# Use Offline data in RL

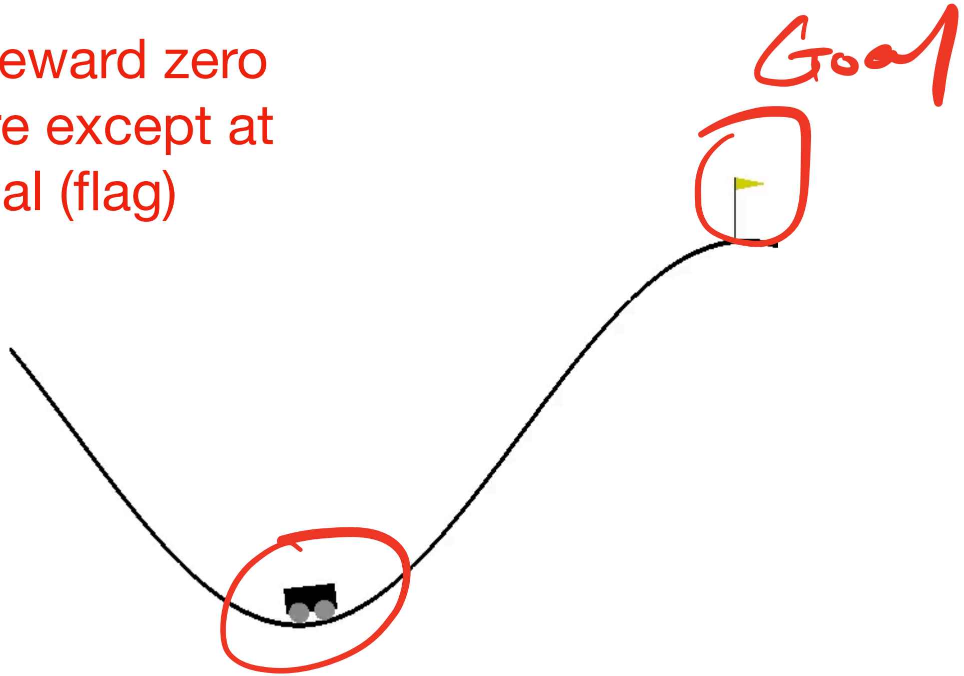
# Annoucements

1. PA3 will be released today, due in three weeks
2. Almost done grading HW2 and Prelim exam
3. No office hour tmr

# Failure mode of Policy Gradient

The mountainCar Example (i.e., the sparse reward problem)

We have reward zero everywhere except at the goal (flag)



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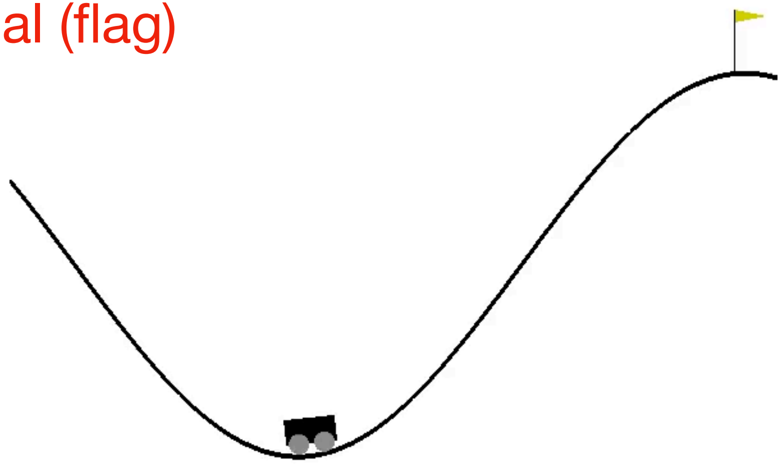

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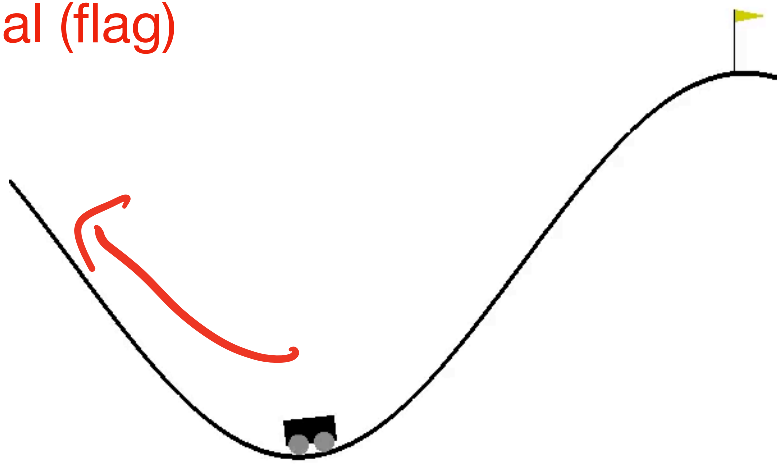

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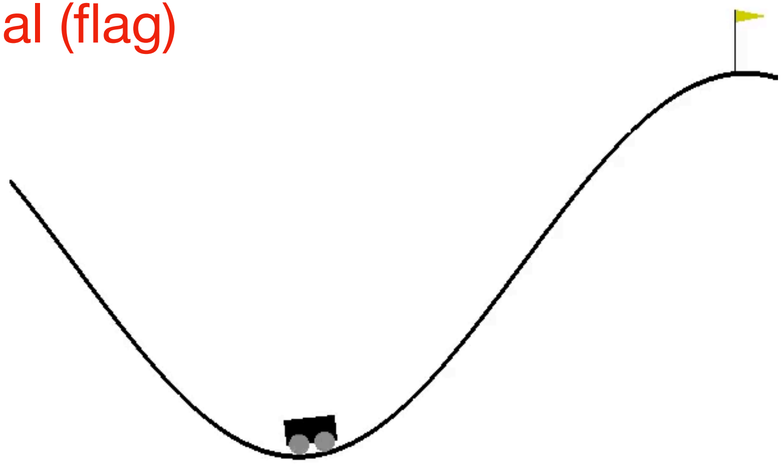

The prob of a random policy hitting the goal is exponentially small $\approx 2^{-H}$

$\tau \sim \pi$

$$\text{PG} := \underbrace{R(\tau)}_{=0} \sum_{h=0}^{H-1} \nabla_\theta \ln \pi_\theta(a_h \mid s_h) \approx 0$$

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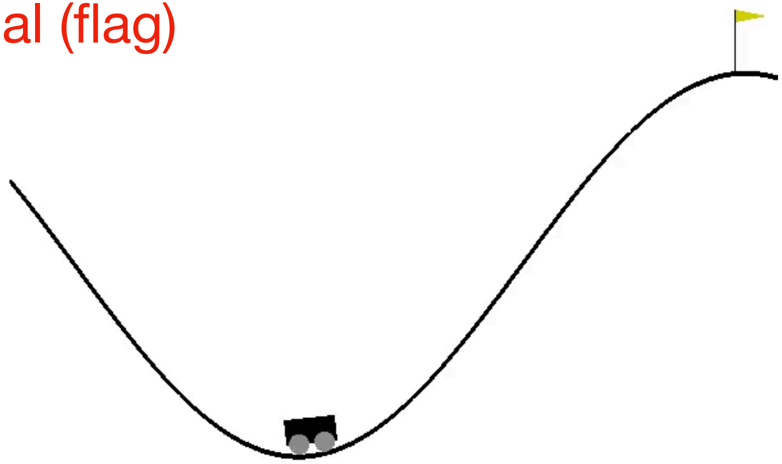

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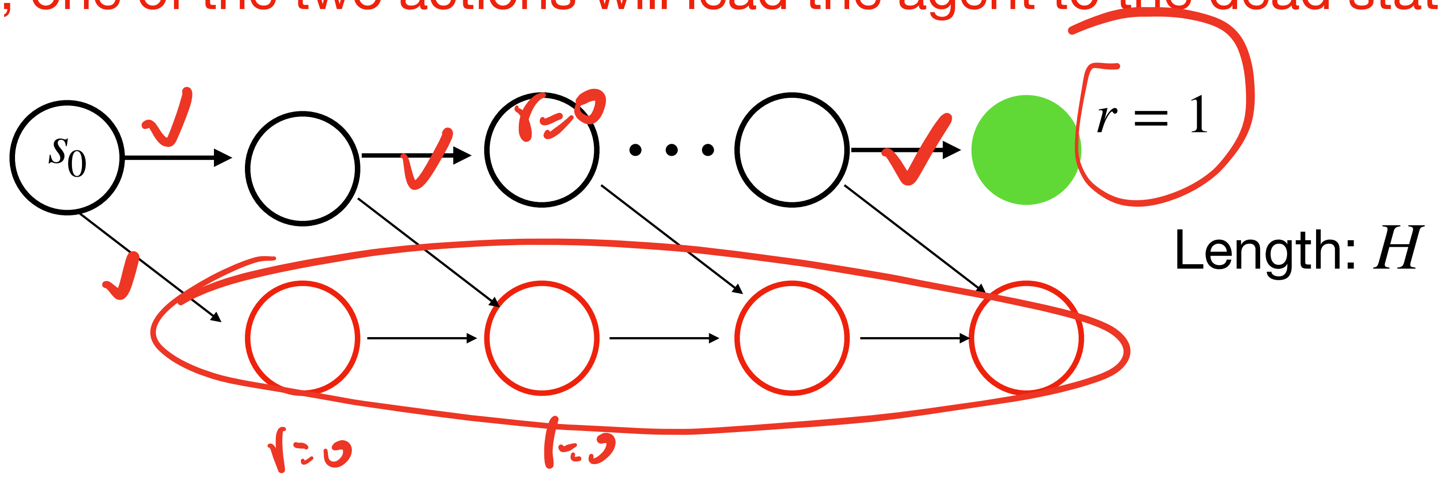
$$\text{PG} := R(\tau) \sum_{h=0}^{H-1} \nabla_\theta \ln \pi_\theta(a_h \mid s_h) \approx 0$$

i.e., a random policy is a perfect locally optimal policy

# Failure model of Policy Gradient

The Combination Lock Example (i.e., the sparse reward problem)

(1) We have reward zero everywhere except at the goal (the right end);
(2) Every black node, one of the two actions will lead the agent to the dead state (red)




$\left(\frac{1}{2}\right)^H$

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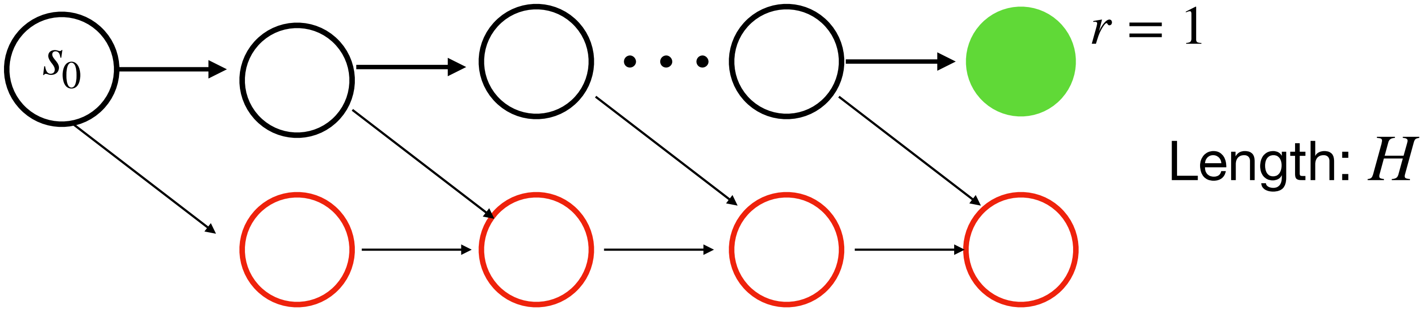



What is the probability of a random policy generating a trajectory that hits the goal?

