

Human and Agent Cooperative Learning

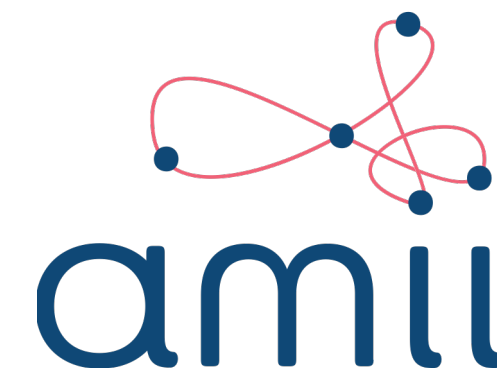
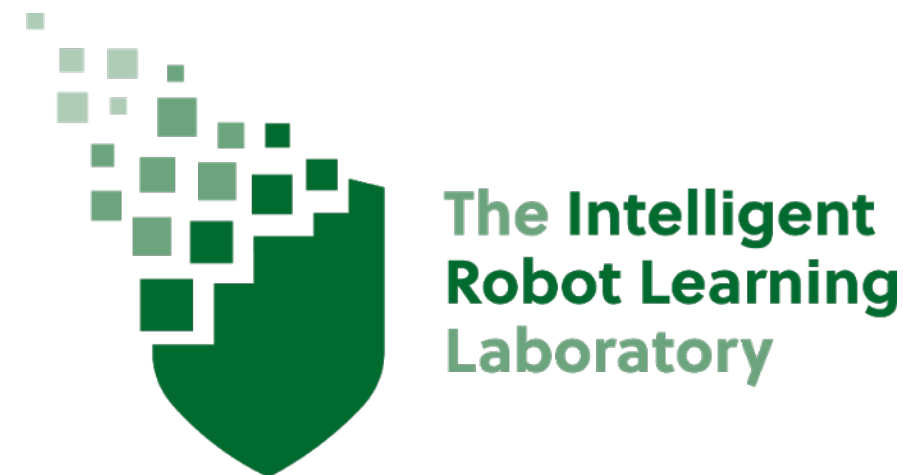
Matt Taylor

University of Alberta: Intelligent Robot Learning Lab (irll.ca)

Fellow-in-Residence: Alberta Machine Intelligence Institute (Amii.ca)

AI Redefined: Research Director (AI-R.com)

Canada CIFAR AI Chair, Amii

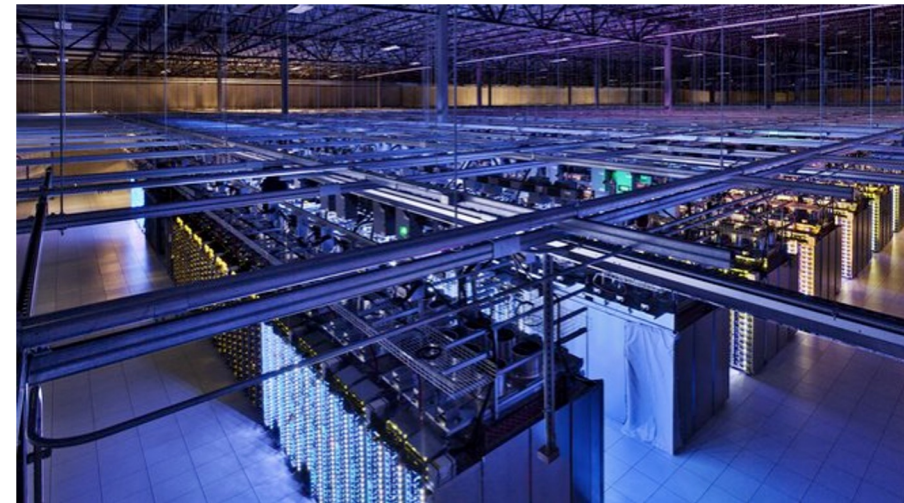


RL Applications

Developing vs. PoC vs. MVP



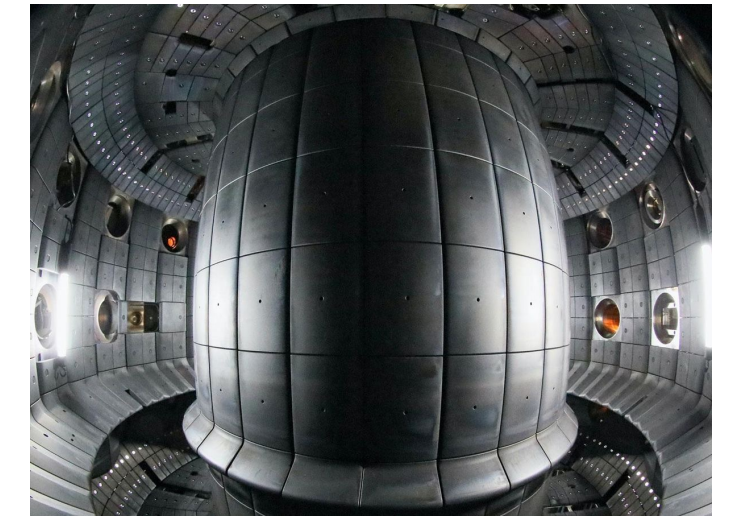
American Options Exercise Policy



Data Center Cooling



Balloon Control



Tokamak Fusion



AlphaGO



Stock Trading



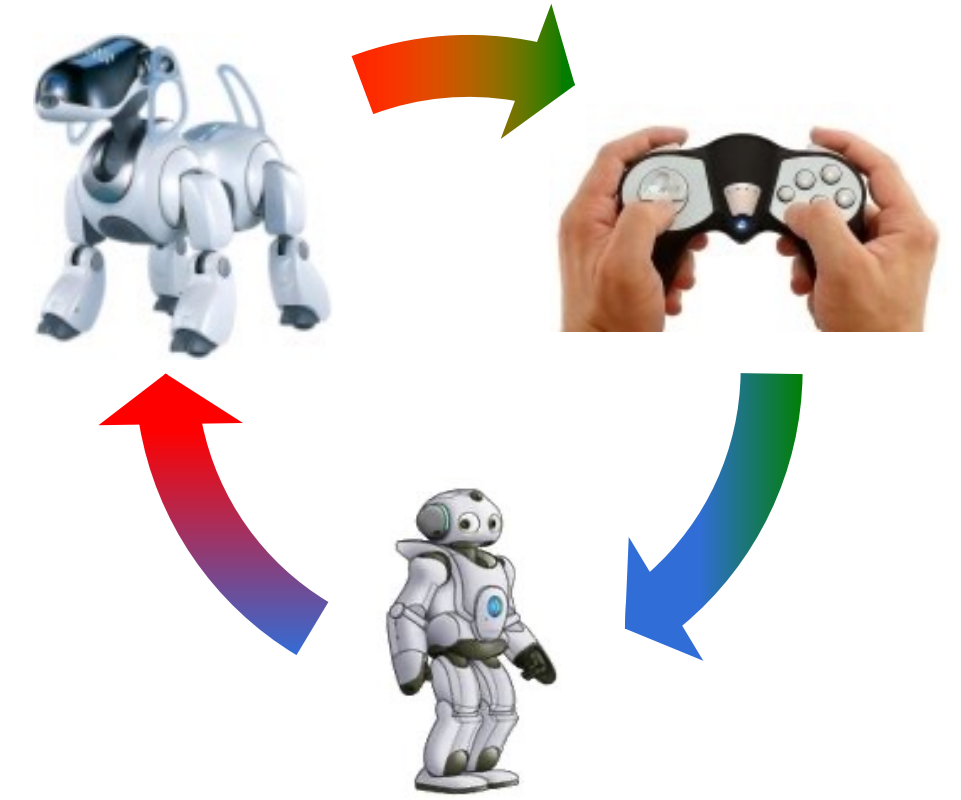
Water Treatment



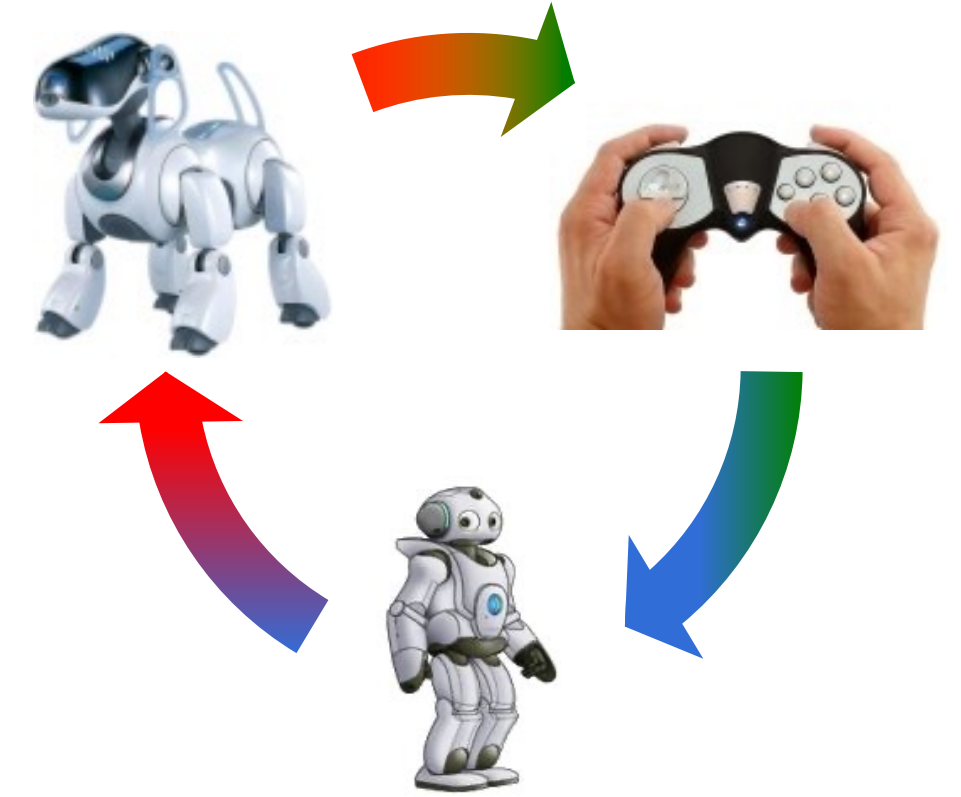
How do we deploy more RL solutions?

- Better understand how to identify, de-risk, and tackle real world problems
 - Challenges of Real-World Reinforcement Learning
- Understand how and when to “cheat” by using external information
 - Existing agents/data
 - Human knowledge

Cooperative Learning



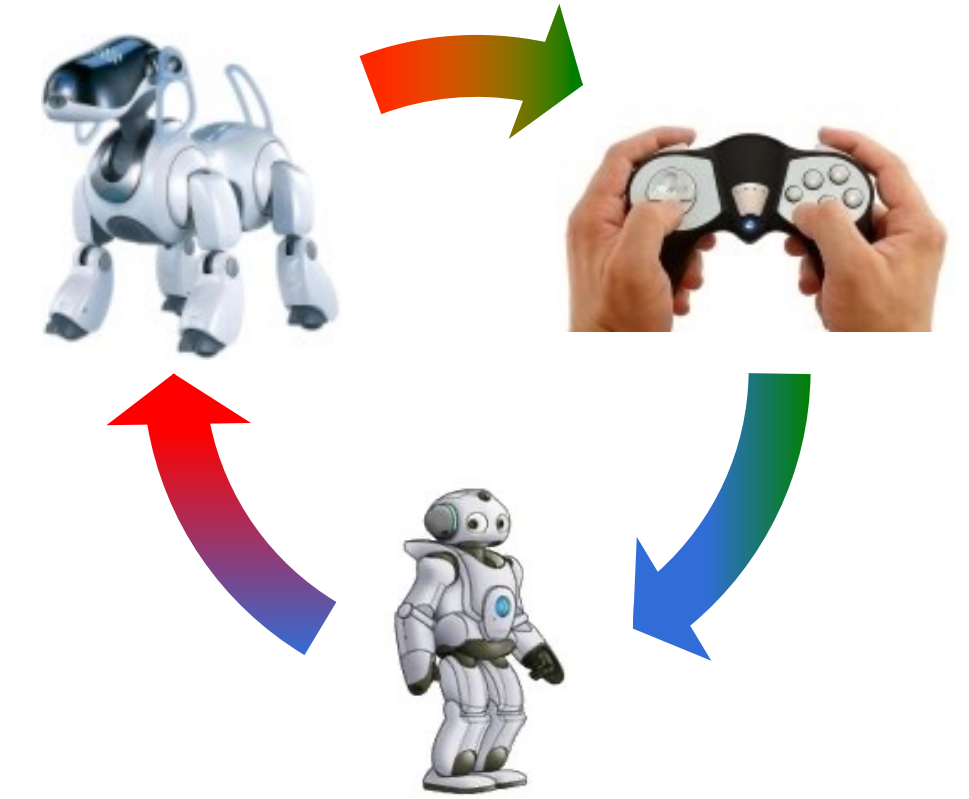
Cooperative Learning



Agent \rightarrow Agent

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice

Cooperative Learning

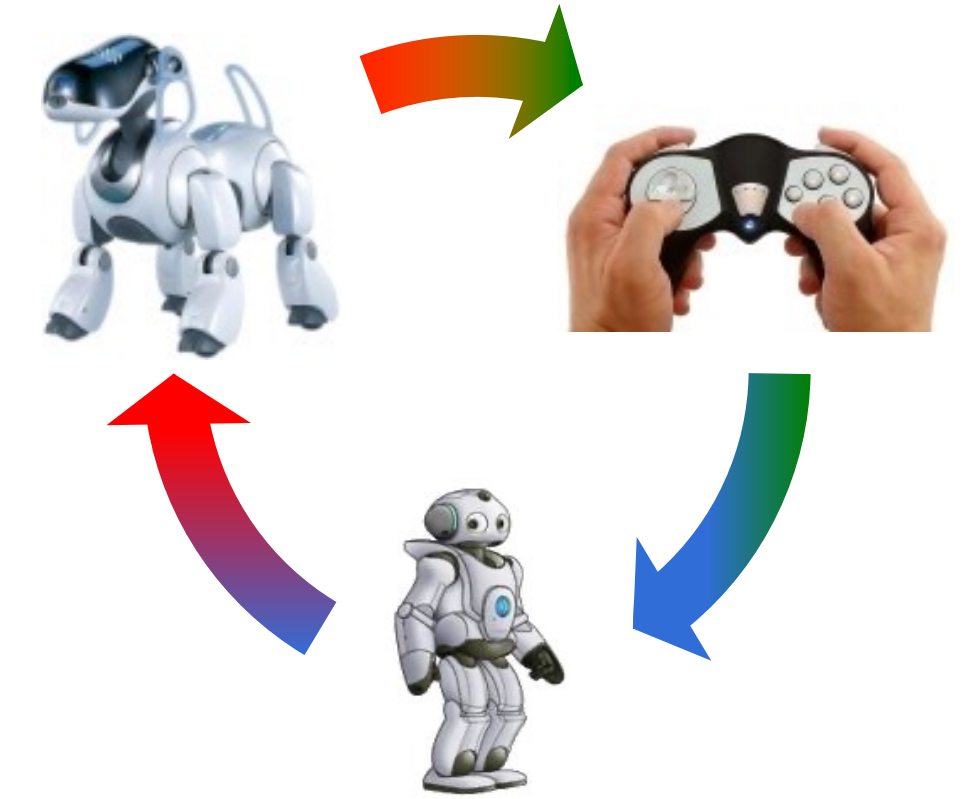


Agent \rightarrow Agent

Human \rightarrow Agent

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Cooperative Learning



Agent → Agent

Human → Agent

Agent → Human

- Intelligent Tutoring Systems

Agent → Agent Bootstrapping

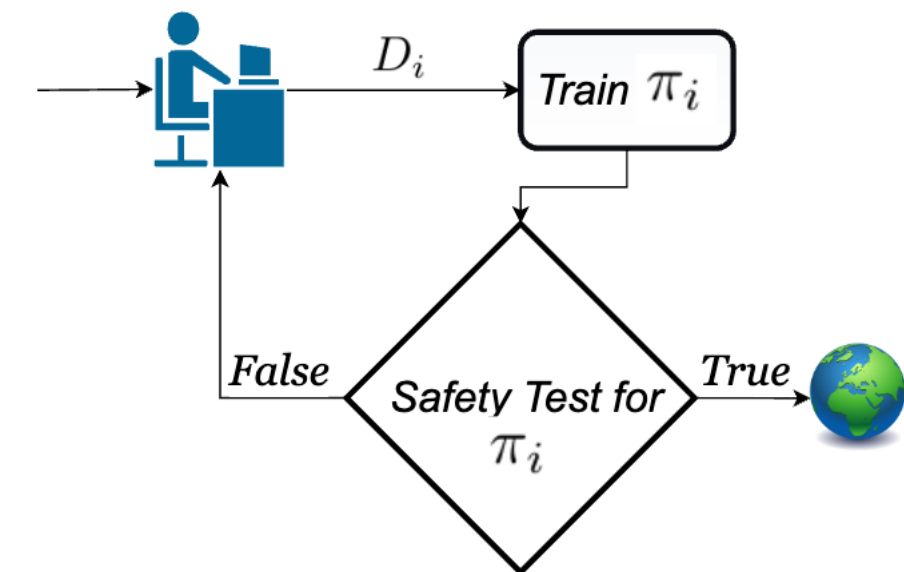
- Offline / Batch RL
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- Advice

Prior agent is ~~optimal~~ OK

How much data do I need?

