Inverse Reinforcement Learning

Chelsea Finn

3/5/2017

Course Reminders:

March 22nd: Project group & title due

April 17th: Milestone report due & milestone presentations

April 26th: Beginning of project presentations

Inverse RL: Outline

1. Motivation & Definition
2. Early Approaches
3. Maximum Entropy Inverse RL
4. Scaling inverse RL to deep cost functions

Inverse RL: Outline

1. Motivation & Definition

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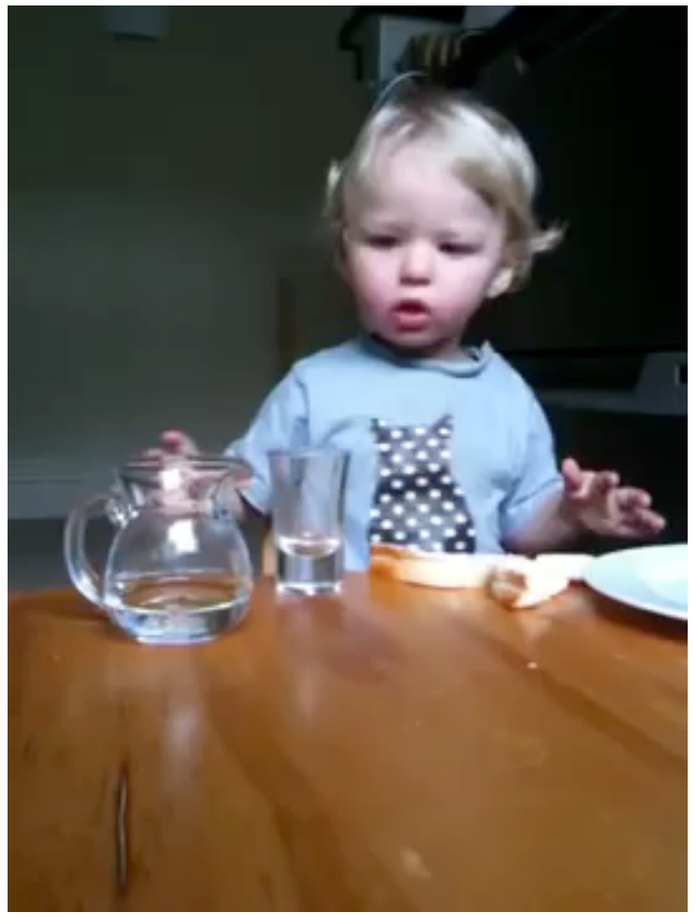
reward

Mnih et al. ’15

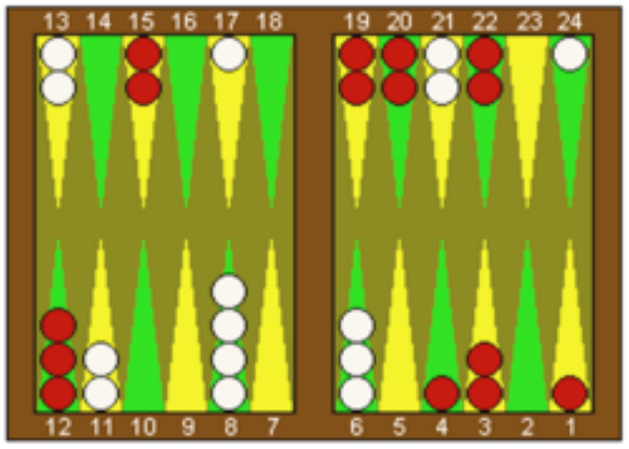


reinforcement learning agent

what is the reward?

In the real world, humans don’t get a score.

video from Montessori New Zealand



Tesauro ’95


Kohl & Stone, ’04


Mnih et al. ’15

AlphaGo

Silver et al. ‘16

reward function is essential for RL

real-world domains: reward/cost often difficult to specify

- robotic manipulation
- autonomous driving
- dialog systems
- virtual assistants
- and more…

Motivation

Behavioral Cloning: Mimic actions of expert

- but no reasoning about outcomes or dynamics
- the expert might have different degrees of freedom

Can we reason about what the expert is trying to achieve?

Inverse Optimal Control / Inverse Reinforcement Learning:
infer cost/reward function from expert demonstrations

(IOC/IRL) (Kalman '64, Ng & Russell '00)

Inverse Optimal Control / Inverse Reinforcement Learning:
infer cost/reward function from demonstrations

given:
- state & action space
- roll-outs from π^*
- dynamics model [sometimes]

goal:
- recover reward function
- then use reward to get policy

Compare to DAgger: no direct access to π^*

Challenges

underdefined problem

difficult to evaluate a learned cost

demonstrations may not be precisely optimal

Early IRL Approaches

All: alternate between solving MDP w.r.t. cost and updating cost

Ng & Russell '00: expert actions should have higher value than other actions, larger gap is better

Abbeel & Ng '04: expert policy w.r.t. cost should match feature counts of expert trajectories

Ratliff et al. '06: max margin formulation between value of expert actions and other actions

How to handle ambiguity? What if expert is not perfect?

Inverse RL: Outline

1. Motivation & Examples
2. Early Approaches
3. **Maximum Entropy Inverse RL**
4. Scaling inverse RL to deep cost functions

Maximum Entropy Inverse RL

(Ziebart et al. '08)

Notation:

$$\tau = \{s_1, a_1, ..., s_t, a_t, ..., s_T\}$$

c_θ: cost with parameters θ [linear case $c_\theta(\tau) = \theta^T \mathbf{f}_\tau = \sum_{s \in \tau} \theta^T \mathbf{f}_s$]

$\mathcal{D}$: dataset of demonstrations $M = |\mathcal{D}|$

T: transition dynamics

Whiteboard

Maximum Entropy Inverse RL

(Ziebart et al. '08)

0. Initialize θ, gather demonstrations $\mathcal{D}$
1. Solve for optimal policy $\pi(a|s)$ w.r.t. c_θ with value iteration
2. Solve for state visitation frequencies $p(s \mid \theta, T)$
3. Compute gradient $\nabla_\theta \mathcal{L} = \frac{1}{M} \sum_{\tau_d \in \mathcal{D}} \mathbf{f}_{\tau_d} + \sum_s p(s \mid \theta, T) \mathbf{f}_s$
4. Update θ with one gradient step using $\nabla_\theta \mathcal{L}$

Inverse RL: Outline

1. Motivation & Examples
2. Early Approaches
3. Maximum Entropy IRL
4. **Scaling IRL to deep cost functions**

Case Study: MaxEnt Deep IRL

MaxEnt IRL with known dynamics (tabular setting), neural net cost

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Maximum Entropy Deep Inverse Reinforcement Learning

