Frugal learning of manipulation skills in robotics

GdR Robotique - Nov 6th, 2024

Sylvain Calinon

https://calinon.ch

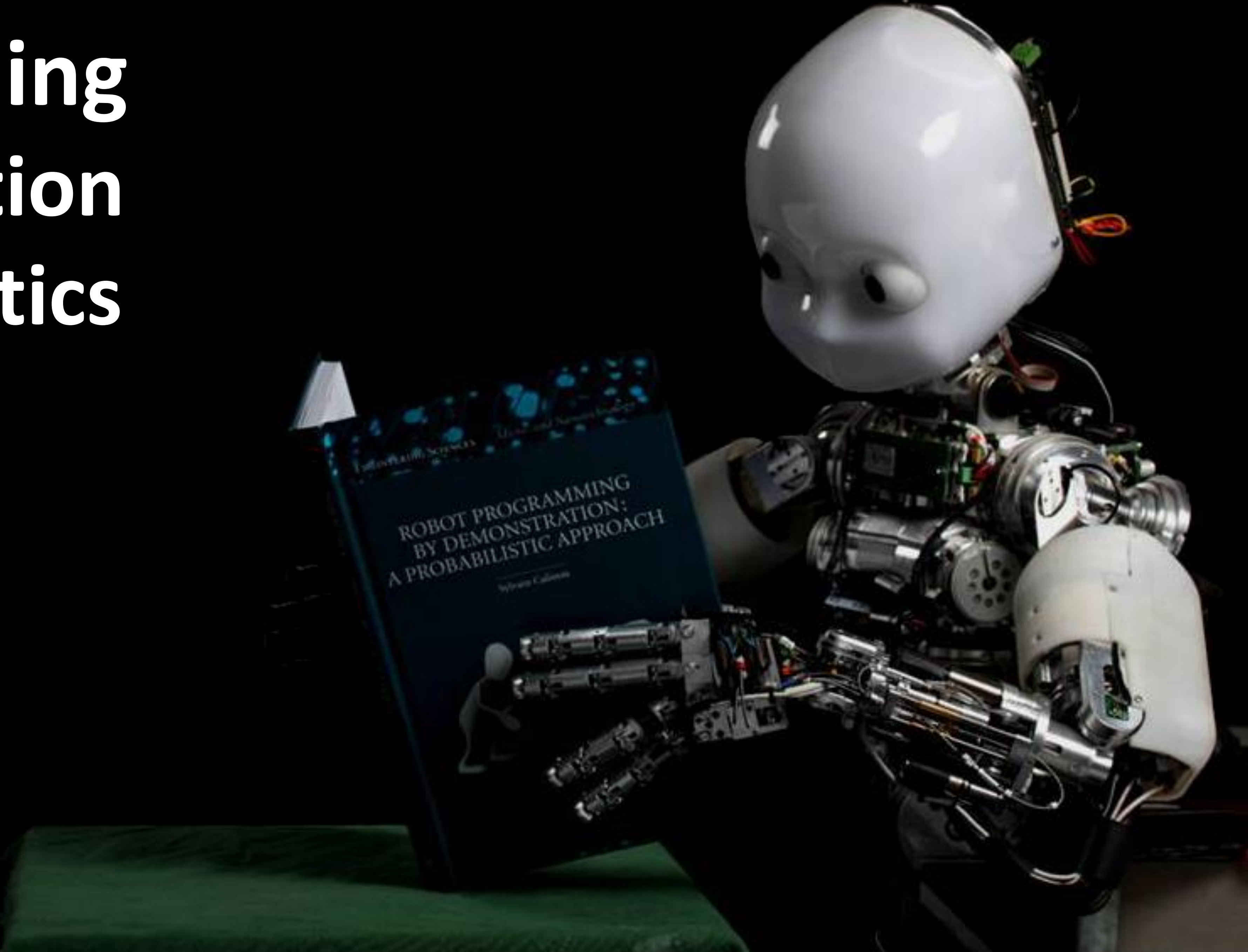
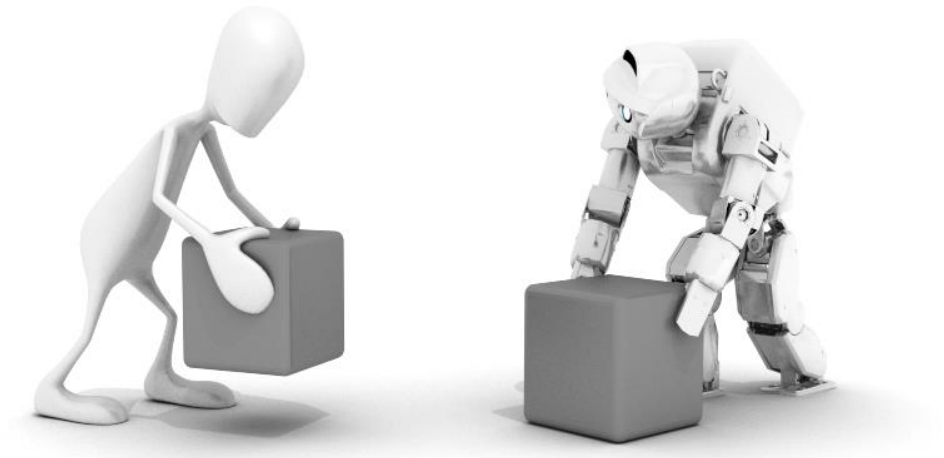


Photo: Basilio Noris - LASA/EPFL

RESEARCH INSTITUTE



Robot Learning & Interaction

Research Programs

Human-AI Teaming	AI for Sustainable & Resilient Societies
AI for Life	AI for Everyone

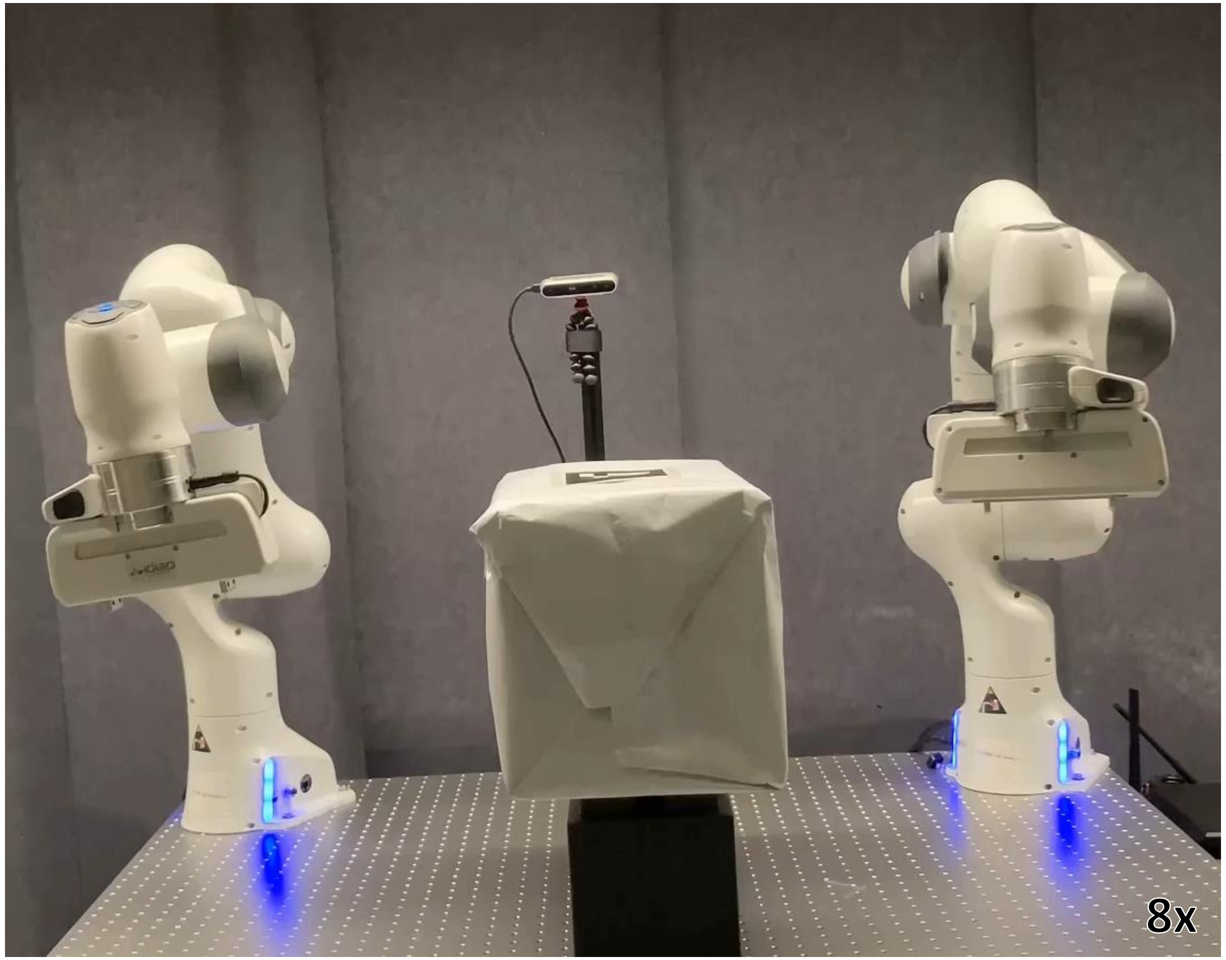
Idiap's 3 missions:

