Lecture 4: Introduction to Deep Reinforcement Learning

Zhi Wang & Chunlin Chen

Department of Control and Systems Engineering
Nanjing University

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For large/continuous state/action spaces

- **Curse of dimensionality**: Computational requirements grow exponentially with the number of state variables
  - Theoretically, all state-action pairs need to be visited infinite times to guarantee an optimal policy
  - In many practical tasks, almost every state encountered will never have been seen before
- **Generalization**: How can experience with a limited subset of the state space be usefully generalized to produce a good approximation over a much larger subset?

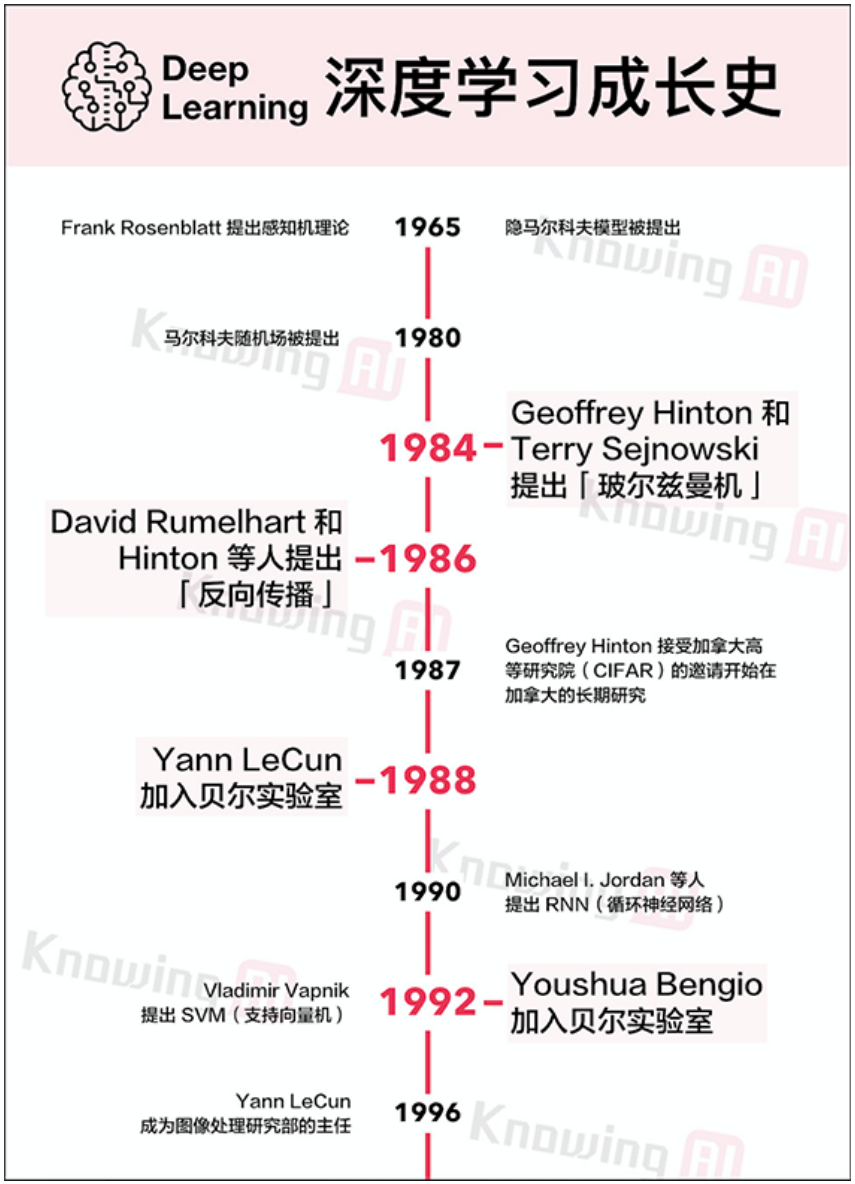
Function approximation

- It takes examples from a desired function (e.g., a value function) and attempts to generalize from them to construct an approximation to the entire function
  - Linear function approximation: $Q(s,a) = \sum_i \phi_i(s,a) w_i$
  - Neural network approximation: $Q(s,a) = Q(s,a;\boldsymbol{\theta})$
- Function approximation is an instance of supervised learning, the primary topic studied in machine learning, artificial neural networks, pattern recognition, and statistical curve fitting
  - In theory, any of the methods studied in these fields can be used in the role of function approximator within RL algorithms
  - RL with function approximation involves a number of **new issues** that do not normally arise in conventional supervised learning, e.g., non-stationarity, bootstrapping, and delayed targets

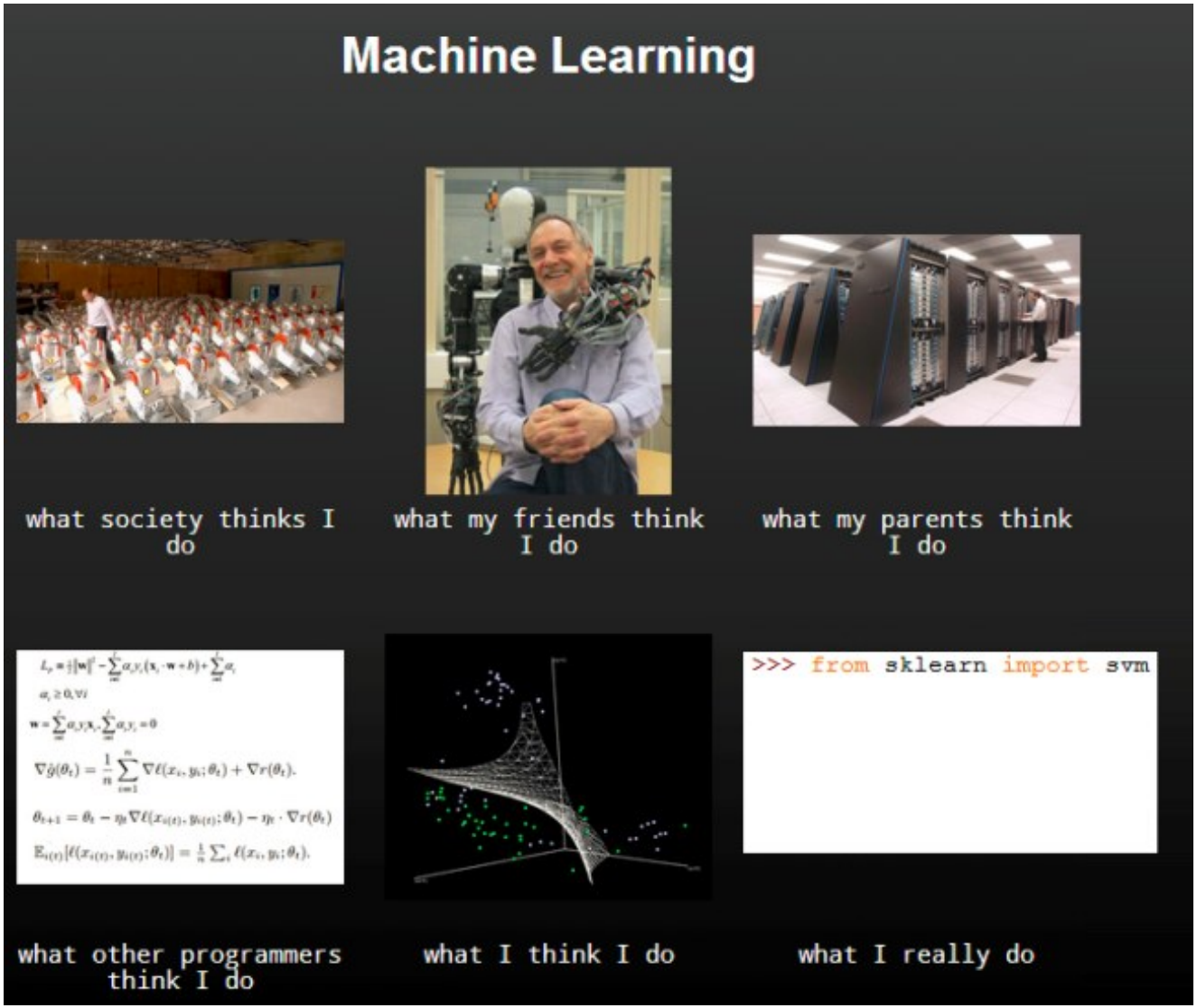
Deep reinforcement learning (DRL)

- The revolution of Deep Learning
  - Turing award 2018 to deep learning godfathers
- DRL = theories of RL + the help of deep function approximators

