# Imitation Learning

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# Outline

- ✓ Introduction
- ✓ Imitation learning challenges
  - ✓ Distribution mismatch
  - ✓ Sequential models
  - ✓ Multimodal actions
- ✓ Advanced topics
  - ✓ Generative imitation learning
  - ✓ Inverse reinforcement learning

# Introduction

# Limitations of learning by (physical) interaction

The agent should have the chance to try (and fail) MANY times

- ✓Hard when safety is a concern
- ✓Hard in general when each interaction takes time

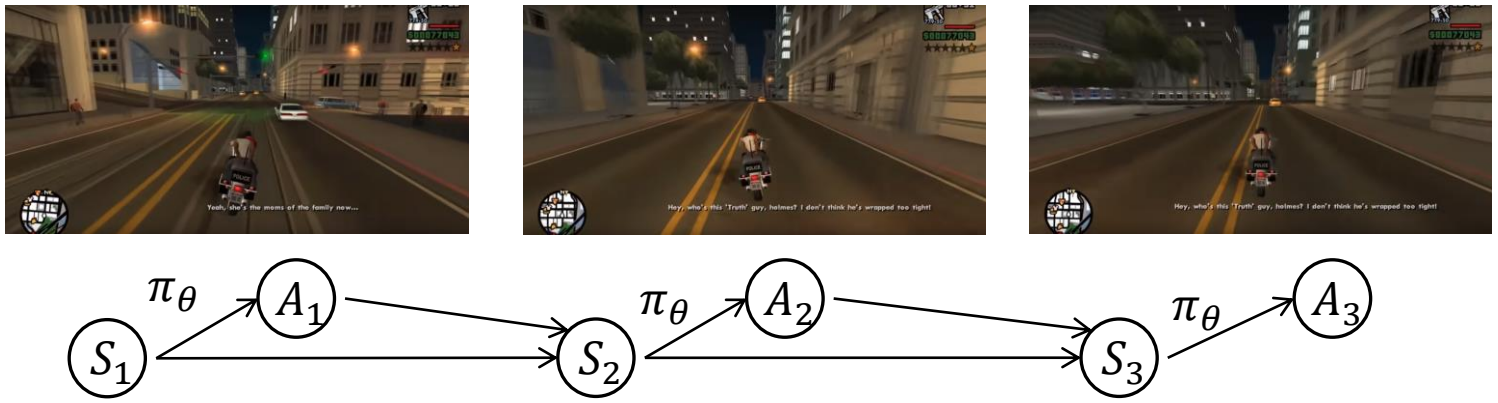
# Imitation Learning

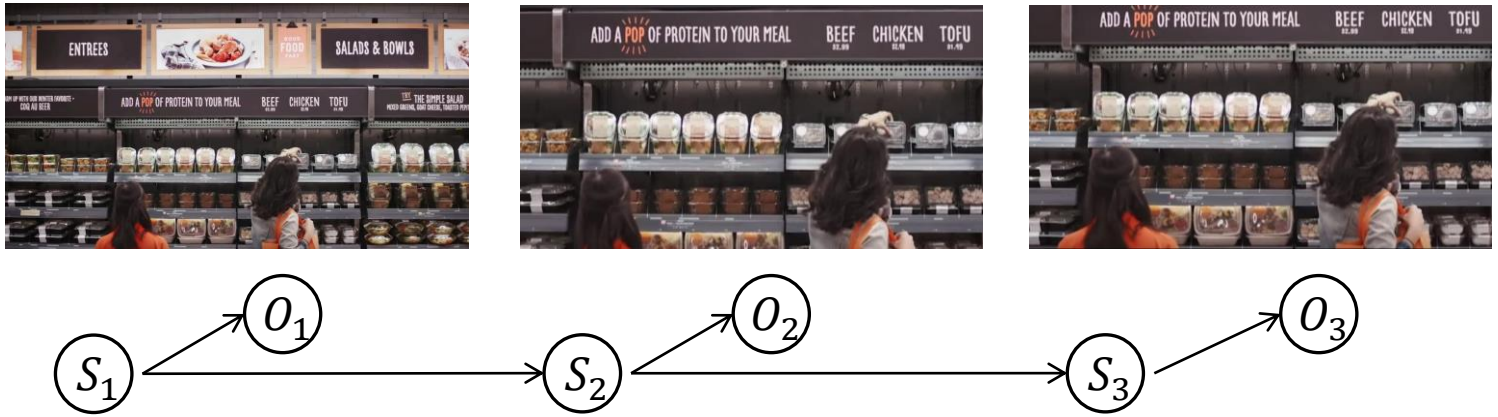
## Learning from demonstrations

- ✓Kinesthetic imitation
  - ✓Teacher takes over the end effectors of the agent.
  - ✓Demonstrated actions are in the action space of the imitator

- ✓Visual imitation
  - ✓The actions of the teacher need to be inferred from visual sensory input and mapped to the action space of the agent

# Imitation Learning Vs Supervised Labelling



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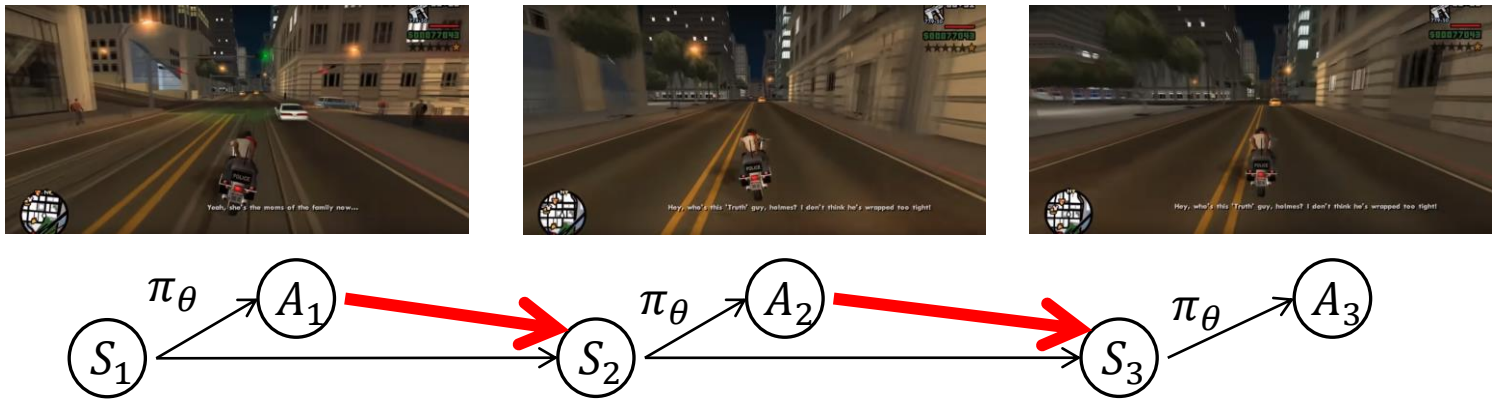
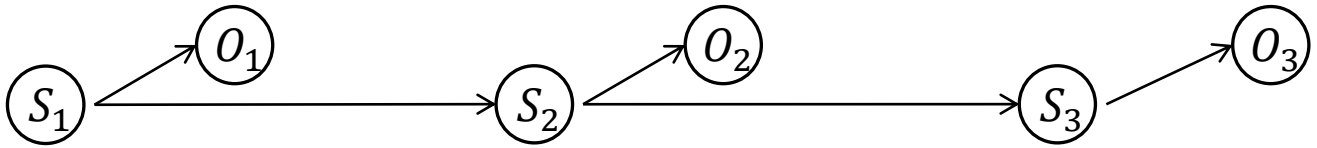


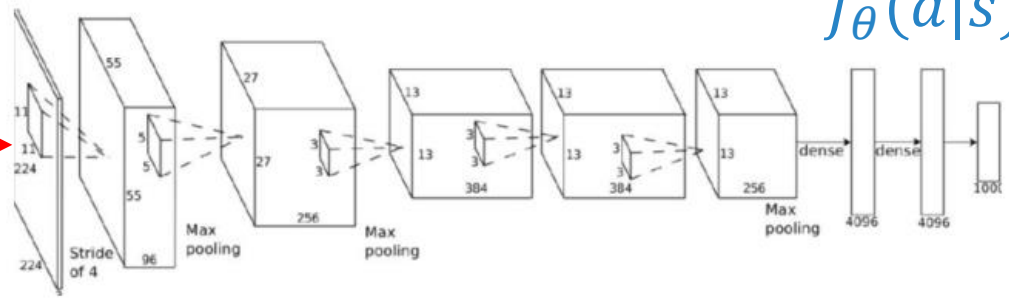
Our actions influence future state and data

