

XPERIENCE

Robots Bootstrapped through Learning from Experience

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XPERIENCE.ORG
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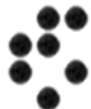
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Xperience: Problem and Approach

- **State of the Art (developmental approach):** Exploration of the world allows acquiring grounded and robust cognitive representations. This is an “**outside-in**”, data-driven process.
- **Human cognitive ability:** We are able to also use **generative mechanisms** based on (e)Xperience for knowledge extension.
 - **Advantage:** This is an “**inside-out**”, model-driven process and much faster!

Approach: XPERIENCE will implement a **complete robot system combining developmental with generative mechanisms** for automating introspective, predictive, and interactive understanding of actions and dynamic situations.

Main Novelty of Xperience

Structural Bootstrapping

An explicit mechanism for generative model construction used for internal simulation to extend knowledge

Structural Bootstrapping

- The process of structural bootstrapping compares a newly observed entity to a model of experienced entities to understand the novel situation and predict consequences of actions.
- The concept is **taken from human language acquisition**
 - Example: Knowledge of “**Fill a bottle with water**”, allows you to infer the role of xxx as something that can be filled with water when hearing the sentence “**Fill the xxx with water**”.
- Xperience **transfers this concept** to the full spectrum of cognitive robotics problems.

Examples for Structural Bootstrapping

1. **Language domain:** Knowing the grammar of English and the category and meaning of the surrounding words in a sentence allows identification of the category and semantic type of an unknown word.
2. **Sensorimotor domain:** Knowing how to peel potatoes with a knife, significantly aids one in learning how to use a potato-peeler. A single demonstration enables understanding in terms of an existing theory of potato peeling, and makes the peeler available for generalization to other plans (other potatoes and other vegetables).

Major Scientific Questions

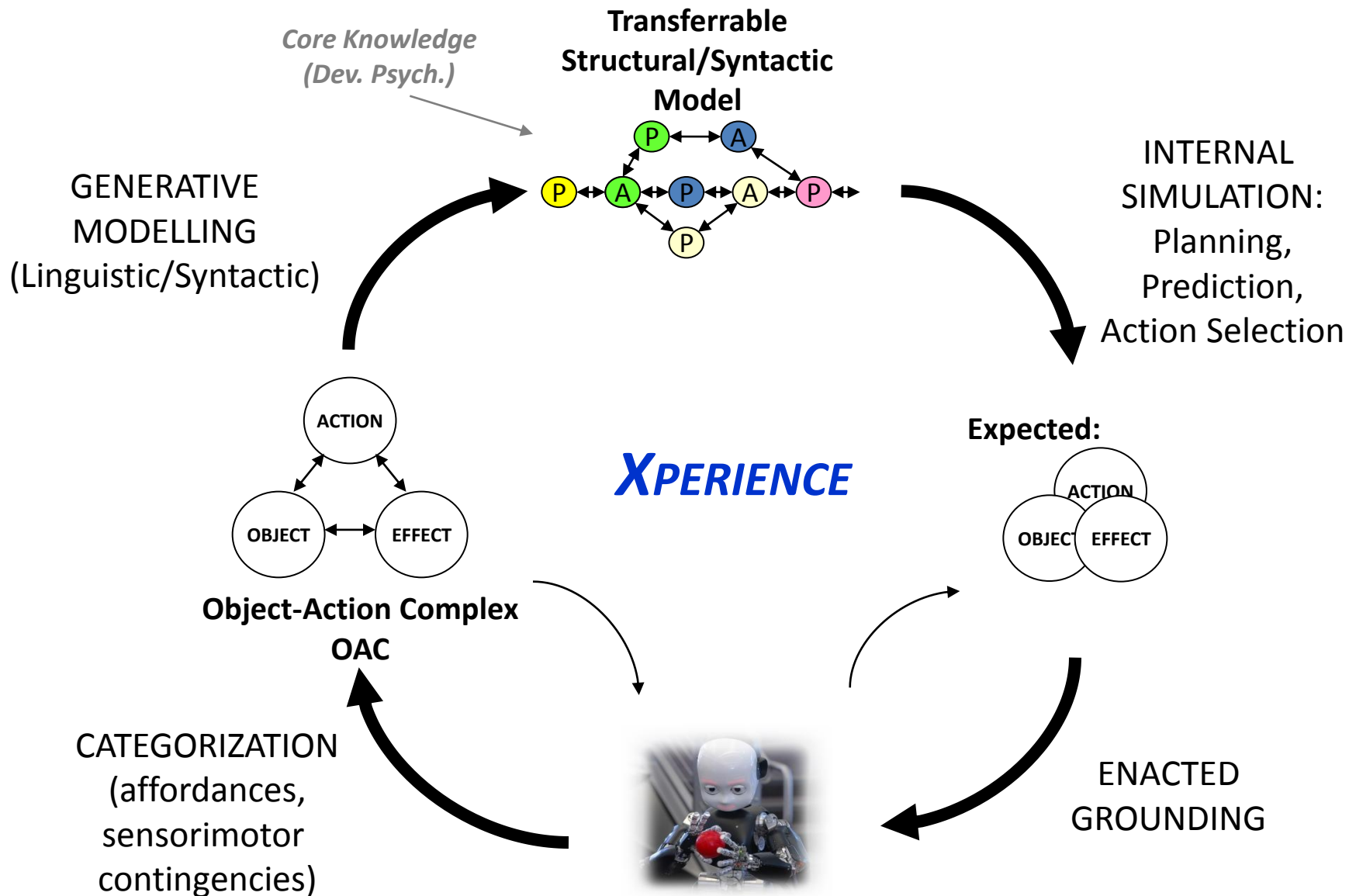
1. How to improve **exploration based knowledge acquisition** (“outside-in” stage)?
2. How to implement the **generative process** of structural bootstrapping (“inside-out” stage)?
3. How to combine these two mechanisms in a **dynamically stable process**?
4. How to **predict** other agents, leading to advanced abilities to **cooperate, interact and communicate**?
5. How to integrate a **complete embodied cognitive system**?