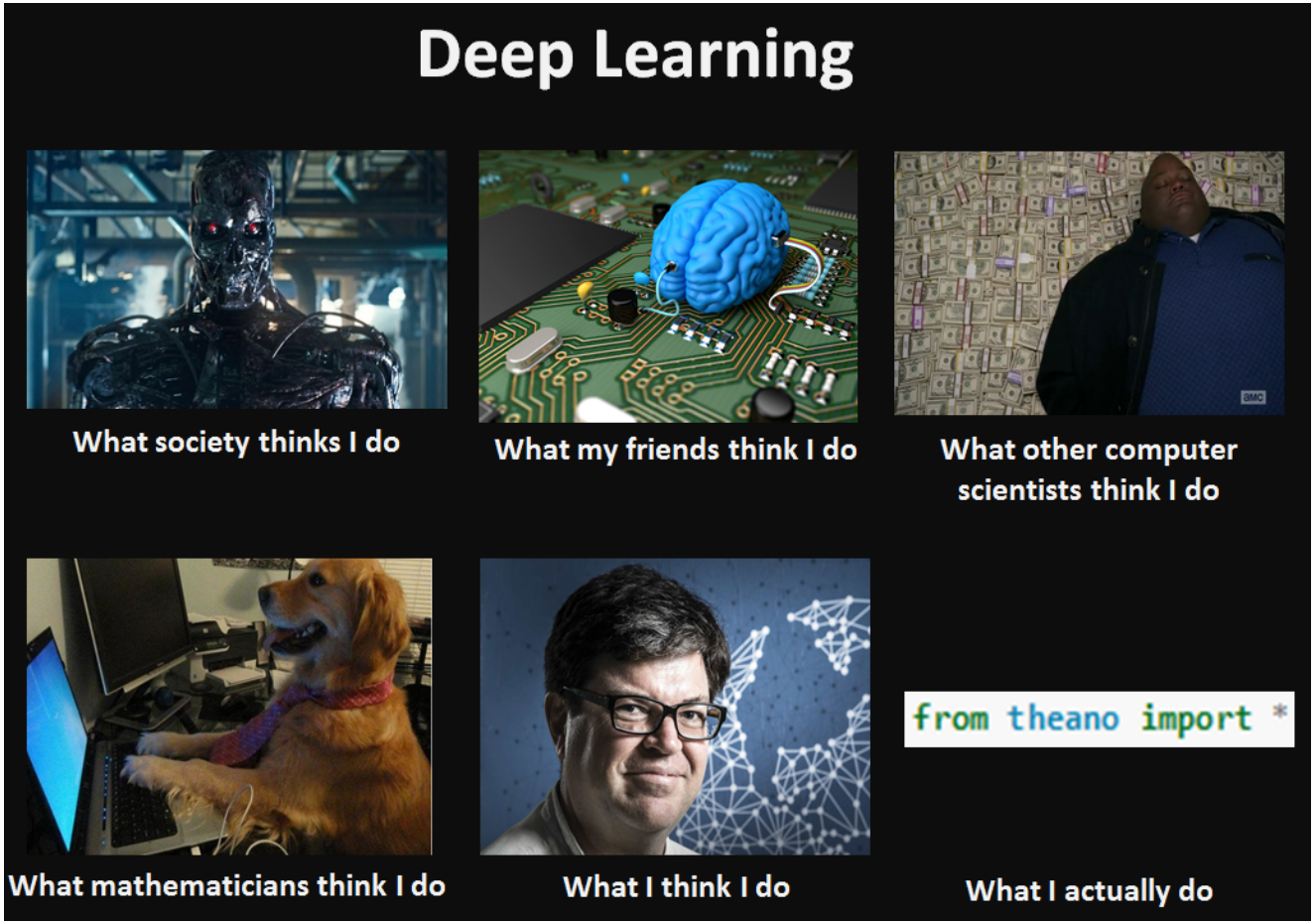
Deep reinforcement learning (DRL)



What do you think machine learning is?



What do you think deep learning is?



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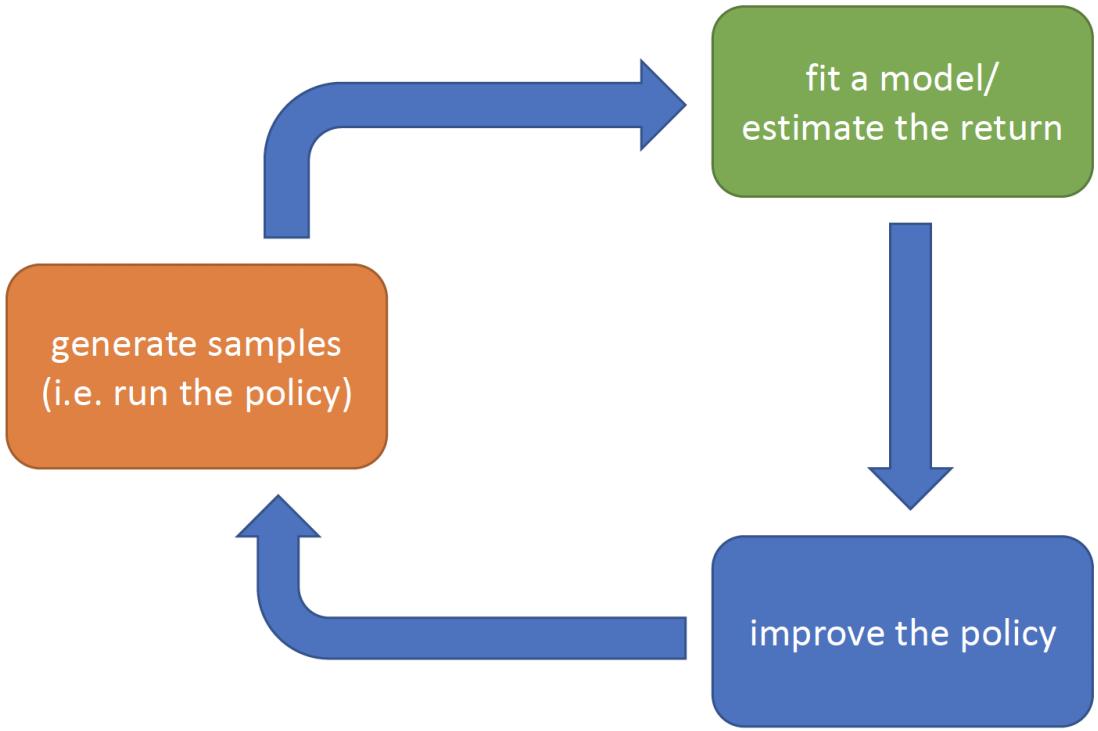
The anatomy of a DRL algorithm



- Following the **Generalized Policy Iteration** framework
  - ... Generate samples $\Rightarrow$ Policy evaluation $\Rightarrow$ Policy improvement ...

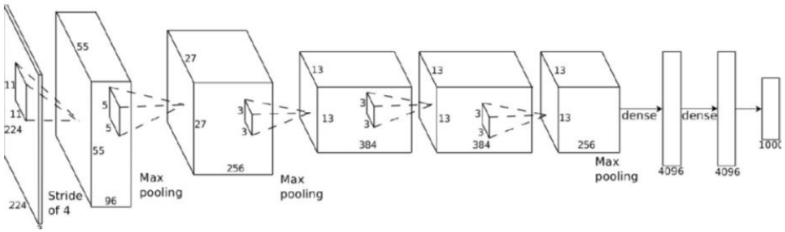
$$\pi_0 \xrightarrow{E} v_{\pi_0} \xrightarrow{I} \pi_1 \xrightarrow{E} v_{\pi_1} \xrightarrow{I} \pi_2 \xrightarrow{E} \ldots \xrightarrow{I} \pi_* \xrightarrow{E} v_*$$

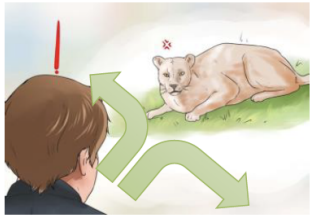
Types DRL algorithms

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta} \in \mathbb{R}^d} \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}(\tau)} \left[\sum_t r(s_t, a_t) \right]$$

- **Policy gradients**: Directly approximate the policy and differentiate the above objective
- **Value function-based**: Estimate state- or action-value function or of the optimal policy (no explicit policy)
- **Actor-critic**: Estimate state- or action-value function or of the current policy, use it to improve policy
- **Model-based RL**: Estimate the transition model, $p(s', r|s, a)$
  - Use it for planning (no explicit policy), use it to improve a policy, etc

DRL - Directly approximate policies





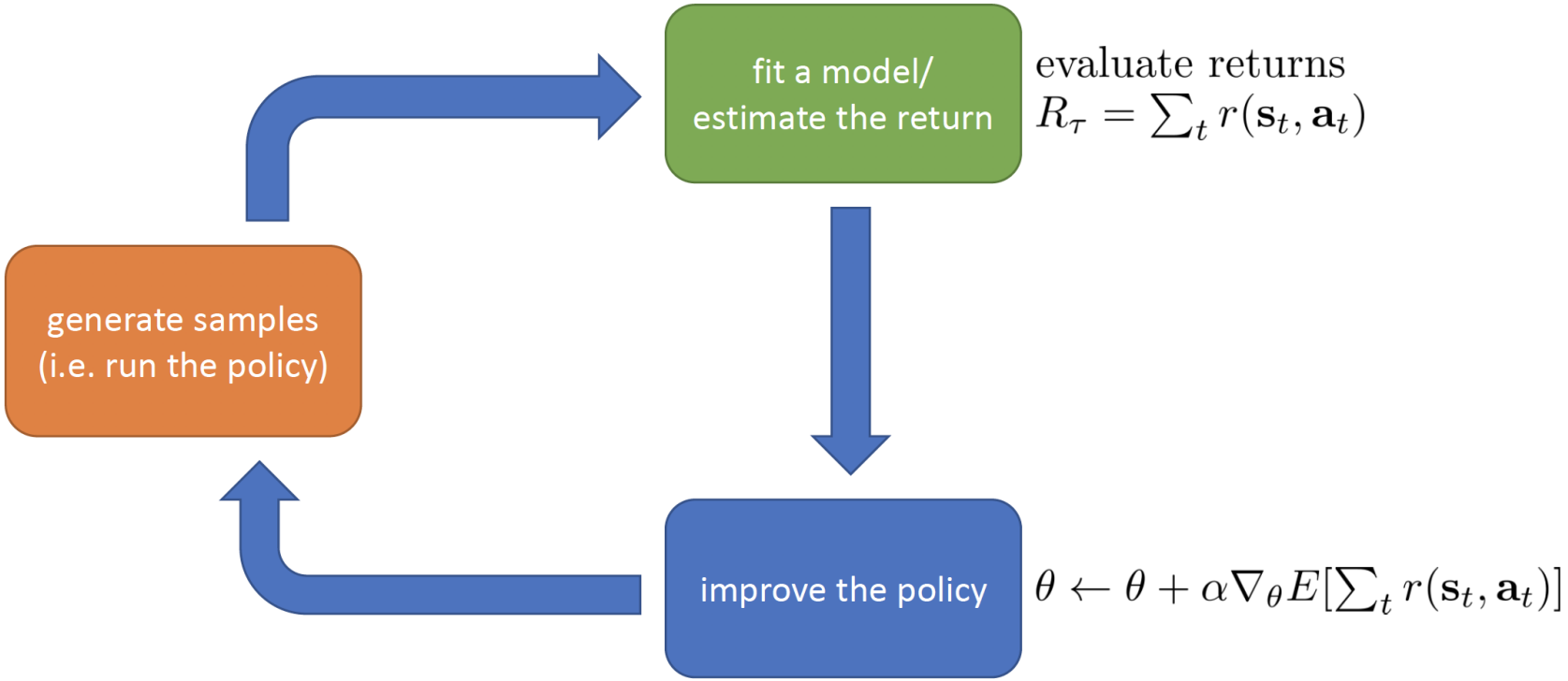
$\mathbf{o}_t$ $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ $\mathbf{a}_t$

