

From weak and narrow to strong and general

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SingularityNET
<https://singularitynet.io>

AI – where are we now?

Programmable → Adaptive

Guided → Autonomous

194?

2019

20??

Weak → Strong

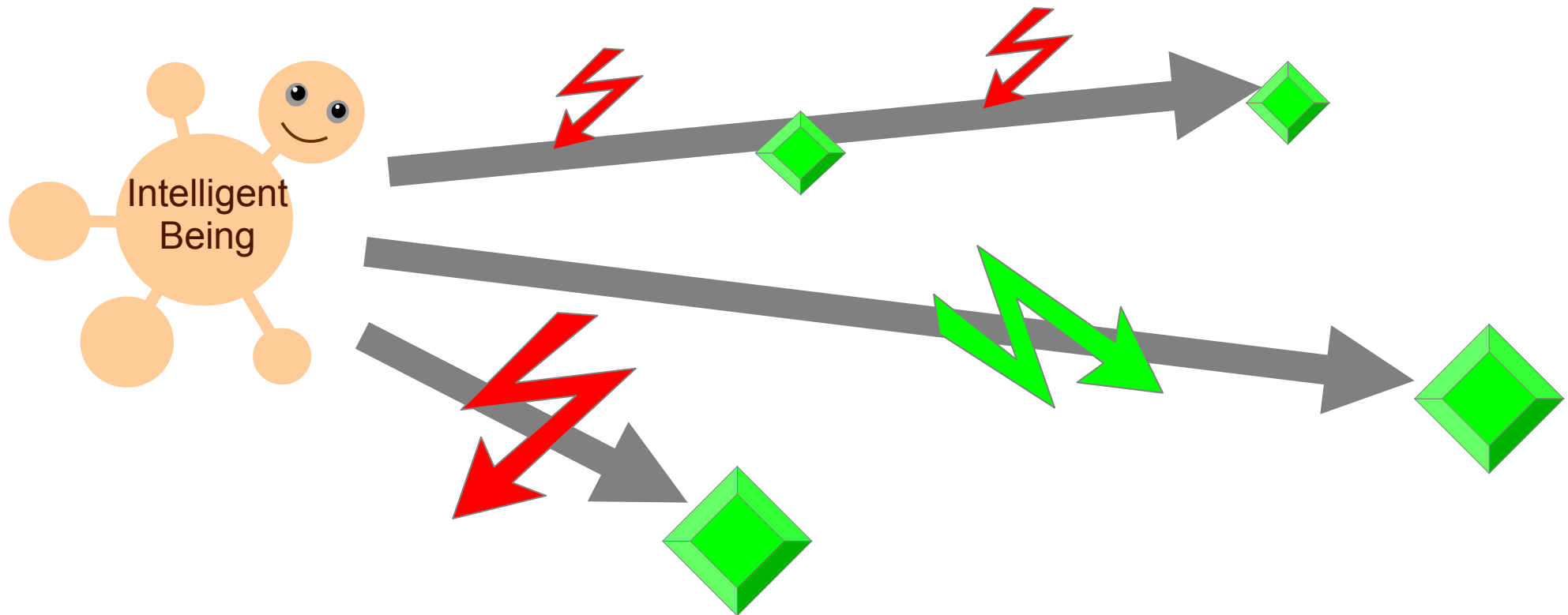
Big Data,
Machine Learning,
Experimental Statistics

Human-level AI (HLAI) → Super-human AI

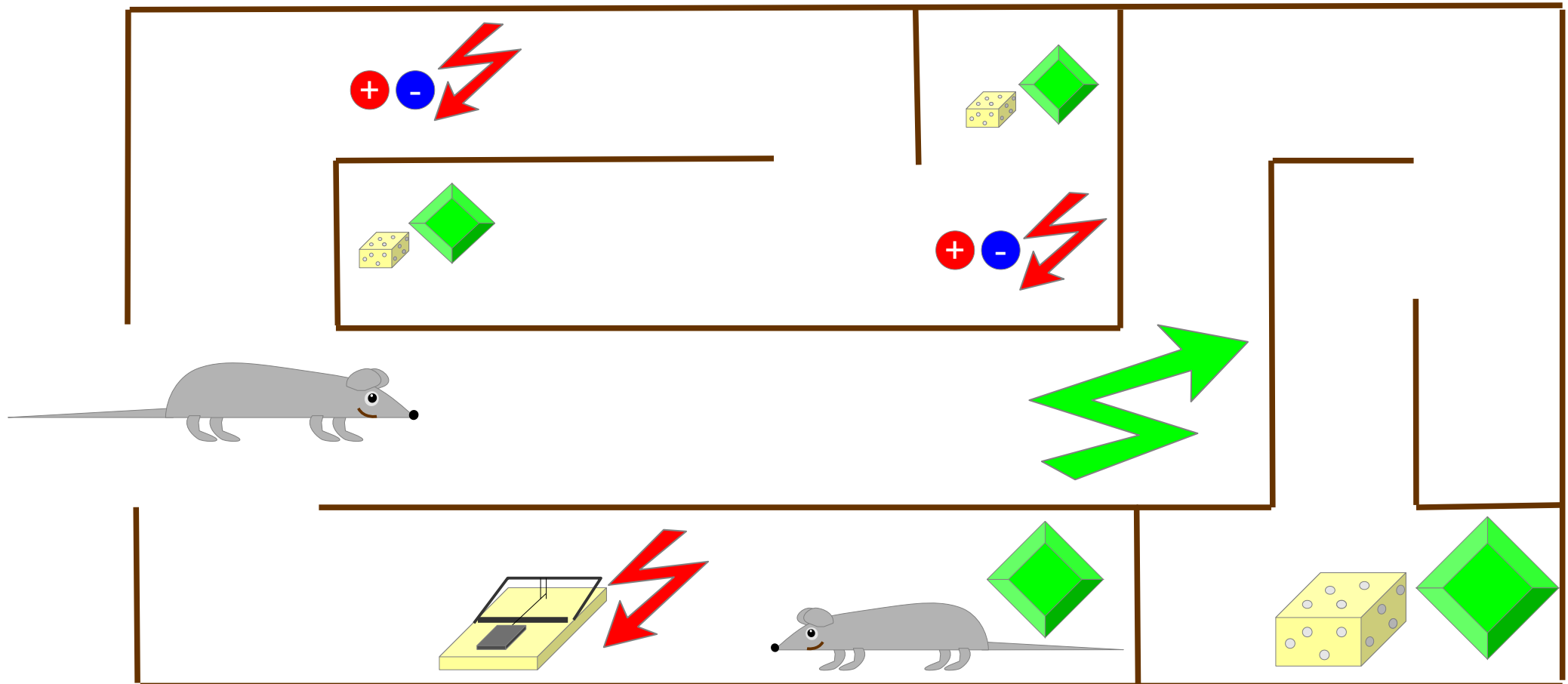
Narrow Artificial Intelligence (AI)

