



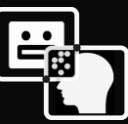
# Lecture 8: The effects of leader-follower dynamics on physical collaboration in human-robot dyads

**Tadej Petrič**

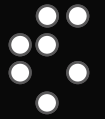
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WWW: <http://cobotat.ijs.si/>



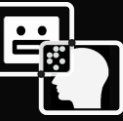
# Examples of human-robot interaction



- Traditional industrial manipulators
- Robot assisted rehabilitation
- Collaborative robot for manufacturing
- Robotic exoskeleton
- Robots for construction
- Elder companionship



# Research questions and challenges

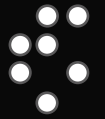


Outline

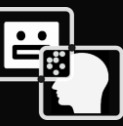
- How can roles (leader-follower) be defined in pHRI?
- What is the optimal level of co-adaptation?
- How can robots learn more like humans?
- How can robots learn more from humans?
- What kind of machine learning can be used in pHRI?



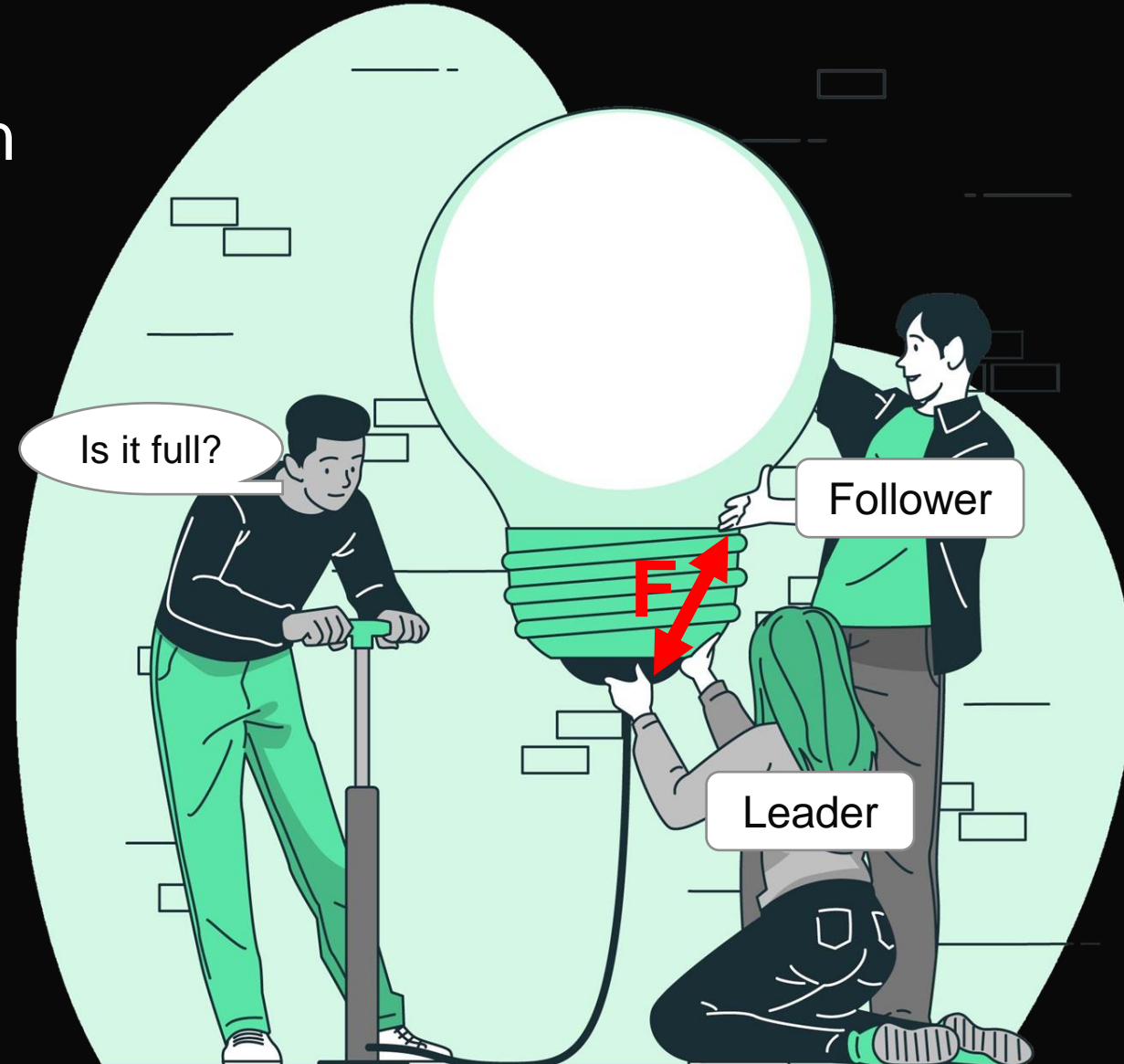




# Collaboration between people

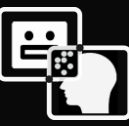


- Daily activity
- Coordination through communication
  - Verbal
  - Non-verbal
- Role allocation
  - important research area for HRC
  - mostly insufficiently researched

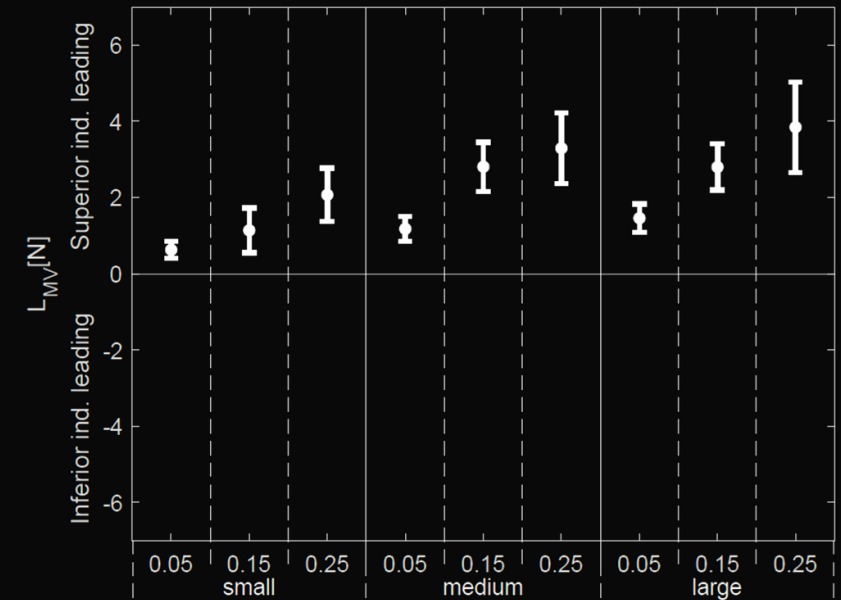
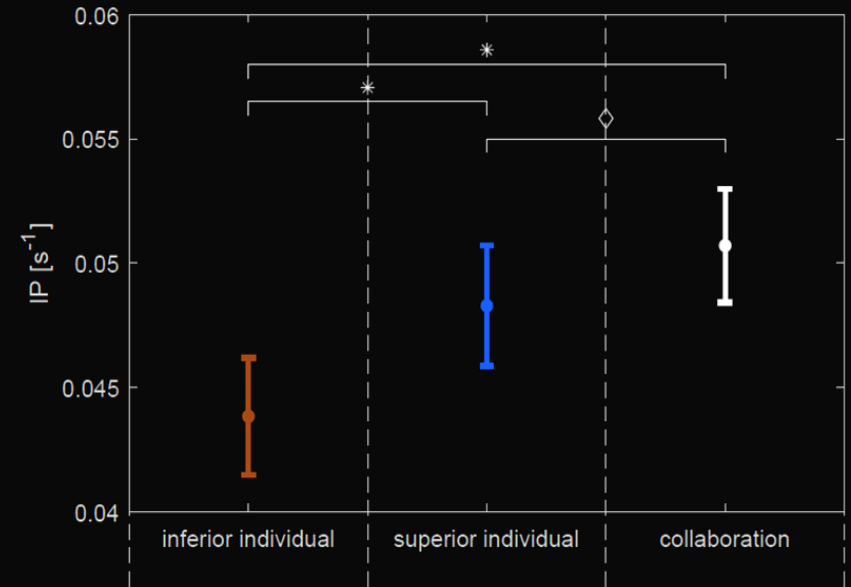
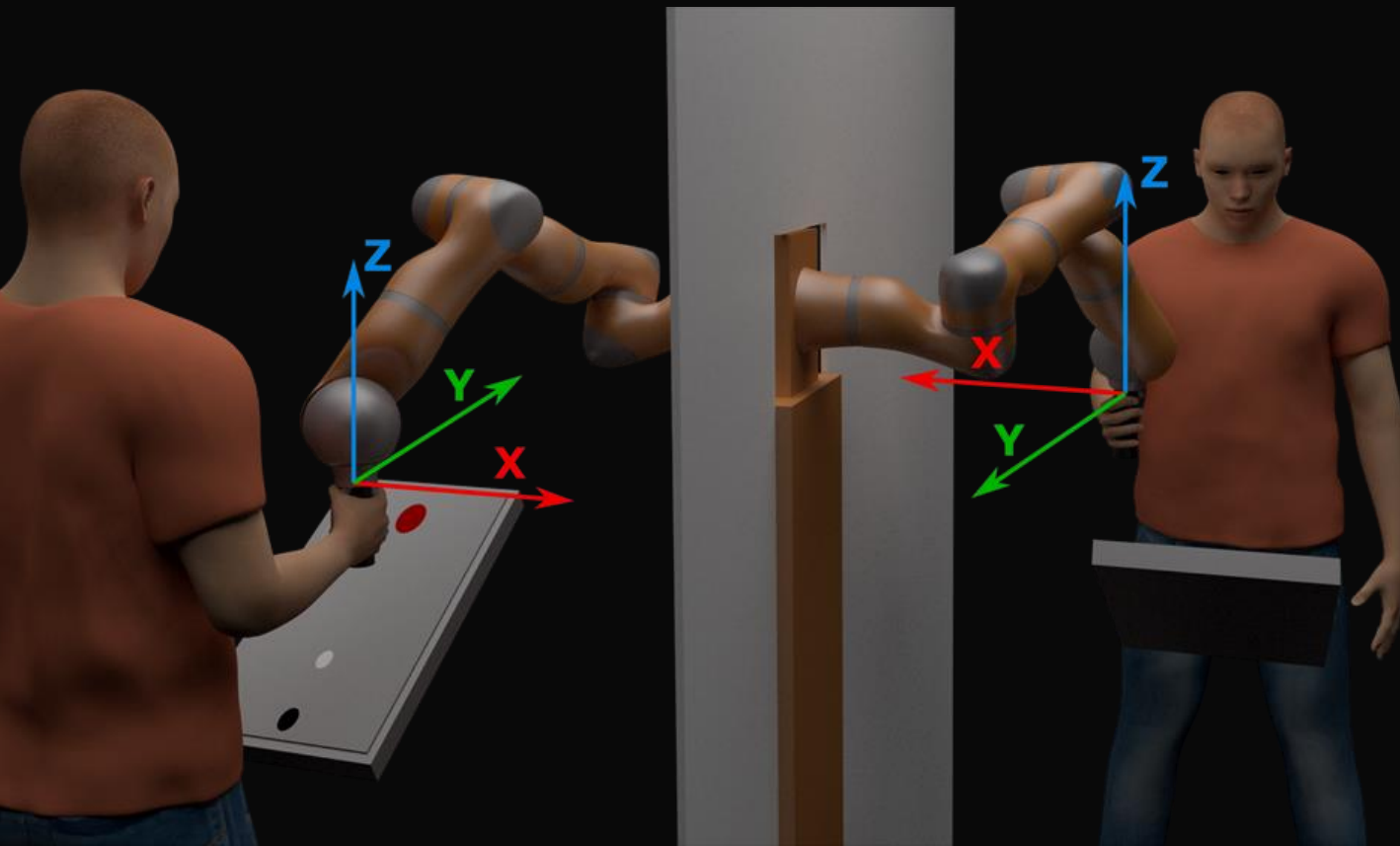




