# Computational Concept and Architecture of Artificial Psyche

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Telegram: akolonin
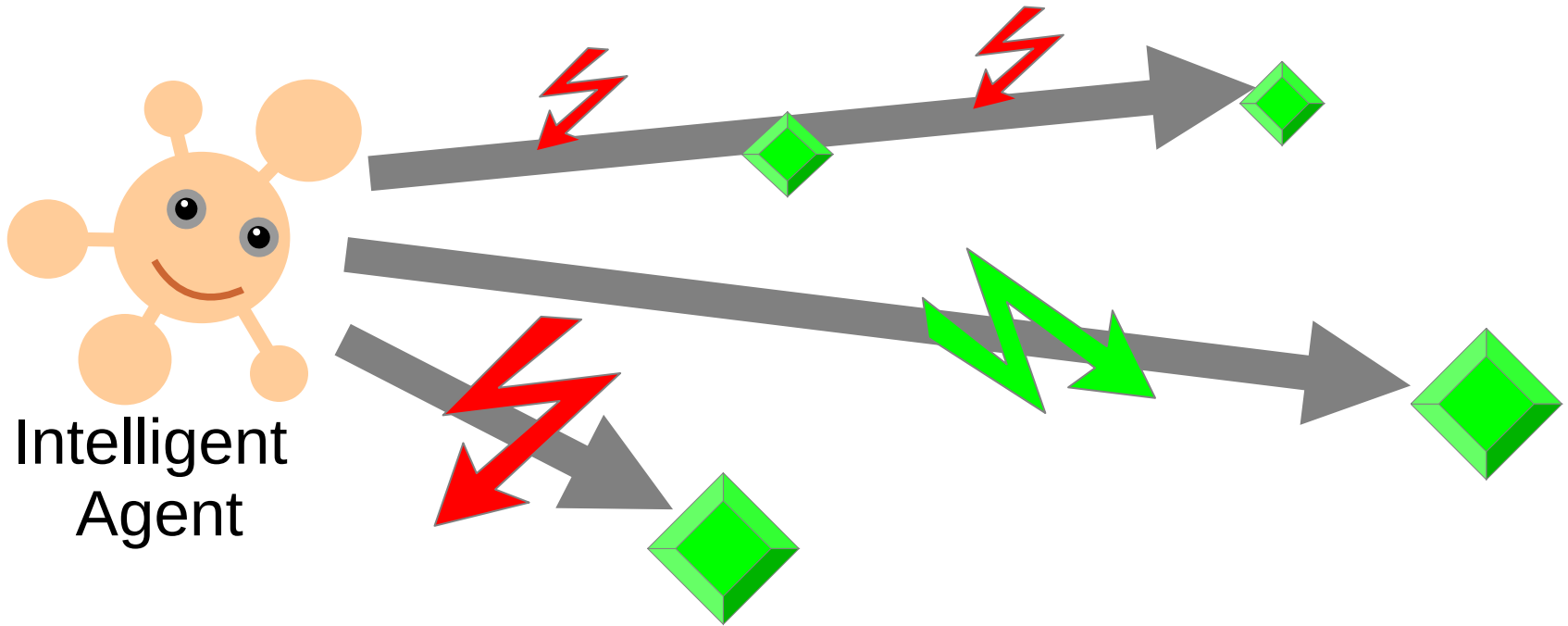
Novosibirsk State University
*THE REAL SCIENCE
https://www.nsu.ru

AIGENTS
https://aigents.com
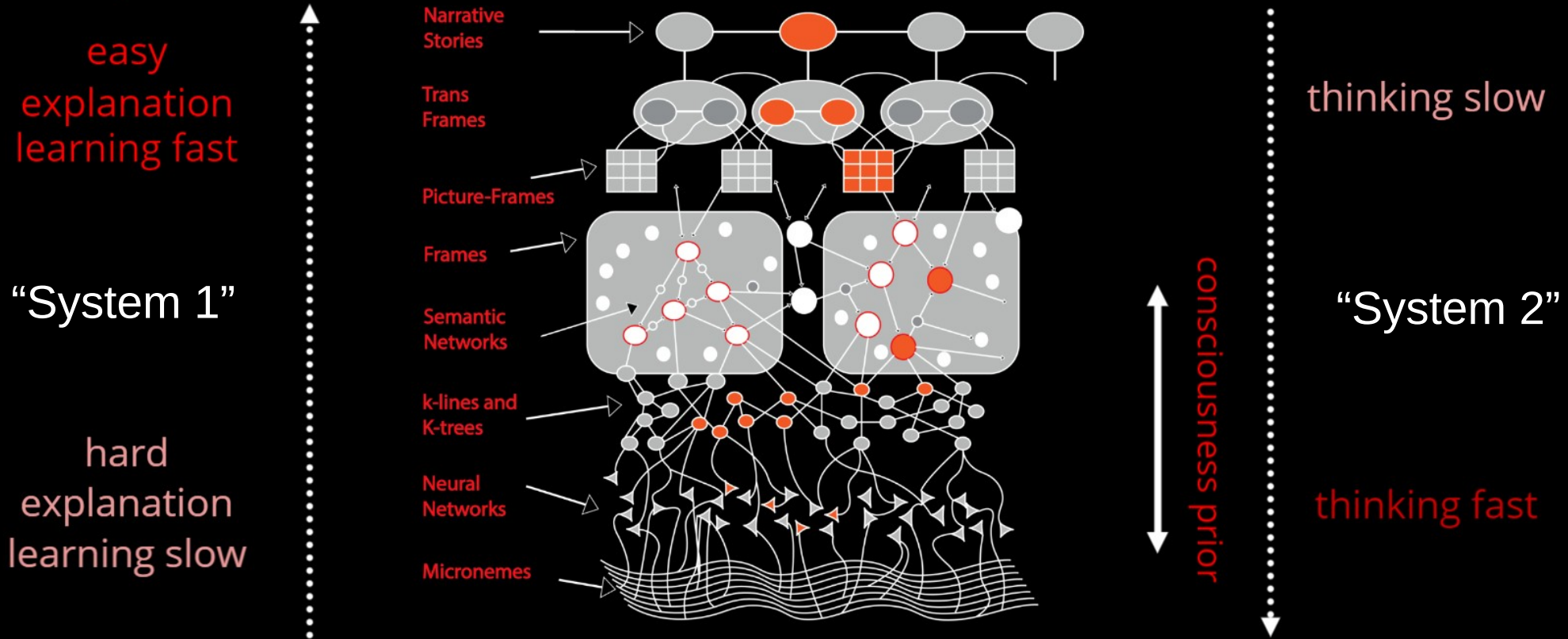
AGI IN RUSSIAN
https://agirussia.org

# General Intelligence:

Reaching complex goals in different complex environments, using limited resources under uncertainty (Ben Goertzel + Pei Wang + Shane Legg + Marcus Hutter)

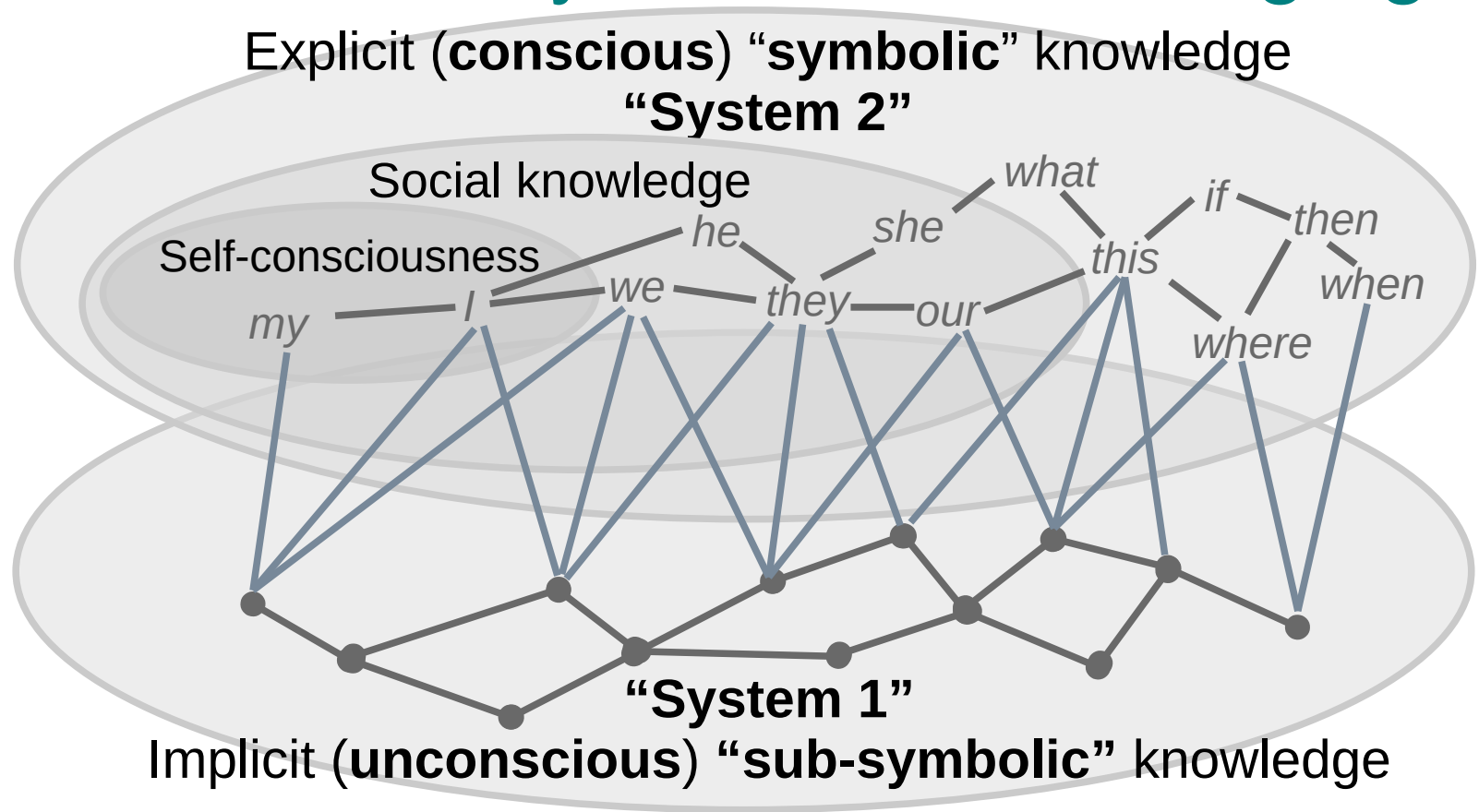Intelligent Agent

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# "Fast and Slow Thinking" – Daniel Kahneman

https://www.linkedin.com/pulse/explainable-ai-vs-explaining-part-1-ahmad-haj-mosa/
Xing, F., Cambria, E., Welsch, R. (2019). Theoretical Underpinnings on Text Mining. In: Intelligent Asset Management. Socio-Affective Computing, vol 9. Springer, Cham.
https://doi.org/10.1007/978-3-030-30263-4_3
M. Minsky, The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind (Simon & Schuster Paperbacks, Princeton, 2007)