OACs as representations in Xperience

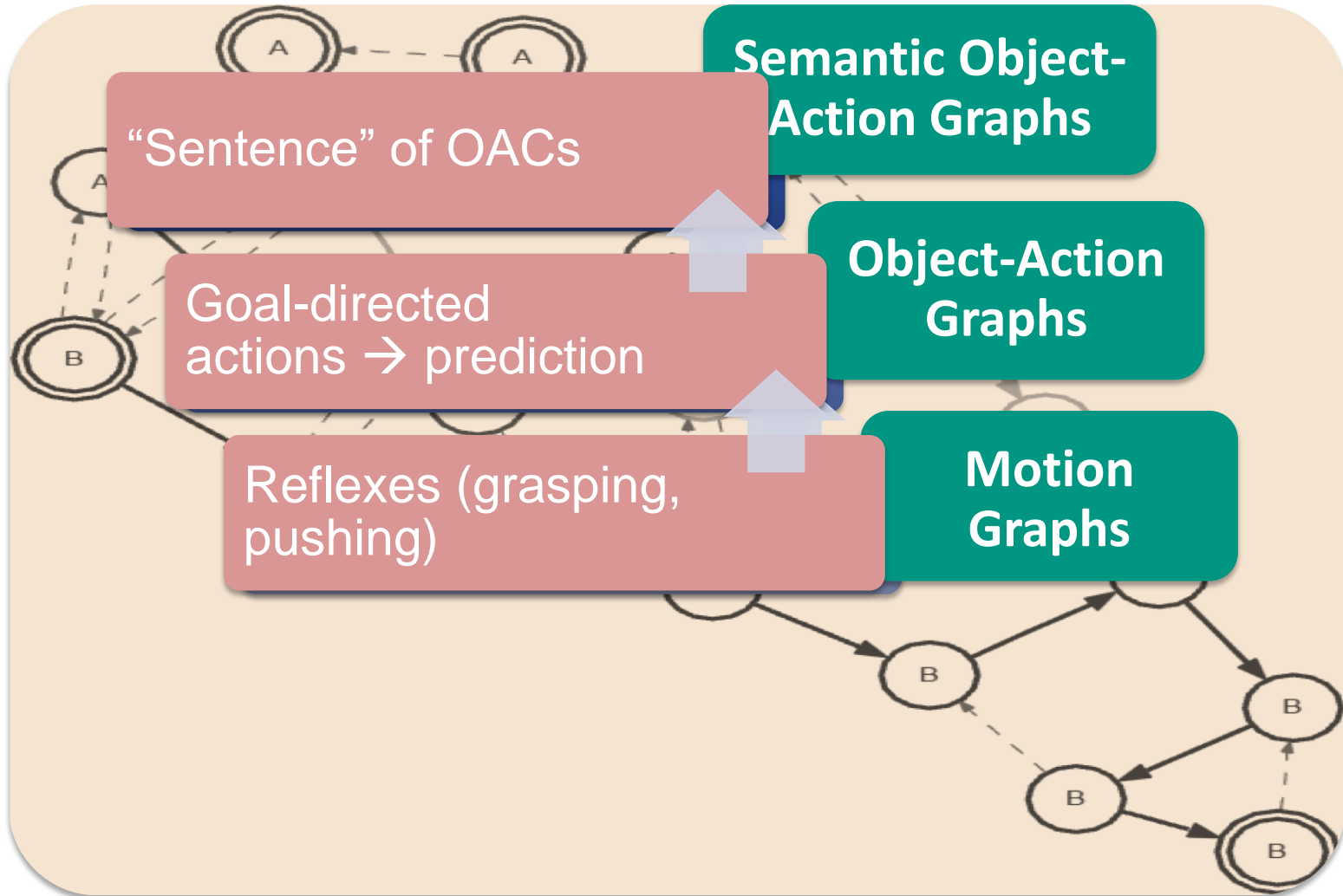
- **Object-Action Complex (OACs, pronounced “oaks”)**
 - **Grounded** abstractions of sensorimotor processes
 - Describes how an object is affected by an action
 - Can be **executed** to actually do it
 - Allows reasoning based on **experience**
 - Combines notions of
 - affordances (perception)
 - prediction (action, state transitions)
 - reasoning (~STRIPS)
- OACs as basis for symbolic representations of sensorimotor experience and behavior.

Krüger et al. 2011. Object–Action Complexes: Grounded abstractions of sensory–motor processes, RAS, 59(10):740-757, 2011

