



XPERIENCE

Robots Bootstrapped through Learning from Experience

XPERIENCE.ORG

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The Consortium

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The starting point

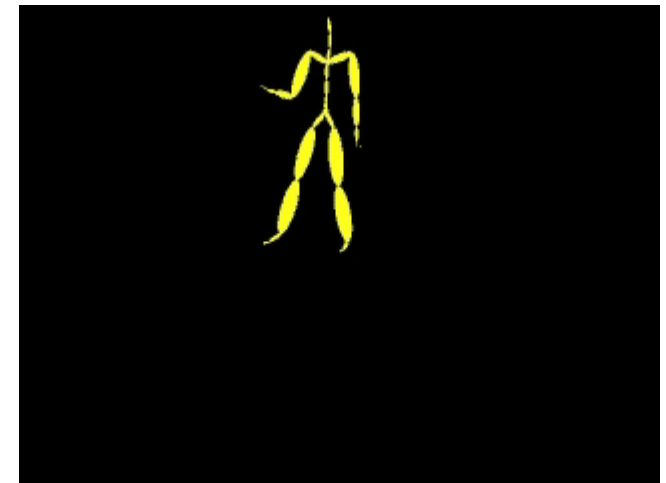
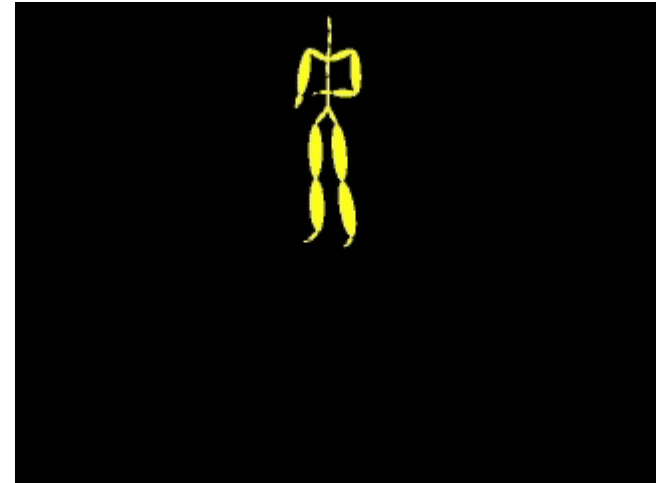
- **Problem:** Representational differences between high-level AI planning and low-level robotics/vision.
 - Continuous Robotics vs. Discrete AI Planning
 - Previous efforts have resulted in largely ad-hoc solutions.
- **Claim: Object Action Complexes (OACs, pronounced “oaks”)** can be used as a “lingua franca” to bridge this representational divide
 - Formalization the requirements for an artificial system to approach some level of cognitive complexity
 - Grounding of entities in the sensorimotor domain
 - Data structures, which can be used on all levels

- EU project PACO-PLUS: www.paco-plus.org

Motivation: Object-Action Complexes

Objects and Actions are inseparably intertwined

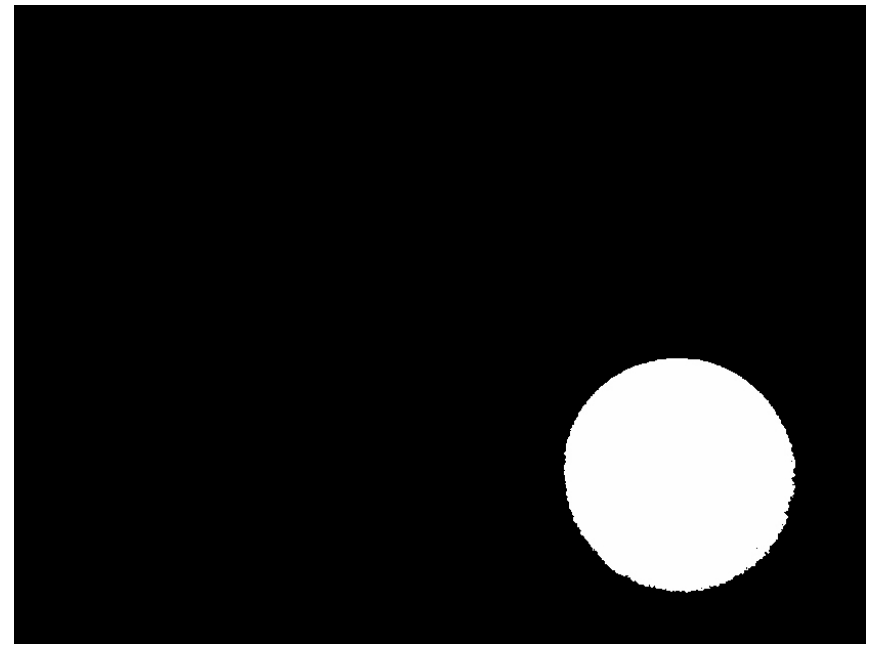
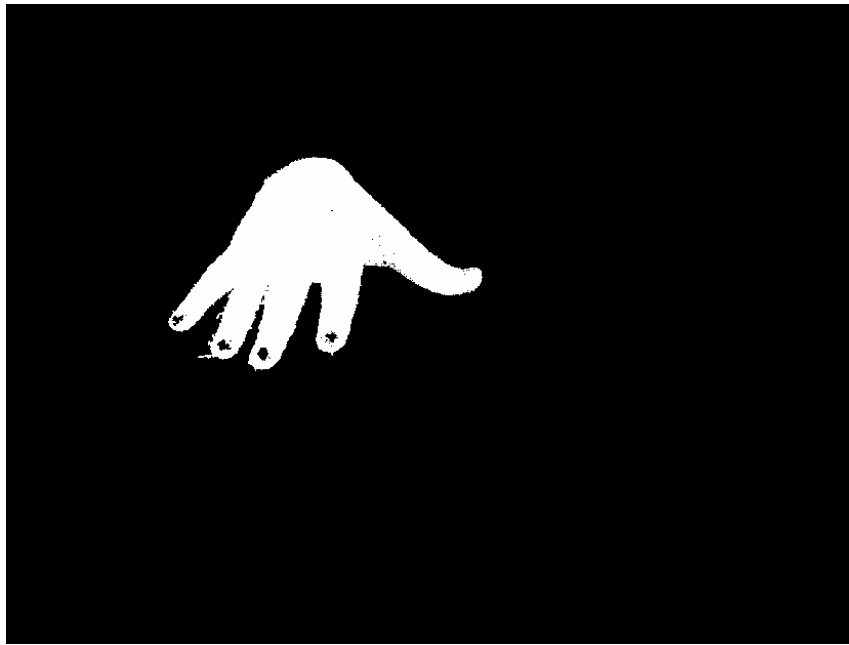
- Visually based object recognition fails
- Visual information is sparse and limited
- Activity involving the object decreases the uncertainty about the object's nature considerably!



CMU Graphics Lab Motion Capture Database
<http://mocap.cs.cmu.edu/>

Motivation: Object-Action Complexes

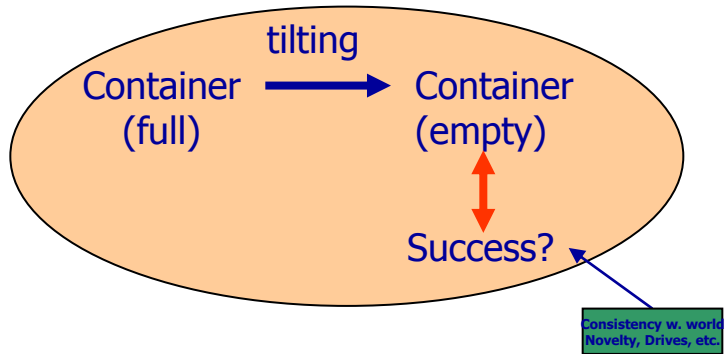
Objects and Actions are inseparably intertwined



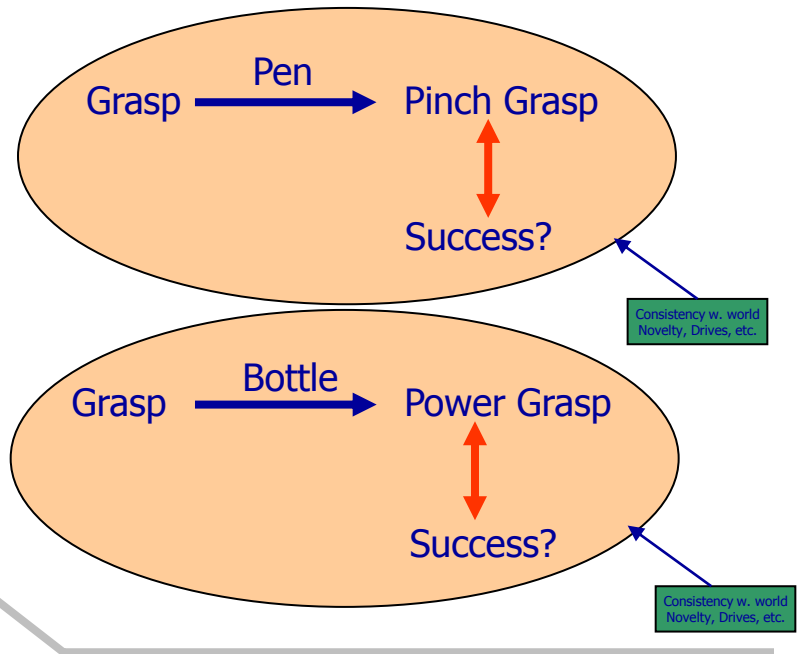
Antonis Argyros, FORTH

Object, Action and Task Perspective

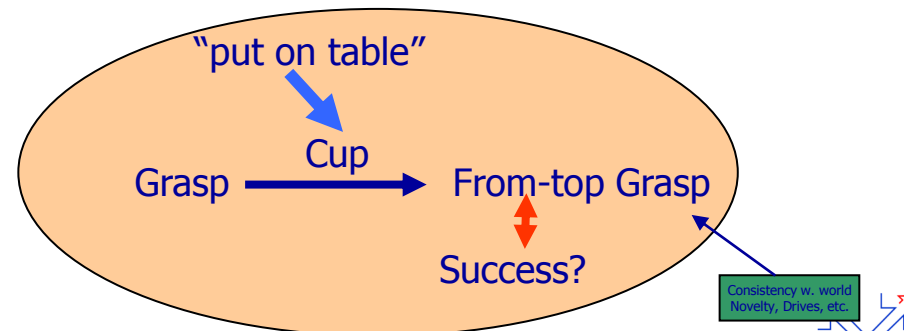
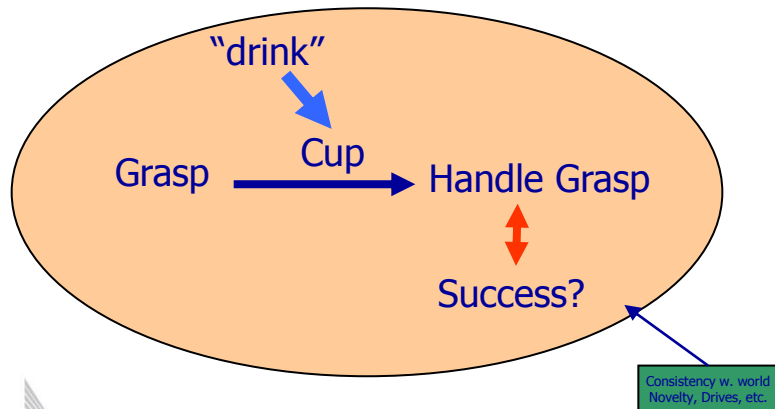
Object Perspective



Action Perspective



Task Perspective



Formal definition of an OAC

Definition

We define an **Object-Action Complex (OAC)** as a triplet

$$(id; T; M) \quad (1)$$

containing

- a unique OAC identifier id ,
- a prediction function $T : \mathcal{S} \rightarrow \mathcal{S}$ (where \mathcal{S} is a global attribute space) that codes the system's belief of how the world (and the robot) will change through the OAC [P2], and
- a statistical measure M representing the success of the OAC within a window over the past [P6].

