

# Behavioral Cloning

CMPT 729 G100

Jason Peng

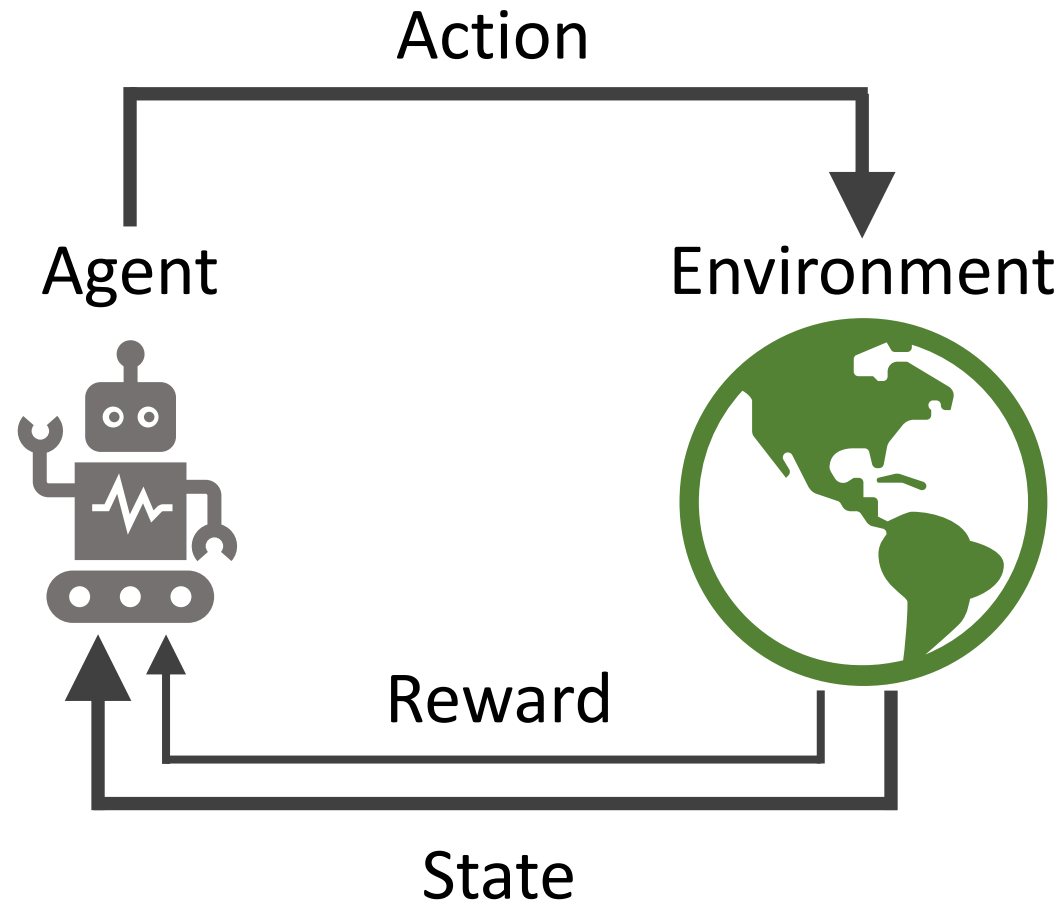
# Overview

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- Behavioral Cloning
- Drift
- Theoretical Analysis
- DAgger
- Applications

# Agent-Environment Interface

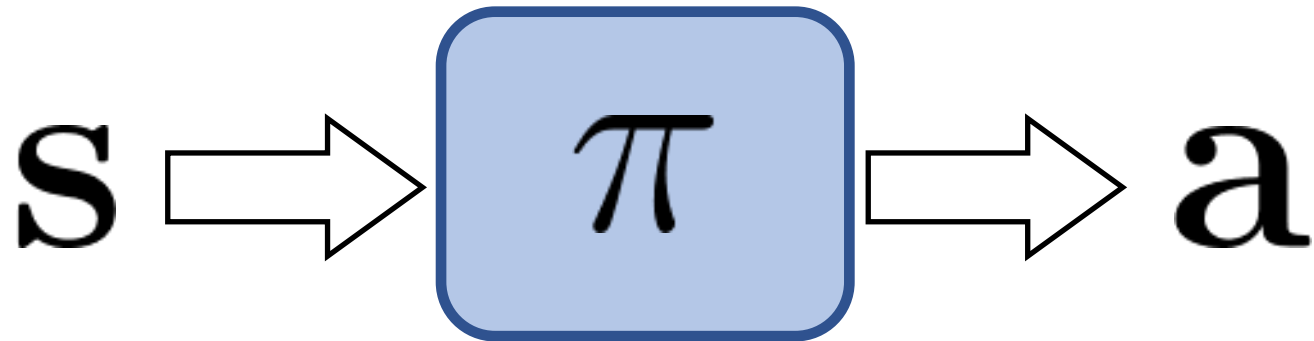
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# Policy

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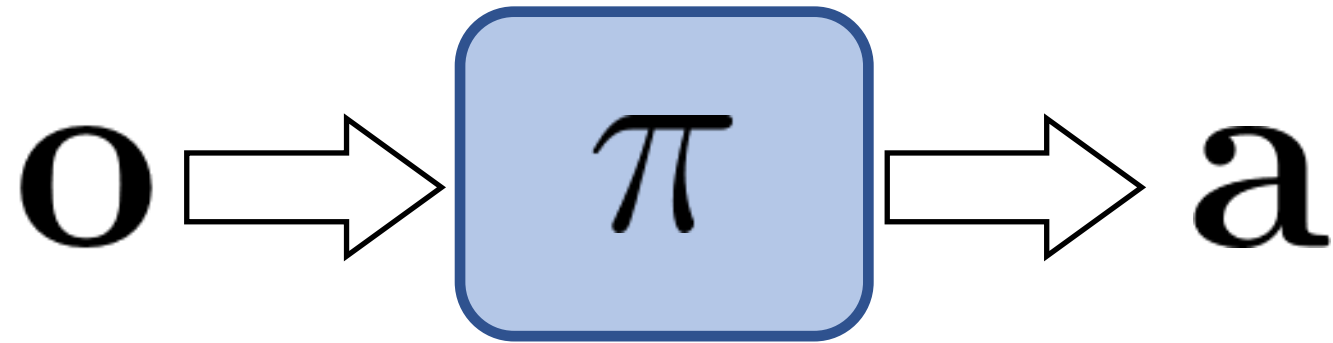
$$\pi(\mathbf{a}|\mathbf{s})$$



# Policy

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$$\pi(\mathbf{a}|\mathbf{o})$$



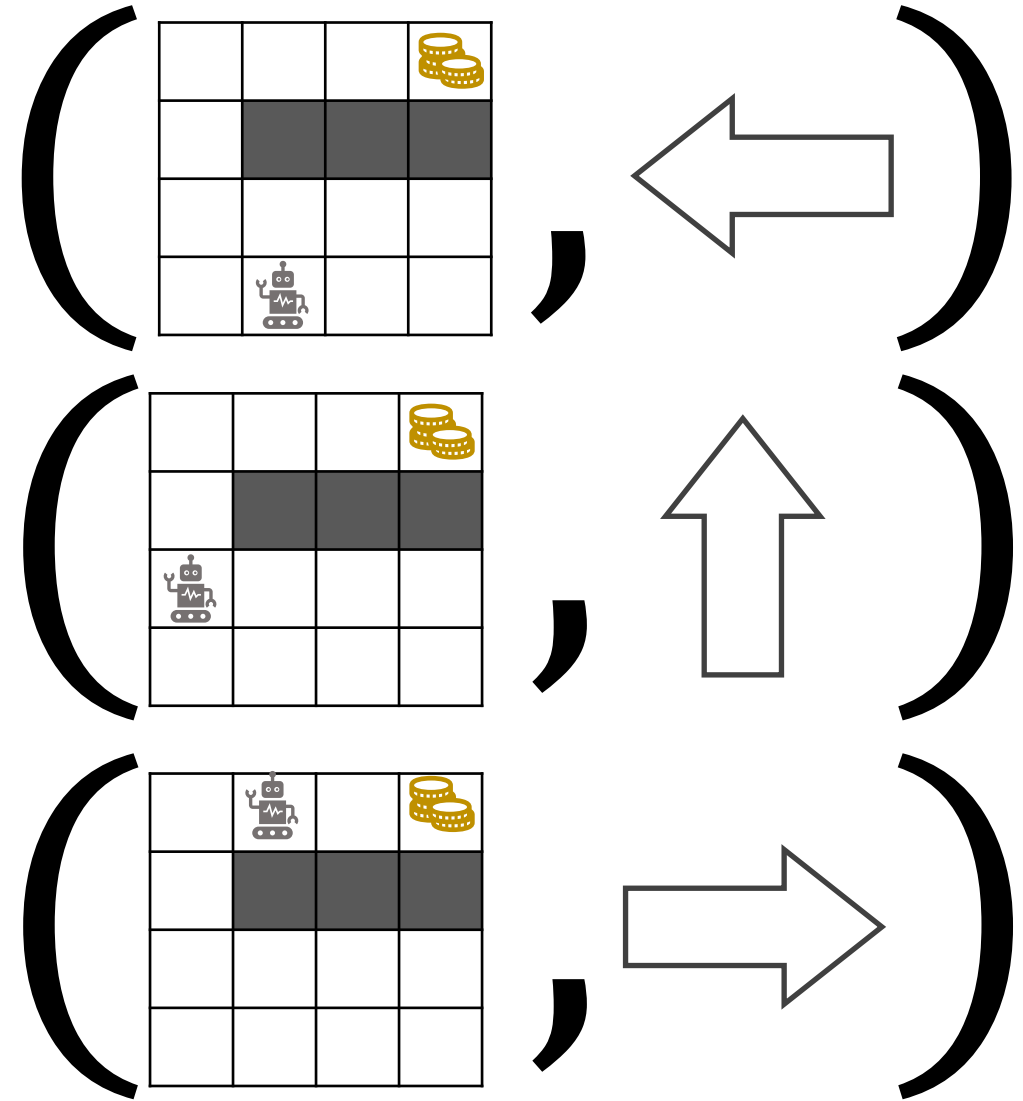
# Supervised Learning

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$\{(\mathbf{o}_0, \mathbf{a}_0), (\mathbf{o}_1, \mathbf{a}_1), \dots\}$



Dataset



# Supervised Learning

$$\{(\mathbf{o}_0, \mathbf{a}_0), (\mathbf{o}_1, \mathbf{a}_1), \dots\}$$



Dataset



Nvidia Automotive Simulation  
[NVIDIA]



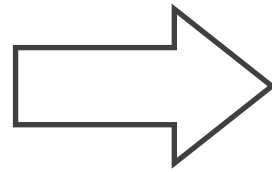
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Dataset



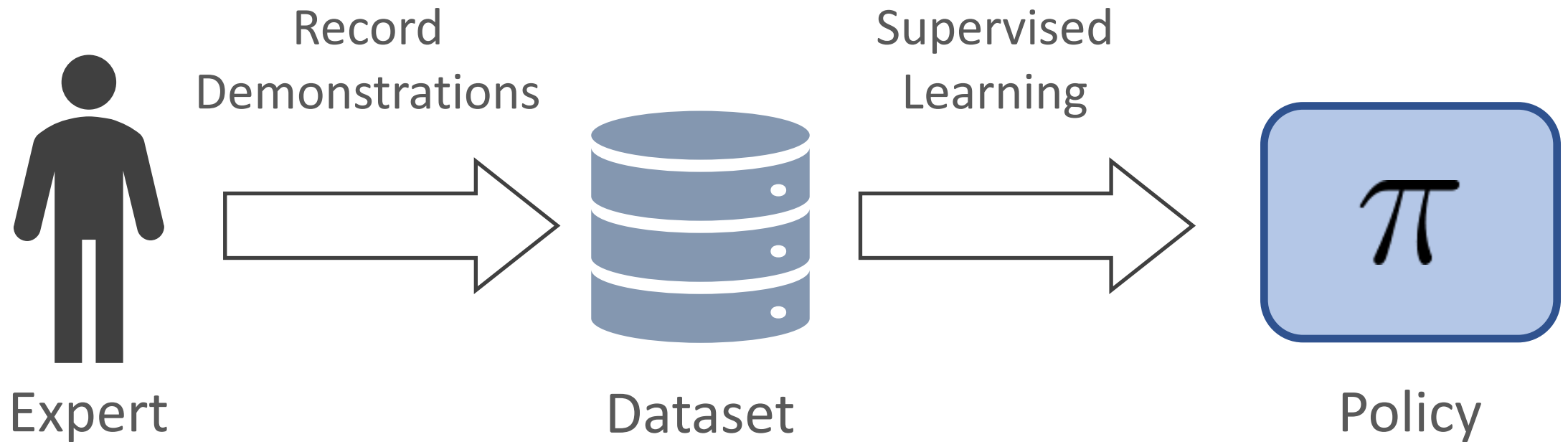
$$\min_{\pi} \mathbb{E}_{(\mathbf{o}, \mathbf{a}) \sim \mathcal{D}} [-\log \pi(\mathbf{a} | \mathbf{o})]$$

