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

CS 330

Introduction

Karol Hausman

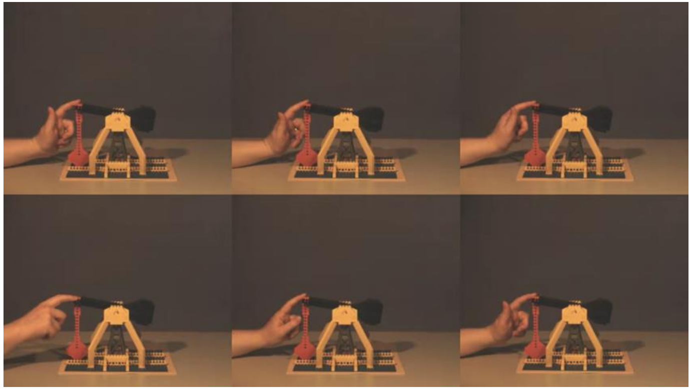
Some background:

- Not a native English speaker so **please please** let me know if you don't understand something
- I like robots ☺
- Studied classical robotics first
- Got fascinated by deep RL in the midd of my PhD a

  a talk by Sergey Levine
- Research Scientist at Robotics @ Google

Why Reinforcement Learning?

Isolated action that doesn't affect the future?



Why Reinforcement Learning?

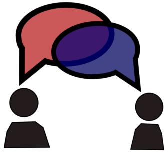
Isolated action that doesn't affect the future?

Supervised learning?

In RL, the actions effect future behaviour.

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 counterparts

Q-learning <— should be review

Multi-task Q-learning

The Plan

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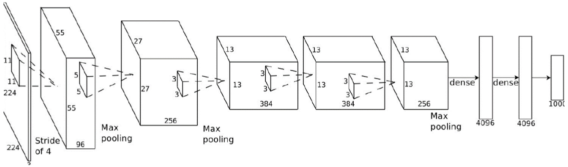
Policy gradients & their multi-task counterparts

Q-learning <— should be review

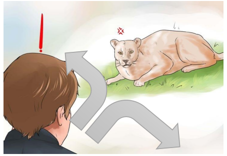
Multi-task Q-learning

Terminology & notation

$\mathbf{o}_t$



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



$\mathbf{a}_t$

1. run away
2. ignore
3. pet

$\pi_\theta(a_t|o_t)$

$\mathbf{s}_t$ – 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

Terminology & notation

$\mathbf{s}_t$ – state

$\mathbf{o}_t$ – observation

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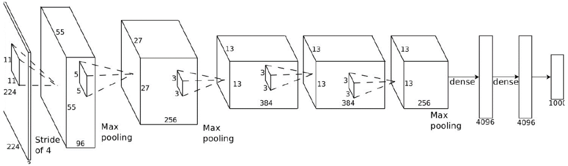
$\mathbf{o}_t$ – observation

$\mathbf{s}_t$ – state

Slide adapted from Sergey Levine

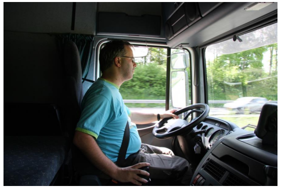
Imitation Learning

$\mathbf{o}_t$



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

$\mathbf{a}_t$



$\mathbf{o}_t$

$\mathbf{a}_t$

training data

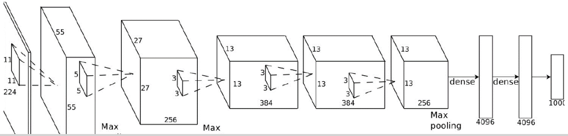
supervised learning

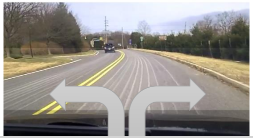
$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

Images: Bojarski et al. '16, NVIDIA

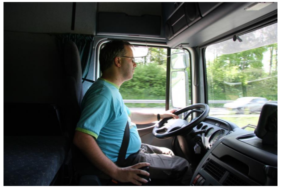
Slide adapted from Sergey Levine

Imitation Learning





Imitation Learning vs Reinforcement Learning?



