DAgger: Taming Covariate Shift with No Regret

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Cornell Bowers CIS
Computer Science

Really cool talk today!

My Six Decade Experience in Visual Imaging

Prof. Don Greenburg

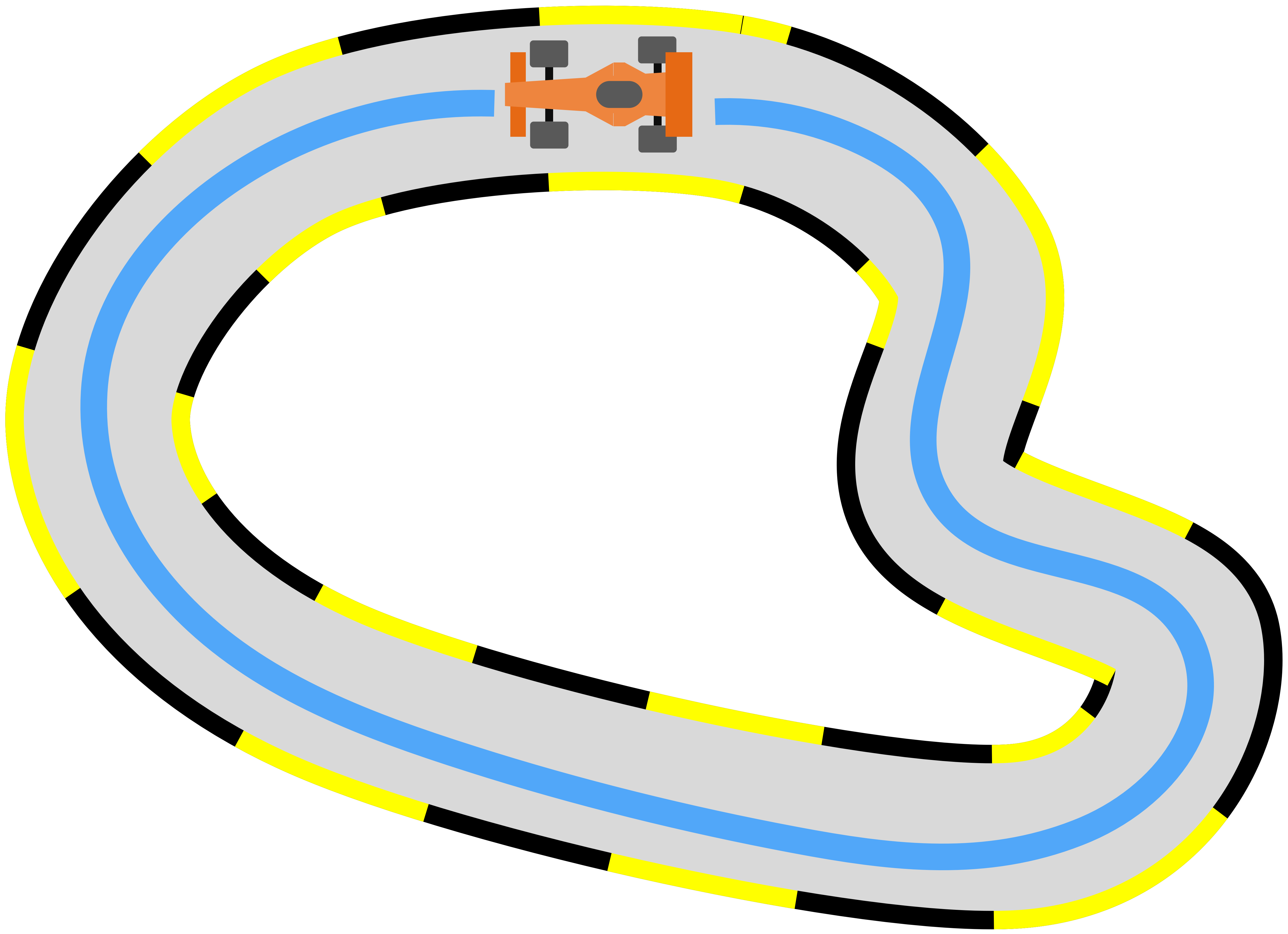
Colloquium at 11:45am, in G01 Gates Hall


RESEARCH NIGHT
Monday
Sept. 16 2024
Panel Discussion
Gates G01 5-6 PM
Poster Session
Gates Atrium 6-7 PM
ACSU
Gates Hall
GATES HALL

Today's class

- What is DAGGER?
- DAGGER in the real world
- Why *aggregate* data?

