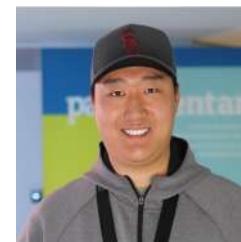
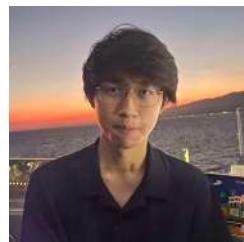


SOPE: Learning to Singulate Objects in Packed Environments using a Dexterous Hand

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¹ Applying to Ph.D
* Equal Contribution

Singulating Objects

- We study the object singulation problem.
 - Given some target in clutter, isolate, grasp, and retrieve it.
- This has many applications.
 - Deformable object manipulation: separating a certain # of layers.
 - Object retrieval: extract item from clutter (e.g., shelves, boxes, bowls).
- Challenges: occlusions, manipulating in clutter, high-precision.

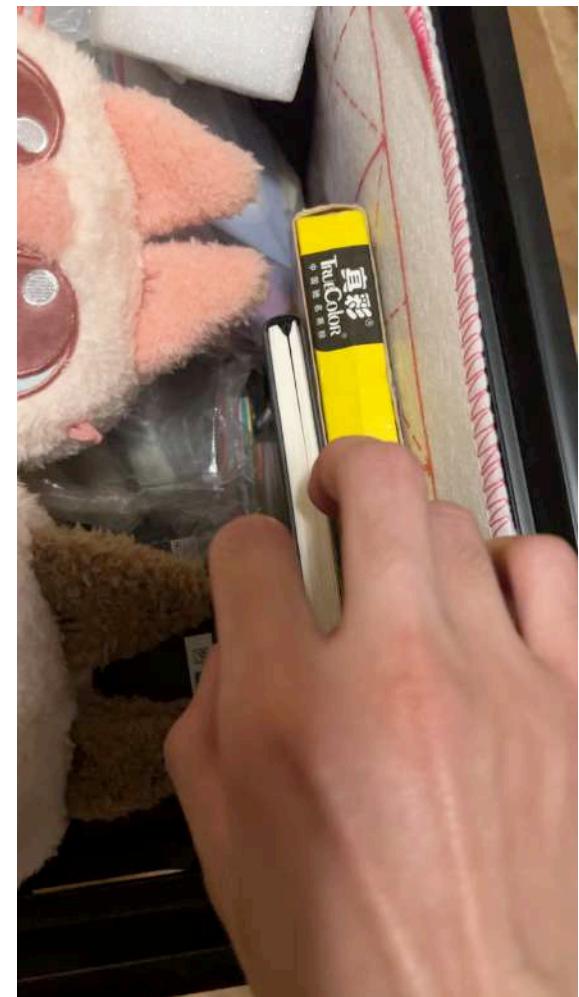
[Tirumala*,
Weng*,
Seita* et al,
IROS 2022]



[Guzey et al.
CoRL 2023]

Singulating Objects in Packed Environments

- We focus on packed environments.
 - What if the object is tightly packed under a clustered environment? Naively “push and then retrieve” may not work.



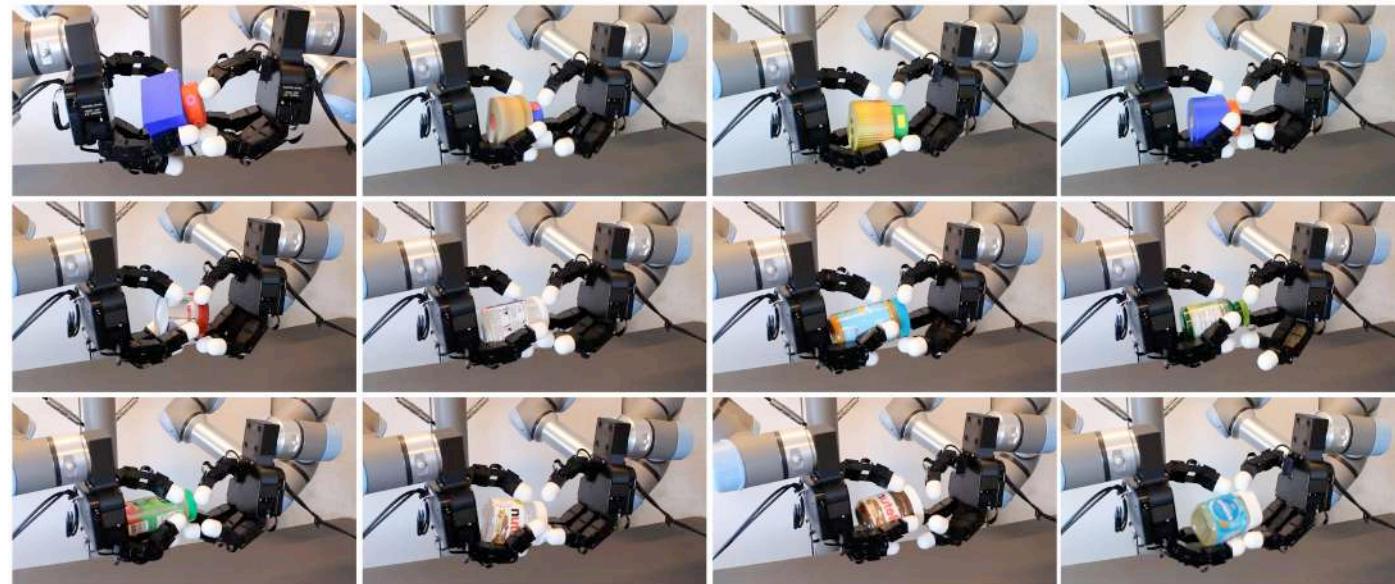
[Marios et al, ICRA 2019]