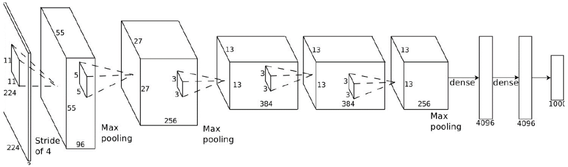
$\mathbf{o}_t$, $\mathbf{a}_t$ → training data → supervised learning → $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

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

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

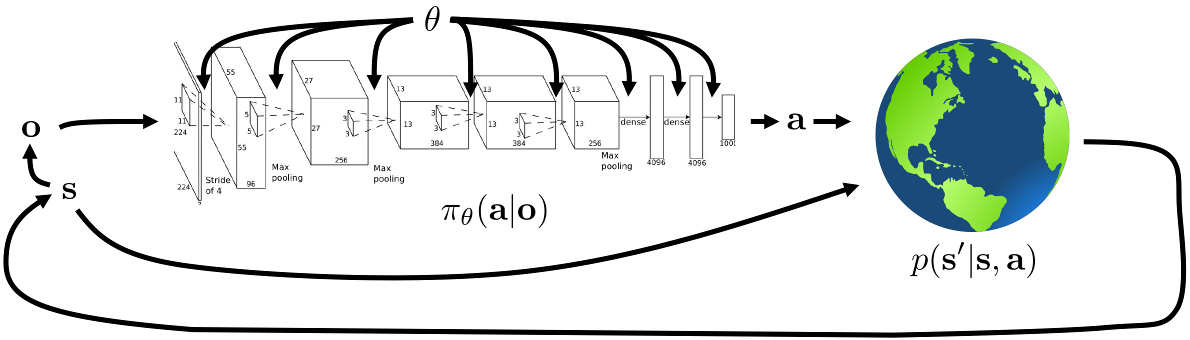
Markov decision process

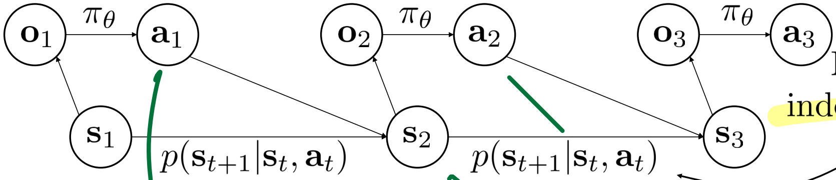
high reward

low reward

Slide adapted from Sergey Levine

The goal of reinforcement learning





Markov property
independent of $\mathbf{s}_{t-1}$

Only depends on S_t

$O_1 \approx r(s_1, a_1)$

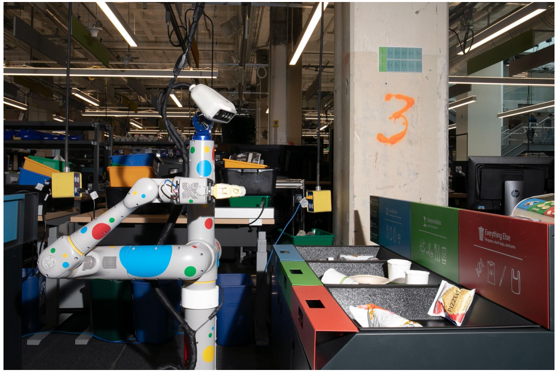
O_2

O_t = Optimality variable

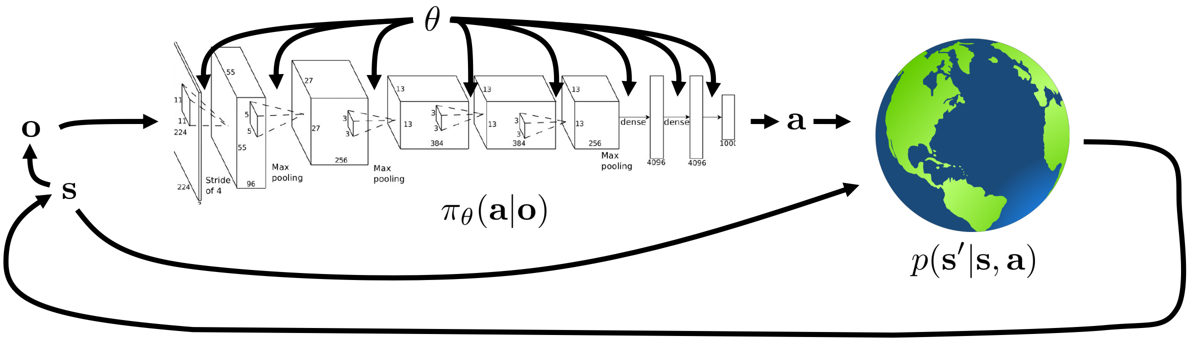
Partial observability

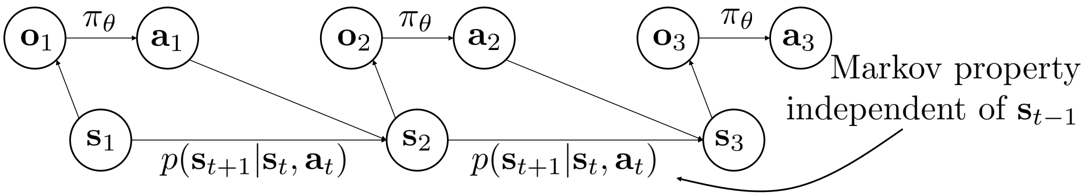
Fully observable?

- Simulated robot performing a reaching task given the goal position and positions and velocities of all of its joints
- Indiscriminate robotic grasping from a bin given an overhead image
- A robot sorting trash given a camera image



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: $\mathcal{T}_i \triangleq \{p_i(\mathbf{x}), p_i(\mathbf{y}|\mathbf{x}), \mathcal{L}_i\}$

