Computational Concept and Architecture of Artificial Psyche

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AIGENTS
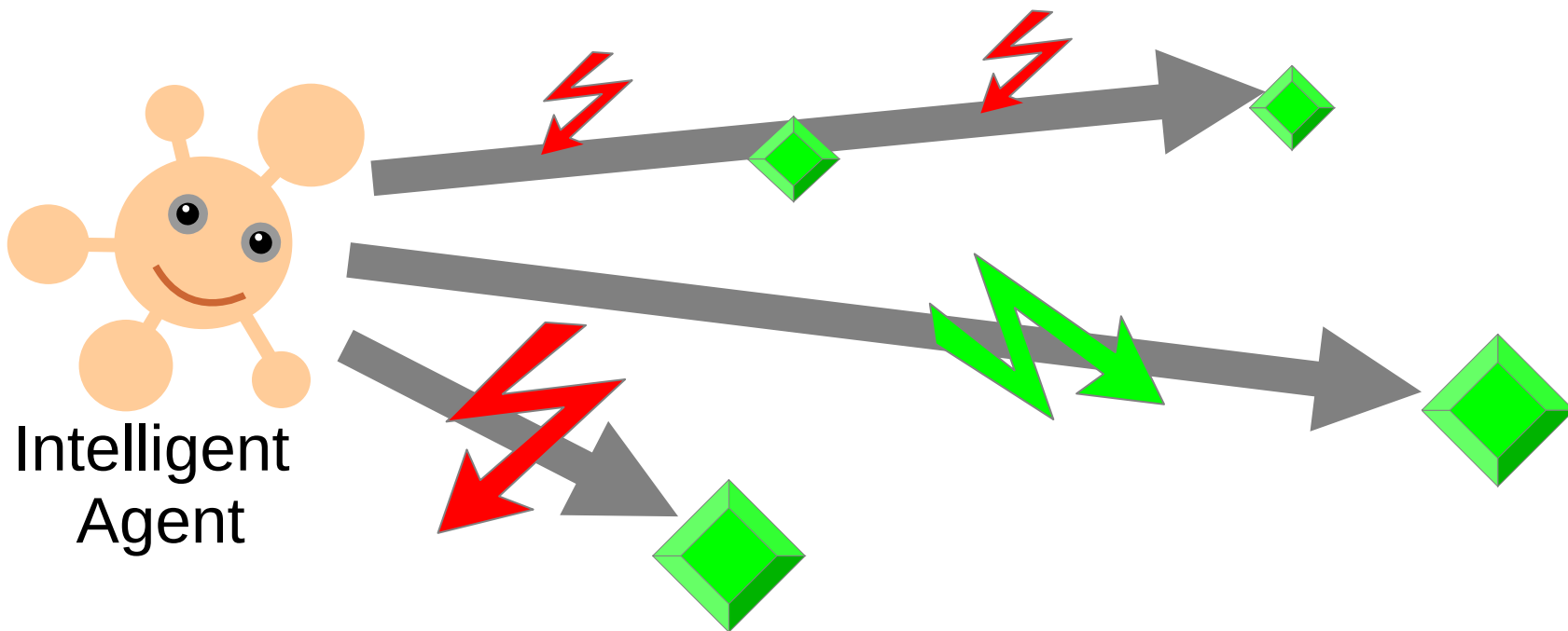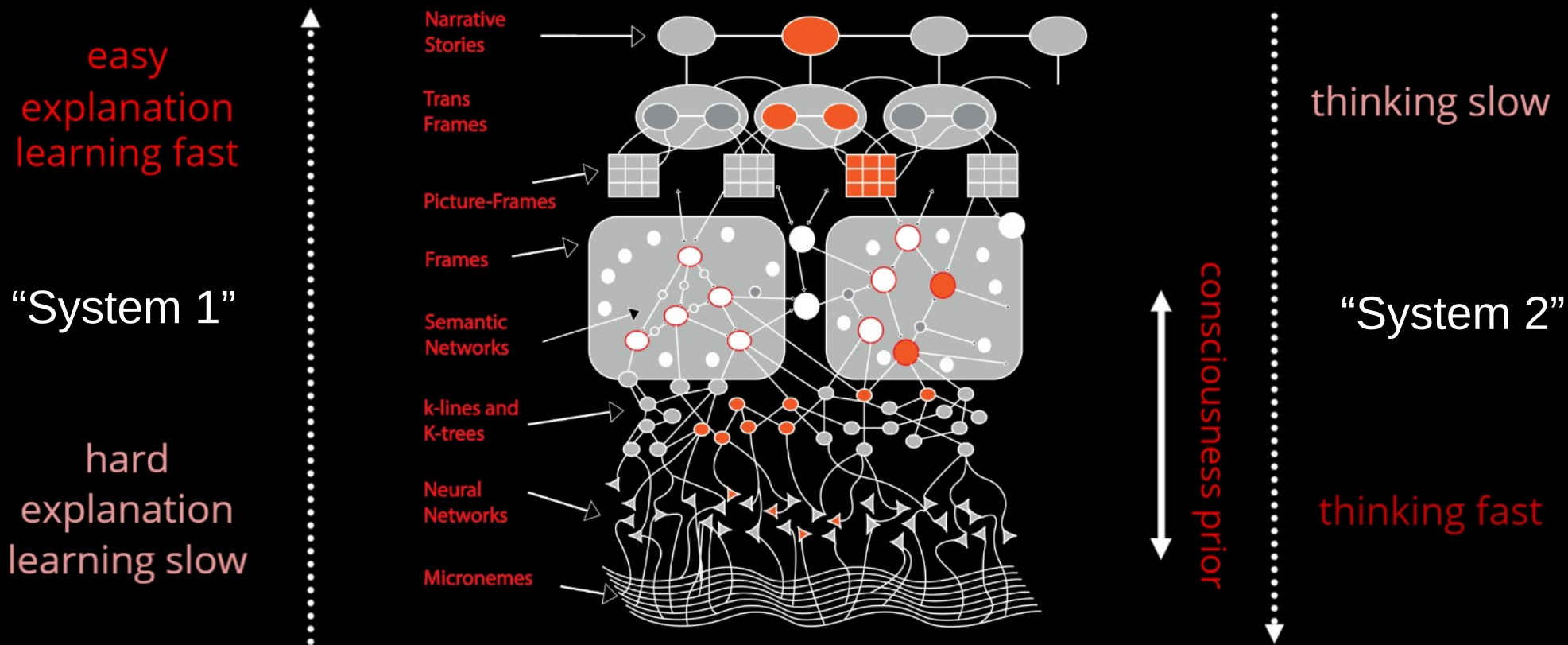https://aigents.com

