Methods of Increasing the Autonomy of Intelligent Robotic Systems

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There is autonomy

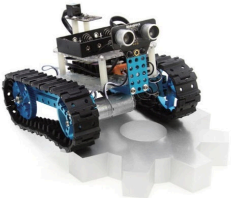
No autonomy

Robotic systems definition

Robot is

- a machine capable of carrying out a complex series of actions automatically, especially one programmable by a computer
- a device that automatically performs complicated often repetitive tasks
- a mechanism guided by automatic controls
- a machine resembling a human being and able to replicate certain human movements and functions automatically
- I don't know what robot is, but I'll distinguish him when I'll see him
- etc.
- etc.

Mobile robots

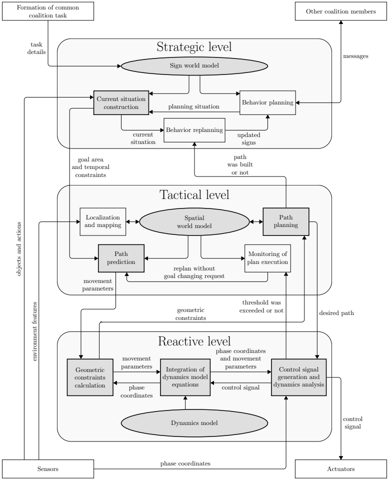


VS

Intelligent robotic system

- Programmable device
  - Possessing high degree of autonomy
  - e.g. ability to operate in the complex environment by itself (without remote control)
- Capable of
  - Adapting to the dynamic environment
  - Interacting with other robots
  - Collaborating with humans

Strategic,tactic,reactive layered architecture



Emel'yanov, S., D. Makarov, A. I. Panov, and K. Yakovlev. "Multilayer cognitive architecture for UAV control". *Cognitive Systems Research*. 2016.

Макаров, Д. А., А. И. Панов и К. С. Яковлев. «Архитектура многоуровневой интеллектуальной системы управления беспилотными летательными аппаратами». *Искусственный интеллект и принятие решений*. 2015.

Rule-based DIS

- Rule is the triple $r = \langle C, A, D \rangle$.
- The set of rules Π is divided into two subsets Π_{CL} and Π_{TR}:

$$\Pi_{CL} = \langle C(t), A(t), D(t) \rangle,$$
$$\Pi_{TR} = \langle C(t), A(t+1), D(t+1) \rangle.$$

- Closure and transition functions:

$$\Phi(\chi(t)) = (CL, \chi(t)) : 2^X \to 2^X,$$
$$\Psi(\chi(t), t) = (TR, \chi(t), t) : 2^X \times T \to 2^X.$$

- A quadruple $D = \langle X, T, \Phi, \Psi \rangle$ is called an intelligent rules-based dynamic system.

Osipov, G. S. "Limit behaviour of dynamic rule-based systems". *Information Theories and Applications.* 2008.

Vinogradov, A. N., G. S. Osipov, and L. Yu. Zhilyakova. "Dynamic intelligent systems: I. Knowledge representation and basic algorithms". *Journal of Computer and Systems Sciences International.* 2002.

Osipov, Gennady S. "Dynamics in Integrated Knowledge-based Systems". *Proceedings of the 1998 IEEE ISIC/CIRA/ISAS Joint Conference.* 1998.

DIS tasks

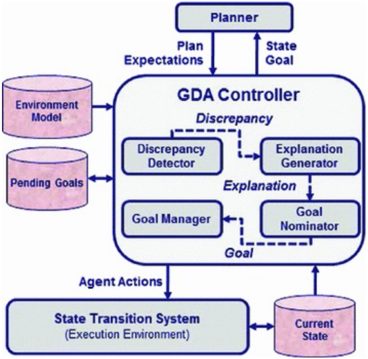
- Generation of the goal-driven behavior.
- Trajectory stability issues.
- Synthesis of control to compensate for disturbances.
- Synthesis of feedback.
- General issues of dynamic systems controllability.

Osipov, G. S. "Limit behaviour of dynamic rule-based systems". *Information Theories and Applications*. 2008.

Vinogradov, A. N., G. S. Osipov, and L. Yu. Zhilyakova. "Dynamic intelligent systems: I. Knowledge representation and basic algorithms". *Journal of Computer and Systems Sciences International*. 2002.

Osipov, Gennady S. "Dynamics in Integrated Knowledge-based Systems". *Proceedings of the 1998 IEEE ISIC/CIRA/ISAS Joint Conference*. 1998.

Goal-setting problem



For example GDA performs goal reasoning in four tasks:

- discrepancy detection,
- explanation,
- goal formulation,
- goal management.

Cox, Michael T. "A Model of Planning, Action and Interpretation with Goal Reasoning". *Advances in Cognitive Systems*. 2016.

Roberts, Mark et al. "Iterative Goal Refinement for Robotics". *Working Notes of the Planning and Robotics Workshop at ICAPS*. 2014.

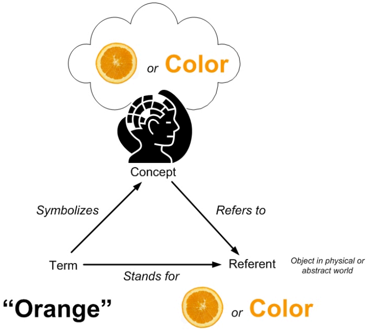
Role distribution problem

- Agents solve a common problem (have a common top-level goal).
- Agents act independently (decentralized control), including the ability to set individual sub-goals and achieve them.
- Agents have different characteristics, both technical and cognitive, i.e. different strategies of behavior.
- Agents possess different knowledge bases.
- Agents operate in a dynamic environment.

Adams, Julie A. "Task Fusion Heuristics for Coalition Formation and Planning Robotics Track". *Proc. ofthe 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018).* 2018.

Roncone, Alessandro, Olivier Mangin, and Brian Scassellati. "Transparent role assignment and task allocation in human robot collaboration". *Proceedings - IEEE International Conference on Robotics and Automation.* 2017.

Symbol grounding problem



Classical methods of artificial intelligence are symbolic (logic, set of rules, planning, learning). However, thinking — is more than symbol manipulation.

This problem is especially relevant in robotics (**symbol anchoring**) — the system should learn symbols based on its own experience.

Barsalou, Lawrence W. "Grounded cognition". *Annual review of psychology*. 2008.
Barsalou, L. W. "Perceptual symbol systems". *The Behavioral and brain sciences*. 1999.
Harnad, Stevan. "Symbol Grounding Problem". *Physica*. 1990.

Psychology and Neurophysiology

- Various applications that require or prefer human-like behaviour and performance.
- Cognitive architectures may serve as a good basis for building mind/brain-inspired, psychologically realistic cognitive agents.
- "Cognitive synergy", wherein different components are specifically integrated in such a way as to compensate for each others scalability weaknesses.
- Bridging the gap between neurophysiological realities and mathematical and computer science concepts.

Goertzel, Ben. "GOLEM: towards an AGI meta-architecture enabling both goal preservation and radical self-improvement". *Journal of Experimental & Theoretical Artificial Intelligence*. 2014.

— ."How Might the Brain Represent Complex Symbolic Knowledge?". *2014 International Joint Conference on Neural Networks (IJCNN)*. 2014.

Hélie, Sébastien and Ron Sun. "Autonomous learning in psychologically-oriented cognitive architectures: A survey". *New Ideas in Psychology*. Aug. 2014.

Sun, Ron and Sébastien Hélie. "Psychologically realistic cognitive agents: taking human cognition seriously". *Journal of Experimental & Theoretical Artificial Intelligence*. 2012.

Knowledge representation as a main issue of AI

- Knowledge representation approaches vs machine learning approaches.
- Representing knowledge in order to design formalisms that will make complex systems easier to design and build.
- Knowledge representation and reasoning also incorporate findings from logic to automate various kinds of reasoning.

Финн, В. К. «Эпистемологические принципы порождения гипотез». *Вопросы философии.* 2014.

— .«Об определении эмпирических закономерностей посредством ДСМ - метода автоматического порождения гипотез». *Искусственный интеллект и принятие решений.* 2010.

Applied semiotics by Pospelov

Semiotic knowledge bases:

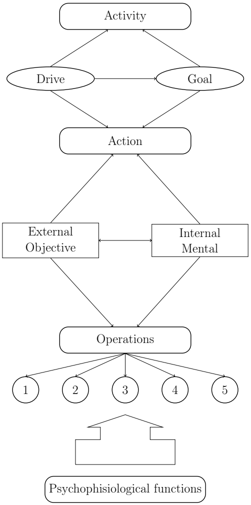
- **Naming**: information unit, which purports to be knowledge, needs to have some tag - name.
- **Structuring**: an information unit must have its own internal structure.
- **Principle of "matryoshka"**: signs are embedded into each other through inheritance relationships, providing a description of entities at different levels.
- **Connectivity**: the signs due to the different relations are combined in the network.
- **Activity**: in sign networks it becomes possible to implement the principle of "knowledge activation is source of procedures activation".
- **Reflexivity**: the appearance of the meta-level allows the system to talk about itself, about the nature of its information about the world.

Osipov, G. S. "Origines of Applied Semiotics". *Proceedings of the Workshop "Applied Semiotics: Control Problems (ASC 2000)". 14th European Conference of Artificial Intelligence (ECAI2000).* 2000.

— ."Applied Semiotics and Intelligent Control". *Proceedings of the Second Workshop on Applied Semiotics, Seventh International Conference on Artificial Intelligence and Information-Control Systems of Robots (AIICSR'97).* 1997.

