#### 16-867 Human-Robot Interaction

# Lecture 12

Safety and Uncertainty

*Q of the Day:* Explain intuitively what mutual information is.



https://forms.gle/AM2ZNkN6ahhxceMq9





### Last Time

[√] active learning

#### This Time

[ ] final presentation logistics[ ] tips on giving a good presentation[ ] safety and uncertainty

# Logistics

- This Thursday Guest lecture from Prof. Sidd Karamcheti on "HRI in the Era of Foundation Models"
- Next Tuesday No Class ©

### **Upcoming Deadlines**

- Dec. 2 Final Project Presentations: Part 1
- Dec. 4 -- Final Project Presentations: Part 2
- Dec. 11 Final Project Report

### Final Project Presentations

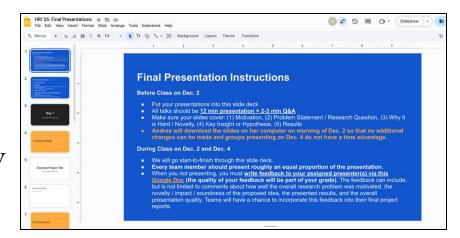
#### **Before Class:**

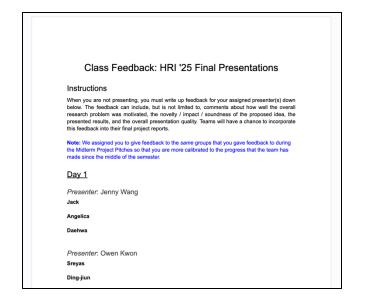
- Put your presentations into the slide deck
- All talks should be <u>12 min presentation + 2-3 min Q&A</u>
- Make sure your slides cover at least these aspects of your project:

   (1) Motivation, (2) Problem Statement / Research Question, (3) Why it is Hard / Novelty, (4) Key Insight or Hypothesis, (5) Results
- Andrea will download the slides on her computer on morning of Dec. 2 so that no additional changes can be made and groups presenting on Dec. 4 do not have a time advantage.

#### **During Class:**

- We will go start-to-finish through this slide deck
- Every team member should **present roughly an equal proportion** of the presentation.
- When you not presenting, you must write feedback to your assigned presenter(s) via the Google Doc (the quality of your feedback will be part of your grade).





### Dec. 11– Final Project Report

- The final report should present your final findings in a research or survey paper format.
- The length should be <u>maximum 6 pages</u>, double-column.
- Follow the template and answer the questions – you should build on your Mid-term Report, address the feedback you got from me, Yilin, and the class!
- You can also see the grading rubric on Canvas. We are looking to see progress throughout the semester relative to where you started.

The final report should present your final findings in a research or survey paper format. The length should be maximum 6 pages, double-column. The grade will be determined based on the content quality and not on the absolute length (please see the grading rubric below).

Please use the attached Latex template and follow the structure of the subsections.

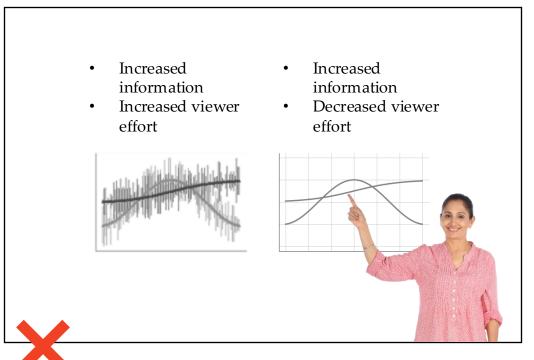


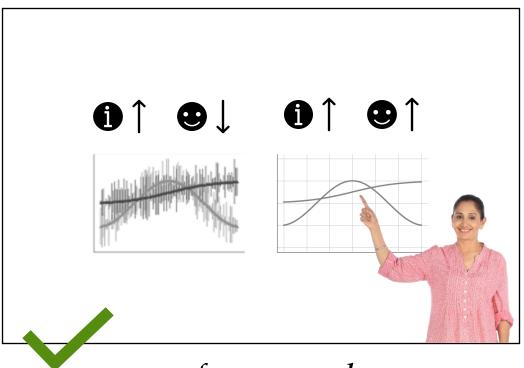
Latex Template (zip file):  $\underline{\text{final-report-latex.zip}}$ 

# Heuristics for good presentations

# Heuristics for good presentations

Sparse; figures over text!





focus on **slide** 

focus on **speaker** 

## Heuristics for presentations

### Distill your ideas and takeaways for the viewer

#### **Key Idea**

- Several reactive control strategies have been developed to deal with pHRI
- But the robot returns to its original motion stems from a fundamental limitation of traditional pHRI strategies: they miss the fact that human interventions are often intentional
- Key idea is that because pHRI is intentional, it is also informative
- pHRI provides observations about the correct robot objective function, and the robot can leverage these observations to learn that correct objective.

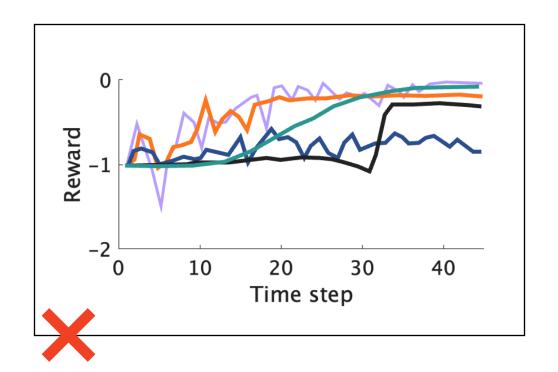
#### **Key Idea**

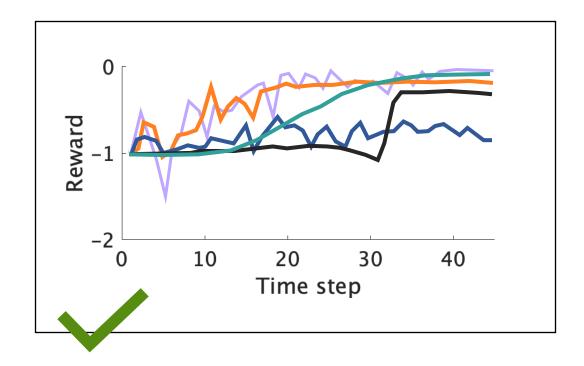
Because pHRI is intentional, it is also informative.

Human corrections are observations about the correct robot objective function

# Heuristics for good presentations

Be visual (e.g., make graphs and break them down)



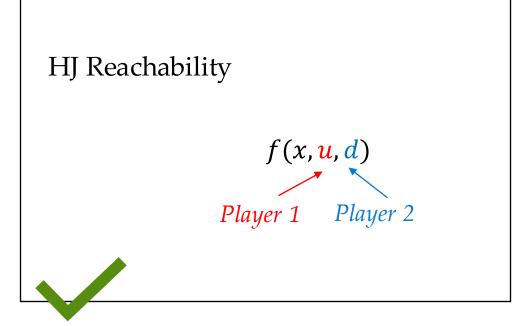


# Heuristics for good presentations

If using equations, explain them and build them up

HJ Reachability

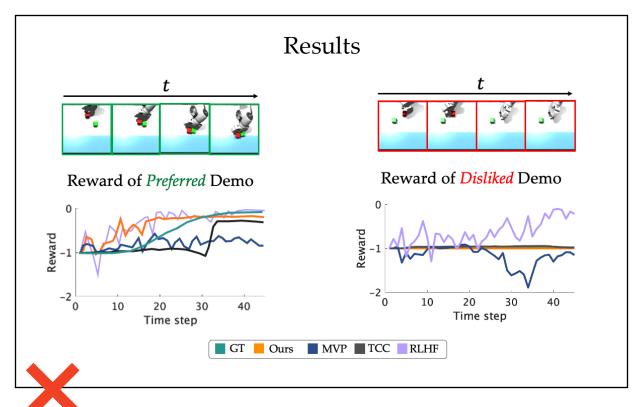
$$\max_{\mathbf{u}} \min_{\mathbf{d}} \nabla_{x} V(x, t)^{\mathsf{T}} f(x, \mathbf{u}, \mathbf{d}) + \frac{\partial V}{\partial t} = 0$$

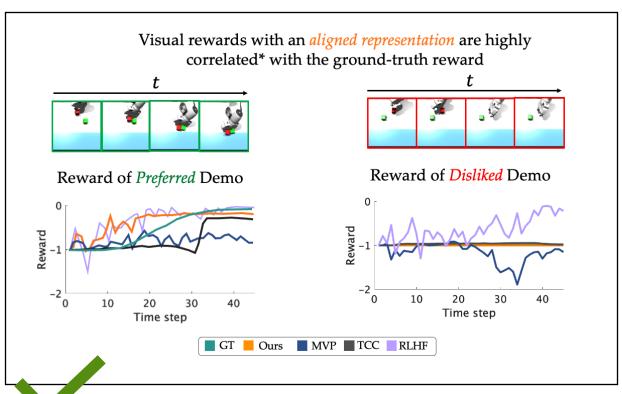




# Heuristics for presentations

Use useful titles





### Go to the Class Website for More Resources

### FAQ

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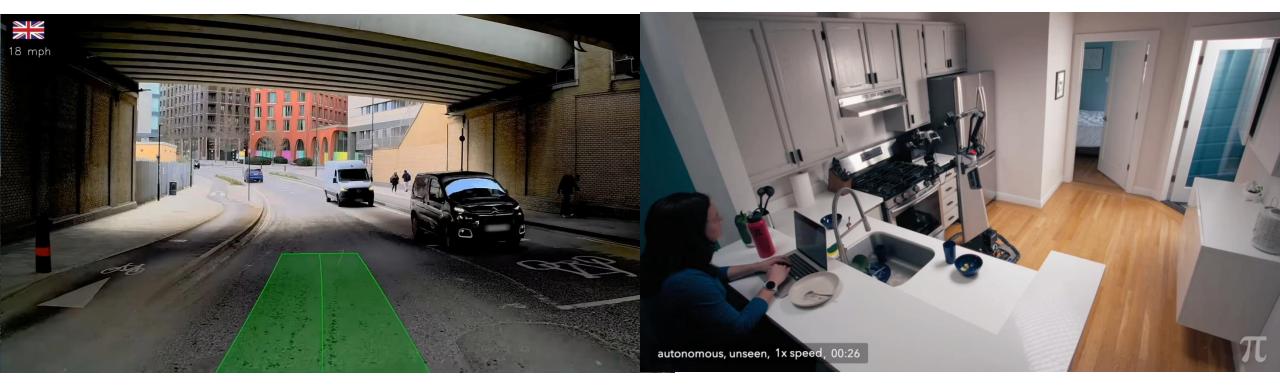
- 1 I don't have access to robots! What can I do?
- 2 I don't have access to compute! What can I do?
- 3 For my class project, I want to test an algorithm with people. Do I need to run a formal user study?
- 4 How can you effectively read a research paper?
- 5 How do you write a good research paper?
- 6 How do I make nice figures for a paper or talk? ←———
- 7 Is there a textbook for the class?

Now onto....

Lecture 12

Safety and Uncertainty

Imagine you are given a robot policy that needs to be deployed. This policy may have to interact *with* or *in service of* an end-user



Wayve

**Physical Intelligence** 

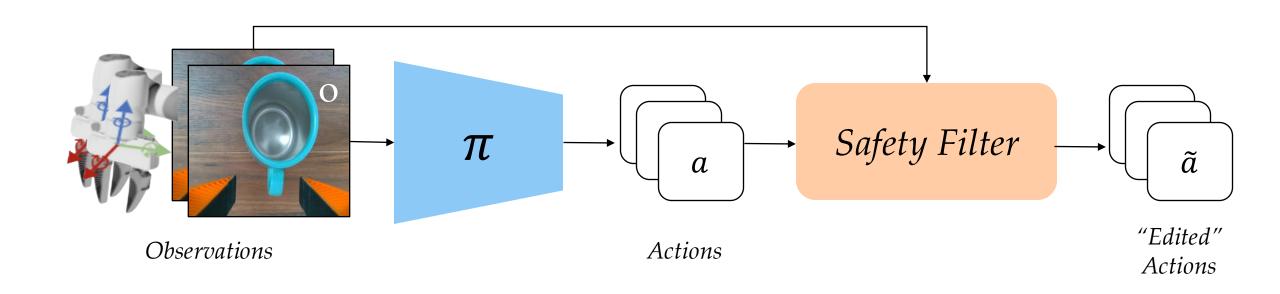
How do we know that the robot will "make safe decisions"? What does "a safe decision" mean more precisely?

Let's start with some ideas from safe control....

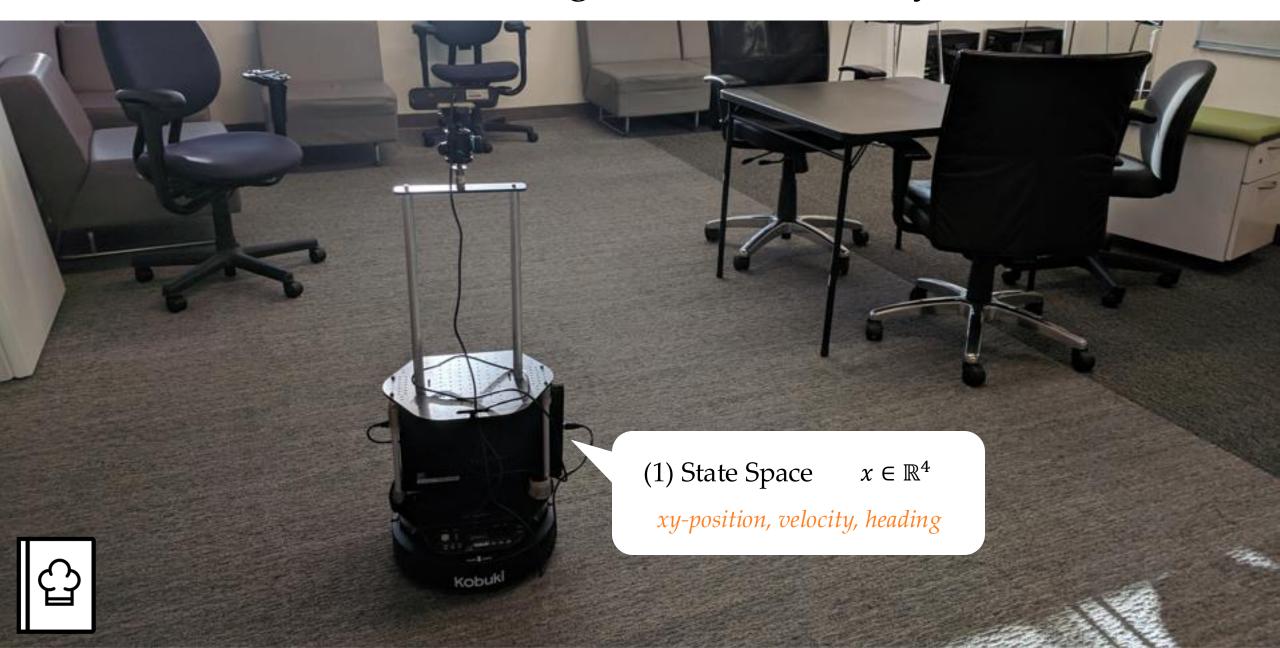
### Idea from safe control:

