Learning for Robot Decision Making: The Big Picture

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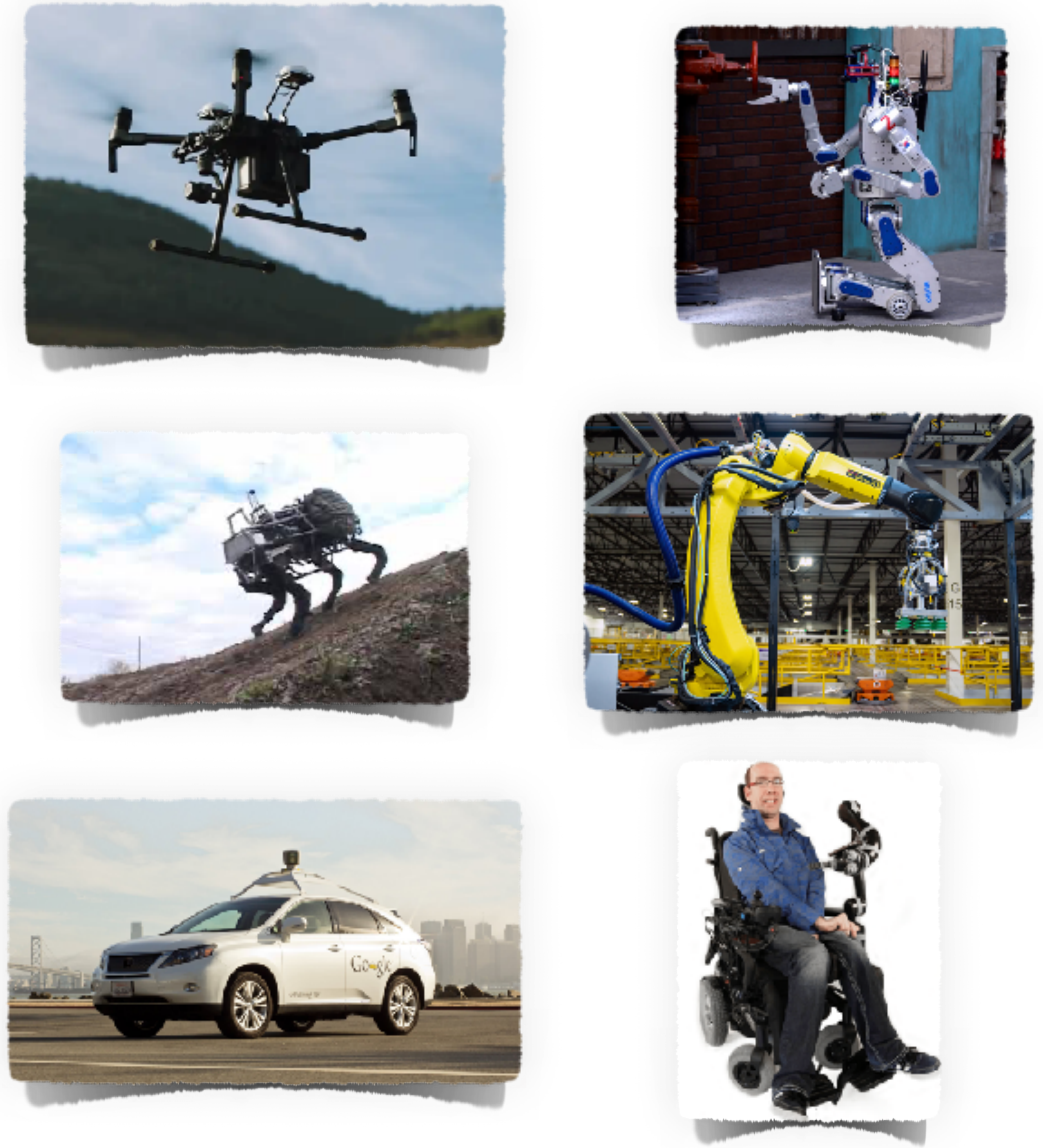
Computer Science

How should robots learn to make good decisions?

WHY ask this question?



Take *any*
robot application

Formulate as a Markov Decision Problem (MDP)

Solve MDPs using an all-purpose toolkit

(Imitation/Reinforcement learning, Model based/free)

Deploy learners in real-world

(Safety, distribution shift, value alignment)

HOW can we answer this question?

Solve

How do you want to represent your policy?
Model-based? Model-free?
Learning: Data? Loss?

Formulate

What is the MDP?
Discrete/Stochastic/Time?
What is known/unknown?

Application

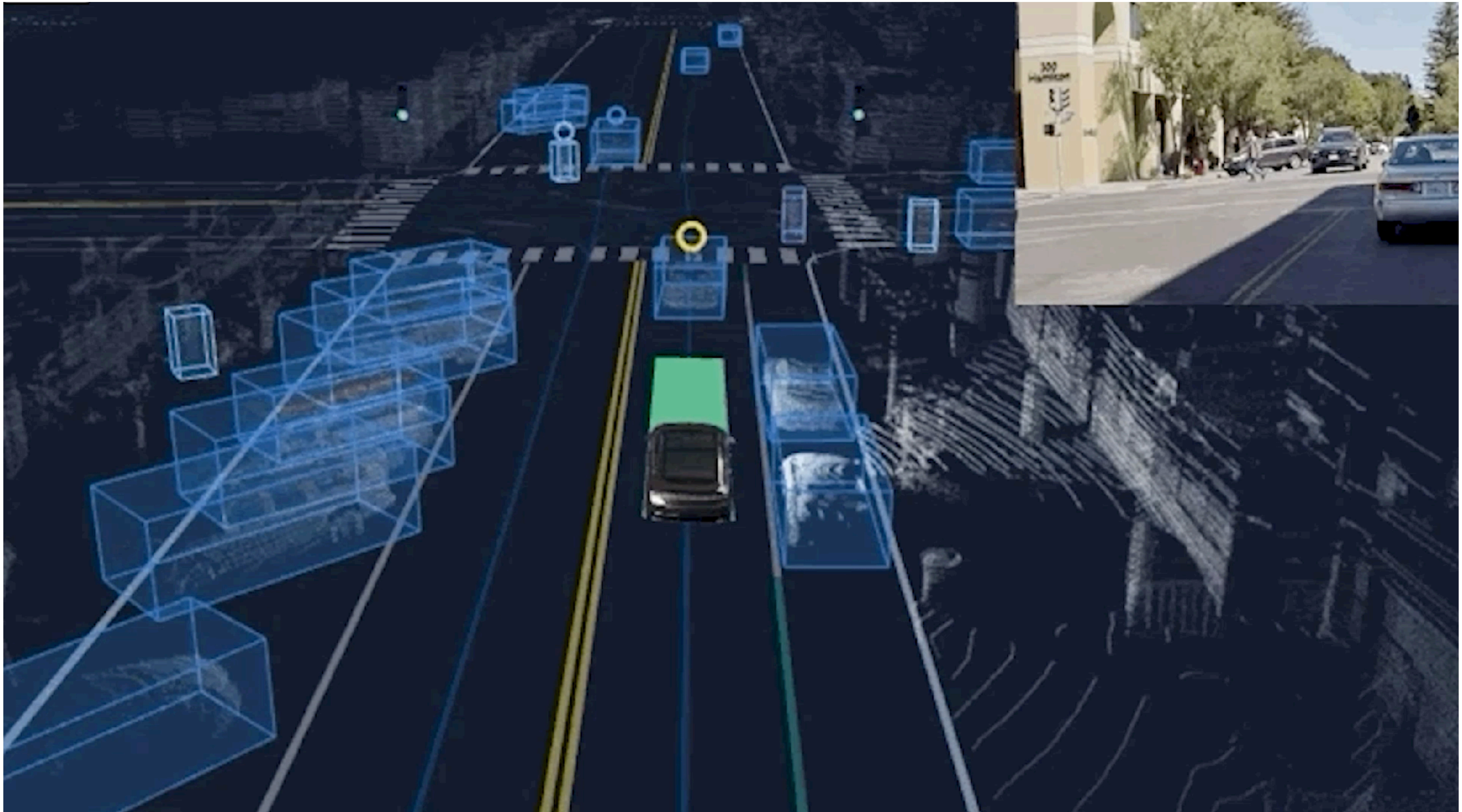
What is the robot?
What is the task?
What are the metrics?
What is good enough?

Backward

Forward

Activity!

Let's solve the Unprotected Left Turn



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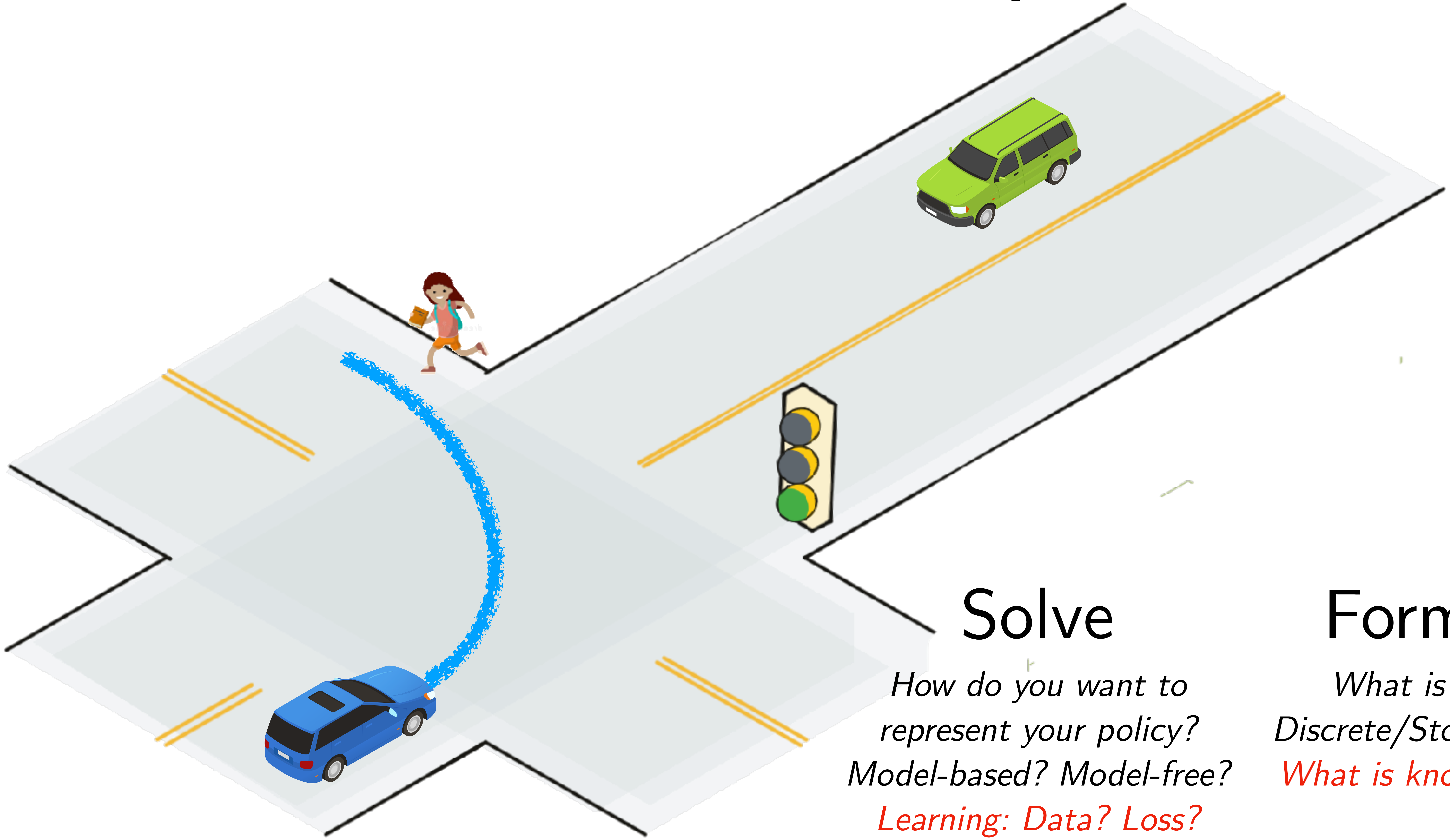

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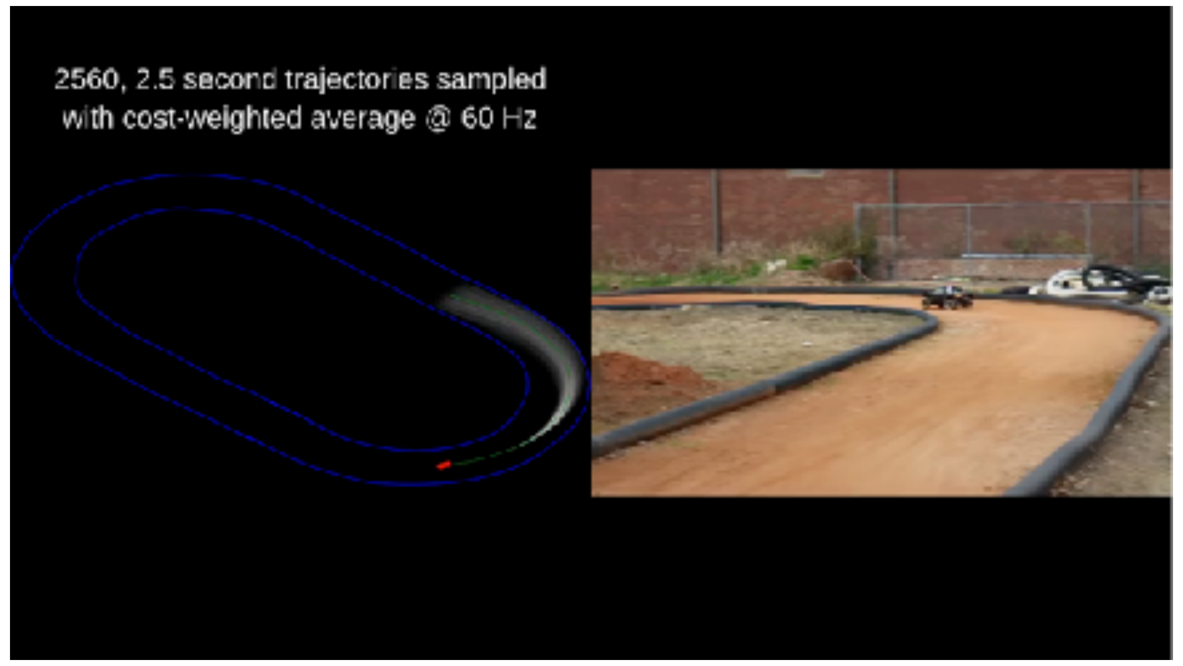
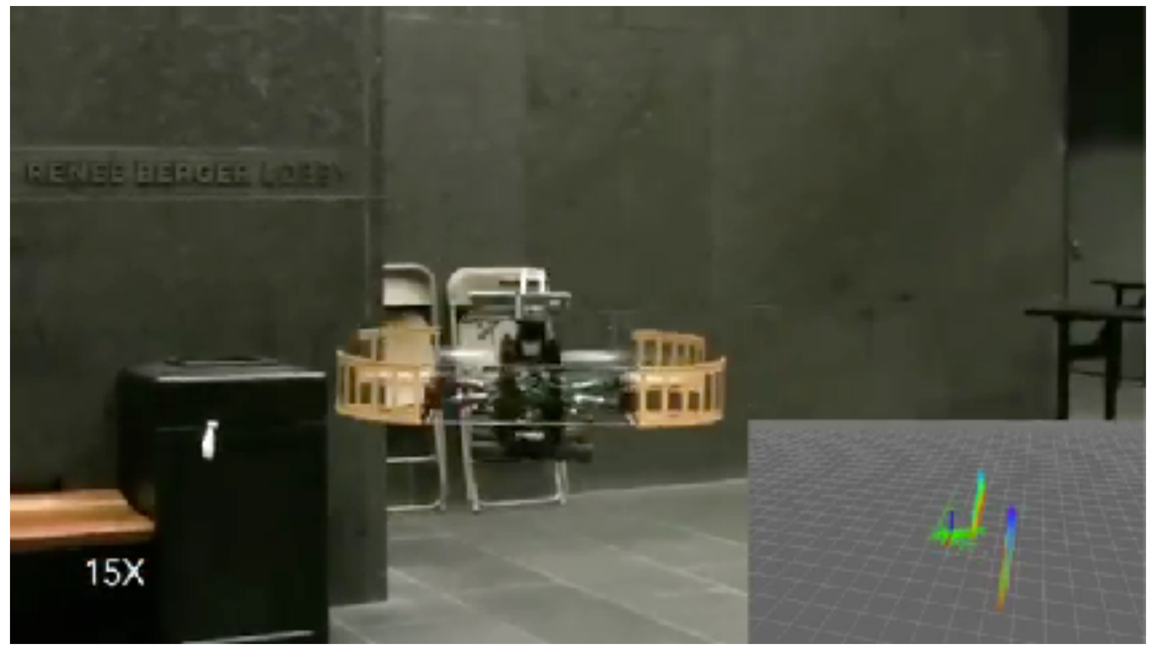
We have worked through many applications in this class …