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NIPS Deep RL workshop 2015

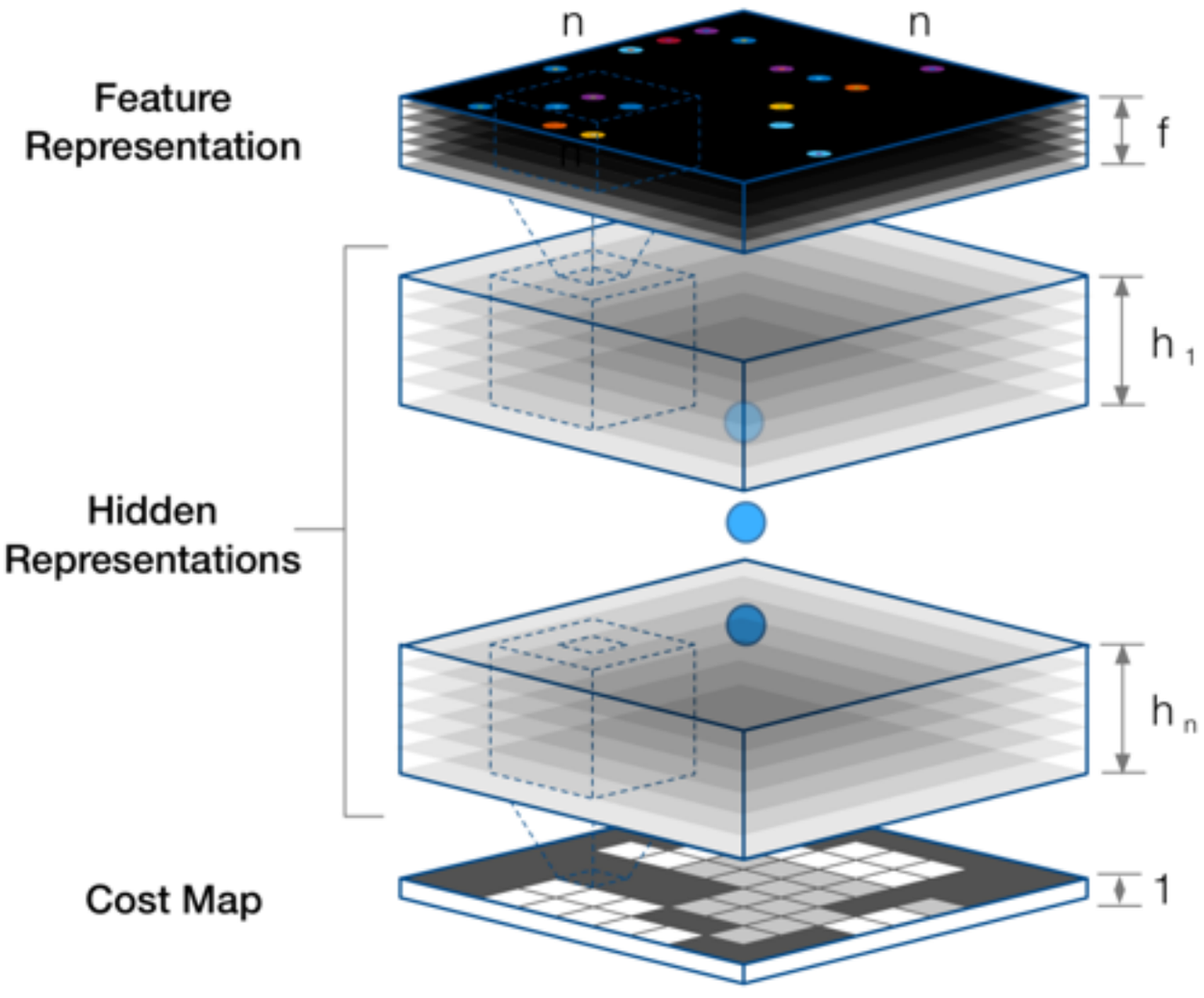
Watch This: Scalable Cost-Function Learning for Path Planning in Urban Environments

Markus Wulfmeier[1], Dominic Zeng Wang[1] and Ingmar Posner[1]

IROS 2016

Case Study: MaxEnt Deep IRL

MaxEnt IRL with known dynamics (tabular setting), neural net cost



Algorithm 1 Maximum Entropy Deep IRL

Input: $\mu_D^a, f, S, A, T, \gamma$

Output: optimal weights θ^*

$\theta^1 = \text{initialise\_weights}()$

Iterative model refinement

for n = 1 : N **do**

  $r^n = \text{nn\_forward}(f, \theta^n)$

  Solution of MDP with current reward

  $\pi^n = \text{approx\_value\_iteration}(r^n, S, A, T, \gamma)$

  $\mathbb{E}[\mu^n] = \text{propagate\_policy}(\pi^n, S, A, T)$

  Determine Maximum Entropy loss and gradients

  $\mathcal{L}_D^n = \log(\pi^n) \times \mu_D^a$

  $\frac{\partial \mathcal{L}_D^n}{\partial r^n} = \mu_D - \mathbb{E}[\mu^n]$

  Compute network gradients

  $\frac{\partial \mathcal{L}_D^n}{\partial \theta_D^n} = \text{nn\_backprop}(f, \theta^n, \frac{\partial \mathcal{L}_D^n}{\partial r^n})$

  $\theta^{n+1} = \text{update\_weights}(\theta^n, \frac{\partial \mathcal{L}_D^n}{\partial \theta_D^n})$

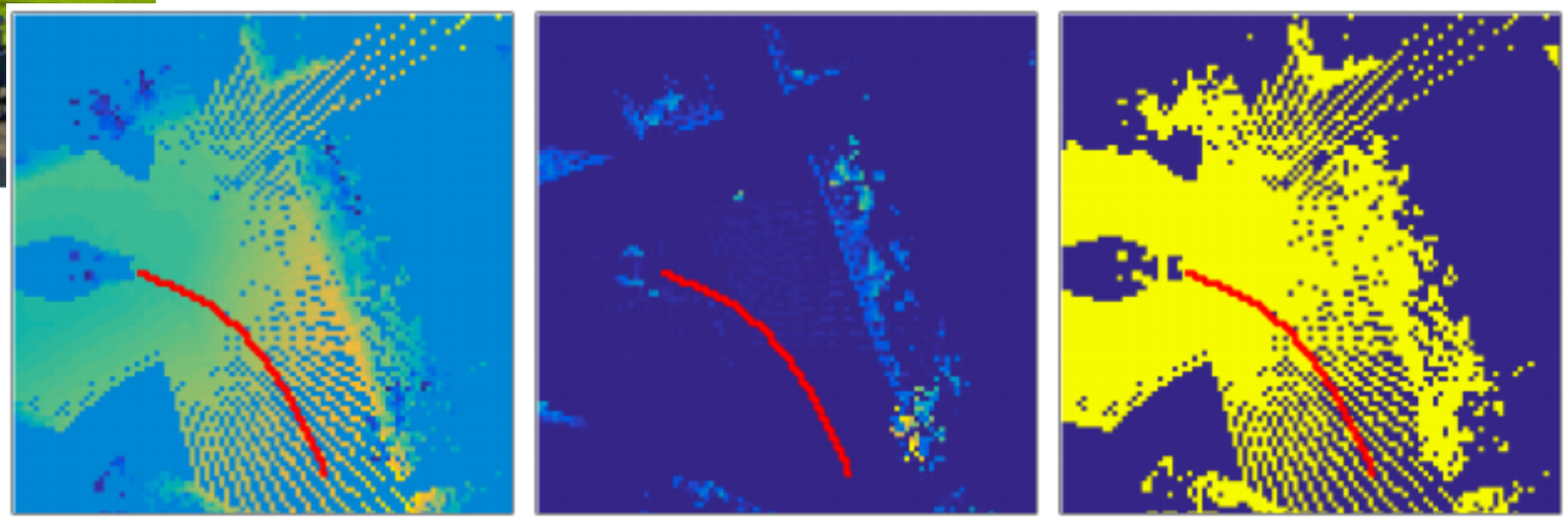
end for

Need to iteratively solve MDP for every weight update

Case Study: MaxEnt Deep IRL

MaxEnt IRL with known dynamics (tabular setting), neural net cost

demonstrations



mean height height variance cell visibility

120km of demonstration data

manually designed cost:

test-set trajectory prediction:

Prediction metrics	Standard FCN	Pooling FCN	MS FCN	Manual CF
NLL	69.35	69.73	65.39	78.13
MHD	0.221	0.230	0.200	0.284

MHD: modified Hausdorff distance

Case Study: MaxEnt Deep IRL

MaxEnt IRL with known dynamics (tabular setting), neural net cost

Strengths

- scales to neural net costs
- efficient enough for real robots

Limitations

- still need to repeatedly solve the MDP
- assumes known dynamics

What about unknown dynamics?

