



Massachusetts Institute of Technology



Empirical Analysis of Sim-and-Real Cotraining

Adam Wei, Abhinav Agarwal, Boyuan Chen, Rohan Bosworth,
Nicholas Pfaff, and Russ Tedrake



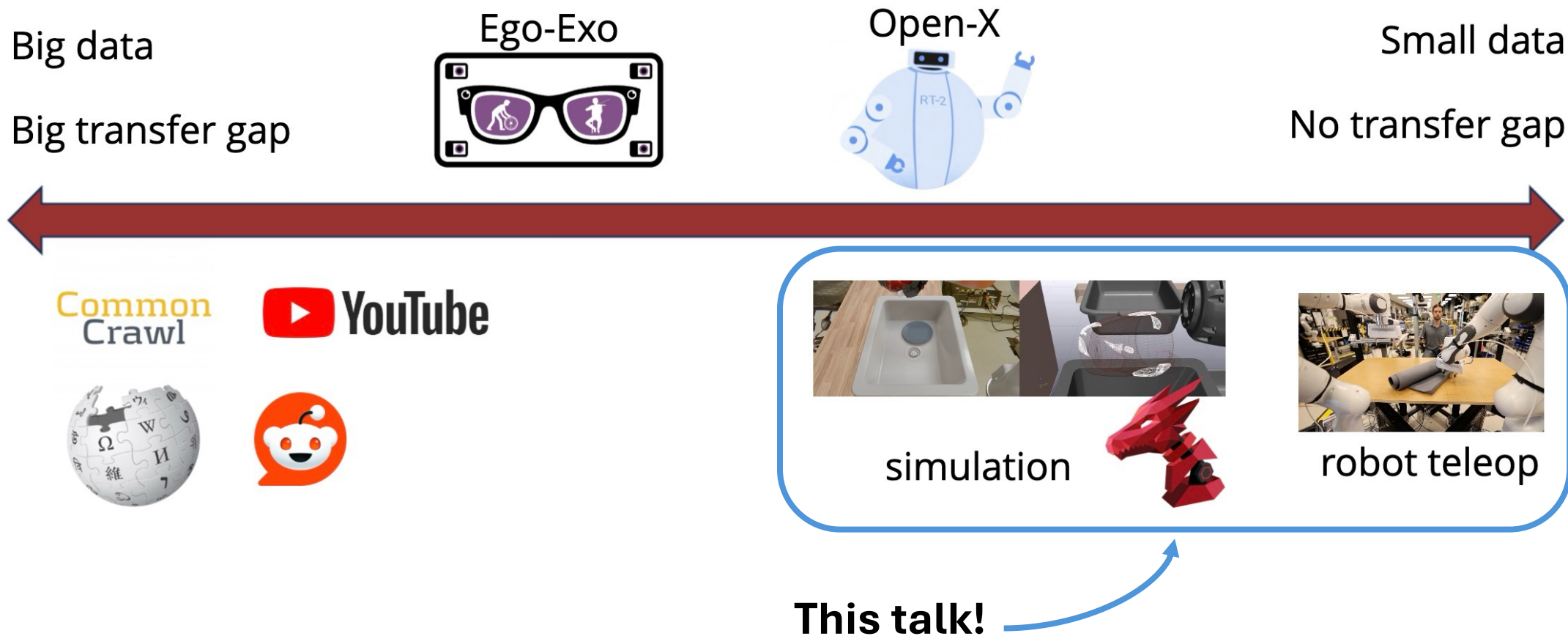
Adam Wei

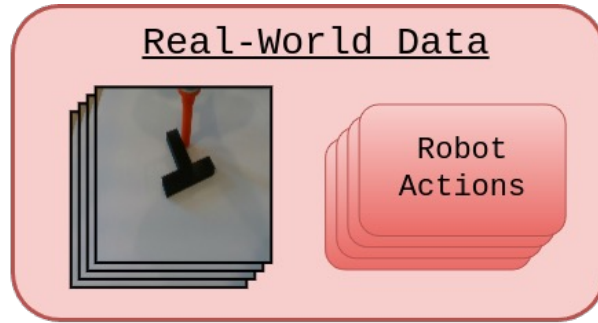
IROS
21 October, 2025



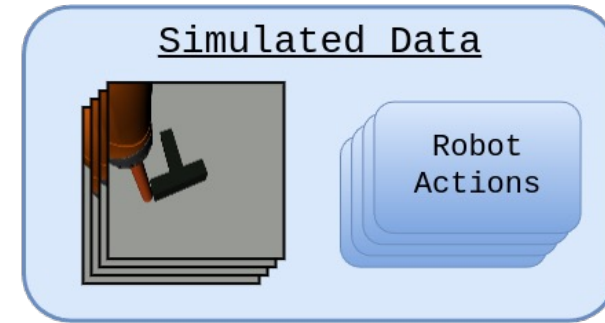
Robot Data Diet

How can we obtain data for robot imitation learning?