Reinforcement learning

action space

dynamics

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

state space

initial state distribution

reward

a Markov decision process

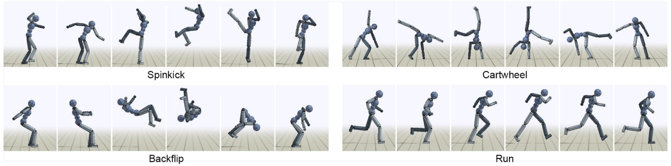
much more than the semantic meaning of task!

Examples Task Distributions

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

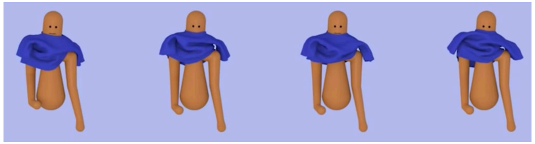
Character animation: across maneuvers

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

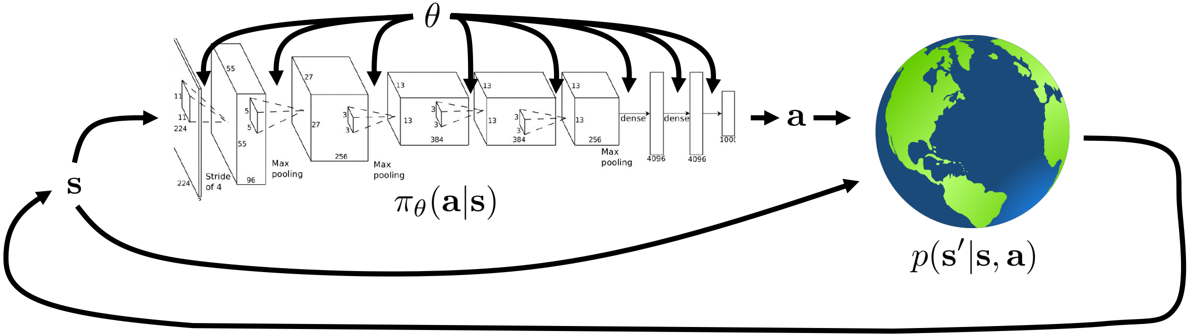
A **task identifier** is part of the state: $\mathbf{s} = (\bar{\mathbf{s}}, \mathbf{z}_i)$

original state — $\bar{\mathbf{s}}$

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

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"

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

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

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

The Plan

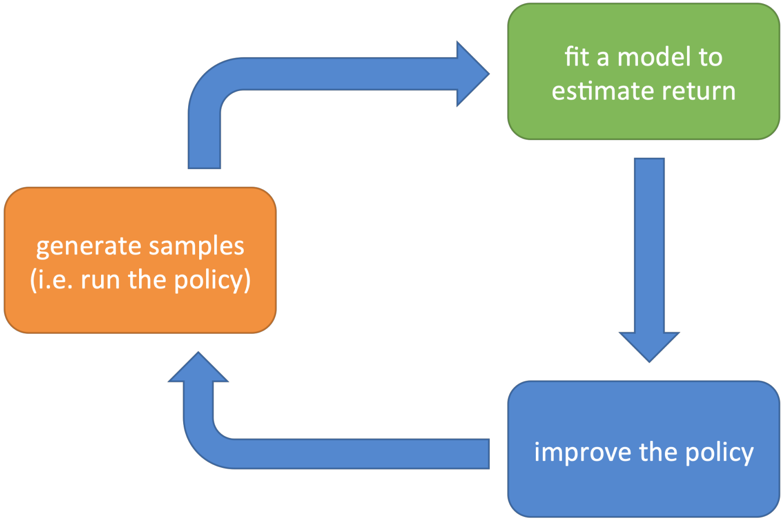
Multi-task reinforcement learning problem

