Inverse Reinforcement Learning: From Maximum Margin to Maximum Entropy

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Setting

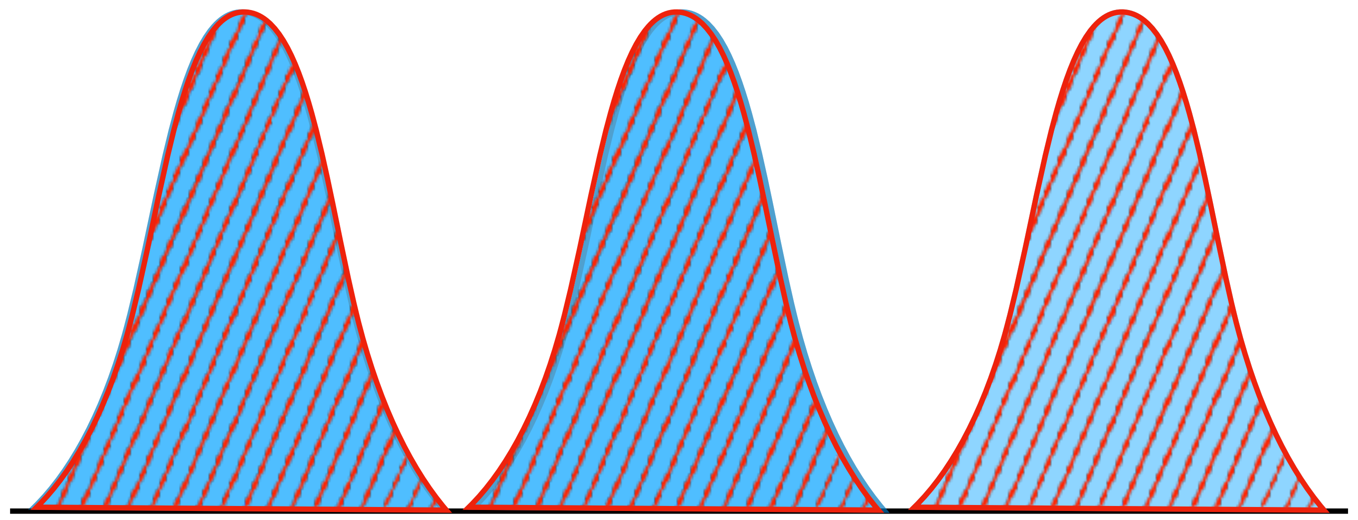
Solution

Easy

Expert is realizable

$\pi^E \in \Pi$

As $N \to \infty$, drive down $\epsilon = 0$ (or Bayes error)



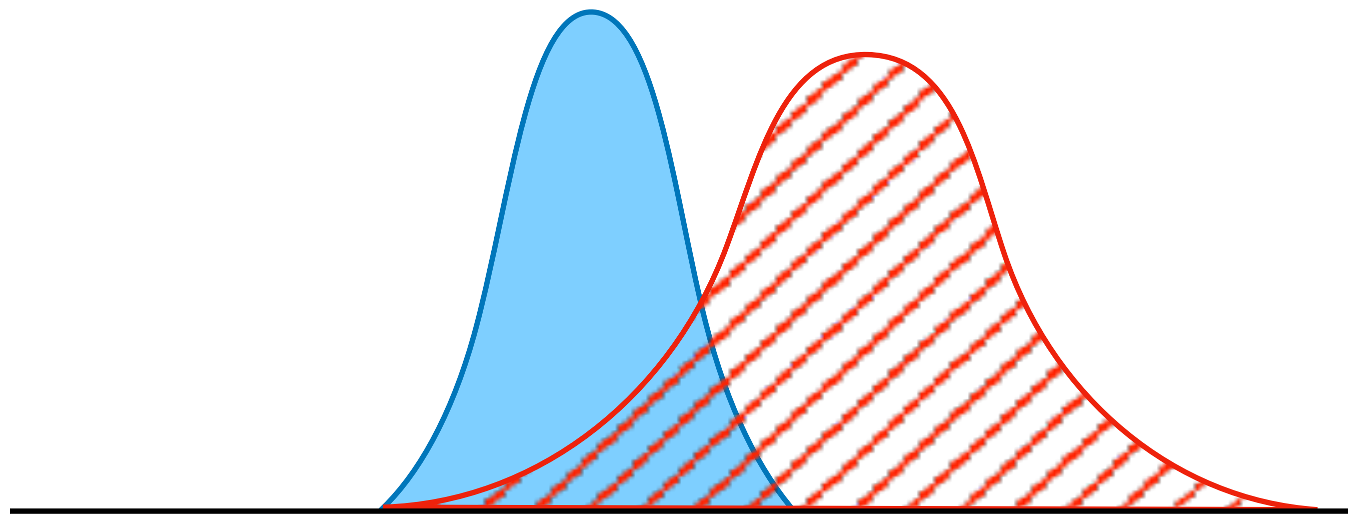
Nothing special.

Collect lots of data and do Behavior Cloning

Hard

Non-realizable expert + limited expert support

Even as $N \to \infty$, behavior cloning $O(\epsilon T^2)$



Requires interactive expert (DAGGER/EIL) to provide labels $\Rightarrow O(\epsilon T)$

Setting

Solution

Easy

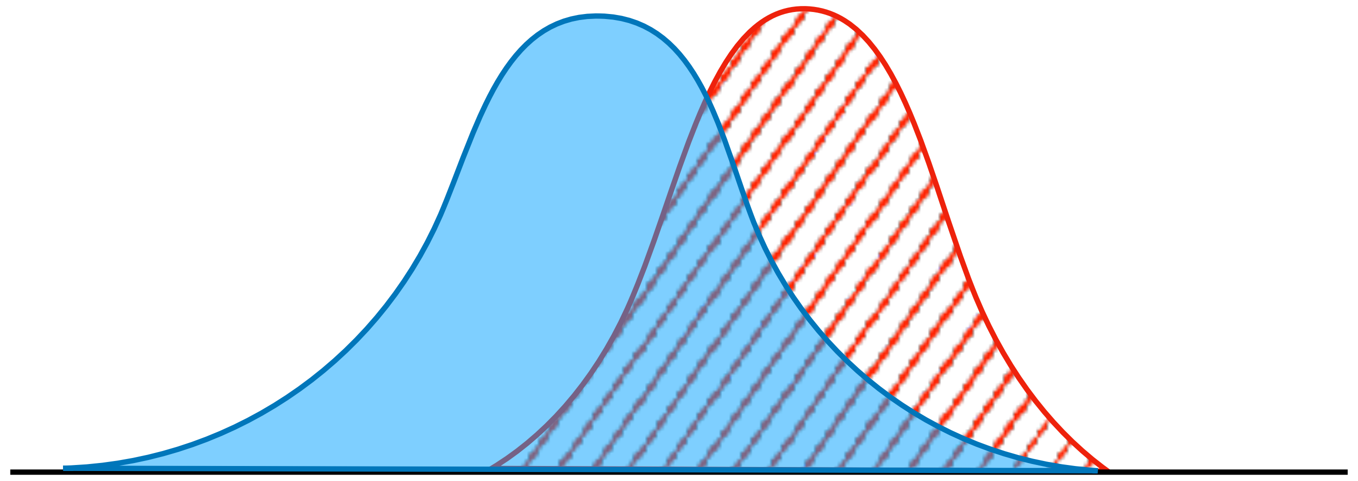
Expert is realizable
$\pi^E \in \Pi$

As $N \to \infty$, drive down
$\epsilon = 0$ (or Bayes error)

Nothing special.
Collect lots of data and
do Behavior Cloning

Medium

Non-realizable expert
but full expert support



?

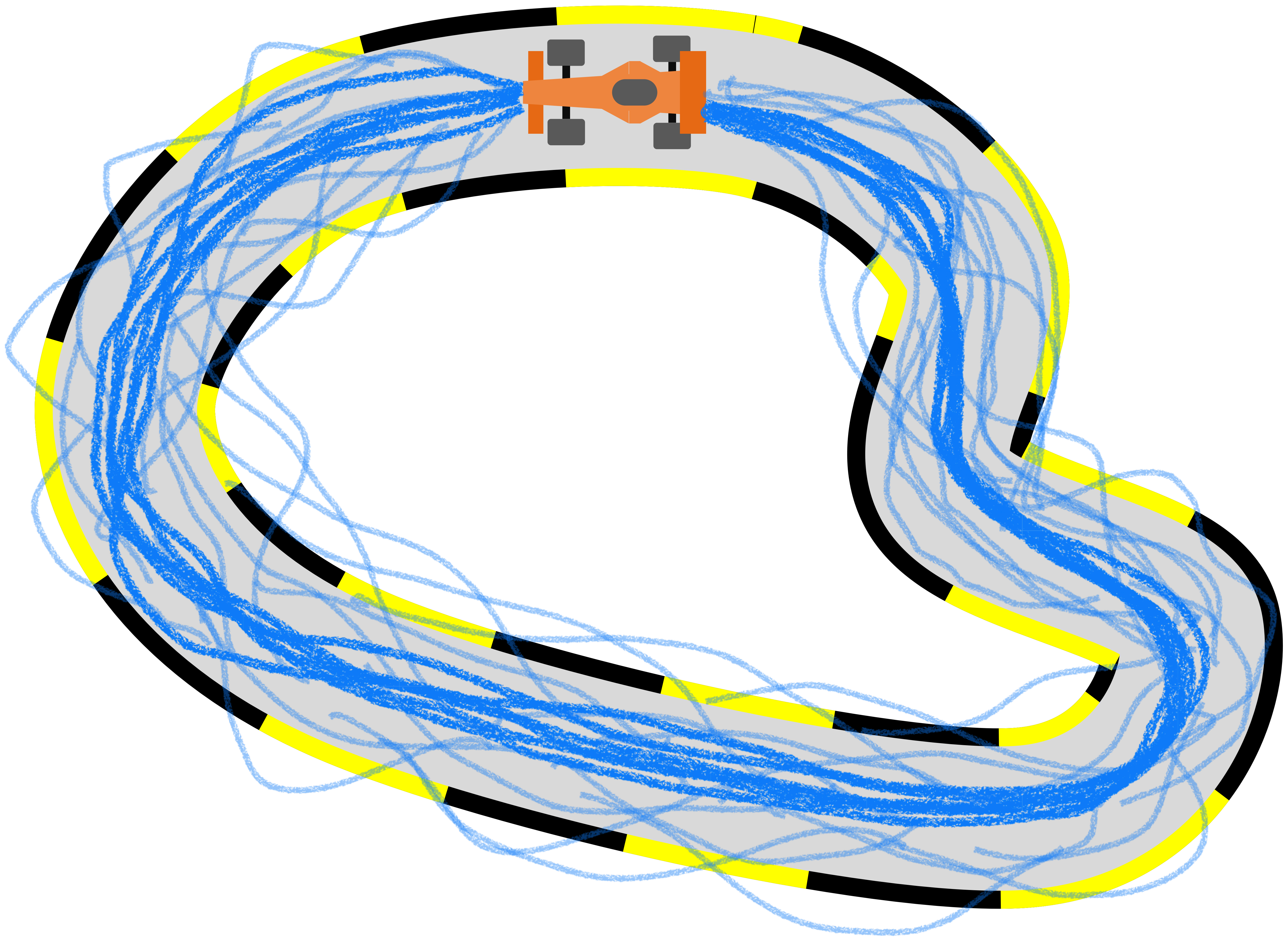
Hard

Non-realizable expert +
limited expert support

Even as $N \to \infty$,
behavior cloning $O(\epsilon T^2)$

Requires interactive expert
(DAGGER/EIL) to provide
labels $\Rightarrow O(\epsilon T)$

Expert demonstrations have full coverage



.. but expert runs away after demonstrations

So expert data has full coverage ...

