Imitation Learning & Behavioral Cloning

Lucas Janson

CS/Stat 184(0): Introduction to Reinforcement Learning

Fall 2024

Today

- Feedback from last lecture
- Recap
- Imitation Learning problem statement
- Behavioral Cloning
- DAgger

Feedback from feedback forms

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1. Thank you to everyone who filled out the forms!

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All Policy Gradient Algorithms in One Slide

Parameterize policy and optimize directly while sampling from MDP

Policy Gradient (PG)

Variance too high

Variance reduction techniques like mini-batches and baselines

Fitted Policy Iteration

Big steps unstable

Trust Region Policy Optimization (TRPO)

Approximation in closed form

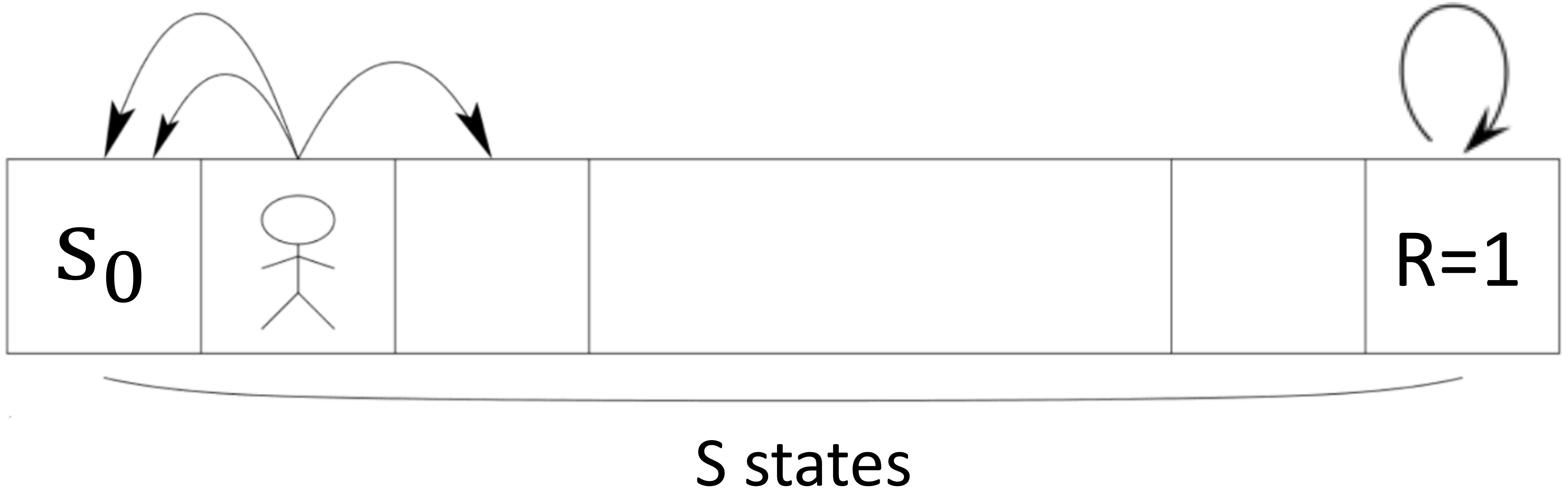
Natural Policy Gradient (NPG)

2nd-order updates expensive

Proximal Policy Optimization (PPO)

PPO gets 2nd-order optimization benefits over PG and 1st-order computation benefits over TRPO/NPG

"Lack of Exploration" leads to Optimization and Statistical Challenges



Thrun '92

- Suppose $H \approx \text{poly}(|S|)$ & $\mu(s_0) = 1$ (i.e. we start at s_0).
- A randomly initialized policy π^0 has prob. $O(1/3^{|S|})$ of hitting the goal state in a trajectory.
- Thus a sample-based approach, with $\mu(s_0) = 1$, require $O(3^{|S|})$ trajectories.
    - Holds for (sample based) Fitted DP
    - Holds for (sample based) PG/TRPO/NPG/PPO
- Basically, for these approaches, there is no hope of learning the optimal policy if $\mu(s_0) = 1$.

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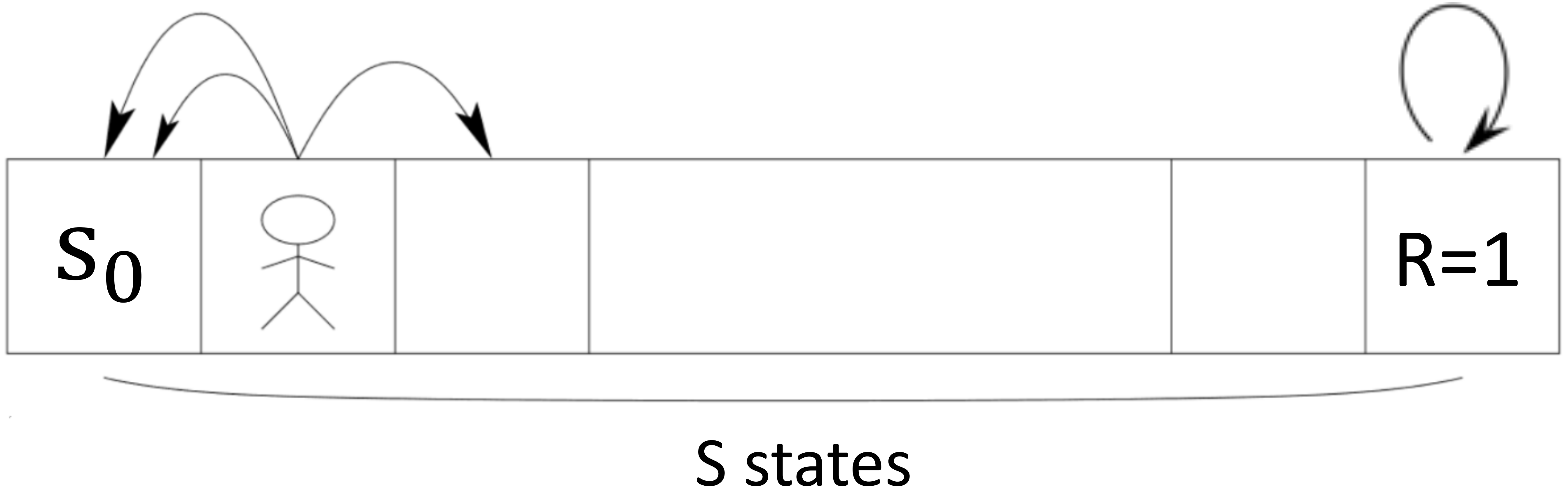

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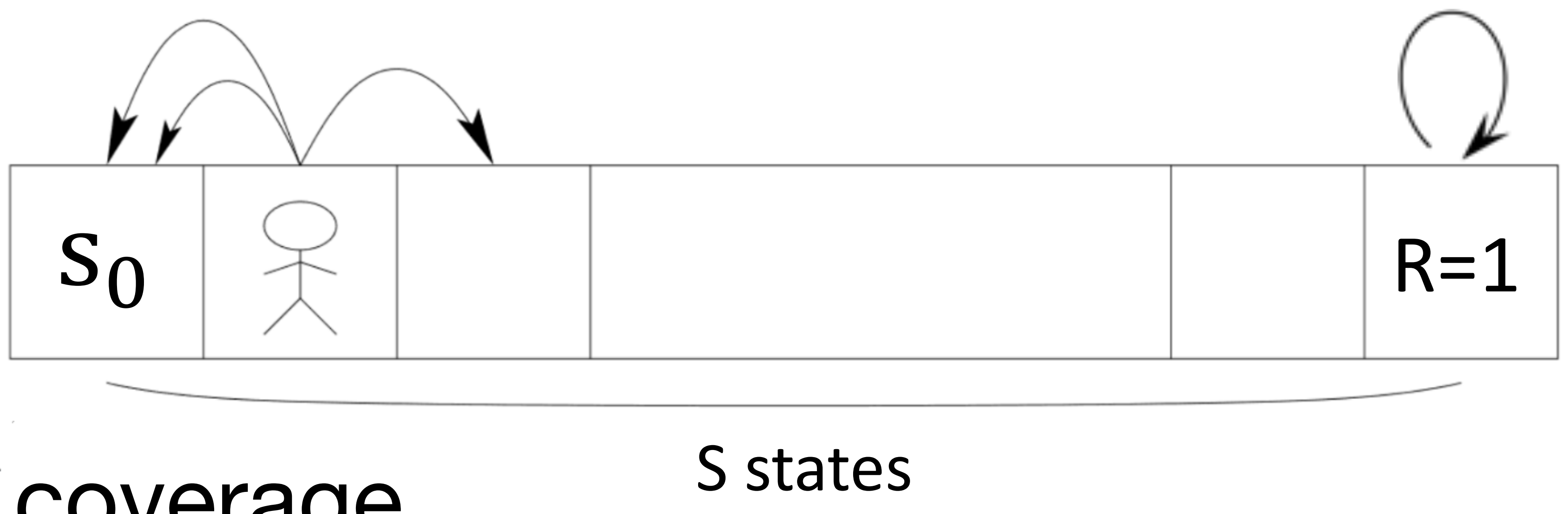
Why not do one trajectory that always moves right?

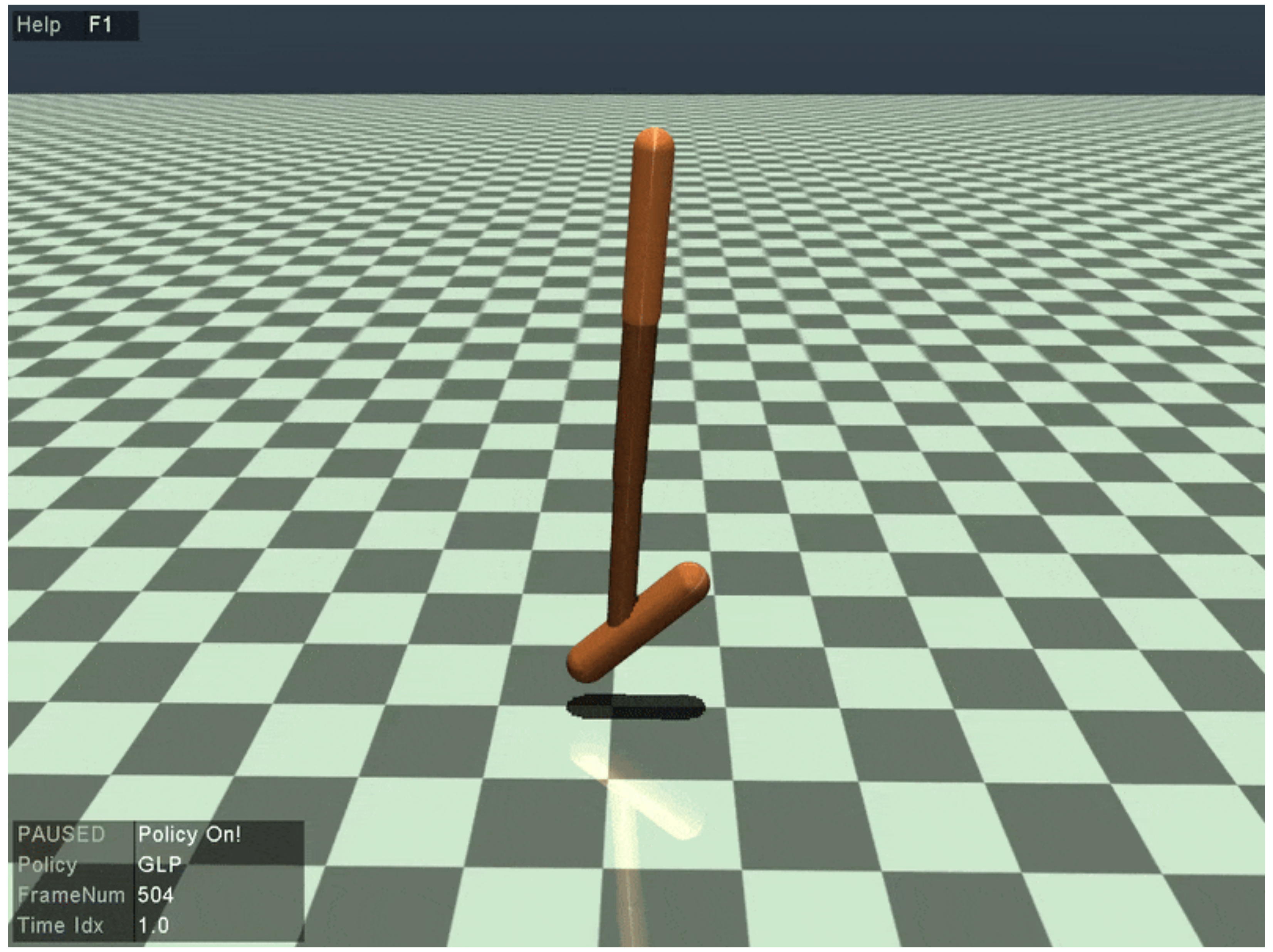
Let's examine the role of μ

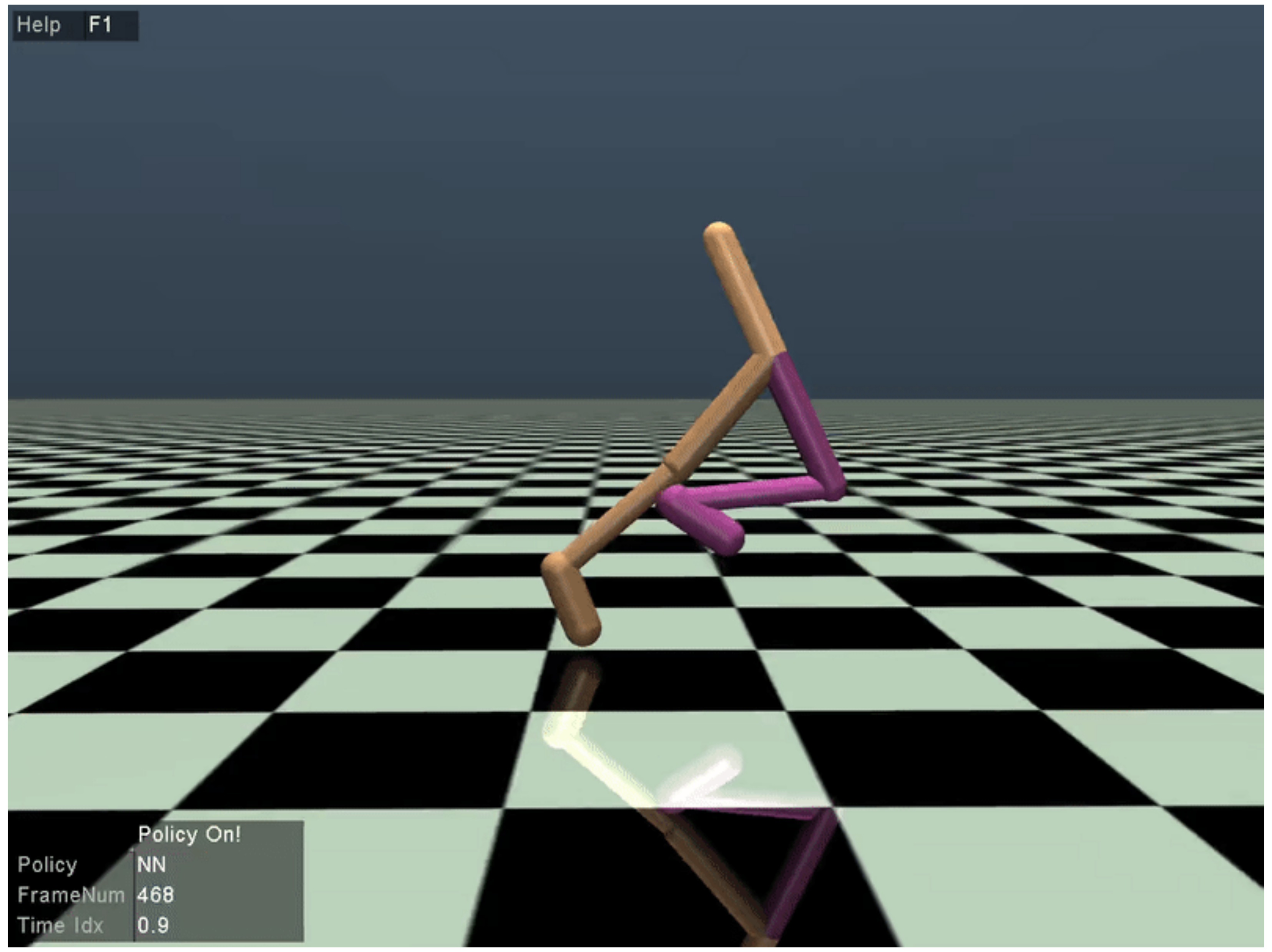


Thrun '92

- Suppose that somehow the distribution μ had better coverage.
  - e.g, if μ was uniform overall states in our toy problem, then all approaches we covered would work (with mild assumptions)
  - Theory: TRPO/NPG/PPO have better guarantees than fitted DP methods (assuming some "coverage")
- Strategies without coverage:
  - If we have a simulator, sometimes we can design μ to have better coverage.
    - this is helpful for robustness as well.
  - Imitation learning (next time).
    - An expert gives us samples from a "good" μ.
  - Explicit exploration:
    - UCB-VI: we'll merge two good ideas!
    - Encourage exploration in PG methods.
  - Try with reward shaping

Aside: Brittle policies if we train starting from only from one configuration!





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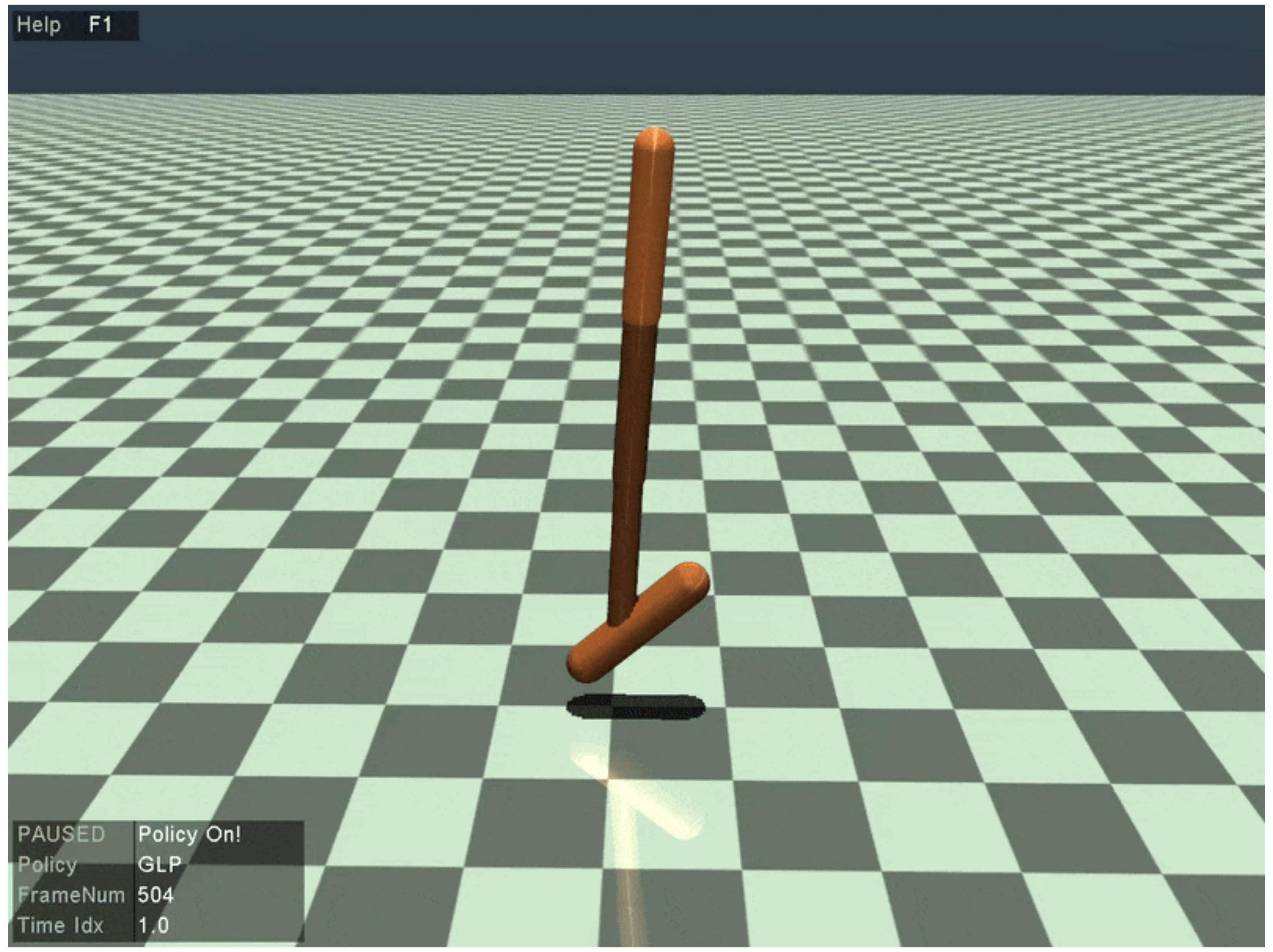