$\mathbf{s}_t$ – state
$\mathbf{o}_t$ – observation
$\mathbf{a}_t$ – action

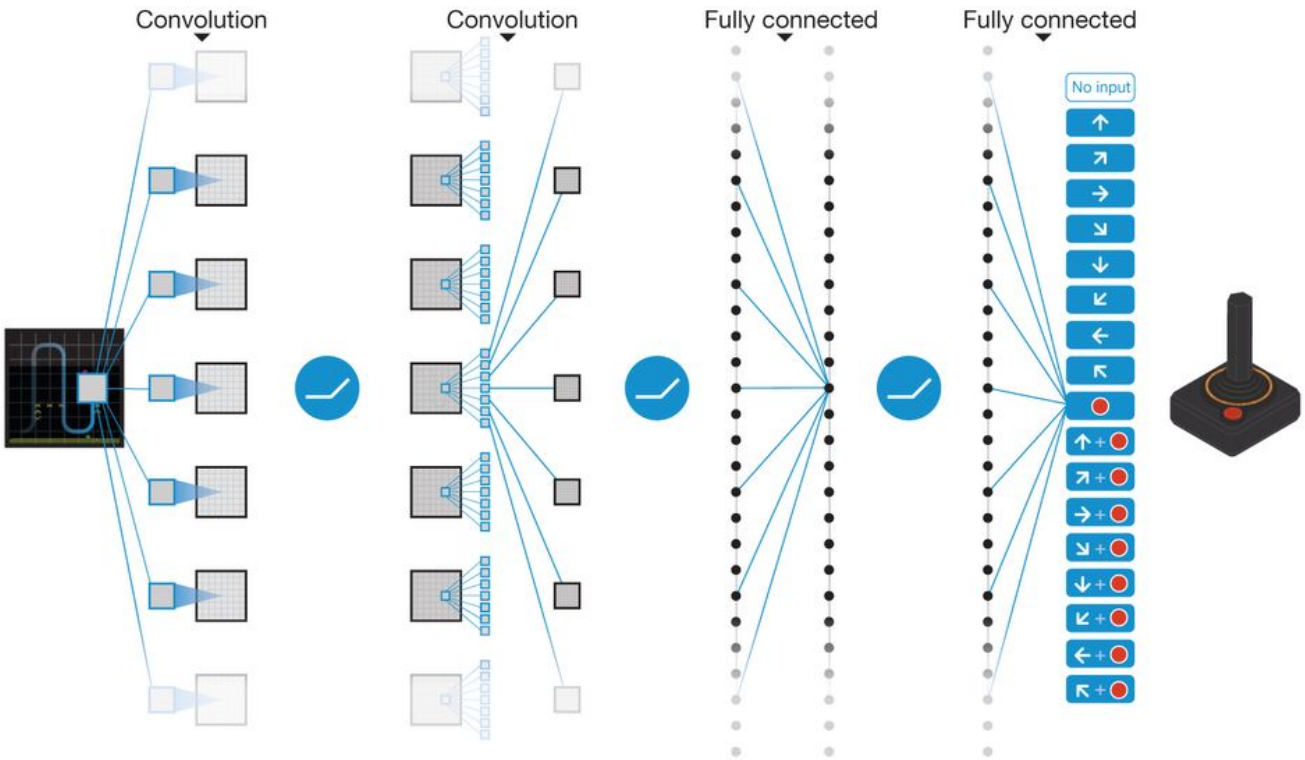
$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ – policy
$\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ – policy (fully observed)

- Usually using deep neural networks
- Optimize the policy network by backpropagation

DRL - Directly approximate policies

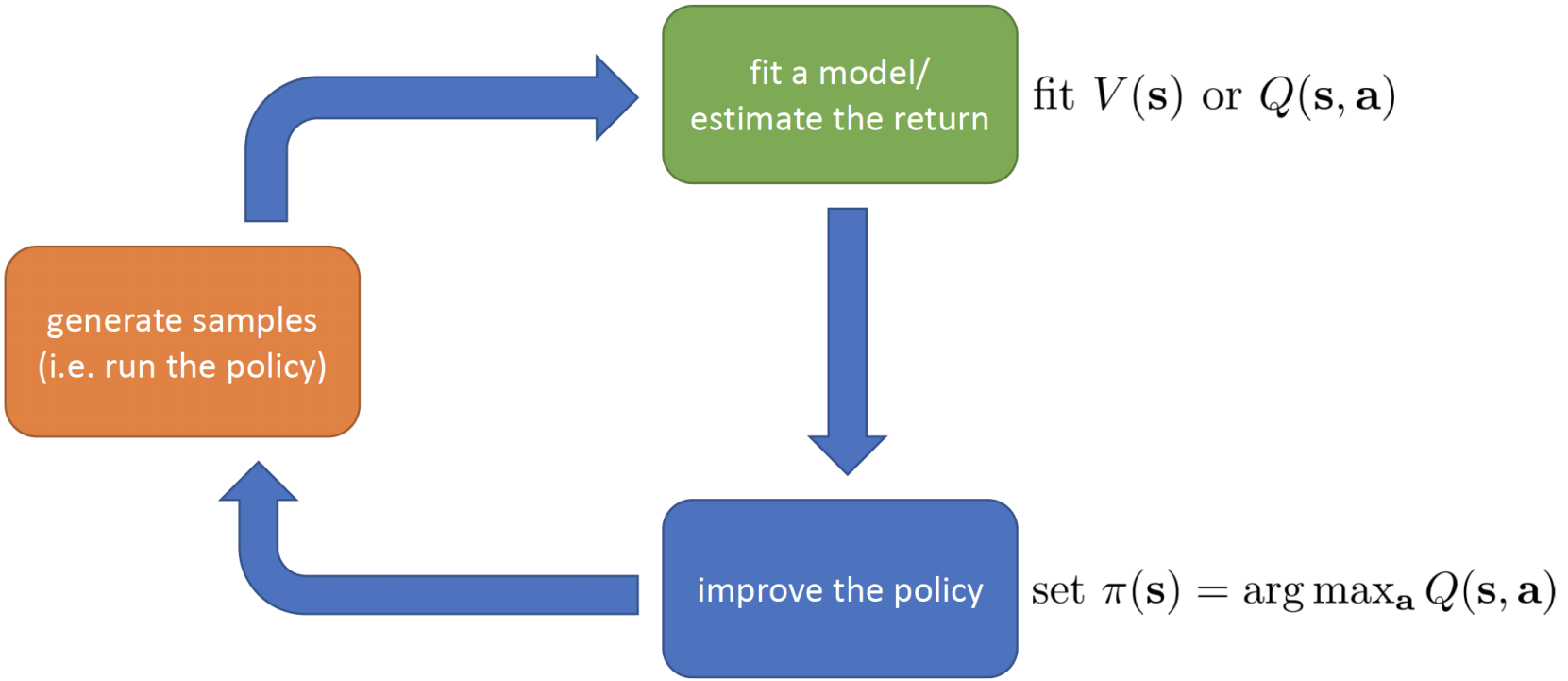


DRL - Approximate value functions



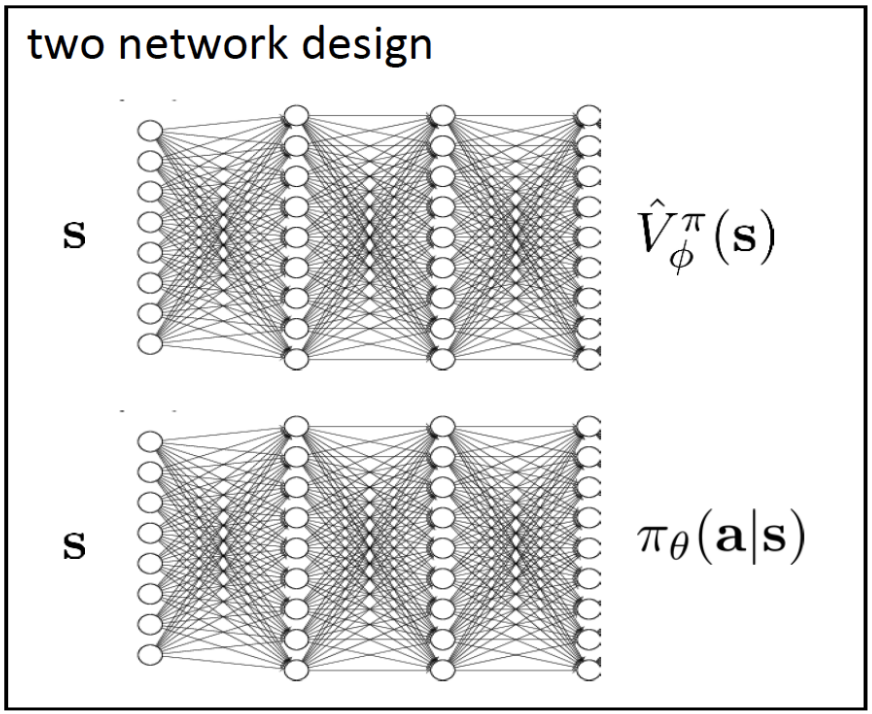
- Usually using deep neural networks
- Optimize the deep Q-network by minimizing the **Bellman residual**