Behavior Cloning

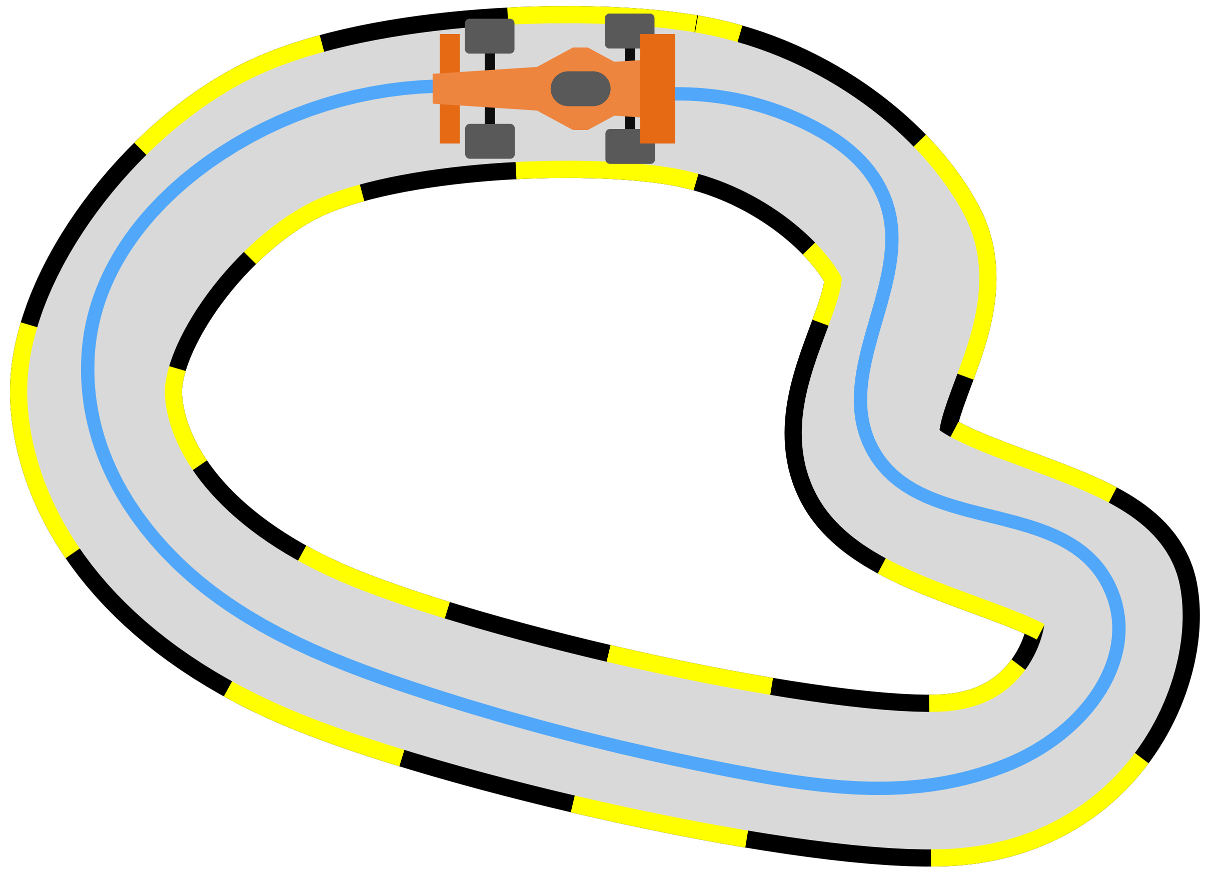


Expert runs
away after
demonstrations

The Big Problem with BC

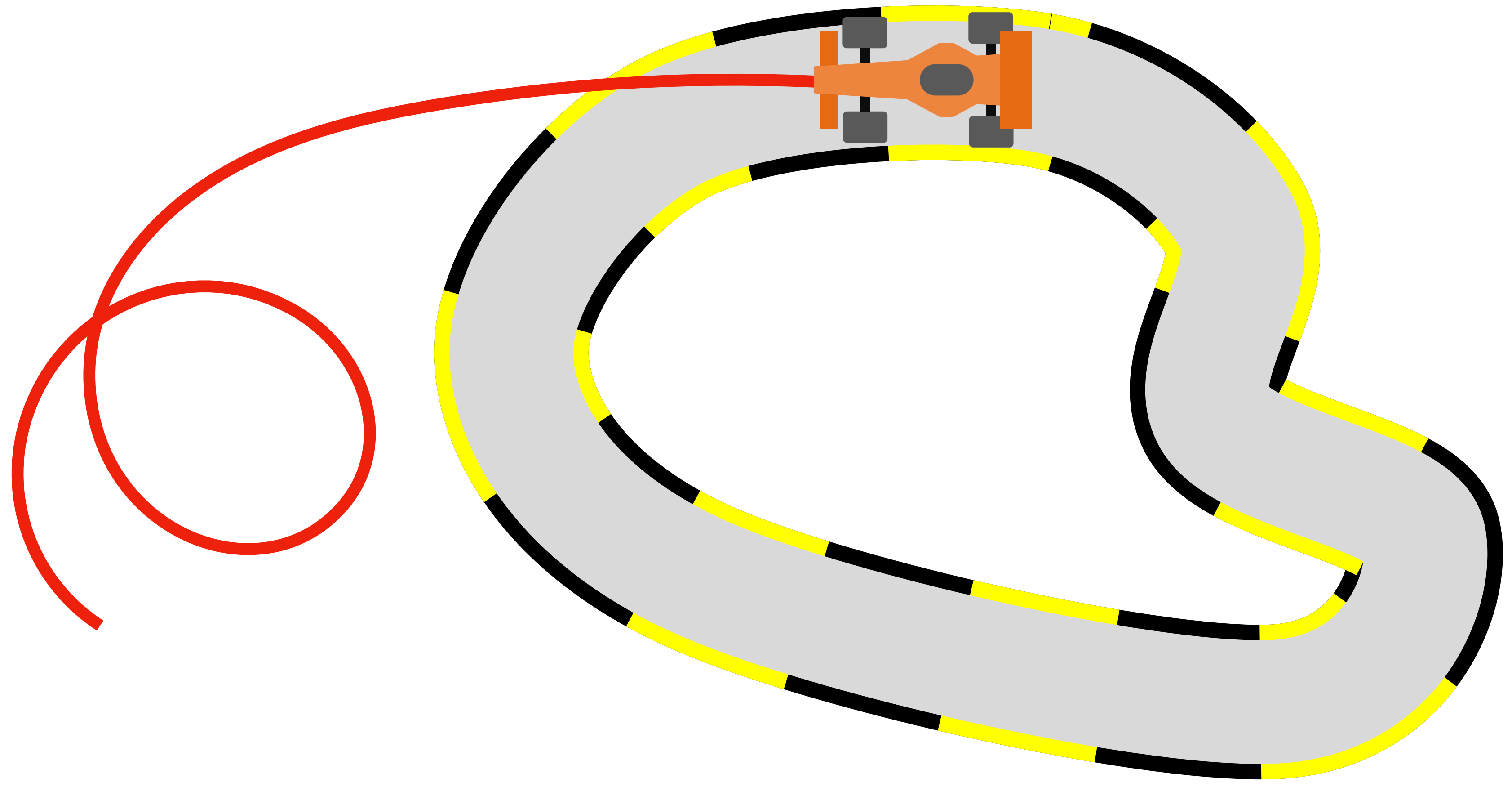
Train

$$\sum_{t=0}^{T-1} \mathbb{E}_{s_t \sim d_t^{\pi^\star}}[\ell(s_t, \pi(s_t))]$$



Test

$$\sum_{t=0}^{T-1} \mathbb{E}_{s_t \sim d_t^{\pi}}[\ell(s_t, \pi(s_t))]$$



Goal: Bound on-policy loss

$$\sum_{t=0}^{T-1} \mathbb{E}_{s_t \sim d_t^{\pi}}[\ell(s_t, \pi(s_t))]$$

If we can bound above, we can bound performance difference

$$J(\pi) - J(\pi^*)$$

What if we interactively queried the expert on states the learner visits?

