



DeepRob

[Group 7] Lecture 7
Dual-arm Manipulation - Learning
by Ryan Roche, Matt Rajala, Adit Kadepurkar
University of Minnesota





What is Bimanual Manipulation?





What is Bimanual Manipulation?

- The term “Bimanual Manipulation” originates from psychological studies on motor skills
- Refers specifically to tasks requiring the use and coordination of both hands acting on an object
- Used in developmental psychology studies of infants and their motor skill development
- Later used in robotics after robotic bimanual manipulators were developed

“Role-differentiated bimanual manipulation (RDBM) is a complementary movement of both hands that requires differentiation between actions of the hands.”

Kimmerle, Marliese et al. “Development of role-differentiated bimanual manipulation during the infant’s first year.” *Developmental psychobiology* vol. 52,2 (2010): 168-80.
doi:10.1002/dev.20428



What is Bimanual Manipulation?

- **The term “Bimanual Manipulation” originates from psychological studies on motor skills**
- **Refers specifically to tasks requiring the use and coordination of both hands acting on an object**
- **Used in developmental psychology studies of infants and their motor skill development**
- **Later used in robotics after robotic bimanual manipulators were developed**

“Role-differentiated bimanual manipulation (RDBM) is a complementary movement of both hands that requires differentiation between actions of the hands.”

Kimmerle, Marliese et al. “Development of role-differentiated bimanual manipulation during the infant’s first year.” *Developmental psychobiology* vol. 52,2 (2010): 168-80.
doi:10.1002/dev.20428

“Behavioral studies provide evidence that bimanual tasks are more than the simple sum of unimanual tasks as they have to consider spatial and temporal coordination as well as the interactions between both hands.”

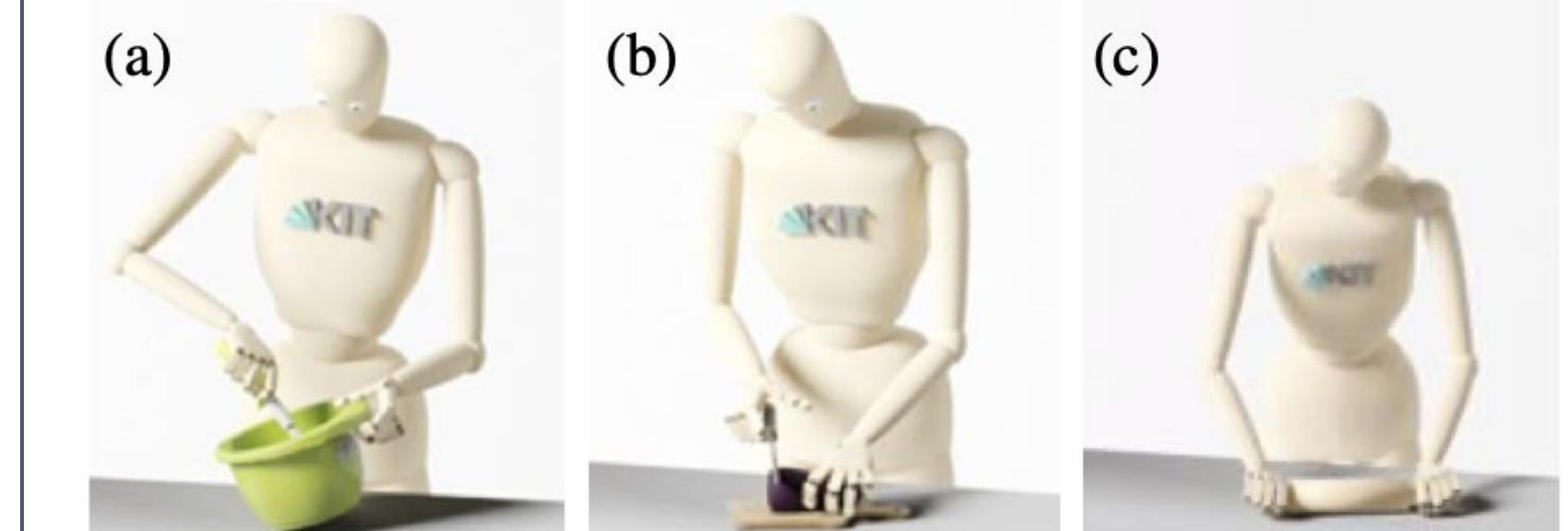
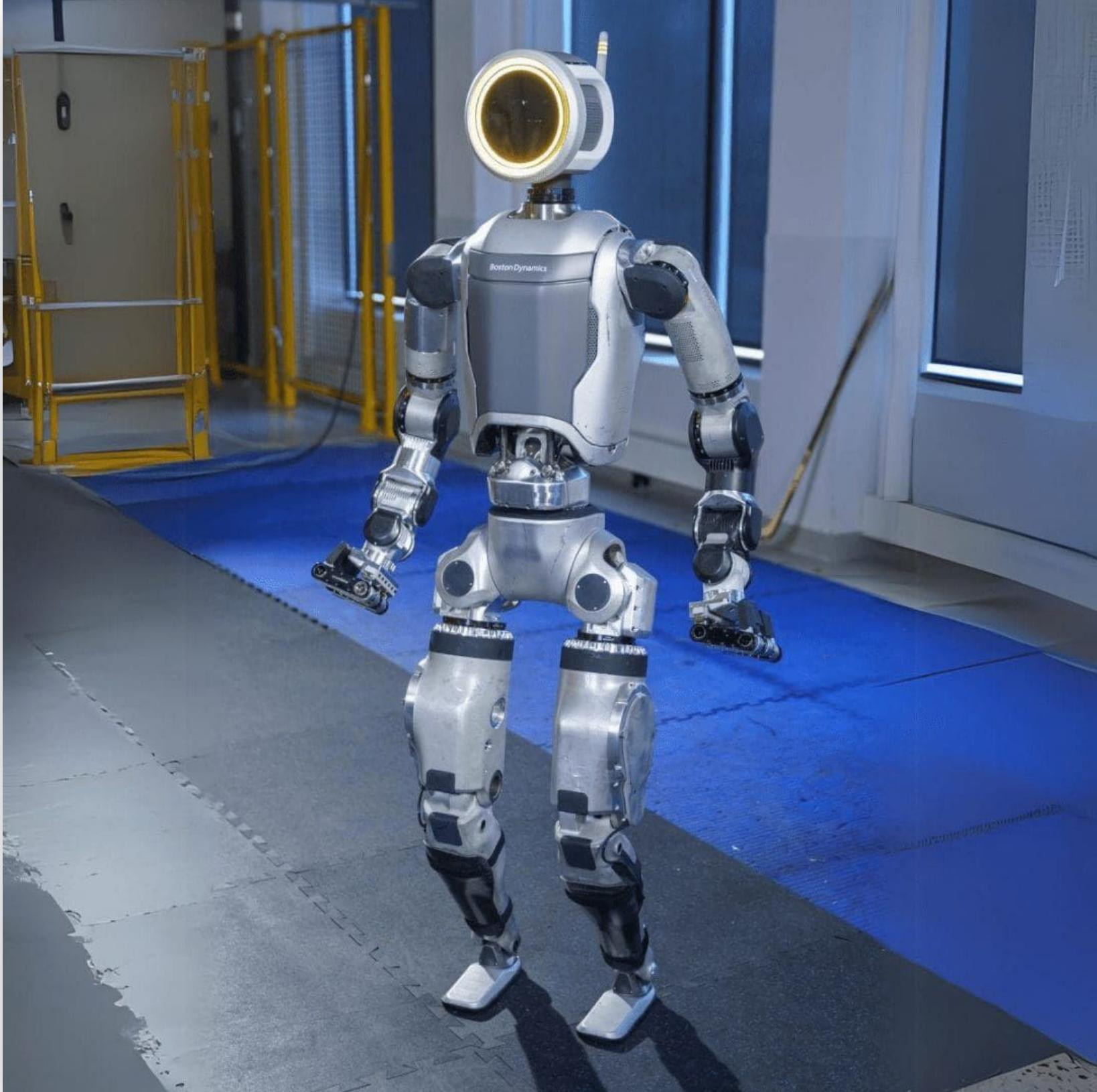


Fig. 1. Examples of bimanual actions: Asymmetric such as stir (a) and cut (b), and symmetric such as rolling (c).

Quote and figure from F. Krebs and T. Asfour, “A Bimanual Manipulation Taxonomy,” in *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11031-11038, Oct. 2022, doi: 10.1109/LRA.2022.3196158



So you're talking about Humanoid Robots, then?

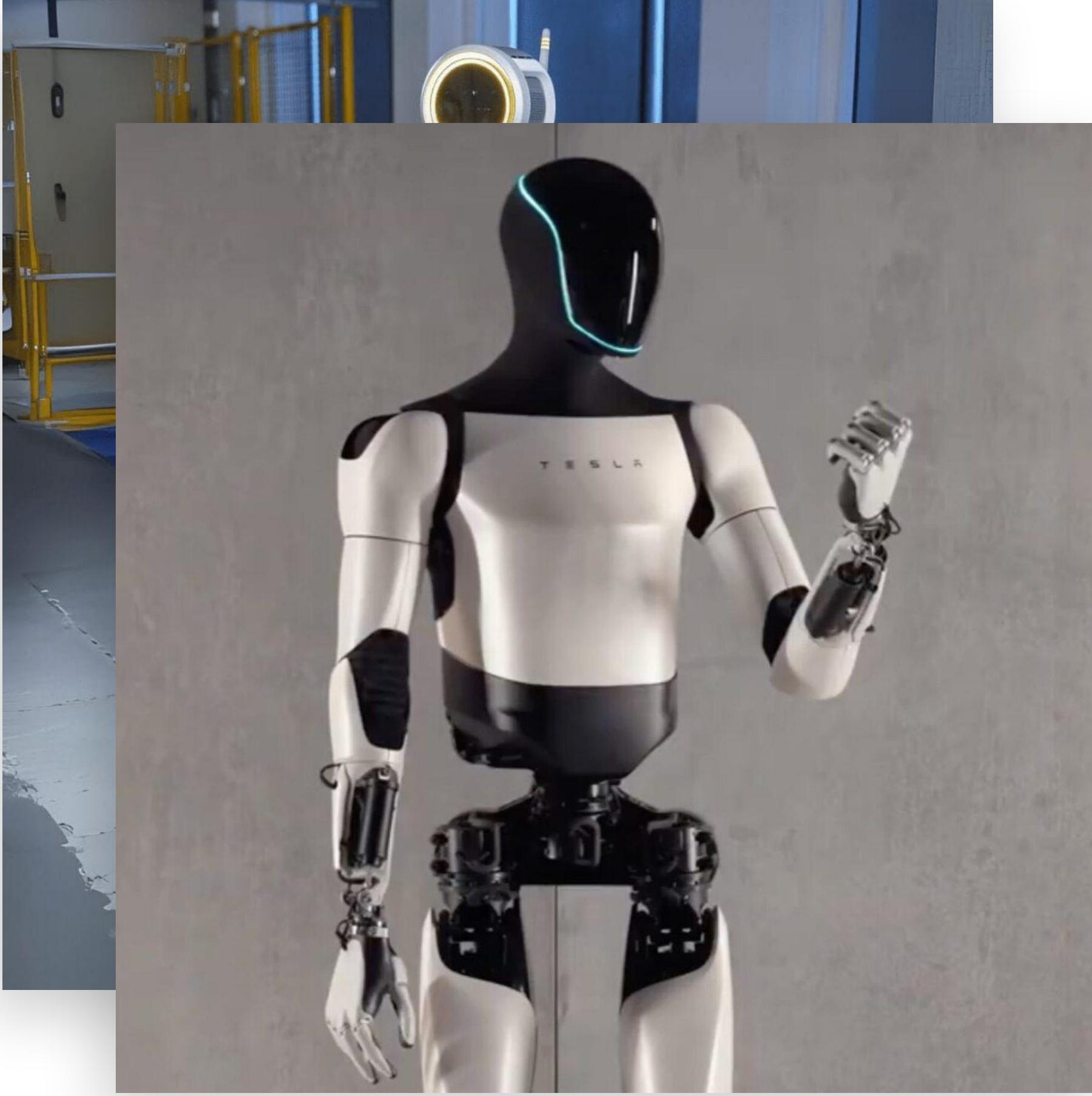


<https://bostondynamics.com/blog/electric-new-era-for-atlas/>





So you're talking about Humanoid Robots, then?



<https://bostondynamics.com/blog/electric-new-era-for-atlas/>

<https://www.teslarati.com/tesla-shows-off-optimus-gen-2-humanoid-robot-video/>





So you're talking about Humanoid Robots, then?



<https://bostondynamics.com/blog/electric-new-era-for-atlas/>

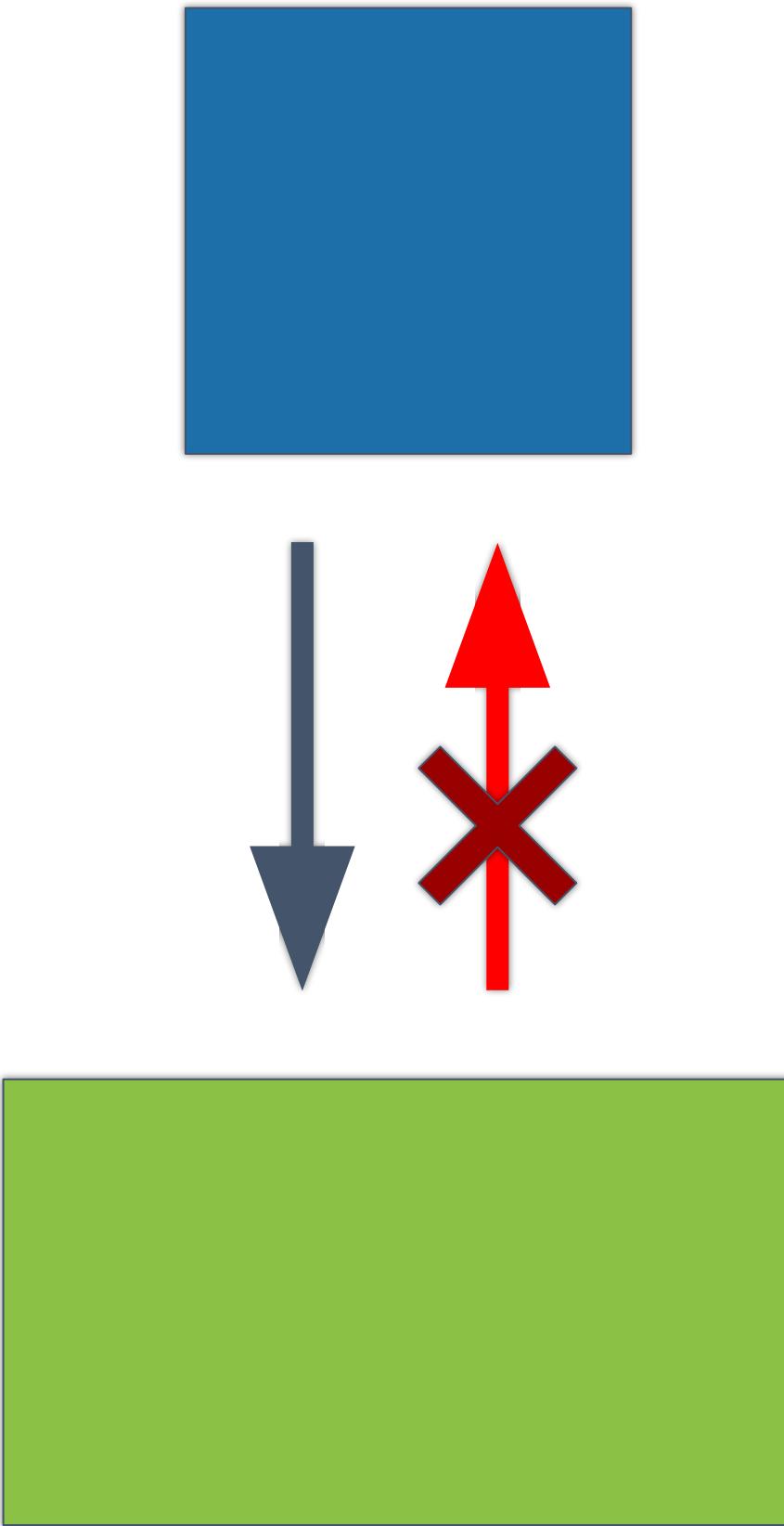
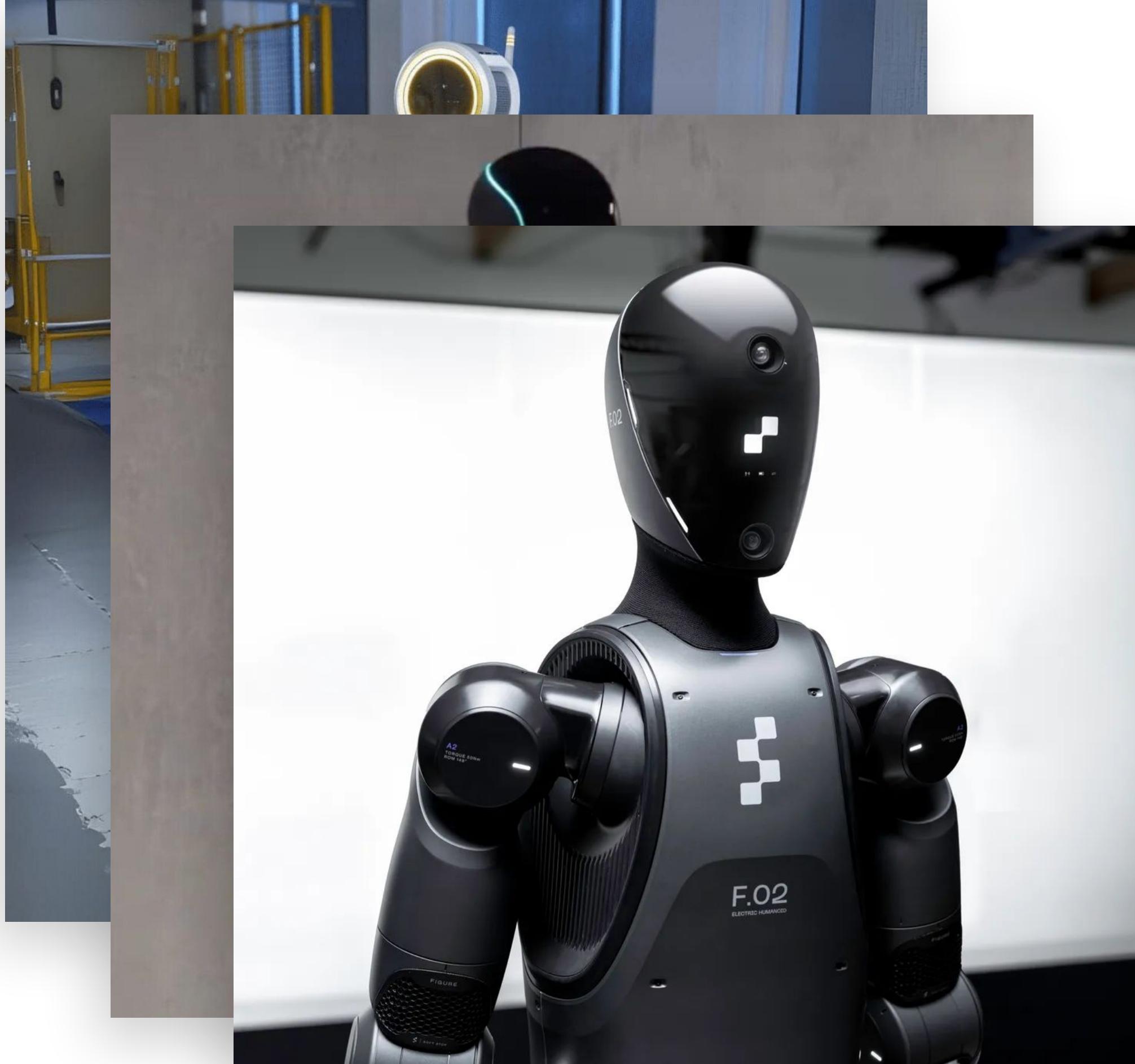
<https://www.teslarati.com/tesla-shows-off-optimus-gen-2-humanoid-robot-video/>

<https://www.therobotreport.com/figure-02-humanoid-robot-is-ready-to-get-to-work/>





So you're talking about Humanoid Robots, then?



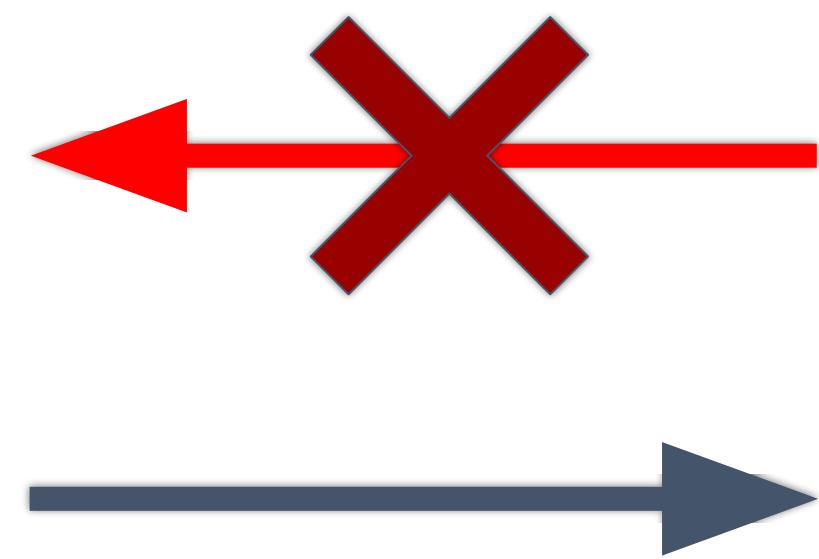
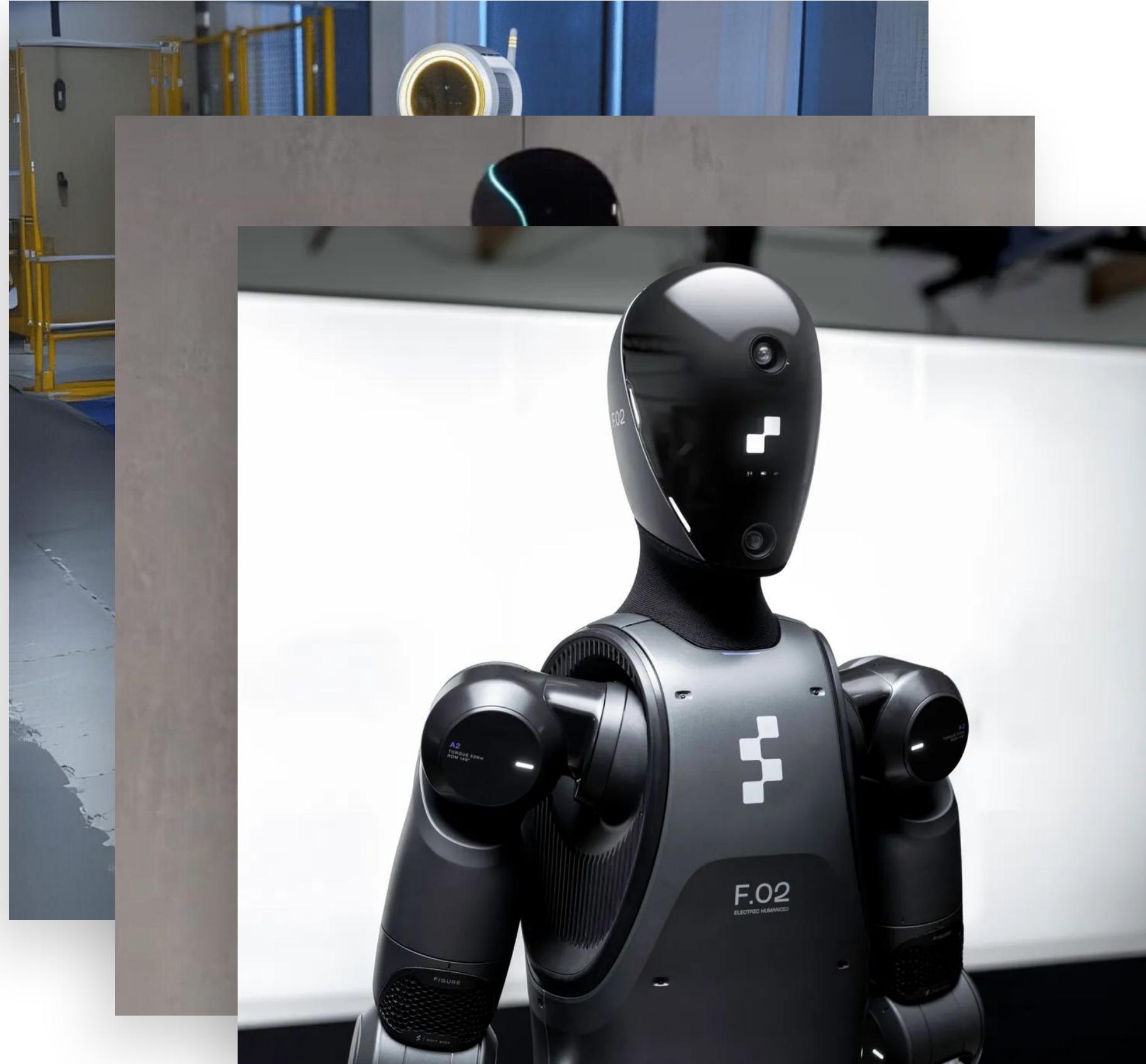
<https://bostondynamics.com/blog/electric-new-era-for-atlas/>

<https://www.teslarati.com/tesla-shows-off-optimus-gen-2-humanoid-robot-video/>

<https://www.therobotreport.com/figure-02-humanoid-robot-is-ready-to-get-to-work/>



So you're talking about Humanoid Robots, then?



<https://bostondynamics.com/blog/electric-new-era-for-atlas/>

https://www.researchgate.net/figure/Robot-stir-fry-is-a-non-prehensile-manipulation-of-semi-fluid-objects-which-requires_fig1_360559814

<https://www.teslarati.com/tesla-shows-off-optimus-gen-2-humanoid-robot-video/>

<https://www.therobotreport.com/figure-02-humanoid-robot-is-ready-to-get-to-work/>



Humanoid Robots are a
subset of Bimanual Robots





Why is Bimanual Manipulation important?





Why is Bimanual Manipulation important?

Objects in human environments are built for dual-arm agents





Why is Bimanual Manipulation important?

We want robots to help humans in their environments.

Objects in human environments are built for dual-arm agents





Why is Bimanual Manipulation important?

We want robots to help humans in their environments.

Objects in human environments are built for dual-arm agents

It makes sense to build bimanual manipulation robots!





Why is Bimanual Manipulation important?

Many policy training
methods require expert
demonstrations



Why is Bimanual Manipulation important?

Many policy training methods require expert demonstrations

It's **much** easier to teleoperate a bimanual robot to record expert demonstrations since we already innately know how to perform these bimanual tasks ourselves!

Why is Bimanual Manipulation important?



<https://www.youtube.com/watch?v=PHXQFE-Rteo>



Why is Bimanual Manipulation important?

- . **Similarity to operator**
 - . Teleoperation becomes near-trivial as the operator's innate bimanual manipulation skills can be applied to the robot's operation





Why is Bimanual Manipulation important?

- . Similarity to operator
 - . Teleoperation becomes near-trivial as the operator's innate bimanual manipulation skills can be applied to the robot's operation
- . **Manipulability**
 - . The ability to manipulate both ends of a task (i.e. peg-in-hole or nut+bolt screw assembly) provides more avenues towards solving a task





Why is Bimanual Manipulation important?

- . Similarity to operator
 - . Teleoperation becomes near-trivial as the operator's innate bimanual manipulation skills can be applied to the robot's operation
- . Manipulability
 - . The ability to manipulate both ends of a task (i.e. peg-in-hole or nut+bolt screw assembly) provides more avenues towards solving a task
- . **Cognitive Motivation**
 - . Humans have an innate understanding of bimanual manipulation, so it becomes much easier to relate to and understand what a manipulator is trying to do





Why is Bimanual Manipulation important?

- . Similarity to operator
 - . Teleoperation becomes near-trivial as the operator's innate bimanual manipulation skills can be applied to the robot's operation
- . Manipulability
 - . The ability to manipulate both ends of a task (i.e. peg-in-hole or nut+bolt screw assembly) provides more avenues towards solving a task
- . Cognitive Motivation
 - . Humans have an innate understanding of bimanual manipulation, so it becomes much easier to relate to and understand what a manipulator is trying to do
- . **Human form factor**
 - . Robots are often expected to operate in environments intended for human use, thus it motivates the creation of humanlike (and thus, bimanual) robots

From *Dual arm manipulation -- A survey*

C. Smith, Y. Karayiannidis, L. Nalpantidis, X. Gratal, P. Qi, D. V. Dimarogonas, D. Kragic

KTH Royal Institute of Technology

DOI 10.1016/j.robot.2012.07.005





Timeline of Bimanual Manipulators

Select milestones from the past 30 years





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

1994

**Yaskawa Motoman introduces
the MRC system**

Allowed for synchronized control and coordination of two robotic arms by “teaching” it a sequence of movements, or programming a task on a PC



<https://ifr.org/robot-history>





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

<https://robotsguide.com/robots/davinci>



**Intuitive Surgical releases first
Da Vinci surgical robot system**

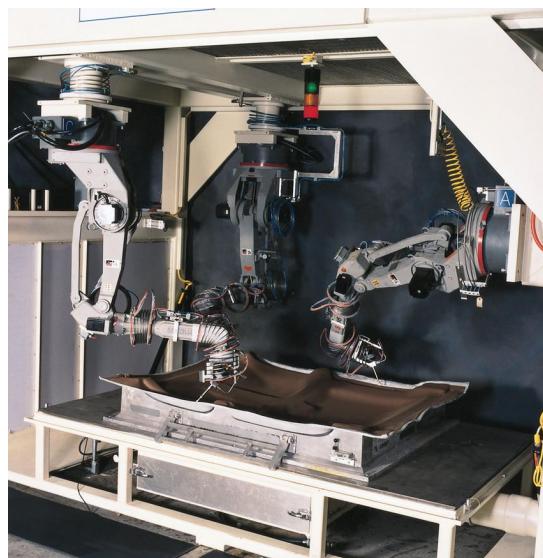
Enables less invasive surgeries
through the use of smaller robotic
tools with bimanual teleoperation

1999

1994

**Yaskawa Motoman introduces
the MRC system**

Allowed for synchronized
control and coordination of
two robotic arms by
“teaching” it a sequence of
movements, or
programming a task on a PC



<https://ifr.org/robot-history>





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

<https://robotsguide.com/robots/davinci>



Intuitive Surgical releases first Da Vinci surgical robot system

Enables less invasive surgeries through the use of smaller robotic tools with bimanual teleoperation

1999

1994

Yaskawa Motoman introduces the MRC system

Allowed for synchronized control and coordination of two robotic arms by “teaching” it a sequence of movements, or programming a task on a PC



<https://ifr.org/robot-history>

2006

Personal Robotics Lab develops Herb (Home Exploring Robot Butler)

Bimanual robot for domestic tasks developed by the Personal Robotics Lab at CMU (now at UW Seattle)



<https://robotsguide.com/robots/herb>





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

<https://robotsguide.com/robots/davinci>



Intuitive Surgical releases first Da Vinci surgical robot system

Enables less invasive surgeries through the use of smaller robotic tools with bimanual teleoperation

<https://robotsguide.com/robots/baxter>



Rethink Robotics releases Baxter

Now-defunct Rethink Robotics releases Baxter, a bimanual manufacturing robot that can be programmed simply by moving its arms by hand

1994

Yaskawa Motoman introduces the MRC system

Allowed for synchronized control and coordination of two robotic arms by “teaching” it a sequence of movements, or programming a task on a PC



<https://ifr.org/robot-history>

1999

Personal Robotics Lab develops Herb (Home Exploring Robot Butler)

Bimanual robot for domestic tasks developed by the Personal Robotics Lab at CMU (now at UW Seattle)



<https://robotsguide.com/robots/herb>

2012

<https://robotsguide.com/robots/baxter>

Rethink Robotics releases Baxter

Now-defunct Rethink Robotics releases Baxter, a bimanual manufacturing robot that can be programmed simply by moving its arms by hand

2006





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

<https://robotsguide.com/robots/davinci>



Intuitive Surgical releases first Da Vinci surgical robot system

Enables less invasive surgeries through the use of smaller robotic tools with bimanual teleoperation

<https://robotsguide.com/robots/baxter>



Rethink Robotics releases Baxter

Now-defunct Rethink Robotics releases Baxter, a bimanual manufacturing robot that can be programmed simply by moving its arms by hand

1999

2012

1994

Yaskawa Motoman introduces the MRC system

Allowed for synchronized control and coordination of two robotic arms by “teaching” it a sequence of movements, or programming a task on a PC



<https://ifr.org/robot-history>

Personal Robotics Lab develops Herb (Home Exploring Robot Butler)

Bimanual robot for domestic tasks developed by the Personal Robotics Lab at CMU (now at UW Seattle)