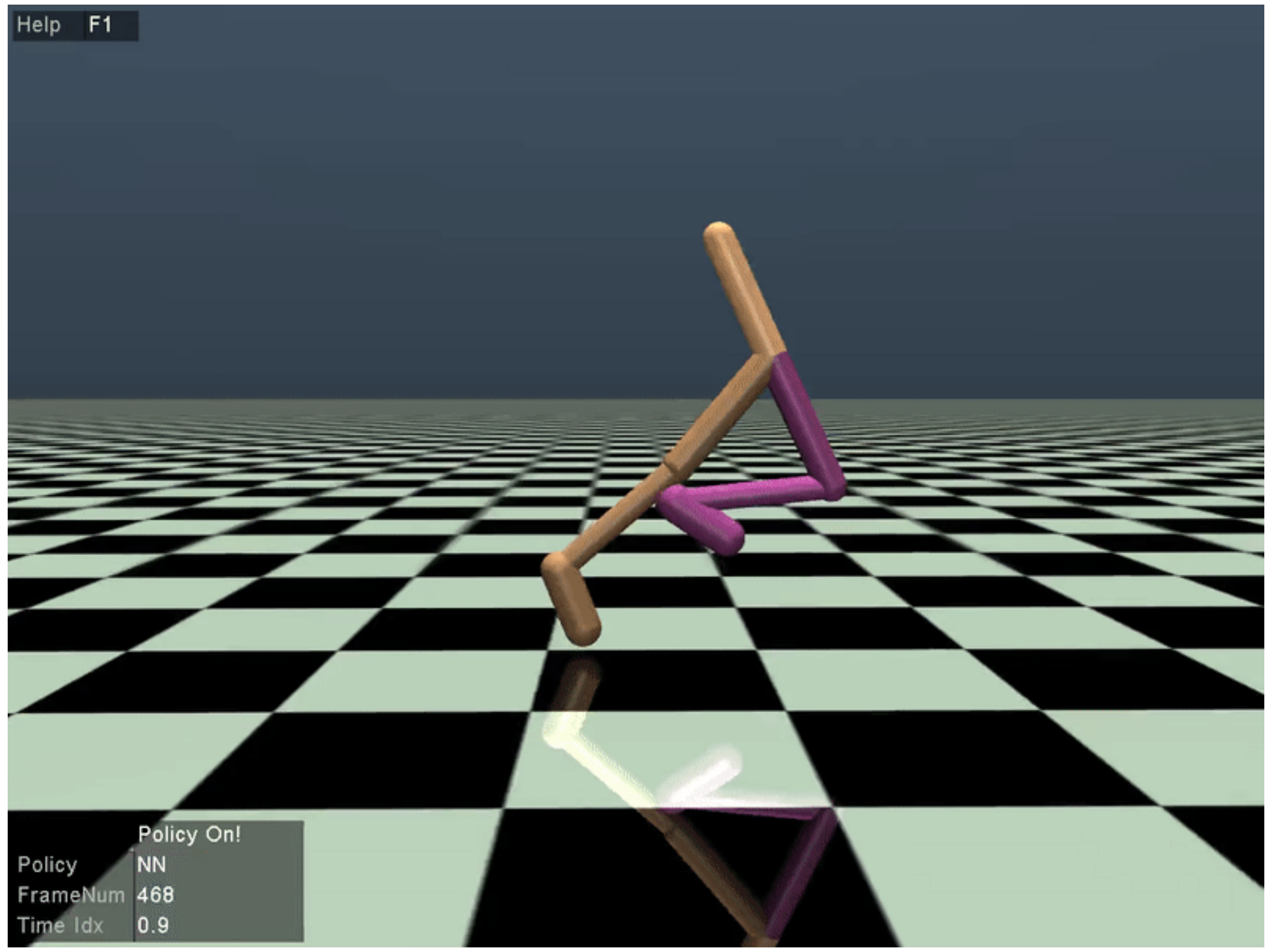

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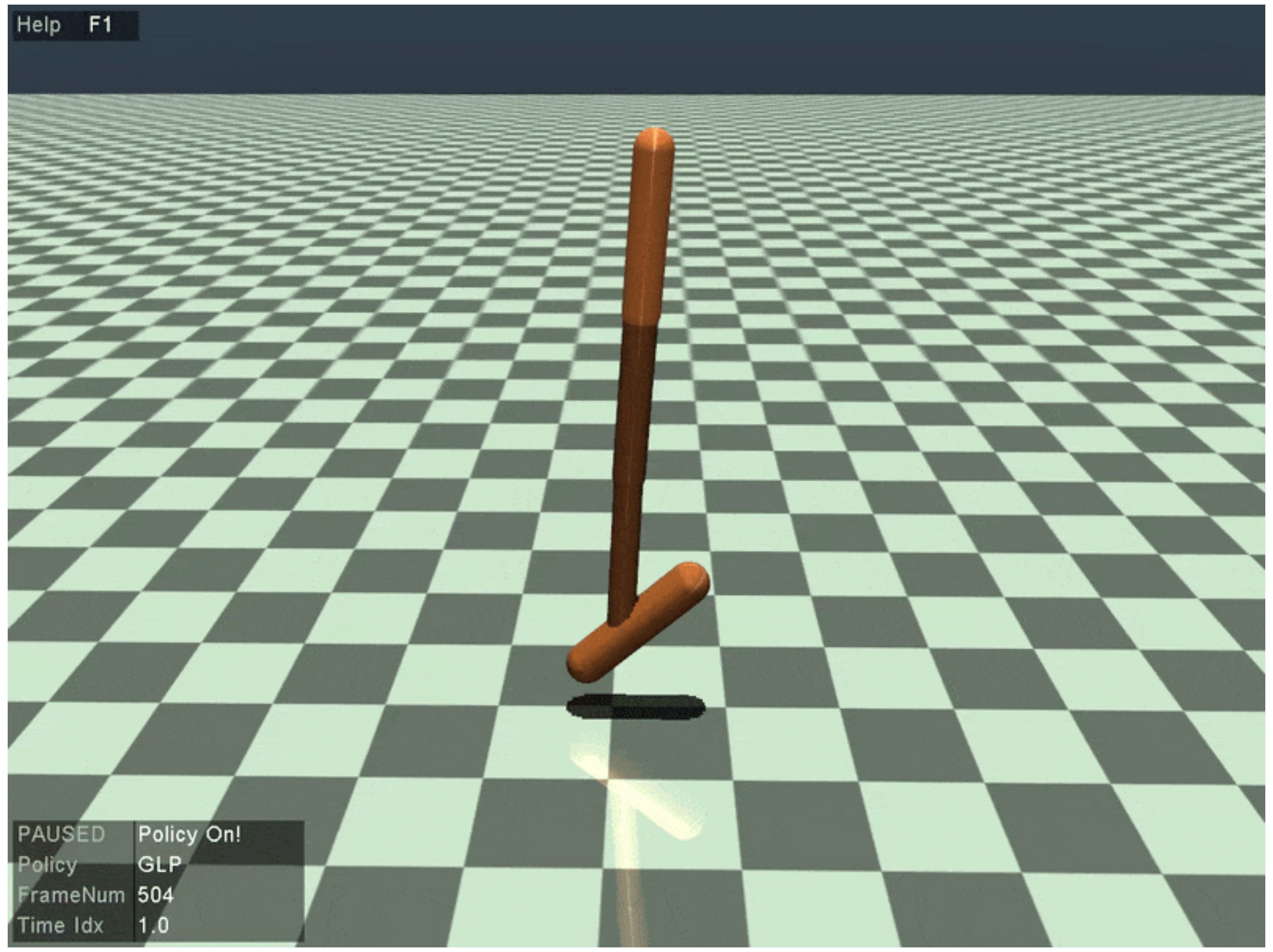

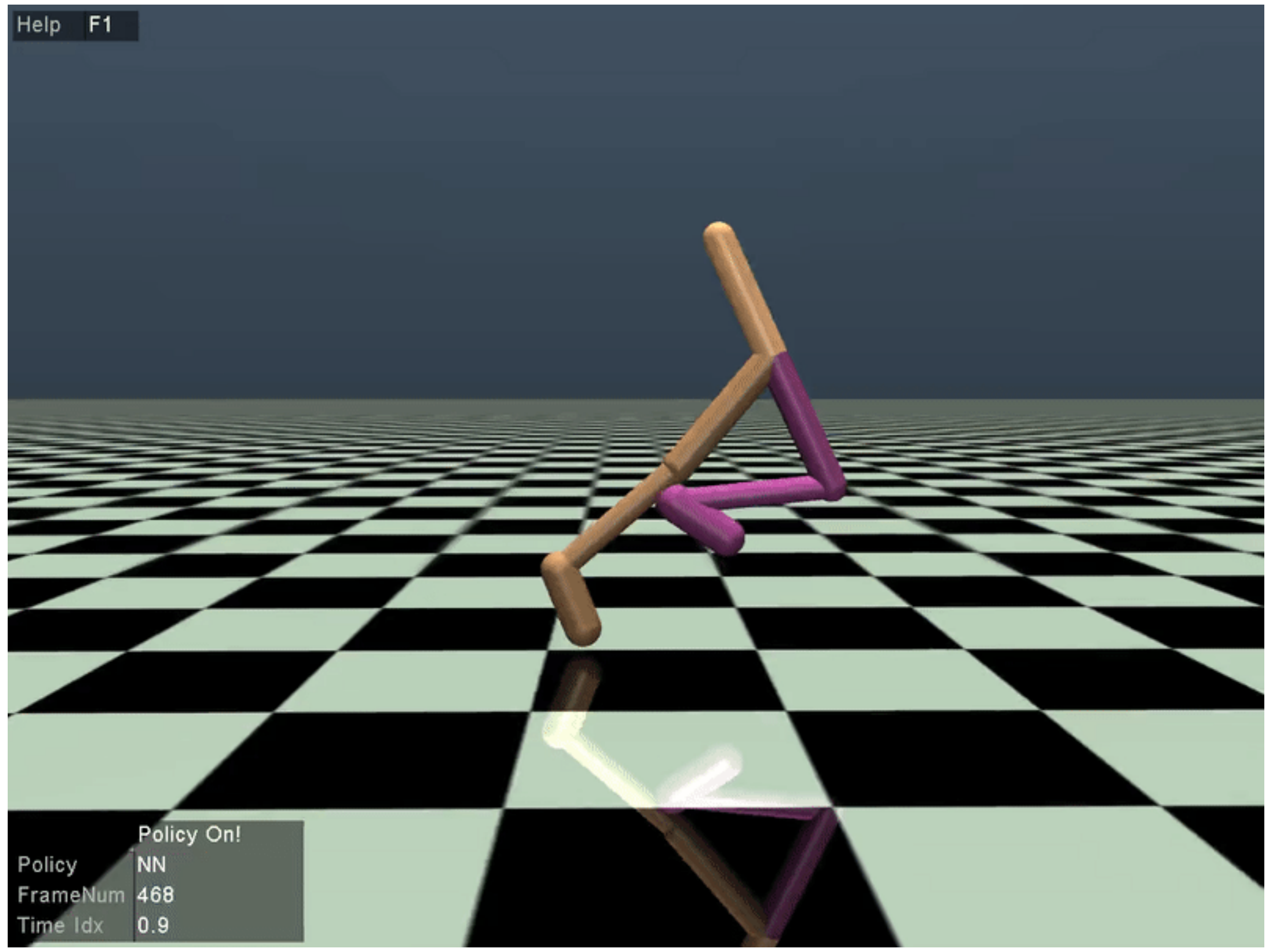

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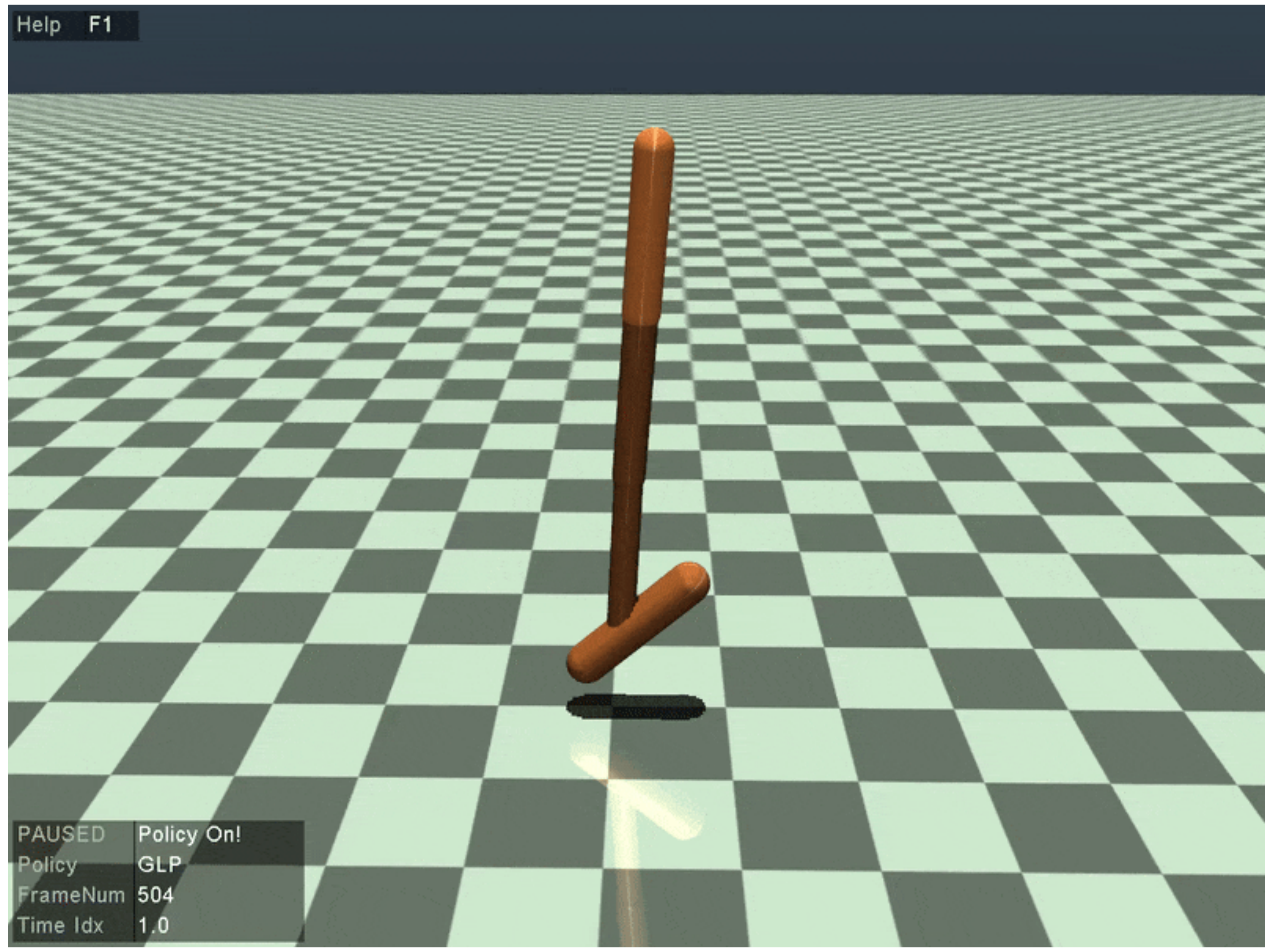

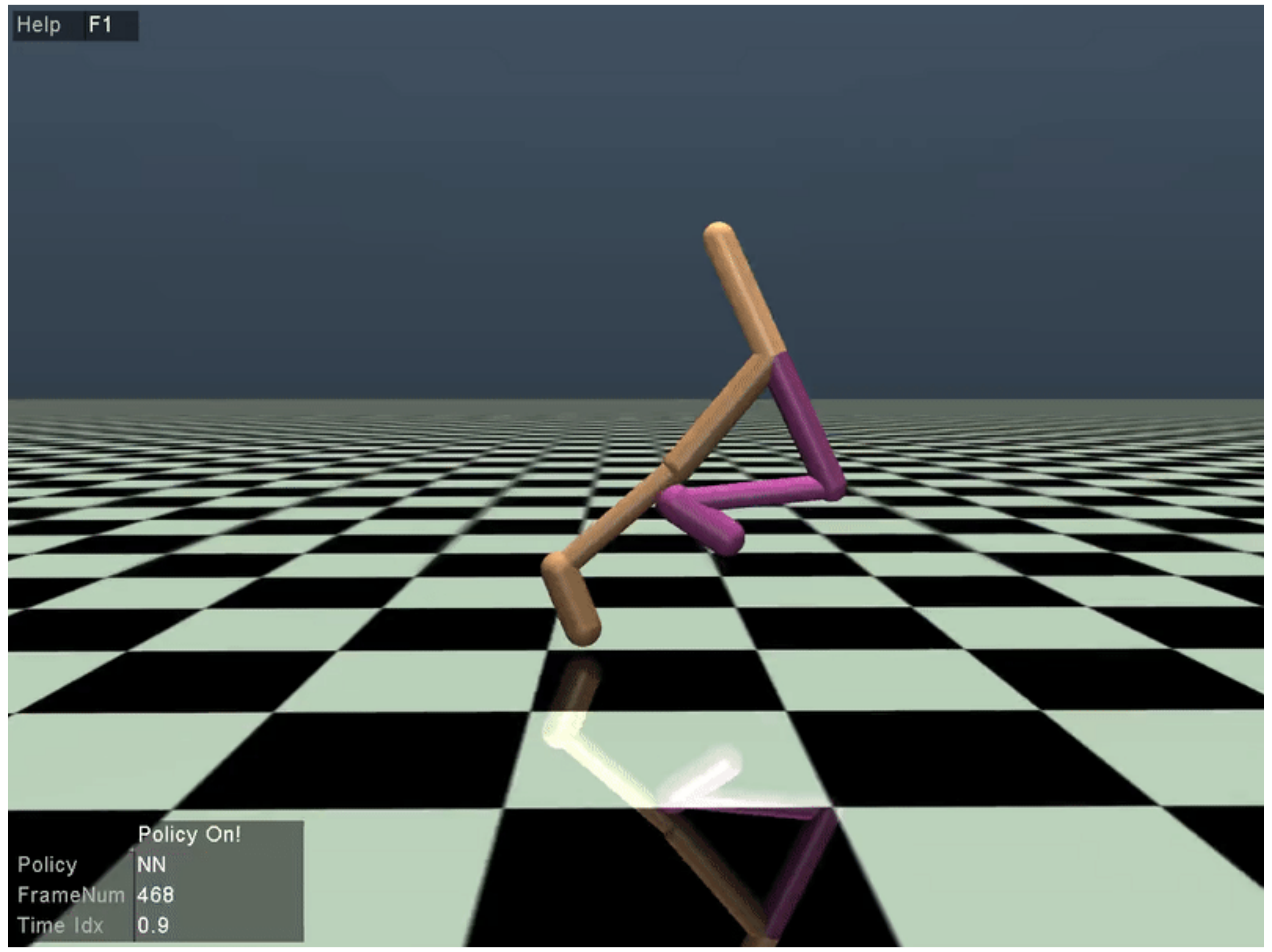

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- How to fix this?
  - Training from different starting configurations sampled from $s_0 \sim \mu$ fixes this:

$$\max_{\theta} \mathbb{E}_{s_0 \sim \mu}[V^{\theta}(s_0)]$$

Even if starting position concentrated at just one point—good for robustness!

OpenAI: progress on dexterous hand manipulation

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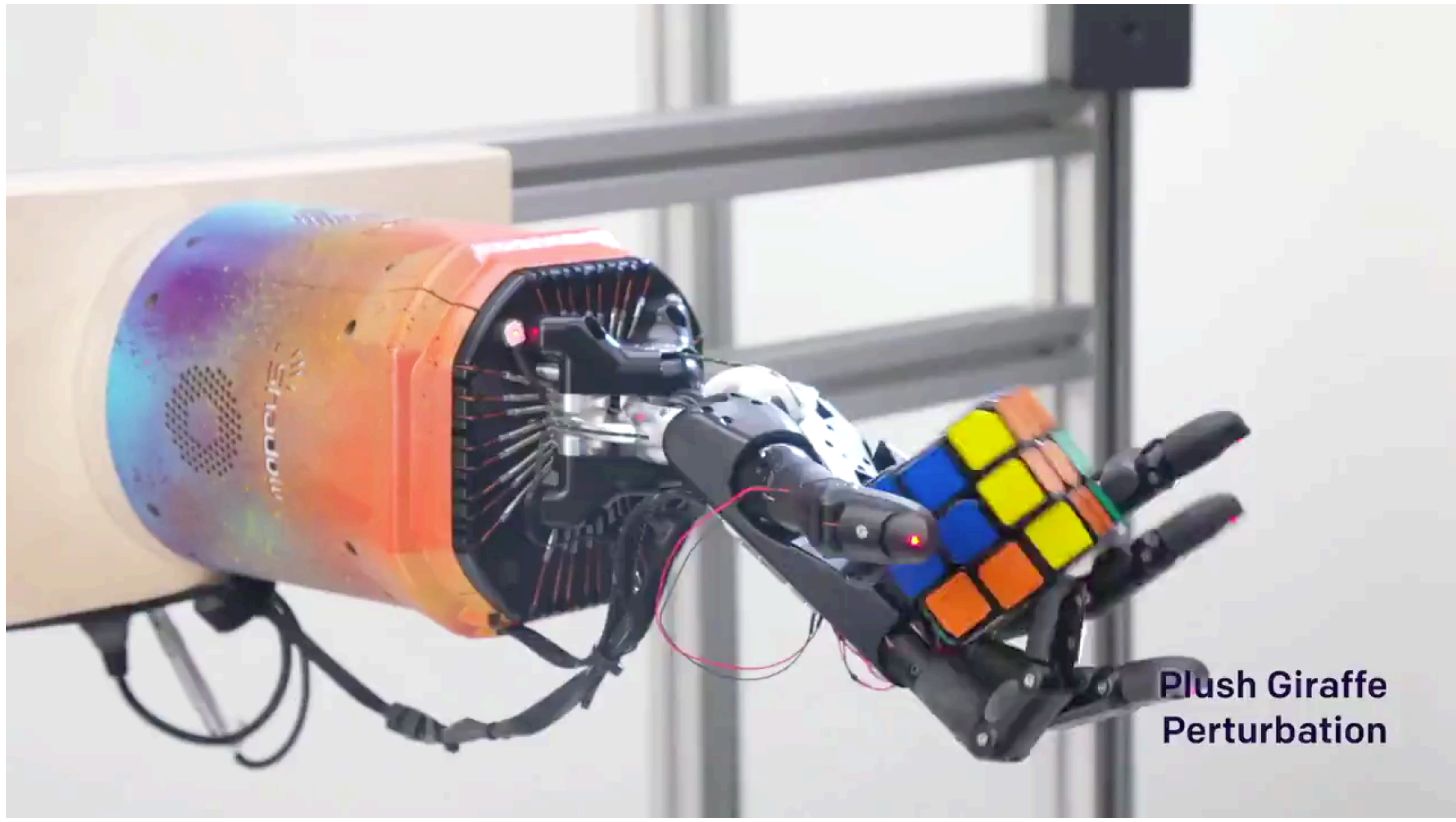
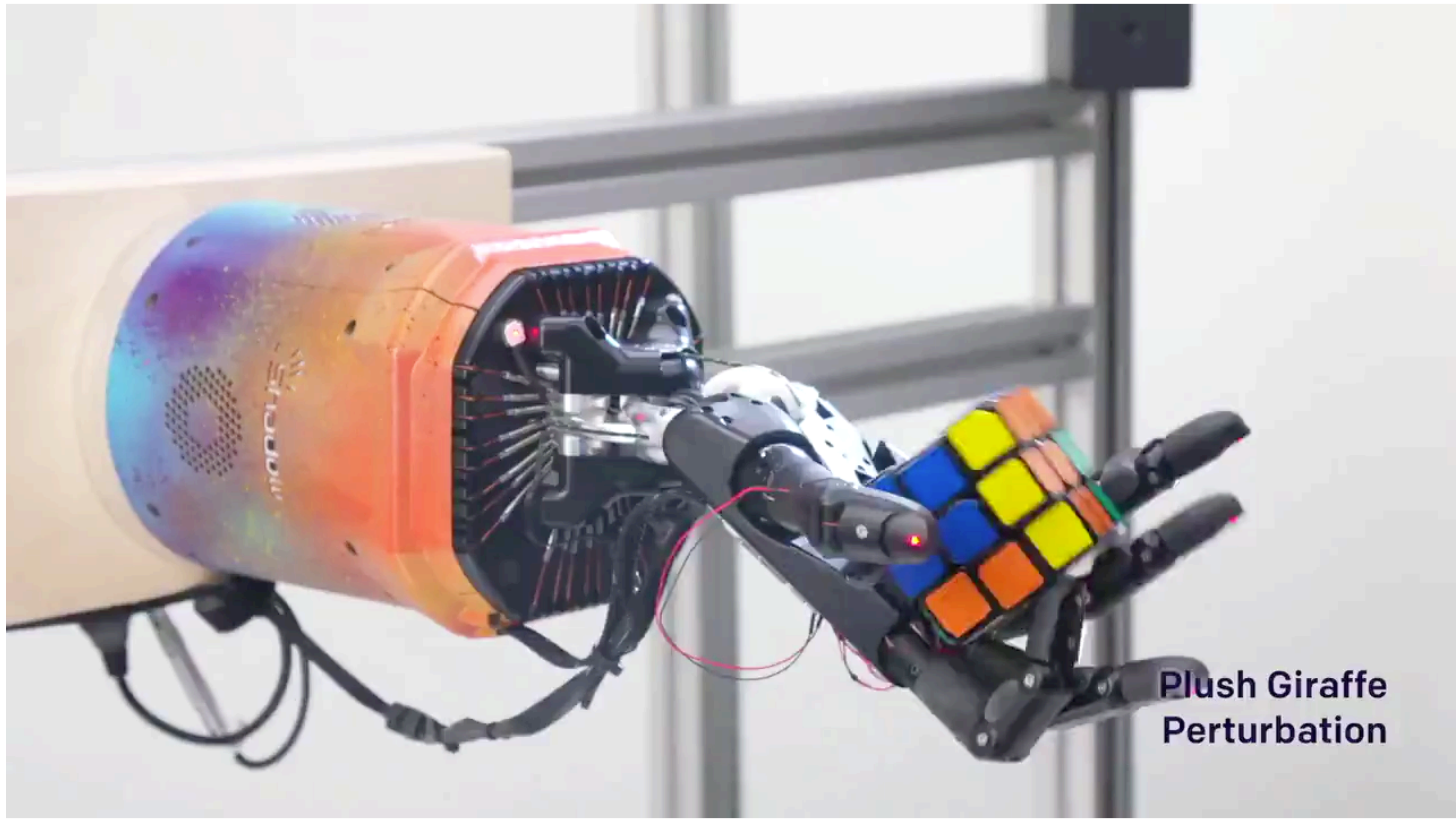