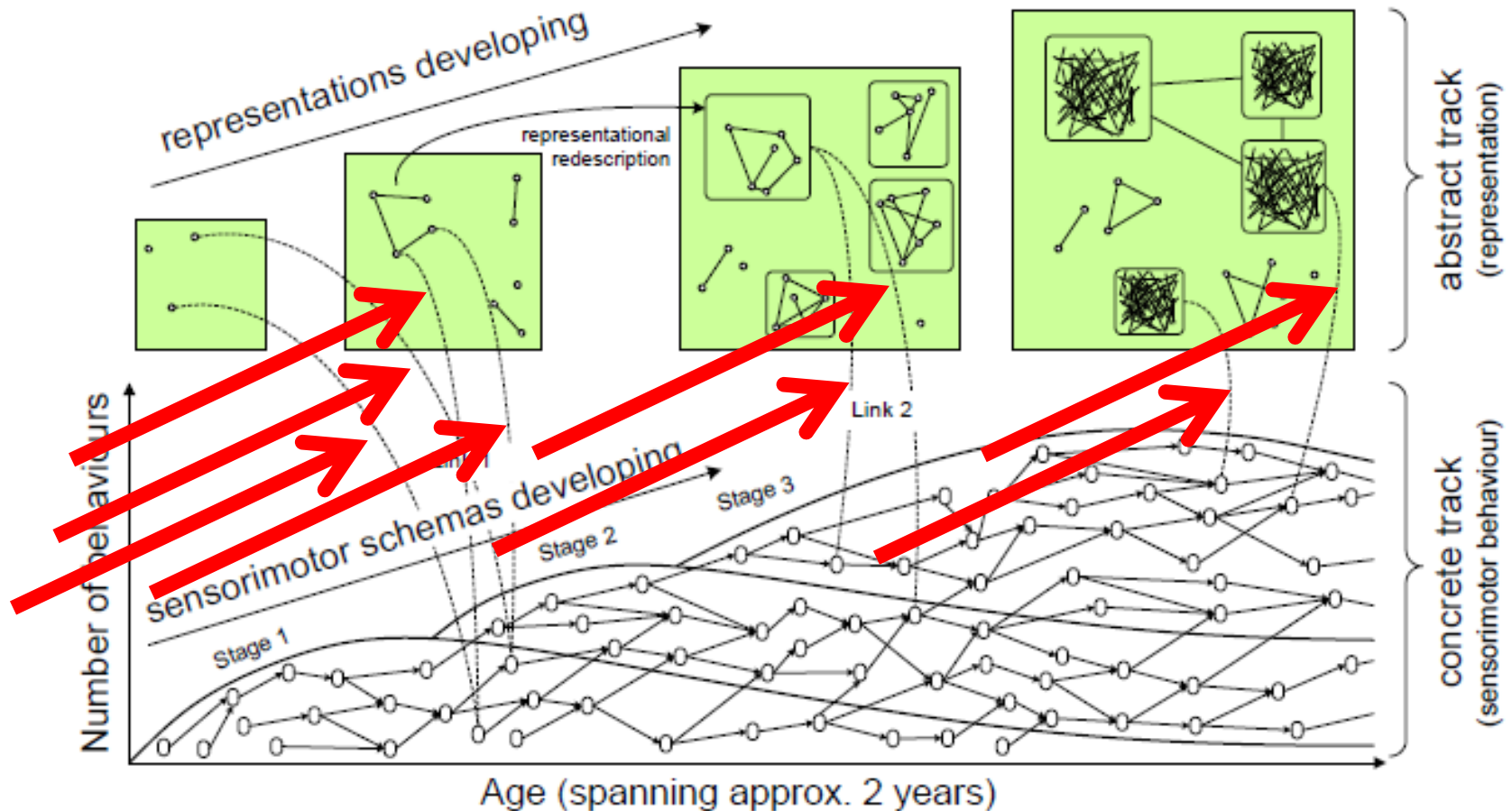
The XPERIENCE Cognitive Architecture



OACs on all levels



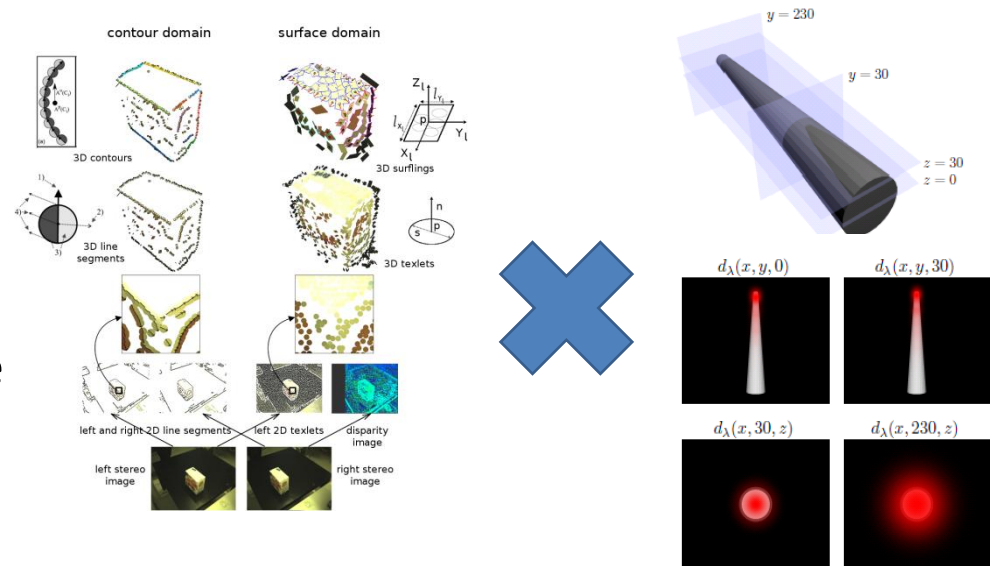
Development and Structural Bootstrapping



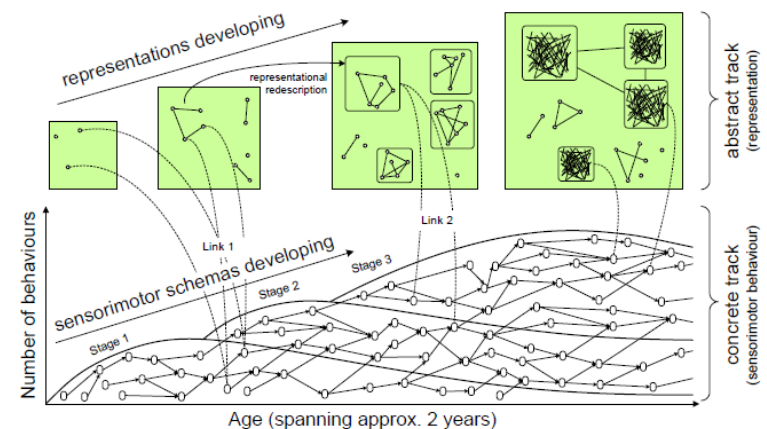
Guerin, Kruger and Kraft (submitted). A Survey of the Ontogeny of Tool Use: from Sensorimotor Experience to Planning

Learning hierarchical and probabilistic sensory-motor spaces: Early Cognitive Vision (ECV) x Probabilistic Grasp Functions (PMFs)

- ECV provides
 - a deep hierarchical, view point invariant, rich, explicit visual representation
- PMFs
 - provide a probabilistic, complete and structured action representation
- OACs
 - provide the required framework for generating, storing and utilizing sensory-motor data
- Structural bootstrapping on a sensory-motor level
 - searches in the cross space ECV x MD for relevant structures
 - to refine existing and create new OACs