Dexterous Manipulation for Object Singulation

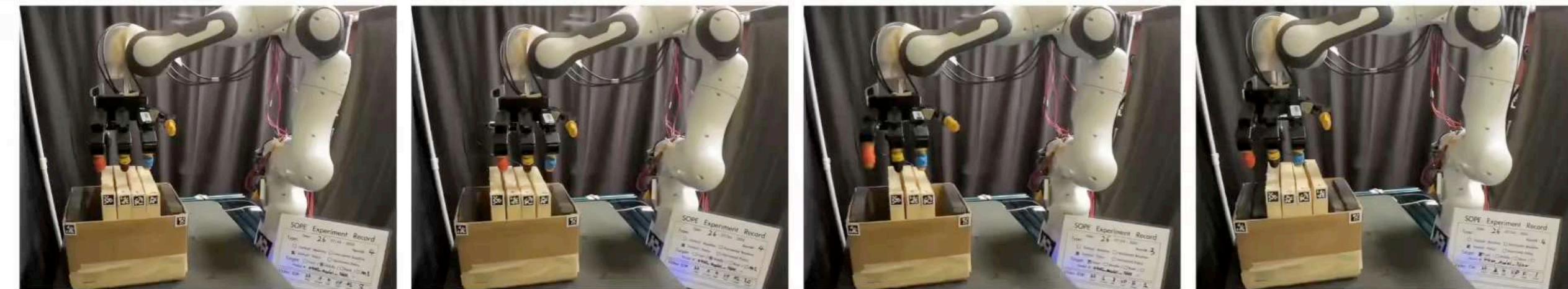
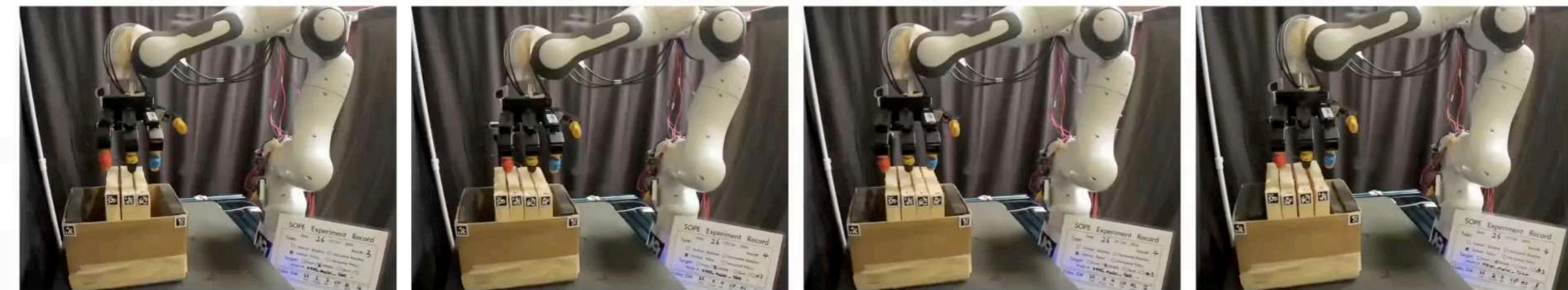
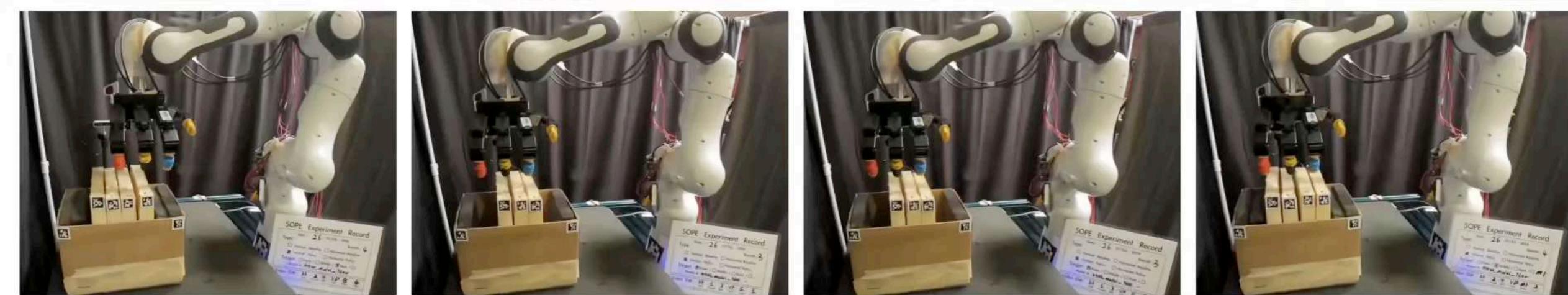
- Just like human, use a high-DOF dexterous hands!
 - Use some fingers to **stabilize** / push other items, while other fingers **act**.
- Dexterous manipulation: in-hand reorientation / rotation / pen spinning / et al



(Allegro Hand)

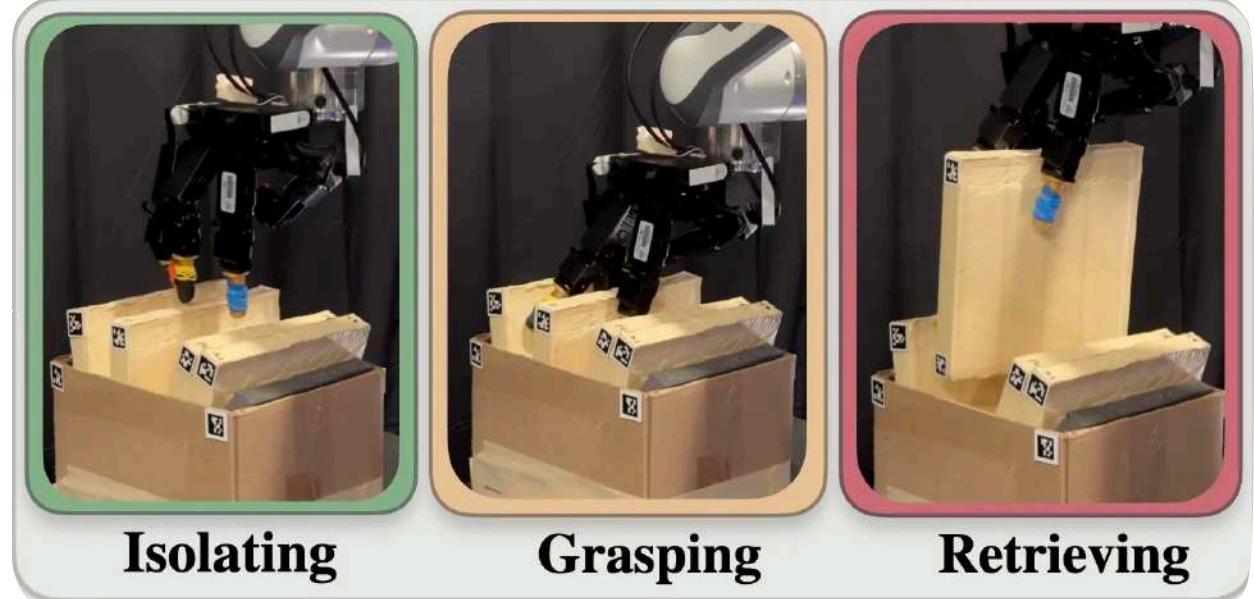
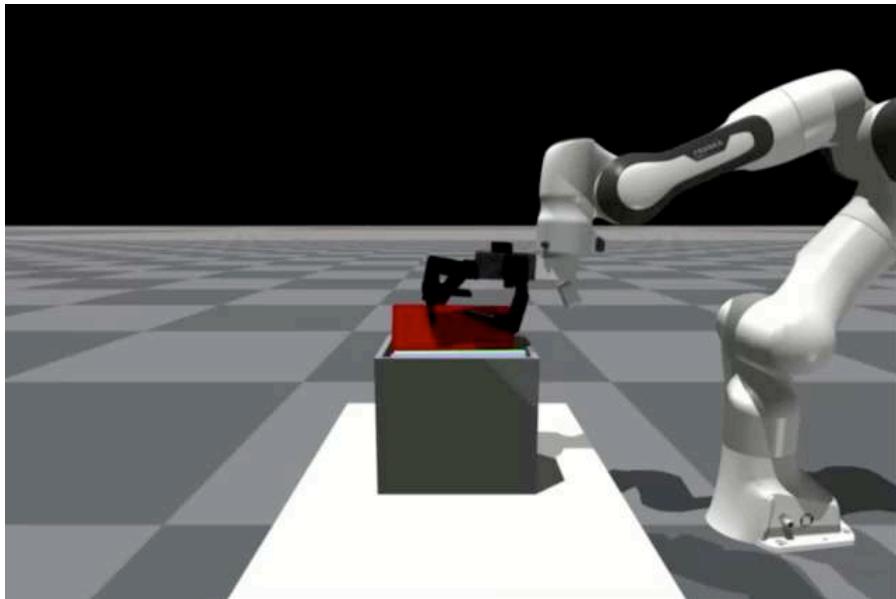