OpenAI: progress on dexterous hand manipulation



Trained with “domain randomization”

Basically, the measure $s_0 \sim \mu$ was diverse.

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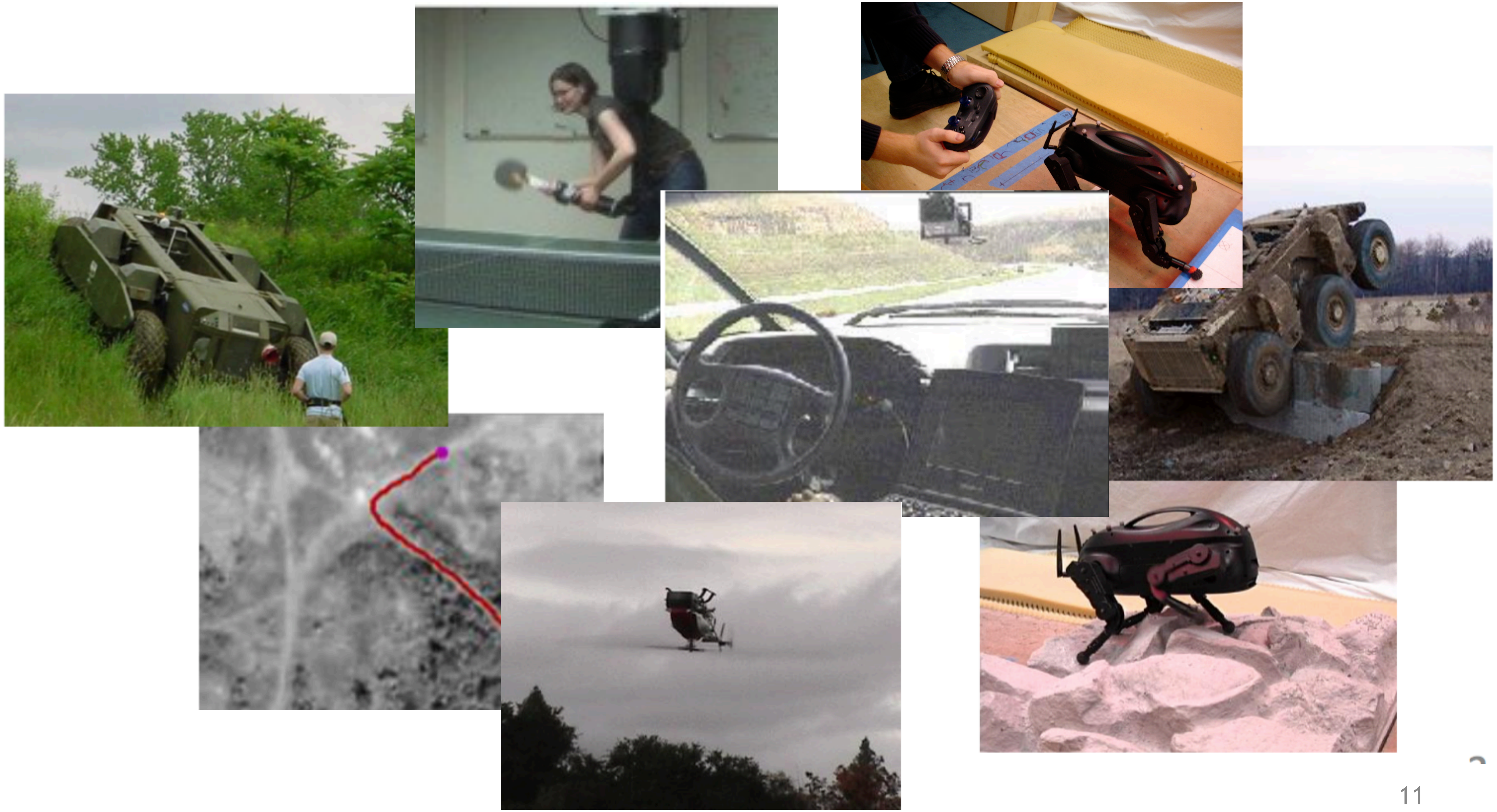

Imitation Learning

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Expert Demonstrations

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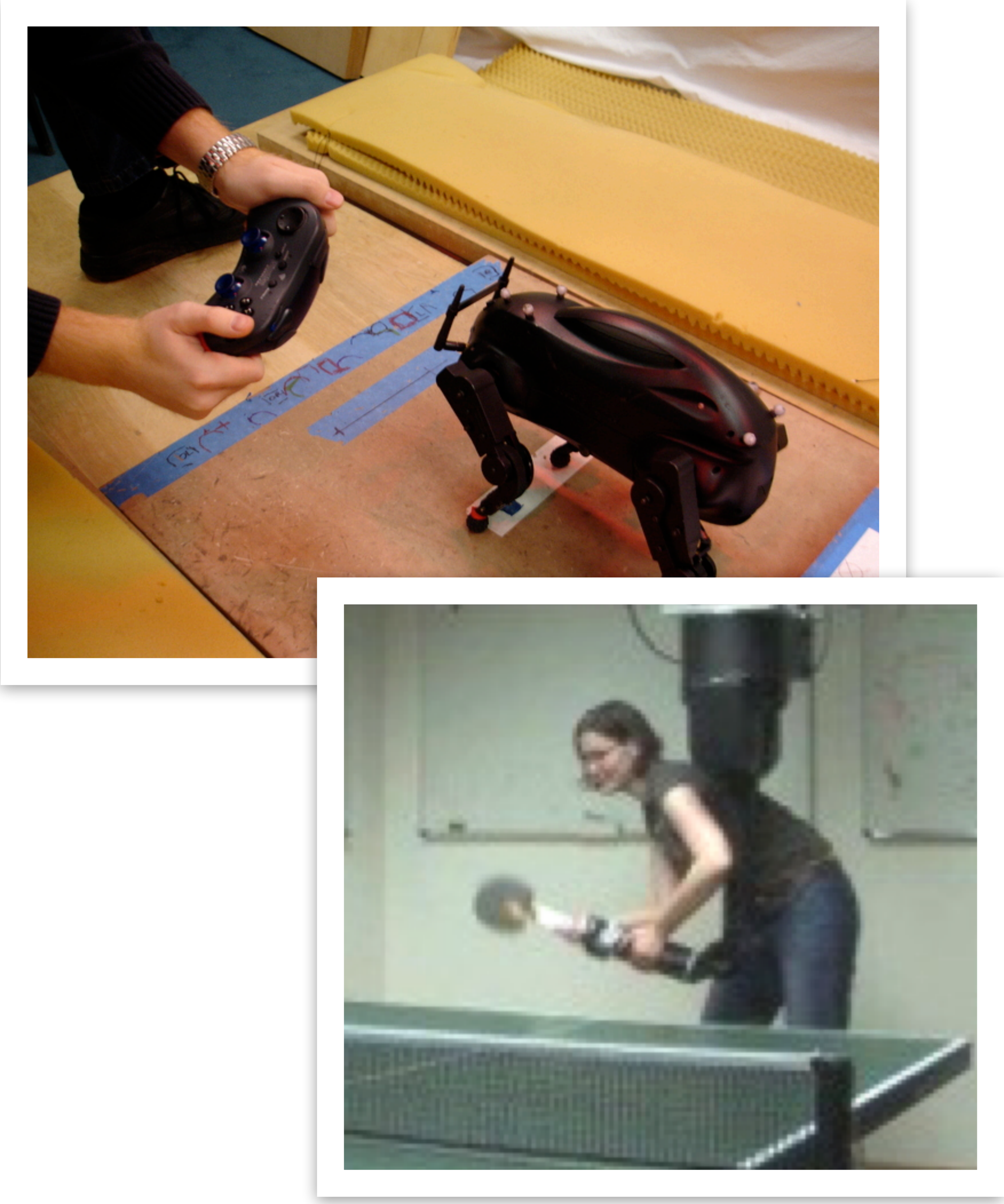
Machine Learning Algorithm



- SVM
- Gaussian Process
- Kernel Estimator
- Deep Networks
- Random Forests
- LWR
- …

Imitation Learning

Expert Demonstrations

Machine Learning Algorithm

Policy π

- SVM
- Gaussian Process
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Maps *states* to <u>actions</u>

Learning to Drive by Imitation

[Pomerleau89, Saxena05, Ross11a]

Input:

Camera Image

Policy

Output:

Steering Angle
in [-1, 1]

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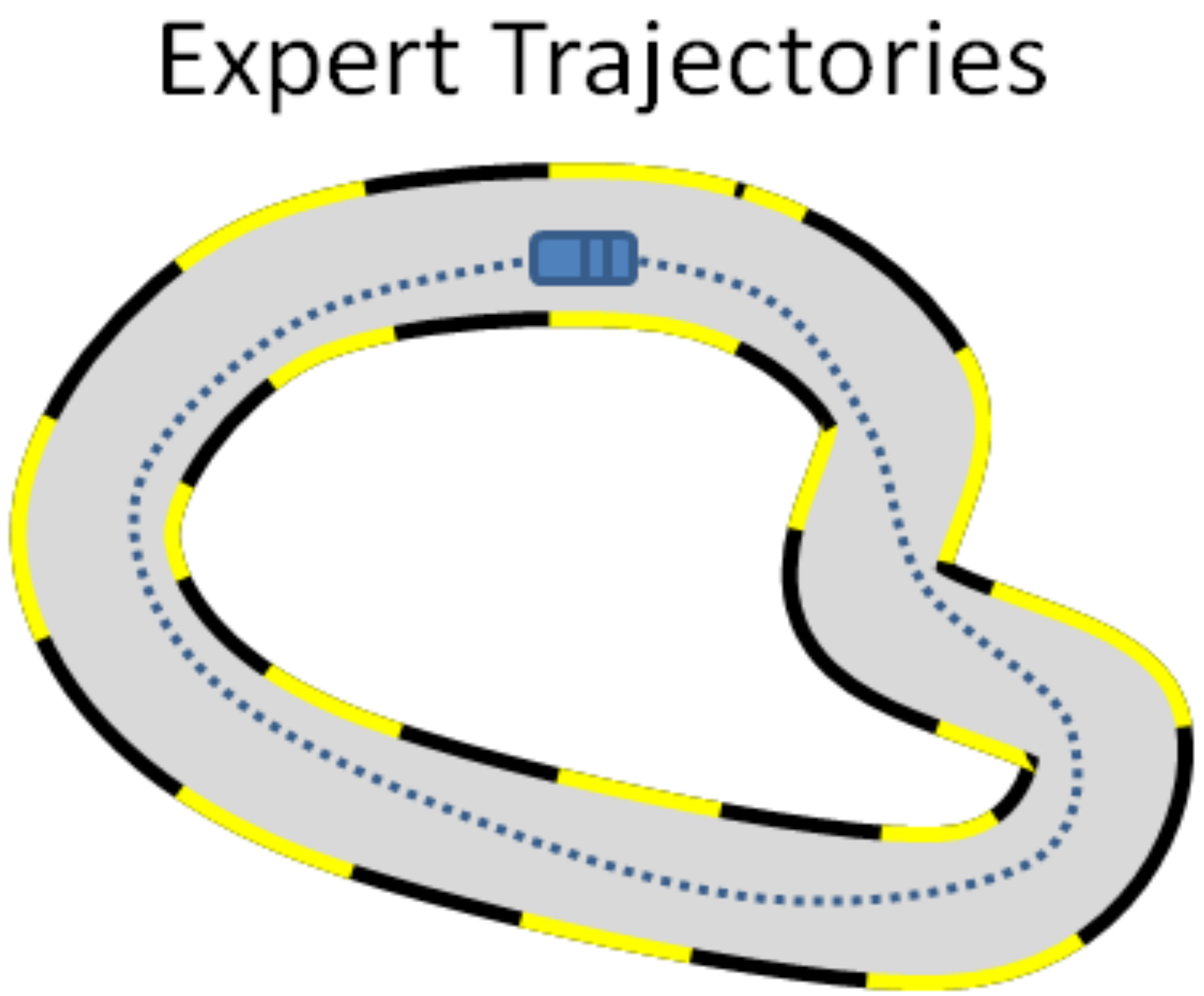
[Widrow64,Pomerleau89]

Supervised Learning Approach: Behavior Cloning



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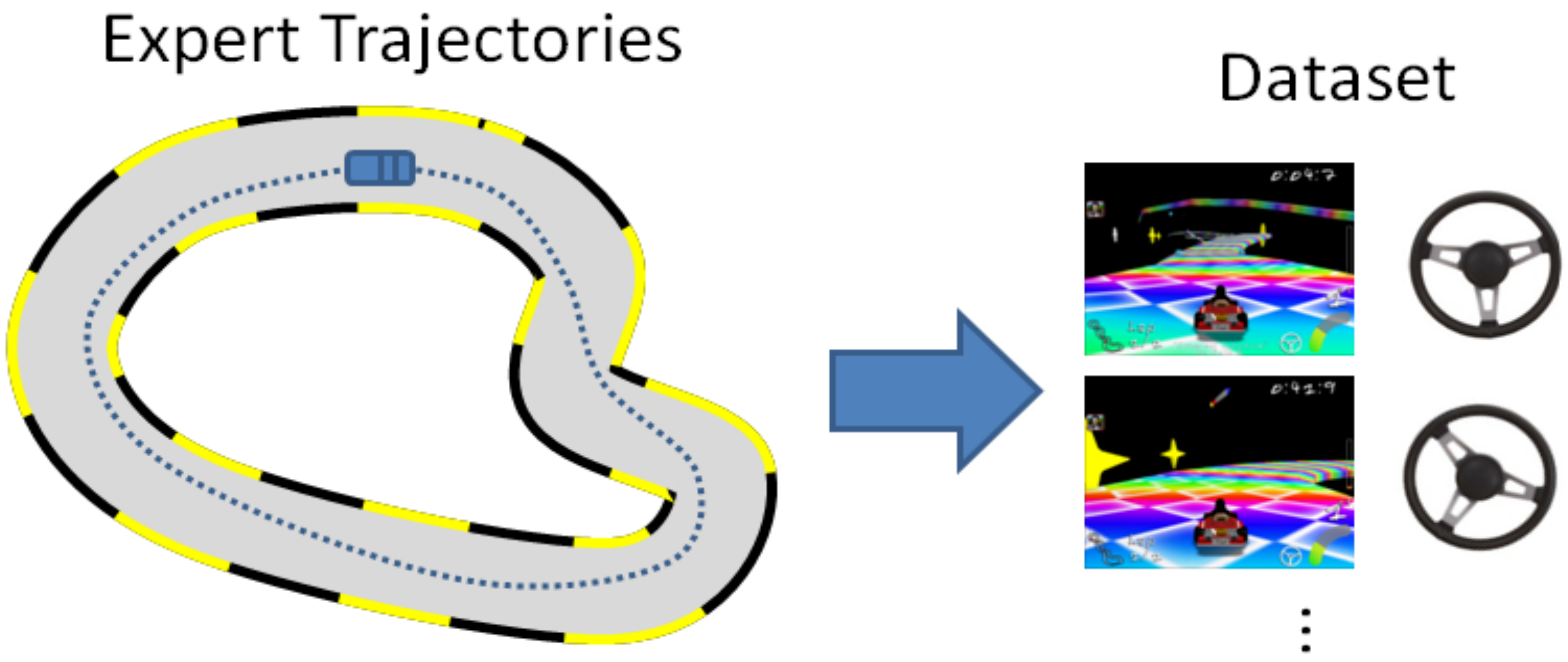

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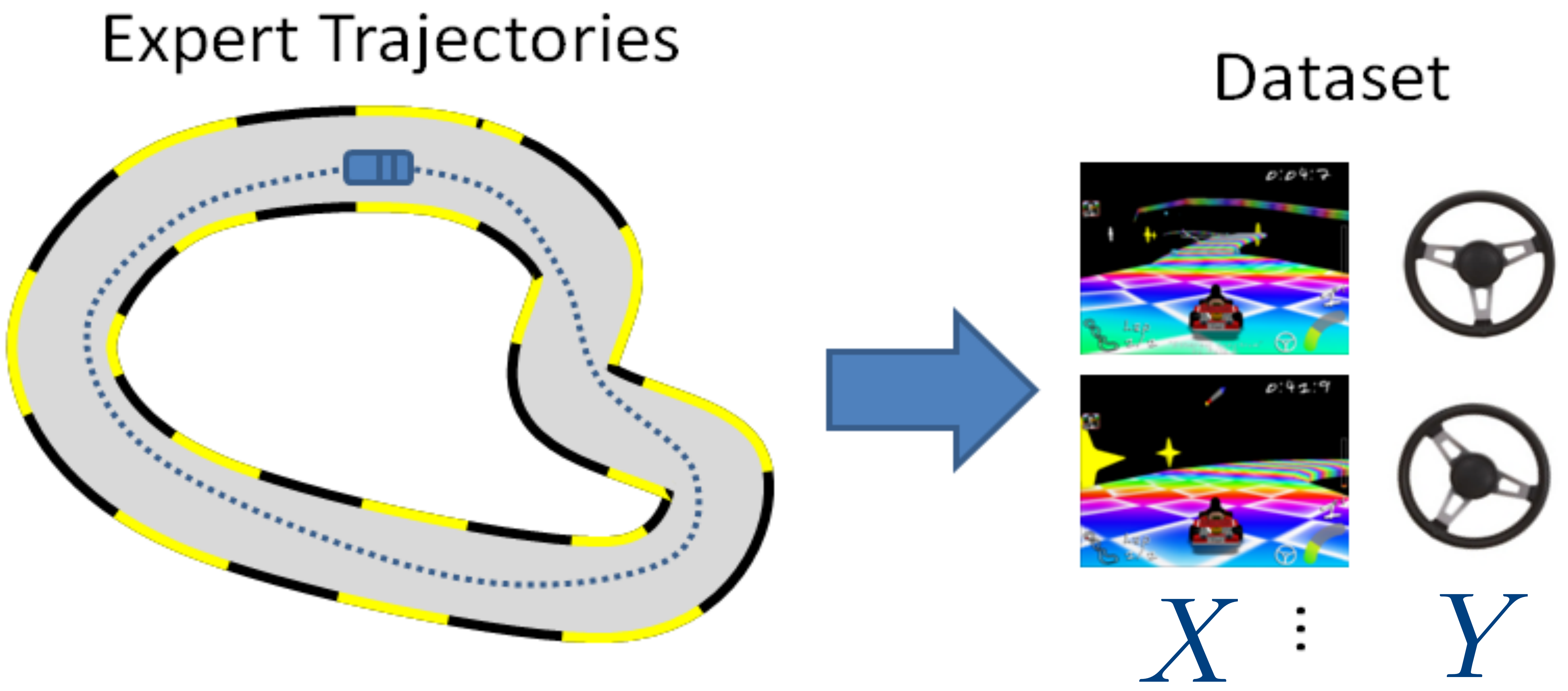