DRL - Approximate value functions

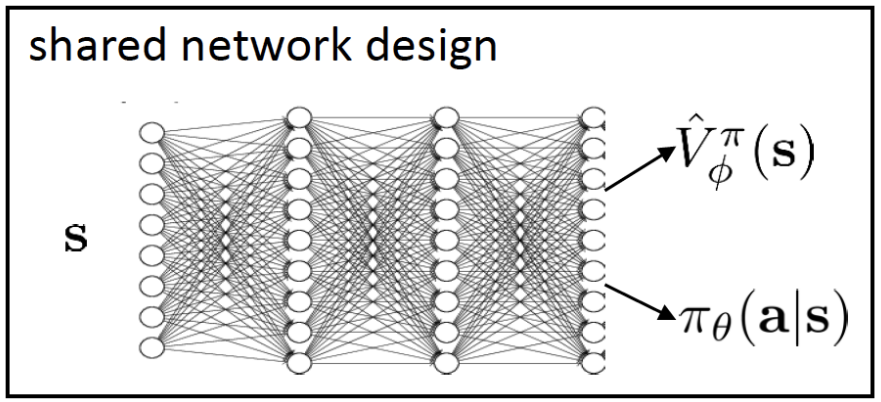


DRL - Approximate both

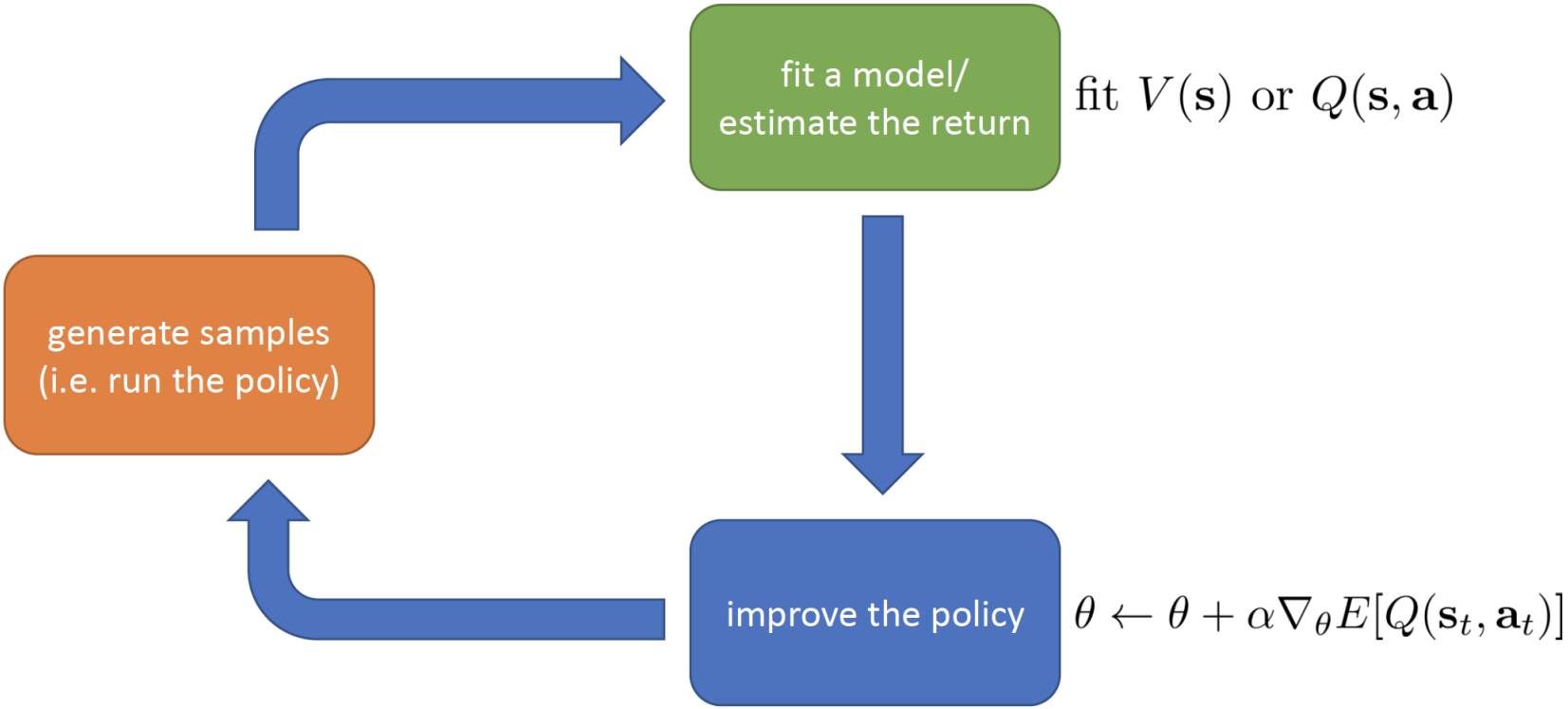
two network design



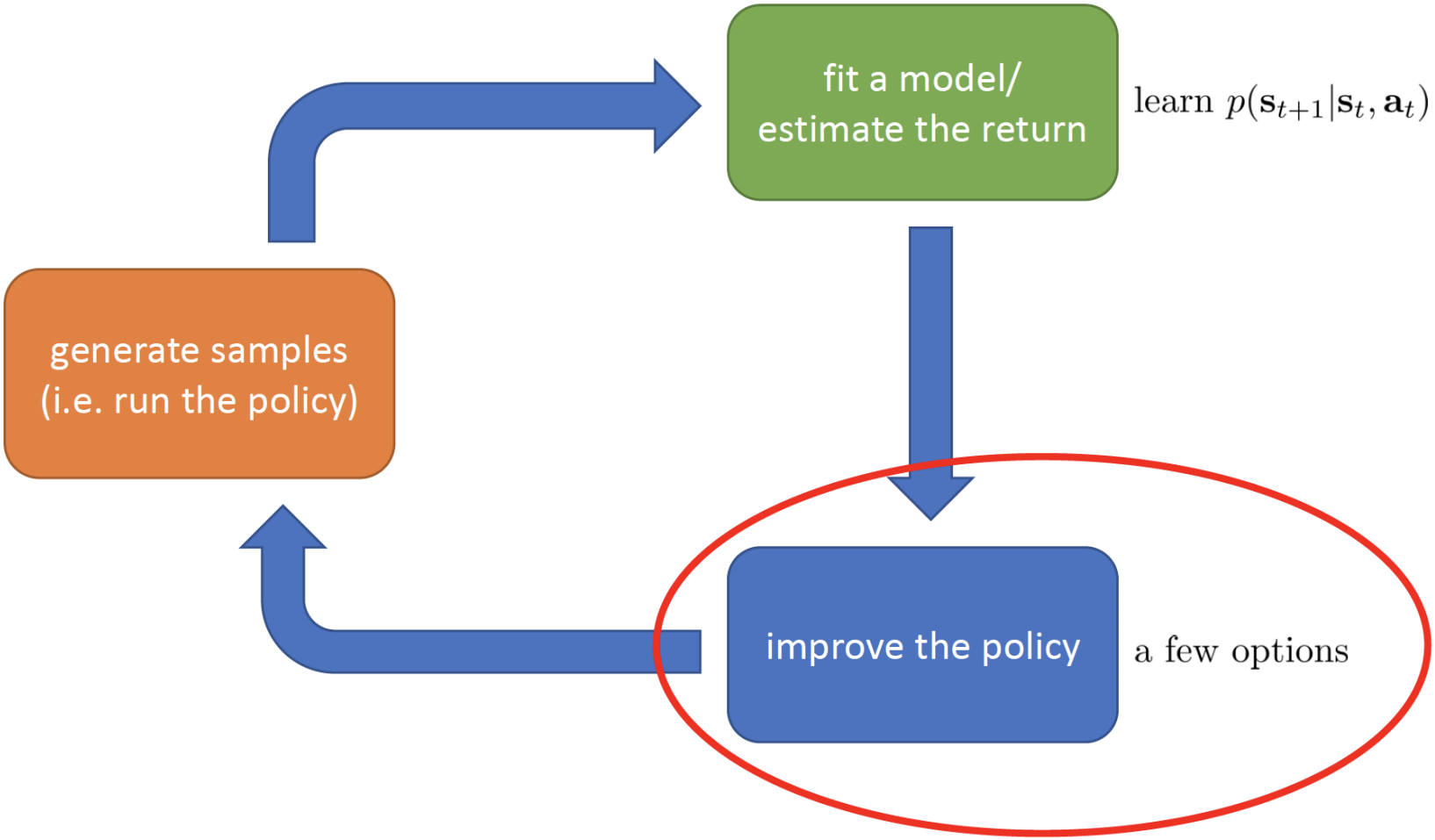
shared network design



DRL - Approximate both



DRL - Model-based

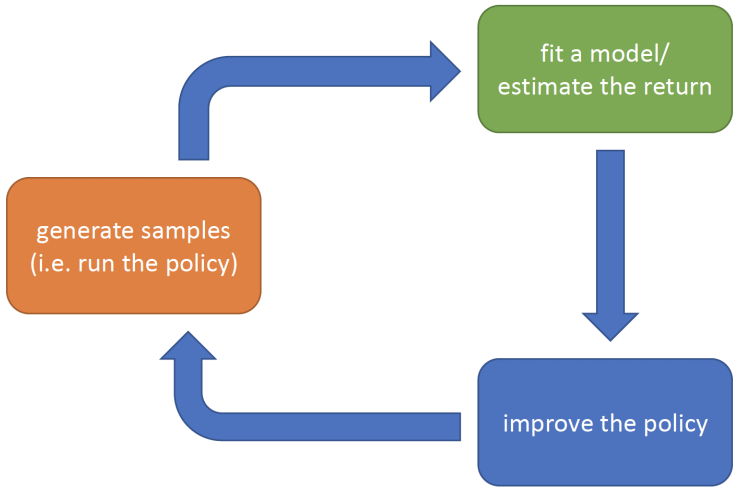


DRL - Model-based

- Just use the model to plan (no explicit policy)
  - Trajectory optimization / optimal control
  - Discrete planning in discrete action spaces, e.g., Monte Carlo tree search
- Backpropagate gradients into the policy
- Use the model to learn a value function
  - Dynamic programming
  - Generate simulated experience for model free learner

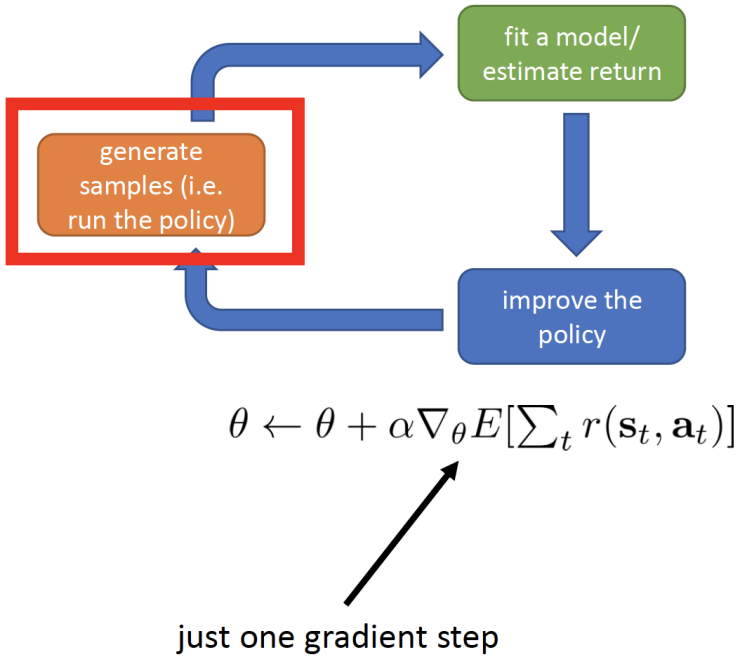
Why so many DRL algorithms?

- Different tradeoffs
  - Sample efficiency – model-based
  - Stability & easy to use – model-free
- Different assumptions
  - Stochastic or deterministic?
  - Continuous or discrete?
  - Episodic or infinite horizon?
- Different things are easy or hard in different settings
  - Easier to represent the policy?
  - Easier to represent the model?

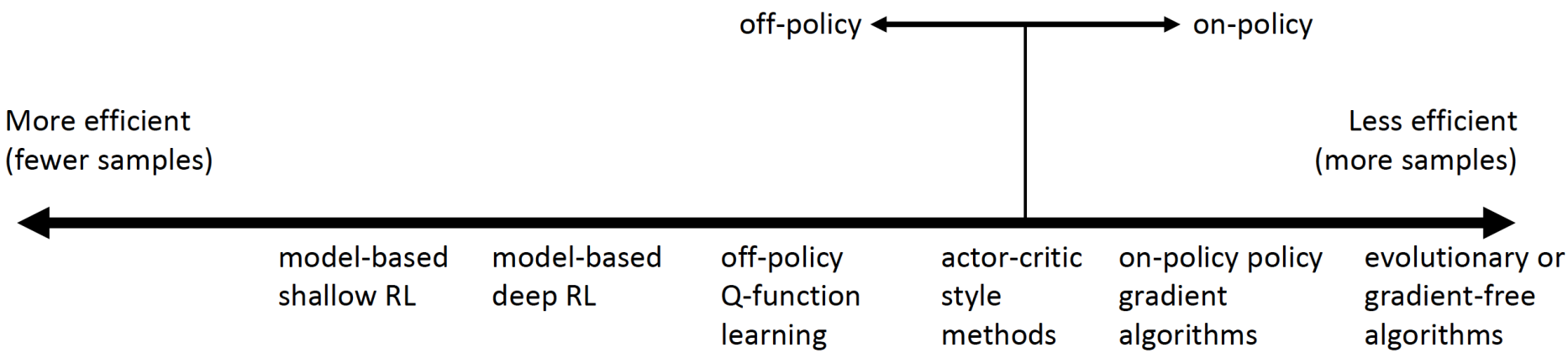


Comparison: Sample efficiency

- Sample efficiency = how many samples do we need to get a good policy?
- Most important question: is the algorithm off-policy?
  - Off-policy: able to improve the policy without generating new samples from that policy
  - On-policy: each time the policy is changed, even a little bit, we need to generate new samples



Comparison: Sample efficiency



Comparison: Stability and ease of use

- Does it converge?
- And if it converges, to what?
- And does it converge every time?

Why is any of this even a question???

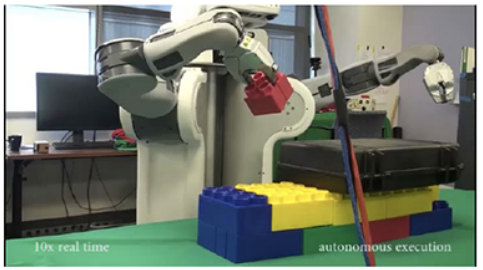
- Supervised learning: almost always gradient descent