.. why don't we just do Behavior Cloning?

Activity!

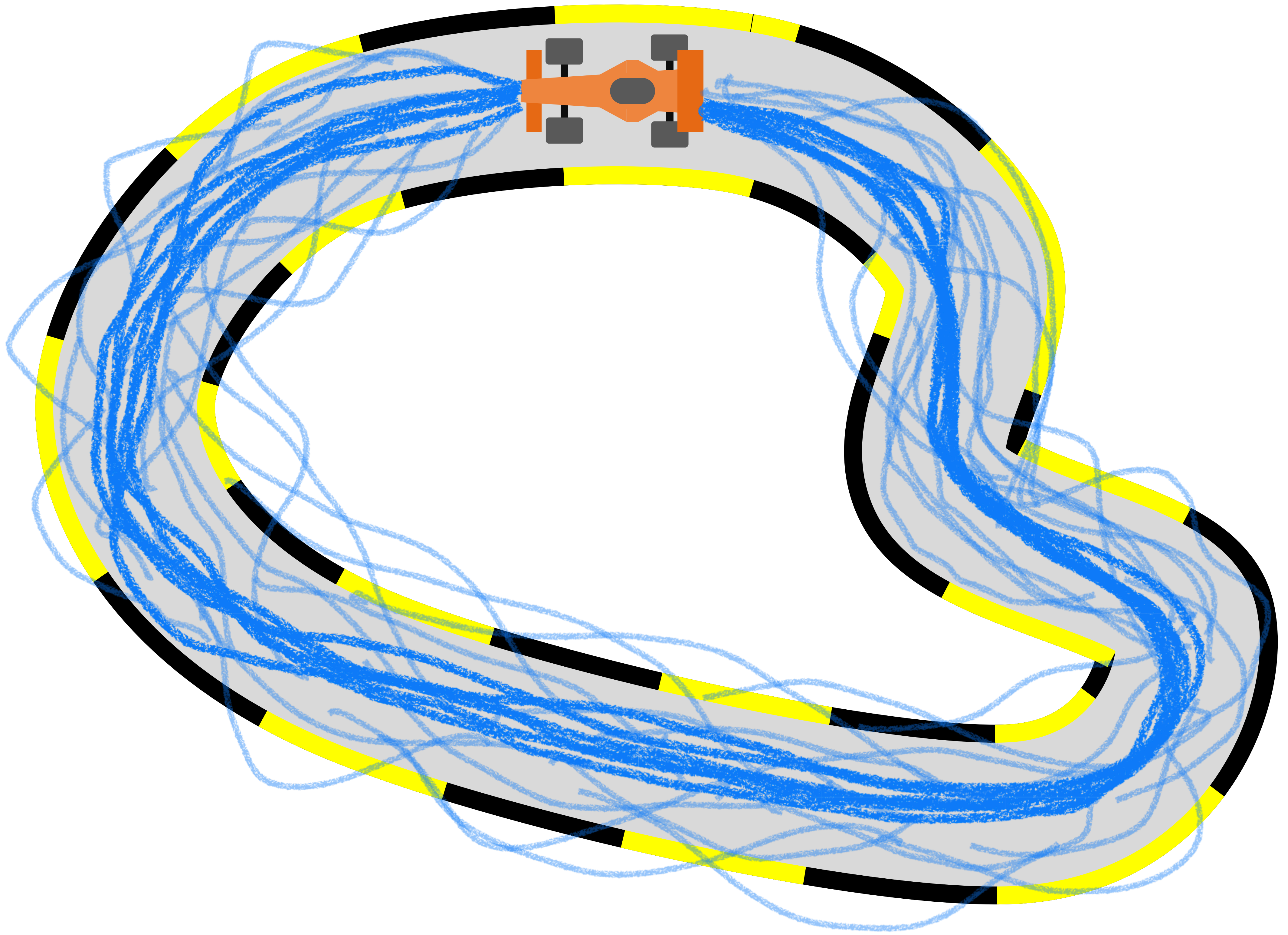
Think-Pair-Share!

To BC, or not to BC!

Think (30 sec): Will BC work? $O(\epsilon T)$ or $O(\epsilon T^2)$?
Make the argument!

Pair: Find a partner

Share (45 sec): Partners exchange ideas



BC results in compounding errors

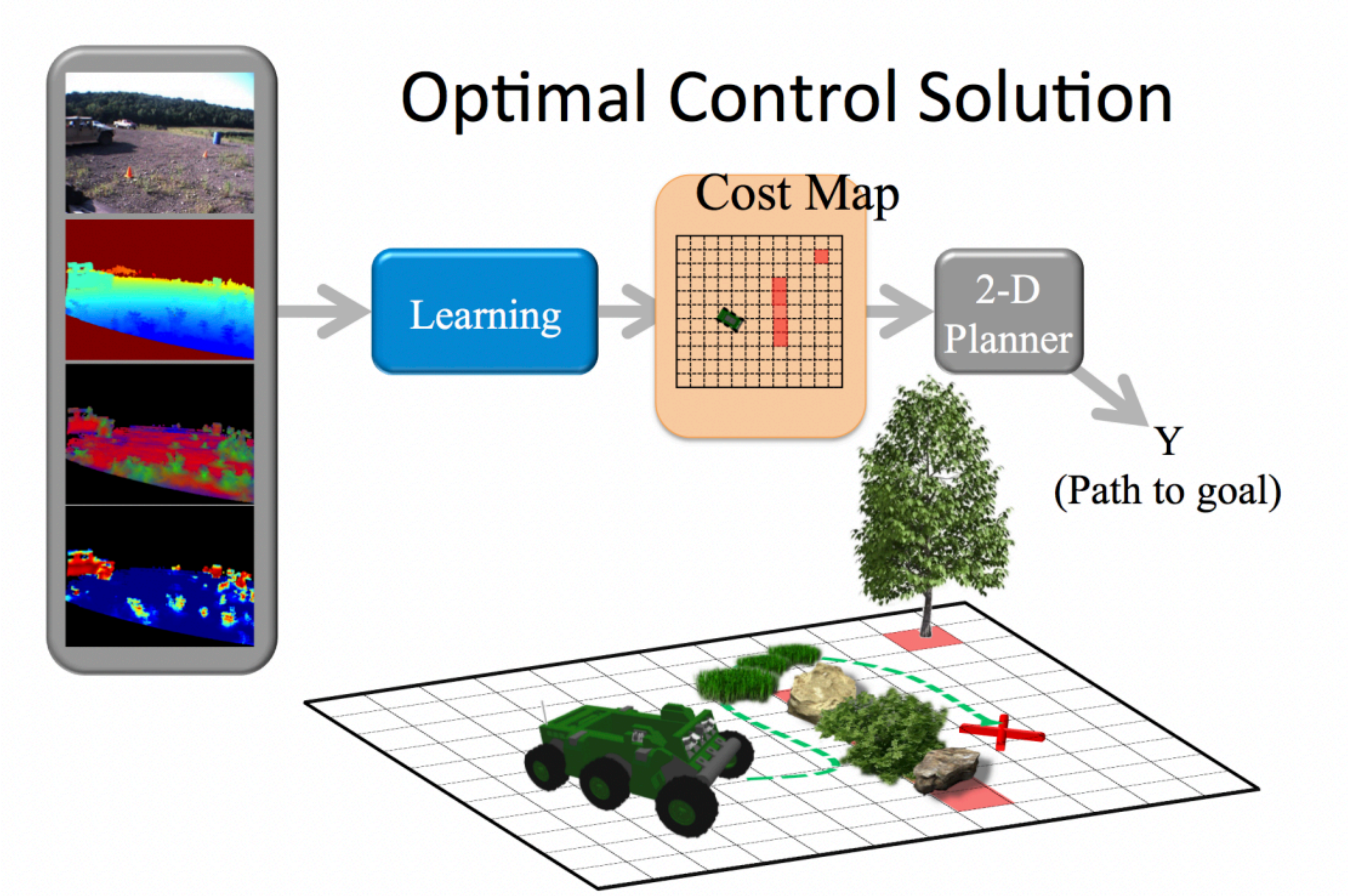
We don't have an interactive expert

What if we knew our MDP (except the cost)?

Or what if we had an interactive simulator?

CRUSHER robot from CMU

Can we learn a cost function for CRUSHER navigation?



Let's formalize!

Learning to Search (LEARCH)

Min distance

Stay on roads

Stay near trees

Learning to Search: Functional Gradient Techniques for Imitation Learning

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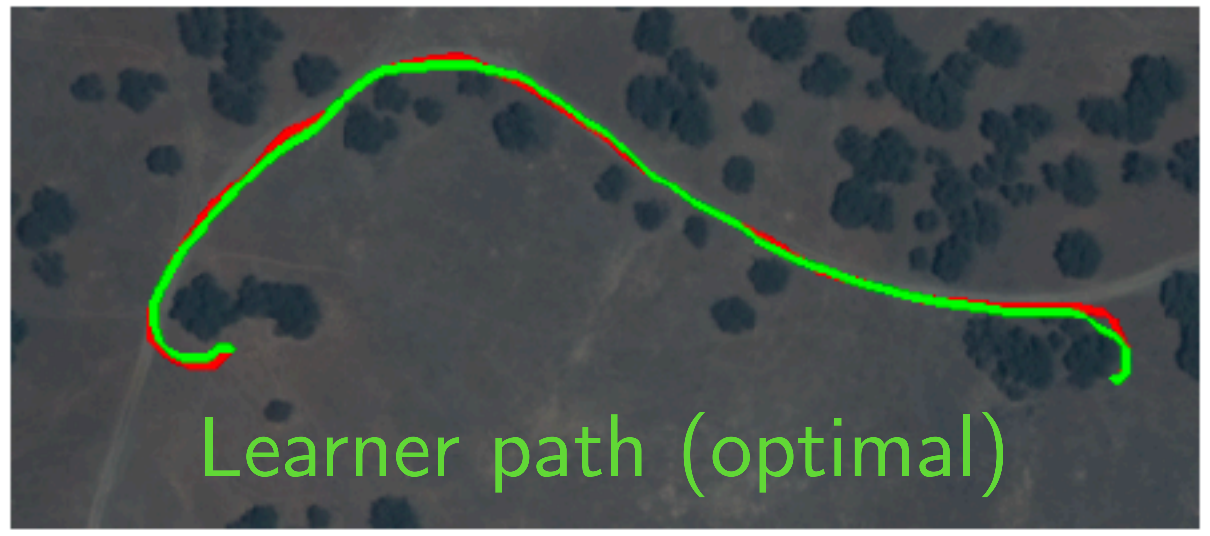
Learning to Search (LEARCH)

