

**Riccardo Caccavale**

**Tutor: Alberto Finzi**

**XXIX Cycle - III year presentation**

**Flexible Task Execution and  
Cognitive Control in  
Human-Robot Interaction**



# Background

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**Graduation MS:** Computer Science (Computational Models) Federico II.

**DIETI groups:** PRISCA laboratory of advanced cognitive science, PRISMA laboratory of industrial robotics.

**Collaborations:** LAAS-CNRS (Toulouse), TUM (Munich)

# Credit Summary

	Credits year 1							Credits year 2							Credits year 3							Total	Check			
	Estimated	1	2	3	4	5	6	Summary	Estimated	1	2	3	4	5	6	Summary	Estimated	1	2	3	4			5	6	Summary
<b>Modules</b>	18					3	14	17	15		3				3	6	7						6	6	29	30-70
<b>Seminars</b>	13				2,8	2,2		5	4	1				5,8		6,8	0							0	12	10-30
<b>Research</b>	34	10	10	8	8	7	5	48	45	9	7	10	10	5	7	48	40	8	8	8	8	8	3	43	139	80-140
	65	10	10	8	11	12	19	70	64	10	10	10	10	11	10	61	47	8	8	8	8	8	9	49	180	180

## Period Abroad:

3/05 – 31/05 and 21/06 – 28/07 at TUM university of Munich.

# Flexible Human-Robot Interaction

In social and industrial robotics **flexible** and **natural** interaction with humans is **needed** to perform structured collaborative tasks.

Robots should be able to **flexibly adapt** action execution to the human behaviors and the environmental changes.

**Plan-based:** relevant works in rely on the *three layer architectures* [Gat et al.] exploiting planning, re-planning [Ayan et al] and plan-adjustment [Estlin et al].

- Sometimes slow to react to unexpected events or human interventions.

**Behavior-based:** some approaches involve *reactive* and *behavior-based* systems [Arkin] to on-line adapt task/plan execution [Nicolescu et al, Proetzsch et al].

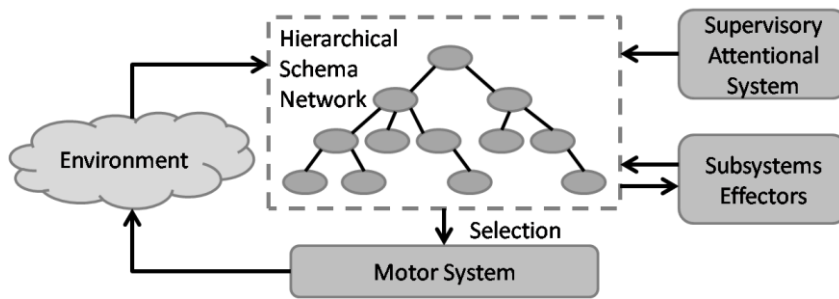
- Need to be orchestrated.

**Cognitive-based:** *cognitive architectures* [Langley et al] have also been proposed to develop flexible and human-friendly robotic frameworks [Anderson et al, Albus et al].

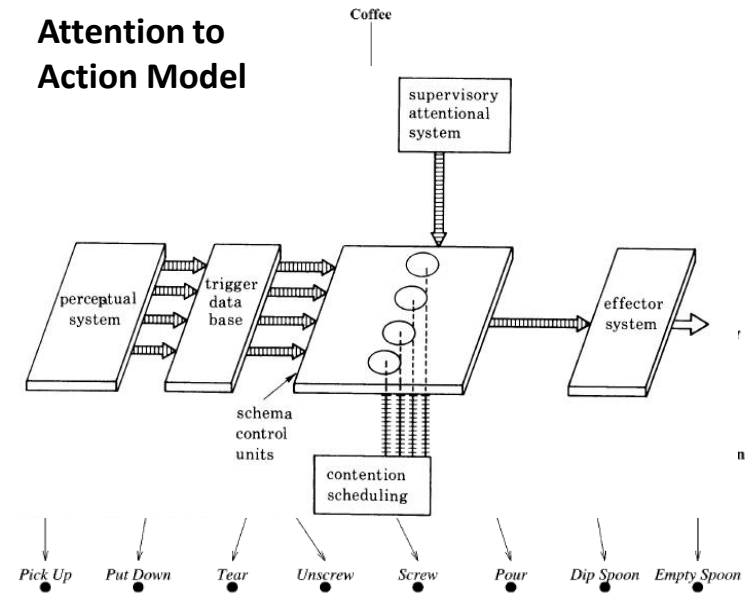
- Focused on psychology rather than robotics.

# Cognitive Control and Attention

**Cognitive control:** ability to configure itself for the performance of specific tasks through appropriate adjustments in perceptual selection, response biasing, and on-line maintenance of contextual information. [Botvinick et al. 2001]

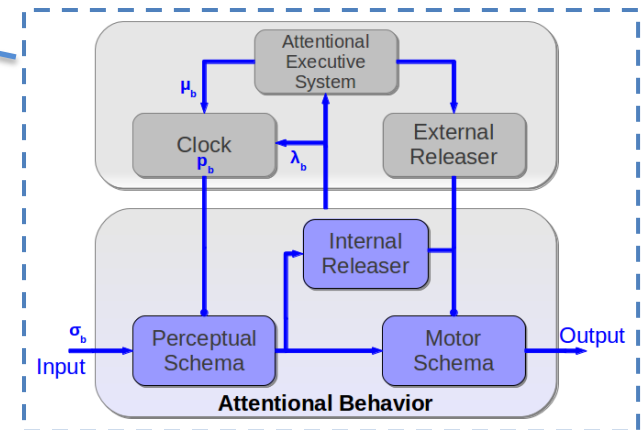
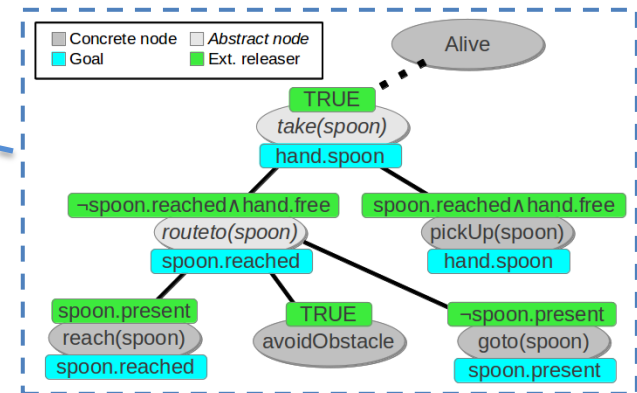
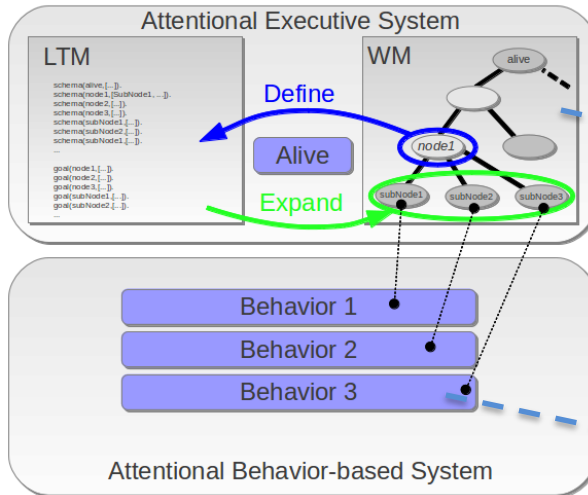


