

T2

Cognitive Systems

2020 edition

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PSI 3560 – COGNITIVE SYSTEMS

class T2

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THE CONCEPT OF COGNITIVE SYSTEM AND THE NATURE OF COGNITION

Cognitive agents, natural versus artificial cognition, cognitive systems, machine learning and AI, paradigms of cognition, examples of cognitive systems and applications.

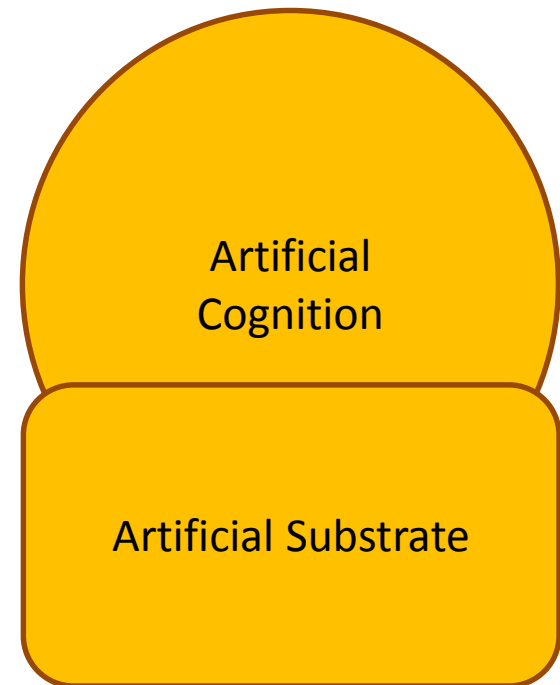
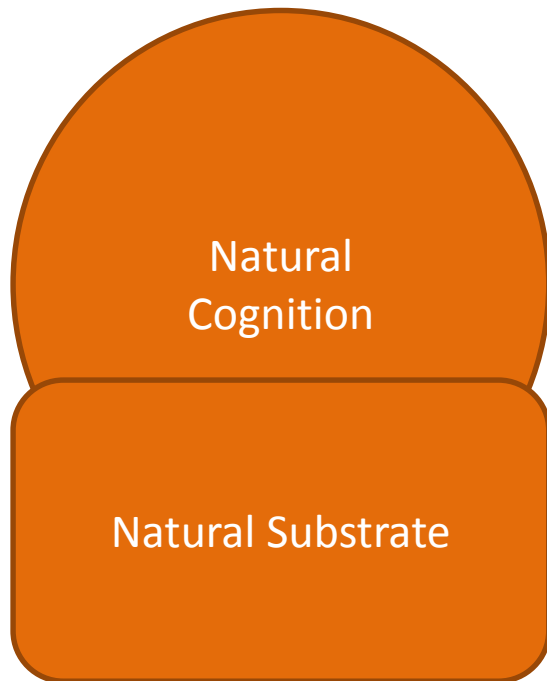
Session T2

Summary

- Coffee break
 - First session (7:30 – 9:00)
- Natural x Artificial cognition
- Machine learning x traditional A.I. overview
- Paradigms of cognition overview
- Examples and counterexamples
 - Coffee break – 9:00 – 9:10
 - Second session (9:10 – 11:00)

