purposeful behavior.

The problem of statistical ambiguity: Statements obtained in the inductive inference may infer contradictory statements.

(L1) - ‘Almost all cases of streptococcus disease are quickly cured by injection of penicillin’;

(L2) - ‘Almost always penicillin-resistant streptococcal infection does not cure after an injection of penicillin’;

(C1) - ‘Jane Jones got a streptococcal infection’;

(C2) - ‘Jane Jones received an injection of penicillin’;

(C3) - ‘Jane Jones has a penicillin-resistant streptococcal infection’.

Explanation 1		Explanation 2	
L1	[r]	L2	[r]
C1,C2		C2,C3	
E		¬E	

$$\begin{array}{l} p(G;F) = r \\ F(a) \\ \hline G(a) \end{array} \quad [r]$$

To eliminate conflicting inferences, Karl Hempel introduced the **Maximum Specificity Requirement** (MSR): If the following statements hold for the class H: $\forall x(H(x) \Rightarrow F(x))$, H (a), then there exists a law p (G; H) = r’ such that r = r’.

The problem of probabilities estimation in derived predictions. They can quickly go to zero and give predictions with a score of 0, which is not a prediction.

This problem is known as the synthesis of logic and probability problem, considered in a series of conferences Progic (Probability + Logic), 2003, 2005, 2009, 2011, 2013, 2015, 2017, 2019.

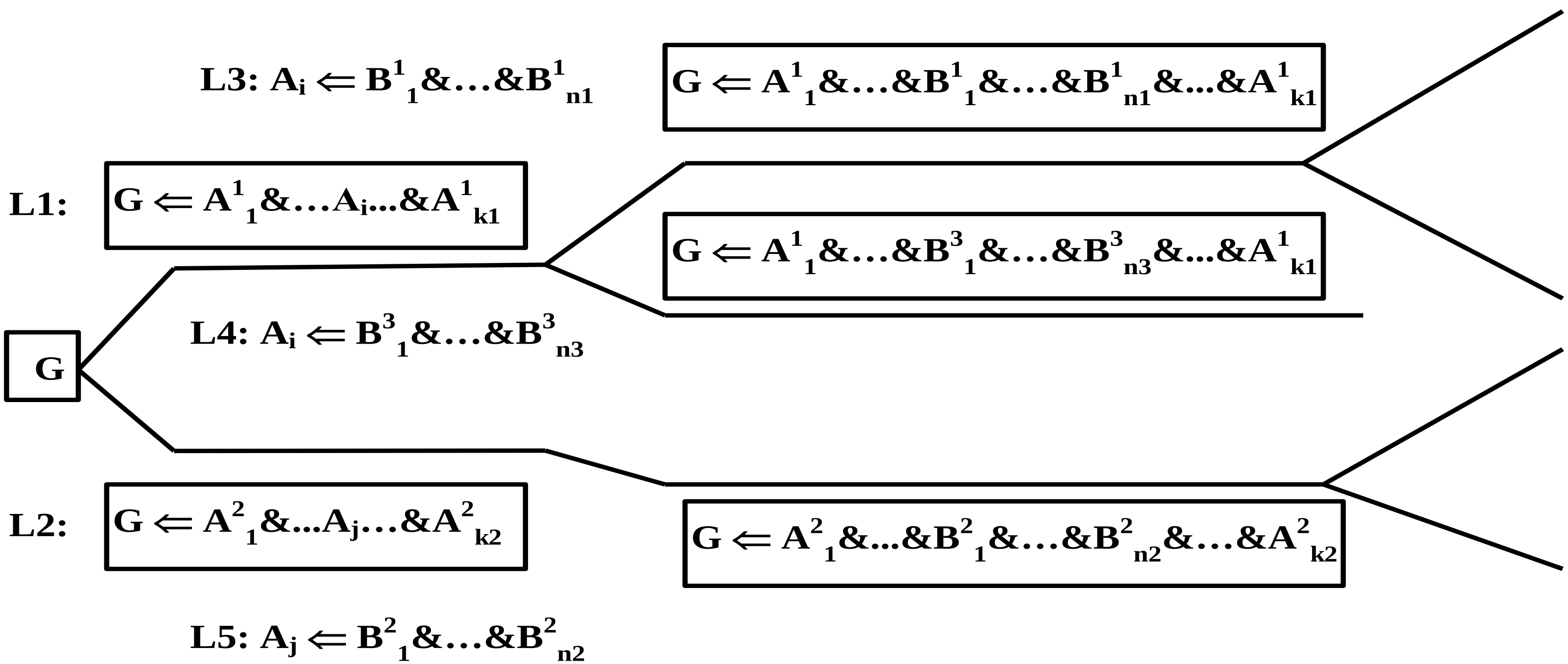
PREDICTIONS INFERENCE IN LOGIC PROGRAMMING

The prediction is formulated as a request G to a program including (statistical) laws $L_1, \ldots, L_m$ and facts $C_1, \ldots, C_n$

If the output to the request G by the program is successful, then:

1. It is true that $\{L_1, \ldots, L_m, C_1, \ldots, C_n\} \vdash \exists x_1, \ldots, x_n G$;
2. The program calculates terms $t_1, \ldots, t_n$: $\{L_1, \ldots, L_m\ C_1, \ldots, C_n\} \vdash G\ [x_1/t_1, \ldots, x_n/t_n]$.

The calculation process can be represented in the form of a tree.



Prediction from the point of view of semantic modeling

Consider the model-theoretical semantics of logical programs, where the facts are statements of the empirical system $\mathfrak{I} = \langle \mathbf{A}; \Omega_{\mathfrak{I}} \rangle$ representing the domain model.

In this case, the process of inference of prediction can be generalized by considering the inference as a calculation of the truth of the predicted fact G, consisting in the discovery of facts $C_1, \ldots, C_n$ of the empirical system $\mathfrak{I}$, from the truth of which the truth of the predicted statement is calculated according to the laws $L_1, \ldots, L_m$.

Then, together with the inference of the fact G, the truth will be:

$$\mathfrak{I} \vDash G[x_1/a_1,\ldots,x_n/a_n].$$

With this view on the inference, it can be generalized, defining new relationships between statements and models. We can consider the inference not only as a verification of the truth on the model, but also as a search for facts in the model, that predict with maximum probability the interested us statement or as a search for the most probable or specific.

Such inference will be called semantical, which will be defined.

The integration project of the Siberian Branch of the Russian Academy of Sciences "Establishing the similarity of the structures of the real physical world with computability structures is becoming so significant in modern science that many researchers consider the concept of computability to be a new paradigm of the philosophy of science."

INDUCTIVE INFERENCE of the THEORY AND KNOWLEDGE in THE SUBJECT DOMAIN

Let domain model (DM) be represented by the empirical system $\mathfrak{I} = \langle A, W \rangle$.

Th($\mathfrak{I}$) – domain model theory – the set of all universal formulas true on $\mathfrak{I}$.

It is known that Th($\mathfrak{I}$) can be represented as the set of all true rules on $\mathfrak{I}$ of the form $C = (L_1 \& \ldots \& L_k \Rightarrow L_0)$, where L_j are letters;

The rule $C = (A_1 \& \ldots \& A_n \Rightarrow A_0)$ is sub-rule of the rule $C' = (L_1 \& \ldots \& L_k \Rightarrow A_0)$ if $\{A_1, \ldots, A_n\} \subset \{L_1, \ldots, L_k\}$, $0 \leq n < k$.

The ***law*** on $\mathfrak{I} = \langle A, W \rangle$ is the rule $C = (L_1 \& \ldots \& L_k \Rightarrow L_0)$ satisfying the conditions:

1. C is true on $\mathfrak{I}$;
2. the premise of the rule is not always false on $\mathfrak{I}$;
3. each subrule of the rule C false on $\mathfrak{I}$.

Let L – is the set of all laws on $\mathfrak{I}$.

Theorem. $L \vdash Th(\mathfrak{I})$.

A ***Probabilistic Law*** (PL) on $\mathfrak{I}$ is a rule C whose conditional probability is strictly greater than the conditional probabilities of all its sub-rules.

The ***Strongest Probabilistic Law*** (SPL) is called the probabilistic law, which is not under the rule of another probabilistic law.

Let LP – is the set of all probability laws on $\mathfrak{I}$.

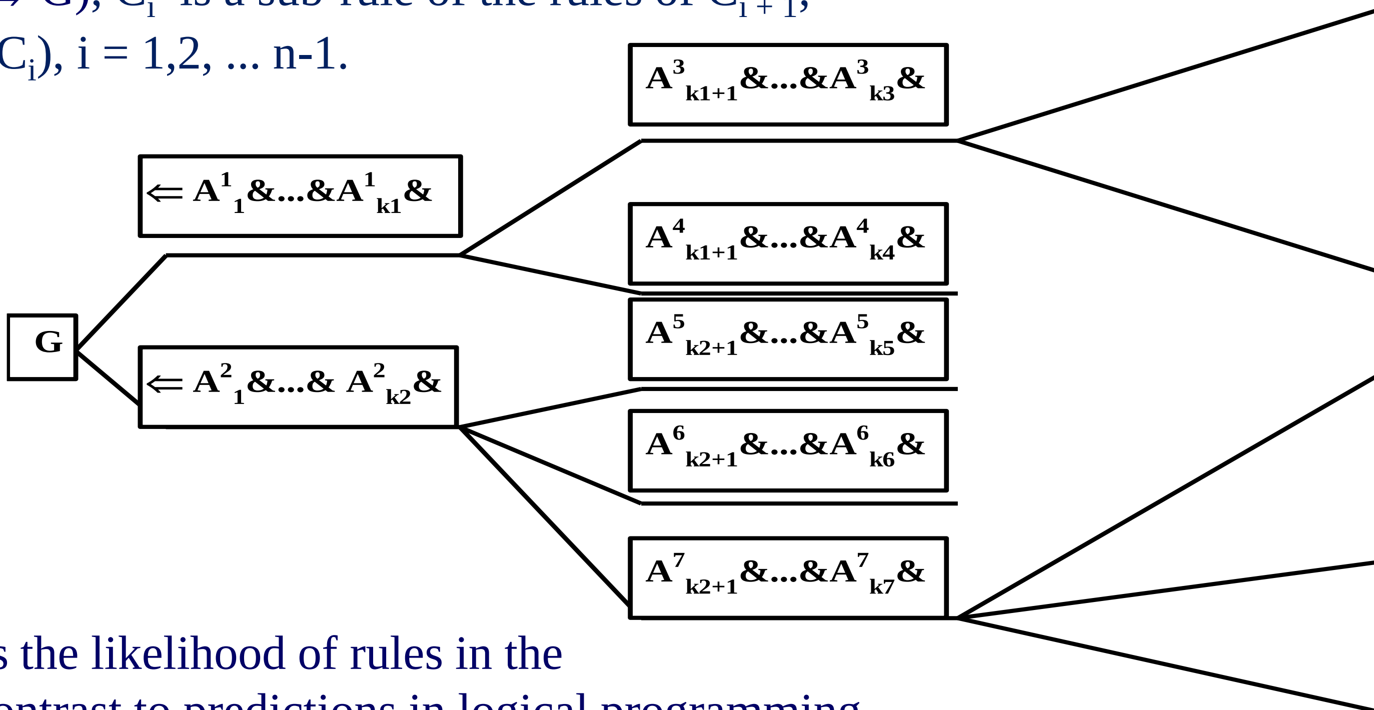
Statement. $L \subset LP$. The set L gives a DM theory, and LP – DM knowledge.