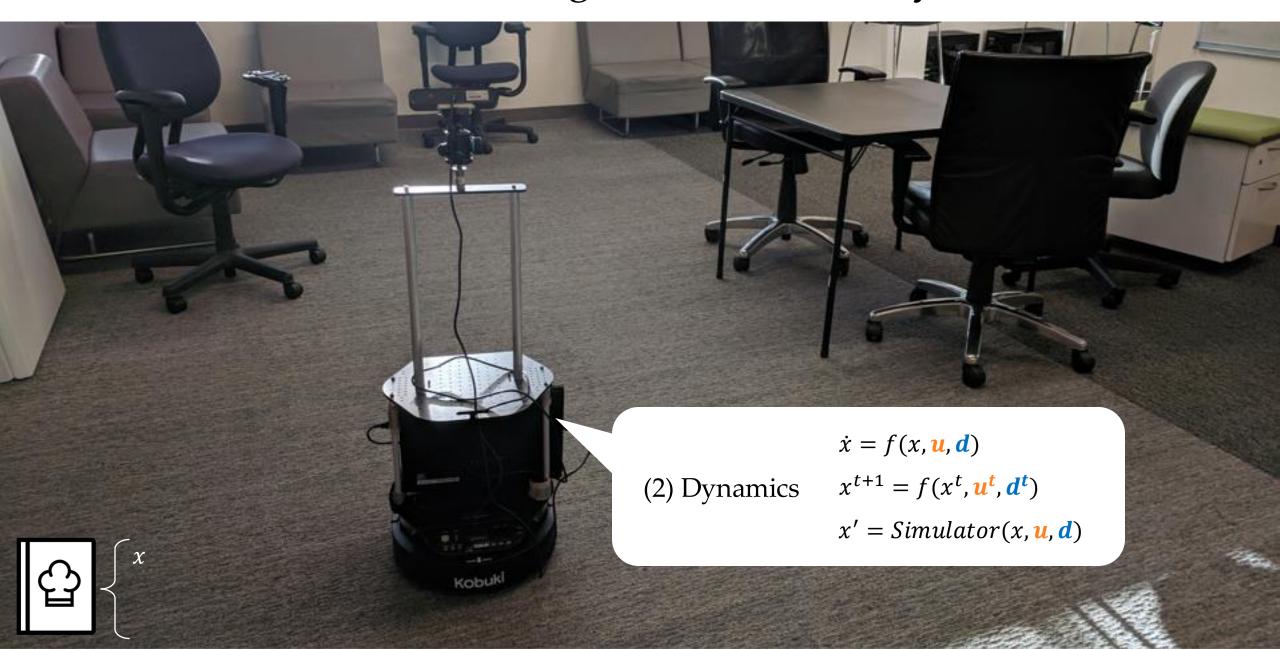
# **Safety filters** modify *any* policy's output so that present actions will not result in future failure

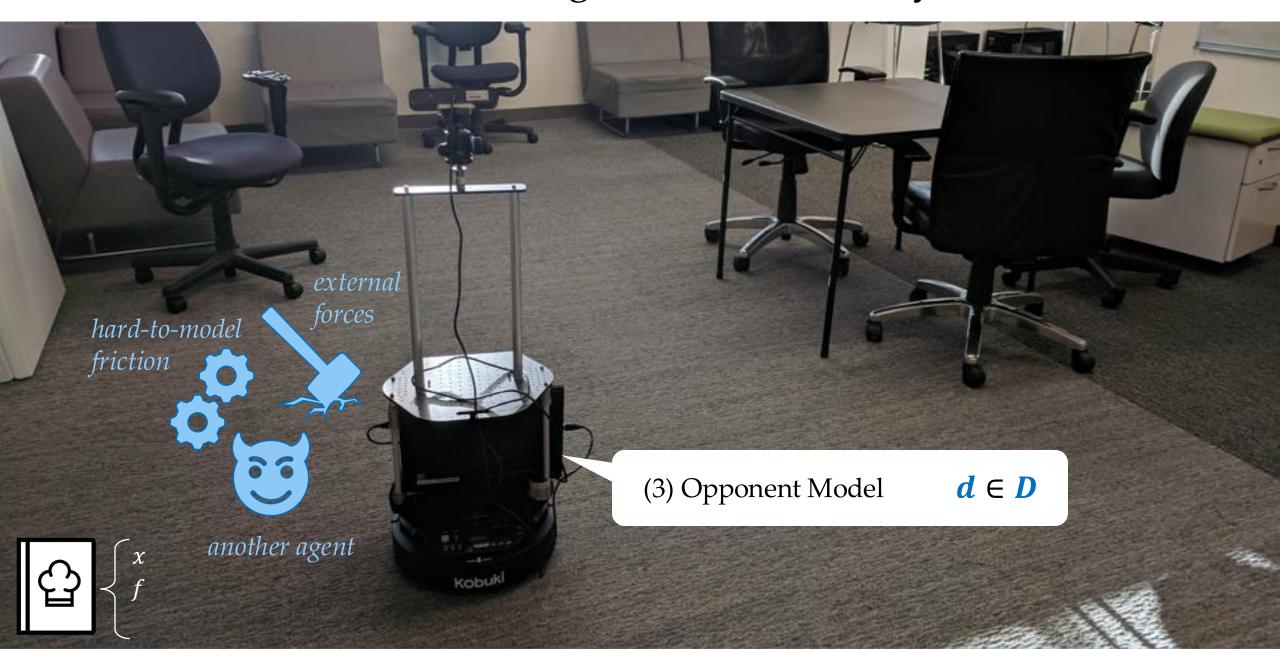
Aside: In LLM land this is called an "output guardrail" ©

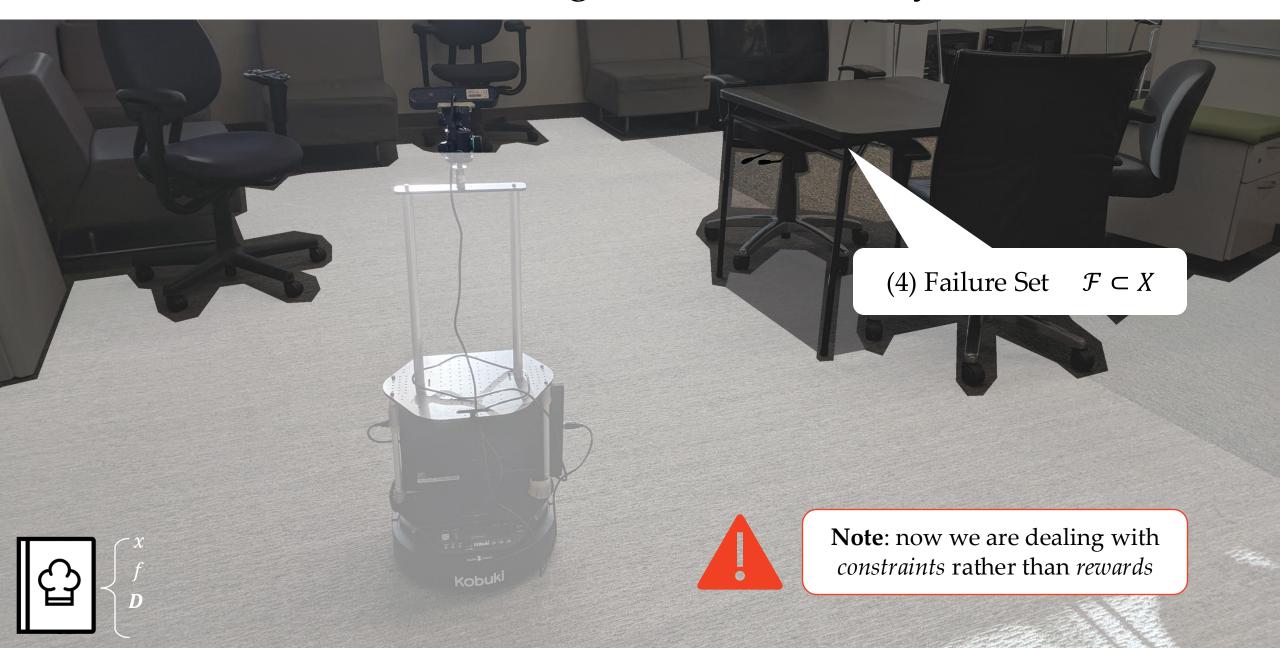


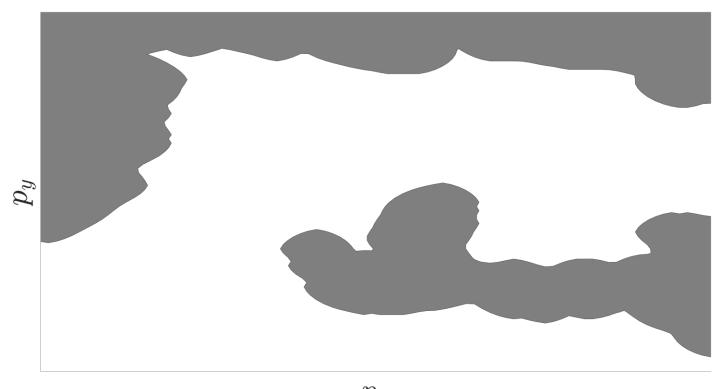








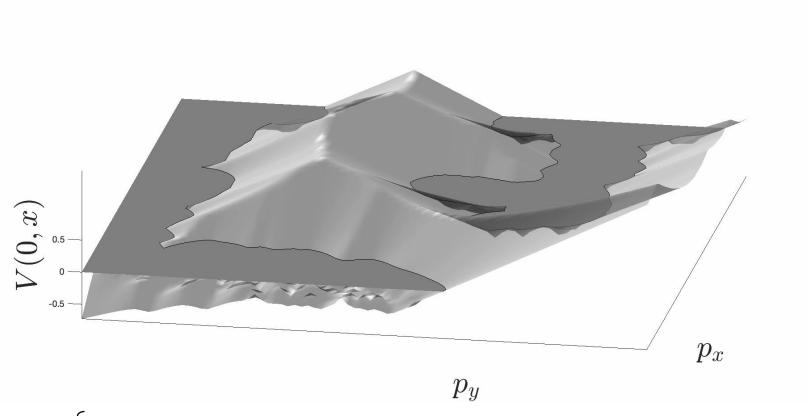




Failure Set (i.e., our safety specification)

 $\mathcal{F} \subset \mathcal{X}$ 

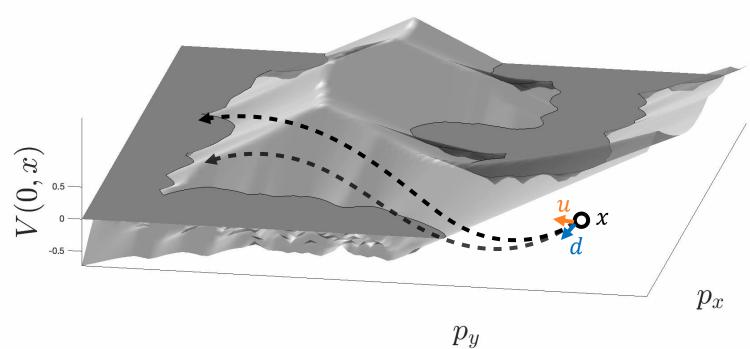




Encode Failure Set

$$\mathcal{F} = \{x : \ell(x) \le 0\}$$

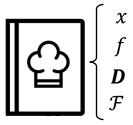


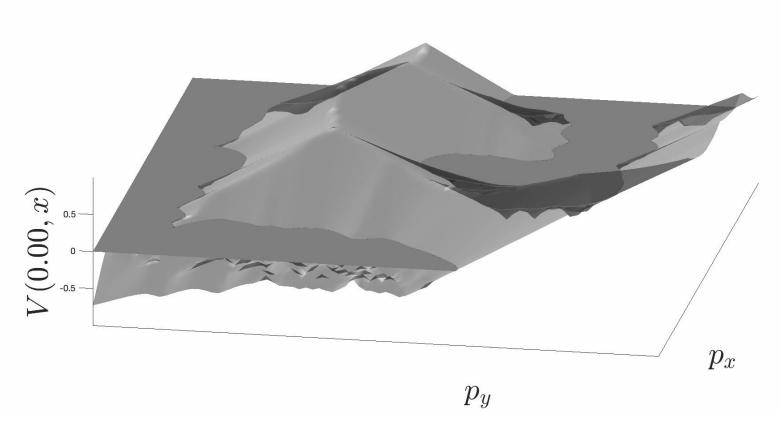


Pose Safety Critical Game

$$V(x) := \max_{\boldsymbol{\pi_u}} \min_{\boldsymbol{\pi_d}} \left( \min_{t \ge 0} \ell(\zeta_x^{\boldsymbol{u}, \boldsymbol{d}}(t)) \right)$$

V "remembers" the closest system got to failure under best robot strategy  $\pi_u$  and worst opponent strategy  $\pi_d$ 





Solve Safety Game

 $V(x) := \max_{\boldsymbol{\pi_u}} \min_{\boldsymbol{\pi_d}} \left( \min_{t \ge 0} \ell(\zeta_x^{\boldsymbol{u}, \boldsymbol{d}}(t)) \right)$ 

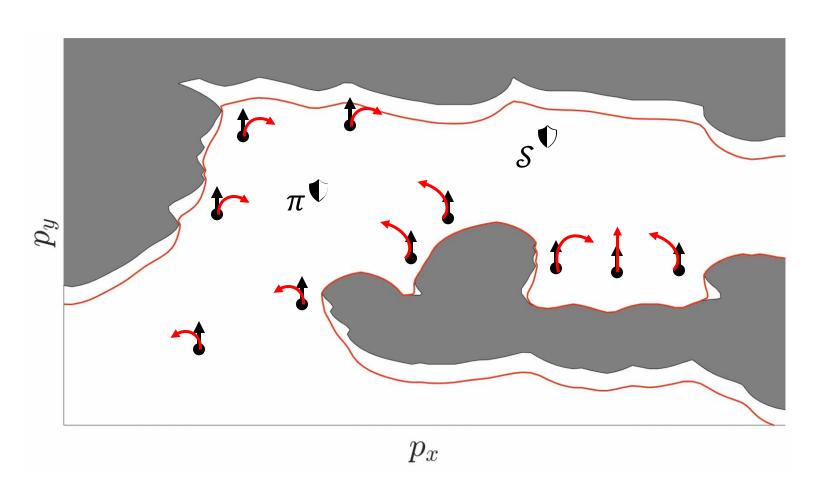
Many solvers: exact grid-based PDE solvers [1], adversarial RL [2,3], self-supervised learning [4]

