Interactive Robotics Lab

Towards Learning Semantic Policies for Human-Robot Collaboration

Heni Ben Amor
Interactive Robotics Laboratory
Arizona State University

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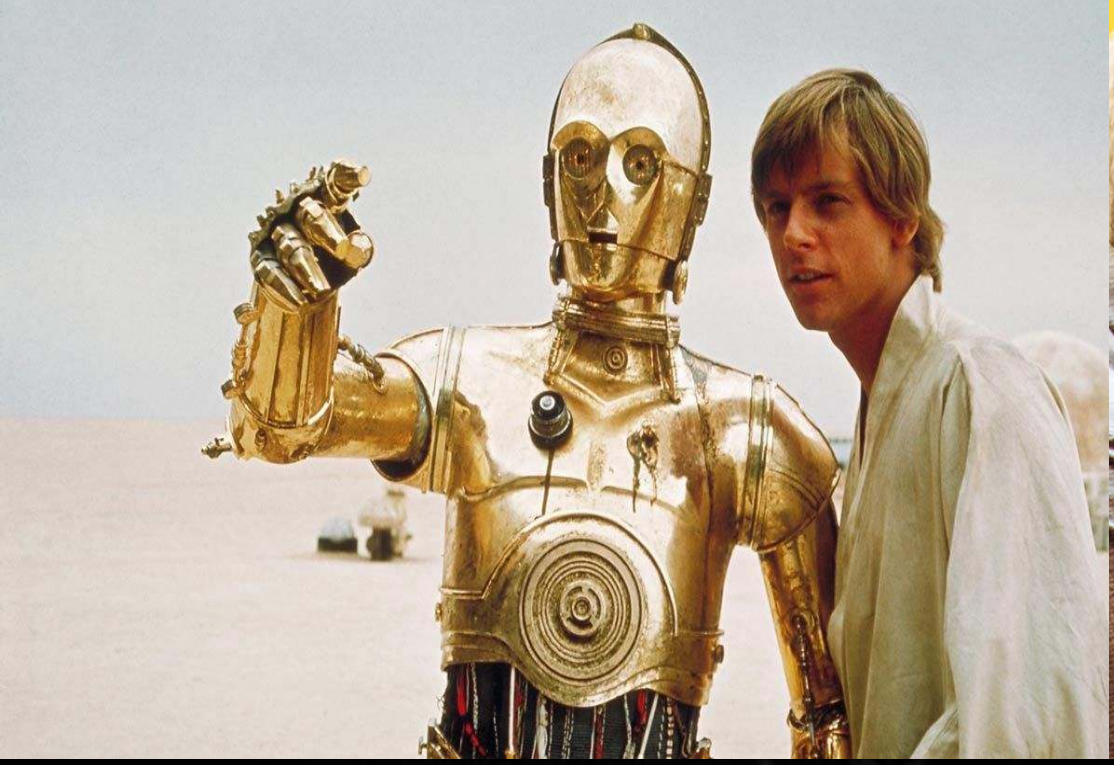
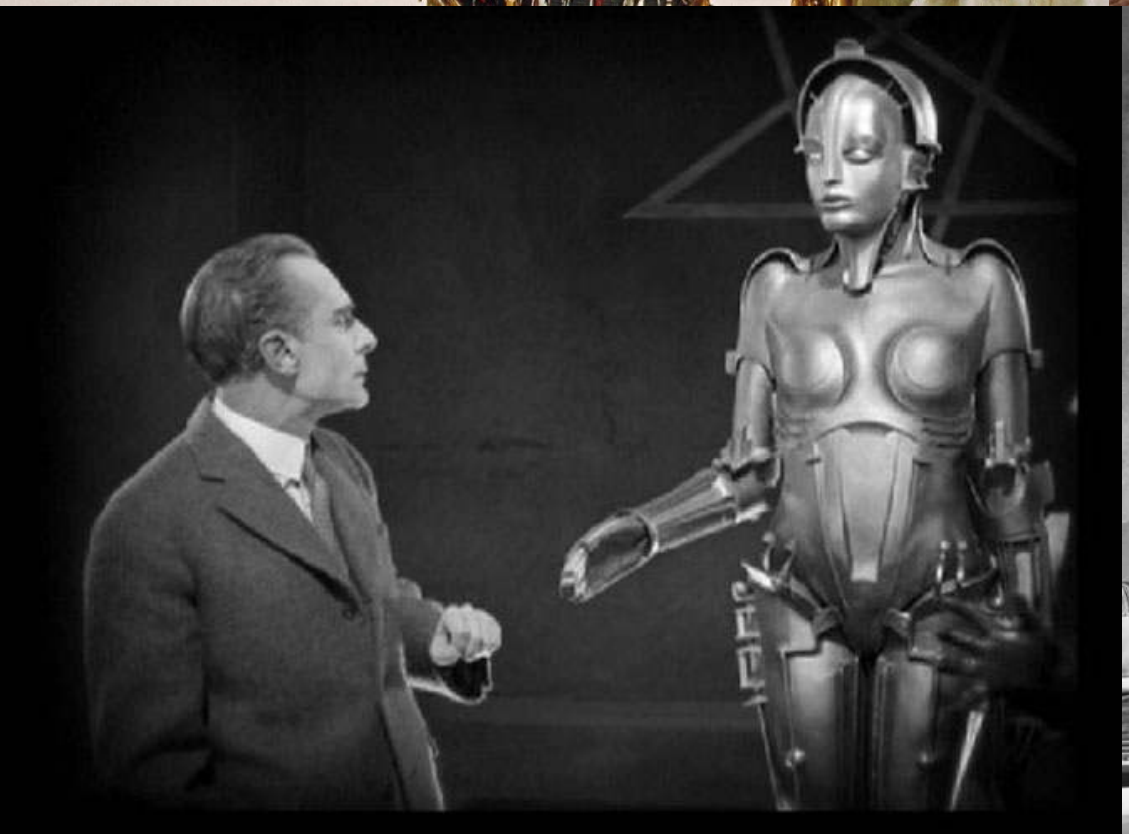
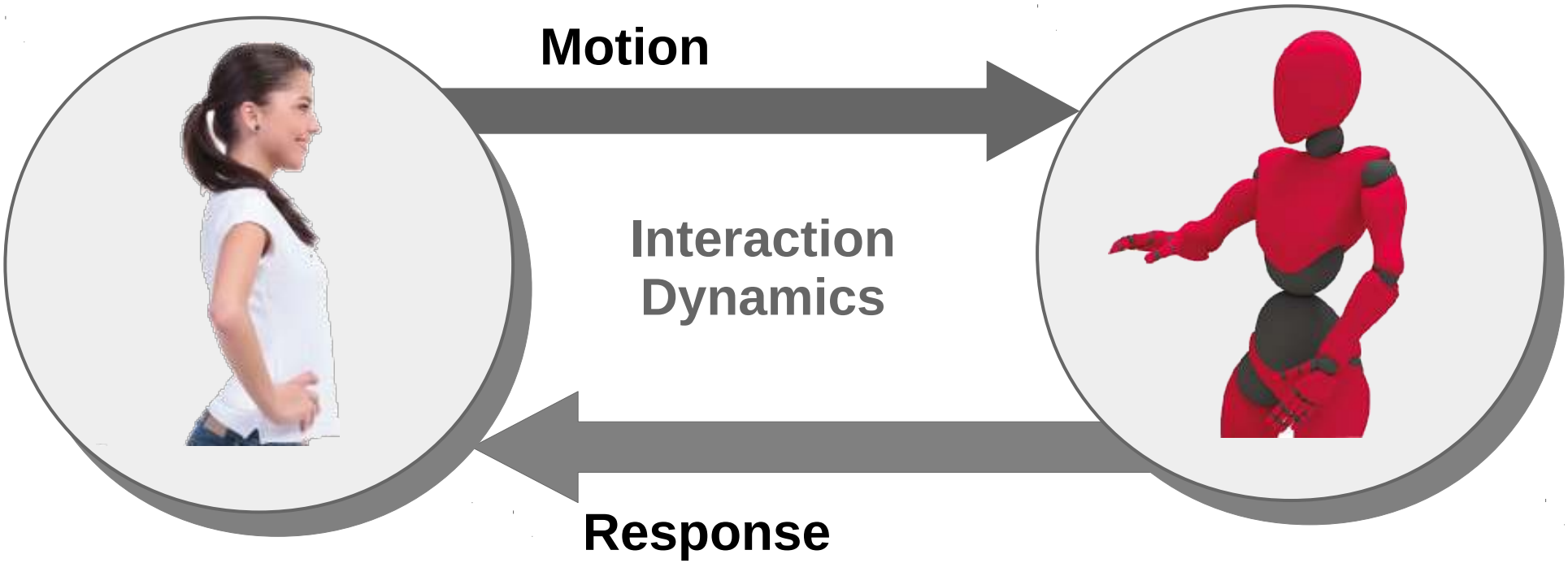




Modeling Human-Robot Collaboration



Learning from Demonstration

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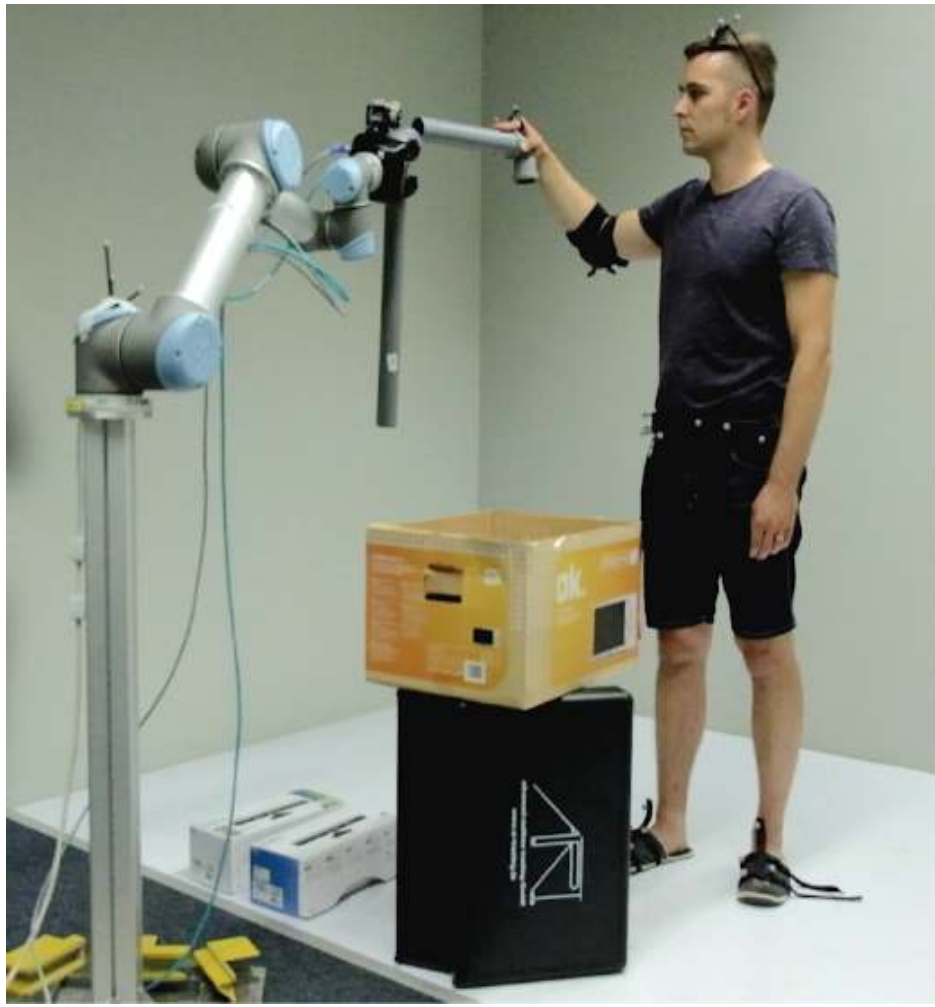
Human-Human Interaction

