Soft Actor-Critic

Maximum Entropy Reinforcement Learning

T. Haarnoja, et al., “Reinforcement Learning with Deep Energy-Based Policies”, ICML 2017

T. Haarnoja, et, al., “Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor”, ICML 2018

T. Haarnoja, et, al., “Soft Actor-Critic Algorithms and Applications”, arXiv preprint 2018

Presented by Dongmin Lee

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Outline

1. Reinforcement Learning
   - Markov Decision Processes (MDPs)
   - Bellman Equation

2. Maximum Entropy Reinforcement Learning
   - Soft MDPs
   - Soft Bellman Equation

3. From Soft Policy Iteration to Soft Actor-Critic
   - Soft Policy Iteration
   - Soft Actor-Critic

4. Results

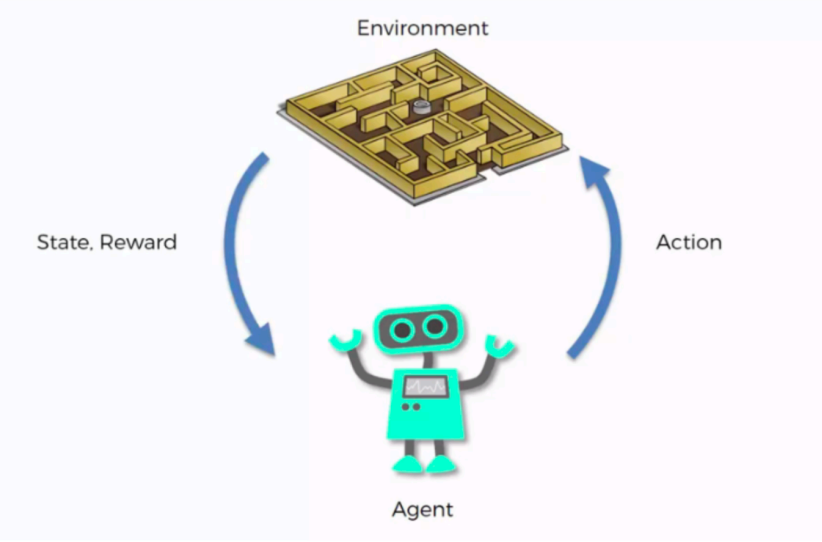
Reinforcement Learning

- State of the environment: $s_t \in S$
- Action determined by the agent: $a_t \in A$
- Reward evaluated the benefit of state and action: $r_t \in R$
- Policy (mapping from state to action): π
  - Deterministic

$$\pi(s_t) = a_t$$

  - Stochastic (randomized)

$$\pi(a|s) = \text{Prob}(a_t = a|s_t = s)$$



→ **Policy is what we want to optimize!**

Reinforcement Learning

What are the challenges of RL?

- Huge # of samples: millions
- Fast, stable learning
- Hyperparameter tuning
- Exploration
- Sparse reward signals
- Safety / reliability
- Simulator

Markov Decision Processes (MDPs)

A Markov decision process (MDP) is a tuple $< S, A, p, r, \gamma >$, consisting of

- S: set of states (state space)
  e.g., $S = \{1, \dots, n\}$ (discrete), $S = \mathbb{R}^n$ (continuous)

- A: set of actions (action space)
  e.g., $A = \{1, \dots, m\}$ (discrete), $A = \mathbb{R}^m$ (continuous)

- p: state transition probability
  $p(s'|s, a) \triangleq \mathrm{Prob}(s_{t+1} = s'|s_t = s, a_t = a)$

- r: reward function
  $r(s_t, a_t) = r_t$

- $\gamma \in (0,1]$: discount factor

Markov Decision Processes (MDPs)

The MDP problem

- To find an optimal policy that maximizes the expected cumulative reward:

$$\max_{\pi \in \prod} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]$$

Value function

- The state value function $V^{\pi}(s)$ of a policy π is the expected return starting from state s under executing π:

$$V^{\pi}(s) \triangleq \mathbb{E}_{\pi} \left[\sum_{\tau=t}^{\infty} \gamma^{\tau-t} r(s_\tau, a_\tau) \,|s_t = s \right]$$

Q-function

- The action value function $Q^{\pi}(s, a)$ of a policy π is the expected return starting from state s, taking action a, and then following π:

$$Q^{\pi}(s, a) \triangleq \mathbb{E}_{\pi} \left[\sum_{\tau=t}^{\infty} \gamma^{\tau-t} r(s_\tau, a_\tau) \,|s_t = s, a_t = a \right]$$

Markov Decision Processes (MDPs)

The MDP problem

- To find an optimal policy that maximizes the expected cumulative reward:

$$\max_{\pi \in \prod} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]$$

Optimal value function

- The optimal value function $V^*(s)$ is the maximum value function over all policies:

$$V^*(s) \triangleq \max_{\pi \in \prod} V^{\pi}(s) = \max_{\pi \in \prod} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \,|s_t = s \right]$$

Optimal Q-function

- The optimal Q-function $Q^*(s, a)$ is the maximum Q-function over all policies:

$$Q^*(s, a) \triangleq \max_{\pi \in \prod} Q^{\pi}(s, a)$$

Bellman Equation

Bellman expectation equation for V^π

- The value function V^π is the unique solution to the following Bellman equation:

$$V^\pi(s) = \mathbb{E}[r(s_t, a_t) + \gamma V^\pi(s_{t+1}) | s_t = s]$$

$$= \sum_{a \in A} \pi(a|s) \left(r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^\pi(s') \right) = \sum_{a \in A} \pi(a|s) Q^\pi(s,a)$$

  - In operator form

$$V^\pi = TV^\pi$$

Bellman expectation equation for Q^π

- The Q-function Q^π satisfies:

$$Q^\pi(s,a) = \mathbb{E}[r(s_t, a_t) + \gamma V^\pi(s_{t+1}) | s_t = s, a_t = a]$$

$$= r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^\pi(s')$$

$$= r(s,a) + \gamma \sum_{s' \in S} \left(p(s'|s,a) \sum_{a' \in A} \pi(a'|s') Q^\pi(s',a') \right)$$

Bellman Equation

Bellman optimality equation for V^*

- The optimal value function V^* must satisfies the self-consistency condition given by the Bellman equation for V^π:

$$V^*(s) = \max_{a_t \in A} \mathbb{E}[r(s_t, a_t) + \gamma V^*(s_{t+1}) | s_t = s]$$

$$= \max_{a \in A} \left(r(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) V^*(s') \right) = \max_{a \in A} Q^*(s, a)$$

  - In operator form

$$V^* = TV^*$$

Bellman optimality equation for Q^*

- The optimal Q-function Q^* satisfies:

$$Q^*(s, a) = \mathbb{E}[r(s_t, a_t) + \gamma V^*(s_{t+1}) | s_t = s, a_t = a]$$

$$= r(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) V^*(s')$$

$$= r(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) \max_{a' \in A} Q^*(s', a')$$

Bellman Equation

The MDP problem

- To find an optimal policy that maximizes the expected cumulative reward:

$$\max_{\pi \in \prod} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]$$

Known model:

- Policy iteration
- Value iteration

Unknown model:

- Temporal-difference learning
- Q-learning

Maximum Entropy Reinforcement Learning

Common issue: exploration

- Is there a value of exploring unknown regions of the environment?
- Which action should we try to explore unknown regions of the environment?

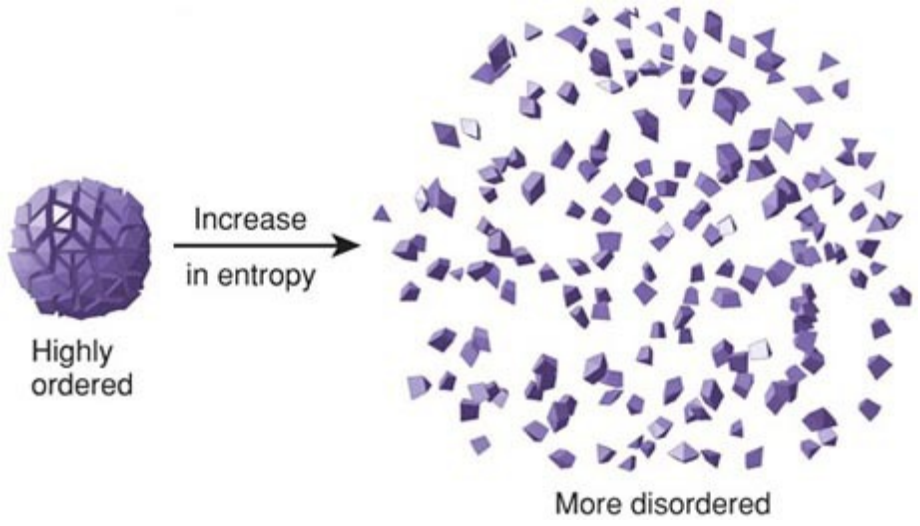
Maximum Entropy Reinforcement Learning

What is entropy?