**Question Today:**

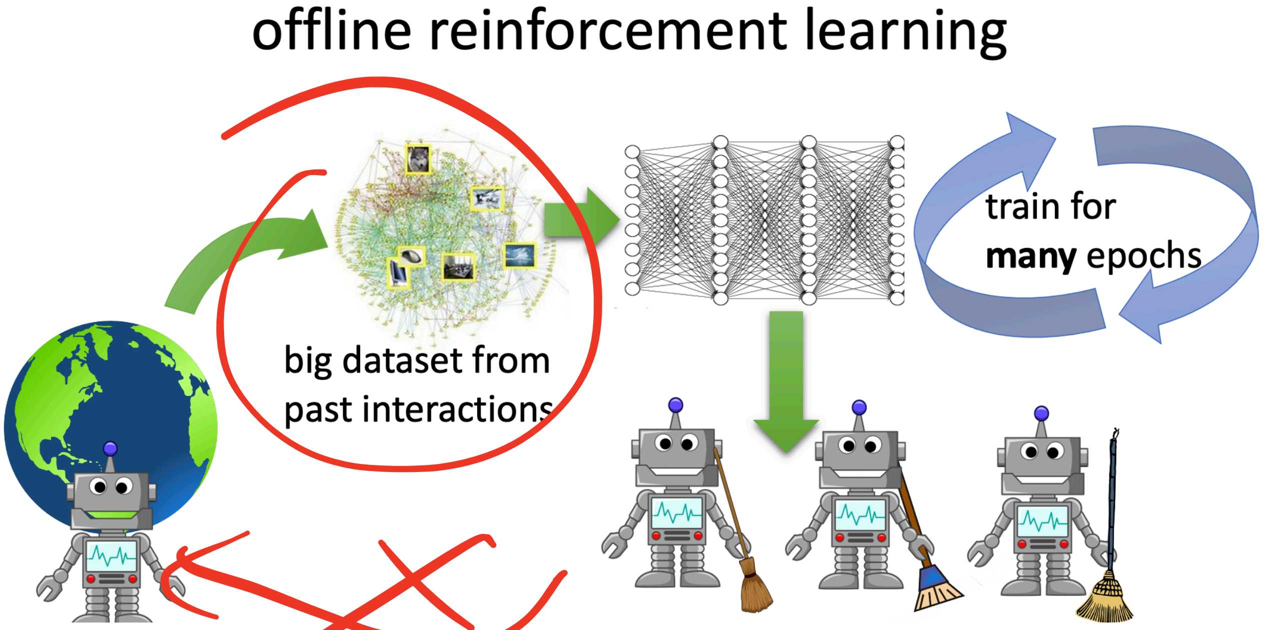
Make RL (DQN and PG/PPO) more efficient by leveraging offline data

# Outline

1. Using offline data in the DQN framework

2. Using offline data in PG via Reset

# Detour: Offline RL, i.e., RL with <u>only</u> pre-collected dataset




Note here loop is
not closed!

The hope:

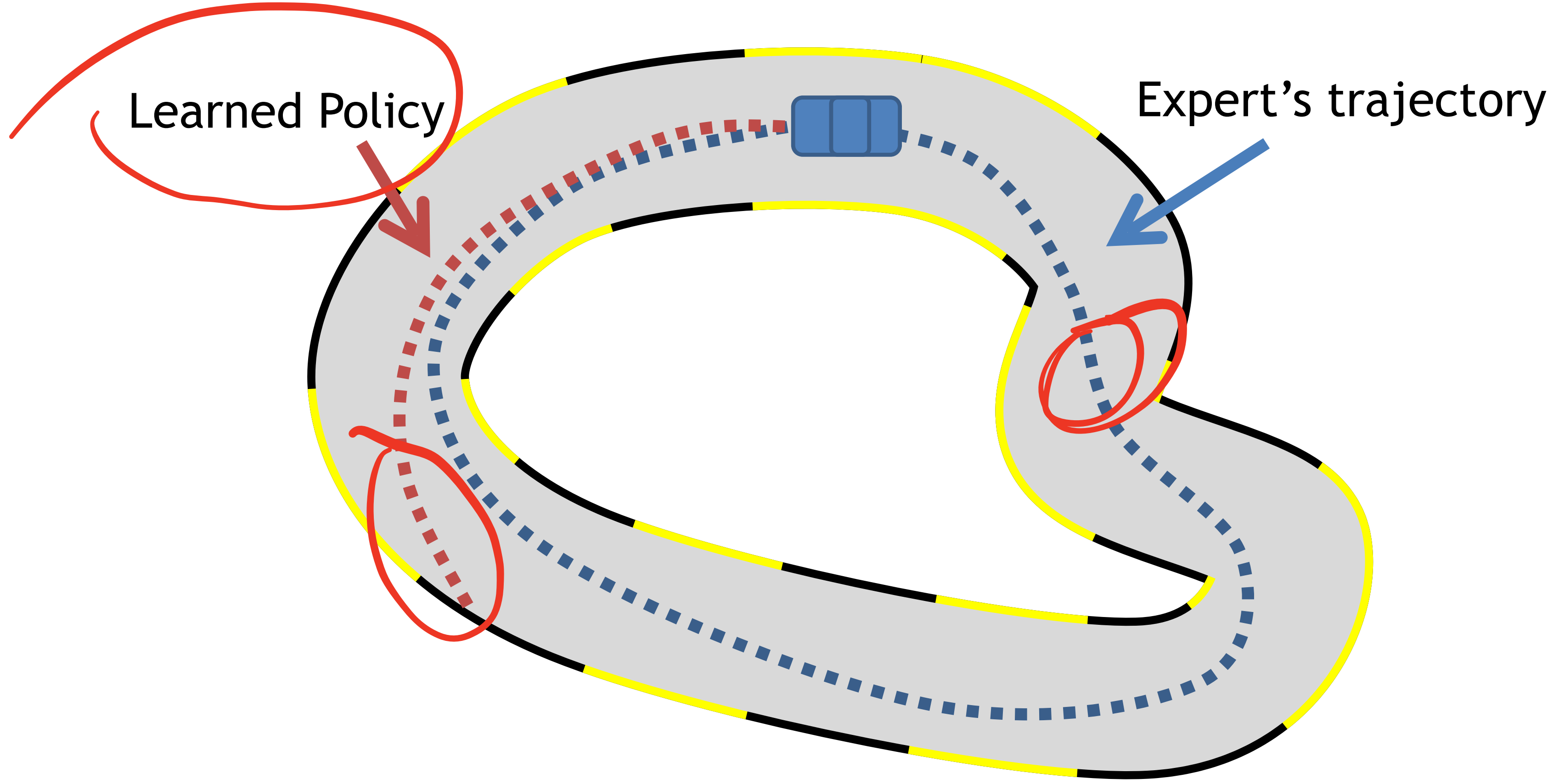
We can pre-train RL on
large logged datasets

[Image from BAIR blog post: https://bair.berkeley.edu/blog/2020/12/07/offline/]

# What could go wrong?

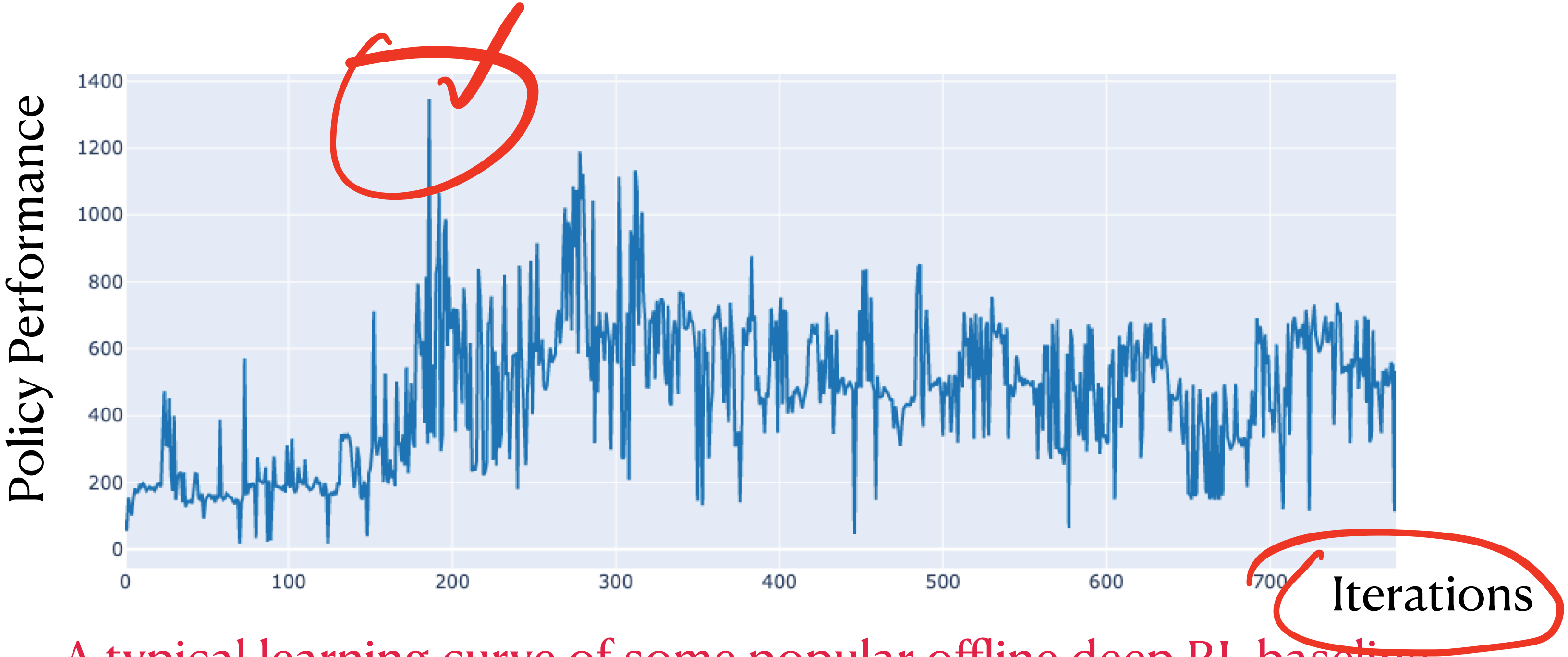
[Pomerleau89,Daume09]

- Distribution shift



# Detour: Offline RL, i.e., RL with only pre-collected dataset

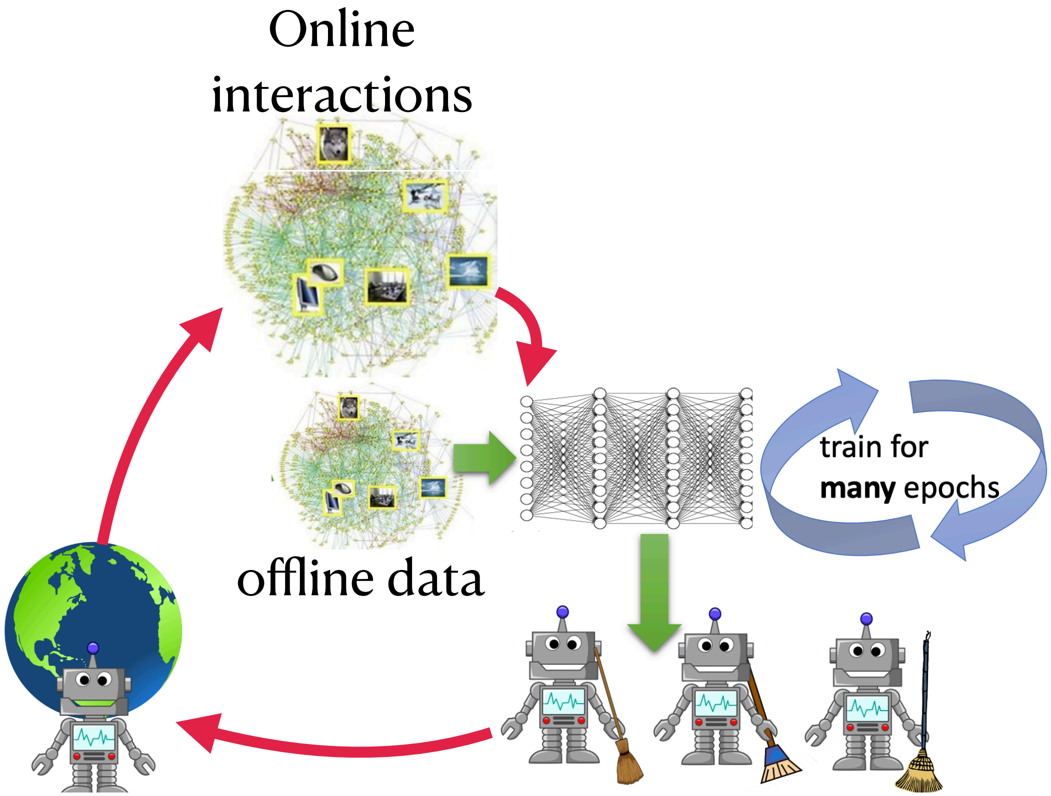
The reality:  Making offline RL work reliably is hard...