## Attention to Action Model



- **Contention Scheduling:** conflicting actions have to compete each other: only the most active actions are executed.
- **Supervisory Attentional System:** is employed to oversee the contention and regulate actions according to the context [Norman and Shallice 80].

# Attentional Executive System



$$e_b = \mu_b \lambda_b$$

**Working Memory:** maintains the **executive state** and the structure of the tasks in the **attentional focus** of the system, including all the task the system is executing or willing to execute.

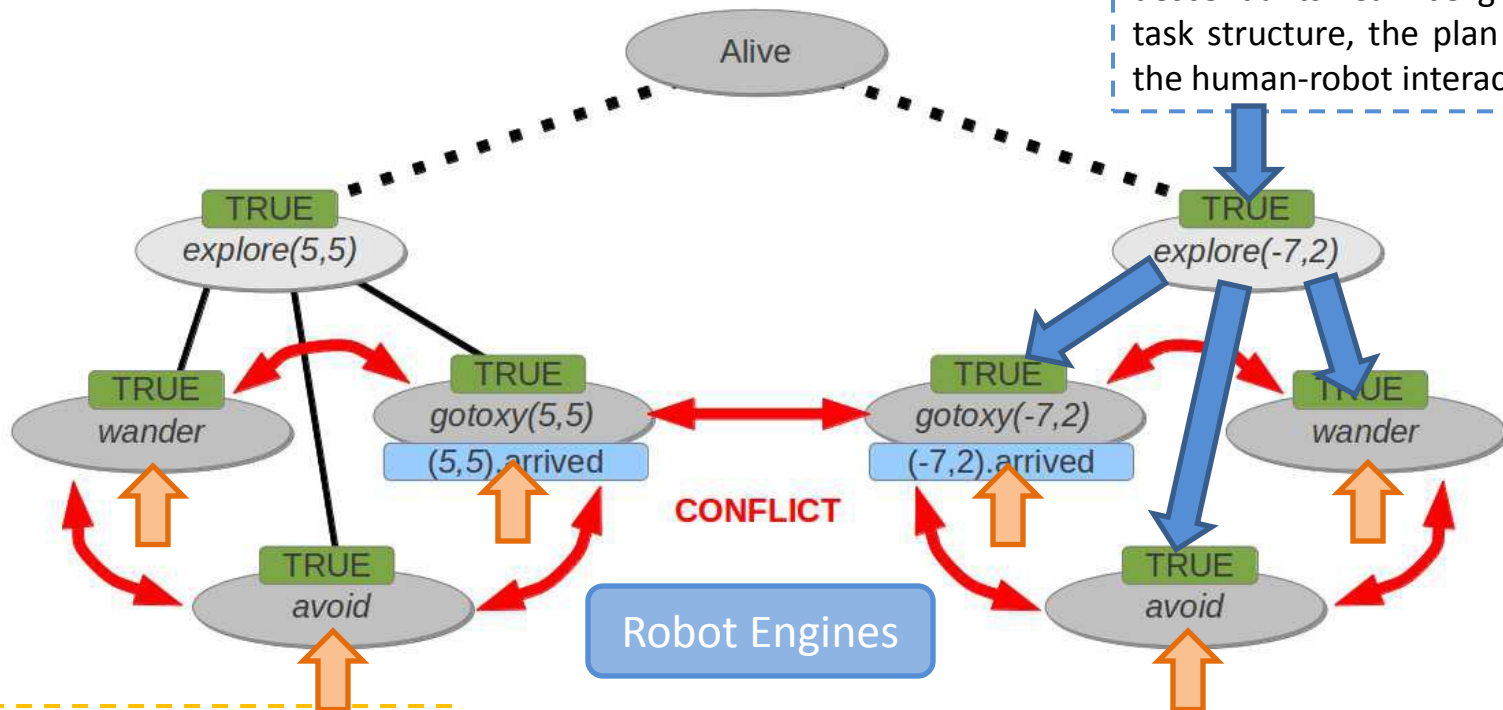
**Long Term Memory:** is a repository which contains the definition of all the **tasks available** to the system.

**Attentional Behaviors:** **elaborates** sensor data (behavior-specific stimuli) producing a pattern of **motor actions**.

**Emphasis:** **integrates** top-down ( $\mu_b$ ) and bottom-up ( $\lambda_b$ ) stimulation to manage the **contention** between behaviors and **clocks**.

# Contention and Regulations

**Top-down:** is inherited by all descendants. Can be given by the task structure, the plan or through the human-robot interaction.