Artificial General Intelligence (AGI)

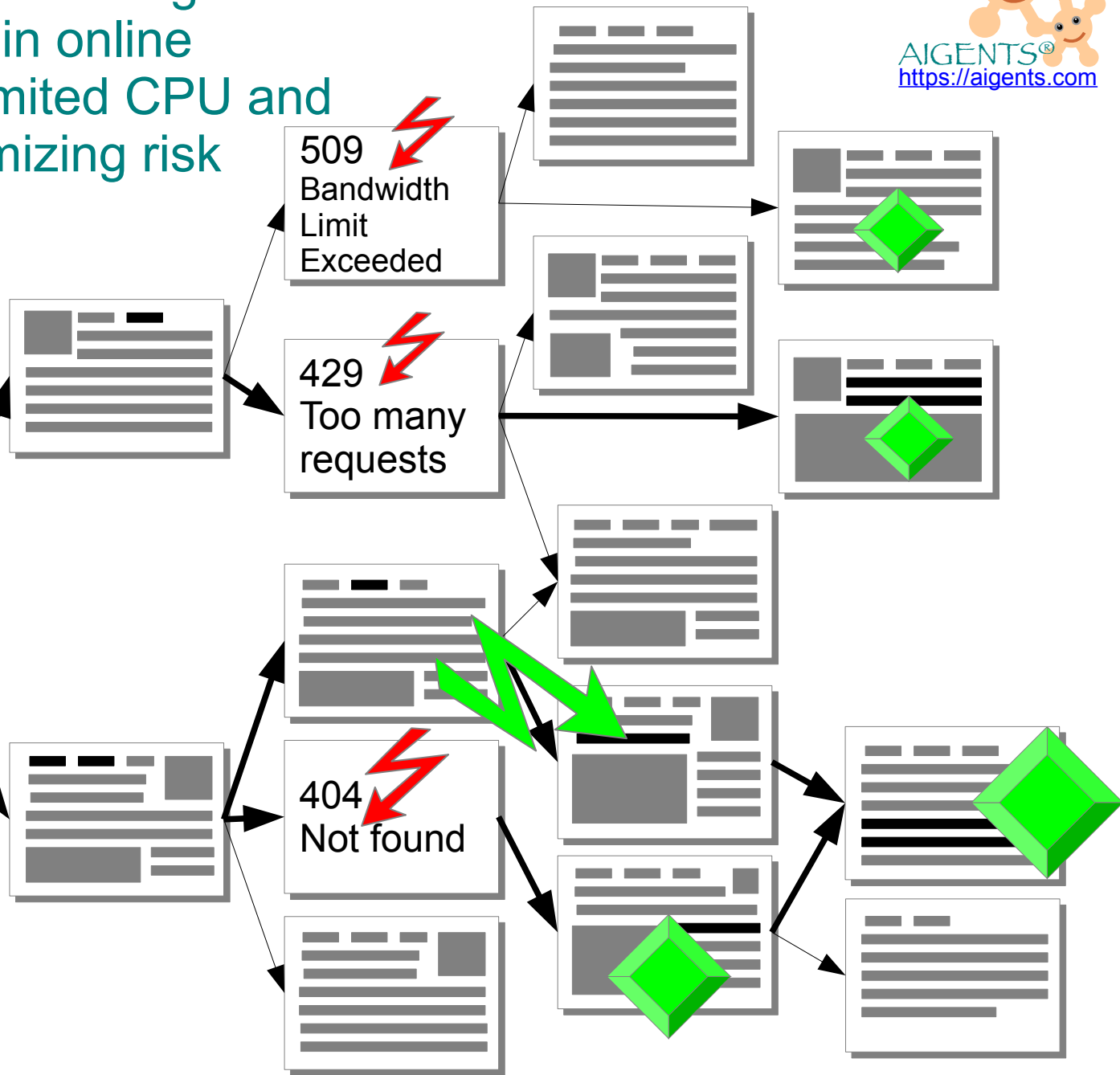
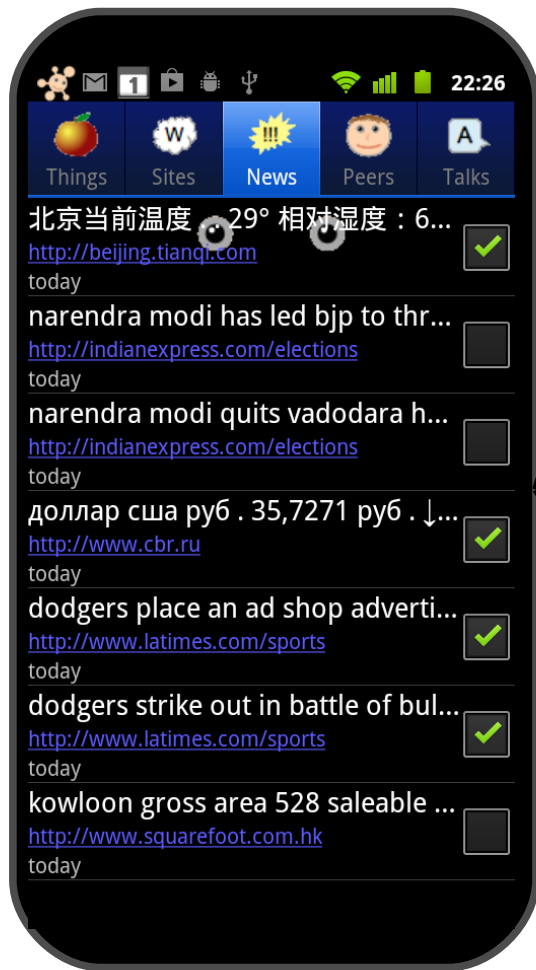
General Intelligence: Reaching complex goals in *different* complex environments, using limited resources and *minimizing risks* (Ben Goertzel, Pei Wang, et al.)



