Interactive Imitation Learning

Recap

The Behavior Cloning algorithm:

Choose regression (for continuous action) or classification loss $\ell(\pi(s), a)$, and perform SL:

$$\widehat{\pi} = \min_{\pi \in \Pi} \sum_{i=1}^{M} \ell(\pi(s_i^\star), a_i^\star)$$

ERM

(s^*, a^*)

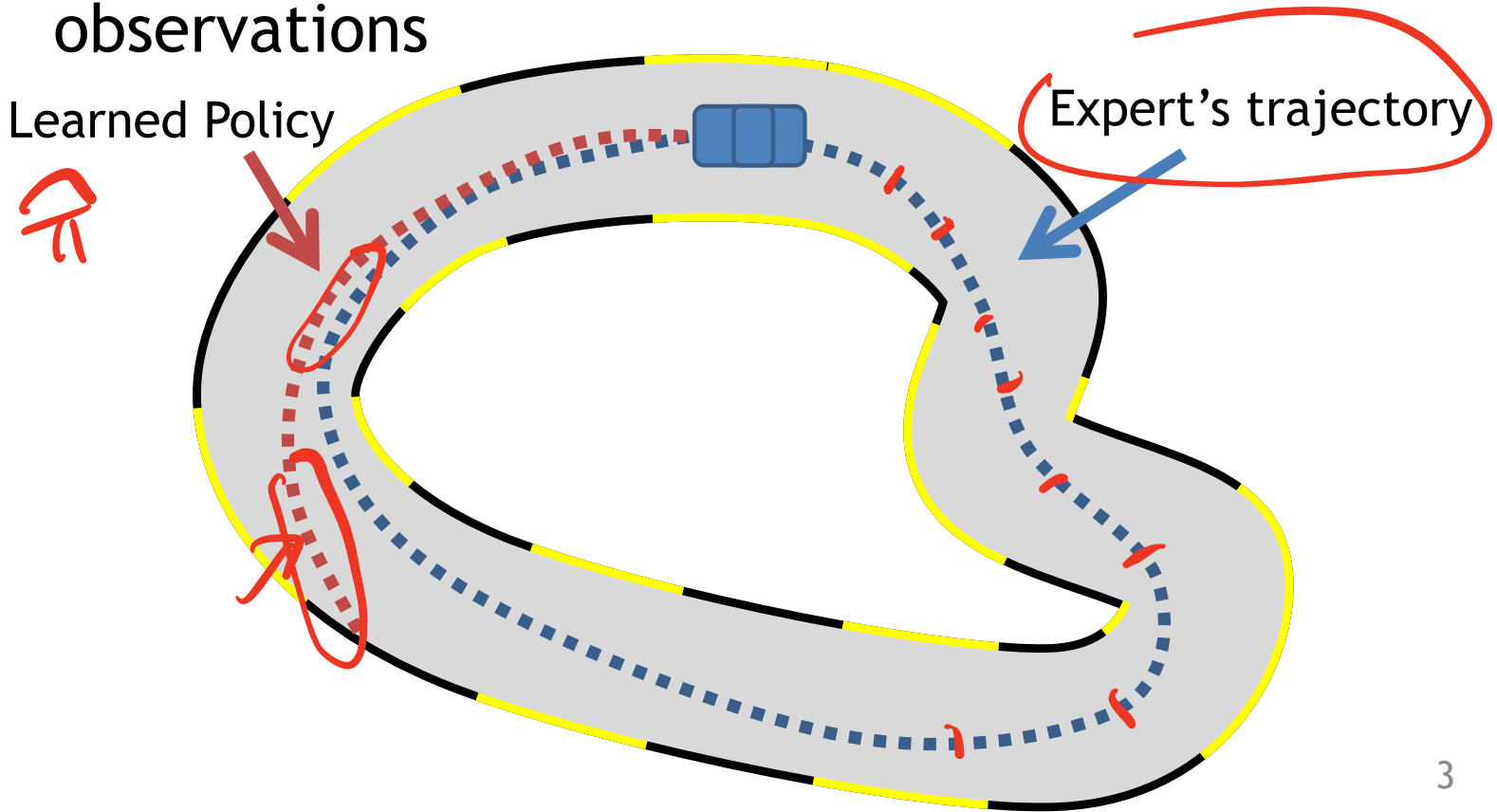
$s^* \sim d^{\pi^*}$

$a^* \sim \pi^*(\cdot | s^*)$

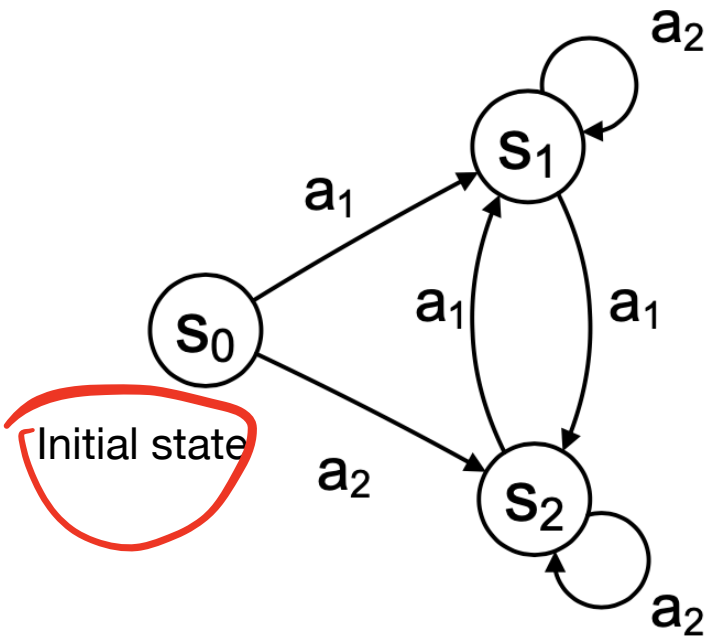
What could go wrong?

[Pomerleau89,Daume09]

- Predictions affect future inputs/ observations



Distribution Shift: Example



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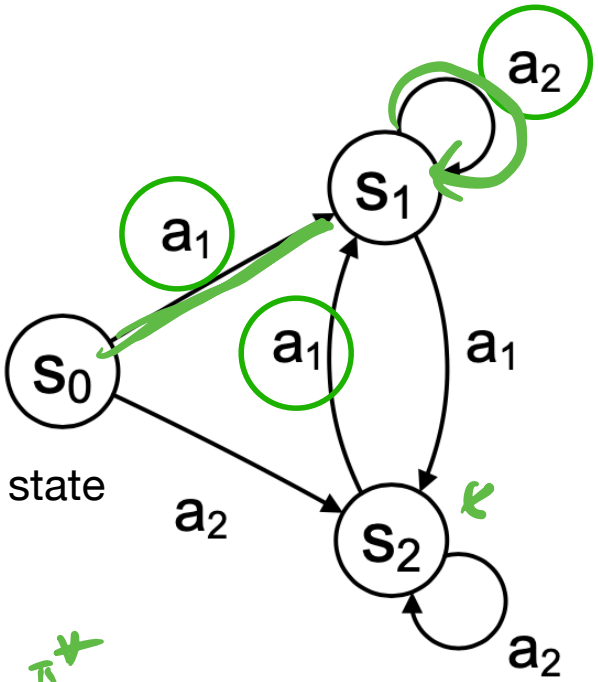

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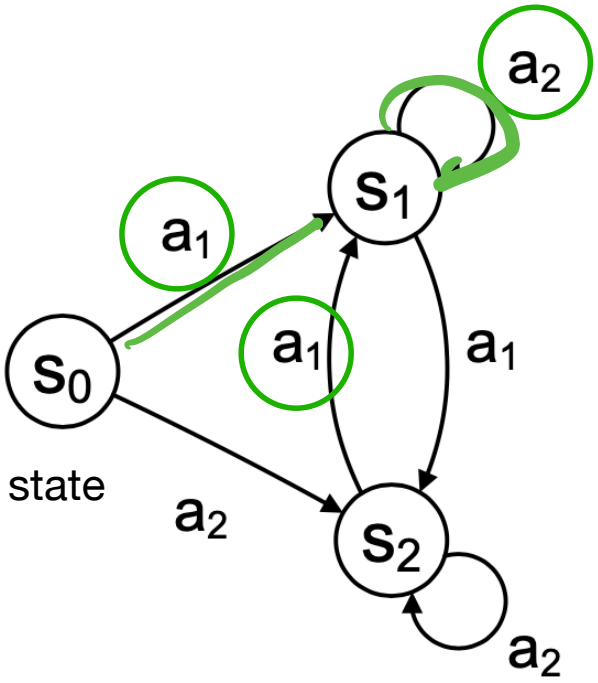

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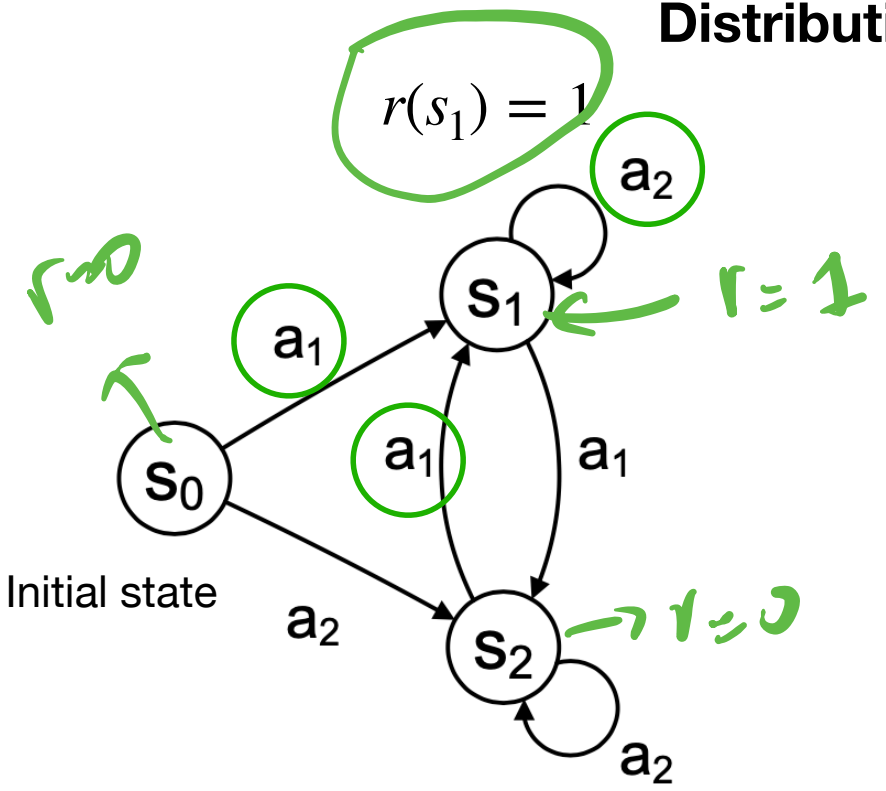

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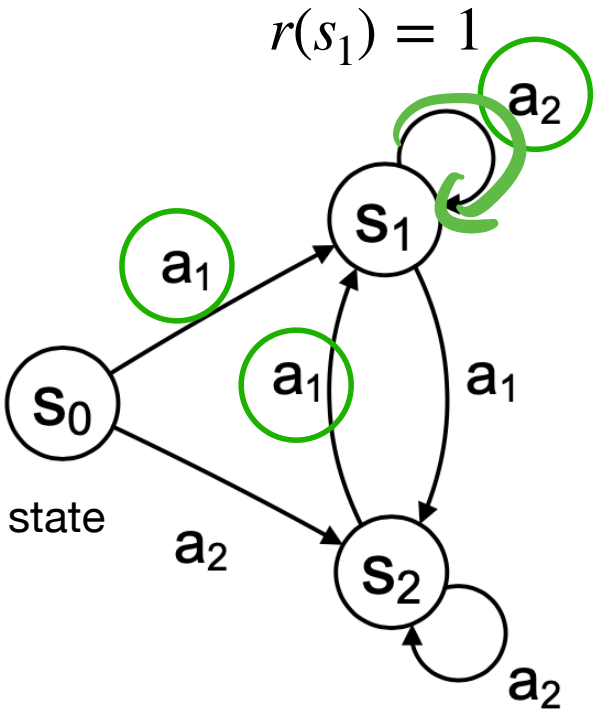

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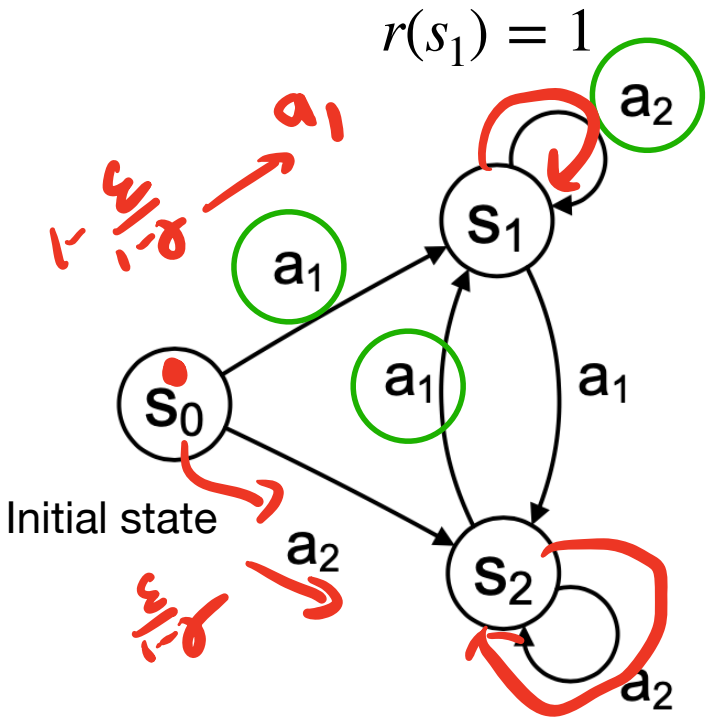