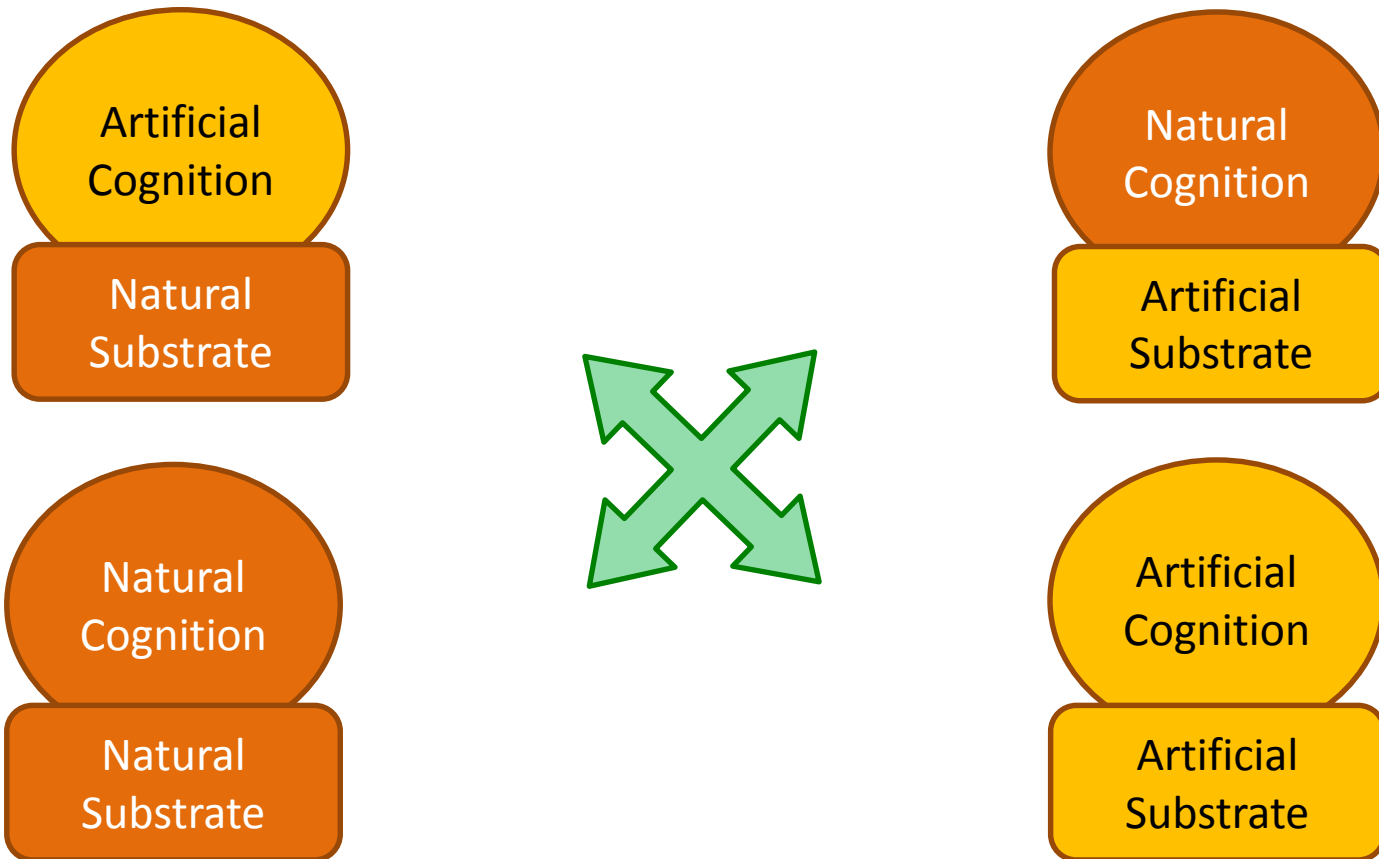
Natural x Artificial cognition

- Cognition x substrate



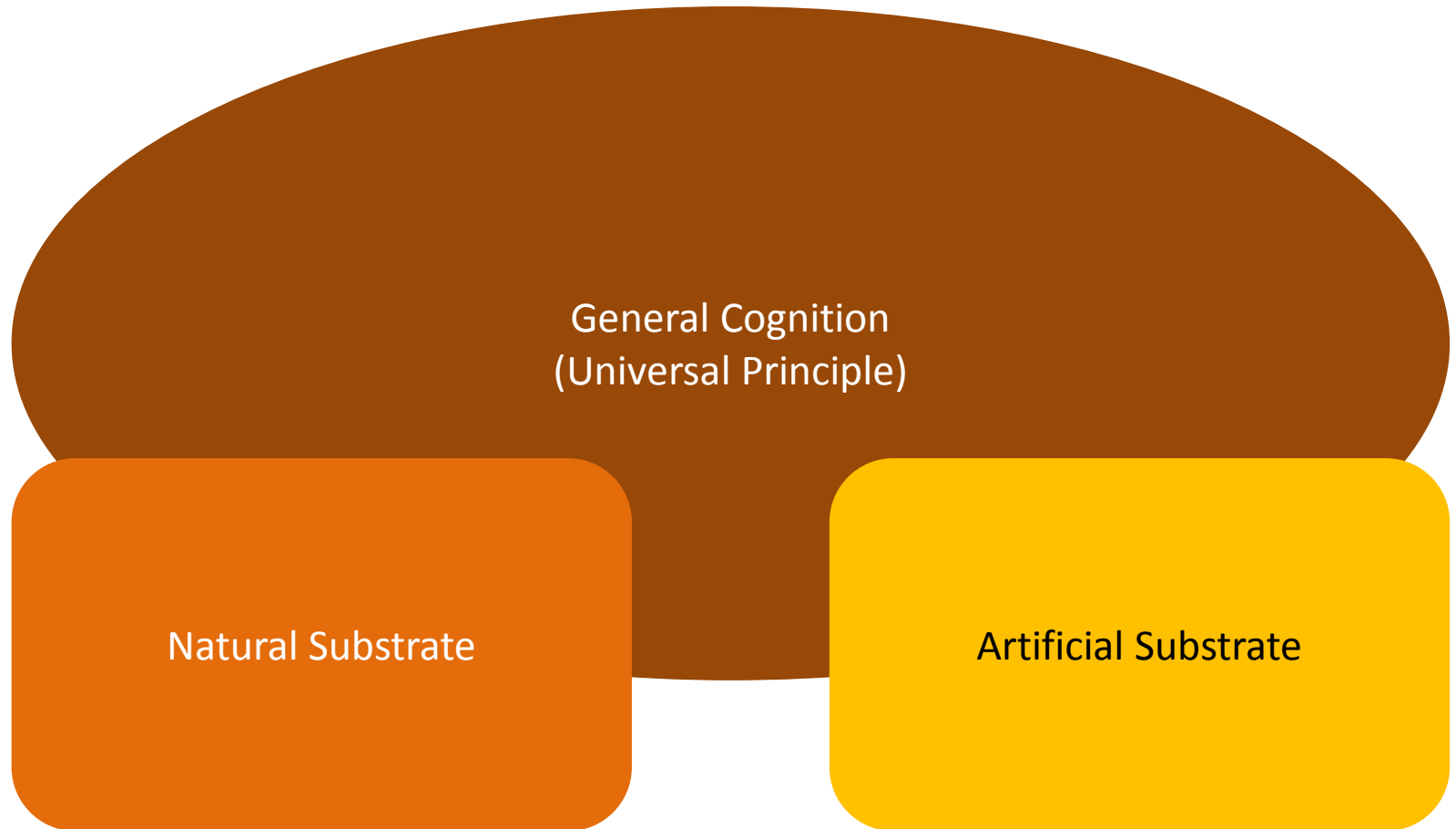
Natural x Artificial cognition

- Cognition x substrate