Pospelov, D. A. and G. S. Osipov. "Knowledge in semiotic models". *Proceedings of the Second Workshop on Applied Semiotics, Seventh International Conference on Artificial Intelligence and Information-Control Systems of Robots (AIICSR'97).* 1997.

Theory of activity by Leontyev



Base concepts:

- Human behavior is a dual hierarchical structure of motives-goals and actions-operations.
- Activity is an active, purposeful process.
- Human actions are subject; their goals are social in nature.
- Consciousness and activity are inextricably linked.

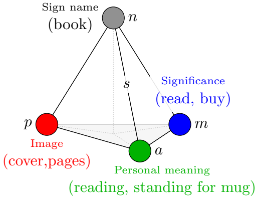
Leontyev, A. N. *The Development of Mind.* 2009.

Cultural and historical approach by Vygotsky

Theory of origin and development of higher mental functions:

- **Social environment** — the main source of personality development.
- Mastery of culture, ways of behavior and thinking.
- The development of cognitive functions occurs primarily through the child's using of **"psychological tools"**, by mastering the system of character signs, such as language, writing, counting.
- External activity, when cultural tools are subject, as mining collapses (**interiorized**) in the internal plan.
- In the first stage of external activity the child does everything in **cooperation** with adults - "zone of proximal development".
- The development is not exactly gradual, and **multi-stage** process.
- Consciousness develops through the **dialogue**: a child's dialogue with an adult or an adult's dialogue with an adult.

Three elements of the sign-based world model

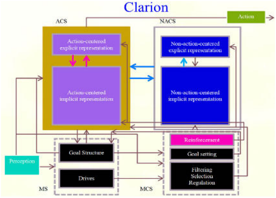


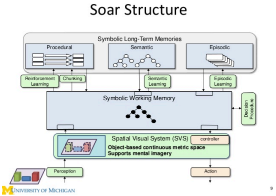
We present an entity as three cause-effect (causal) structures:

- image structure - representation of the relationship of external signals and internal characteristics of the subject (agent) - sensorimotor representation,
- value structure - generalized knowledge of relations in the outside world, agreed in some group of subjects (agents),
- the structure of the personal meaning - situational requirement of motivational interpretation of knowledge about the relationships in the external environment ("the value for me").

Oizumi, Masafumi, Larissa Albantakis, and Giulio Tononi. "From the Phenomenology to the Mechanisms of Consciousness: Integrated Information Theory 3.0". *PLoS Computational Biology*. 2014.

Cognitive architectures





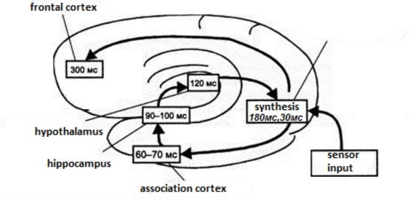
Disadvantages of modern cognitive architectures:

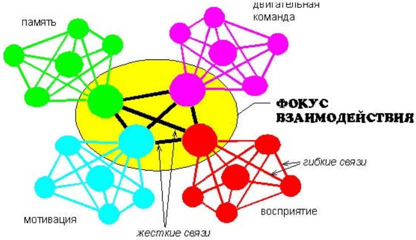
- The conceptually unresolved problems of binding symbols (symbol grounding problem) - CLARION.
- The lack of the activity model of the system behavior, there is implementation of only some cognitive aspects
- Hierarchy of knowledge representations (4D/RCS).
- The possibility of implementing a hierarchical planning.
- Implementation of conceptual knowledge learning - Cognitive Mario.
- Modeling of the reflexive behavior.

Besold, Tarek R. and Kai Uwe Kuhnberger. "Towards integrated neural-symbolic systems for human-level AI: Two research programs helping to bridge the gaps". *Biologically Inspired Cognitive Architectures.* 2015.

Sun, Ron. "Autonomous generation of symbolic representations through subsymbolic activities". *Philosophical Psychology.* 2013.

Three elements of the sign-based world model





A.Ivanitsky (*information synthesis*), G.Edelman (*theory of re-entry*): the emergence of sensations, i.e. activation of some element of the personal knowledge, occurs with the closure of contour of the nervous excitement distribution from the sensory input. The value of the signal (the hippocampus) and emotional relations (hypothalamus) impose on the received sensory information.

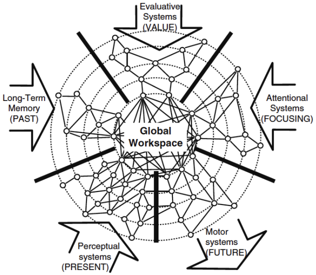
Ivanitsky, A. M. “Brain science on the way to solving the problem of consciousness”. *Herald of the Russian Academy of Sciences*. 2010.

Izhikevich, Eugene M. and Gerald M. Edelman. “Large-scale model of mammalian thalamocortical systems”. *Proceedings of the National Academy of Sciences of the United States of America*. 2008.

Ivanitsky, A. M. “Information synthesis in key parts of the cerebral cortex as the basis of subjective experience”. *Neuroscience and Behavioral Physiology*. 1997.

Edelman, G. M. *Neural Darwinism: The Theory Of Neuronal Group Selection*. 1987.

Three elements of the sign-based world model

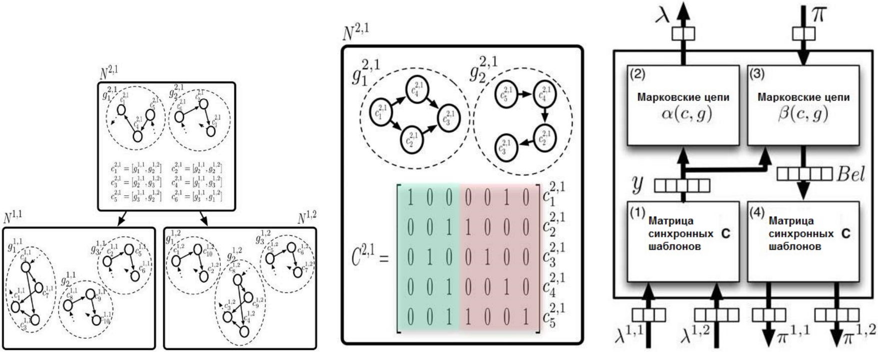


- Conscious cognitive content is globally available for diverse cognitive processes including attention, evaluation, memory, and verbal report.
- Global availability is necessarily limited to a single stream of content.
- Sensory stimuli mobilize excitatory neurons with long-range cortico-cortical axons, leading to the genesis of a global activity pattern among workspace neurons.
- Any such global pattern can inhibit alternative activity patterns among workspace neurons.

Dehaene, Stanislas, Lucie Charles, Jean-Rémi King, and Sébastien Marti. "Toward a computational theory of conscious processing". *Current Opinion in Neurobiology*. 2014.

Baars, Bernard J., Stan Franklin, and Thomas Zoega Ramsoy. "Global workspace dynamics: Cortical "binding and propagation" enables conscious contents". *Frontiers in Psychology*. 2013.

An elementary unit



The main principles of the learning mechanism are:

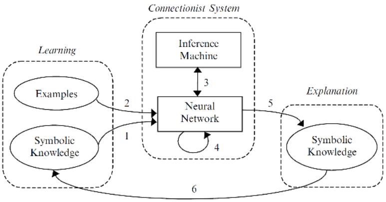
- using a hierarchy of computing nodes with bottom-up and top-down streams,
- using Hebbian rules for learning,
- separation of spatial and temporal poolers,
- suppression of secondary activation for the formation of sparse representations.

George, D. et al. "A generative vision model that trains with high data efficiency and breaks text-based CAPTCHAs". *Science*. Oct. 2017.

Billaudelle, Sebastian and Subutai Ahmad. "Porting HTM Models to the Heidelberg Neuromorphic Computing Platform". 2015.

George, Dileep and Jeff Hawkins. "Towards a mathematical theory of cortical micro-circuits". *PLoS computational biology*.

Neural symbolic computation



Basic idea: encoding a symbol by a vector of numbers and then representing that vector by links in an ensemble of artificial neurons (embedding).

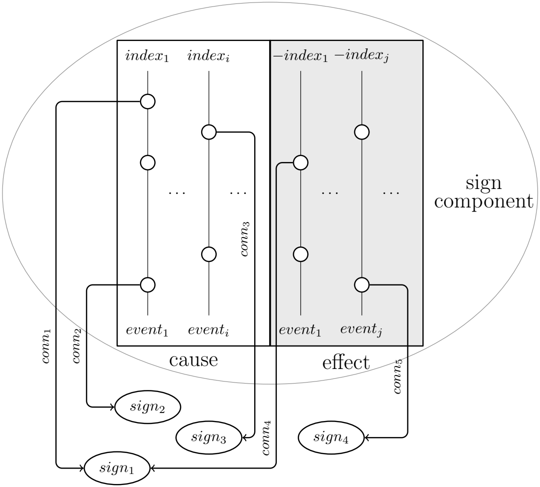
The main result: by introducing special rules on the distribution of activity in neural networks some simple logic circuits are implemented.

Main drawback: limited integration of learning.

Garcez, Avila et al. "Neural-Symbolic Learning and Reasoning : Contributions and Challenges". *Knowledge Representation and Reasoning: Integrating Symbolic and Neural Approaches: Papers from the 2015 AAAI Spring Symposium*. 2015.

