AA203
Optimal and Learning-based Control

Imitation Learning

Stanford University

Autonomous Systems Lab

The basics of Imitation Learning

- Assume access to a dataset $\mathcal{D} = \{(\mathbf{x}_n, \mathbf{u}_n)\}_{n=1}^N$ of state-control pairs collected by an expert
- At a high-level, approaches to IL belong to two main categories:
  - *Behavior Cloning* — *"learn the policy used by expert"*
  - *Inverse Reinforcement Learning (a.k.a. Inverse Optimal Control)* — *"learn the objective optimized by the expert"*

Behavior Cloning

$$\pi_\theta(\mathbf{u}|\mathbf{x})$$

Inverse Reinforcement Learning

$$R : \mathcal{X} \times \mathcal{U} \to \mathbb{R}$$

Outline

- Imitation Learning:
  - Behavior Cloning (BC)
    - Common pitfalls
    - Design strategies for effective IL
    - Other paradigms (RvS)
  - Inverse Reinforcement Learning (IRL)

Recap: BC as "supervised learning of behavior"

1. SL: learn a (parametric) mapping from inputs **x** to outputs **y** by minimizing a measure of prediction error

$\mathbf{x} =$ 

$\xrightarrow{f : \mathcal{X} \to \mathcal{Y}}$ $\mathcal{Y} = \{0, 1, \ldots, C\}$

$\mathcal{D} = \{(\mathbf{x}_n, \mathbf{y}_n)\}_{n=1}^N$ e.g., mean squared error (MSE)

$\boldsymbol{\theta}^* = \underset{\theta}{\operatorname{argmin}} \mathcal{L}(\theta; \mathcal{D})$ $\mathcal{L} = \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{x},\mathbf{y}) \in \mathcal{D}} \|\mathbf{y} - \hat{\mathbf{y}}\|_2^2, \quad \text{where } \hat{\mathbf{y}} = f_\theta(\mathbf{x})$

2. Skeleton of a BC algorithm:
   - Collect a dataset of "expert" demonstrations $\mathcal{D} = \{(\mathbf{x}_n, \mathbf{u}_n)\}_{n=1}^N$ 
   - Train policy $\pi_\theta(\mathbf{u}|\mathbf{x})$ to mimic expert:

$$\mathcal{L} = \frac{1}{|\mathcal{D}|} \sum_{(\mathbf{x},\mathbf{u}) \in \mathcal{D}} \|\mathbf{u} - \hat{\mathbf{u}}\|_2^2, \quad \text{where } \hat{\mathbf{u}} = \pi_\theta(\mathbf{x})$$

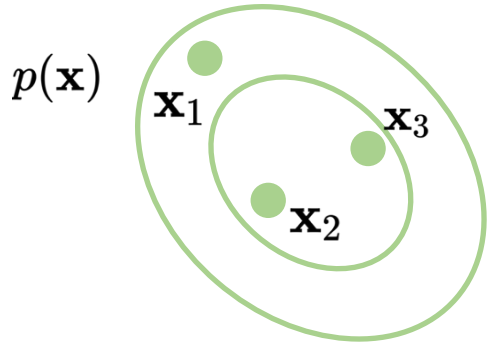
   - Deploy

Is this it?

Today:
- What could go wrong?
- Strategies to address these challenges

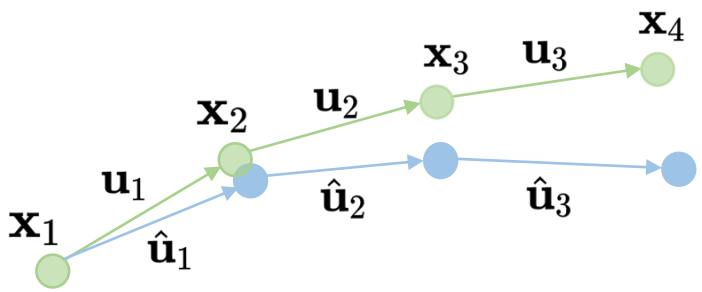
Common Pitfalls: 1) Compounding Errors

In statistical learning theory, data is assumed to be independent and identically distributed (i.i.d)



When learning behavior policies however:

- Predicted controls influence future states
- Even small errors can lead to drift away from the data distribution
- Errors compound



This leads to the *state distributions* under the expert and the learner to diverge

$$p_{\text{expert}}(\mathbf{x}) \neq p_{\pi_\theta}(\mathbf{x})$$

"covariate shift"

Probability of making mistakes grows quadratically with the length of the trajectory

$$\mathcal{O}(\epsilon T^2)$$

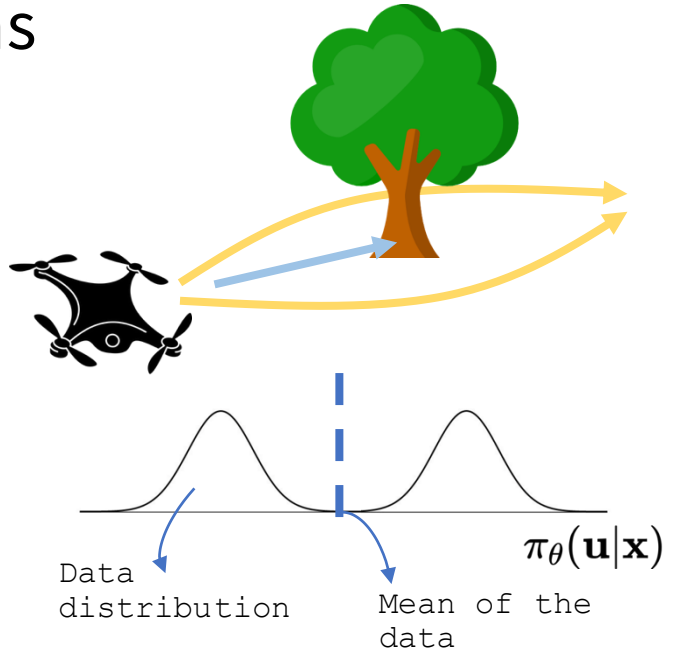
[Ross & Bagnell '10]

Common Pitfalls: 2) Multimodal behavior

- In many tasks, there exist multiple (equivalent) solutions
- In IL, this becomes relevant the moment the dataset is characterized by multimodal demonstrations

  e.g., fitting multimodal behavior using MSE

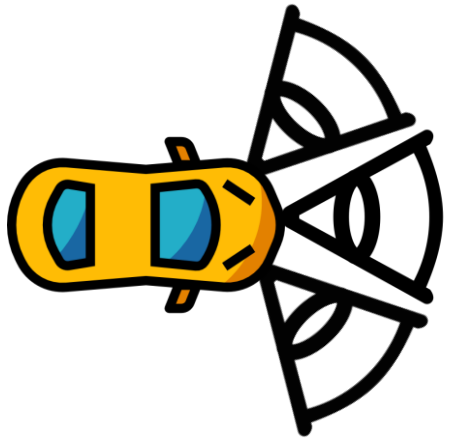
- This is extremely common in practice, e.g., data collected by multiple experts

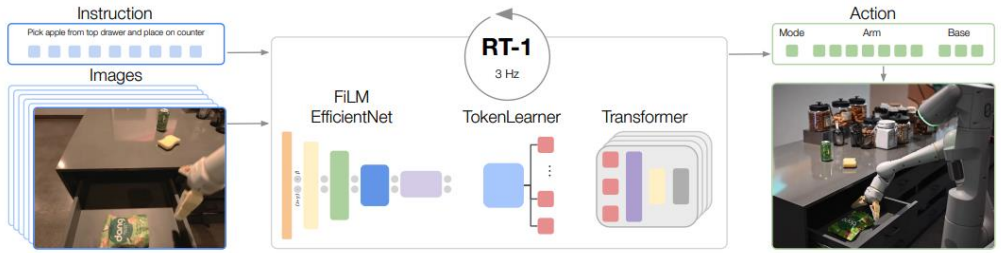


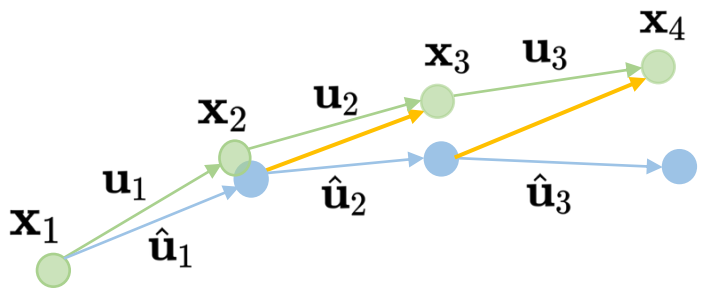
A useful mental model

We can address these challenges in a few different ways:

- Targeted algorithms
- Smart data collection (and augmentation)
- Use expressive models (e.g., that are able to capture the multi-modality of behavior data)







