

From Passive Robot Learner to *Pro-Active Inter-Active* Robot Learner

The Role of Interaction in Robot Learning

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TU Wien, DLR

Imitation Learning



Why Imitation Learning from Humans?

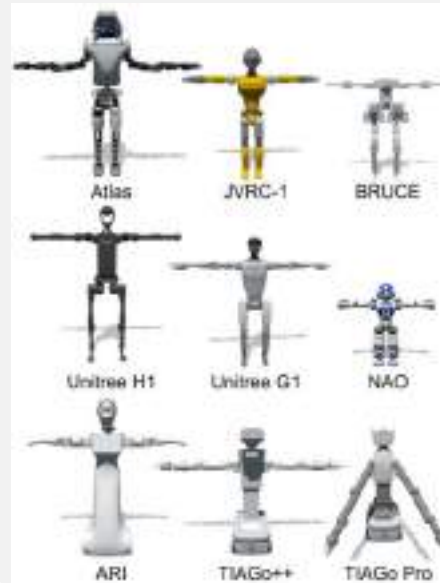
Democratizing Robot Programming



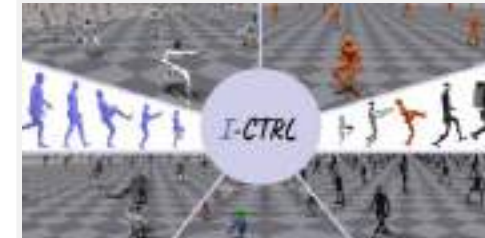
Expressive Robot Motions



To Any Robots



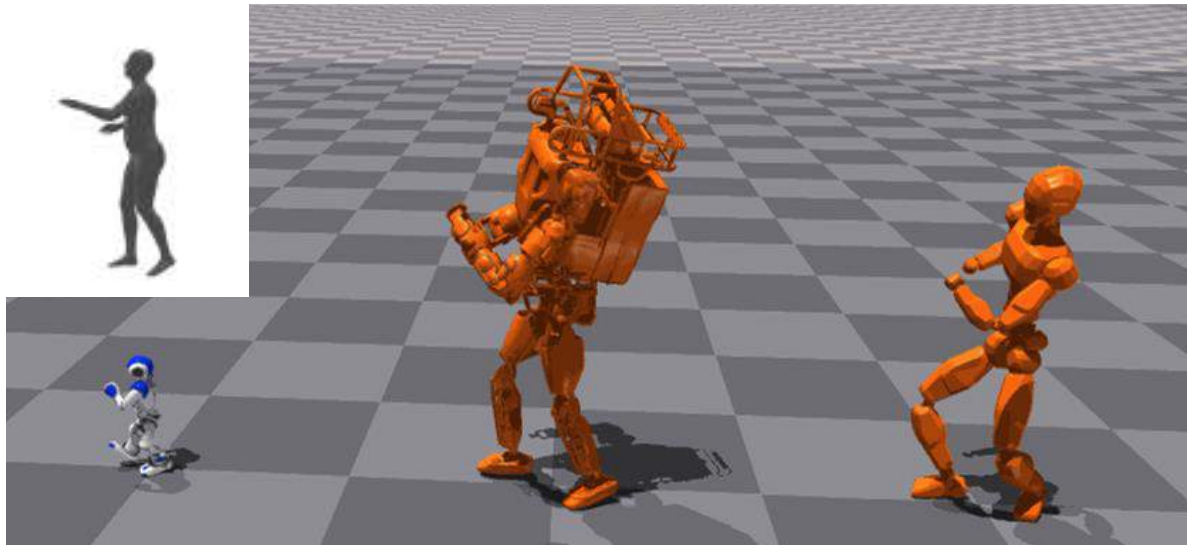
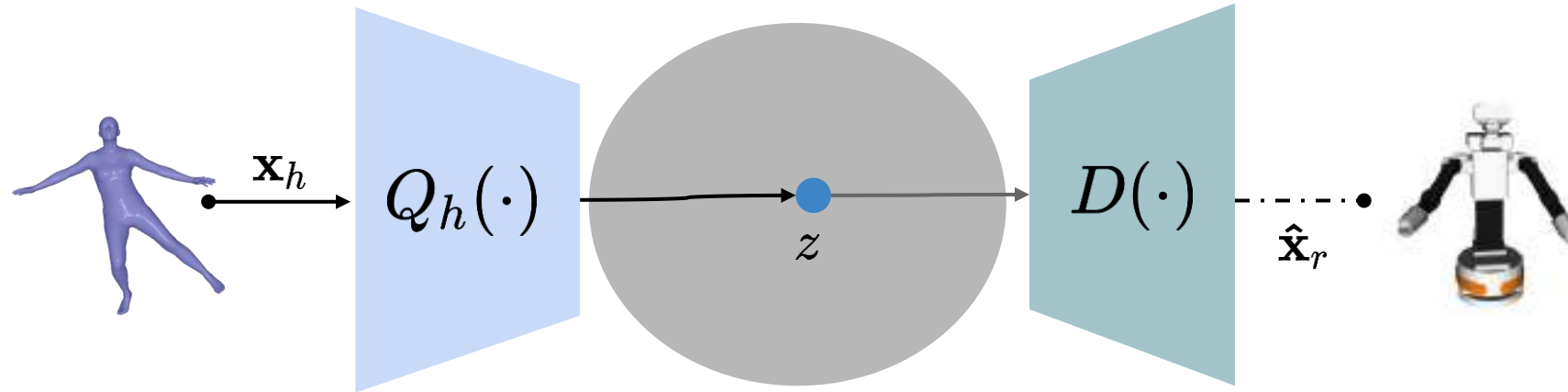
Fast Efficient Skill Learning



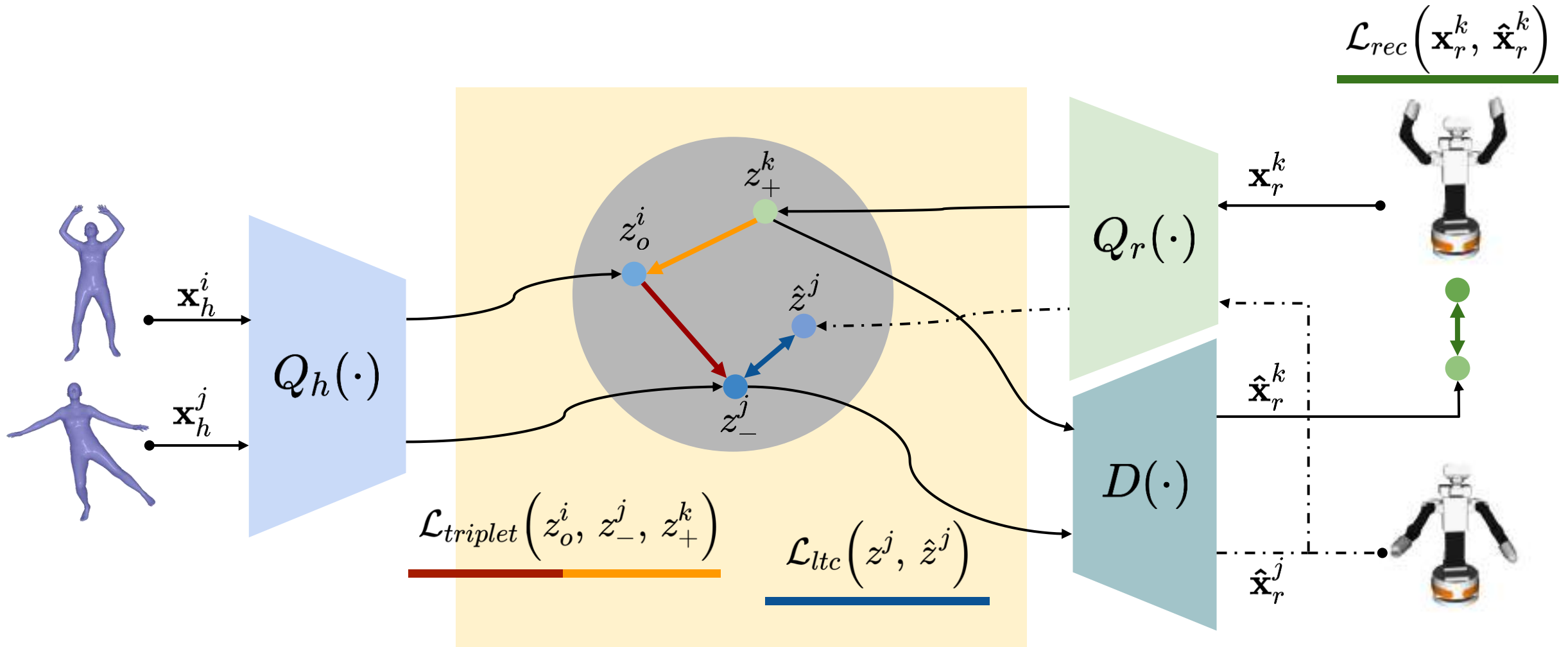
Natural Human-Robot Interaction



ImitationNet is an **unsupervised** DL method for human-to-robot retargeting via expressive shared latent space.



Shared latent space is built in unsupervised manner.



Imitation Learning from Humans



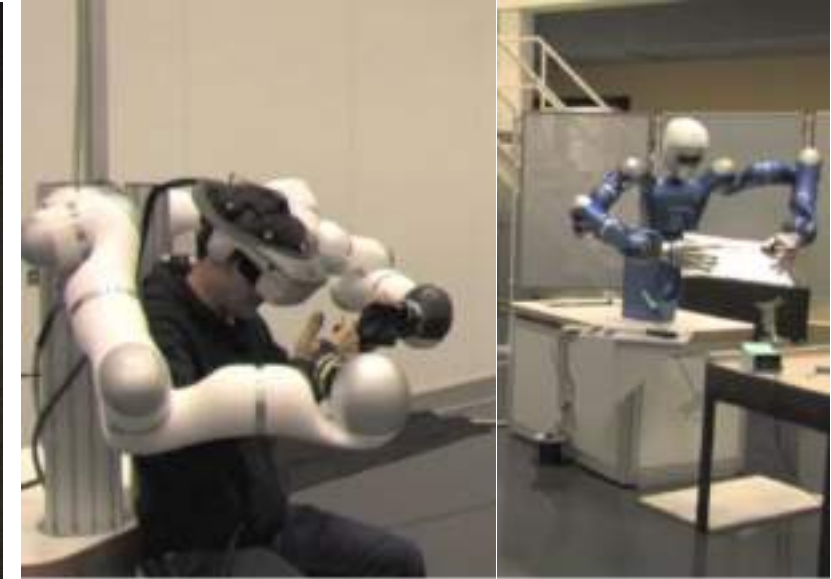
Motion Imitation

[Humanoids 2008, SYROCO2012, AT 2012, ICRA11, ICRA2014, etc]



Kinesthetic teaching

[Autonomous Robots 2011, IROS 2010, ICRA 2015, etc]

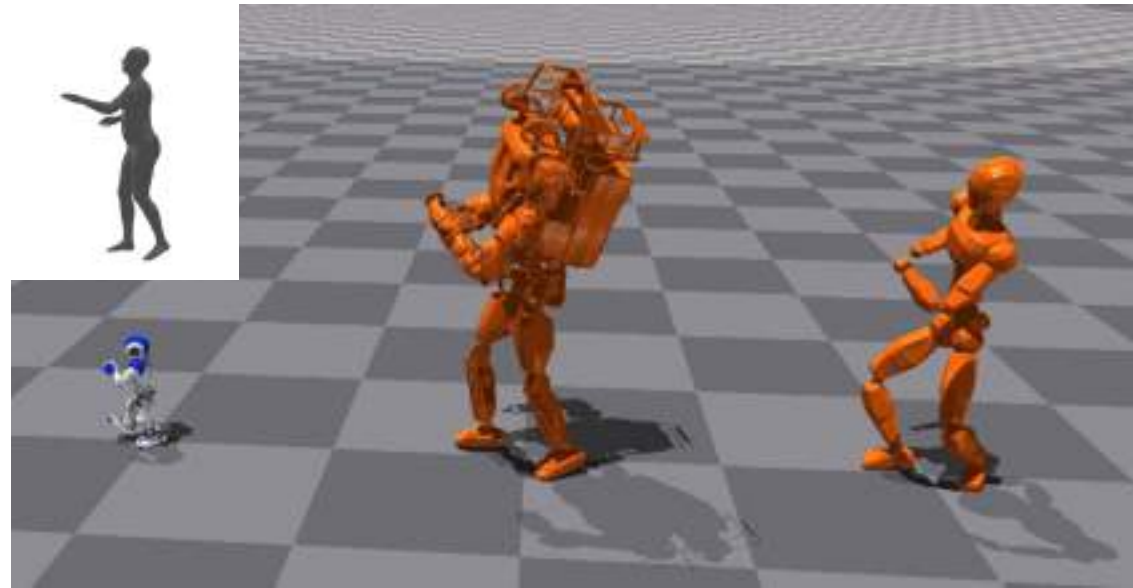


Teleoperation

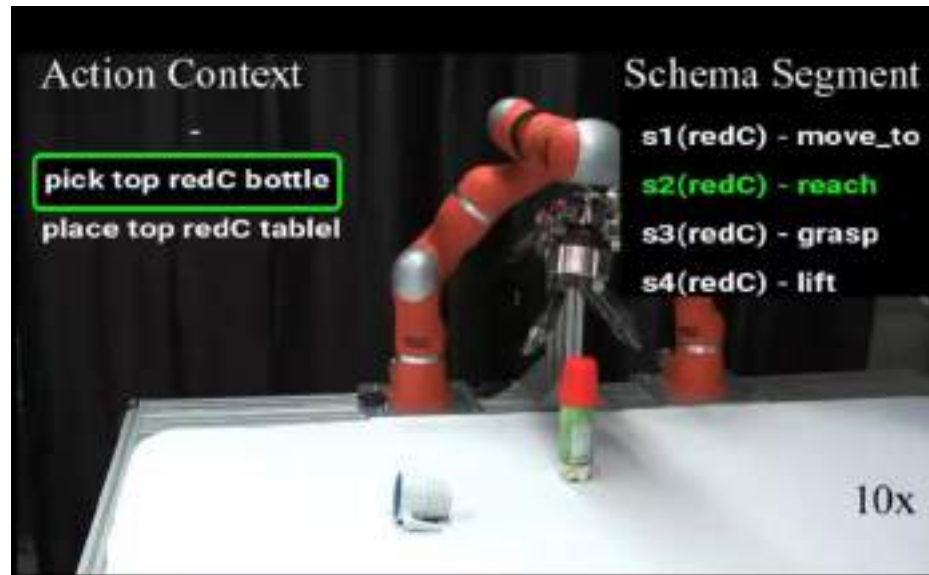
[IROS 2011, WHC 2017, AURO2019, ICRA 2020, RAL 2021, TRO 2022, RAL 2023, RAL 2024, etc]