<sup>[1]</sup> Mitchell, Journal of Scientific Computing 2008

<sup>[2]</sup> Pinto, et al. ICML 2017

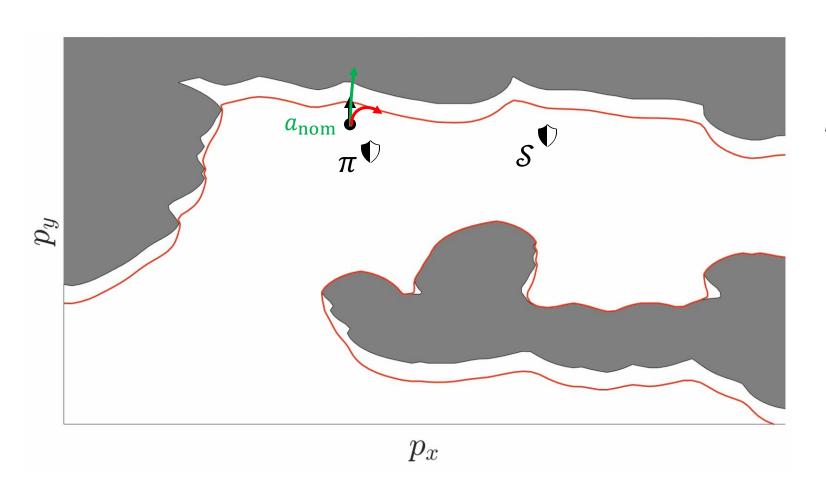
<sup>[3]</sup> Hsu, et al. L4DC 2023

<sup>[4]</sup> Bansal & Tomlin, ICRA 2021



Safety **Policy** 

$$\pi^{\P}$$
,  $\mathcal{S}^{\P} = \{x : V(x) > 0\}$   
Safe Set (i.e., "Monitor")

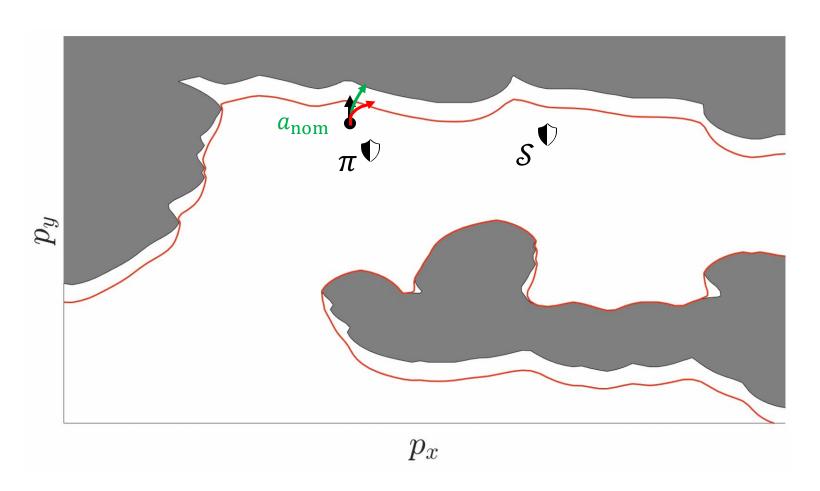


Safety **Policy** 

$$\pi^{\P}$$
,  $S^{\P} = \{x : V(x) > 0\}$   
Safe Set (i.e., "Monitor")

Safety **Filter** 

$$a^* = \begin{cases} \pi^{\P}, & x \text{ near bdry } S^{\P} \\ \text{[any policy here]}, & x \in S^{\P} \end{cases}$$



Safety **Policy** 

$$\pi^{\P}$$
,  $\mathcal{S}^{\P} = \{x : V(x) > 0\}$   
Safe Set (i.e., "Monitor")

Safety **Filter** 

$$a^* = \arg\min_{a} ||a - a_{\text{nom}}||_2^2$$
  
s. t.  $V(x(t + \delta)) \ge 0$ 

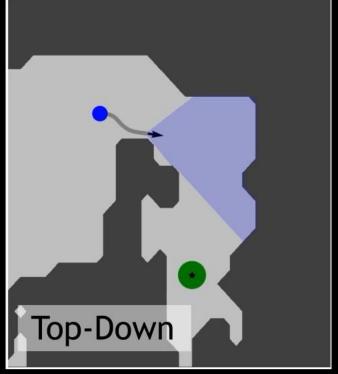
\*Note: there are many filtering variants!

[Wabersich, et al. "Data-driven safety filters." Control Systems Magazine, 2023]

[Hsu, et al. "The Safety Filter." Annual Review of Control, Robotics, and Autonomous Systems, 2023]

"Find an action that is similar to the base policy as long as the next state is still safe"

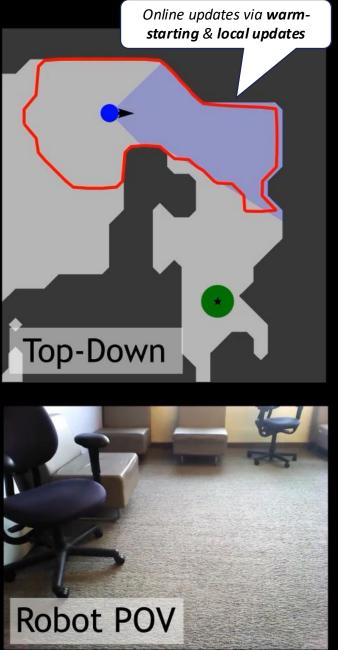




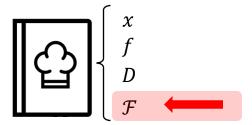


[Bajcsy\*, et al. CDC 2019]





# What "matters" about safe robot behavior can be hard to specify ...



### So far, the safety representations we have seen are....

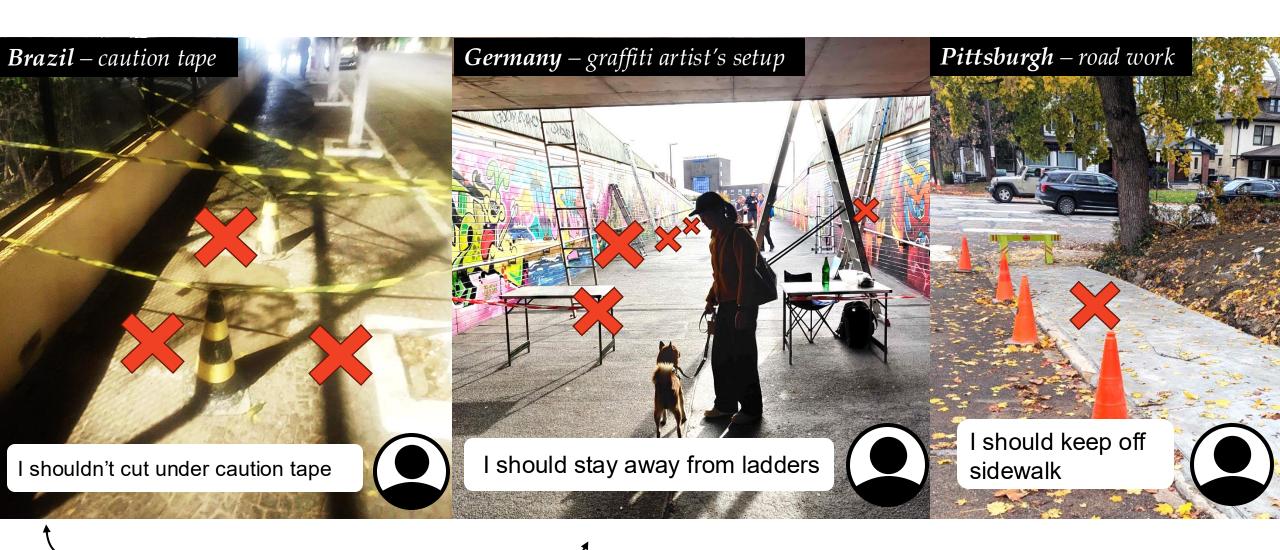




$$\mathcal{F} = \{x : \| x_R - x_H \|_2 \le \epsilon \}$$

$$\mathcal{F} = \{x : \| x - \text{SLAM}(x) \|_2 \le \epsilon \}$$

### But in the open world, there are many more constraints....



Real images taken by my students!

### But in the open world, there are many more constraints....











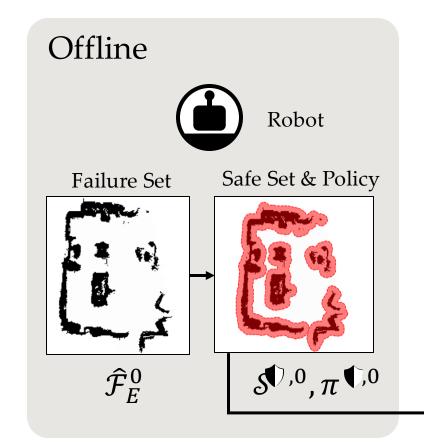
How can robots refine their safety representations to include semantically-meaningful safety constraints?

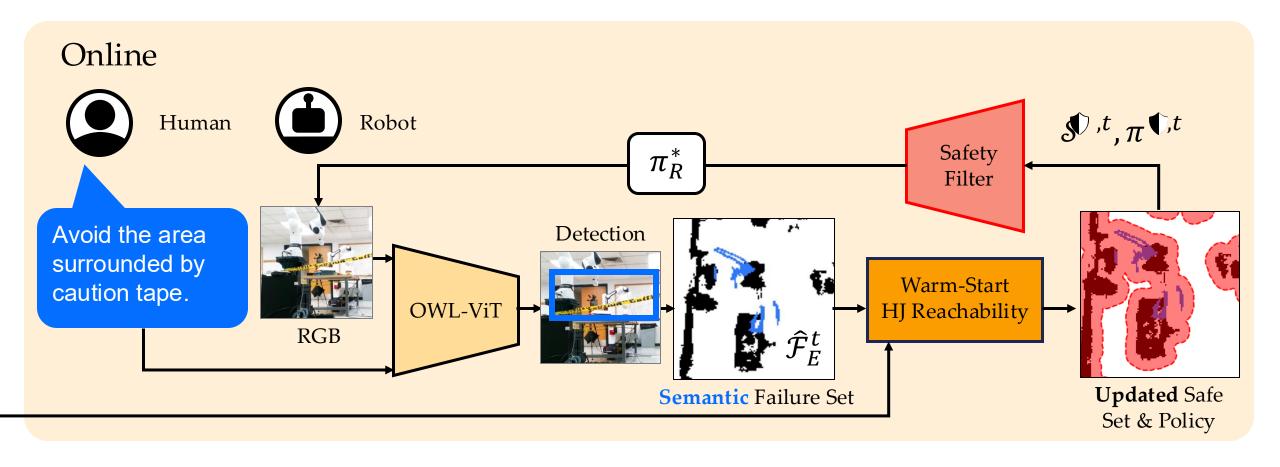
#### Language Feedback



#### Idea:

Vision-language models enable a flexible way to communicate safety constraints to the robot





## From the human's POV...

#### Language Feedback



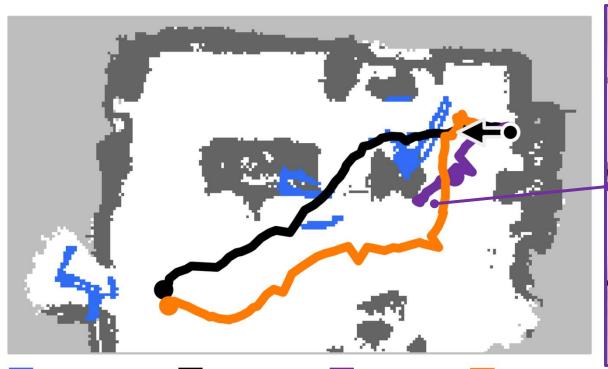


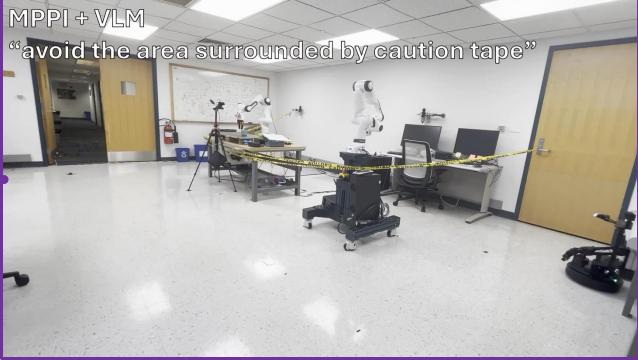
## From the robot's POV...





### Quantitative & Qualitative Hardware Results





Semantic Fail	Plan-SLAM	Plan-Lang	Safe-Lang
---------------	-----------	-----------	-----------

	Caution Tape Scenario			
Method	Plan Time (ms)	t-to-Goal	Abides $\mathcal{F}_E^*$	$\pi^{f 0}_{\mathcal R}$ On
Plan-SLAM	7 (±1)	17.647	Х	N/A
<b>Plan-Lang</b>	$40 \ (\pm 30)$	$\infty$	×	N/A
Safe-Lang	31 (±29)	26.176	✓	29.37%

All modules run asynchronously

So far, we have been safeguarding the robot by *switching*.....

$$a^* = \begin{cases} \pi^{\P}, & x \text{ near bdry } S^{\P} \\ [any policy here], & x \in S^{\P} \end{cases}$$

Can we do better?