SEMANTIC PROBABILISTIC INFERENCE
Solution of the statistical ambiguity problem

Semantic Probabilistic Inference (SPI) is a sequence of probabilistic laws: $C_1 \sqsupset C_2 \sqsupset \ldots \sqsupset C_n$, where C_n is a strongest probabilistic law

$C_i = (A^i_1 \& \ldots \& A^i_{ki} \Rightarrow G)$, C_i is a sub-rule of the rules of C_{i+1};

$Prob(C_{i+1}) > Prob(C_i)$, $i = 1,2, \ldots n-1$.



SPI is strictly increases the likelihood of rules in the inference process, in contrast to predictions in logical programming.

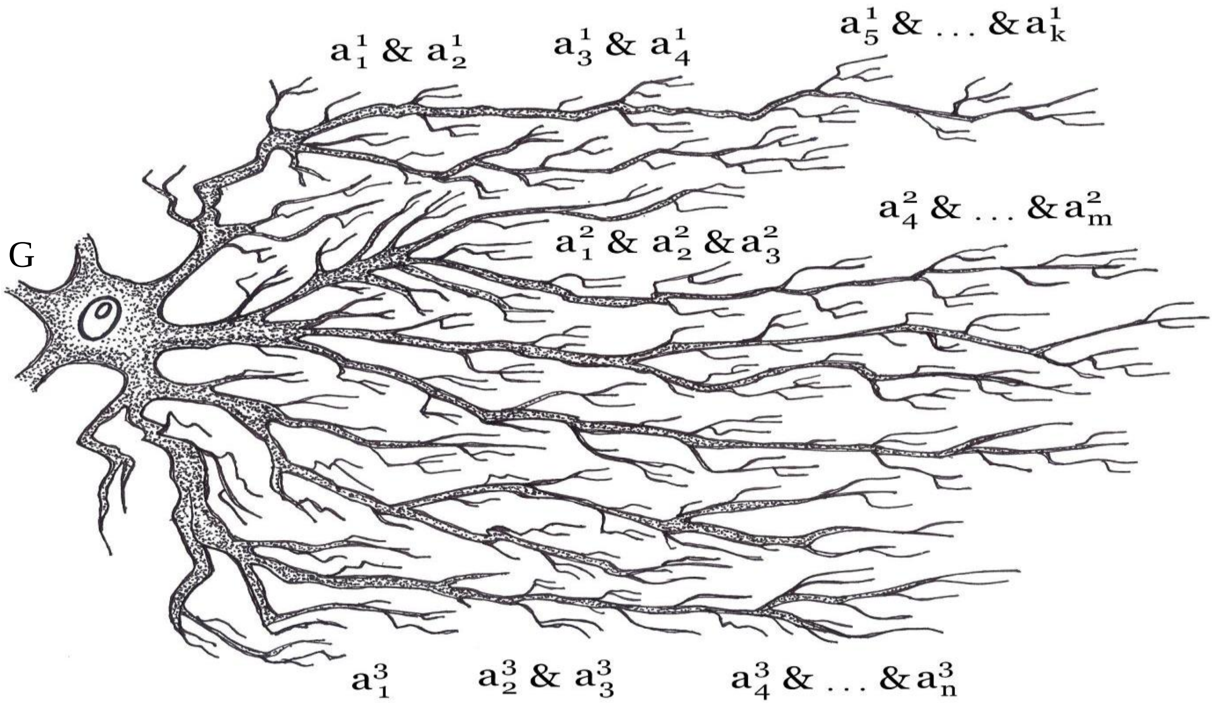
By the ***maximal specific rule*** MS(G) of the inference of the atom G we mean the SPL-rule of the inference tree G, having the maximum value of the conditional probability.

Theorem. (Solution of the statistical ambiguity problem):

I-S inference that use only MSR rules is consistent. $L \subset MSR \subset LP$.

Vityaev, E., Odintsov, S. How to predict consistently? // Trends in Mathematics and Computational Intelligence In: Studies in Computational Intelligence, 796, María Eugenia Cornejo (ed), 2019, 35-41.

Semantic probabilistic inference as a formal model of neuron



If G denotes a stimulus, on which the neuron responds unconditionally, then the stimuli arriving at the dendrites can establish conditional connections with excitation of the neuron G.

New stimulus are added to the rule only if they increase its conditional probability. This is a manifestation of the conditional connections closure at the level of a neuron, its plasticity.

Neurons respond faster to the most probable conditional connections and hence first of all on Maximum Specific Rules.

Vityaev E.E. A formal model of neuron that provides consistent predictions // Biologically Inspired Cognitive Architectures 2012. Proceedings of the Third Annual Meeting of the BICA Society. In Advances in Intelligent Systems and Computing, v.196, Springer. 2013, pp. 339-344.

Emotion switching function

Semantic probabilistic inference also formalizes the concepts of ***probabilistic forecasting*** and ***probability***, introduced in I.M. Feigenberg and the Iinformation Theory of Emotions (ITE) P.V. Simonov:

"Summing up the results of our own experiments and literature data, we came to the conclusion that emotion is a reflection by the brain of humans and animals of any actual need (its quality and magnitude) and the likelihood of satisfying it ...".

Simonov P.V. Higher nervous activity of a person (motivational-emotional aspects). M., 1975.

Simonov P.V. Emotional brain. M .: Nauka, 1981.

In TFS, decision-making is carried out by choosing one specific action plan taking into account the probability of this forecast and emerging emotions, which is an important addition of the information theory of emotions to TFS.

Emotions are a necessary criterion for choosing between different ways of achieving a goal, taking into account the probability of achieving a goal, complexity and laboriousness, as well as authorizing afferentations when need is satisfied.

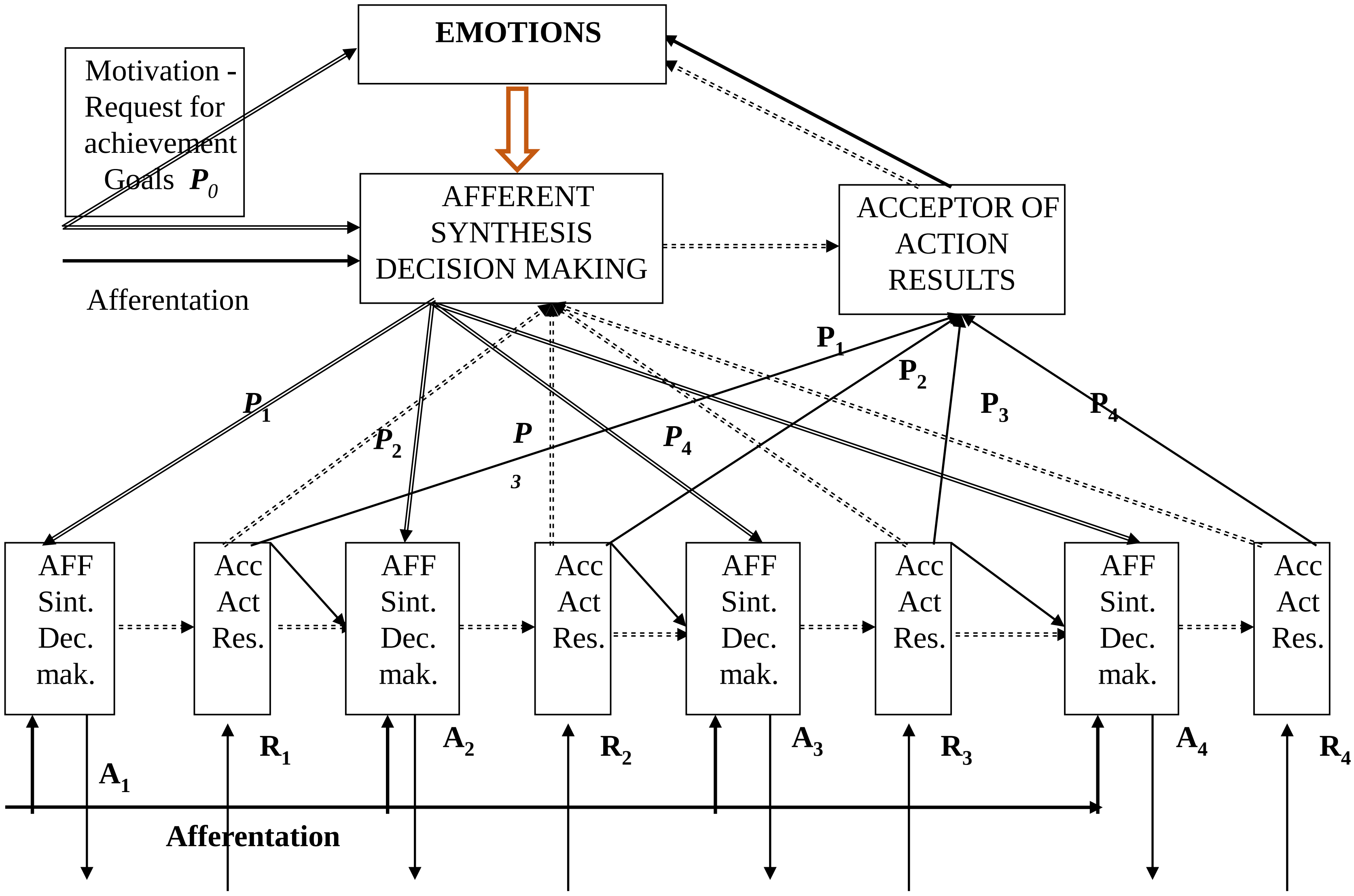
Therefore, decision-making and the choice of a specific way to achieve the goal is carried out by the ***switching function of emotions***.