Human demonstration

Human demonstration



Given dataset: $\{\xi_i^h, \phi_i\}_{i=1}^N$

(Human demo) *(Map)*

Solve for cost $C_\theta(\xi)$

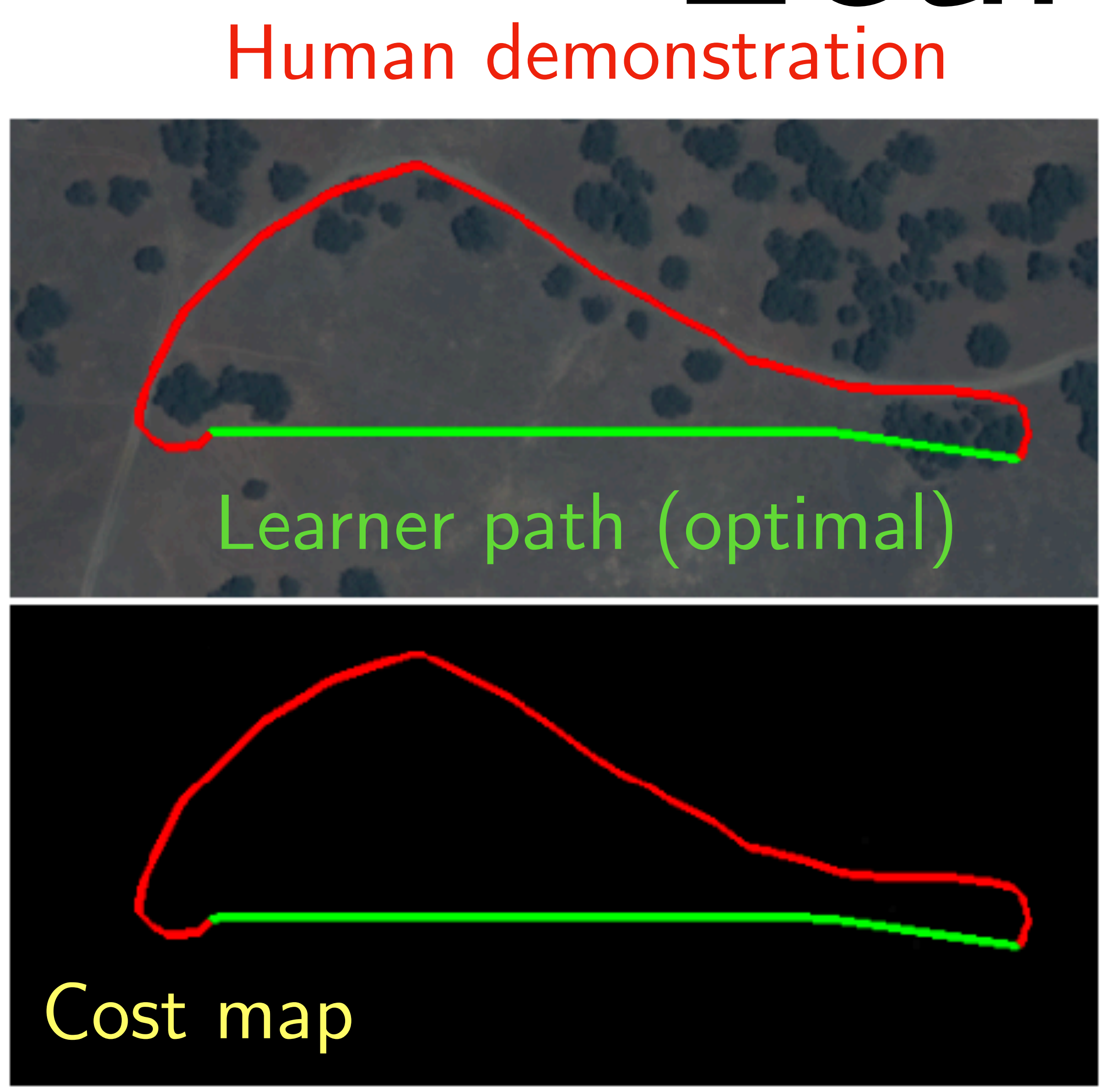
$$\min_\theta \frac{1}{N} \sum_{i=1}^N \left(C_\theta(\xi_i^h, \phi_i) - \min_\xi [C_\theta(\xi, \phi_i) - \underbrace{\gamma(\xi, \xi^h)}_{\text{(Margin)}}] \right) + R(\theta)$$

Human Cost

Learner Cost

Regularizer

Learning to Search (LEARCH)



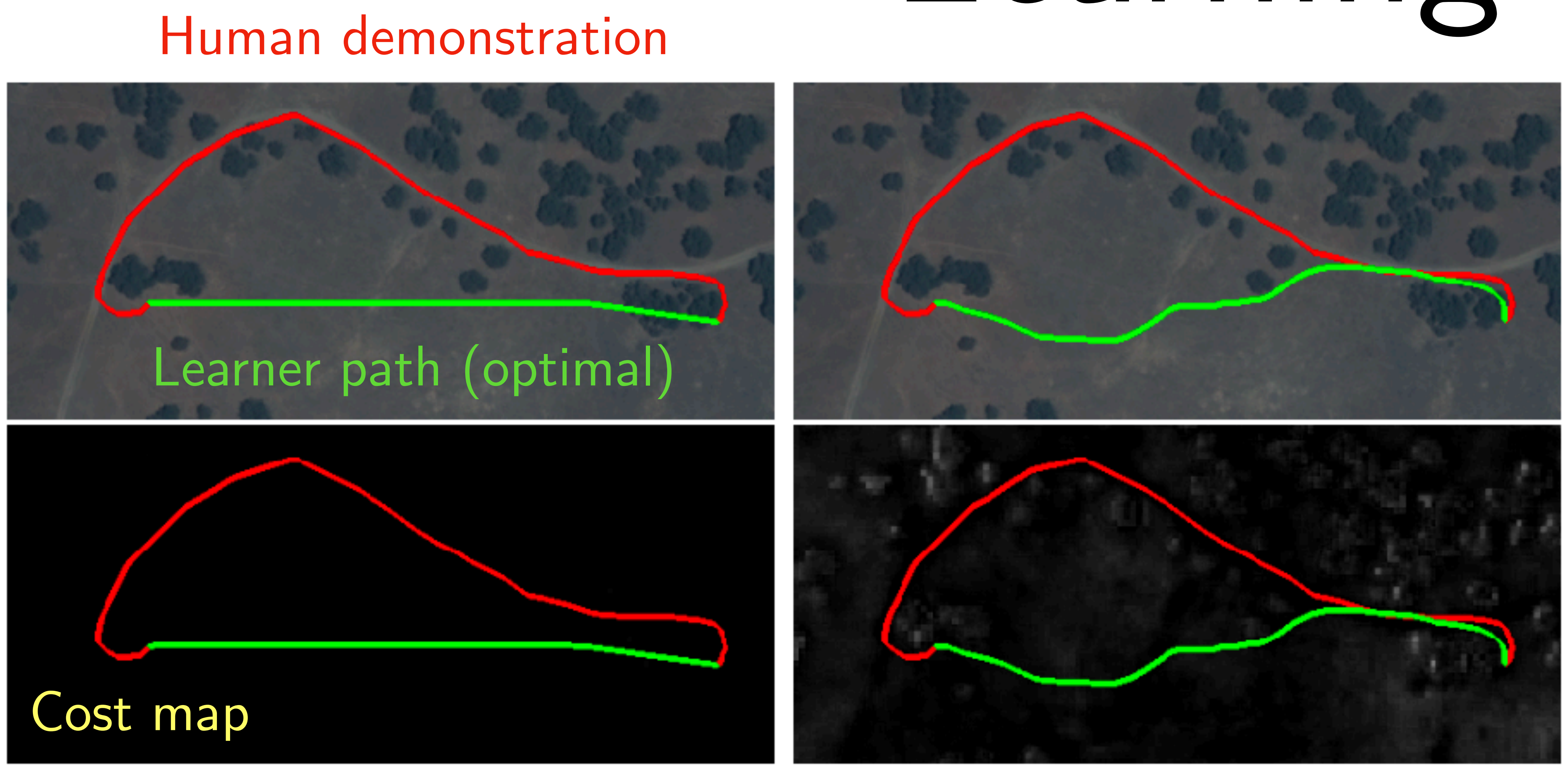
for $i = 1, \ldots, N$ # Loop over datapoints

$$\xi_i^* = \min_{\xi}[C_\theta(\xi, \phi_i) - \gamma(\xi, \xi^h)]$$ # Call planner!

$$\theta^+ = \theta - \eta[\nabla_\theta C_\theta(\xi_i^h, \phi_i) - \nabla_\theta C_\theta(\xi_i^*, \phi_i) + \nabla_\theta R(\theta)]$$

(Push down human cost) *(Push up planner cost)* # Update cost

Learning to Search



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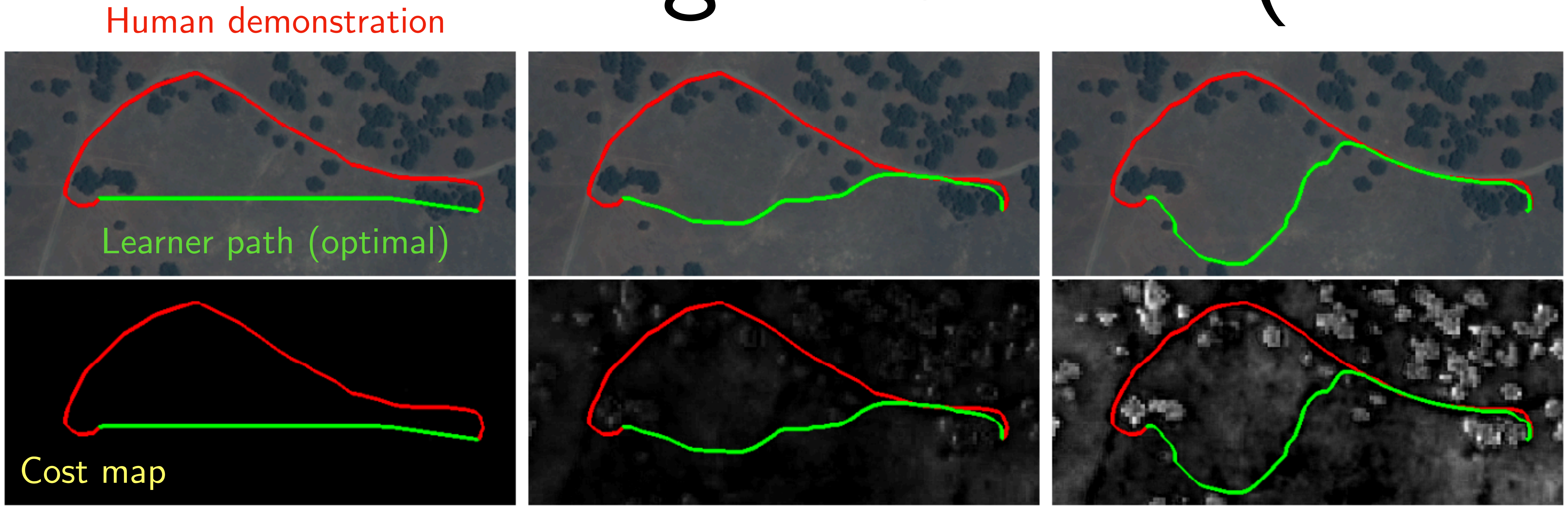