N. Krüger, C. Geib, J. Piater, R. Petrick, M. Steedman, F. Wörgötter, A. Ude, T. Asfour, D. Kraft, D. Omrčen, A. Agostini, and R. Dillmann. **Object-Action Complexes: Grounded Abstractions of Sensorimotor Processes**, Robotics and Autonomous Systems, 59(10):740-757, doi:10.1016/j.robot.2011.05.009, 2011.

Affordance and OACs

“The Affordances of the environments are what it offers the animal, what it provides or furnishes, either for good or ill”
(Gibson, 1986)



Thanks to Jose-Santos Victor for this example

OACs vs. Affordances

- Affordances are “**unidirectional**”
 - Objects affords actions
- OACs are “**bidirectional**”
 - Object affords actions
 - Actions suggest objects
- OACs can be **chained** (new complex OACs from simpler OACs “Tasks from skills = Planning”)
- OACs (unlike affordances) are **fully formalized** and **(partly) implemented**

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

Xperience: Problem and Approach

- **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.
 - 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

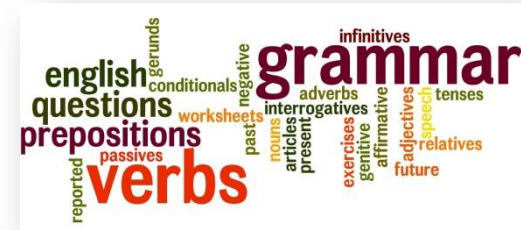
- The process of structural bootstrapping compares a newly observed entity to a model of experienced entities to understand the novel situation and predict consequences of actions
- The concept is taken from **human language acquisition** (syntactic bootstrapping, Gleitman 1990)
 - Example: Knowledge 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).



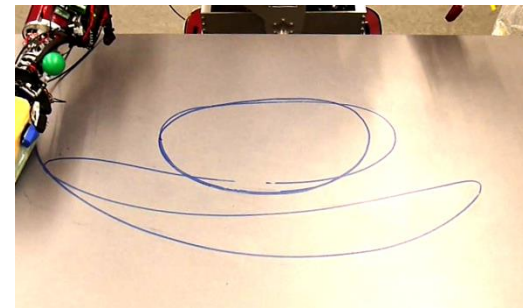
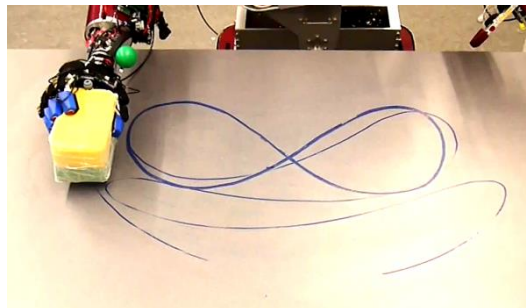
Other Examples

- **Joint space vs. task space**
 - For certain tasks better execution in the joint space:
 - More accurate, simpler representations
 - Examples:
 - Screws tightening, pouring
- **Bootstrapping:**
 - Concept of the execution in the joint space is “discovered” (e.g. when tightening screws)
 - Same for pouring



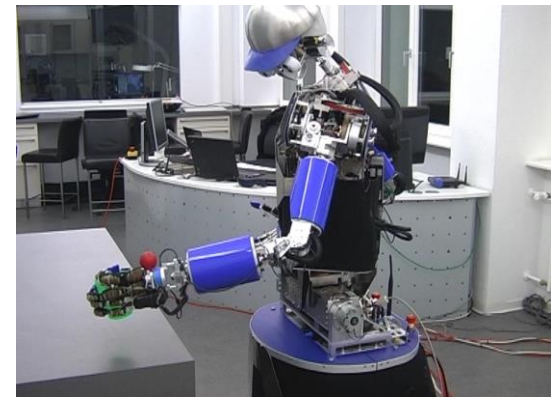
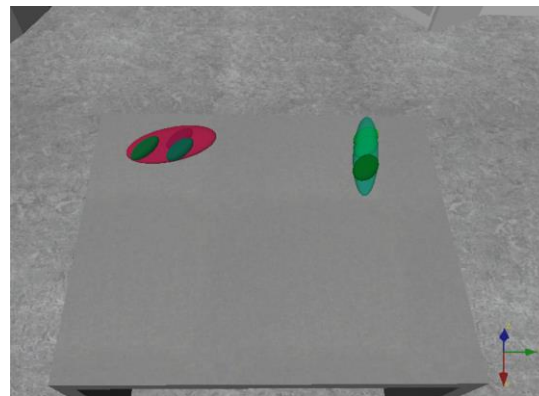
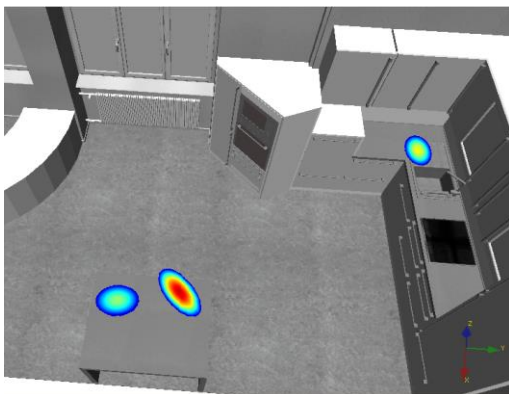
Other Examples

- **Object replacement**
 - Stir with a spoon or knife possible
- **Action replacement**
 - Different types of wiping movements



Other Examples

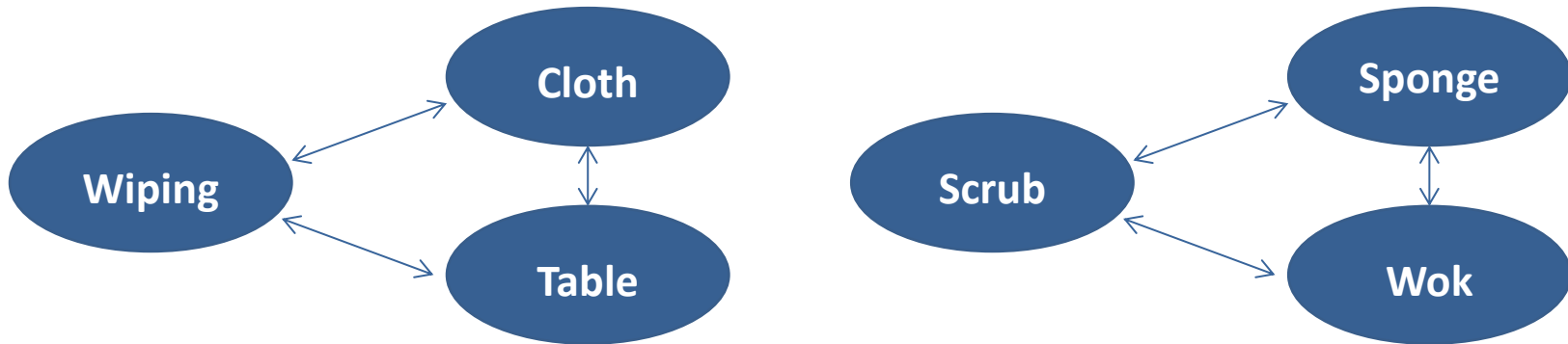
- **Common object locations** provides information about possible function
 - Probability of object location
 - Cutlery in the drawer
 - Cans in the lower cabinet
 - Important for planning and search tasks



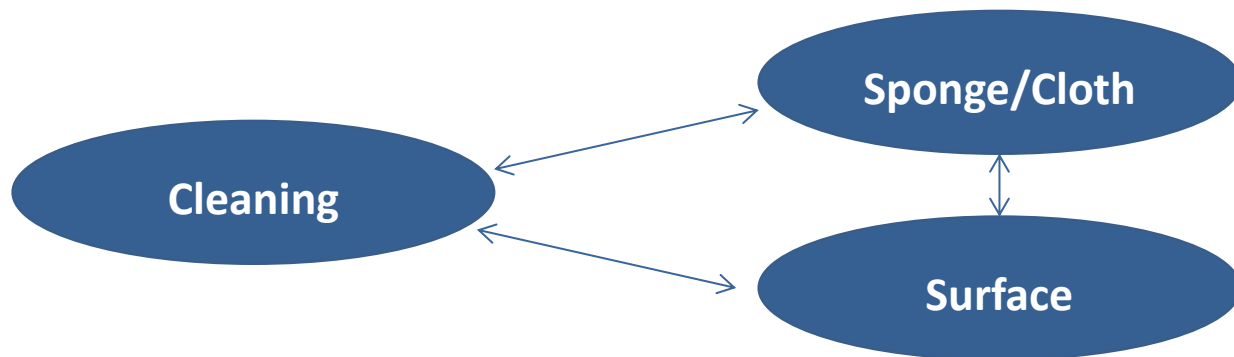
Other Examples

- **Object and/or action replacement**
 - Cleaning objects with different cleaning “tools” (cloth, sponge, ...)
 - Two actions and two objects
 - Obj₁: Cloth, Table A₁: Wipe E: Clean
 - Obj₂: Sponge, Wok A₂: Scrub E: Clean

In OACs words “pictures”



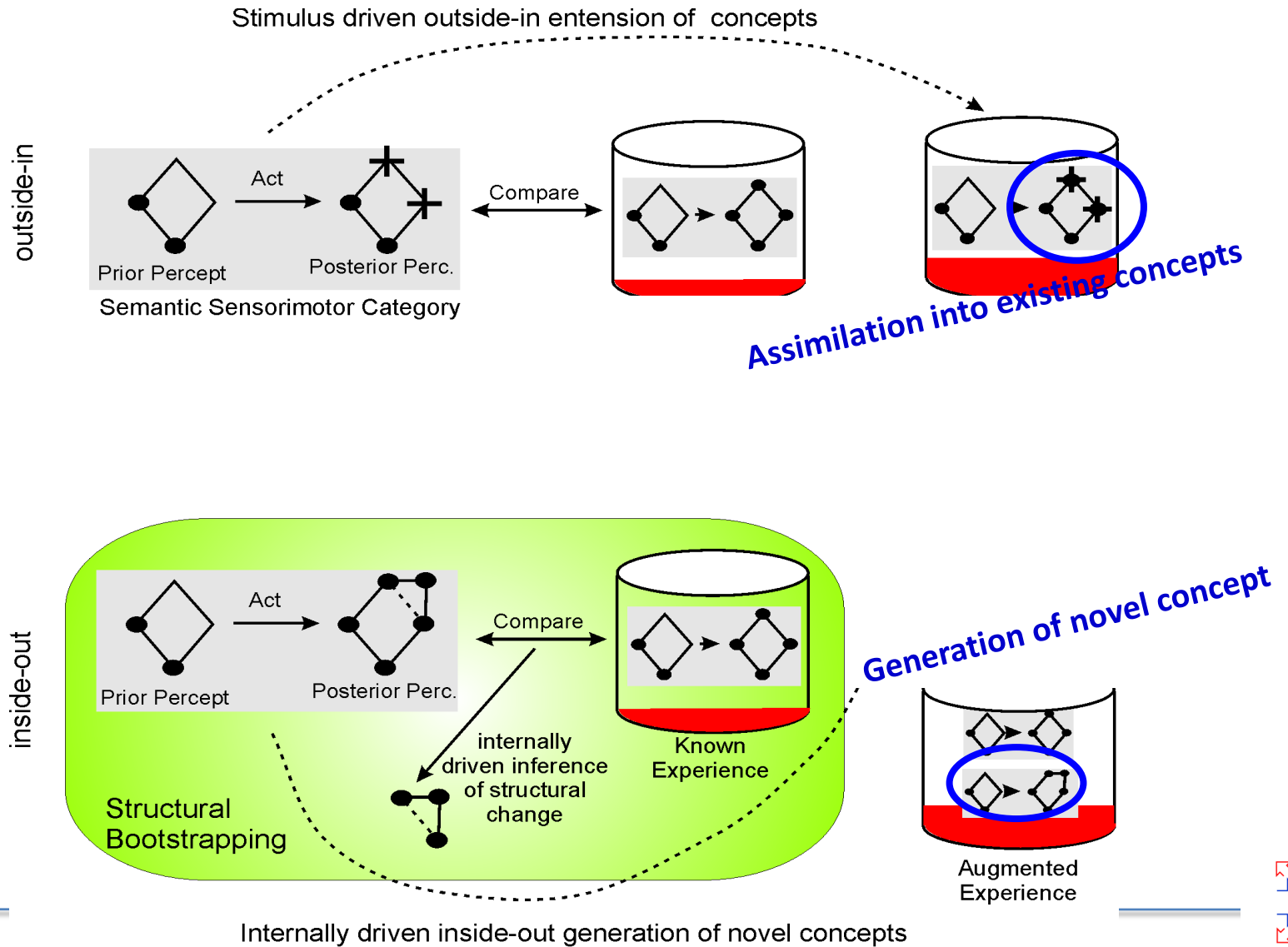
- Bootstrapping: Action and object categorization