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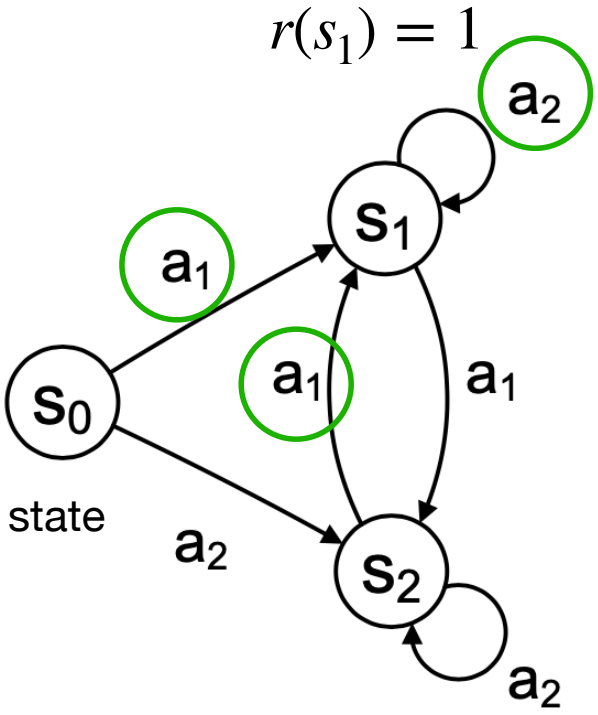

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We will have good supervised learning error:

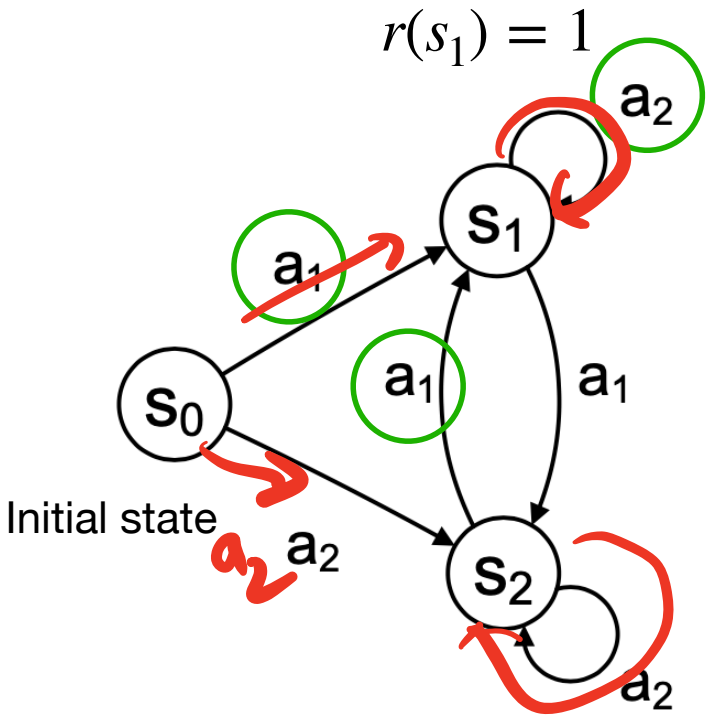
$$\mathbb{E}_{s \sim d_{s_0}^{\pi^\star}} \mathbb{E}_{a \sim \widehat{\pi}(\cdot|s)} \mathbf{1}\left(a \neq \pi^\star(s)\right) = \epsilon$$

$V^{\widehat{\pi}} \leftrightarrow V^{\pi^\star}$

Δ

Train Dis $d_{s_0}^{\pi^\star}$

Distribution Shift: Example



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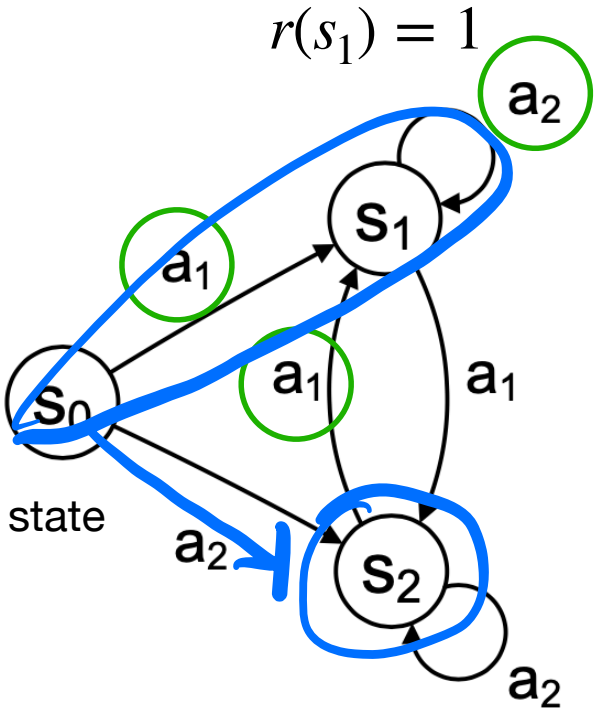

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Issue: once we make a mistake at s_0, we end up in s_2 which is not in the training data!

$\frac{\epsilon\cdot\gamma}{(1-\gamma)^2}$

An Autonomous Land Vehicle In A Neural Network *[Pomerleau, NIPS '88]*

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Question for today:

How to mitigate the distribution shift issue?

Solution:

Interactive Imitation Learning Setting

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we can query expert $\pi^\star$ at any time and any state during training

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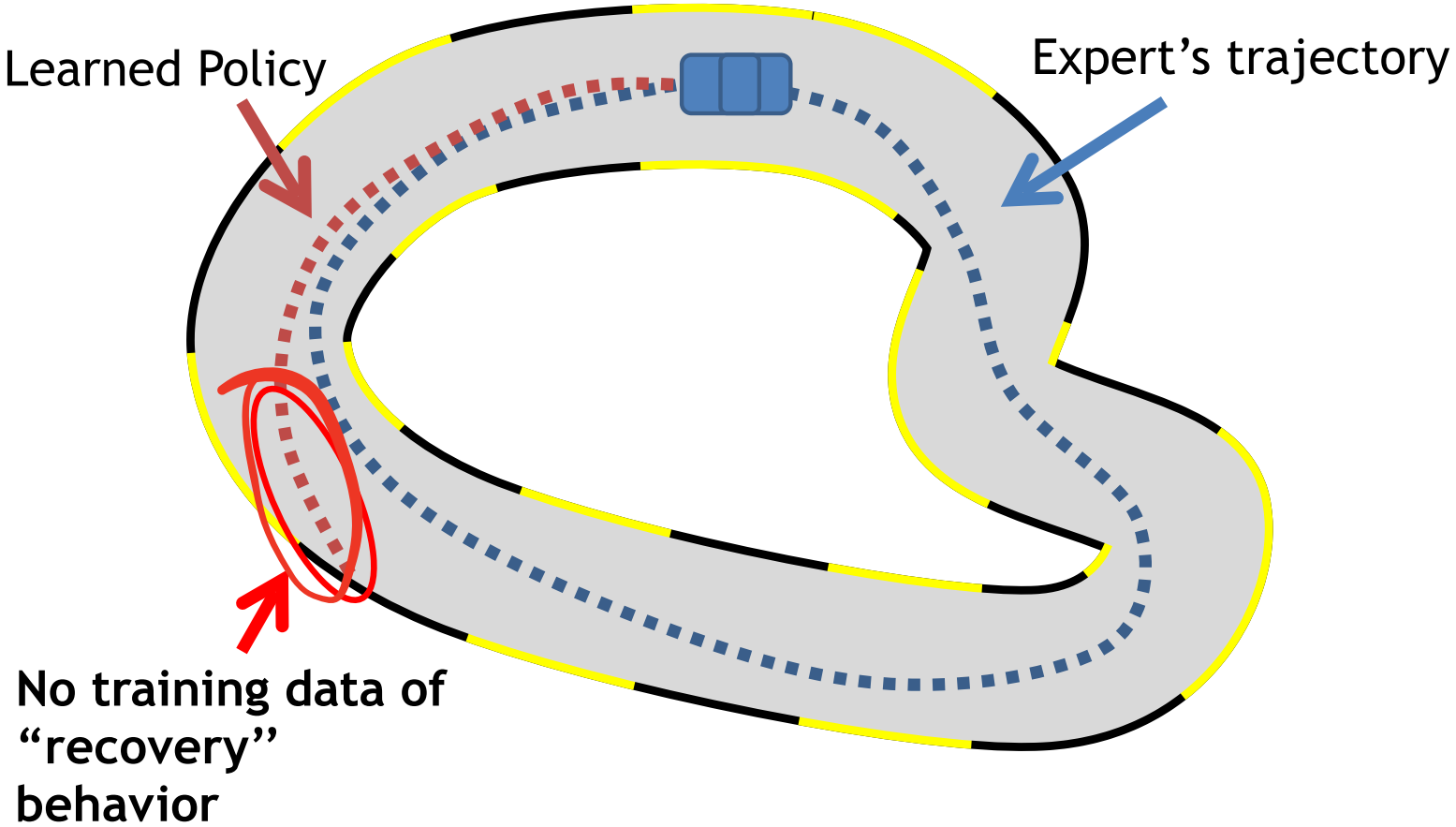
(Recall that previously we only had an offline dataset $\mathscr{D} = (s_i^\star, a_i^\star)_{i=1}^M \sim d_\mu^{\pi^\star}$)

Outline for today:

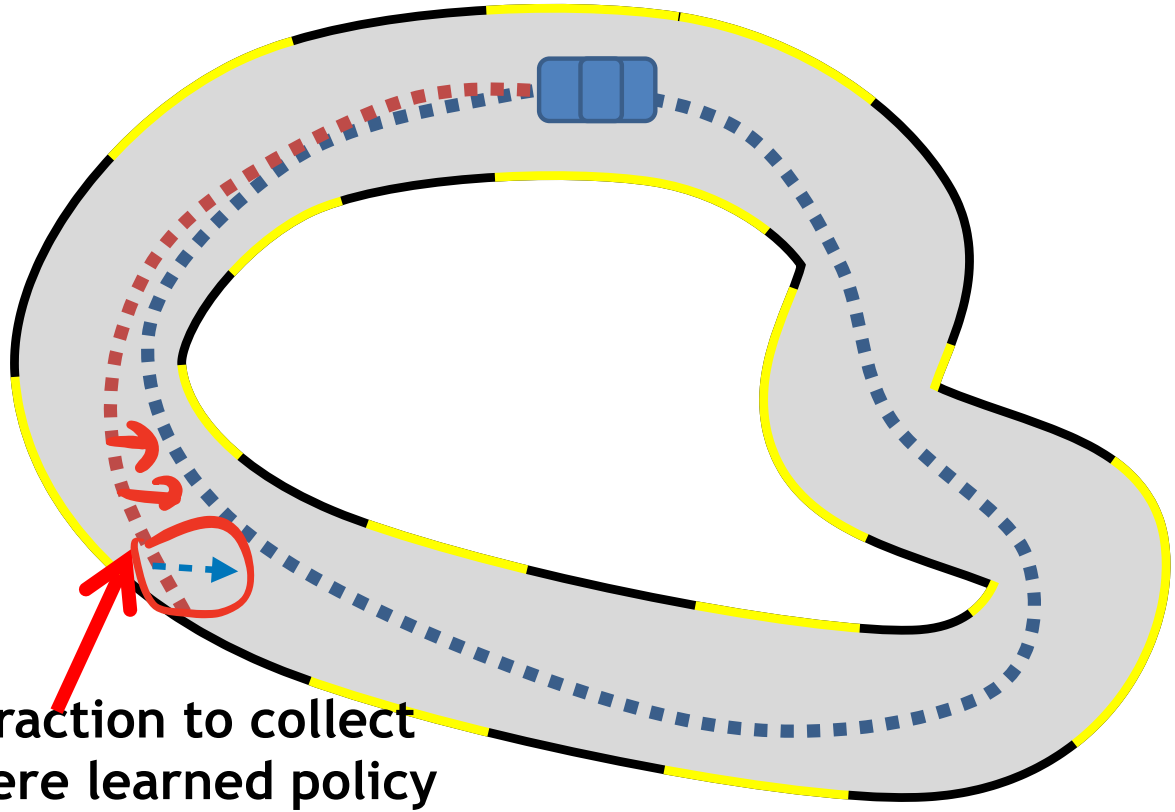
1. The DAgger (Data Aggregation) Algorithm

2. Analysis of DAgger: DAgger as online learning

Recall the Main Problem from Behavior Cloning:

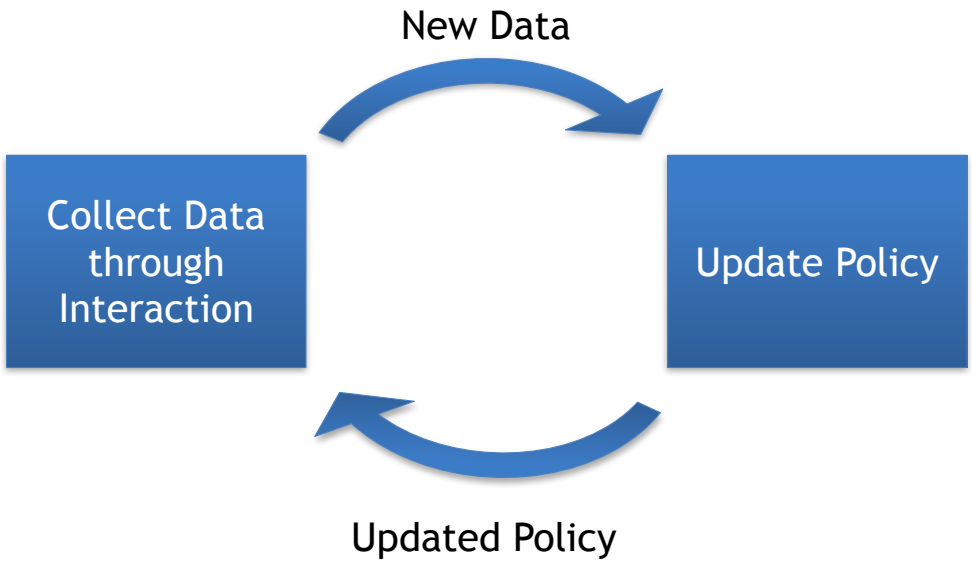


Intuitive solution: **Interaction**



Use interaction to collect data where learned policy goes

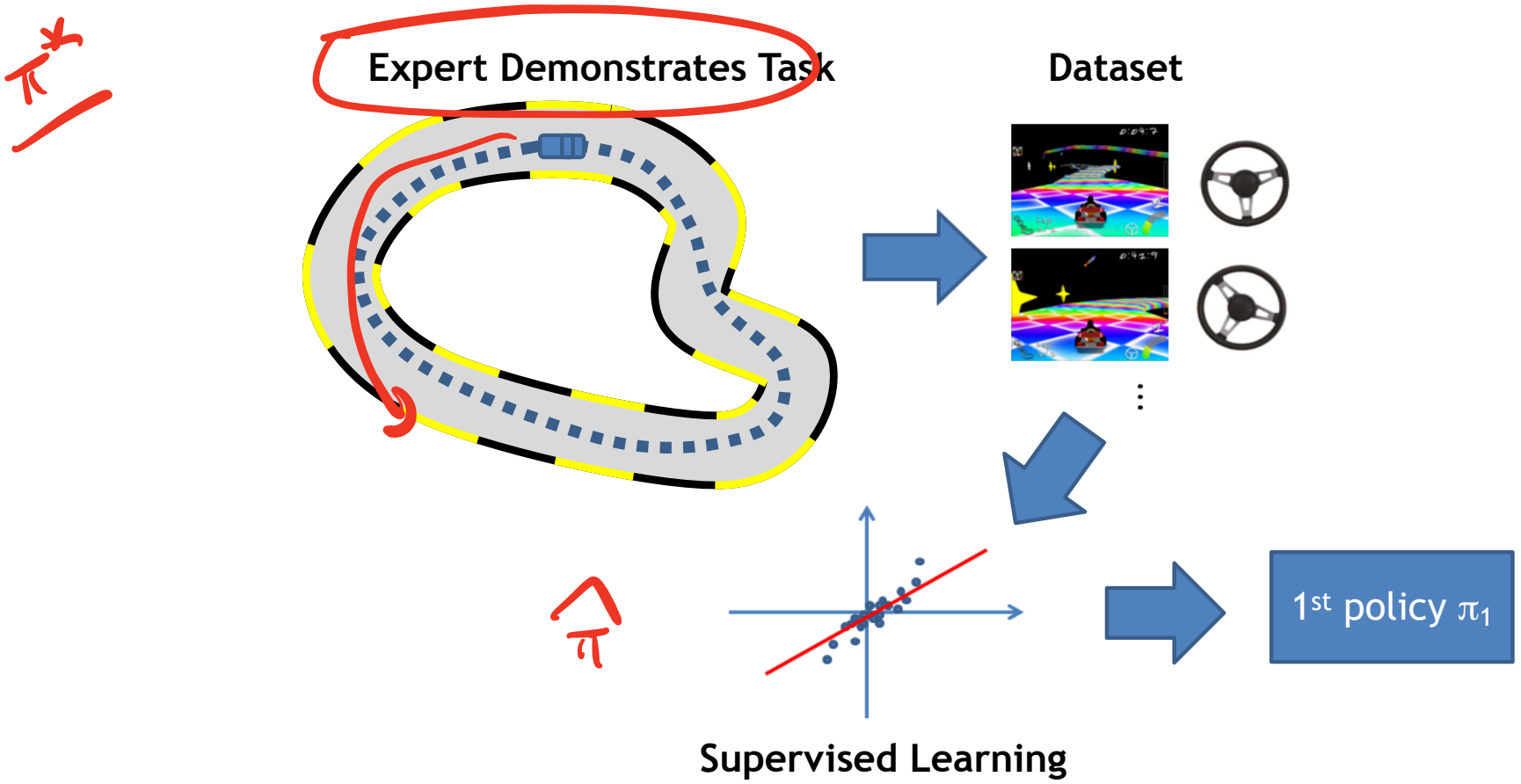
General Idea: Iterative Interactive Approach



All DAgger slides credit: Drew Bagnell, Stephane Ross, Arun Venktraman

DAgger: Dataset Aggregation [Ross11a]

0th iteration



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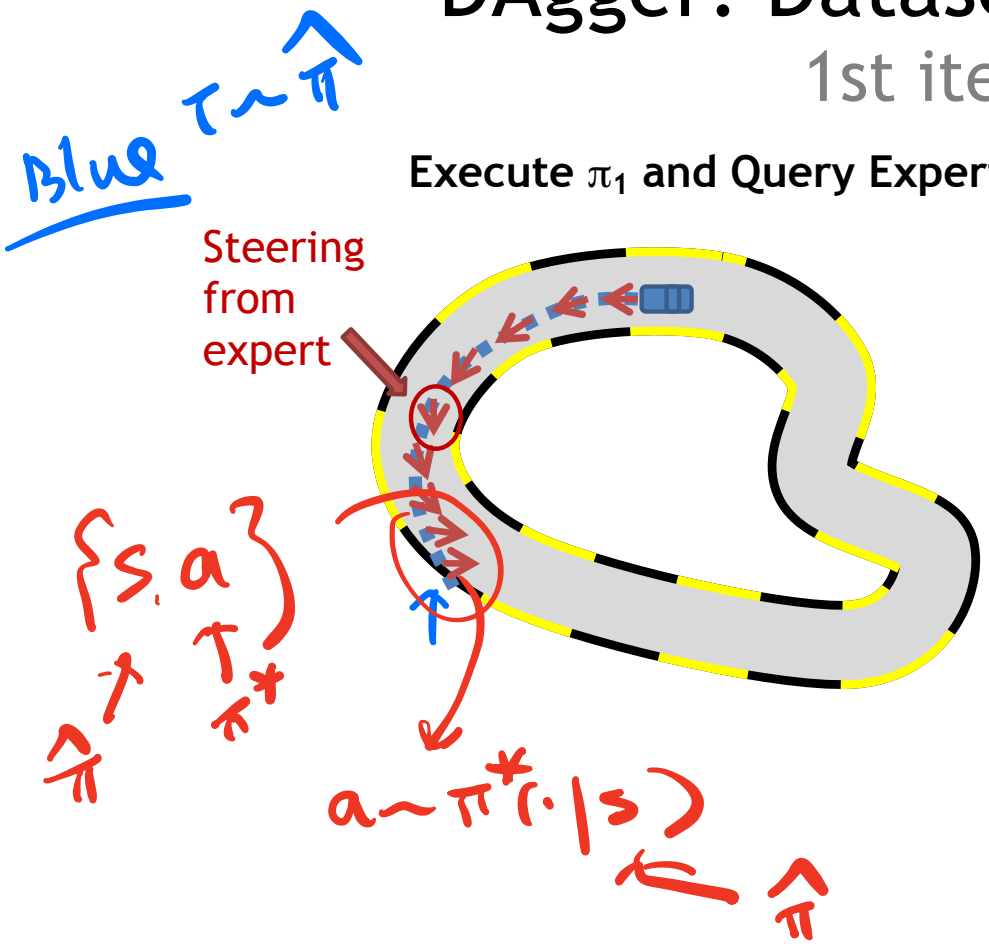
1st iteration

Execute π_1 and Query Expert



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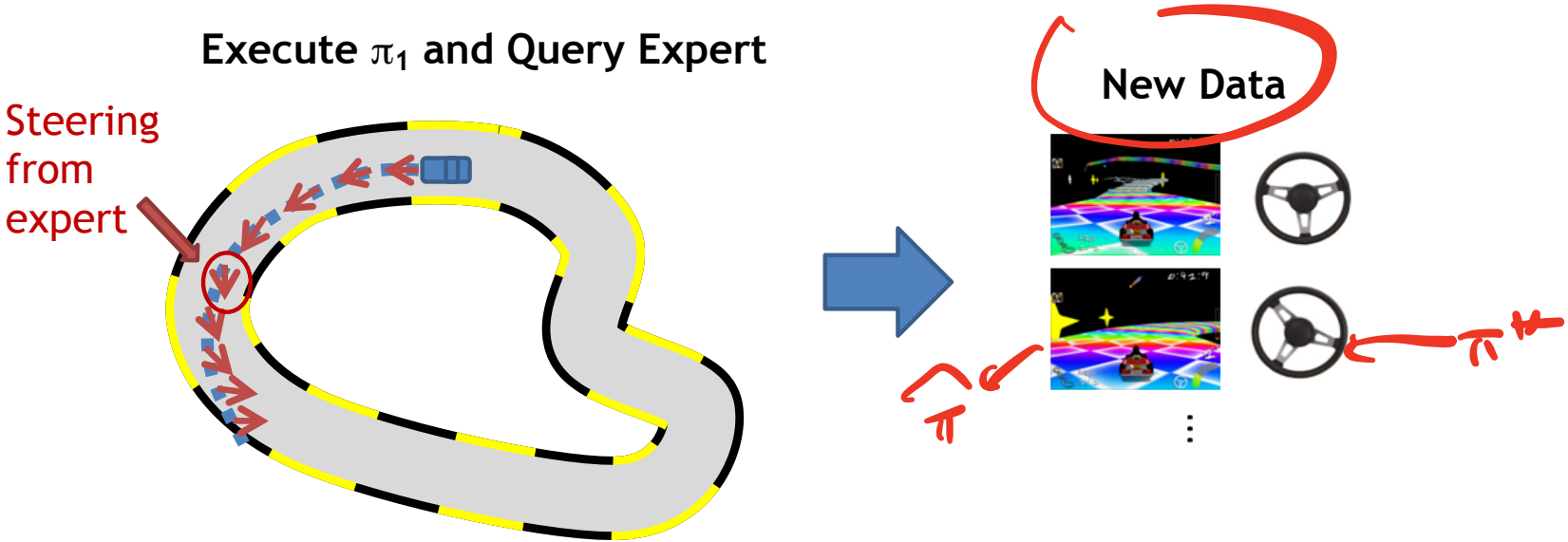

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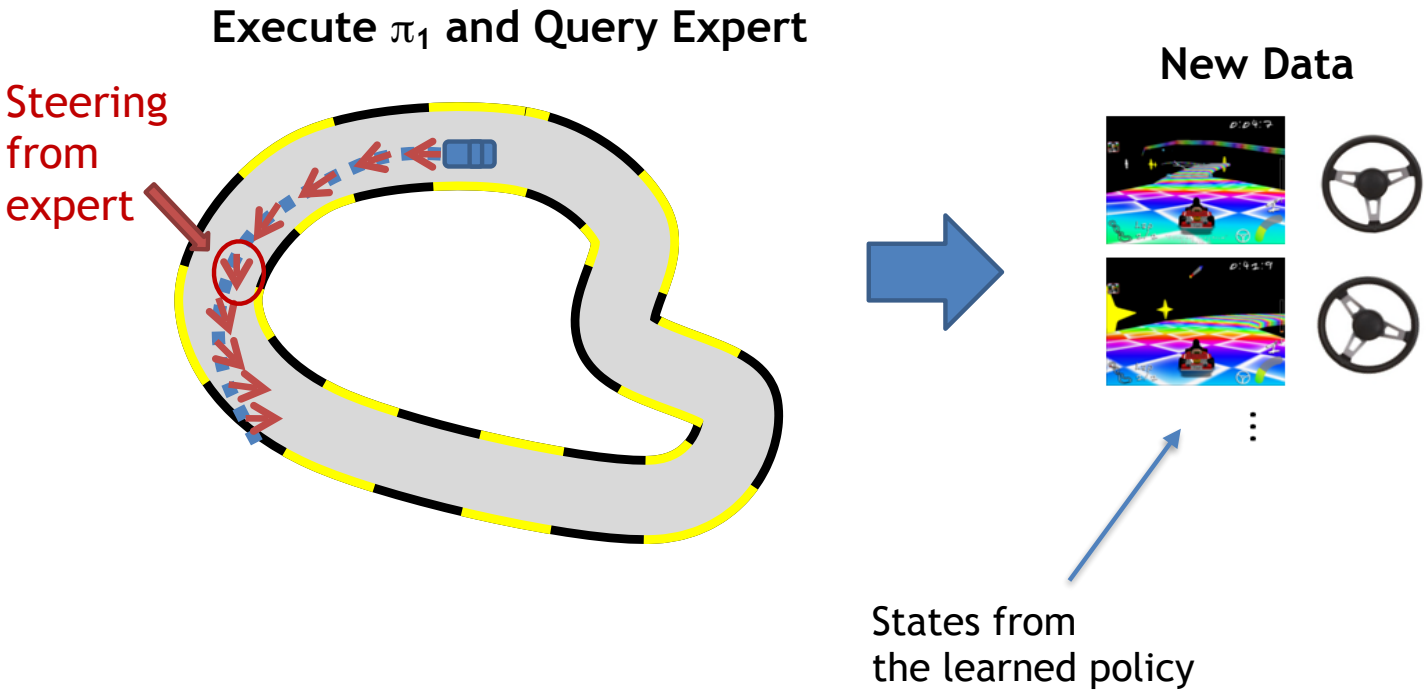