In Artificial Intelligence for intelligent agents such criterion is called ***utility***.

In mathematics, there is a field of research dealing with utility, for example:

Fishburn, Peter C. Utility theory for decision making // Peter C. Fishburn New York, 1970.

Emotion switching function



Multilevel organization of movements according to N.A. Bernstein

In work of N.A. Bernstein «About building movements» investigated the multi-level organization of movements: “The level of organization of movements B is body ownership”; “The movements of the level C of the spatial field are primarily of a clearly defined target nature, they lead “from somewhere” to “somewhere” and “for some reason”; “Leading motive at the level of actions D is not an object in itself, like a geometric form, but the semantic side of actions with an object ...”.

Let us define these levels through the chain of actions and the results that they achieve.

We introduce the concept of a ***probabilistic goal-result of actions*** so that they can be formed automatically in the learning process:

1. goal-result increases the likelihood of achieving the final result;
2. the goal-result has the branching property: if a certain goal-result is achieved in the course of chain of actions, then further chain of actions can develop differently in accordance with the hierarchy of goal-results;
3. when goal is reached, the result should be fixed by a set of signs, fixing completeness of the chain of actions and the possibility of moving to the next chain of actions;
4. achievement of the goal-result is supported by emotion, which captures an increase of the probability of achieving the final goal.

Achieving these goals-results can be considered as the automatic formation of functional subsystems that achieve these goals-results.

Demin A.V., Vityaev E.E. The logical model of an adaptive control system. Neuroinformatics, 2008, Volume 3, No. 1, pp. 79-107.

Clarification of the Task concept

The ***domain model*** is a ***model of the external world***, which is obtained as a result of the MSR rules detection in the internal circuit of the brain;

A ***request*** (Goal) is a need to be satisfied, indicated by the predicate P_0;

The ***task solution*** is the object, the situation, perceived by the "totality of afferent stimuli" ***a***, on which the predicate P_0 is true $P_0(a)$ (satisfies the need), which is the ***criterion of the task solution***. There may be several such solutions, the choice of a particular solution is carried out by a ***switching function of emotions***.

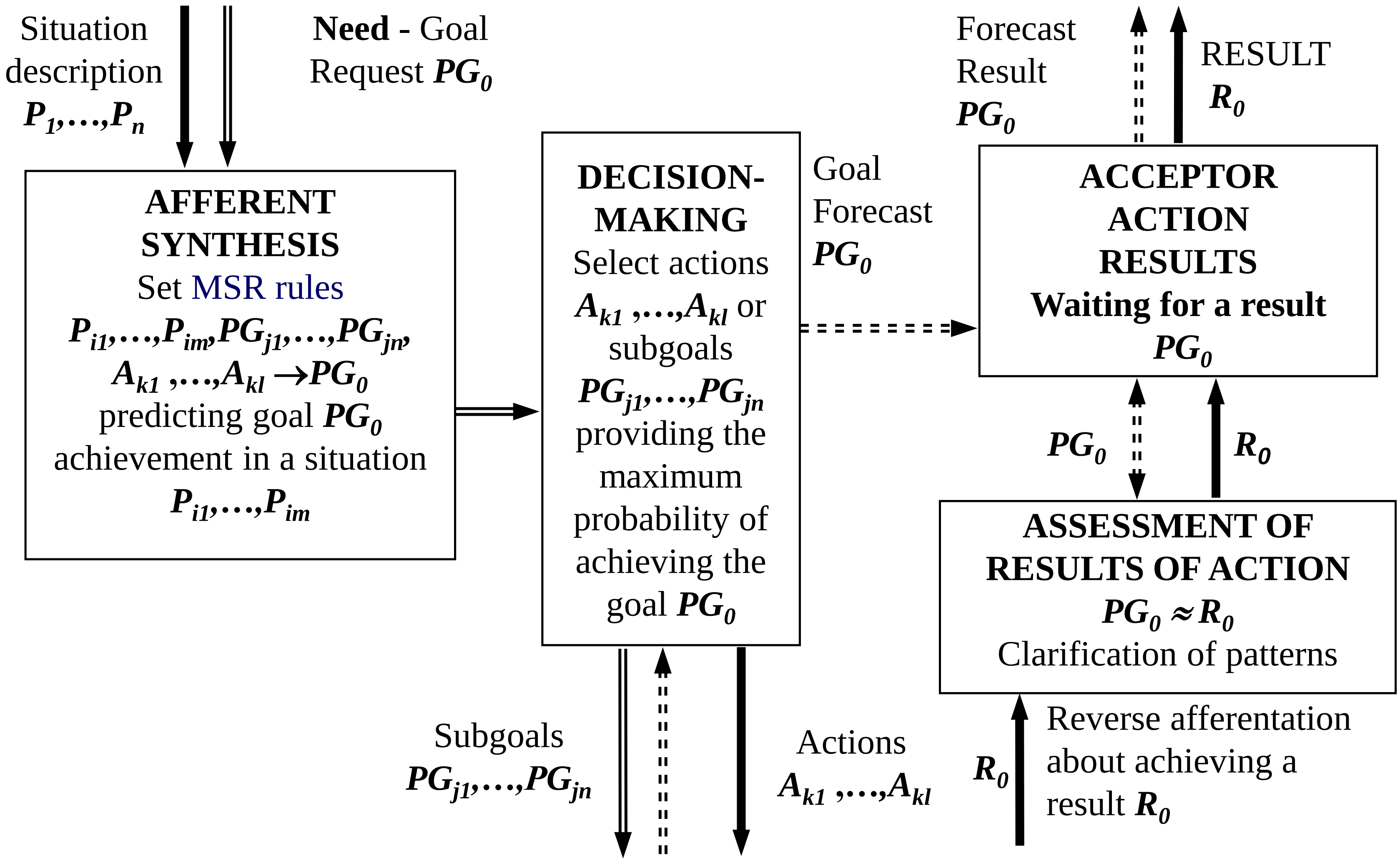
Decisions making is carried out by choosing a ***particular action plan*** taking into account the probabilistic forecast and the maximum emotional reaction for the corresponding action plan, which is formed based on:

- the basis of existing experience and available MSR, which predict the achievement of a goal according to the model of the external world (object achievement, situation ***a***, making the predicate P_0 true);
- hierarchical planning of the goal achievement, using probabilistic goal-results and available MSR;
- semantic modeling, predicting by I-S inference the goal achievement, using MSR and existing knowledge about the domain model.

A ***particular action plan*** converts the request-goal into a ***particular request-goal***, giving the way of the desired object ***a*** finding together with the totality of the subrequests-goals and goal-results (***acceptor of the results of actions***).

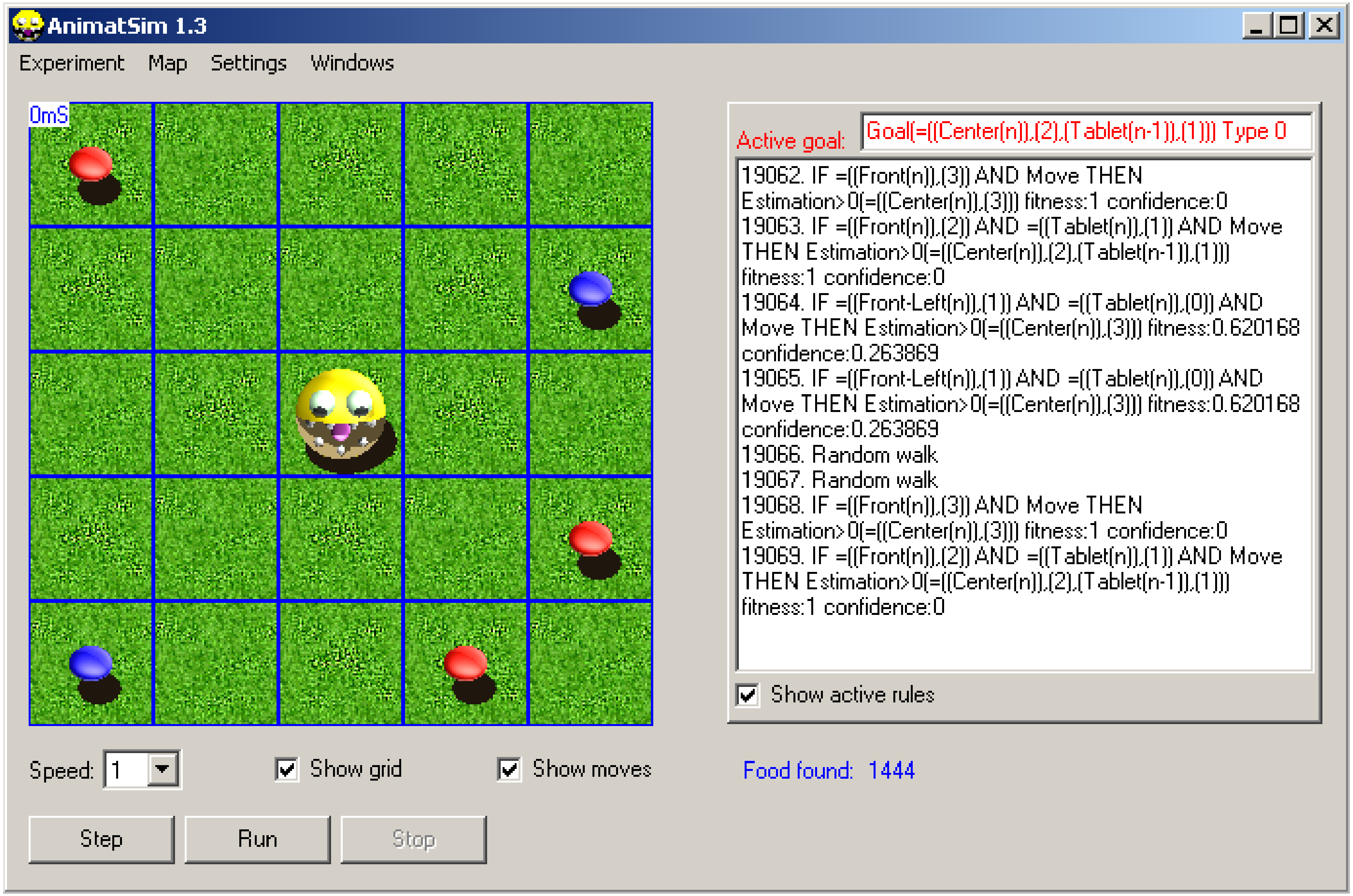
Scheme of the tasks solution and work of functional systems

$Prob(PG_0|R)=Prob(R)Prob(PG_{j1})\ldots Prob(PG_{jn})$, где **$R=P_{i1},\ldots,P_{im},PG_{j1},\ldots,PG_{jn},A_{k1},\ldots,A_{kl}\rightarrow PG_0$**



Vityaev E.E. The logic of the brain. Approaches to modeling thinking. (collection edited by Doctor of Physics and Mathematics V.G. Redko). URSS Editorial, Moscow, 2014, pp. 120-153.

