

Learning Deep Sensorimotor Policies for Shared Autonomy

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Deep shared autonomy vision



assistive control for tasks of daily living

Basic challenges

- **Intent:** robot must understand what the person is trying to do
- **Assistance:** robot must offer assistance in a way that is natural and maintains human control
- **Perception:** robot must be able to perceive objects in the world from its on-board sensors

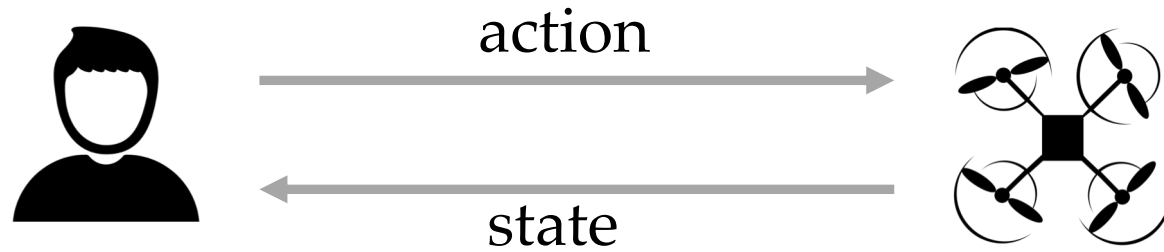
Algorithmic foundations

- Algorithms for **inverse reinforcement learning:** inferring the goals of the human from observing their behavior
- **Imitation learning:** learning how to perform a task from observing human behavior, even when it differs in terms of embodiment or capability
- **Shared autonomy:** learning how to perform a task **together** with a person