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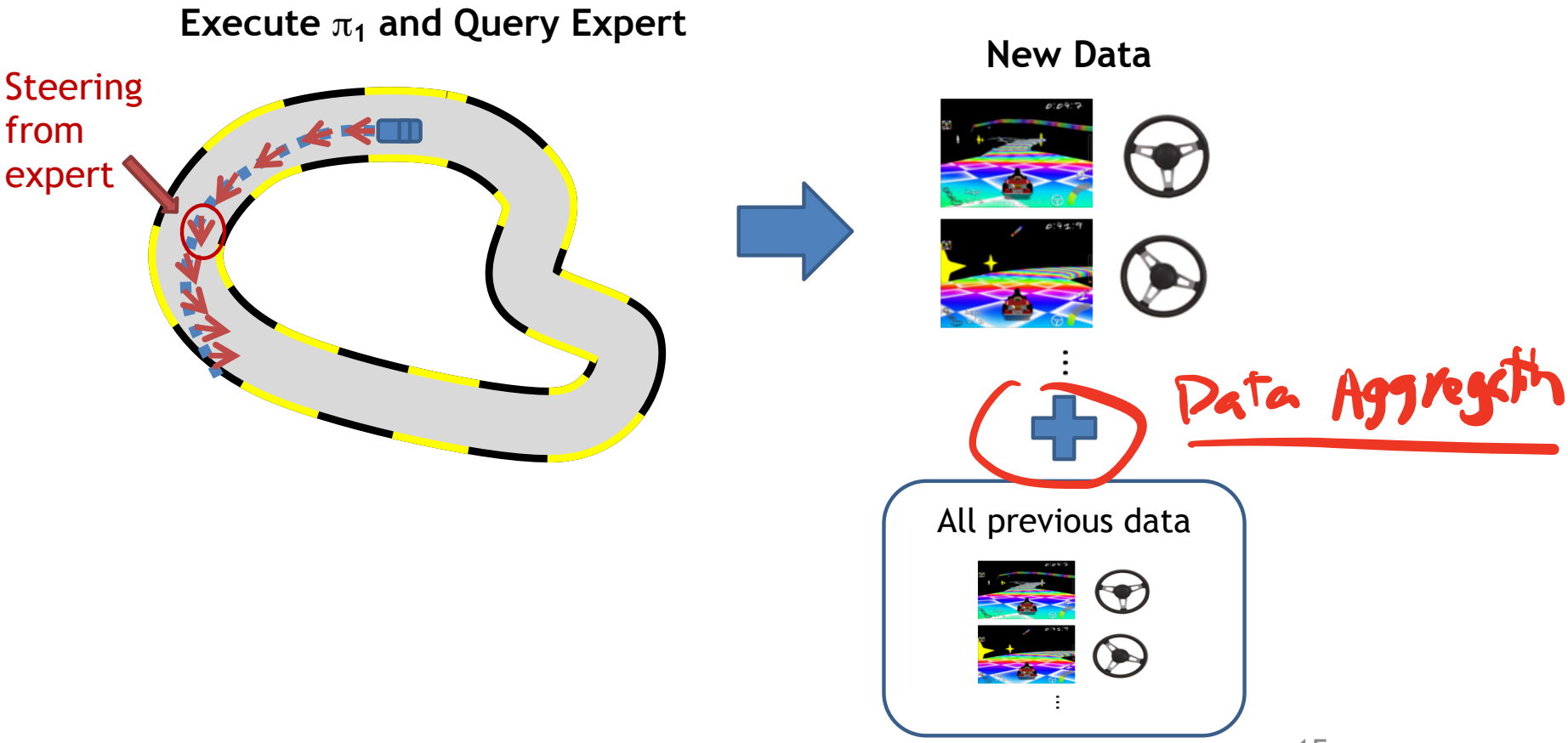

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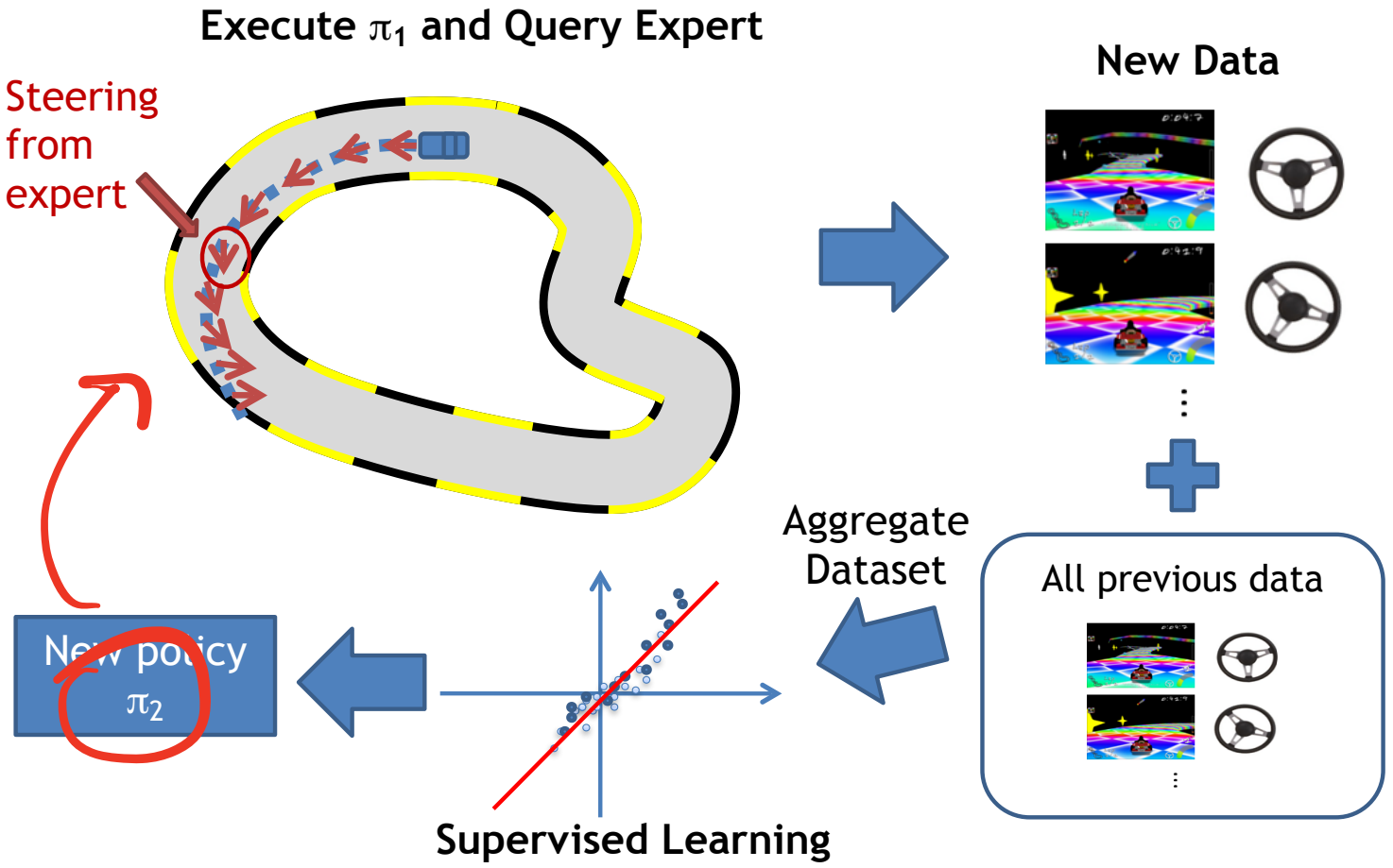

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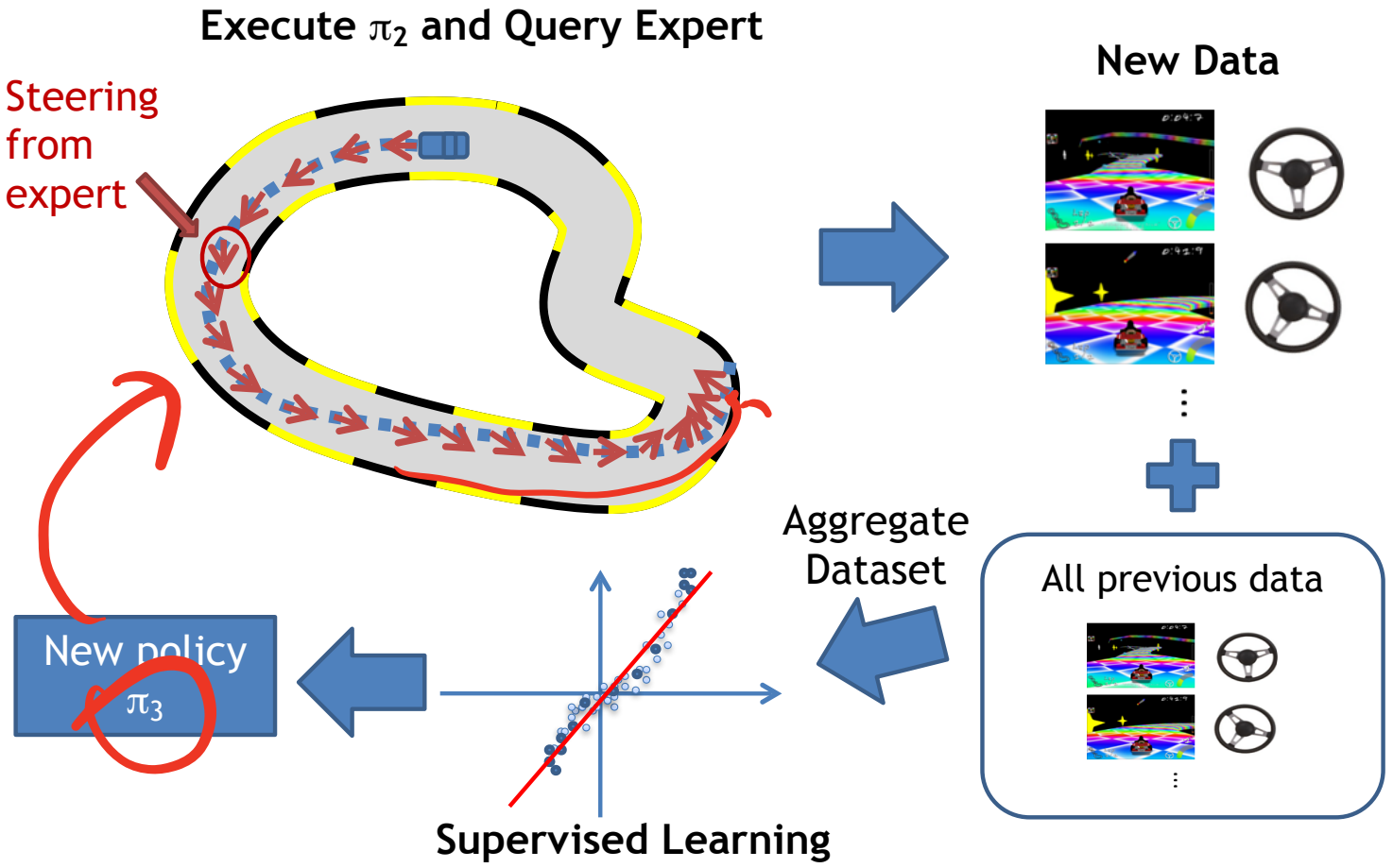
2nd iteration