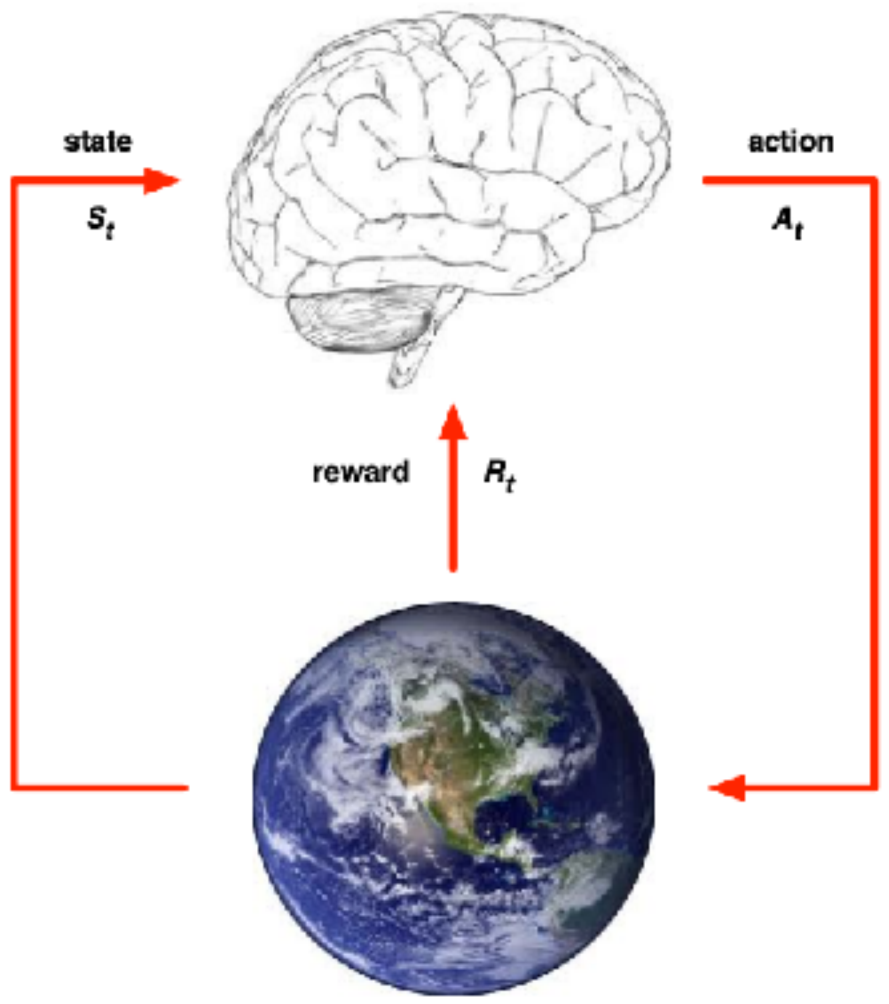




Model-Based OR Model Free?

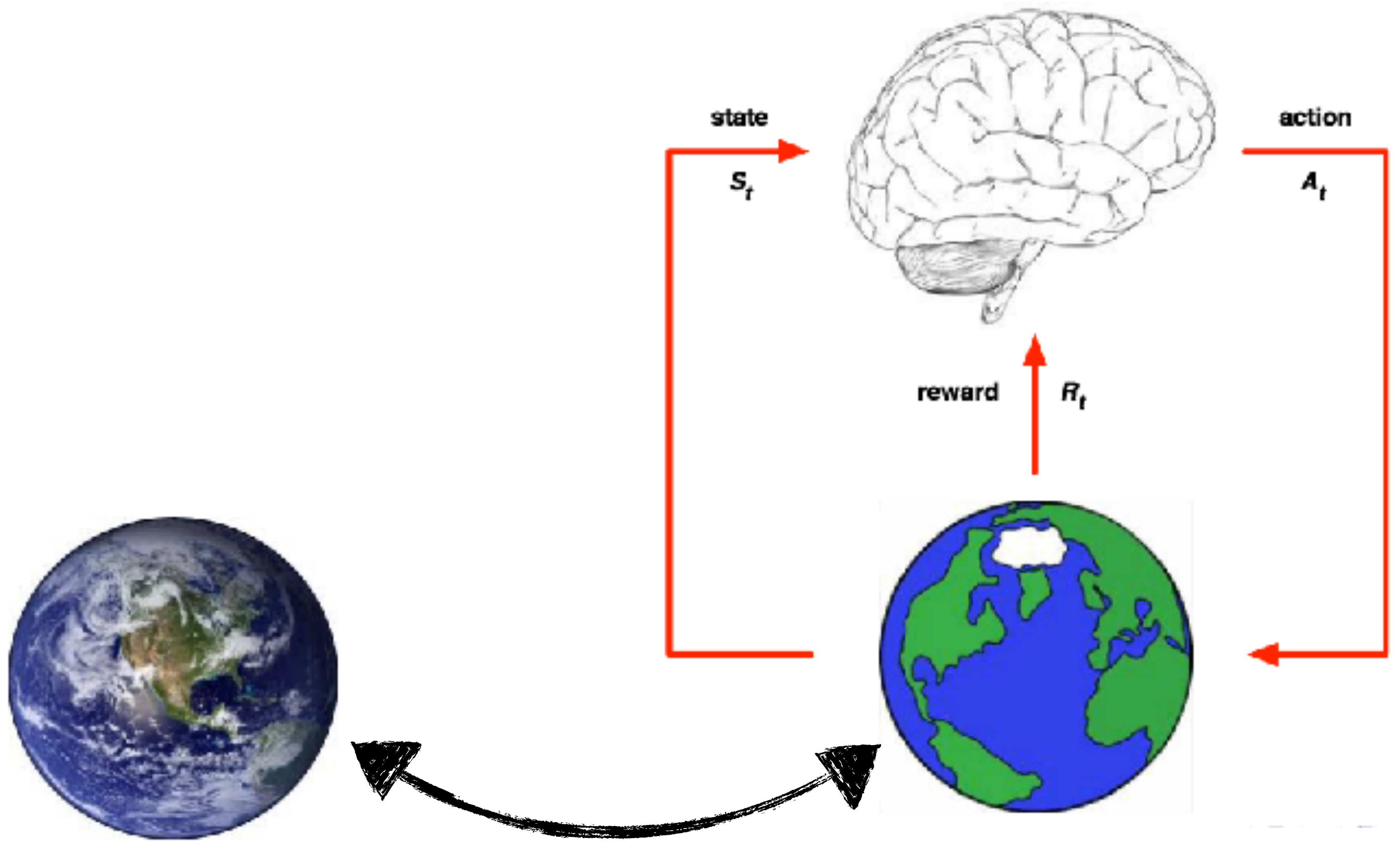
Model Free

Directly learn
π or $Q(s,a)$



Model Based

Learn a model
$P(s'|s,a)$, plan with
model to find π



Model-Based OR Model Free?

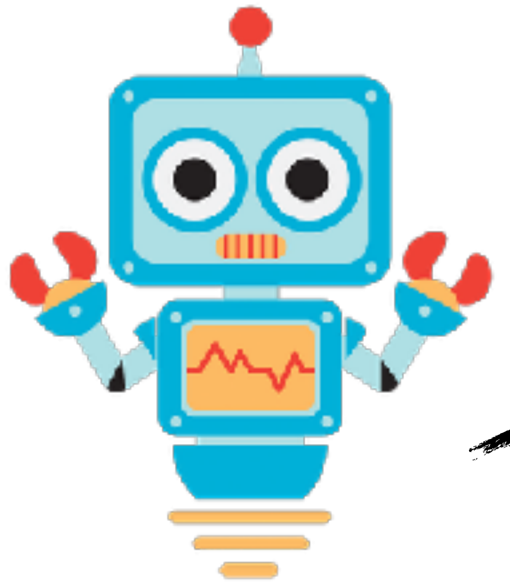
Model Free	Model Based
There exists a good enough reactive policy	You need to reason about many likely options
State space is too big to search exhaustively	Small state space / compressible state space

Model-Based ~~OR~~ *AND* Model Free

Model Based

Model Free

$$s' = \hat{M}(s, a)$$



Use model to plan

$$Q_M^*(s_T, a_T)$$

Use model-free terminal value function

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Goal

Minimize value difference between robot and the human

PDL

Apply Bellman, express perf. difference as sum of Q value differences on states the robot visits

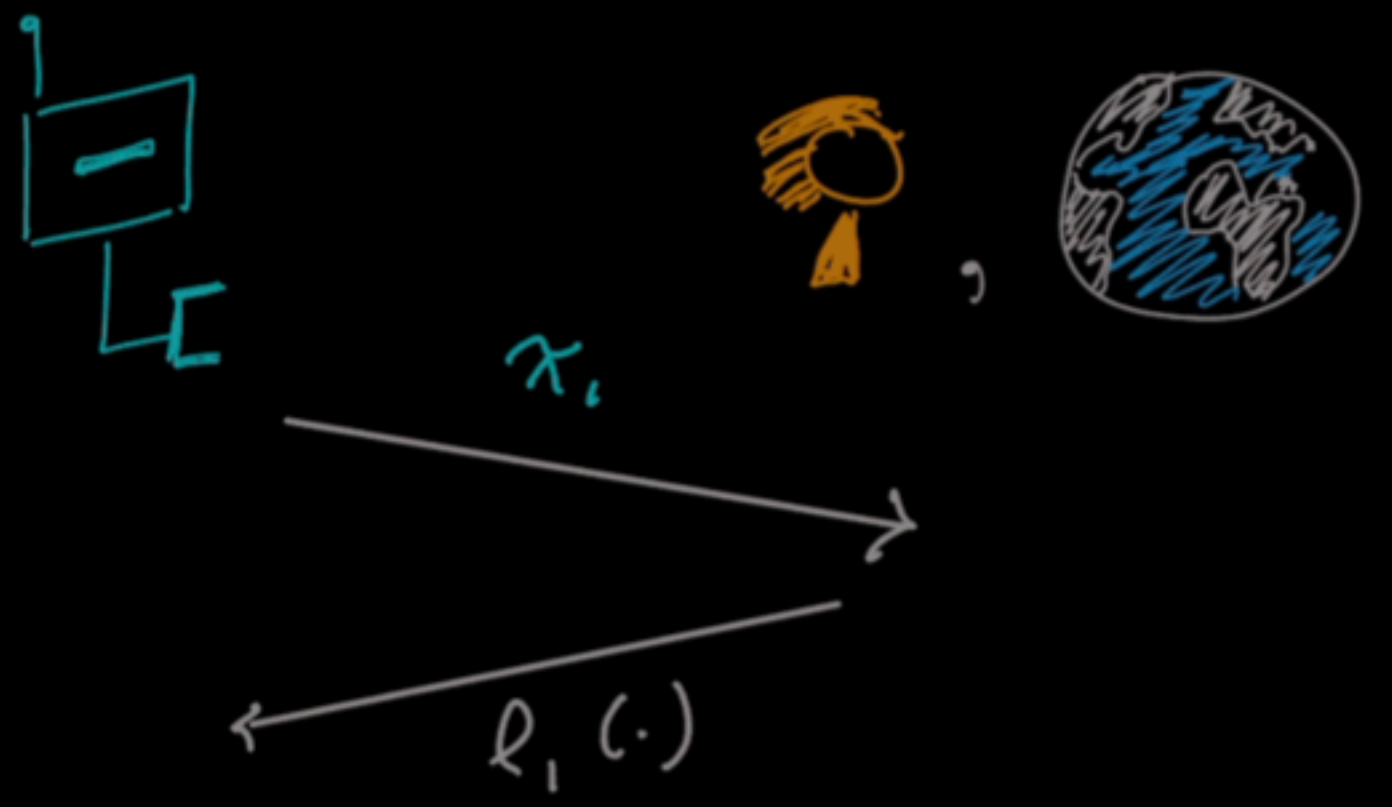
A Game

Q values are not known, must be estimated from feedback from human or the world.
Create a game between robot policy and Q value estimate, solve via no-regret online learning

5 Levels

of

Robot Learning



$$\min_{\substack{\pi \\ \text{ROBOT}}} \max_{\substack{Q^* \\ \text{ACTION VALUE}}} \sum_{i=1}^{N} Q^*(s, \pi(s)) - Q^*(s, \pi^*(s))$$

FIND A POLICY $\pi : S \to A$ SUCH THAT THE

VALUE DIFFERENCE

$$ \underbrace{J(\pi)}_{\text{ROBOT}} - \underbrace{J(\pi^*)}_{\text{HUMAN}} $$

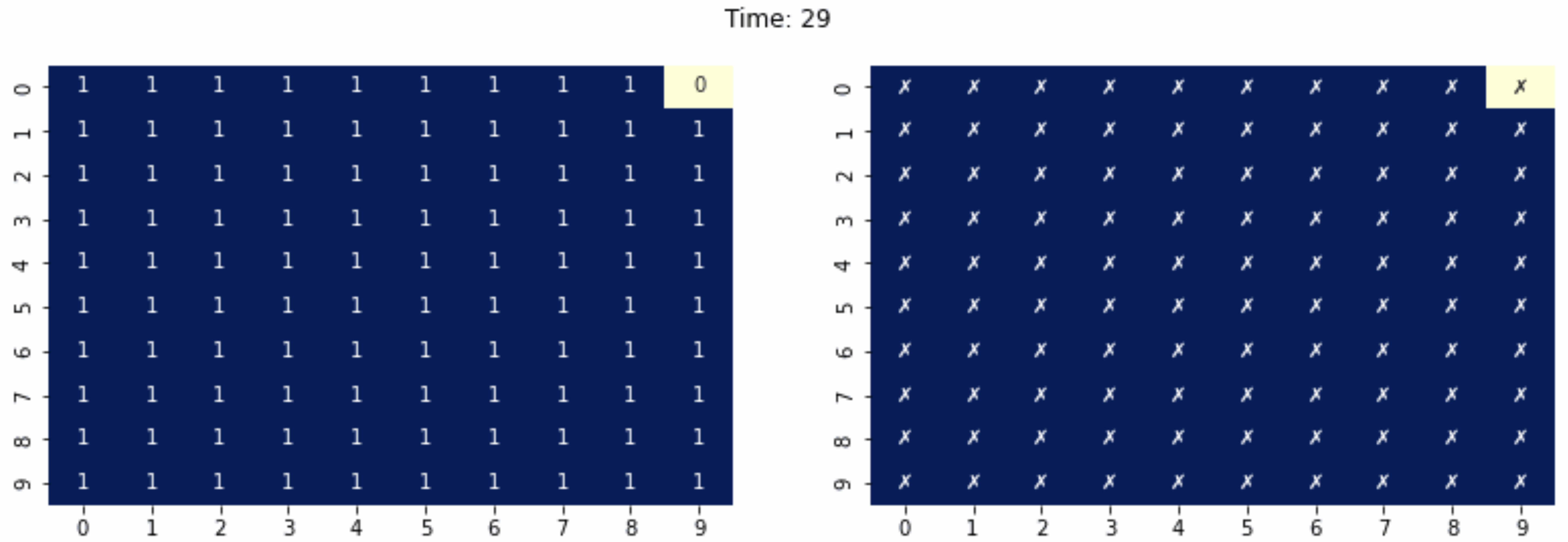
FOR ANY VALUE $J(\cdot)$ THE HUMAN CARES ABOUT

$$

$$V^*(s_t) = \min_{a_t}\left[\underset{??}{C}(s_t, a_t) + \mathbb{E}_{s_{t+1}\sim \underset{??}{P}(\cdot \mid s_t, a_t)} V^*(s_{t+1}) \right]$$

LEARN OPTIMAL VALUE BY INTERACTIONS W/ HUMAN + WORLD

Two Fundamental Approaches

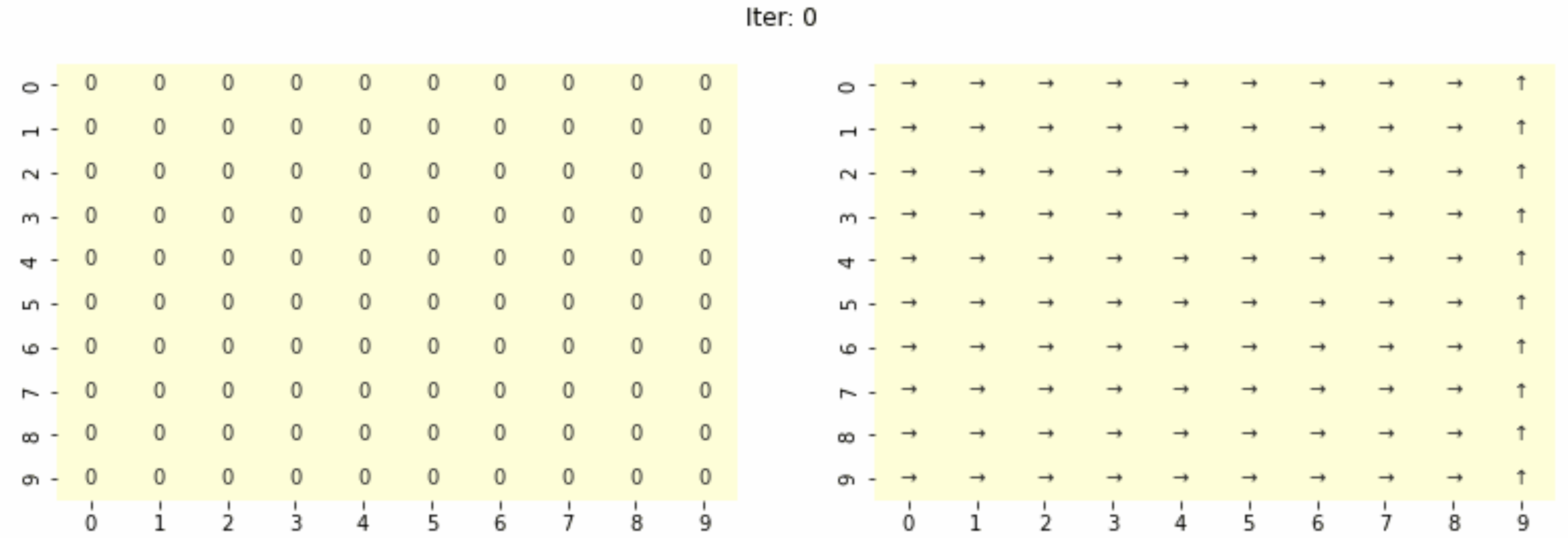


$V^*(s_t) = \min_a[c(s_t, a) + V^*(s_{t+1})]$ $\pi^*(s_t) = \arg\min_a[c(s_t), a) + V^*(s_{t+1})]$