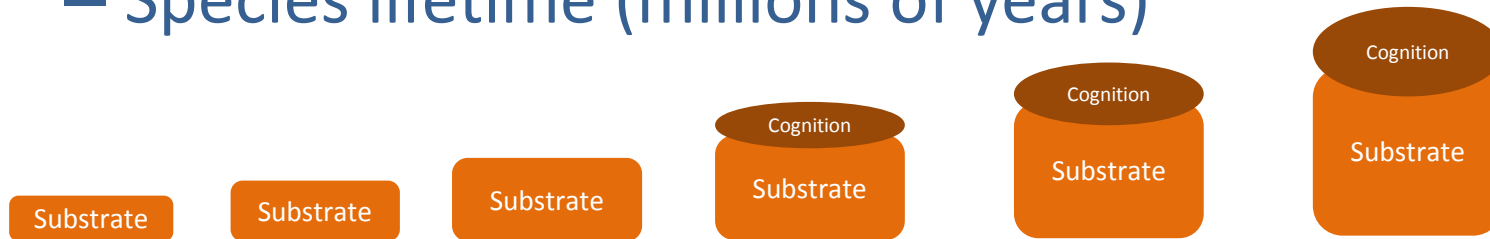
Natural x Artificial cognition

- Cognition x substrate

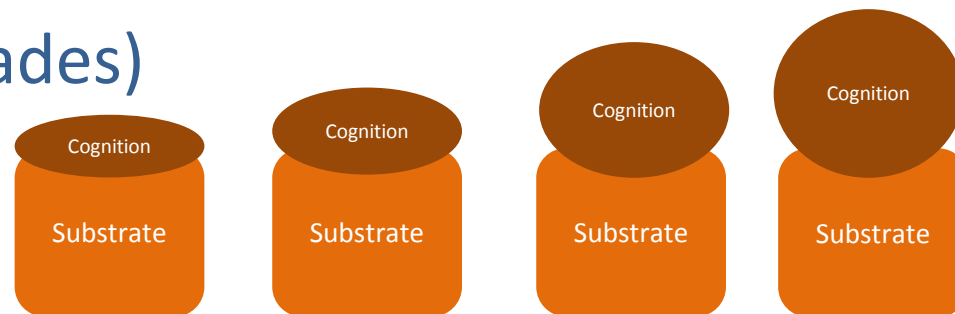


Cognition

- Species evolution ()
 - Species lifetime (millions of years)