A typical learning curve of some popular offline deep RL baseline tested under a standard D4RL benchmark

# The rescue:

## Offline data + Online Interaction



# Offline data + Online is widely used in practice

1. In robotics, we typically combine offline expert demonstration with online interaction [e.g., Rajeswaran et al 17, Nair et al., 20, Zhu et al., 19]

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1. In robotics, we typically combine offline expert demonstration with online interaction [e.g., Rajeswaran et al 17, Nair et al., 20, Zhu et al., 19]

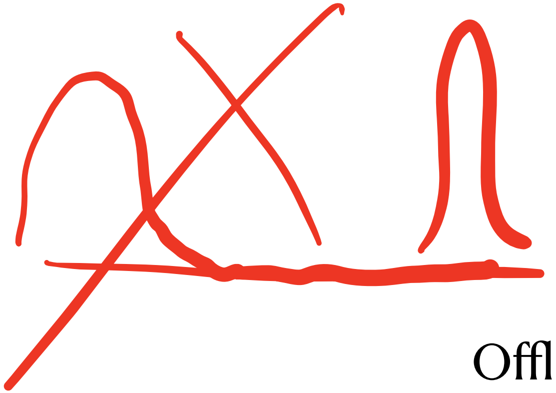
2. In games, we combine human demonstrations with online interaction, e.g., first version of AlphaGo [deepmind], playing Hanabi [Meta AI, Hu et al, 22]

# Offline data distribution

Offline data is sampled from offline distributions $\nu$

$$\mathcal{D}_{off} = \{s, a, r, s'\}_{i=1}^{m}, \text{ where } s, a \sim \nu, s' \sim P(\cdot \mid s, a)$$

$r(s,a)$



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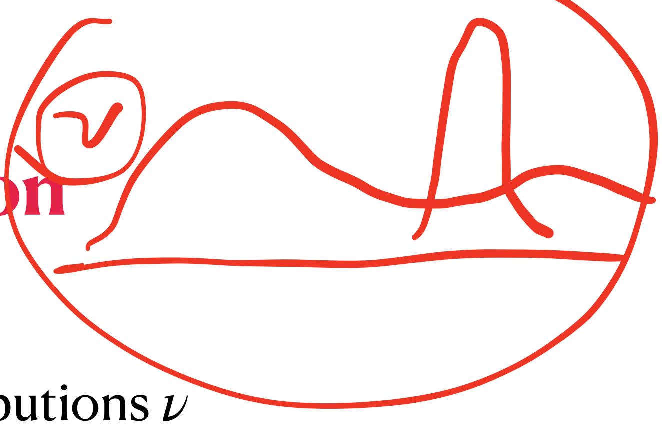


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$$\mathcal{D}_{off} = \{s, a, r, s'\}_{i=1}^{n}, \text{ where } s, a \sim \nu, s' \sim P(\cdot \mid s, a)$$

We assume offline distributions “cover” some high quality policy’s traces

$\pi^*$

$$\frac{d^{\pi}(s,a)}{\nu(s,a)} < \infty$$

# Algorithm: Hybrid (Deep) Q Learning (Hy-Q)

In high level, it iteratively runs DQN on combination of offline and online data

Initialize $Q_{\theta_0}$, online replay buffer $\mathscr{D}_{on} = \emptyset$, initial state $s$, set target network $\widetilde{Q} = Q_{\theta_0}$

While true:

1. Run $\epsilon$-greedy of $Q_{\theta_t}$ to collect a transition data $(s, a, r, s')$, $s' \sim P(s, a)$
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3. **W/ prob 0.5, sample batch $\mathcal{B}$ from $\mathcal{D}_{on}$, and otherwise from $\mathcal{D}_{off}$**
4. Q-update: $\theta_{t+1} \Leftarrow \theta_t - \eta \frac{1}{|\mathcal{B}|} \sum_{s,a,r,s' \in \mathcal{B}} \left( Q_{\theta_t}(s, a) - r - \gamma \max_{a'} \tilde{Q}(s', a') \right) \nabla_{\theta_t} Q_{\theta_t}(s, a)$

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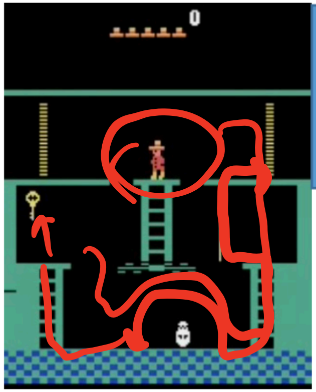
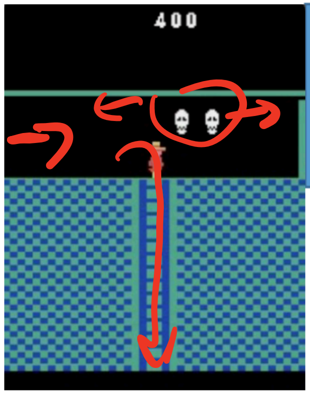
5. Set $s \Leftarrow s'$, and update target network once a while

# How does such a simple algorithm work in practice?

Montezuma's Revenge




Reward
0
Room #
1




Reward
400
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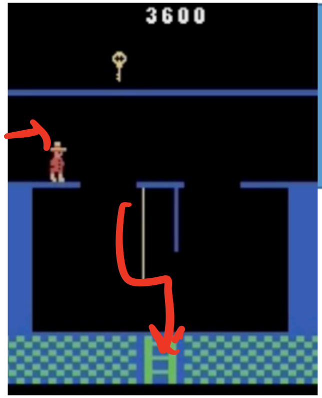
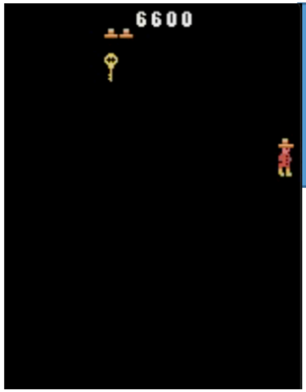
2




Reward
3600
Room #
14




Reward
6600
Room #
23

# Comparison to Empirical Deep RL baseline

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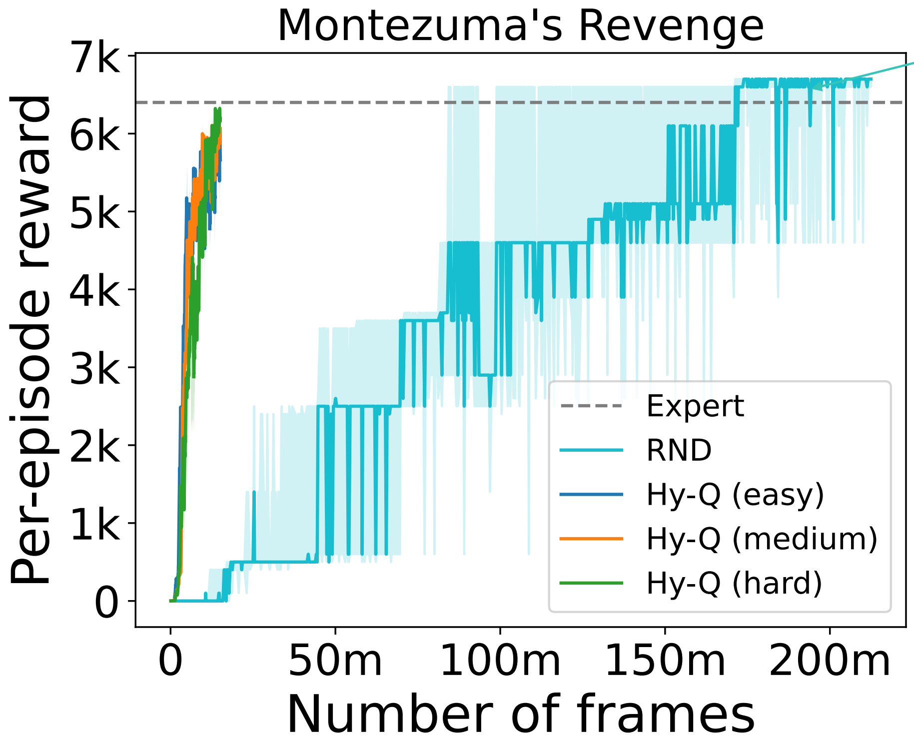

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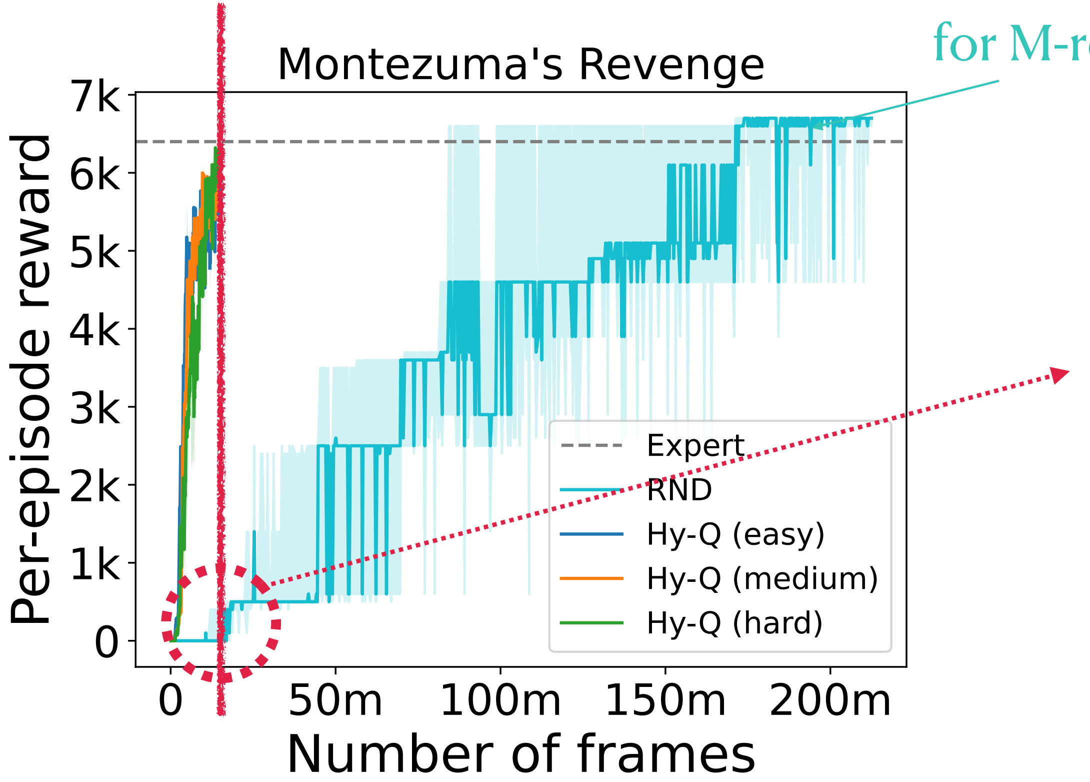