Sun, Ron. *Integrating Rules and Connectionism for Robust Commonsense Reasoning*. 1994.

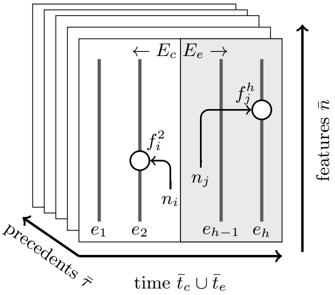
Causal matrix



Osipov, Gennady S. and Aleksandr I. Panov. "Relationships and operations in agent's sign-based model of the world". *Scientific and Technical Information Processing*. 2018.

Panov, Aleksandr I. "Behavior Planning of Intelligent Agent with Sign World Model". *Biologically Inspired Cognitive Architectures*. 2017.

Causal tensor



A causal tensor $T(n) = T[n, \bar{n}, \bar{t}_c, \bar{\tau}]$ is a three-dimensional array of real numbers of dimension $r \times q \times h$, which is provided with an identifier n and three reference vectors:

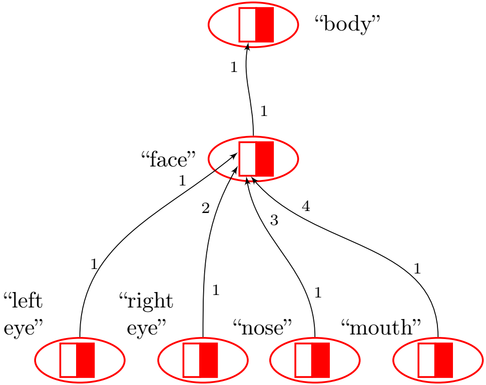
- an indicative vector $\bar{n} = (n_1, n_2, ..., n_q)$;
- a temporary vector $\bar{t}_c = (t_1, t_2, ..., t_{h_c})$;
- a case vector $\bar{\tau} = (\tau_1, \tau_2, ..., \tau_r)$.

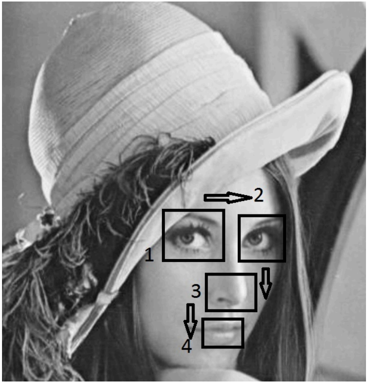
Causal network

Causal network $W = (\mathbf{T}, \mathbf{L})$ is a directed labeled multigraph where the set of vertices $\mathbf{T}$ with the tags $\{n_1, n_2, ...\}$ corresponds to the set of causal tensors $\{T(n_1), T(n_2), \dots\}$ and set of arcs $\mathbf{L}$ consists of arcs $l_i = T(n_i) \to T(n_j) = (T[n_i, \bar{n}_i, \bar{t}_{ci}, \bar{\tau}_i], T[n_j, \bar{n}_j, \bar{t}_{cj}, \bar{\tau}_j])$ such that $n_i \in \bar{n}_j$, and marked by triplet $\{\varepsilon_1, \varepsilon_2, \varepsilon_3\}$ where

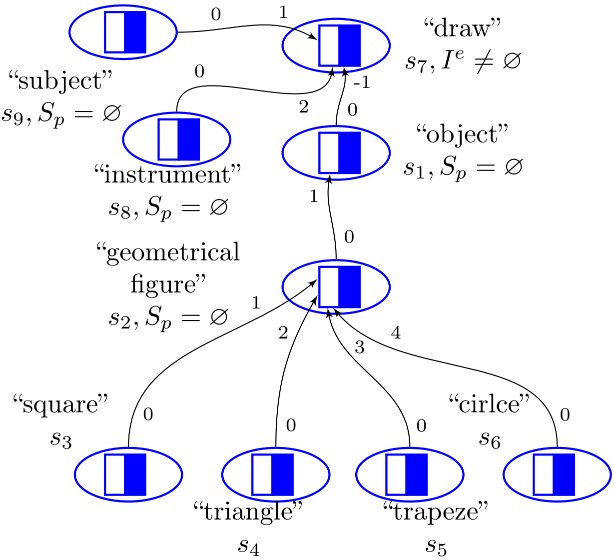
- $\varepsilon_1 = \tau_k$ such that $\tau_k \in \bar{\tau}_j$ and $\exists e_u = (f_1^u, f_2^u, \dots, f_q^u) \in E_c(n_j) \cup E_e(n_j)$, in which $\exists f_v^u > \theta^f$, that is, this label corresponds to such a precedent in the tensor $T(n_j)$ for which an event exists in the causal matrix in which the tensor-trait $T(n_i)$ manifests itself with a value above the threshold θ^f;
- $\varepsilon_2 = t_k$ so $t_k > 0$ then $t_k \in \bar{t}_{cj}$ and $e_{t_k} = (f_1^{t_k}, f_2^{t_k}, \dots, f_q^{t_k}) \in E_c(n_j) \cup E_e(n_j)$ exists $f_v^{t_k} > \theta^f$ and if $t_k < 0$, then $t_k \in \bar{t}_{ej}$ and in $e_{t_k} = (f_1^{t_k}, f_2^{t_k}, \dots, f_q^{t_k}) \in E_c(n_j) \cup E_e(n_j)$ $f_v^{t_k} > \theta^f$ i.e. this label corresponds to such an event in the precedent $\varepsilon_1 = \tau_k$ of the tensor $T(n_j)$, for which there is a tensor-feature $T(n_i)$ in the causal matrix, manifesting with a value above the threshold θ^f;
- $\varepsilon_3 = \tau_w$ such that if $\tau_w > 0$, then $\tau_w \in \bar{\tau}_i$, i.e. defines a precedent in the tensor $T(n_i)$, which encodes the trait for the tensor $T(n_j)$, if $\tau_w = 0$, then the trait is encoded by all precedents of the tensor $T(n_i)$.

Causal network on images

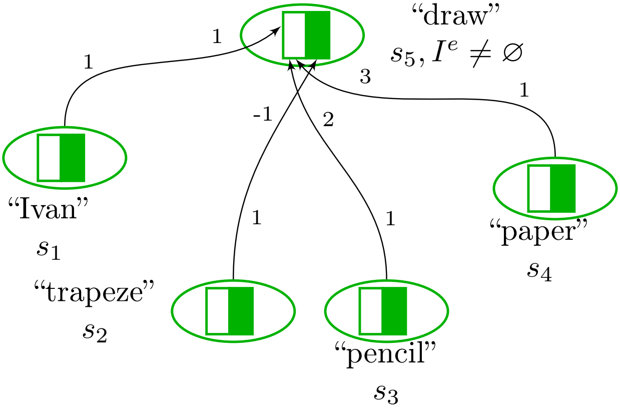




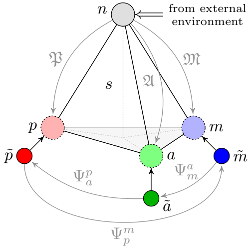
Causal network on significances

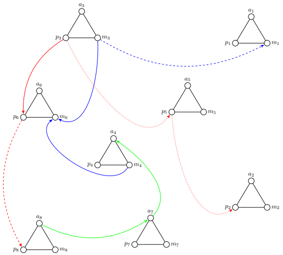


Causal network on personal meanings



Sign and semiotic network





Sign $s(n)$ with name n is the quadruple $\langle n, T^p(n), T^m(n), T^a(n)\rangle$ such that all the three ratios are satisfied: $\Psi_a^p \Psi_m^a \Psi_p^m(T^p(n)) = T^p(n)$, $\Psi_p^a \Psi_a^p \Psi_m^a(T^m(n)) = T^m(n)$ and $\Psi_m^a \Psi_p^m \Psi_a^p(T^a(n)) = T^a(n)$, i.e., for any composition of linking functions the three tensors $(T^p(n), T^m(n), T^a(n))$ is a stationary point.

Semiotic network is the triple $\langle W_n, \mathbf{W}, \mathbf{\Psi}, \mathbf{\Phi}\rangle$, where $\mathbf{W} = \{W_p, W_m, W_a\}$ is a family of causal networks on images, significances and personal meanings, $\mathbf{\Psi} = \{\Psi_p^m, \Psi_m^a, \Psi_a^p\}$ is a family of linking functions, $\mathbf{\Phi}$ is a family of rules of activity propagation in causal networks, $W_n = (N, R_n)$ - a semantic network on the names, where the set of vertices N is the set of names of characters $N = \{n : \Psi_a^p \Psi_m^a \Psi_p^m(T^p(n)) = T^p(n)\}$, and a family of relationships R_n sets to linguistic communication on the set sign names and is a translation of the relations on the set of sign components(collections R_p, R_m, R_a).

Osipov, G. S. "Sign-based representation and word model of actor". *2016 IEEE 8th International Conference on Intelligent Systems (IS).* 2016.

Osipov, Gennady S. "Signs-Based vs. Symbolic Models". *Advances in Artificial Intelligence and Soft Computing.* 2015.