## Safety with Agency: Human-Centered Safety Filter with Application to Al-Assisted Motorsports

Donggeon David Oh\*, Justin Lidard\*, Haimin Hu, Himani Sinhmar, Elle Lazarski, Deepak Gopinath, Emily Sumner, Jonathan DeCastro, Guy Rosman, Naomi Leonard, Jaime Fernández Fisac





#### Safety **Filter** (before)

$$a^* = \begin{cases} \pi^{\P}, & V(x) \approx 0 \\ [any policy here], & V(x) > 0 \end{cases}$$

Safety **Filter** (now)

$$a^* = \arg\min_{a \in A} ||a - a_{\text{nom}}||_2^2$$
  
s. t.  $Q(x, a) \ge \alpha V(x)$ 

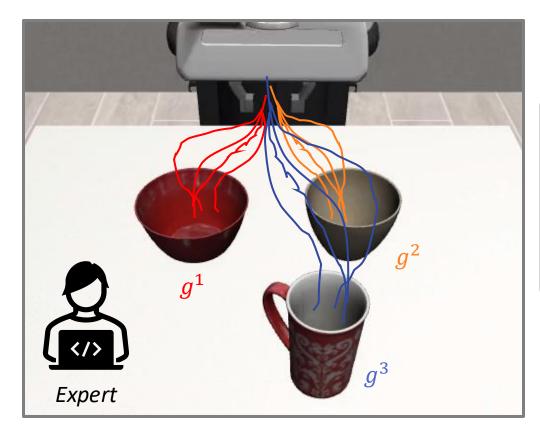
 $\alpha \in [0,1)$  design parameter controls how quickly the safety value function is allowed to decrease over a single timestep

"Find an action that is similar to the base policy as long as the next state is still safe"

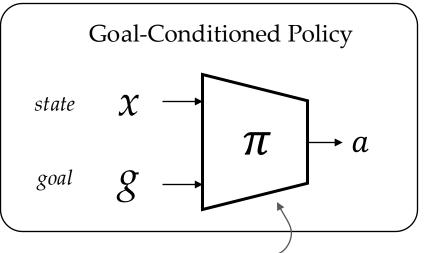




## Goal-conditioned imitation learned policies are useful



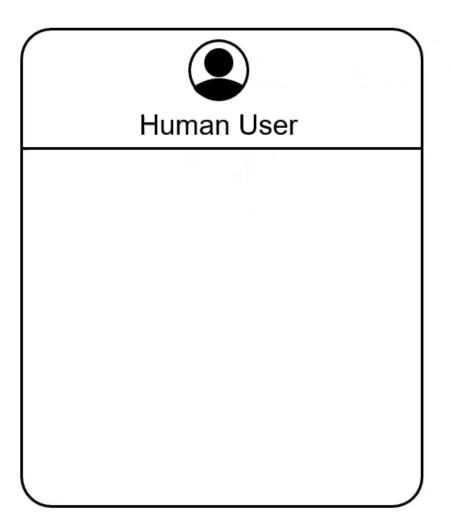
100 successful demos per target object

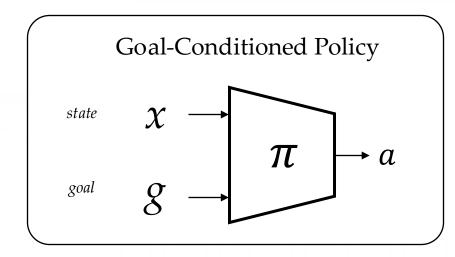


Training via Behavior Cloning

$$\mathcal{L}_{BC}(\mathcal{D}) = \mathbb{E}_{(x^i, a^i, g^i) \sim \mathcal{D}} \left| \left| \pi(x^i; g^i) - a^i \right| \right|_2^2$$

# Goal-conditioned imitation learned policies are useful but they aren't guaranteed to safely succeed









### Idea:

alternative suggestion can be modeled as **safety filtering in** *goal space*, rather than action space

# alternative suggestion can be modeled as **safety filtering in** *goal space*, rather than action space

#### Before

$$a^* = \arg\min_{a \in A} ||a - a_{\text{nom}}||_2^2$$

s.t. 
$$V(x(t+\delta)) \ge 0$$

"Find an action that is similar to the base policy as long as the next state is still safe"

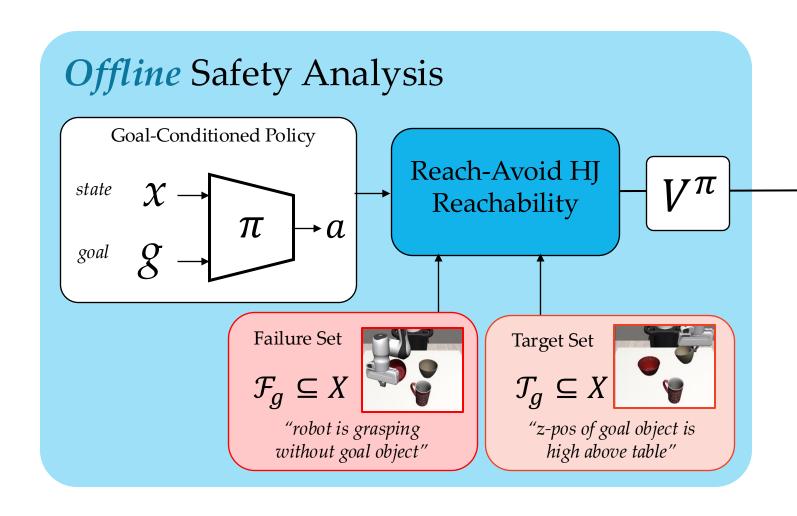
#### Ours

$$g_R = \arg\min_{g \in G} ||g - g_H||_2^2$$

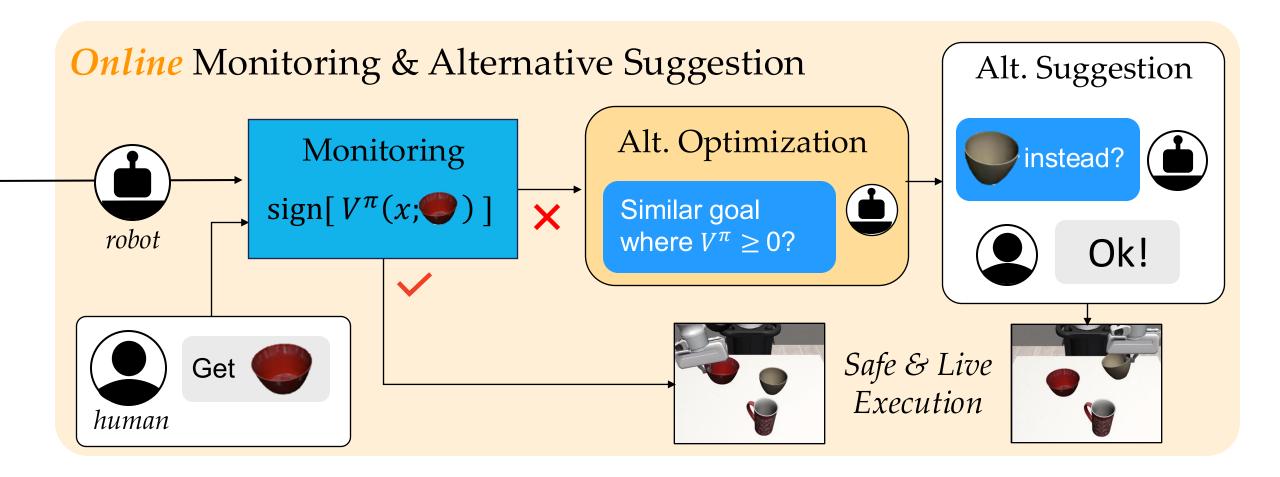
s. t. 
$$V^{\pi}(x; g) \ge 0$$

"Find a goal that is similar to the human's original goal as long as the pre-trained policy is safe"

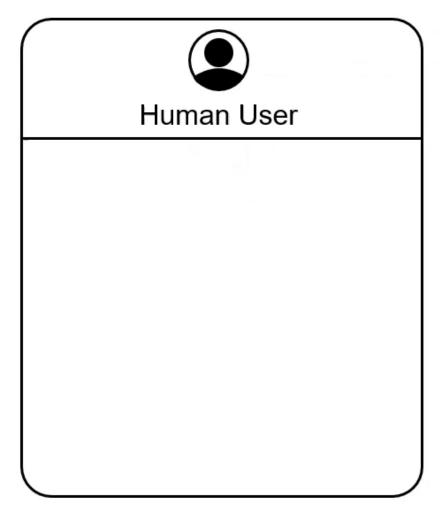
## SALT: safety filter goals to suggest Safe ALTernatives



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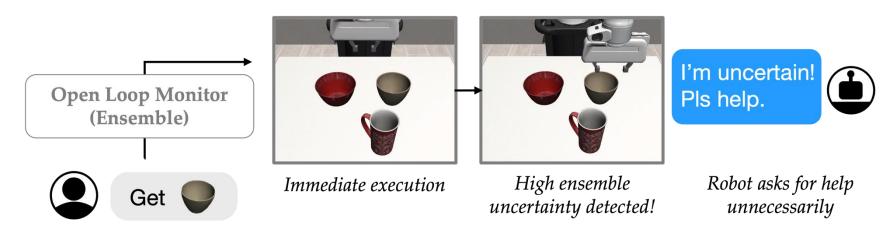


## SALT: safety filter goals to suggest Safe ALTernatives



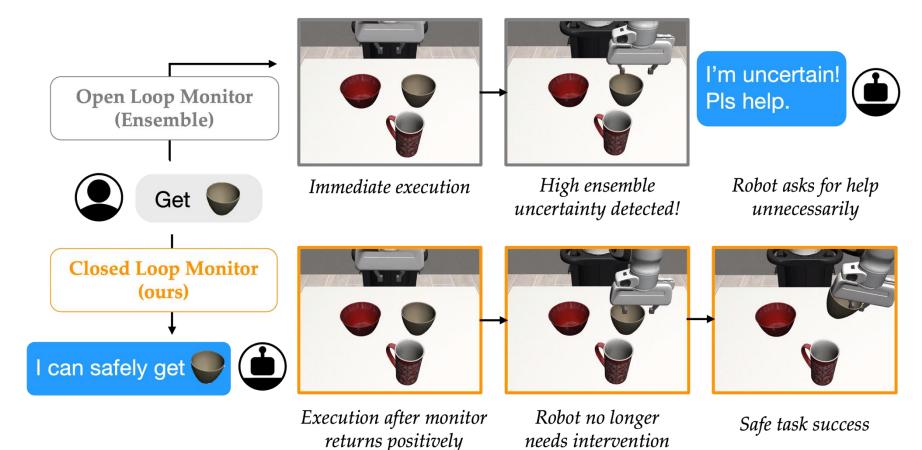
## What is the Benefit of SALT as a Runtime Monitor?

		Manipulation			
	Method	TNR % (†)	TPR % (†)	FPR % (↓)	FNR % (↓)
$Open-Loop \rightarrow Closed-Loop \left\{\right.$	Ensemble RewardSum SALT (ours)	34.61 (±1.68) 64.47 (±1.61) 61.21 (±1.91)	$27.45 (\pm 1.96)$ $4.67 (\pm 0.68)$ $13.23 (\pm 1.56)$	$32.65 (\pm 1.27)$ $8.85 (\pm 1.01)$ $13.23 (\pm 1.23)$	5.26 (±0.89) 22.01 (±1.21) 12.33 (±0.85)

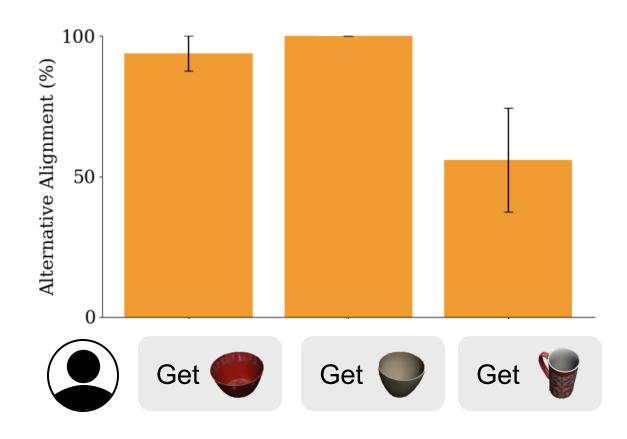


## What is the Benefit of SALT as a Runtime Monitor?

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Open-Loop →	Ensemble	34.61 (±1.68)	27.45 (±1.96)	32.65 (±1.27)	5.26 (±0.89)
Closed-Loop ⟨	RewardSum	$64.47 (\pm 1.61)$	$4.67 \ (\pm 0.68)$	$8.85 (\pm 1.01)$	$22.01 (\pm 1.21)$
Closed-Loop	SALT (ours)	$61.21\ (\pm 1.91)$	$13.23 \ (\pm 1.56)$	$13.23 \ (\pm 1.23)$	$12.33\ (\pm0.85)$



## How Acceptable Are The Proposed Alternatives?



Human's original goal ( $g_H$ )

10 expert users from labs at CMU and UC San Diego.

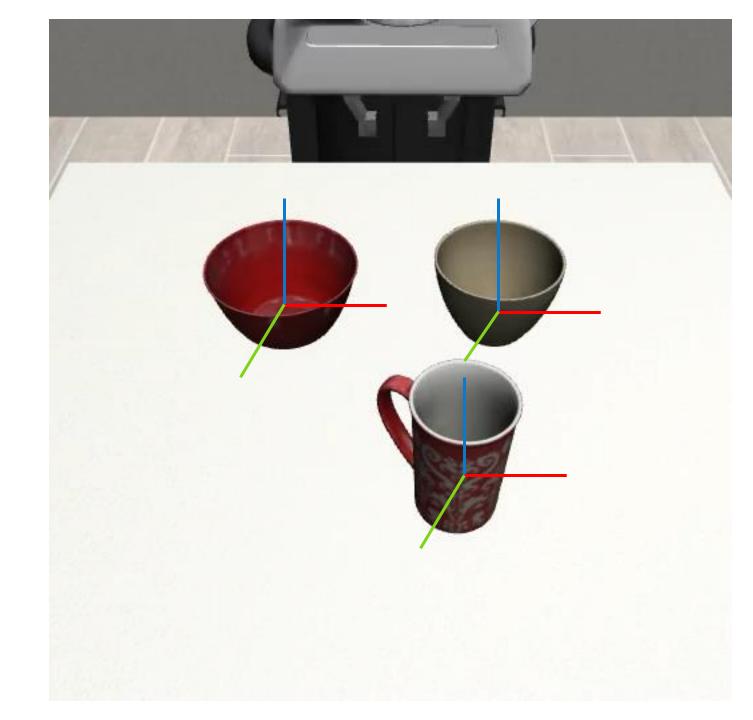
1,000 random initial conditions  $x^0$  for each  $g_H$  and  $g_R$  suggested by SALT







