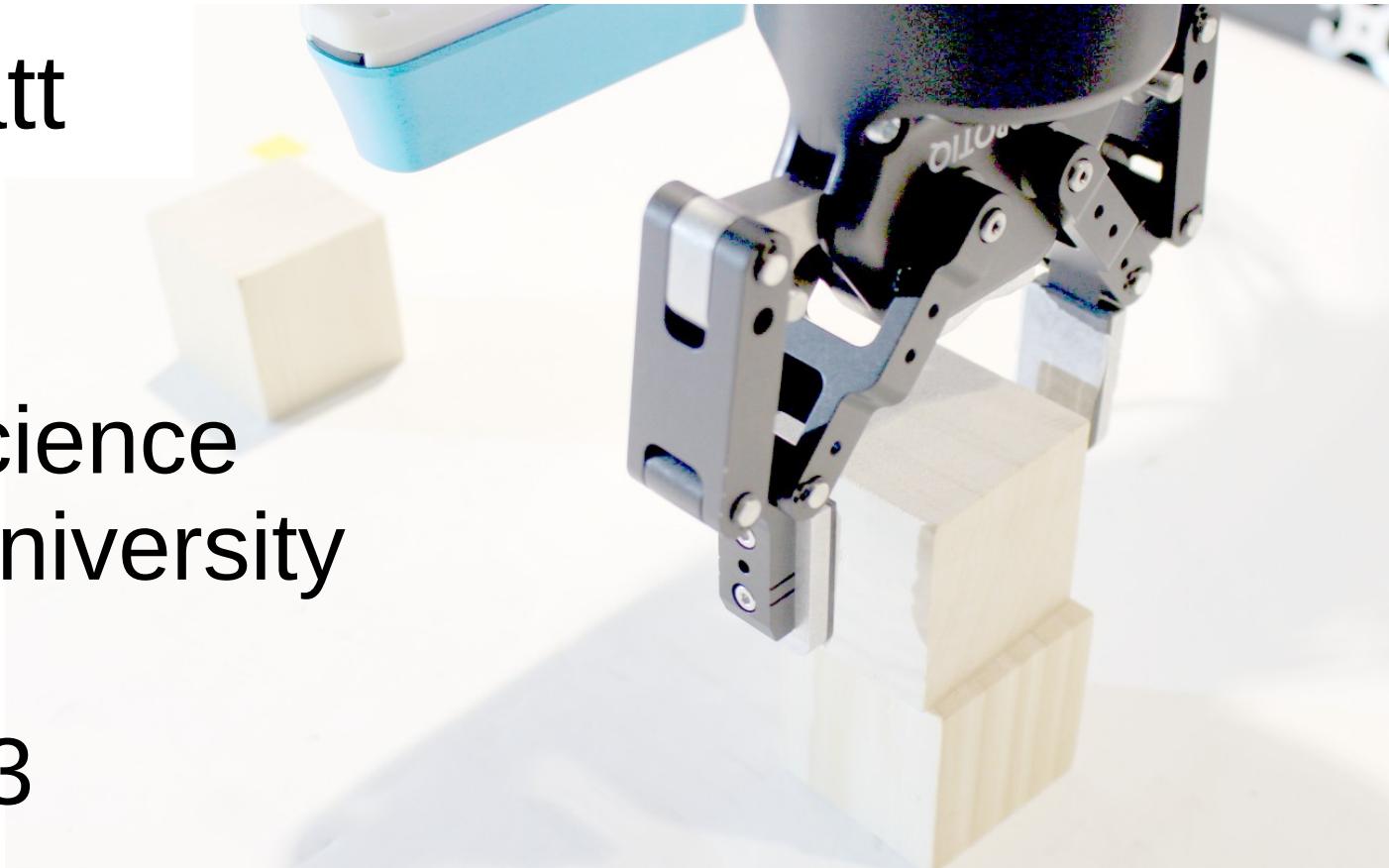


Applications of Symmetry to Robotics

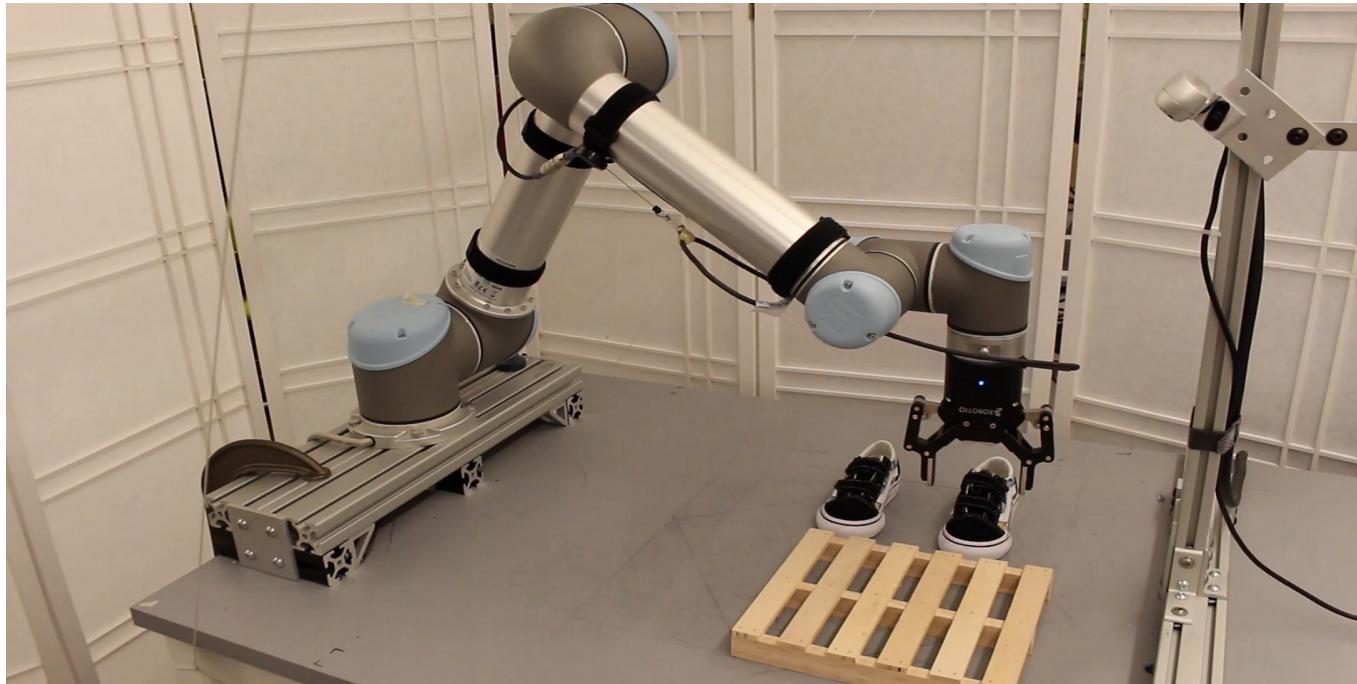
Rob Platt

Computer Science
Northeastern University

4/7/2023



Problem: Find Robot Control Policy

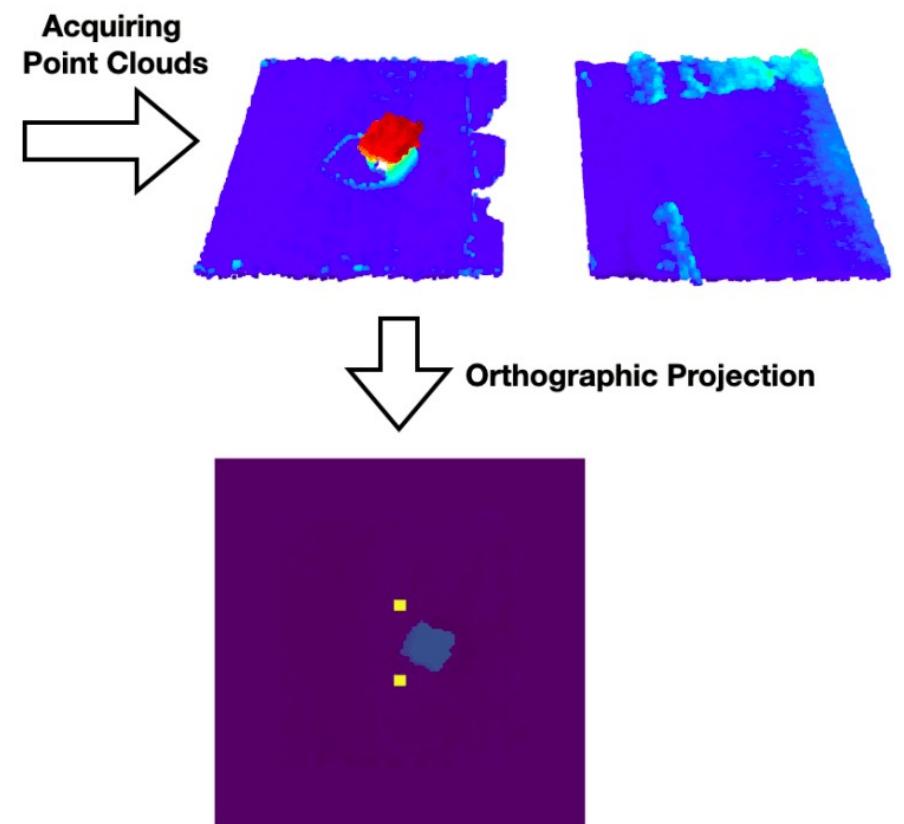
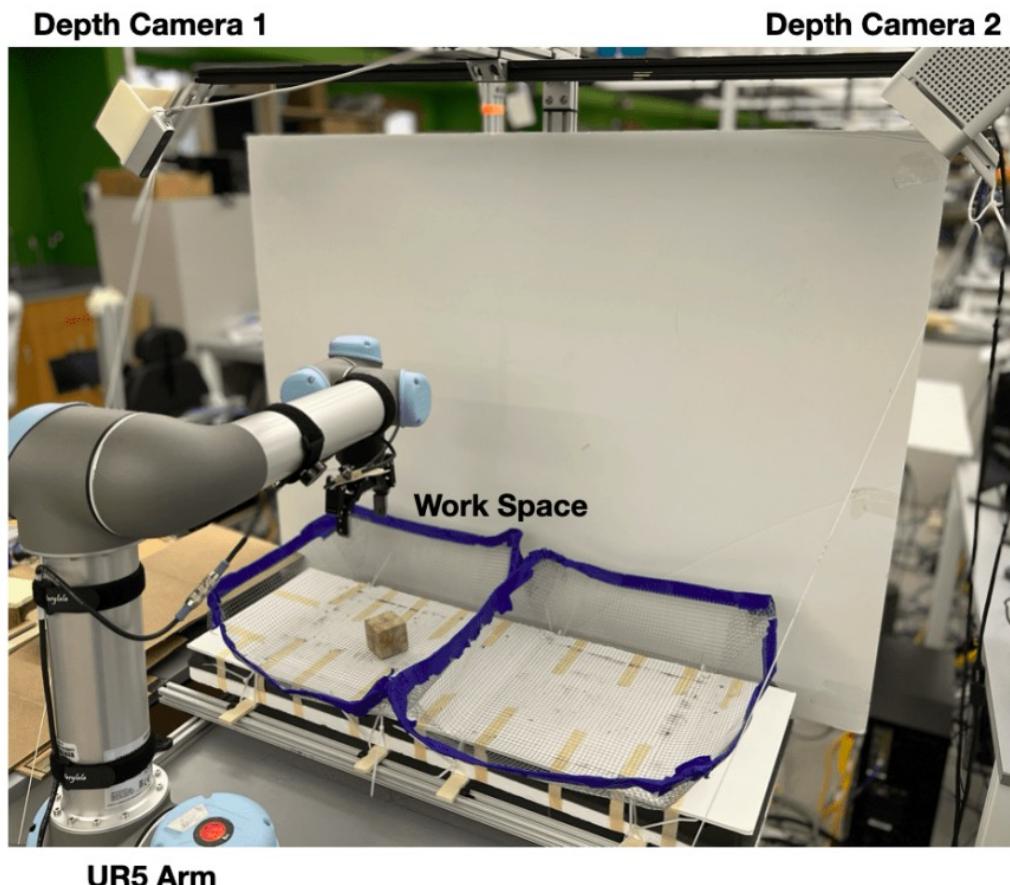


Learn Control Policy: $a = \pi(s)$

Control signal

Image, lidar,
force, tactile, etc.

Robotics Problems Often Have Geometric Structure



Symmetry In Transition Dynamics

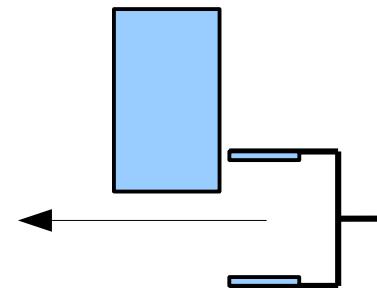
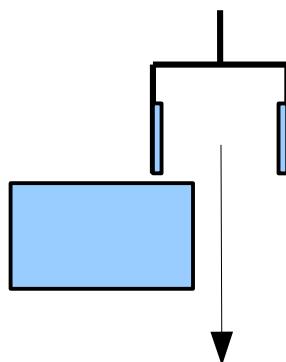


Image: $s \in \mathbb{R}^{h \times w}$

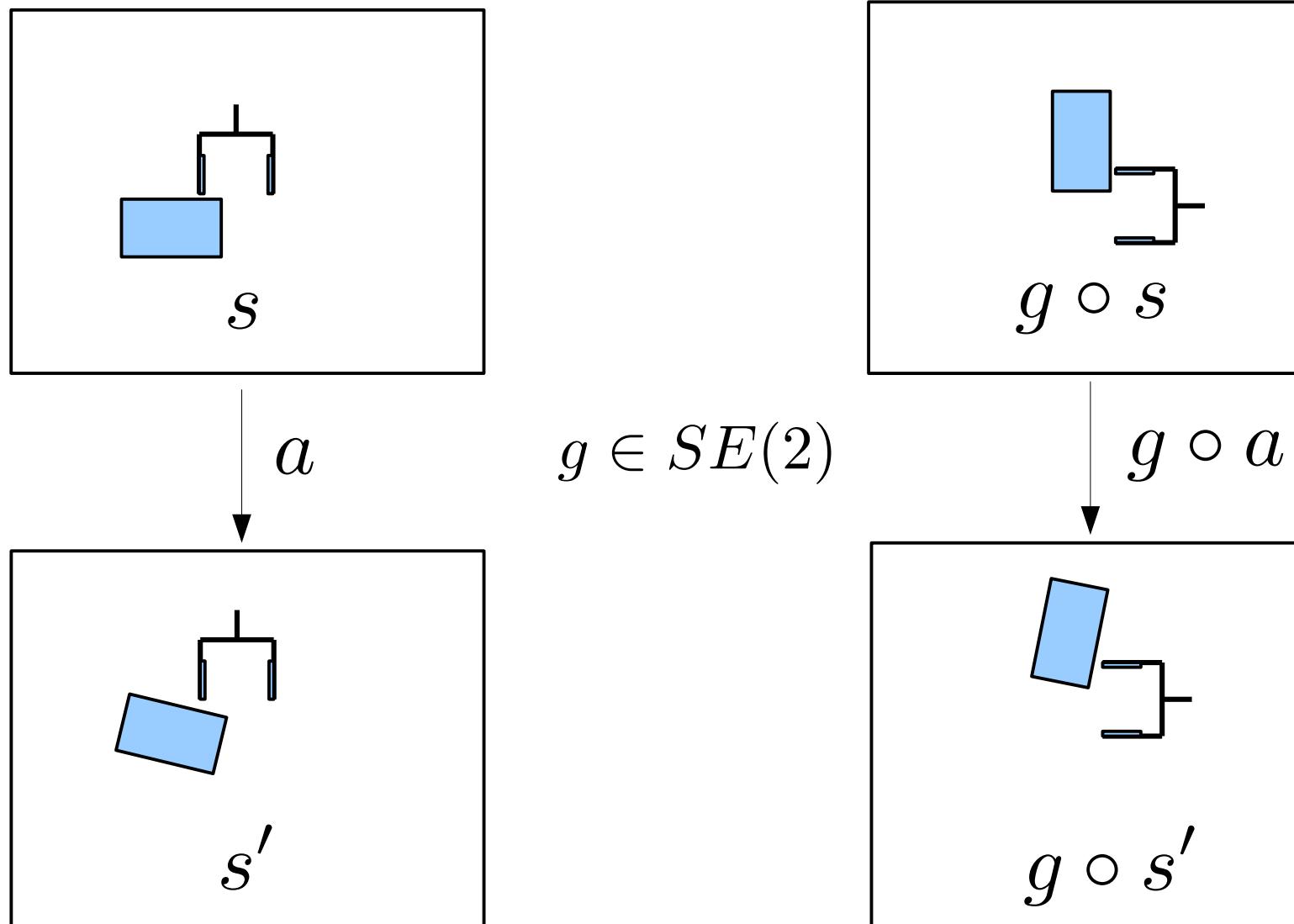
Velocity: $a \in \mathbb{R}^2$

$g \in SE(2)$

$g \circ s$

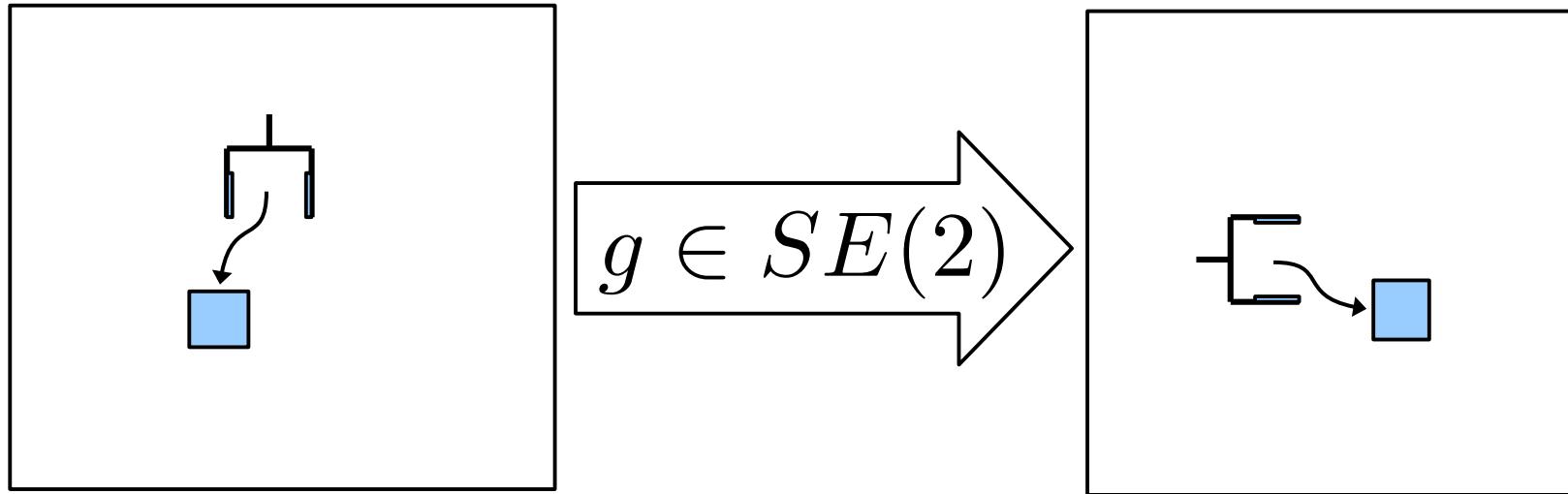
$g \circ a$

Symmetry In Transition Dynamics



$$p(s'|s, a) = p(g \circ s'|g \circ s, g \circ a)$$

Translates to Policy Symmetries



Policy: $a = \pi(s)$

Policy Symmetry: $g \circ \pi(s) = \pi(g \circ s)$

Symmetric MDPs Have Symmetric Optimal Value Functions and Policies

Definition 4.1 (G -invariant MDP). A G -invariant MDP $\mathcal{M}_G = (S, A, T, R, G)$ is an MDP $\mathcal{M} = (S, A, T, R)$ that satisfies the following conditions:

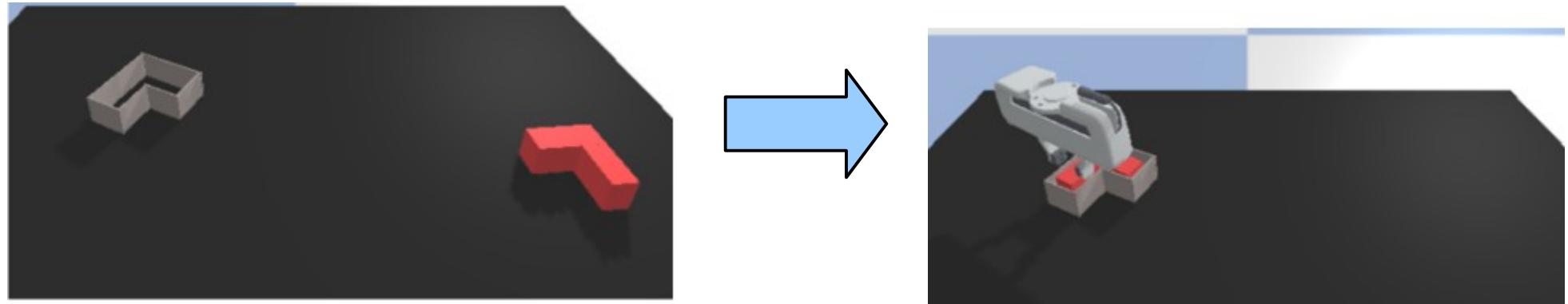
1. Reward Invariance: *The reward function is invariant to the action of the group element $g \in G$, $R(s, a) = R(gs, ga)$.*
2. Transition Invariance: *The transition function is invariant to the action of the group element $g \in G$, $T(s, a, s') = T(gs, ga, gs')$.*

Proposition 4.1. Let \mathcal{M}_G be a group-invariant MDP. Then its optimal Q -function is group invariant, $Q^*(s, a) = Q^*(gs, ga)$, and its optimal policy is group-equivariant, $\pi^*(gs) = g\pi^*(s)$, for any $g \in G$.

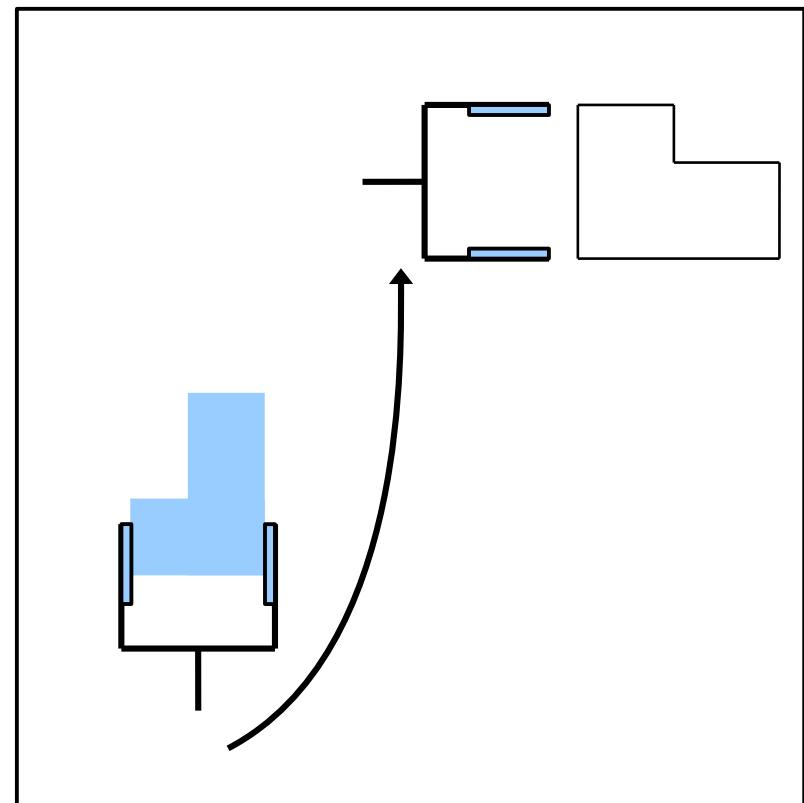
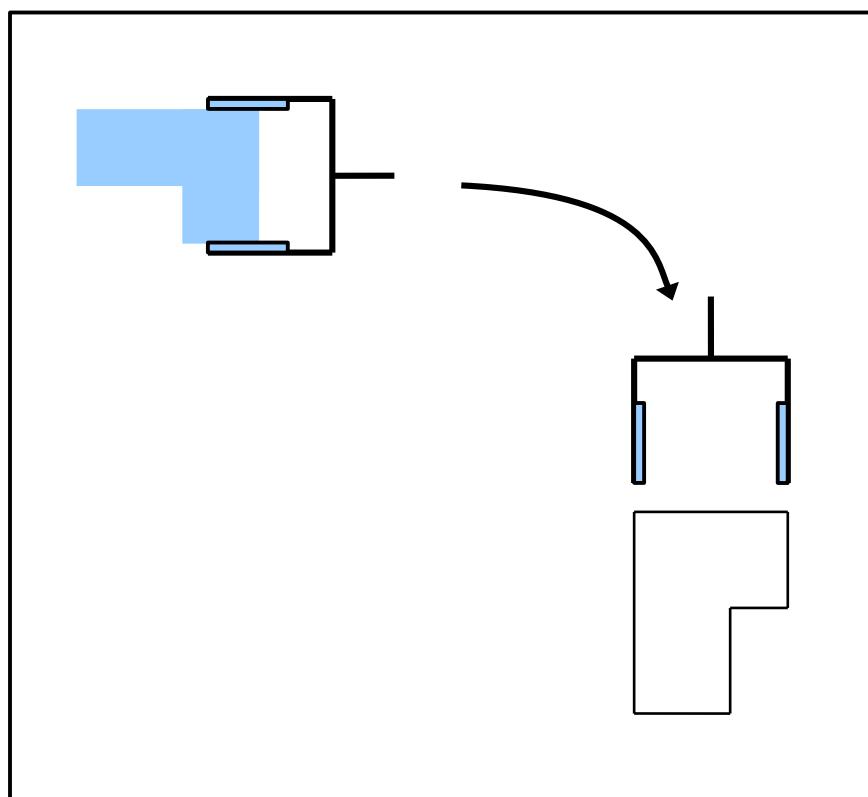
Hard code symmetries into solutions:

$$Q(s, a) = Q(g \circ s, g \circ a)$$
$$g \circ \pi(s) = \pi(g \circ s)$$

Object Factored Symmetries



Object Factored Symmetries



$$g \in SE(2) \times SE(2)$$

Symmetries in SE(3)



Gameplan: Use escnn, e3nn, etc.

General E(2)-Equivariant Steerable CNNs

[Documentation](#) | [Experiments](#) | [Paper](#) | [Thesis](#) | [new escnn library](#)

E(n)-equivariant Steerable CNNs (*escnn*)

[Documentation](#) | [Paper ICLR 22](#) | [Paper NeurIPS 19](#) | [e2cnn library](#) | [e2cnn experiments](#) | [Thesis](#)

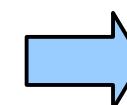
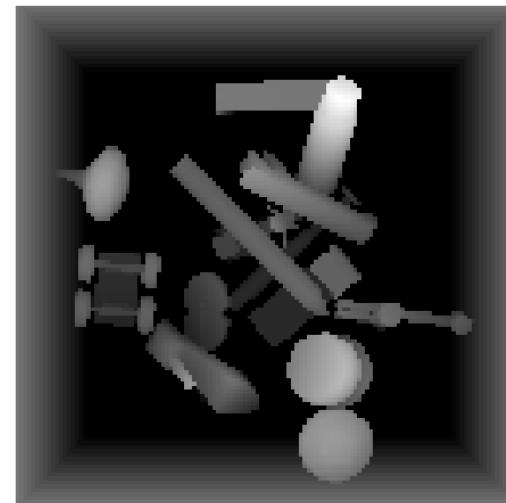
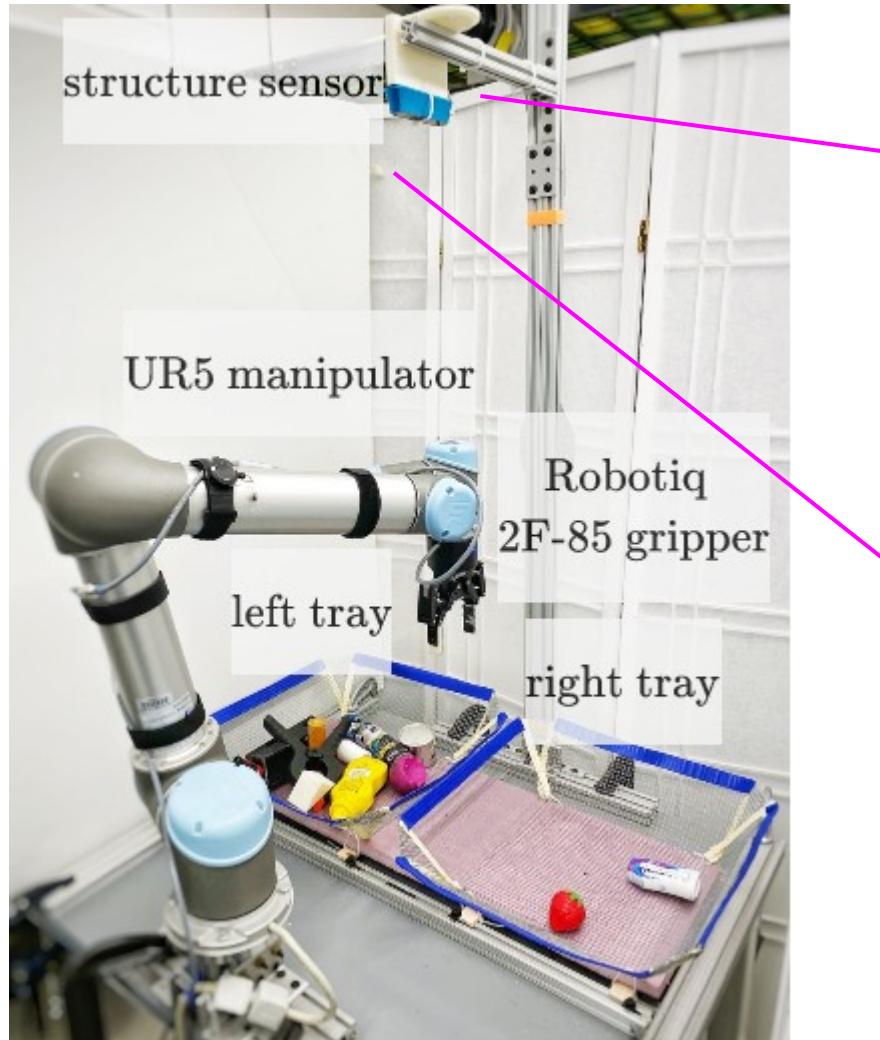
Euclidean neural networks

[coverage 96%](#) [DOI 10.5281/zenodo.7430260](#)

[Documentation](#) | [Code](#) | [ChangeLog](#) | [Colab](#)

The aim of this library is to help the development of E(3) equivariant neural networks. It contains fundamental mathematical operations such as [tensor products](#) and [spherical harmonics](#).

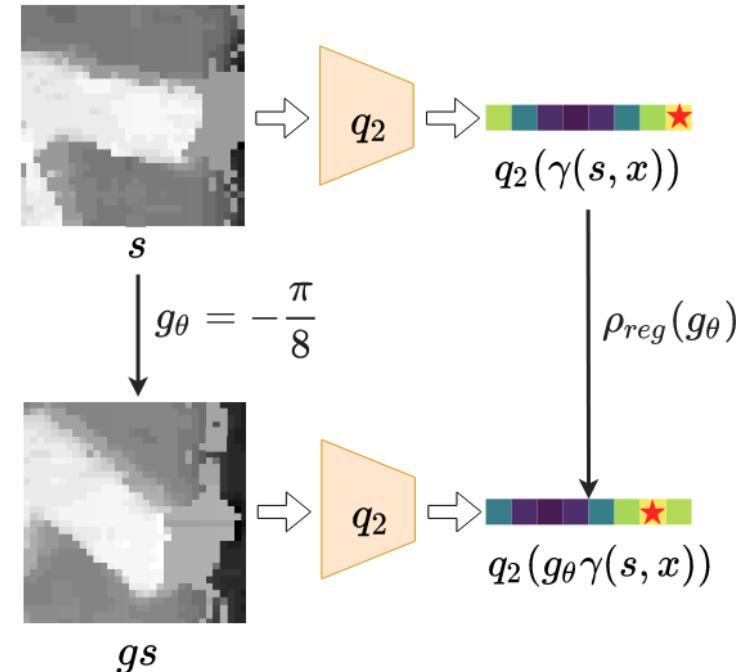
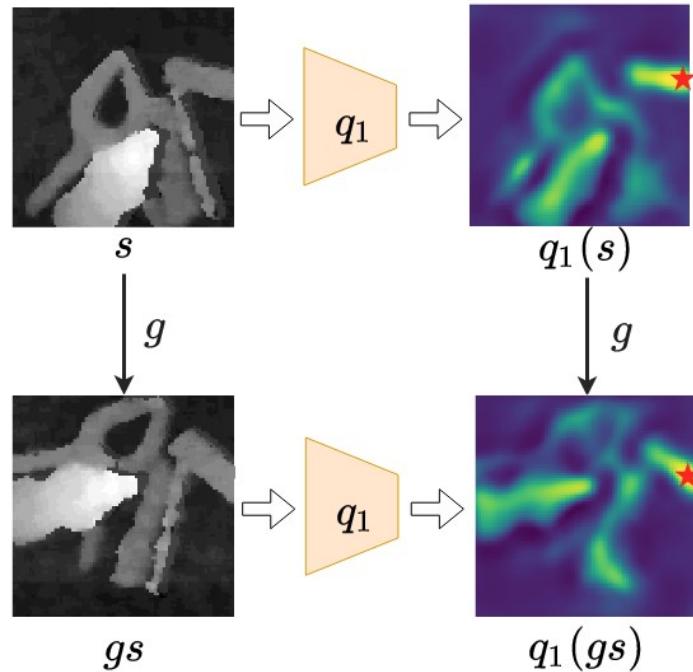
#1) Grasp Learning in SE(2)



Grasp pose
 (x, y, θ)

Depth image

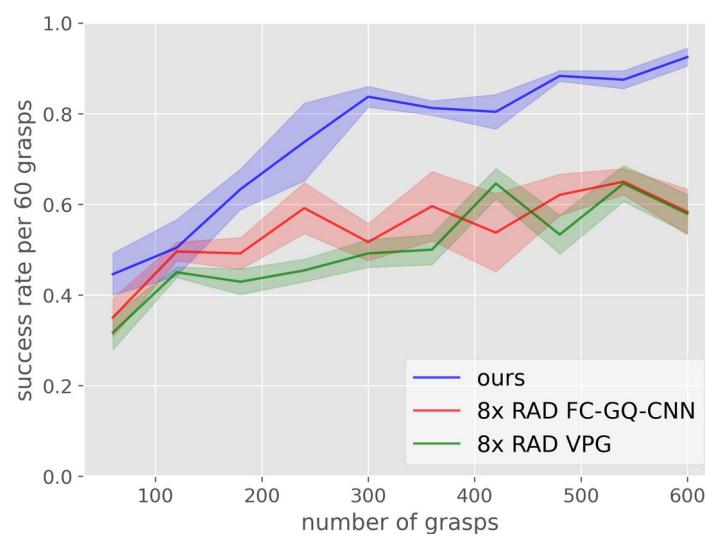
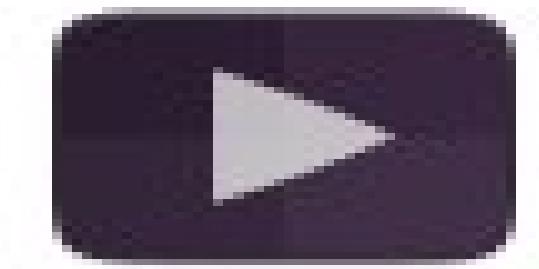
#1) Grasp Learning in SE(2)



Type of equivariance: as input image rotates, output image also rotates.