Relationships on the set of images

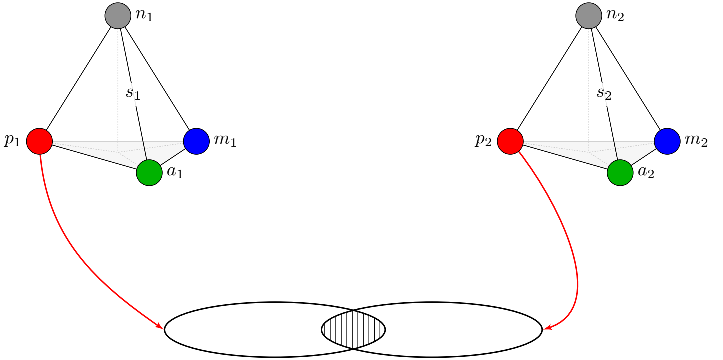


Image similarity

Relationships on the set of images

Image inclusion

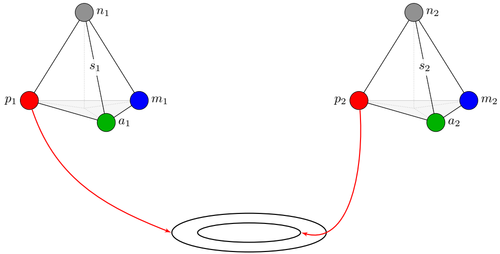
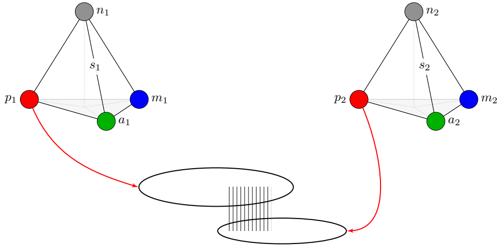
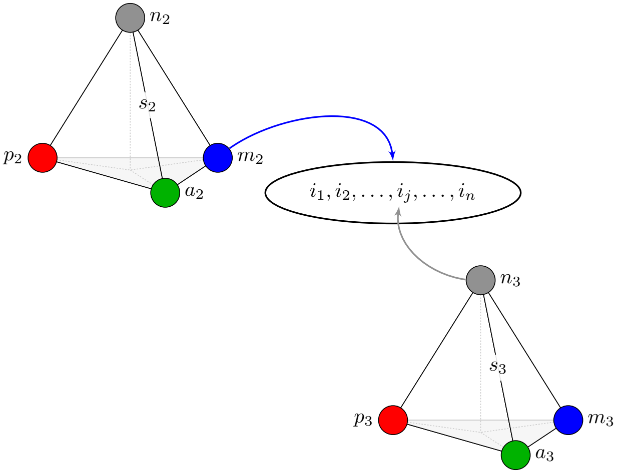


Image opposition



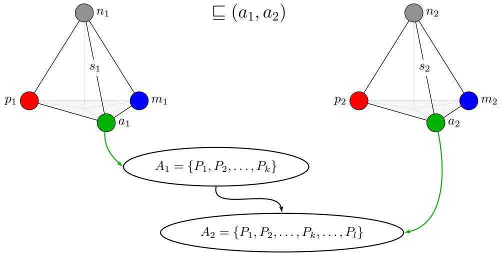
Relationships on the set of significances



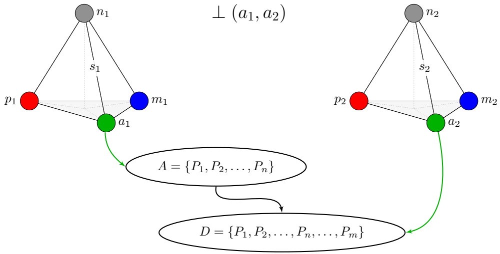
Script on significances

Relationships on the set of personal meaning

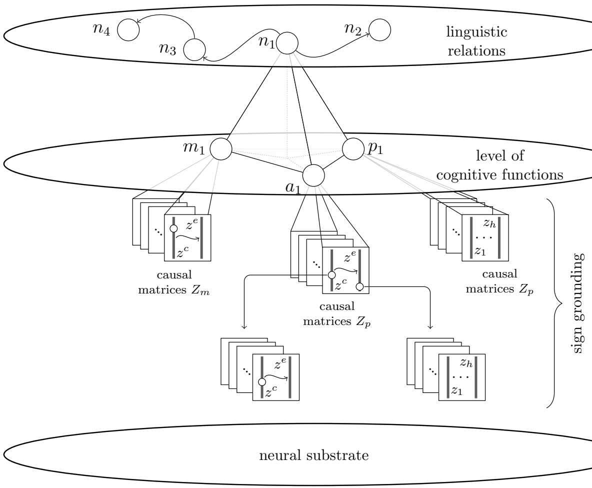
Agglutination of personal meanings



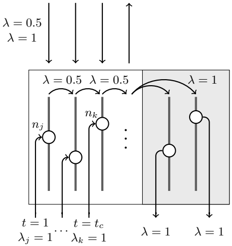
Opposition of personal meanings



Network on sign names

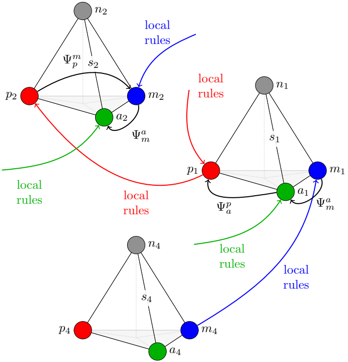


Local rules of activity propogation



- *The upward rule*: if at time t the tensor $T(n_j)$ such that $n_j \in \bar{n}$ and $\lambda_j = 1$, then all nonzero elements of (j, t, τ_l) tensor $T(n_i)$ in each precedent of τ_l becomes active, i.e., $\lambda_{jtl} = 1$.
- *The predicting rule*: if at time t, the event e_t of the precedent τ_l in the tensor $T(n_i)$ is active (i.e., $\forall f_k^t \in e_t : f_k^t > 0 \wedge \lambda_{ktl} = 1$) and $t < t_c$, then all nonzero elements of $(k, t+1, \tau_l)$ events in e_{t+1} be a semi-active, i.e., $\lambda_{jt+1l} = 0.5$.
- *The downward rule*: if at time t in each active precedent (i.e. $\forall u > 0 : u \leq t$ is e_u - active) tensor $T(n_i)$, the event e_t - active (i.e., $\forall f_k^t \in e_t : f_k^t > 0 \wedge \lambda_{ktl} = 1$), then all tensors $T(n_j)$ corresponding to the nonzero elements of $(j, t+1, \tau_l)$ events in e_{t+1} in each precedent of τ_l becomes semi-active.
- *The causal rule*: if $t = t_c$ event e_{t_c} is active at the time, then the predictive rule and the downward rule are applied consistently for all effect events, adjusted for the fact that full activity is propagated, i.e. $\lambda_{jtl} = 1$.

The model of the cognitive function



A cognitive function model is the sequence of signs $(s_1, s_2, \dots)$ such that $\forall s_i(n_i)$ tensors for each component in $T^p(n_i)$, $T^m(n_i)$, $T^a(n_i)$ are simultaneously active, i.e. the propogation of activity leads to the activation of these causal tensors, which form a sign on each stage of the activity propogation.

Perception and categorization

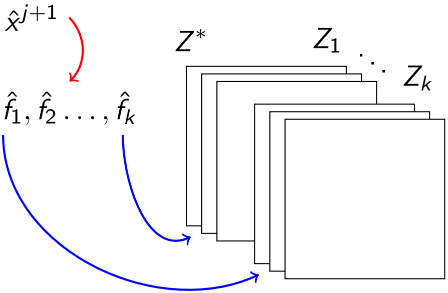
$\hat{f}_1, \hat{f}_2 \ldots, \hat{f}_k$