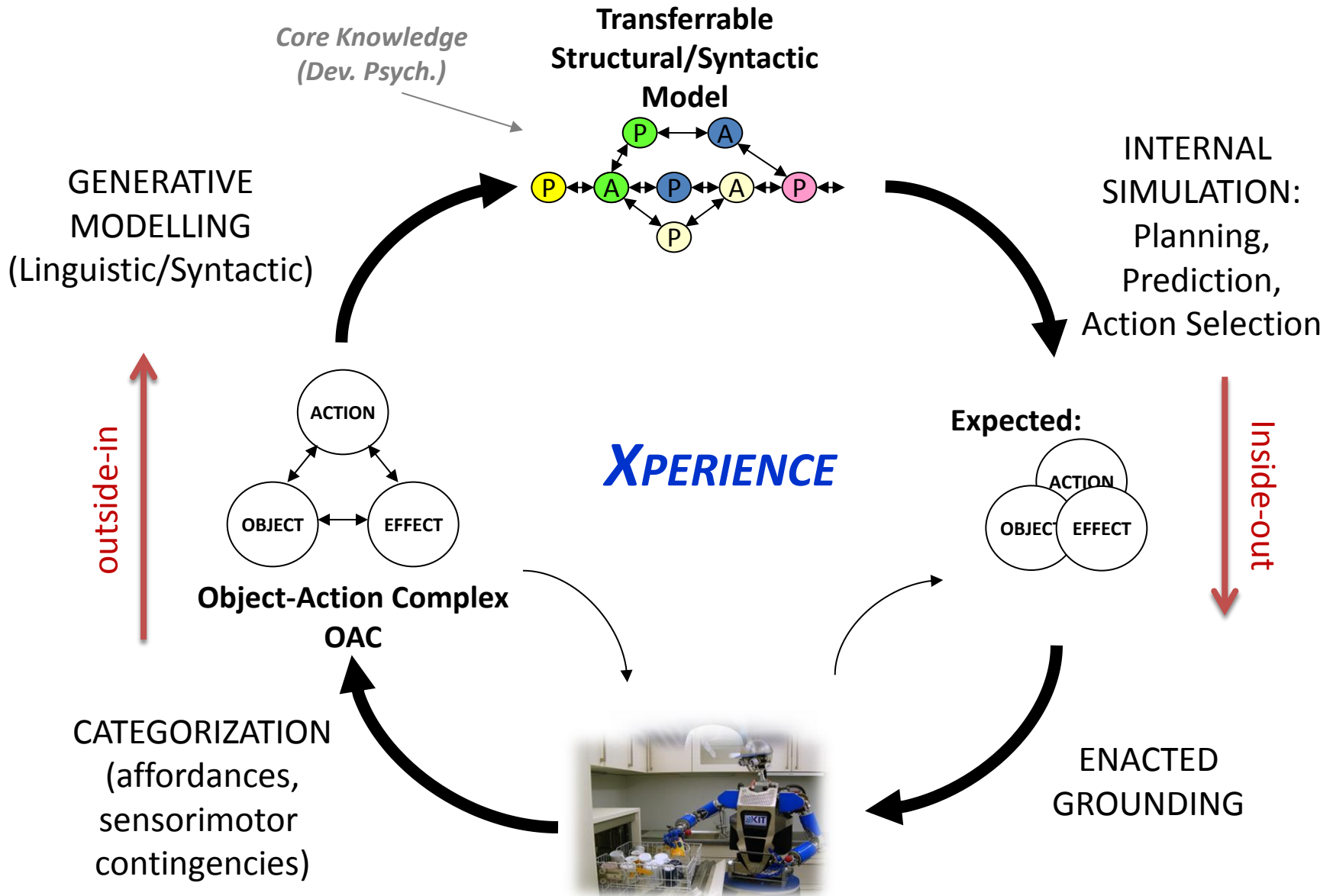
Xperience Major Scientific Questions

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**?