- Average rate at which information is produced by a stochastic source of data
- The well-known standard Shannon-Gibbs entropy:

$$H(P) \triangleq \underset{X\sim P}{\mathbb{E}}\left[-\log\left(P(X)\right)\right] = -\sum_{x\in X} P(x)\log P(x)$$

- More generally, entropy refers to **disorder**



Maximum Entropy Reinforcement Learning

What's the benefit of high entropy policy?

- Entropy of policy:

$$H(\pi(\cdot\,|s)) \triangleq \mathop{\mathbb{E}}_{a\sim\pi}\left[-\log\left(\pi(a|s)\right)\right] = -\sum_{a}\pi(a|s)\log\pi(a|s)$$

- Higher disorder in policy π
- Try new risky behaviors: Potentially explore unexplored regions

Soft MDPs

Standard MDP problem:

$$\max_{\pi} \mathbb{E}_{\pi}\left[\sum_{t} \gamma^{t} r(s_t, a_t)\right]$$

Maximum entropy MDP problem:

$$\max_{\pi} \mathbb{E}_{\pi}\left[\sum_{t} \gamma^{t} \left(r(s_t, a_t) + H\left(\pi_t(\cdot\,|s_t)\right)\right)\right]$$

Soft Bellman Equation

Theorem 1 (Soft value functions and Optimal policy)

Soft Q-function:

$$Q^{\pi}_{\text{soft}}(s_t, a_t) \triangleq r(s_t, a_t) + \mathbb{E}_{\pi}\left[\sum_{l=1}^{\infty} \gamma^l \left(r(s_{t+l}, a_{t+l}) + H\big(\pi(\cdot\,|s_{t+l})\big)\right)\right]$$

Soft value function:

$$V^{\pi}_{\text{soft}}(s_t) \triangleq \log \int \exp\big(Q^{\pi}_{\text{soft}}(s_t, a)\big)\, da$$

Optimal value functions:

$$Q^{*}_{\text{soft}}(s_t, a_t) \triangleq \max_{\pi} Q^{\pi}_{\text{soft}}(s_t, a_t)$$

$$V^{*}_{\text{soft}}(s_t) \triangleq \log \int \exp\big(Q^{*}_{\text{soft}}(s_t, a)\big)\, da$$

Soft Bellman Equation

Proof.

Maximum entropy MDP problem:

$$\max_{\pi} \mathbb{E}_{\pi}\left[\sum_{t} \gamma^{t}\left(r(s_t, a_t) + H\left(\pi_t(\cdot\,|s_t)\right)\right)\right]$$

Soft value function:

$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{\pi}\left[\sum_{\tau=t} \gamma^{\tau-t}(r(s_\tau, a_\tau) - \log \pi(a_\tau|s_\tau))\,|s_t = s\right]$$
$$= \mathbb{E}_{\pi}[r(s_t, a_t) - \log \pi(a_t|s_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1})|s_t = s]$$

Soft Q-function:

$$Q^{\pi}_{\text{soft}}(\mathrm{s}, a) = \mathbb{E}_{\pi}\left[\sum_{\tau=t} \gamma^{\tau-t}(r(s_\tau, a_\tau) - \log \pi(a_\tau|s_\tau))\,|s_t = s, a_t = a\right]$$
$$= \underbrace{\mathbb{E}_{\pi}[r(s_t, a_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1})|s_t = s, a_t = a]}$$

note that $Q^{\pi}_{\text{soft}}(\mathrm{s}, a)$ is the same with the original form

Soft Bellman Equation

Proof.

Soft value function:

$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{\pi}\left[\sum_{\tau=t} \gamma^{\tau-t}(r(s_\tau, a_\tau) - \log \pi(a_\tau|s_\tau)) \,|s_t = s\right]$$
$$= \mathbb{E}_{\pi}[r(s_t, a_t) - \log \pi(a_t|s_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1})|s_t = s]$$

Soft Q-function:

$$Q^{\pi}_{\text{soft}}(\mathrm{s}, a) = \mathbb{E}_{\pi}\left[\sum_{\tau=t} \gamma^{\tau-t}(r(s_\tau, a_\tau) - \log \pi(a_\tau|s_\tau)) \,|s_t = s, a_t = a\right]$$
$$= \mathbb{E}_{\pi}[r(s_t, a_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1})|s_t = s, a_t = a]$$

Soft value function (rewrite):

$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{\pi}[r(s_t, a_t) - \log \pi(a_t|s_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1})|s_t = s]$$
$$= \mathbb{E}_{\pi}[Q^{\pi}_{\text{soft}}(s_t, a_t) - \log \pi(a_t|s_t) \,|s_t = s]$$

Soft Bellman Equation

Proof.

Given a policy π_{old}, define a new policy π_{new} as:

$$\pi_{\text{new}}(a|s) \propto \exp\left(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a)\right)$$

$$\pi_{\text{new}}(a|s) = \frac{\exp(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a))}{\int \exp(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a'))\, da'} = \text{soft}\max_{a \in A} Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a)$$

$$= \exp(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a) - V_{\text{soft}}^{\pi_{\text{old}}}(s)) = \exp(A_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a))$$

Substitute $\pi_{\text{new}}(a|s)$ into $V_{\text{soft}}^{\pi}(s)$:

$$V_{\text{soft}}^{\pi}(s) = \mathbb{E}_{a\sim\pi}\left[Q_{\text{soft}}^{\pi}(\text{s}, a) - \log\left(\frac{\exp\left(Q_{\text{soft}}^{\pi}(\text{s}, a)\right)}{\int \exp\left(Q_{\text{soft}}^{\pi}(\text{s}, a')\right) da'}\right)\right]$$

$$= \mathbb{E}_{a\sim\pi}\left[Q_{\text{soft}}^{\pi}(\text{s}, a) - \log\exp\left(Q_{\text{soft}}^{\pi}(\text{s}, a)\right) + \log\int \exp\left(Q_{\text{soft}}^{\pi}(\text{s}, a')\right) da'\right]$$

Soft Bellman Equation

Proof.

Substitute $\pi_{\text{new}}(a|s)$ into $V^{\pi}_{\text{soft}}(s)$:

$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{a\sim\pi}\left[Q^{\pi}_{\text{soft}}(\mathrm{s},a) - \log\exp\left(Q^{\pi}_{\text{soft}}(\mathrm{s},a)\right) + \log\int \exp\left(Q^{\pi}_{\text{soft}}(\mathrm{s},a')\right)da'\right]$$

$$= \mathbb{E}_{a\sim\pi}\left[\log\int \exp\left(Q^{\pi}_{\text{soft}}(\mathrm{s},a')\right)da'\right]$$

independent from a

$$= \log\int \exp\left(Q^{\pi}_{\text{soft}}(\mathrm{s},a')\right)da'$$

$$\therefore V^{\pi}_{\text{soft}}(s) = \log\int \exp\left(Q^{\pi}_{\text{soft}}(\mathrm{s},a)\right)da$$

Soft Bellman Equation

Theorem 1 (Soft value functions and Optimal policy)

Soft Q-function:

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Soft value function:

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$$Q^{*}_{\text{soft}}(s_t, a_t) \triangleq \max_{\pi} Q^{\pi}_{\text{soft}}(s_t, a_t)$$

$$V^{*}_{\text{soft}}(s_t) \triangleq \log \int \exp\big(Q^{*}_{\text{soft}}(s_t, a)\big)\, da$$

Soft Bellman Equation

Theorem 2 (Soft policy improvement theorem)

Given a policy π_{old}, define a new policy π_{new} as:

$$\pi_{\text{new}}(a|s) \propto \exp\left(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a)\right)$$

Assume that throughout our computation, Q is bounded and $\int \exp\big(Q(s,a)\big)\, da$ is bounded for any s (for both π_{old} and π_{new}).