How good is my policy? (OPE)

How sure am I about the policy's performance? (HCOPE)



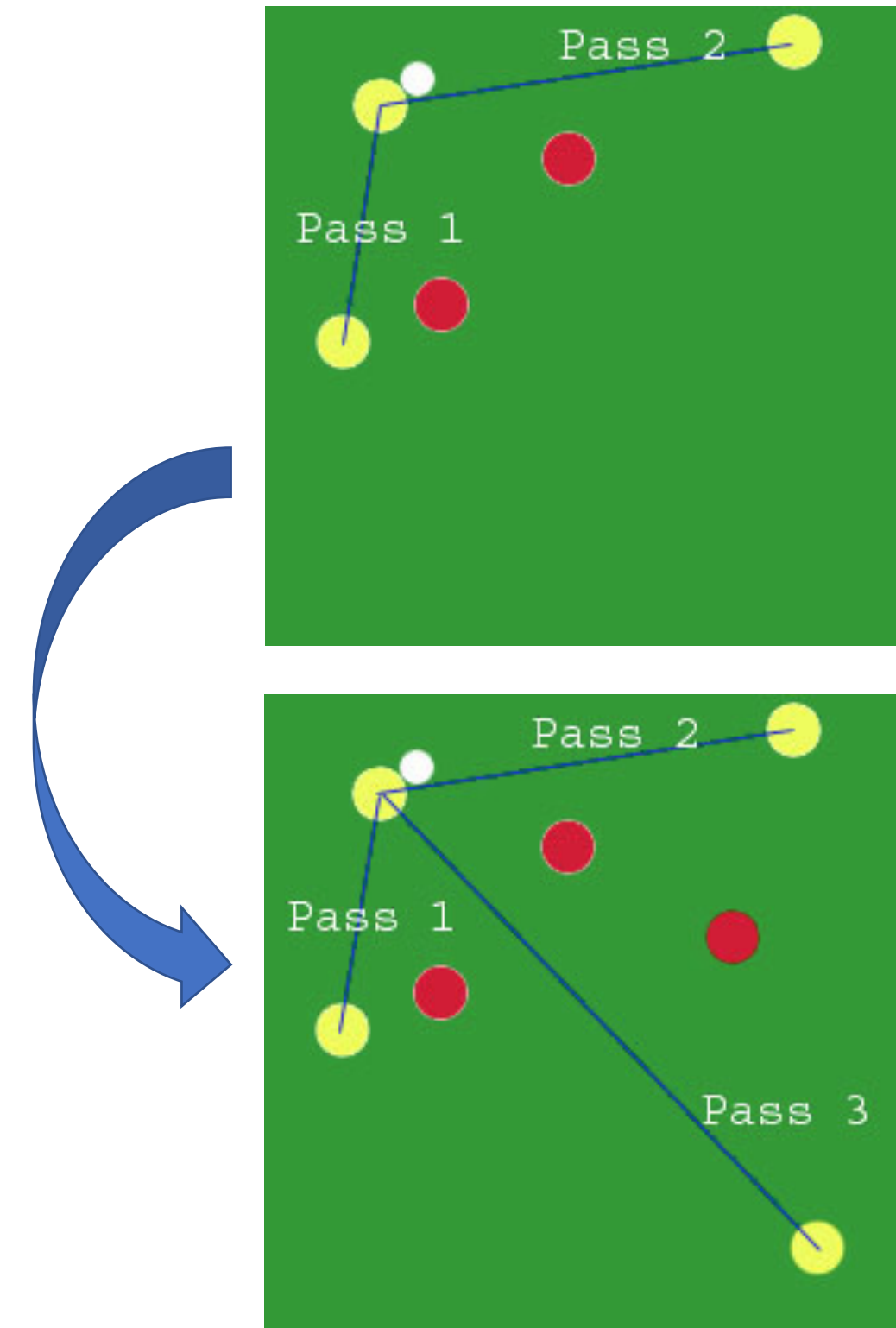
Agent \rightarrow Agent Transfer

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice

What to transfer? (From whom to transfer?)

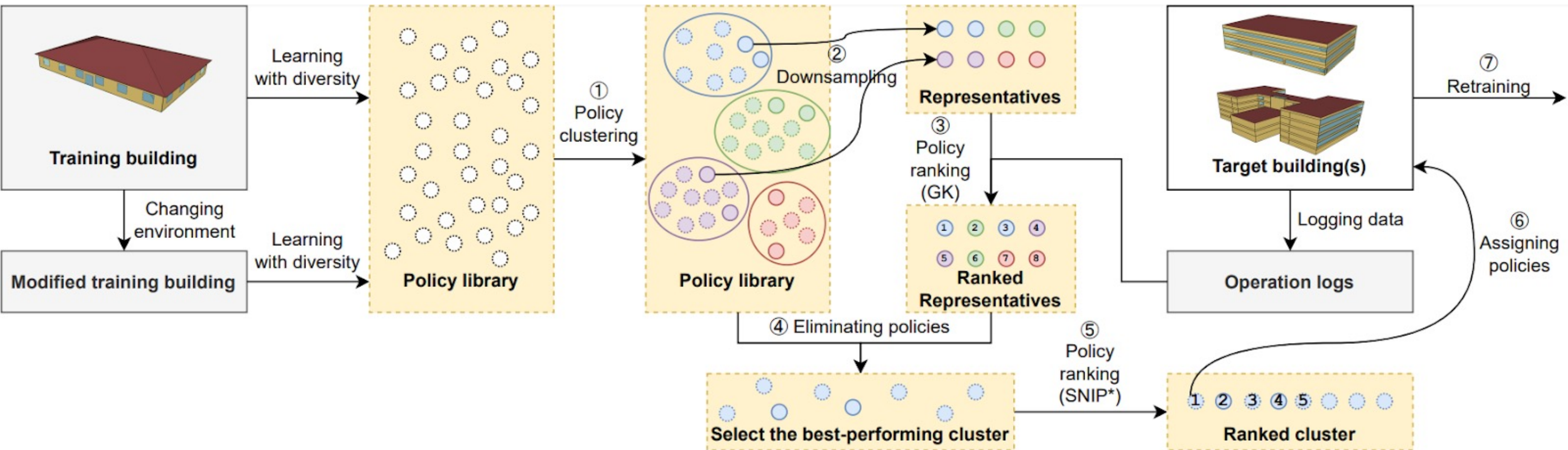
How to transfer?

When to transfer?



Agent → Agent Transfer

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice

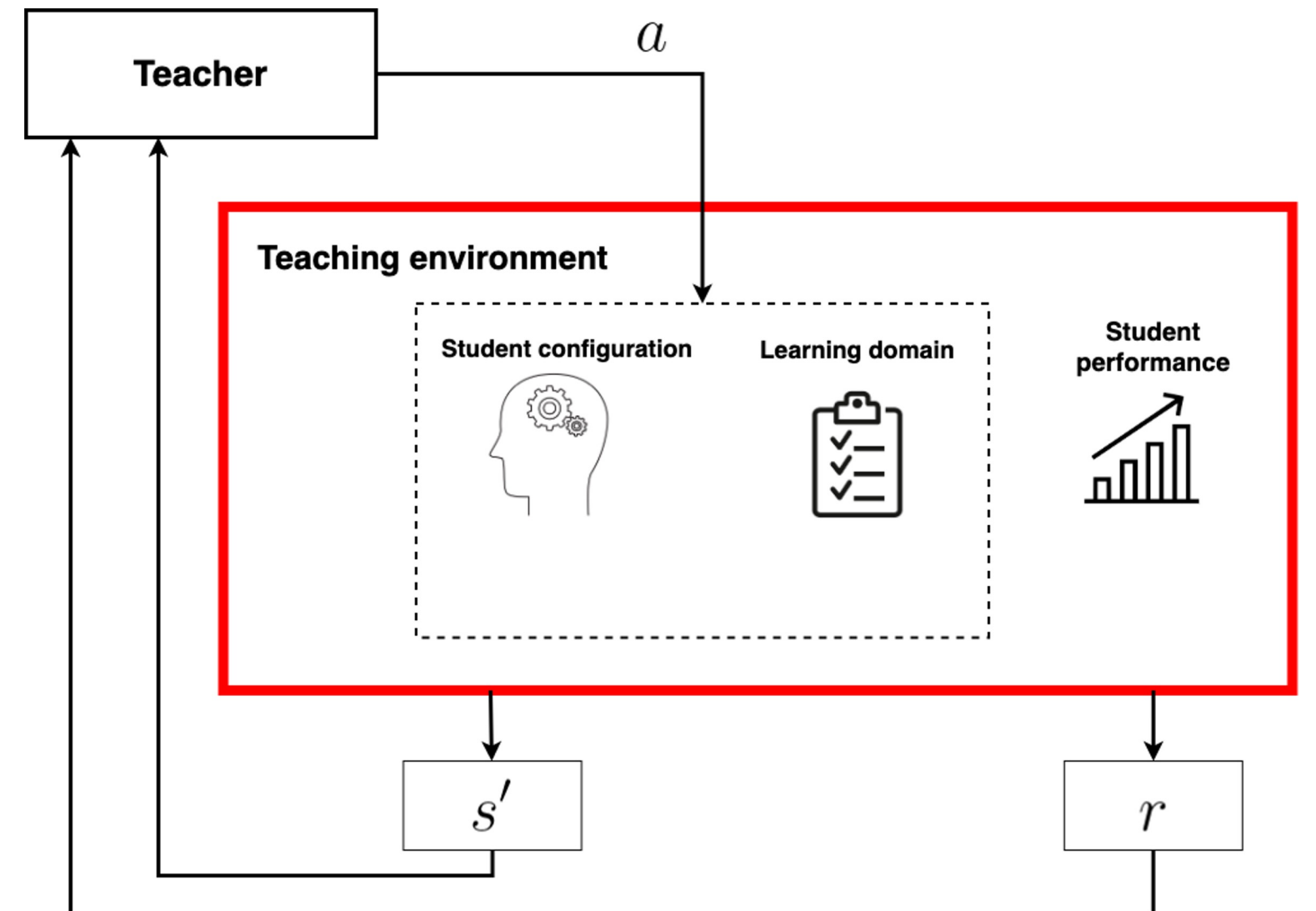
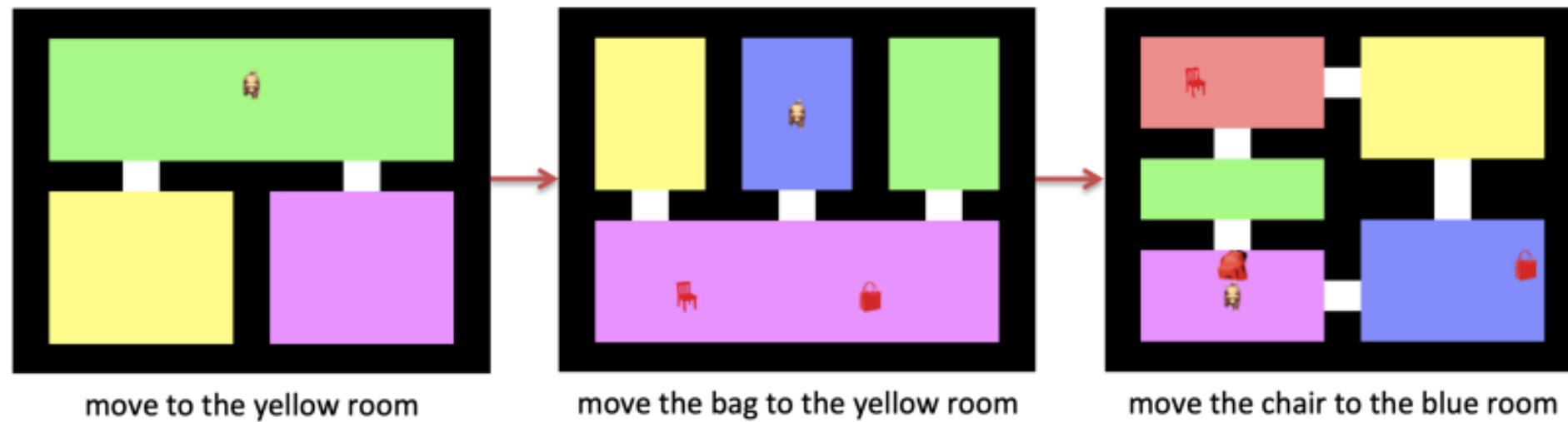


“Mitigating an Adoption Barrier of Reinforcement Learning-based Control Strategies in Buildings.” Aakash Krishna G.S., Tianyu Zhang, Omid Ardakanian, Taylor. Energy & Buildings, 2023

Agent → Agent Online Learning

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice

Curriculum Learning Meta RL



“Curriculum Learning for Reinforcement Learning Domains: A Framework and Survey.”
Sanmit Narvekar, Bei Peng, Matteo Leonetti, Jivko Sinapov, Taylor, and Peter Stone. 2020.

Muslimani, Lewandowski, Luo, Schuurmans

Agent → Agent Advice

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice

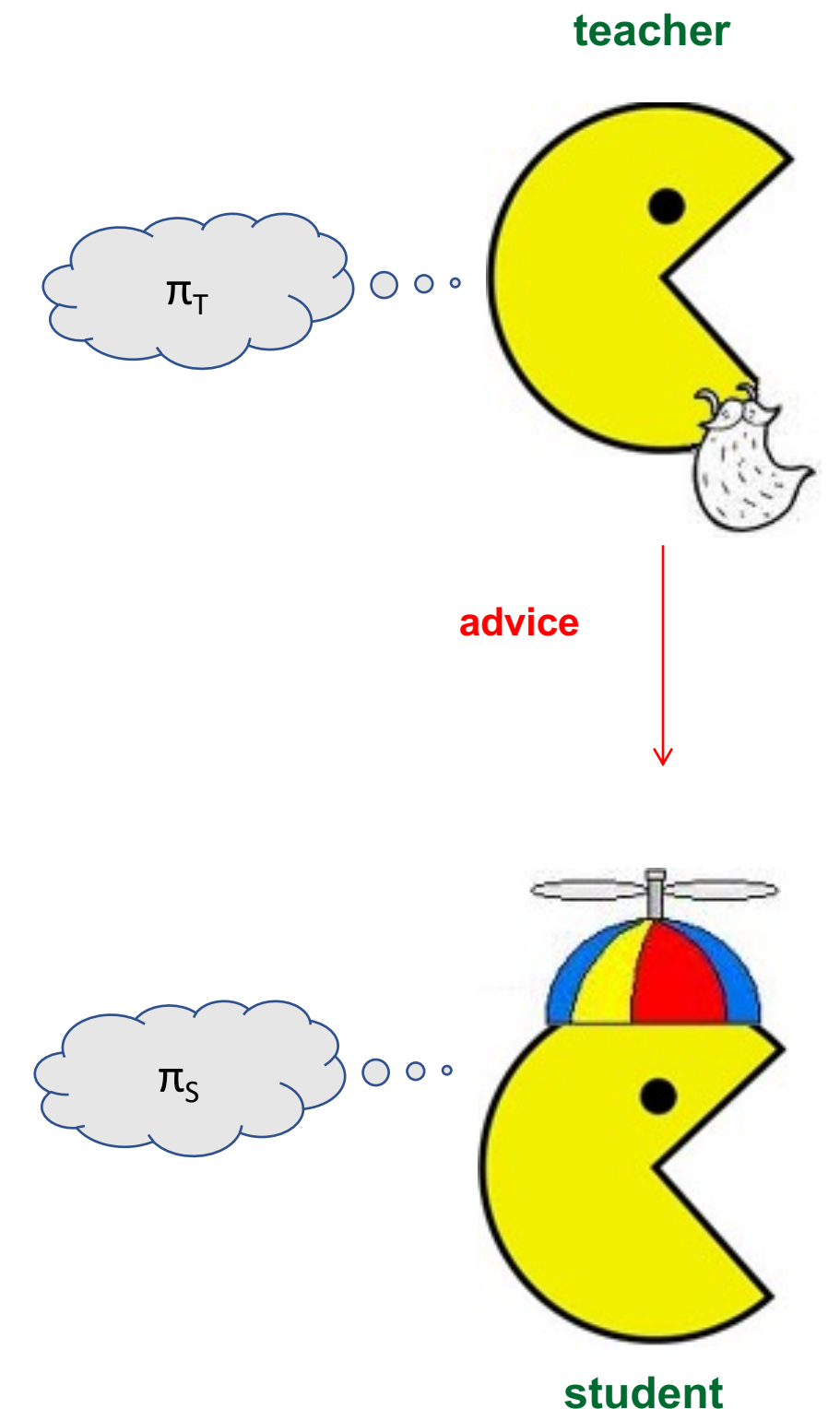
On-demand advice

Who initiates?