Whiteboard

Case Study: Guided Cost Learning

Guided Cost Learning: Deep Inverse Optimal Control via Policy Optimization

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ICML 2016

Goals:

- remove need to solve MDP in the inner loop
- be able to handle unknown dynamics
- handle continuous state & actions spaces

guided cost learning algorithm

initial policy π_0

human demonstrations

generate policy samples from π

Update cost using samples & demos

update π w.r.t. cost

policy π

cost c

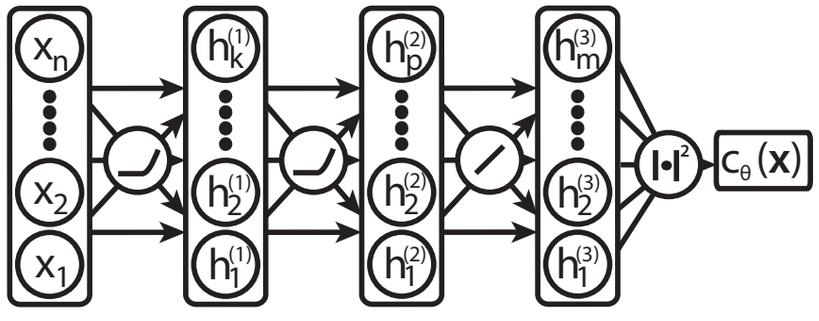
guided cost learning algorithm

initial policy π_0

human demonstrations

generate policy samples from π

generator



Update cost using samples & demos

discriminator

policy π

update π w.r.t. cost (partially optimize)

cost c

update cost in inner loop of policy optimization

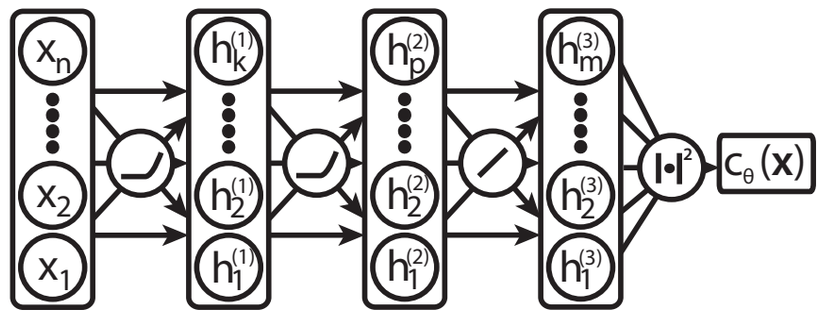
guided cost learning algorithm

initial policy π_0

human demonstrations

generate policy samples from π

generator



Update cost using samples & demos

discriminator

policy π

update π w.r.t. cost (partially optimize)

cost c

Ho et al., ICML '16, NIPS '16

What about unknown dynamics?

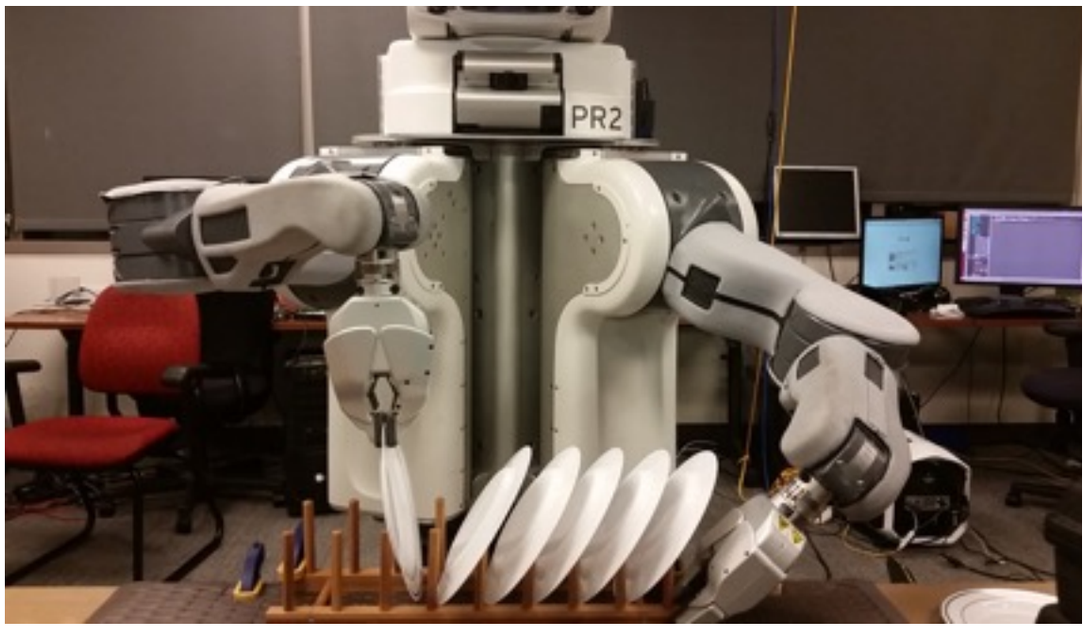
Adaptive importance sampling

1: Initialize $q_k(\tau)$ as either a random initial controller or from demonstrations
2: **for** iteration $i = 1$ to I **do**
3: Generate samples $\mathcal{D}_{\text{traj}}$ from $q_k(\tau)$
4: Append samples: $\mathcal{D}_{\text{samp}} \leftarrow \mathcal{D}_{\text{samp}} \cup \mathcal{D}_{\text{traj}}$
5: Use $\mathcal{D}_{\text{samp}}$ to update cost c_θ using gradient descent
6: Update $q_k(\tau)$ using $\mathcal{D}_{\text{traj}}$ and the method from (Levine & Abbeel, 2014) to obtain $q_{k+1}(\tau)$
7: **end for**
8: **return** optimized cost parameters θ and trajectory distribution $q(\tau)$