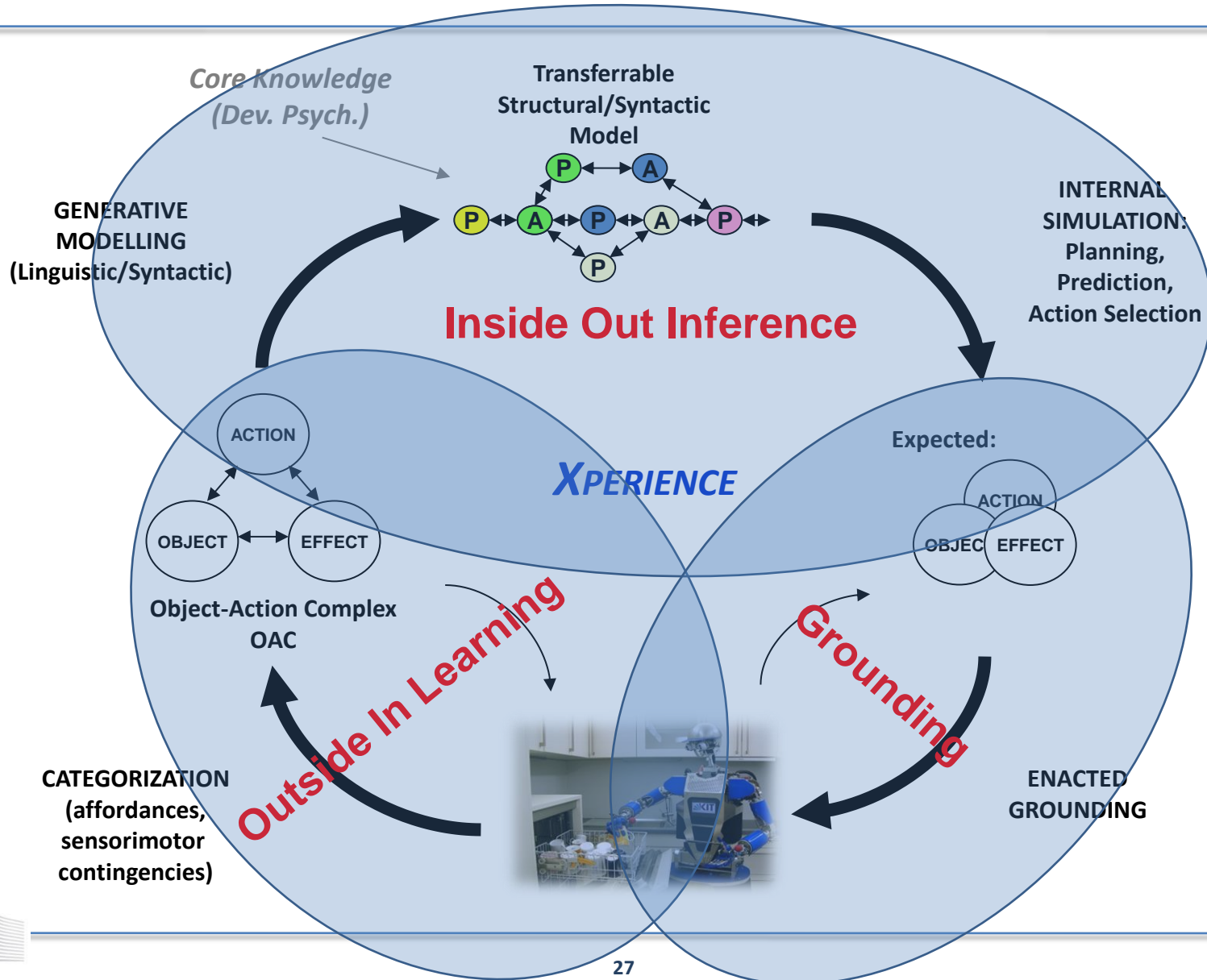
Xperience-based knowledge extension



The XPERIENCE Cycle



The Xperience Cycle



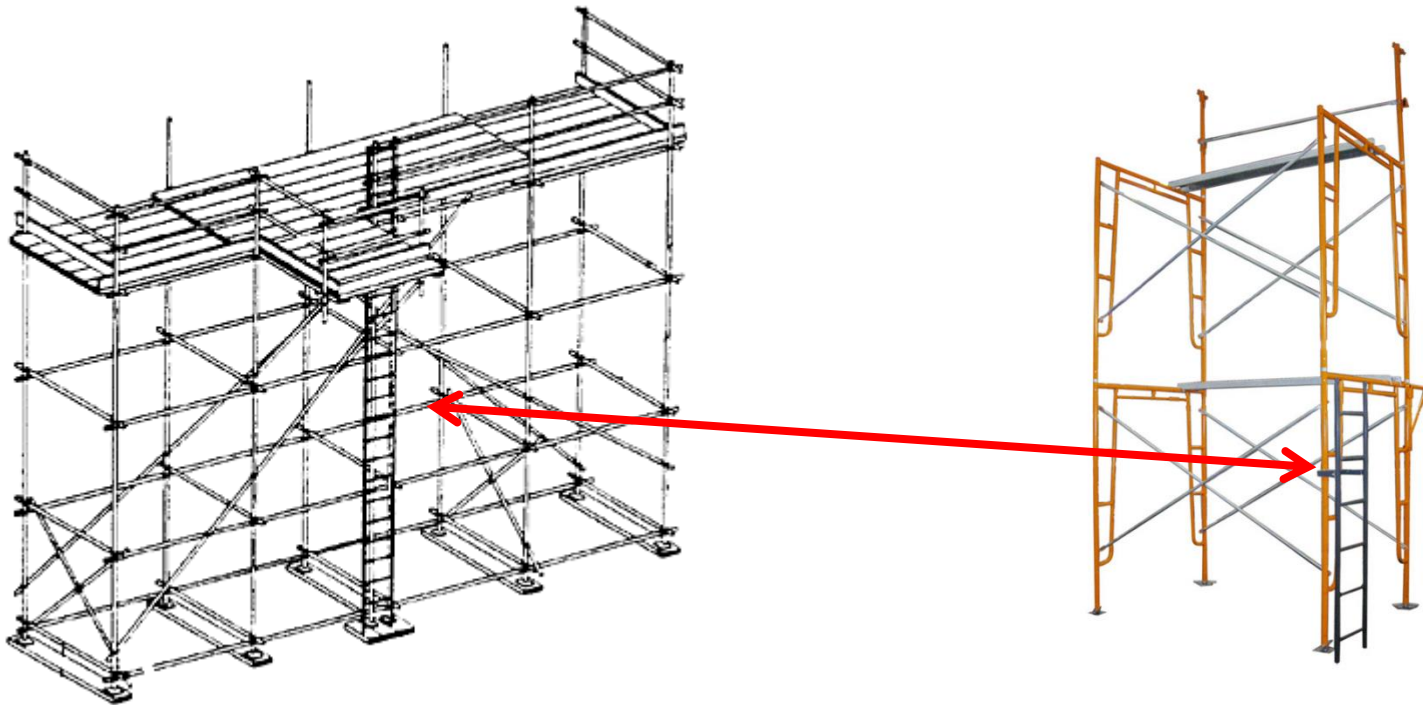


Structural Bootstrapping: Proof of Concept

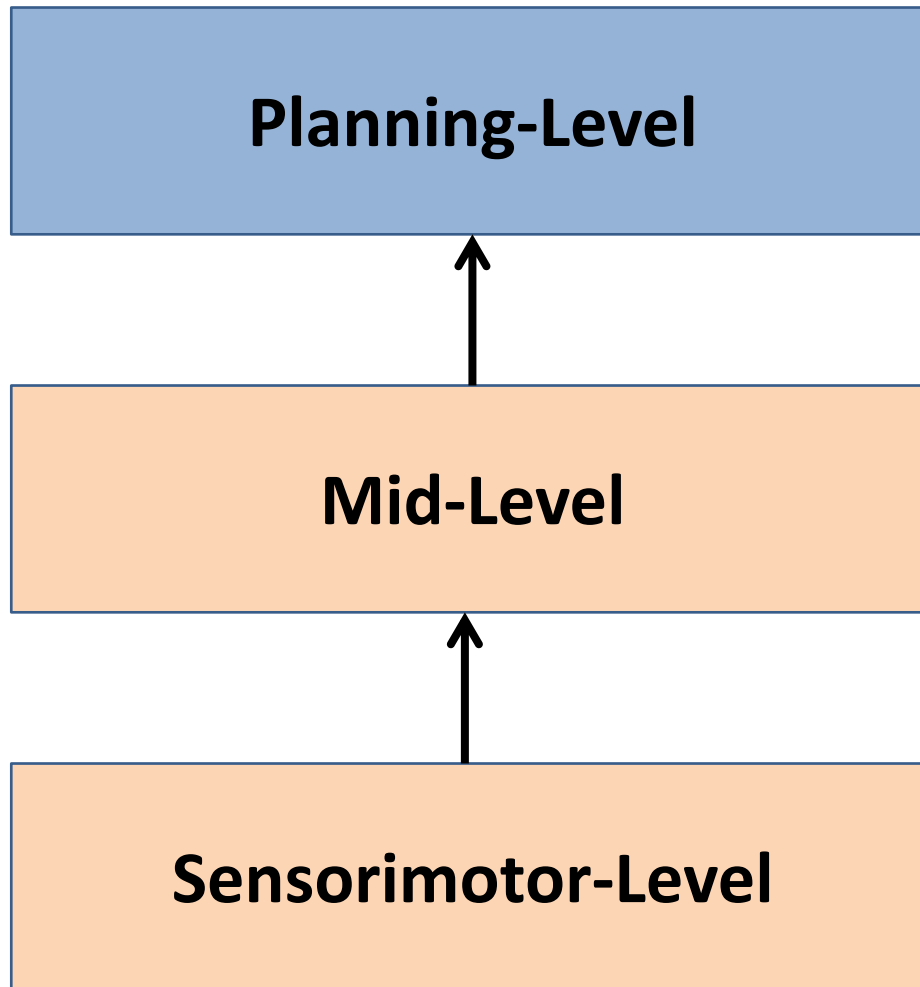


Goal

- Devise an example and the required algorithmic steps for Structural Bootstrapping through-out the different levels of the Xperience architecture.
 - Semantic Scaffolds and Syntactic elements

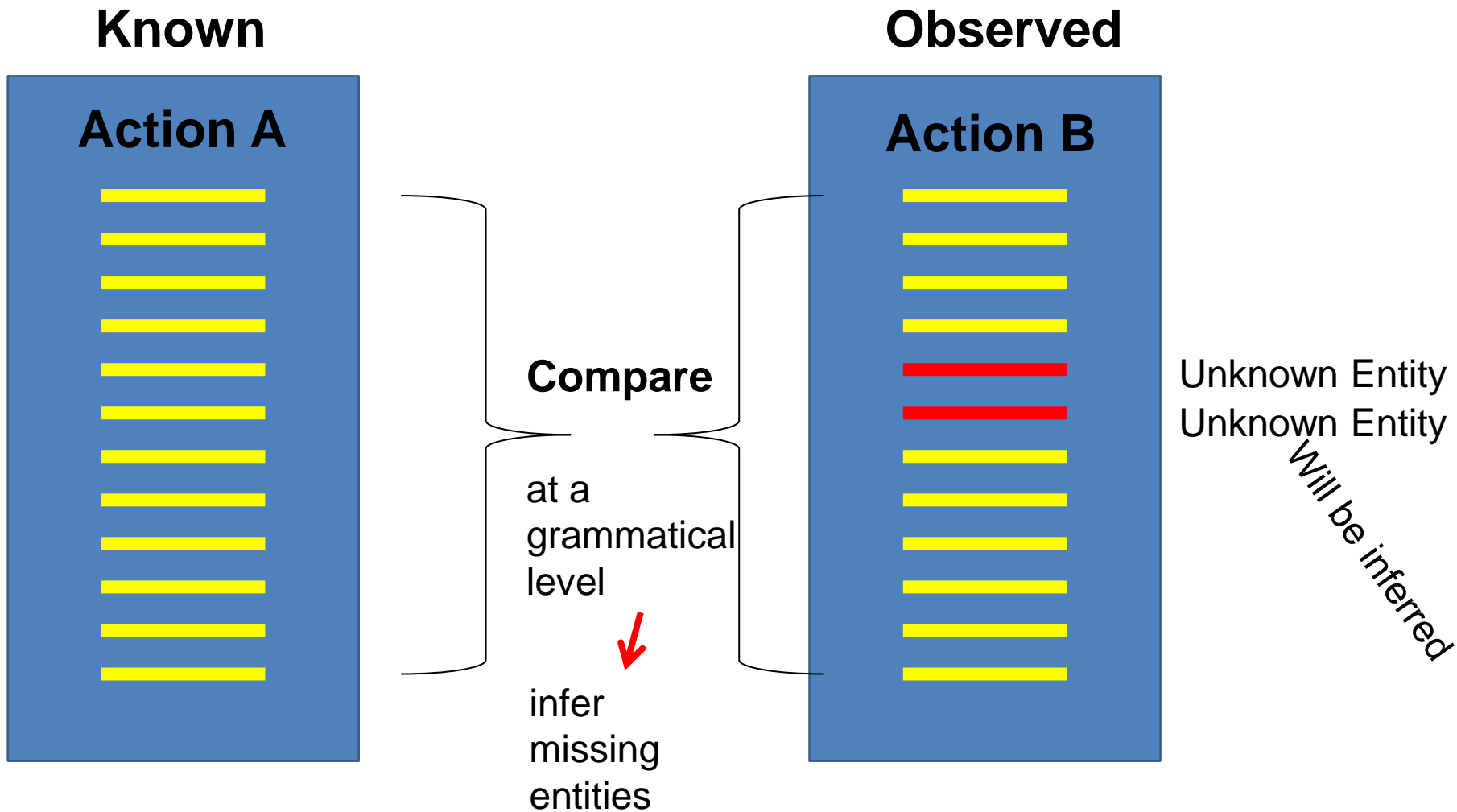


Rather traditional 3-Layer Architecture



Feedback
not indicated

Structural Bootstrapping at any level: utilizing grammatical correlations



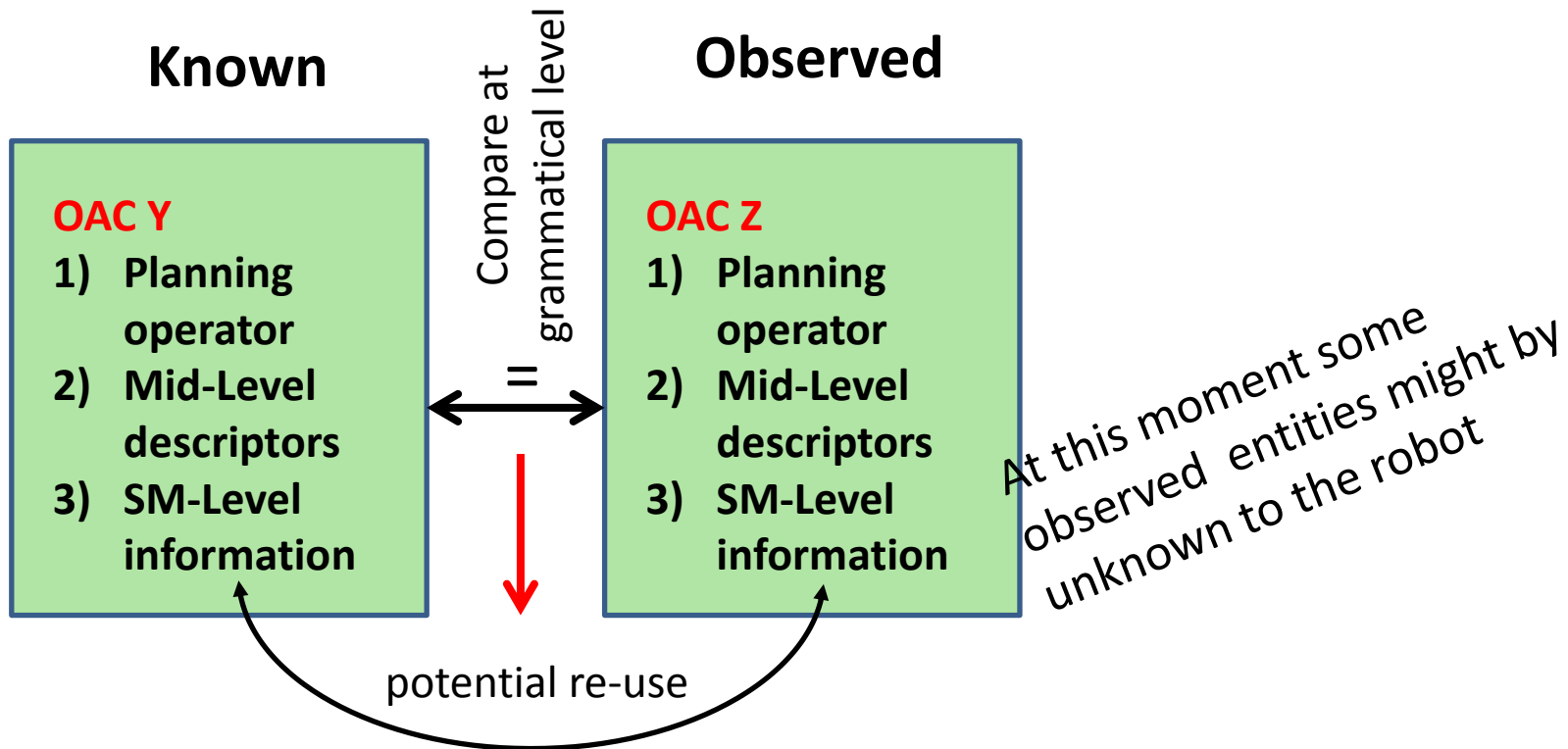
The „Innards“: Structure of an Executable (OAC)

Outside-in: Learned (and stored) OACs

OAC

- 1) Planning operator**
- 2) Mid-Level descriptors**
- 3) SM-Level information**

Structural Bootstrapping at any level: utilizing grammatical correlations



Bootstrapping via Re-use avoids full-fledged new-learning (outside in) and requires hopefully only „adjustments“.

