Cognitive Architecture for Neuro-Symbolic Experiential Learning

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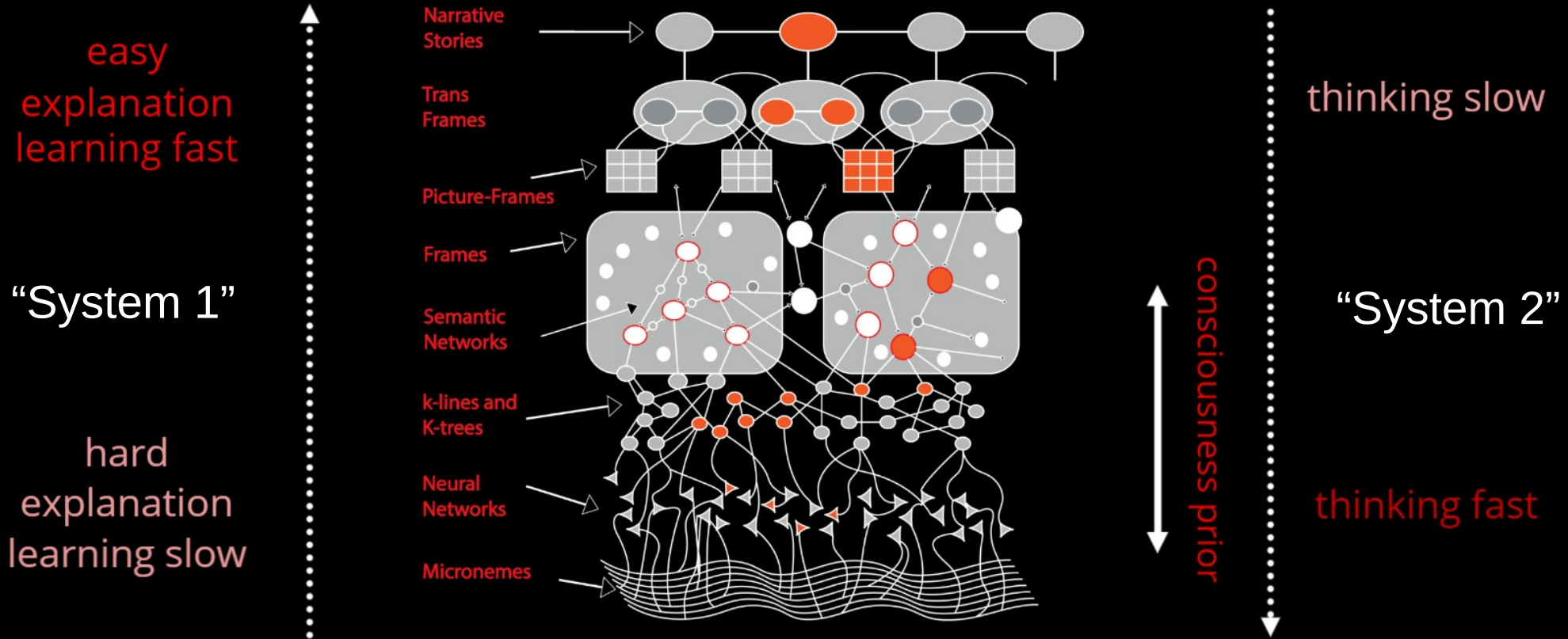Novosibirsk State University