GCL Experiments

Real-world Tasks

dish placement



state includes goal plate pose

pouring almonds

state includes unsupervised visual features [Finn et al. ’16]

action: joint torques

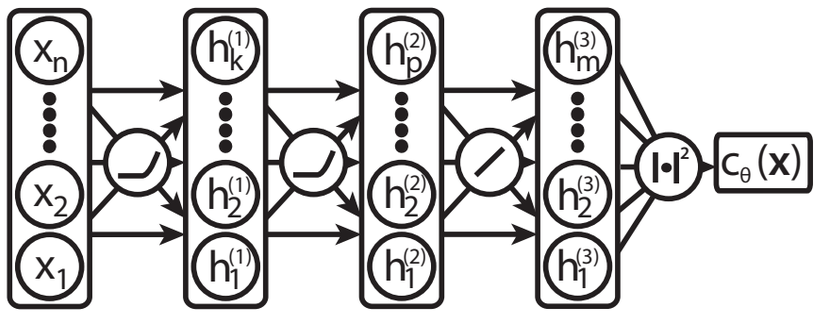
Comparisons

Path Integral IRL (Kalakrishnan et al. '13)

initial distribution q_0

generate policy samples from q

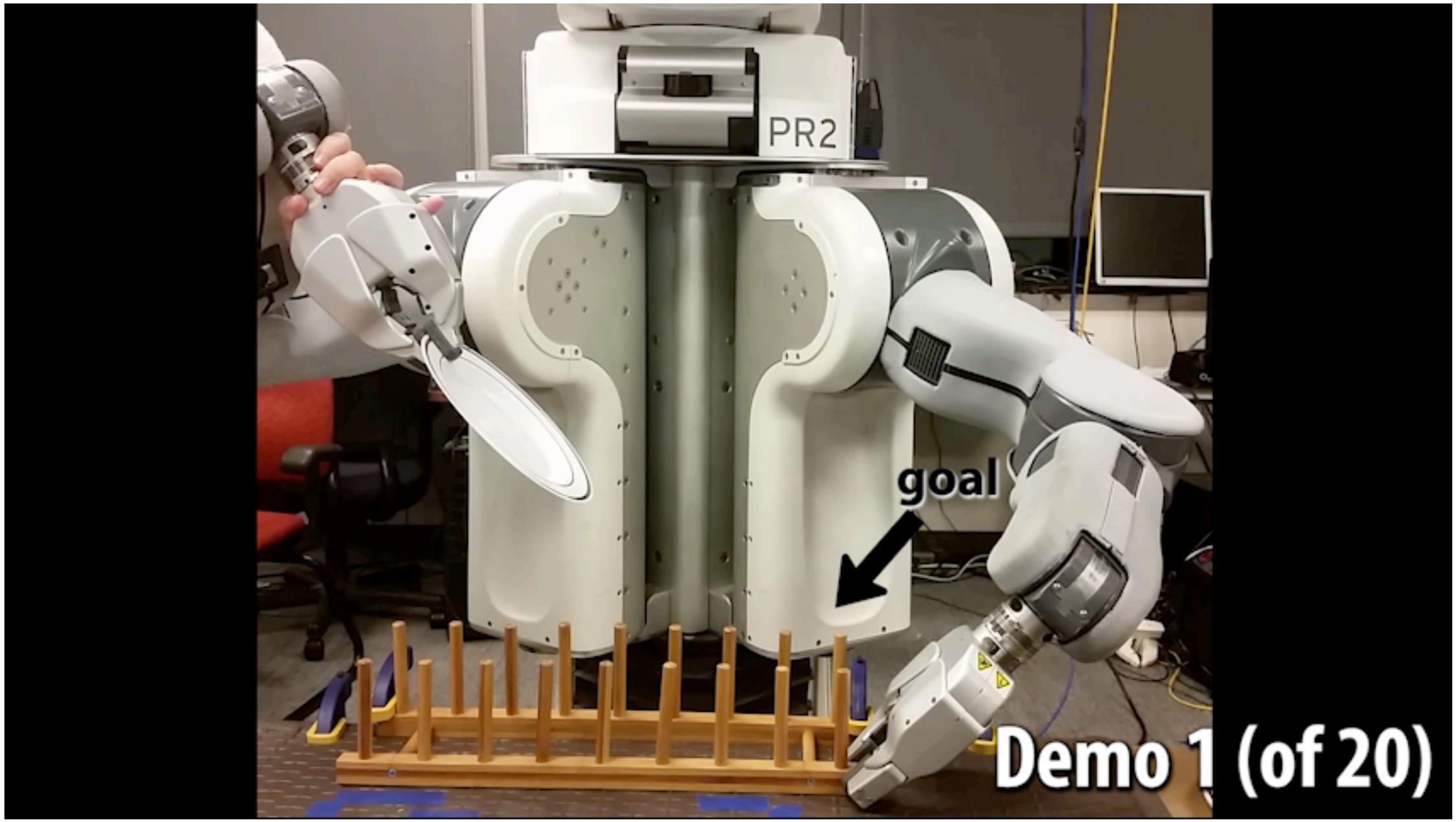
Relative Entropy IRL (Boularias et al. '11)