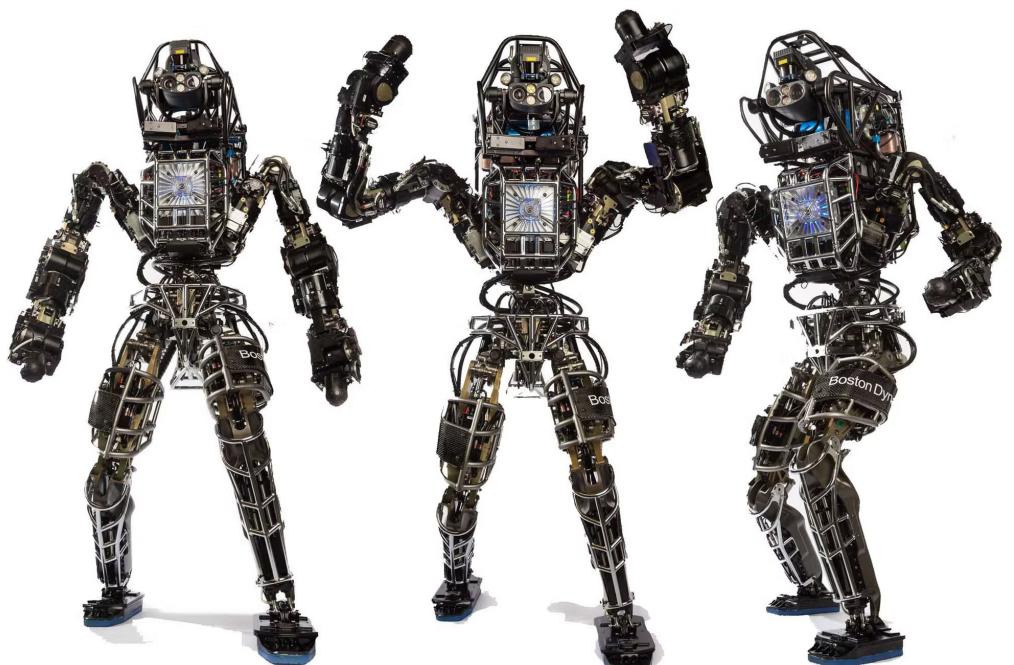
<https://robotsguide.com/robots/herb>

2013

Boston Dynamics develops first iteration of Atlas Robot

Developed as a disaster-response robot for the Defence Advanced Research Projects Agency

<https://robotsguide.com/robots/atlas2013>





Timeline of Bimanual Manipulators

Select milestones from the past 30 years

<https://robotsguide.com/robots/davinci>



Intuitive Surgical releases first Da Vinci surgical robot system

Enables less invasive surgeries through the use of smaller robotic tools with bimanual teleoperation



<https://robotsguide.com/robots/baxter>

Rethink Robotics releases Baxter

Now-defunct Rethink Robotics releases Baxter, a bimanual manufacturing robot that can be programmed simply by moving its arms by hand

1994

Yaskawa Motoman introduces the MRC system

Allowed for synchronized control and coordination of two robotic arms by “teaching” it a sequence of movements, or programming a task on a PC



<https://ifr.org/robot-history>

<https://robotsguide.com/robots/herb>



Personal Robotics Lab develops Herb (Home Exploring Robot Butler)

Bimanual robot for domestic tasks developed by the Personal Robotics Lab at CMU (now at UW Seattle)

2012

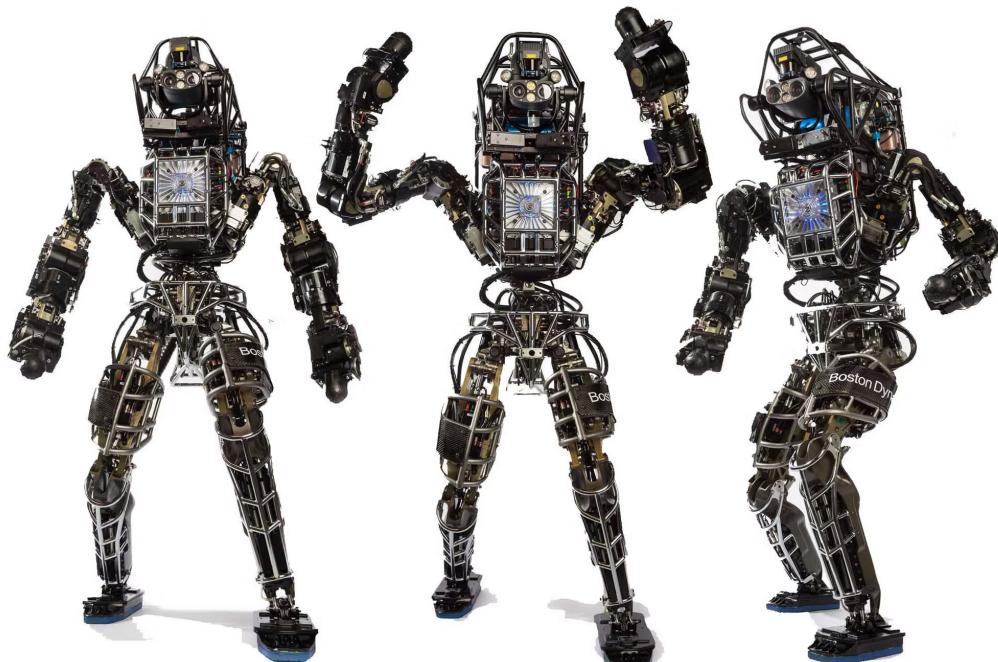
2006

2013

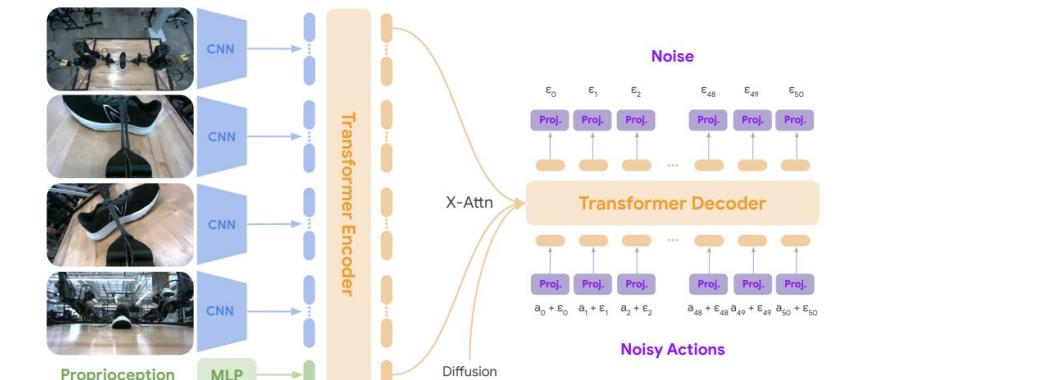
Boston Dynamics develops first iteration of Atlas Robot

Developed as a disaster-response robot for the Defence Advanced Research Projects Agency

<https://robotsguide.com/robots/atlas2013>



<https://aloha-unleashed.github.io/>



ALOHA Unleashed

Diffusion policy-backed imitation learning framework capable of learning complex bimanual tasks with deformable objects

2024



Humanoid Robots, too!

2000

NASA Completes first iteration of Robonaut

<https://robotsguide.com/robots/pr2>



2010

Willow Garage releases humanoid PR2 Robot

<https://robotsguide.com/robots/pr2>



2020

1X Technologies releases EVE humanoid robot

<https://robotsguide.com/robots/eve>



Why stop at two manipulators?



- Multi-arm robotic apple picker
- While the robot has more than two arms, it's effectively multiple single-arm manipulation tasks in parallel
- Robots with more arms tend to be more specialized towards specific tasks
- We want a robot that can be generalized to as many domestic tasks as possible

<https://www.youtube.com/watch?v=TUOmZCcRKbI>



Why stop at two manipulators?

Recall, we want to be able to perform as many tasks as possible in a domestic environment.



Why stop at two manipulators?





Challenges



Task Variety

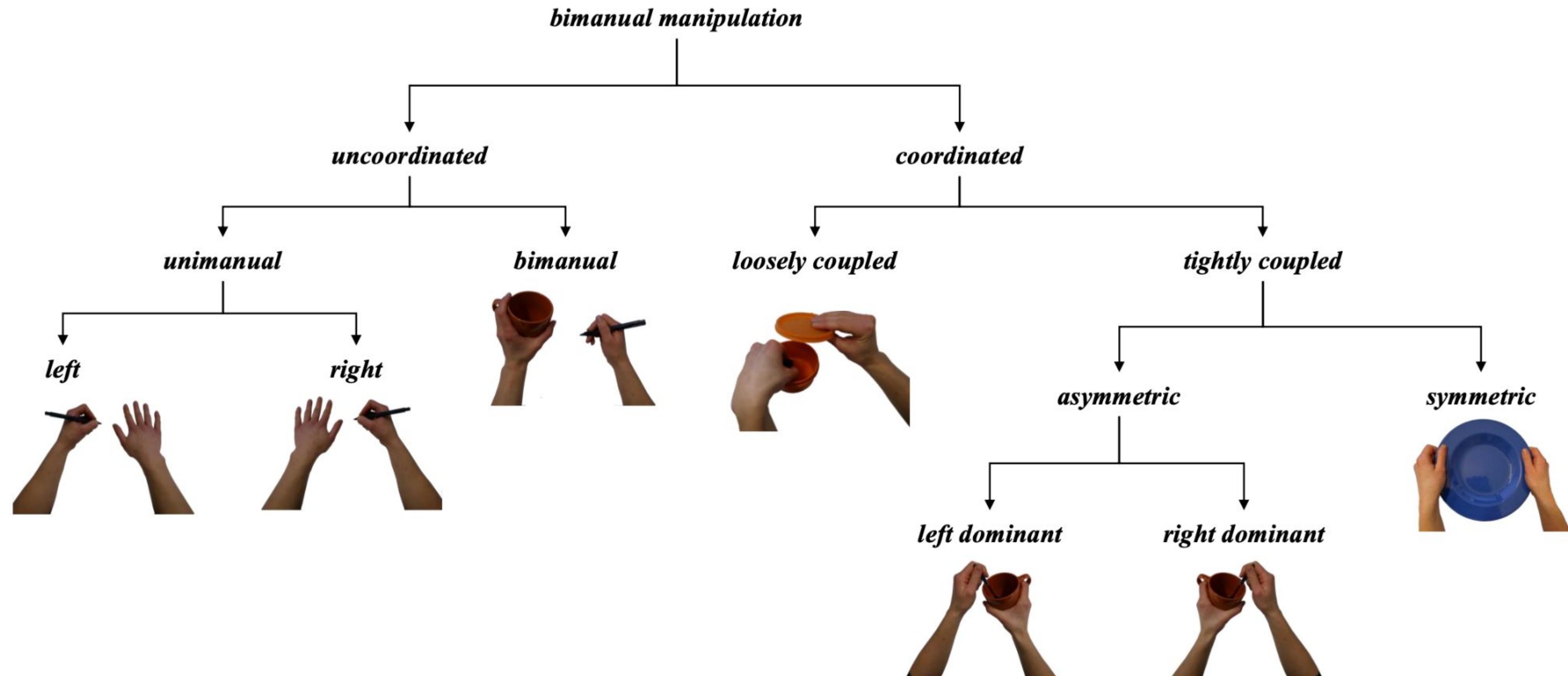


Fig. 2. Bimanual manipulation taxonomy. Tasks are classified based on the aspects *coordination*, *interaction*, *hand role* and *symmetry*.

Figure from F. Krebs and T. Asfour, "A Bimanual Manipulation Taxonomy," in *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11031-11038, Oct. 2022, doi: 10.1109/LRA.2022.3196158

Task Variety

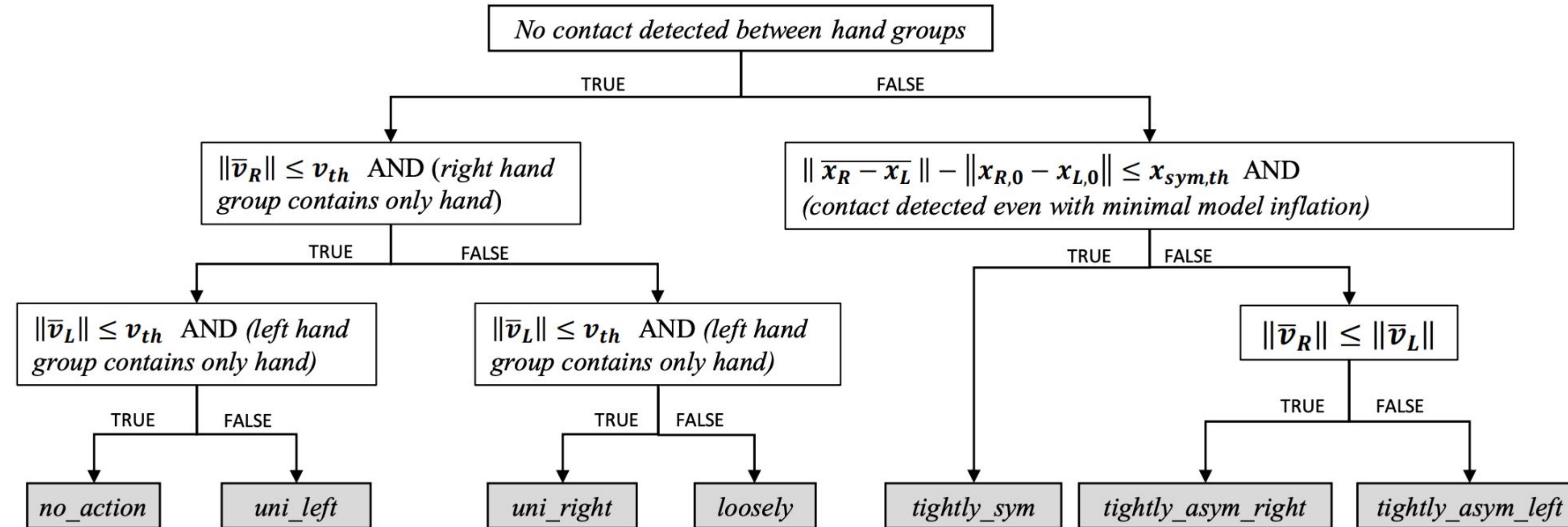


Fig. 4. Decision tree for the rule-based classification



Figure from F. Krebs and T. Asfour, "A Bimanual Manipulation Taxonomy," in *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11031-11038, Oct. 2022, doi: 10.1109/LRA.2022.3196158

Coordination

With regards to the task(s)...

- Each type of the task as defined by the decision tree shown previously warrants its own planning strategy
 - Sometimes the arms are each doing their own, uncoordinated tasks
 - Other times forces transfer between end effectors
 - Constraints for each effector can interact with each other
- The category of a task can change partway through!

Coordination

With regards to the task(s)...

- Each type of the task as defined by the decision tree shown previously warrants its own planning strategy
 - Sometimes the arms are each doing their own, uncoordinated tasks
 - Other times forces transfer between end effectors
 - Constraints for each effector can interact with each other
- The category of a task can change partway through!

With regards to the manipulators...

- The addition of a second manipulator constitutes an added, dynamic set of obstacles for each manipulator
- Imposes a whole new set of constraints upon the configuration space (more details later)
- Manipulators take on “roles” (leader + follower, fixed transformation...)



Methodologies





Methodologies

Control based method

- . IK
- . Control
- . Manipulation

Policy learning methods

- . ALOHA
- . VLAs
- . Π_0



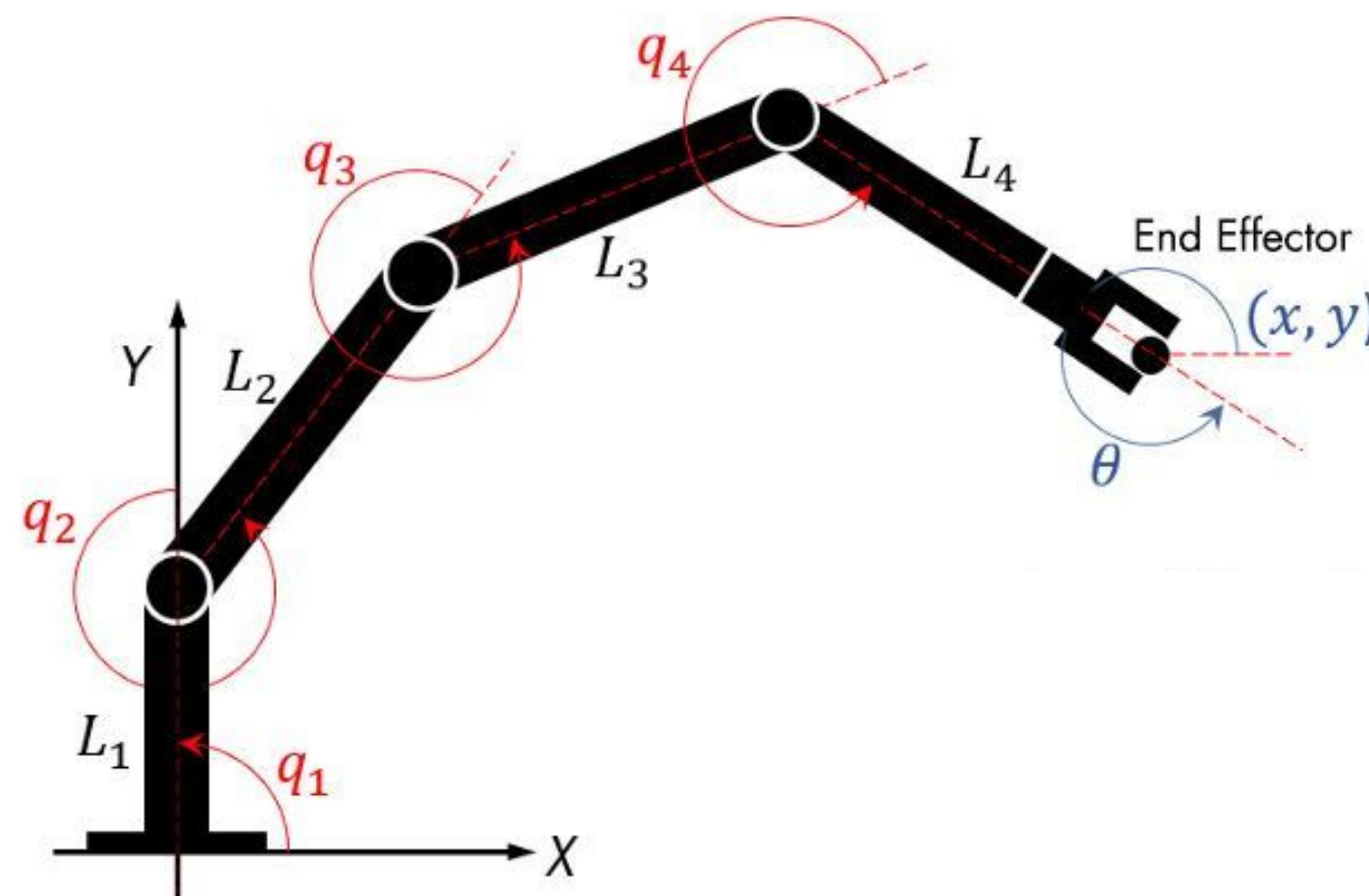


Kinematic-based methodologies



Forward Kinematics (FK)

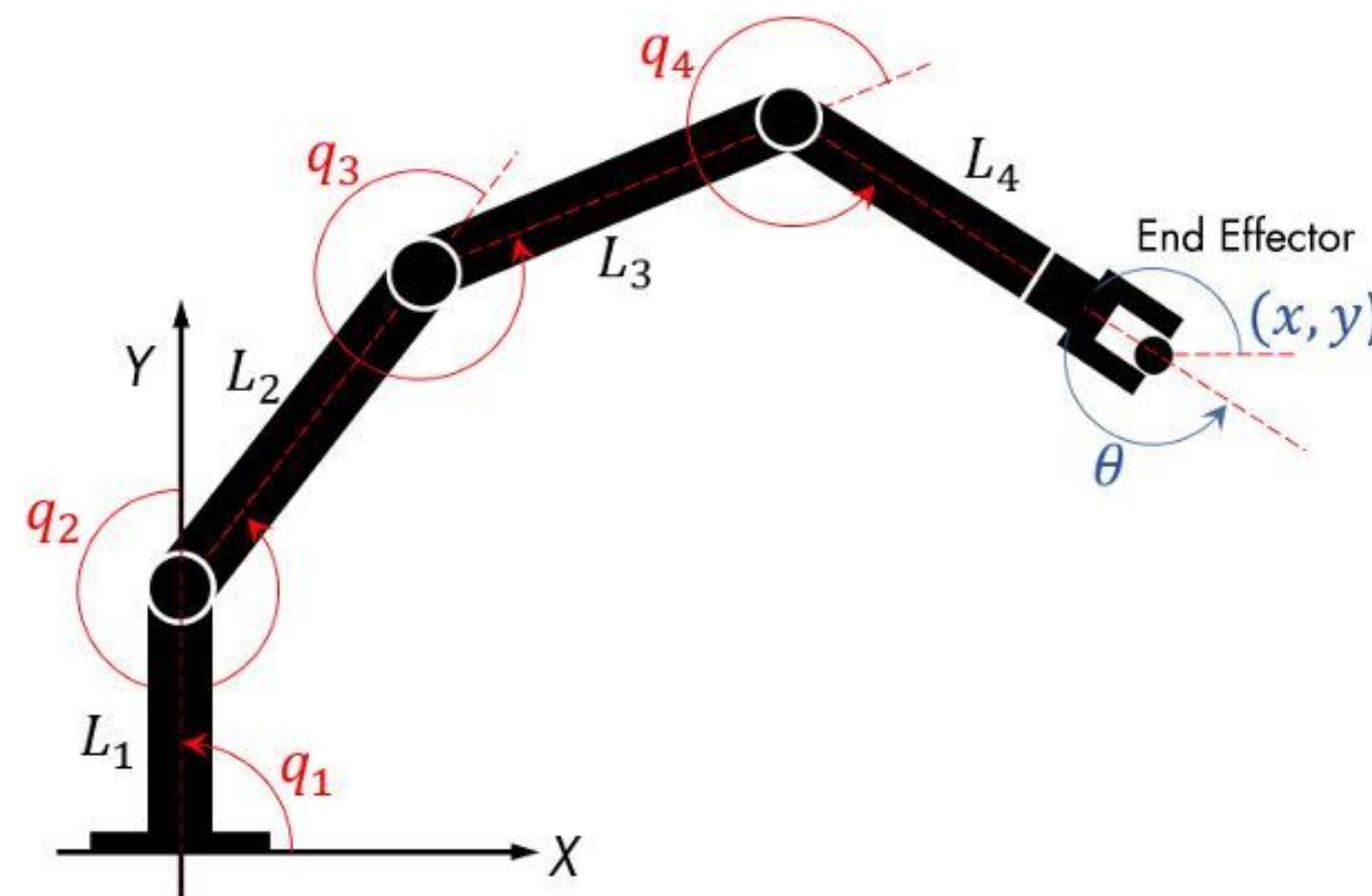
- . What is “forward kinematics”



<https://www.mathworks.com/discovery/inverse-kinematics.html>

Forward Kinematics (FK)

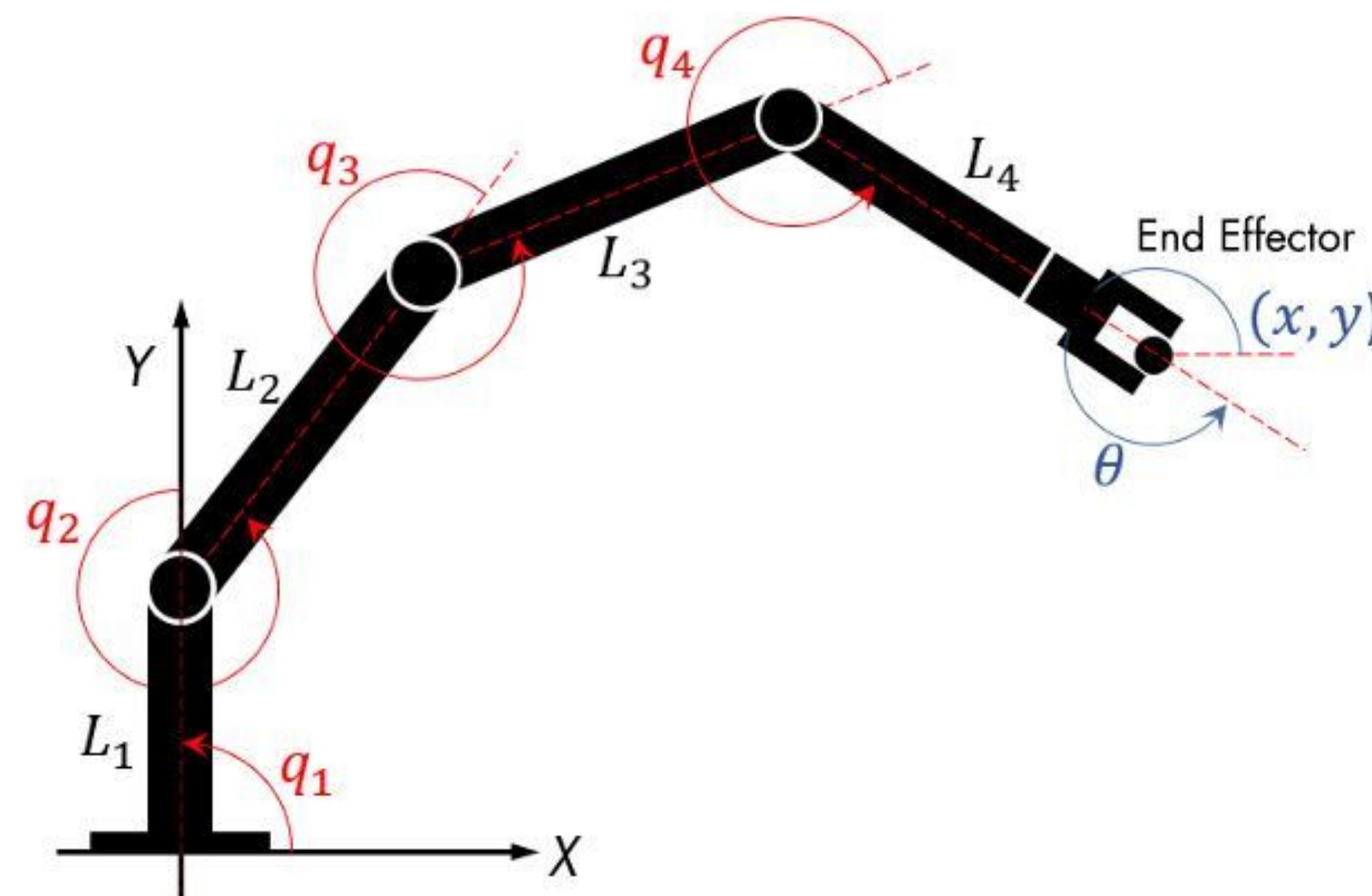
- . Given each joint position, determine the end effector pose
- . Singular solution for each configuration



<https://www.mathworks.com/discovery/inverse-kinematics.html>

Forward Kinematics (FK)

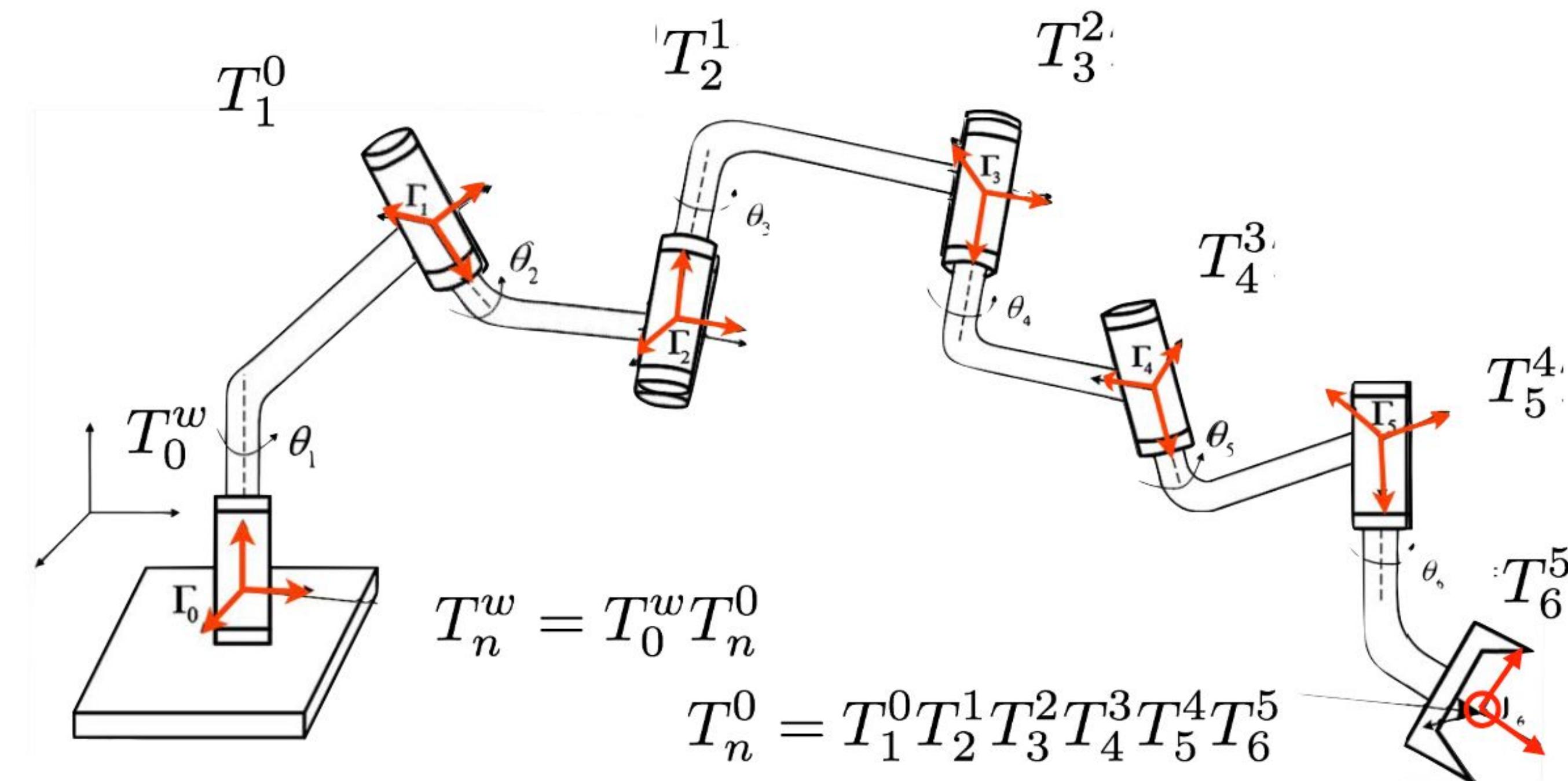
- . Given each joint position, determine the end effector pose
- . Singular solution for each configuration



<https://www.mathworks.com/discovery/inverse-kinematics.html>

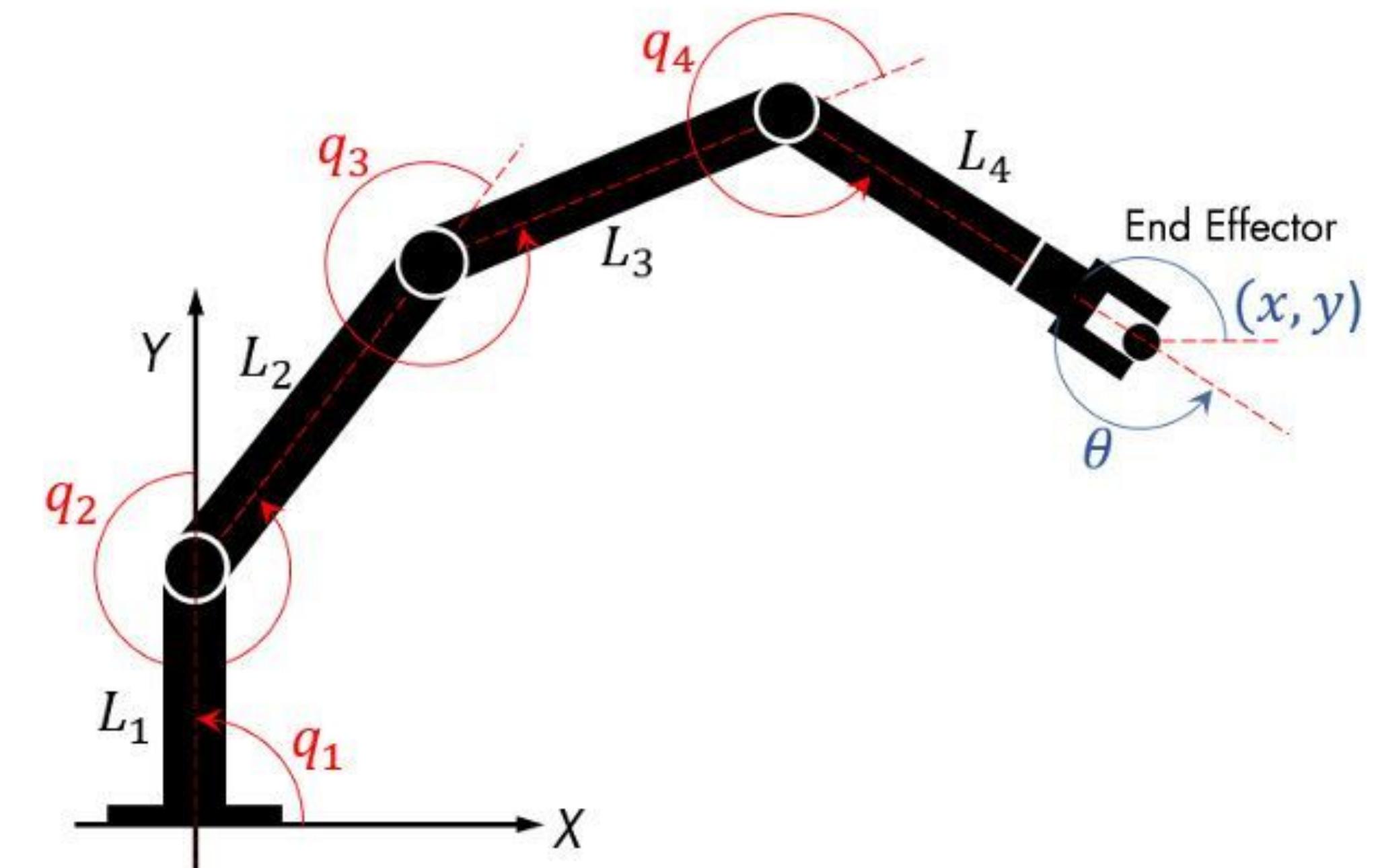
Forward Kinematics (FK)

- Each joint has its own coordinate frame
- Transformations between each joint represented by homogeneous transformations



Inverse Kinematics (IK)

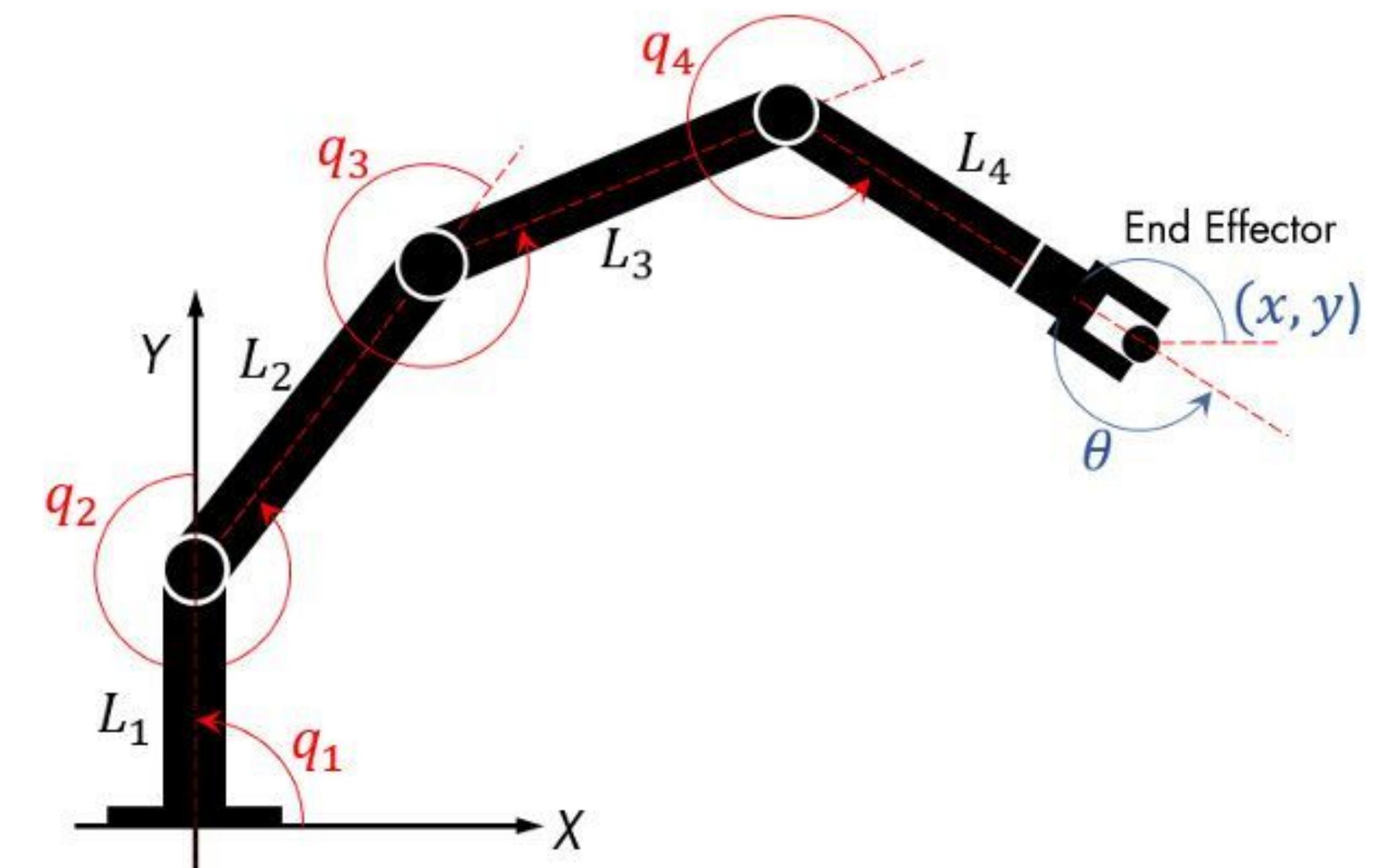
- . What is “inverse kinematics”?