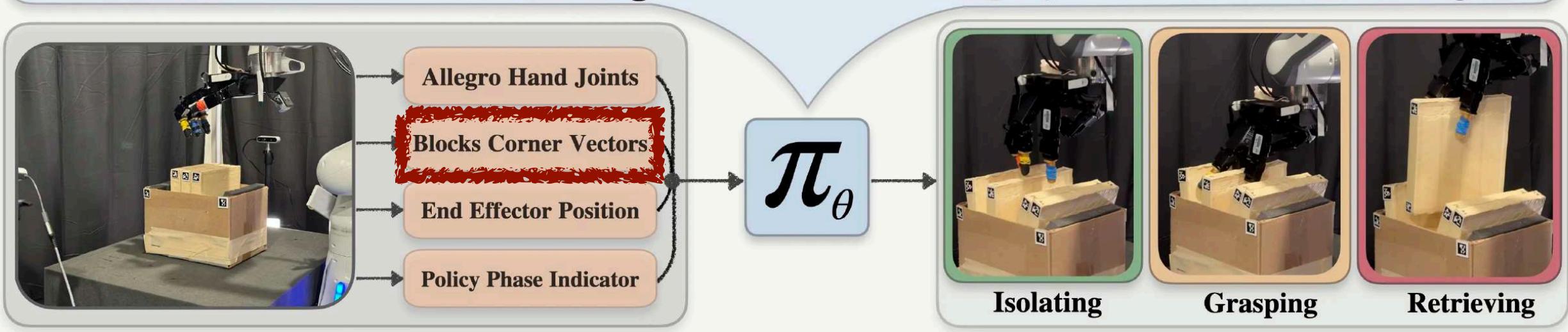
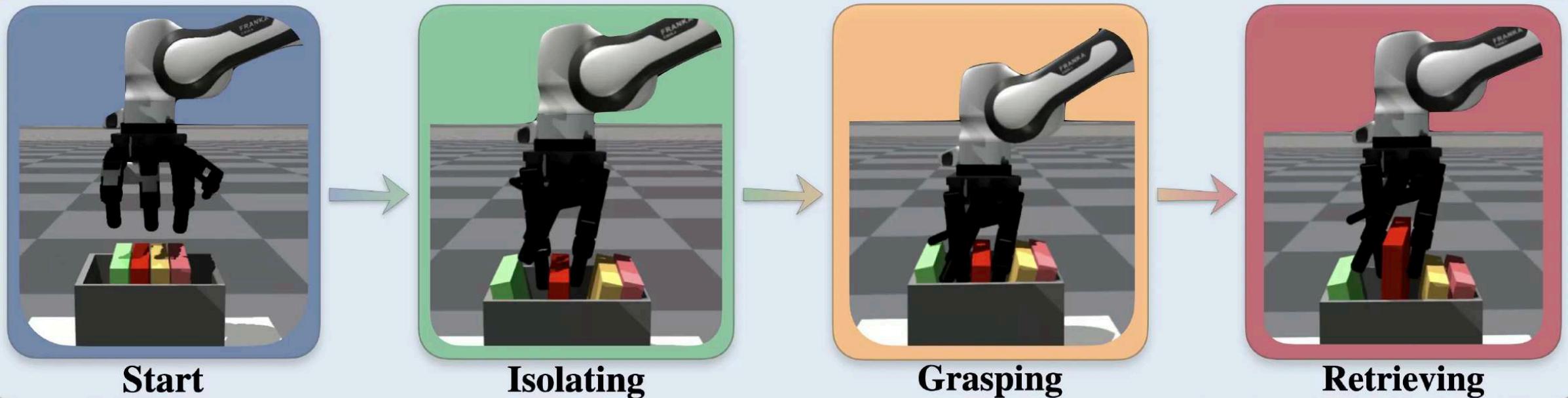
(Example of Acting & Stabilizing but with Two Hands)
[Toru Lin, Zhao-Heng Yin, et al, CoRL 2024]