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

2

"Fast and Slow Thinking" – Daniel Kahneman

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* *when* *where*

(**System 1**)
Implicit (**unconscious**) "**sub-symbolic**" knowledge
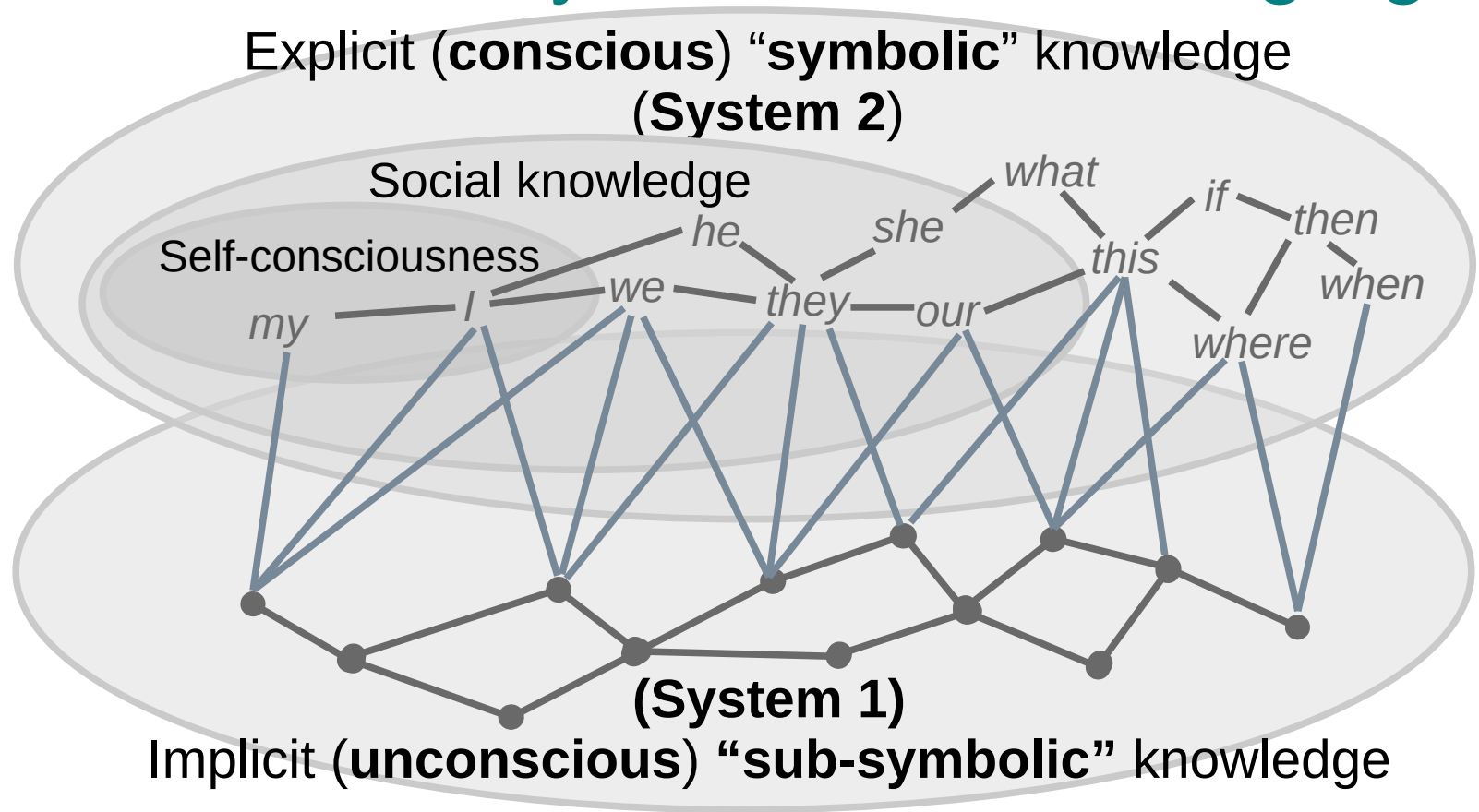
Neuro-Symbolic Integration for Interpretable AI
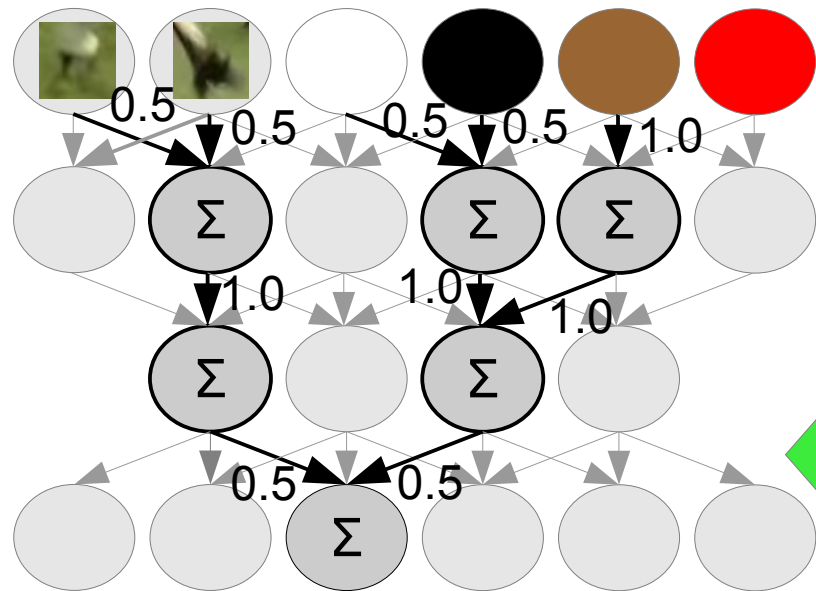
Explain

Transfer

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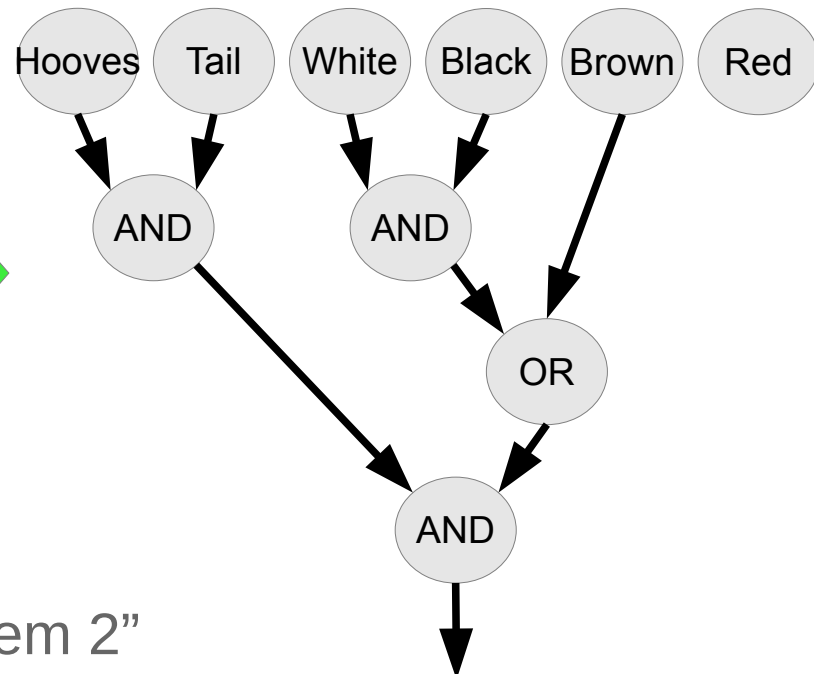
(Hooves AND Tail) AND NOT Red
((White and Black) OR Brown)