<https://www.mathworks.com/discovery/inverse-kinematics.html>

Inverse Kinematics (IK)

- . Given the end effector pose, determine each joint position
- . Can be many solutions for each joint position
- . Summarized by these equations (numerical):



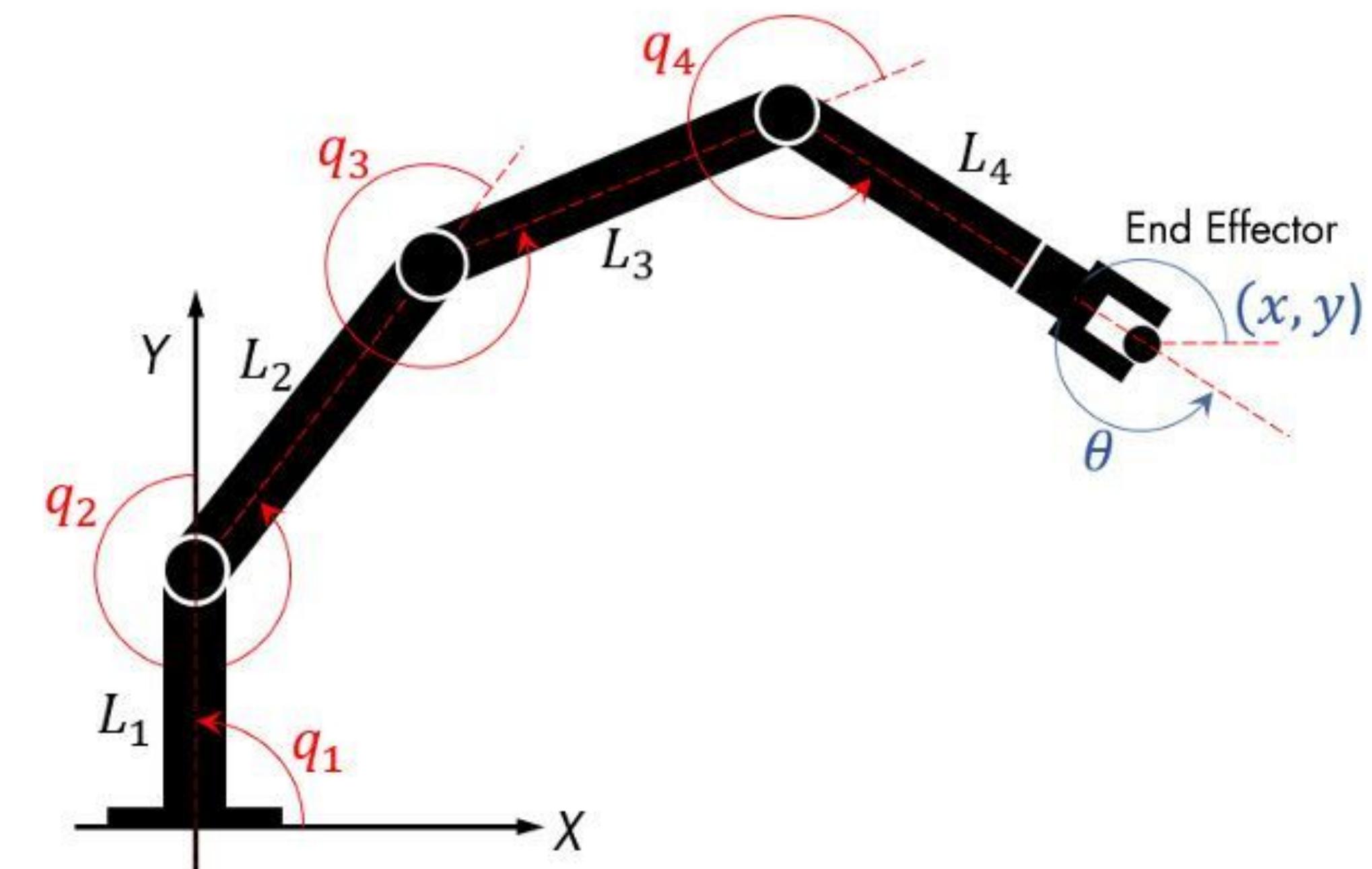
<https://www.mathworks.com/discovery/inverse-kinematics.html>

Inverse Kinematics (IK)

- . Given the end effector pose, determine each joint position
- . Can be many solutions for each joint position
- . Summarized by these equations (numerical):

$$\Delta \mathbf{x}_n = \mathbf{x}_d - \mathbf{x}_n$$

Start with error from end point



https://rpm-lab.github.io/CSCI5551-Spr24/assets/slides/lec08_manipulation_3_ik_jacobian.pdf

<https://www.mathworks.com/discovery/inverse-kinematics.html>

Inverse Kinematics (IK)

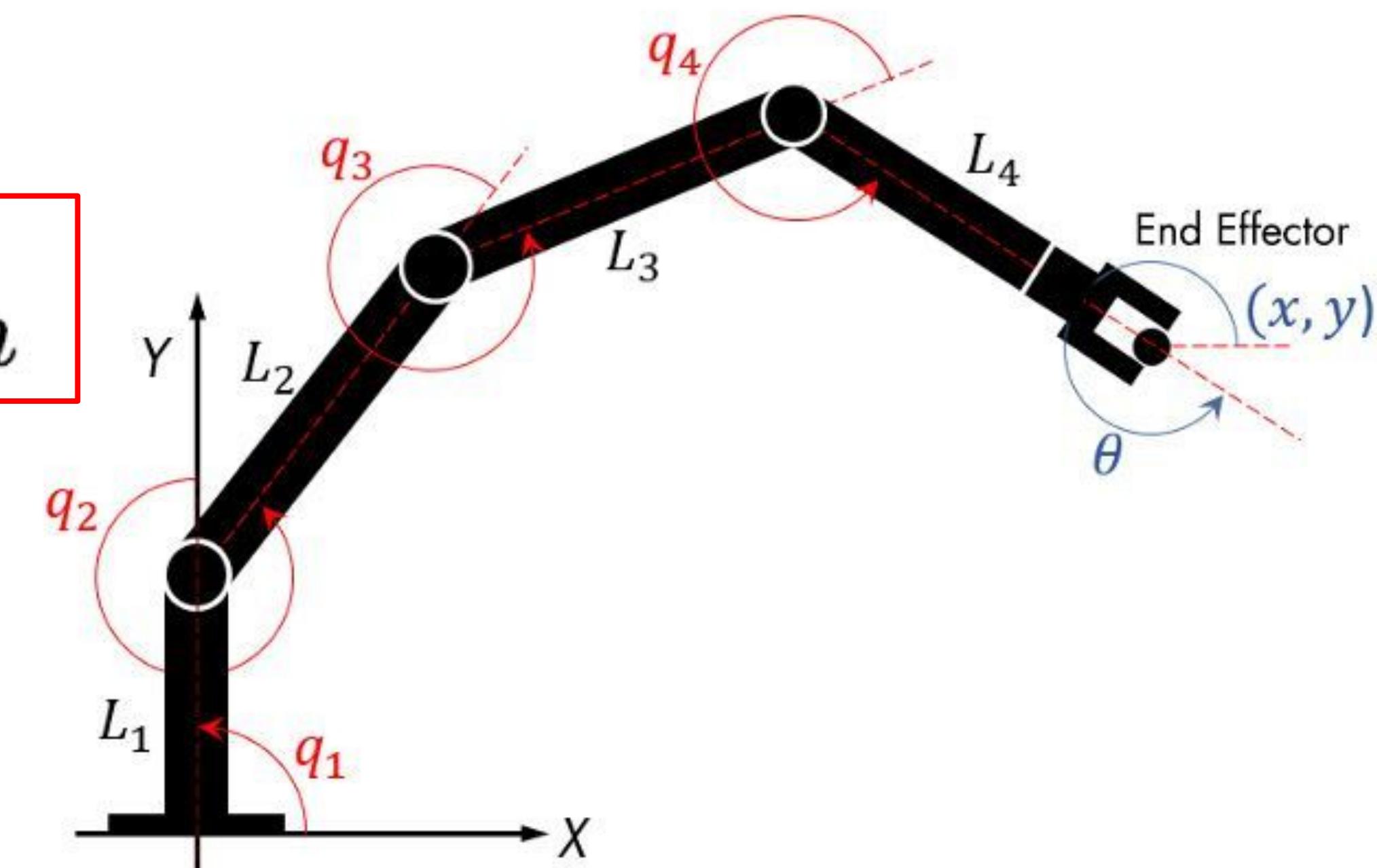
- Given the end effector pose, determine each joint position
- Can be many solutions for each joint position
- Summarized by these equations (numerical):

$$\Delta \mathbf{x}_n = \mathbf{x}_d - \mathbf{x}_n$$

$$\boxed{\Delta \mathbf{q}_n = J(\mathbf{q}_n)^{-1} \Delta \mathbf{x}_n}$$

Find the direction to move

https://rpm-lab.github.io/CSCI5551-Spr24/assets/slides/lec08_manipulation_3_ik_jacobian.pdf



<https://www.mathworks.com/discovery/inverse-kinematics.html>

Inverse Kinematics (IK)

- Given the end effector pose, determine each joint position
- Can be many solutions for each joint position
- Summarized by these equations (numerical):

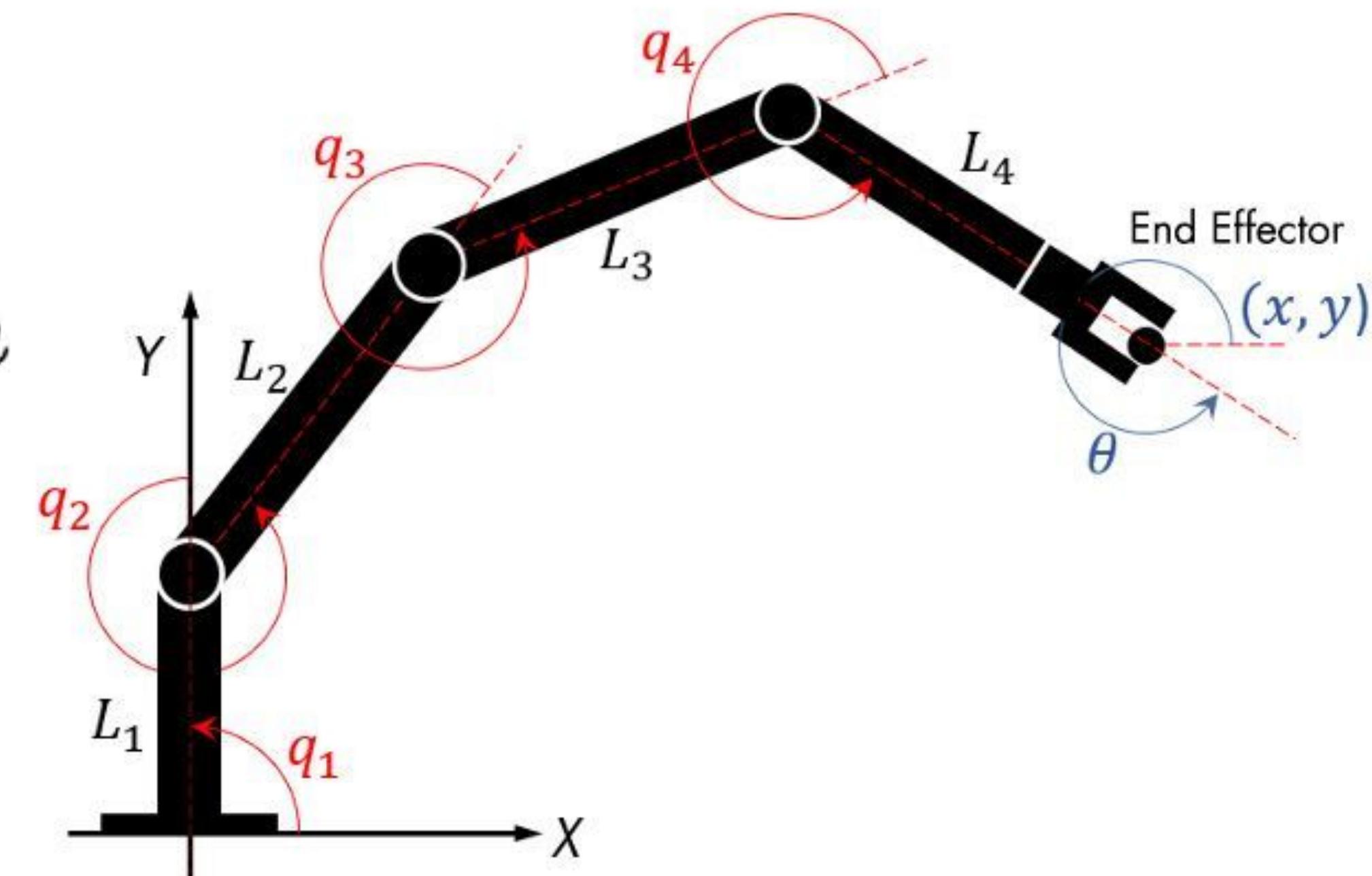
$$\Delta \mathbf{x}_n = \mathbf{x}_d - \mathbf{x}_n$$

$$\Delta \mathbf{q}_n = J(\mathbf{q}_n)^{-1} \Delta \mathbf{x}_n$$

$$\mathbf{q}_{n+1} = \mathbf{q}_n + \gamma \Delta \mathbf{q}_n$$

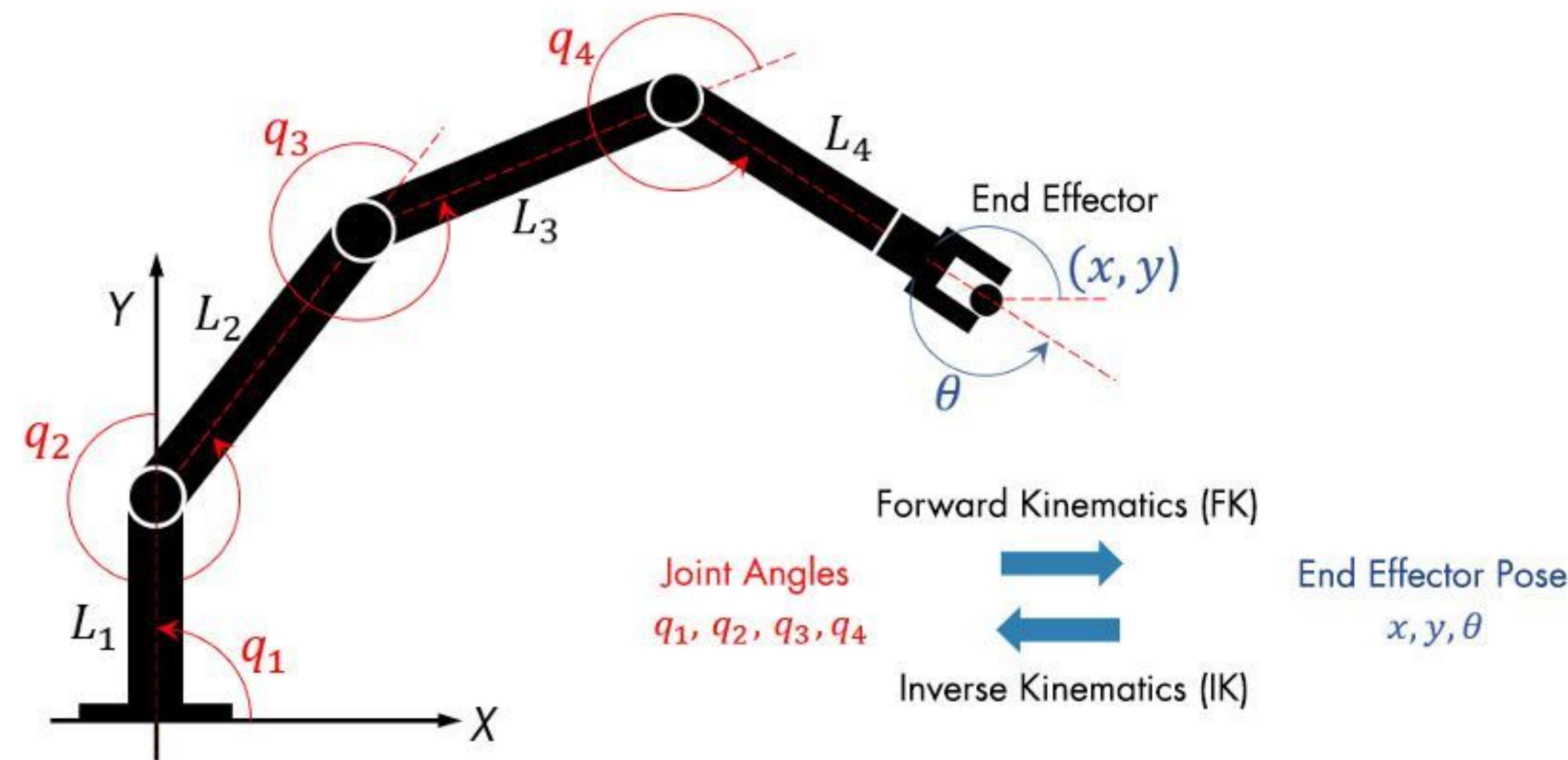
https://rpm-lab.github.io/CSCI5551-Spr24/assets/slides/lec08_manipulation_3_ik_jacobian.pdf

Take a step in that direction!



<https://www.mathworks.com/discovery/inverse-kinematics.html>

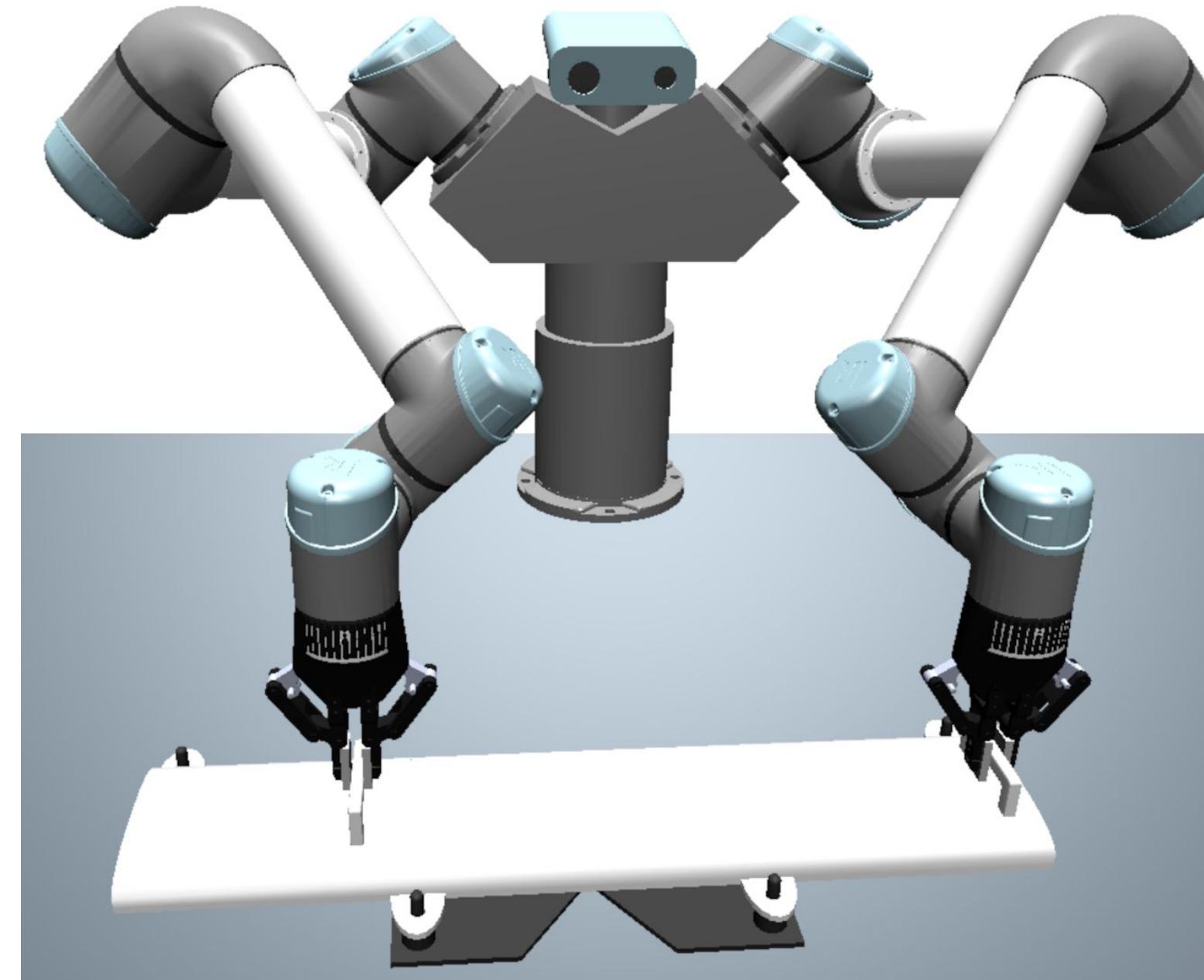
Forward vs Inverse Kinematics



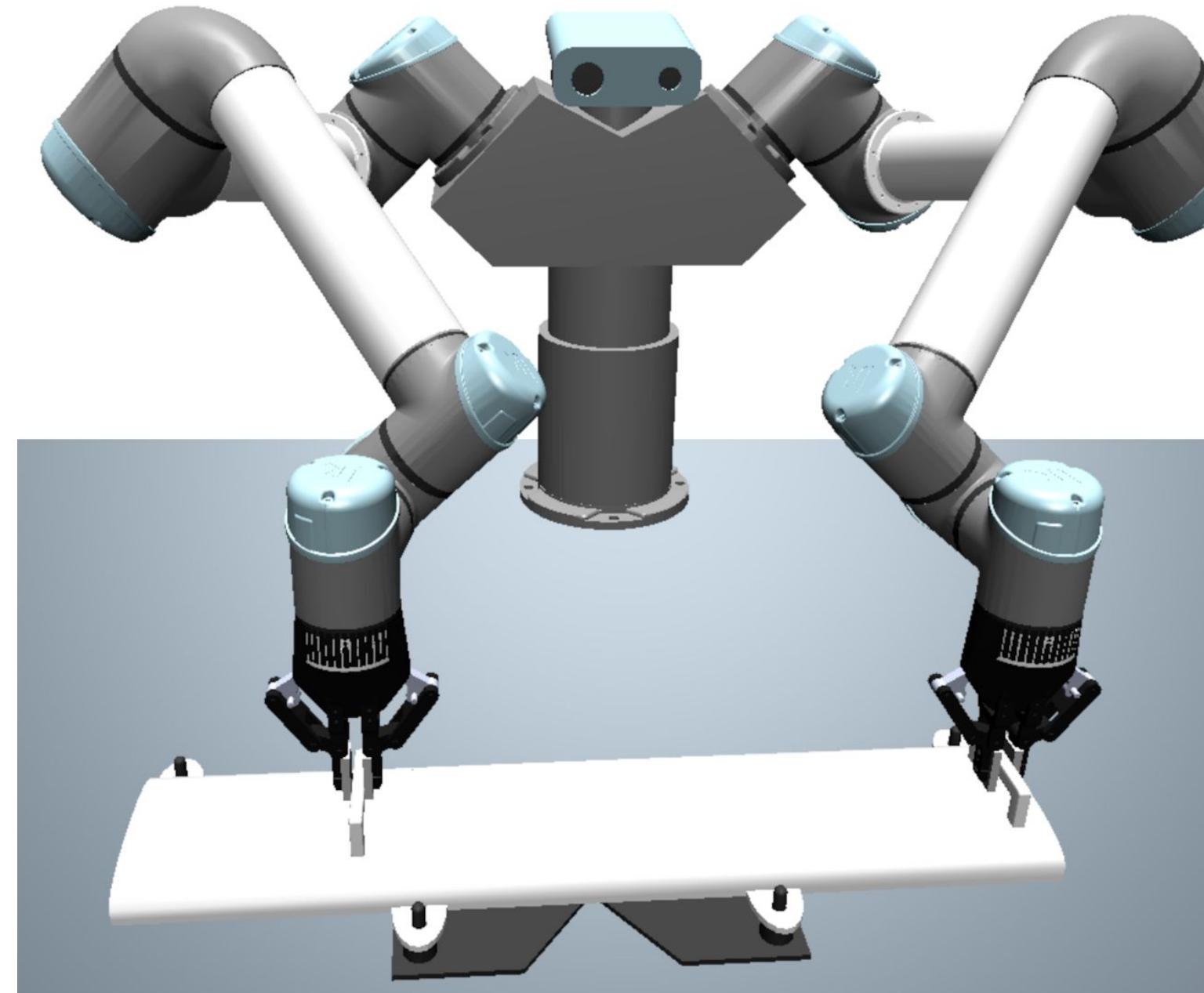
<https://www.mathworks.com/discovery/inverse-kinematics.html>



In the case of dual arm manipulation, is it as simple as applying IK to both arms?



In the case of dual arm manipulation, is it as simple as applying IK to both arms?

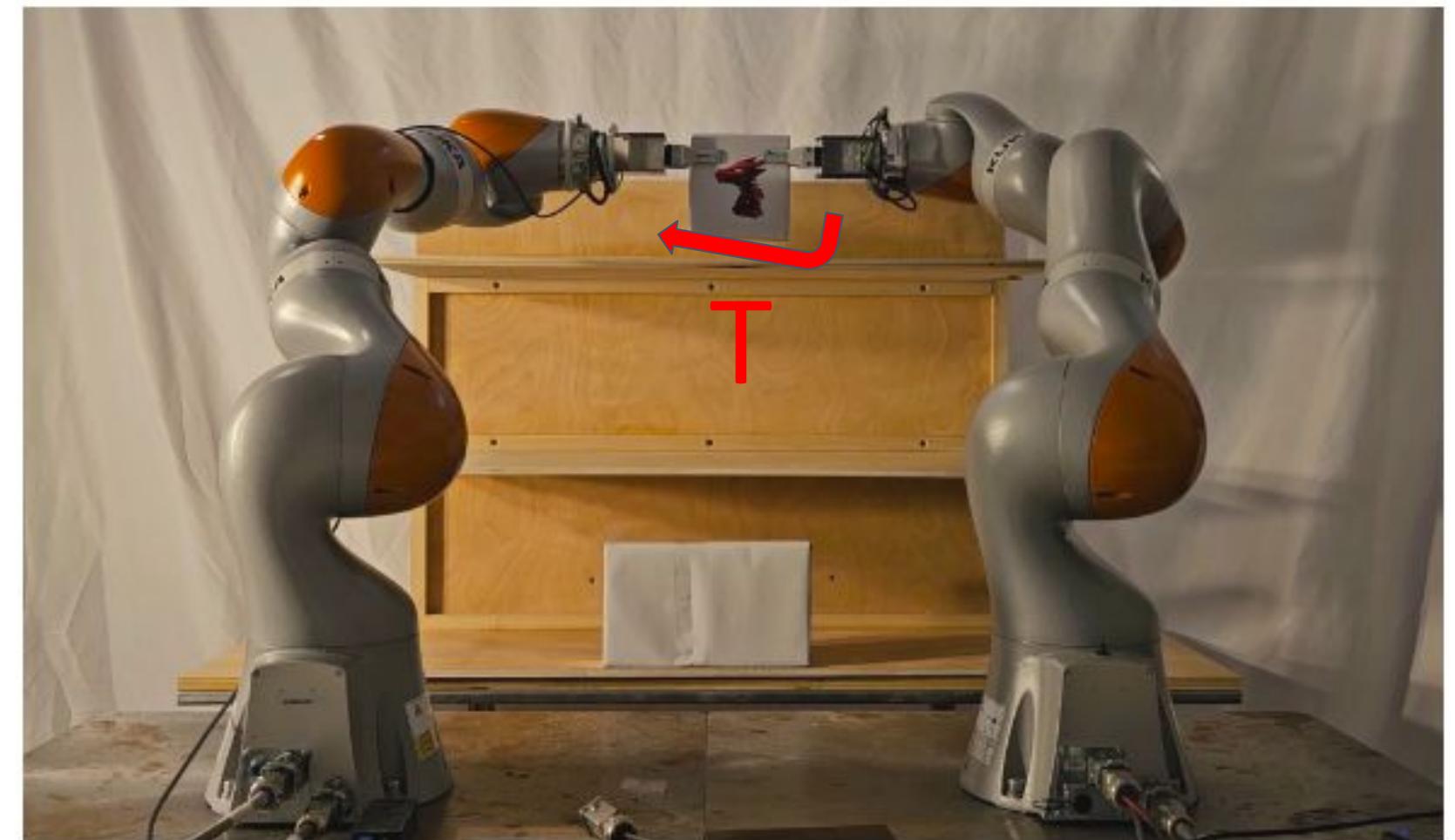


Maybe a bit more involved...