Predicted labels do not influence future

# Action Labelling

A mapping from states/observations to action labels


$f_\theta(a|s)$




Buying poultry

Assume action labels in an annotated video are i.i.d

Train a classifier to map observations to labels at each time step


$s_t$

$a_t$

Training Data

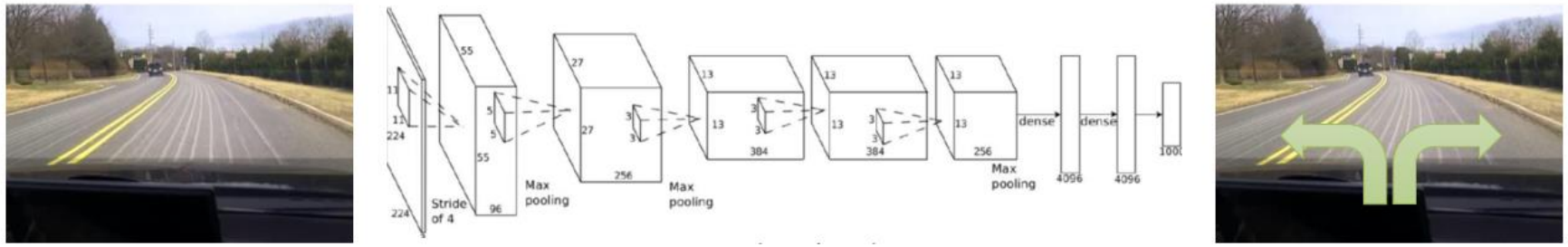
Supervised learning

$f_\theta(a|s)$

# Imitation Learning (Behaviour Cloning)

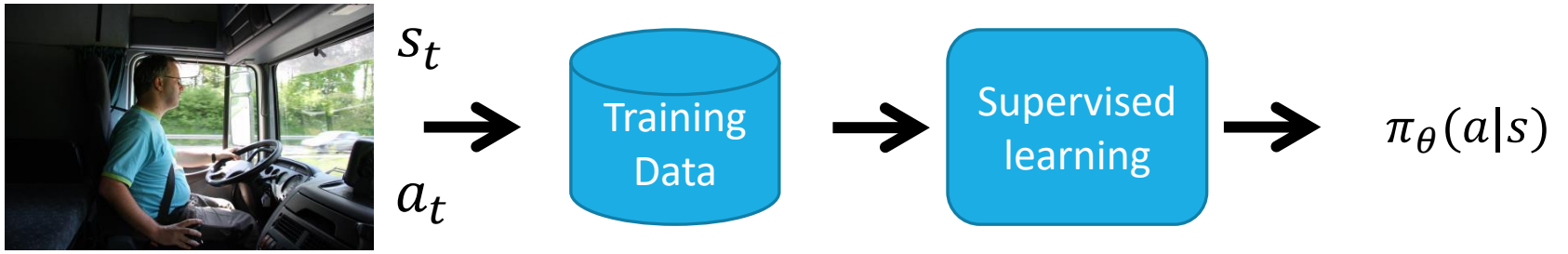
Policy - A mapping from observations to actions

$\pi_\theta(a|s)$



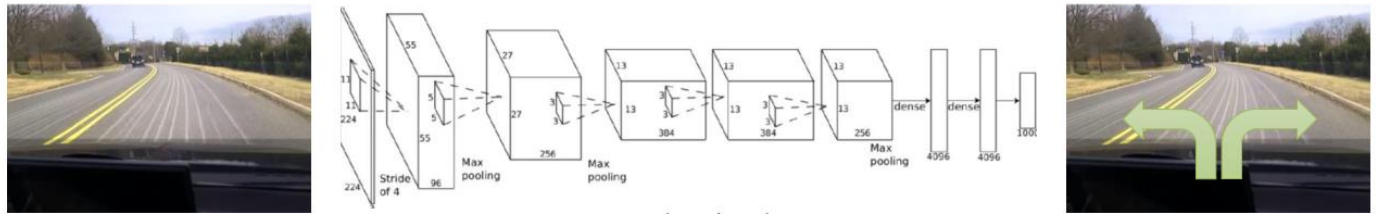

Assume actions in the expert trajectories are i.i.d

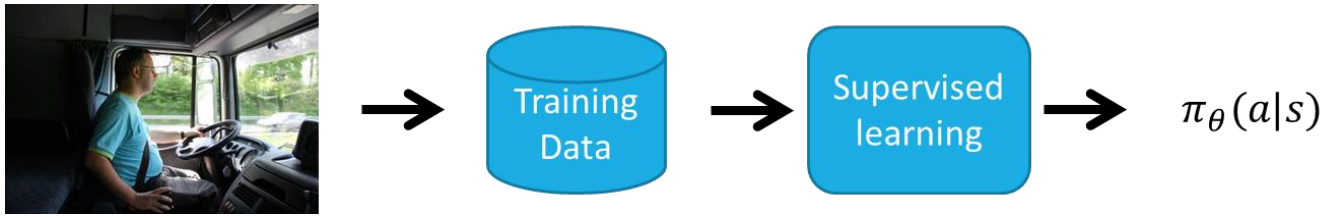
Train a function to map observations to actions at each time step



# What Possibly Can Go Wrong?

- ✓Compounding errors
  - ✓Data augmentation
- ✓Non-markovian observations
  - ✓Recurrent models
- ✓Stochastic expert actions
  - ✓Generative modelling

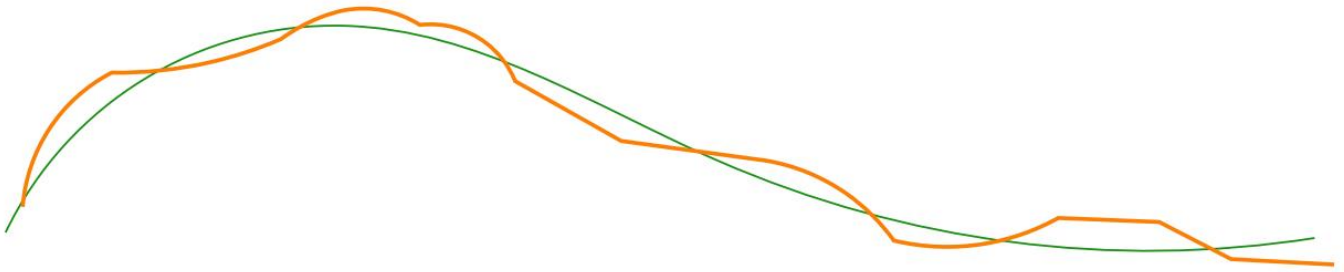


# Distribution Shifts

# Independent in Time Error

At each time step t, the agent wakes up on a state drawn from the state distribution of the expert trajectories, and executes an action

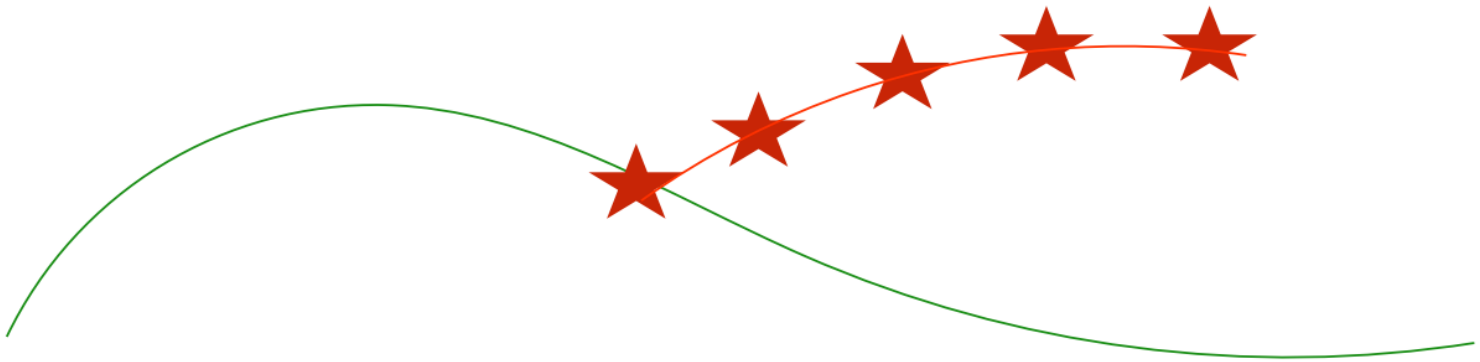


✓Error at each time t step bounded by $\epsilon$

✓Expected total error for T steps: $\mathbb{E}[E] \leq \epsilon T$

# Compounding Errors

At each time step t, the agent wakes up on a state drawn from the state distribution resulting from executing the action suggested by the learned policy previously