**Bottom-up (stimuli-driven):** given by salient elements of the environment (objects, landmarks, obstacles, etc.).

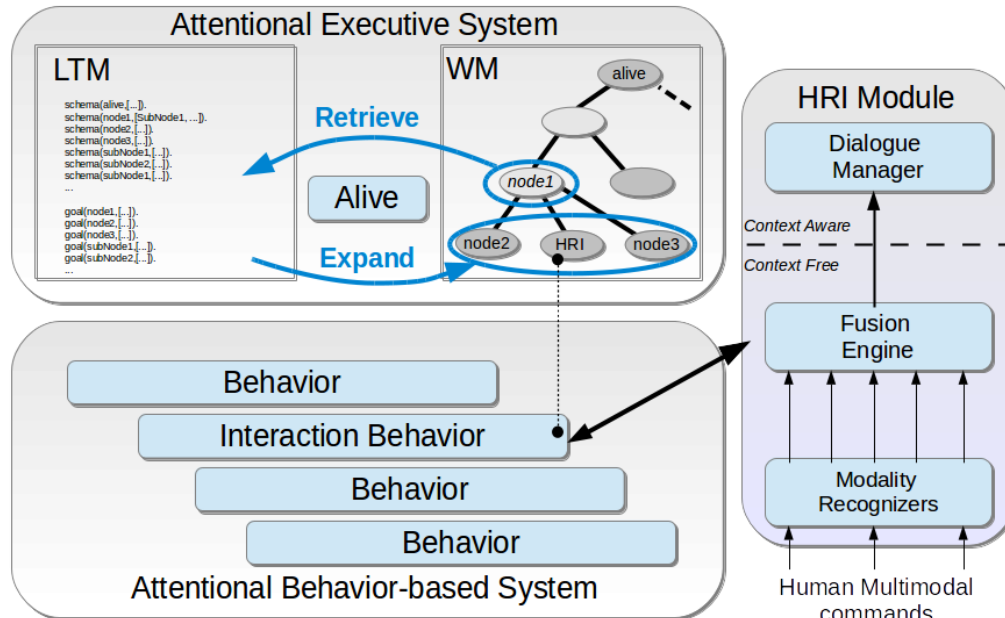
**Contentions** among behaviors competing for mutually exclusive state variables are solved following a *winner-takes-all* approach. The most emphasized behavior is selected with the exclusive access.

# Summary

- In many robotic contexts a robotic systems should be able to dynamically execute activities, react to human behaviors and environmental changes.
- Prominent approaches rely on planning/re-planning processes during the task execution that are time consuming.
- In the proposed approach we exploit contention scheduling and supervisory attention during the task execution.
- The system includes attentional regulations mechanisms for the flexible orchestration of robotic sensorimotor processes.
- During this PhD, the proposed system has been applied in different robotic contexts including HRI, flexible plan execution, and learning...



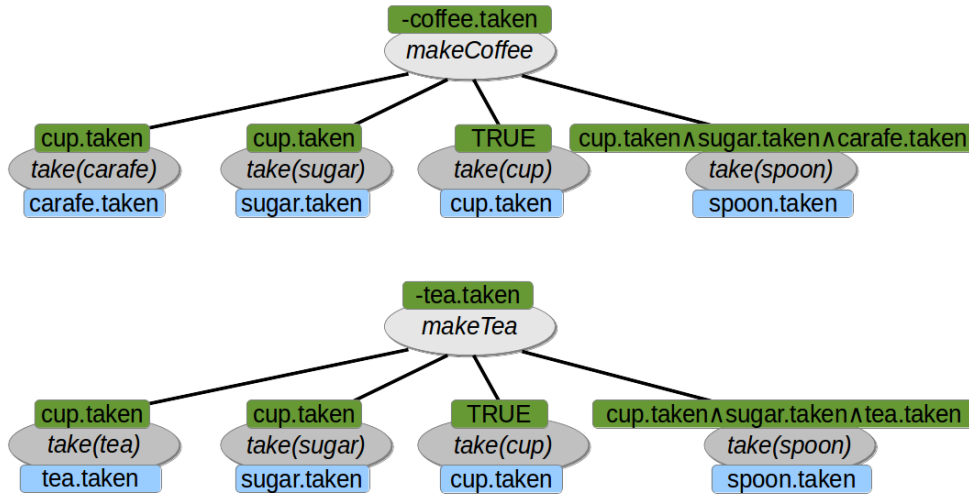
# Attentional Regulations in HRI



1. **Recognition layer** acquires the input from sensors and provide a classification for each interaction modality.
  1. Speech: Julius based recognition.
  2. Gestures: Latent Dynamic Conditional Random Fields (LDCRF).
2. **Fusion Layer** acquires the N-best gestures and speech from the classifiers to produce a list of N-best users intention.
3. **Dialogue Layer** integrates information about the dialogue history that is represented as a Partially Observable Markov Decision Process (POMDP) producing a user intention according to his policy.

- Commands recognized by the HRI module are associated with tasks to be allocated in WM.
- Tasks can be instantiated with contextual subtasks and arguments, while their execution is regulated by top-down/bottom-up attentional mechanisms.

# Interaction Ambiguities: Coffee or Tea?



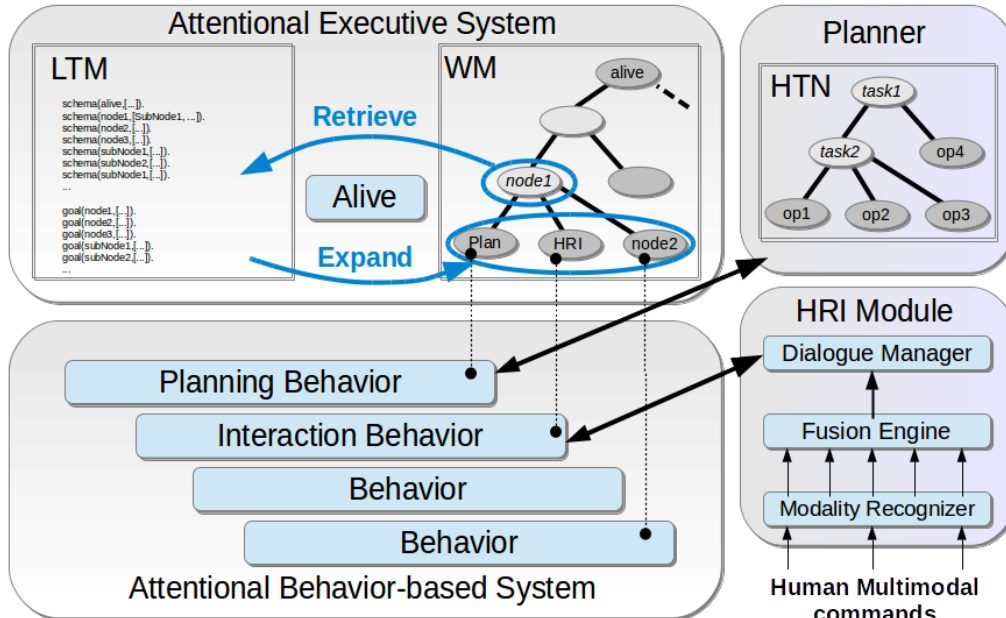
**Interactive Commands:** some user's acts are not explicit commands, therefore the system should interpret the human intention supporting the human activity with a proactive behavior.

**Test Scenario:** we consider the system at work in a kitchen scenario where two ambiguous tasks (make-coffee and make-tea) should be interpreted by the system.