$$g_R = \arg\min_{g} ||g - g_H||_2^2$$
  
s.t.  $V^{\pi}(x; g) \ge 0$ 







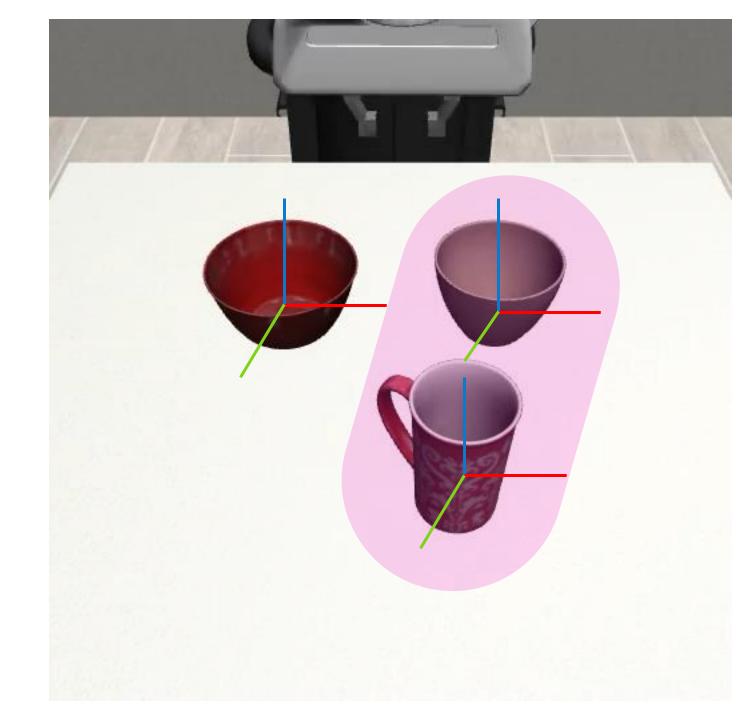


$$g_R = \arg\min_{g} ||g - g_H||_2^2$$

s.t. 
$$V^{\pi}(x; g) \ge 0$$







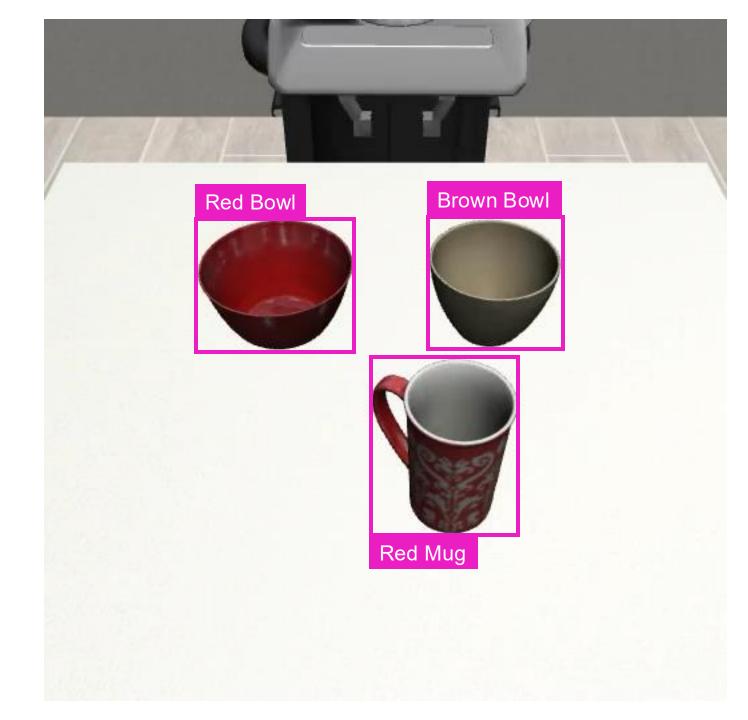






$$g_R = \arg\min_{g} \frac{d(\mathcal{E}(g), \mathcal{E}(g_H))}{d(\mathcal{E}(g), \mathcal{E}(g_H))}$$

s.t. 
$$V^{\pi}(x; g) \ge 0$$



$$g_R = \arg\min_{g} \frac{d(\mathcal{E}(g), \mathcal{E}(g_H))}{1}$$



ChatGPT V

We: You are a robot in a kitchen. You have a set of items in front of you.

We: The items are: Red Mug, Red Bowl,

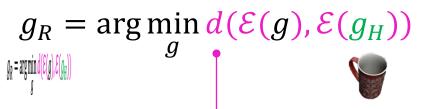
**Brown Bowl** 

We: Given Red Mug, which item is the most similar? Please answer with only one of the letters. The user is organizing their kitchen items by color.

You:

- A) Brown Bowl
- B) Red Bowl





We: You are a robot in a kitchen. You have a set of items in front of you.

We: The items are: Red Mug, Red Bowl,

**Brown Bowl** 

We: Given Red Mug, which item is the most similar? Please answer with only one of the letters. The user is organizing their kitchen items by color.

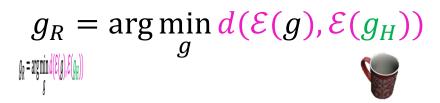
You:

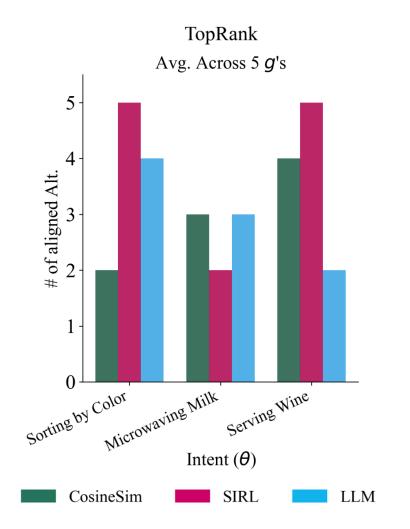
- A) Brown Bowl
- B) Red Bowl

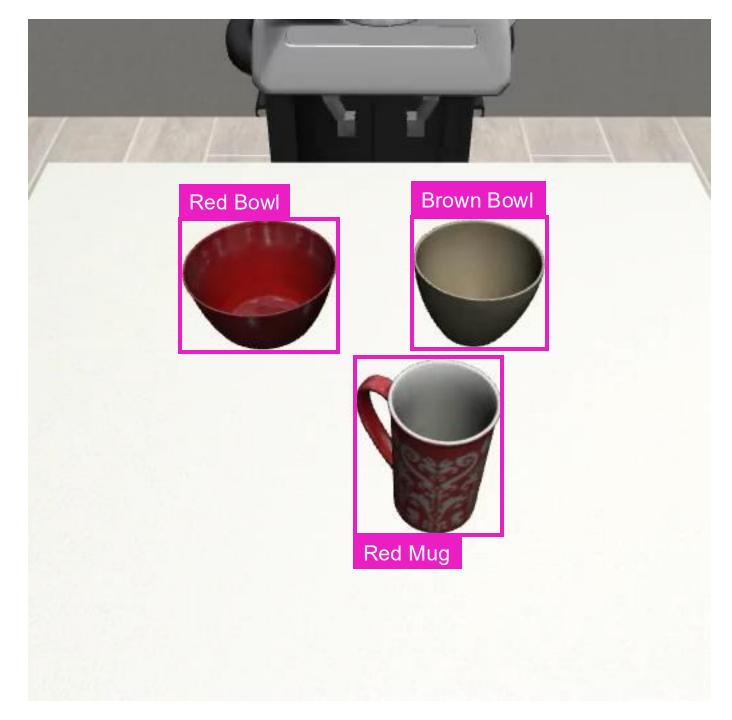




B) Red Bowl













$$g_R = \arg\min_{g} \frac{d(\mathcal{E}(g), \mathcal{E}(g_H))}{d(\mathcal{E}(g), \mathcal{E}(g_H))}$$

s.t. 
$$V^{\pi}(x; g) \ge 0$$



instead?

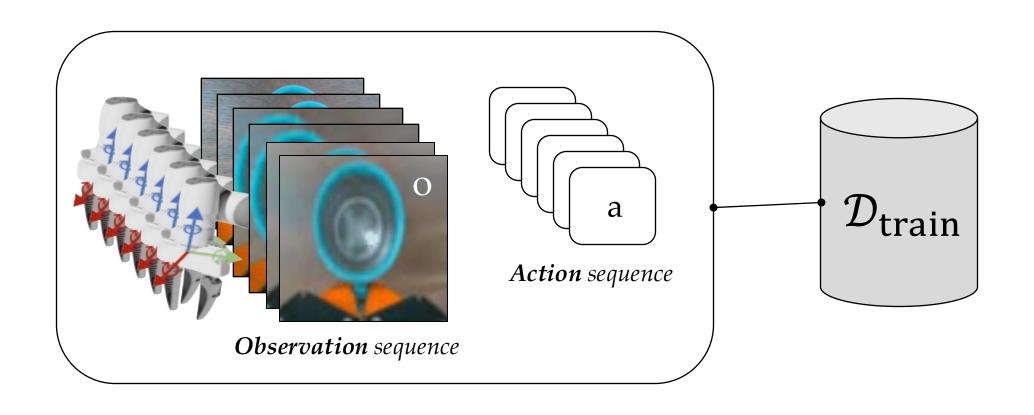




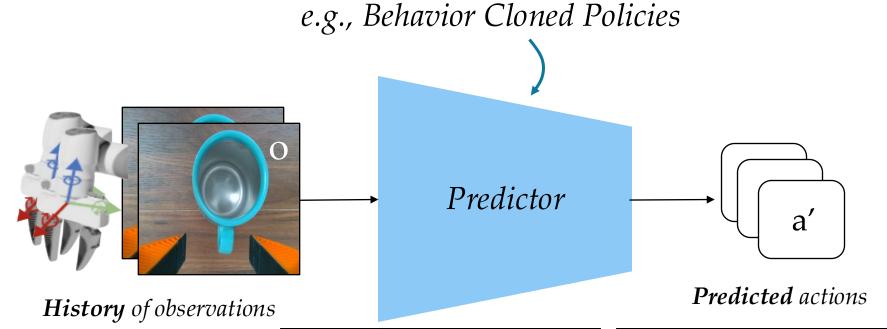
Hmm... so maybe safety is more than just avoiding collisions.

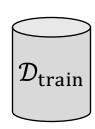
What are other safety problems for robots, and *how can humans help*?

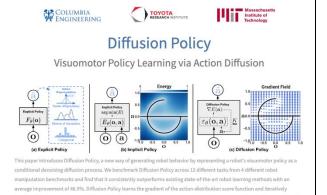
Let's talk about robot models that are trained on data like...



## .... and these models learn to predict actions ...



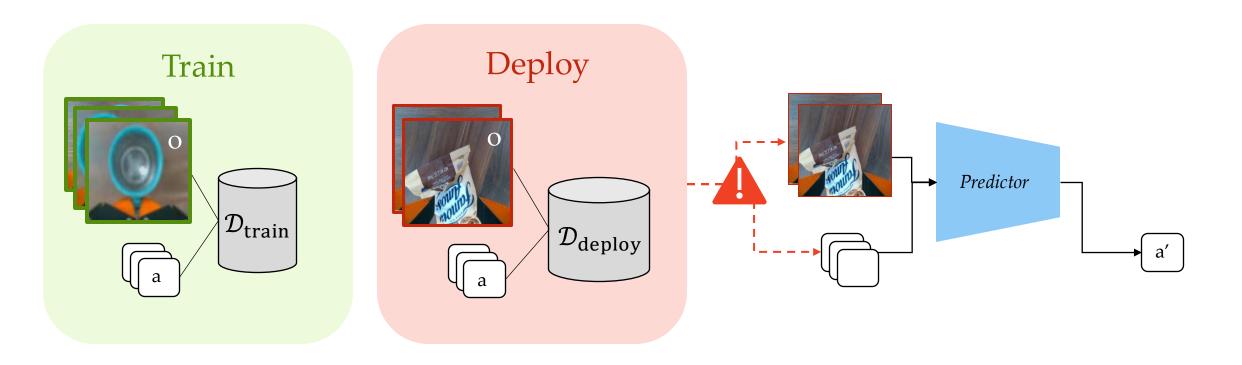






...(& many more)...

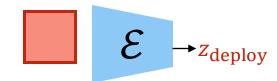
## How do we detect *out-of-distribution* (OOD) scenarios in these models like these?

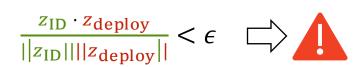


## How do we detect *out-of-distribution* (OOD) scenarios in these models like these?

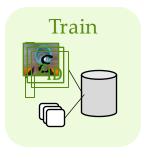
Embedding Distances (e.g., Cosine Sim)

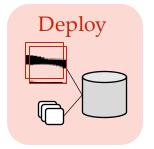






[Majumdar et al., arXiv 2025] [Sinha et al., RSS 2024] [Luo et al., ICRA 2024]

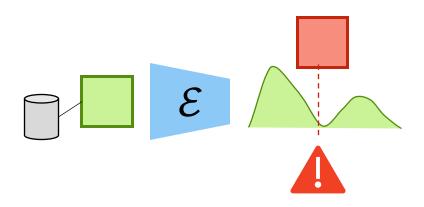




Foundation Models



[Ganai et al., arXiv 2025] [Sinha et al., RSS 2024] [Elhafsi et al., Autonomous Robots 2023] Density Estimators

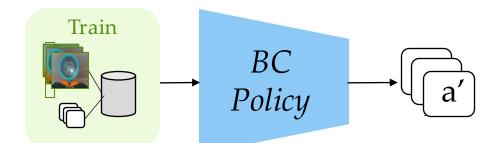


[Xu et al., RSS 2025] [Liu et al., Neurips 2021]

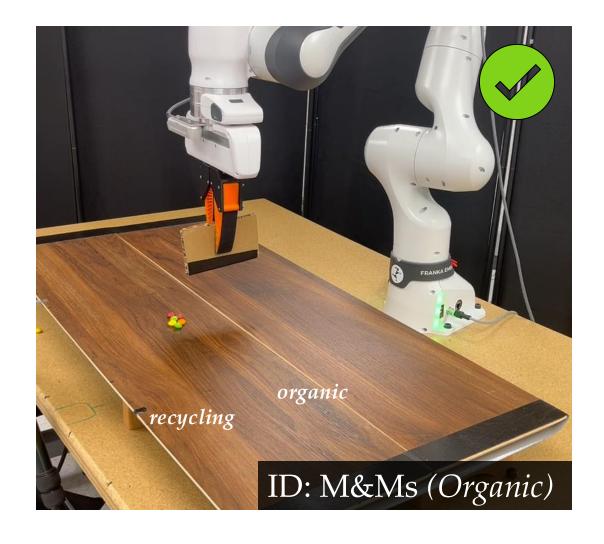
...(& many more)...

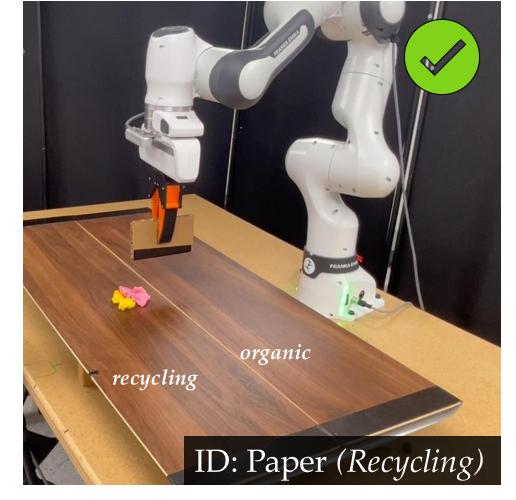
# But what should robots *do* once they detect an OOD condition?

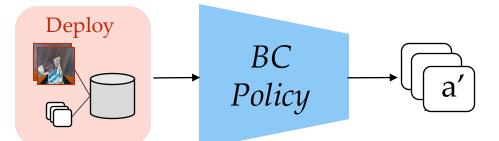
# How do we go from *detection* to *mitigation* of OOD conditions?



