



UNIVERSITY OF TECHNOLOGY  
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# Deep Reinforcement Learning

Maximum Entropy RL

Julien Vitay

Professur für Künstliche Intelligenz - Fakultät für Informatik

# 1 - Maximum Entropy RL

# Hard RL

- All methods seen so far search the optimal policy that maximizes the return:

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_t \gamma^t r(s_t, a_t, s_{t+1}) \right]$$

- The optimal policy is deterministic and greedy by definition.

$$\pi^*(s) = \arg \max_a Q^*(s, a)$$

- Exploration is ensured externally by :
  - applying  $\epsilon$ -greedy or softmax on the Q-values (DQN),
  - adding exploratory noise (DDPG),
  - learning stochastic policies that become deterministic over time (A3C, PPO).
- Is “hard” RL, caring only about **exploitation**, always the best option?

## Need for soft RL

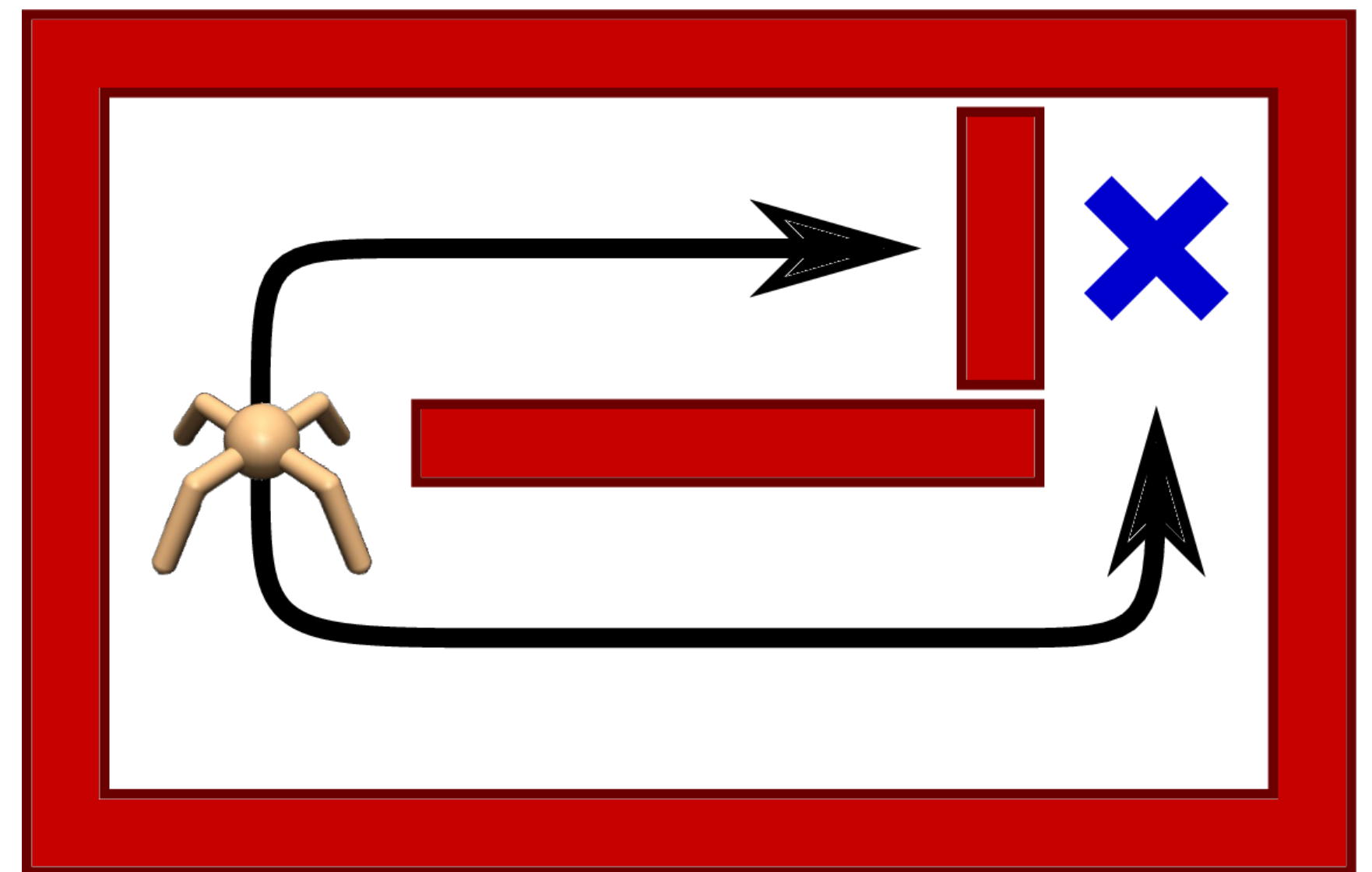
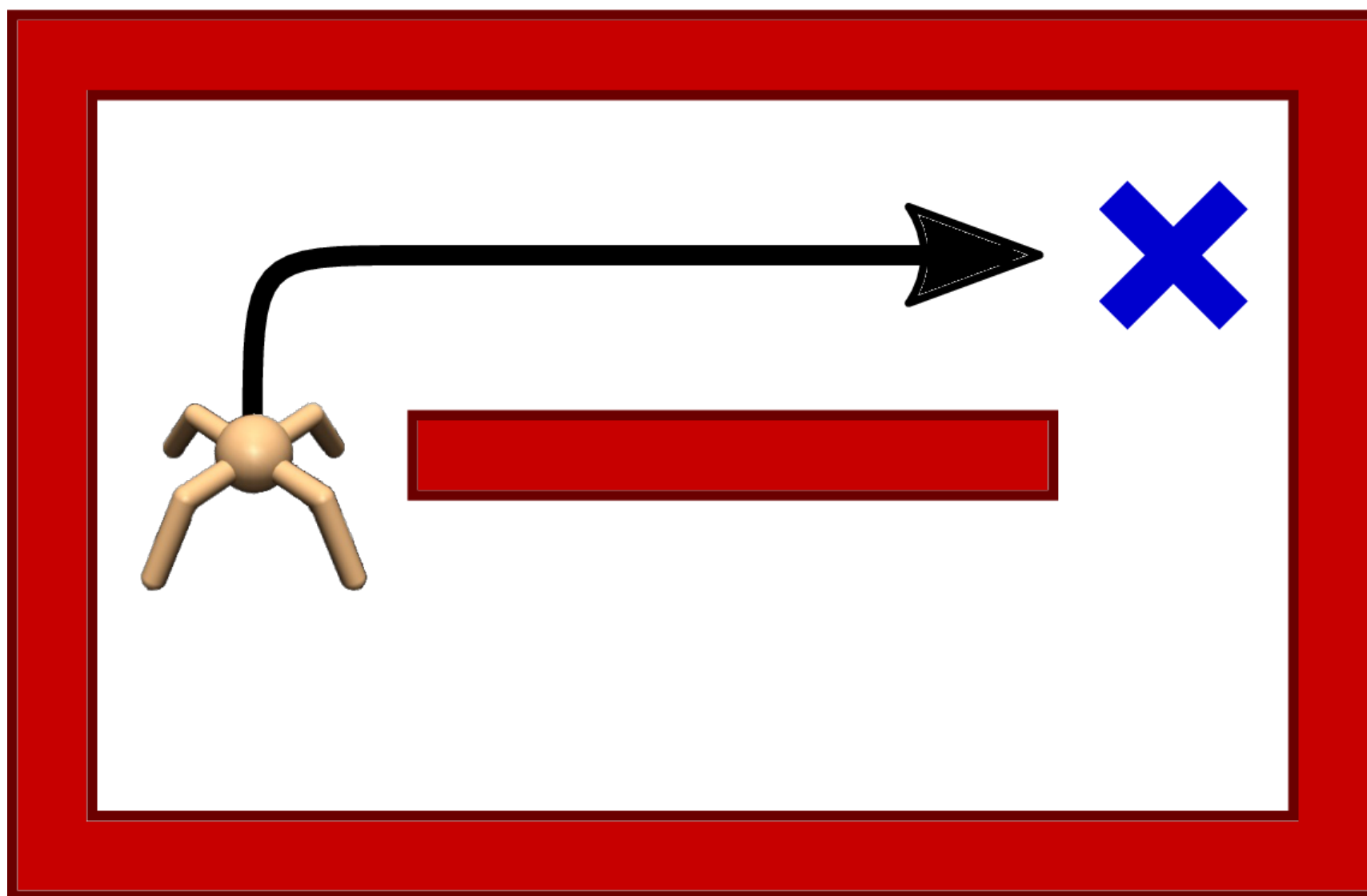


Source: <https://www.chess.com/article/view/announcing-the-chess-com-gif-maker>

- The optimal policy is only greedy for a MDP, not obligatorily for a POMDP.
- Games like chess are POMDPs: you do not know what your opponent is going to play (missing information).
- If you always play the same moves (e.g. opening moves), your opponent will adapt and you will end up losing systematically.
- **Variety** in playing is beneficial in POMDPs: it can counteract the uncertainty about the environment.