	Success	Correction	Failures
Percent.	56.6%	26.7%	16.7%
Hum. Act.	1.48	2.25	3.6
Std.	0.67	0.42	0.52



# Flexible Plan Execution



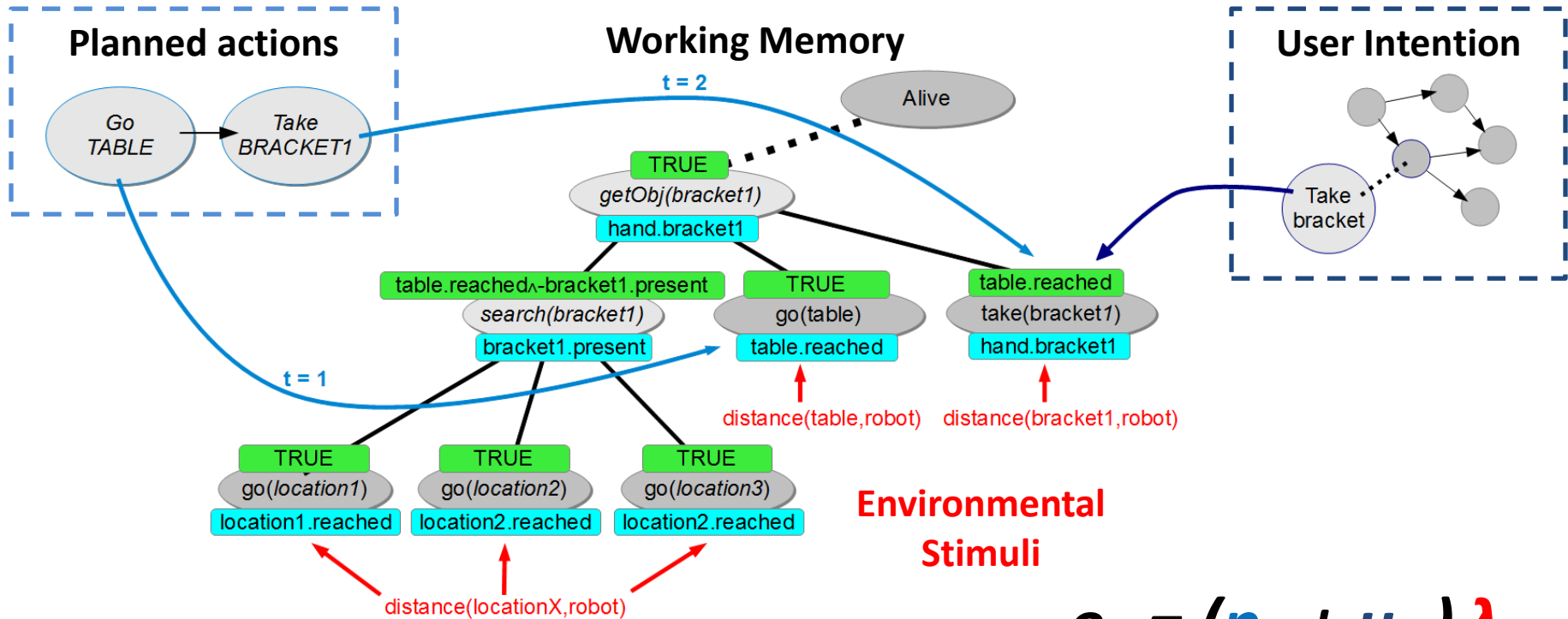
**Hierarchical Task Network (HTN):** Planning problems are specified in a hierarchical network providing a set of *primitive*, *compound* or *goal* tasks.

**Human-Aware Task Planner (HATP):** is an HTN planner that produces a different sequence of actions for each agent (human or robot).

- The planner suggests to the attentional system actions or subtasks to perform.
- The attentional system integrates the plan with the user commands and the environmental context in order to flexibly react to unexpected events.



# Attentional Regulations



**Environmental Stimuli**

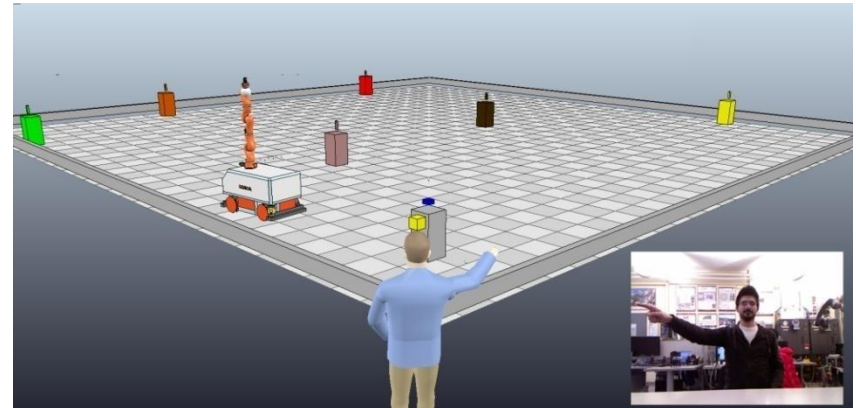
$$e_b = (p_b + u_b) \lambda_b$$

Attentional Regulation and Action Selection:

- The action selected by the plan and the user are **emphasized** (top-down).
- The bottom-up stimulations emphasizes actions that are **more accessible** to the robot.
- The **most emphasized** actions among all active actions are selected for the execution.

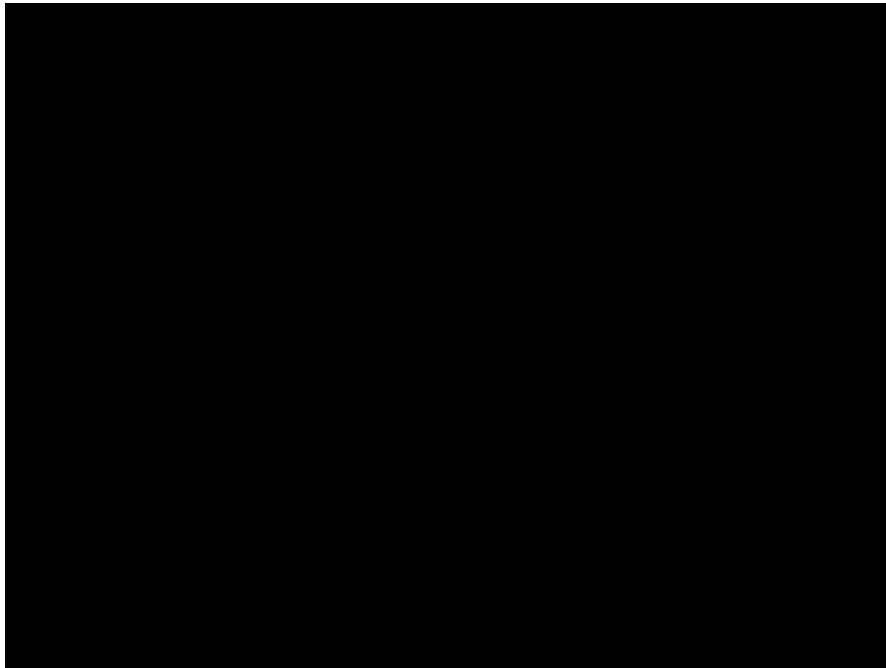
# Testing and Results

**Simulated Scenario:** We consider the system at work in a simulated scenario where a mobile robot can execute pick-carry-and-place tasks in the presence of multiple colored objects.