Experimental evaluation

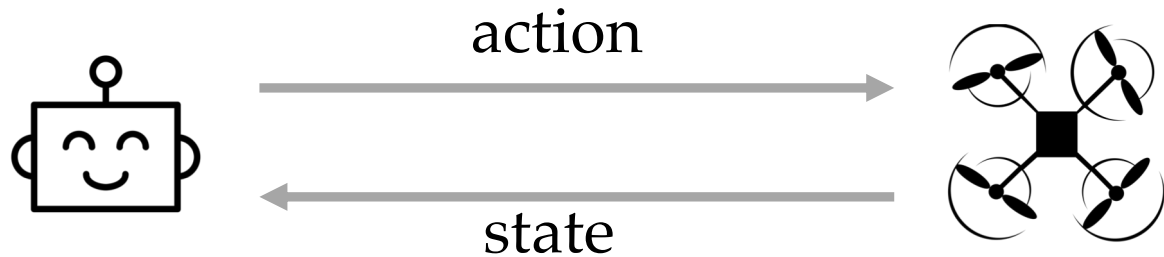
- **Robot-assisted feeding**

Augmenting human control with deep Q-learning



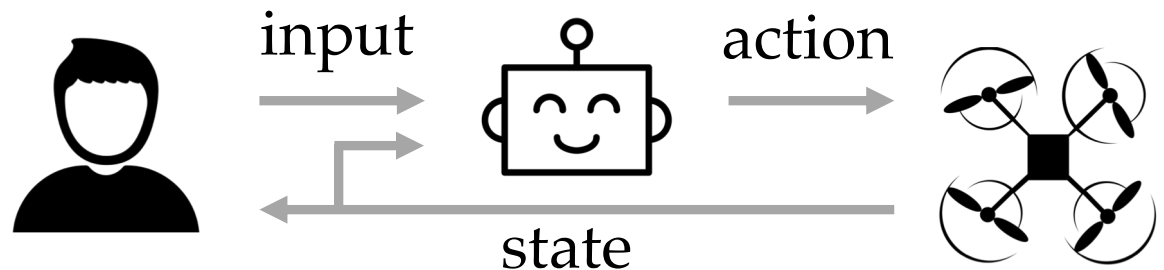
Solo Human Pilot

Knows intent, suboptimal ability



Autonomous Robotic Pilot

Doesn't know intent, near-optimal ability

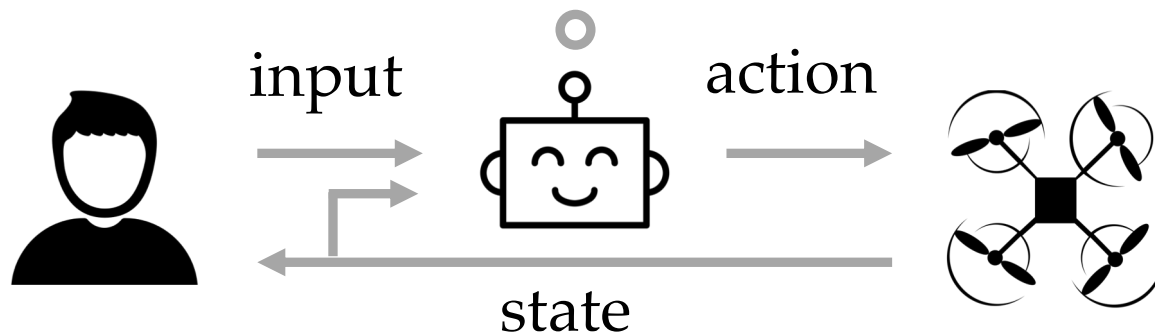
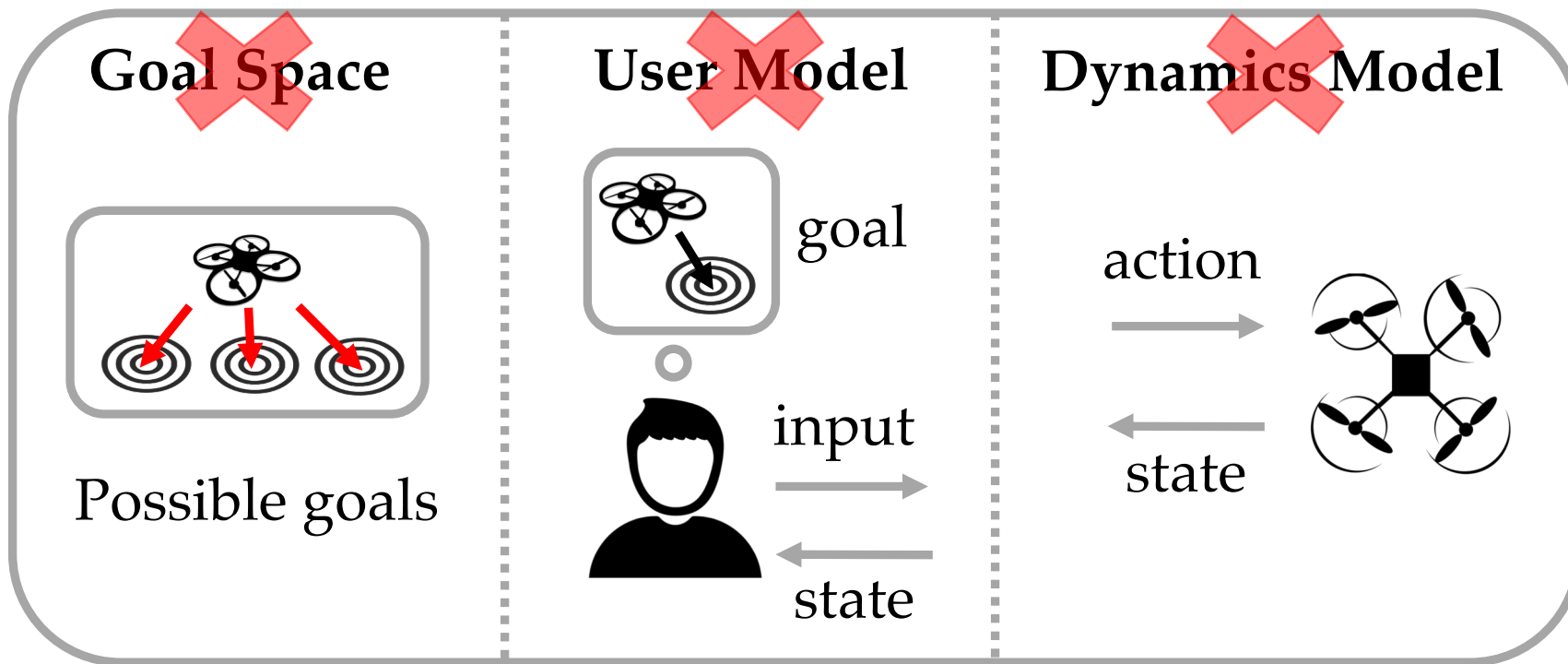


Shared Autonomy:

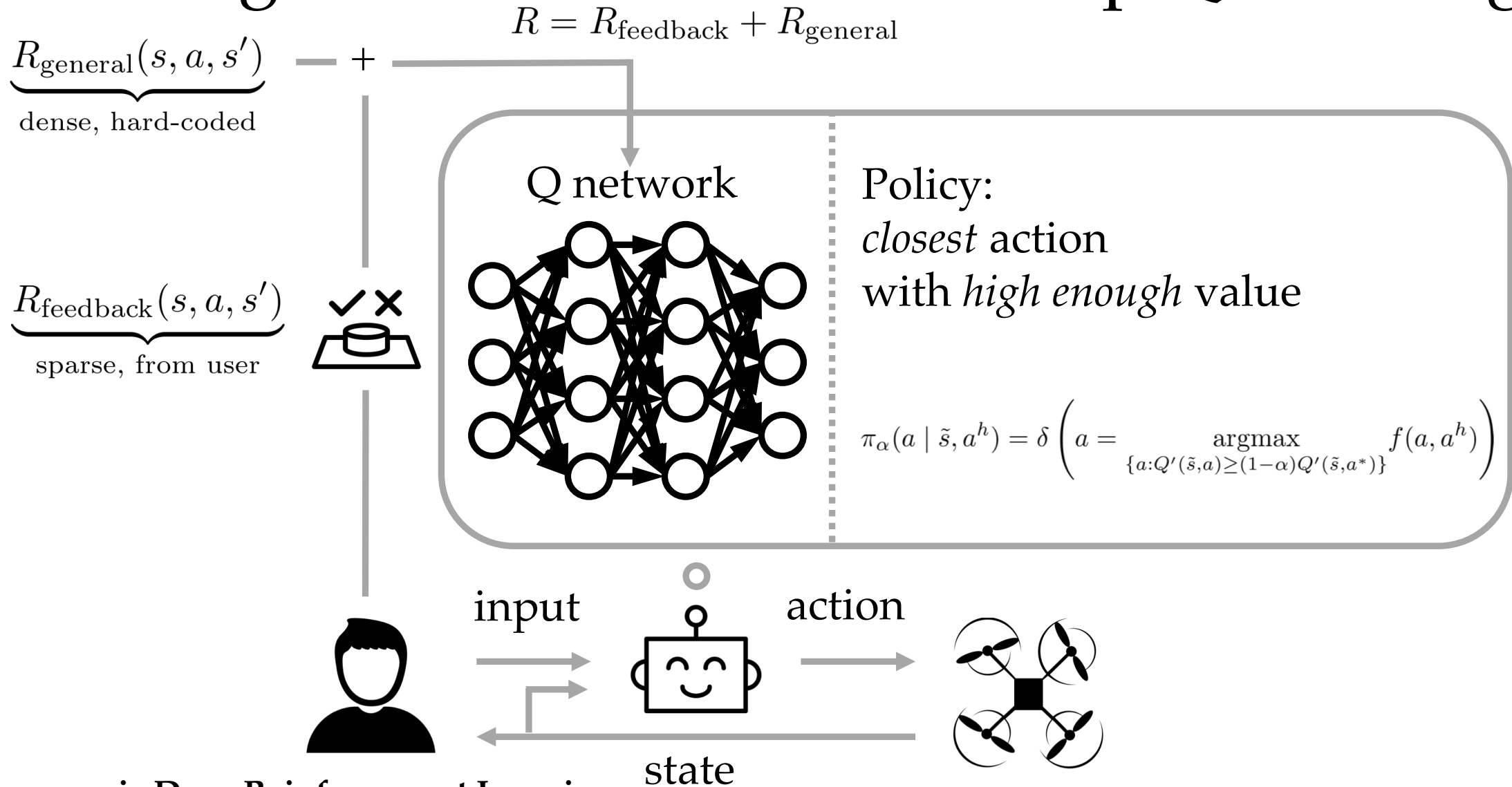
Human Pilot + Robotic Copilot

Knows intent, near-optimal ability