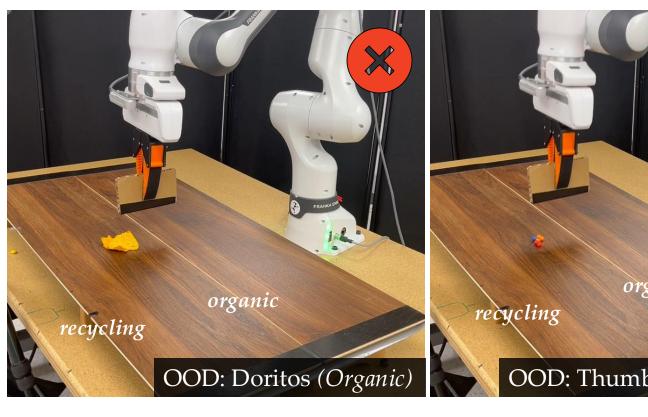
### Task: Sort Organic & Recycling Waste

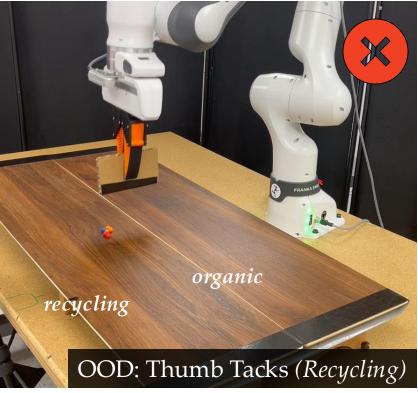


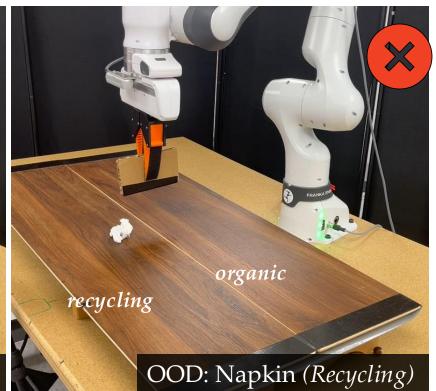




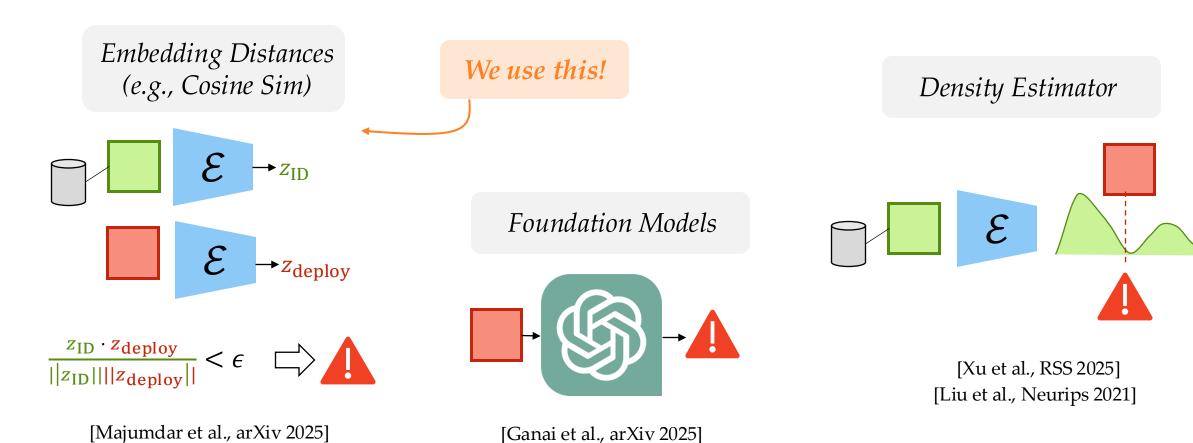
## Task: Sort Organic & Recycling Waste







## Here is where we can return to these OOD detection methods from before....



[Sinha et al., RSS 2024]

[Elhafsi et al., Autonomous Robots 2023]

[Sinha et al., RSS 2024]

[Luo et al., ICRA 2024]

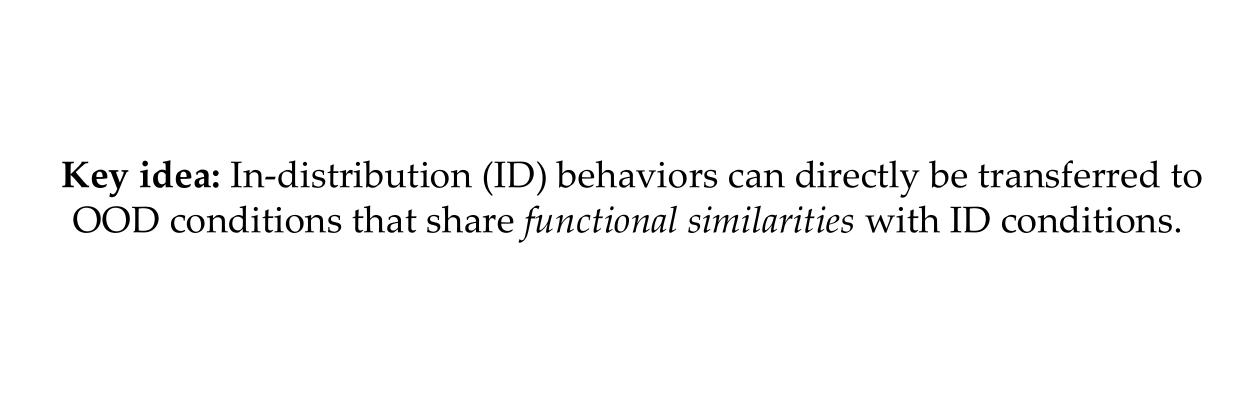
So, what should happen next?

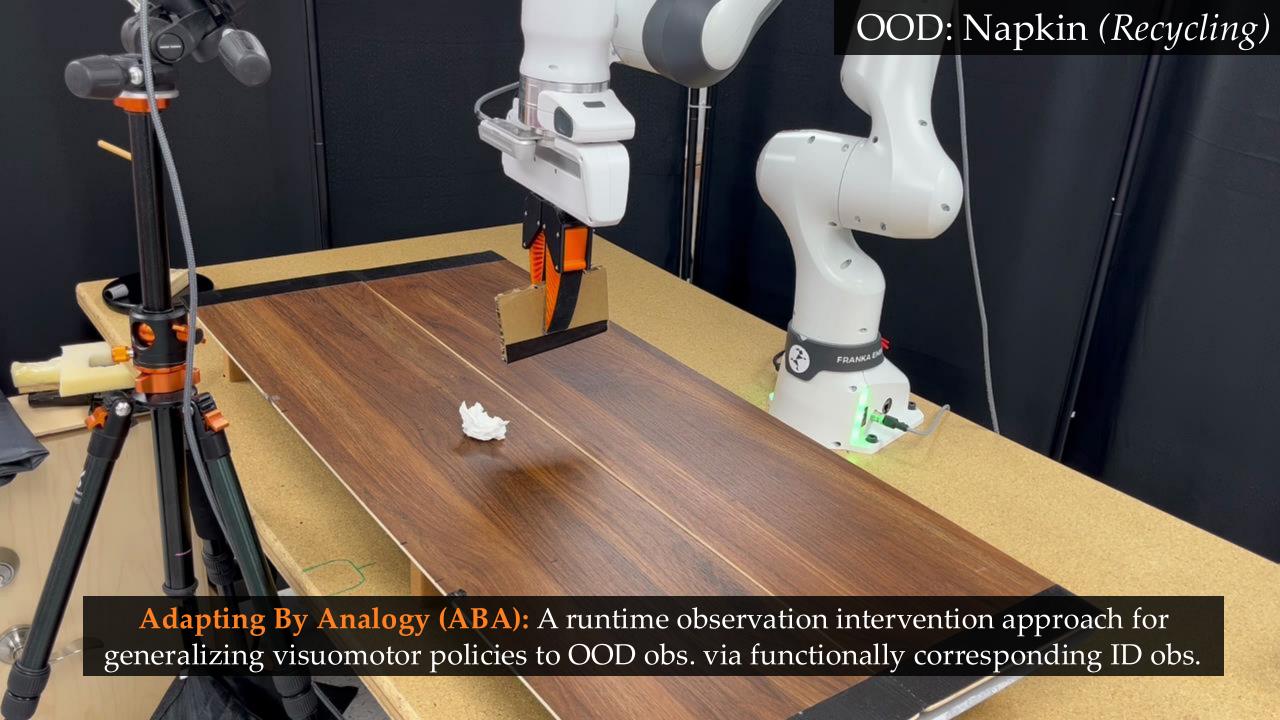
It may be tempting to collect more demonstration data but...

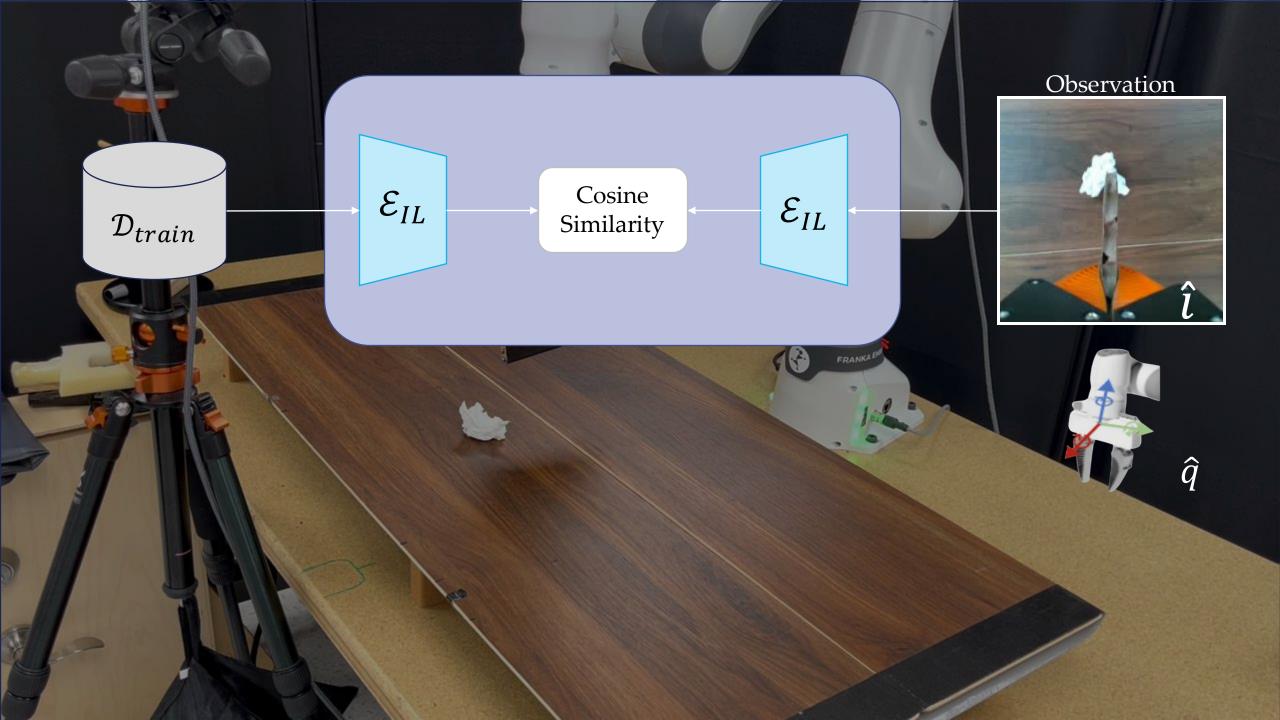
The robot already knows the right behavior in its model, but it doesn't understand correct mapping