*THE REAL SCIENCE

https://www.nsu.ru

AIGENTS

https://aigents.com

AGI IN RUSSIAN

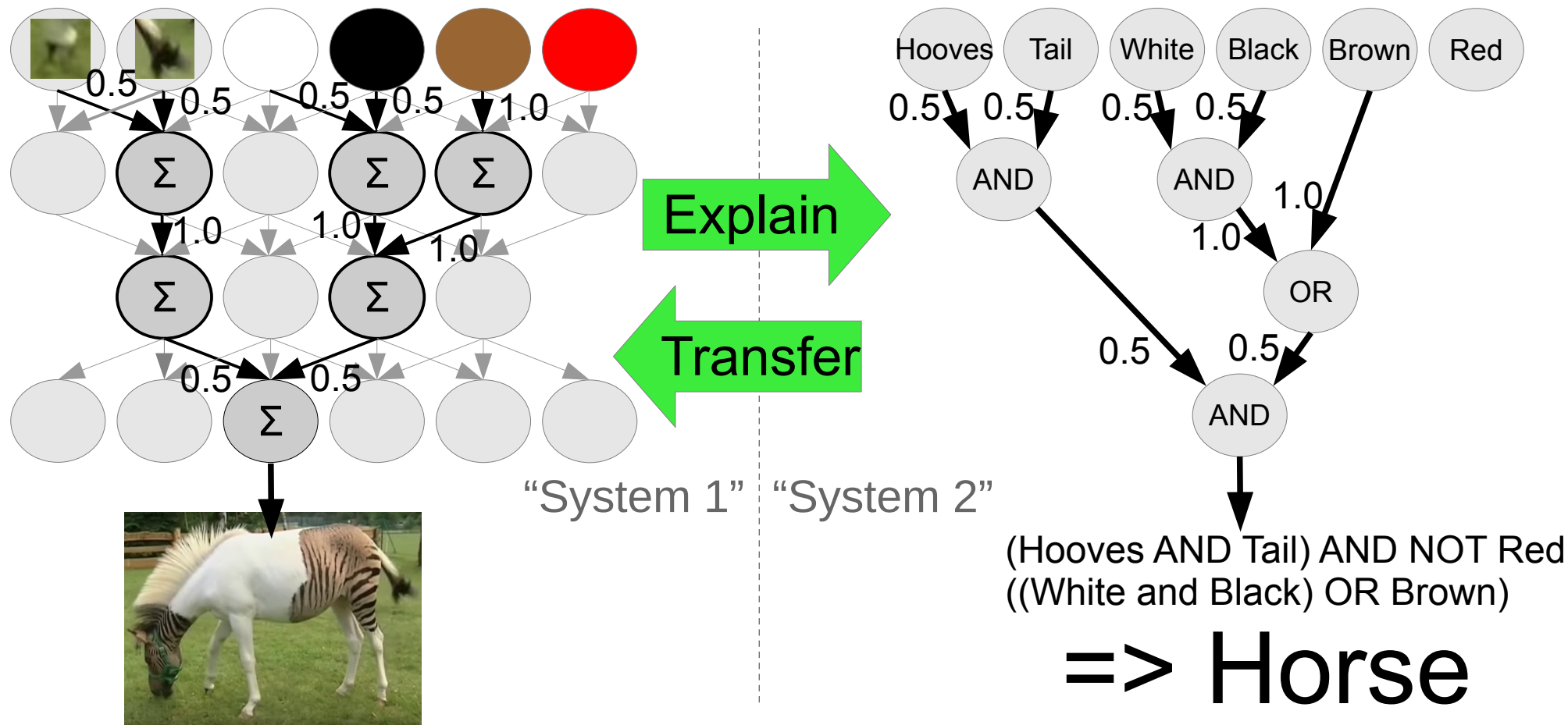https://agirussia.org

"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.
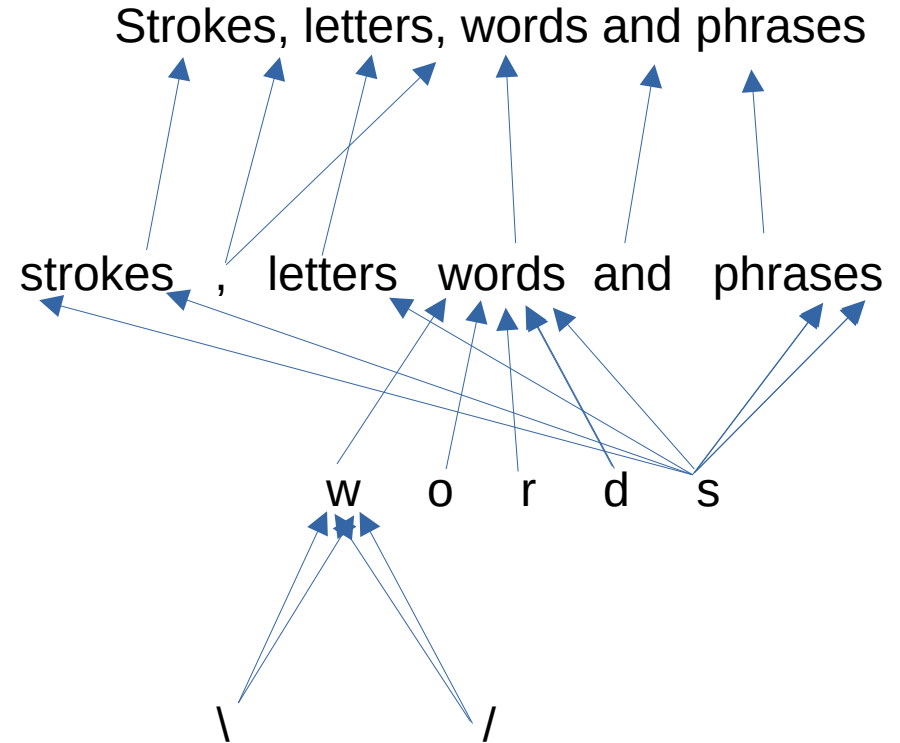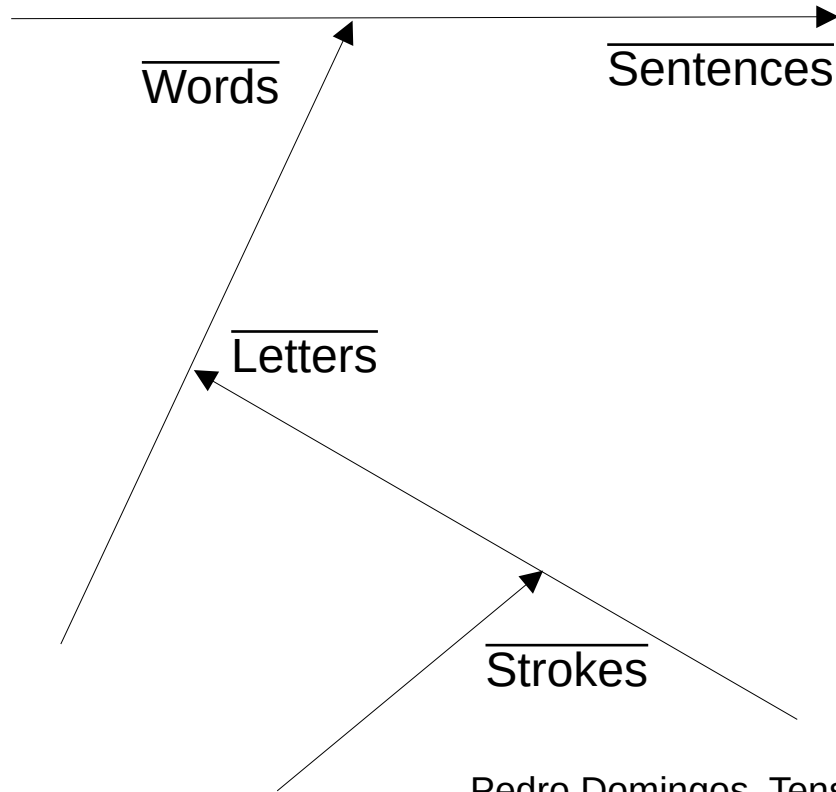https://doi.org/10.1007/978-3-030-30263-4_3
M. Minsky, The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind (Simon & Schuster Paperbacks, Princeton, 2007)

Neuro-Symbolic Integration for Interpretable AI

(Hooves AND Tail) AND NOT Red
((White and Black) OR Brown)

=> Horse

"System 1" "System 2"

3

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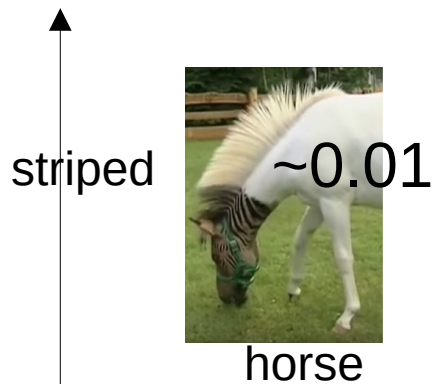
Truth-Value Tensor
(NARS/PLN)
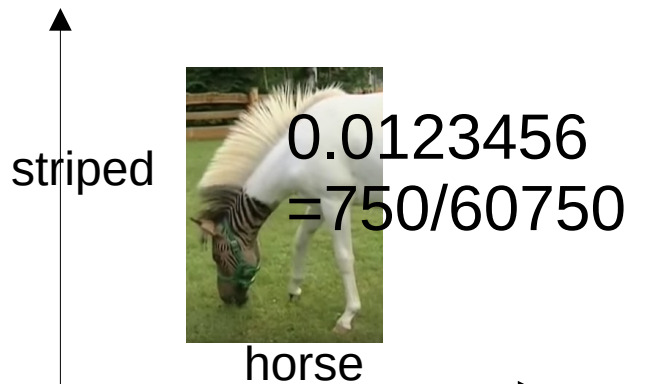
Numerical Tensor
(ANN/Bayesian Logic)

