



# Imitation Learning

CS 224R

# Course reminders

- Start forming final project groups (survey due Weds April 16)
- Homework 1 out today, due Fri April 18
- PyTorch tutorial today at 1:30 pm in Gates B1

# Partial Recap

state  $\mathbf{s}_t$  - the state of the “world” at time  $t$

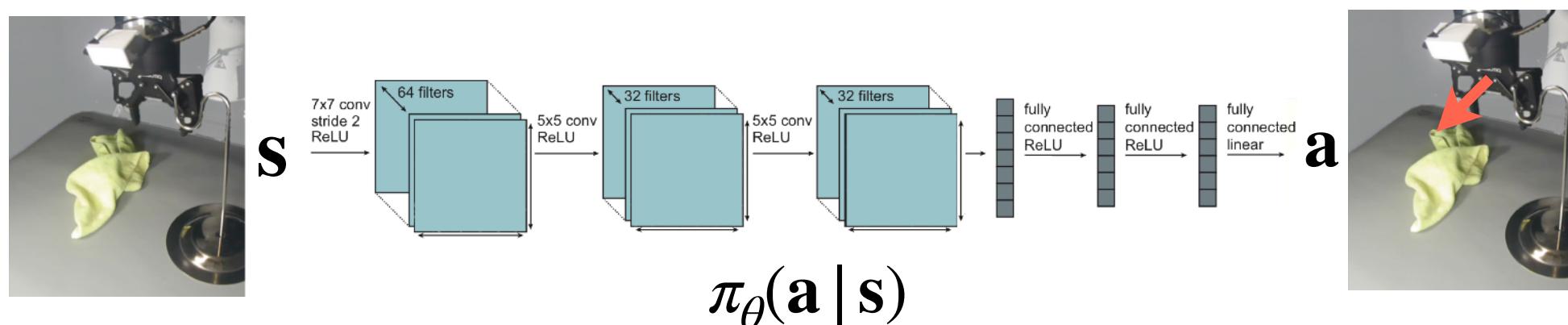
observation  $\mathbf{o}_t$  - what the agent observes at time  $t$

action  $\mathbf{a}_t$  - the decision taken at time  $t$

trajectory  $\tau$  - sequence of states/observations and actions

$$(\mathbf{s}_1, \mathbf{a}_1, \mathbf{s}_2, \mathbf{a}_2, \dots, \mathbf{s}_T, \mathbf{a}_T)$$

reward function  $r(\mathbf{s}, \mathbf{a})$  - how good is  $\mathbf{s}, \mathbf{a}$ ?



policy  $\pi(\mathbf{a}_t | \mathbf{s}_t)$  or  $\pi(\mathbf{a}_t | \mathbf{o}_{t-m:t})$  - behavior, usually what we are trying to learn

can be represented using a generative model

# The plan for today

## Imitation Learning

1. Imitation learning basics
2. Learning expressive policy distributions
3. Learning from online interventions
4. Time permitting: how to collect demonstrations

} Topic of homework 1!

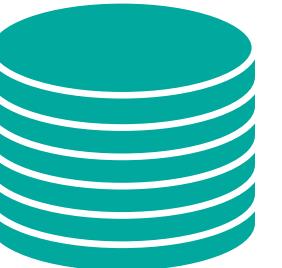
## Key learning goals:

- how to represent distributions with neural networks
- why expressive distributions matter for imitation learning
- what are compounding errors and how to address them

# What is the goal of imitation learning?

**Data:** Given trajectories collected by an expert

“demonstrations”  $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \dots, \mathbf{s}_T)\}$



(sampled from some unknown policy  $\pi_{\text{expert}}$ )



- Dataset from human drivers
- Sensor readings + steering commands

**Goal:** Learn a policy  $\pi_\theta$  that performs at the level of the expert policy, by mimicking it.

# Imitation learning - version 0

Deterministic policy

0. Given demonstrations collected by an expert  $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \dots, \mathbf{s}_T)\}$

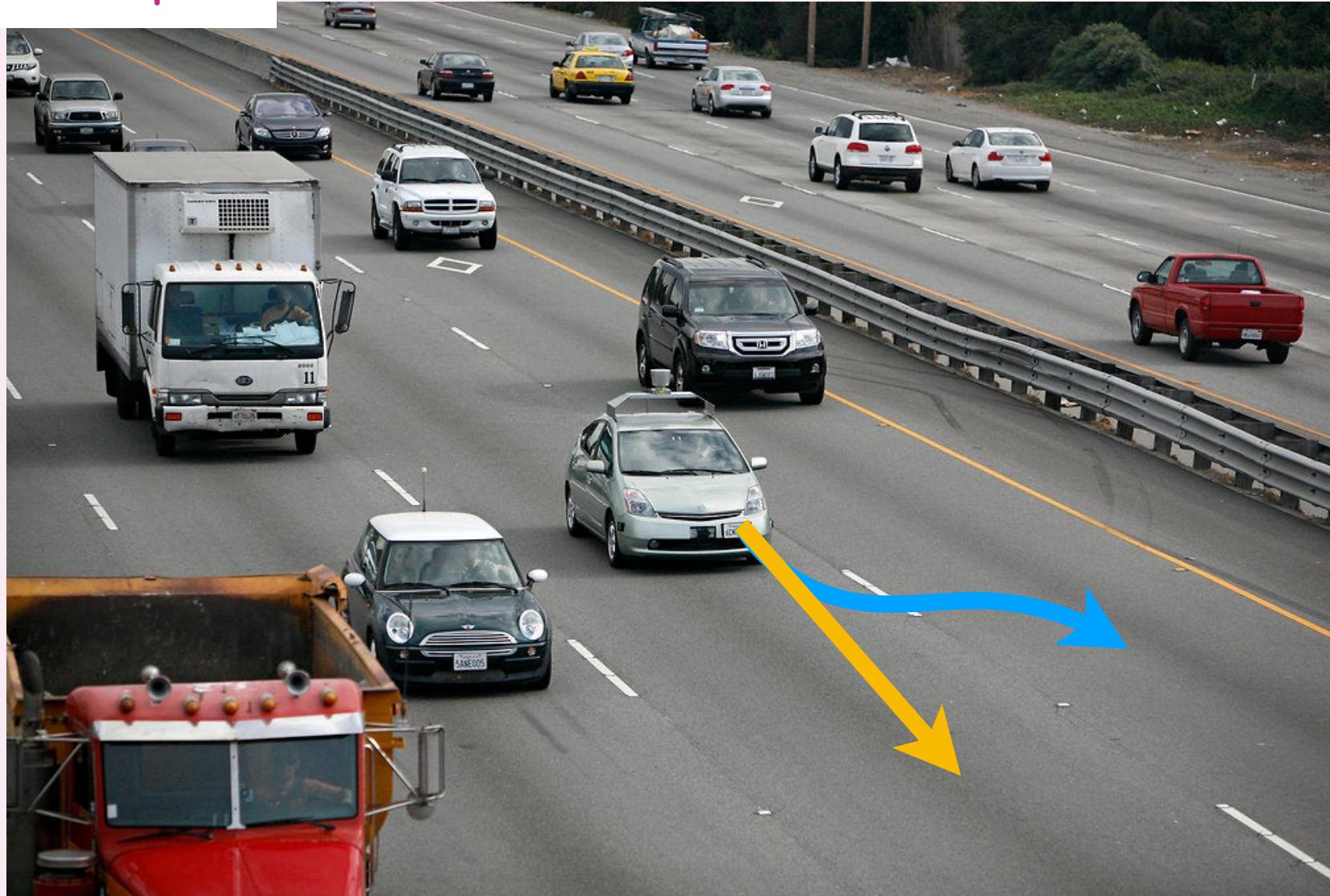
1. For deterministic policy, supervised regression to the expert's actions

$$\min_{\theta} \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{s}, \mathbf{a}) \in \mathcal{D}} \|\mathbf{a} - \hat{\mathbf{a}}\|^2 \quad \text{where } \hat{\mathbf{a}} = \pi_{\theta}(\mathbf{s})$$