DAGGER: A meta-algorithm for imitation learning

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning

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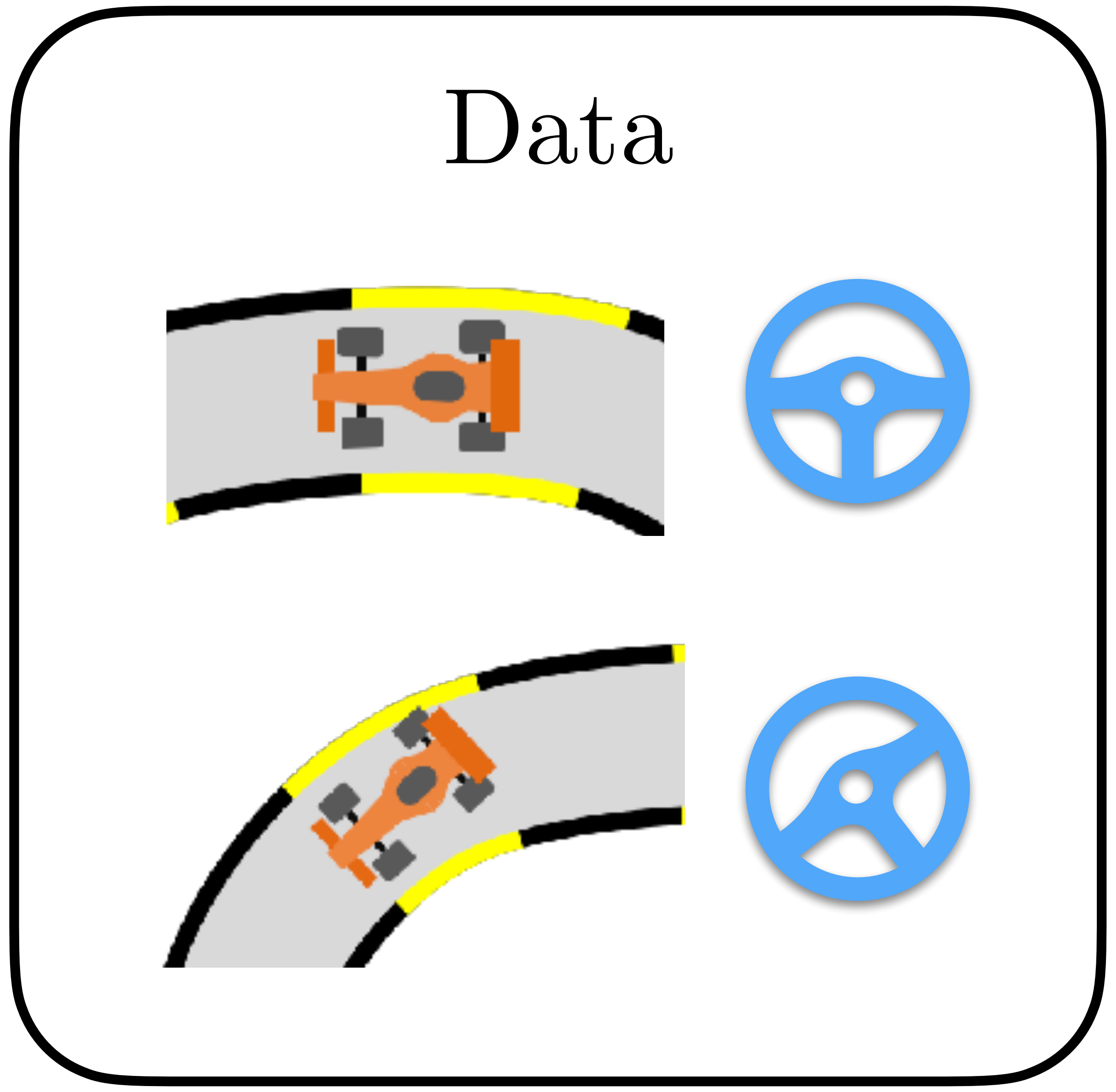
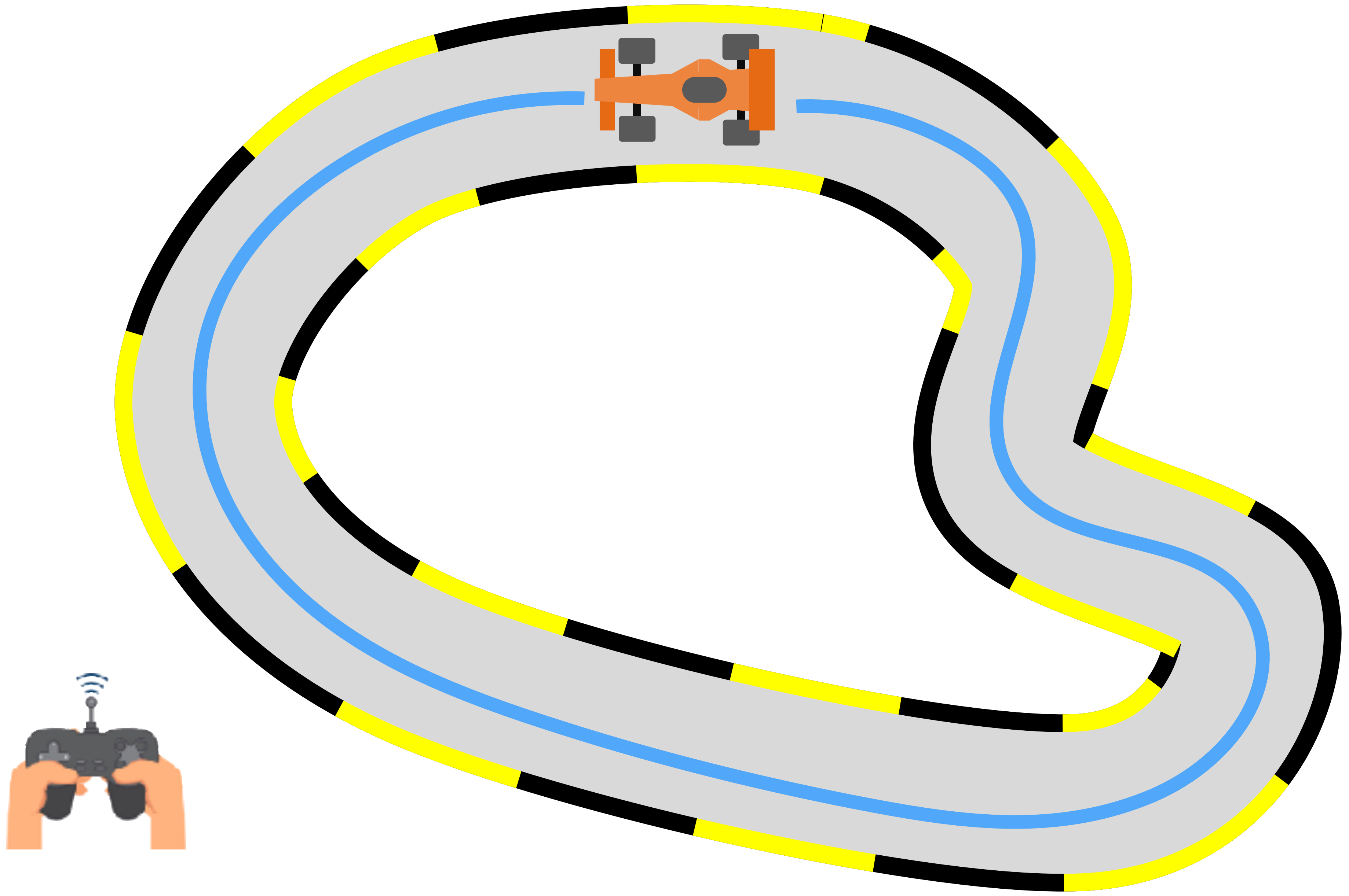
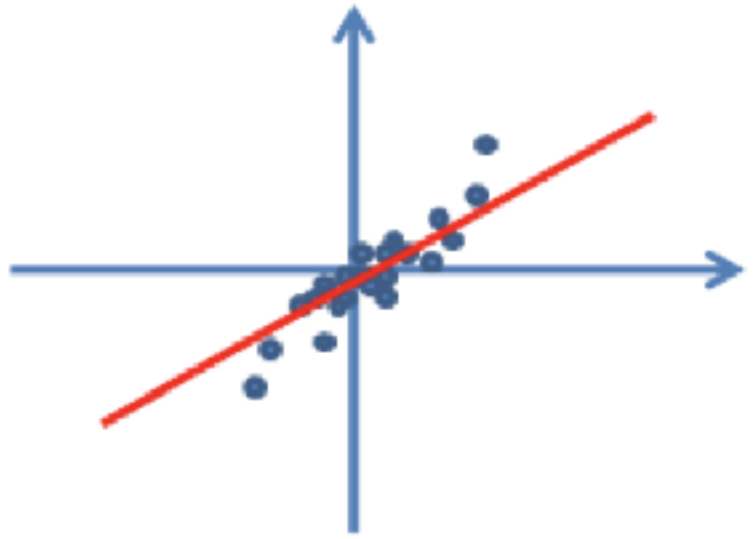
[Ross et al’11]

