Meta-Reinforcement Learning:

Learning to Explore

CS224R

Reminders

Homework 3 due **tonight**

(and HW4 out today)

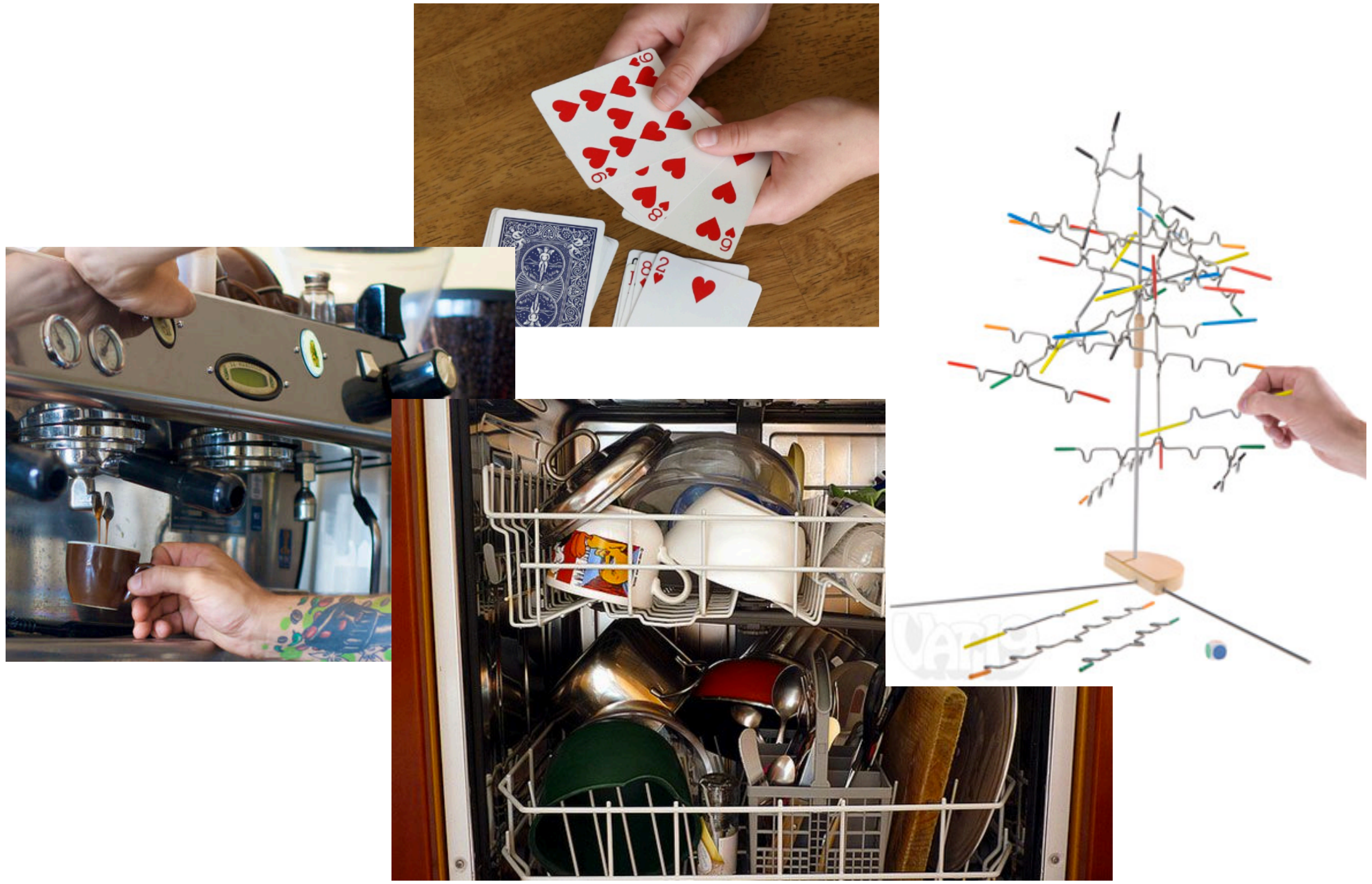
Project milestone due **next Wednesday**

Following up on high-res feedback:

- Wanting homeworks to require more conceptual understanding
- Request for summary table of approaches
- Unofficial lecture notes

Why meta-reinforcement learning?

Why are humans good at RL?



People have previous experience.

They have developed **representations** that facilitate exploration & learning.

Our RL agents start tabula rasa.

Can we allow RL agents to leverage prior experience?

Source: https://i.imgur.com/hJIVfZ5.jpg

Should we be using the same exploration algorithm for:

- Learning to navigate an environment
- Learning to make recommendations to users
- Learning a policy for computer system caching
- Learning to physically operate a new tool or machine

This is how we currently approach exploration.

Today's Lecture

Can we *learn exploration strategies* based on experience from other tasks in that domain?

Outline

Brief Recap on Meta-RL

Algorithms for Learning to Explore

End-to-End Optimization of Exploration Strategies

Alternative Decoupled Exploration Strategies

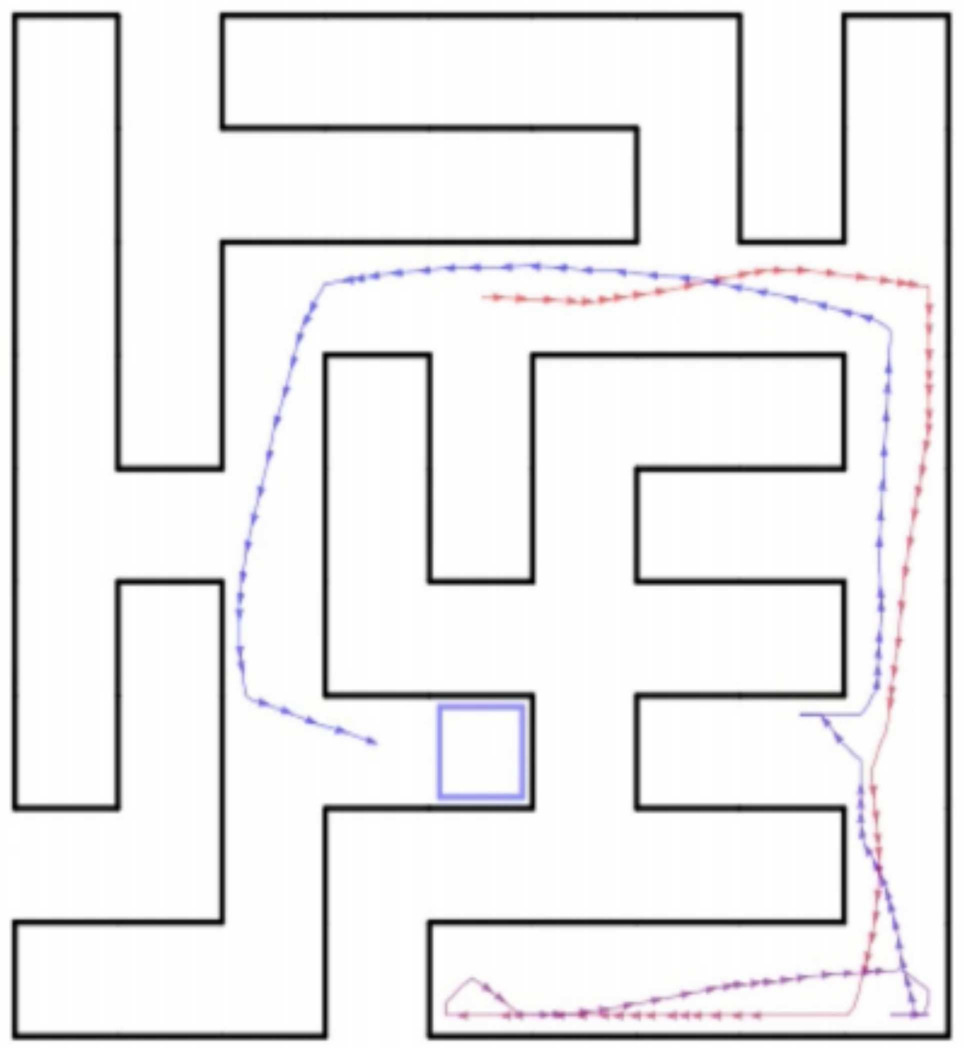
Decoupled but Consistent Exploration & Exploitation

Case Study: Applying Meta-RL to CS Education

A brief recap of meta-reinforcement learning

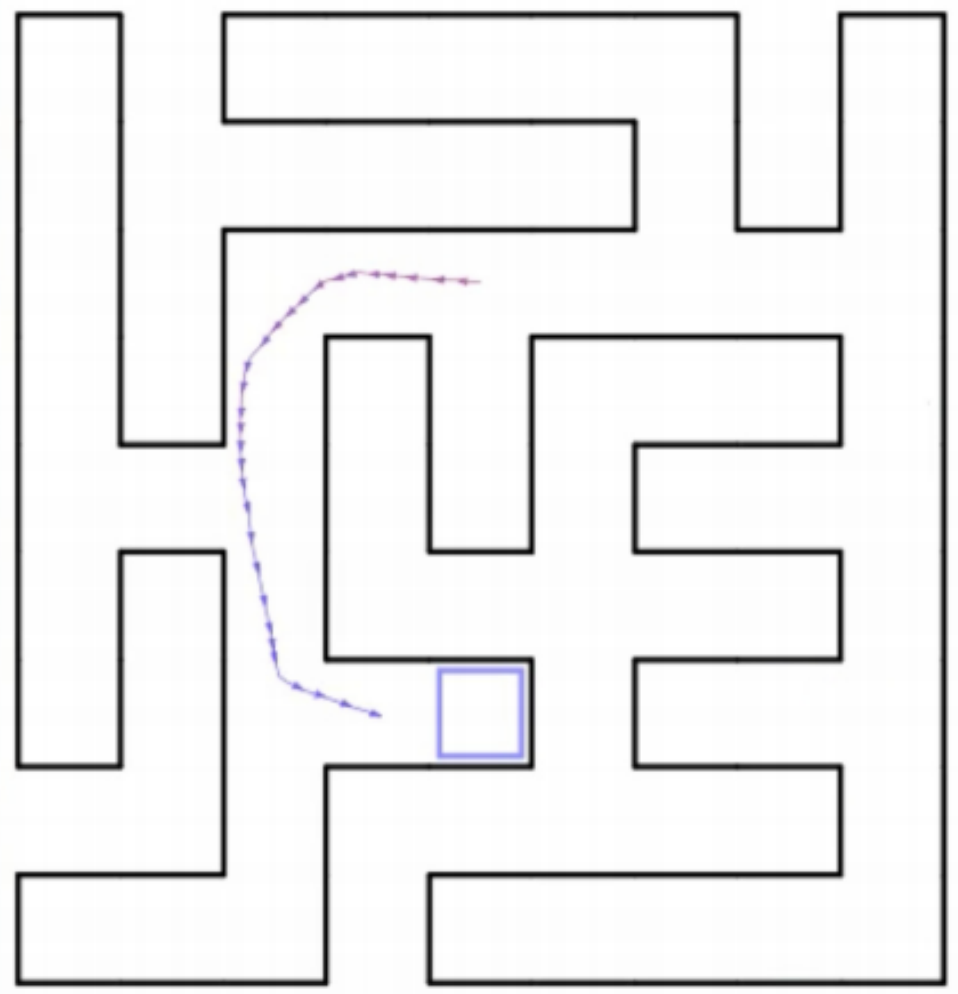
Goal:

Collect small amount of
experience in new MDP



Collect $\mathscr{D}_{\mathrm{tr}} \sim \pi^{\mathrm{exp}}$

Learn policy that
solves that MDP



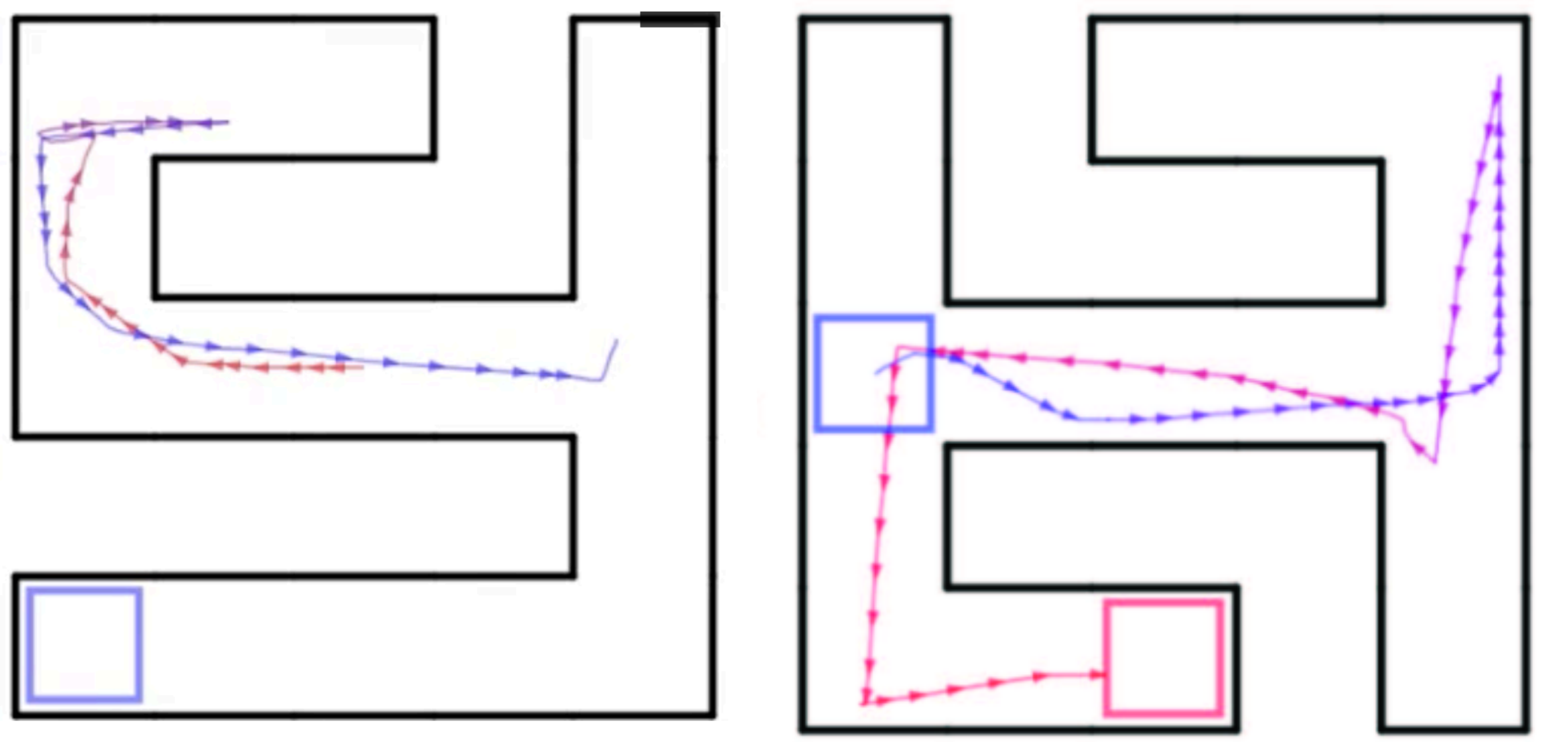
$\mathscr{D}_{\mathrm{tr}} \rightarrow \pi^{\mathrm{task}}$

diagram adapted from Duan et al. ‘17

A brief recap of meta-reinforcement learning

Meta-Train Time:

Learn how to efficiently explore & solve many MDPs:

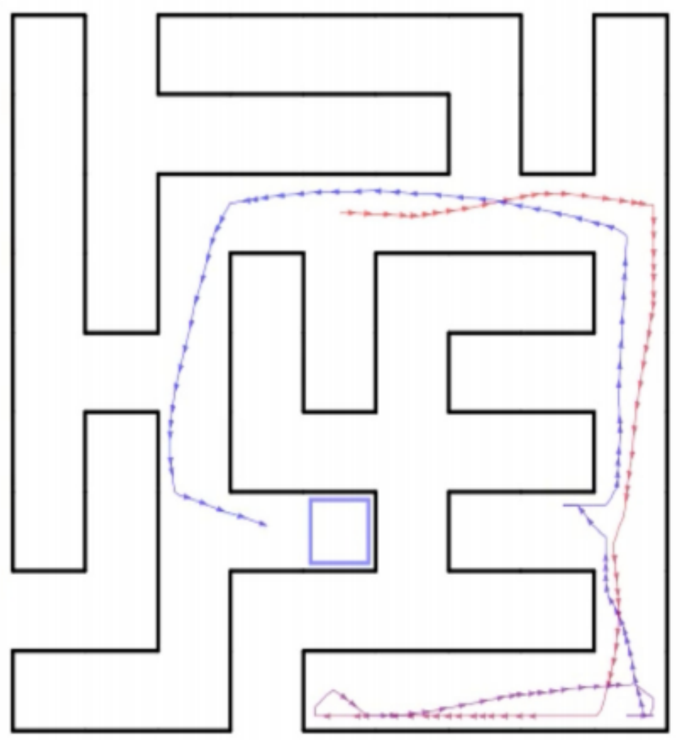


. . . meta-training tasks

Meta-train $\pi^{\text{exp}}, \pi^{\text{task}}$

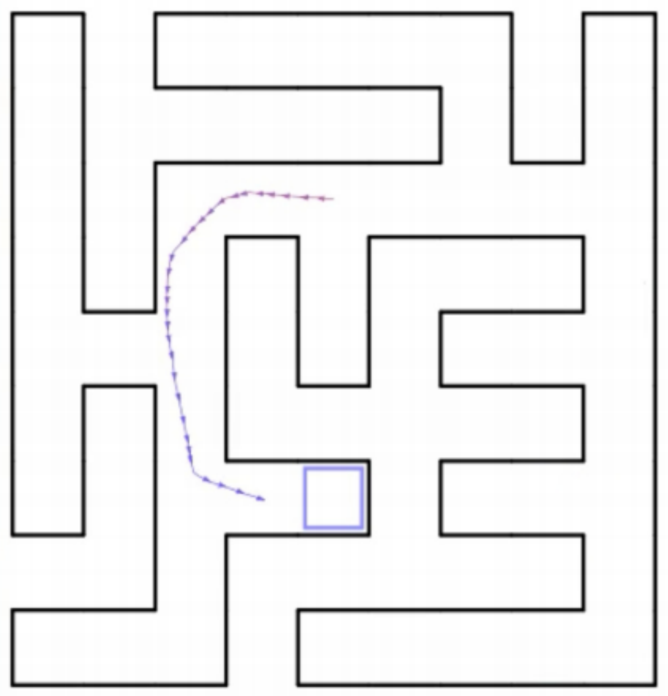
Meta-Test Time:

Collect small amount of experience in new MDP



Collect $\mathscr{D}_{\text{tr}} \sim \pi^{\text{exp}}$

Learn policy that solves that MDP



$\mathscr{D}_{\text{tr}} \rightarrow \pi^{\text{task}}$

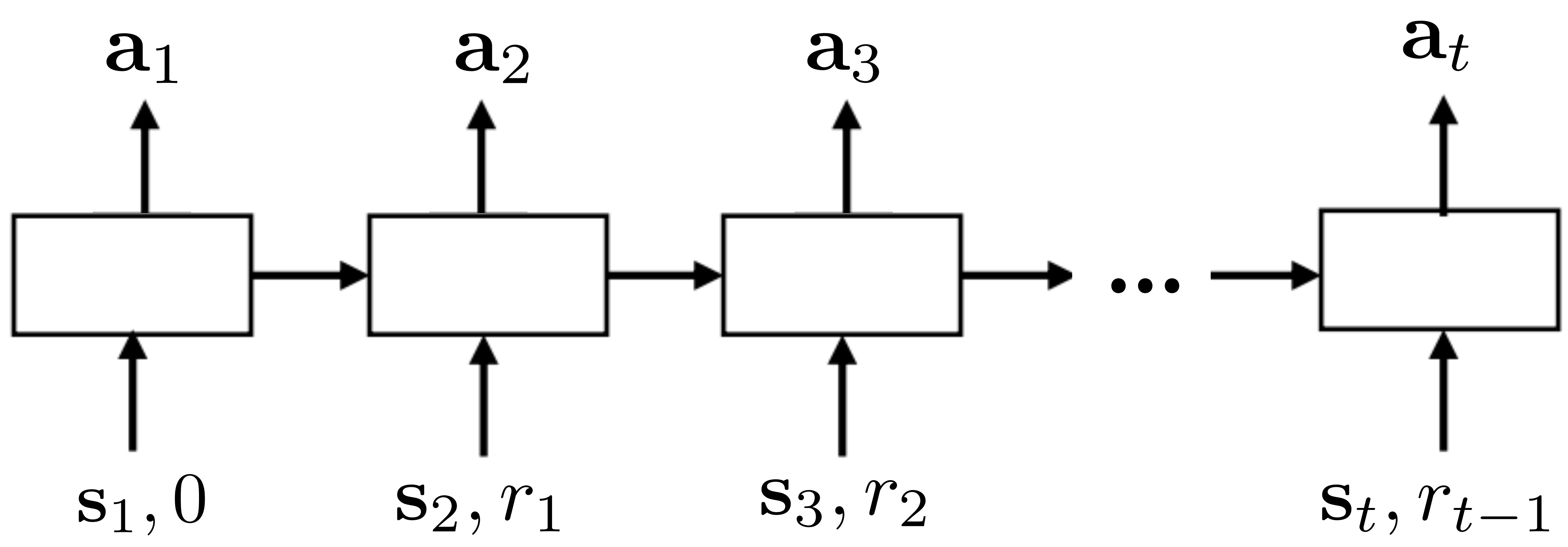
Key assumption: Meta-training & meta-testing MDPs come from same distribution.

(so that we can expect generalization)

diagram adapted from Duan et al. ‘17

A brief recap of meta-reinforcement learning

Common approach: Implement the learning procedure with a recurrent network.



Is this just a recurrent policy?

Hidden state maintained *across episodes* within a task!

Trained across a *family of MDPs* with varying dynamics, rewards.