Augmenting human control with deep Q-learning



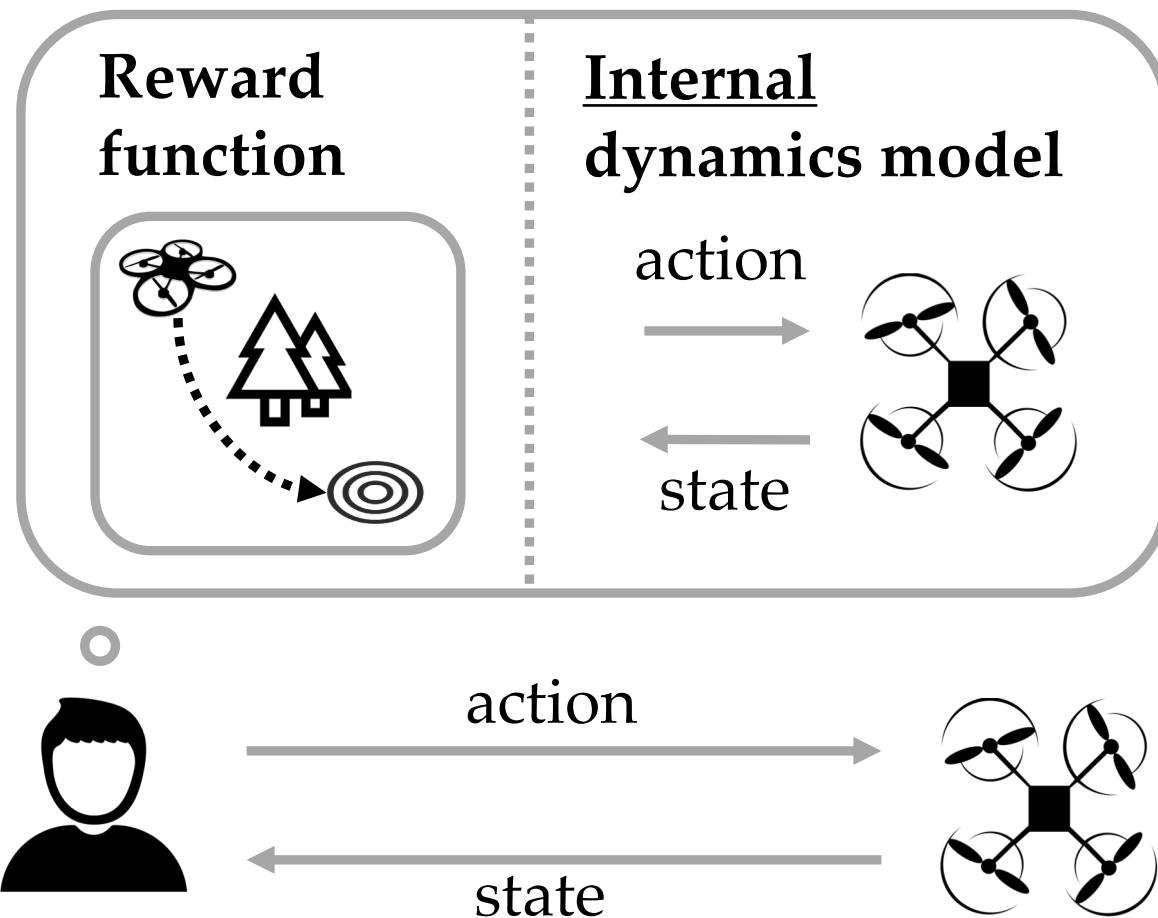
Augmenting human control with deep Q-learning