DAgger: Initializations





Human drives

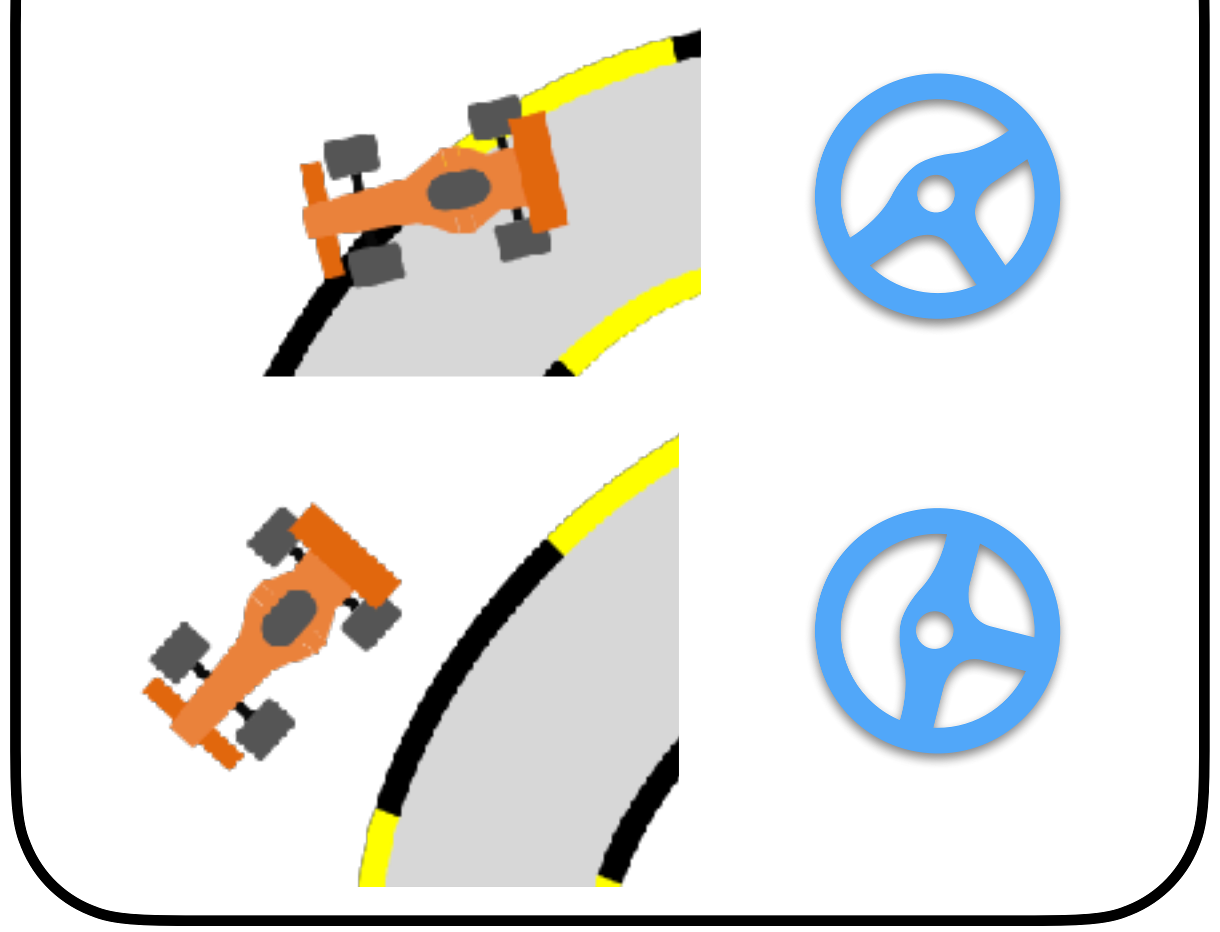


Policy
π_1

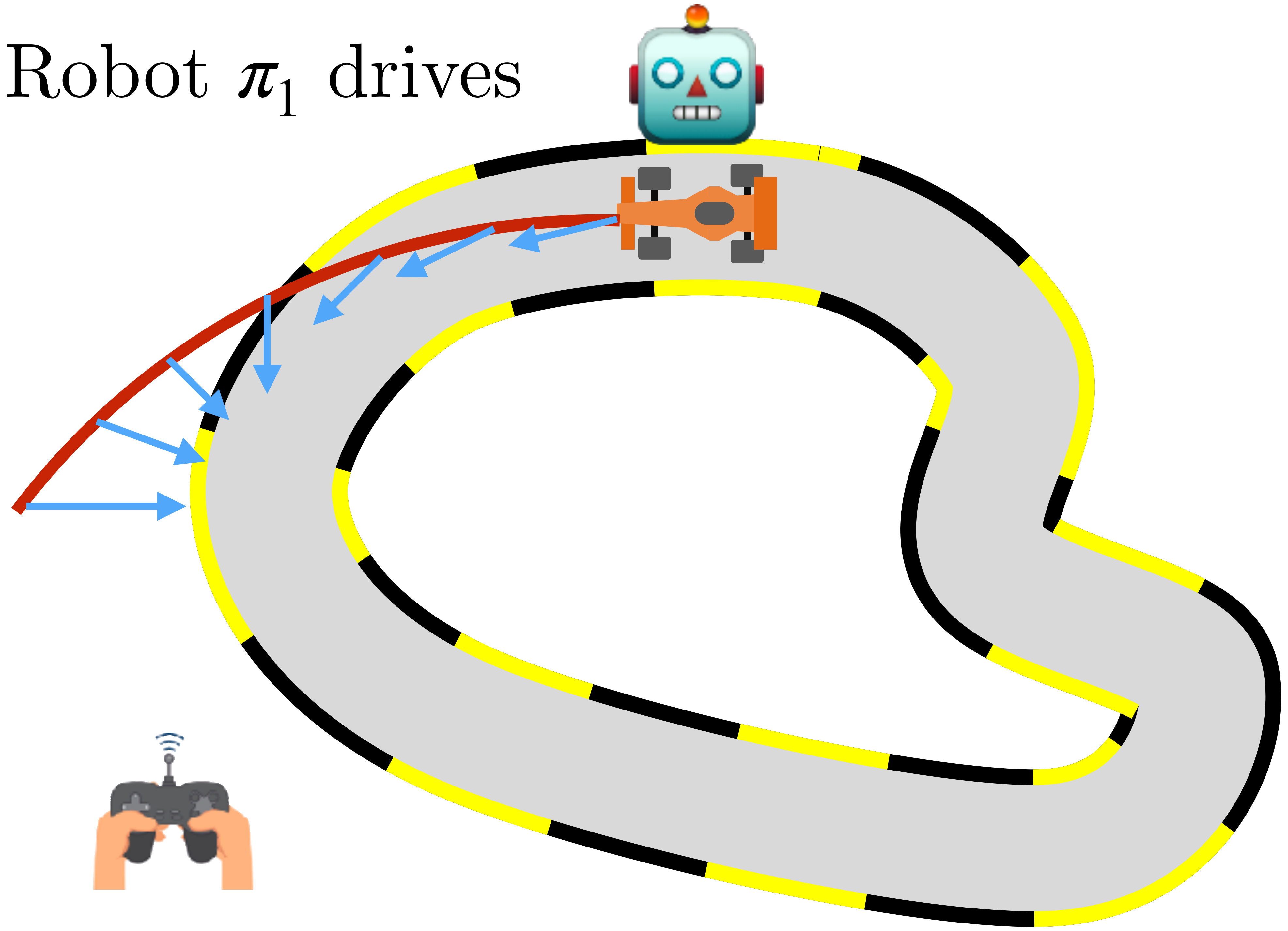
[Ross et al'11]