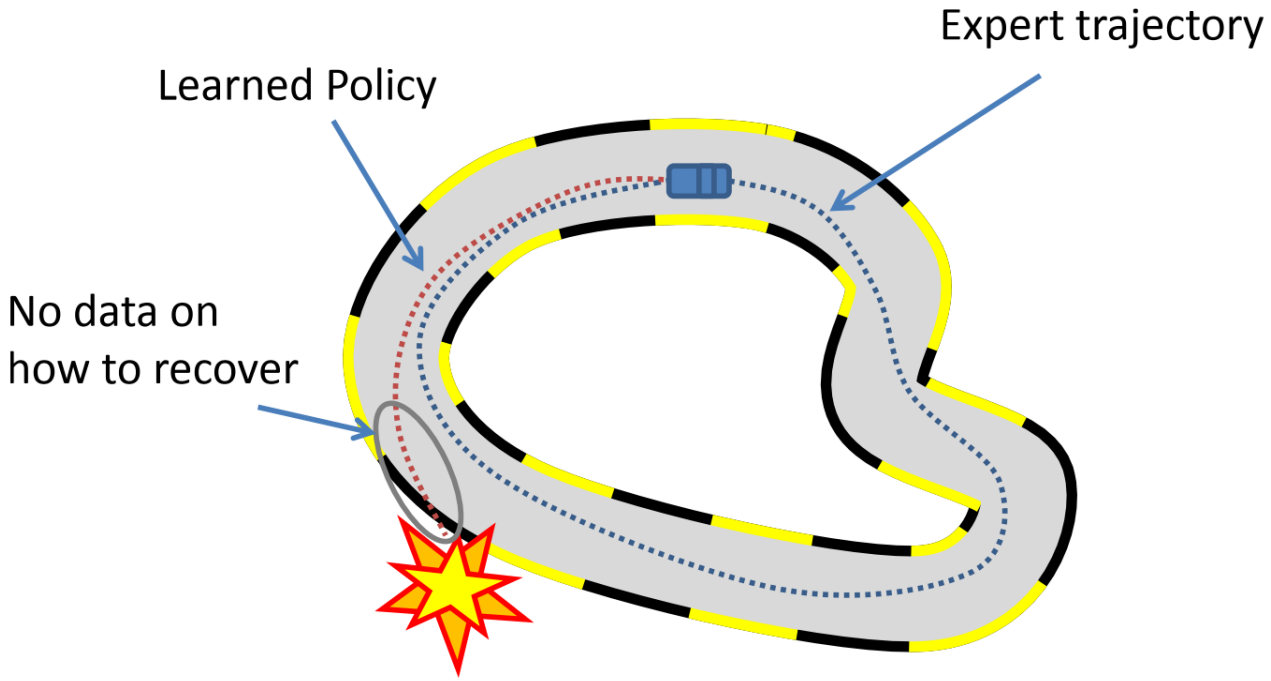
✓Error at each time t step bounded by $\epsilon$

✓Expected total error for T steps: $\mathbb{E}[E] \leq \epsilon\,(T + (T-1) + (T-2) + \cdots) \propto \epsilon T^2$

# Distribution Mismatch (Distribution Shift)

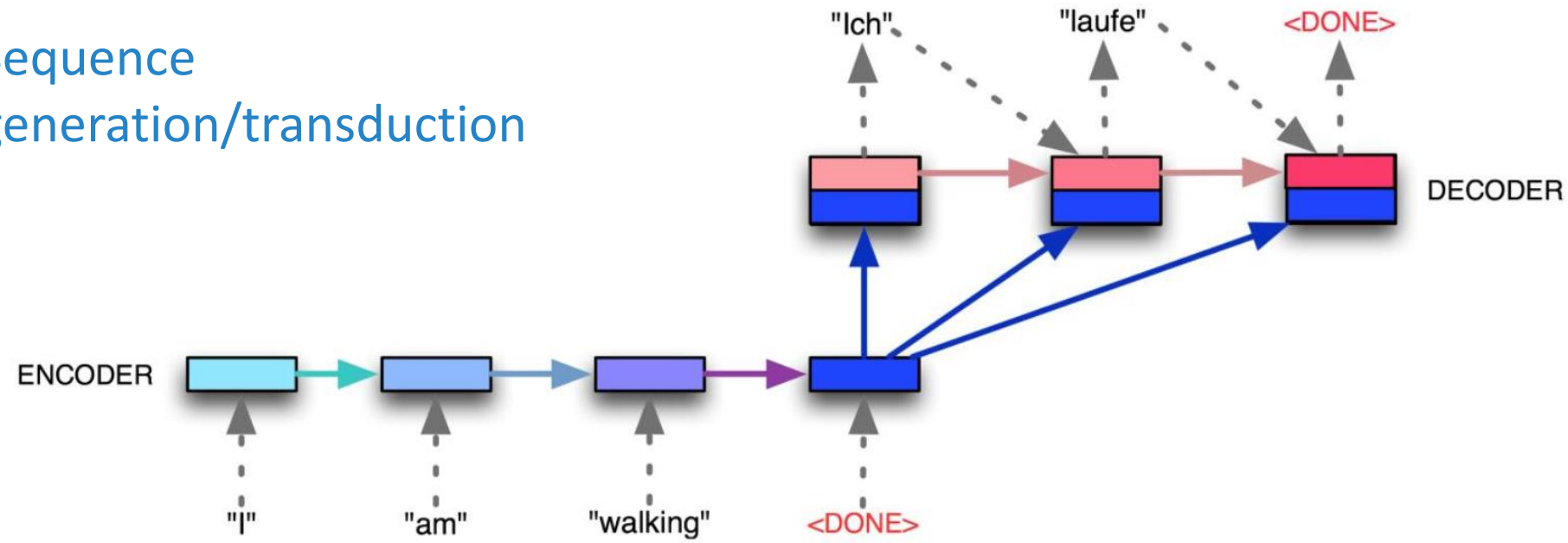
Due to the interdependence between our action at time step $t$ and the state at $t+1$, states seen at test time may come from a different distribution than those seen at training time

$$P_{\pi^*}(S_t) \neq P_{\pi_\theta}(S_t)$$



# Something Similar Happens in..

Sequence generation/transduction




Solutions use teacher forcing with annealed schedule

# Scheduled Sampling

- ✓ Initial training phase
  - ✓ Conditioning states come from the Teacher (training data)
- ✓ Later training phase
  - ✓ States/observations are sampled from the output of the model
- ✓ Ground-truth for the next time step still from the expert
  - ✓ Model learns to handle its mistakes
  - ✓ Pushing deviating generated sequences back to the right track

# Distribution Mismatch (DM)

| | Supervised Learning | Supervised learning + Control |
|---|---|---|
| **Train** | $(x, y) \sim P(D)$ | $s_t \sim P_{\pi^*}(\boldsymbol{s})$ |
| **Test** | $(x, y) \sim P(D)$ | $s_t \sim P_{\pi_\theta}(\boldsymbol{s})$ |