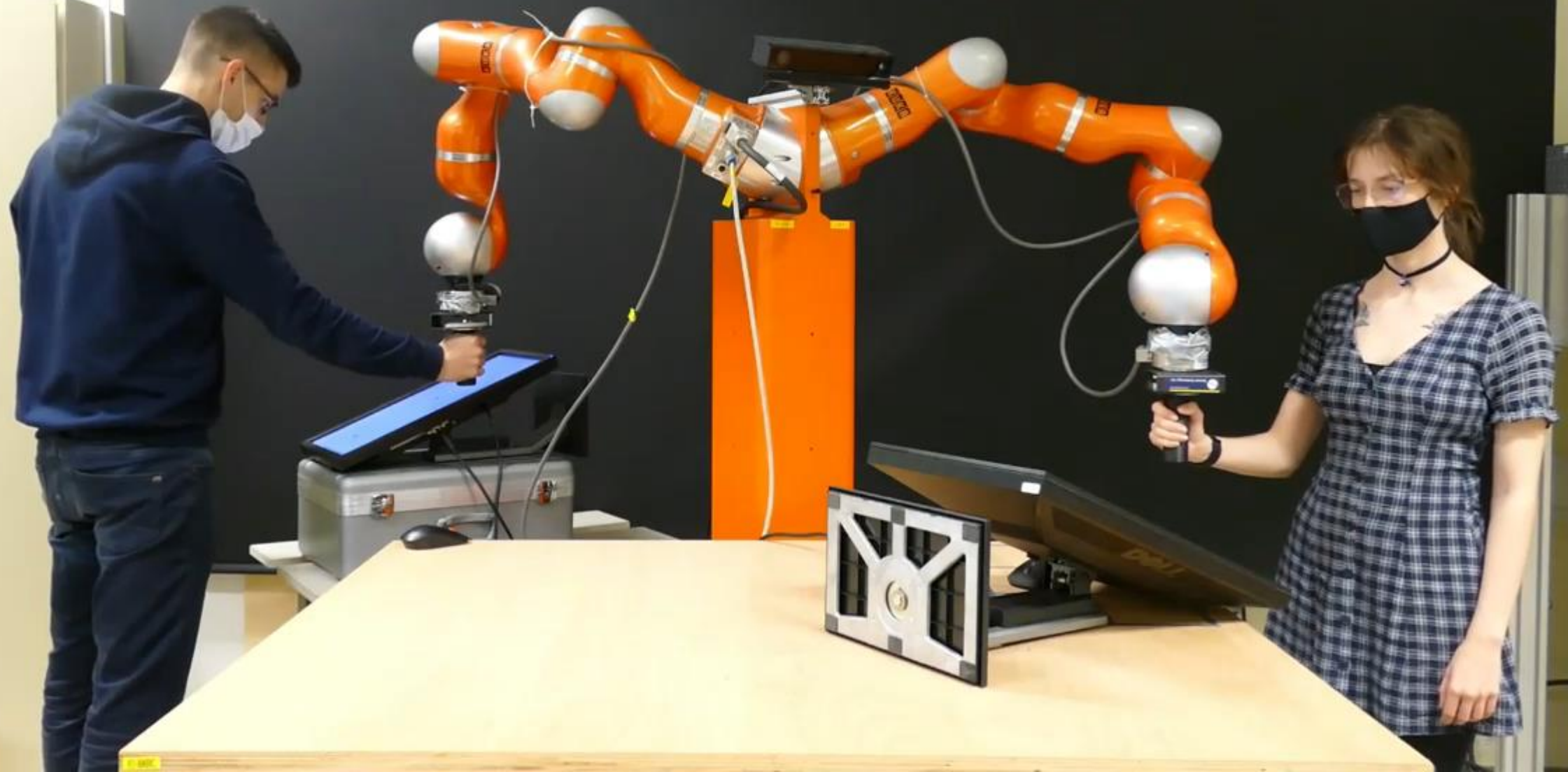
# Study on leader-follower dynamics



- Increased performance in collaboration
  - Slower individual significant improvement
  - Faster individual no significant improvement or deterioration
- **Hypothesis:** leader has the greatest influence in task without start and aiming

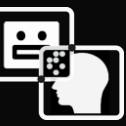


in the individual task  
the two robots aren't connected

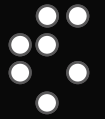




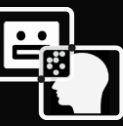
# Human-robot control evaluation



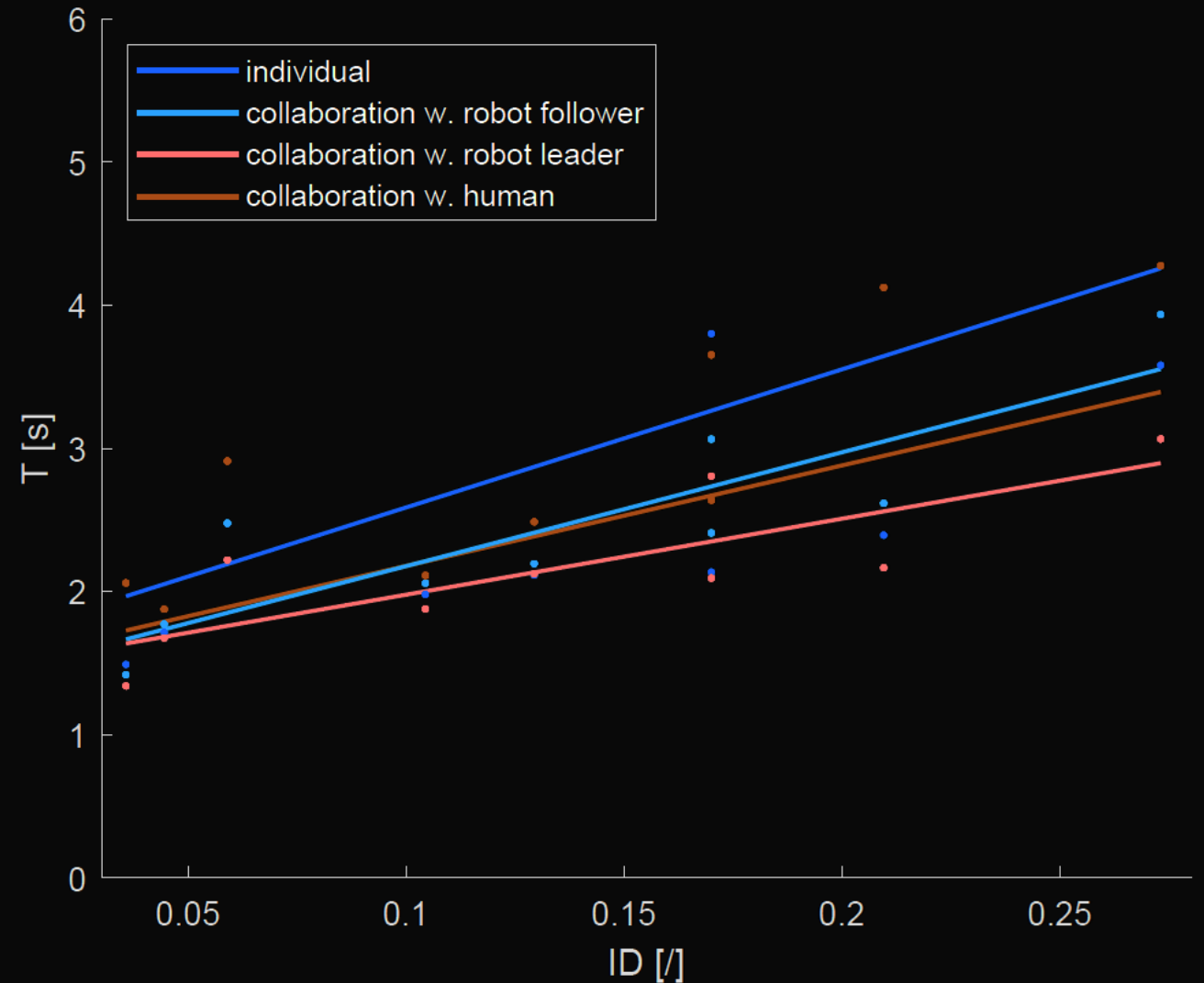
- Objective evaluation:
  - Fitts' law model
    - Time to complete the task depending on the complexity of the target
    - Lower time = better performance
- Subjective evaluation:
  - Nasa-TLX (Task Load Index)
- Turing test
  - "If you chose one of the experiments that you found easiest?"
  - "For each experiment, choose whether you performed the task yourself, with a human, or with a robot."