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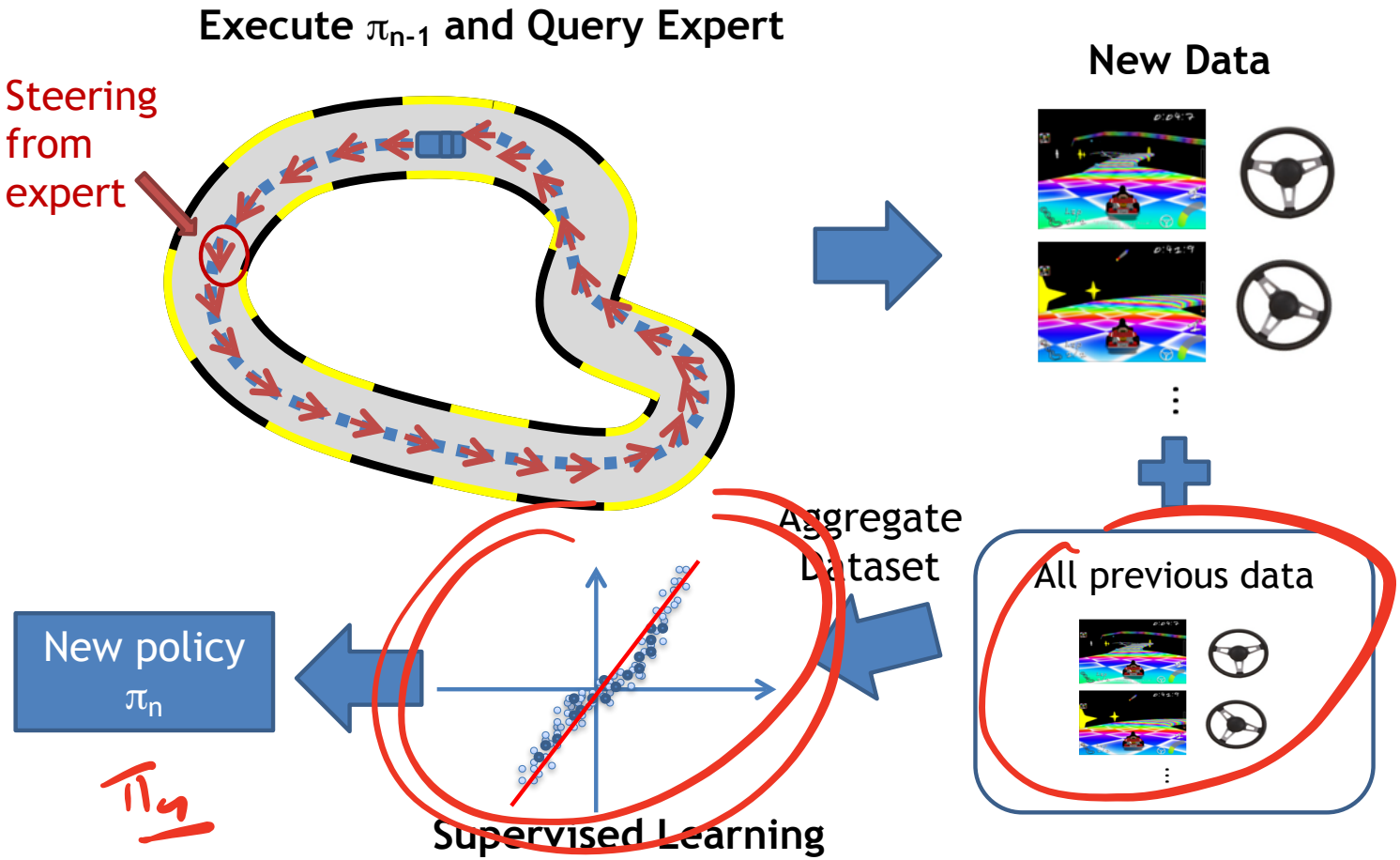
n^{th} iteration



Success!

[Ross AISTATS 2011]

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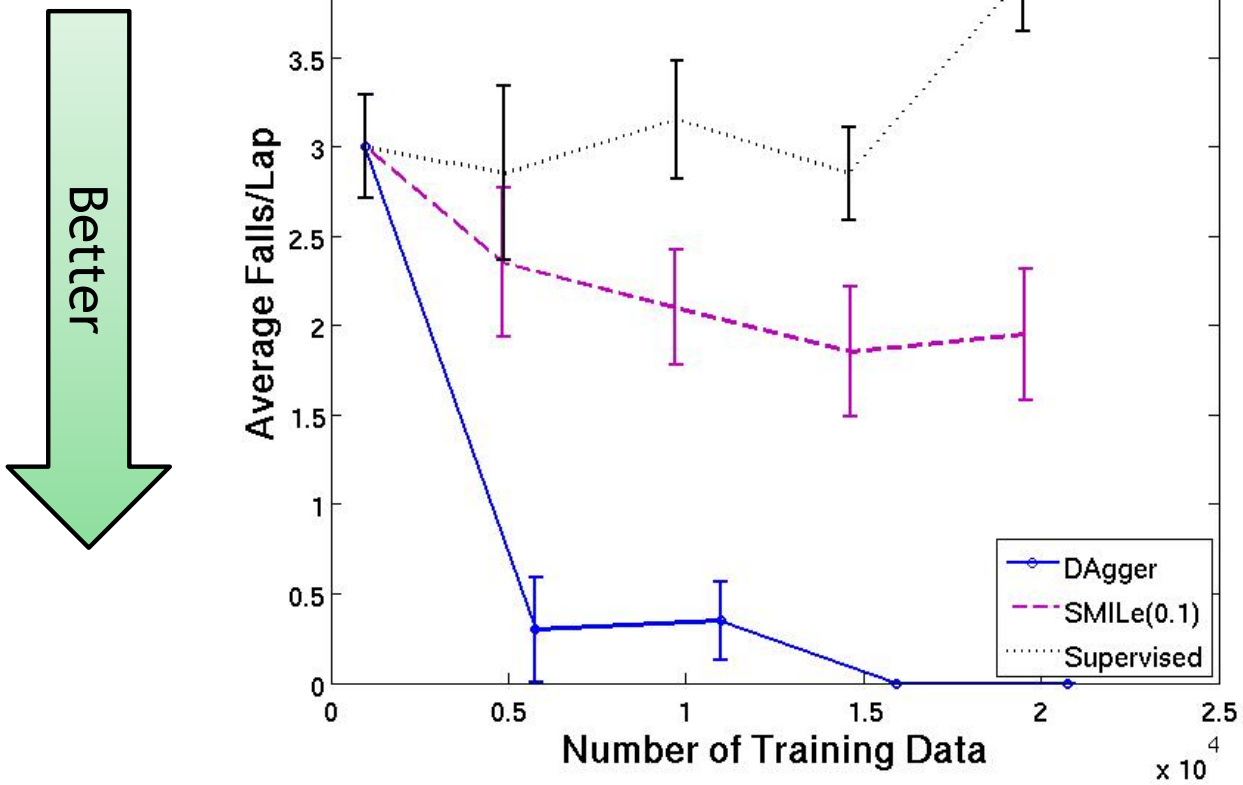
Average Falls/Lap




FPS: 24
Attempt: 1 of 1
AgentLinear
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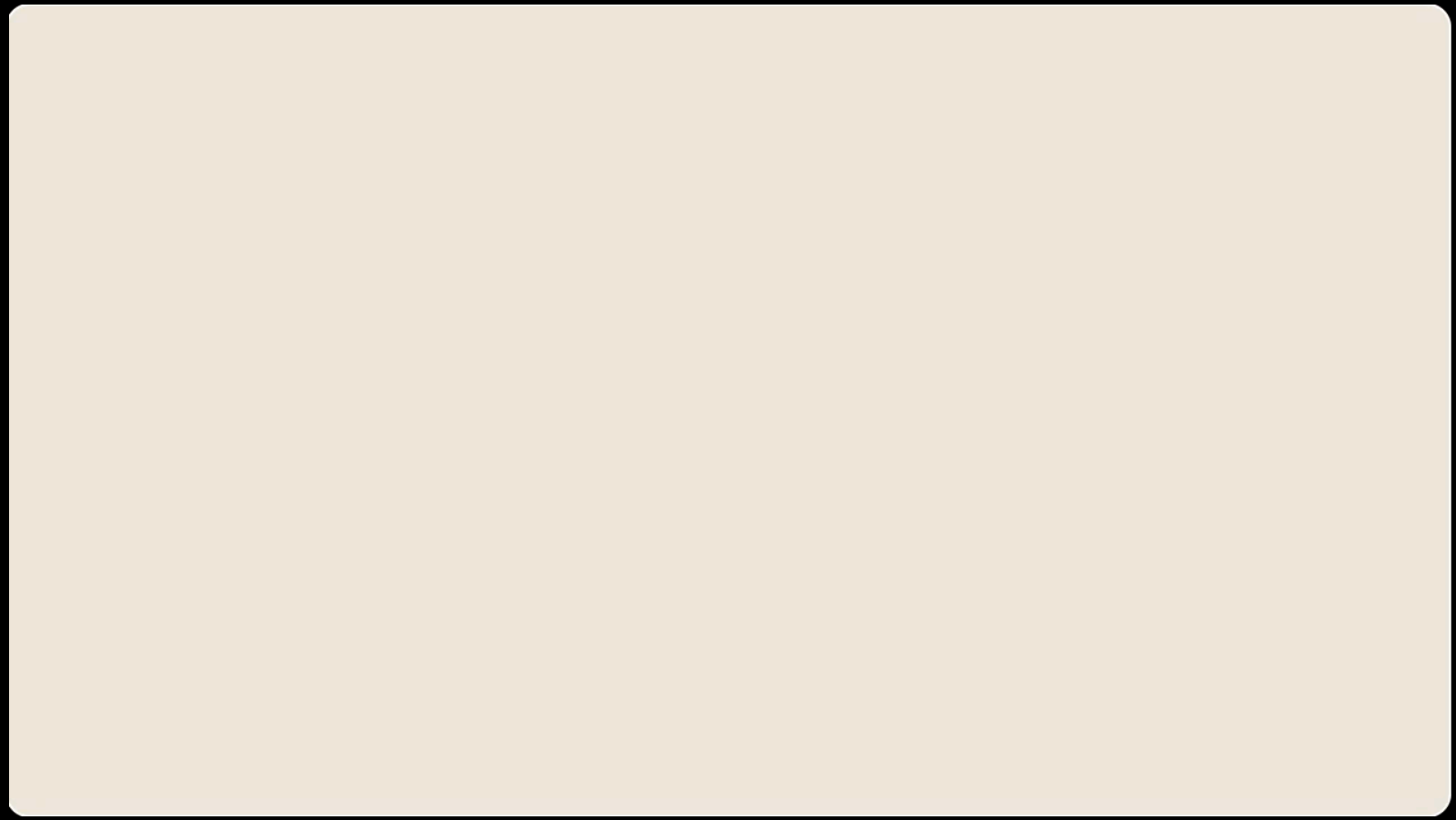

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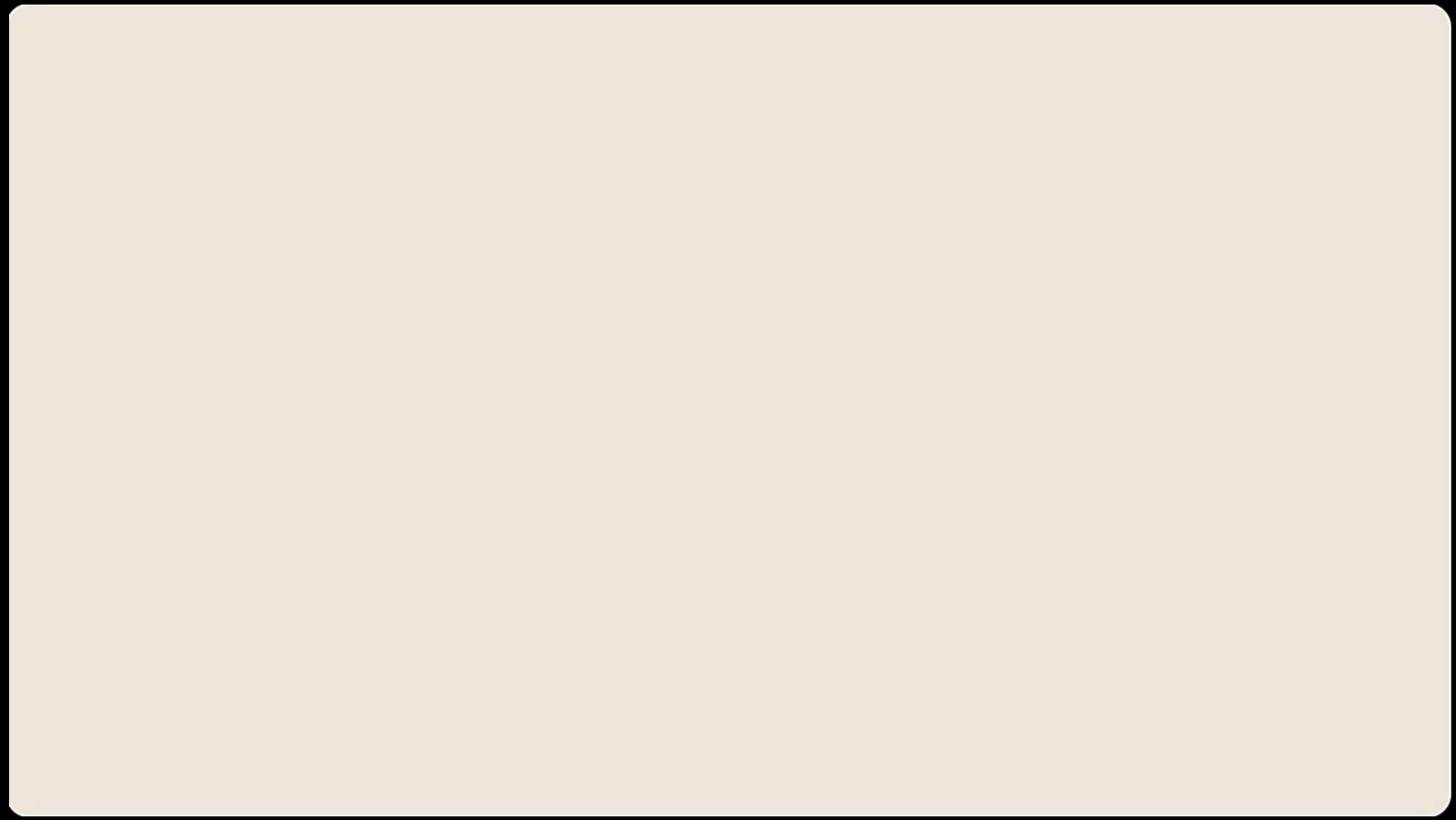