Story line: robot making a cake

The task is to pour two ingredients (e.g. flour and water) and mix them together to obtain batter.

Experience from outside-in learning:

- Robot has learned earlier to execute the following actions :
 - pick up object;
 - put down object;
 - pour ingredient;
 - mix with a mixer.
- In addition, robot has learned earlier to execute wiping with a sponge.
- Furthermore the robot has a repository of objects-with-roles.

Story line: unknown situation

Let us assume a situation where mixer is not available, but a spoon is on the table.

- Robot can not make a plan for making batter as it only knows mixing with a mixer.
- Human demonstrates to a robot the procedure:
 - pour ingredient_1;
 - pour ingredient_2;
 - mix with a spoon.

Structural bootstrapping at three levels

- Planning Level
 - Grammatical categories
- Mid Level
 - SECs
- Sensorimotor Level
 - Several examples

Structural bootstrapping at three levels

- **Planning level**
 - Robot derives gramatical category for mixing with the spoon;
- Mid level
 - Robot infers mid-level from SEC similarity.
- Sensorimotor level
 - Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.
 - Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!
 - Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.
 - Robot enters the new object into the data-base of „objects-for-mixing“

Planning Details: Domain Specification

% foundations

```
types: [obj, hand, ingredient, bowl];
```

```
objects: [left:hand,right:hand,liquid1:ingredient,  
          liquid2:ingredient,mixingBowl:bowl,beaker:obj,  
          cup2:obj,mixer1:obj];
```

```
predicates: [haveBatterP( )];
```

% category definitions

```
category: pickC(hand,obj);
```

```
category: placeC(hand,obj);
```

% pour (add ingredient)

```
category: aiC(hand,ingredient,obj,bowl);
```

% making batter

```
category: mbC(ingredient,ingredient,bowl) [haveBatterP( )]  
        { [haveBatterP( )] > 0.01;  
          [!haveBatterP(0)] > 0.99; };
```

Planning Details (cont.)

% action definitions

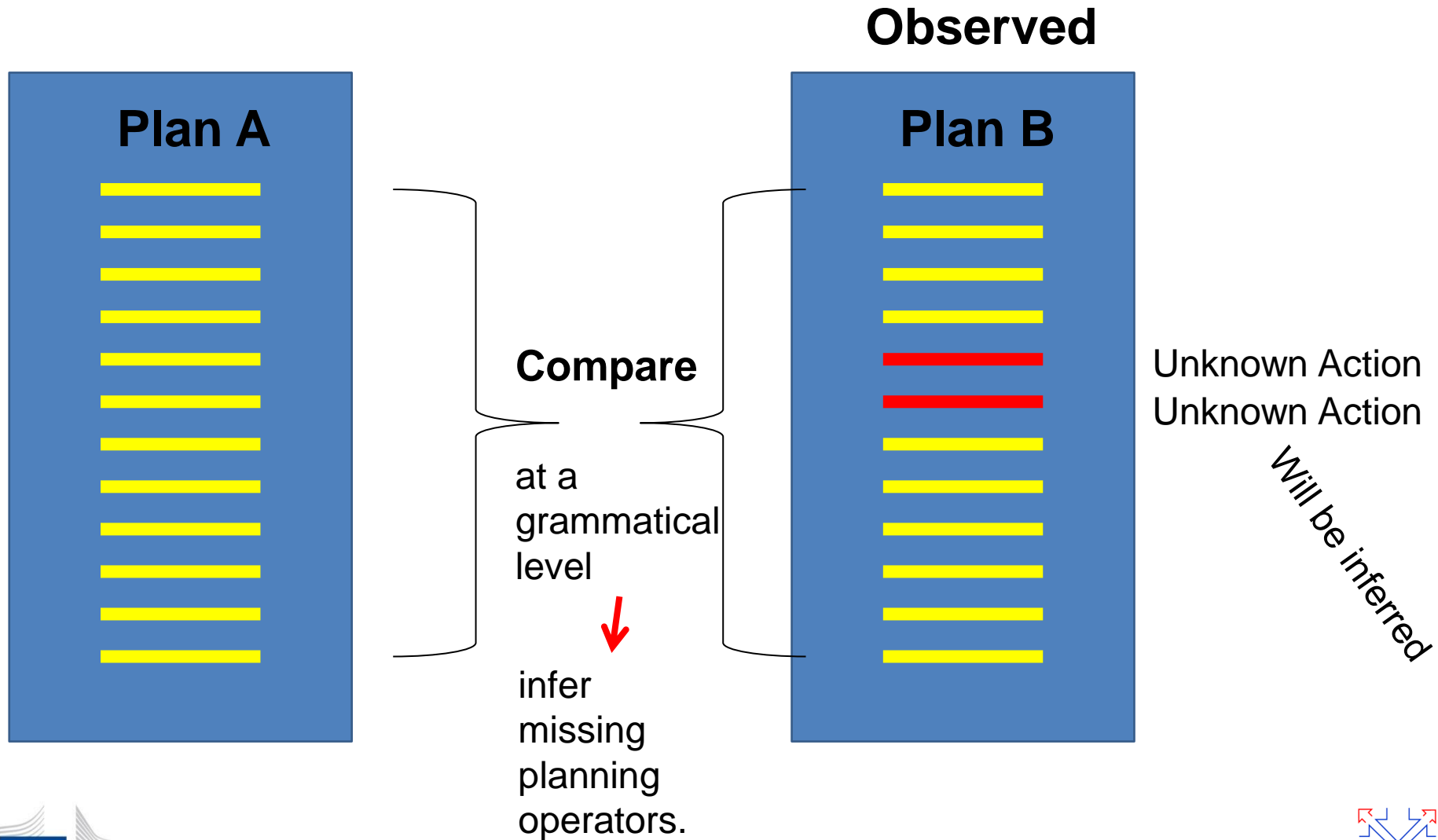
```
action: pickobj(hand,obj)
       [pickC(0,1)];
```

```
action: placeobj(hand,obj)
       [placeC(0,1)];
```

```
action: pour(hand, ingredient, obj, bowl )
       [((aiC(0,1,2,3))/placeC(0,2))\pickC(0,2)];
```

```
action: mix(obj,ingredient,ingredient,bowl)
       [((mbC(1,2,3))/placeC(4,0))\aiC(5,1,6,3),aiC(7,2,8,3 ),
       pickC(4,0)];
```

The actual inference process



The actual inference process

Recognizable instance of the original plan

```
testName: xpermix;  
initialState: [ ];  
observations: [  
  pickobj( left, beaker ),  
  pour( left, liquid1, beaker, mixingBowl ),  
  placeobj( left, beaker ),  
  pickobj( left, cup2 ),  
  pour( left, liquid2, cup2, mixingBowl ),  
  placeobj( left, cup2 ),  
  pickobj( right, mixer1 ),  
  mix( mixer1, liquid1, liquid2, mixingBowl )  
];
```

Observed instance of plan to learn the new action from

```
testName: xpermixnew;  
initialState: [ ];  
observations: [  
  pickobj( left, beaker ),  
  pour( left, liquid1, beaker, mixingBowl ),  
  placeobj( left, beaker ),  
  pickobj( left, cup2 ),  
  pour( left, liquid2, cup2, mixingBowl ),  
  placeobj( left, cup2 ),  
  pickobj( right, spoon1 ),  
  UNKNACT( UNKNOBJ, liquid1, liquid2, mixingBowl )  
];
```



Constructing the new executable (OAC)

- Planning Level: **System learns**

- Category for UNKNACT1 is the same as action mix category because it results in the same state of the world.

- action:

```
UNKNACT1(obj, ingredient, ingredient, bowl) [((mbC(1, 2, 3)) /  
{placeC(4, 0)}) \ {aiC(5, 1, 6, 3), aiC(7, 2, 8, 3), pickC(4, 0)}];
```

- Initial hypothesis of the action's preconditions and effects.

- Mid-level.....still missing

- Sensorimotor level.....still missing

Structural bootstrapping at three levels

- Planning level
 - Robot derives grammatical category for mixing with the spoon;
- **Mid level**
 - **Robot infers mid-level from SEC similarity.**
- Sensorimotor level
 - Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.
 - Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!
 - Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.
 - Robot enters the new object into the data-base of „objects-for-mixing“

Mid-Level Similarities using SECs + Semantic Outcomes as descriptors

Picking up

hand, beaker 0 1

Putting down

hand, beaker 1 0

Pouring

hand, beaker 1 1 1 1 1

beaker, mixbowl 0 1 1 1 0

beaker, liquid2 1 1 1 0 0

mixbowl, liquid2 0 0 1 1 1

Mixing with a mixer

hand, mixer 0 1 1 1 0

mixer, dough 0 0 1 0 0

Stirring with a spoon (???)

hand, ??? 0 1 1 1 0

???, dough 0 0 1 0 0

Wiping

hand, sponge 0 1 1 1 0

sponge, tray 0 0 1 0 0

Mid-Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of SECs**

The here-found similarity suggests that the mixing-SEC could be used to encode the stirring action at mid-level, too.

Mixing with a mixer

hand, mixer 0 1 1 1 0

mixer, dough 0 0 1 0 0

=

Stirring with a spoon (???)

hand, ??? 0 1 1 1 0

???, dough 0 0 1 0 0

Constructing the new executable (OAC)

- Planning Level

- Category for UNKNACT1 is the same as action `mix` category because it results in the same state of the world.
 - action: `UNKNACT1(obj, ingredient, ingredient, bowl) [((mbC(1, 2, 3)) / {placeC(4, 0)}) \ {aiC(5, 1, 6, 3), aiC(7, 2, 8, 3), pickC(4, 0)}] ;`
- Initial hypothesis of the action's preconditions and effects

- Mid-level

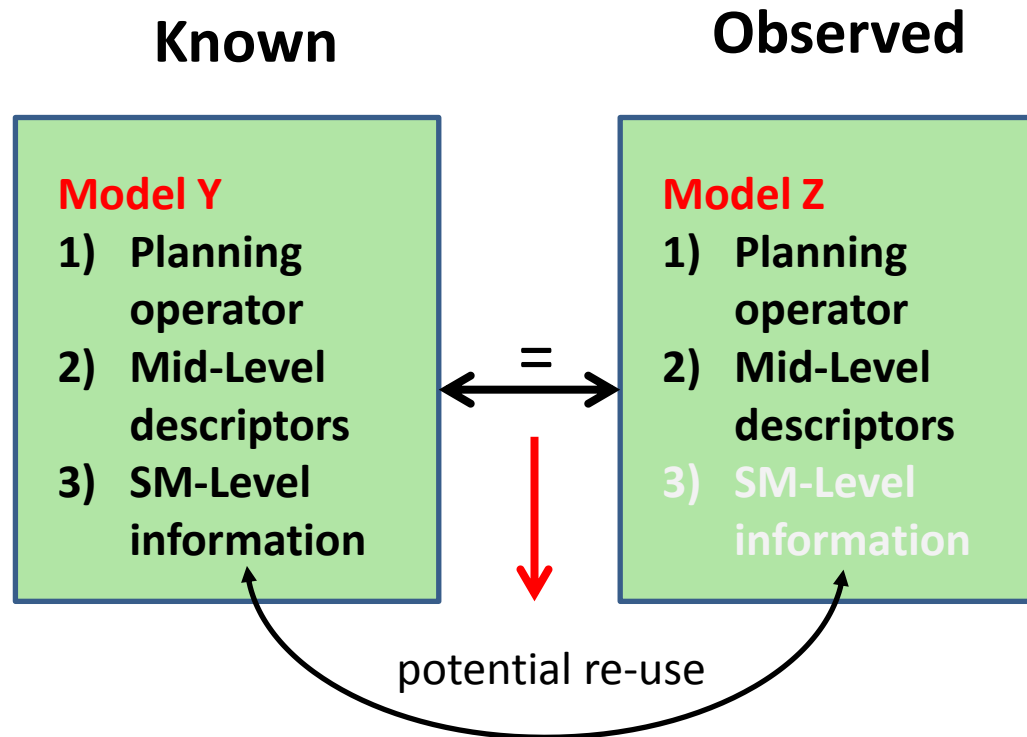
- SEC: hand, ??? 0 1 1 1 0
 ???, dough 0 0 1 0 0

As the SEC from mixing is (ideally) identical to the new one we use the (blue) mixing SEC to encode the new operation, too.