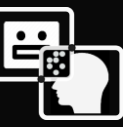
# Human-robot Fitts' law performance evaluation



- Performing the task in collaboration improves efficiency
- Best performance when human collaborates with a robot that is leading



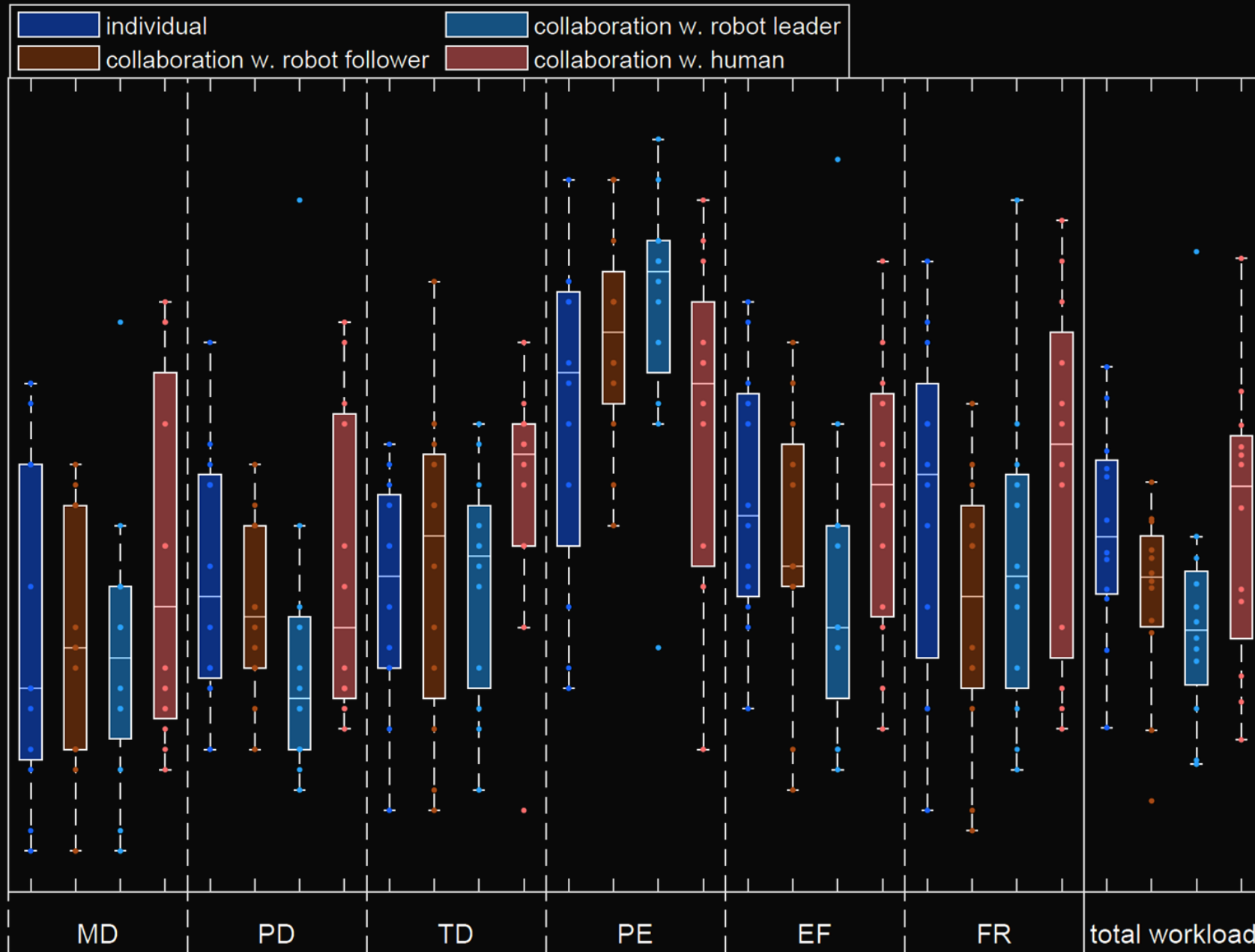




# Nasa-TLX grades

high

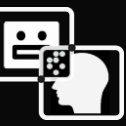
low



- Best result when human collaborate with a robot that is leading
- The most dispersed assessments when two humans are collaborating



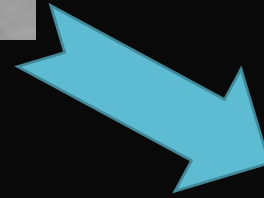
# Turing test



1. If you chose one of the experiments that you found easiest?
  - Individual  $\rightarrow$  2/12
  - Human-robot collaboration (robot is follower)  $\rightarrow$  1/12
  - Human-robot collaboration (robot is leader)  $\rightarrow$  7/12
  - Human-human collaboration  $\rightarrow$  2/12
  
2. For each experiment, choose whether you performed the task yourself, with a human, or with a robot.
  - Individual  $\rightarrow$  9/12
  - Human-robot collaboration (robot is follower)  $\rightarrow$  4/12
    - (wrong: 5 Individual, 1 with human)
  - Human-robot collaboration (robot is leader)  $\rightarrow$  8/12
    - (wrong: 3 with human, 2 individual)
  - Human-human collaboration  $\rightarrow$  9/12



# How do we bridge the gap?



Robots should learn more like humans

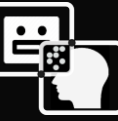
- Learning internal dynamic models
- Learning task specific dynamics



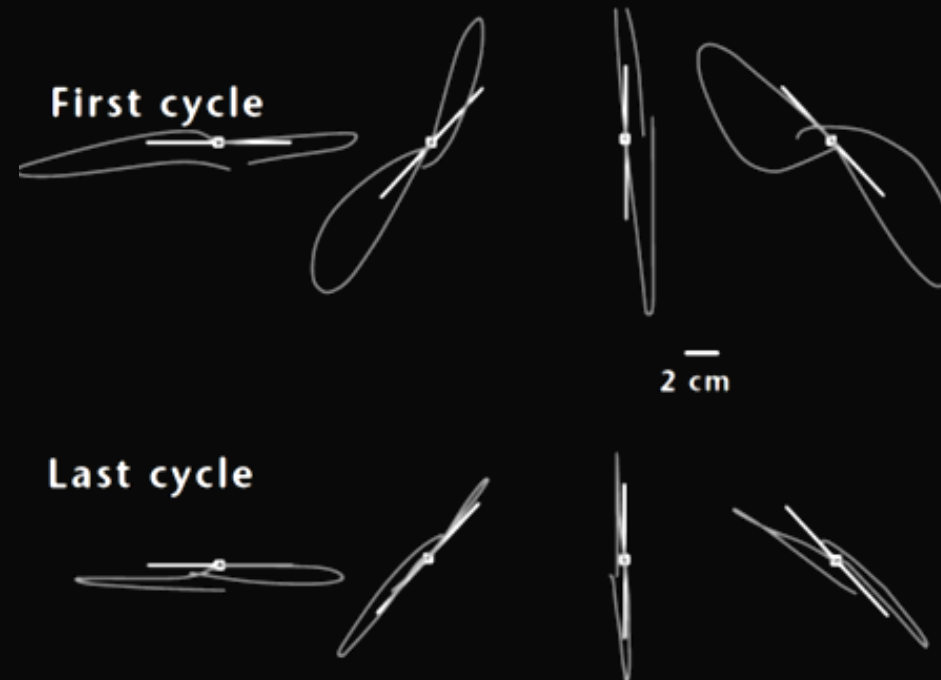
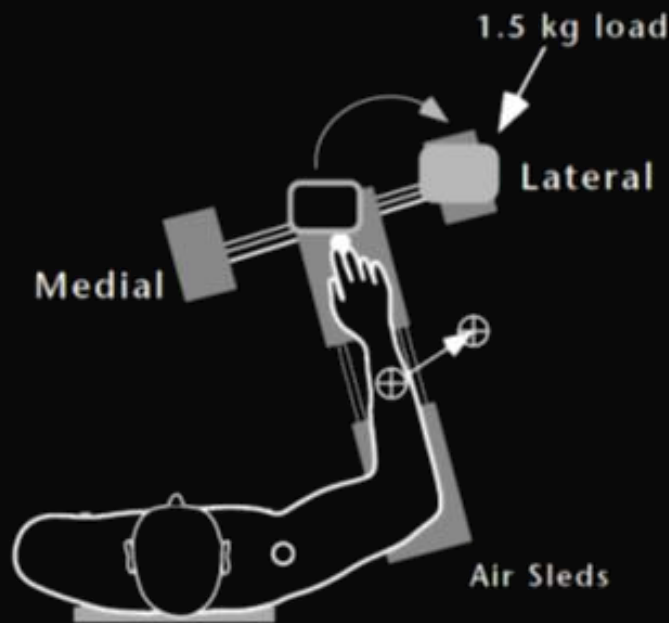
7.2



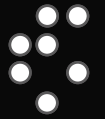
# Humans



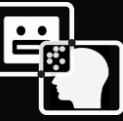
- Krakauer, et al. (1999), Nature Neuroscience:
  - ... hand **kinematics** are learned from **errors in extent and direction** in an **extrinsic coordinate system**, whereas **dynamics** are learned from **proprioceptive errors** in an **intrinsic coordinate** system...