Then,

$$Q_{\text{soft}}^{\pi_{\text{new}}}(\text{s}, a) \geq Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a) \quad \forall s, a$$

→ **Monotonic policy improvement!**

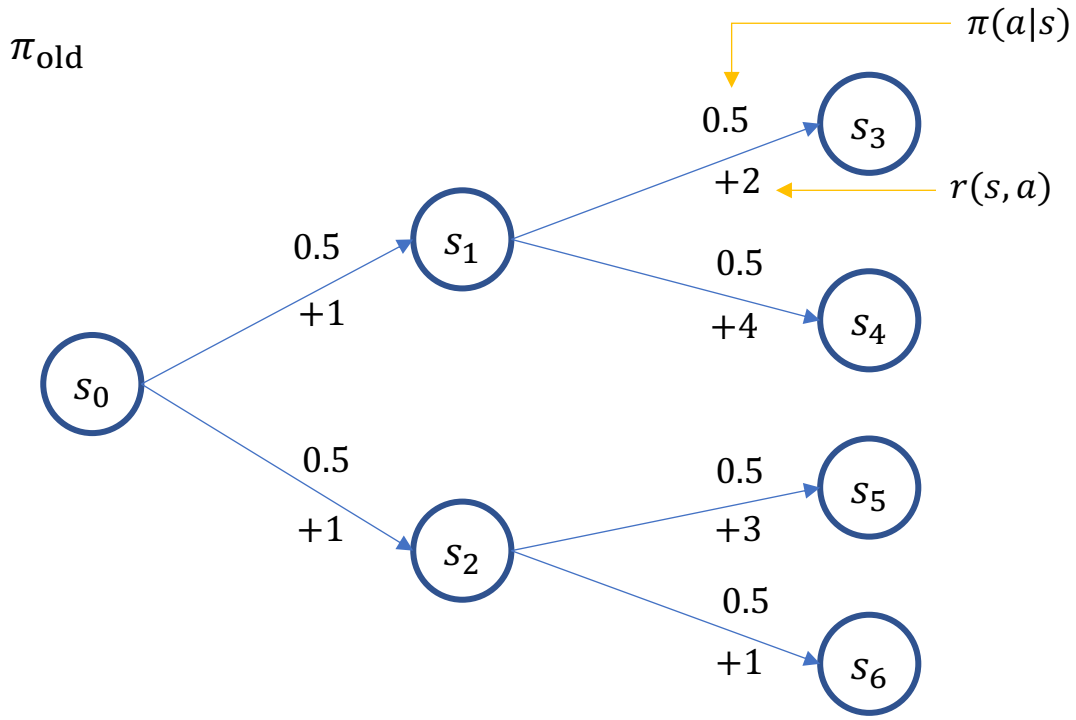
Soft Bellman Equation

Proof.

If one greedily maximize the sum of entropy and value with one-step look-ahead, then one obtains π_{new} from π_{old}:

$$H\left(\pi_{\text{old}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{old}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s,a)\right] \leq H\left(\pi_{\text{new}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{new}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s,a)\right]$$

Example



Soft Bellman Equation

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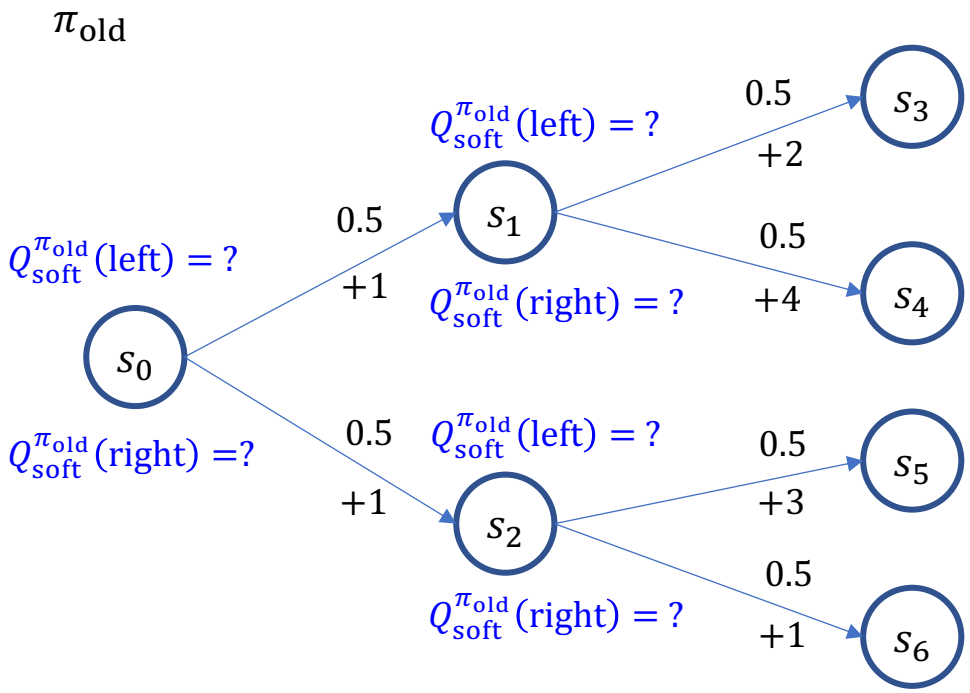

Soft Q-function:

$$Q_{\text{soft}}^{\pi}(s,a) \triangleq r(s_t,a_t) + \mathbb{E}_{\pi}\left[\sum_{l=1}^{\infty}\gamma^l\left(r(s_{t+l},a_{t+l}) + H\left(\pi(\cdot\,|s_{t+l})\right)\right)\right]$$
$$= r(s,a) + \gamma p(s'|s,a)V_{\text{soft}}^{\pi}(s')$$

Soft value function:

$$V_{\text{soft}}^{\pi}(s) = \sum_a \pi(a|s)(Q_{\text{soft}}^{\pi}(s,a) - \log\pi(a|s))$$

Entropy of policy:

$$H(\pi(\cdot\,|s)) \triangleq -\sum_a \pi(a|s)\log\pi(a|s)$$

Soft Bellman Equation

Proof.

If one greedily maximize the sum of entropy and value with one-step look-ahead, then one obtains π_{new} from π_{old}:

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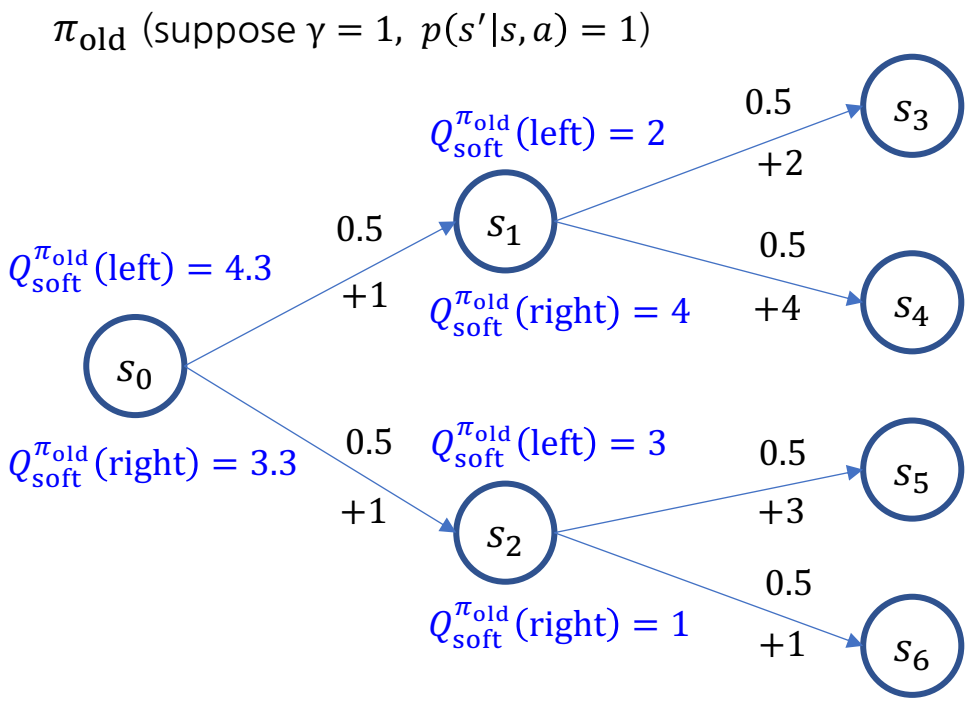