2. Deploy learned policy  $\pi_{\theta}$

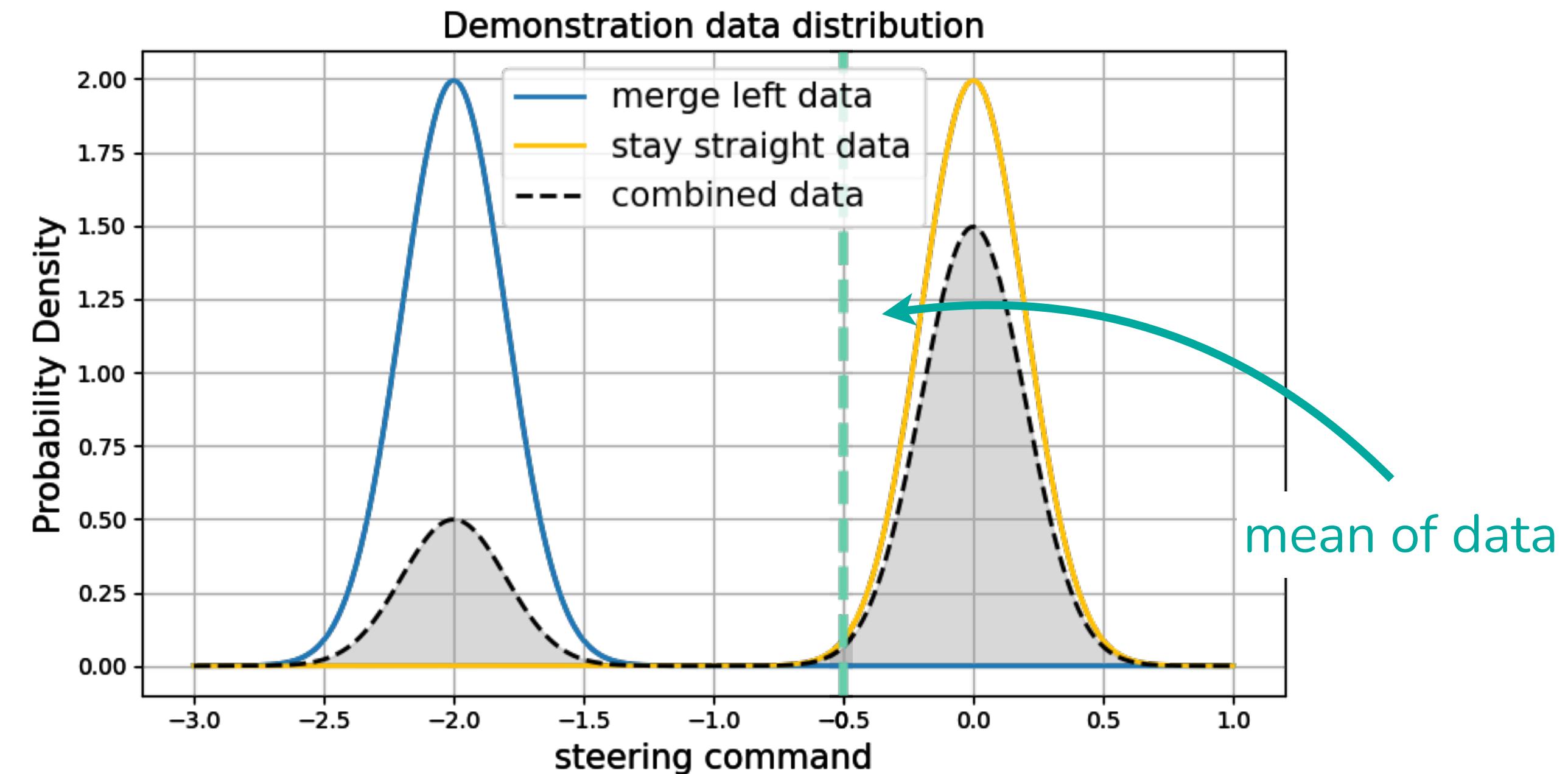
# What could go wrong?

## Example



- Dataset from human drivers
- Sensor readings + steering commands

Question: what might policy trained with  $\ell_2$ -regression do?

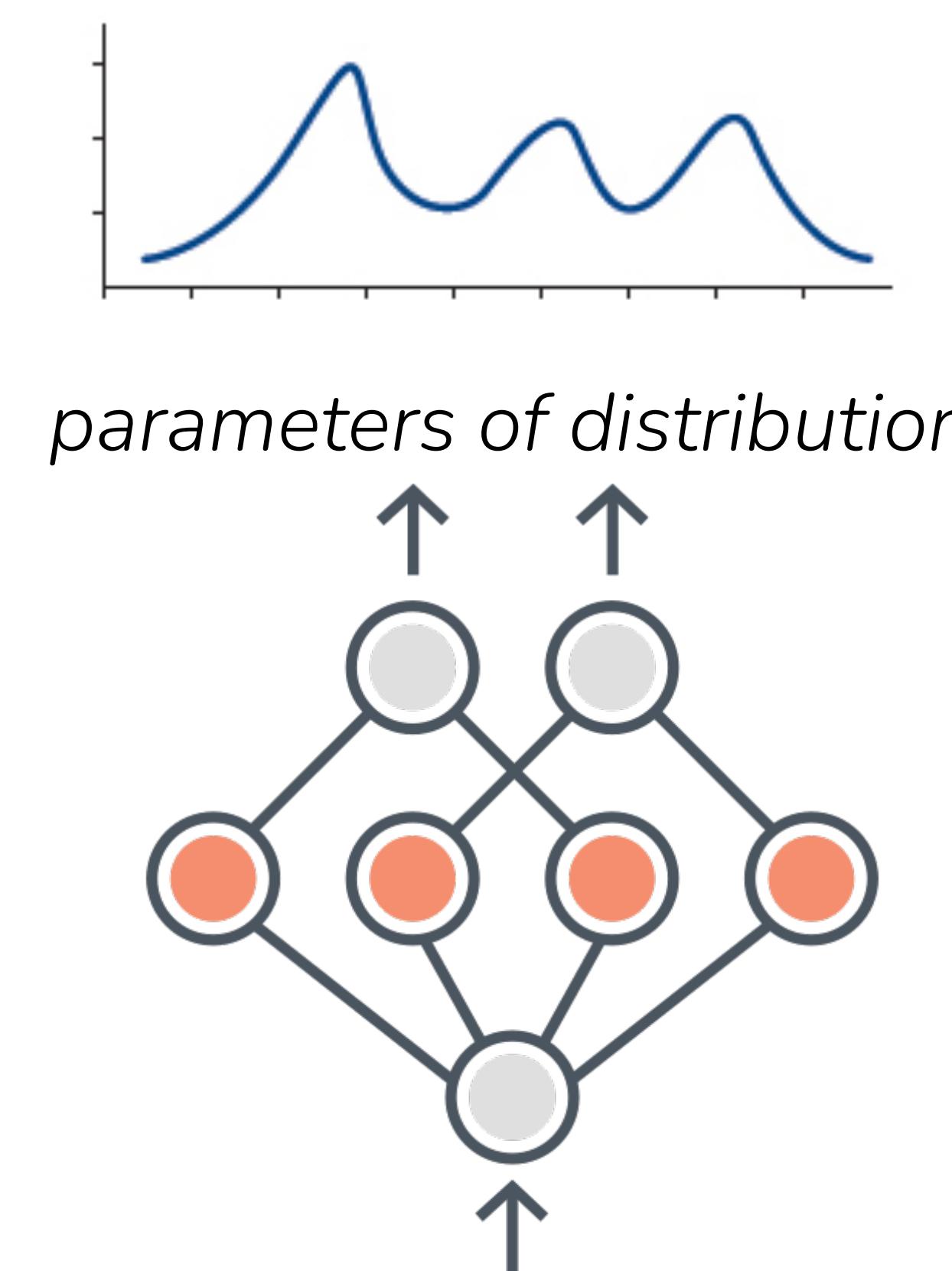


How often does this happen in practice? All the time!

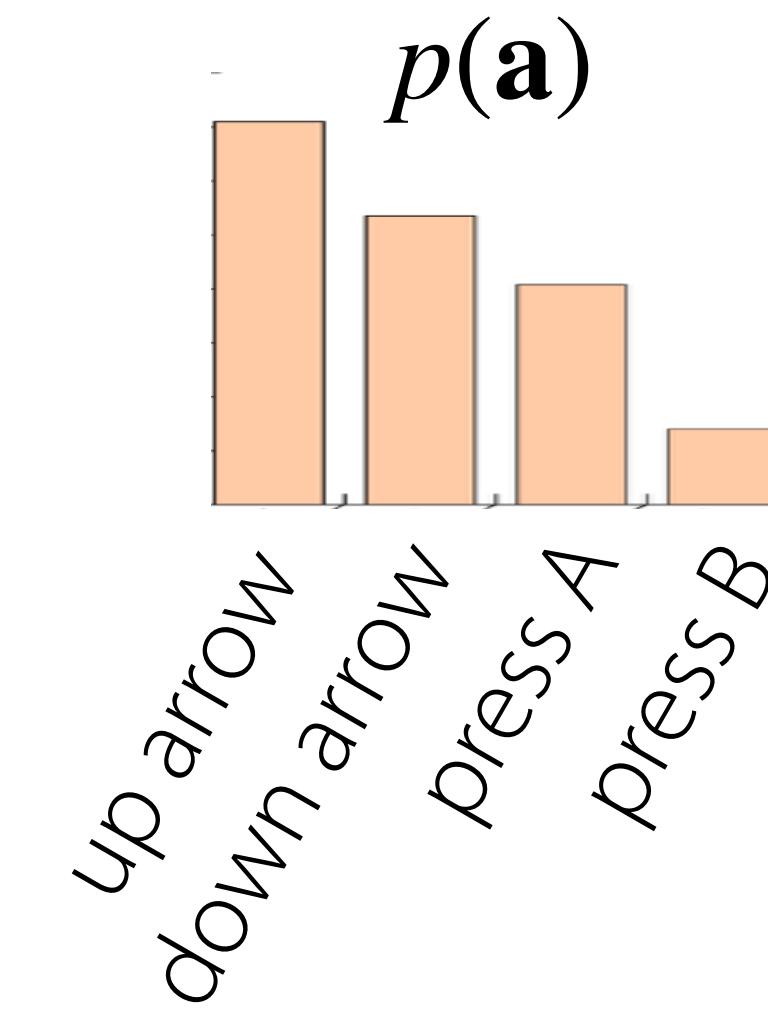
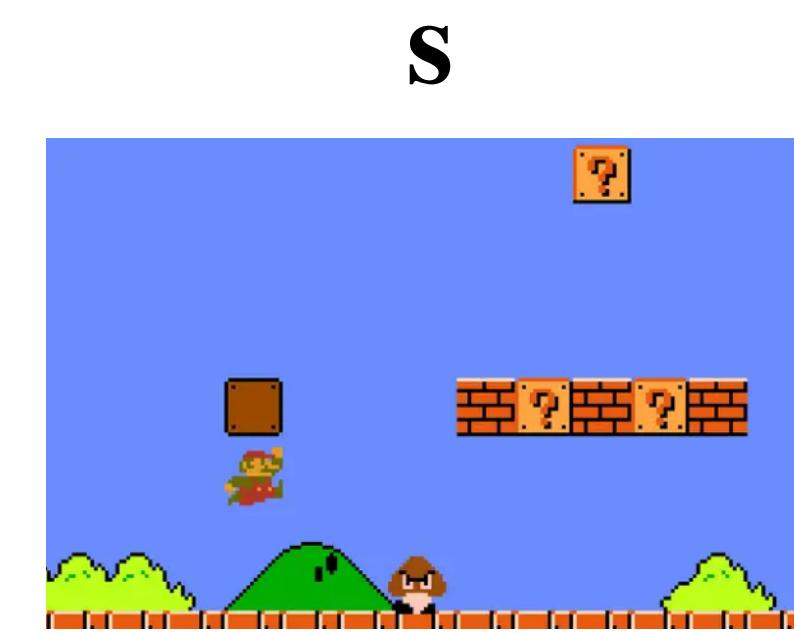
Esp. when data collected by multiple people.