# Compliant Movement Primitives (CMP)



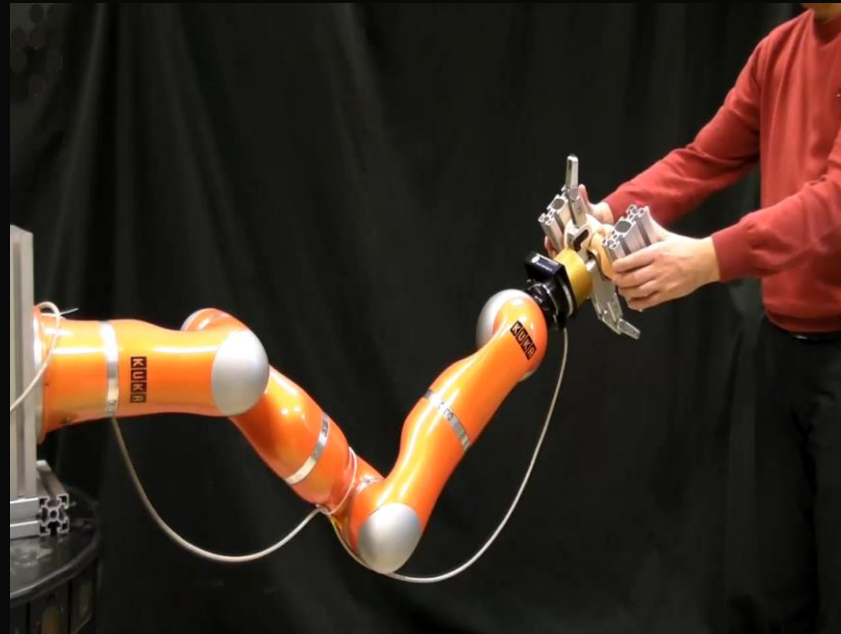
- CMP defines a task as a pair of signals:  $h(t) = [q_d(t), \tau_f(t)]$