Bimanual manipulation kinematics

Challenges:

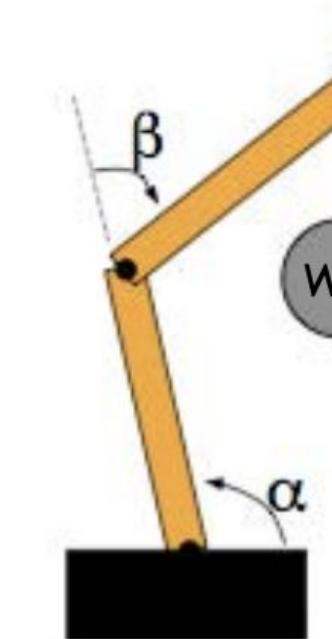
- . The transform between the end effectors must remain fixed



Bimanual manipulation kinematics challenges:

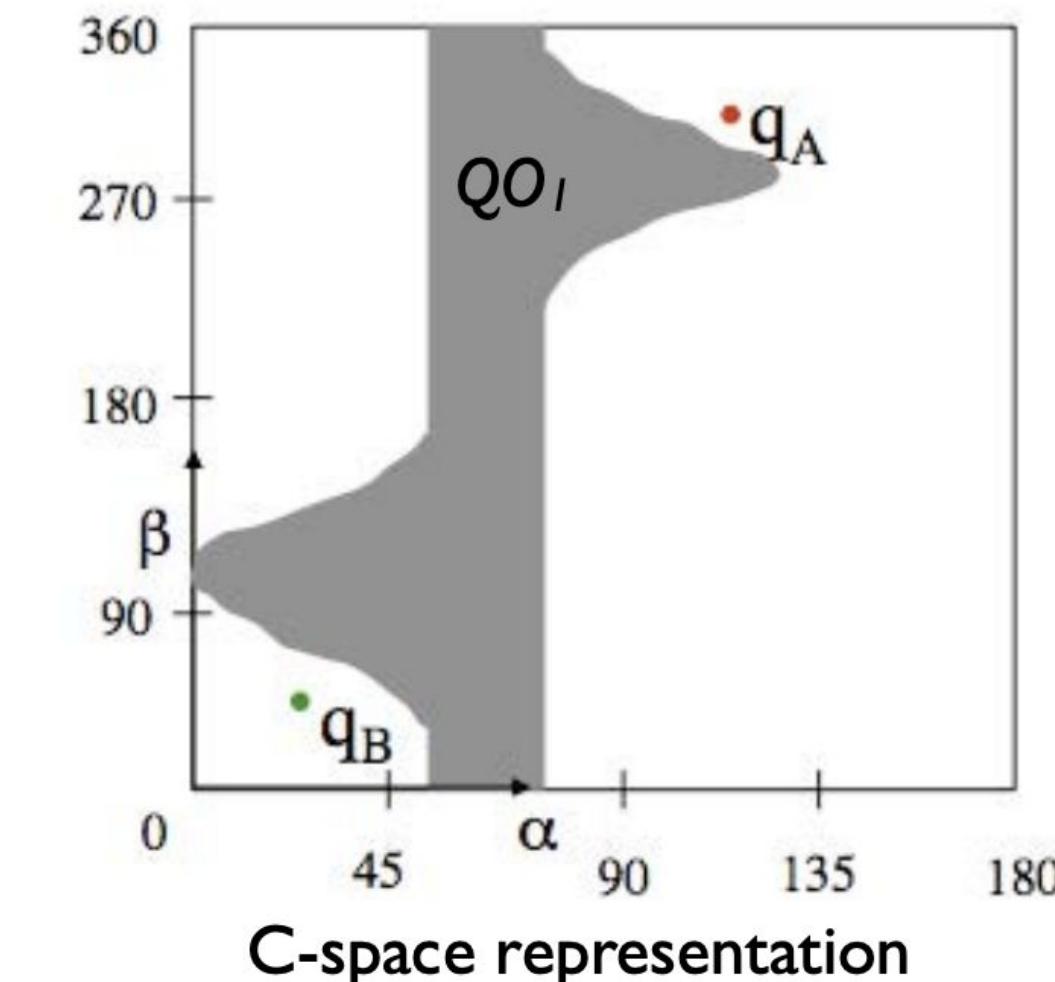
- . The transform between the end effectors must remain fixed
- . Configuration space becomes a non-linear mess with obstacles and other arm

- Workspace: set of all reachable eeff points
- Configuration space: all possible configurations for the robots joints



Circular obstacle in workspace

Obstacles in T^2

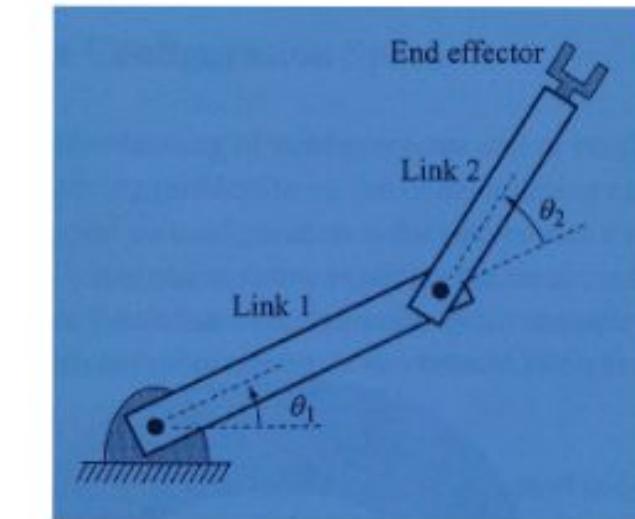


C-space representation

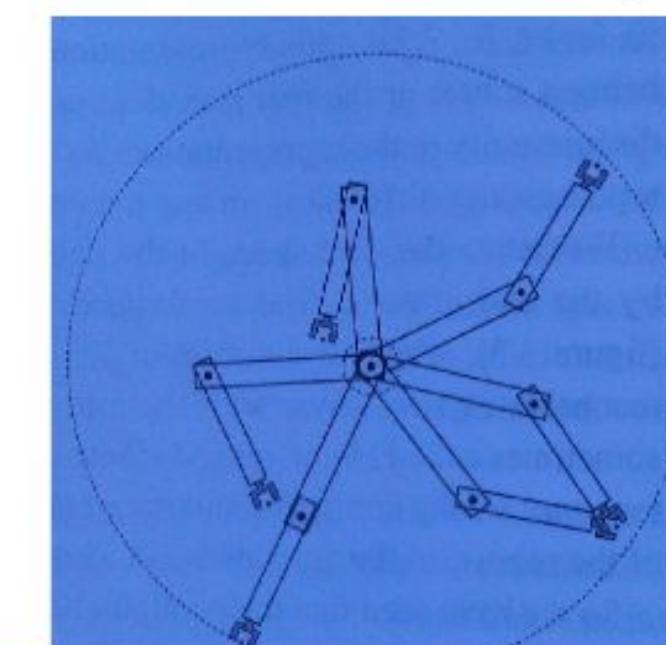
Bimanual manipulation kinematics challenges:

- . The transform between the end effectors must remain fixed
- . Configuration space becomes a non-linear mess with obstacles and other arm

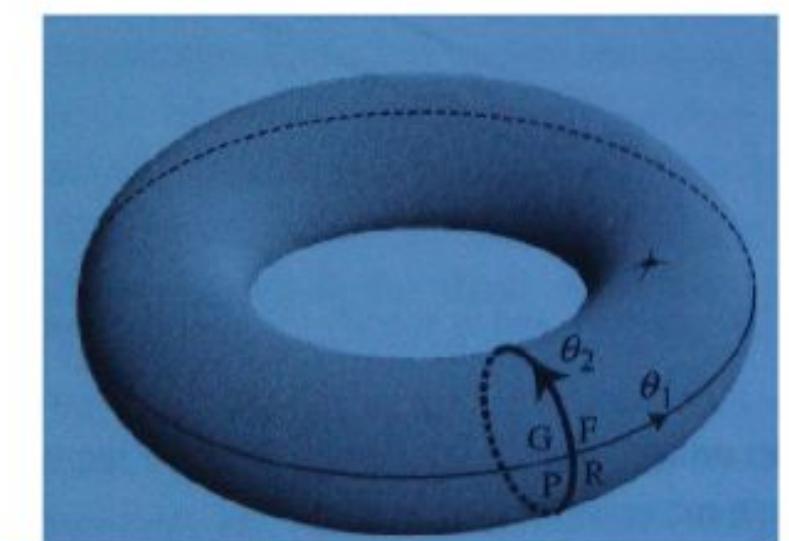
- Workspace: set of all reachable eeff points
- Configuration space: all possible configurations for the robots joints



Workspace is w.r.t. end-effector position (x, y)



C-space is w.r.t. joint angles (Θ_1, Θ_2)





Bimanual manipulation kinematics challenges:

- . The transform between the end effectors must remain fixed
- . Configuration space becomes a non-linear mess with obstacles and other arm
- . Numeric IK becomes very computationally expensive





Bimanual manipulation kinematics challenges:

- . The transform between the end effectors must remain fixed
- . Configuration space becomes a non-linear mess with obstacles and other arm
- . Numeric IK becomes very computationally expensive
- . How would we tackle all of these?





One neat approach:



One neat approach:

Constrained Bimanual Planning with Analytic Inverse Kinematics

Thomas Cohn, Seiji Shaw, Max Simchowitz, and Russ Tedrake

Abstract—In order for a bimanual robot to manipulate an object that is held by both hands, it must construct motion plans such that the transformation between its end effectors remains fixed. This amounts to complicated nonlinear equality constraints in the configuration space, which are difficult for trajectory optimizers. In addition, the set of feasible configurations becomes a measure zero set, which presents a challenge to sampling-based motion planners. We leverage an analytic solution to the inverse kinematics problem to parametrize the configuration space, resulting in a lower-dimensional representation where the set of valid configurations has positive measure. We describe how to use this parametrization with existing motion planning algorithms, including sampling-based approaches, trajectory optimizers, and techniques that plan through convex inner-approximations of collision-free space.

I. INTRODUCTION

Enabling bimanual robots to execute coordinated actions with both arms is essential for achieving (super)human-like skill in automation and home contexts. There exists a variety of tasks that are only solvable when two arms manipulate in concert [1], such as carrying an unwieldy object, folding clothes, or assembling parts. In many manipulation tasks, one gripper can be used to provide fixture to the manipuland, while the other performs the desired action [2]; such tasks include opening a bottle, chopping vegetables, and tightening a bolt. Furthermore, some tools explicitly require two arms to use, such as hand mixers, rolling pins, and can openers.

To accomplish many of these desired tasks, the motion of the robot arms becomes subject to equality constraints imposed in task space. For example, when moving an object that is held by both hands, the robot must ensure that the transformation between the end effectors remains constant. Such task space constraints appear as complicated nonlinear equality constraints in configuration space, posing a major challenge to traditional motion planning algorithms.

In the existing literature, there are general techniques for handling task-space constraints in configuration-space planning. Sampling-based planners can project samples onto the constraint manifold [3] or use numerical continuation [4] to construct piecewise-linear approximations. Constraints can also be relaxed [5] or enforced directly with trajectory optimization [6]. In the case of certain bimanual planning problems, there is additional structure that is not exploited

This work was supported by Amazon.com, PO No. 2D-06310236, the MIT Quest for Intelligence, and the National Science Foundation Graduate Research Fellowship Program under Grant No. 2141064. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The authors are with the Computer Science and Artificial Intelligence Laboratory (CSAIL), Massachusetts Institute of Technology, Cambridge, Massachusetts [tcohn, seiji, msimchow, russtj@mit.edu]

arXiv:2309.08770v2 [cs.RO] 13 Mar 2024



Fig. 1: Hardware setup for our experiments. The two arms must work together to move an objects between the shelves, avoiding collisions and respecting the kinematic constraint.

by these general methods. For certain classes of robot arms, *analytic inverse kinematics* (analytic IK) can be used to map an end-effector pose (along with additional parameters to resolve kinematic redundancy) to joint angles in closed form. Such solutions are specific to certain classes of robot arms, but are a powerful tool to be leveraged if available. Fortunately, analytic IK is available for many popular robot arms available today, including the KUKA iiwa. See Figure 1.

If a robot must move an object that it is holding with both hands, we propose constructing a plan for one “controllable” arm, and then the other “subordinate” arm can be made to follow it via an analytic IK mapping. Configurations where the subordinate arm cannot reach the end-effector of the primary arm, or where doing so would require violating joint limits, are treated as obstacles. In this way, we parametrize the constraint manifold so that the feasible set has positive measure in the new planning space. Because we no longer have to consider the equality constraints, sampling-based planning algorithms can be applied without modification. We can also differentiate through the IK mapping, enabling the direct application of trajectory optimization approaches.

The remainder of this paper is organized as follows. First, we give an overview of the existing techniques used for constrained motion planning, and describe the available analytic IK solutions. Then, we present our parametrization of the constraint manifold for bimanual planning, and discuss its relevant geometric and topological properties. We describe the slight modifications which are necessary to adapt standard planning algorithms (including sampling-based planning and trajectory optimization) to operate in this framework. We then present a technique for generating



Analytic IK

- . Rather than gradient descent - find closed form solution for joint angles instead...



Analytic IK

- Rather than gradient descent - find closed form solution for joint angles instead...
- Geometric algebra can be very difficult, many common configurations are already solved

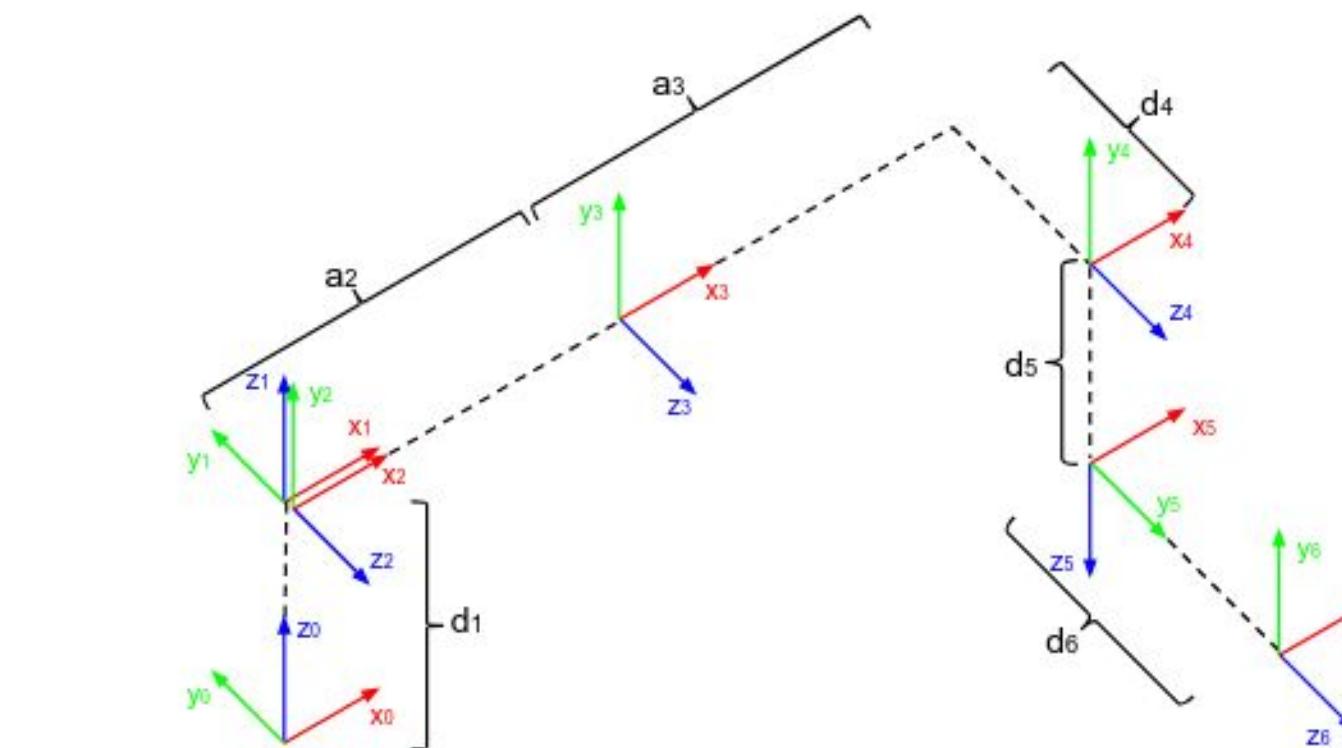
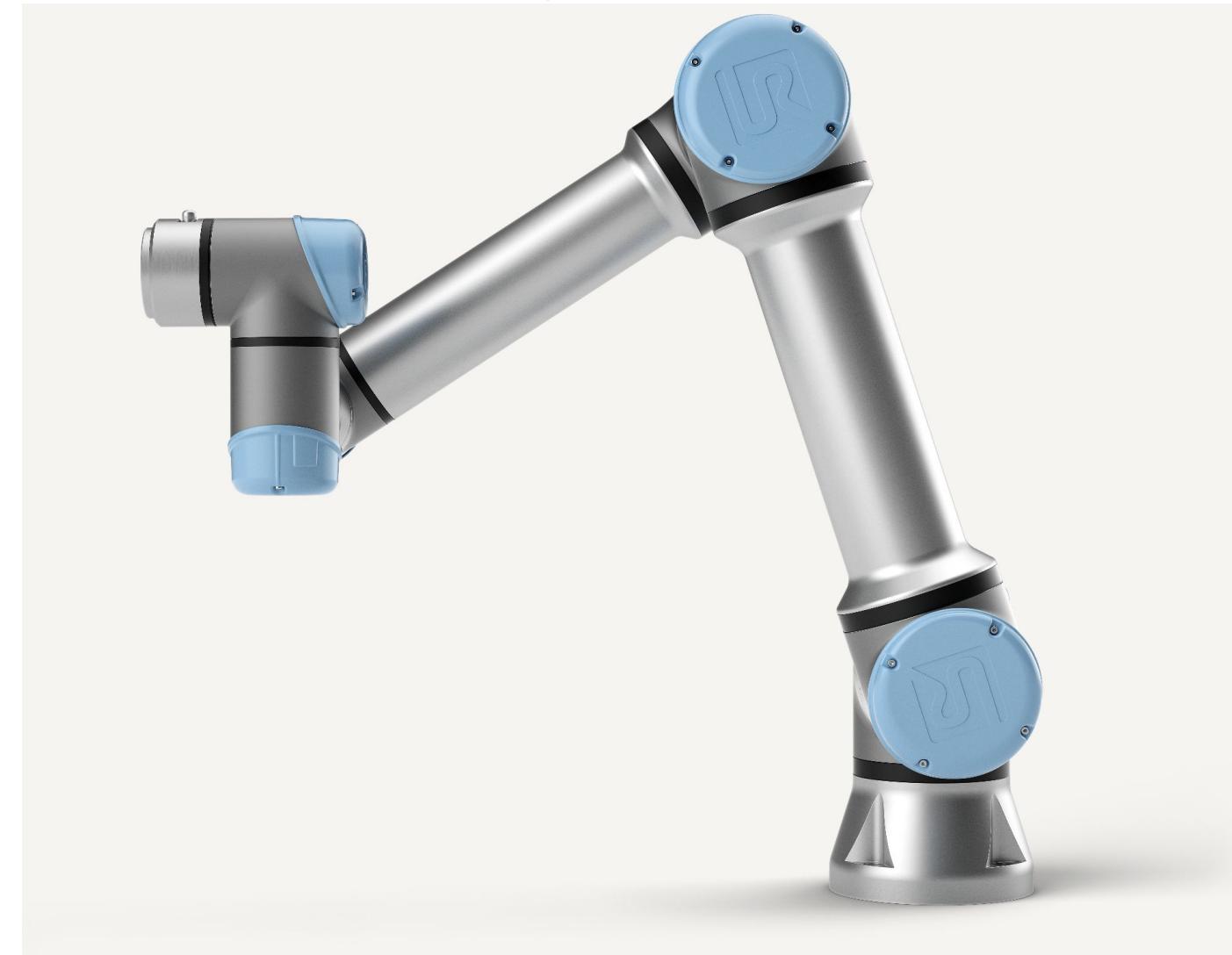


Figure 1: Coordinate frames for UR arm. Joints rotate around the z-axes and are pictured at $\theta_i = 0$ for $1 \leq i \leq 6$.

i	d_i	a_i	α_i
0	-	0	0
1	d_1	0	$\pi/2$
2	0	a_2	0
3	0	a_3	0
4	d_4	0	$\pi/2$
5	d_5	0	$-\pi/2$
6	d_6	-	-

Table 1: Denavit-Hartenberg parameters for the UR Arms

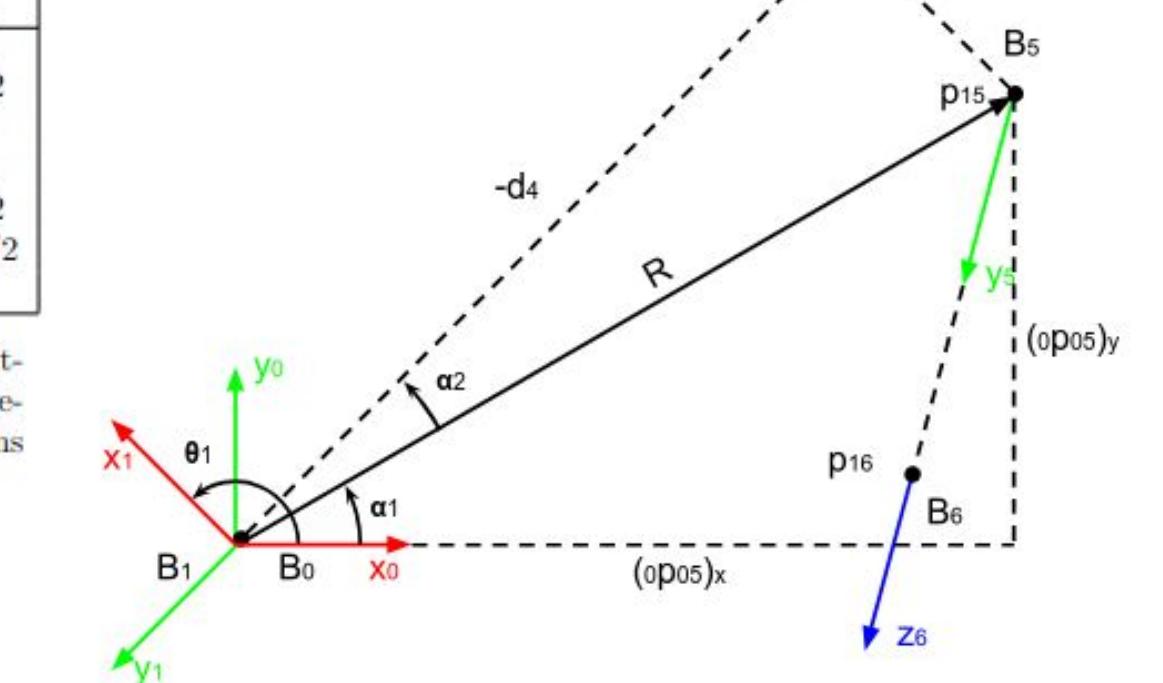


Figure 2: Illustration of the geometry of finding θ_1 . This is essentially an overhead view of the robot, looking down on the x-y plane.

<https://www.universal-robots.com/products/ur5-robot/>

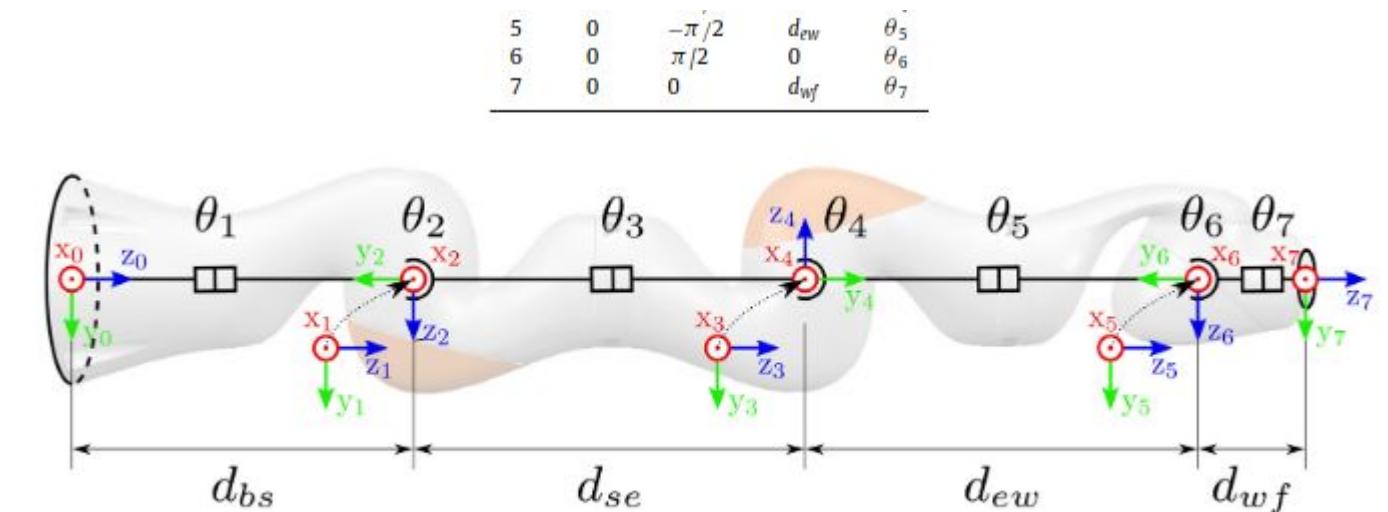
<https://repository.gatech.edu/server/api/core/bitstreams/e56759bc-92c8-43df-aa62-0dc47581459d/content>

Analytic IK

- Rather than gradient descent - find closed form solution for joint angles instead...
- Geometric algebra can be very difficult, many common configurations are already solved



<https://www.kuka.com/en-se/products/robotics-systems/industrial-robots/lbr-iiwa>



6.2. Trajectory example

Fig. 1. Manipulator generic structure, joint variables and DH frames assigned. The 7-DoF manipulator model of LBR iiwa 7 R800 from KUKA AG is used to depict the shape of an anthropomorphic arm without offsets.

To demonstrate the redundancy resolution strategy, we created an example linear trajectory to be performed by the robot manipulator. The robot is purposely positioned at a configuration near its mechanical joint limits. The robot starts at the joint angles in degrees:

$$\theta^c = [-5.4101 \quad -26.4986 \quad -48.1542 \quad -61.6500 \quad 152.6198 \quad 114.4466 \quad 8.1812] \quad (37)$$

which correspond to the global configuration $GC = 3$, arm angle $\psi = 58.5882^\circ$ and pose:

$${}^0\mathbf{T}_7^c = \begin{bmatrix} -0.2634 & -0.9112 & -0.3166 & -0.1174 \\ 0.3014 & -0.3895 & 0.8703 & -0.1464 \\ -0.9164 & 0.1338 & 0.3773 & 1.0203 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (38)$$

The manipulator performs a linear motion in Cartesian space, keeping the same end-effector orientation but translating its position along the z-axis (${}^0\mathbf{R}_{7,z}$) of a distance of 0.25 m, ending at the target pose:

$${}^0\mathbf{T}_7^d = \begin{bmatrix} -0.2634 & -0.9112 & -0.3166 & -0.1966 \\ 0.3014 & -0.3895 & 0.8703 & 0.0712 \\ -0.9164 & 0.1338 & 0.3773 & 1.1146 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (39)$$

The path is interpolated and a new pose is passed to the redundancy resolution algorithm (Fig. 10) every iteration. The global configuration remains unchanged throughout the trajectory, and the arm angle varies according to the parameters defined (α and K_j).⁵

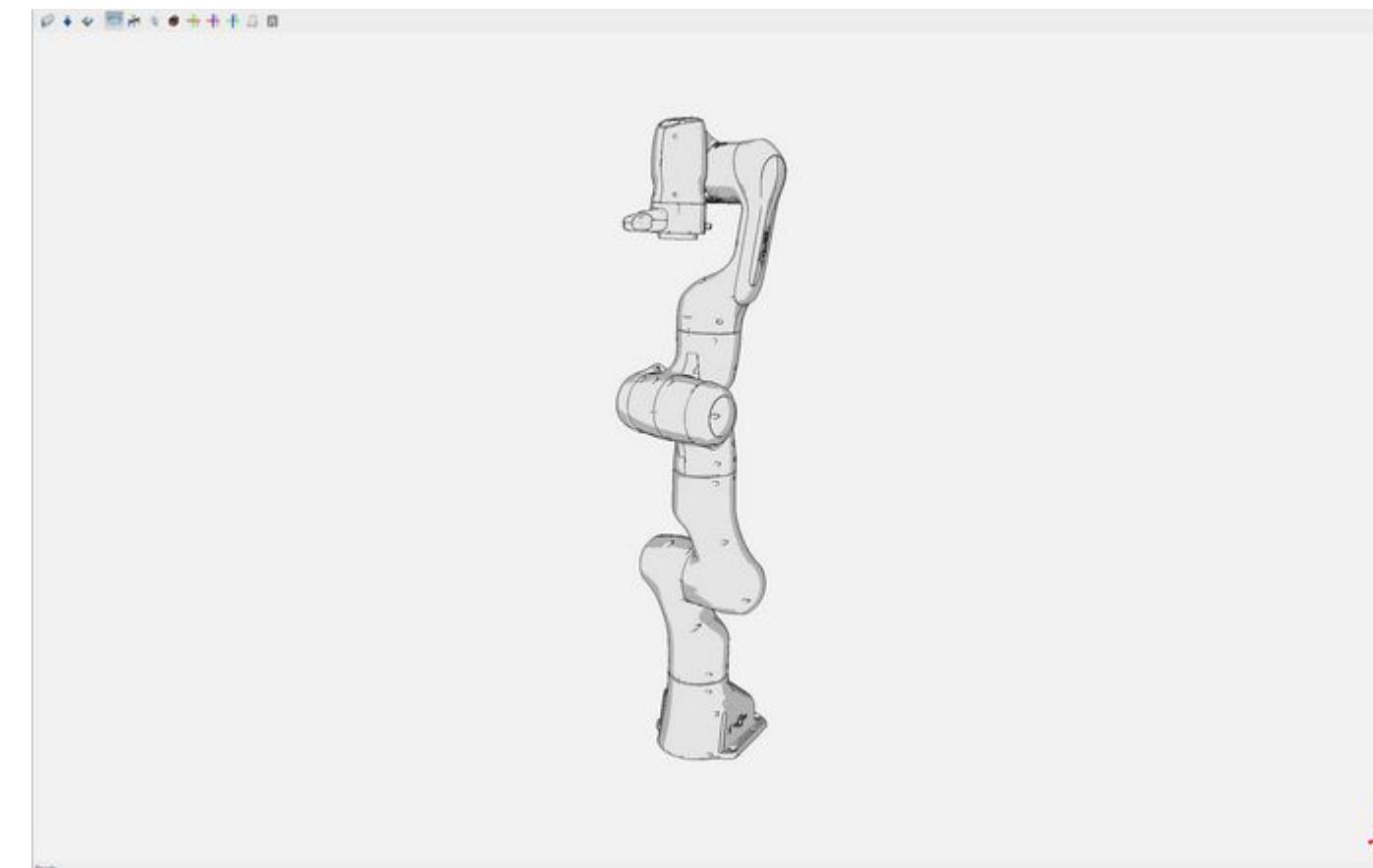
<https://www.sciencedirect.com/science/article/pii/S0094114X17306559>



Analytic IK

- . Rather than gradient descent - find closed form solution for joint angles instead...
- . Look towards existing software solutions, OpenRAVE IK Fast

 ROS



Self-motion

- . TL;DR - There are a degree of freedom that exists by virtue of 7 DoF arms (such as the Kuka) that allows for movement without changing end-effector position.
- . Show JS example...