Value Iteration

Iterate over *optimal* value

min() operator in value iteration step



$V^\pi(s) = c(s, \pi(s)) + \gamma \mathbb{E}_{s' \sim \mathcal{T}(s,a)} V^\pi(s')]$ $\pi^+(s) = \arg\min c(s, a) + \gamma \mathbb{E}_{s' \sim \mathcal{T}(s,a)} V^\pi(s')]$

Policy Iteration

Evaluate value of current policy, then improve

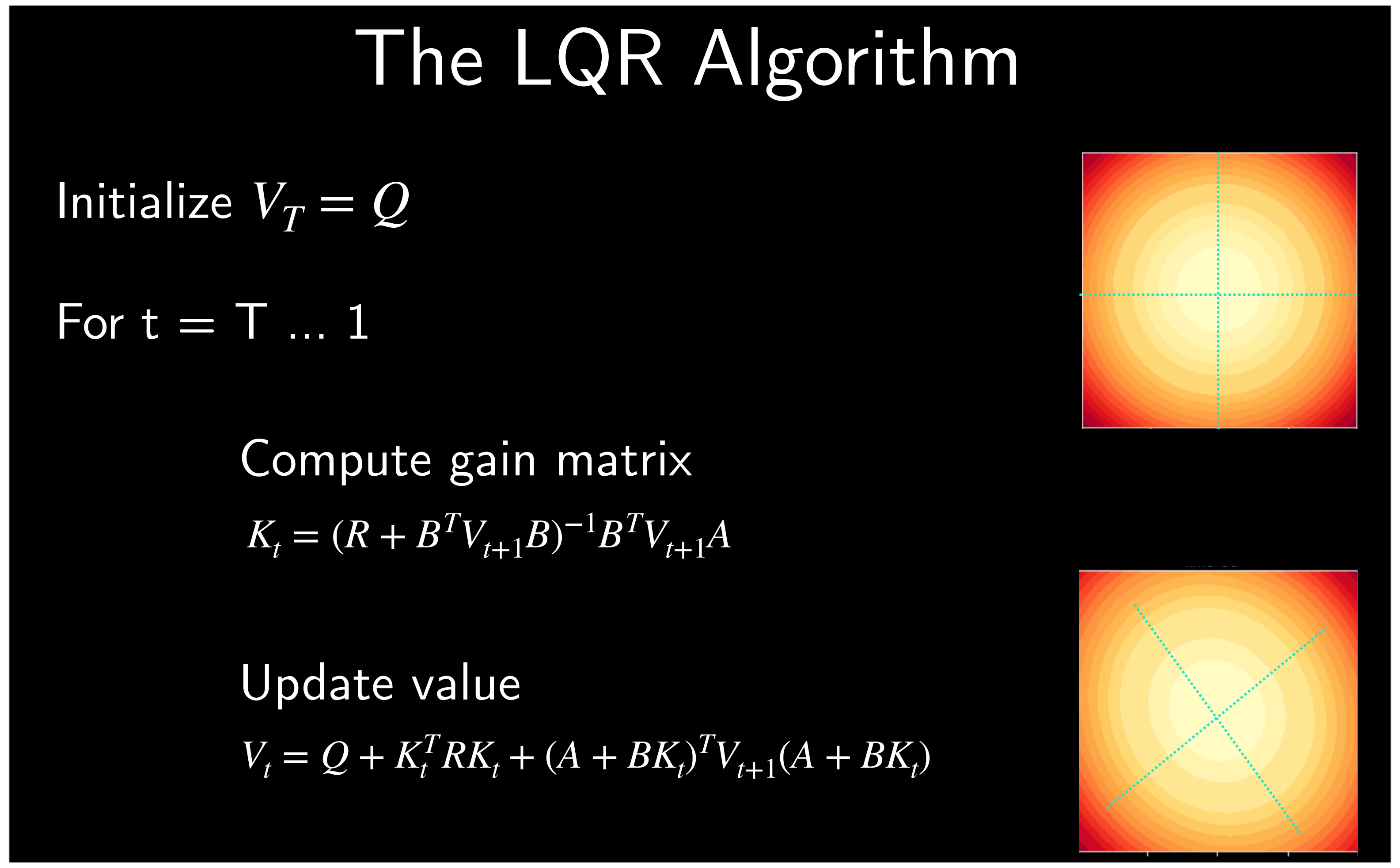
min() operator in policy improvement

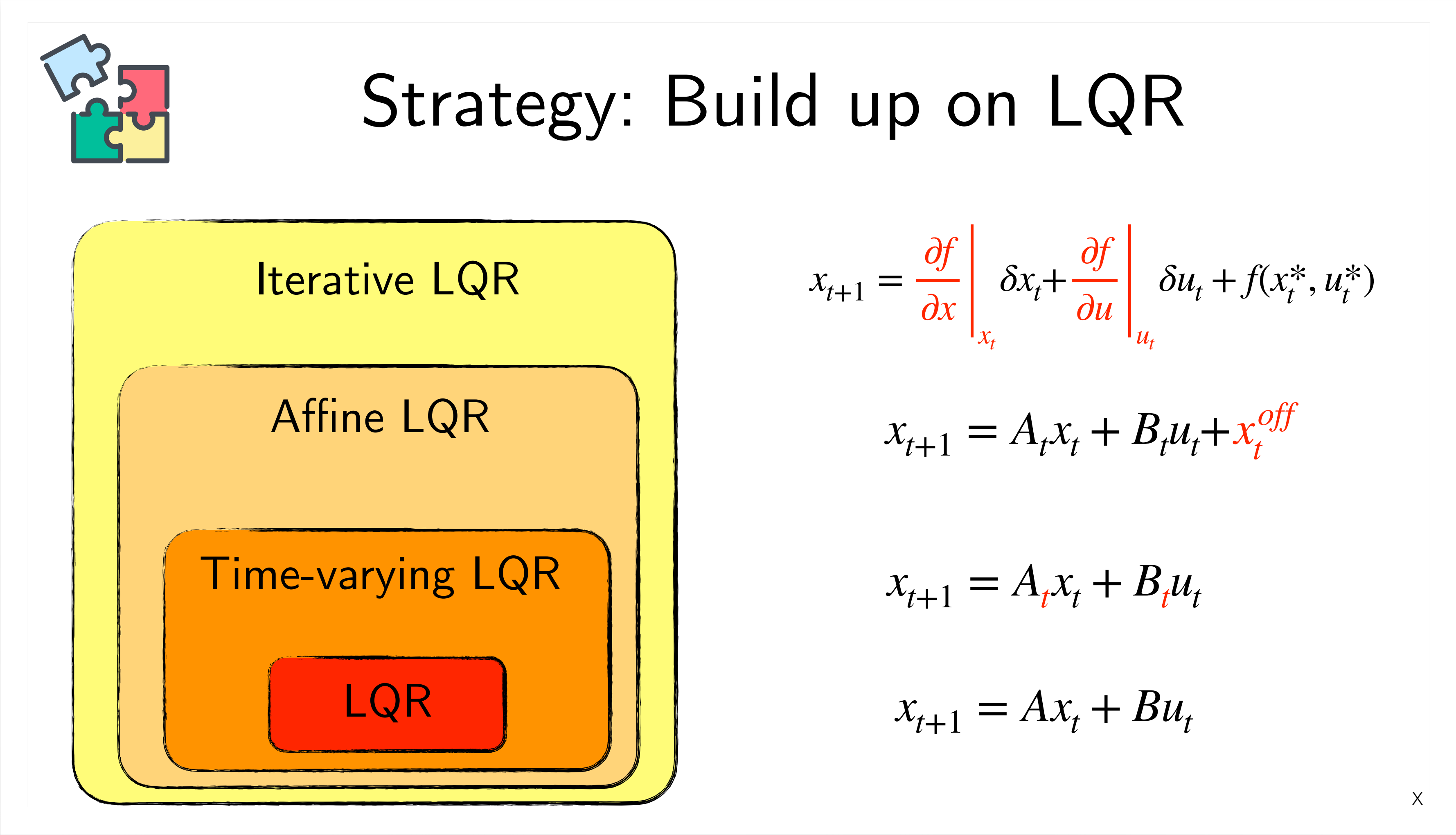
How do we scale these approaches?

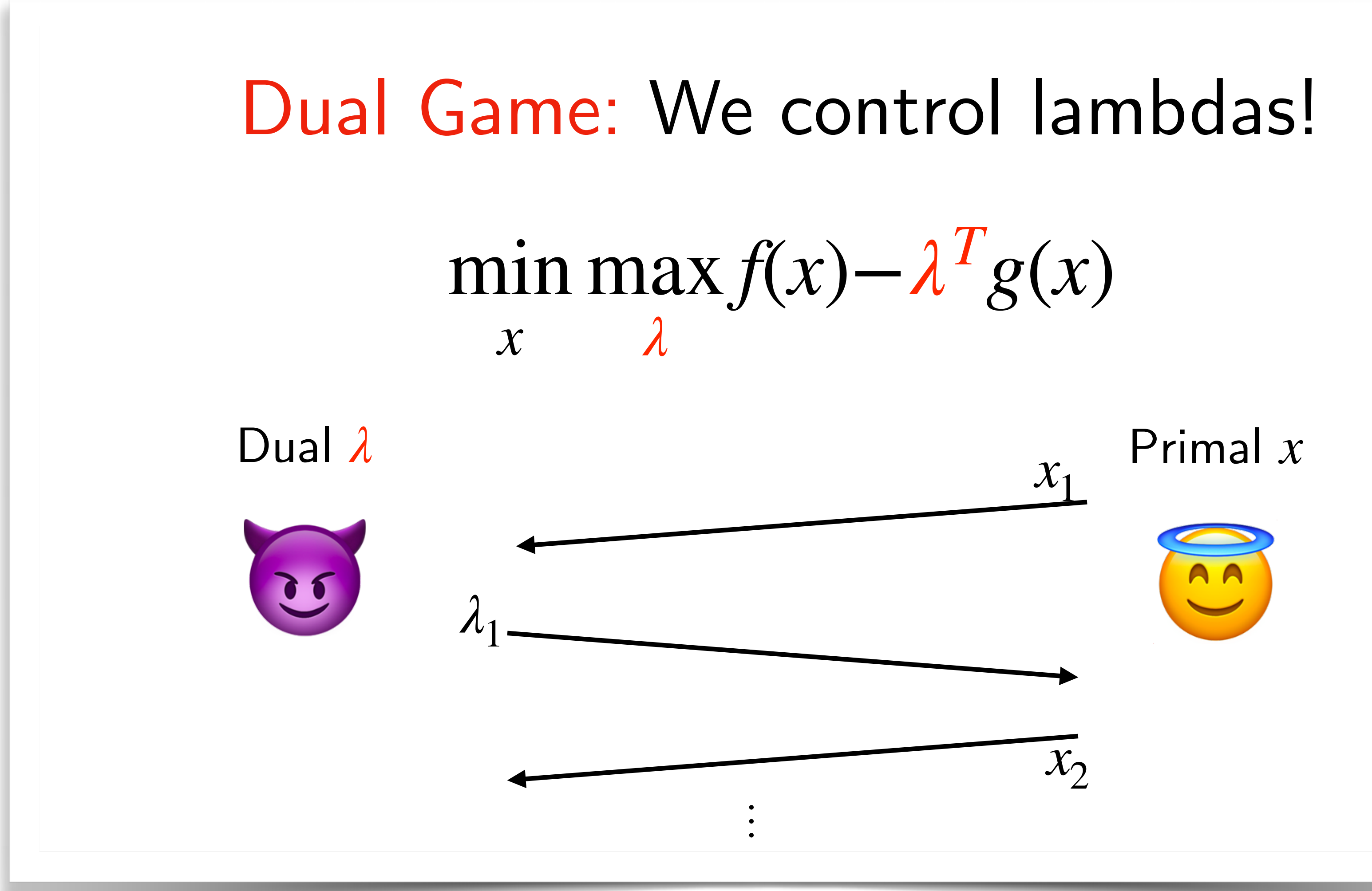
For continuous MDP (but linear)?

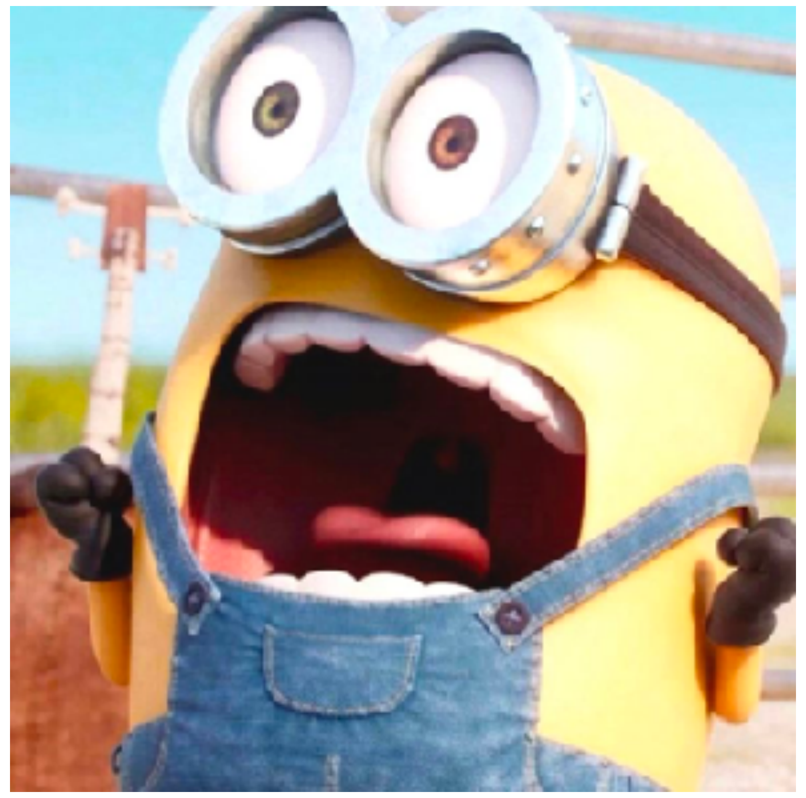
For non-linear MDP?

Handle constraints?





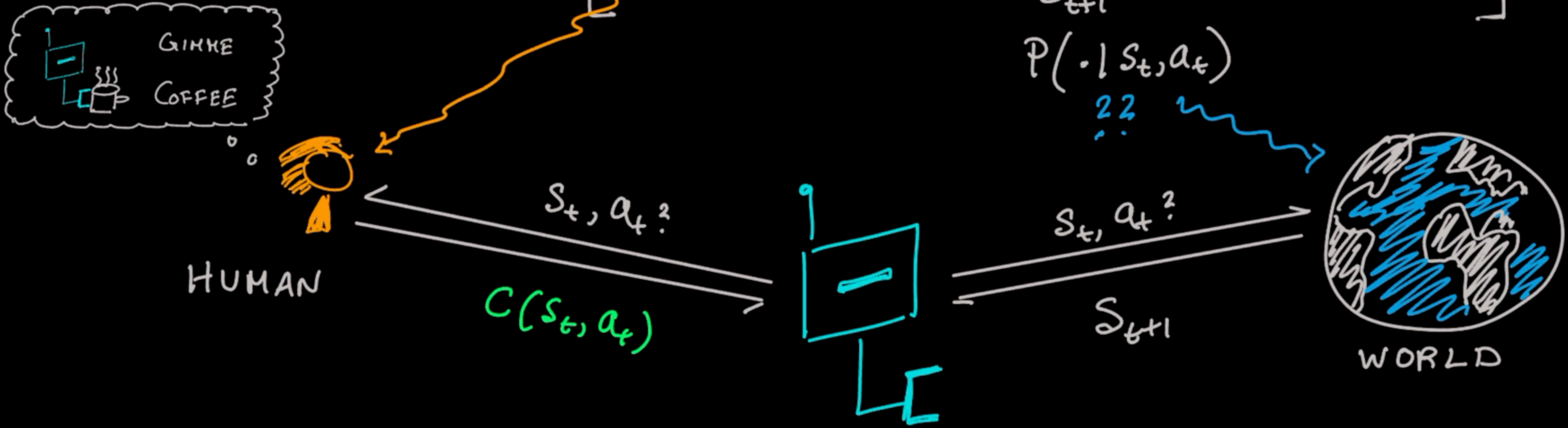




… What if your MDP is really complex?