- Research
- Education
- Technology transfer

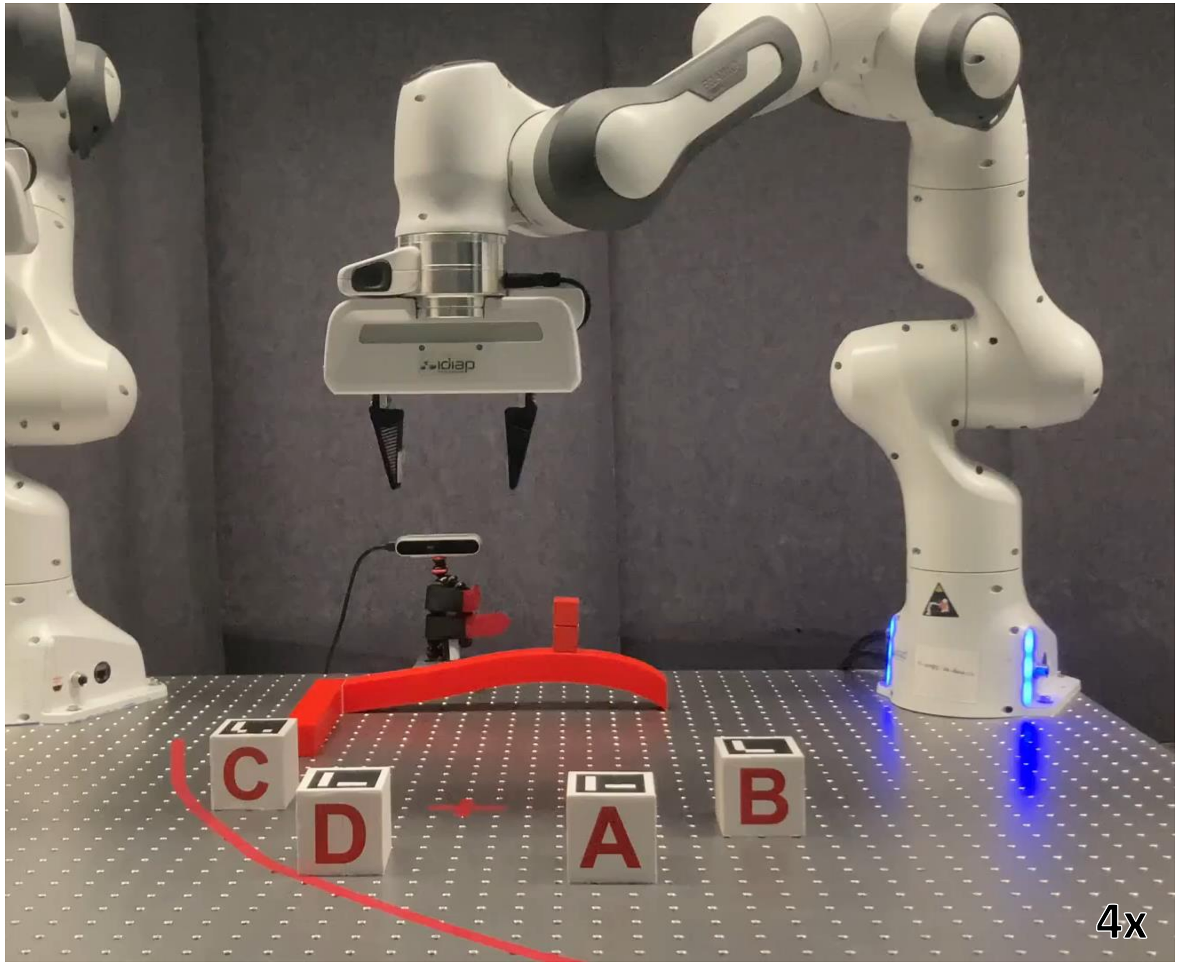
Joint development plan with:

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Prehensile manipulation



Bimanual skills / whole-body contacts [ICRA'2024]

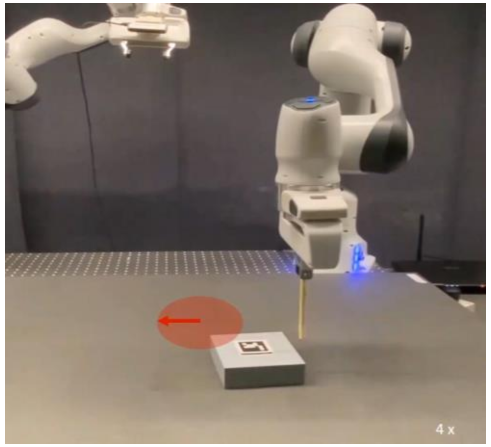


Object affordances / use of tools [ICRA'2024]

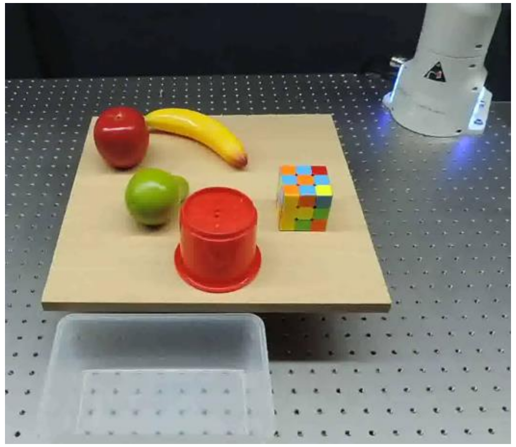
Non-prehensile manipulation

Pushing skills

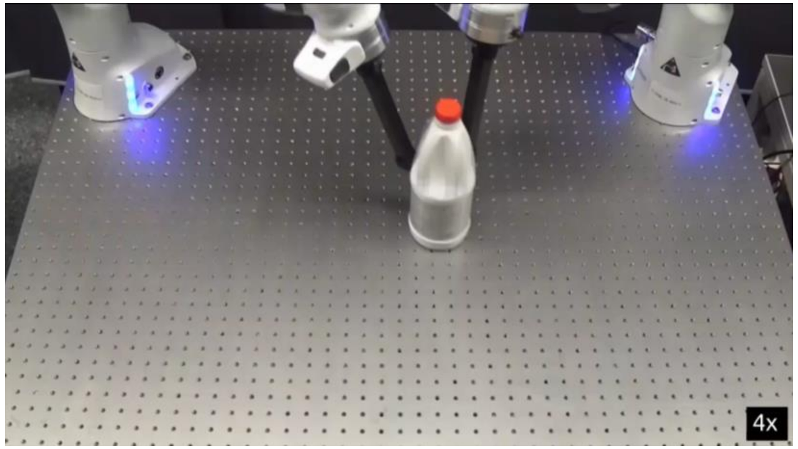
[IEEE RA-L 2023]



[ICLR'2024]

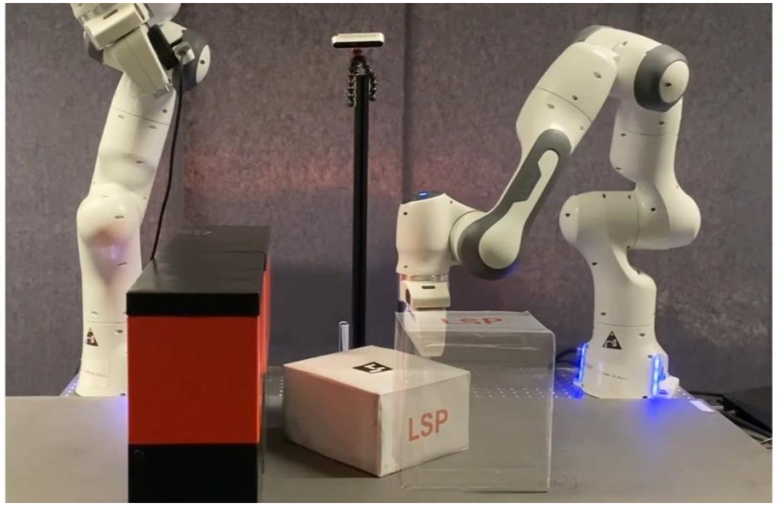


[IROS'2023]



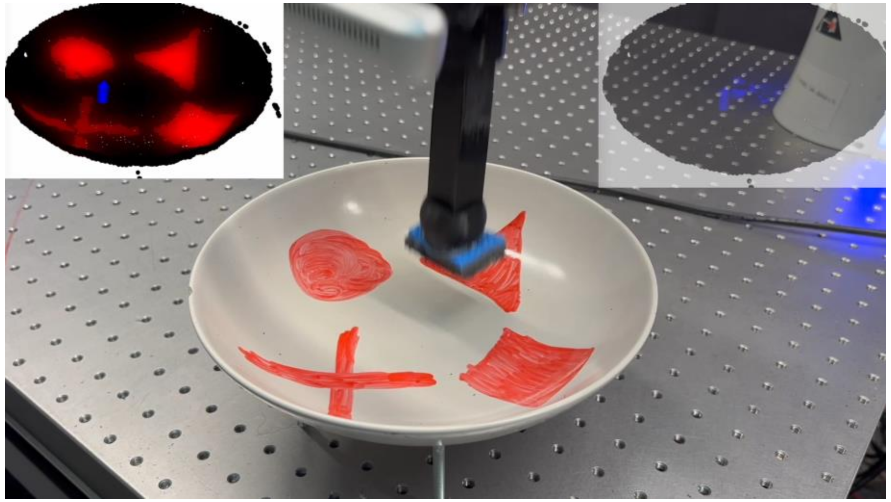
[IJRR 204, conditionally accepted]

Box pulling and pivoting



[RSS'2024]

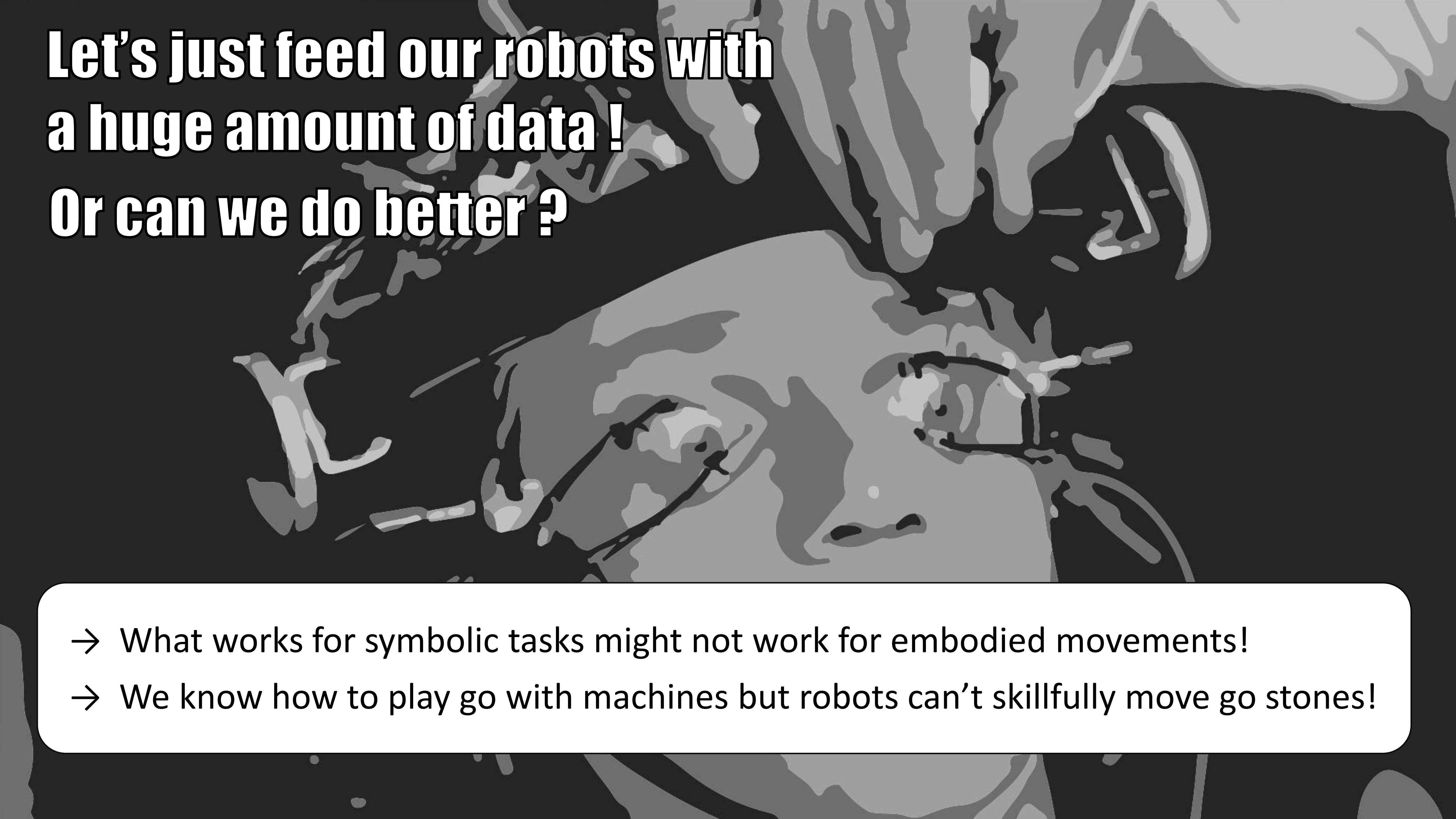
Washing/cleaning



[arXiv 2024]

Hitting skills

Winner of Air Hockey Challenge, NeurIPS'2023



Let’s just feed our robots with a huge amount of data !

