



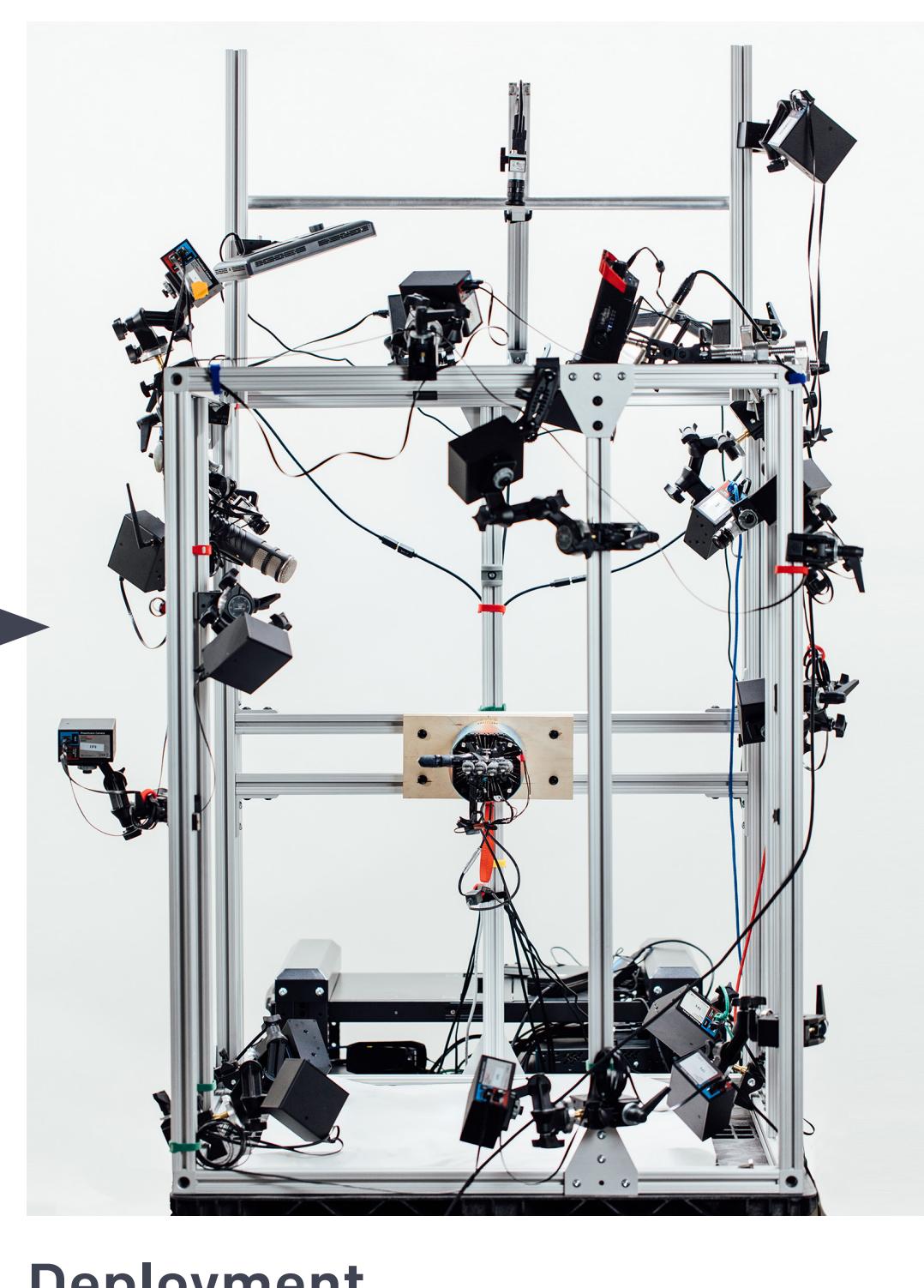
Setup & Task

Simulation Environment



Training

Real-World Environment



Deployment

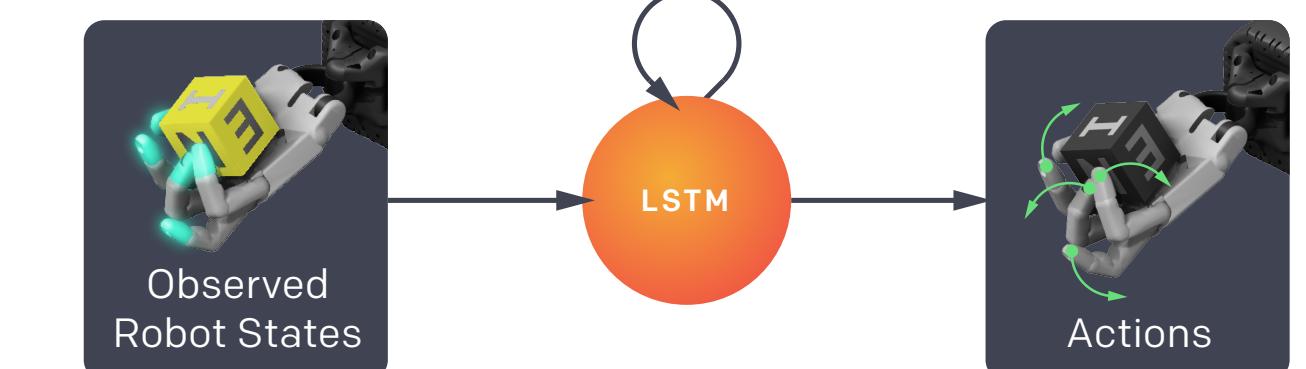
Transfer

System Overview

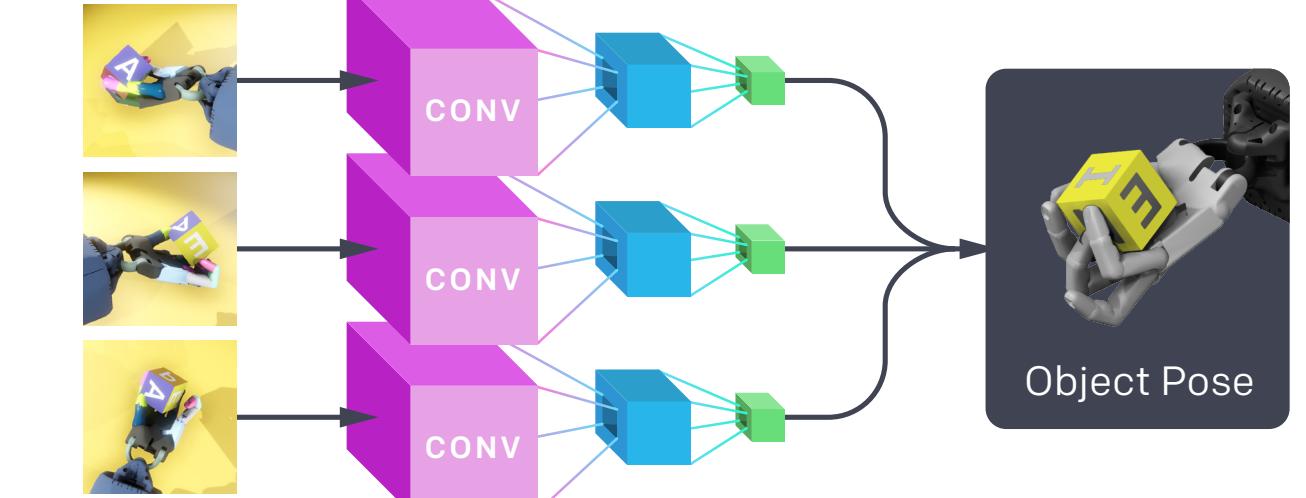
A Distributed workers collect experience on randomized environments at large scale.



B We train a control policy using reinforcement learning. It chooses the next action based on fingertip positions and the object pose.



C We train a convolutional neural network to predict the object pose given three simulated camera images.



D We combine the pose estimation network and the control policy to transfer to the real world.



Goal

Train entirely in simulation and achieve zero-shot transfer to real robot hand.