Behavioral Cloning



# Behavioral Cloning

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# Behavioral Cloning

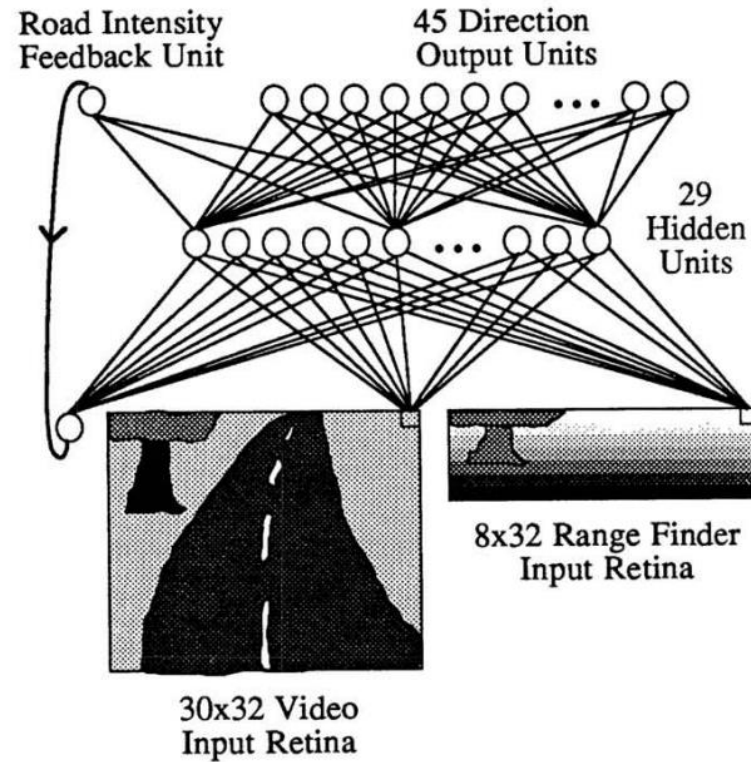


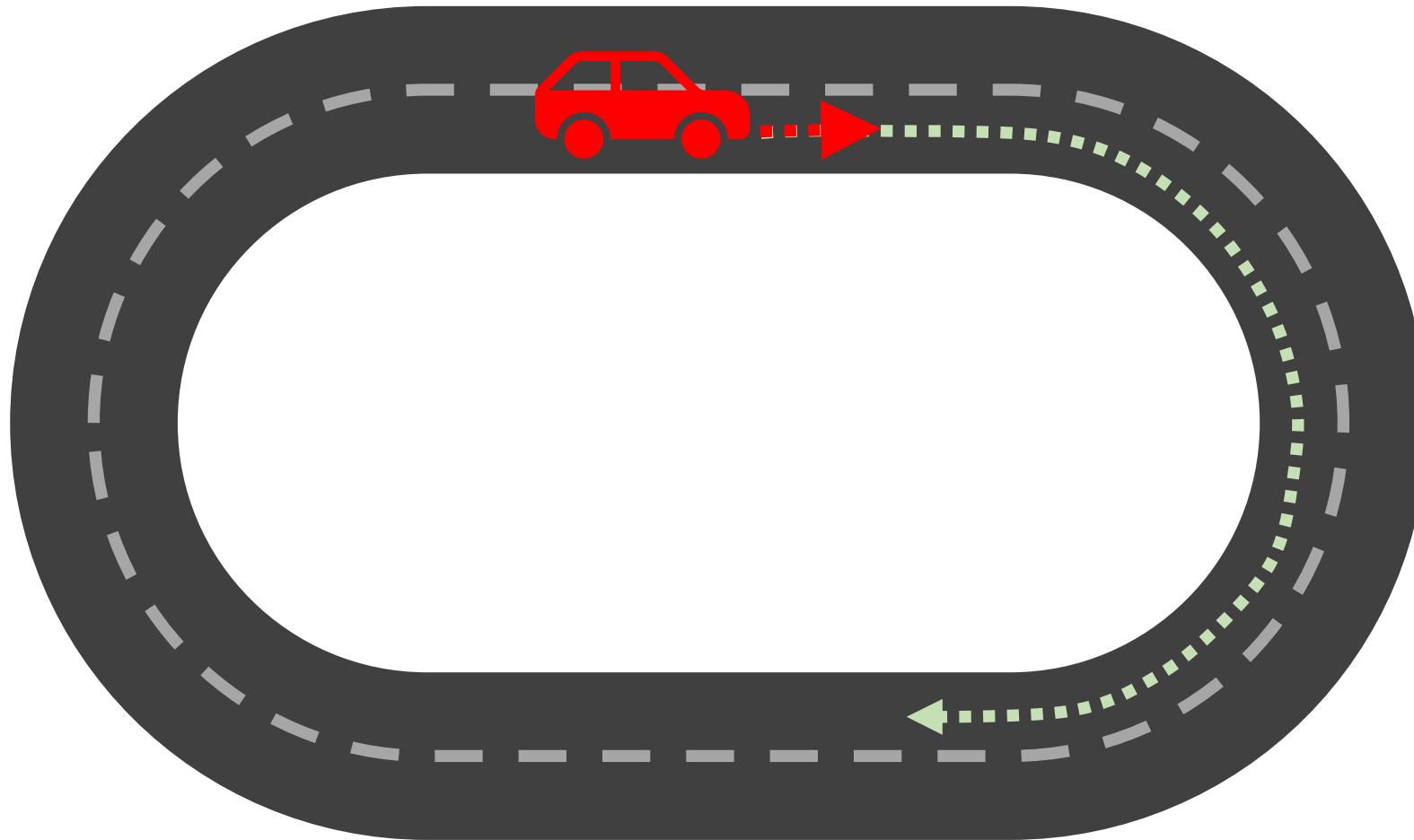
Figure 1: ALVINN Architecture



ALVINN: An Autonomous Land Vehicle in a Neural Network  
[Pomerleau 1989]

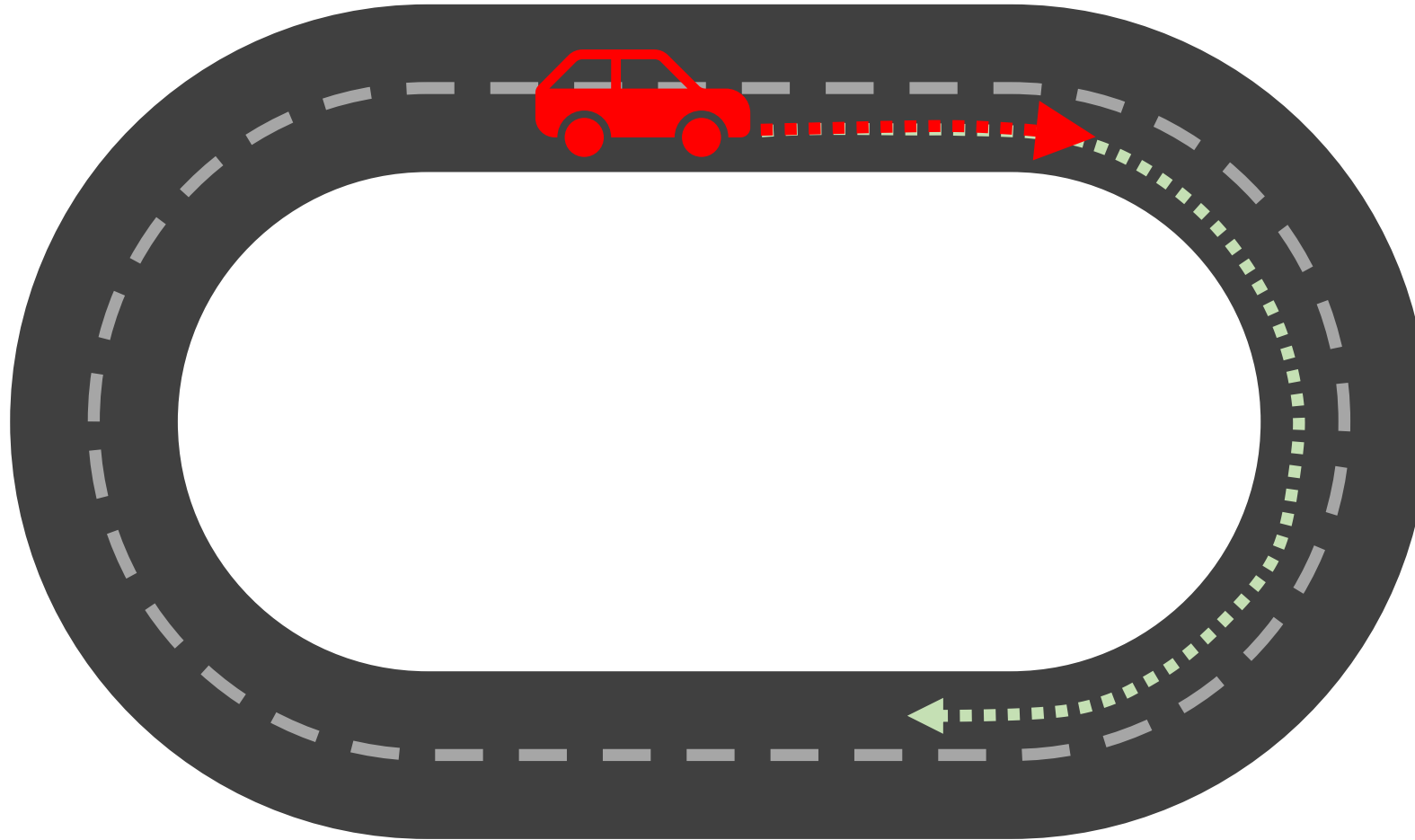
# Does it work?