Or can we do better ?

- → What works for symbolic tasks might not work for embodied movements!
- → We know how to play go with machines but robots can’t skillfully move go stones!

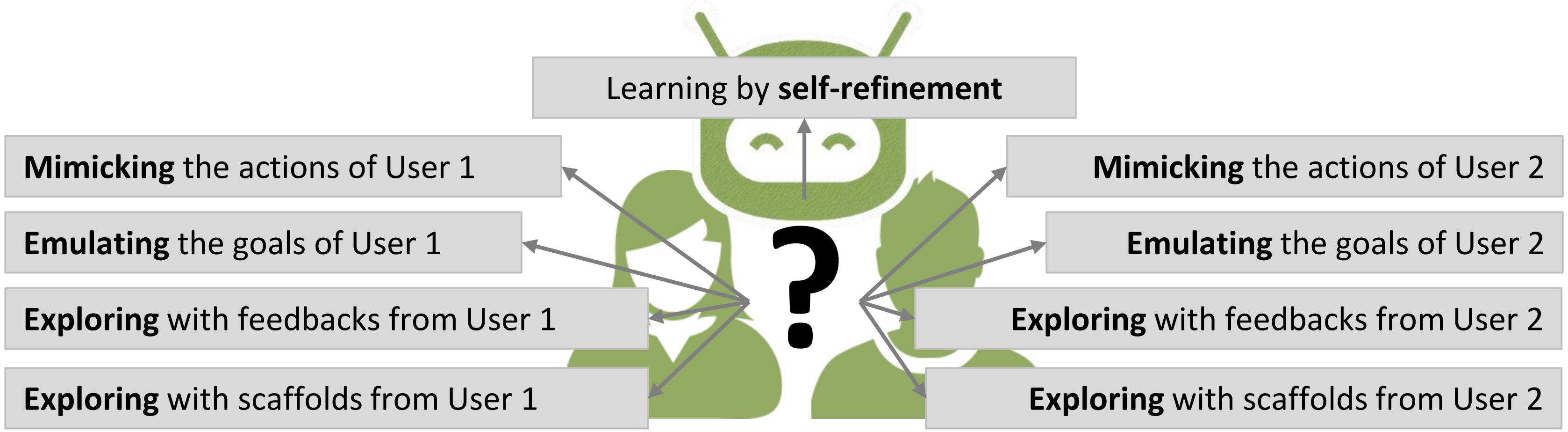
Human-in-the-loop learning

Machine teaching

Active learning

Curriculum learning

Interaction

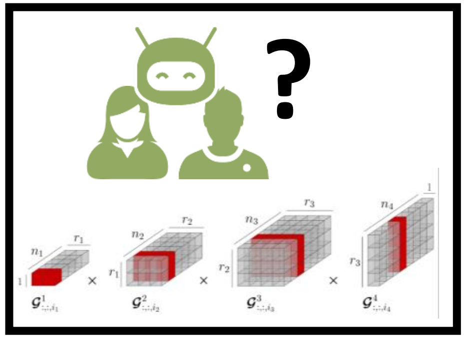


Skill acquisition by exploiting multiple learning strategies

Learning as a scaffolding process

[Kulak and Calinon, IEEE Trans. on Cognitive and Developmental Systems, 2023]

Outline



Models built from self-generated data

Tensor networks Vs neural networks

Ergodic control

Learning for control Vs control for learning

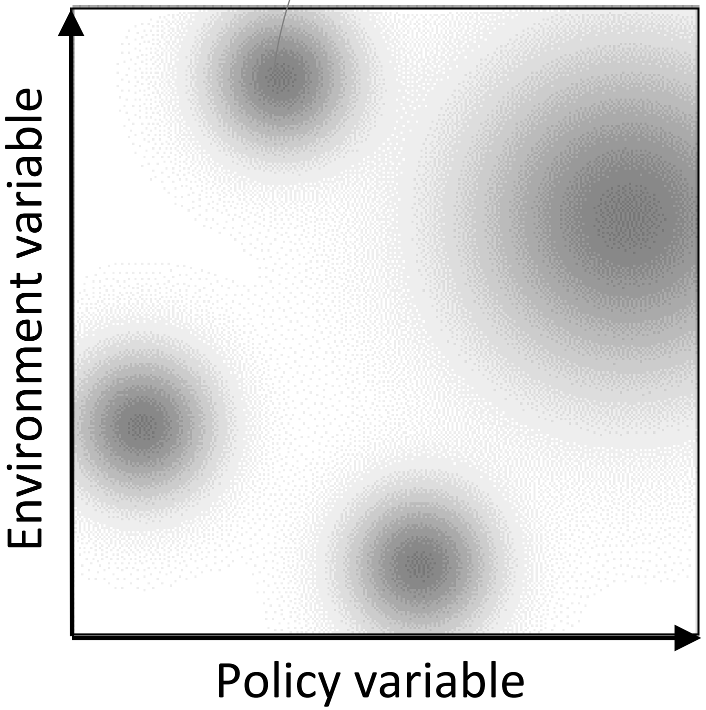
Geometry-informed models

Object-centric, distances and manifold representations

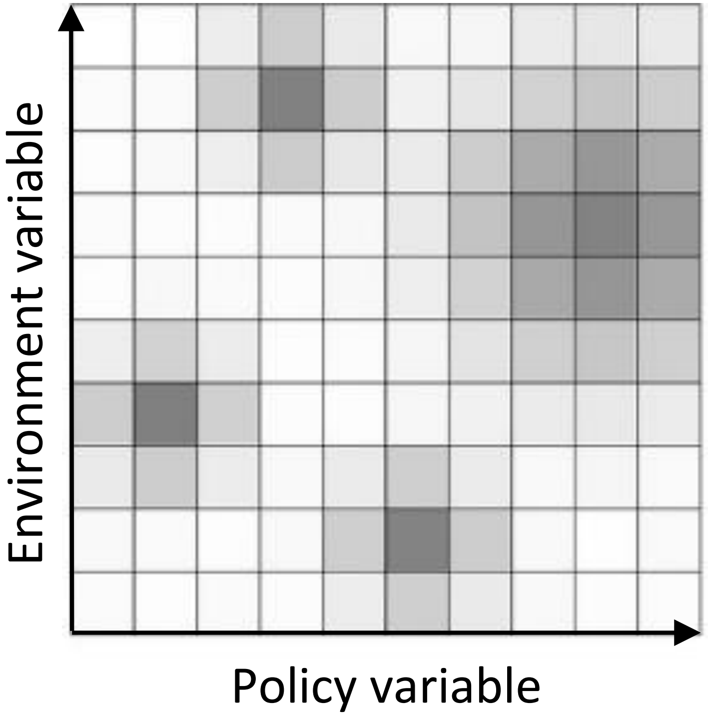
Combining environment scaffolding and policy demonstrations

Cost function as a distribution

Task parameters,
current situations,
objects locations, …



Actions, motions,
controllers, behaviors, …



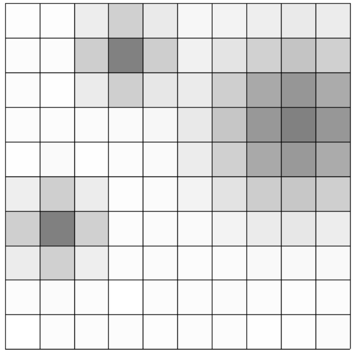
Adaptive skill acquisition = Estimating this distribution
Skill generation = Conditional sampling

[Shetty, Lembono, Löw and Calinon, IJRR, 2024]
(Best article award, IEEE RAS TC OptRob)

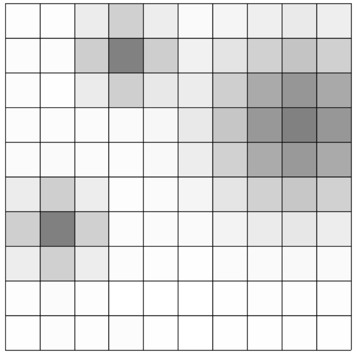
Active data sampling for low-rank factorization

Dr Suhan Shetty

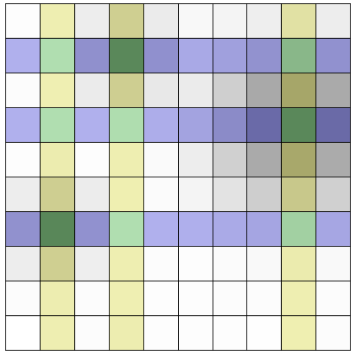
Cross approximation (skeleton decomposition) of a probability distribution:



Original distribution



Reconstructed distribution (rank 3 approximation)



$$\boldsymbol{X}_{i,j,k,\ldots} = \sum_{r=1}^{R} \boldsymbol{U}_{i,r} \boldsymbol{V}_{j,r} \boldsymbol{W}_{k,r} \cdots$$

→ Can be used to approximate an unknown matrix with an algorithm **querying rows and columns of the matrix** in an iterative manner, while estimating its rank

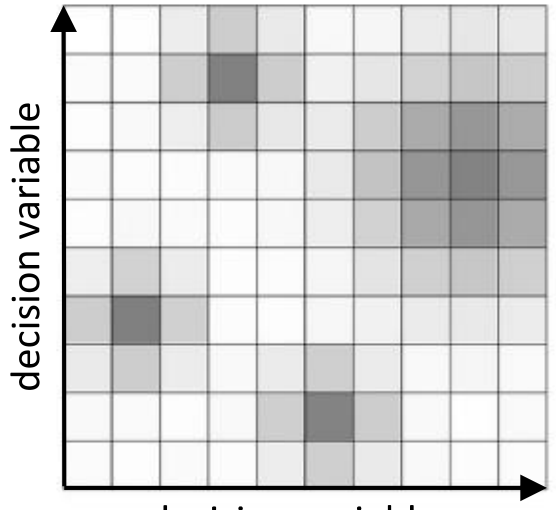
→ In contrast to NN and GMM that first require to sample points to approximate the function, **Tensor Trains recursively generates the required data to build the model**

[Shetty, Lembono, Löw and Calinon, IJRR, 2024]
(Best article award, IEEE RAS TC OptRob)