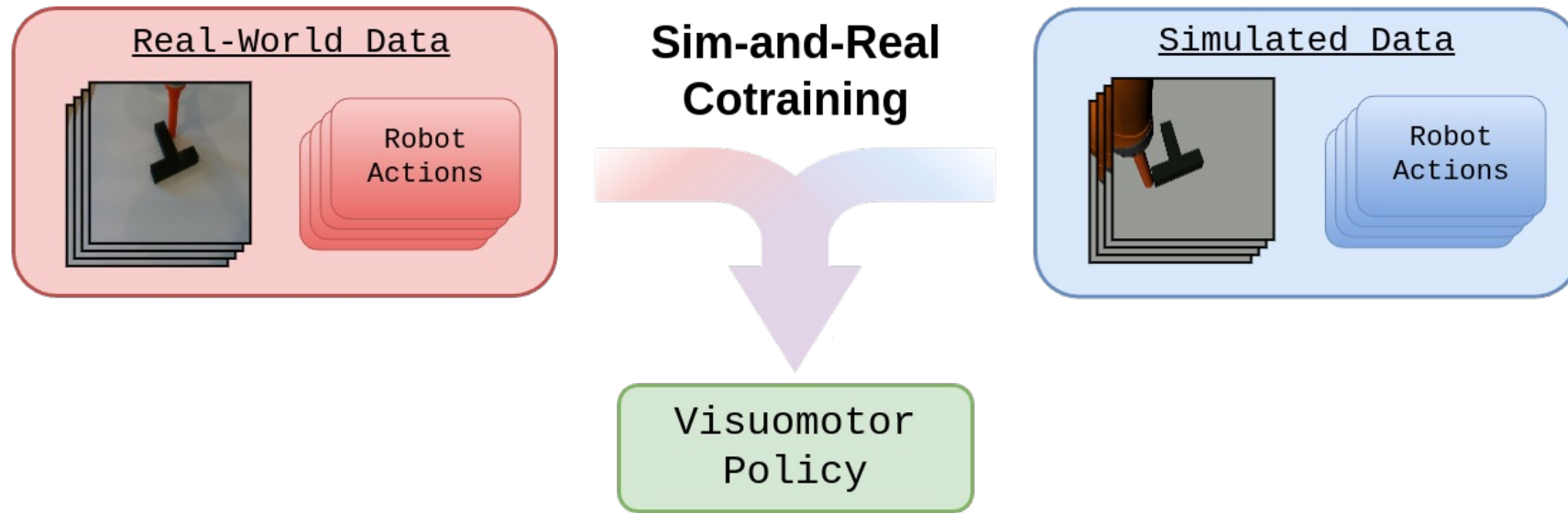




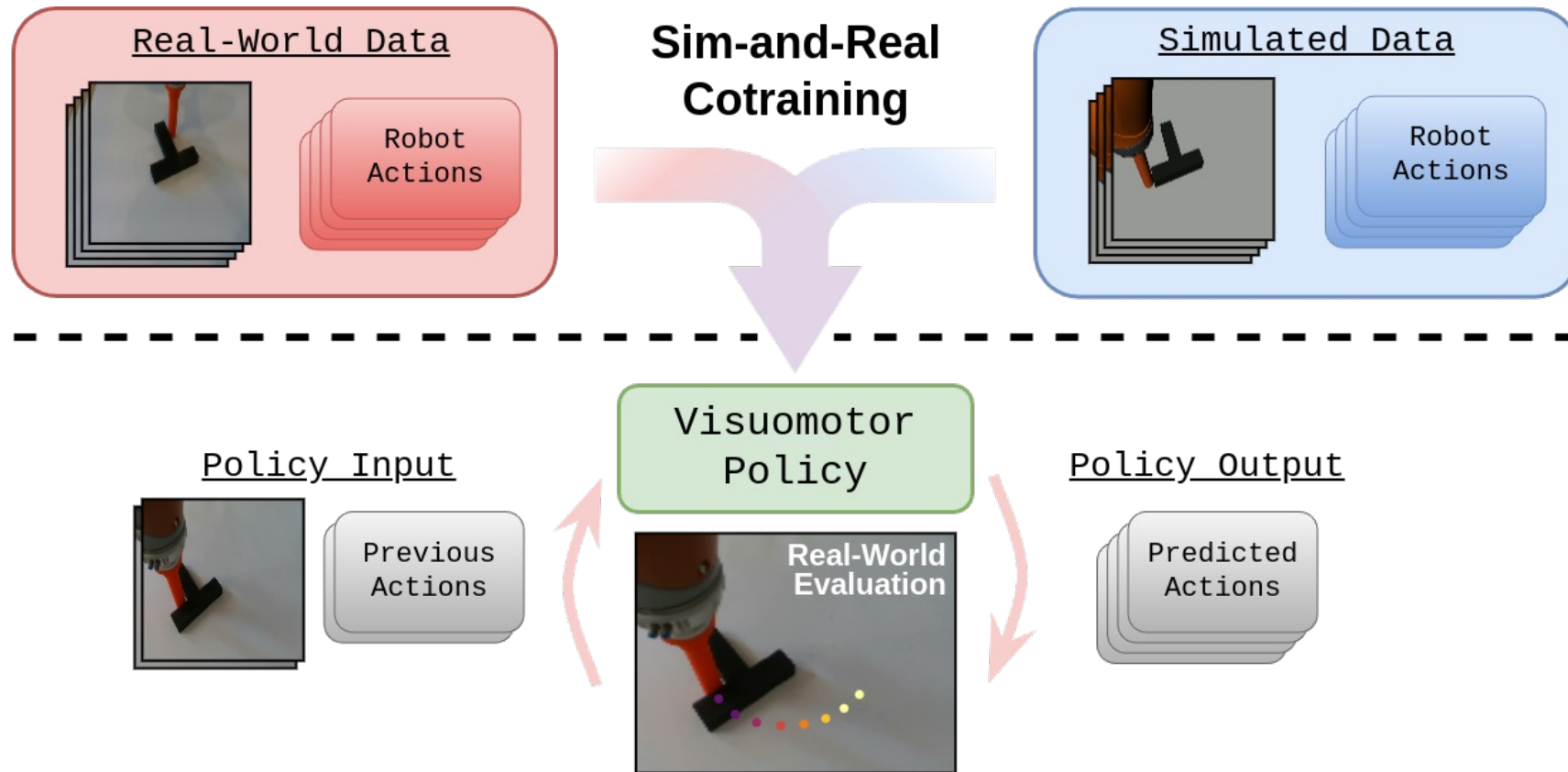
Sim-and-Real Cotraining



Cotraining: use *both datasets* to train a *model* that maximizes a real-world *performance objective*



Cotraining: use *both datasets* to train a *model* that maximizes a real-world *performance objective*



Cotraining: use *both datasets* to train a *model* that maximizes a real-world *performance objective*

Cotraining: use *both datasets* to train a *model* that maximizes a real-world *performance objective*

Performance Objective:

Success rate on planar pushing from pixels



Focusing on a single canonical task enables controlled and thorough analysis