PROGRAM MODELING ANIMATE AND ITS ENVIRONMENT



ANIMATE DESCRIPTION

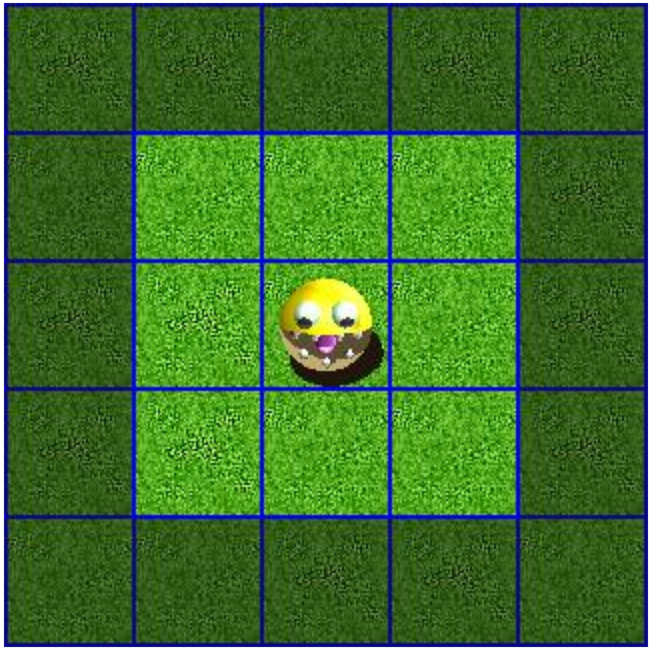
Actions

Step forward, Turn 90^0 to the left, Turn 90^0 to the right.

Sensors

Nine sensors informing the animat about the state of surrounding cells. Sensors take the values “empty”, “obstacle”, “food” or “pill”.

One sensor "there is a tablet", informing the animat about the presence of a tablet and assuming the values "yes" or "no."



Sensors location

Predicates

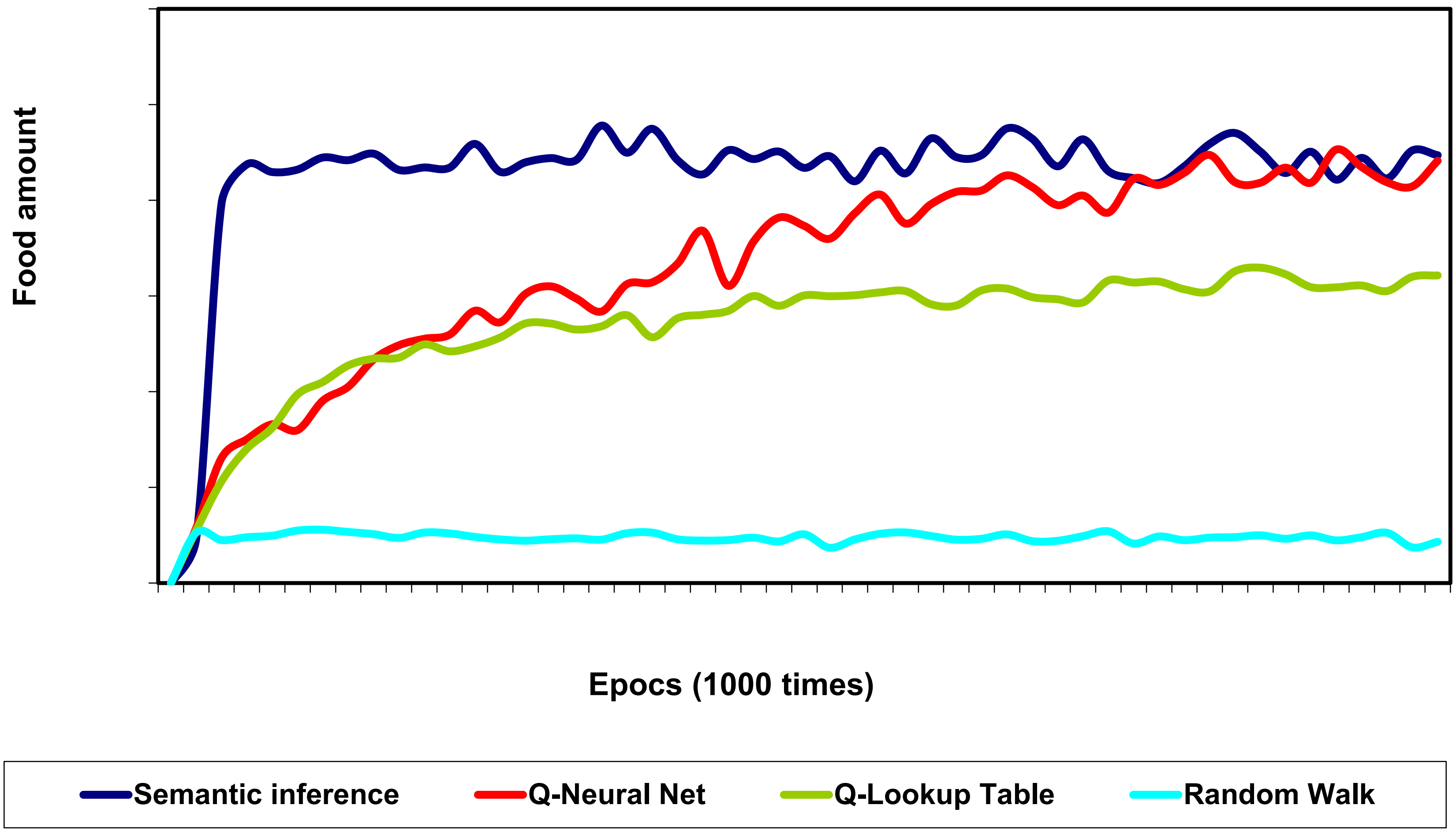
<s = "empty">, <s = "obstacle">, <s = "food">, <s = "pill">, where s is the surrounding cell, and <"there is a pill" = "yes">.

Primary goal

Achieving the situation of the simultaneous presence of a pill and finding food in the central cell.

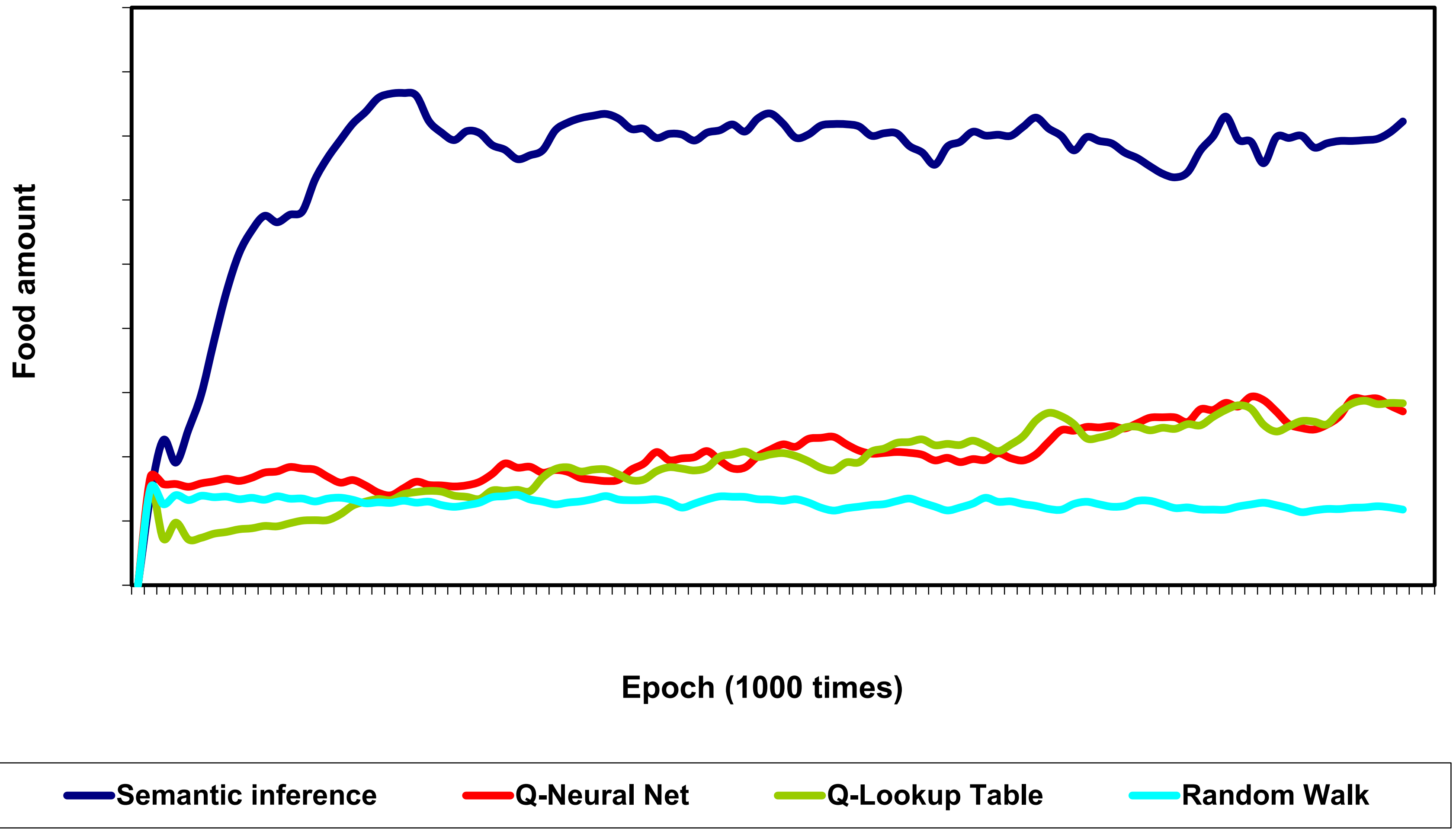
Goal predicate: <“central cell” = “food” AND “eat a pill” = “yes”>.