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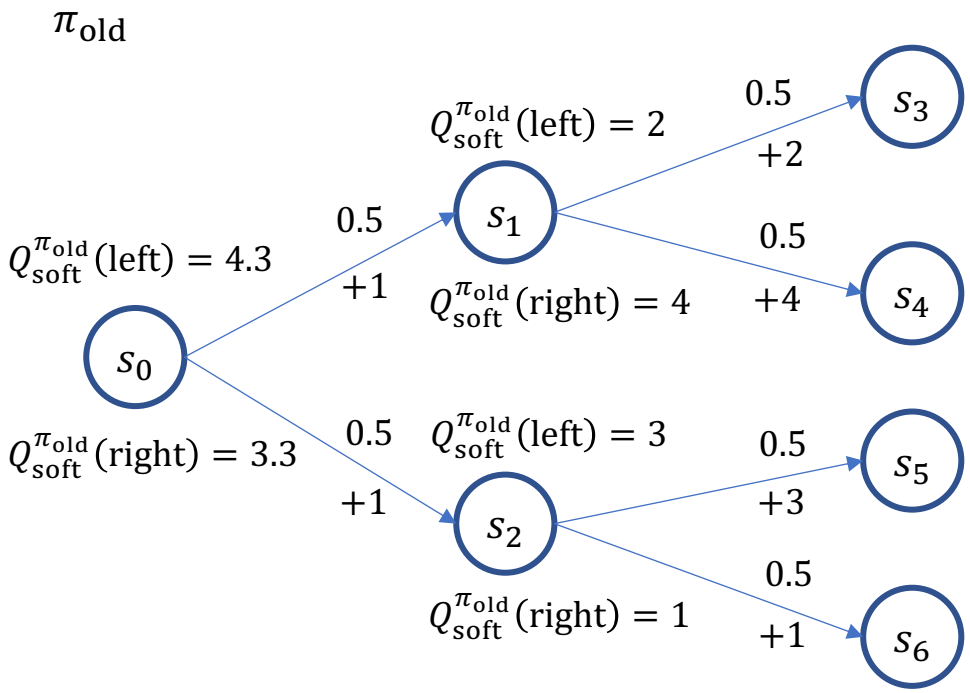
$$H\left(\pi_{\text{old}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{old}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a)\right] \leq H\left(\pi_{\text{new}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{new}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a)\right]$$

Example



A new policy π_{new}:

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$$= \exp(Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a) - V_{\text{soft}}^{\pi_{\text{old}}}(s))$$

Soft Bellman Equation

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If one greedily maximize the sum of entropy and value with one-step look-ahead, then one obtains π_{new} from π_{old}:

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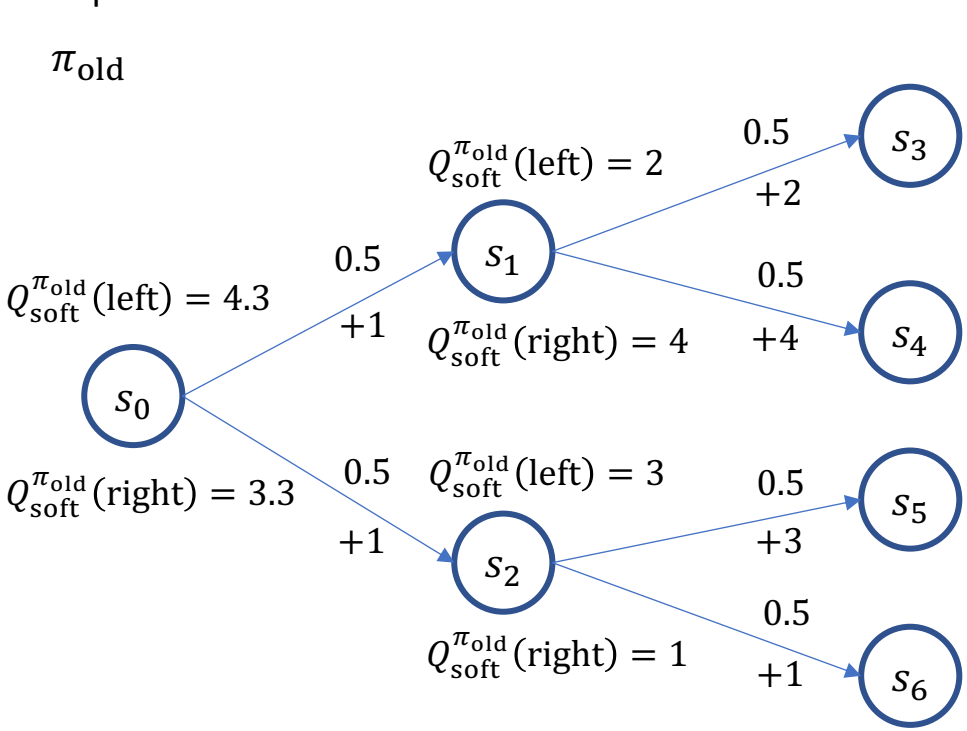
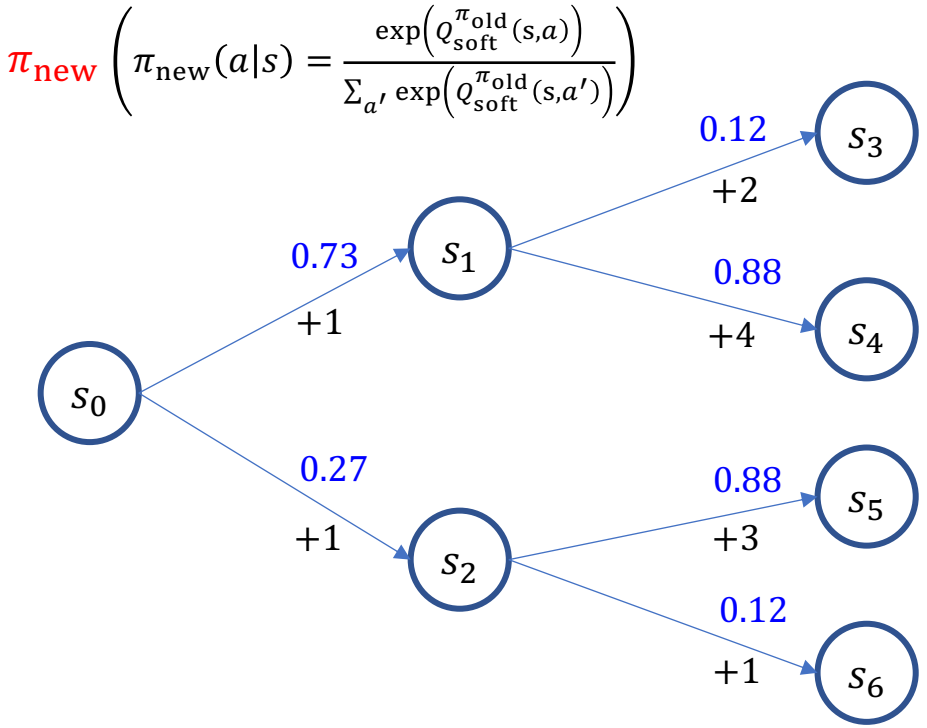




Soft Bellman Equation

Proof.

If one greedily maximize the sum of entropy and value with one-step look-ahead, then one obtains π_{new} from π_{old}:

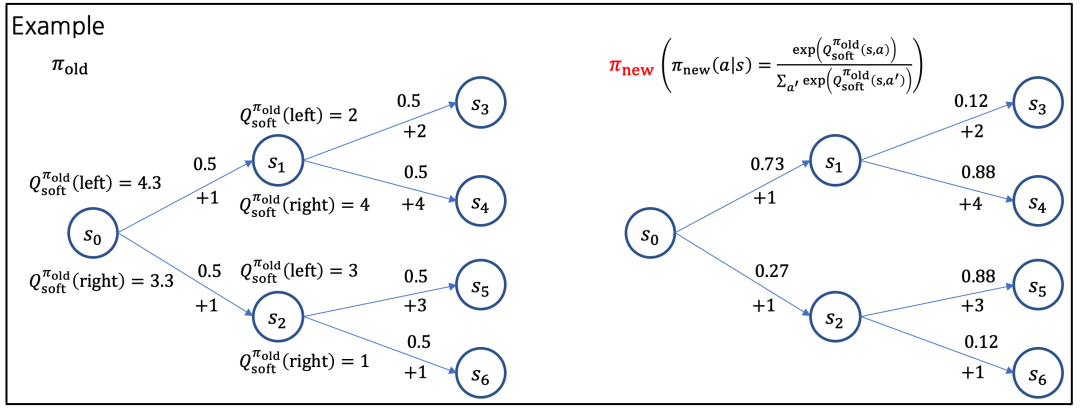
$$H\left(\pi_{\text{old}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{old}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s,a)\right] \leq H\left(\pi_{\text{new}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{new}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s,a)\right]$$

So, Substitute s_0, a_0 for s, a:

$$H\left(\pi_{\text{old}}(\cdot\,|s_0)\right) + \mathbb{E}_{\pi_{\text{old}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s_0,a_0)\right] \leq H\left(\pi_{\text{new}}(\cdot\,|s_0)\right) + \mathbb{E}_{\pi_{\text{new}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(s_0,a_0)\right]$$

$$0.3 + 3.8 \leq 0.25 + 4.03$$

$$4.1 \leq 4.28$$



Soft Bellman Equation

Proof.