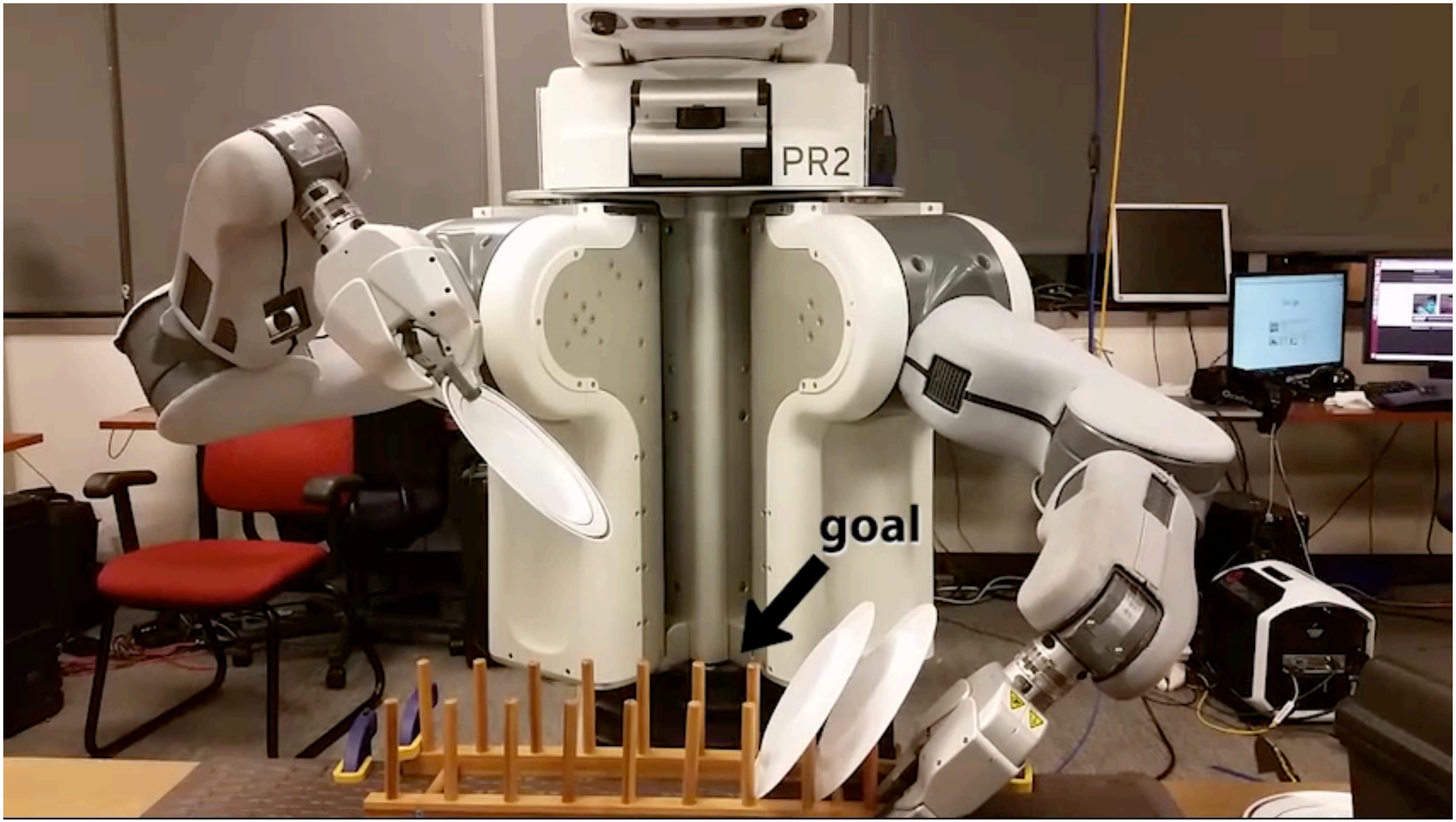
Update cost using samples & demos

cost c

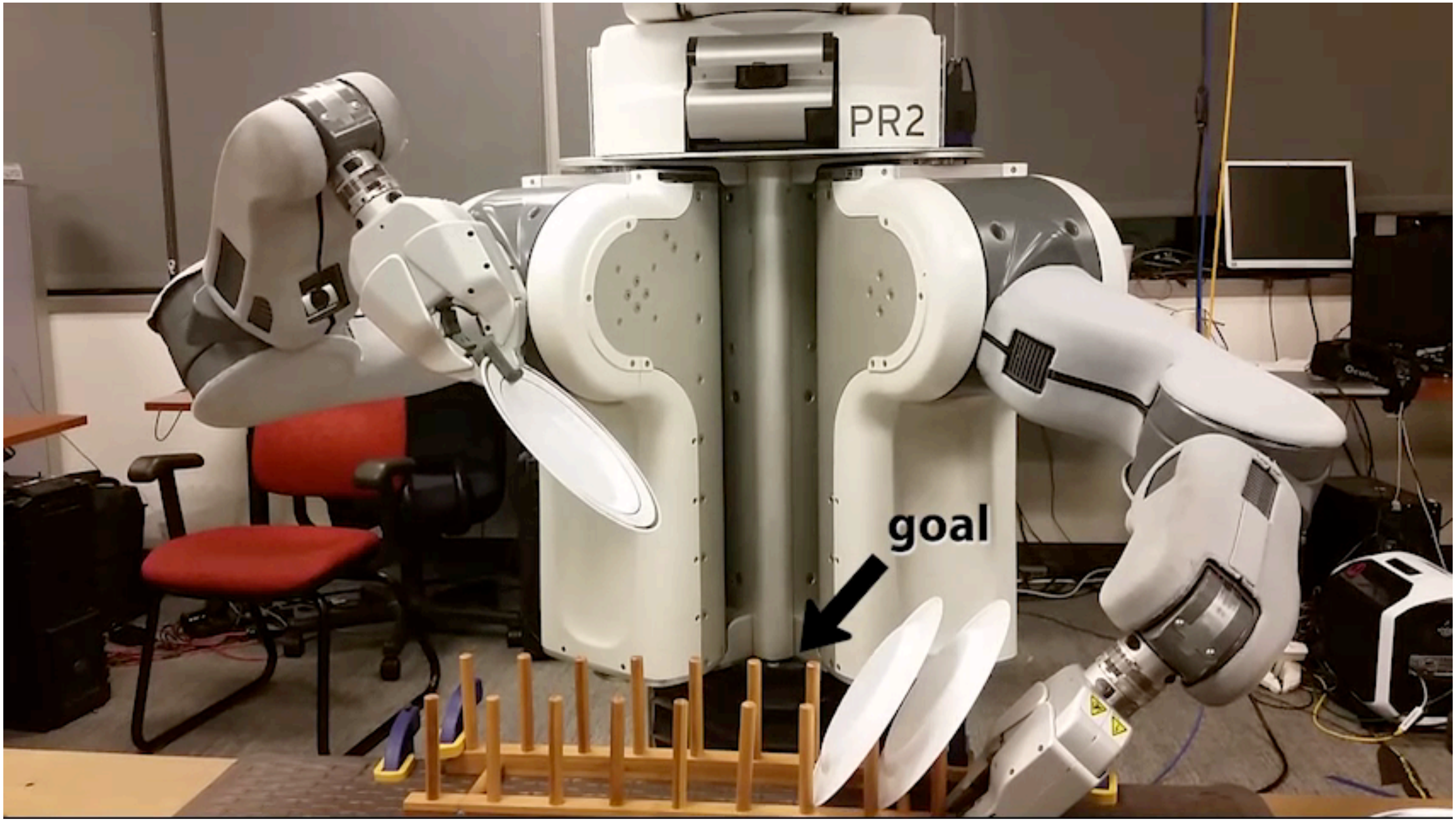
Dish placement, demos



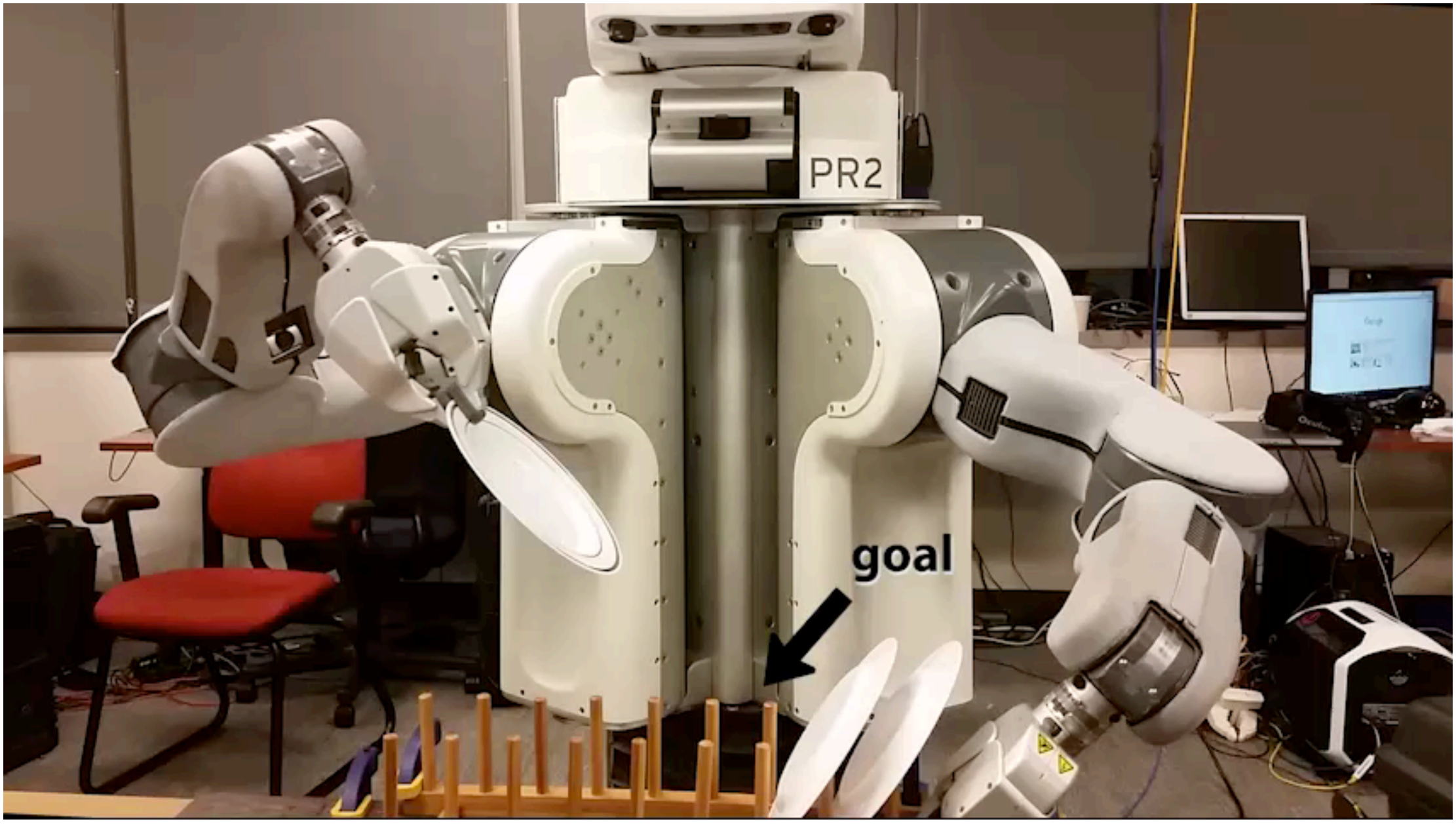
Dish placement, standard cost



Dish placement, RelEnt IRL

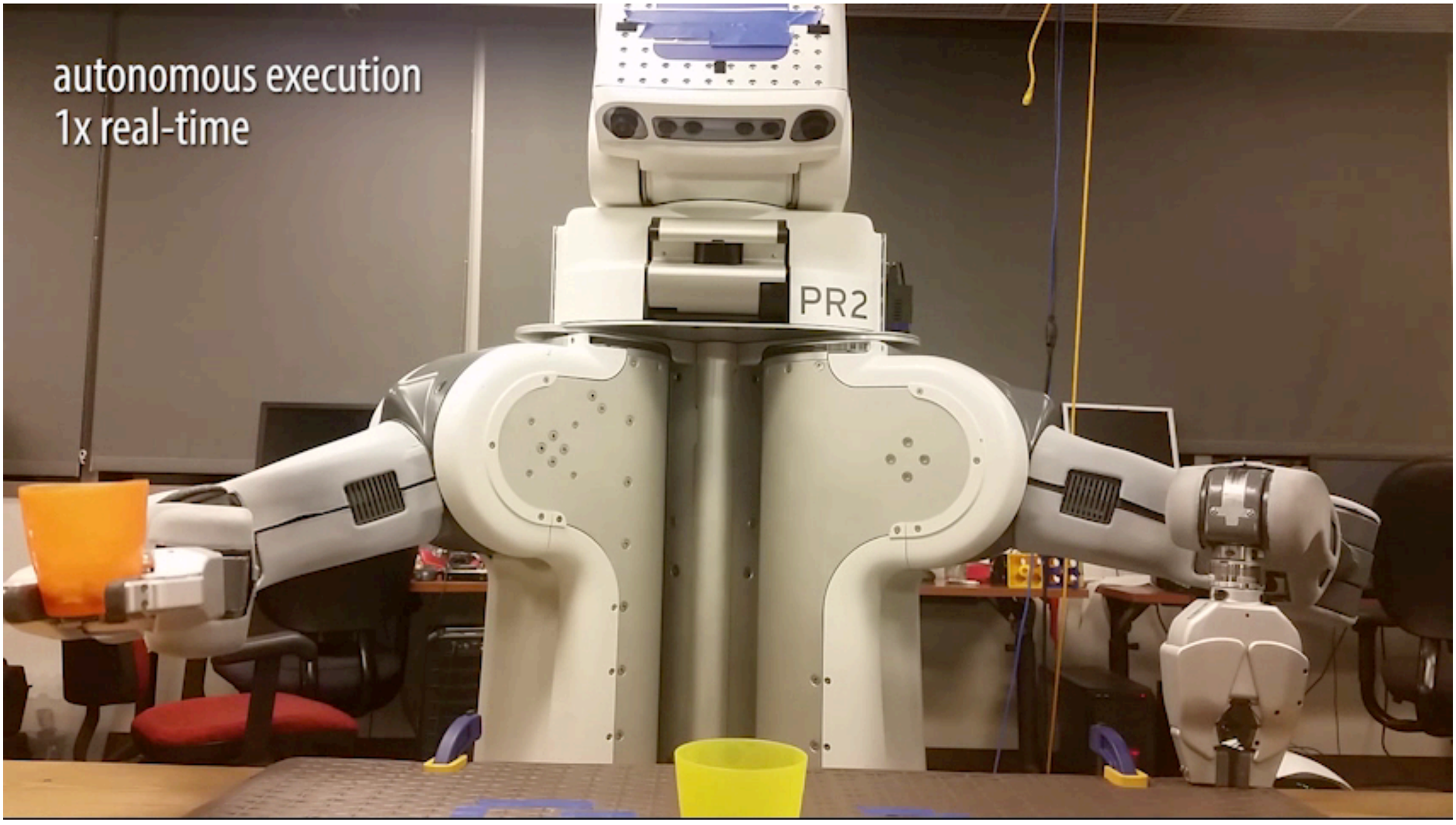


Dish placement, GCL policy

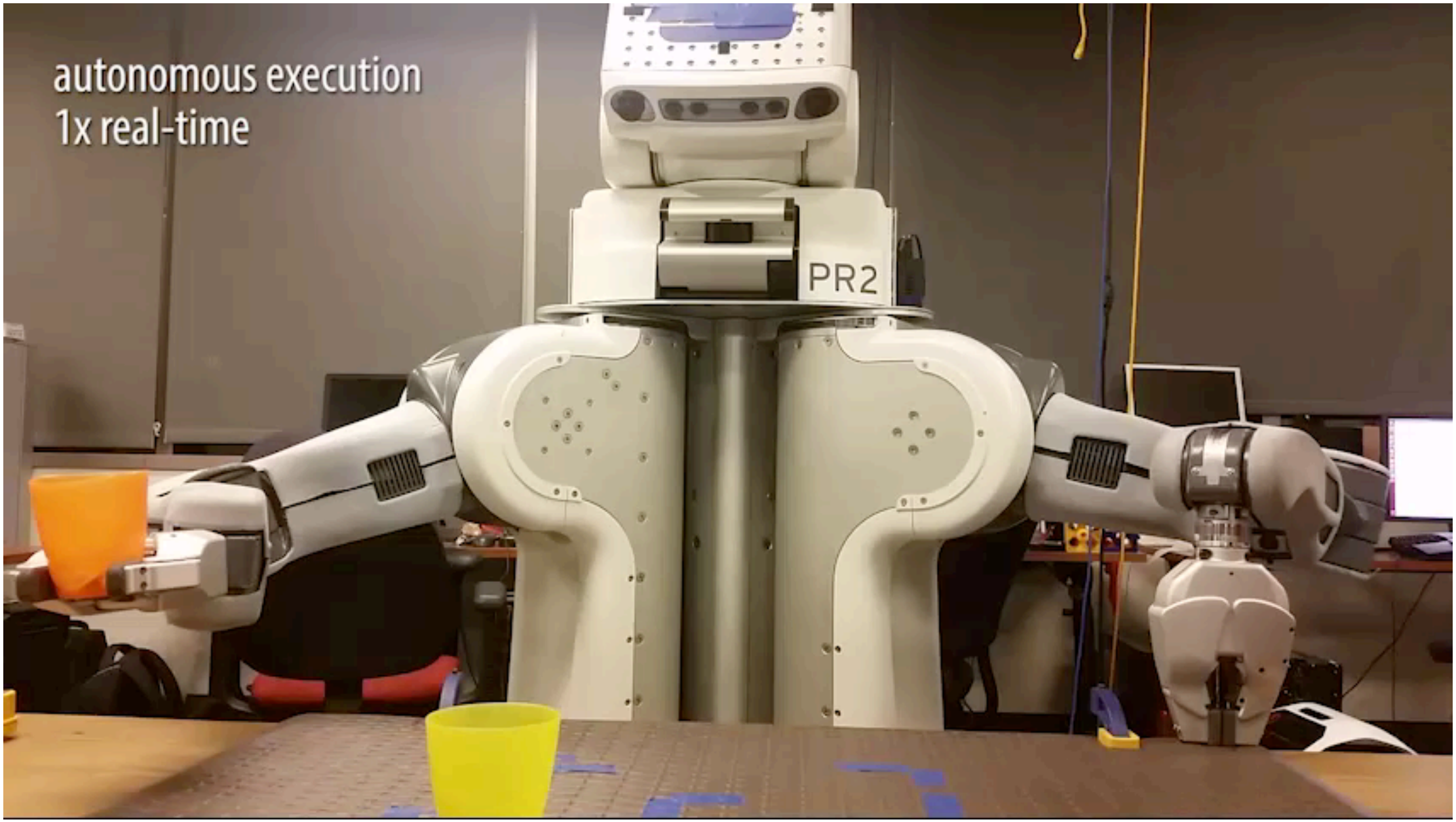


Pouring, demos

Pouring, RelEnt IRL



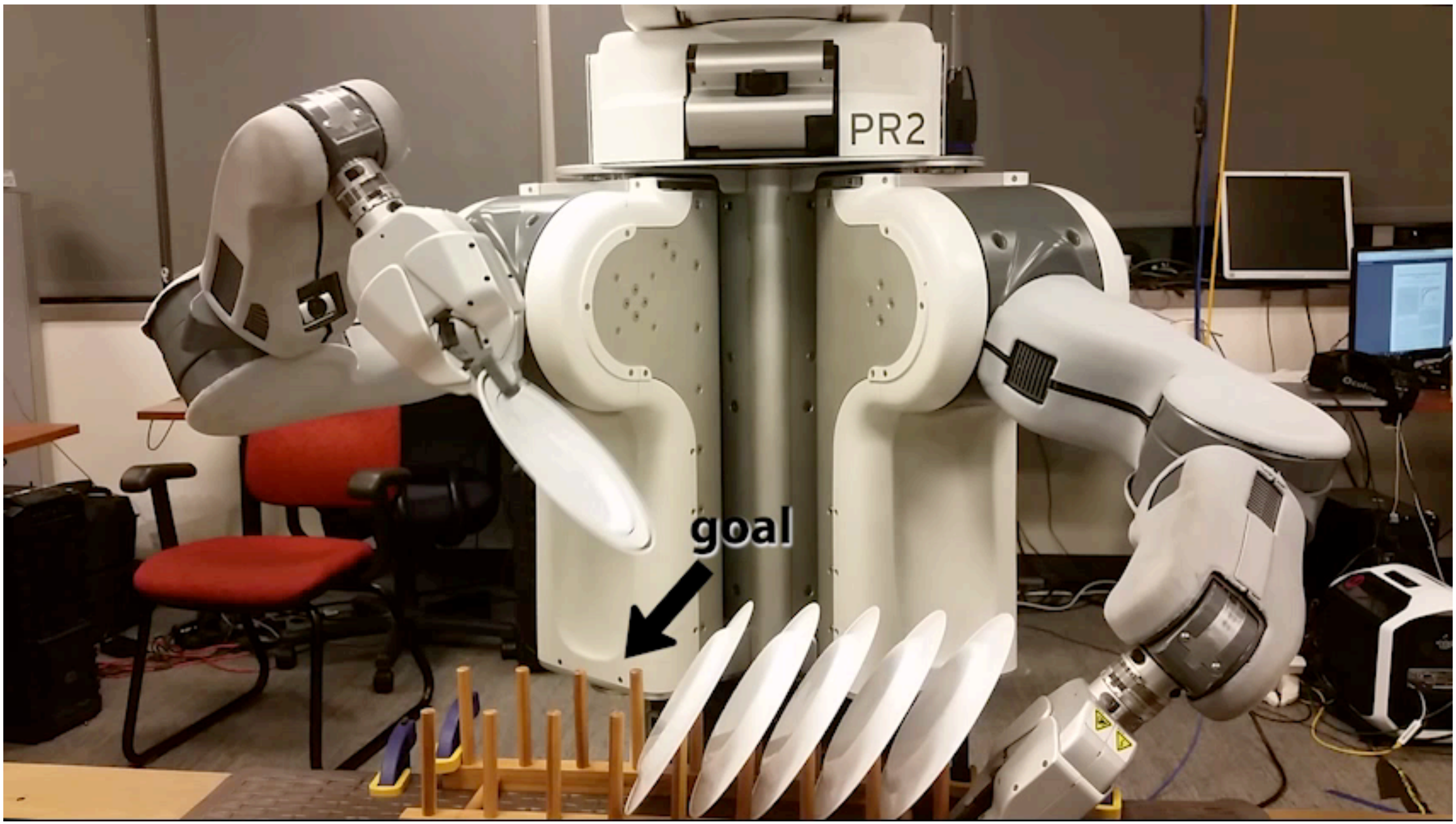
Pouring, GCL policy