Boolean Tensor
(Boolean Logic)
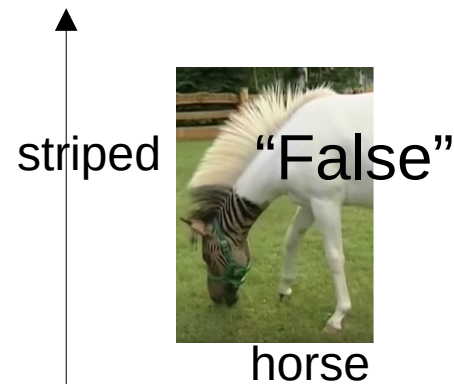
Property

striped

0.0123456
=750/60750
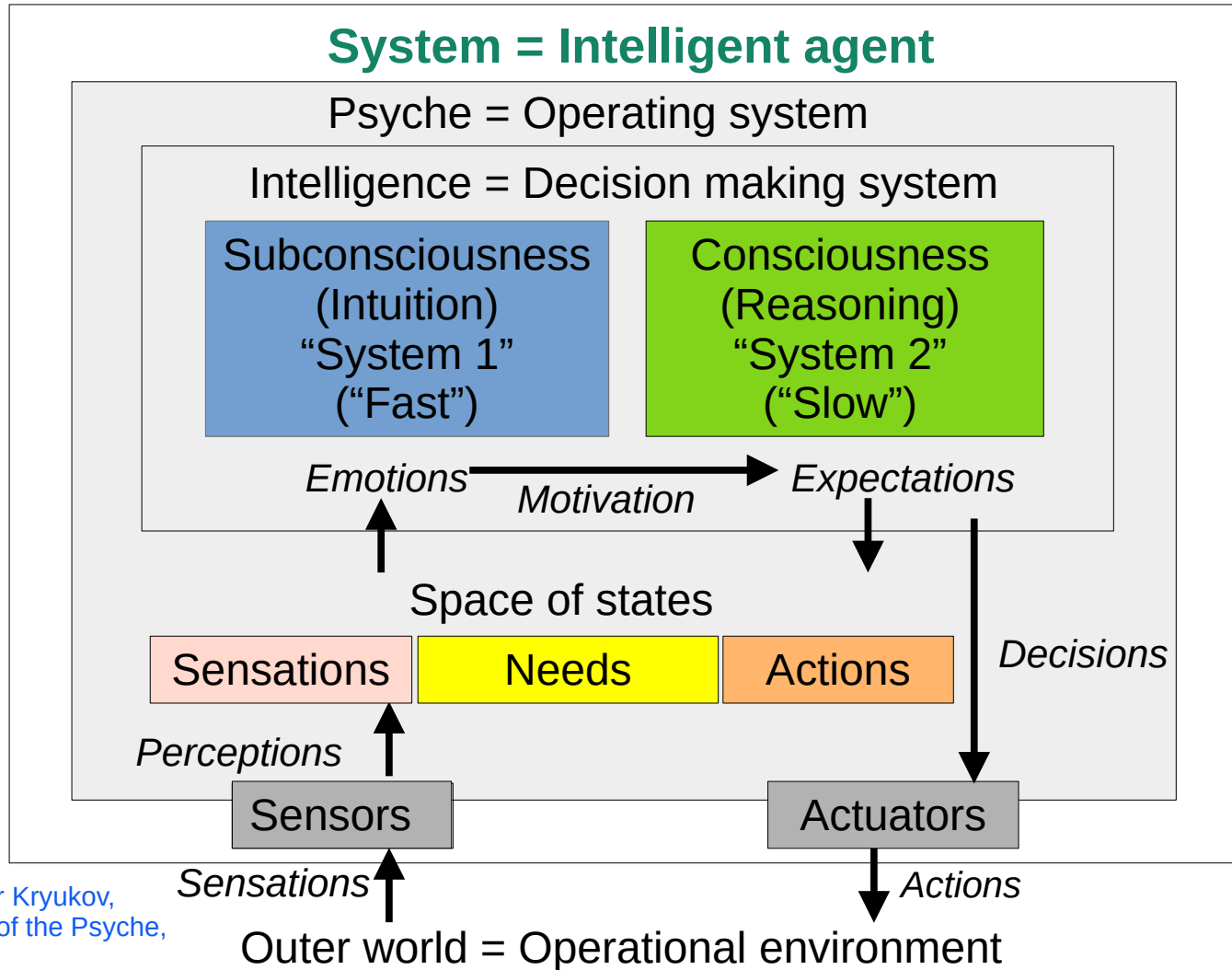
horse

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

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

Psyche = Operating system
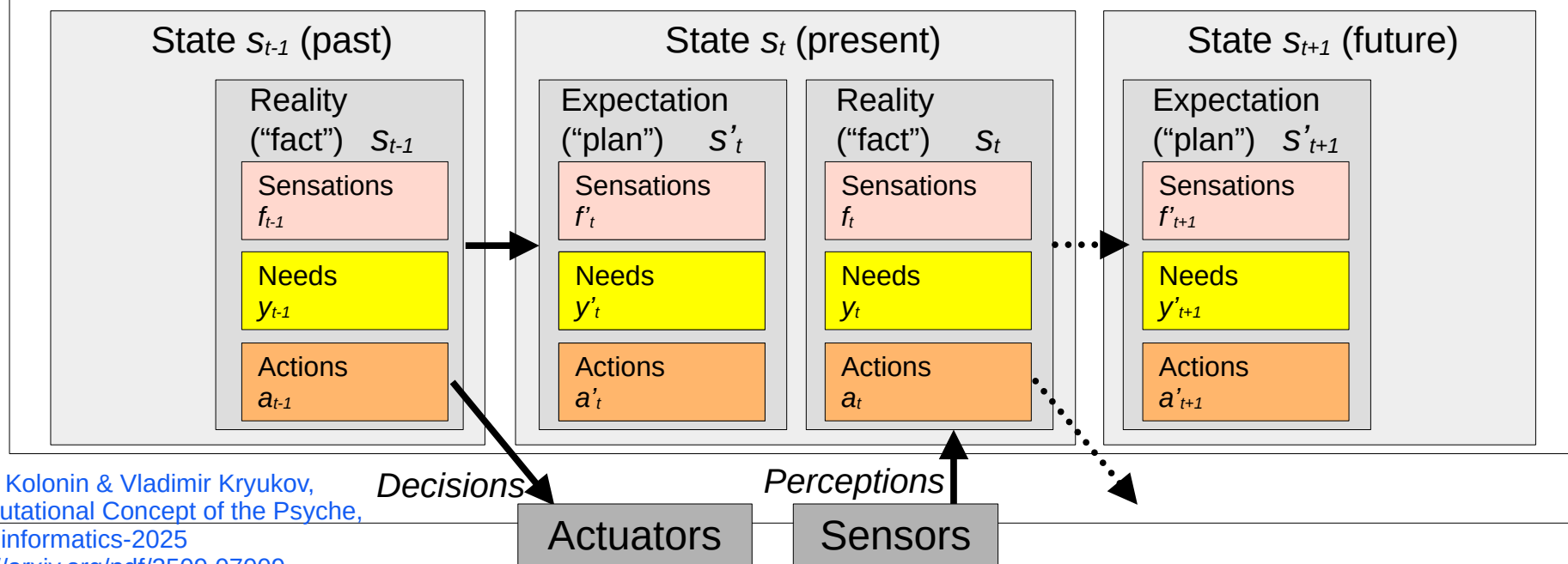
Intelligence = Decision making system