Human-Robot Interaction



Human-Robot Collaboration @ IRL

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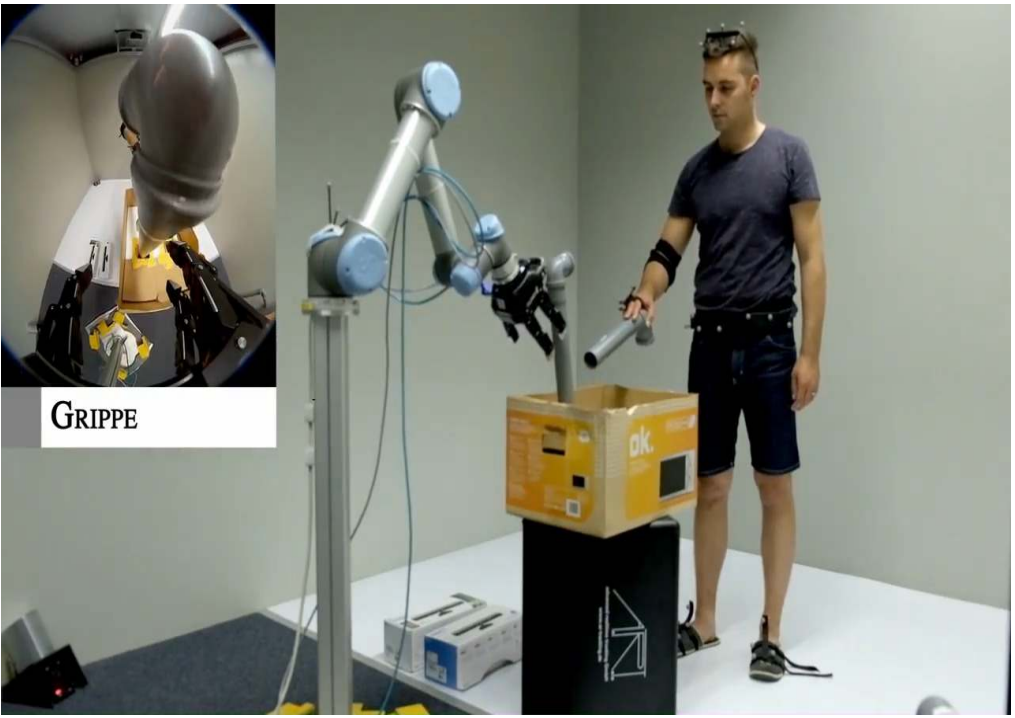

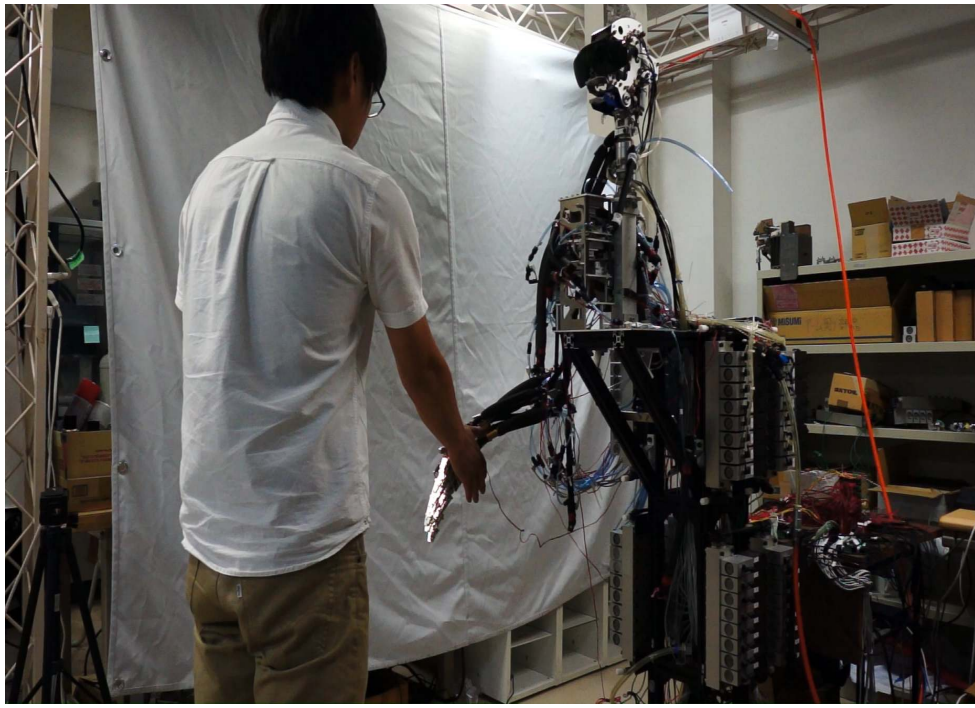

[Collaborators David Vogt, Shuhei Ikemoto, Koh Hosoda]

Modeling Human-Robot Collaboration

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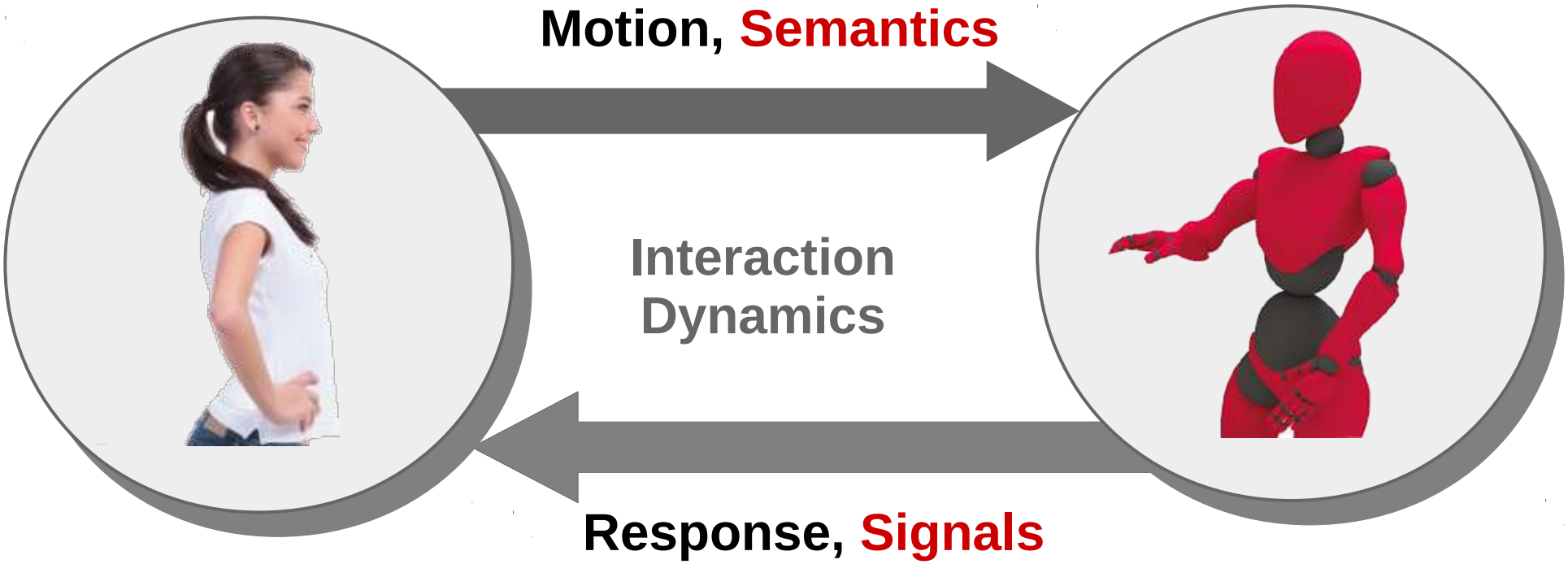

Human Motion and Robot Response

Encoding Interaction Dynamics

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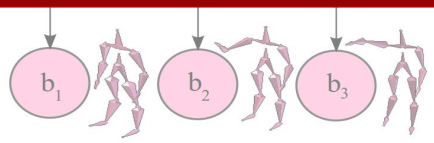
- How to specify joint behavior?
- How to model the mutual dependency?
- Requires both:

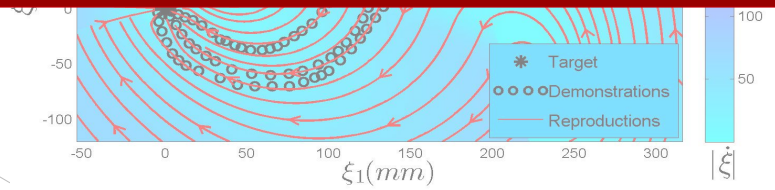
Action Recognition

Hidden Markov Models [Brand et al., 1997]



Action Generation

DMP [Ispeert et al., 2002]



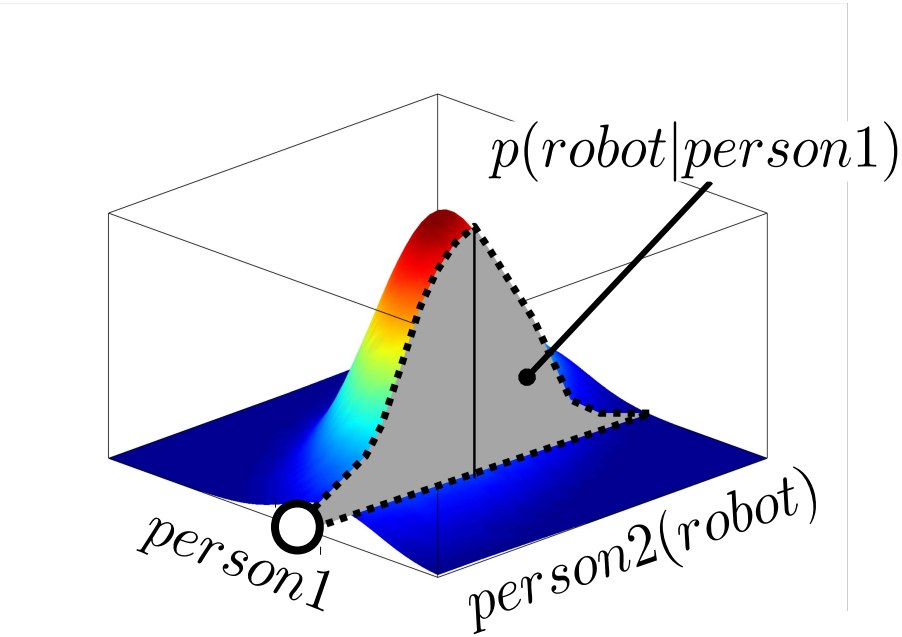
Mind the gap:

Interaction Primitives

Ben Amor et al. (ICRA, 2014): Interaction Primitives for Human-Robot Cooperation Tasks

Interaction Primitives

- **Modeling** correlations among agents as a joint probability distribution
- Action generation through Bayesian **inference**
- **Enables:**
  - Action Generation
  - Action Recognition
  - Action Prediction



Ben Amor et al. (ICRA, 2014): Interaction Primitives for Human-Robot Cooperation Tasks

Interaction Primitives: Basic Approach

- Represent movement as weighted basis-functions

$$\mathbf{y}(t) = \begin{bmatrix} q(t) \\ \dot{q}(t) \end{bmatrix} = \begin{bmatrix} \psi(t) \\ \dot{\psi}(t) \end{bmatrix} \omega + \epsilon_y$$

- Fit a probability distribution into basis weights ω

$$\omega \sim p(\omega; \theta) \qquad \theta = \{\mu_\omega, \Sigma_\omega\}$$

- Probability of trajectory

$$p(\mathbf{y}_t; \theta) = \int p(\mathbf{y}_t|\omega) p(\omega; \theta) d\omega = \mathcal{N}(\mathbf{y}|\psi_t^T \mu_\omega, \psi_t^T \mathbf{\Sigma}_\omega \psi_t + \Sigma_y)$$

- Also closed form for inference; posterior
- For two agents:

$$\mathbf{y}(t) = \begin{bmatrix} \mathbf{p}(t) \\ \dot{\mathbf{p}}(t) \\ \mathbf{q}(t) \\ \dot{\mathbf{q}}(t) \end{bmatrix}$$

Person 1

Person 2

$$\omega = [\omega^A, \omega^B]$$

Example: High-Five

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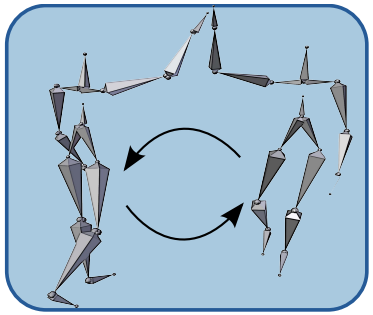
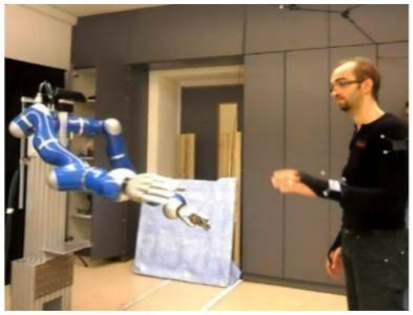
Demonstrations

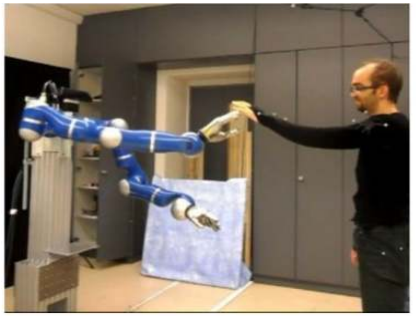
Learning

Conditioning

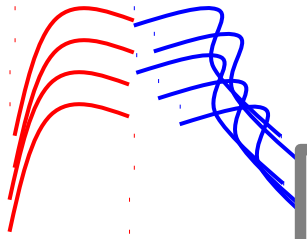
Response





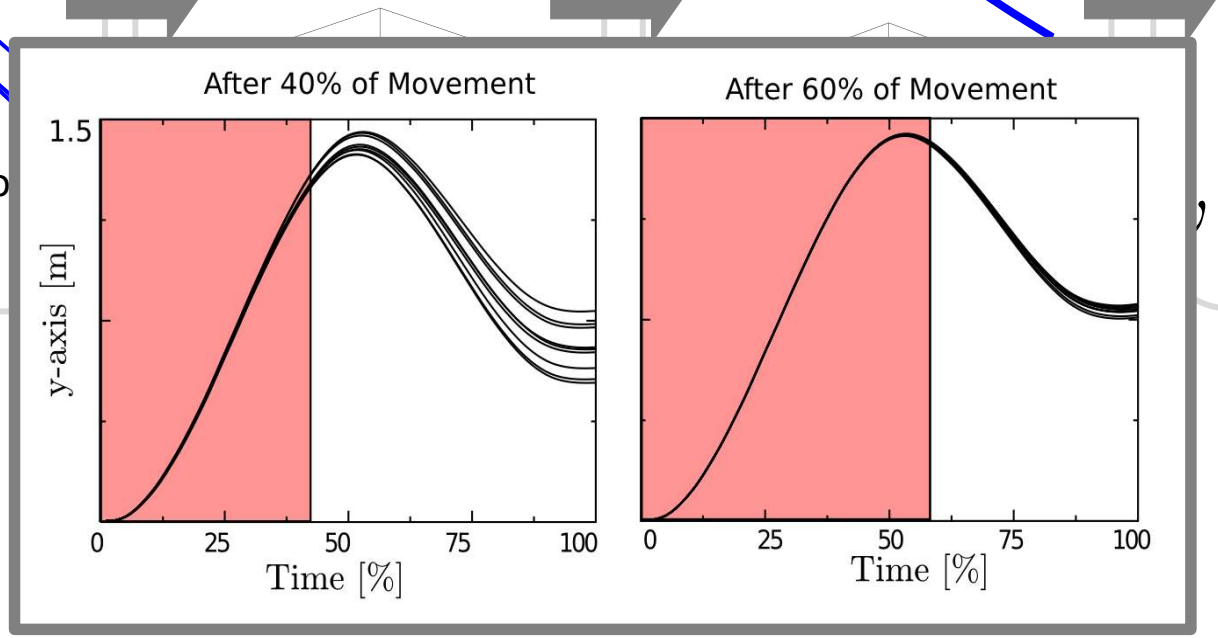


N Demonstrations



Person 2

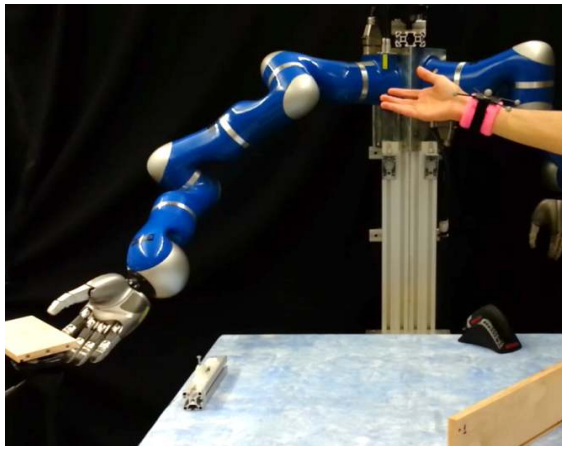
Perso



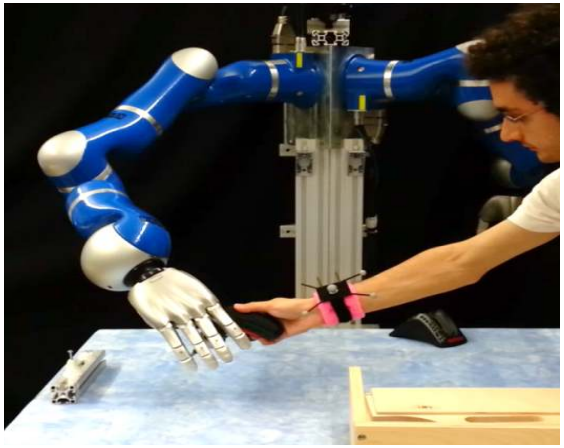
$$= [\omega^A, \omega^B]$$

Mixture of Interaction Primitives

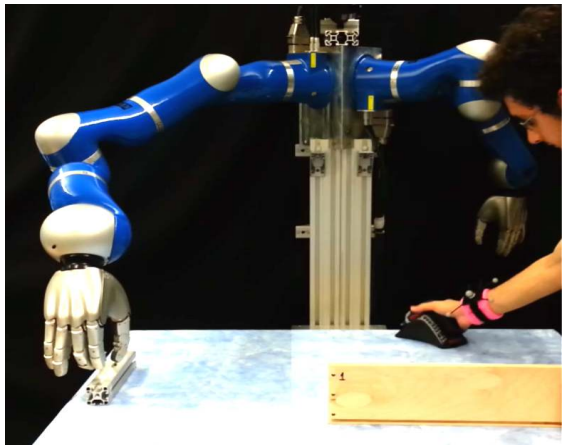
Hand over plate



Hold screwdriver



Hand over screw



What is the most likely current task k given observation $\mathbf{y}_{1:N}$?

$$p(k|\mathbf{y}_{1:T}) \propto p(\mathbf{y}_{1:T}|\theta_k)\ p(k)$$

Posterior Likelihood Prior

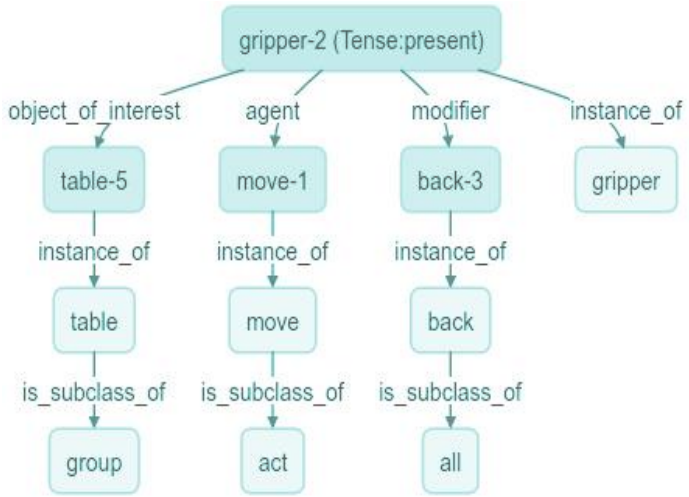
Solution $\underset{k}{\operatorname{argmax}}\ p(k|\mathbf{y}_{1:T})$

Example: Collaborative Assembly

What's missing?

Nearly everything!

It's more than just synchronized motion.