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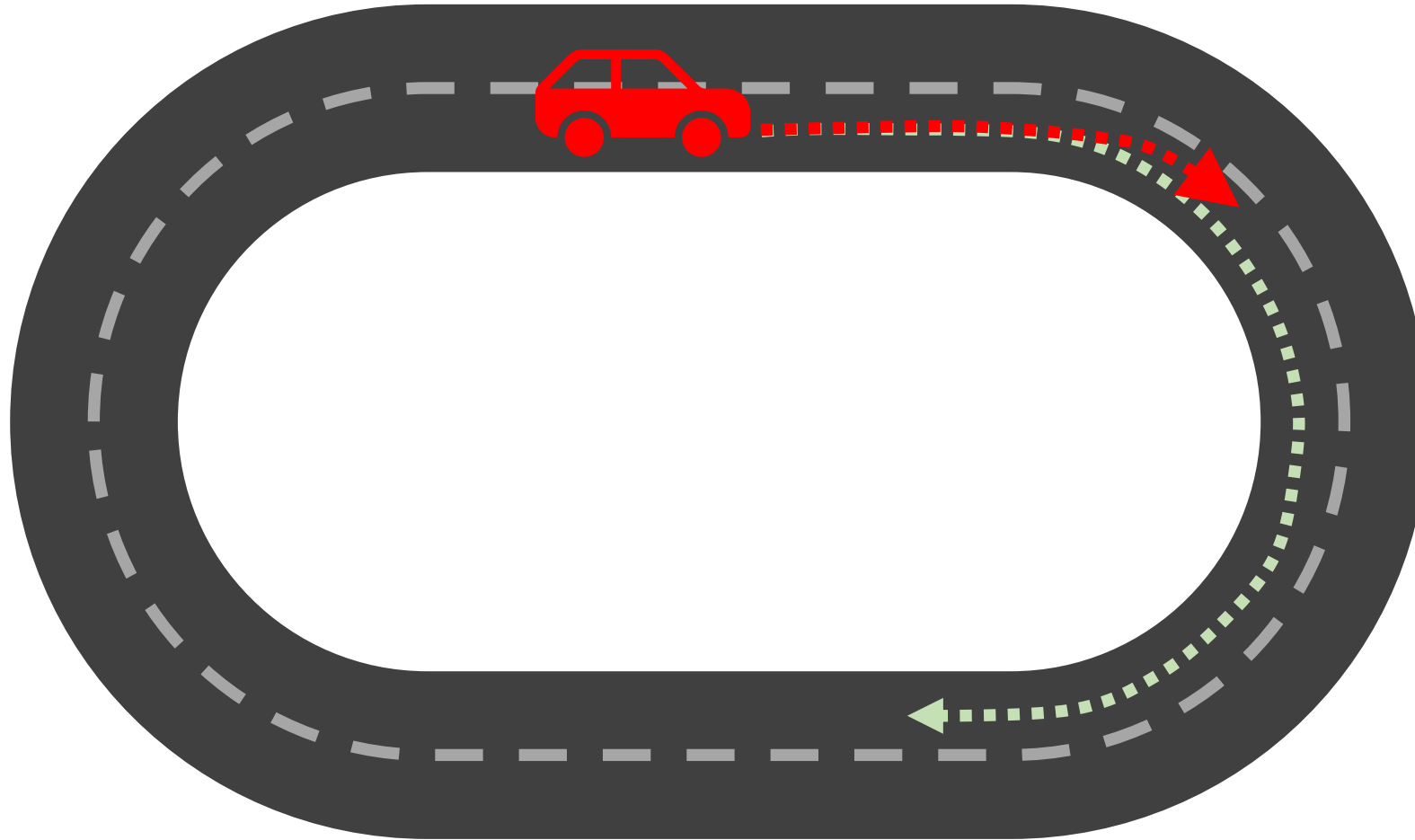
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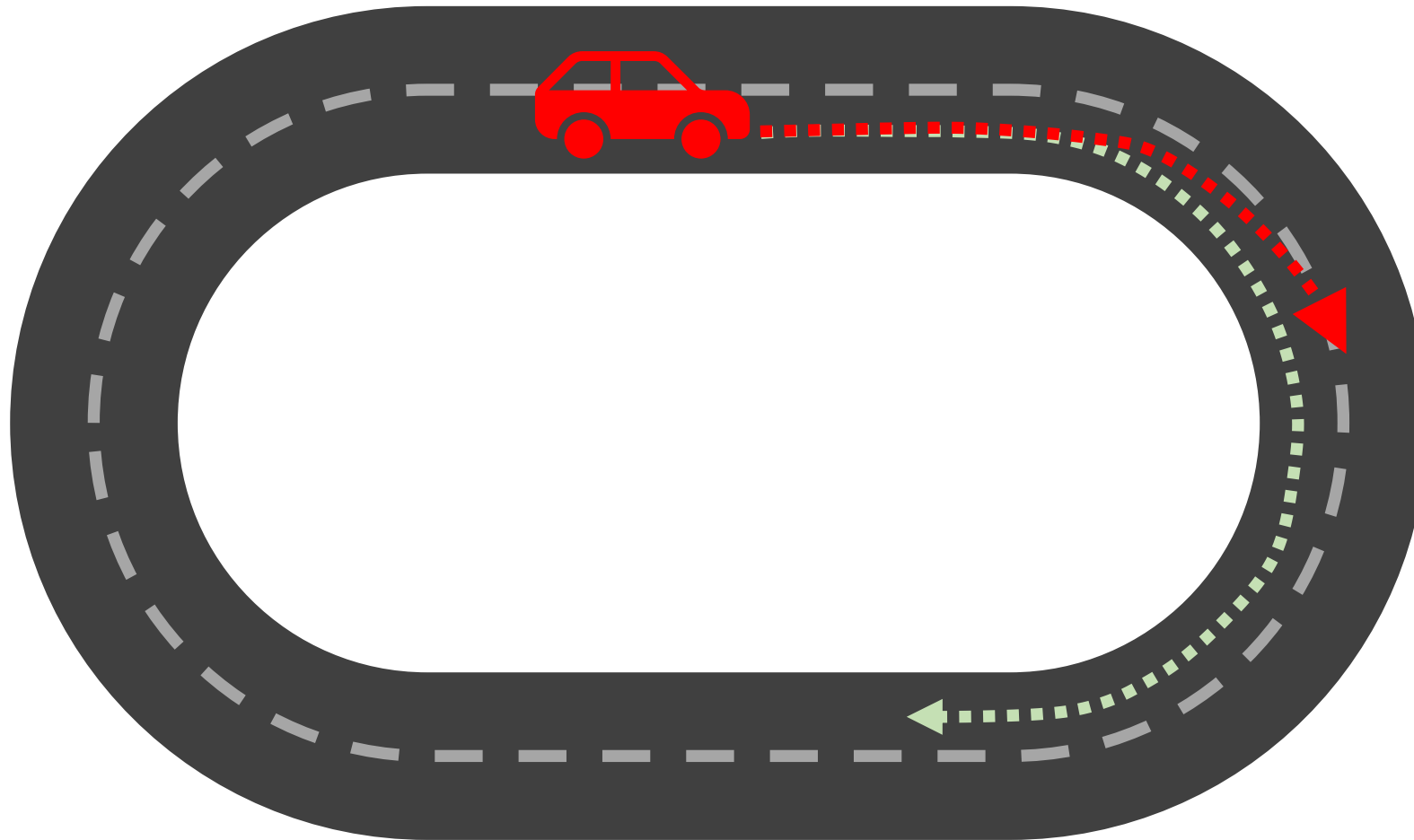
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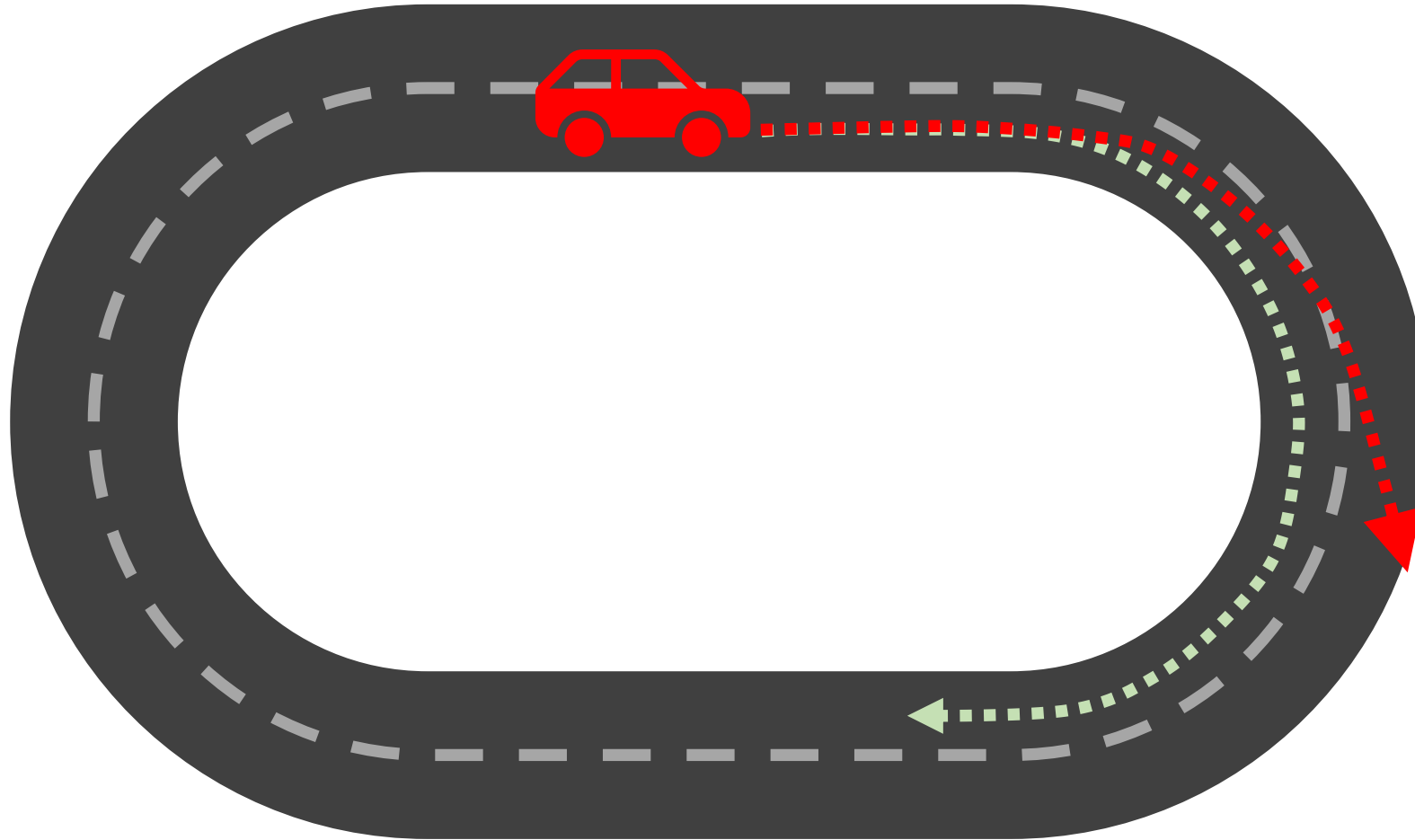
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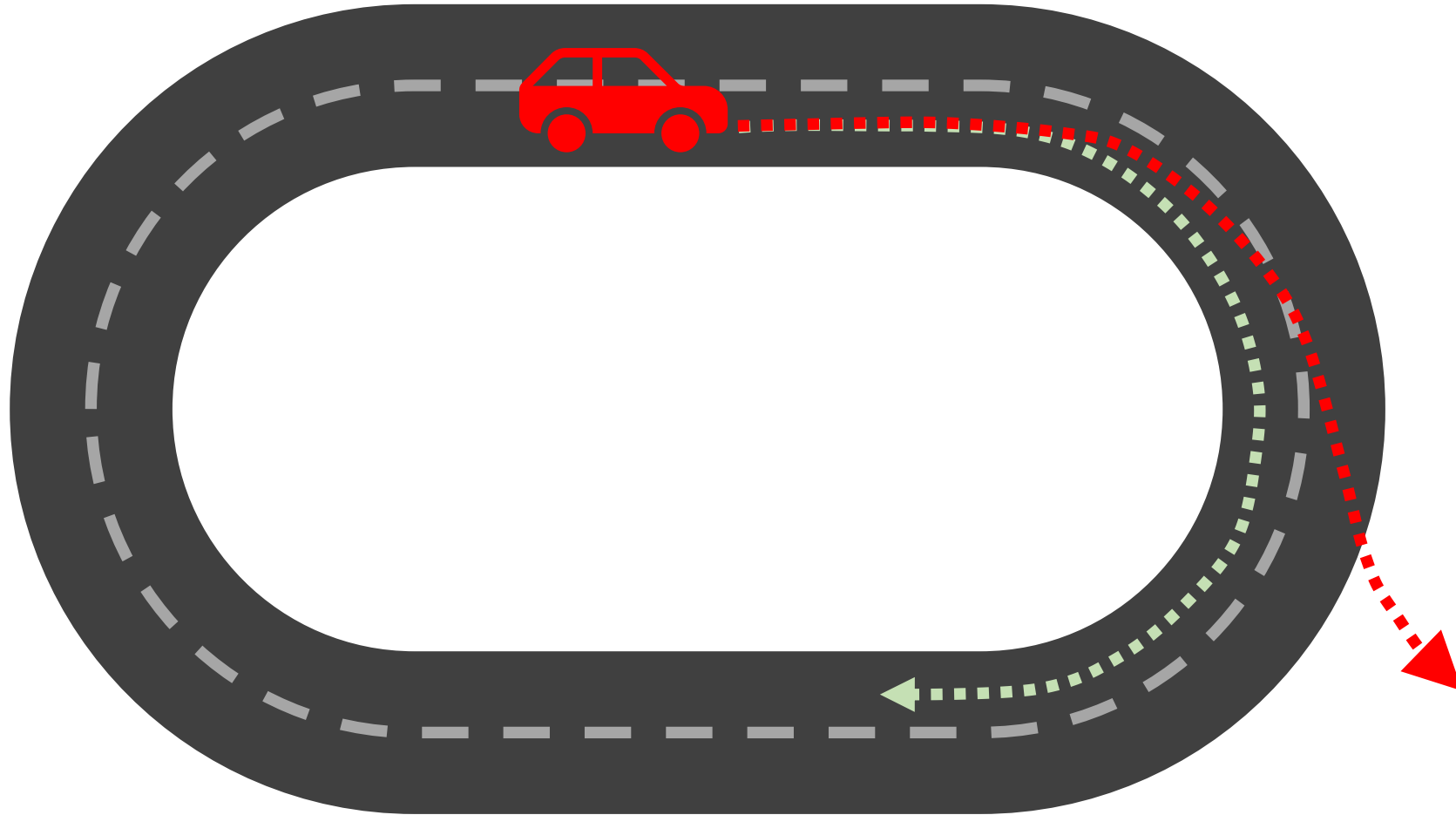
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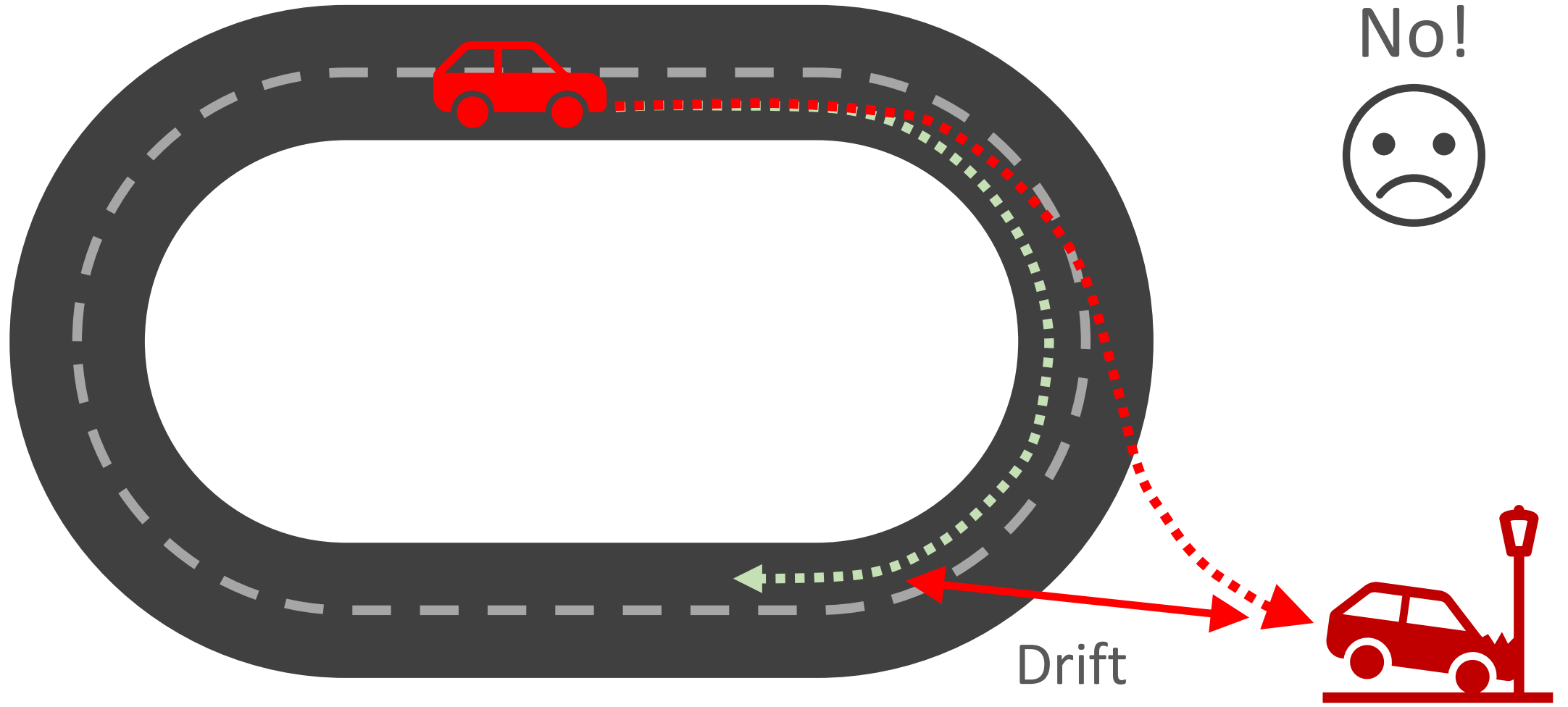
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# Does it work?