- Sensorimotor level.....still missing

Sensorimotor-Level: Using mid-level similarity to infer control-level cross-functionalities

Outside-in: Learned (and stored) conjectures



Bootstrapping via Re-use avoids full-fledged new-learning (outside in) and requires hopefully only „adjustments“.

Structural bootstrapping at three levels

- Planning level
 - Robot derives grammatical category for mixing with the spoon;
- Mid level
 - Robot infers mid-level from SEC similarity.
- **Sensorimotor level**
 - **Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.**
 - Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!
 - Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.
 - Robot enters the new object into the data-base of „objects-for-mixing“

Mid-Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of Motion**

The here-found similarity suggests that transfer of known control information from wiping to stirring should be possible! **Here Motion**

Stirring with a spoon (???)

hand, ??? 0 1 1 1 0

???, dough 0 0 1 0 0

=

Wiping

hand, sponge 0 1 1 1 0

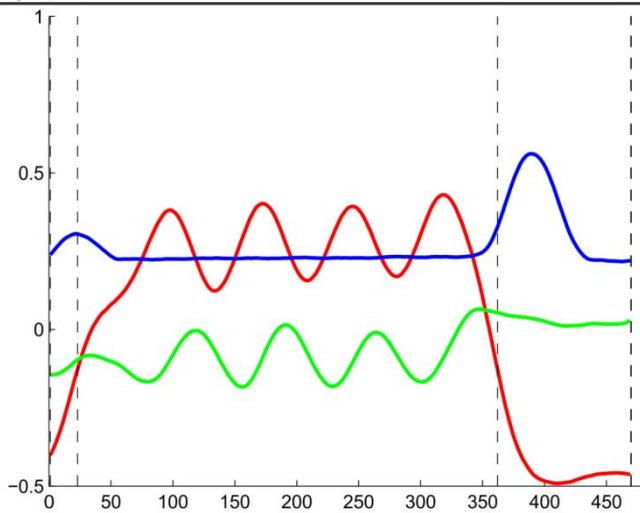
sponge, tray 0 0 1 0 0

Mid-level based Sensori-Motor Level Similarities: Wipe and Stir: **Transfer of Motion**

Wipe: Motion Encoding (e.g. DMP parameters)

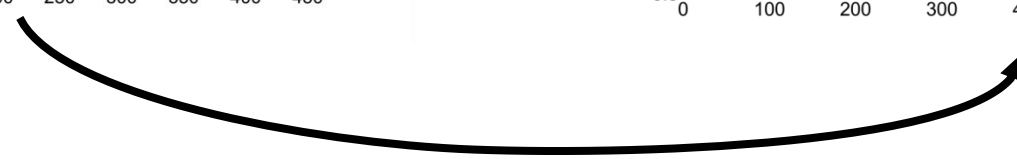
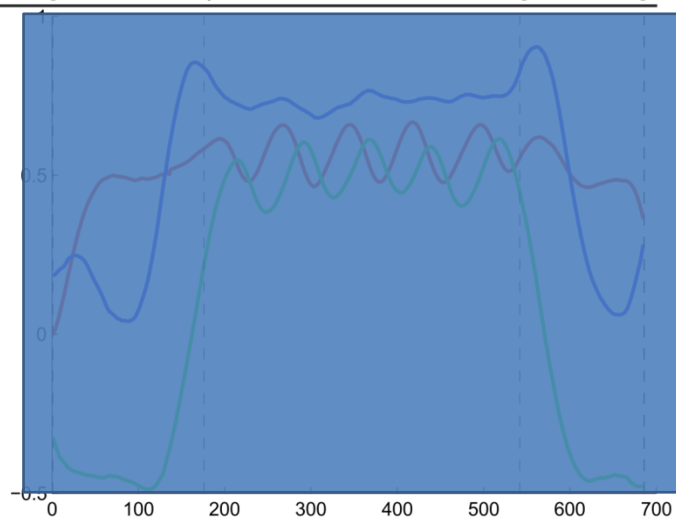
SEC wipe

Hand, Sponge	1	1	1	0
Sponge, Tray	0	1	0	0



SEC stir

Hand, Spoon	1	1	1	0
Spoon, Bowl	0	1	0	0



Transfer!

Constructing the new executable (OAC)

- Planning Level

- Category for UNKNACT1 is the same as action mix's category because it results in the same state of the world.

- `action: UNKNACT1 (obj, ingredient, ingredient, bowl) [((mbC (1, 2, 3)) / {placeC (4, 0)}) \ {aiC (5, 1, 6, 3), aiC (7, 2, 8, 3), pickC (4, 0)}] ;`

- Initial hypothesis of the action's preconditions and effects

- Mid-level

- SEC: hand, ??? 0 1 1 1 0
 ???, dough 0 0 1 0 0

- Sensorimotor level

- Stir motion: = Wipe-Motion Encoding (e.g. DMP parameters)

Structural bootstrapping at three levels

- Planning level
 - Robot derives grammatical category for mixing with the spoon;
- Mid level
 - Robot infers mid-level from SEC similarity.
- **Sensorimotor level**
 - Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.
 - **Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!**
 - Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.
 - Robot enters the new object into the data-base of „objects-for-mixing“

Mid-Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of Objects**

The here-found similarity suggests that transfer of known control information from wiping to stirring **also about objects should be possible!**

Stirring with a spoon (???)

hand, ??? 0 1 1 1 0

???, dough 0 0 1 0 0

=

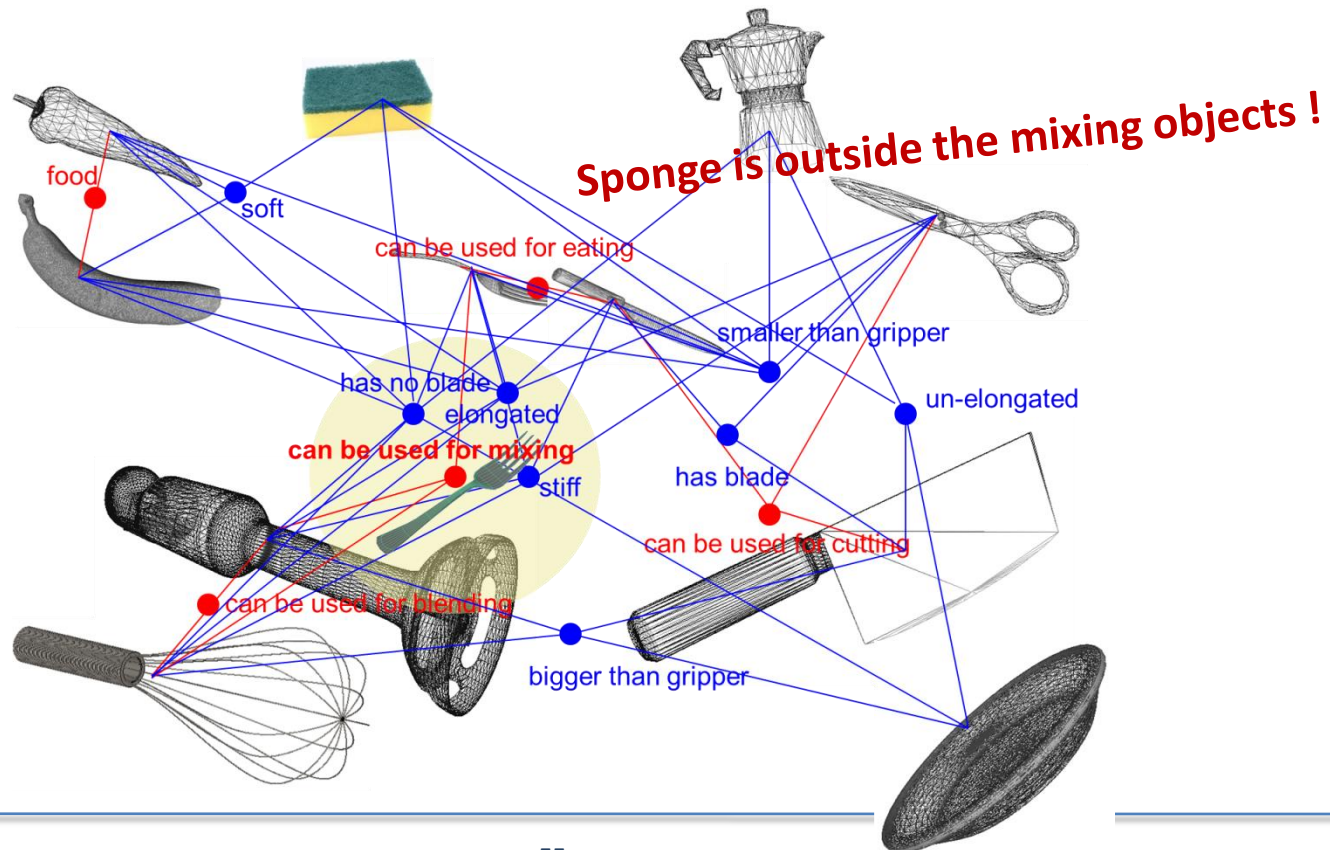
Wiping

hand, sponge 0 1 1 1 0

sponge, tray 0 0 1 0 0

Mid Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of Objects**

- Sponges should be „Objects for Mixing“
- Correction via the repository of objects-with-roles: mixing



Structural bootstrapping at three levels

- Planning level
 - Robot derives grammatical category for mixing with the spoon;
- Mid level
 - Robot infers mid-level from SEC similarity.
- **Sensorimotor level**
 - Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.
 - Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!
 - **Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.**
 - Robot enters the new object into the data-base of „objects-for-mixing“

Mid Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of Objects**

The here-found similarity suggests that the one could **look into the cluster of objects for mixing to find another possible object.**