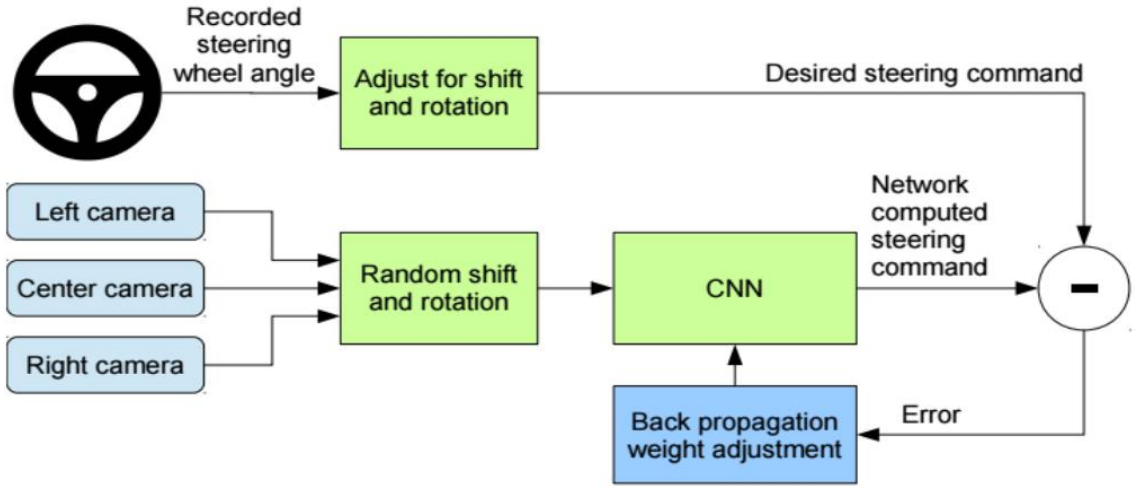
Fundamental assumption in (standard) supervised learning is that training and test data distributions match

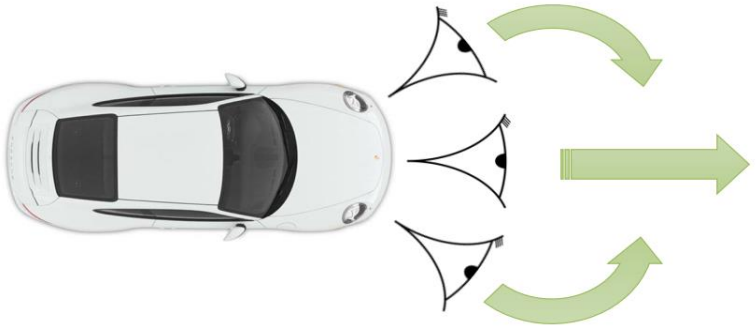
# DM Solution - Augment Data

- ✓Change $P_{\pi^*}(\boldsymbol{s})$ by augmenting the expert demonstration trajectories
  - ✓Add examples in expert demonstration trajectories to cover the states where the agent will land when trying out its own policy
- ✓Approaches
  - ✓Generate synthetic data in simulation (ALVINN 1989)
  - ✓Collecting additional data via clever tricks
  - ✓Interactively query the experts in additional datapoints

# Clever Tricks – NVIDIA 2016

*End to End Learning for Self-Driving Cars , Bojarski et al. 2016*



Additional, left and right cameras with automatic ground-truth labels to recover from mistakes

# NVIDIA 2016 Demo

https://youtu.be/NJU9ULQUwng

# Incremental Dataset Growing - DAgger

How can we make $P_{\pi^*}(\boldsymbol{s}) \approx P_{\pi_\theta}(\boldsymbol{s})$?

Key Idea - If we cannot be clever on $P_{\pi_\theta}(\boldsymbol{s})$ let us be clever on $P_{\pi^*}(\boldsymbol{s})$

**DAgger – Dataset Aggregation**

✓Collect training data from $P_{\pi_\theta}(\boldsymbol{s})$ in place of $P_{\pi^*}(\boldsymbol{s})$

✓Collect observations by running $\pi_\theta(a_t|s_t)$ and ask someone for labels $a_t$

# Incremental Dataset Growing - DAgger

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**DAgger – Dataset Aggregation**

1. Train $\pi_\theta(a_t|s_t)$ from expert data $\mathcal{D} = \{\boldsymbol{s}_1, \boldsymbol{a}_1, \dots, \boldsymbol{s}_N, \boldsymbol{a}_N\}$
2. Run $\pi_\theta(a_t|s_t)$ to get data $\mathcal{D}_\pi = \{\boldsymbol{s}_1, \dots, \boldsymbol{s}_N\}$
3. Ask expert to label $\mathcal{D}_\pi$ with action $\boldsymbol{a}_n$
4. Aggregate $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$

Potential issues

- Execute an unsafe/partially trained policy
- Repeatedly query the expert
- Expert is queried for an action without experiencing the state

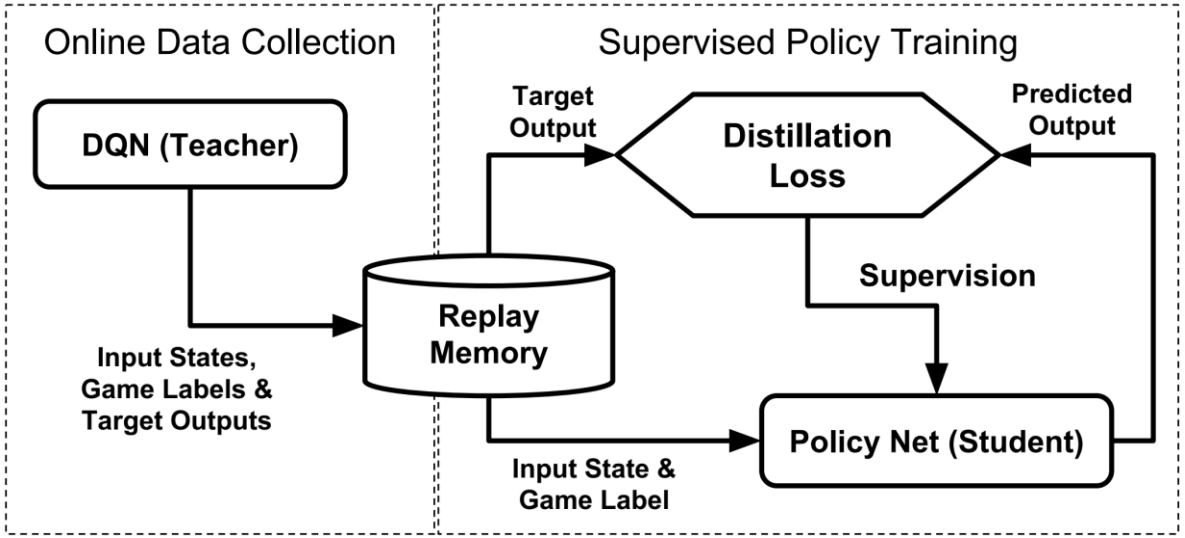
# Dagger Demo

*Ross et al, Learning monocular reactive UAV control in cluttered natural environments, 2013*


https://youtu.be/hNsP6-K3Hn4

# Beyond Vanilla Dagger

- ✓Experts do not need to be humans
  - ✓Generative learning can be used for imitating expert policies
  - ✓Solving simpler optimization in a constrained part of the state space
- ✓Imitation then means distilling knowledge of constrained policies into a general policy that can do well in all scenarios




*Rusu, Policy distillation, ICLR 2016*

# Meeting the Expert Expectations

# Non-Markovian Behaviour

$$\pi_\theta(a_t|s_t)$$

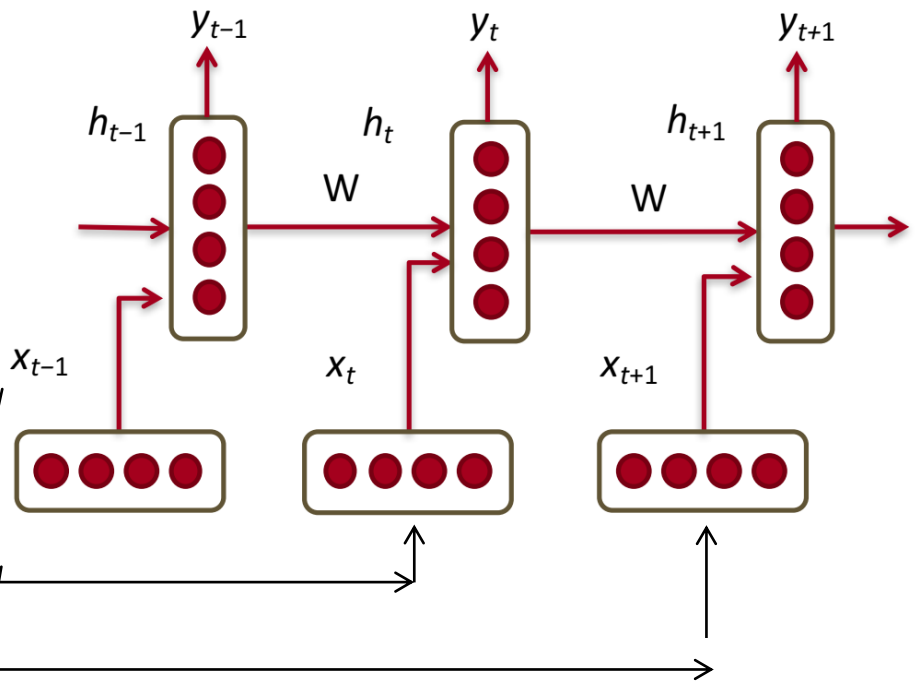
If we see the same thing twice, we do the same thing twice, regardless of what happened before