**How can we represent  
more than the mean?**

# Learning distributions with neural networks

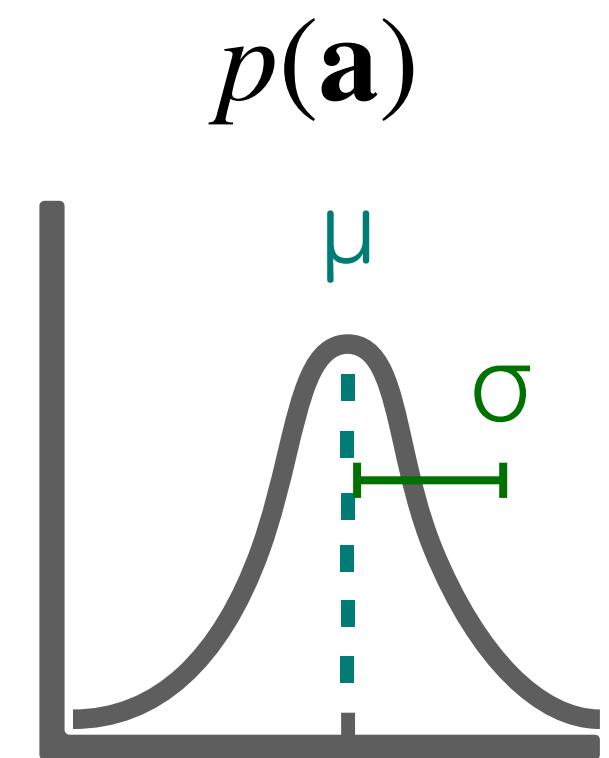
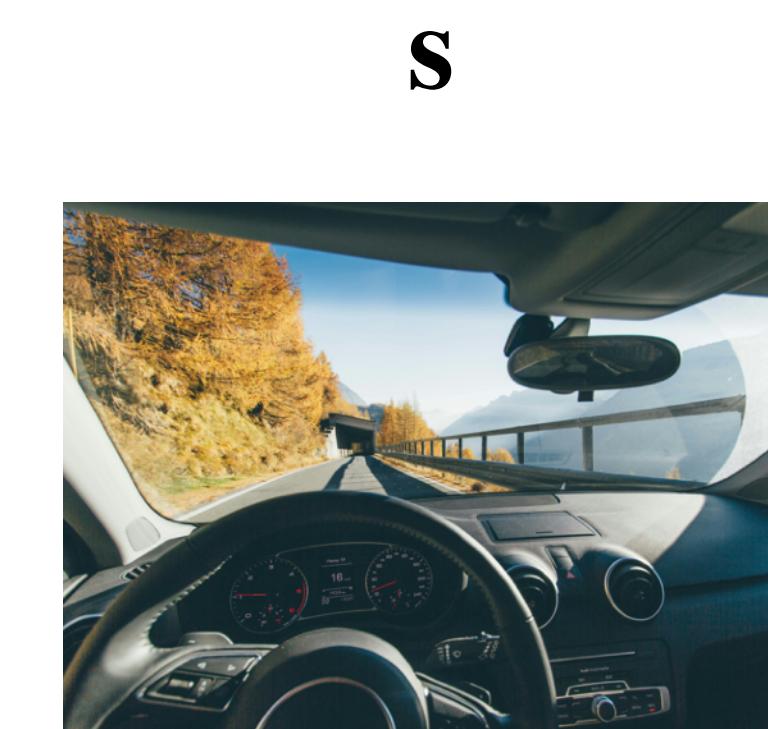


## 1D discrete actions



Neural net outputs  $p(\text{up}), p(\text{down}), \dots$   
represent categorical distribution.  
Maximally expressive

## Continuous actions



next steering angle

Neural net outputs  $\mu, \sigma$  to represent  
Gaussian distribution.  
Not very expressive!

# Learning *distributions* with neural networks

💡 Can we use generative modeling?

image diffusion models



autoregressive models

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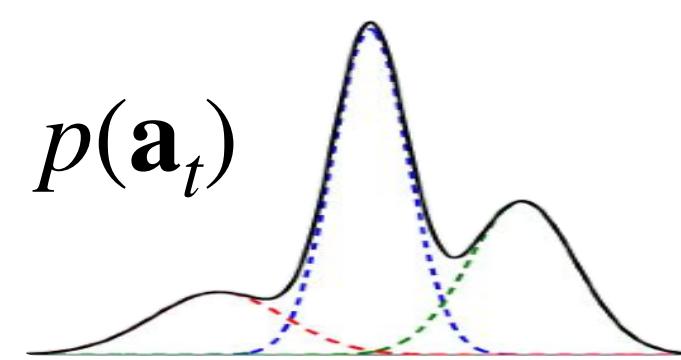
learning  $p(\text{image} \mid \text{text description})$

learning  $p(\text{next word} \mid \text{words so far})$

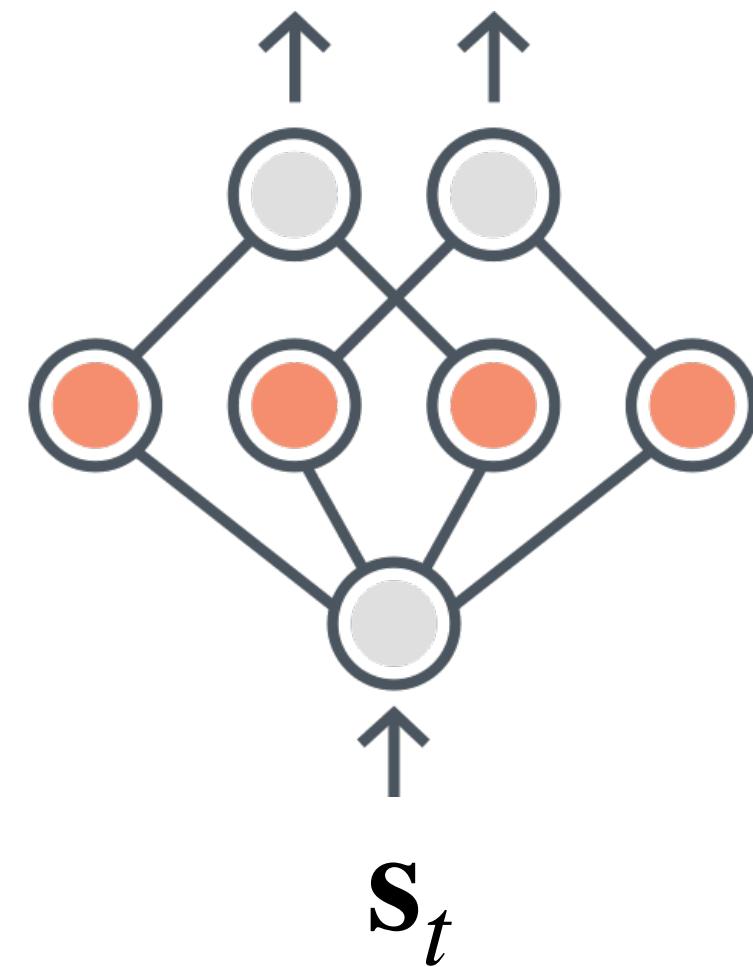
Our goal: learning  $p(\text{action} \mid \text{observations})$