Shared Autonomy via Deep Reinforcement Learning

Siddharth Reddy, Anca D. Dragan, Sergey Levine

Inferring beliefs about dynamics from behavior

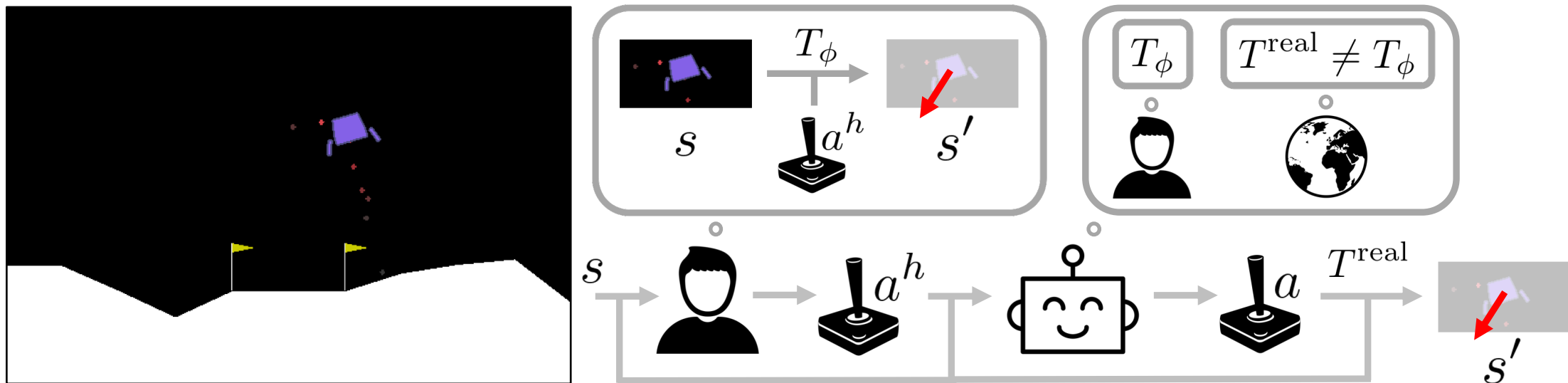


Inferring beliefs about dynamics from behavior

- Training time: **learning from demonstrations**

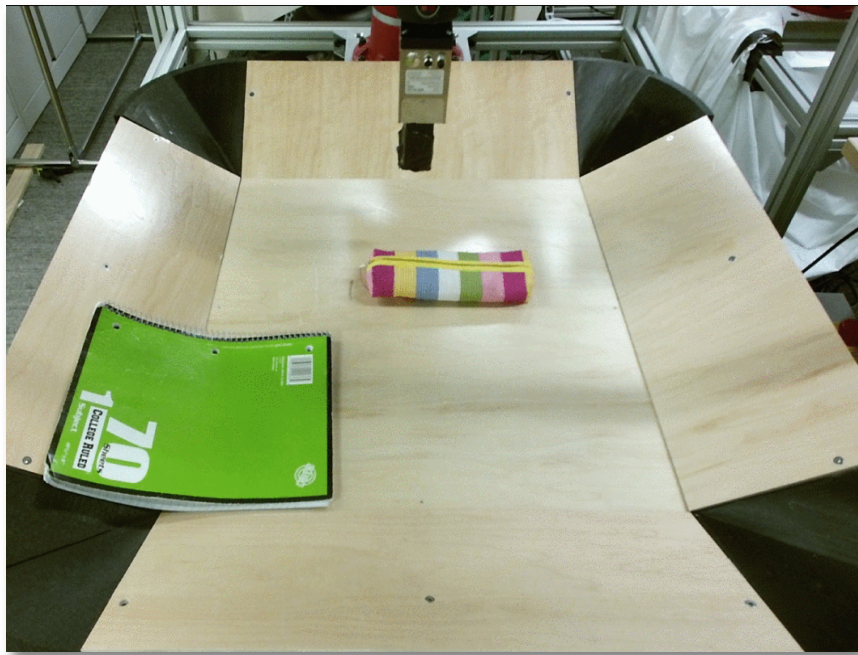


- Test time: **shared autonomy via internal-to-real dynamics transfer**



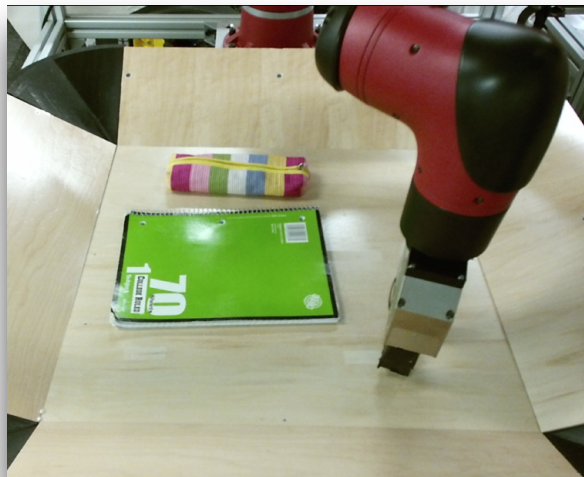
Where Do You Think You're Going?: Inferring Beliefs about Dynamics from Behavior