Cotraining: use *both datasets* to train a *model* that maximizes a real-world *performance objective*

Performance Objective:

Success rate on planar pushing from pixels

Model:

Diffusion Policy

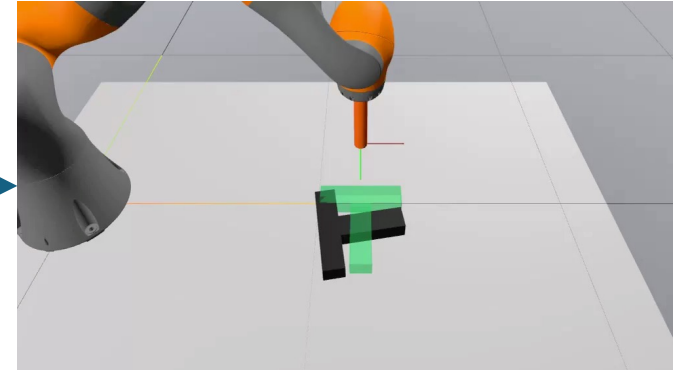
$$\mathcal{L}_{\mathcal{D}^\alpha} = \alpha \mathcal{L}_{\mathcal{D}_R} + (1 - \alpha) \mathcal{L}_{\mathcal{D}_S}$$

Real-World Dataset:



Simulated Dataset:

Model-based
Motion Planner



sim2real gap!

Does Cotraining Improve Performance?

Policy trained with
50 real demos, 0 sim demos



Success rate: **10/20**

Policy cotrained with
50 real demos, 2000 sim demos



Success rate: **18/20**

1.8x improvement!

Does Cotraining Improve Performance?