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# Drift

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- Expert is too good
- Lack of corrective feedback
- Policy inaccuracies
- Errors compound over time

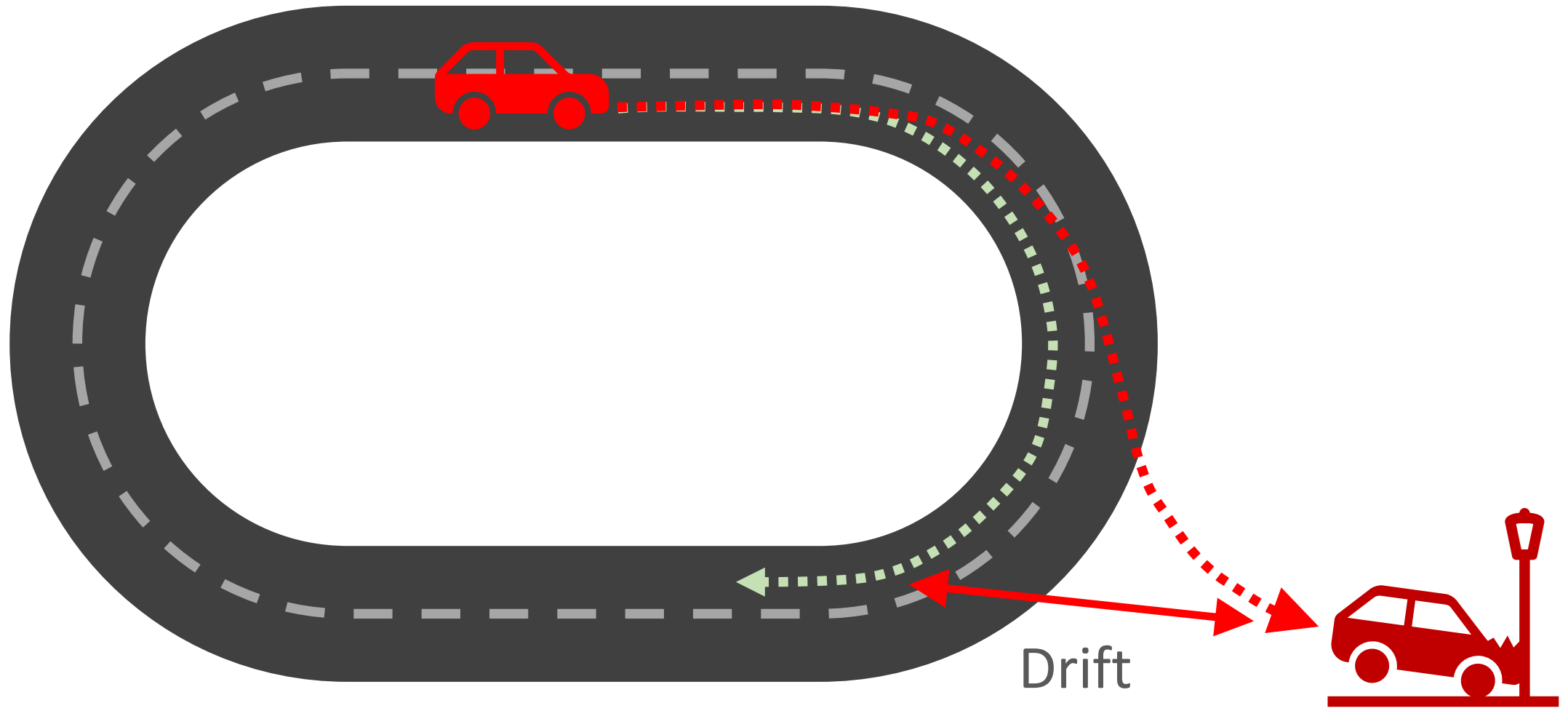
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# Feedback

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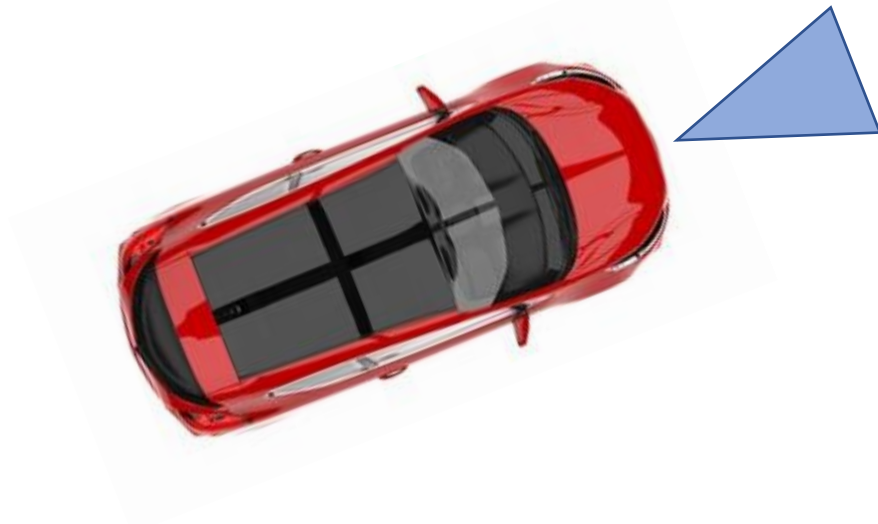
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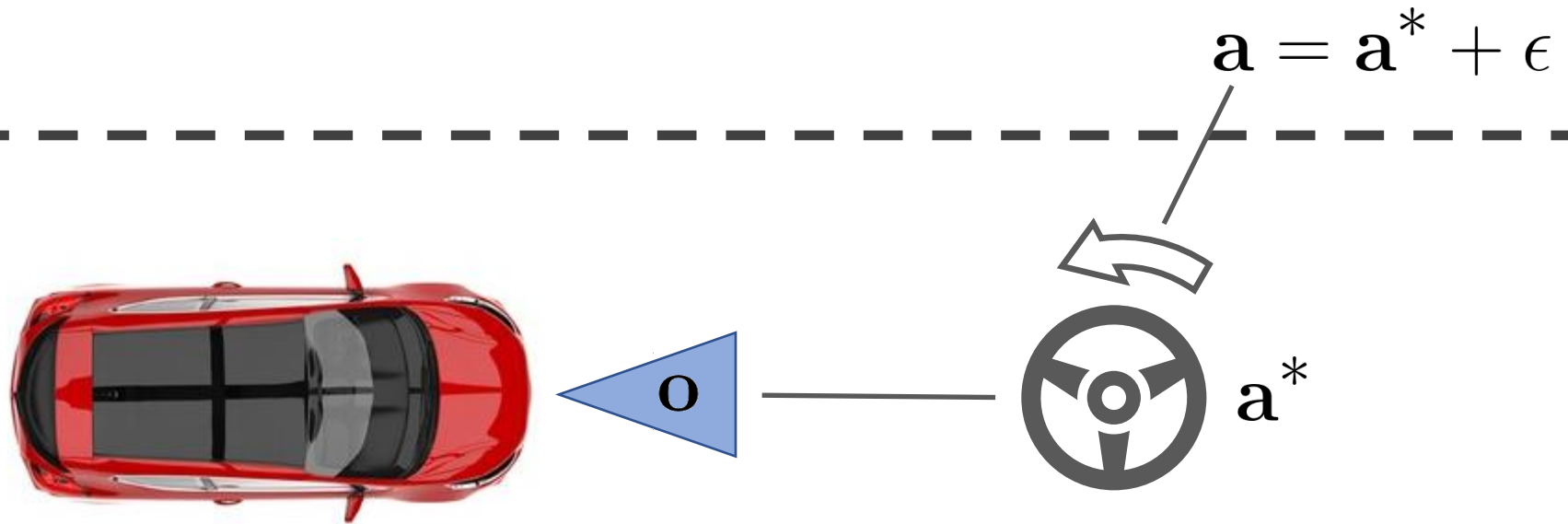
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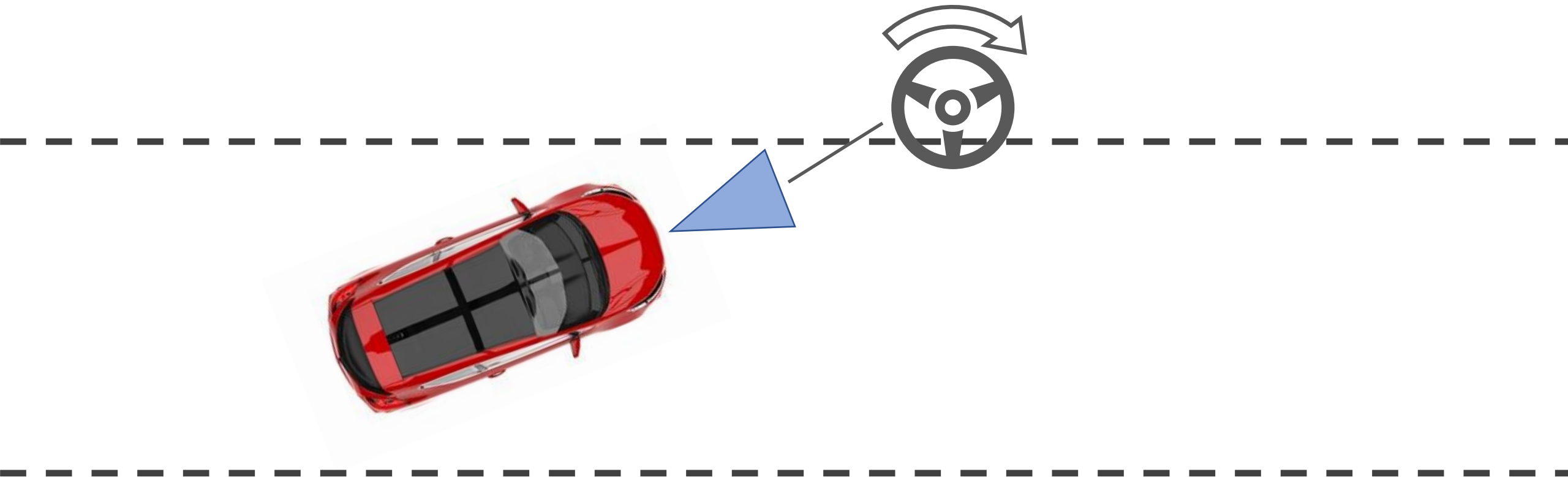
# Noise Injection