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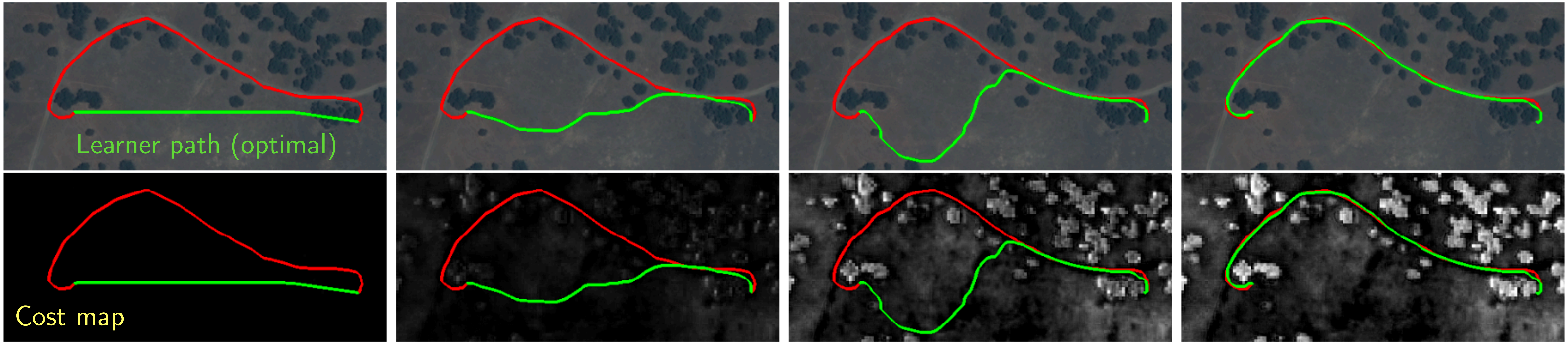
Learning to Search (LEARCH)



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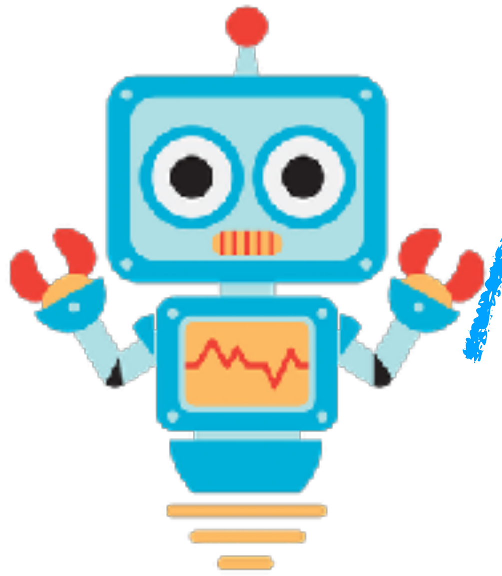
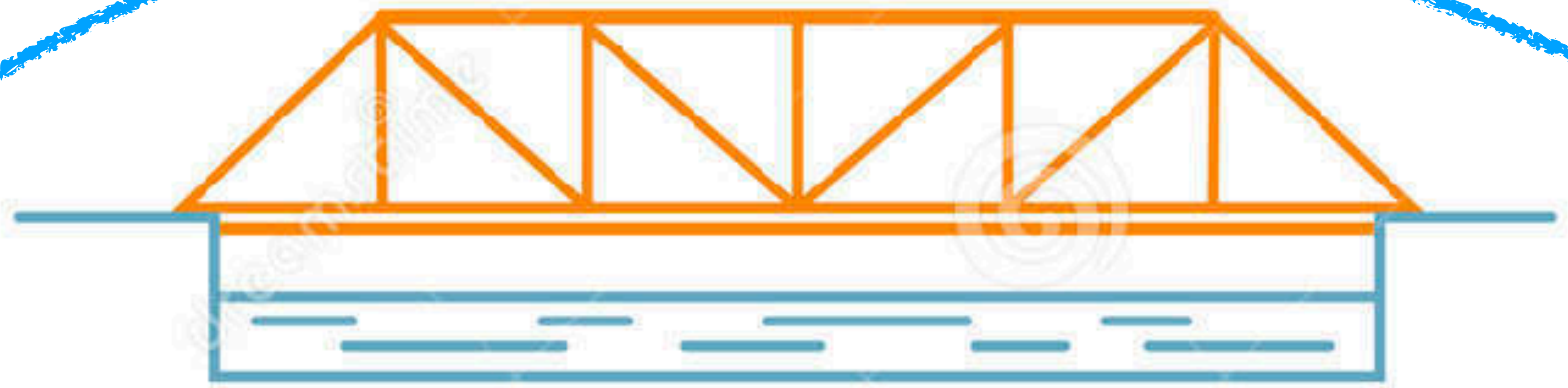
(Push down human cost) *(Push up planner cost)* # Update cost

What happens when the expert is stochastic / noisy / suboptimal?

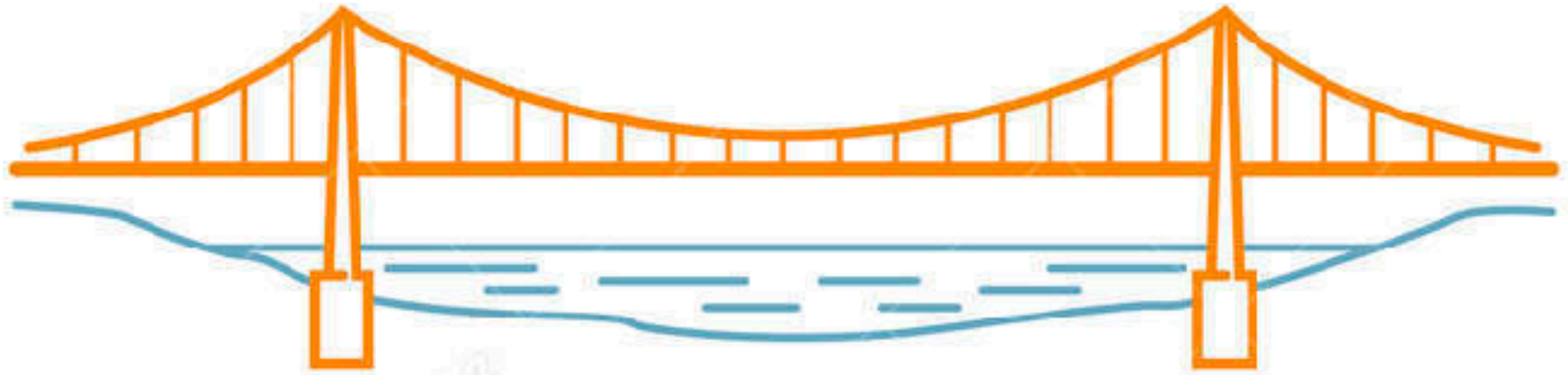
Learning which bridge to cross

Demonstrations always pick Bridge 1





$f = [1 \quad 0 \quad 0]$

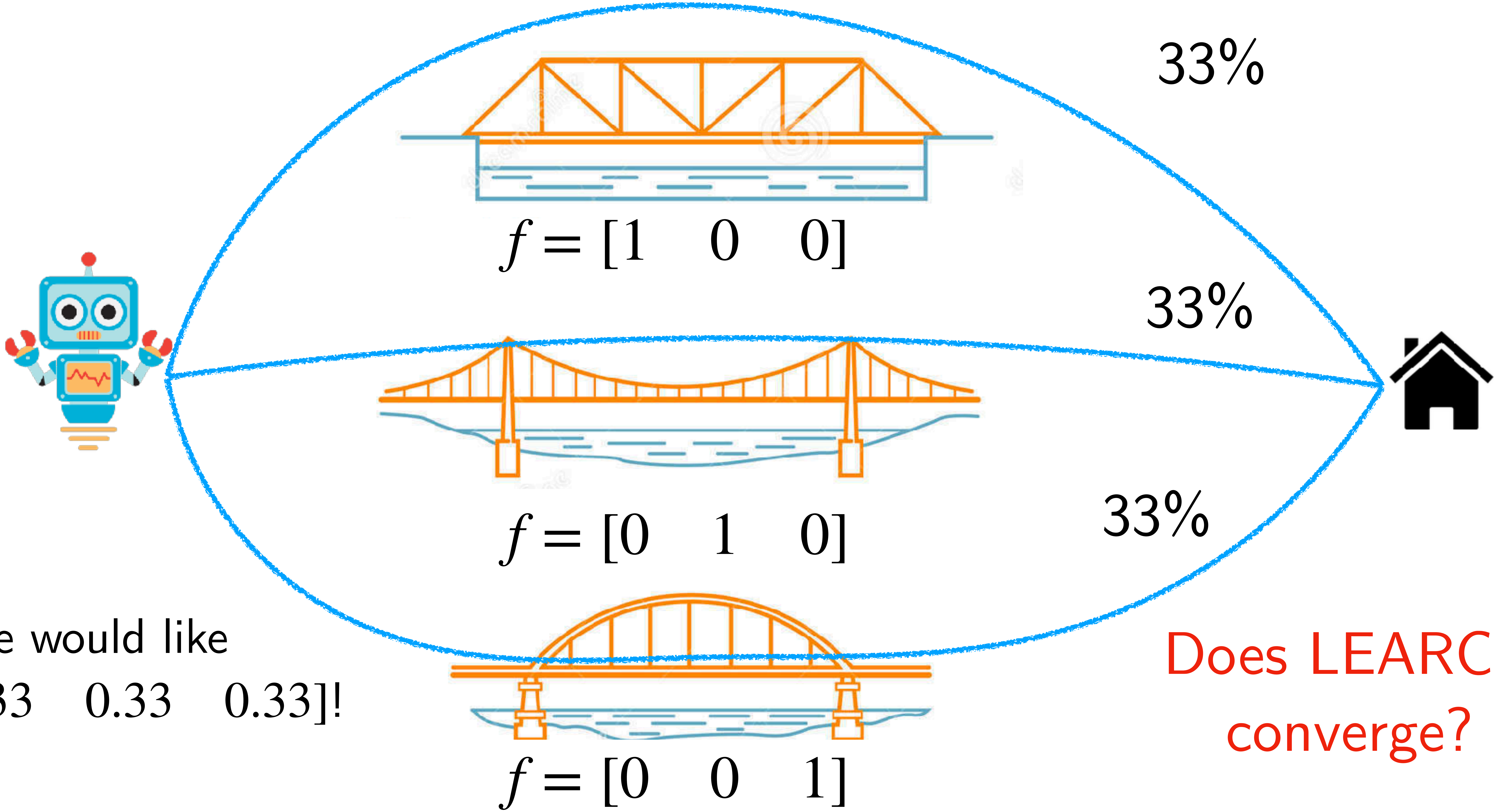


$f = [0 \quad 1 \quad 0]$

$f = [0 \quad 0 \quad 1]$

LEARCH converges to $w = [1 \quad 0 \quad 0]$!

Learning which bridge to cross



We would like
$w = [0.33 \quad 0.33 \quad 0.33]$!

Does LEARCH converge?

