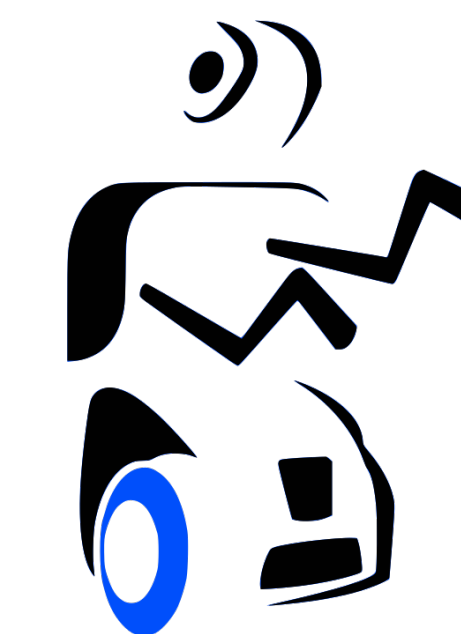


Intent Prediction in Robotic Teleoperation Tasks Using Inverse Reinforcement Learning



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Motivation

To work toward a lower abandonment rate, how do we make assistive robotic arms easier to control for day-to-day use?

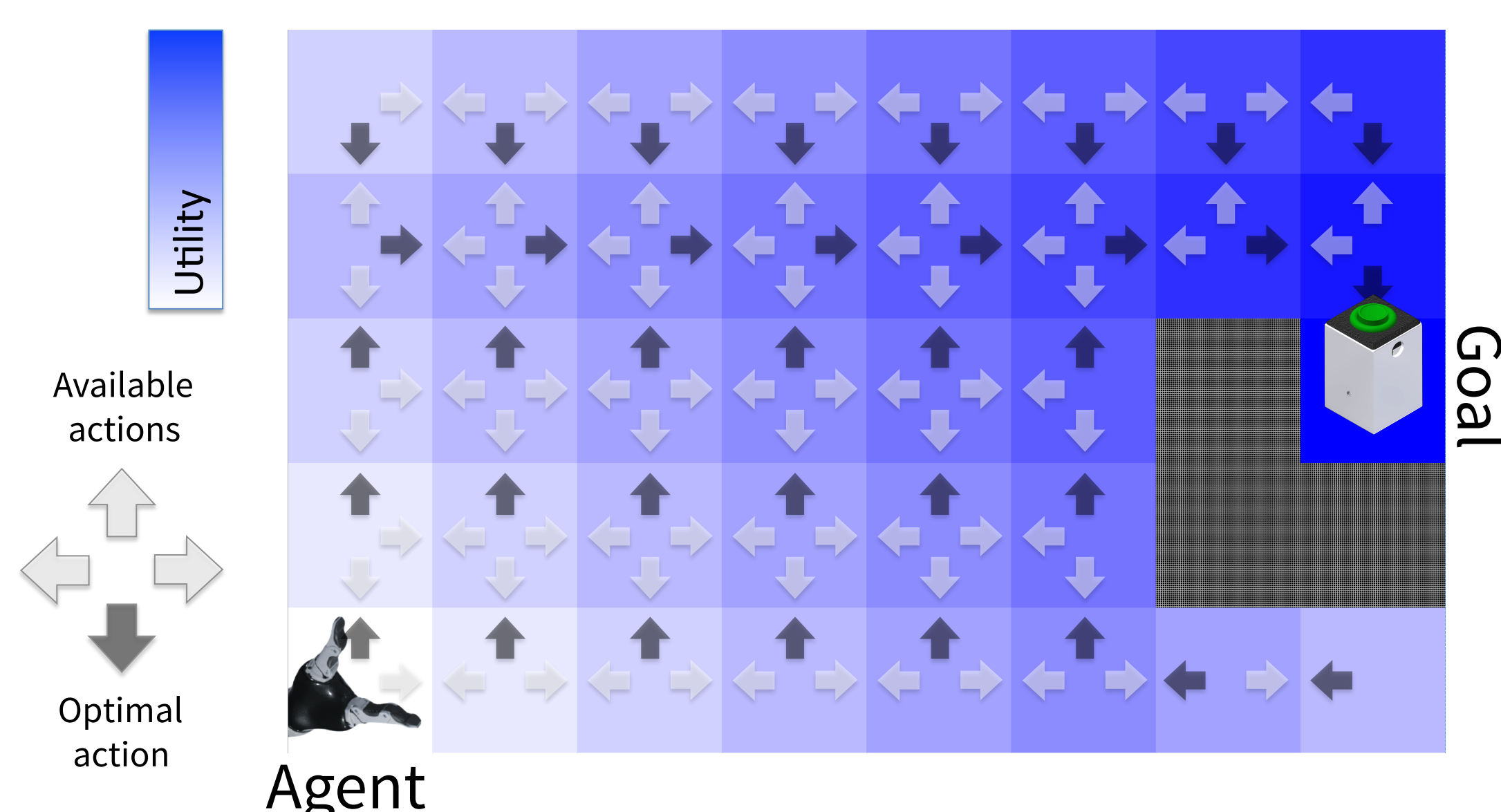


Task Representation

- A Markov Decision Process (MDP) consists of

$$\langle U, A(s), T(s, a), R(s) \rangle$$

- We model the user as an agent in an MDP, where achieving some goal has a high reward
- An agent has a policy, π
- In reinforcement learning, we look for an optimal policy given a reward function

