Reinforcement Learning:
A Primer, Multi-Task, Goal-Conditioned

CS 330

Logistics

Homework 2 due **Wednesday.**

Homework 3 out on **Wednesday.**

Project proposal due **next Wedesday.**

Why Reinforcement Learning?

When do you <u>not</u> need sequential decision making?

When your system is making a single isolated decision, e.g. classification, regression.
When that decision does not affect future inputs or decisions.

Common applications

robotics

language & dialog

autonomous driving

business operations

finance

(most deployed ML systems)

+ a key aspect of intelligence

The Plan

Multi-task reinforcement learning problem

Policy gradients & their multi-task/meta counterparts

Q-learning <— should be review

Multi-task Q-learning

object classification

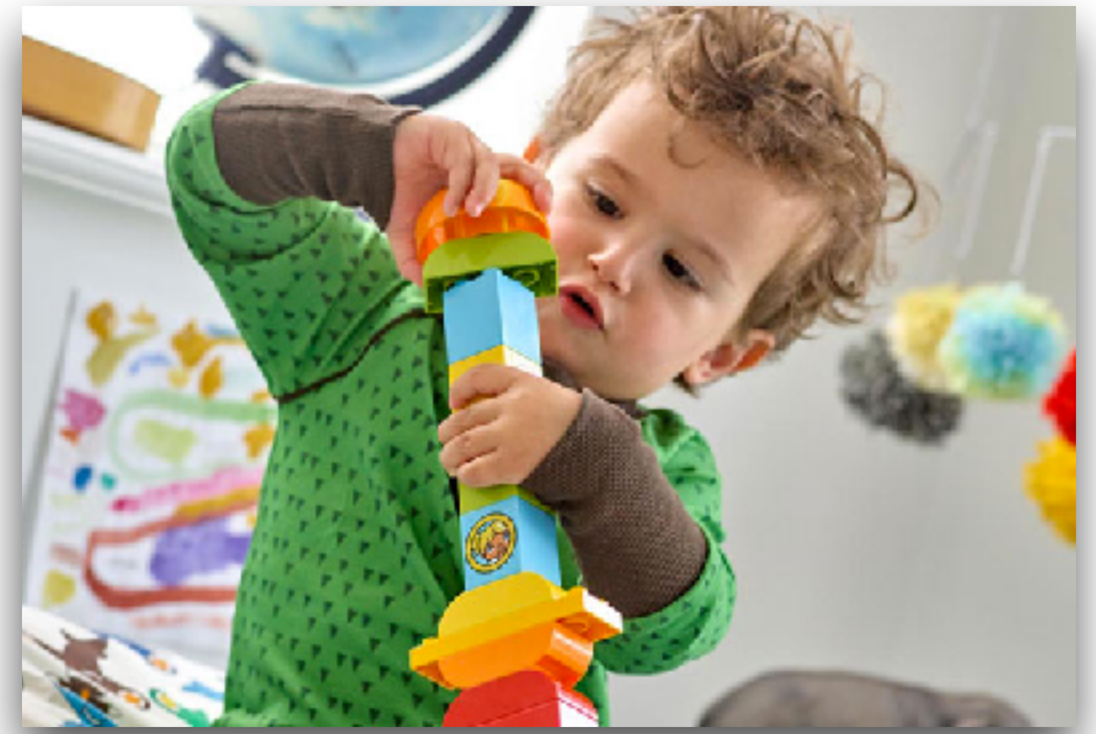
supervised learning

iid data

large labeled, curated dataset

well-defined notions of success

object manipulation



sequential decision making

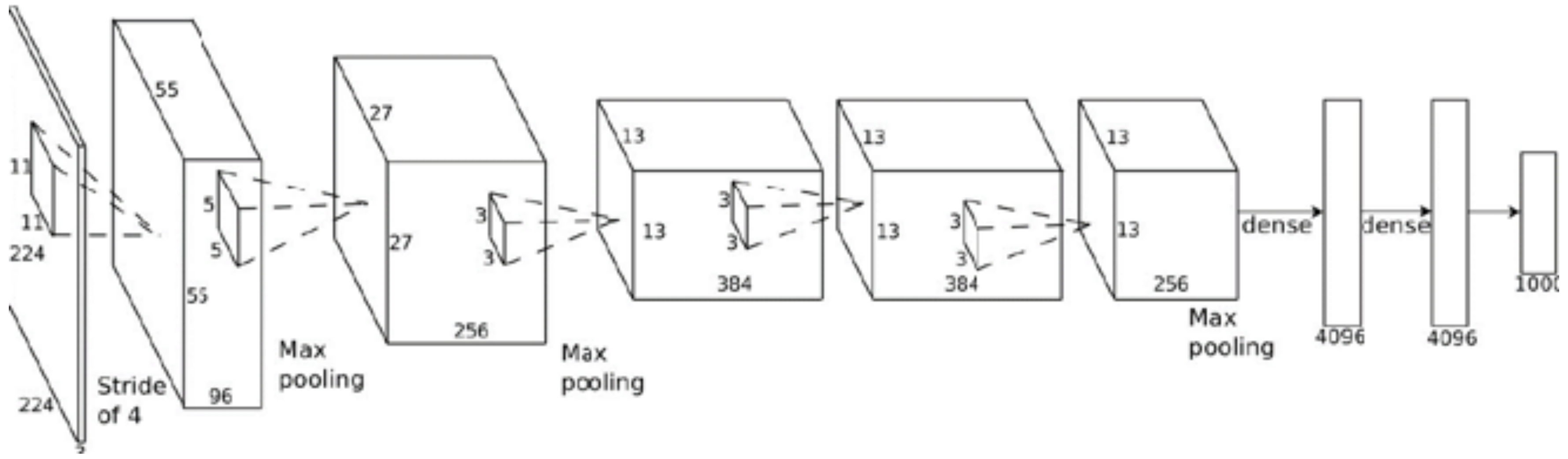
action affects next state

how to collect data?
what are the labels?

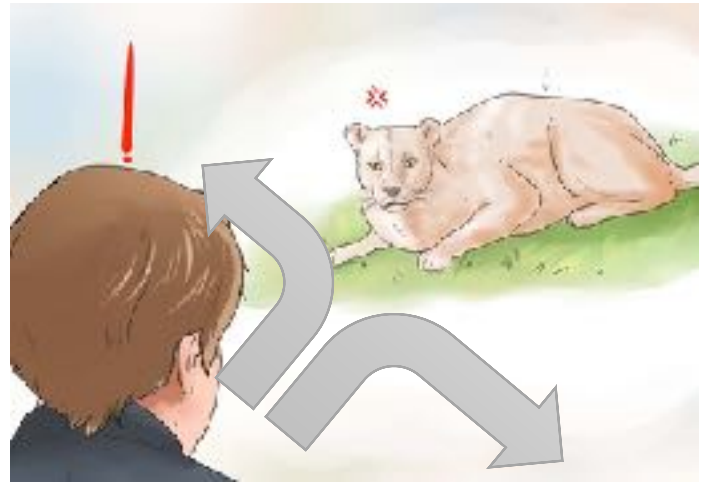
what does success mean?

Terminology & notation

$\mathbf{o}_t$



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

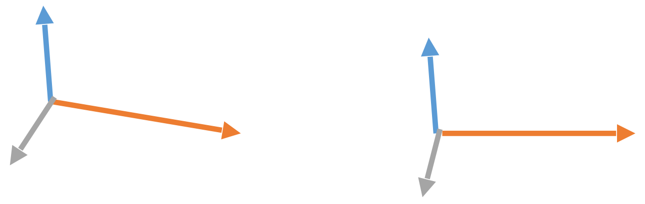


$\mathbf{a}_t$

$\mathbf{s}_t$ – 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)

$\mathbf{o}_t$ – observation

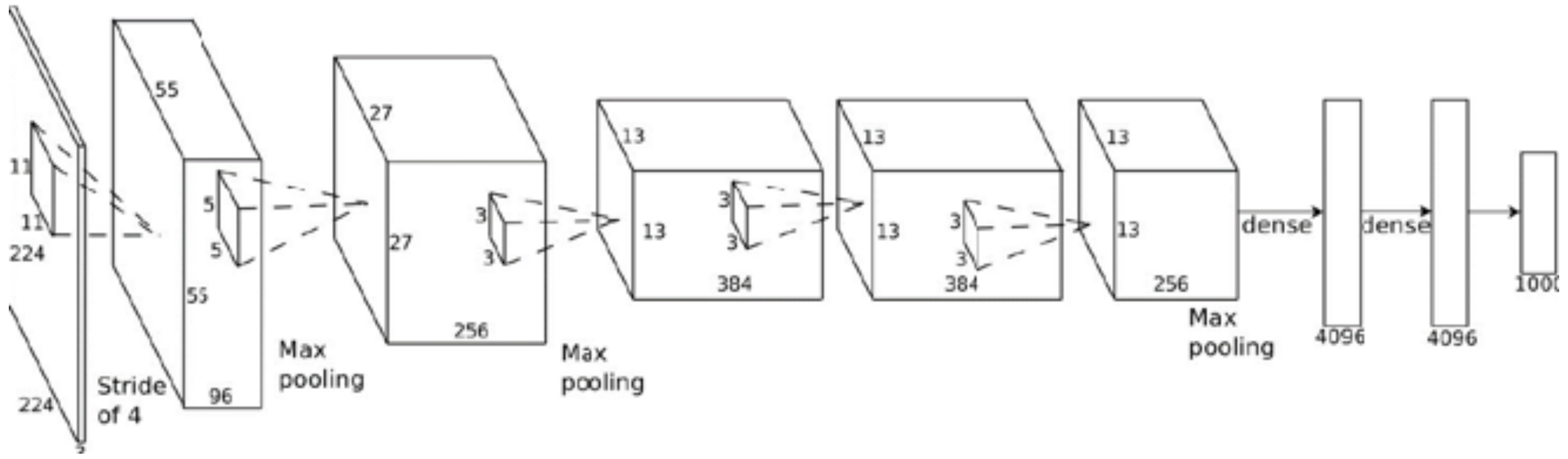


$\mathbf{s}_t$ – state

Slide adapted from Sergey Levine

Imitation Learning

$\mathbf{o}_t$



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

$\mathbf{a}_t$

$\mathbf{o}_t$

$\mathbf{a}_t$

→ training data → supervised learning

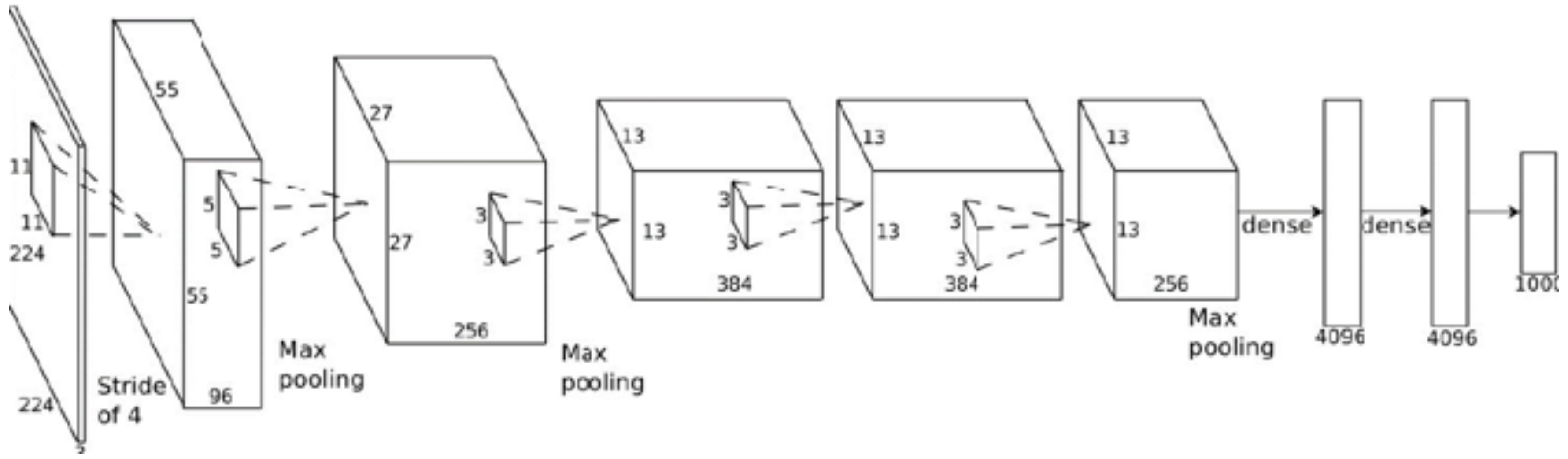
$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

Images: Bojarski et al. '16, NVIDIA

Slide adapted from Sergey Levine

Reward functions

$\mathbf{o}_t$



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

$\mathbf{a}_t$

which action is better or worse?

$r(\mathbf{s}, \mathbf{a})$: reward function

tells us which states and actions are better

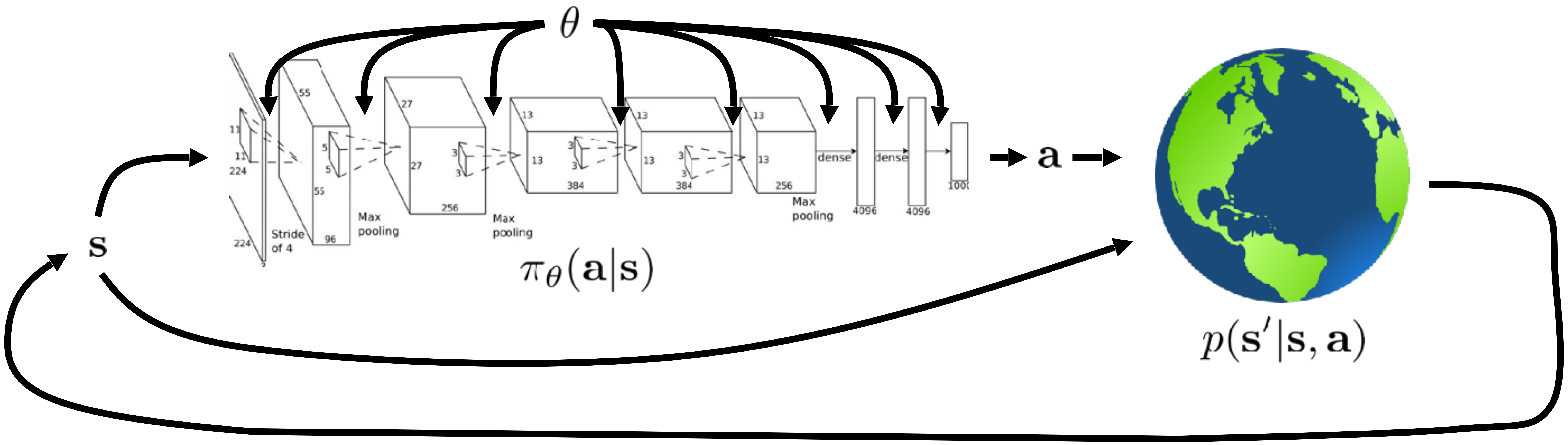
high reward

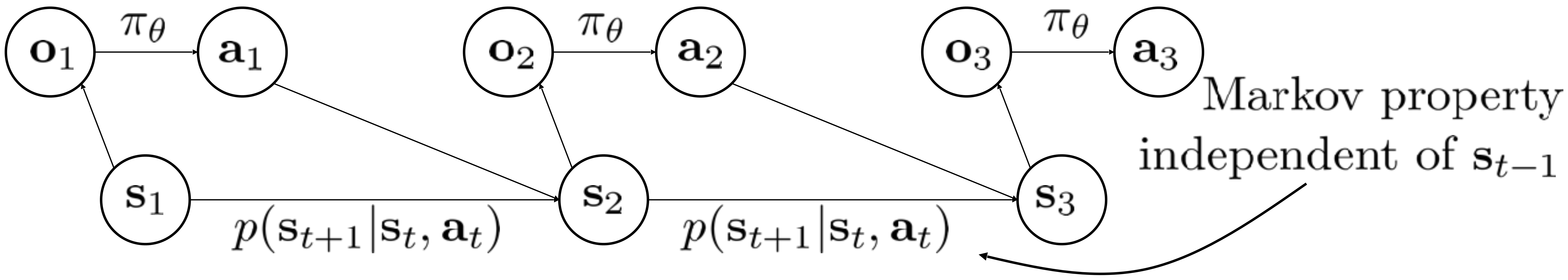
low reward

$\mathbf{s}$, $\mathbf{a}$, $r(\mathbf{s}, \mathbf{a})$, and $p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$ define Markov decision process

Slide adapted from Sergey Levine

The goal of reinforcement learning





$$\theta^\star = \arg\max_\theta E_{(\mathbf{s},\mathbf{a})\sim p_\theta(\mathbf{s},\mathbf{a})}[r(\mathbf{s},\mathbf{a})]$$

infinite horizon case

$$\theta^\star = \arg\max_\theta \sum_{t=1}^{T} E_{(\mathbf{s}_t,\mathbf{a}_t)\sim p_\theta(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t)]$$

finite horizon case

Slide adapted from Sergey Levine

What is a reinforcement learning task?