When the expert

is Suboptimal /

is Noisy /

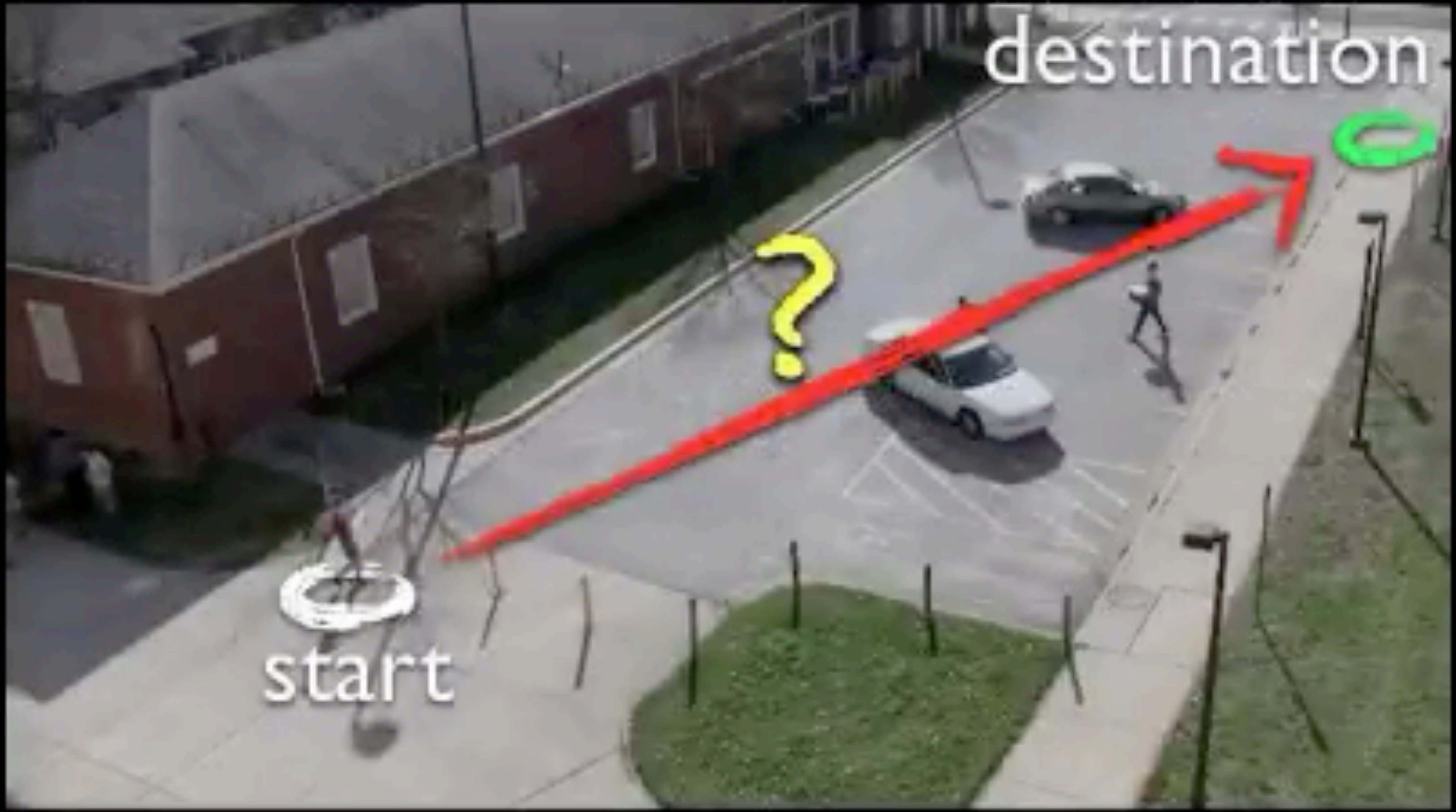
Has Privileged Information

LEARCH does NOT converge!!

Activity Forecasting

Kris M. Kitani, Brian D. Ziebart, J. Andrew Bagnell, and Martial Hebert

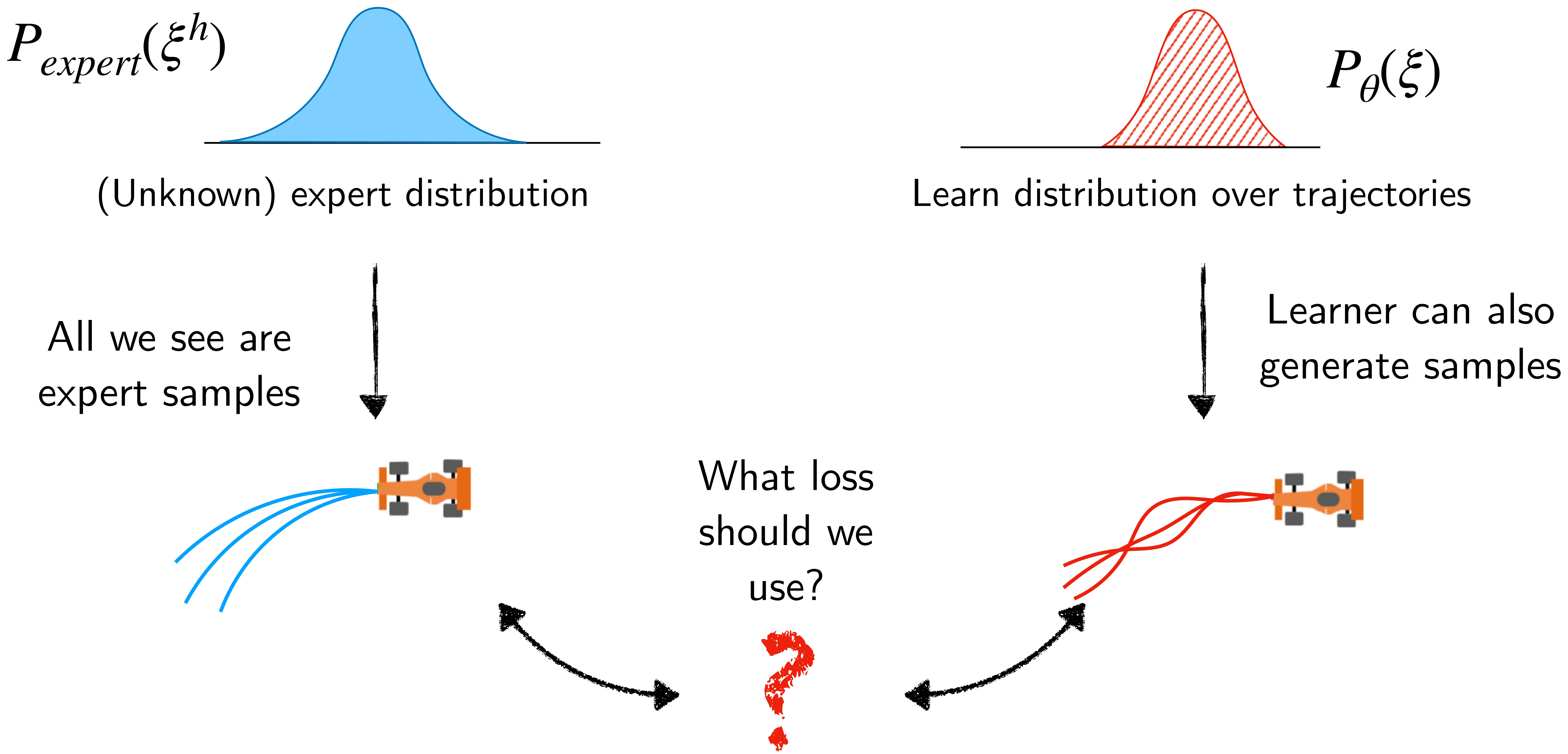
Carnegie Mellon University, Pittsburgh, PA 15213 USA
{kkitani,bziebart}@cs.cmu.edu, {dbagnell,hebert}@ri.cmu.edu



Expert demonstrations are coming from some (unknown) distribution ..

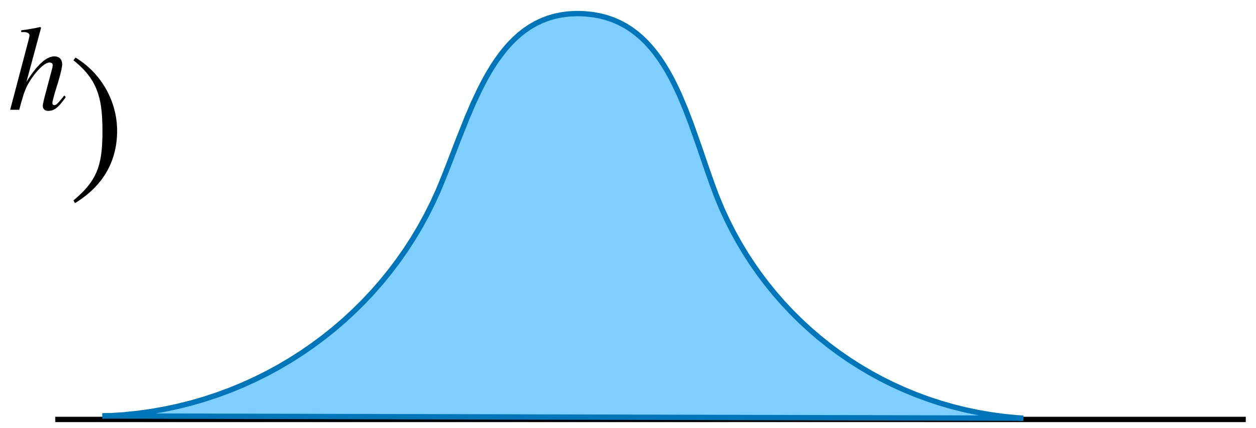
Can we learn this distribution?

The Distribution Matching Problem

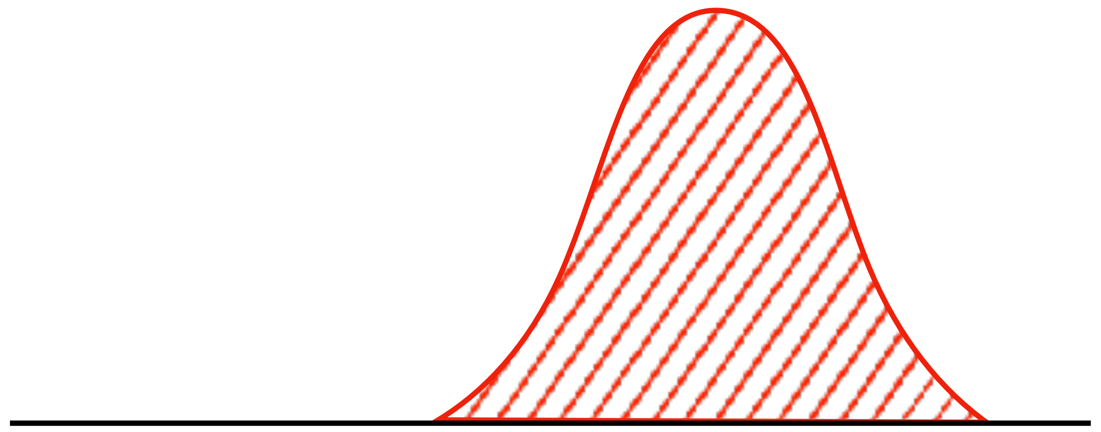


Proposal: Match expected features!