## Need for soft RL

- There are sometimes more than one way to collect rewards, especially with sparse rewards.
- If exploration decreases too soon, the RL agent will “overfit” one of the paths.
- If one of the paths is suddenly blocked, the agent would have to completely re-learn its policy.
- It would be more efficient if the agent had learned all possible paths, even if some of them are less optimal.



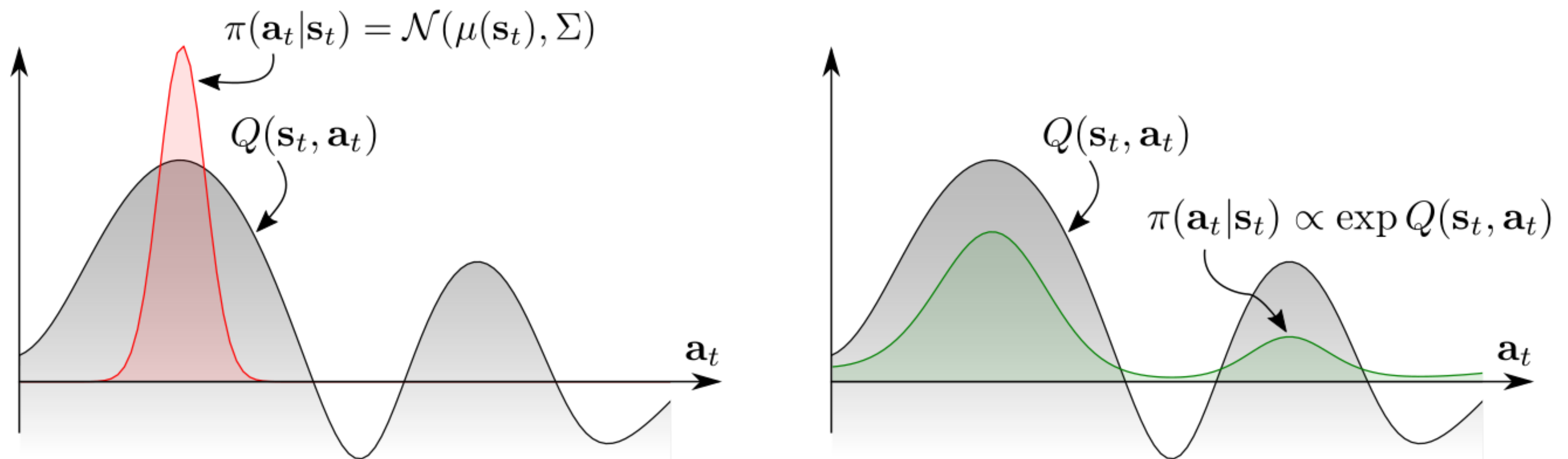
Source: <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/>

# Soft policies

- Softmax policies allow to learn **multimodal** policies, but only for discrete action spaces.

$$\pi(s, a) = \frac{\exp Q(s, a)/\tau}{\sum_b \exp Q(s, b)/\tau}$$

- Continuous Gaussian policies are still **unimodal policies**: they mostly sample actions around the mean  $\mu_\theta(s)$  and the variance  $\sigma_\theta(s)$  decreases to 0 with learning.
- If we want a multimodal policy that learns different solutions, we need to learn a **Softmax** distribution (Gibbs / Boltzmann) over the continuous action space.



Source: <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/>

# Maximum Entropy RL

- A solution to force the policy to be **multimodal** is to force it to be as stochastic as possible by **maximizing its entropy**.
- Instead of searching for the policy that “only” maximizes the returns:

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_t \gamma^t r(s_t, a_t, s_{t+1}) \right]$$

we search for the policy that maximizes the returns while being as stochastic as possible:

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[ \sum_t \gamma^t r(s_t, a_t, s_{t+1}) + \alpha H(\pi(s_t)) \right]$$

- This new objective function defines the **maximum entropy RL** framework.
- The entropy of the policy **regularizes** the objective function: the policy should still maximize the returns, but stay as stochastic as possible depending on the parameter  $\alpha$ .
- Entropy regularization can always be added to PG methods such as A3C.
- It is always possible to fall back to hard RL by setting  $\alpha$  to 0.

# Entropy of a policy

- The entropy of a policy in a state  $s_t$  is defined by the expected negative log-likelihood of the policy:

$$H(\pi_\theta(s_t)) = \mathbb{E}_{a \sim \pi_\theta(s_t)} [-\log \pi_\theta(s_t, a)]$$

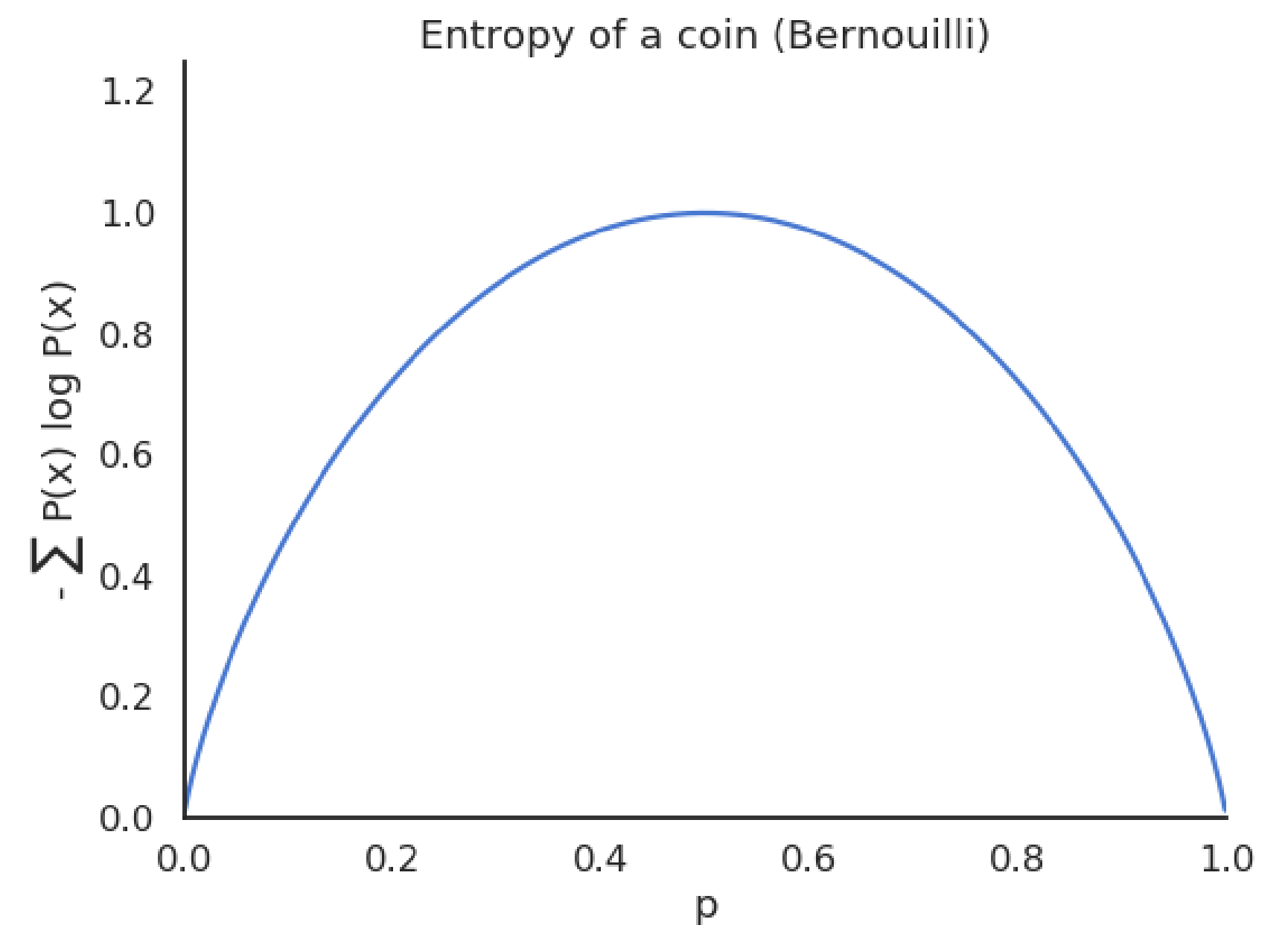
- For a discrete action space:

$$H(\pi_\theta(s_t)) = - \sum_a \pi_\theta(s_t, a) \log \pi_\theta(s_t, a)$$

- For a continuous action space:

$$H(\pi_\theta(s_t)) = - \int_a \pi_\theta(s_t, a) \log \pi_\theta(s_t, a) da$$

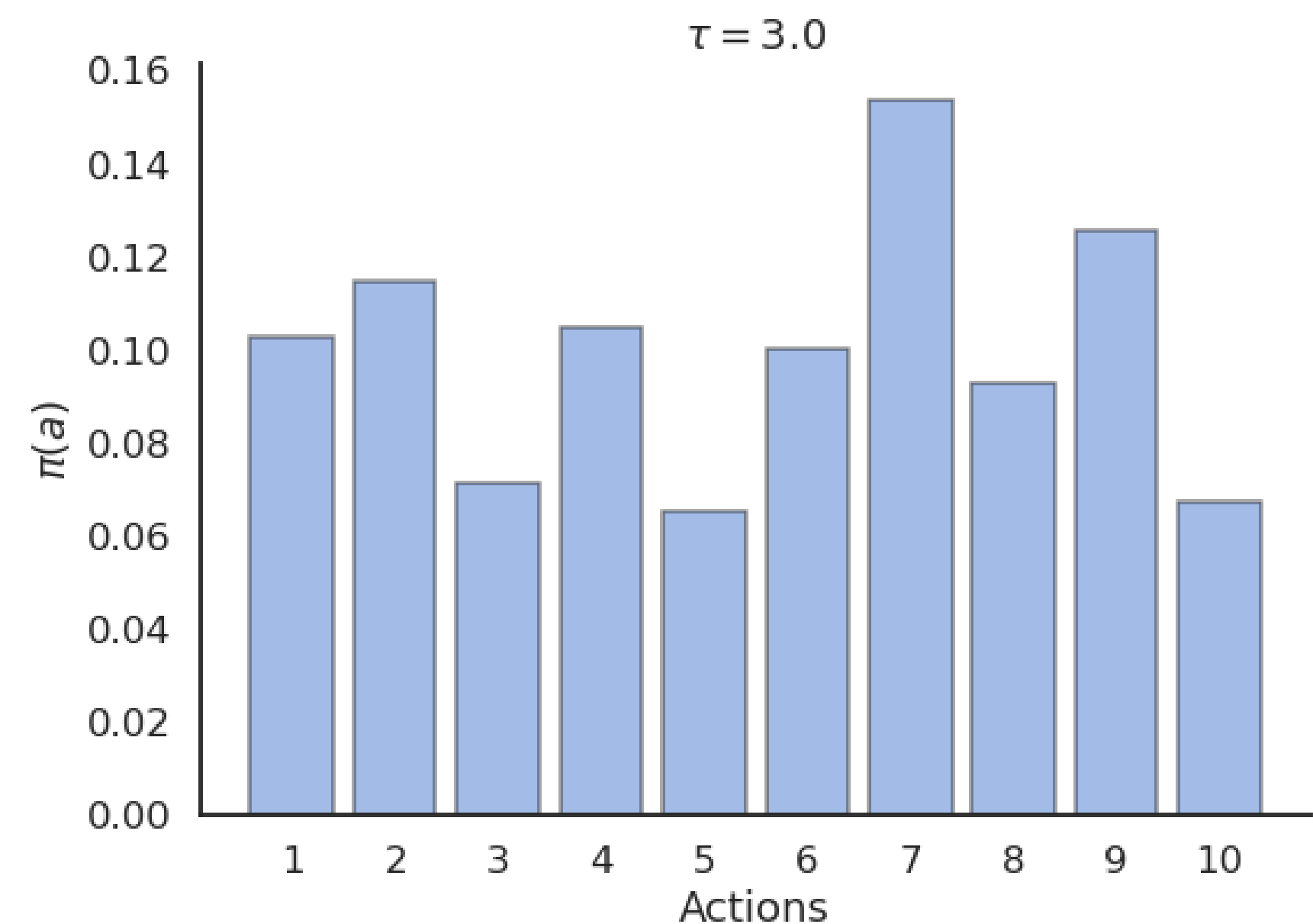
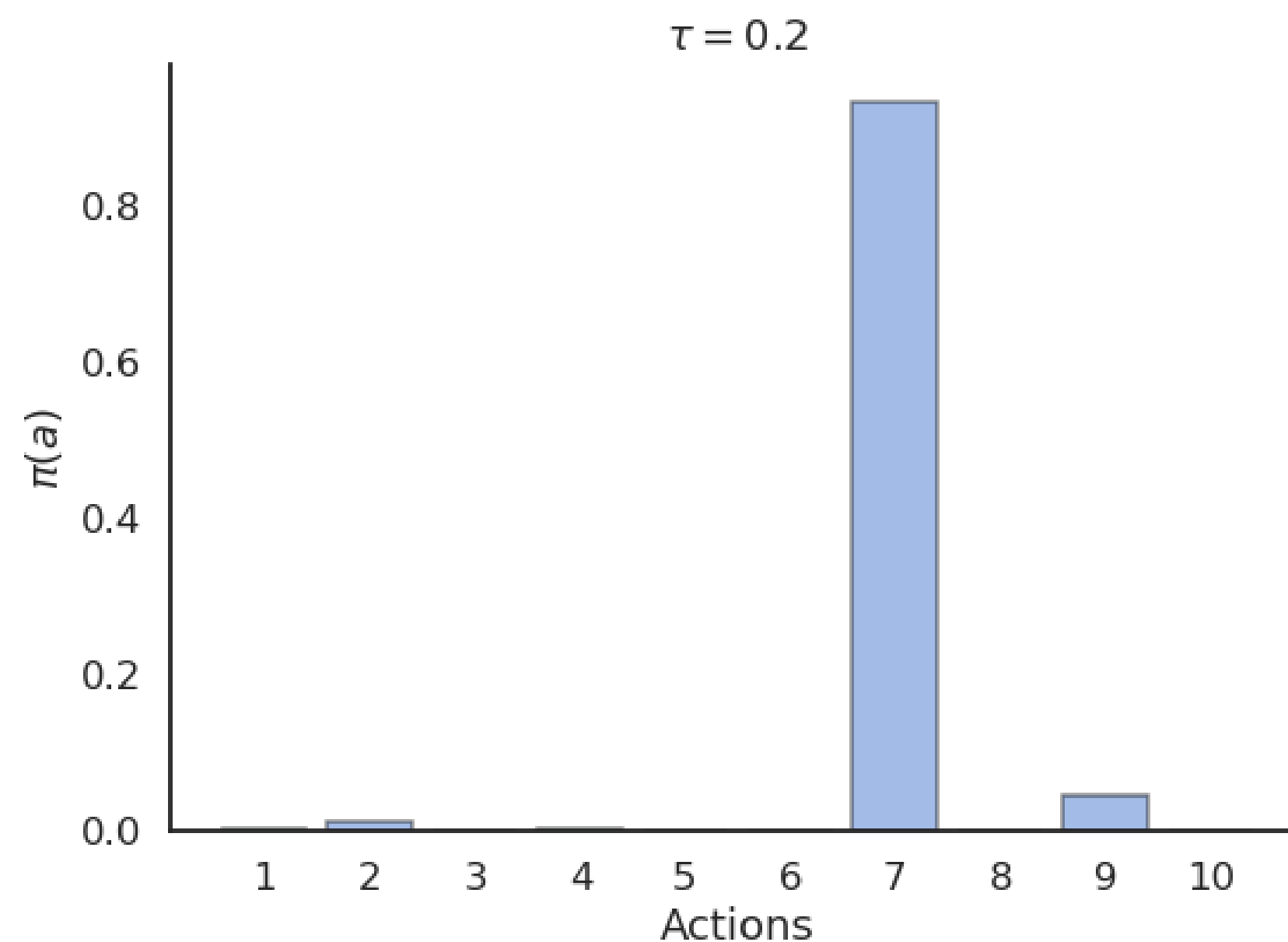
- The entropy necessitates to sum or integrate the **self-information** of each possible action in a given state.





# Entropy of a policy

- A **deterministic** (greedy) policy has zero entropy, the same action is always taken: **exploitation**.
- A **random** policy has a high entropy, you cannot predict which action will be taken: **exploration**.