Recall: supervised learning

data generating distributions, loss

A task: $\mathscr{T}_i \triangleq \{p_i(\mathbf{x}), p_i(\mathbf{y} \mid \mathbf{x}), \mathscr{L}_i\}$

Reinforcement learning

action space

dynamics

A task: $\mathscr{T}_i \triangleq \{\mathscr{S}_i, \mathscr{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}' \mid \mathbf{s}, \mathbf{a}), r_i(\mathbf{s}, \mathbf{a})\}$

state space

initial state distribution

reward

a Markov decision process

much more than the semantic meaning of task!

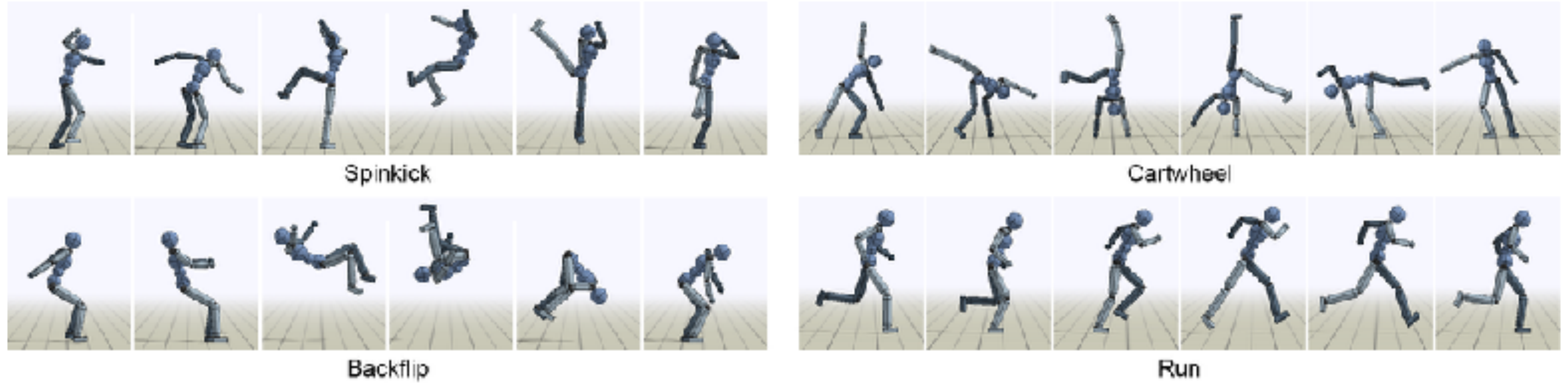
Examples Task Distributions

A task: $\mathcal{T}_i \triangleq \{\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a}), r_i(\mathbf{s},\mathbf{a})\}$

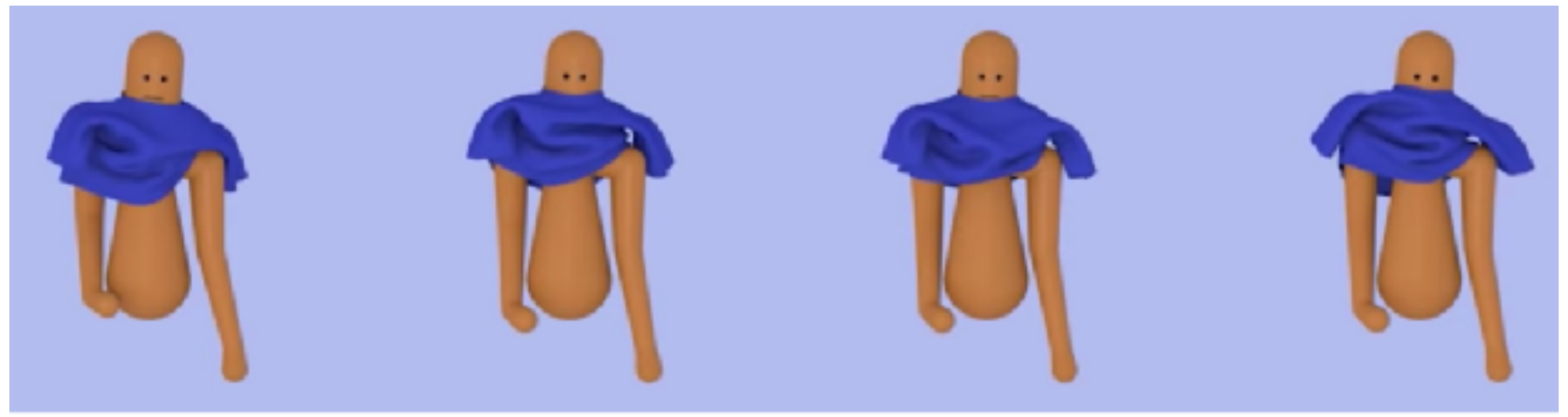
Personalized recommendations: $p_i(\mathbf{s}'|\mathbf{s},\mathbf{a}), r_i(\mathbf{s},\mathbf{a})$ vary across tasks

Character animation:

across maneuvers
$r_i(\mathbf{s},\mathbf{a})$ vary



across garments &
initial states
$p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a})$ vary



Multi-robot RL:

$\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a})$ vary

What is a reinforcement learning task?

Reinforcement learning

A task: $\mathcal{T}_i \triangleq \{\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p_i(\mathbf{s}'|\mathbf{s},\mathbf{a}), r_i(\mathbf{s},\mathbf{a})\}$

action space: $\mathcal{A}_i$

dynamics: $p_i(\mathbf{s}'|\mathbf{s},\mathbf{a})$

state space: $\mathcal{S}_i$

initial state distribution: $p_i(\mathbf{s}_1)$

reward: $r_i(\mathbf{s},\mathbf{a})$

An alternative view:

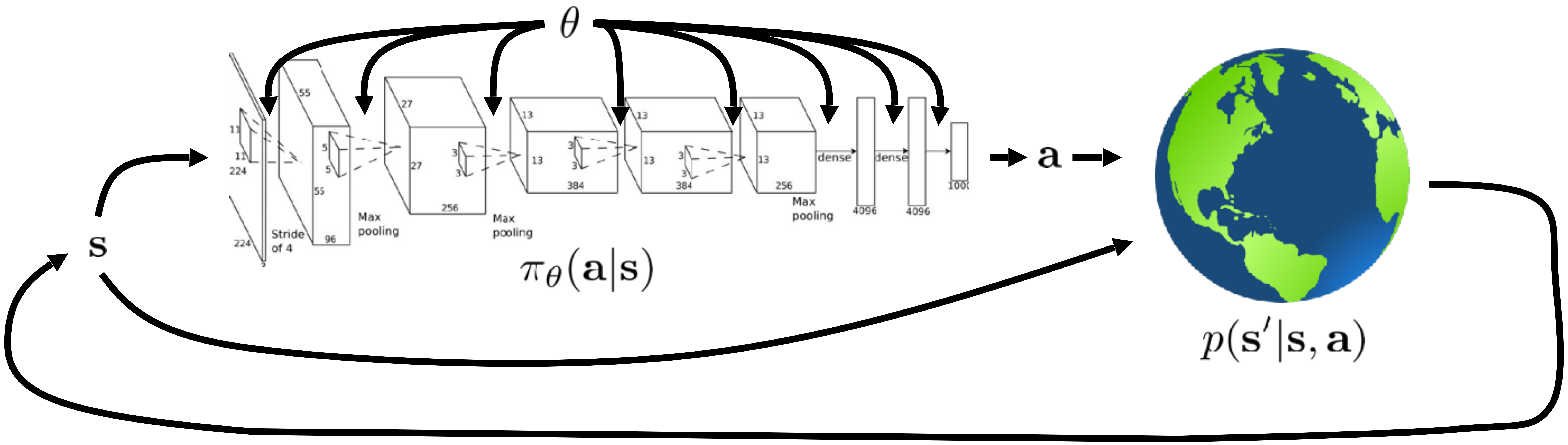
A **task identifier** is part of the state: $\mathbf{s} = (\bar{\mathbf{s}}, \mathbf{z}_i)$

original state: $\bar{\mathbf{s}}$

$$\mathcal{T}_i \triangleq \{\mathcal{S}_i, \mathcal{A}_i, p_i(\mathbf{s}_1), p(\mathbf{s}'|\mathbf{s},\mathbf{a}), r(\mathbf{s},\mathbf{a})\} \longrightarrow \{\mathcal{T}_i\} = \left\{\bigcup \mathcal{S}_i, \bigcup \mathcal{A}_i, \frac{1}{N}\sum_i p_i(\mathbf{s}_1), p(\mathbf{s}'|\mathbf{s},\mathbf{a}), r(\mathbf{s},\mathbf{a})\right\}$$

It can be cast as a **standard Markov decision process**!

The goal of multi-task reinforcement learning



Multi-task RL

The same as before, **except**:

a **task identifier** is part of the state: $\mathbf{s} = (\bar{\mathbf{s}}, \mathbf{z}_i)$

e.g. one-hot task ID

language description

desired goal state, $\mathbf{z}_i = \mathbf{s}_g$ ← "**goal-conditioned** RL"

If it's still a **standard Markov decision process**,

then, why not apply standard RL algorithms? You can! You can often do better.

What is the reward?

The same as before

Or, for goal-conditioned RL:

$r(\mathbf{s}) = r(\bar{\mathbf{s}}, \mathbf{s}_g) = -d(\bar{\mathbf{s}}, \mathbf{s}_g)$

Distance function d examples:

- Euclidean ℓ_2
- sparse 0/1

The Plan

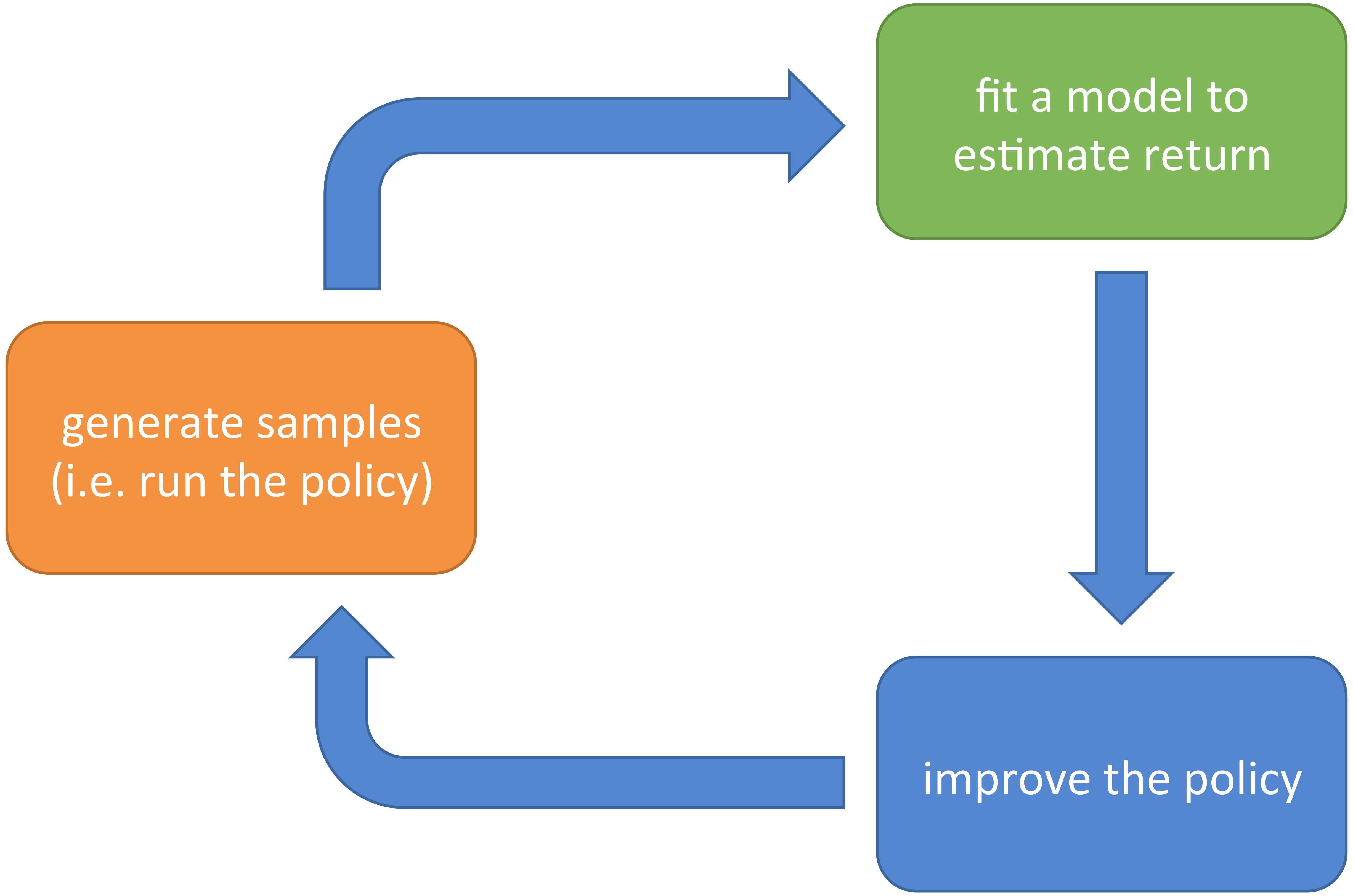
Multi-task reinforcement learning problem