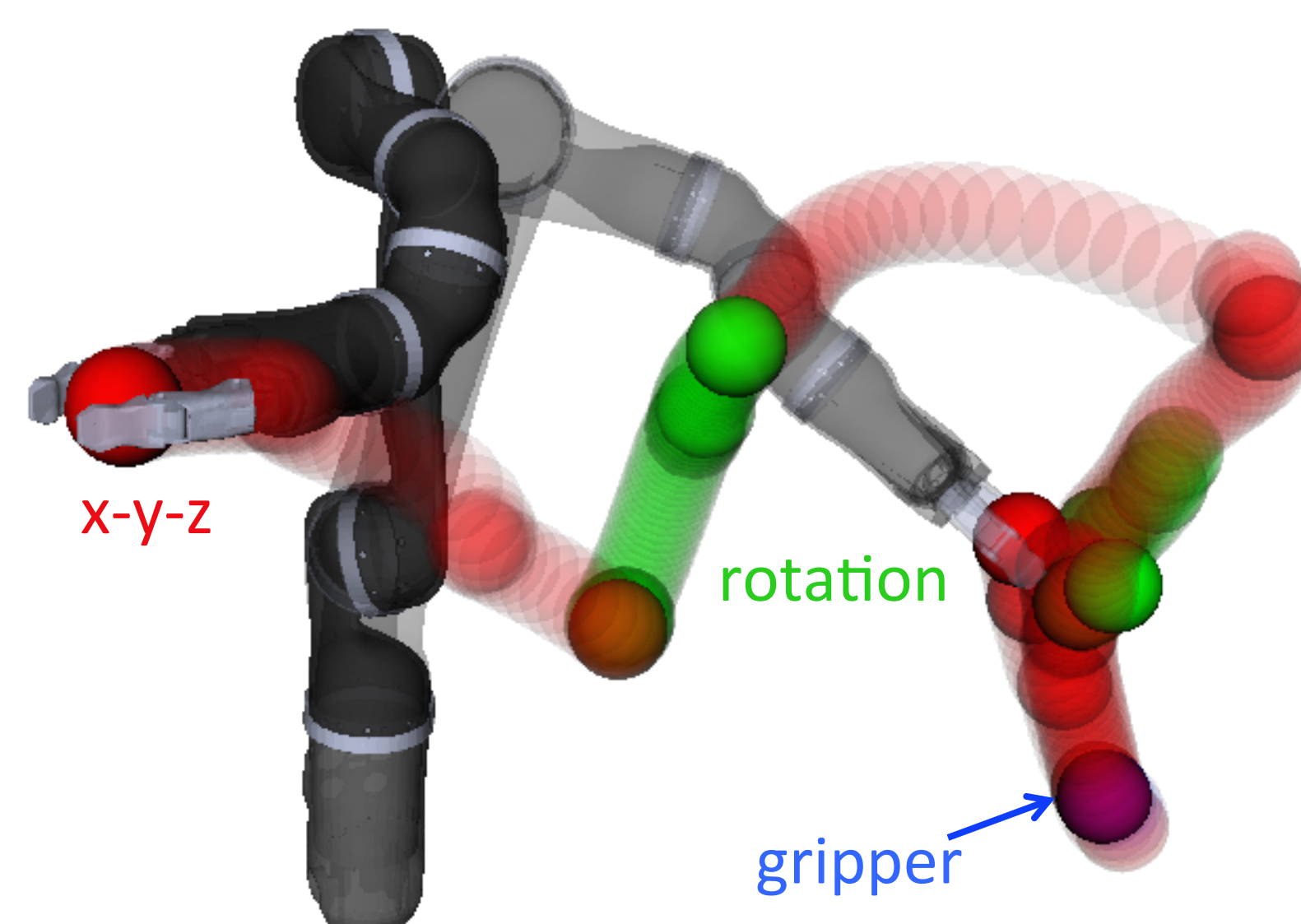


Inverse Reinforcement Learning

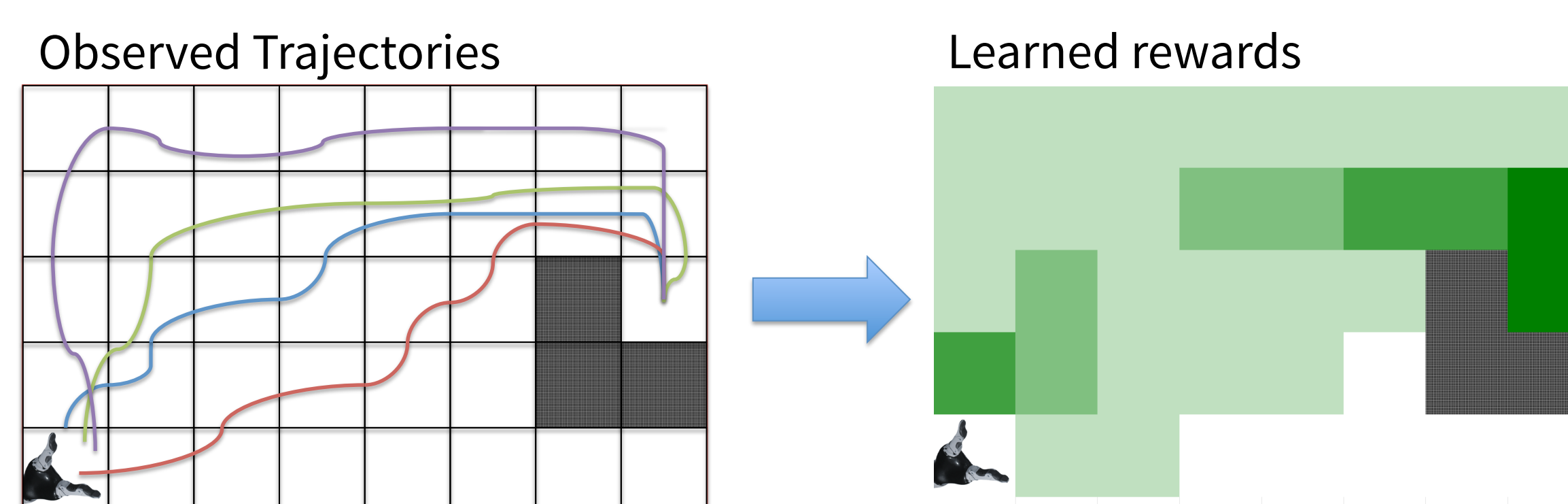