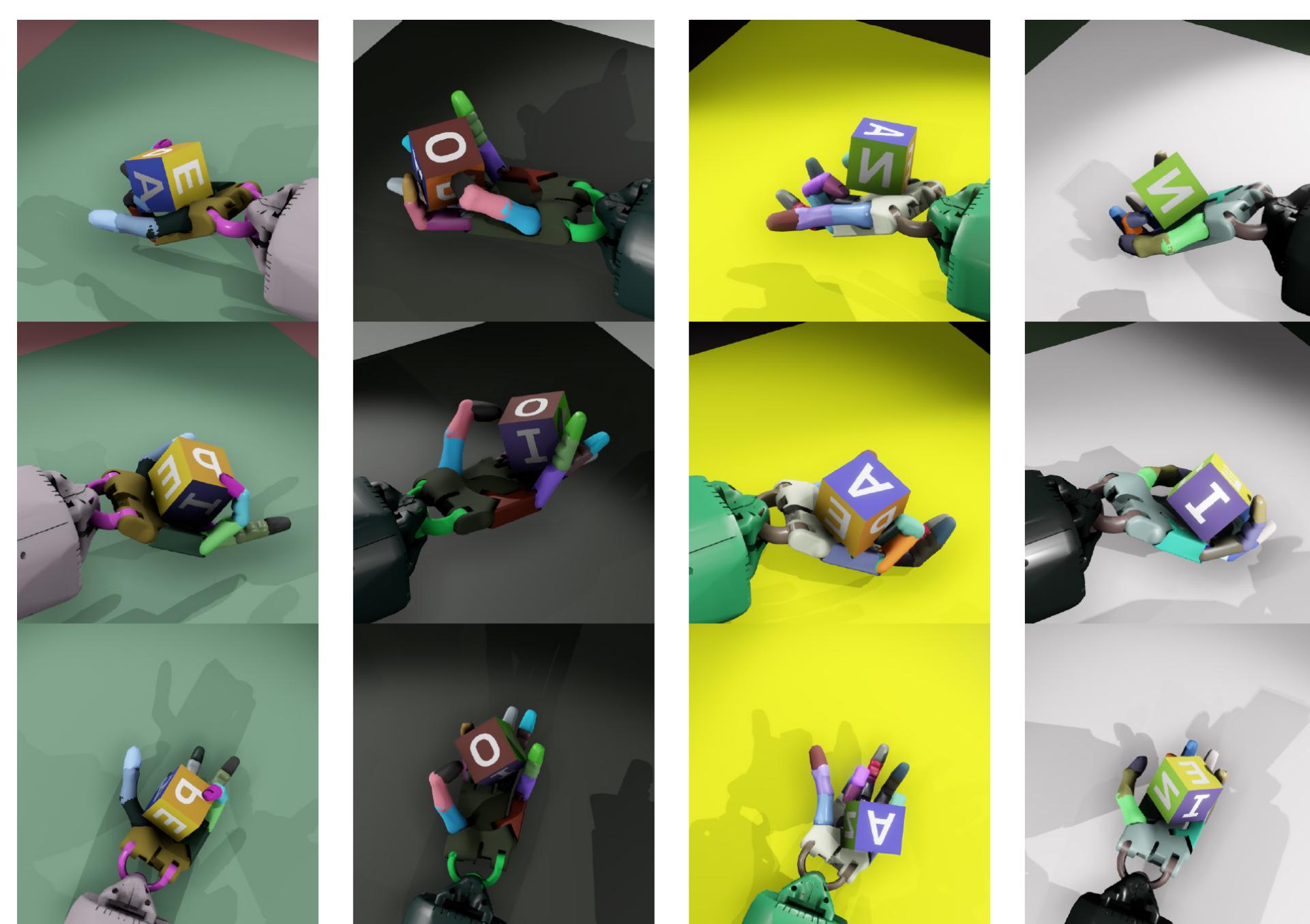
Key Elements

1. Domain Randomization

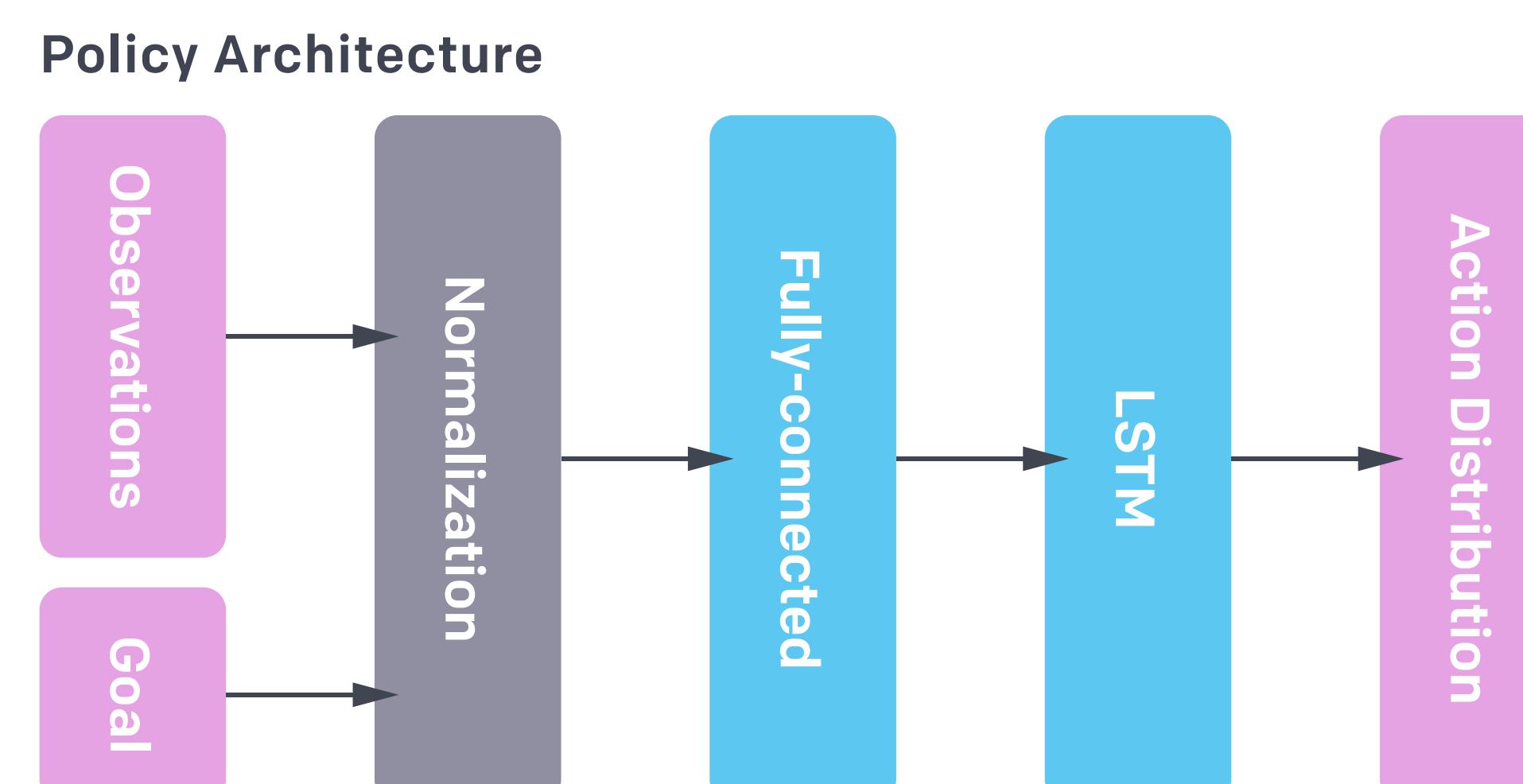
Physics Randomizations

Object Dimensions	Actuator Force Gains
Object And Robot Link Masses	Joint Limits
Surface Friction	Gravity Vector
Robot Joint Damping	Noisy Observations
Backlash	Noisy Actions