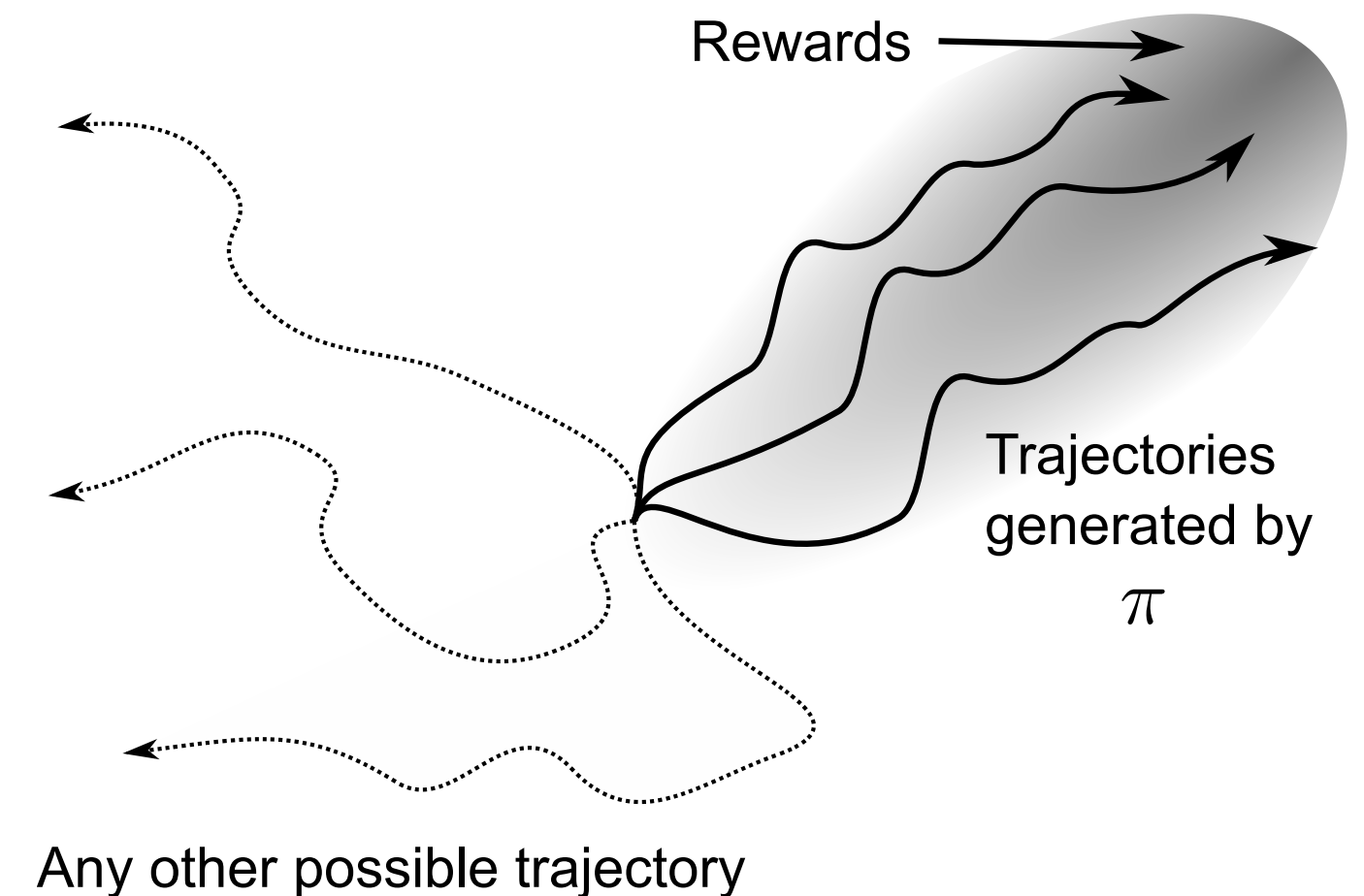
- Maximum entropy RL embeds the exploration-exploitation trade-off inside the objective function instead of relying on external mechanisms such as the softmax temperature.

# Soft Q-learning

- In **soft Q-learning**, the objective function is defined over complete trajectories:

$$\mathcal{J}(\theta) = \sum_t \gamma^t \mathbb{E}_{\pi} [r(s_t, a_t, s_{t+1}) + \alpha H(\pi(s_t))]$$

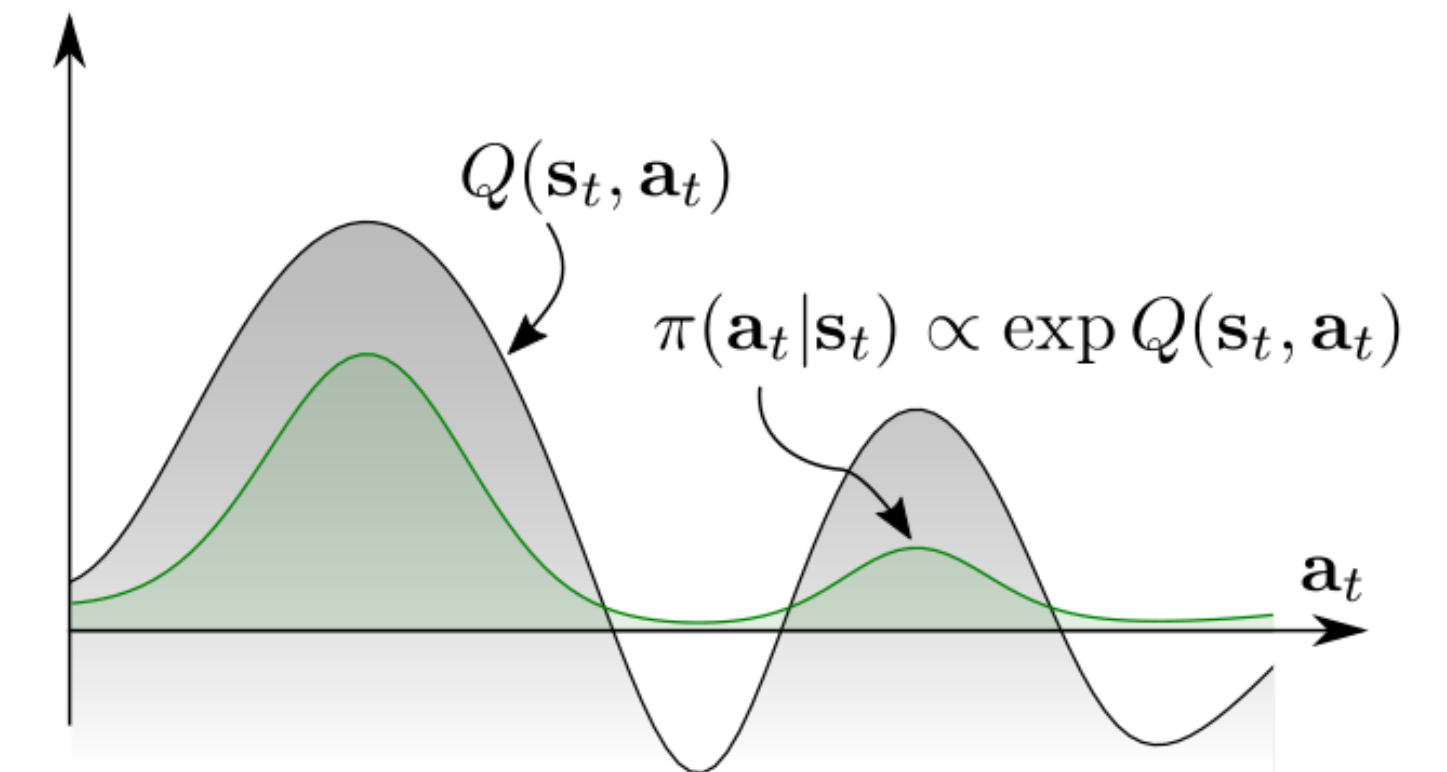
- The goal of the agent is to generate trajectories associated with a lot of rewards (high return) but only visiting states with a high entropy, i.e. where the policy is random (exploration).
- The agent can decide how the trade-off is solved via regularization:
  - If a single action leads to high rewards, the policy may become deterministic.
  - If several actions lead to equivalent rewards, the policy must stay stochastic.



# Soft Q-learning

- In soft Q-learning, the policy is implemented as a softmax over **soft Q-values**:

$$\pi_{\theta}(s, a) = \frac{\exp \frac{Q_{\theta}^{\text{soft}}(s, a)}{\alpha}}{\sum_b \exp \frac{Q_{\theta}^{\text{soft}}(s, b)}{\alpha}} \propto \exp \frac{Q_{\theta}^{\text{soft}}(s, a)}{\alpha}$$



- $\alpha$  plays the role of the softmax temperature parameter  $\tau$ .