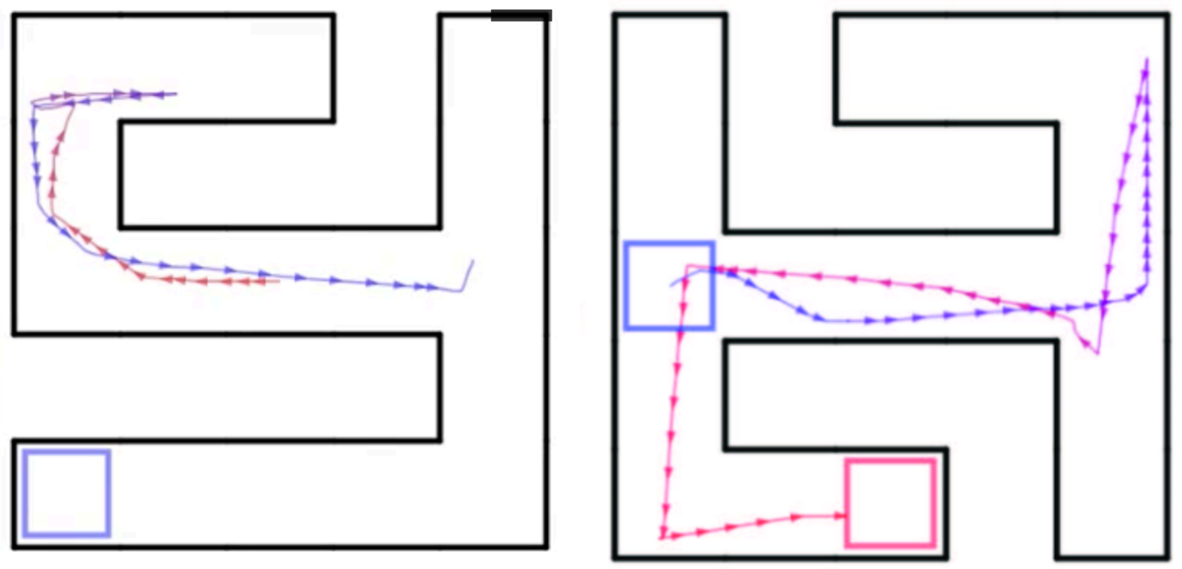
RL[2] with Policy Gradients: $$\nabla_\theta J(\theta) = E_{\tau\sim\pi_\theta,\mathcal{T}_i}\left[\left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t, \mathcal{D}_i^{\text{tr}})\right)\left(\sum_t r_i(\mathbf{s}_t,\mathbf{a}_t)\right)\right]$$

Wang et al. Learning to Reinforcement Learn. 2017; Duan et al. RL[2]. 2017

A brief recap of meta-reinforcement learning

Examples of meta-RL tasks

Navigation through different mazes

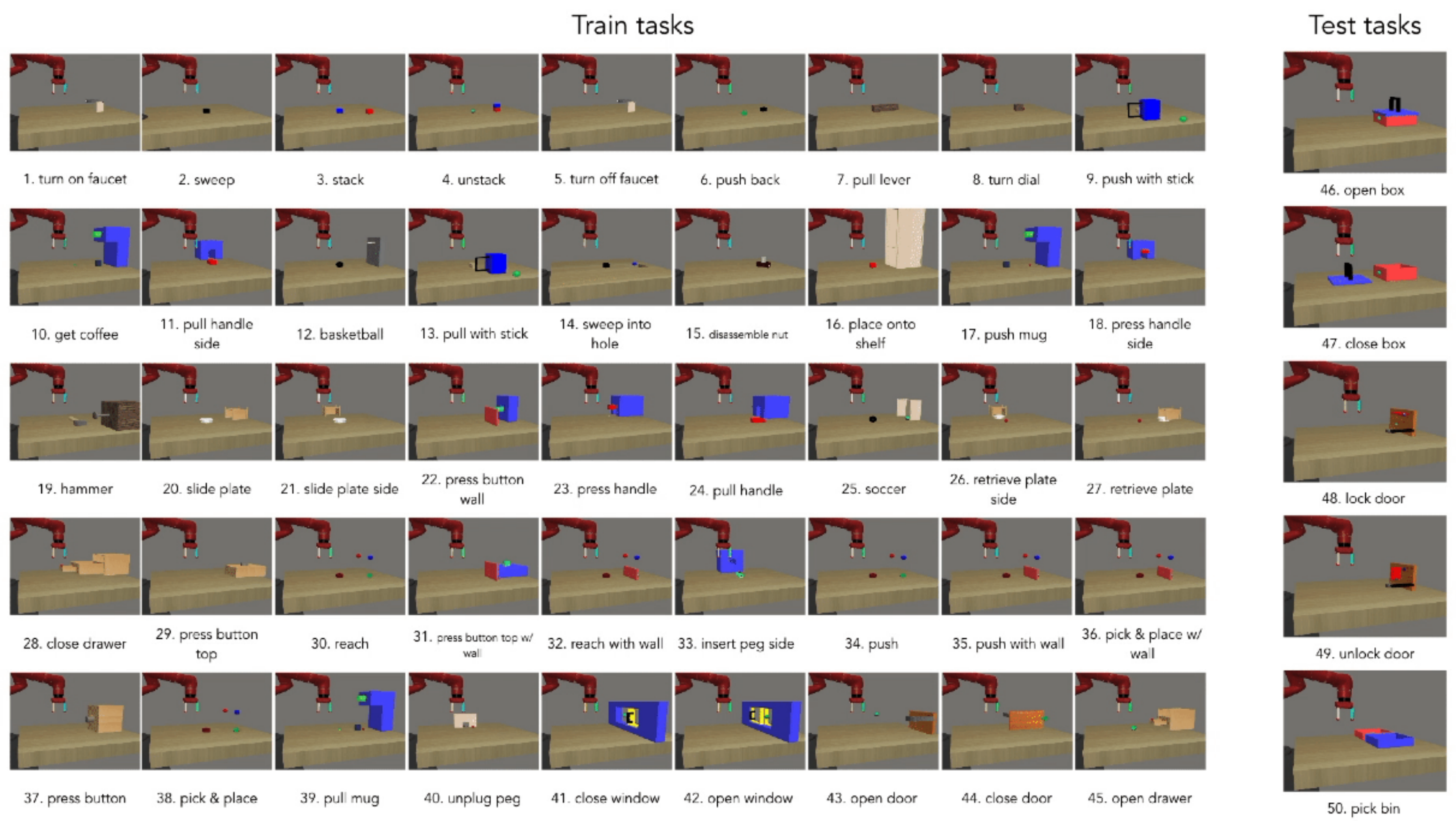


. . .

Locomotion on different terrains, slopes

. . .

Object manipulation with different objects, goals



Dialog with different users w/ different preferences

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How Do We Learn to Explore?

Solution #1: Optimize for Exploration & Exploitation *End-to-End* w.r.t. Reward

(Duan et al., 2016, Wang et al., 2016, Mishra et al., 2017, Stadie et al., 2018, Zintgraf et al., 2019, Kamienny et al., 2020)

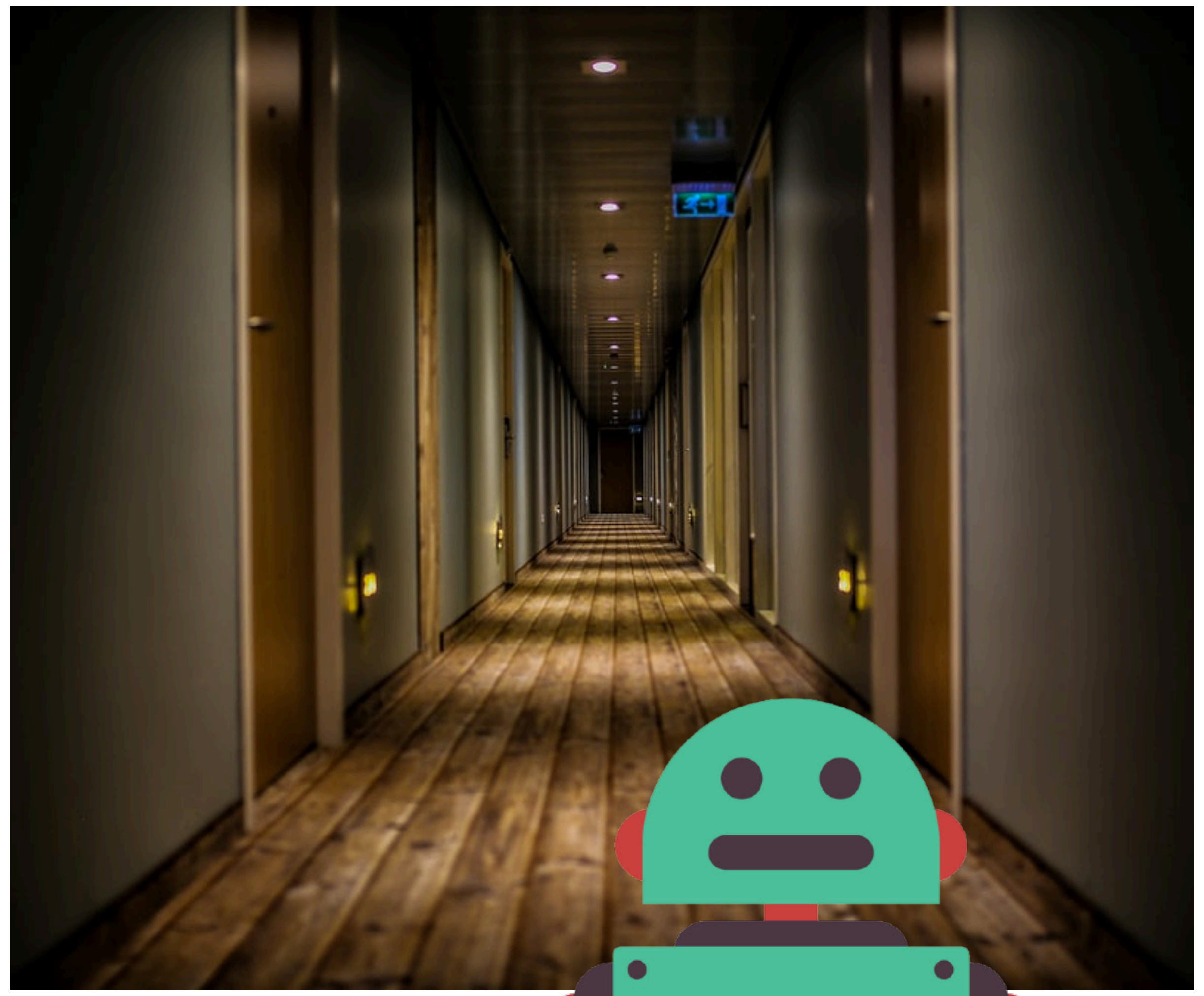
+ simple
+ leads to optimal strategy in principle

-- challenging optimization when exploration is hard

A simple, running example

Hallway 1

Hallway 2



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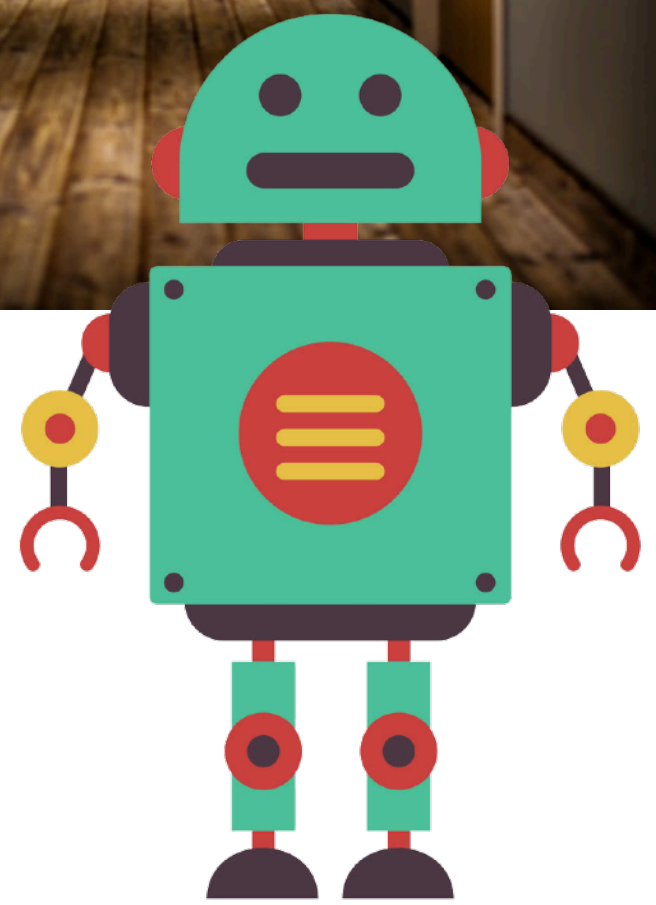
Hallway N



agent

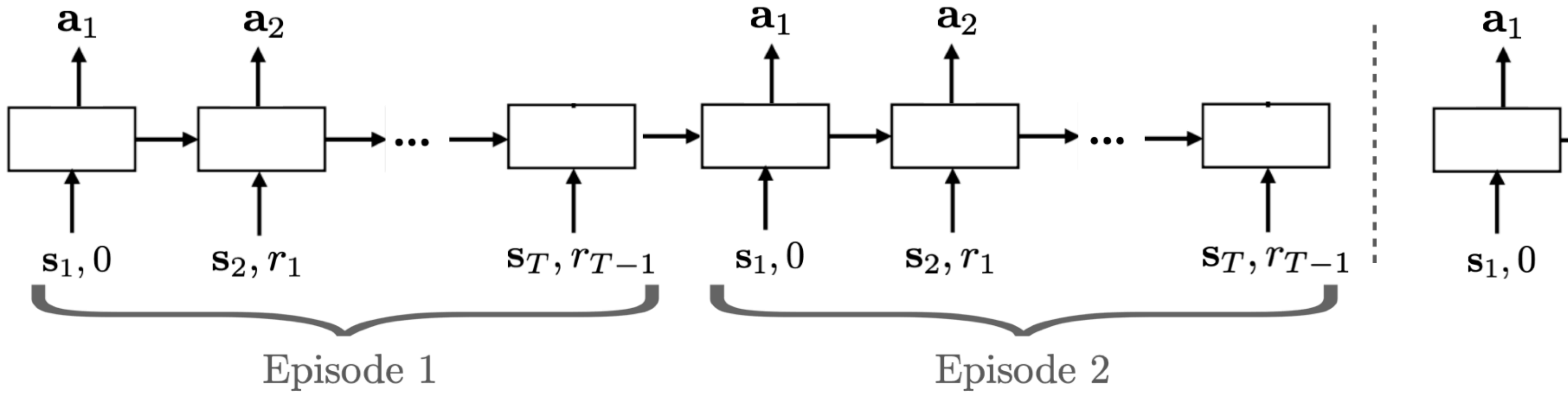
information on where to go

Different tasks: navigating to the ends of different hallways

How Do We Learn to Explore?

Solution #1: Optimize for Exploration & Exploitation *End-to-End* w.r.t. Task Reward

(Duan et al., 2016, Wang et al., 2016, Mishra et al., 2017, Stadie et al., 2018, Zintgraf et al., 2019, Kamienny et al., 2020)



Example episodes during meta-training:

agent goes to the end of the correct hallway

- gets positive reward for current task, but $\mathcal{D}_i^{\text{tr}}$ won't be different than for any other task

agent goes to wrong hallway then correct hallway

+/- provides signal on a **suboptimal** exploration + exploitation strategy

agent looks at the instructions

- good exploratory behavior, but won't get any reward for this behavior

It's hard to learn exploration & exploitation at the same time!

Another Example of a Hard Exploration Meta-RL Problem

Learned cooking tasks in previous kitchens

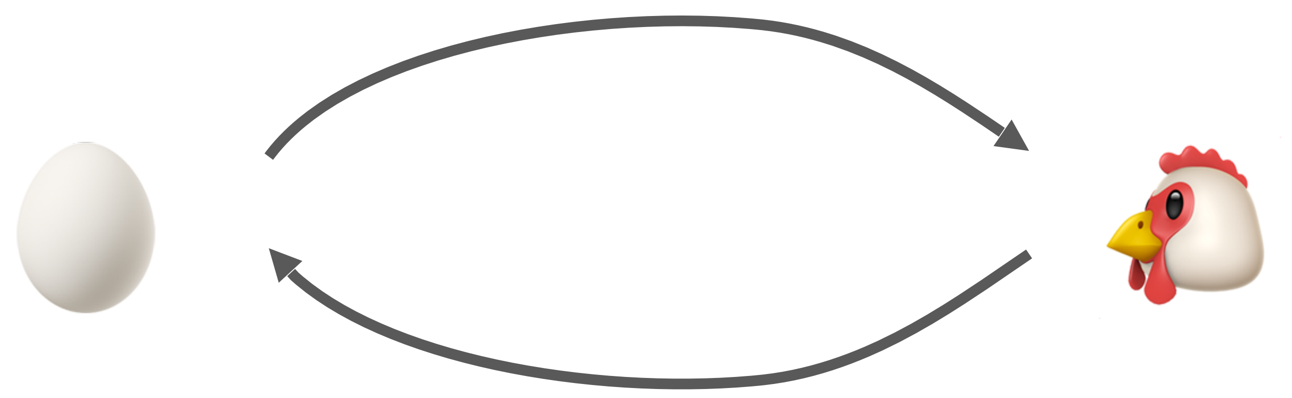
meta-training

Goal: Quickly learn tasks in a new kitchen.

meta-testing

Why is End-to-End Training Hard in This Example?

End-to-end approach: optimize exploration and execution episode behaviors end-to-end to maximize reward of execution



Learning to cook (execution)

Learning to find ingredients (exploration)

Ingredient not found (bad exploration) → Cannot learn to cook (bad execution)

Cannot cook (bad execution) → Low reward for **any** exploration

Coupling problem: learning exploration and execution depend on each other

—> can lead to poor local optima, poor sample efficiency

Liu, Raghunathan, Liang, Finn. ***Decoupling Exploration and Exploitation for Meta-Reinforcement Learning without Sacrifices***. ICML 2021

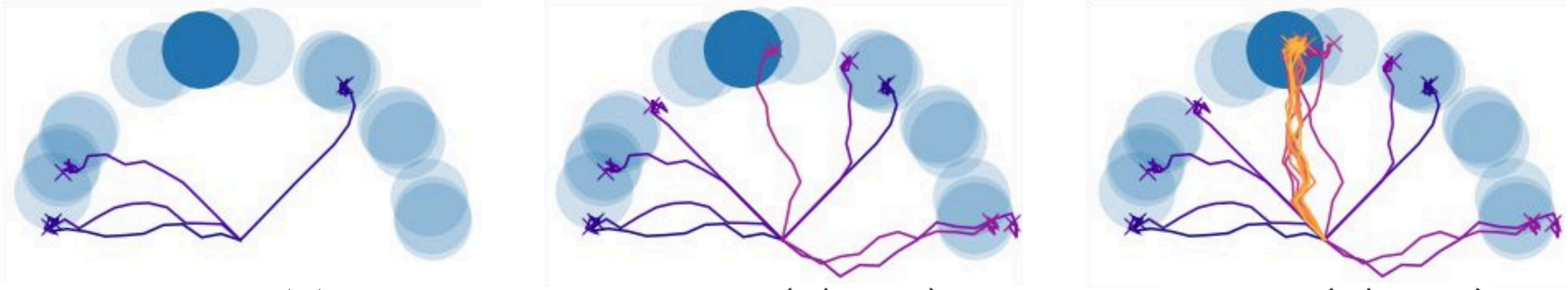
Solution #2: Leverage Alternative Exploration Strategies

2a. Use posterior sampling
(also called Thompson sampling)

PEARL (Rakelly, Zhou, Quillen, Finn, Levine. ICML '19)

i. Learn distribution over latent task variable $p(\mathbf{z}), q(\mathbf{z} \mid \mathscr{D}_{\text{tr}})$ and corresponding task policies $\pi(\mathbf{a} \mid \mathbf{s}, \mathbf{z})$

ii. Sample $\mathbf{z}$ from current *posterior* and sample from policy $\pi(\mathbf{a} \mid \mathbf{s}, \mathbf{z})$



$\mathbf{z} \sim p(\mathbf{z})$ $\qquad$ $\mathbf{z} \sim q_\phi(\mathbf{z}|c_{1:10})$ $\qquad$ $\mathbf{z} \sim q_\phi(\mathbf{z}|c_{1:30})$

When might posterior sampling be bad? Eg. Goals far away & sign on wall that tells you the correct goal.

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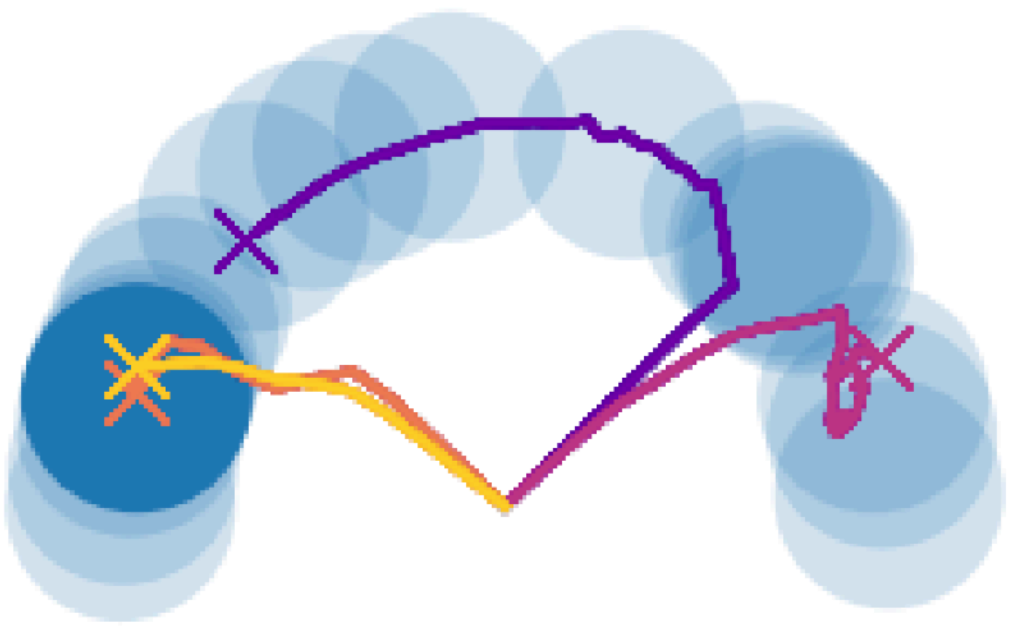
2b. Use intrinsic rewards — MAME (Gurumurthy, Kumar, Sycara. CoRL '19)

2c. Task dynamics & reward prediction — MetaCURE (Zhang, Wang, Hu, Chen, Fan, Zhang. '20)

i. Train model $f(\mathbf{s}', r | \mathbf{s}, \mathbf{a}, \mathcal{D}_{\text{train}})$

ii. Collect $\mathcal{D}_{\text{train}}$ so that model is accurate.



When might this be bad?

Lots of distractors,
or complex, high-dim state dynamics

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\+ easy to optimize

\+ many based on principled strategies

-- suboptimal by arbitrarily large amount in some environments.

Can we avoid the chicken-and-egg problem without sacrificing optimality?

(best of both worlds?)

Yes!

Solution #3

Idea from solution #2b: Train model $f(\mathbf{s}', r \mid \mathbf{s}, \mathbf{a}, \mathcal{D}_{\text{tr}})$ & collect $\mathcal{D}_{\text{tr}}$ so that model is accurate.

Do we have to learn a *full dynamics & reward model*?

Idea 3.0: Label each training task with a unique ID μ

Meta training

Exploration policy: train policy $\pi^{\text{exp}}(\mathbf{a} \mid \mathbf{s})$ and task identification model $q(\mu \mid \mathcal{D}_{\text{tr}})$

such that $\mathcal{D}_{\text{tr}} \sim \pi^{\text{exp}}$ allows accurate task prediction from f

Execution policy: train ID-conditioned policy $\pi^{\text{exec}}(\mathbf{a} \mid \mathbf{s}, \mu_i)$

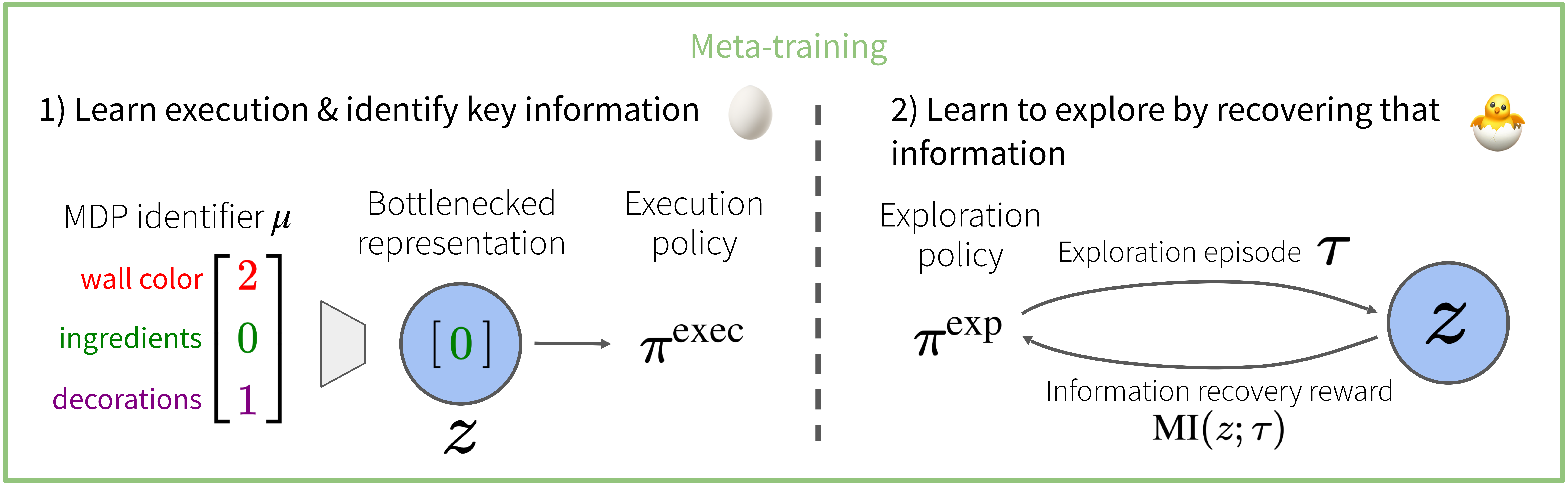
Meta testing

Explore: $\mathcal{D}_{\text{tr}} \sim \pi^{\text{exp}}(\mathbf{a} \mid \mathbf{s})$ Infer task: $\hat{\mu} \sim q(\mu \mid \mathcal{D}_{\text{tr}})$ Perform task: $\pi^{\text{exec}}(\mathbf{a} \mid \mathbf{s}, \hat{\mu})$

+ no longer need to model dynamics, rewards

— may not generalize well for one-hot μ

Solution #3: Decouple by acquiring representation of task relevant information



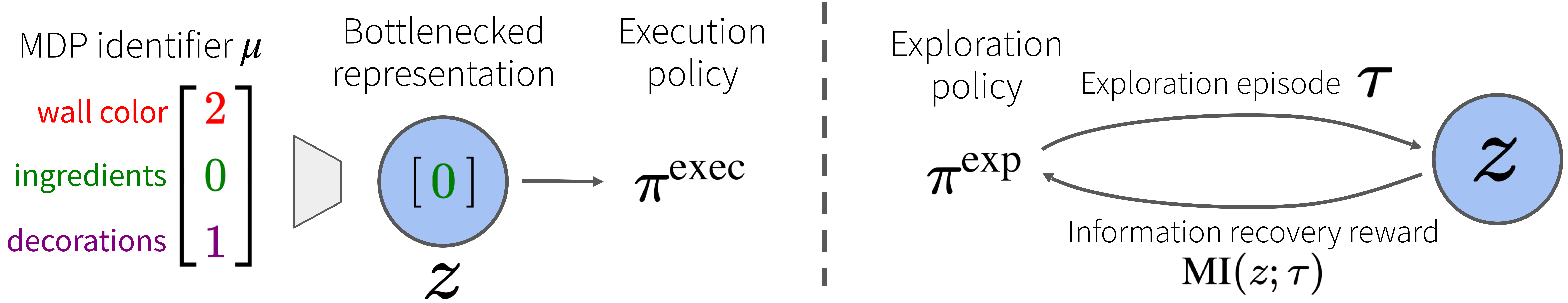
Liu, Raghunathan, Liang, Finn. *Decoupling Exploration and Exploitation for Meta-Reinforcement Learning without Sacrifices*. ICML 2021

Solution #3: Decouple by acquiring representation of task relevant information

Meta-training

1) Learn execution & identify key information

2) Learn to explore by recovering that information



Train $\pi^{\text{exec}}(\mathbf{a} \,|\, \mathbf{s}, z_i)$ and encoder $F(z_i \,|\, \mu_i)$ to:

$$\max \sum_i \mathbb{E}_{\pi^{\text{exec}}}[r_i] - D_{\text{KL}}\left(F(z_i|\mu_i) \| \mathcal{N}(0,1)\right)$$

Train π^{exp} such that collected $\mathscr{D}_{\text{tr}}$ is predictive of z_i.