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# Medium: "neuro-symbolic" "knowledge graph"



Explicit (**conscious**) "**symbolic**" knowledge
**"System 2"**

Social knowledge

Self-consciousness

*my* · *I* · *we* · *he* · *they* · *she* · *our* · *what* · *this* · *if* · *then* · *where* · *when*

**"System 1"**

Implicit (**unconscious**) "**sub-symbolic**" knowledge

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# Neuro-Symbolic Integration for Interpretable AI
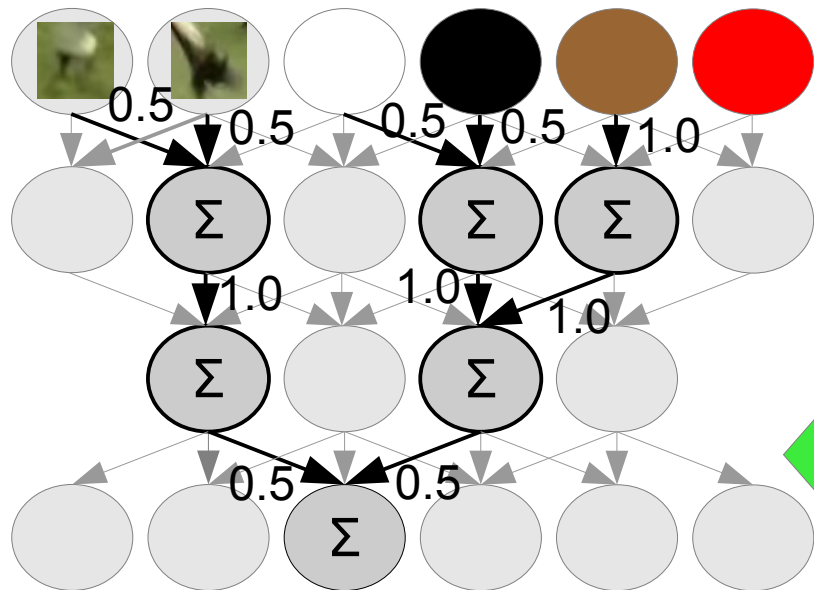


Explain

Transfer

"System 1" | "System 2"
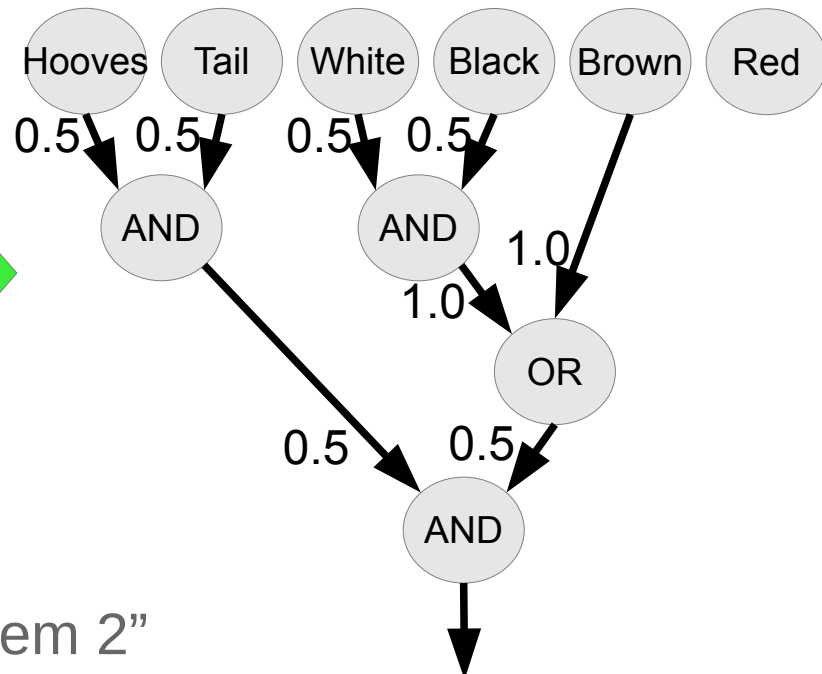
(Hooves AND Tail) AND NOT Red
((White and Black) OR Brown)

=> Horse

https://arxiv.org/abs/2006.13155
https://arxiv.org/abs/2006.06465
https://arxiv.org/abs/1904.11694
https://arxiv.org/abs/1910.08629
https://www.ijcai.org/proceedings/2025/0555.pdf
https://www.springerprofessional.de/neuro-symbolic-architecture-for-experiential-learning-in-discret/20008336

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# Functional equivalence of ~~neural network~~ tensor and graph (symbolic) models

Words

Sentences

Letters

Strokes

Strokes, letters, words and phrases

strokes , letters words and phrases

w o r d s

\ /

Pedro Domingos, Tensor Logic: The Language of AI
https://arxiv.org/pdf/2510.12269
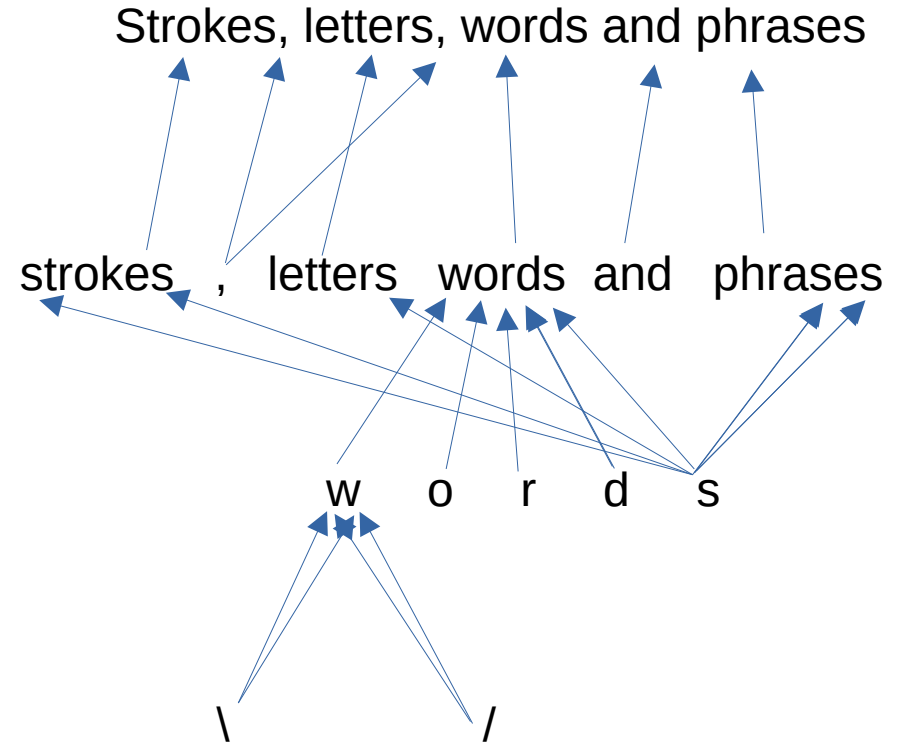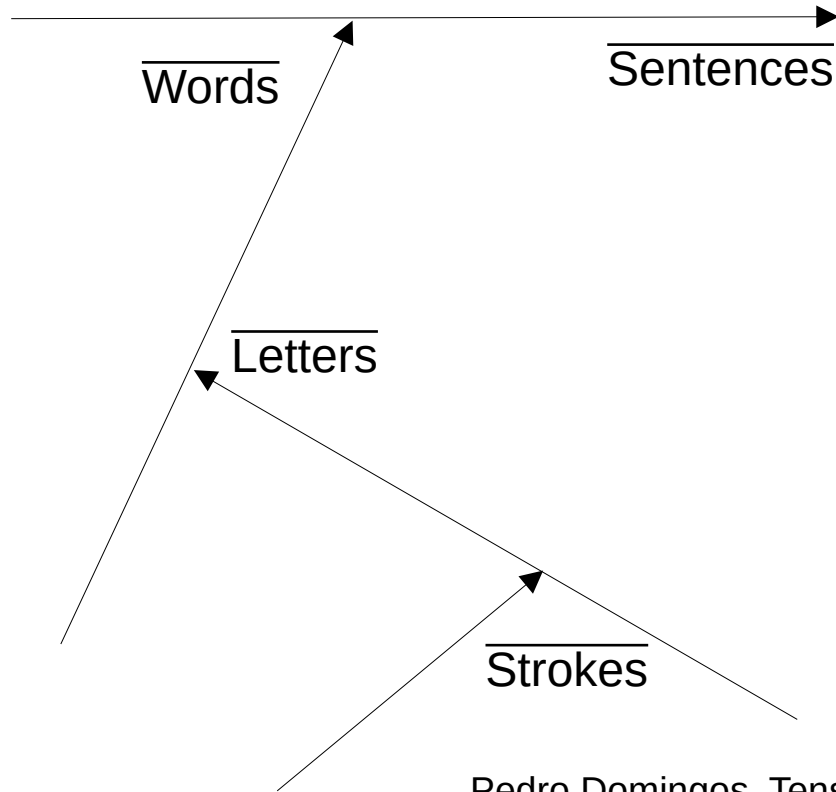
# Typed tensor logic for different kinds of AI-s (logical, sub-symbolic, probabilistic/non-axiomatic)

**Truth-Value Tensor**
(NARS/PLN)
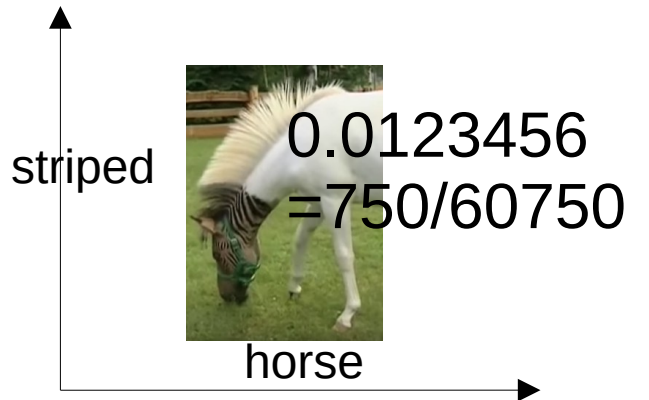
**Numerical Tensor**
(ANN/Bayesian Logic)
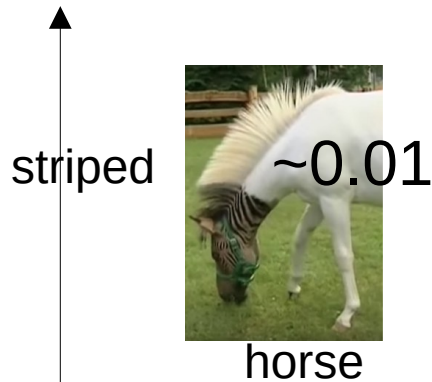
**Boolean Tensor**
(Boolean Logic)



Property

striped

0.0123456
=750/60750

horse

Subject



Property

striped

~0.01

horse

Subject



Property

striped

"False"

horse
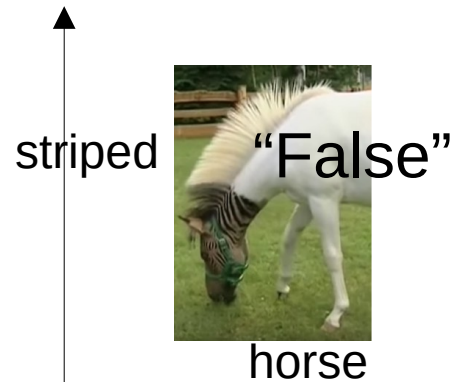
Subject

Life-long learning?