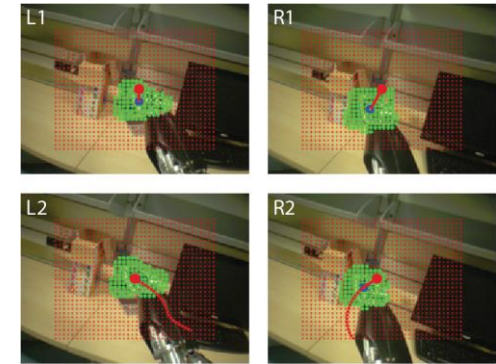


ECV \times MD

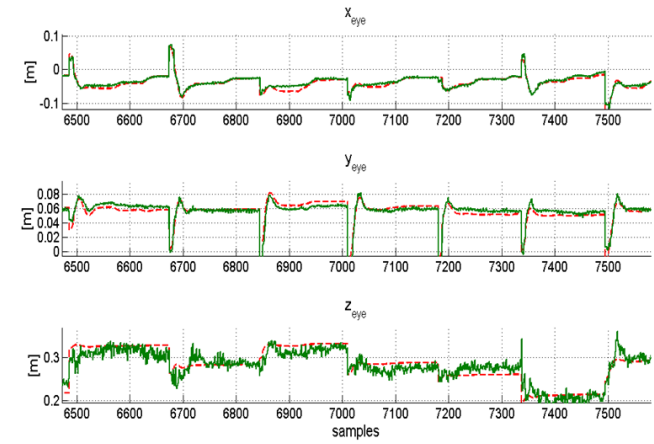
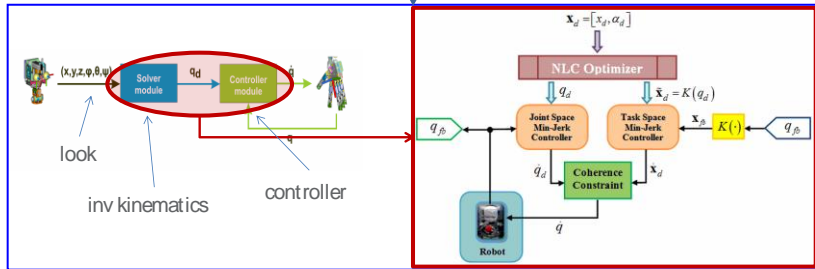


Machine Learning techniques for exploration-based ...

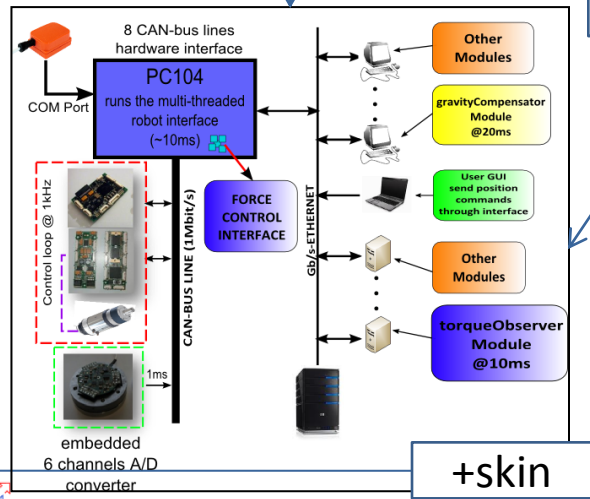
visually identified target,
e.g. using motion



Learning

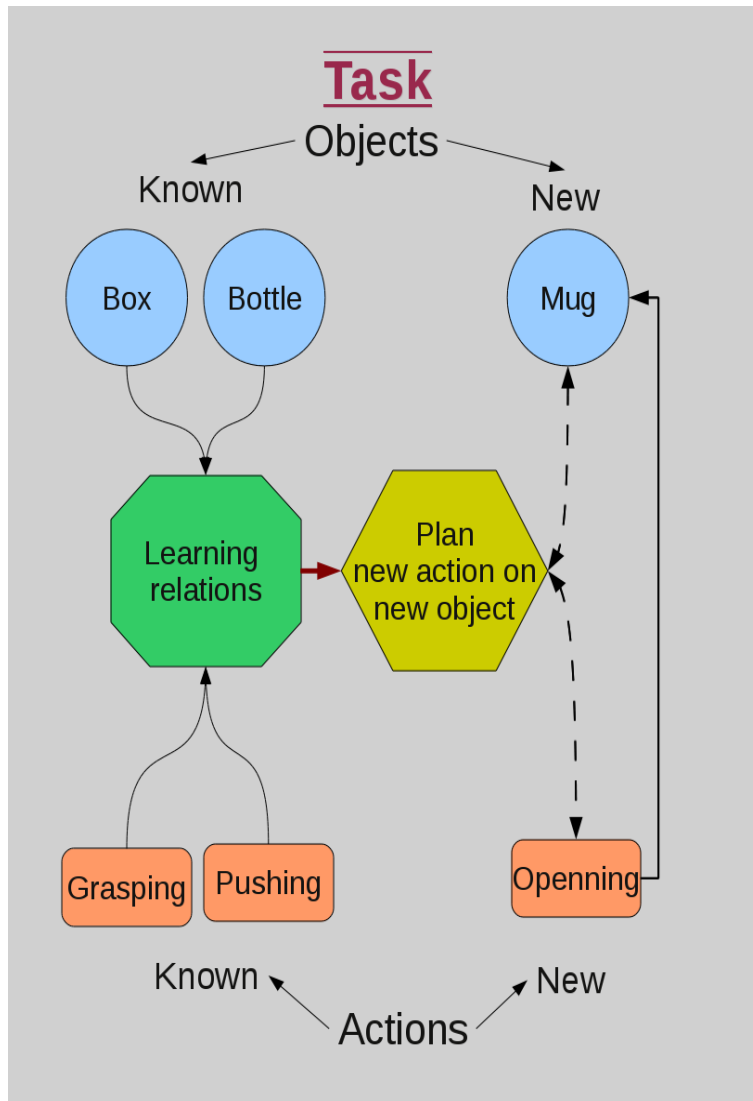


Learning



Learning to reach from optical flow data and self-calibration (plot shows the desired vs. learnt compensatory signals during reaching tasks)