Policy gradients & their multi-task/meta counterparts

Q-learning

Multi-task Q-learning

The anatomy of a reinforcement learning algorithm



compute $\hat{Q} = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$ (MC policy gradient)
fit $Q_\phi(\mathbf{s}, \mathbf{a})$ (actor-critic, Q-learning)
estimate $p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$ (model-based)

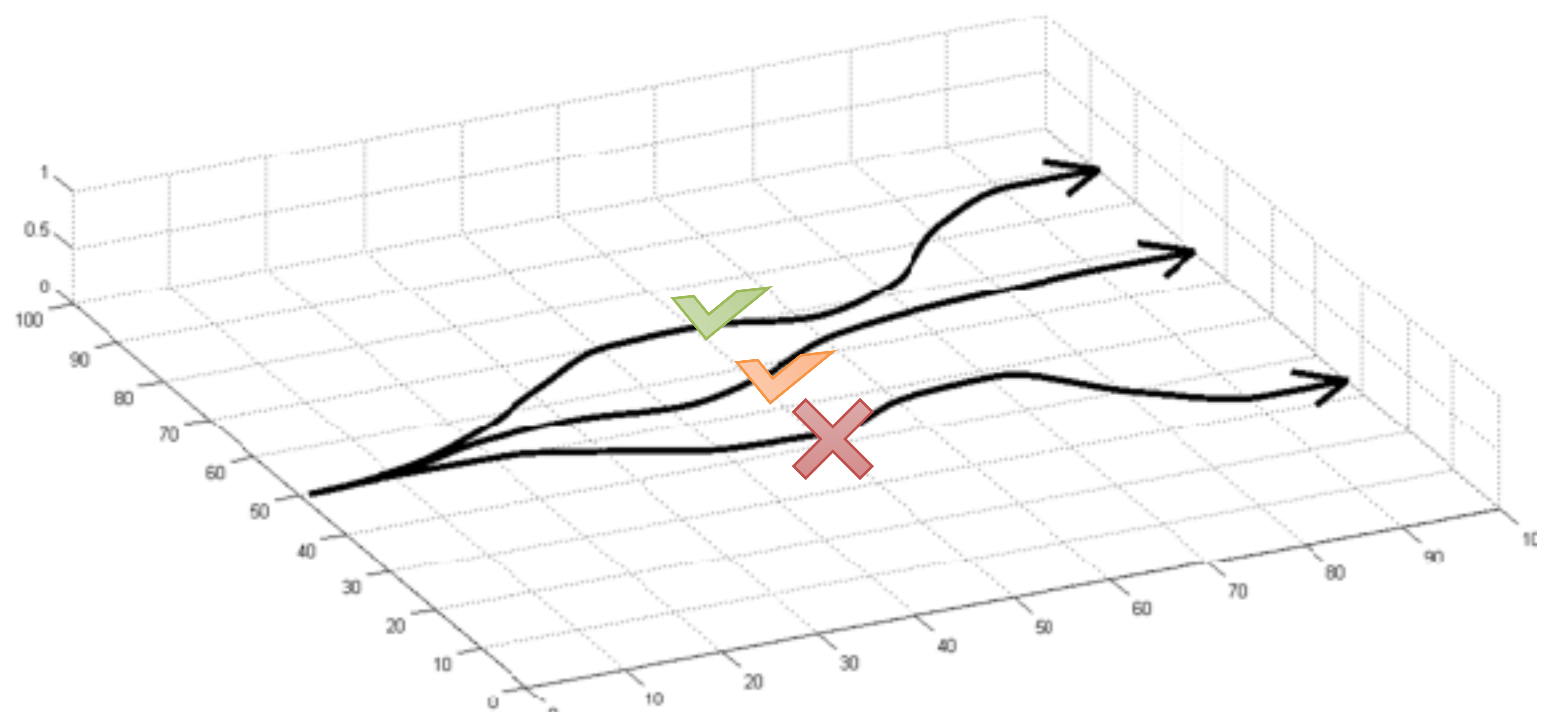
$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$ (policy gradient)
$\pi(\mathbf{s}) = \arg\max Q_\phi(\mathbf{s}, \mathbf{a})$ (Q-learning)
optimize $\pi_\theta(\mathbf{a}|\mathbf{s})$ (model-based)

This lecture: focus on model-free RL methods (policy gradient, Q-learning)

11/6: focus on model-based RL methods

Evaluating the objective

$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right]}_{J(\theta)}$$



$$J(\theta) = E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right] \approx \frac{1}{N}\sum_i \sum_t r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$$

sum over samples from π_θ

Slide adapted from Sergey Levine

Direct policy differentiation

$$\theta^\star = \arg\max_\theta \underbrace{E_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t,\mathbf{a}_t)\right]}_{J(\theta)}$$

a convenient identity

$$\pi_\theta(\tau)\nabla_\theta \log\pi_\theta(\tau) = \pi_\theta(\tau)\frac{\nabla_\theta\pi_\theta(\tau)}{\pi_\theta(\tau)} = \nabla_\theta\pi_\theta(\tau)$$

$$J(\theta) = E_{\tau\sim\pi_\theta(\tau)}[\underbrace{r(\tau)}_{\sum_{t=1}^{T} r(\mathbf{s}_t,\mathbf{a}_t)}] = \int \pi_\theta(\tau)r(\tau)d\tau$$

$$\nabla_\theta J(\theta) = \int \nabla_\theta\pi_\theta(\tau)r(\tau)d\tau = \int \pi_\theta(\tau)\nabla_\theta\log\pi_\theta(\tau)r(\tau)d\tau = E_{\tau\sim\pi_\theta(\tau)}[\nabla_\theta\log\pi_\theta(\tau)r(\tau)]$$

Slide adapted from Sergey Levine

Direct policy differentiation

$$\theta^\star = \arg\max_\theta J(\theta)$$

$$J(\theta) = E_{\tau\sim\pi_\theta(\tau)}[r(\tau)]$$

$$\underbrace{\pi_\theta(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)}_{\pi_\theta(\tau)} = p(\mathbf{s}_1)\prod_{t=1}^{T}\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

log of both sides

$$\log \pi_\theta(\tau) = \log p(\mathbf{s}_1) + \sum_{t=1}^{T} \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

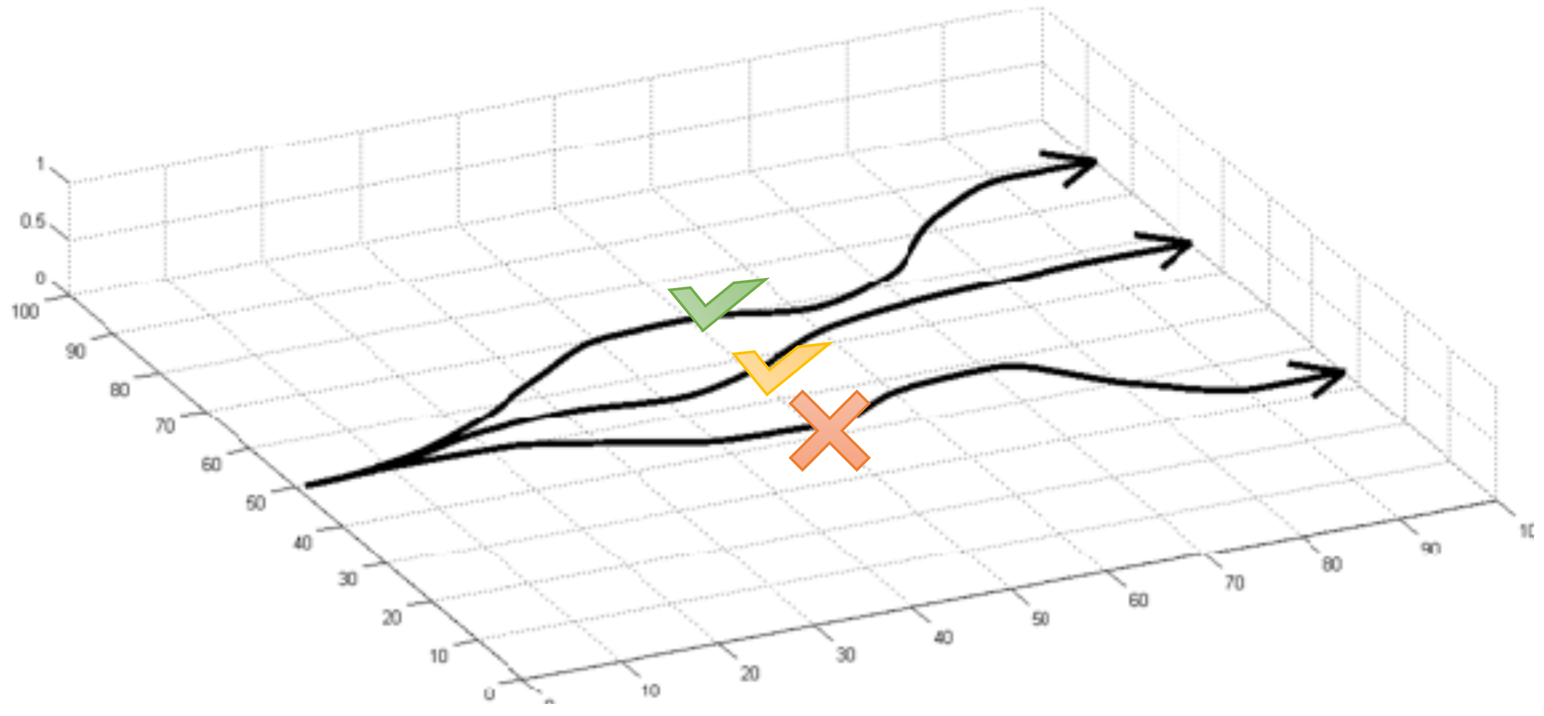
$$\nabla_\theta J(\theta) = E_{\tau\sim\pi_\theta(\tau)}[\nabla_\theta \log \pi_\theta(\tau) r(\tau)]$$

$$\nabla_\theta \left[\cancel{\log p(\mathbf{s}_1)} + \sum_{t=1}^{T} \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \cancel{\log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}\right]$$

$$\nabla_\theta J(\theta) = E_{\tau\sim\pi_\theta(\tau)}\left[\left(\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)\right)\left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)\right)\right]$$

Slide adapted from Sergey Levine

Evaluating the policy gradient

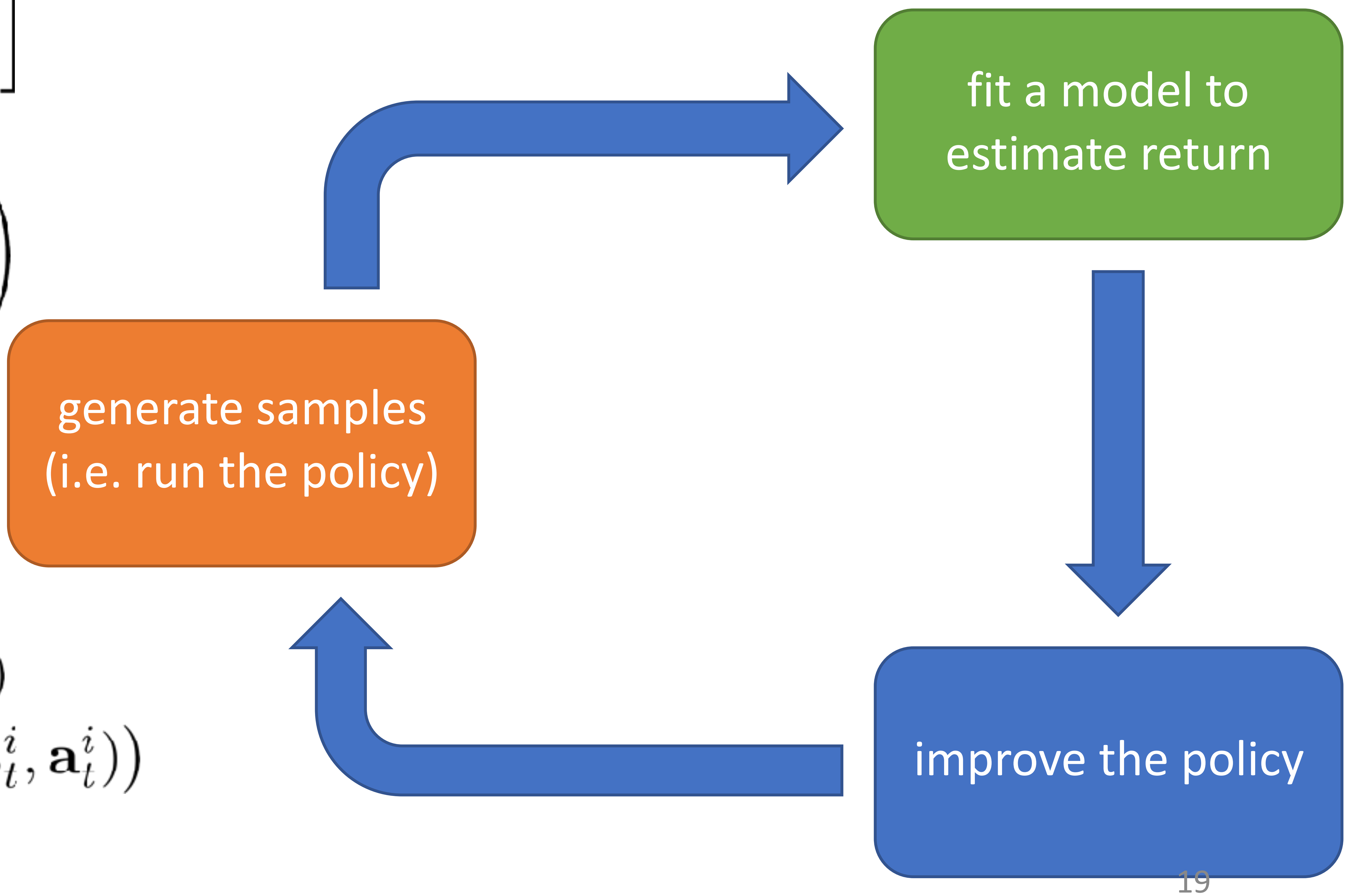


recall: $J(\theta) = E_{\tau \sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right] \approx \frac{1}{N}\sum_i \sum_t r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$

$$\nabla_\theta J(\theta) = E_{\tau \sim \pi_\theta(\tau)}\left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)\right)\left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)\right)\right]$$

$$\nabla_\theta J(\theta) \approx \underline{\frac{1}{N}\sum_{i=1}^{N}}\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})\right)\underline{\left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})\right)}$$

$$\underline{\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)}$$



REINFORCE algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ (run the policy)
2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right)\left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i)\right)$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Slide adapted from Sergey Levine