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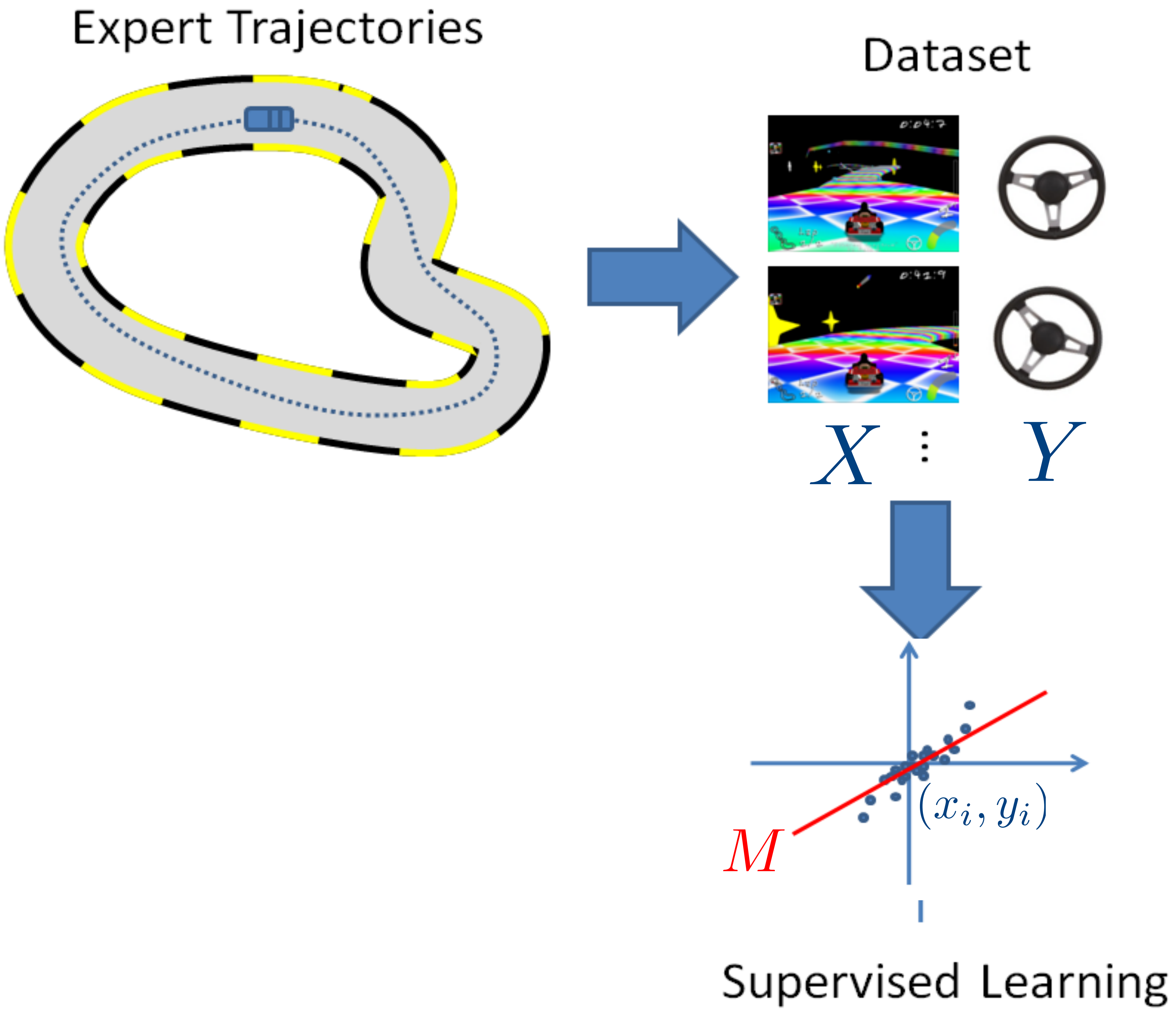

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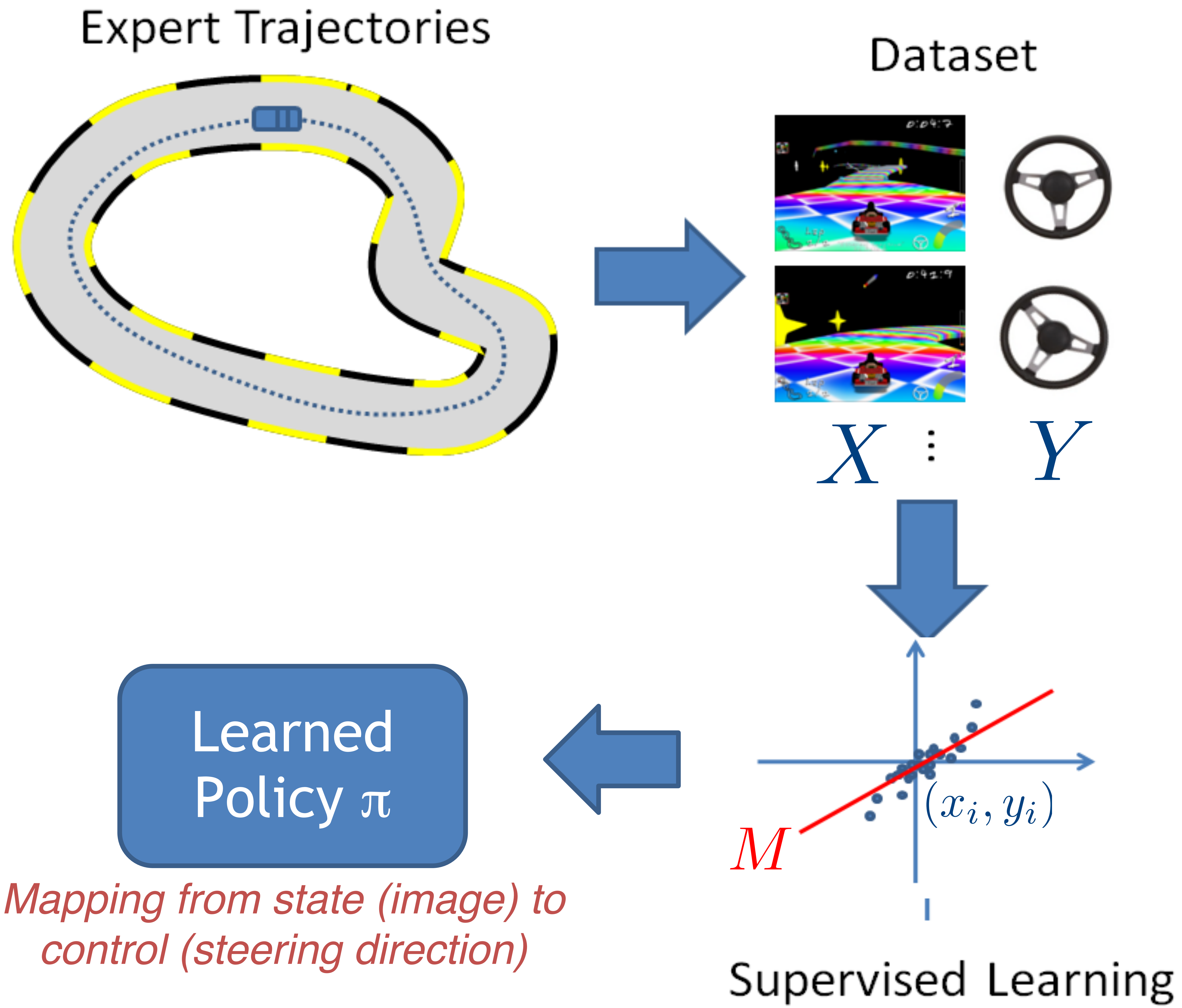
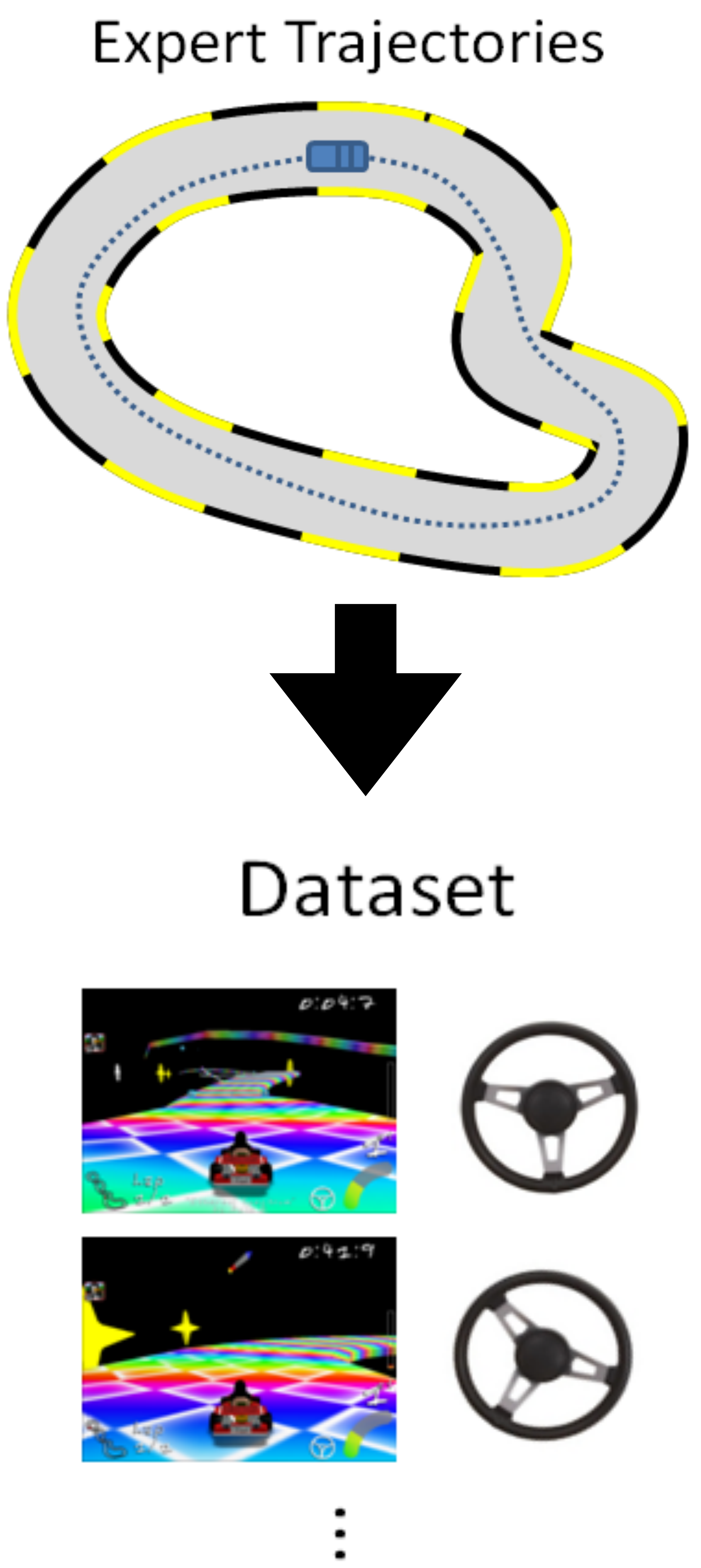


Let’s formalize the offline IL Setting and the Behavior Cloning algorithm



Finite horizon MDP $\mathscr{M}$

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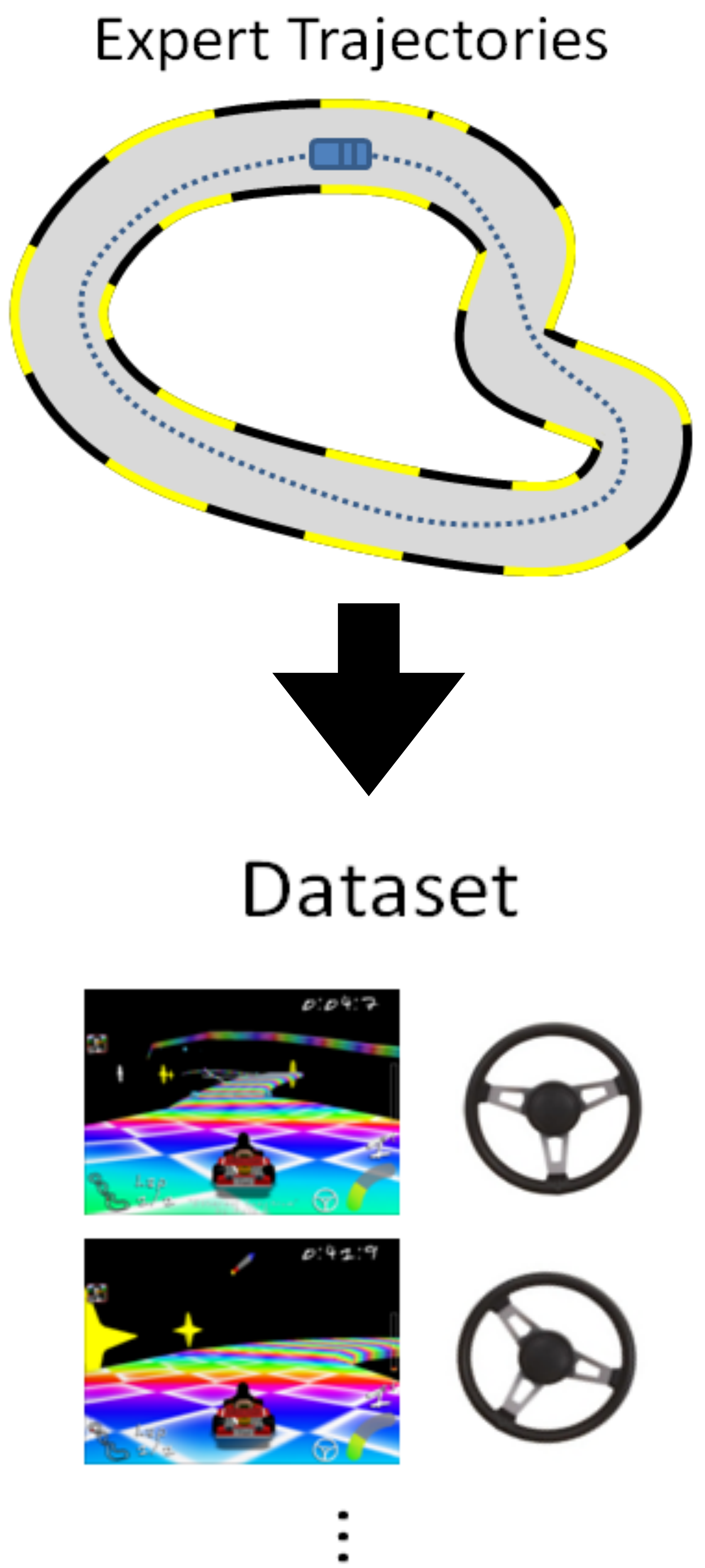

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Assume the expert has a good policy $\pi^\star$ (not necessarily opt)

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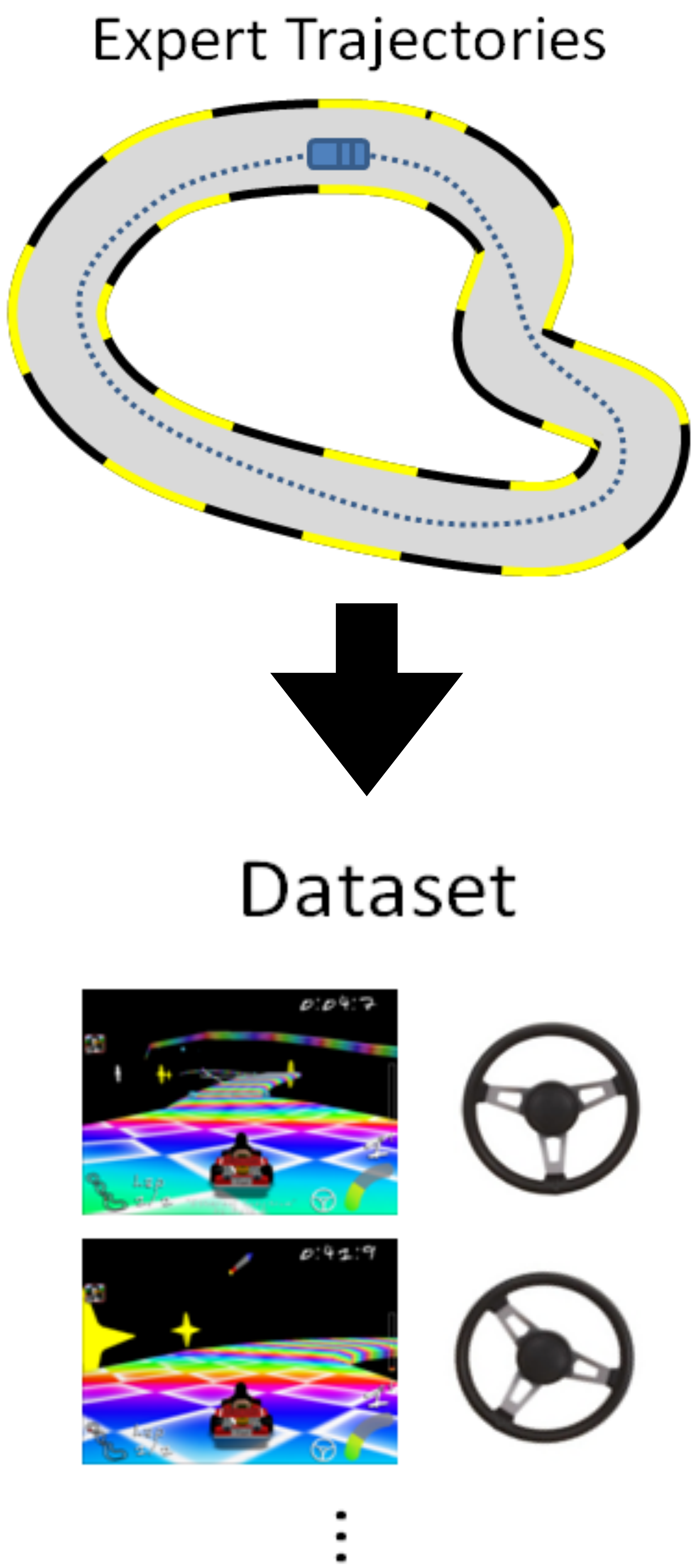

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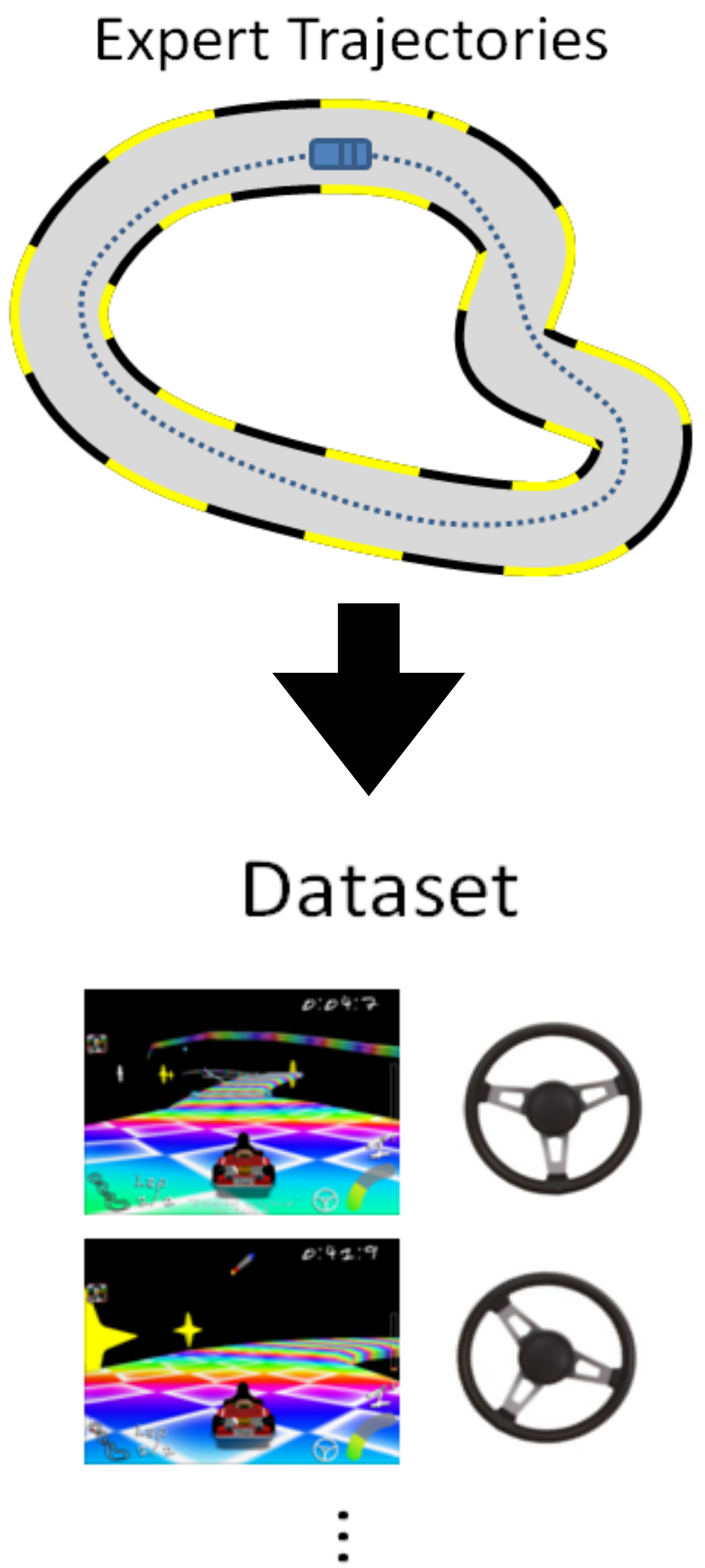

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Goal: learn a policy from $\mathscr{D}$ that is as good as the expert $\pi^\star$

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BC Algorithm input: a restricted policy class $\Pi = \{\pi : S \mapsto \Delta(A)\}$

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3. square loss (i.e., regression for continuous action): $\ell(\pi, s, a) = \|\pi(s) - a\|_2^2$

Theorem: IL is (almost) as easy as SL

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The quadratic amplification is annoying

Proof:

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$$|V^{\pi^\star}(s) - V^{\widehat{\pi}}(s)| = \left|\mathbb{E}_{\tau \sim \rho_{\pi^\star}}\left[\sum_{h=0}^{H-1} A_h^{\widehat{\pi}}(s_h, a_h)\right]\right|$$

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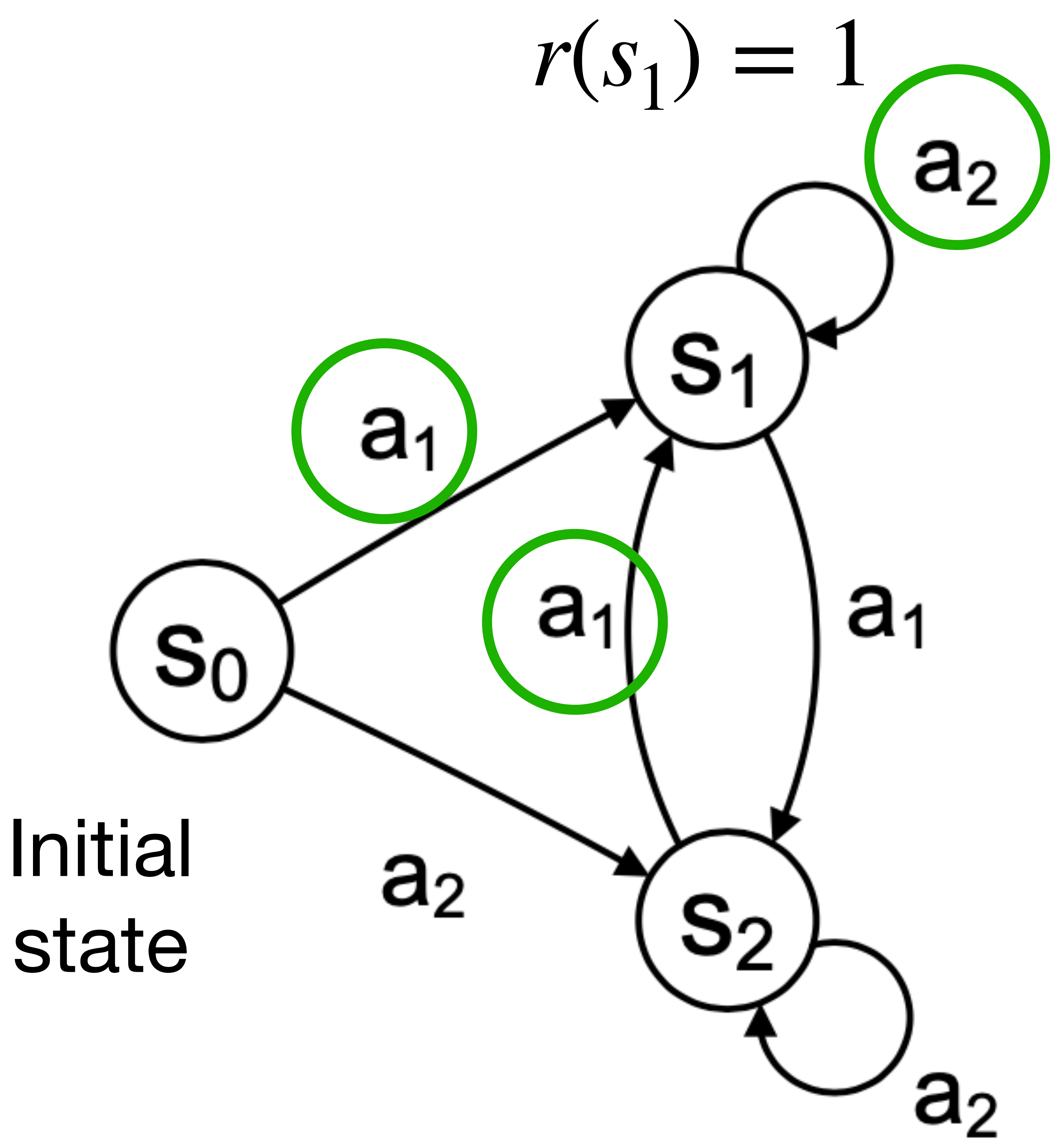
$$\leq H^2\epsilon$$

Distribution Shift Example (H^2 factor is tight)



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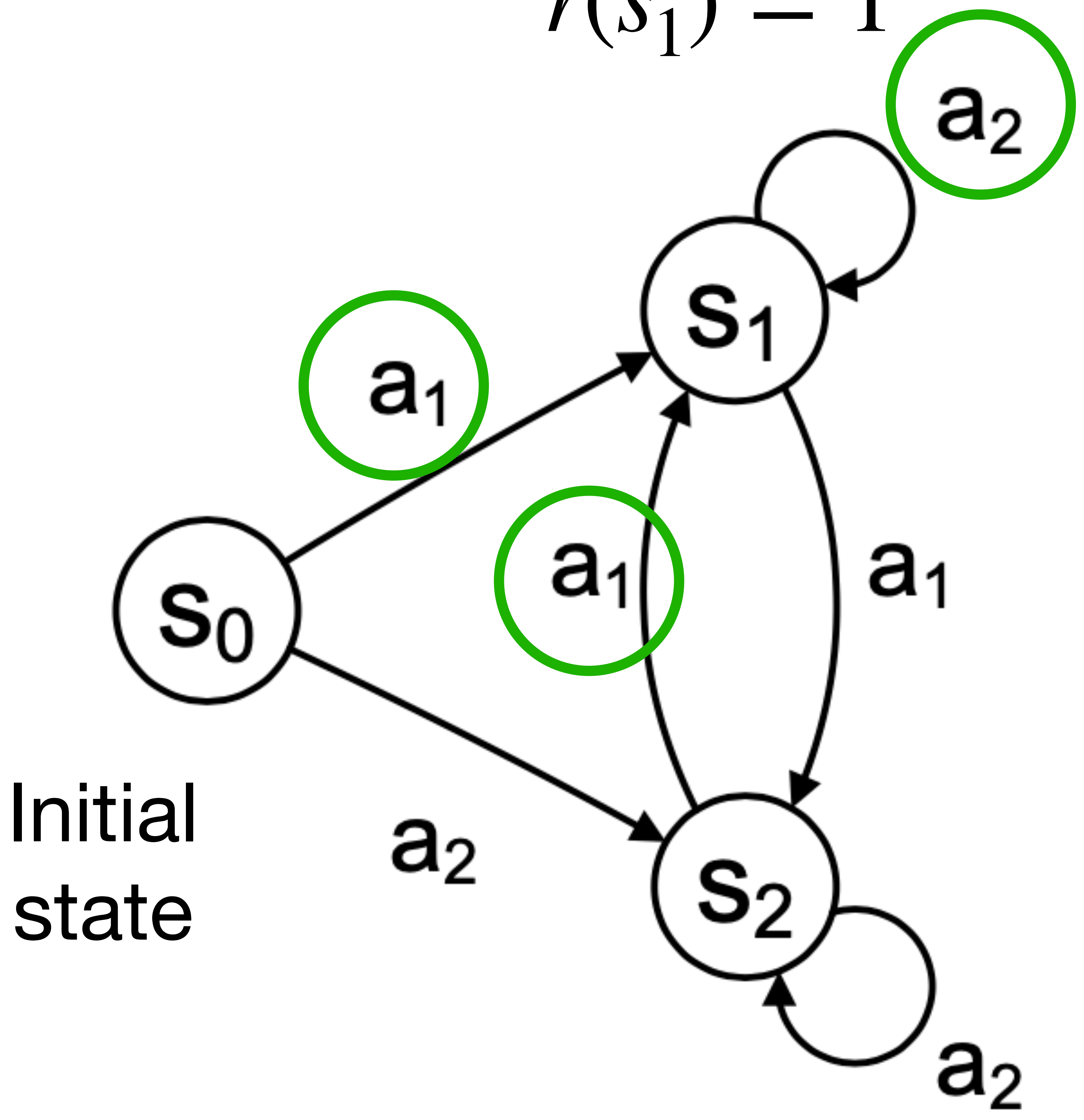

Opt policy:

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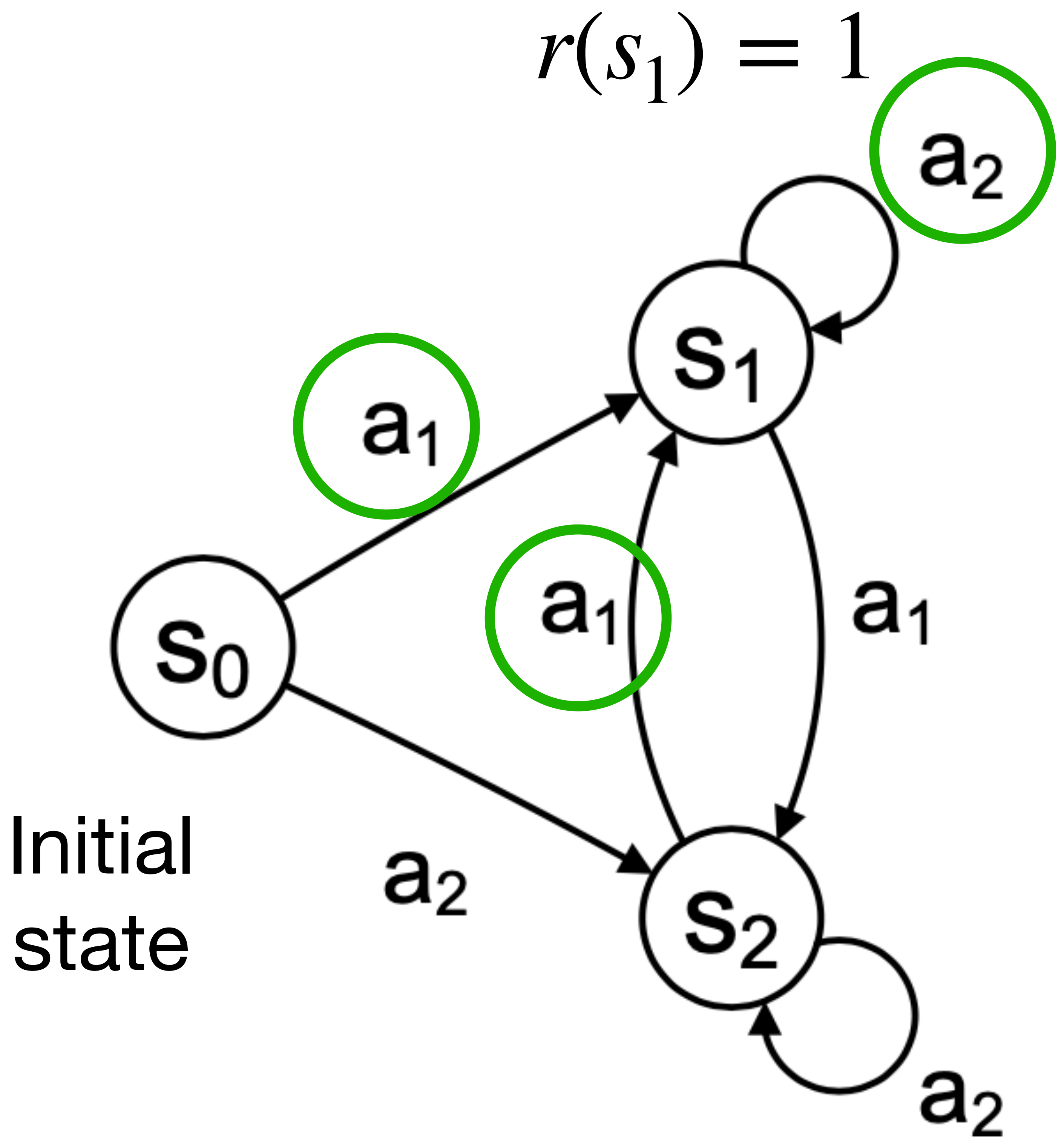

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Under $\rho_{\pi^\star}$, trajectory is $s_0, s_1, s_1, \ldots$

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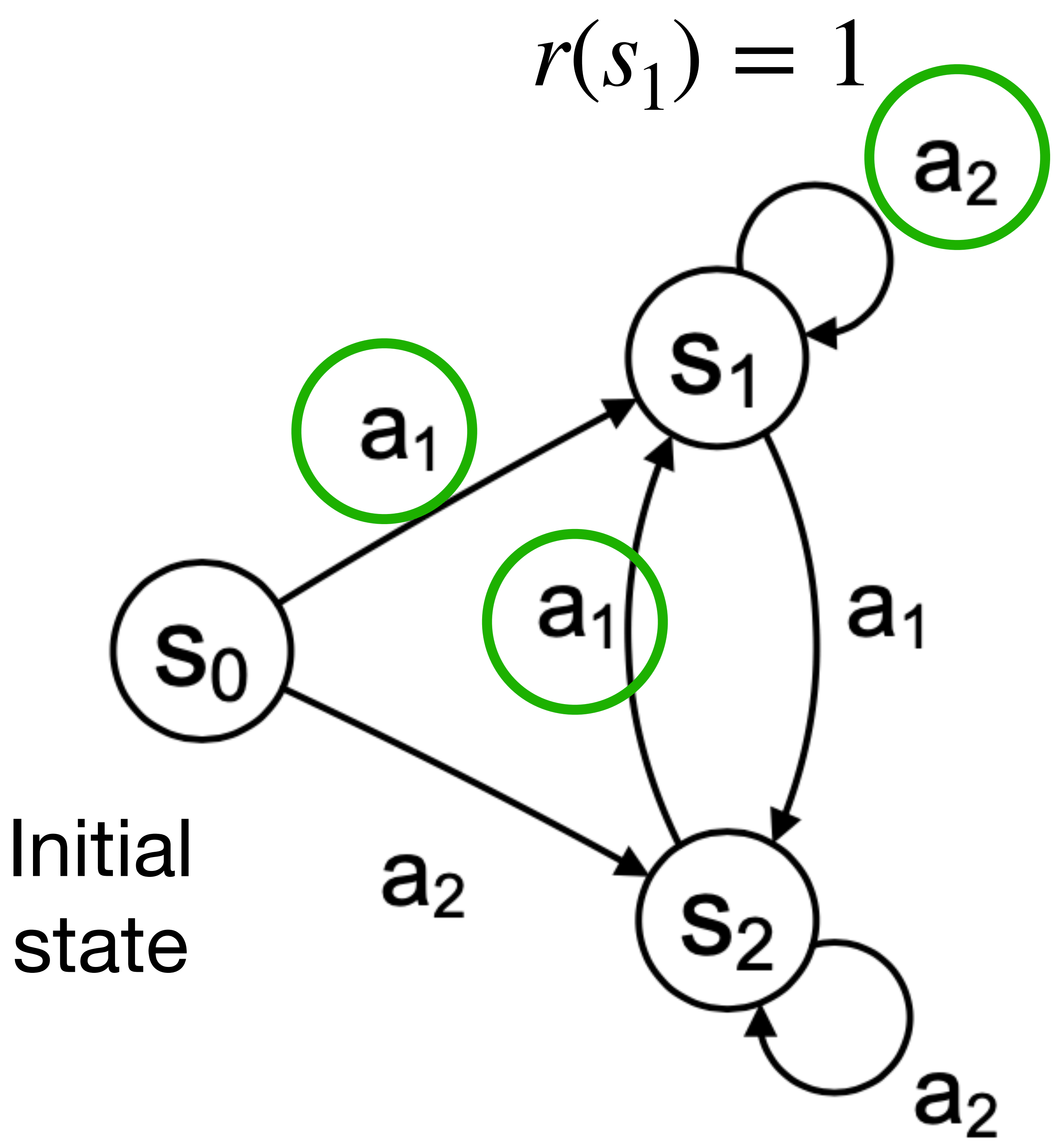

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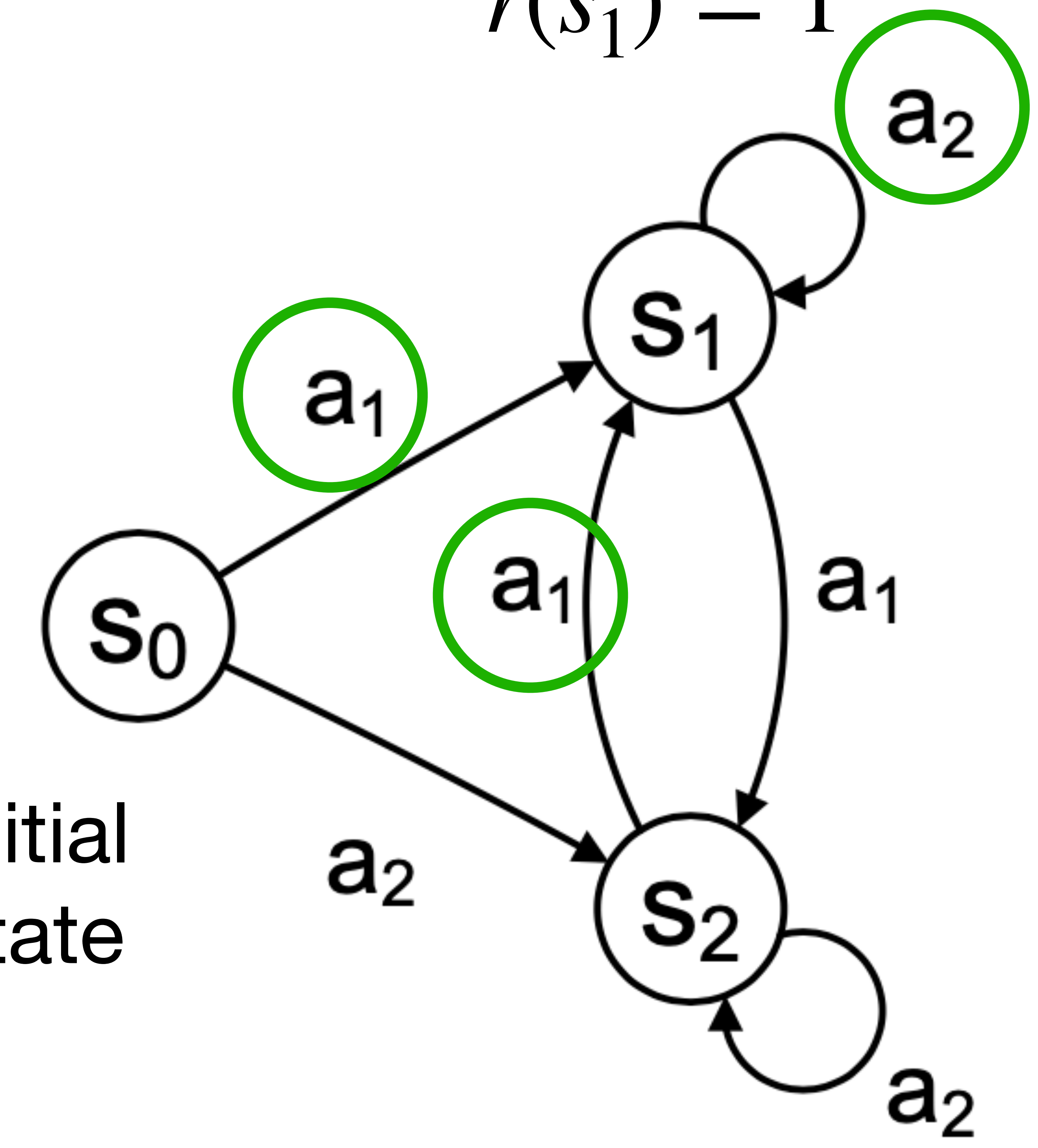

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$V_0^{\pi^\star}(s_0) = H - 1$

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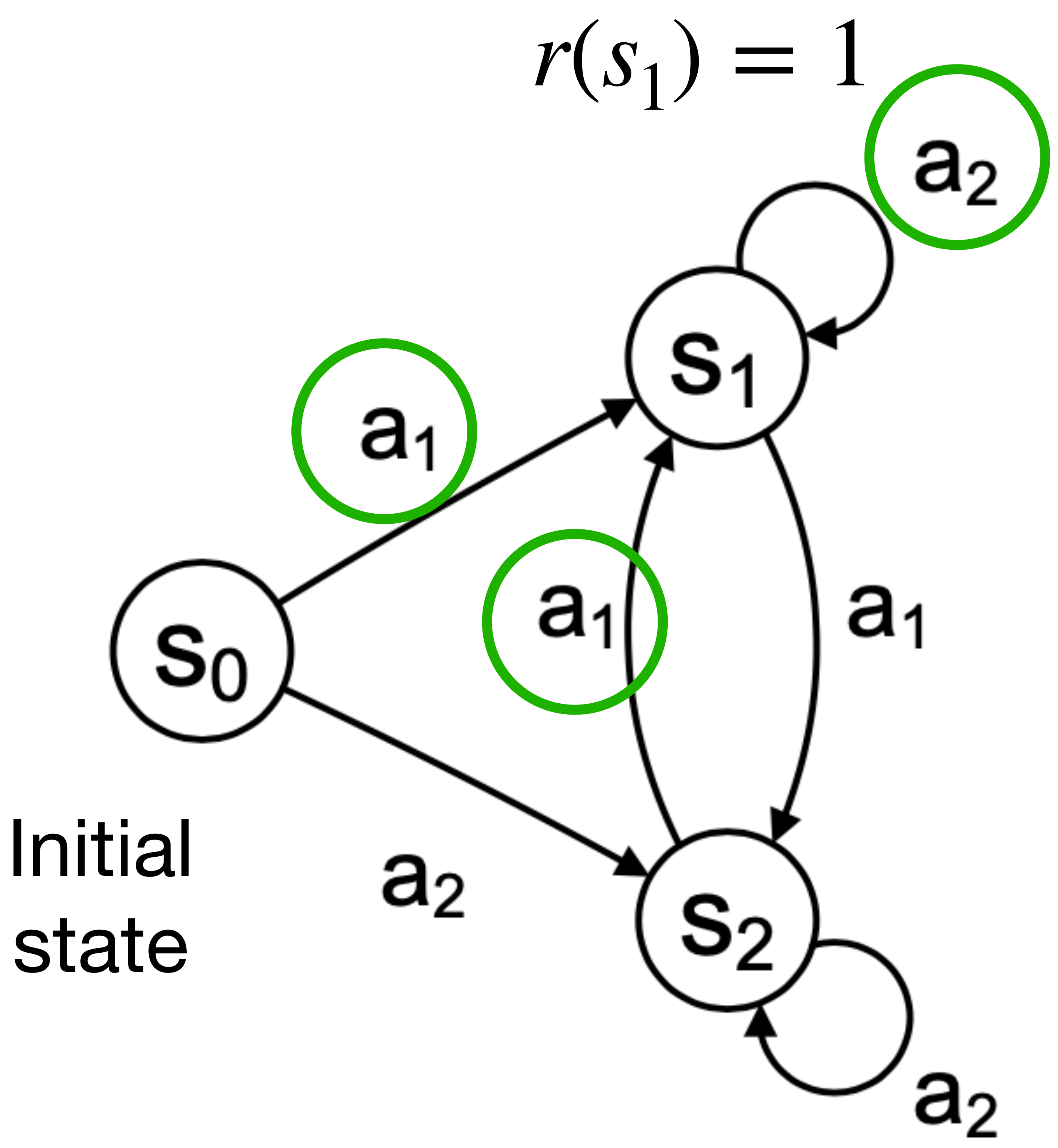