- Multi step process

1. Motion trajectory  $q_d(t)$  is learned by human demonstration



2. Iterative leaning of torque primitives  $\tau_f(t)$  is updated based on kinematics



3. Movement and torque primitives are learned, stored and executed

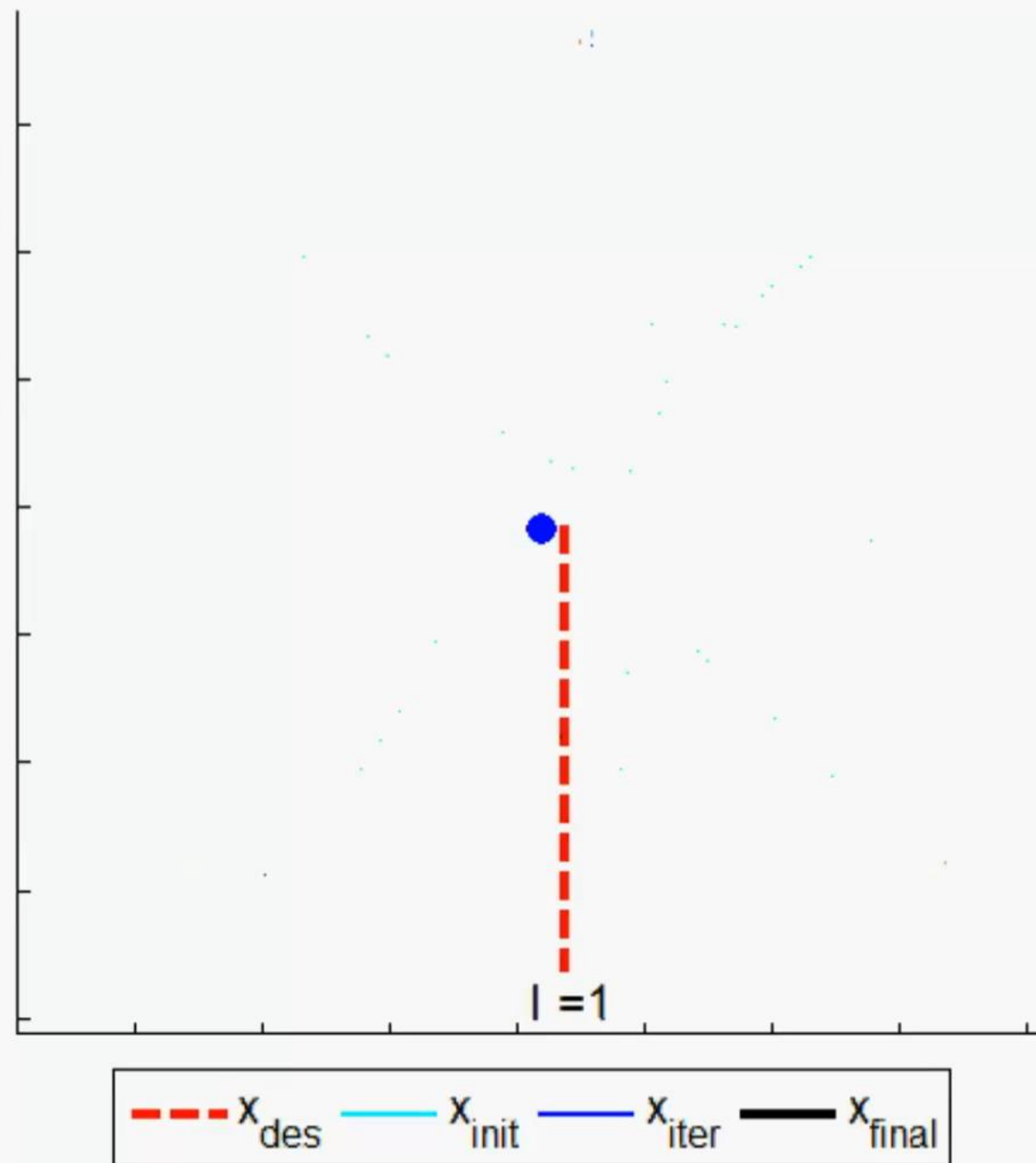


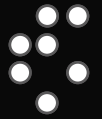
# Human

First cycle

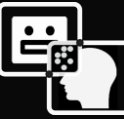


Last cycle

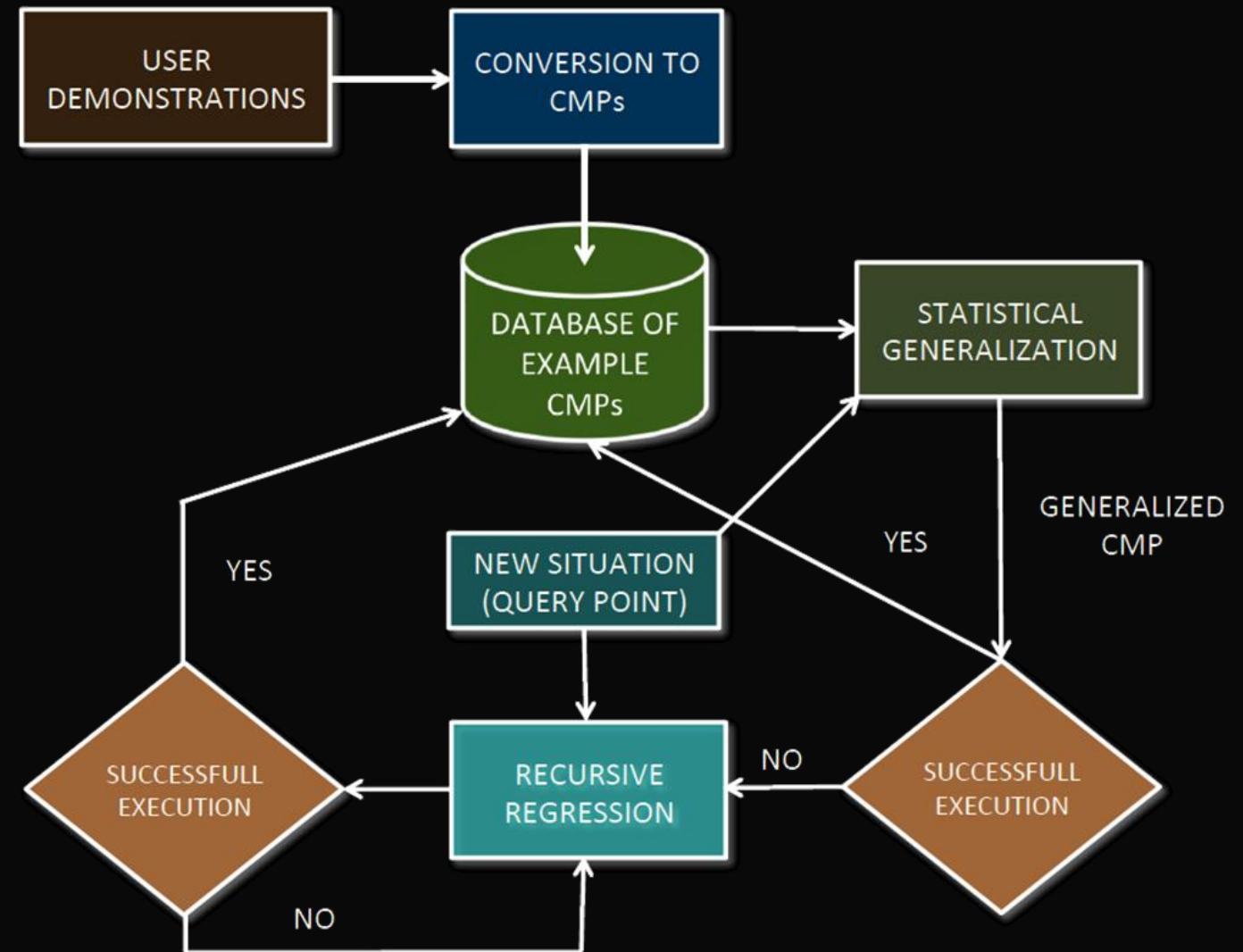


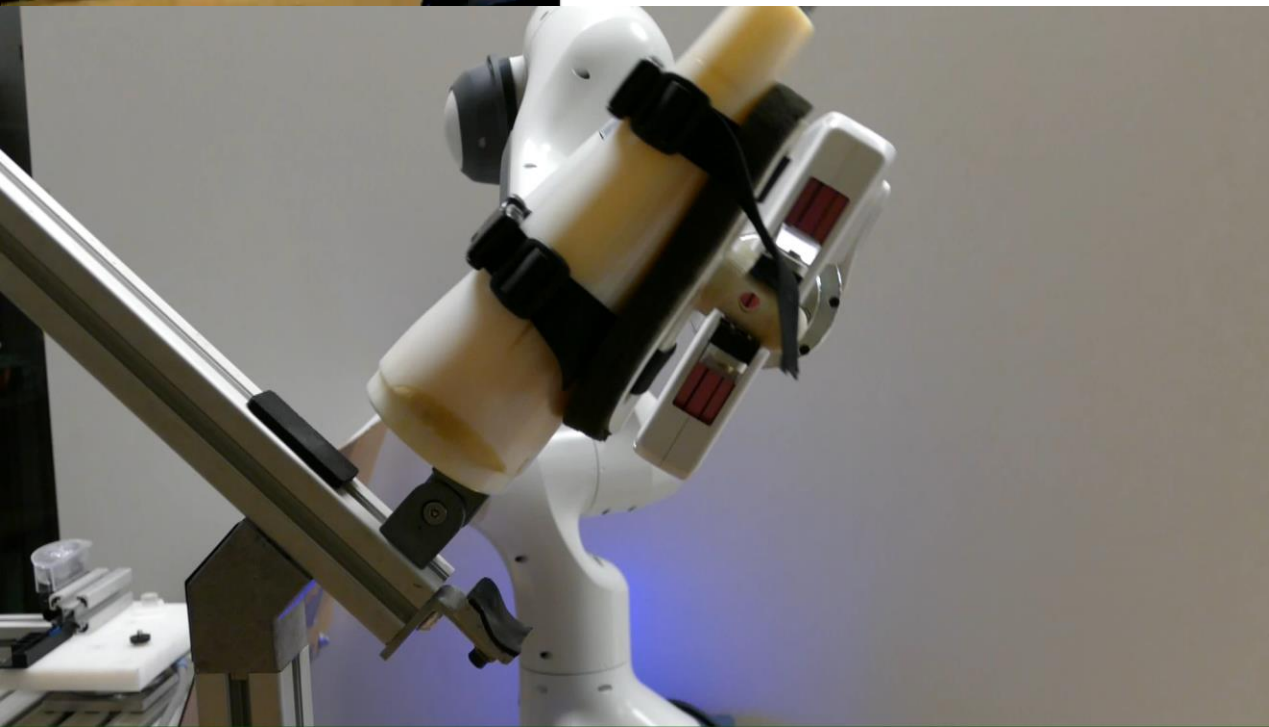
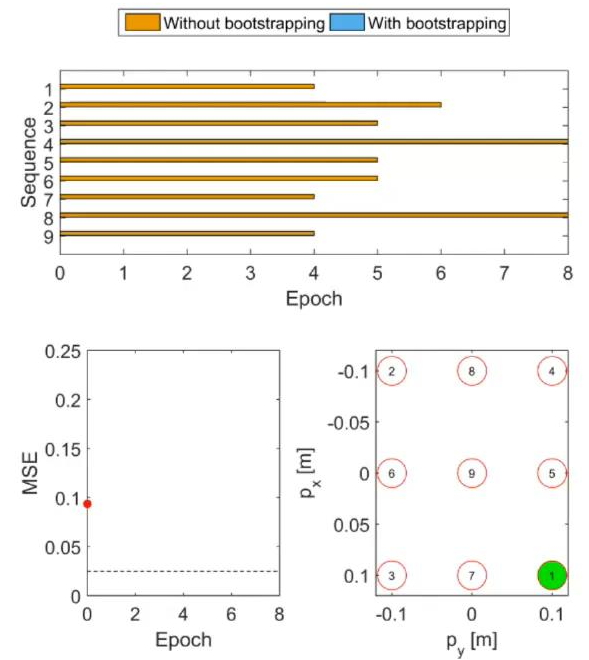
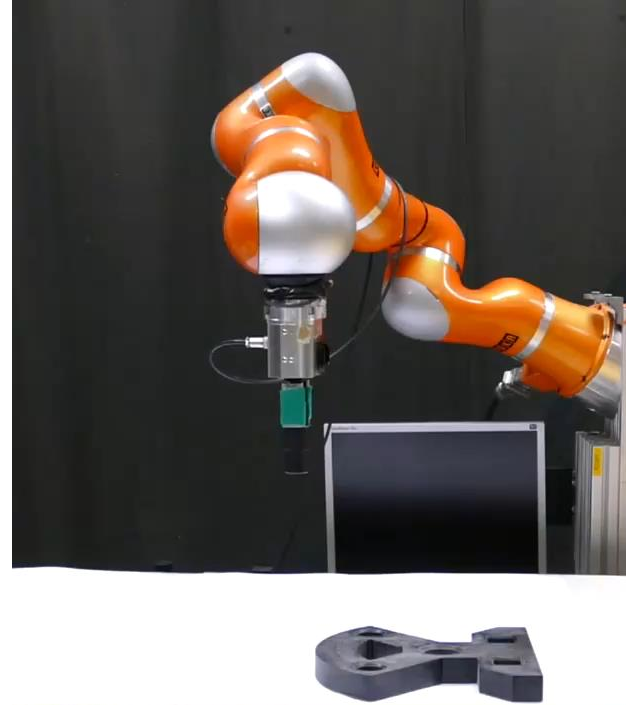
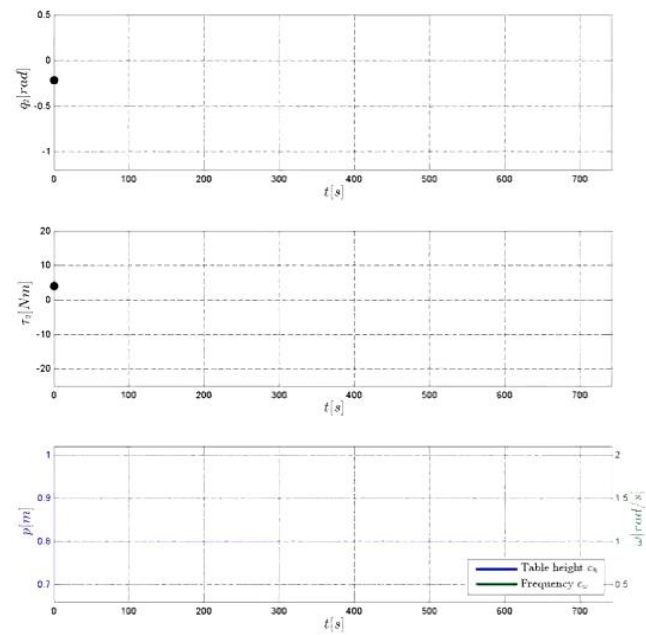
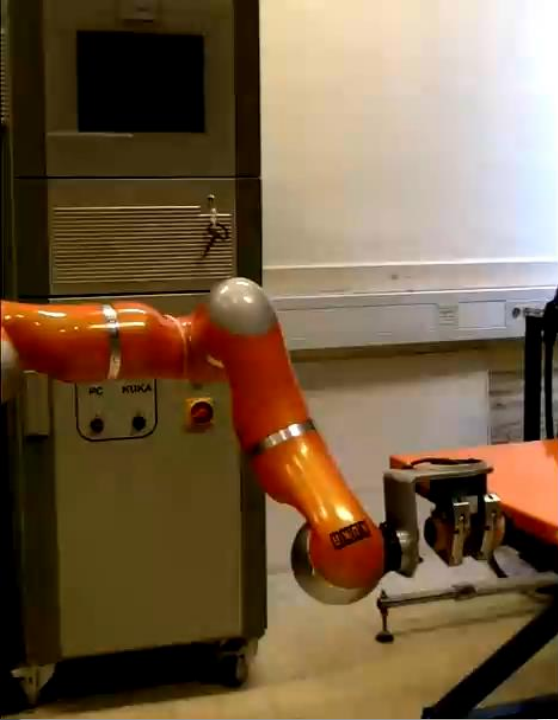


# Generating database of CMPs



- CMPs have to be learned for every variation of the task.
- Different error metric can be used for determining if new CMPs should be added to the database.
- Learning can be, avoided or significantly accelerated by using statistical generalization.

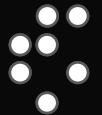




## Part 2:

### *Generalization of Discrete CMPs*





# Robots should learn more from humans

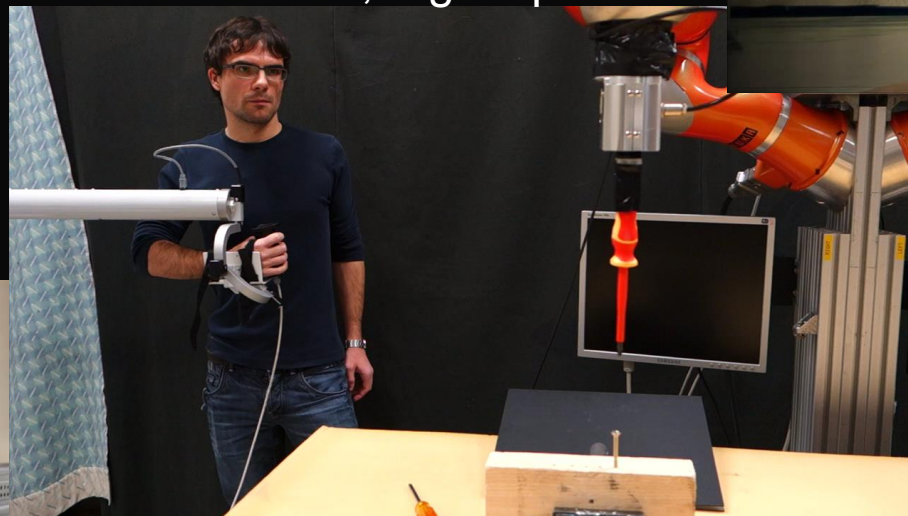


Complexity of skill

Progress of SotA

Learning task relevant information, e.g. impedance

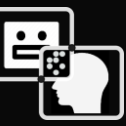
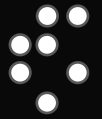
Learning by demonstration