Biological Intelligence: Reaching food and parents for self-reproduction in natural environments using limited physical resources and minimizing existential risks



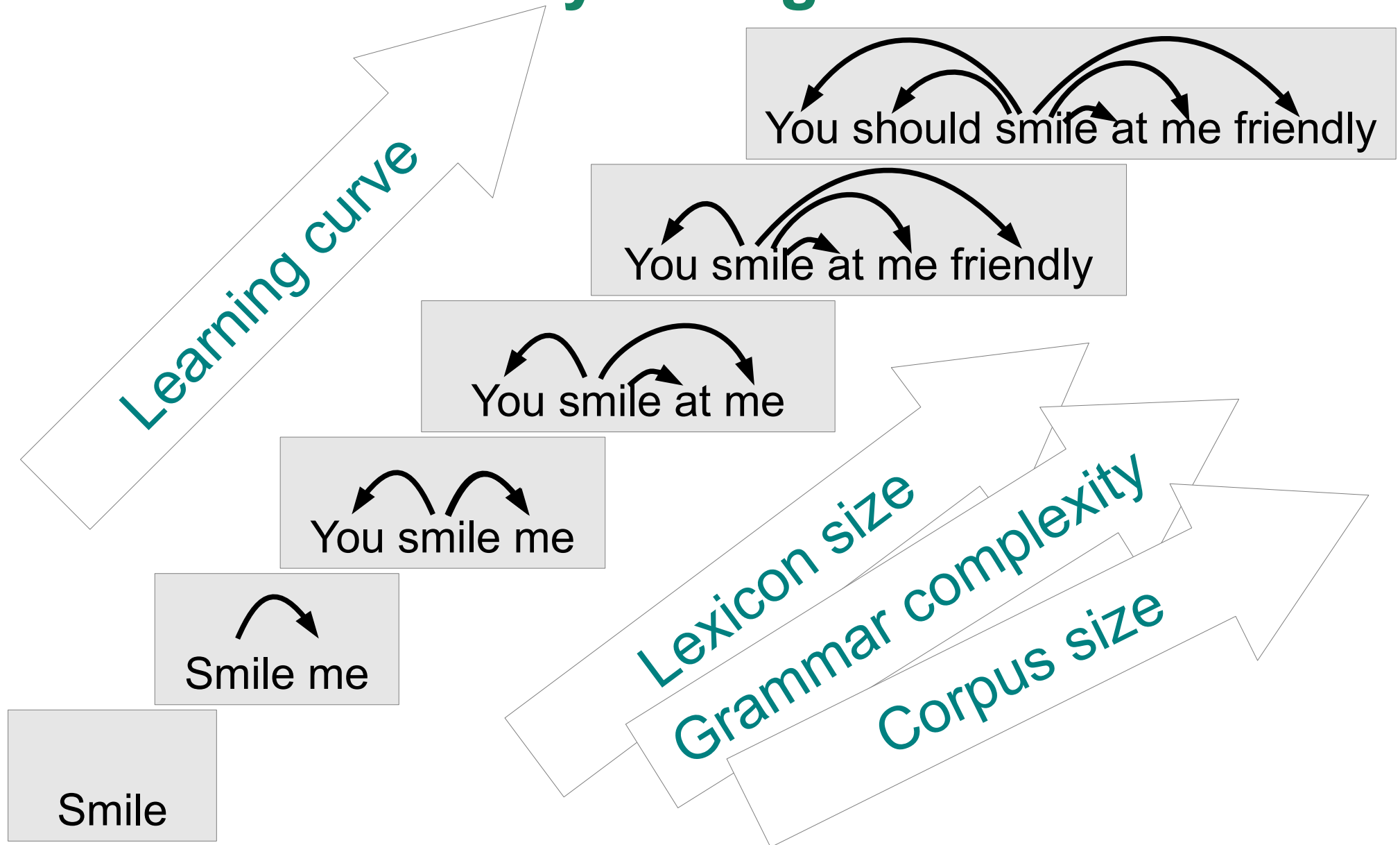
Personal Internet Assistant Aigents®: Reaching information in online environments using limited CPU and RAM resources, minimizing risk of being banned