Semantics and Signals

Semantics from Language

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ASU Multimodal Assembly Dataset

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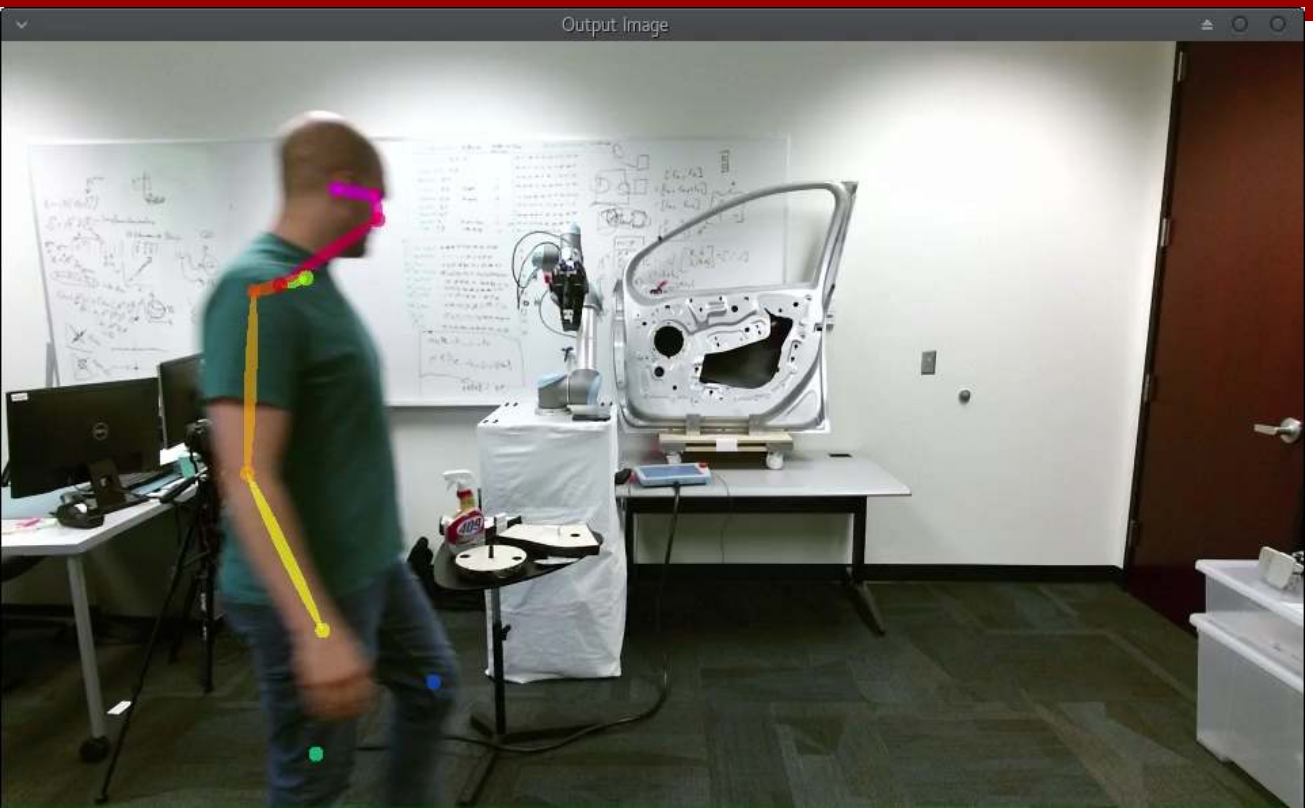

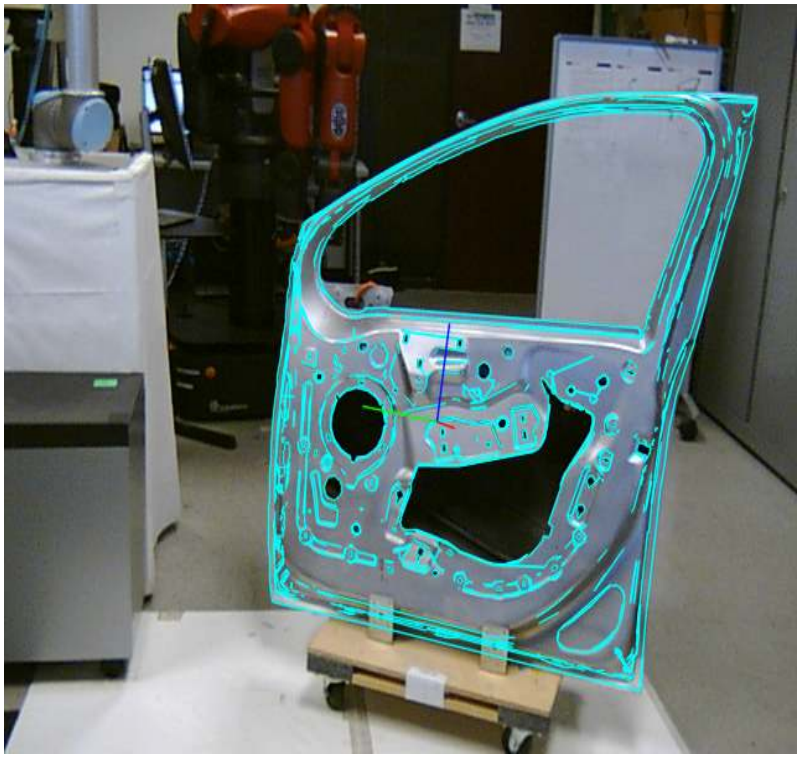

1. Free-form Speech
2. Transcripted Text
3. Object Tracking
4. Skeletal Tracking
5. Robot Proprioception

Variability in Human Verbal Instructions

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User 1	User 2
0:10 I am starting	0:17 start experiment
0:14 I pick up	0:19 move gripper to first object
0:16 the glue	0:23 close gripper
0:22 I want to go to glue the door for the circular piece	0:25 move gripper to cardoor to place object
0:30 I am gluing the door	0:34 open gripper
0:33 I will go back and put the glue down	0:37 move gripper back to grab second object
0:40 now I am putting the glue down	0:45 close gripper
0:42 Now I am going to pick up the circular object	0:47 move gripper to cardoor to place second object
0:48 Ready to pick up the circular object	1:00 open gripper
0:53 Alright now we are moving it to the door	

Semantic Segmentation

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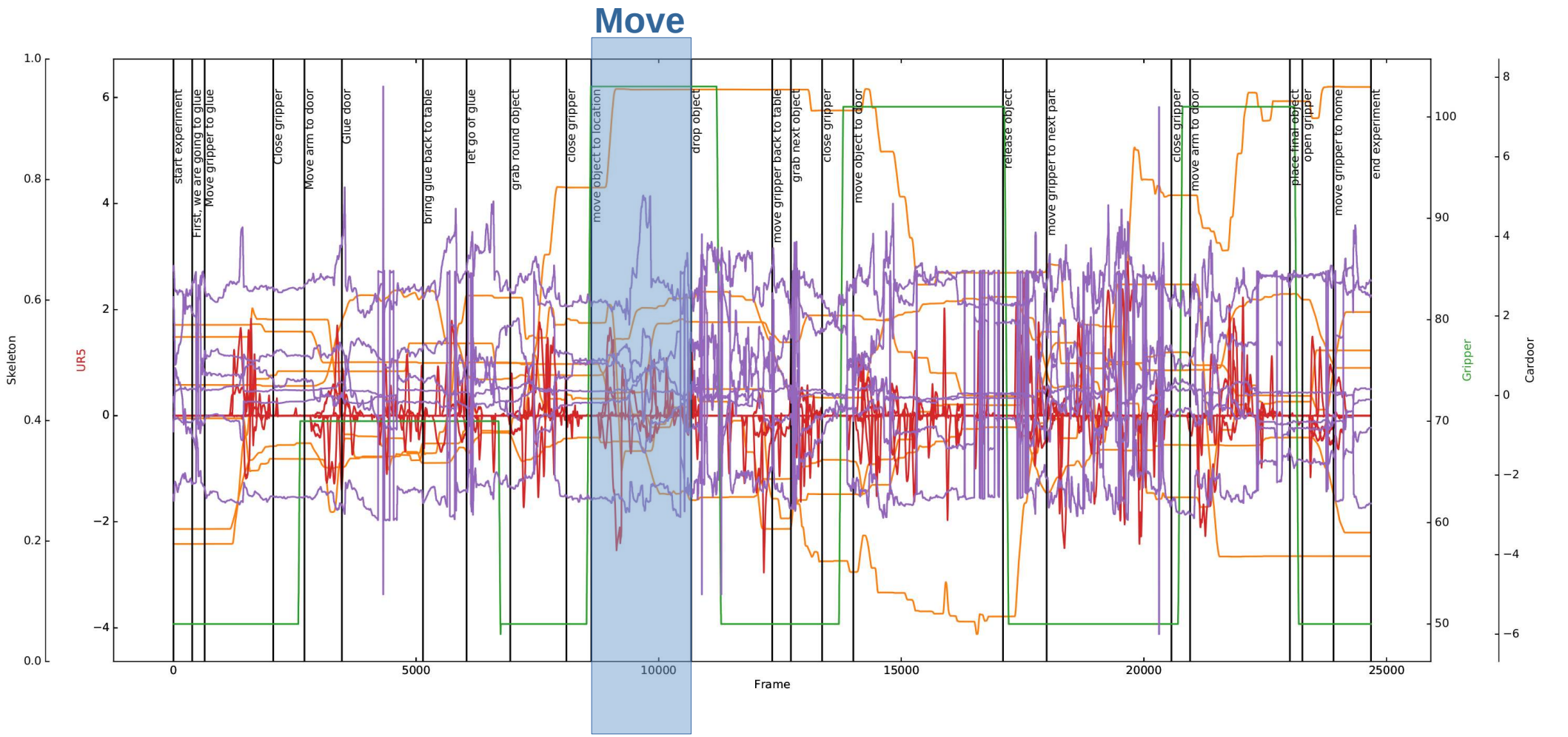