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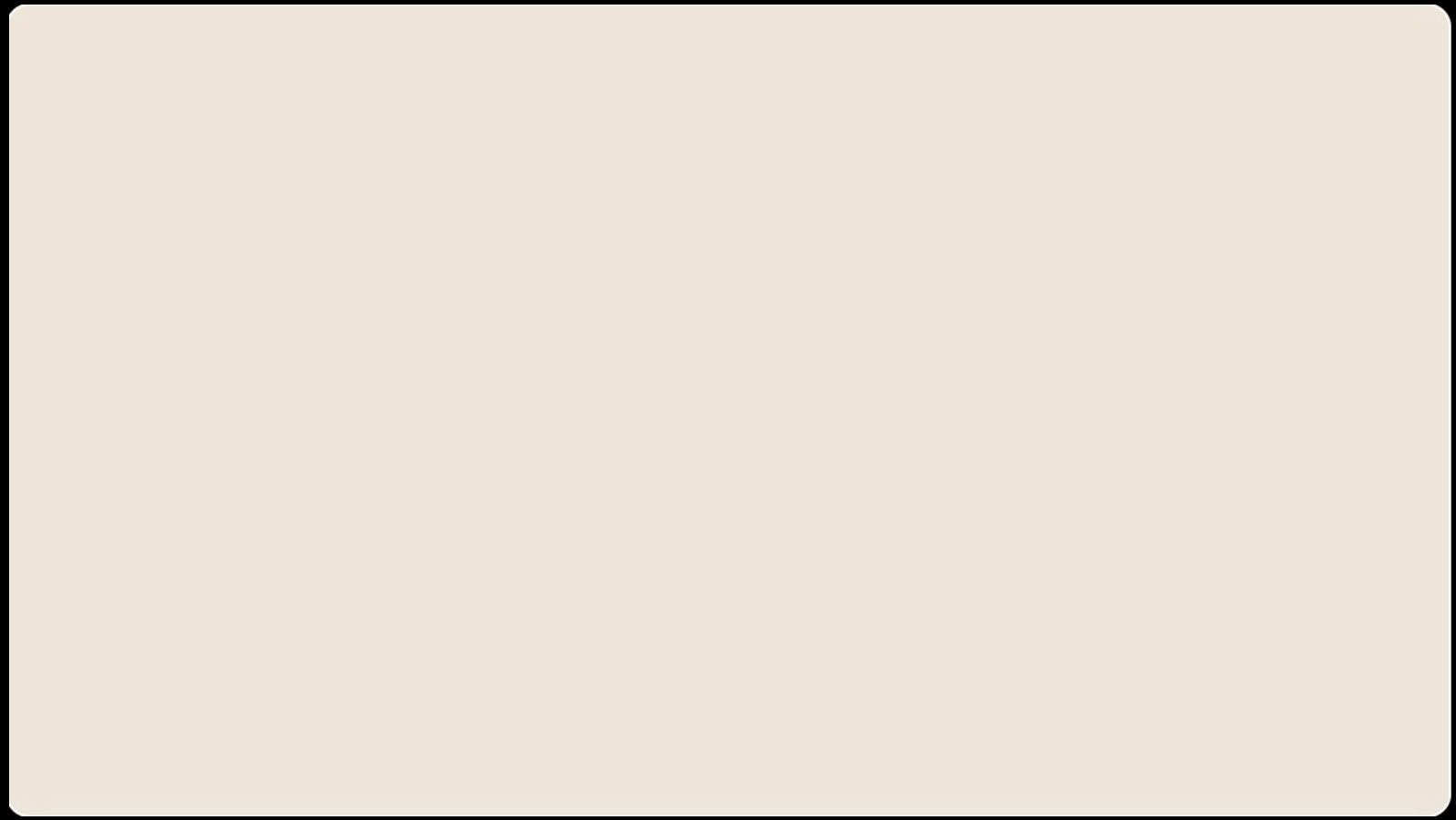

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Forms of the Interactive Experts

Interactive Expert is expensive, especially when the expert is human…

But expert does not have to be human…

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Fig. 4: The AutoRally car and the test track.

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Goal: learn a racing control policy that maps from data on cheap on-board sensors (raw-pixel imagine) to low-level control (steer and throttle)

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→ Steering + throttle

(a) raw image

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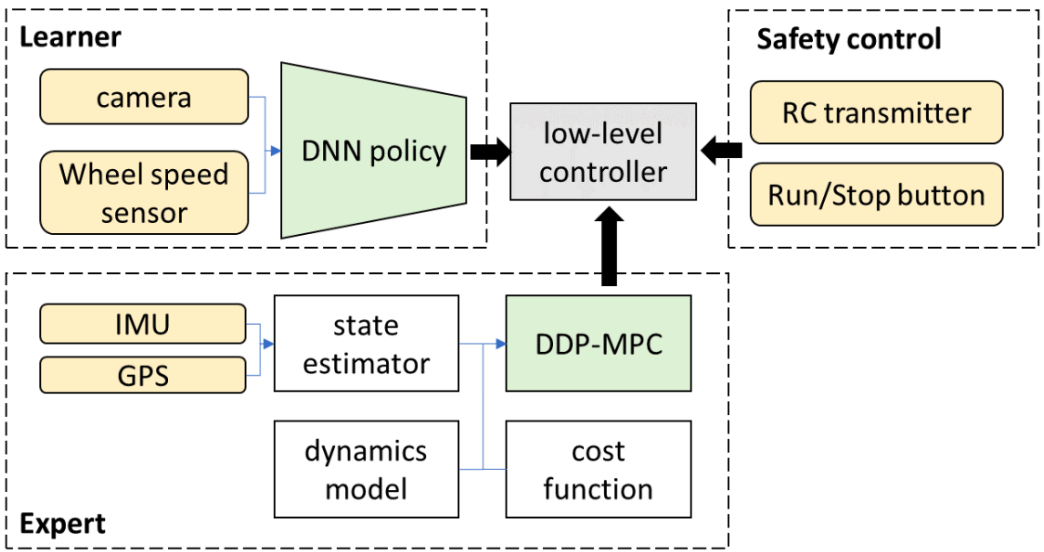

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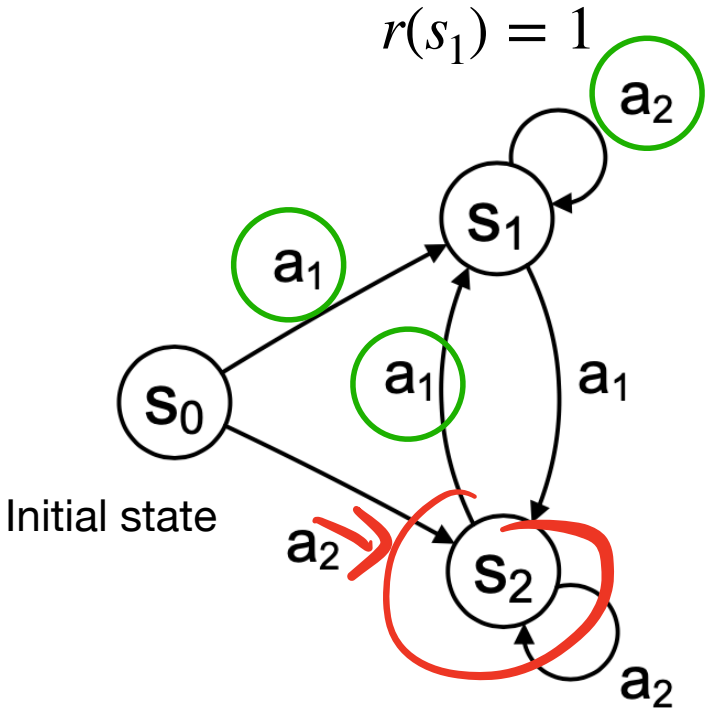

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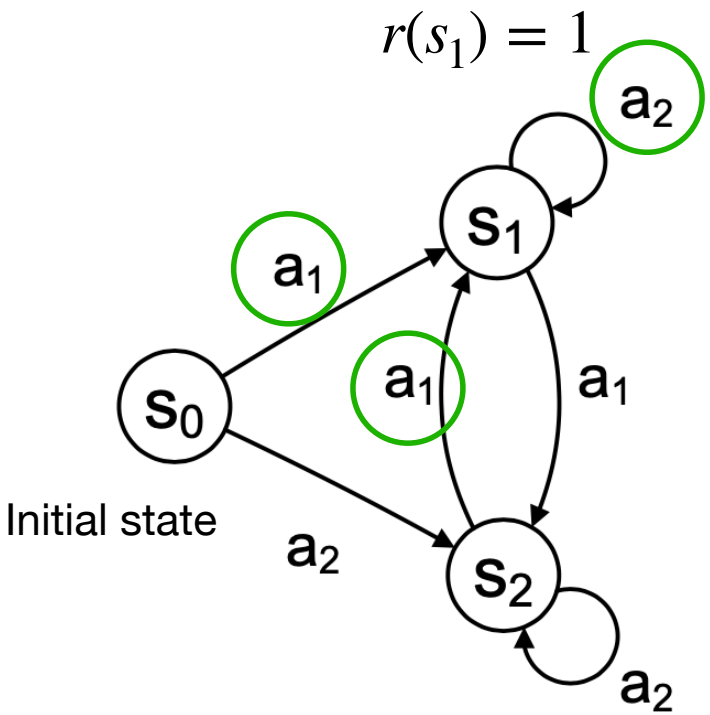

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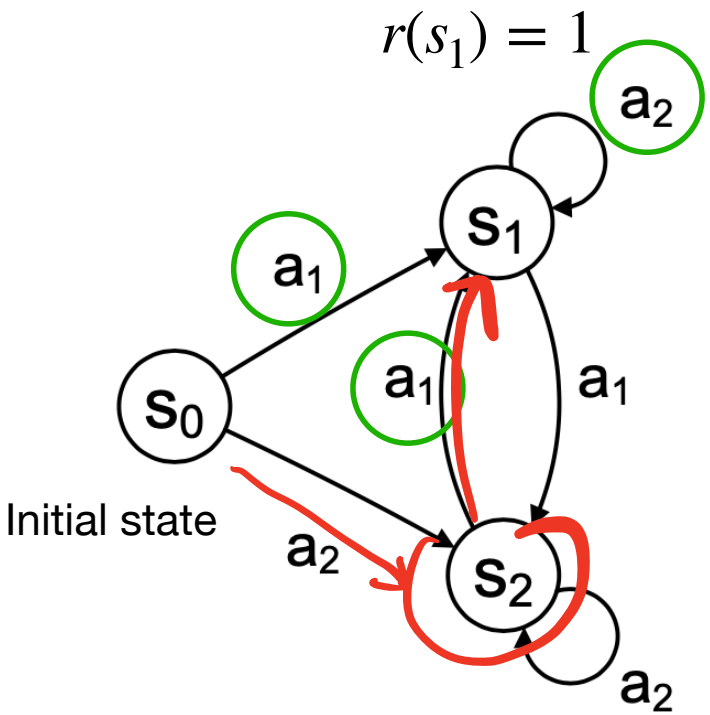

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Why DAgger can fix this problem?