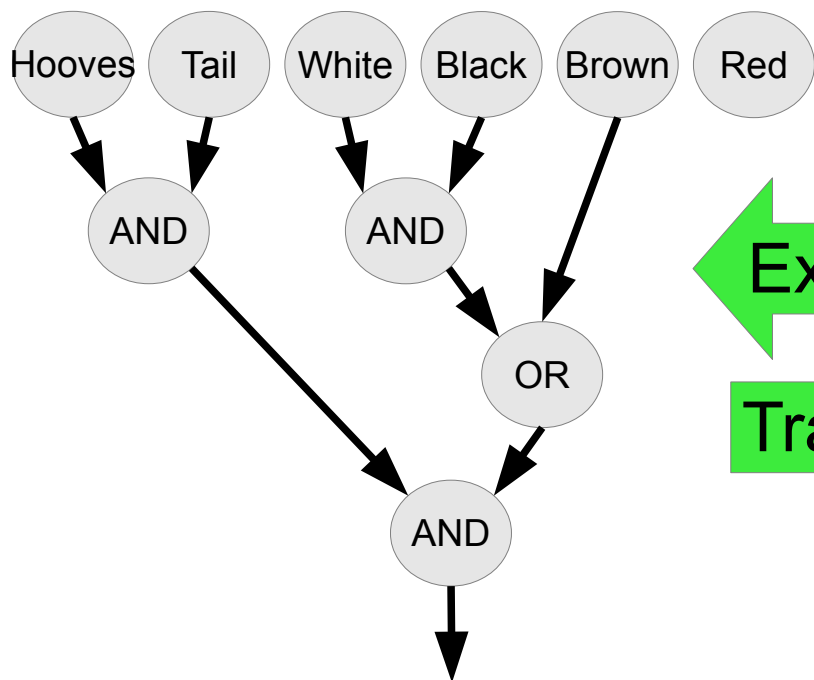
Current AI/AGI frontiers

- Neuro-Symbolic integration – progress in 2019
- Explainable AI – progress in 2019
- Transfer learning – progress in 2019
- One shot (few-shot) learning
- Strong generalization
- Generative models
- Structured prediction and learning
- Fighting catastrophic forgetting
(and catastrophic remembering)
- Incremental learning and life-time learning
- New “Turing Test” (e.g., “Baby Turing Test”)
- Solving the “consciousness” problem

Incremental development and Baby Turing Test

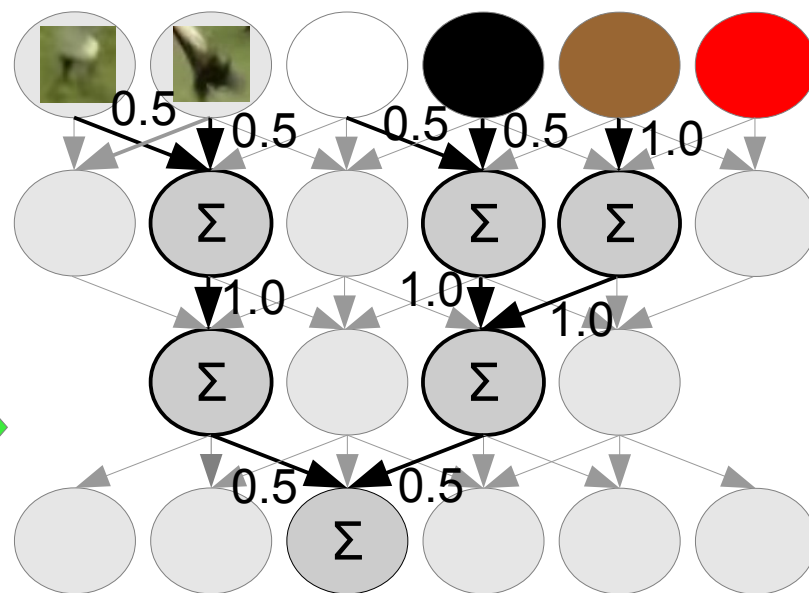
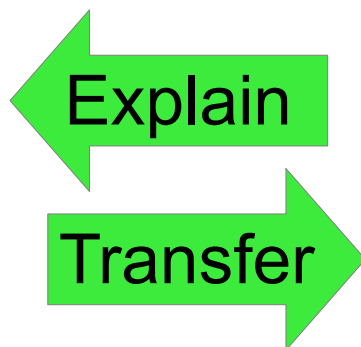


Bridging the Symbolic-Subsymbolic gap for “explainable AI” and “transfer learning”