COMPARISON RESULTS ON THE EXAMPLE OF THE DECISION OF THE CLASSICAL FEEDING PROBLEM

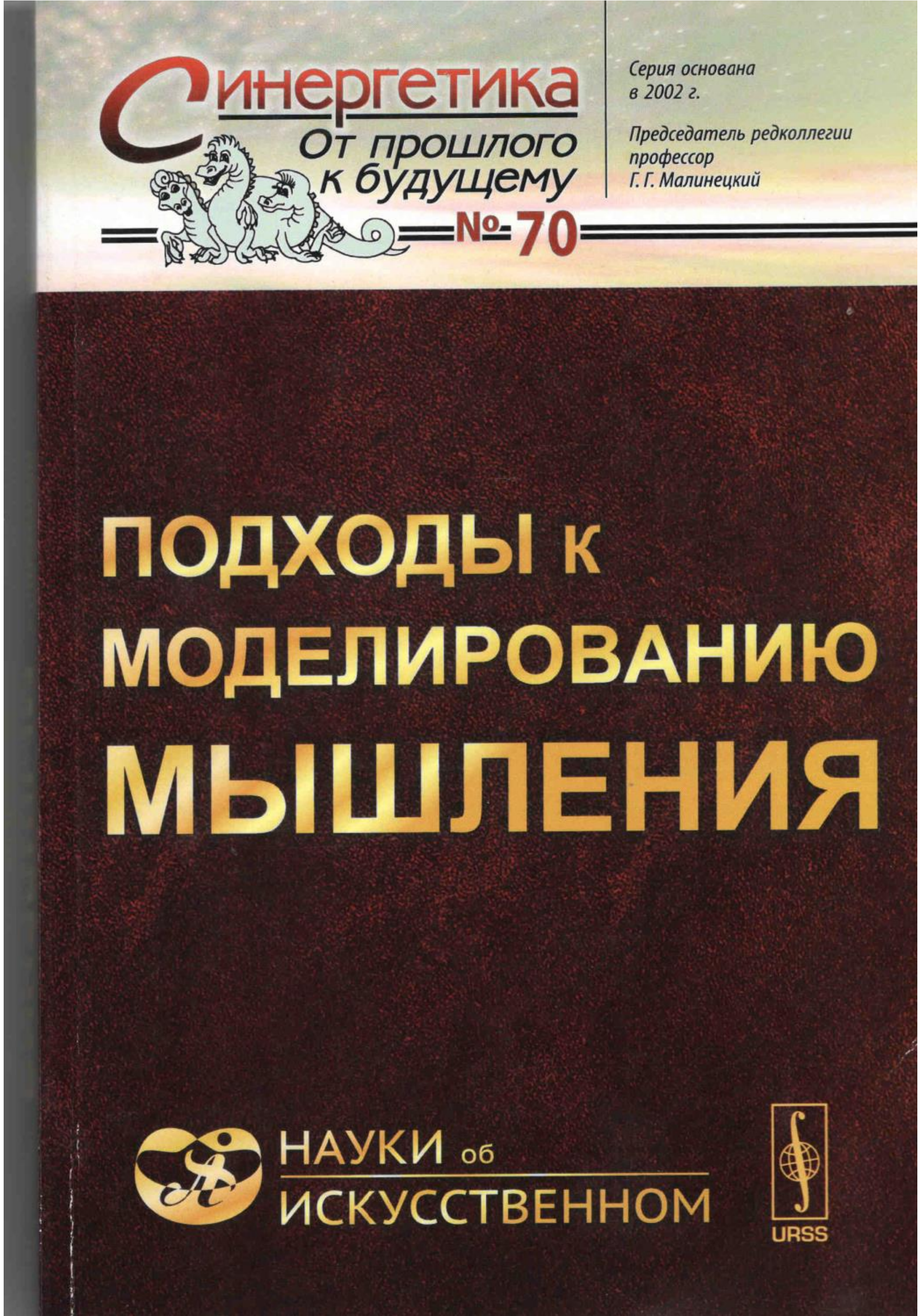


The amount of "food" collected by the animat in different control systems

COMPARISON RESULTS ON THE EXAMPLE OF SOLUTION OF THE FEEDING PROBLEM WITH FORMATION OF SUB-GOALS



The amount of "food" collected by the animat in different control systems

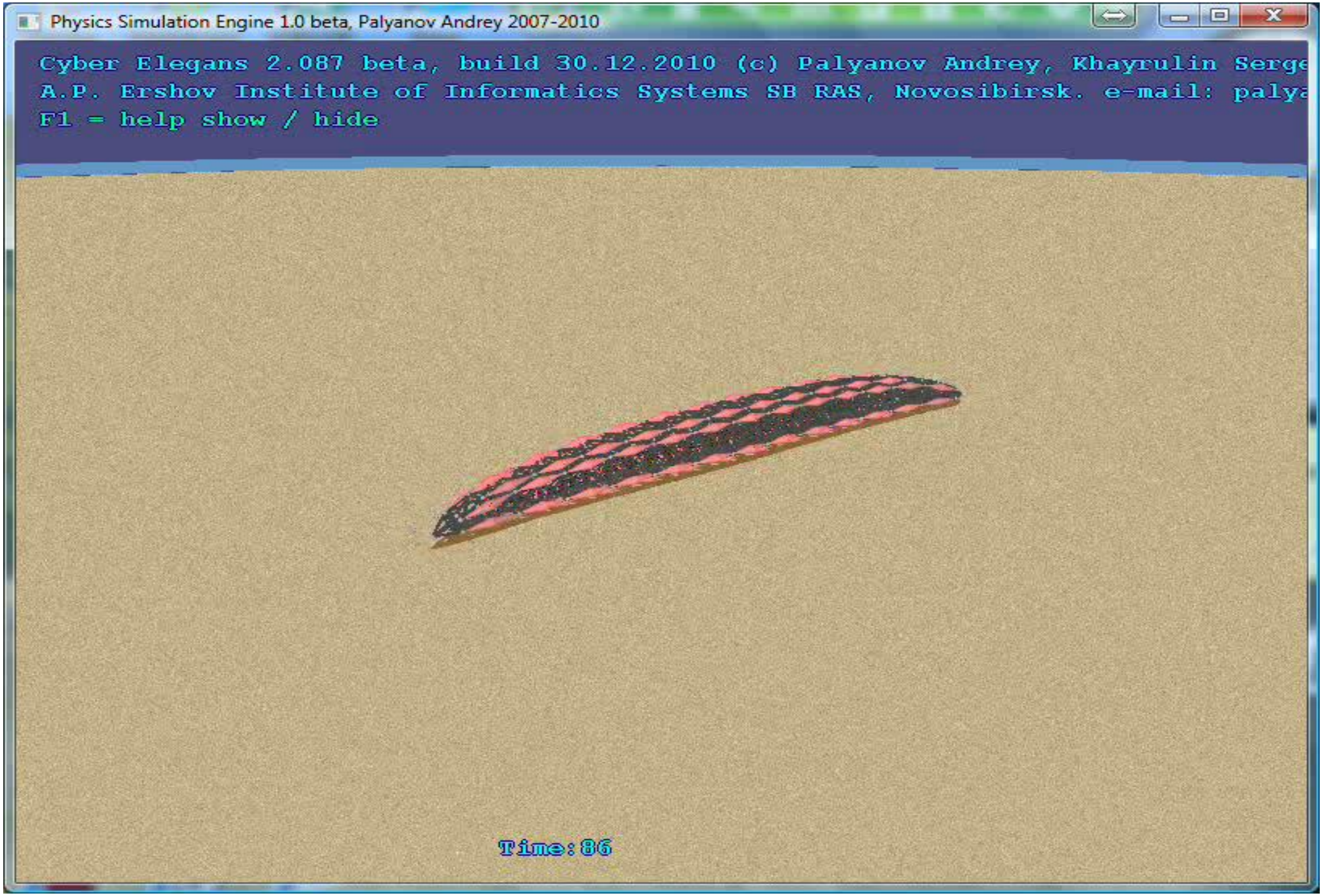


Vityaev E.E. The logic of the brain // Approaches to modeling thinking. (collection edited by Doctor of Physics and Mathematics V.G. Redko). URSS Editorial, Moscow, 2014, pp. 120-153. (in Russian)