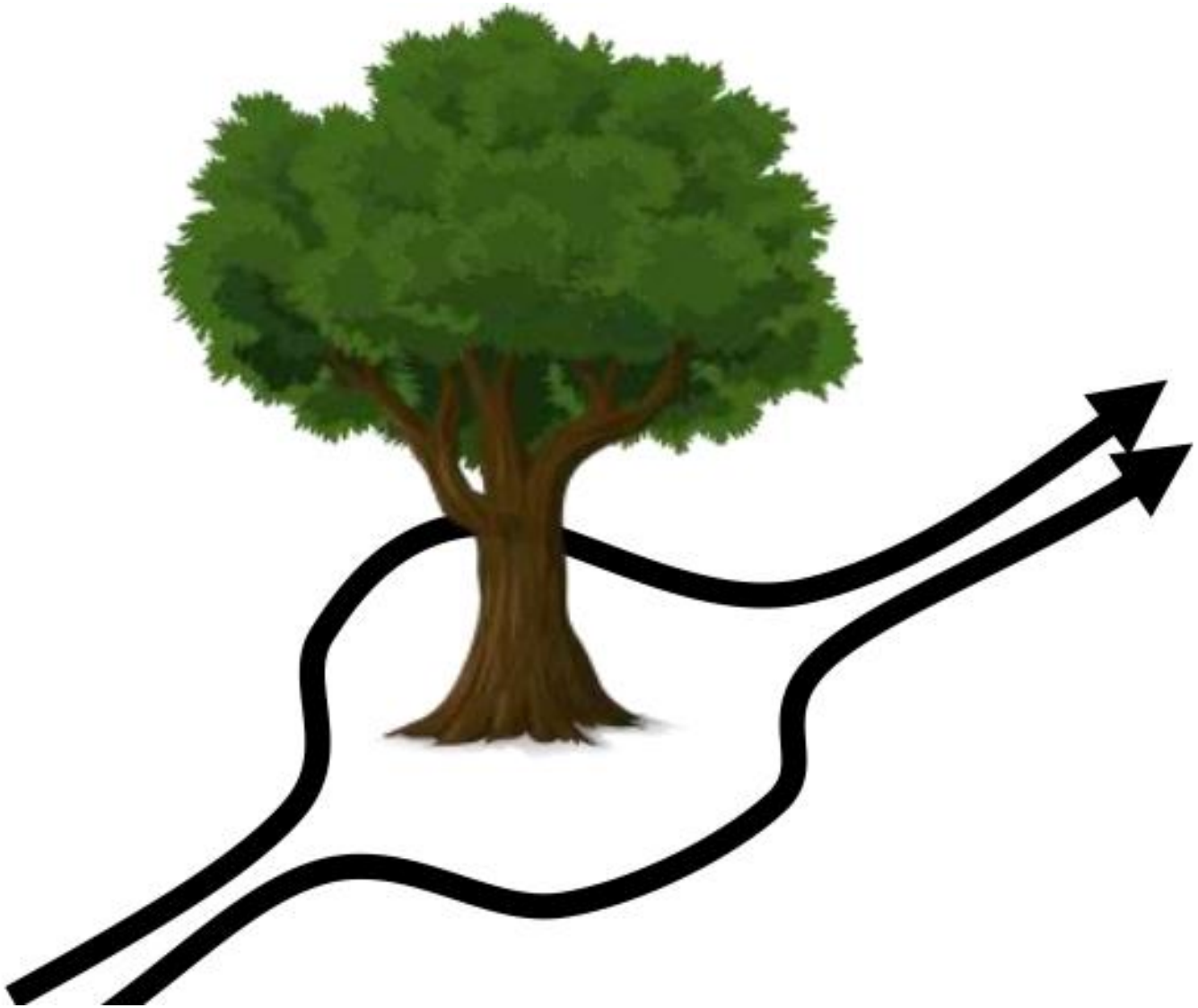
$$\pi_\theta(a_t|s_t, s_{t-1}, \dots, s_0)$$

Behavior depends on the history of past observations

# Non-Markovian Behaviour – How to?

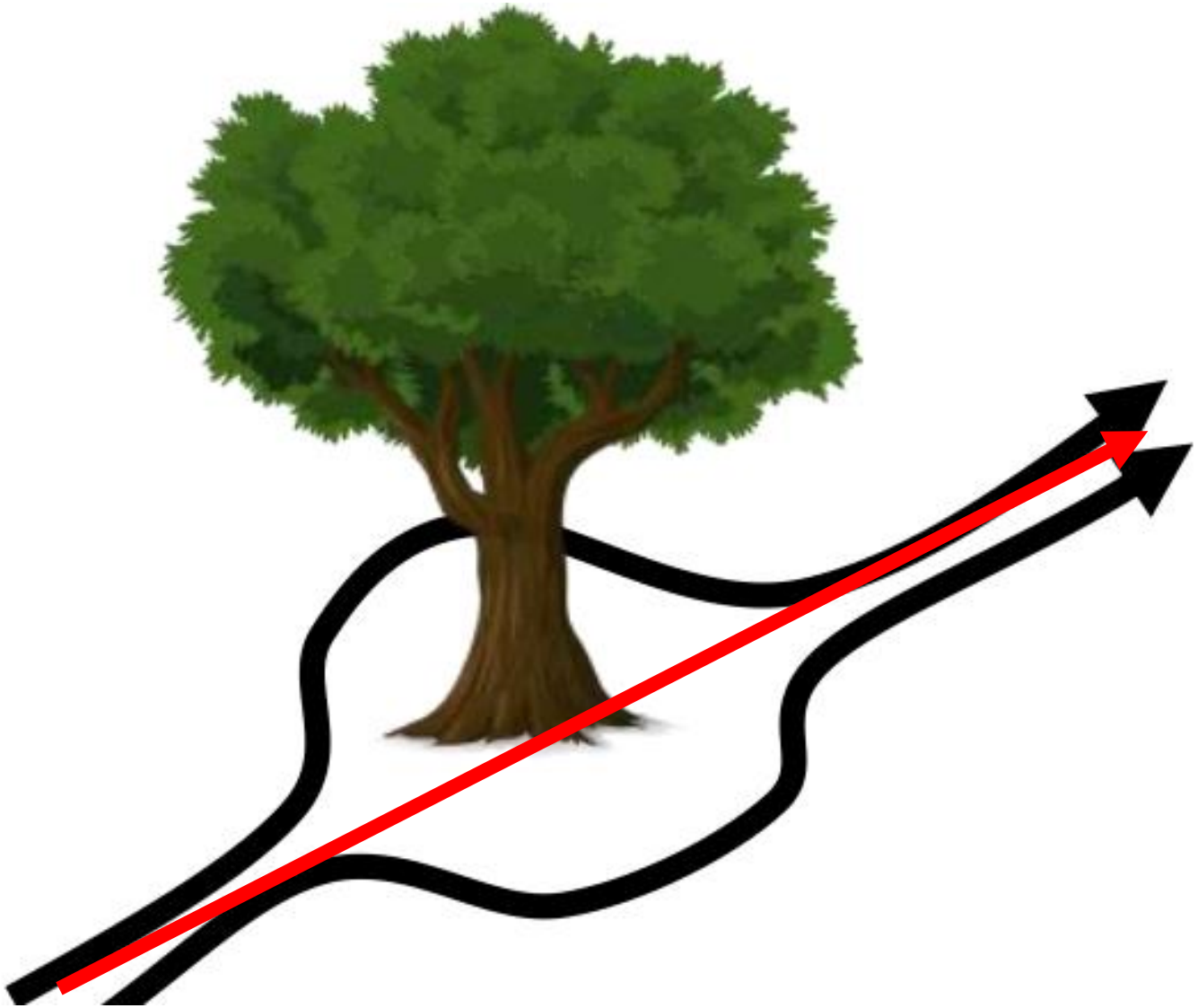

**Recurrent neural network**
(gated to say the least)





# Multimodal Behaviour

- ✓ Avoiding an obstacle for an expert is easy
- ✓ Take one of the two steering angles