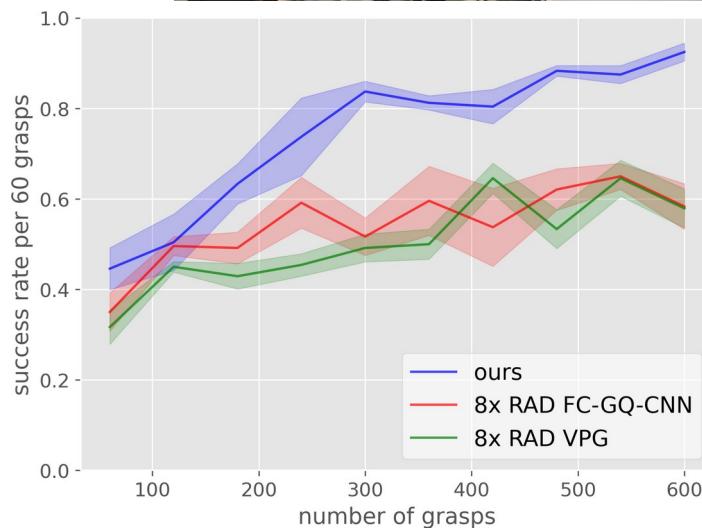
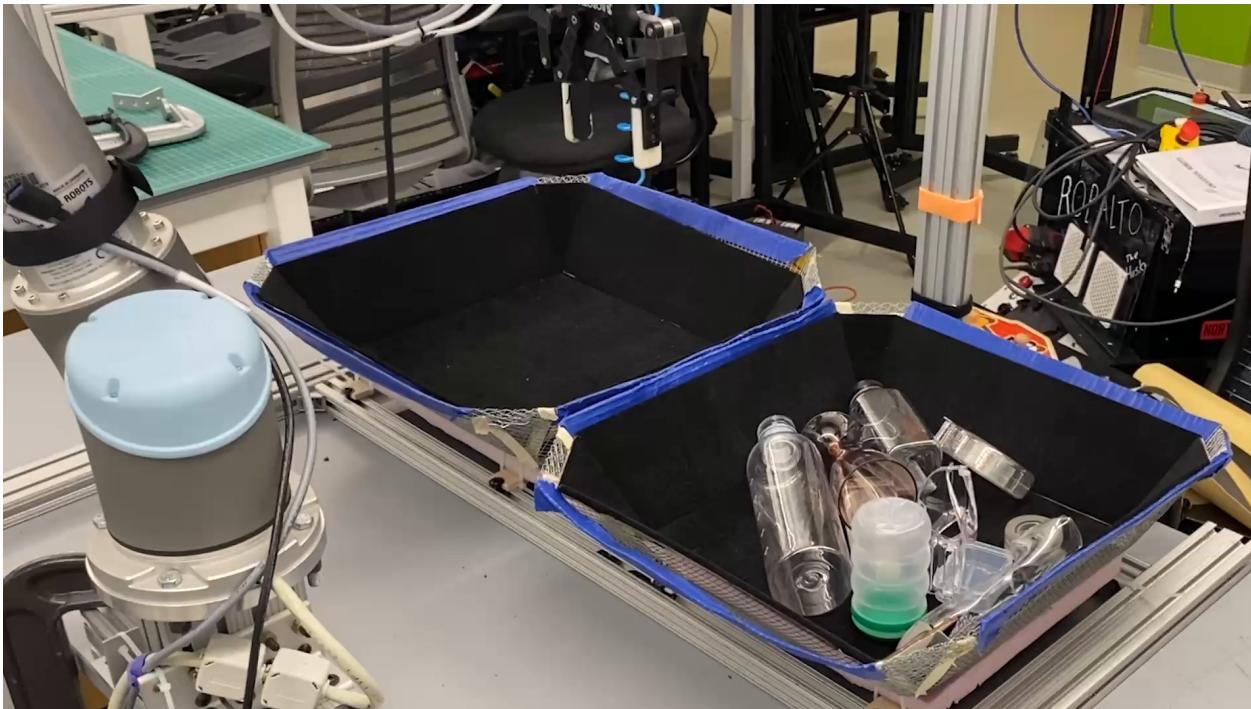
Type of equivariance: as input image rotates, output vector does circular shift.

#1) Grasp Learning in SE(2)

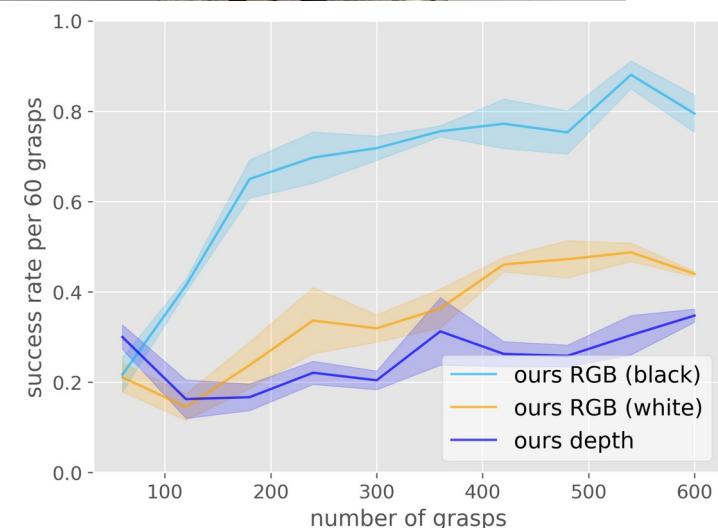


600 grasps = 1 hr, 20 min

#1) Grasp Learning in SE(2)

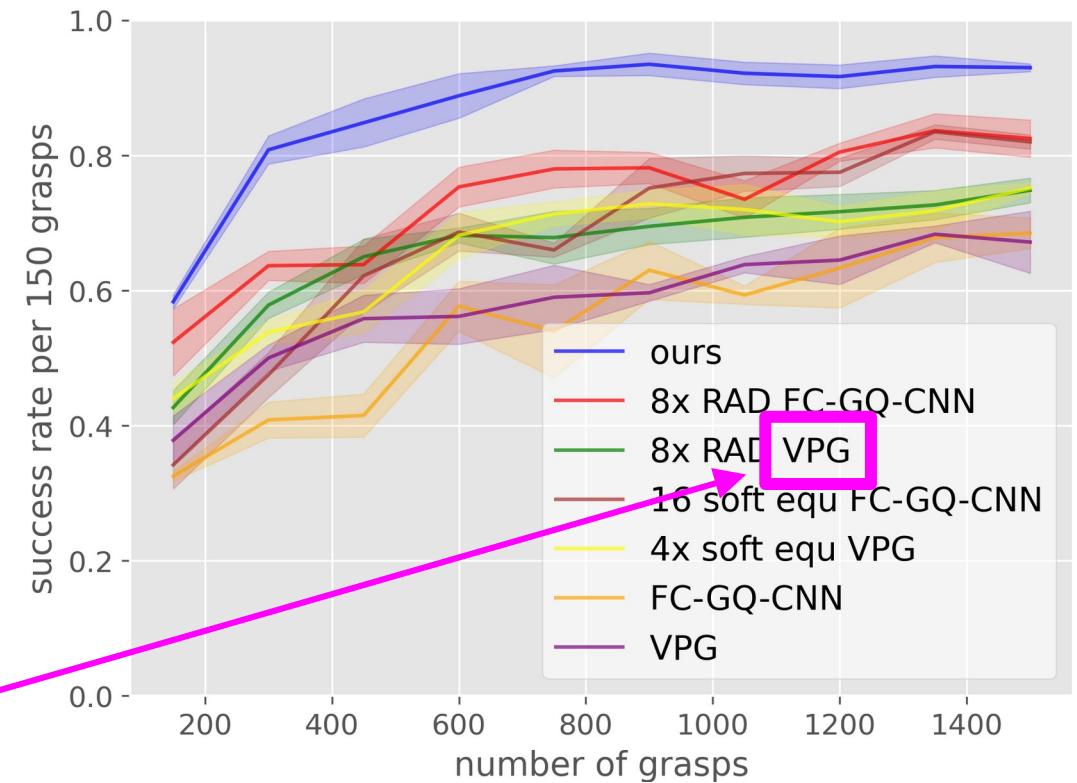
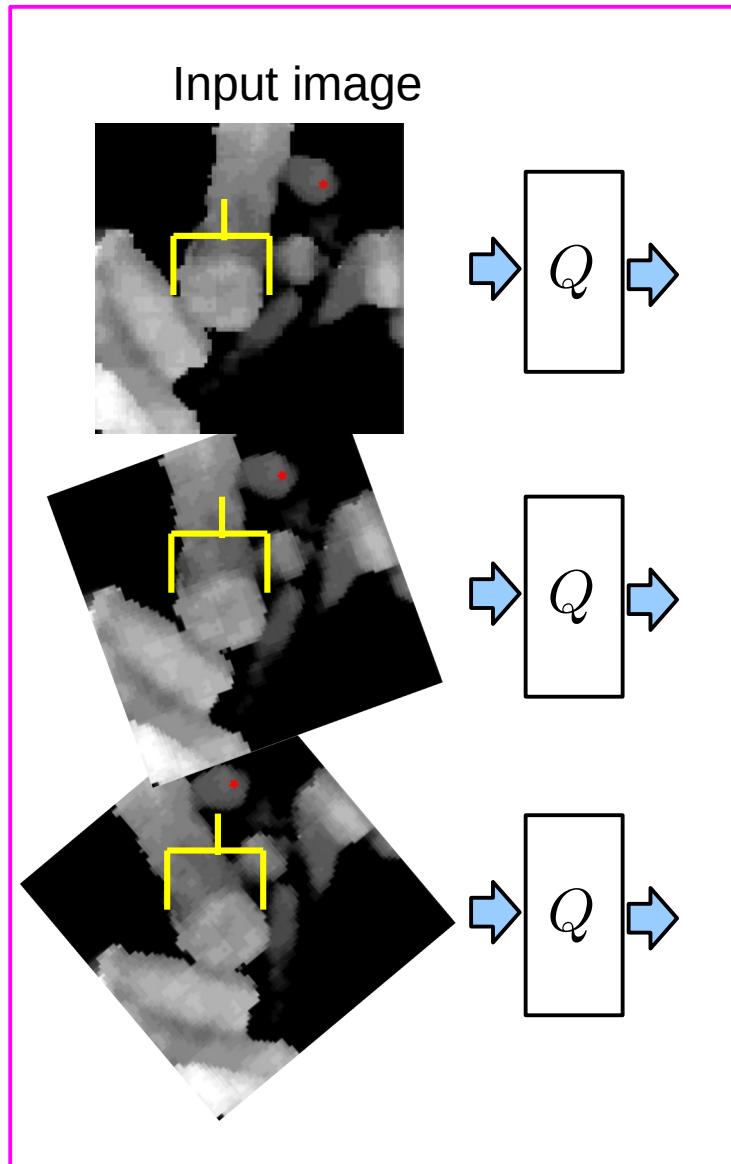


opaque



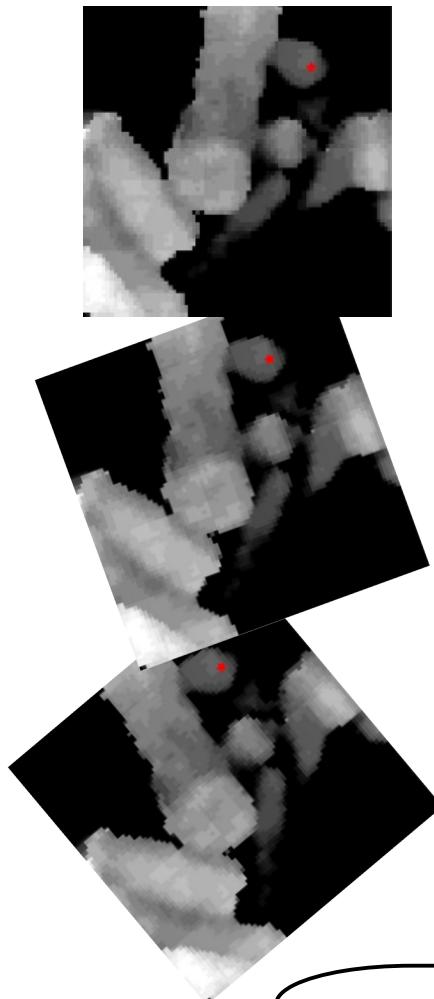
transparent

Equivariance via canonicalization

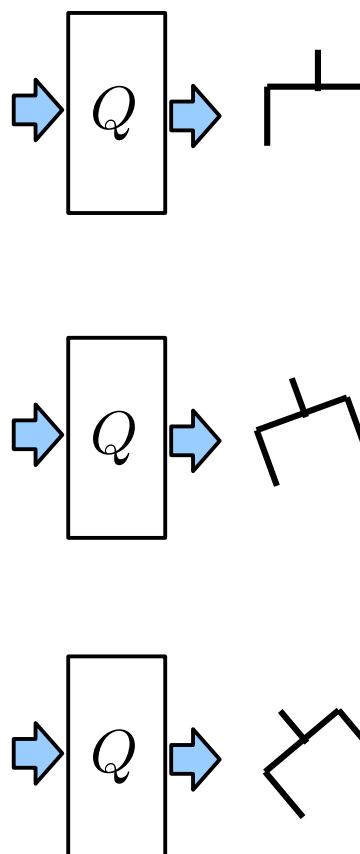


Data Augmentation

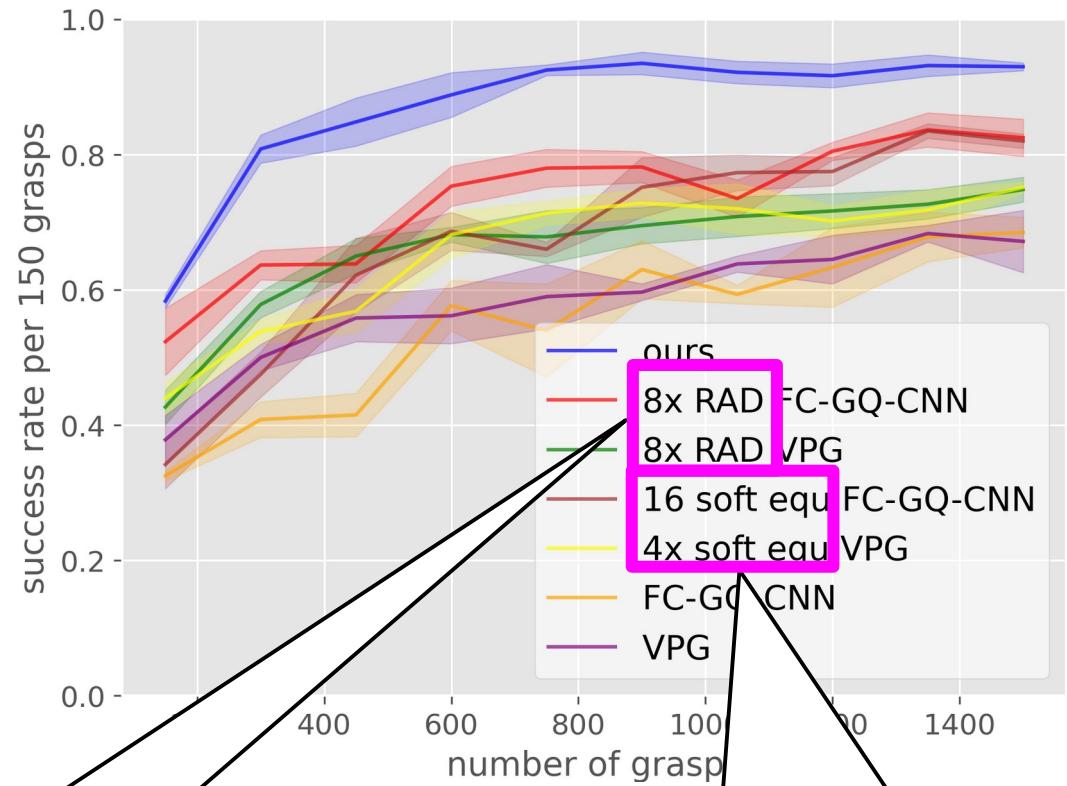
Input image



Output grasp

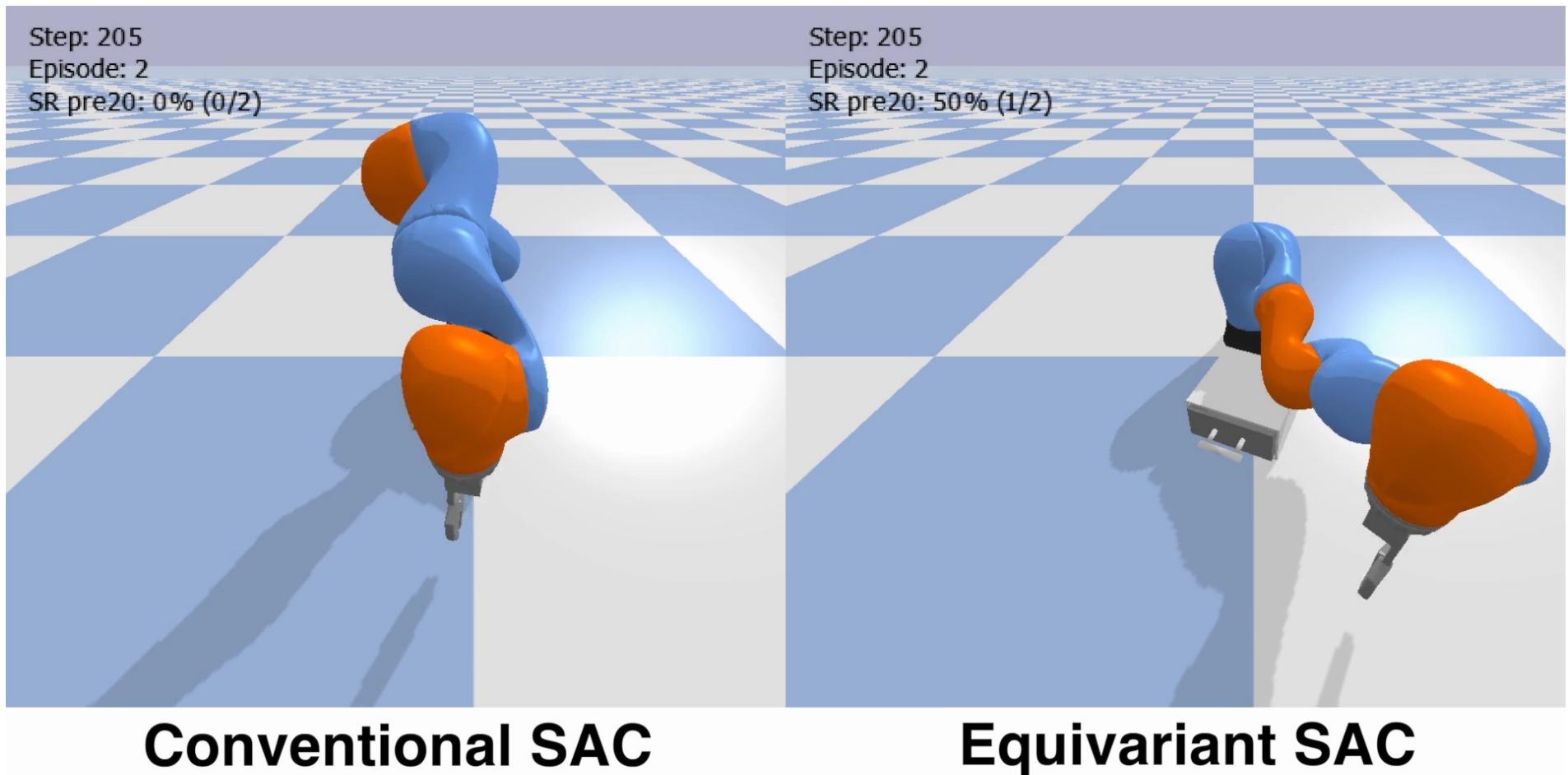


8 SGD steps per grasp
-- each step is performed on a minibatch
-- each frame in mb is translated/rotated



16 or 4 SGD steps per grasp
-- each step is performed on a 1/16 minibatch
-- each frame in mb is augmented 16 times