When do they provide?

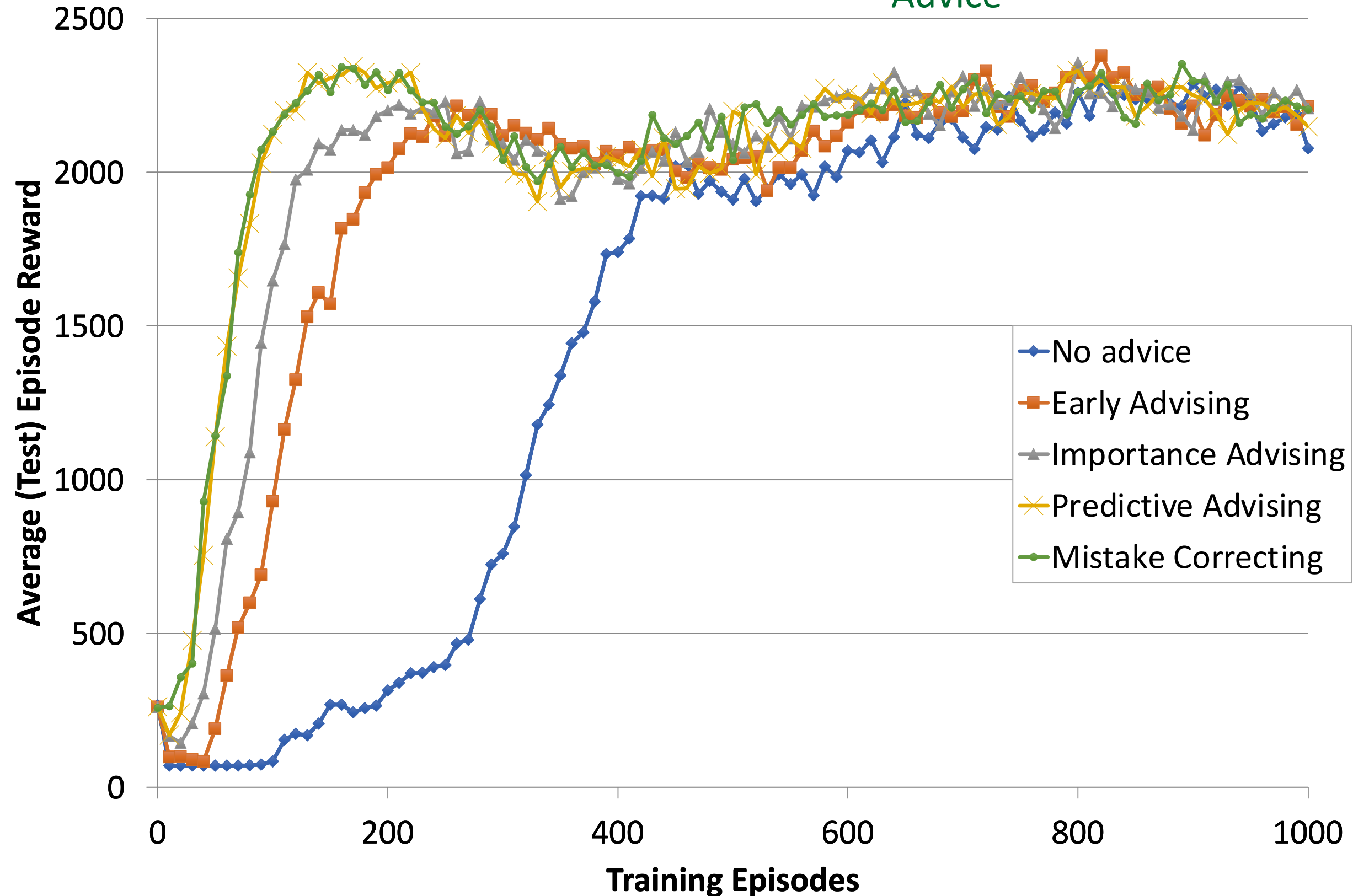
Is there a cost?

Are there multiple teachers?



Agent → Agent Advice

- Offline / Batch RL
- Transfer Learning
- Curriculum Learning / Meta RL
- Advice



“Integrating Reinforcement Learning with Human Demonstrations of Varying Ability.” Taylor, Halit Bener Suay, and Sonia Chernova. AAMAS-11.

Multi-Agent Advisor Q-Learning.

Subramanian, S., Taylor, K. Larson, & M. Crowley. JMLR-22



Sriram Ganapathi Subramanian

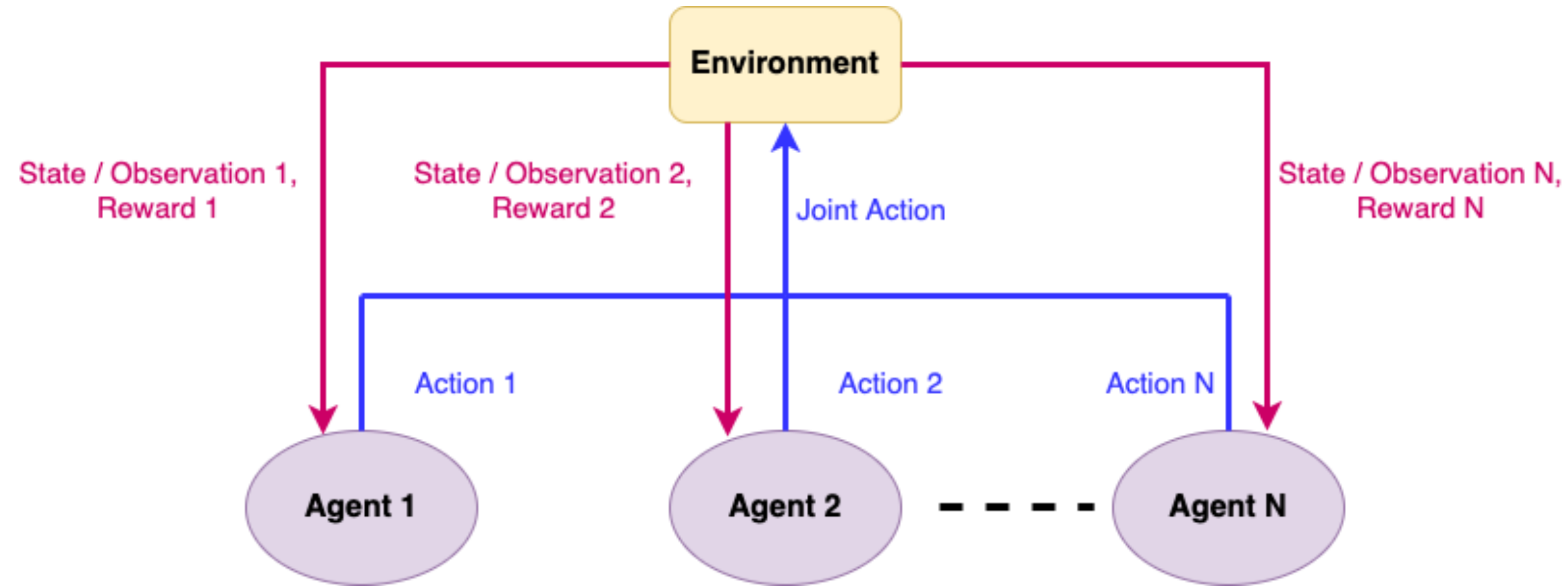


Kate Larson



Mark Crowley

ADvising Multiple Intelligent Agents (ADMIRAL)



Improving MARL sample efficiency

- We introduce: **Multi-agent action advising** for MARL
 - General methods (**no assumption** on advisor or type of environment)
 - **Two practical algorithms** to learn from advisor
 - **Principled method** to evaluate the advisor
 - **Theoretical guarantees** of convergence

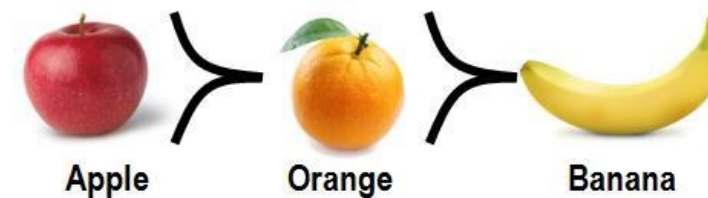
Human → Agent

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Reward signal?

No

- Demonstrations
- Feedback
- Preferences



Yes

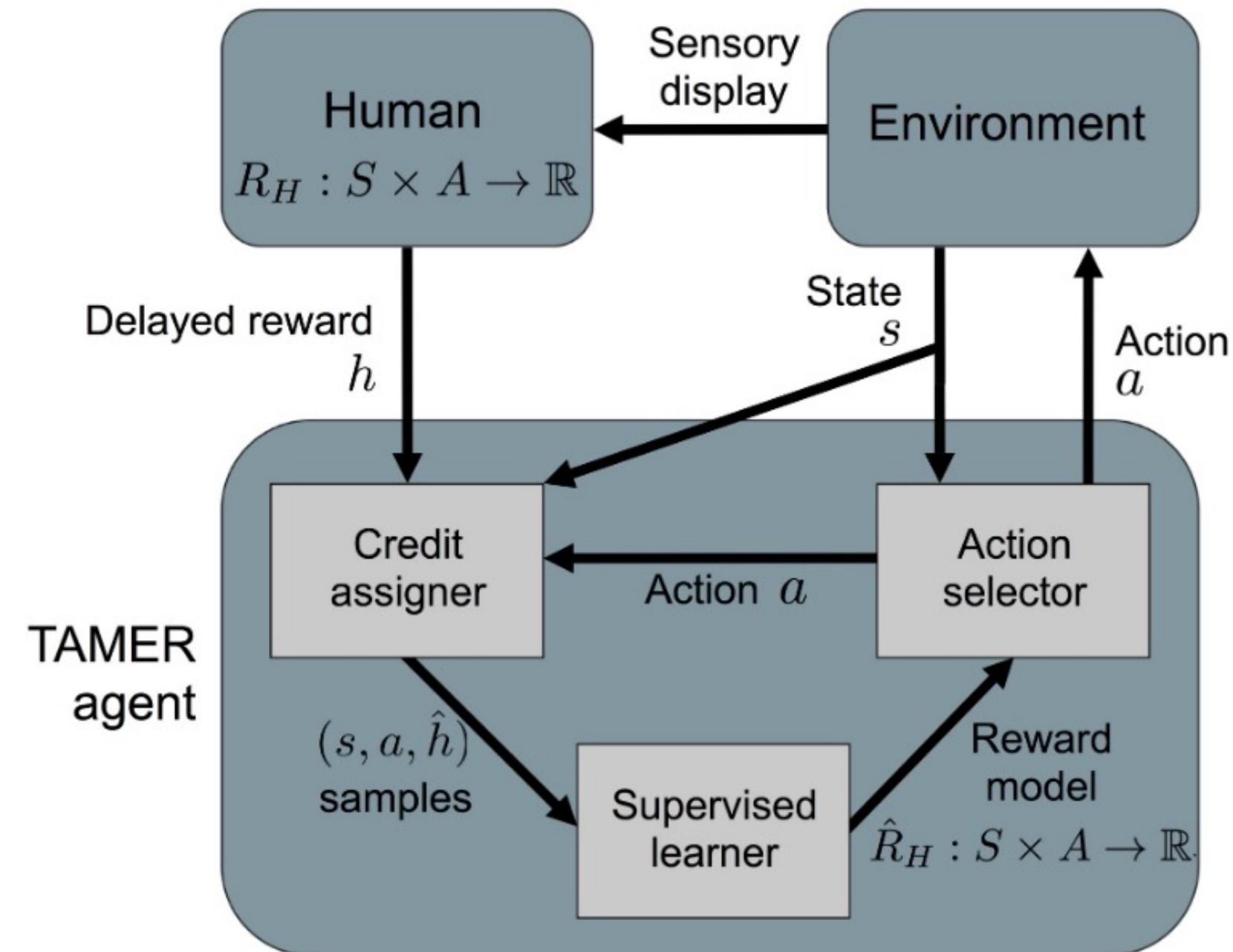
- Demonstrations
- Feedback
- Preferences
- Action Advice
- Shaping Rewards

Human \rightarrow Agent Feedback (!R)

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Thomaz & Breazeal 2006: Anticipator

TAMER, Knox & Stone 2009



Human → Agent Feedback (!R)

- Offline / Batch RL
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- Advice

Thomaz & Breazeal 2006: Anticipator

TAMER, Knox & Stone 2009: Numeric, Return

SABL, Loftin+ 2015

Feedback history h

Observation: “sit”, Action:  , Feedback: “Bad Dog”

Observation: “sit”, Action:  , Feedback: “Good Boy”

...

Really make sense to assign numeric rewards to these?

Human → Agent Feedback (!R)

- Offline / Batch RL
- Demonstrations
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- Advice