Pedro Domingos, Tensor Logic: The Language of AI
https://arxiv.org/pdf/2510.12269

# Problem of dimensionality (reduction) and discreteness (increase)

Retail store optimization case for "trousers"
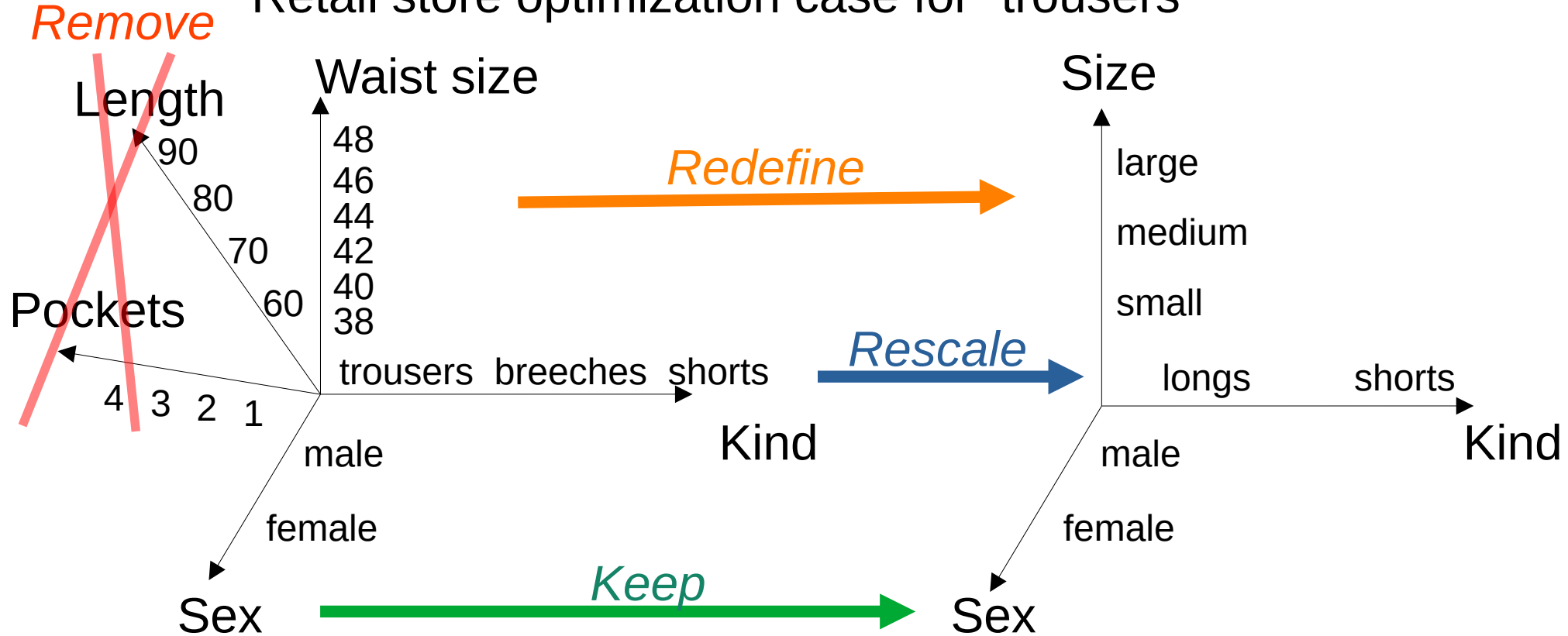
The psyche /ˈsaɪki/ is currently used to describe the totality of the human mind, conscious and unconscious.
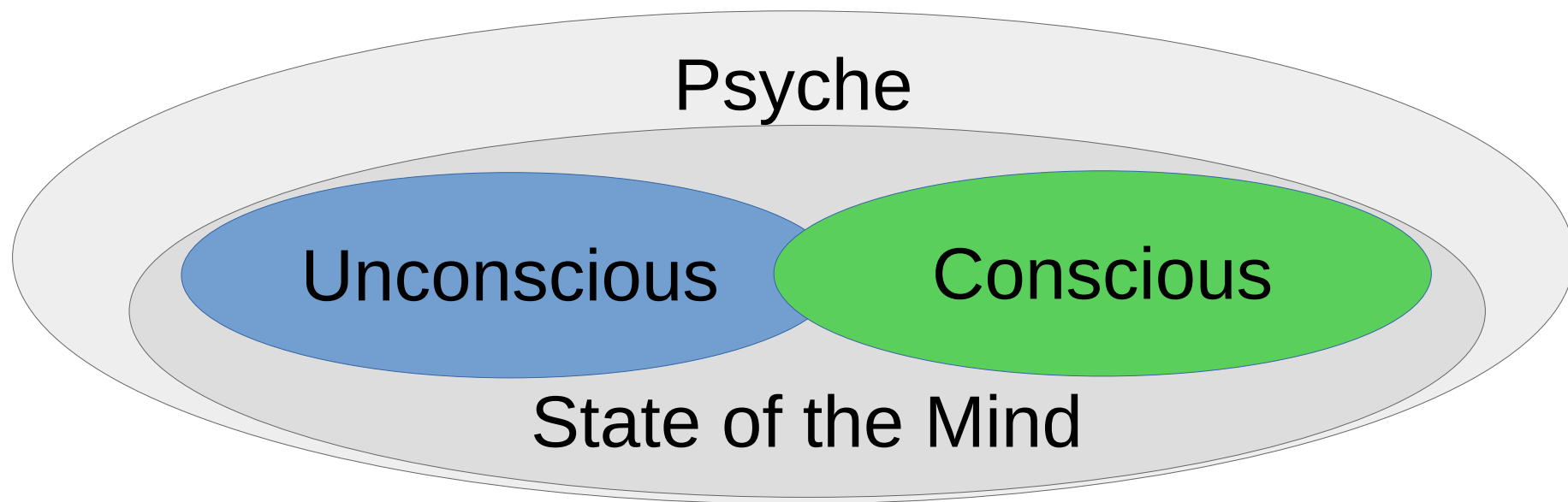
# System = Intelligent agent
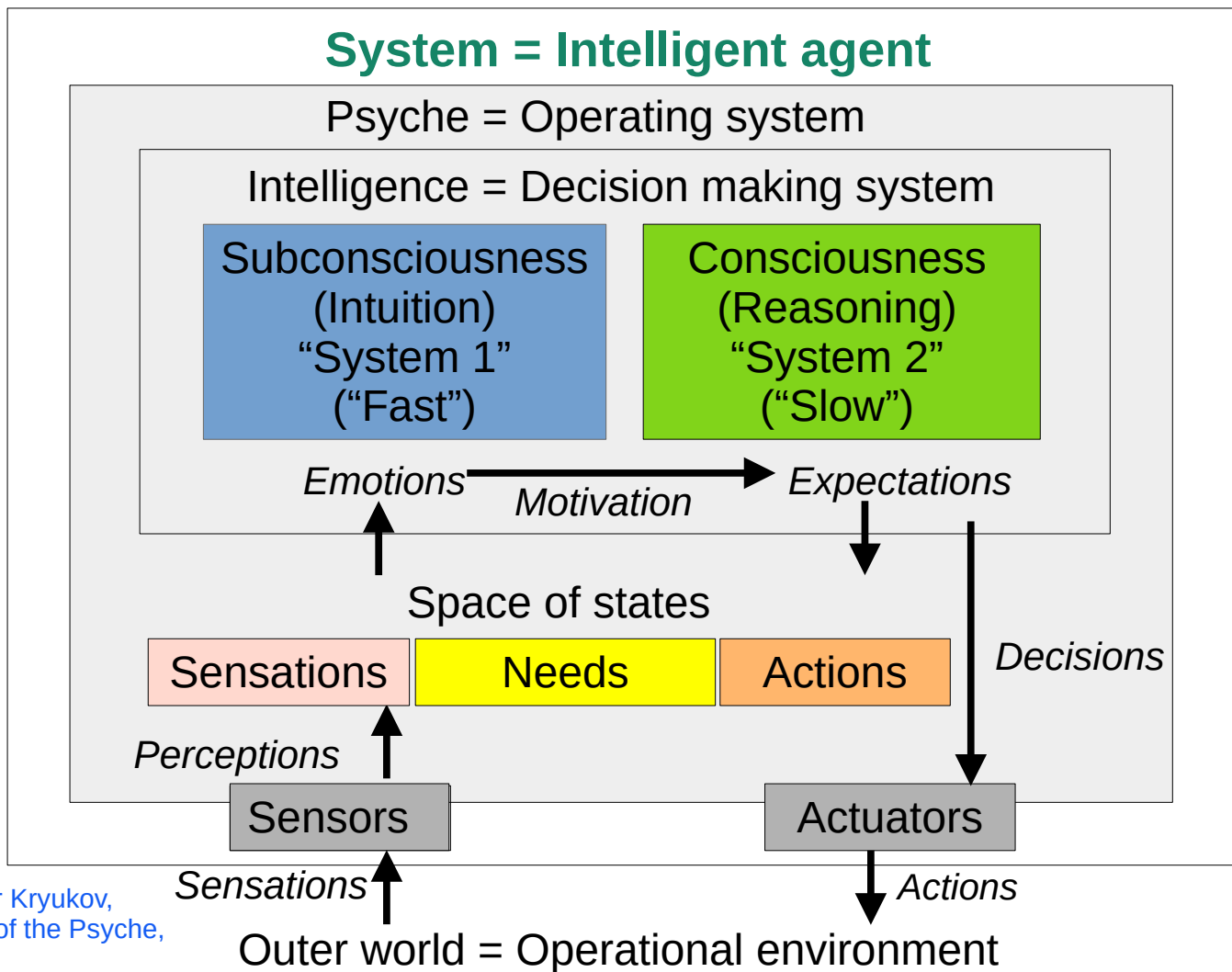
## Psyche = Operating system