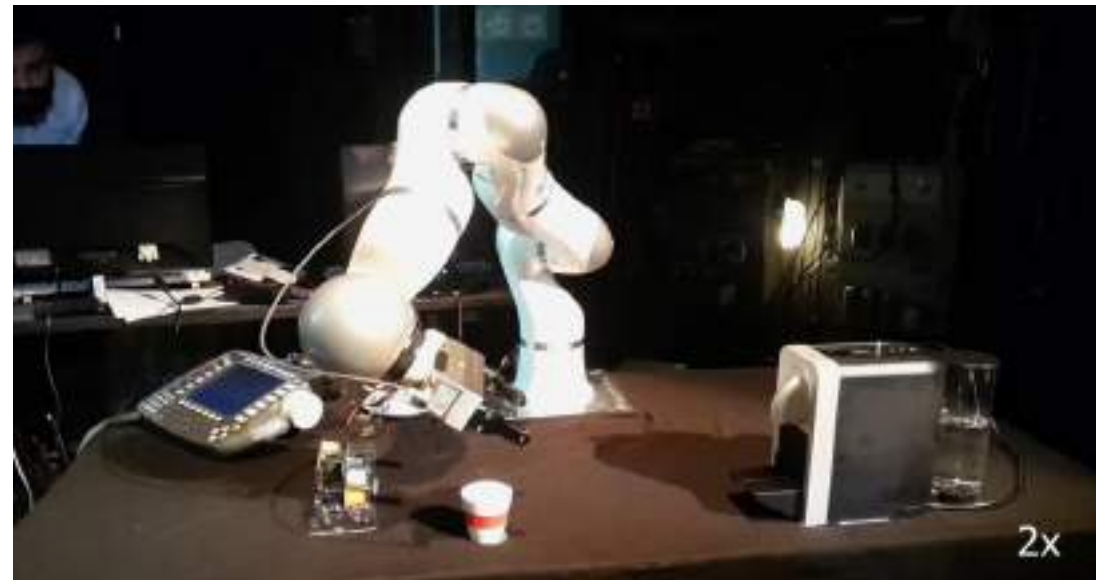
[Pervez and Lee, 2018]



[Yan+, 2023, 2025]

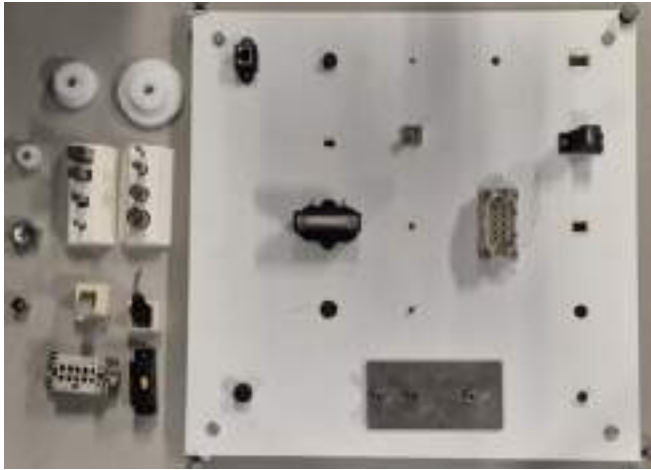


[Agostini+, RAL, 2020]



Bayerischer Rundfunk Zuendfunk Netzkongress, 2016

Embodied Intelligence: Contact-rich Manipulation



[Sliwowski+, REASSEMBLE, RSS 2025]



[Xue, RSS 2025]



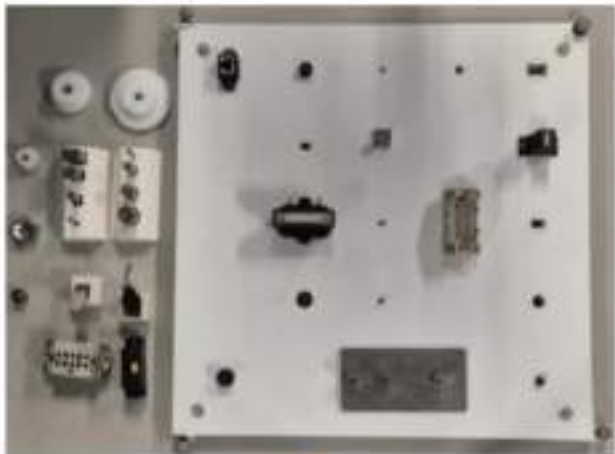
[Willibald & Lee, IJRR 2025]

REASSEMBLE Dataset

RSS 2025



NIST Task Board #1



Assembly



Disassembly



REASSEMBLE

Robotic asse**mbly** dis**ASSEMBLY** datase**t**



4551 Contact-rich Task Demonstration

- ★ 4035 Successful
- ★ 516 Failed



Multimodal data

- ★ Event camera
- ★ Force & Torque Sensor
- ★ 3 RGB cameras
- ★ 3 Microphones
- ★ Robot Proprioception



Multiple Task annotations

- ★ Motion Policy Learning
- ★ Temporal Action Segmentation
- ★ Success / Anomaly Detection

Sensors

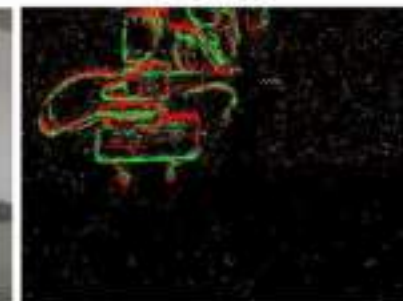
External View



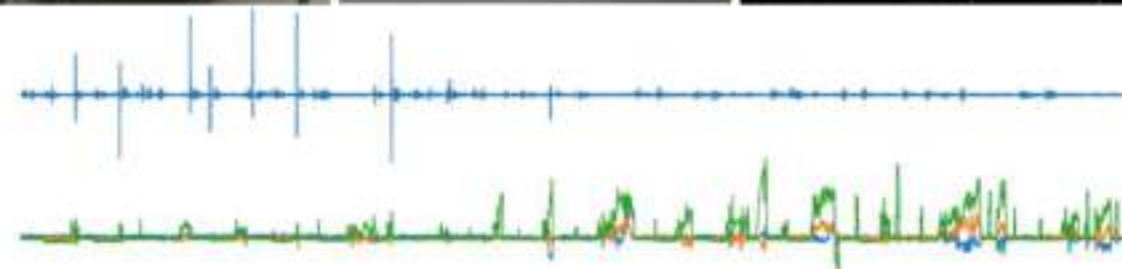
Wrist View



Events



Force Audio



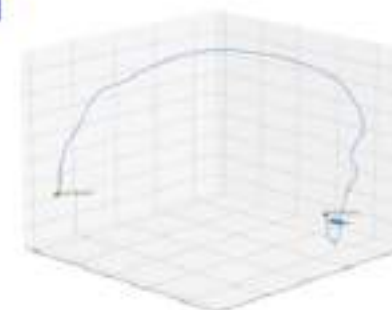
Tasks

Temporal Action Segmentation

1 2 3 4

1. Idle
2. Pick Ethernet
3. Insert Ethernet
4. Idle

Motion Policy Learning



Success/Anomaly Detection

Success

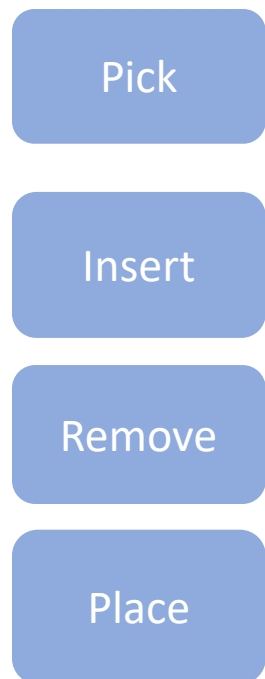


Failure

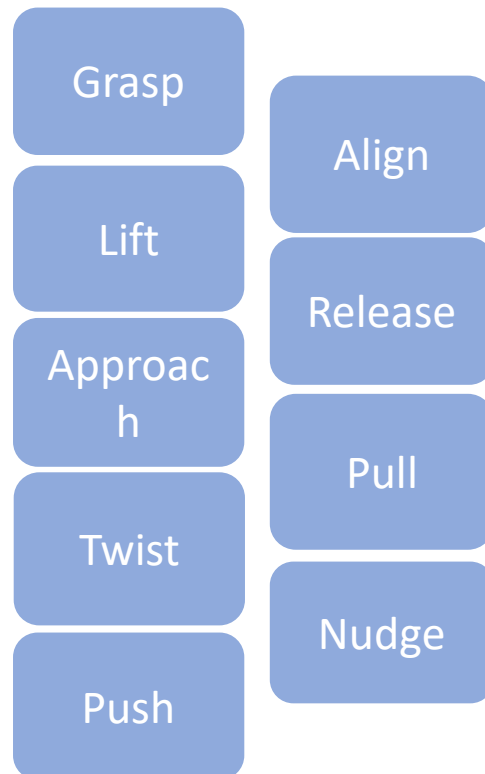


REASSEMBLE Dataset

4 High-level Action



9 low-level skills



68 Unique action-object instances

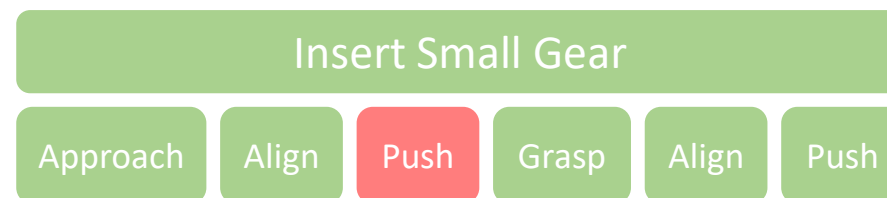
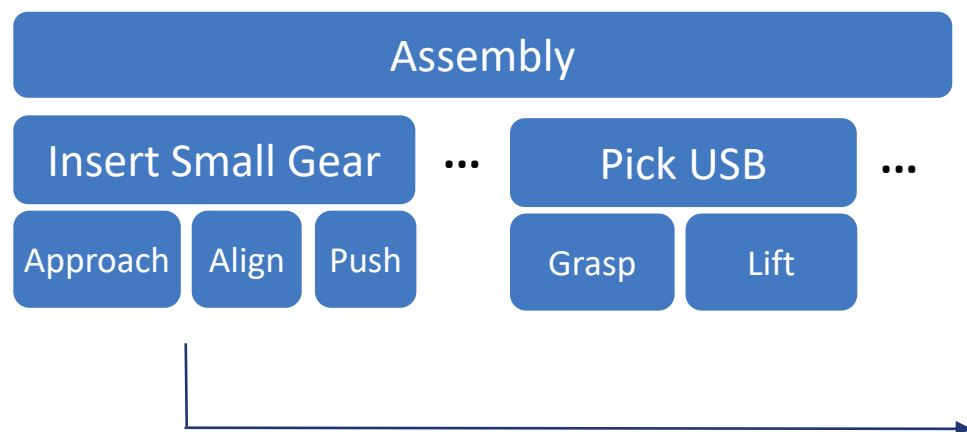
17 Objects



121 Unique skill-object instances

REASSEMBLE

Hierarchical skill execution



Imitation learning process is often designed as

passive, unidirectional, batch learning

Are we leveraging potential benefits of **HRI**
in robot learning?