If one greedily maximize the sum of entropy and value with one-step look-ahead, then one obtains π_{new} from π_{old}:

$$H\left(\pi_{\text{old}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{old}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a)\right] \leq H\left(\pi_{\text{new}}(\cdot\,|s)\right) + \mathbb{E}_{\pi_{\text{new}}}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a)\right]$$

Then, we can show that:

$$\begin{aligned}
Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s}, a) &= \mathbb{E}_{s_1}\left[r_0 + \gamma\left(H\left(\pi_{\text{old}}(\cdot\,|s_1)\right) + \mathbb{E}_{a_1\sim\pi_{\text{old}}}[Q_{\text{soft}}^{\pi}(s_1, a_1)]\right)\right] \\
&\leq \mathbb{E}_{s_1}\left[r_0 + \gamma\left(H\left(\pi_{\text{new}}(\cdot\,|s_1)\right) + \mathbb{E}_{a_1\sim\pi_{\text{new}}}[Q_{\text{soft}}^{\pi}(s_1, a_1)]\right)\right] \\
&= \mathbb{E}_{s_1}\left[r_0 + \gamma\left(H\left(\pi_{\text{new}}(\cdot\,|s_1)\right) + r_1\right)\right] + \gamma^2\mathbb{E}_{s_2}\left[H\left(\pi_{\text{old}}(\cdot\,|s_2)\right) + \mathbb{E}_{a_2\sim\pi_{\text{old}}}[Q_{\text{soft}}^{\pi}(s_2, a_2)]\right] \\
&\leq \mathbb{E}_{s_1}\left[r_0 + \gamma\left(H\left(\pi_{\text{new}}(\cdot\,|s_1)\right) + r_1\right)\right] + \gamma^2\mathbb{E}_{s_2}\left[H\left(\pi_{\text{new}}(\cdot\,|s_2)\right) + \mathbb{E}_{a_2\sim\pi_{\text{new}}}[Q_{\text{soft}}^{\pi}(s_2, a_2)]\right] \\
&= \mathbb{E}_{s_1, a_2\sim\pi_{\text{new}}, s_2}\left[r_0 + \gamma\left(H\left(\pi_{\text{new}}(\cdot\,|s_1)\right) + r_1\right) + \gamma^2 H\left(\pi_{\text{new}}(\cdot\,|s_2)\right) + r_2\right] + \gamma^3\mathbb{E}_{s_3}\left[H\left(\pi_{\text{new}}(\cdot\,|s_3)\right) + \mathbb{E}_{a_3\sim\pi_{\text{new}}}[Q_{\text{soft}}^{\pi}(s_3, a_3)]\right] \\
&\vdots \\
&\leq \mathbb{E}_{\tau\sim\pi_{\text{new}}}\left[r_0 + \textstyle\sum_{t=1}^{\infty}\gamma^t\left(H\left(\pi_{\text{new}}(\cdot\,|s_t)\right) + r_t\right)\right] \\
&= Q_{\text{soft}}^{\pi_{\text{new}}}(\mathrm{s}, a)
\end{aligned}$$

Soft Bellman Equation

Theorem 2 (Soft policy improvement theorem)

Given a policy π_{old}, define a new policy π_{new} as:

$$\pi_{\text{new}}(a|s) \propto \exp\left(Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a)\right)$$

Assume that throughout our computation, Q is bounded and $\int \exp\big(Q(s,a)\big)\, da$ is bounded for any s (for both π_{old} and π_{new}).

Then,

$$Q_{\text{soft}}^{\pi_{\text{new}}}(\text{s}, a) \geq Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a) \quad \forall s, a$$

→ **Monotonic policy improvement!**

Soft Bellman Equation

Comparison to standard MDP: Bellman expectation equation

Standard:

$$Q^{\pi}(s,a) = \mathbb{E}[r(s_t,a_t) + \gamma V^{\pi}(s_{t+1}) | s_t = s, a_t = a]$$
$$= r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^{\pi}(s')$$
$$V^{\pi}(s) = \sum_{a \in A} \pi(a|s) Q^{\pi}(s,a)$$

Maximum entropy:

$$Q^{\pi}_{\text{soft}}(s,a) = \mathbb{E}_{\pi}[r(s_t,a_t) + \gamma V^{\pi}_{\text{soft}}(s_{t+1}) | s_t = s, a_t = a]$$
$$= r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^{\pi}_{\text{soft}}(s')$$
$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{\pi}[Q^{\pi}_{\text{soft}}(s_t,a_t) - \log \pi(a_t|s_t) \, | s_t = s]$$
$$= \log \int \exp\left(Q^{\pi}_{\text{soft}}(s,a)\right) da$$

Maximum entropy variant:

- Add explicit temperature parameter α

$$V^{\pi}_{\text{soft}}(s) = \mathbb{E}_{\pi}[Q^{\pi}_{\text{soft}}(s_t,a_t) - \alpha \log \pi(a_t|s_t) \, | s_t = s]$$
$$= \alpha \log \int \exp\left(\frac{1}{\alpha} Q^{\pi}_{\text{soft}}(s,a)\right) da$$

Soft Bellman Equation

Comparison to standard MDP: Bellman optimality equation

Standard:

$$Q^*(s,a) = \mathbb{E}[r(s_t,a_t) + \gamma V^*(s_{t+1})|s_t = s, a_t = a]$$
$$= r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^*(s')$$

$$V^*(s) = \max_{a \in A} Q^*(s,a)$$

Maximum entropy variant:

$$Q^*_{\text{soft}}(\text{s},a) = \mathbb{E}_\pi[r(s_t,a_t) + \gamma V^*_{\text{soft}}(s_{t+1})|s_t = s, a_t = a]$$
$$= r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^*_{\text{soft}}(s')$$

$$V^*_{\text{soft}}(s) = \max_{a \in A}(Q^*_{\text{soft}}(s,a) - \alpha \log \pi(a|s))$$
$$= \alpha \log \int \exp\left(\frac{1}{\alpha} Q^*_{\text{soft}}(\text{s},a)\right) da$$

Connection:

- Note that as $\alpha \to 0$, $\exp\left(\frac{1}{\alpha} Q^*_{\text{soft}}(\text{s},a)\right)$ emphasizes $\max_{a \in A} Q^*(s,a)$:

$$\alpha \log \int \exp\left(\frac{1}{\alpha} Q^*_{\text{soft}}(\text{s},a)\right) da \to \max_{a \in A} Q^*(s,a) \quad \text{as } \alpha \to 0$$

Soft Bellman Equation

Comparison to standard MDP: Policy

Standard:

$$\pi_{\text{new}}(a|s) \in \arg\max_{a} Q^{\pi_{\text{old}}}(s,a)$$

→ Deterministic policy

Maximum Entropy:

$$\pi_{\text{new}}(a|s) = \frac{\exp\left(\frac{1}{\alpha} Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s},a)\right)}{\int \exp\left(\frac{1}{\alpha} Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s},a')\right) da'} = \exp\left(\frac{1}{\alpha}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\mathrm{s},a) - V_{\text{soft}}^{\pi_{\text{old}}}(s)\right]\right)$$

→ Stochastic policy

Soft Bellman Equation

So, what's the advantage of maximum entropy?

- Computation:
  No maximization involved
- Exploration:
  High entropy policy
- Structural similarity:
  Can combine it with many RL methods for standard MDP

From Soft Policy Iteration to Soft Actor-Critic

Soft Actor-Critic:
Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

Tuomas Haarnoja [1] Aurick Zhou [1] Pieter Abbeel [1] Sergey Levine [1]

Version 1 (Jan 4 2018)

Soft Actor-Critic Algorithms and Applications

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

Version 2 (Dec 13 2018)

Idea:

- Maximum entropy + off-policy actor-critic

Advantages:

- Exploration
- Sample efficiency
- Stable convergence
- Little hyperparameter tuning

Soft Policy Iteration

Soft policy evaluation

Modified Bellman operator:

$$T^{\pi}Q^{\pi}(s,a) \triangleq r(s,a) + \gamma \sum_{s' \in S} p(s'|s,a) V^{\pi}_{\text{soft}}(s')$$

where $V^{\pi}(s) = \mathbb{E}_{\pi}[Q^{\pi}_{\text{soft}}(s,a) - \alpha \log \pi(a|s)]$

Repeatedly apply T^{π} to Q_k:

$$Q_{k+1} \leftarrow T^{\pi}Q_k$$

- **Result: Q_k converges to Q^{π}!**

Soft Policy Iteration

Soft policy improvement

If no constraint on policies,

$$\pi_{\text{new}}(a|s) = \exp\left(\frac{1}{\alpha}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s}, a) - V_{\text{soft}}^{\pi_{\text{old}}}(s)\right]\right)$$