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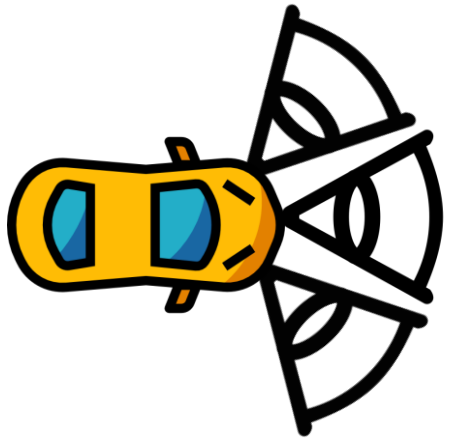
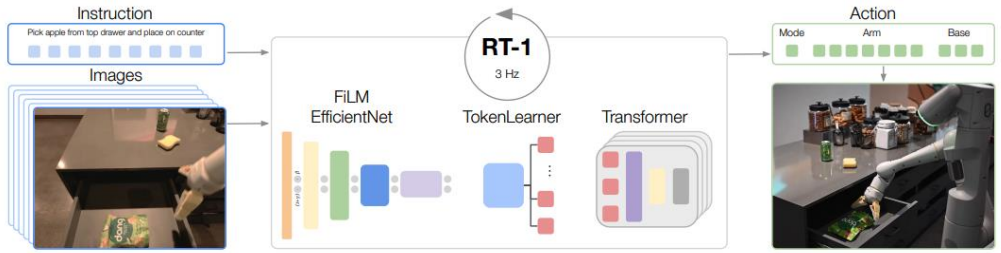
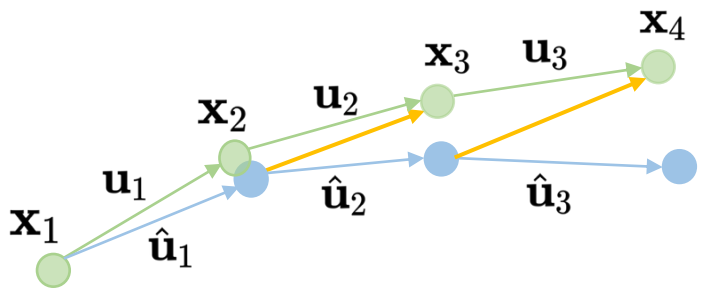


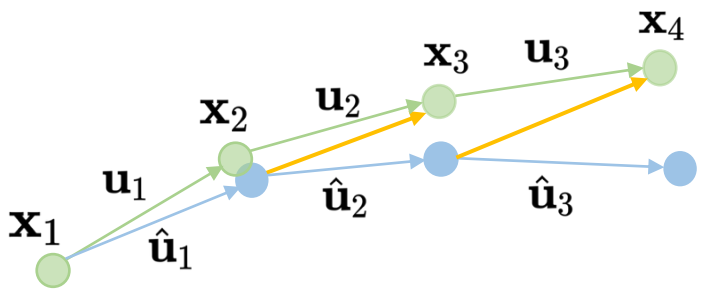




The value of corrective data

- A lot of the methods that make naïve BC work try to leverage the fact that, during deployment, we can recover from mistakes
  - Modify the learning problem to allow BC to learn how to correct from mistakes

- Paradox:
  - Learning from a broader set of trajectories that make some mistakes (and recoveries) is likely to work better than learning from a narrow set of perfect demonstration data



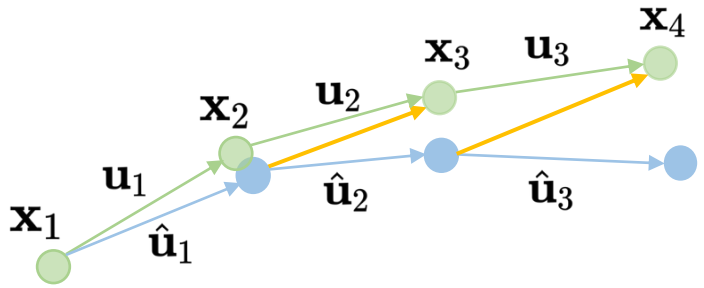
Learning from interventions: DAgger

DAgger is a well-known method for addressing the covariate shift problem through data aggregation techniques

DAgger seeks to reduce the covariate shift by explicitly gathering expert demonstrations under the state distribution induced by the learner.

$$p_{\text{expert}}(\mathbf{x}) \neq p_{\pi_\theta}(\mathbf{x})$$

"covariate shift"



At its core, DAgger defines an iterative procedure:

Algorithm 22.3: DAGGER Algorithm

Data: Initial dataset of expert demonstrations, $\mathcal{D}$, initial policy, π_θ^1, number of iterations, N

Result: Trained policy, π_θ^N

for $i = 1, 2, \ldots, N$ **do**

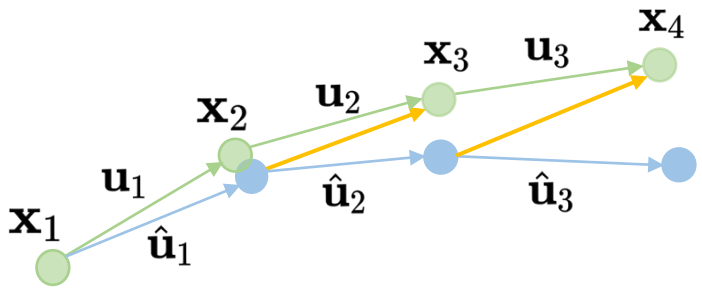
- Collect trajectories, $\tau = \{(\boldsymbol{x}_t, \boldsymbol{u}_t^{\text{learner}})\}$, using the policy π_θ^i.
- Gather dataset of states visited by the learner and actions given by the expert, $\mathcal{D}^i = \{(\boldsymbol{x}_t, \boldsymbol{u}_t^{\text{expert}})\}$.
- Aggregate the dataset, $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}^i$.
- Train the policy π_θ^{i+1} on the updated dataset, $\mathcal{D}$.

return Trained policy, π_θ^N.

Learning from interventions: DAgger

Essentially, DAgger operates as a form of iterative supervised learning:

- Reduces the amount of expert data required (i.e., the alternative would be collecting an extremely broad dataset of demonstrations)



+ data-efficient way of querying the expert
- querying the expert can be expensive

Many algorithms have been developed that follow a similar scheme:

- Confidence-based methods: "*query the expert when the agent is uncertain about its decisions*"
- Human-gated DAgger: "*query the expert when the policy makes a mistake*"

A useful mental model

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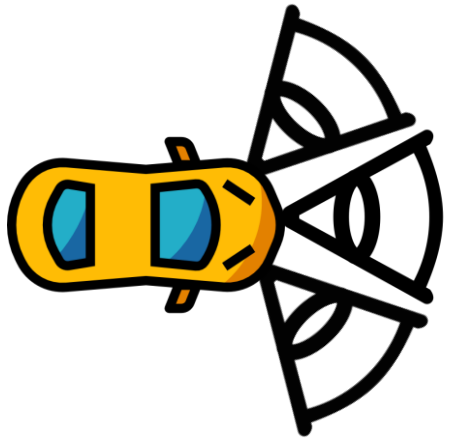
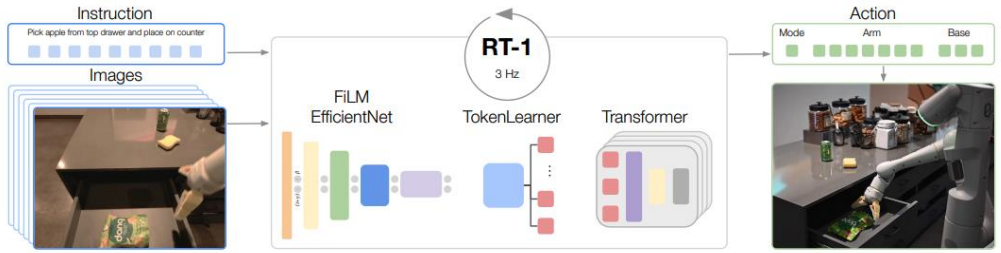
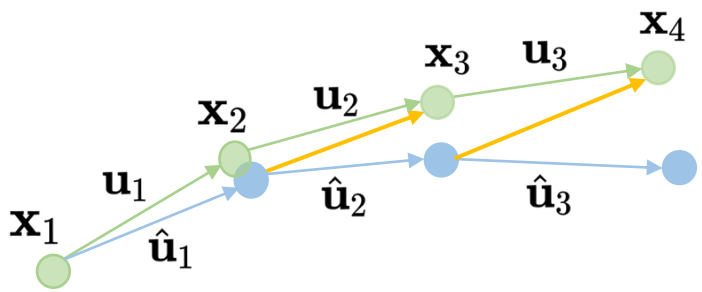
- Use expressive models (e.g., that are able to capture the multi-modality of behavior data)