### Intelligence = Decision making system

| Subconsciousness (Intuition) "System 1" ("Fast") | Consciousness (Reasoning) "System 2" ("Slow") |
|---|---|

*Emotions* → *Motivation* → *Expectations*

Space of states

| Sensations | Needs | Actions |
|---|---|---|

*Decisions*

*Perceptions*

Sensors          Actuators

*Sensations* ↑          *Actions* ↓

Outer world = Operational environment

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# Psyche = Operating system

Intelligence = Decision making system

Models $s$ ("invariants") of states with utilities $U$ and probabilities $P$ of transitions

$$U(\{s_\tau\}_{\tau\in\{-T,-1\}}, s'_0) = L(\ x\cdot(y_t - y_{t-1}),\ (s'_t - s_t),\ E(a_{t-1}))\qquad s'_t=argmax_s(U(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t), P(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t))$$

*Experiential learning*    *Decision making*

Space of states and episodic memory ("precedents")

| State $s_{t-1}$ (past) | State $s_t$ (present) | | State $s_{t+1}$ (future) |

**State $s_{t-1}$ (past)**

Reality ("fact") $s_{t-1}$
- Sensations $f_{t-1}$
- Needs $y_{t-1}$
- Actions $a_{t-1}$

**State $s_t$ (present)**

Expectation ("plan") $s'_t$
- Sensations $f'_t$
- Needs $y'_t$
- Actions $a'_t$

Reality ("fact") $s_t$
- Sensations $f_t$
- Needs $y_t$
- Actions $a_t$

**State $s_{t+1}$ (future)**

Expectation ("plan") $s'_{t+1}$
- Sensations $f'_{t+1}$
- Needs $y'_{t+1}$
- Actions $a'_{t+1}$

*Decisions*    *Perceptions*

Actuators    Sensors

**Psyche = Operating system**

Energy-efficiency *of a*

Optimal decision and expectation of s

Predictability *of s*

Expected utility of s

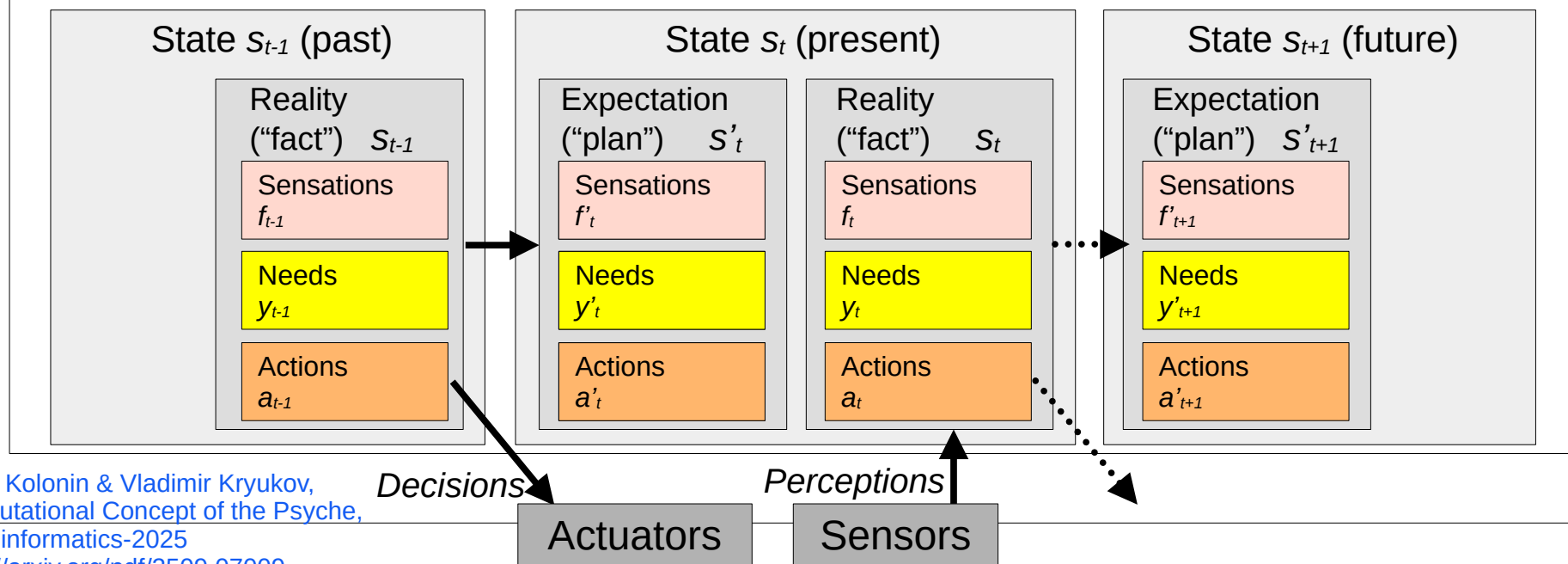Intelligence = Decision making system

Models s ("invariants") of states with utilities $U$ and probabilities $P$ of transitions

$$U(\{s_\tau\}_{\tau\in\{-T,-1\}}, s'_0) = L(\, x\cdot(y_t - y_{t-1}),\, (s'_t - s_t),\, E(a_{t-1}))\qquad s'_t = argmax_s(U(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t), P(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t))$$

Satisfaction *of y*

Expected probability of s

↑ *Experiential learning*    ↓ *Decision making*

Space of states and episodic memory ("precedents")

**State $s_{t-1}$ (past)**

Reality ("fact")   $s_{t-1}$

Sensations $f_{t-1}$

Needs $y_{t-1}$

Actions $a_{t-1}$

**State $s_t$ (present)**

Expectation ("plan")   $s'_t$

Sensations $f'_t$

Needs $y'_t$

Actions $a'_t$

Reality ("fact")   $s_t$

Sensations $f_t$

Needs $y_t$

Actions $a_t$

**State $s_{t+1}$ (future)**

Expectation ("plan")   $s'_{t+1}$

Sensations $f'_{t+1}$

Needs $y'_{t+1}$

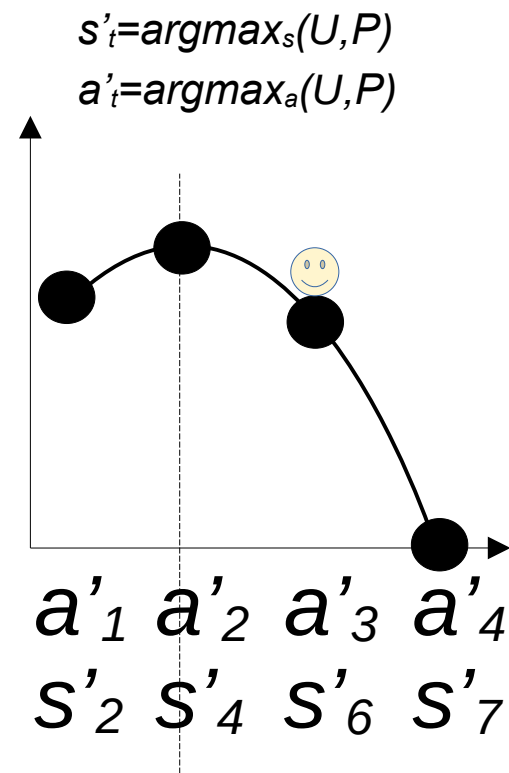Actions $a'_{t+1}$

*Decisions*

*Perceptions*

Actuators

Sensors

$x\cdot y_t$ − "motivation vector"
V. F. Petrenko and A. P. Suprun, "Goal oriented systems, evolution, and the subjective aspect in systemology," Tr. Inst. Sistem. Analiza RAN 62 (1) (2012)

# Decision making as operational risk management

| $s_t$ | $s'_{t+1}$ | $s'_{t+1}$ | | | $U$ | $P$ | $\sum U*P$ |
|---|---|---|---|---|---|---|---|
| | | $a'$ | $y'$ | $f'$ | | | |
| $s_1$ | $s'_2$ | $a'_1$ | $y'_1$ | ... | 1.0 | 0.5 | **_0.7_** |
| $s_1$ | $s'_3$ | $a'_1$ | $y'_2$ | ... | 0.4 | 0.5 | |
| $s_1$ | $s'_4$ | $a'_2$ | $y'_3$ | ... | 1.0 | 0.8 | **_0.8_** |
| $s_1$ | $s'_5$ | $a'_2$ | $y'_4$ | ... | 0.0 | 0.2 | |
| $s_1$ | $s'_6$ | $a'_3$ | $y'_5$ | ... | 0.6 | 1.0 | **_0.6_** |
| $s_1$ | $s'_7$ | $a'_4$ | $y'_6$ | ... | 0.0 | 1.0 | **_0.0_** |

$s'_t = argmax_s(U,P)$
$a'_t = argmax_a(U,P)$



$a'_1 \; a'_2 \; a'_3 \; a'_4$
$s'_2 \; s'_4 \; s'_6 \; s'_7$

Tversky & Kahneman:
most people choose $a'_3$ и $s'_6$
(*"smaller profit with greater reliability"*)

# Mutual dependency of state variable ~~subgraphs~~ tensors
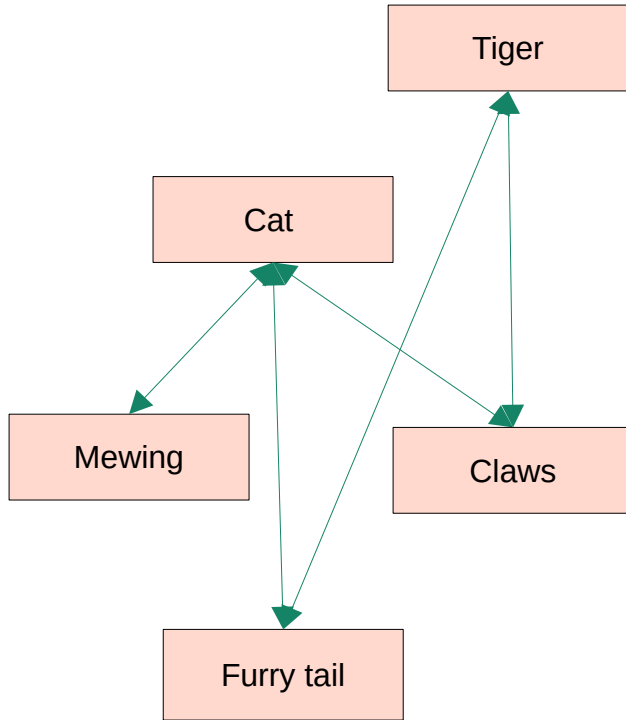
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# Hierarchy of values/goals/subtasks/tasks/subtasks