Policy gradients & their multi-task 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)

10/19: focus on model-based RL methods

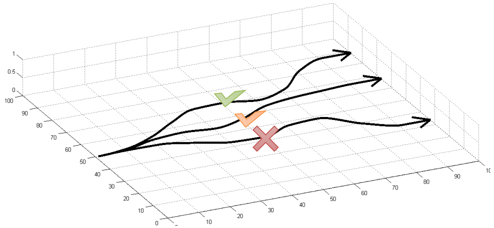
On-policy vs Off-policy

- Data comes from the current policy
- Compatible with all RL algorithms
- Can't reuse data from previous policies

- Data comes from any policy
- Works with specific RL algorithms
- Much more sample efficient, can re-use old data

Evaluating the objective (Policy-Gradient)

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



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

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

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

$$\nabla_x \log f(x) = \frac{1}{f(x)} \nabla_x f(x)$$

$$\Rightarrow \nabla_x f(x) = f(x) \nabla_x \log f(x)$$

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

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

Slide adapted from Sergey Levine

Direct policy differentiation

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

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

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

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

log of both sides

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

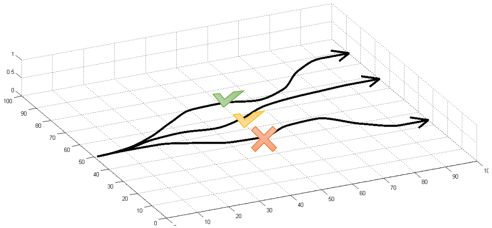
$$\nabla_\theta\left[\cancel{\log p(\mathbf{s}_1)} + \sum_{t=1}^T \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \cancel{\log p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}\right]$$

does not depend on θ

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

Slide adapted from Sergey Levine

Evaluating the policy gradient

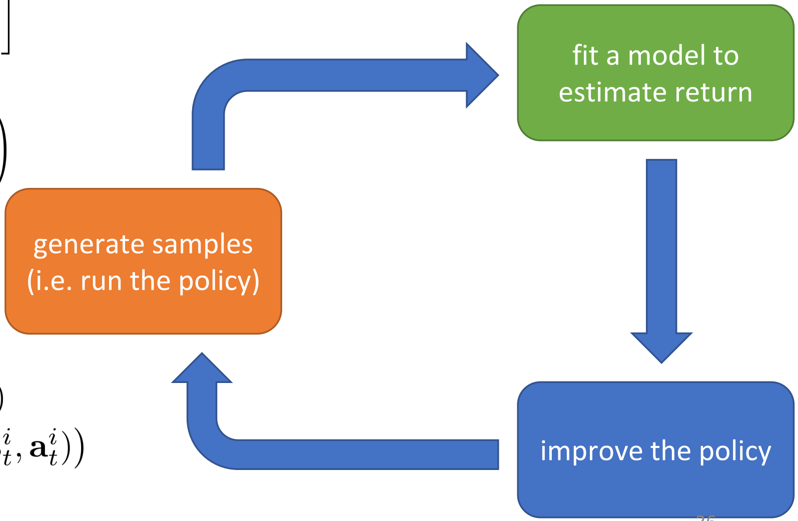


recall: $J(\theta) = E_{\tau \sim p_\theta(\tau)}\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right] \approx \frac{1}{N}\sum_i \sum_t r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t})$

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

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

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



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

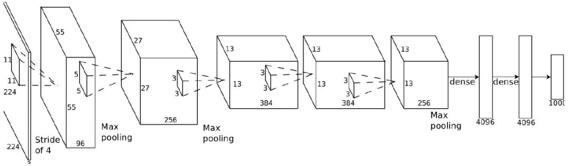
Comparison to maximum likelihood

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

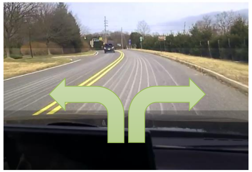
Multi-task learning algorithms can readily be applied!

