

### **SEIL: Simulation-augmented Equivariant Imitation Learning** Robin Walters David Klee Dian Wang\* Xupeng Zhu

 $Rot~90^\circ$ 

Mingxi Jia\*

## Contributions

- Transition Simulation: Utilizes point cloud projection as a simulation of transitions to augment expert data.
- Equivariant Imitation Learning: Incorporates symmetry into imitation learning that allows direct generalization on rotations and reflections.

## Method

## **Transition Simulation (TS)**

Simulates new expert state-action pairs within the vicinity of existing expert transitions by projecting observation images from the observed point cloud.



Figure 1. Overview of Transition Simulation.



(a) Transition simulation on one transition



simulation

Figure 2. Concept of transition simulation. (a) shows how transition simulation is accomplished for one specific transition. (b) shows how two types of transition simulation are accomplished for one specific transition.

## Equivariant Behavioral Cloning (EquiBC)

EquiBC utilizes the existing O(2) (i.e., planar rotation and reflection) symmetry in robotic manipulation to make the policy automatically generalize over different O(2) transformed states.

# Guanang Su

 $\rho s$ 

Northeastern University

Figure 3. Equivariant Behavioral Cloning: The rotation equivariant property in the state and action space. The (x, y) action rotates as the state rotates; the other action components stay invariant.

## Experiments



(b) Block in Bowl (c) Drawer Opening (d) Shoe Packing

## Figure 4. Simulation environments in PyBullet

	Bloc	ck Stac	king	Blo	ck in B	owl	Draw	ver Ope	ening	Sho	be Pack	king	
Method	1	5	10	1	5	10	1	5	10	1	5	10	
CNN BC	18.5	73.5	79.0	19.0	93.5	99.0	31.0	66.5	76.0	2.0	4.7	12.0	
Implicit BC [1]	11.0	9.5	51.0	13.0	99.5	100	31.0	63.5	71.5	0.5	5.5	12.0	
CNN BC + TS	41.0	75.0	87.0	52.2	91.0	96.5	53.5	76.0	75.0	7.5	13.0	22.0	
Equi BC (Ours) SEIL (Ours)	33.5 <b>71.5</b>	87.5 <b>99.5</b>	93.0 <b>98.5</b>	46.5 <b>75.0</b>	<b>99.5</b> 98.0	99.5 <b>100</b>	62.5 <b>78.5</b>	<b>88.5</b> 87.5	91.0 <b>93.5</b>	1.5 <b>16.5</b>	22.5 <b>57.3</b>	39.5 <b>68.0</b>	

Table 1. Baseline comparisons in simulation. Task success rates averaged over four runs.



Figure 5. Ablation study. The figure shows how every component of our method improves performance. All tasks use one demonstration. Results averaged over four runs.

- m=3



(a) Block Stacking

## \*Equal Contribution







	Trash Tidying			Blo	Block in Bowl			Drawer Opening			Shoe Packing		
Method	1	5	10	1	5	10	1	5	10	1	5	10	
CNN BC SEIL (Ours)	0.0 <b>30.0</b>	3.3 <b>60.0</b>	20.0 <b>93.3</b>	0.0 <b>36.7</b>	50.0 <b>90.0</b>	76.7 <b>100.0</b>	23.3 <b>86.7</b>	60.0 <b>96.7</b>	70.0 <b>100.0</b>	10.0 <b>13.3</b>	46.7 <b>60.0</b>	70.0 <b>90.0</b>	

Table 2. Baseline comparisons in real-world experiments. Task success rates averaged over 30 episodes across three seeds.





(a) Table Tidying

## QR code for videos.





(a) CNN pick

Figure 7. Comparison of SEIL and CNN BC in Shoe Packing. SEIL is able to pack the shoes with reasonable orientations, but CNN cannot.

- transition with contact.
- tasks like color-based sorting.

[1] Pete Florence, Corey Lynch, Andy Zeng, Oscar A Ramirez, Ayzaan Wahid, Laura Downs, Adrian Wong, Johnny Lee, Igor Mordatch, and Jonathan Tompson. Implicit behavioral cloning. In Aleksandra Faust, David Hsu, and Gerhard Neumann, editors, Proceedings of the 5th Conference on Robot Learning, volume 164 of Proceedings of Machine Learning Research, pages 158–168. PMLR, 08–11 Nov 2022.

# Robert Platt







(b) Block in Bowl (c) Drawer Opening (d) Shoe Packing

Figure 6. Real-world experiments. SEIL on four real-world tasks. Refer to the



(b) CNN place

(c) SEIL pick



(d) SEIL place

## Limitations

Transition Simulation only simulates transitions without contact between the gripper and the environment. Can be improved by learning an environment model to predict the outcome of the

Observations are based on depth images without color information, preventing the agent from solving more complex

## References