- Specimen development (ontology / epistemology)
 - Lifetime (decades)



Natural x Artificial cognition

- Human \leftrightarrow Human “Symbiosis”

- Senses

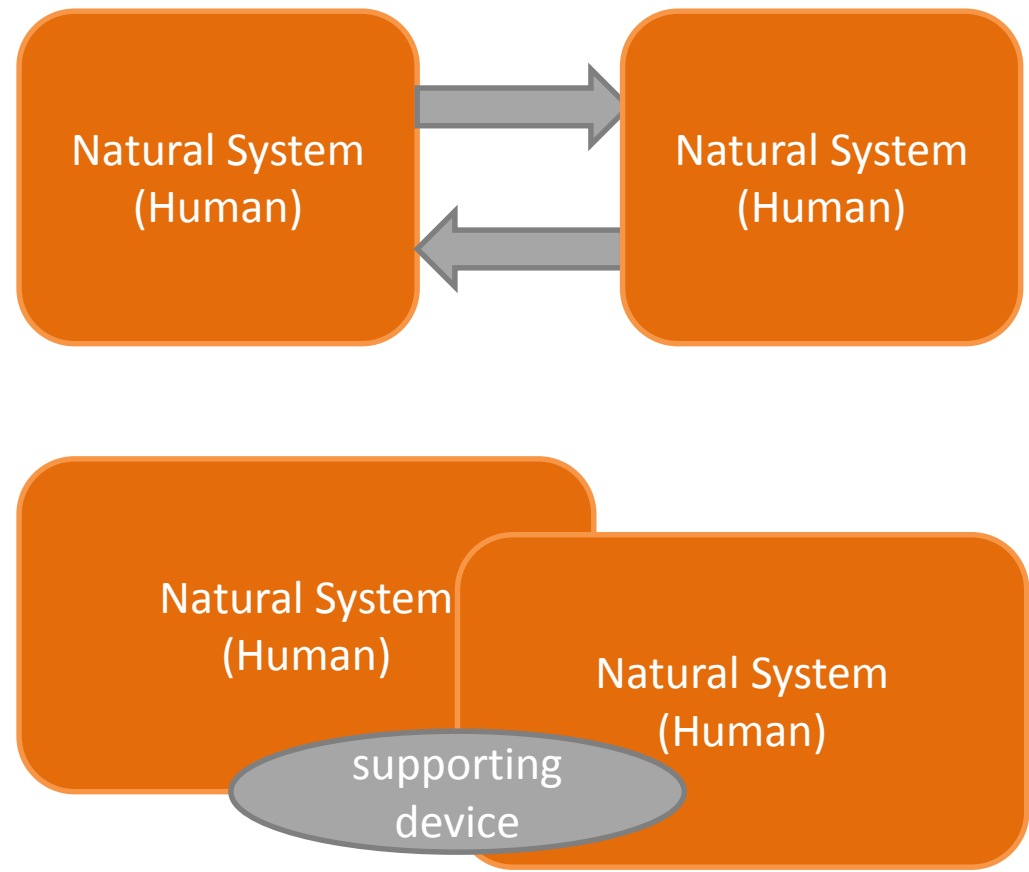
- Perception

- Cognition

- Level

- Assistance

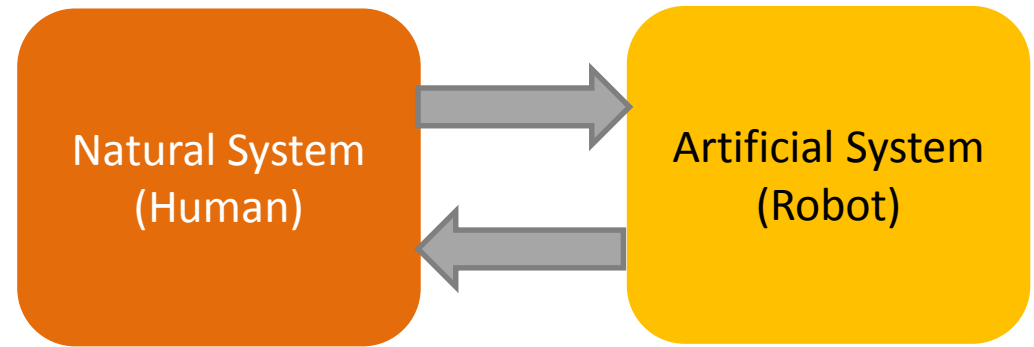
- Sharing / Merging abilities??