Perception and categorization

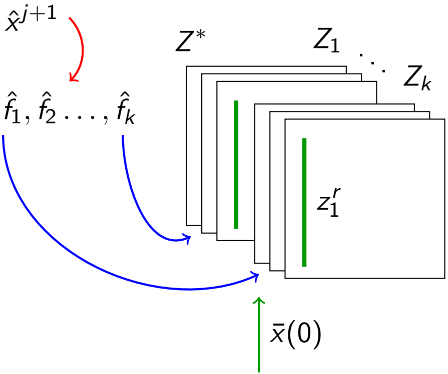
$$\hat{x}^{j+1}$$

$$\hat{f}_1, \hat{f}_2 \ldots, \hat{f}_k$$

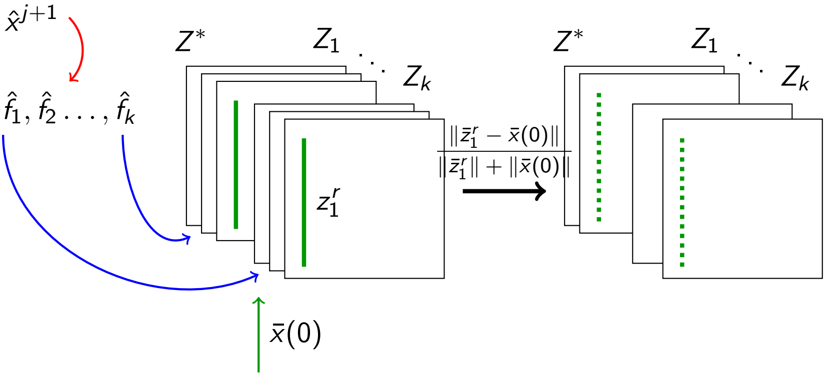
Perception and categorization



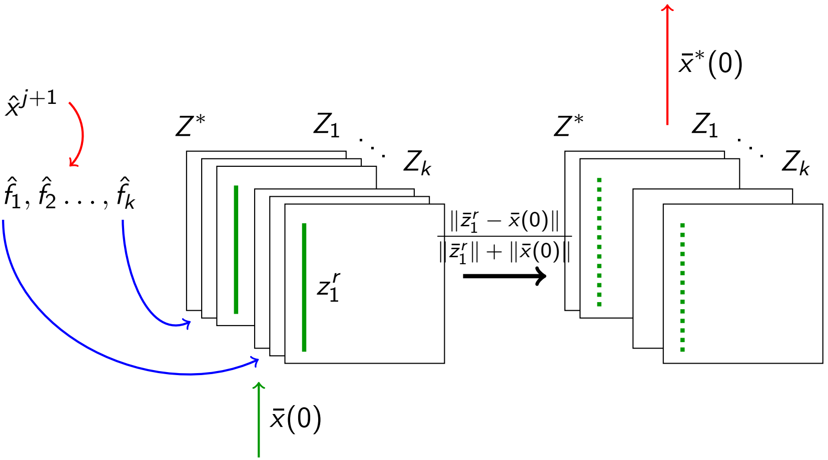
Perception and categorization



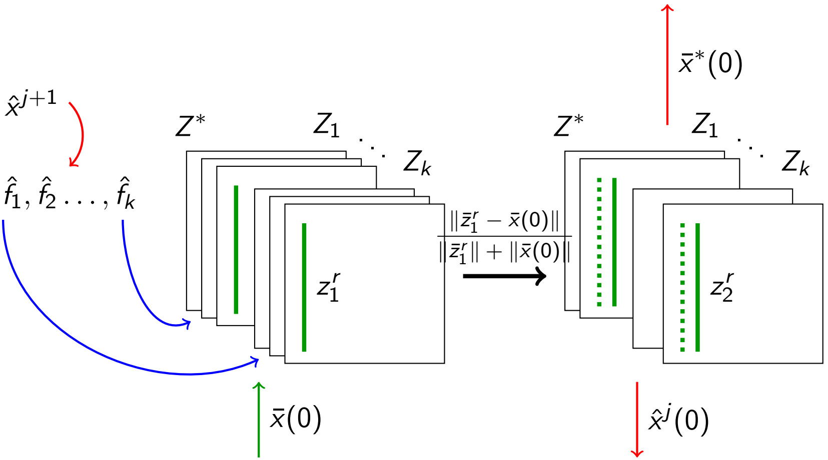
Perception and categorization



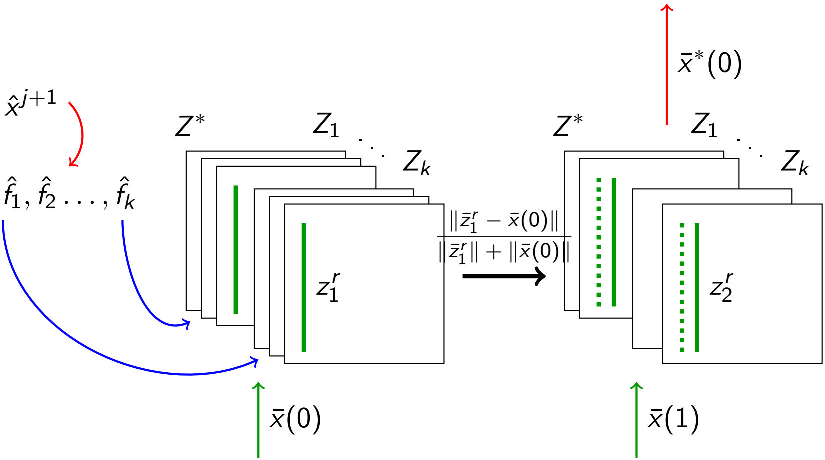
Perception and categorization



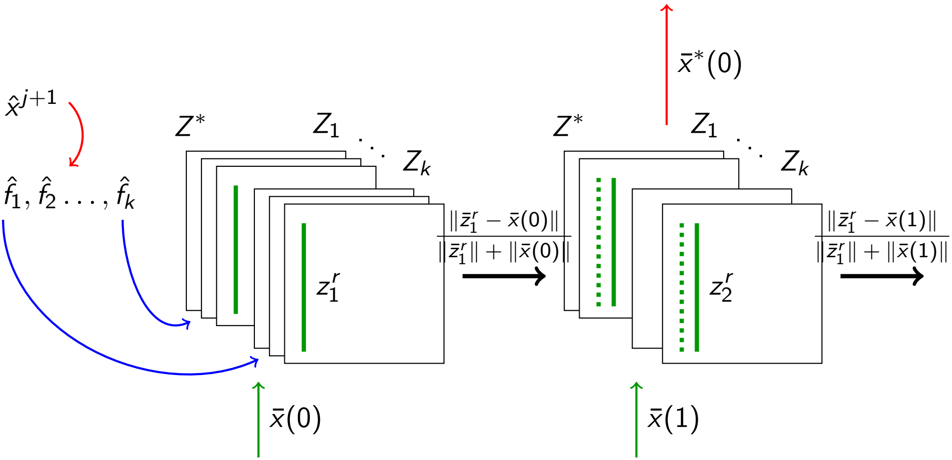
Perception and categorization



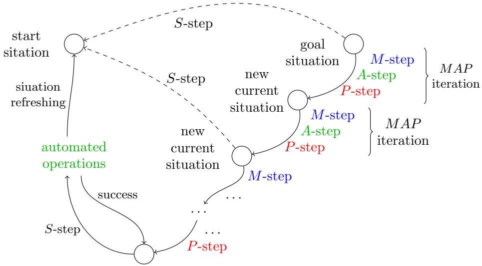
Perception and categorization



Perception and categorization



Schema of the algorithm MAP



Kiselev, G. A. and A. I. Panov. "Sign-based Approach to the Task of Role Distribution in the Coalition of Cognitive Agents". *SPIIRAS Proceedings*. 2018.

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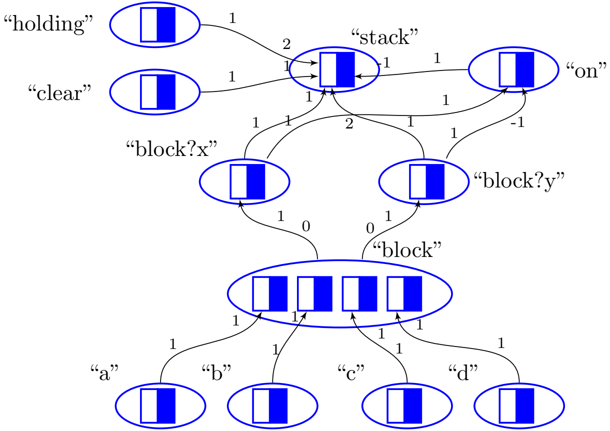
Panov, Aleksandr I. and Konstantin S. Yakovlev. "Psychologically Inspired Planning Method for Smart Relocation Task". *Procedia Computer Science*. 2016.

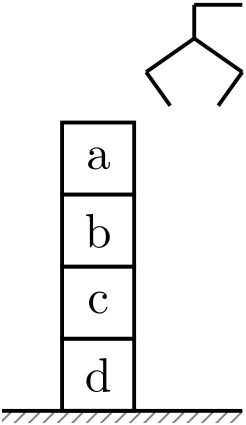
The hierarchical planning process begins with the finish situation and seeks to achieve the start situation.

MAP iteration:

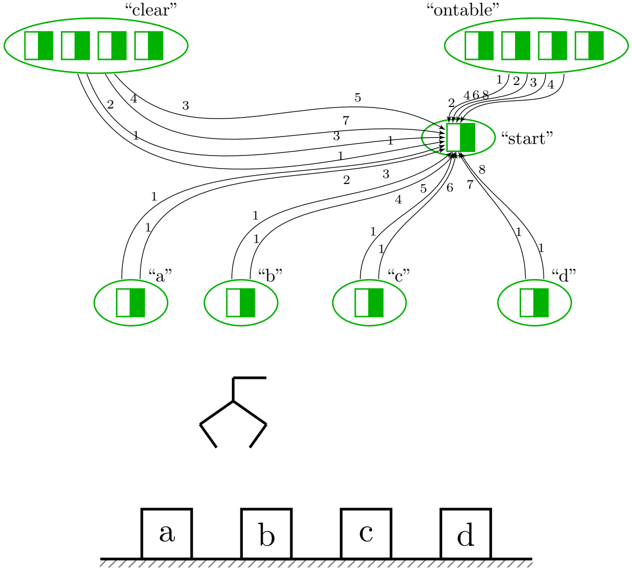
- *S-step* – search of precedents of the action implementation for the current conditions,
- M-step – find applicable actions on the significance network,
- A-step – generation of personal meanings corresponding to the found significances,
- P-step – construct a new current situation from the set of features of the conditions of the found actions.