- Reinforcement learning: often not gradient descent
  - Q-learning: Bellman fixed point iteration
  - Model-based RL: model is not optimized for expected reward
  - Policy gradient: is gradient descent, but also often the least efficient!

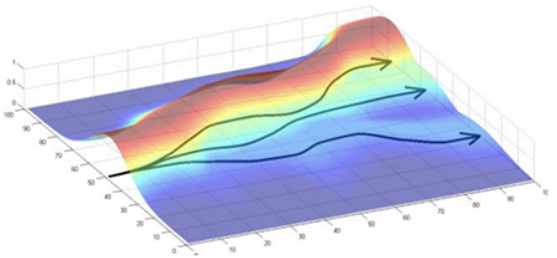
Comparison: Stability and ease of use

- Value function fitting
  - At best, minimizes error of fit ("Bellman error"), not the same as expected reward
  - At worst, doesn't optimize anything. Many popular deep RL value fitting algorithms are not guaranteed to converge to anything in the nonlinear case
- Model-based RL
  - Model minimizes error of fit. This will converge.
  - No guarantee that better model = better policy
- Policy gradient
  - The only one that actually performs gradient descent (ascent) on the true objective

Comparison: Assumptions

- Common assumption 1: full observability
  - Generally assumed by value function fitting methods
  - Can be mitigated by adding recurrence
- Common assumption 2: episodic learning
  - Often assumed by pure policy gradient methods
  - Assumed by some model-based RL methods
- Common assumption 3: continuity or smoothness
  - Assumed by some continuous value function learning methods
  - Often assumed by some model-based RL methods





Examples of specific algorithms

- Policy gradient methods
  - REINFORCE
  - Natural policy gradient
  - Trust region policy optimization
- Value function fitting methods
  - Fitted value iteration, fitted Q-iteration
  - Deep Q-network, deep Q-learning
- Actor-critic algorithms
  - Deep deterministic policy gradient (DDPG)
  - Asynchronous advantage actor-critic (A3C)
  - Soft actor-critic (SAC)
- Model based RL algorithms
  - Dyna
  - Guided policy search

We'll learn about most of these in the next few weeks!