Needs/Values

Goals

Subgoals

Tasks

Subtasks

Actions

*Give a birth to next generations*

*Get married*

*Make a marriage offer*

*Make the visit*

*Spell the words*

*Reach the house*

*Climb the stairs*

*Knock at the door*

*Make a step on the way...*

*Bend a knee*

*Straighten a leg*

# Space of needs/goals/values



Psychological

Physical
(Physiological)

*Self-determination...*

*Self-implementation...*

*Feeding and self-cleaning...*

*Survival and reproduction...*

According to the ideas of A. Maslow, any goal can be represented as a combination (superposition) of basic needs

Routine
(Everyday)

Existential
(Life-long)

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# Attention, context, model and memories



Attention focus
*Attention period*

Short-term memory (STM)
"Context"
*Context period*

"Model"
GPT/DNN Parameters    Invariants, Rules, Indexes
*"Model size"*

Long-term memory (LTM), including "episodic memory"
Precedents or "Data"
*Retention period*

Scope
(modalities)
&
Accuracy
(precision)

# Attention, context, model and memories



Attention focus

*Attention period*

Short-term memory (STM) "Context"

*Context period*

"Model"

GPT/DNN Parameters     Invariants, indexes

*"Model size"*

Remembering & Learning

Recalling & Deciding

Forgetting & Compressing

Long-term memory (LTM), including "episodic memory" "Data"

*Retention period*

Scope (modalities) & Accuracy (precision)

# Application cases
## A) Automated Process Control Systems (APCS)
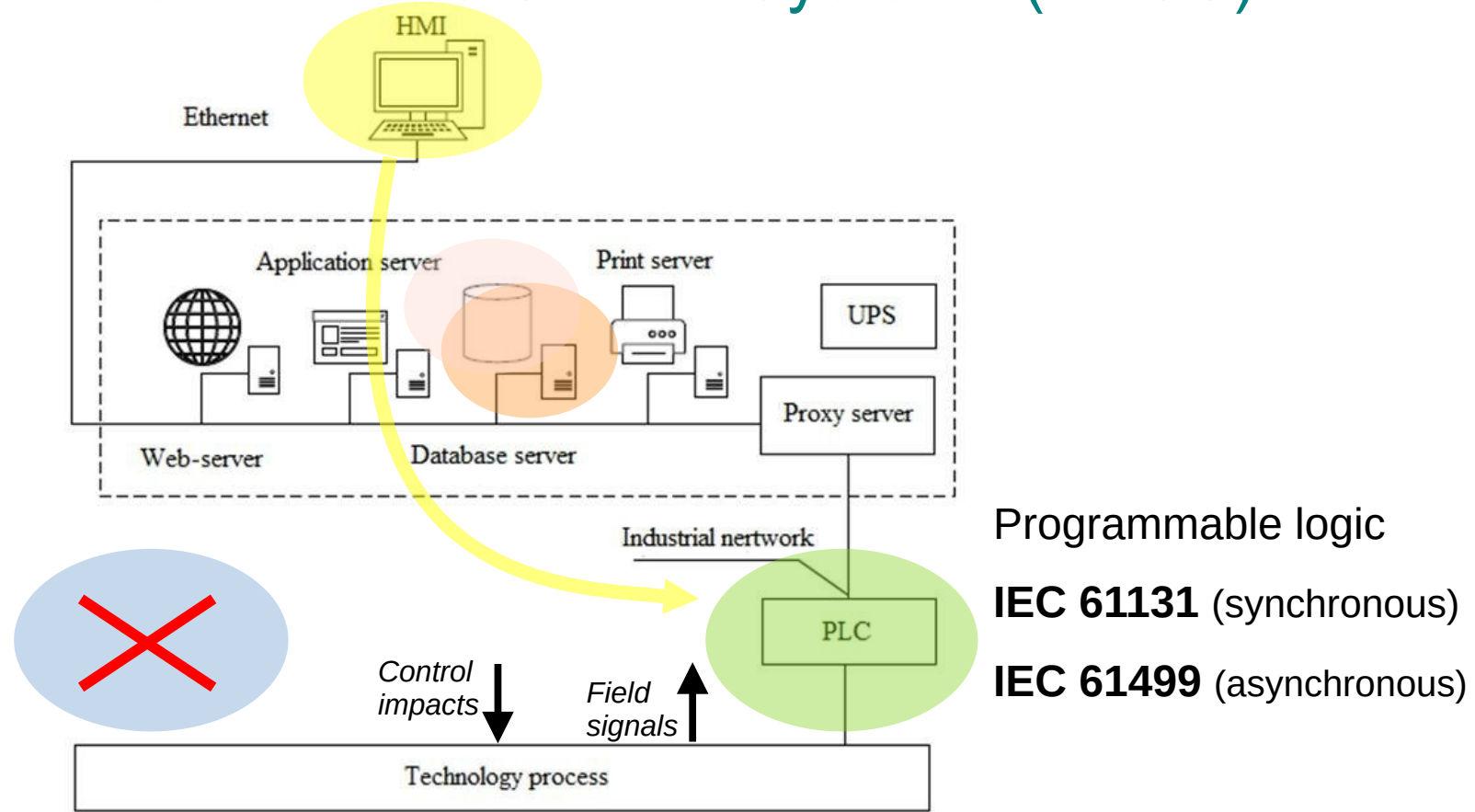


Programmable logic

**IEC 61131** (synchronous)

**IEC 61499** (asynchronous)

# Application cases
## B) "Smart Home"

**User Intents**

**PRESENTATION LAYER**
(User Interfaces: Mobile Apps, Web UI, Voice Assistants)
Home Assistant UI / Mobile App (Android/iOS) / Smart Speakers (Google Assistant, Alexa) / Custom Dashboards / Voice Interfaces

**LOGIC LAYER**
(Automation, Scenes, AI/NLP, Decision Engine)
Home Assistant Automations & Scripts / AI/NLP Integration (e.g., OpenAI GPT, Rasa, etc.) / Voice/Text Intent Handling / Context Engine / User Preferences

- Predictive models?
- Automation rules and scripts
- Sensory and Command Logs

**INTEGRATION / SERVICE LAYER**
(APIs, Device Managers, Cloud Services, 3rd Party APIs)
Home Assistant Integrations / OpenAI API / Weather APIs, Location Services / Voice Services (STT/TTS engines, e.g., Whisper, Polly) / HomeKit, Google Smart Home, Alexa APIs

*Control impacts*

*Field signals*

**DEVICE ABSTRACTION LAYER**
(Drivers, Protocol Adapters, Message Brokers)
MQTT Broker / Zigbee/Z-Wave Adapters (e.g., Zigbee2MQTT, Z-Wave JS) / Bluetooth/Wi-Fi Controllers / Device Drivers (Light, Thermostat, Lock, etc.)

**PHYSICAL DEVICE LAYER**
(Actual smart home devices and sensors)
Smart Bulbs, Switches, Plugs / Thermostats, Cameras, Motion Sensors / Door Locks, Blinds, HVAC / Custom DIY Sensors (ESPHome, Tasmota, etc.)

# Implementation options
## 1) Reinforcement learning based on "actor-critic" model
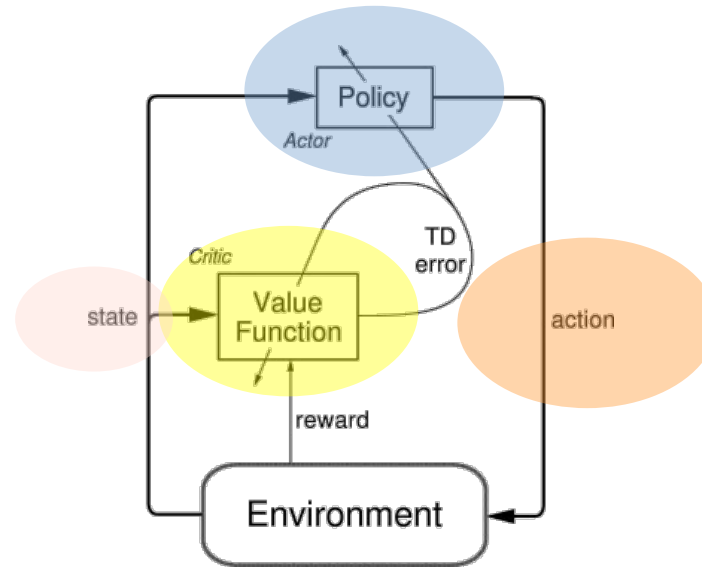
# Implementation options