=> Horse

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

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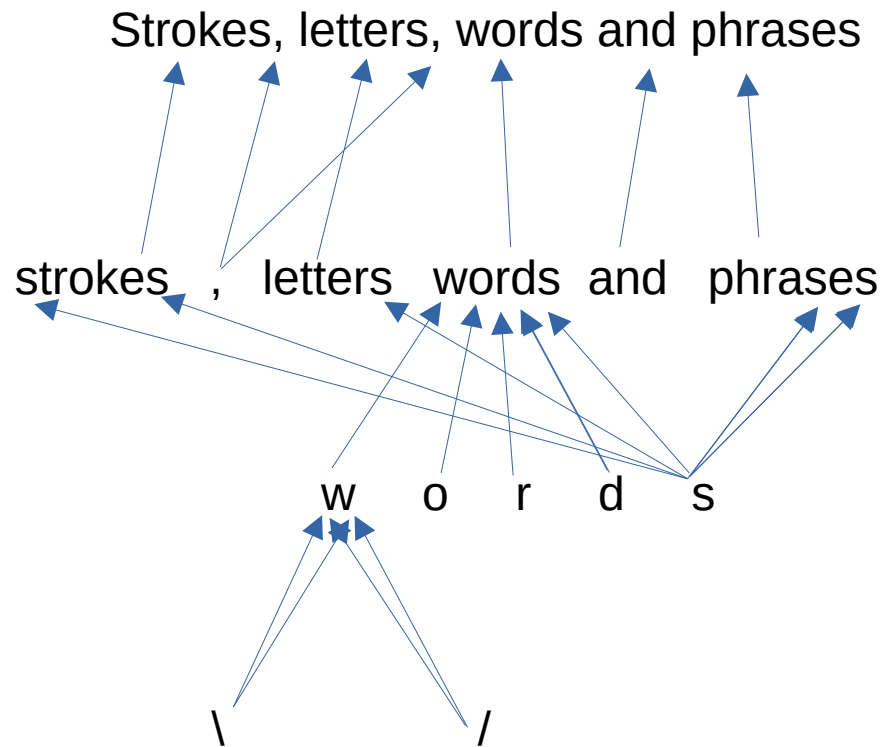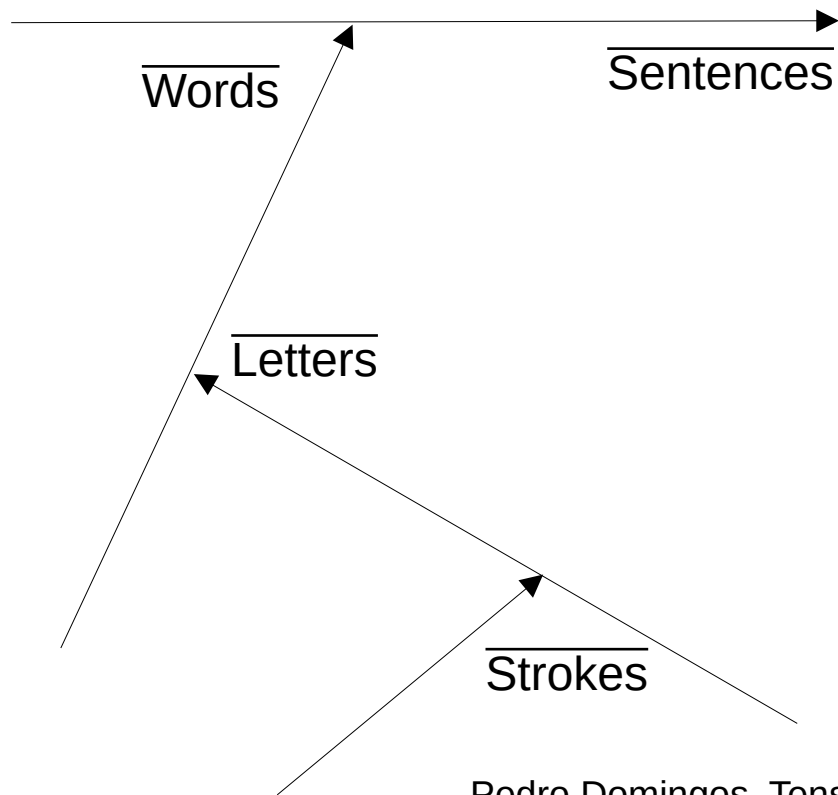
Pedro Domingos, Tensor Logic: The Language of AI
https://arxiv.org/pdf/2510.12269

The psyche /ˈsaɪki/ is currently used to describe the totality of the human mind, conscious and unconscious.

Unconscious   Conscious
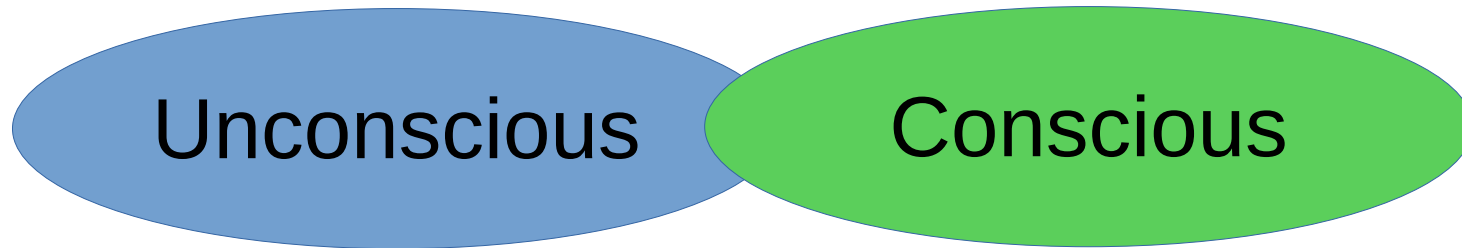
System = Intelligent agent