Part I

Interactive Robot Learning

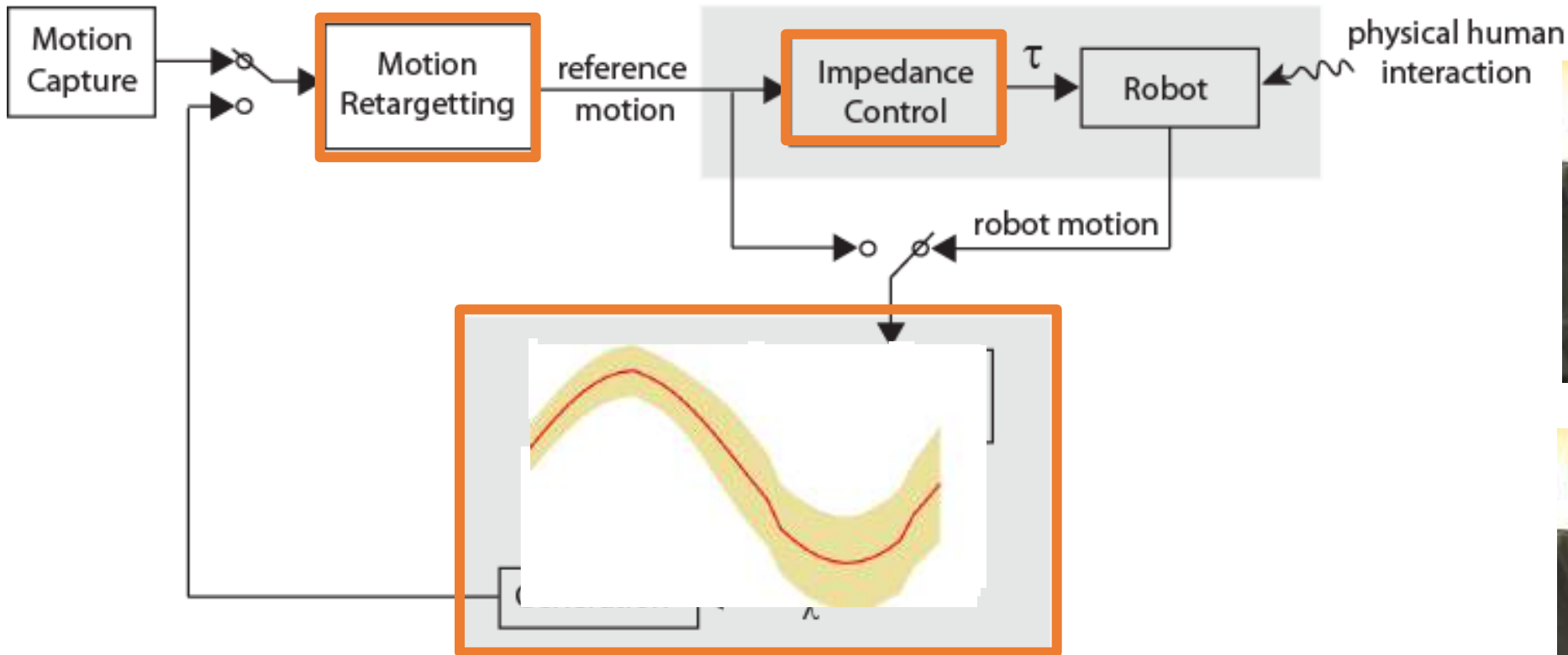
Teaching Pulp Fiction Twist Dance



The **demonstrator's intent** was not clearly conveyed to the robot.

Refine by kinesthetic teaching

$$\tau = g(q) + M(q)\ddot{q}_d + C(q, \dot{q})\dot{q}_d - D\ddot{\tilde{q}} - s(\tilde{q})$$



Interactive incremental learning
with **heterogeneous teaching modalities**
could communicate the **demonstrator's intent** better.

Report

Longitudinal evidence that infants develop their imitation abilities by being imitated

Samuel Essler,^{1,2,5,*} Tamara Becher,¹ Carolina Pletti,^{1,3} Burkhard Gniewosz,⁴ and Markus Paulus¹

¹Ludwig-Maximilians-Universität München, Leopoldstr. 13, 80802 Munich, Germany

²FOM University of Applied Sciences, Leimkugelstraße 6, 45141 Essen, Germany

³University of Vienna, Universitätsring 1, 1010 Vienna, Austria

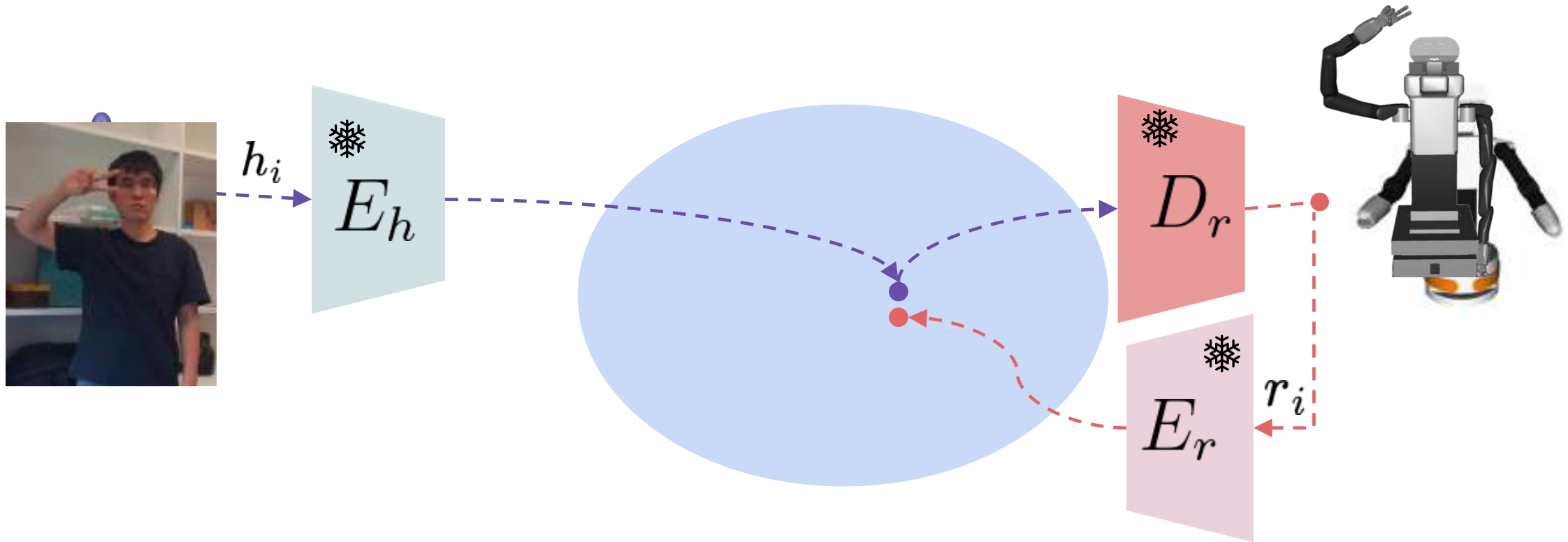
⁴Paris-Lodron-University, Kapitelgasse 4/6, 5020 Salzburg, Austria

⁵Lead contact

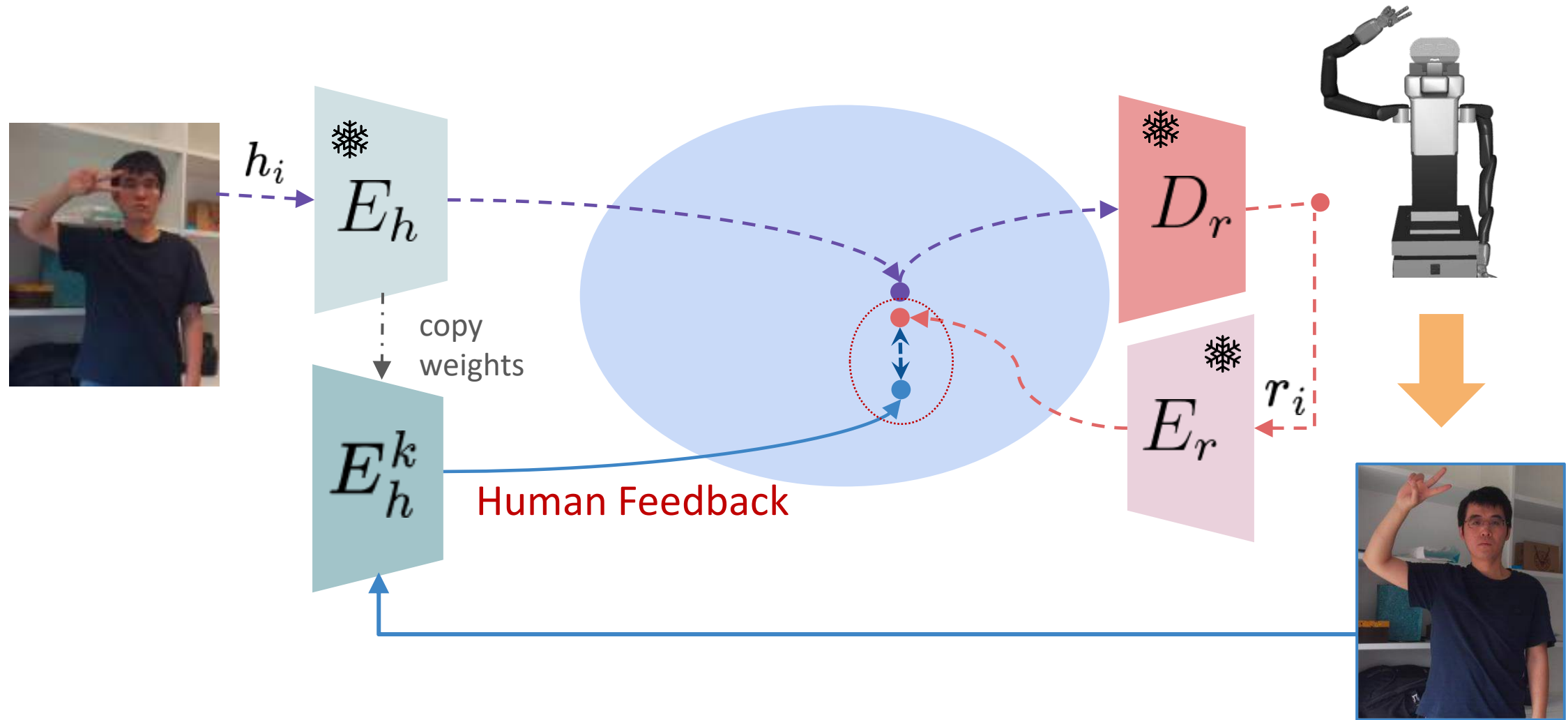
*Correspondence: samuel.essler@psy.lmu.de

<https://doi.org/10.1016/j.cub.2023.08.084>

ImitationNet: Unsupervised Human Motion Retargeting



ImitationNet Finetuning using a few Human Feedback data

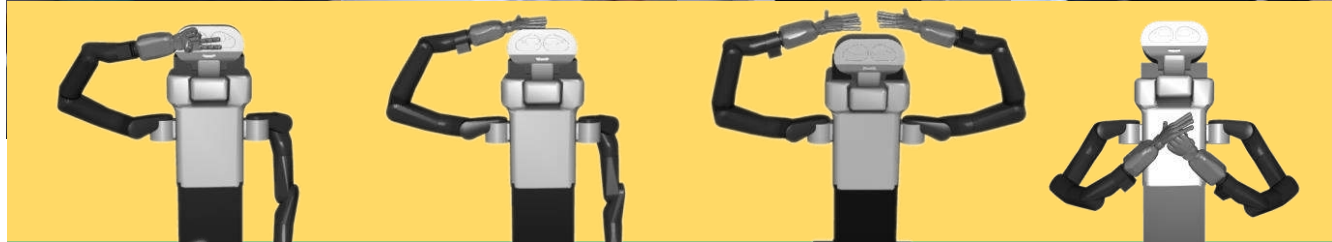


Performance of Personalized Motion Retargetting

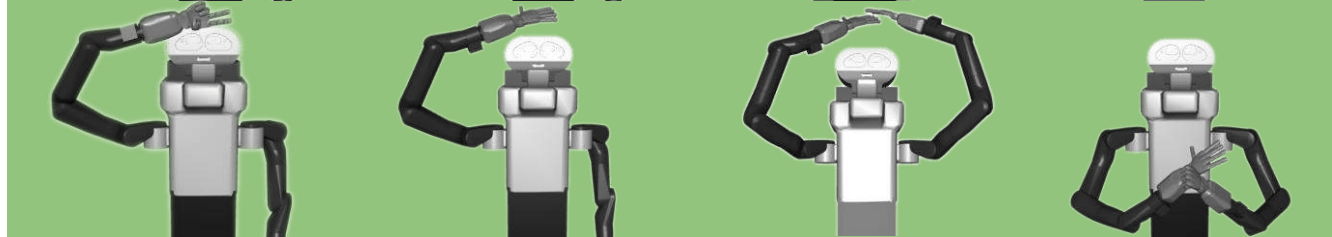
Human



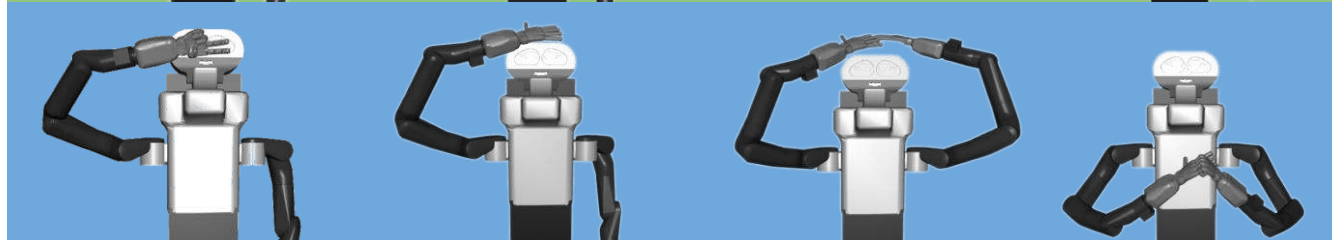
Ground True



ImitationNet



Ours



Human feedback

- reduces the gap between **robot's perception of human motion** and **human's perception of robot motion**.
- reinforces the **coactivation of visual and motor representations**

We saw *Interactive robot learning* procedure,
but via **human's feedback**.