Source: <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/>

- Soft Q-learning belongs to **energy-based models**, as  $-\frac{Q_{\theta}^{\text{soft}}(s, a)}{\alpha}$  represents the energy of the Boltzmann distribution (see restricted Boltzmann machines).
- The **partition function**  $\sum_b \exp \frac{Q_{\theta}^{\text{soft}}(s, b)}{\alpha}$  is untractable for continuous action spaces, as one would need to integrate over the whole action space, but it will disappear from the equations anyway.

# What are soft values?

- Soft V and Q values are the equivalent of the hard value functions, but for the new objective:

$$\mathcal{J}(\theta) = \sum_t \gamma^t \mathbb{E}_\pi [r(s_t, a_t, s_{t+1}) + \alpha H(\pi(s_t))]$$

- The soft value of an action depends on the immediate reward and the soft value of the next state (soft Bellman equation):

$$Q_\theta^{\text{soft}}(s_t, a_t) = \mathbb{E}_{s_{t+1} \in \rho_\theta} [r(s_t, a_t, s_{t+1}) + \gamma V_\theta^{\text{soft}}(s_{t+1})]$$

- The soft value of a state is the expected value over the available actions plus the entropy of the policy.

$$V_\theta^{\text{soft}}(s_t) = \mathbb{E}_{a_t \in \pi} [Q_\theta^{\text{soft}}(s_t, a_t)] + H(\pi_\theta(s_t)) = \mathbb{E}_{a_t \in \pi} [Q_\theta^{\text{soft}}(s_t, a_t) - \log \pi_\theta(s_t, a_t)]$$

- Haarnoja et al (2017) showed that these soft value functions are the solution of the entropy-regularized objective function.
- All we need is to be able to estimate them... Soft Q-learning uses complex optimization methods (variational inference) to do it, but SAC is more practical.

## 2 - Soft Actor-Critic (SAC)

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# Soft Actor-Critic Algorithms and Applications

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**Tuomas Haarnoja<sup>\*†‡</sup>**   **Aurick Zhou<sup>\*†</sup>**   **Kristian Hartikainen<sup>\*†</sup>**   **George Tucker<sup>‡</sup>**  
**Sehoon Ha<sup>‡</sup>**   **Jie Tan<sup>‡</sup>**   **Vikash Kumar<sup>‡</sup>**   **Henry Zhu<sup>†</sup>**   **Abhishek Gupta<sup>†</sup>**  
**Pieter Abbeel<sup>†</sup>**   **Sergey Levine<sup>†‡</sup>**

# Soft Actor-Critic (SAC)

- Putting these equations together:

$$Q_{\theta}^{\text{soft}}(s_t, a_t) = \mathbb{E}_{s_{t+1} \in \rho_{\theta}} [r(s_t, a_t, s_{t+1}) + \gamma V_{\theta}^{\text{soft}}(s_{t+1})]$$

$$V_{\theta}^{\text{soft}}(s_t) = \mathbb{E}_{a_t \in \pi} [Q_{\theta}^{\text{soft}}(s_t, a_t) - \log \pi_{\theta}(s_t, a_t)]$$

we obtain:

$$Q_{\theta}^{\text{soft}}(s_t, a_t) = \mathbb{E}_{s_{t+1} \in \rho_{\theta}} [r(s_t, a_t, s_{t+1}) + \gamma \mathbb{E}_{a_{t+1} \in \pi} [Q_{\theta}^{\text{soft}}(s_{t+1}, a_{t+1}) - \log \pi_{\theta}(s_{t+1}, a_{t+1})]]$$

- If we want to train a **critic**  $Q_{\varphi}(s, a)$  to estimate the true soft Q-value of an action  $Q_{\theta}^{\text{soft}}(s, a)$ , we just need to sample  $(s_t, a_t, r_{t+1}, a_{t+1})$  transitions and minimize:

$$\mathcal{L}(\varphi) = \mathbb{E}_{s_t, a_t, s_{t+1} \sim \rho_{\theta}} [(r_{t+1} + \gamma Q_{\varphi}(s_{t+1}, a_{t+1}) - \log \pi_{\theta}(s_{t+1}, a_{t+1}) - Q_{\varphi}(s_t, a_t))^2]$$

- The only difference with a SARSA critic is that the negative log-likelihood of the next action is added to the target.
- In practice,  $s_t$ ,  $a_t$  and  $r_{t+1}$  can come from a replay buffer, but  $a_{t+1}$  has to be sampled from the current policy  $\pi_{\theta}$  (but not taken!).
- SAC is therefore an **off-policy actor-critic algorithm**, but with stochastic policies!

## Soft Actor-Critic (SAC)

- But how do we train the actor? The policy is defined by a softmax over the soft Q-values, but the log-partition  $Z$  is untractable for continuous spaces:

$$\pi_{\theta}(s, a) = \frac{\exp \frac{Q_{\varphi}(s, a)}{\alpha}}{\sum_b \exp \frac{Q_{\varphi}(s, b)}{\alpha}} = \frac{1}{Z} \exp \frac{Q_{\varphi}(s, a)}{\alpha}$$

- The trick is to make the **parameterized actor**  $\pi_{\theta}$  learn to be close from this softmax, by minimizing the KL divergence:

$$\mathcal{L}(\theta) = D_{\text{KL}}(\pi_{\theta}(s, a) || \frac{1}{Z} \exp \frac{Q_{\varphi}(s, a)}{\alpha}) = \mathbb{E}_{s, a \sim \pi_{\theta}(s, a)} \left[ -\log \frac{\frac{1}{Z} \exp \frac{Q_{\varphi}(s, a)}{\alpha}}{\pi_{\theta}(s, a)} \right]$$

- As  $Z$  does not depend on  $\theta$ , it will automatically disappear when taking the gradient!

$$\nabla_{\theta} \mathcal{L}(\theta) = \mathbb{E}_{s, a} [\alpha \nabla_{\theta} \log \pi_{\theta}(s, a) - Q_{\varphi}(s, a)]$$

- So the actor just has to implement a Gaussian policy and we can train it using soft-Q-value.



## Soft Actor-Critic (SAC)

- **Soft Actor-Critic (SAC)** is an **off-policy actor-critic** architecture for **maximum entropy RL**:

$$\mathcal{J}(\theta) = \sum_t \gamma^t \mathbb{E}_{\pi} [r(s_t, a_t, s_{t+1}) + \alpha H(\pi(s_t))]$$

- Maximizing the entropy of the policy ensures an efficient exploration. It is even possible to learn the value of the parameter  $\alpha$ .
- The critic learns to estimate soft Q-values that take the entropy of the policy into account:

$$\mathcal{L}(\varphi) = \mathbb{E}_{s_t, a_t, s_{t+1} \sim \rho_{\theta}} [(r_{t+1} + \gamma Q_{\varphi}(s_{t+1}, a_{t+1}) - \log \pi_{\theta}(s_{t+1}, a_{t+1}) - Q_{\varphi}(s_t, a_t))^2]$$

- The actor learns a Gaussian policy that becomes close to a softmax over the soft Q-values:

$$\pi_{\theta}(s, a) \propto \exp \frac{Q_{\varphi}(s, a)}{\alpha}$$

$$\nabla_{\theta} \mathcal{L}(\theta) = \mathbb{E}_{s, a} [\alpha \nabla_{\theta} \log \pi_{\theta}(s, a) - Q_{\varphi}(s, a)]$$



## SAC vs. TD3

- In practice, SAC uses **clipped double learning** like TD3: it takes the lesser of two evils between two critics  $Q_{\varphi_1}$  and  $Q_{\varphi_2}$ .
- The next action  $a_{t+1}$  comes from the current policy, no need for target networks.
- Unlike TD3, the learned policy is **stochastic**: no need for target noise as the targets are already stochastic.
- See <https://spinningup.openai.com/en/latest/algorithms/sac.html> for a detailed comparison of SAC and TD3.
- The initial version of SAV additionally learned a soft V-value critic, but this turns out not to be needed.