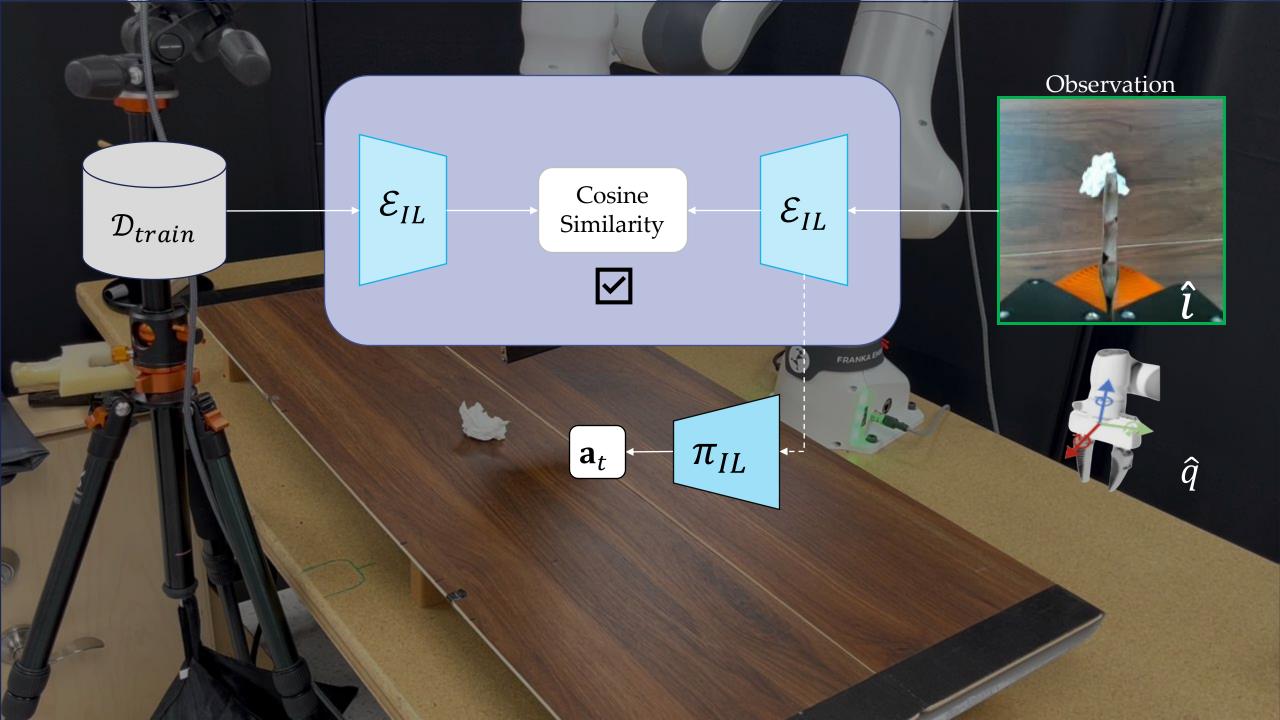


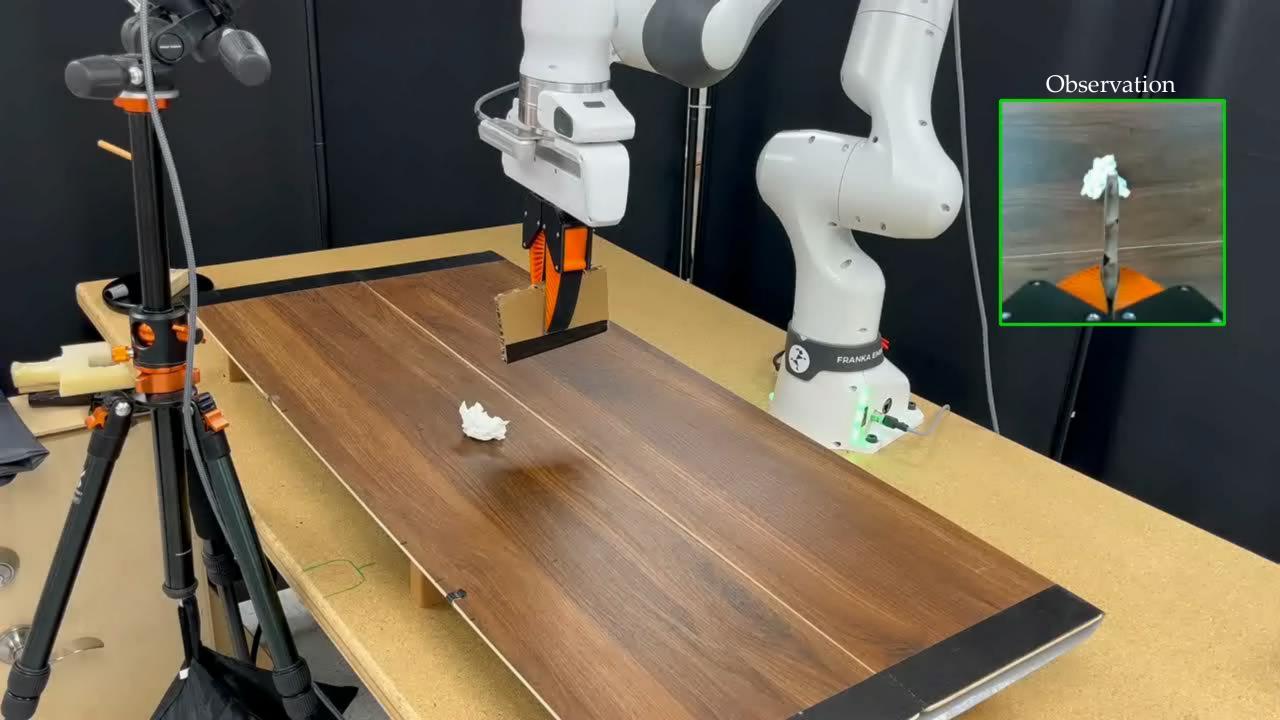


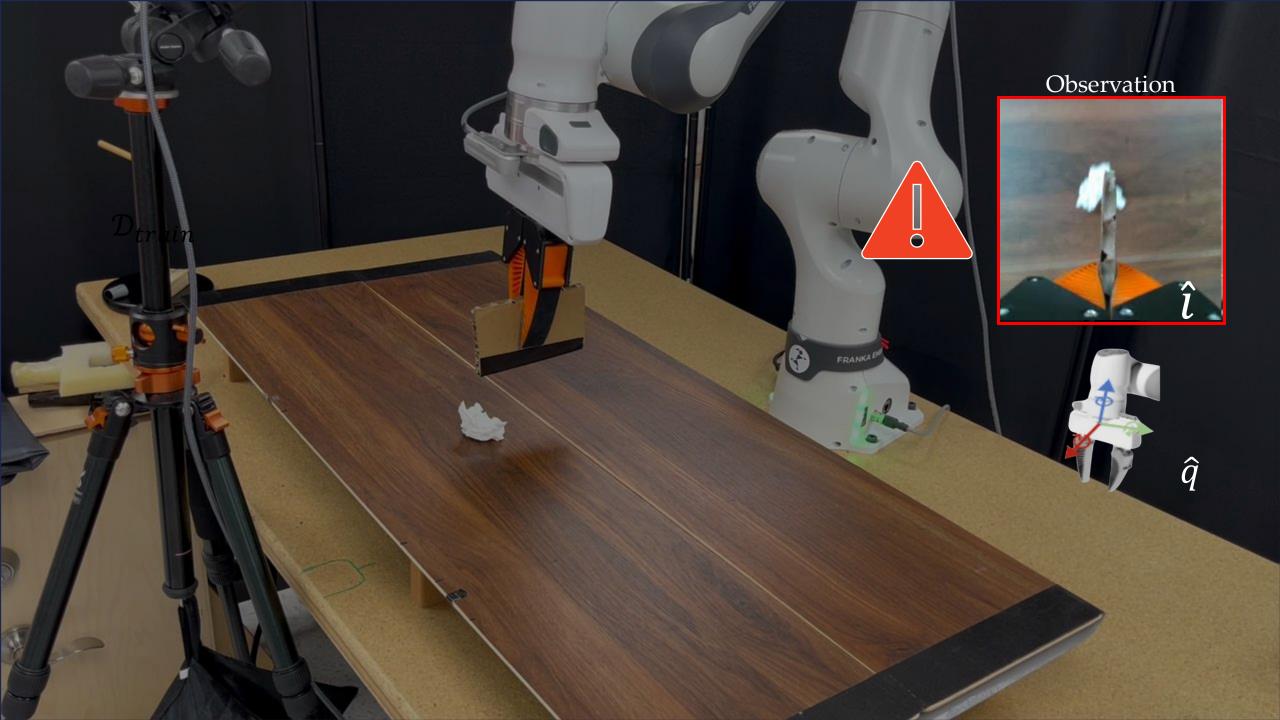


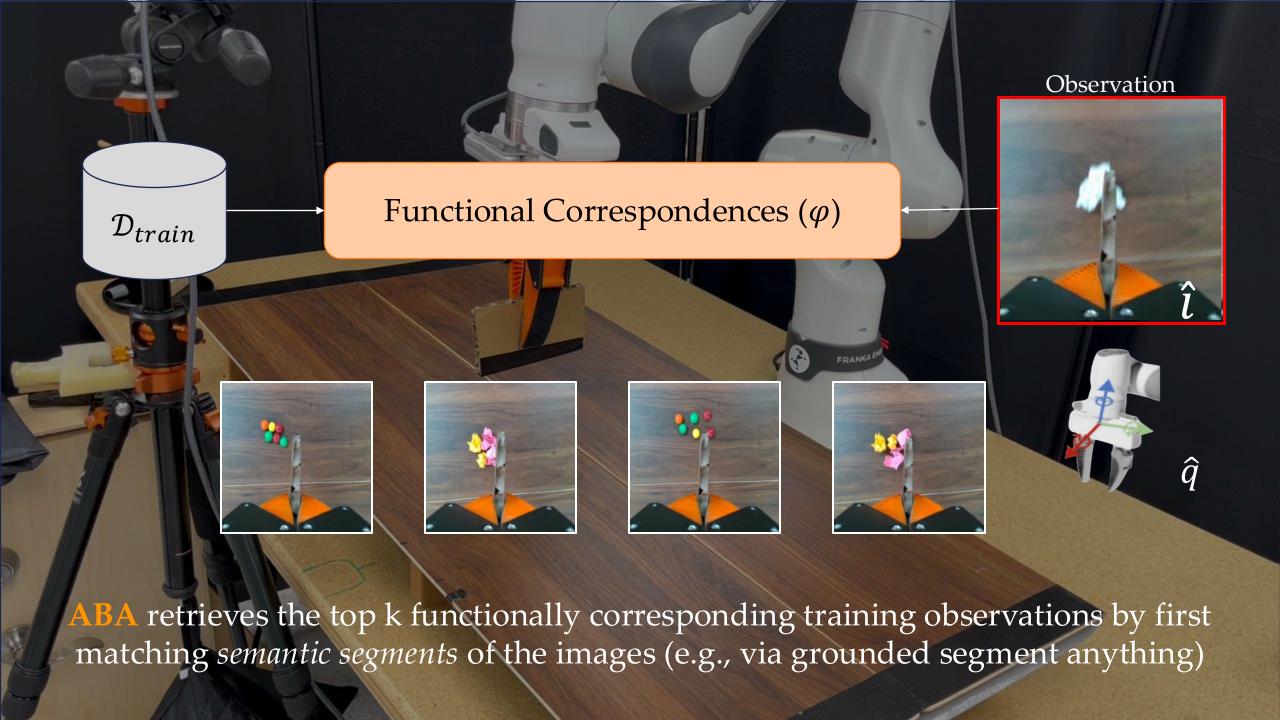


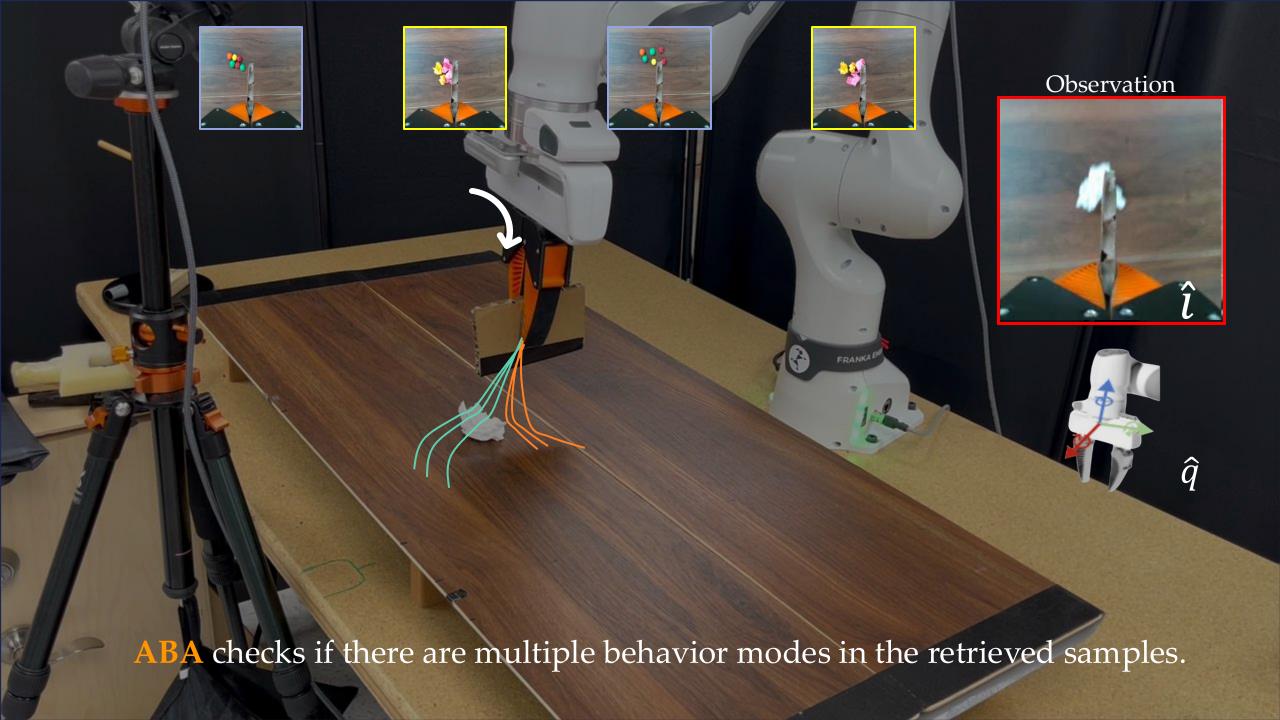


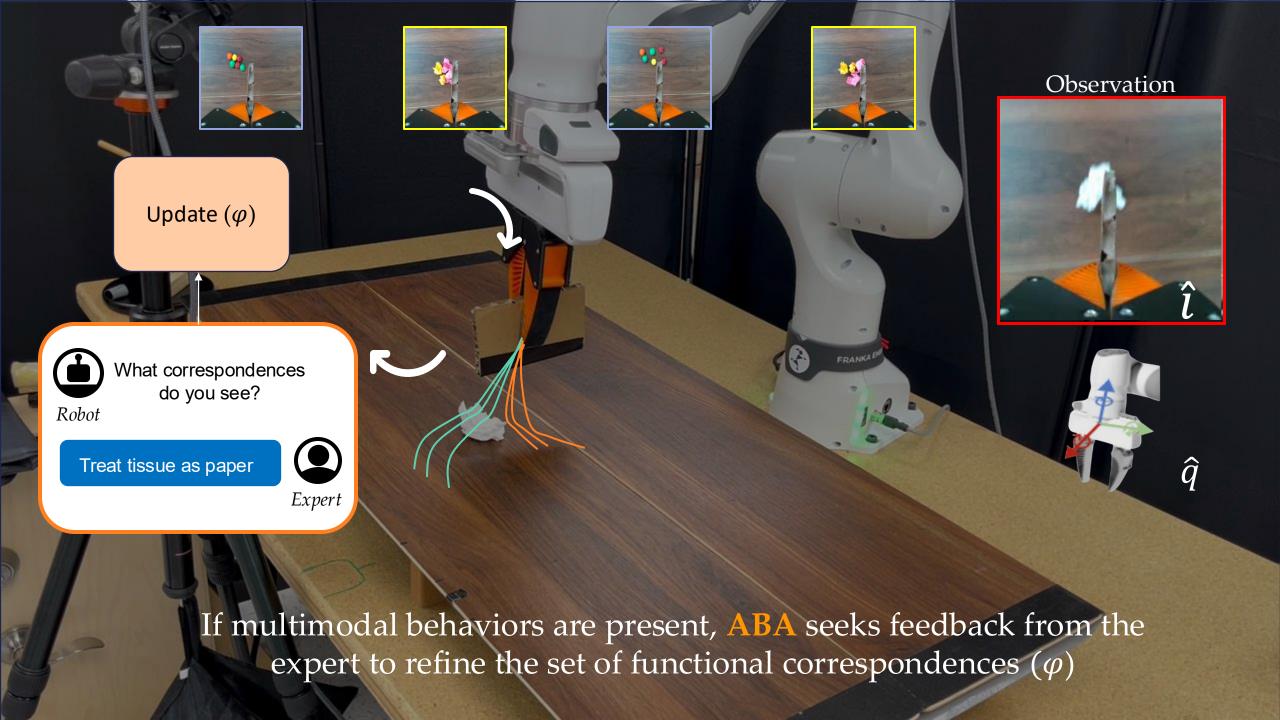


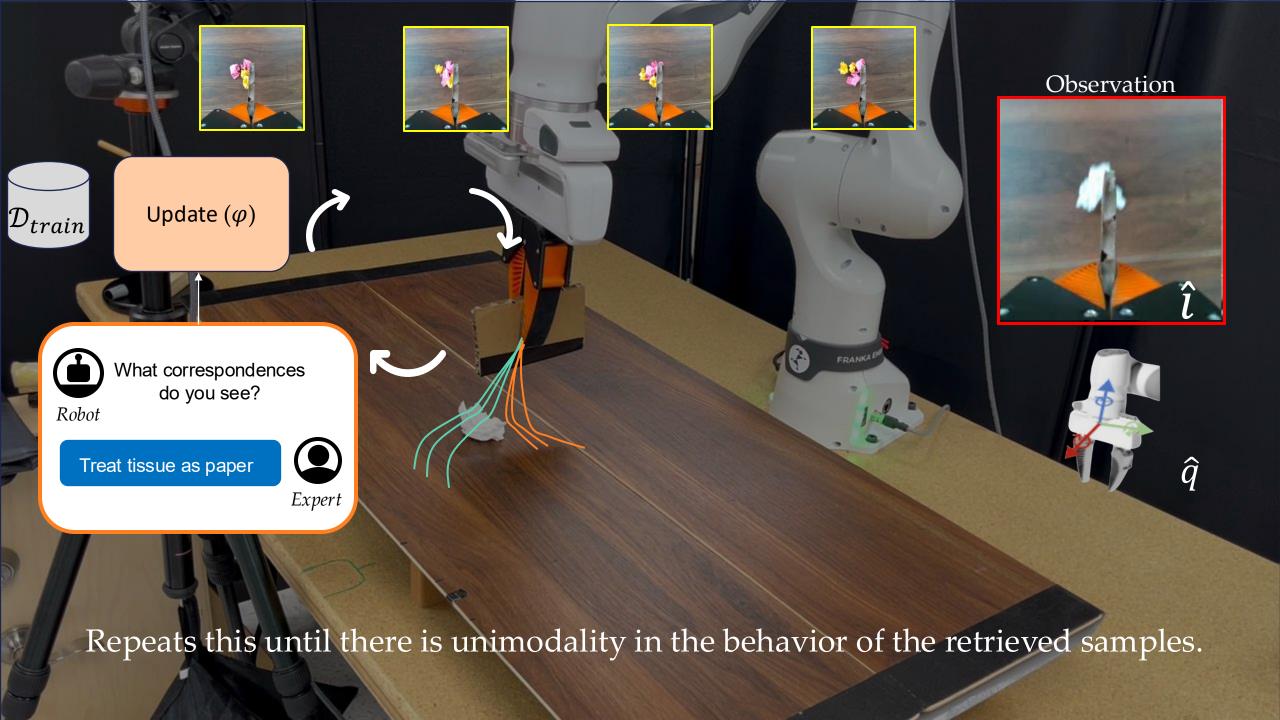


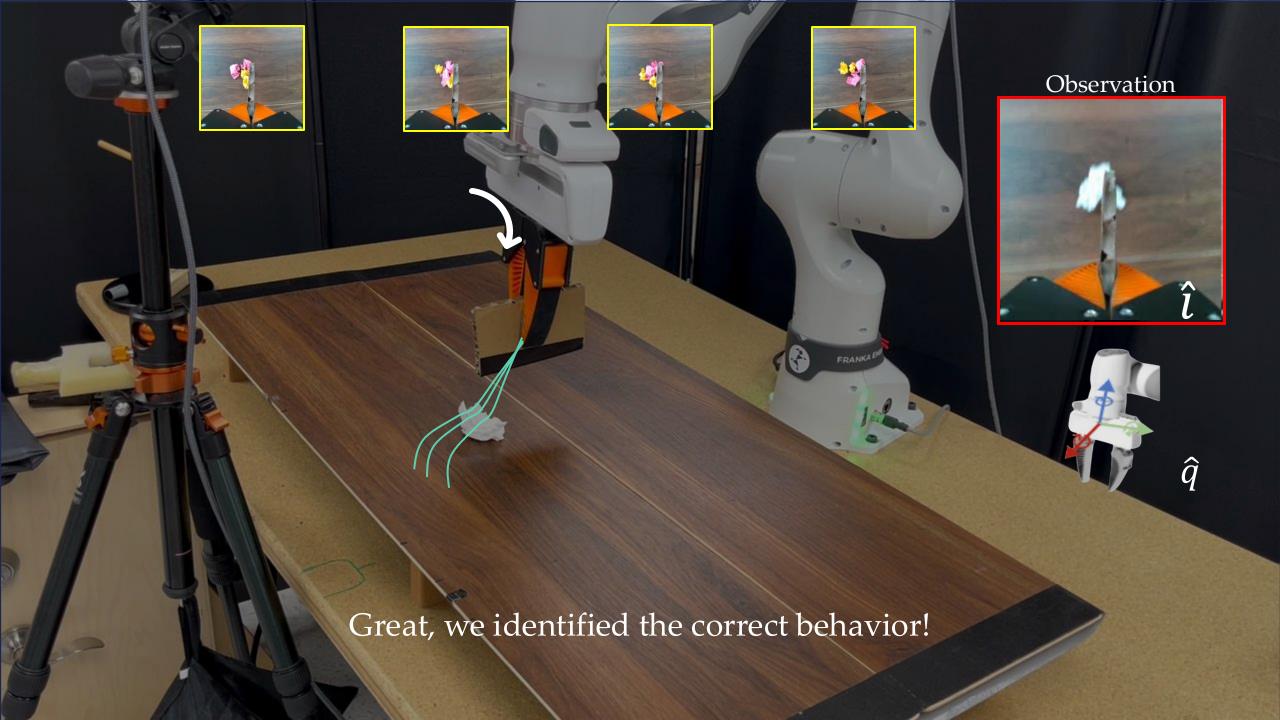


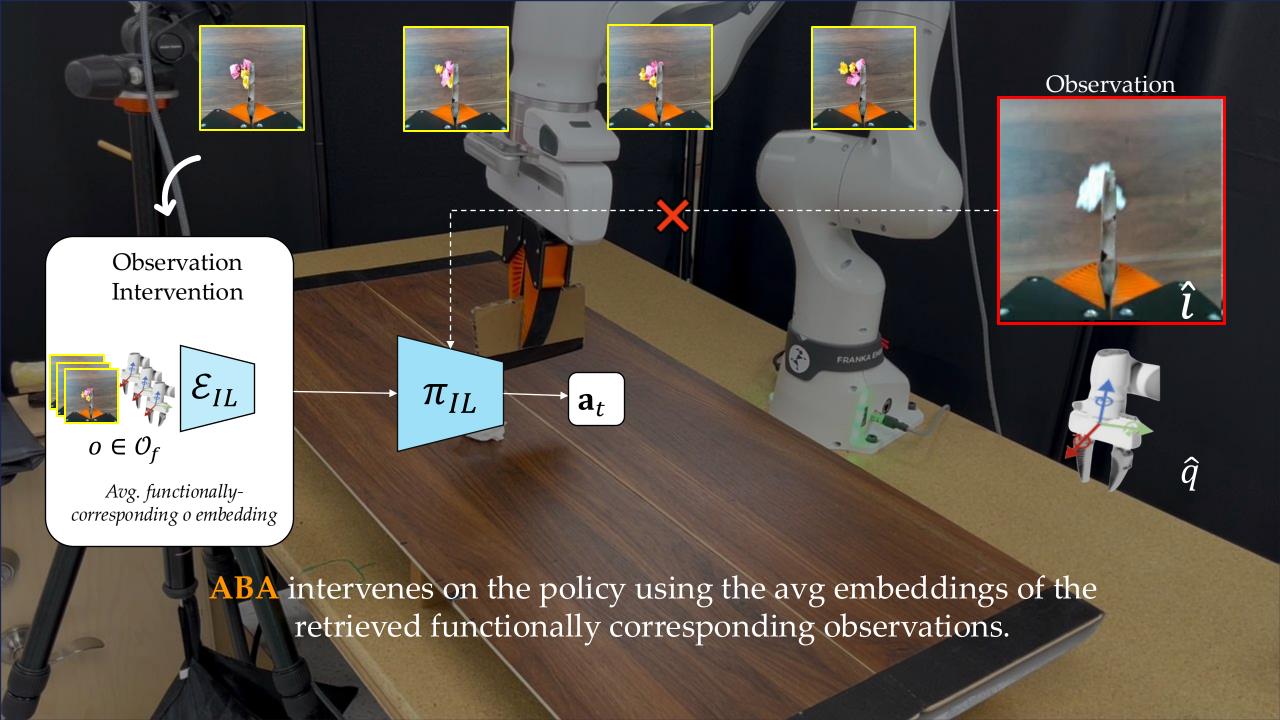


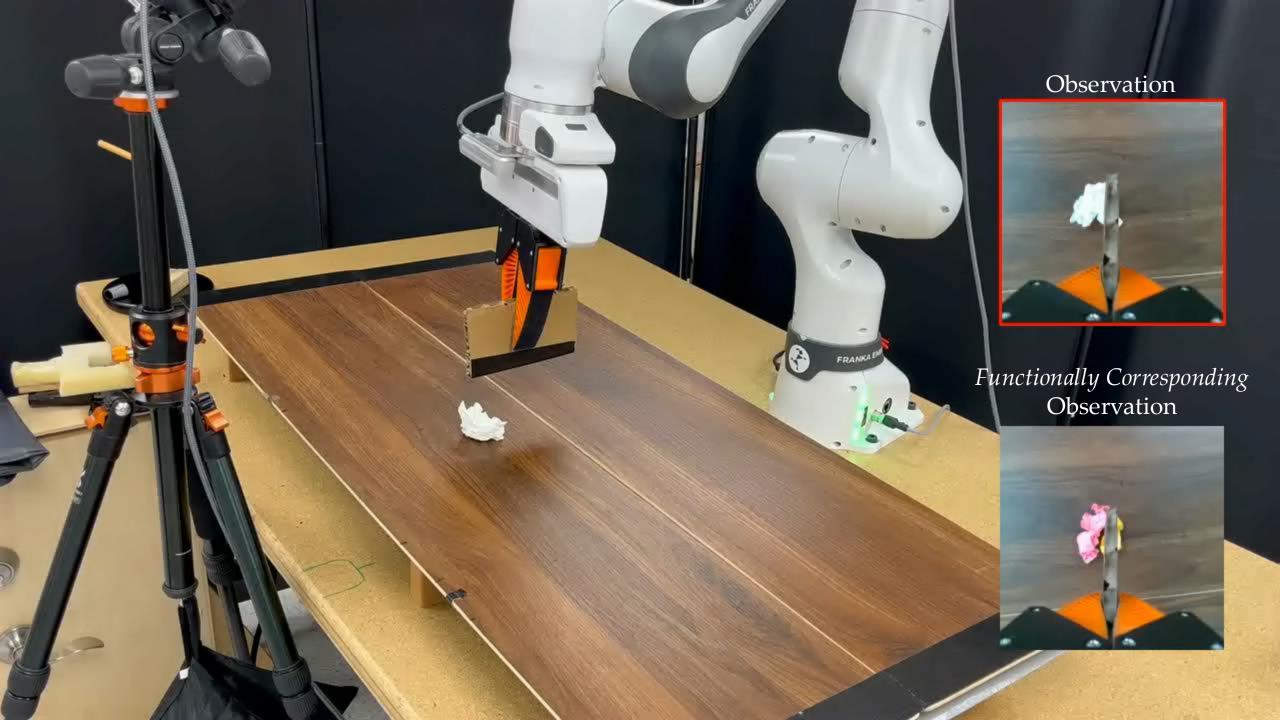












### What kind of features maximally help observation interventions?

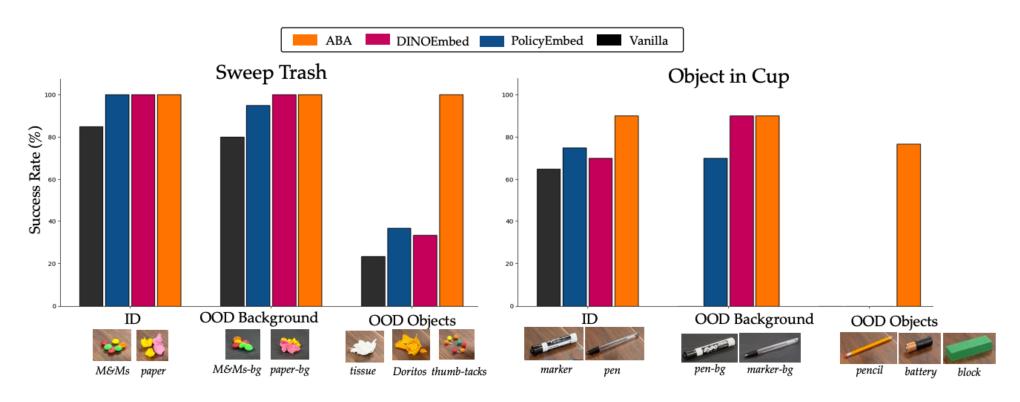


Figure 3: **Task Success in ID and OOD Environments.