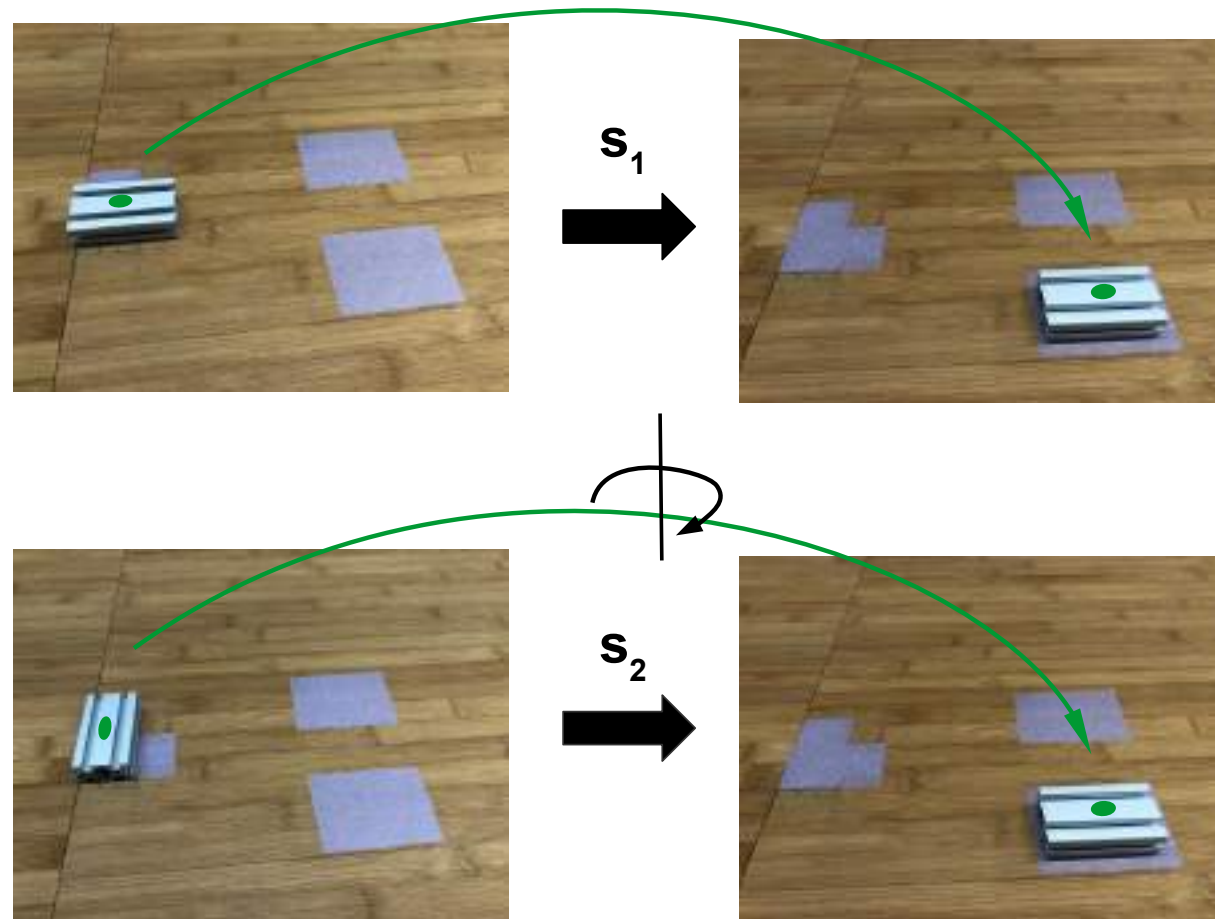
Robots remained *passive*.

Part II

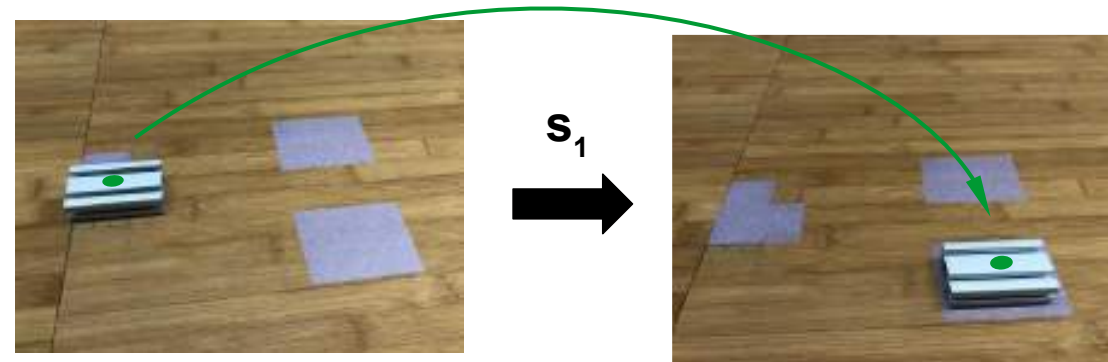
Pro-Active Robot Learning

Policy Learning by Noticing Anomalies

Proprioceptive Policy Learning without Vision



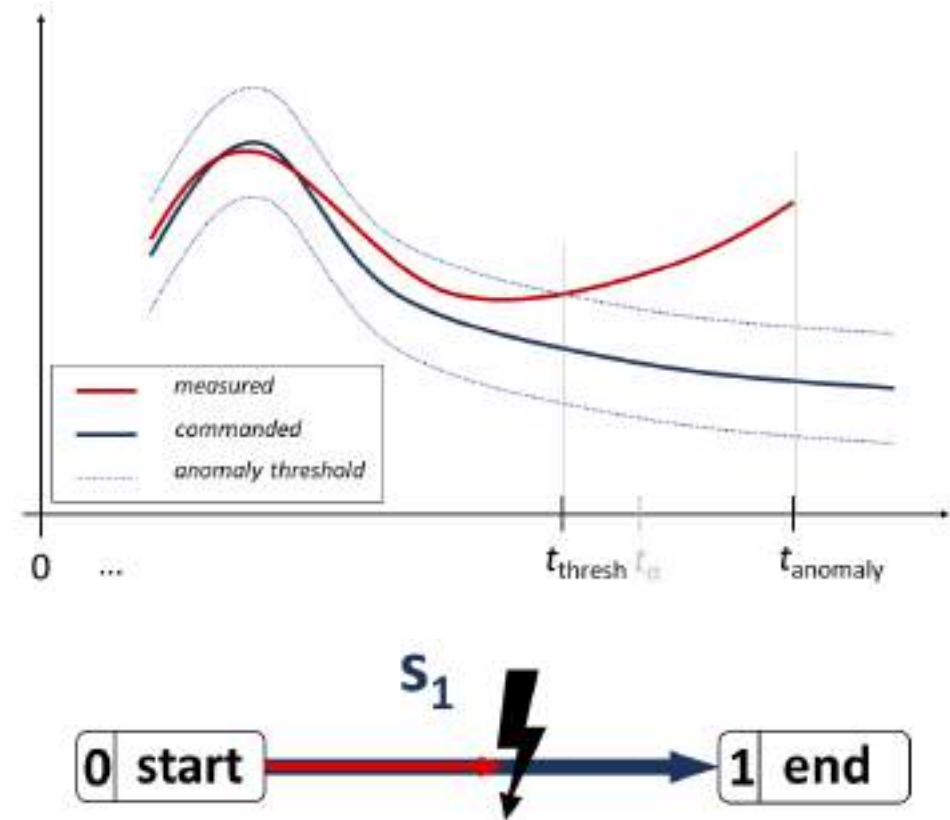
Initial Demonstration

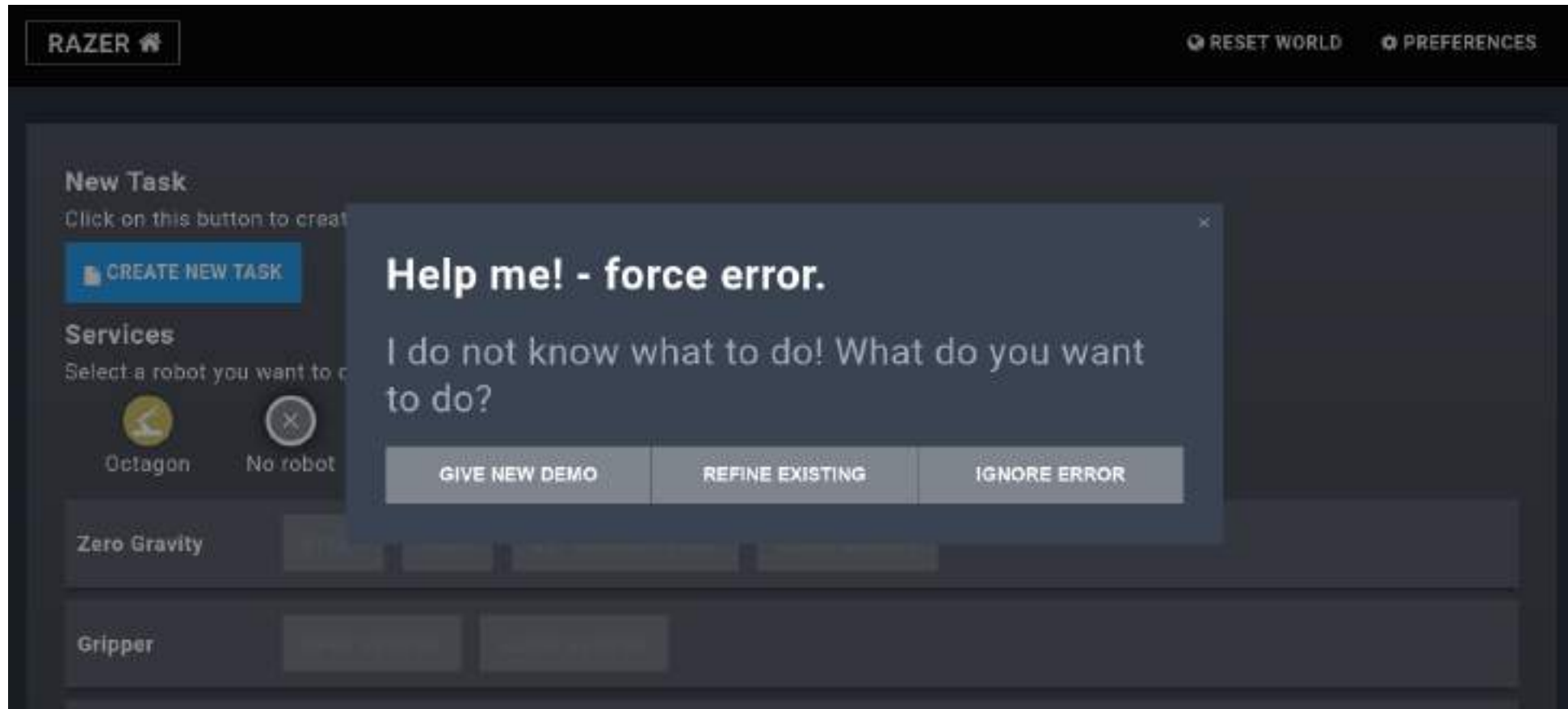


Task-Graph Generation

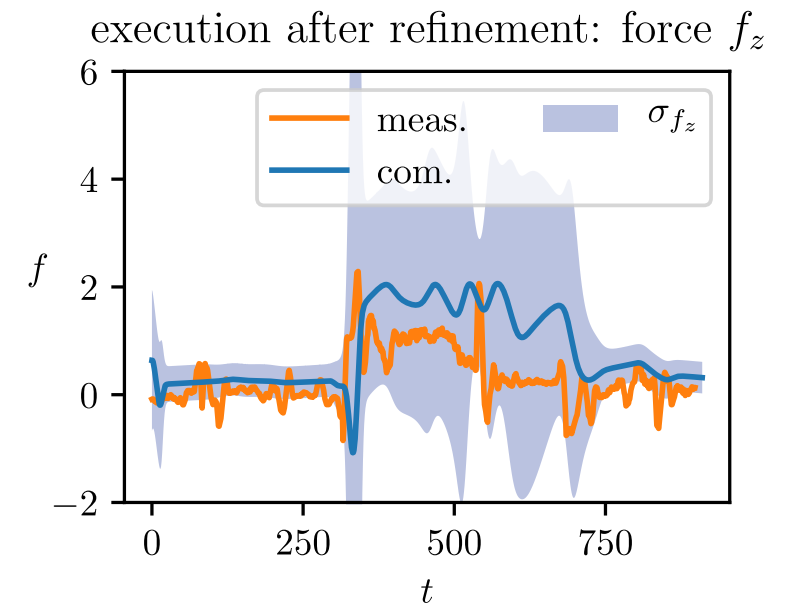
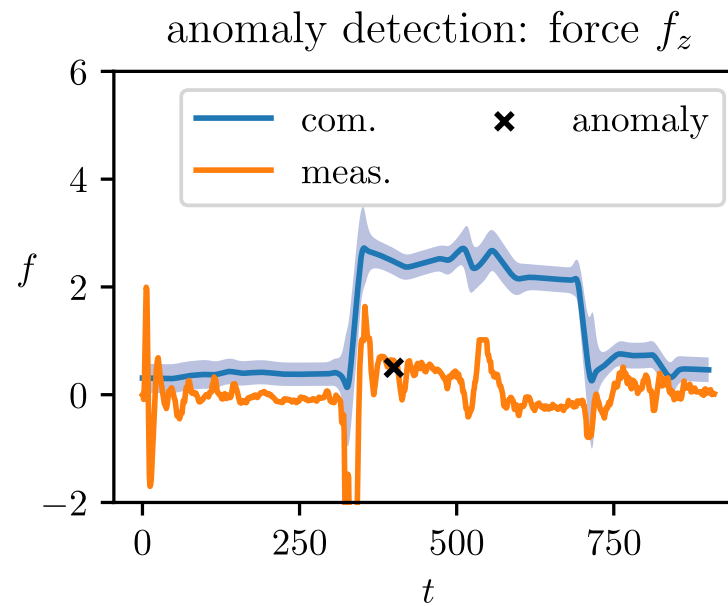
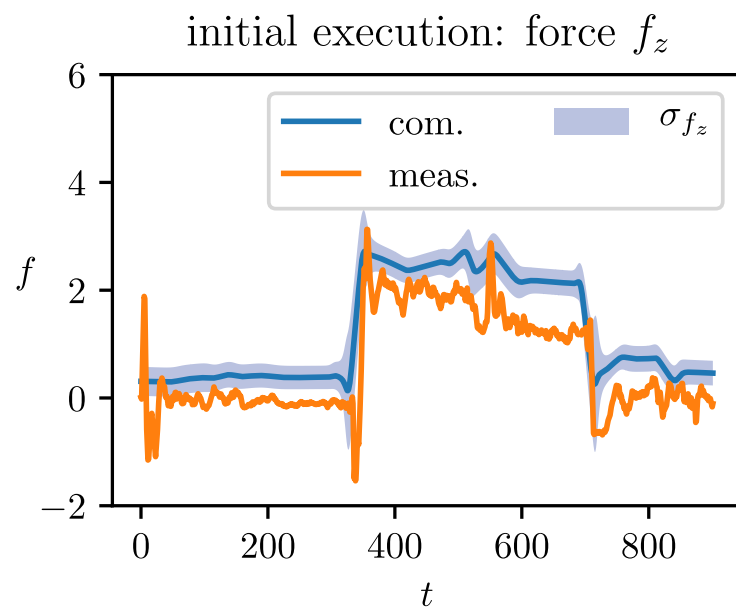