Finding Structure in Objects x Features x Actions

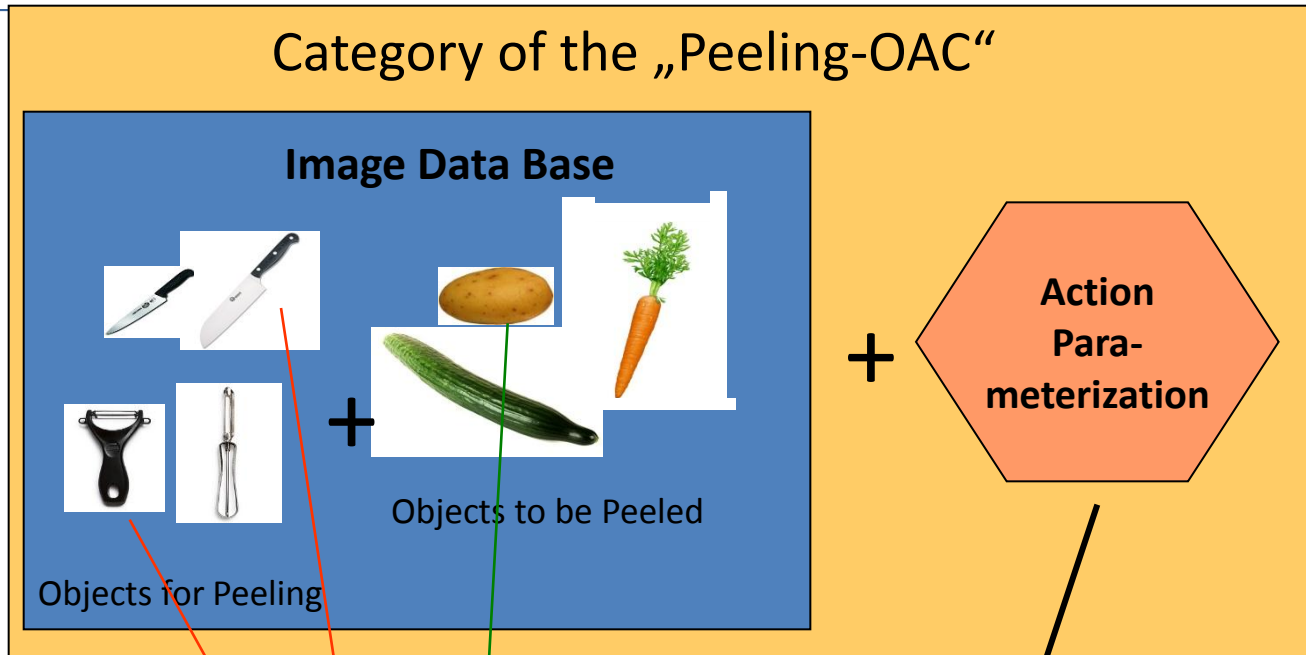


- Predict highly interdependent relations between objects and actions
 - Identify relevant features determining the relations
 - Use known objects (and their interrelations) to predict properties and affordances of unknown objects (even if they share features only indirectly)
- Methods to collect representative sample data

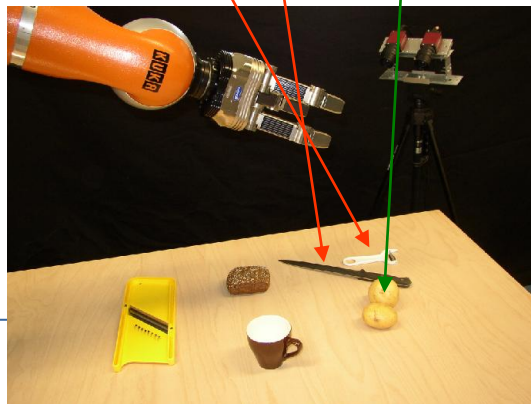
Generalizing Objects by Analyzing Language (“GOAL”)

Different Example

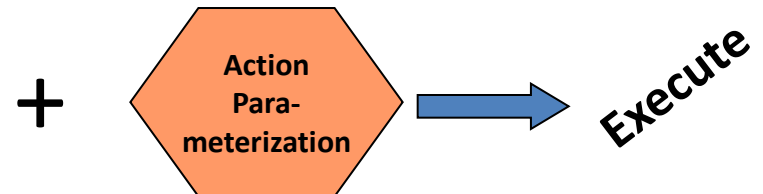
What can be peeled with what?



Search for these objects in the scene



Retrieve Action Parameterization



Generalizing Objects by Analyzing Language (“GOAL”)

For Example asking the robot:

What can be cut with what?

(without having seen any of the objects before!)

Algorithm: Generalize, starting with the sentence:

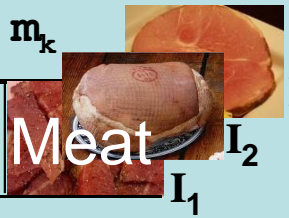
“Cut the salami with a knife”

use the Internet to **replace nouns** in this sentence and then **attach images** to the new nouns (again from the internet) .

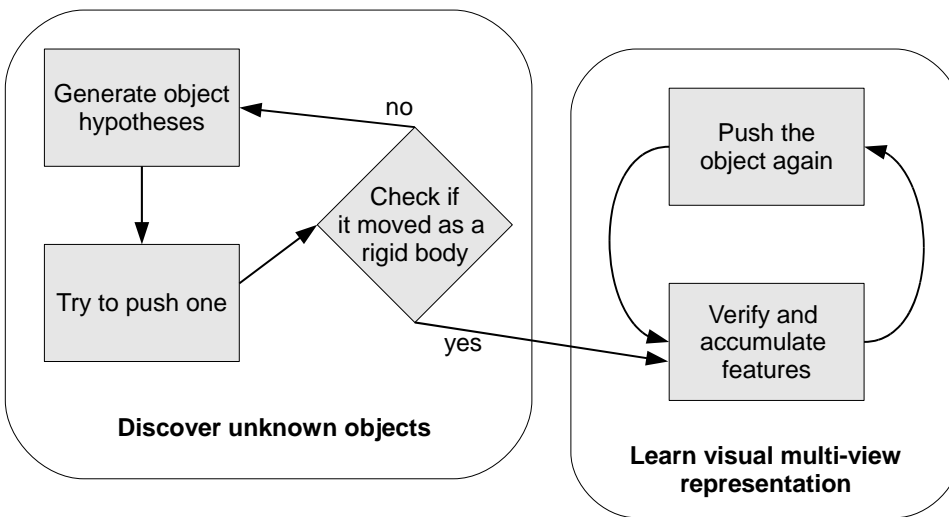
Store a verb-labeled “**Picture Book**” of what can be cut with what.