## 2) Cognitive architecture based on LLM and (active) GraphRAG
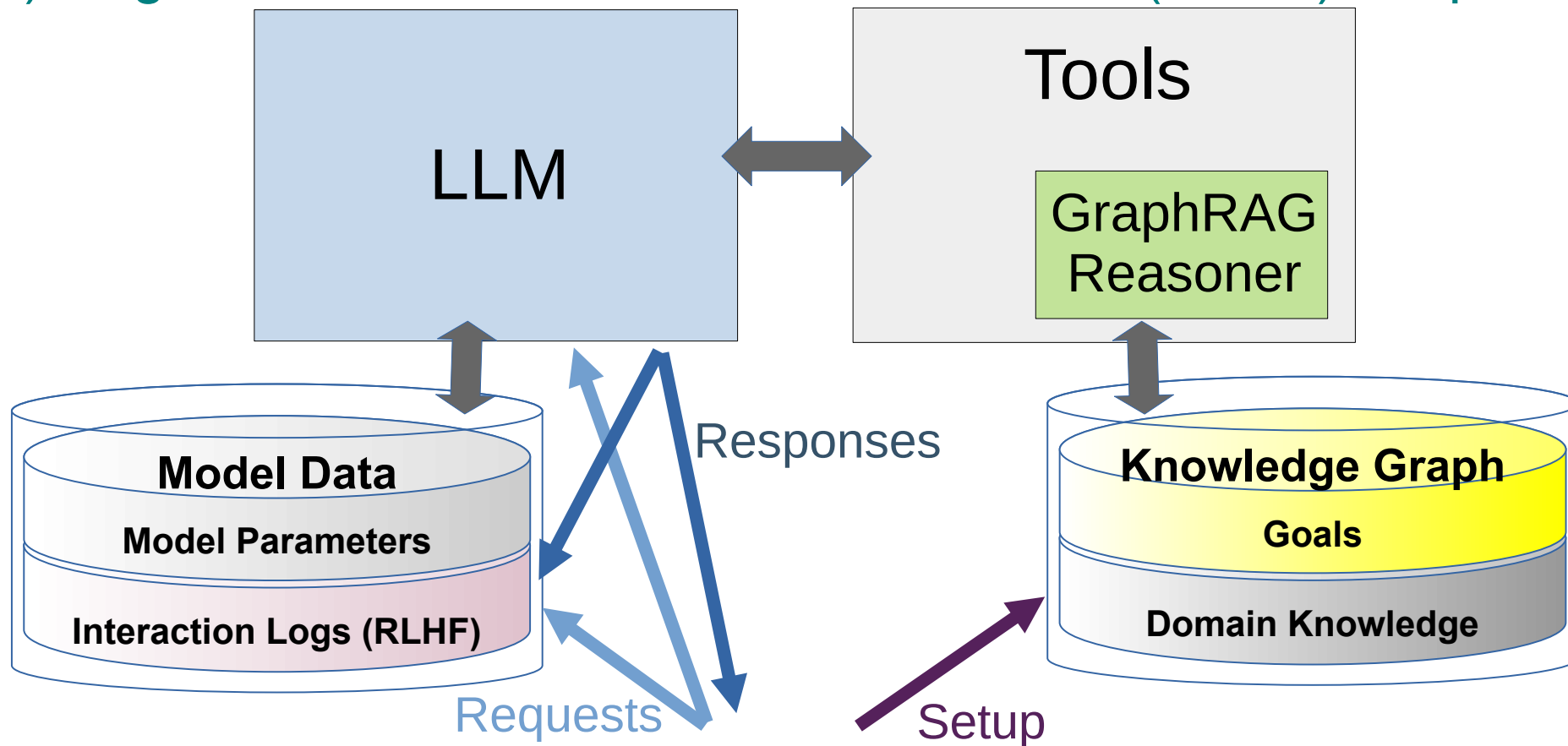


Leonie Monigatti, "The Evolution from RAG to Agentic RAG to Agent Memory", November 3, 2025
https://www.leoniemonigatti.com/blog/from-rag-to-agent-memory.html

# Implementation options

## 3) Cognitive architecture based on probabilistic logic

Motivation-Request to achieve a goal **G**

Afferentation about situation $P_1,...,P_m$

**AFFERENT SYNTHESIS**
Set **PR** of rules $\langle P_1,...,P_k, A \rangle \rightarrow G$
that forecast achievement of the goal *G* in situation $P_1,...,P_m$ if fulfil *A* and subgoals $P_1,...,P_n$

Forecast for result **G**

RESULT **R**

**ACTIONS RESULTS ACCEPTOR**
Anticipation of result **G**
**RESULT EVALUATION**
$G \approx R$
*Reinforcement/ punishment*

**DECISION MAKING**
Selection of actions *A* and subgoals $P_1,...,P_n$, providing maximum probability of the goal *G* achievement

Forecast for goal **G** achievement

Subgoals $P_1,..., P_n$

Actions **A**

Forecast for subgoals $P_1,..., P_n$

**RESULT R** Backward afferentation

**RESULTS** $R_1,...,R_n$

$$Pr\,ob(\,G\mid P_1,...,P_k\,,P_1,...,P_n\,,A\,) = Pr\,ob(\,rule\,)\cdot Pr\,ob(\,P_1\,)\cdot...\cdot Pr\,ob(\,P_n\,)$$

Evgenii Vityaev, Alexander Demin: Adaptive Control of Modular Robots // Conference Paper in Advances in Intelligent Systems and Computing, Conference: First International Early Research Career Enhancement School on Biologically Inspired Cognitive Architectures, Springer, August 2018

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.

Витяев Е.Е. Логика работы мозга. Подходы к моделированию мышления. (сборник под ред. д.ф.-м.н. В.Г. Редько). УРСС Эдиториал, Москва, 2014г., стр. 120-153.
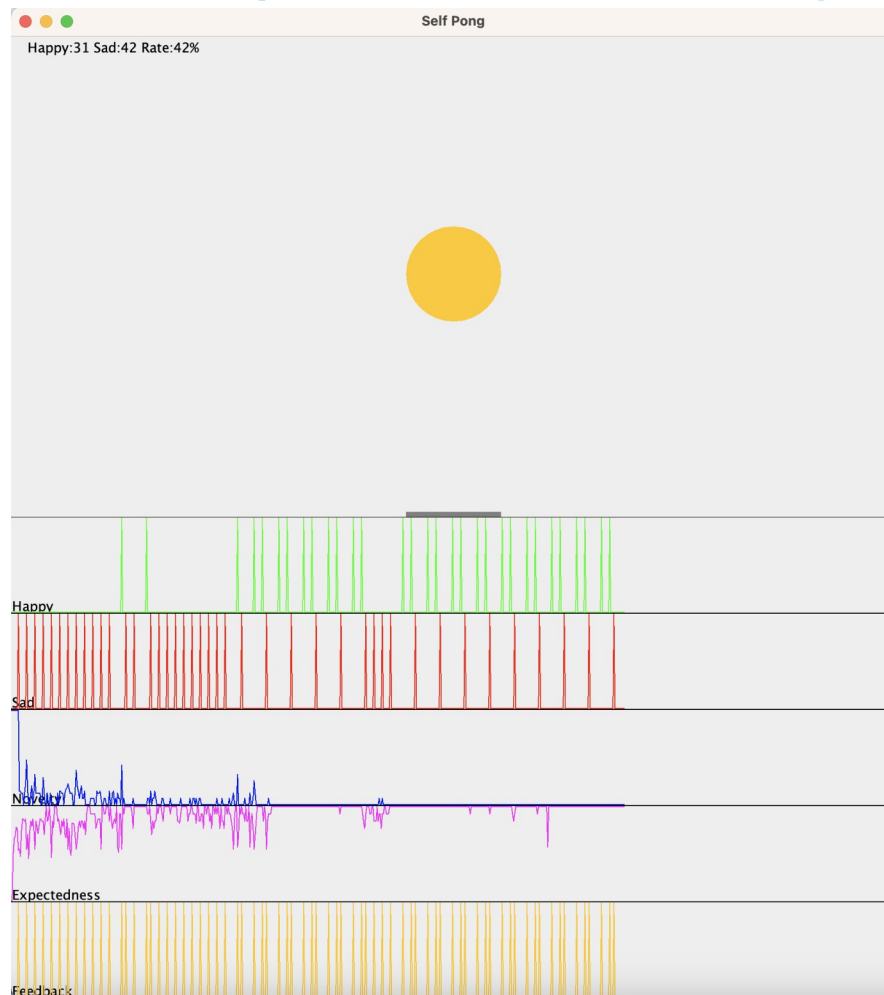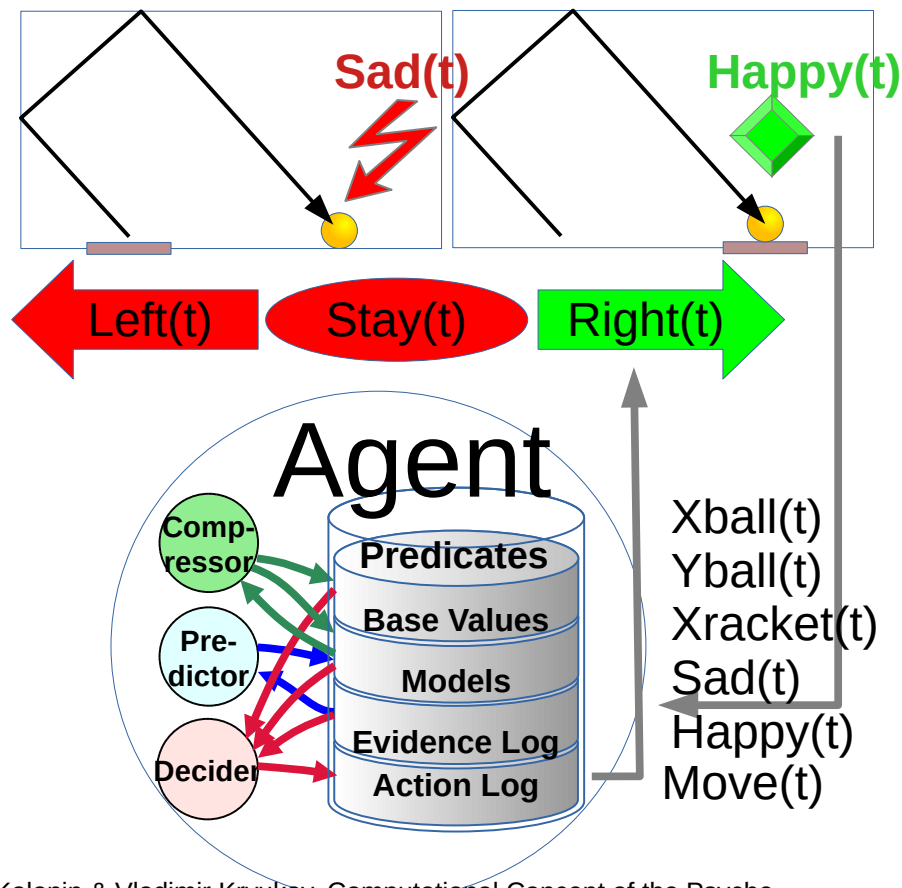
# Implementation options
## 4) Cognitive architecture of value-based experiential learning
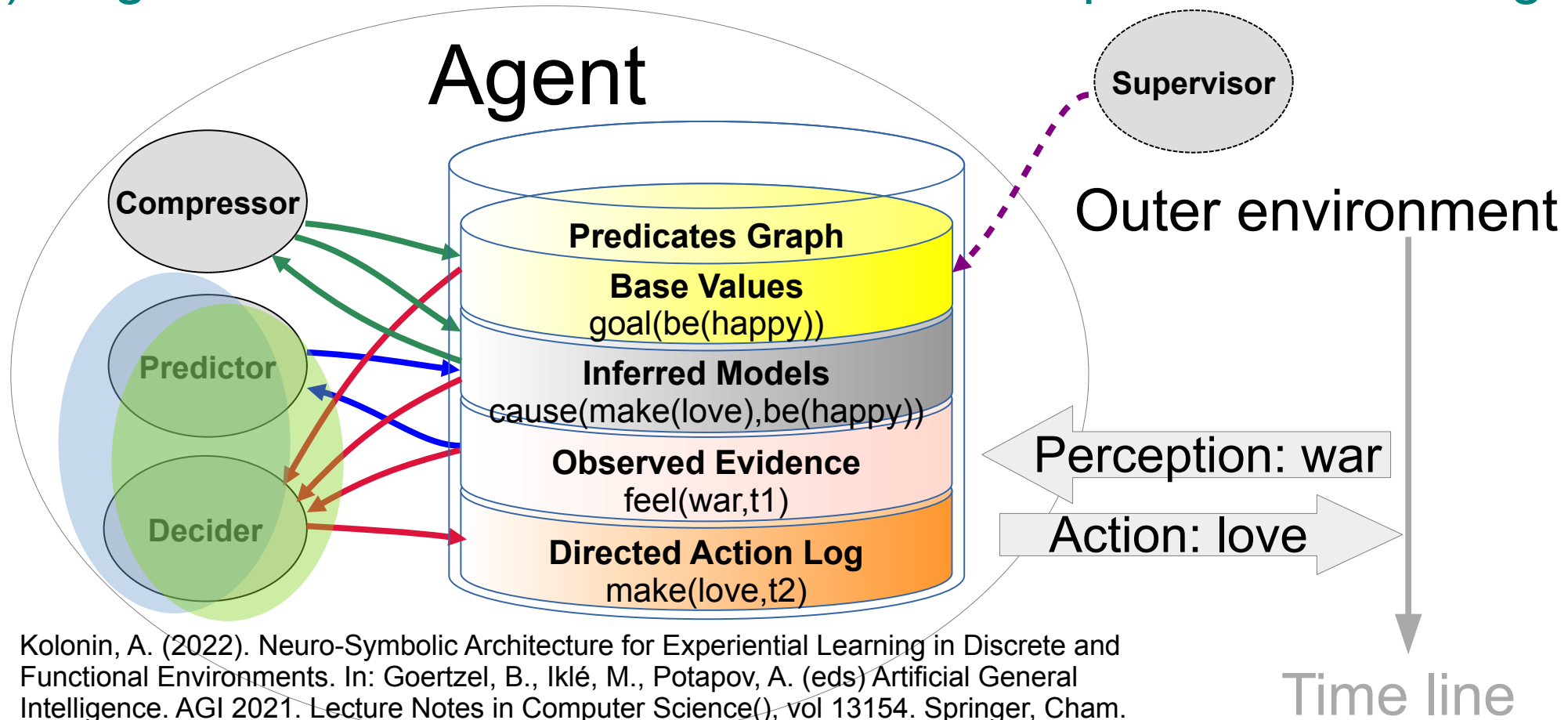