Monitored Execution: Anomaly Detection

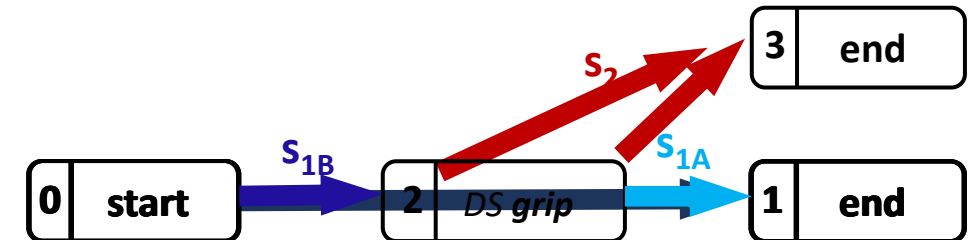
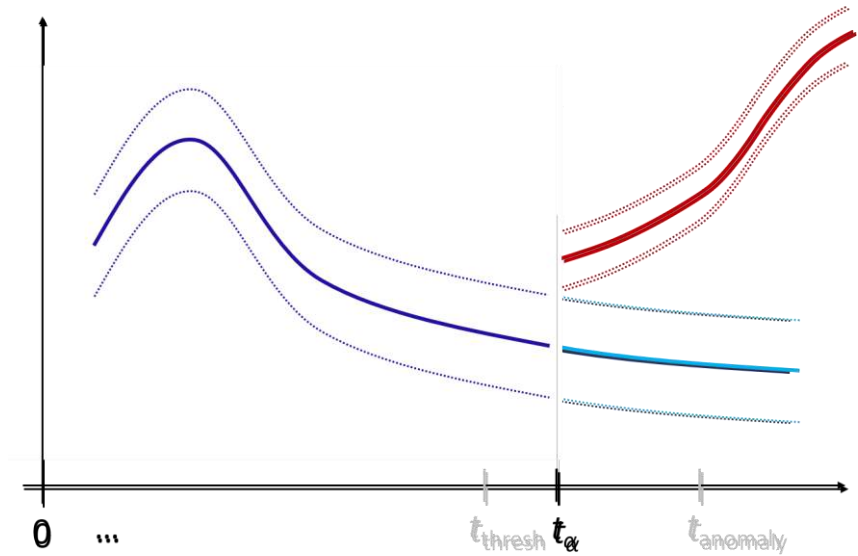







Skill Refinement



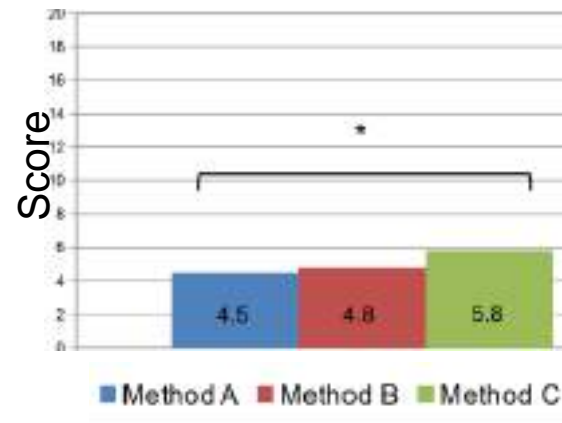
Add a New Skill to Task-Graph



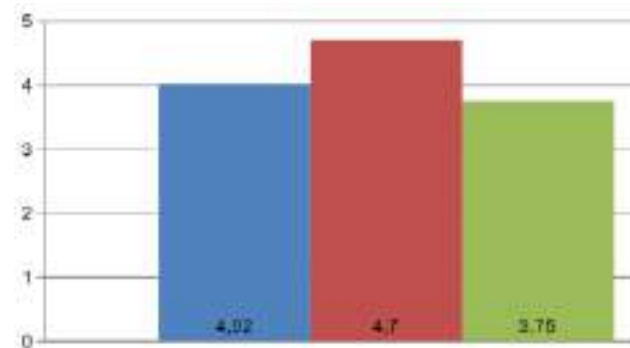
User Study on Interactive Programming and UI

	Sequential Batch Programming (SBP)	Collaborative Incremental Programming (CIP)	User-triggered Incremental Programming (UIP)
Knowledge representation	sequential 	sequential & branching 	sequential & branching 
Teaching Interaction	Unidirectional: passive data acquisition	Bidirectional: active data request	Unidirectional: passive data acquisition

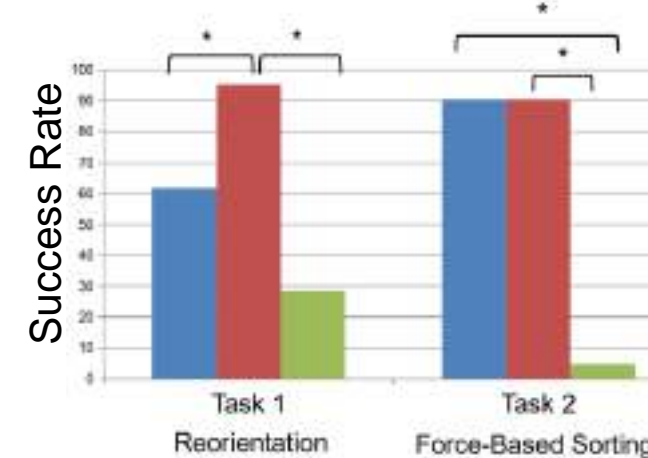
NASA-TLX



QUESI



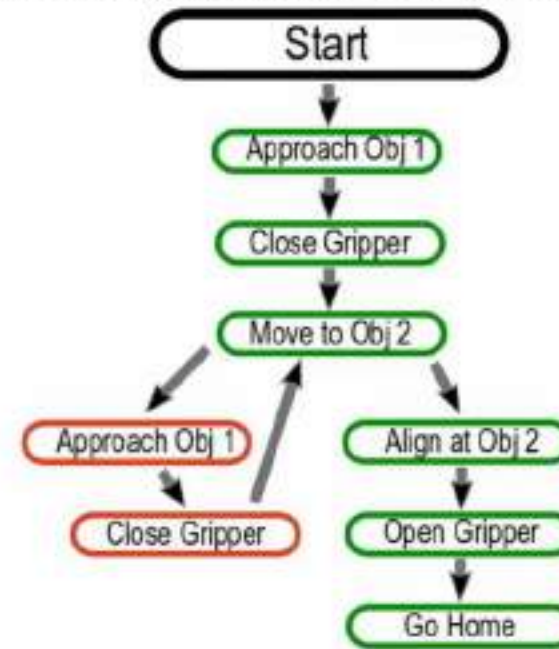
Task Performance



Online task programming: Segmentation and Anomalies



Task Graph with Recovery Behavior



Can I put spatula on cutting board?



Did I open the top drawer?



Yes

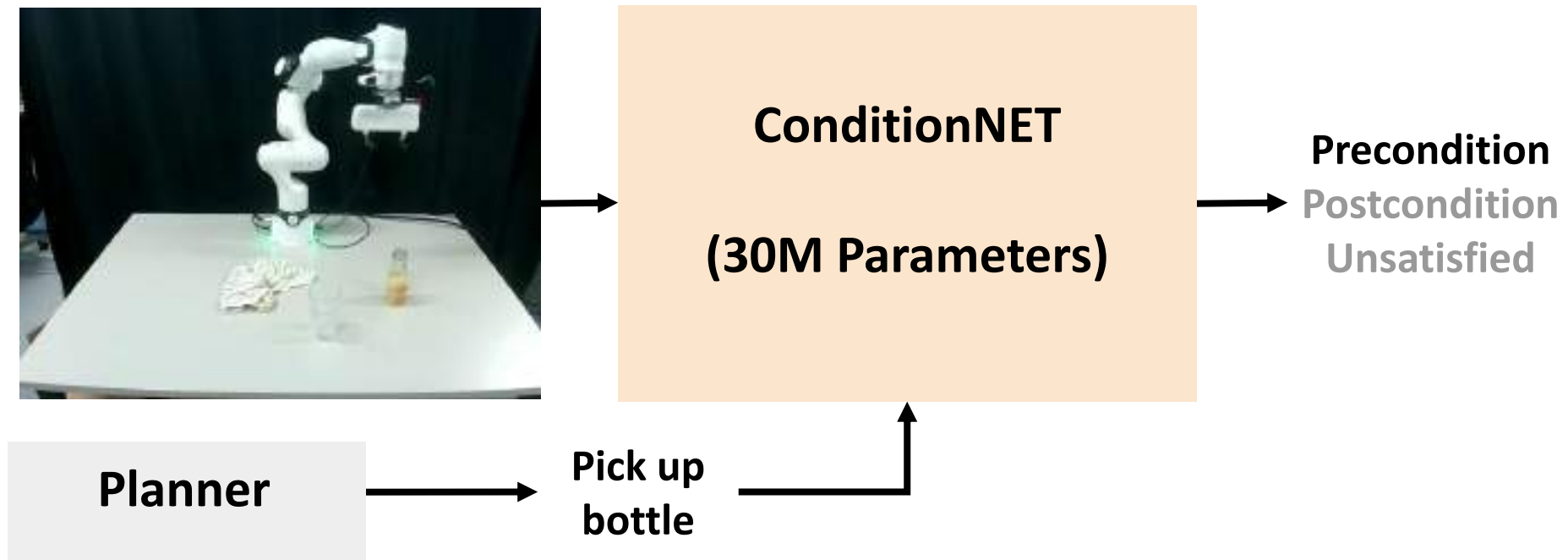
No



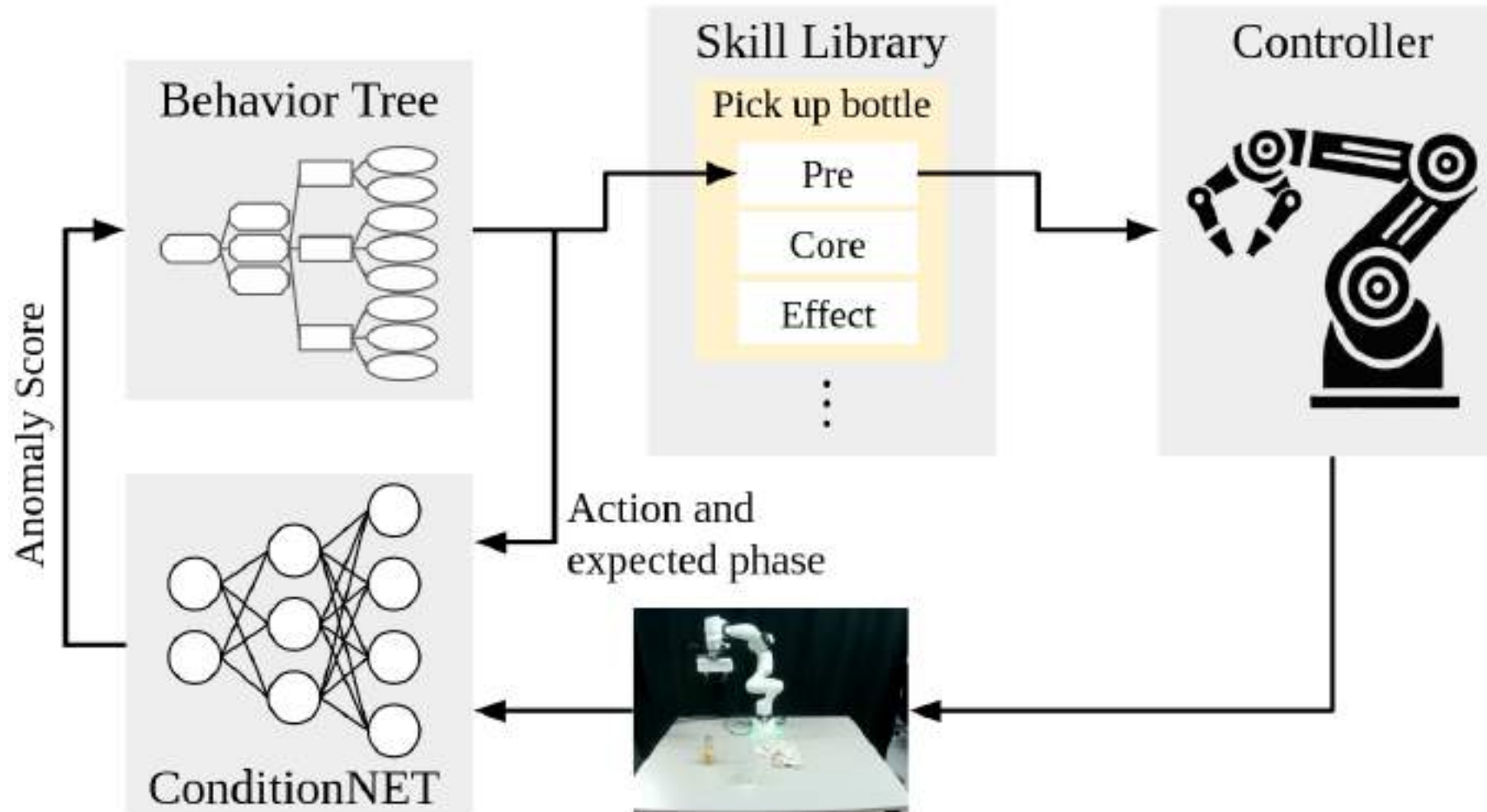
Anomaly Detection based on Pre- and Post-condition Learning

ConditionNET

- Visual-language model for action preconditions and effects.
- Training for consistent action representation
- Real-time execution monitoring.