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

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

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
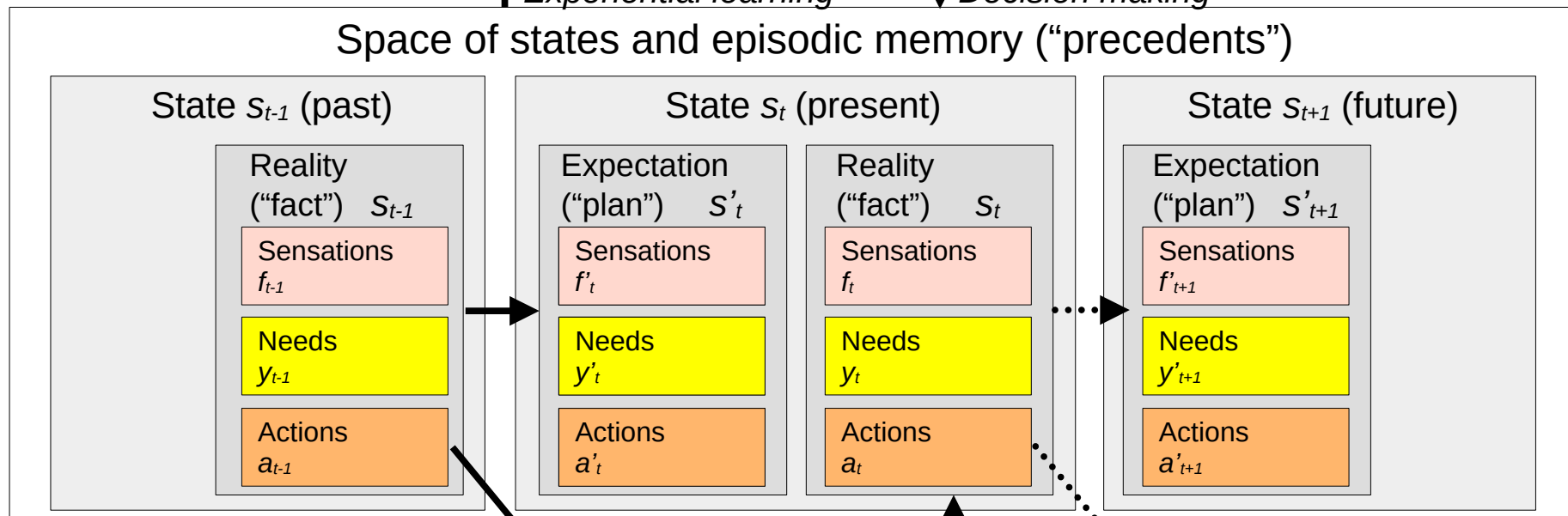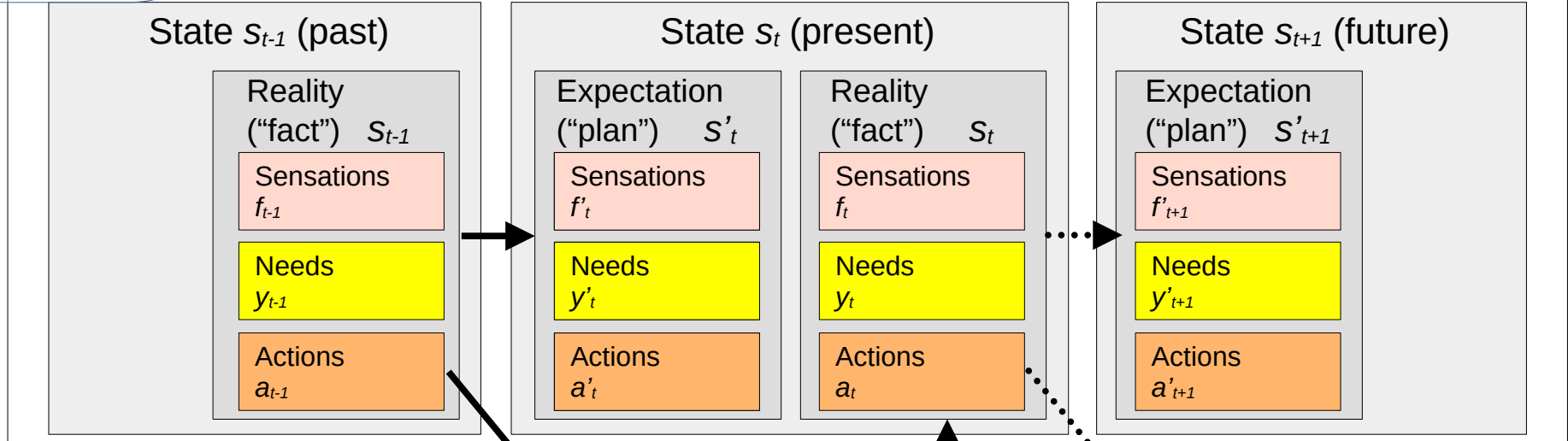
Intelligence = Decision making system

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

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$\uparrow$ *Experiential learning* $\downarrow$ *Decision making*

Space of states and episodic memory ("precedents")

Energy-efficiency *of a*

Optimal decision and expectation of *s*

Predictability *of s*

Expected utility of *s*

Satisfaction *of y*

Expected probability of *s*

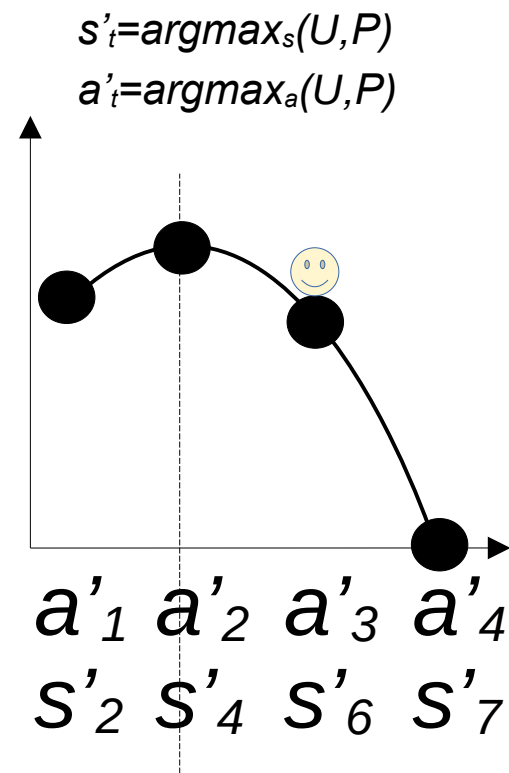| State s_{t-1} (past)	State s_t (present)		State s_{t+1} (future)
Reality ("fact") s_{t-1}	**Expectation ("plan")** s'_t	**Reality ("fact")** s_t	**Expectation ("plan")** s'_{t+1}
Sensations f_{t-1}	Sensations f'_t	Sensations f_t	Sensations f'_{t+1}
Needs y_{t-1}	Needs y'_t	Needs y_t	Needs y'_{t+1}
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)
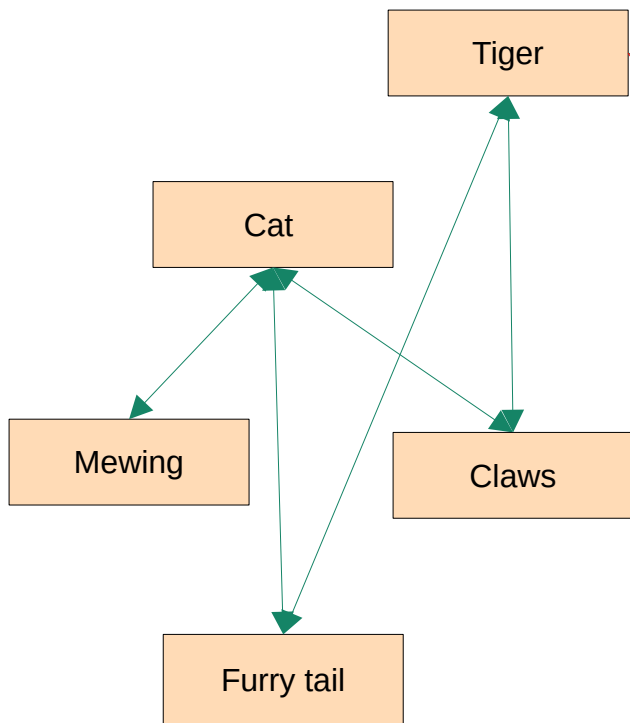
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Decision making as operational risk management

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

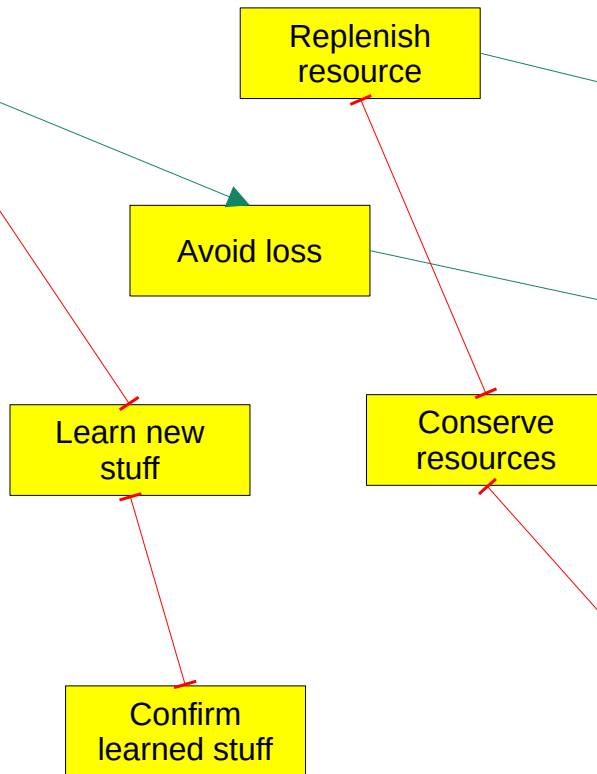Tversky & Kahneman: most people choose a'_3 и s'_6 ("smaller profit with greater reliability")