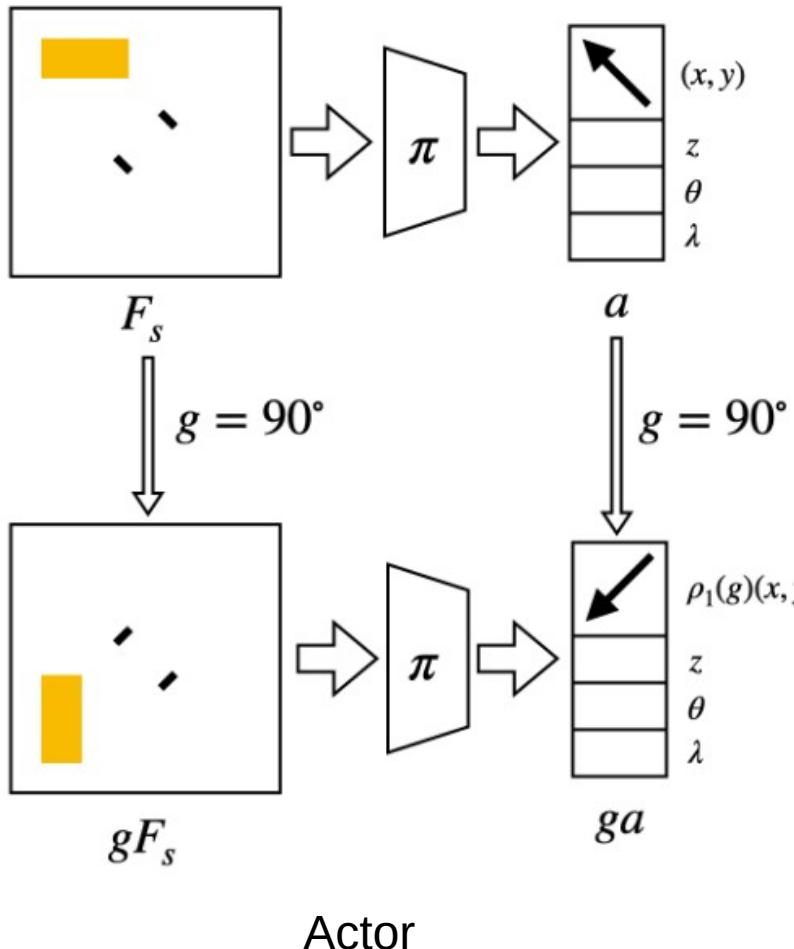
#2) O(2) Equivariant SAC



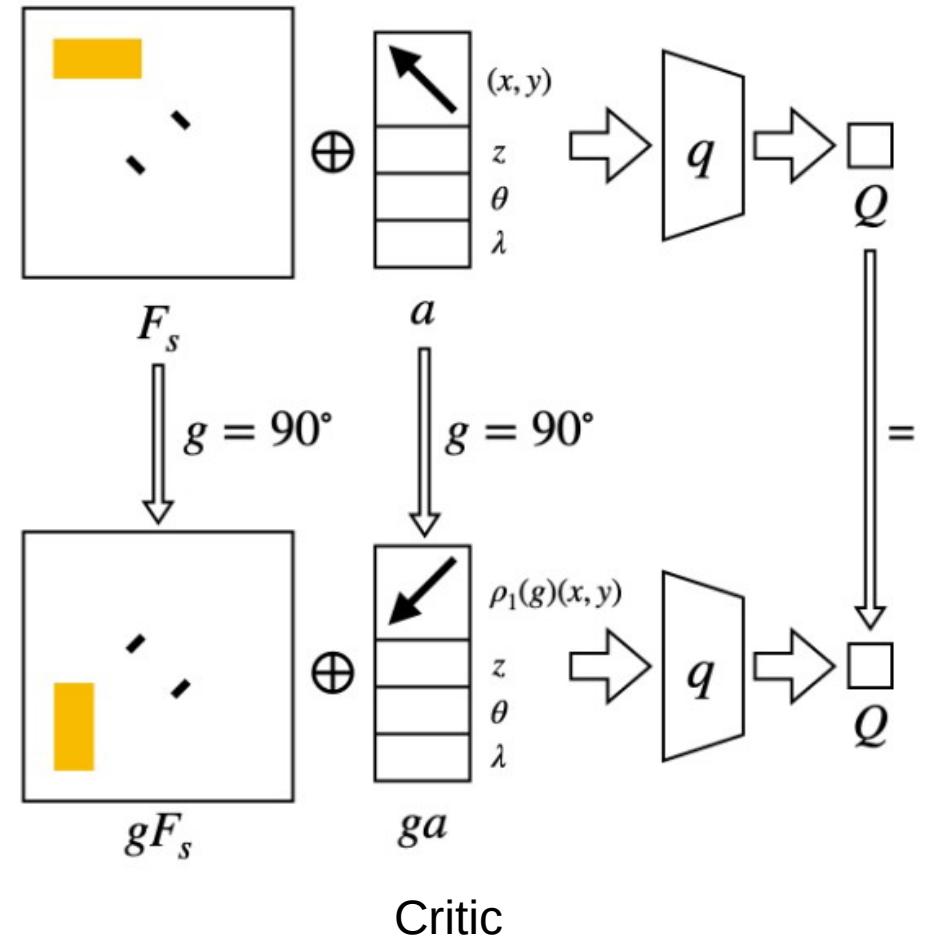
Wang, Walters, Platt, SO(2)-Equivariant Reinforcement Learning, ICLR 2022

Wang, Jia, Zhu, Walters, Platt, On-Robot Policy Learning with O(2)-Equivariant SAC, arXiv preprint arXiv:2203.04923

#2) O(2) Equivariant SAC



Actor

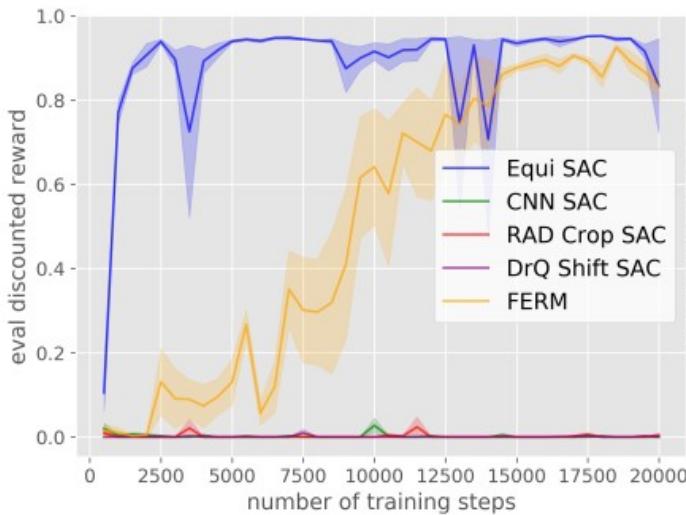


Critic

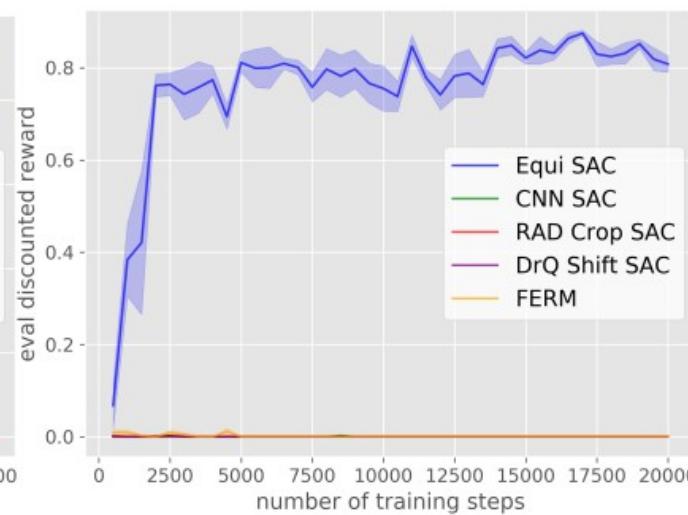
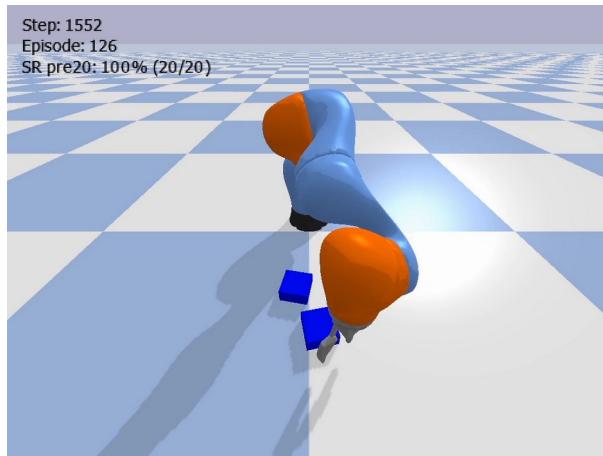
Wang, Walters, Platt, SO(2)-Equivariant Reinforcement Learning, ICLR 2022

Wang, Jia, Zhu, Walters, Platt, On-Robot Policy Learning with O(2)-Equivariant SAC, arXiv preprint arXiv:2203.04923.

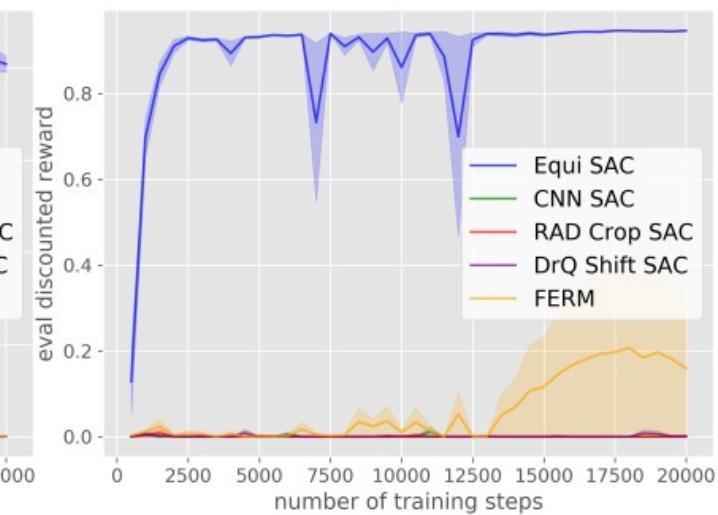
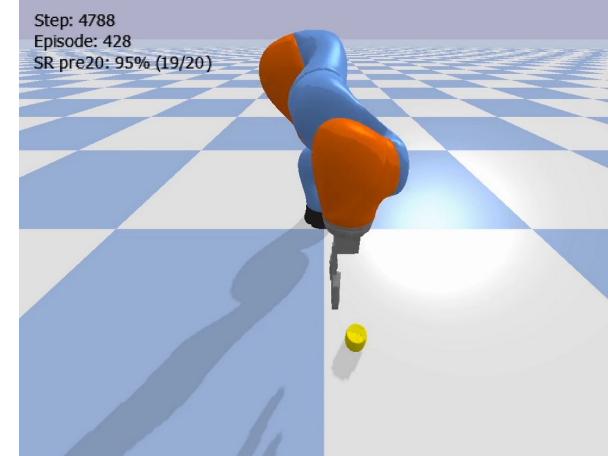
#2) O(2) Equivariant SAC



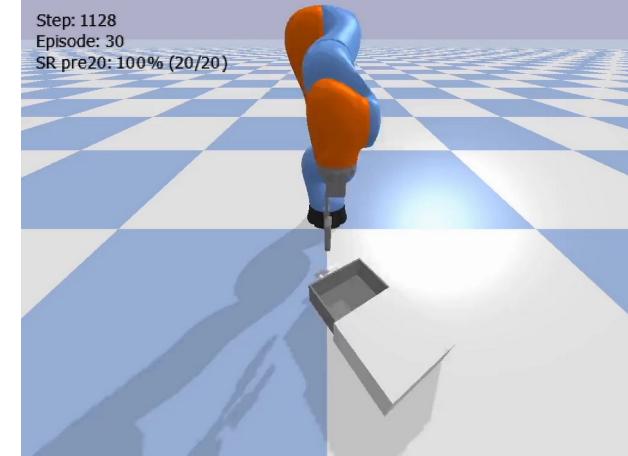
(a) Block Pulling



(b) Object Picking



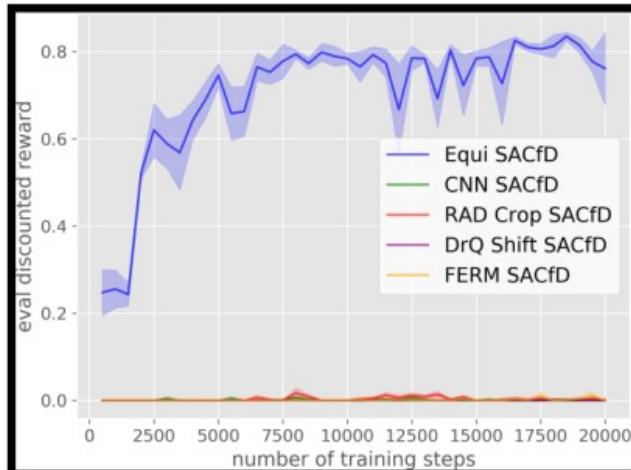
(c) Drawer Opening



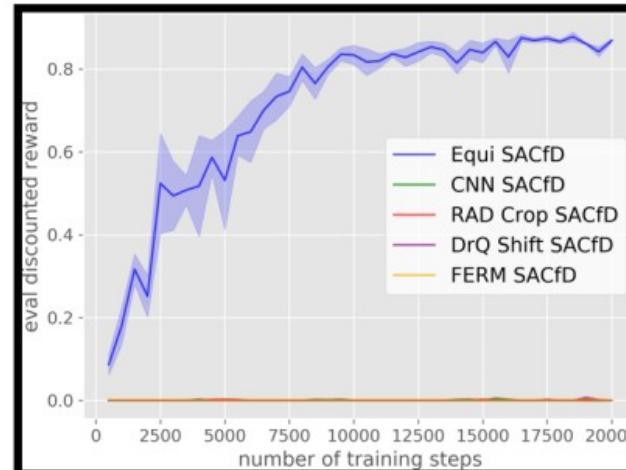
Wang, Walters, Platt, SO(2)-Equivariant Reinforcement Learning, ICLR 2022

Wang, Jia, Zhu, Walters, Platt, On-Robot Policy Learning with O(2)-Equivariant SAC, CoRL 2022

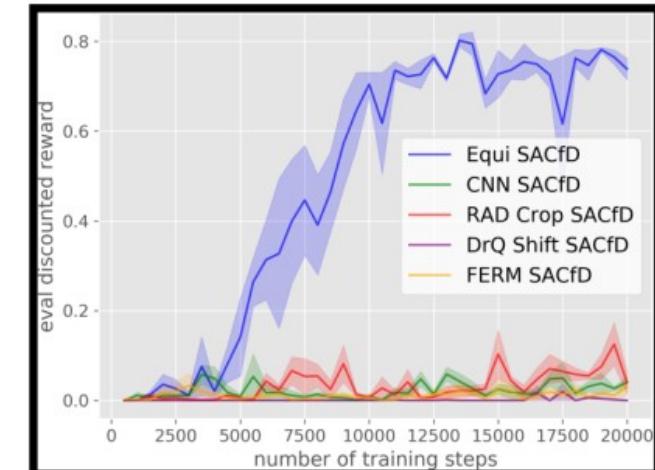
#2) O(2) Equivariant SAC



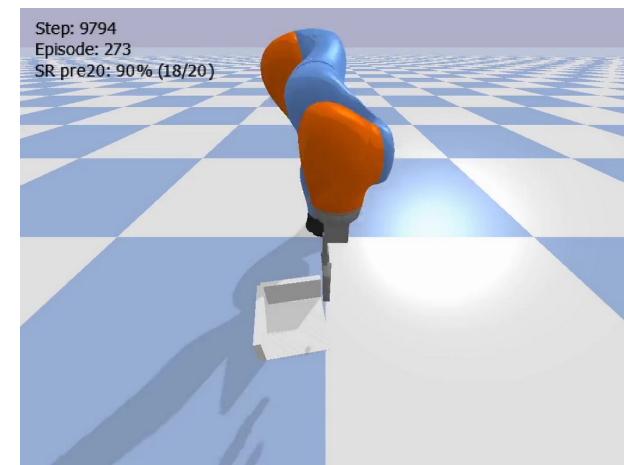
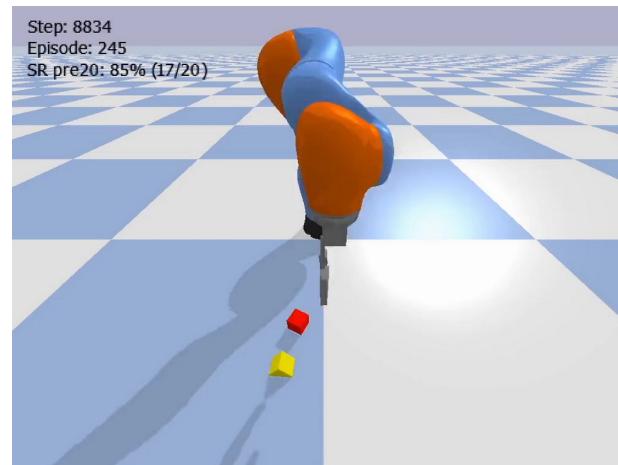
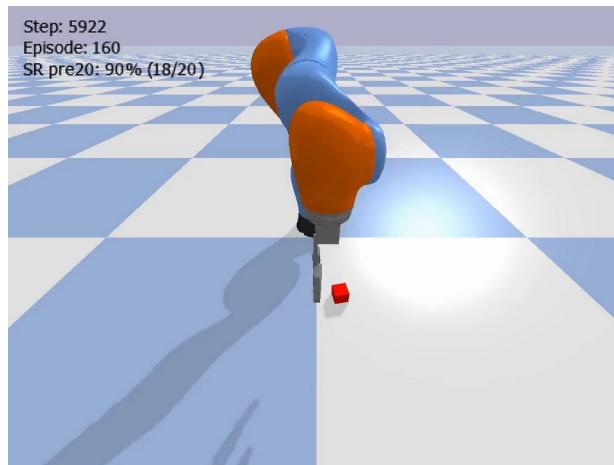
Block Stacking