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Opt policy:

Under $\rho_{\pi^\star}$, trajectory is $s_0, s_1, s_1, \ldots$

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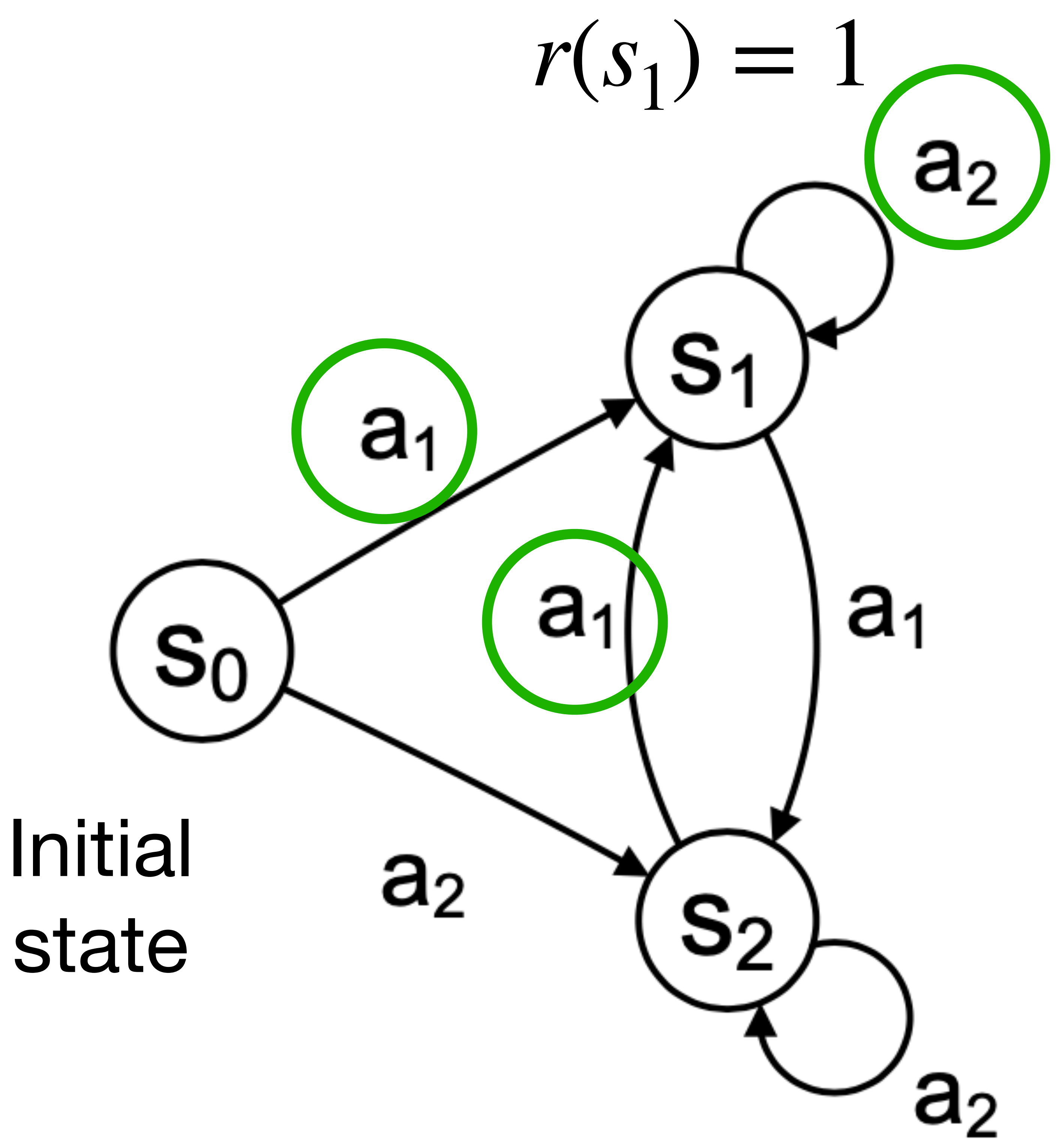

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$$\mathbb{E}_{\tau \sim \rho_{\pi^\star}} \left[\frac{1}{H} \sum_{h=0}^{H-1} \mathbf{1} \left[\widehat{\pi}(s_h) \neq \pi^\star(s_h) \right] \right] = \epsilon$$

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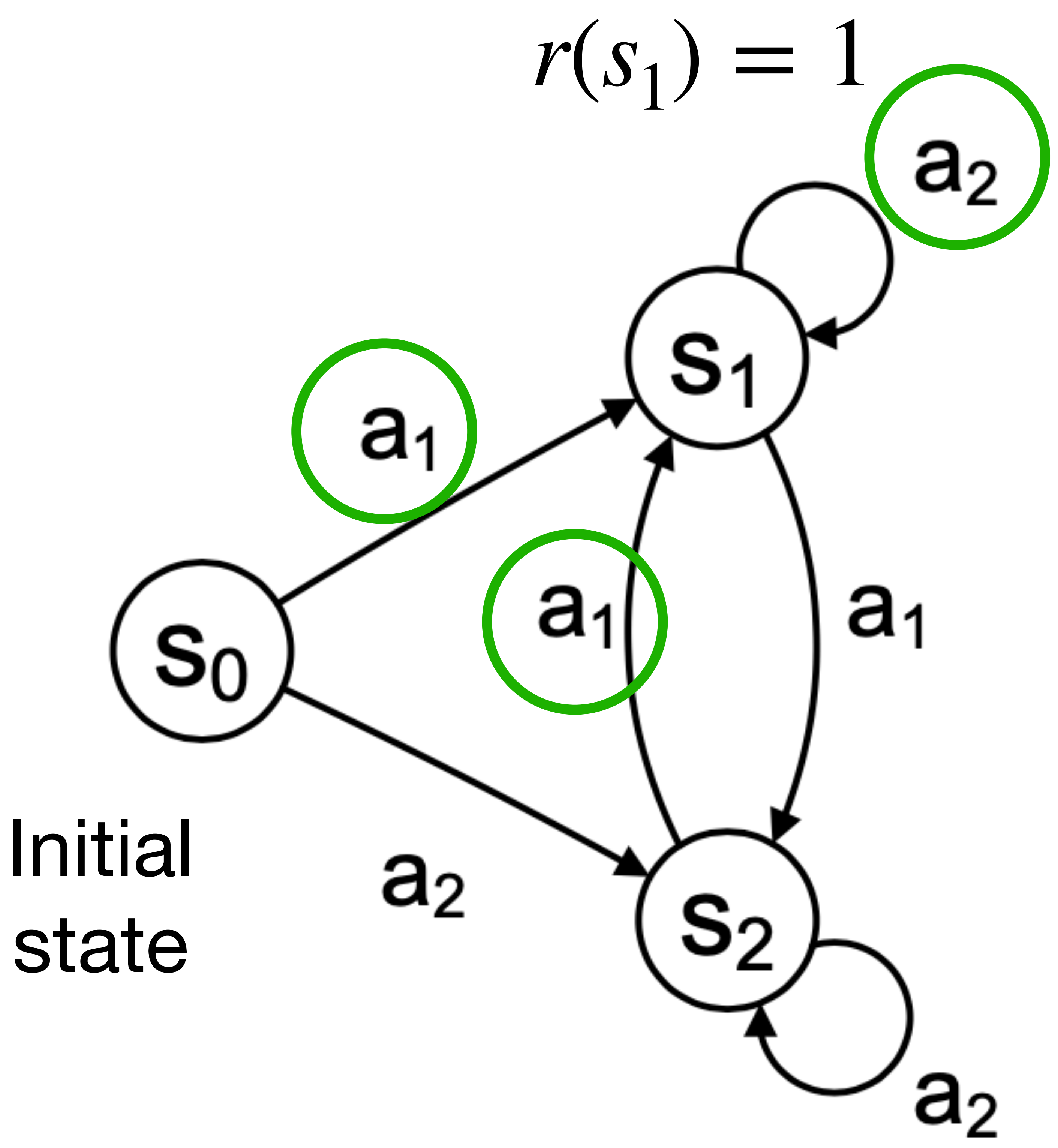

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$$V_0^{\widehat{\pi}}(s_0) = (1 - H\epsilon) \cdot V_0^{\pi^\star}(s_0) + H\epsilon \cdot 0 = V_0^{\pi^\star}(s_0) - \epsilon H(H-1)$$

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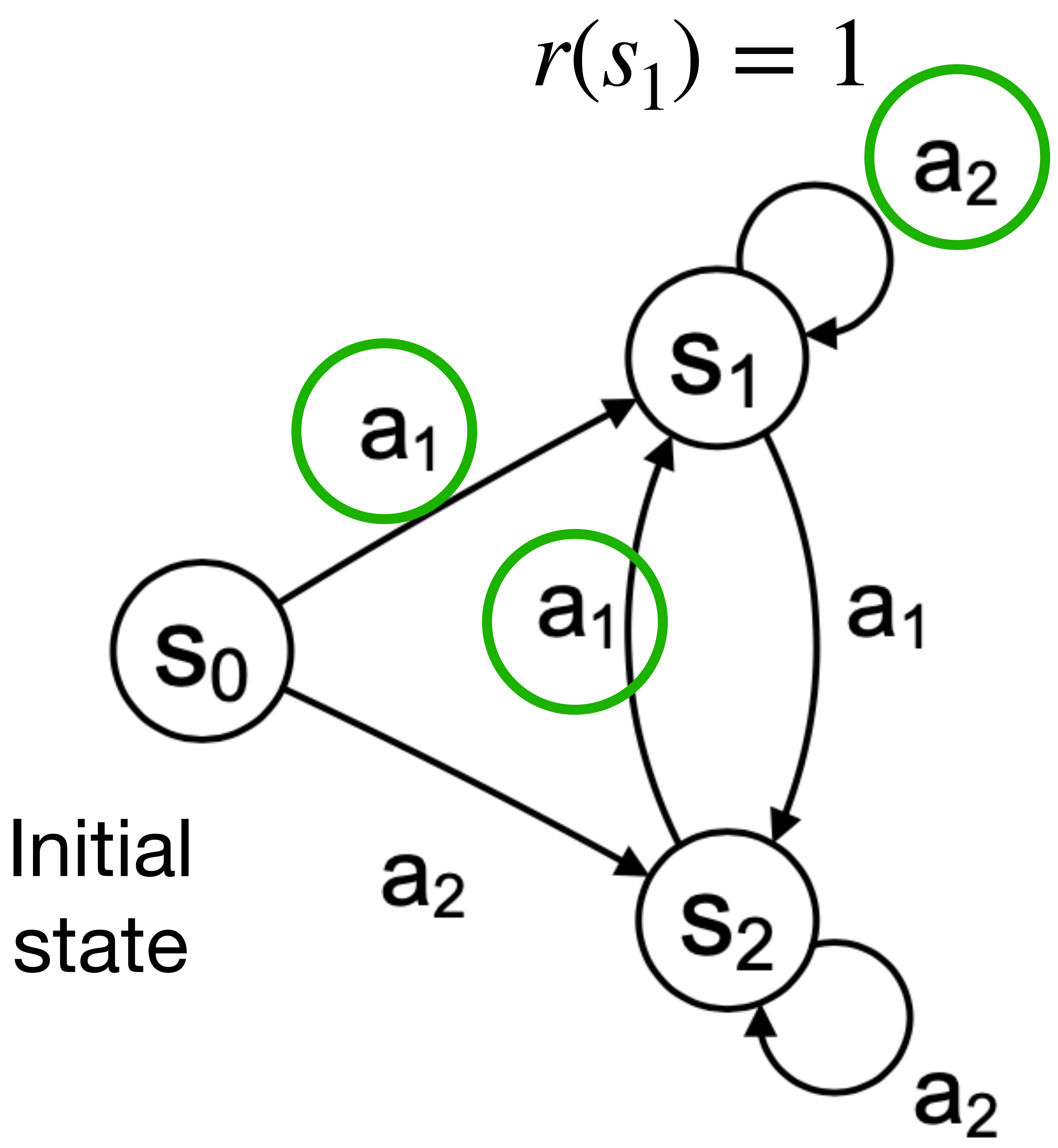

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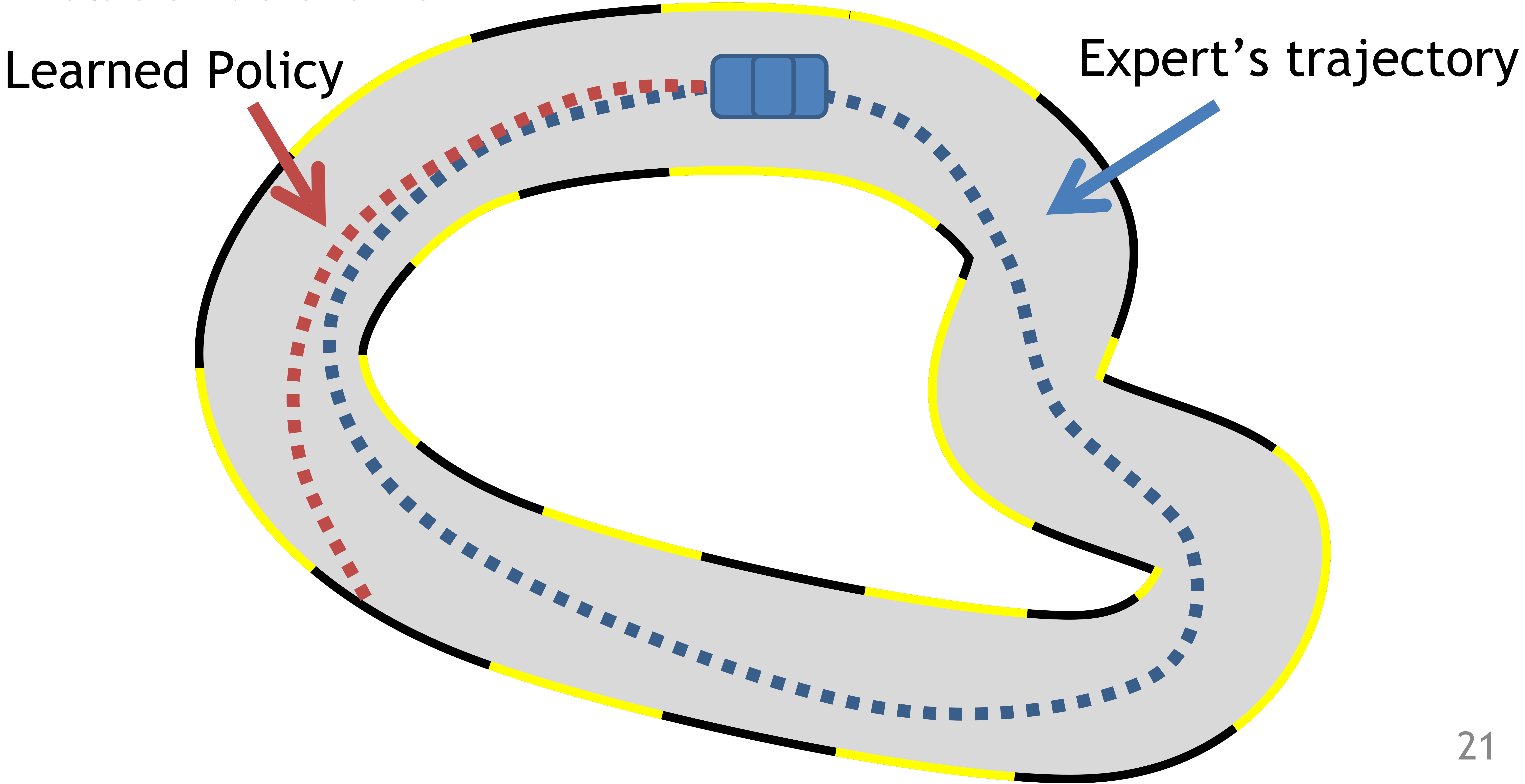
Intuition: once we make a mistake at s_0, we end up in s_2 which is not in the training data!

What could go wrong?

- Predictions affect future inputs/ observations



Expert Demos


Ready!


Ready!

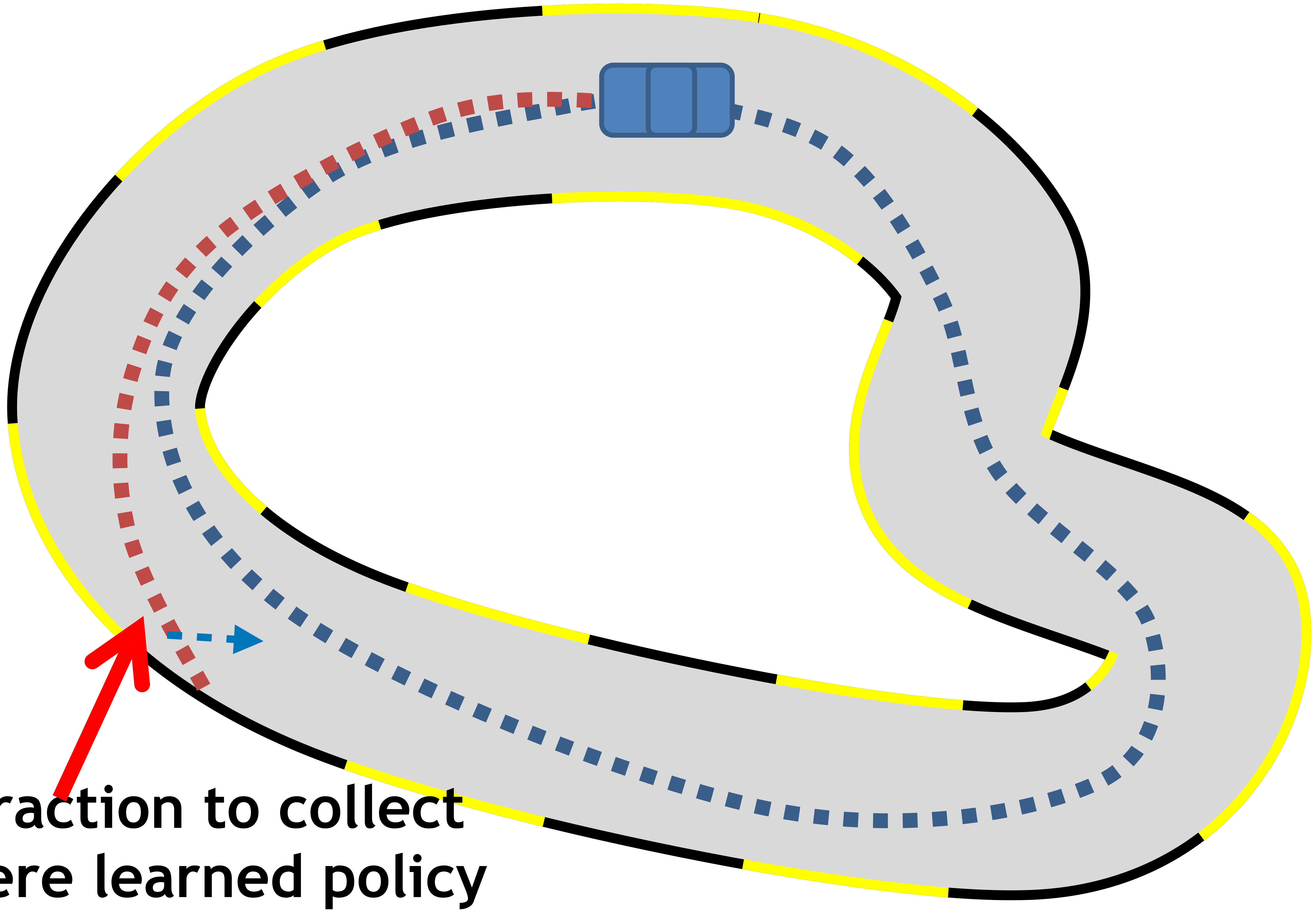

Features
Ready!


Features
Ready!