Mutual dependency of state variable ~~subgraphs~~ tensors

Percept feelings: Tiger, Cat, Mewing, Claws, Furry tail

Satisfied needs: Replenish resource, Avoid loss, Learn new stuff, Conserve resources, Confirm learned stuff

Decided & committed actions: Get resource, Make step, Stretch leg, Bend leg
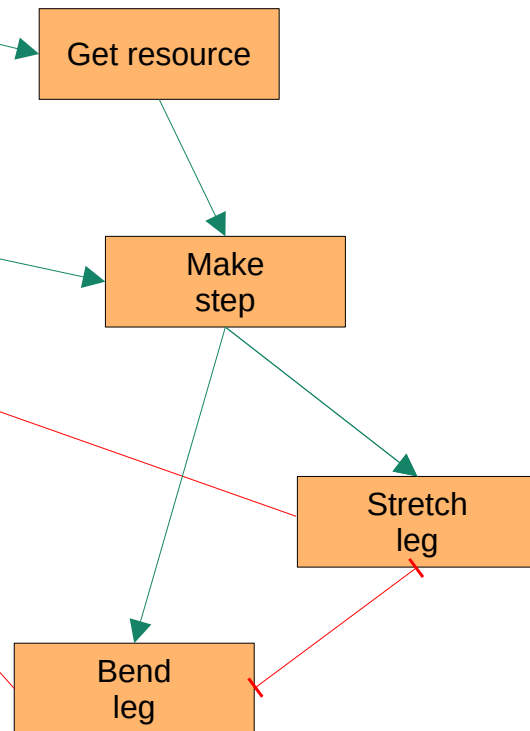
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Space of needs/goals/values

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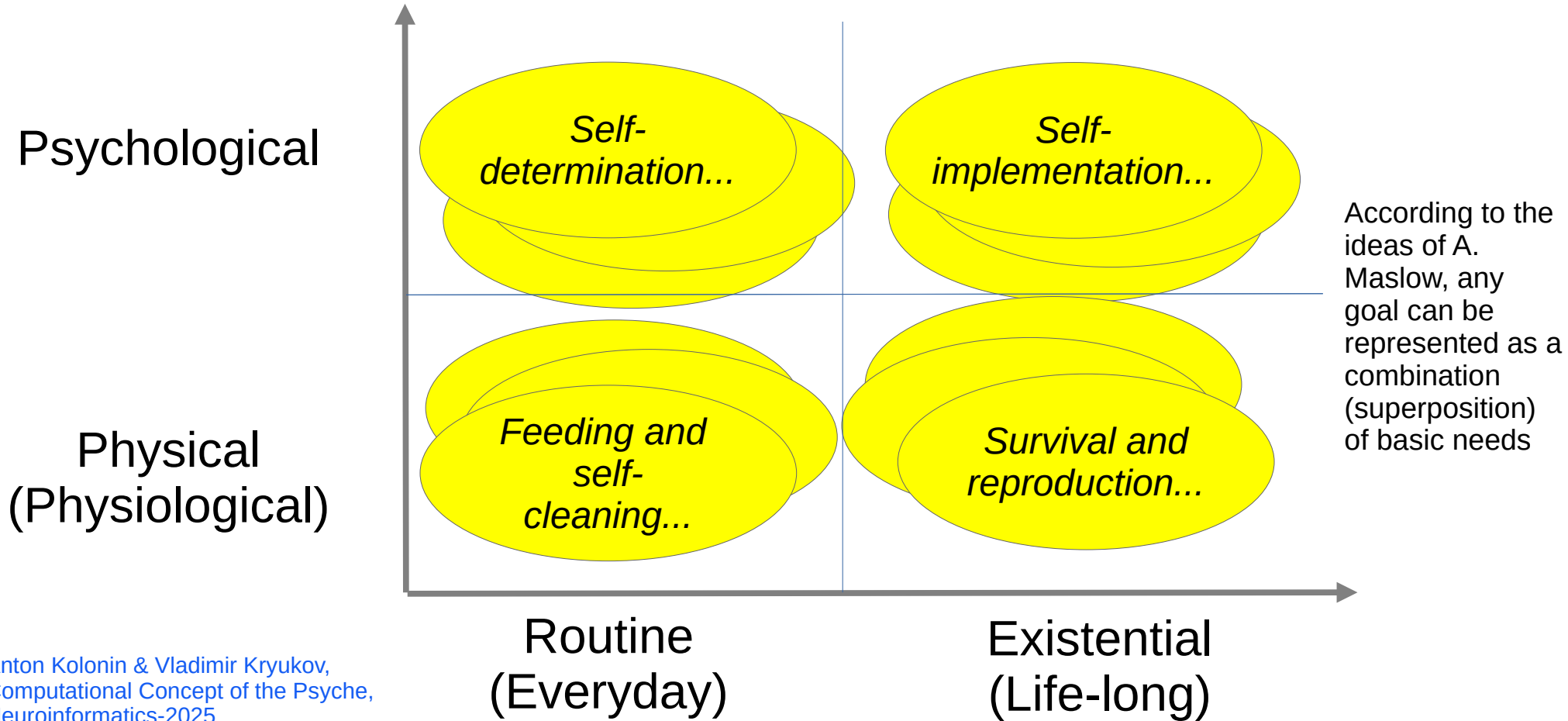
Application cases
A) Automated Process Control Systems (APCS)

Programmable logic

IEC 61131 (synchronous)