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?

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

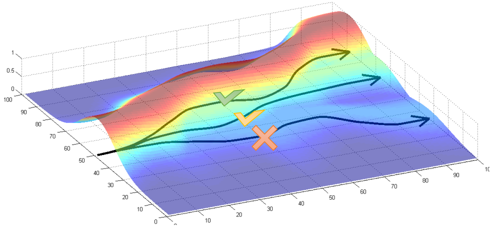
$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \underbrace{\nabla_\theta \log \pi_\theta(\tau_i)}_{\sum_{t=1}^{T} \nabla_\theta \log_\theta \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t})} r(\tau_i)$$

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. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Slide adapted from Sergey Levine

Policy Gradients

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

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

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 $\pi^\star$: $\underline{Q^\star(\mathbf{s}_t, \mathbf{a}_t) = \mathbb{E}_{\mathbf{s}' \sim p(\cdot|\mathbf{s},\mathbf{a})}\left[r(\mathbf{s}, \mathbf{a}) + \gamma \max_{\mathbf{a}'} Q^\star(\mathbf{s}', \mathbf{a}')\right]}$

Bellman equation

Value-Based RL

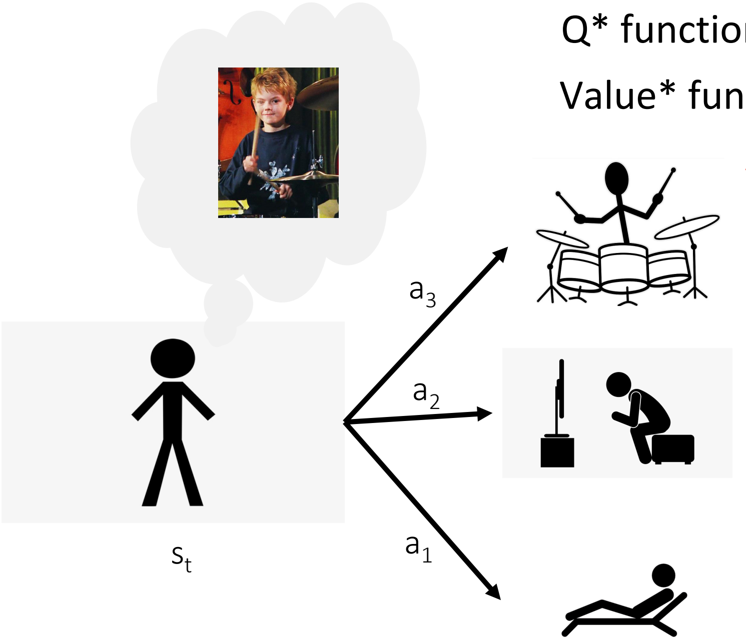
Value function: $V^{\pi}(\mathbf{s}_t) = ?$

Q function: $Q^{\pi}(\mathbf{s}_t, \mathbf{a}_t) = ?$

Q* function: $Q^{*}(\mathbf{s}_t, \mathbf{a}_t) = ?$

Value* function: $V^{*}(\mathbf{s}_t) = ?$

Reward = 1 if I can play it in a month, 0 otherwise



if, Current $\pi(a_1|s) = 1$

$V^{\pi}(s_t) = 1$

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.

Current $\pi(\mathbf{a}_1|\mathbf{s}) = 1$

Fitted Q-iteration Algorithm

full fitted Q-iteration algorithm:

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 $\phi \leftarrow \arg\min_\phi \frac{1}{2} \sum_i \|Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{y}_i\|^2$

$K \times$

Algorithm hyperparameters

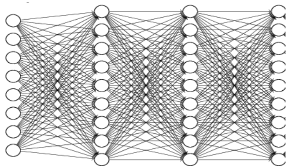
dataset size N, collection policy

iterations K

gradient steps S

$\mathbf{s}$

$\mathbf{a}$



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

parameters ϕ

Result: get a policy $\pi(\mathbf{a}|\mathbf{s})$ 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