Policy trained with
10 real demos, 0 sim demos



Success rate: **2/20**

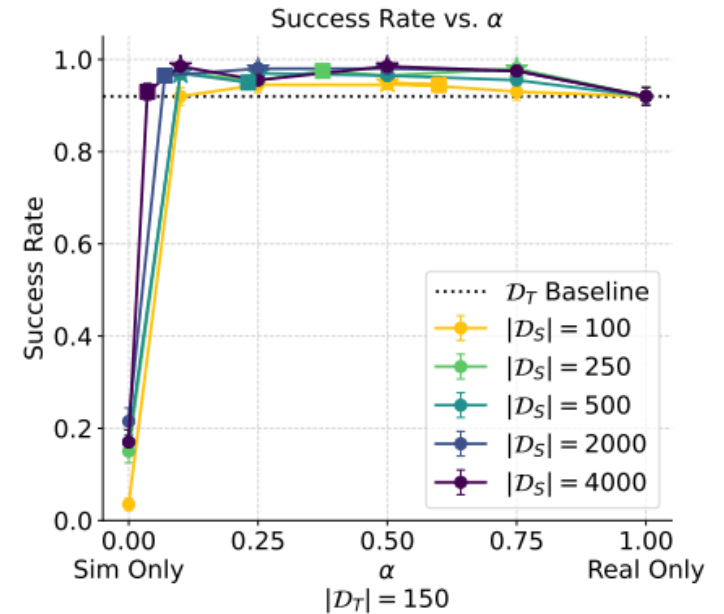
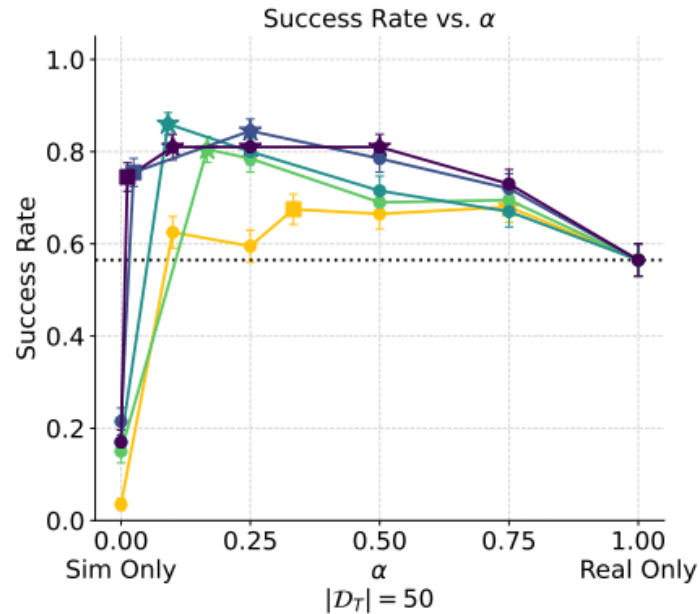
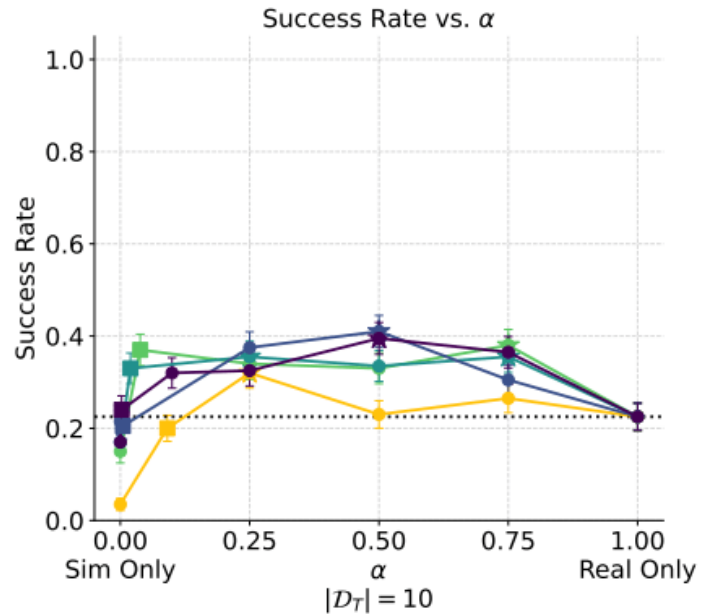
Policy cotrained with
10 real demos, 2000 sim demos



Success rate: **14/20**

—————→
7x improvement!