When constraint need to be satisfied (i.e., $\pi \in \prod$),
Information projection:

$$\pi_{\text{new}}(\cdot\,|s) \in \underset{\pi'(\cdot|s)\in\prod}{\arg\min}\, D_{KL}\left(\pi'(\cdot\,|s) \,\|\, \underbrace{\exp\left(\frac{1}{\alpha}\left[Q_{\text{soft}}^{\pi_{\text{old}}}(\text{s},\cdot) - V_{\text{soft}}^{\pi_{\text{old}}}(s)\right]\right)}_{\text{target policy}}\right)$$

- **Result: Monotonic improvement on policy!** (π_{new} better than π_{old})

Soft Actor-Critic

Model-Free version of soft policy iteration: Soft actor-critic

Soft policy iteration: maximum entropy variant of policy iteration

Soft actor-critic (SAC): maximum entropy variant of actor-critic

- Soft critic:
  evaluates soft Q-function Q_θ of policy π_ϕ

- Soft actor:
  improves maximum entropy policy using critic's evaluation

- Temperature parameter alpha:
  automatically adjusts entropy for maximum entropy policy using alpha α

Soft Actor-Critic

Soft critic: evaluates soft Q-function Q_θ of policy π_ϕ

Idea: DQN + Maximum entropy

- Training soft Q-function:

$$\min_\theta J_Q(\theta) \triangleq \mathbb{E}_{(s_t,a_t)}\left[\frac{1}{2}\left(Q_\theta(s_t,a_t) - \underbrace{\left[r(s_t,a_t) + \gamma \mathbb{E}_{s_{t+1}}[V_{\theta^-}(s_{t+1})]\right]}_{\text{target}}\right)^2\right]$$

- Stochastic gradient:

$$\hat{\nabla}_\theta J_Q(\theta) = \nabla_\theta Q_\theta(s_t,a_t) \times \Big[Q_\theta(s_t,a_t) - \big[r(s_t,a_t) + \gamma \underbrace{\big(Q_{\theta^-}(s_{t+1},a_{t+1}) - \alpha \log \pi_\phi(a_{t+1}|s_{t+1})\big)}_{\text{sample estimate of } \mathbb{E}_{s_{t+1}}[V_{\theta^-}(s_{t+1})]}\big]\Big]$$

Soft Actor-Critic

Soft actor: updates policy using critic's evaluation

Idea: Policy gradient + Maximum entropy

- Minimizing the expected KL-divergence:

$$\min_{\phi} D_{KL}\left(\pi_{\phi}(\cdot|s_t) \,\|\, \underbrace{\exp\left(\frac{1}{\alpha}[Q_{\theta}(s_t,\cdot) - V_{\theta}(s_t)]\right)}_{\text{target policy}}\right)$$

which is equivalent to

$$\min_{\phi} J_{\pi}(\phi) \triangleq \mathbb{E}_{s_t}\left[\mathbb{E}_{a_t \sim \pi_{\phi}(\cdot|s_t)}[\alpha \log \pi_{\phi}(a_t|s_t) - Q_{\theta}(s_t, a_t)]\right]$$

Soft Actor-Critic

Reparameterization trick

Reparameterize the policy as

$$a_t \triangleq f_\phi(\epsilon_t; s_t)$$

which ϵ_t is an input noise with some fixed distribution (e.g., Gaussian)

Benefit: lower variance

Rewrite the policy optimization problem as

$$\min_\phi J_\pi(\phi) \triangleq \mathbb{E}_{s_t,\epsilon_t}\left[\alpha \log \pi_\phi\left(f_\phi(\epsilon_t; s_t)\middle|s_t\right) - Q_\theta\left(s_t, f_\phi(\epsilon_t; s_t)\right)\right]$$

Stochastic gradient:

$$\hat{\nabla}_\phi J_\pi(\phi) = \nabla_\phi \alpha \log \pi_\phi(a_t|s_t) + \left[\nabla_{a_t} \alpha \log \pi_\phi(a_t|s_t) - \nabla_{a_t} Q_\theta(s_t, a_t)\right] \times \nabla_\phi f_\phi(\epsilon_t; s_t)$$

which a_t is evaluated at $f_\phi(\epsilon_t; s_t)$

Soft Actor-Critic

Automating entropy adjustment

Why do we have to do automatic temperature parameter α adjustment?

- Choosing the optimal temperature α_t^* is non-trivial, and the temperature needs to be tuned for each task.
- Since the entropy $H(\pi_t)$ can vary unpredictably both across tasks and during training as the policy becomes better, this makes the temperature adjustment particularly difficult.
- Thus, simply forcing the entropy to a fixed value is a poor solution, since the policy should be free to explore more in regions.

Soft Actor-Critic

Automating entropy adjustment

Constrained optimization problem (suppose $\gamma = 1$):

$$\max_{\pi_0,\ldots,\pi_T} \mathbb{E}\left[\sum_{t=0}^{T} r(s_t, a_t)\right] \quad \text{s.t. } H(\pi_t) \geq H_0 \; \forall t$$

where H_0 is a desired minimum expected entropy threshold

Rewrite the objective as an iterated maximization employing an (approximate) dynamic programming approach:

$$\max_{\pi_0}\left(\mathbb{E}[r(s_0, a_0)] + \max_{\pi_1}\left(\mathbb{E}[\ldots] + \max_{\pi_T} \mathbb{E}[r(s_T, a_T)]\right)\right)$$

Subject to the constraint on entropy

Start from the last time step T:

$$\max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T, a_T)]$$

Subject to $\mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[-\log \pi_T(a_T|s_T)] - H_0 \geq 0$

Soft Actor-Critic

Automating entropy adjustment

Change the constrained maximization to the dual problem using Lagrangian:

1. Create the following function:

$$f(\pi_T) = \begin{cases} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T)], & \text{s.t. } h(\pi_T) \geq 0 \\ -\infty, & \text{otherwise} \end{cases}$$

$$h(\pi_T) = H(\pi_T) - H_0 = \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[-\log \pi_T(a_T|s_T)] - H_0$$

2. So, rewrite the objective as

$$\max_{\pi_T} f(\pi_T) \quad \text{s.t. } h(\pi_T) \geq 0$$

3. Use Lagrange multiplier:

$$\min_{\alpha_T \geq 0} L(\pi_T, \alpha_T) = f(\pi_T) + \alpha_T h(\pi_T)$$

where α_T is the dual variable

4. Rewrite the objective using Lagrangian as

$$\max_{\pi_T} f(\pi_T) = \min_{\alpha_T \geq 0} \max_{\pi_T} L(\pi_T, \alpha_T) = \min_{\alpha_T \geq 0} \max_{\pi_T} f(\pi_T) + \alpha_T h(\pi_T)$$

Soft Actor-Critic

Automating entropy adjustment

Change the constrained maximization to the dual problem using Lagrangian:

$$\begin{aligned}\max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T)] &= \max_{\pi_T} f(\pi_T) \\ &= \min_{\alpha_T\geq 0} \max_{\pi_T} L(\pi_T,\alpha_T) = \min_{\alpha_T\geq 0} \max_{\pi_T} f(\pi_T) + \alpha_T h(\pi_T) \\ &= \min_{\alpha_T\geq 0} \max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T)] + \alpha_T\left(\mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[-\log\pi_T(a_T|s_T)] - H_0\right) \\ &= \min_{\alpha_T\geq 0} \max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T) - \alpha_T\log\pi_T(a_T|s_T)] - \alpha_T H_0 \\ &= \min_{\alpha_T\geq 0} \max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T) + \alpha_T H(\pi_T) - \alpha_T H_0]\end{aligned}$$

We can solve for

- Optimal policy π_T^* as

$$\pi_T^* = \arg\max_{\pi_T} \mathbb{E}_{(s_T,a_T)\sim\rho_\pi}[r(s_T,a_T) + \alpha_T H(\pi_T) - \alpha_T H_0]$$

- Optimal dual variable α_T^* as

$$\alpha_T^* = \arg\min_{\alpha_T\geq 0} \mathbb{E}_{(s_T,a_T)\sim\rho_{\pi^*}}[\alpha_T H(\pi_T^*) - \alpha_T H_0]$$

Thus,

$$\max_{\pi_T} \mathbb{E}[r(s_T,a_T)] = \mathbb{E}_{(s_T,a_T)\sim\rho_{\pi^*}}[r(s_T,a_T) + \alpha_T^* H(\pi_T^*) - \alpha_T^* H_0]$$