Example 1: Atari games with deep Q-networks

- Playing Atari with deep reinforcement learning
- Q-learning with convolutional neural networks

Example 2: robots and model-based RL

- End-to-end training of deep visuomotor policies
- Guided policy search (model-based RL) for image based robotic manipulation

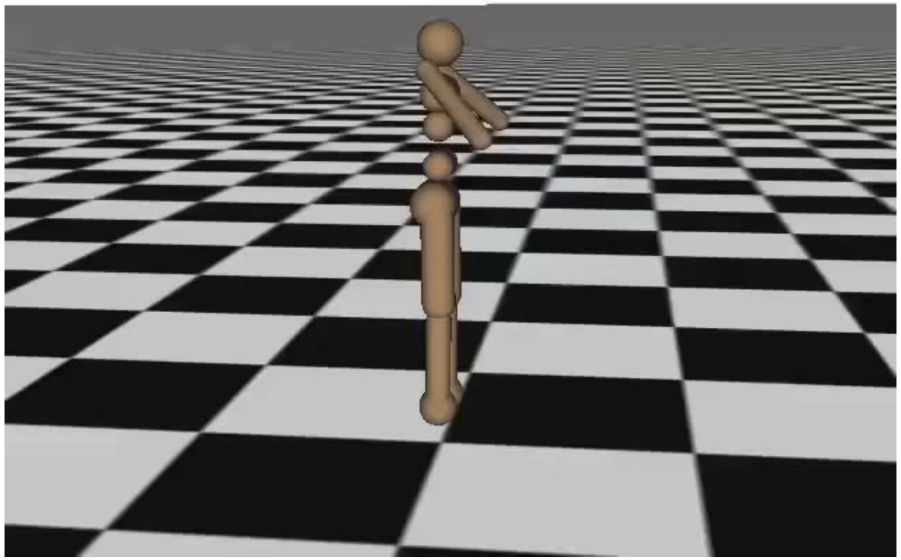
2018 IEEE International Conference on Robotics and Automation (ICRA)
May 21-25, 2018, Brisbane, Australia

Neural Network Dynamics for Model-Based Deep Reinforcement Learning with Model-Free Fine-Tuning

Anusha Nagabandi, Gregory Kahn, Ronald S. Fearing, Sergey Levine
University of California, Berkeley

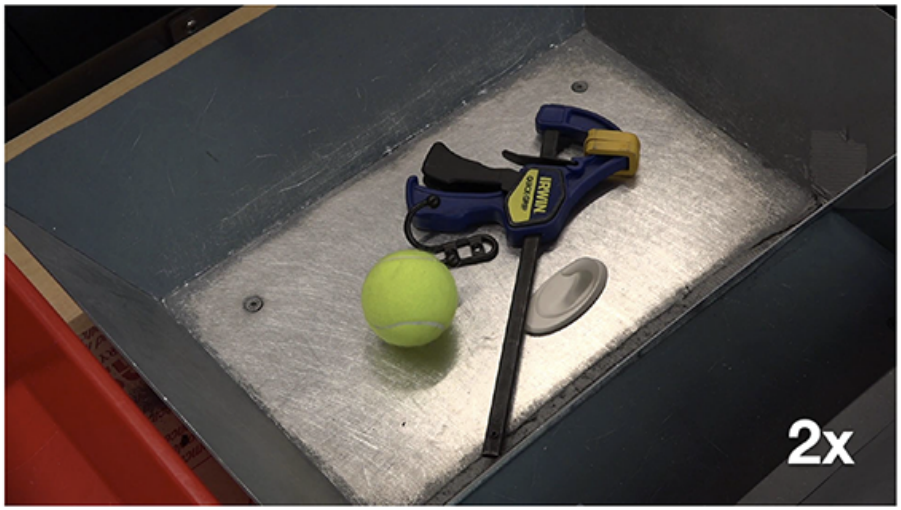
Example 3: walking with policy gradients

- High-dimensional continuous control with generalized advantage estimation
- Trust region policy optimization with value function approximation



Example 4: robotic grasping with Q-functions

- Q learning from images for real world robotic grasping



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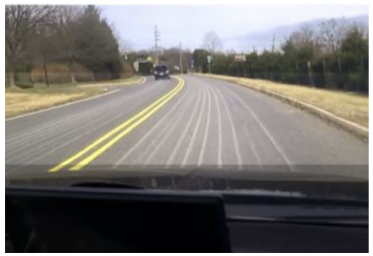
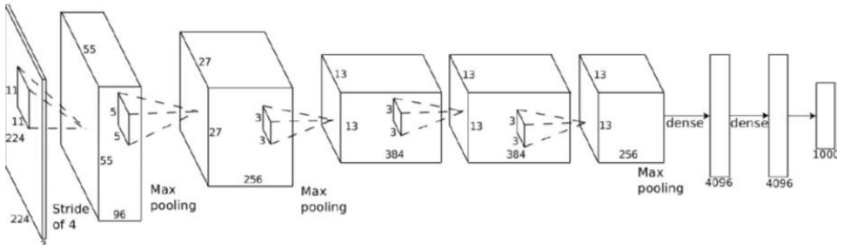
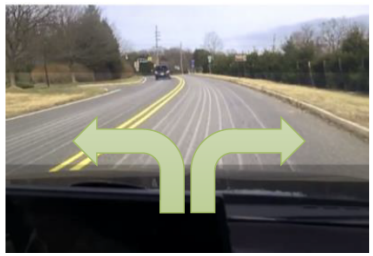
Imitation learning - Imitating expert demonstrations



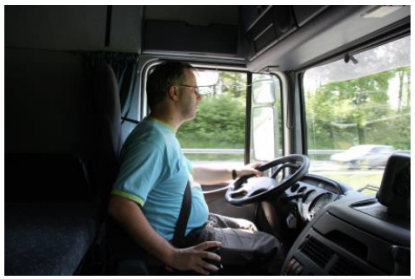
$\mathbf{o}_t$



$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

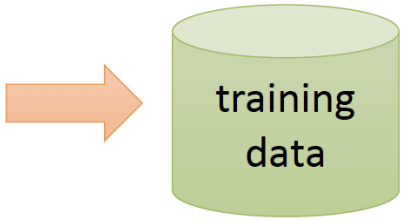


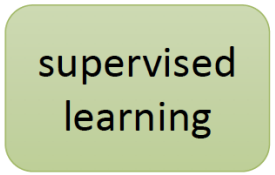
$\mathbf{a}_t$



$\mathbf{o}_t$

$\mathbf{a}_t$

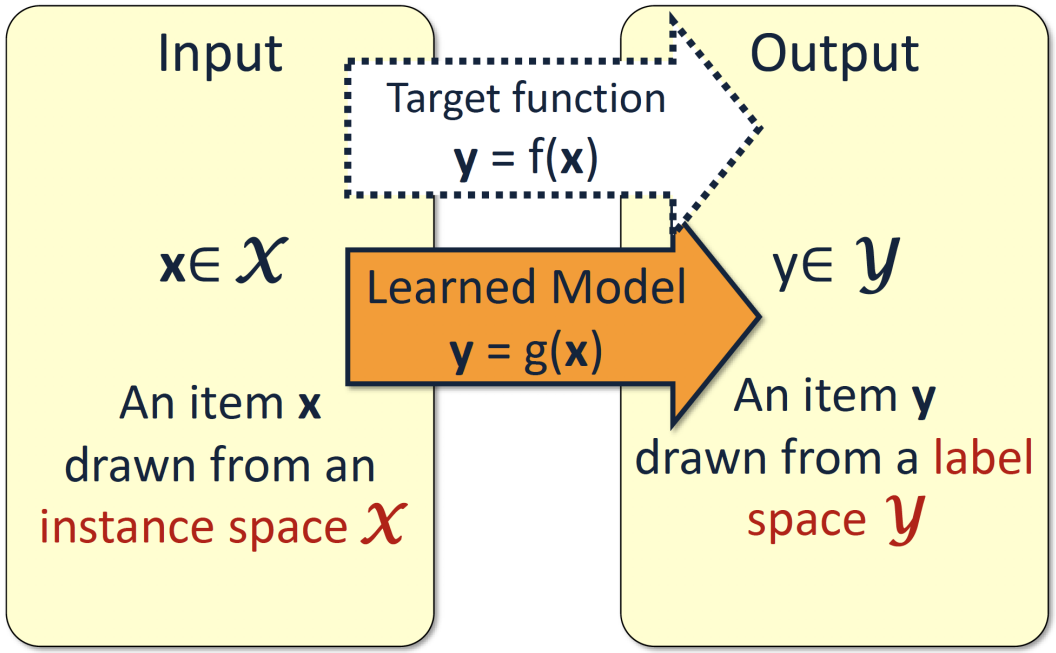




$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

- Behavior cloning
- Supervised training has better stability than many RL methods

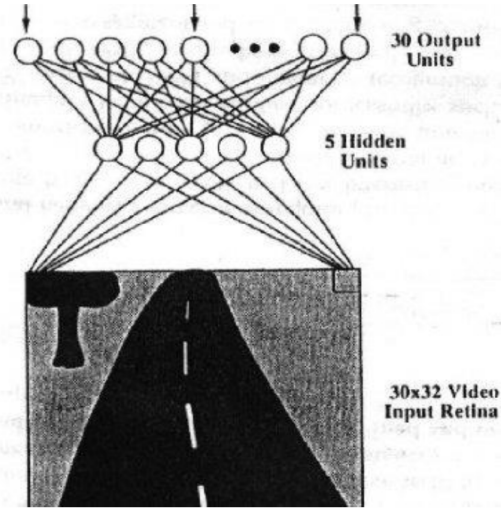
Recall: supervised learning



- We need to choose what kind of model we want to learn
  - Linear model, nonlinear model...
  - Parametric model, nonparametric model...
  - Decision trees, neural networks, Gaussian processes...