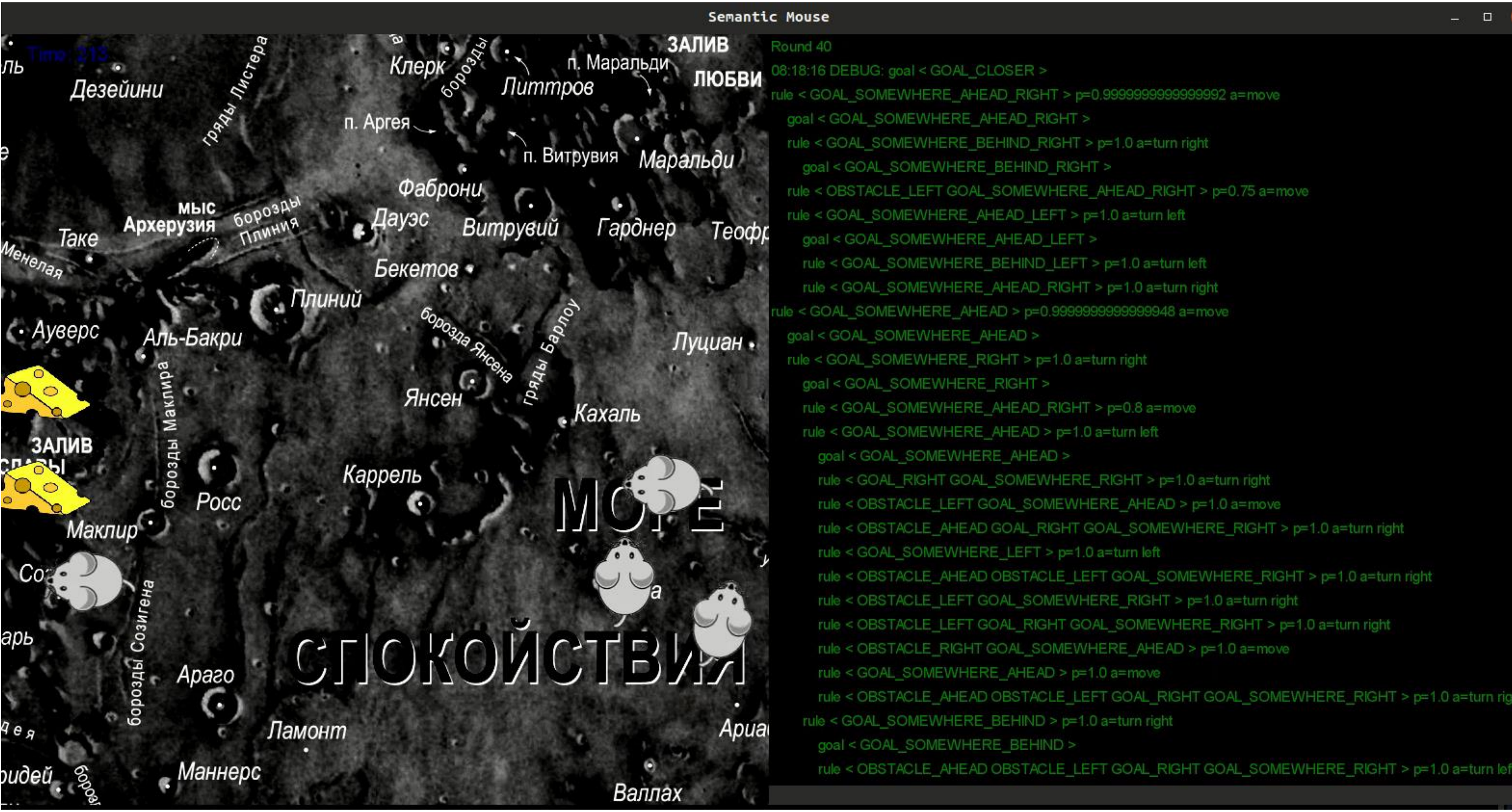
Vityaev E.E., Neupokoev N.V. A formal model of perception and image as a fixed point of anticipation // Approaches to modeling thinking. (collection edited by Doctor of Physics and Mathematics V.G. Redko). URSS Editorial, Moscow, 2014, pp. 155-172. (in Russian)

Evgenii Vityaev. Consciousness as a logically consistent and prognostic model of reality // Cognitive Systems Research, 2019 Elsevier, 59 (2020), 231–246.

Vityaev E.E. Consciousness is a logically consistent predictive model of reality // Nonlinear Dynamics in Cognitive Research (Proceedings of the V All-Russian Conference on Cognitive Sciences), Nizhny Novgorod, IPP RAS, 2017, p. 67-70. (in Russian)

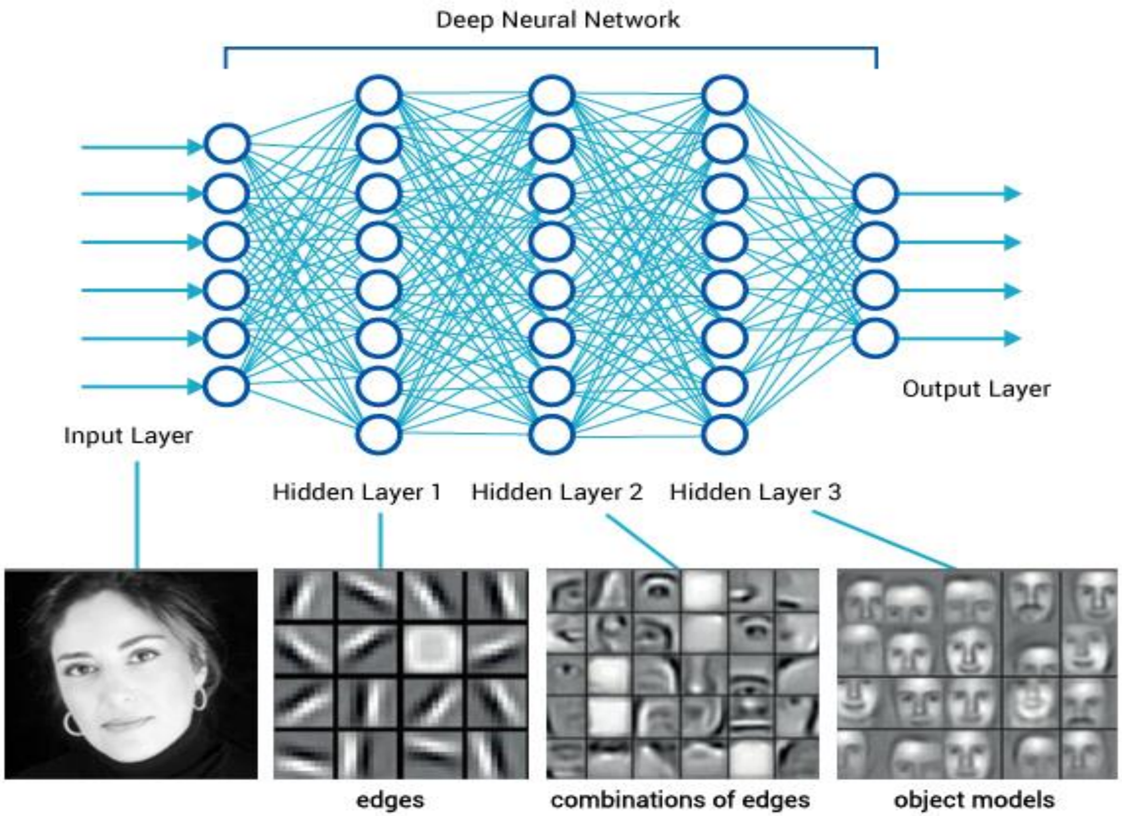


https://www.youtube.com/watch?v=eMqt_E4uKbI



https://www.youtube.com/watch?v=985Fw3yKeOM

Deep learning



J. Gibson "Ecological theory of perception": The world is hierarchically structured: "small elements are contained in larger ones ... therefore I introduce a special term for it: ***embeddedness***. "... in any part of the earth's surface, in fact, the same elements are found. The size of grains of sand, wherever they meet, is always about the same. Grass stems are also more or less the same everywhere. The same can be said about stones, bunches of grass, bushes, etc. ... And although their repeatability is devoid of metric regularity, they still have ***stochastic regularity***, that is, they are regular in the probabilistic sense. "

“Natural” concepts in cognitive sciences

In the works of Eleanor Rosch, the principles of categorization of “natural” categories were formulated:

The structure of the perceived world: “the perceived world is not an unstructured set of equally likely properties, on the contrary, the objects of the perceived world have ... a ***highly correlated structure***. ... combinations of what we perceive as attributes of real objects do not occur evenly. Some pairs, triples, etc. likely enough ... others are rare; others do not occur logically or empirically. ”

Basic objects are information-rich bundles of observable and functional properties that form a natural discontinuity that creates categorization.

“Categories can be considered in terms of their pure cases, if the perceiver pays attention to the ***correlation structure of perceived attributes*** ... By ***category prototypes*** we generally mean pure cases of category membership.”

In the future, the theory of "natural" concepts Eleanor Rosch was called the ***prototype theory of categorization*** (prototype theory).

Further research revealed that models based on attributes, similarities, and prototypes are not enough to describe classes. It is necessary to consider causal and ontological knowledge related to class objects. For example, people not only know that birds have wings, they can fly and make nests in trees, but also that birds make nests in trees, because they can fly, and fly because they have wings.

Given these studies, Bob Rehder put forward the ***causal-model theory***, in which the relationship of an object to a category is no longer based on a variety of features and proximity by features, but on the basis of the ***similarity of the causative mechanism***.

To describe causal models, Bob Rehder used a “sweep” of causal models using Bayesian networks. However, Bayesian networks do not support cycles and therefore cannot model cyclic causal relationships.

We propose a ***new mathematical apparatus*** – ***probabilistic generalization of the formal concepts*** for formalization of the "natural" concepts, based on the ***formalization of cyclic causal relationships***.

During the perception of “natural” objects, these causal relationships become closed to themselves, forming a certain “resonance” of cyclic causal relationships, which gives causal models.

Formal concept analysis

Formal context K = ⟨G, M, I⟩, $I \subseteq G \times M$,

G — objects, M — features, I — object- features relation

Derivation operators $A \subseteq G,$ $A' = \{ m \in M \mid \forall g \in A (gIm) \}$

$B \subseteq M$ $B' = \{ g \in G \mid \forall m \in B (gIm) \}$

A formal concept in the context of K = ⟨G, M, I⟩ is a pair

$$(A, B), A \subseteq G, B \subseteq M, A' = B, B' = A$$

A – is the set of all objects from G that have all the attributes from B, and B is the set of all features from M that all the objects from A possess.

ANIMALS	preying	flying	bird	mammal
LION	×			×
FINCH		×	×	
EAGLE	×	×	×	
HARE				×
OSTRICH			×	

Probabilistic generalization of formal concepts

J. St. Mill wrote that: “Natural groups ... are determined by features ... However, this takes into account not only the features that are certainly common to all objects included in the group, but the totality of those features, of which all occur in most of these objects, and majority in all".