Things for Cutting & Things to Cut

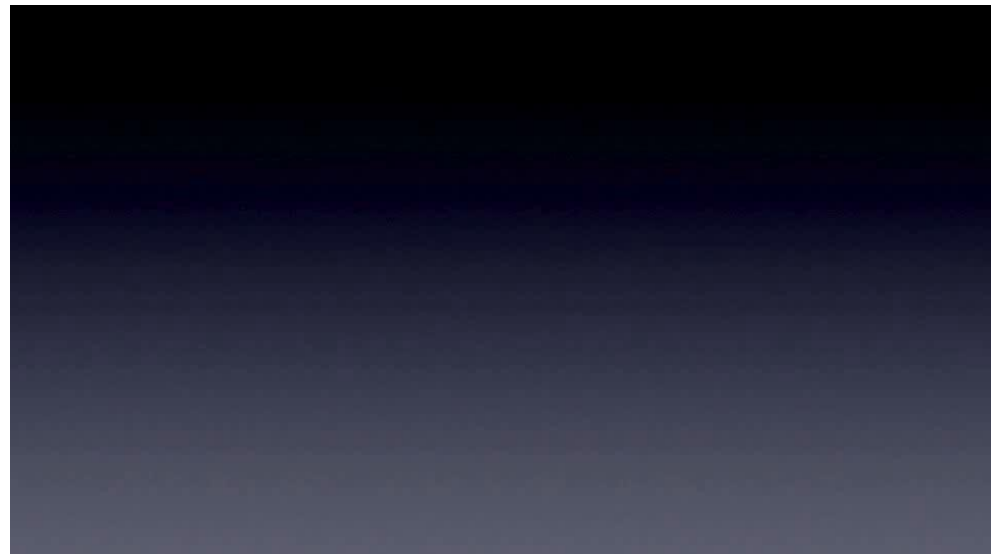
	i=1	2 ...	m_k	
k=1	Salami	Bread	...	Meat  I_1 I_2 $I_{r_{k,i}}$
2	Knife	Peeler		
⋮	⋮	⋮		
	...	$X_v[\tilde{I}]$		
n				

Pushing reflex for learning object representations



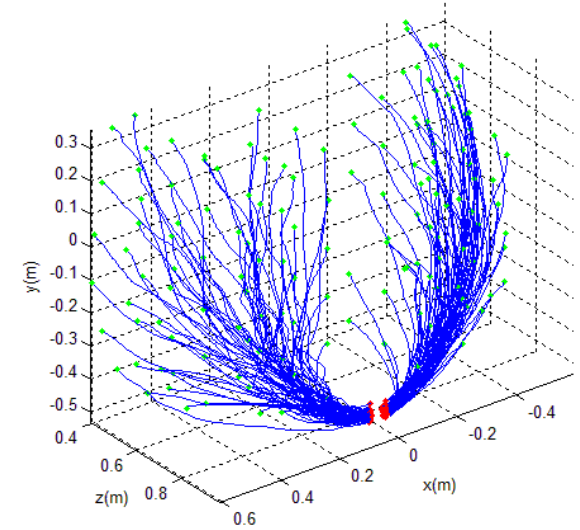
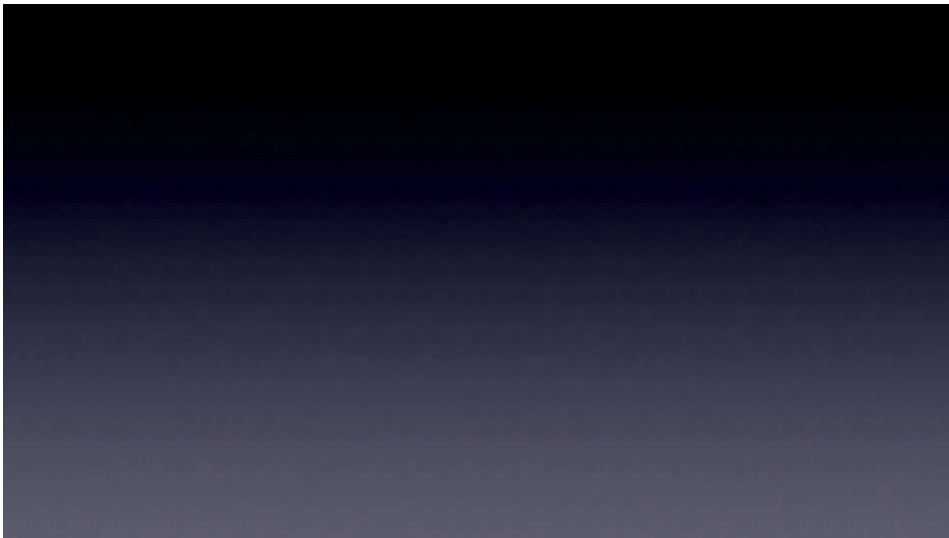
- Predefined (innate) pushing behavior
- Triggered by regular image structures

- Data accumulation for learning

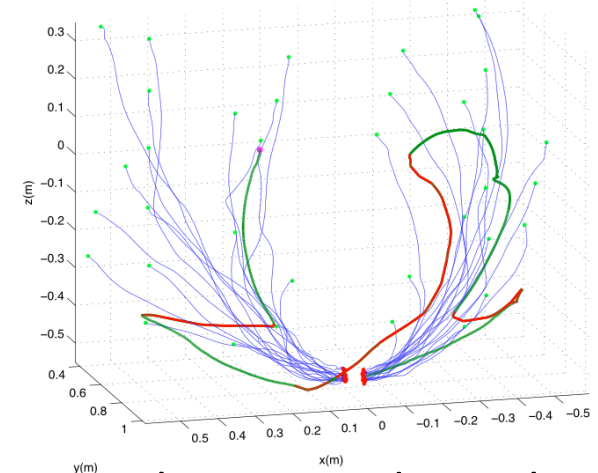


Switching Motor Primitives in Collaborative Tasks

- Data acquisition by kinesthetic guiding.
- Real-time generation of Dynamic Movement Primitives (DMPs) by Gaussian process regression.
- Updating and switching to new motor primitives based on force sensing enables collaborative task execution.