Human in the loop learning

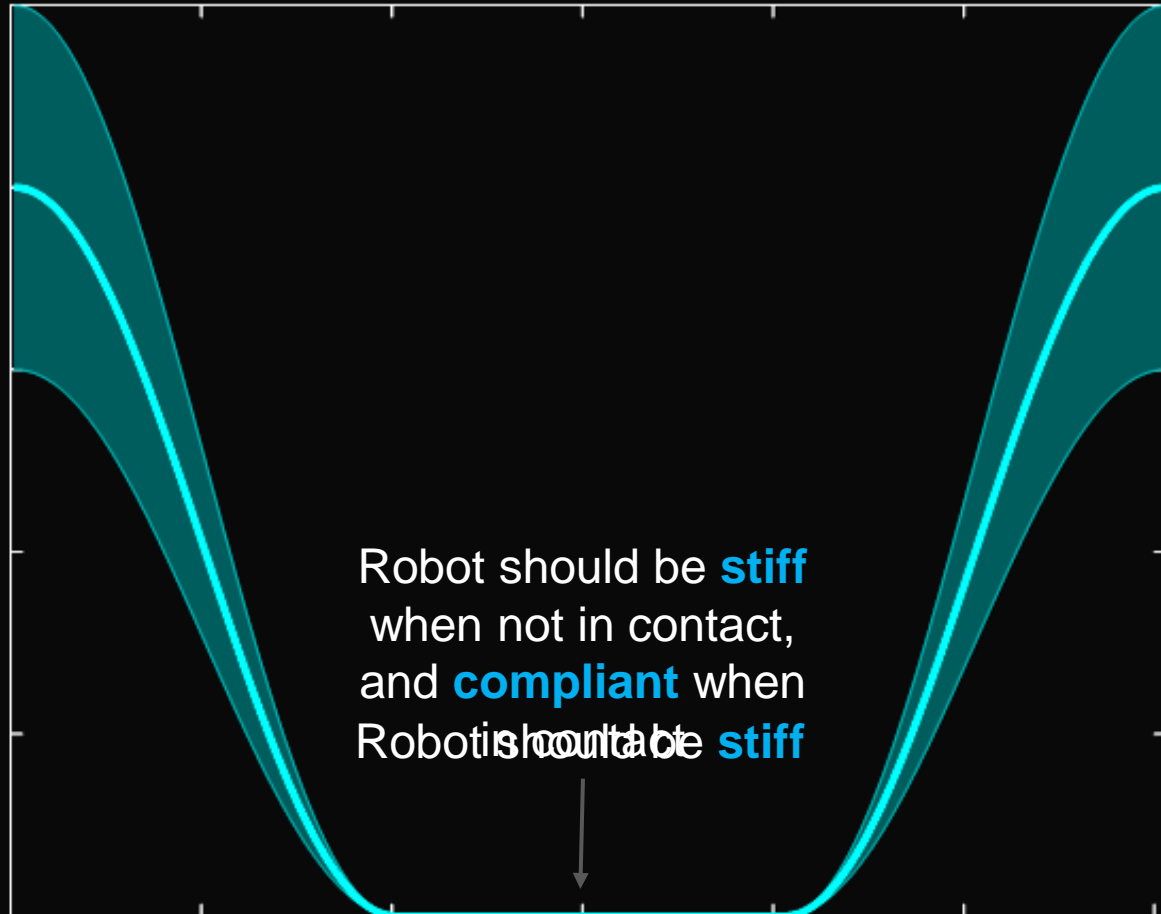


Acquisition of skill

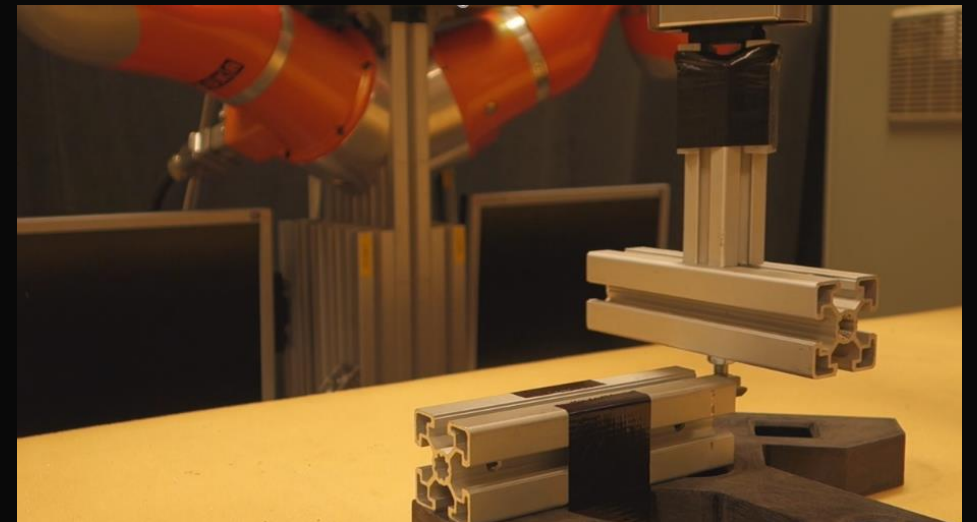


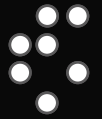
# How to transfer compliance?

- Path and standard deviation

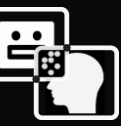


- When not in contact SD can be associated with robot compliance
- When the robot is in contact with environment we must use different strategy



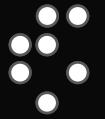


# Dataset correspondence

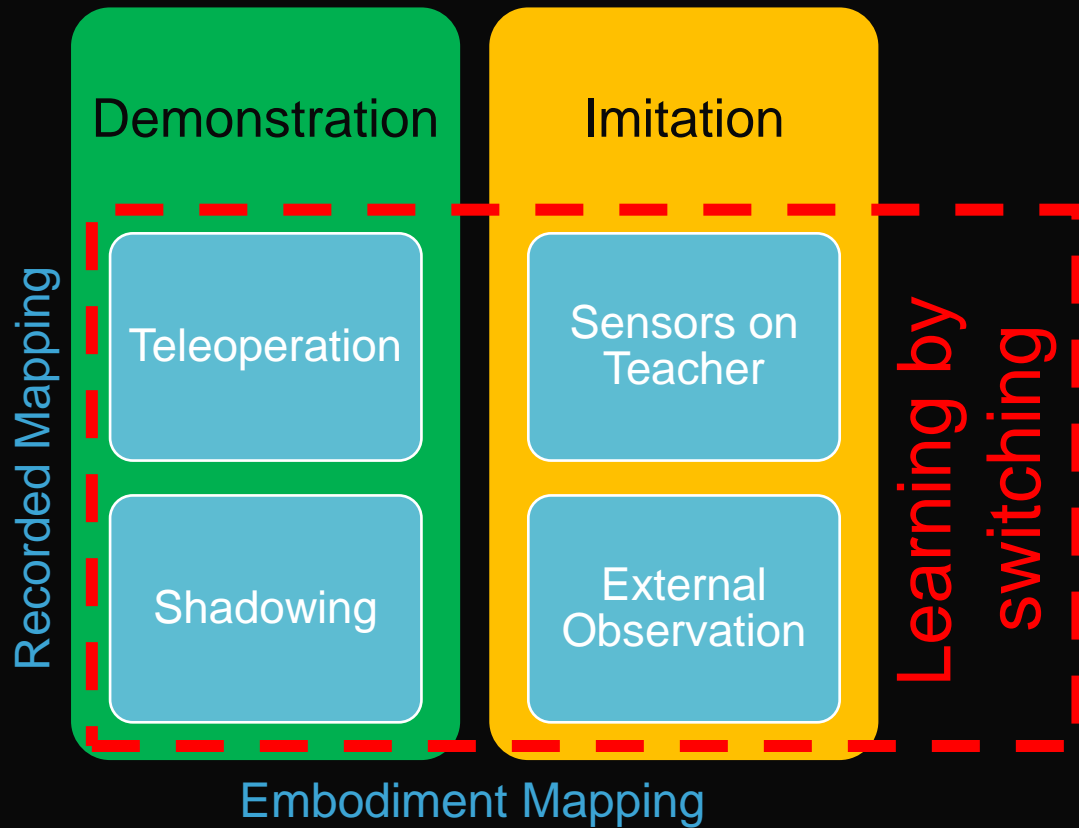
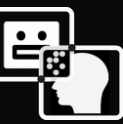


- Because of differences in the teacher's sensors and actuators (human eyes, human joints) and the robot's sensors and actuators, a direct transfer of information from teacher to student is often difficult
- This issue, called **correspondence**, and can be broken down into two categories:
  - Record mapping: correspondence between teacher's actions and recorded data
  - Embodiment mapping: correspondence between recorded data and learner's execution





# Acquired dataset with the recorded and the embodied mapping...

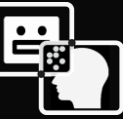


...enables:

- Learning and control strategies for reactive behaviors
- Learning and control strategies for anticipative behaviors
- Subspace learning for physical collaboration
- Tennis example:

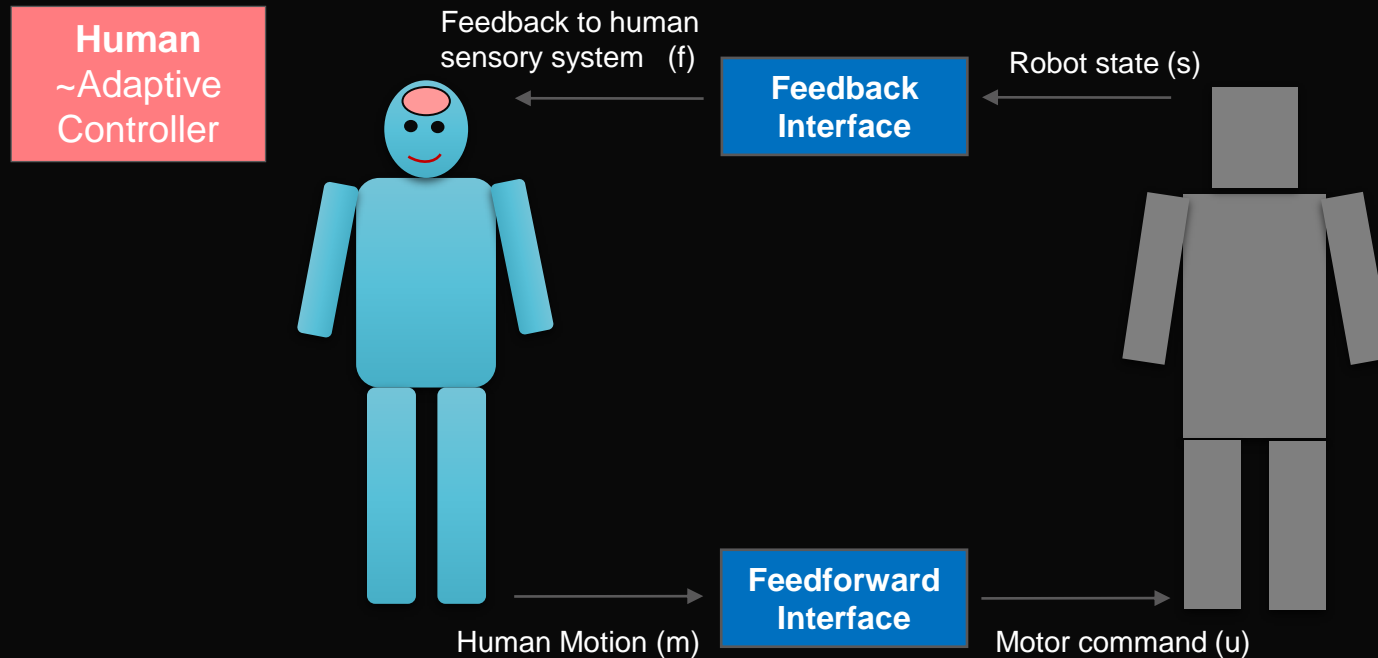


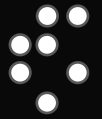




# The paradigm

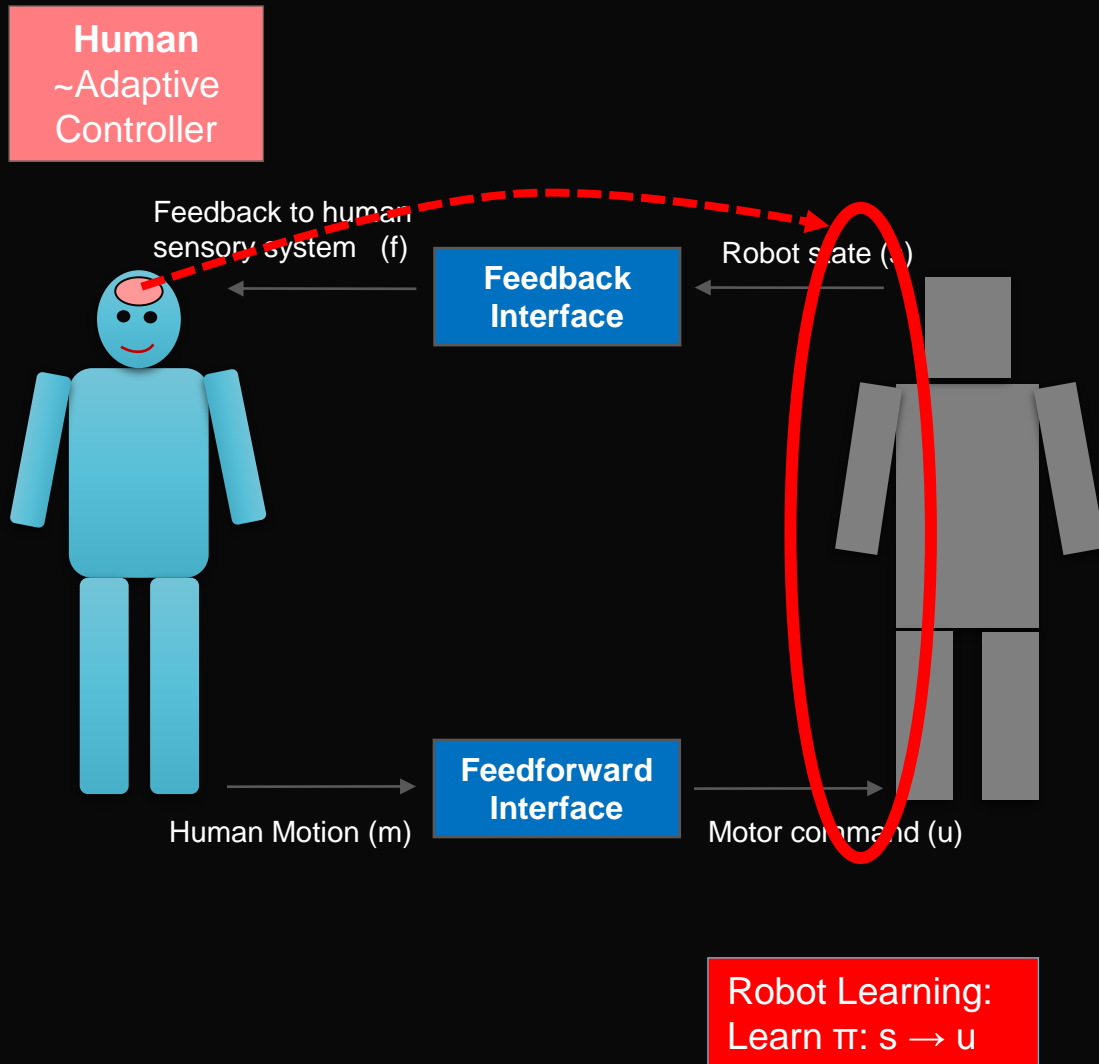
- Use human **sensorimotor learning** ability to obtain robot behaviors
  - Include the human in the control loop
  - May ask human to do extensive training
  - Utilize the human brain as the adaptive controller



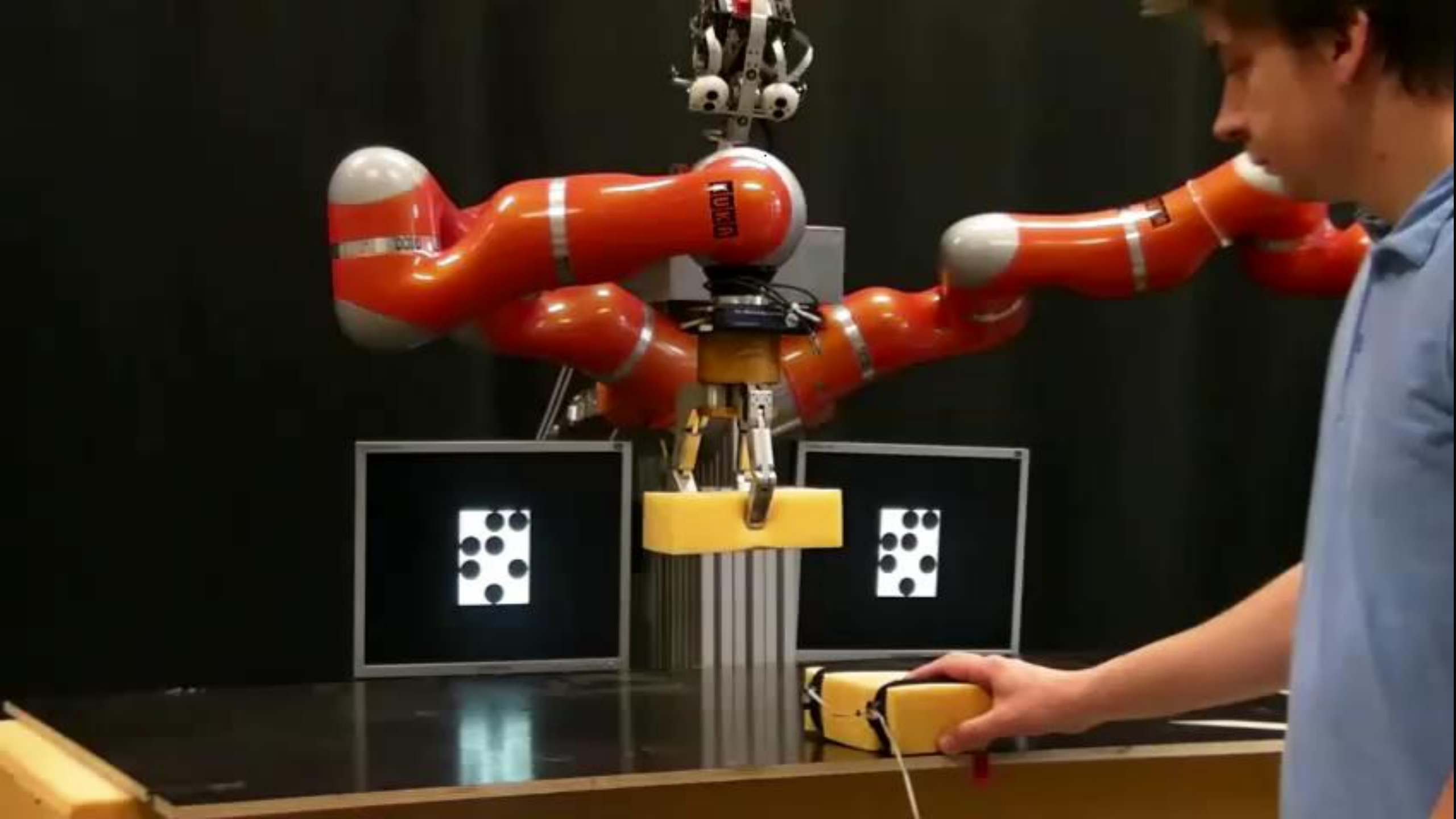


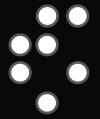
# Skill synthesis for autonomy

- Why should this paradigm work?