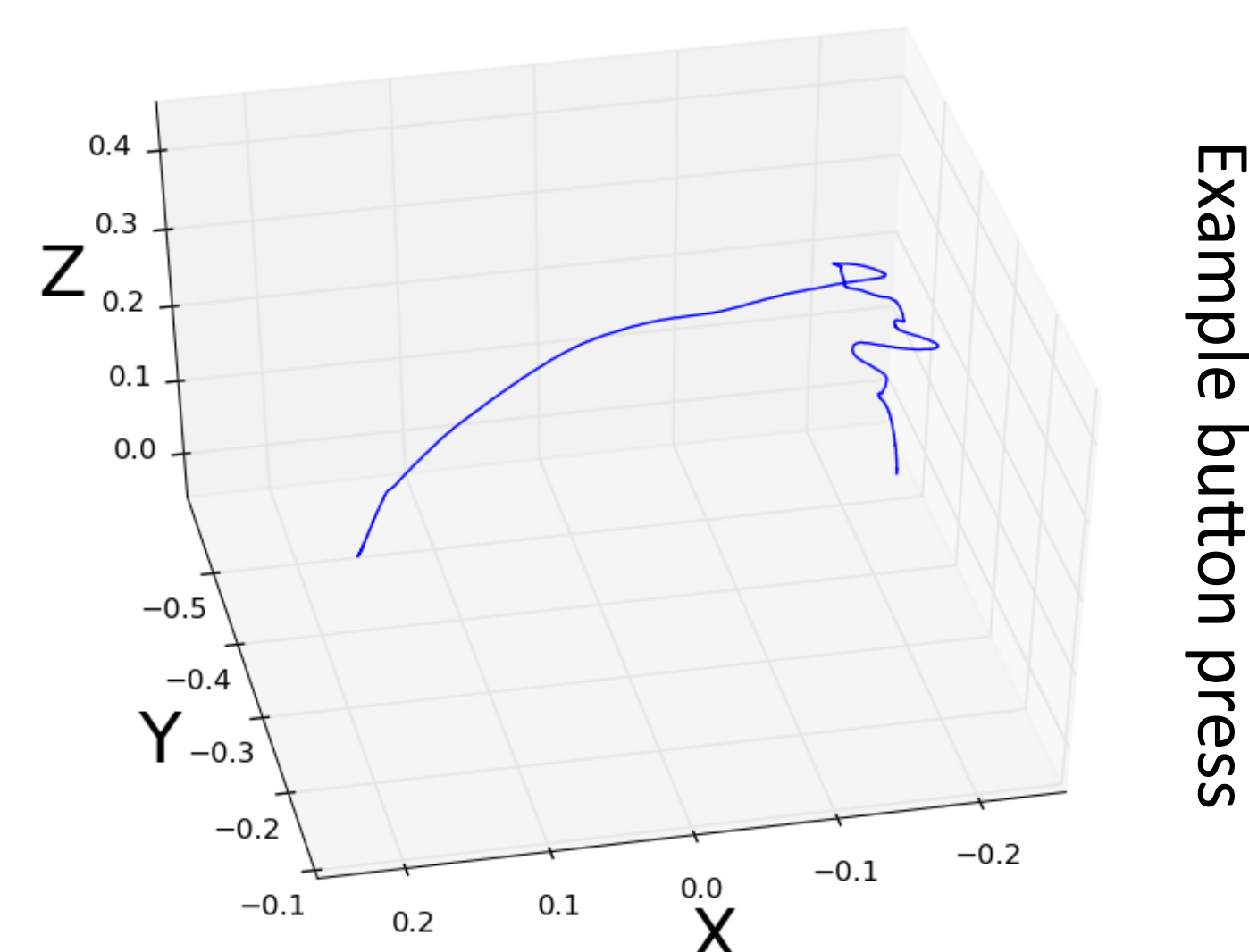
- We have some “expert” trajectories (recorded by users) and we want to learn a cost function
- We have a hypothesis set of reward functions
- We find the one that maximizes the probability of the observed trajectories