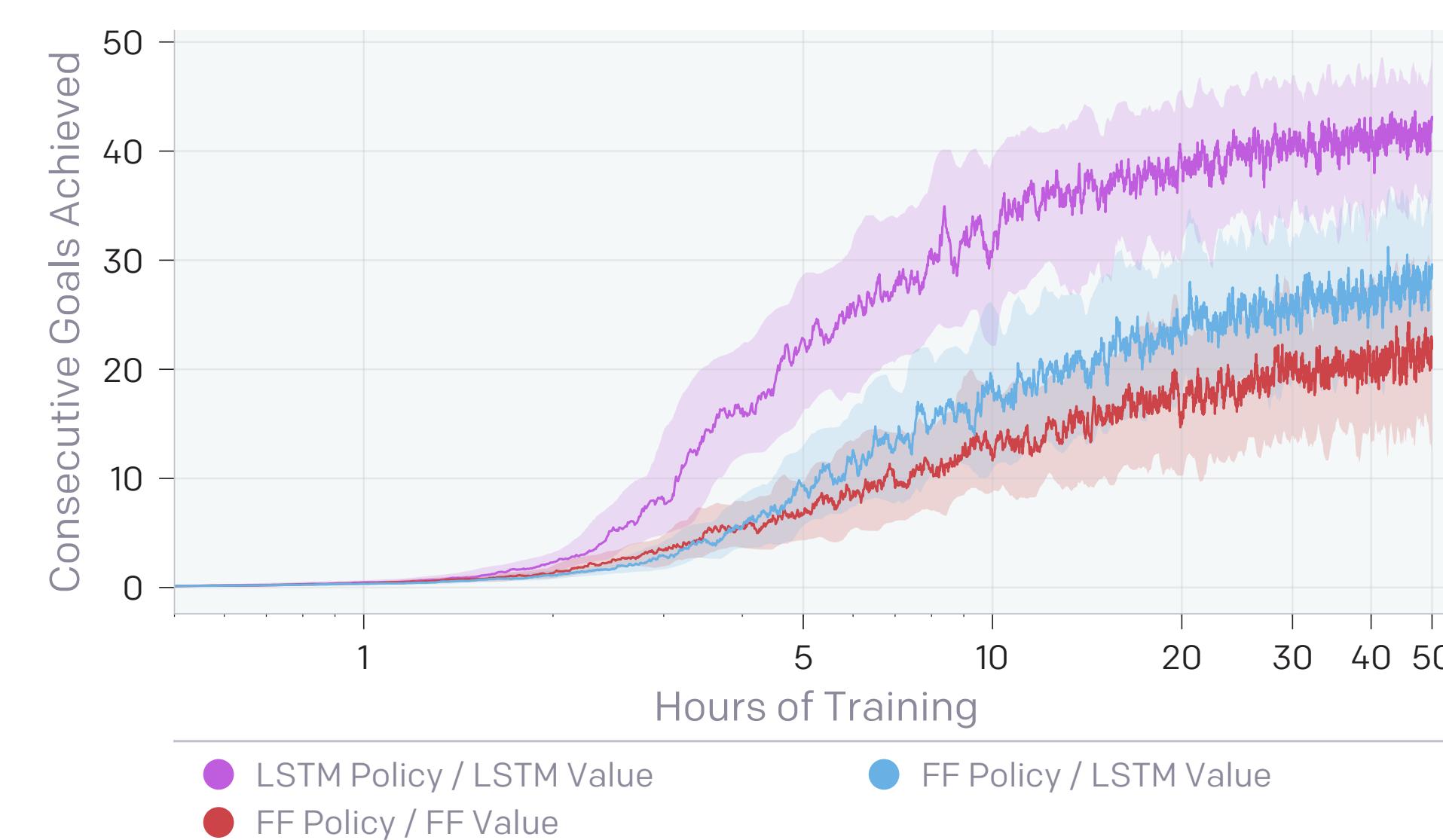
Appearance Randomizations



2. Memory Augmented Policy

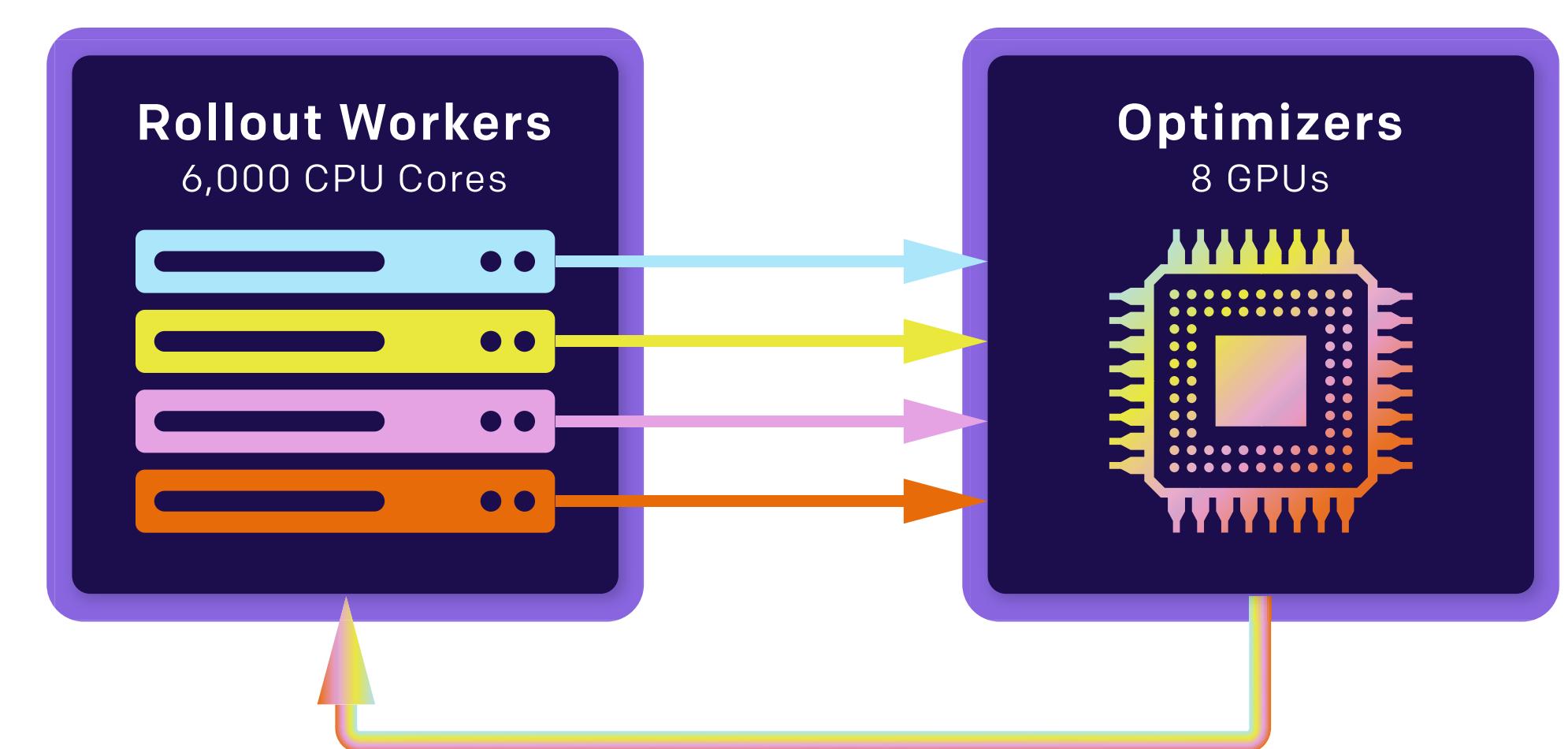


Effect of Memory in Simulation

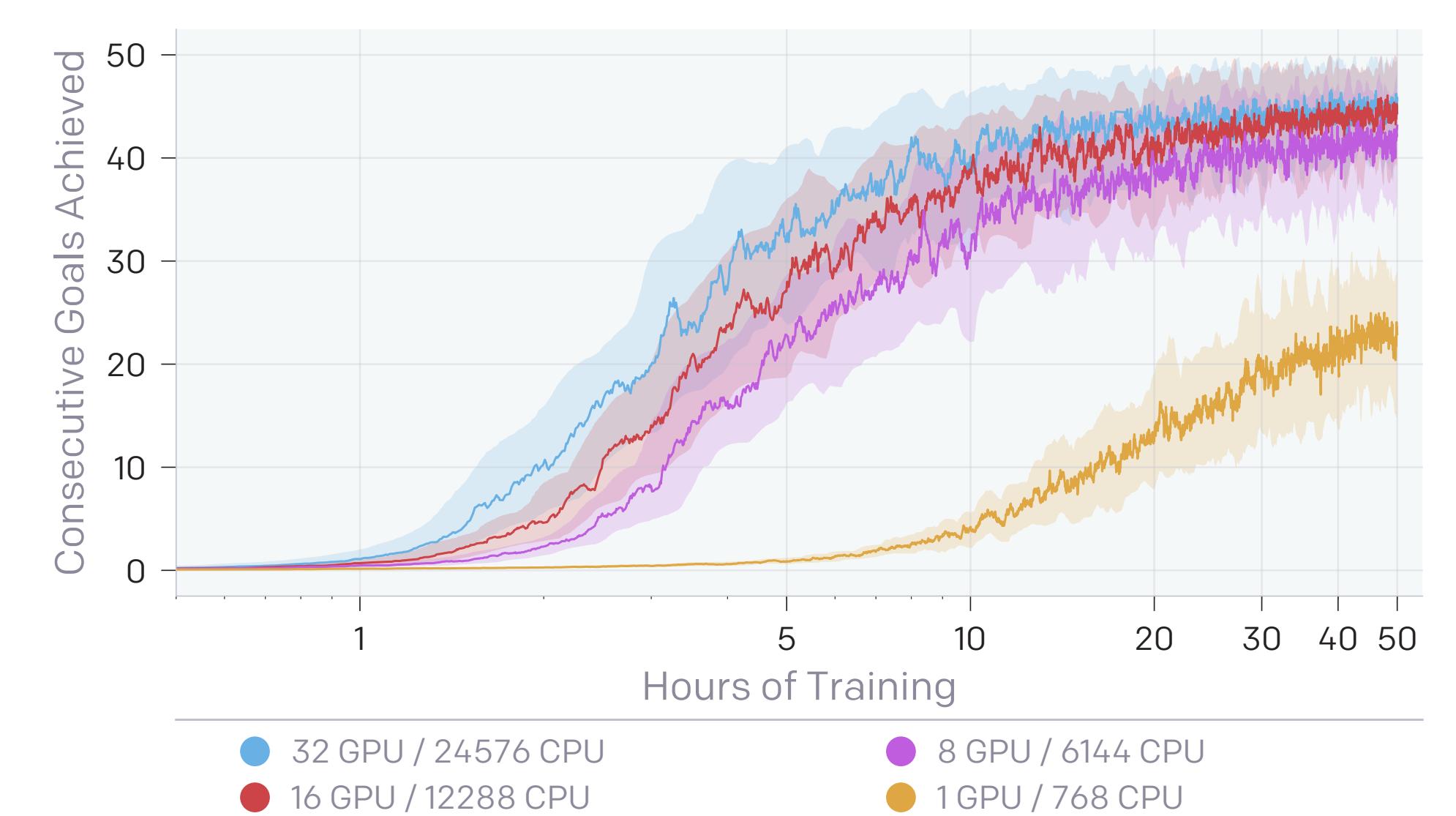


3. Large Scale RL

Distributed Training with Rapid



Effect of Scale in Simulation