PERFORMANCE			ERRORS	
Accuracy	Precision	Recall	Violation	Worsening
0.9439	0.9375	0.9868	0.8333	0.3333

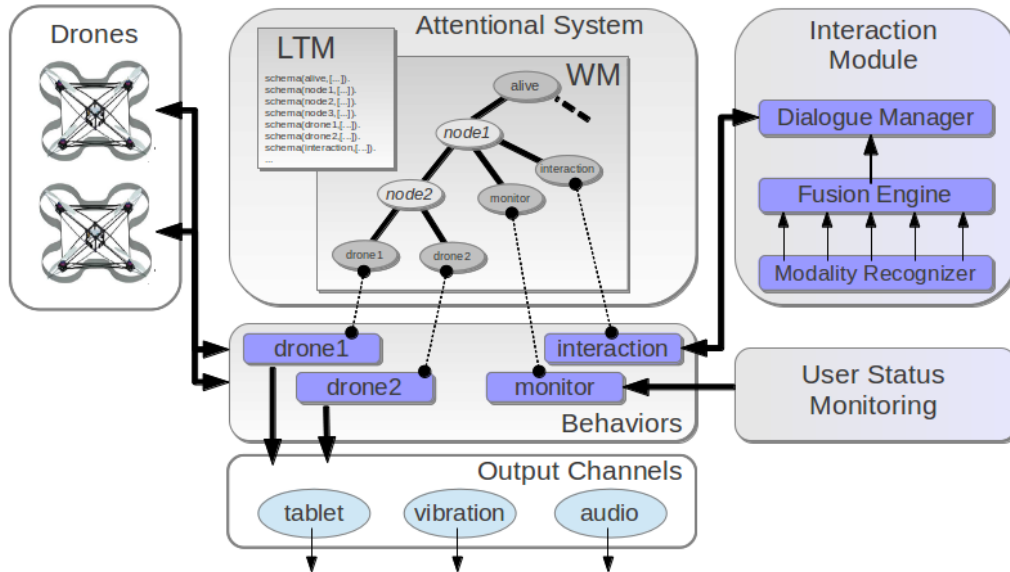
**Real Scenario:** We studied the system at work in a real-world scenario evaluating how the integrated system can flexibly adapt the execution to unexpected behaviors of the human avoiding replan.



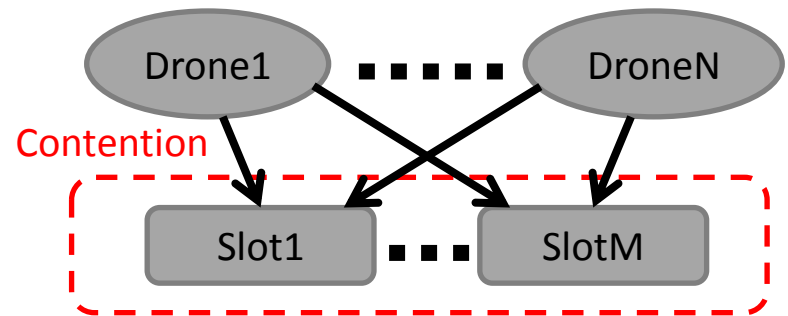
# The SHERPA Context



# Attentional Cognitive Filtering



We assume the drones communication as a problem of contention for shared resources (communication slots).

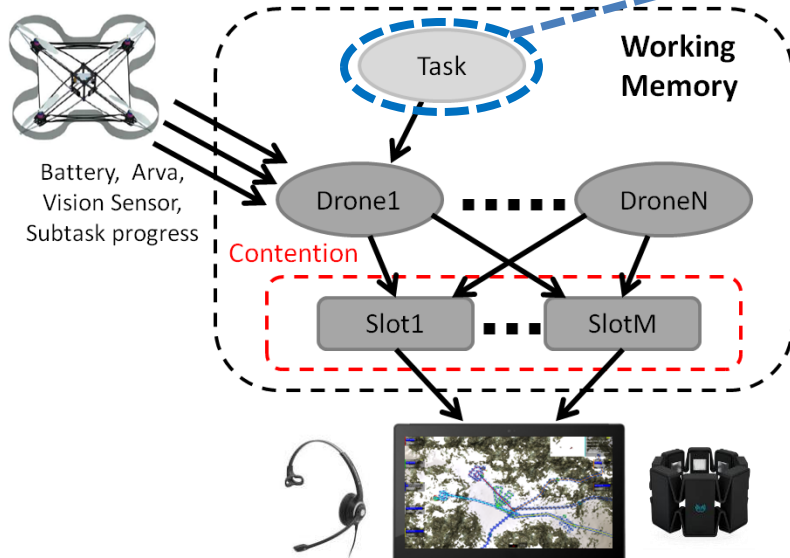


The number of available slots reduces with respect to the users cognitive load.

- Top-down and bottom-up attentional regulations used to emphasize relevant information.
- Hierarchical representation of the active tasks (WM).
- Monitoring processes with adaptive activations (frequency).
- Contention scheduling to manage conflicts (N-winner-take-all).

# Attentional Regulations

- The **top-down** regulation is given by the mission state represented in WM by an annotated tree.
- The **bottom-up** regulation is given by the on-board sensors of the drones.