Assistance

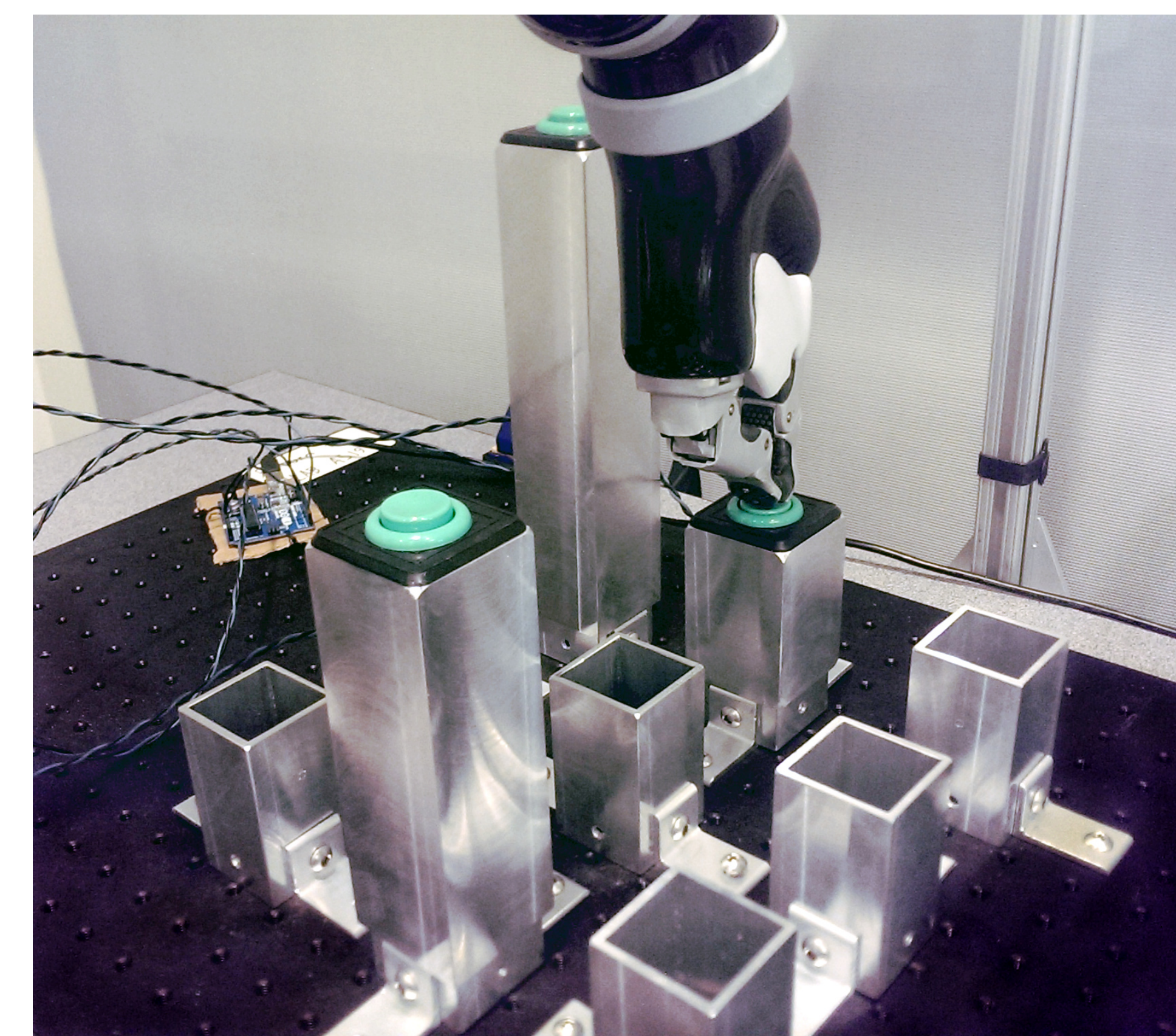
- When the arm has more degrees of freedom than the input, modes allow the user to choose which ones to control



- Can we apply IRL to this?
 - We might accidentally learn something about the interface instead of the task
 - All observed trajectories control x-y-z and rotation separately
- To explore possibilities, we’re currently gathering trajectory data



Testing Apparatus



- We set up targets at arbitrary positions in a 3x3x3 grid
 - The user pushes a button with the arm
 - Non-modal dataset: All buttons have the same orientation, and the gripper only moves in x-y-z
 - Modal dataset: Buttons are aligned with one x-y plane and have varying orientations; the user must switch modes to press them
- Collecting these datasets separately will allow us to more precisely determine users’ optimal policies
- Possible factors in cost function: mode switching, maximum speed, visibility of the path

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