DAgger: Iteration 1

Data



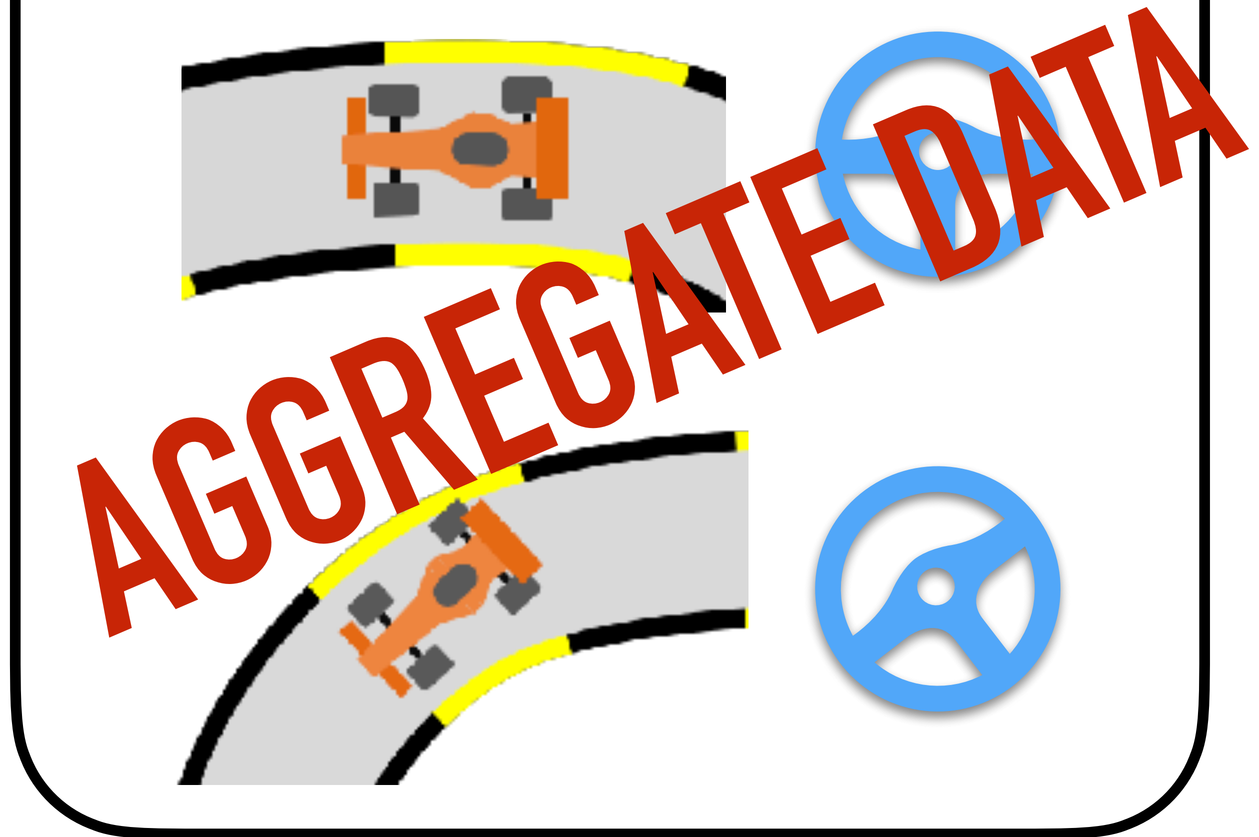
Robot π_1 drives

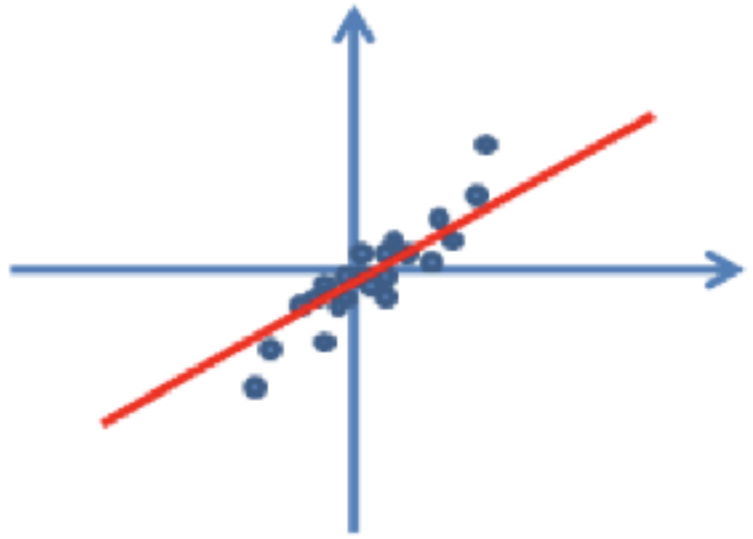


Human corrects!