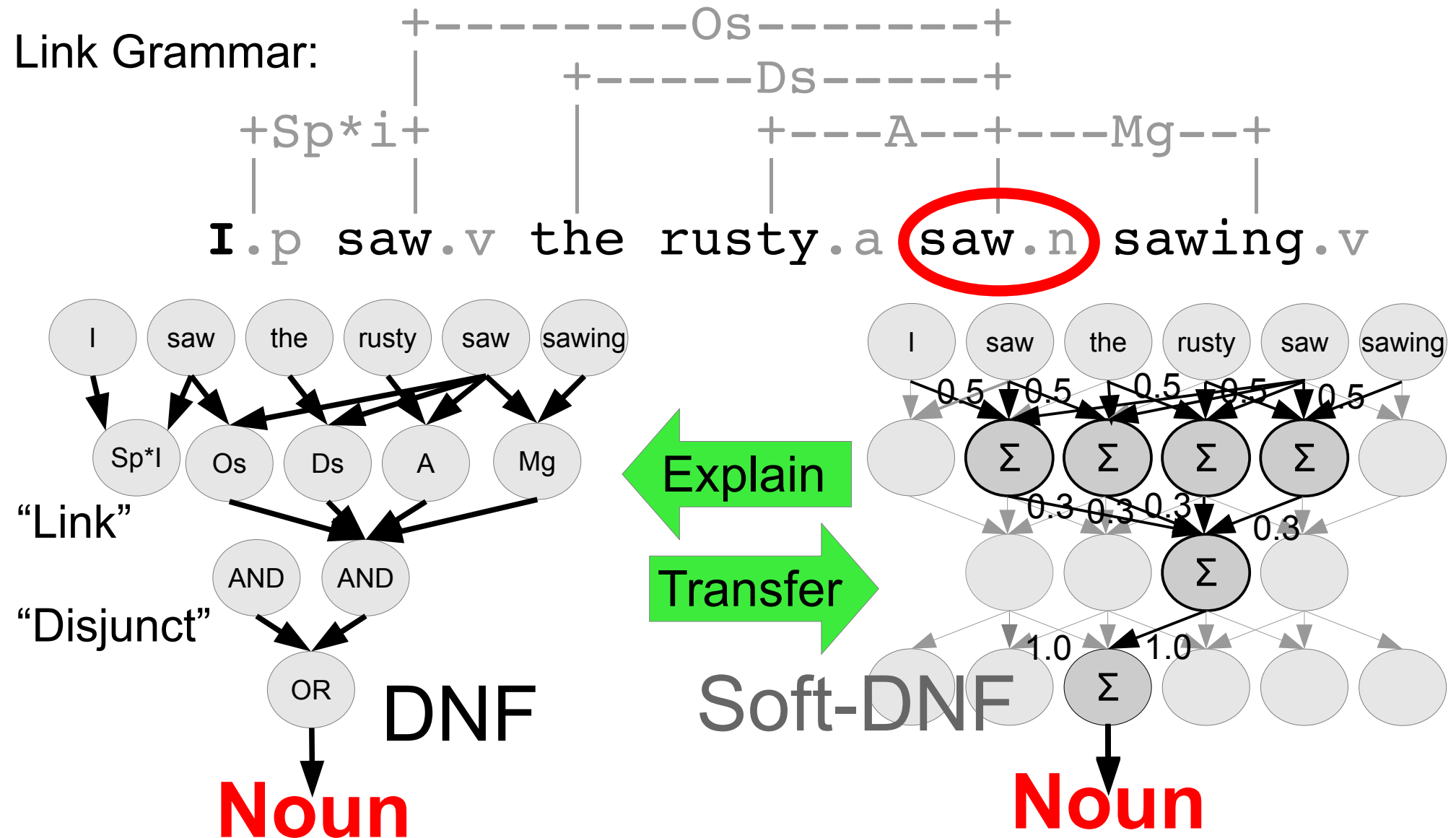


(Hooves AND Tail) AND
((White and Black) OR Brown)