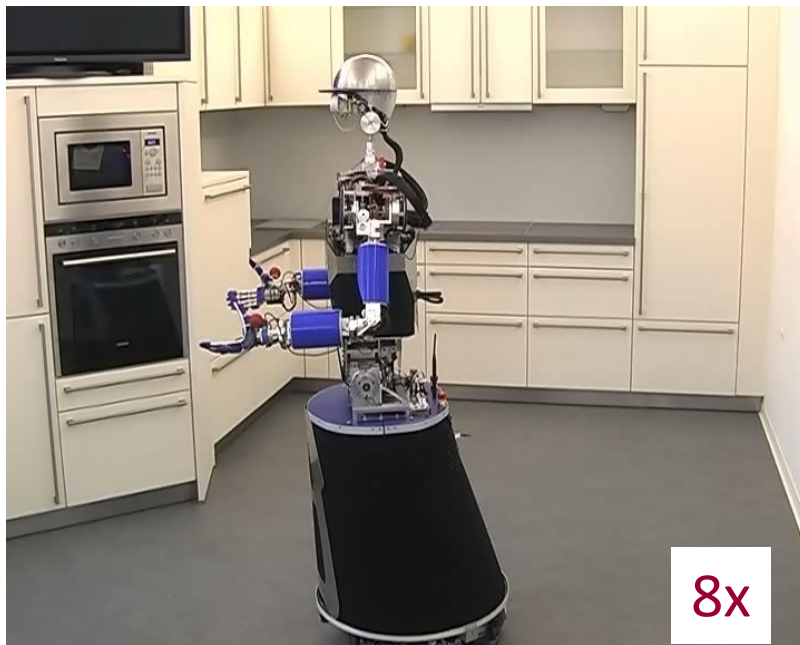
Training trajectories



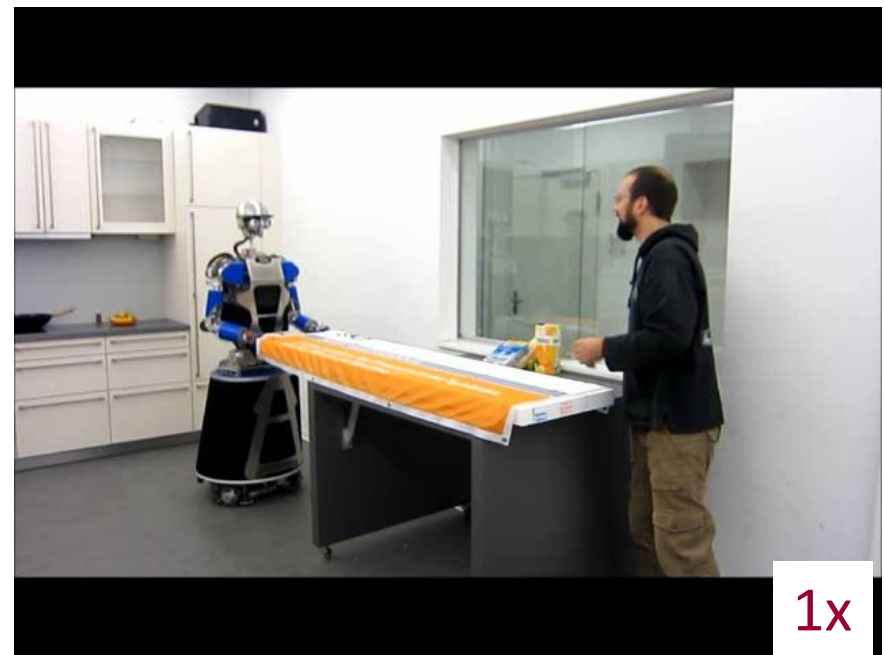
On-line generalization and switching

Tightly-coupled physical human-robot interaction

Use human motion models and sensorimotor experience for prediction and role assignment in tightly coupled cooperative tasks



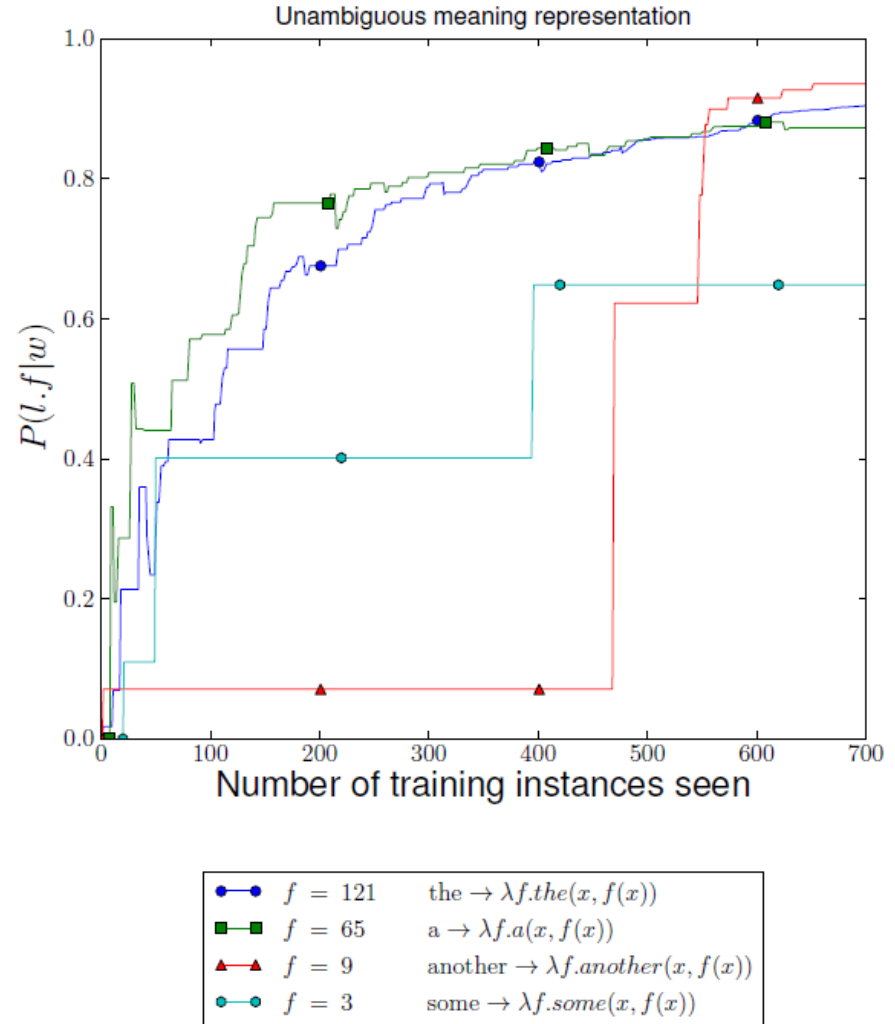
Coaching through tightly-coupled interaction