# Multimodal Behaviour in Regression

- ✓Regression fails in multimodality
- ✓MSE minimum is the average
- ✓Which might not be advisable…

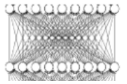
# Multimodal Behaviour in Regression

- ✓….unless you know how to do this

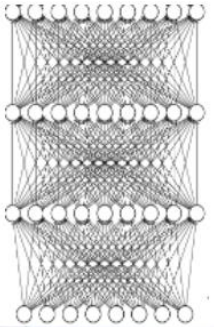
# Multimodality - Can we fix it?

- ✓ Autoregressive discretization
  - ✓ Discretize the action space and train a classifier that predicts a categorical distribution it
  - ✓ Do it progressively on the original features to avoid curse of dimensionality (e.g. PixelRNN)
- ✓ Gaussian mixture model output
  - ✓ Predict mixture components weights, means and variances
  - ✓ Need to guess number of modes
- ✓ Density model
  - ✓ Density networks
  - ✓ Variational Autoencoders
  - ✓ Generative Adversarial Network

$P(a_2|a_1)$



$P(a_1)$



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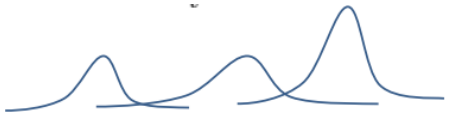
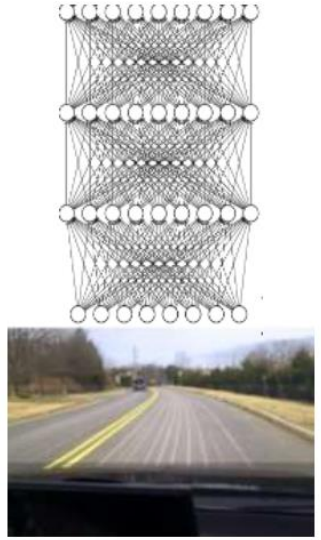
$$\pi_\theta(a|s) = \sum_i w_i \mathcal{N}(\mu_i, \Sigma_i)$$





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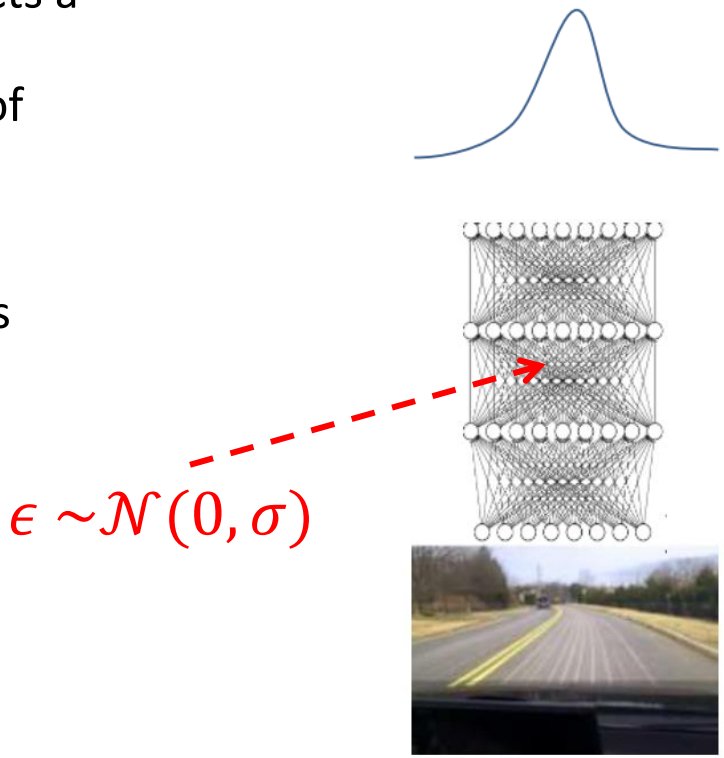
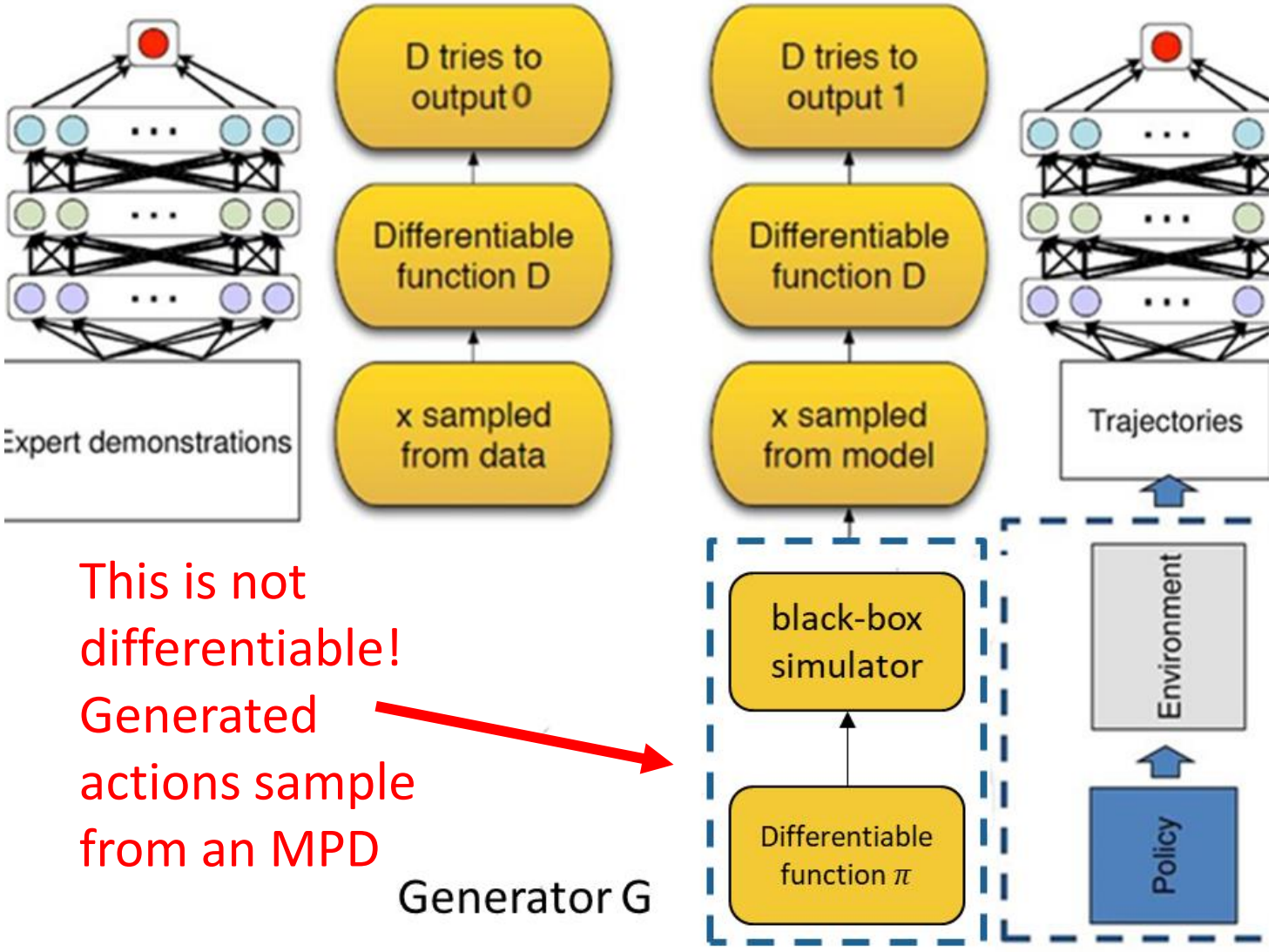