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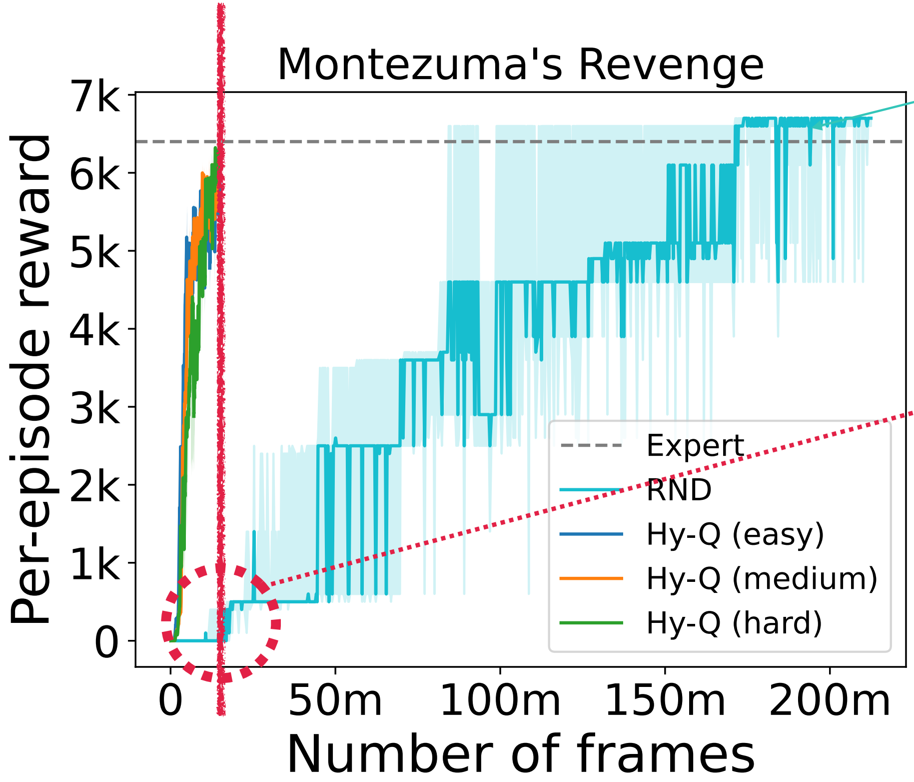


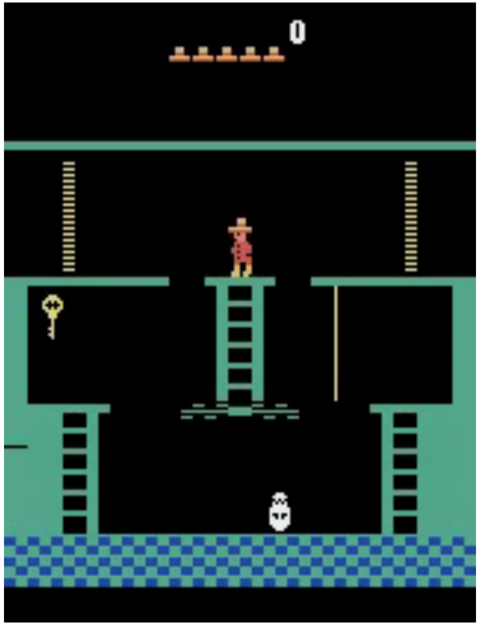

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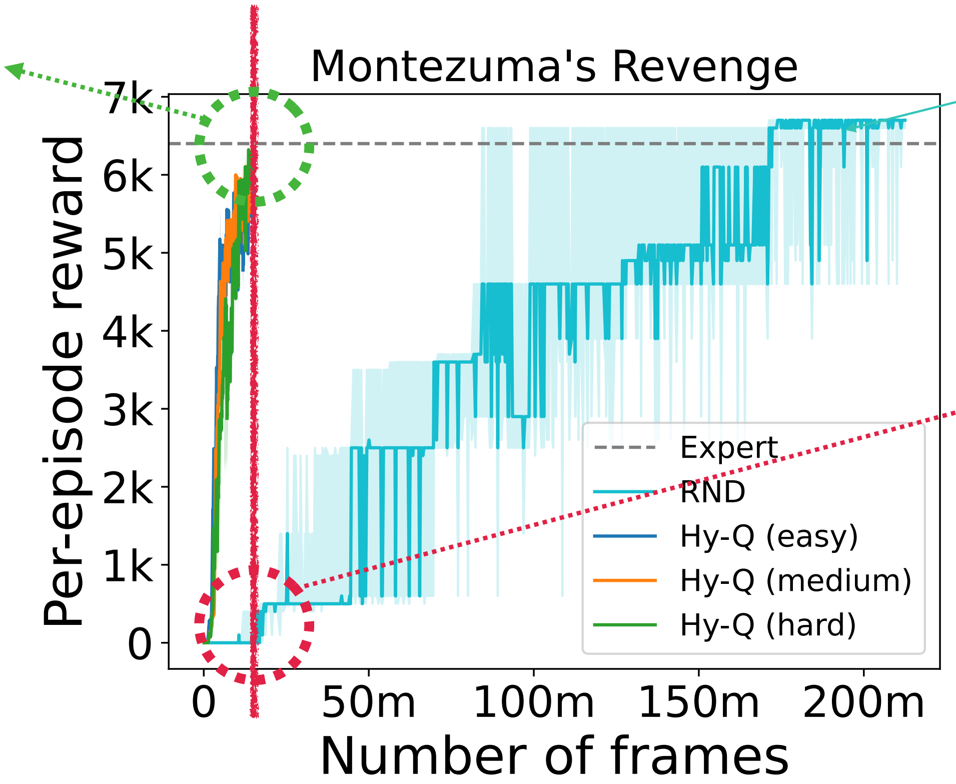


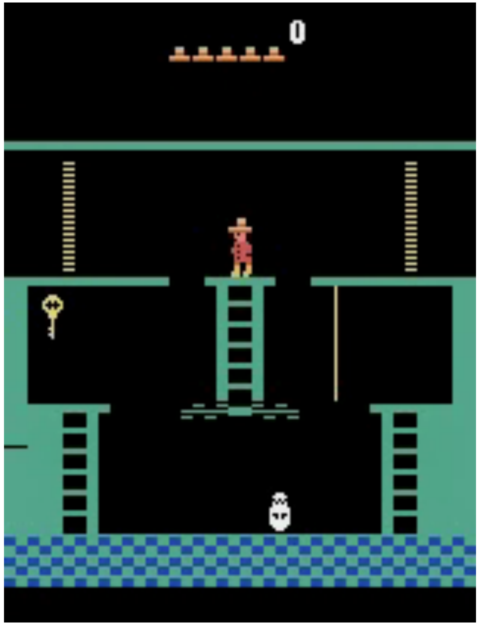

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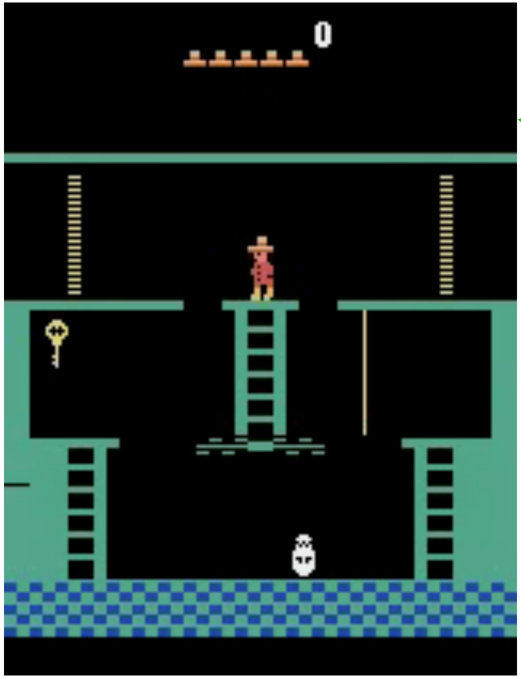