Key Takeaways: Performance Gains

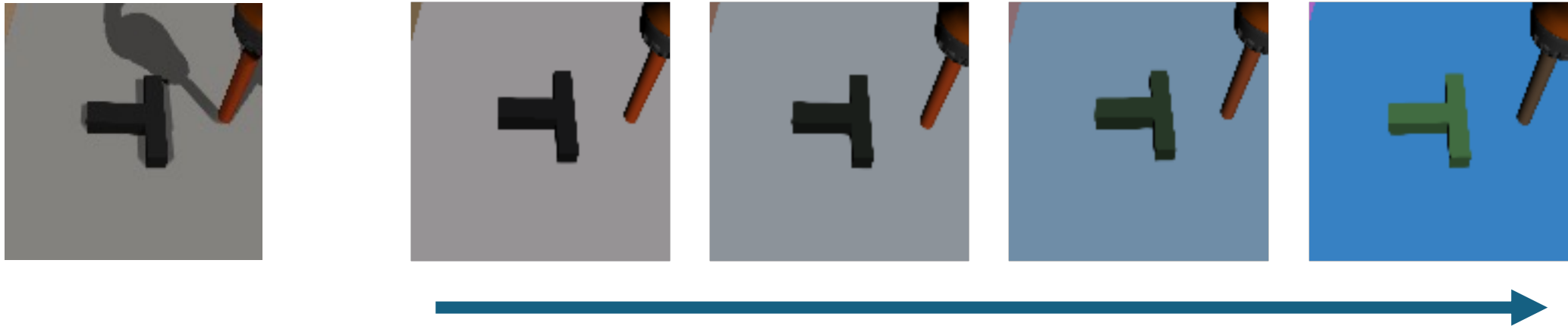


- Cotraining improved performance *up to 7x!*
- Cotraining is most effective in the *low to medium* data regime.
- Scaling simulated data alone is insufficient!

The Effect of Sim2Real Gaps (i.e. distribution shifts)

Which *sim2real gaps* affect the *value* of simulated data?

Example: Analyzing Color Shift



“True” Color

Increasing “Color Shift”

Ex. Analyze policies trained on increasing intensities of color shift

The Effect of Sim2Real Gaps (i.e. distribution shifts)

Visual Gaps

Color Shift

Color Randomization

Camera Pose Shift

Physical Gaps

Center of Mass Shift

Task Gaps

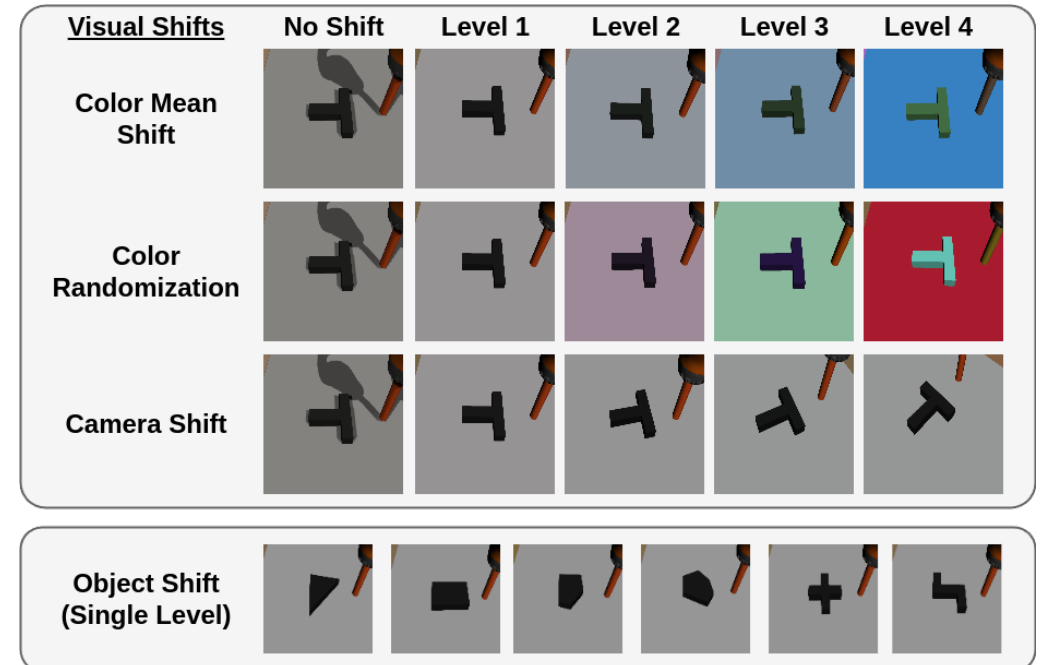
Target Shift

Object Mismatch



Key Takeaways: Sim2Real Gaps

- *Cotraining still improves performance...
but all gaps reduce the value of sim data*
- Physics & task gaps were most impactful
- *Better rendering* improves performance,
but *perfect rendering* hurts performance!



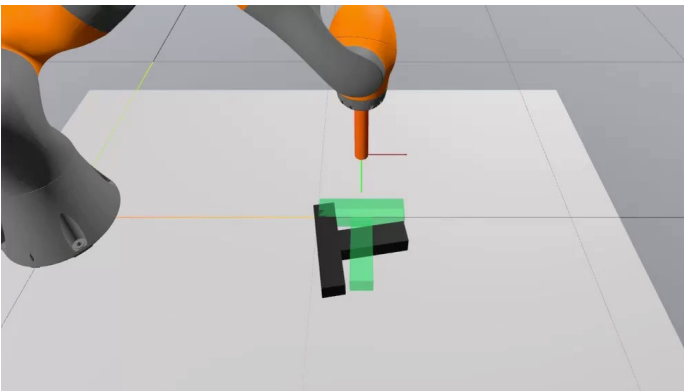
Sim vs Real “Expert”