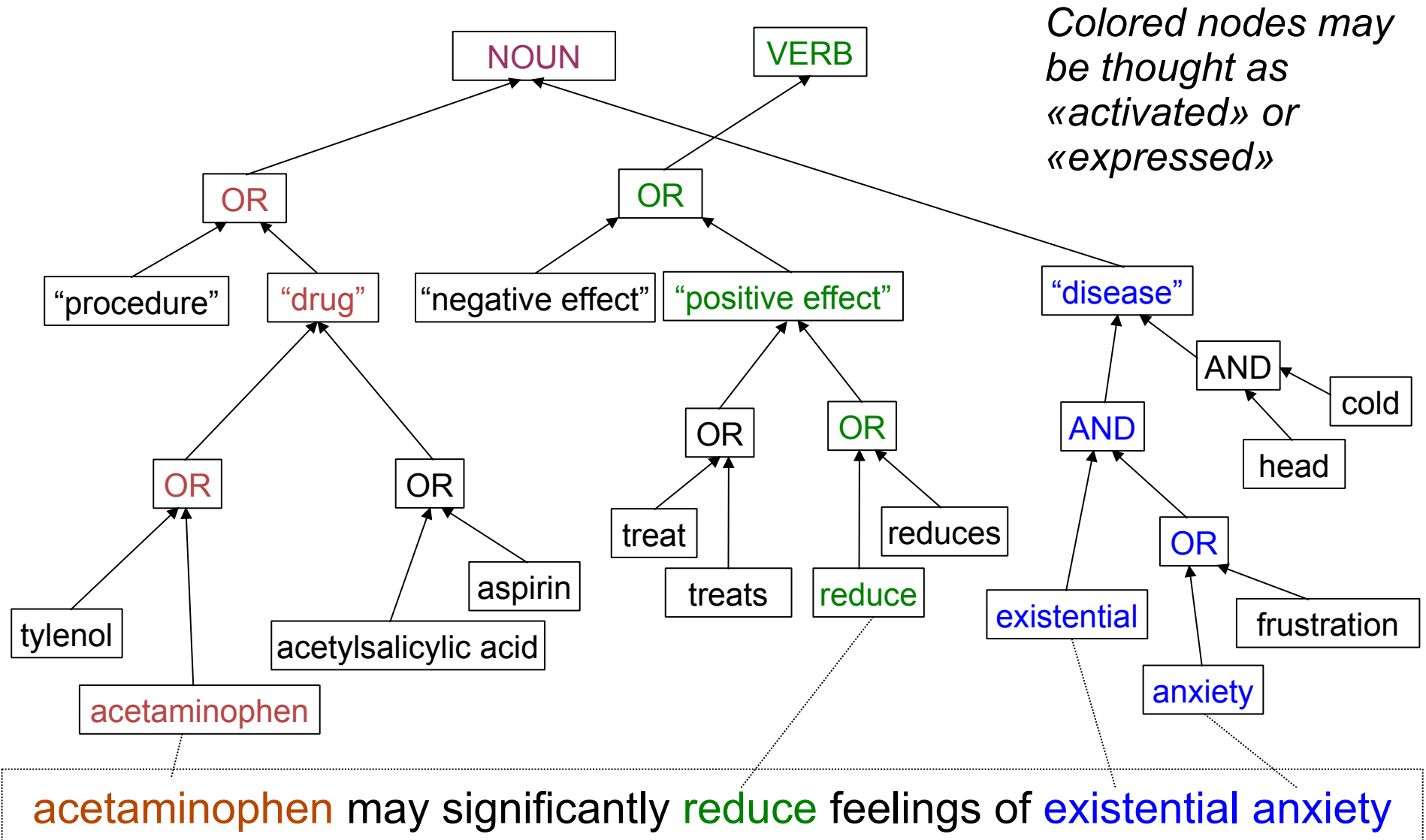
=> **Horse**



Bridging the Symbolic-Subsymbolic gap in NLP between distributed representations and formal grammars with ontologies



Aigents® “Deep Patterns” - Language Model



Aigents[®] “Deep Patterns” - Text Mining

<set> := <disjunctive-set> | <conjunctive-set> | <M-skip-N-gram>
<disjunctive-set> := { <pattern> * }
<conjunctive-set> := (<pattern> *)
<N-gram> := [<pattern> *]
<pattern> := <token> | <regexp> | <variable> | <set>

Variables may have domain restrictions in ontology and/or refer to other patterns as subgraphs

Example:

{[\$description catheter] [\$coating coating] [\$inner-diameter diameter inner-diameter]} [\$tip tip] [\$pattern pattern]}