# Generative models for policies (approximating $p(\mathbf{a} | \mathbf{s})$ )

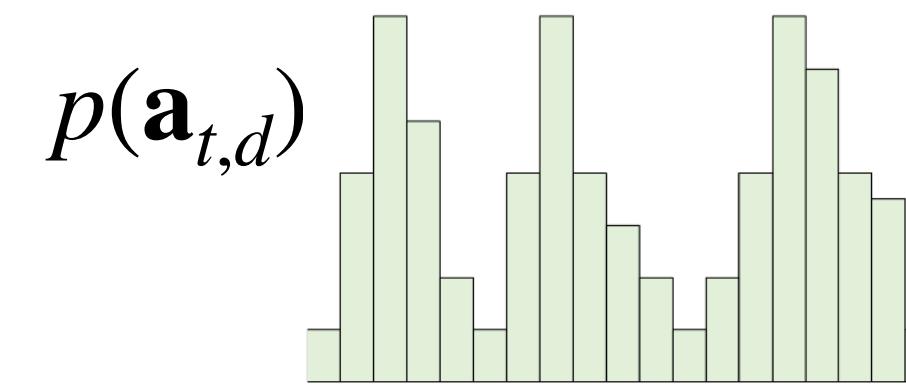
## Mixture of Gaussians



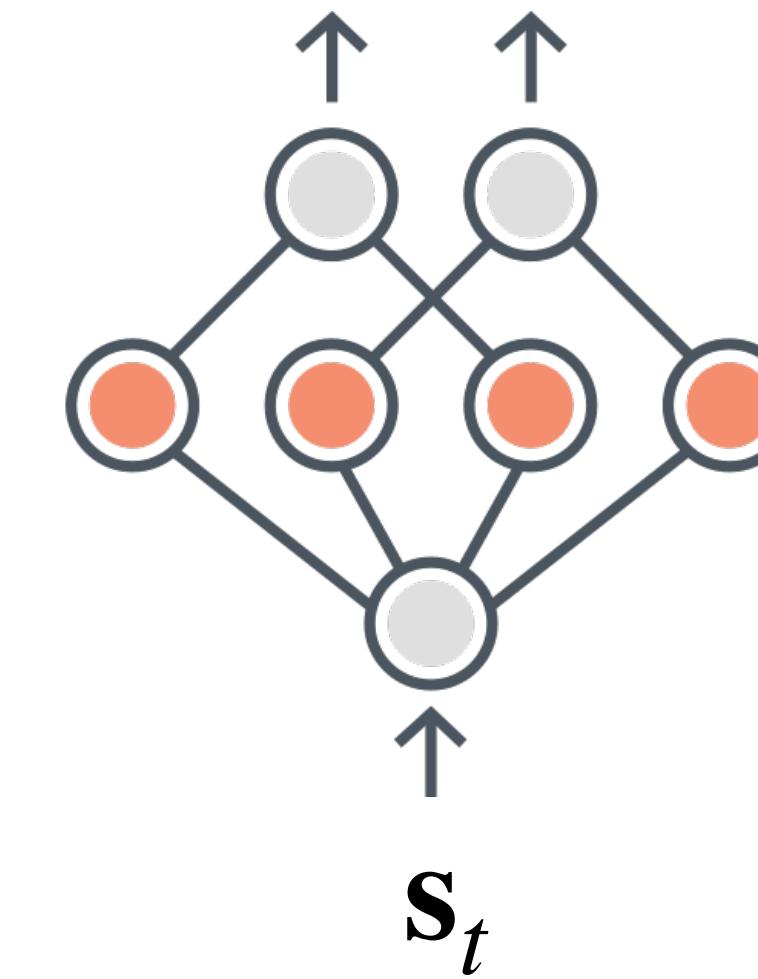
output  $\mu_1, \sigma_1, w_1, \mu_2, \sigma_2, w_2, \dots$



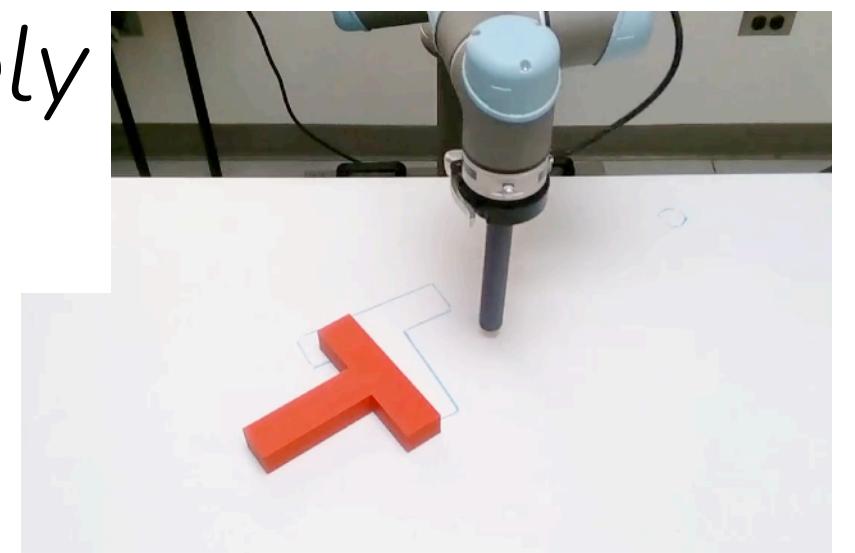
## Discretize + Autoregressive



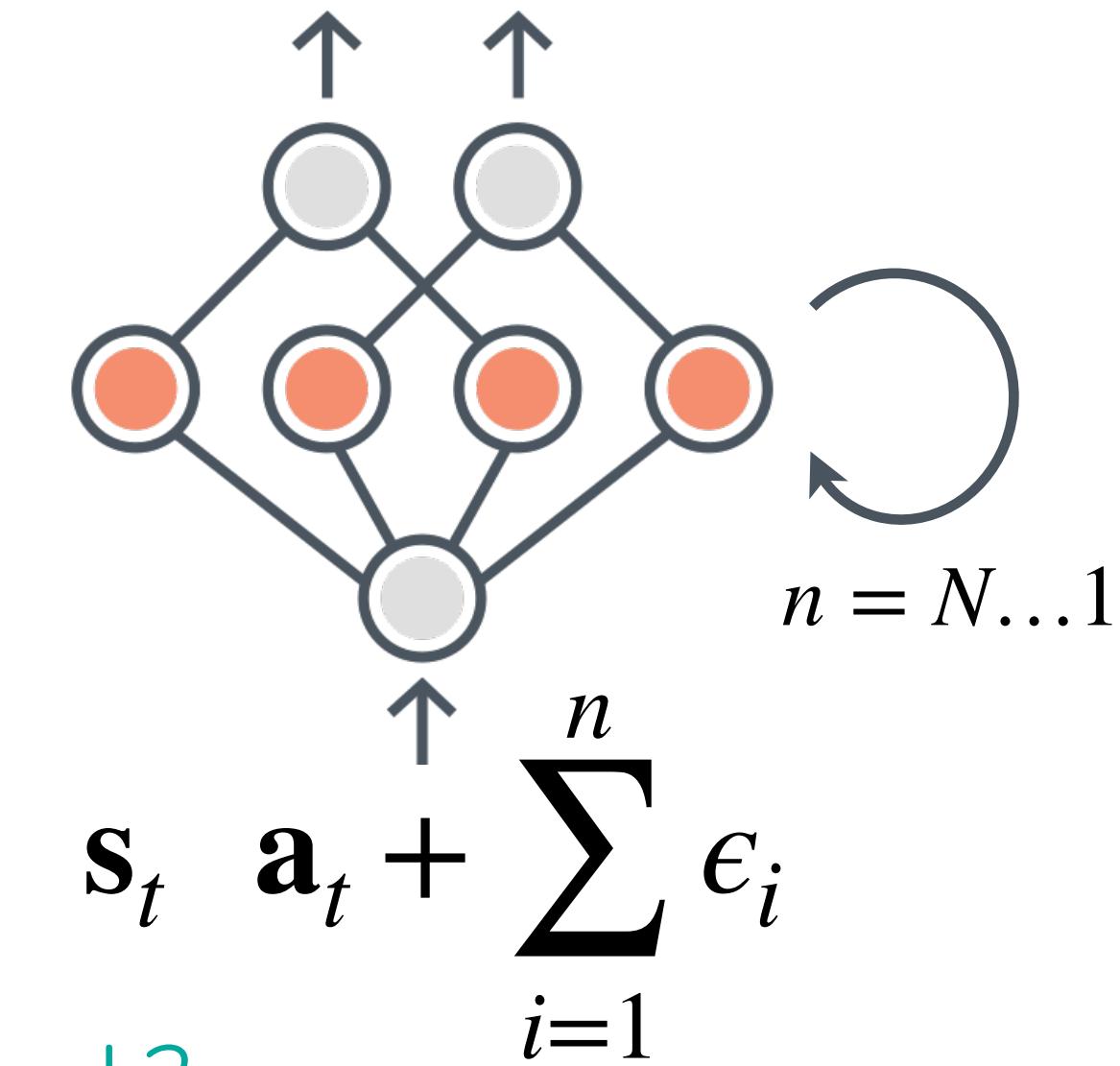
output  $p(\mathbf{a}_{t,1}), p(\mathbf{a}_{t,2} | \hat{\mathbf{a}}_{t,1}), p(\mathbf{a}_{t,3} | \hat{\mathbf{a}}_{t,1:2}), \dots$



## Diffusion



output  $\epsilon_n$



Question: how are these different from  $\ell_2$  loss with larger network?