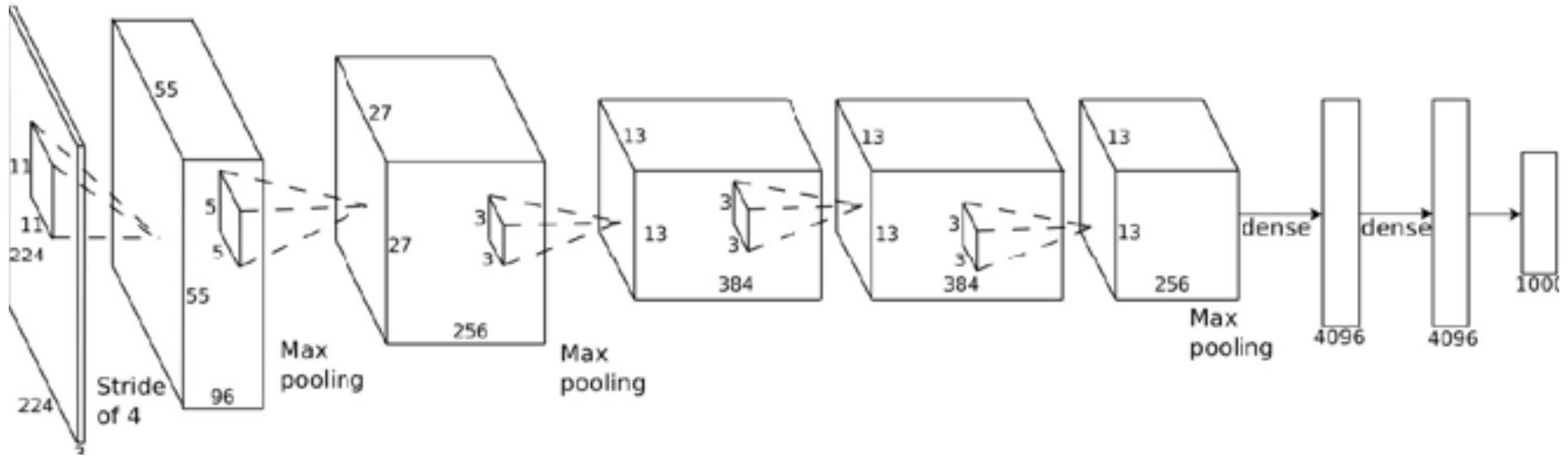
Comparison to maximum likelihood

policy gradient: $\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$

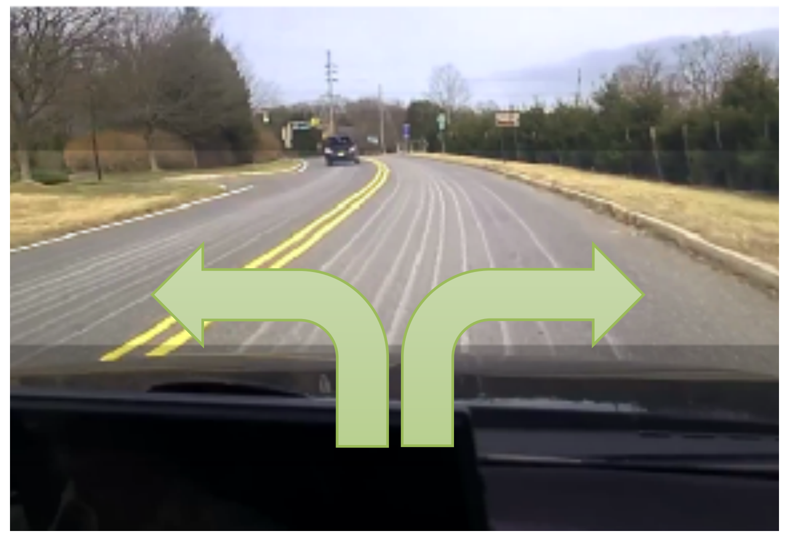
Multi-task learning algorithms can readily be applied!

maximum likelihood: $\nabla_\theta J_{\mathrm{ML}}(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right)$


$\mathbf{s}_t$



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


$\mathbf{a}_t$

$\mathbf{s}_t$

$\mathbf{a}_t$

→ training data → supervised learning → $\pi_\theta(\mathbf{a}_t | \mathbf{s}_t)$

Slide adapted from Sergey Levine

What did we just do?

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

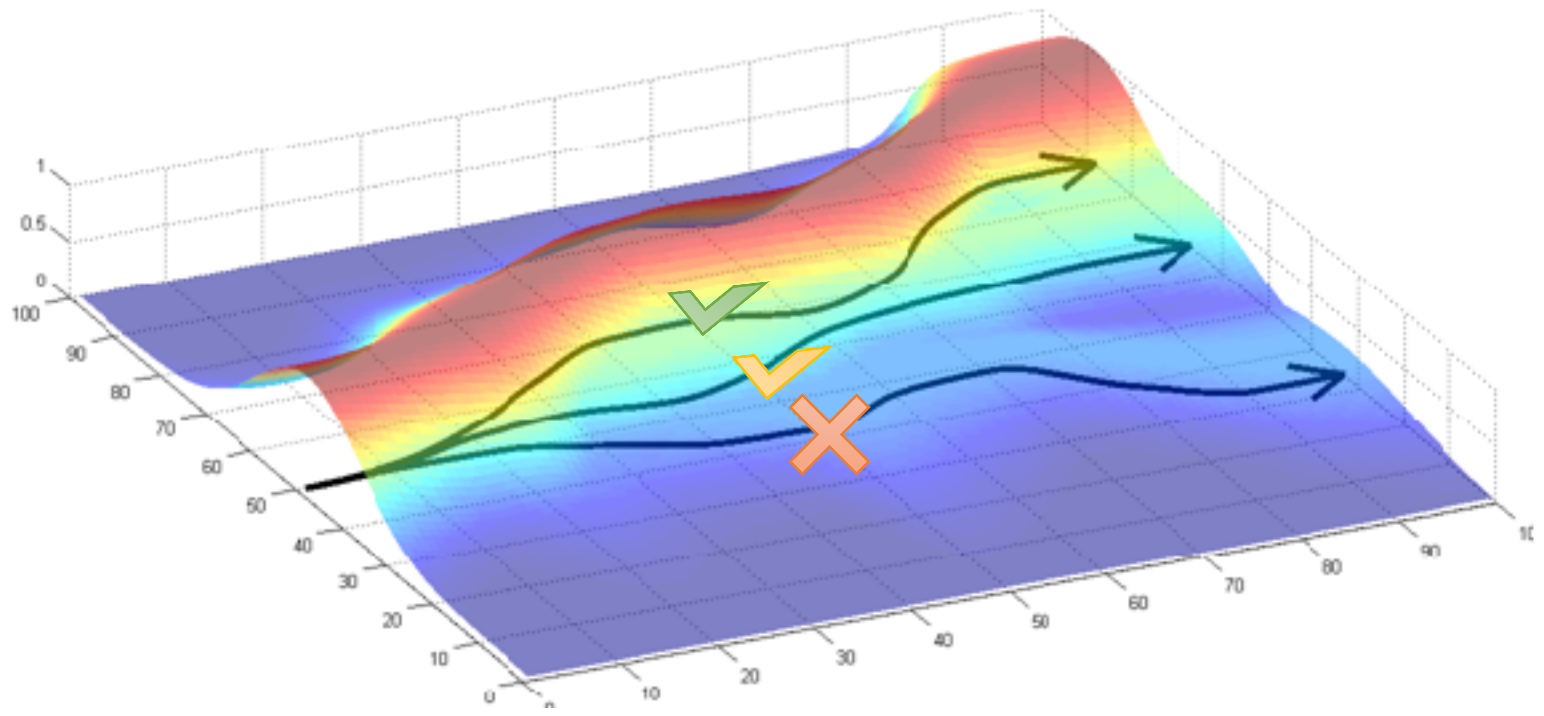
$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \underbrace{\nabla_\theta \log \pi_\theta(\tau_i)}_{\sum_{t=1}^{T} \nabla_\theta \log_\theta \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})} r(\tau_i)$$

maximum likelihood: $\nabla_\theta J_{\mathrm{ML}}(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log \pi_\theta(\tau_i)$

good stuff is made more likely

bad stuff is made less likely

simply formalizes the notion of “trial and error”!

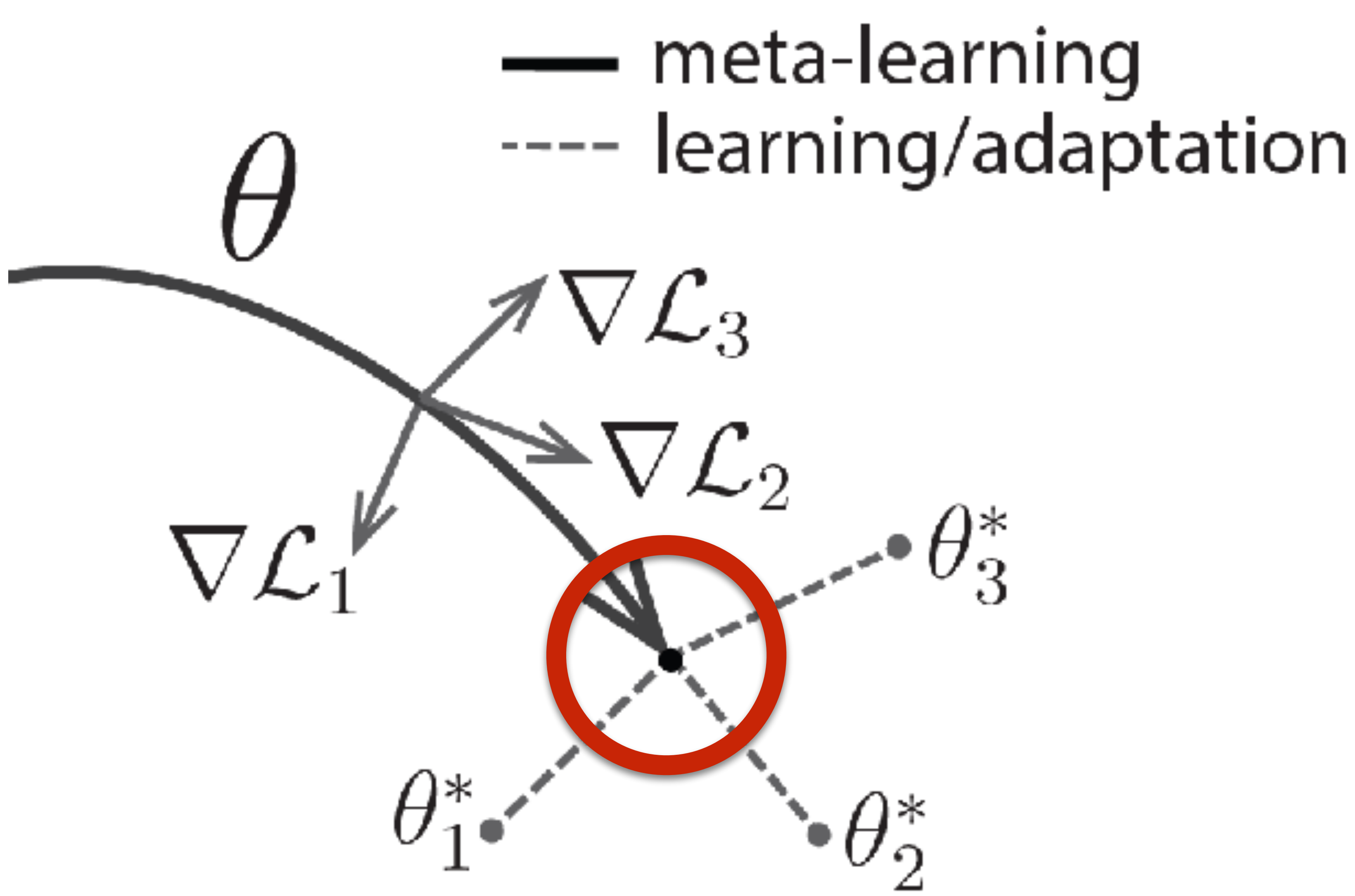


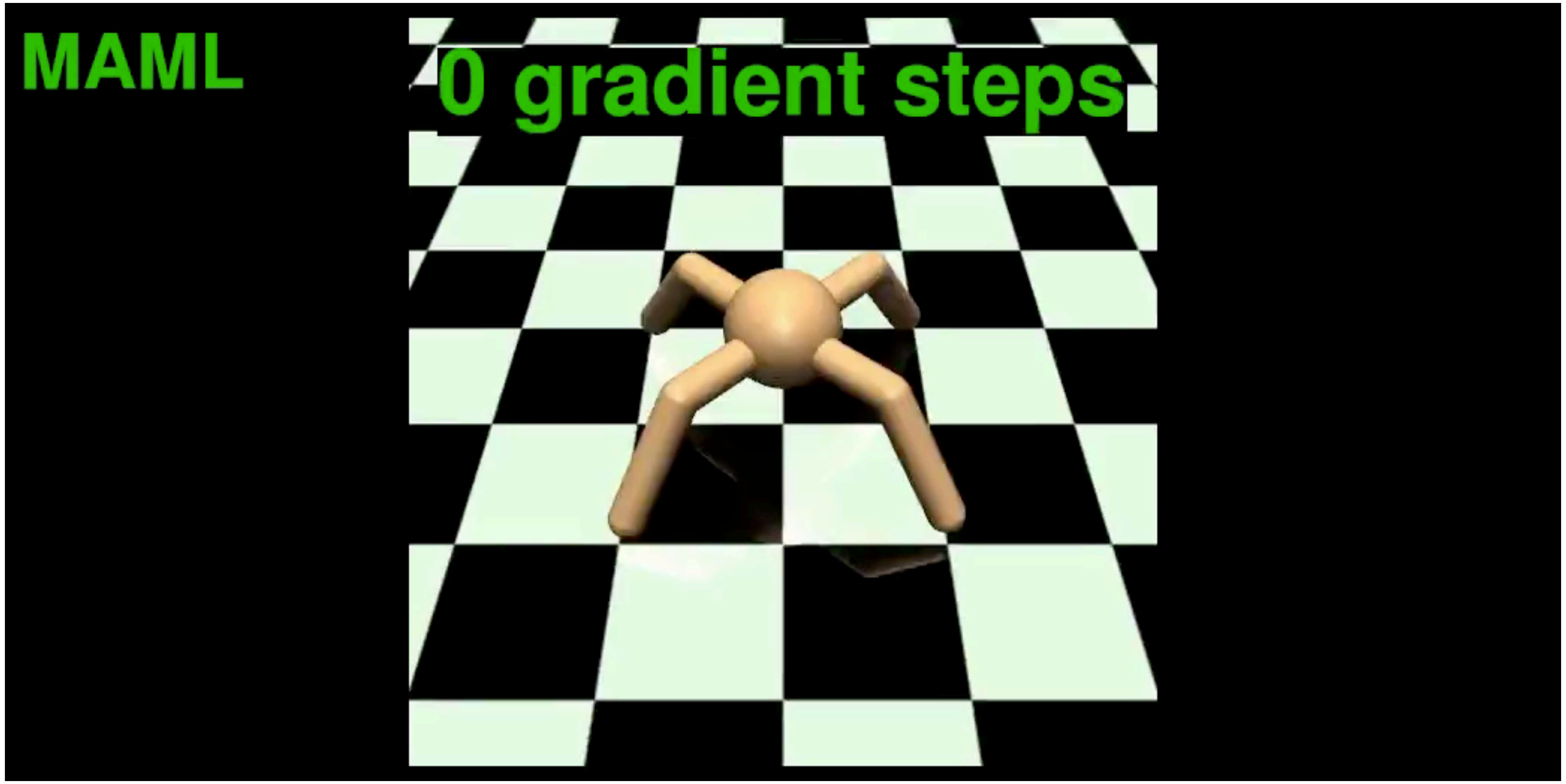
REINFORCE algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ (run it on the robot)
2. $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t \nabla_\theta \log \pi_\theta(\mathbf{a}_t^i|\mathbf{s}_t^i)\right) \left(\sum_t r(\mathbf{s}_t^i, \mathbf{a}_t^i)\right)$
3. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Can we use **policy gradients** with **meta-learning**?