The fragment of the significance network

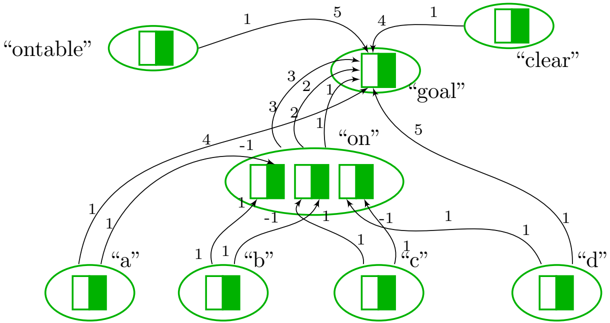


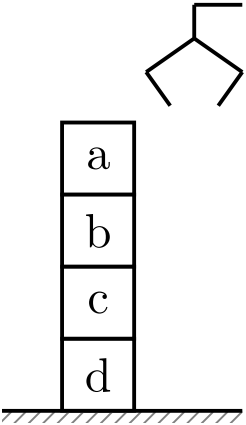


Personal meaning network - start situation

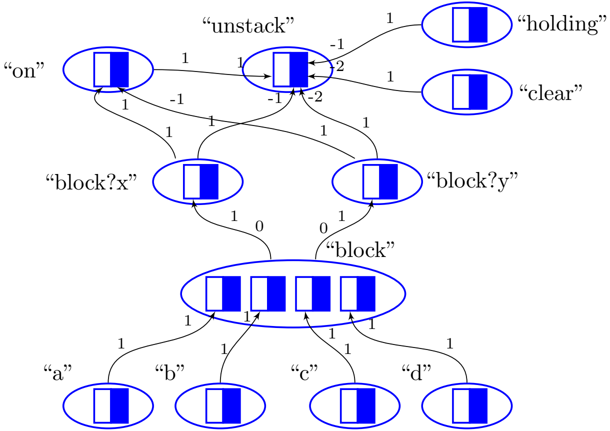


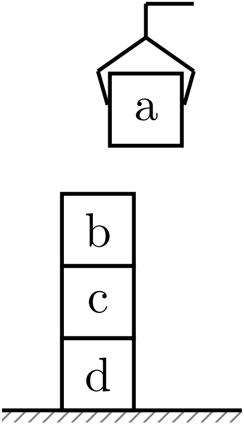
Personal meaning network - final situation