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)

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*

Predictability *of s*

Optimal decision and expectation 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")

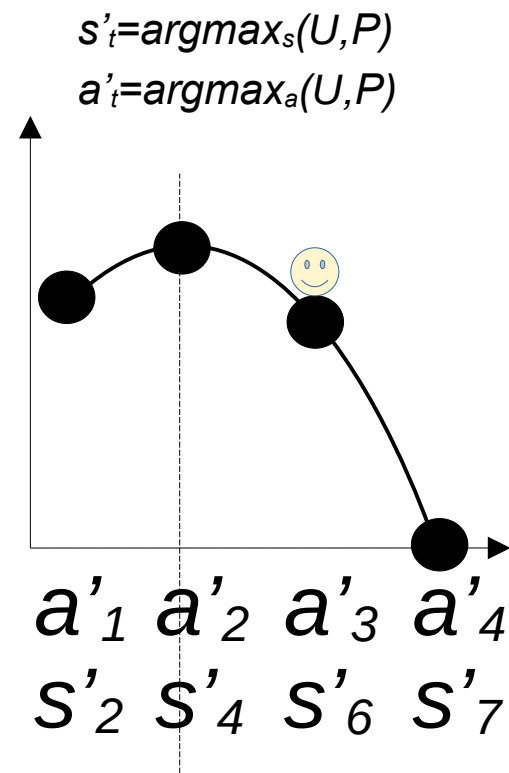| State s_{t-1} (past)	State s_t (present)		State s_{t+1} (future)
Reality ("fact") s_{t-1}	Expectation ("plan") s'_t	Reality ("fact") s_t	Expectation ("plan") s'_{t+1}
Sensations f_{t-1}	Sensations f'_t	Sensations f_t	Sensations f'_{t+1}
Needs y_{t-1}	Needs y'_t	Needs y_t	Needs y'_{t+1}
Actions a_{t-1}	Actions a'_t	Actions a_t	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"*)

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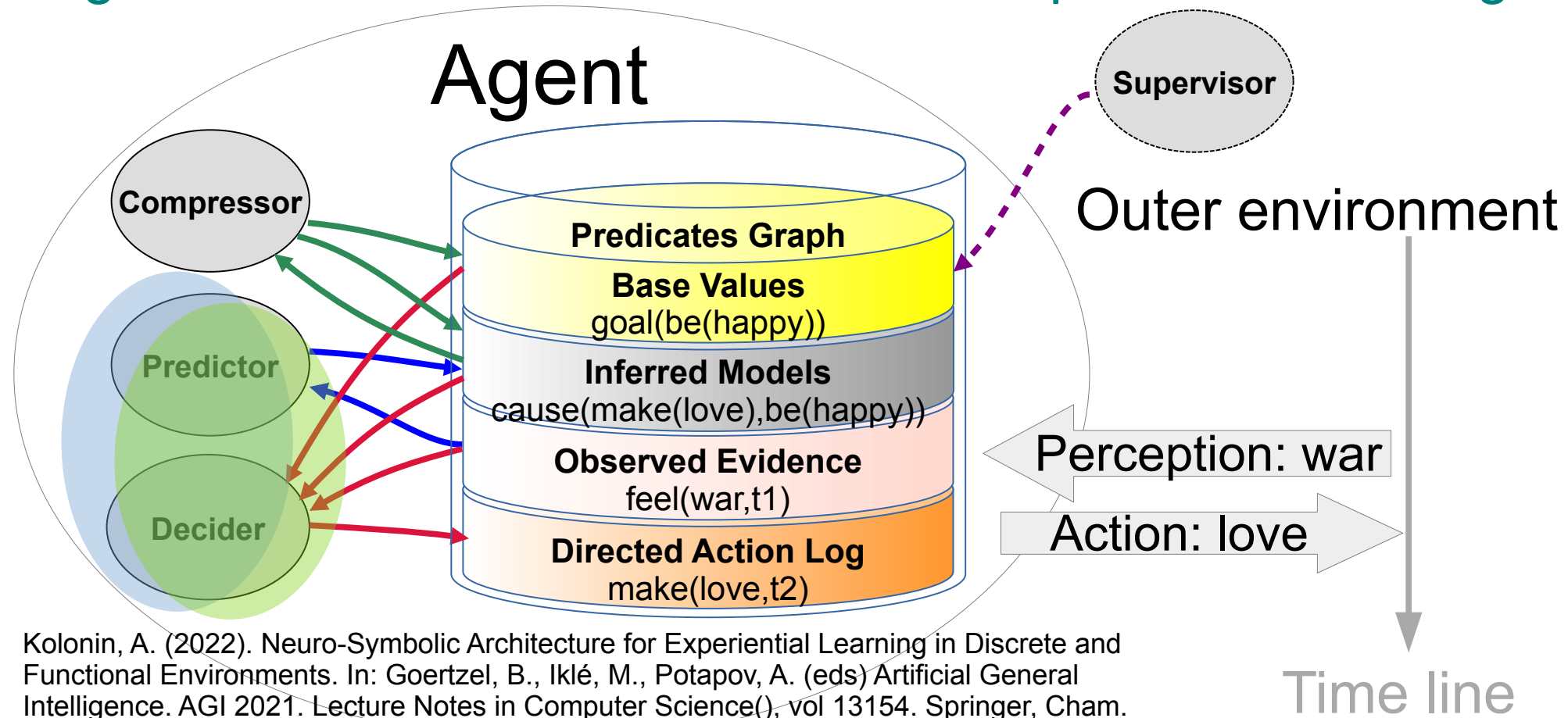
Kolonin, A. (2022). Neuro-Symbolic Architecture for Experiential Learning in Discrete and Functional Environments. In: Goertzel, B., Iklé, M., Potapov, A. (eds) Artificial General Intelligence. AGI 2021. Lecture Notes in Computer Science(), vol 13154. Springer, Cham. https://doi.org/10.1007/978-3-030-93758-4_12