Example: MAML + policy gradient

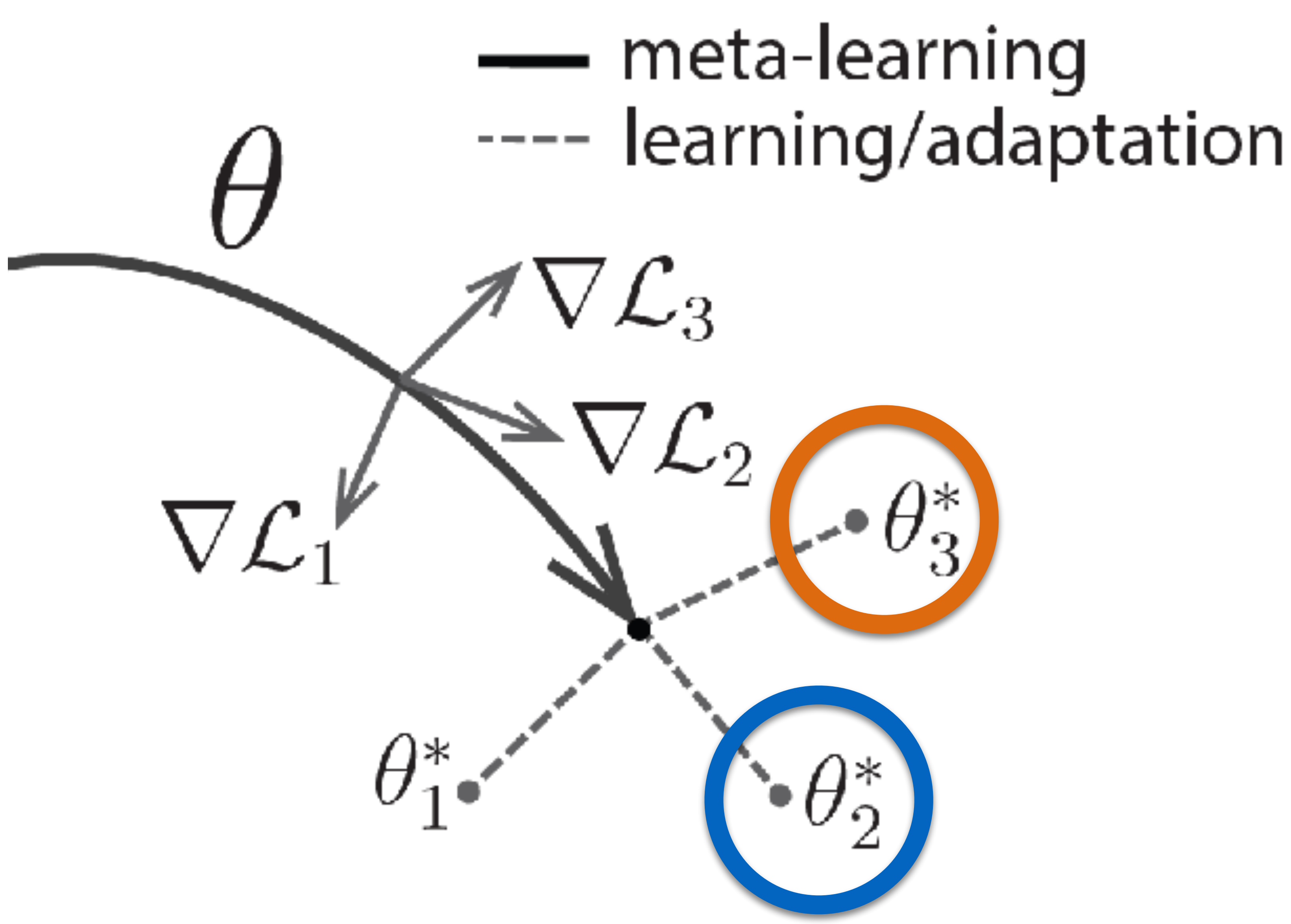


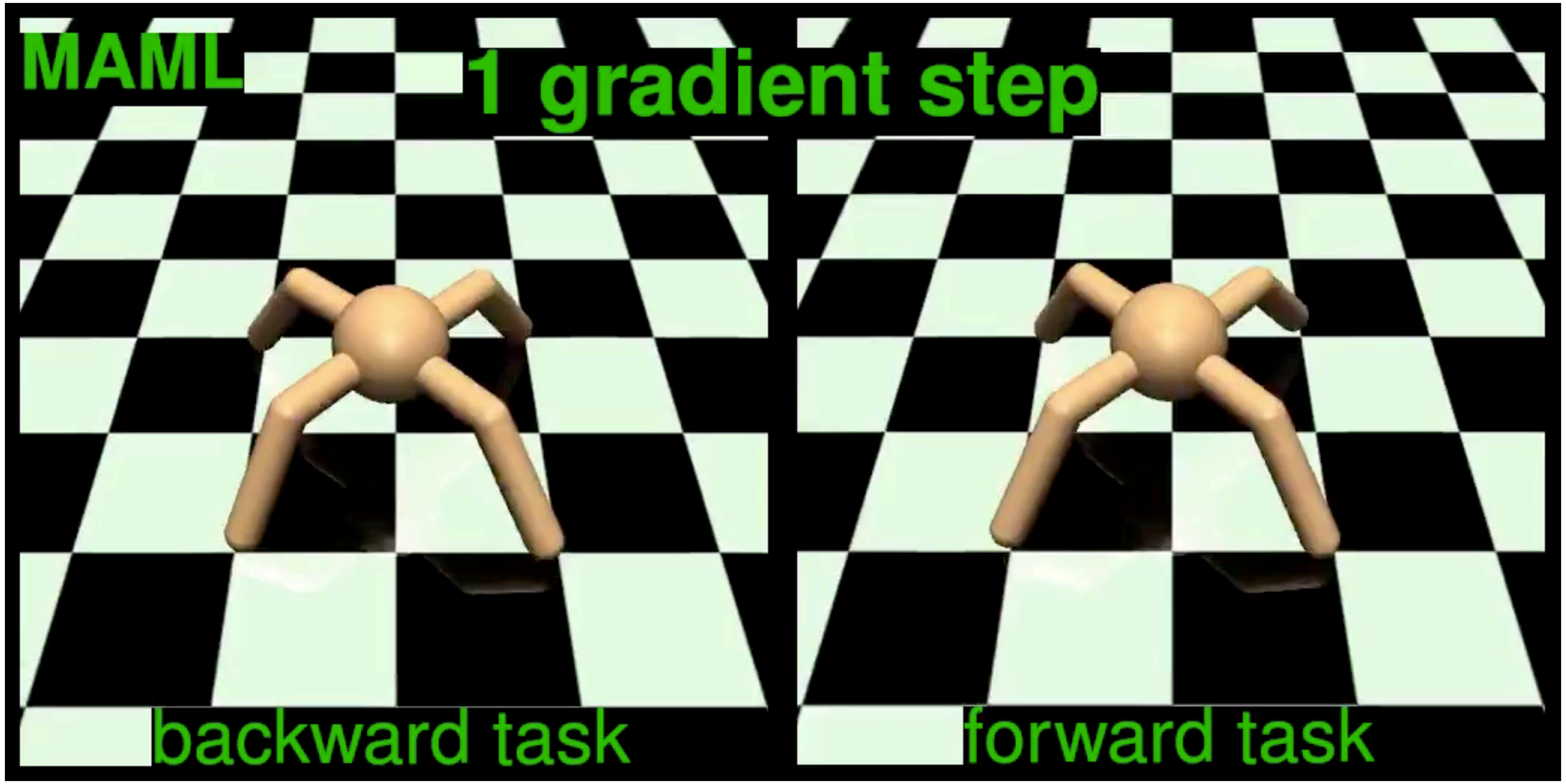


two tasks: running backward, running forward

Finn, Abbeel, Levine. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. ICML '17

Example: MAML + policy gradient





two tasks: running backward, running forward

There exists a **representation** under which **RL** is **fast** and **efficient.**

Finn, Abbeel, Levine. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. ICML '17

Example: Black-box meta-learning + policy gradient

Experiment: Learning to visually navigate a maze

- train on 1000 small mazes
- test on held-out small mazes and large mazes

Mishra, Rohaninejad, Chen, Abbeel. A Simple Neural Attentive Meta-Learner ICLR'18

Policy Gradients

$$\text{policy gradient:} \quad \nabla_\theta J(\theta) = E_{\underline{\tau \sim \pi_\theta(\tau)}} \left[\left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t | \mathbf{s}_t) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t) \right) \right]$$

Pros:

+ Simple
+ Easy to combine with **existing multi-task & meta-learning algorithms**

Cons:

- Produces a **high-variance** gradient
  - Can be mitigated with **baselines** (used by all algorithms in practice), trust regions
- Requires **on-policy** data
  - Cannot reuse existing experience to estimate the gradient!
    - **Importance weights** can help, but also high variance

The Plan

Multi-task reinforcement learning problem

Policy gradients & their multi-task/meta counterparts

Q-learning

Multi-task Q-learning

Value-Based RL: Definitions

Value function: $V^\pi(\mathbf{s}_t) = \sum_{t'=t}^{T} \mathbb{E}_\pi \left[r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \mid \mathbf{s}_t \right]$ total reward starting from $\mathbf{s}$ and following π

"how good is a state"

Q function: $Q^\pi(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{T} \mathbb{E}_\pi \left[r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \mid \mathbf{s}_t, \mathbf{a}_t \right]$ total reward starting from $\mathbf{s}$, taking $\mathbf{a}$, and then following π

"how good is a state-action pair"

They're related: $V^\pi(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t \sim \pi(\cdot|\mathbf{s}_t)} \left[Q^\pi(\mathbf{s}_t, \mathbf{a}_t) \right]$

If you know Q^π, you can use it to improve π.

Set $\pi(\mathbf{a}|\mathbf{s}) \leftarrow 1$ for $\mathbf{a} = \arg\max_{\bar{\mathbf{a}}} Q^\pi(\mathbf{s}, \bar{\mathbf{a}})$ New policy is at least as good as old policy.

Value-Based RL: Definitions

Value function: $V^{\pi}(\mathbf{s}_t) = \sum_{t'=t}^{T} \mathbb{E}_{\pi}\left[r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \mid \mathbf{s}_t\right]$ total reward starting from $\mathbf{s}$ and following π

"how good is a state”

Q function: $Q^{\pi}(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{T} \mathbb{E}_{\pi}\left[r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \mid \mathbf{s}_t, \mathbf{a}_t\right]$ total reward starting from $\mathbf{s}$, taking $\mathbf{a}$, and then following π

"how good is a state-action pair”

For the optimal policy $\pi^{\star}$: $\underbrace{Q^{\star}(\mathbf{s}_t, \mathbf{a}_t) = \mathbb{E}_{\mathbf{s}'\sim p(\cdot|\mathbf{s},\mathbf{a})}\left[r(\mathbf{s}, \mathbf{a}) + \gamma \max_{\mathbf{a}'} Q^{\star}(\mathbf{s}', \mathbf{a}')\right]}_{\text{Bellman equation}}$

Fitted Q-iteration Algorithm

full fitted Q-iteration algorithm:

$K\times$

1. collect dataset $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$ using some policy
2. set $\mathbf{y}_i \leftarrow r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \max_{\mathbf{a}'_i} Q_\phi(\mathbf{s}'_i, \mathbf{a}'_i)$
3. set $\phi \leftarrow \arg\min_\phi \frac{1}{2}\sum_i \|Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{y}_i\|^2$

Algorithm hyperparameters

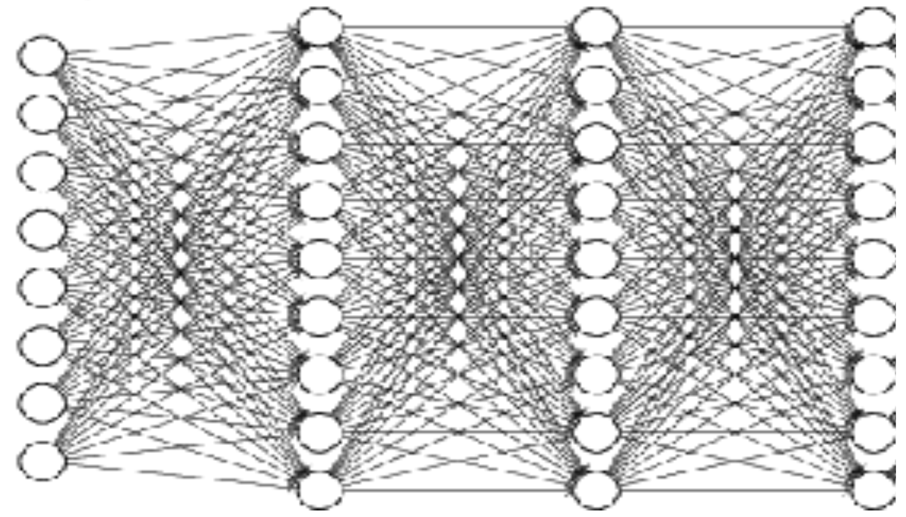
dataset size N, collection policy

iterations K

gradient steps S

$\mathbf{s}$

$\mathbf{a}$



$Q_\phi(\mathbf{s}, \mathbf{a})$

parameters ϕ

Result: get a policy $\pi(\mathbf{a} \mid \mathbf{s})$ from $\arg\max_{\mathbf{a}} Q_\phi(\mathbf{s}, \mathbf{a})$

Important notes:

We can **reuse data** from previous policies!

an **off-policy** algorithm using replay buffers

This is **not** a **gradient descent** algorithm!

Can be readily extended to multi-task/goal-conditioned RL

Slide adapted from Sergey Levine

The Plan

Multi-task reinforcement learning problem

Policy gradients & their multi-task/meta counterparts

Q-learning

Multi-task Q-learning

Multi-Task RL Algorithms

Policy: $\pi_\theta(\mathbf{a} \mid \bar{\mathbf{s}})$ —> $\pi_\theta(\mathbf{a} \mid \bar{\mathbf{s}}, \mathbf{z}_i)$

Q-function: $Q_\phi(\bar{\mathbf{s}}, \mathbf{a})$ —> $Q_\phi(\bar{\mathbf{s}}, \mathbf{a}, \mathbf{z}_i)$

Analogous to multi-task supervised learning: stratified sampling, soft/hard weight sharing, etc.

What is different about **reinforcement learning**?

The **data distribution** is controlled by the agent!

Should we share **data** in addition to sharing **weights**?

You may know **what aspect(s) of the MDP** are changing across tasks.

Can we leverage this knowledge?

An example

Task 1: passing

Task 2: shooting goals

What if you accidentally perform a good pass when trying to shoot a goal?