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# Noise Injection

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DART: Noise Injection for Robust Imitation Learning  
[Laskey et al. 2017]



# Noise Injection

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**ALGORITHM 2:** BC with Noise Injection

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- 1:  $\mathcal{D} \leftarrow \emptyset$  initialize dataset
  - 2: **for** timestep  $t$  **do**
  - 3:    $\mathbf{o}_t \leftarrow$  record observation
  - 4:    $\mathbf{a}_t^* \leftarrow$  query expert for an action
  - 5:    $\epsilon_t \leftarrow$  sample noise
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  - 7:   Apply  $\mathbf{a}_t$  to environment
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  - 9: **end for**
  - 10:  $\pi^{\text{BC}} = \arg \min_{\pi} \mathbb{E}_{(\mathbf{o}_i, \mathbf{a}_i) \sim \mathcal{D}} [-\log \pi(\mathbf{a}_i | \mathbf{o}_i)]$
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DART: Noise Injection for Robust Imitation Learning  
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# Noise Injection

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- ✓ Simple method to get corrective feedback
- ✓ Can work well in practice
- ✗ Dangerous for expert!
- ✗ Difficult to pick effective perturbations

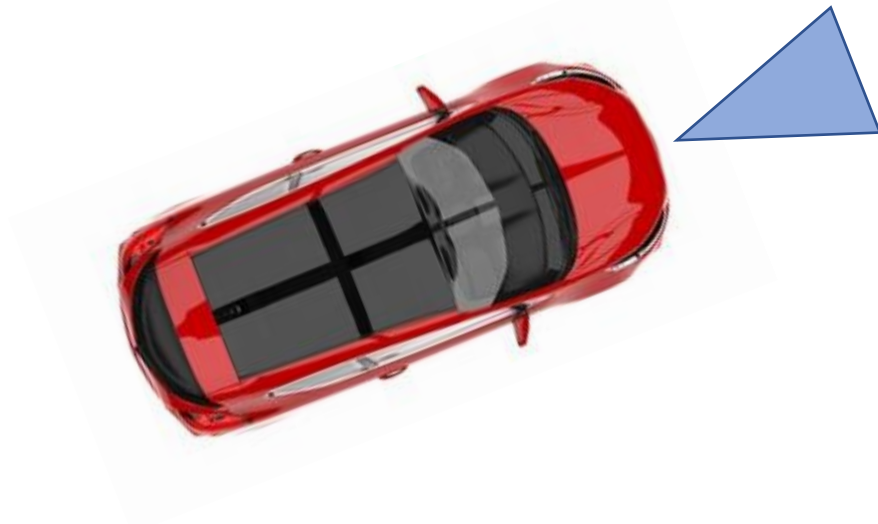
# Data Augmentation

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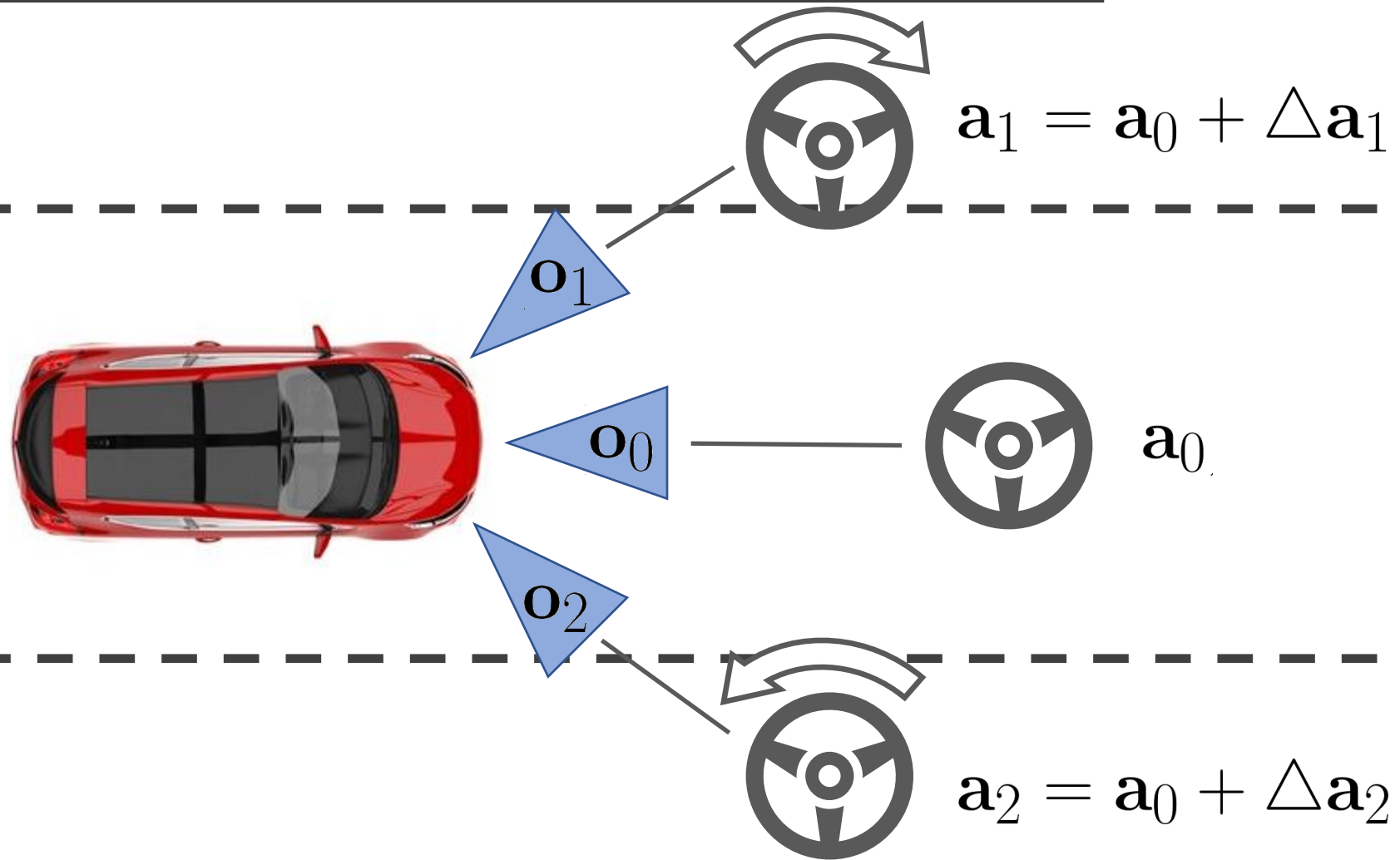
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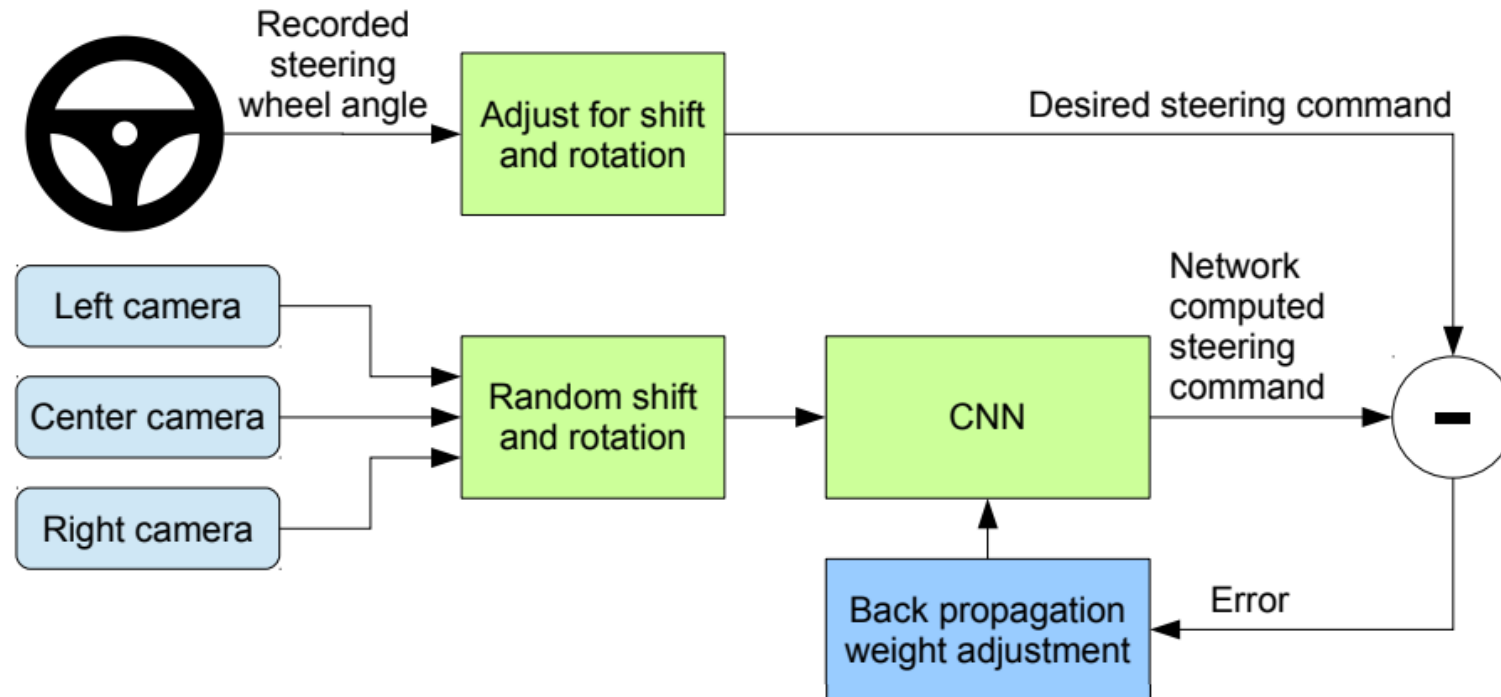
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# Data Augmentation

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End to End Learning for Self-Driving Cars  
[Bojarski et al. 2016]