**Important Note:** Neural network expressivity is often distinct from distribution expressivity!

# Imitation learning - version 1

Expressive policies

0. Given demonstrations collected by an expert  $\mathcal{D} := \{(\mathbf{s}_1, \mathbf{a}_1, \dots, \mathbf{s}_T)\}$

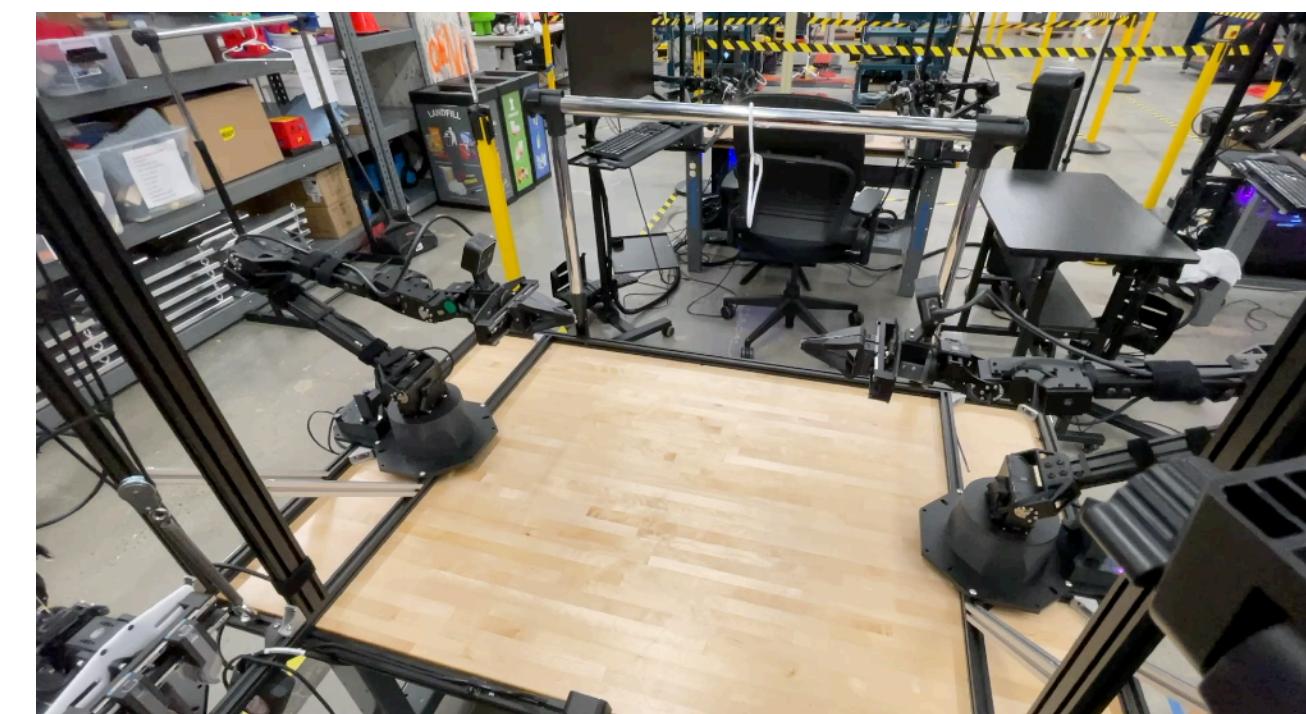
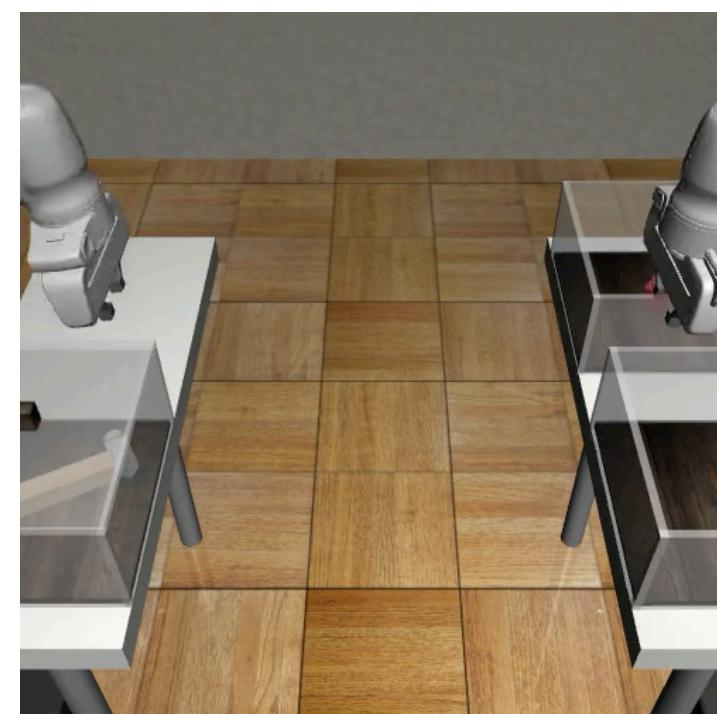
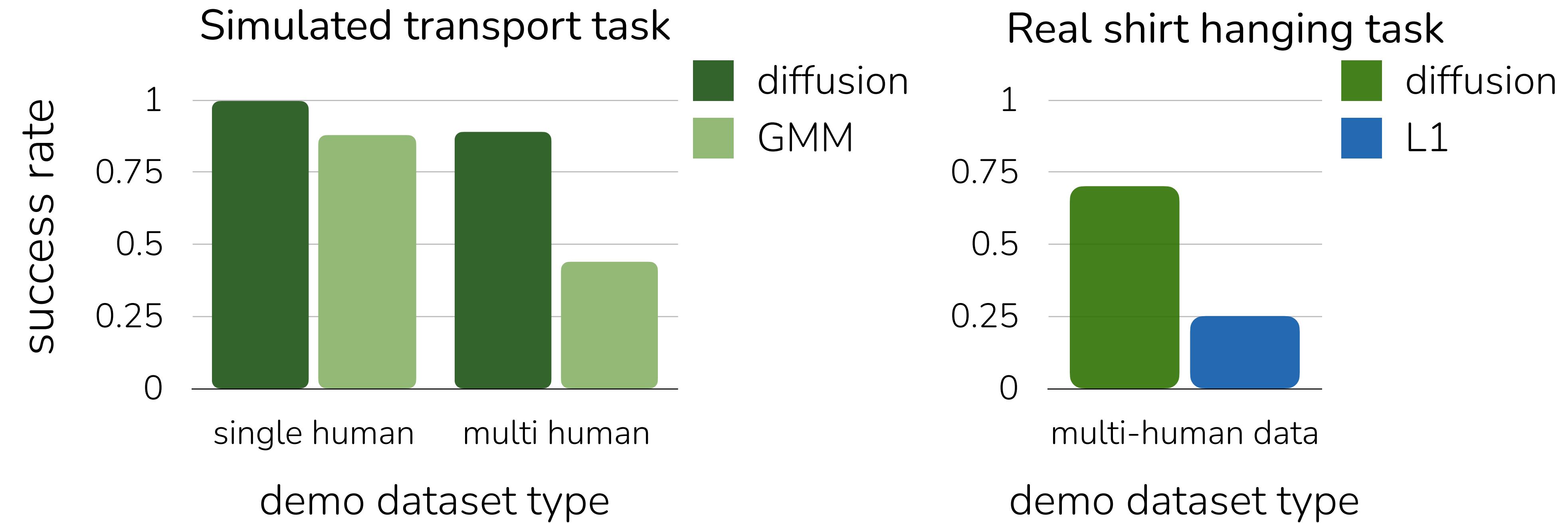
1. Train **generative model** of the expert's actions

$$\min_{\theta} - \mathbb{E}_{(\mathbf{s}, \mathbf{a}) \sim \mathcal{D}} [\log \underline{\pi}_{\theta}(\mathbf{a} | \mathbf{s})] \quad \text{with expressive distribution } \pi(\cdot | \mathbf{s})$$

2. Deploy learned policy  $\pi_{\theta}$

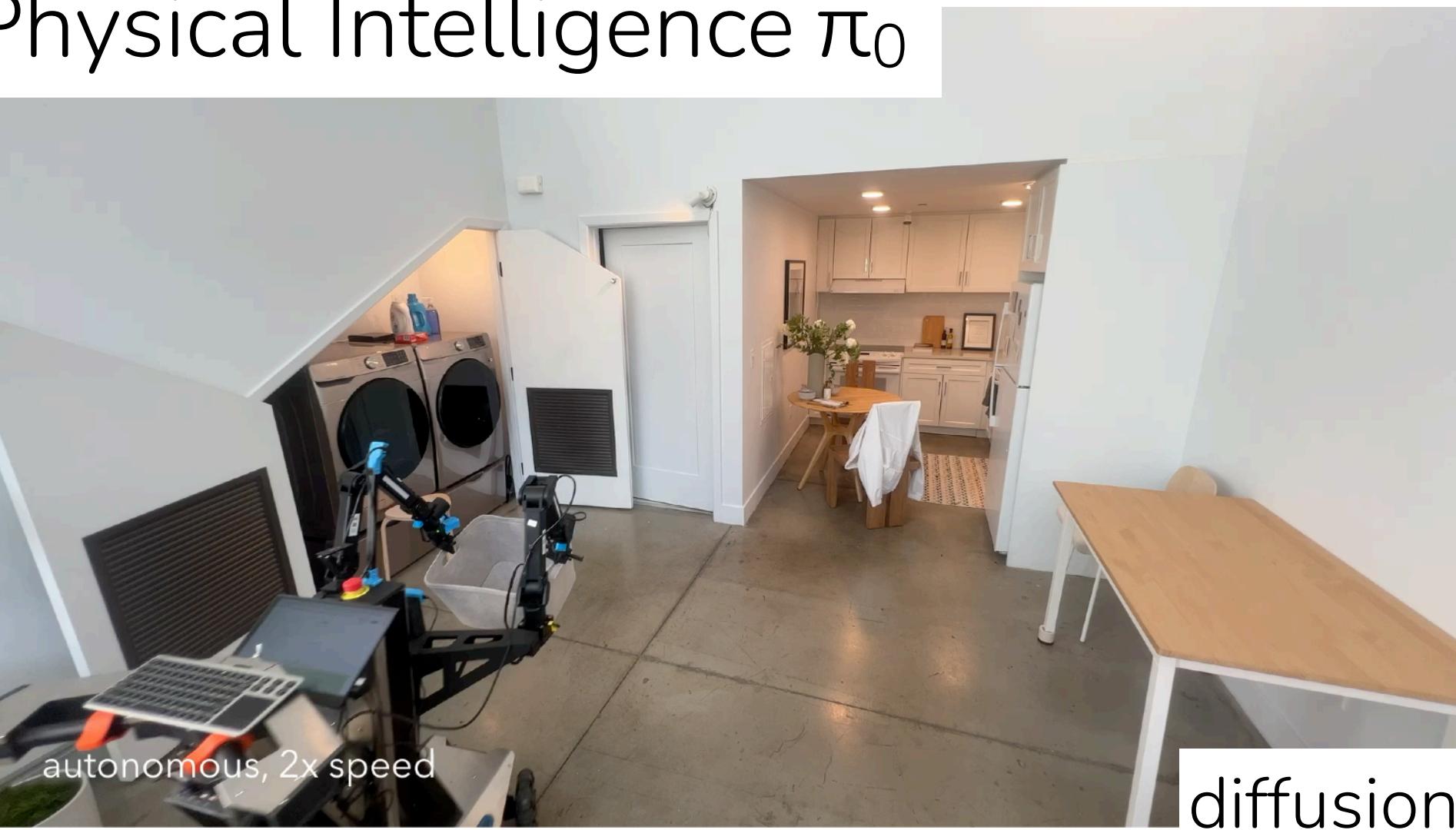
maximize the **log probability** of the  
**demo actions** under the **policy**