House Building



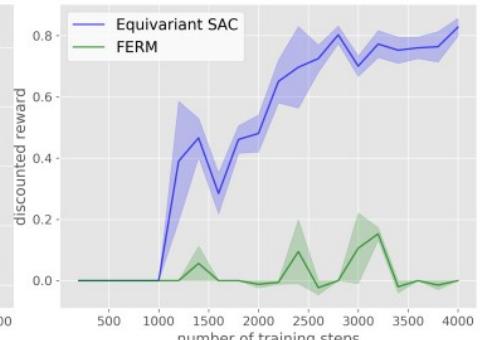
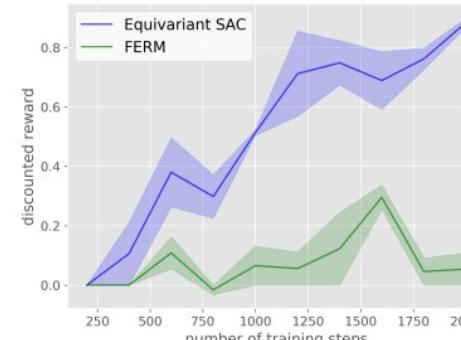
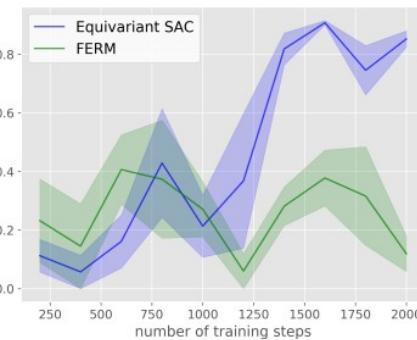
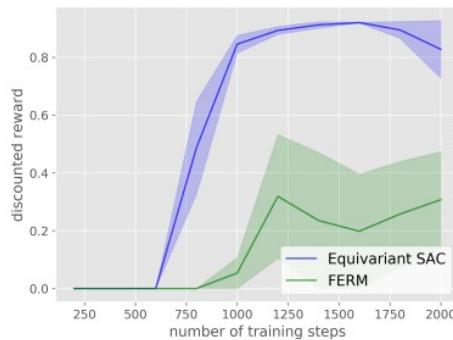
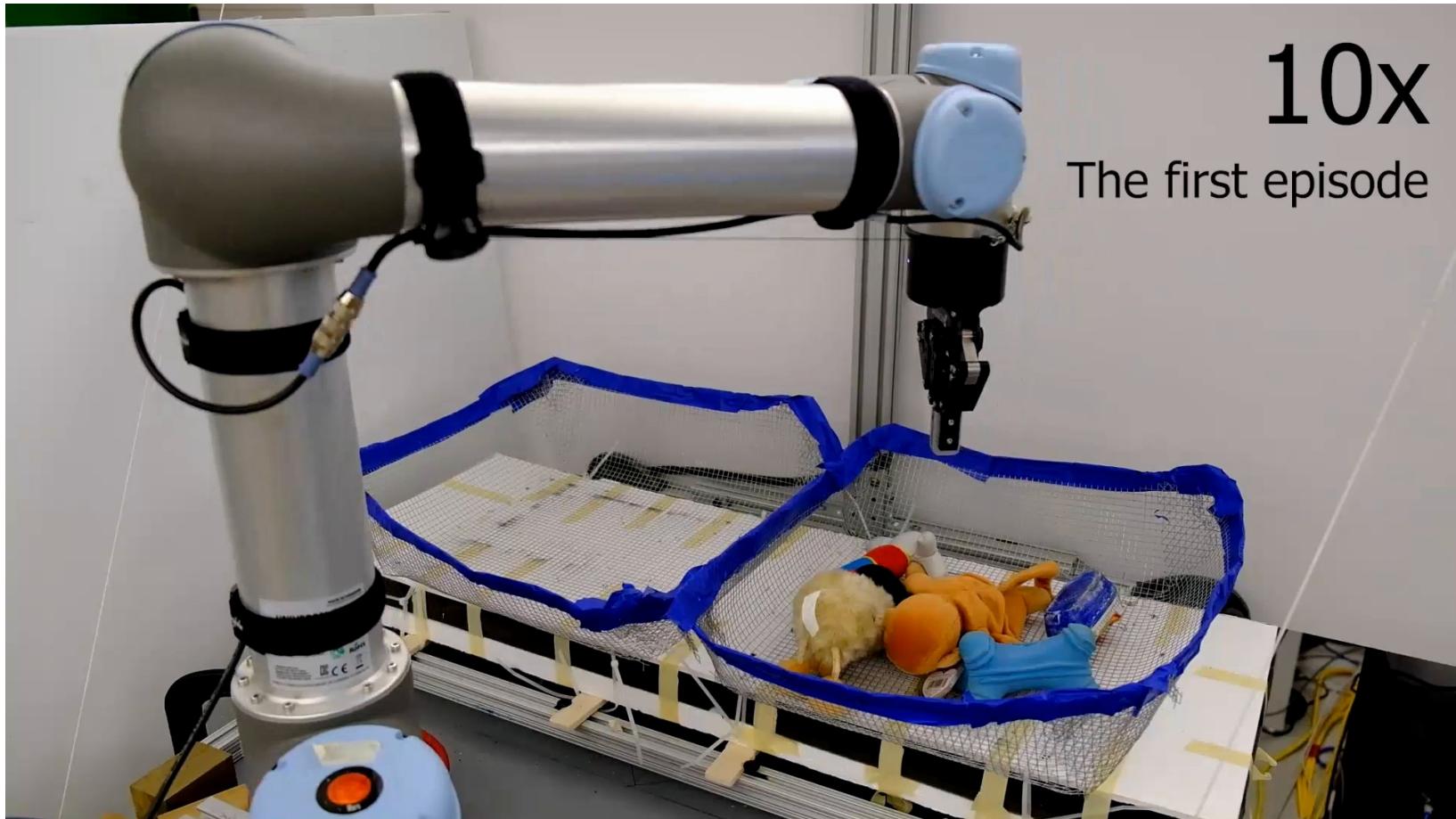
Corner Picking



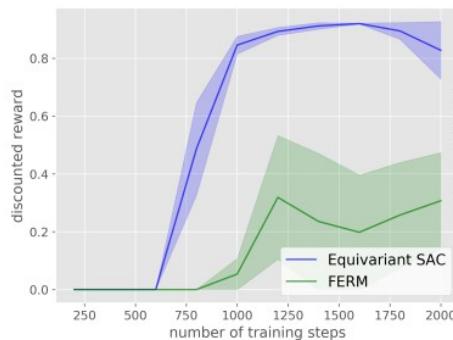
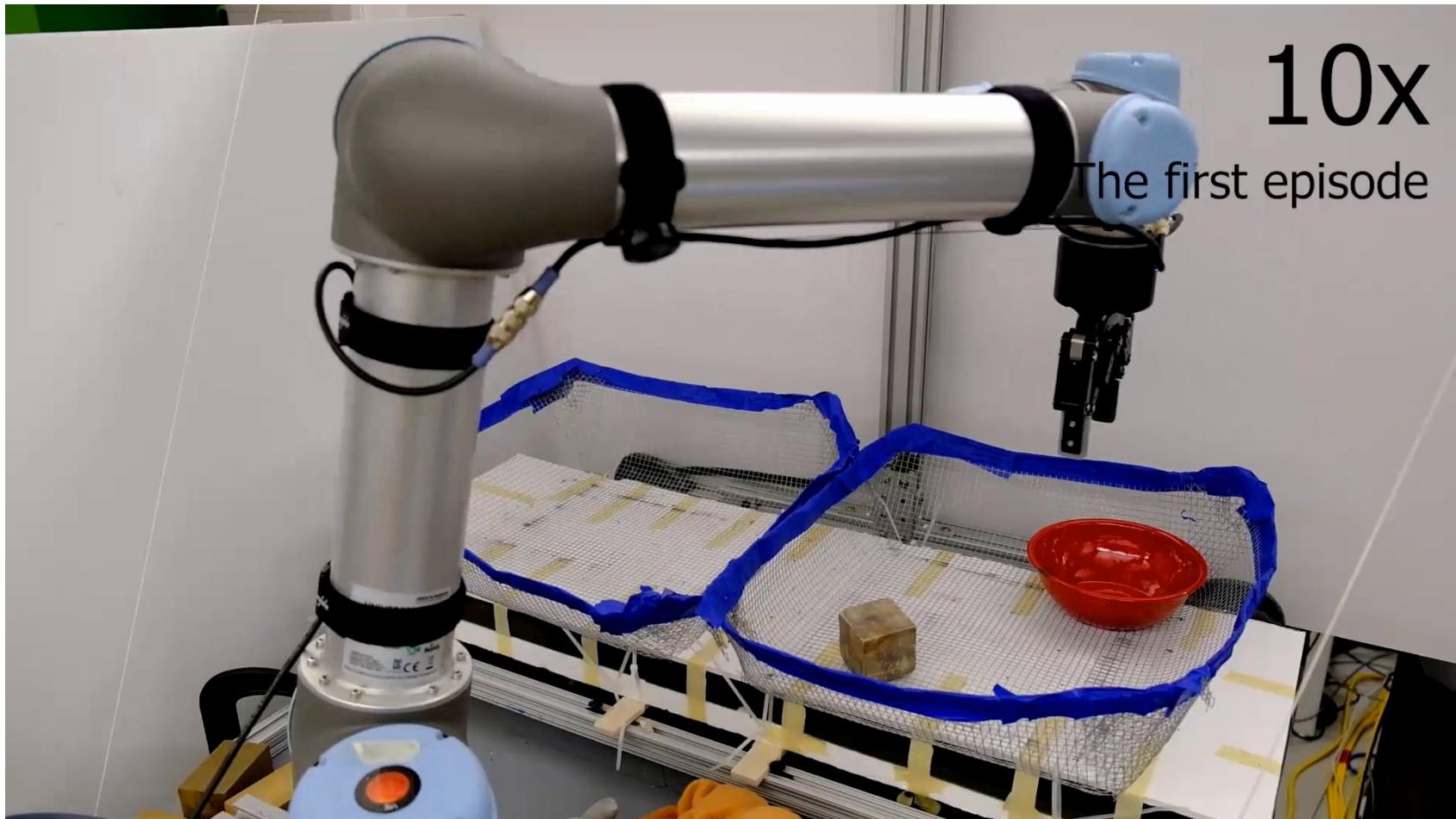
Wang, Walters, Platt, SO(2)-Equivariant Reinforcement Learning, ICLR 2022

Wang, Jia, Zhu, Walters, Platt, On-Robot Policy Learning with O(2)-Equivariant SAC, CoRL 2022

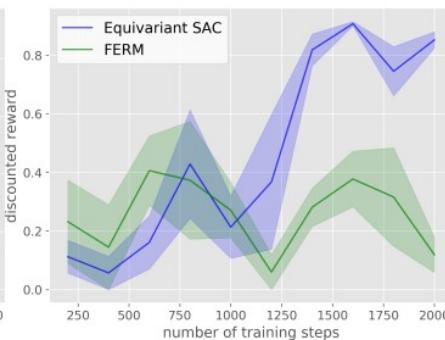
#2) O(2) Equivariant SAC



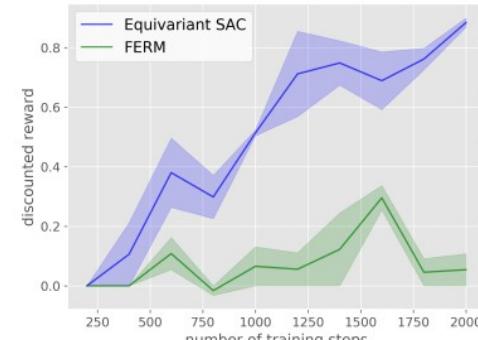
#2) O(2) Equivariant SAC



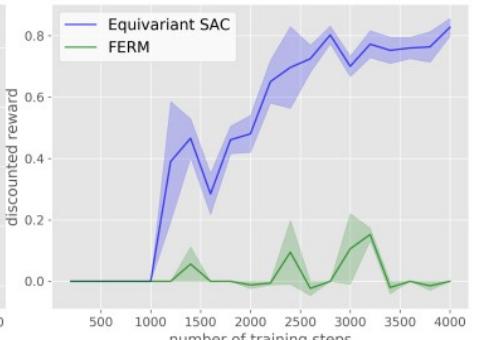
(a) Block Picking



(b) Clutter Grasping

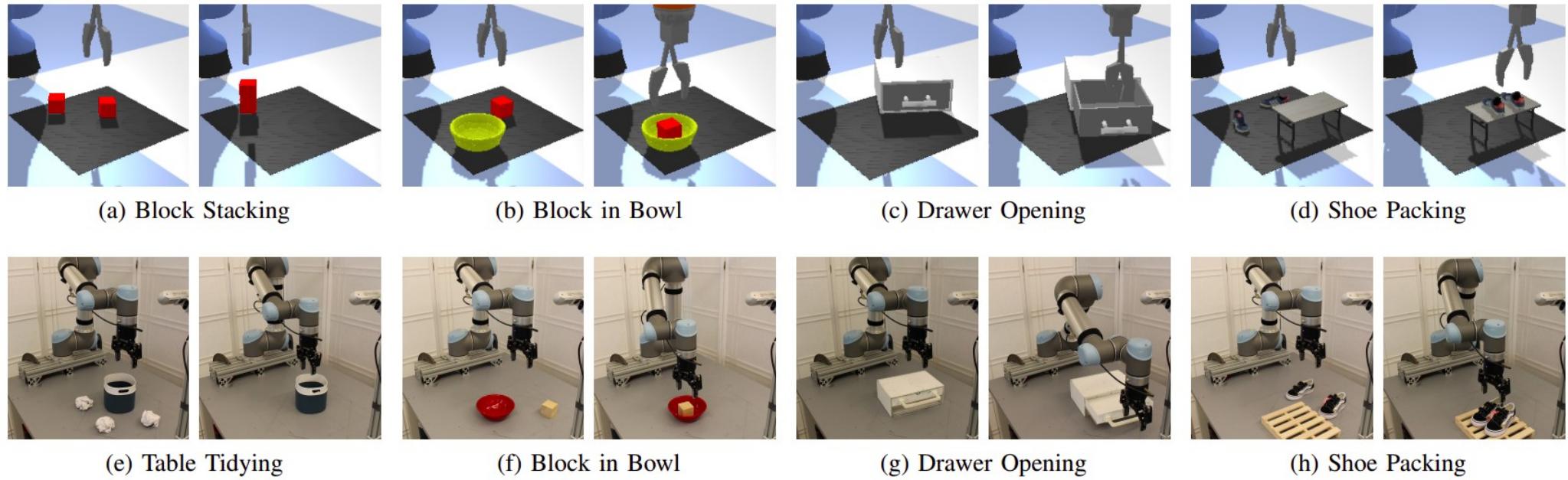


(c) Block Pushing



(d) Block in Bowl

#3) O(2) Equivariant IL



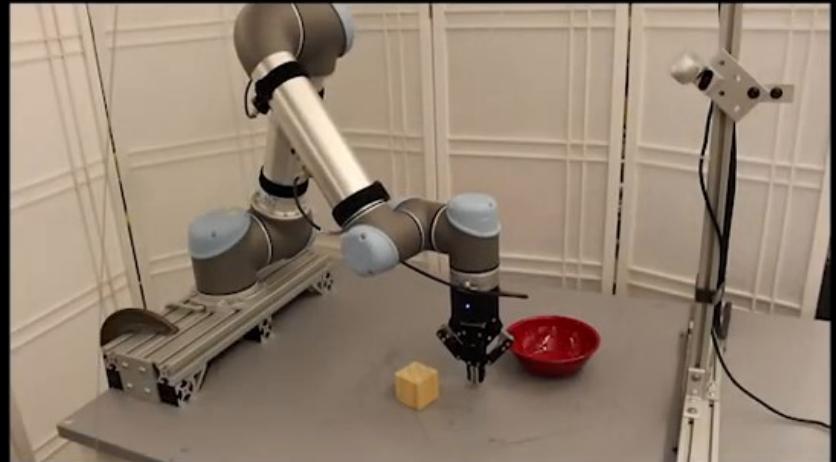
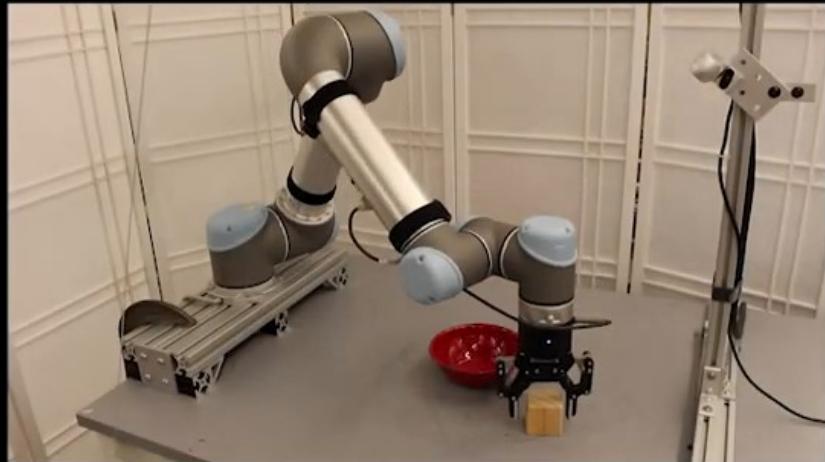
Method	Block Stacking				Block in Bowl				Drawer Opening				Shoe Packing			
	1	5	10	100	1	5	10	100	1	5	10	100	1	5	10	100
CNN BC	18.5	73.5	79.0	90.5	19.0	93.5	99.0	100	31.0	66.5	76.0	88.5	2.0	4.7	12.0	20.0
Implicit BC	11.0	9.5	51.0	80.5	13.0	99.5	100	100	31.0	63.5	71.5	81.5	0.5	5.5	12.0	13.0
CNN BC + TS	41.0	75.0	87.0	92.0	52.2	91.0	96.5	98.5	53.5	76.0	75.0	84.5	7.5	13.0	22.0	26.0
Equi BC (Ours)	33.5	87.5	93.0	100	46.5	99.5	99.5	100	62.5	88.5	91.0	100	1.5	22.5	39.5	75.0
SEIL (Ours)	71.5	99.5	98.5	100	75.0	98.0	100	100	78.5	87.5	93.5	96.5	16.5	57.3	68.0	72.0