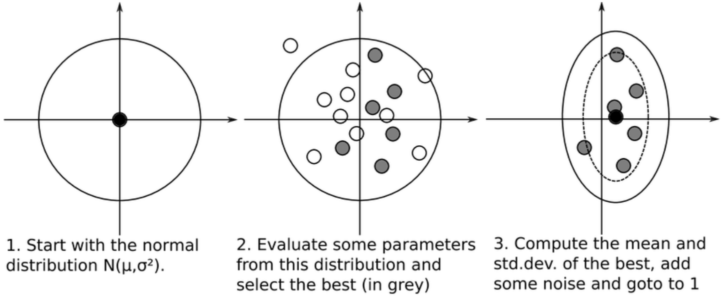
Slide adapted from Sergey Levine

Example: Q-learning Applied to Robotics

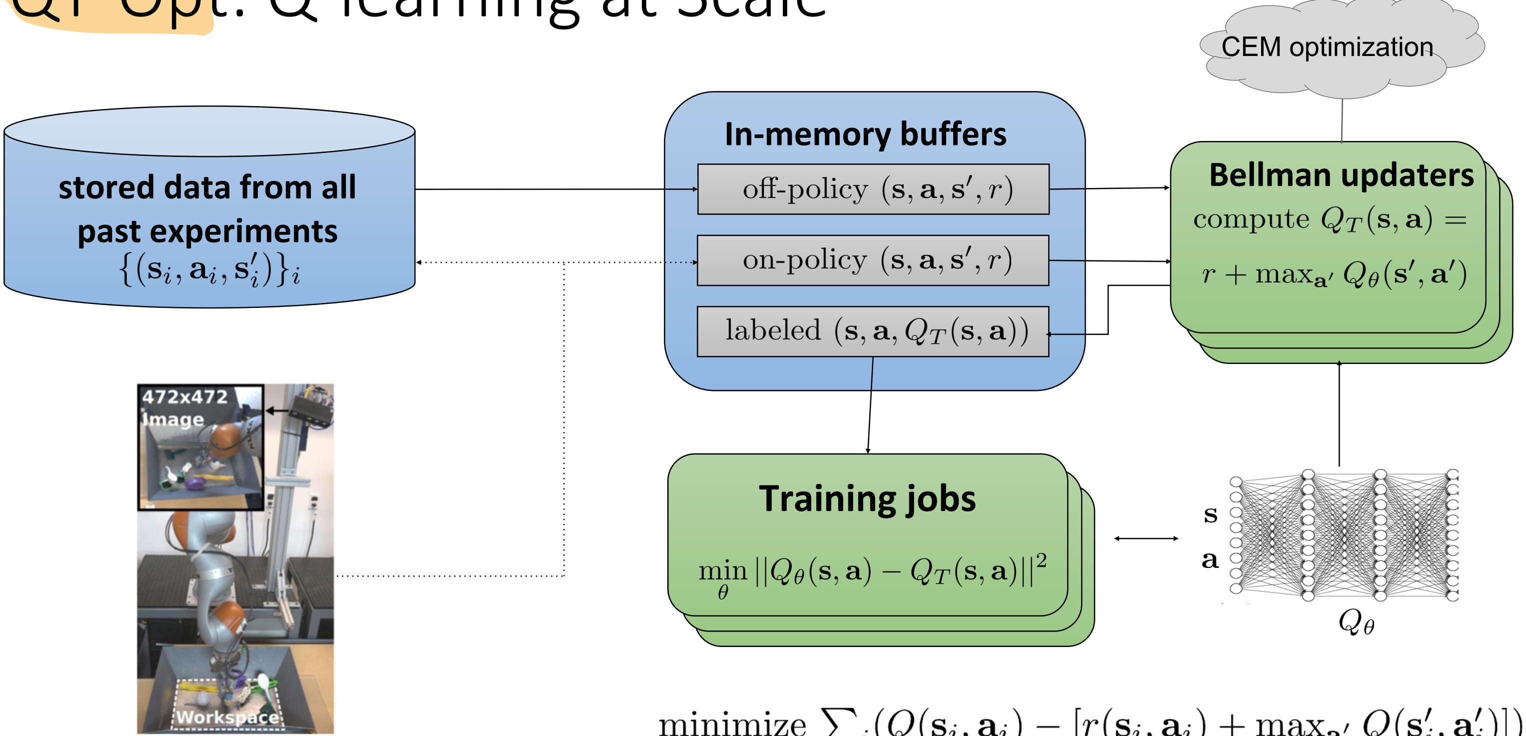
1. collect dataset $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$ using some policy
2. set $\mathbf{y}_i \leftarrow r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \max_{\mathbf{a}'_i} Q_\phi(\mathbf{s}'_i, \mathbf{a}'_i)$
3. set $\phi \leftarrow \arg\min_\phi \frac{1}{2} \sum_i \|Q_\phi(\mathbf{s}_i,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

Continuous action space?