In practice: (1) and (2) can be trained simultaneously.

Liu, Raghunathan, Liang, Finn. *Decoupling Exploration and Exploitation for Meta-Reinforcement Learning without Sacrifices*. ICML 2021

Solution #3: Decouple by acquiring representation of task relevant information

Meta-training

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Train π^{exp} such that collected $\mathcal{D}_{\text{tr}}$ is predictive of z_i.

How to formulate the *reward function* for π^{exp}?

(a) Train model $q(z_i \mid \mathcal{D}_{\text{tr}})$ (b) r_t = per-step information gain

$$r_t = \text{prediction error from } \tau_{1:t-1} - \text{prediction error from } \tau_{1:t}$$

Decoupled **R**eward-free **E**xplor**A**tion and Execution in **M**eta-Reinforcement Learning (DREAM)

Liu, Raghunathan, Liang, Finn. *Decoupling Exploration and Exploitation for Meta-Reinforcement Learning without Sacrifices*. ICML 2021

Aside: How can we bottleneck the information in a neural net's representation?

V0: Add noise the representation.

$\epsilon \sim \mathcal{N}(0,I) \quad \bar{\mathbf{z}} = \mathbf{z} + \epsilon$

+ will discard information 😊

- if done at test time, my discard good info

- if done during training, model can increase magnitude of $\mathbf{z}$

Key ideas:

1. Add Gaussian noise during training
2. Prevent the model from increasing magnitude

V1: Variational information bottleneck

Add noise before passing representation to next layer: $\epsilon \sim \mathcal{N}(0,I) \quad \bar{\mathbf{z}} = \mathbf{z} + \epsilon$

Modify loss term:

$$L_{\text{tr}} + ||\mathbf{z}||^2$$

-> equivalent to $D_{KL}\left(F(z \mid \mu_i) || \mathcal{N}(0,1)\right)$.

Alemi, Fischer, Dillon, Murphy. ***Deep Variational Information Bottleneck***. ICLR 2017.

Solution #3: Decouple by acquiring representation of task relevant information

(Informal) Theoretical Analysis

(1) DREAM objective is ***consistent*** with end-to-end optimization. [under mild assumptions]

-> can in principle recover the optimal exploration strategy

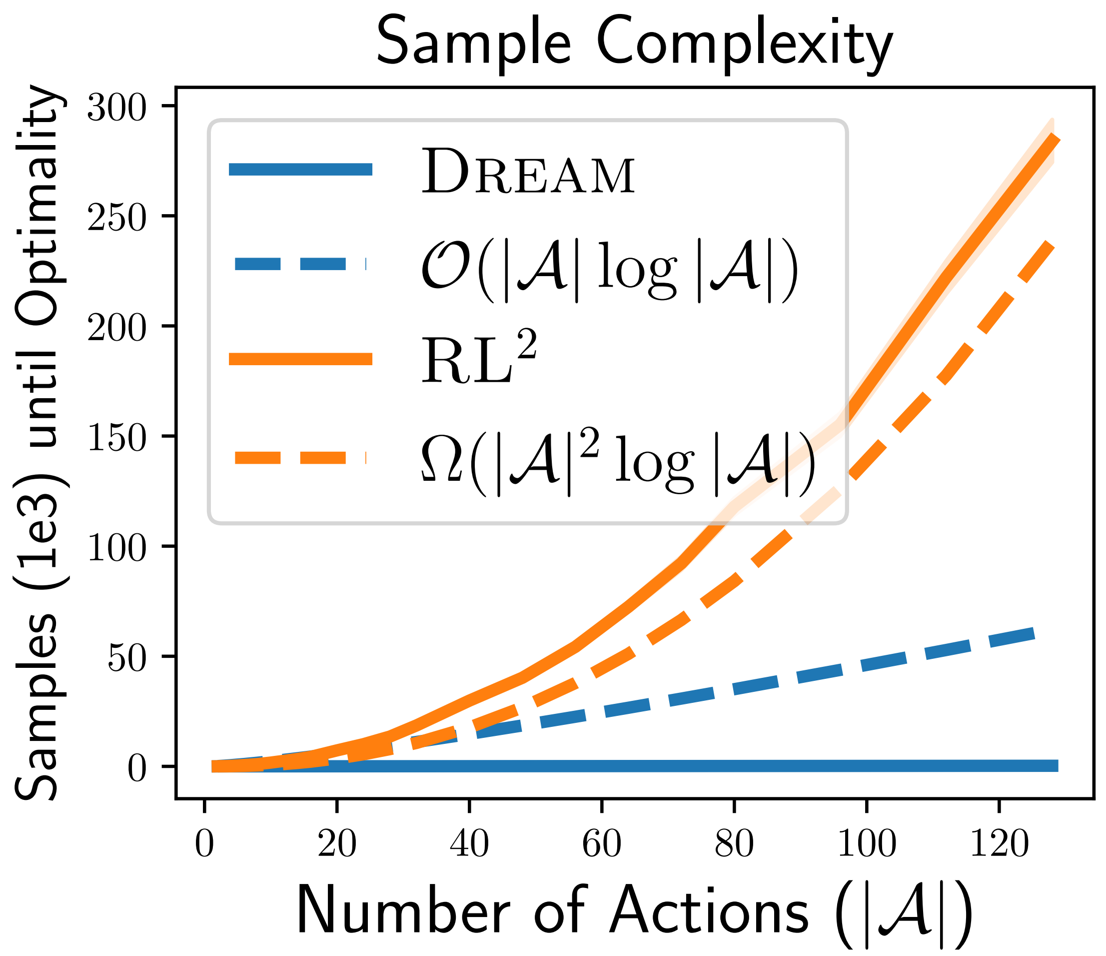
(2) Consider a bandit-like setting with $|\mathcal{A}|$ arms.

In MDP i, arm i yields reward. In all MDPs, arm 0 reveals the rewarding arm.

RL² requires $\Omega(|\mathcal{A}|^2 \log |\mathcal{A}|)$ samples for meta-optimization.

DREAM requires $\mathcal{O}(|\mathcal{A}| \log |\mathcal{A}|)$ samples for meta-optimization.

[assuming Q-learning with uniform outer-loop exploration]



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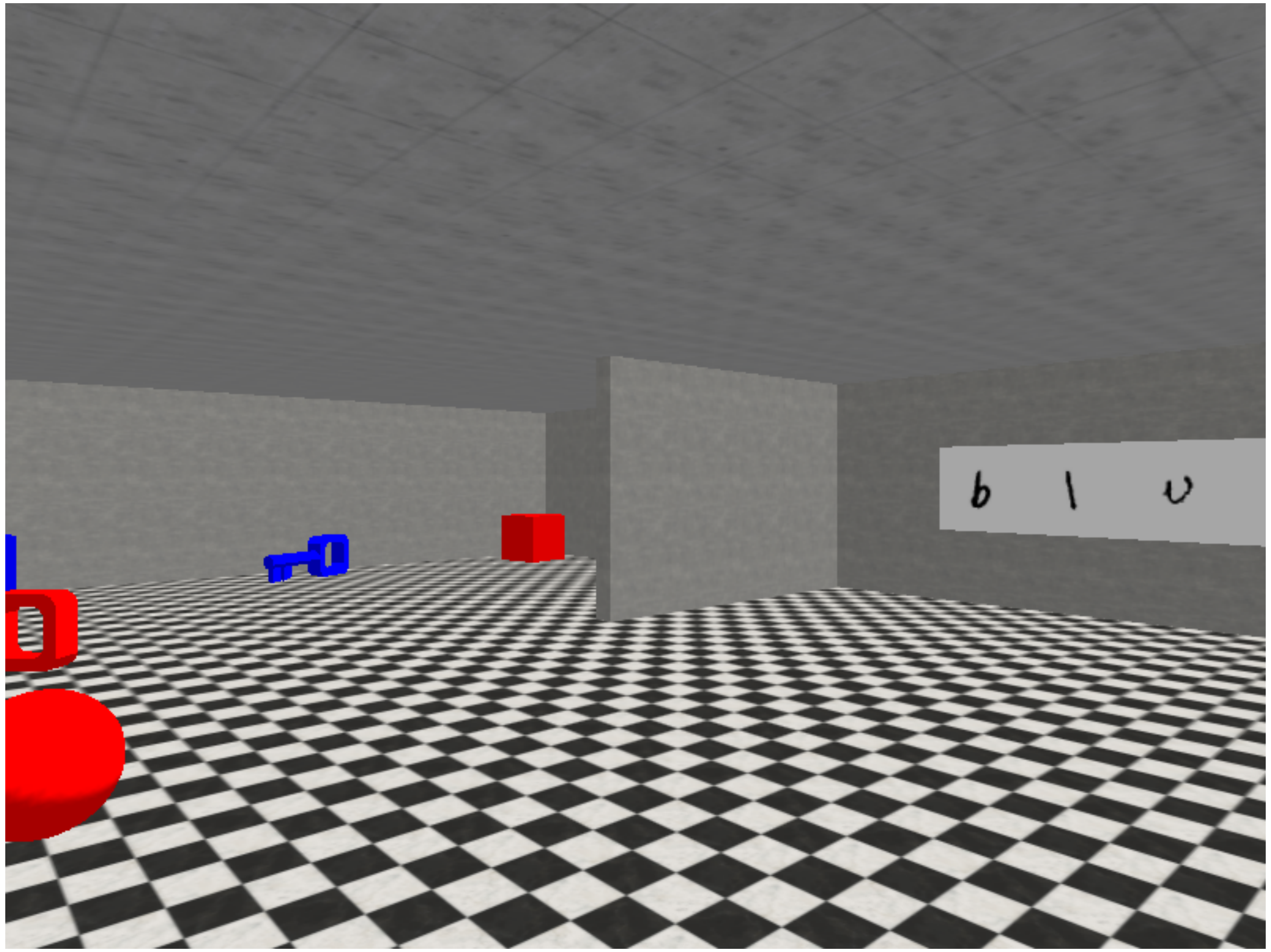
Empirical Comparison: Sparse Reward 3D Visual Navigation Problem

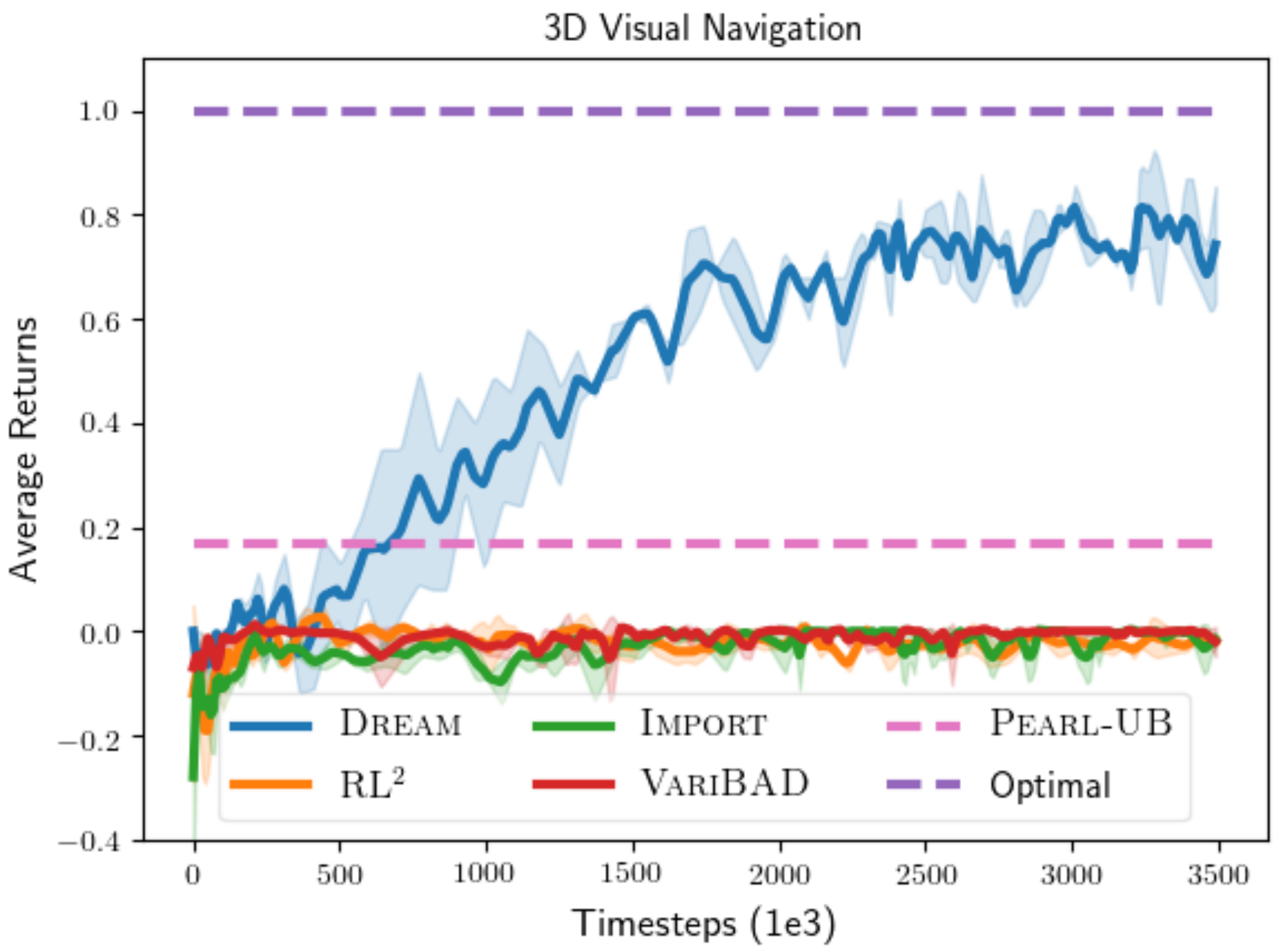


More challenging variant of task from Kamienny et al., 2020

- Task: go to the (key / block / ball), color specified by the sign
- Agent starts on other side of barrier, must walk around to read the sign
- Pixels observations (80 x 60 RGB)
- Sparse binary reward

Liu, Raghunathan, Liang, Finn. ***Explore then Execute: Adapting without Rewards via Factorized Meta-RL***. ICML 2021

Quantitative Comparison



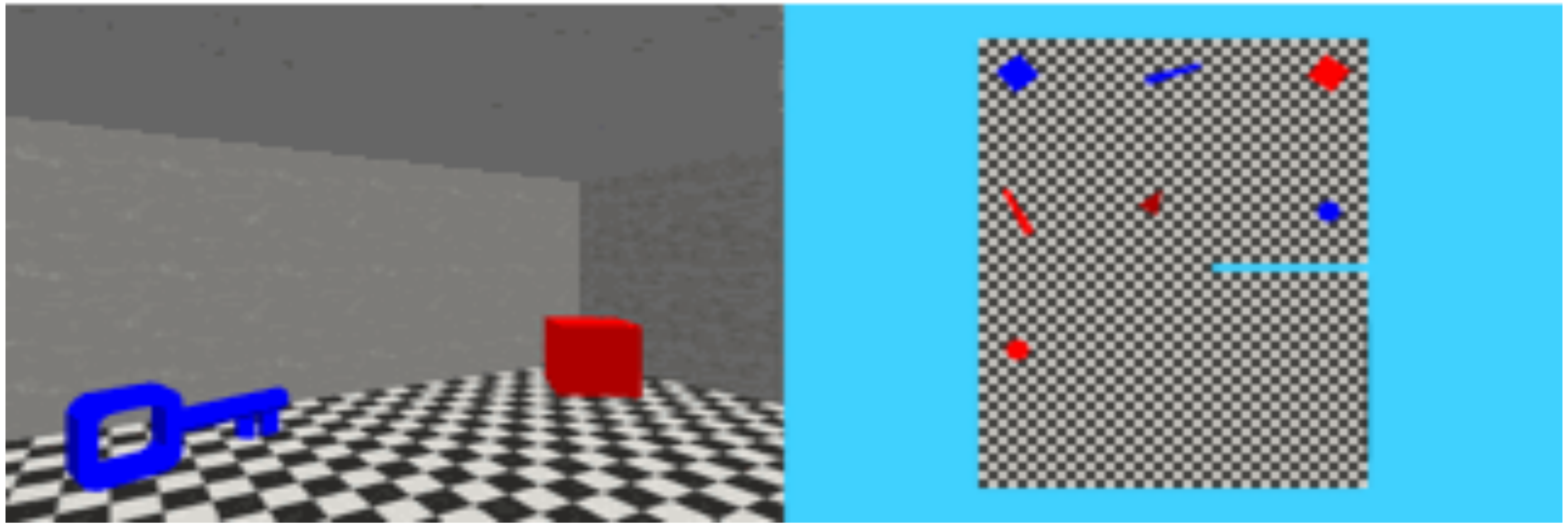
- End-to-end algorithms (RL²,IMPORT, VARIBAD) perform poorly due to **coupling**
- PEARL-UB: Upper-bound on PEARL: optimal policy and Thompson-Sampling exploration, does not learn the optimal exploration strategy
- DREAM achieves near-optimal reward

RL² (Duan et al., 2016), IMPORT (Kamienny et al., 2020), VARIBAD (Zintgraf et al., 2019), PEARL (Rakelly, et. al., 2019), Thompson, 1933

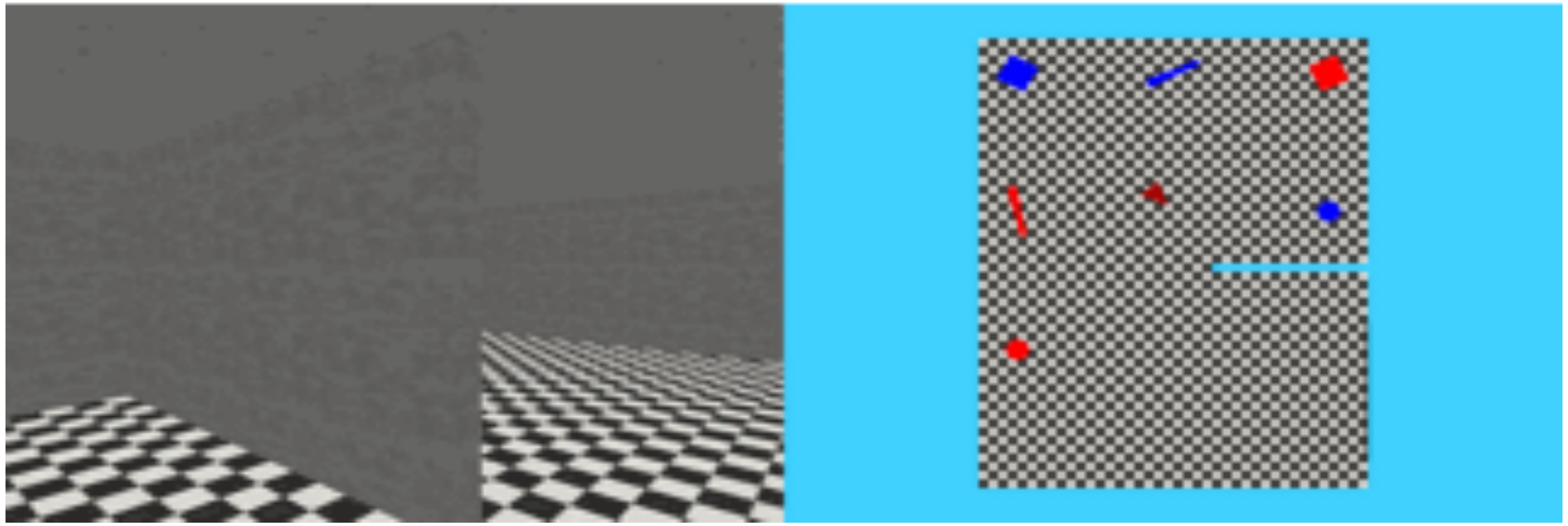
Liu, Raghunathan, Liang, Finn. *Explore then Execute: Adapting without Rewards via Factorized Meta-RL*. ICML 2021

Qualitative Results for DREAM

Exploration episode



Execution episode
Goal: Go to key



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End-to-End

+ leads to optimal strategy in principle

-- challenging optimization when exploration is hard

Alternative Strategies

+ easy to optimize
+ many based on principled strategies

-- suboptimal by arbitrarily large amount in some environments.