# Imitation learning - version 1 vs version 0



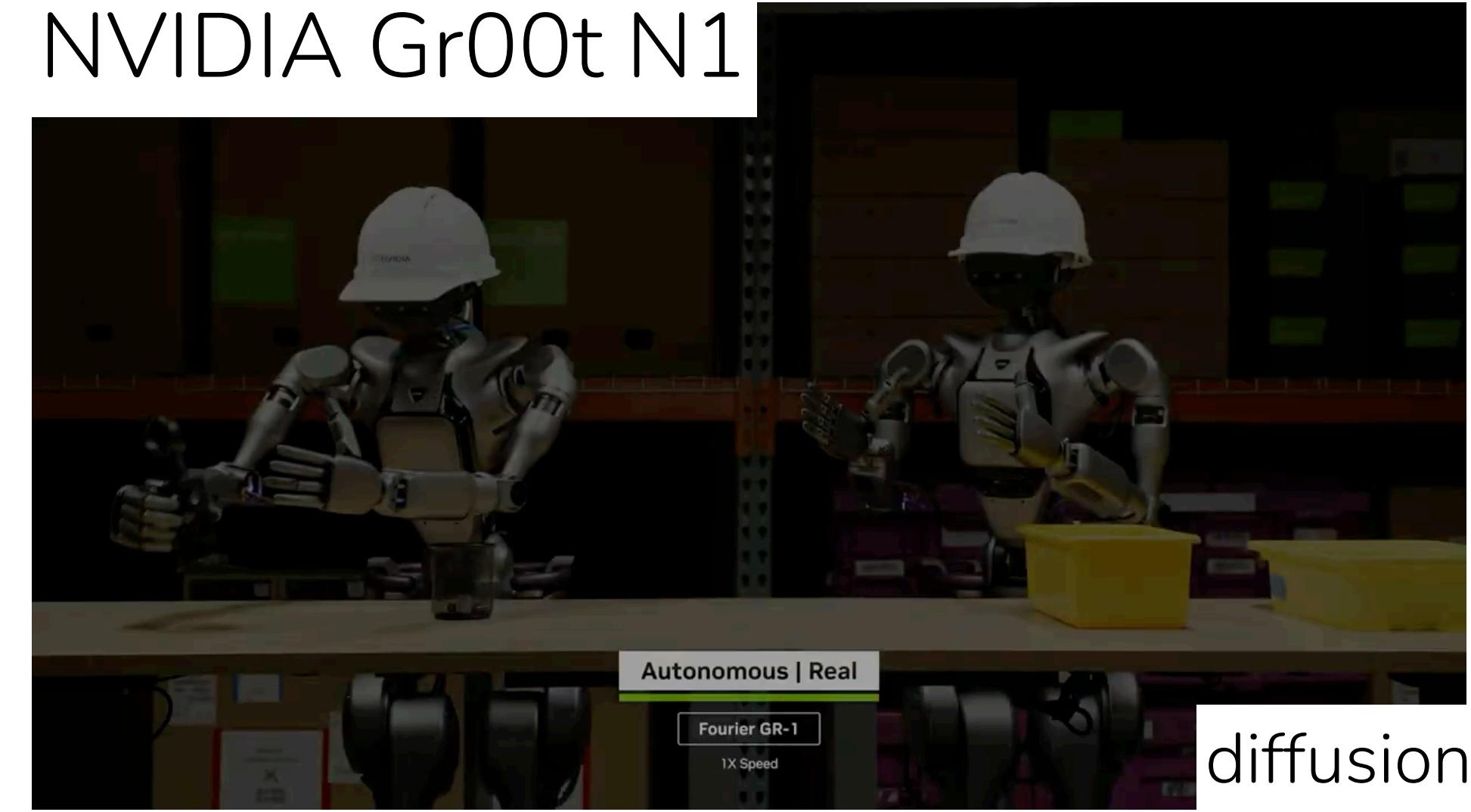
# Robotics: Imitation learning + expressive policies

Physical Intelligence  $\pi_0$



diffusion

NVIDIA Gr00t N1



diffusion

Figure Helix



diffusion 13

OpenVLA



discretize + autoregressive prediction

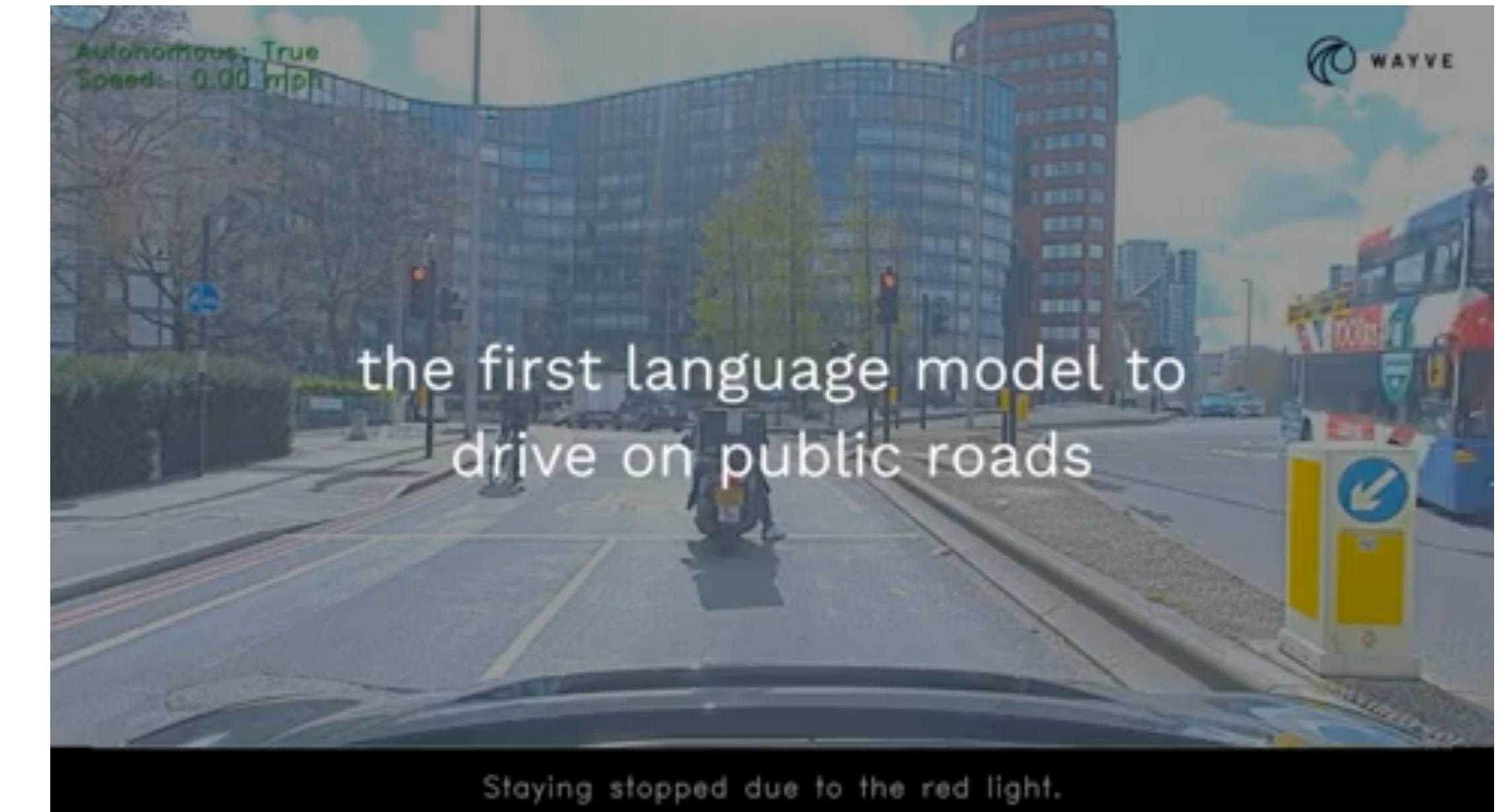
# Autonomous driving: Imitation learning + expressive policies

Waymo EMMA



discretize + autoregressive prediction

Wayve LINGO-2



discretize + autoregressive prediction

# Summary so far

Data from one consistent demonstrator



Unimodal policy distribution is enough

Multimodal data, e.g. from multiple demonstrators



Need expressive generative model for policy

# Summary so far

- Key idea: Train expressive policy class via generative modeling on dataset of demonstrations.
- Algorithm is fully *offline*
  - + no need for data from policy (online data can be unsafe, expensive to collect)
  - + no need to define a reward function
  - may need **a lot** of data for reliable performance

Definitions.

*offline*: using only an existing dataset, no new data from learned policy

*online*: using new data from learned policy

# The plan for today

## Imitation Learning

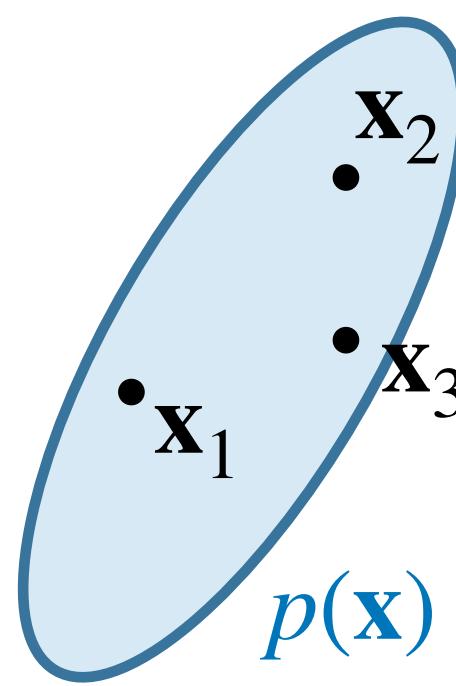
1. Imitation learning basics
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4. Time permitting: how to collect demonstrations

} Topic of homework 1!