+

Old Data

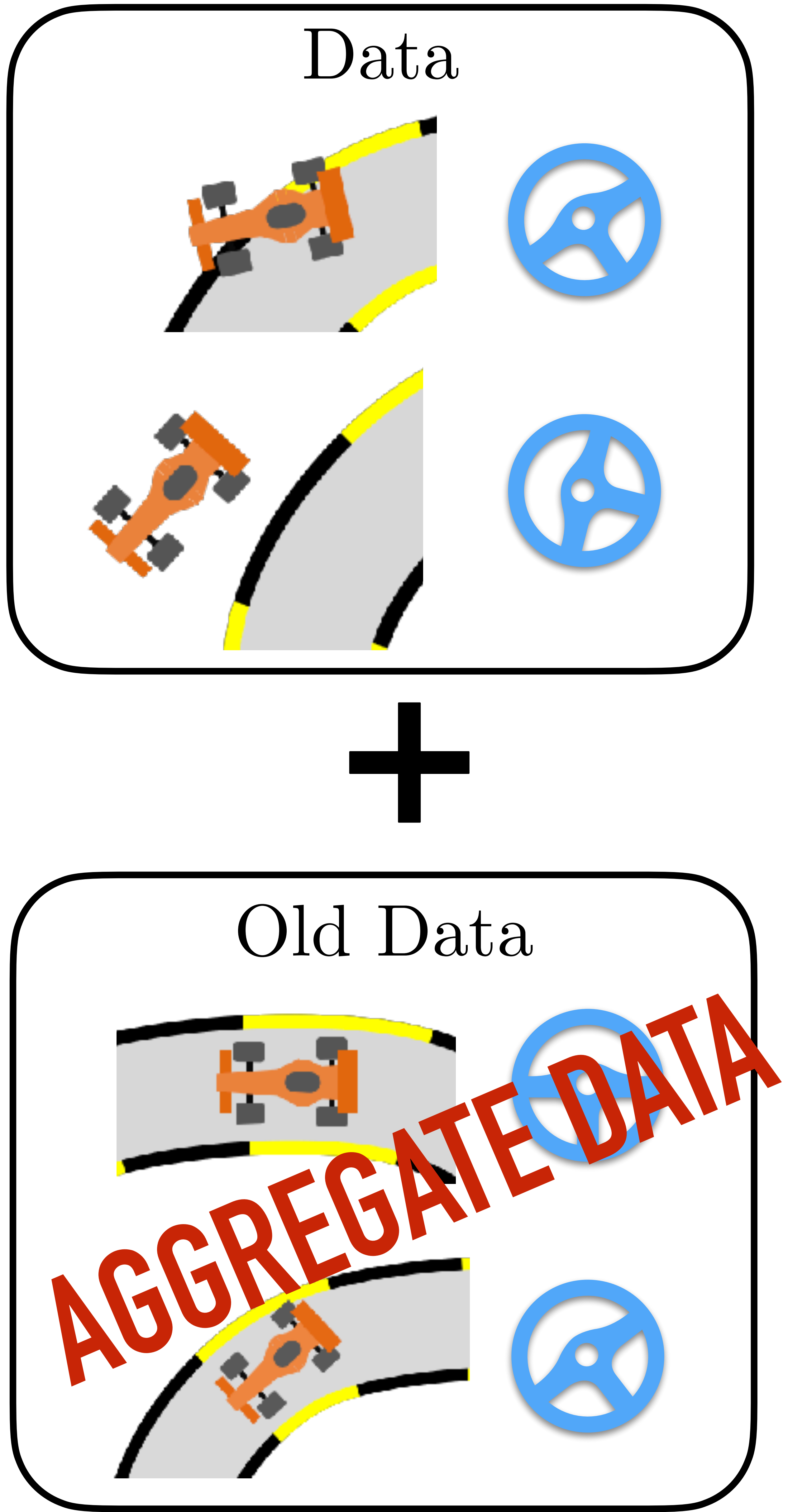




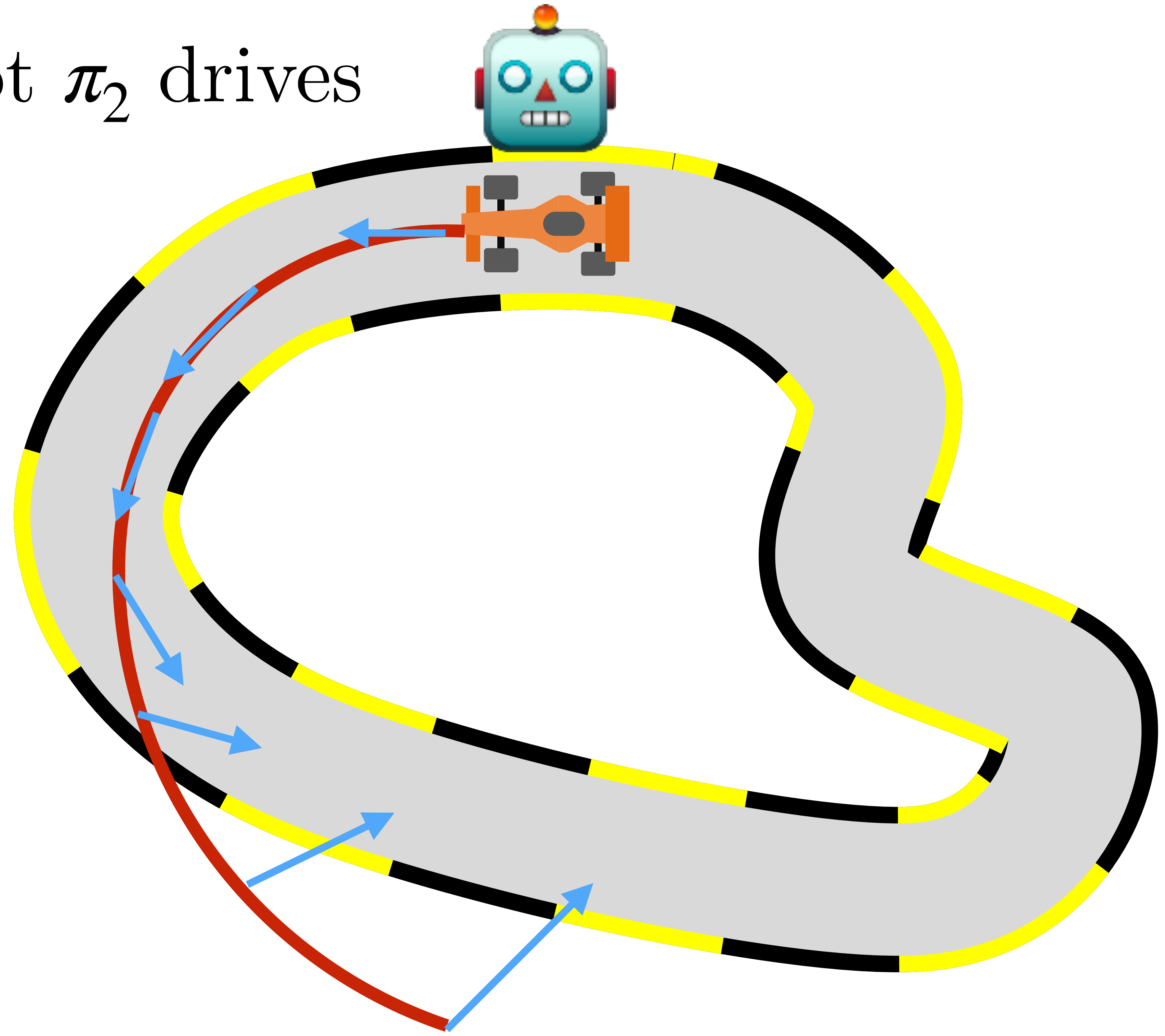
Policy
π_2

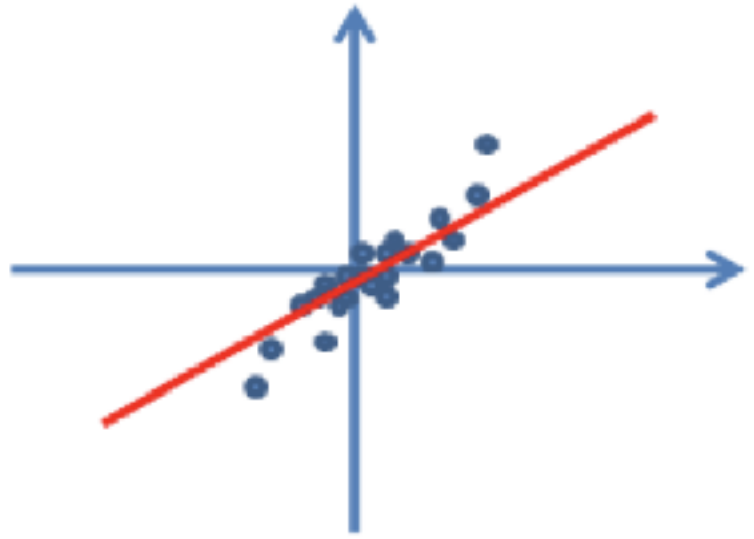
[Ross et al'11]