Case Study 1

End to End Learning for Self-Driving Cars

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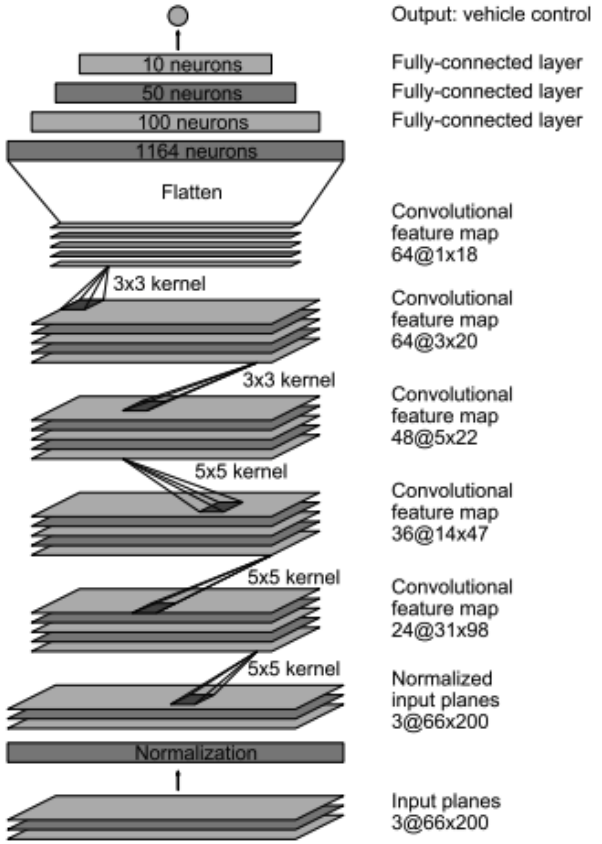
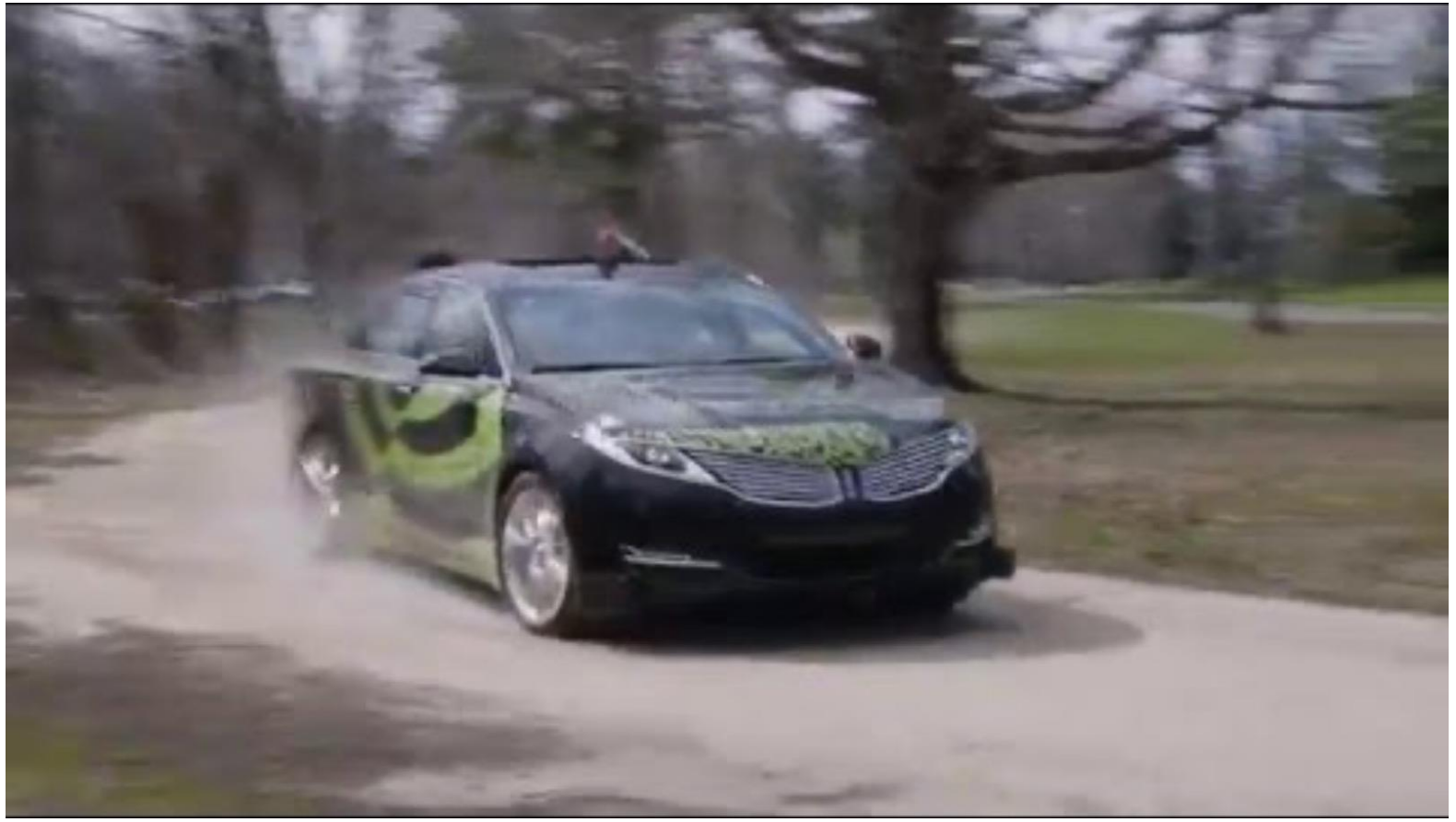
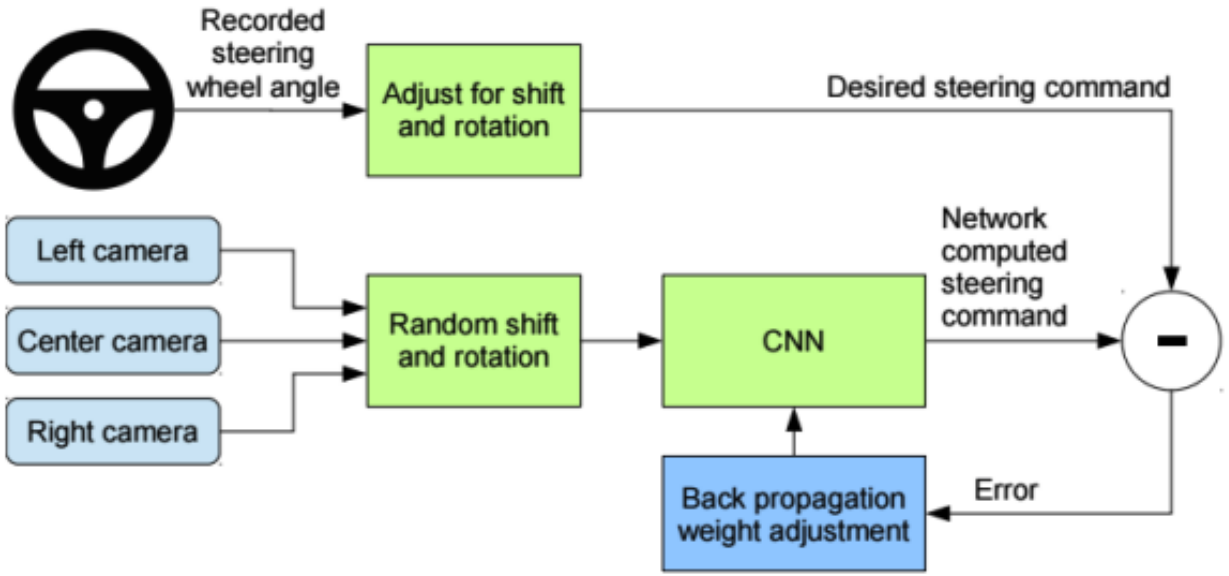