Siddharth Reddy, Anca D. Dragan, Sergey Levine



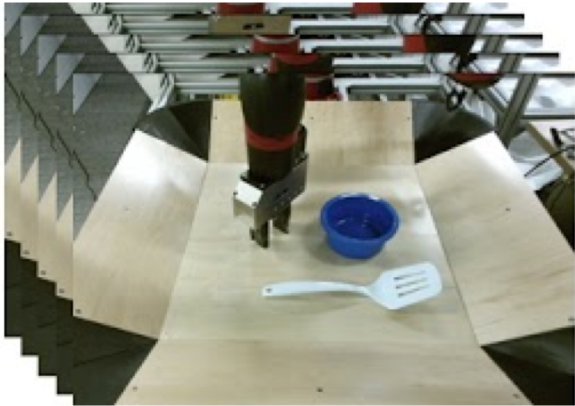
“what” & “how”

Do we need the entire demonstration to infer the goal?



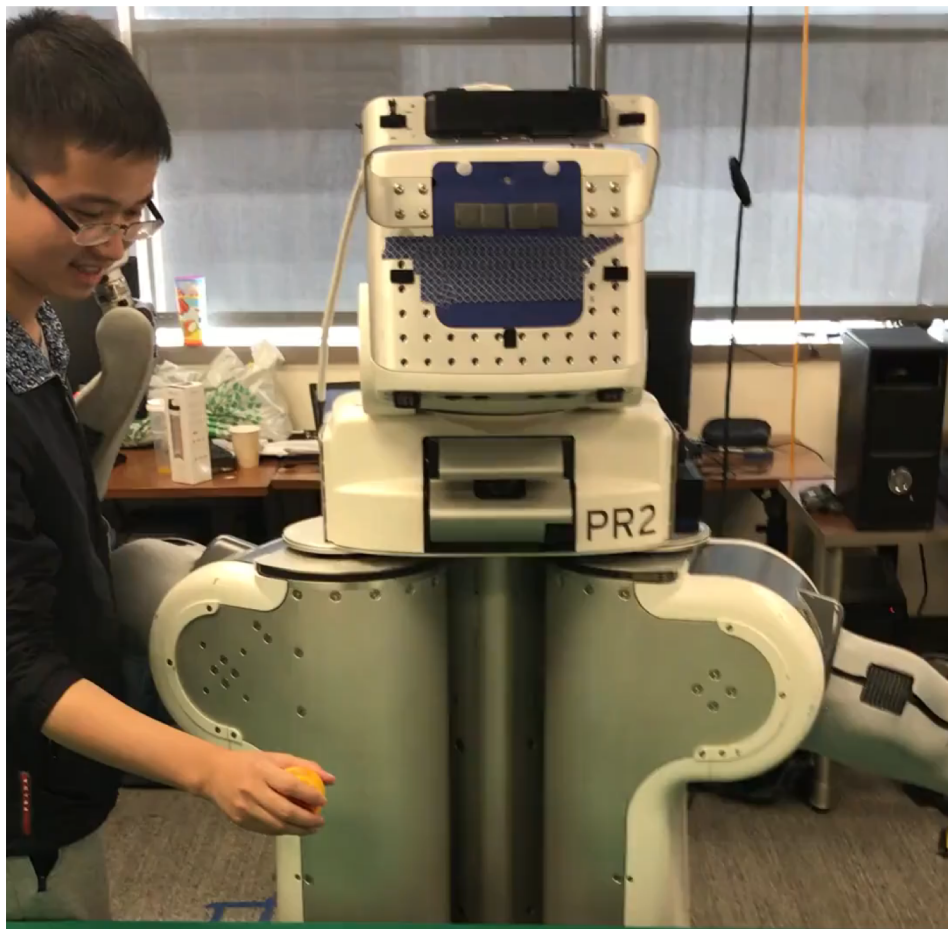
“what”