The SOPE Pipeline

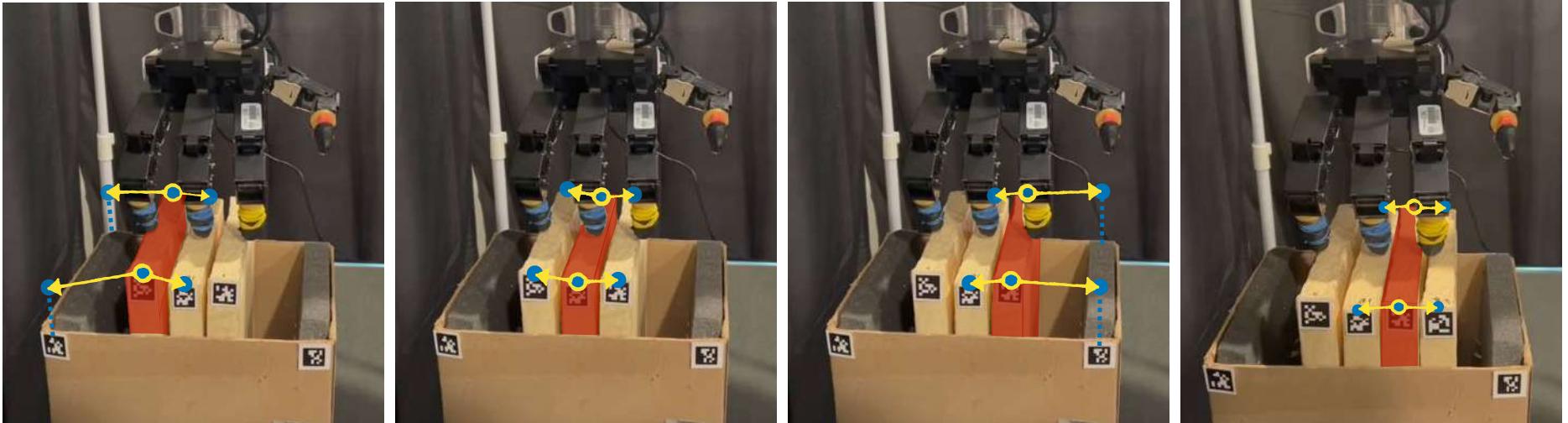
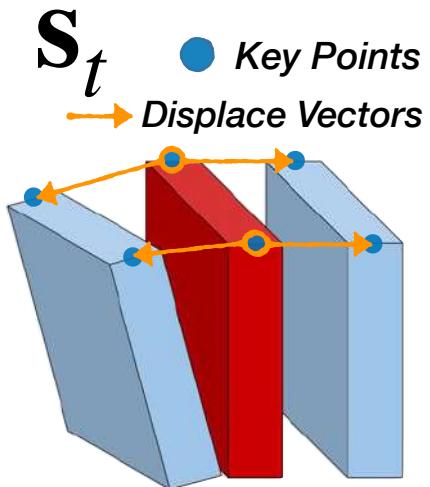
- Use reinforcement learning with Proximal Policy Optimization.
- Reward based on extracting the target.
- Zero-shot sim2real using NVIDIA IsaacGym.



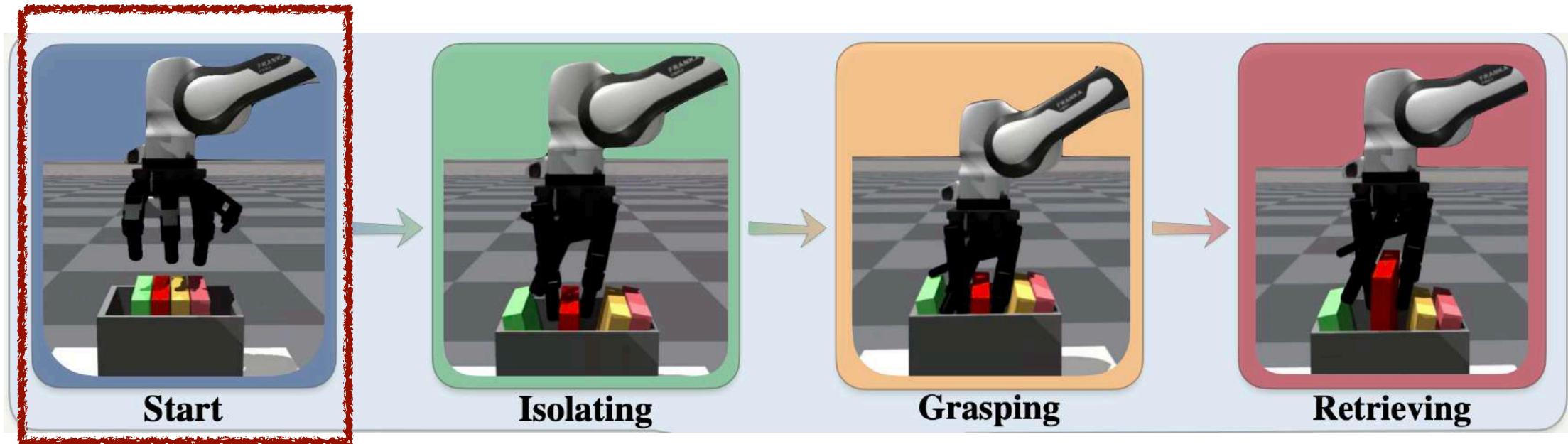


Vector Displacement State Representation

- Use a displacement-based state representation for the blocks.
 - Detect using AprilTag markers in real (or corner detection methods).
- Why?
 - Captures essence of the task: separating target from nearby objects.
 - Easier to bridge sim2real gap, e.g., compared to images.