Today

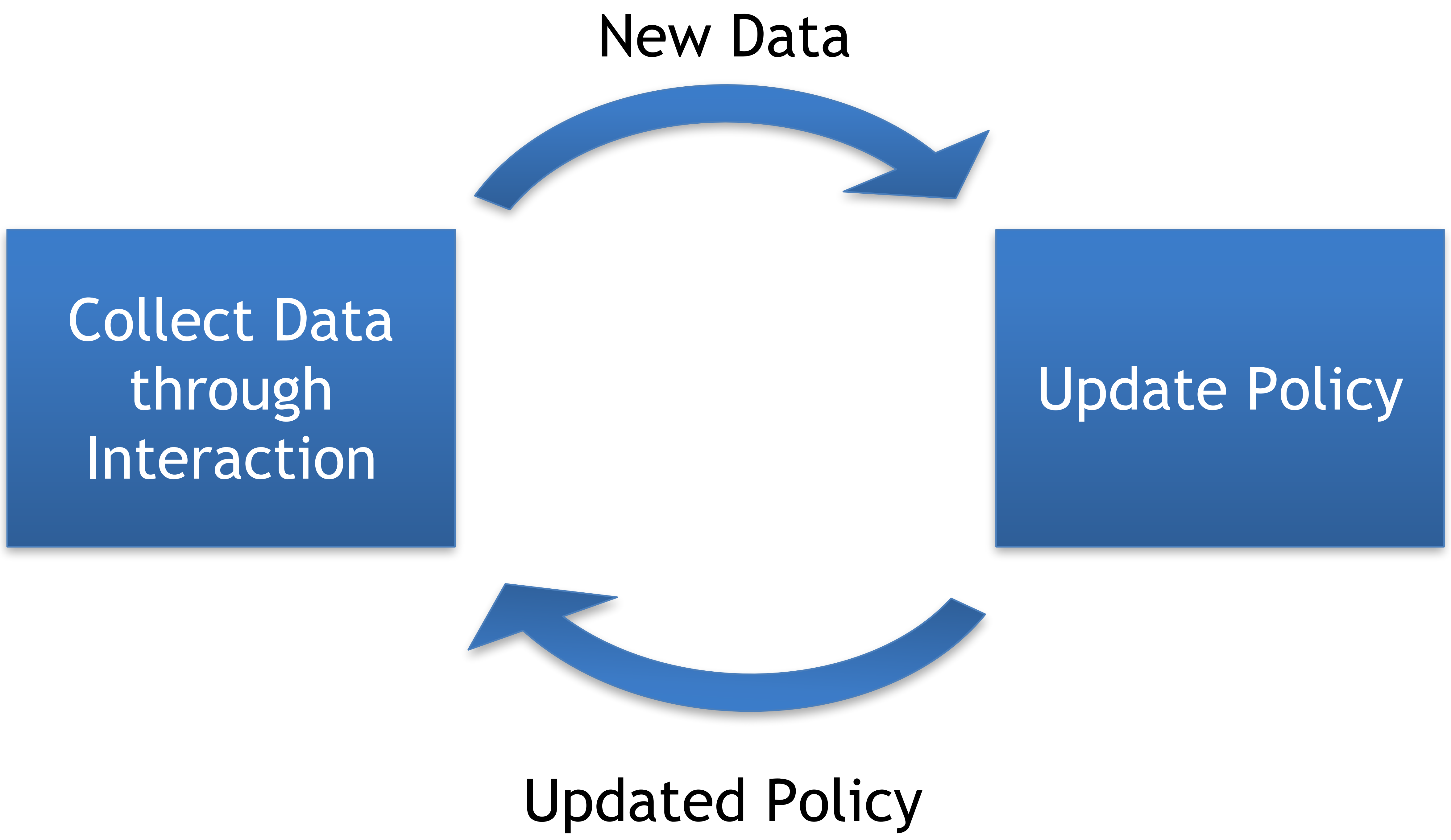
- Feedback from last lecture
- Recap
- Imitation Learning problem statement
- Behavioral Cloning
- DAgger

Intuitive solution: **Interaction**



Use interaction to collect data where learned policy goes

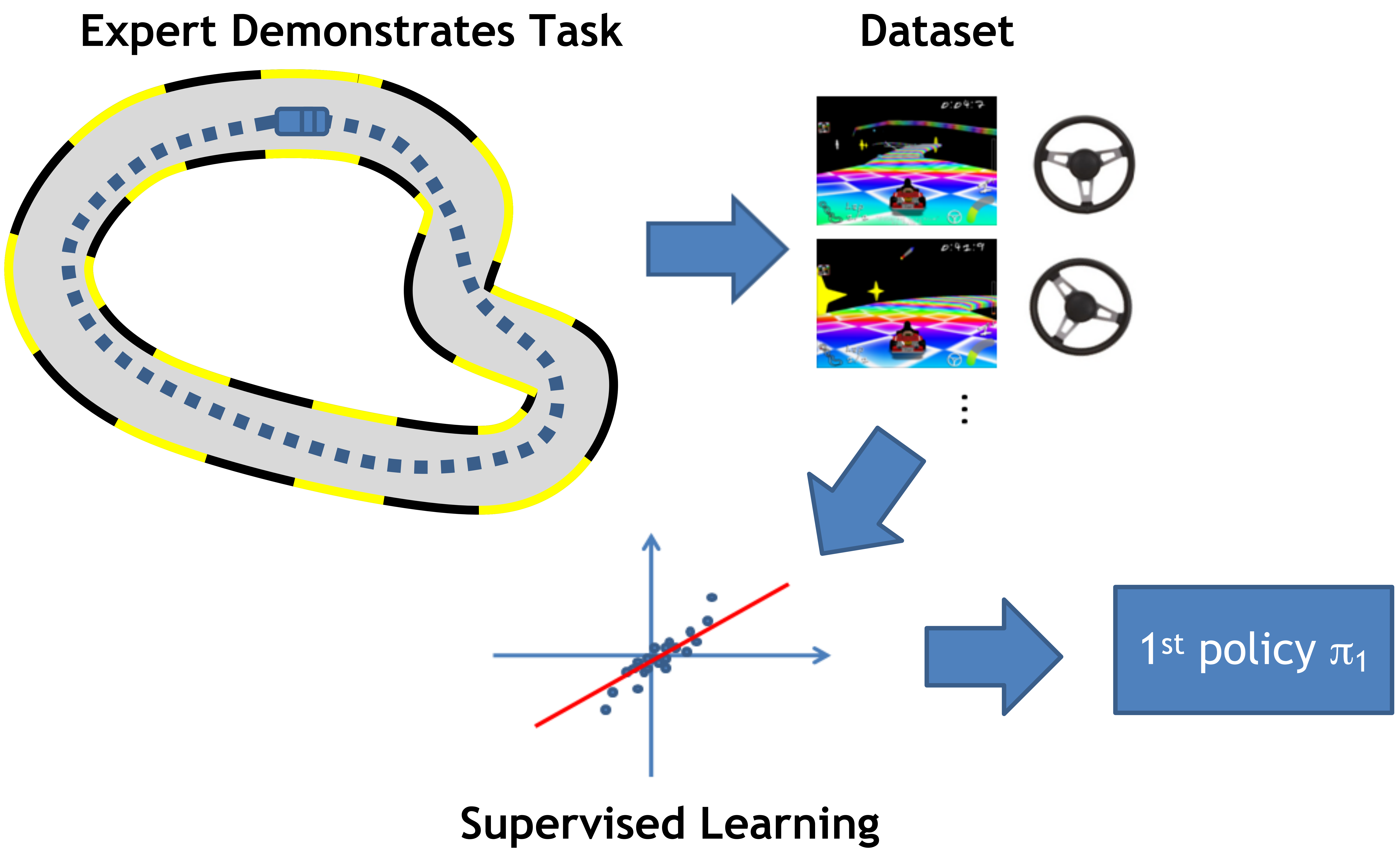
General Idea: Iterative Interactive Approach



DAgger: Dataset Aggregation

[Ross11a]

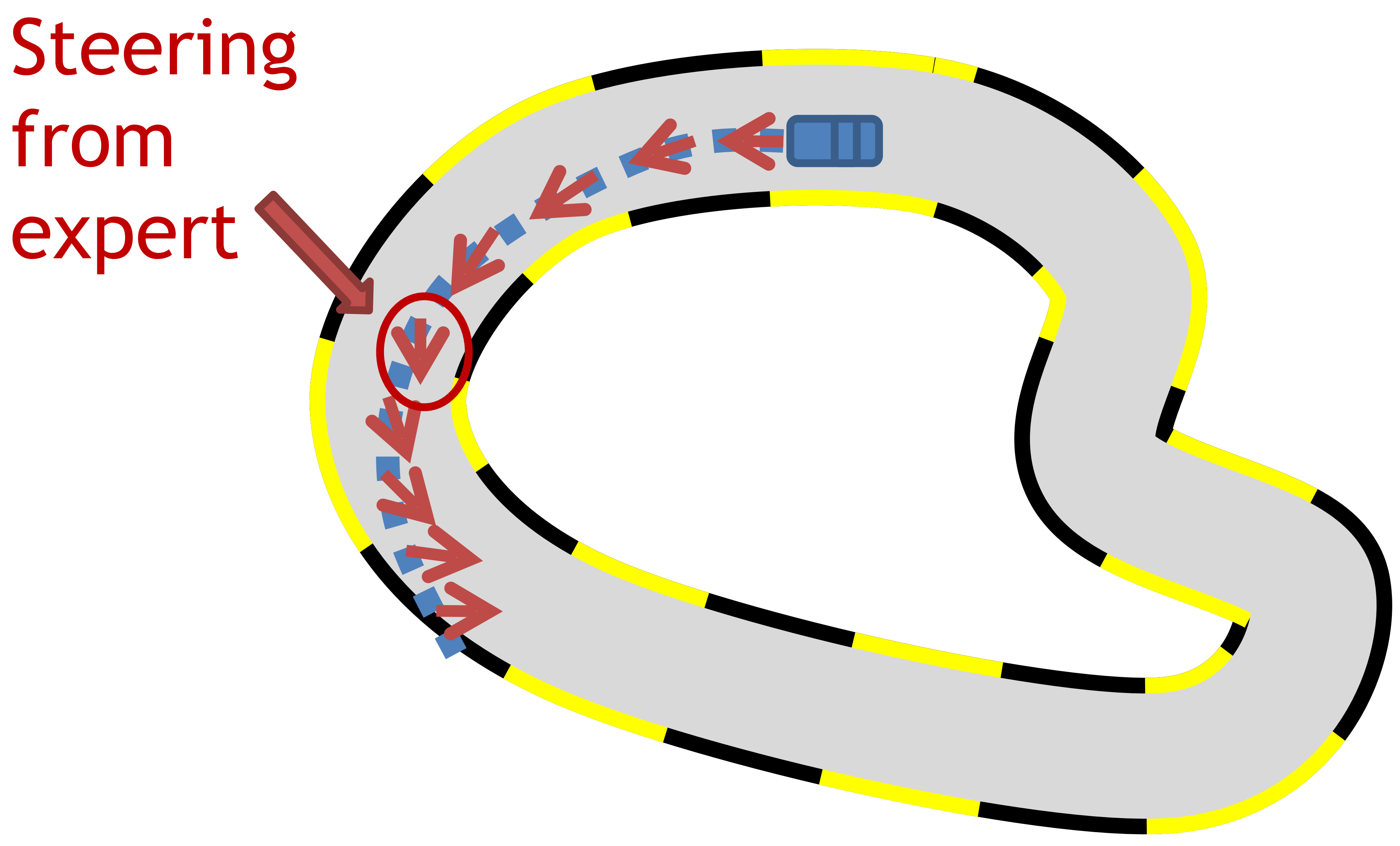
0th iteration



DAgger: Dataset Aggregation [Ross11a]

1st iteration

Execute π_1 and Query Expert



DAgger: Dataset Aggregation

[Ross11a]

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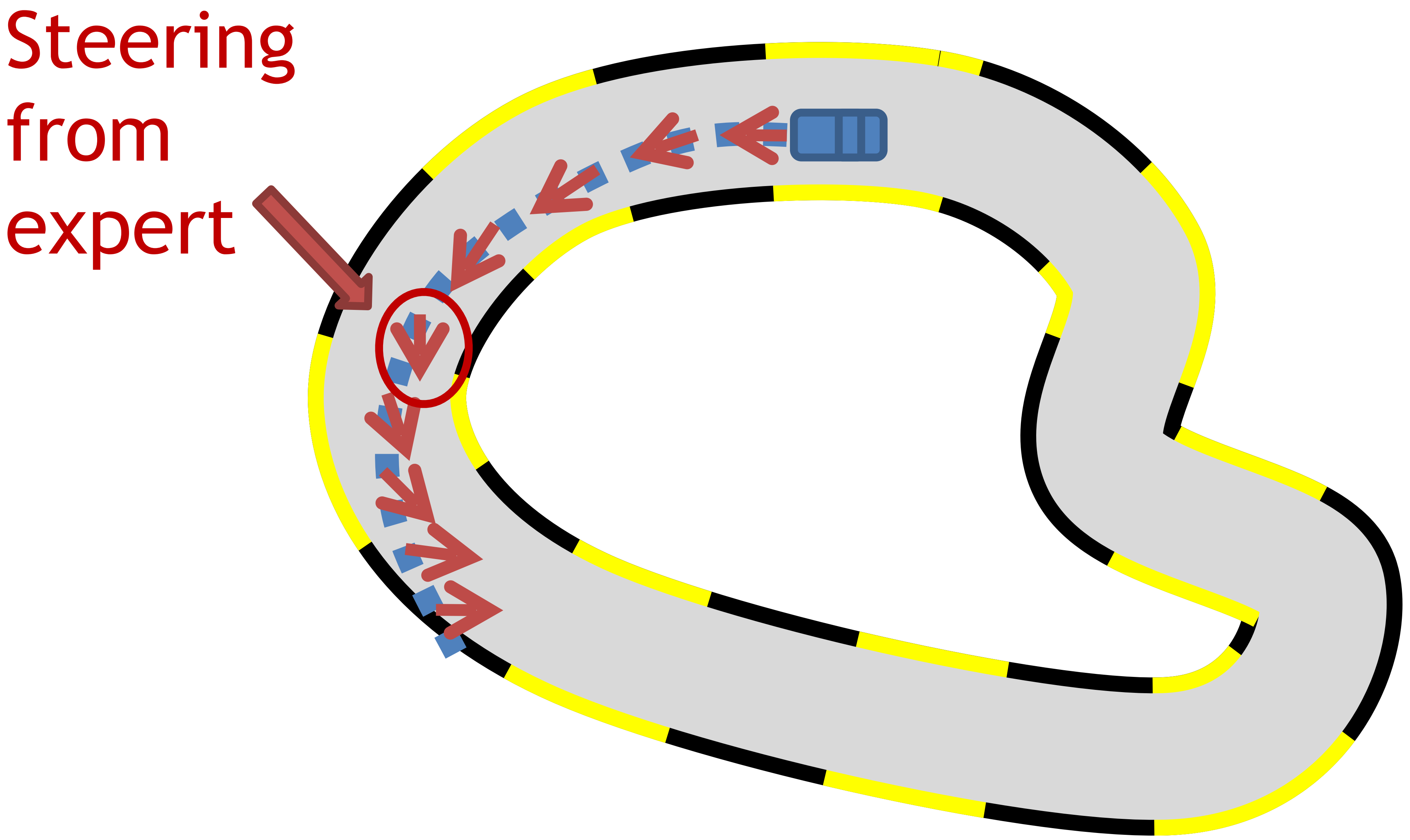
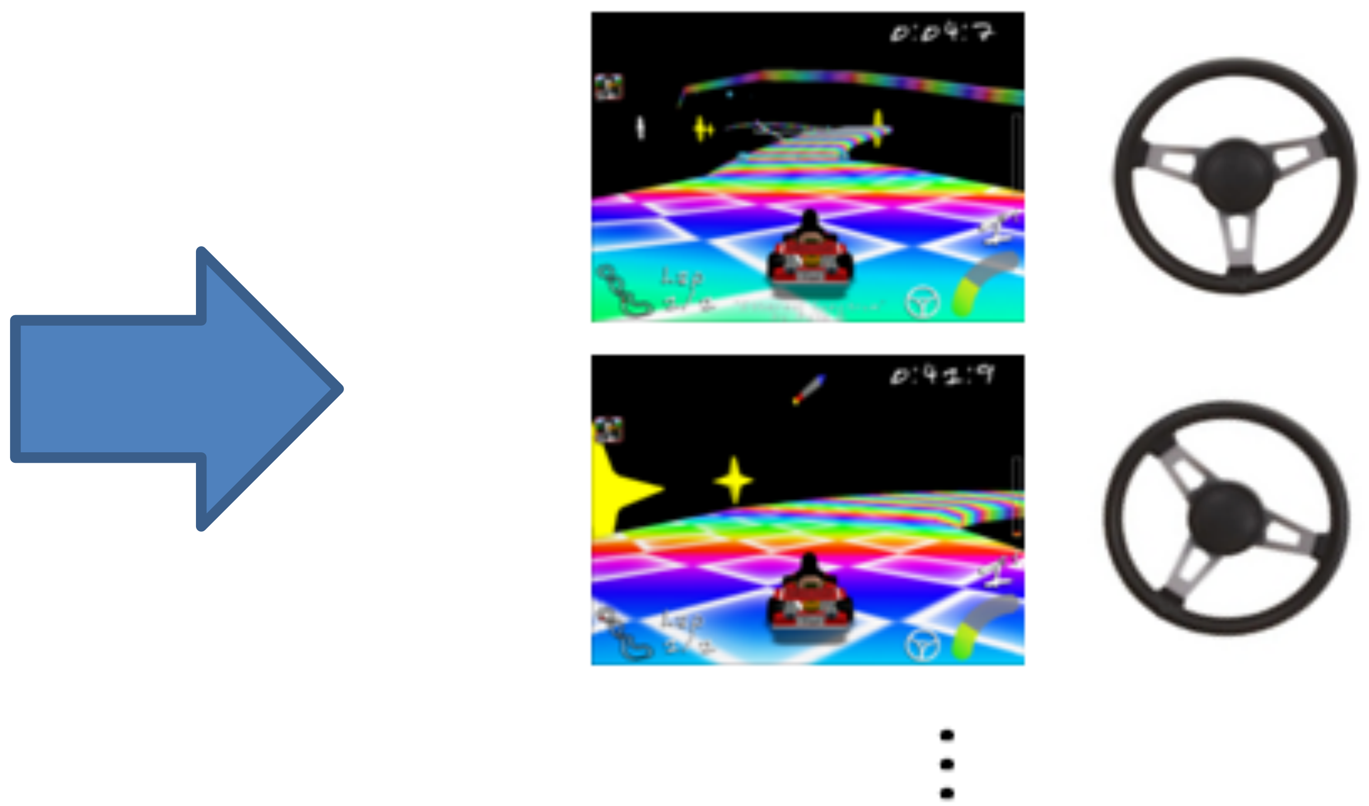


New Data



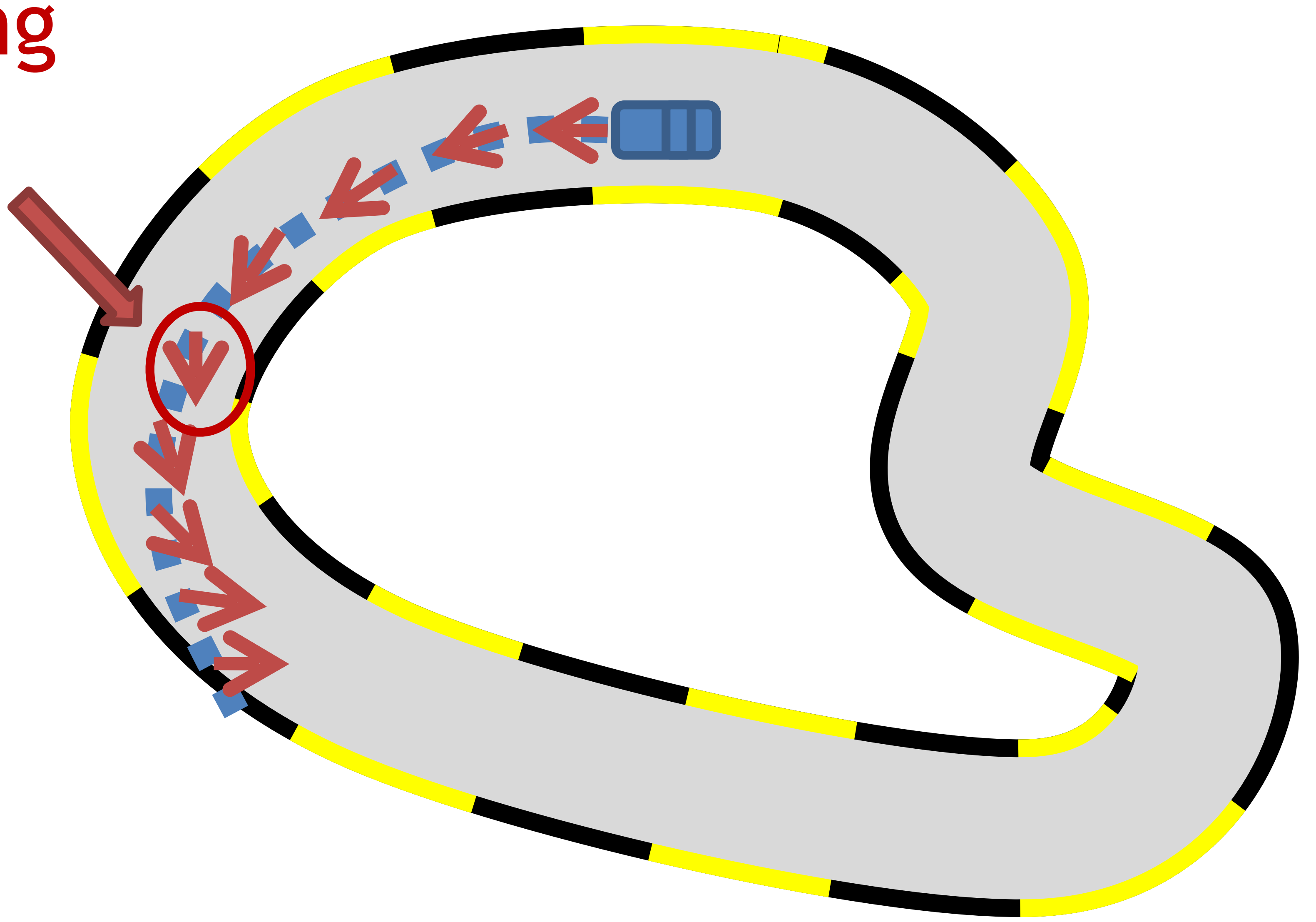
DAgger: Dataset Aggregation

[Ross11a]