IEC 61499 (asynchronous)
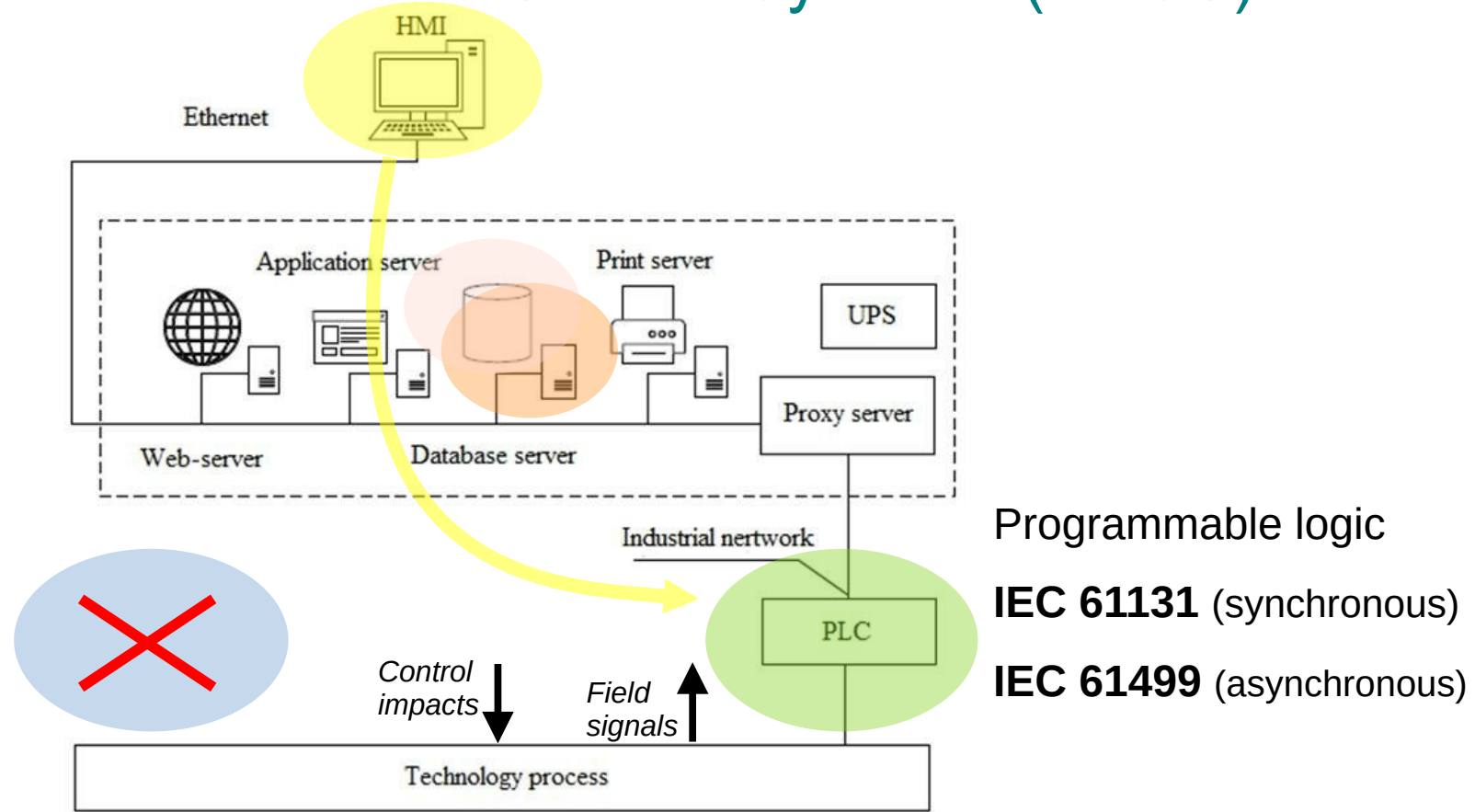
https://www.researchgate.net/publication/311662442_Adaptive_Intelligent_Manufacturing_Control_Systems

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