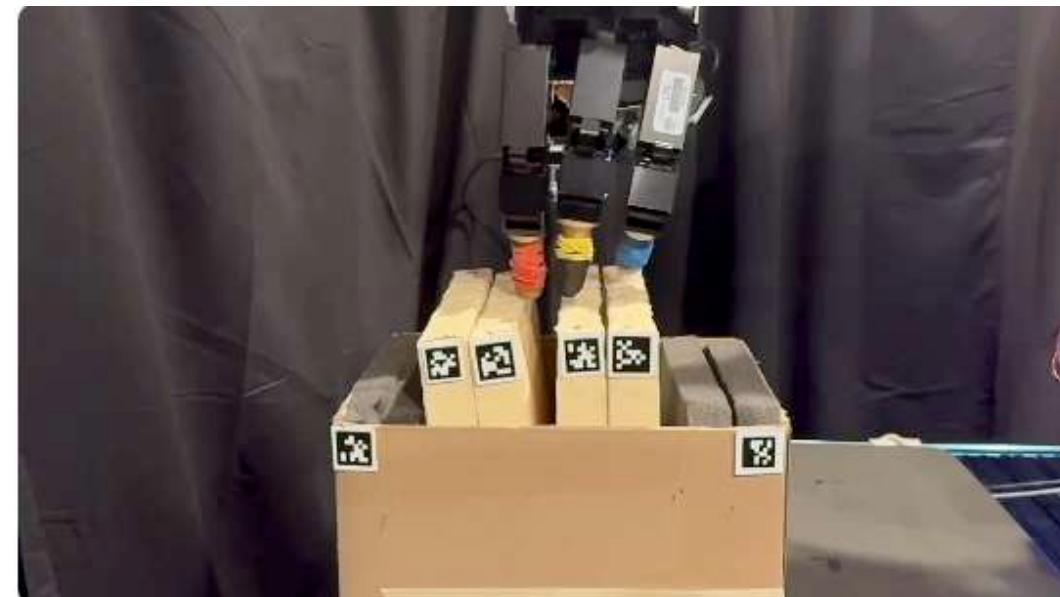
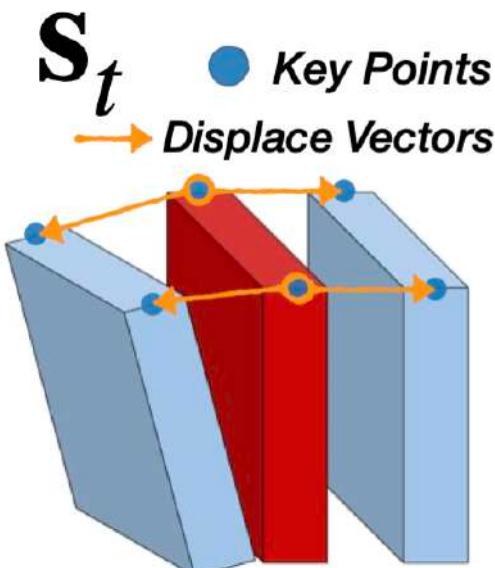
Multi-Phase Training Pipeline



- Proceed through each phase sequentially, each phase has unique:
 - Pre-engineered End-Effector Height
 - Reward Design

Isolating Phase

- Avoid lifting the other blocks
- Maximize the “**Displace Vectors**”

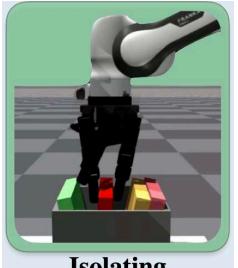


Slowed-down isolation phase



Grasping Phase

- Avoid lifting the other blocks
- Minimize the Euclidean distance between fingertips and the block's surface
 - Encourage at least two contacts for force closure



Isolating



Grasping



Retrieving

Retrieving Phase

- Avoid lifting the other blocks
- Maximize the height of the target block
 - Encourage strong grasp for previous phase