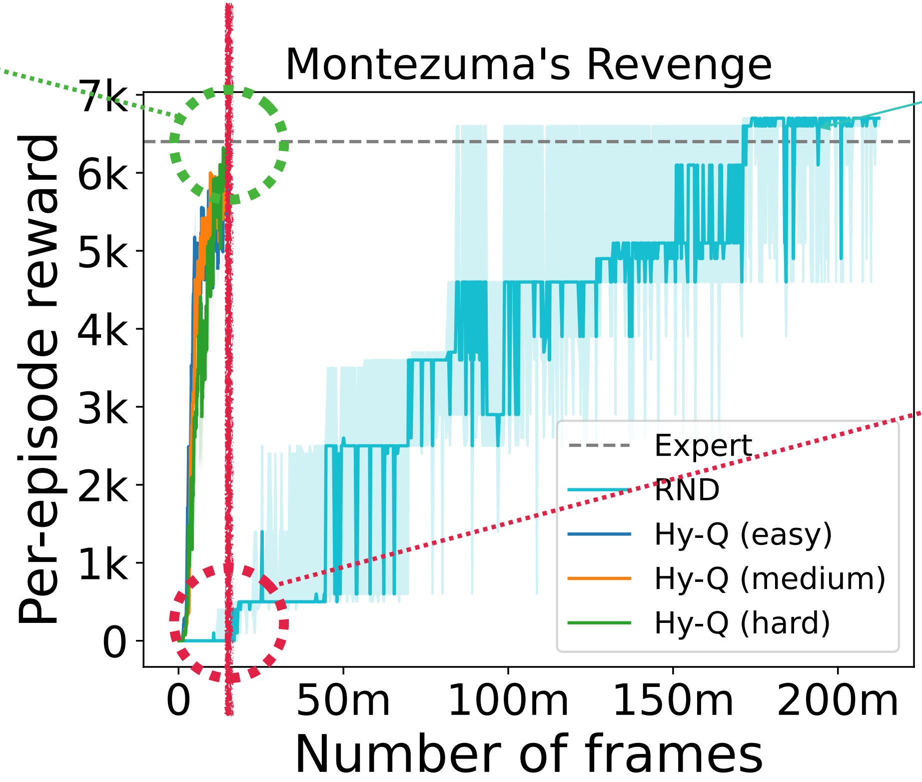


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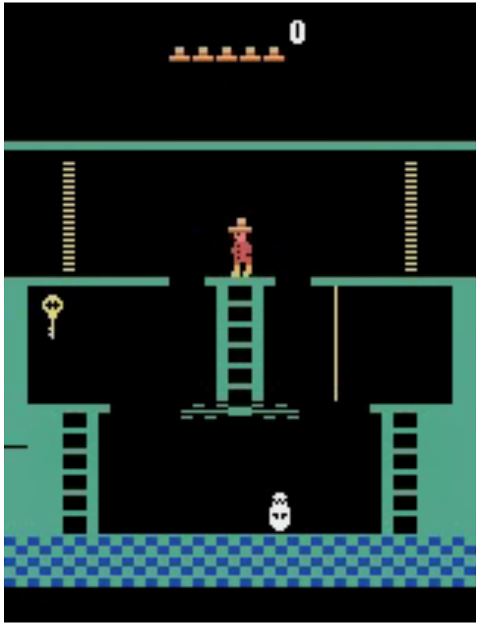
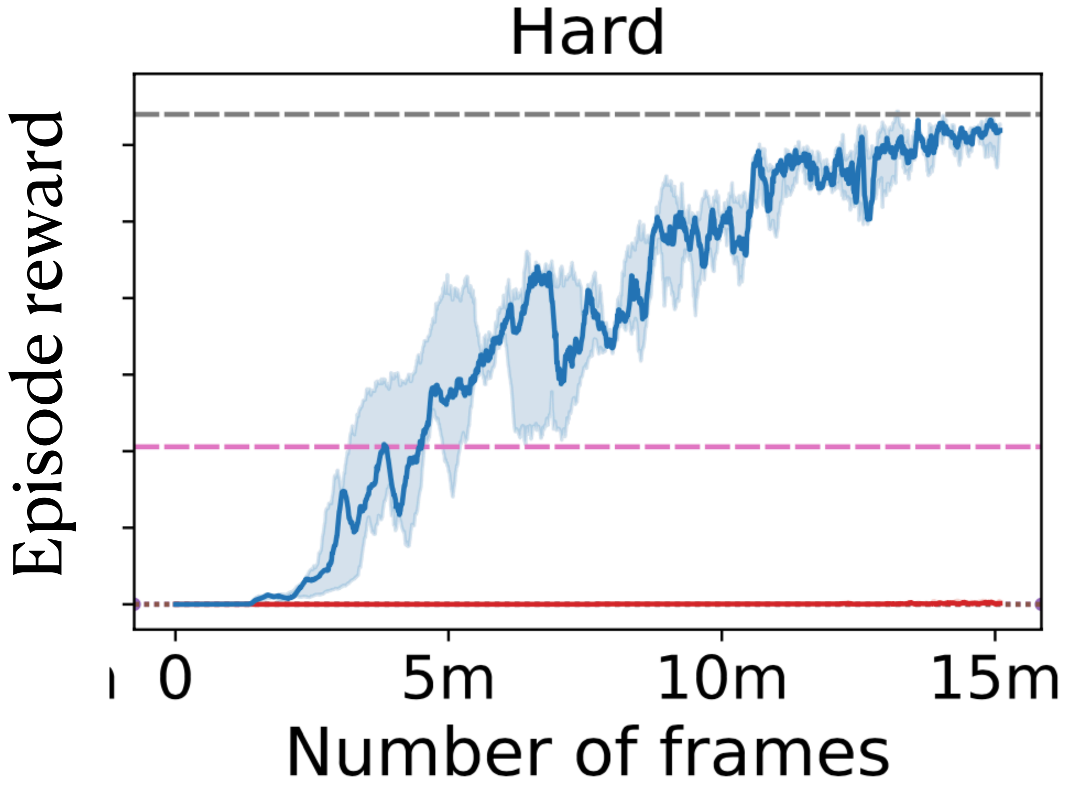


# Comparison to Pure Offline RL & Imitation Learning baselines



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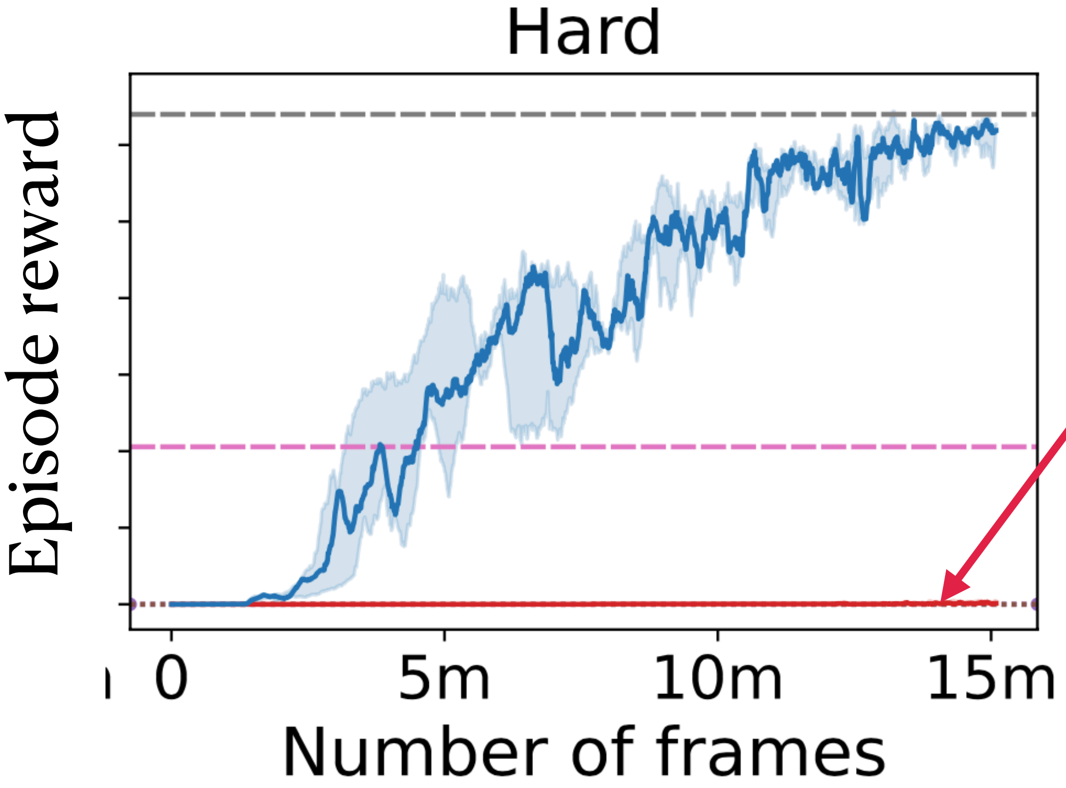



Offline RL (and imitation learning) baselines fail completely

# Further reading:

Hybrid RL: Using Both Offline and Online Data Can Make RL Efficient

Yuda Song[*] Yifei Zhou[†] Ayush Sekhari[‡] J. Andrew Bagnell[§] Akshay Krishnamurthy[¶] Wen Sun[‖]

March 14, 2023

https://arxiv.org/pdf/2210.06718

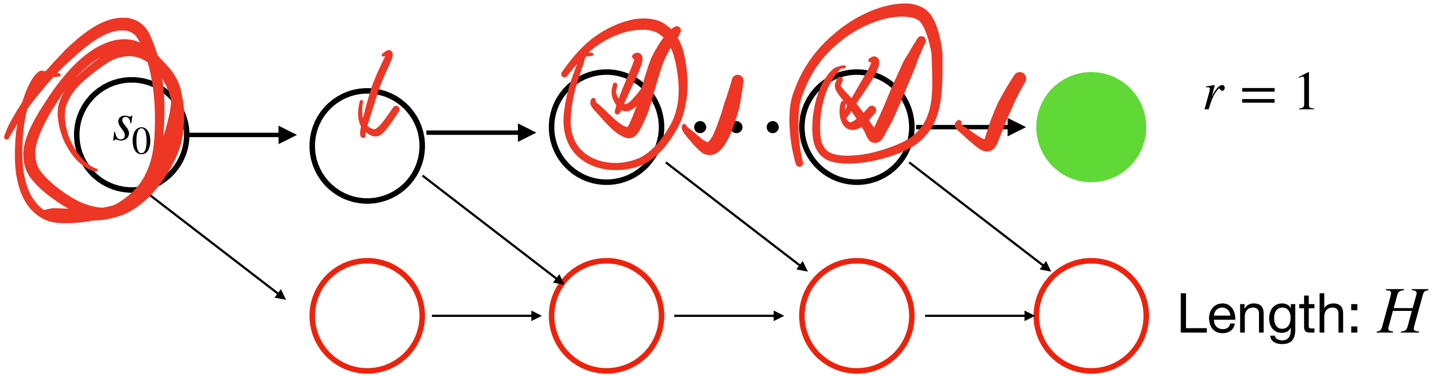
# Outline

1. Using offline data in the DQN framework

2. Using offline data in PG via Reset

The Combination Lock Example (i.e., the sparse reward problem)

Instead of always starting from the $s_0$, what if we can start **everywhere**?



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We again assume offline distribution "cover" some high quality policy's traces

$$\frac{d^{\pi^*}(s)}{\nu(s)} \le c < +\infty$$

# Taking advantage of offline data via reset

In high level, let's run PPO with $\nu$ (offline data) as the new initial state distribution

Initialize $\theta_0$ for the policy

$s_0 \sim \mu$

$\forall s \quad \frac{d^{q}(s)}{\nu(s)} < \infty$

For $t = 0 \rightarrow T$:

$\tau_1, \tau_2 \ldots \tau^{n}$

Run $\pi_\theta$ to collect multiple trajectories where **each traj's $s_0$ is randomly picked from $\mathscr{D}_{off}$**

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Construct the policy loss and the value loss using the trajectories

(GAE)

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Construct the policy loss and the value loss using the trajectories

Update policy and value loss with gradient descents

# Case study in post-training LLMs

# Modeling text generation as an RL / MDP problem

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LLM as a policy $\pi$: $\underbrace{\textbf{a sequence of tokens so far}}_{s}$ => $\underset{a}{\underline{\textbf{the next token}}}$ (i.e., action)

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prompt

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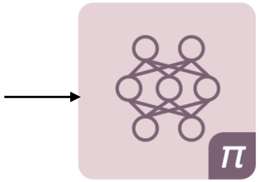

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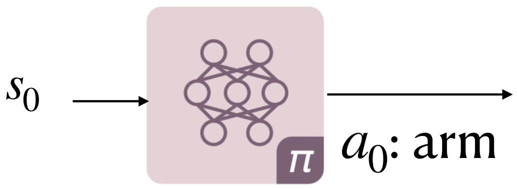

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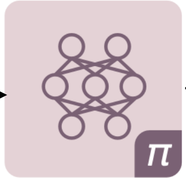
$s_0$ →




→ $s_1 = s_0 \oplus a_0$

$a_0$: arm

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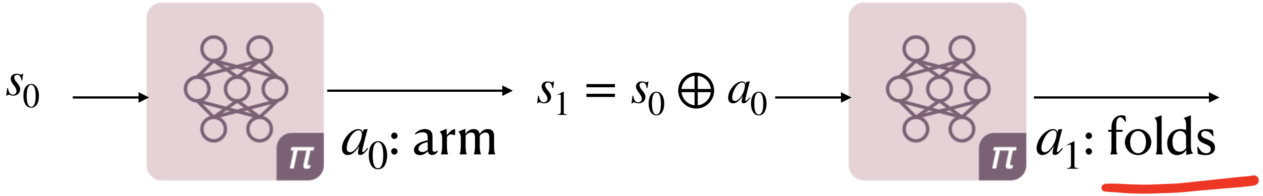

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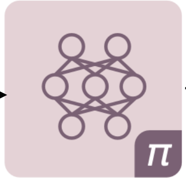
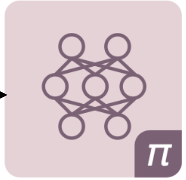
$s_0$ →


→ $a_0$: arm → $s_1 = s_0 \oplus a_0$ →


→ $a_1$: folds → $s_2 = s_1 \oplus a_1$

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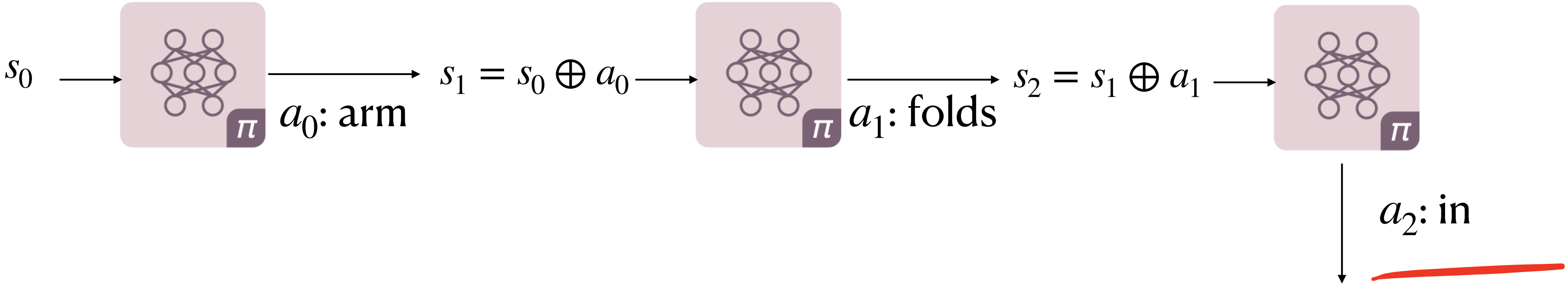