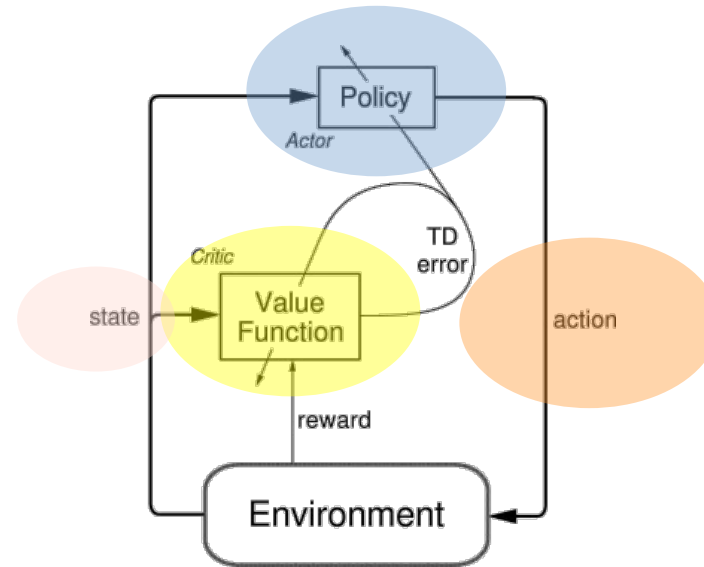
Implementation options
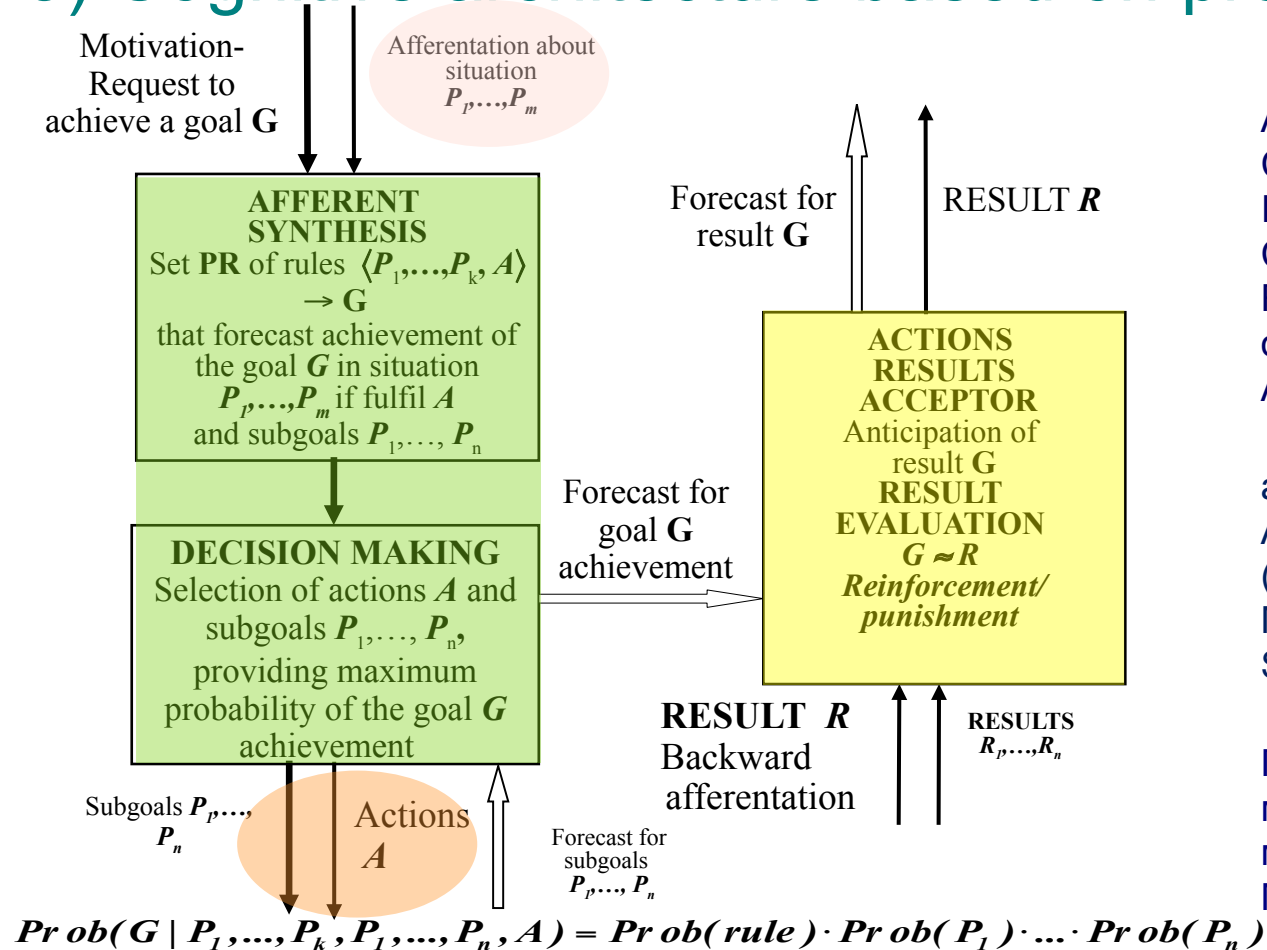## 2) Cognitive architecture based on LLM and (active) GraphRAG
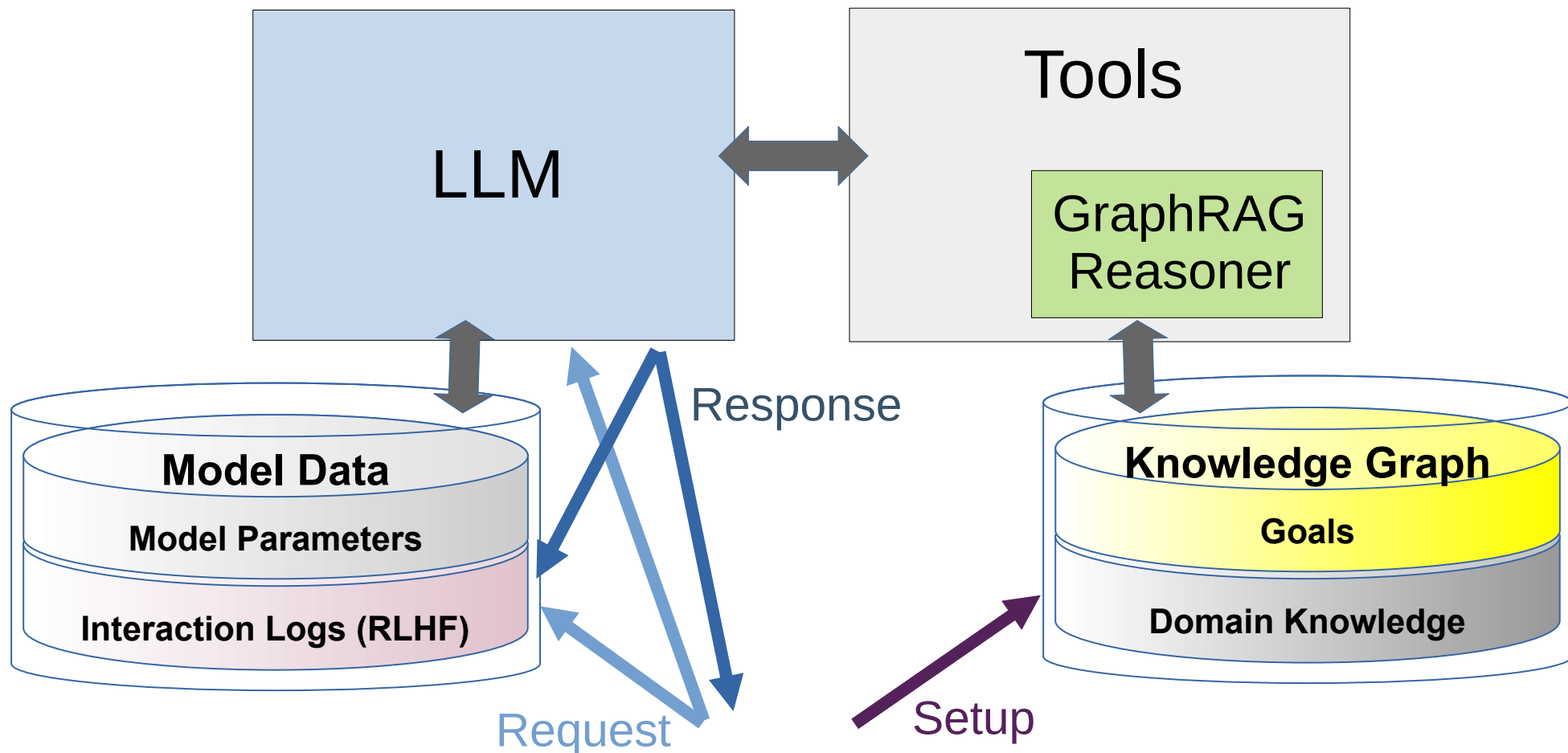
Implementation options