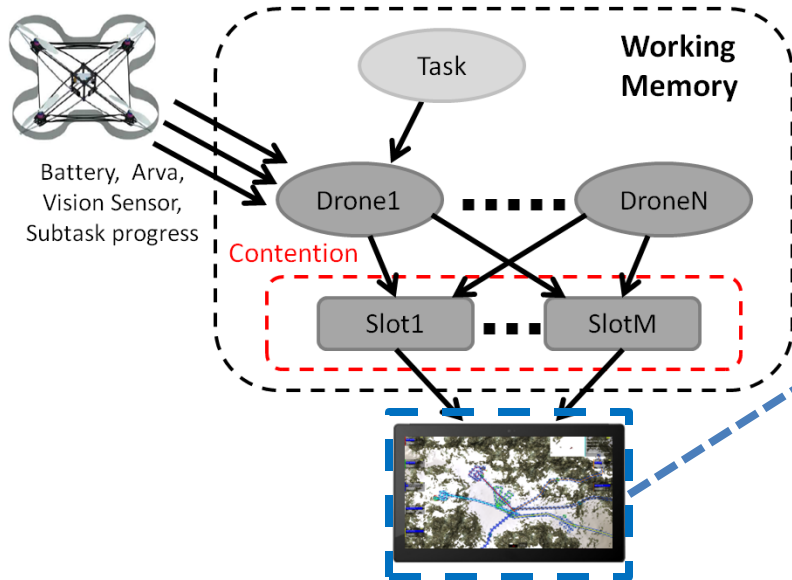


$$e = \mu_{task} (\lambda_{arva} + \lambda_{battery} + \lambda_{vision})$$



# Adaptive Interface

- Background: map of the area with positions and trajectories
  - Multiple target monitoring [Alvarez & Cavanagh 2005]
- Foreground: info-box about the drones and streaming
  - Attentional shift [Posner et al. 1980]



Not Relevant

Weakly Relevant

Relevant

Trajectory

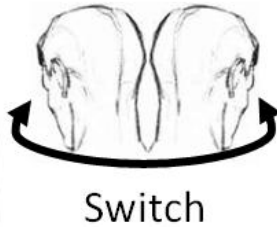
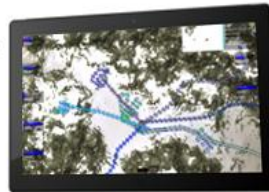
ARVA signal

# Testing and Results

Secondary Task



Primary Task



- **Interface-monitoring** (*primary*): the user has to monitor 8 drones during their search activities.
- **Word-counting** (*secondary*): the user should count the letters contained in each word of a list.

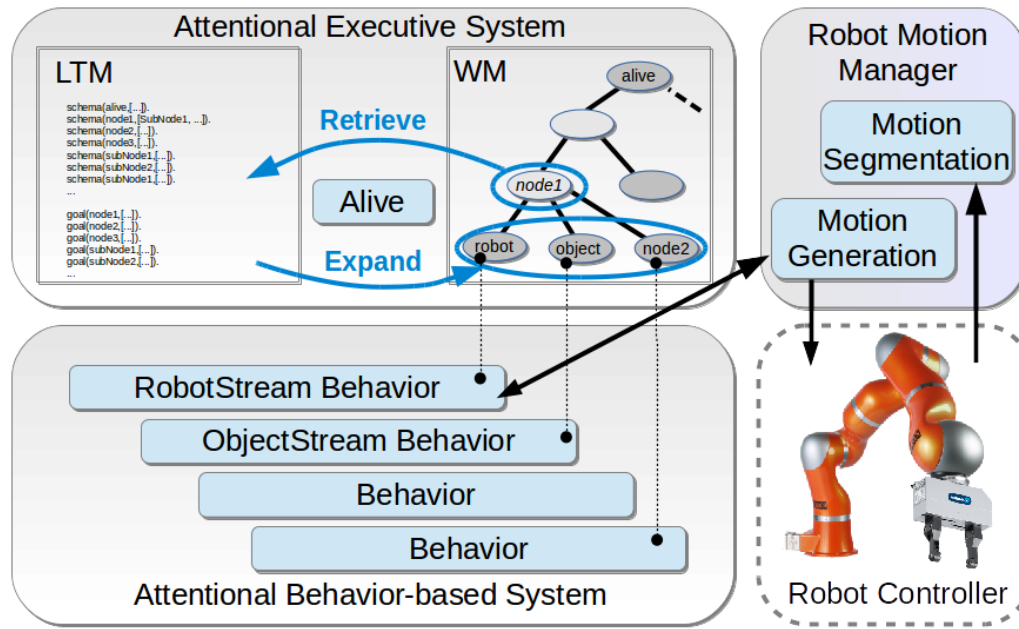
- **Adaptive**: the number of communication slots is reduced to one (maximum cognitive load).

	Events Occurred		Events Missed		Victims Missed	
	avg	std	avg	std	avg	std
<b>No-Adapt</b>	19.22	1.69	3.67	3	0.33	0.25
<b>Adapt</b>	11.44	2.28	1.22	0.69	0.11	0.11

- **No-adaptive**: fixed size of info-boxes and multiple parallel communications allowed.

no-Adaptive		Adaptive		Improvement	
avg	std	avg	std	avg	std
19.4%	1%	10.6%	0.4%	8.9%	0.4%