Store experience as normal. *and* **Relabel** experience with task 2 ID & reward and store.

"hindsight relabeling" "hindsight experience replay" (HER)

Goal-conditioned RL with hindsight relabeling

$k{+}{+}$

1. Collect data $\mathscr{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_g, r_{1:T})\}$ using some policy
2. Store data in replay buffer $\mathscr{D} \leftarrow \mathscr{D} \cup \mathscr{D}_k$
3. Perform hindsight relabeling:
   a. Relabel experience in $\mathscr{D}_k$ using last state as goal:
   $\mathscr{D}'_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_T, r'_{1:T}\}$ where $r'_t = -d(\mathbf{s}_t, \mathbf{s}_T)$
   b. Store relabeled data in replay buffer $\mathscr{D} \leftarrow \mathscr{D} \cup \mathscr{D}'_k$
4. Update policy using replay buffer $\mathscr{D}$

<— Other relabeling strategies?

use any state from the trajectory

Result: exploration challenges alleviated

Kaelbling. Learning to Achieve Goals. IJCAI '93
Andrychowicz et al. Hindsight Experience Replay. NeurIPS '17

Multi-task RL with relabeling

k++

1. Collect data $\mathcal{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{z}_i, r_{1:T})\}$ using some policy
2. Store data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_k$
3. Perform hindsight relabeling:
   a. Relabel experience in $\mathcal{D}_k$ for task $\mathcal{T}_j$:
   $\mathcal{D}'_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{z}_j, r'_{1:T}\}$ where $r'_t = r_j(\mathbf{s}_t)$
   b. Store relabeled data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}'_k$
4. Update policy using replay buffer $\mathcal{D}$

<— Which task $\mathcal{T}_j$ to choose?

- randomly
- task(s) in which the trajectory gets high reward

When can we apply relabeling?

- reward function form is known, evaluatable
- dynamics consistent across goals/tasks
- using an off-policy algorithm*

Kaelbling. Learning to Achieve Goals. IJCAI ‘93
Andrychowicz et al. Hindsight Experience Replay. NeurIPS ‘17

Hindsight relabeling for goal-conditioned RL

Example: goal-conditioned RL, simulated robot manipulation

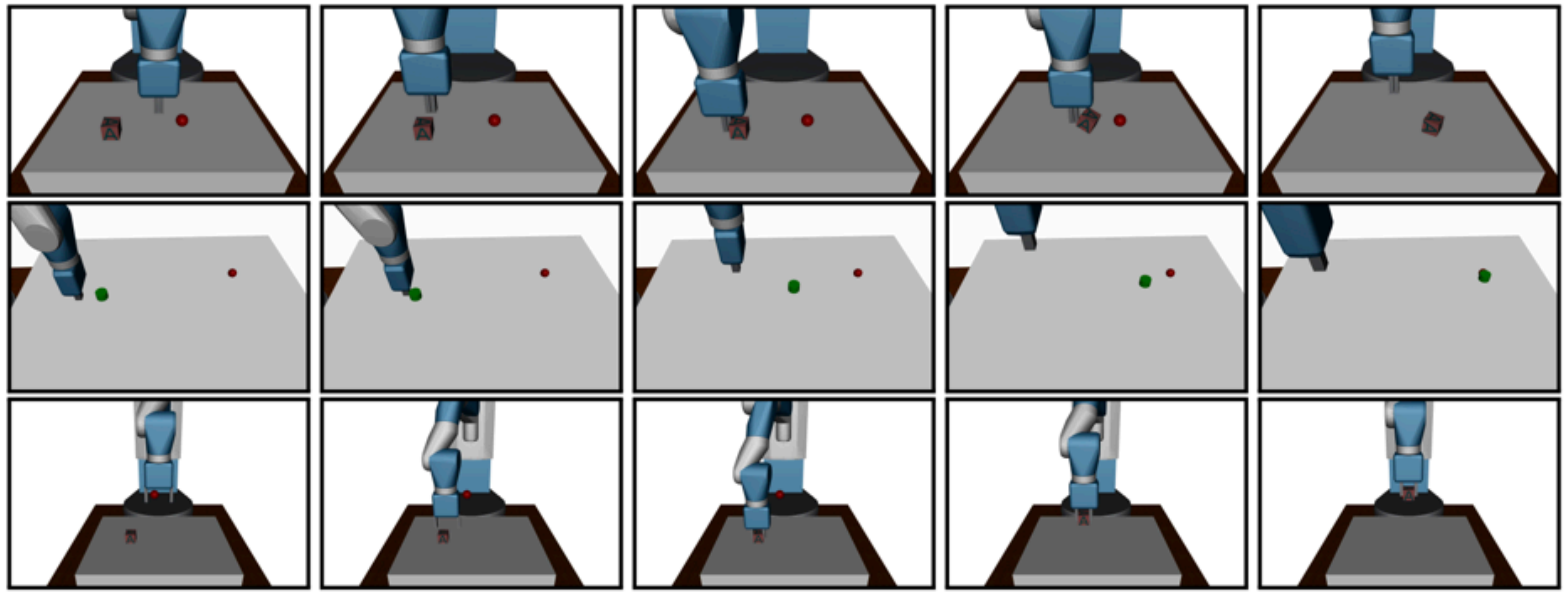
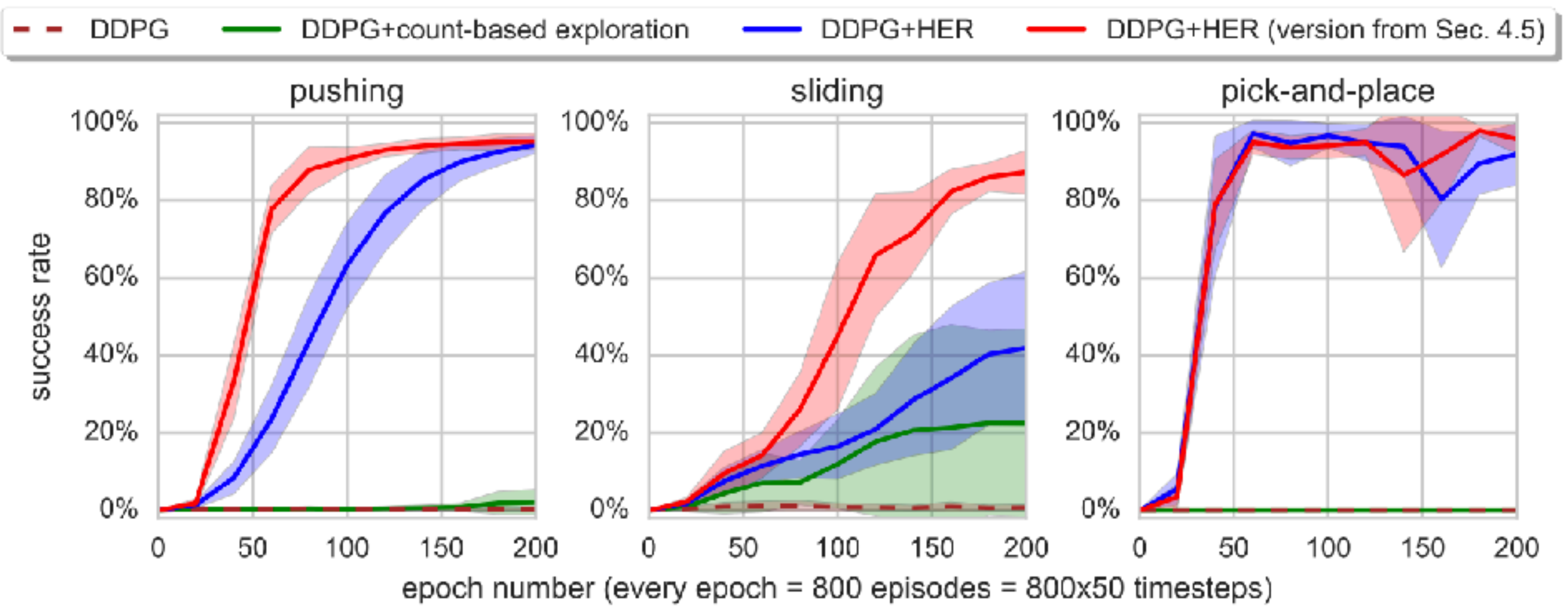


Figure 2: Different tasks: *pushing* (top row), *sliding* (middle row) and *pick-and-place* (bottom row). The red ball denotes the goal position.



Kaelbling. Learning to Achieve Goals. IJCAI '93
Andrychowicz et al. Hindsight Experience Replay. NeurIPS '17

Time Permitting: What about image observations?

Recall: need a distance function between current and goal state!

$$r'_t = -d(\mathbf{s}_t, \mathbf{s}_T)$$

Use binary 0/1 reward? Sparse, but accurate.

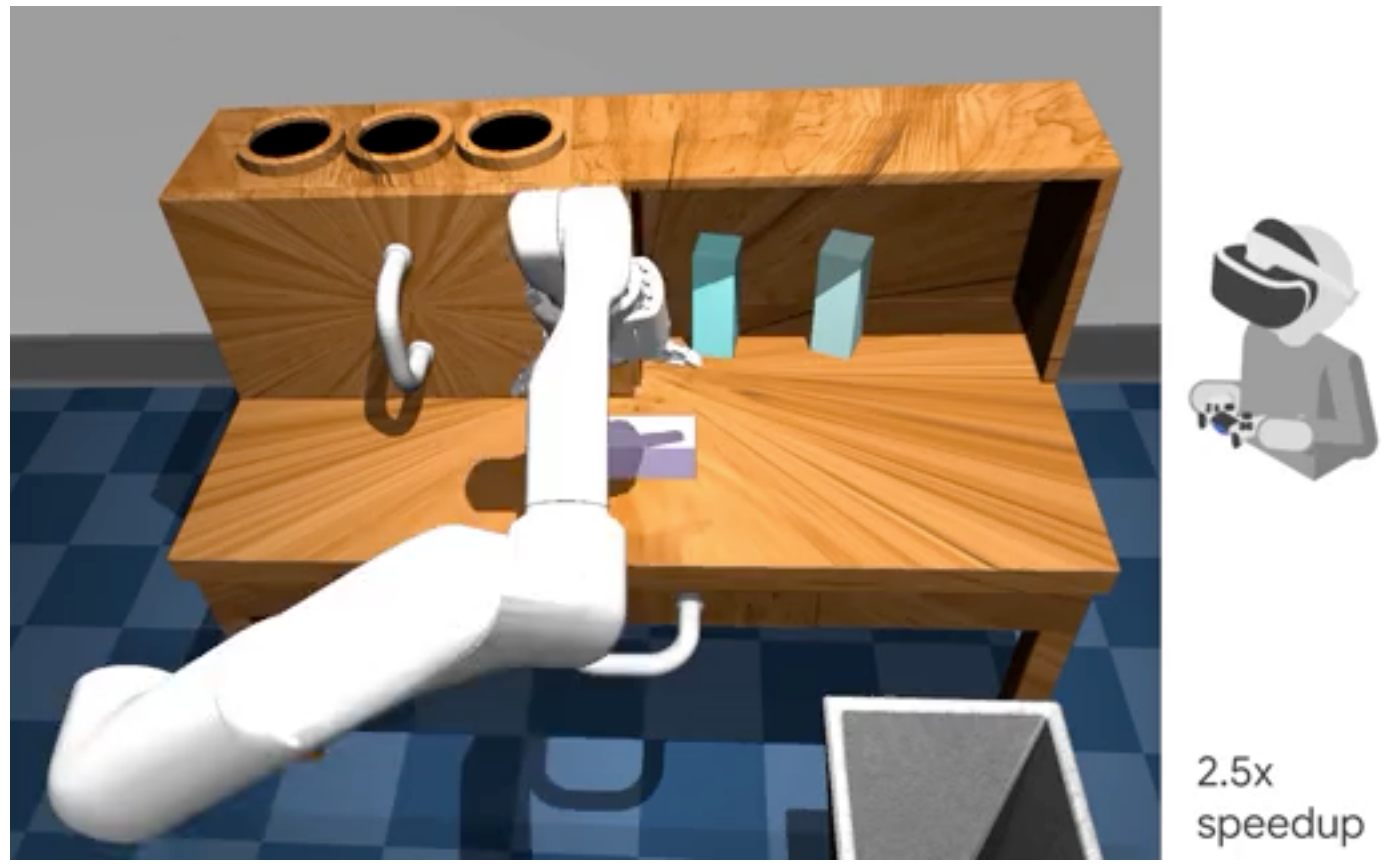
Random, unlabeled interaction is *optimal* under the 0/1 reward of reaching the last state.

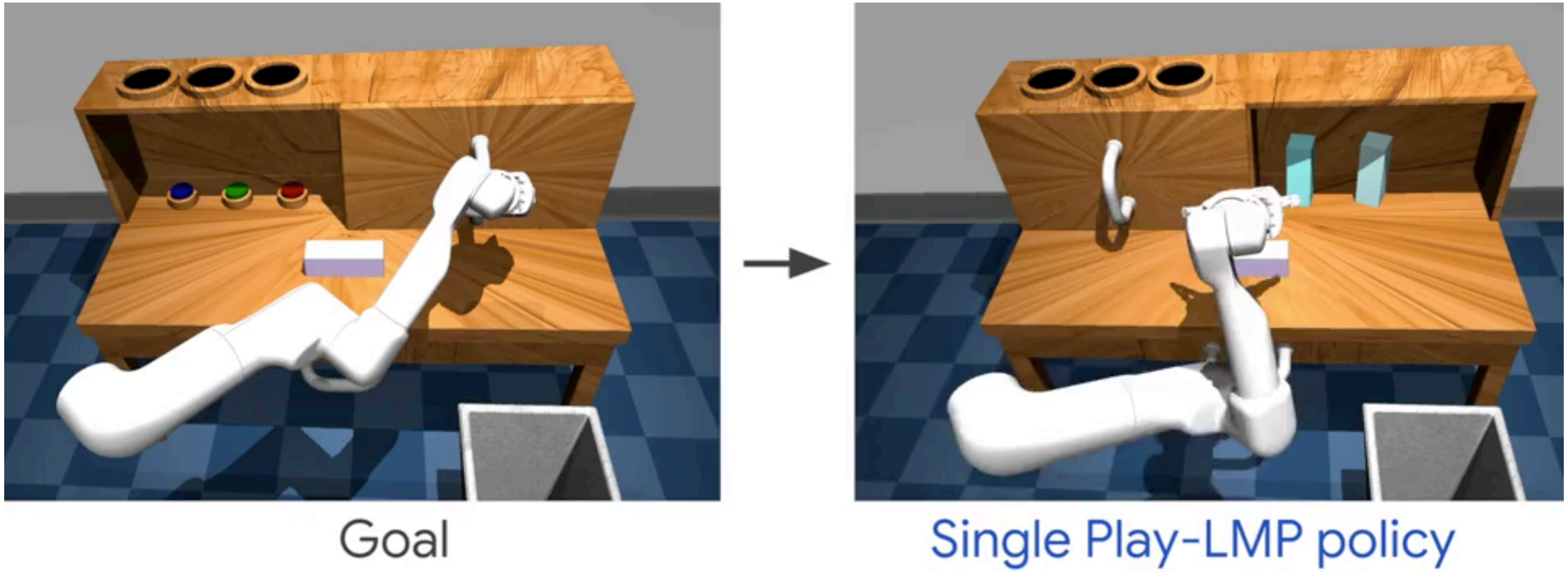
Can we use this insight for **better learning**?