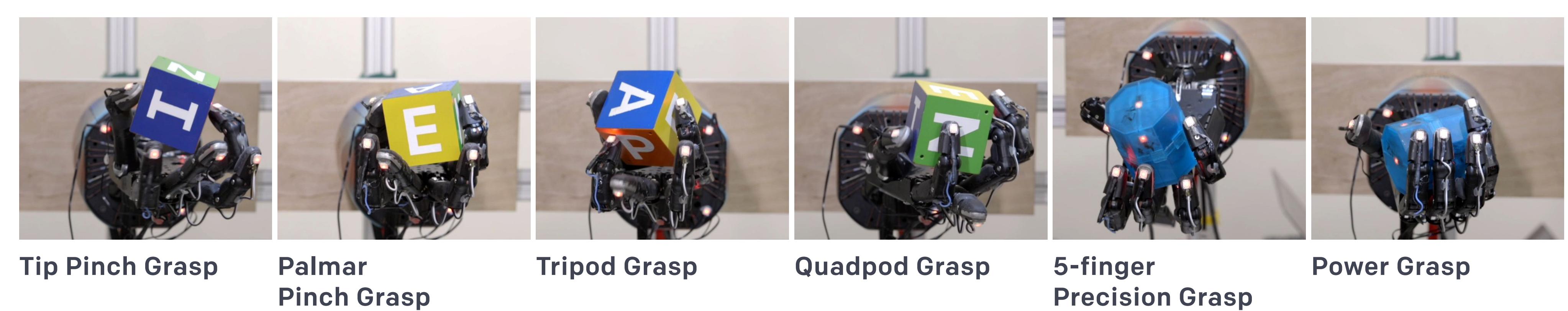


Quantitative Results

Randomizations	Object Tracking	Policy	Number of Successes*		
			Median	Mean	Max
None	Motion Tracking	LSTM	0	1.1 ± 1.9	6
All	Motion Tracking	FF	3.5	4.7 ± 4.1	15
All	Motion Tracking	LSTM	13	18.8 ± 17.1	50
All	Vision	LSTM	11.5	15.2 ± 14.3	46

* Measured across 10 trials. Each trial ends when the block is dropped or if 50 successes are achieved.

Qualitative Results



Classified according to "The GRASP Taxonomy of Human Grasp Types", Feix et al., 2016.

Learn More



<https://blog.openai.com/learning-dexterity/>



<https://arxiv.org/abs/1808.00177>



<https://youtu.be/jwSbzNHGfIM>