Decoupled Exploration & Execution

+ leads to optimal strategy in principle
+ easy to optimize in practice

-- requires task identifier

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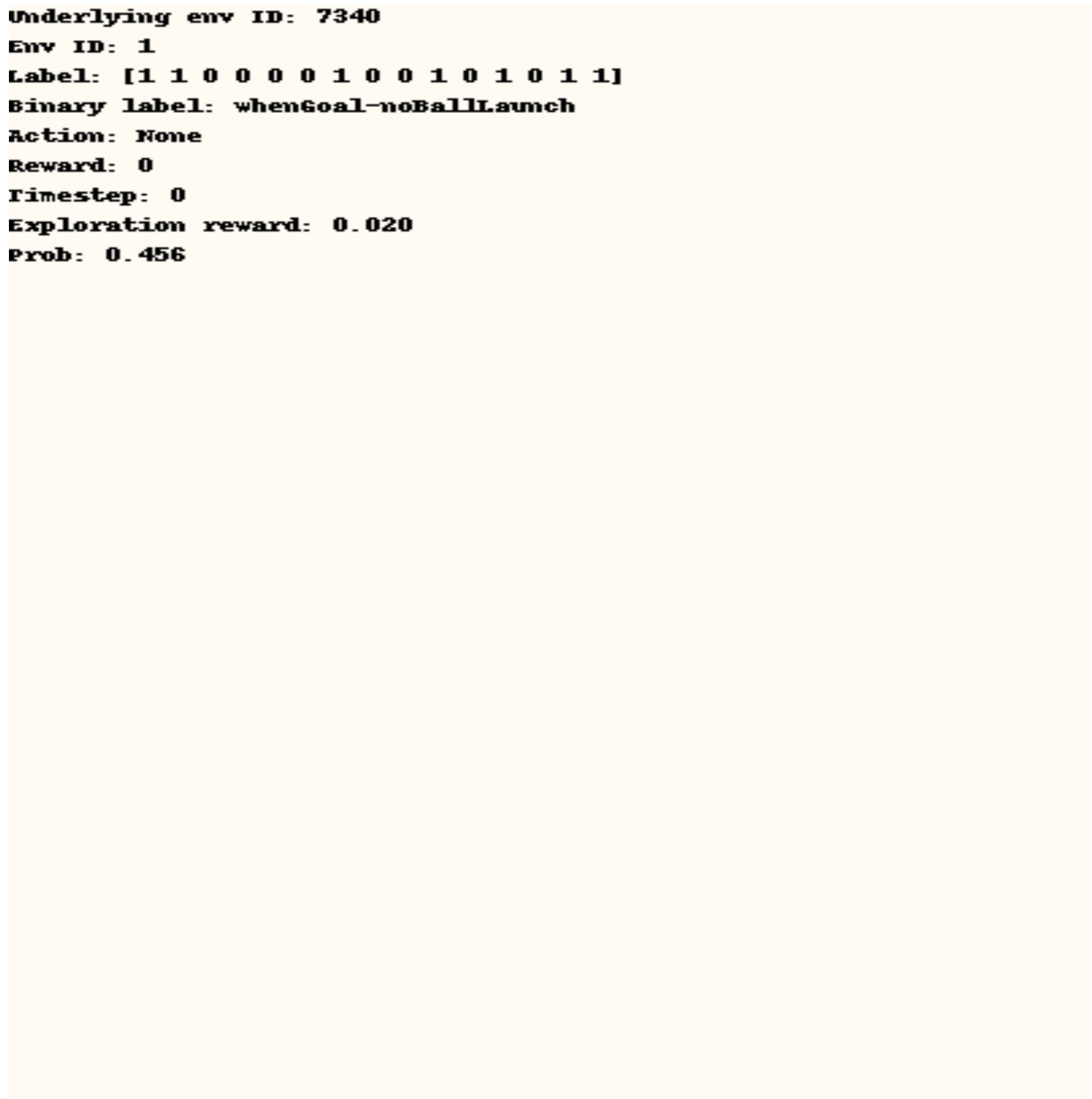
Case Study: Applying Meta-RL to CS Education

Problem: Providing Feedback on Interactive Software

Common CS assignment: **interactive software**



Bounce assignment
(Code.org)

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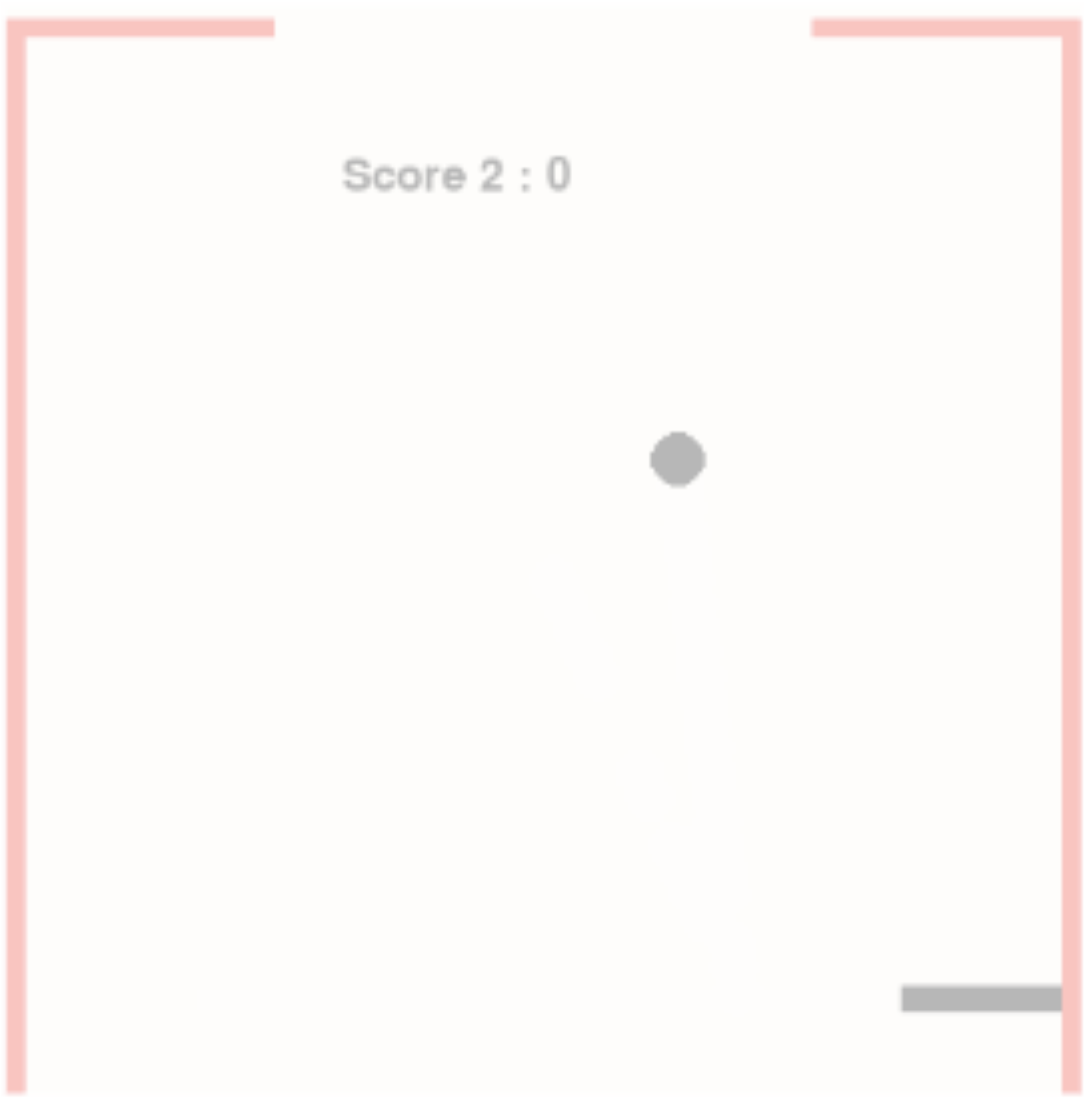

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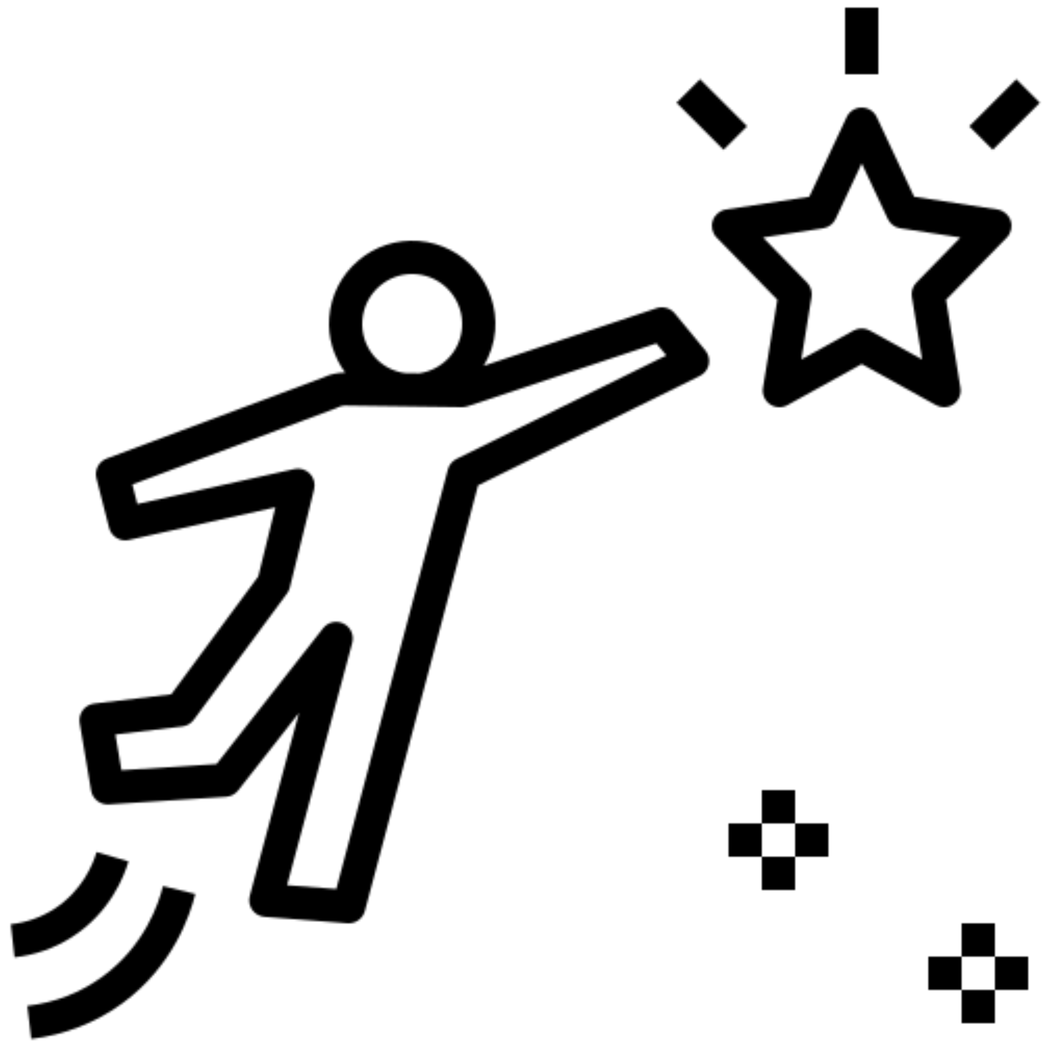

Motivating and engaging (fun!)
⇒ can enrich learning (Pfaffman et al., 2003)

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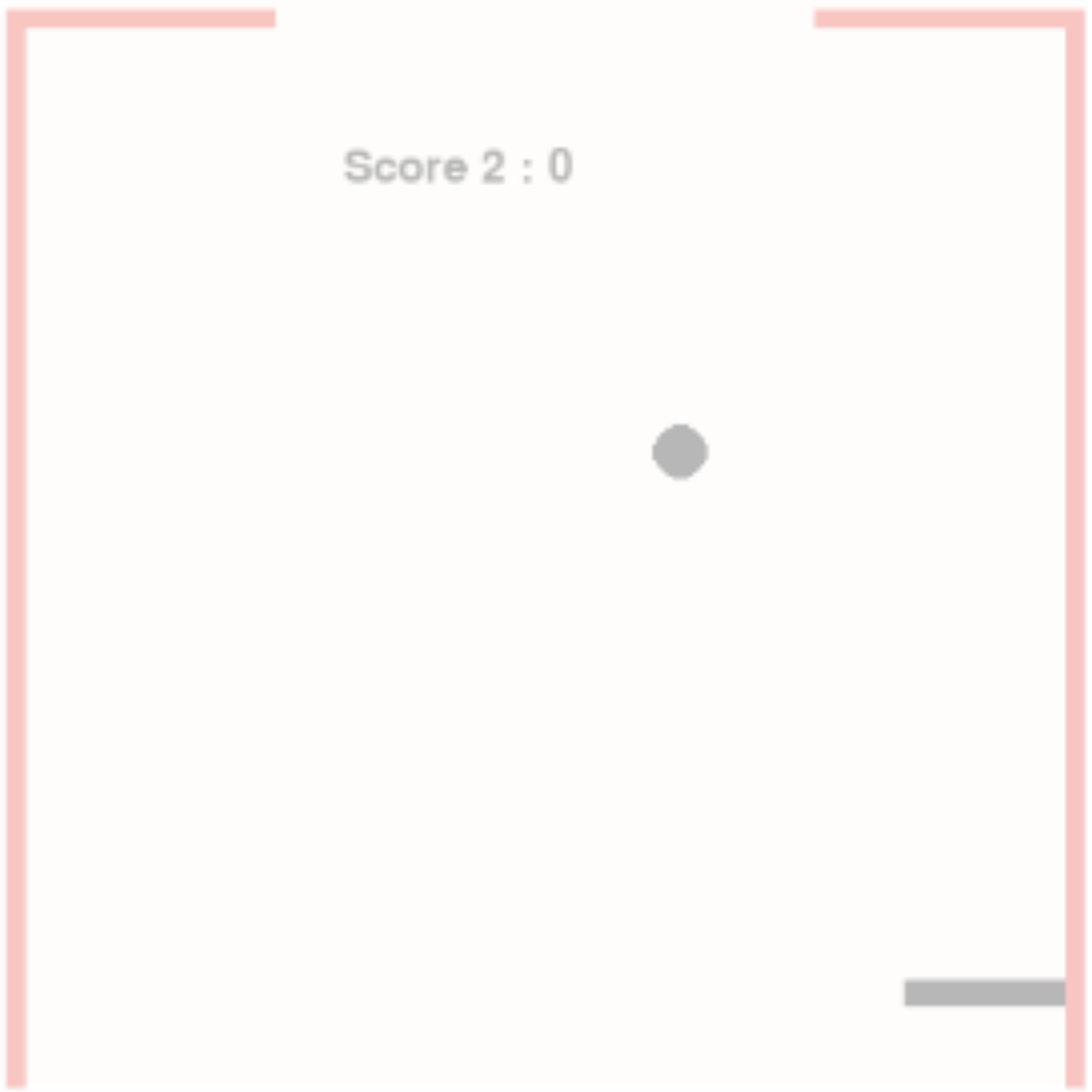

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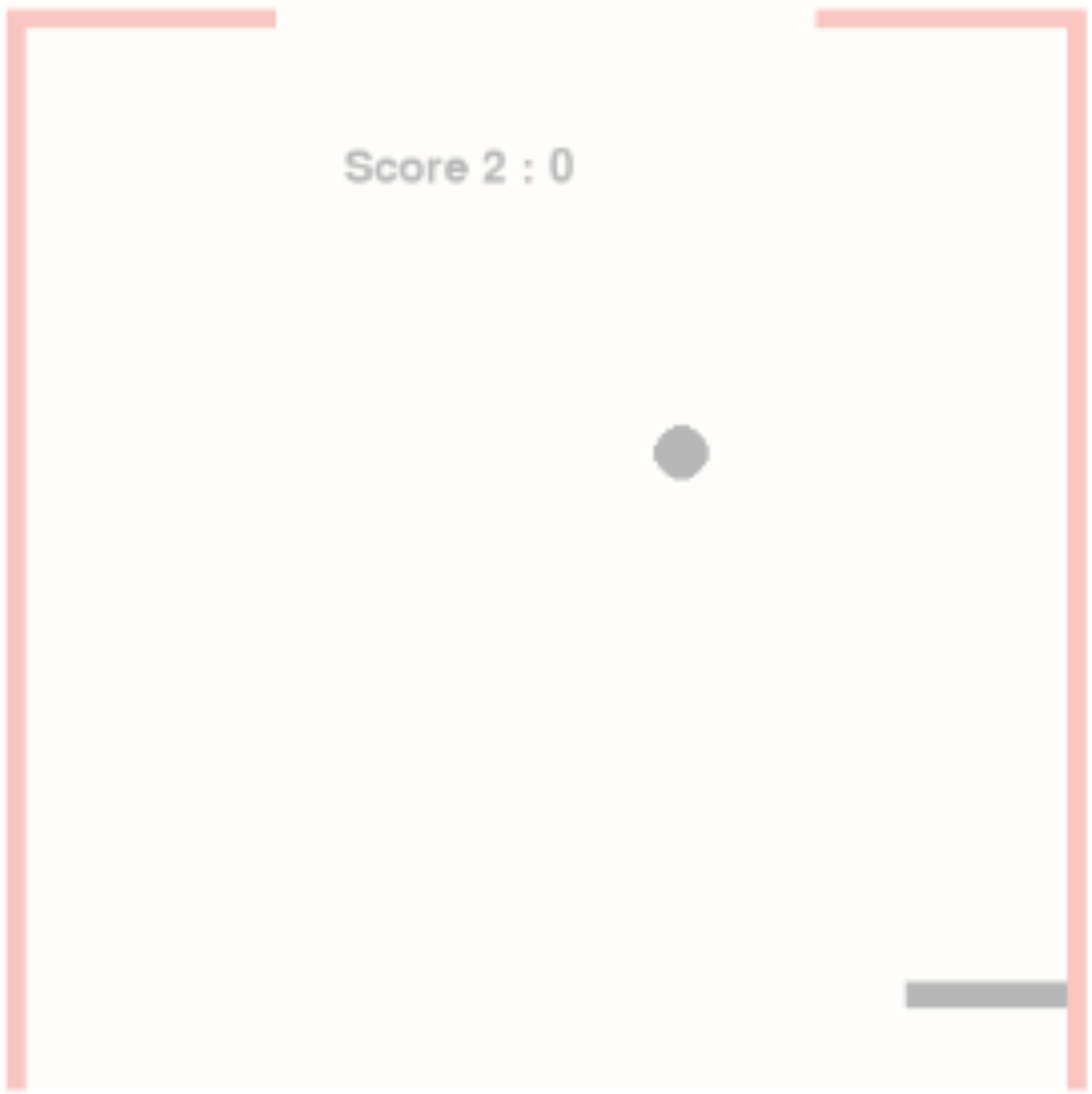
Harvard CS50
UC Berkeley CS61B
UCLA CS32
Stanford CS106A
Code.org
Camp K12
Tynker
Google Applied CS Skills
...

Increasingly found everywhere

Problem: Providing Feedback on Interactive Software

Providing feedback / grading is hard



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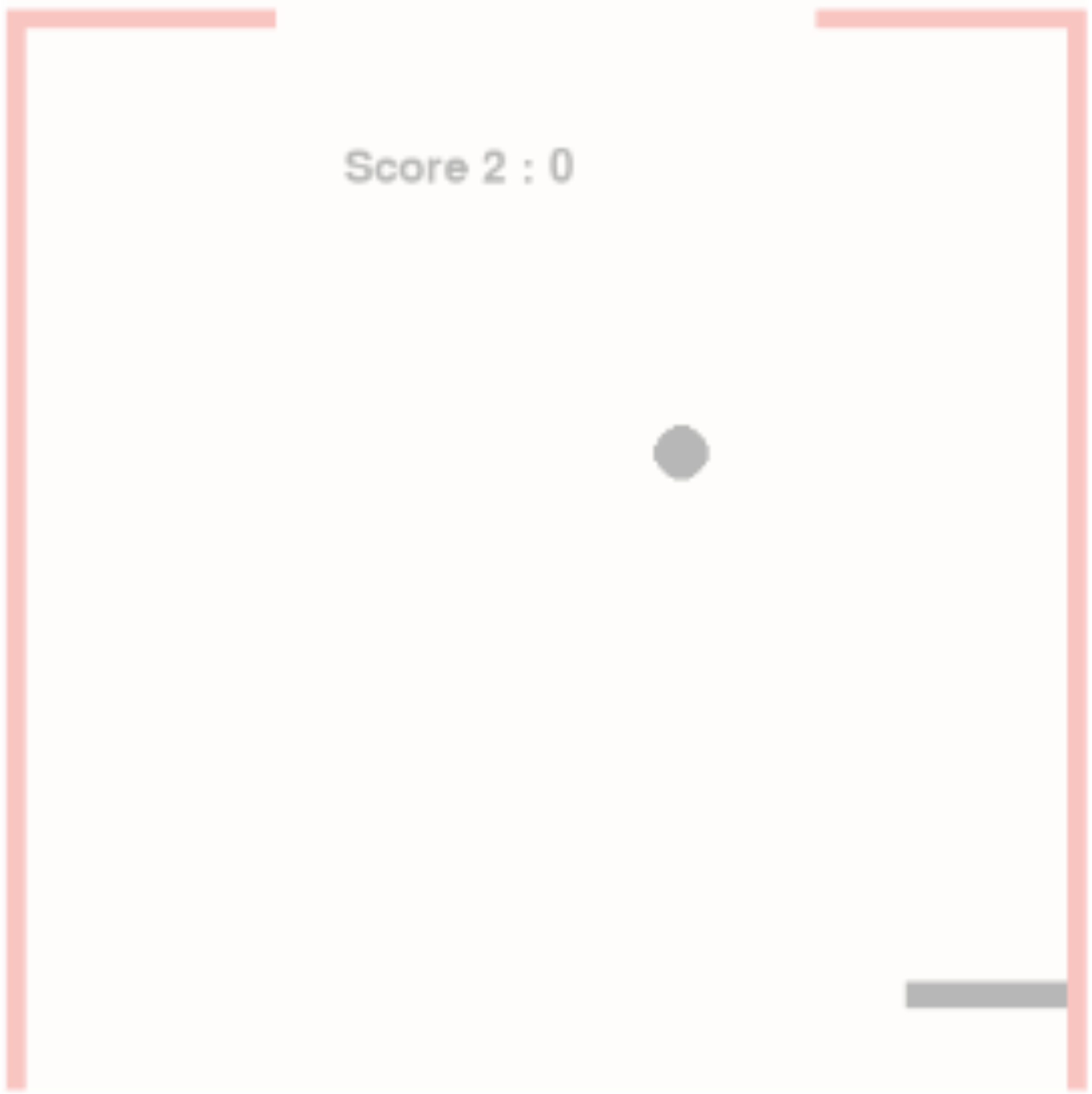

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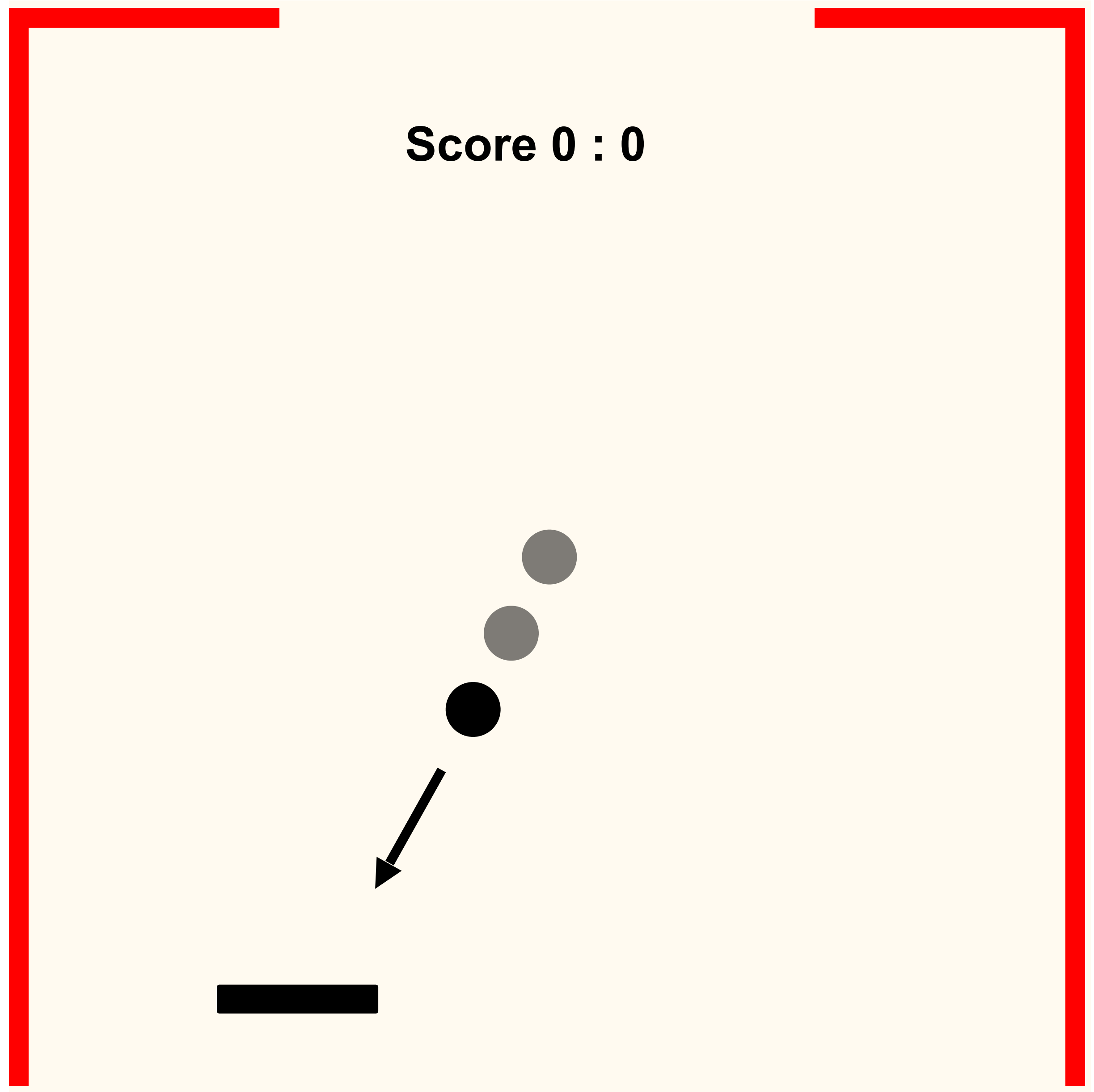