# Structured Tasks Learning



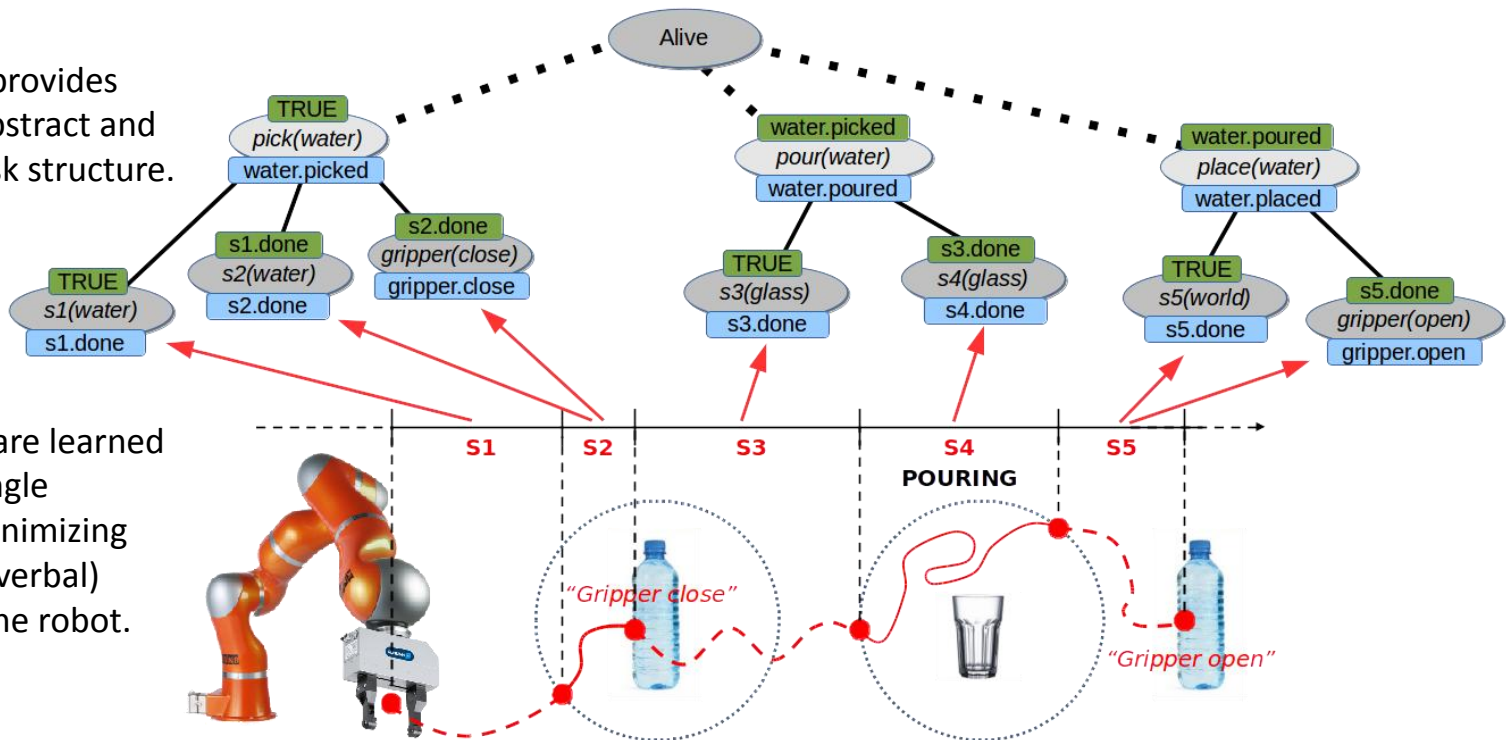
- 1. Modality switching (teach/execute).**
  - *Kinesthetic Teaching.*
  - *Trajectory Execution.*
- 2. Online actions segmentation.**
  - *Object Proximity:* end effector enters/leaves a near-object area.
  - *Open/Close Gripper:* open/close gripper command is received (speech).
- 3. Online motion generation.**
  - *Far-Object-Action (FOA):* actions far from the object are executed with a point-to-point motion (less accurate).
  - *Near-Object-Action (NOA):* actions near the object are executed with Dynamic Movement Primitives (more accurate).

- *The Robot Manager:* responsible for robotic motion, it splits the demonstration (teaching mode) in sub-segments.
- *The Attentional System:* contains the definition of all the **tasks available** to the system, updates the task according with the given sub-segments, select the most relevant action for the execution/learning.

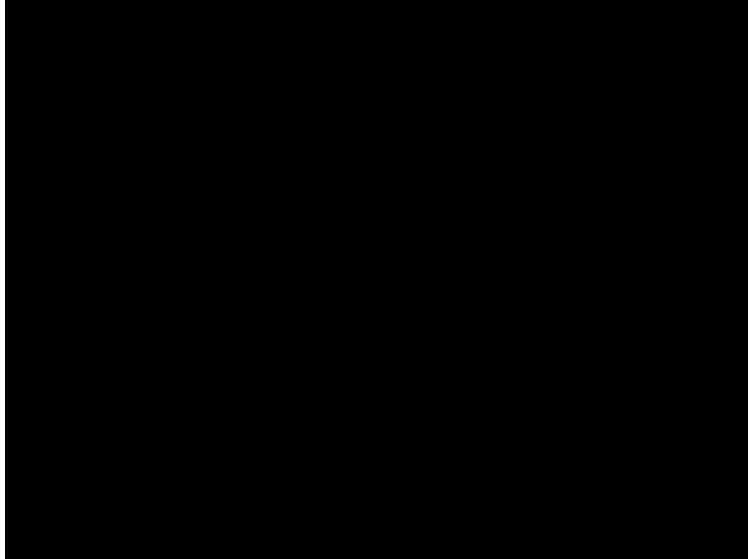
# Segmentation and Task Update

- The attentional system tracks and monitors both the human and the robot task execution:
  - It is responsible for flexible and cooperative task execution;
  - During teaching it associates trained motion primitives to tasks and sub-tasks.

The user provides only an abstract and simple task structure.



# Testing and Results



- **Add-water task** (*simple*): take and pour the water in the cup.
- **Prepare-coffee task** (*complex*): prepare the instant coffee.
- **Prepare-tea task** (*re-usage*): prepare tea reusing some prepare-coffee subtasks.

	Teaching time (avg $\pm$ std)	Execution time (avg $\pm$ std)	Success Rate
add-water	50.4 $\pm$ 2.0	77.5 $\pm$ 2.3	1
prepare-coffee	165.7 $\pm$ 12.8	224.5 $\pm$ 2.9	0.9

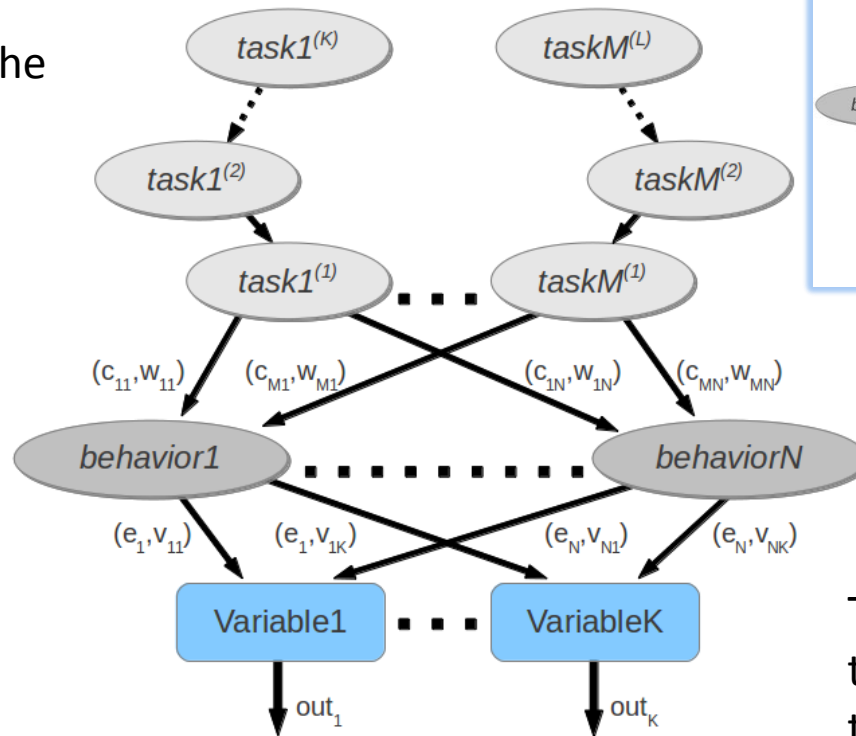
	Teaching time (avg $\pm$ std)
No Re-usage	84.2 $\pm$ 2.9
Re-usage	39.6 $\pm$ 2.4

47% faster!