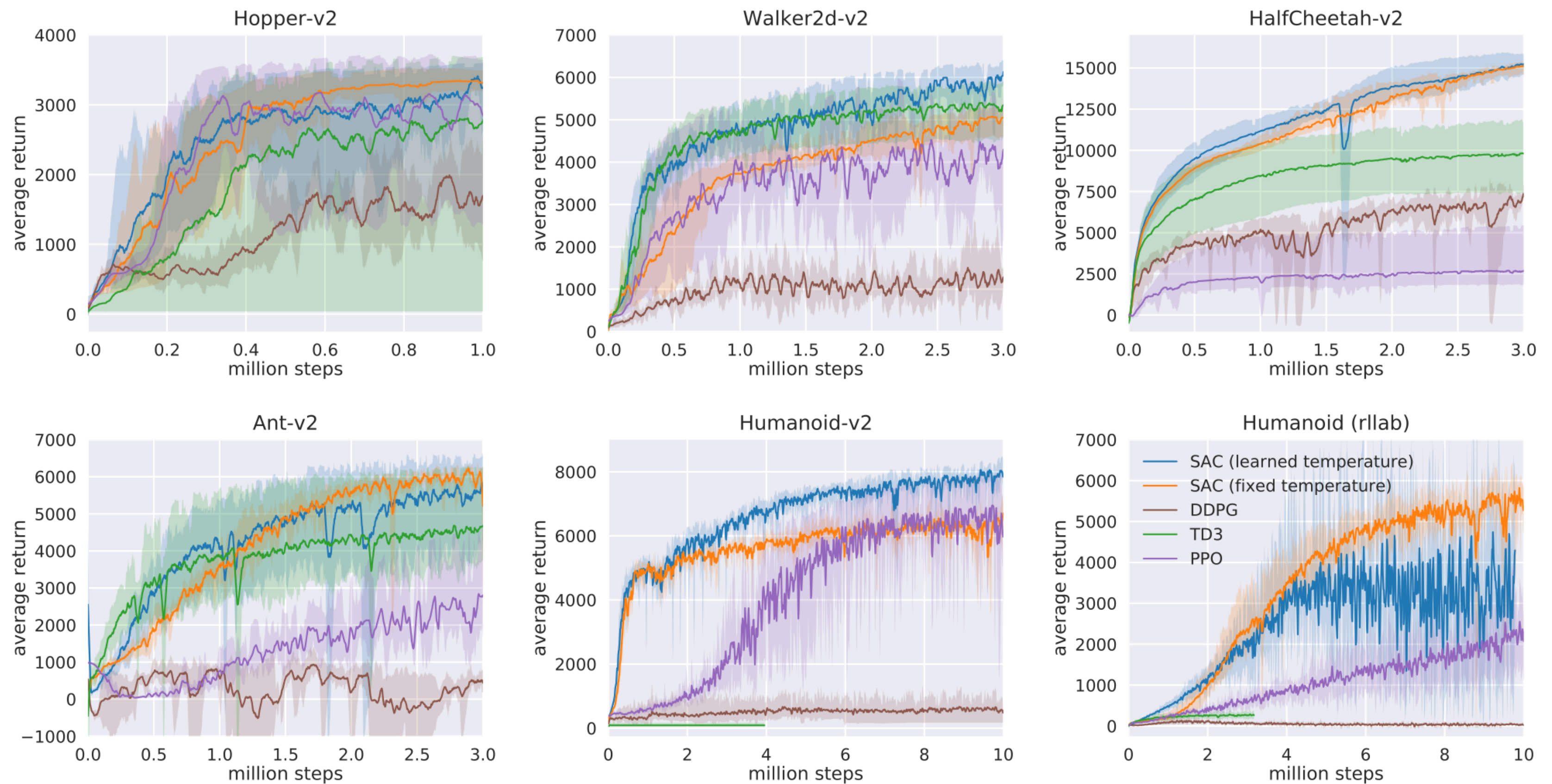
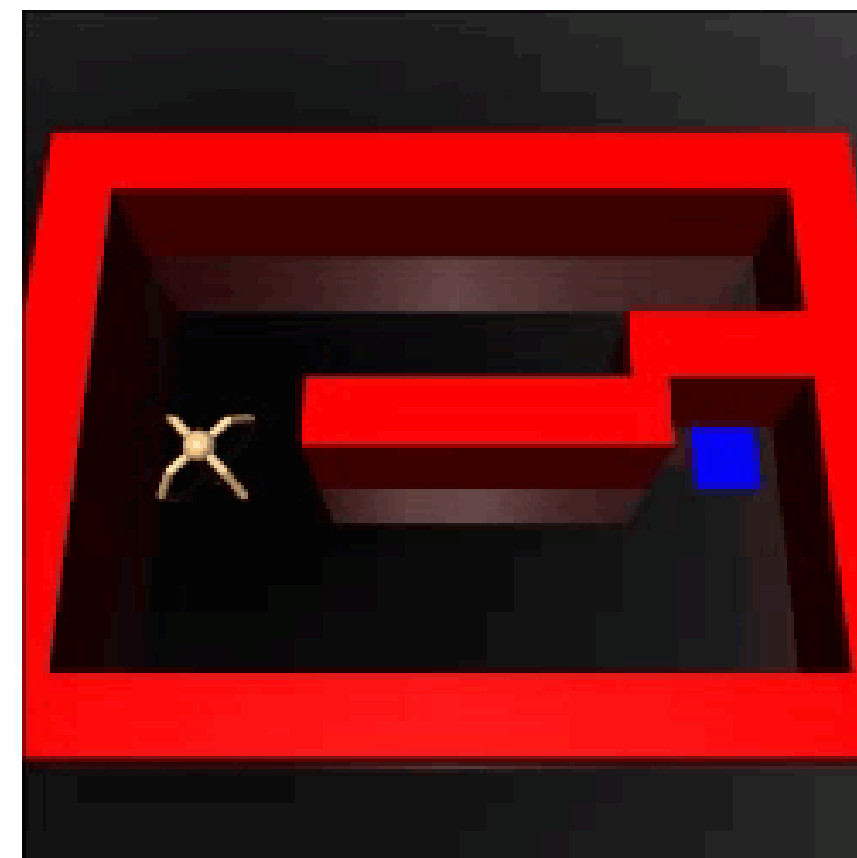
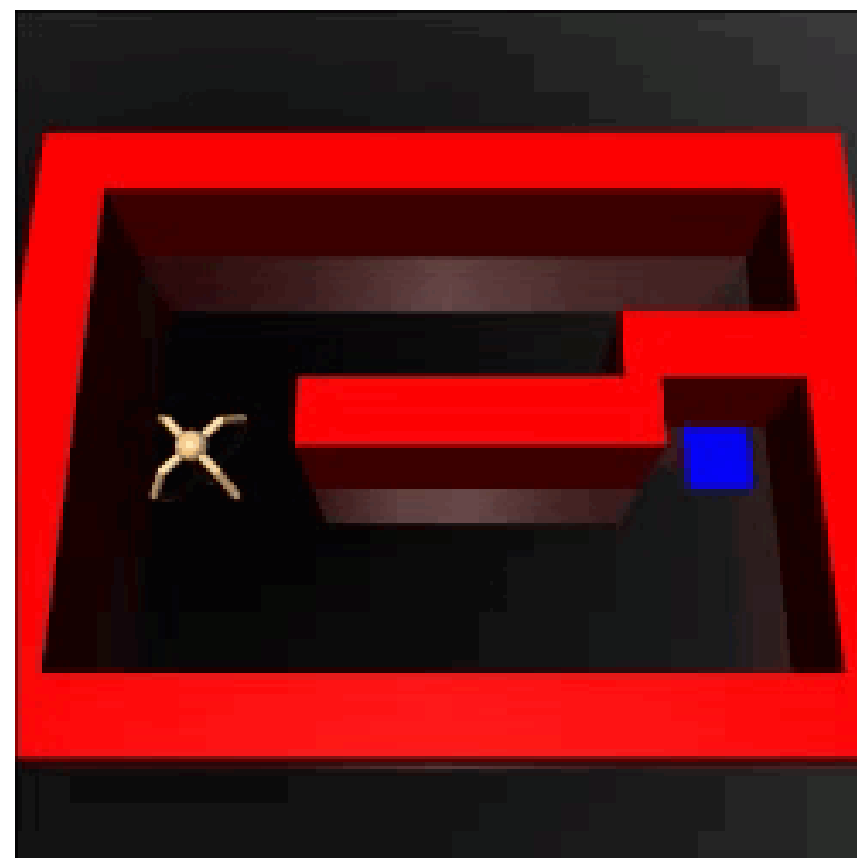
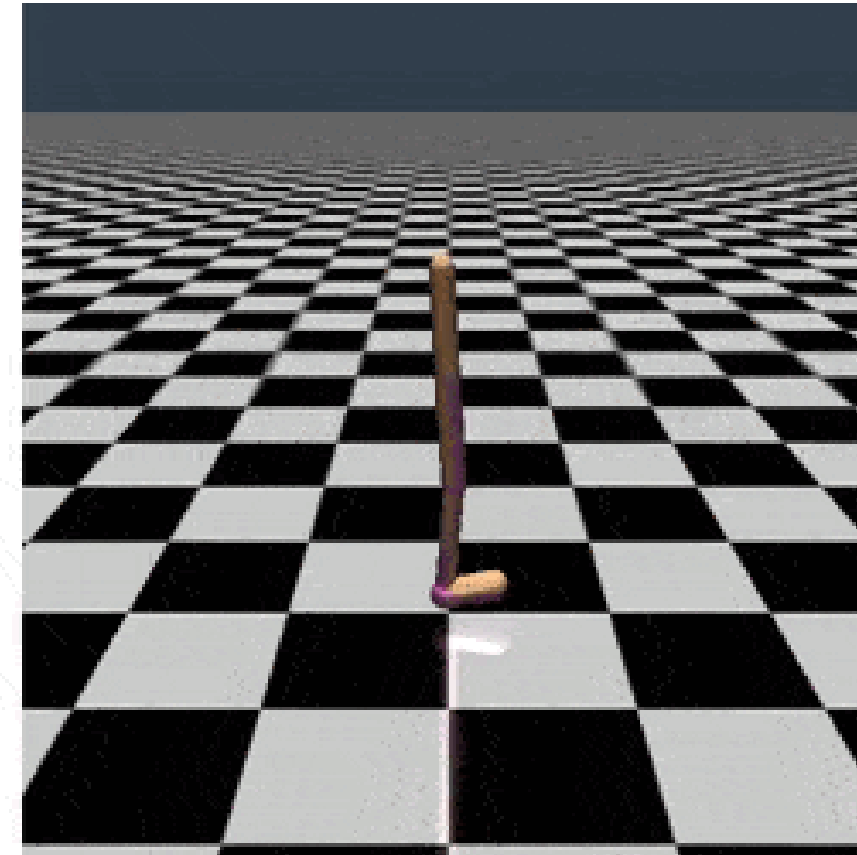
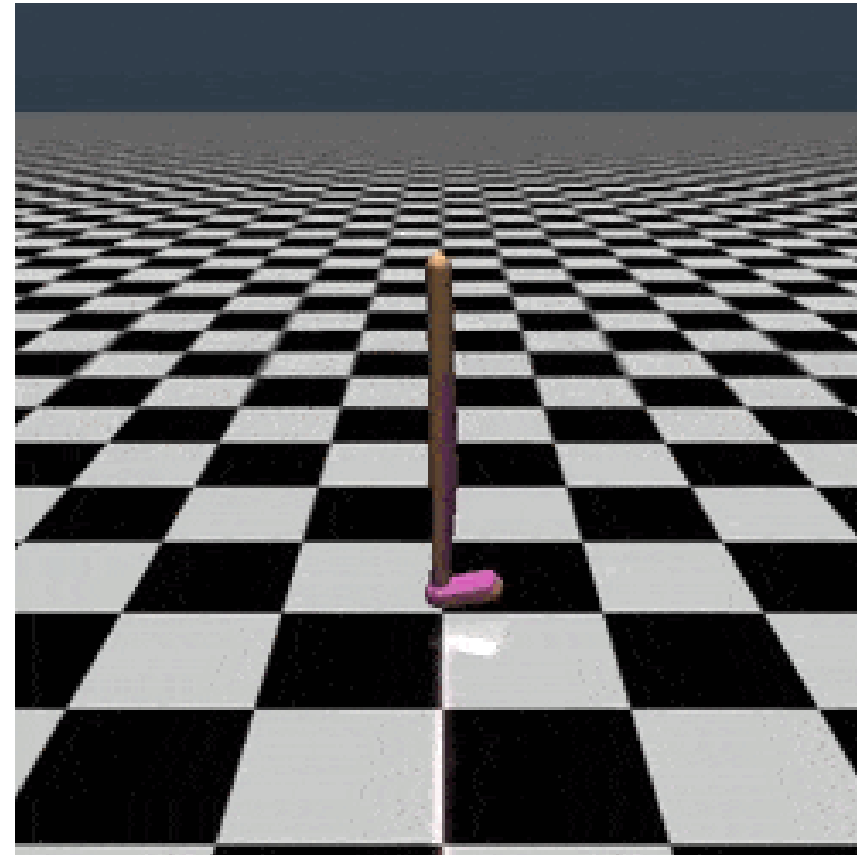