10

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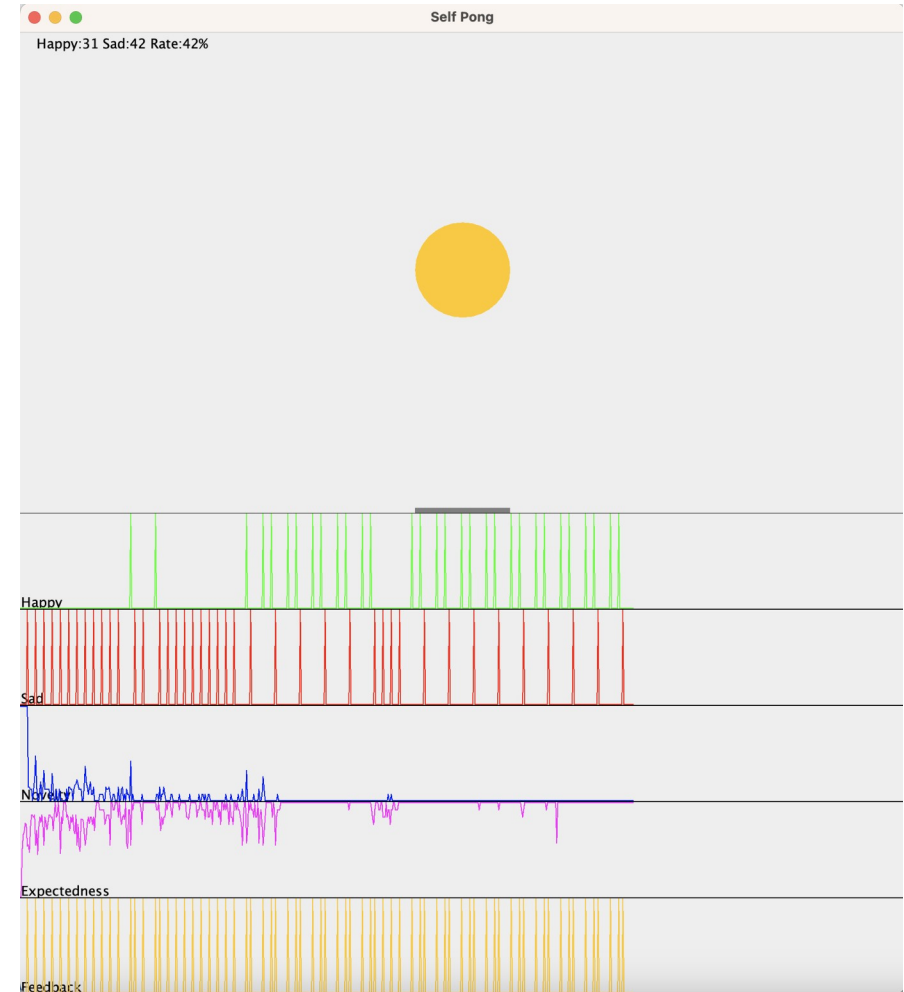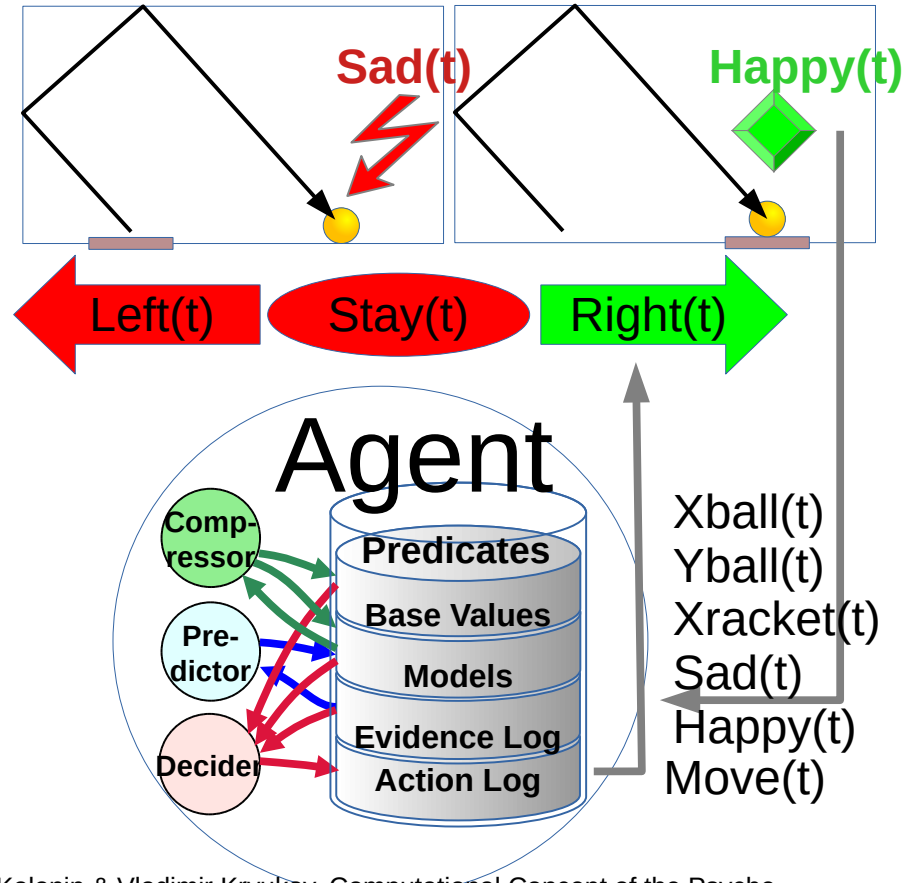
Anton Kolonin & Vladimir Kryukov, Computational Concept of the Psyche
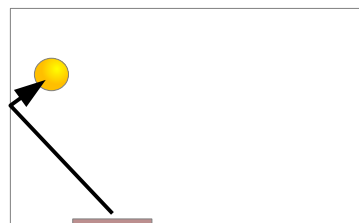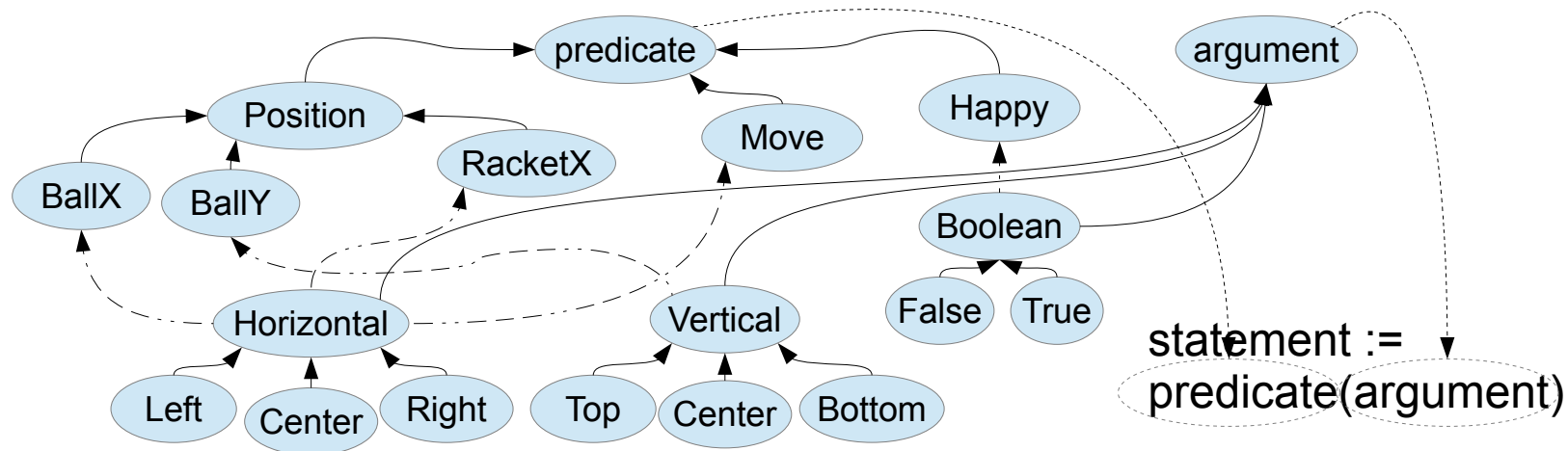https://arxiv.org/pdf/2509.07009
Anton Kolonin, Neuro-Symbolic Architecture for Experiential Learning in Discrete and Functional Environments
https://doi.org/10.1007/978-3-030-93758-4_12