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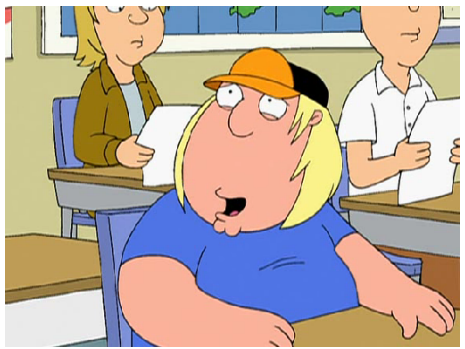
2. Analysis of DAgger: DAgger as online learning

Online Learning

Learner



convex Decision set Θ

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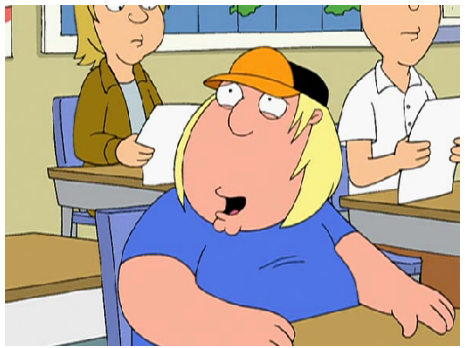
Adversary

[Vovk92,Warmuth94,Freund97,Zinkevich03,Kalai05,Hazan06,Kakade08]

Online Learning

Learner



convex Decision set Θ

Learner picks a decision θ_0

(x, y) **Adversary**

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[Vovk92,Warmuth94,Freund97,Zinkevich03,Kalai05,Hazan06,Kakade08]

Online Learning

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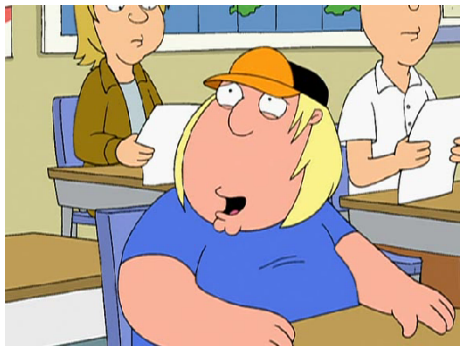


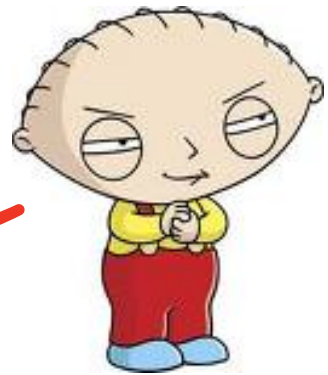
convex Decision set Θ

Learner picks a decision θ_0

Adversary picks a loss $\ell_0 : \Theta \to \mathbb{R}$

$\ell_0(\theta_0)$
$= (\theta_0^T x_0 - y_0)^2$

Adversary



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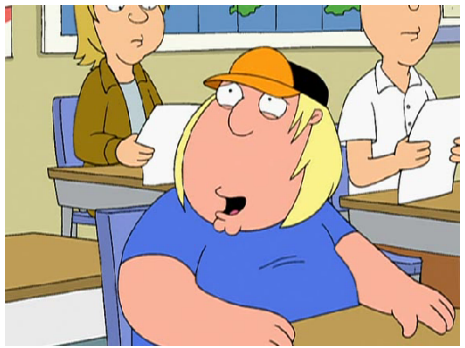
[Vovk92,Warmuth94,Freund97,Zinkevich03,Kalai05,Hazan06,Kakade08]

Online Learning

Learner



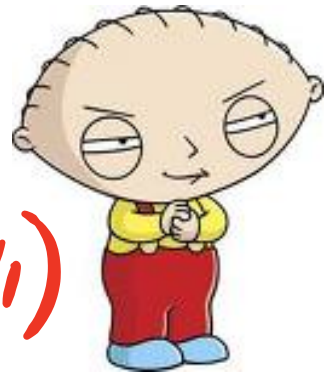
convex Decision set Θ

Learner picks a decision θ_0

Adversary picks a loss $\ell_0 : \Theta \to \mathbb{R}$

Learner picks a new decision θ_1

Adversary



(x_1, y_1)

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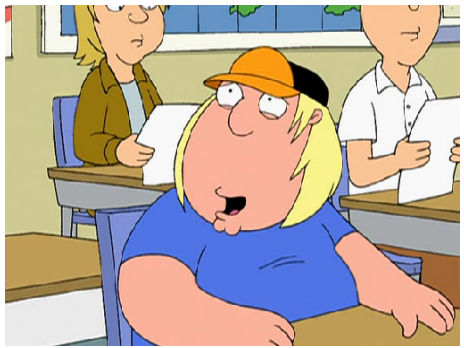

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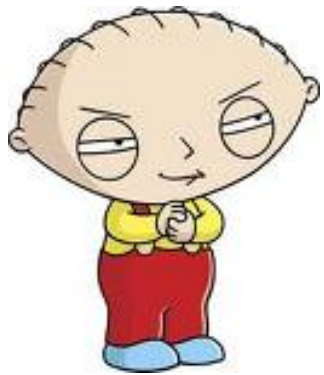

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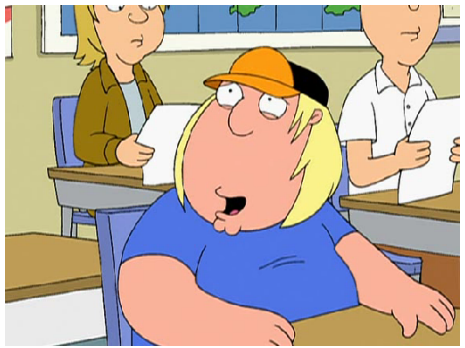

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$$\text{Regret} = \sum_{t=0}^{T-1} \ell_t(\theta_t) - \min_{\theta \in \Theta} \sum_{t=0}^{T-1} \ell_t(\theta)$$

[Vovk92,Warmuth94,Freund97,Zinkevich03,Kalai05,Hazan06,Kakade08]

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Can we perform linear regression in online fashion with non i.i.d (or even adversary) data?

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(see θ_t)

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Adversary seems too powerful…

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$$\sum_{i=0}^{T-1} \ell_i(\theta_i) - \min_{\theta \in \text{Ball}} \sum_{i=0}^{T-1} \ell_i(\theta) = O\left(\sqrt{T}\right)$$

Avg-Reg $= \frac{\sqrt{T}}{T} \to 0$

Generally, Follow-the-Regularized-Leader is no-regret

At time step t, learner has seen $\ell_0, \ldots \ell_{t-1}$, which new decision she could pick?

FTRL: $\theta_t = \min_{\theta \in \Theta} \sum_{i=0}^{t-1} \ell_i(\theta) + \lambda R(\theta)$

Ex $\|\theta\|_2^2$

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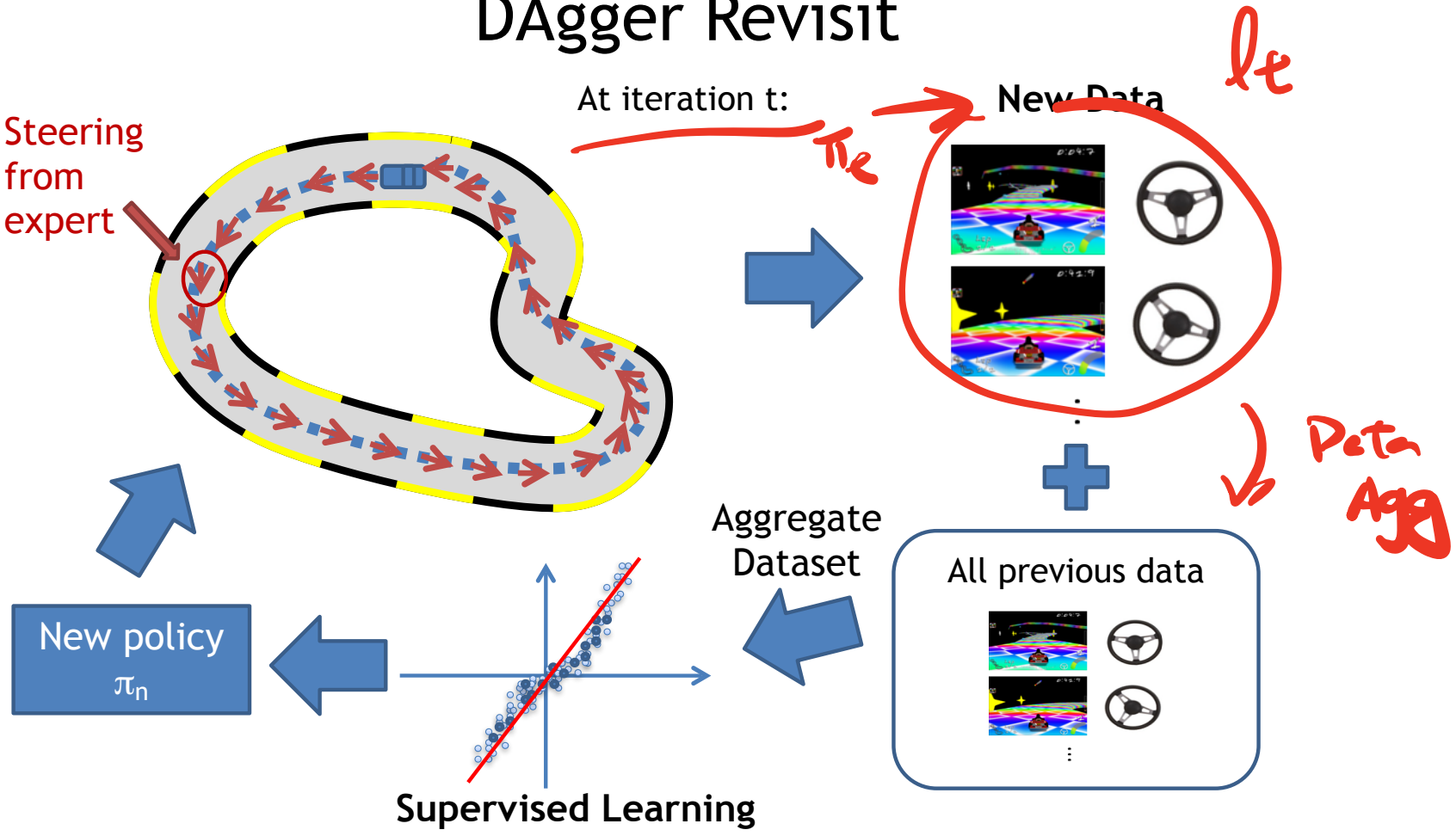
Informal Theorem (FTRL): when things are convex, FTRL is no-regret, i.e.,

$$\frac{1}{T}\left[\sum_{t=0}^{T-1} \ell_t(\theta_t) - \min_{\theta \in \Theta} \sum_{t=0}^{T-1} \ell_t(\theta)\right] = O\left(1/\sqrt{T}\right)$$

DAgger Revisit



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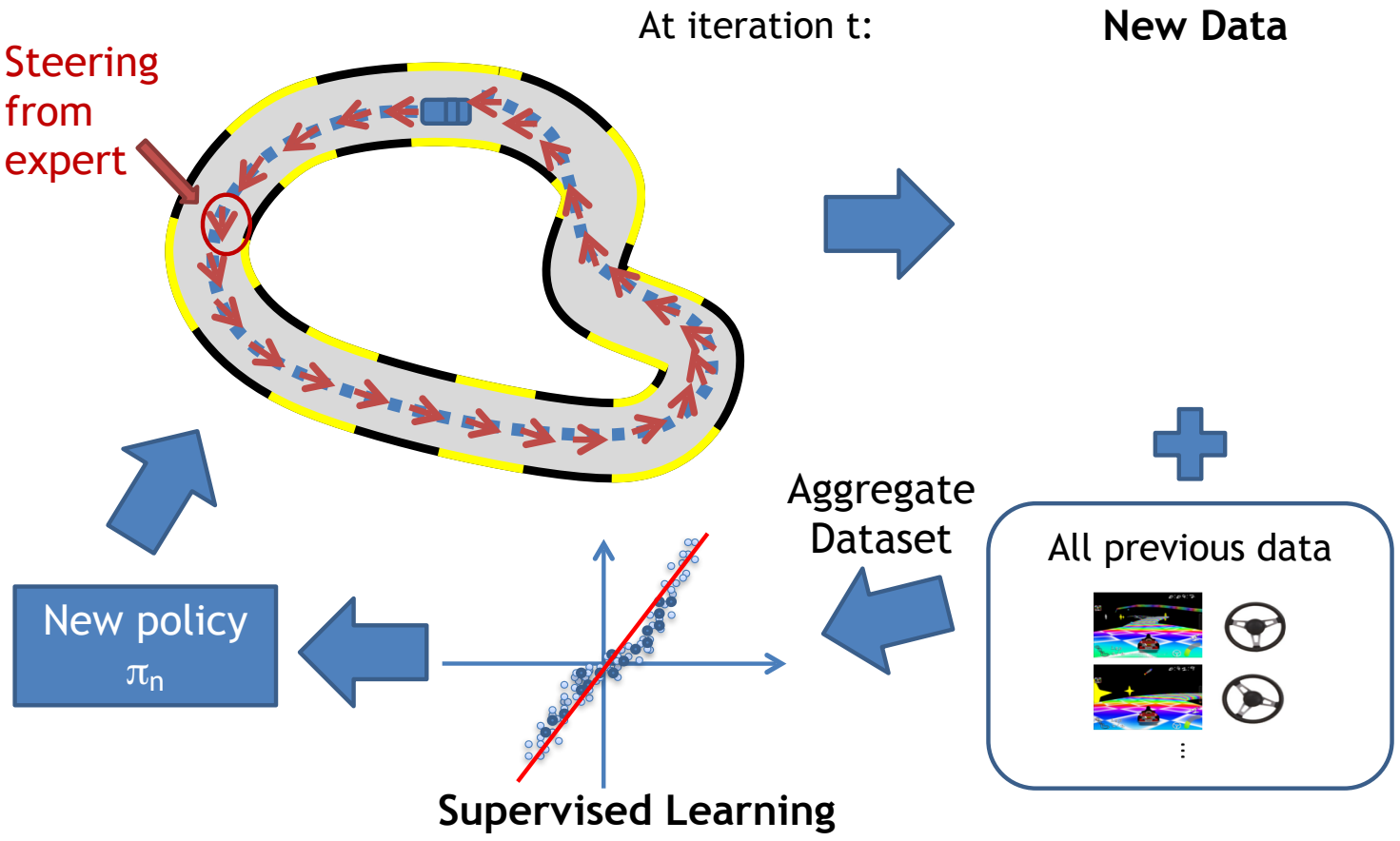
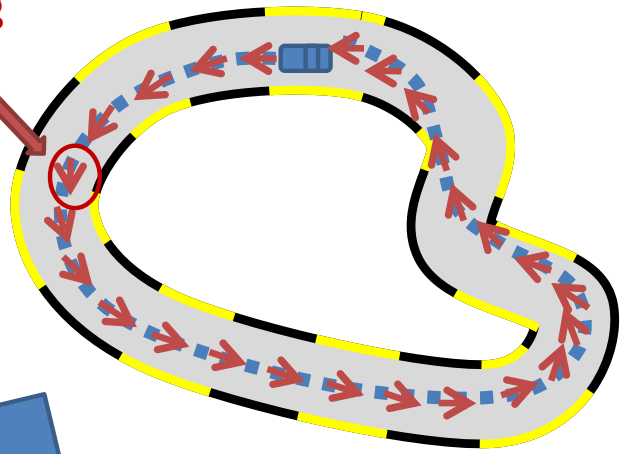