We assess the system performances executing 10 learning sessions and 5 executions for each task (randomly changing objects positions) measuring times and success rate.

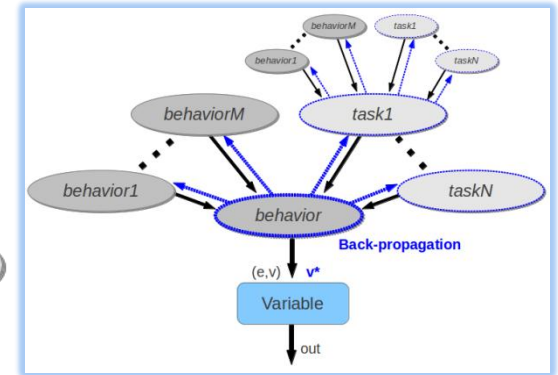
# Work in Progress...

Each edge of the WM can be associated with a weight that regulates the intensity of the attentional influence.



The *emphasis* value of each node is obtained as a weighted sum:

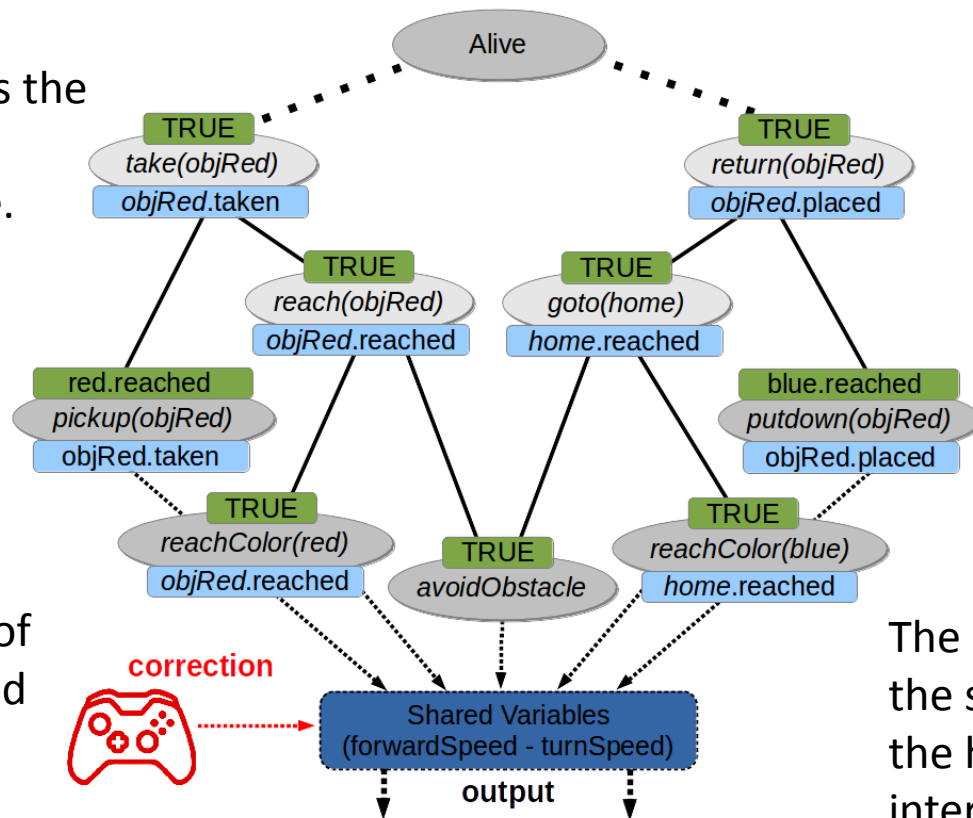
$$e_i = \sum w_{ji} c_{ji}$$



The difference between the system behavior and the human correction is interpreted as an error to be back-propagated.

# Work in Progress...

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The difference between the system behavior and the human correction is interpreted as an error to be back-propagated.

# Conclusions

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- We proposed a robotic cognitive control framework for the flexible execution of structured complex tasks in the context of human-robot interaction.
- The framework was applied in different incremental scenarios, facing aspects of human-robot interaction, flexible plan execution, filtering and learning.
- Some of the applicative scenarios was also framed in the context of EU projects (SAPHARI and SHERPA).
- We assessed the framework performance in the different proposed contexts, considering simulations and real robotic scenarios.



# Productions

## **Journal Papers:**

- Flexible task execution and attentional regulations in human-robot interaction, IEEE Transactions on Cognitive and Developmental Systems, 2016.
- Kinesthetic teaching and attentional supervision of structured tasks in human-robot interaction, Autonomous Robots Journal, Springer, 2016. [Submitted]

## **Conference Papers:**

- Attentional regulations in a situated human-robot dialogue. *IEEE RO-MAN*, 2014.
- Attentional top-down regulation and dialogue management in human-robot interaction. HRI, ACM, 2014.
- Plan Execution and Attentional Regulations for Flexible Human-Robot interaction. IEEE SMC, 2015.
- Attentional supervision of human-robot collaborative plans. *IEEE RO-MAN*, 2016.
- Attentional multimodal interface for mult drone search in the Alps. IEEE SMC, 2016.
- Cognitive control and adaptive attentional regulations of robotic task execution. EuCognition meeting, 2016.

## **Book Chapters:**

- Attentional Top-Down Regulations in a Situated Human-Robot Dialogue ICRA 2014 WS Robots in Homes and Industry: Where to Look First?
- Integrating Multimodal Interaction and Kinesthetic Teaching for Flexible Human-Robot Collaboration. HFR-2015.

## **Workshop Papers:**

- Attentional Top-Down Regulations in a Situated Human-Robot Dialogue ICRA 2014 WS Robots in Homes and Industry: Where to Look First?
- Integrating Multimodal Interaction and Kinesthetic Teaching for Flexible Human-Robot Collaboration. HFR-2015.
- Attentional Plan Execution for Human-Robot Cooperation. AI\*IA-2015 Italian Workshop on Artificial Intelligence and Robotics (AIRO2015).
- A human-robot interaction framework for search and rescue in the Alps, AI\*IA-2016 Italian Workshop on Artificial Intelligence and Robotics (AIRO2016).
- Integrated task learning and kinesthetic teaching for human-robot cooperation, AI\*IA-2016 Italian Workshop on Artificial Intelligence and Robotics (AIRO2016).

*Thanks for Your attention*