Large state space, stochastic, continuous actions …

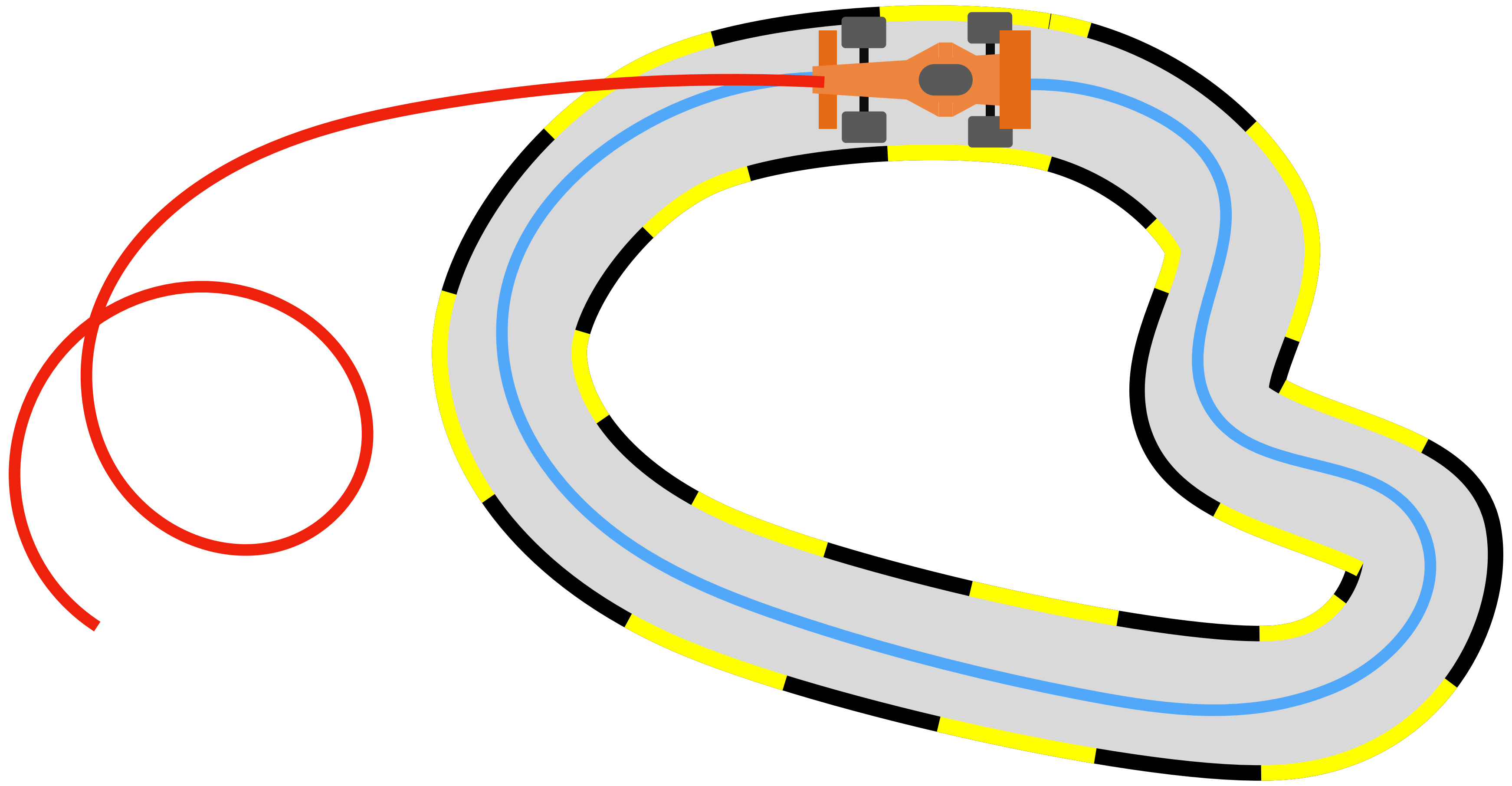
$$V^*(s_t) = \min_{a_t} \left[C(s_t, a_t) + \mathop{\mathbb{E}}_{s_{t+1} \sim P(\cdot \mid s_t, a_t)} V^*(s_{t+1}) \right]$$



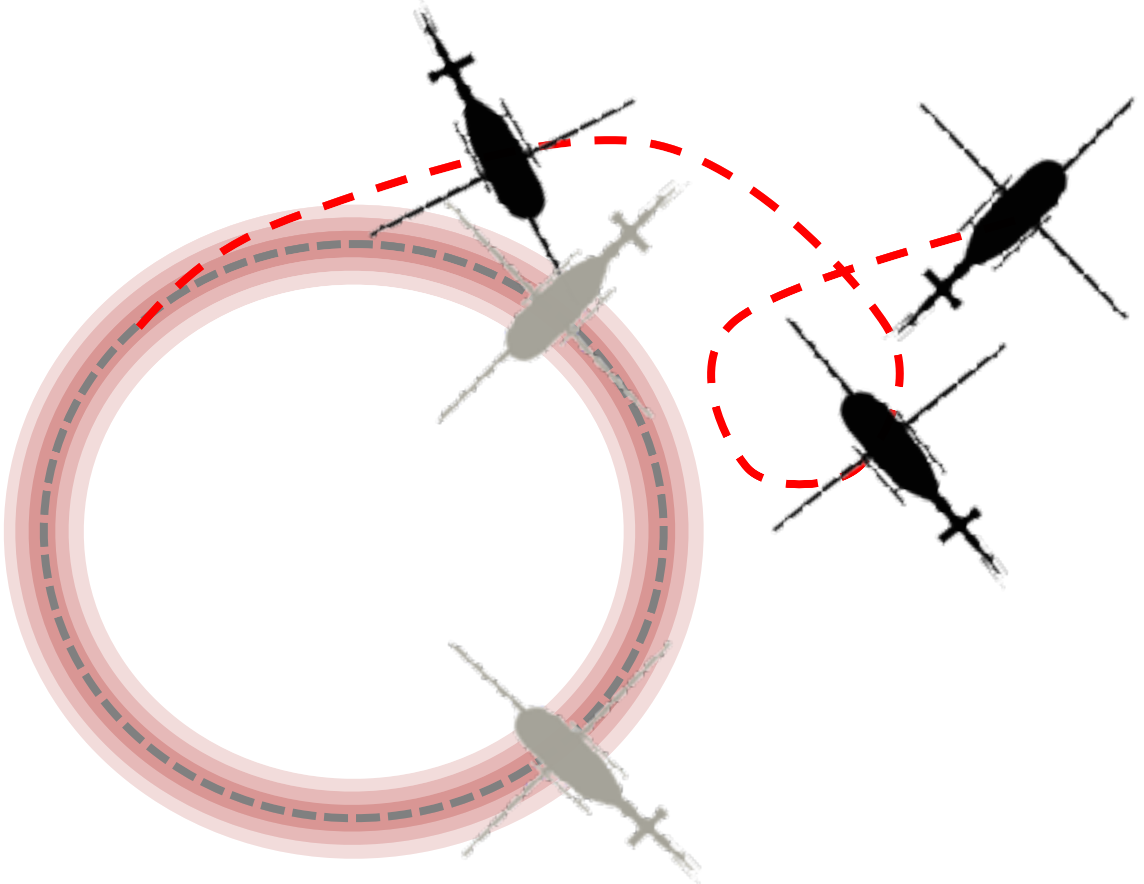
LEARN OPTIMAL VALUE BY INTERACTIONS W/ HUMAN + WORLD

Where all did we see covariate shift?

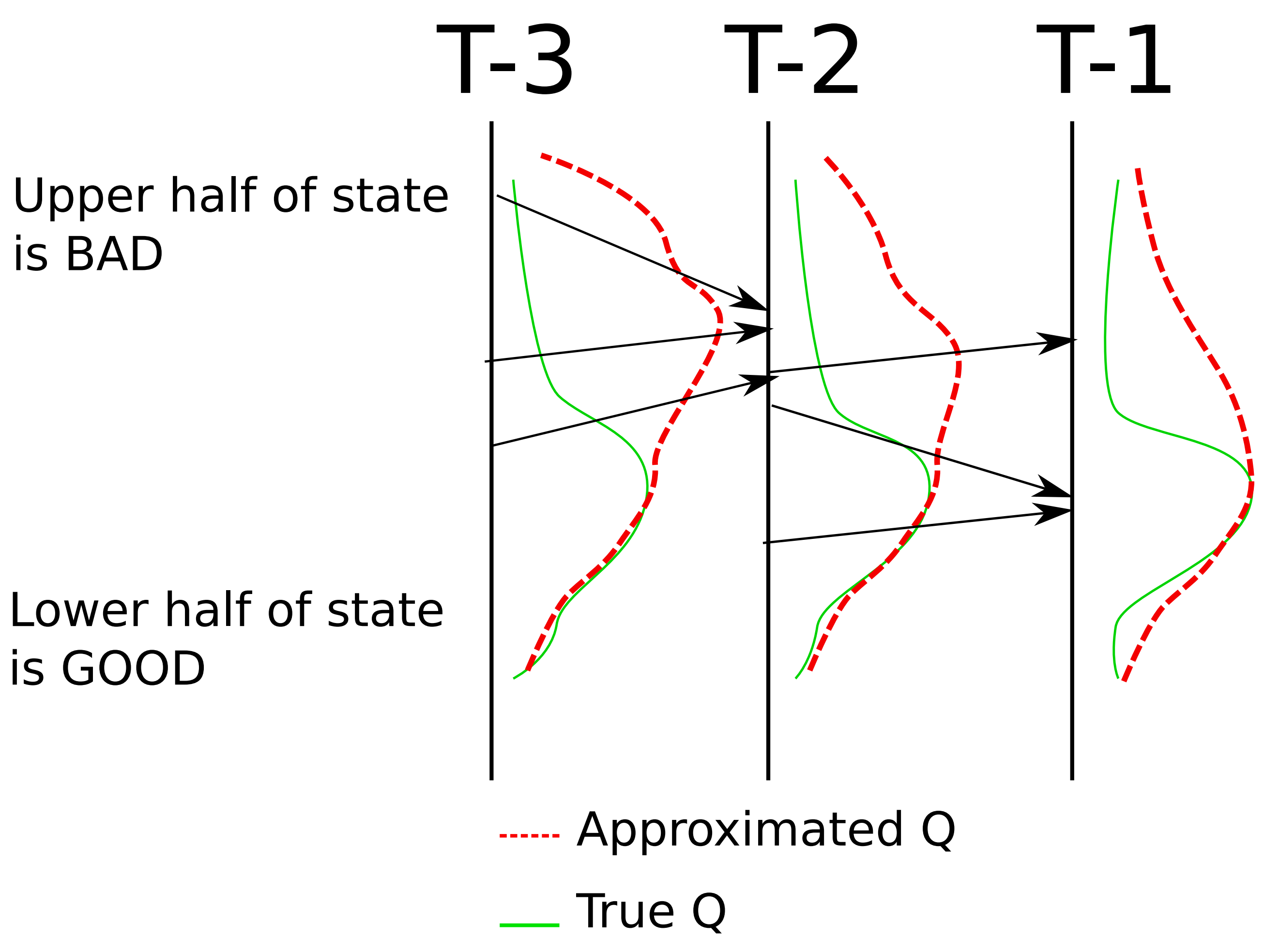
Imitation Learning?



Model Based RL?



Approximate Dynamic Programming?



Interactive Learning

Learner | Adversary

Initialize policy

π_1 [policy]

Chooses loss

$l_1(.)$ [loss]

Update policy

π_2

Chooses loss

$l_2(.)$

⋮ ⋮

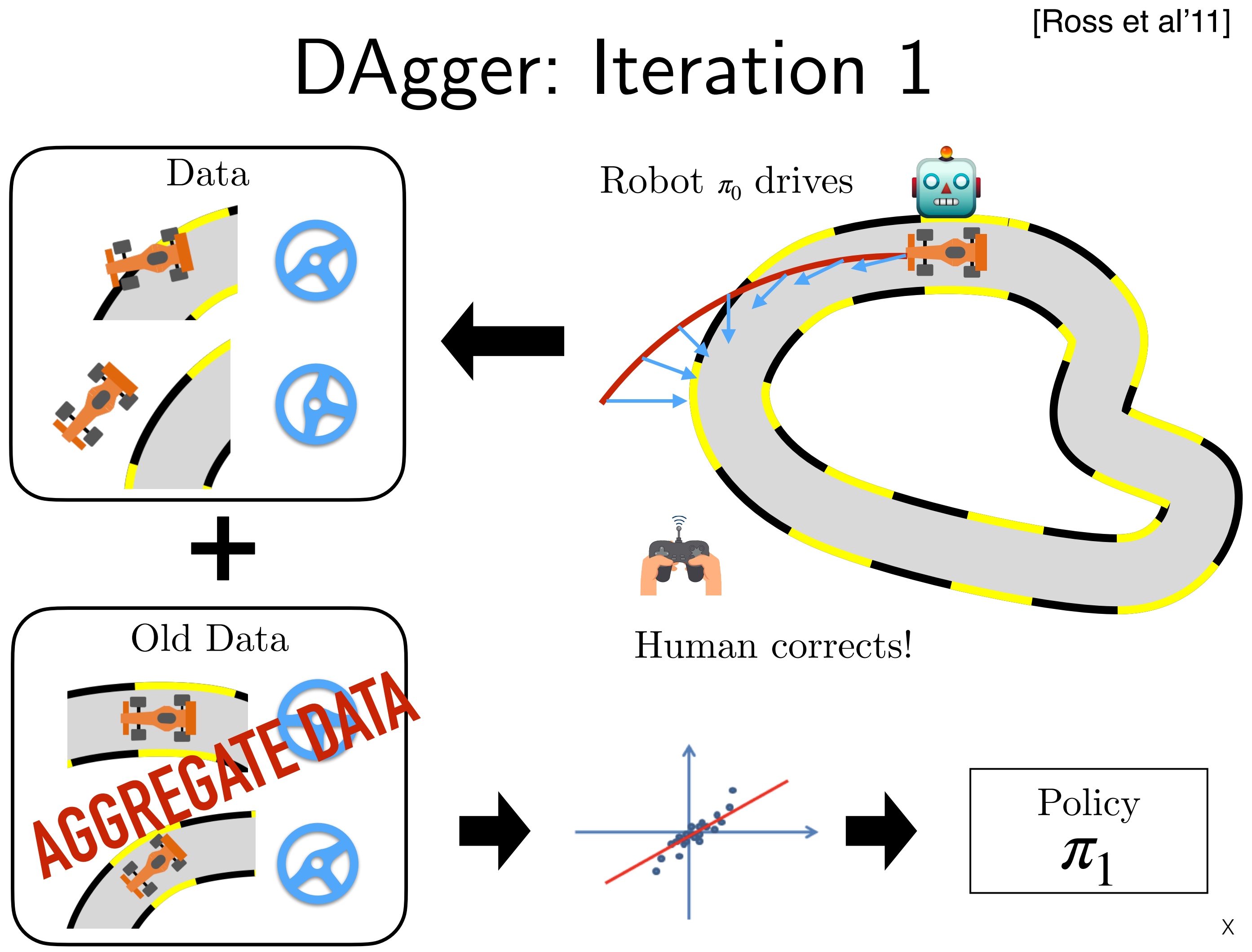
Learning is a Game!