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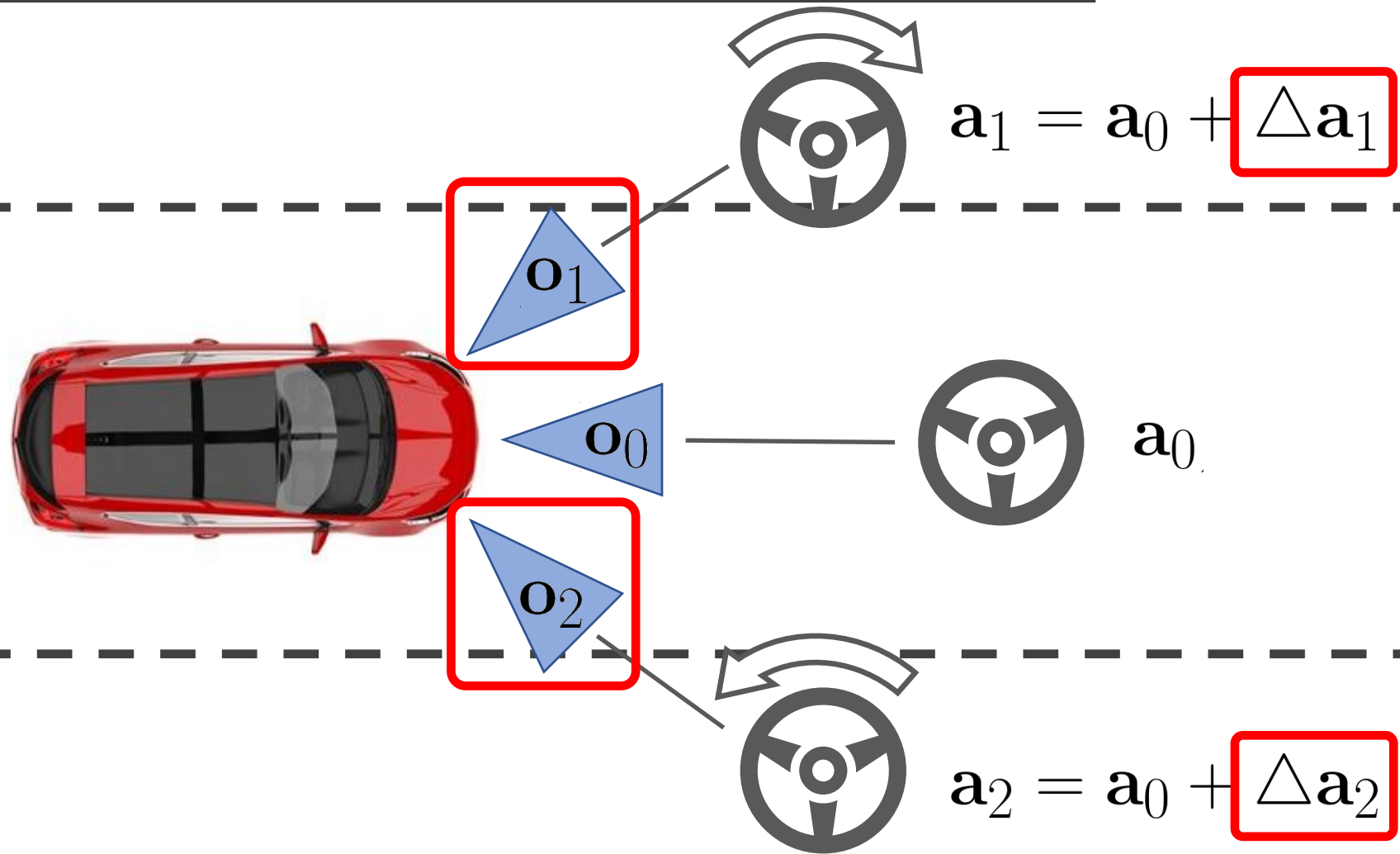
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End to End Learning for Self-Driving Cars  
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# Data Augmentation

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# Drift

---

- Expert is too good
- Lack of corrective feedback
- Policy inaccuracies
- Errors compound over time

# Theoretical Analysis

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Analyze the number of mistakes  $\pi$  makes over time

Spoiler:

- Number of mistakes  $O(\epsilon T^2)$

# Theoretical Analysis

---

Given dataset sampled from  $p_{\text{data}}(\mathbf{s}, \mathbf{a})$

$$\min_{\pi} \mathbb{E}_{(\mathbf{s}, \mathbf{a}) \sim p_{\text{data}}(\mathbf{s}, \mathbf{a})} [-\log \pi(\mathbf{a} | \mathbf{s})]$$

Such that

$$\pi(\mathbf{a} \neq \pi^*(\mathbf{s}) | \mathbf{s}) \leq \epsilon \text{ for all } \mathbf{s} \sim p_{\text{data}}(\mathbf{s})$$

i.e. the probability of  $\pi$  making a mistake is bounded.

$$\text{Cost: } c(\mathbf{s}, \mathbf{a}) = \begin{cases} 0 & \text{if } \mathbf{a} = \pi^*(\mathbf{s}) \\ 1 & \text{otherwise} \end{cases}$$

# Theoretical Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$\underline{p_{\pi}^t(\mathbf{s})} = (1 - \epsilon)^t p_{\text{data}}^t(\mathbf{s}) + (1 - (1 - \epsilon)^t) p_{\text{mistake}}^t(\mathbf{s})$$

probability of being in  $\mathbf{s}$  after following  $\pi$  for  $t$  timesteps

# Theoretical Analysis

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\pi}^t(\mathbf{s}) = \underbrace{(1 - \epsilon)^t}_{\text{no mistakes in } t \text{ timesteps}} p_{\text{data}}^t(\mathbf{s}) + (1 - (1 - \epsilon)^t) p_{\text{mistake}}^t(\mathbf{s})$$

no mistakes in  $t$  timesteps

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no mistakes in  $t$  timesteps

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$$\sum_t \mathbb{E}_{p_{\pi}^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})]$$

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expected cost

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$$\sum_t \mathbb{E}_{\underline{p_{\pi}^t(\mathbf{s})}} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] = \sum_t \sum_{\underline{\mathbf{s}}} p_{\pi}^t(\mathbf{s}) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})]$$

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

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$$\begin{aligned} \sum_t \mathbb{E}_{p_{\pi}^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] &= \sum_t \sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &= \sum_t \sum_{\mathbf{s}} \left( p_{\pi}^t(\mathbf{s}) - \underbrace{p_{\text{data}}^t(\mathbf{s}) + p_{\text{data}}^t(\mathbf{s})}_{=0} \right) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \end{aligned}$$

# Theoretical Analysis

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\pi}^t(\mathbf{s}) = (1 - \epsilon)^t p_{\text{data}}^t(\mathbf{s}) + (1 - (1 - \epsilon)^t) p_{\text{mistake}}^t(\mathbf{s})$$

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# Theoretical Analysis

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\pi}^t(\mathbf{s}) = (1 - \epsilon)^t p_{\text{data}}^t(\mathbf{s}) + (1 - (1 - \epsilon)^t) p_{\text{mistake}}^t(\mathbf{s})$$

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# Theoretical Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

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# Theoretical Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

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# Theoretical Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

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# Theoretical Analysis

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

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# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$
$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - \underline{(1-\epsilon)^t p_{\text{data}}^t(\mathbf{s})} = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) - \underbrace{\left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})} = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s}) - \underbrace{\left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})}$$

# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - \underbrace{(1-\epsilon)^t p_{\text{data}}^t(\mathbf{s})} - \underbrace{\left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})} = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s}) - \left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})$$



# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s})$$

# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) - \left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s}) = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s}) - \left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) = \left(1 - (1-\epsilon)^t\right) \sum_{\mathbf{s}} p_{\text{mistake}}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s})$$

$$\leq \left(1 - (1-\epsilon)^t\right) \underbrace{\sum_{\mathbf{s}} \left| p_{\text{mistake}}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \right|}_{\text{total variation distance} \leq 2}$$

total variation distance  $\leq 2$

# Theoretical Analysis

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$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) = \sum_{\mathbf{s}} (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) + \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - (1-\epsilon)^t p_{\text{data}}^t(\mathbf{s}) - \left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s}) = \sum_{\mathbf{s}} \left(1 - (1-\epsilon)^t\right) p_{\text{mistake}}^t(\mathbf{s}) - \left(1 - (1-\epsilon)^t\right) p_{\text{data}}^t(\mathbf{s})$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) = \left(1 - (1-\epsilon)^t\right) \sum_{\mathbf{s}} p_{\text{mistake}}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s})$$

$$\leq \left(1 - (1-\epsilon)^t\right) \sum_{\mathbf{s}} \left| p_{\text{mistake}}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \right|$$

$$\leq 2 \left(1 - (1-\epsilon)^t\right)$$

**Note:**  $(1-\epsilon)^t \geq 1 - \epsilon t$  for  $\epsilon \in [0, 1]$

$$\leq 2\epsilon t$$

$$\sum_{\mathbf{s}} p_{\pi}^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \leq 2\epsilon t$$

# Theoretical Analysis

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$$\begin{aligned} \sum_t \mathbb{E}_{p_\pi^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] &= \sum_t \sum_{\mathbf{s}} p_\pi^t(\mathbf{s}) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \epsilon T + \sum_t \underbrace{\sum_{\mathbf{s}} \left( p_\pi^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \right)}_{\leq 2\epsilon t} \underbrace{\mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})]}_{\leq 1} \end{aligned}$$

# Theoretical Analysis

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$$\begin{aligned}\sum_t \mathbb{E}_{p_\pi^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] &= \sum_t \sum_{\mathbf{s}} p_\pi^t(\mathbf{s}) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \epsilon T + \sum_t \sum_{\mathbf{s}} \left( p_\pi^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \right) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \epsilon T + \sum_t 2\epsilon t\end{aligned}$$

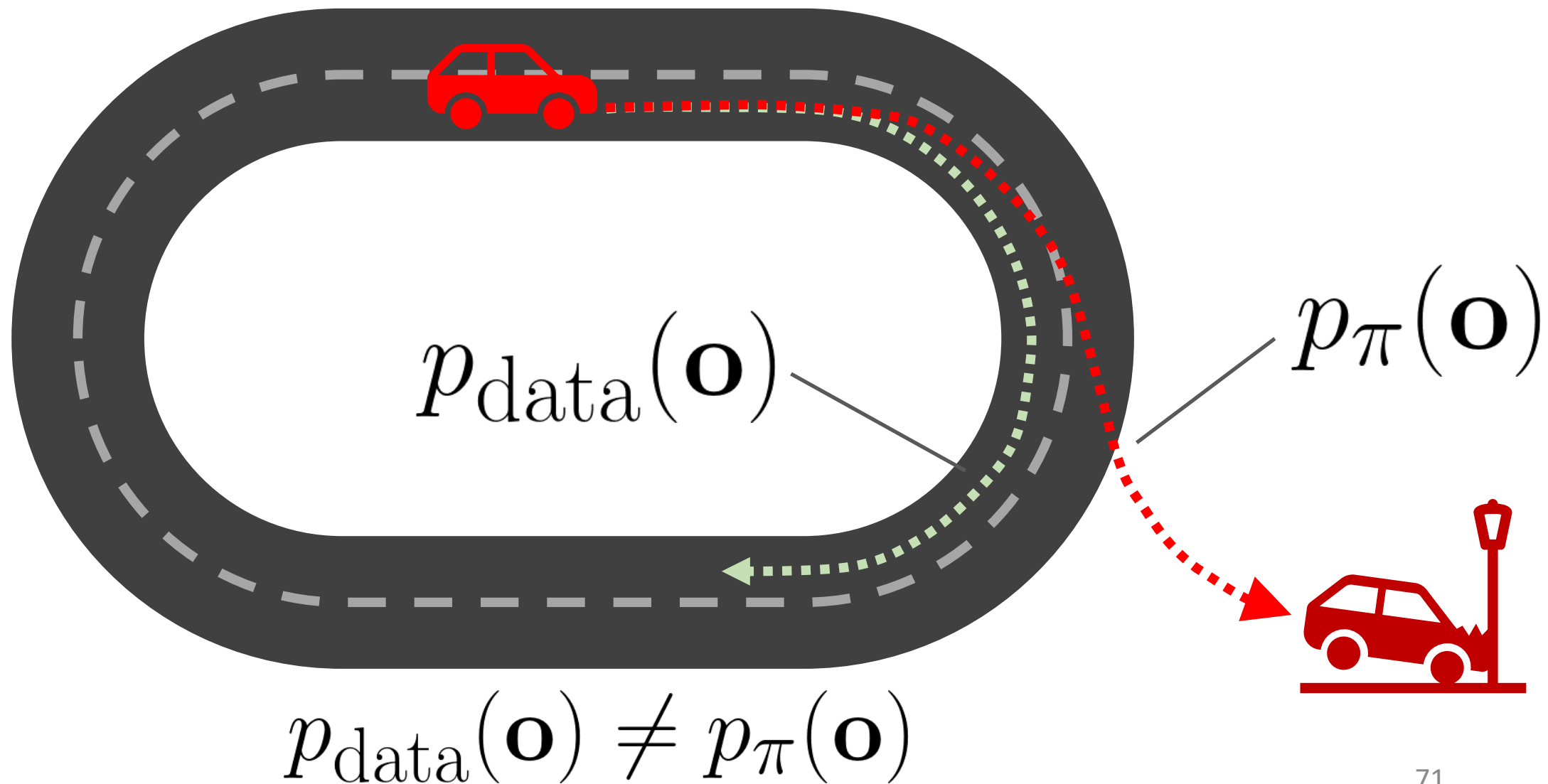
# Theoretical Analysis

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$$\begin{aligned} \sum_t \mathbb{E}_{p_\pi^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] &= \sum_t \sum_{\mathbf{s}} p_\pi^t(\mathbf{s}) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \epsilon T + \sum_t \sum_{\mathbf{s}} \left( p_\pi^t(\mathbf{s}) - p_{\text{data}}^t(\mathbf{s}) \right) \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \epsilon T + \sum_t 2\epsilon t \\ &\leq \epsilon T + 2\epsilon T^2 \in \boxed{O(\epsilon T^2)} \end{aligned}$$

# Distribution Shift

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# Dataset Aggregation

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Can we make  $p_{\text{data}}(\mathbf{o}) = p_{\pi}(\mathbf{o})$  ?