Simple optimization algorithm -> Cross Entropy Method (CEM)



QT-Opt: Q-learning at Scale

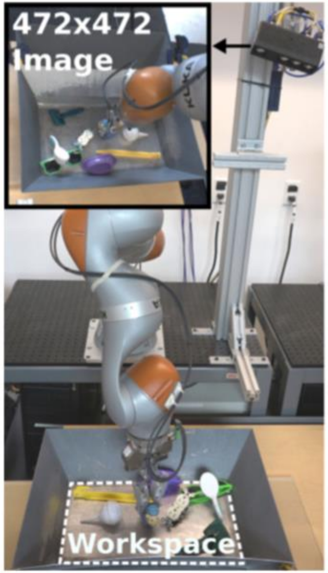


$$\text{minimize } \sum_i (Q(\mathbf{s}_i, \mathbf{a}_i) - [r(\mathbf{s}_i, \mathbf{a}_i) + \max_{\mathbf{a}'_i} Q(\mathbf{s}'_i, \mathbf{a}'_i)])^2$$

Slide adapted from D. Kalashnikov

QT-Opt: Kalashnikov et al. '18, Google Brain

QT-Opt: MDP Definition for Grasping

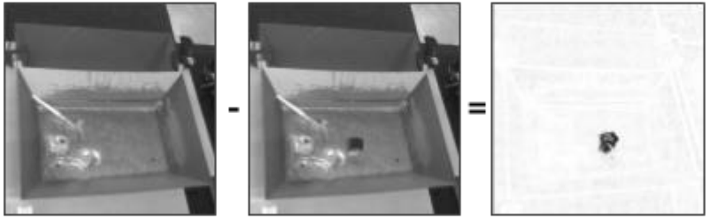


State: over the shoulder RGB camera image, no depth

Action: 4DOF pose change in Cartesian space + gripper control

Reward: binary reward at the end, if the object was lifted. Sparse. No shaping

Automatic success detection:



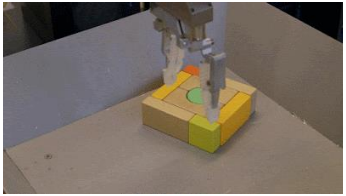
Slide adapted from D. Kalashnikov

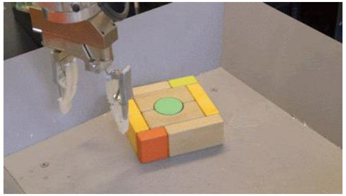
QT-Opt: Setup and Results

7 robots collected 580k grasps

Unseen test objects

96% test success rate!





Q-learning

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

Pros:

+ More **sample efficient** than on-policy methods
+ Can incorporate **off-policy data** (including a fully offline setting)
+ Can updates the policy even without seeing the reward
+ Relatively easy to parallelize

Cons:

- Harder to apply standard meta-learning algorithms (DP algorithm)
- Lots of “tricks” to make it work
- Potentially could be harder to learn than just a policy

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

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!

Why mention it now?

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

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 $\mathcal{D}_k = \{(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}, \mathbf{s}_g, r_{1:T})\}$ using some policy
2. Store data in replay buffer $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_k$
3. 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 $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}'_k$
4. Update policy using replay buffer $\mathcal{D}$

< strategies?

e trajectory

Result: exploration challenges alleviated

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

Why mention it now?

Task 1: close a drawer

Task 2: open a drawer

Can we use episodes from drawer opening task for drawer closing task?

How does that answer change for Q-learning vs Policy Gradient?