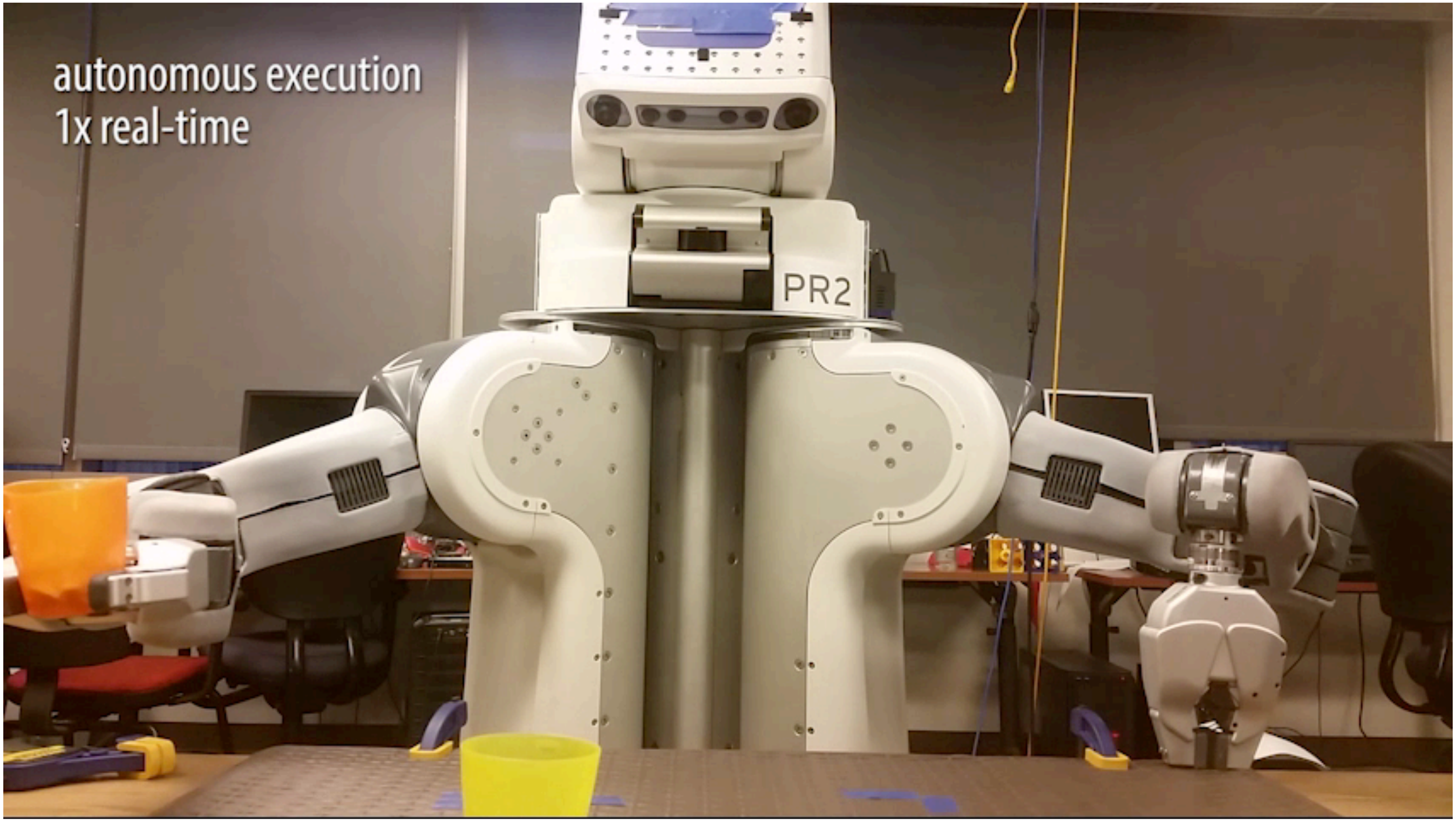
Conclusion: We can recover successful policies for new positions.

Is the cost function also useful for new scenarios?

Dish placement - GCL reopt.



Pouring - GCL reopt.



Note: normally the GAN discriminator is discarded

Case Study: Generative Adversarial Imitation Learning

Generative Adversarial Imitation Learning

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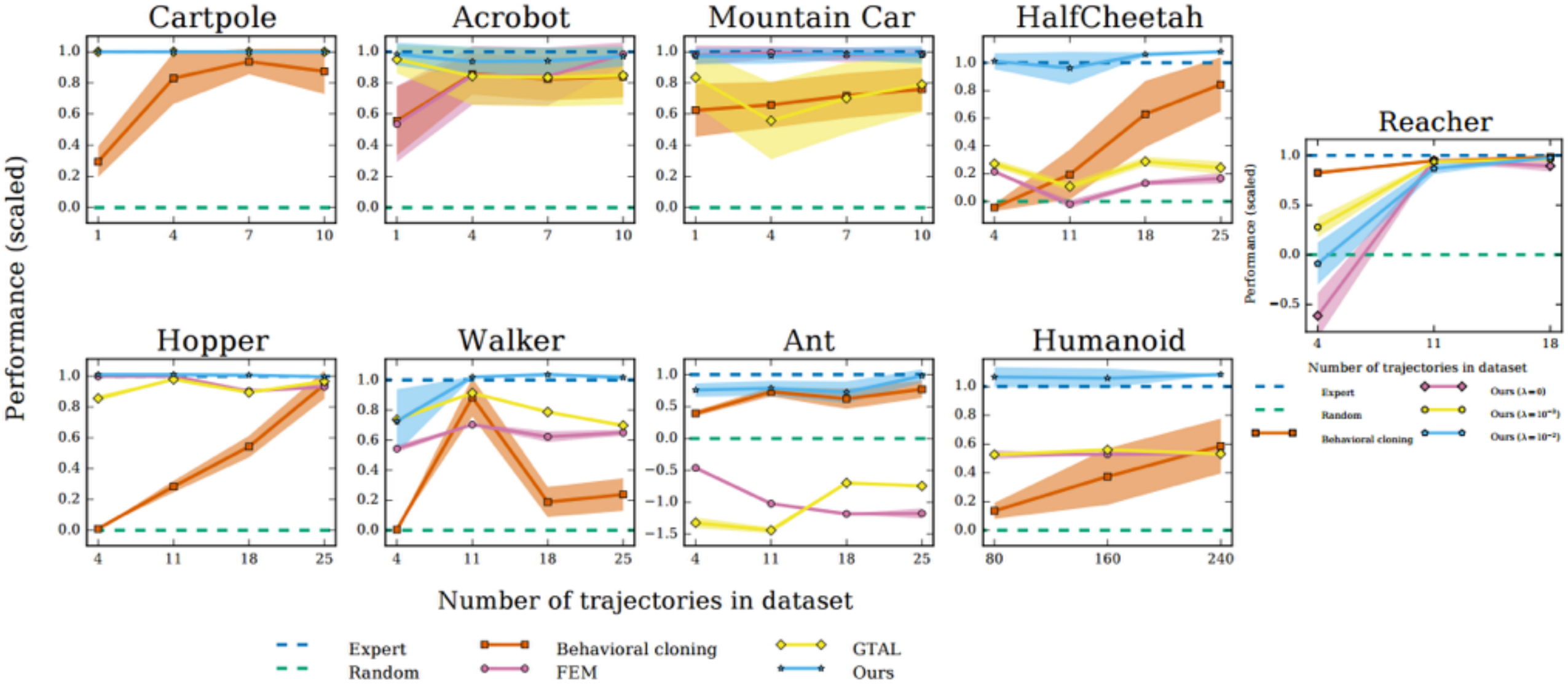
NIPS 2016

Case Study: Generative Adversarial Imitation Learning

- demonstrations from TRPO-optimized policy
- use TRPO as a policy optimizer
- OpenAI gym tasks



Guided Cost Learning & Generative Adversarial Imitation Learning

Strengths

- can handle unknown dynamics
- scales to neural net costs
- efficient enough for real robots

Limitations

- adversarial optimization is hard
- can’t scale to raw pixel observations of demos
- demonstrations typically collected with kinesthetic teaching or teleoperation (first person)

Next Time:

Back to forward RL (advanced policy gradients)

IOC is under-defined

need regularization:

- encourage slowly changing cost

$$g_{\text{lcr}}(\tau) = \sum_{x_t \in \tau} [(c_\theta(x_{t+1}) - c_\theta(x_t)) - (c_\theta(x_t) - c_\theta(x_{t-1}))]^2$$

- cost of demos decreases strictly monotonically in time

$$g_{\text{mono}}(\tau) = \sum_{x_t \in \tau} [\max(0, c_\theta(x_t) - c_\theta(x_{t-1}) - 1)]^2$$

Regularization ablation