** We report the task success rate averaged across 10 rollouts (per each ID and OOD conditions) and averaged across ID, OOD background, or OOD object conditions. For both the sweep-trash and the object-in-cup tasks, we see that **ABA** consistently achieves the highest task success rate compared to baselines.

#### How efficient is ABA at seeking expert feedback in OOD environments?

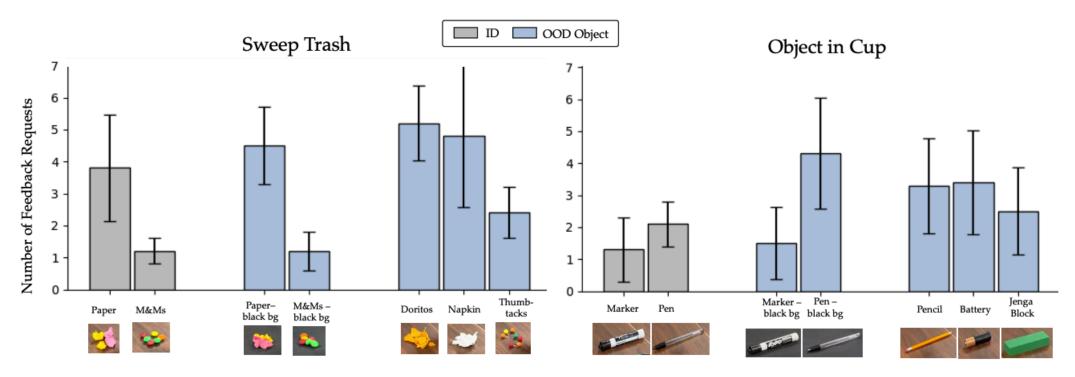


Figure 4: Expert Feedback Requested by ABA. We show mean and standard error for the number of feedback requests across 10 rollouts per each environment. We find that ABA infrequently queries the expert for correspondances, given that sweep-trash has 70 timesteps and object-in-cup has 120.

### This is just a small *slice* of the problem of safely deploying robots...