Kolonin, A. (2022). Neuro-Symbolic Architecture for Experiential Learning in Discrete and Functional Environments. In: Goertzel, B., Iklé, M., Potapov, A. (eds) Artificial General Intelligence. AGI 2021. Lecture Notes in Computer Science(), vol 13154. Springer, Cham. https://doi.org/10.1007/978-3-030-93758-4_12

# Cognitive architecture of value-based experiential learning



Sad(t)

Happy(t)

Left(t)  Stay(t)  Right(t)

Agent

Comp-ressor

Pre-dictor

Decider

Predicates

Base Values

Models

Evidence Log

Action Log

Xball(t)
Yball(t)
Xracket(t)
Sad(t)
Happy(t)
Move(t)

Self Pong

Happy:31 Sad:42 Rate:42%

Happy

Sad

Novelty

Expectedness

Feedback

Anton Kolonin & Vladimir Kryukov, Computational Concept of the Psyche
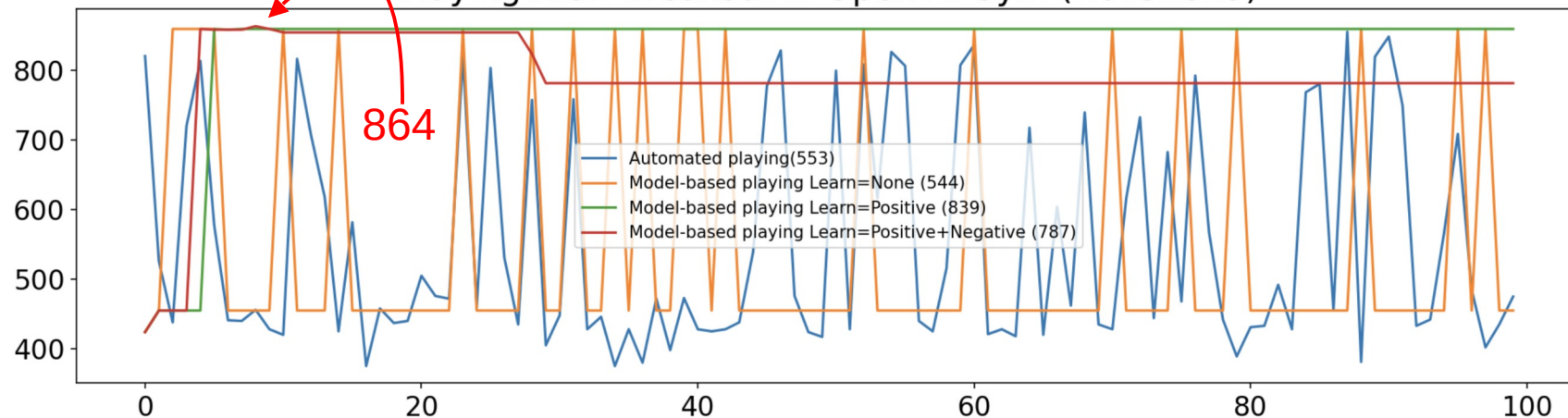https://arxiv.org/pdf/2509.07009
Anton Kolonin, Neuro-Symbolic Architecture for Experiential Learning in Discrete and Functional Environments
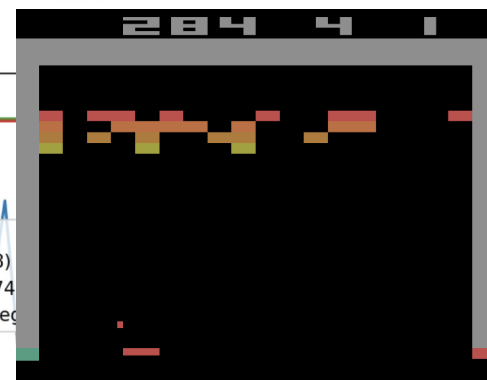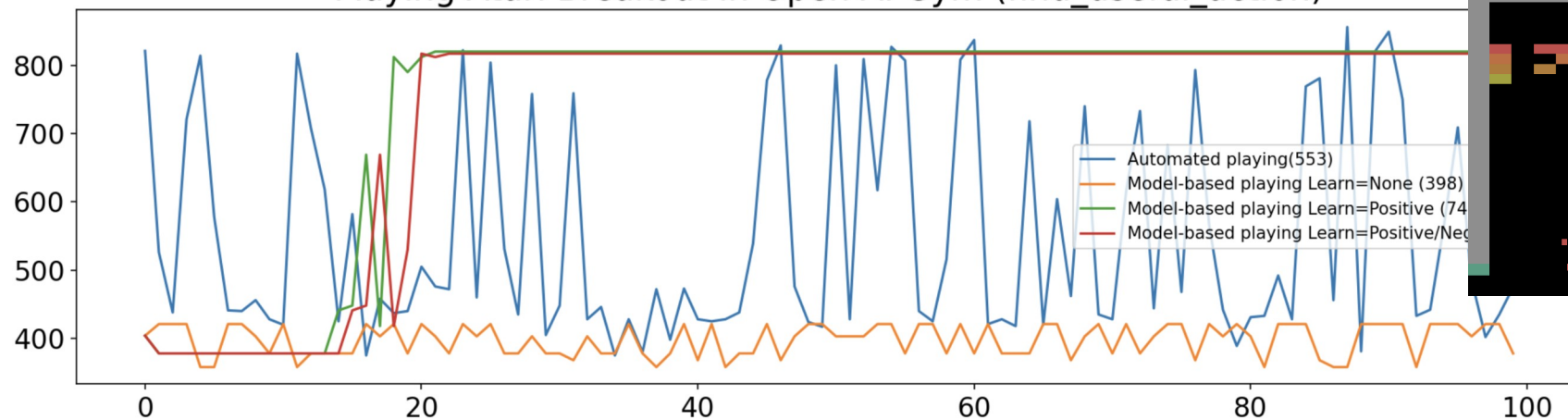https://doi.org/10.1007/978-3-030-93758-4_12

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# Imitation learning – decision making on "pre-trained" model



Playing Atari Breakout in Open AI Gym (Nov32025)

864

- Automated playing(553)
- Model-based playing Learn=None (544)
- Model-based playing Learn=Positive (839)
- Model-based playing Learn=Positive+Negative (787)

Playing Atari Breakout in Open AI Gym (find_useful_action)

- Automated playing(553)
- Model-based playing Learn=None (398)
- Model-based playing Learn=Positive (74...)
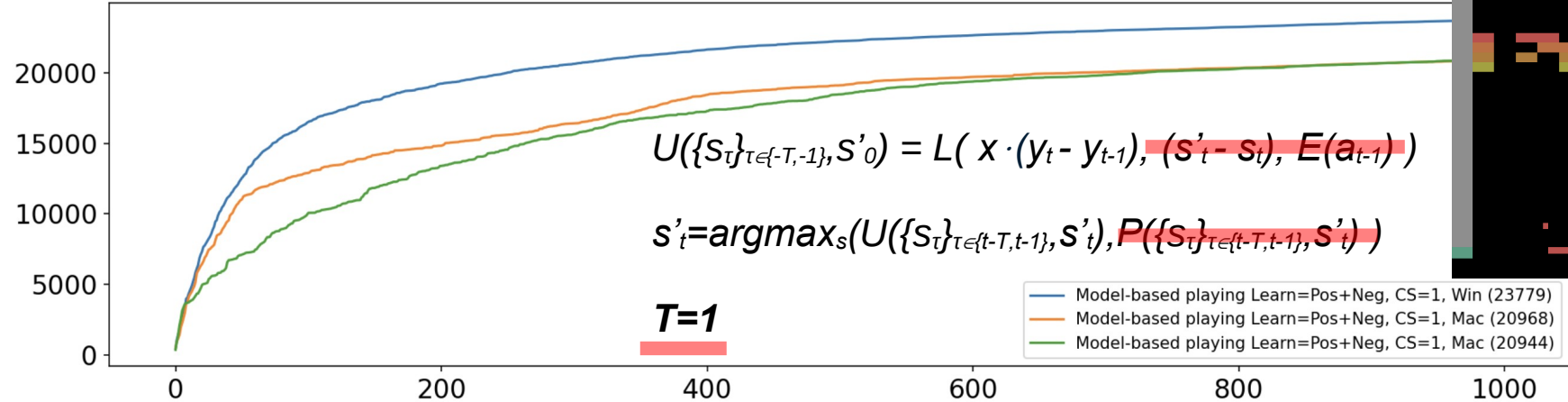- Model-based playing Learn=Positive/Neg...