#3) O(2) Equivariant IL

Block in Bowl (5 Demos)

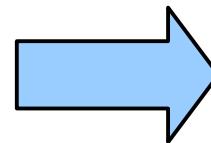
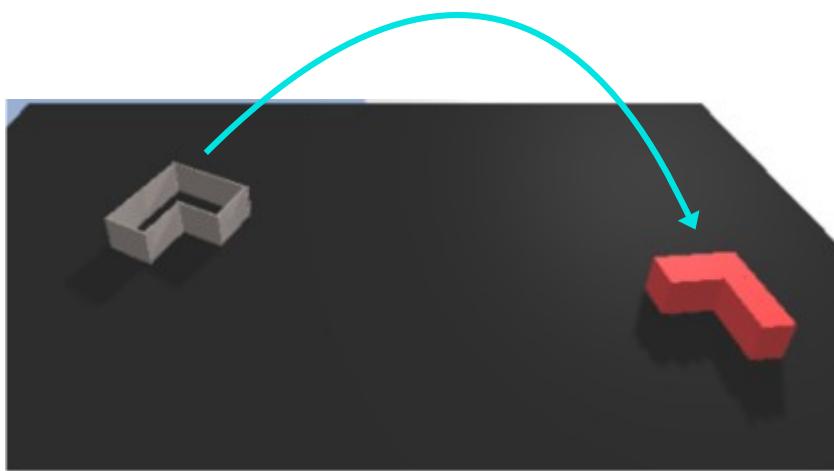
SEIL (ours)

CNN BC

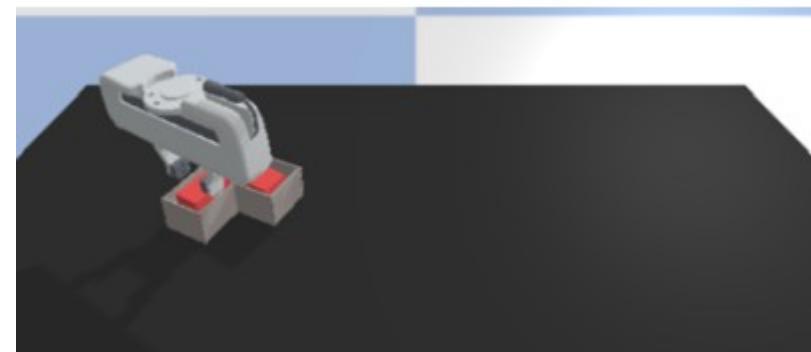


#4) Pick and Place

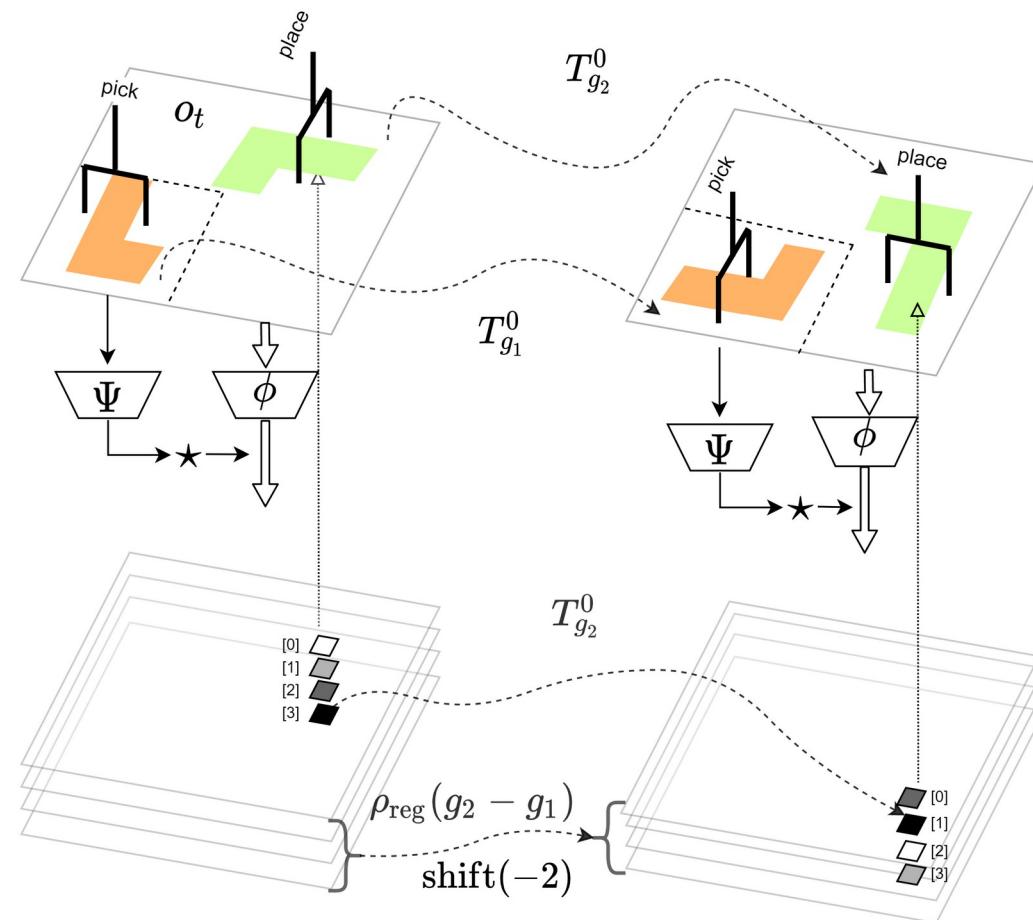
Demonstration



Control Policy

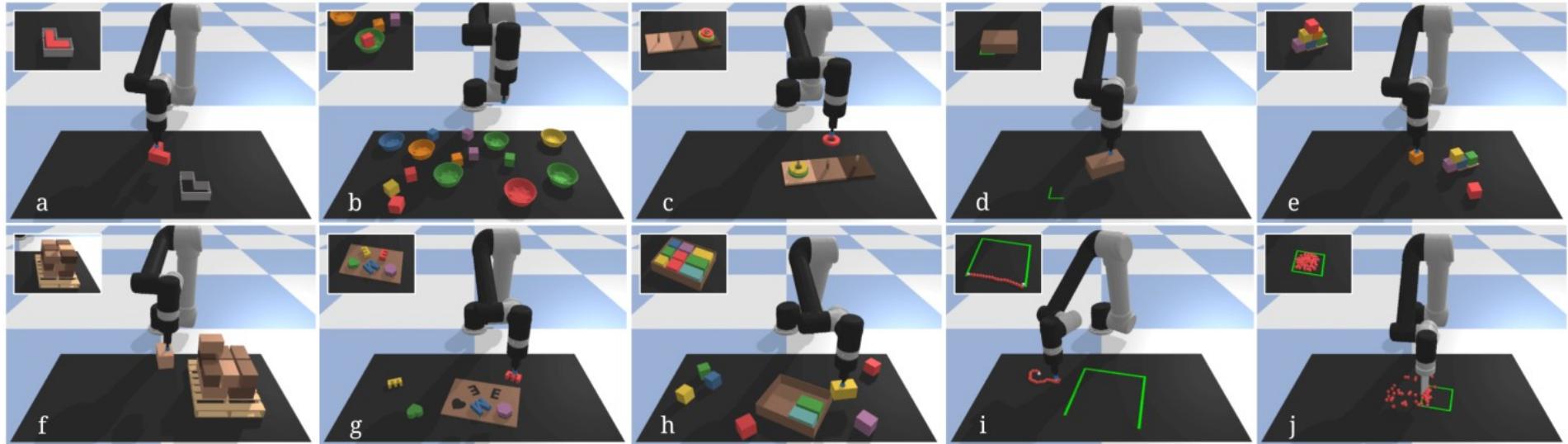


#4) Pick and Place



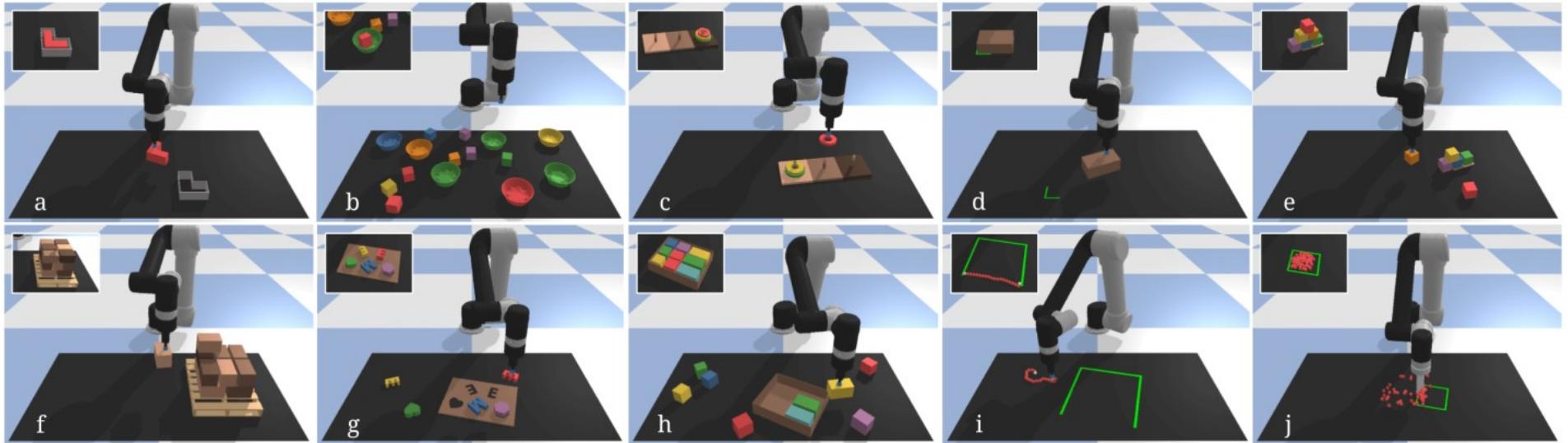
Equivariant over both pick and place pose: $SE(2) \times SE(2)$

#4) Pick and Place



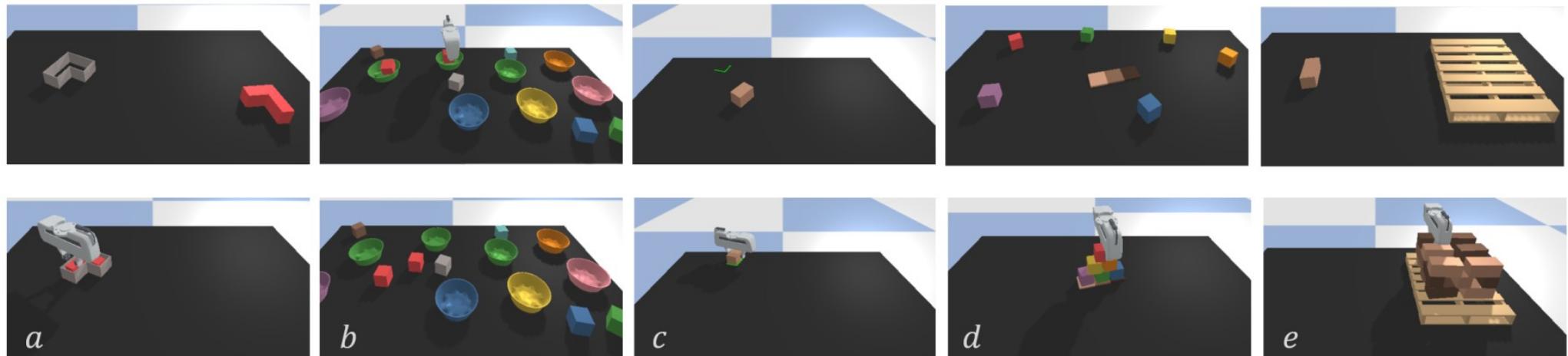
Method	block-insertion				place-red-in-green				towers-of-hanoi				align-box-corner				stack-block-pyramid			
	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000
Equivariant Transporter	100	100	100	100	98.5	100	100	100	88.1	95.7	100	100	41.0	99.0	100	100	34.6	80.0	90.8	95.1
Transporter Network	100	100	100	100	84.5	100	100	100	73.1	83.9	97.3	98.1	35.0	85.0	97.0	98.0	13.3	42.6	56.2	78.2
Form2Fit	17.0	19.0	23.0	29.0	83.4	100	100	100	3.6	4.4	3.7	7.0	7.0	2.0	5.0	16.0	19.7	17.5	18.5	32.5
Conv. MLP	0.0	5.0	6.0	8.0	0.0	3.0	25.5	31.3	0.0	1.0	1.9	2.1	0.0	2.0	1.0	1.0	0.0	1.8	1.7	1.7
GT-State MLP	4.0	52.0	96.0	99.0	0.0	0.0	3.0	82.2	10.7	10.7	6.1	5.3	47.0	29.0	29.0	59.0	0.0	0.2	1.3	15.3
GT-State MLP 2-Step	6.0	38.0	95.0	100	0.0	0.0	19.0	92.8	22.0	6.4	5.6	3.1	49.0	12.0	43.0	55.0	0.0	0.8	12.2	17.5
palletizing-boxes					assembling-kits				packing-boxes				manipulating-rope				sweeping-piles			
	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000
Equivariant Transporter	75.3	98.9	99.6	99.6	63.8	90.6	98.6	100	98.3	99.4	99.6	100	31.0	85.0	92.3	98.4	97.9	99.5	100	100
Transporter Network	63.2	77.4	91.7	97.9	28.4	78.6	90.4	94.6	56.8	58.3	72.1	81.3	21.9	73.2	85.4	92.1	52.4	74.4	71.5	96.1
Form2Fit	21.6	42.0	52.1	65.3	3.4	7.6	24.2	37.6	29.9	52.5	62.3	66.8	11.9	38.8	36.7	47.7	13.2	15.6	26.7	38.4
Conv. MLP	31.4	37.4	34.6	32.0	0.0	0.2	0.2	0.0	0.3	9.5	12.6	16.1	3.7	6.6	3.8	10.8	28.2	48.4	44.9	45.1
GT-State MLP	0.6	6.4	30.2	30.1	0.0	0.0	1.2	11.8	7.1	1.4	33.6	56.0	5.5	11.5	43.6	47.4	7.2	20.6	63.2	74.4
GT-State MLP 2-Step	0.6	9.6	32.8	37.5	0.0	0.0	1.6	4.4	4.0	3.5	43.4	57.1	6.0	8.2	41.5	58.7	9.7	21.4	66.2	73.9