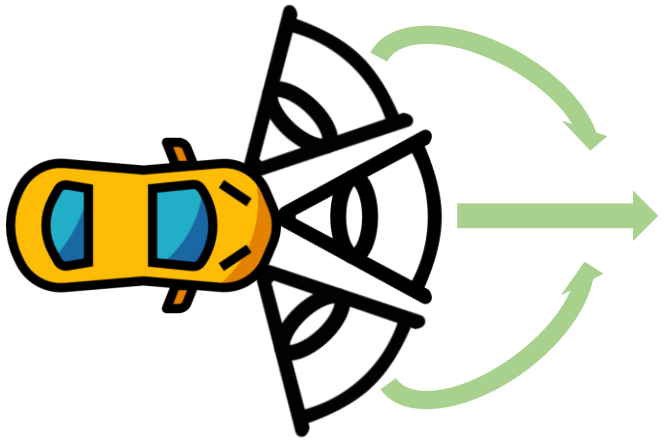
Case Study 1



Bojarski et al. ‘16, NVIDIA

An important detail

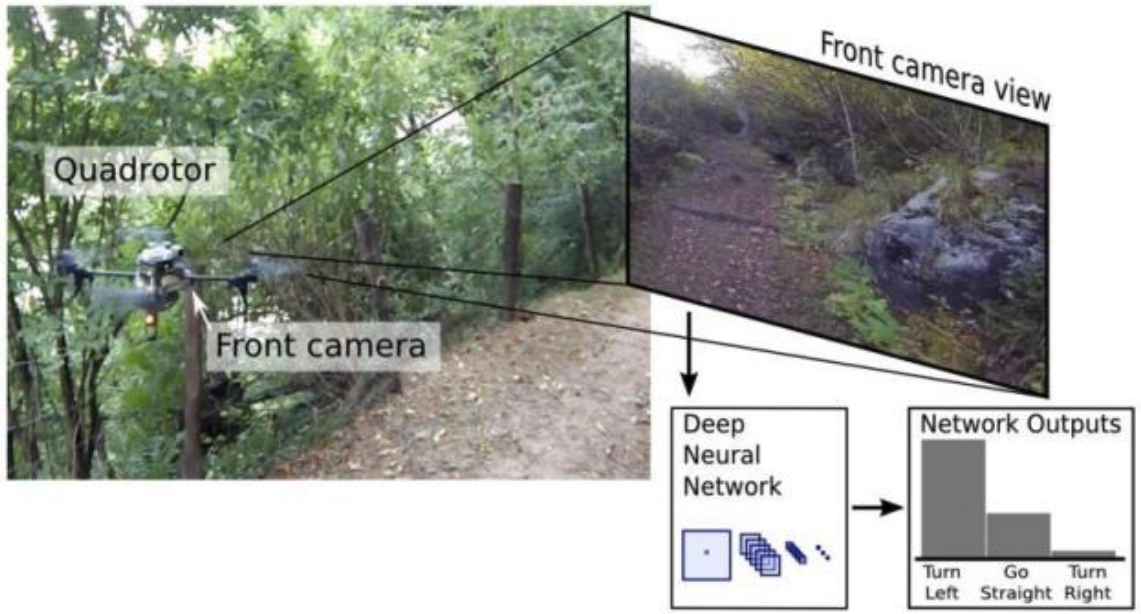




Case Study 2

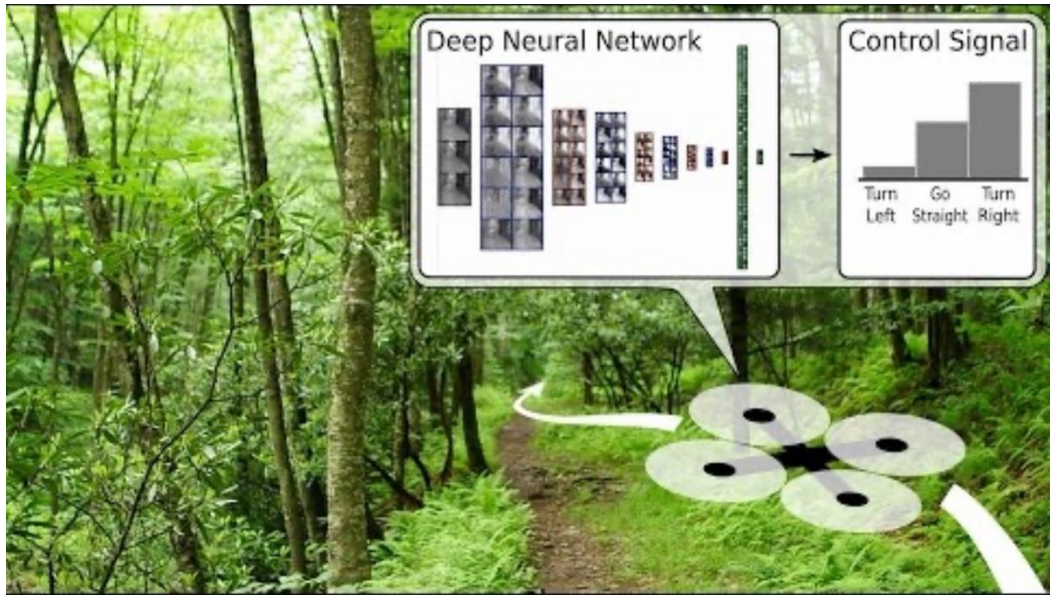
A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robots

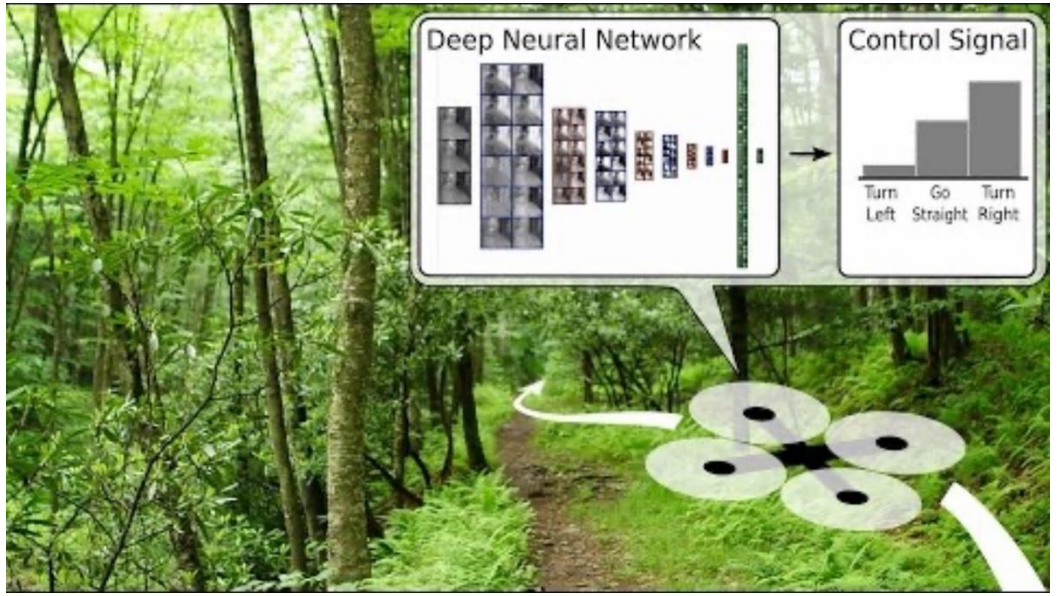
Alessandro Giusti[1], Jérôme Guzzi[1], Dan C. Cireşan[1], Fang-Lin He[1], Juan P. Rodríguez[1]
Flavio Fontana[2], Matthias Faessler[2], Christian Forster[2]
Jürgen Schmidhuber[1], Gianni Di Caro[1], Davide Scaramuzza[2], Luca M. Gambardella[1]



Case Study 2


Training the classifier


Deep Neural Network
Control Signal
Turn Left
Go Straight
Turn Right


Deep Neural Network
Control Signal
Turn Left
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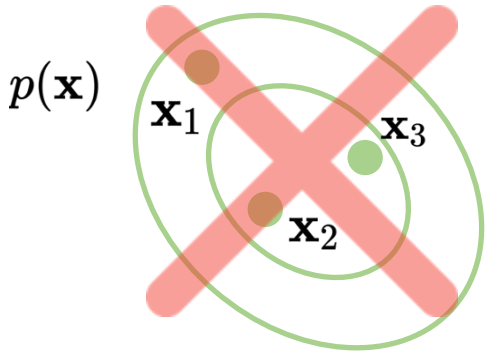
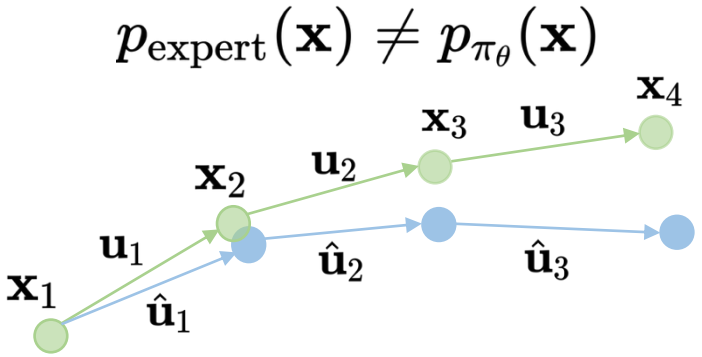
Key idea: Being intentional with data collection





Intentionally add **mistakes** and **corrections** to your data:

- Augment your collection pipeline with "fake" demonstrations of corrections (e.g., side cameras)
- Use algorithms that automate the collection of correction data where it matters more (e.g., DAgger)

A useful mental model

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- Targeted algorithms
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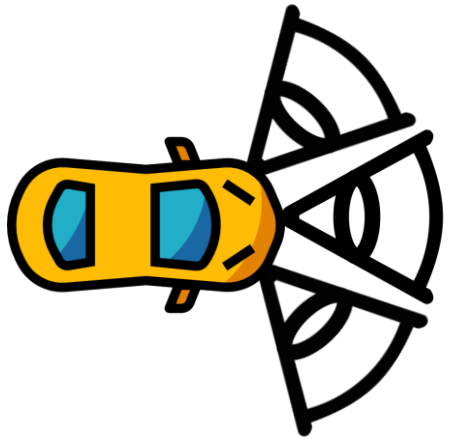
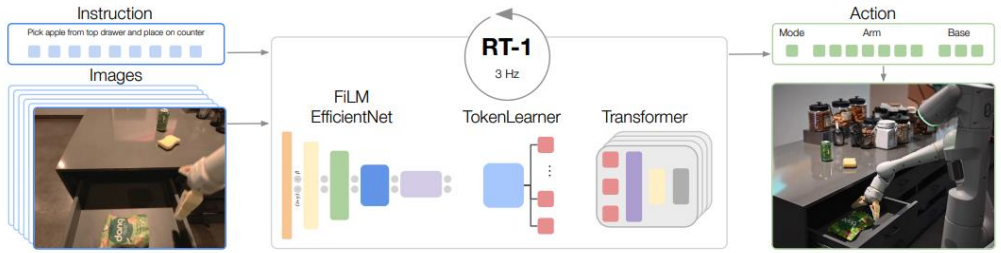
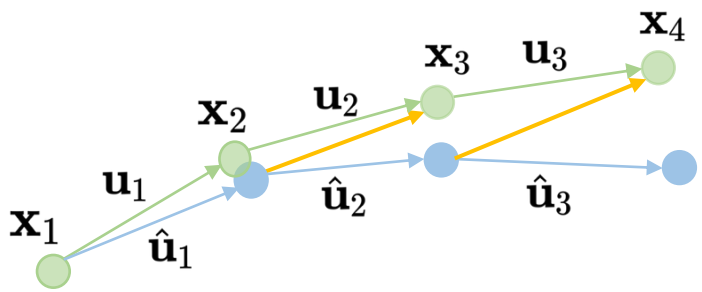
- Use expressive models (e.g., that are able to capture the multi-modality of behavior data)







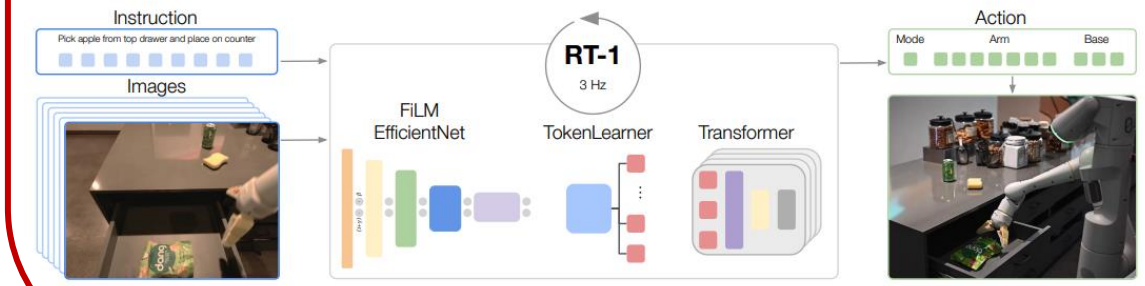
Improving the expert's predictions

At a high level, two main classes of methods:

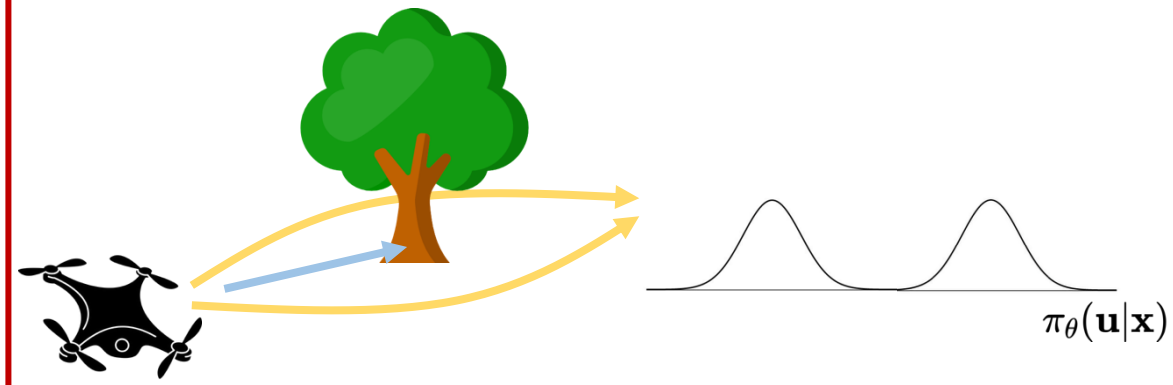
Include history of observations

$$\pi(\mathbf{u}_t|\mathbf{x}_t)$$

$$\pi(\mathbf{u}_t|\mathbf{x}_t, \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-H})$$



Expressive function class



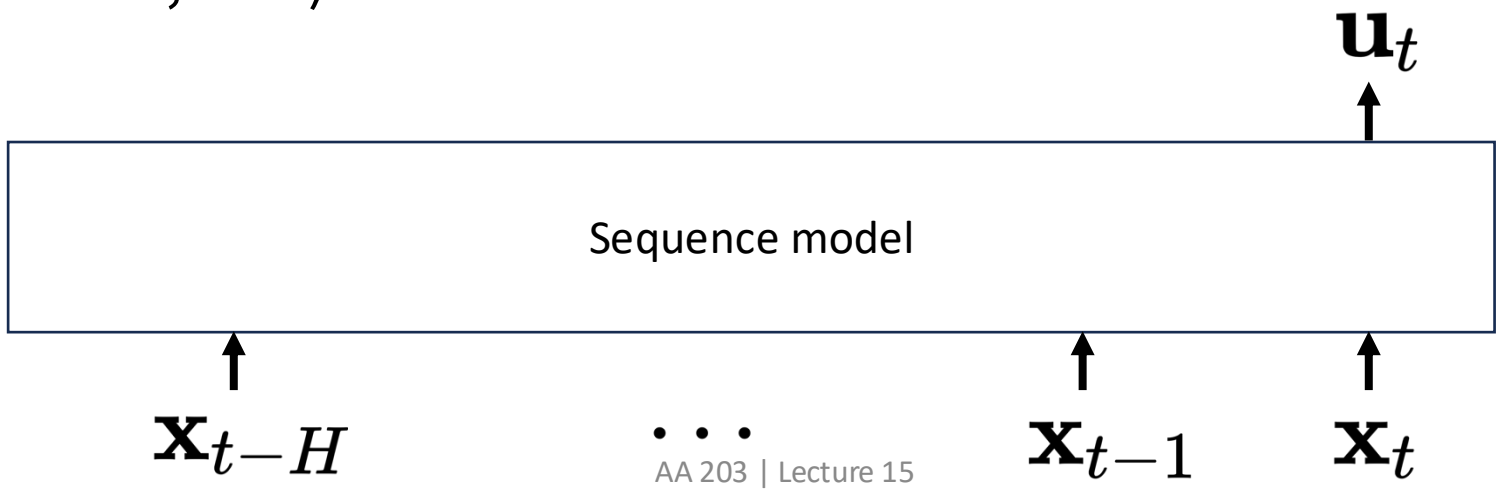
E.g., mixture of Gaussians, conditional VAEs, diffusion models, etc.

Non-Markovian behavior

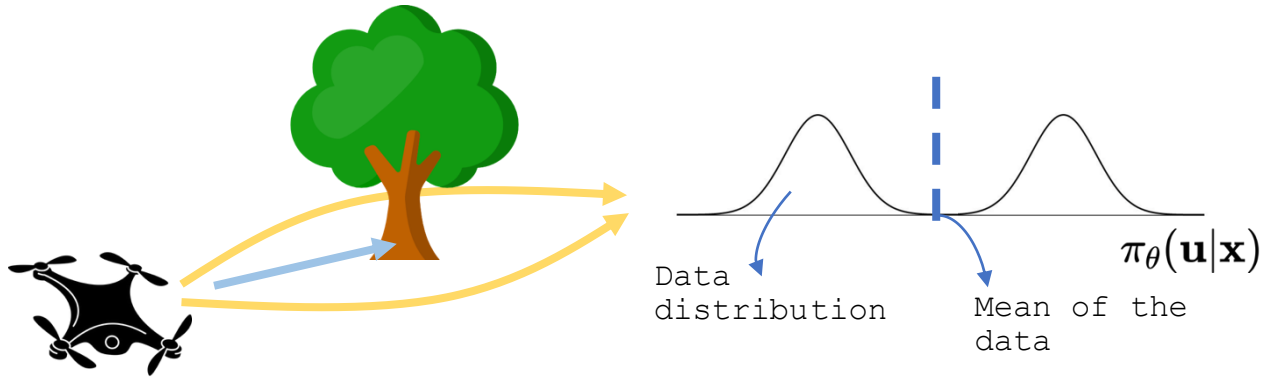
Often, the behavior observed in demonstration data does not depend only on the current observation

$$\pi(\mathbf{u}_t|\mathbf{x}_t) \qquad \pi(\mathbf{u}_t|\mathbf{x}_t, \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-H})$$

Idea: represent the policy via any sequence model (e.g., Transformers, LSTM/GRU cells, etc.)



Capturing the data distribution

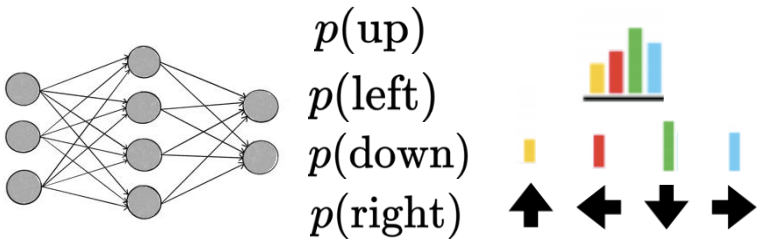


- Minimizing average prediction error is inherently limited in presence of more complex data distributions
- Goal: represent the entire distribution (as opposed to e.g., only the mean)

Parametrizing distributions

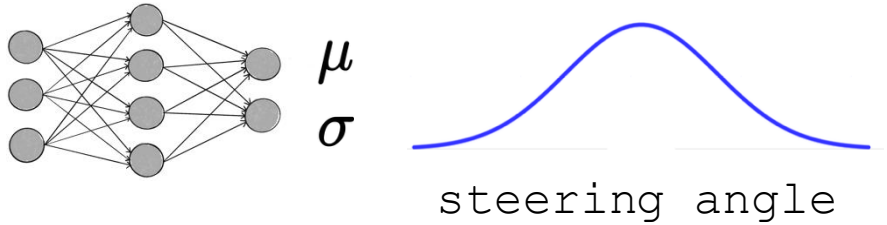
- Use a parametric function (e.g., a neural network) to output the parameters of a distribution

1D discrete distribution



+ handles multimodality
- scaling to high-dim action spaces

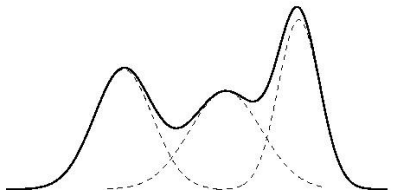
Continuous distribution



+ captures the continuous nature of actions
- not very expressive (e.g., unimodal)