Figure 1: Training curves on continuous control benchmarks. Soft actor-critic (blue and yellow) performs consistently across all tasks and outperforming both on-policy and off-policy methods in the most challenging tasks.

# SAC results

- The enhanced exploration strategy through maximum entropy RL allows to learn robust and varied strategies that can cope with changes in the environment.

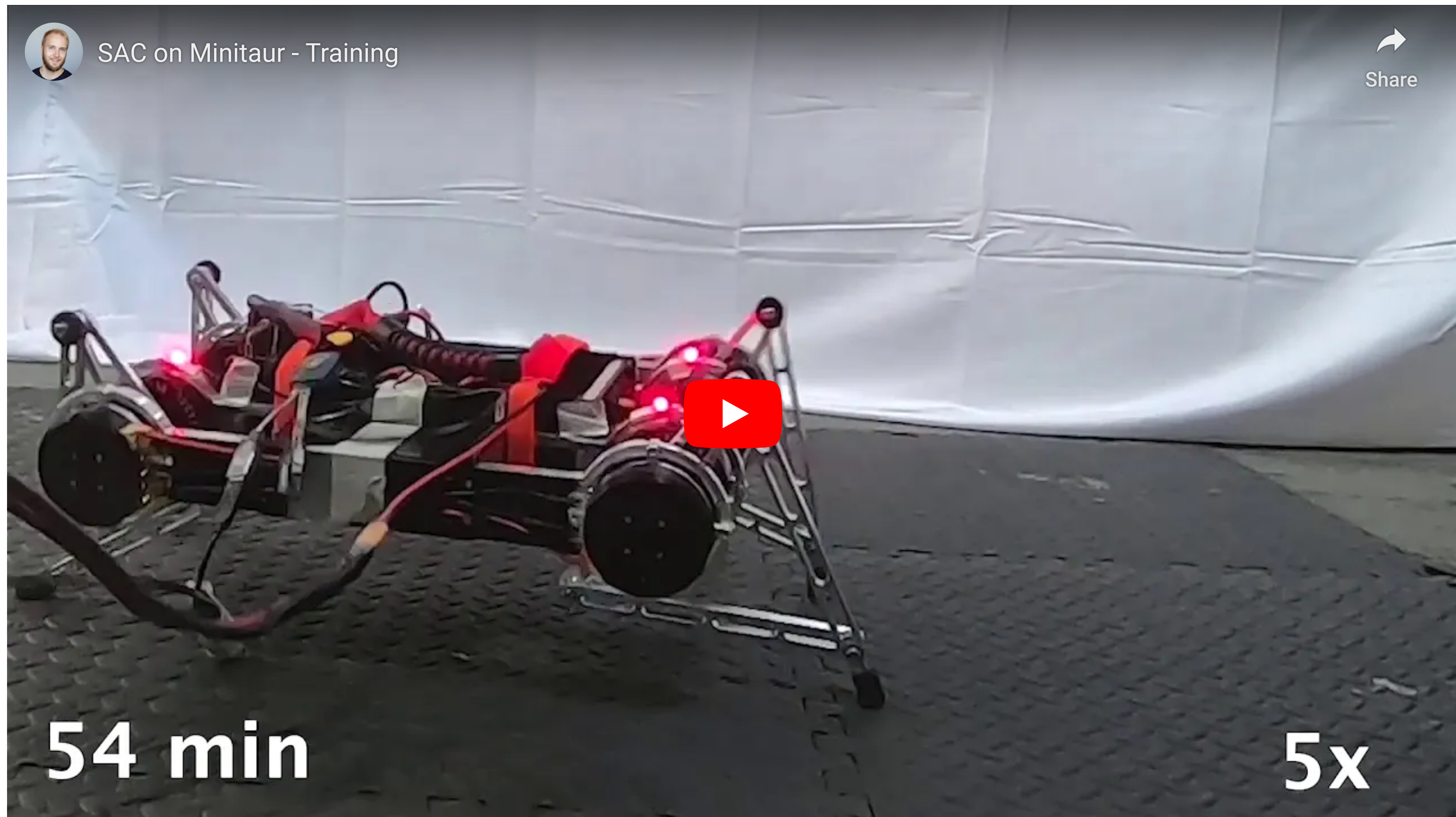


Source: <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/>



# Real-world robotics

- The low sample complexity of SAC allows to train a real-world robot in less than 2 hours!