#4) Pick and Place



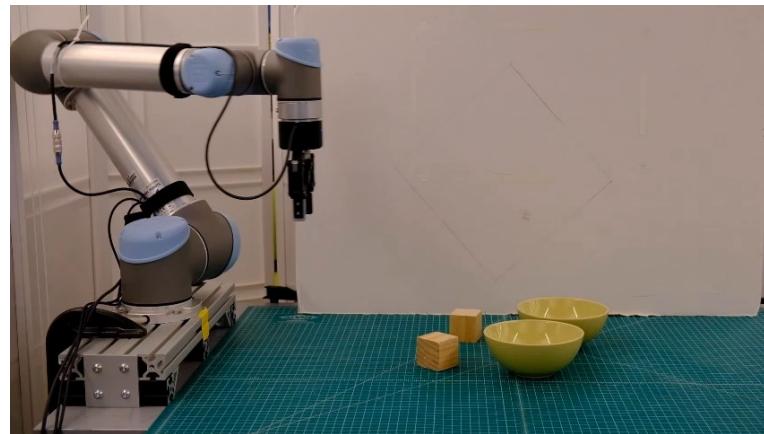
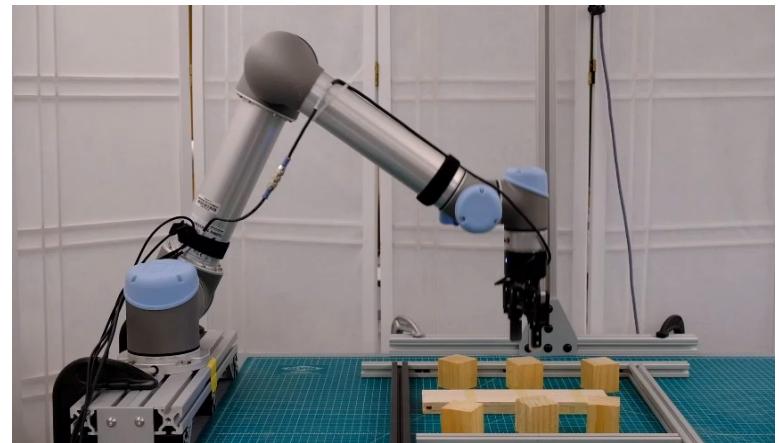
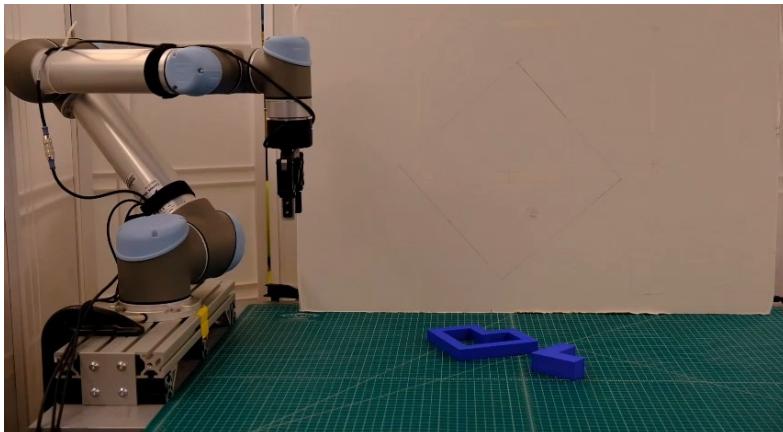
Method	block-insertion				place-red-in-green				towers-of-hanoi				align-box-corner				stack-block-pyramid			
	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000
Equivariant Transporter	100	100	100	100	98.5	100	100	100	88.1	95.7	100	100	41.0	99.0	100	100	34.6	80.0	90.8	95.1
Transporter Network	100	100	100	100	84.5	100	100	100	73.1	83.9	97.3	98.1	35.0	85.0	97.0	98.0	13.3	42.6	56.2	78.2
Form2Fit	17.0	19.0	23.0	29.0	83.4	100	100	100	3.6	4.4	3.7	7.0	7.0	2.0	5.0	16.0	19.7	17.5	18.5	32.5
Conv. MLP	0.0	5.0	6.0	8.0	0.0	3.0	25.5	31.3	0.0	1.0	1.9	2.1	0.0	2.0	1.0	1.0	0.0	1.8	1.7	1.7
GT-State MLP	4.0	52.0	96.0	99.0	0.0	0.0	3.0	82.2	10.7	10.7	6.1	5.3	47.0	29.0	29.0	59.0	0.0	0.2	1.3	15.3
GT-State MLP 2-Step	6.0	38.0	95.0	100	0.0	0.0	19.0	92.8	22.0	6.4	5.6	3.1	49.0	12.0	43.0	55.0	0.0	0.8	12.2	17.5
palletizing-boxes					assembling-kits				packing-boxes				manipulating-rope				sweeping-piles			
					1	10	100	1000	1	10	100	1000	1	10	100	1000	1	10	100	1000
Equivariant Transporter	75.3	98.9	99.6	99.6	63.8	90.6	98.6	100	98.3	99.4	99.6	100	31.0	85.0	92.3	98.4	97.9	99.5	100	100
Transporter Network	63.2	77.4	91.7	97.9	28.4	78.6	90.4	94.6	50.8	58.3	72.1	81.3	21.9	73.2	85.4	92.1	52.4	74.4	71.5	96.1
Form2Fit	21.6	42.0	52.1	65.3	3.4	7.6	24.2	37.6	29.9	52.5	62.3	66.8	11.9	38.8	36.7	47.7	13.2	15.6	26.7	38.4
Conv. MLP	31.4	37.4	34.6	32.0	0.0	0.2	0.2	0.0	0.3	9.5	12.6	16.1	3.7	6.6	3.8	10.8	28.2	48.4	44.9	45.1
GT-State MLP	0.6	6.4	30.2	30.1	0.0	0.0	1.2	11.8	7.1	1.4	33.6	56.0	5.5	11.5	43.6	47.4	7.2	20.6	63.2	74.4
GT-State MLP 2-Step	0.6	9.6	32.8	37.5	0.0	0.0	1.6	4.4	4.0	3.5	43.4	57.1	6.0	8.2	41.5	58.7	9.7	21.4	66.2	73.9

#4) Pick and Place



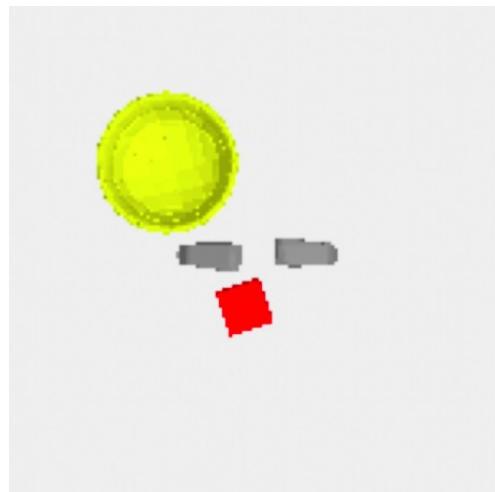
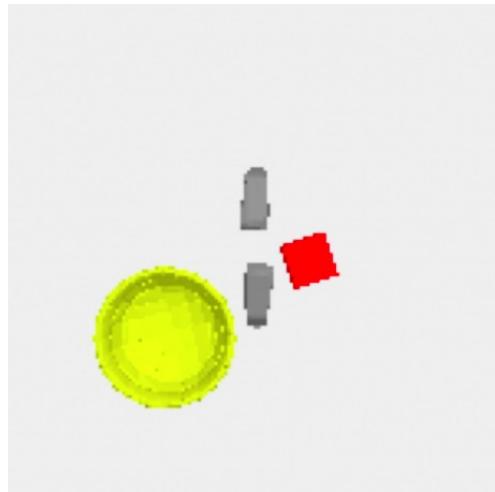
Method	block-insertion			place-red-in-green			palletizing-boxes			align-box-corner			stack-block-pyramid		
	1	10	100	1	10	100	1	10	100	1	10	100	1	10	100
Equivariant Transporter	100	100	100	95.6	100	100	96.1	100	100	64.0	99.0	100	62.1	85.6	98.3
Transporter Network	98.0	100	100	82.3	94.8	100	84.2	99.6	100	45.0	85.0	99.0	16.6	63.3	75.0

#4) Pick and Place

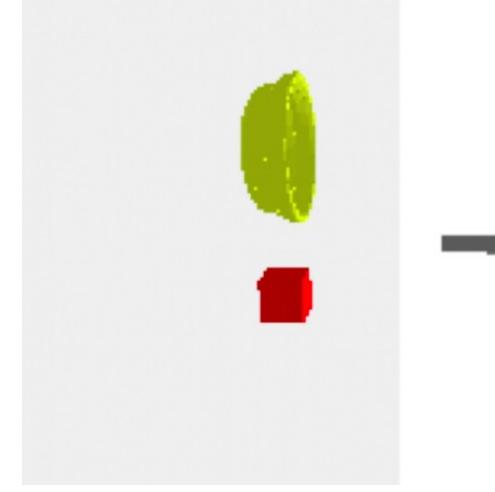
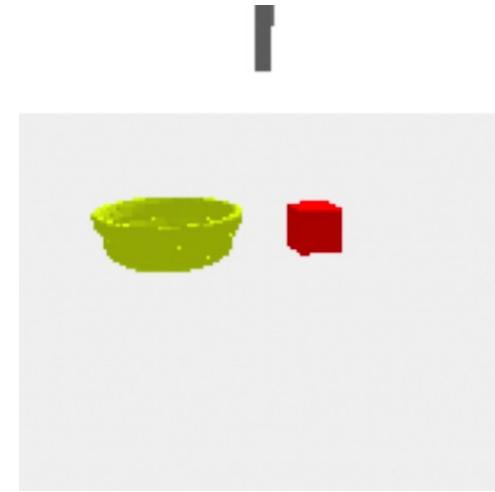


Task	# demos	# completions / # trials	success rate
stack-block-pyramid	10	17/20	95.8%
place-box-in-bowl	10	20/20	100%
block-insertion	10	20/20	100%

#5) Symmetry Mismatch

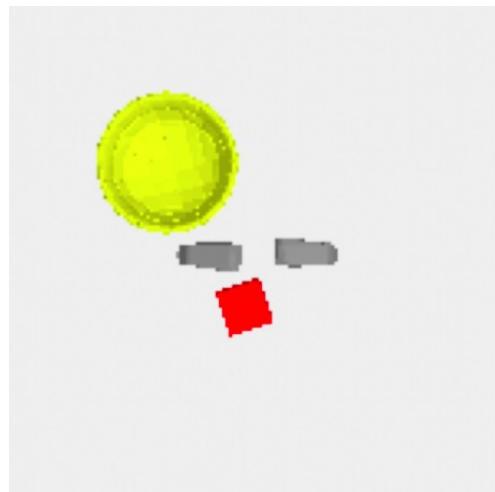
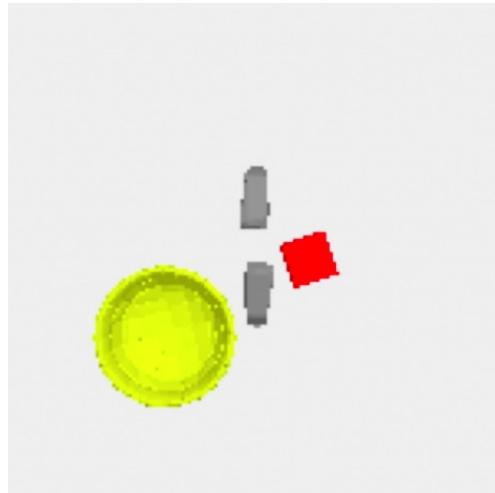


Model symmetry matches
domain symmetry

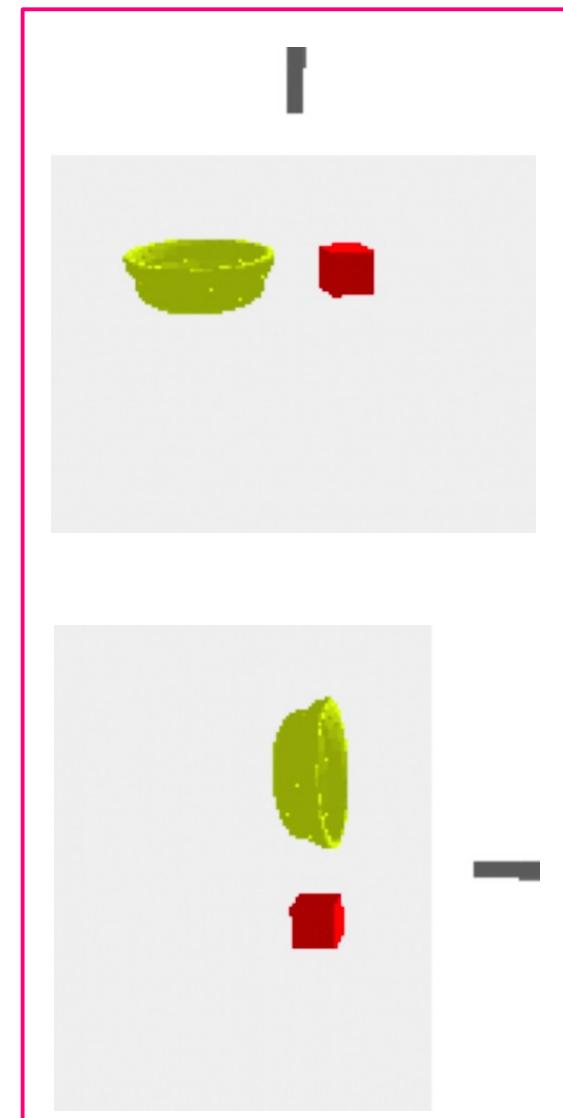


Model symmetry **does not**
match domain symmetry

#5) Symmetry Mismatch

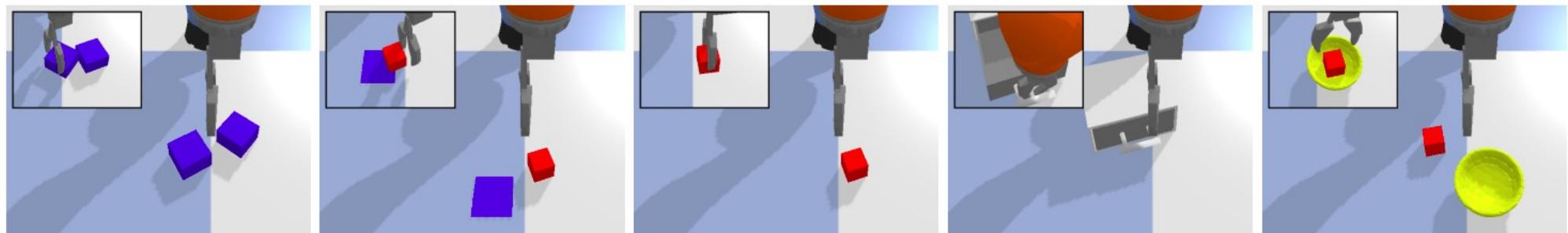


Model symmetry matches
domain symmetry



Model symmetry **does not**
match domain symmetry

#5) Symmetry Mismatch



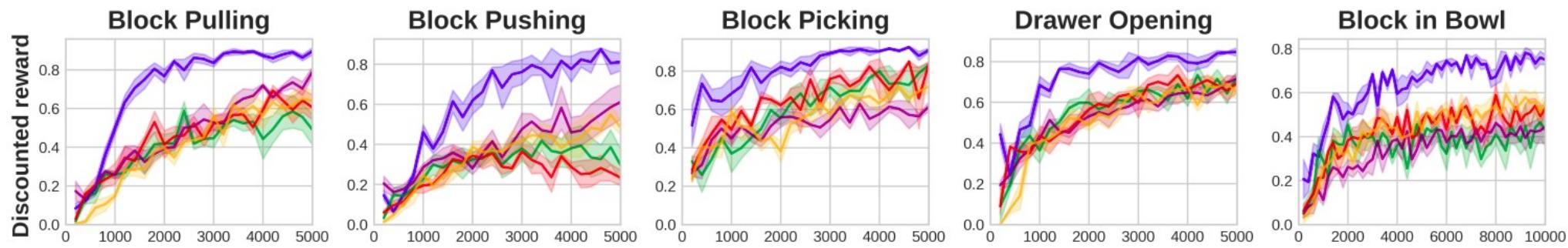
(a) Block Pulling

(b) Block Pushing

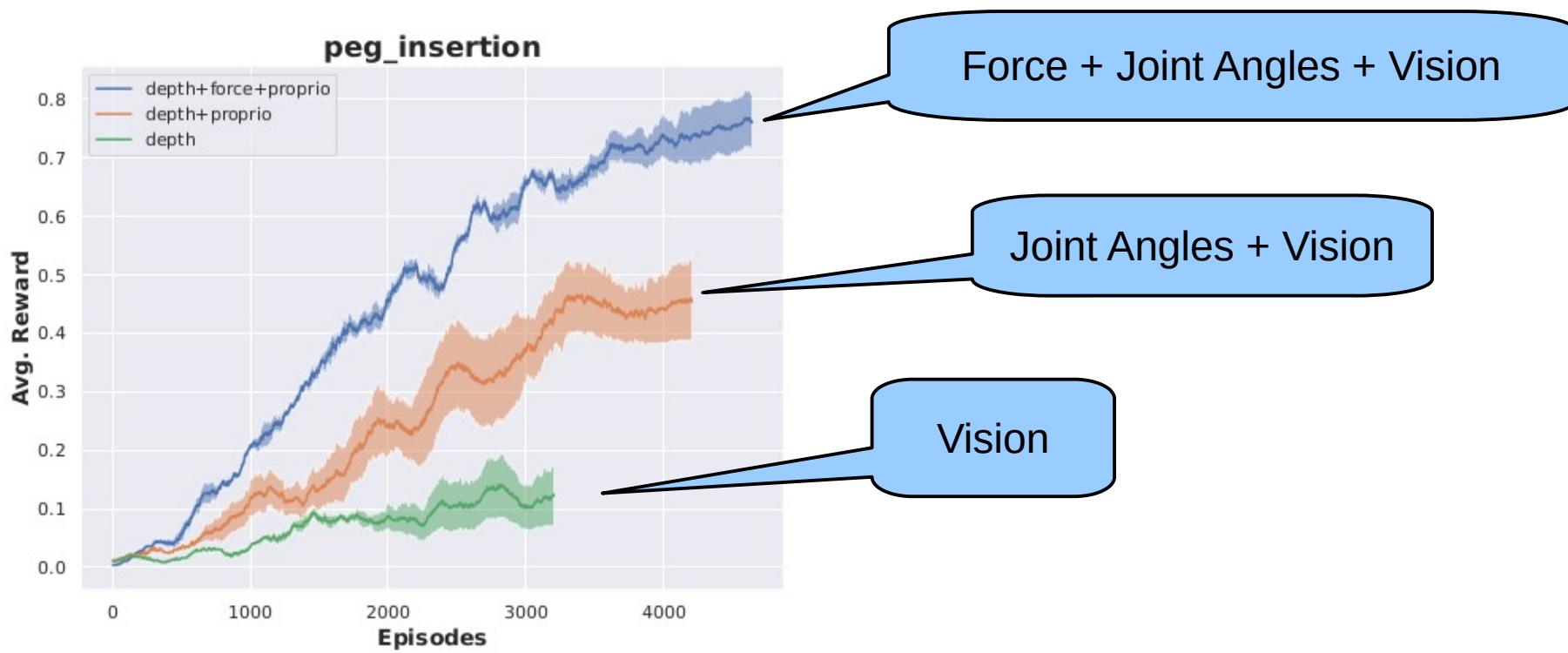
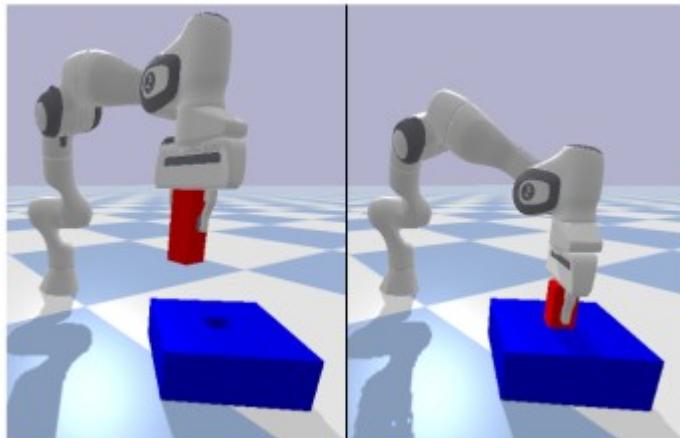
(c) Block Picking

(d) Drawer Opening

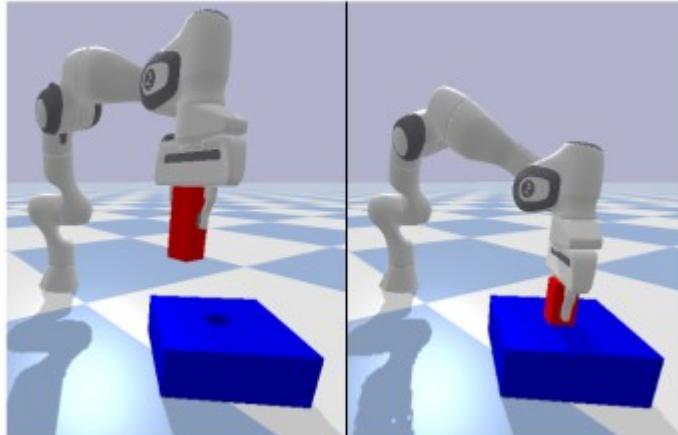
(e) Block in Bowl



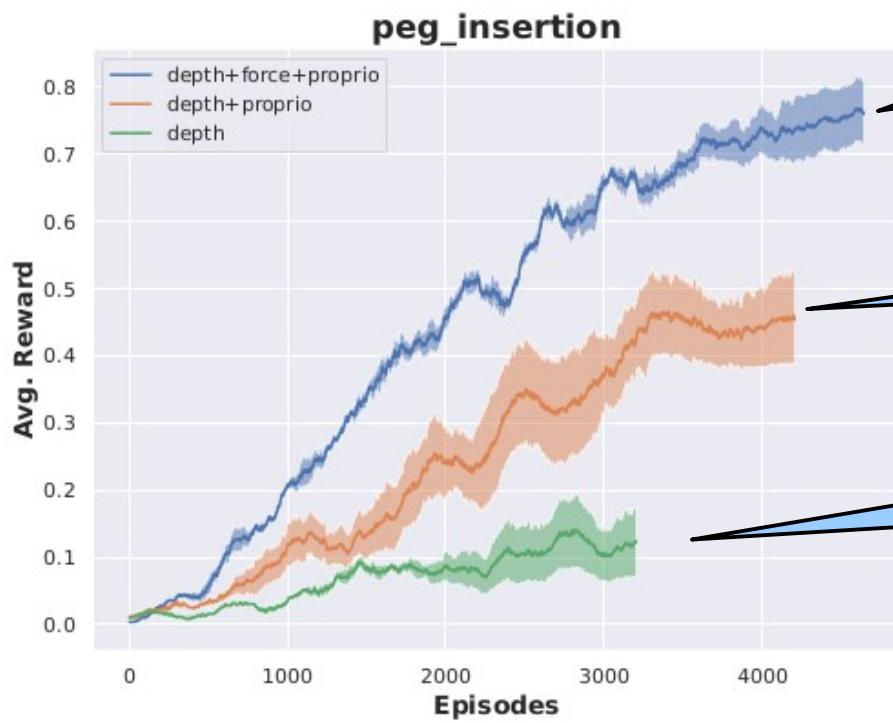
#6) Force Feedback



#6) Force Feedback



Imperfect symmetries
are essential here!