# Generative Imitation Learning




# Generative Adversarial Imitation Learning (GAIL)

- ✓Use a policy network as generator (state conditioned)
- ✓Find a policy that makes it impossible for a discriminator network to distinguish between state-actions from the expert demonstrations and state-actions visited by the learnt policy
- ✓Generator needs to be trained using RL

Ho and Ermon, Generative Adversarial Imitation Learning, NIPS 2016

# GAIL Algorithm

**Algorithm 1** Generative adversarial imitation learning

1: **Input:** Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator parameters $\theta_0, w_0$
2: **for** $i = 0, 1, 2, \ldots$ **do**
3: Sample trajectories $\tau_i \sim \pi_{\theta_i}$
4: Update the discriminator parameters from $w_i$ to $w_{i+1}$ with the gradient

$$\hat{\mathbb{E}}_{\tau_i}[\nabla_w \log(D_w(s,a))] + \hat{\mathbb{E}}_{\tau_E}[\nabla_w \log(1 - D_w(s,a))] \tag{17}$$

Discriminator provides reward function

5: Take a policy step from $\theta_i$ to $\theta_{i+1}$, using the TRPO rule with cost function $\log(D_{w_{i+1}}(s,a))$. Specifically, take a KL-constrained natural gradient step with

$$\hat{\mathbb{E}}_{\tau_i}[\nabla_\theta \log \pi_\theta(a|s) Q(s,a)] - \lambda \nabla_\theta H(\pi_\theta), \tag{18}$$
$$\text{where } Q(\bar{s},\bar{a}) = \hat{\mathbb{E}}_{\tau_i}[\log(D_{w_{i+1}}(s,a)) \,|\, s_0 = \bar{s}, a_0 = \bar{a}]$$

Entropy-based policy regularizer

Trust-Region policy gradient

6: **end for**

# Rewards are not always as explicit

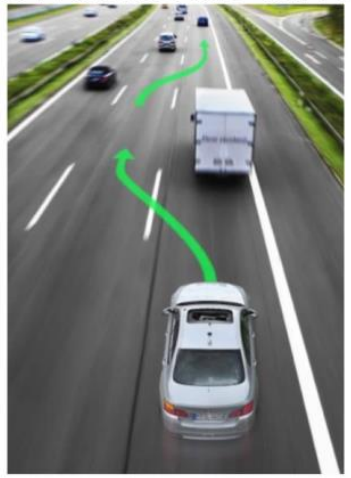
reward

Mnih et al. ‘15

robotics

dialog

autonomous driving



what is the reward?
often use a proxy

# Inverse Reinforcement Learning (IRL)

- ✓An alternative to imitation learning
  - ✓Use demonstrations to learn a reward function
  - ✓Train a policy using learnt reward function
- ✓Least expensive form of supervision
  - ✓Does not need full demonstrations
  - ✓RL phase can “fill in” missing behavior given partial demonstrations
- ✓Argued to be a more comprehensive model of expert behavior
  - ✓Learning why the expert did something instead of mapping states to actions
  - ✓Can potentially generalize better

GAIL is a particular form of inverse RL that learns a reward function that tries to match state distributions between the expert and imitator

# More Formally

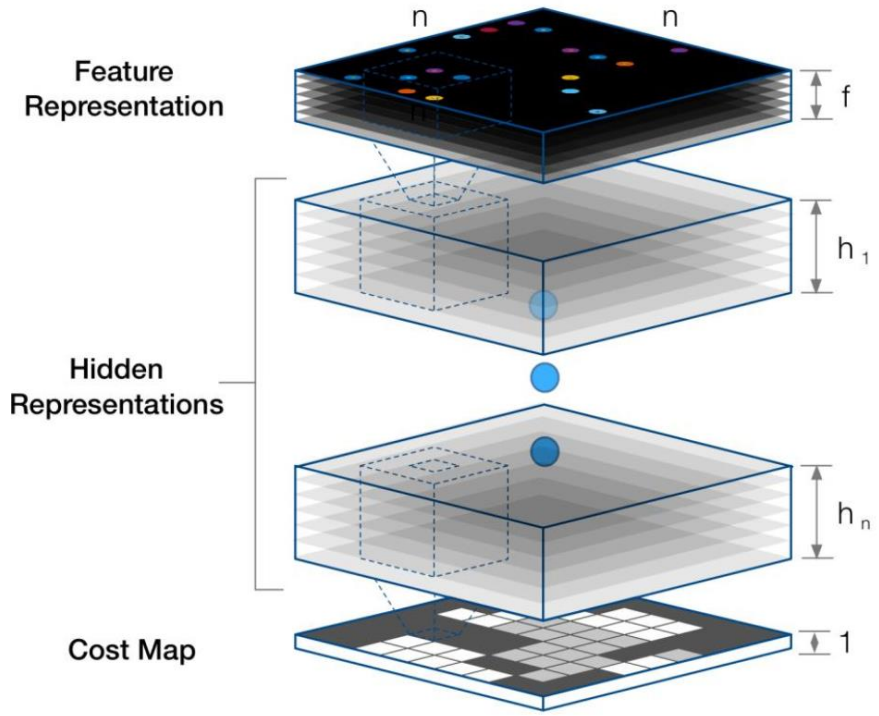
## Forward Reinforcement Learning

- ✓ Given
  - ✓ States $s \in \mathcal{S}$ and actions $a \in \mathcal{A}$
  - ✓ Transitions $P_{ss'}^{a}$ (sometimes)
  - ✓ Reward function $\mathcal{R}_{s}^{a}$
- ✓ Learn or infer policy $\pi^{*}(a|s)$

## Inverse Reinforcement Learning

- ✓ Given
  - ✓ States $s \in \mathcal{S}$ and actions $a \in \mathcal{A}$
  - ✓ Transitions $P_{ss'}^{a}$ (sometimes)
  - ✓ Sampled episodes from expert $(s, a) \sim \pi^{*}(a|s)$
- ✓ Learn a reward function $r_{\phi}(a, s)$, with $\phi$ being adaptive parameters
- ✓ …and use $r_{\phi}(a, s)$ to learn/infer $\pi^{*}(a|s)$

# Solving IRL – MaxEntropy Deep IRL




Wulfmeier et al, Maximum Entropy Deep Inverse Reinforcement Learning, 2015

**Algorithm 1** Maximum Entropy Deep IRL

**Input:** $\mu_D^a, f, S, A, T, \gamma$

**Output:** optimal weights $\theta^*$

1: $\theta^1 = \text{initialise\_weights}()$

**Iterative model refinement**

2: **for** n = 1 : N **do**

3: $r^n = \text{nn\_forward}(f, \theta^n)$

**Solution of MDP with current reward**

4: $\pi^n = \text{approx\_value\_iteration}(r^n, S, A, T, \gamma)$

5: $\mathbb{E}[\mu^n] = \text{propagate\_policy}(\pi^n, S, A, T)$

**Determine Maximum Entropy loss and gradients**

6: $\mathcal{L}_D^n = \log(\pi^n) \times \mu_D^a$

7: $\frac{\partial \mathcal{L}_D^n}{\partial r^n} = \mu_D - \mathbb{E}[\mu^n]$

**Compute network gradients**

8: $\frac{\partial \mathcal{L}_D^n}{\partial \theta_D^n} = \text{nn\_backprop}(f, \theta^n, \frac{\partial \mathcal{L}_D^n}{\partial r^n})$

9: $\theta^{n+1} = \text{update\_weights}(\theta^n, \frac{\partial \mathcal{L}_D^n}{\partial \theta_D^n})$