Learning Play "Pong" at Object Level

statement :=
predicate(argument)
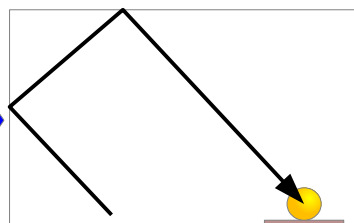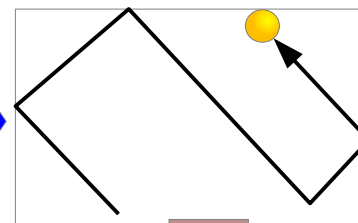
BallY(Top)
BallX(Left)
RacketX(Left)
Happy(False)
=> **Move(Left)**
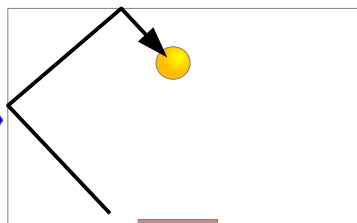
BallY(Top)
BallX(Center)
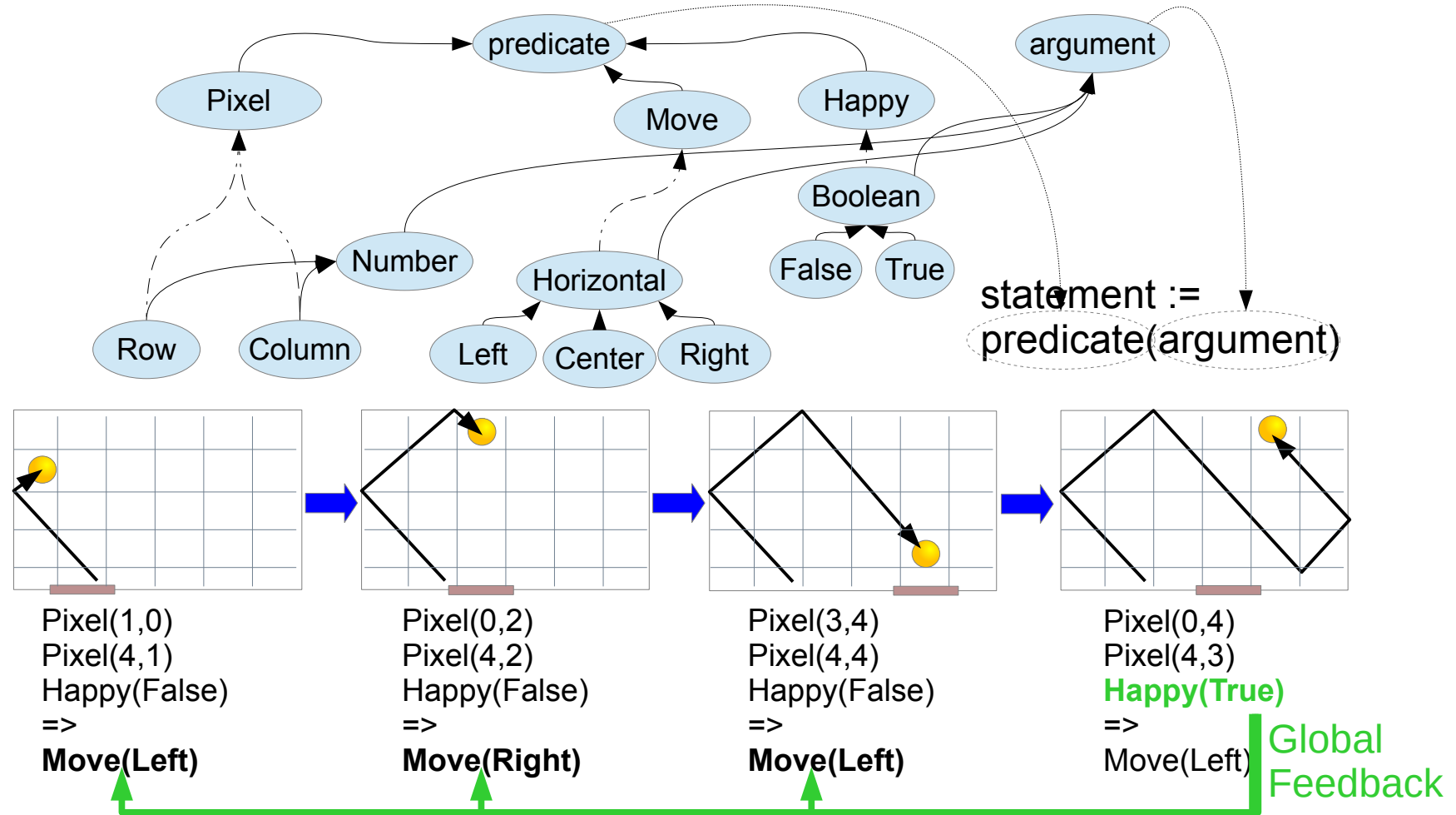RacketX(Center)
Happy(False)
=> **Move(Right)**

BallY(Bottom)
BallX(Right)
RacketX(Right)
Happy(False)
=> **Move(Right)**

BallY(Bottom)
BallX(Right)
RacketX(Right)
Happy(True)
=> **Move(Left)**

Global
Feedback

Learning Play "Pong" at Pixel Level

statement := predicate(argument)

Pixel(1,0)
Pixel(4,1)
Happy(False)
=>
Move(Left)

Pixel(0,2)
Pixel(4,2)
Happy(False)
=>
Move(Right)

Pixel(3,4)
Pixel(4,4)
Happy(False)
=>
Move(Left)