Cooperative manipulation of large objects

Language and planning domain

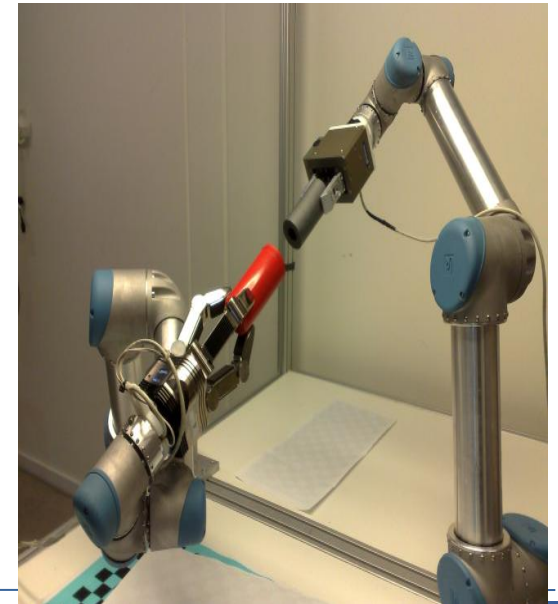
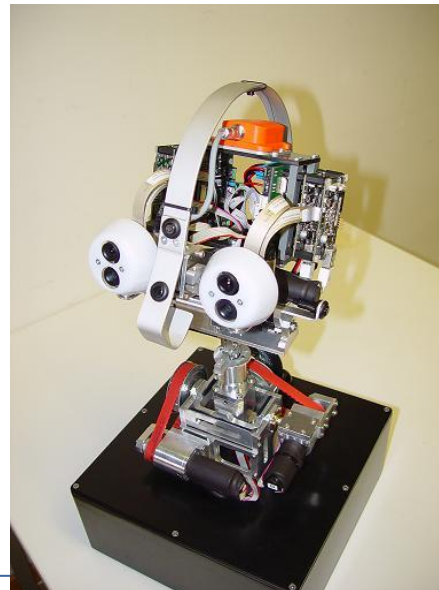
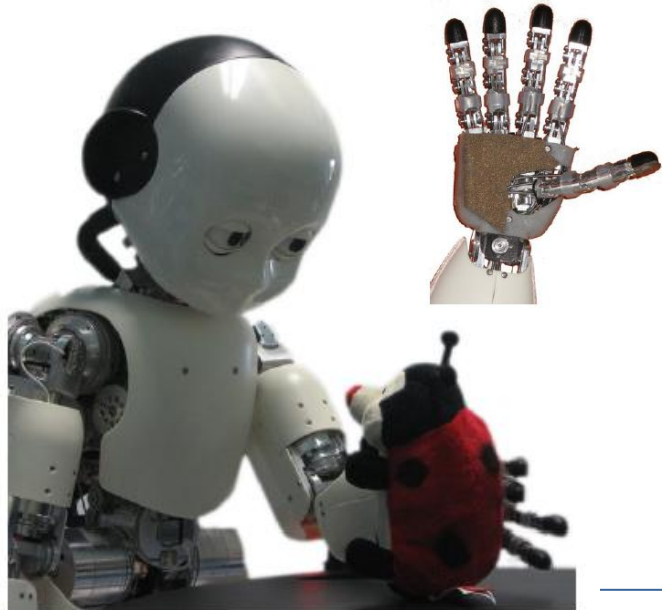
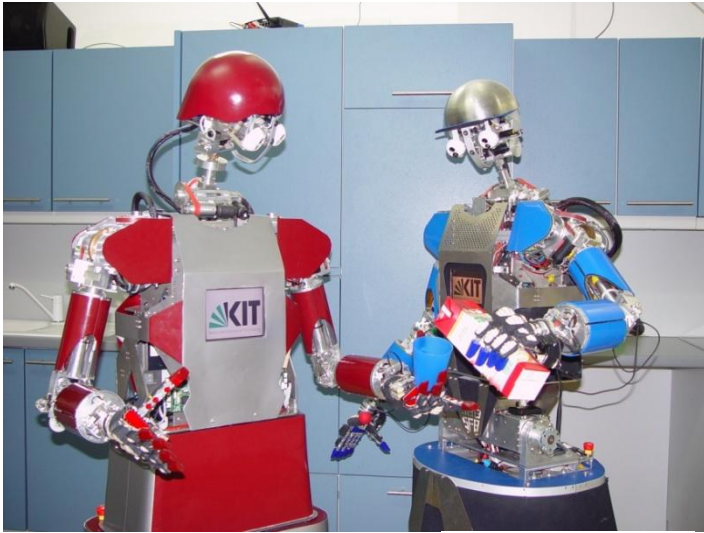
- Working demonstrations of bootstrapping in both supervised and semi-supervised language learning
- PKS planner to support noisy numerical properties
- Learning Action Semantics



Scenario: “Human Living Space”

- Multiple agents performing exploration and learning from demonstrations using structural bootstrapping
- We investigate:
 - bimanual manipulation and grasping
 - robot-robot interaction
 - human-robot interaction and communication
- Robots will interact with humans for:
 - learning and execution of a cooking recipe
 - clearing and rearranging a room in cooperation with a human

Robot Platforms in Xperience



Thank you for your attention!

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