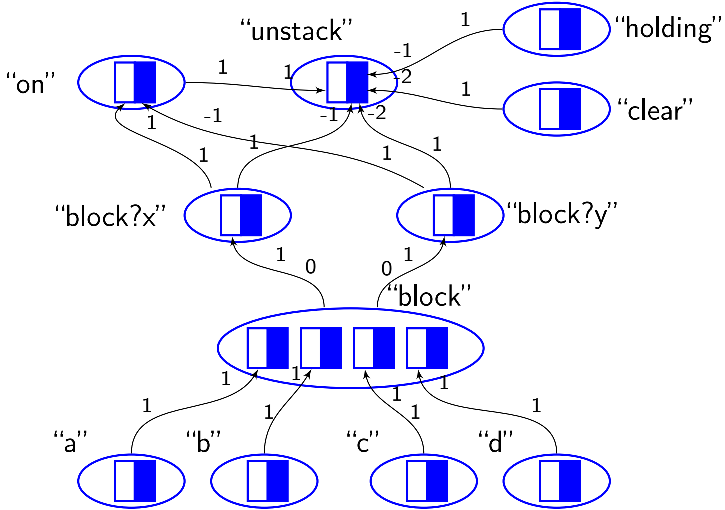


The fragment of the significance network

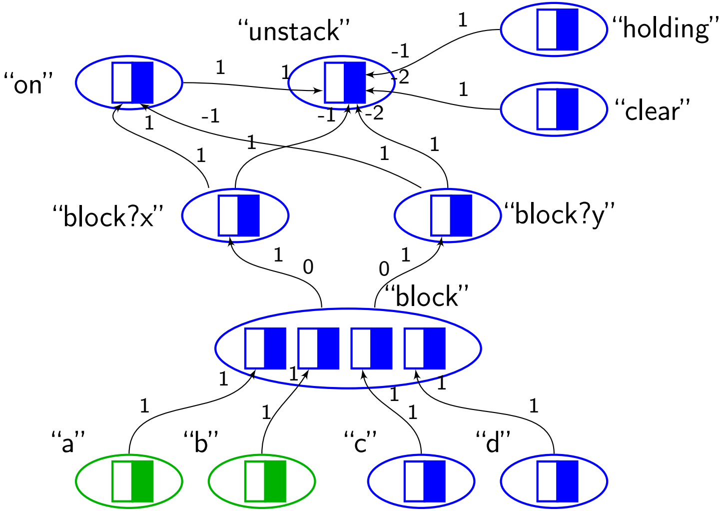




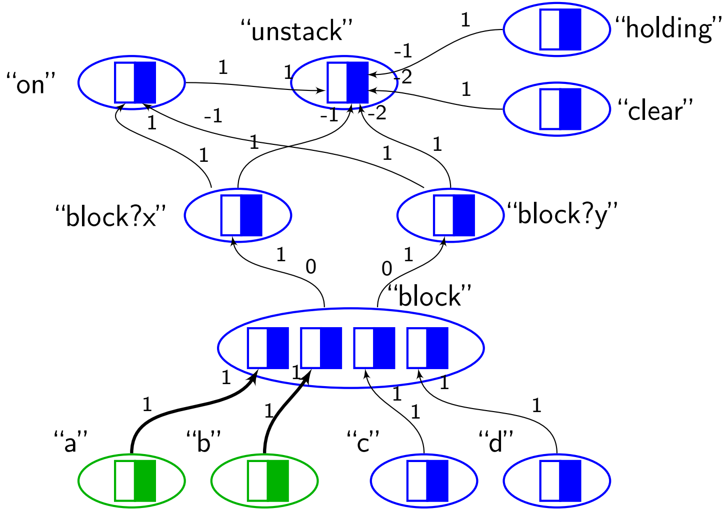
Generation of the next situation



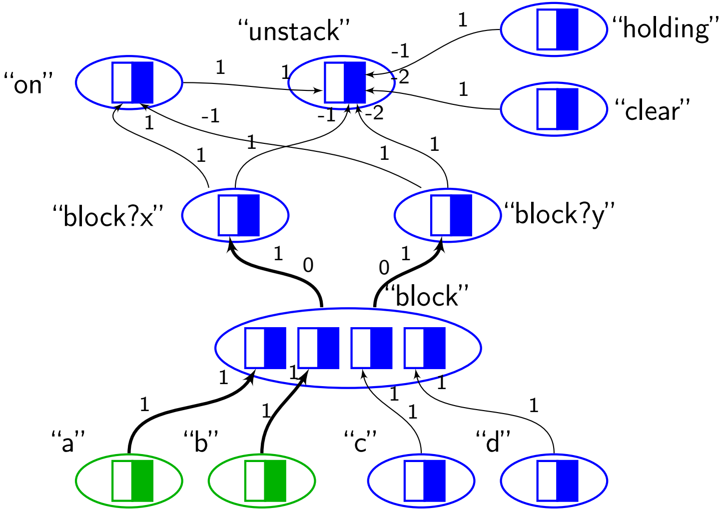
Generation of the next situation



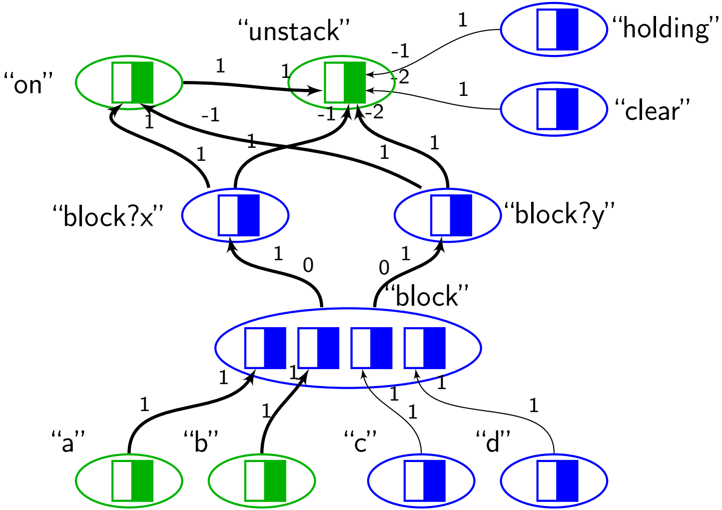
Generation of the next situation



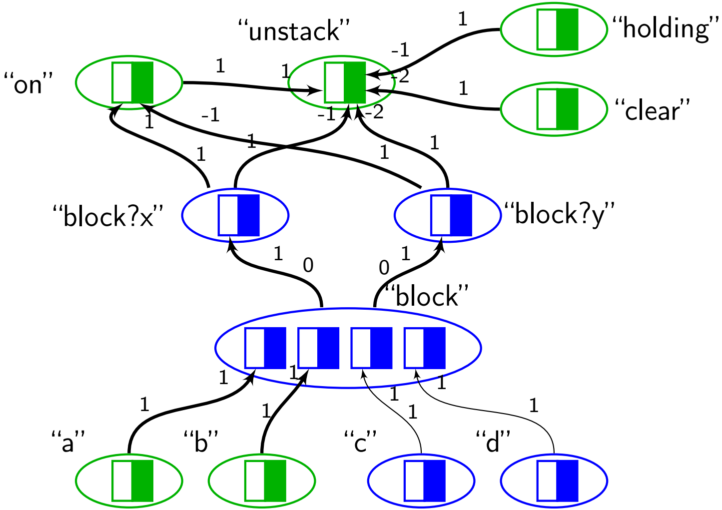
Generation of the next situation



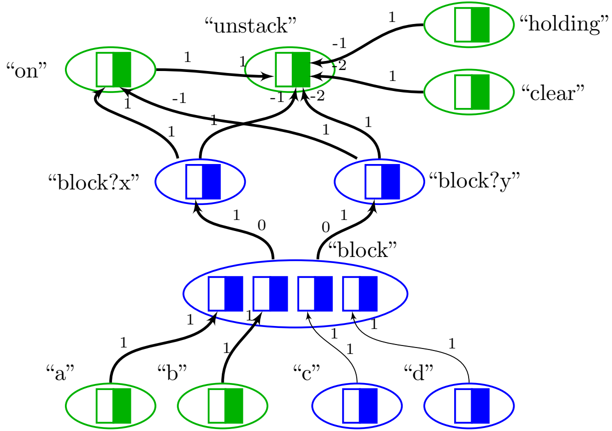
Generation of the next situation

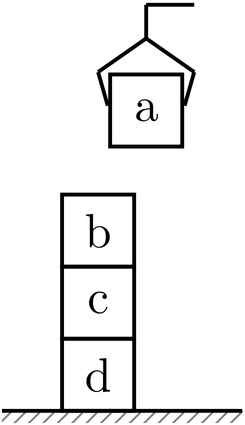


Generation of the next situation



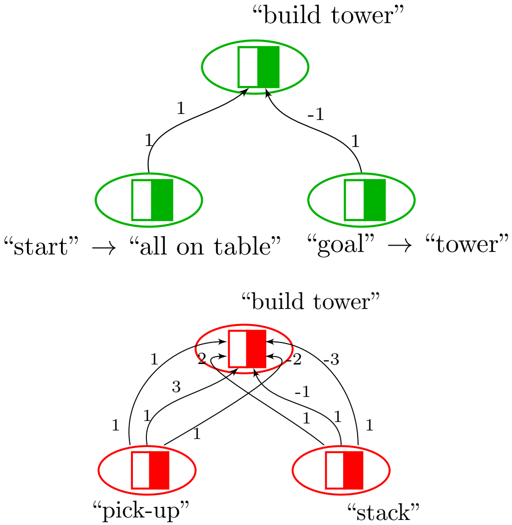
The current situation



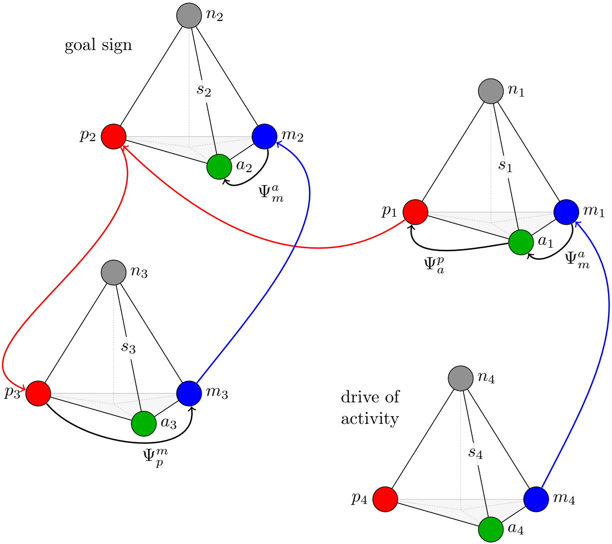


Formation of the new sign

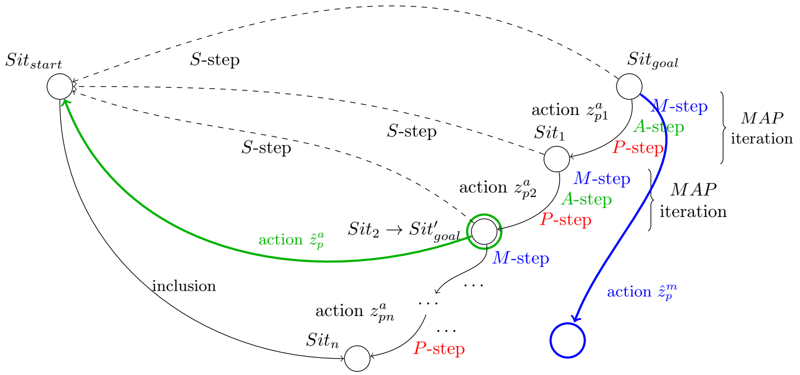
Formation of a new rule and learning a new sign - formation of new causal matrices.



Goal-setting on the syntactic level



Goal-setting in planning



Панов, А. И. «Целеполагание и синтез плана поведения когнитивным агентом». *Искусственный интеллект и принятие решений*. 2018.

Samsonovich, Alexei V. “Goal reasoning as a general form of metacognition in BICA”. *Biologically Inspired Cognitive Architectures*. 2014.

Iterative and unsupervised learning

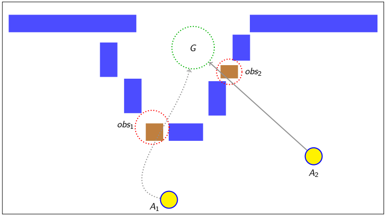
We construct an algorithm $\mathfrak{A}_{pm}$ to determine the function Ψ_p^m, which provides the formation of such an image from the set of features $\hat{F}$, in which the generated sign value converges to the given value $\tilde{m}^0 = \{f_p^0\}$.

The proposed learning algorithm is based on the hierarchical temporal memory (HTM) approach and consists of the following basic steps:

1. Formation of spatial representation.
2. Search for time sequences.
3. Identification of the causal relationship.

Панов, А. И. и А. В. Петров. «Иерархическая временная память как модель восприятия и её автоматное представление». *Шестая Международная конференция "Системный анализ и информационные технологии"САИТ-2015 (15-20 июня 2015 г., г. Светлогорск, Россия): Труды конференции. В 2-х т.* 2015.

Smart Relocation Tasks (SRT)



3 levels of control:

- Transformable environment
- Different types of obstacles (some – can be destroyed)
- Agents with different capabilities (some agents can destroy obstacles, others – can not)
- Common spatial goal (ALL agents must reach this region in order goal to be achieved)

Problem

Goal area can not be achieved by some agents on their own (using standalone task and path planning methods)

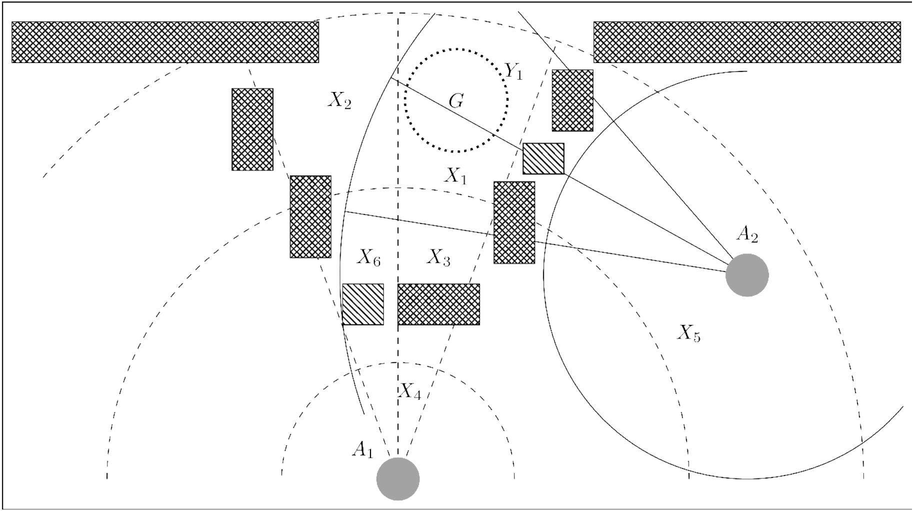
Solution

Agents must communicate and some agents must alter their "selfish" plans in order to construct coalition plan

Panov, A. I. and K. S. Yakovlev. "Behavior and path planning for the coalition of cognitive robots in smart relocation tasks". *Robot Intelligence Technology and Applications 4.* 2016.

Panov, Aleksandr I. and Konstantin S. Yakovlev. "Psychologically Inspired Planning Method for Smart Relocation Task". *Procedia Computer Science.* 2016.

Spatial knowledge representation



Spatial knowledge representation

Relocation actions — signs s_t (features f_t, t — relocation type), with corresponding prediction matrices Z_t consist of 3 columns:

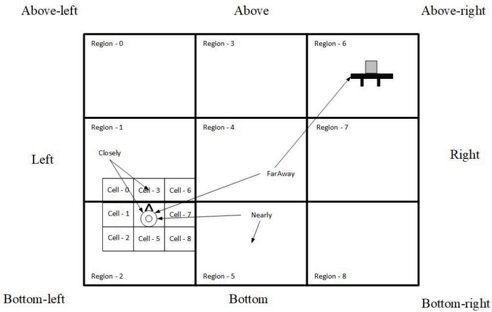
$$z_1 = (l_x, I), z_2 = (l_y, d_u, E), z_3 = (l_y, I, t_v),$$

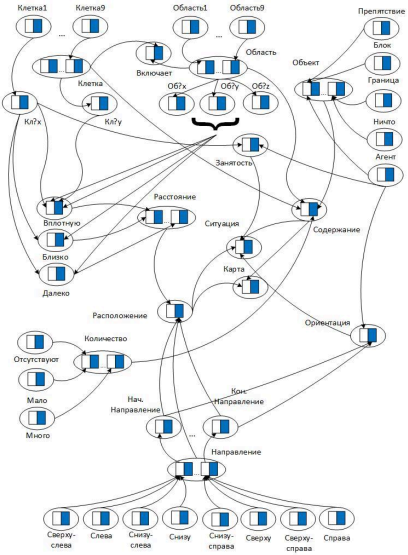
- l_x, l_y — features represented category of distance in a spatial logic (e.g., “far”, “closely” etc.),
- d_u — features represented category of direction in a spatial logic (e.g., “left”, “straight” etc.),
- t_v — features represented category of time in temporal logic (e.g., “soon”, “not soon” etc.),
- I — feature of agent presence,
- E — feature of obstacle absence.