Parsing Free-Form Speech: Example 1

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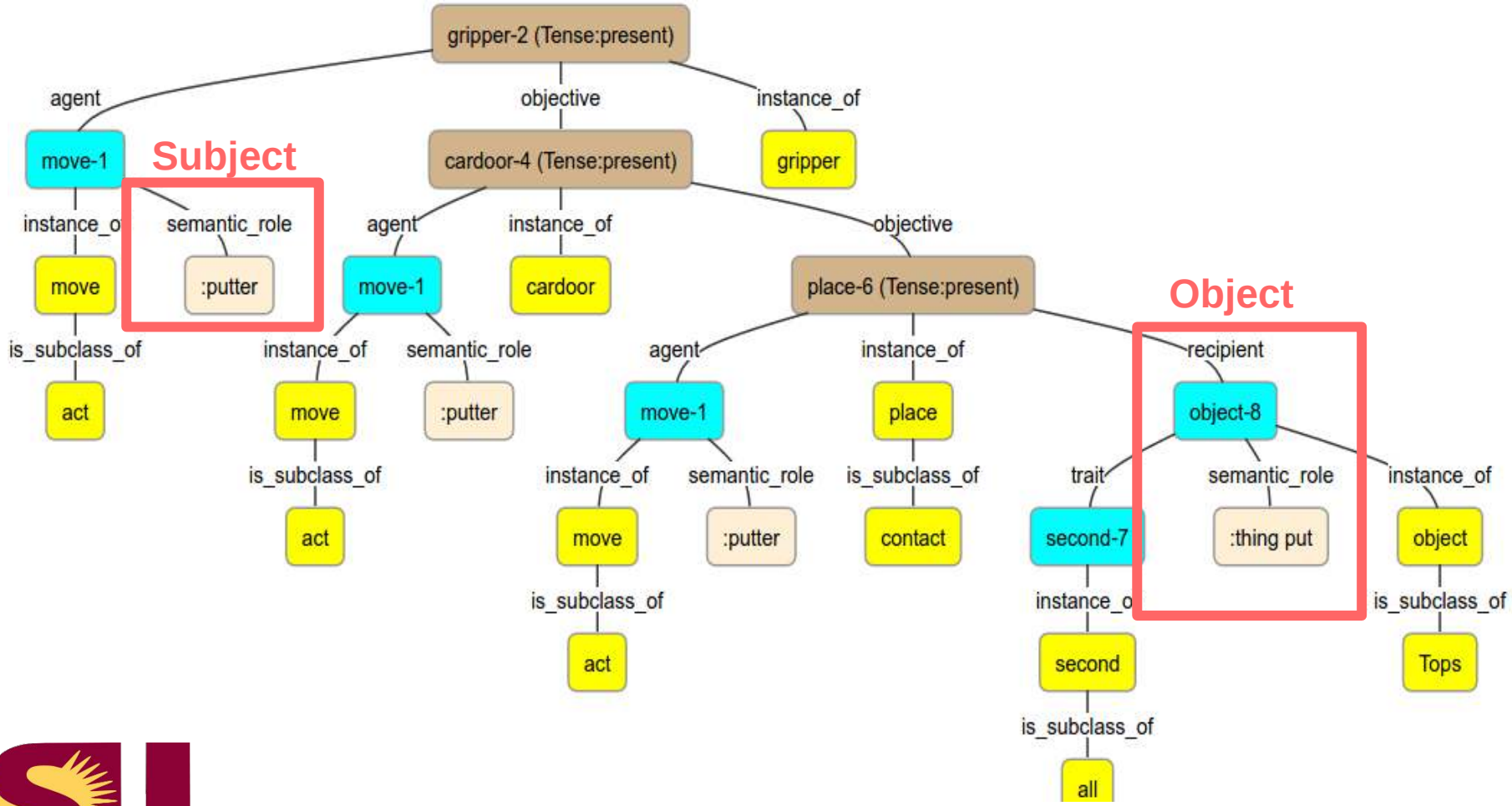
Human: **“Move Gripper to cardoor to place second object.”**



Kparser.org (Arizona State University)

Event | Entity | Class | Semantic Role | Co-referents

Parsing Free-Form Speech: Example 1

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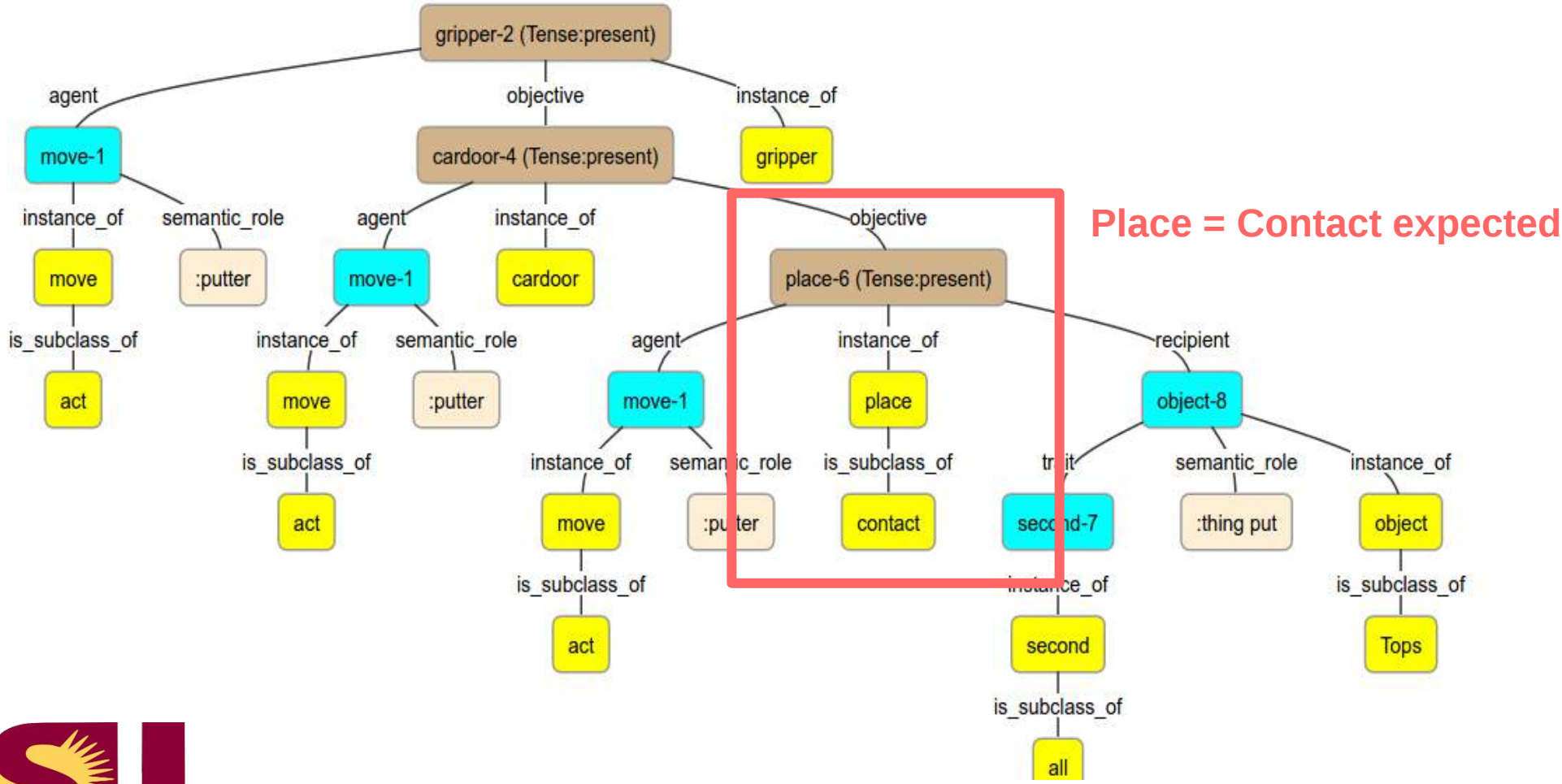
Human: **“Move Gripper to cardoor to place second object.”**



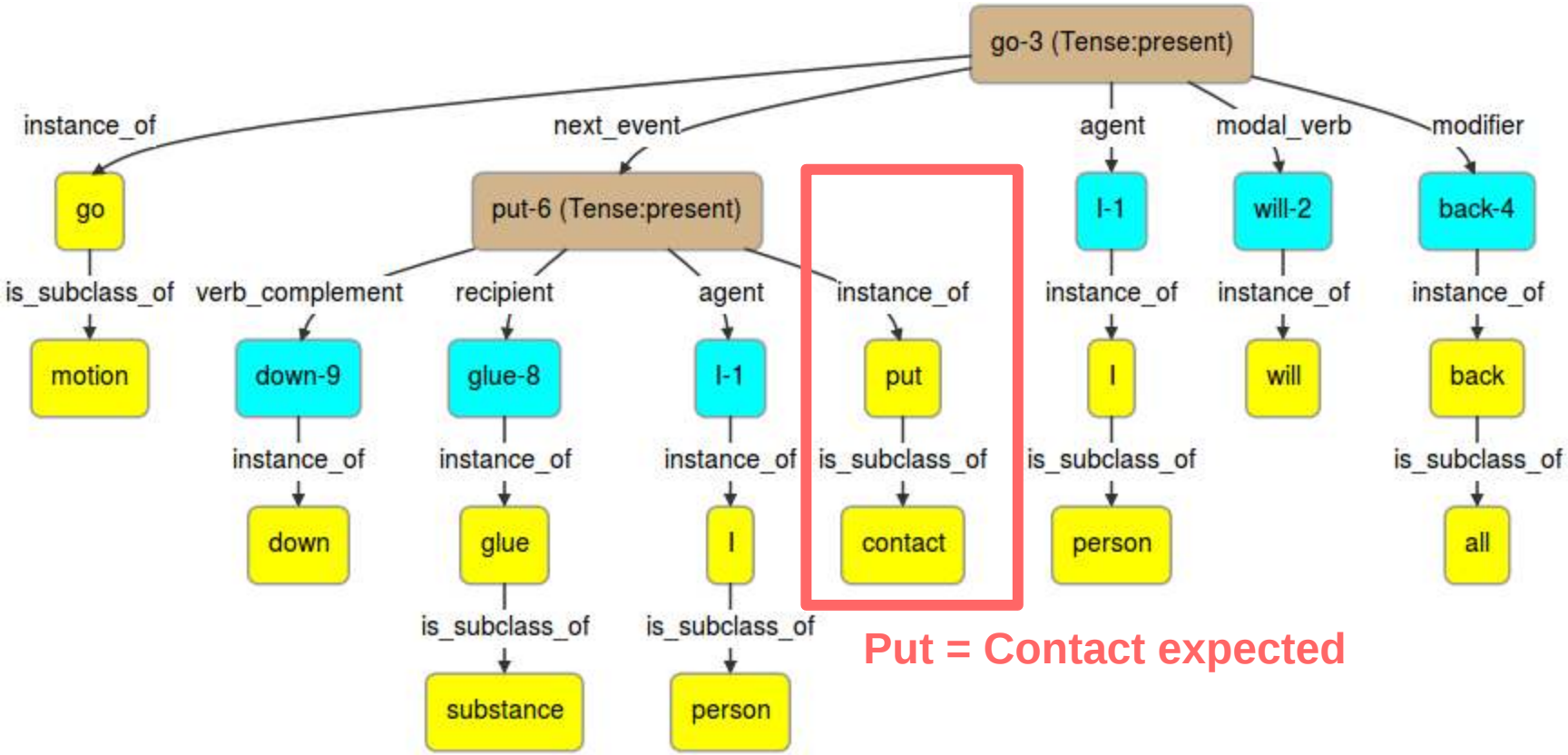
Place = Contact expected

Kparser.org (Arizona State University)