Stochasticity

Problem: Providing Feedback on Interactive Software

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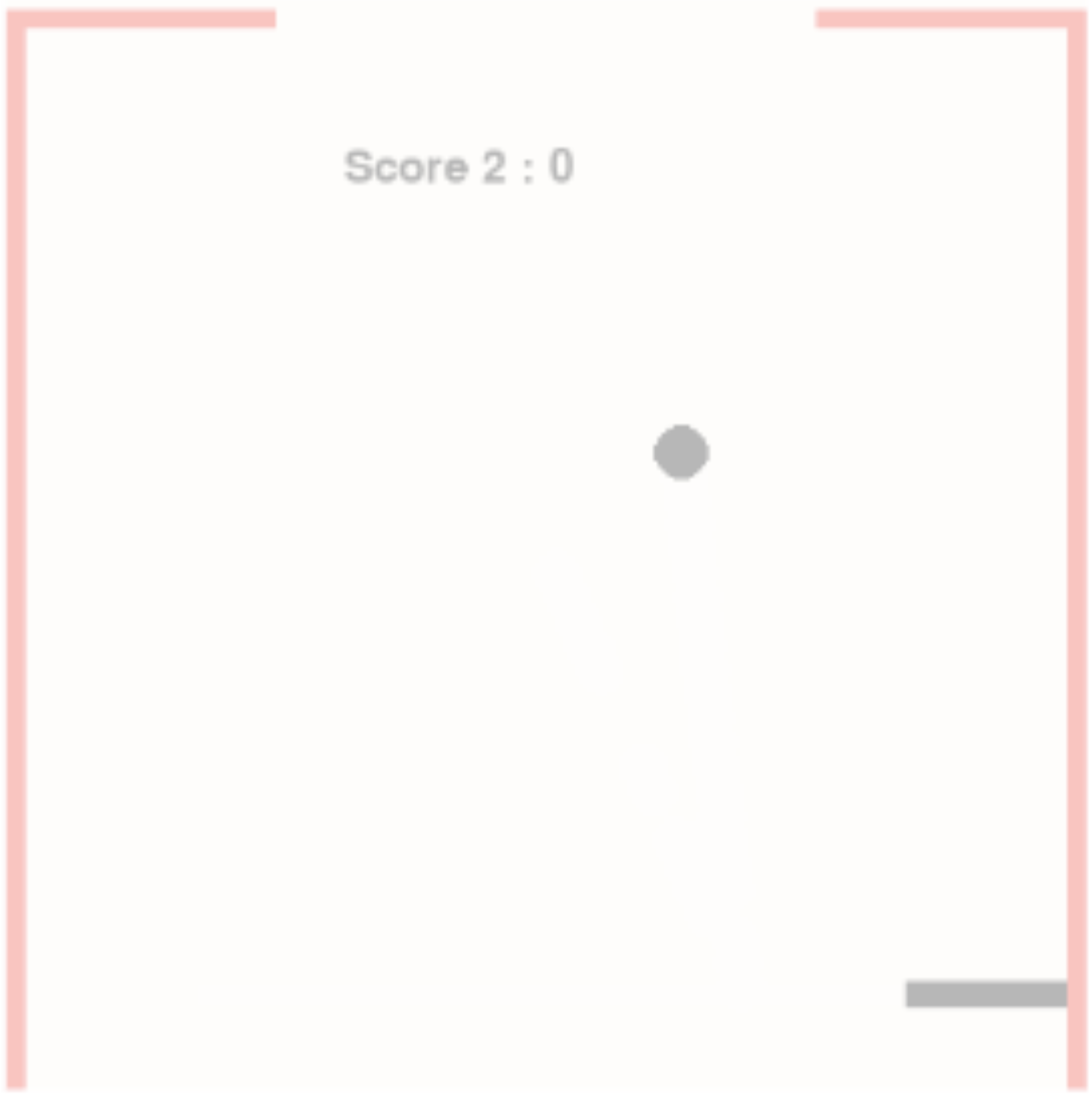

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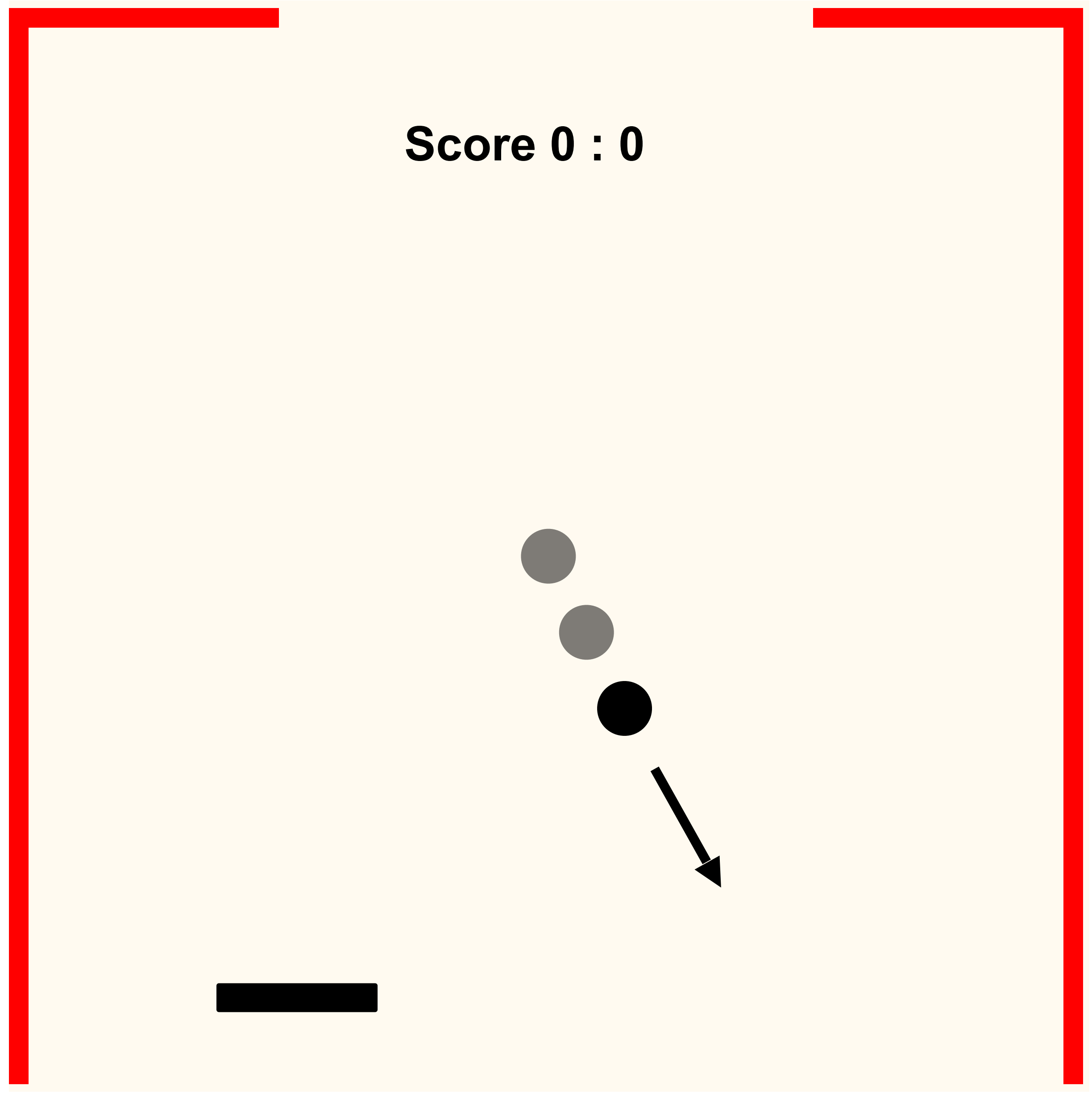

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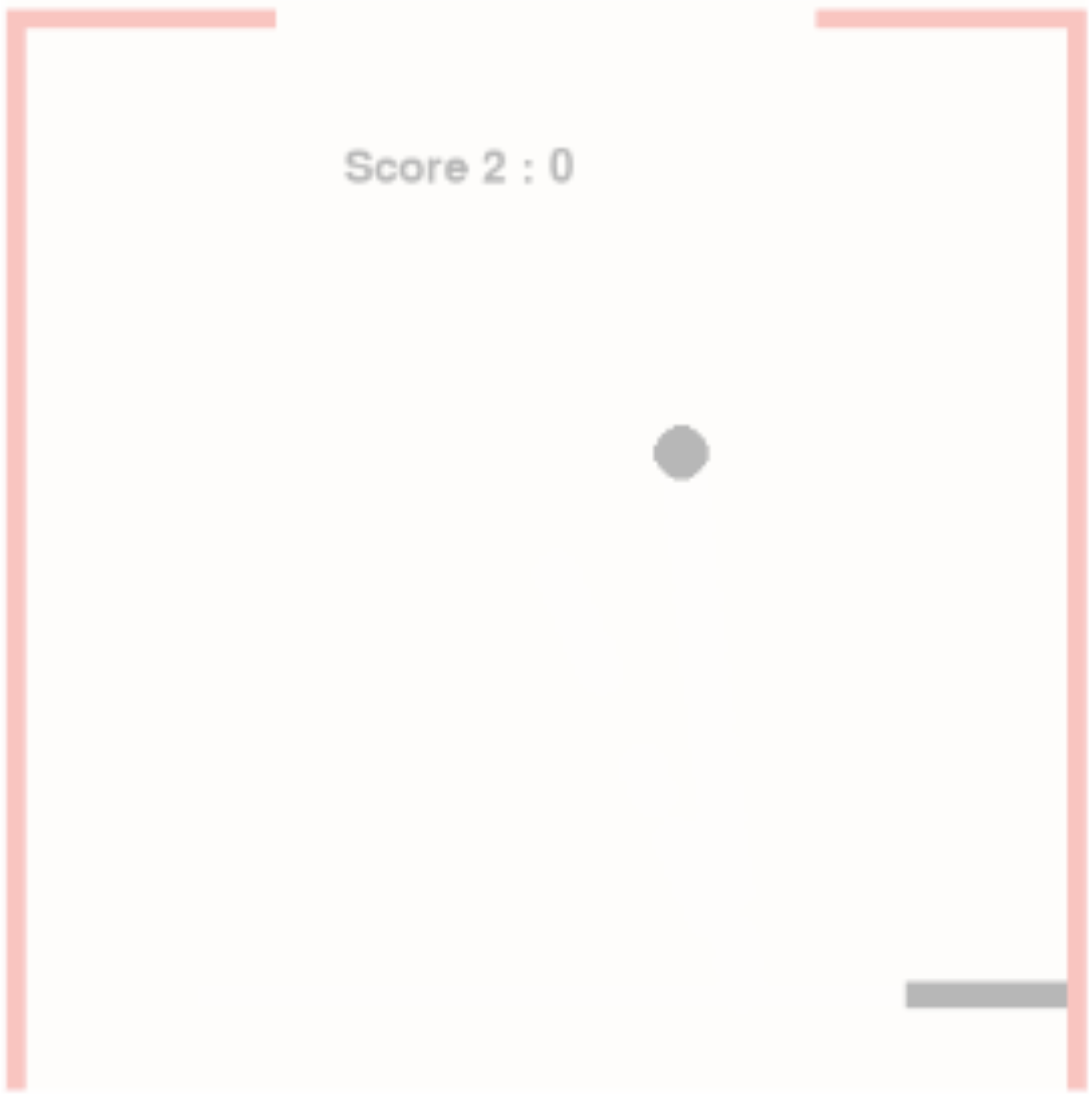

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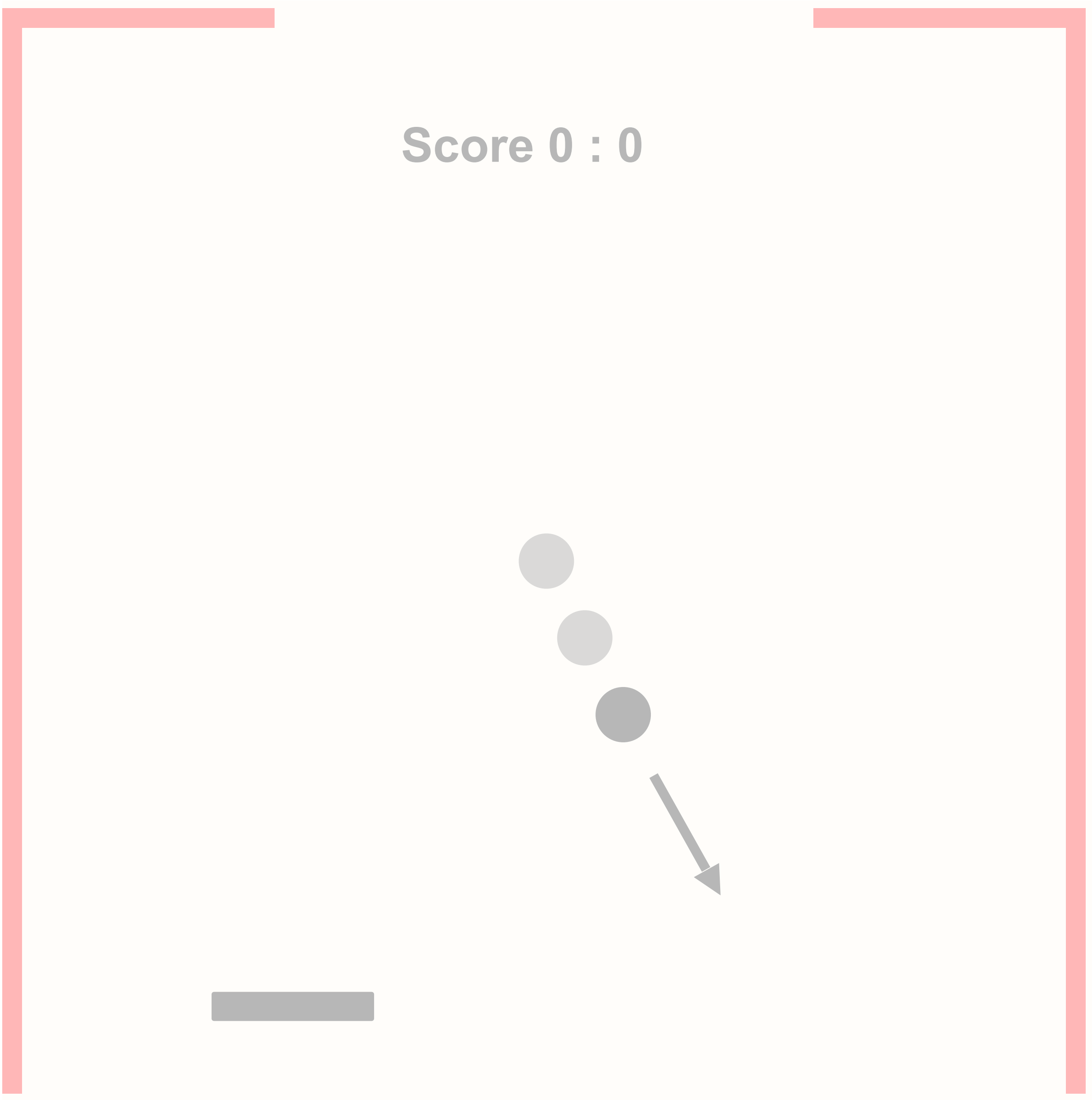
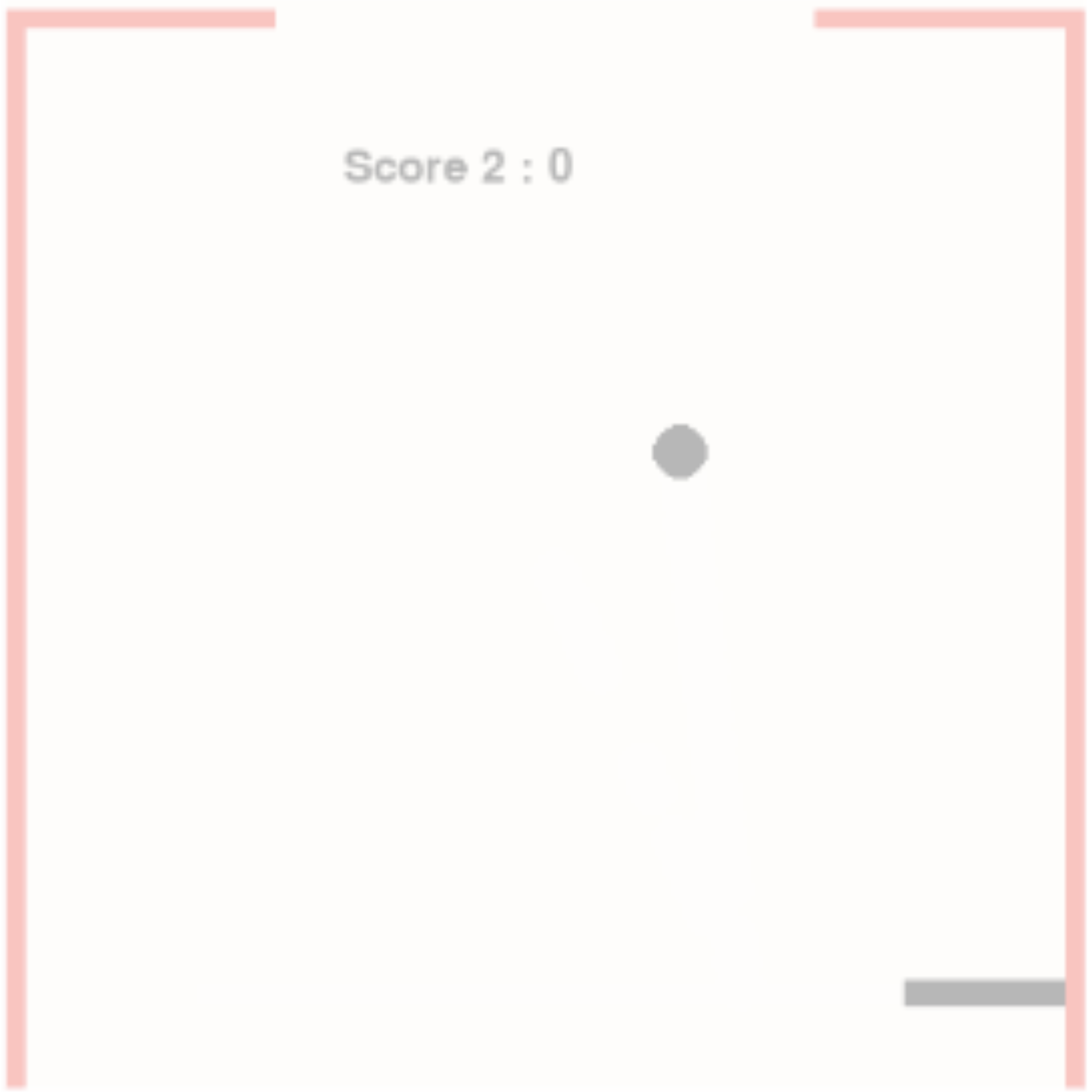


Stochasticity

Student creativity

Problem: Providing Feedback on Interactive Software



Bounce assignment
(Code.org)

3+ min manual grading
per assignment

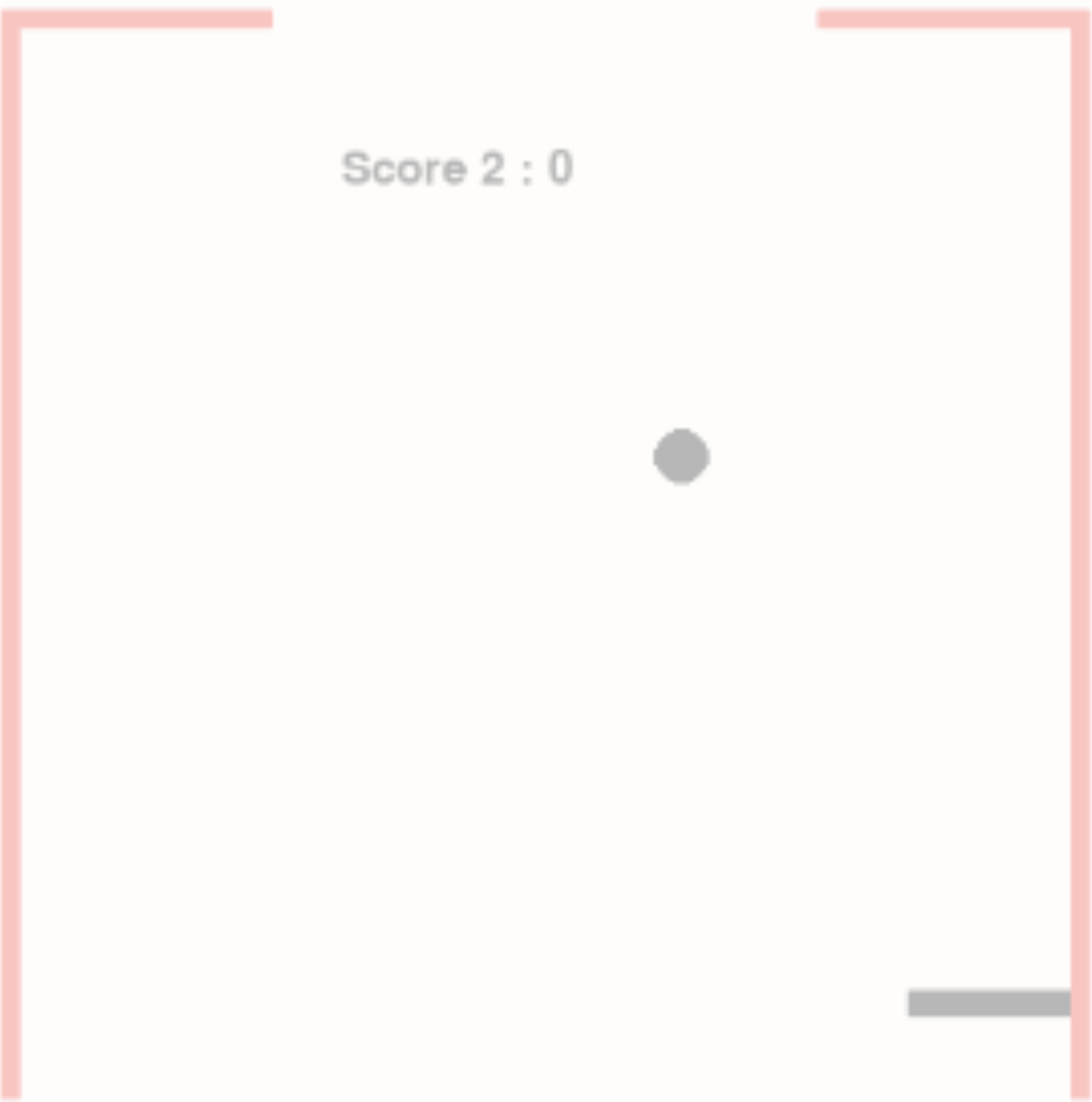
X

70M+
enrolled students

=

300+ years
of grading work

Problem: Providing Feedback on Interactive Software



Bounce assignment
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3+ min manual grading
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70M+
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Our goal: Automatically provide feedback

- ⭐ Reduce enormous human grading burden
- ⭐ Provide *faster* and *iterative* feedback

Setting

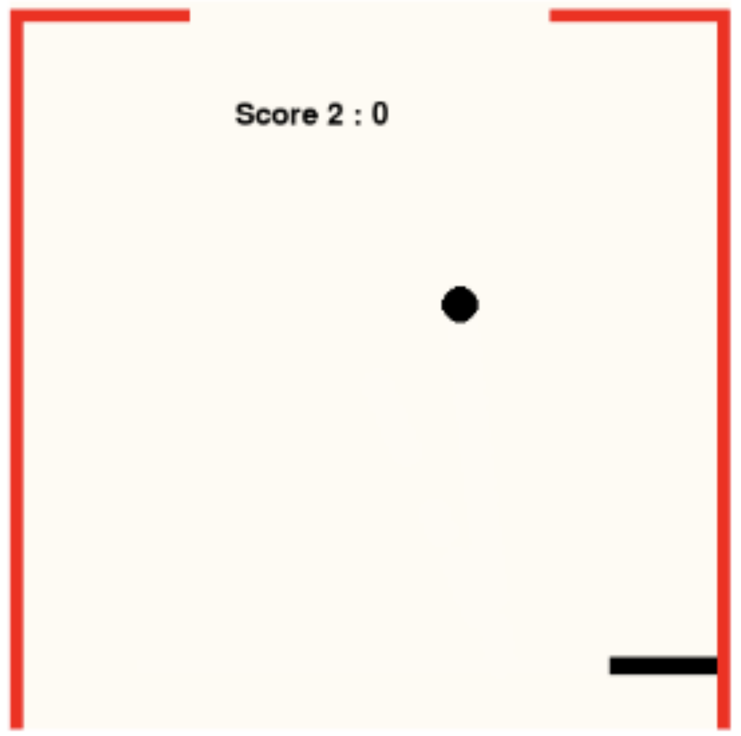
Rubric: List of possible errors

```
moveError

whenWall-newBallError

whenGoal-scoreError

...
```

Setting

Training (~3500 labeled programs)

Program μ



Label y: Subset of rubric items present in program

`moveError`

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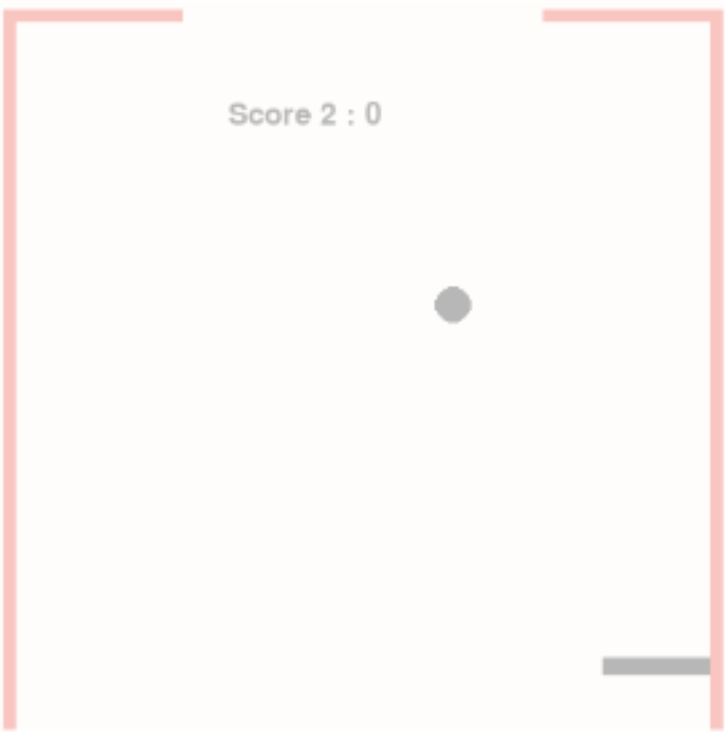