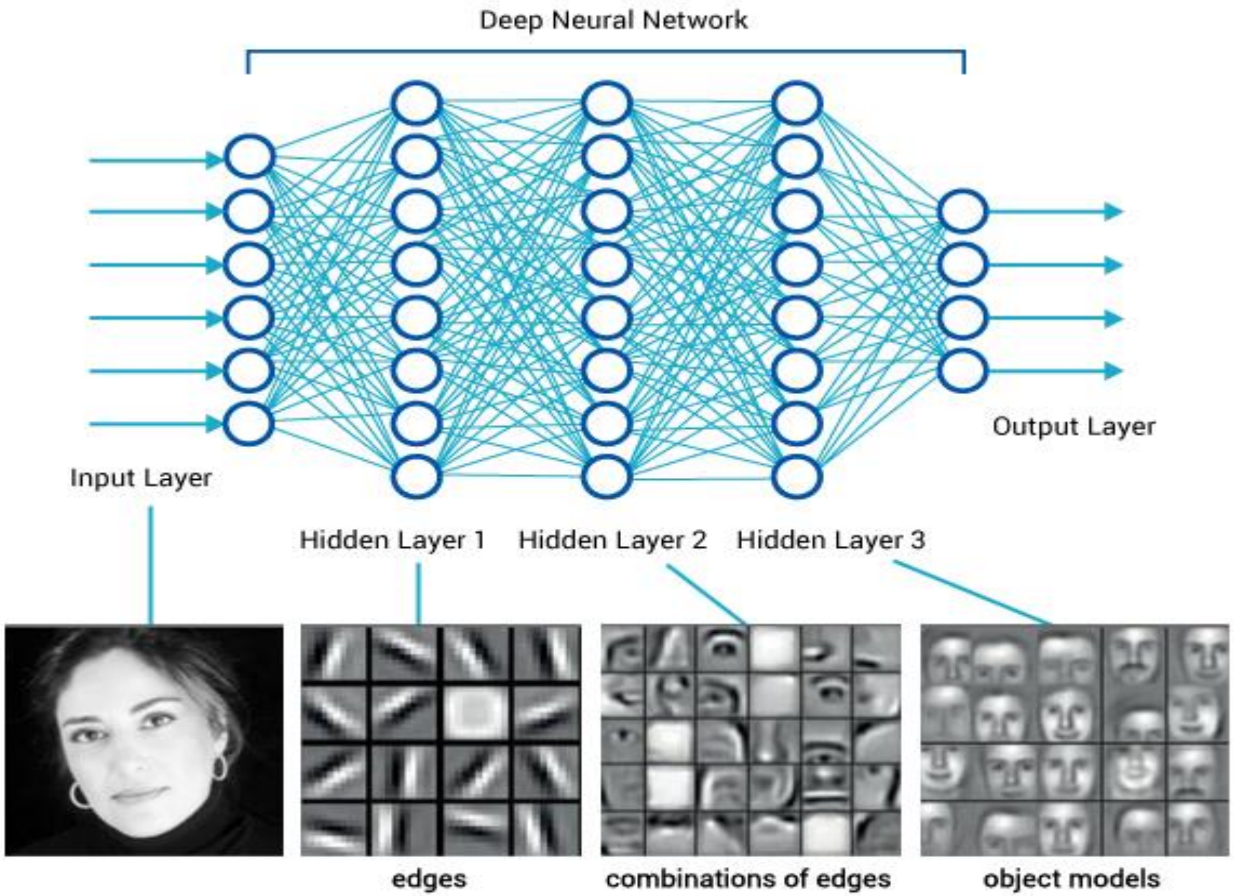
Stages of probabilistic generalization of formal concepts:

1. Define formal concepts as fix-points of implications;
2. Implications were replaced by the most specific causal relationships;
3. Define probabilistic formal concepts as fixed-points of maximally specific causal relationships;
4. Prove that these fix-points are logically consistent;
5. Define “natural” concepts as probabilistic formal concepts.

Alexander Demin, Denis Ponomaryov, Evgeny Vityaev. Probabilistic Concepts in Formal Contexts // Lecture Notes in Computer Science, Vol. 7162, Springer Verlag, 2012, p. 394-410

E. E. Vityaev, V. V. Martinovich. Probabilistic Formal Concepts with Negation // A. Voronkov, I. Virbitskaite (Eds.): PCI 2014, LNCS 8974, 2015, pp.385-399.

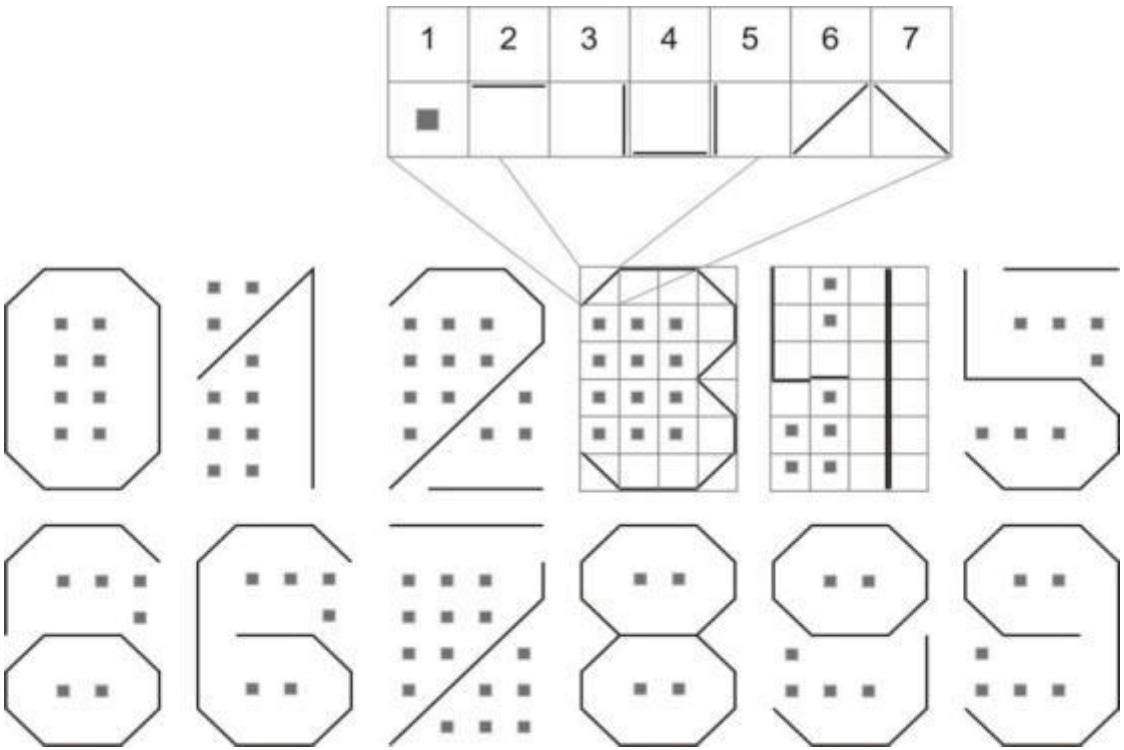
Probabilistic explainable deep learning.



Stochastic regularity and secondary features are also described by probabilistic formal concepts, so the hierarchy of probabilistic formal concepts:

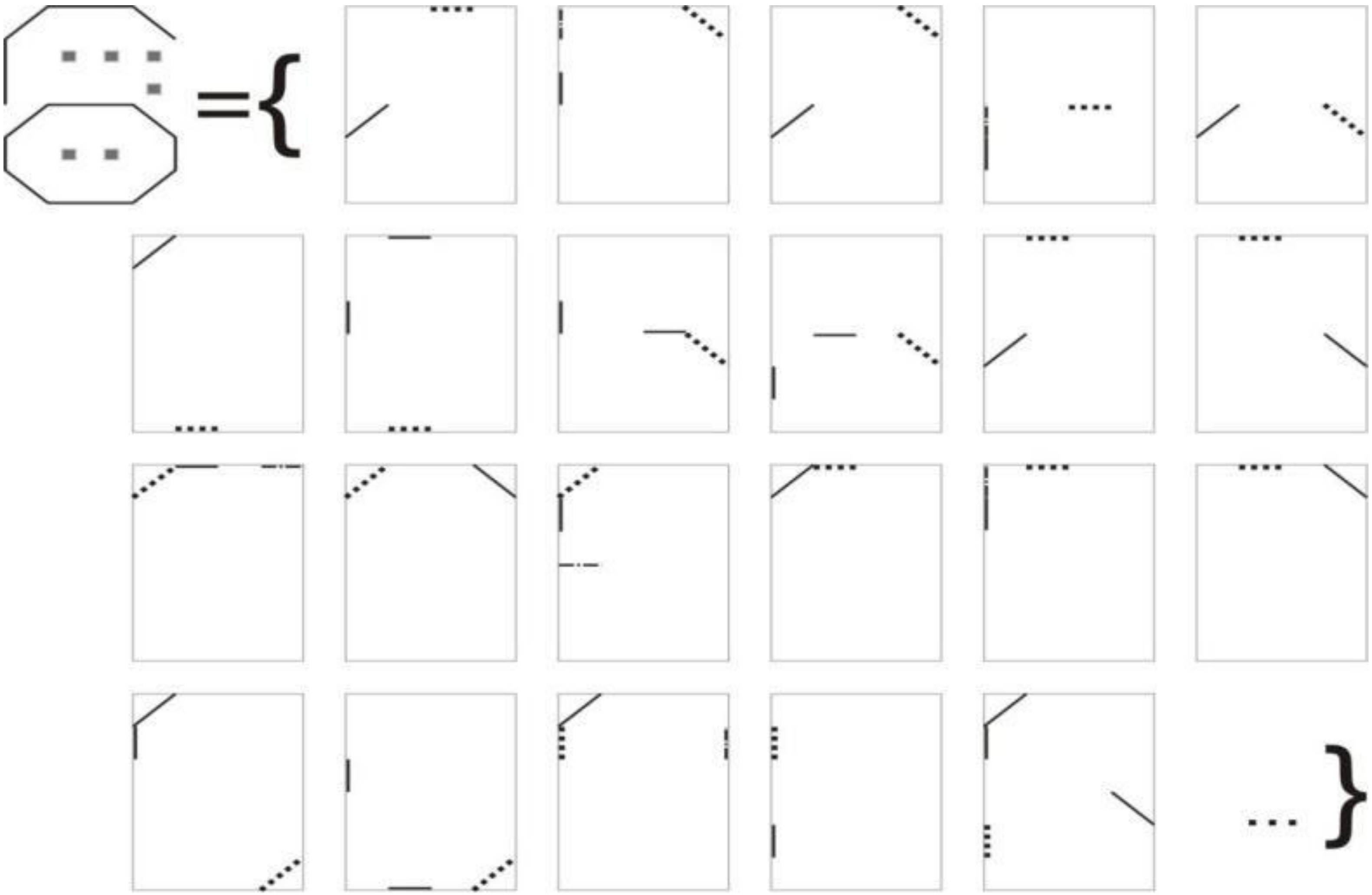
- automatically detect a hierarchy of secondary characteristics;
- form classes as fix-points explainable, accurately and consistently;
- transparent and explainable.