Real-World Demos



- Fixes orientation first, then translation

Sim Demos



- Fixes orientation and translation *simultaneously*

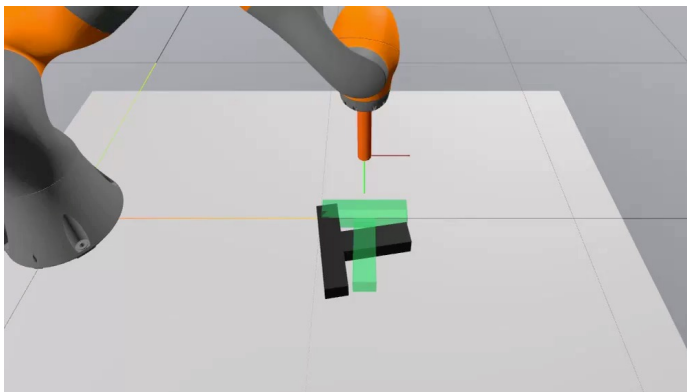
Sim & real behaviors
are characteristically
different

Sim vs Real “Expert”

Real-World Demos



Sim Demos



50
demos

2000
demos

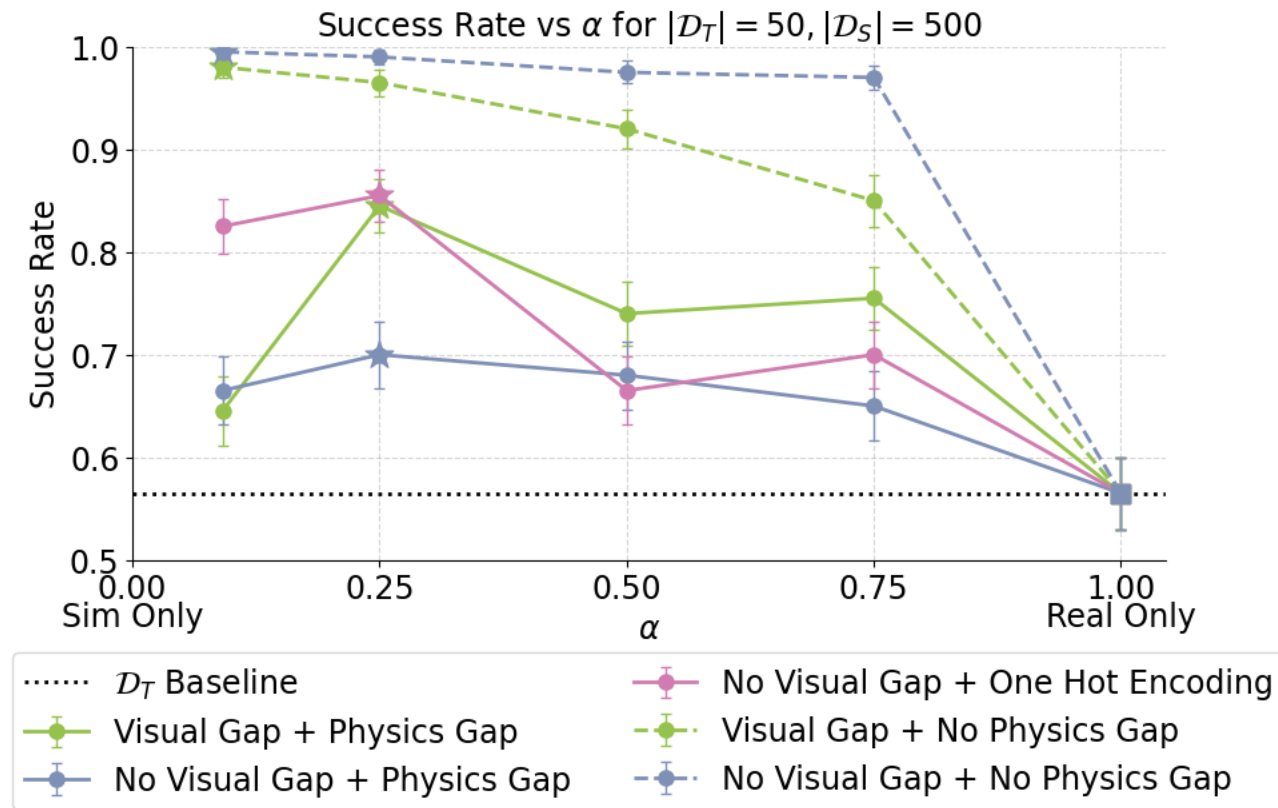
Distinctly more similar
to real-world expert!