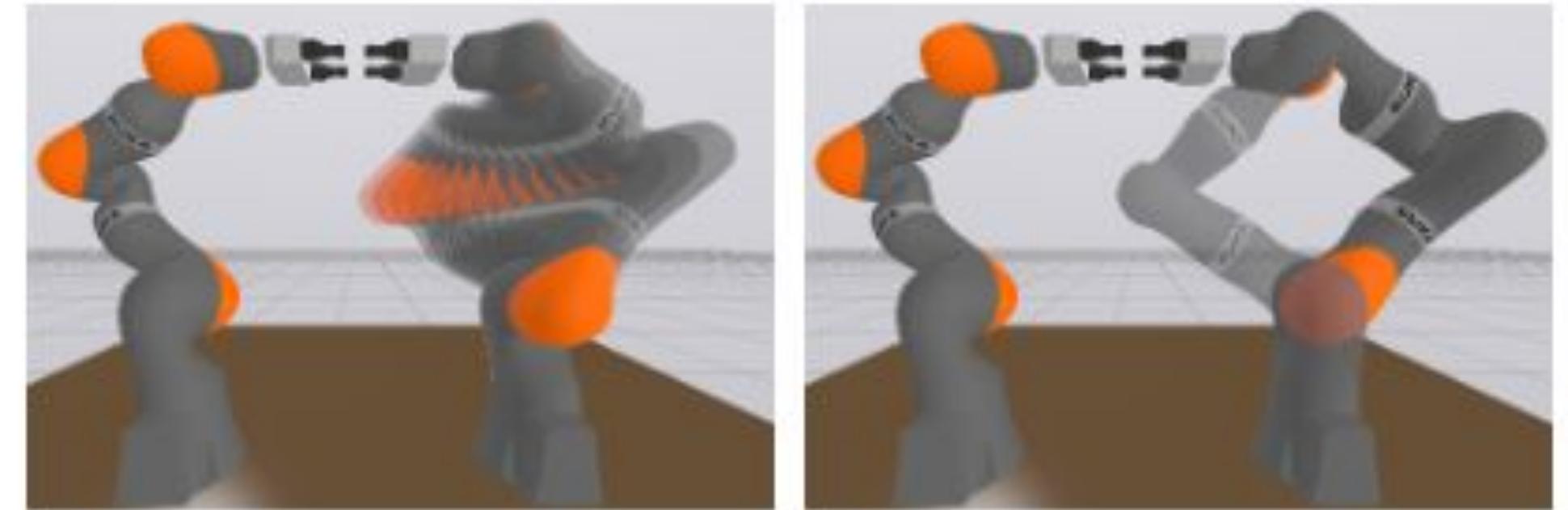
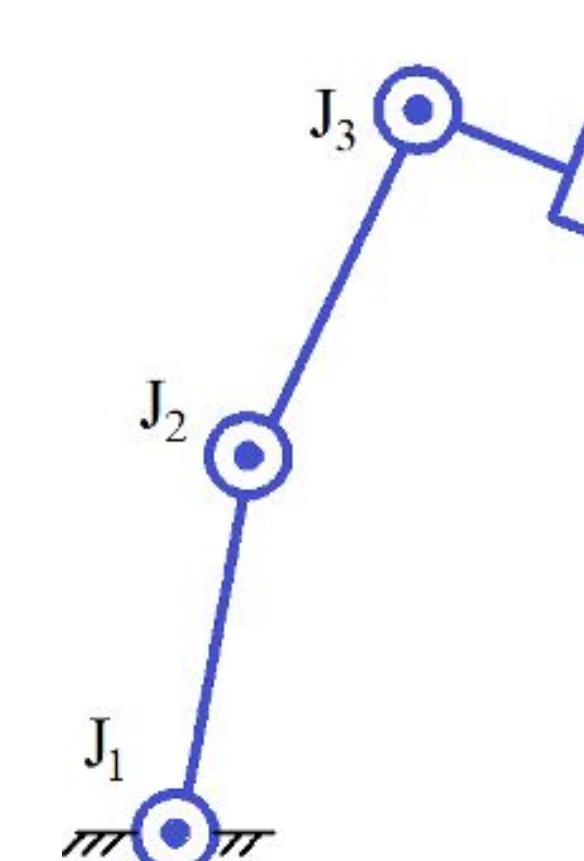


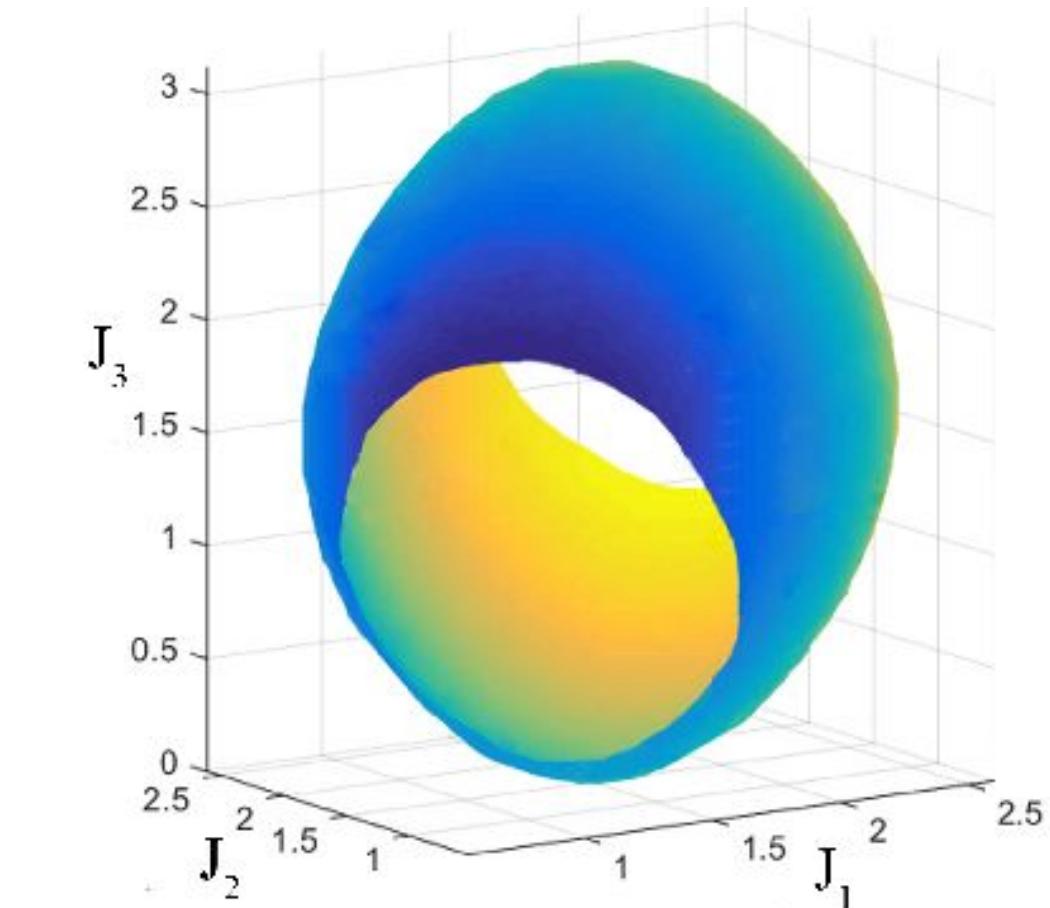
Fig. 3: Continuous (left) and discrete (right) self-motions of a 7DoF arm. The continuous self-motion yields an additional degree of freedom for the planner to consider, whereas the discrete self-motion is not utilized.

Constrained configuration space

- . Constantly checking configuration space to determine the following:
 - . Are there any collisions?
 - . Is the transformation between end effectors the same?
- . Constraint manifold - set of possible configurations that satisfy the systems constraints
 - . Requires offline planning to build



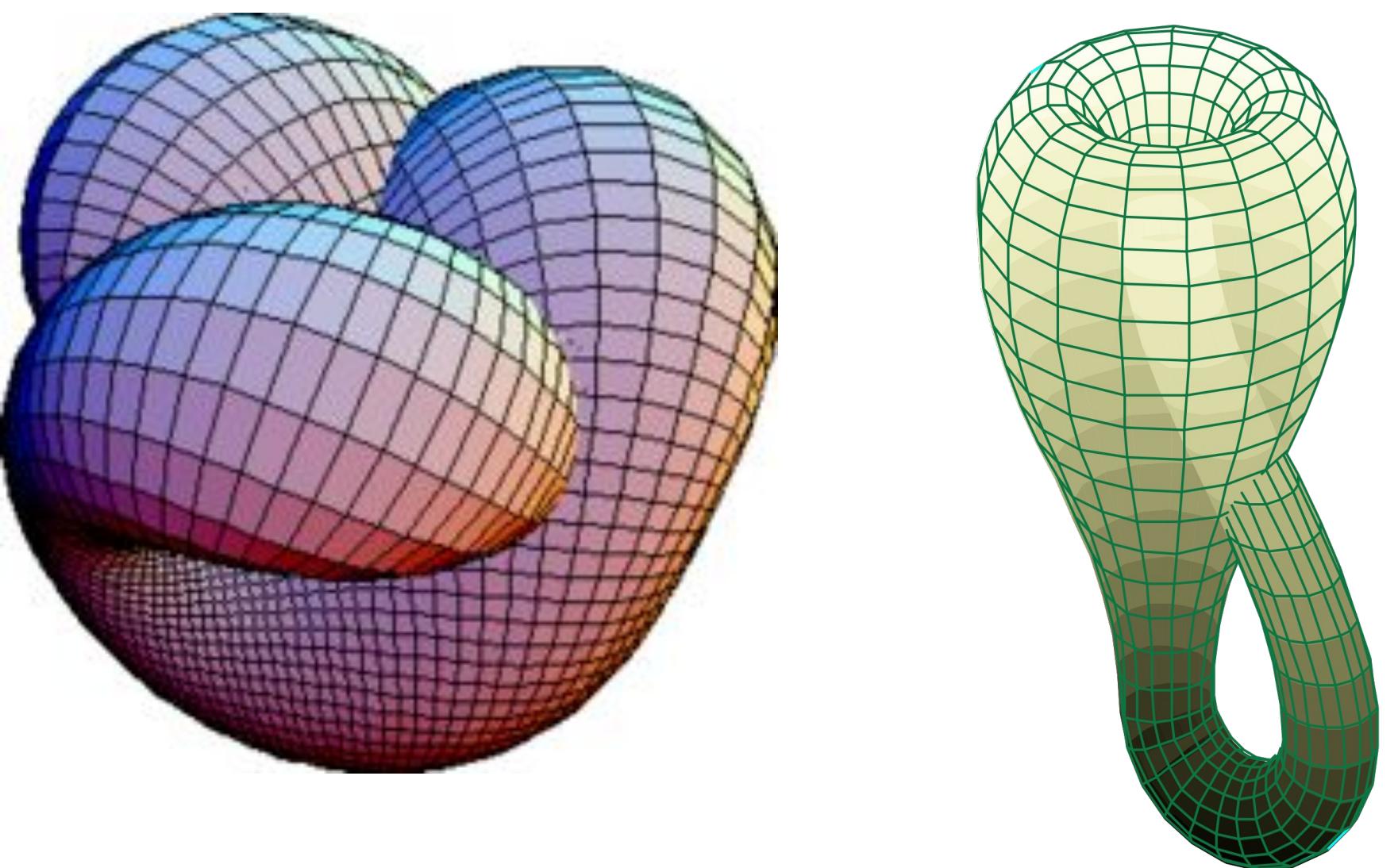
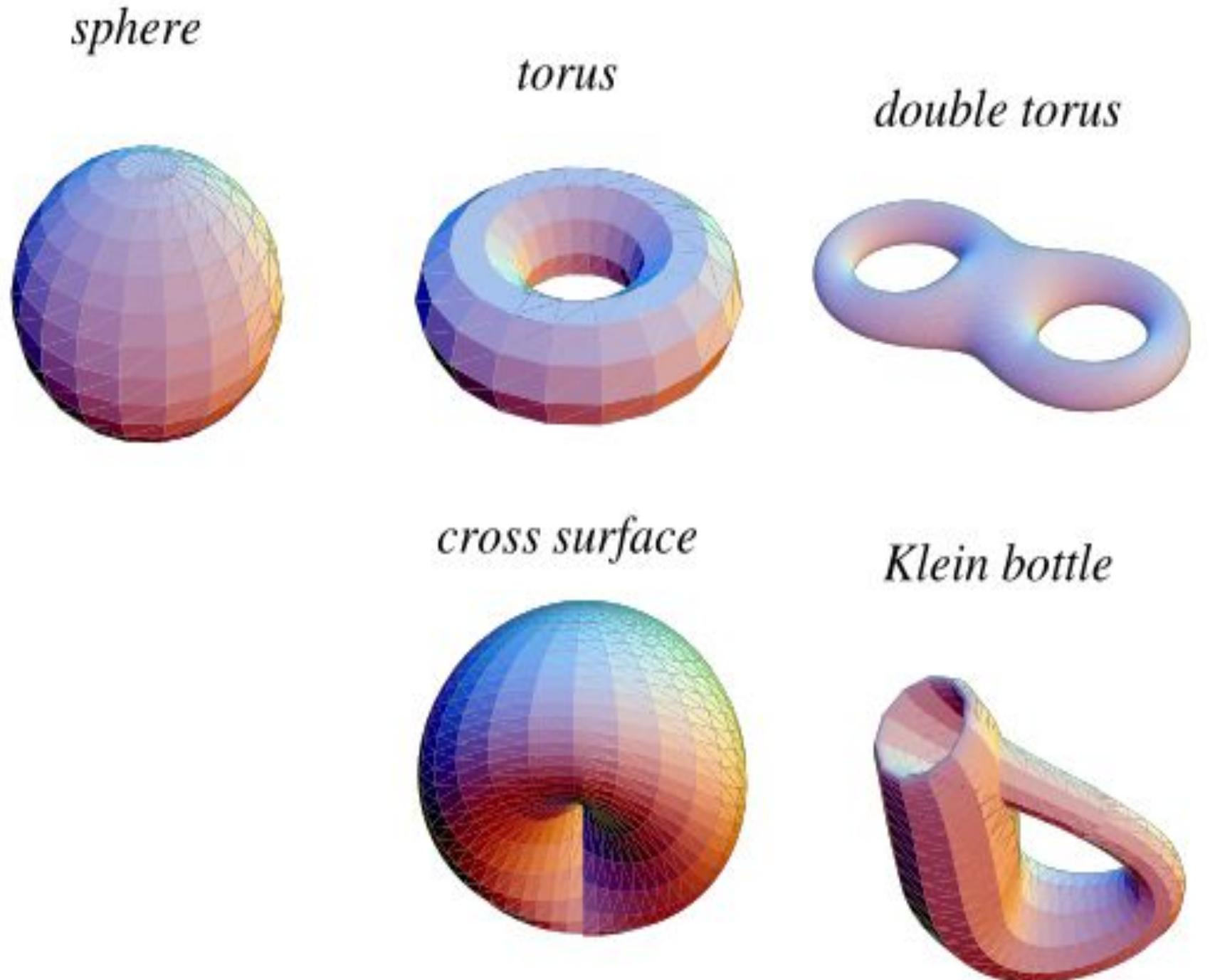
(a) 3-DOF robot



(b) Constraint manifold

Quick aside - Manifolds

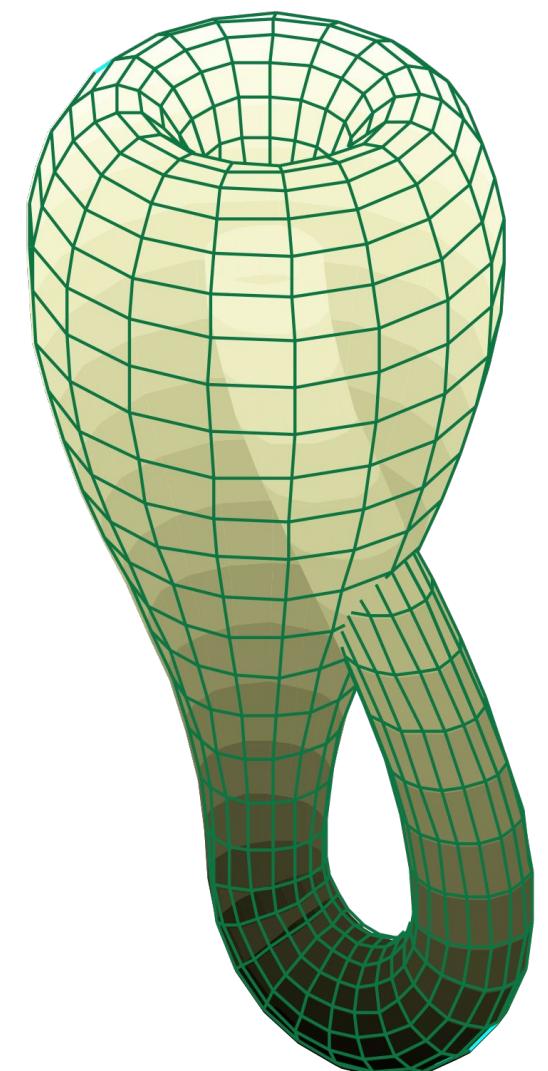
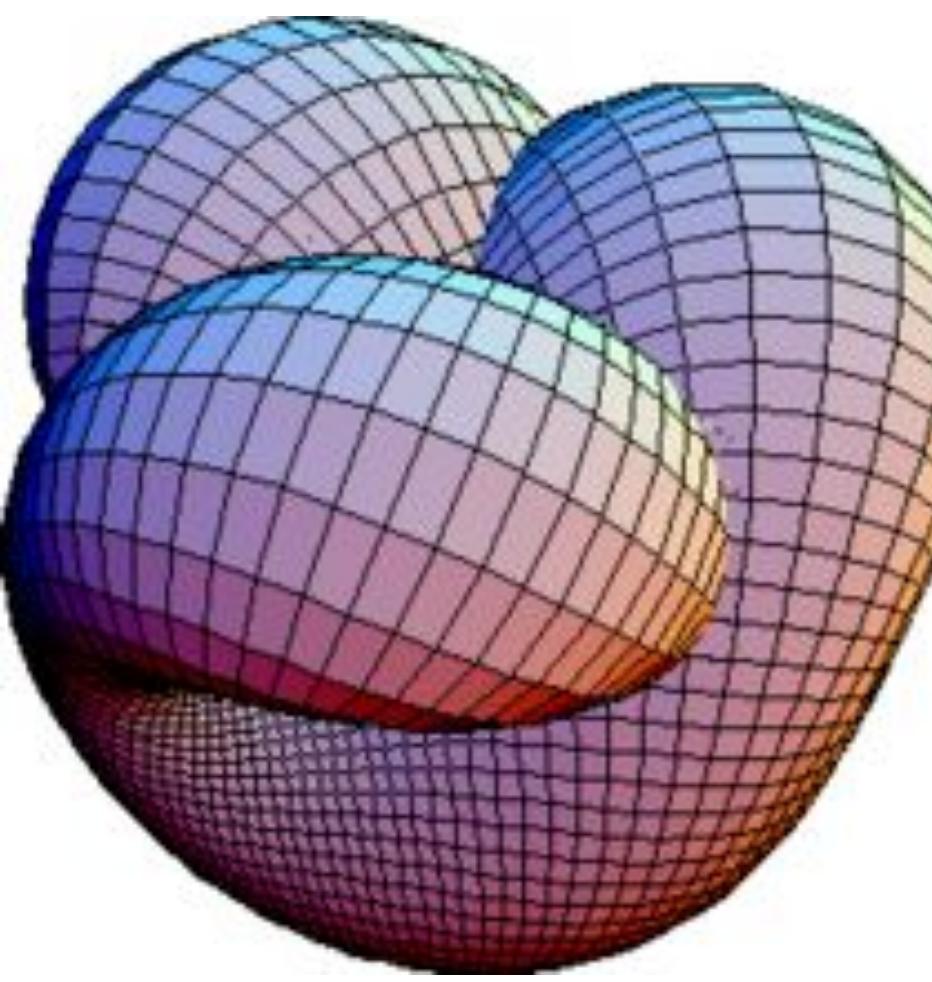
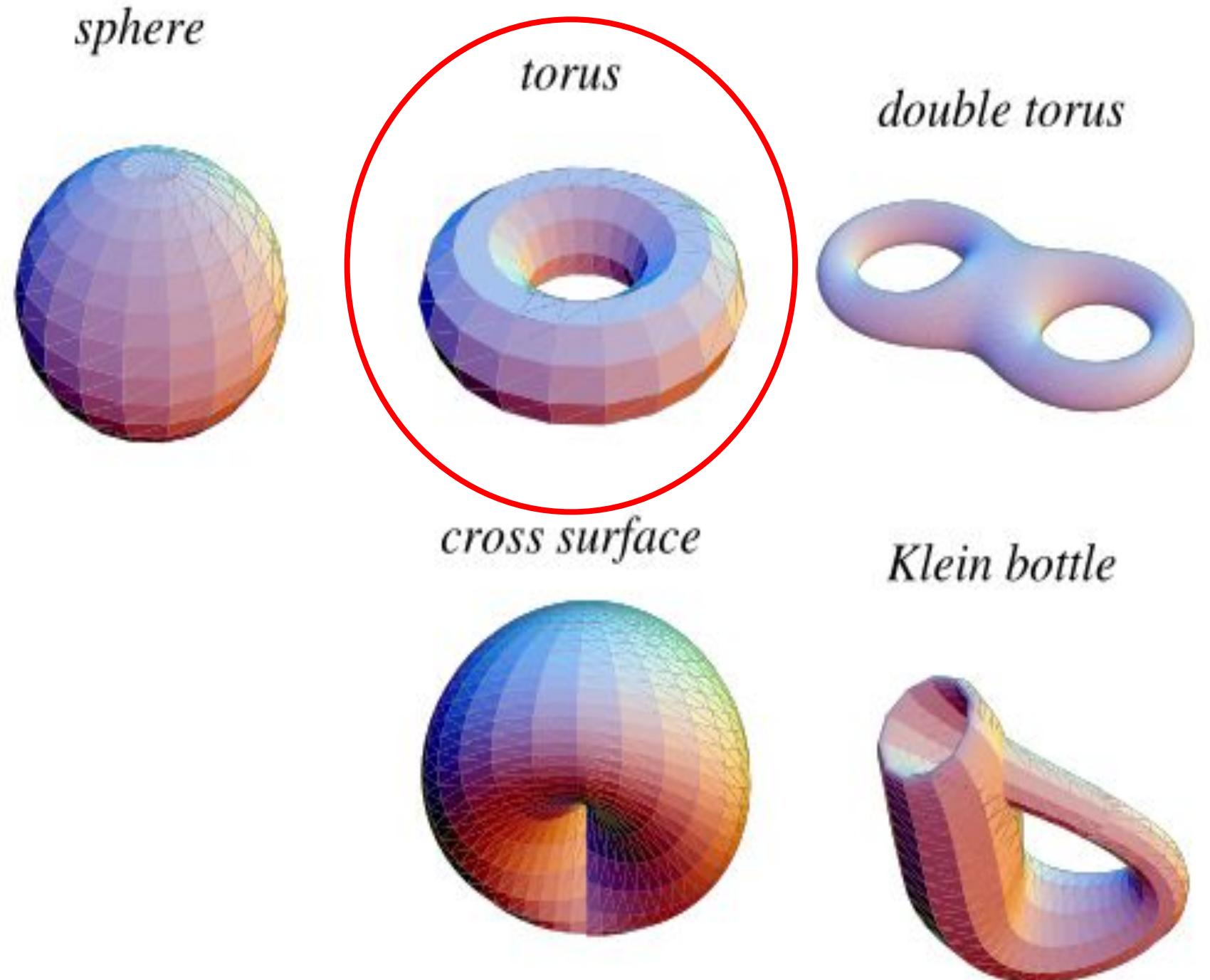
- . Set of points resembling Euclidean space
- . Connectedness is defined



<https://en.wikipedia.org/wiki/Manifold>

Quick aside - Manifolds

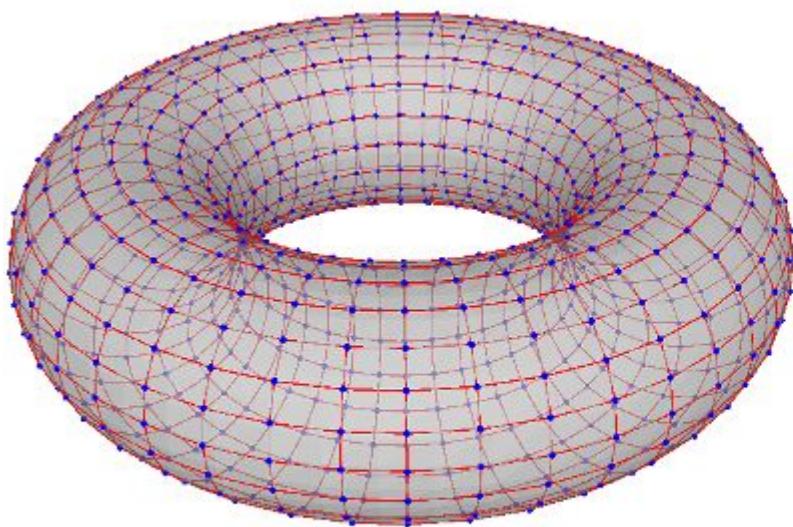
- . Set of points resembling Euclidean space
- . Connectedness is defined



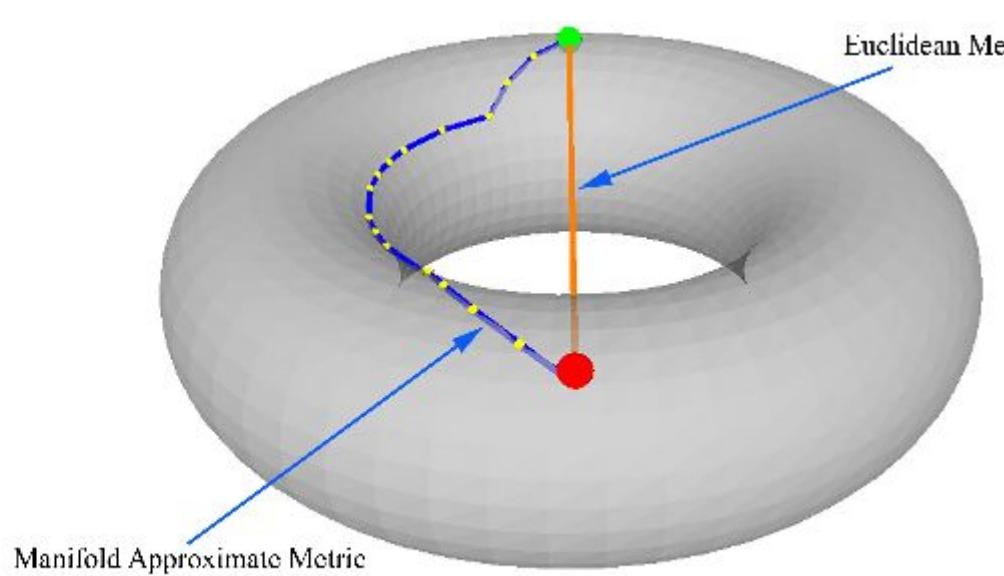
<https://en.wikipedia.org/wiki/Manifold>

Path and motion planning

- . Planning occurs in configuration space using constraint manifold

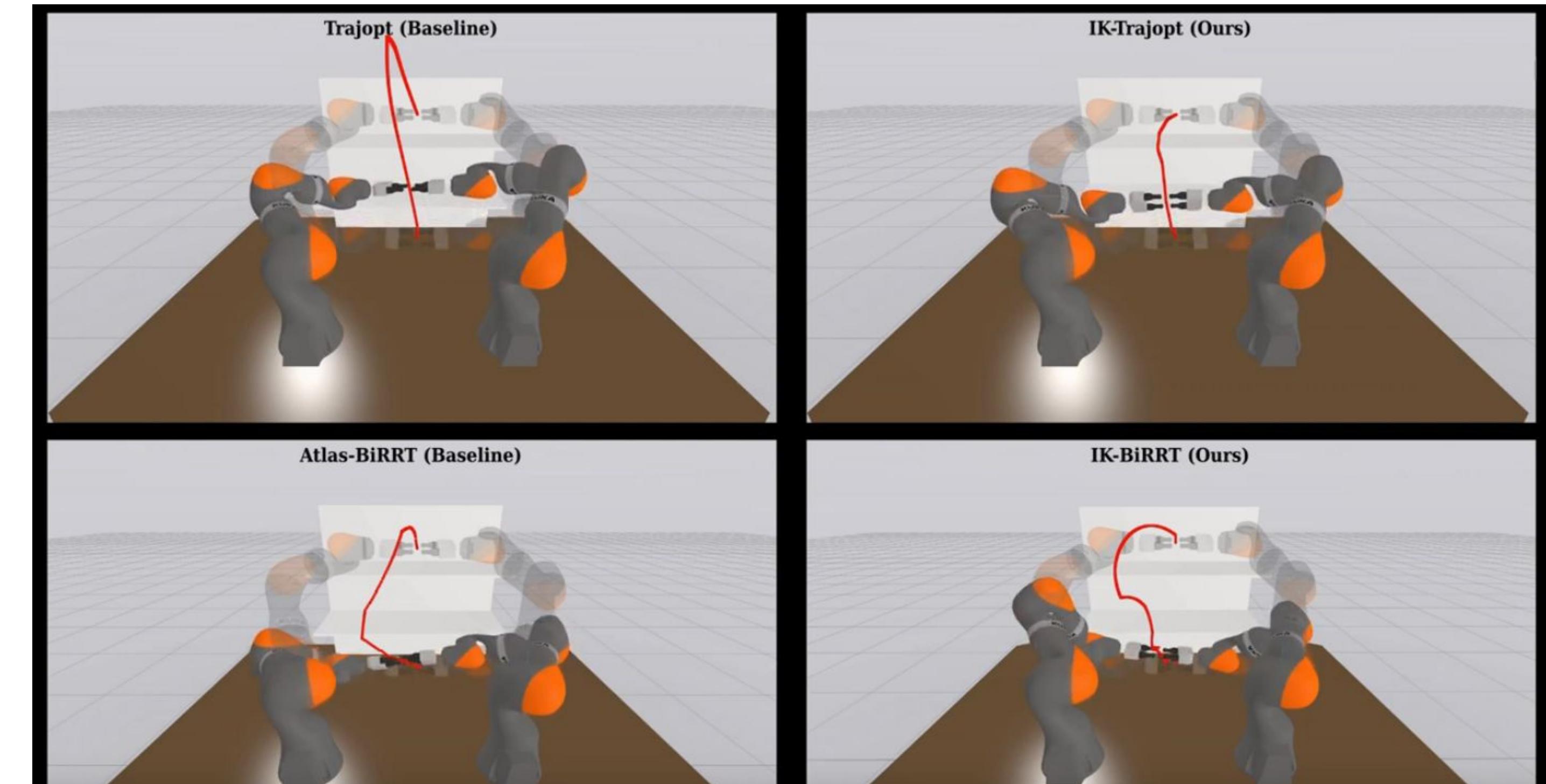


(a) Manifold approximate graph



(b) Manifold approximate metric

Zha, Fusheng, Yizhou Liu, Wei Guo, Pengfei Wang, Mantian Li, Xin Wang, and Jingxuan Li. "Learning the metric of task constraint manifolds for constrained motion planning." *Electronics* 7, no. 12 (2018): 395.



<https://www.youtube.com/watch?v=vmujyn4EgTU>

Cohn, Thomas, Seiji Shaw, Max Simchowitz, and Russ Tedrake. "Constrained bimanual planning with analytic inverse kinematics." In *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 6935-6942. IEEE, 2024.

Path and motion planning

- . Common path planning/graph algorithms can be used

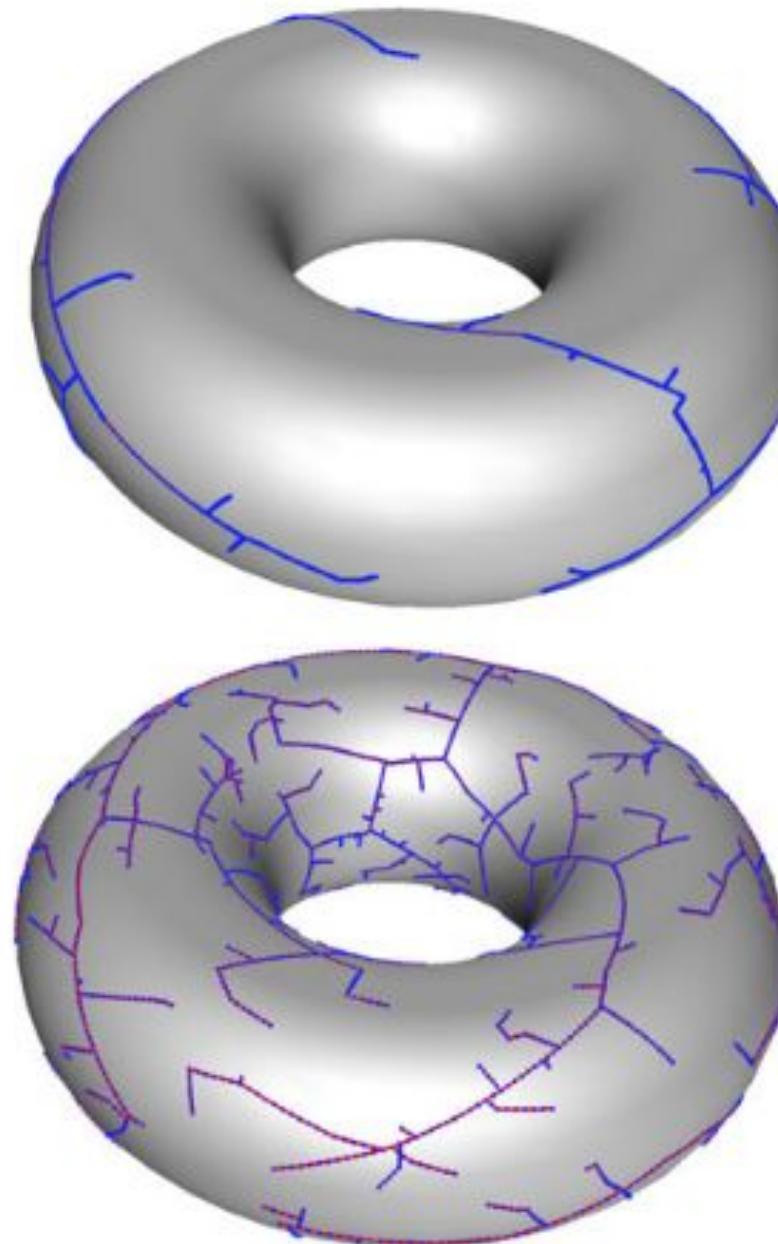


Fig. 2. Two RRTs of 500 samples built on a torus-like manifold. (Top) With an ambient space sampling method, the exploration focuses on the outer parts of the torus, and many samples do not produce a tree extension. (Bottom) With an AtlasRRT, the diffusion process is largely independent of the ambient space, which improves the coverage.