Follow the leader is aggressive

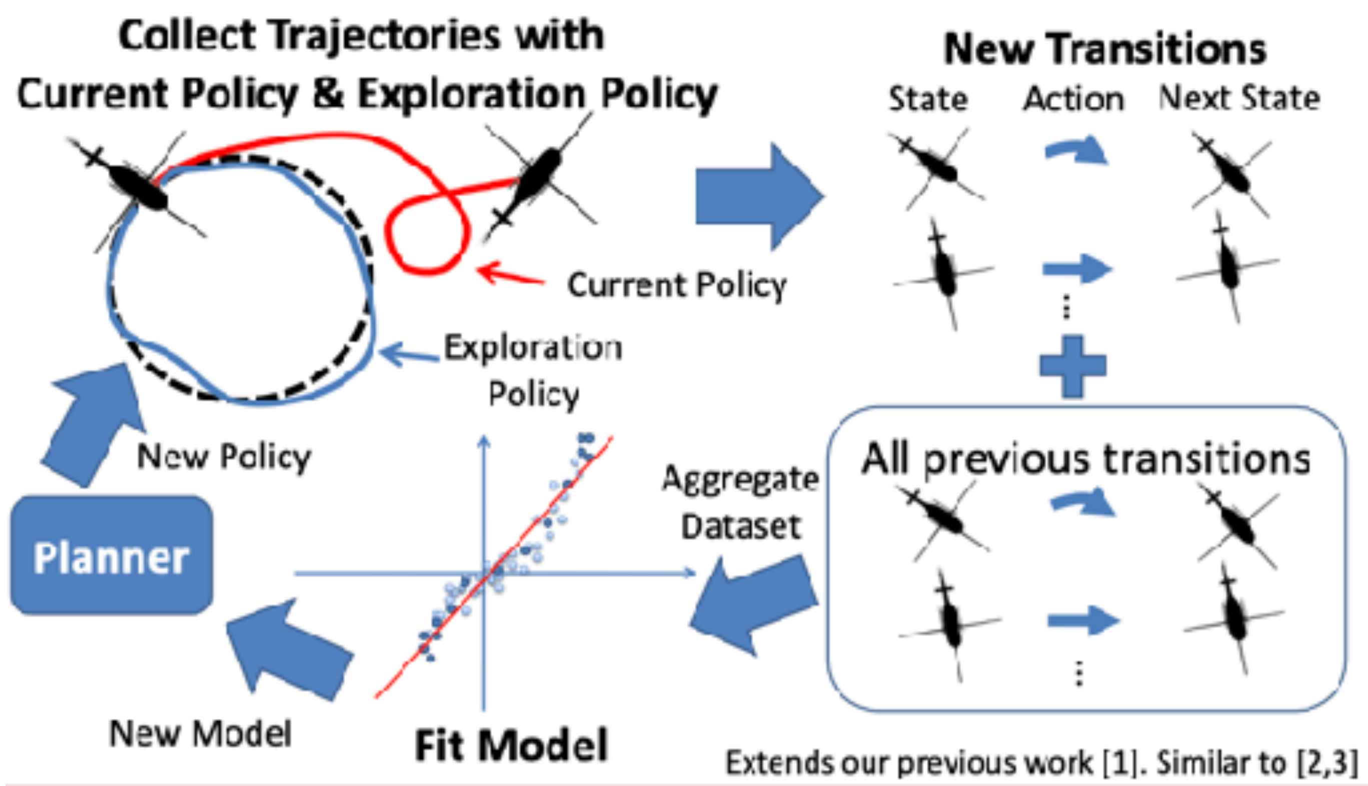
Slowly change predictions, achieve no-regret

No regret solves all!

DAgger



DAgger for SysID



Conservative policy iteration

Idea 1: Conservative Policy Iteration (CPI)

$$\pi' = (1 - \alpha)\pi + \alpha\pi_{greedy}$$

Mix in old policy and greedy policy

Can prove that performance difference is bounded by

$$V^{\pi'}(s) - V^{\pi}(s) \geq \alpha A_{greedy} - 2\alpha^2 \frac{\gamma}{1 - \gamma}$$

How much greedy policy improves based on estimate

How much distribution shift hurts!

GOAL: MINIMIZE

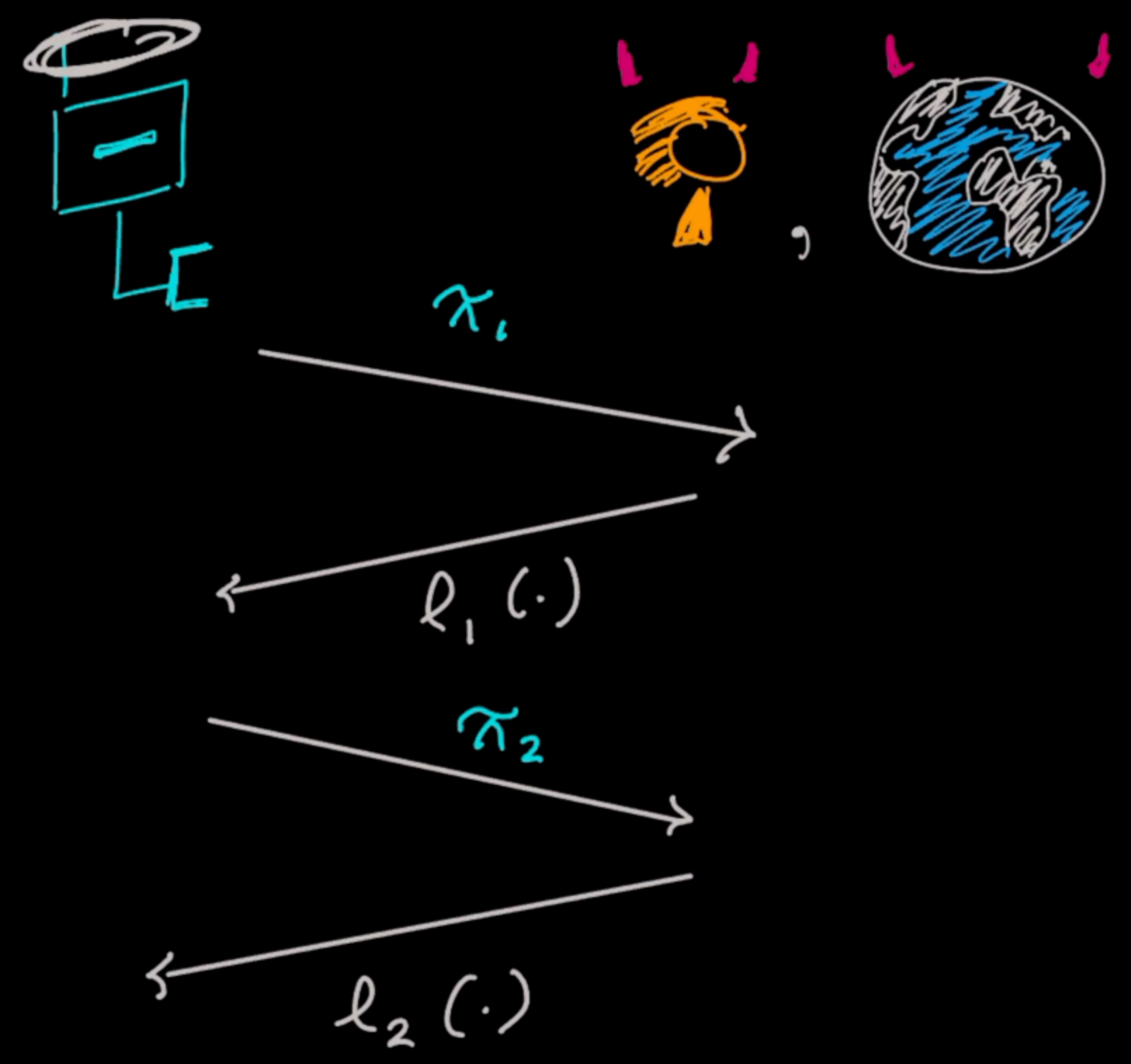
AVG. REGRET

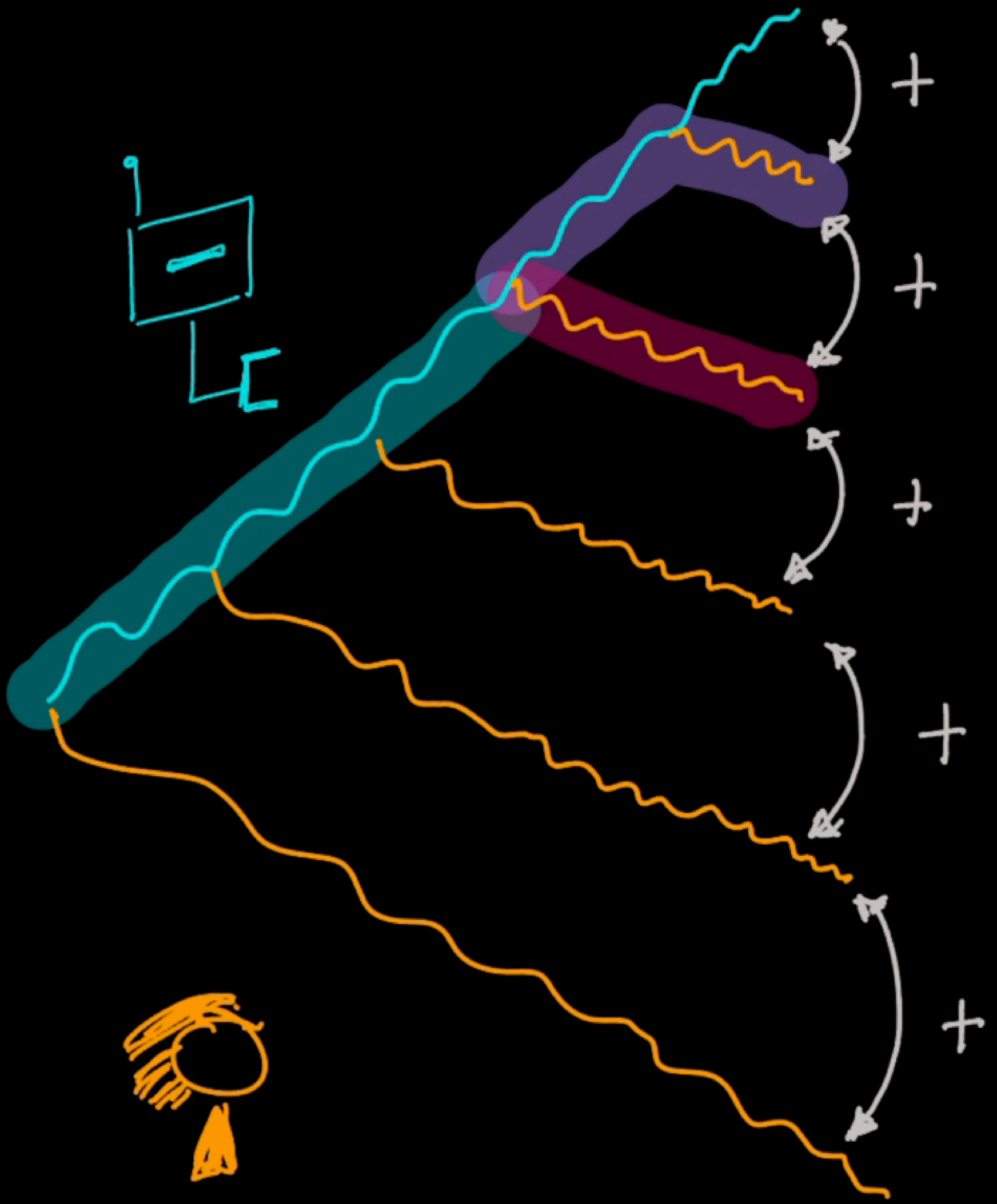
$$\frac{1}{N}\left[\sum_{i=1}^{N} \underbrace{l_i(\pi_i)}_{\text{LEARNER LOSS}} - \underbrace{\min_{\pi^*} \sum_{i=1}^{N} l_i(\pi^*)}_{\text{BEST LOSS}}\right]$$

AS $N \to \infty$, AVG REGRET $\to 0$

"DO AS WELL AS YOU COULD HAVE IF YOU HAD ALL THE DATA UPFRONT"

INTERACTIVE ONLINE LEARNING





Performance Difference Lemma

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

$$= \sum_{t=1}^{T} \underbrace{\mathbb{E}_{s_t \sim d_\pi}}_{\text{States the robot visits}} \underbrace{\Big[\underbrace{Q^*(s_t, \pi(s_t))}_{\text{Action value of robot}} - \underbrace{Q^*(s_t, \pi^*(s_t))}_{\text{Action value of human}} \Big]}_{\text{"Disadvantage"}}$$

Loss

$\ell(s, \pi(s))$

Reinforcement Learning: Brass Tacks

We don't know the MDP, all we see are traces (s,a,s')

Model Based:
Learn a model. Plan with the model.

Model Free:
Forget about models. Learn the policy.