Isolating



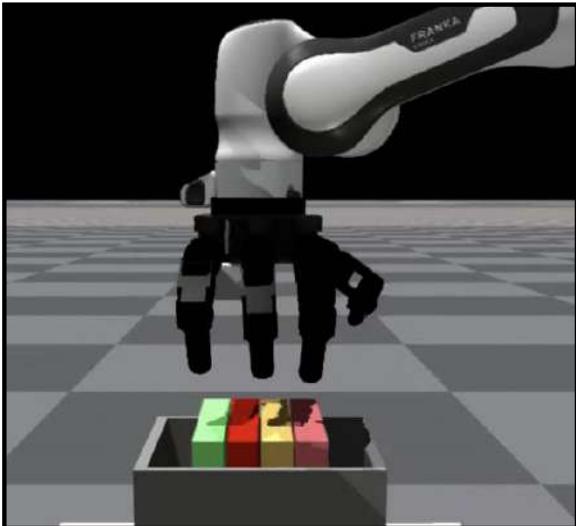
Grasping



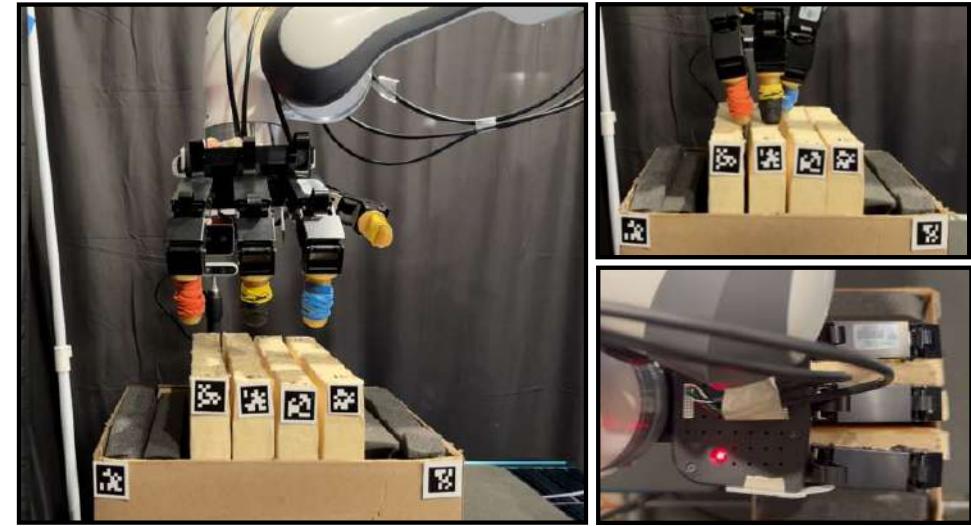
Retrieving

Sim-to-Real

Isaac Gym Simulation



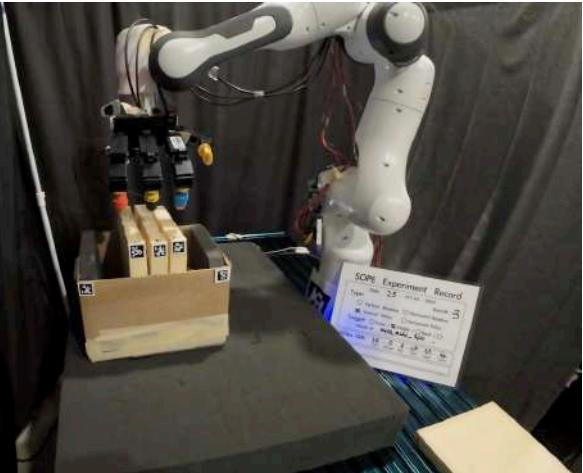
Real World



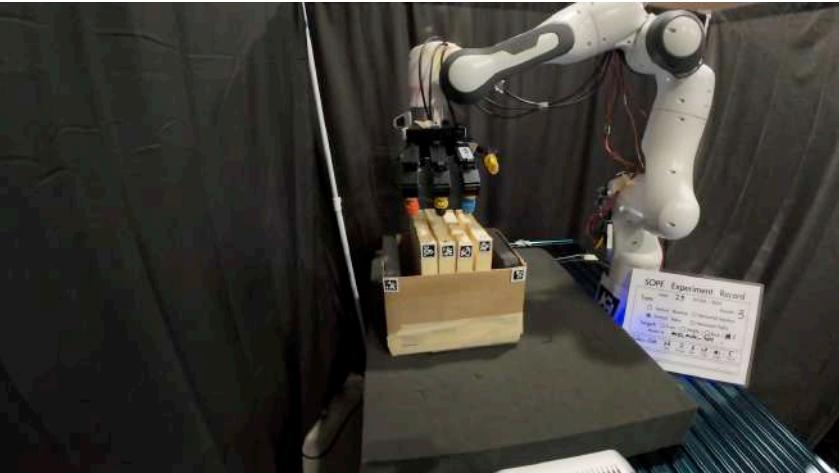
- Domain Randomization
 - Neighbor Blocks Spacing
 - Hand Initial Position
 - Physical Properties (e.g. mass)
 - Observation & Action Space

- State Representation Design
- System Identification (PD Parameter Tuning)
- Other Techniques
 - EMA Smoothing Factor
 - 3D Printed Thinner Fingertip

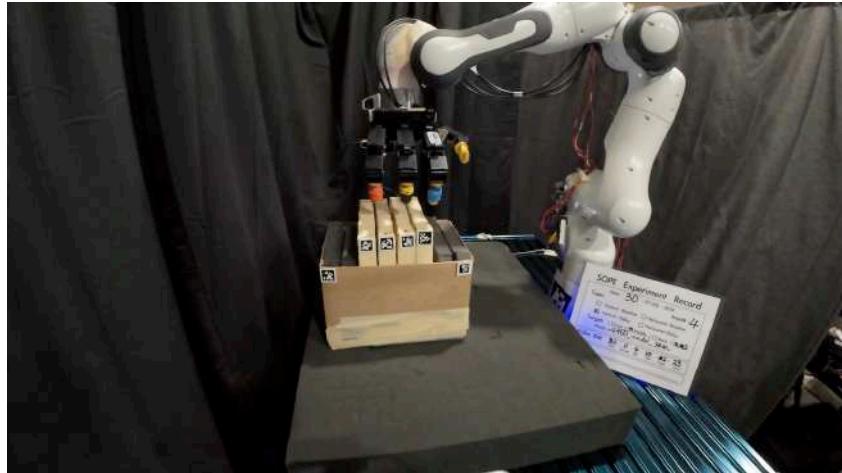
Generalize Over Different Settings



Three Blocks



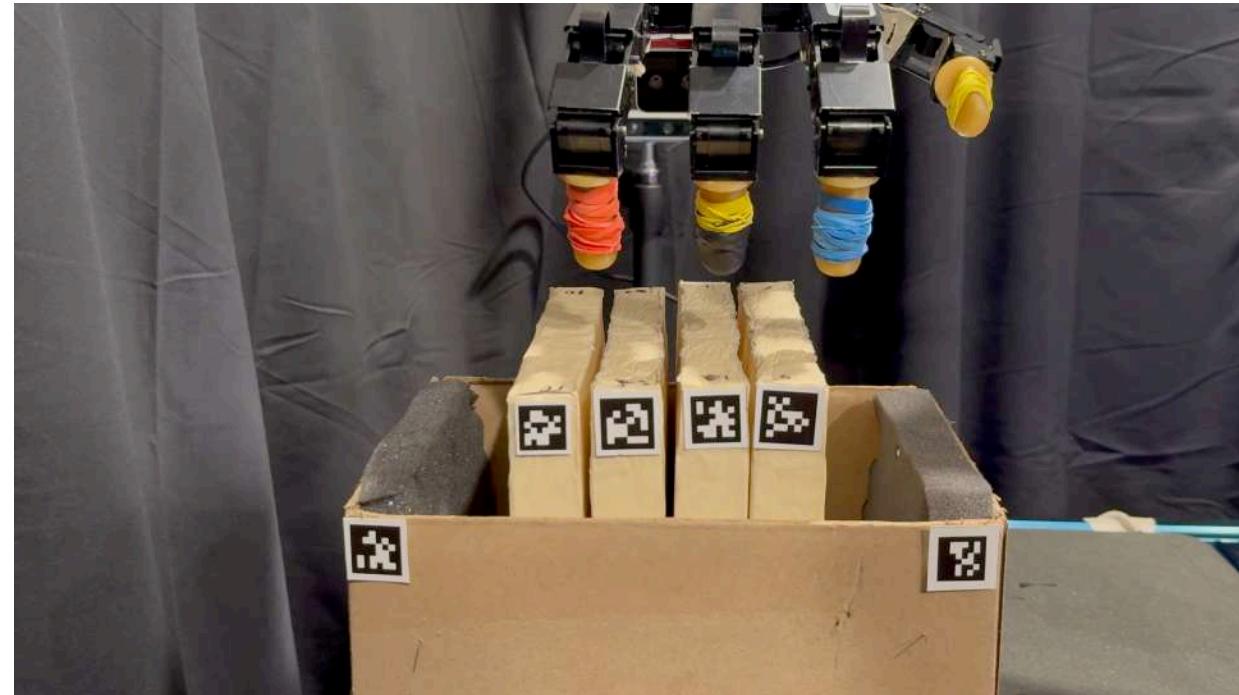
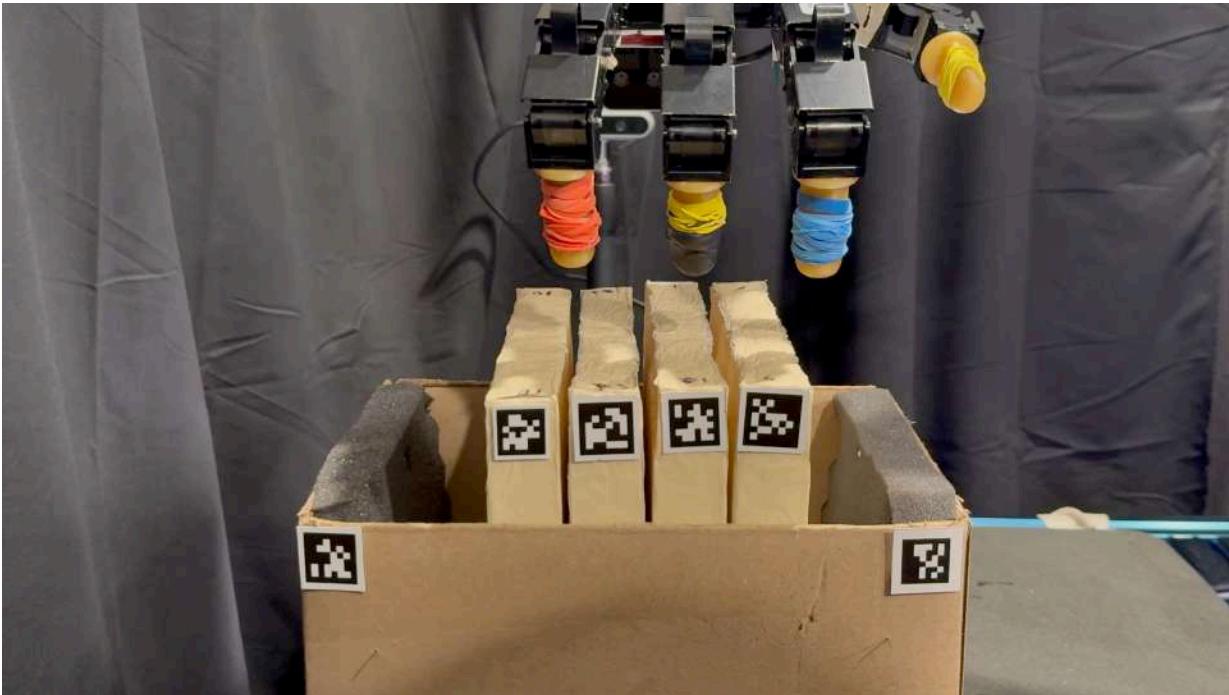
Four Blocks (Normal)