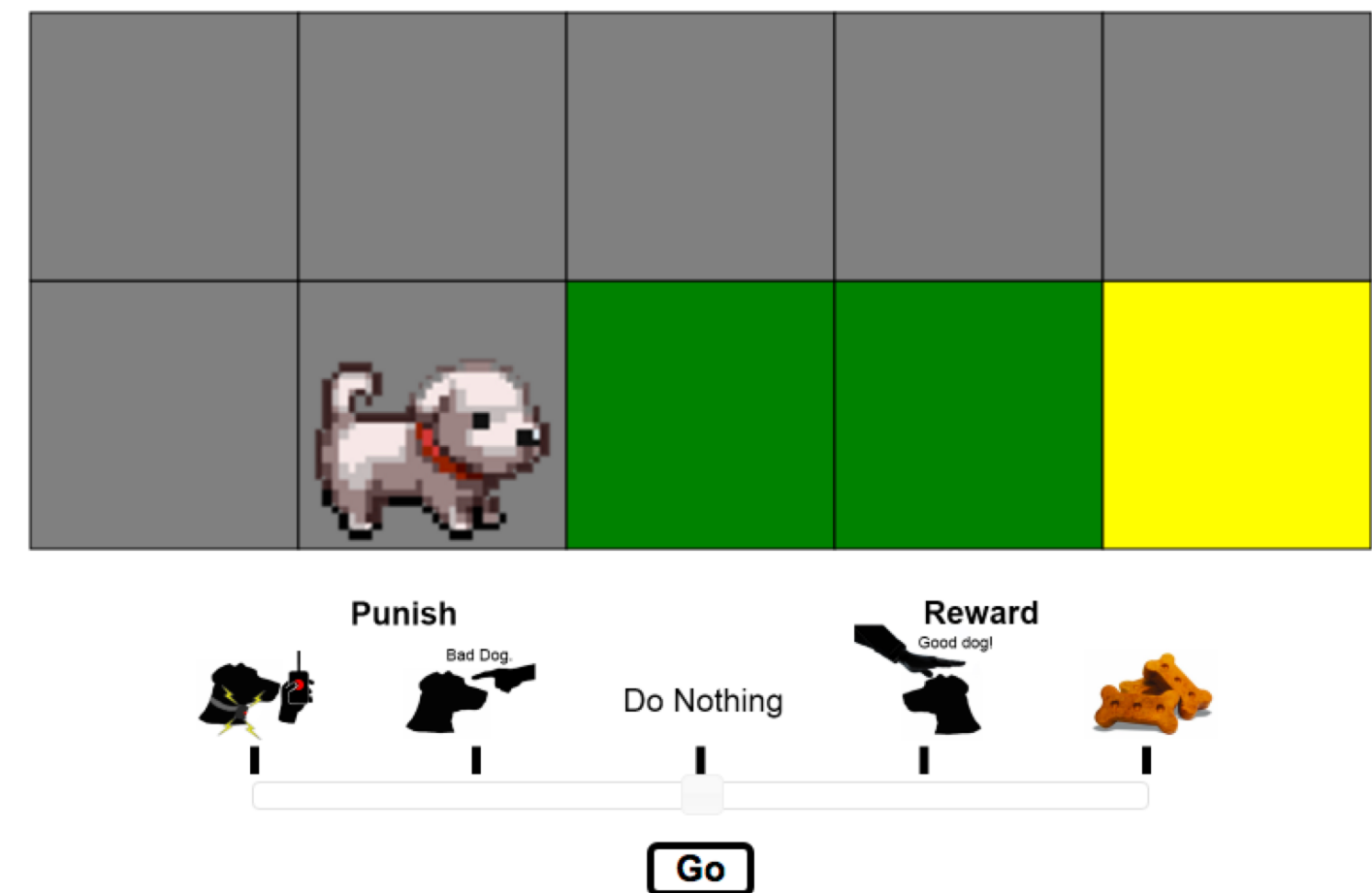
Thomaz & Breazeal 2006: Anticipator

TAMER, Knox & Stone 2009: Numeric, Return

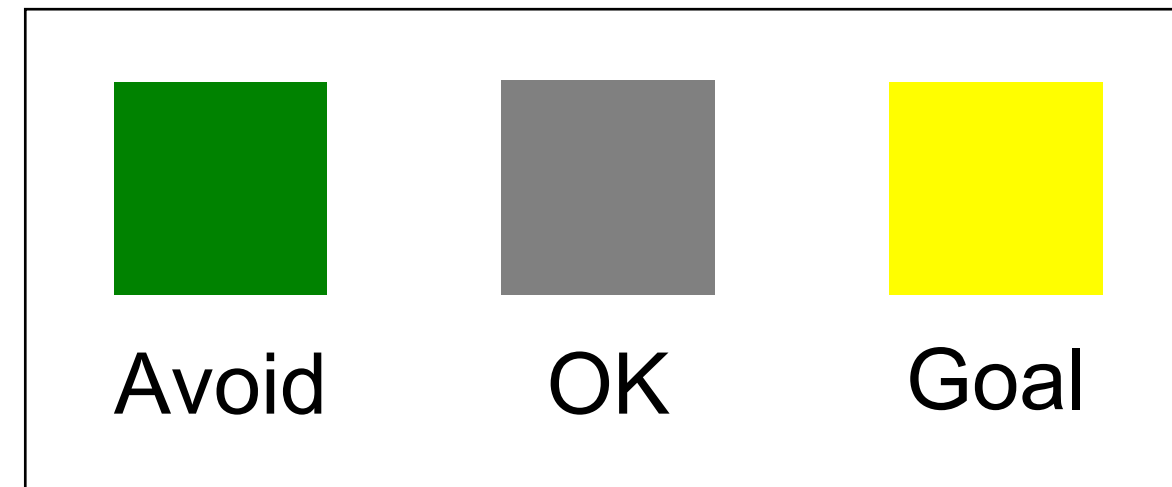
SABL, Loftin+ 2015: Categorical

COACH, McGlashlin+ 2017

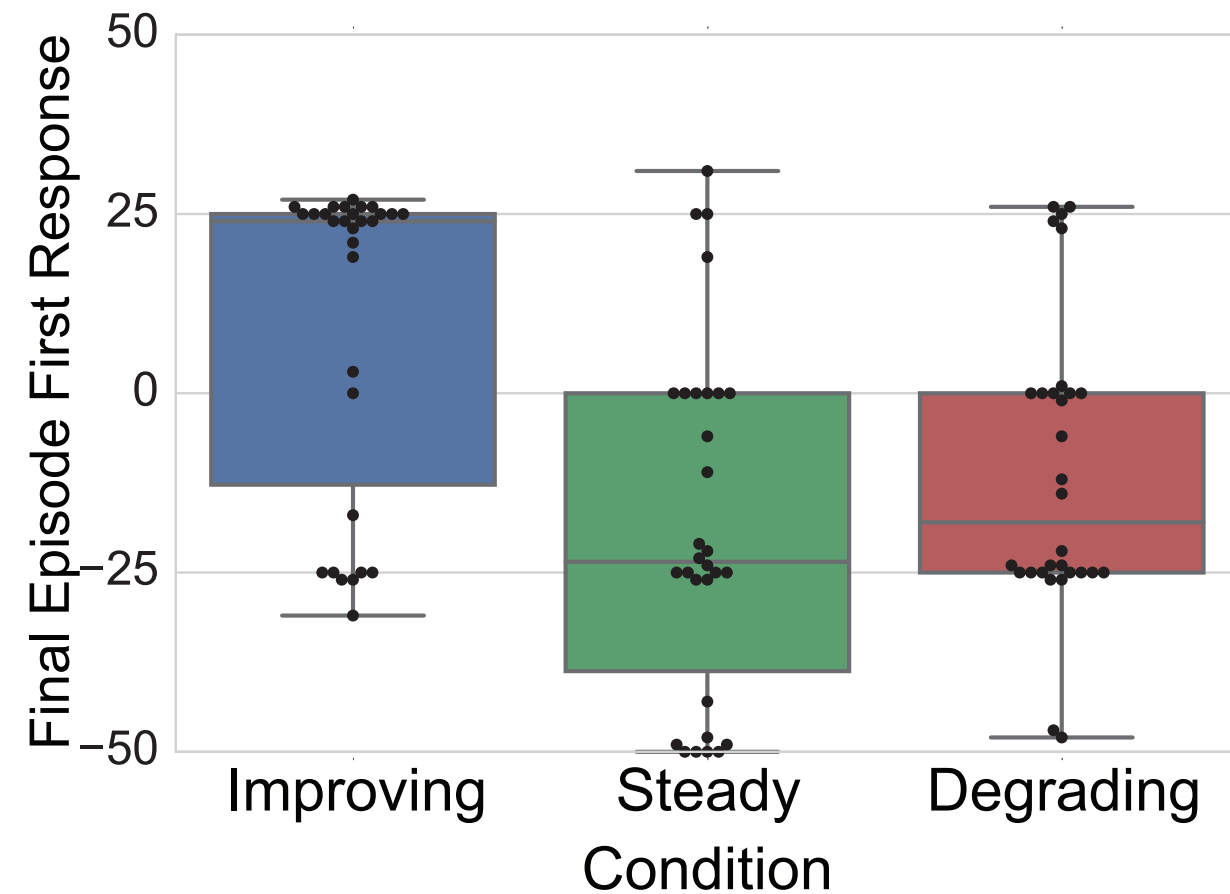
Click 'Go' to start today's training.



Feedback can be Relative

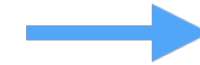


Feedback can be Relative

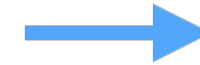


Improving Condition:

bad



bad



alright

Steady Condition:

alright



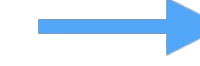
alright



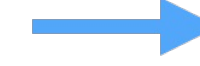
alright

Degrading Condition:

good



good



alright

Advantage Function!

Human → Agent Feedback (!R)

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Thomaz & Breazeal 2006: Anticipator

TAMER, Knox & Stone 2009: Numeric, Return

SABL, Loftin+ 2015: Categorical

COACH, McGlashlin+ 2017: Advantage Function

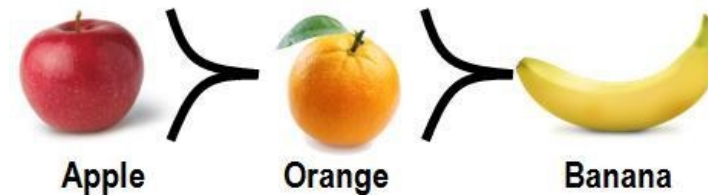
Human → Agent

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Reward signal?

No

- Demonstrations
- Feedback
- Preferences



Yes

- Demonstrations
- Feedback
- Preferences
- Action Advice
- Shaping Rewards

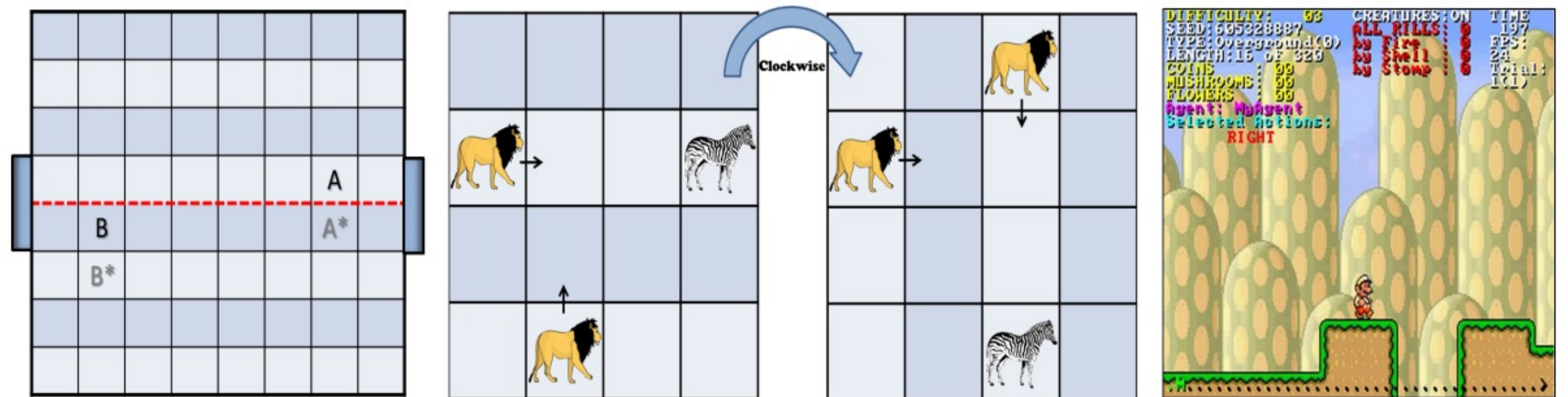
Human → Agent Bootstrapping

- Offline / Batch RL
- Demonstrations
- Curriculum Learning / Meta RL
- Advice

Lay person

Subject Matter Expert

Programmer



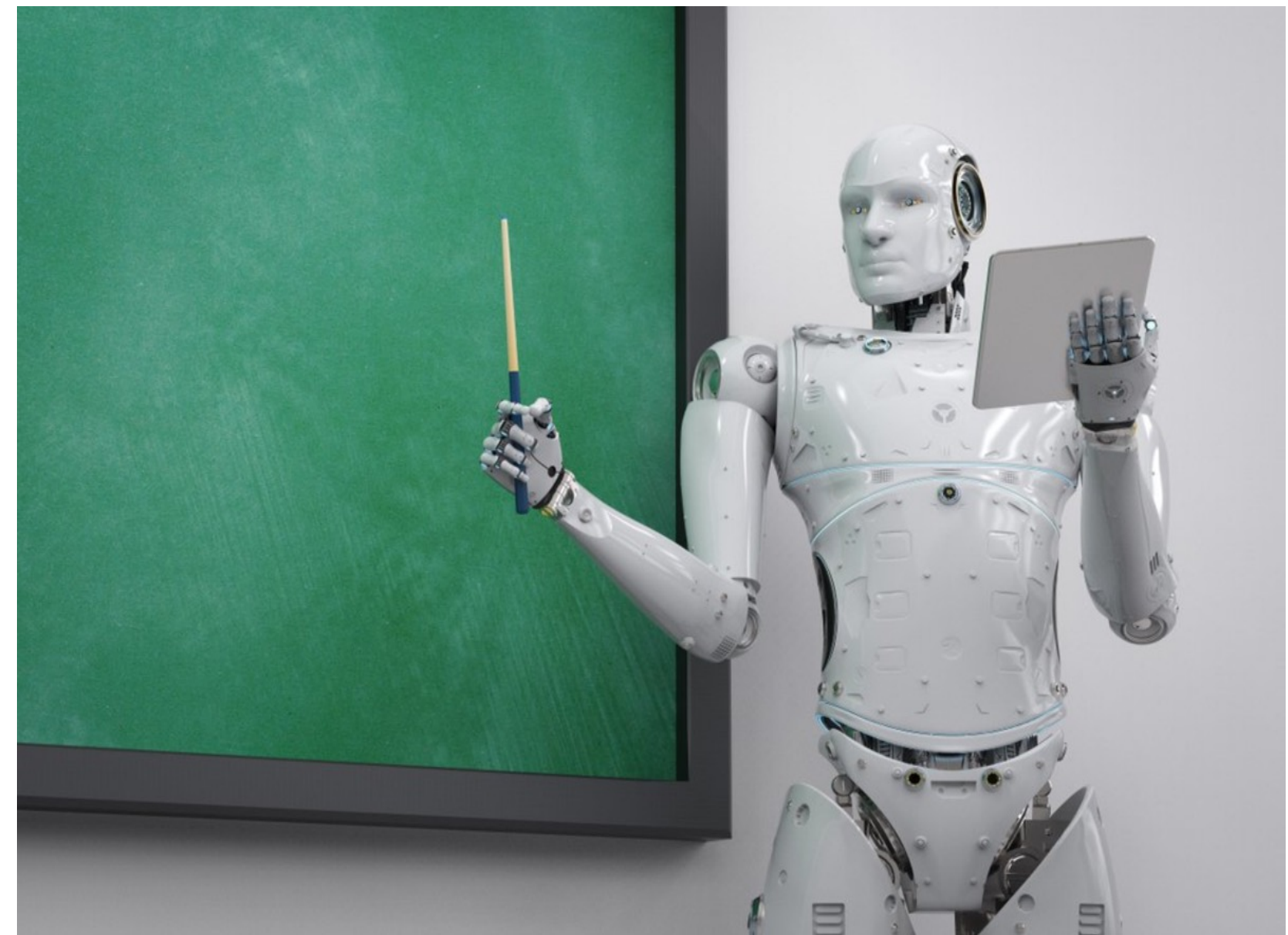
Agent → Human: ITS

Convey information

Model user's understanding

Model user's learning

→ Sequential decision tasks



<https://hassanmachmouchiblog.files.wordpress.com/2021/01/robot-teachers.png>

Agent → Human: ITS

How to practice
How to support
When to support

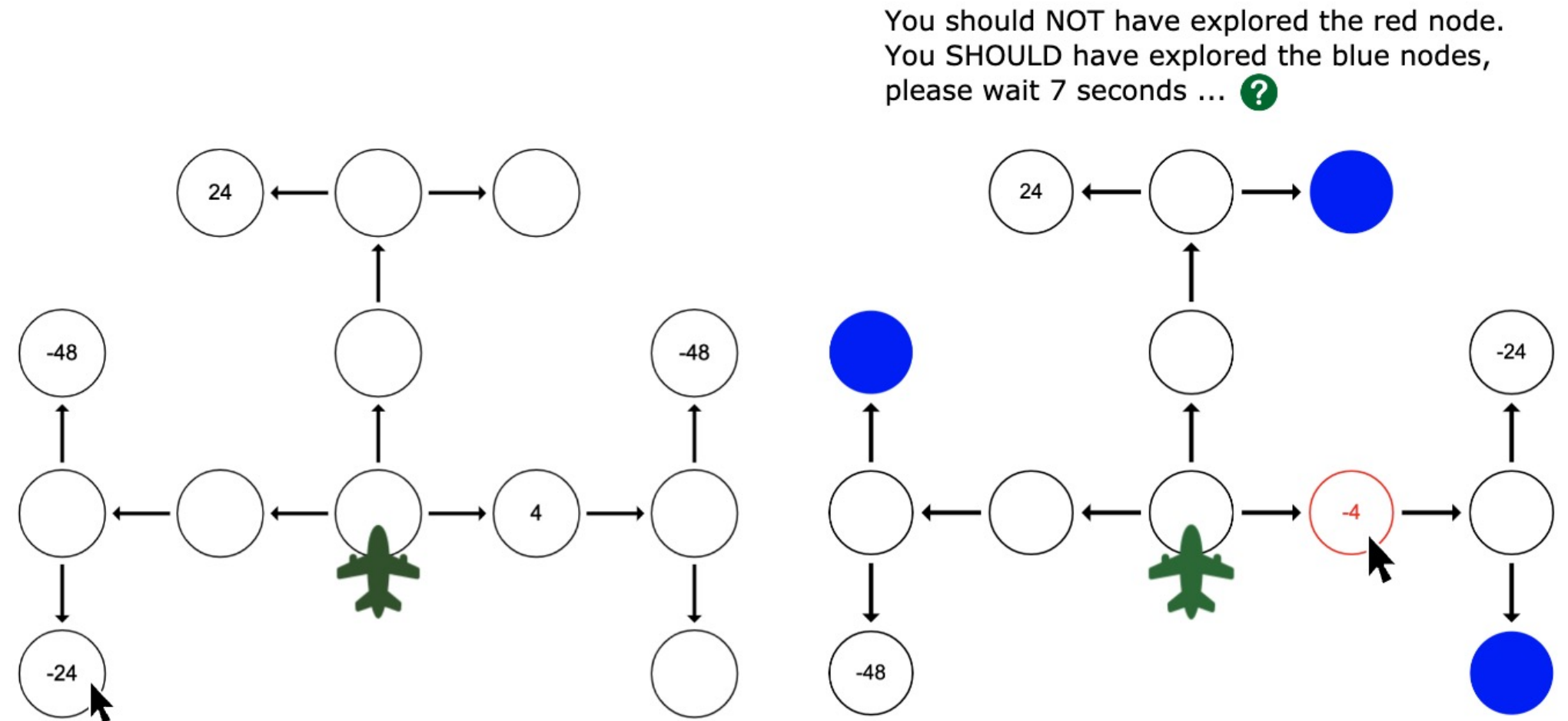


Fig. 1: The Mouselab-MDP paradigm. (Left) Participants click to reveal the value at future states. (Right) ITS provides feedback on each planning operation. The question mark represents optional elaborated feedback.