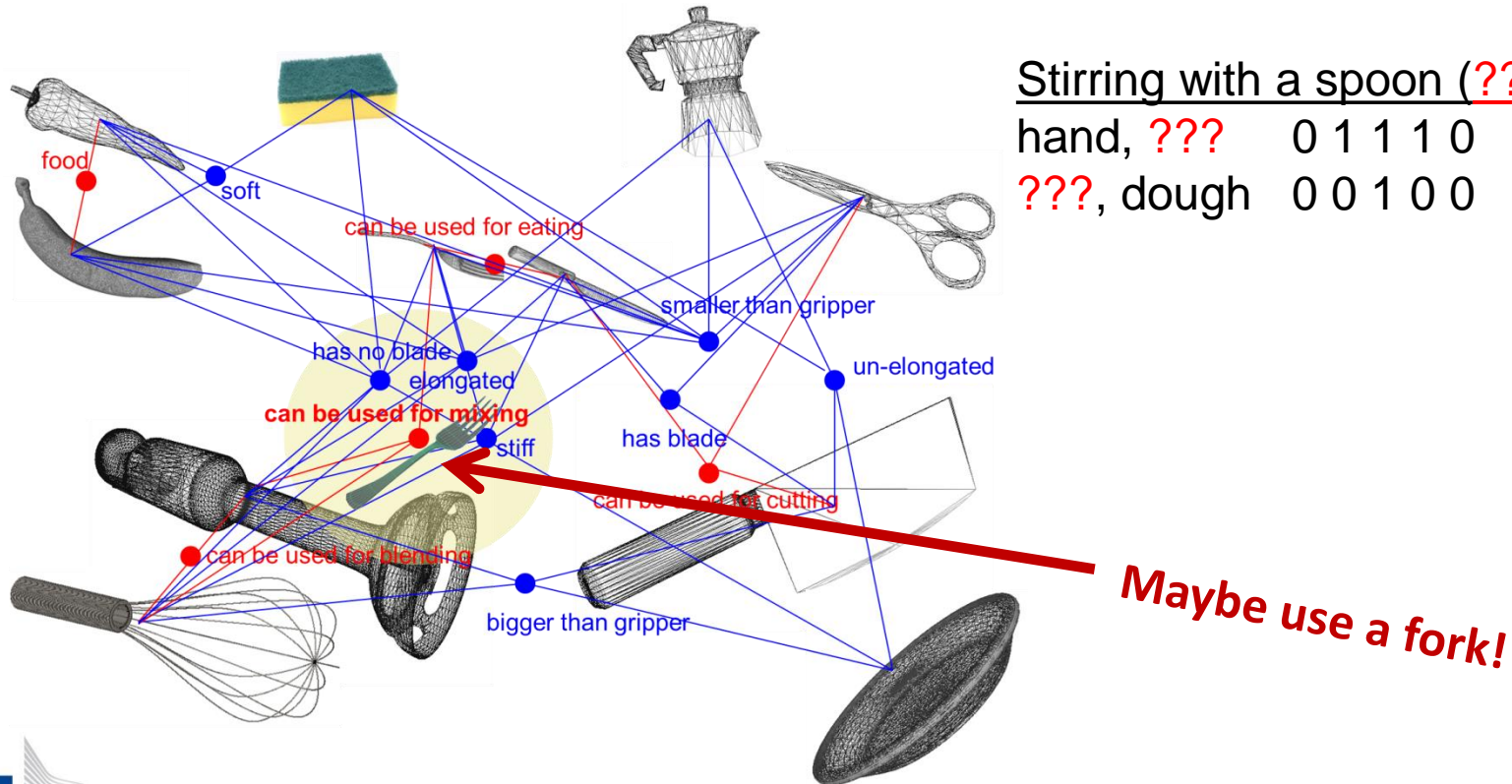
Mixing with a mixer

hand, mixer	0	1	1	1	0
mixer, dough	0	0	1	0	0

=

Stirring with a spoon (???)

hand, ???	0	1	1	1	0
???, dough	0	0	1	0	0



Maybe use a fork!

Constructing the new executable (OAC)

- Planning Level

- Category for UNKNACT1 is the same as action mix's category because it results in the same state of the world.

- action: UNKNACT1(obj, ingredient, ingredient, bowl) [((mbC(1, 2, 3)) / {placeC(4, 0)}) \ {aiC(5, 1, 6, 3), aiC(7, 2, 8, 3), pickC(4, 0)}] ;

- Initial hypothesis of the action's preconditions and effects

- Mid-level

- SEC: hand, ??? 0 1 1 1 0
 ???, dough 0 0 1 0 0

- Sensorimotor level

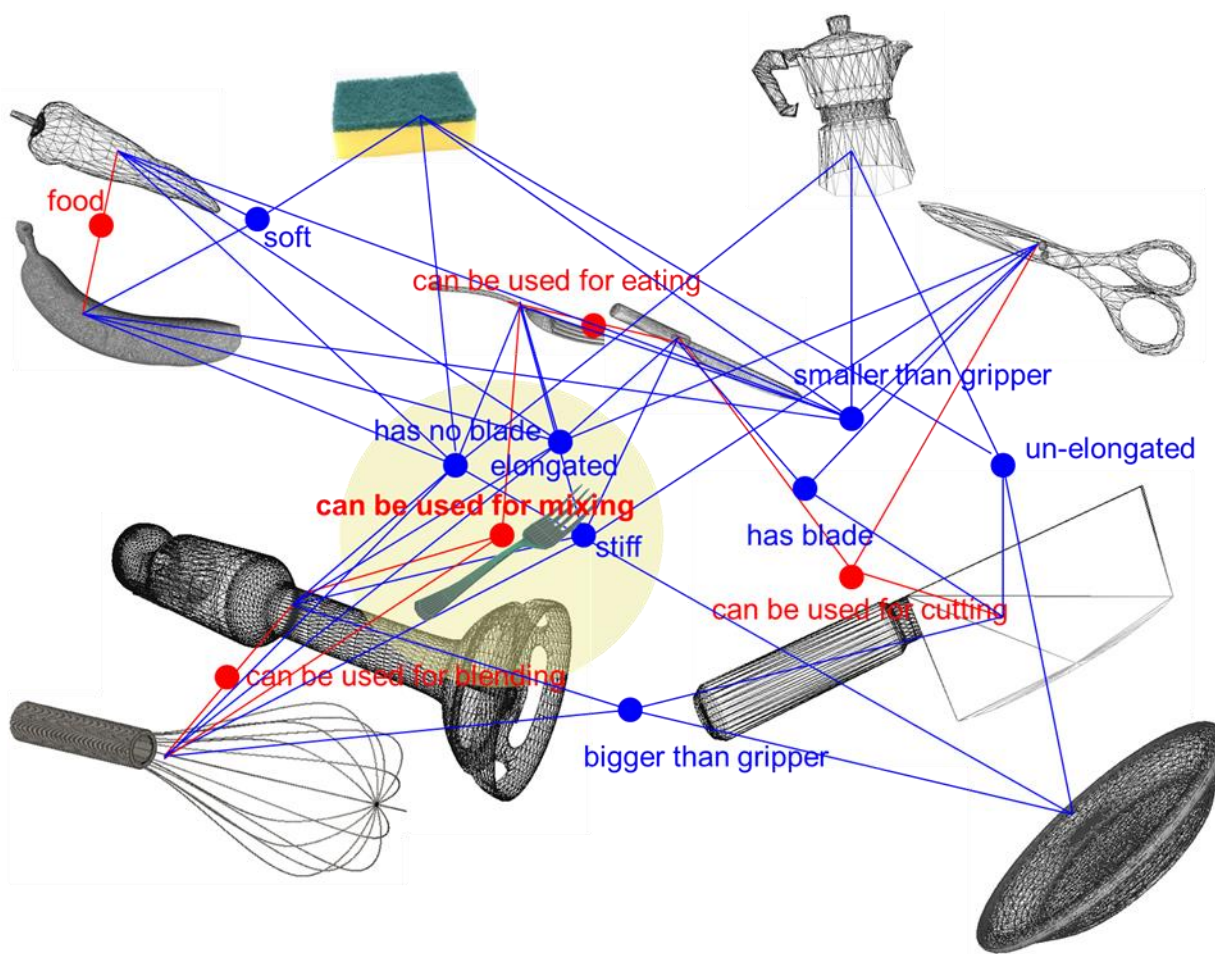
- Stir motion: = Wipe-Motion Encoding (e.g. DMP parameters)

- Object: „Fork“ or else

Structural bootstrapping at three levels

- Planning level
 - Robot derives grammatical category for mixing with the spoon;
- Mid level
 - Robot infers mid-level from SEC similarity.
- **Sensorimotor level**
 - Robot derives that mixing with a spoon is similar to wiping with a sponge and re-uses the wiping program.
 - Robot generalizes in the same way into objects and suggests to use a sponge. Countercheck yields rejection!
 - Robot retrieves an object-for-mixing from the data-base of objects-for-mixing.
 - **Robot enters the new object into the data-base of „objects-for-mixing“**

Mid Level Similarities using SECs + Semantic Outcomes as descriptors: **Transfer of Objects**

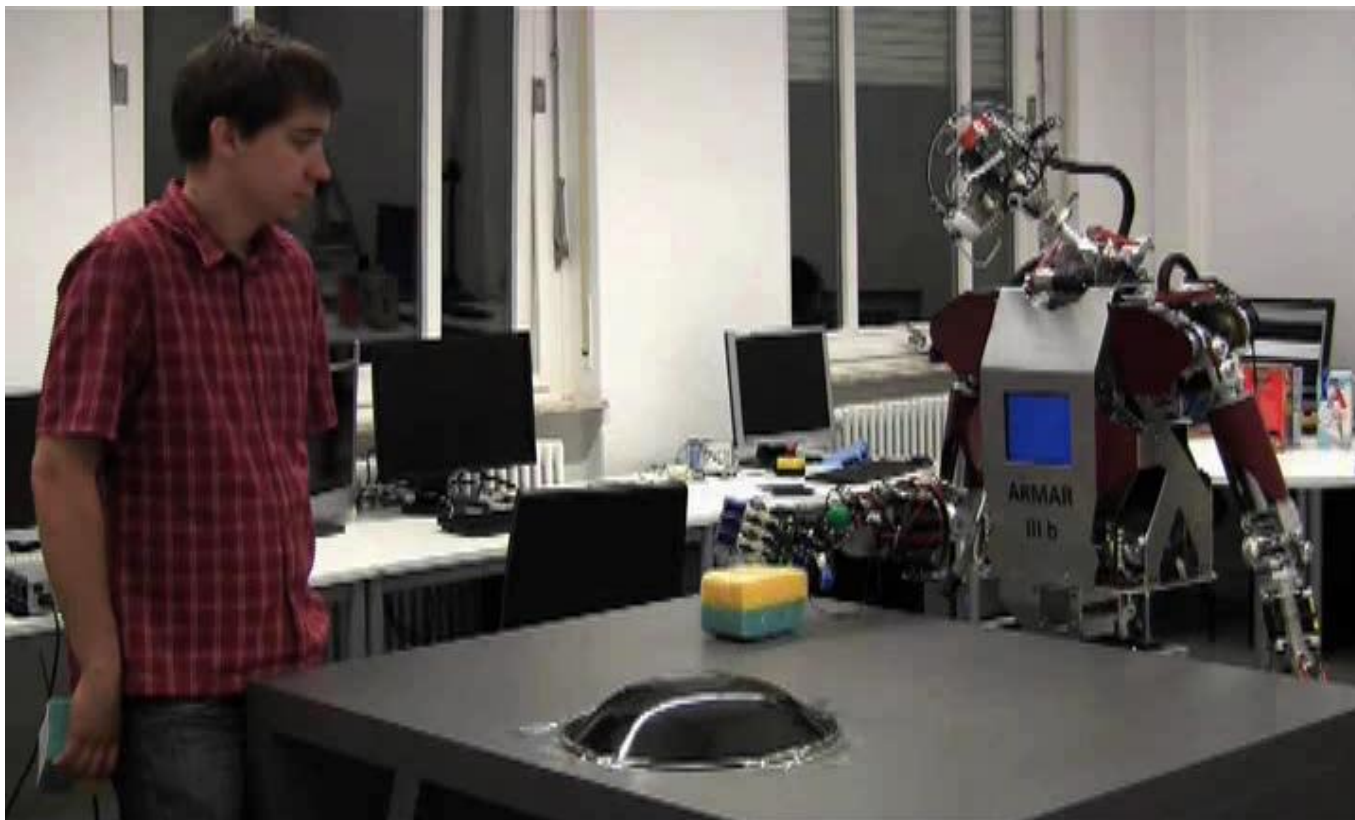


Spoon is entered in the repository (its features need to be extracted to do this!)