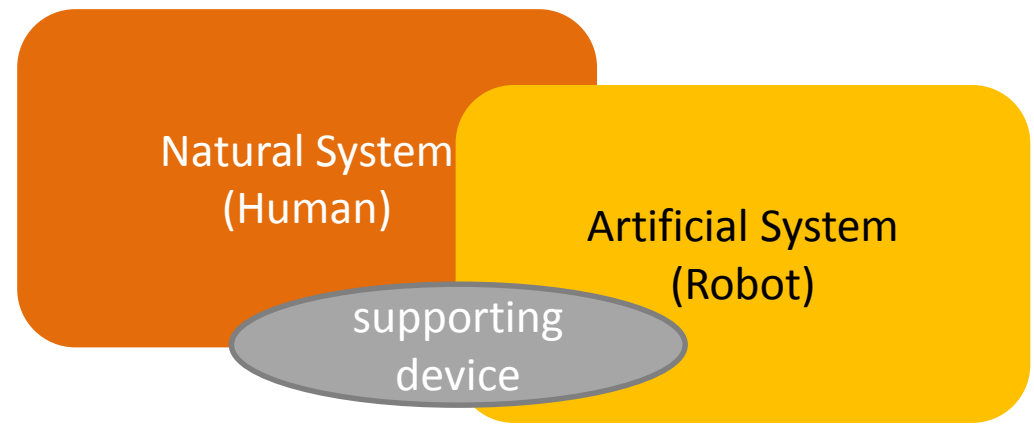
Natural x Artificial cognition

- Human \leftrightarrow Machine “Symbiosis”

- Senses
- Perception
- Cognition



- Level
- Assistance
- Sharing / Merging abilities??

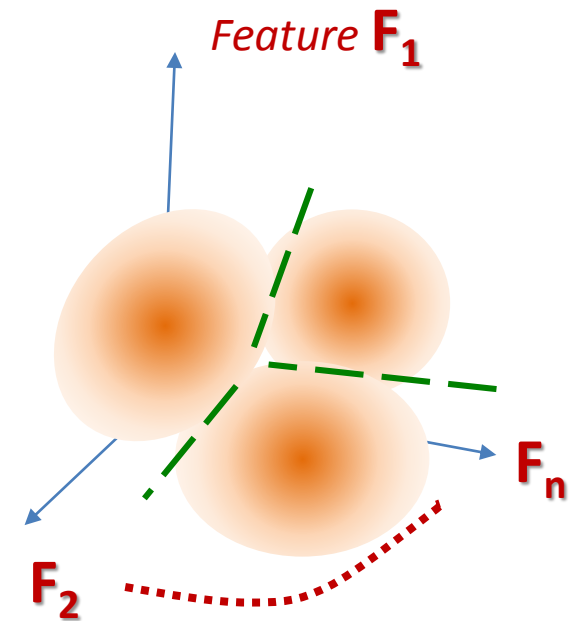


Machine Learning x traditional A.I.

- “Traditional” or “old” A.I.
 - Symbolic representation
 - Logical processing → deductive

If A and/or/not B → then C

- Machine Learning (“new” A.I.)
 - Multi-feature representation
 - Statistical processing → inductive



Paradigms of cognition

- Cybernetics approach
 - Wiener, McCulloch & Pitts, Turing, Von Neumann (1940-1956)
 - Logical formal neuron, self-organization, autonomy
- Symbolic intelligence approach
 - Simon, Minsky, Chomsky, McCarthy, Newell, Anderson (1956-1990... still alive) *Dartmouth Conference*
 - Symbolic representation, rule-based, formal architectures
- Connectionist approach
 - Rosenblatt, Hebb, Hinton & Sejnowsky, Hopfield, Rummelhart & McClelland (1962-...)
 - Synaptic plasticity, statistical learning, emergence
- Enactivist approach
 - Maturana, Varela, Thompson, Rosch, Clarck, Chalmers, Noë (1992-....)
 - “Embodied, embedded, enacted” cognition

EXAMPLES AND COUNTEREXAMPLES OF COGNITIVE SYSTEMS AND APPLICATIONS.