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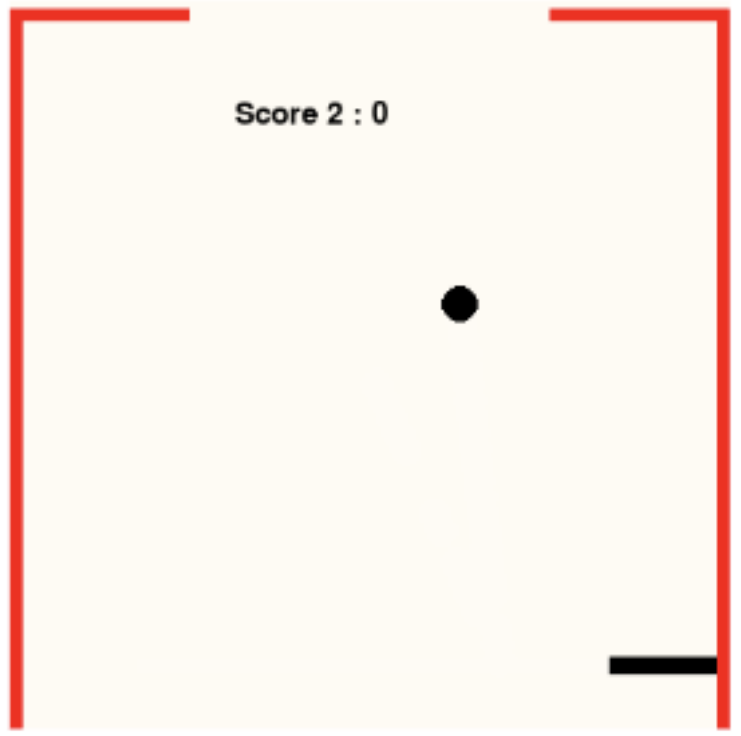
Testing

New student program



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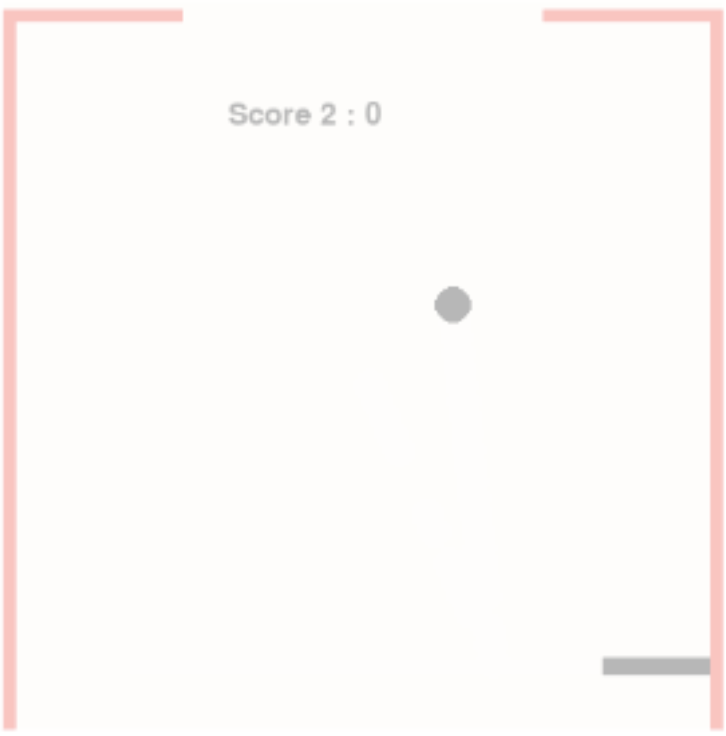

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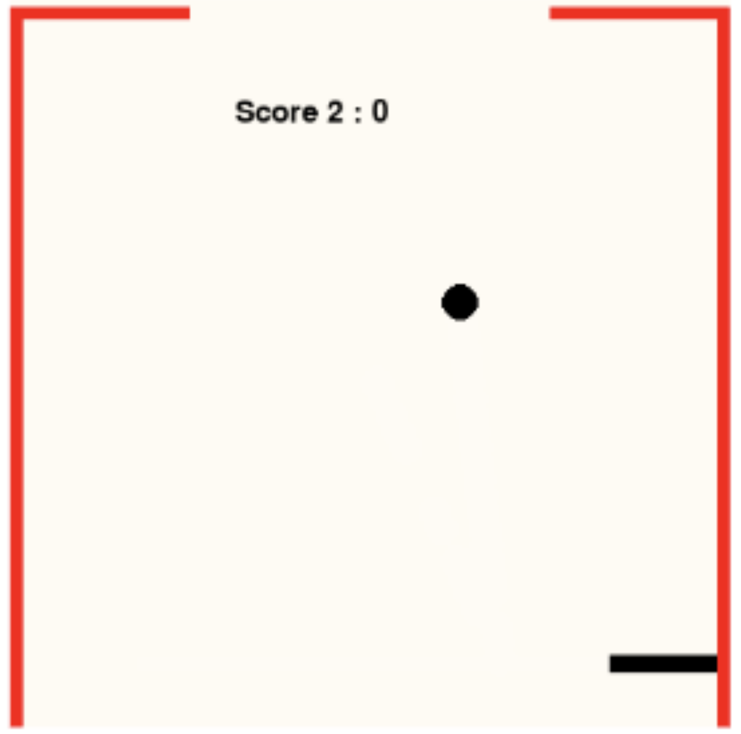


Goal: Output which bugs are in the program (i.e., predict the label)

Related Work: Two Paradigms for Automated Feedback

Analyze program *code*
(Singh et al., ‘13, Piech et al., ‘15, Bhatia et al., ‘16, , Rivers et al., ‘17, Paaβen et al., ‘17, Wang et al., ‘17, Malik et al., ‘19, Wu et al., ‘19, Wu et al., ‘21)

Works well for shorter programs (e.g., <50 lines of code)

Existing methods struggle to scale to longer programs

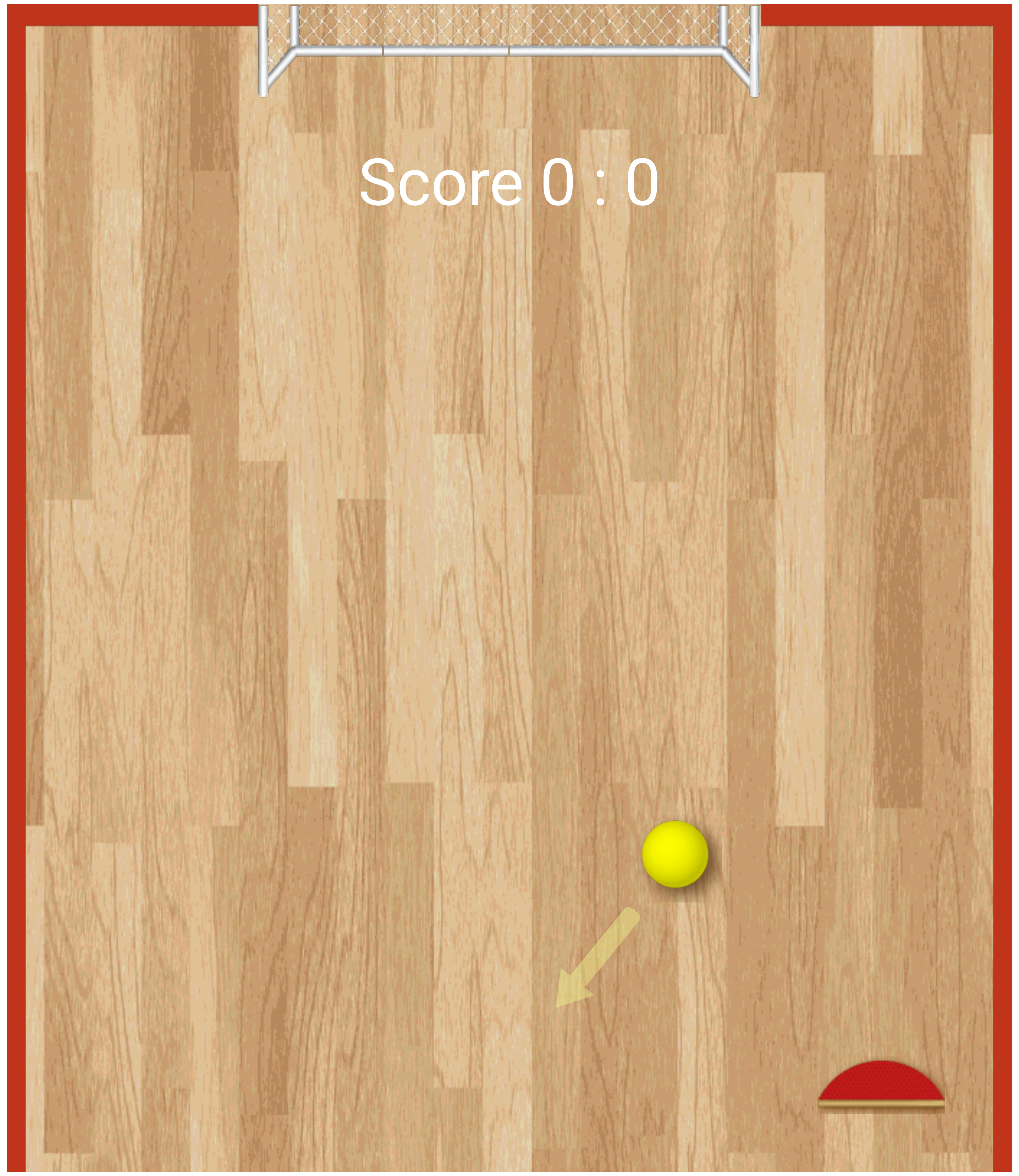
Analyze program *behavior*
(King et al., ‘76, Godefroid et al., ‘08, Zheng et al., ‘19, Nie et al., ‘21, Gordillo et al., ‘21)

Independent of program length

Assumes that the program can compile and run

We opt for this approach

The Play-to-Grade Paradigm



Agent interacts with program like human

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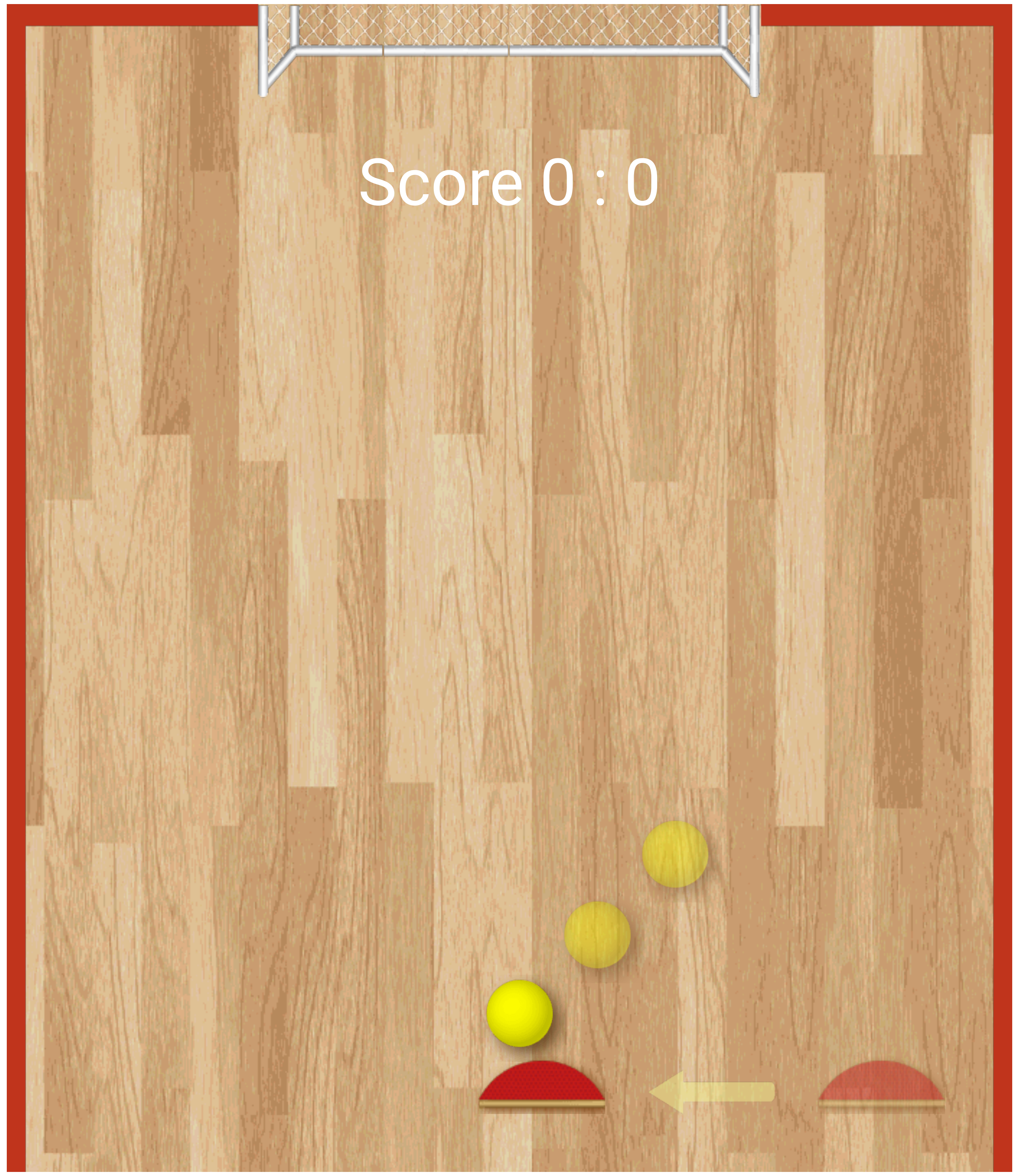

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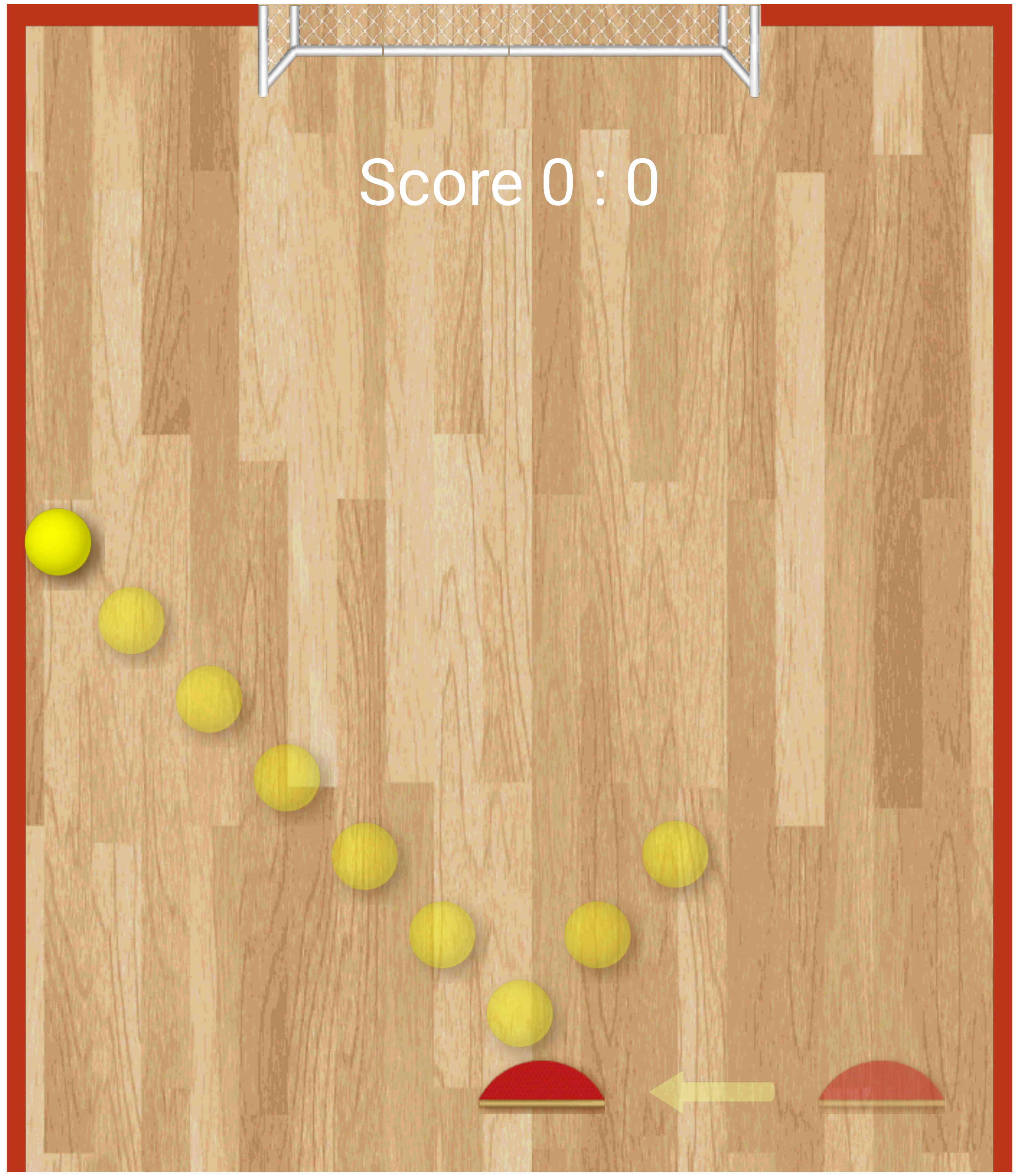

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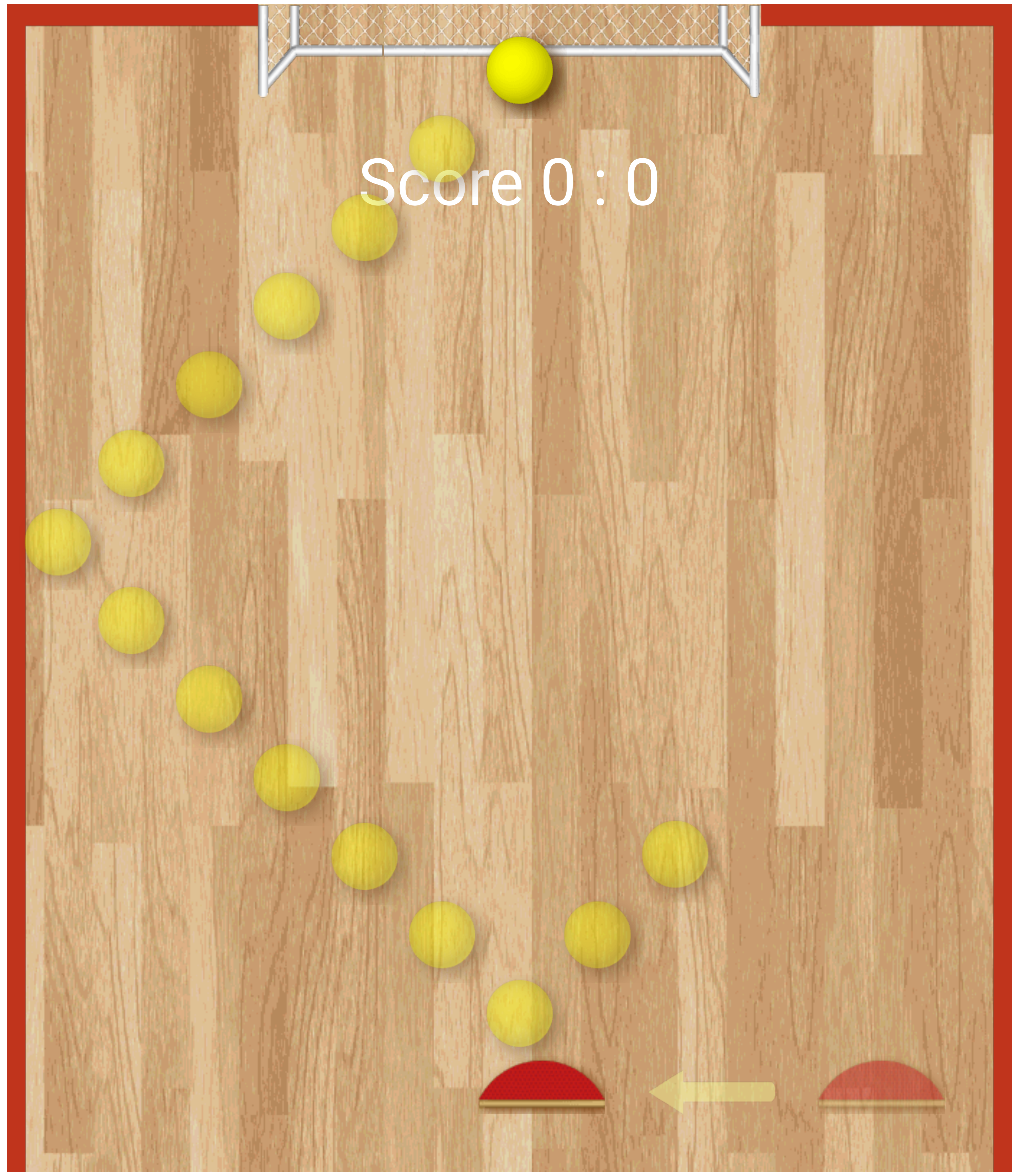

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Agent outputs feedback

The Play-to-Grade Paradigm

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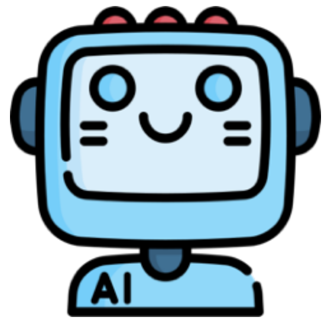
Existing work (Nie et al., '21):
Coarse binary feedback



The program is incorrect

Agent outputs feedback

Not **specific** enough for student to learn and correct mistakes

The Play-to-Grade Paradigm

Agent interacts with program like human

Existing work (Nie et al., '21):
Coarse binary feedback

The program is incorrect

Not **specific** enough for student to learn and correct mistakes

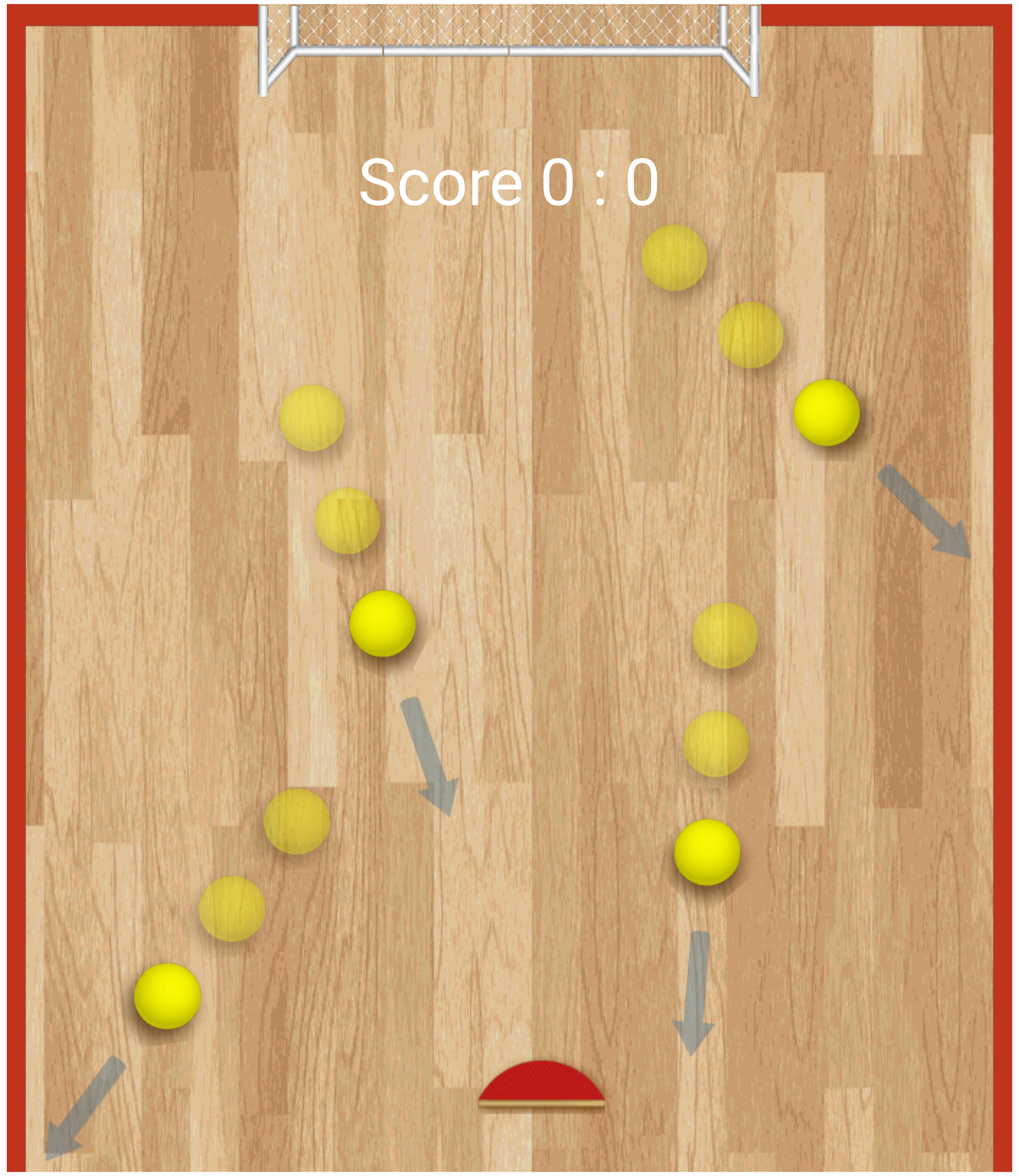
Our goal: **Fine-grained** feedback

The ball incorrectly bounces off the goal

Agent outputs feedback

What makes providing feedback hard?