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 $P_1,…,P_n$

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

Forecast for result **G**

RESULT **R**

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

Forecast for goal **G** achievement

Subgoals $P_1,…, P_n$

Actions A

Forecast for subgoals $P_1,…, P_n$

RESULT **R**
Backward afferentation

RESULTS $R_1,…,R_n$

$$Prob(G \mid P_1,…,P_k, P_1,…,P_n, A) = Prob(rule) \cdot Prob(P_1) \cdot … \cdot Prob(P_n)$$

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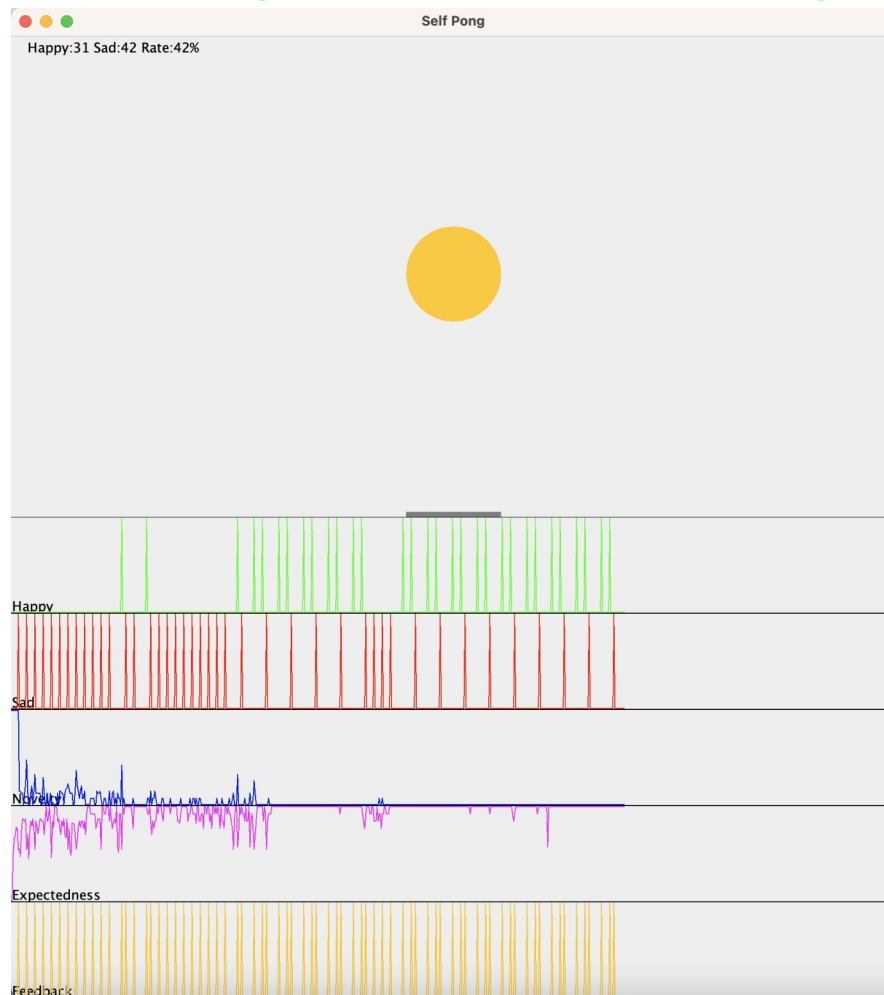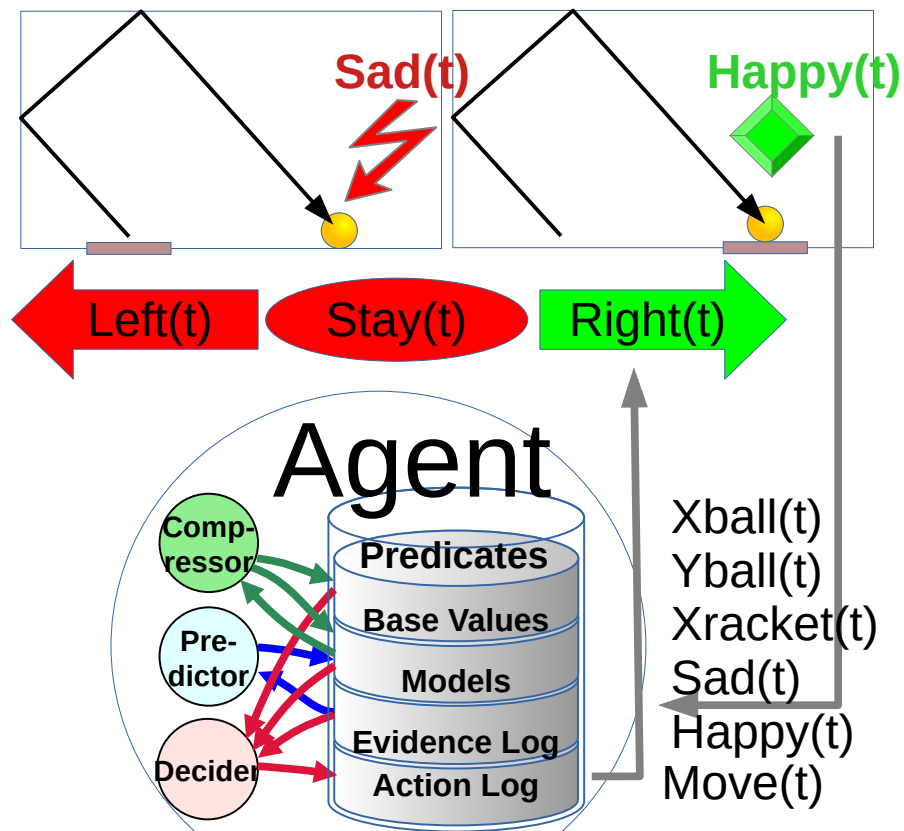
Implementation options
4) Cognitive architecture of value-based experiential learning
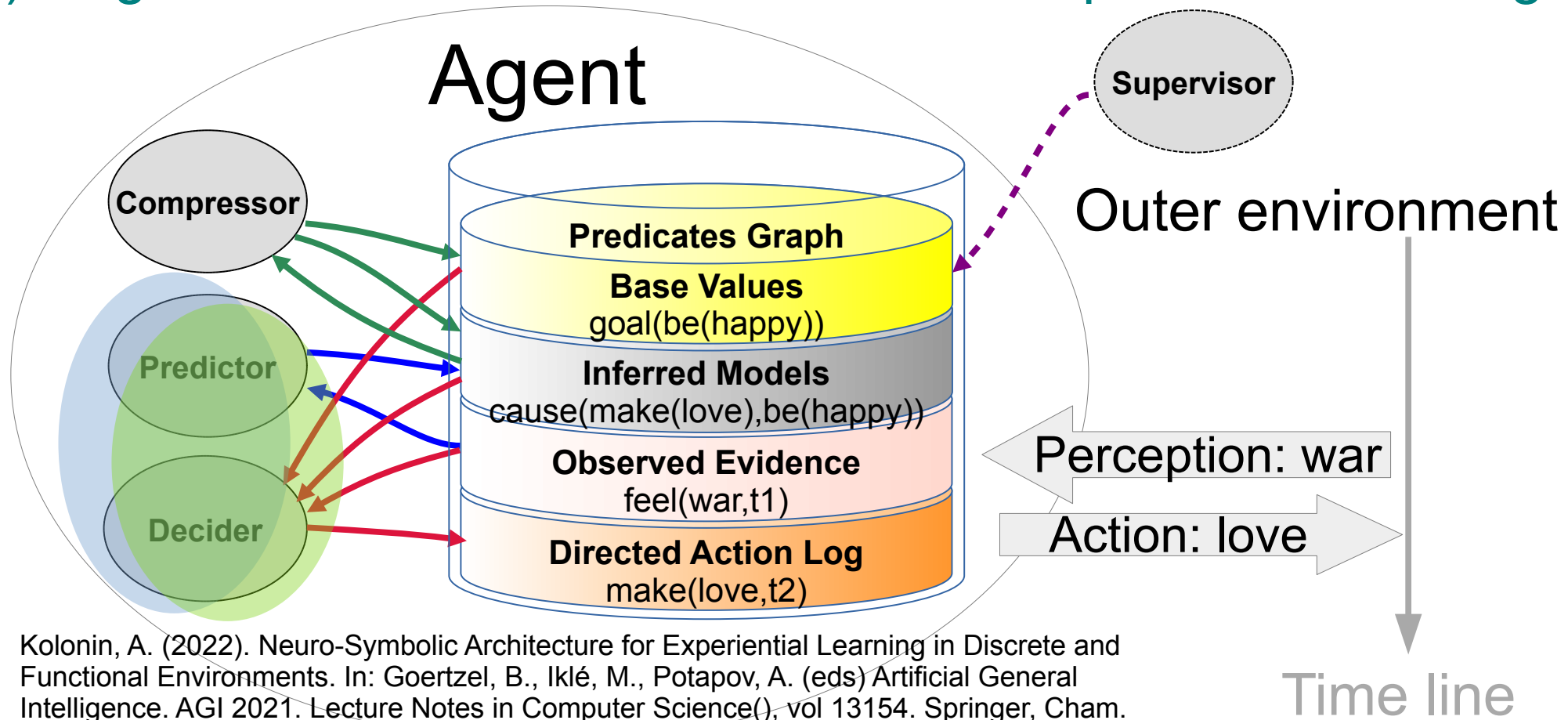
Kolonin, A. (2022). Neuro-Symbolic Architecture for Experiential Learning in Discrete and Functional Environments. In: Goertzel, B., Iklé, M., Potapov, A. (eds) Artificial General Intelligence. AGI 2021. Lecture Notes in Computer Science(), vol 13154. Springer, Cham. https://doi.org/10.1007/978-3-030-93758-4_12

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)
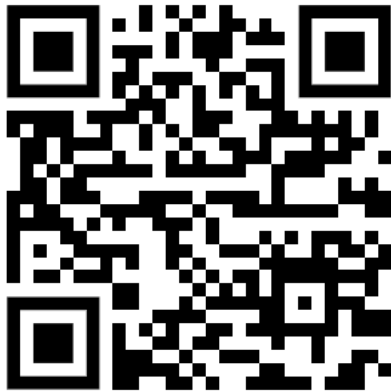Move(t)

Self Pong

Happy:31 Sad:42 Rate:42%

Happy
Sad
Novelty
Expectedness
Feedback

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