DAgger: Iteration 2



Robot π_2 drives

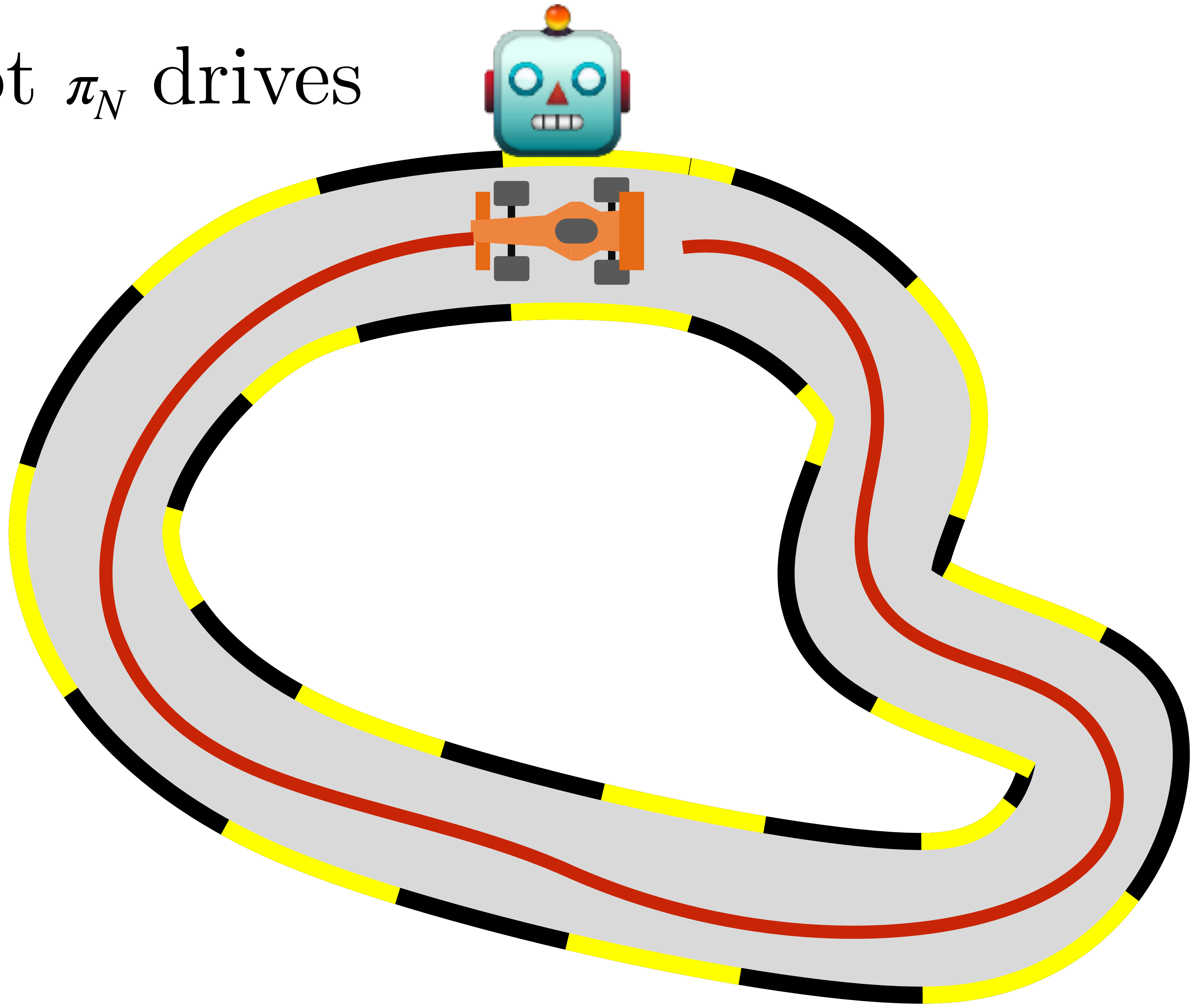




Policy π_3

DAgger: Iteration N

Robot π_N drives



After many iterations ....
we are able to drive like a human!

DAgger (Dataset Aggregation)

Initialize with a random policy π_1 # Can be BC

Initialize empty data buffer $\mathcal{D} \leftarrow \{\}$

For $i = 1, \ldots, N$

Execute policy π_i in the real world and collect data

$$\mathcal{D}_i = \{s_0, a_0, s_1, a_1, \ldots\}$$ # Also called a rollout

Query the expert for the optimal action on learner states

$$\mathcal{D}_i = \{s_0, \pi^\star(s_0), s_1, \pi^\star(s_1), \ldots\}$$

Aggregate data $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$

Train a new learner on this dataset $\pi_{i+1} \leftarrow \text{Train}(\mathcal{D})$

Select the best policy in $\pi_{1:N+1}$

The DAGGER Guarantee

DAGGER returns a policy π such that

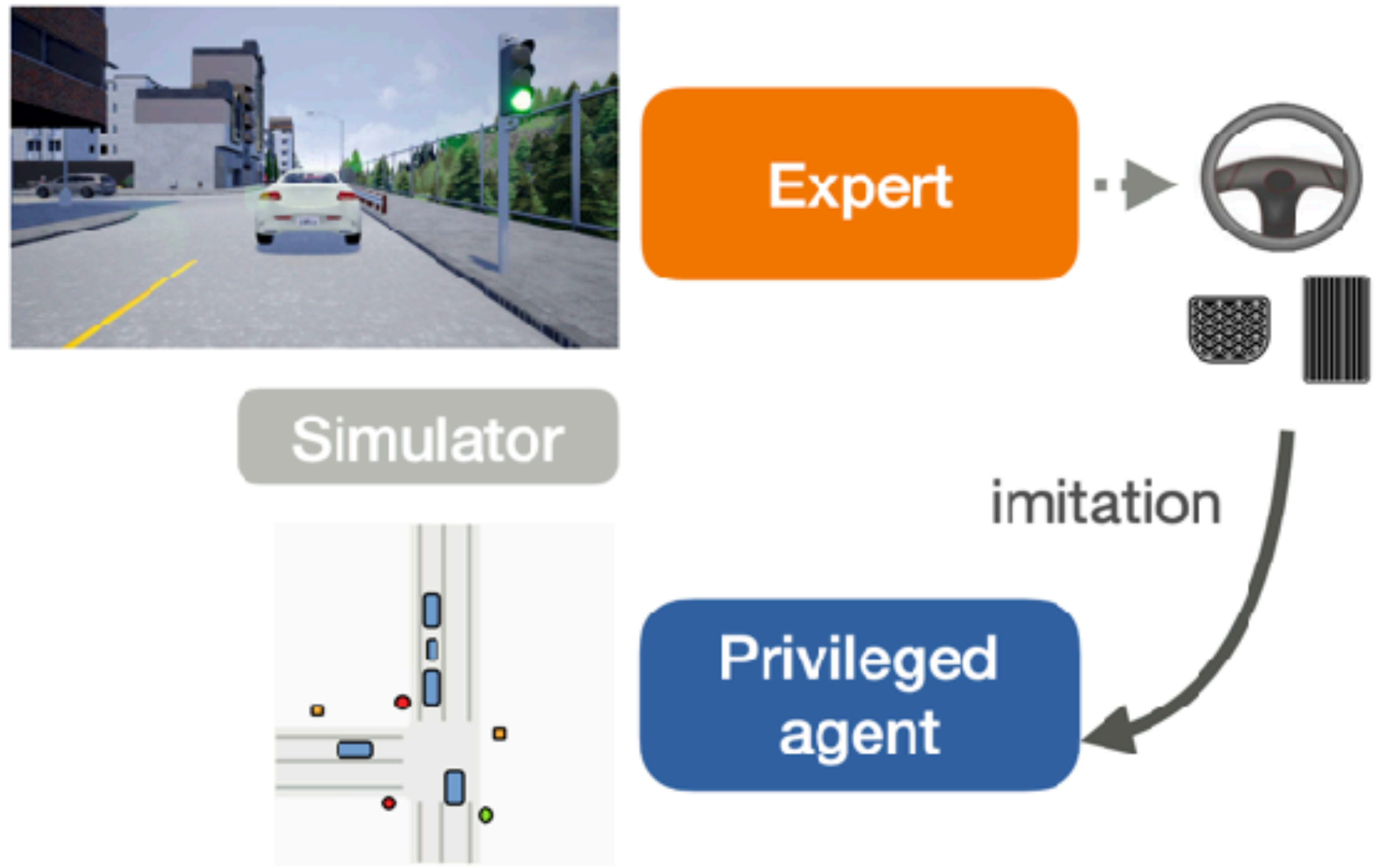
$$\sum_{t=0}^{T-1} \mathbb{E}_{s_t \sim d_t^{\pi}}[\ell(s_t, \pi(s_t))] \leq O(\epsilon T)$$