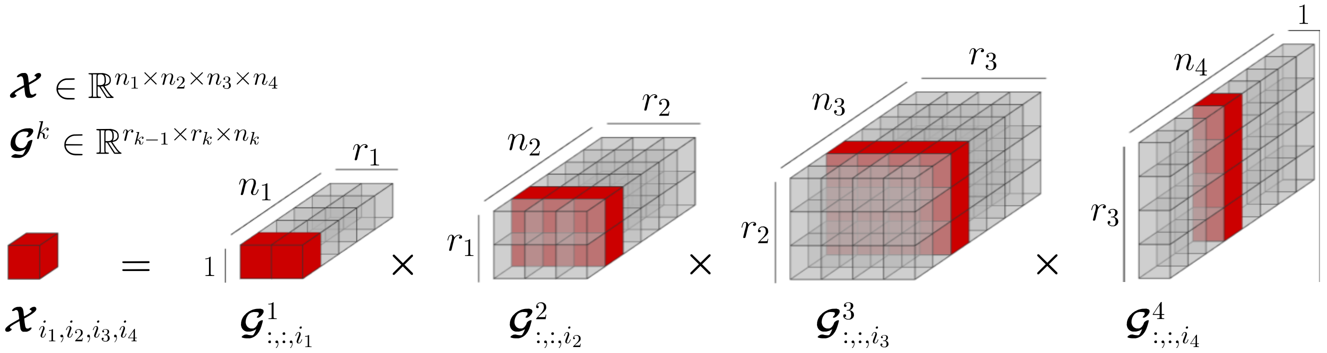
Tensor train for global optimization (TTGO)

Dr Suhan Shetty

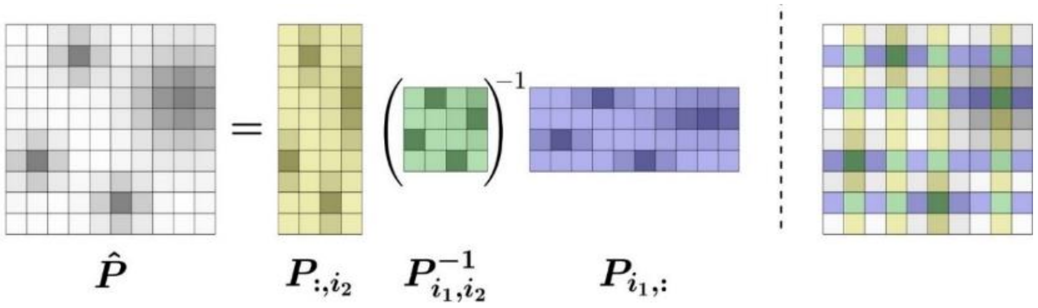
For 2D decision variables:



For nD decision variables:



Tensor train (TT) for data factorization



[Shetty, Lembono, Löw and Calinon, IJRR, 2024]
(Best article award, IEEE RAS TC OptRob)

Tensor train for global optimization (TTGO)

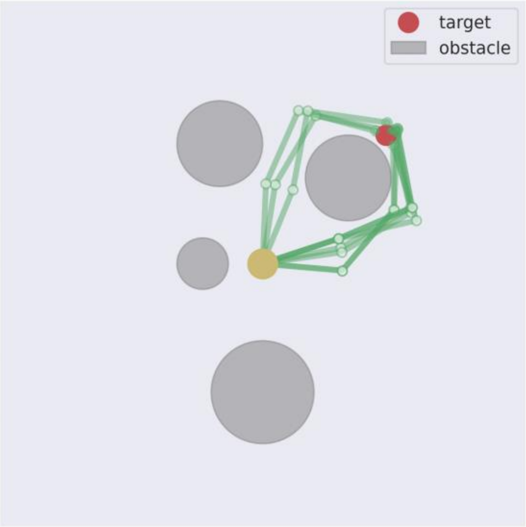
Dr Suhan Shetty

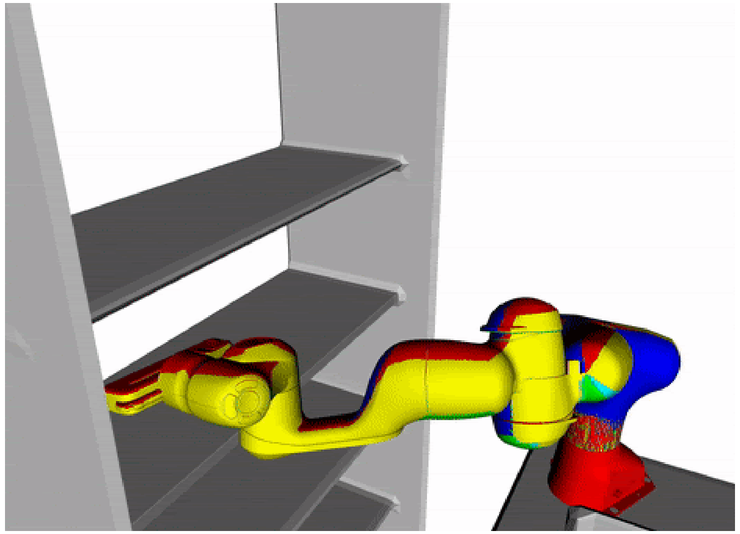
- **Generates multiple solutions** → faster adaptation to sudden changes
- **Data-efficient** alternative to reinforcement learning
- Optimization for **discrete and continuous** decision variables (alternative to TAMP)
- Variables stay within **a boundary domain**
- Easy extensions to **human-guided learning** (incl. LfD and scaffolding)

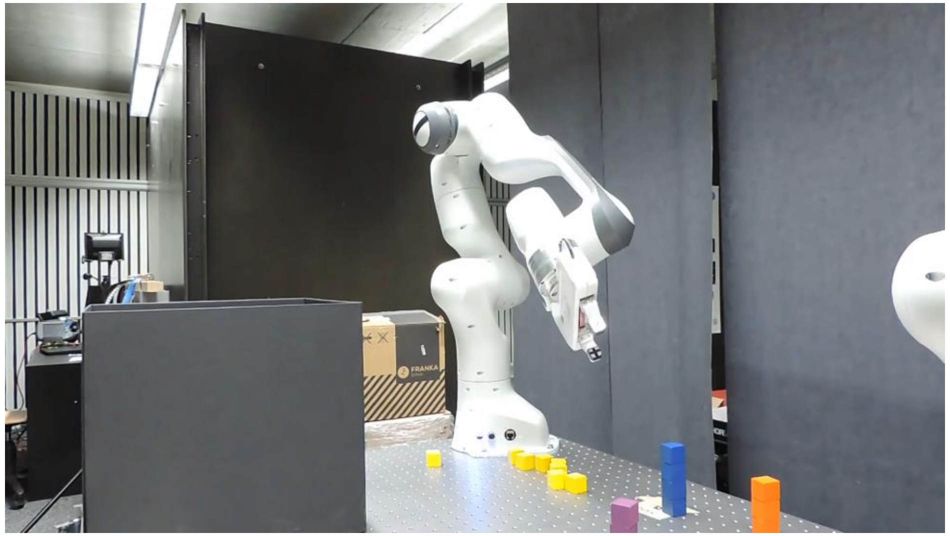
Inverse kinematics (success rate)	Number of samples			
	1	10	100	1000
TTGO	94.00%	98.00%	98.00%	99.00%
Uniform	37.75%	45.50%	59.25%	75.00%

Target reaching (success rate)	Number of samples			
	1	10	100	1000
TTGO	62.00%	86.00%	86.00%	88.00%
Uniform	19.25%	28.75%	41.00%	53.50%

Pick-and-place (success rate)	Number of samples			
	1	10	100	1000
TTGO	70.00%	81.00%	79.00%	89.00%
Uniform	23.75%	30.25%	39.5%	44.25%







[Shetty, Lembono, Löw and Calinon, IJRR, 2024]
(Best article award, IEEE RAS TC OptRob)

Frugal AI with tensor data in robotics: which tools to use?

Neural networks Vs Tensor networks

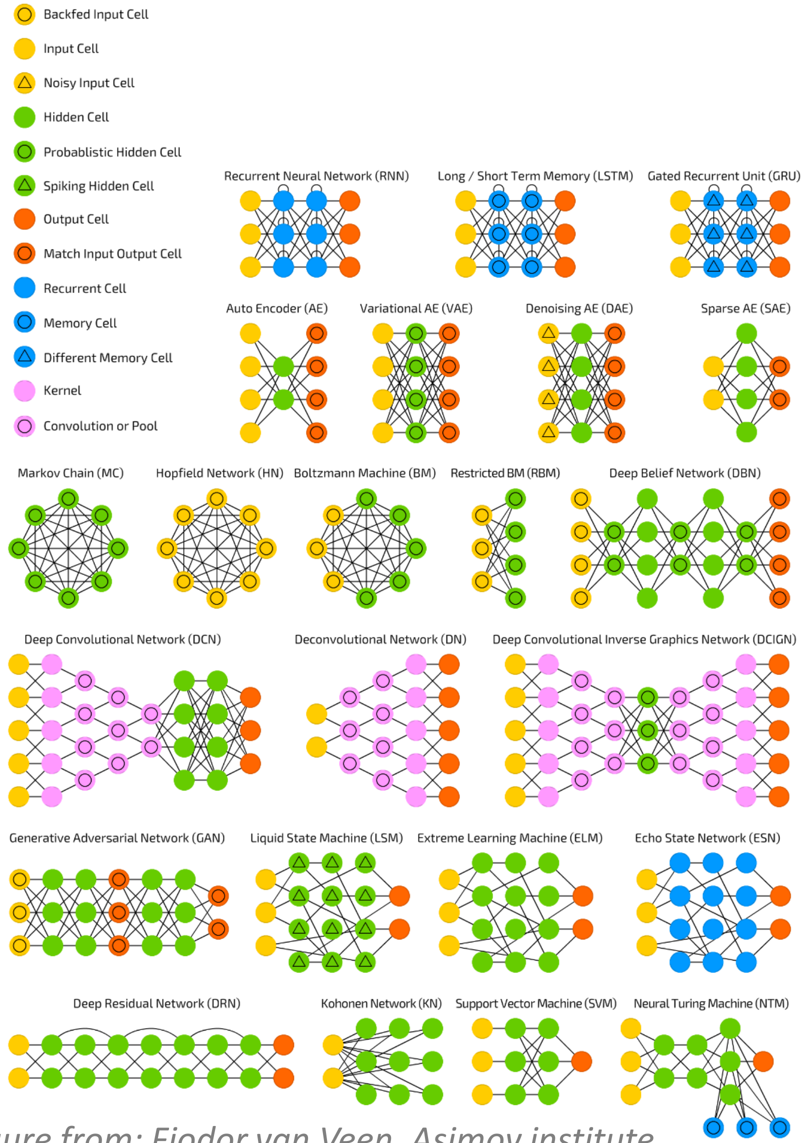
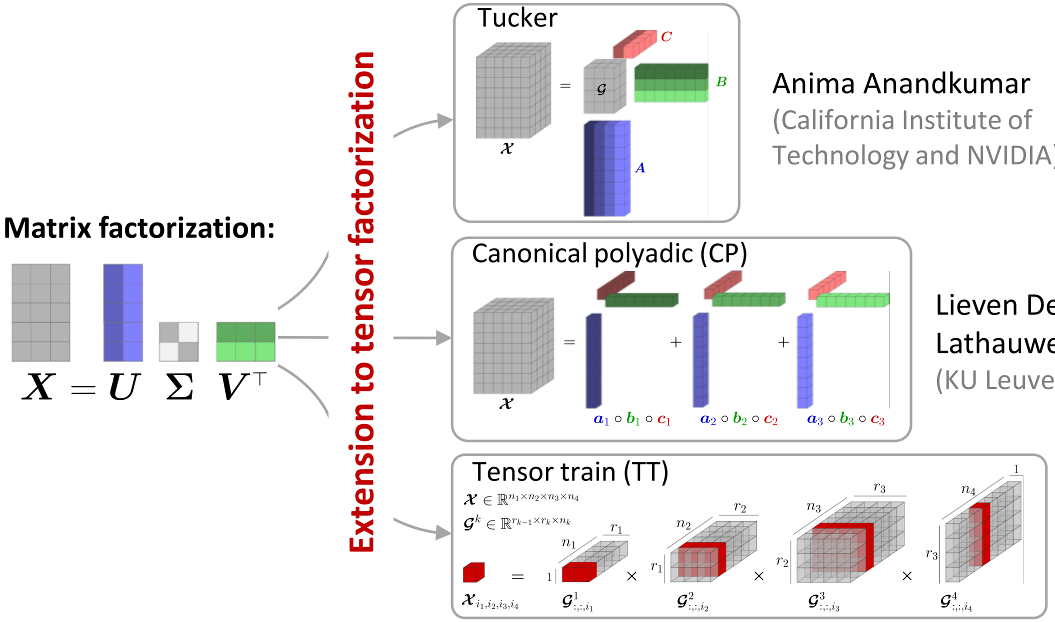