Multi-task RL with relabeling

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 $\mathcal{D}$

$k++$

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

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

Eysenbach et al. Rewriting History with Inverse RL
Li et al. Generalized Hindsight for RL

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

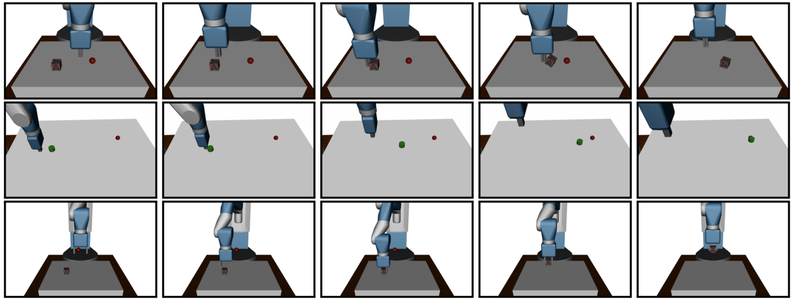
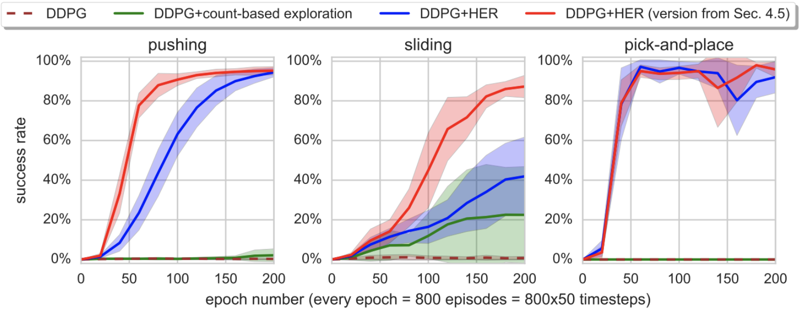


Figure 2: Different tasks: *pushing* (top row), *sliding* (middle row) and *pick-and-place* (bottom row). The red ball denotes the goal position.



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.

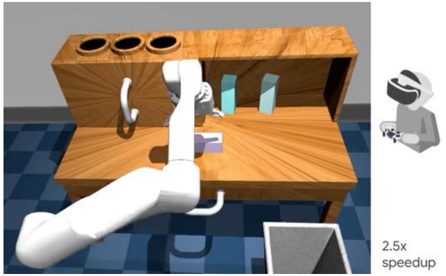
Random, unlabeled interaction is *optimal* under the 0/1 reward of reaching the last state.

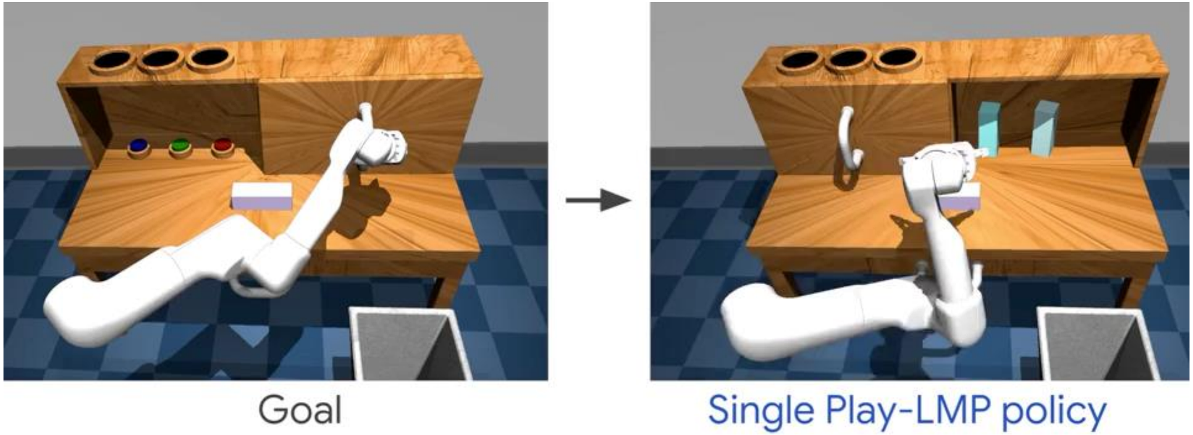
Can we use this insight for **better learning**?

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

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 Three Weeks

How can we use a **model** in multi-task RL?	Model-based RL - **Oct 19**
What about **meta-RL** algorithms?	Meta-RL - **Oct 21**
Can we learn **exploration strategies** across tasks?	Meta-RL: Learning to explore - **Oct 26**
What about **hierarchies** of tasks?	Hierarchical RL - **Nov 2**

Additional RL Resources

Stanford CS234: Reinforcement Learning

UCL Course from David Silver: Reinforcement Learning

Berkeley CS285: Deep Reinforcement Learning