$P_{expert}(\xi^h)$



(Unknown) expert distribution

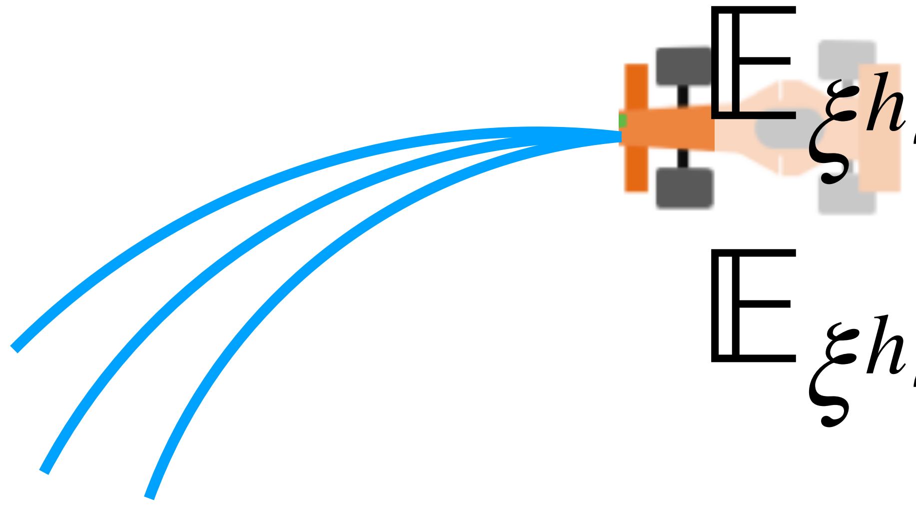


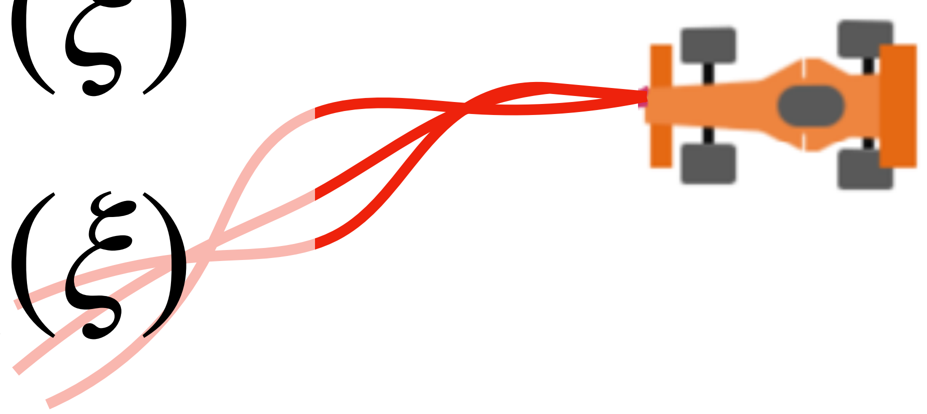
$P_\theta(\xi)$

Learn distribution over trajectories

All we see are expert samples

Learner can also generate samples





$$\mathbb{E}_{\xi^h \sim P_{expert}(.)}\, f_1(\xi^h) = \mathbb{E}_{\xi \sim P_\theta(.)}\, f_1(\xi)$$

$$\mathbb{E}_{\xi^h \sim P_{expert}(.)}\, f_2(\xi^h) = \mathbb{E}_{\xi \sim P_\theta(.)}\, f_2(\xi)$$

$$\vdots$$

$$\mathbb{E}_{\xi^h \sim P_{expert}(.)}\, f_k(\xi^h) = \mathbb{E}_{\xi \sim P_\theta(.)}\, f_k(\xi)$$

Let's

formalize!

Maximum Entropy Inverse Optimal Control

Maximum Entropy Inverse Reinforcement Learning

Brian D. Ziebart, Andrew Maas, J.Andrew Bagnell, and **Anind K. Dey**
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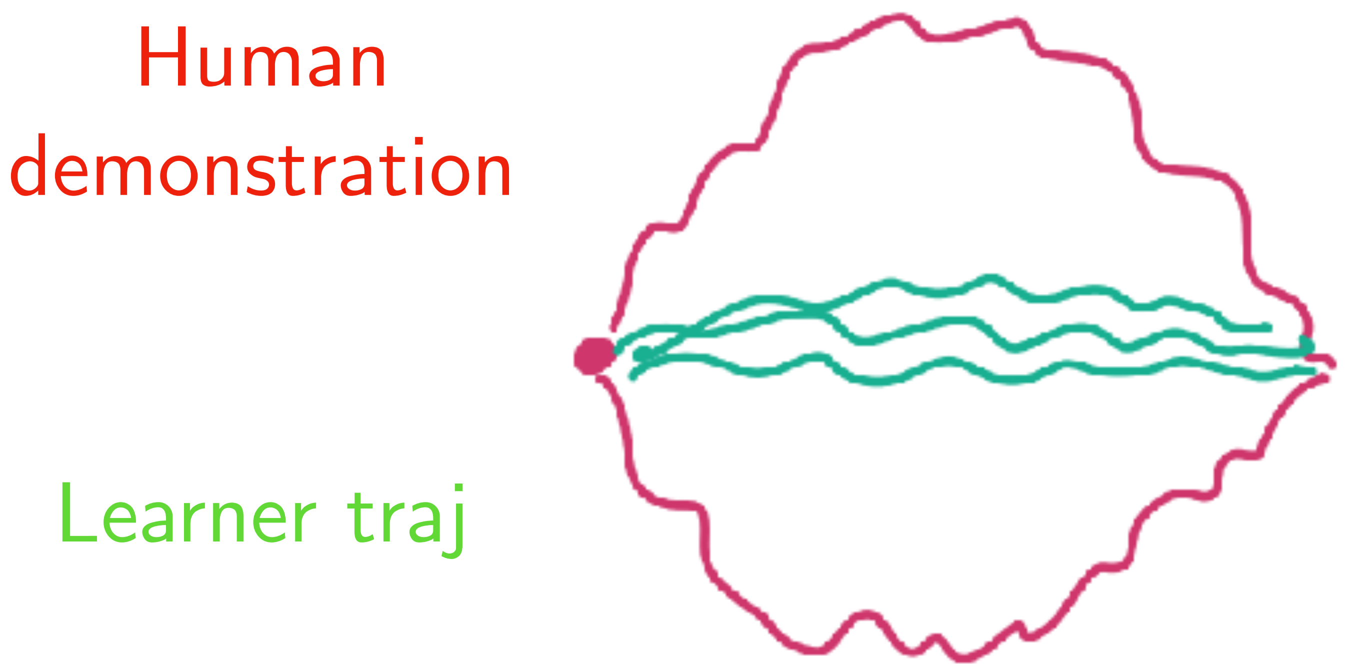
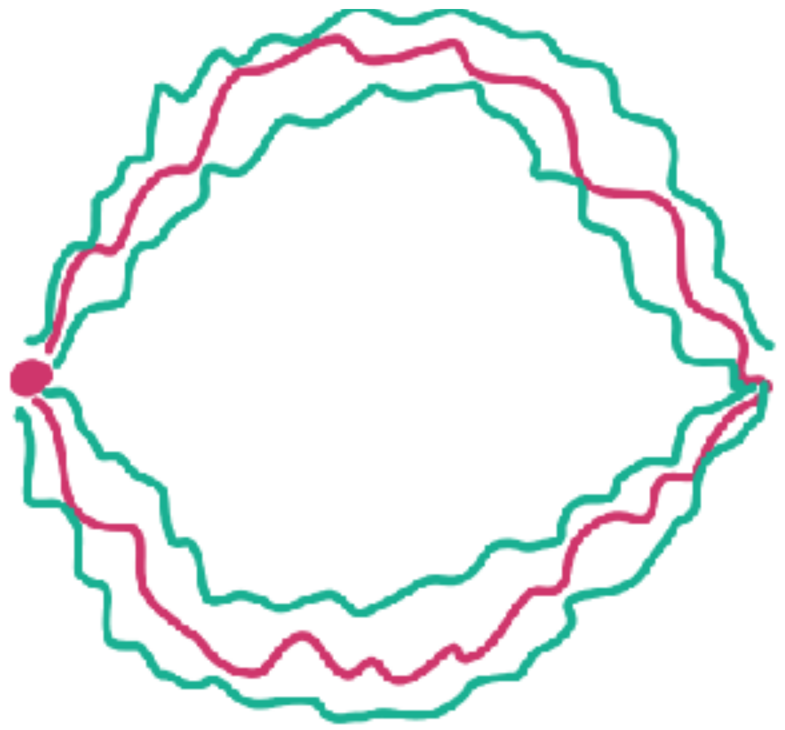
Maximum Entropy Inverse Optimal Control

LEO: Learning Energy-based Models in Factor Graph Optimization

Paloma Sodhi[1,2], Eric Dexheimer[1], Mustafa Mukadam[2], Stuart Anderson[2], Michael Kaess[1]
[1]Carnegie Mellon University, [2] Facebook AI Research

Maximum Entropy Inverse Optimal Control





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(Human demo) *(Map)*

Solve for cost $C_\theta(\xi)$

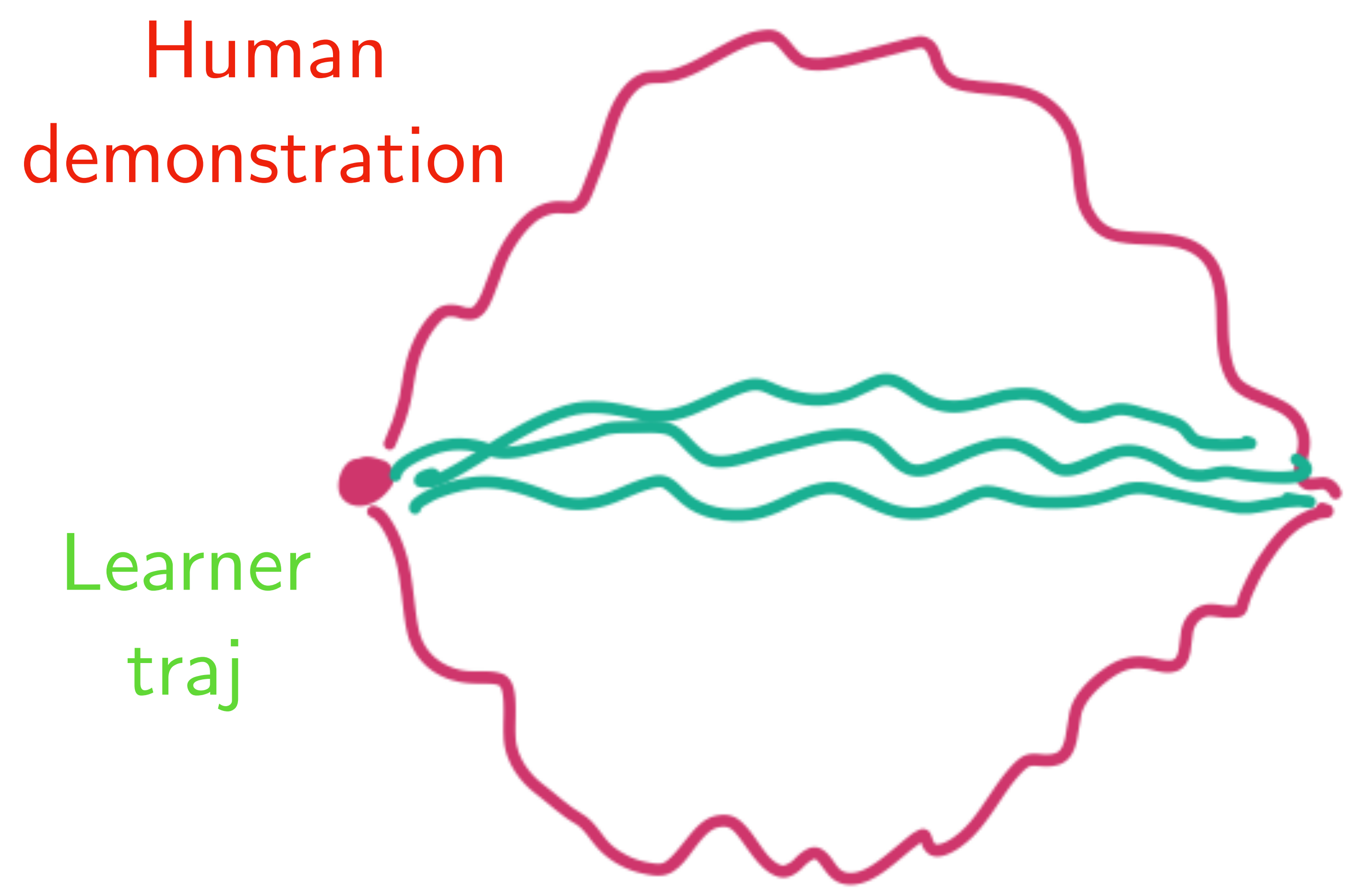
$$\min_\theta \frac{1}{N} \sum_{i=1}^{N} -\log P_\theta(\xi_i^h \mid \phi_i)$$