Kiselev, G. A. and A. I. Panov. “Sign-based Approach to the Task of Role Distribution in the Coalition of Cognitive Agents”. *SPIIRAS Proceedings*. 2018.

Kiselev, Gleb A. and Aleksandr I. Panov. “Synthesis of the Behavior Plan for Group of Robots with Sign Based World Model”. *Interactive Collaborative Robotics*. 2017.

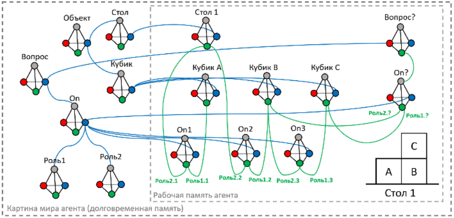
Spatial knowledge representation





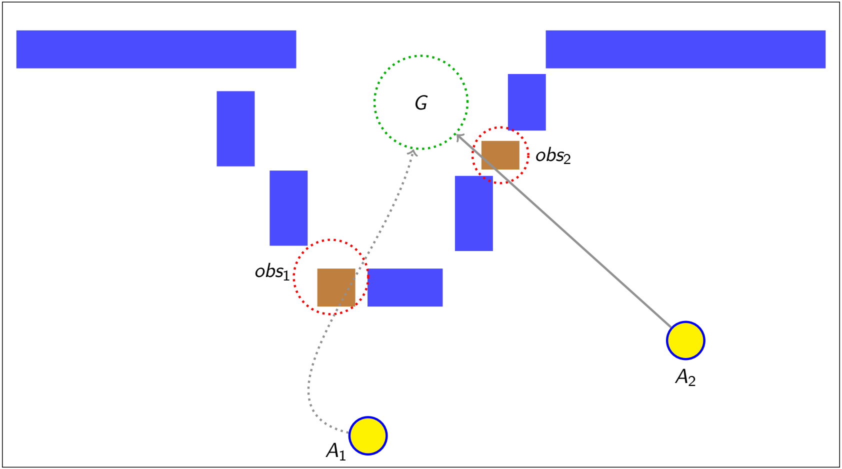
Sign-based spatial reasoning

- **Abstraction** $inst2prot(\hat{S})$ is the transition along an edge from the sign-instance to the corresponding sign-prototype.
- **Concretization** to the instance $prot2inst(\dot{S})$ is the transition along the edge from the sign-prototype to the corresponding sign-instance.
- **Generalization** $class2supercl(\dot{S})$ is the transition along the edge from the sign-prototype of the class to the sign-prototype of the super-class.
- **Concretization** to a subclass $class2subcl(\dot{S})$ is a transition along the edge from a sign-prototype of a class to a sign-prototype of a subclass.

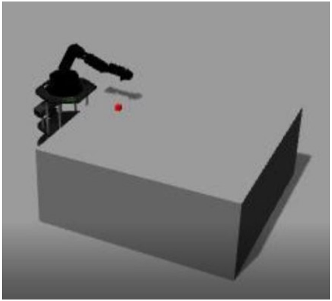


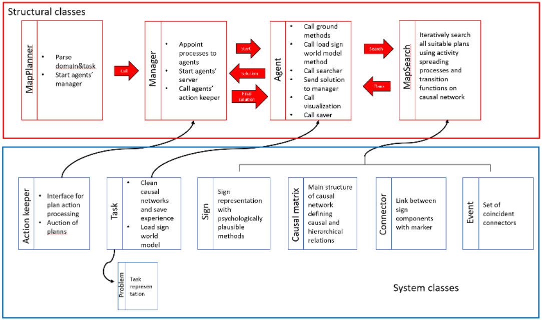
Kiselev, Gleb, Alexey Kovalev, and Aleksandr I Panov. "Spatial reasoning and planning in sign-based world model". *Artificial Intelligence*. 2018.

Model scenario of interaction



Robotic implementation





https://github.com/cog-isa/map-planner

The task of Reinforcement learning

Base concepts:

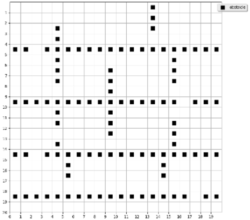
- $a_t : s_t \to s_{t+1}$ - actions of the agent in environment,
- r_t - reward from environment,
- goal of the agent – maximization of the total reward $R = \sum_t \gamma^t r_t$, $0 < \gamma \leq 1$,
- $\pi : S \to A$ - agent's policy (ϵ-greedy method).

Solution:

- If we know $T(s_t, a_t, s_{t+1})$ и $r(s_t, a_t)$, planning task – *Bellman equation*.
- Evaluation of state value function $V(s) = \mathbf{E}[R|s, \pi]$ or state-action value function $Q(s, a) = \mathbf{E}[R|s, a, \pi]$.

Reinforcement learning for the relocation task

- $E = (M, G)$ - environment where M - grid map, $G(p_s, p_f)$ - reward function,
- $a_t = p_t \rightarrow p_{t+1}$ - relocation action of the agent,
- $s_t \in R^{(2d)^2}$ - agent's observation (sensor image).



Пусть $Q^*(s_t, a_t) = \max_\pi \mathbf{E}[R|s_t, a_t, \pi]$ - optimal value function according to R Bellman equation:

$$Q^*(s, a) = \mathbf{E}_{s_t \sim E}\left[r_t + \gamma \max_{a_t} Q^*(s_t, a_t) \middle| s, a \right]$$

Reinforcement learning with approximation

Different approximations of the value function are used to solve Bellman equations by iterative methods $Q^*(s,a)$: $Q(s,a;\theta) \approx Q^*(s,a)$.

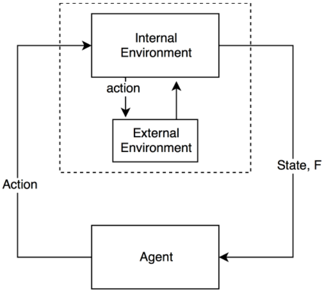
In the process of learning, the parameters θ are adjusted as a result of minimizing the loss function $L(\theta)$:

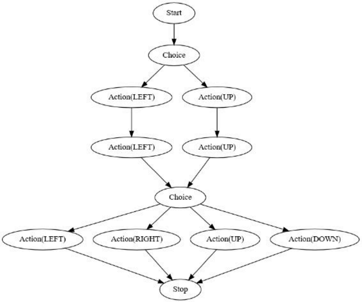
$$L_i(\theta_i) = \mathbf{E}_{s,a\sim\rho(\cdot)}\left[\left(\boxed{y_i} - Q(s,a;\theta_i)\right)^2\right],$$

$$y_i = \boxed{\mathbf{E}_{s_t\sim E}\left[r_t + \gamma \max_{a_t} Q(s_t,a_t;\theta_{i-1}) | s,a\right]}$$

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbf{E}_{s,a\sim\rho(\cdot);s_t\sim E}\left[\left(r_t + \gamma \max_{a_t} Q(s_t,a_t;\theta_{i-1}) - \right.\right.$$
$$\left.\left. - Q(s,a;\theta_i)\right) \nabla_{\theta_i} Q(s,a;\theta_i)\right].$$

RL for formation of causal matrices





- **Hierarchical reinforcement learning** to form representation of new actions.
- The alternation of the processes of action abstraction and abstraction of states of the environment.
- Automatic formation of the hierarchy of operations.

Panov, Aleksandr I. and Aleksey Skrynnik. "Automatic formation of the structure of abstract machines in hierarchical reinforcement learning with state clustering". *ICML\IJCAI Workshop on Planning and Learning (PAL-18)*. 2018.

RL for mobile robot movement

RL for robot manipulator

Publications

Kiselev, G. A. and A. I. Panov. "Sign-based Approach to the Task of Role Distribution in the Coalition of Cognitive Agents". *SPIIRAS Proceedings*. 2018.

Osipov, Gennady S. and Aleksandr I. Panov. "Relationships and operations in agent's sign-based model of the world". *Scientific and Technical Information Processing*. 2018.

Panov, Aleksandr I. and Aleksey Skrynnik. "Automatic formation of the structure of abstract machines in hierarchical reinforcement learning with state clustering". *ICML\IJCAI Workshop on Planning and Learning (PAL-18)*. 2018.

Панов, А. И. «Формирование образной компоненты знаний когнитивного агента со знаковой картиной мира». *Информационные технологии и вычислительные системы*. 2018.

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Osipov, G. S. "Sign-based representation and word model of actor". *2016 IEEE 8th International Conference on Intelligent Systems (IS)*. 2016.

Panov, A. I. and K. S. Yakovlev. "Behavior and path planning for the coalition of cognitive robots in smart relocation tasks". *Robot Intelligence Technology and Applications 4*. 2016.

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Osipov, G. S., A. I. Panov, and N. V. Chudova. "Behavior Control as a Function of Consciousness. II. Synthesis of a Behavior Plan". *Journal of Computer and Systems Sciences International*. 2015.

Osipov, Gennady S. "Signs-Based vs. Symbolic Models". *Advances in Artificial Intelligence and Soft Computing*. 2015.

Osipov, G. S., A. I. Panov, and N. V. Chudova. "Behavior control as a function of consciousness. I. World model and goal setting". *Journal of Computer and Systems Sciences International*. 2014.

Thank you for your attention!

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