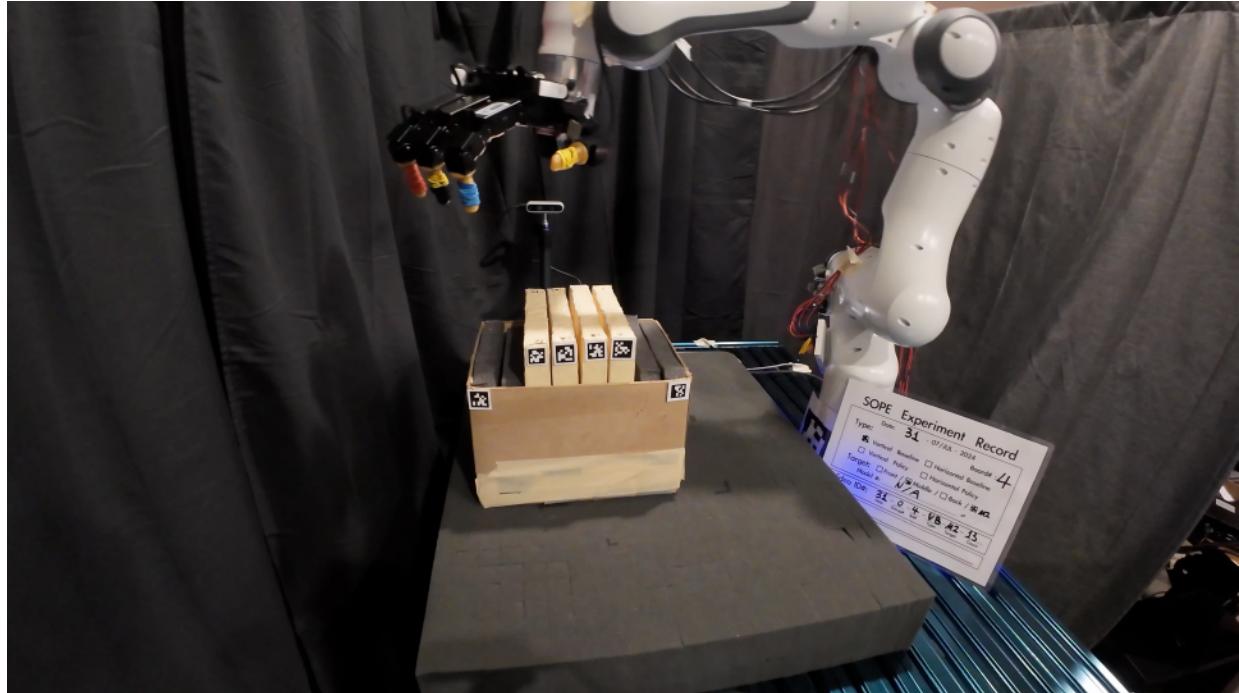
Four Blocks (Packed)

- Our policy and adapt to different levels of *packing densities*.
 - Our state representation is invariant to object arrangements.
 - Domain Randomization enables robustness.