Model Free RL: Actor Critic

Actor

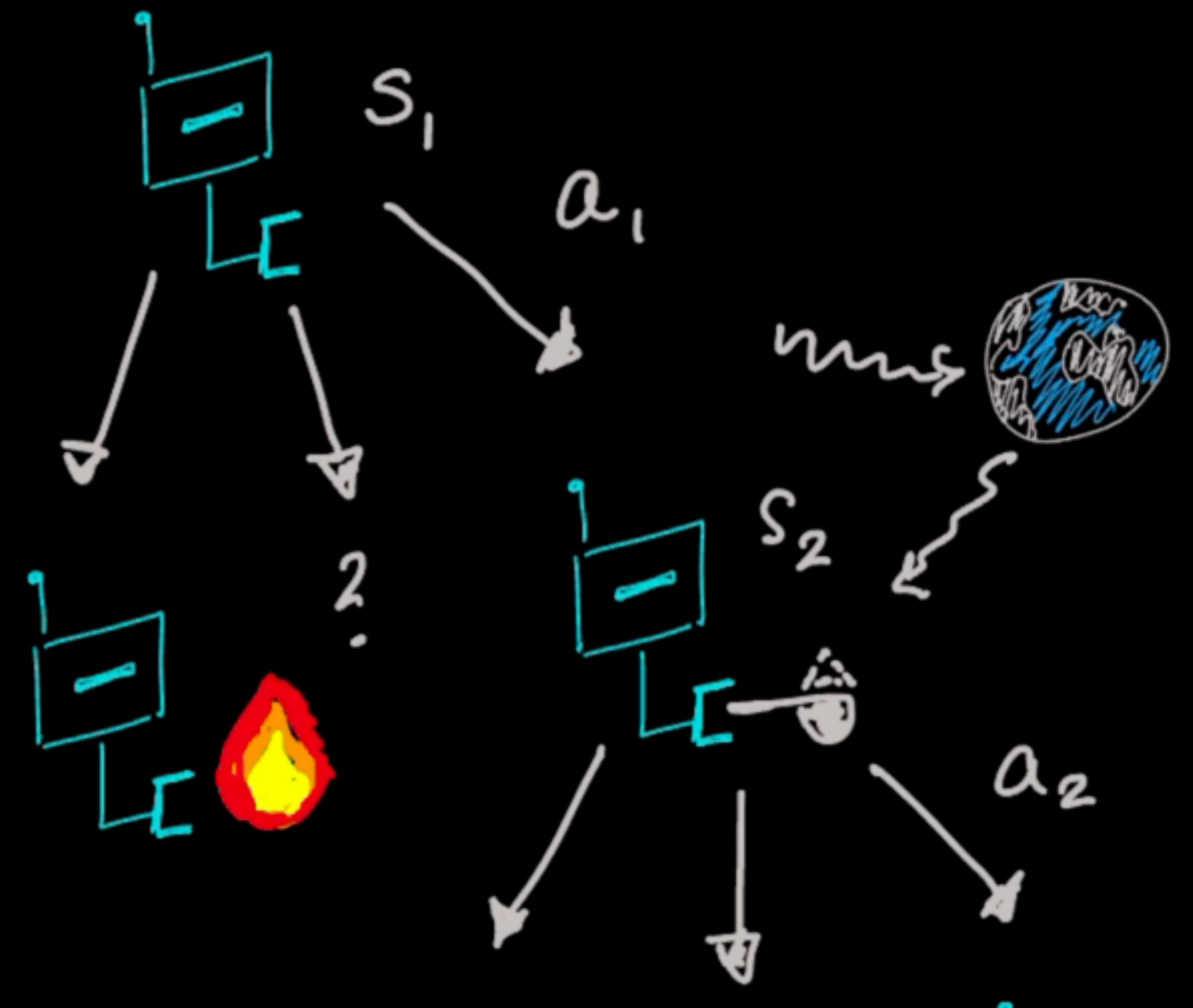
Critic

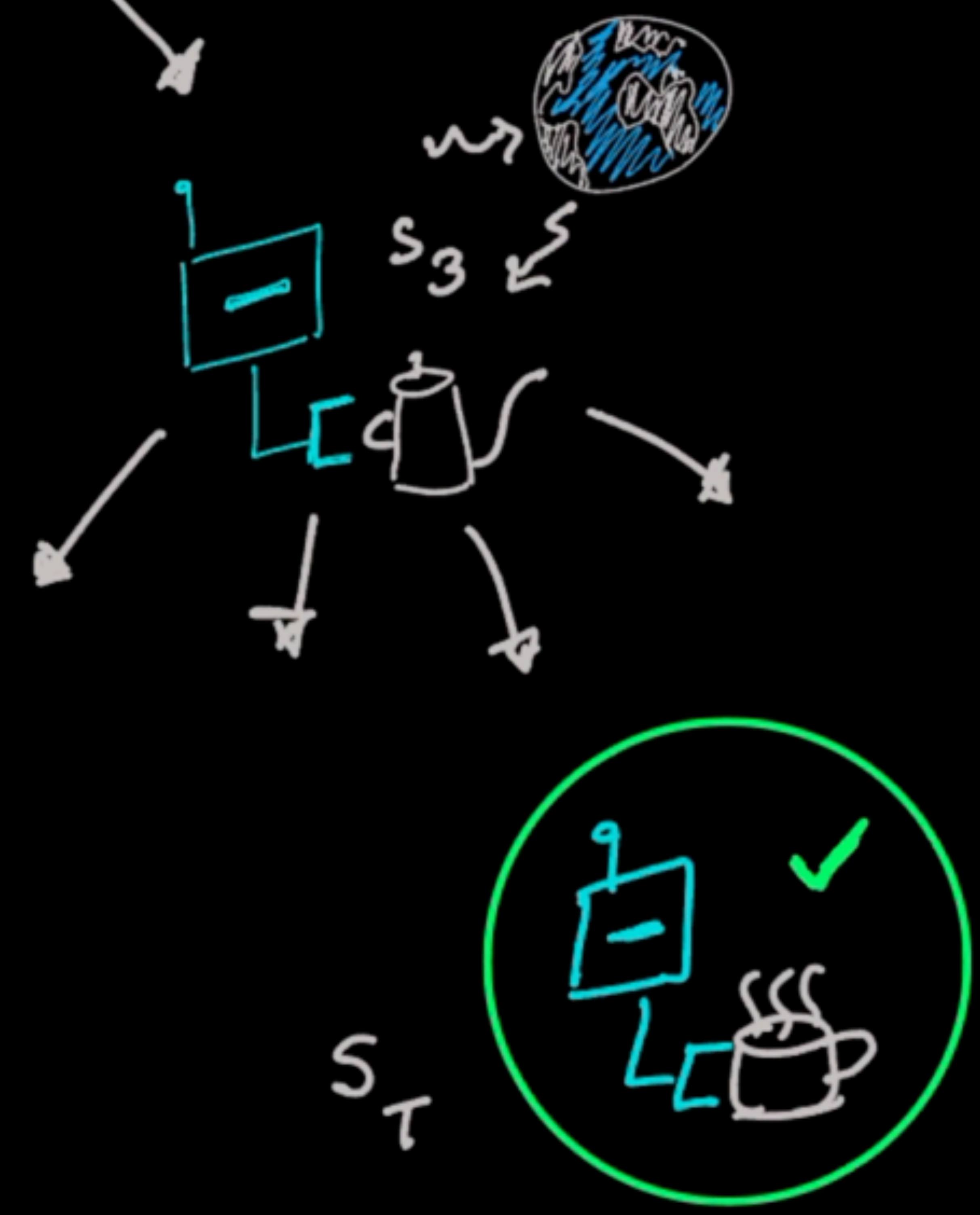
Policy improvement of π

Estimates value functions $Q^{\pi}_{\phi}/V^{\pi}_{\phi}/A^{\pi}_{\phi}$

(Natural) Policy Gradient

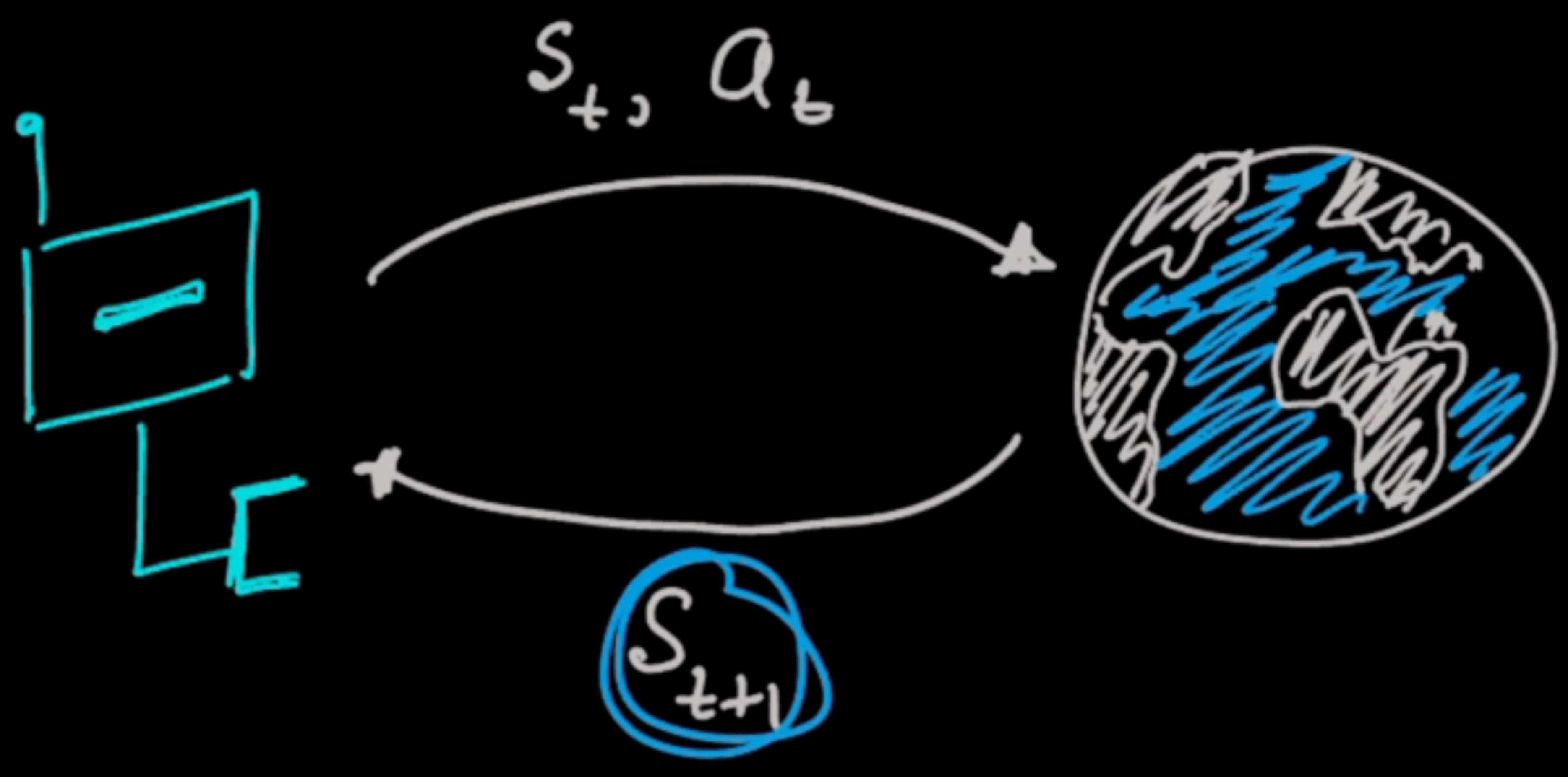
TD, MC





Explore all actions to see next state to estimate Q^*.

Reinforcement Learning



Estimate $Q^*(s_t, a_t)$ such that

$$Q^*(s_t, a_t) = c(s_t, a_t) + \underset{s_{t+1}}{E} \min_{a_{t+1}} Q^*(s_{t+1}, a_{t+1})$$

i.e. Bellman consistent

Imitation Learning: Brass Tacks

We don't know the MDP, all we see are human actions (a*)

Learn Cost:

Learn a cost that makes human look cheap, learner look expensive

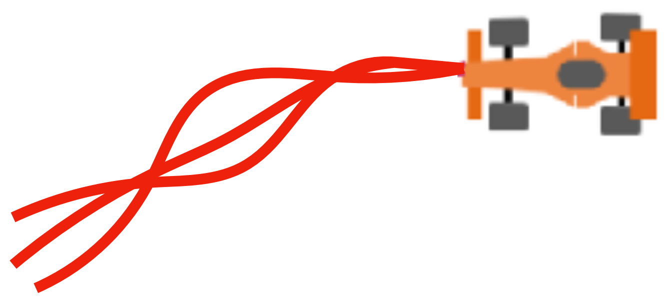
Learn Values:

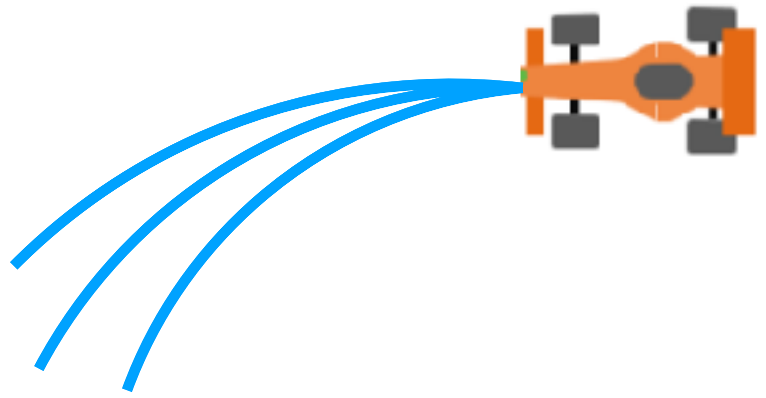
Learn Q* that makes human look cheap, learner look expensive

Inverse Optimal Control (Learn Cost)

Make human look cheap, learner look expensive

$$\max_{\phi} \min_{\theta} \; \mathbb{E}_{s_t, a_t \sim \pi_\theta}[C_\phi(s_t, a_t)] - \mathbb{E}_{s_t^*, a_t^* \sim \pi^*}[C_\phi(\xi)]$$



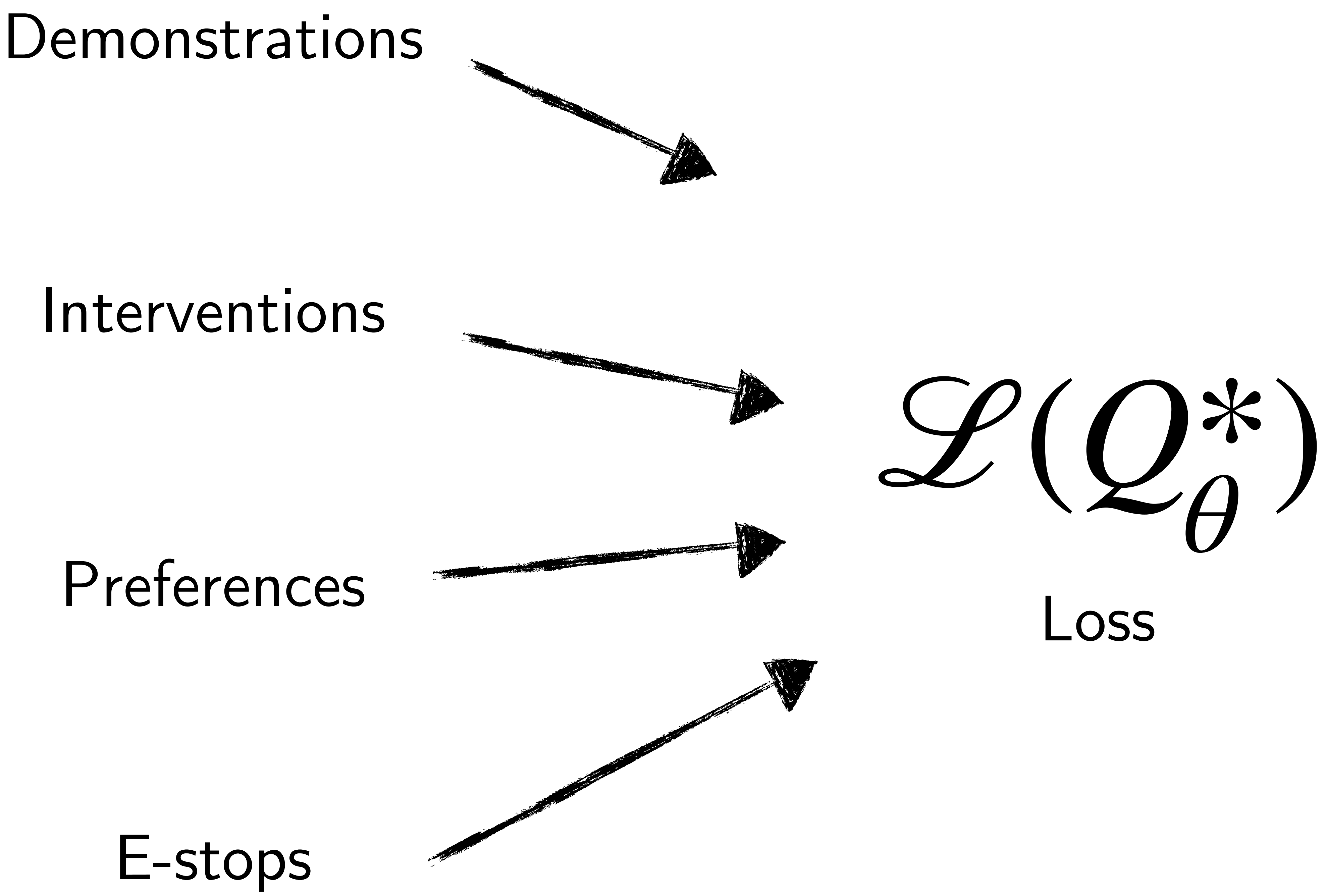


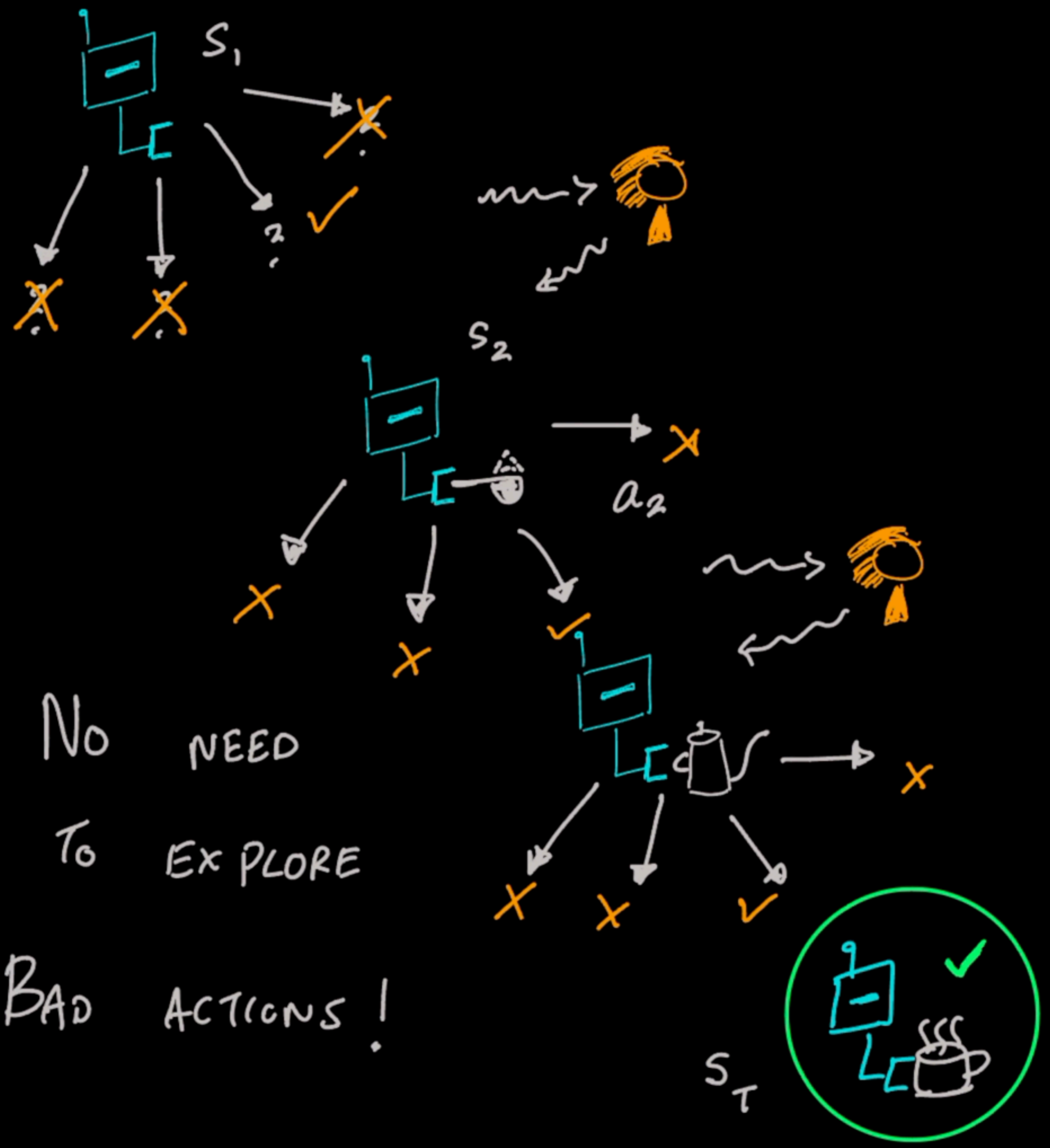
Cost of Learner

Cost of Expert

Learn Values

Estimate Q* from demonstrations, interventions, preferences, ..
and even E-stops!