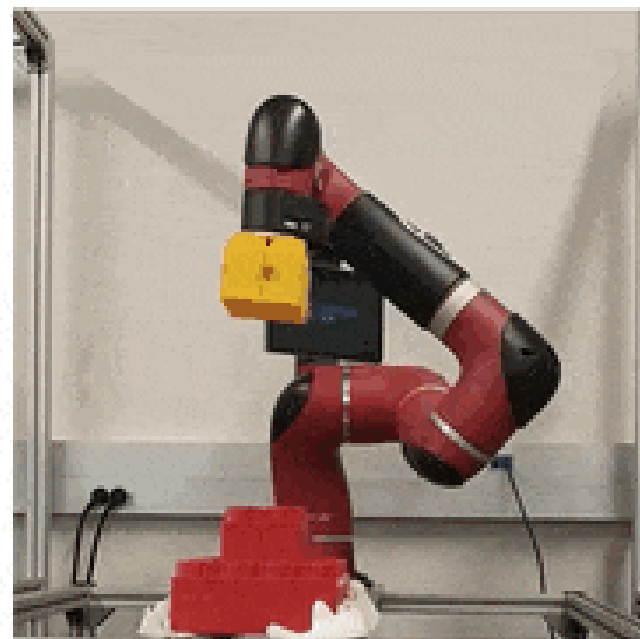
# Real-world robotics

- Although trained on a flat surface, the rich learned stochastic policy can generalize to complex terrains.

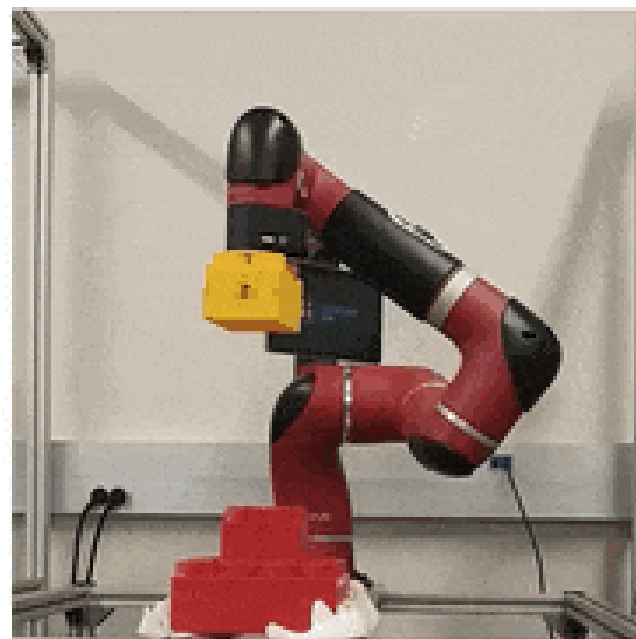


# Real-world robotics

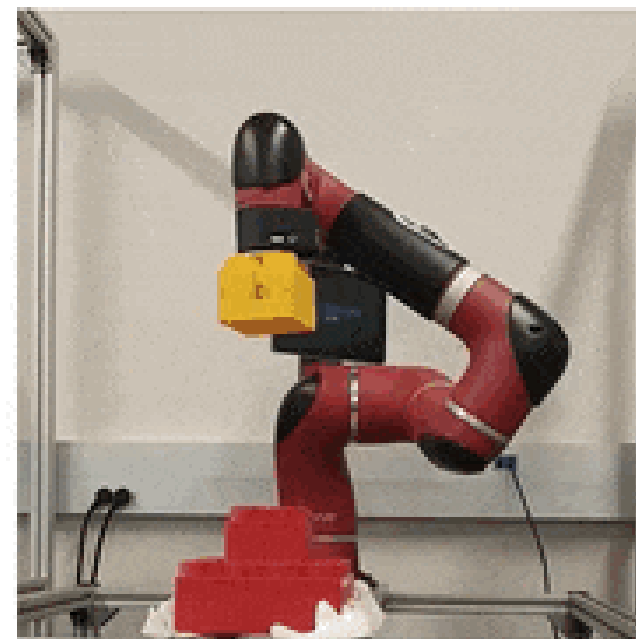
- When trained to stack lego bricks, the robotic arm learns to explore the whole state-action space.



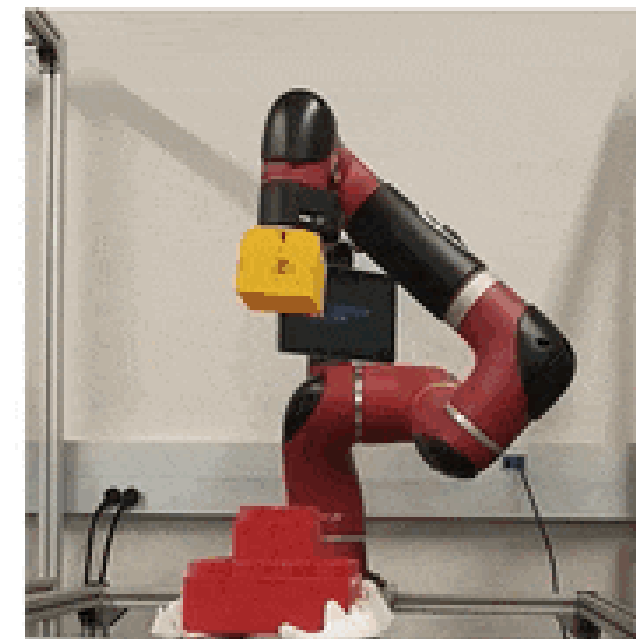
untrained



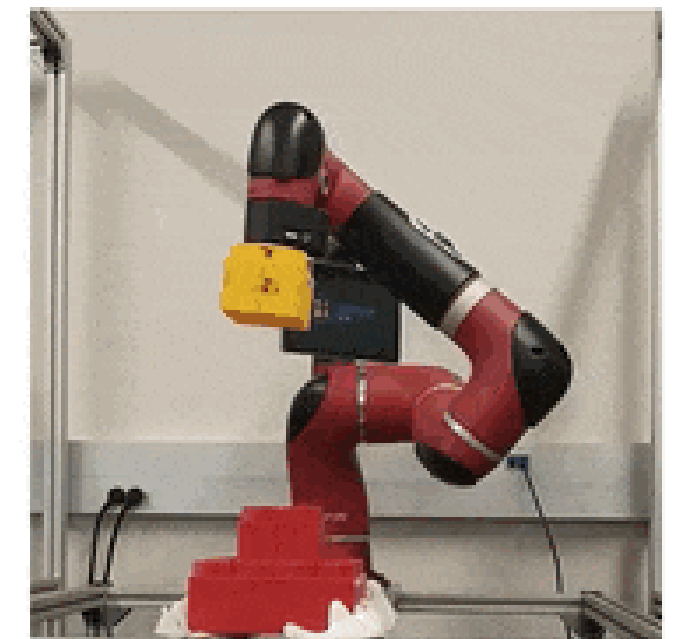
12 min later



30 min later

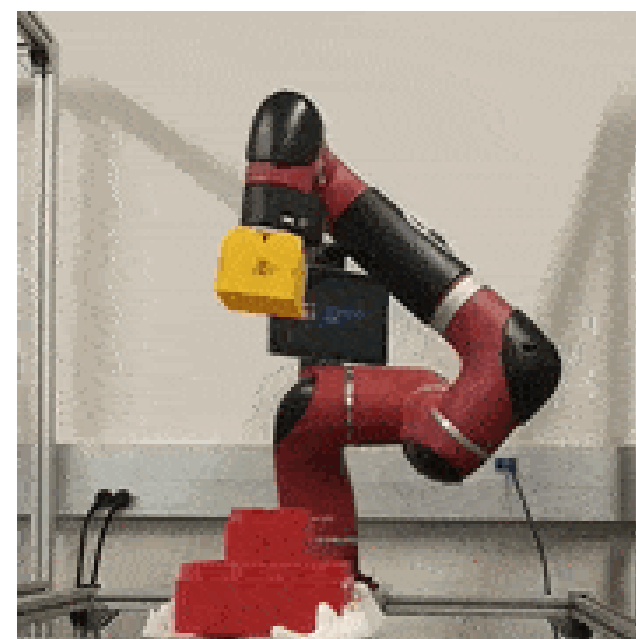


1 hour later



2 hours later

- This makes it more robust to external perturbations after training:



Source: <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/>

## Additional reading

- <https://ai.googleblog.com/2019/01/soft-actor-critic-deep-reinforcement.html>
- <https://towardsdatascience.com/in-depth-review-of-soft-actor-critic-91448aba63d4>
- <https://towardsdatascience.com/soft-actor-critic-demystified-b8427df61665>
- <https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning>
- <https://arxiv.org/abs/1805.00909>

# References

- Haarnoja, T., Tang, H., Abbeel, P., and Levine, S. (2017). Reinforcement Learning with Deep Energy-Based Policies. <http://arxiv.org/abs/1702.08165>.
- Haarnoja, T., Zhou, A., Hartikainen, K., Tucker, G., Ha, S., Tan, J., et al. (2018). Soft Actor-Critic Algorithms and Applications. <http://arxiv.org/abs/1812.05905>.