Targeted exploration



Adaptive exploration

Approach: DreamGrader

Exploration policy π:
Takes program μ and produces trajectories τ

Feedback classifier g:
Takes trajectories τ and predicts label y

`whenWall-newBallError`

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...

Approach: DreamGrader

Exploration policy π:
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Maximize probability of correct label

$$\mathcal{J}(\pi, g) = \underbrace{\mathbb{E}_{\mu \sim p(\mu), \tau \sim \pi(\mu)}}_{\text{Sample a program and roll out exploration policy}} \left[\overline{g(y \mid \tau)}\right]$$

Sample a program and roll out exploration policy

Approach: DreamGrader

Exploration policy π**:**
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Naive approach:
Treat this as end-of-episode reward

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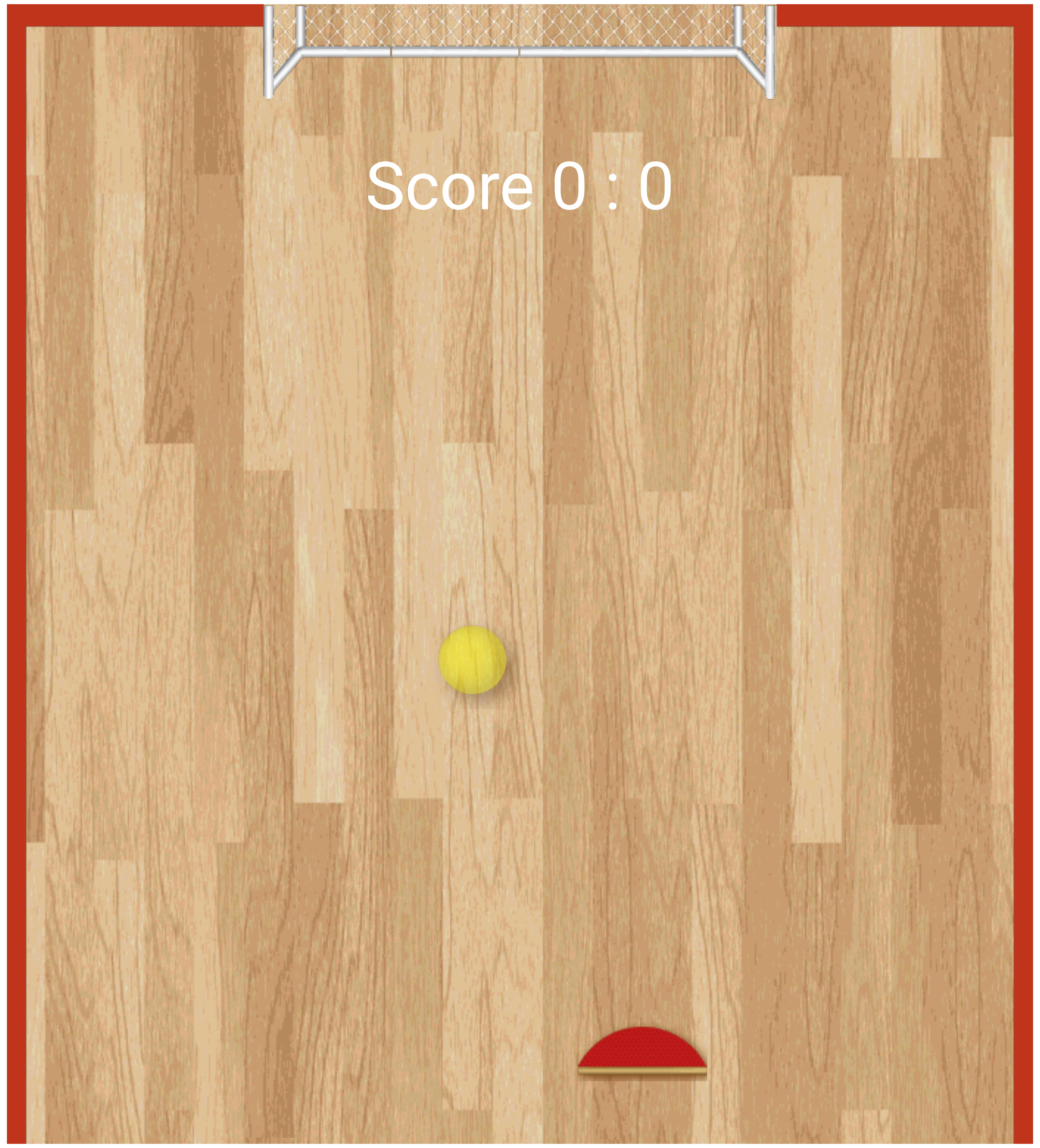

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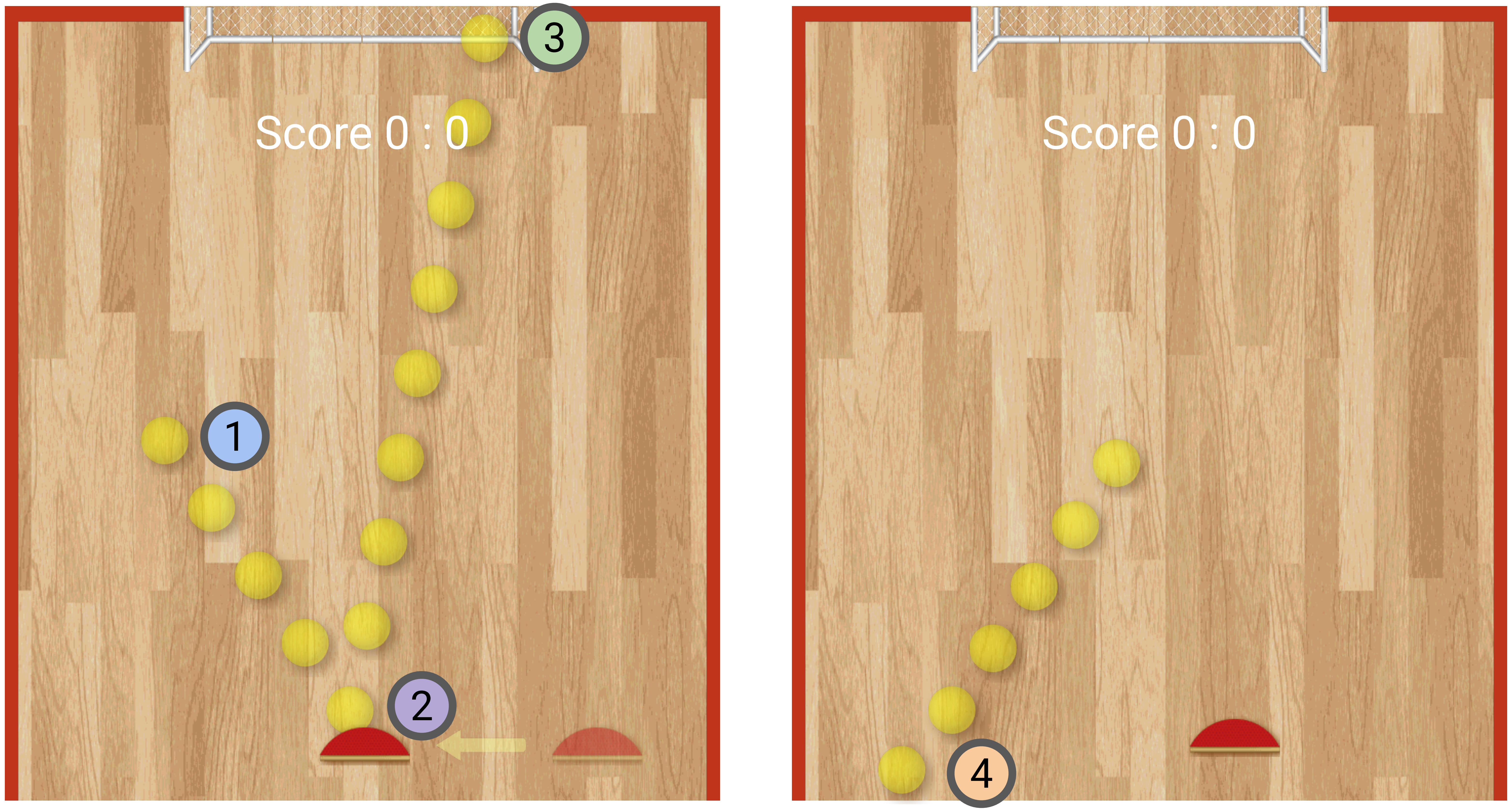

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Reward given at 4 but bug discovered at 3

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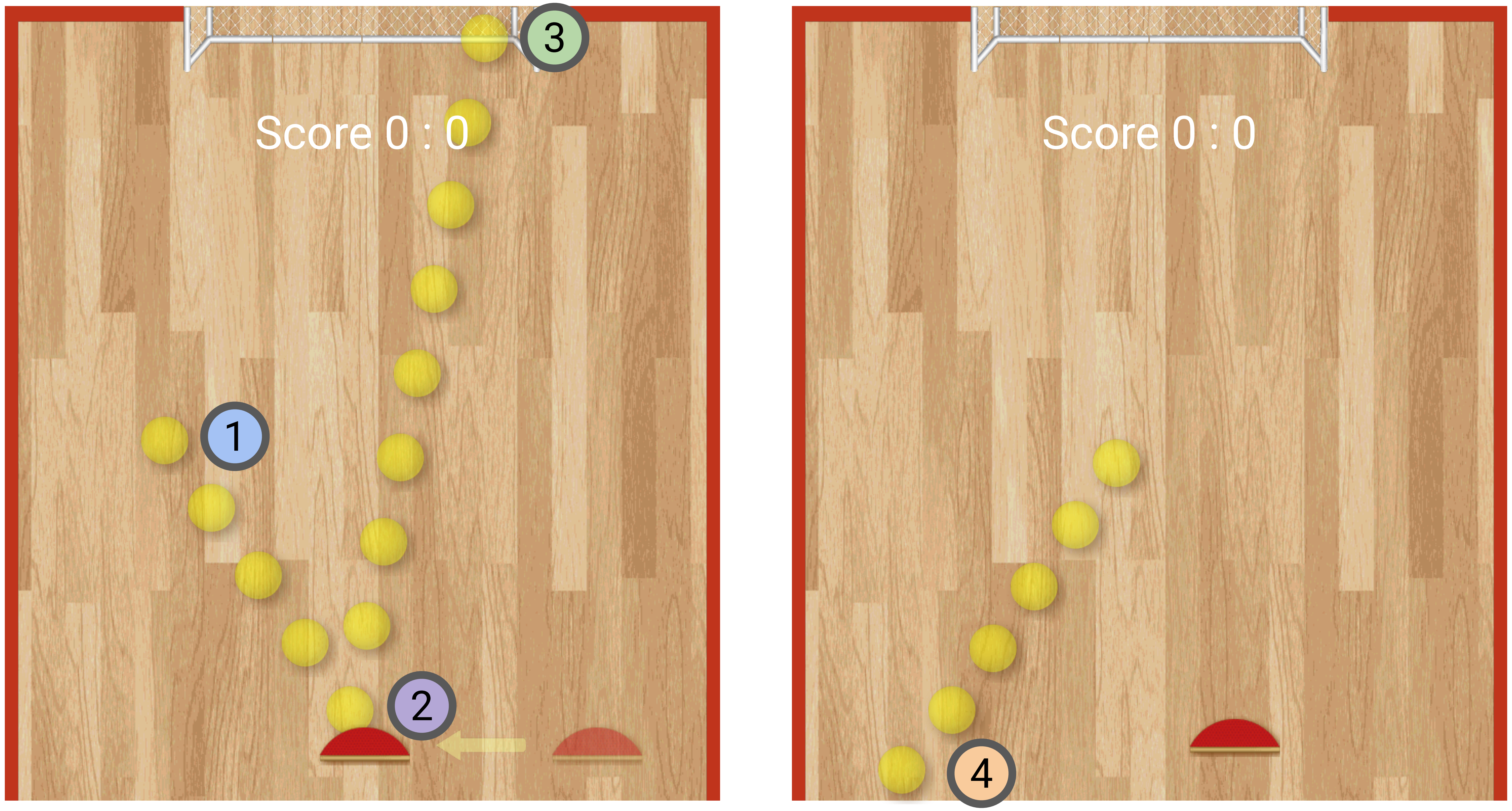

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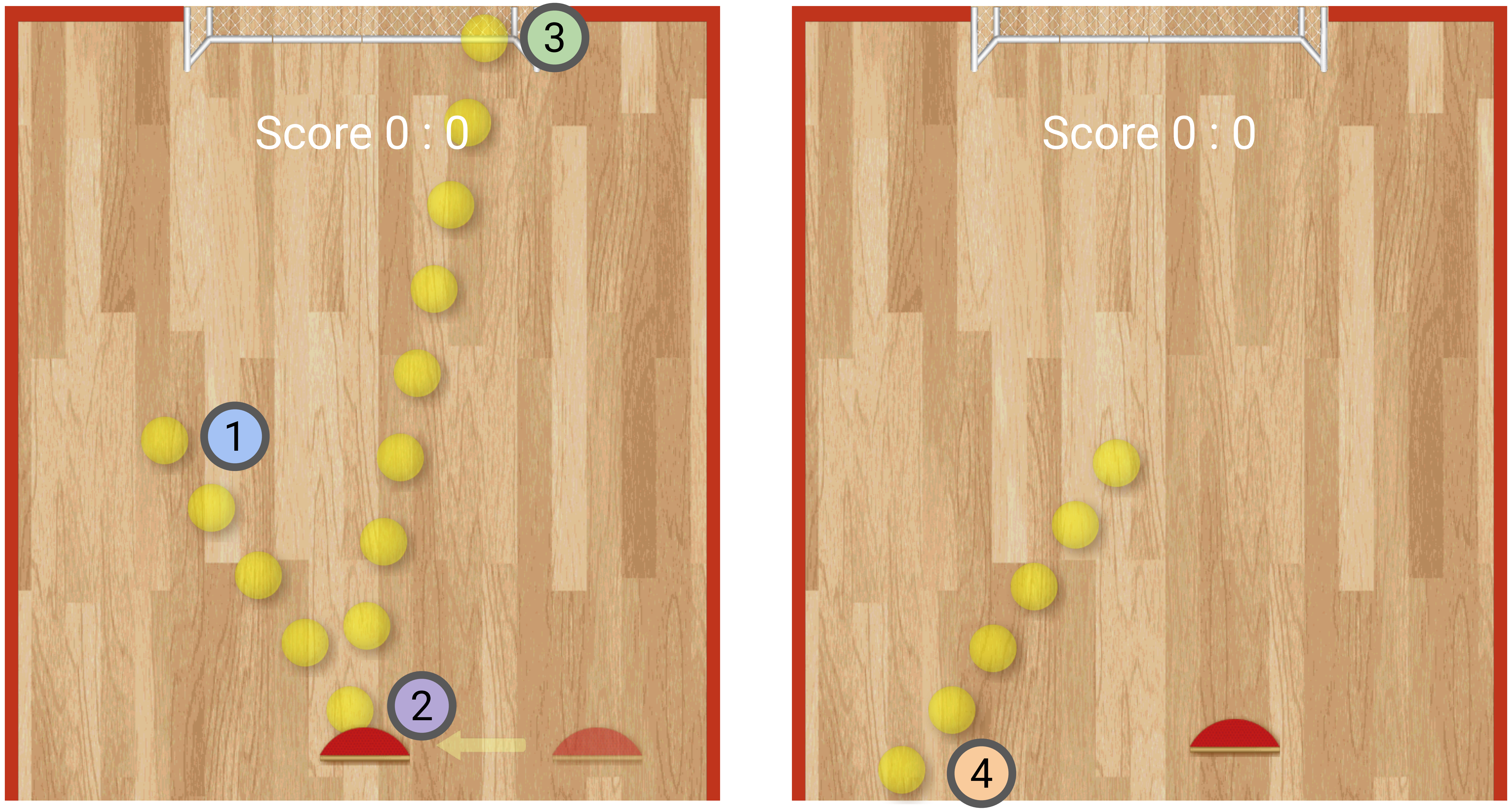

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Intuition: maximize information gain

$$r_t = \log \frac{g(y \mid \tau_{:t+1})}{g(y \mid \tau_{:t})}$$

Approach: DreamGrader

Why does the Dream meta-RL algorithm apply here?

Few-shot meta-RL:

1) Agent is given new task

2) Agent gets to explore for a few episodes

3) Agent uses exploration to maximize returns on new episode

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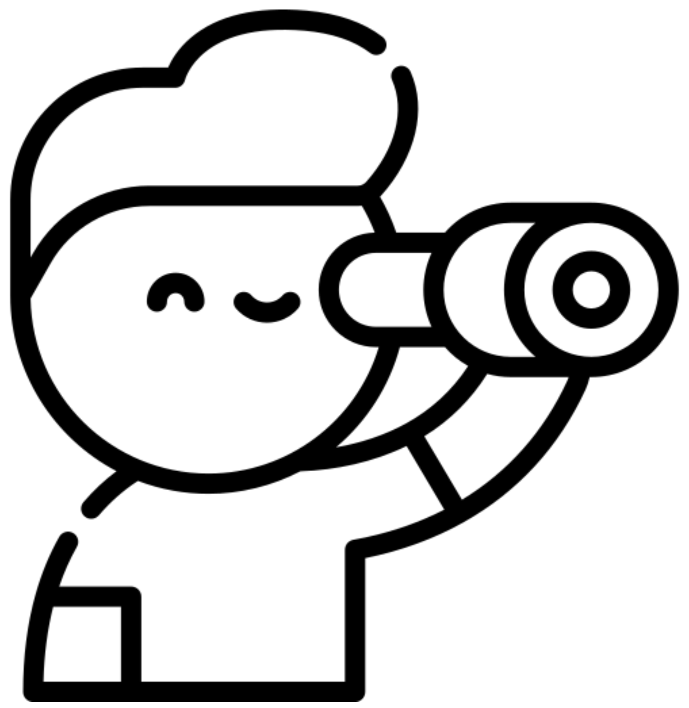

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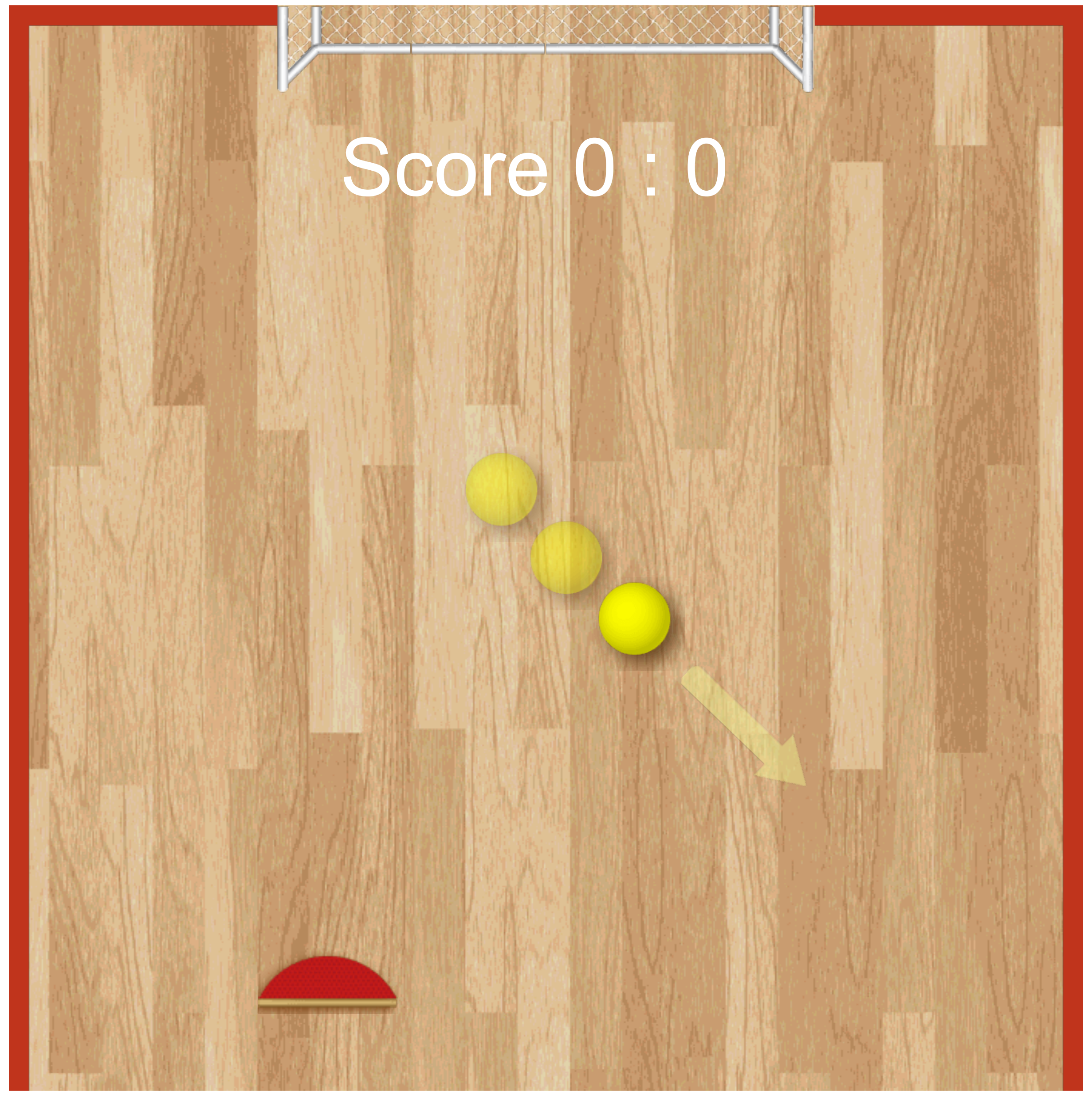

Bounce programming assignment from Code.org

Dataset of ~700K real student submissions, released by Nie et al., ‘21

Train systems on 3,500 programs — hold out the rest

Experiments: Questions

How feasible is automated feedback generation?

Humans

Naive approach of direct maximization

Existing state-of-the-art approach (Nie et al., ‘21)

Can automated feedback generation handle student creativity?