Agent → Human: Pilot Training

Shortage of pilots
Lots of knowledge
Hands on training

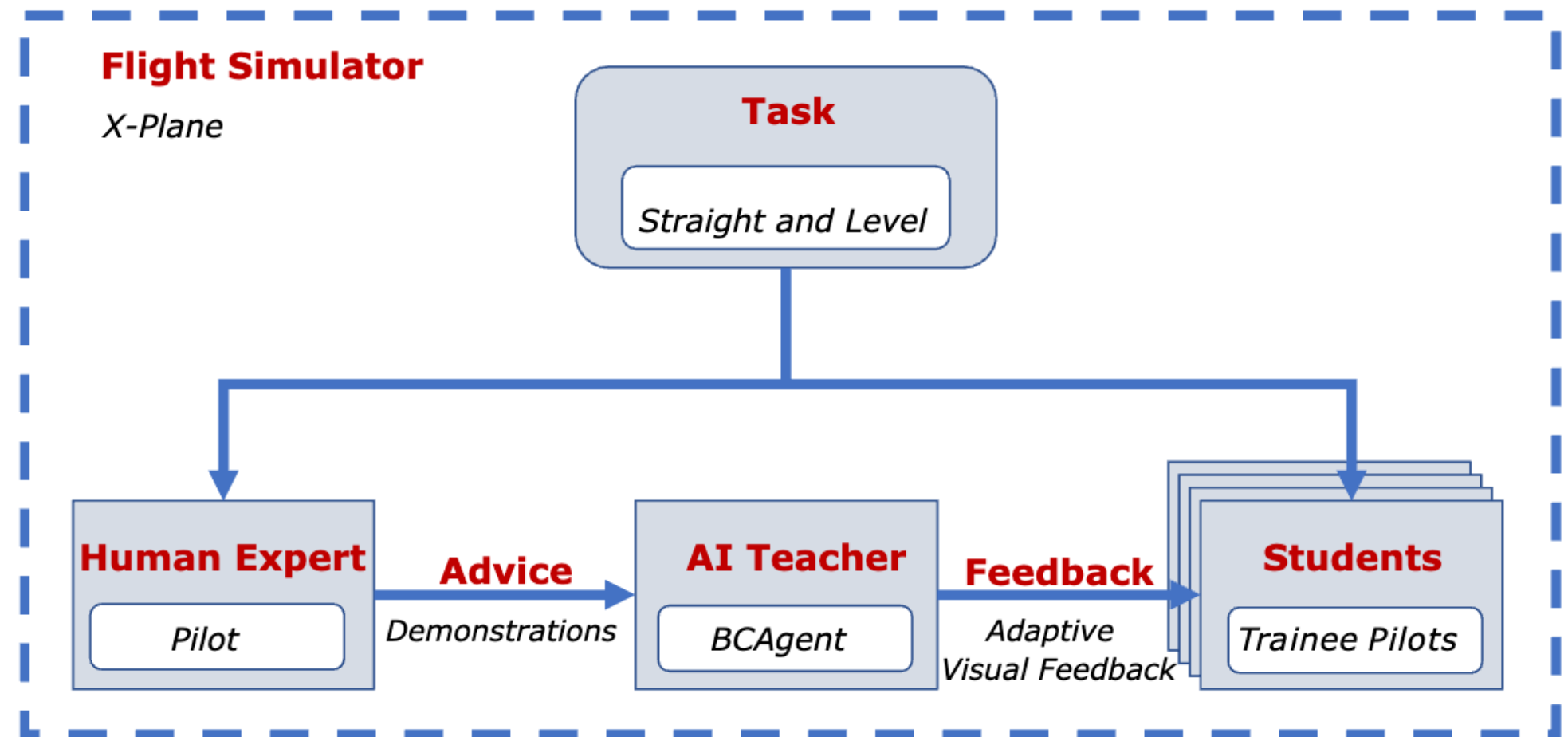


Figure 1: System Architecture



D.A.T VOLTS
24 E
20:04

200
180
160
140
120
100
80
60
40
AL SPEED
KNO
TAS

9
8
7
6
5
4
3
2
1
0
ALT
FEET
10000
5000
0

33
30
27
24
21
18
15
12
9
6
3
0
3
6
9
12
15
18
21
24
27
30
33
N
W
E
S
NAV
OBS

FUEL
20
15
10
5
0
QTY
LEFT
RIGHT

FF
UL
EO
LW
100
50
0
-100

DC REC
TURN COORDINATOR
L
R
2 MIN
NEWBY
PITCH
ROLL
YAW

21
24
30
33
9
12
15
18
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3
0
3
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120
125
130
135
140
145
150
VERTICAL
SPEED
FEET
PER
MIN

33
30
27
24
21
18
15
12
9
6
3
0
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12
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24
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N
W
E
S
NAV
OBS

COM1 COM2 DME NAV1 NAV2 ADF
SENS COM1 MIC COM2 MIC
PILOT
3-PLANE 530
COM 1 121.800 DTK Trk 210°
121.800
VLOC 1 111.70
111.70
111.70
150
35me
GS 103
VLOC
COM/VLOC
CDI OBS HDG FFL VNAV
PUSH
3-PLANE 430
COM 2 121.800

Program Synthesis

Write better code faster

Program Optimization with Locally Improving search (POLIS)

- A system for improving programs w.r.t. reward
- Local search algorithm exploits program structure
- Generate effective & short programs

```
1 def max_sum_slice(xs):  
2     max_ending = max_so_far = 0  
3     for x in xs:  
4         max_ending = max(0, max_ending + x)  
5         max_so_far = max(max_so_far, max_ending)  
6     return max_so_far
```

 Copilot

POLIS

polis, plural **poleis**, ancient Greek city-state.... There were several hundred poleis, the history and constitutions of most of which are known only sketchily most ancient Greek history is recounted in terms of the histories of Athens, Sparta, and a few others.

Episode: 1

Original program

Average score ~ -75

POLIS

Episode: 1

```
def initial(o):  
    if o[1] > 1 and o[1] < 1.1 and (o[4] < 0.12):  
        action = 2  
    elif o[1] > 1 and o[3] < -0.7 and o[0] < -0.05:  
        action = 3  
    elif o[1] > 1 and o[3] < -0.8 and o[0] > 0.1:  
        action = 1  
    elif o[0] < -0.15 and o[4] > 0.1:  
        action = 3  
    elif o[0] < 0.13 and o[4] < -0.1:  
        action = 1  
    elif o[1] < 0.8 and o[1] > 0.2:  
        action = 2  
    elif o[1] <= 0.2 and o[4] > 0.1:  
        action = 3  
    elif o[1] <= 0.2 and o[4] < -0.1:  
        action = 1  
    else:  
        action = 0  
    return action
```

```
def improved(o):  
    if o[3] > -0.038:  
        action = 0  
    elif o[7] > 0.036:  
        action = 2  
    elif o[5] < -0.1:  
        action = 1  
    elif o[0] and o[6]:  
        action = 2  
    elif o[5] > 0.959:  
        action = 0  
    elif o[3] < -0.388:  
        action = 2  
    elif o[4] > 0.1:  
        action = 3  
    elif o[2] > 0.28:  
        action = 1  
    else:  
        action = 3  
    return action
```

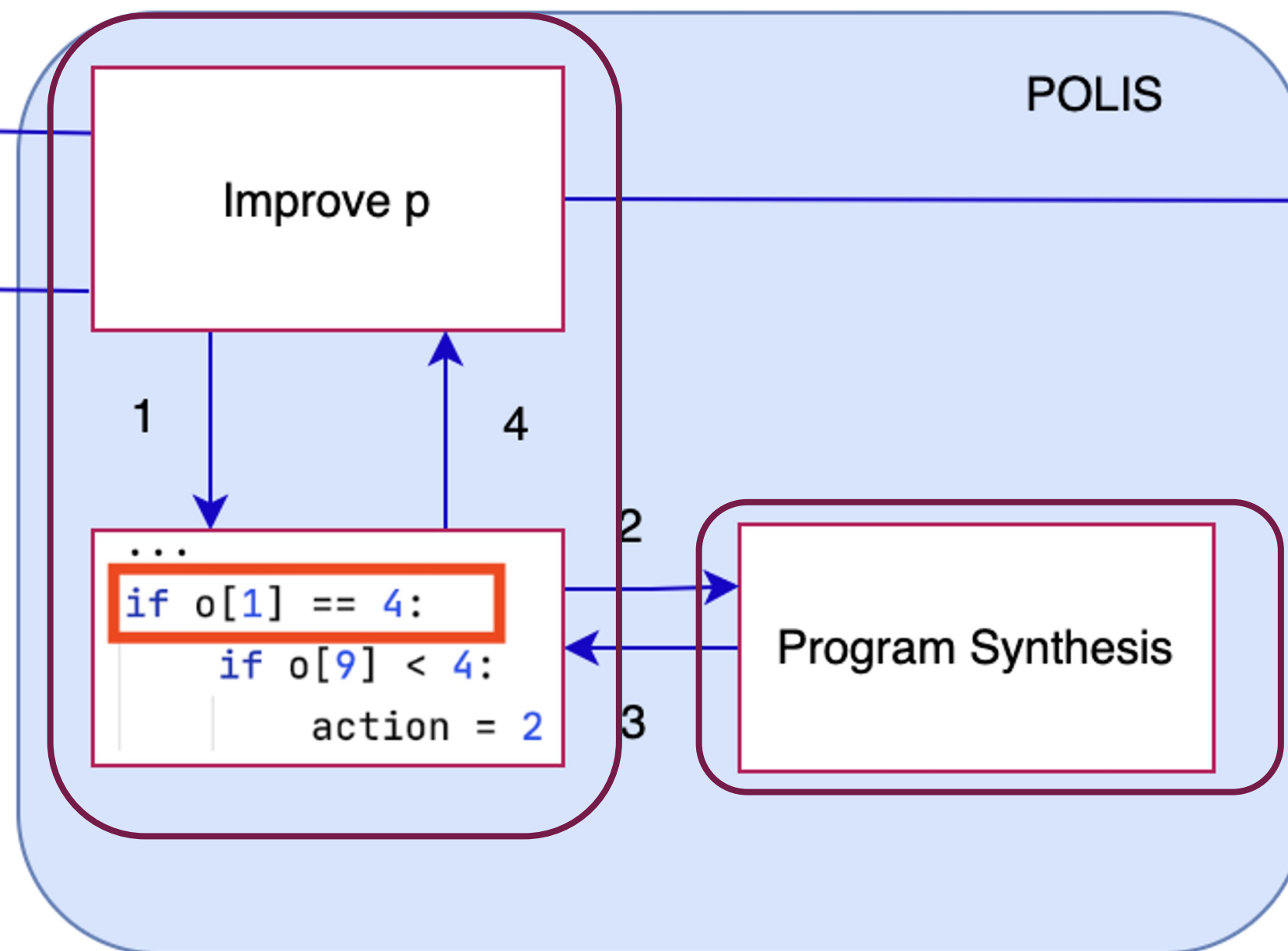
POLIS improved program

Average score ~
+190

POLIS

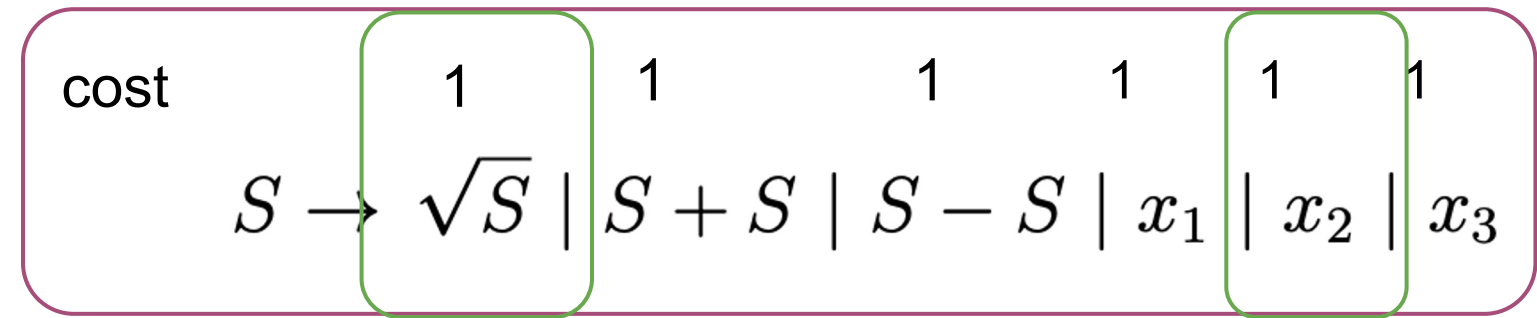
```
...  
if o[1] == 4:  
    if o[9] < 4:  
        action = 2  
    else:  
        action = 0  
else:  
    action = 0  
...
```

Objective function F



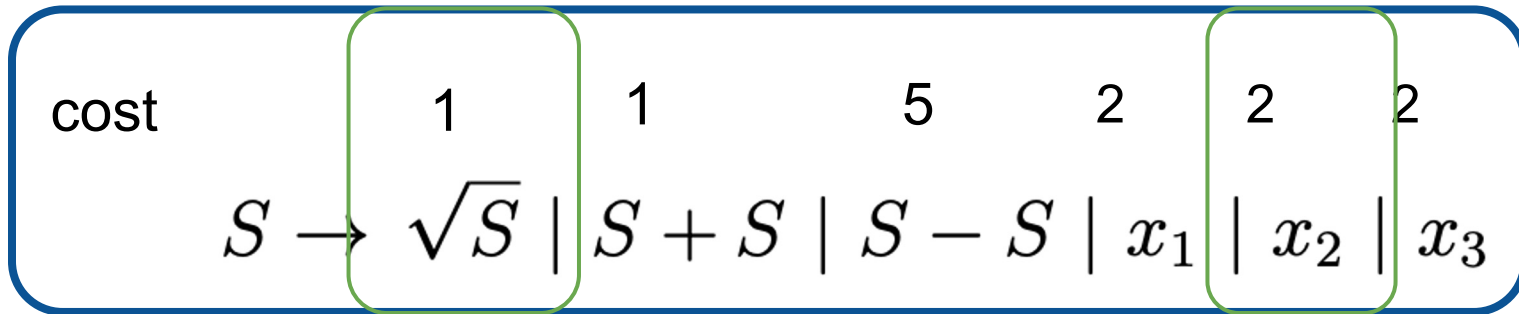
Improved program $p' \cong \operatorname{argmax} F(p)$

Bottom-Up Search (BUS)



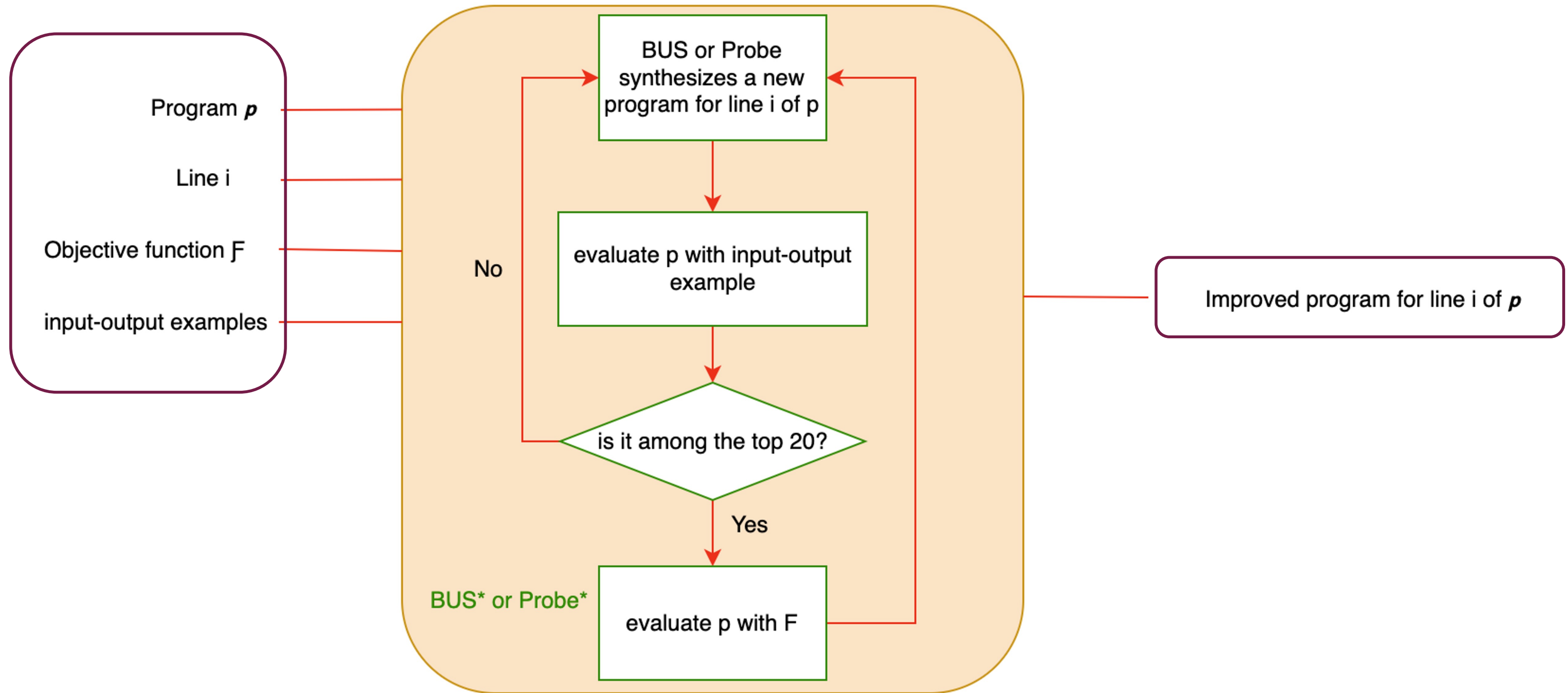
Cost	# Programs	Bank
1	3	$\{x_1, x_2, x_3\}$
2	3	$\{\sqrt{x_1}, \sqrt{x_2}, \sqrt{x_3}\}$
3	75	$\{\sqrt{\sqrt{x_1}}, \sqrt{\sqrt{x_2}}, \sqrt{\sqrt{x_3}}, x_1 + x_1, \dots, x_1 - x_1, x_1 - x_2, \dots\}$
4	147	$\{\sqrt{\sqrt{\sqrt{x_1}}}, \dots, \sqrt{x_1 + x_1}, \dots, \sqrt{x_1 - x_1}, \dots, \sqrt{x_1 + x_1}, \dots, \sqrt{x_1 - x_1}, \dots\}$
5	12K	$\{\dots\}$
6	70K	$\{\dots\}$
7	...	$\{\dots, \sqrt{\sqrt{x_1 + x_2 + x_3}}, \dots\}$