# What can go wrong in imitation learning?

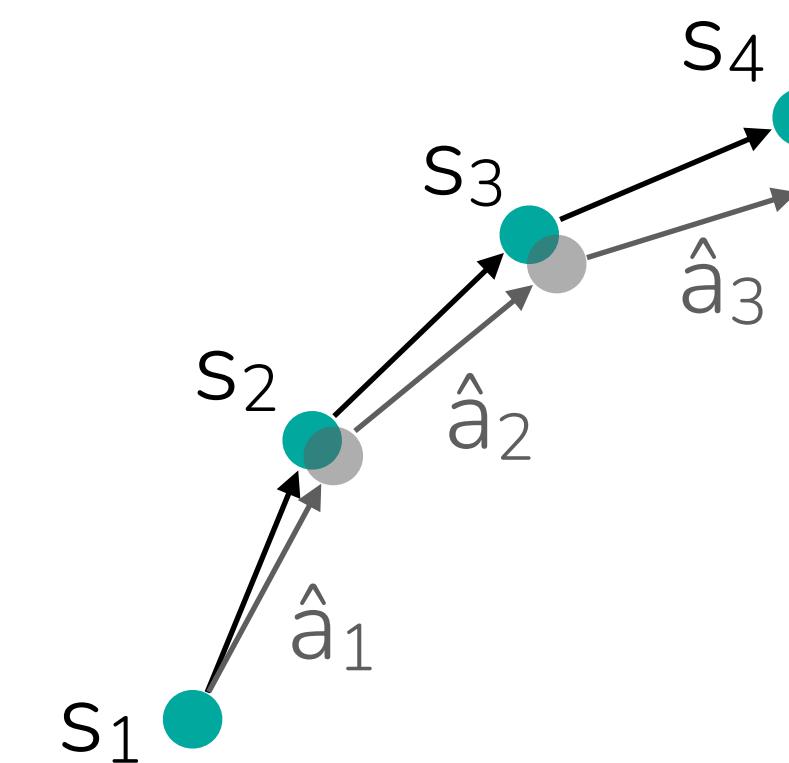
## Compounding errors

### Supervised learning



Inputs independent  
of predicted labels  $\hat{\mathbf{y}}$

### Supervised learning of behavior



Predicted actions affect  
next state.

Errors can lead to drift  
away from the data  
distribution!

Errors can then compound!

$$\underline{p_{expert}(\mathbf{s})} \neq \underline{p_{\pi}(\mathbf{s})}$$

states visited  
by expert

states visited by  
learned policy  $\pi$

“covariate shift”

# What can go wrong in imitation learning?

## Compounding errors

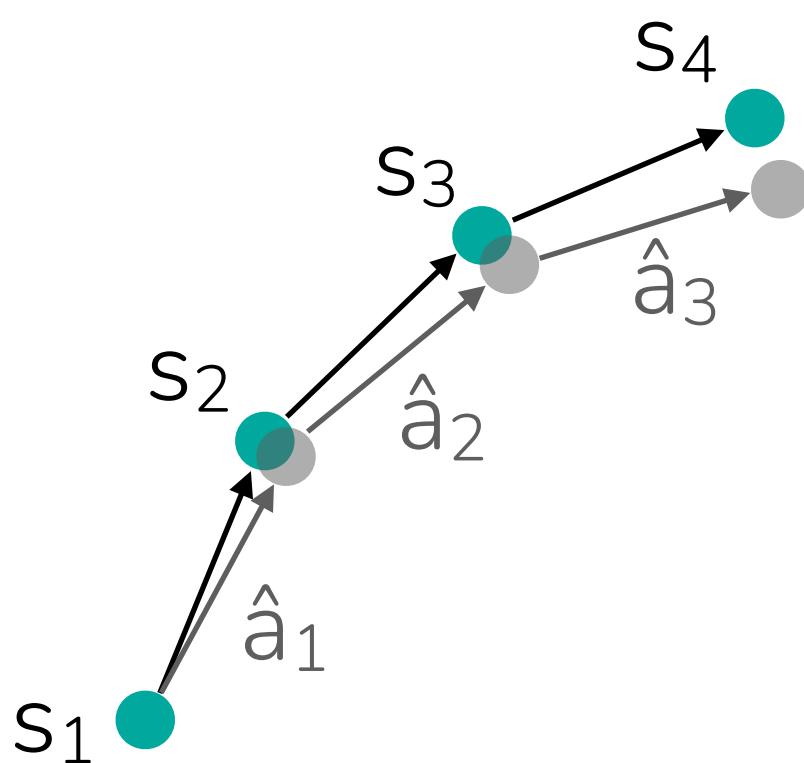
### Supervised learning of behavior

Predicted actions affect next state.

Errors can lead to drift away from the data distribution!

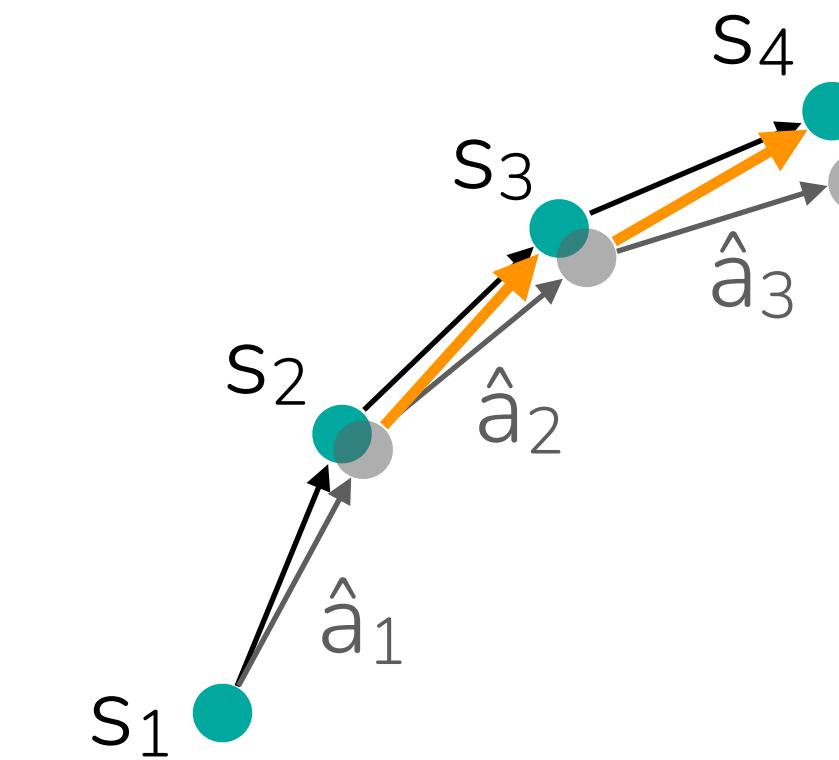
Errors can then compound!

$$p_{expert}(\mathbf{s}) \neq p_{\pi}(\mathbf{s})$$



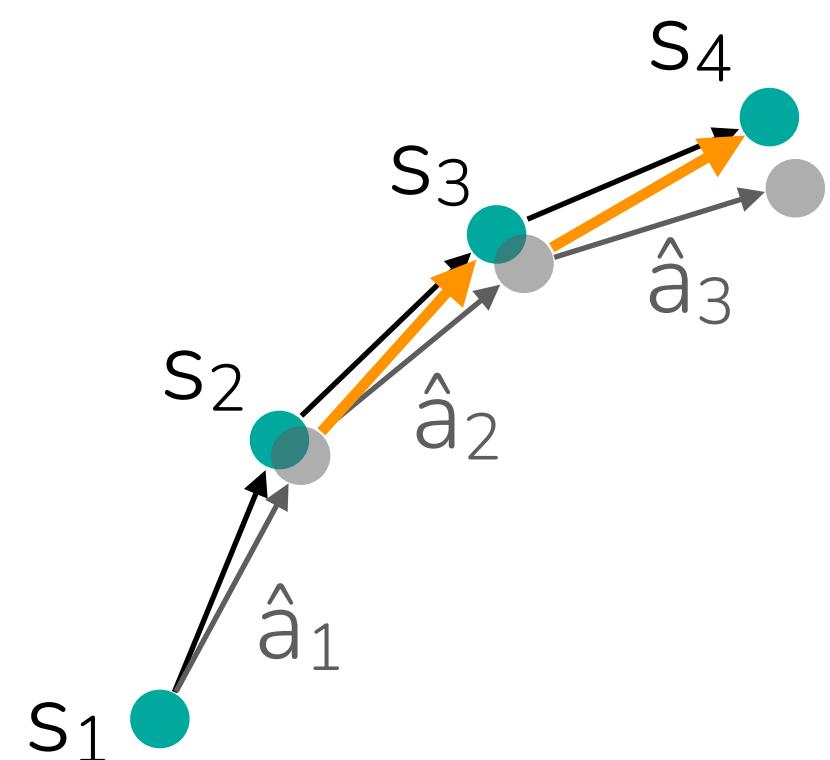
### Solutions?