<https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6352929>

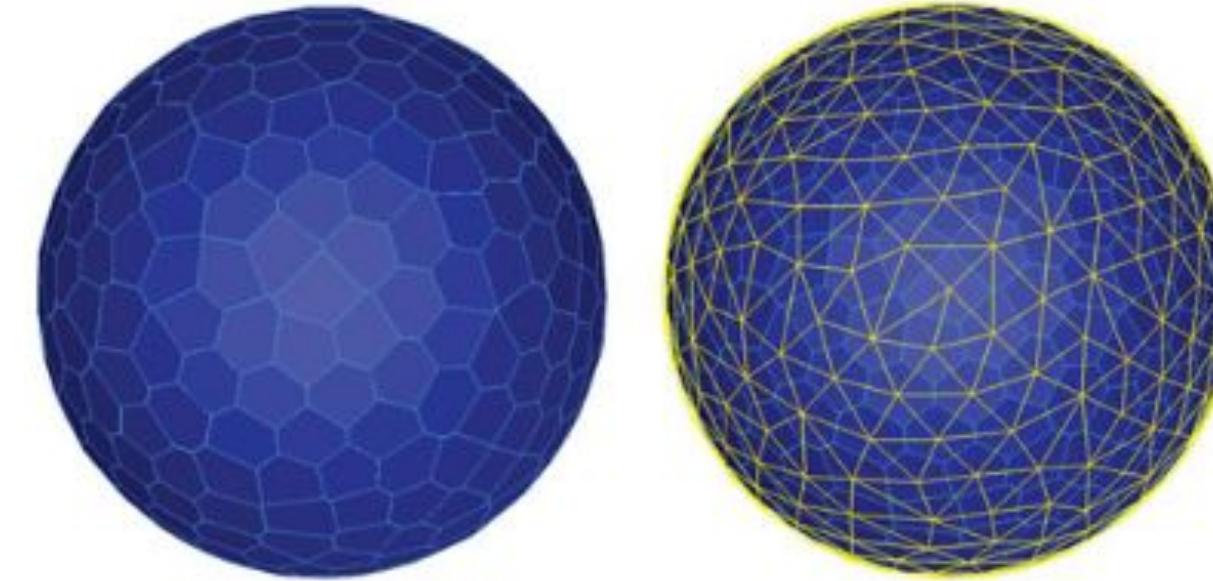


Fig. 6. (Left) Atlas of a sphere. Each polygonal patch corresponds to a given \mathcal{P}_i : a conservative approximation of the validity area for the associated chart. (Right) A roadmap can be extracted from the atlas where the nodes are the chart centers and where the edges are given by the neighborhood relations between charts. This roadmap could be used to devise collision free paths between any two given configurations.

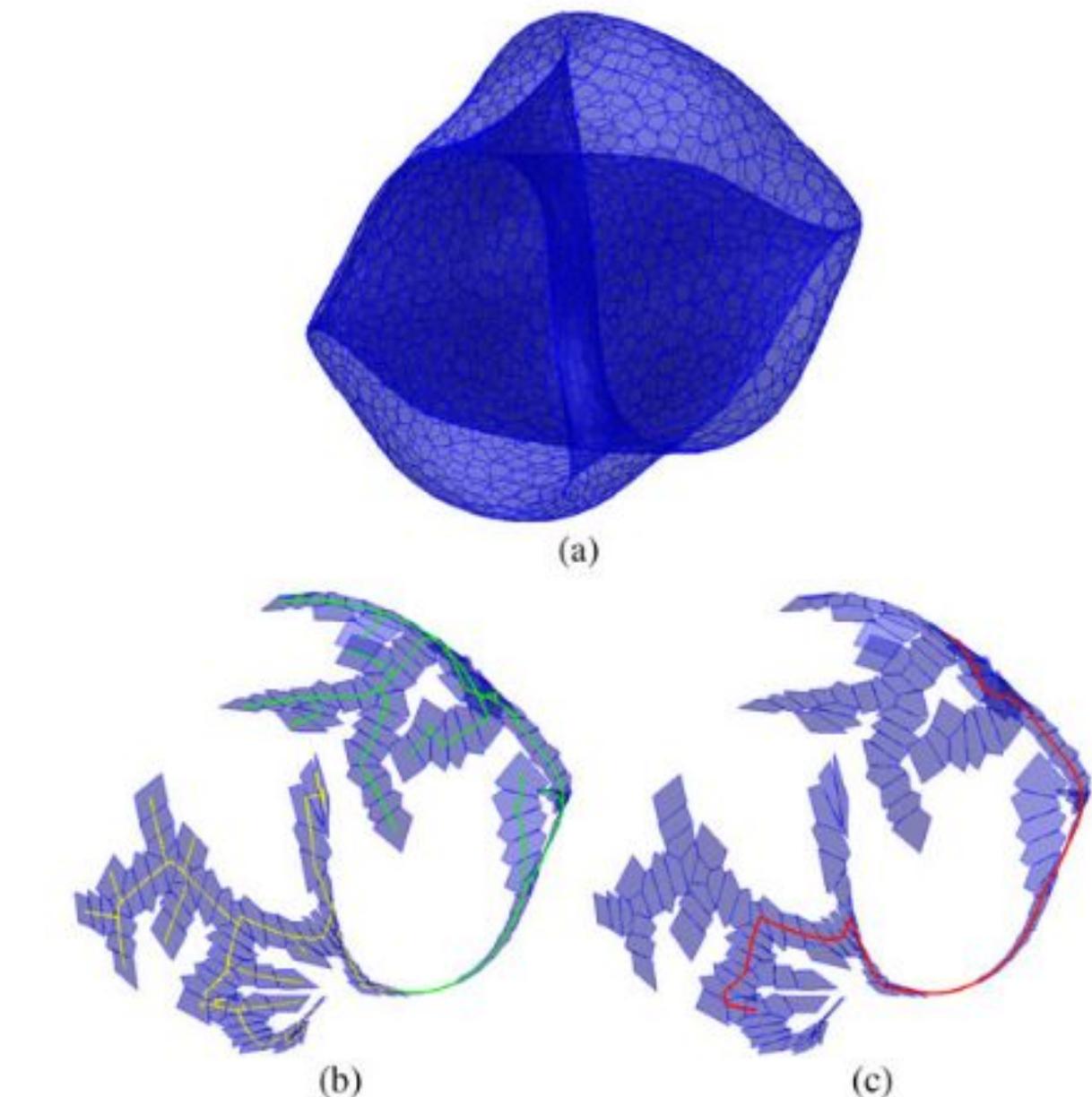
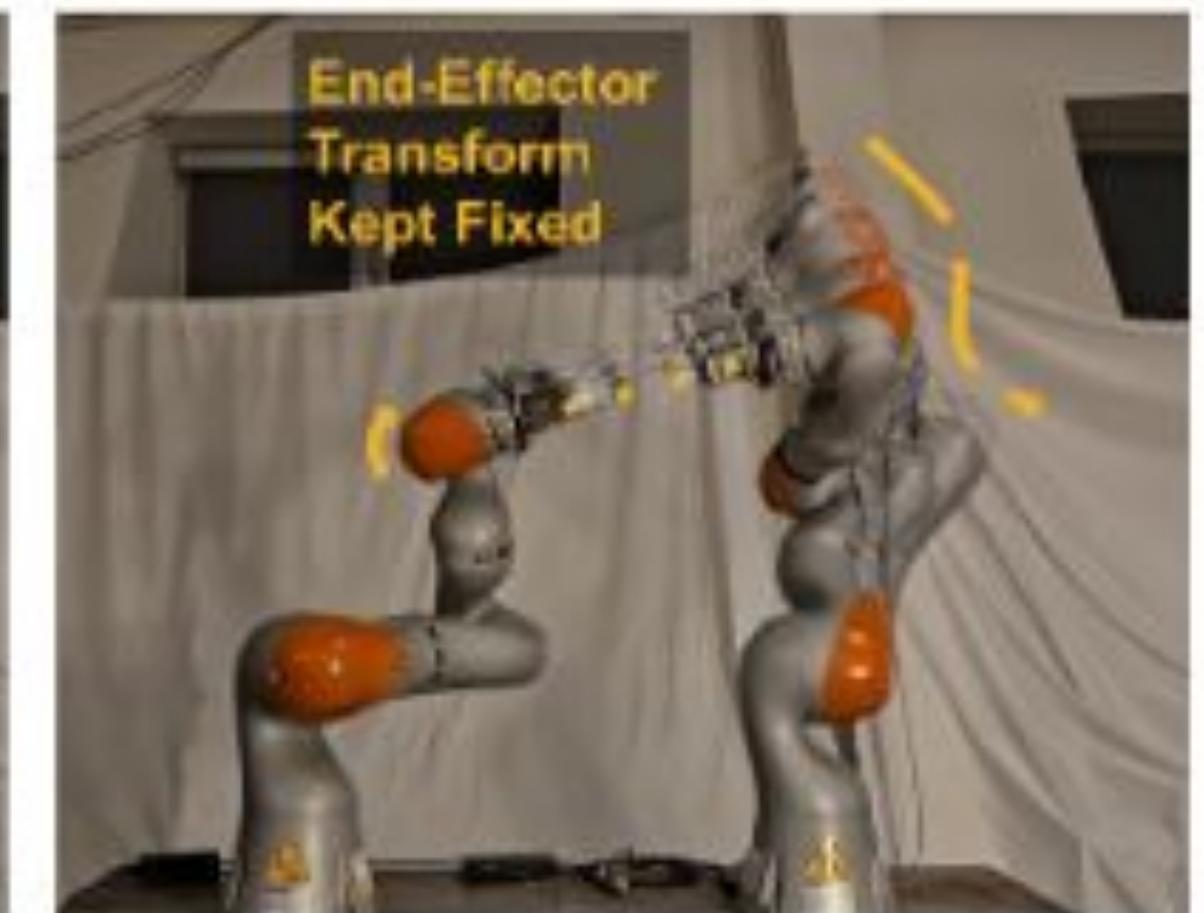
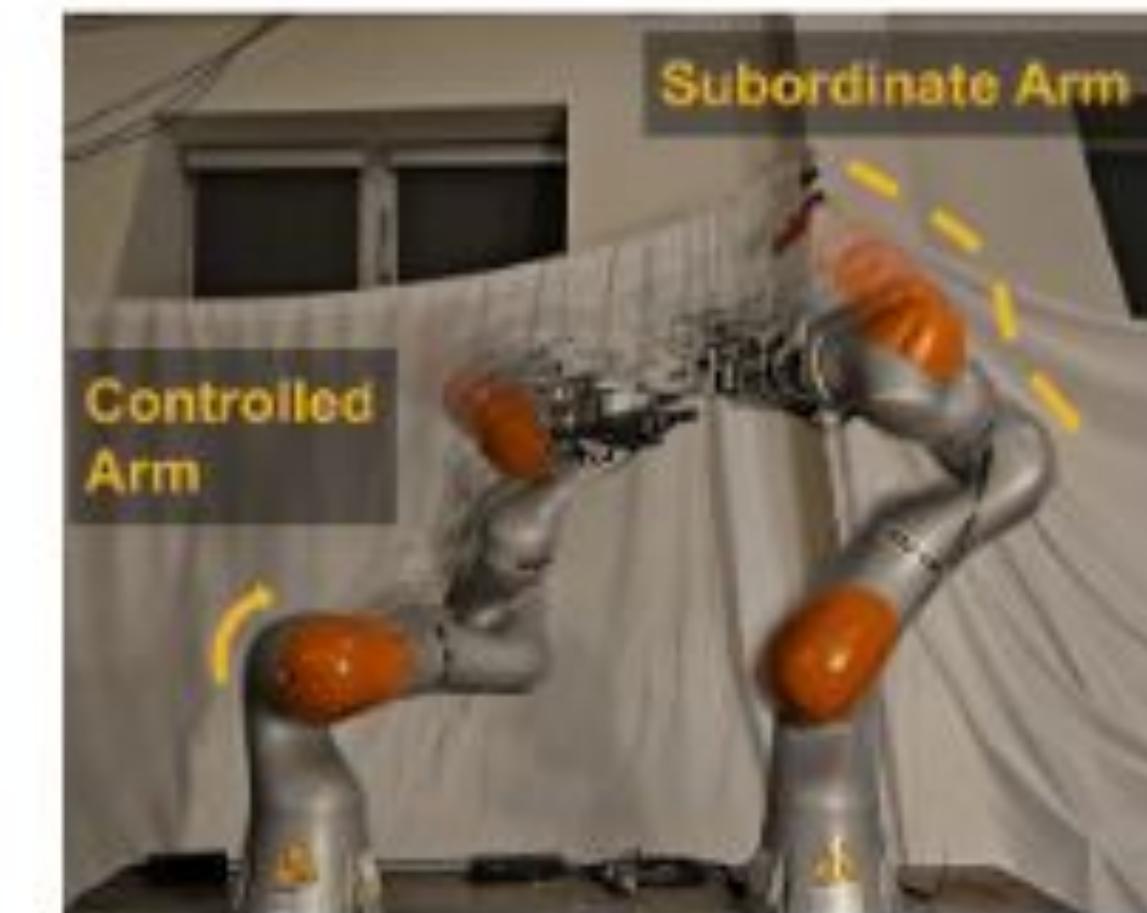


Fig. 1. Example of exploration with AtlasRRT. (a) Full atlas of the bidimensional configuration space of the cyclooctane. (b) AtlasRRT intertwines the construction of a bidirectional RRT with an atlas construction. The trees rooted at the start and goal configurations are represented in yellow and green, respectively. (c) When the two RRTs are connected, a solution path (represented in red) can be readily computed. Observe that only a small fraction of the full atlas is necessary to connect the query configurations.

Intuition for the papers method

- . Constrain manifold is created using with obstacle collisions for each arm
- . If the transformation between end effectors differs, that is treated as an obstacle
- . The left arm is controlled
- . Right arm follows
- . Any path planning algorithm can be used for trajectories



Results - setup

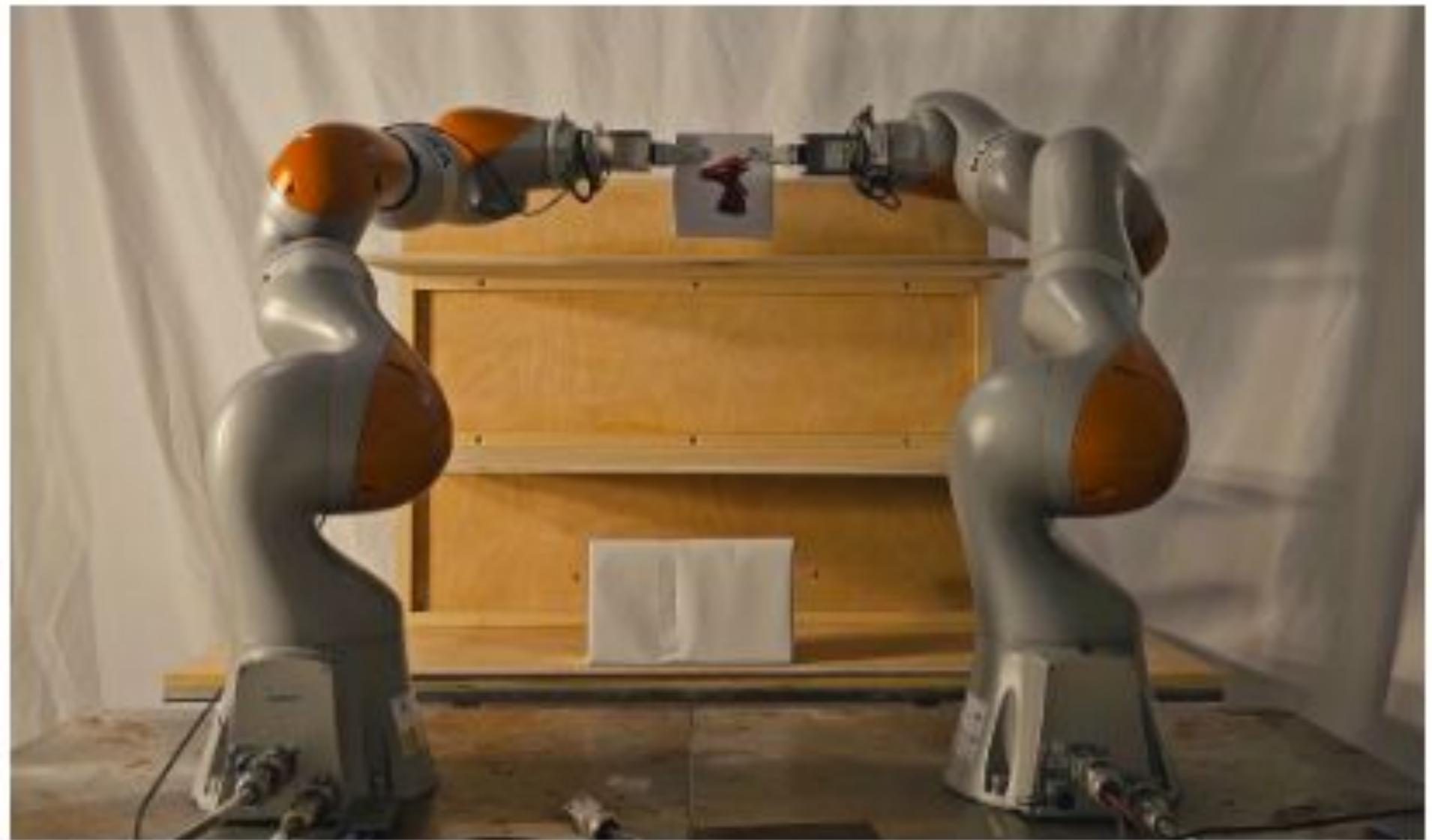
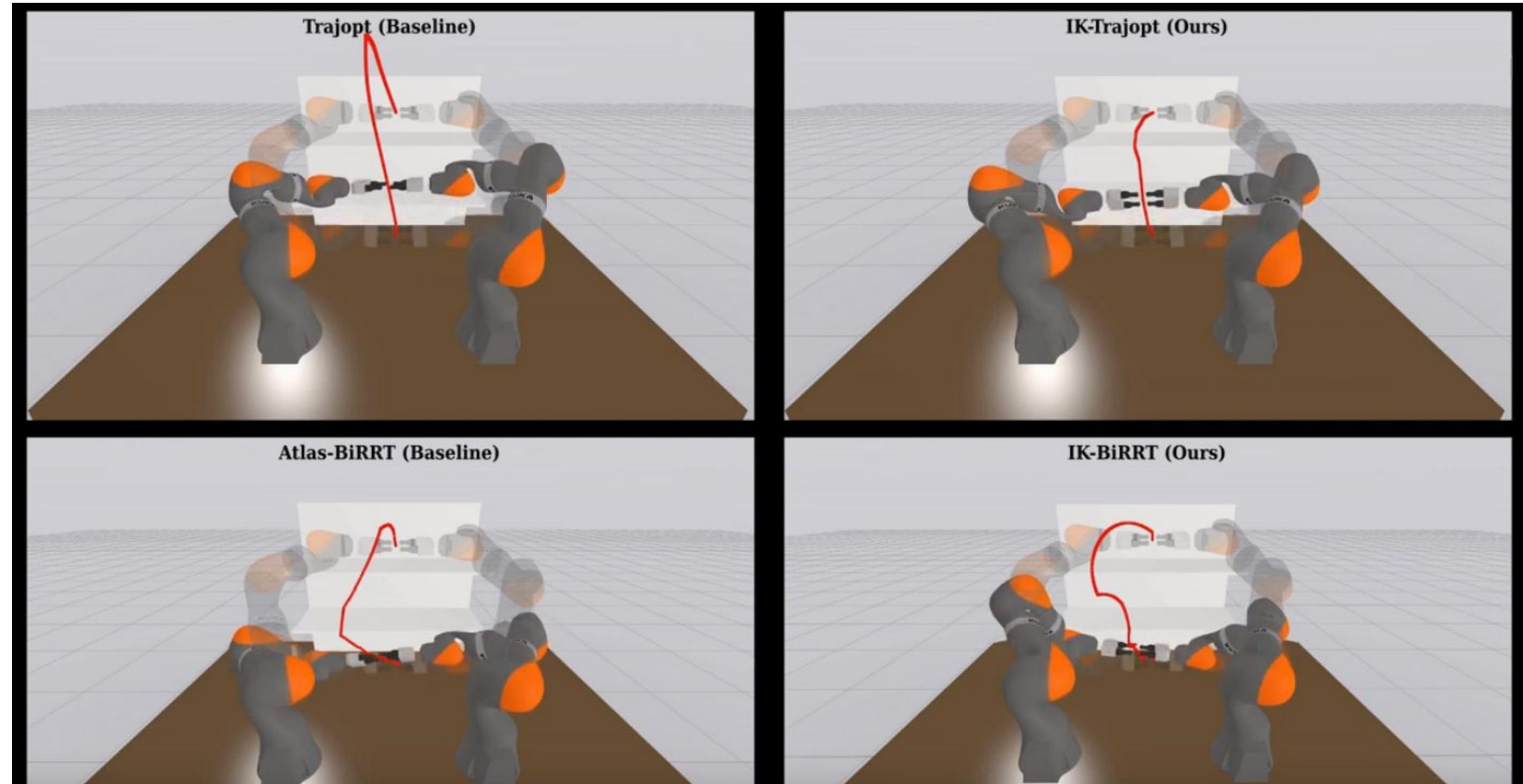


Fig. 1: Hardware setup for our experiments. The two arms must work together to move an objects between the shelves, avoiding collisions and respecting the kinematic constraint.





Results

Method	Top to Middle	Middle to Bottom	Bottom to Top
Trajopt	4.58*	2.85*	4.35*
Atlas-BiRRT	4.72	5.04	6.61
Atlas-PRM	5.43	5.67	6.99
IK-Trajopt	4.24*	1.81*	8.87
IK-BiRRT	9.91	8.69	11.42
IK-PRM	4.67	8.93	9.21
IK-GCS	2.09	3.32	5.62

TABLE I: Path lengths (measured in configuration space) for each method with various start and goal configurations. Paths marked with an asterisk were not collision-free.

path arc length (feet)

Method	Top to Middle	Middle to Bottom	Bottom to Top
Trajopt	10.37	5.36	7.25
Atlas-BiRRT	140.82	155.91	201.32
Atlas-PRM	0.69	0.86	0.96
IK-Trajopt	19.48	18.70	22.29
IK-BiRRT	49.42	52.53	54.10
IK-PRM	0.46	0.64	0.61
IK-GCS	3.41	2.32	3.32

TABLE II: Online planning time (in seconds) for each method with various start and goal configurations. Atlas-BiRRT runtimes were only averaged over successful runs (not including timeouts).





Results

Method	Top to Middle	Middle to Bottom	Bottom to Top
Trajopt	4.58*	2.85*	4.35*
Atlas-BiRRT	4.72	5.04	6.61
Atlas-PRM	5.43	5.67	6.99
IK-Trajopt	4.24*	1.81*	8.87
IK-BiRRT	9.91	8.69	11.42
IK-PRM	4.67	8.93	9.21
IK-GCS	2.09	3.32	5.62

TABLE I: Path lengths (measured in configuration space) for each method with various start and goal configurations. Paths marked with an asterisk were not collision-free.

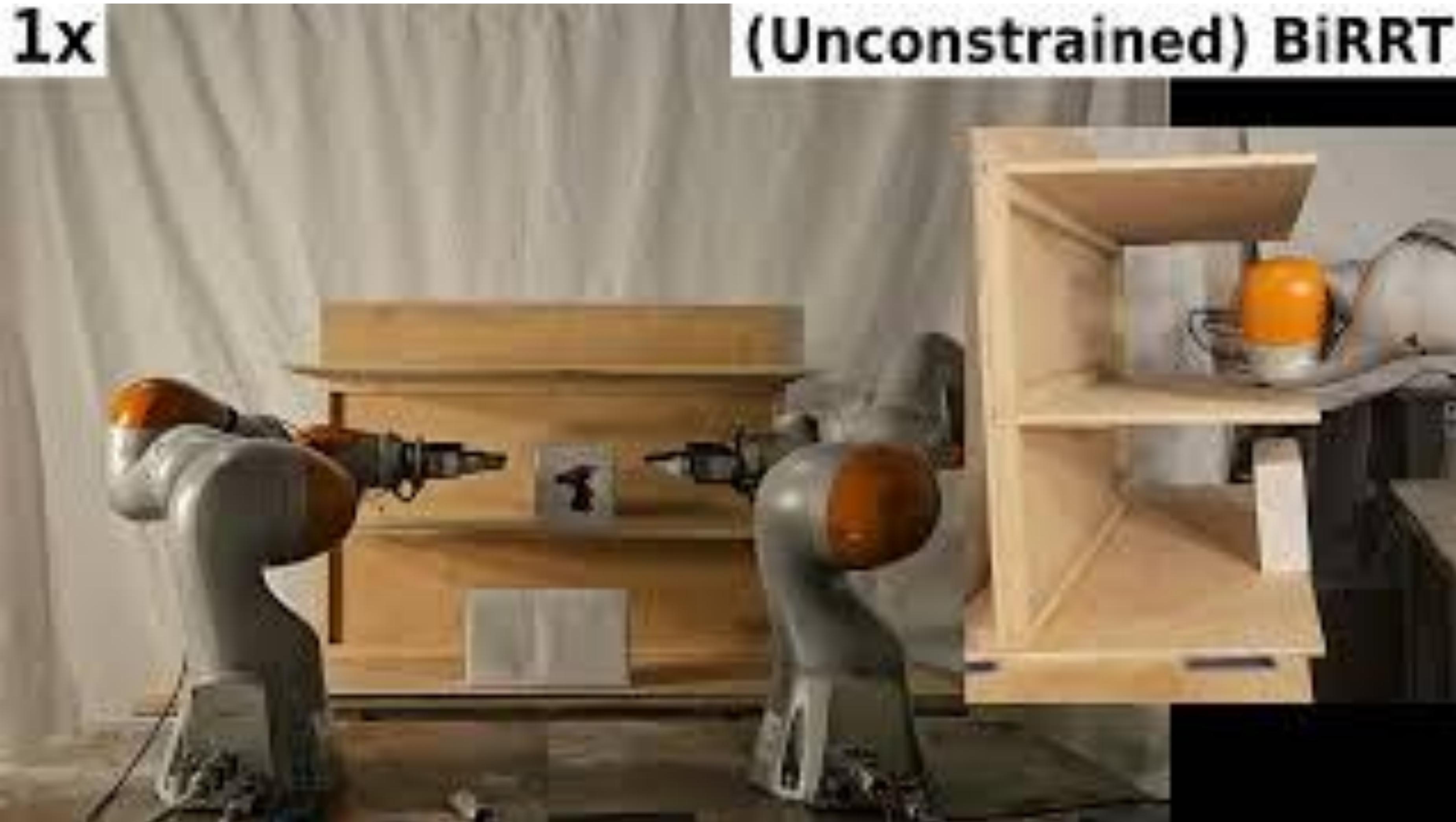
path arc length (feet)

Method	Top to Middle	Middle to Bottom	Bottom to Top
Trajopt	10.37	5.36	7.25
Atlas-BiRRT	140.82	155.91	201.32
Atlas-PRM	0.69	0.86	0.96
IK-Trajopt	19.48	18.70	22.29
IK-BiRRT	49.42	52.53	54.10
IK-PRM	0.46	0.64	0.61
IK-GCS	3.41	2.32	3.32

TABLE II: Online planning time (in seconds) for each method with various start and goal configurations. Atlas-BiRRT runtimes were only averaged over successful runs (not including timeouts).



Results



<https://www.youtube.com/watch?v=vmujyn4EgTU>

Cohn, Thomas, Seiji Shaw, Max Simchowitz, and Russ Tedrake. "Constrained bimanual planning with analytic inverse kinematics." In 2024 IEEE International Conference on Robotics and Automation (ICRA), pp. 6935-6942. IEEE, 2024.

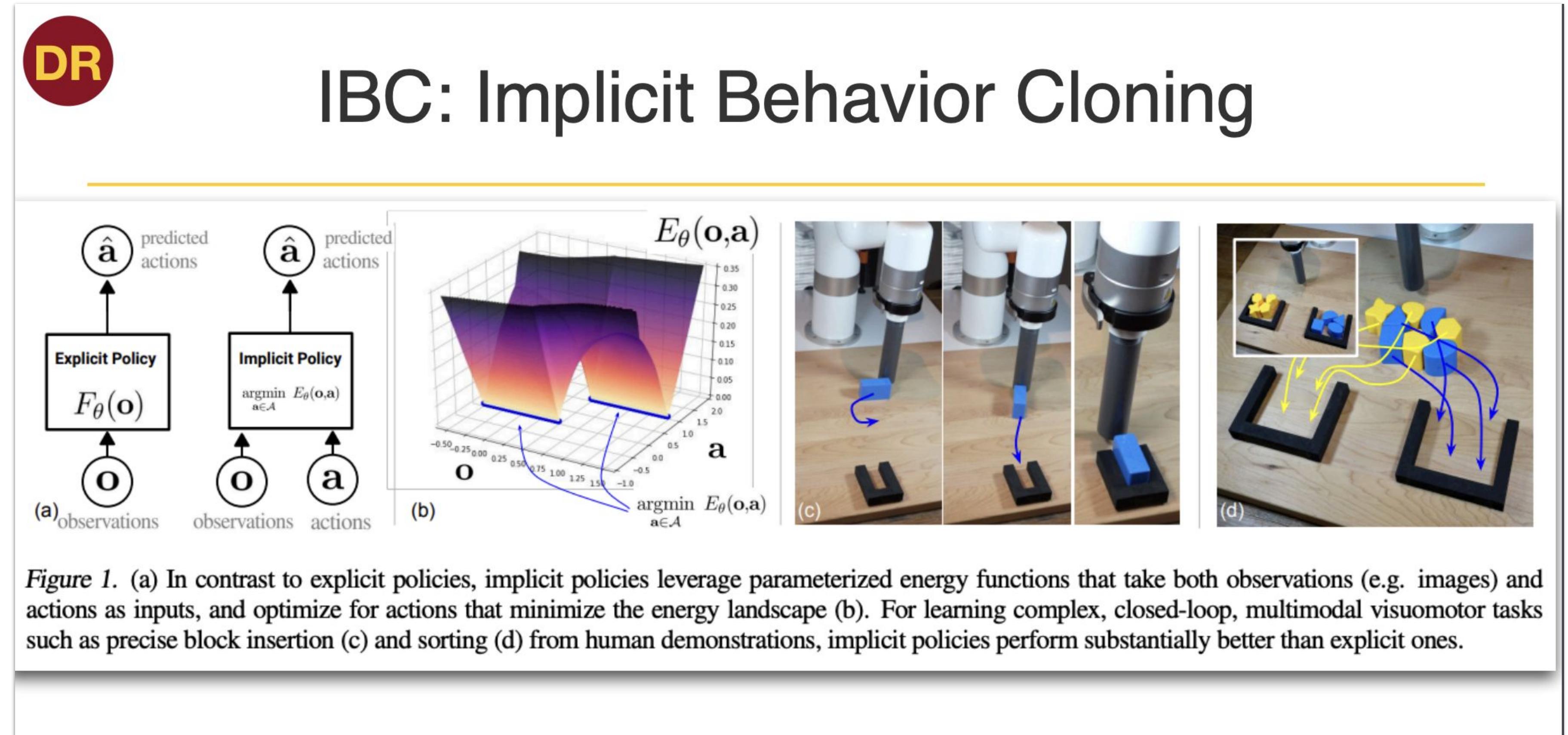


Policy learning approaches



Methods - Imitation Learning

Recall:



Much more sample efficient than RL!