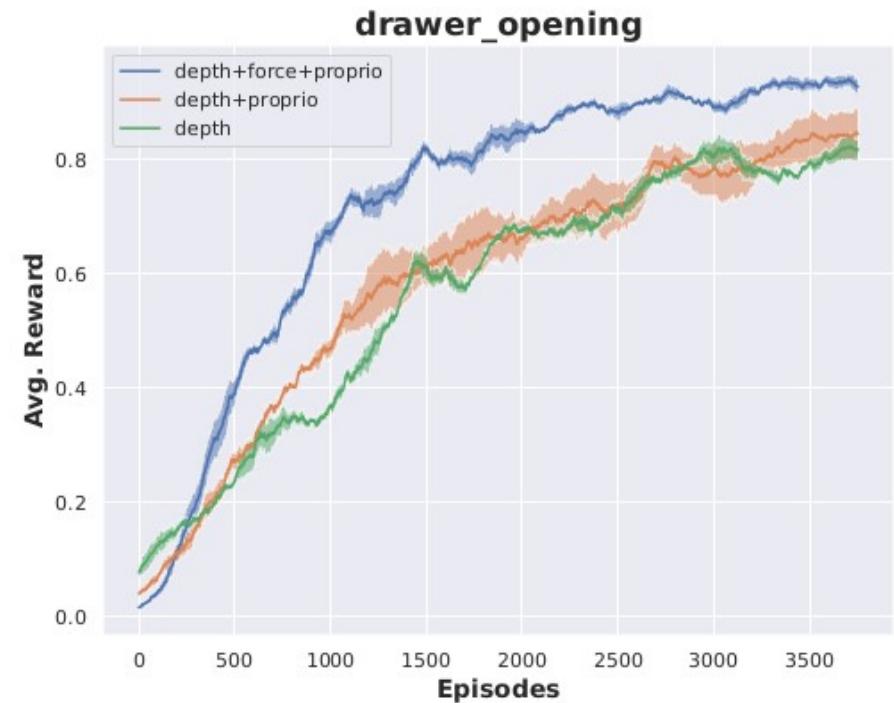
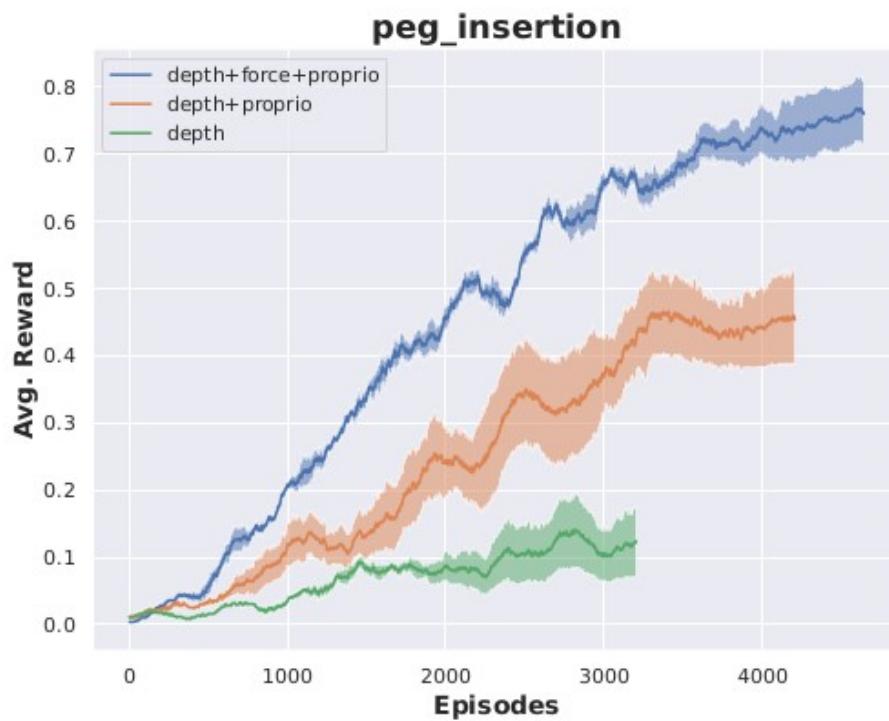
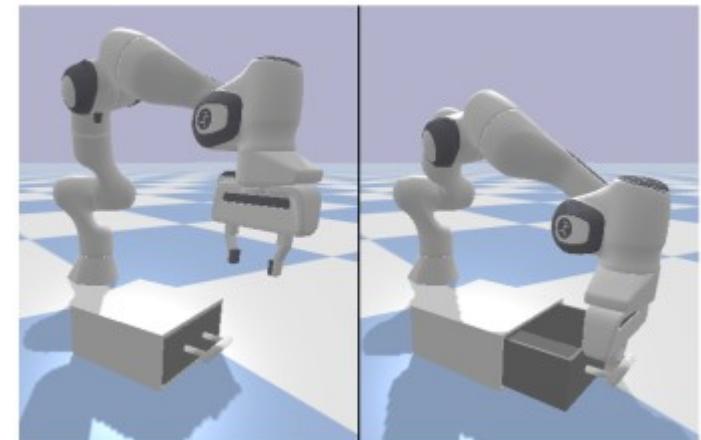
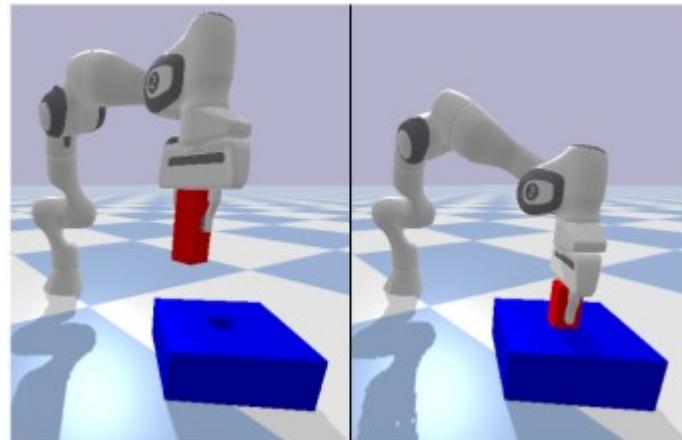


Force + Joint Angles + Vision

Joint Angles + Vision

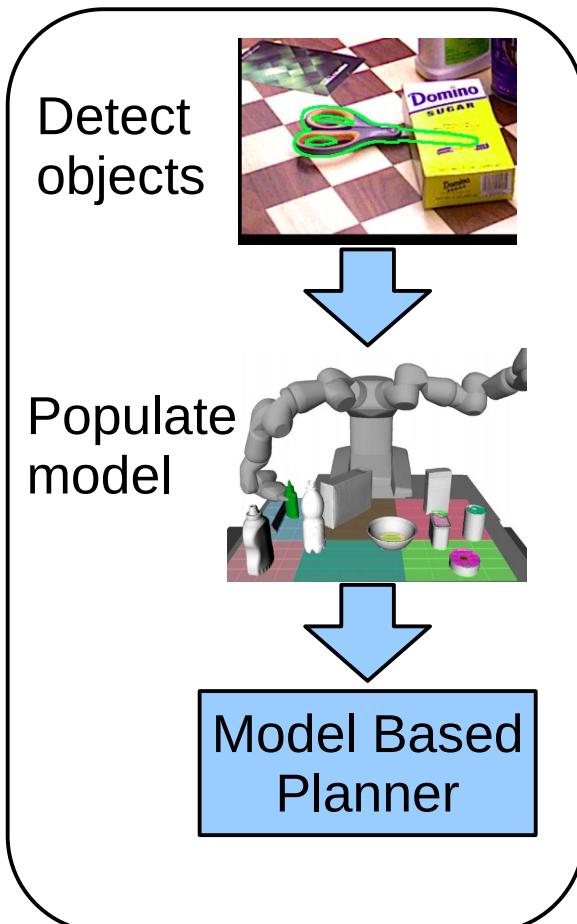
Vision

#6) Force Feedback



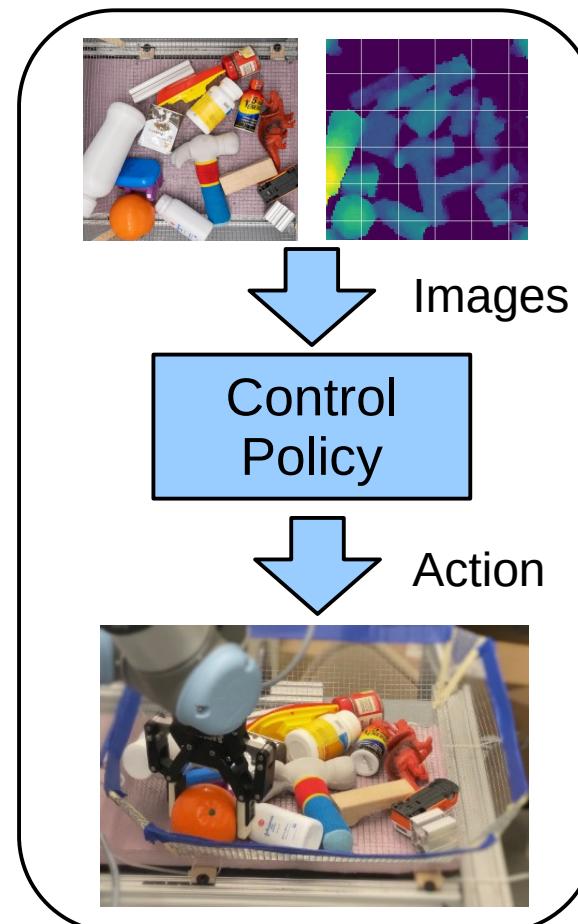
Perspective

Model Based



Powerful, but makes
a lot of assumptions

Model Free



Robust, but hard to
scale up

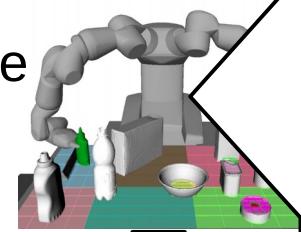
Perspective

Model Based

Detect objects



Populate model



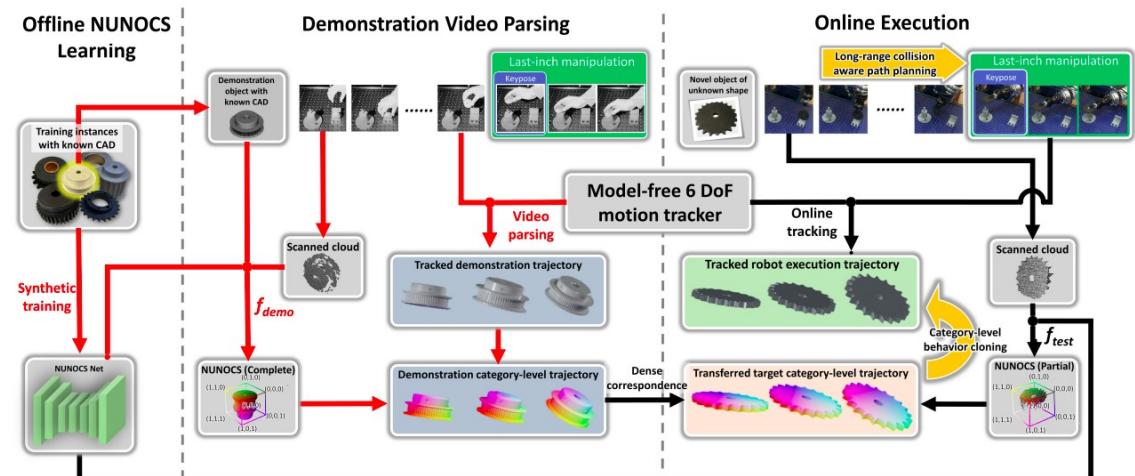
Model Based Planner

Powerful, but makes a lot of assumptions

Model Free



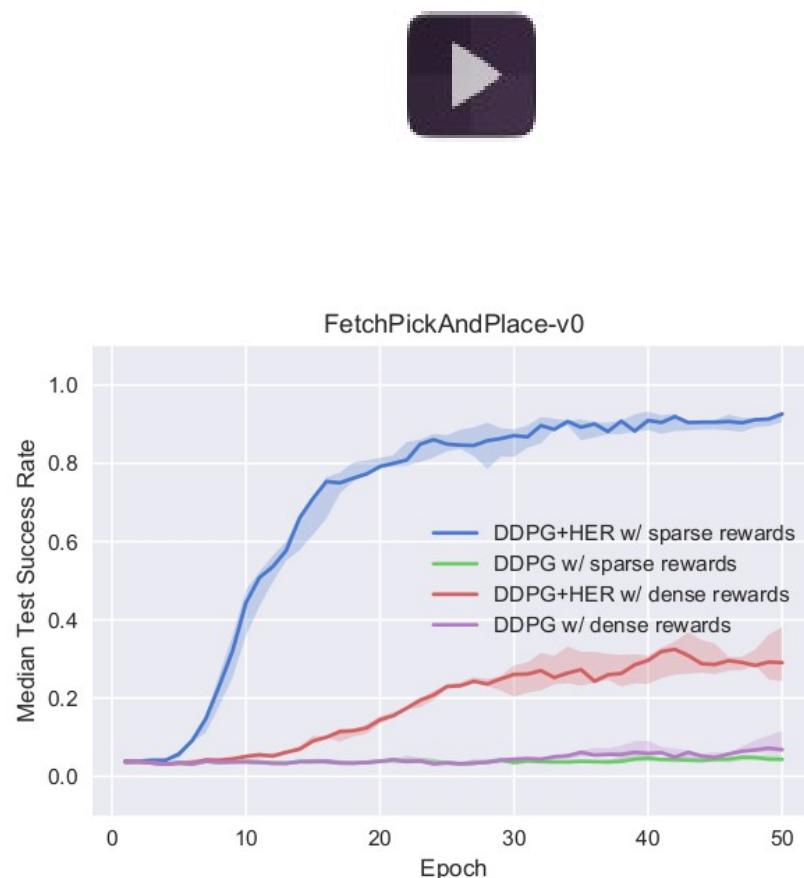
Example: YODO



Wen, Lian, Bekris, Schaal, *You Only Demonstrate Once: Category-Level Manipulation from Single Visual Demonstration*, RSS 2022 Best Paper

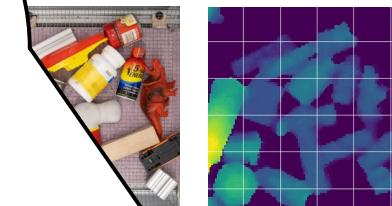
Perspective

Example: OpenAI Baselines



Plappert et al., *Multi-Goal Reinforcement Learning: Challenging Robotics Environments and Request for Research*, ArXiv 2018

Model Free



Images

Control Policy

Action



bust, but hard to scale up

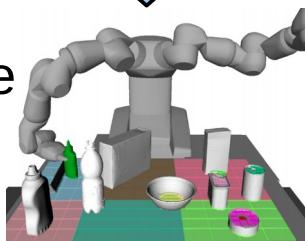
Perspective

Model Based

Detect objects



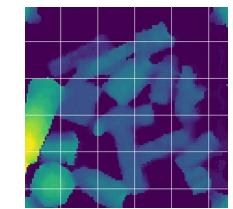
Populate model



Model Based Planner

A few thousand parameters?

Model Free



Images

Control Policy

Action



Millions of parameters

A few dozen parameters

Perspective

Model Based

Detect objects



Populate model



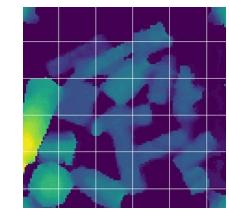
Model Based Planner

A few dozen parameters

Model Free

Constrained Model Free

Symmetric policies



Images

Control Policy

Action



Millions of parameters