Cognitive tools and agents. Cognitive robots and vehicles. Applications from Universities and Companies. Find the non-cognitive ones !

Class T2

Examples of where one can embed cognition

- **Artificial Pets**
 - Convincing expressions, learn abilities
- **Artificial Butler**
 - Understanding people, providing what they should be looking for
- **Artificial Worker**
 - Understanding situations, acting to solve problems
- **Smart Building / Vehicle**
 - Recognizing traffic cases, behaving accordingly, being adaptive
- **Smart City / Traffic**
 - Recognizing traffic cases, behaving accordingly, being adaptive

- **Cognitive Robotics**

SCOPE:

- There is growing need for robots that can interact safely with people in everyday situations. These robots have to be able to anticipate the effects of their own actions as well as the actions and needs of the people around them.
- To achieve this, two streams of research need to merge, one concerned with physical systems specifically designed to interact with unconstrained environments and another focusing on control architectures that explicitly take into account the need to acquire and use experience.

Aldebaran Robots



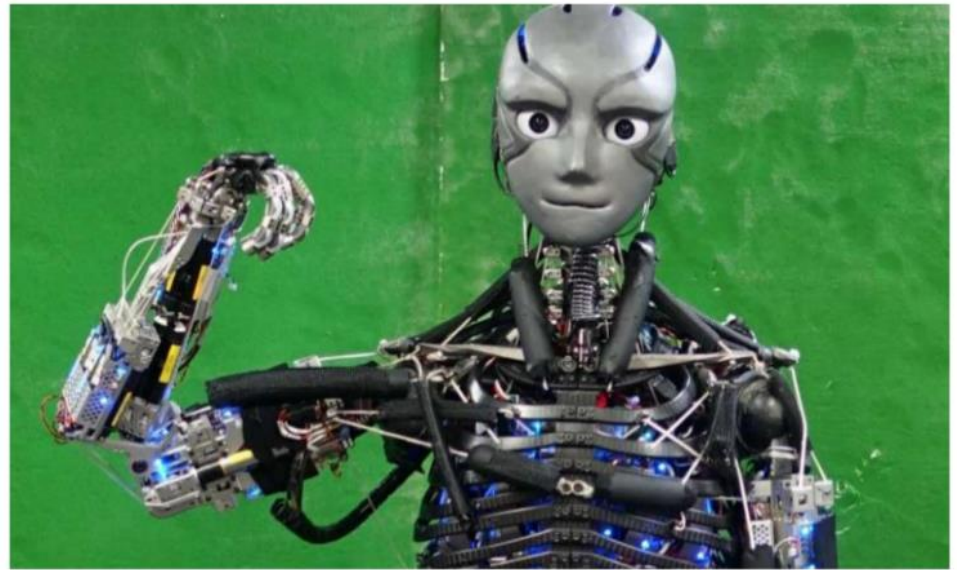
Pepper



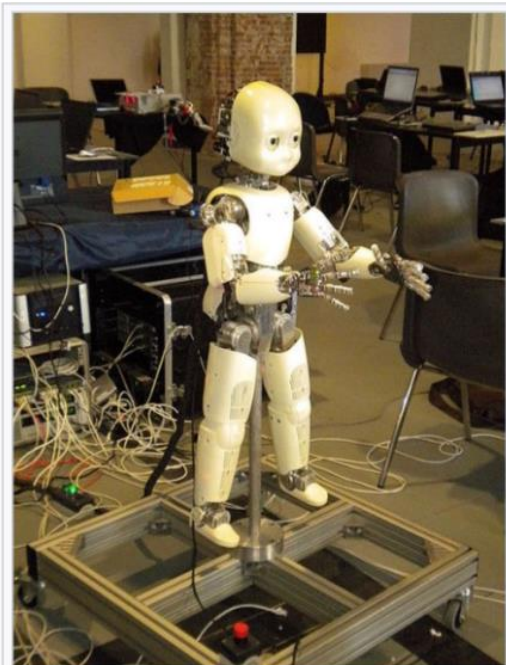
Nao



Romeo



The humanoid Kengoro. Credit: Asano, Okada, Inaba, Sci. Robot. 2, eaaq0899 (2017)