Soft Actor-Critic

Automating entropy adjustment

Then, the soft Q-function can be computed as

$$\begin{aligned} Q_{T-1}(s_{T-1}, a_{T-1}) &= r(s_{T-1}, a_{T-1}) + \mathbb{E}[Q_T(s_T, a_T) - \alpha_T \log \pi_T(a_T|s_T)] \\ &= r(s_{T-1}, a_{T-1}) + \mathbb{E}[r(s_T, a_T)] + \alpha_T H(\pi_T) \end{aligned}$$

$$Q^*_{T-1}(s_{T-1}, a_{T-1}) = r(s_{T-1}, a_{T-1}) + \max_{\pi_T} \mathbb{E}[r(s_T, a_T)] + \alpha^*_T H(\pi^*_T)$$

Now, given the time step $T-1$, we have:

$$\begin{aligned} &\max_{\pi_{T-1}} \Big(\mathbb{E}[r(s_{T-1}, a_{T-1})] + \max_{\pi_T} \mathbb{E}[r(s_T, a_T)] \Big) \\ &= \max_{\pi_{T-1}} \big(Q^*_{T-1}(s_{T-1}, a_{T-1}) - \alpha^*_T H(\pi^*_T) \big) \\ &= \min_{\alpha_{T-1} \geq 0} \max_{\pi_{T-1}} \big(Q^*_{T-1}(s_{T-1}, a_{T-1}) - \alpha^*_T H(\pi^*_T) + \alpha_{T-1}(H(\pi_{T-1}) - H_0) \big) \\ &= \min_{\alpha_{T-1} \geq 0} \max_{\pi_{T-1}} (Q^*_{T-1}(s_{T-1}, a_{T-1}) - \alpha_{T-1} H(\pi_{T-1}) - \alpha_{T-1} H_0) - \alpha^*_T H(\pi^*_T) \end{aligned}$$

Soft Actor-Critic

Automating entropy adjustment

We can solve for

- Optimal policy π^*_{T-1} as

$$\pi^*_{T-1} = \arg\max_{\pi_{T-1}} \mathbb{E}_{(s_{T-1},a_{T-1})\sim\rho_\pi}[Q^*_{T-1}(s_{T-1},a_{T-1}) + \alpha_{T-1}H(\pi_{T-1}) - \alpha_{T-1}H_0]$$

- Optimal dual variable α^*_{T-1} as

$$\alpha^*_{T-1} = \arg\min_{\alpha_{T-1}\geq 0} \mathbb{E}_{(s_{T-1},a_{T-1})\sim\rho_{\pi^*}}[\alpha_{T-1}H(\pi^*_{T-1}) - \alpha_{T-1}H_0]$$

In this way, we can proceed backwards in time and recursively optimize constrained optimization problem. Then, we can solve the optimal dual variable α^*_t after solving for Q^*_t and π^*_t:

$$\alpha^*_t = \arg\min_{\alpha_t} \mathbb{E}_{a_t\sim\pi^*_t}[-\alpha_t \log \pi^*_t(a_t|s_t) - \alpha_t H_0]$$

Soft Actor-Critic

Temperature parameter alpha: automatically adjusts entropy for maximum entropy policy using alpha α

Idea: Constrained optimization problem + Dual problem

- Minimizing the dual objective by approximating dual gradient descent:

$$\min_{\alpha} \mathbb{E}_{a_t \sim \pi_t}[-\alpha \log \pi_t(a_t|s_t) - \alpha H_0]$$

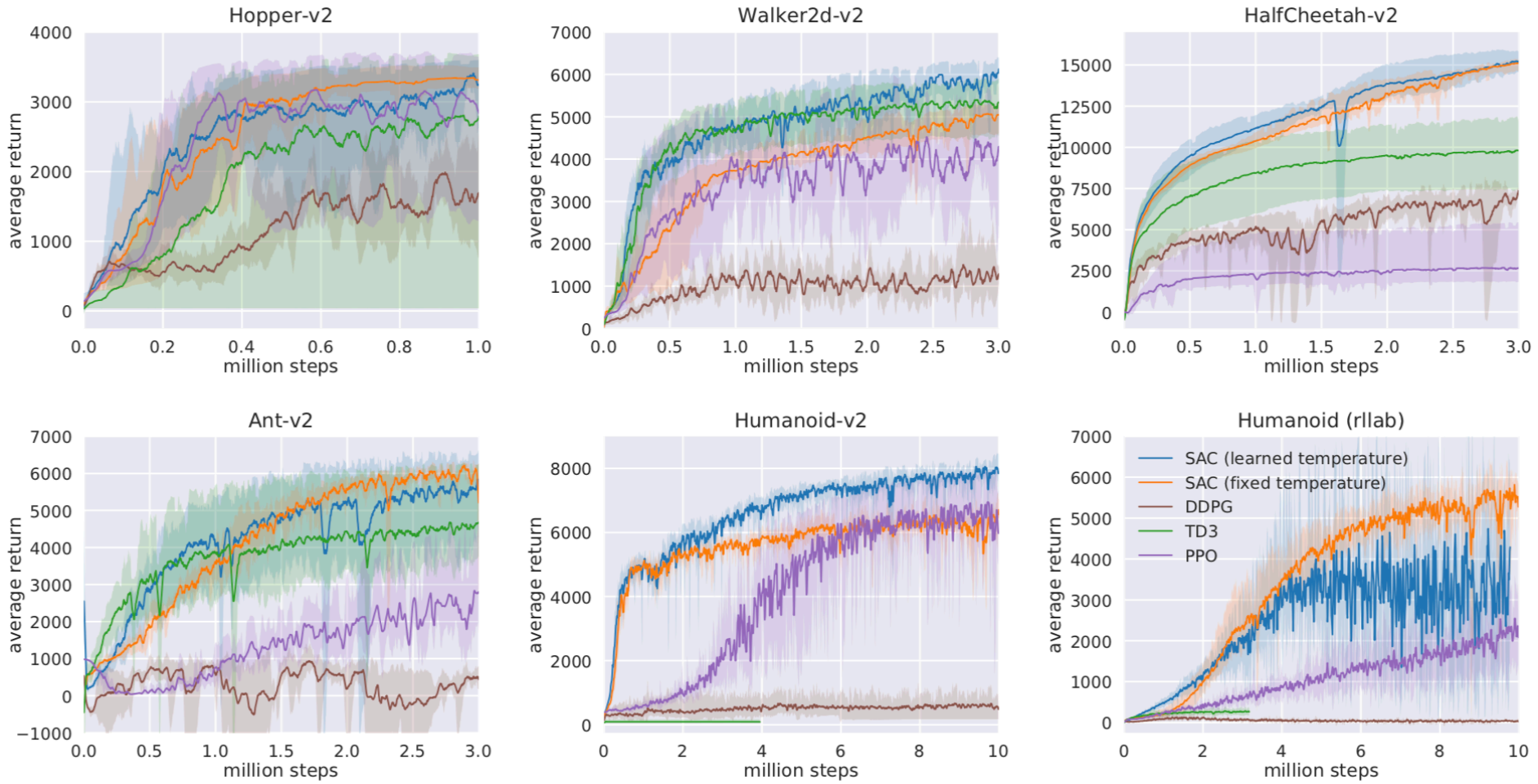
Soft Actor-Critic

Putting everything together: Soft Actor-Critic (SAC)

Algorithm 1 Soft Actor-Critic

Input: θ_1, θ_2, ϕ ▷ Initial parameters
$\bar{\theta}_1 \leftarrow \theta_1, \bar{\theta}_2 \leftarrow \theta_2$ ▷ Initialize target network weights
$\mathcal{D} \leftarrow \emptyset$ ▷ Initialize an empty replay pool
for each iteration **do**
  for each environment step **do**
    $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$ ▷ Sample action from the policy
    $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ ▷ Sample transition from the environment
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$ ▷ Store the transition in the replay pool
  end for
  for each gradient step **do**
    $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$ ▷ Update the Q-function parameters
    $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$ ▷ Update policy weights
    $\alpha \leftarrow \alpha - \lambda \hat{\nabla}_\alpha J(\alpha)$ ▷ Adjust temperature
    $\bar{\theta}_i \leftarrow \tau\theta_i + (1-\tau)\bar{\theta}_i$ for $i \in \{1, 2\}$ ▷ Update target network weights
  end for
end for
Output: θ_1, θ_2, ϕ ▷ Optimized parameters

Results



- 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.