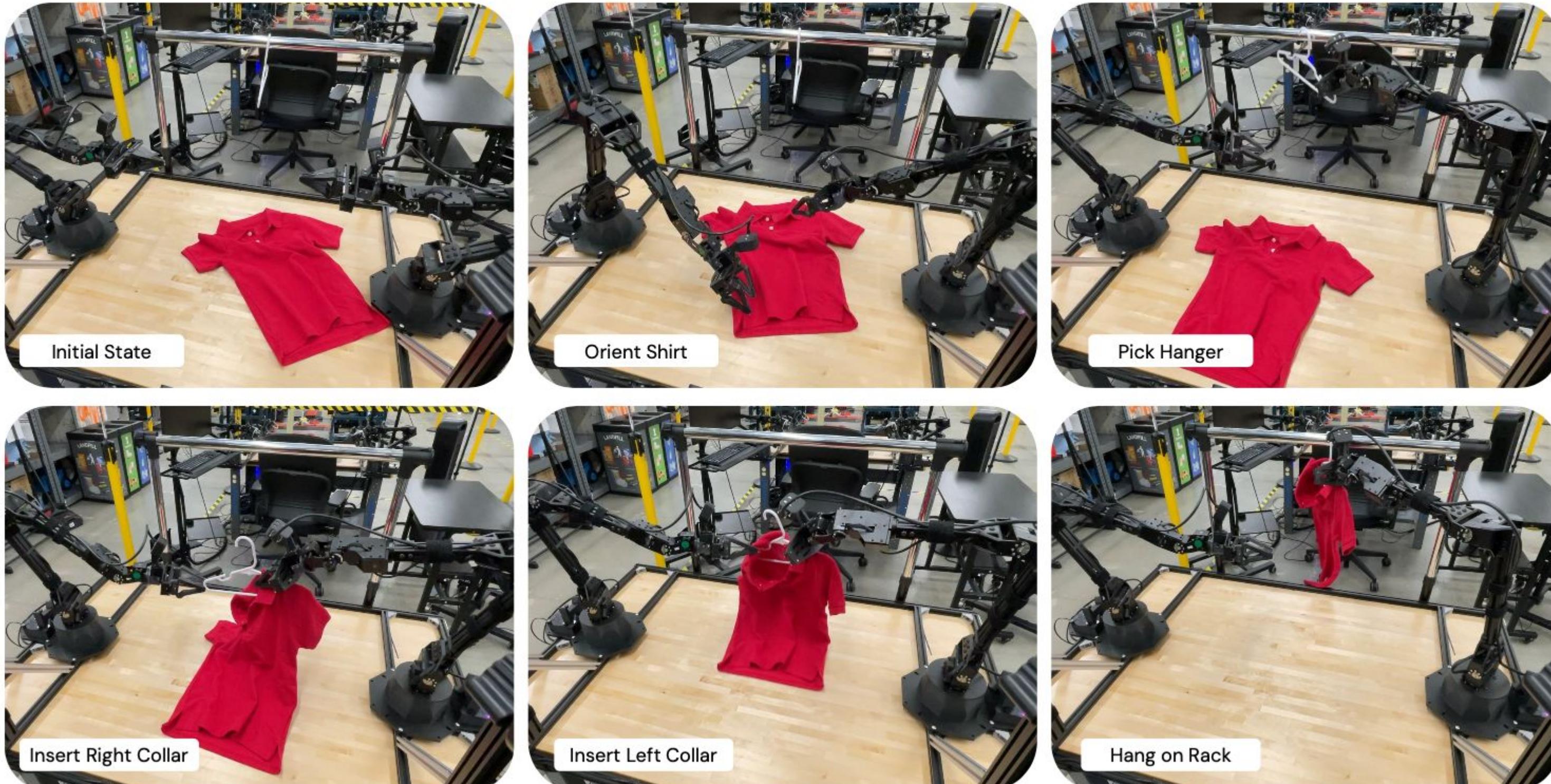


ALOHA Unleashed



T. Z. Zhao, J. Tompson, D. Driess, P. Florence, S. K. S. Ghasemipour, C. Finn, and A. Wahid. ALOHA unleashed: A simple recipe for robot dexterity. In 8th Annual Conference on Robot Learning, 2024. URL <https://openreview.net/forum?id=gvdXE7ikHI>.

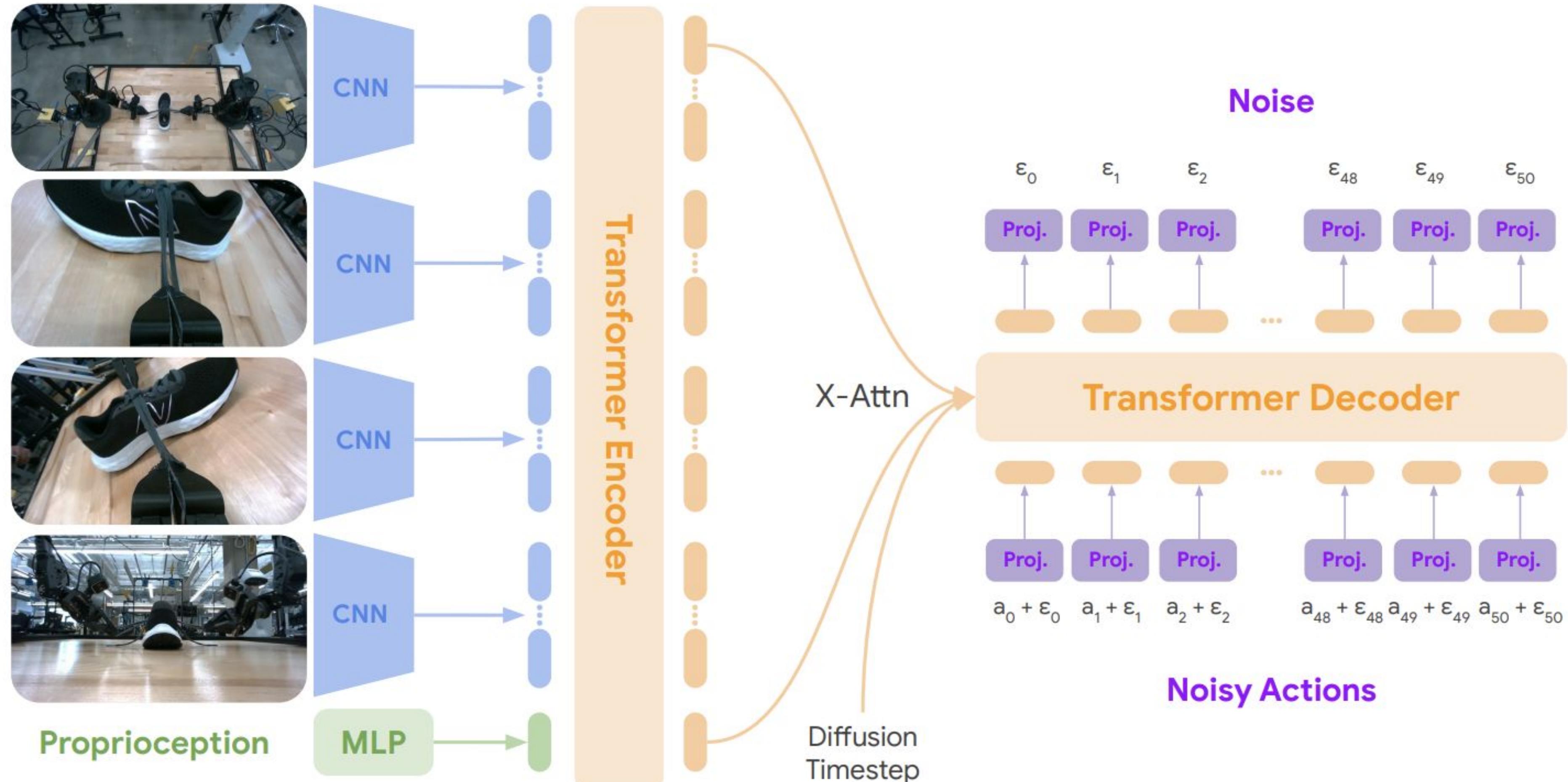
ALOHA Unleashed - Data



- ALOHA allows bimanual teleoperation for data collection
- 5 different tasks
- Tasks are somewhat long horizon and require precision and dexterity

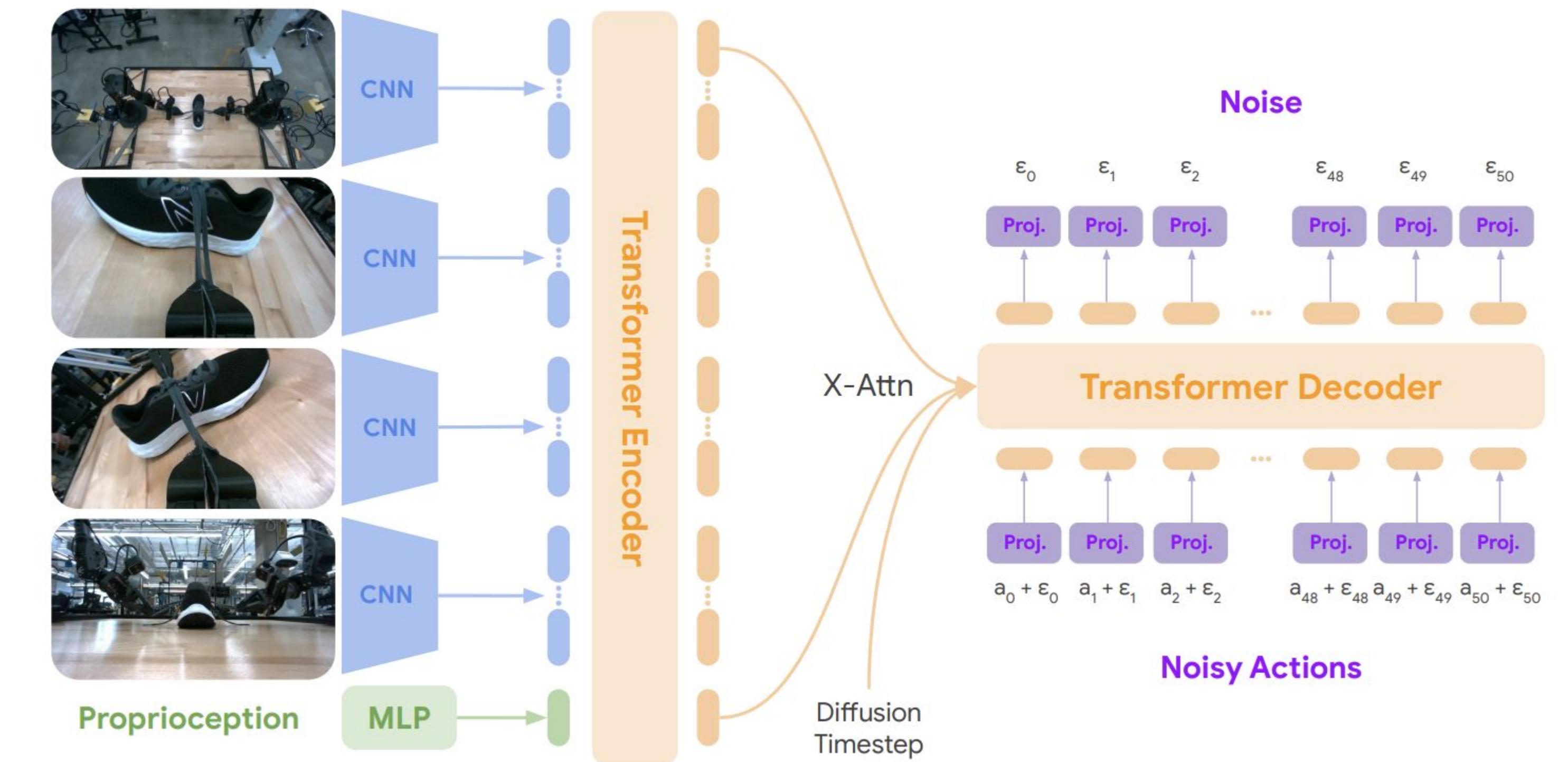


ALOHA Unleashed - Architecture



ALOHA Unleashed - Architecture

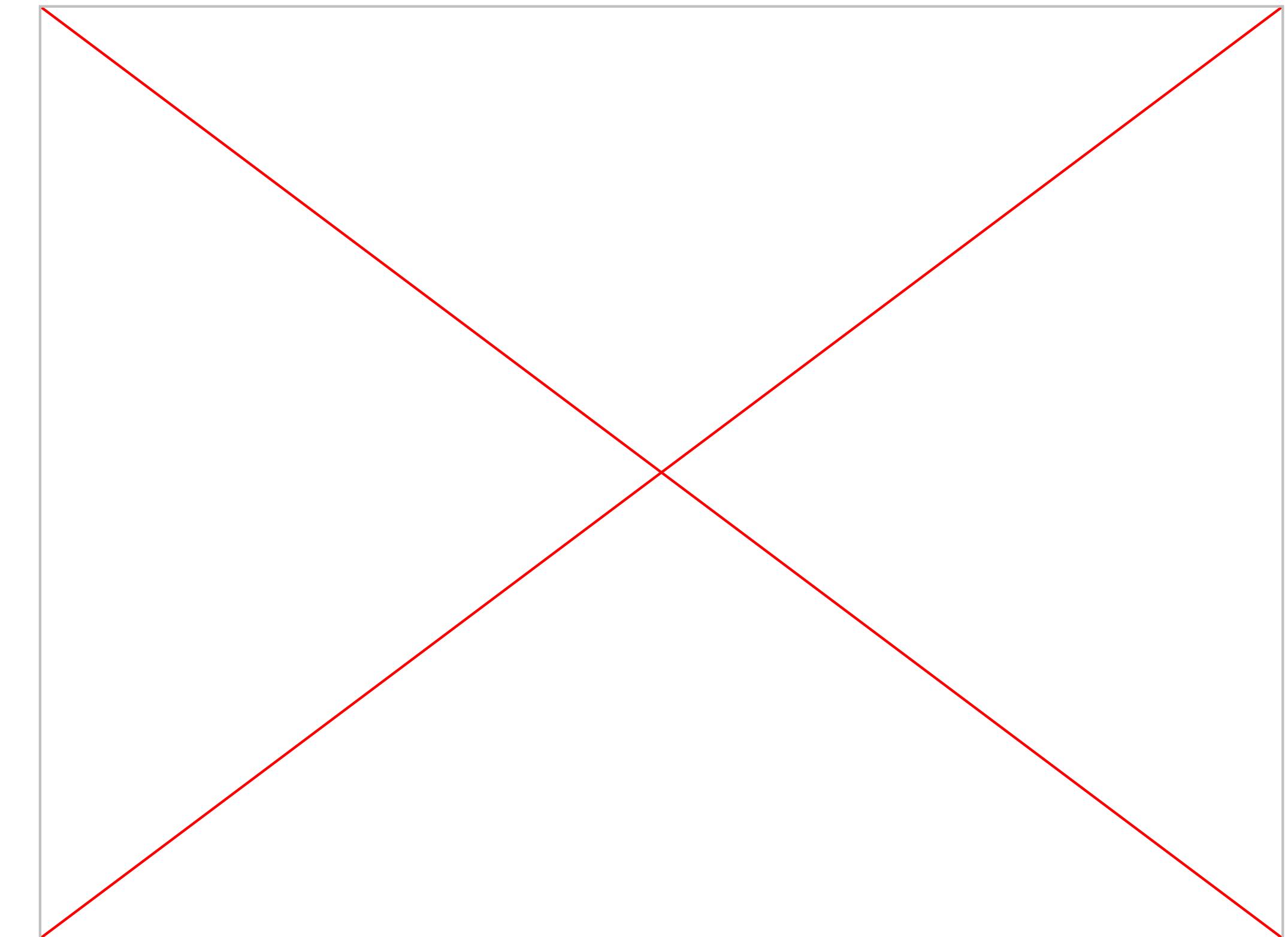
- Encoder-decoder architecture with diffusion loss
- 4 cameras + proprioception
- CNNs are ResNet-50s
- 50 diffusion steps(ie: during inference decoder runs 50 times)
- This is just diffusion policy!



ALOHA Unleashed - Results

- Messy demonstrations help the agent learn to recover from mistakes

Task	Success Rate	Number of Demonstrations
ShirtEasy	75%	
ShirtMessy	70%	8658 (5345 Easy; 3313 Messy)
LaceEasy	70%	
LaceMessy	40%	5133 (2212 Easy; 2921 Messy)
FingerReplace	75%	5247
GearInsert-1	95%	
GearInsert-2	75%	4005
GearInsert-3	40%	
RandomKitchen-Bowl	95%	
RandomKitchen-Bowl+Cup	65%	3198 (216 In-Domain)
RandomKitchen-Bowl+Cup+Fork	25%	





ALOHA Unleashed - Results

- Messy demonstrations help the agent learn to recover from mistakes

Task	Success Rate	Number of Demonstrations
ShirtEasy	75%	
ShirtMessy	70%	8658 (5345 Easy; 3313 Messy)
LaceEasy	70%	
LaceMessy	40%	5133 (2212 Easy; 2921 Messy)
FingerReplace	75%	5247
GearInsert-1	95%	
GearInsert-2	75%	4005
GearInsert-3	40%	
RandomKitchen-Bowl	95%	
RandomKitchen-Bowl+Cup	65%	3198 (216 In-Domain)
RandomKitchen-Bowl+Cup+Fork	25%	

Task	DP (S)	DP (XS-LowRes)	ACT (XS-LowRes)	Num Demos
SingleInsertion (sim)	72	58 ±3	32	522
DoubleInsertion (sim)	60	48 ±2	58	201
MugOnPlate (sim)	80	74 ±0	40	550
Task	DP (S)	ACT (150M)	Num Demos	
ShirtMessy (real)	70	25	8658	

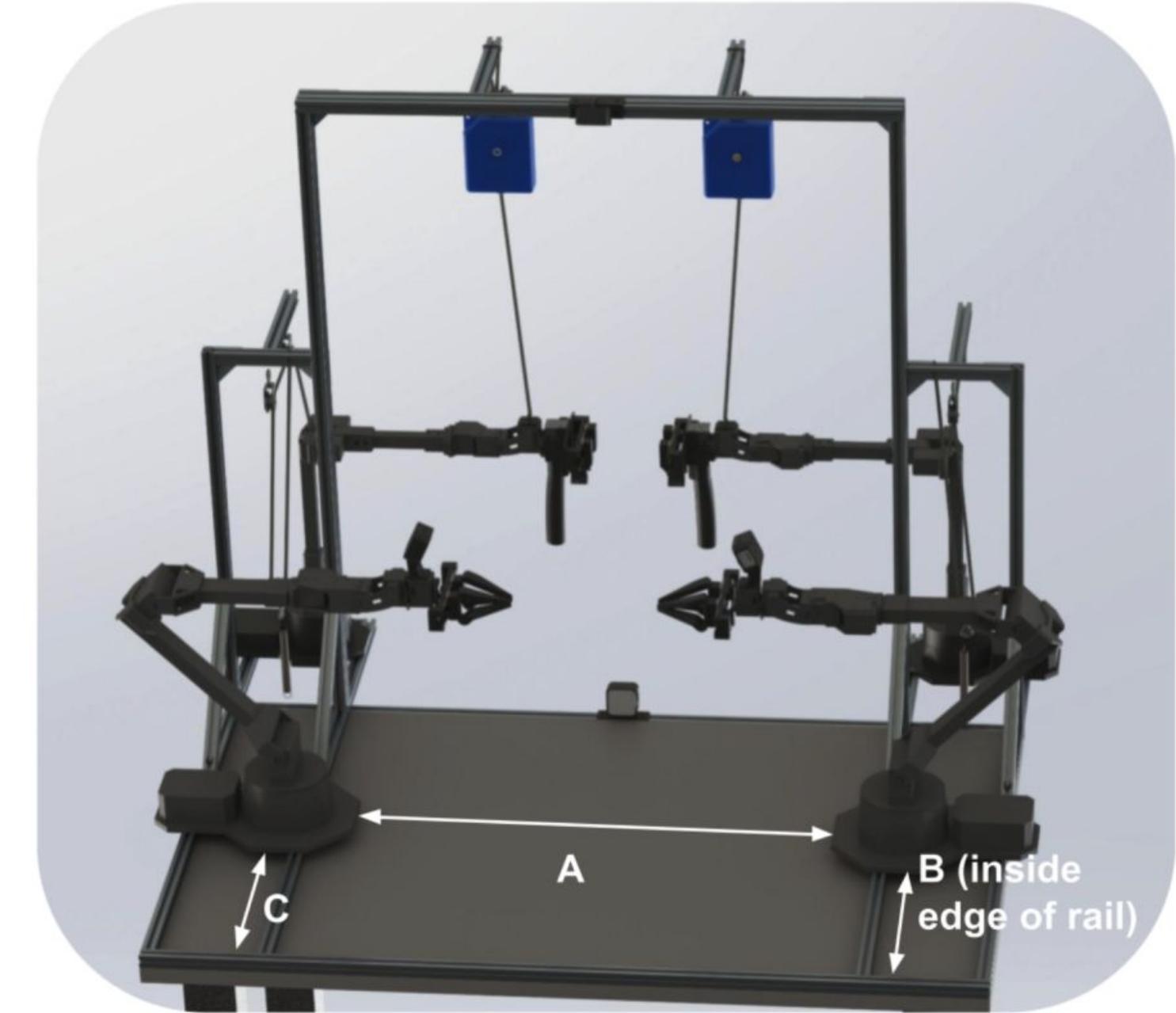
- Outperforms previous methods significantly



ALOHA Unleashed - Results

- Ridiculous number of demonstrations required
- Messy demonstrations help the agent learn to recover from mistakes

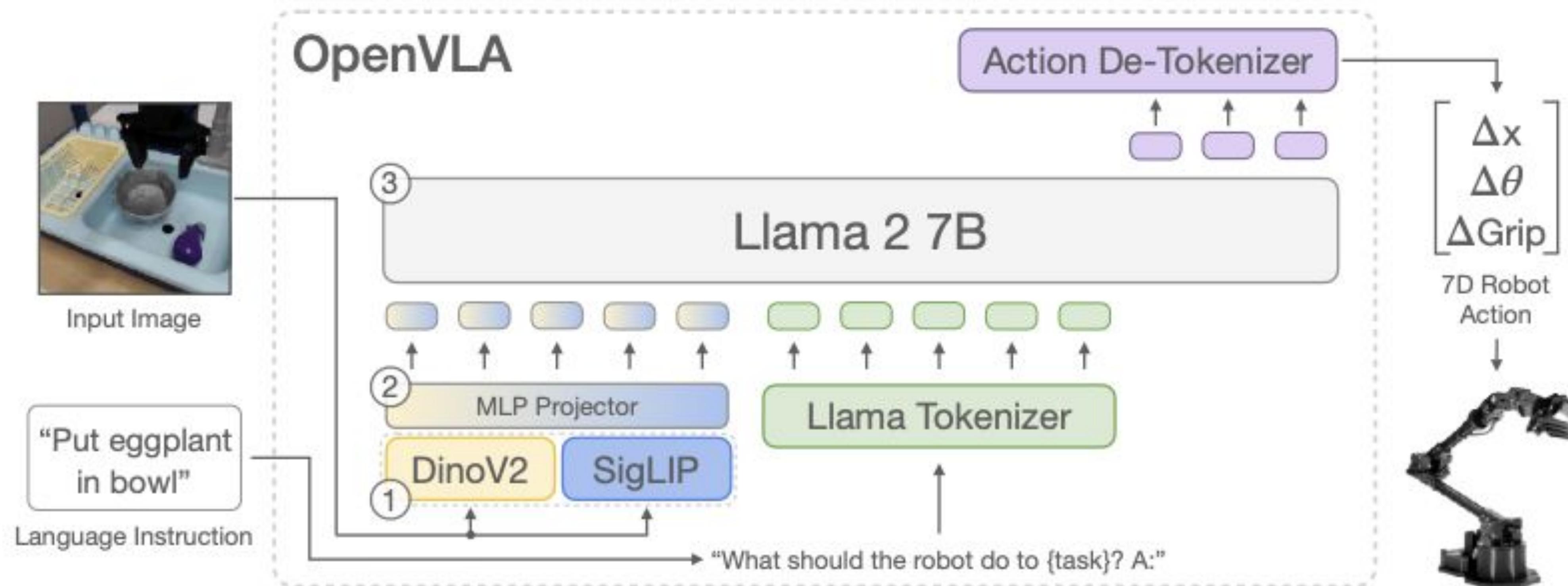
Task	Success Rate	Number of Demonstrations
ShirtEasy	75%	8658 (5345 Easy; 3313 Messy)
ShirtMessy	70%	
LaceEasy	70%	5133 (2212 Easy; 2921 Messy)
LaceMessy	40%	
FingerReplace	75%	5247
GearInsert-1	95%	
GearInsert-2	75%	4005
GearInsert-3	40%	
RandomKitchen-Bowl	95%	
RandomKitchen-Bowl+Cup	65%	3198 (216 In-Domain)
RandomKitchen-Bowl+Cup+Fork	25%	



Ridiculous amount of demonstrations.

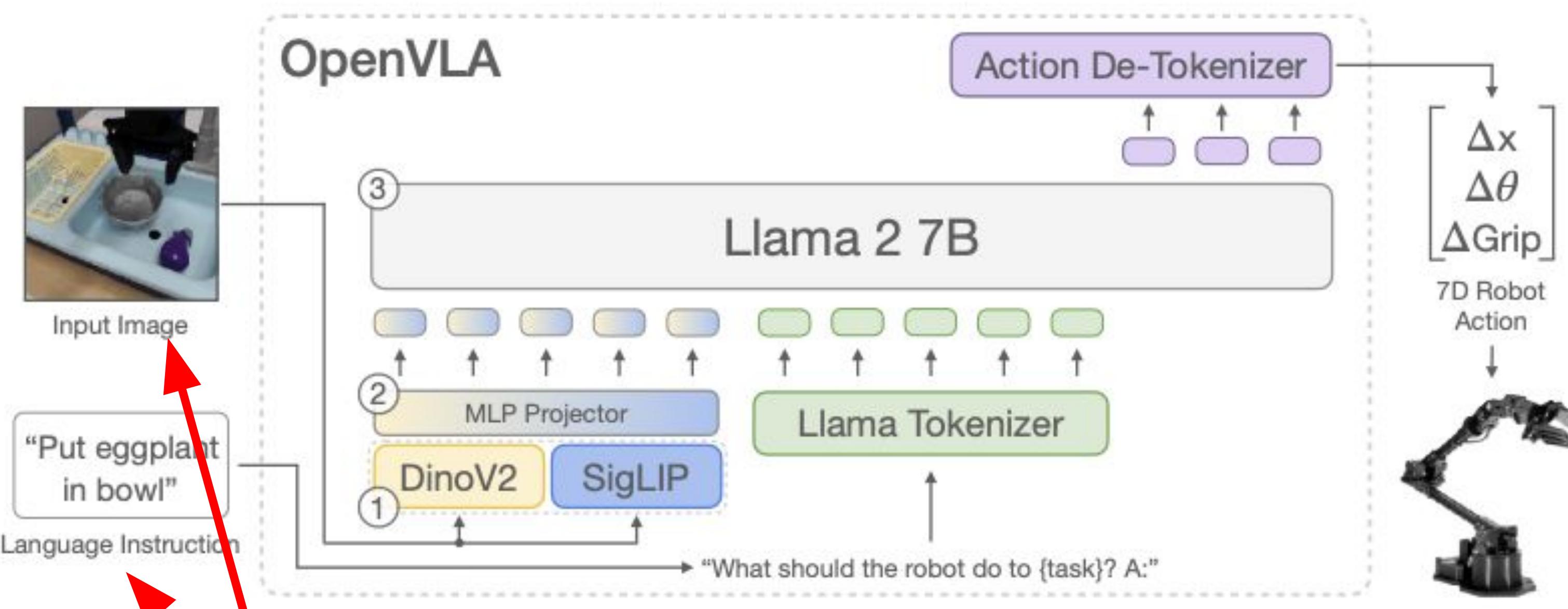


VLAs - Briefly



VLAs - Briefly

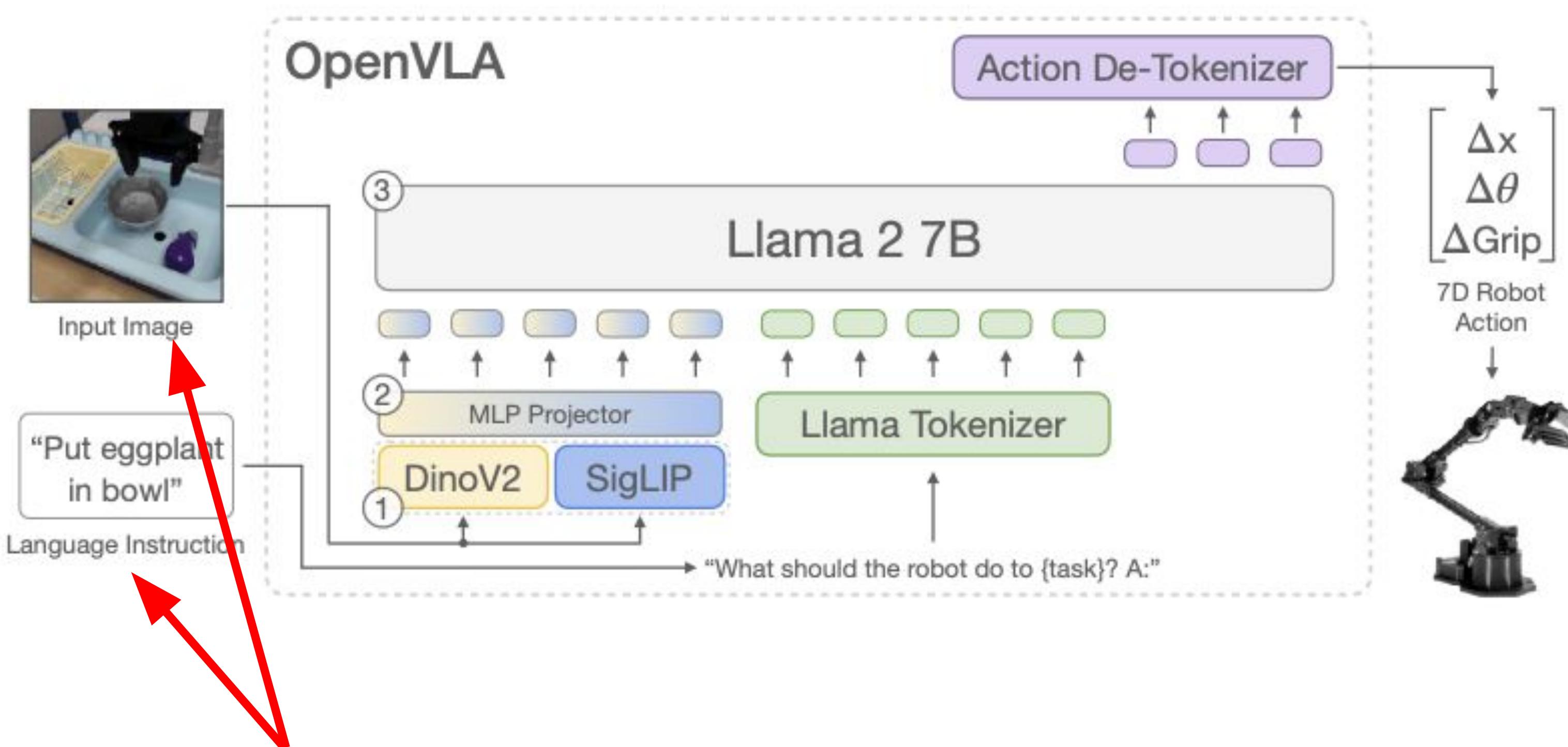
- Make use of LLMs
- Visual understanding from SigLIP and DinoV2



- Takes in visual observation + textual input



VLAs - Briefly



- Takes in visual observation + textual input

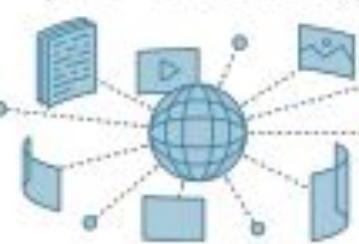
- Make use of LLMs
- Visual understanding from SigLIP and DinoV2
- The output translates to robot actions