10: **end for**

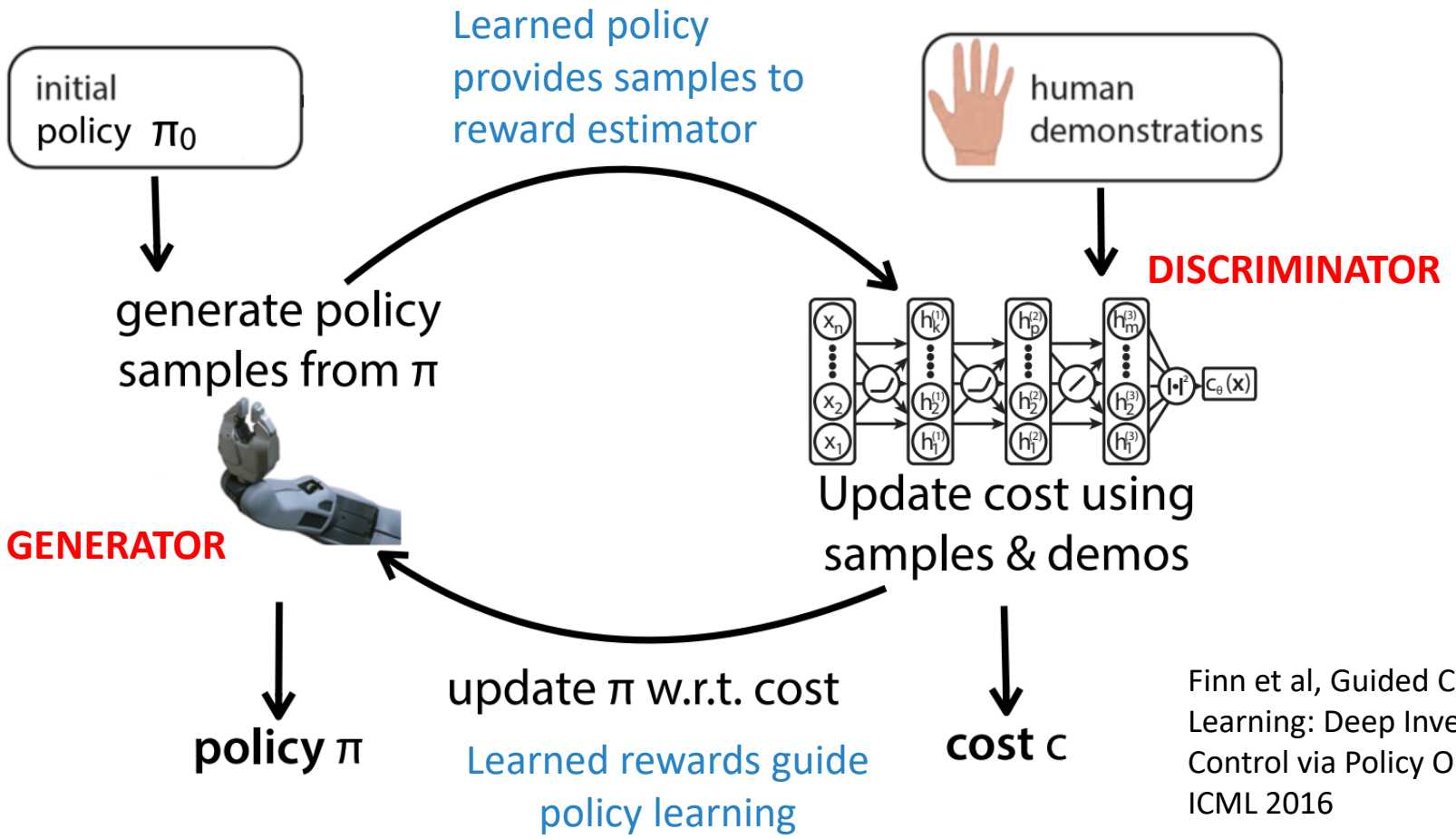
Expert state-action frequencies

Finds $Q$ and $V$ and infers $\pi^n$

Expected state visiting frequencies by sampling with $\pi^n$

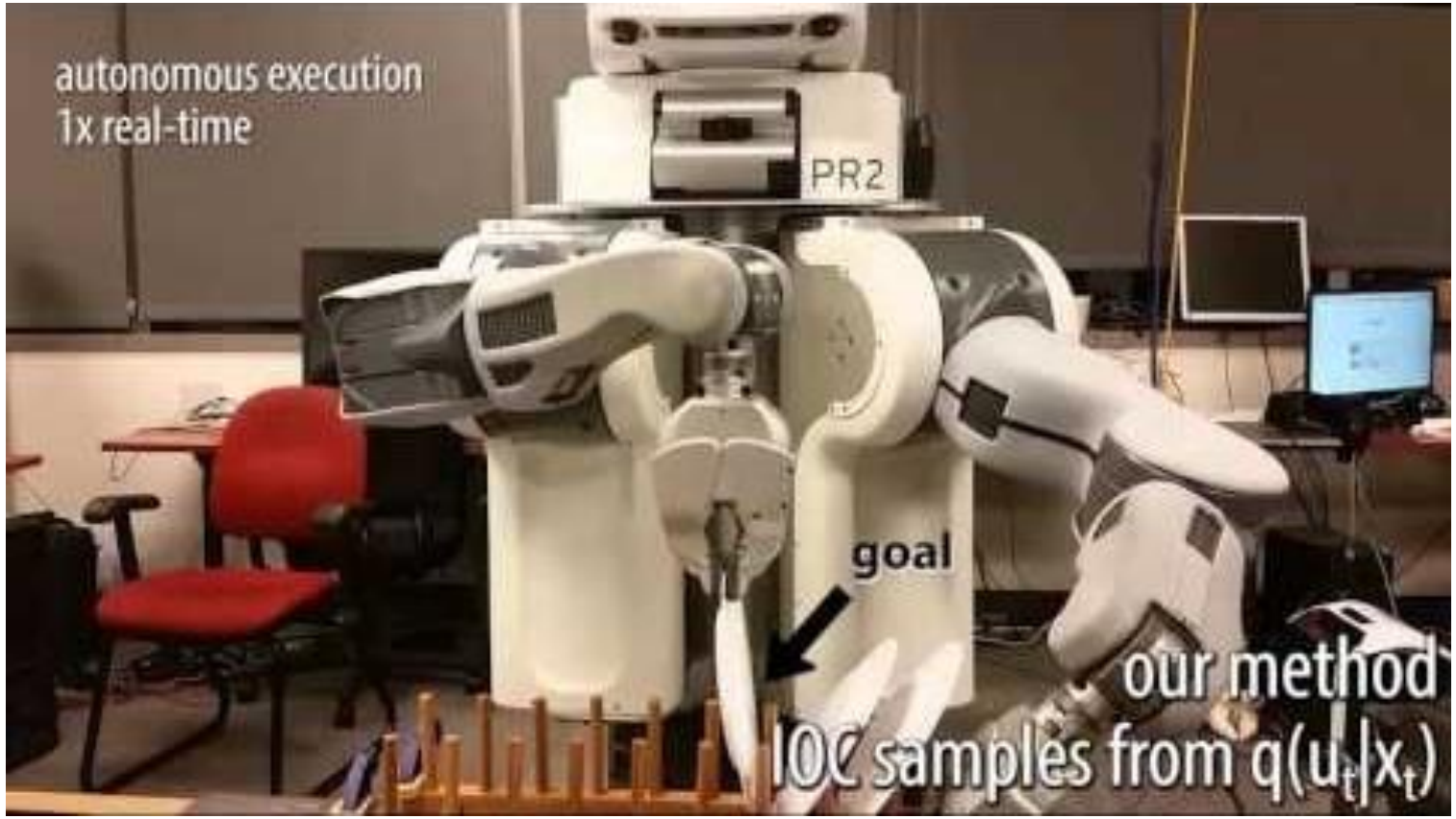
MAP of observing expert samples

# Guided Cost Learning




Finn et al, Guided Cost Learning: Deep Inverse Optimal Control via Policy Optimization, ICML 2016

# GCL Demo




https://youtu.be/hXxaepw0zAw

# Wrap-up

# Take home messages

- ✓Effective imitation learning is much about managing distribution shift and relaying less on human demonstration
- ✓Using a learnable model of reward can serve the purpose of reducing the extent of human labelling (inverse reinforcement learning)
- ✓Much left unsaid
  - ✓Off-policy learning from imitation policy
  - ✓Q-learning as natural off-policy imitation learner
    - ✓Just drop demonstrations into the replay buffer
  - ✓Inverse reinforcement learning Vs generative adversarial learning