1. Collect A LOT of demo data & hope for the best.
2. Collect **corrective behavior data**



# Addressing Compounding Errors with Interventions

Collect corrective behavior data



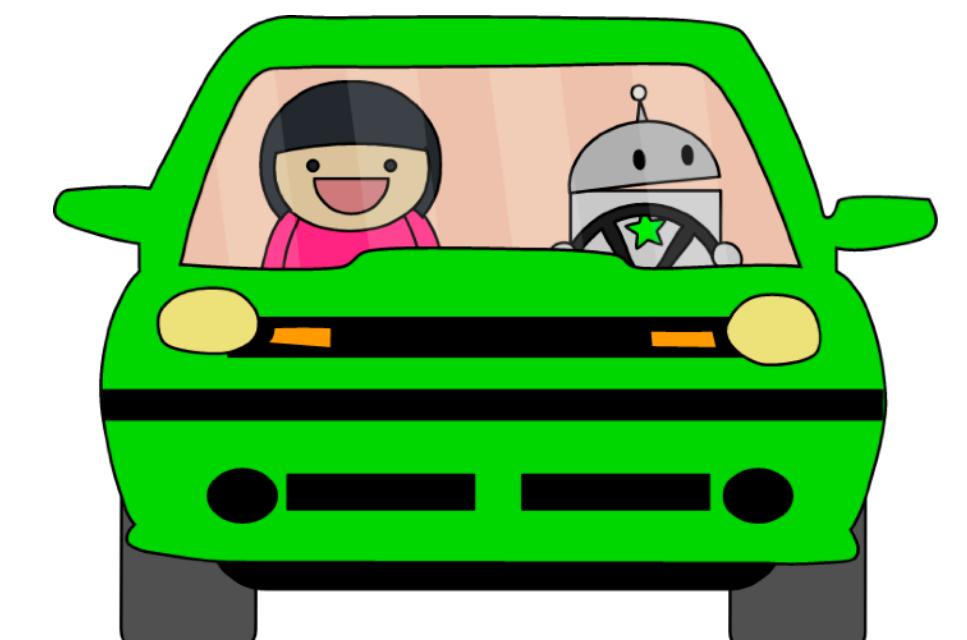
1. Roll out learned policy  $\pi_\theta: \mathbf{s}'_1, \hat{\mathbf{a}}_1, \dots, \mathbf{s}'_T$
2. Query expert action at visited states  $\mathbf{a}^* \sim \pi_{expert}(\cdot | \mathbf{s}')$
3. Aggregate corrections with existing data  $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}', \mathbf{a}^*)\}$
4. Update policy  $\min_\theta \mathcal{L}(\pi_\theta, \mathcal{D})$

“dataset aggregation” (DAgger)

+ data-efficient way to learn from an expert

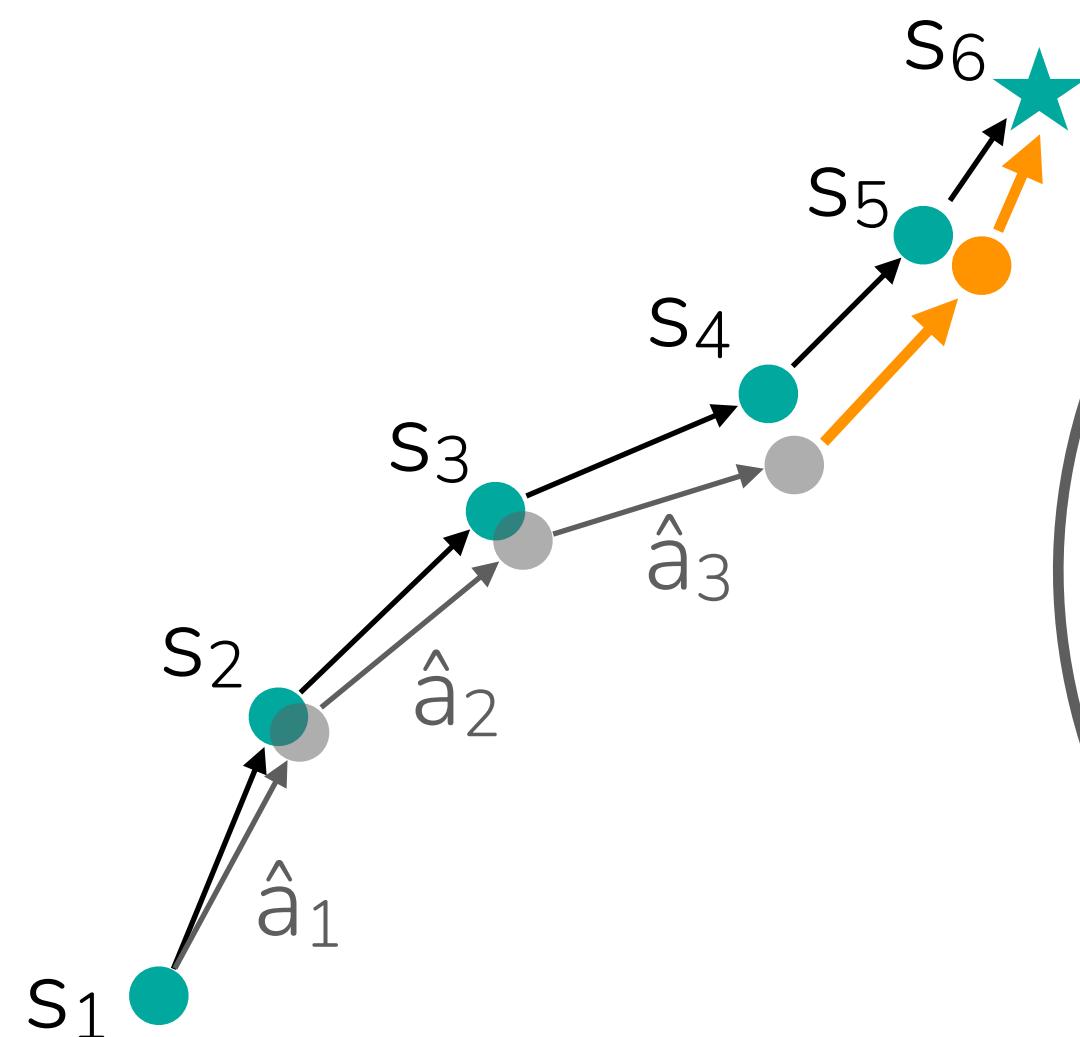
- can be challenging to query expert when agent has control

Is there another way to collect corrective data?



# Addressing Compounding Errors with Interventions

Collect corrective behavior data while taking full control



1. Start to roll-out learned policy  $\pi_\theta$ :  $s'_1, \hat{a}_1, \dots, s'_t$
2. Expert intervenes at time  $t$  when policy makes mistake
3. Expert provides (partial) demonstration  $s'_t, a^*_t, \dots, s'_T$
4. Aggregate new demos with existing data  $\mathcal{D} \leftarrow \mathcal{D} \cup \{(s'_i, a^*_i)\}; i \geq t$
5. Update policy  $\min_{\theta} \mathcal{L}(\pi_\theta, \mathcal{D})$

“human gated DAgger”

- + (much) more practical interface for providing corrections
- can be hard to catch mistakes quickly in some application domains

Question: could you automatically detect when intervention is needed?

# The plan for today

## Imitation Learning

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} Topic of homework 1!

# How to collect demonstrations?

In some domains: People already collect demonstrations that can be recorded  
e.g. driving cars, writing text messages

What about robotics?

Kinesthetic teaching



+ easy interface

- human visible in scene

Remote controllers



~ interface ease varies,  
can have high latency

Puppeteering



+ easy interface

- requires double hardware

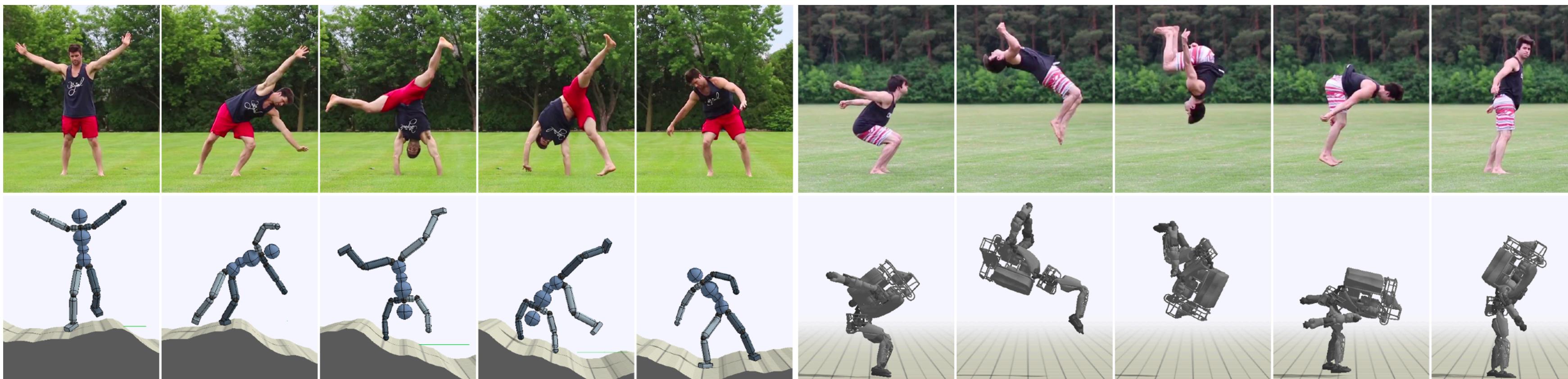
In other domains: It may not be viable to collect demos! (e.g. quadruped robot)

# Can robots directly use videos of people, animals?

Embodiment gap:

- difference in appearance
- difference in physical capabilities, degrees of freedom

Hard to directly imitate human & animal data, but can potentially guide exploration.



# Summary

## Part 1: Train policy to mimic offline demonstrations

- best if policy is an expressive generative model over actions
- algorithm is fully *offline*

often referred to as  
**behavior cloning (BC)**

## Part 2: Improve policy using online interventions

- requires interface for human or expert intervention
- algorithm involves running policy *online*

often referred to as  
**Dagger**, or **HG-Dagger**

- + offline BC: simple, no need for data from policy (online data can be unsafe, expensive)
- + Dagger: possible path to reliable performance, more data-efficient than offline BC
- + no need to define a reward function
- may need **impractically large amount** of data for reliable performance
- doesn't provide a framework for improving on own (from "practicing")

Many successful methods **combine** imitation learning and reinforcement learning!

# The plan for today

## Imitation Learning

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## Key learning goals:

- how to represent distributions with neural networks
- why expressive distributions matter for imitation learning
- what are compounding errors and how to address them

# Next time

Start of *reinforcement learning algorithms*

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- Homework 1 out today, due Fri April 18
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