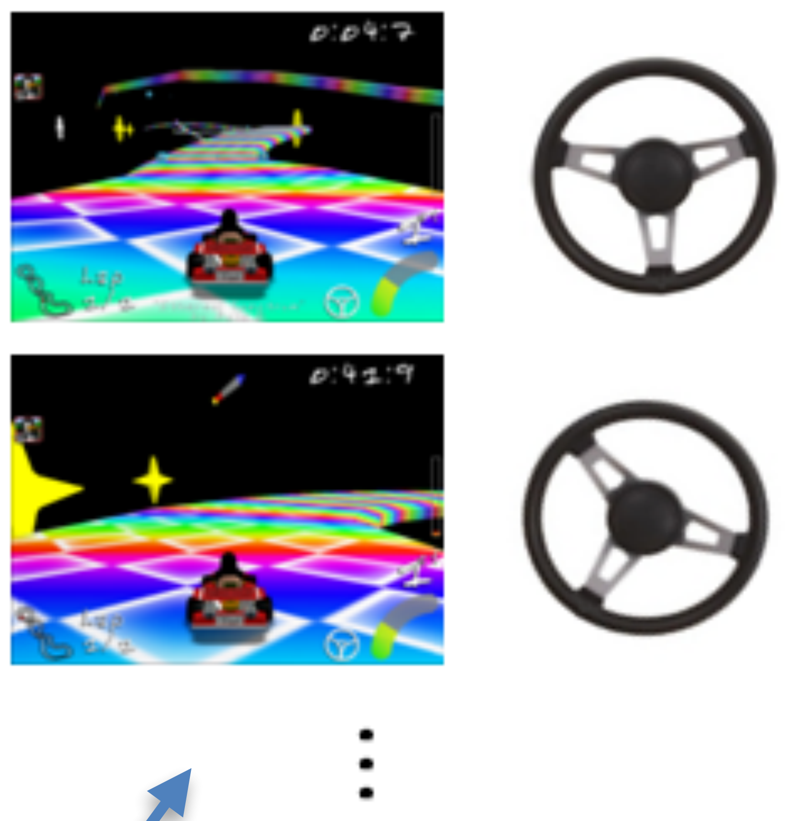
1st iteration

Execute π_1 and Query Expert

Steering
from
expert



New Data



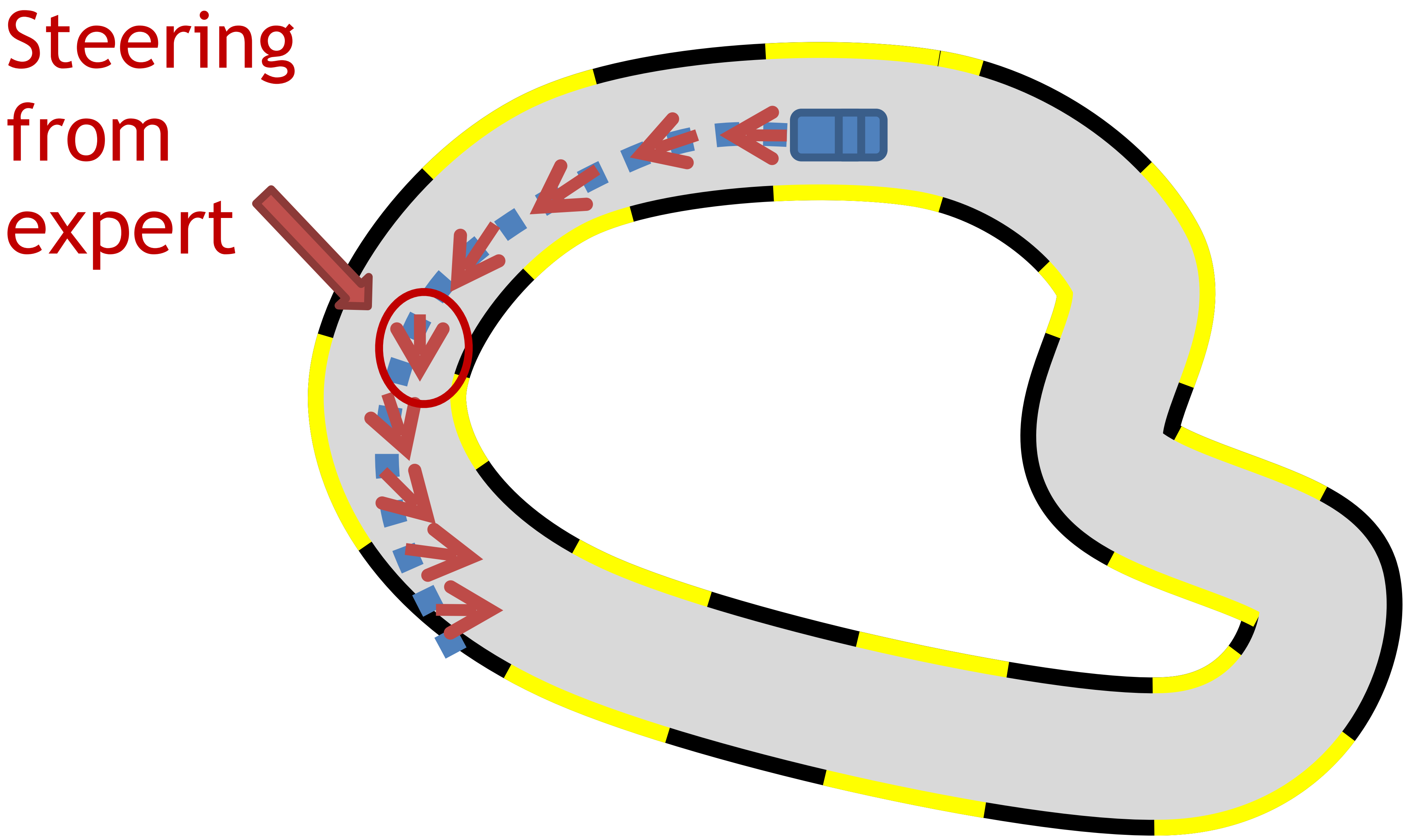
States from
the learned policy

DAgger: Dataset Aggregation

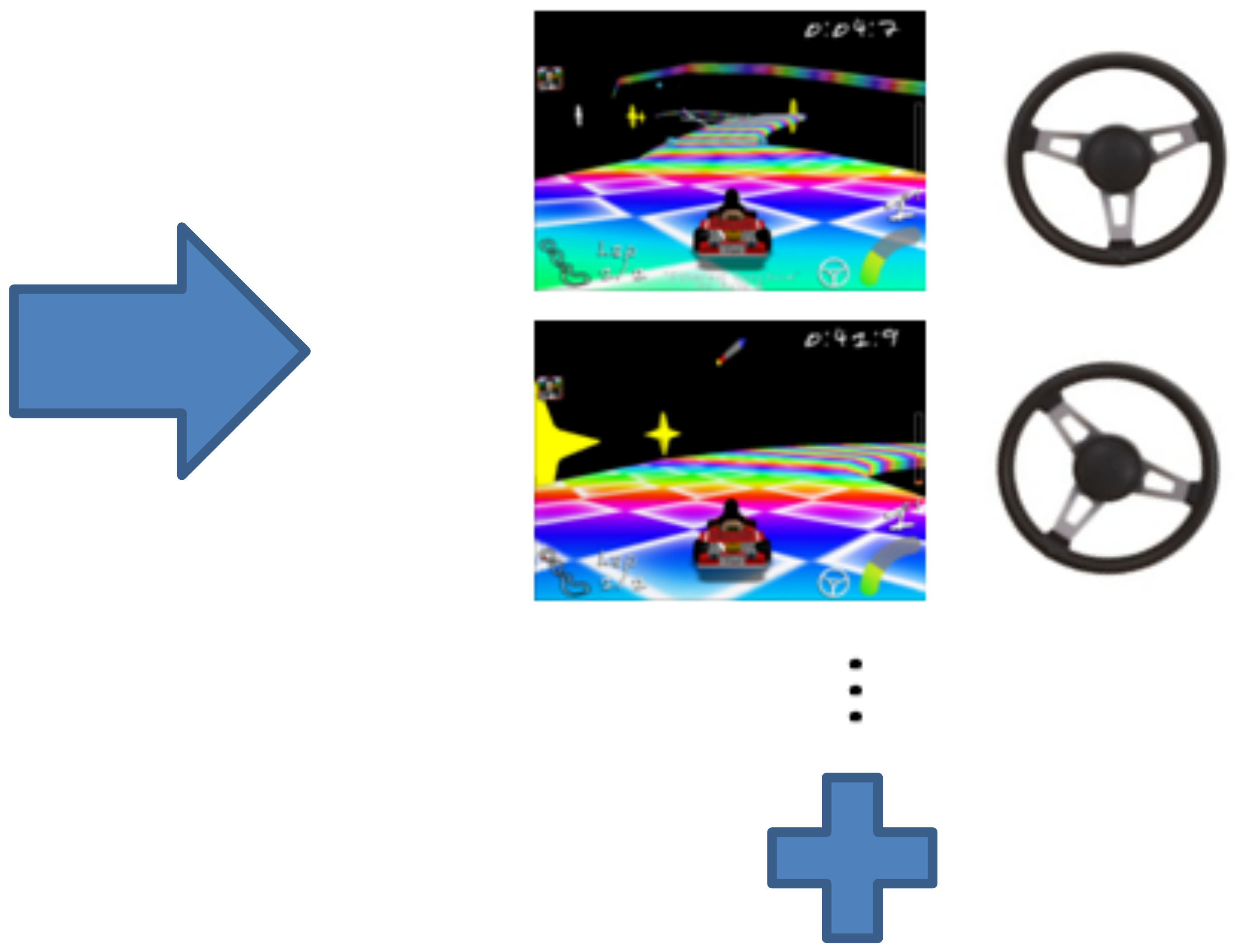
[Ross11a]

1st iteration

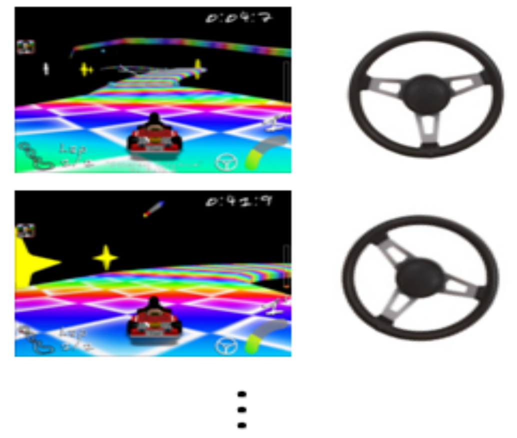
Execute π_1 and Query Expert



New Data



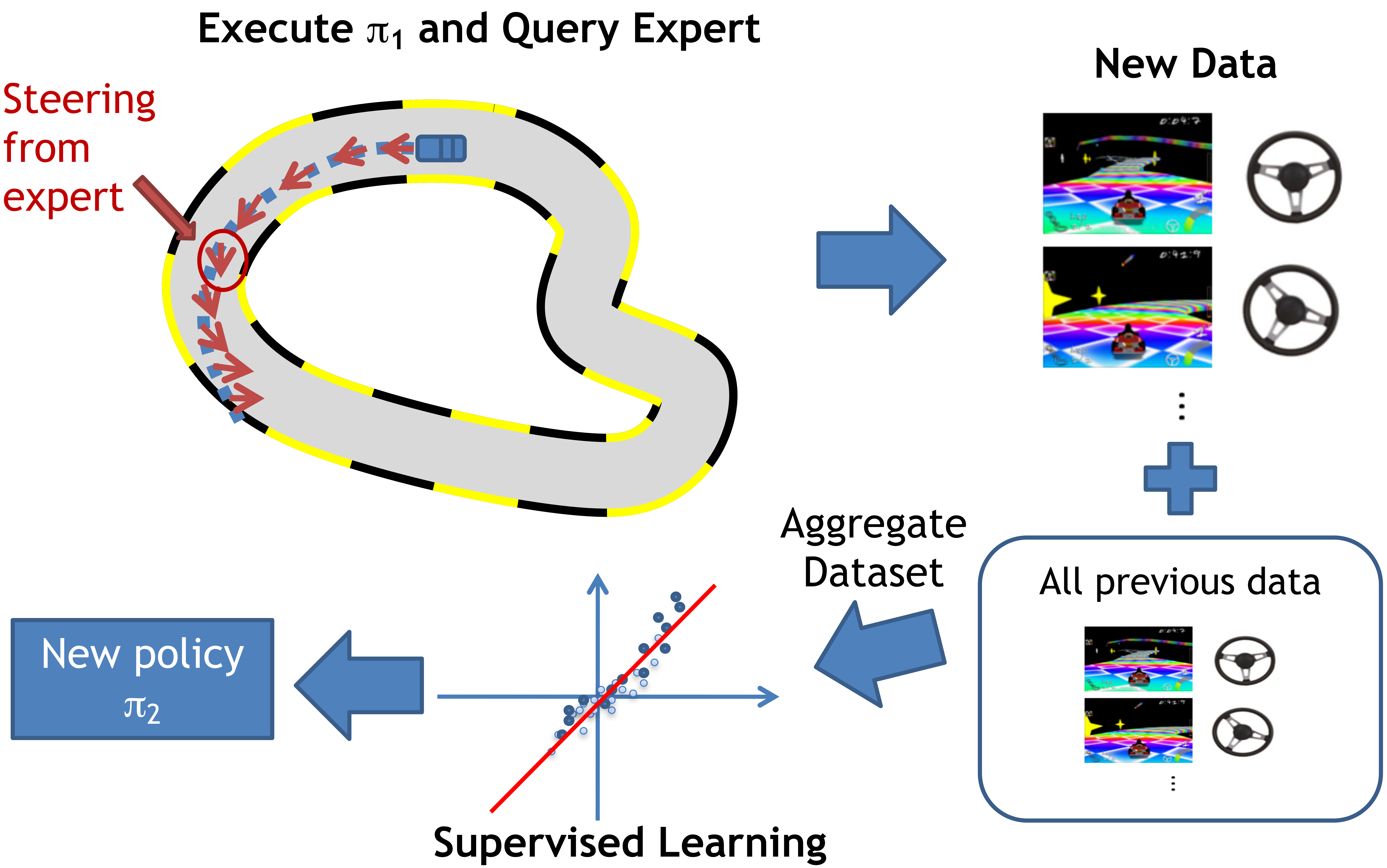
All previous data



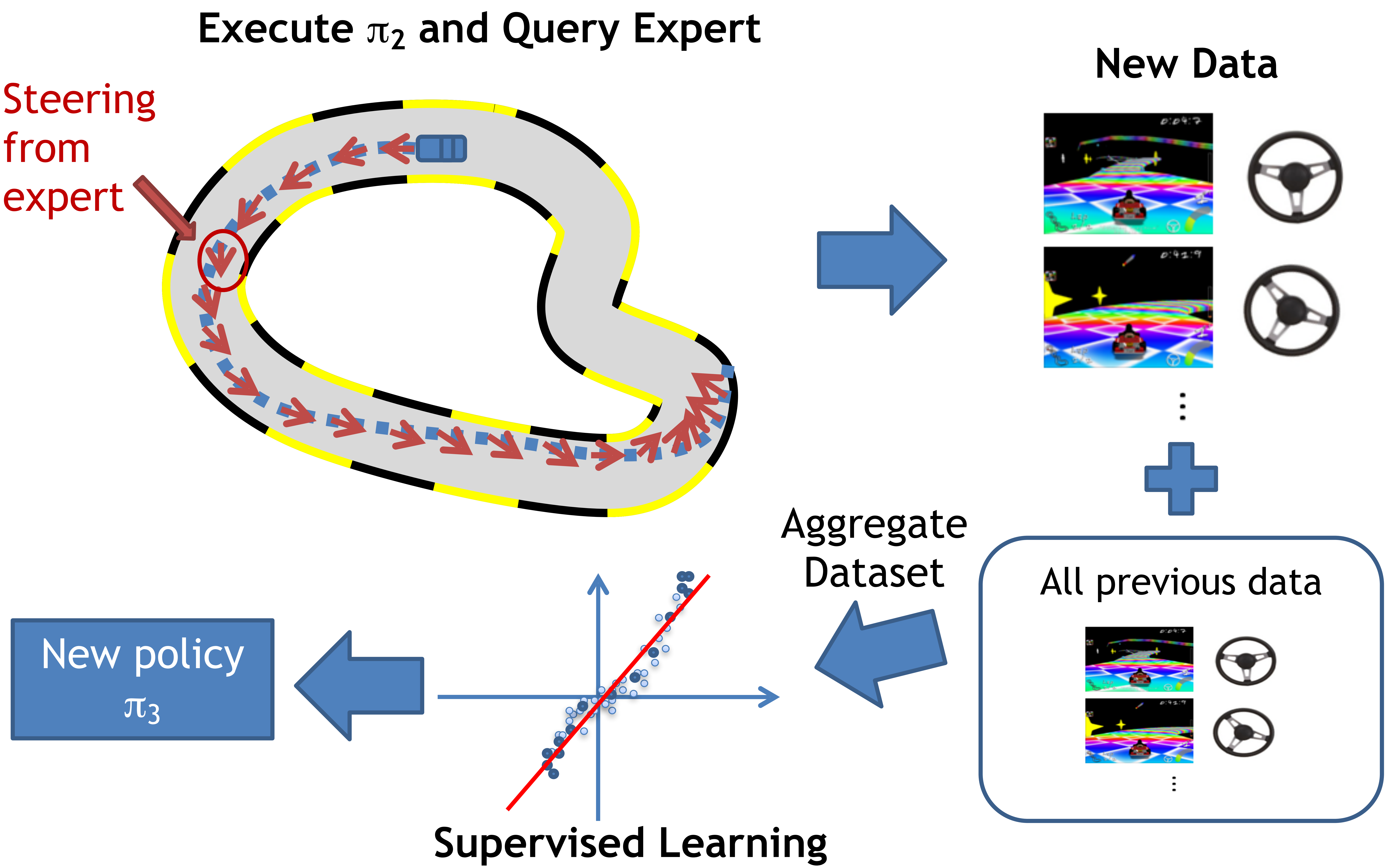
DAgger: Dataset Aggregation

[Ross11a]

1st iteration

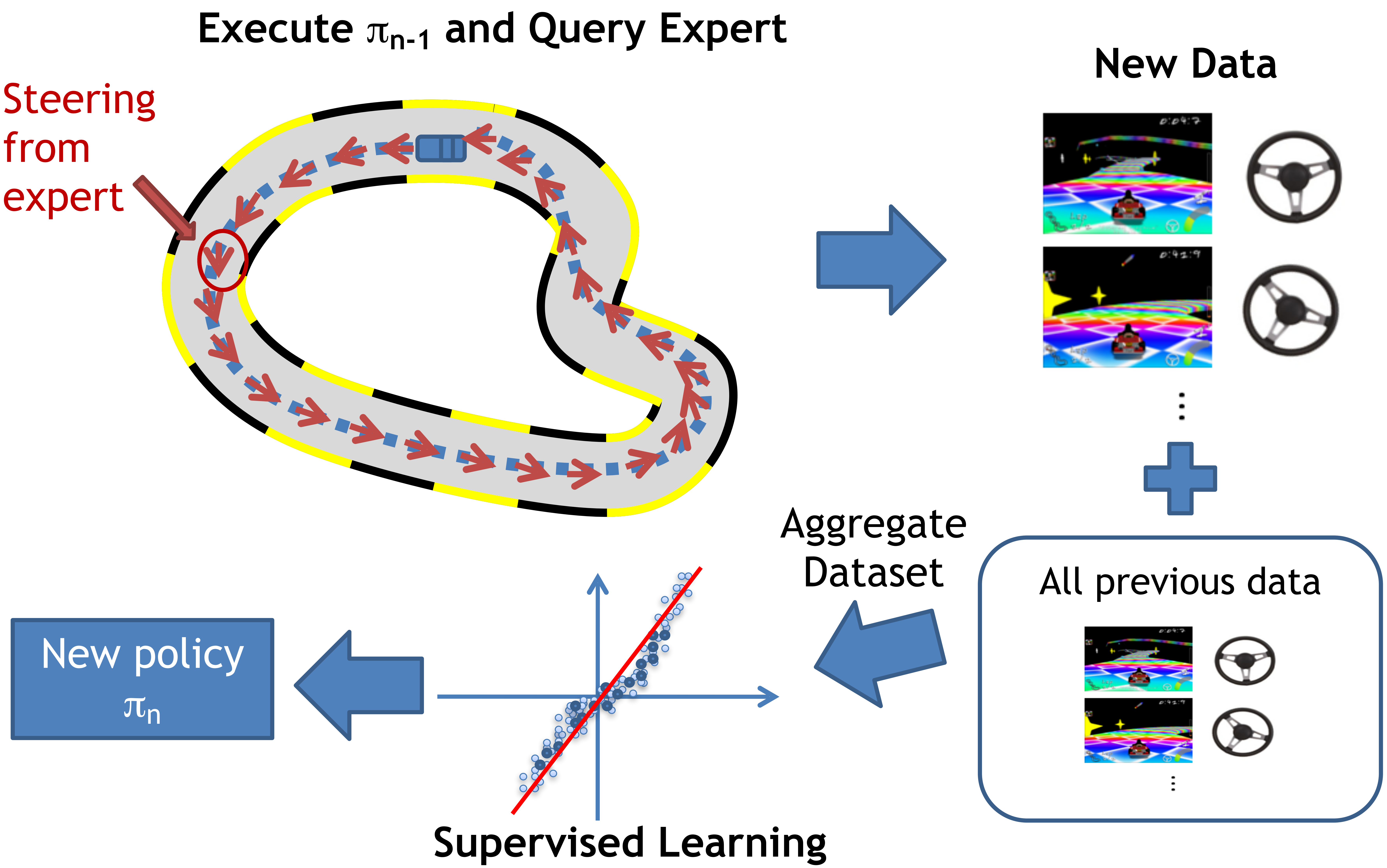


DAgger: Dataset Aggregation [Ross11a]
2nd iteration



DAgger: Dataset Aggregation [Ross11a]

n^{th} iteration



The DAgger algorithm

Initialize π^0, and dataset $\mathscr{D} = \emptyset$

For $t = 0 \rightarrow T - 1$:

The DAgger algorithm

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For $t = 0 \to T - 1$:

1. W/ π^t, generate dataset of trajectories $\mathscr{D}^t = \{\tau_1, \tau_2, \ldots\}$
where for all trajectories $s_h \sim \rho_{\pi^t}$, $a_h = \pi^\star(s_h)$

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3. **Update policy via Supervised-Learning**: $\pi^{t+1} = \text{SL}\left(\mathscr{D}\right)$

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In practice, the DAgger algorithm requires less human labeled data than BC.

[Informal Theorem] Under more assumptions + assuming ϵ SL error is achievable,
the DAgger algorithm has error: $|V^{\pi^\star} - V^{\widehat{\pi}}| \leq H\epsilon$

Success!

[Ross AISTATS 2011]

Success!

[Ross AISTATS 2011]

Today

- Feedback from last lecture
- Recap
- Imitation Learning problem statement
- Behavioral Cloning
- DAgger

Summary:

1. IL can help a lot to explore the space
2. BC pretty good but brittle -> quadratic-in-horizon error
3. Online expert feedback can help with robustness -> linear-in-horizon error

Attendance:

bit.ly/3RcTC9T

Feedback:

bit.ly/3RHtlxy