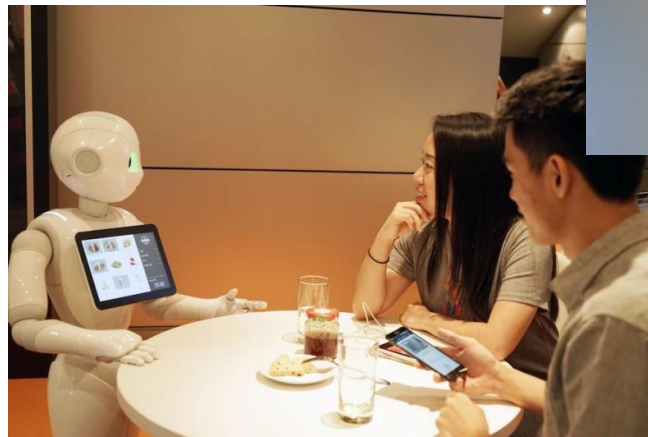


An iCub robot mounted on a supporting frame. The robot is 104 cm high and weighs around 22 kg



Sophia

World's First Robot Citizen



Humanoid Cognitive Robots

Artificial Cognitive Systems

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- Institute for Cognitive Systems
- Humanoid Robots
- Embedding Cognition on Robots
 - narrow ACS approach
 - cooker & waiter

Artificial Cognitive Systems

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Home

Institute for Cognitive Systems

The Institute for Cognitive Systems deals with the fundamental understanding and creation of cognitive systems.

As our research interests fall in line with the notion of "Understanding through Creating", three essential aspects motivate our approach [Cheng et. al. 2007; Cheng 2014]:

- In **Engineering** - Engineers can gain a great deal of understanding through the studies of biological systems, which can provide guiding principles for developing sophisticated and robust artificial systems;
- **Scientifically** - Building of a human-like machine and the reproduction of human-like behaviours can in turn teach us more about how humans deal with the world, and the plausible mechanisms involved.
- For **society** - In turn we will gain genuine knowledge toward the development of systems that can better serve our society.

Institute for Cognitive Systems (ICS)

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Biologically-Inspired
Humanoid Vision



Cognitive Architecture
for Skill Acquisition



Artificial Robot Skin



NeuroRobotics: (BCR)
Brain Compatible Robotics



Humanoid Dynamic
Locomotion



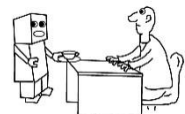
Sociable Robots:
SLICK-BOTS



Affective Brain-Computer
Interface



Semantic Reasoning about
Human Activities



Social Robotics

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- **Engineering** - Engineers can gain a great deal of understanding through the studies of biological systems, which can provide guiding principles for developing sophisticated and robust artificial systems;
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Outline

Abstract

Keywords

1. Introduction
 2. State-of-the-art
 3. Definition and extraction of visual information
 4. Inference of the demonstrator's goal
 5. Goal transfer to the robot and execution
 6. Examples of everyday human activities
 7. Results
 8. Conclusions
- Acknowledgements
Appendix A. Supplementary material
References

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Figures (19)



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Tables (2)

- Table 1
- Table 2

Extras (1)

- MMC 1



Artificial Intelligence

Volume 247, June 2017, Pages 95-118



Transferring skills to humanoid robots by extracting semantic representations from observations of human activities

Karinne Ramirez-Amaro , Michael Beetz , Gordon Cheng 

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<https://doi.org/10.1016/j.artint.2015.08.009>

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Abstract

In this study, we present a framework that infers human activities from observations using semantic representations. The proposed framework can be utilized to address the difficult and challenging problem of transferring tasks and skills to humanoid robots. We propose a method that allows robots to obtain and determine a *higher-level* understanding of a demonstrator's behavior via semantic representations. This abstraction from observations captures the "essence" of the activity, thereby indicating which aspect of the demonstrator's actions should be executed in order to accomplish the required activity. Thus, a *meaningful semantic* description is obtained in terms of human motions and object properties. In addition, we validated the semantic rules obtained in different conditions, i.e., three different and complex kitchen activities: 1) making a pancake; 2) making a sandwich; and 3) setting the table. We present quantitative and qualitative results, which demonstrate that without any further training, our system can deal with time restrictions, different execution styles of the same task by several participants, and different labeling strategies. This means, the rules obtained from one scenario are still valid even for new situations, which demonstrates that the inferred representations do not depend on the task performed. The results show that our system correctly recognized human behaviors in *real-time* in around 87.44% of cases, which was even better than a random participant recognizing the behaviors of another human (about 76.68%). In particular, the semantic rules acquired can be used to effectively improve the dynamic growth of the ontology-based knowledge representation. Hence, this method can be used flexibly across different demonstrations and constraints to infer and achieve a similar goal to that observed. Furthermore, the inference capability introduced in this study was integrated into a joint space control loop for a humanoid robot, an iCub, for achieving similar goals to the human demonstrator *online*.