 π_0

π cross-embodiment robot dataset



Internet-scale pre-training



Open X-Embodiment Dataset



π_0 vision-language-action model



High-quality post-training data



Zero-shot in-distribution tasks



Specialized post-training to difficult tasks



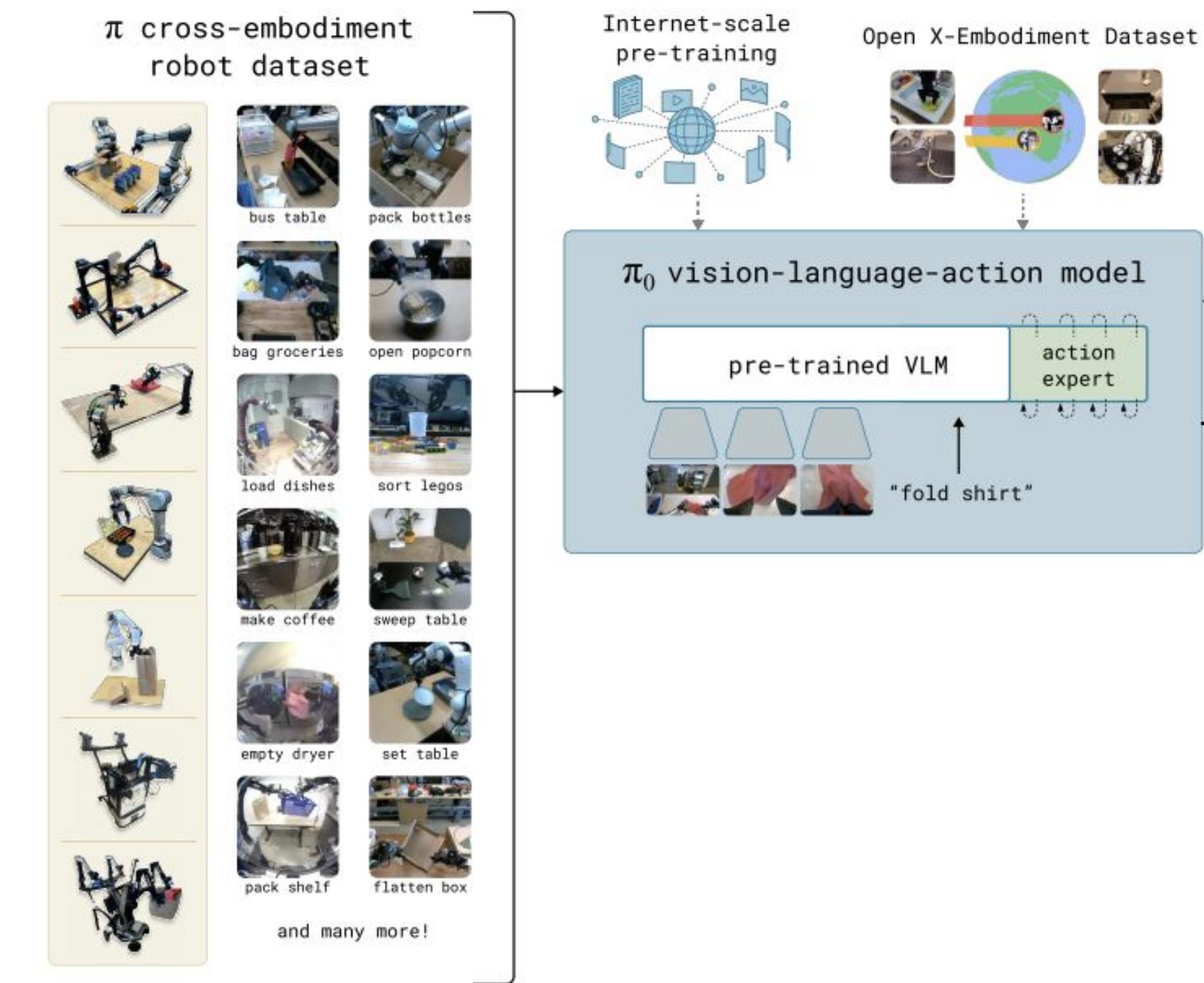
Efficient post-training to unseen tasks



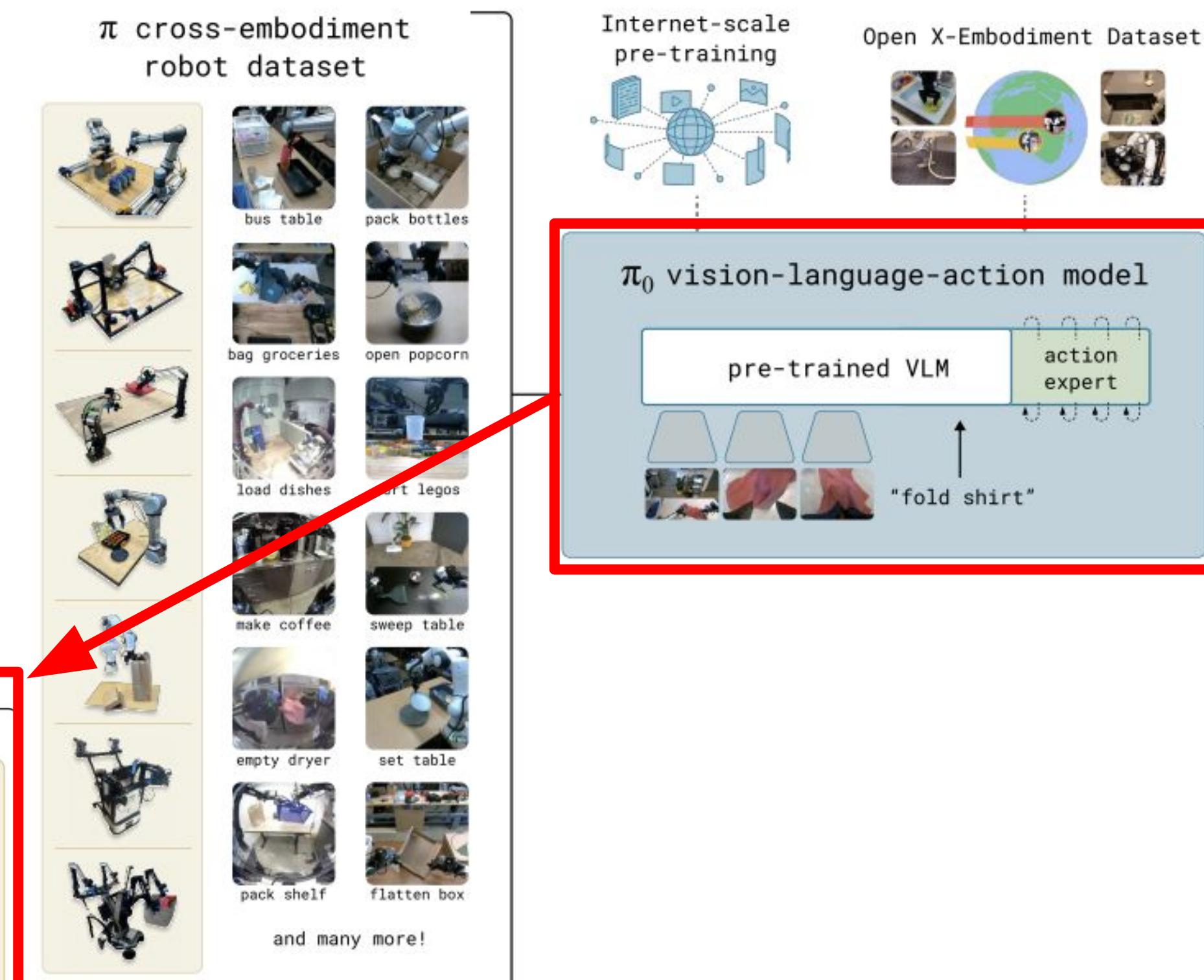
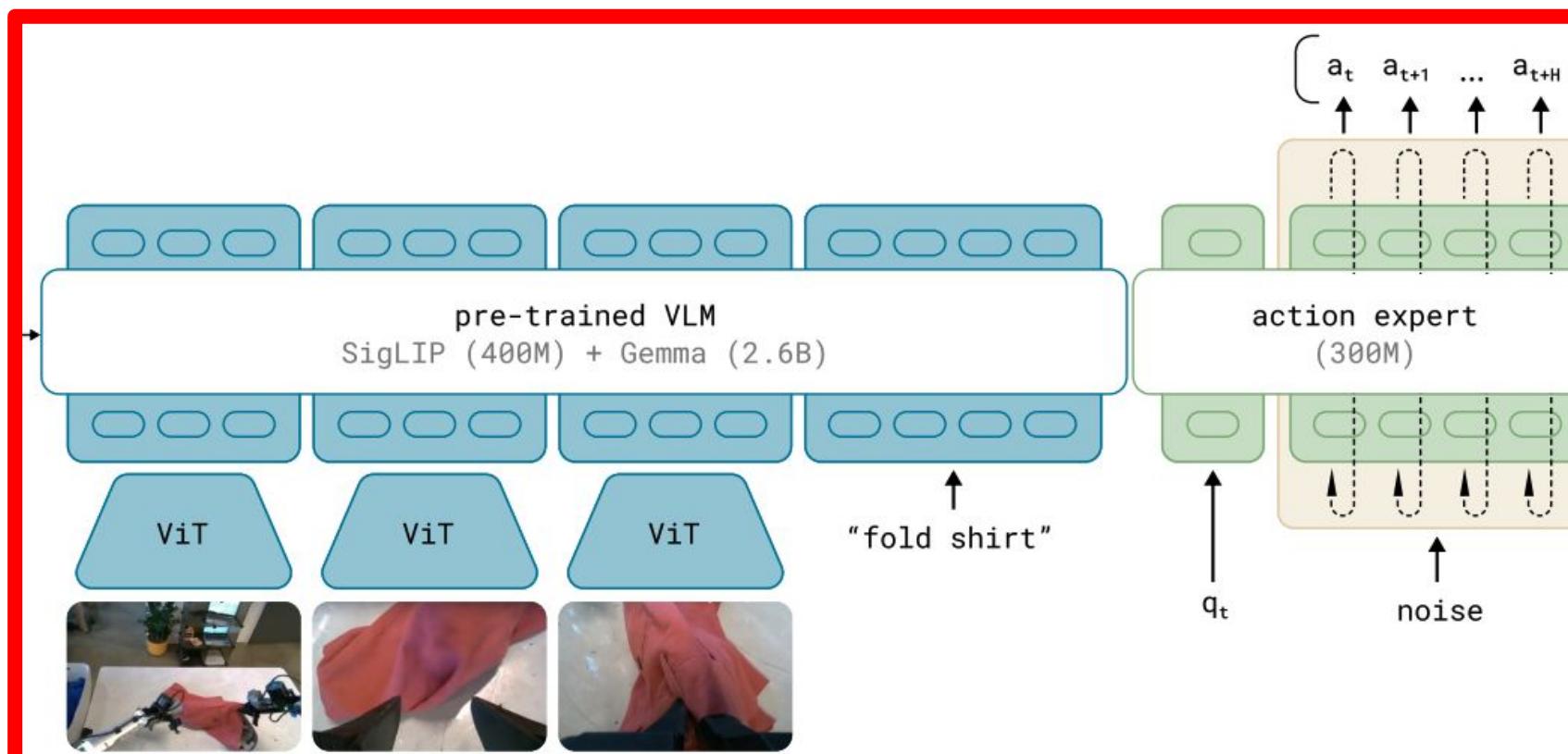


π_0

- A general framework for training generalist policies

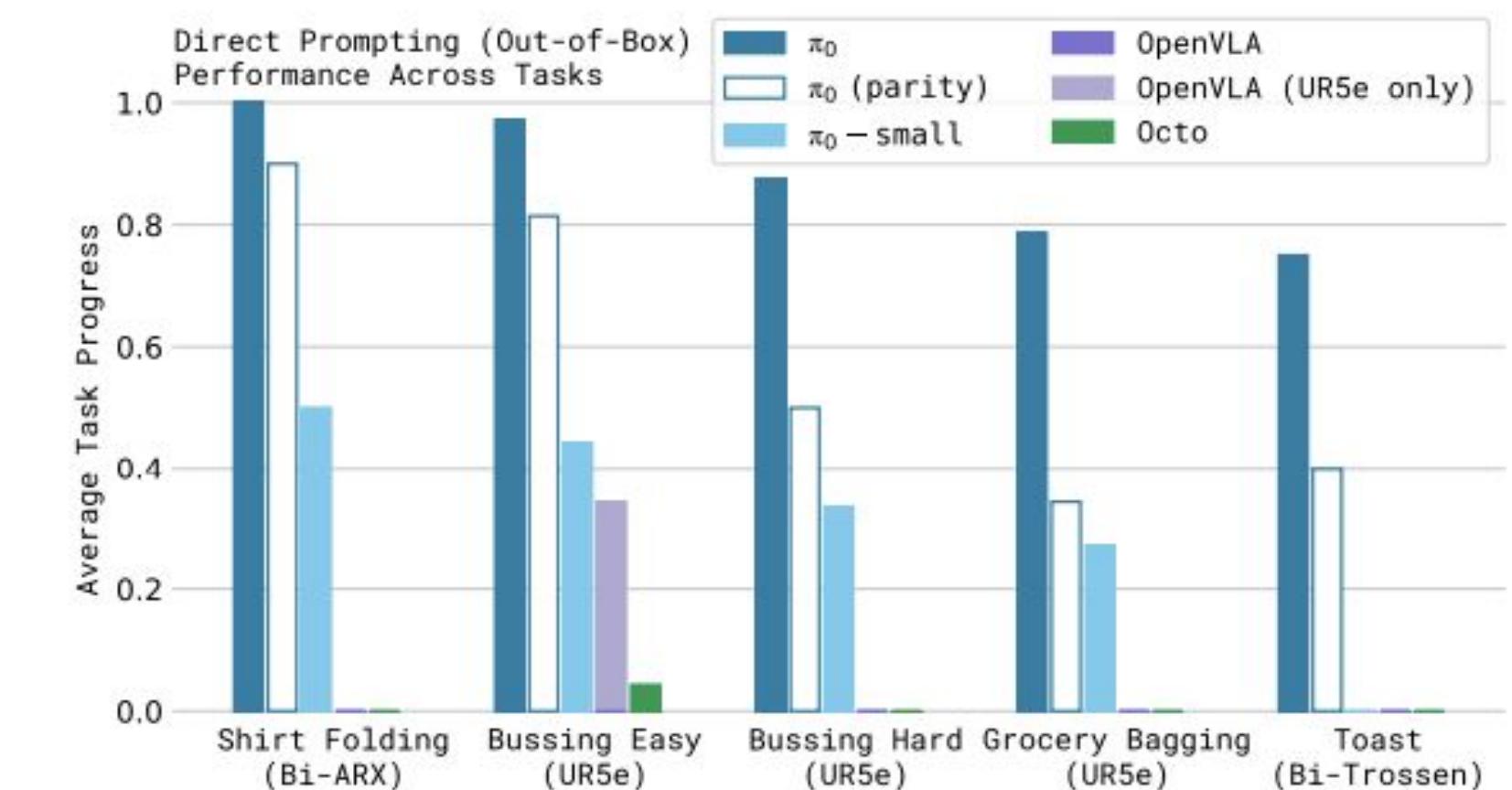
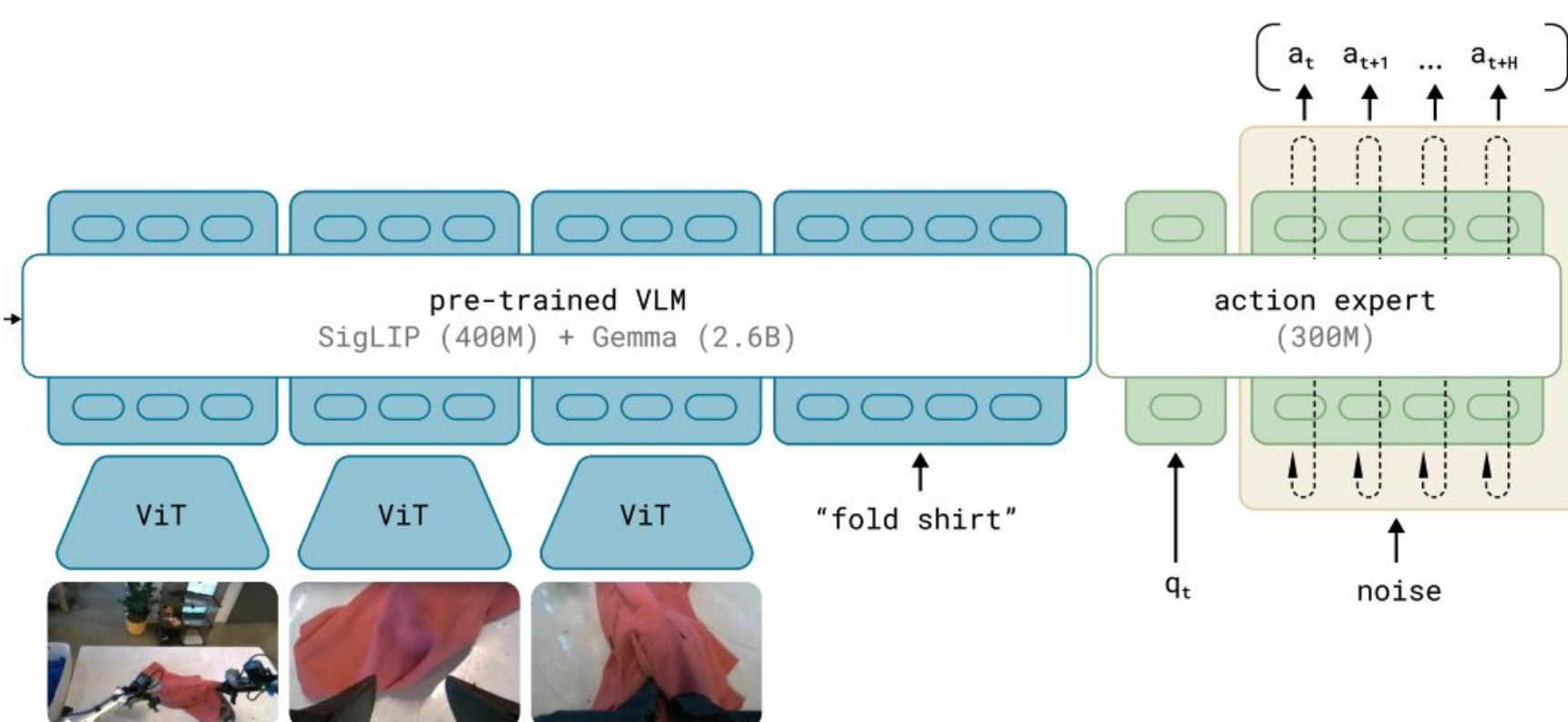


- A general framework for training generalist policies
- VLMs + diffusion variant(flow matching)



Results

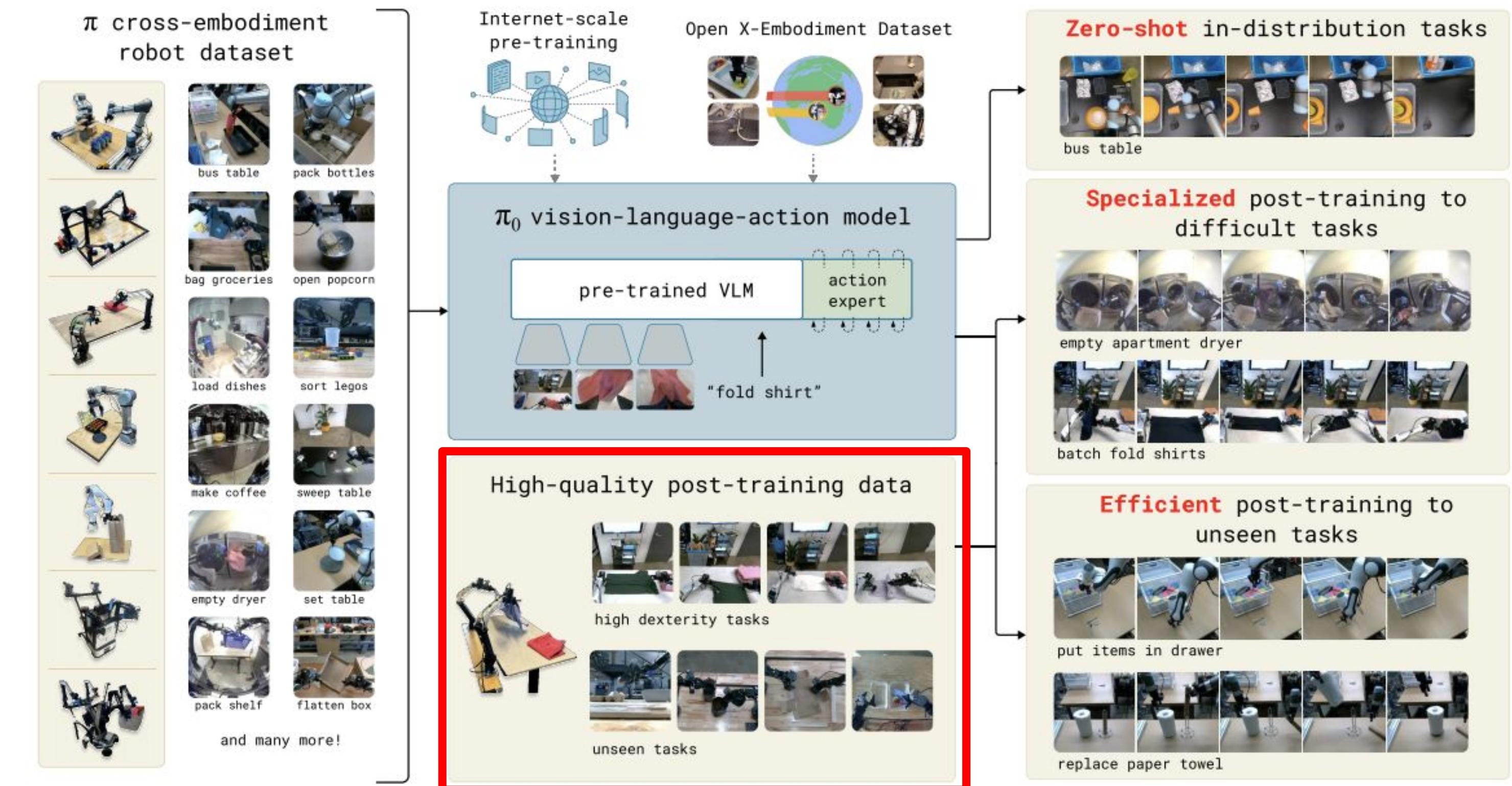
- Outperforms previous methods(OpenVLA, Octo) by a large margin



Performance out of the box

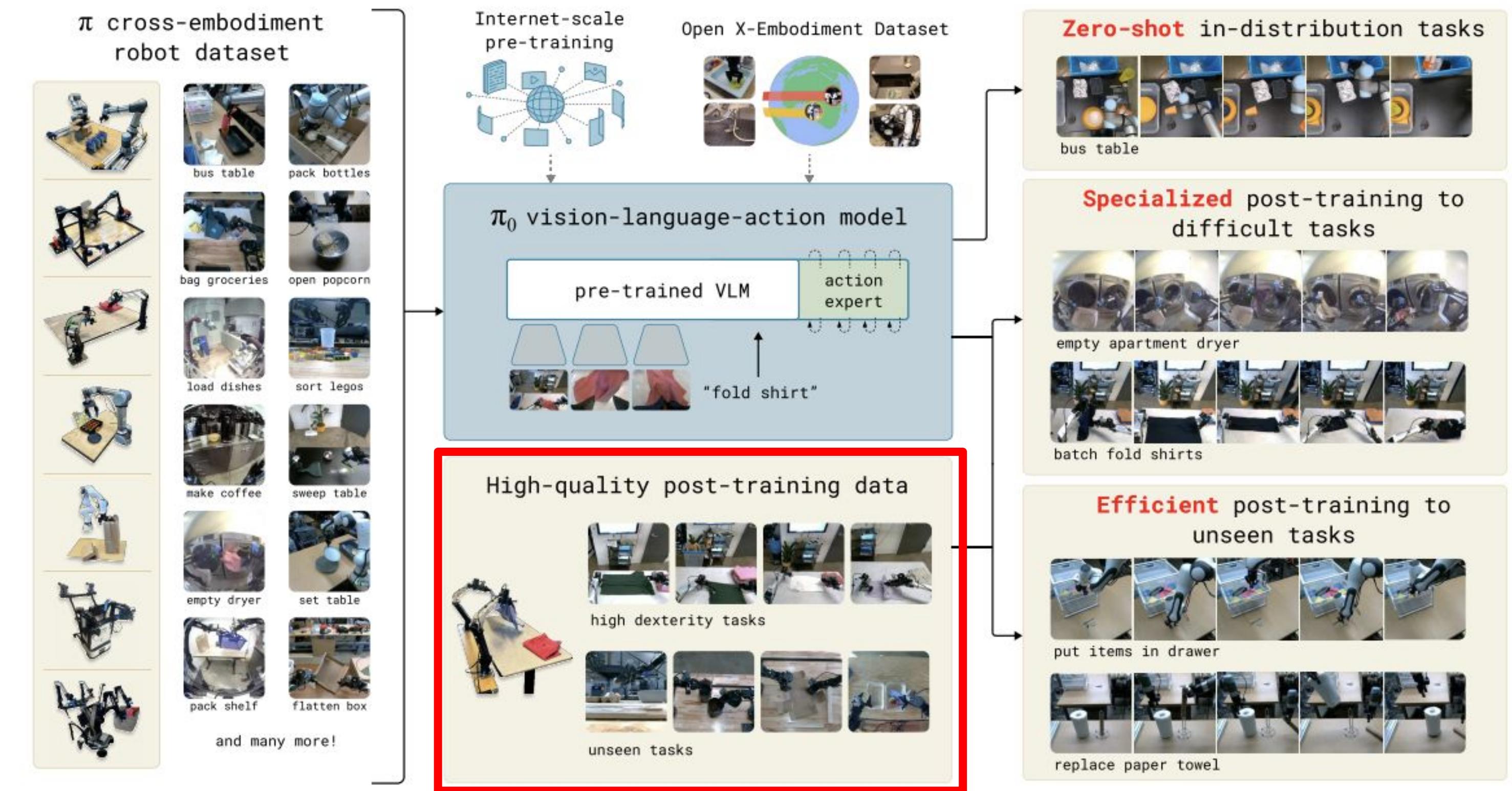
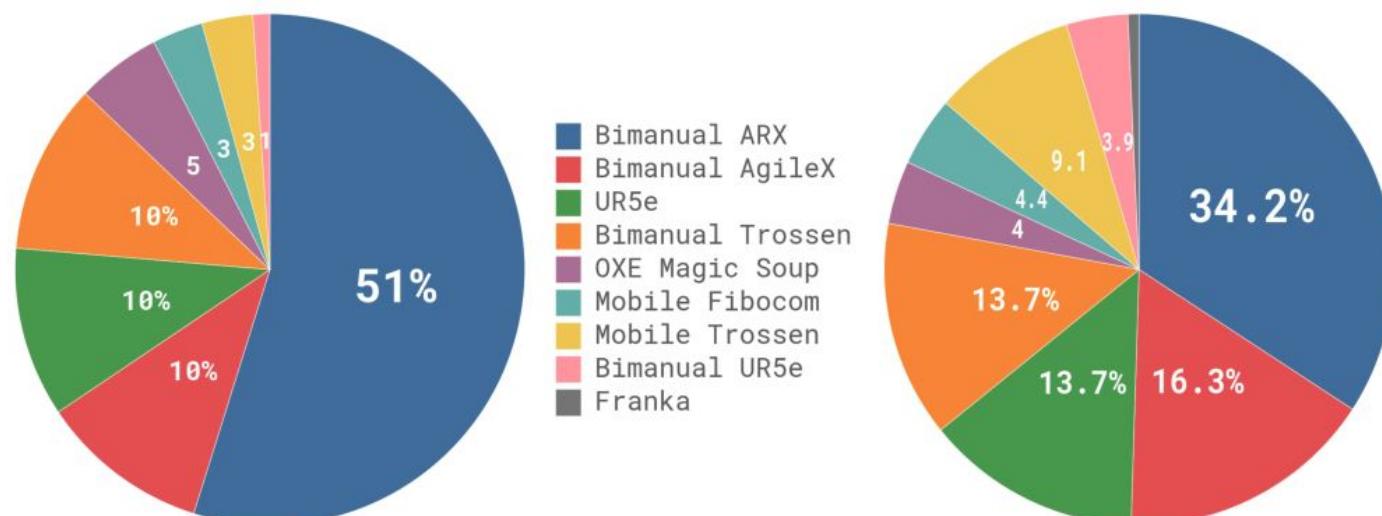
 π_0

- A general framework for training generalist policies
- VLMs + diffusion variant(flow matching)



π_0

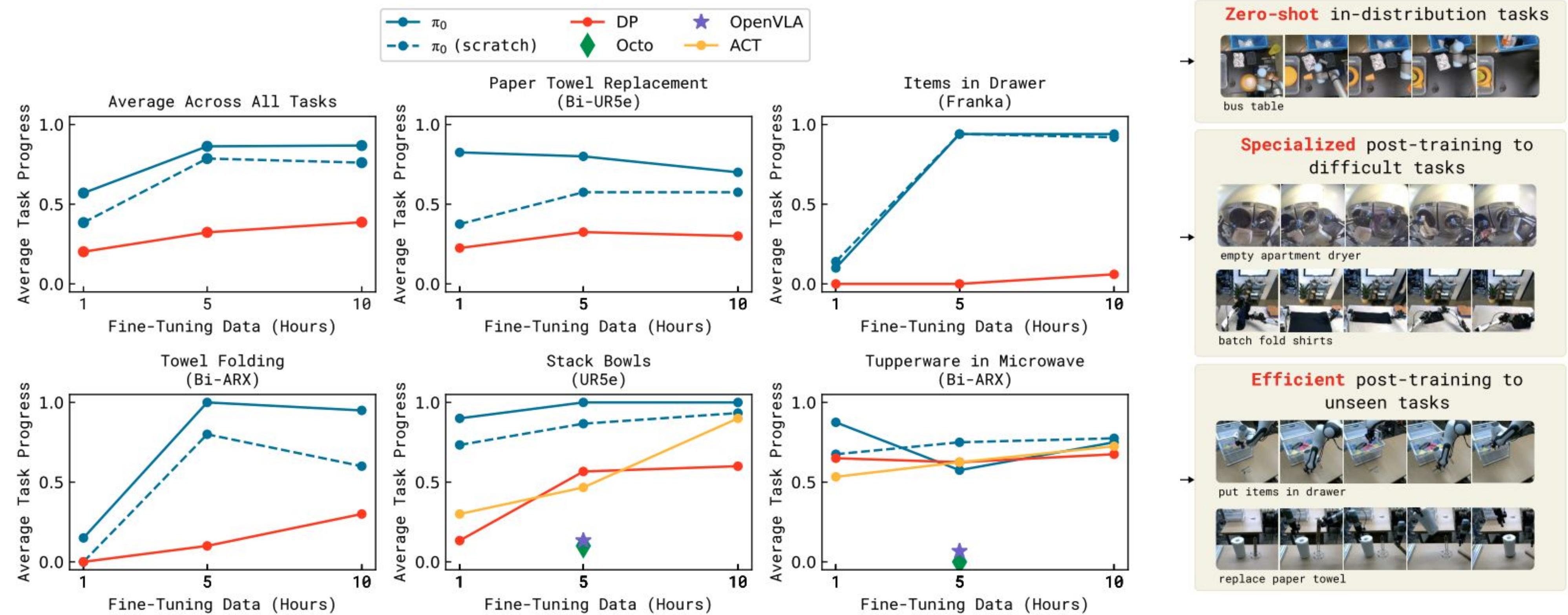
- Some difficult tasks needed 100s of hours of data
- Their dataset(below) contained 970M timesteps



- Post training fine tunes for difficult tasks.

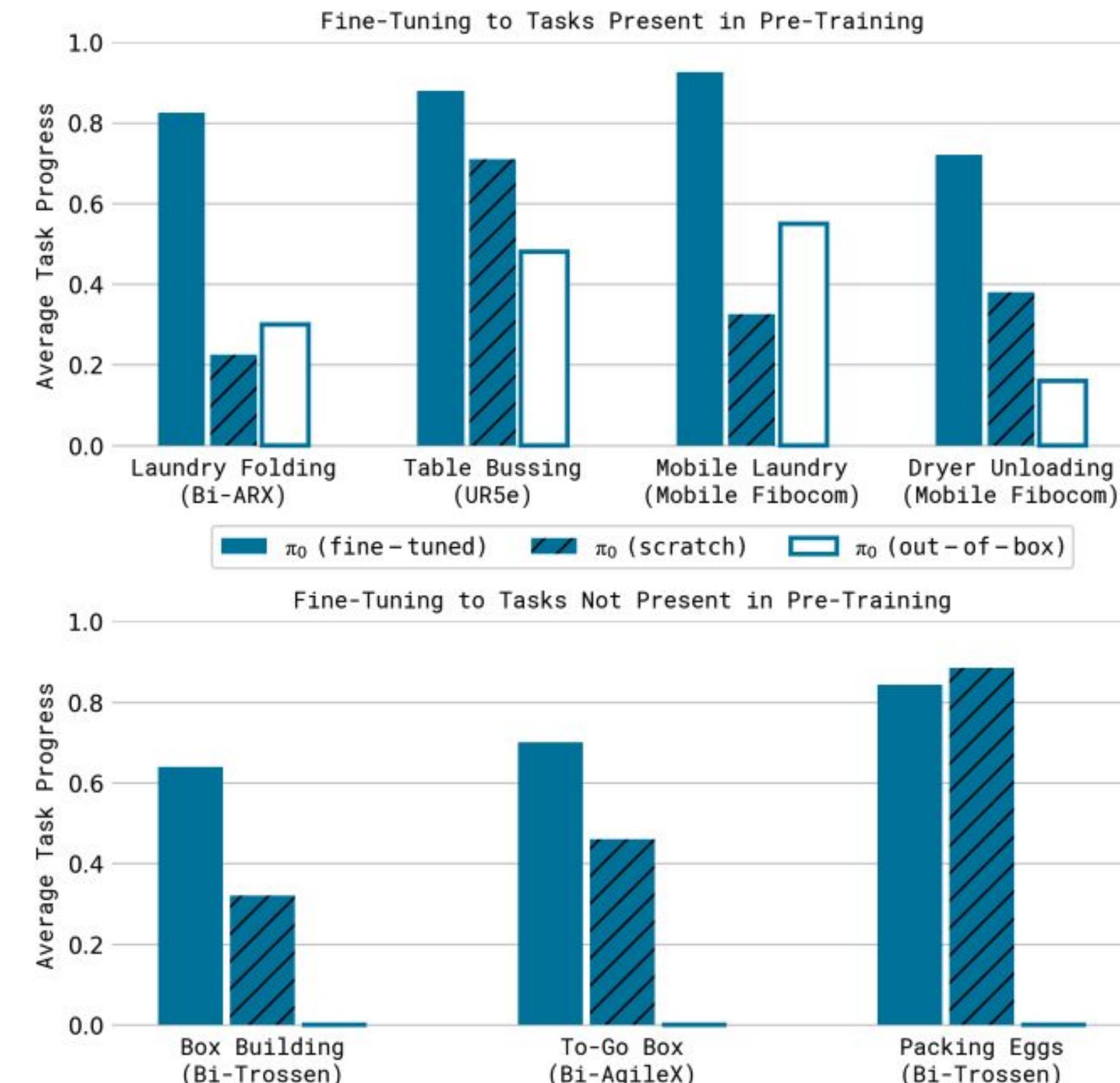


Results



Results

- More complex tasks that bring together smaller tasks in pre-training





π_0 from Physical Intelligence





Next Lecture:

Student Lecture 8

Foundational Models and Robot Manipulation





Reminder for Final Project Check-ins

Edstem post

12/04 Model Check-in: The presentations should include a discussion of the neural network models, loss functions, details on the training data and the test data, visualization of data and the amount of data, loss curves (train vs. test), and any other information you would like to share. Please upload your google-slides (not more than 4 slides per group) as "G#_model_training" in this [folder](#). **Due 9am 12/04**

12/11 Evaluation Check-in: Using the trained model, how accurate is the task performance on the manipulation task? What scenarios are you experimenting with, etc.? How is your method compared to baseline(s)? What are your ongoing experiments? Please upload your google-slides (not more than 4 slides per group) as "G#_evaluation_baselines" in this [folder](#). **Due 9am 12/11**





DeepRob

[Group 7] Lecture 7
Dual-arm Manipulation - Learning
by Ryan Roche, Matt Rajala, Adit Kadepurkar
University of Minnesota