Event | Entity | Class | Semantic Role | Co-referents

Parsing Free-Form Speech: Example 2

Human: **“I will go back and put the glue down.”**

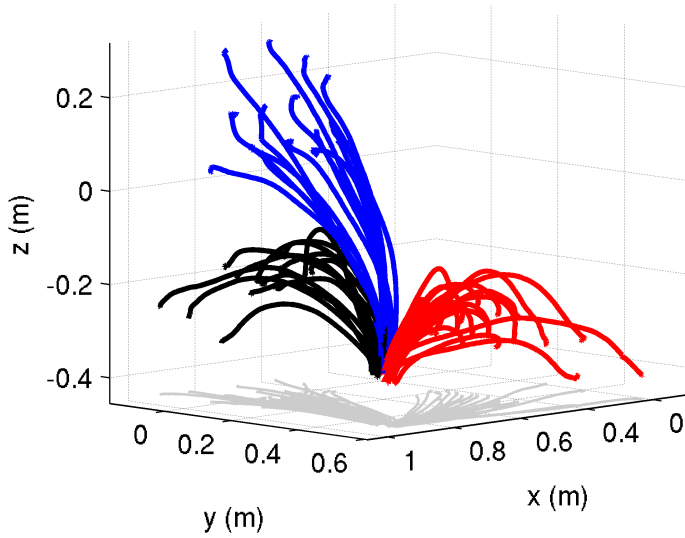


Kparser.org (Arizona State University)

Event | Entity | Class | Semantic Role | Co-referents

Determining Policy Variables

- Which objects part of the state?
- Relevant objects from speech
- Policy parametrized by object

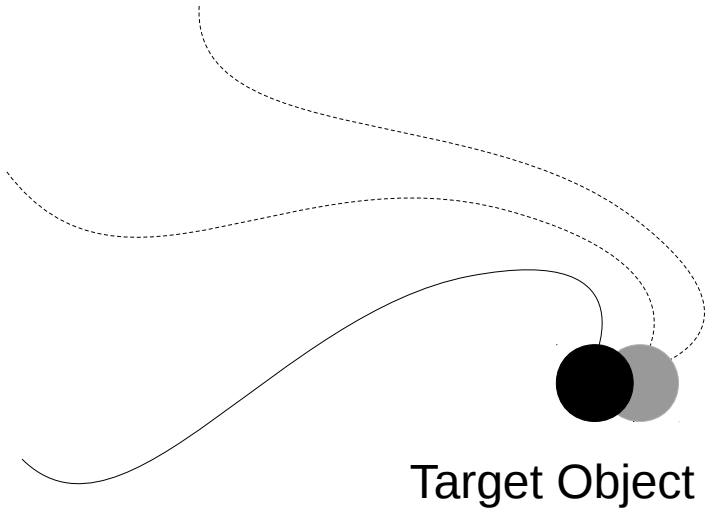


During Learning:

Make object part of the state

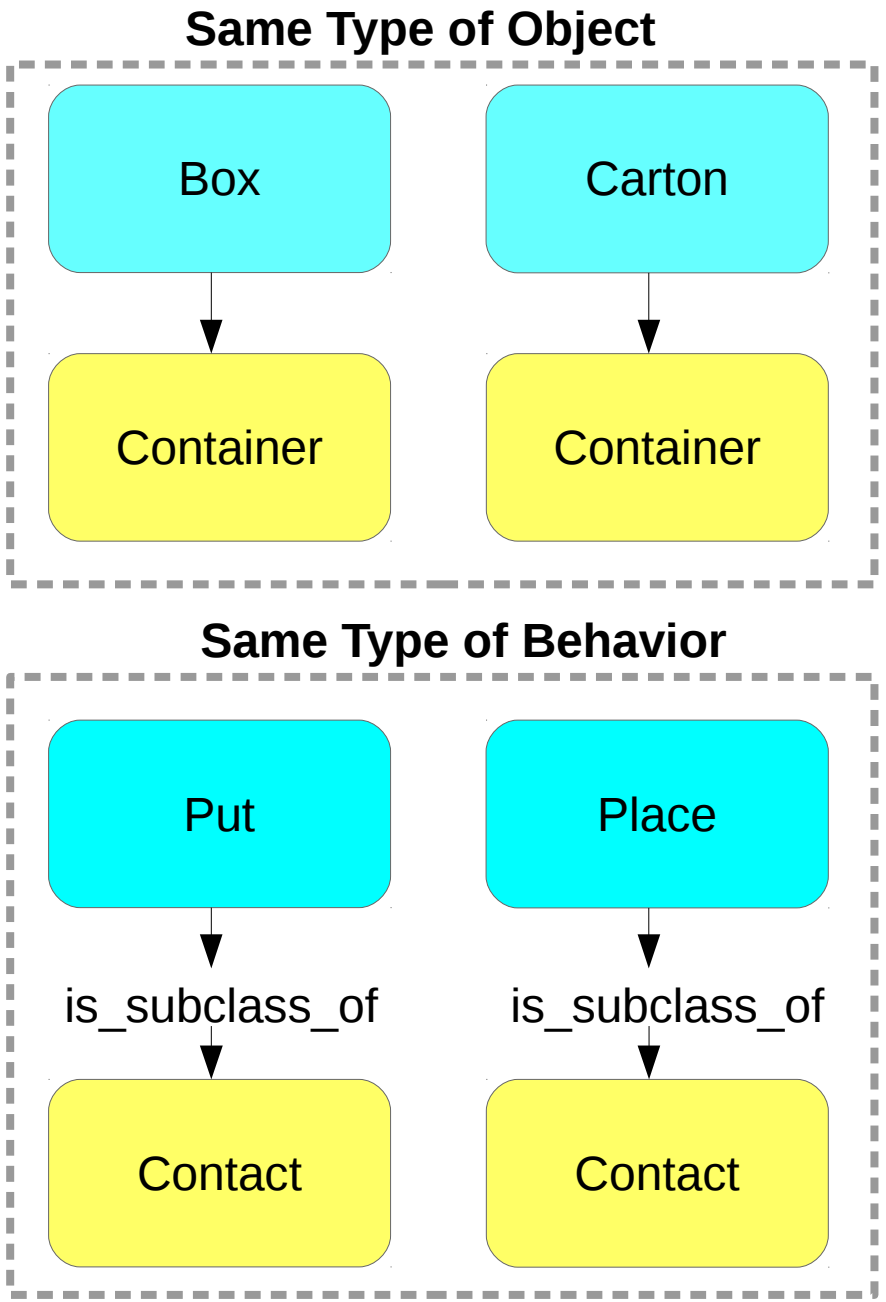
During Reproduction:

Condition on object



Abstraction for Interaction Primitives

- Aggregate data
- Combine data for similar objects
- Combine for similar behaviors
- E.g. behavior for containers
- E.g. contact behavior
- If object missing, look for type



Signals through Intention Projection

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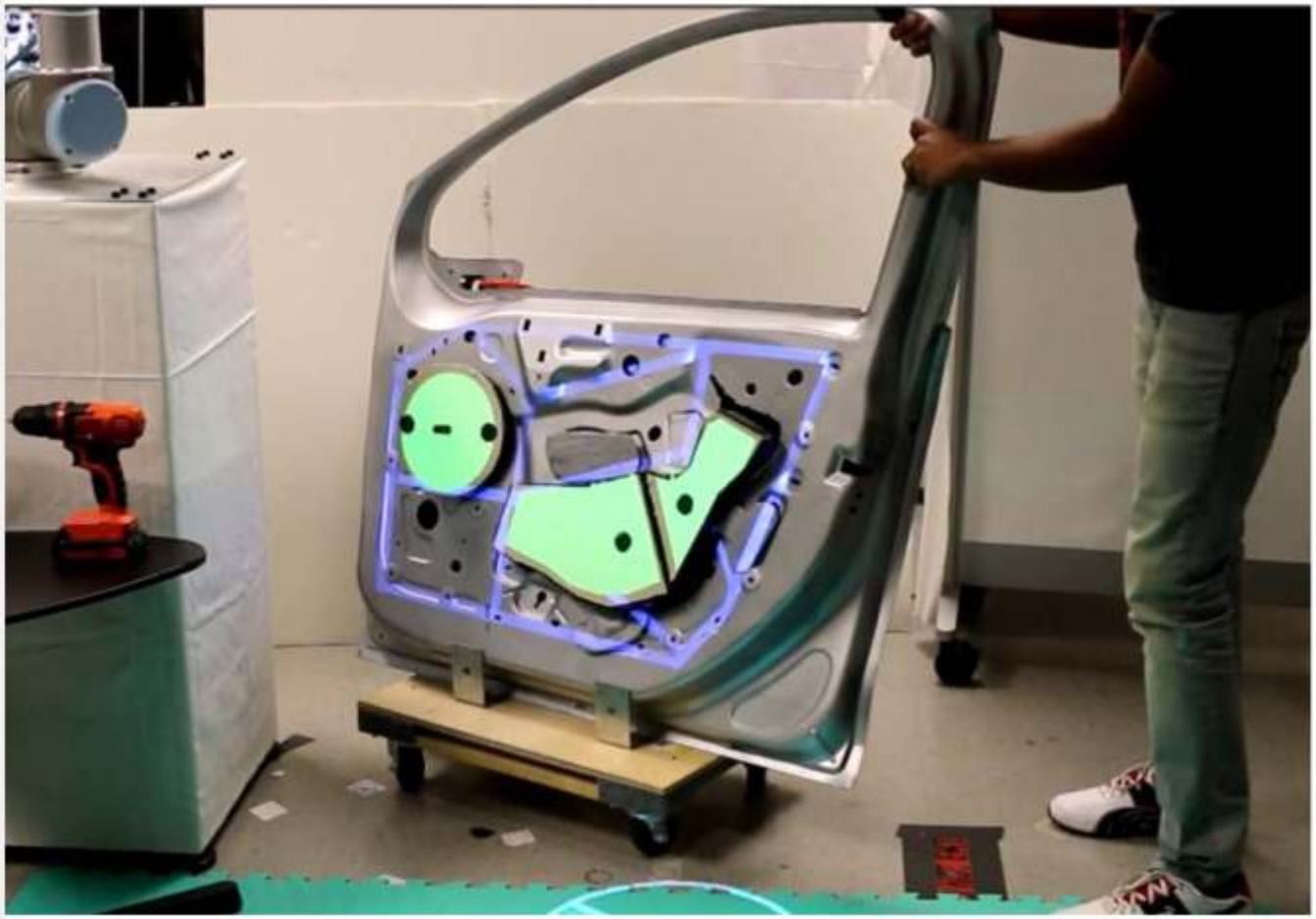