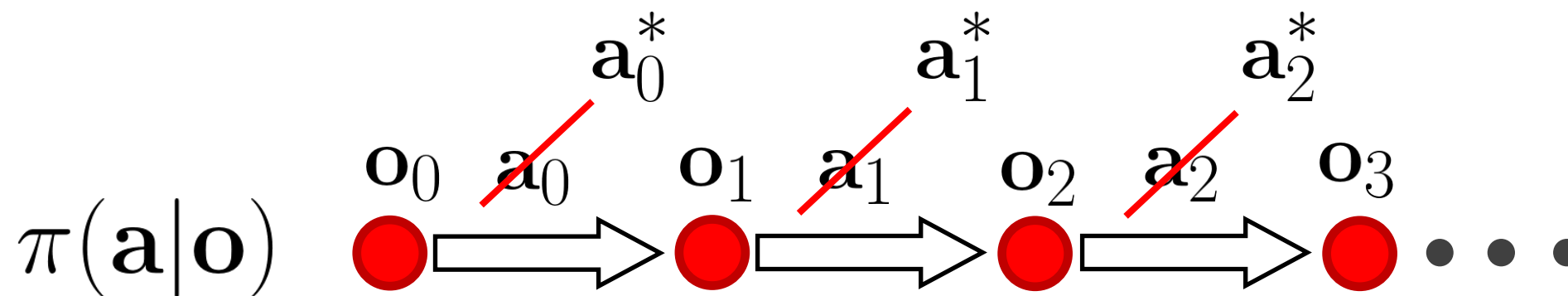
Key idea:

- Collect observations from  $p_{\pi}(\mathbf{o})$  instead of  $p_{\text{data}}(\mathbf{o})$
- Label actions with expert
- DAgger: Dataset Aggregation [Ross et al. 2011]



# DAgger

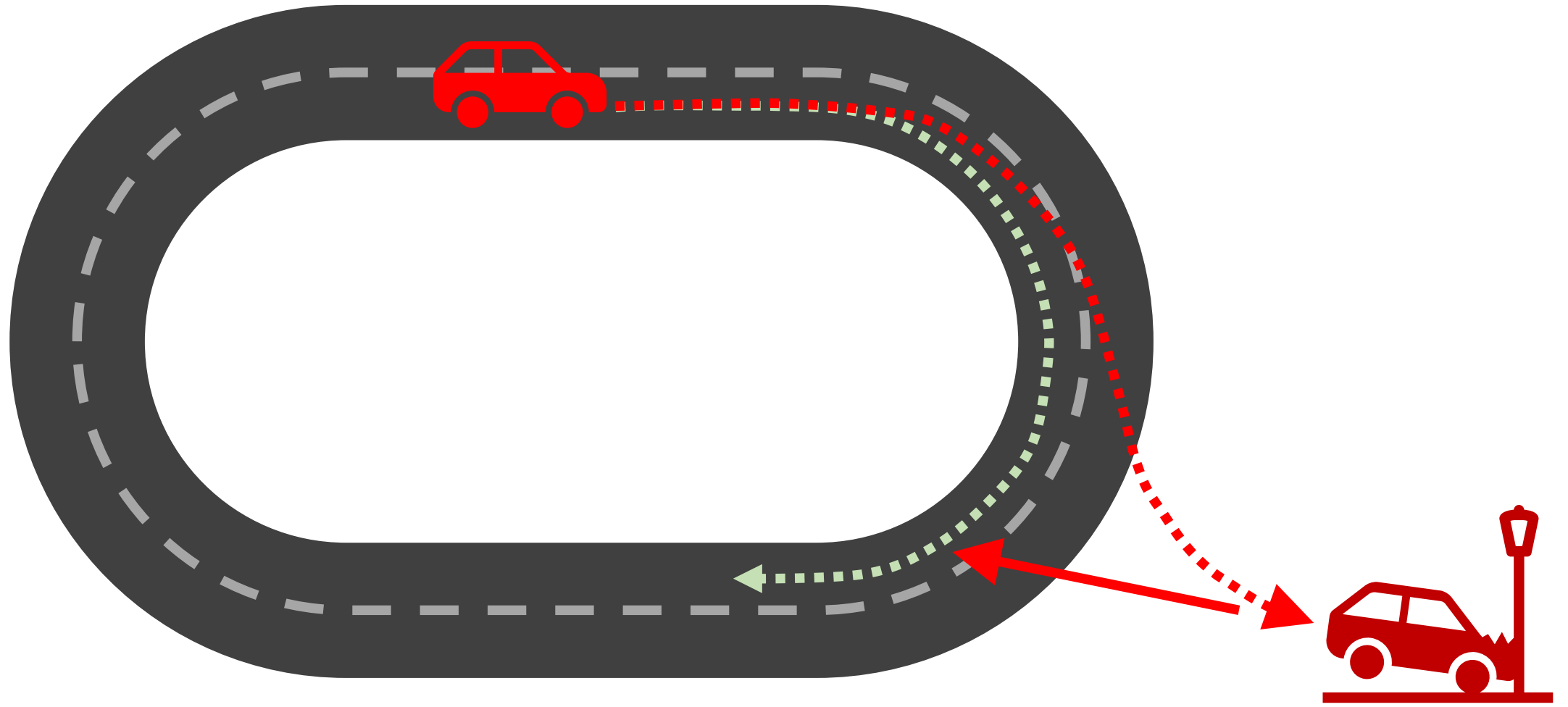
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Train with  $(\mathbf{o}_i, \mathbf{a}_i^*)$

# Dagger

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# DAgger

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**ALGORITHM:** DAgger

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- 1: **for** iteration  $i = 0, \dots, k - 1$  **do**
  - 2:   train  $\pi(\mathbf{a}|\mathbf{o})$  from dataset  $\mathcal{D} = \{\mathbf{o}_0, \mathbf{a}_0, \mathbf{o}_1, \mathbf{a}_0, \dots\}$
  - 3:   run  $\pi(\mathbf{a}|\mathbf{o})$  to collect dataset  $\mathcal{D}_\pi = \{\mathbf{o}_0, \mathbf{o}_1, \dots\}$
  - 4:   Label  $\mathcal{D}_\pi$  with actions  $\mathbf{a}_i$  from expert
  - 5:   Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$
  - 6: **end for**
- 

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning  
[Ross et al. 2011]

# DAgger

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**ALGORITHM: DAgger**

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# DAgger

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**ALGORITHM:** DAgger

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# DAgger

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**ALGORITHM:** DAgger

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# DAgger

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**ALGORITHM: DAgger**

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# DAgger

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**ALGORITHM:** DAgger

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- 

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning  
[Ross et al. 2011]



# DAgger

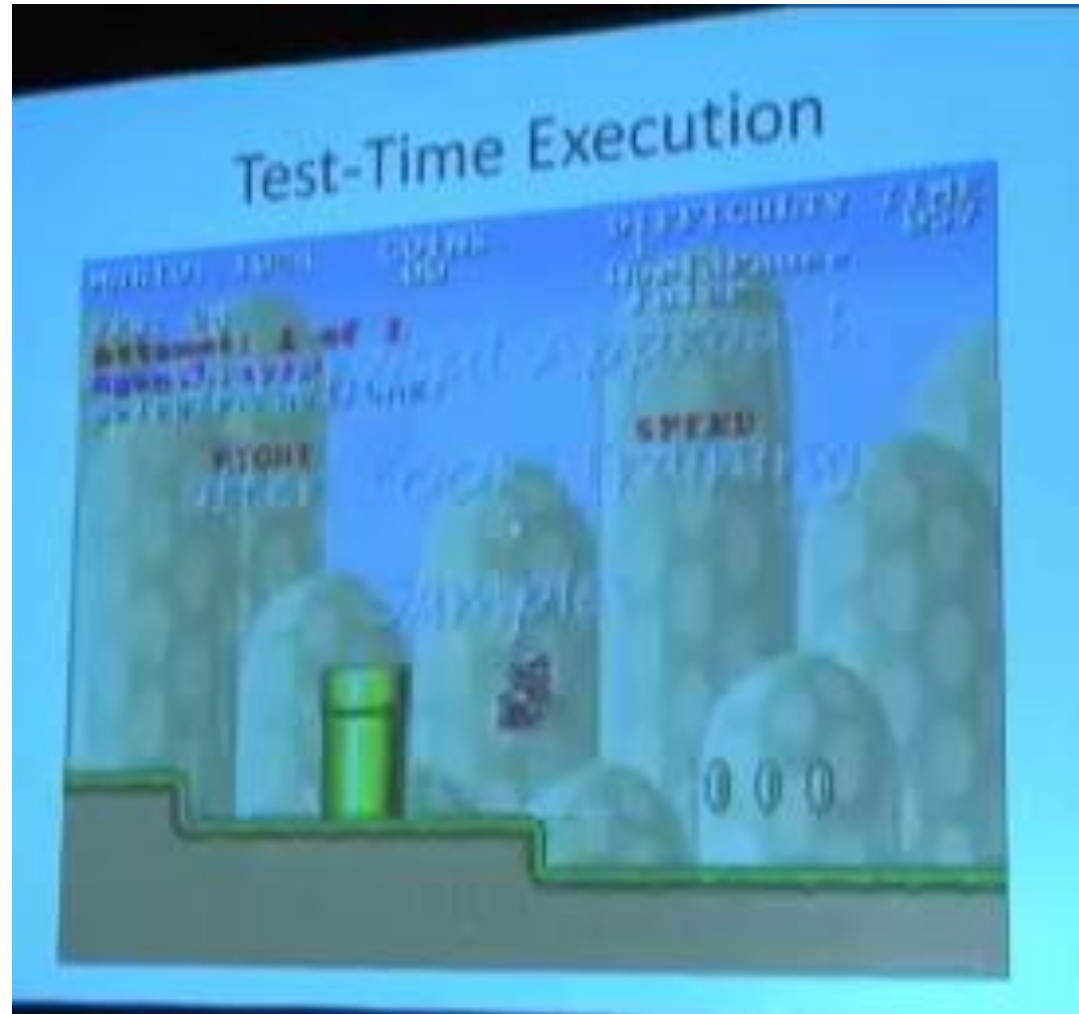
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A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning  
[Ross et al. 2011]

# DAgger

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A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning  
[Ross et al. 2011]

# DAgger Analysis

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Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\text{data}}(\mathbf{s}) = p_{\pi}(\mathbf{s})!$$

$$\begin{aligned} p_{\pi}^t(\mathbf{s}) &= (1 - \epsilon)^t p_{\text{data}}^t(\mathbf{s}) + (1 - (1 - \epsilon)^t) p_{\text{mistake}}^t(\mathbf{s}) \\ &= p_{\text{data}}^t(\mathbf{s}) \end{aligned}$$