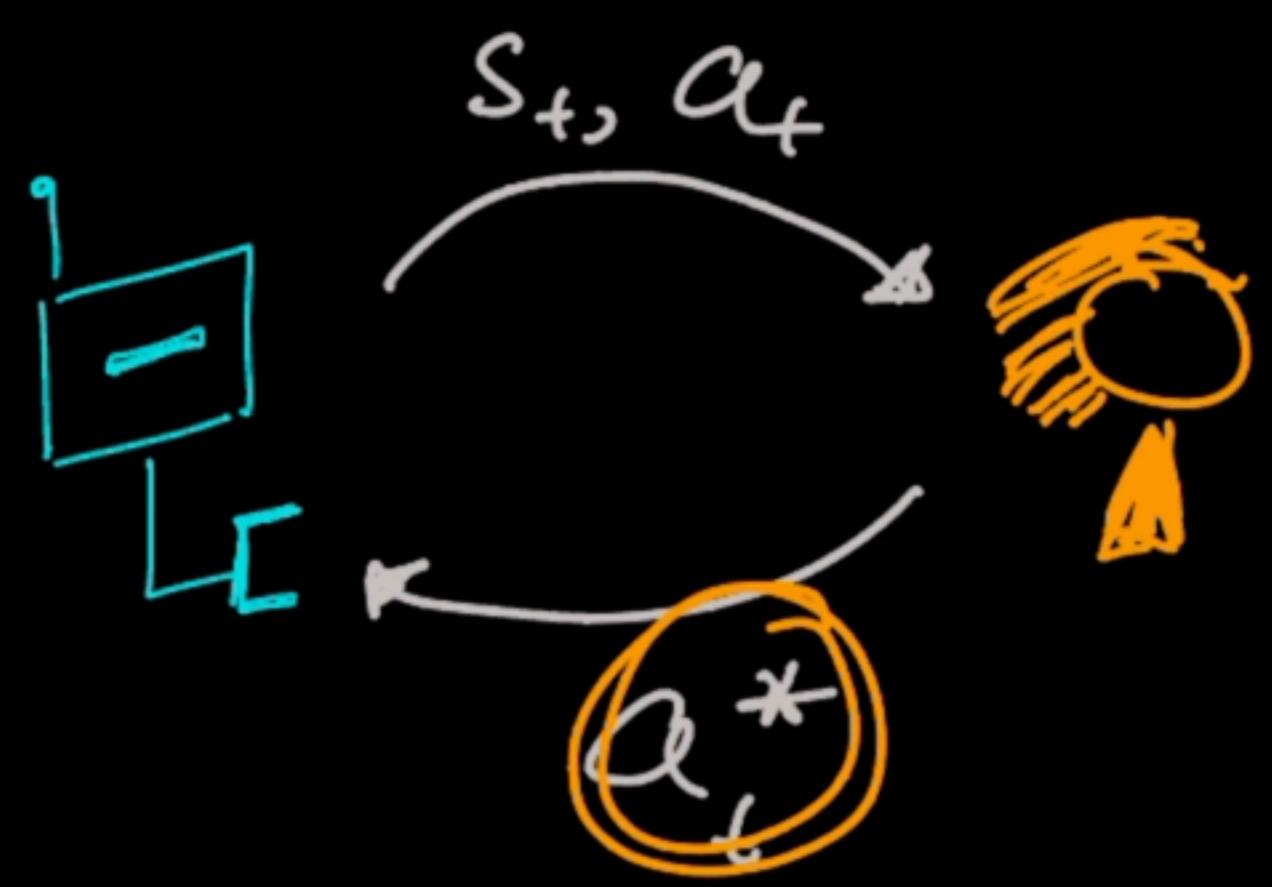




No need to explore

Bad actions!

Imitation Learning



Estimate $Q^*(s_t, a_t)$ such that

$$Q^*(s_t, a_t) = \min_{a_t'} Q^*(s_t, a_t')$$

i.e. Human is optimal

The Imitation Game

We have an interactive expert.

Apply PDL in forward direction: roll-in learner, roll-out expert

$$\min_{\pi} \quad \max_{Q^*} \sum_{t=1}^{T} \mathbb{E}_{s_t \sim \pi}[Q^*(s_t, \pi(s_t)) - Q^*(s_t, \pi^*(s_t))]$$

😇 😈

Use no-regret learning to solve the game!

$$O(\epsilon T)$$

The RL Game

We don't have interactive expert.

Apply PDL in reverse direction: roll-in expert, roll-out learner

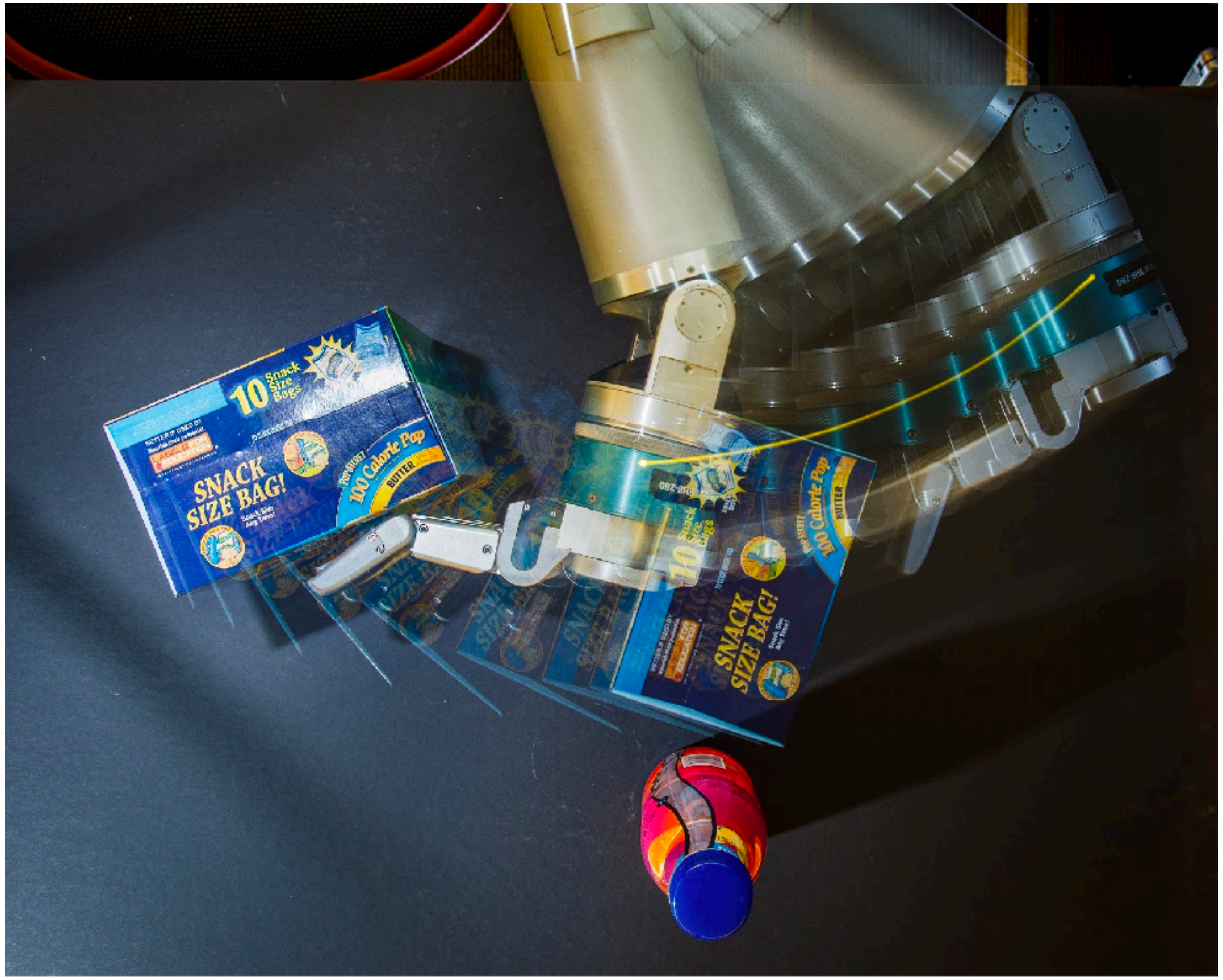
$$\min_{\pi} \quad \max_{Q^{\pi}} \sum_{t=1}^{T} \mathbb{E}_{s \sim \pi^*} Q^{\pi}(s, \pi(s)) - Q^{\pi}(s, \pi^*(s))$$

😇 😈

Use no-regret learning to solve the game! $O(\epsilon T^2)$

A grand unification of IL / RL Games?

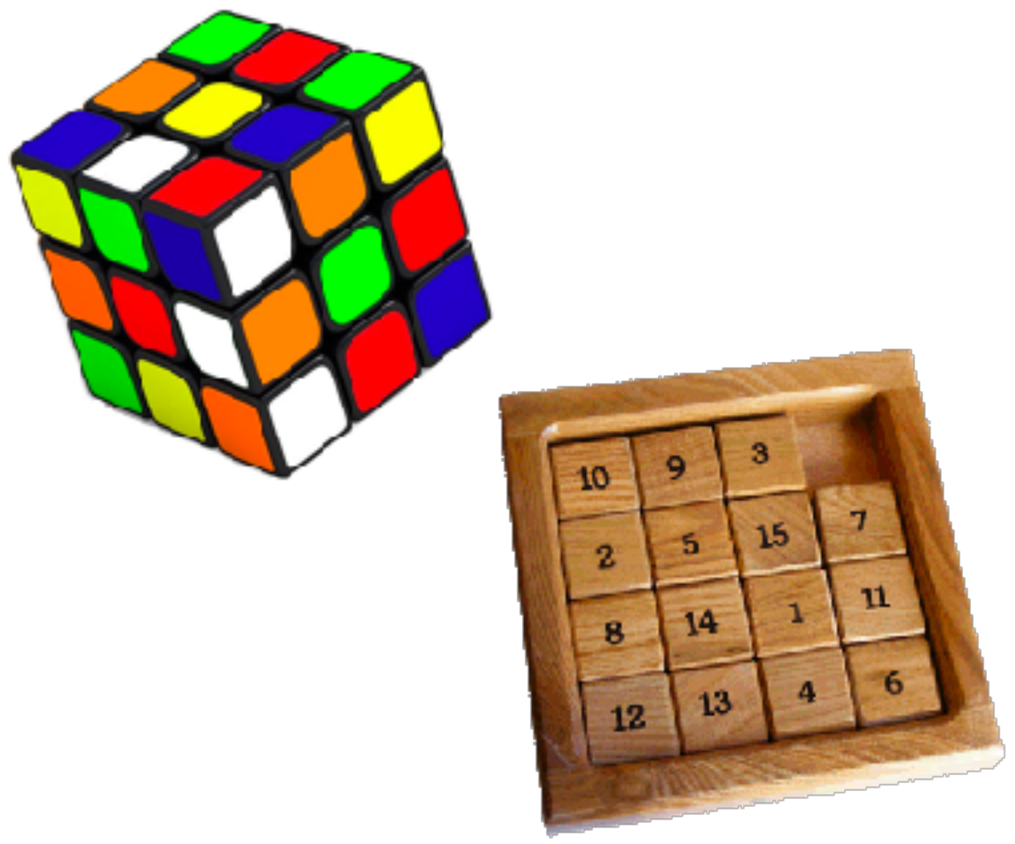
A simple question:
Can learning help us build better planners?



A prospective grad student:
“Is planning just A*?”

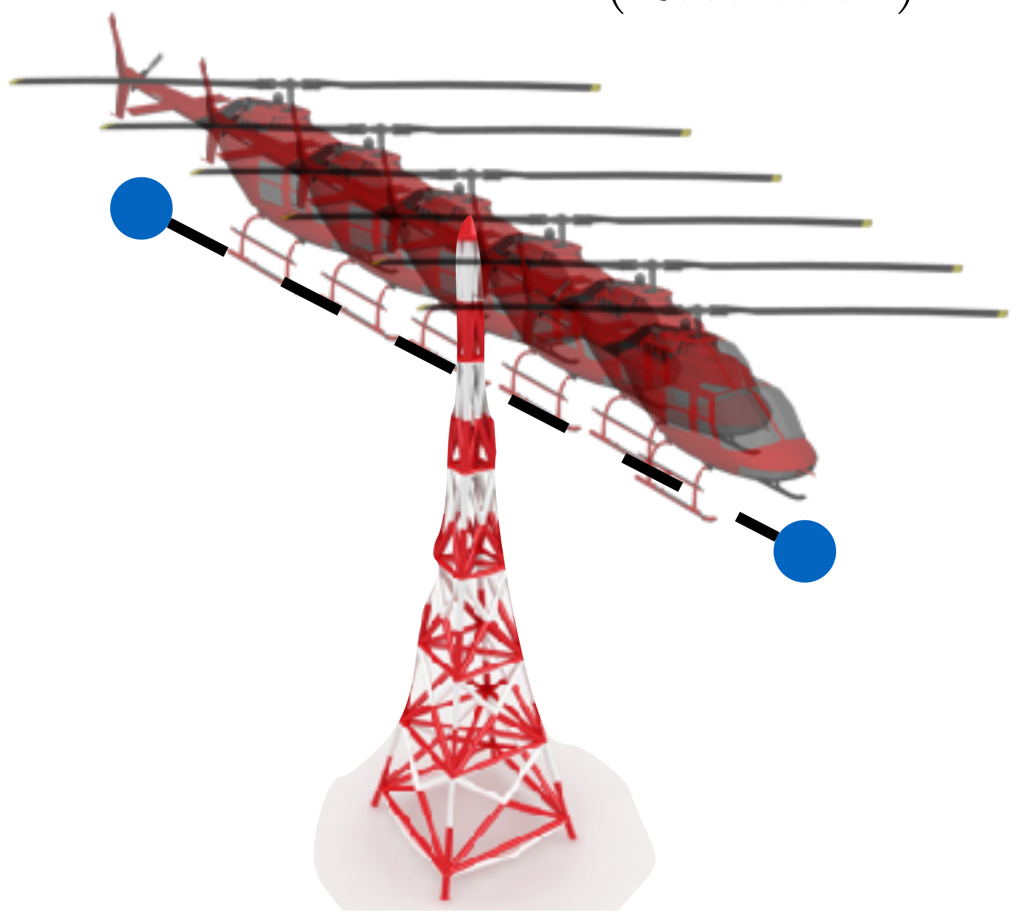
Motion Planning: Dealing with expensive collision checking

Trivial

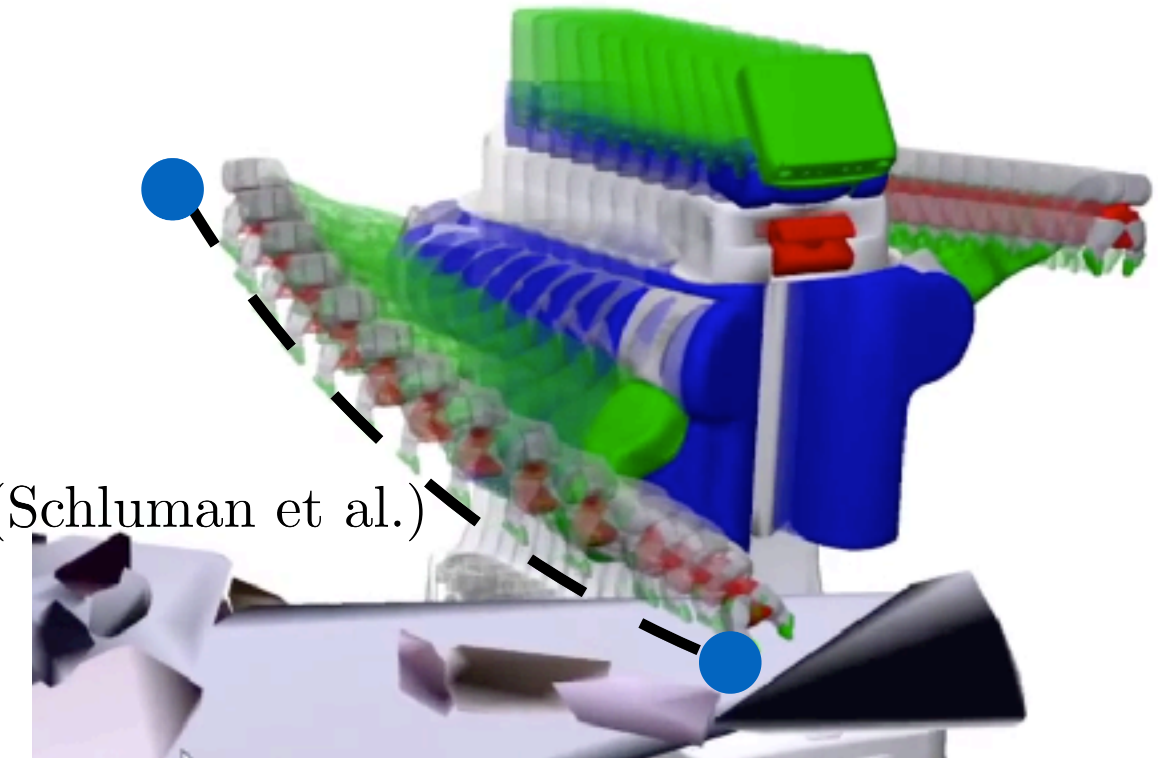


Medium

(Ross et al.)