Today's class

- ☑ What is DAGGER?
- ☐ DAGGER in the real world
- ☐ Why *aggregate* data?

Many cool applications of DAGGER in robotics

Lee et al, Learning quadrupedal locomotion over challenging terrain (2020)



Chen et al Learning by Cheating(2020)

Choudhury et al, Data Driven Planning via Imitation Learning (2018)

Pan et al Imitation learning for agile autonomous driving (2019)

How do we actually apply DAGGER in practice?

Asking a *human* expert to label every state the robot visits is hard

Option 1: Extend DAGGER to different degrees of human feedback

Can we extend DAGGER to handle easier forms of human feedback preferences, interventions, etc?

Yes (*Future lectures!)

Option 2: Use an algorithmic oracle

What if we had a powerful algorithm
that we can run in train time
but not at test time?

With audio

Learning quadrupedal locomotion over challenging terrain

Joonho Lee[1], Jemin Hwangbo[1,2 †], Lorenz Wellhausen[1], Vladlen Koltun[3], Marco Hutter[1]

[1] Robotic Systems Lab, ETH Zurich
[2] Robotics & Artificial Intelligence Lab, KAIST
[3] Intelligent Systems Lab, Intel

†Substantial part of the work was carried out during his stay at 1

ETH zürich

RSL Robotic Systems Lab

intel Intelligent Systems Lab

Quiz: Is the teacher policy realizable?

When poll is active respond at **PollEv.com/sc2582**

Send **sc2582** to **22333**

Today's class

- ☑ What is DAGGER?
- ☑ DAGGER in the real world
- ☐ Why *aggregate* data?

But why does *aggregating* data work?

Why aggregate data?

Initialize with a random policy π_1

Initialize empty data buffer $\mathcal{D} \leftarrow \{\}$

For $i = 1, \ldots, N$

Execute policy π_i in the real world and collect data

$$\mathcal{D}_i = \{s_0, a_0, s_1, a_1, \ldots\}$$

Query the expert for the optimal action on learner states

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Aggregate data $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$

Train a new learner on this dataset $\pi_{i+1} \leftarrow \text{Train}(\mathcal{D})$

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From
Imitation Learning
to
Interactive
No-Regret Learning

Interactive Learning

Learner

Adversary

$$\min_{\pi} l(\pi)$$

Choose $l(\pi)$

Interactive Learning

Learner		Adversary
Initialize policy	π_1 [policy] →	
	← $l_1(\,.\,)$ [loss]	Chooses loss
Update policy	π_2 →	
	← $l_2(\,.\,)$	Chooses loss
⋮		⋮

What is the best that I can do in such an adversarial setting?

From
Imitation Learning
to
Interactive
No-Regret Learning

How do we design algorithms that are no-regret?

$$\text{Regret} = \sum_{i=1}^{N} l_i(\pi_i) - \min_{\pi^*} \sum_{i=1}^{N} l_i(\pi^*)$$

(Learner) (Best in hindsight)

At every round t, choose the best policy in hindsight

$$\pi_i = \arg\min_{\pi} \sum_{j=1}^{i-1} l_j(\pi)$$

(lowest total loss)

$\sum l_i$		l_1
- -	Policy 1 	$\boxed{1.0}$
- -	Policy 2 	0.2
- -	Policy 3 	0.5

Avg. Regret: - -

$\sum l_i$		l_1	l_2
1.0	Policy 1 	$\boxed{1.0}$	0.5
0.2	Policy 2 	0.2	$\boxed{0.5}$
0.5	Policy 3 	0.5	0.2

Avg. Regret: 0.80

$\sum l_i$		l_1	l_2	l_3
1.5	Policy 1 	$\boxed{1.0}$	0.5	0.5
0.7	Policy 2 	0.2	$\boxed{0.5}$	$\boxed{1.0}$
0.7	Policy 3 	0.5	0.2	0.2

Avg. Regret: 0.40

$\sum l_i$		l_1	l_2	l_3	l_4
2.0	Policy 1 	$\boxed{1.0}$	0.5	0.5	1.0
$\boxed{1.7}$	$\boxed{\text{Policy 2}}$ 	0.2	$\boxed{0.5}$	$\boxed{1.0}$	0.2
0.9	Policy 3 	0.5	0.2	0.2	$\boxed{0.5}$

Avg. Regret: **0.53**

$\sum l_i$		l_1	l_2	l_3	l_4	l_5
3.0	Policy 1 	$\boxed{1.0}$	0.5	0.5	1.0	0.5
1.9	Policy 2 	0.2	$\boxed{0.5}$	$\boxed{1.0}$	0.2	1.0
1.4	Policy 3 	0.5	0.2	0.2	$\boxed{0.5}$	$\boxed{0.2}$

Avg. Regret: 0.40

$\sum l_i$		l_1	l_2	l_3	l_4	l_5	l_6
3.5	Policy 1 	$\boxed{1.0}$	0.5	0.5	1.0	0.5	1.0
2.9	Policy 2 	0.2	$\boxed{0.5}$	$\boxed{1.0}$	0.2	1.0	0.5
$\boxed{1.6}$	$\boxed{\text{Policy 3}}$ 	0.5	0.2	0.2	$\boxed{0.5}$	$\boxed{0.2}$	$\boxed{0.2}$

Avg. Regret: 0.32

$\sum l_i$		l_1	l_2	l_3	l_4	l_5	l_6
4.5	Policy 1 	$\boxed{1.0}$	0.5	0.5	1.0	0.5	1.0
3.4	Policy 2 	0.2	$\boxed{0.5}$	$\boxed{1.0}$	0.2	1.0	0.5
$\boxed{1.8}$	$\boxed{\text{Policy 3}}$ 	0.5	0.2	0.2	$\boxed{0.5}$	$\boxed{0.2}$	$\boxed{0.2}$

Avg. Regret: 0.26

Is FTL no-regret?

FTL is no-regret if

1. We are in the continuous setting
2. Loss is strongly convex

Back to the proof!