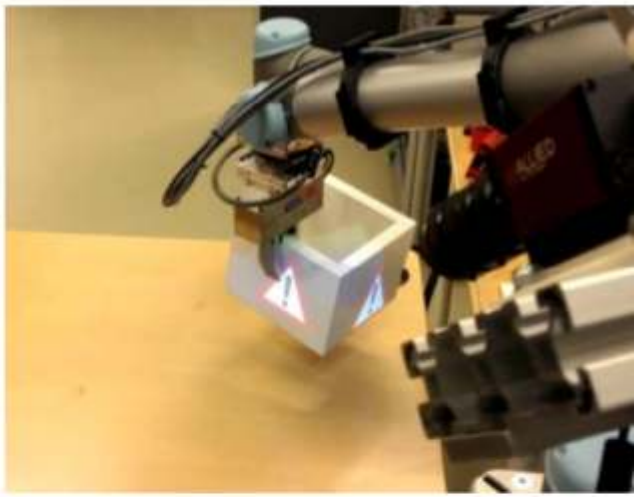

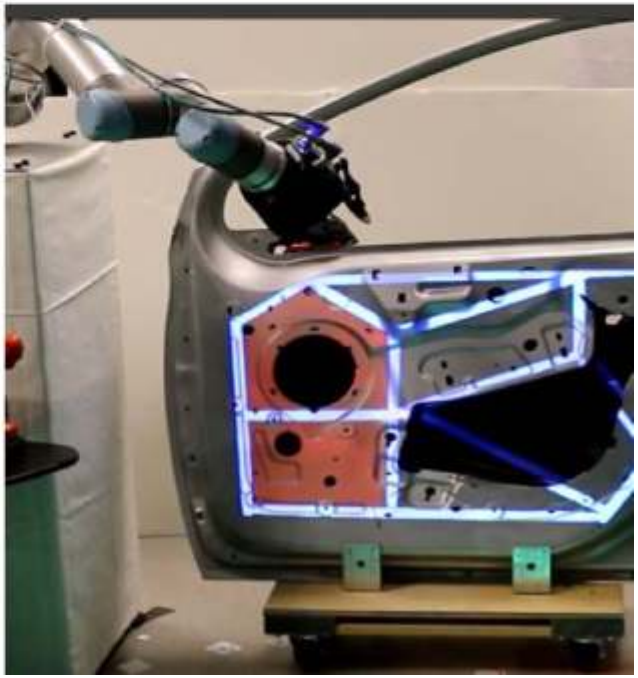

Projection System

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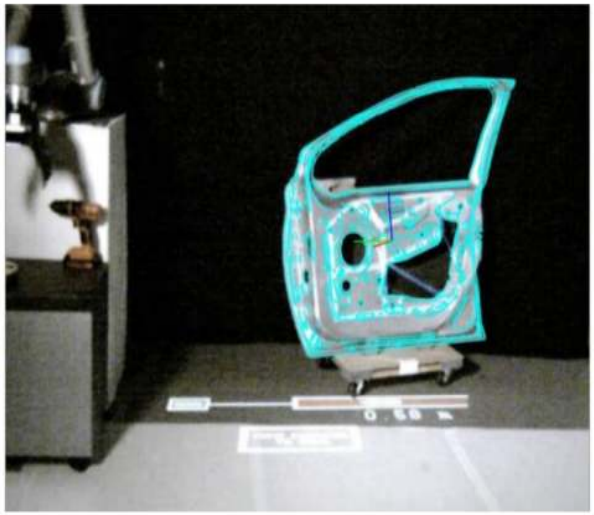
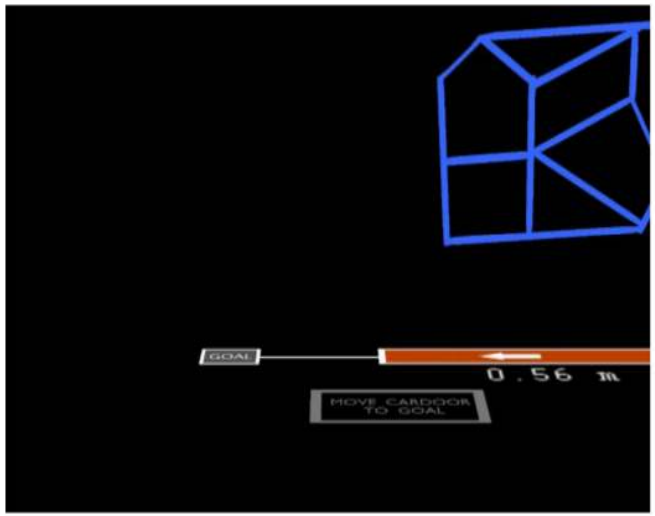
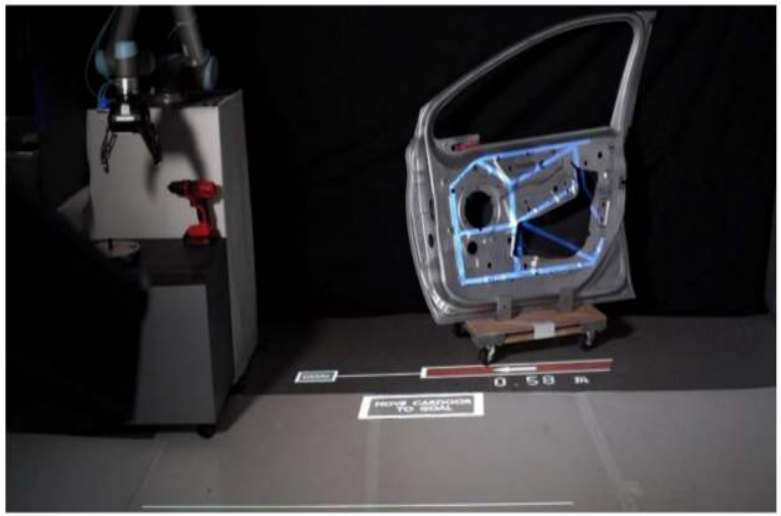


Track Object

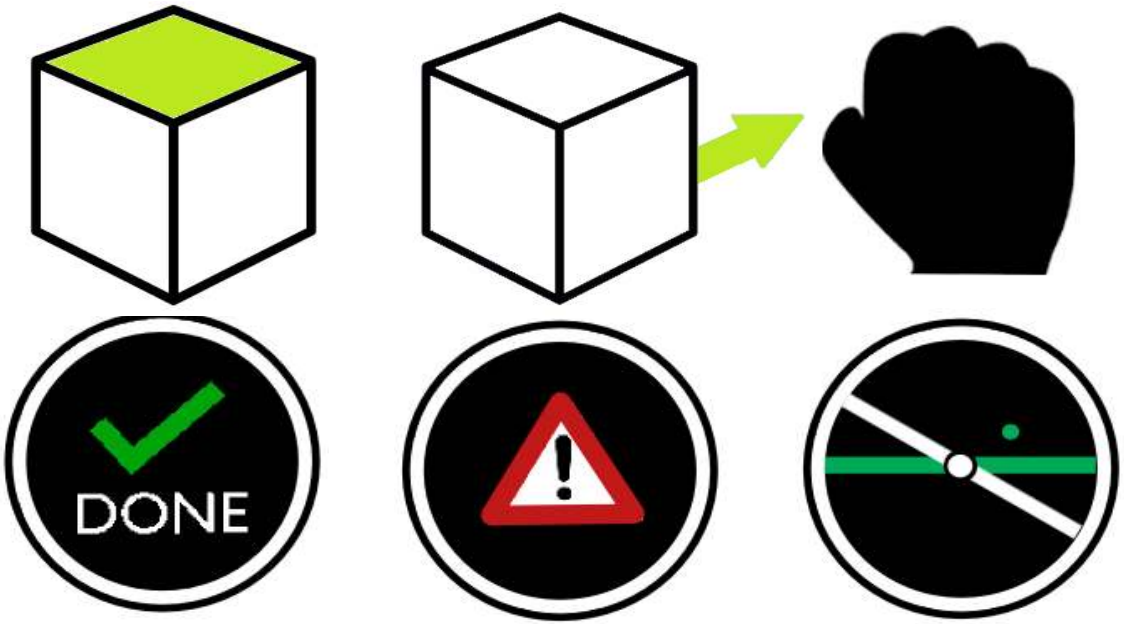


Render

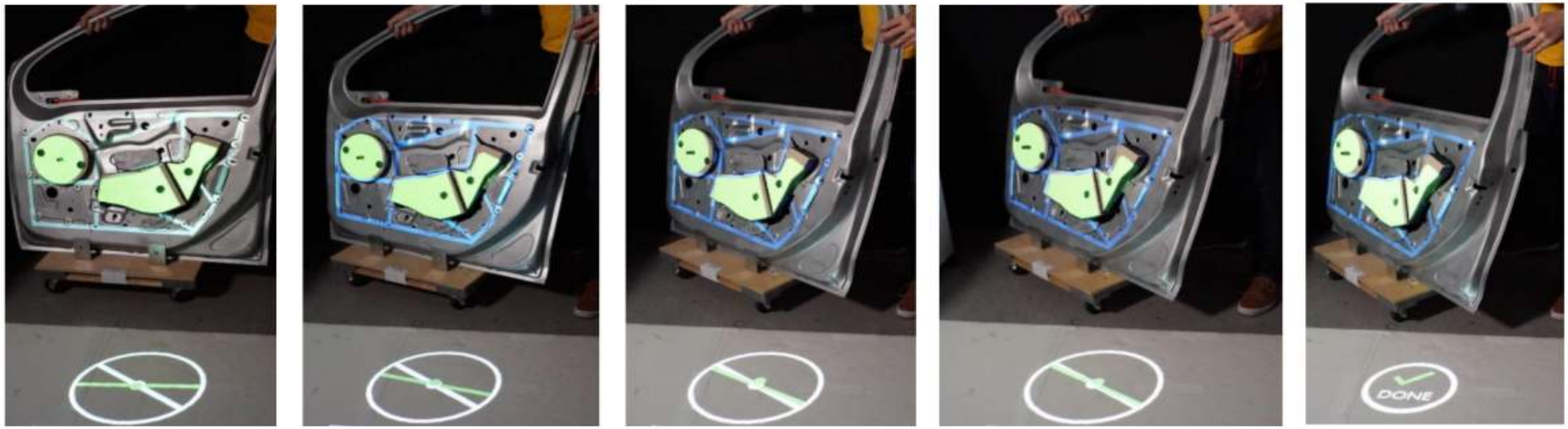


Project

Visual Signals



- move_to(X,Y)
- remove(X)
- align(X, Y)
- left_of(X, Y)
- object(X)
- location(X)