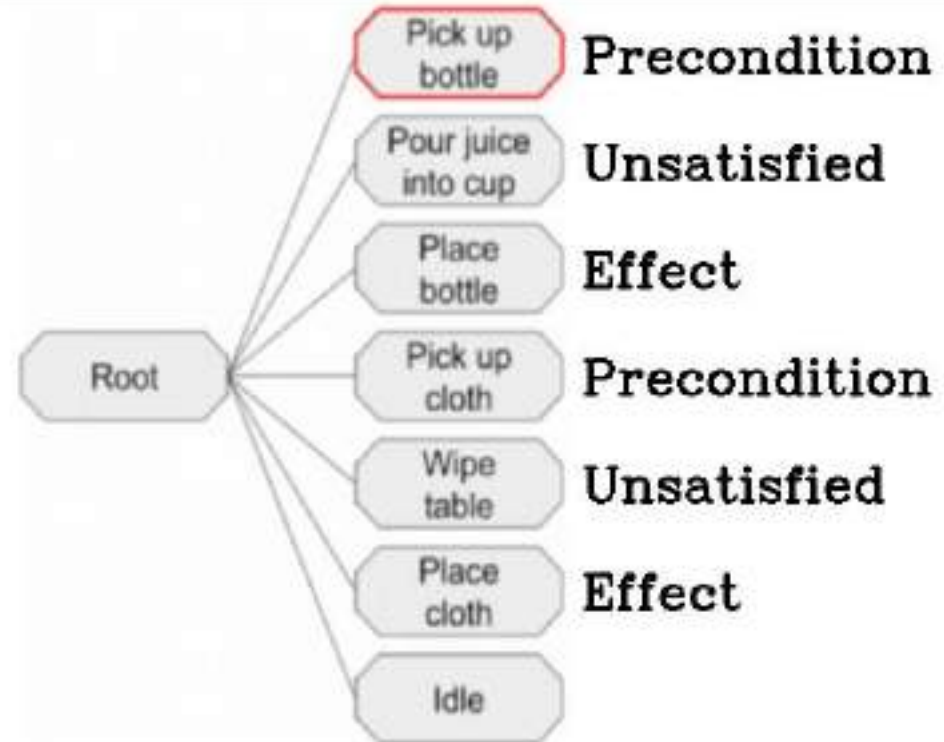


Planning, Execution, and Monitoring



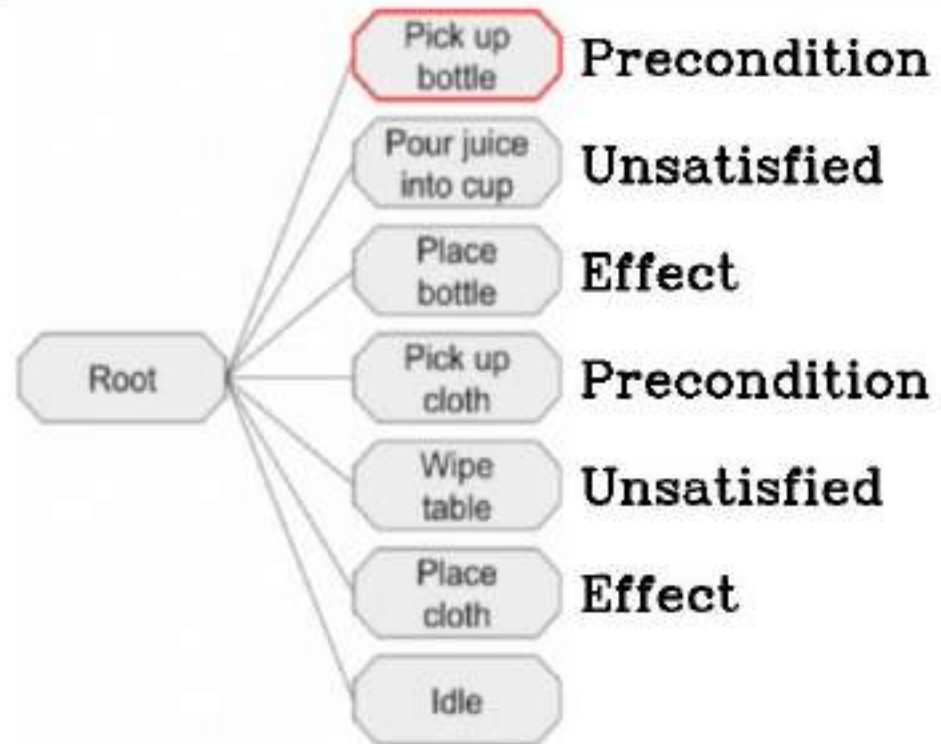
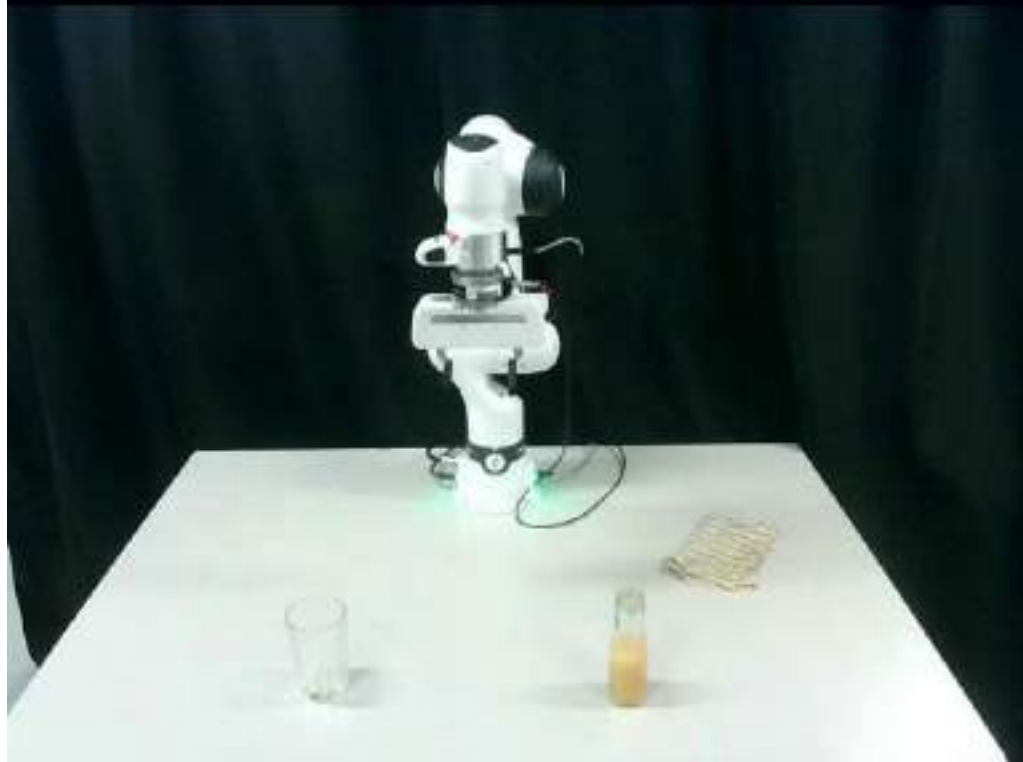
Monitoring Pre-/Post- Condition of Actions

Human perturbation – taking away items



Monitoring Pre-/Post- Condition of Actions

Human perturbation – spilling and taking away items

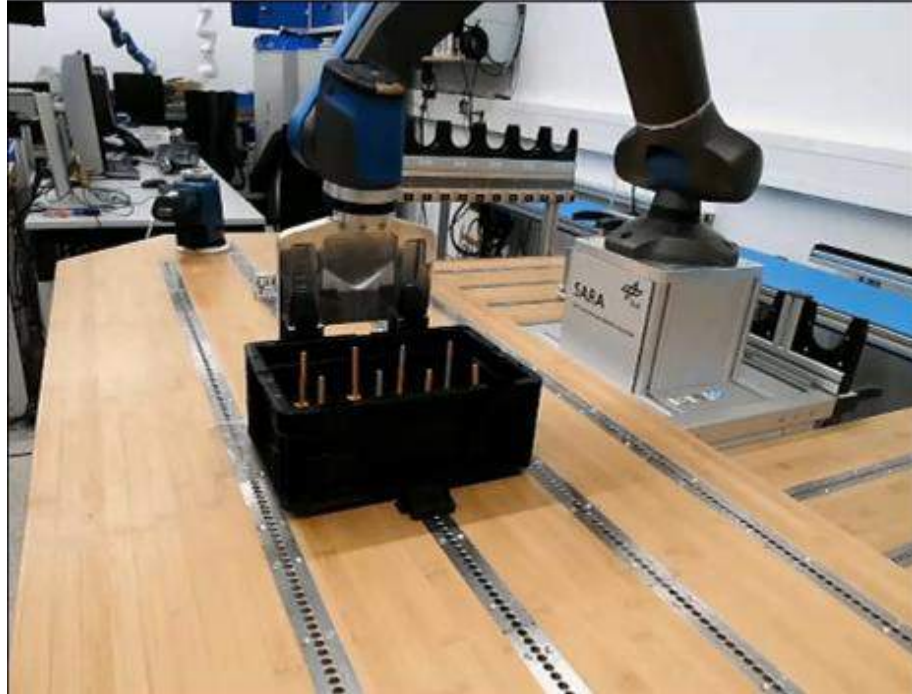


ConditionNET Evaluation on two datasets

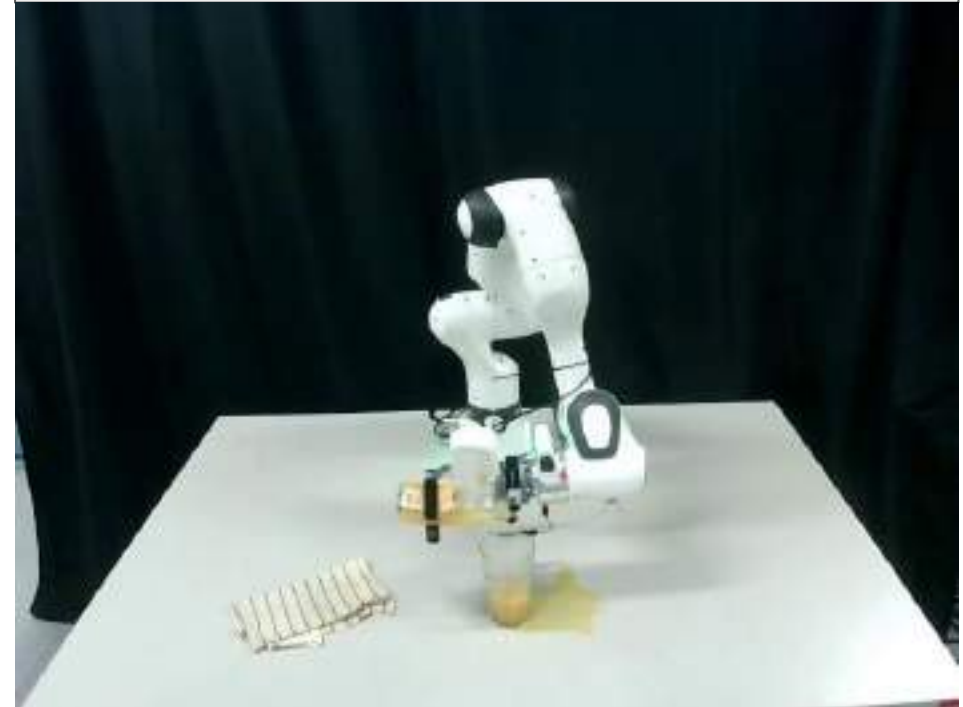
TABLE I: Quantitative evaluation.