Max lik. of human traj

$$P_\theta(\xi \mid \phi) = \frac{1}{Z(\theta, \phi)} \exp(-C_\theta(\xi, \phi))$$

More costly traj, less likely

Maximum Entropy Inverse Optimal Control



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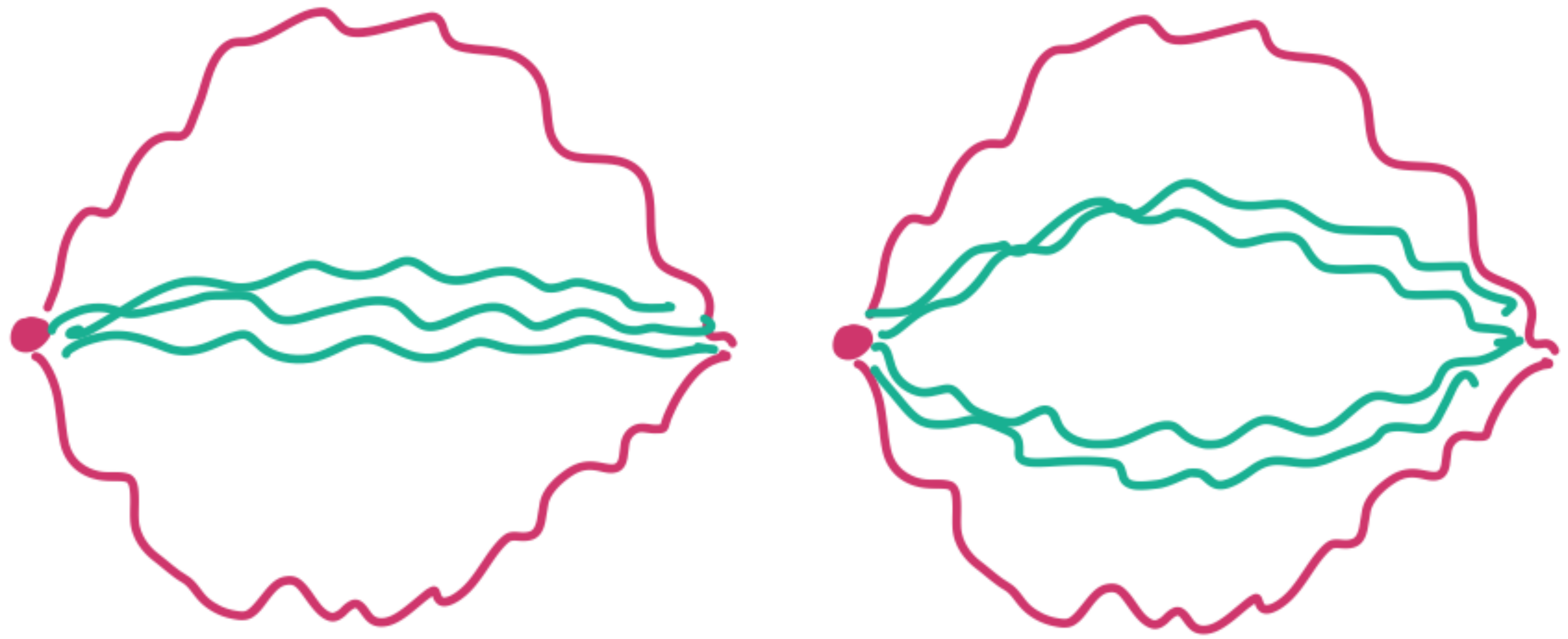
$$\theta^+ = \theta - \eta[\nabla_\theta C_\theta(\xi_i^h, \phi_i) - \nabla_\theta C_\theta(\xi_i, \phi_i)]$$ # Update cost

(Push down human cost) *(Push up planner cost)*

Maximum Entropy Inverse Optimal Control



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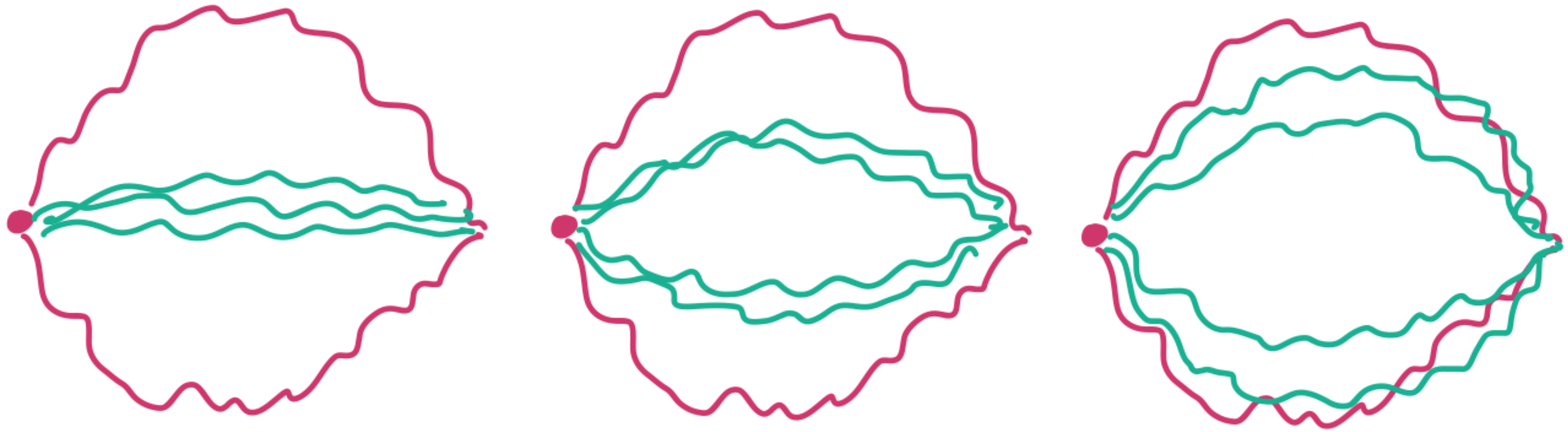

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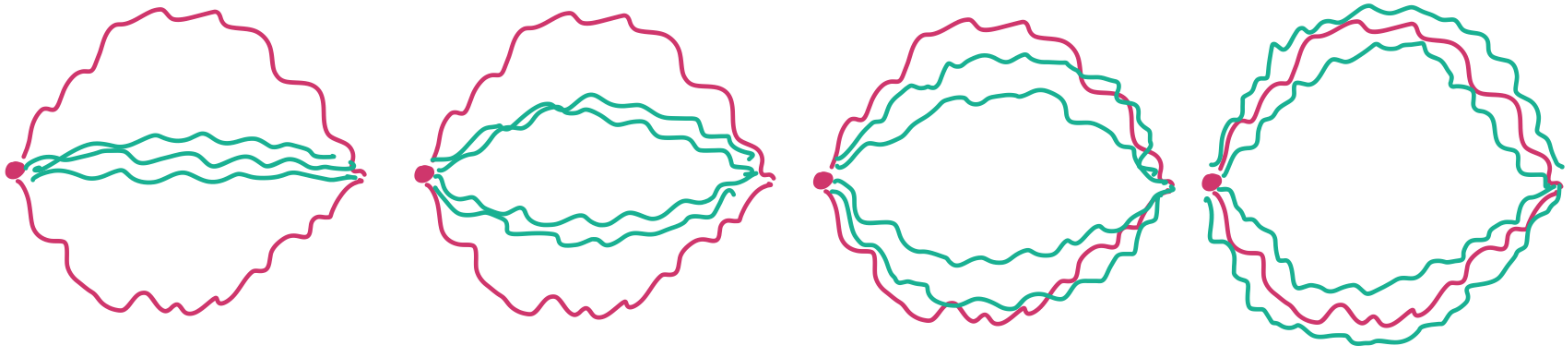
Maximum Entropy Inverse Optimal Control



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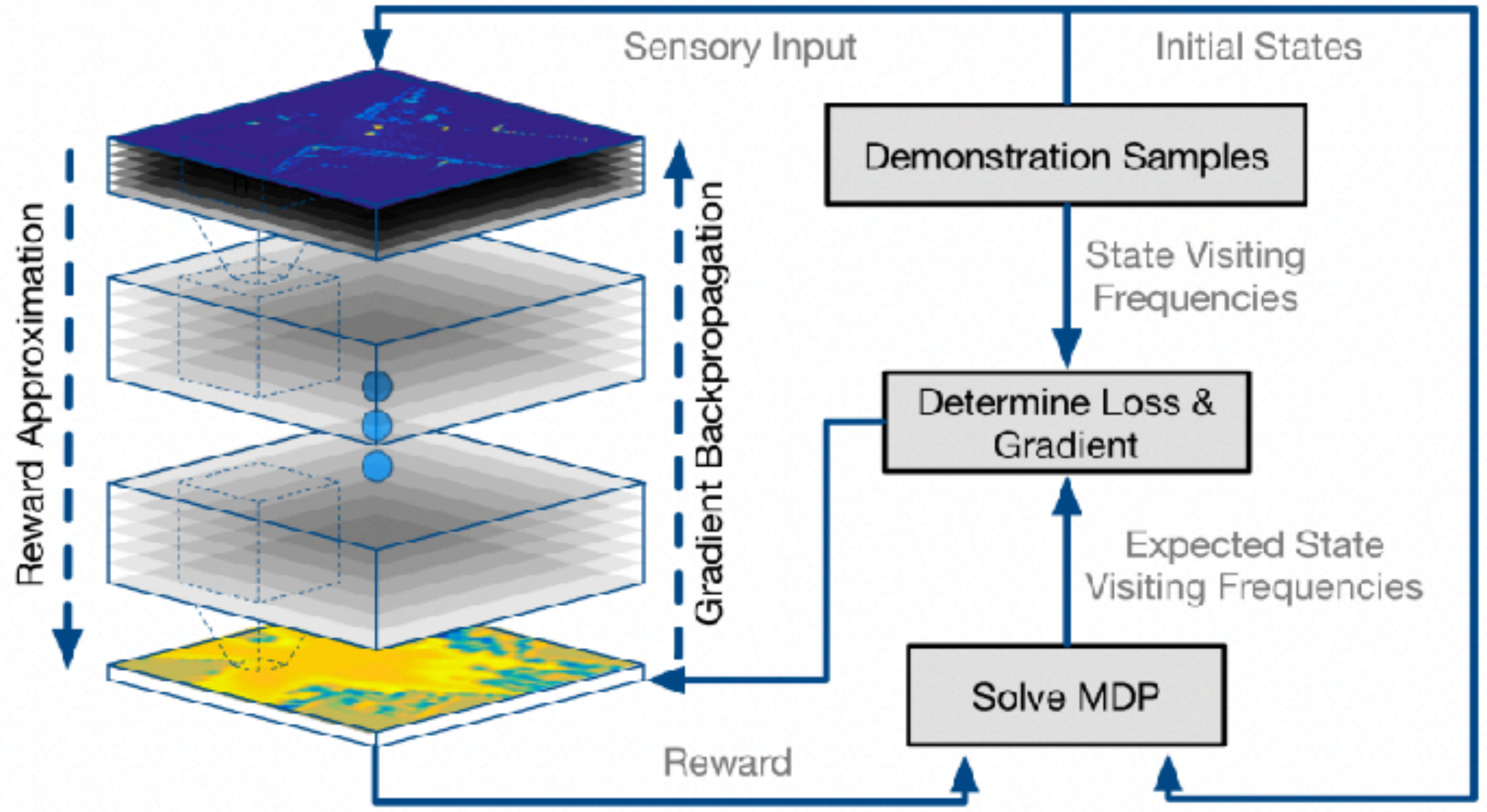
Deep Max Ent