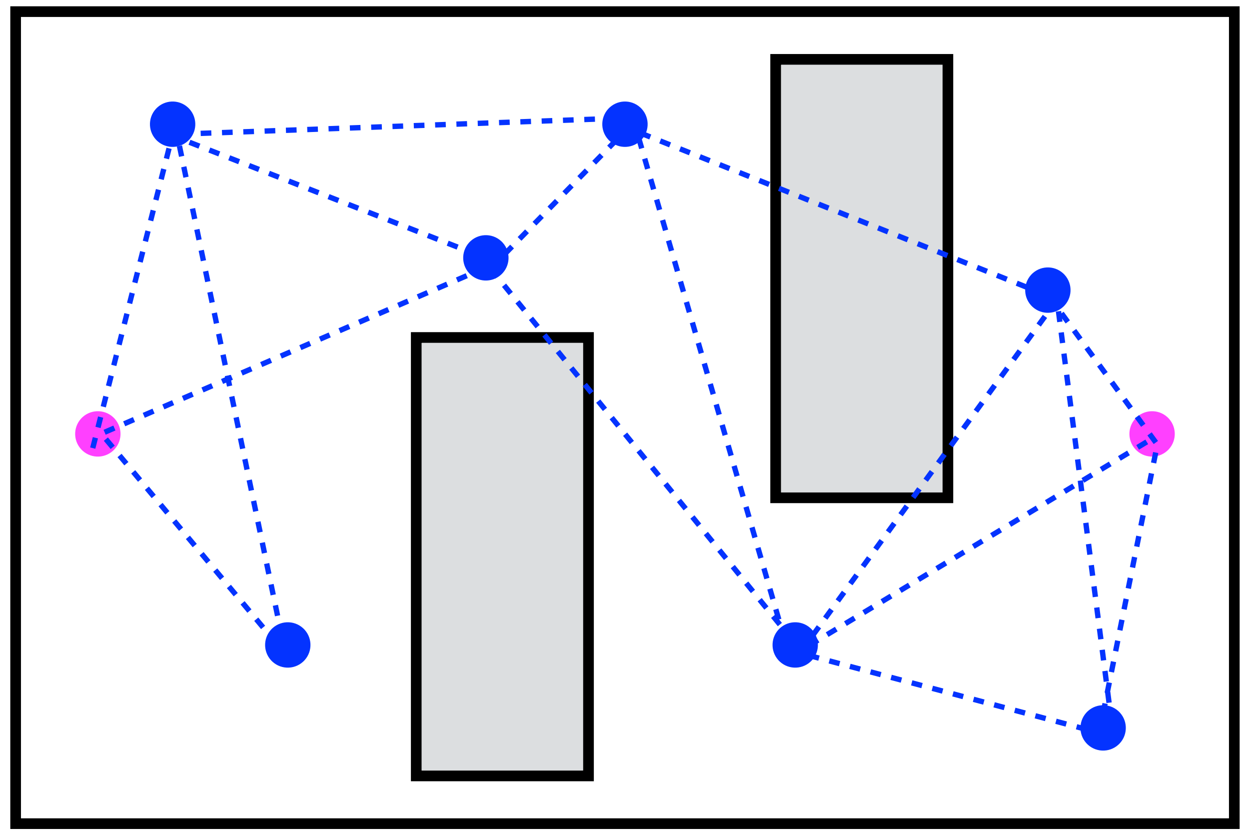
Expensive



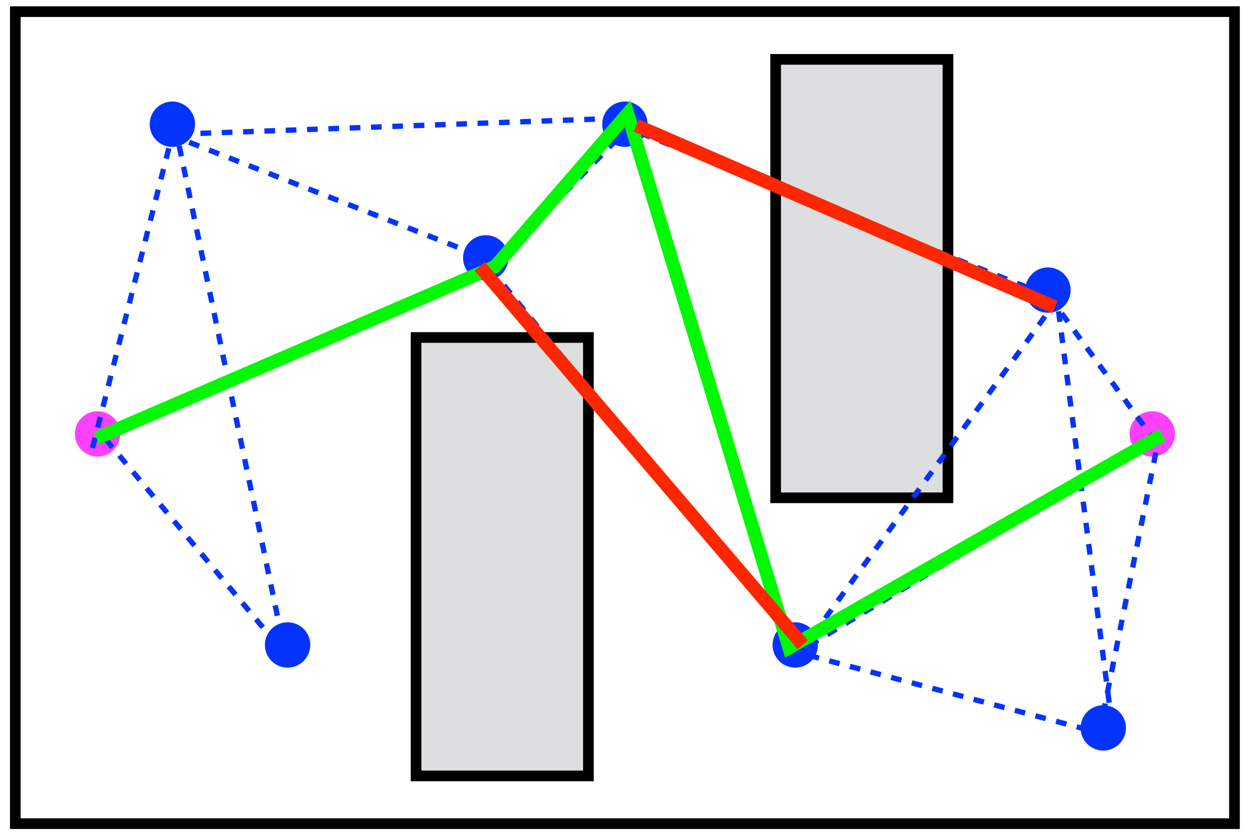
(Schluman et al.)

(LaValle'06, Bialkowski'11, Hauser'15, ...)

General framework for motion planning



Create a graph



Search the graph

Interleave

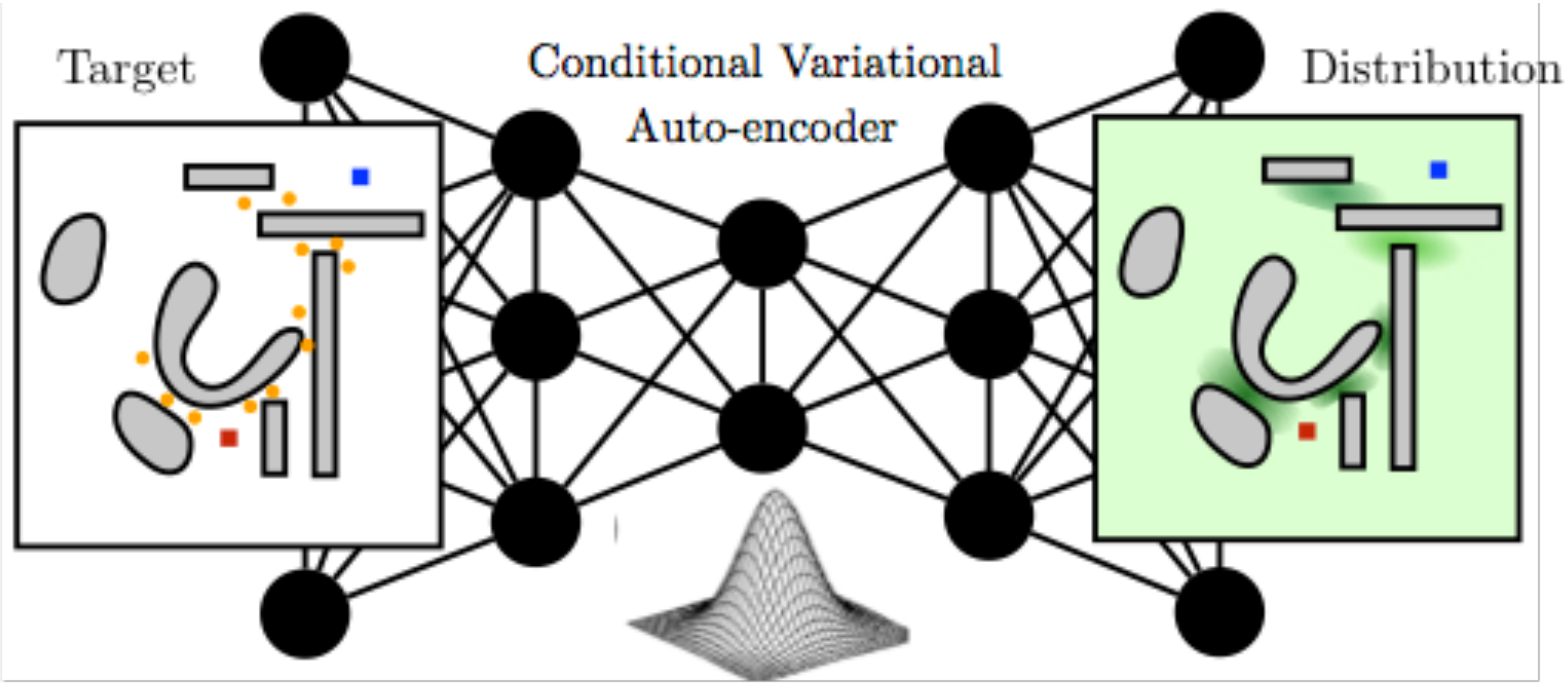
General framework for motion planning

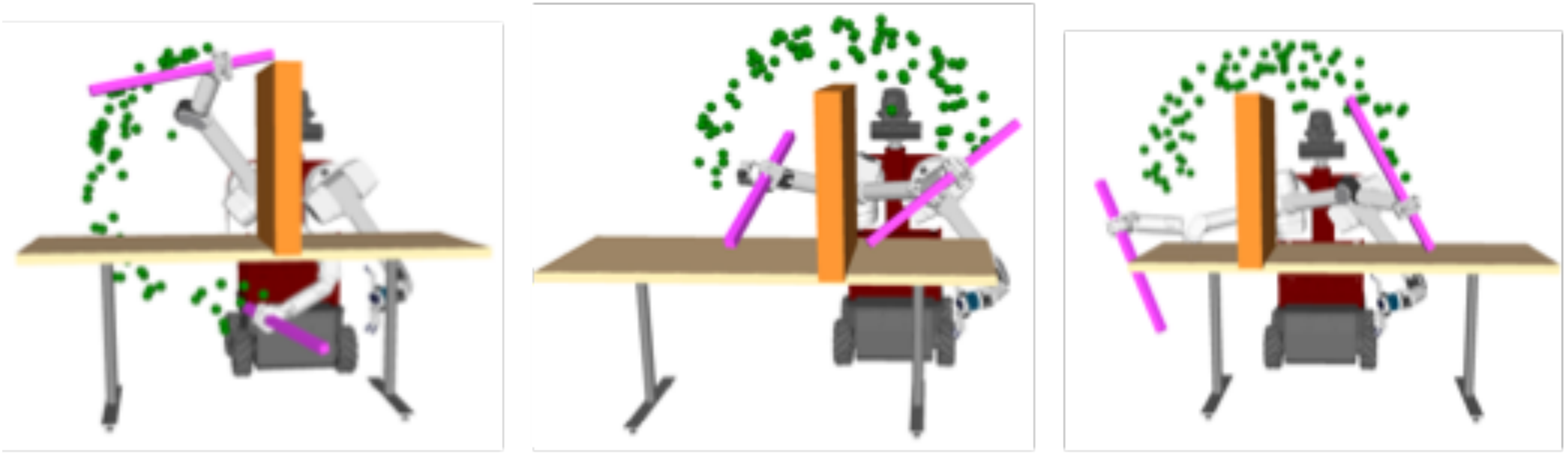
Any planning algorithm		Create graph		Search graph		Interleave
	=	e.g. fancy random sampler	×	e.g. fancy heuristic	×	e.g. fancy way of densifying
		Learn sampler!		Learn heuristic!		

LEGO: Leveraging Experience in Roadmap Generation for Sampling-Based Planning

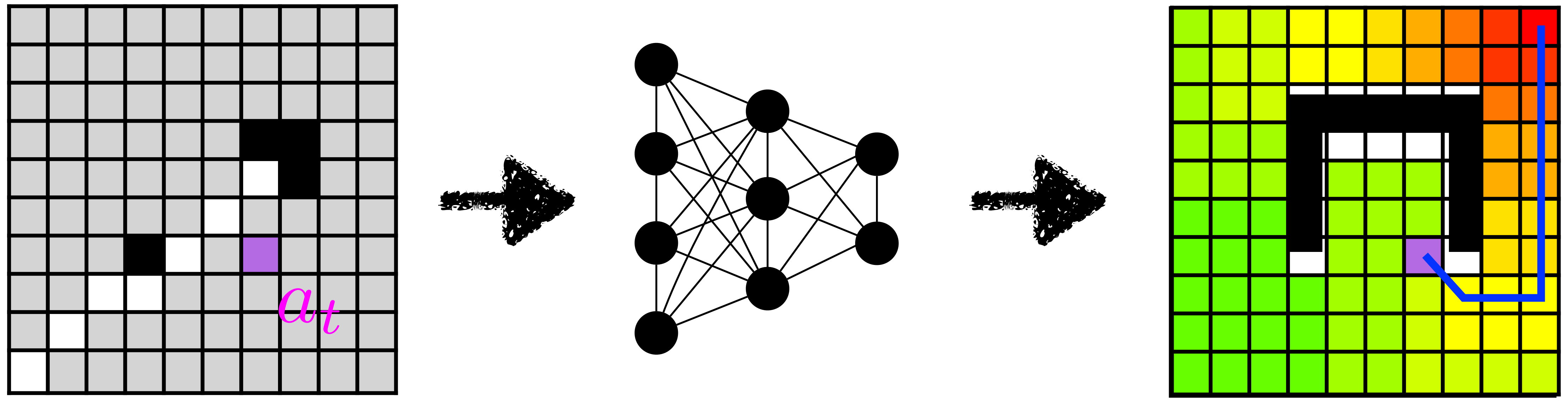
Rahul Kumar*[1], Aditya Mandalika*[2], Sanjiban Choudhury*[2] and Siddhartha S. Srinivasa*[2]

Learning a Sampler

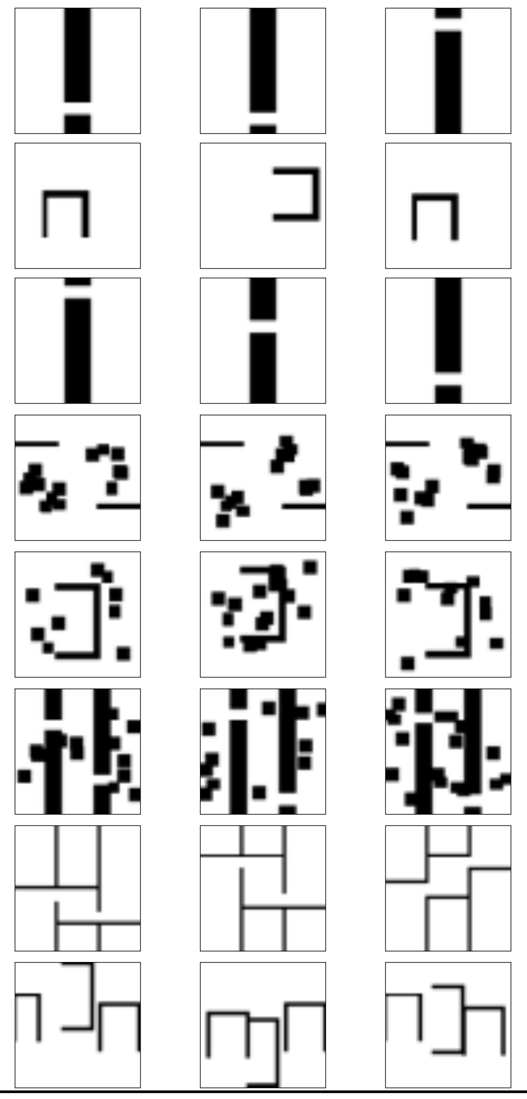




Learn a Heuristic



search tree → train heuristic → imitate true cost-to-go



	Ours	Baseline Learning			Baseline Handcrafted			
	SAIL	**SL**	**CEM**	**QL**	$h_{\mathbf{EUC}}$	$h_{\mathbf{MAN}}$	**A***	**MHA***
alternating_gap	0.039	0.432	0.042	1.000	1.000	1.000	1.000	1.000
single_gap	**0.158**	0.214	0.057	1.000	0.184	0.192	1.000	0.286
shifting_gap	0.104	0.464	1.000	1.000	0.506	0.589	1.000	0.804
forest	0.036	0.043	0.048	0.121	0.041	0.043	1.000	0.075
bugtrap_forest	0.147	0.384	0.182	1.000	0.410	0.337	1.000	0.467
gaps_forest	0.221	1.000	1.000	1.000	1.000	1.000	1.000	1.000
maze	0.103	0.238	0.479	0.399	0.185	0.171	1.000	0.279
multiple_bugtrap	0.479	0.480	1.000	0.835	0.648	0.617	1.000	0.876


Open Challenges