given 5 examples of
success

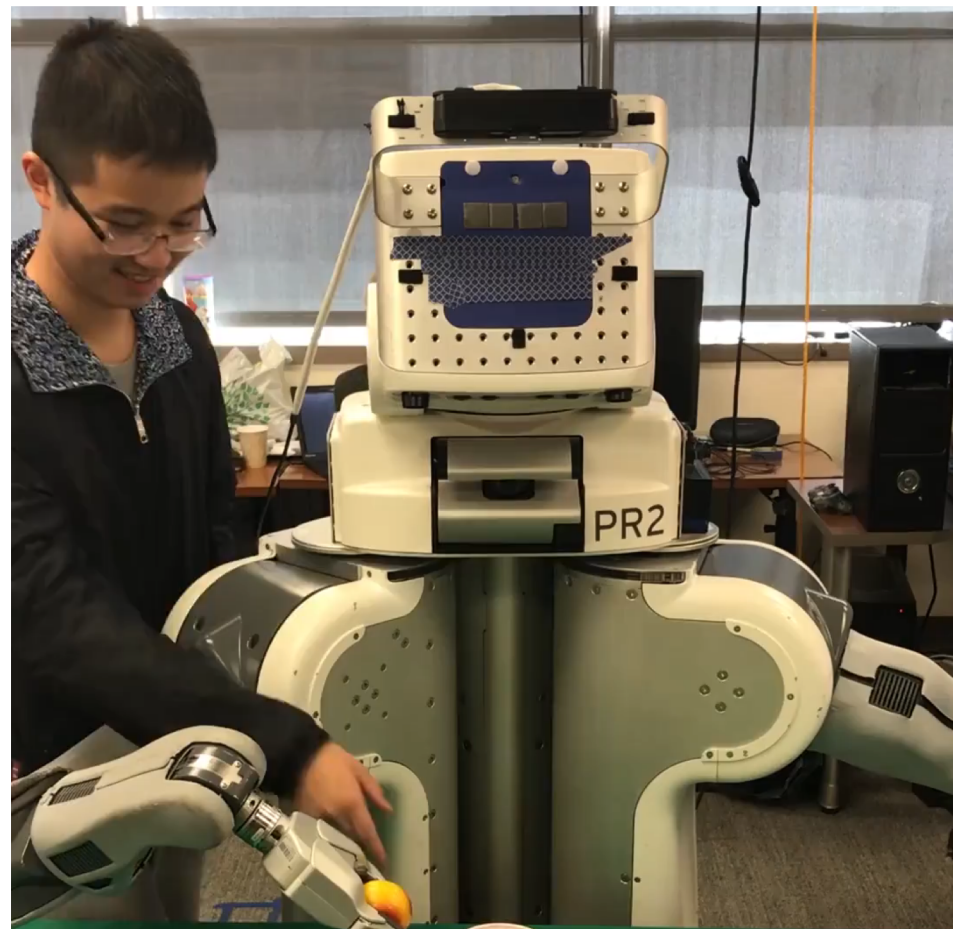


using the classifier as
reward for control





demonstration



testing

Robot-assisted feeding

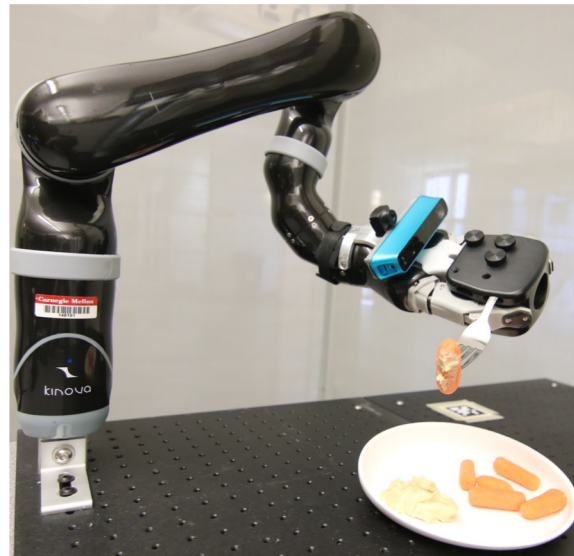
High-level goal: Enabling an assistive robot to feed a person with upper extremity disabilities

High-impact task:

- An activity of daily living (ADL)
- 56.7 million people had disability (Brault, 2012)
- 12.3 million people needed assistance with ADLs (Perry, 2008)

Problem decomposition:

- **Bite acquisition:** food perception, manipulating deformable objects
- **Timing for bite transfer:** understanding the cadence of social dining



bite acquisition



bite transfer

Robot-Assisted Feeding

Transfer depends on Acquisition:
Analyzing Manipulation Strategies for Robotic Feeding

The robotic system uses **multimodal sensing** to acquire food and transfer it using different food **item-dependent manipulation primitives**

Timing for bite transfer



- Features such as **gaze direction (speaker or plate), conversation, mouth (closed or open), and time since last bite** are informative of bite timing
- Represented as a state-transition model
 - **More states than bite acquisition and eating**, e.g., people waiting with full fork vs. empty fork

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