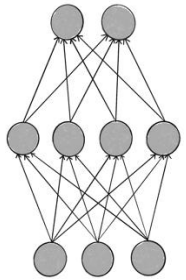
Expressive policy architectures

Gaussian Mixture Model



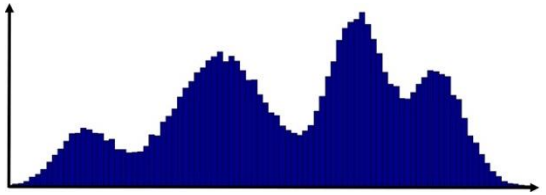
$$\pi(\mathbf{u}_t|\mathbf{x}_t) = \sum_{i=1}^{k} w_i \mathcal{N}(\mu_i, \Sigma_i)$$

$$w_1, \mu_1, \Sigma_1, \ldots, w_k, \mu_k, \Sigma_k$$

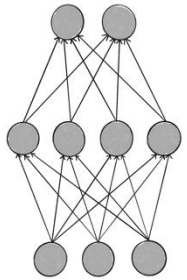


$\mathbf{x}_t$

Discretize + Autoregressive

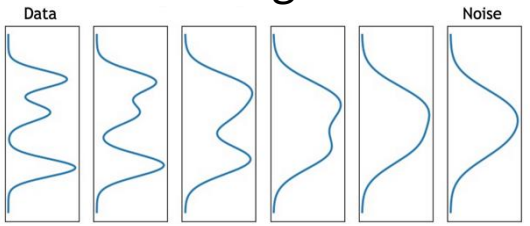


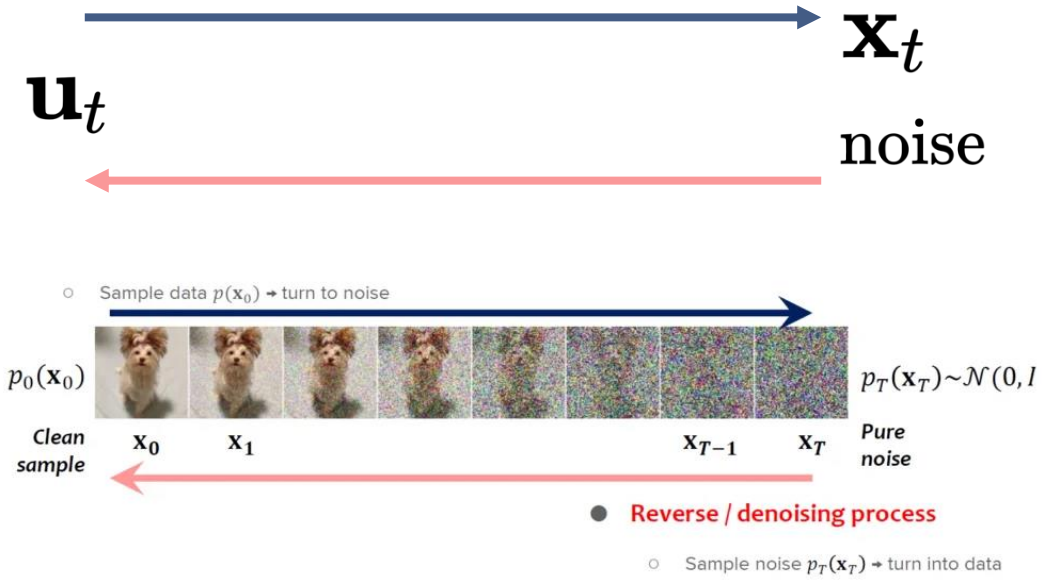
$$\pi(\mathbf{u}_t|\mathbf{x}_t) = \prod_{i=1}^{D} p(\mathbf{u}_{t,i}|\mathbf{u}_{t,<i}, \mathbf{x}_t)$$



$\mathbf{x}_t \quad \mathbf{u}_{t,<i}$

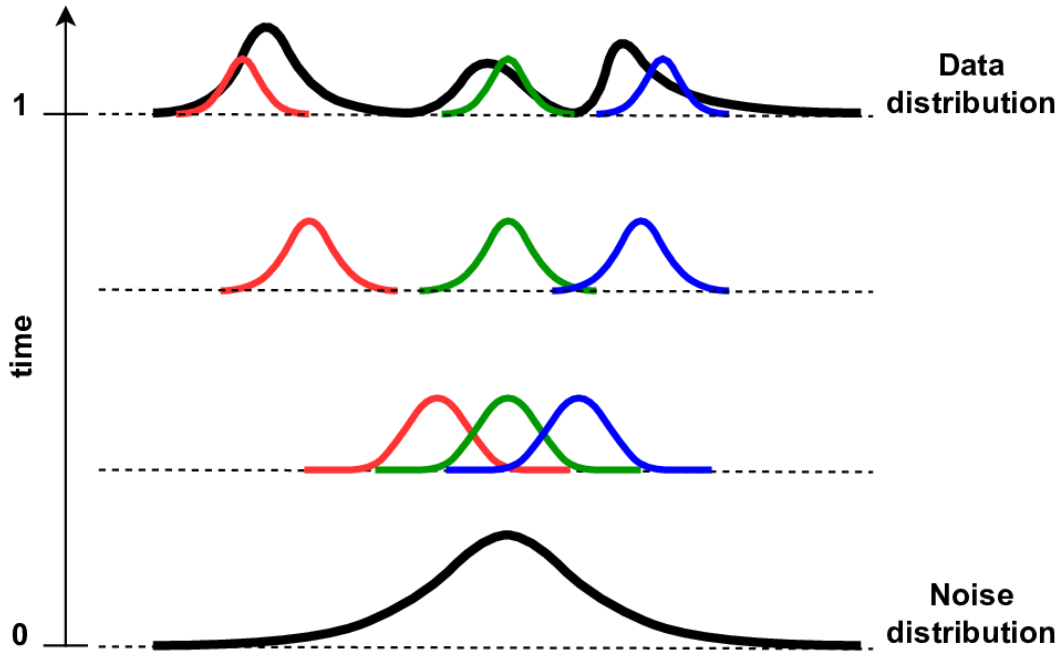
Flow Matching & Diffusion





Flow Matching

Main idea: learn a vector field for iterative denoising



Sampling (inference):

- Sample $\mathbf{x}_0 \sim p_0(\mathbf{x}_0)$
- Integrate the vector field $v_\theta(\mathbf{x}_t, t)$ to get:

$$\mathbf{x}_1 = \mathbf{x}_0 + \int_0^1 v(\mathbf{x}_t, t) dt$$

(e.g., Euler integration)

$$\text{for } t \in \{0, \Delta t, 2\Delta t, 3\Delta t, \ldots, 1 - \Delta t\}:$$
$$\mathbf{x}_{t+\Delta t} \leftarrow \mathbf{x}_t + v(\mathbf{x}_t, t)\Delta t$$

Training:

- Sample $\mathbf{x}_0 \sim p_0(\mathbf{x}_0)$
- Sample $\mathbf{x}_1 \in \mathcal{D}$
- Sample $t \sim p(t)$, e.g., $p(t) = \mathcal{U}(0, 1)$
- Linearly interpolate $\mathbf{x}_t = t\mathbf{x}_1 + (1-t)\mathbf{x}_0$
- Update $v_\theta(\mathbf{x}_t, t)$ to minimize $\|v(\mathbf{x}_t, t) - (\mathbf{x}_1 - \mathbf{x}_0)\|^2$

Source: https://jmtomczak.github.io/blog/18/18_fm.html

Action chunking

A simple trick that works quite well in practice

(Standard) Feedback policy discussed so far:

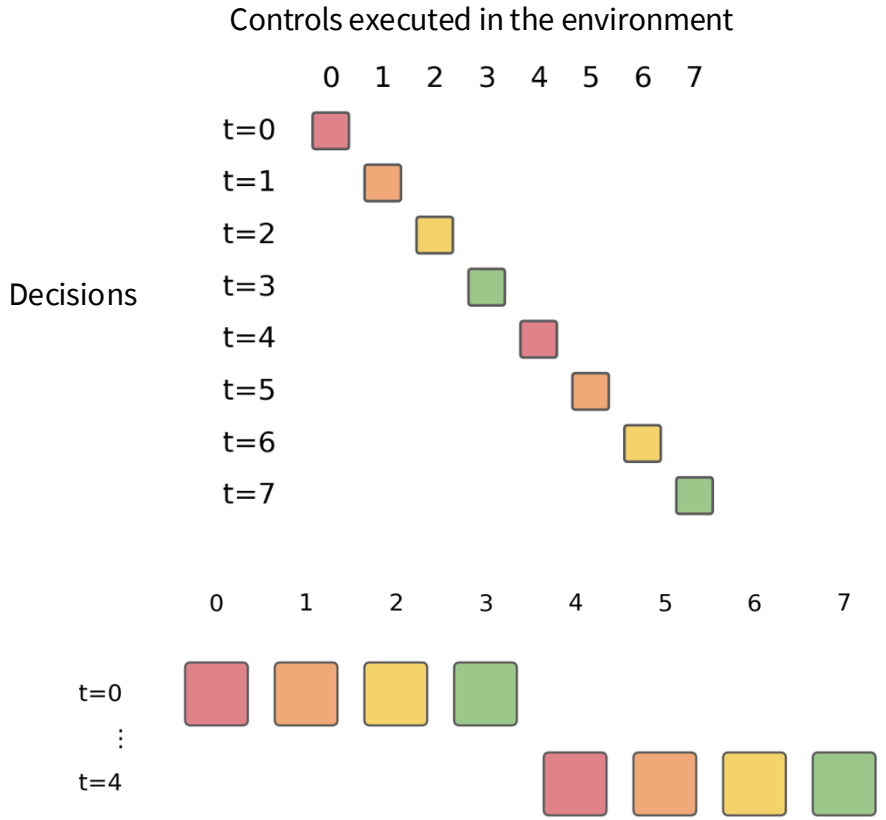
- Observe state $\mathbf{x}_t$
- Sample action $\mathbf{u}_t \sim \pi(\mathbf{u}_t|\mathbf{x}_t)$
- Execute in the environment
- Observe $\mathbf{x}_{t+1}$ and repeat

With action chunking:

- Observe state $\mathbf{x}_t$
- Sample $\mathbf{u}_{t+K} \sim \pi(\mathbf{u}_{t+K}|\mathbf{x}_t)$
- Execute in the environment
- Observe and repeat $\mathbf{x}_{t+K+1}$

In practice:

- Allows more time for inference
- Generally, “smoother” control trajectories



Diffusion Policy

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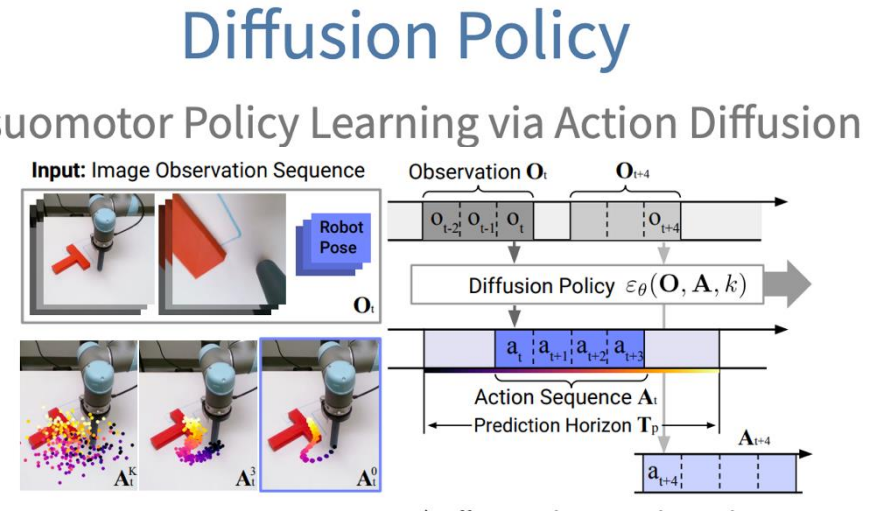

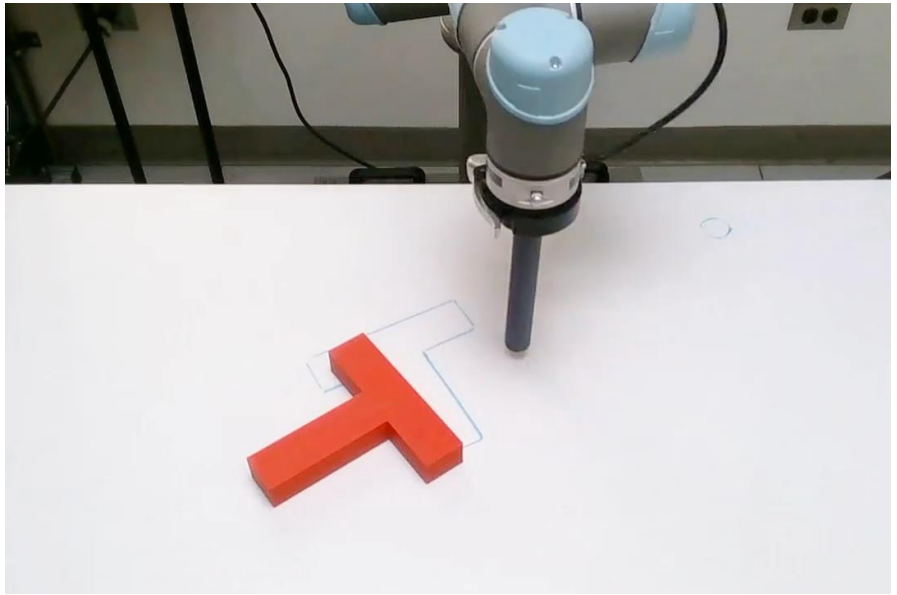

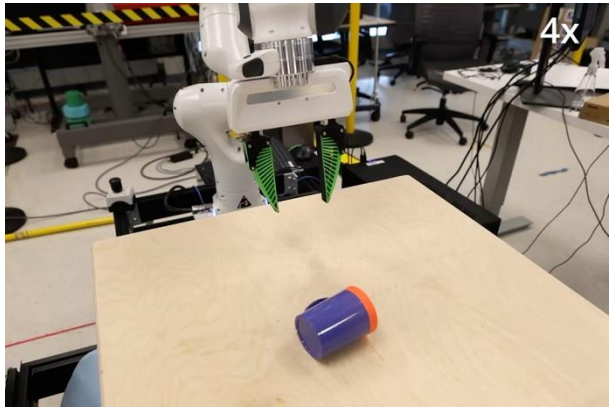

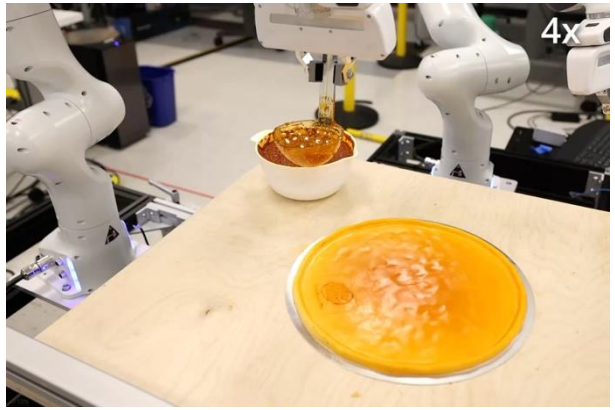

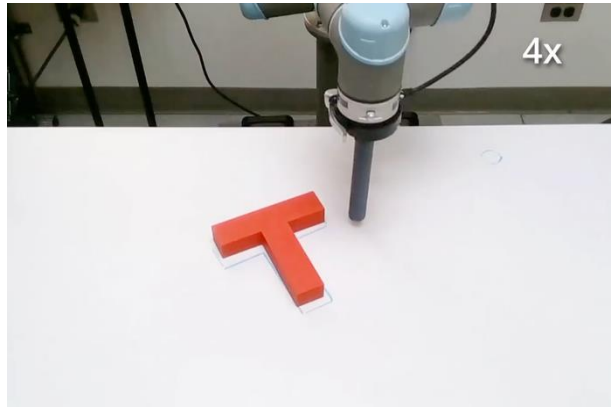

Robotics Transformer

RT-1: Robotics Transformer
for Real-World Control at Scale

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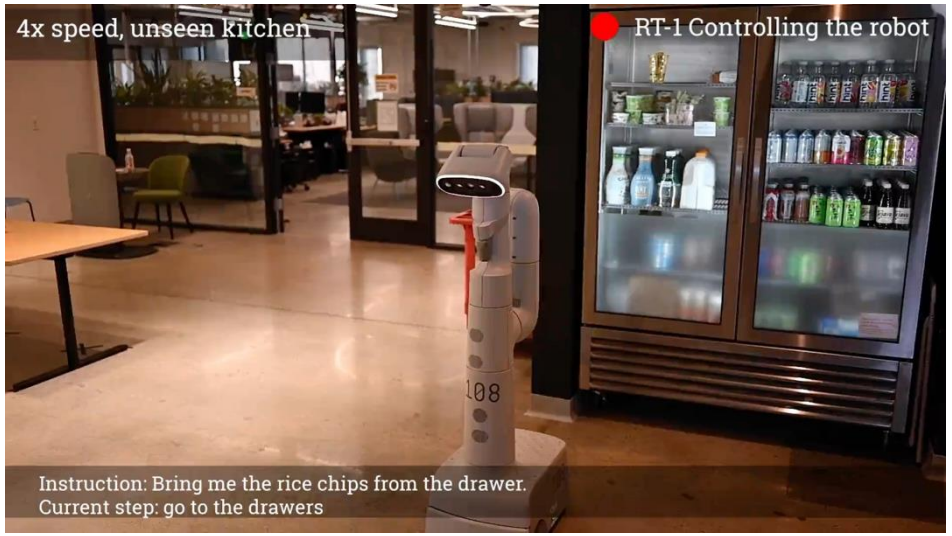
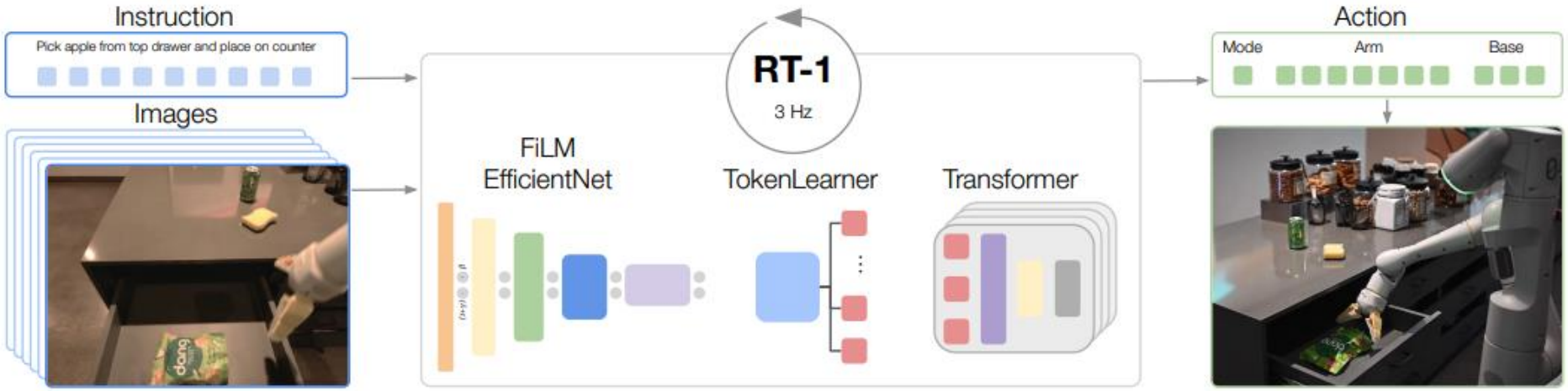
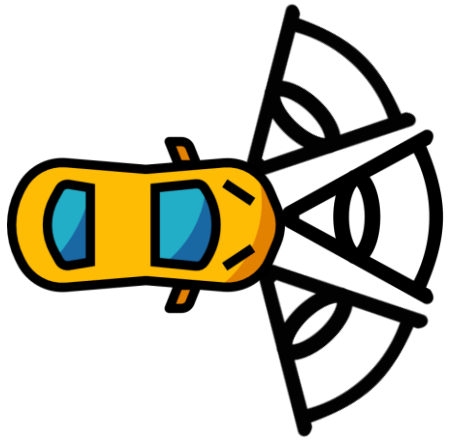