Assembly Scenario

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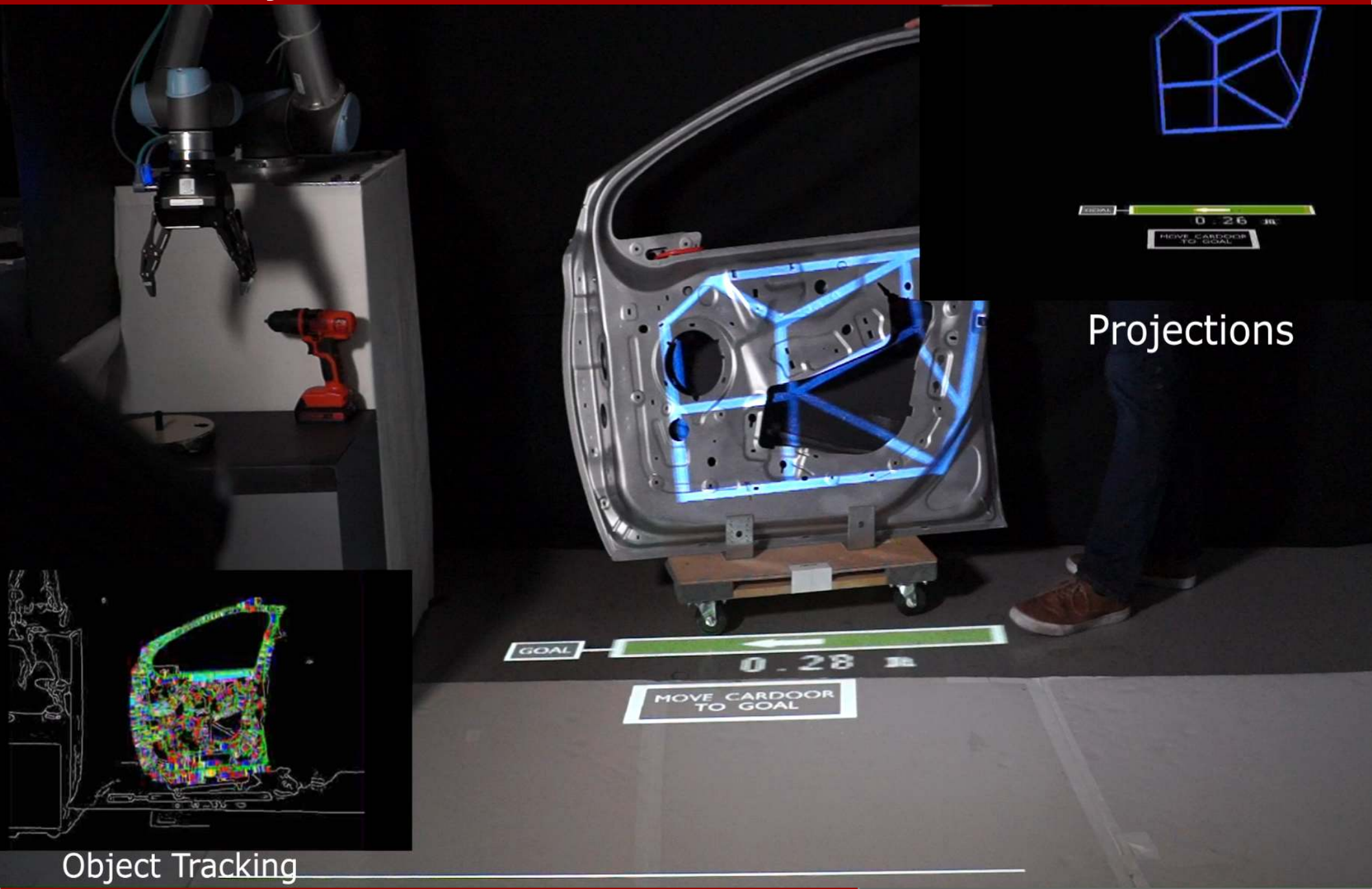

Table-top Scenario

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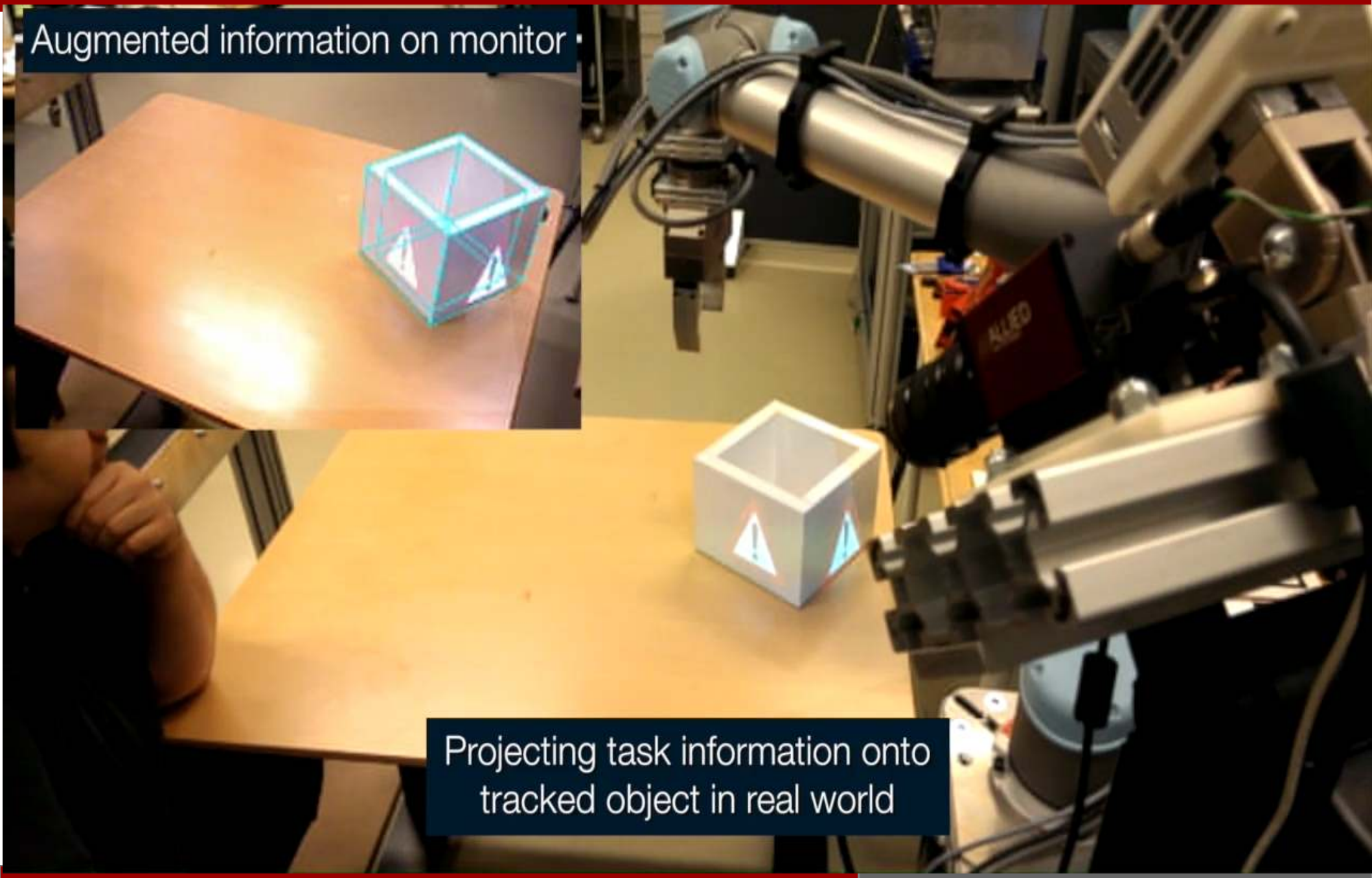
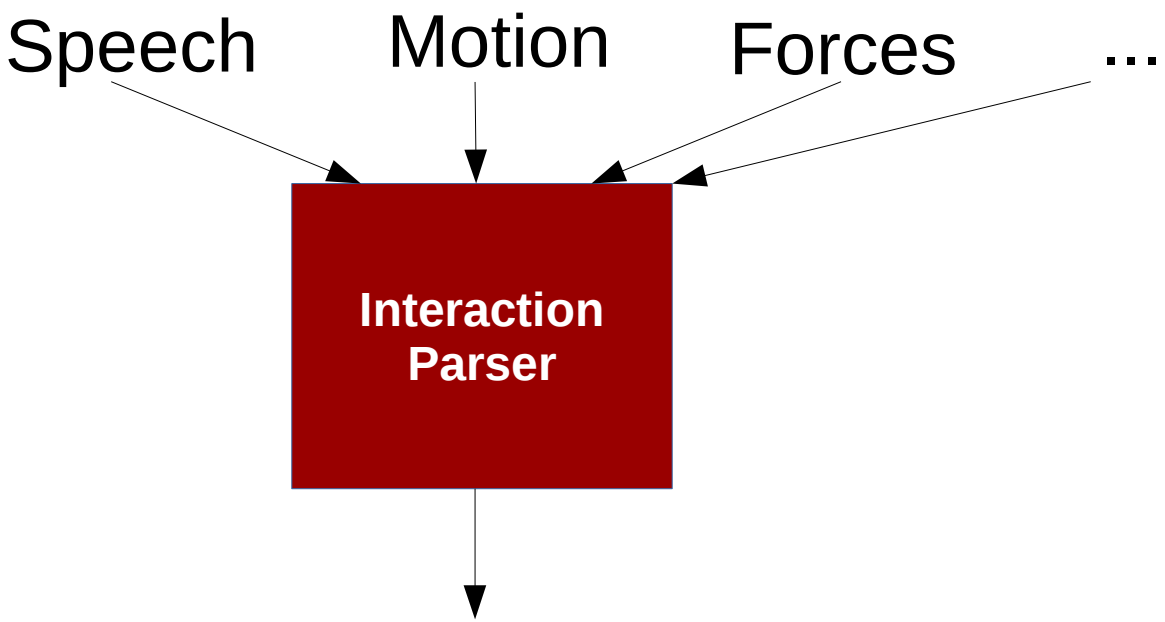
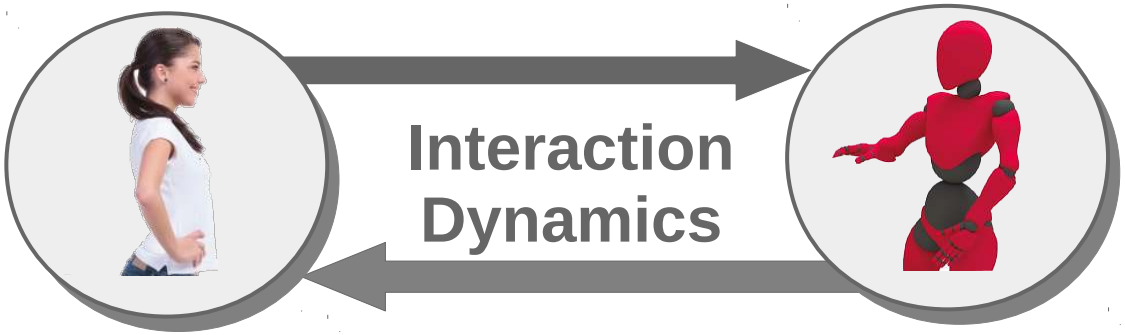


Future Work & Ultimate Goal



Semantic Policy of Interaction Dynamics



Thank you very much!