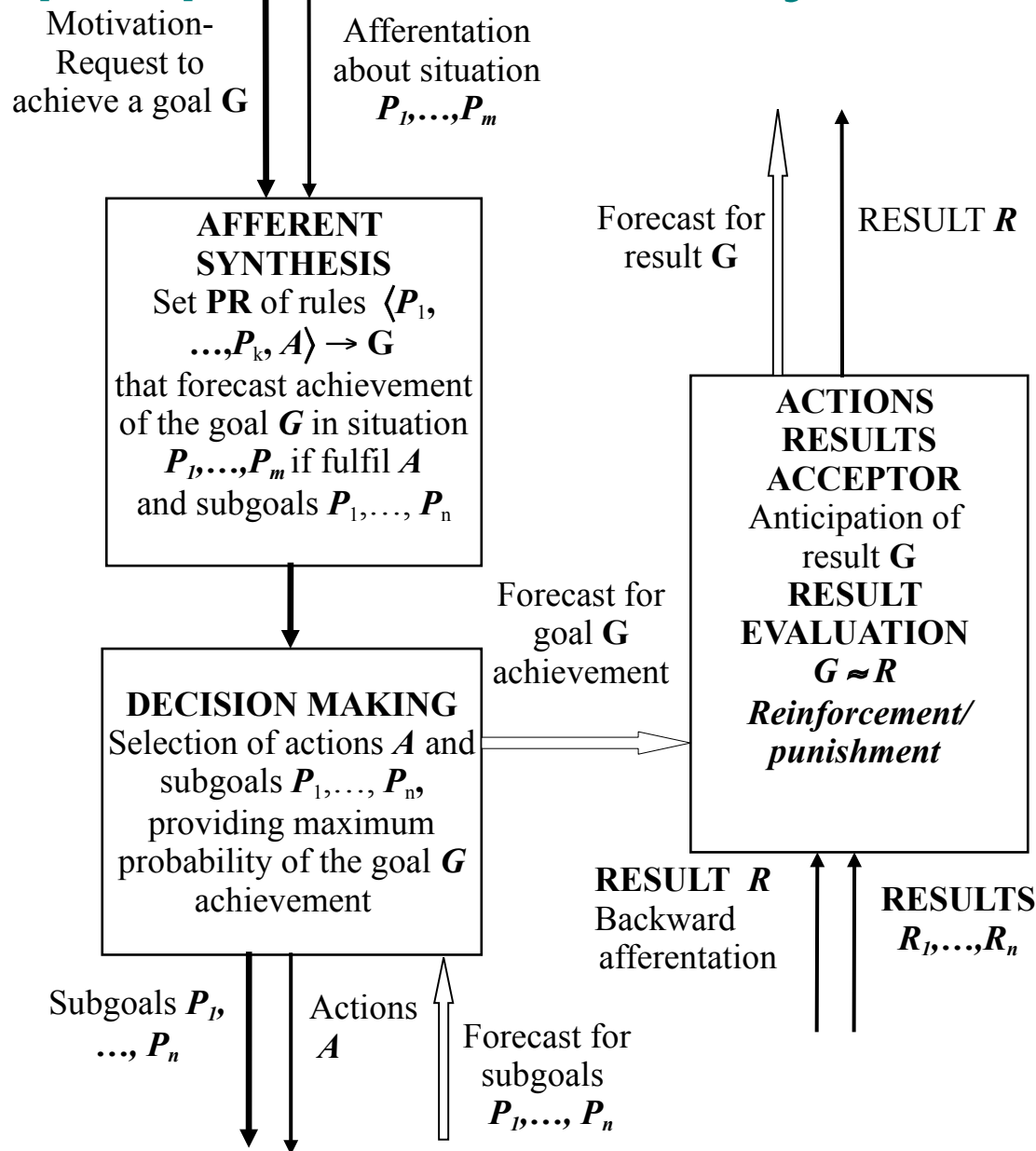
X

“Convey Guiding Catheter. Unique hydrophilic coating.
Small atraumatic soft tip. Ultra-thin 1 × 2 flat wire braid pattern”

=

{ coating : "hydrophilic", description : "convey guiding",
pattern : "ultra-thin 1 × 2 flat wire braid", tip : "soft" }

Applying theory of functional systems for purposeful activity learning (P.Anokhin)



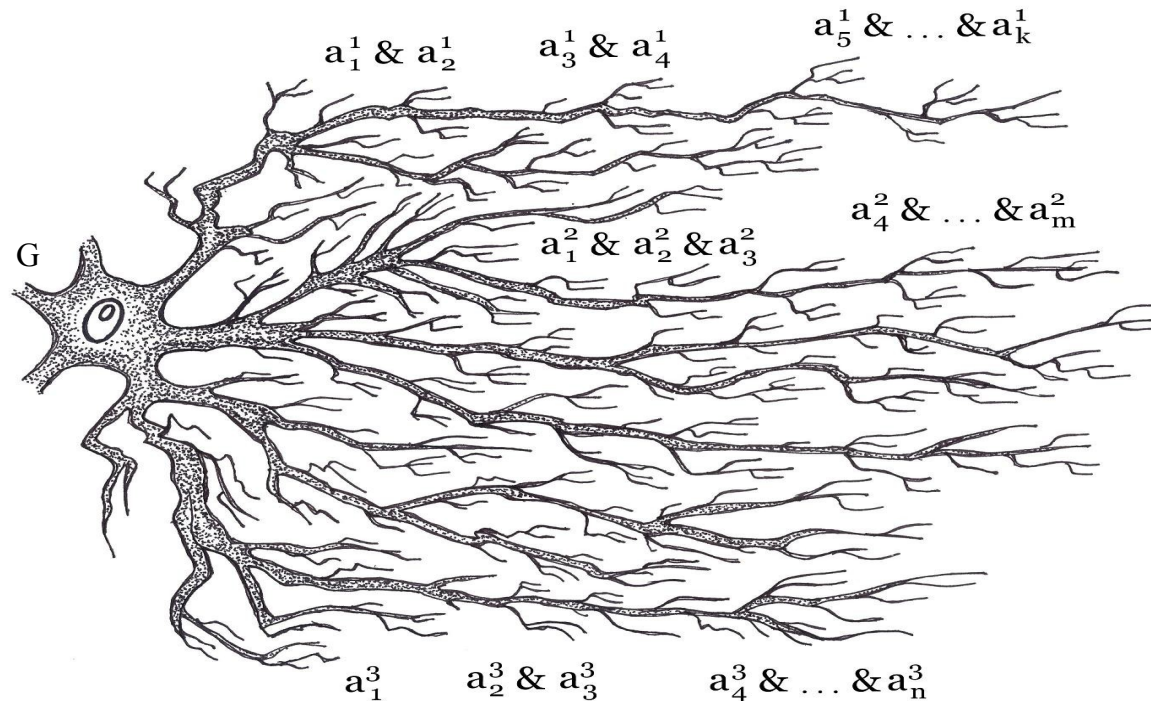
Evgenii Vityaev, Alexander Demin: Adaptive Control of Modular Robots // Conference Paper in Advances in Intelligent Systems and Computing, Conference: First International Early Research Career Enhancement School on Biologically Inspired Cognitive Architectures, Springer, August 2018

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.

$$Pr ob(G | P_1, \dots, P_k, P_1, \dots, P_n, A) = Pr ob(rule) \cdot Pr ob(P_1) \cdot \dots \cdot Pr ob(P_n)$$

Semantic probabilistic inference as the formal model of neuron (E.Vityaev)