Pixel(0,4)
Pixel(4,3)
Happy(True)
=>
Move(Left)
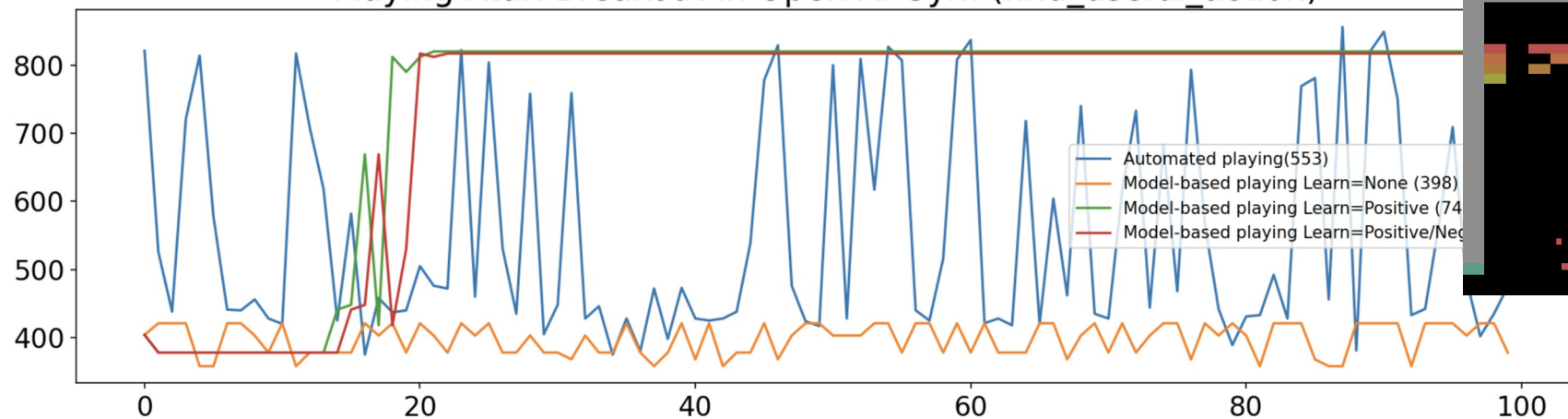
Global Feedback

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)
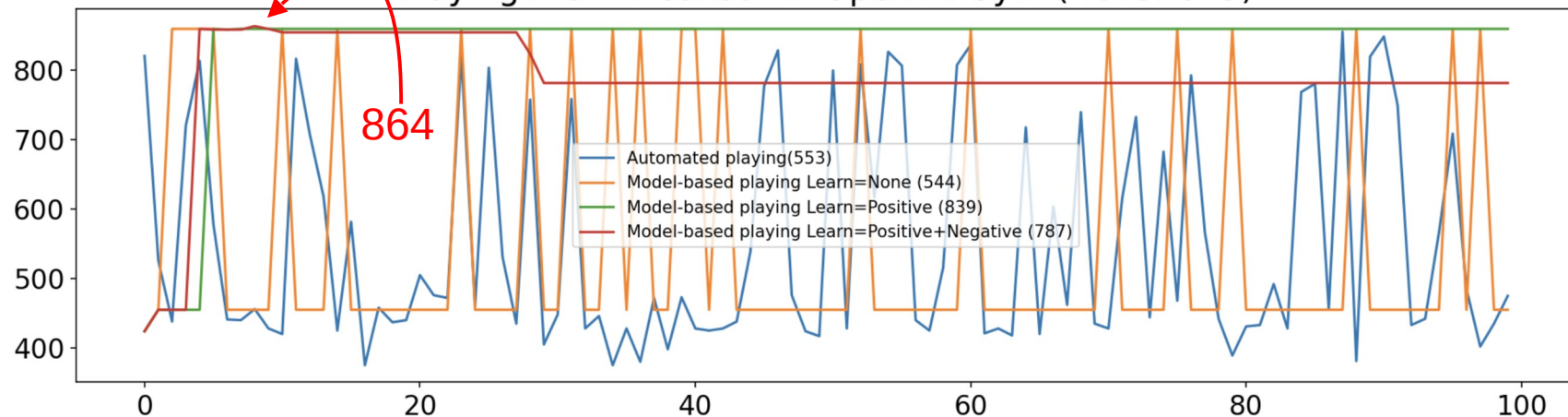
Playing Atari Breakout in Open AI Gym (find_useful_action)

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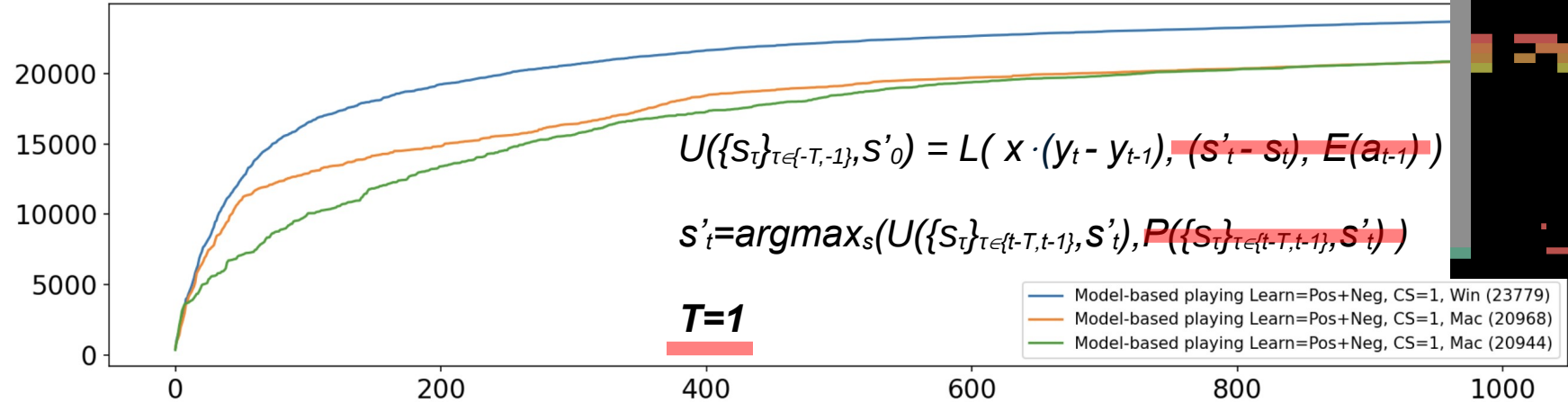- Model-based playing Learn=Positive/Neg...