Figure from: Fjodor van Veen, Asimov institute



Anima Anandkumar (California Institute of Technology and NVIDIA)

Lieven De Lathauwer (KU Leuven)

Ivan Oseledets (Skolkovo Institute of Science and Technology)

$$\boldsymbol{X}_{i,j,k,\ldots} = \sum_{r=1}^{R} \boldsymbol{U}_{i,r} \boldsymbol{V}_{j,r} \boldsymbol{W}_{k,r} \cdots$$

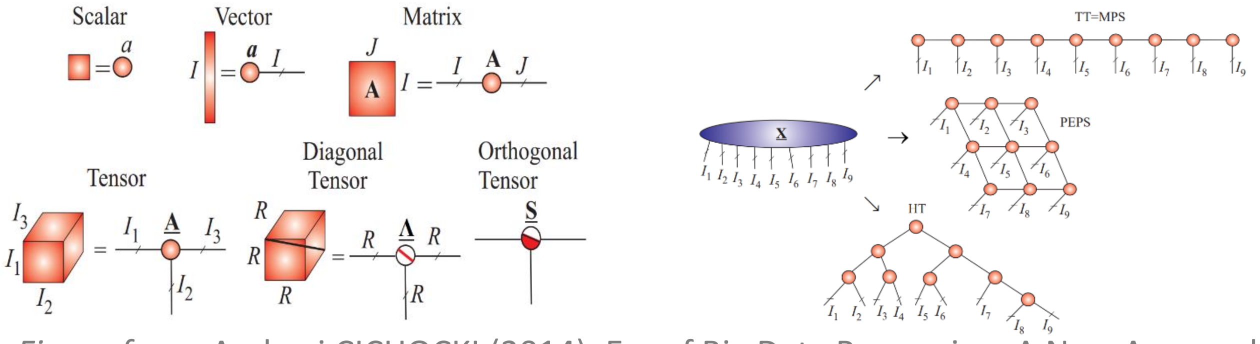
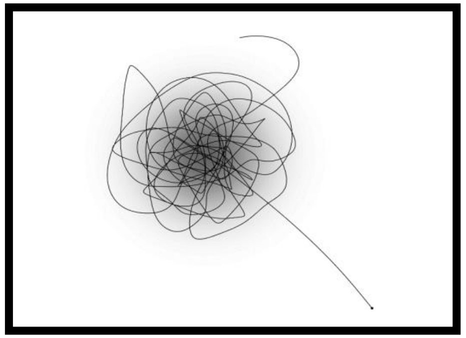


Figure from: Andrzej CICHOCKI (2014), Era of Big Data Processing: A New Approach via Tensor Networks and Tensor Decompositions

Outline

Models built from self-generated data

Tensor networks Vs neural networks



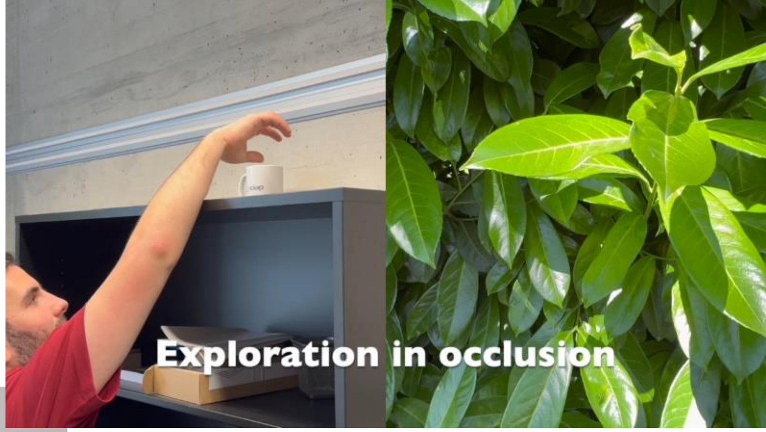
Ergodic control

Learning for control Vs control for learning

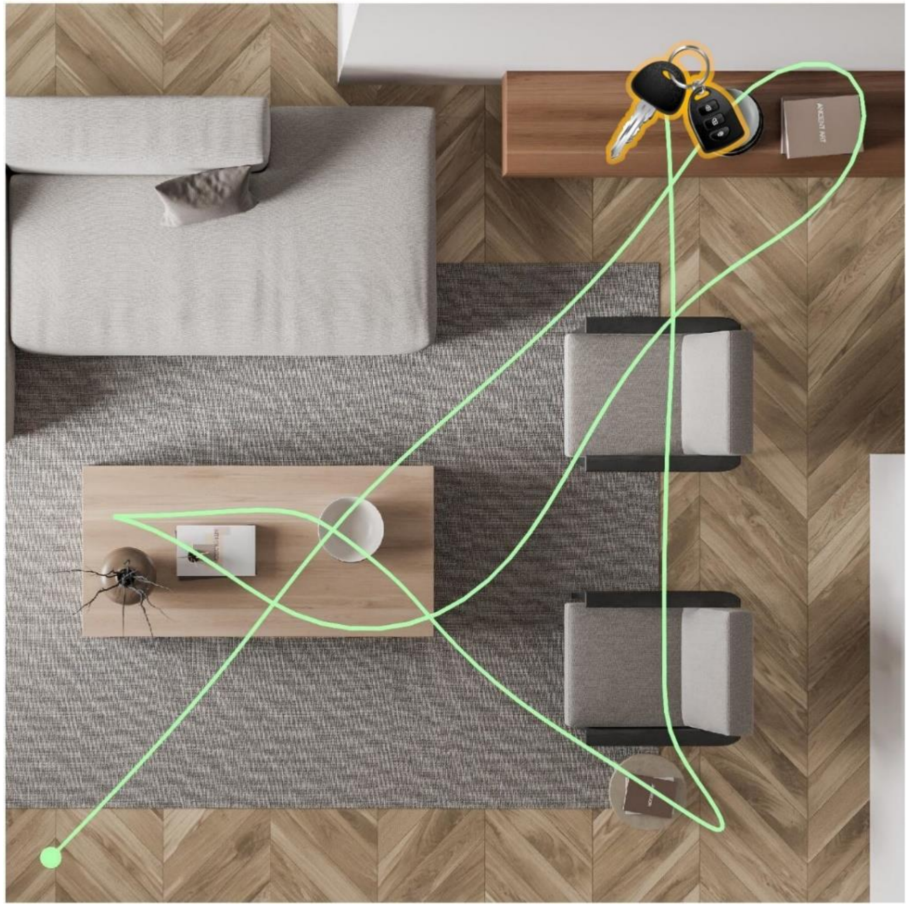
Geometry-informed models

Object-centric, distances and manifold representations

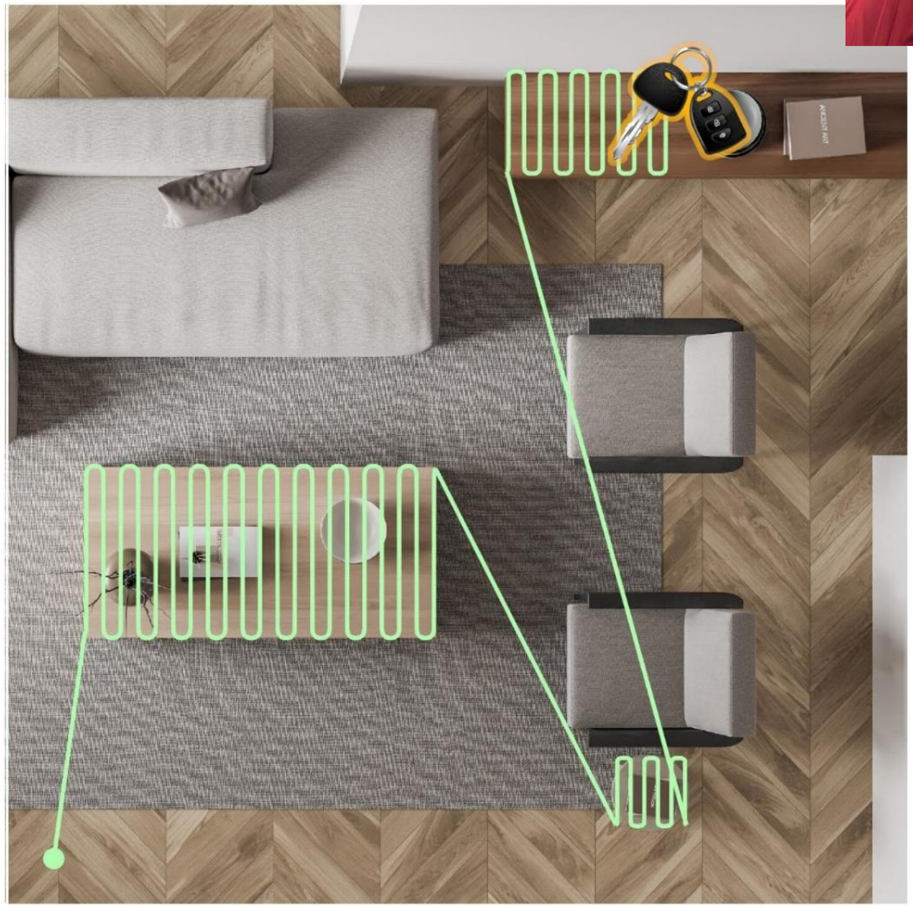
Ergodic control for search and exploration