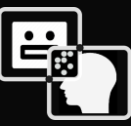


- The ability of the brain to learn novel control tasks by forming **internal models**. The robot can be considered as a tool (e.g. as driving a car, playing an instrument, using chopsticks)
- The flexibility of the **body schema**; extensive human training modifies the body schema so that the robot can be naturally controlled

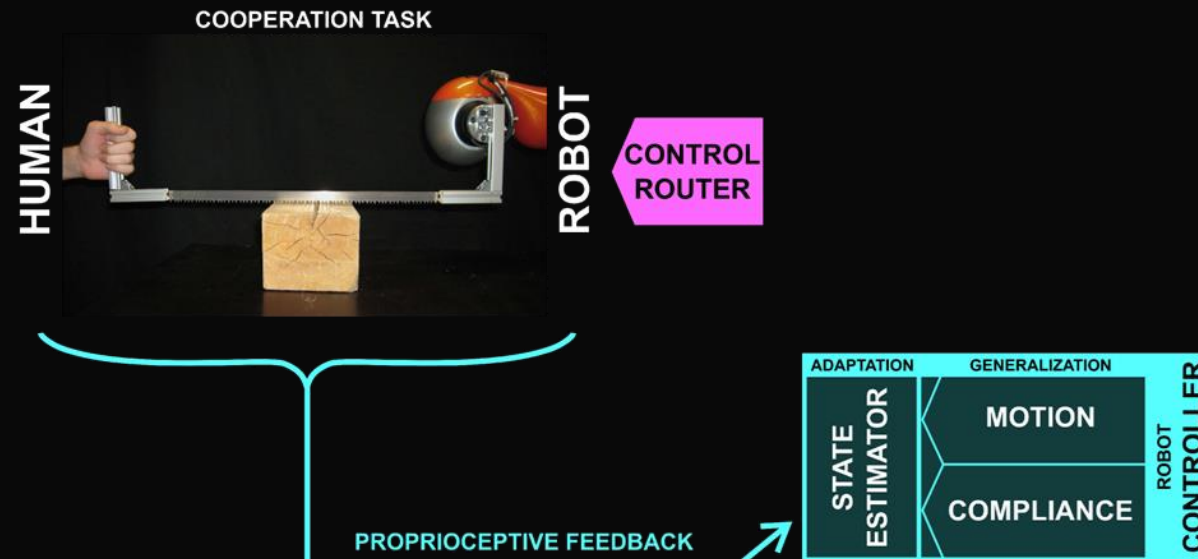




# Cooperative dynamic manipulation

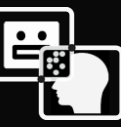


- Teach the robot to perform the manipulation tasks in collaboration with a human partner
- Online learning and adaptations
- Gradually transfer control responsibility from the human teacher to the autonomous robot controller

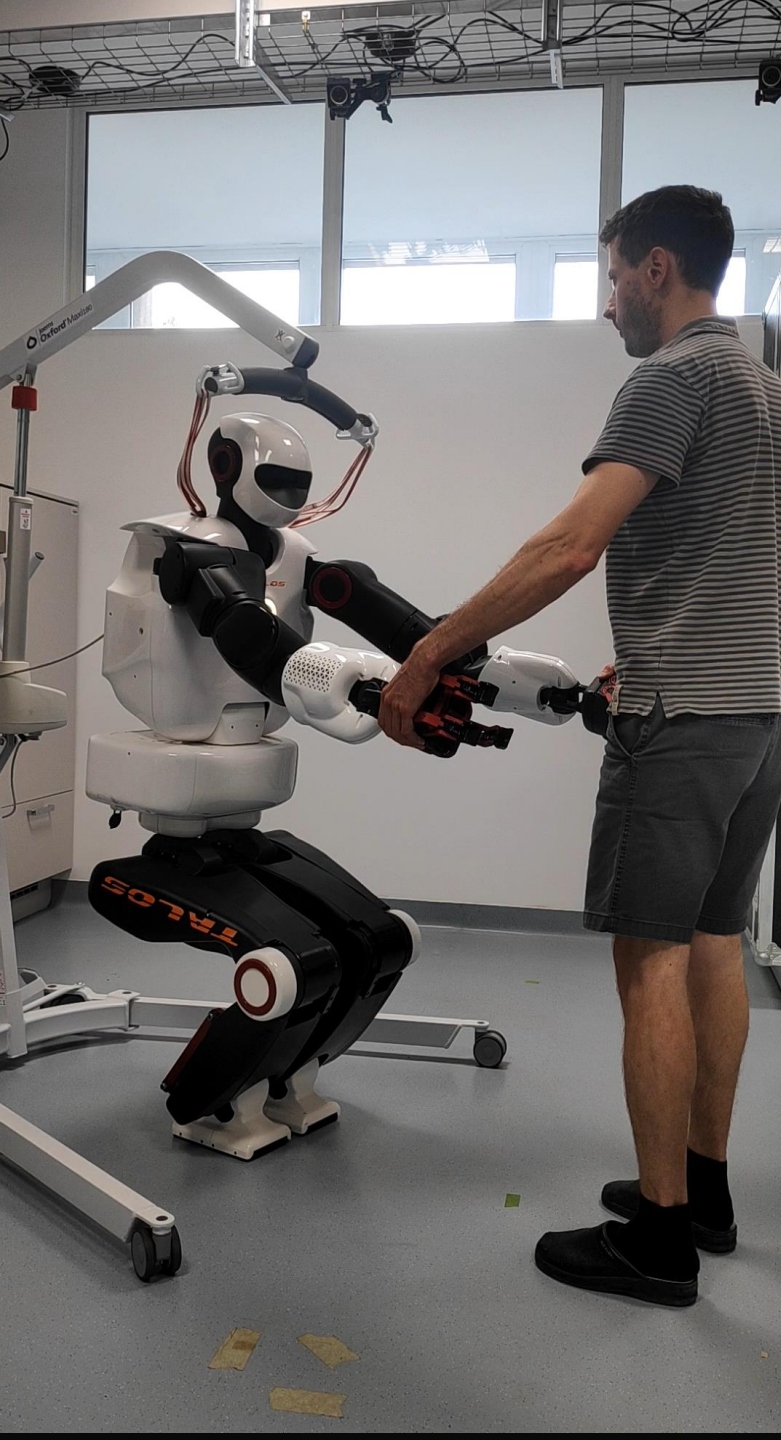








# Stand-up example



Vision and haptic sensing on human



Generalize skill by learning the inverse

Human motion and force interaction



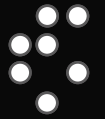
Interaction forces

PSS

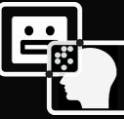
CMP

Motion & torque references





# Robot control for enhanced collaboration



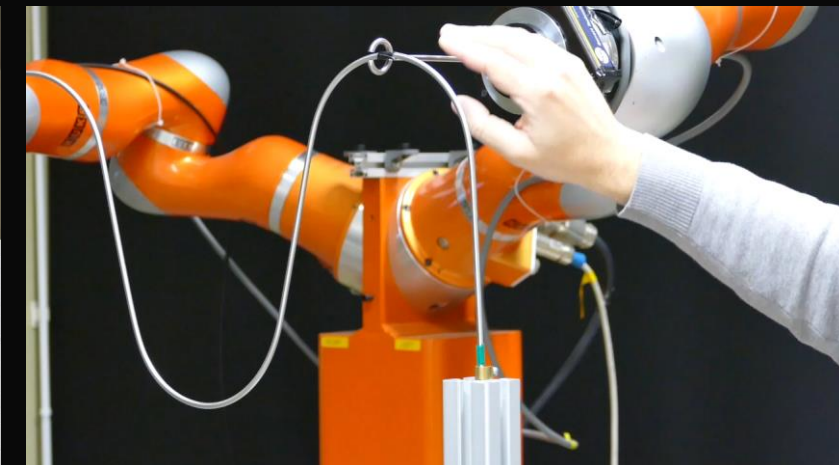
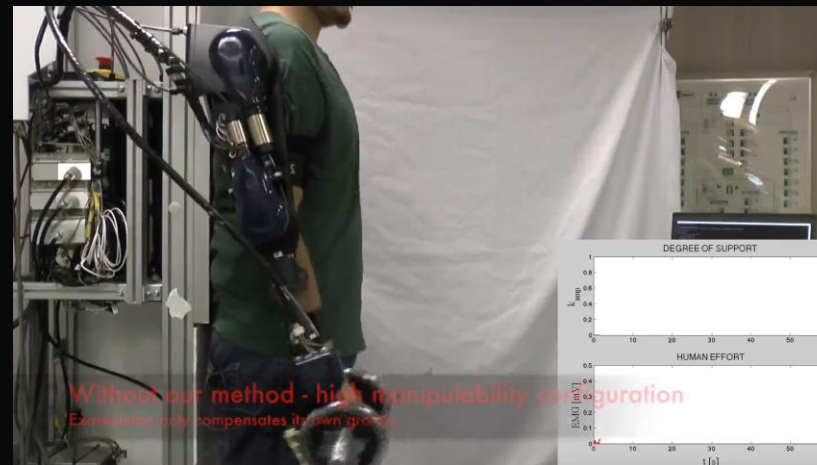
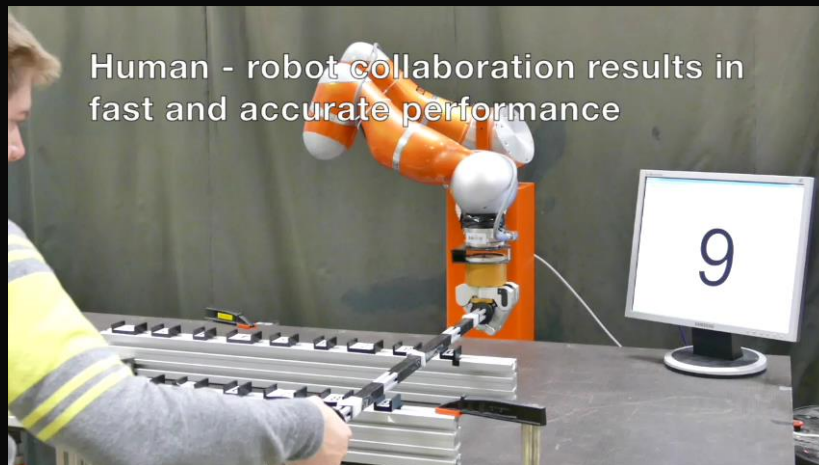
- Robots and humans collaborate in such a way as to enhance and emphasize the qualities of each other

Robots gain:

- Workload
- Proprioception
- Cognition

Humans will:

- Improve speed-accuracy trade-off (Fitts' law)
- Extend the efficient workspace (Manipulability)
- Reduce the variability of motion (Virtual guides)



- **T. Petrič**, M. Cevzar, and J. Babič. "Utilizing speed-accuracy trade-off models for human-robot coadaptation during cooperative groove fitting task." *IEEE Humanoids 2017*
- **T. Petrič**, C.S. Simpson, A. Ude and A. J. Ijspeert, "Hammering Does Not Fit Fitts' Law." *Frontiers in computational neuroscience*, 2017
- **T. Petrič**, L. Peternel, J. Morimoto and J. Babič "Assistive Arm-Exoskeleton Control Based on Human Muscular Manipulability." *Front. Neurorobot.* 2019
- L. Žlajpah, and **T. Petrič**. "Unified Virtual Guides Framework for Path Tracking Tasks." *Robotica*, 2019



# TAKE HOME MESSAGE

Neuromechanical modeling is a powerful tool that can be successfully used as the underlying basis for control of collaborative robots.