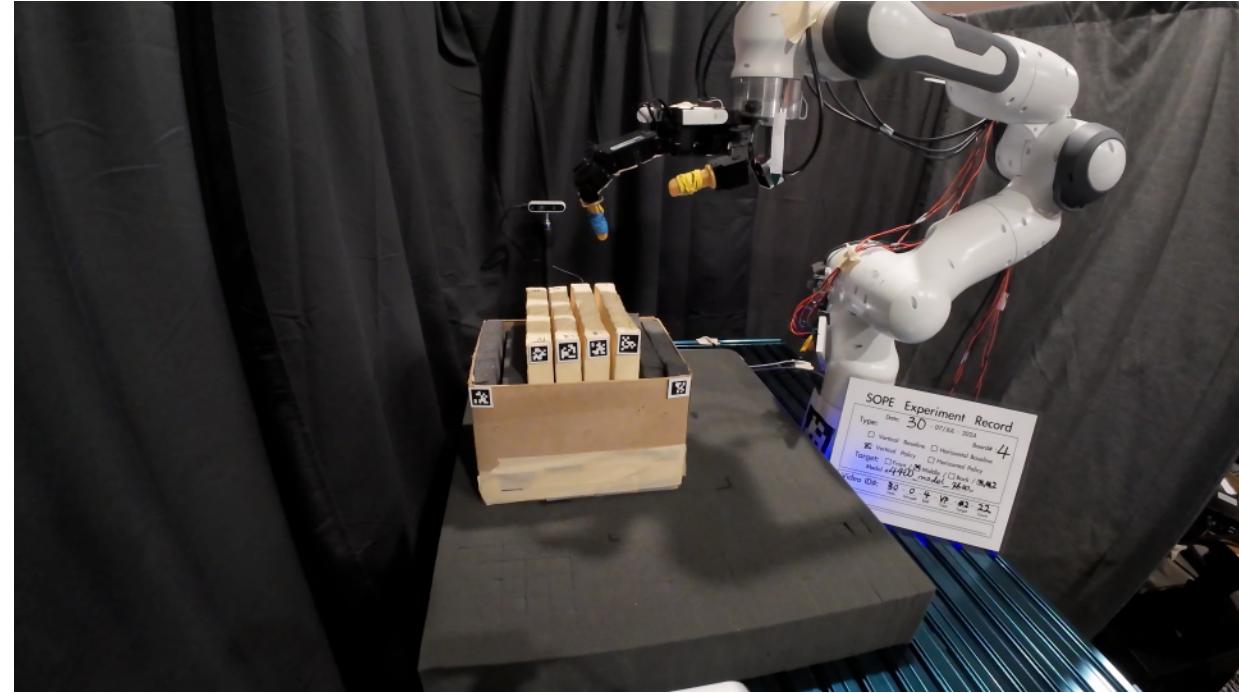
Robustness Under Human Intervention



Comparison with Non-learning Baseline



(S2SS&P Baseline)



(Ours)

(Target block: second from right)

Numerical Results

Environment	Method	Front	Middle-1	Middle-2	Back	Overall
Normal	S2SS&P	10/10	6/10	10/10	10/10	36/40
Normal	Ours	9/10	8/10	9/10	7/10	31/40
Constrained	S2SS&P	0/10	0/10	0/10	0/10	0/40
Constrained	Ours	7/10	6/10	5/10	10/10	28/40

- Constrained environment is more challenging.
- Once we make the container more “packed”, the non-learning baseline immediately failed.
- Better simulation result does not imply better real world result.
- (We release all of the experiments videos.)

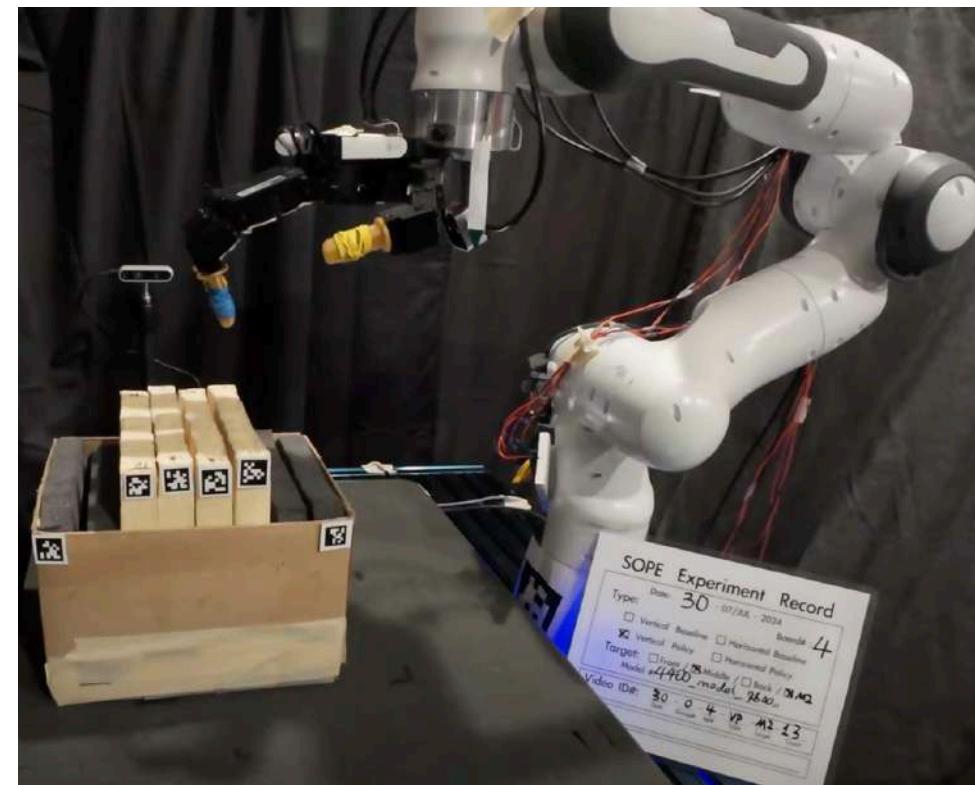
Aside: Lessons Learned during Experiments

- We need to record videos of every experiment → Put all in spreadsheet.
- But also, use a “Clapperboard system” → Helps us remember what we did!
- We encourage the community to consider similar methods for full transparency.

Videos of All Experiments

To maximize transparency, we provide our full experiment record with videos of all trials in the table below. Check out our Clapperboard system - it helps us keep tabs on every experiment and makes it super easy for you to see what we've been up to.

Four Blocks Constrai ned Ours	SOPE-ExperimentData-PublicAccess : Exp Data							
	4	Vertical Policy	Middle - 1	10	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 1	11	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 1	12	No	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 1	13	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 1	14	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	15	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 2	16	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 2	17	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	18	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 2	19	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Back	20	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Back	21	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Back	22	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Back	23	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Back	24	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	25	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	26	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	27	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 2	28	Yes	No	No Lifting	YouTube Link
	4	Vertical Policy	Middle - 1	29	Yes	Yes	Policy	YouTube Link
	4	Vertical Policy	Middle - 1	30	No	No	No Lifting	YouTube Link



Failure Cases

Isolating Failure



Lifting Failure



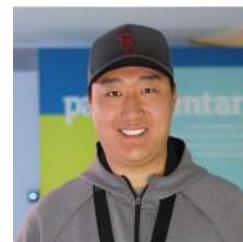
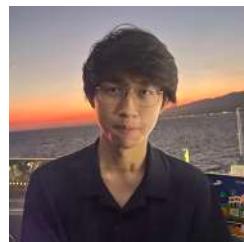
SOPE: Conclusions and Takeaways

- Vector-based states enable high-DOF simulation.
- Sim2Real is possible with this contact-rich task.
- Limitation:
 - Requires AprilTag markers.
 - Potential Method: Learning from Point Clouds.
 - Objects are “equal” irrespective of semantics.
 - Potential Method: Incorporate semantic info to train with diverse objects.
 - Requires an engineered setup for occlusions.
 - Representation may not generalize to deformable objects.



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