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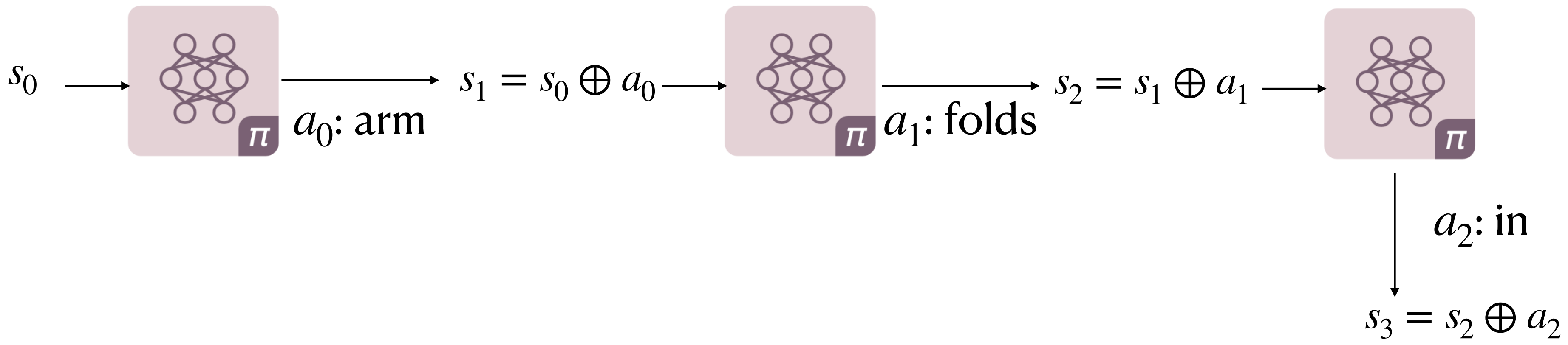

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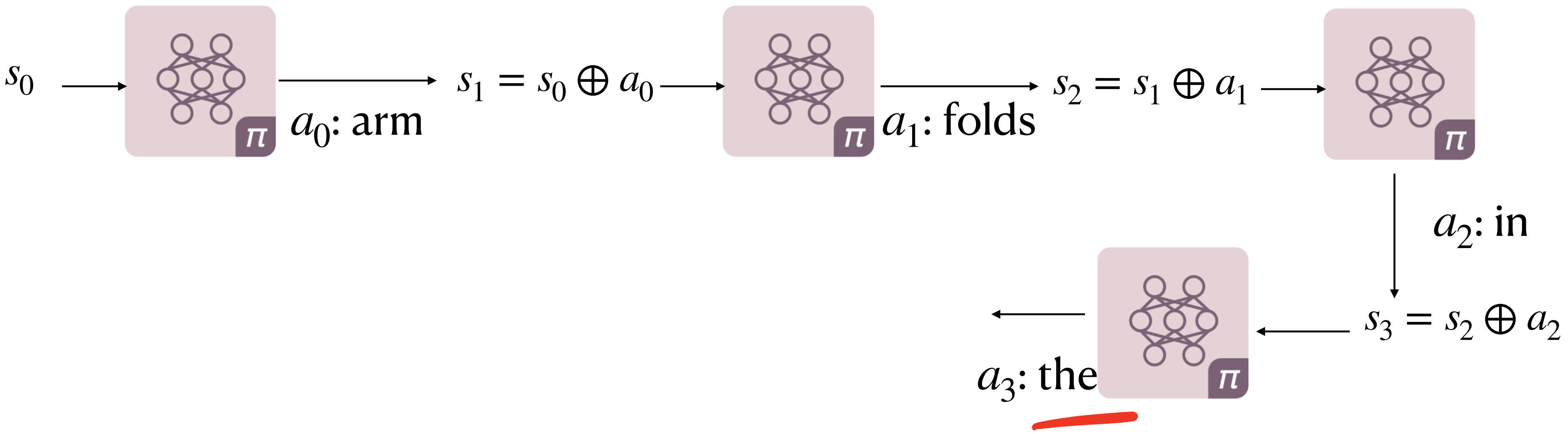

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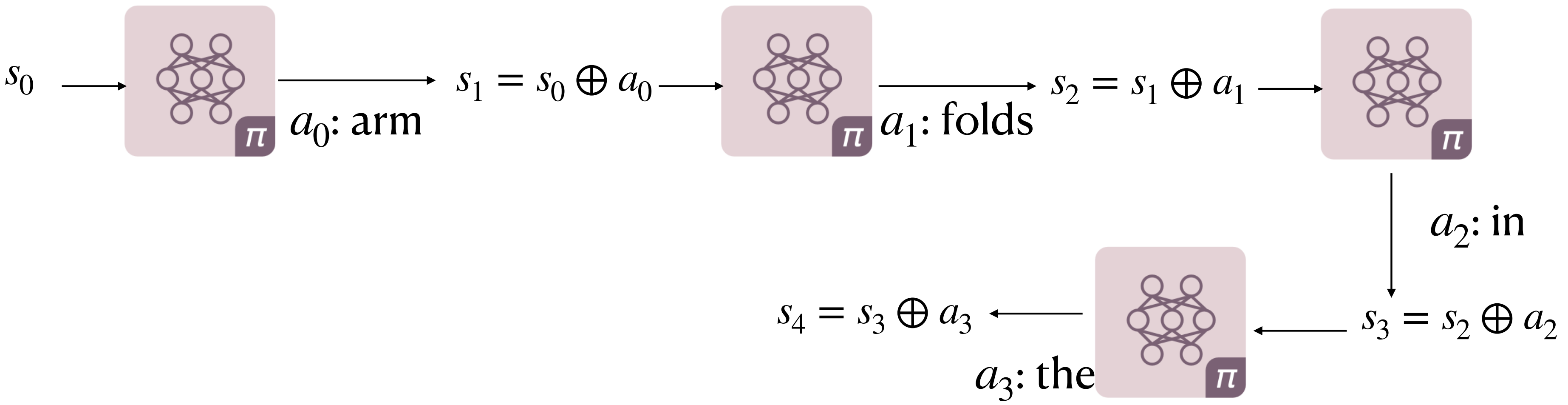

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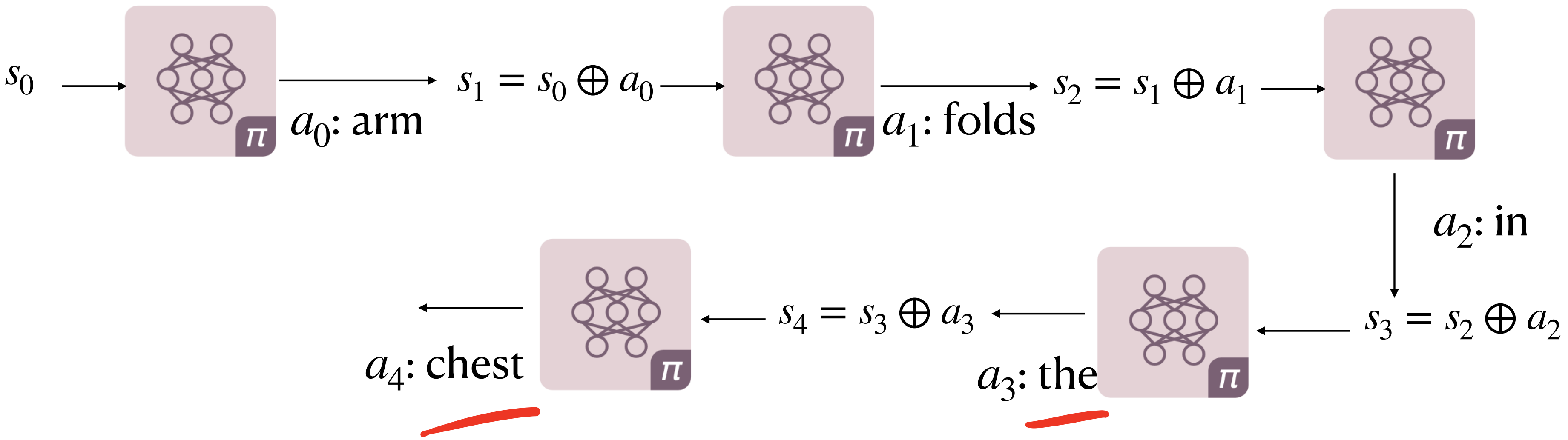

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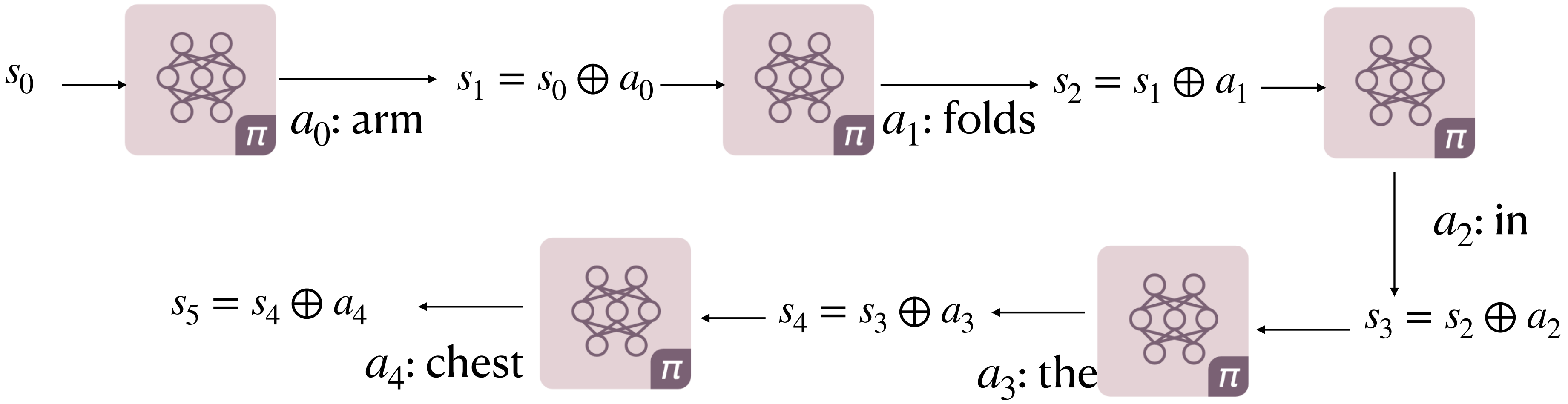

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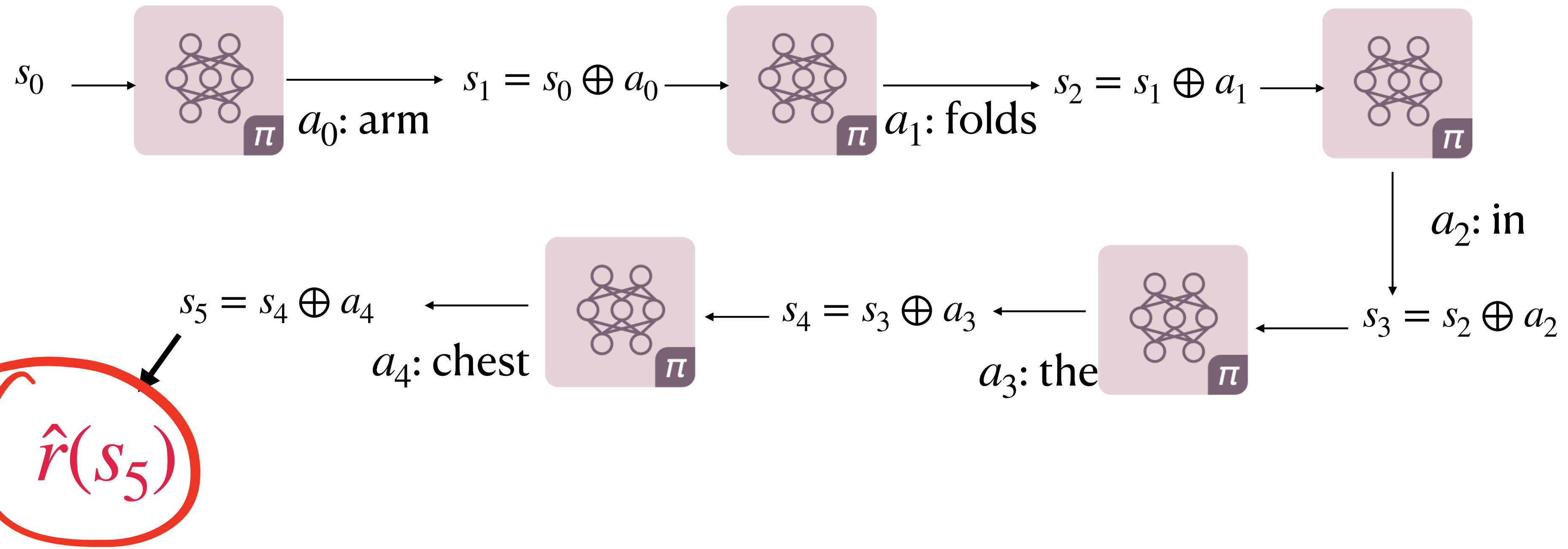