Cotrained Policy



Binary probes show that policies are
learning to **distinguish sim from real!**

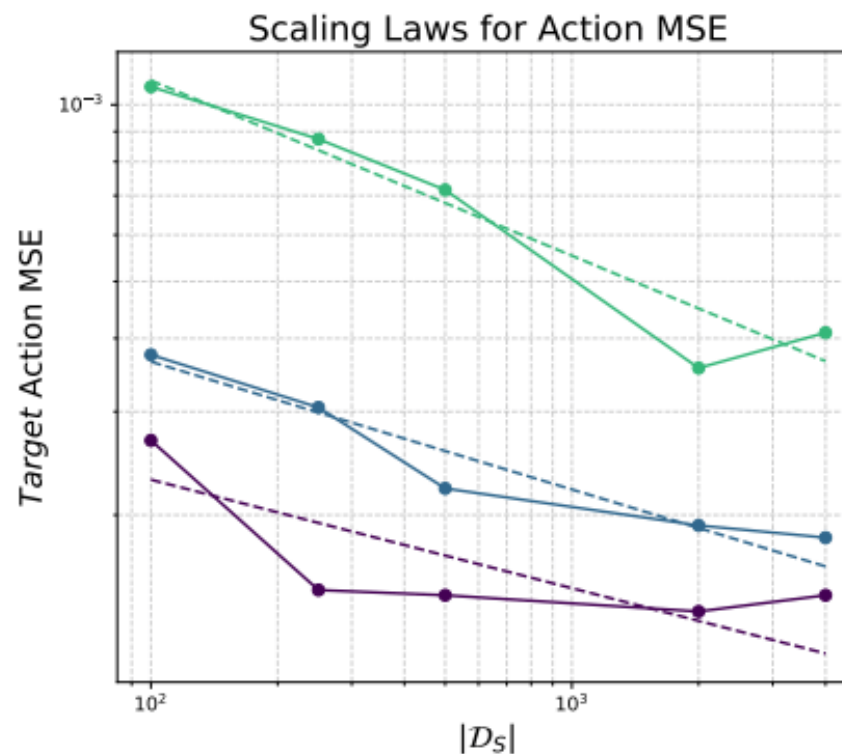
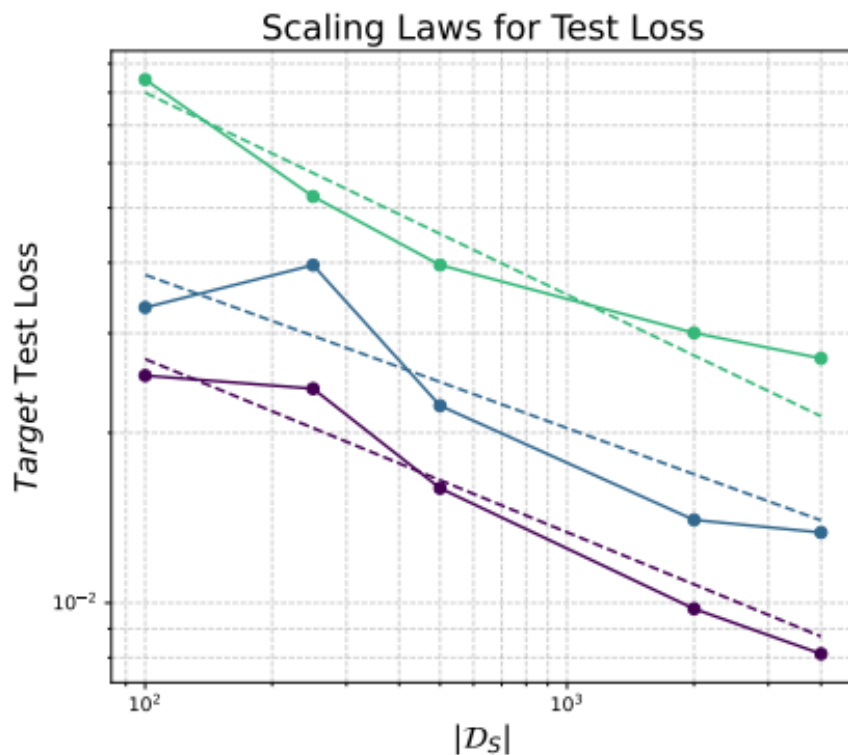
Sim & Real Discernability



High-performing policies must learn to *identify sim vs real*
since the *physics* of each environment *requires different actions*