Implementation: SEC on ARMAR



Let's wipe the table

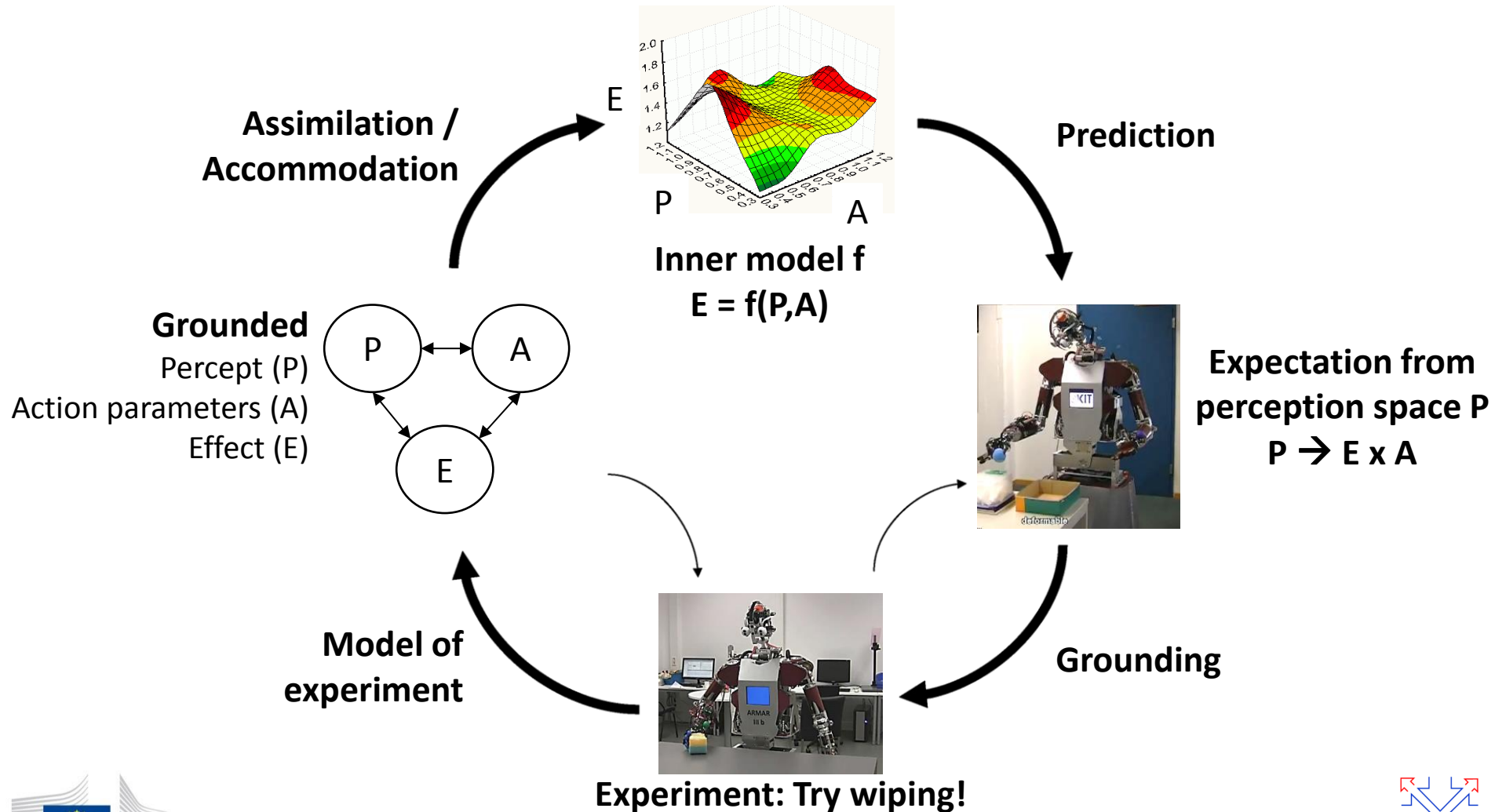


Joint work with Ales Ude, Andre Gams

SB in wiping

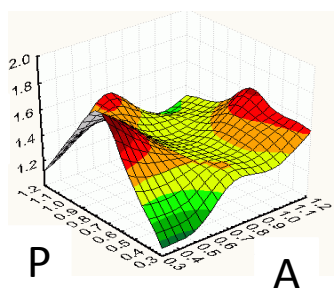
- **Objective:** Specification of action parameters based on perceptual information (visual, haptics, etc.)
 - Actions represented as generalized movement primitives
 - Instantiation with appropriate action parameters leads to a goal-directed execution
- **Evaluation:** wiping OAC in Xperience learning cycle
 - Robot examines an object (deformability, size,...)
 - Robot wipes the table
 - Online evaluation of current wiping process and parameter space exploration
 - Evaluation of cleaning success and forces exerted on the TCP
- **Search the cross space (object features X action parameters) for correlations which allow the creation and refinement of a wiping OAC**

Wiping in the Xperience Learning Cycle (1)



Wiping in the Xperience Learning Cycle (2)

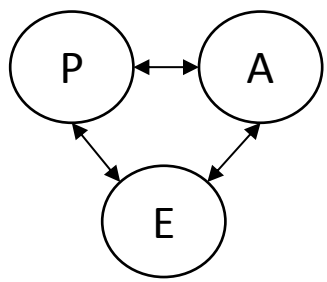
Support Vector Regression to train model



Inner model f
 $D = f((d,h),a)$

- Assessment of object height h and deformability d
- Estimation of initial amplitude a

Grounded
 deform.(d), height (h)
 amplitude (a)
 Dirt Level (D)



Variation of amplitude a

- Assessment of dirt level D (cleaning success)
- Measuring forces exerted on TCP

Collect training data



Execute periodic wiping DMP

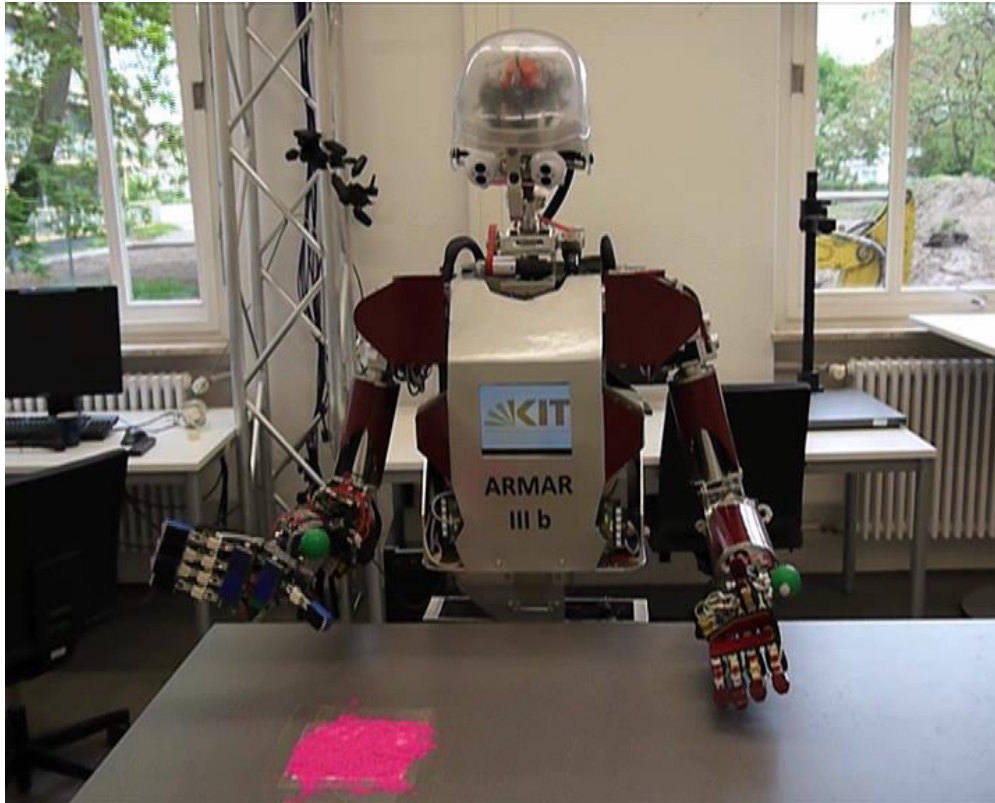
Wiping Scenario: Spaces and Skills (1)

- Perceptual Space (P)
 - **Object height** is measured when an object is detected to be in hand. Height equivalent to distance between thumb and index finger
 - **Object deformability** denotes the extent of deformation which an object experiences when being squeezed
- Effect (E)
 - **Dirt level** is measured using vision. The dirty area is detected and segmented visually. The dirt level denotes the ratio between the remaining dirt within the initial area and the area size
 - **Forces** acting on the TCP should not exceed a certain magnitude to avoid damage on the robot

Wiping Scenario: Spaces and Skills (2)

- Action Parameter Space (A):
 - Wiping action encoded as a transient periodic DMP
 - Initially learned from demonstrations of human wiping movements in x-y plane
 - DMP extended by third transformation system to encode the adaptation movement towards the surface to be wiped
 - **Amplitude** scales the movements. The amplitude is considered to be appropriate when
 - Forces acting on the TCP are within a tolerable range
 - Modify amplitude when forces are too high
 - Dirt level is gradually decreasing
 - Increase amplitude when dirt level is too high and remains unchanged during wiping

Demonstration on ARMAR



Training objects

Deformability	Height	Amplitude
33.67	79.0	1.0
10.18	87.0	1.928
41.29	102.0	3.249
45.37	91.0	1.264

Test objects

Deformability	Height	Estimated Amplitude
29.0	79.0	1.26
6.6	91.0	2.21
45.9	97.0	2.26

Model representing the cross space $P \times A$ is determined using regression techniques (Support Vector Regression)

Wiping: Planned Work

- Extend perceptual space **P**
 - Intrinsic object properties (size, deformability, weight, texture)
 - Extrinsic object properties (object pose in hand)
- Extend action parameter space **A**:
 - Adaptive force thresholds
 - Frequency
- Universal model based on comprehensive data collected during exploration and action execution
- Incremental model refinement
- ...



Challenges and Future Work

- Strengthen the connections between the language/planning and robotics
- Define appropriate quantitative metrics that demonstrate the effectiveness of the constructed bootstrapping systems
- Hierarchical representations that allow for re-use of previously learned components.

Take Home Message

- We found bootstrapping mechanisms
 - at different levels (planning, mid-level, sensorimotor),
 - with respect to different aspects (e.g. motion, objects) as well as
 - targeting different outcomes (e.g. action filling-in or memory augmentation). Other ways of bootstrapping might be possible, too, but have not yet been discovered by this consortium.
- Problems:
 - Many of the technical aspects described here do not yet work fully automatically.
 - Hard problems exist especially in the regime of relevant-feature recognition as well as when performing action chunking and motion-parameter extraction.
 - Furthermore, at the moment we have focused only on one example of an action plan.
- Current main effort
 - resolving the technical problems
 - integrating the here-discussed bootstrapping mechanism more and more in an automatical way
 - analyzing more action plans
- Especially the last aspect might then lead to the discovery of more possible bootstrapping mechanisms.

Exercise

- Provide examples for Structural Bootstrapping on
 - Planning level
 - mid-level
 - Sensorimotor level
- One beer for each “correct” example!



Thanks ...

XPERIENCE.ORG

Jan 2011 - Dec 2015



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Thank you for your attention

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