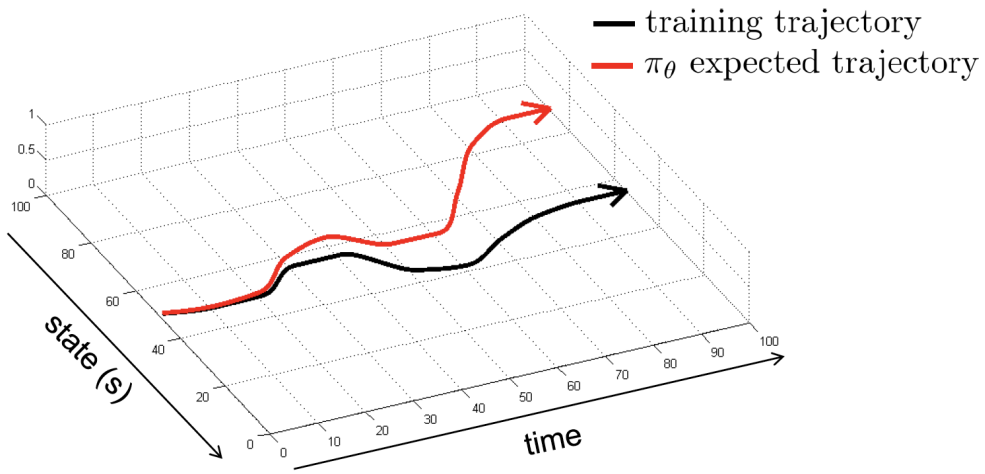
The original deep imitation learning system

ALVINN: **A**utonomous **L**and **V**ehicle **I**n a **N**eural **N**etwork
1989

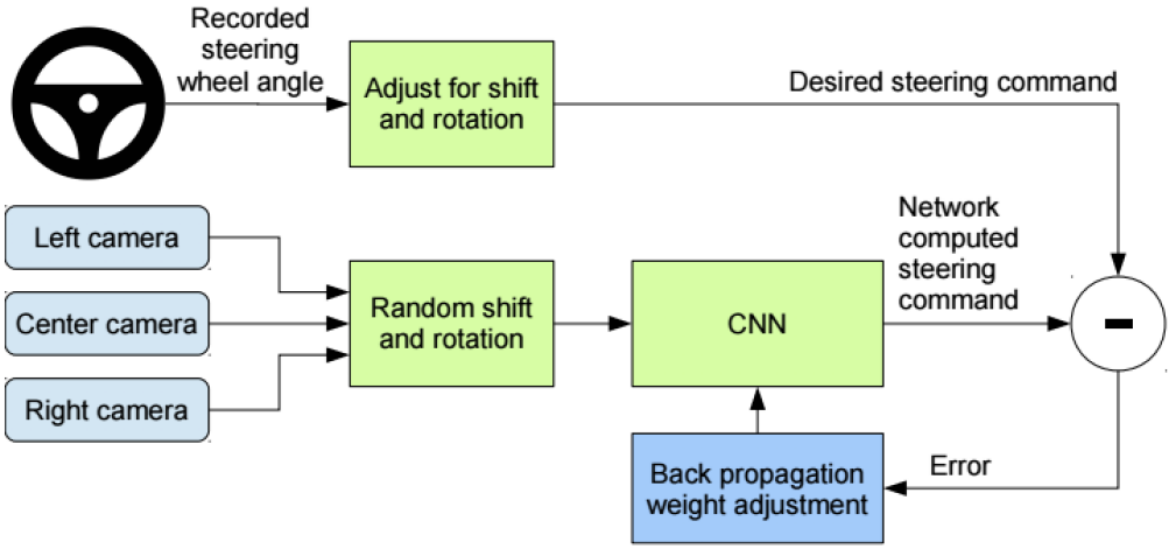


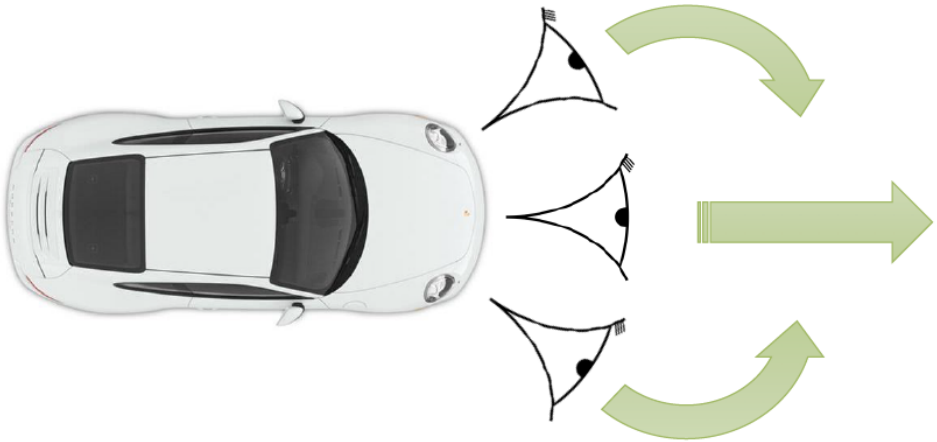
Deep imitation learning system

- Input: states/observations $\boldsymbol{o}_t$
- Output: actions $\hat{\boldsymbol{a}}_t = \pi_\theta(\cdot|\boldsymbol{o}_t)$
- Label/ground truth: actions $\boldsymbol{a}_t$ provided by human



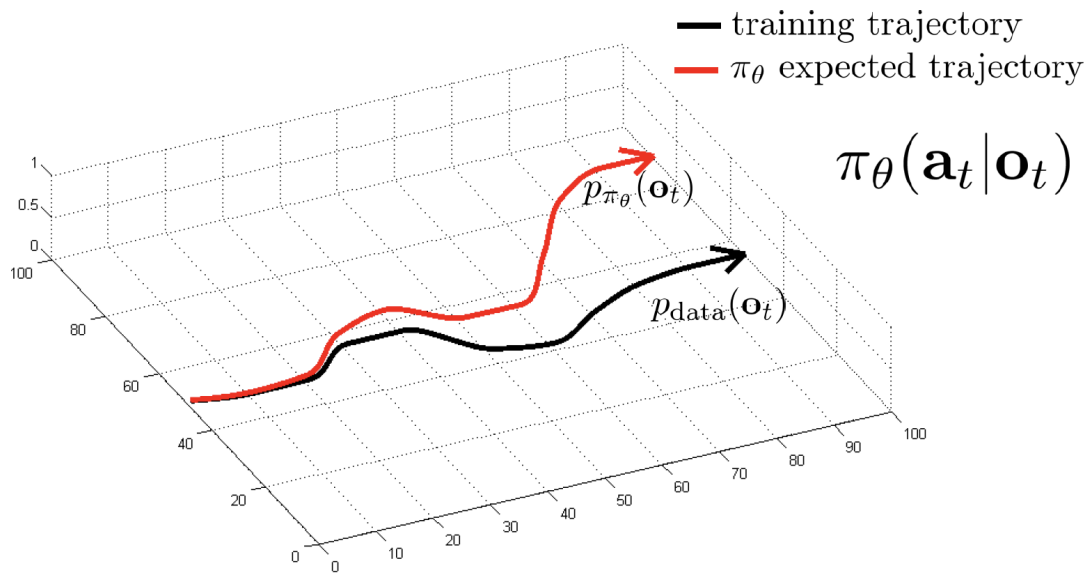
The original deep imitation learning system





Challenge: distribution shift

- Error accumulates fast in a trajectory and put us into situations that we never deal with before
  - Analogous to the key challenge in mode-based RL



Can we make $p_{data}(\boldsymbol{o}_t) = p_{\pi_\theta}(\boldsymbol{o}_t)$?

Alternative solution

Can we make $p_{data}(\boldsymbol{o}_t) = p_{\pi_\theta}(\boldsymbol{o}_t)$?

Idea: instead of being clever about $p_{\pi_\theta}(\boldsymbol{o}_t)$, be clever about $p_{data}(\boldsymbol{o}_t)$

DAgger: **D**ataset **A**ggregation

Goal: collect training data from $p_{\pi_\theta}(\boldsymbol{o}_t)$ instead of $p_{data}(\boldsymbol{o}_t)$

How? Just run $p_{\pi_\theta}(\boldsymbol{o}_t)$

But need labels $\boldsymbol{a}_t$!

1. train $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ from human data $\mathcal{D} = \{\mathbf{o}_1, \mathbf{a}_1, \ldots, \mathbf{o}_N, \mathbf{a}_N\}$
2. run $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ to get dataset $\mathcal{D}_\pi = \{\mathbf{o}_1, \ldots, \mathbf{o}_M\}$
3. Ask human to label $\mathcal{D}_\pi$ with actions $\mathbf{a}_t$
4. Aggregate: $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$

What is the problem?

- One of the biggest challenge is collecting expert demonstrations
  - Unless it has a huge business potential, the attached cost can be prohibitive
- The trained policy is only as good as the demonstrations
  - Initialize a policy from expert demonstrations, finetune it using RL

1. train $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ from human data $\mathcal{D} = \{\mathbf{o}_1, \mathbf{a}_1, \ldots, \mathbf{o}_N, \mathbf{a}_N\}$
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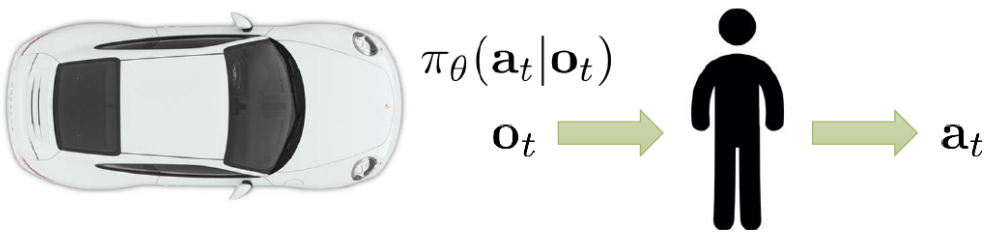
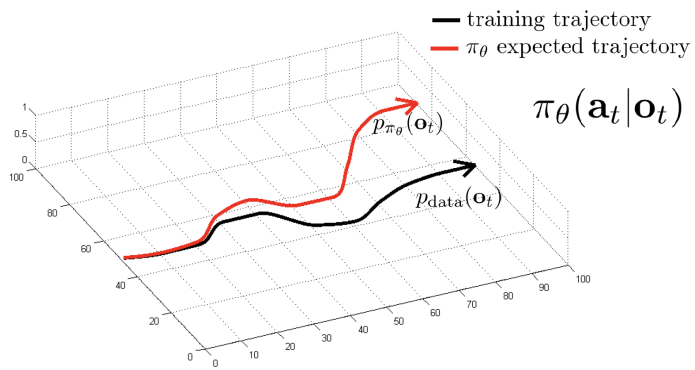


Deep imitation learning in practice

- DAgger addresses the problem of distributional "drift"
- What if our model is so good that it doesn't drift?
- Need to mimic expert behavior very accurately
- But don't overfit



Why might we fail to fit the expert?