Guided BUS: Probe (Barke et. al. 2020)

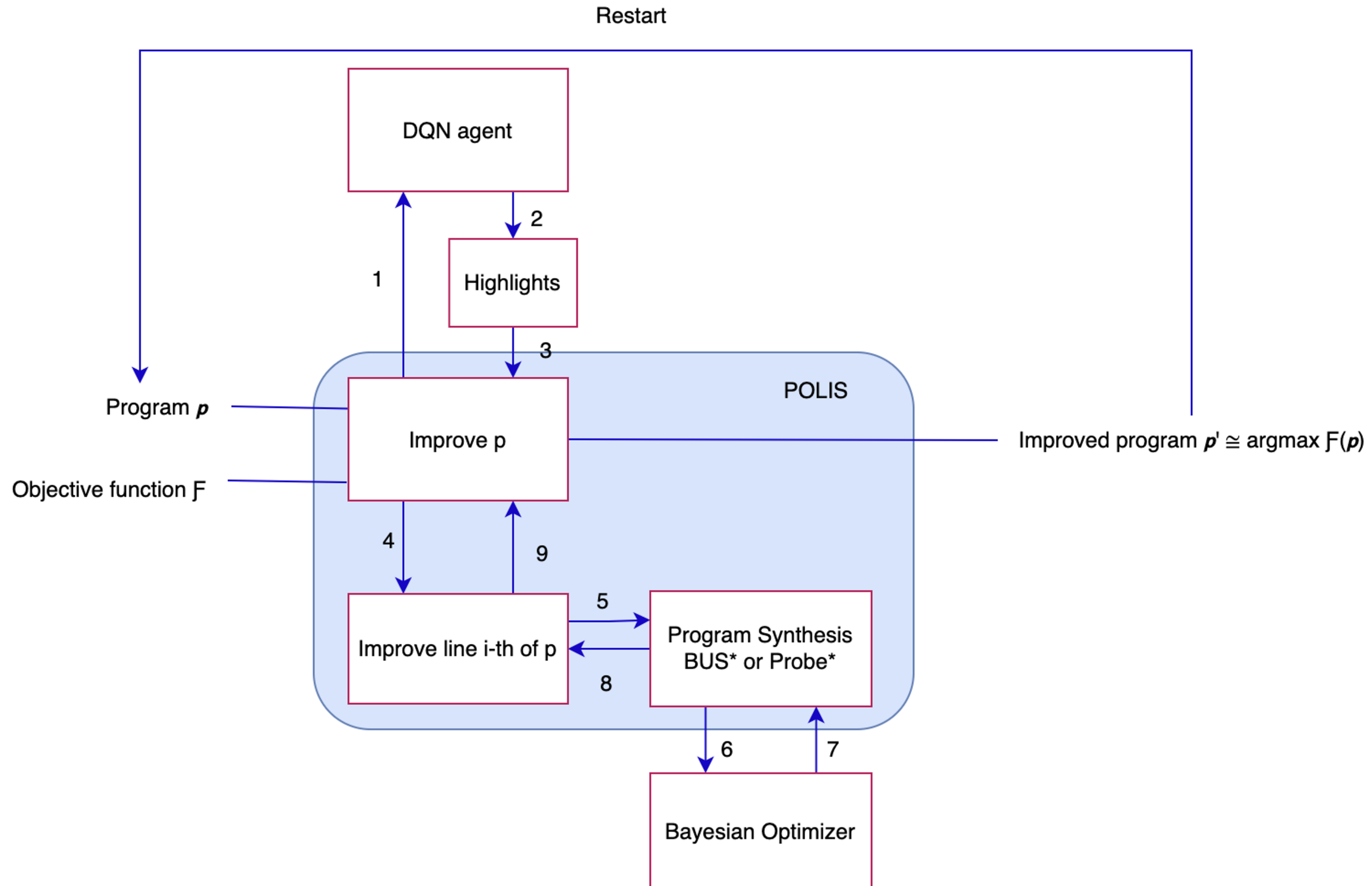


Cost	# Programs	Bank
2	3	$\{x_1, x_2, x_3\}$
3	3	$\{\sqrt{x_1}, \sqrt{x_2}, \sqrt{x_3}\}$
4	3	$\{\sqrt{\sqrt{x_1}}, \sqrt{\sqrt{x_2}}, \sqrt{\sqrt{x_3}}\}$
5	12	$\{\sqrt{\sqrt{\sqrt{x_1}}}, \dots, x_1 + x_1, x_1 + x_2, x_1 + x_3, \dots\}$
6	48	$\{\sqrt{\sqrt{\sqrt{x_1}}}, \dots, \sqrt{x_1 + x_2}, \dots, x_1 + \sqrt{x_1}, \dots, \sqrt{x_1} + x_1\}$
7	93	$\{\dots\}$
8	354	$\{\dots\}$
9	3200	$\{\dots\}$
10	...	$\{\dots, \sqrt{\sqrt{x_1 + x_2 + x_3}}, \dots\}$

How does POLIS use BUS and Probe?



Experimental details



Episode: 1



```
def initial(o):
```

```
if (o[5] == o[1] and o[5]-o[1] > 200) or\  
    (o[9] == o[1] and o[9]-o[1] > 200):
```

```
    action = 4
```

```
elif (o[5] == o[1] and o[5]-o[1] <= 200) or\  
     (o[9] == o[1] and o[9]-o[1] <= 200):
```

```
    if o[1] == 4:
```

```
        if o[9] < 4:
```

```
            action = 2
```

```
        else:
```

```
            action = 0
```

```
    else:
```

```
        action = 0
```

```
else:
```

```
    action = 3
```

```
return action
```

Score ~6.8

Episode: 1



```
def improved(o):
```

```
if o[1] and o[3]:
```

```
    action = 4
```

```
elif (o[5] == o[1] and o[5]-o[1] <= 200) or\  
     (o[9] == o[1] and o[9]-o[1] <= 200):
```

```
    if o[1] == o[5]:
```

```
        if o[1] < 7.93:
```

```
            action = 2
```

```
        else:
```

```
            action = 0
```

```
    else:
```

```
        action = 2
```

```
else:
```

```
    action = 1
```

```
return action
```