# Reinforcement learning – experiential learning and decision making

## Playing Atari Breakout in Open AI Gym (Nov32025)



Legend:
- Model-based playing Learn=Pos+Neg, CS=1, Win (10)
- Model-based playing Learn=Pos+Neg, CS=1, Mac (16)
- Model-based playing Learn=Pos+Neg, CS=1, Mac (14)

Average human level

## N of States in the Model (Nov32025)



$$U(\{s_\tau\}_{\tau\in\{-T,-1\}}, s'_0) = L(\ x\cdot(y_t - y_{t-1}),\ (s'_t - s_t),\ E(a_{t-1})\ )$$

$$s'_t = argmax_s(U(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t), P(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t)\ )$$

*T=1*

Legend:
- Model-based playing Learn=Pos+Neg, CS=1, Win (23779)
- Model-based playing Learn=Pos+Neg, CS=1, Mac (20968)
- Model-based playing Learn=Pos+Neg, CS=1, Mac (20944)

# Reinforcement learning – experiential learning and decision making



Playing Atari Breakout in Open AI Gym (Nov32025)

- Model-based playing Learn=Pos+Neg, CS=2, Win (33)
- Model-based playing Learn=Pos+Neg, CS=2, Mac (45)

Average human level

N of States in the Model (Nov32025)

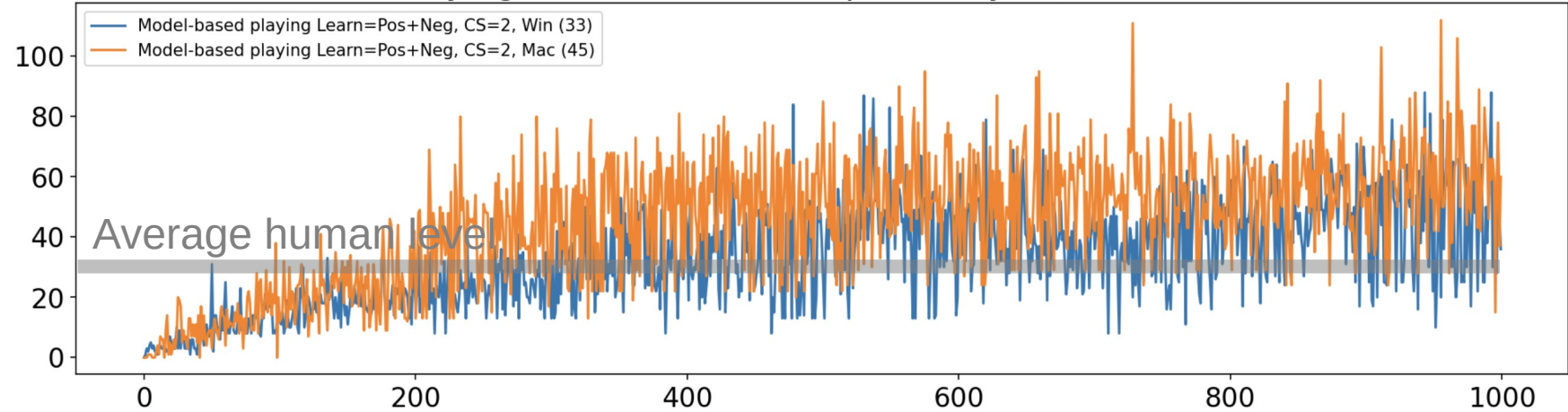$$U(\{s_t\}_{\tau \in \{-T,-1\}}, s'_0) = L( x \cdot (y_t - y_{t-1}), (s'_t - s_t), E(a_{t-1}) )$$

$$s'_t = argmax_s(U(\{s_t\}_{\tau \in \{t-T, t-1\}}, s'_t), P(\{s_t\}_{\tau \in \{t-T, t-1\}}, s'_t) )$$

**T=2, Similarity=0.99**

- Model-based playing Learn=Pos+Neg, CS=2, Win (21034)
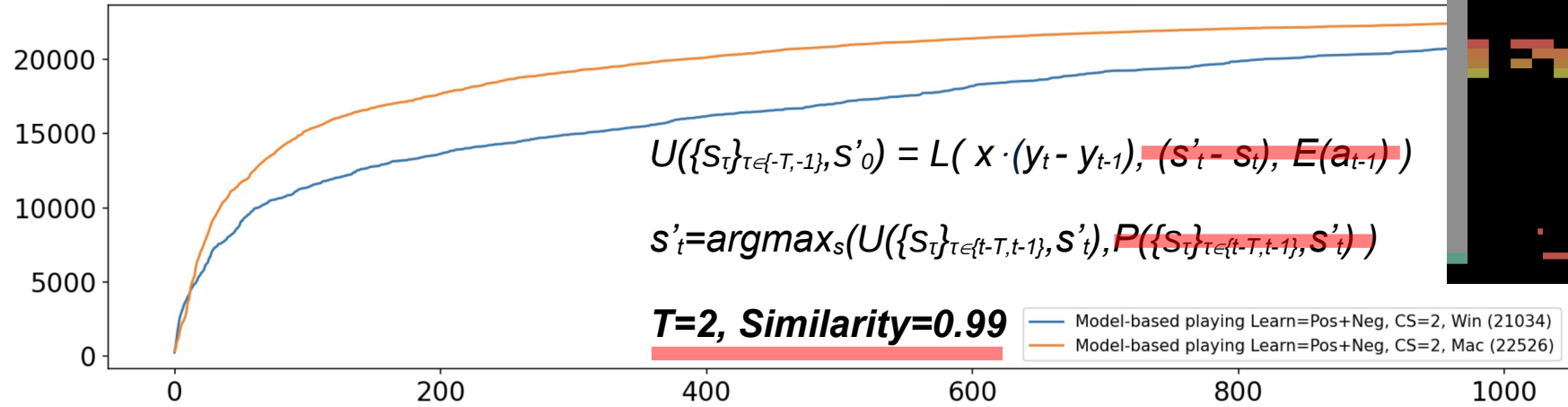- Model-based playing Learn=Pos+Neg, CS=2, Mac (22526)

# Reinforcement learning – experiential learning and decision making



Playing Atari Breakout in Open AI Gym (Nov32025)

- Model-based playing Learn=Pos+Neg, CS=2, SS=0.9 Mac (175)
- Model-based playing Learn=Pos+Neg, CS=2, SS=0.9 Win (7)

Top DQN level

Average DQN level

Average human level

N of States in the Model (Nov32025)

- Model-based playing Learn=Pos+Neg, CS=2, SS=0.9 Mac (18127)
- Model-based playing Learn=Pos+Neg, CS=2, SS=0.9 Win (13210)

$$U(\{s_\tau\}_{\tau\in\{-T,-1\}}, s'_0) = L( \ x \cdot (y_t - y_{t-1}), \ (s'_t - s_t), \ E(a_{t-1}) \ )$$

$$s'_t = argmax_s(U(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t), P(\{s_\tau\}_{\tau\in\{t-T,t-1\}}, s'_t) \ )$$

**T=2, Similarity=0.9**

29
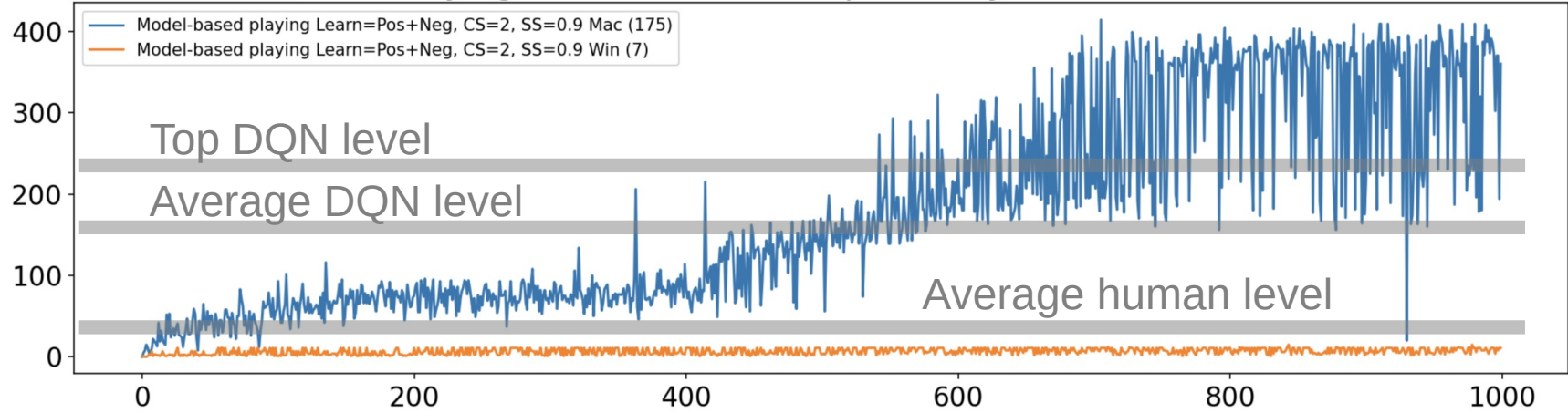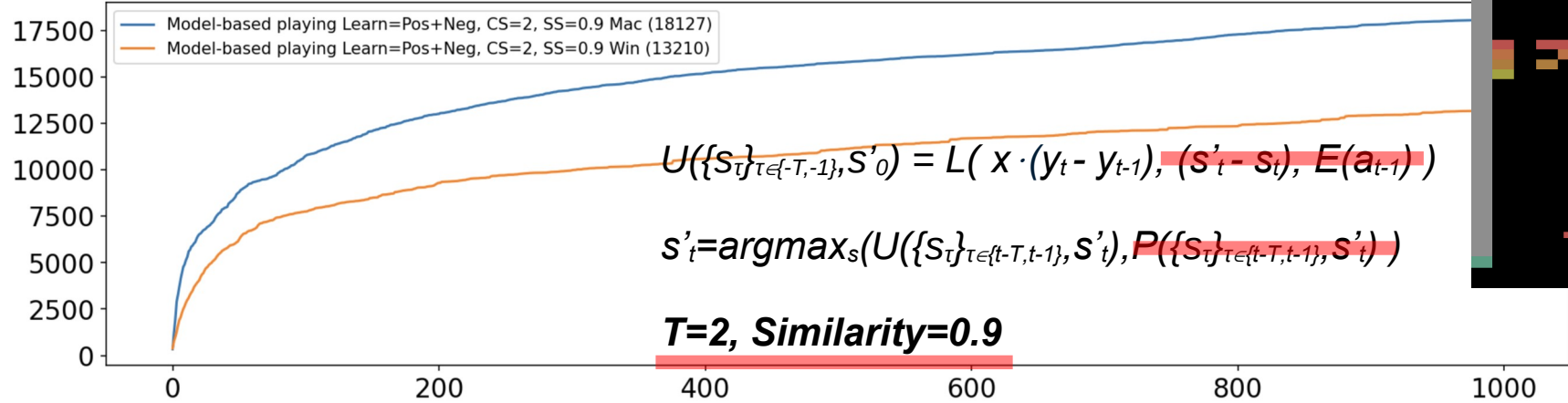
# Thank you for attention! Questions?

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Telegram/GitHub: akolonin

Workshop recording on the subject

Anton Kolonin & Vladimir Kryukov, Computational Concept of the Psyche, Neuroinformatics-2025