# DAgger Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\text{data}}(\mathbf{s}) = p_{\pi}(\mathbf{s})!$$

$$p_{\pi}^t(\mathbf{s}) = p_{\text{data}}^t(\mathbf{s})$$

$$\sum_t \mathbb{E}_{p_{\pi}^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] = \sum_t \mathbb{E}_{p_{\text{data}}^t(\mathbf{s})} \underbrace{\mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})]}_{\leq \epsilon}$$

# DAgger Analysis

---

Assume:  $\pi(\mathbf{a} \neq \pi^*(\mathbf{s})|\mathbf{s}) \leq \epsilon$  for all  $\mathbf{s} \sim p_{\text{data}}(\mathbf{s})$

$$p_{\text{data}}(\mathbf{s}) = p_{\pi}(\mathbf{s})!$$

$$p_{\pi}^t(\mathbf{s}) = p_{\text{data}}^t(\mathbf{s})$$

$$\begin{aligned} \sum_t \mathbb{E}_{p_{\pi}^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] &= \sum_t \mathbb{E}_{p_{\text{data}}^t(\mathbf{s})} \mathbb{E}_{\pi(\mathbf{a}|\mathbf{s})} [c(\mathbf{s}, \mathbf{a})] \\ &\leq \sum_t \epsilon \\ &\leq \epsilon T \in O(\epsilon T) \end{aligned}$$

# DAgger

---

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**ALGORITHM: DAgger**

---

- 1: **for** iteration  $i = 0, \dots, k - 1$  **do**
  - 2:   train  $\pi(\mathbf{a}|\mathbf{o})$  from expert dataset  $\mathcal{D} = \{\mathbf{o}_0, \mathbf{a}_0, \mathbf{o}_1, \mathbf{a}_0, \dots\}$
  - 3:   run  $\pi(\mathbf{a}|\mathbf{o})$  to collect dataset  $\mathcal{D}_\pi = \{\mathbf{o}_0, \mathbf{o}_1, \dots\}$
  - 4:   Label  $\mathcal{D}_\pi$  with actions  $\mathbf{a}_i$  from expert
  - 5:   Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$
  - 6: **end for**
- 

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning  
[Ross et al. 2011]

# DAgger

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**ALGORITHM: DAgger**

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

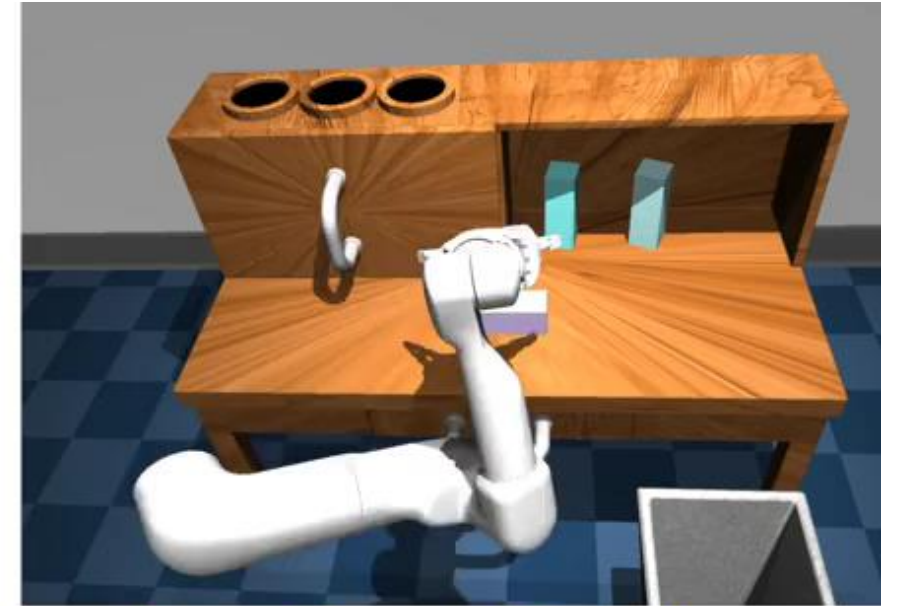


# Applications

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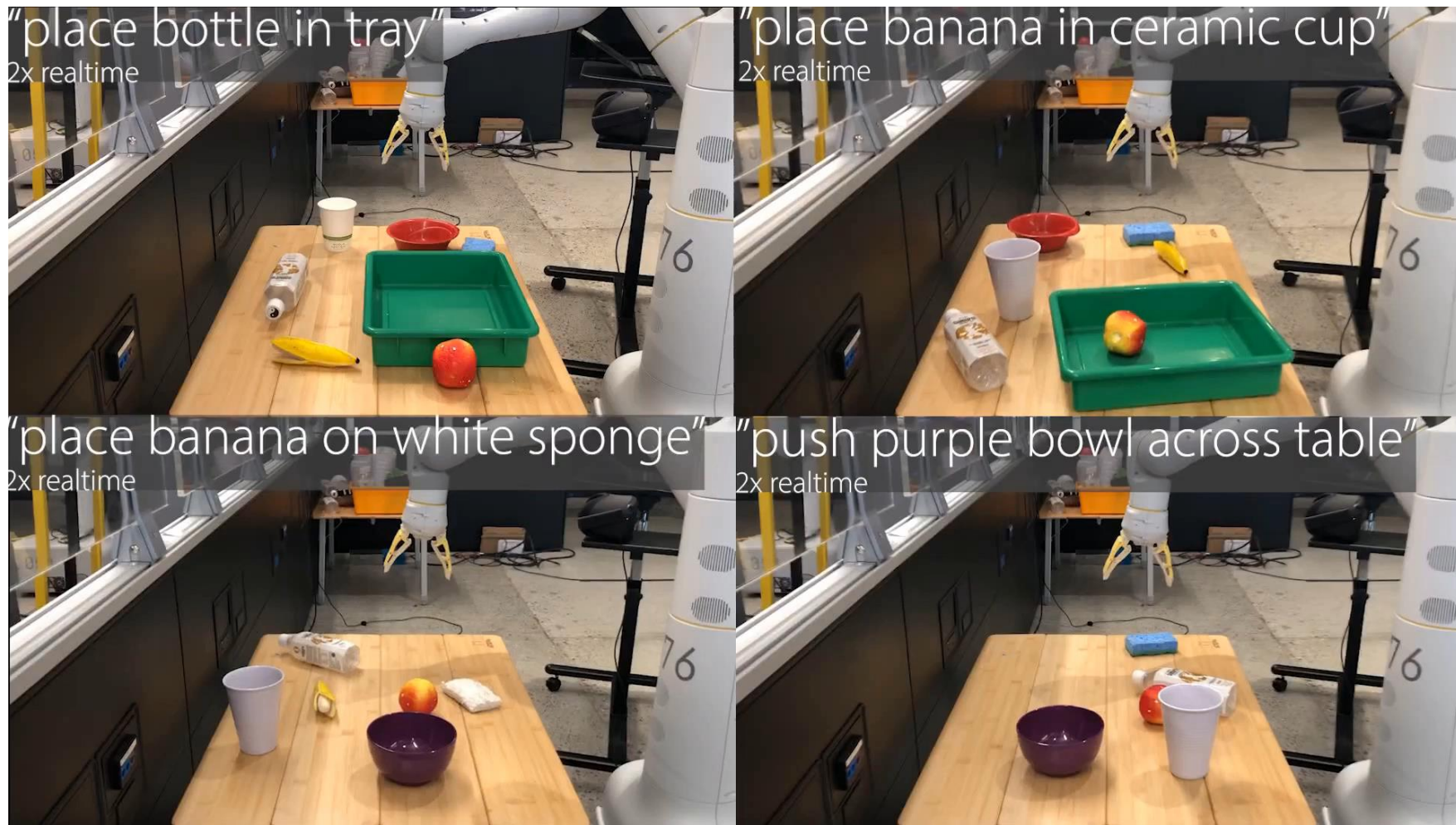
Goal



Single Play-LMP policy

Learning Latent Plans from Play  
[Lynch et al. 2019]

# Applications



BC-Z: Zero-Shot Task Generalization with Robotic Imitation Learning  
[Jang et al. 2021]

# Summary

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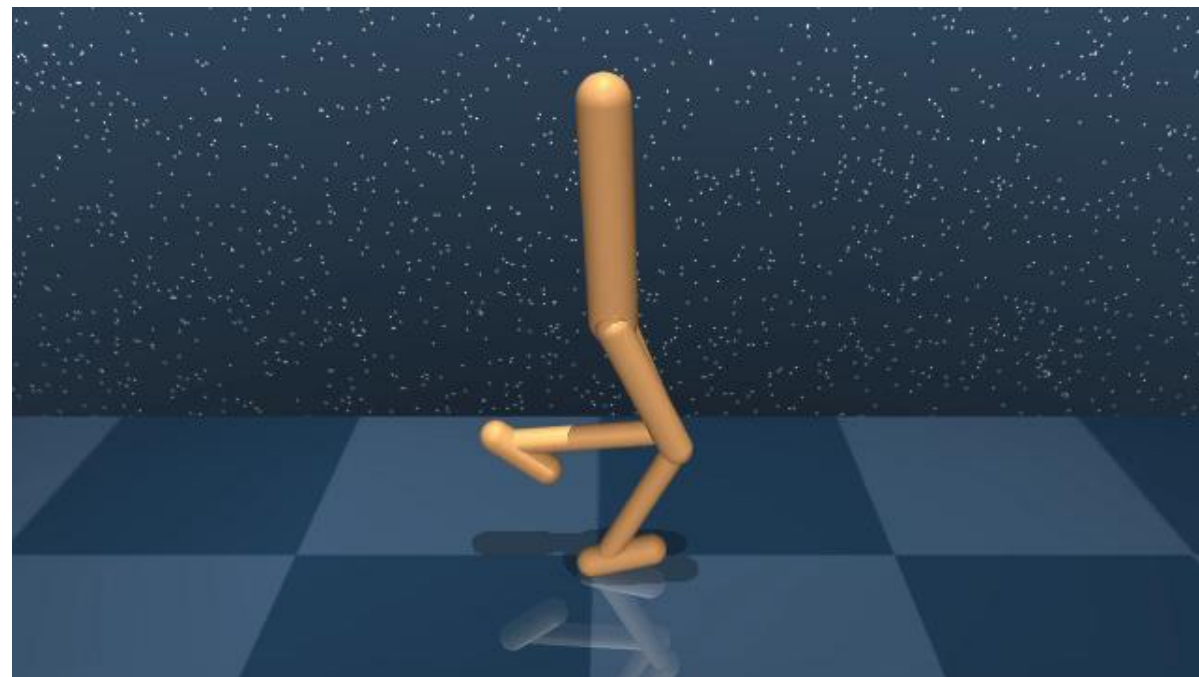
- Behavioral Cloning
- Drift
- Theoretical Analysis
- DAgger
- Applications

# Assignment 1: Behavioral Cloning

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Cheetah



Walker



# Assignment 1: Behavioral Cloning

The screenshot shows the GitHub interface for the repository `xbpeng / rl_assignments`. The repository is public and has 3 stars, 2 watchers, and 3 forks. The main branch is `main`, with 1 branch and 0 tags. The repository contains a commit by Jason Peng titled "fixing potential laoding issueg" (note the typo) 19 hours ago, with 4 commits. The file list includes folders `a1`, `data`, `envs`, `learning`, `tools`, and `util`, and files `.gitignore`, `LICENSE`, and `README.md`. The right sidebar shows the repository's metadata: no description, BSD-3-Clause license, 3 stars, 2 watchers, and 3 forks. There are no releases or packages published.

xbpeng / rl\_assignments Public

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main 1 branch 0 tags Go to file Add file Code

Jason Peng fixing potential laoding issueg 55b171e 19 hours ago 4 commits

folder	a1	a1	2 days ago
folder	data	a1	2 days ago
folder	envs	a1	2 days ago
folder	learning	fixing potential laoding issueg	19 hours ago
folder	tools	a1	2 days ago
folder	util	a1	2 days ago
file	.gitignore	a1	2 days ago
file	LICENSE	a1	2 days ago
file	README.md	readme	2 days ago

About No description, website, or topics provided.

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Releases No releases published Create a new release

Packages

github.com/xbpeng/rl\_assignments