If the data is **optimal**, can we use **supervised imitation learning**?

1. Collect data $\mathcal{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T})\}$ using some policy
2. Perform hindsight relabeling:
   a. Relabel experience in $\mathcal{D}_k$ using last state as goal:
   $\mathcal{D}'_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_T, r'_{1:T}\}$ where $r'_t = -d(\mathbf{s}_t, \mathbf{s}_T)$
   b. Store relabeled data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}'_k$
3. Update policy using **supervised imitation** on replay buffer $\mathcal{D}$

Collect data from "human play", perform goal-conditioned imitation.





Lynch, Khansari, Xiao, Kumar, Tompson, Levine, Sermanet. Learning Latent Plans from Play. ‘19

Can we use this insight to **learn a better goal representation**?

Which representation, when used as a reward function, will cause a planner to choose the observed actions?

1. Collect random, unlabeled interaction data: $\{(s_1, a_1, \ldots, a_{t-1}, s_t)\}$
2. Train a latent state representation $s \rightarrow x$ & latent state model $f(x' | x, a)$ s.t. if we plan a sequence of actions w.r.t. goal state s_t, we recover the observed action sequence.
3. Throw away latent space model, return goal representation x.

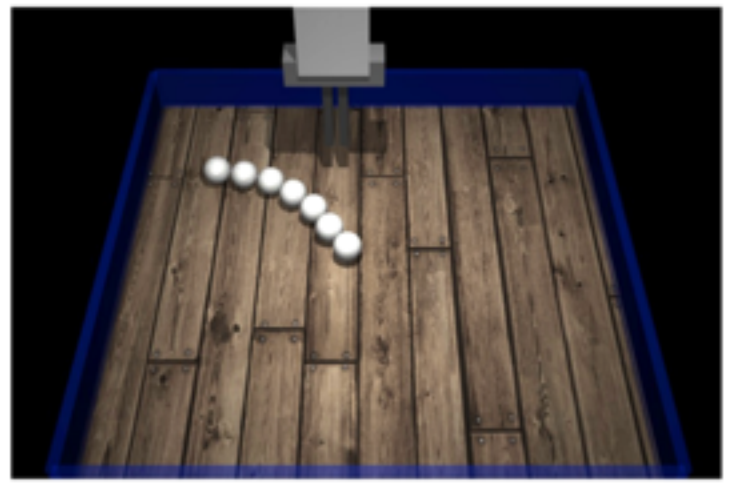
"distributional planning networks"

Srinivas, Jabri, Abbeel, Levine Finn. Universal Planning Networks. ICML '18
Yu, Shevchuk, Sadigh, Finn. Unsupervised Visuomotor Control through Distributional Planning Networks. RSS '19

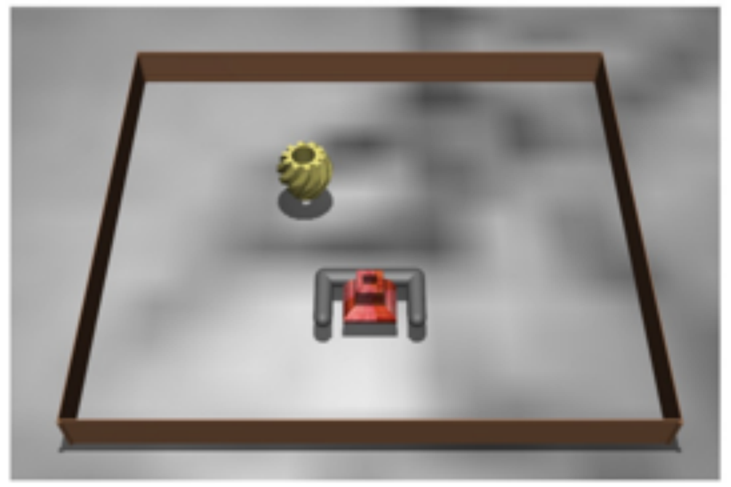
Evaluate metrics on achieving variety of goal images

reaching

rope manipulation

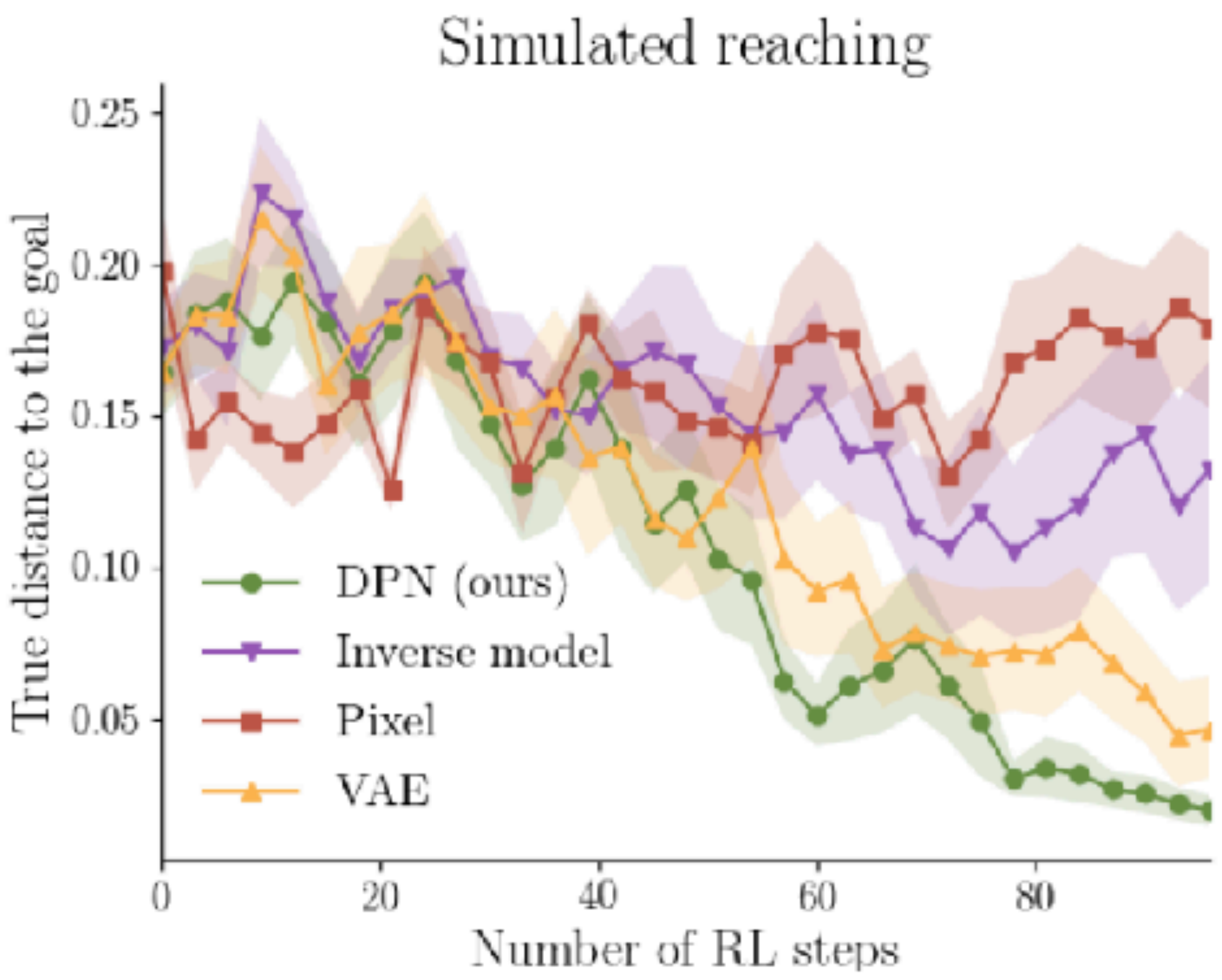


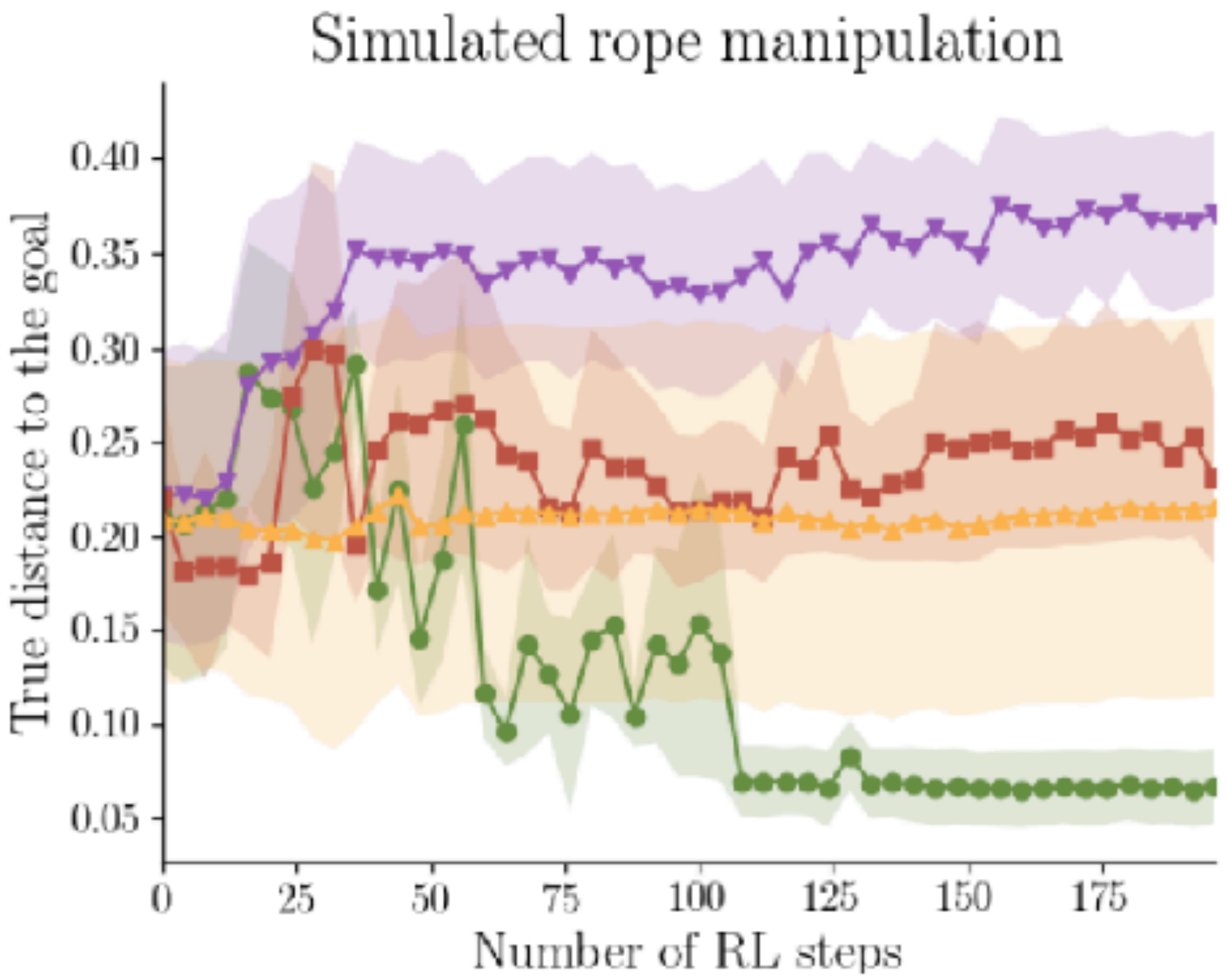
pushing

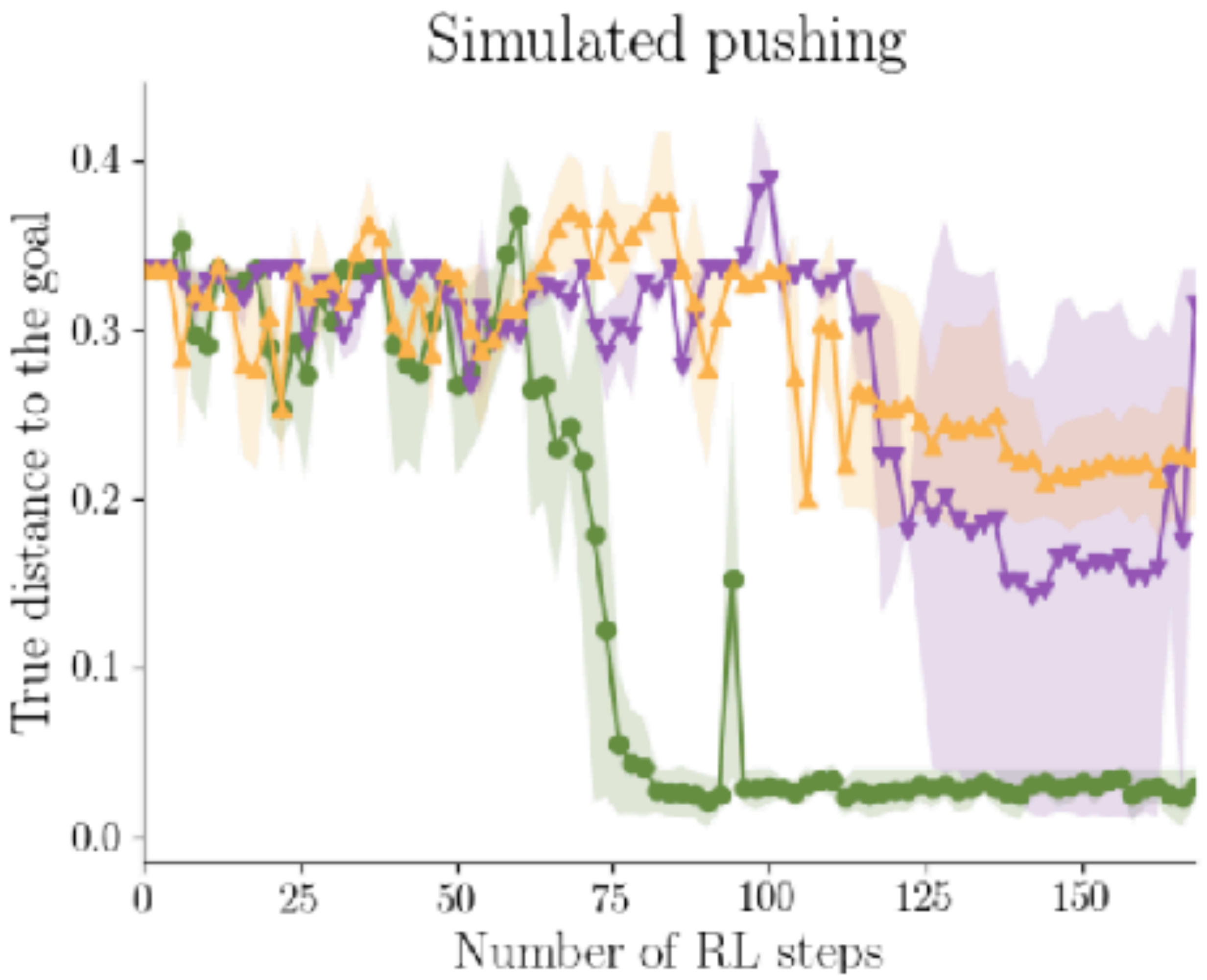


Compare:

- metric from **DPN** (ours)
- **pixel distance**
- distance in **VAE** latent space
- distance in **inverse model** latent space

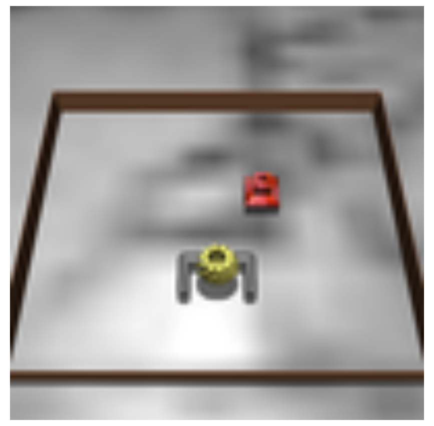


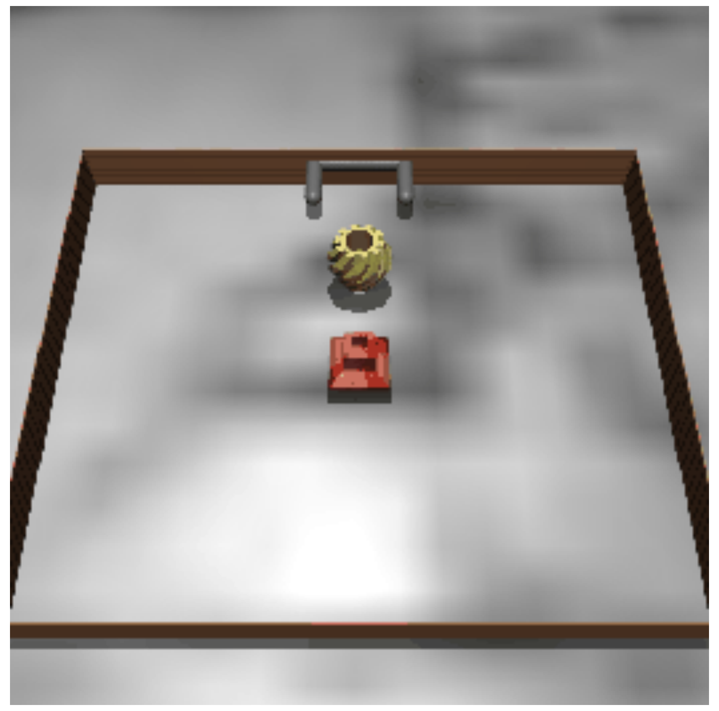




goal

goal

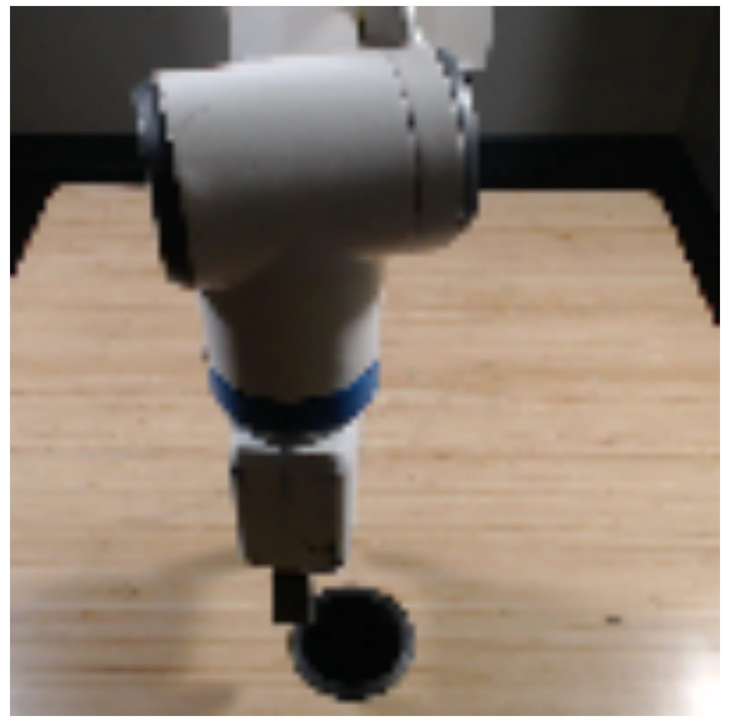




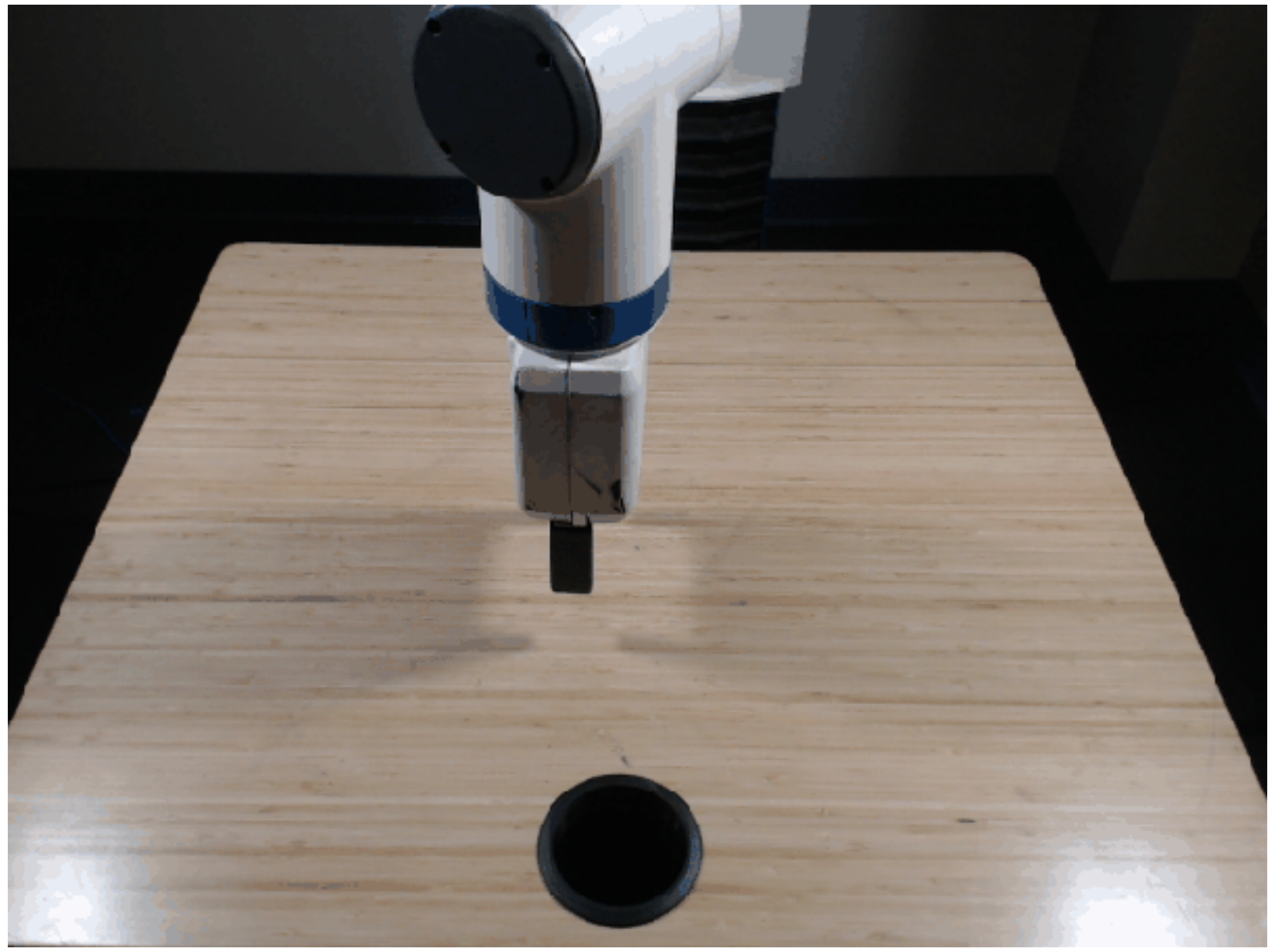
Yu, Shevchuk, Sadigh, Finn. Unsupervised Visuomotor Control through Distributional Planning Networks. RSS '19

Evaluate metrics on achieving variety of goal images

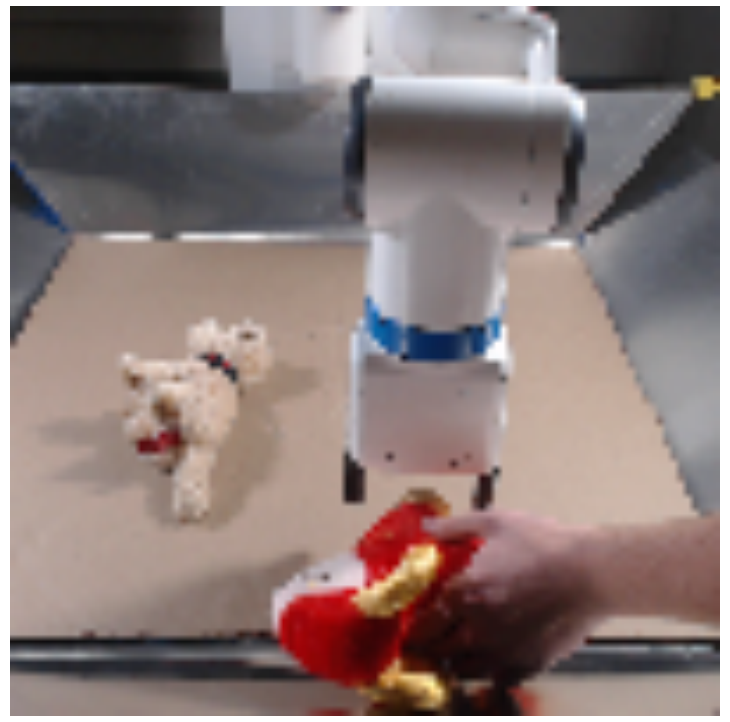
goal



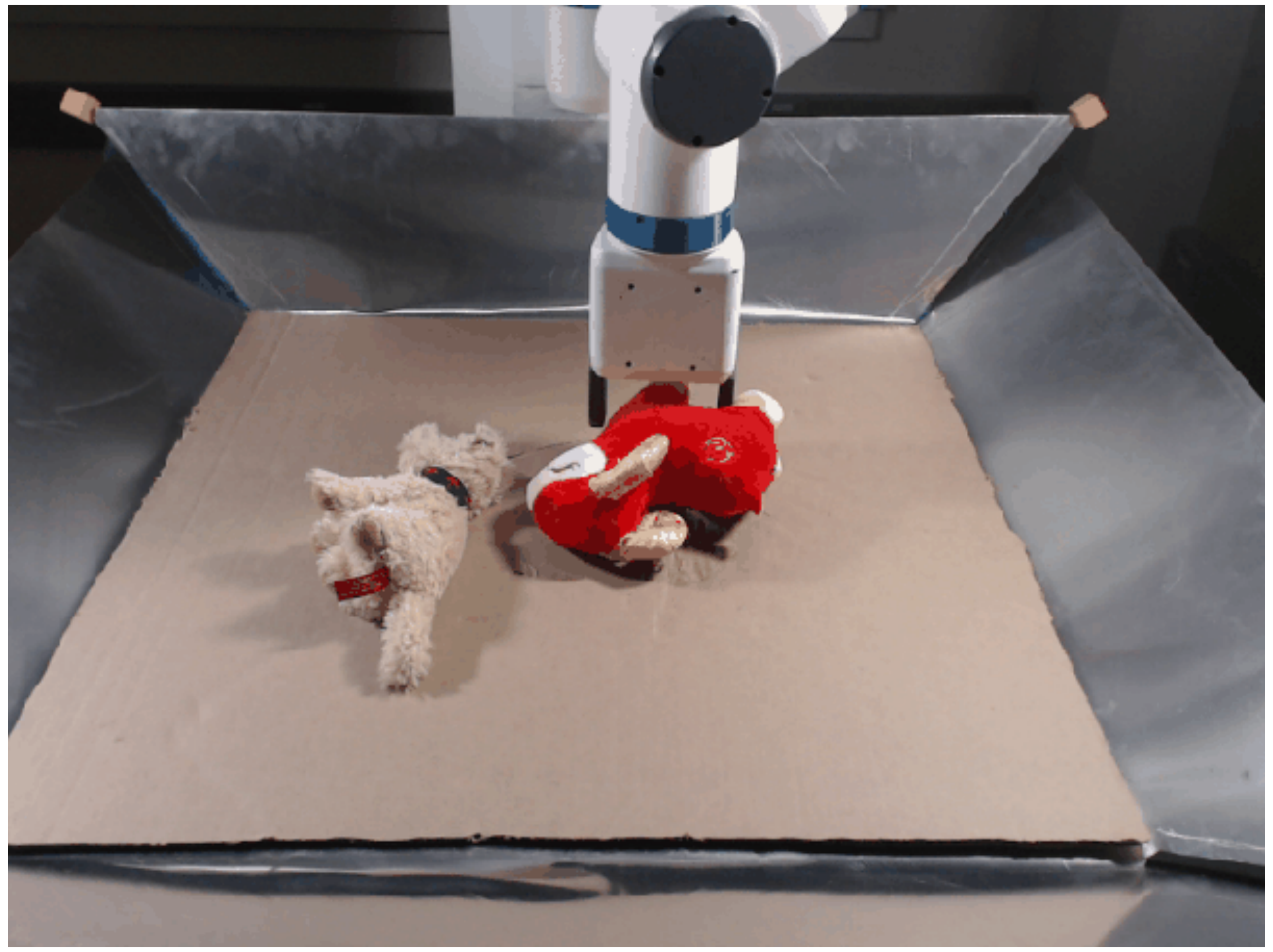
learned policy



goal



learned policy



Yu, Shevchuk, Sadigh, Finn. Unsupervised Visuomotor Control through Distributional Planning Networks. RSS '19

The Plan

Multi-task reinforcement learning problem

Policy gradients & their multi-task/meta counterparts

Q-learning

Multi-task Q-learning

How **data** can be **shared** across tasks.

Many Remaining Questions: The Next Two Weeks

Can we use **auxiliary tasks** to accelerate learning?

What about **hierarchies** of tasks?

Can we learn **exploration strategies** across tasks?

What **do** meta-RL algorithms learn?

Wednesday paper presentations
Auxiliary tasks & state representation learning

Monday paper presentations
Hierarchical reinforcement learning

Next Wednesday:
Meta-Reinforcement Learning
(*Kate Rakelly guest lecture*)

Monday 11/4:
Emergent Phenomenon

Additional RL Resources

Stanford CS234: Reinforcement Learning

UCL Course from David Silver: Reinforcement Learning

Berkeley CS285: Deep Reinforcement Learning

Reminders

Homework 2 due **Wednesday.**

Homework 3 out on **Wednesday.**

Project proposal due **next Wedesday.**