Positive Transfer: Scaling Law

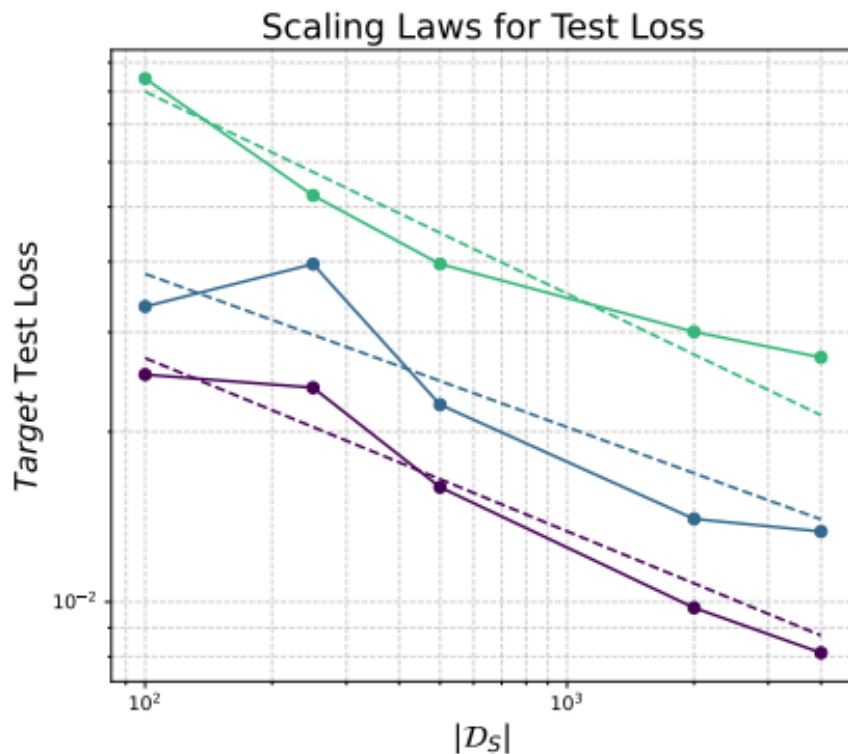
Scaling sim data improves real-world test loss according to a power law!



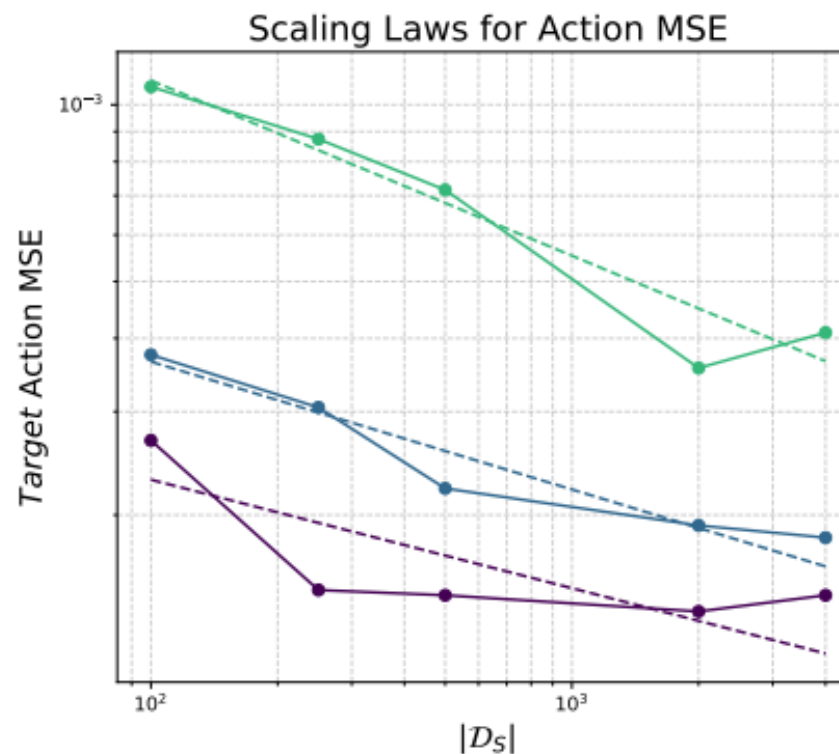
$$\mathcal{L}_{\mathcal{D}_T^{\text{test}}} \propto |\mathcal{D}_S|^{-0.332} \cdot |\mathcal{D}_T|^{-0.397}, \quad R^2 = 0.945$$
$$\text{MSE}_{\mathcal{D}_T^{\text{test}}} \propto |\mathcal{D}_S|^{-0.285} \cdot |\mathcal{D}_T|^{-0.587}, \quad R^2 = 0.975$$

Positive Transfer: Scaling Law

Scaling sim data improves real-world test loss according to a power law!



$$\mathcal{L}_{D_T^{\text{test}}} \propto |D_S|^{-0.332} \cdot |D_T|^{-0.397}, \quad R^2 = 0.945$$
$$\text{MSE}_{D_T^{\text{test}}} \propto |D_S|^{-0.285} \cdot |D_T|^{-0.587}, \quad R^2 = 0.975$$



A sim demo is worth ~0.5-0.8 real demos

Empirical Analysis of Sim-and-Real Cotraining

- Simulation is a promising tool for *scaling data generation in robotics*
- We study the principles and mechanisms of cotraining from both sim and real data



Our Paper
Scan to learn more!



Personal Website (Adam Wei)
Feel free to reach out!