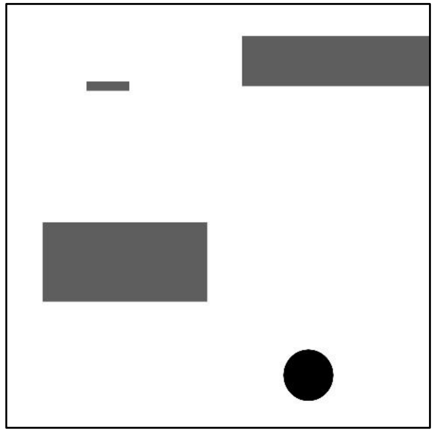
Ergodic search



Patterned search



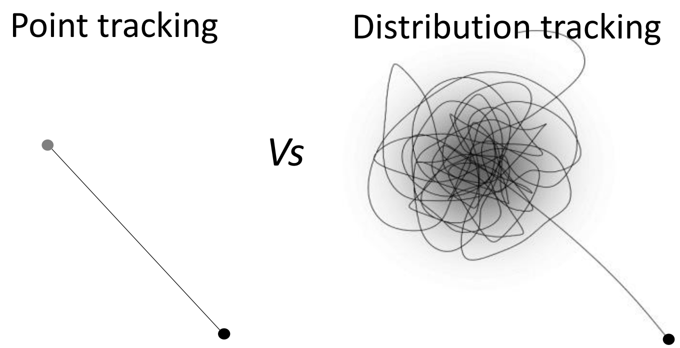
Input as distribution



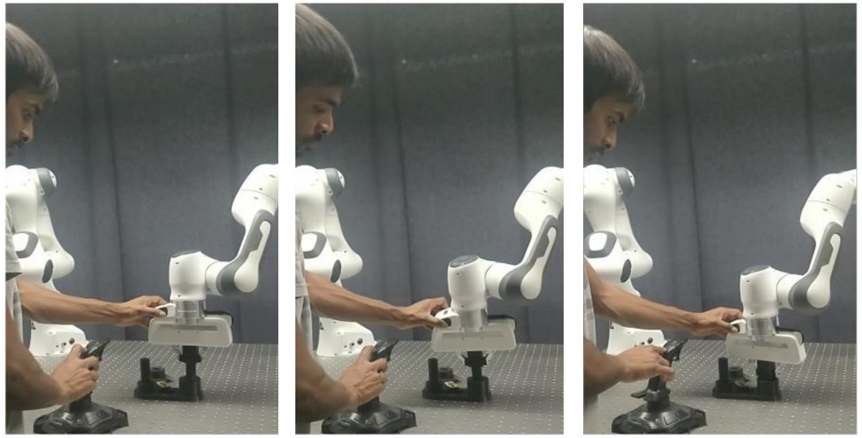
[Shetty, Silvério and Calinon, IEEE Trans. on Robotics, 2022]
https://ergodiccontrol.github.io (Tutorial at ICRA'2024)

Ergodic control to handle uncertainty

Ergodic control as search behavior

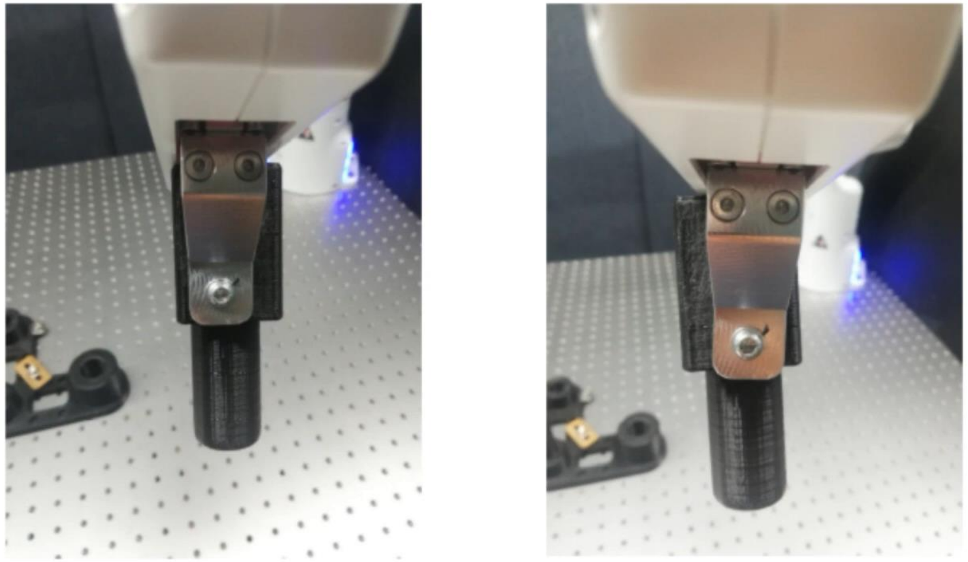


Insertion task (Siemens gears benchmark):



Demonstration of insertion pose variations to provide a spatial reference distribution

We evaluate the proposed approach using two different peg grasps:



Grasp #1 Grasp #2

[Shetty, Silvério and Calinon, IEEE Trans. on Robotics, 2022]
https://ergodiccontrol.github.io (Tutorial at ICRA'2024)

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Tensor networks Vs neural networks

Ergodic control

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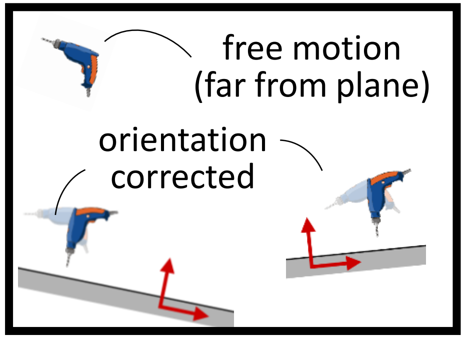
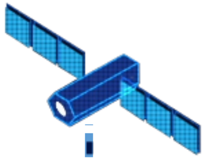


Geometry-informed models

Object-centric, distances and manifold representations

Object-centric representations

DexROV



https://dexrov.eu
EC, H2020 (2015-2018)

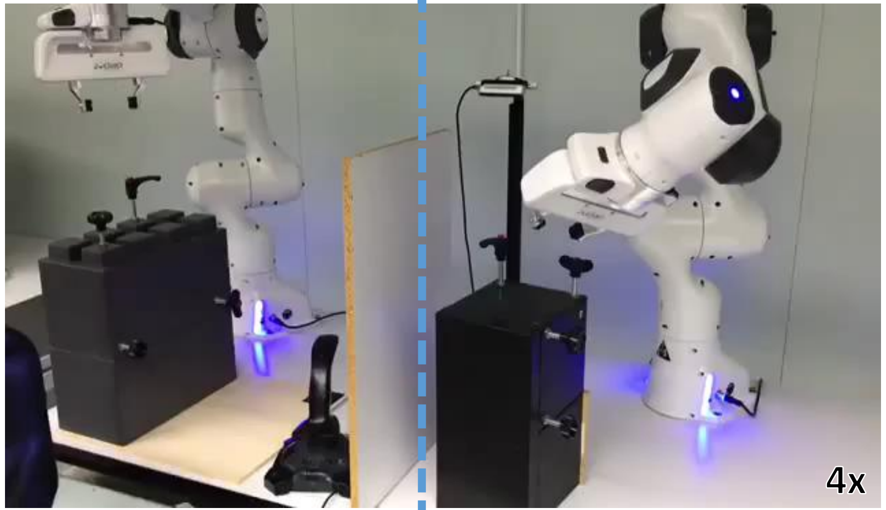
Task-parameterized representation of movements

[Pignat and Calinon, RAS, 2017]

Teleoperator side (VR)

Remote robot side

[Birk *et al.*, IEEE RAM, 2018]



Teleoperated manipulation task

Generation on the targeted robot

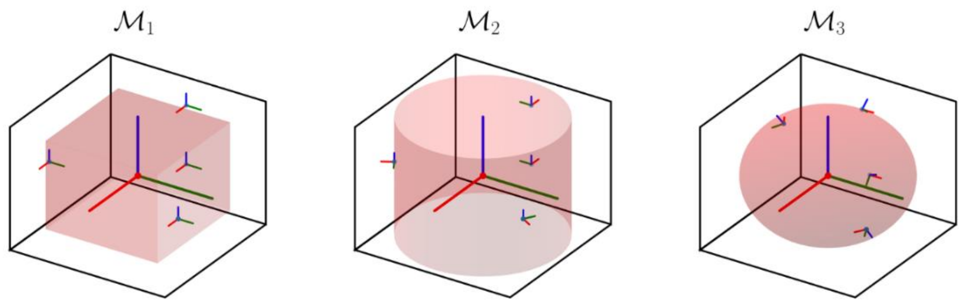
[Gao, Silvério, Pignat, Calinon, Li and Xiao, RA-L, 2021]

Robot learning guided by geometry

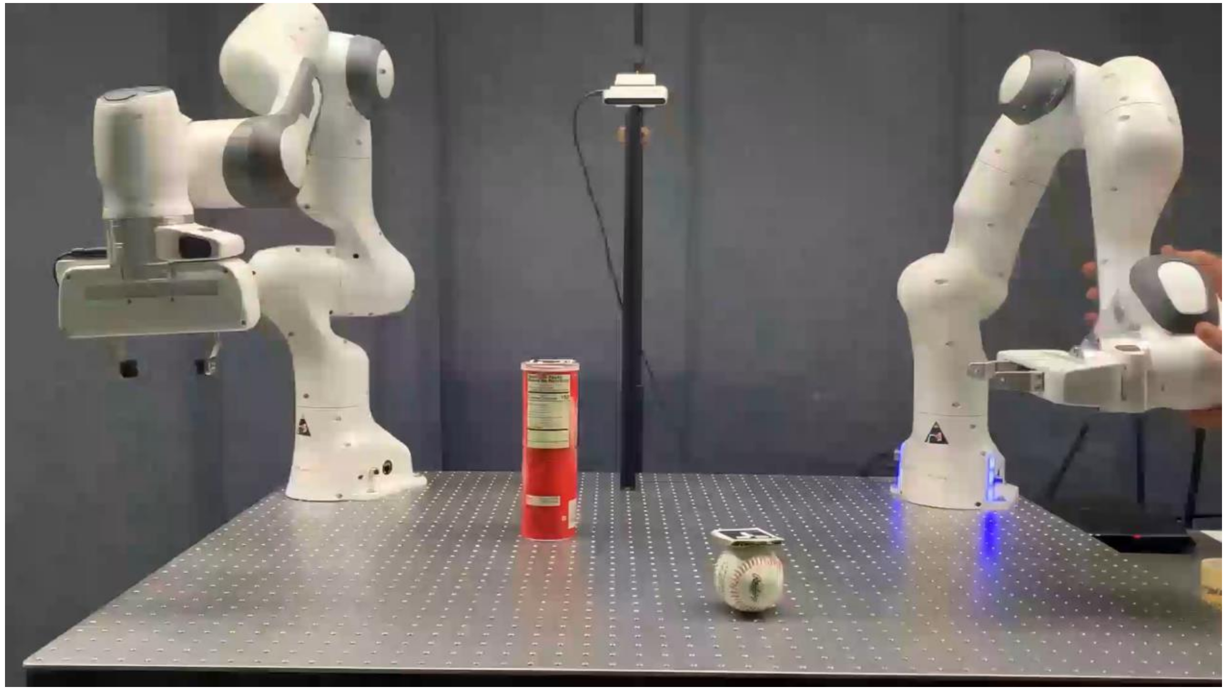
INTELLIMAN
AI-powered manipulation system for advanced robotic service, manufacturing and prosthetics

Sestosenso

Dictionary of candidate manifolds to represent the skill:

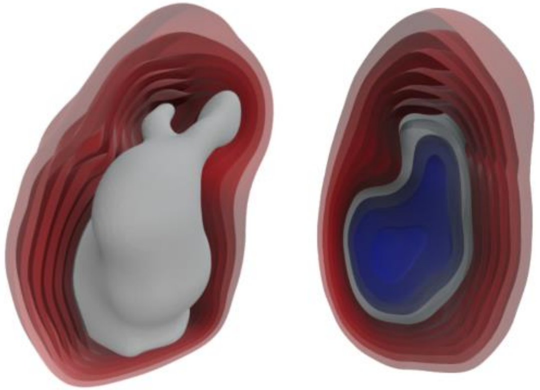


Dr Boyang Ti

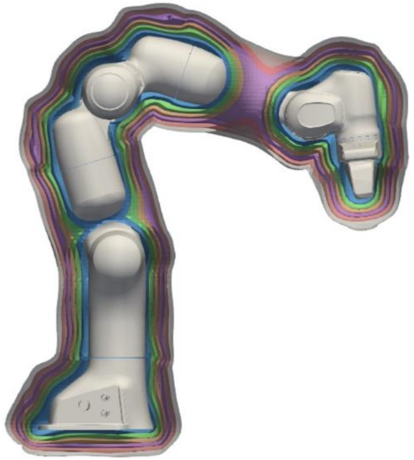


[Ti, Razmjoo, Gao, Zhao and Calinon, RAS, 2023]

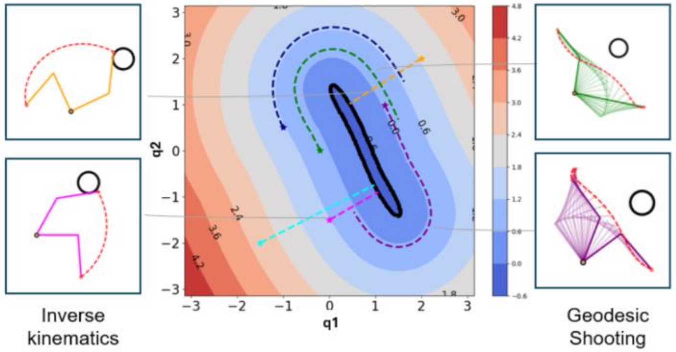
Distance fields and coordinate fields:



Signed distance field (SDF)
[Marić *et al.*, IEEE RA-L 2024]



Robot distance field (RDF)
[Li *et al.*, ICRA'2024]



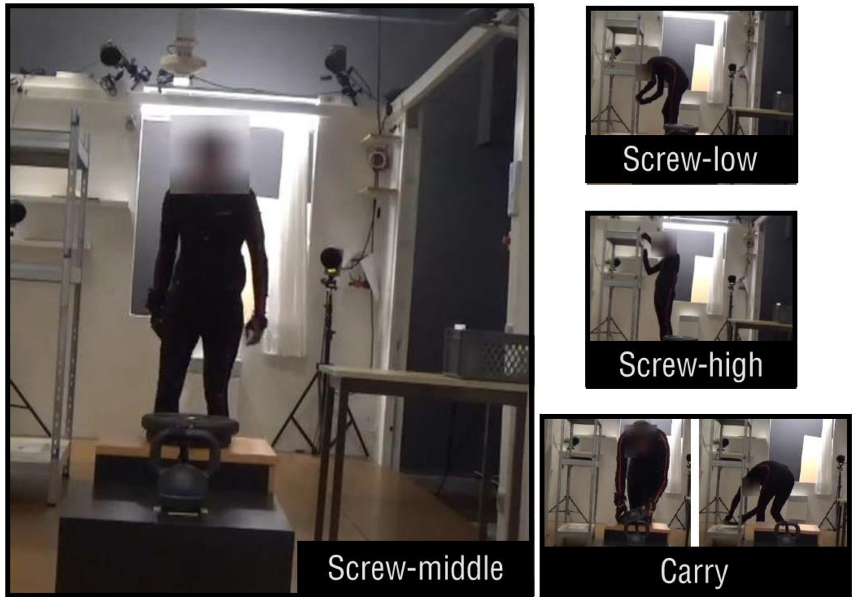
Configuration distance field (CDF)
[Li *et al.*, RSS'2024]

Outstanding Paper Award Finalist at RSS'24

Ante Marić

Yiming Li

Transfer of skills between different kinematic chains



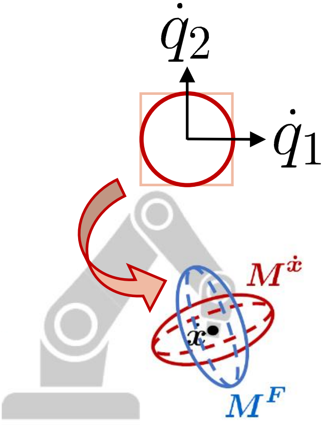
Dr Noémie Jaquier

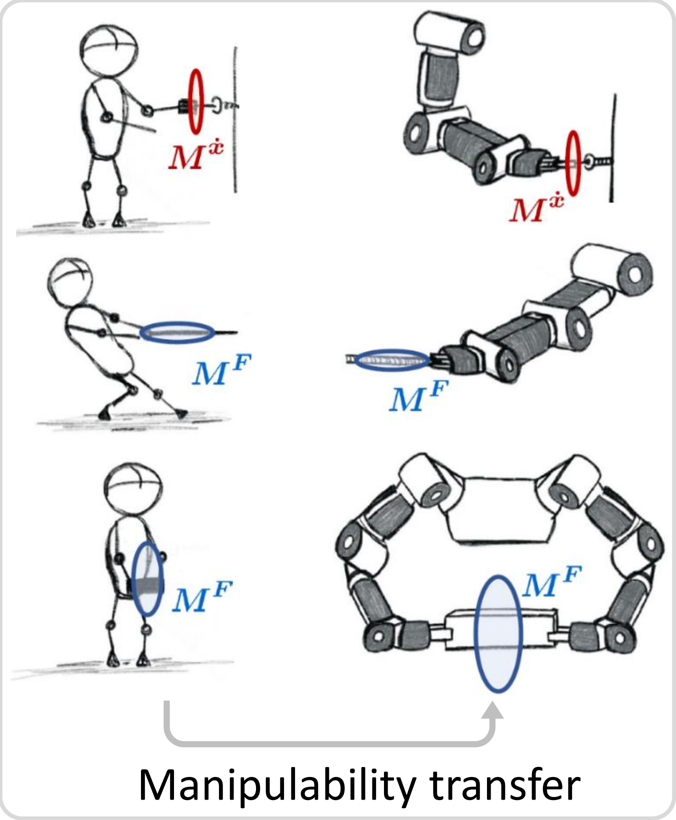
Exploited dataset:

[Maurice, Malaisé, Amiot, Paris, Richard, Rochel and Ivaldi (2019), *Human movement and ergonomics: An industry oriented dataset for collaborative robotics*, IJRR]

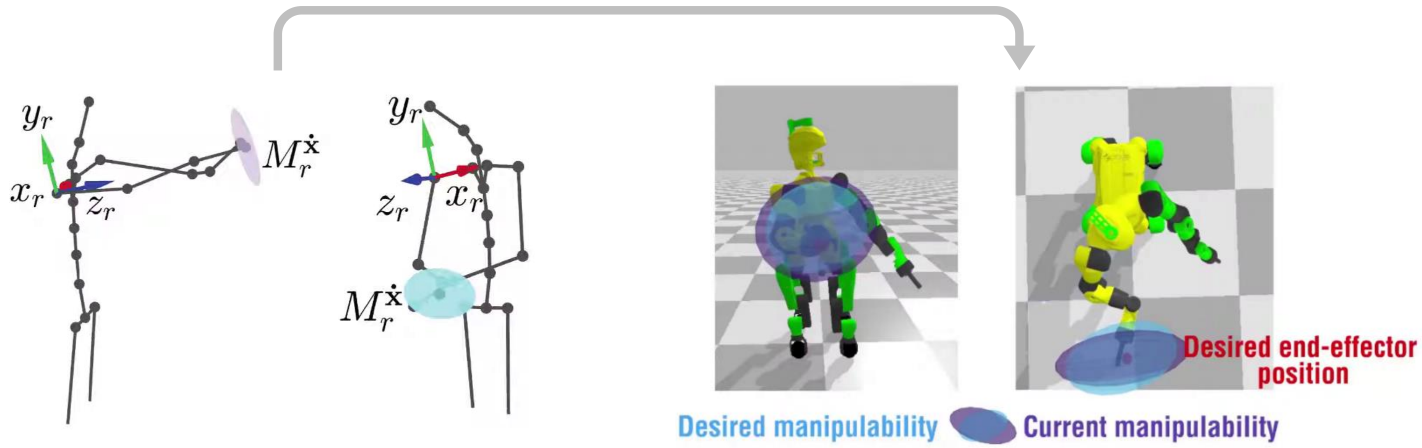
Manipulability ellipsoids as task descriptor: $\boldsymbol{M}(\boldsymbol{q}) = \boldsymbol{J}(\boldsymbol{q})\boldsymbol{J}(\boldsymbol{q})^{\top}$

→ Directions in which velocity/acceleration/force can best reject perturbations





Transfer of manipulation skills

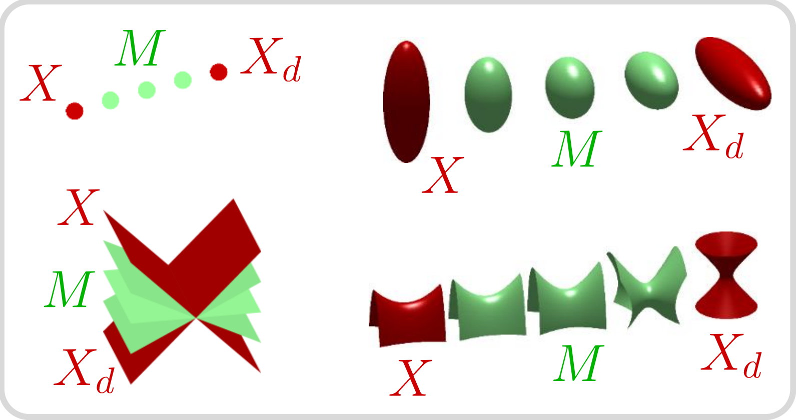


[Jaquier, Rozo, Caldwell and Calinon, IJRR, 2021] [Jaquier, Rozo and Calinon, IROS'2020]