DAgger Revisit

At iteration t:

Steering from expert

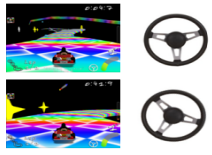


New Data

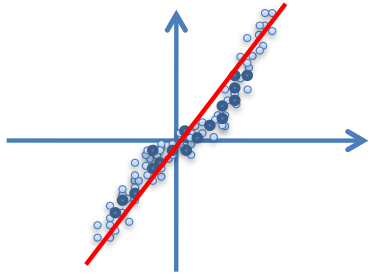
$$\ell_t(\pi) = \sum_{i=1}^{m} \|\pi(s^i) - \pi^\star(s^i)\|_2^2$$

Aggregate Dataset

All previous data



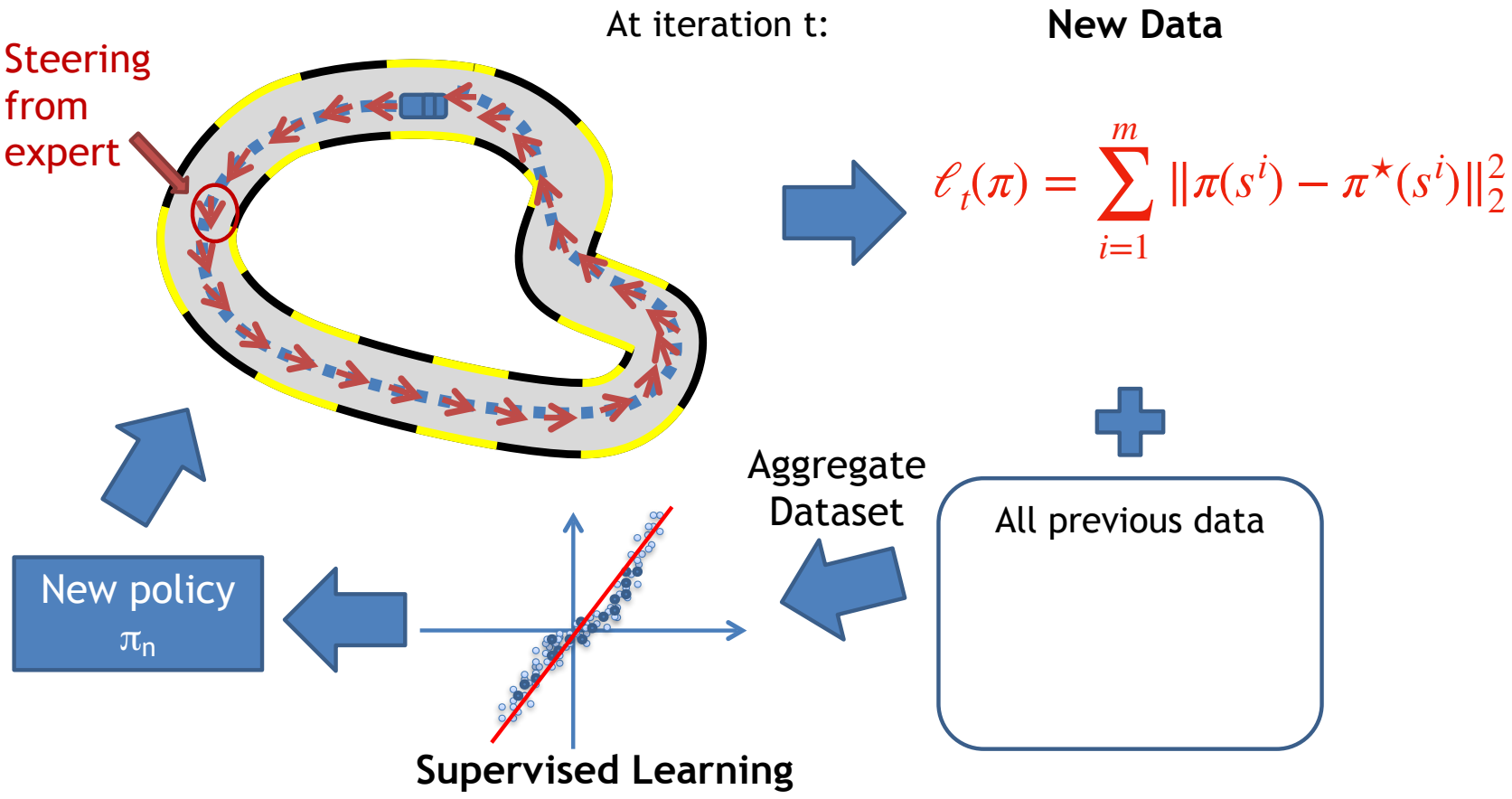
⋮



Supervised Learning

New policy π_n

DAgger Revisit



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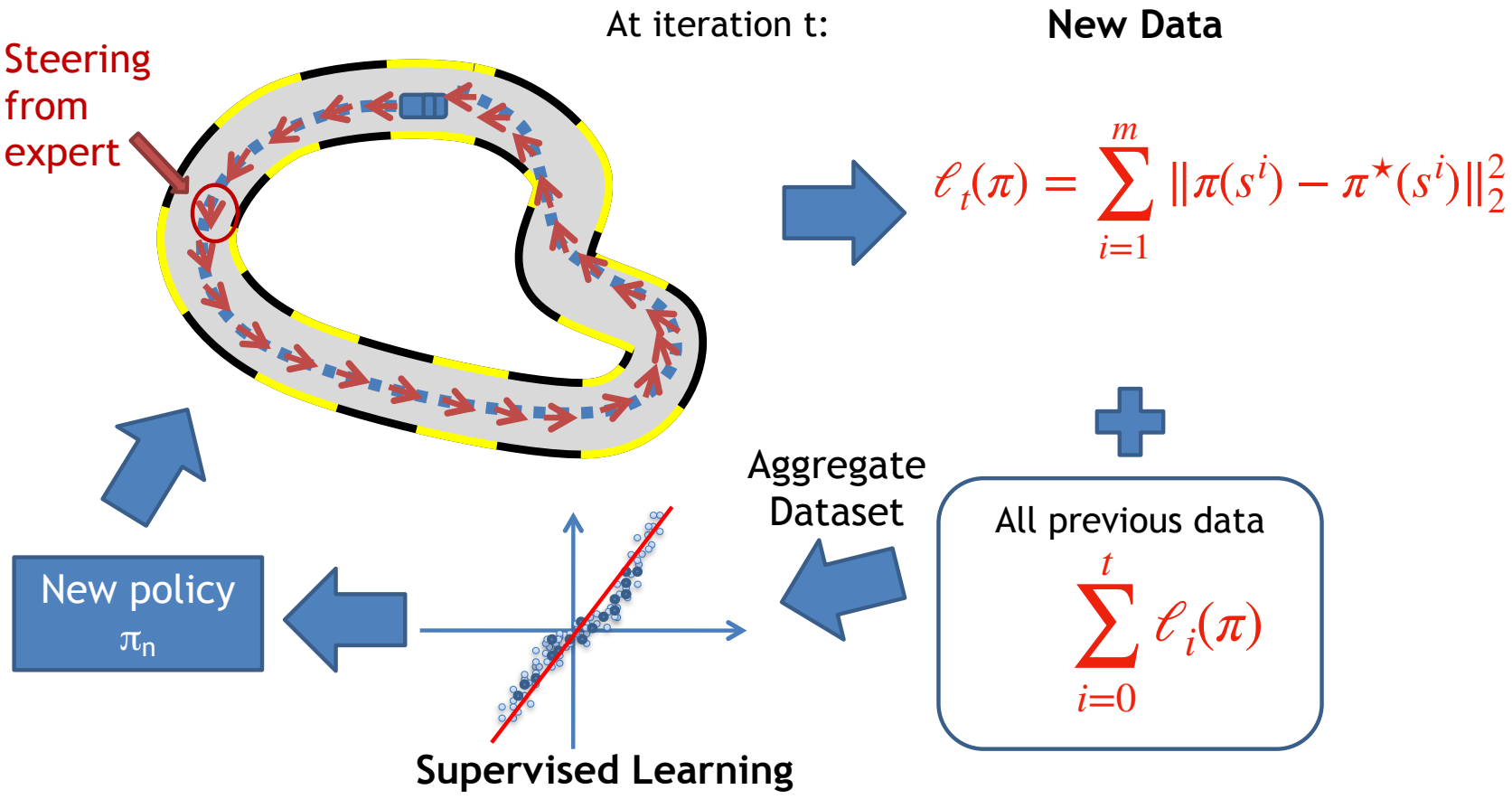

DAgger Revisit

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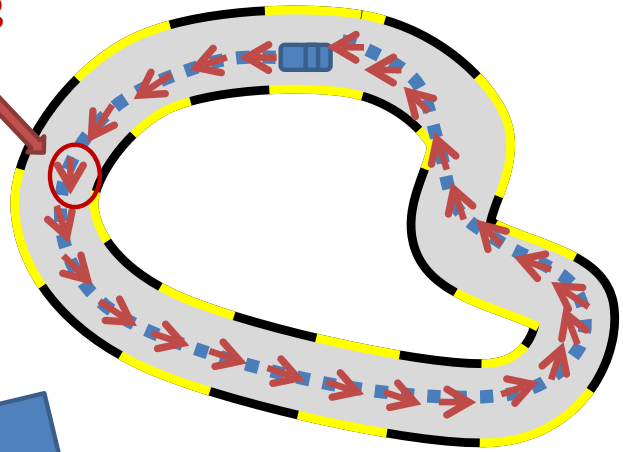

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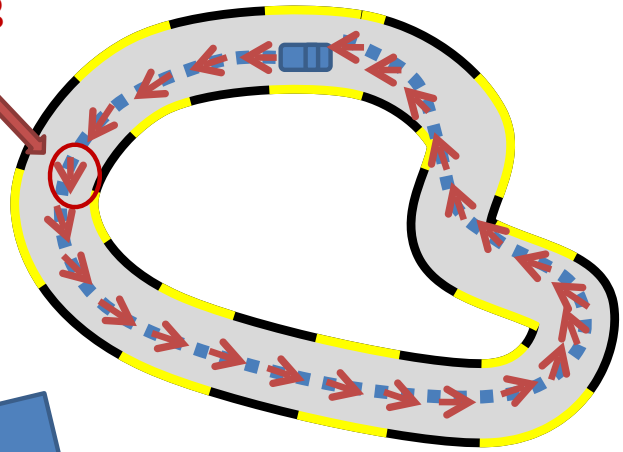

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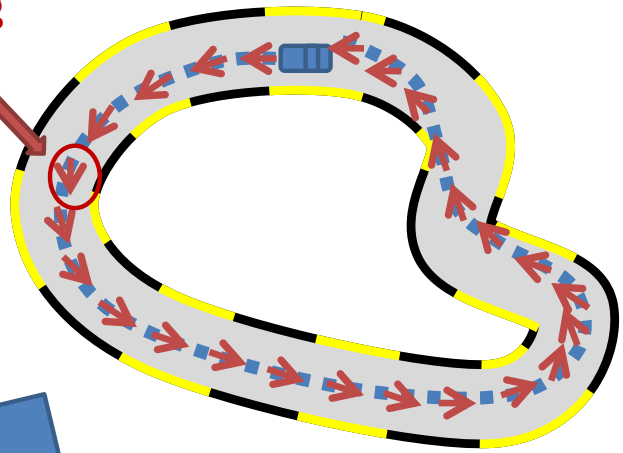

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Supervised Learning

Data Aggregation = Follow-the-Regularized-Leader Online Learner

Summary for Today

1. The DAgger algorithm

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

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

1. W/ π^t, generate dataset $\mathscr{D}^t = \{s_i, a_i^\star\}, s_i \sim d_\mu^{\pi^t}, a_i^\star = \pi^\star(s_i)$
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2. We can see that DAgger is essentially an online-learning algorithm (FTRL)