14

Reinforcement learning – experiential learning and decision making

Playing Atari Breakout in Open AI Gym (Nov32025)

Average human level

- 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)

N of States in the Model (Nov32025)

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

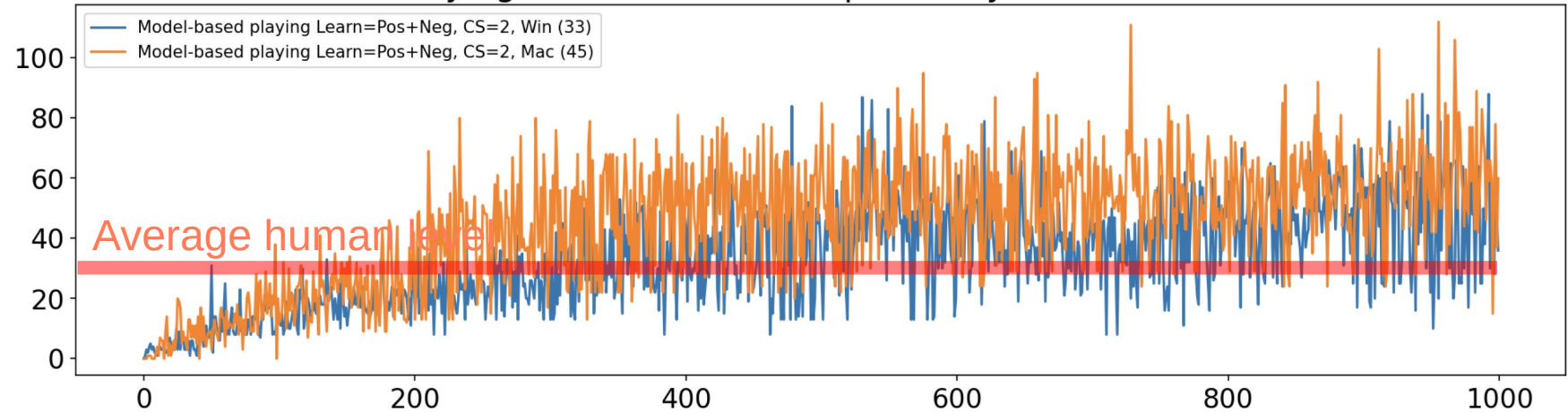$$s'_t = argmax_s(U(\{s_\tau\}_{\tau\in\{t-T,t-1\}},s'_t),P(\{s_\tau\}_{\tau\in\{t-T,t-1\}},s'_t)\ )$$

$T=1$

- 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)

15
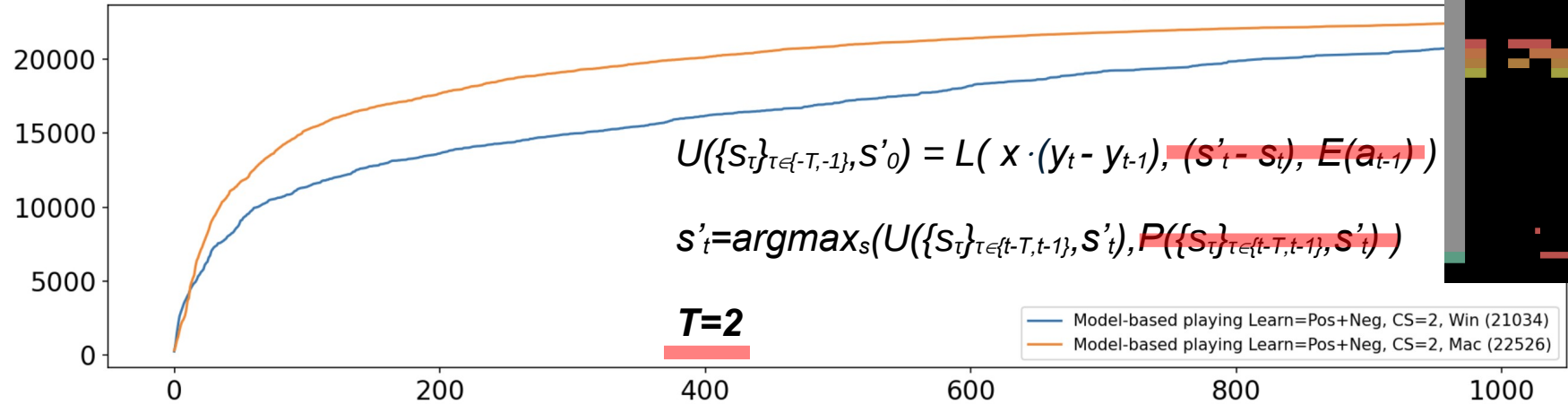
Reinforcement learning – experiential learning and decision making

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)

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

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

T=2

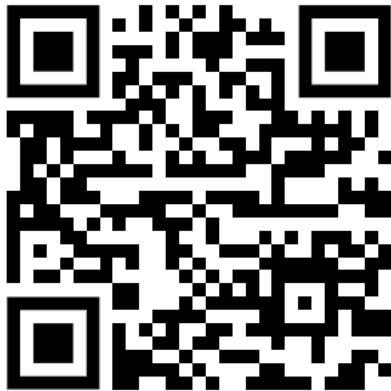- Model-based playing Learn=Pos+Neg, CS=2, Win (21034)
- Model-based playing Learn=Pos+Neg, CS=2, Mac (22526)

16
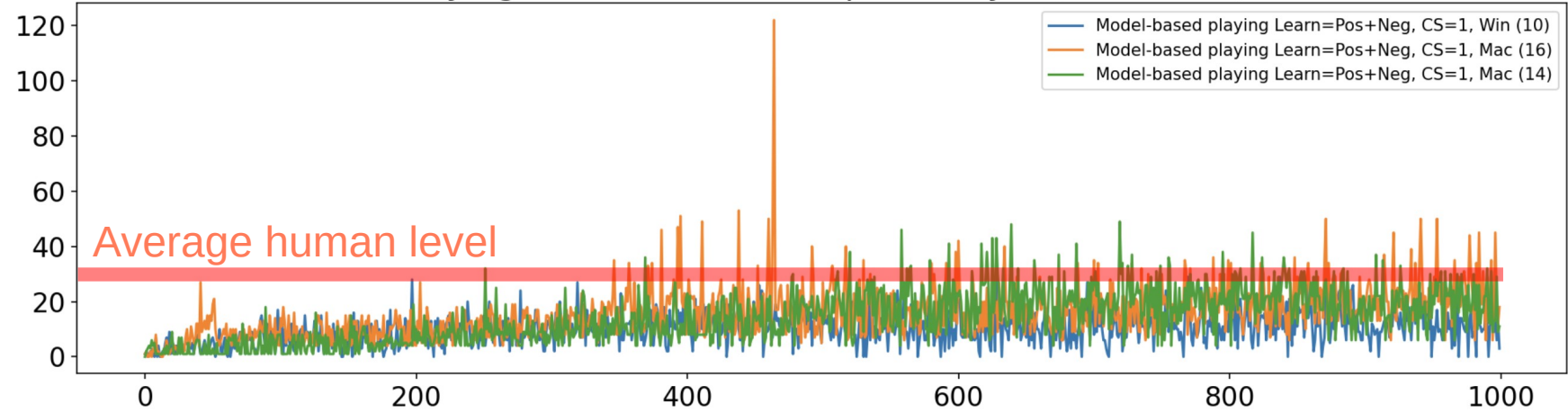
Thank you for attention! Questions?

Anton Kolonin

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Workshop recording
on the subject

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