Watch This: Scalable Cost-Function Learning for Path Planning in Urban Environments

Markus Wulfmeier[1], Dominic Zeng Wang[1] and Ingmar Posner[1]




autonomous execution
1x real-time
PR2
goal
our method
IOC samples from $q(u_t|x_t)$

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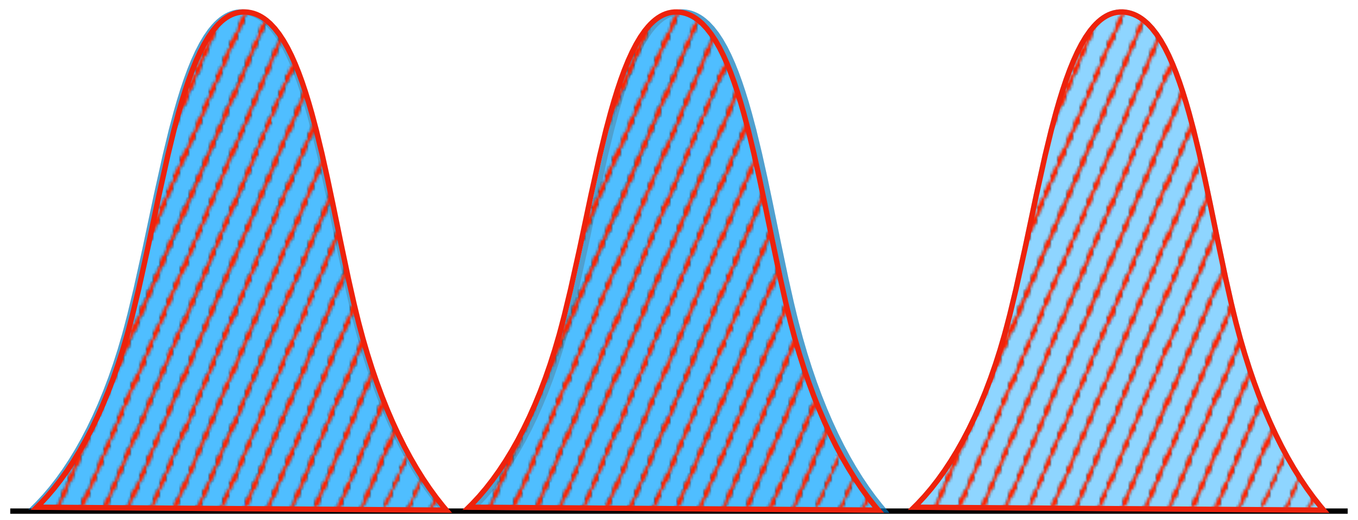


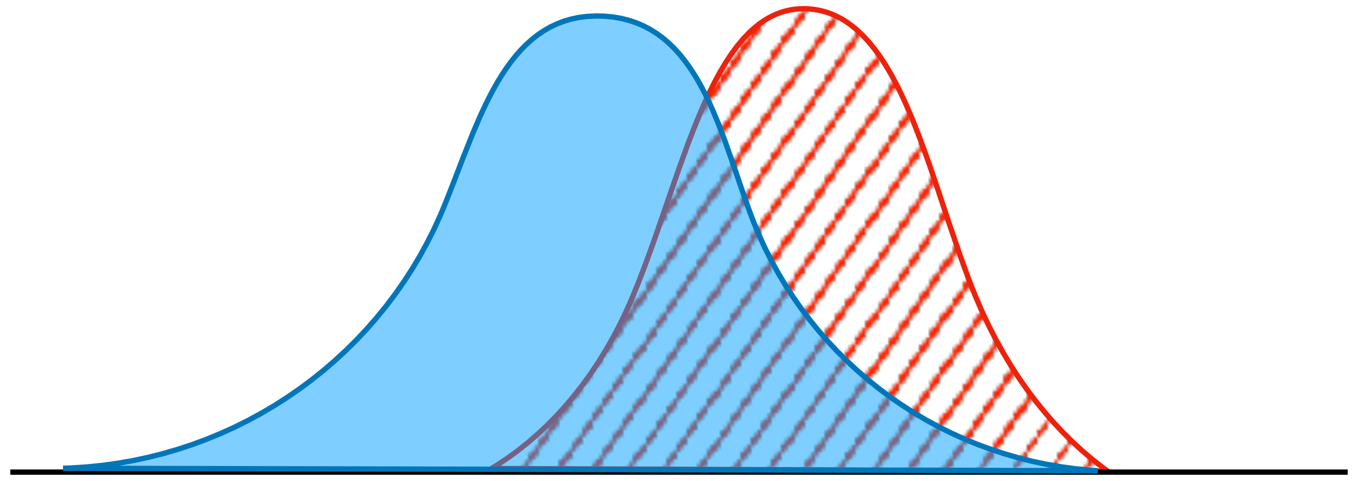
Nothing special. Collect lots of data and do Behavior Cloning

Medium

Non-realizable expert but full expert support

Even as $N \to \infty$, behavior cloning $O(\epsilon C T)$

where C is conc. coeff

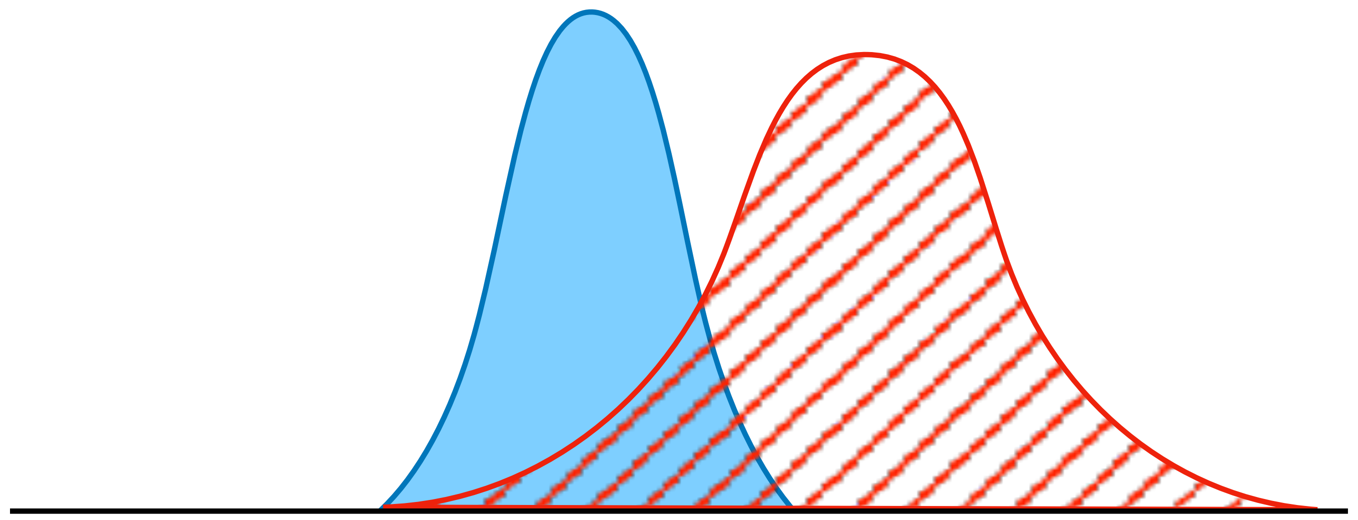


Requires interactive simulator (MaxEntIRL) to match distribution $\Rightarrow O(\epsilon T)$

Hard

Non-realizable expert + limited expert support

Even as $N \to \infty$, behavior cloning $O(\epsilon T^2)$



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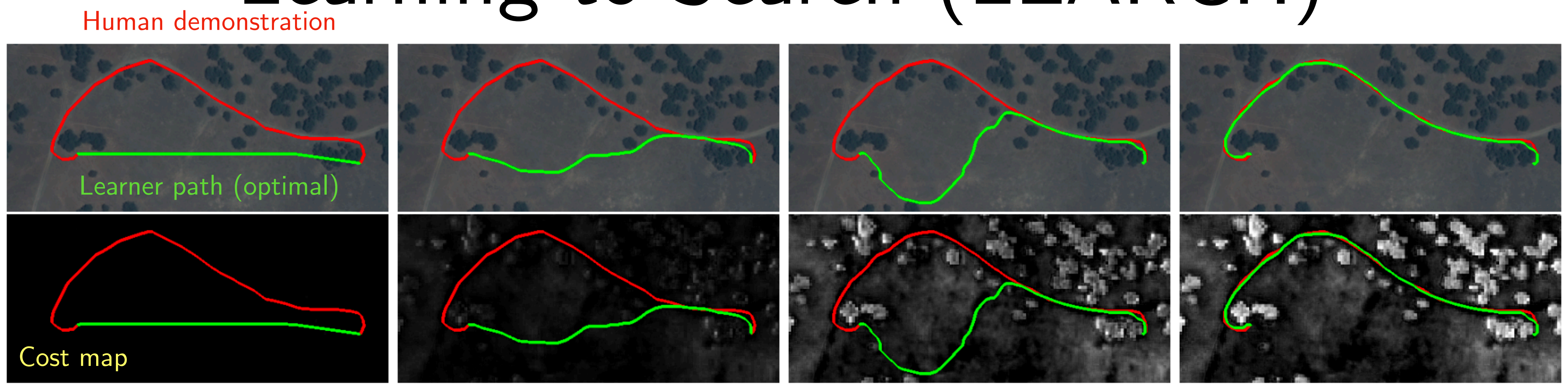
tl;dr

Learning to Search (LEARCH)



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x

When the expert is

Suboptimal

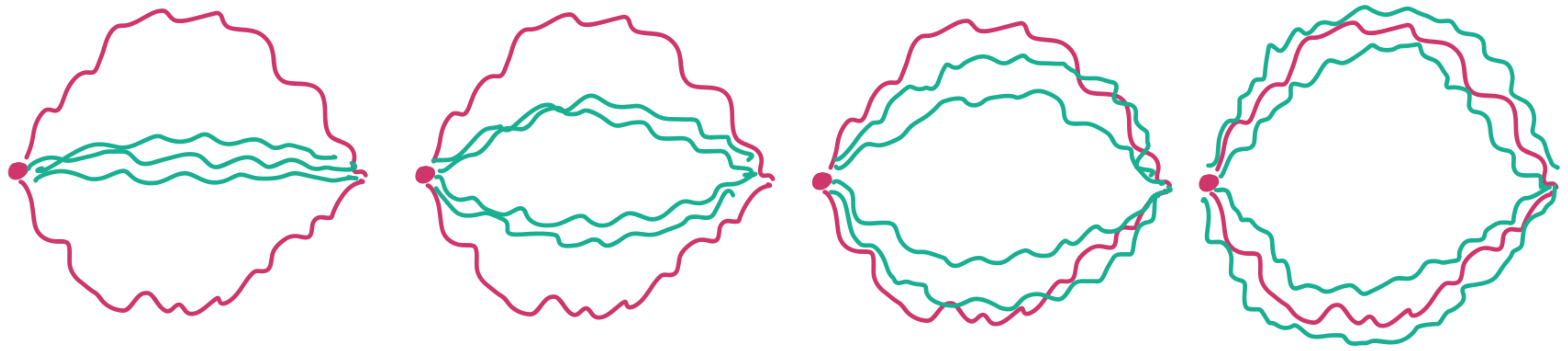
Noisy

Privileged Information

LEARCH does NOT converge!!

x

Maximum Entropy Inverse Optimal Control



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