Part of special issue:

Special Issue on AI and Robotics

Edited by Kanna Rajan, Alessandro Saffiotti

Other articles from this issue 

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Artificial Intelligence, Volume 247, June 2017, pp. 10-44

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Artificial Cognitive Systems

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- Transferring skills to humanoid robots by extracting semantic representations from observations of human activities
- How to
 - Extract semantic representations?
 - Transfer these skills to humanoid robots?
- The robots need to be designed with such ability (to receive and recognize these skills)

Artificial Cognitive Systems

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- Cooker & waiter robot
 - Learn movements (refined): embodiment
 - Able to recognize the environment & to understand it
 - Able to perform adaptively some specific assigned tasks
 - Learn copying human behavior on the same tasks
 - Learn to cooperate with peers
 - Learn to share

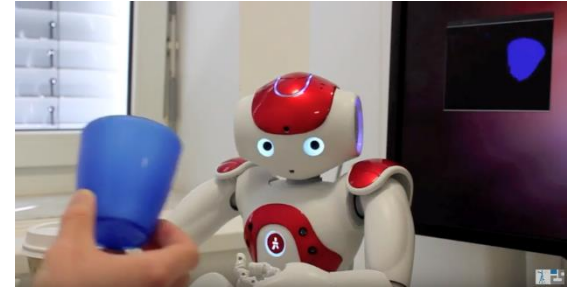
- Next, some videos showing the development of main robot features

Artificial Cognitive Systems

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Progressive Learning of Sensory-Motor Maps through Spatiotemporal Predictors

[video](#)



- Developmental robotics suggests that the forward and inverse kinematics should be learned through a sensory-motor mapping, instead of being programmed in advance. Motor babbling and goal babbling are two common approaches to generate training samples used to acquire a sensory-motor mapping. Motor babbling typically needs a considerable amount of training data and time to acquire a sufficient mapping, while goal babbling poses difficulties on how to select appropriate goals. In this paper, we propose a neurobiologically-inspired system to progressively learn a sensory-motor mapping bootstrapped from a simple constrained DOF exploration, which generates much less training data than motor babbling. Our proposed system is designed according to two neurobiologically-inspired paradigms: spatiotemporal prediction and uniformity. The spatiotemporal prediction capability facilitates the acquisition of sensory-motor mappings with less amount of training data on the one hand, and facilitates robust behavior on the other hand. The uniform system design structure is the foundation for building a scalable architecture for cognitive development. We use an improved version of our predictive action selector (PAS) as building block of our system. We validate a PAS on a 2 DOF robot head where the robot learns object tracking and evading. Then we validate a second PAS on a 5 DOF arm where it learns reaching.

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Transferring Skills to Humanoid Robots by Extracting Semantic Representations

[video](#)

- Video media attachment to the following journal paper: Transferring Skills to Humanoid Robots by Extracting Semantic Representations from Observations of Human Activities. Karinne Ramirez-Amaro, Michael Beetz, Gordon Cheng. Artificial Intelligence Journal, 2015



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PR2 Autonomous Multi floor Navigation at TUM ICS

[video](#)

- The service robot , PR2, autonomously takes the elevator, goes from basement to the 2nd floor, rings the bell, and then goes back to the room in the basement. This video was made in 2014



Artificial Cognitive Systems

Soul Machines

- <https://www.soulmachines.com/>



Autonomous Driving Systems examples



- Autonomous Driving
- TUM – assisted driving – remote driving
- USP São Carlos (Taxi & Truck)

Which ones are cognitive applications?

Invitation

- Students are invited to search for Cognitive Systems Institutes, Laboratories, Projects, etc., worldwide, and to add their links to our course pages (STOA & Facebook)
 - This intends to enrich our dataset on interesting subjects

This is all for today.

See you next week !