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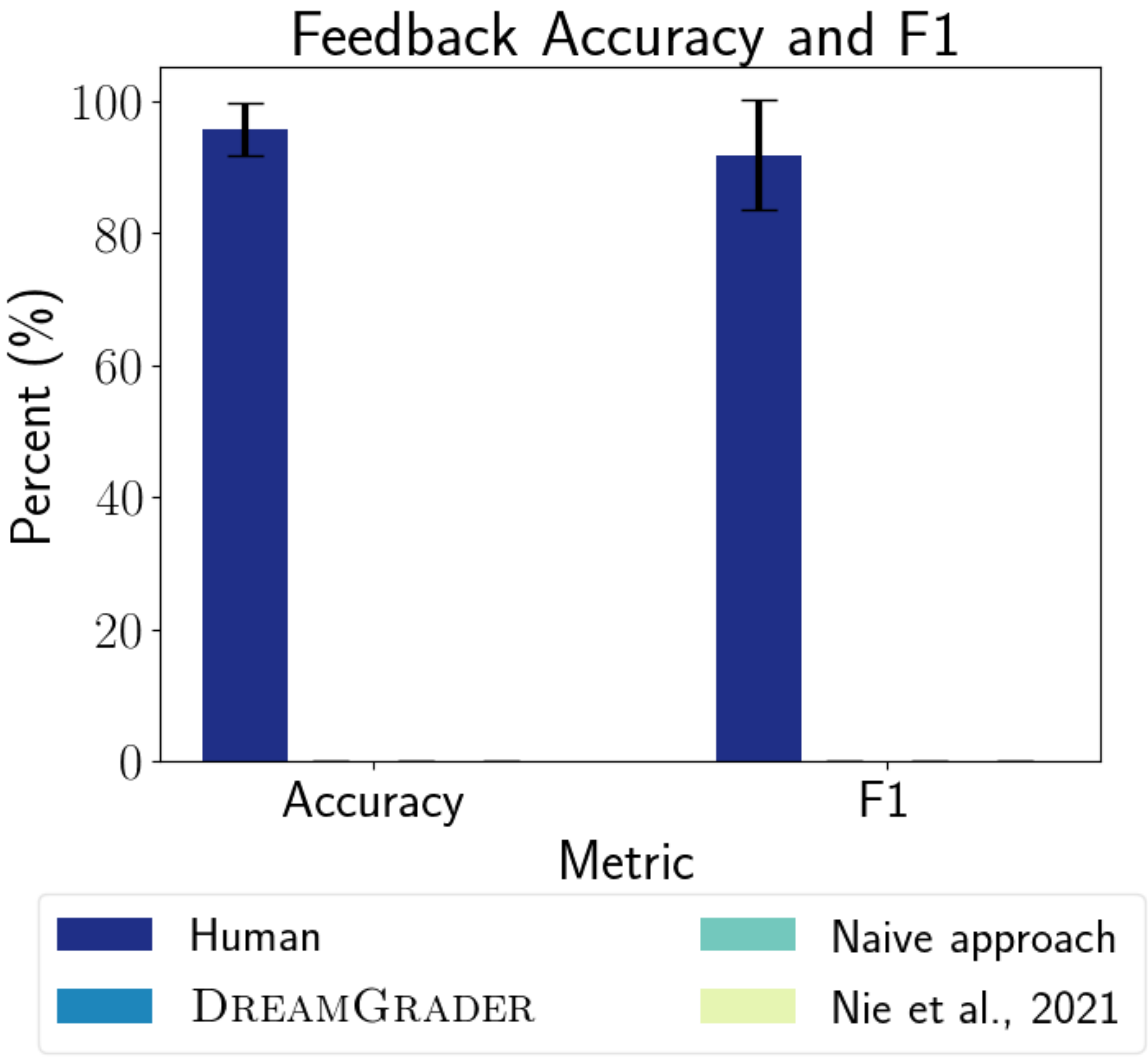
Experiments: How Feasible is Automated Feedback?



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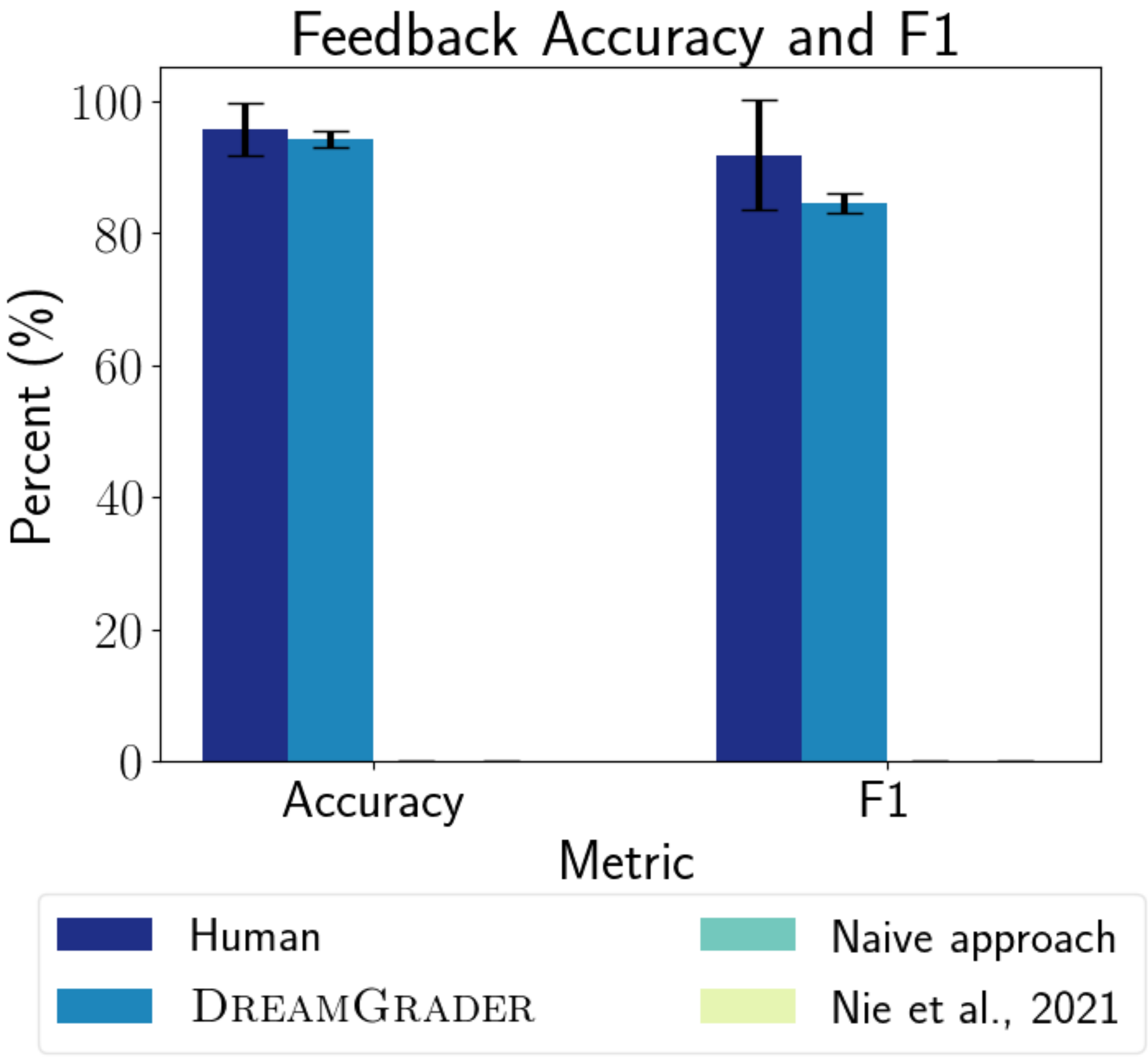

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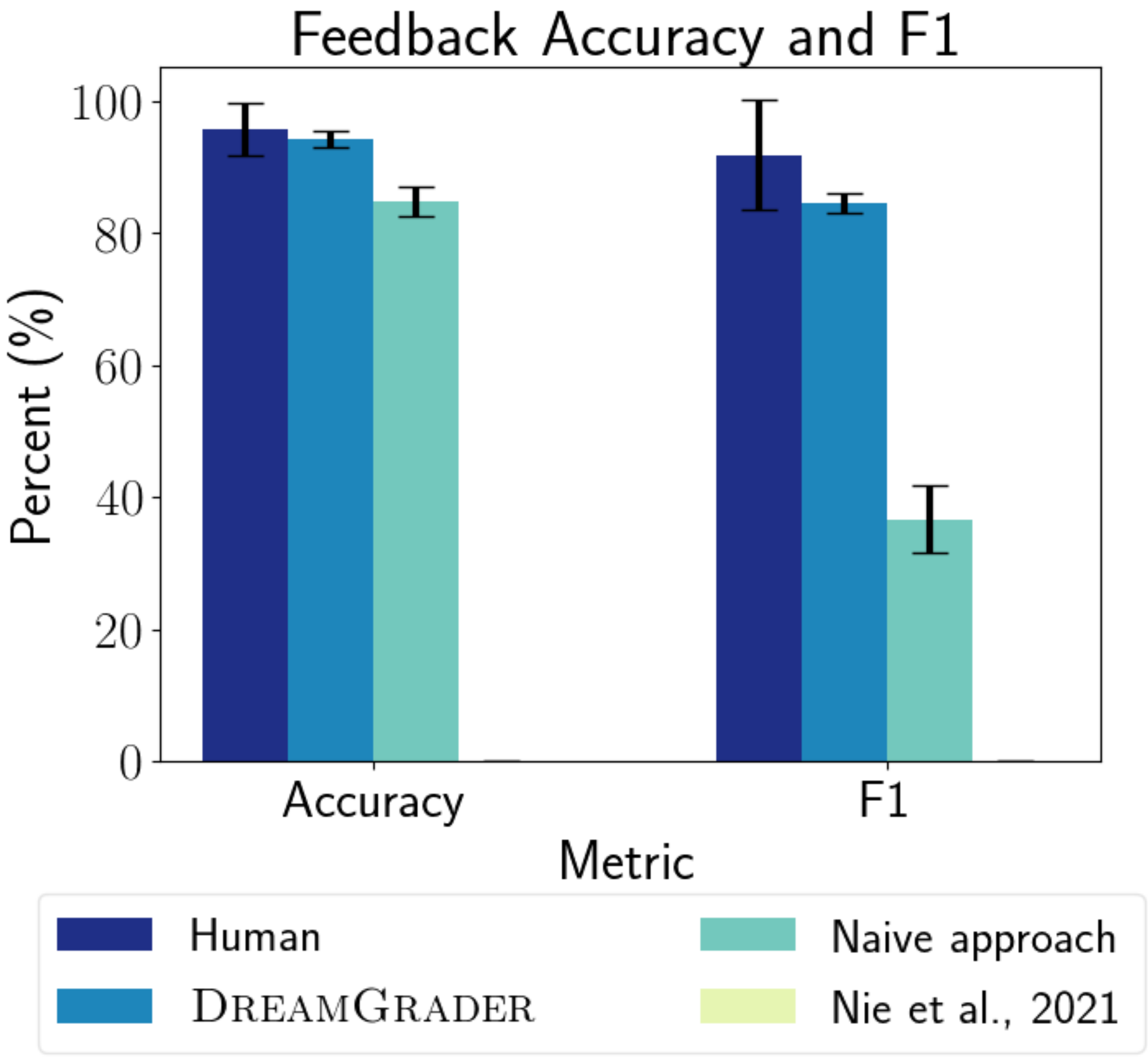

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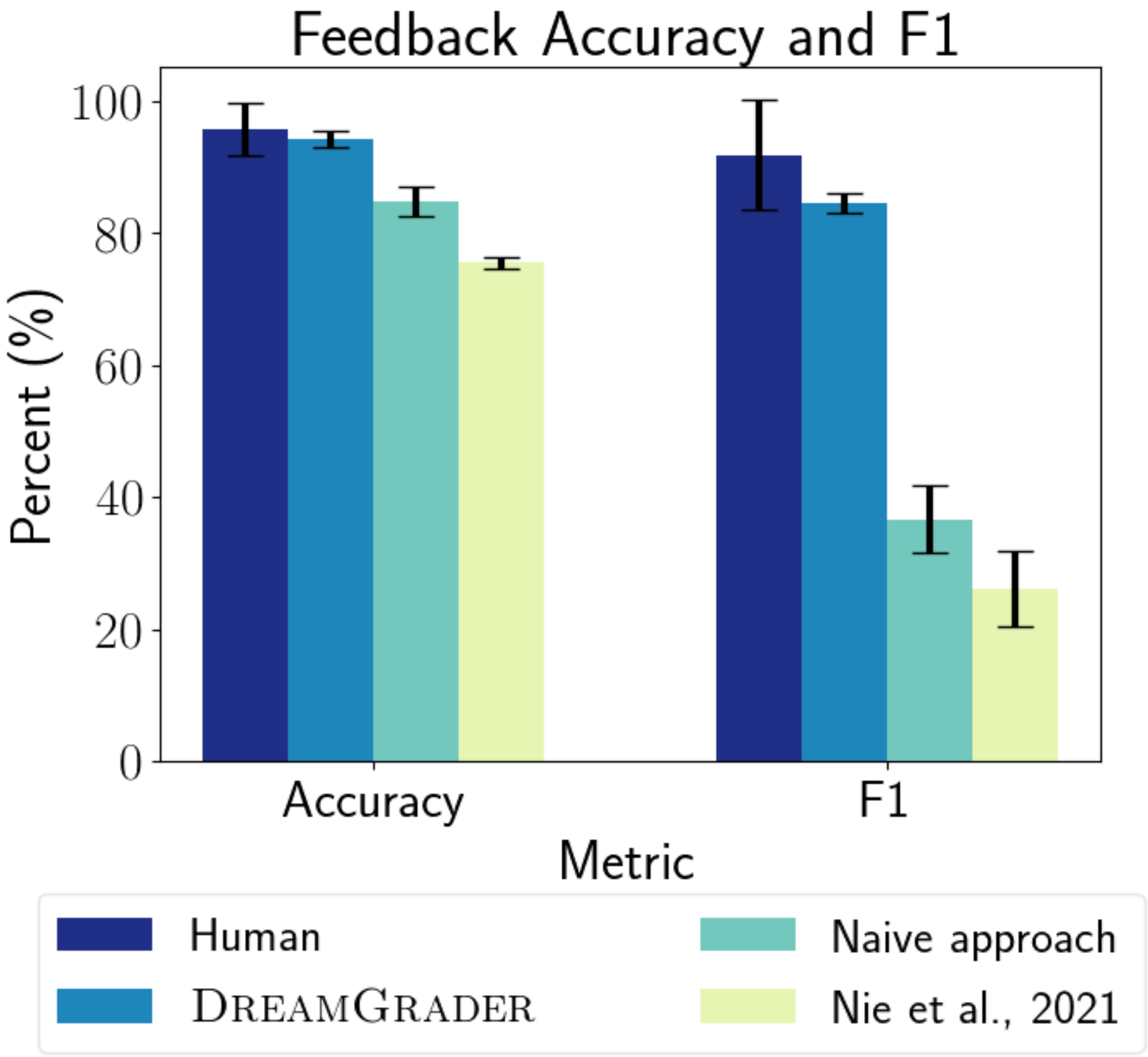

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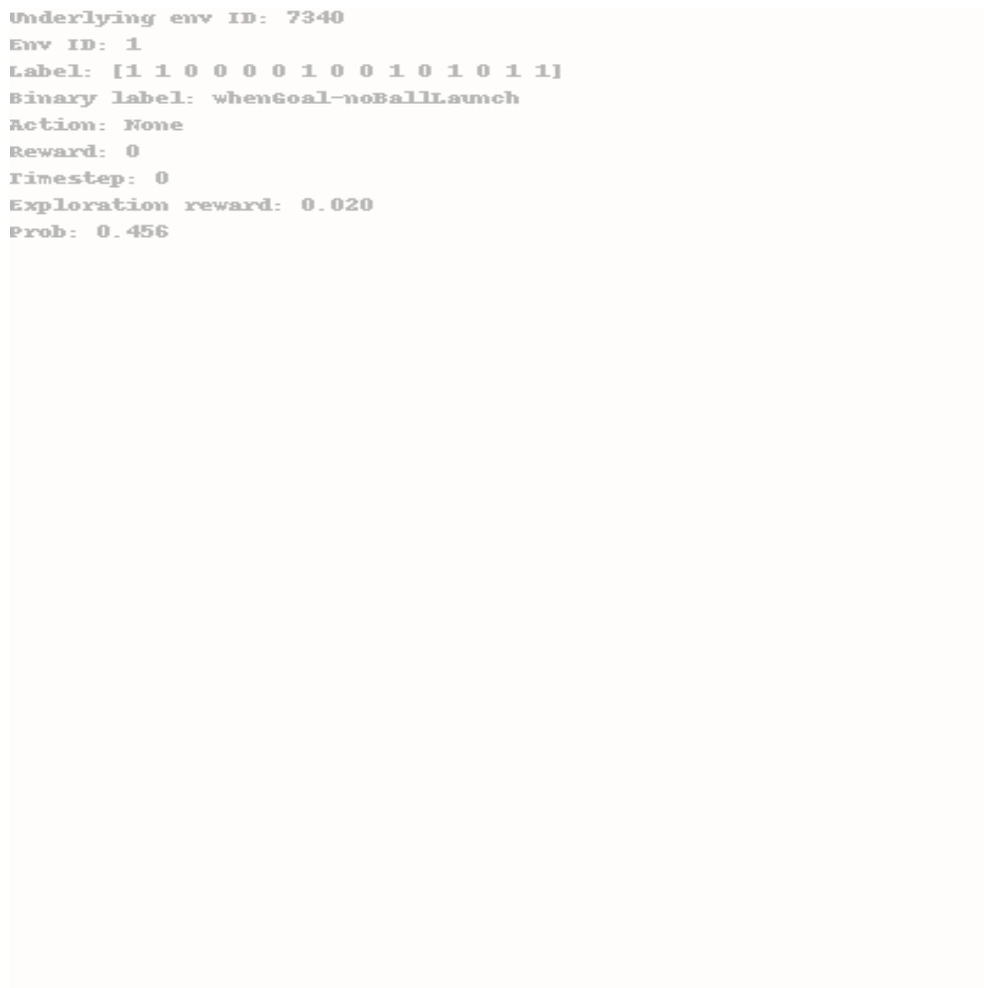
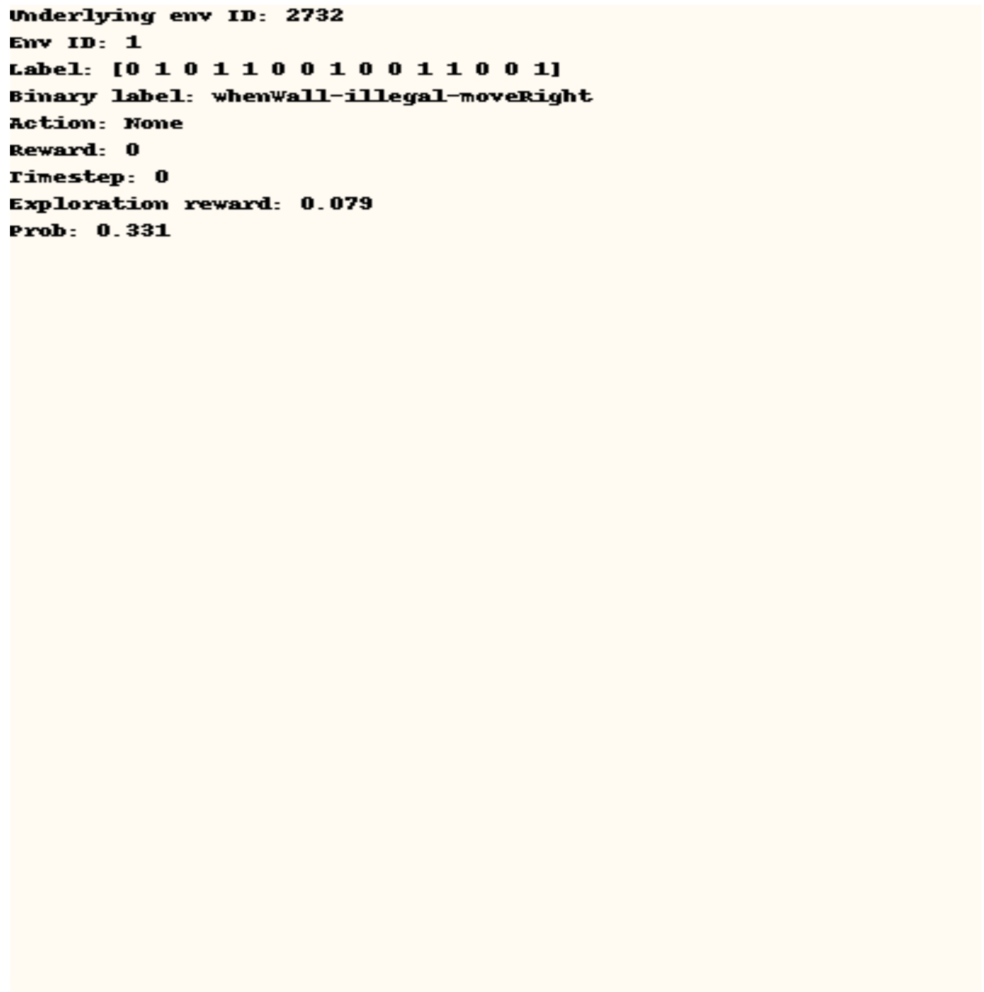
Appropriate credit assignment is **critical** for learning effective exploration

Improves on existing methods by **18.8%**

Experiments: Learned Exploration Behavior





What happens when… the ball hits the goal? the ball hits the floor? the ball hits the wall?

Main gap with humans appears in these sorts of programs with many balls

Experiments: Can We Handle Some Student Creativity?

One type of student creativity in the dataset: ball and paddle speed

- Test handling student creativity by evaluating on held out ball and paddle speeds

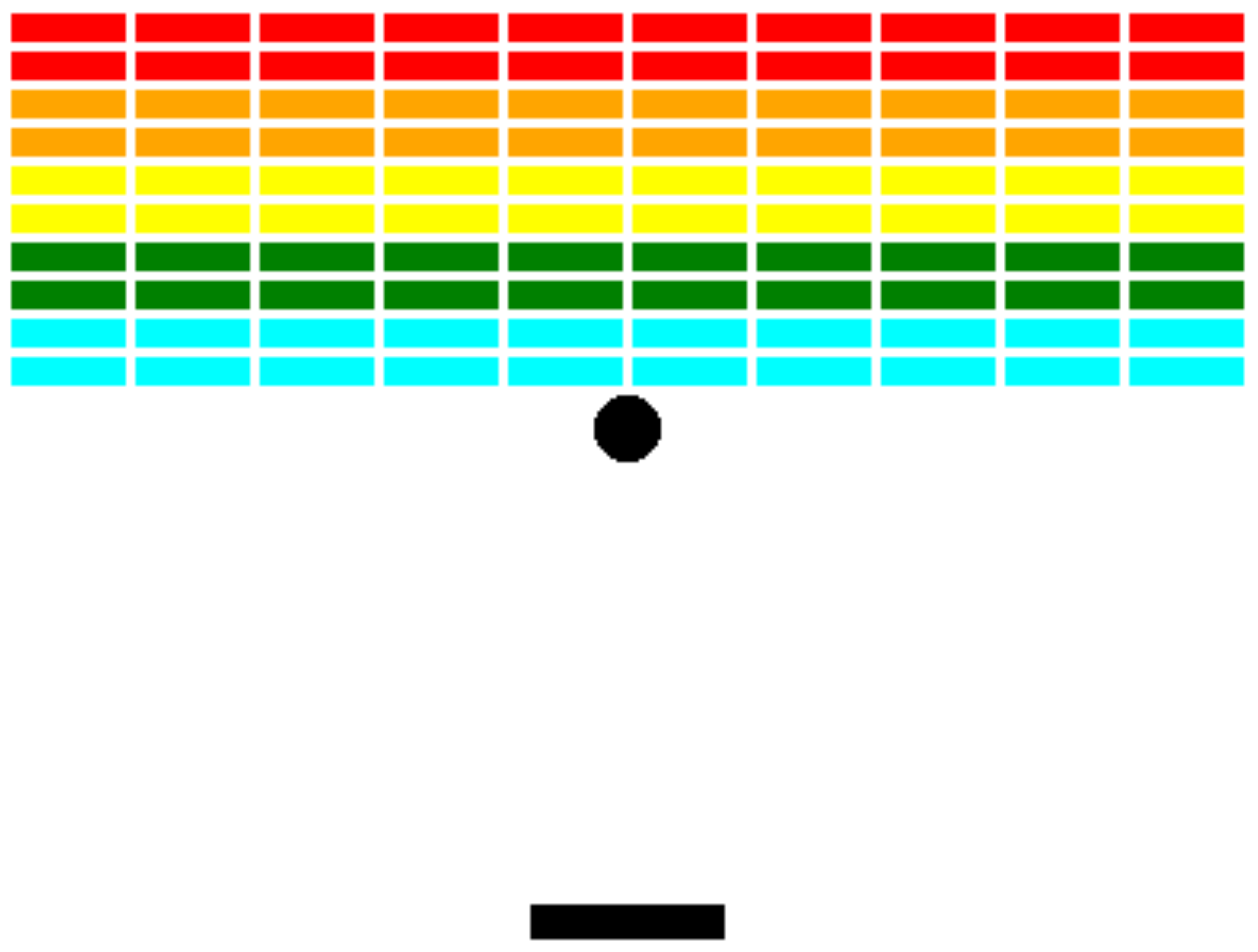
	Both held out	Held out ball speed	Held out paddle speed	Neither held out
Accuracy	88.0%	88.8%	88.2%	88.4%
Precision	38.8%	41.6%	44.9%	38.6%
Recall	82.1%	87.2%	91.4%	85.6%
F1	52.8%	56.3%	60.2%	53.2%

🌟 Performance on held out speeds roughly matches speeds seen during training

Bonus Experiment: Beyond Code.org bounce game?

- Stanford CS106A: Students program Breakout in homework assignment
- Ball “skewering” bug: common mistake, most difficult to detect/grade

Learned exploration policy



Outline

Brief Recap on Meta-RL

Algorithms for Learning to Explore

End-to-End Optimization of Exploration Strategies

Alternative Decoupled Exploration Strategies

Decoupled but Consistent Exploration & Exploitation

Case Study: Applying Meta-RL to CS Education

Reminders

Homework 3 due **tonight**

(and HW4 out today)

Project milestone due **next Wednesday**

Next week: Can we make reinforcement learning more autonomous?

Can RL agents discover skills themselves?

Can we do hierarchical RL?