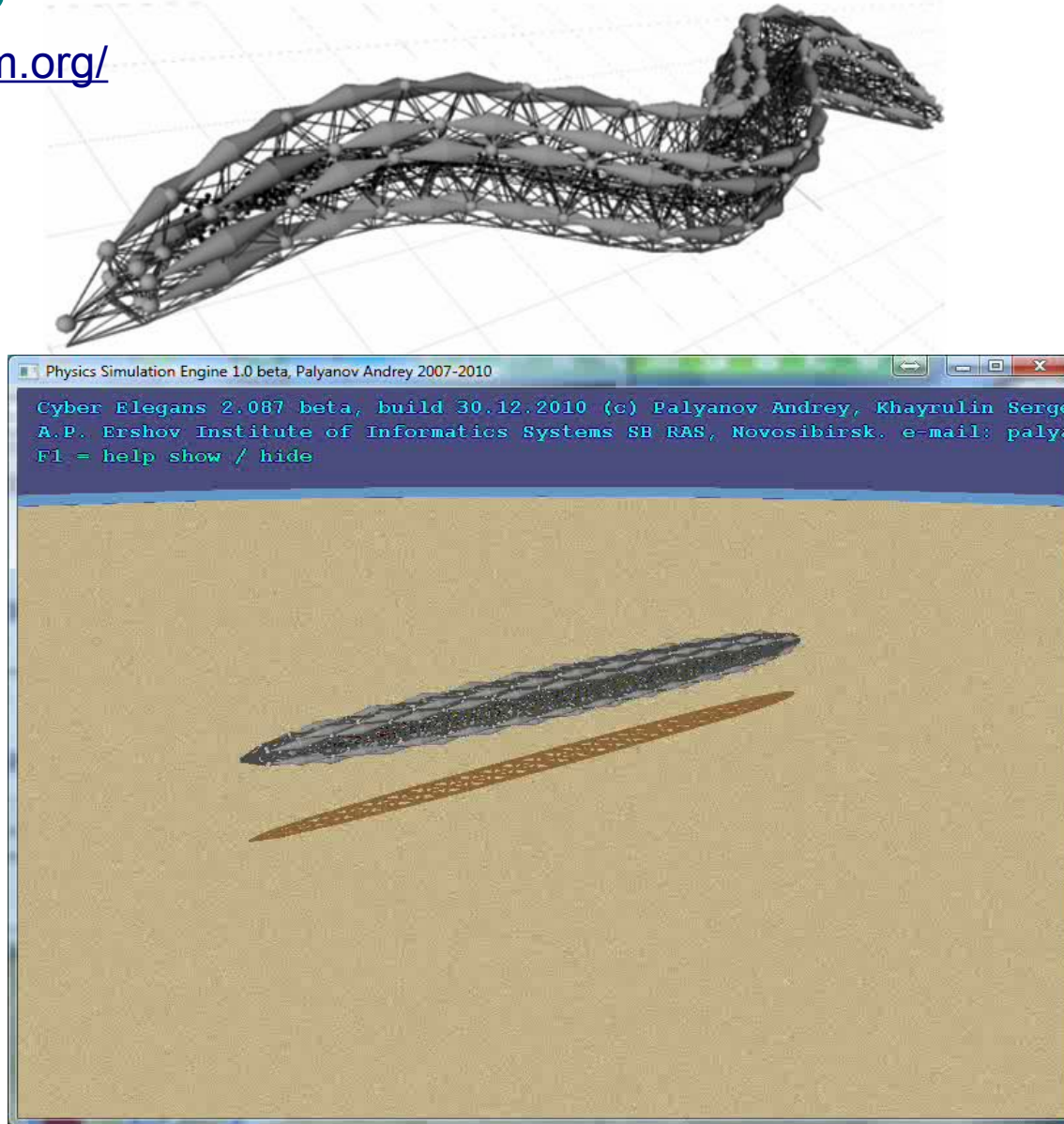
The learning causal relations along the dendrites and the goal feature G may be presented by semantic probabilistic inference – it add to the premise of causal relation all new features that increase the conditional probability of the goal feature G excitation.

Vityaev E.E. A formal model of neuron that provides consistent predictions // Biologically Inspired Cognitive Architectures 2012. Proceedings of the Third Annual Meeting of the BICA Society. 196, Springer: Heidelberg, New York, Dordrecht, London. 2013, pp. 339-344.

E.E. Vityaev, L.I. Perlovsky, B.Y. Kovalerchuk, S.O. Speransky. Probabilistic dynamic logic of cognition // Biologically Inspired Cognitive Architectures. Special issue: Papers from the Fourth Annual Meeting of the BICA Society (BICA 2013), v.6, October, Elsevier, 2013, pp.159-168

C. elegans nematode model learning

<http://openworm.org/>



A.V. Demin, E.E. Vityaev. Learning in a virtual model of the C. elegans nematode for locomotion and chemotaxis // *Biologically Inspired Cognitive Architectures*. (2014) v.7, pp.9–14.

https://www.youtube.com/watch?v=eMqt_E4uKbl

Thank you stay in touch!

Telegram: @AGIRussia

<https://www.facebook.com/groups/agirussia/>

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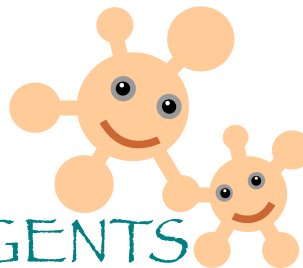


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University
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