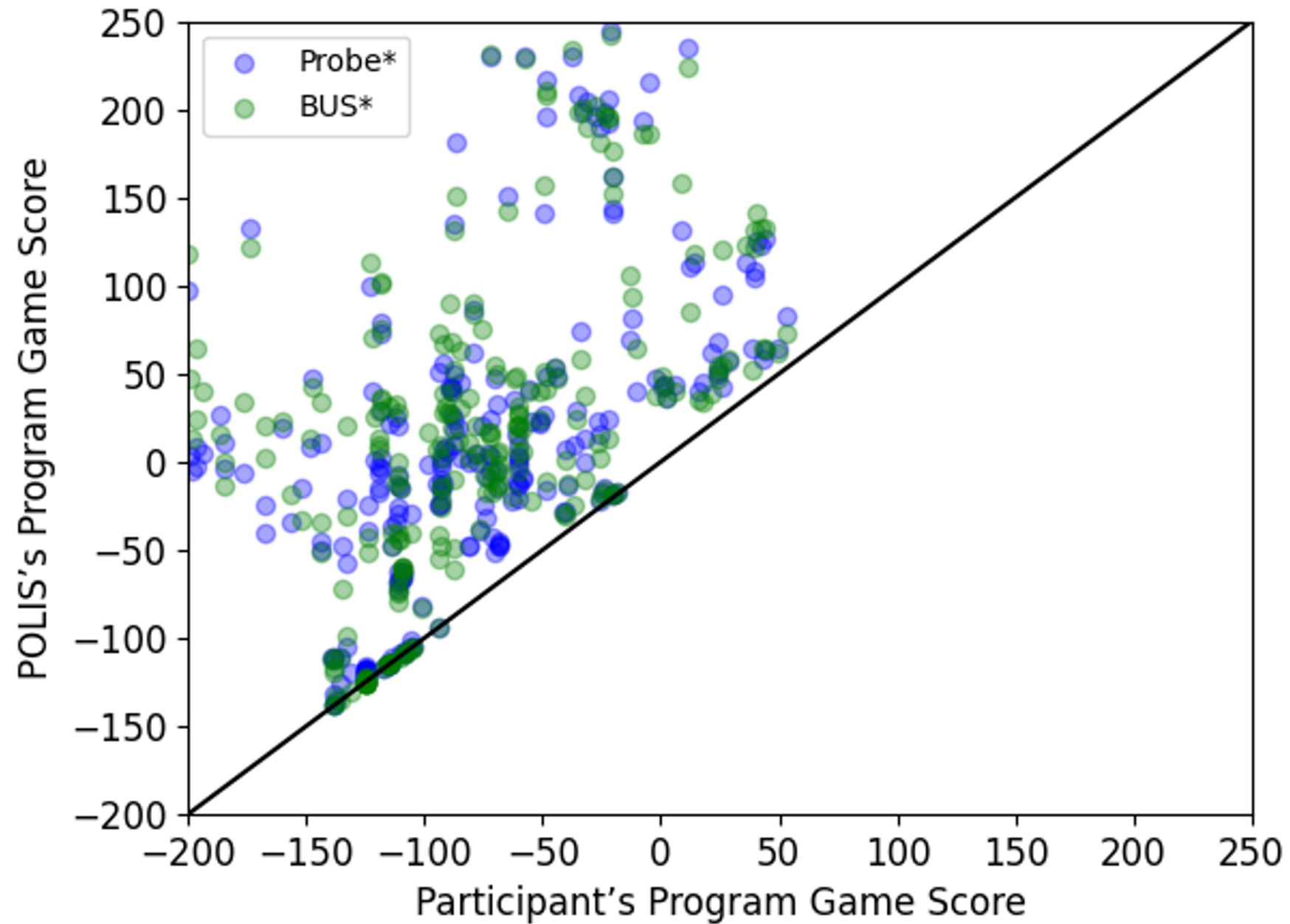
Score ~39

Instead of left, go to the right

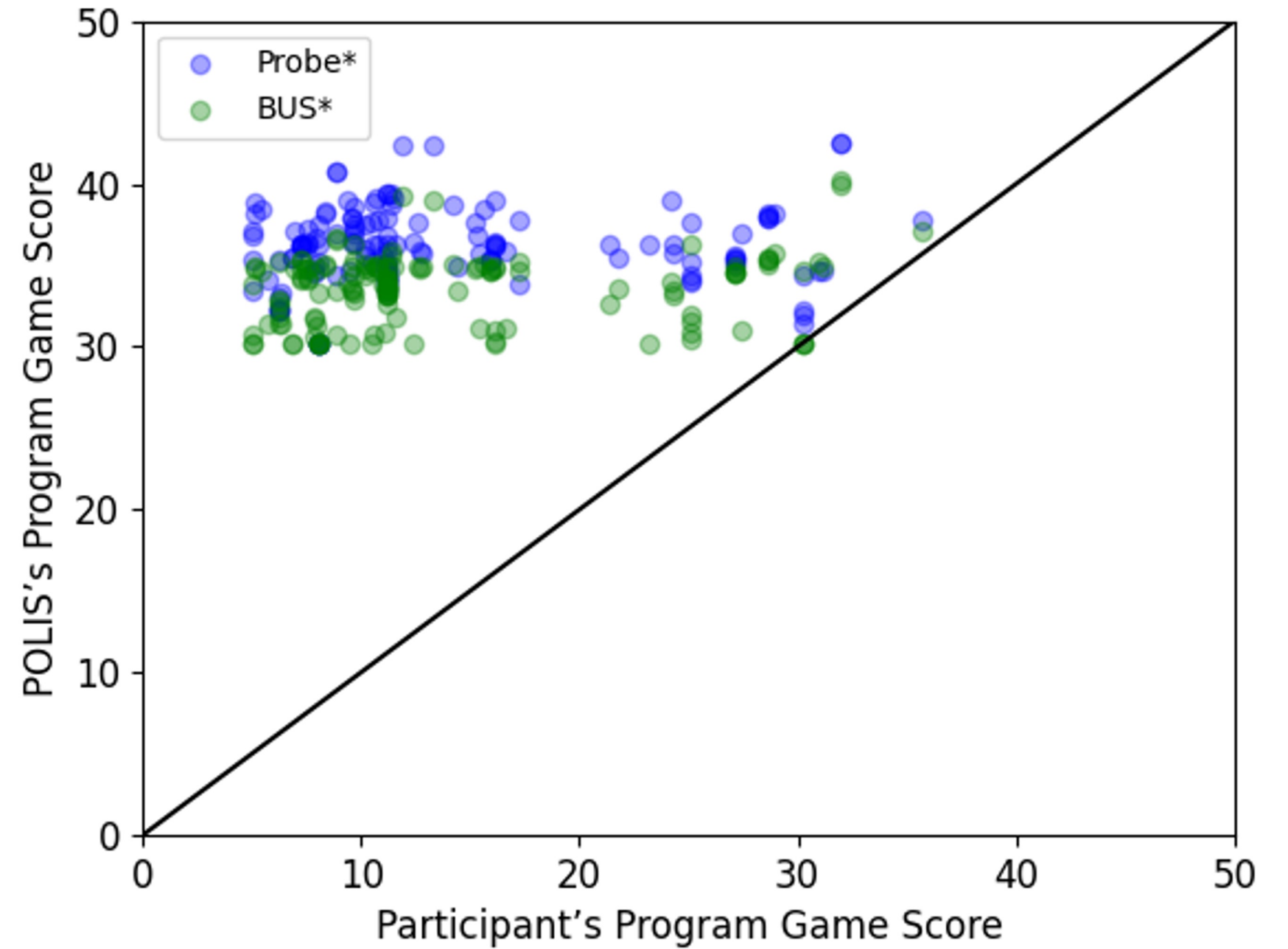
Do nothing instead of increasing speed

Computational results: POLIS results

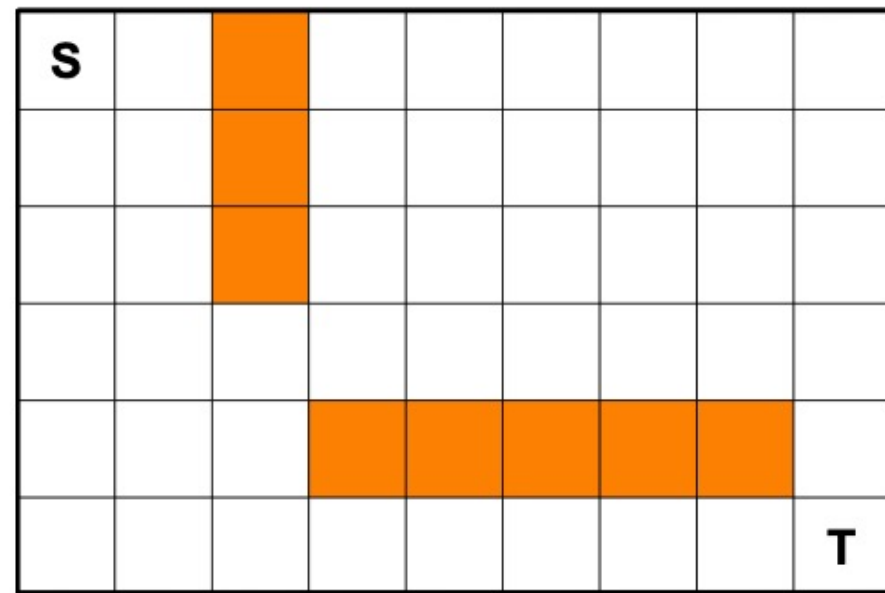
Lunar Lander



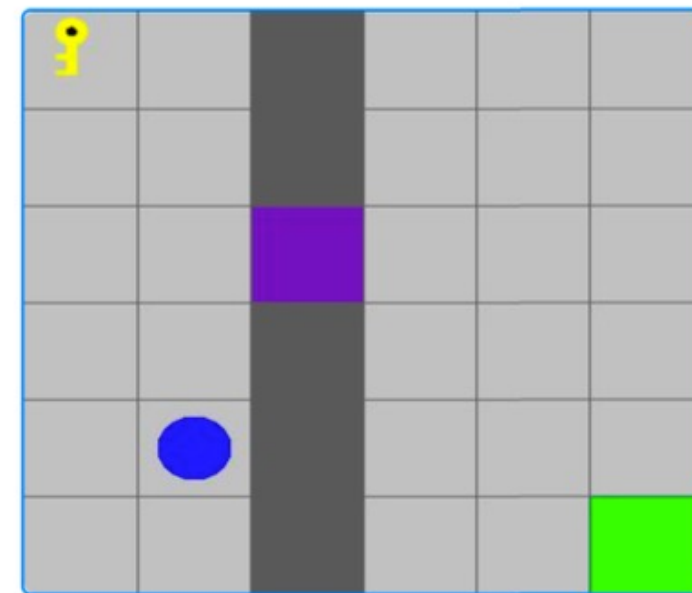
Highway



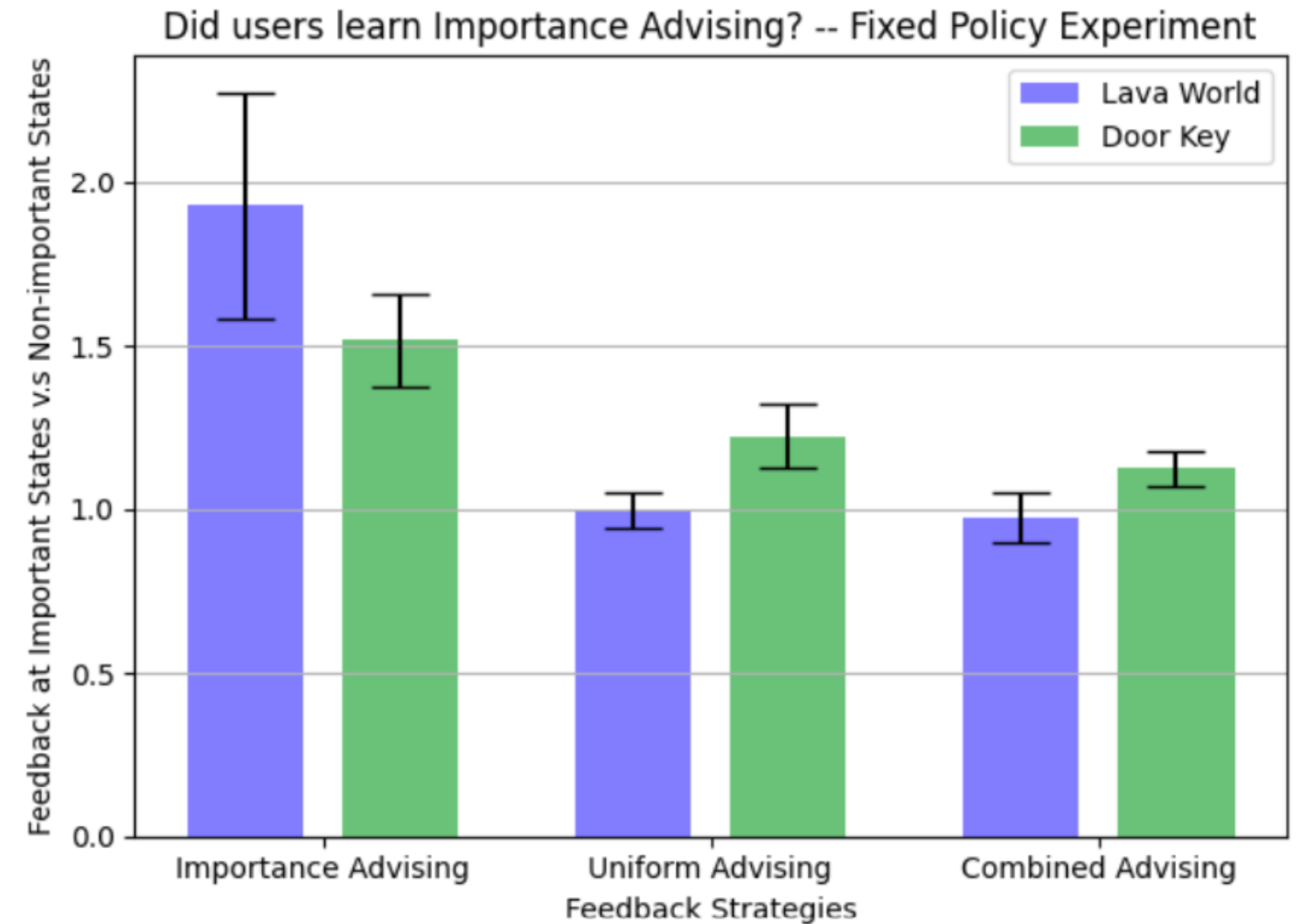
Research Question 1: Can we teach people how to be better teachers?



(a) Lava World

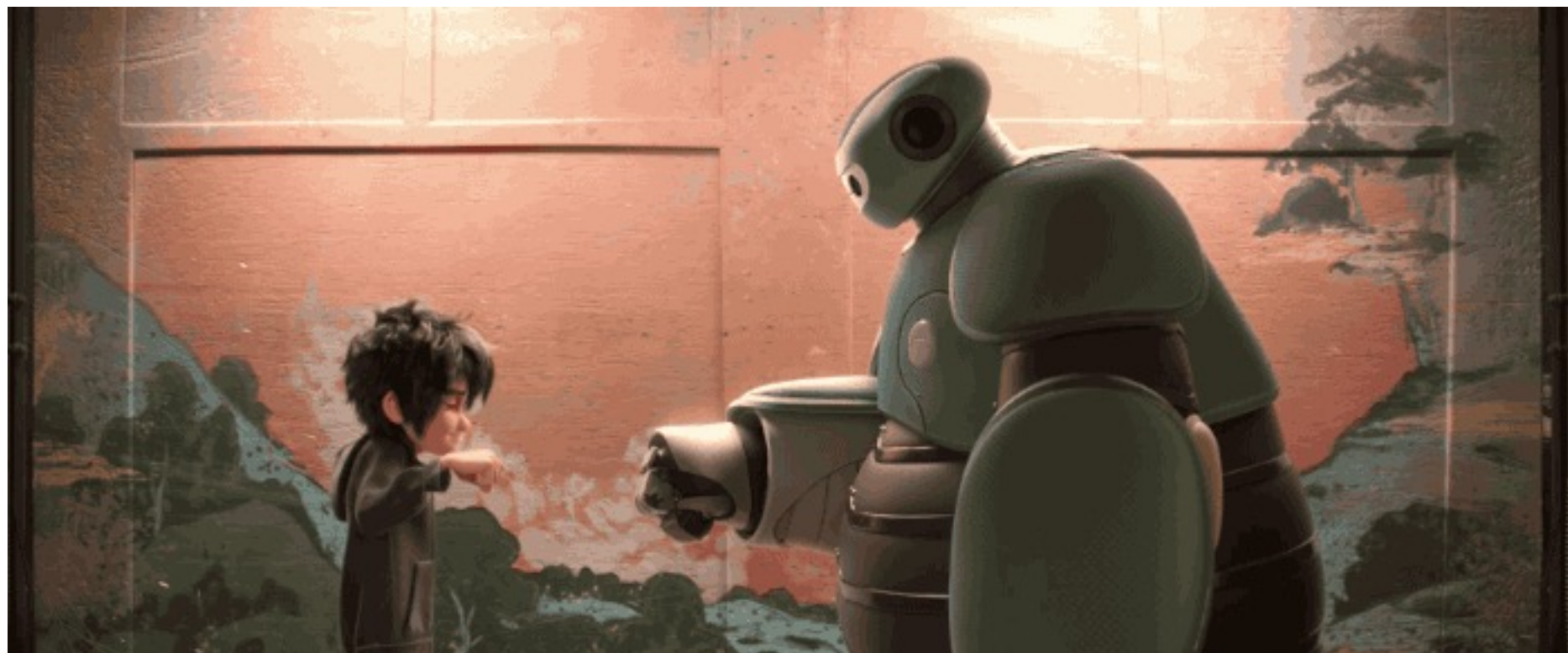


(b) Door Key



Research Question 2: Can we adapt our algorithms to better learn from human teachers?

- Figure out what human feedback means?



Research Question 2: Can we adapt our algorithms to better learn from human teachers?

- Figure out what human feedback means?

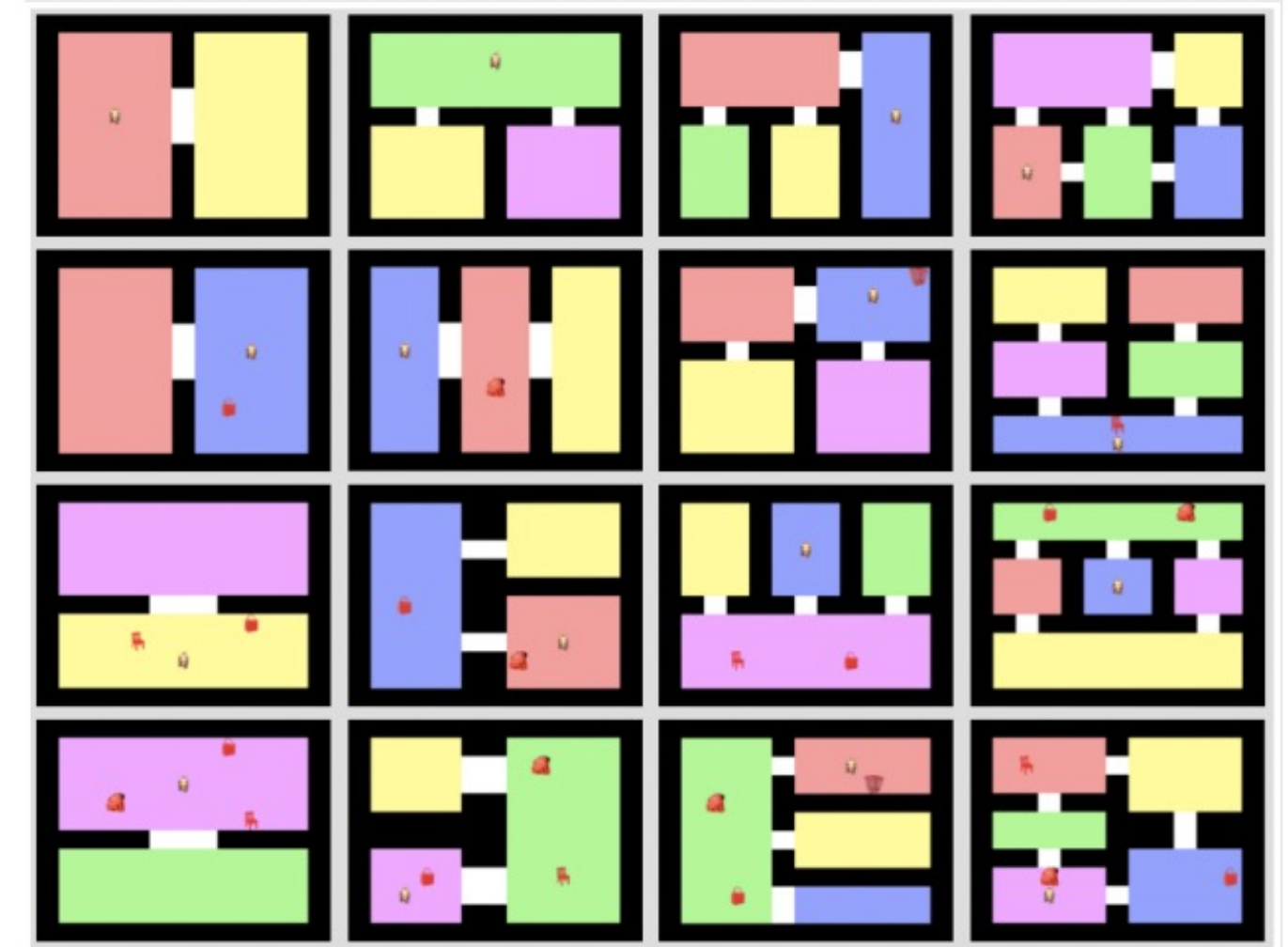
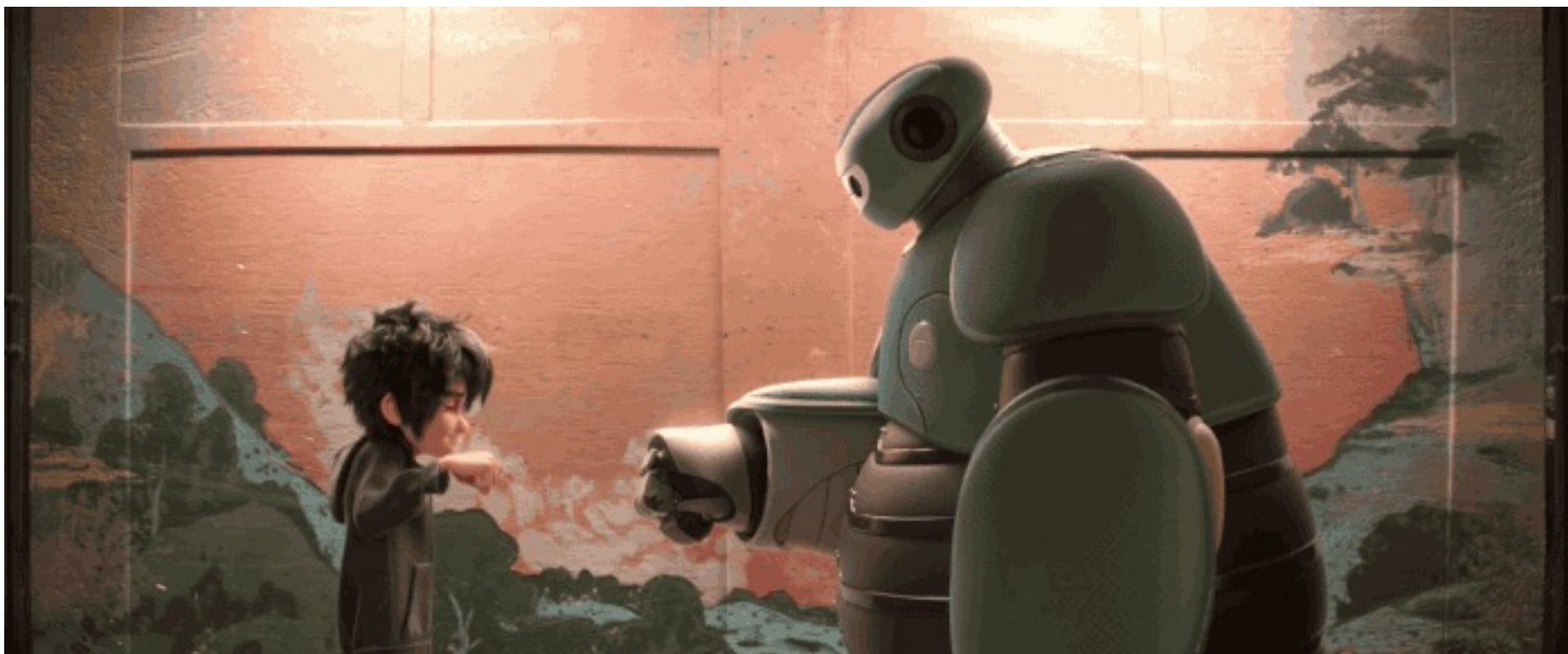
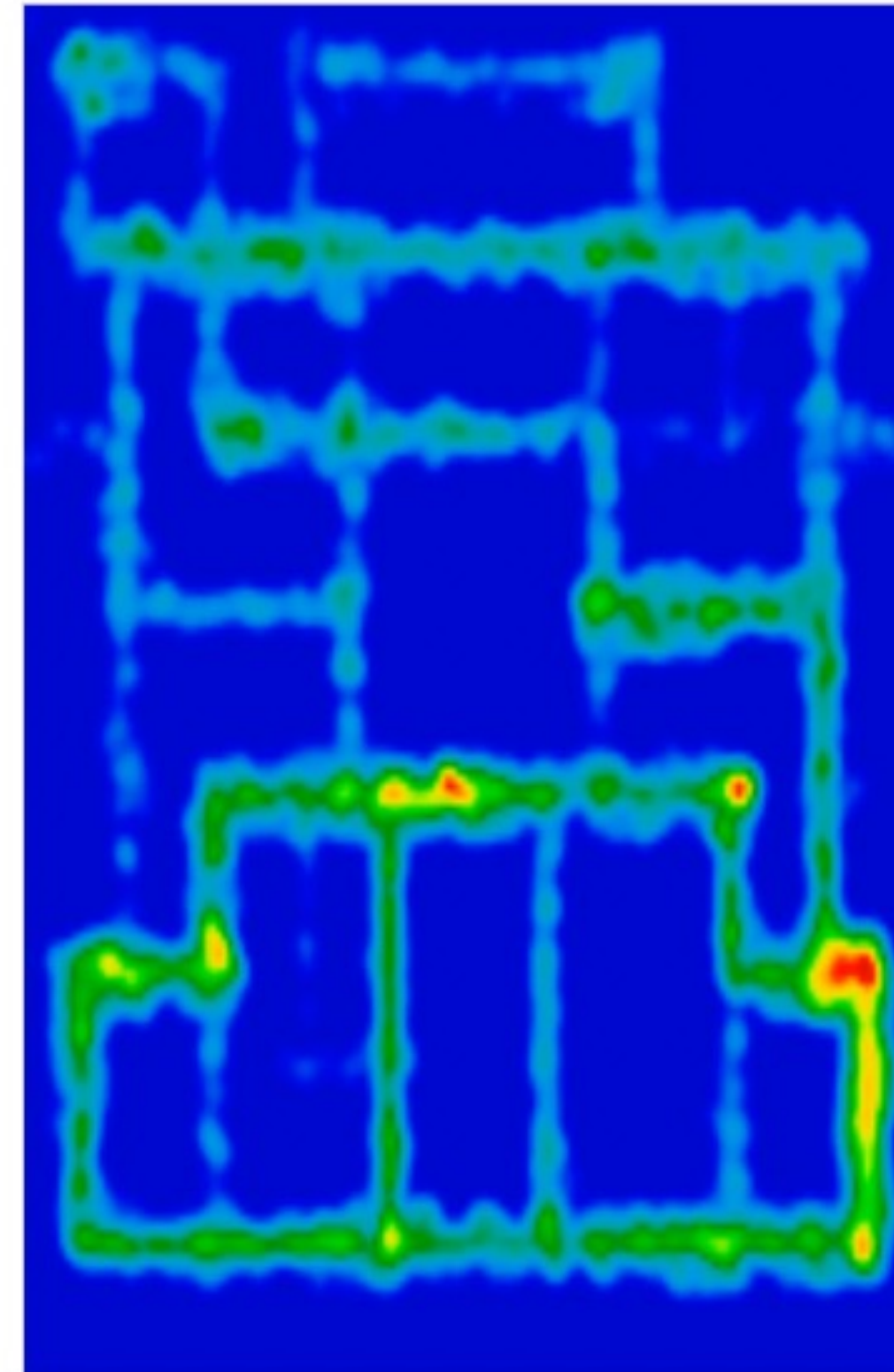