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*He folds his arms over his chest, then he folds his arms over.*

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Transformer

*He folds his arms over his chest, then he folds his arms over.*

$s_6$

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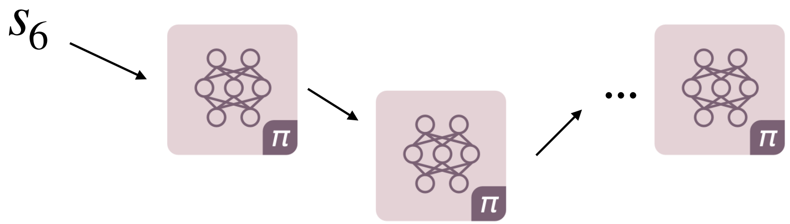

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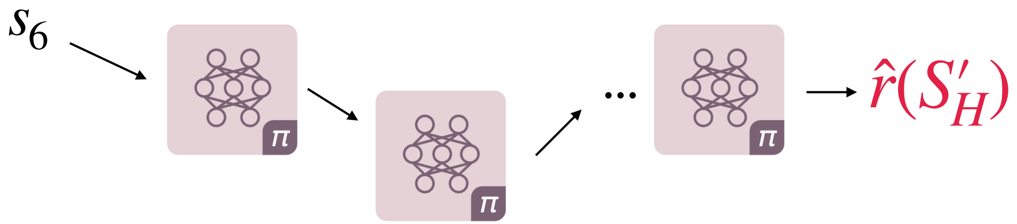

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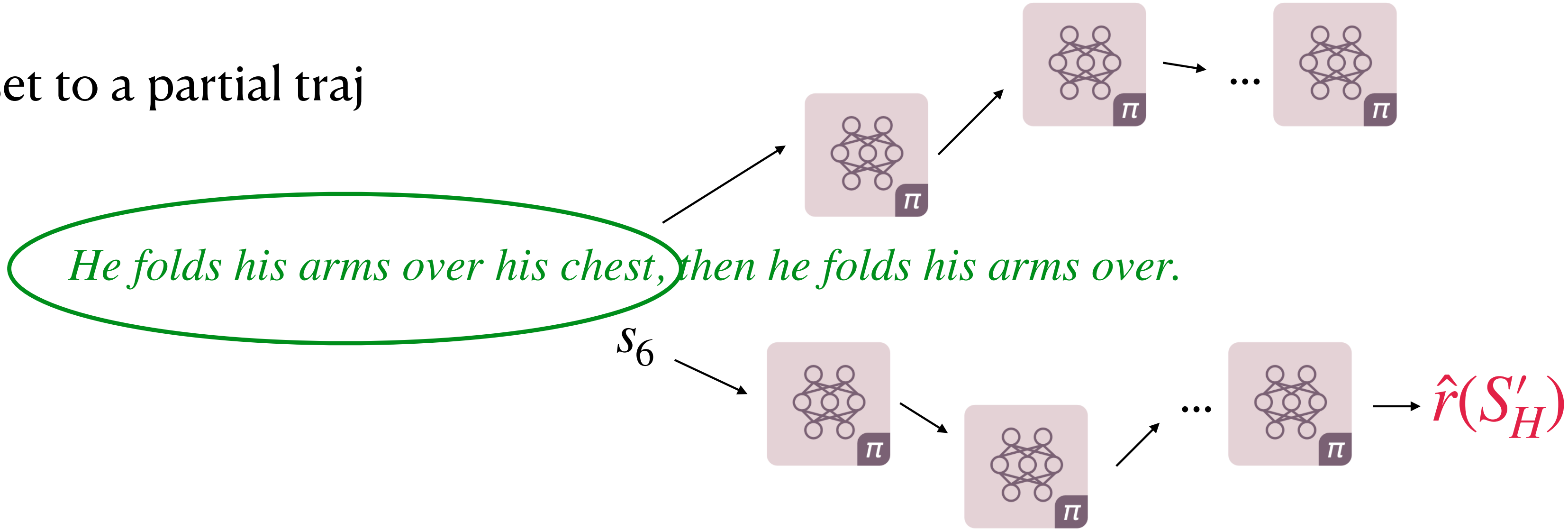

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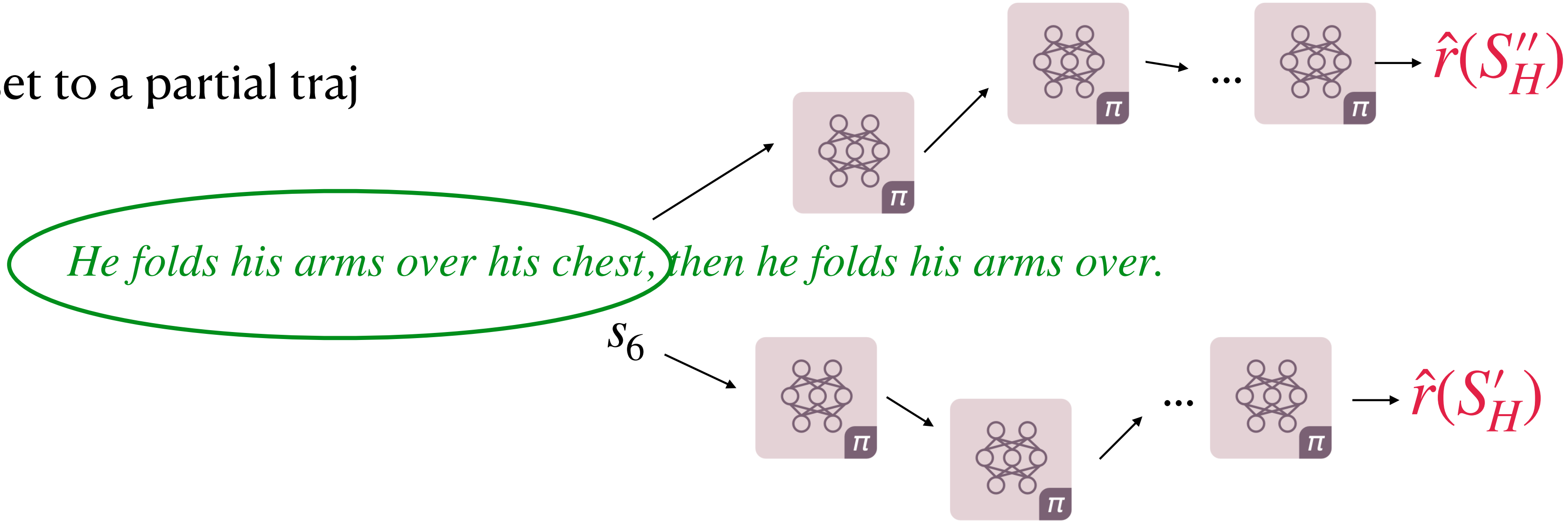

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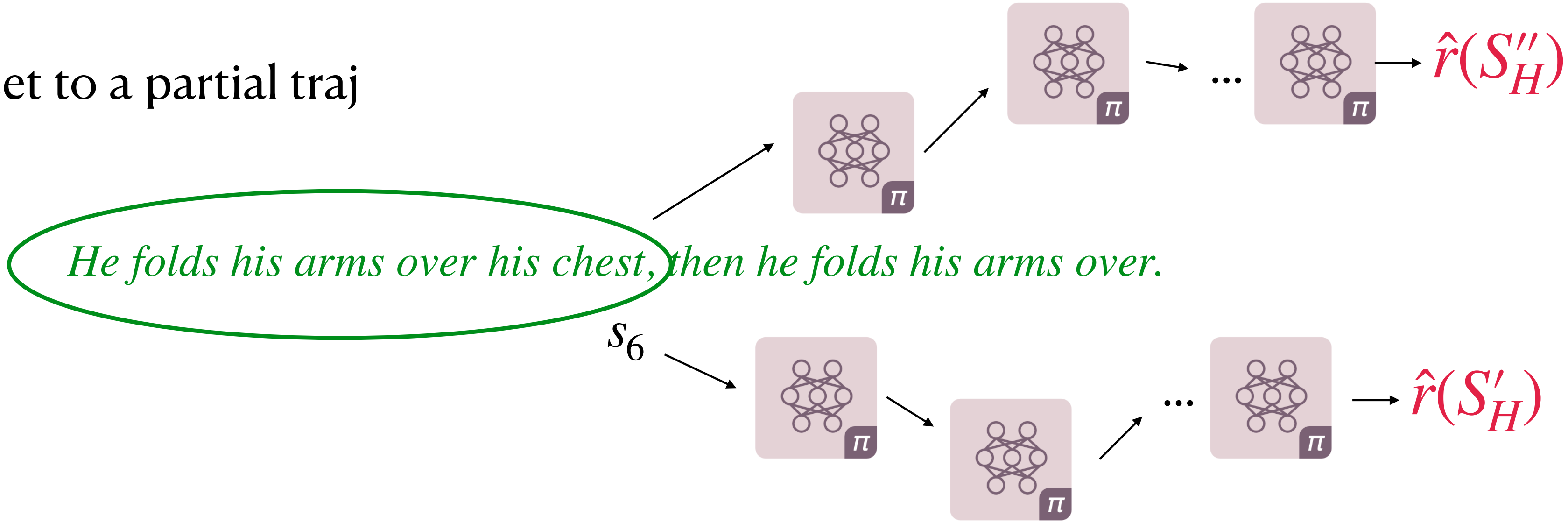


Reset is a game-changer in RL, both theory and practice (e.g., AlphaGo and MCTS)

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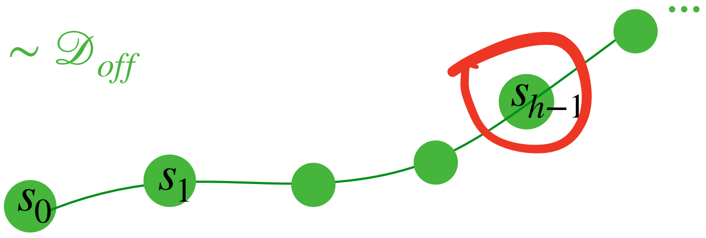

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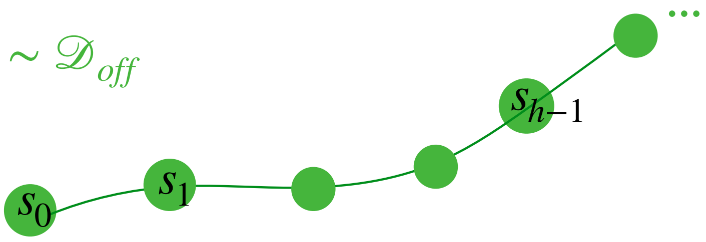


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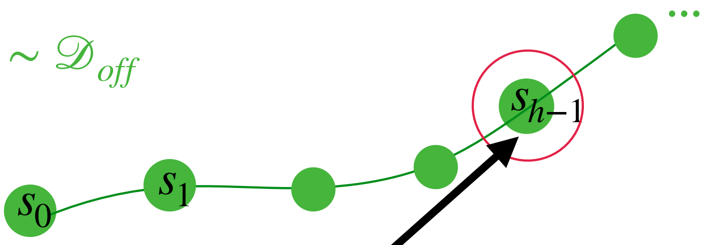