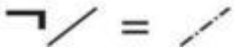
“Natural” concepts as probabilistic formal concepts



1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24

Fix-point





Regularities use an attribute negation

Data mining in terms of task-driven approach
Knowledge discovery on model data (software)

The task concept includes the subject domain and knowledge about the subject domain, presented in the form of its ***model***.

Consider the problem of ***inductive inference of knowledge on the data of the model using data mining methods***.

We can extract from the properties, characteristics and attributes of data only knowledge that is interpreted in the domain ontology.

By themselves, the numerical values of the quantities do not contain any knowledge. The knowledge about quantities contained in numerical values plus interpretation: 5 meters, 5 liters, 5 kg.

Data knowledge is defined by its scales – empirical systems $\mathfrak{I} = \langle \mathbf{A}; \Omega_{\mathfrak{I}} \rangle$, where
A – is the set of values of a quantity;
$\Omega_{\mathfrak{I}}$ – set of relationships and operations interpreted in the domain ontology.

Scale of names: $\langle A; =, \approx \rangle$,
Order scale $\langle A; =, <, > \rangle$,
Interval scale $\langle A \times A; =, <, > \rangle$, defined on the intervals $\langle a,b \rangle$,
Scale of relations $\langle A; =, <, >, +, -, \bullet, / \rangle$

Scales are determined up to ***permissible scale transformations***.

Ontology of Data Mining (DM) and Machine Learning (ML) methods

Knowledge discovered by Data Mining and Machine Learning methods is expressed by their ontology not by ontology of the subject domain.

1-st International Workshop on Philosophies and Methodologies for Knowledge discovery. 22-26 Audust 2005, Copengagen, Denmark.

Evgenii Vityaev, Keith Rennolls. Guest Editorial. Philosophies and methodologies for knowledge discovery // *Intelligent Data Analysis*. Special issue on "Philosophies and Methodologies for Knowledge Discovery and Intelligent Data Analysis" eds. Keith Rennolls, Evgenii Vityaev. v.12(2), IOS Press, 2008.

Data Mining and Machine Learning methods ontology:

1) data types the method works with;
2) a priori hypothesis classes that the method tests.

To obtain knowledge by DM and ML methods, it is necessary that the ***method ontology was interpretable in the subject domain ontology***:

1) data types of the method must be interpretable in the domain ontology;
2) a priori classes of hypotheses also must be interpretable in the domain ontology – the method should use only mathematical relations and operations interpretable in the domain ontology.

If conditions 1-2 are not fulfilled, then the method will not be invariant with respect to the choice of units of measurement and permissible scale transformations and most machine learning methods don't invariant.

Ontological approach to extracting subject domain knowledge

An ontological approach to extracting domain knowledge is to:

1. determine data ontology, using subject domain ontology and scale of quantities;
2. present data in the domain ontology as part of a domain model;
3. define an arbitrary hypothesis class H of interest to us, which should be specified by an expert in the subject domain, for which this knowledge is needed.
4. discover knowledge by testing hypotheses class H on this data and also discover:
    a) subject domain theory;
    b) all rules with maximum conditional probabilities;
    c) all most specific rules that allows you to make consistent predictions.

A “Discovery” system was developed that implements semantic probabilistic inference and discovers rule classes $L \subset MSR \subset LP$.

The ***domain model*** in semantic modeling ***can be enriched by the rules $L \subset MSR \subset LP$***, which give domain theory and probabilistic knowledge.

Evgenii Vityaev, Boris Kovalerchuk. Ontological Data Mining // Uncertainty Modeling: Dedicated to Professor Boris Kovalerchuk on his Anniversary. Studies in Computational Intelligence 683, V. Kreinovich (ed.), Springer, 2017, pp. 277-292.

Boris Kovalerchuk and Evgenii Vityaev. Data Mining in Finance: Advances in Relational and Hybrid Methods, Kluwer Acad. Pub., 2000.

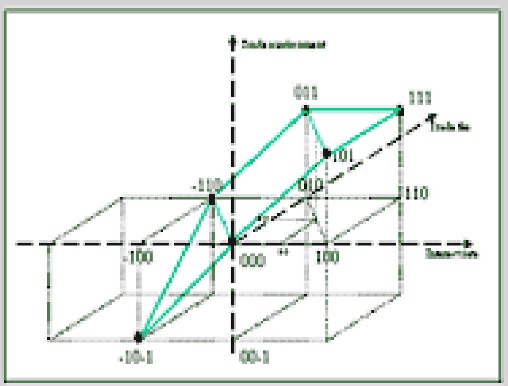
DATA MINING IN FINANCE

Advances in Relational and Hybrid Methods

by

Boris Kovalerchuk

Evgenii Vityaev



Kluwer Academic Publishers

Е.Е. Витяев

ИЗВЛЕЧЕНИЕ ЗНАНИЙ ИЗ ДАННЫХ
КОМПЬЮТЕРНОЕ ПОЗНАНИЕ
МОДЕЛИ КОГНИТИВНЫХ ПРОЦЕССОВ

ANNEX IN FINANCIAL FORECASTING

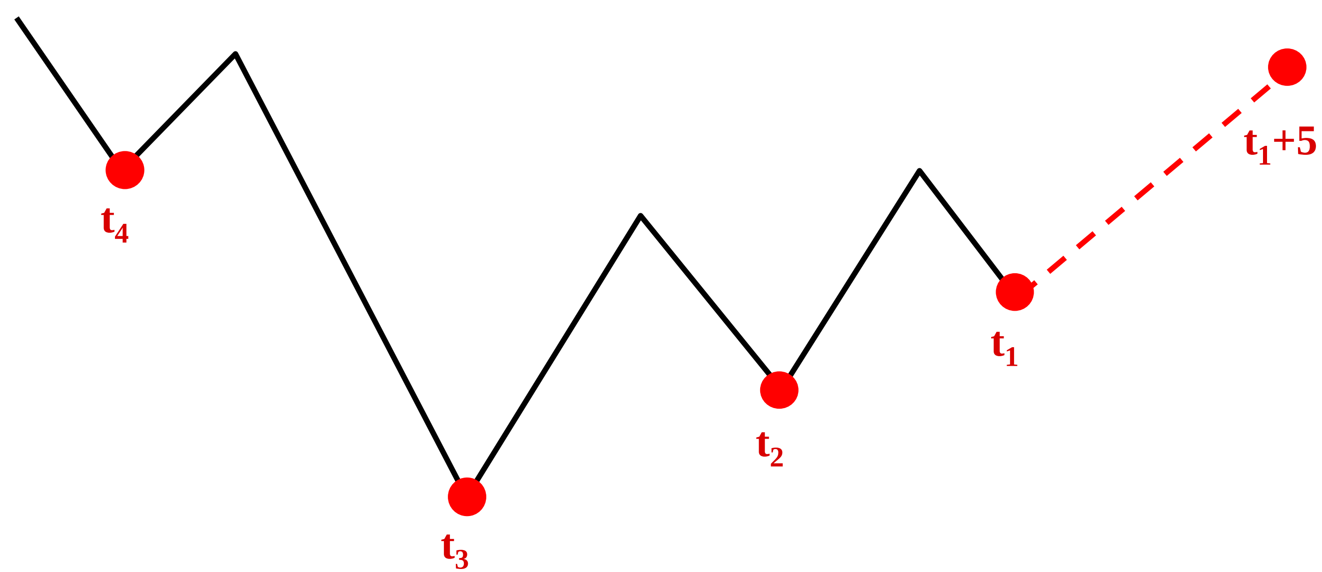
structure1	structure2	structure3	structure4	weekday	week
			forecast for	Friday	forecast week
		forecast for		Thursday	forecast week
			up	Wednesday	forecast week
	forecast for	up		Tuesday	forecast week
forecast for				Monday	forecast week
	up		current day	Friday	current week
				Thursday	current week
up		current day	down	Wednesday	current week
	current day	down		Tuesday	current week
current day			anchor2	Monday	current week
	down	anchor2		Friday	one week ago
	anchor2			Thursday	one week ago
	down anchor1	down		Wednesday	one week ago
down				Tuesday	one week ago
		anchor1		Monday	one week ago
			up	Friday	two weeks ago
				Thursday	two weeks ago
anchor2				Wednesday	two weeks ago
				Tuesday	two weeks ago
up			anchor1	Monday	two weeks ago
anchor1				Friday	three weeks ago
				Thursday	three weeks ago
				Wednesday	three weeks ago
				Tuesday	three weeks ago
				Monday	three weeks ago
training 0.74	training 0.72	training 0.7	training 0.7		
testing 0.78	testing 0.73	testing 0.71	testing 0.82		

TECHNICAL ANALYSIS FIGURES DISCOVERY

Example rule:

FOR ANY t_1 THERE ARE t_2, t_3, t_4 such that
IF t_1, t_2, t_3, t_4 are local minima AND close(t3) < close(t2) AND close(t2) < close(t1) AND close(t1) < close(t4)
THEN close(t1) < close(t1 +5)

The figure described by the rule:



Rules for breast cancer diagnostic system

Diagnostic rule	F-criterion for features		total significance of F-criterion			Accuracy of diagnosis for test cases (%)
			0.01	0.05	0.1	
IF NUMber of calcifications per cm^2 is between 10 and 20 AND VOLume > 5 cm^3 THEN Malignant	NUM VOL	0.0029 0.0040	+ +	+ +	+ +	93.3
IF TOTal number of calcifications >30 AND VOLume > 5 cm^3 AND DENSITY of calcifications is moderate THEN Malignant	TOT VOL DEN	0.0229 0.0124 0.0325	- - -	+ + +	+ + +	100.0
IF VARiation in shape of calcifications is marked AND NUMber of calcifications is between 10 and 20 AND IRRegularity in shape of calcifications is moderate THEN Malignant	VAR NUM IRR	0.0044 0.0039 0.0254	+ + -	+ + +	+ + +	100.0
IF variation in SIZE of calcifications is moderate AND Variation in SHAPE of calcifications is mild AND IRRegularity in shape of calcifications is mild THEN Benign	SIZE SHAPE IRR	0.0150 0.0114 0.0878	- - -	+ + -	+ + +	92.86

Scientific Discovery

Thank you for the attention

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Scientific Discovery website

http://www.math.nsc.ru/AP/ScientificDiscovery

Open Source for animats development:

http://math.nsc.ru/AP/ScientificDiscovery/soft/FS.html