FAILURE [19]								
Model	Anomaly Detection				Condition Learning			
	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
CLIP+MLP	0.81	0.81	0.81	0.81	0.8	0.77	0.71	0.74
DINO+MLP	0.82	0.82	0.84	0.8	0.78	0.72	0.67	0.69
FinoNET [19]	0.79	0.79	0.79	0.79	-	-	-	-
TP-VQA [2]	0.62	0.67	0.82	0.73	0.44	0.75	0.24	0.37
ConditionNET	0.89	0.91	0.89	0.88	0.88	0.85	0.79	0.82
(Im)PerfectPour								
CLIP+MLP	0.86	0.91	0.86	0.87	0.93	0.79	0.77	0.78
DINO+MLP	0.72	0.88	0.72	0.74	0.85	0.74	0.7	0.72
FinoNET [19]	0.74	0.80	0.74	0.74	-	-	-	-
TP-VQA [2]	0.76	0.81	0.9	0.85	0.44	0.74	0.17	0.27
ConditionNET	0.97	0.97	0.97	0.97	0.99	0.98	0.97	0.97

Jamming Gripper

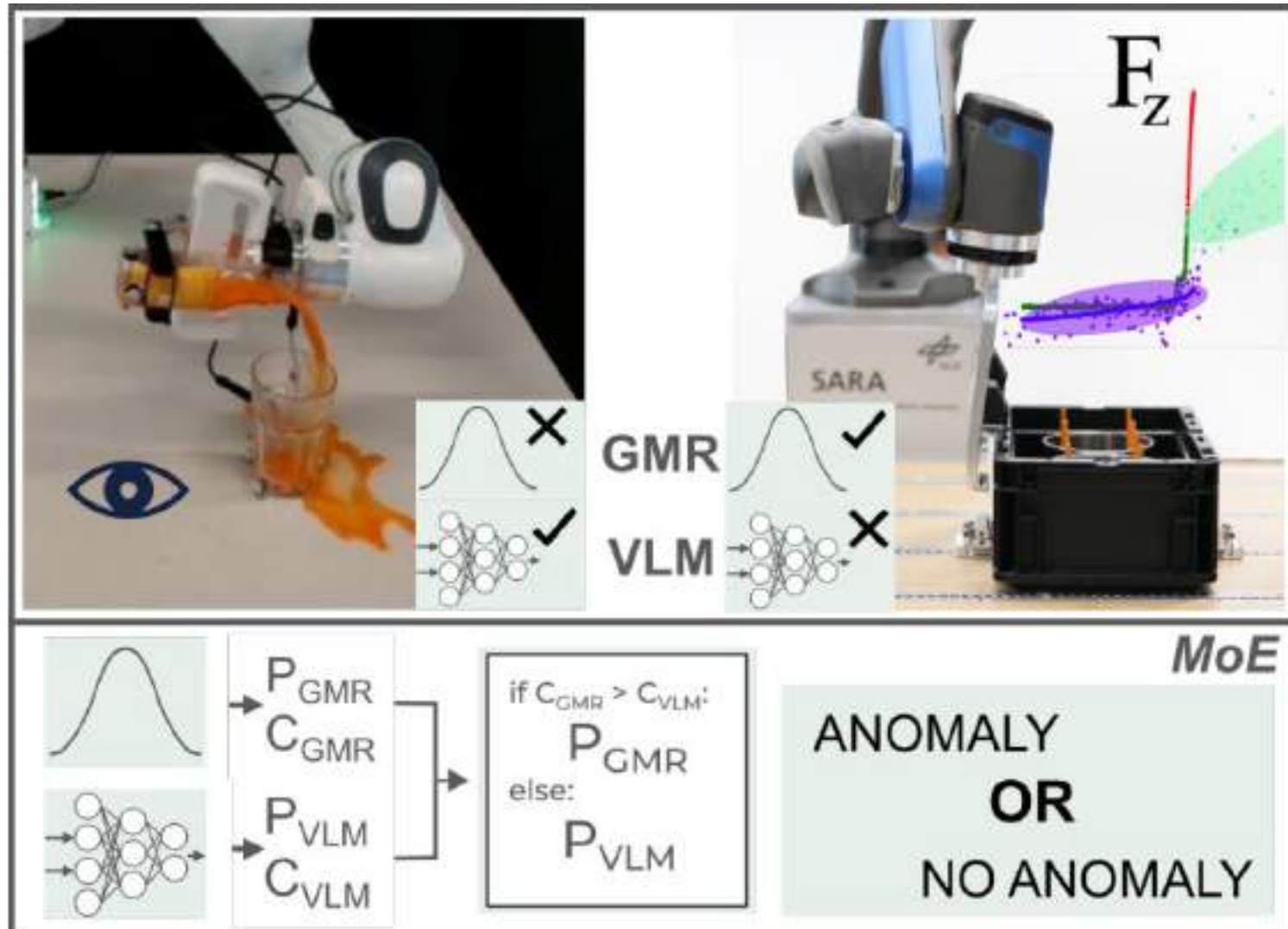


Spill Drink



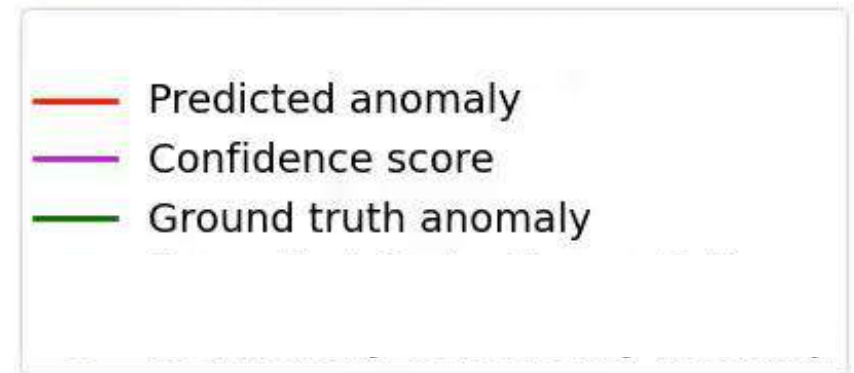
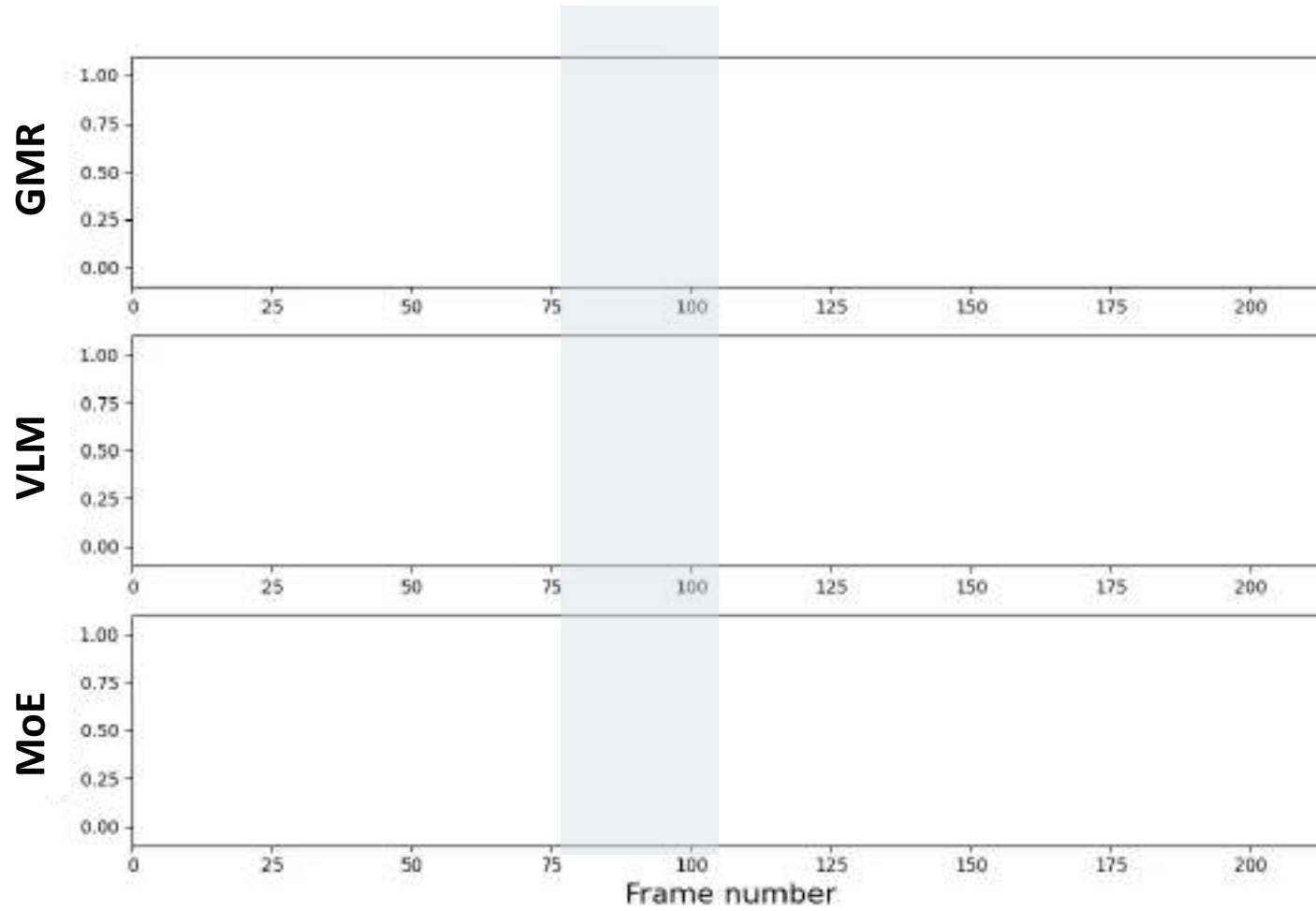
**Mixture of Expertise: Proprioception
and Exteroception**

Multimodal anomaly detection



Push while Pouring

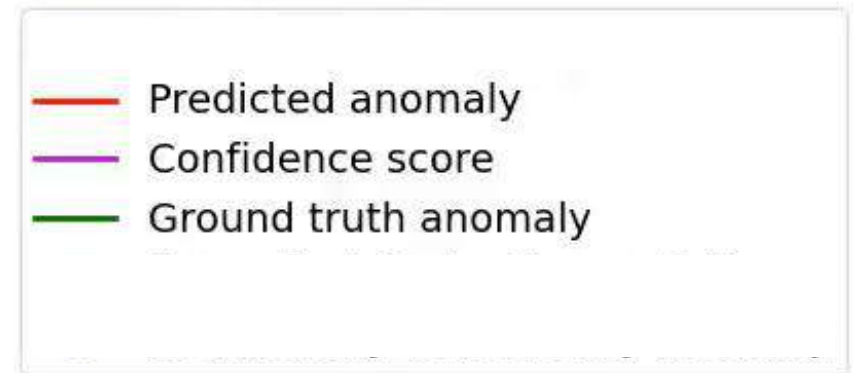
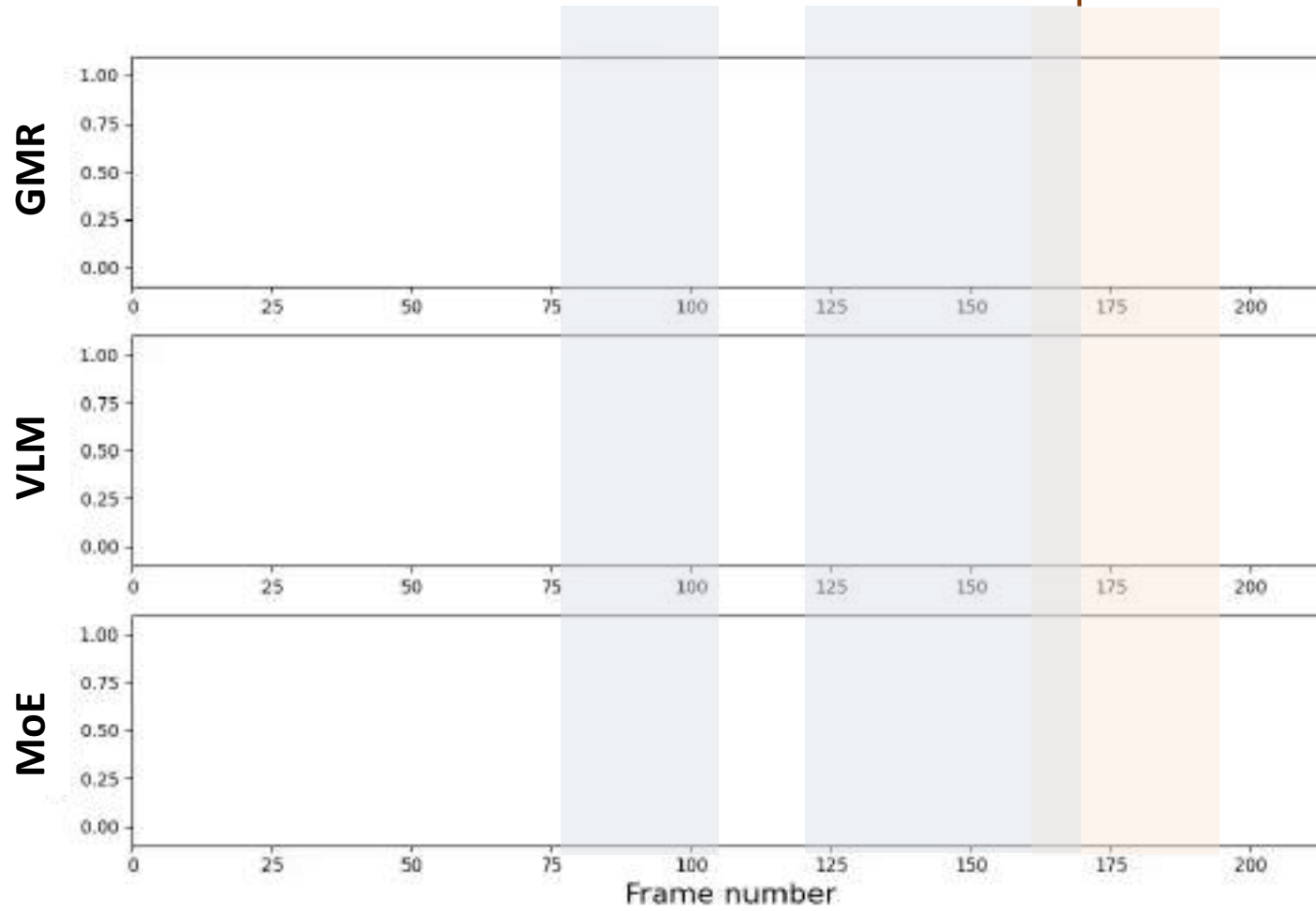
Propriocept expert
detects push.