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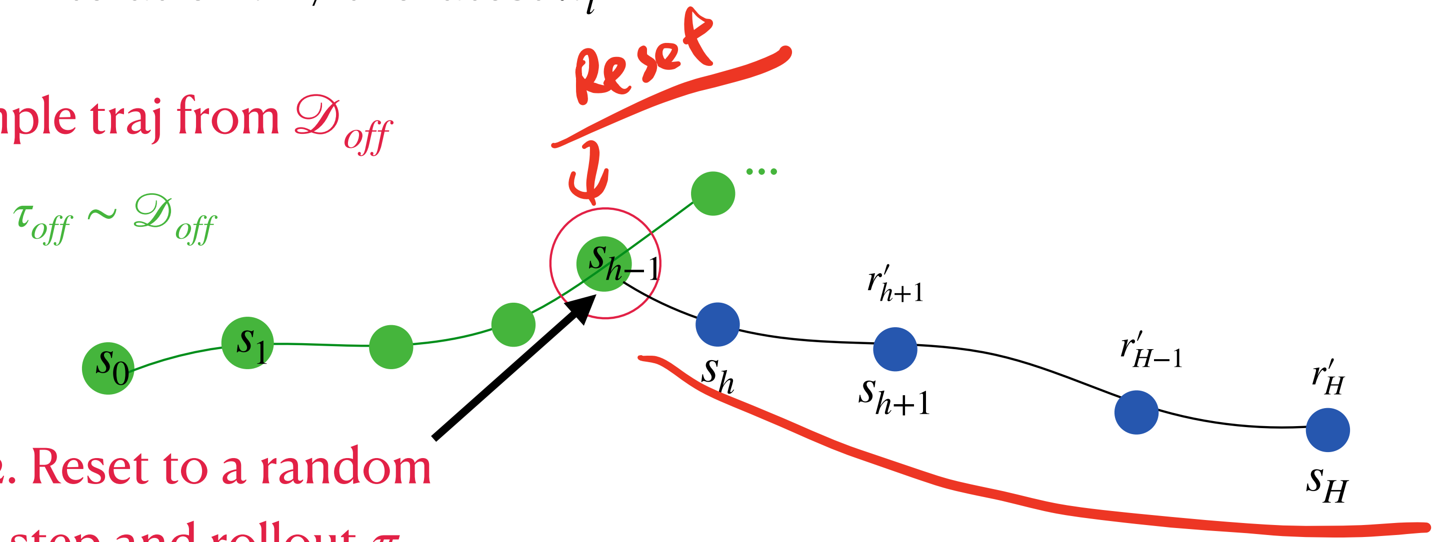


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Repeat this sampling process n times,

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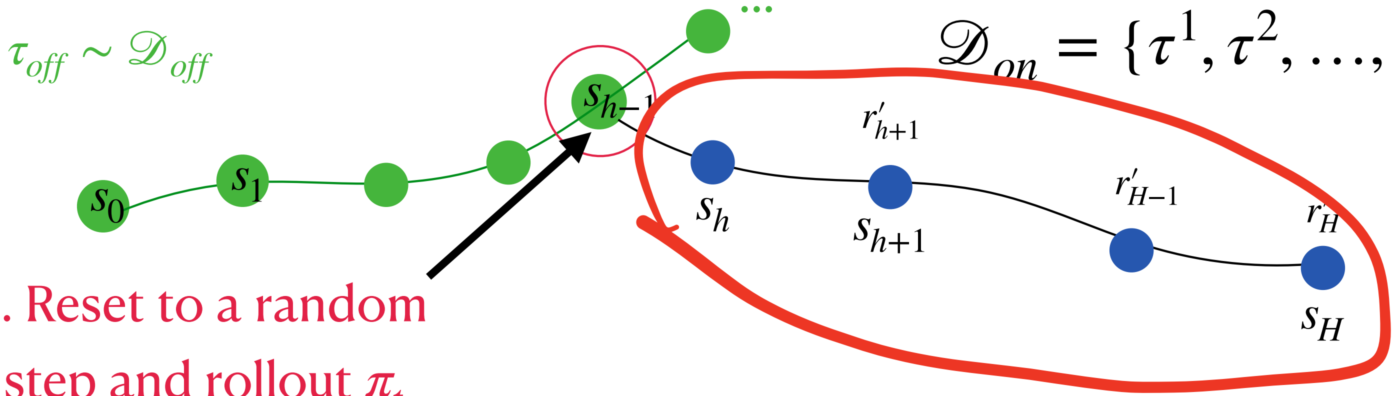


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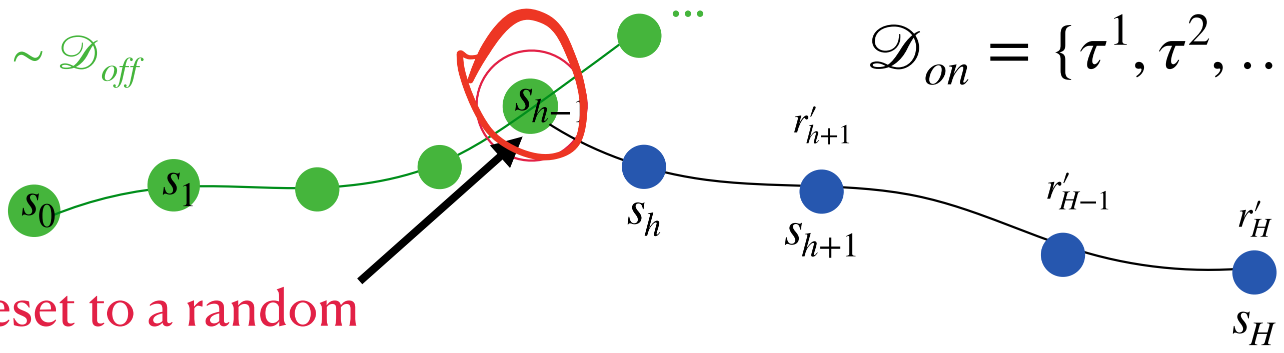


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3. Policy update using $\mathscr{D}_{on}$

$$\pi_{t+1} \Leftarrow \text{policy-update}(\mathscr{D}_{on}, \pi_t)$$

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PPO collects online data by always resetting to $s_0$

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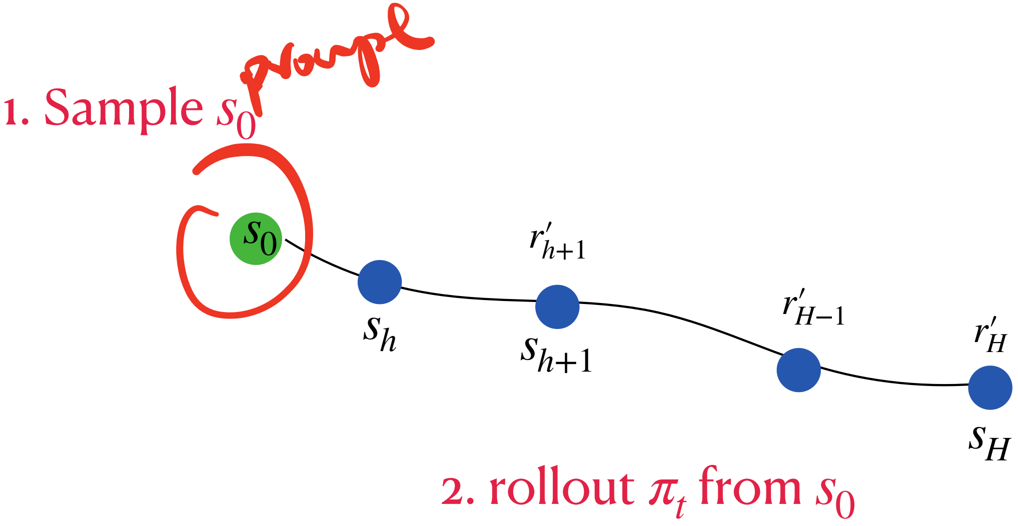

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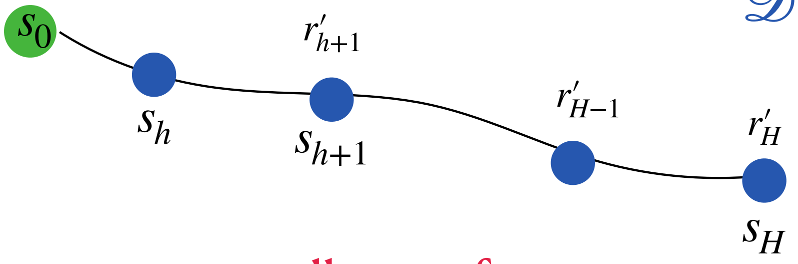


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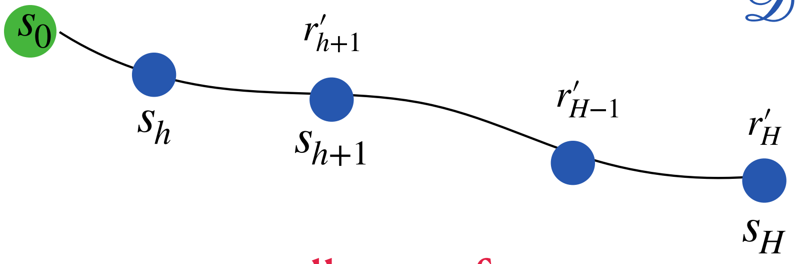


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# Task: TL;DR Summarization

## Task Statement

Given a reddit post, write a TL;DR (short summary).

[Stiennon et.al, 17]

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## Dataset Composition

Reset

- 210K Prompts total
  - 117K Prompts with *Human written summaries*
  - 93K Prompts with *Human Preference Labels*

$\hat{R}$

# Performance again human

(Policy: 7B Pythia model + RoLA)

| Algorithms | TL;DR Summarization | | | | | |
|---|---|---|---|---|---|---|
| | Win Rate (↑) | RM Score (↑) | $KL(\pi \| \| \pi_{ref})$ (↓) | Rouge 1 (↑) | Rouge 2 (↑) | RougeL (↑) |
| SFT | $31.6 \pm 0.2\%$ | $-0.51 \pm 0.04$ | - | $32.17 \pm 1.01$ | $12.27 \pm 0.67$ | $24.87 \pm 1.22$ |
| DPO | $52.6 \pm 0.4\%$ | - | $37.33 \pm 2.01$ | $30.03 \pm 3.23$ | $7.93 \pm 1.02$ | $22.05 \pm 0.83$ |
| PPO | $62.3 \pm 2.5\%$ | $1.17 \pm 0.13$ | $\mathbf{16.32 \pm 1.46}$ | $\mathbf{33.73 \pm 2.34}$ | $\mathbf{11.97 \pm 0.91}$ | $24.97 \pm 1.03$ |
| DR-PO | $\mathbf{70.2 \pm 1.7\%}$ | $\mathbf{1.52 \pm 0.09}$ | $16.84 \pm 0.83$ | $33.68 \pm 1.78$ | $11.90 \pm 0.06$ | $\mathbf{25.12 \pm 0.76}$ |

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Message: DR-PO outperforms PPO *at no extra cost of computation or memory*

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| `DPO` | 6.0% | 20.71 | 9.47 | 15.70 |
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Message 1: DR-PO > PPO

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Zero-shot transfer: evaluate trained models directly on CNN Daily mail news articles

Message 2: DR-PO's zero-shot > supervised learning model trained on CNN DM

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Message 1: DR-PO > PPO

# Further reading:

## Dataset Reset Policy Optimization for RLHF


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https://arxiv.org/abs/2404.08495

# Summary

1. Offline data can boost RL performance

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2. Two approaches for taking advantage of offline data:

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2. Two approaches for taking advantage of offline data:

- Mixing offline data into a replay buffer (e.g., Hybird Q-learning)
- Resetting to the offline data in policy optimization (e.g., DR-PO)