- RL: temporally correlated
- Imitation learning: Non-Markovian behavior

$$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$$

behavior depends only on current observation

$$\pi_\theta(\mathbf{a}_t|\mathbf{o}_1, ..., \mathbf{o}_t)$$

behavior depends on all past observations

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

Often very unnatural for human demonstrators

Recall: Markov property

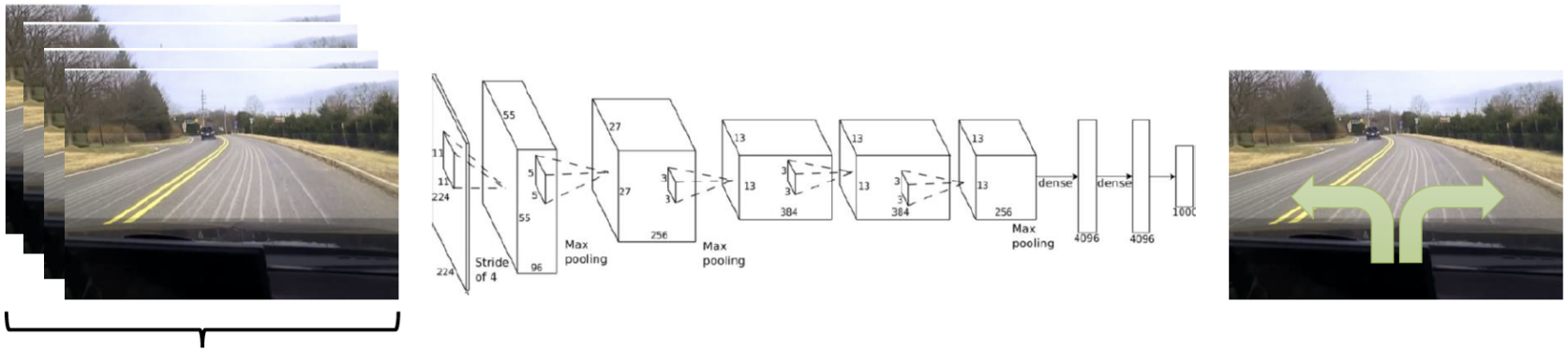
$$p(s', r|s, a) = Pr\{S_t = s', R_t = r|S_{t-1} = s, A_{t-1} = a\}$$

$$\sum_{s' \in \mathcal{S}} \sum_{r \in \mathcal{R}} p(s', r|s, a) = 1, \quad \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$$

- The probabilities given by p completely characterize the environment's dynamics
- **Markov Property**
  - The probability of each possible value for S_t and R_t depends only on the immediately preceding state S_{t-1} and action A_{t-1}, not at all on earlier states and actions
  - $p(S_t, R_t|S_{t-1}, A_{t-1}) =$
    $p(S_t, R_t|S_{t-1}, A_{t-1}, S_{t-2}, A_{t-2}, S_{t-3}, A_{t-3}, ...)$
- Recall supervised learning $p(X_i|X_j) = 0$

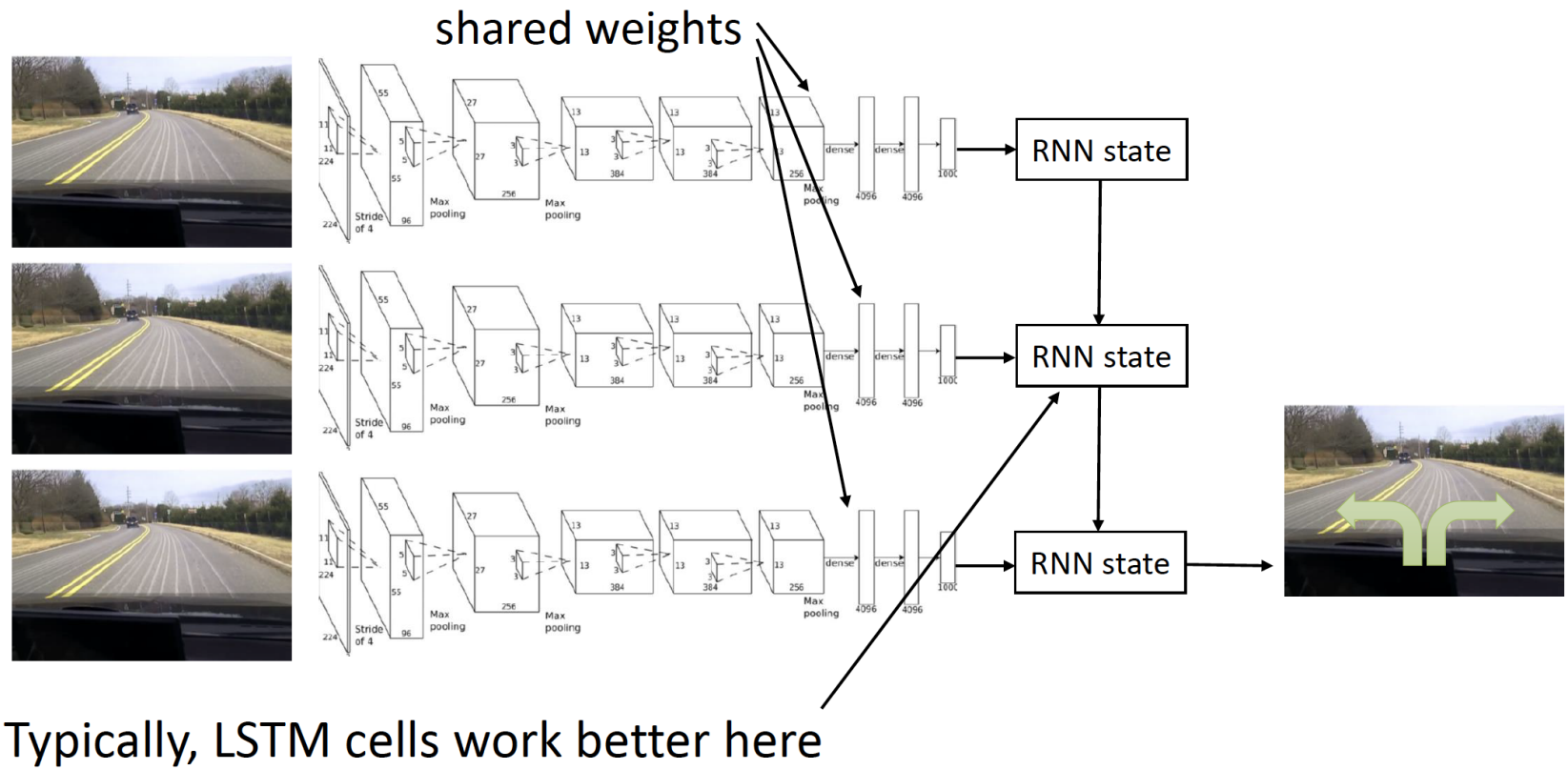
How can we use the whole history?

- Use multiple frames as the input
- The input dimension will be too high

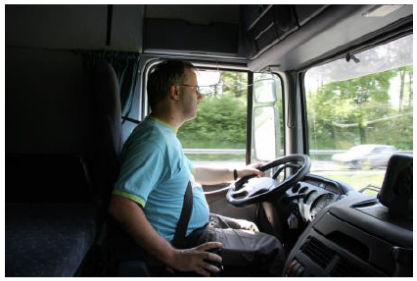


How can we use the whole history?

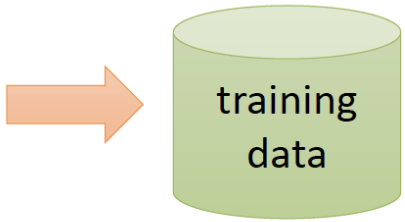
- Use recurrent neural network (RNN) as the encoder
- Embed the summary of past states into the internal **memory**

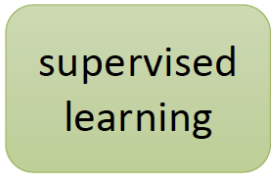


Recap: Imitation learning



$\mathbf{o}_t$
$\mathbf{a}_t$





$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

- Often (but not always) insufficient by itself
  - Distribution mismatch problem
- Sometimes work well
  - Samples from a stable trajectory distribution
  - Add more **on-policy** data, e.g., using Dagger
  - Better models that fit more accurately

Learning objectives of this lecture

- You should be able to...
  - Understand the function approximation mechanism for RL problems with large or continuous state-action spaces
  - Know the main types of DRL algorithms, and their differences
  - Understand the anatomy of imitation learning

References

- Lecture 2 & 4 of CS285 at UC Berkeley, *Deep Reinforcement Learning, Decision Making, and Control*
  - `http://rail.eecs.berkeley.edu/deeprlcourse/static/slides/lec-2.pdf`
  - `http://rail.eecs.berkeley.edu/deeprlcourse/static/slides/lec-4.pdf`

THE END