Geometric Algebra to learn manipulation skills

Tobias Löw

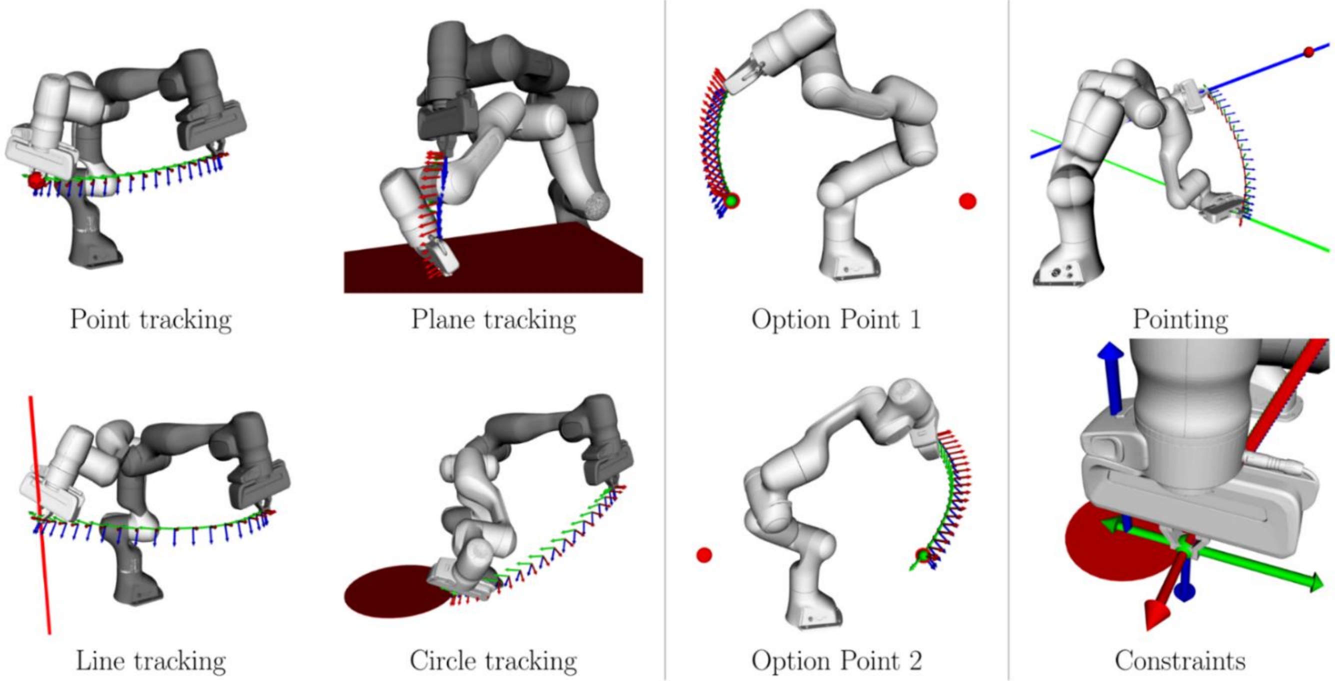
$$M = f(X, X_d)$$



→ Datapoints representing **orientations/spheres/planes/lines**

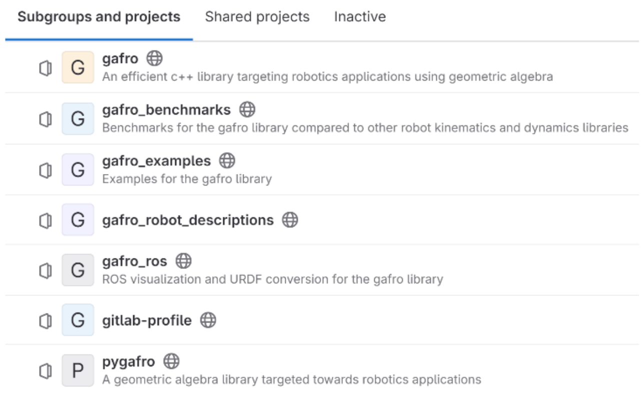
→ **Compact computer codes** with single function working for all these geometric objects

→ **Efficient computation** without switching between different algebra



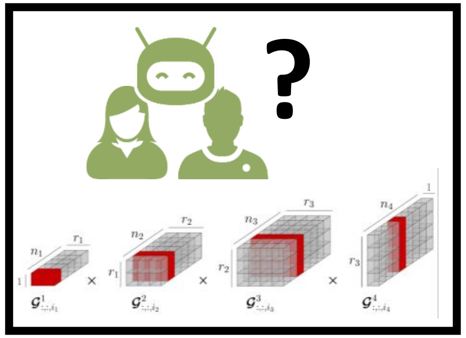
GAFRO - Geometric Algebra For RObotics
Toolbox for efficient learning and control in robotics using conformal geometric algebra

https://gitlab.com/gafro/

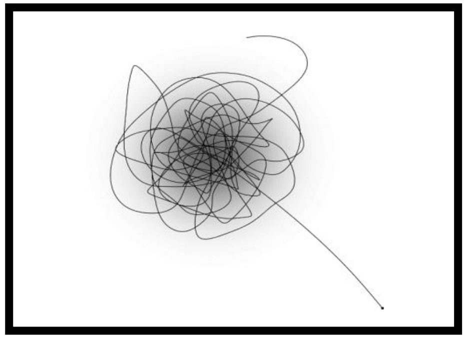


[Löw and Calinon, IEEE Transactions on Robotics, 2023]
[Löw and Calinon, IEEE Robotics & Automation Magazine, 2024]

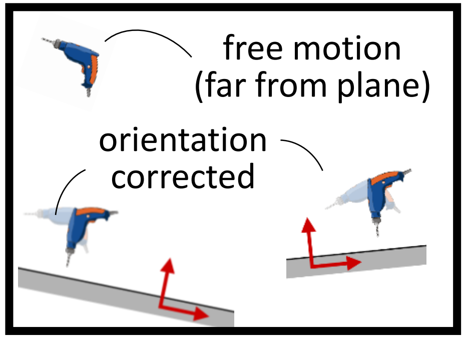
Summary



Tensor trains can build models by actively sampling data, while allowing **human-in-the-loop learning**



In **ergodic control**, the targets to reach take the form of distributions → a good fit for sparse data and low-tech



Manipulation skills acquisition can be facilitated by using **object-centric** and **geometric** representations

Contact:
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Swiss National Science Foundation

European Commission

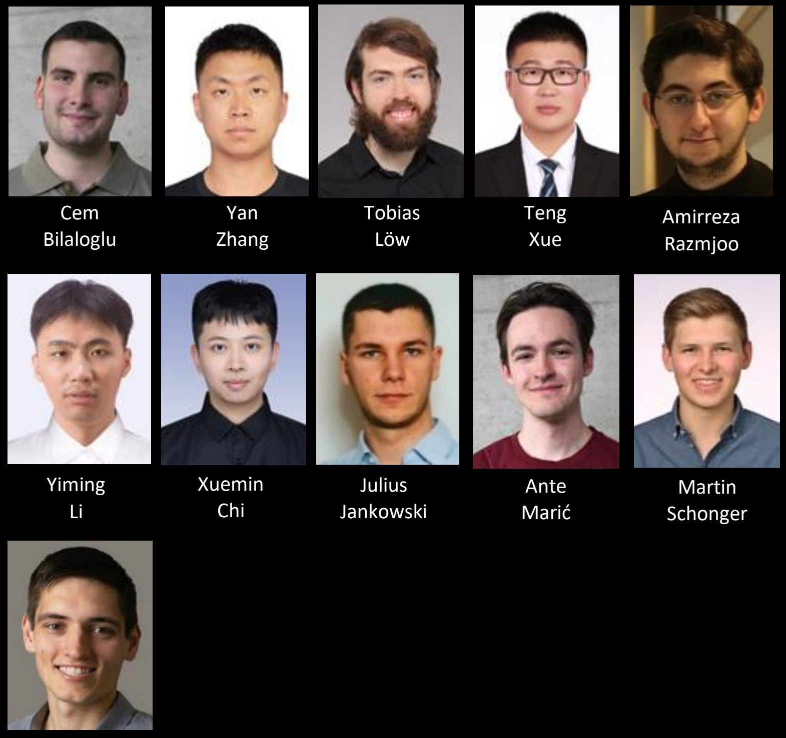
Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

China Scholarship Council

idiap

Robot Learning & Interaction group at Idiap:

Current group members

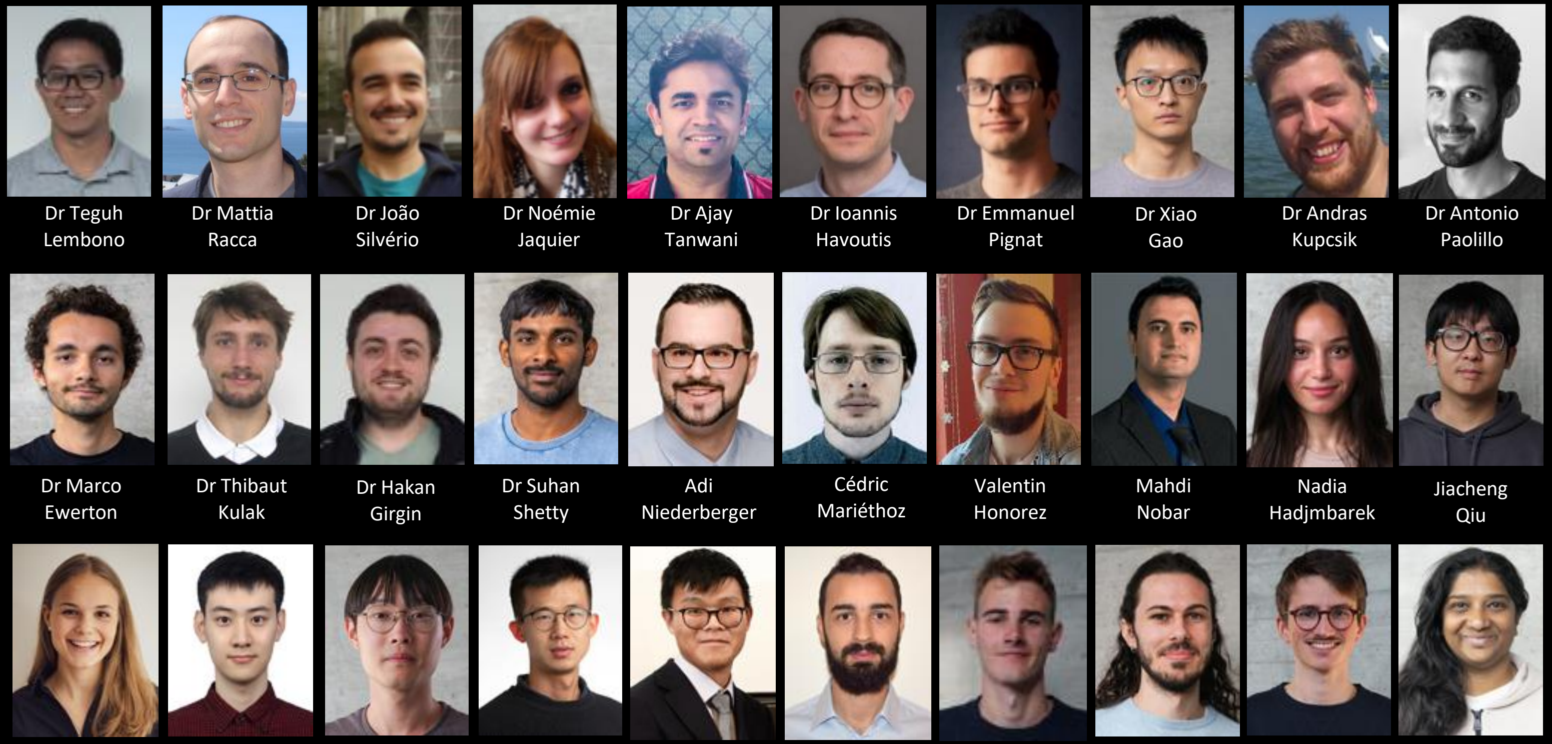


Cem Bilaloglu, Yan Zhang, Tobias Löw, Teng Xue, Amirreza Razmjoo, Yiming Li, Xuemin Chi, Julius Jankowski, Ante Marić, Martin Schonger, Dr James Hermus

R&D Engineers group

Jérémy Maceiras, Philip Abbet, Guillaume Clivaz

Alumni (2015-2024)



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