Figure 2: The library of 16 environments is organized by the number of rooms and objects. There is a command list for each environment.

Research Question 3: Will Explainability Help?

- Explanations can help people select better agent and/or better anticipate agent's actions

Heatmap of Visits Per Coordinate

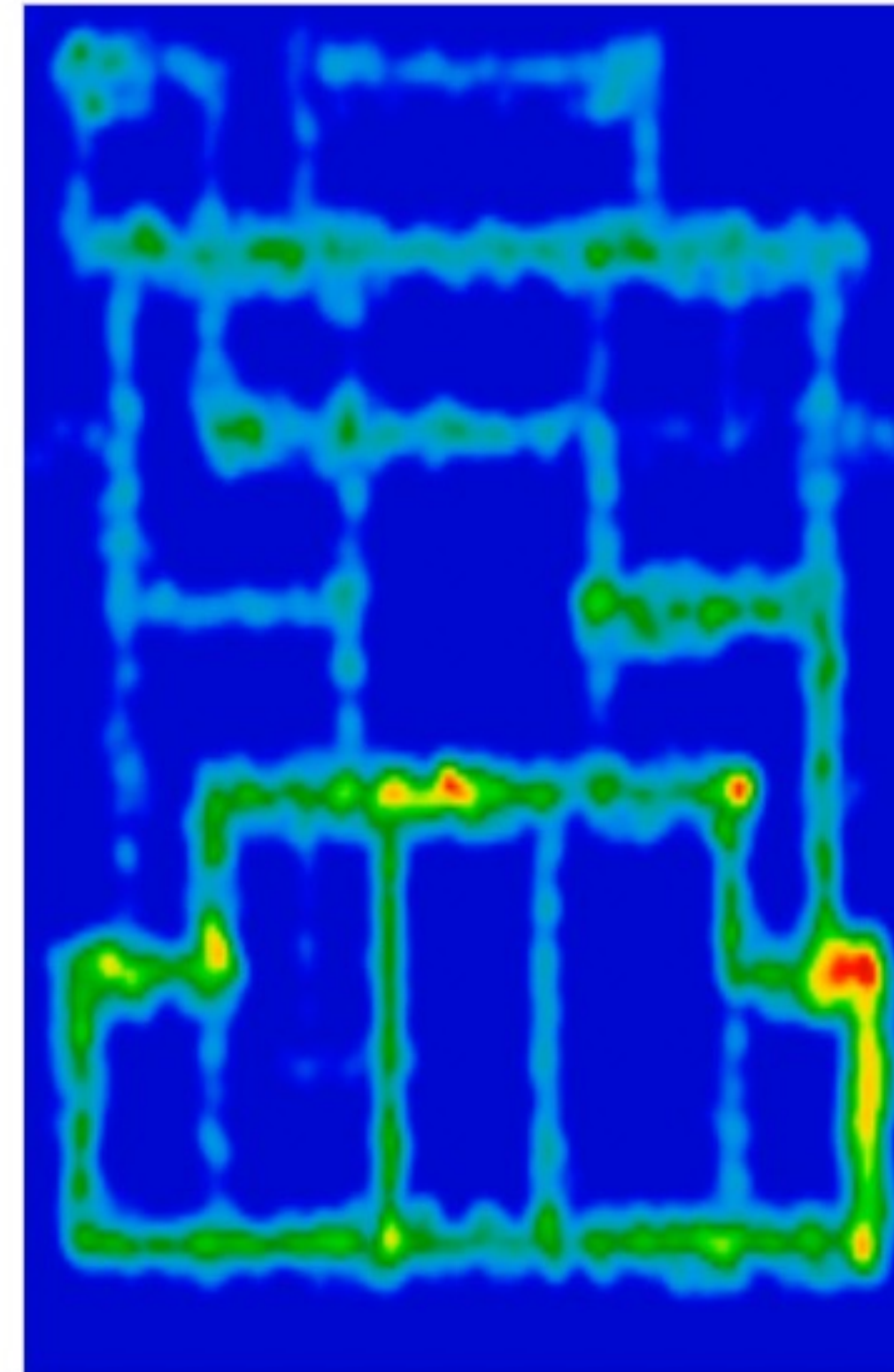


Davis-Pearson et al.,
under submission

Research Question 3: Will Explainability Help?

- Explanations can help people select better agent and/or better anticipate agent's actions
- Knowing what the agents knows should let teacher better target how they help
→ seems obvious...

Heatmap of Visits Per Coordinate

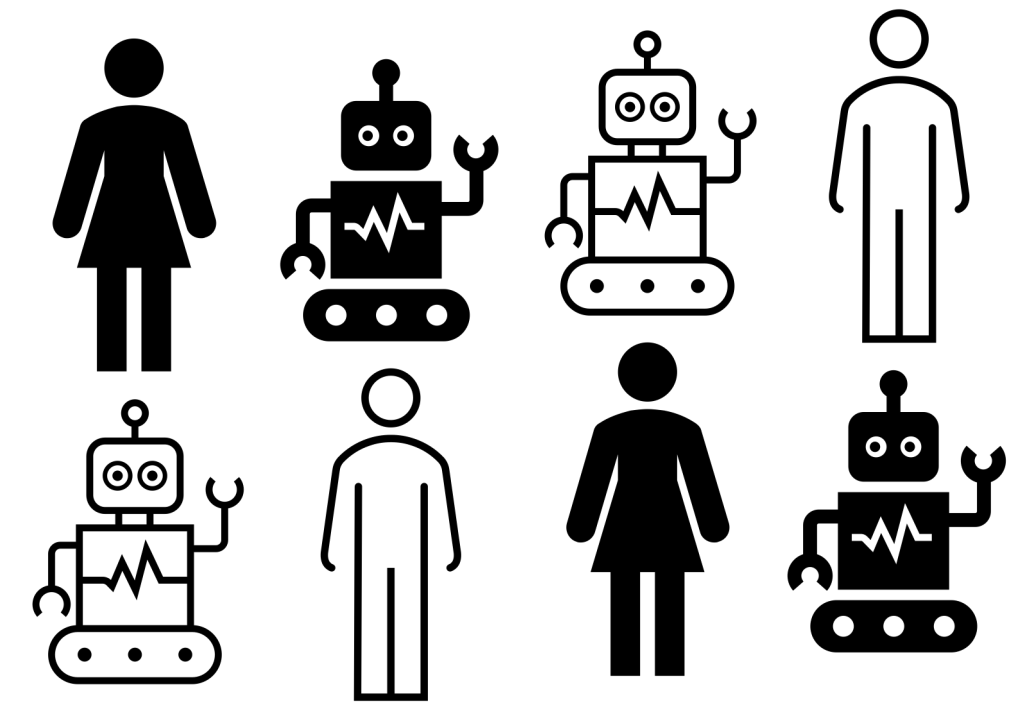


Davis-Pearson et al.,
under submission

Research Question 4: When is one type of help preferred?

- Teacher competence?
- Student capabilities?
- Speed of simulation?
- ...

Multi-agent, Multi-human Teaming



cogmentTM

The **first platform** to allow the design, training, and deployment of complex **intelligence ecosystems**, mixing **humans and artificial agents** of various kinds

It orchestrates heterogeneous ML & non-ML agents with real-time human interaction.



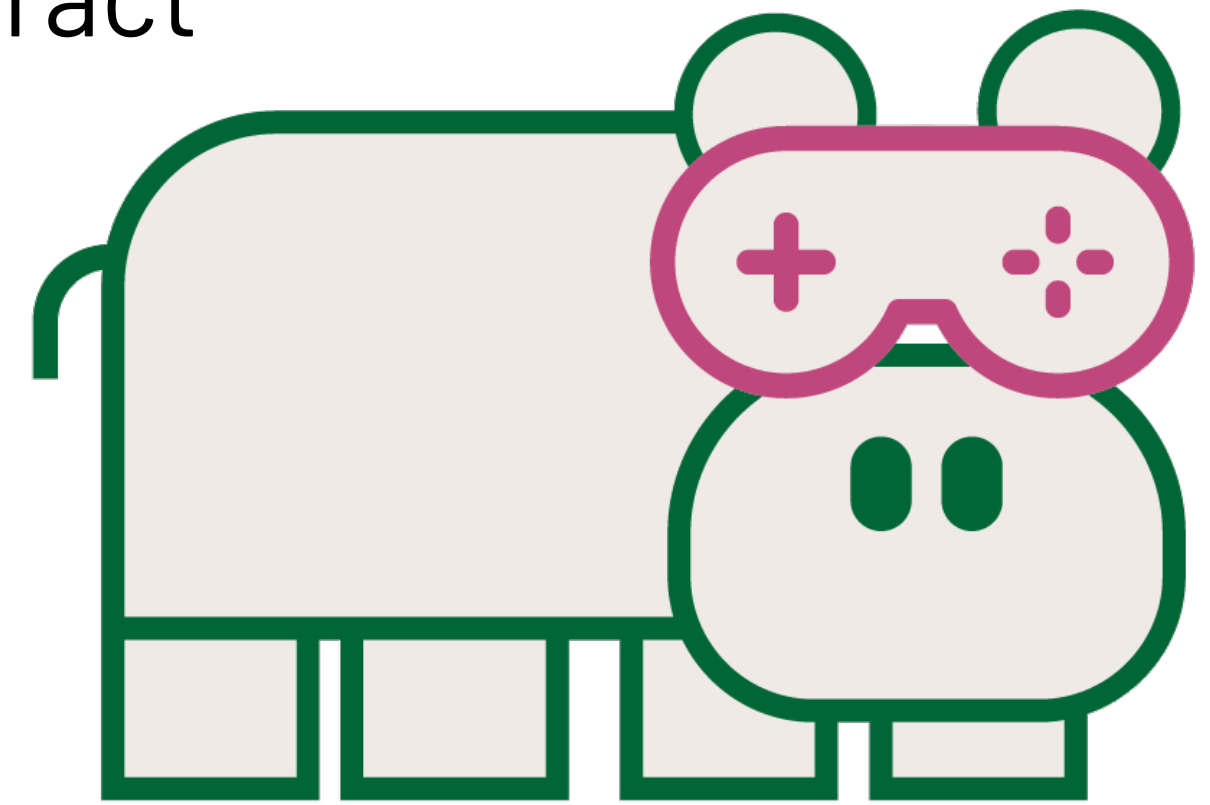
Human Input Parsing Platform for Openai Gym

In a **web browser**, human subjects can interact with Atari **games**, MuJuCo **robots**, etc.

- Give **demonstrations**
- Provide **feedback**
- Identify errors

Enable scaling up & out of HitL RL

- Built-in AWS support
- Integrate with MTurk



HIPPO GYM

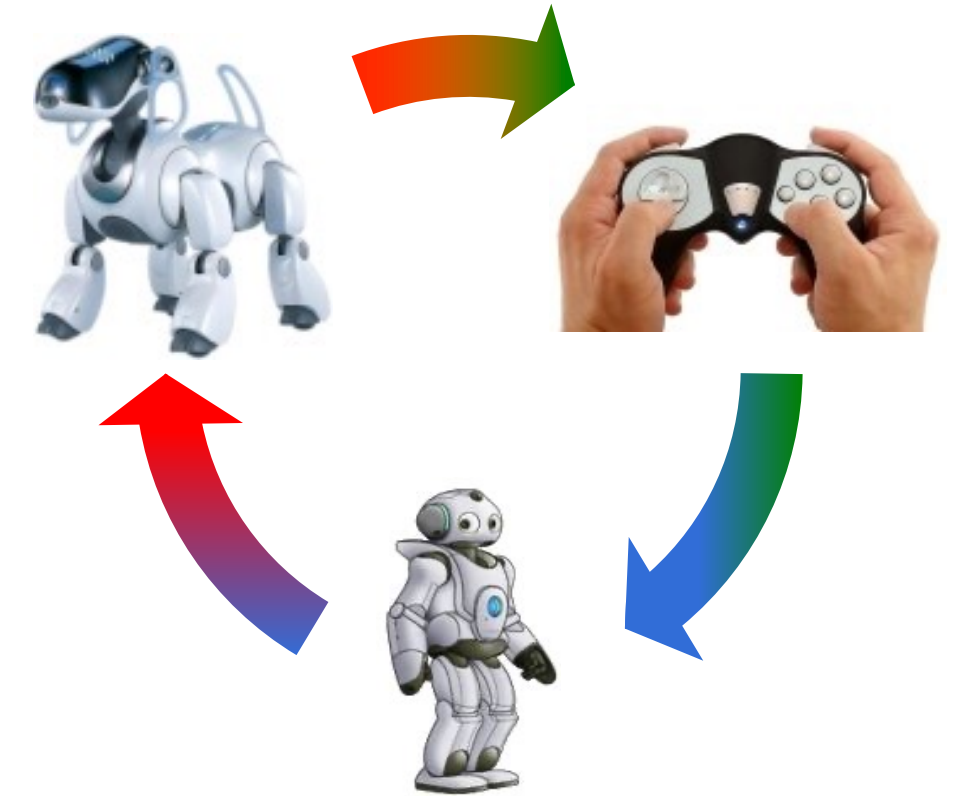
hippogym.irll.ca

Conclusion: Many more questions!

We should cheat whenever possible

Lots of room for improvement

- Learning from agents/data
- Learning from humans
- Teaching humans



**The Intelligent
Robot Learning
Laboratory**

<http://irll.ca>
<http://cogment.ai/>