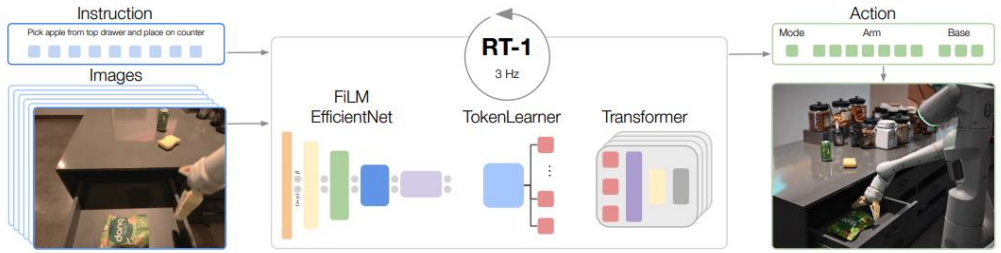


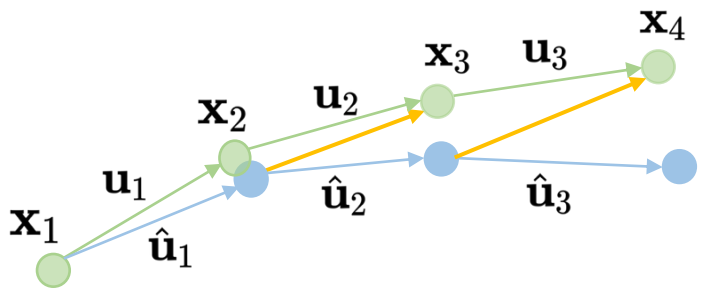
A useful mental model

We can address these challenges in a few different ways:

- Targeted algorithms
- Smart data collection (and augmentation)
- Use expressive models (e.g., that are able to capture the multi-modality of behavior data)







Pros and Cons

Until now, we discussed IL (namely, Behavior Cloning) as the problem of learning to "mimic" the behavior of an expert from demonstrations

Pros:

- *Simplicity*: essentially, SL; easy to implement and monitor
- *Efficiency*: no need for trial-and-error learning (as in RL)
- *No need for an explicit reward signal:* bypasses the task of designing a reward function; only demonstrations are needed

Cons:

- *Dependence on demonstration quality:* poor demos lead to suboptimal policies
- *Generalization and compounding errors*: struggles with covariate shift
- *No exploration:* does not explore the space of solutions for better policies

Outline

- Imitation Learning:
  - Behavior Cloning (BC)
    - Common pitfalls
    - Design strategies for effective IL
    - Other paradigms (RvS)
  - Inverse Reinforcement Learning (IRL)

Reinforcement Learning via Supervised Learning (RvS)

Recent work has explored the idea of converting the reinforcement learning problem (more in the next lecture) into a *conditional*, *filtered*, or *weighted* imitation learning problem.

Key idea: rather than relying solely on "optimal" demonstrations, leverage a broader set of demonstrations from, e.g., suboptimal policies, related tasks, etc.

Two main classes of methods:

1. Filtering or Weighting Demonstrations
2. Goal or Reward Conditioning

Filtering or Weighting Demonstrations

One common approach to RvS is to filter or weight the expert demonstrations based on their quality

Filtering: A simple approach could entail ranking the expert demonstrations based on their return:

$$r(\tau) = \sum_{t=0}^{T-1} \gamma^t R(\mathbf{x}_t, \mathbf{u}_t)$$

Then, we filter the dataset to include only the top-*k%* of trajectories:

$$\mathcal{D} = \{\tau \in \mathcal{D} \mid r(\tau) \geq \bar{r}\}.$$

Weighting: A different approach might involve weighting each individual transition of a trajectory based on its reward, rather than filtering entire trajectories.

$$\mathcal{D} = \{(\mathbf{x}_n, \mathbf{u}_n)\}_{n=1}^N \quad \text{NLL}(\theta) = -\frac{1}{N} \sum_{n=1}^N \log \pi_\theta(\mathbf{u}|\mathbf{x}) R(\mathbf{x}, \mathbf{u}) \quad \hat{\boldsymbol{\theta}}_{\text{mle}} = \underset{\boldsymbol{\theta}}{\text{argmin}}\, \text{NLL}(\boldsymbol{\theta})$$

Goal or Reward Conditioning

Conditioning on *outcomes* is particularly useful in settings where the expert demonstrations are suboptimal or collected from a different task.

Each trajectory might be described using different outcomes, such as the final state of the trajectory, the total reward obtained, or a specific state that was visited during the trajectory.

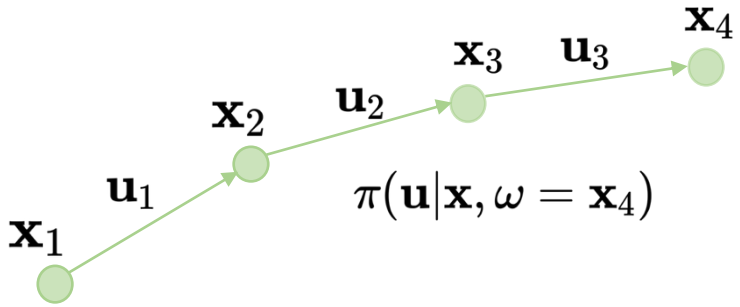
$$\text{NLL}(\theta) = -\frac{1}{N}\sum_{n=1}^{N} \log \pi_\theta(\mathbf{u}|\mathbf{x}, \omega)$$

Goal-conditioning: $\omega = \mathbf{x} \in \mathcal{X}$

Reward-conditioning: $\omega = \sum_{t=0}^{T-1} R(\mathbf{x}_t, \mathbf{u}_t)$

Pros:

- Easily derivable from demonstration data
- Allows to extract useful behavior from suboptimal data
- Improved generalization; decouples the process of achieving desired outcomes from the reward structure



Outline

- Imitation Learning:
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Inverse Reinforcement Learning (IRL)

IRL takes an orthogonal approach to IL, by attempting to recover a reward function from a policy, or from demonstrations of a policy

Example: (BC vs IRL)
A warehouse robot must navigate from a starting point to a goal while avoiding obstacles.
Behavior Cloning:
- Collect demonstration data, train a policy that imitates the demonstrations
- Effective in familiar scenarios, however, it may struggle if the layout changes substantially

Inverse RL:
- Collect the same demonstration data, infer the reward function (e.g., positive for moving closer to the goal, negative for moving close to obstacles)
- The reward function encapsulates the underlying principles of the task

Inverse Reinforcement Learning (IRL)

- Formally, the goal of IRL is to recover a reward function $R : \mathcal{X} \times \mathcal{U} \to \mathbb{R}$ from a dataset of demonstrations $\mathcal{D} = \{(\mathbf{x}_n, \mathbf{u}_n)\}_{n=1}^{N}$
- In practice, the reward is parametrized by some parameters $\mathbf{w}$. Therefore, the goal is to find the value of $\mathbf{w}$ that better explains the expert demonstrations
- Most IRL algorithms follow an iterative learning process:

Algorithm 22.4: High-level IRL Algorithm

Data: Expert demonstrations, $\mathcal{D}$, initialized reward function parameters, w, initialized policy parameters, θ
Result: Learned reward function parameters, w, learned policy parameters, θ
while *not converged* **do**
  Update the reward function parameters, w.
  Update the policy parameters, θ, to maximize the current estimate of the reward function.
return Optimized reward and policy parameters: w, θ.

Key challenge: *reward ambiguity* (i.e., many reward functions explain the same data)

Popular algorithms:
- Apprenticeship learning
- Maximum Margin Planning
- Maximum entropy IRL

Recap

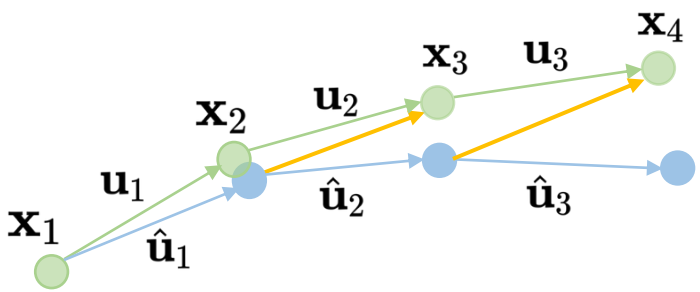
Skeleton of a BC algorithm:

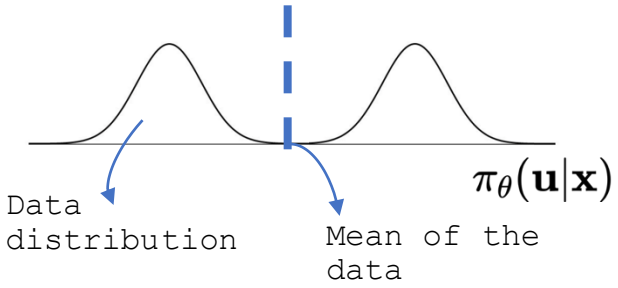
1) Collect a dataset of "expert" demonstrations
2) Train policy $\pi_\theta(\mathbf{u}|\mathbf{x})$ to mimic expert:

$$\mathcal{D} = \{(\mathbf{x}_n, \mathbf{u}_n)\}_{n=1}^{N}$$

Main Challenges:

- Compounding errors
- Multimodal behavior





Potential Solutions:

- Smart data collection
- Targeted algorithms
- Use expressive models

RvS:

Leverage broader set of demonstrations under the same "BC" paradigm

IRL:

Learn the reward function from demonstrations

Next class

- Reinforcement Learning

Additional References:

- Stanford CS 224R
- Berkeley CS285