Push while Pouring

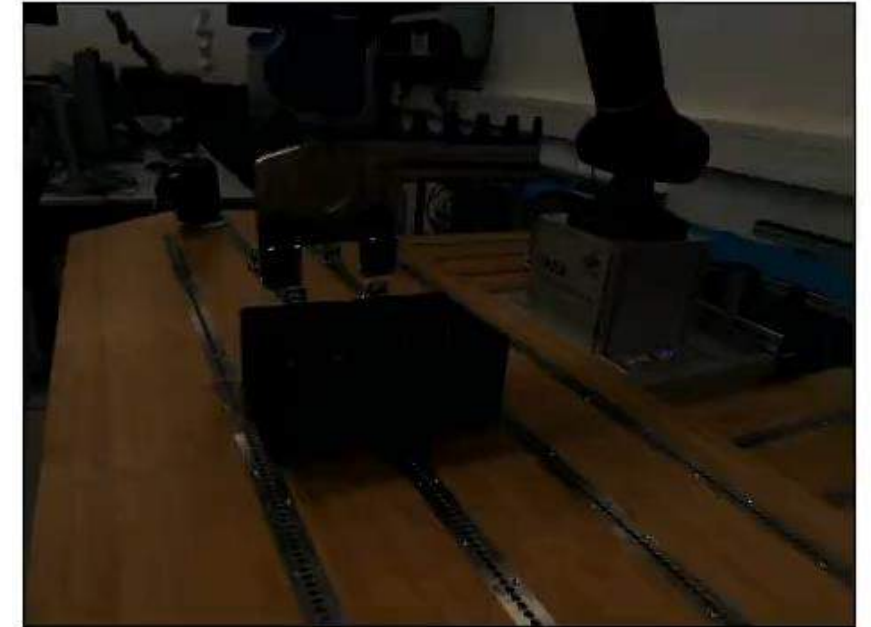
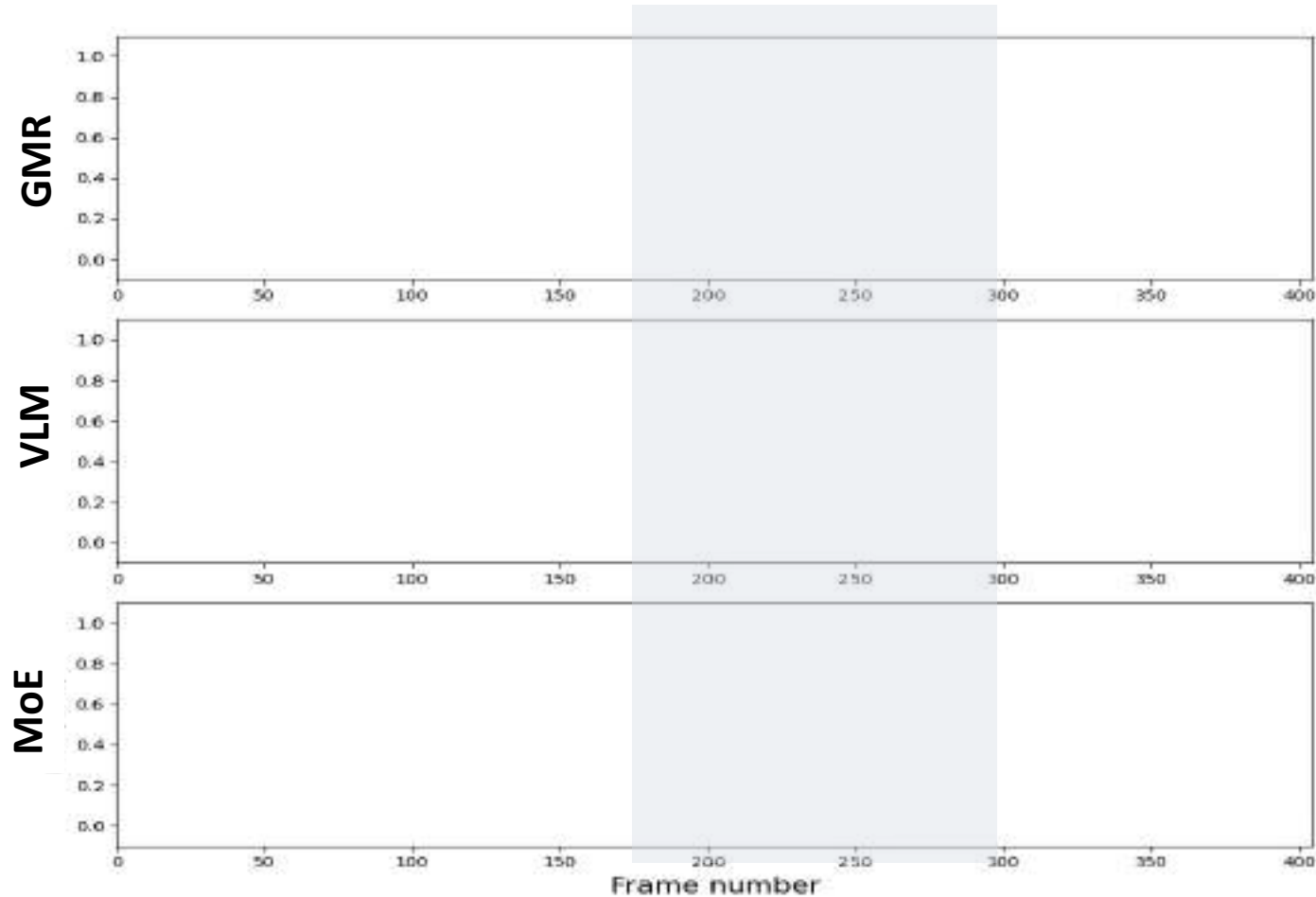
Propriocept expert
detects push.

VLM detects
spill.



Hardware Failure

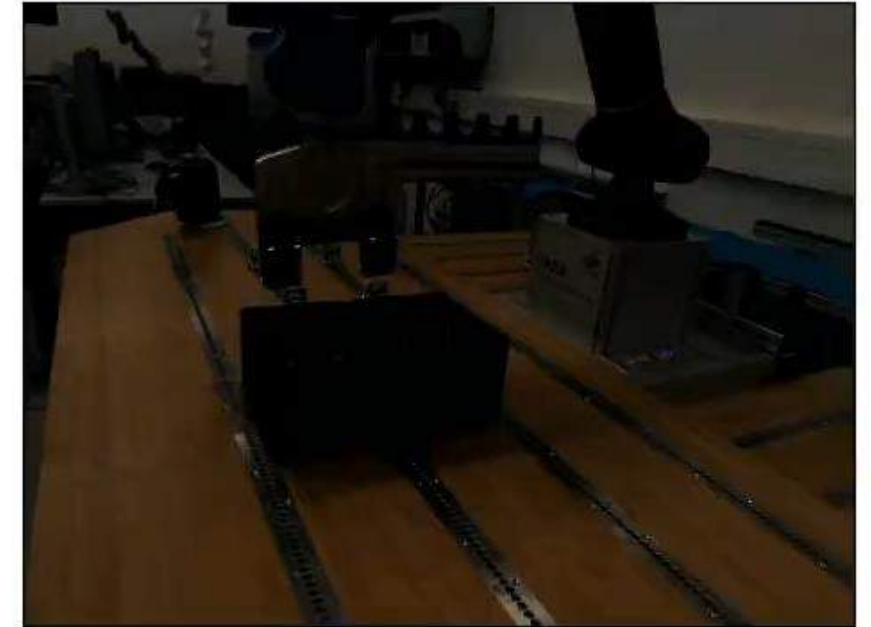
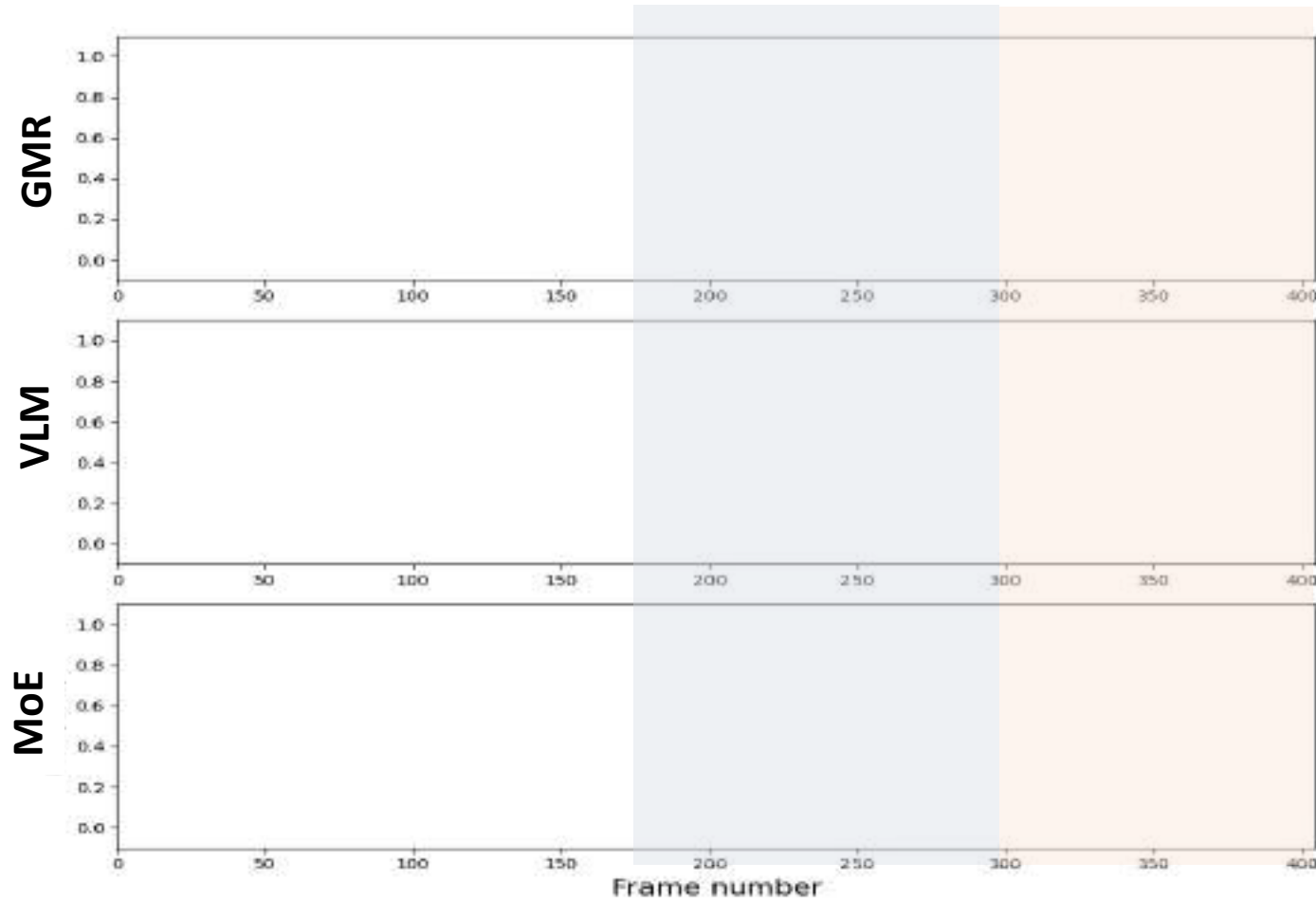
Propriocept expert
detects jamming.



- Predicted anomaly
- Confidence score
- Ground truth anomaly

Hardware Failure

Propriocept expert
detected jamming.
VLM detected
it later.



- Predicted anomaly
- Confidence score
- Ground truth anomaly

MoE improves Performance of individual Detectors

Method	Box-grasping					
	Acc	Pre	Rec	F1	F1@50	Del
MoE (our)	88.1	96.6	82.6	88.3	86.4	0.47
GMR	88.8	100	81.7	87.4	78.9	1.20
CondNET	79.8	95.9	73.2	81.6	75.0	1.23

Method	Pouring					
	Acc	Pre	Rec	F1	F1@50	Del
MoE (our)	88.7	88.7	88.1	87.2	84.7	-0.3
GMR	84.5	86.9	81.0	83.3	76.7	-0.4
CondNET	75.8	88.0	67.2	70.2	69.3	0.4

Summary

- Go beyond *Passive Unidirectional Batch* Learning
- ***Interactive Continual*** Learning clarifies the teacher's intended goal of the task.
- ***Proactive Interactive Continual*** Learning: Self-Awareness can lead to Proactive Learner and leap at learning speed and task performance.

What's the holy grail in robot learning?

**Proactive
Interactive
continual learning**

**Foundation VLA
model**

pretrained with
web-scale data

For embodied intelligence, tactile and proprioception is essential.

22nd IEEE International Conference on Advanced Robotics and its Social Impact (ARSO 2026)

Vienna, Austria 10th – 12th June 2026



Organized Session proposals
9th December 2025

Full Paper submission
22nd January 2026

Notification of acceptance
22nd March 2026

Final paper submission
23rd April 2026

**venue & access in
the middle of Europe**



General Co-Chairs



Dongheui Lee



Sebastian Schlund



Thank you for your attention

Thanks to team members and collaborators



Thomas Eiband



Christoph Willibald



Daniel Sliwowski



Victor Kowalski



Christian Ott



Shail Jadav



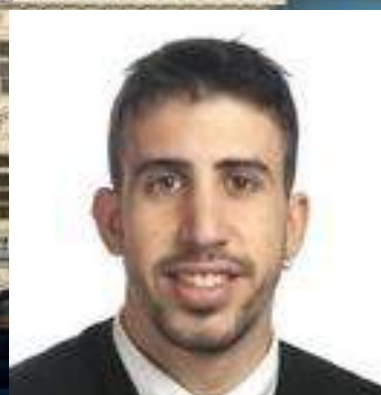
Matteo Saveriano



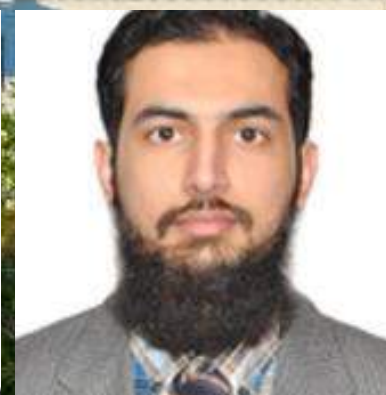
Chengxi Li



Yashuai Yan



Esteve Valls



Affan Pervez



Alejandro Agostini