Results

Soft Actor-Critic:
Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

Tuomas Haarnoja [1] Aurick Zhou [1] Pieter Abbeel [1] Sergey Levine [1]

Version 1 (Jan 4 2018)

Soft Actor-Critic Algorithms and Applications

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Sehoon Ha‡ Jie Tan‡ Vikash Kumar‡ Henry Zhu† Abhishek Gupta†
Pieter Abbeel† Sergey Levine†‡

Version 2 (Dec 13 2018)

Idea:

- Maximum entropy + off-policy actor-critic

Advantages:

- Exploration
- Sample efficiency
- Stable convergence
- Little hyperparameter tuning

Results

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Version 2 (Dec 13 2018)

Idea:

- Maximum entropy + off-policy actor-critic

Advantages:

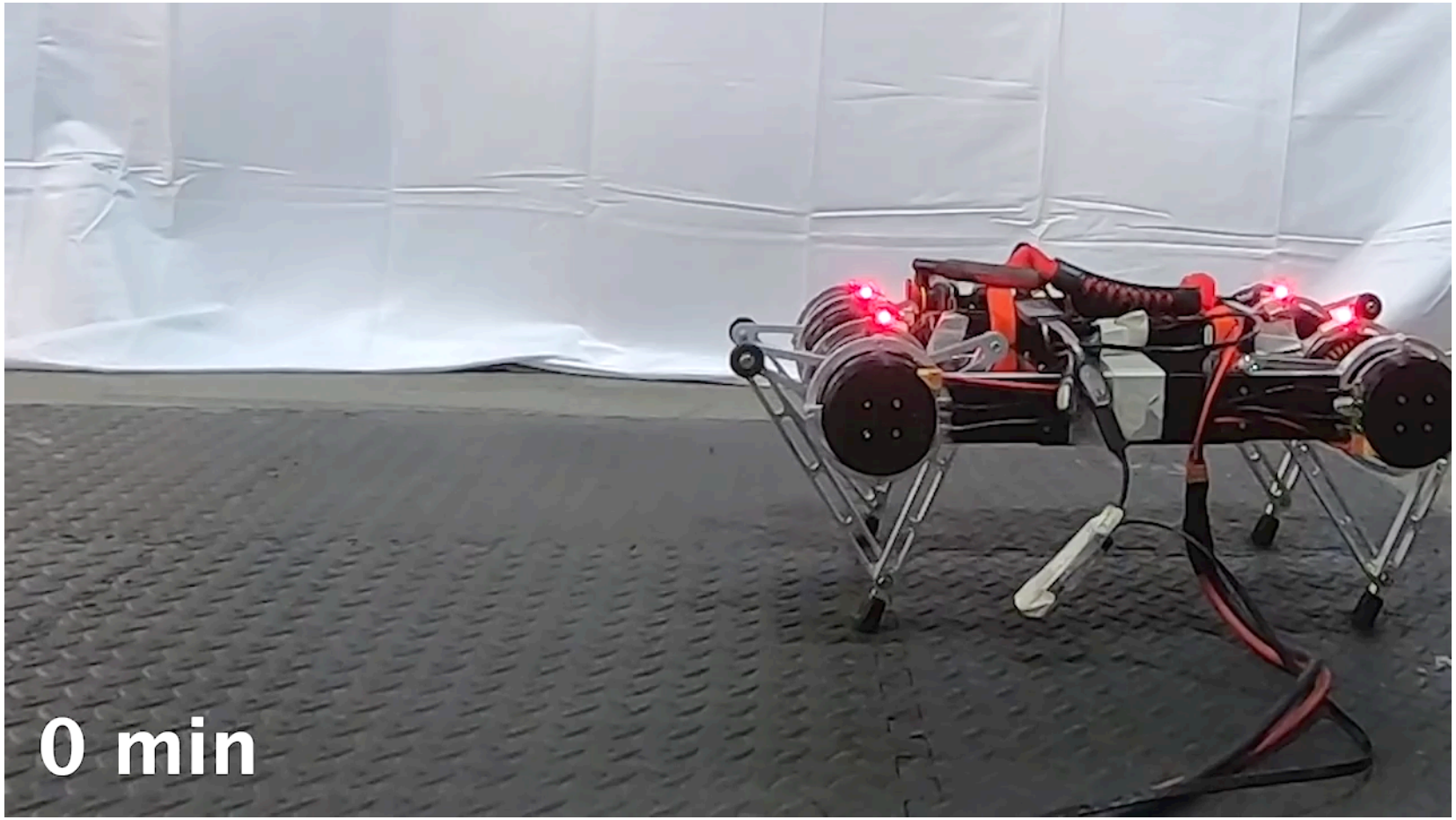
- Exploration
- Sample efficiency
- Stable convergence
- Little hyperparameter tuning

Disadvantages:

- Performance loss
- Coefficient of entropy term
- Different types of entropy

Results

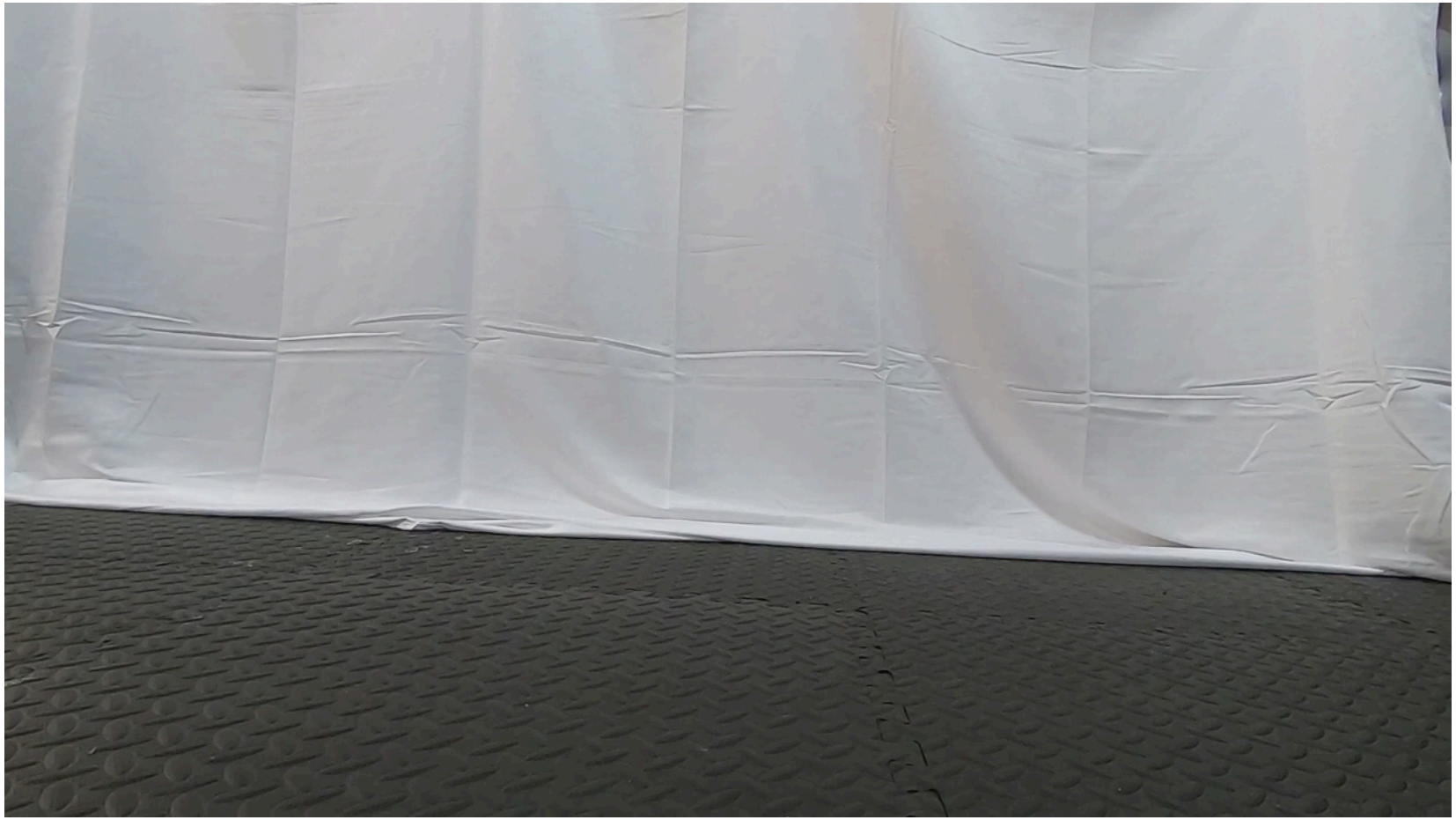
- Soft Actor-Critic on Minitaur - Training



https://sites.google.com/view/sac-and-applications

Results

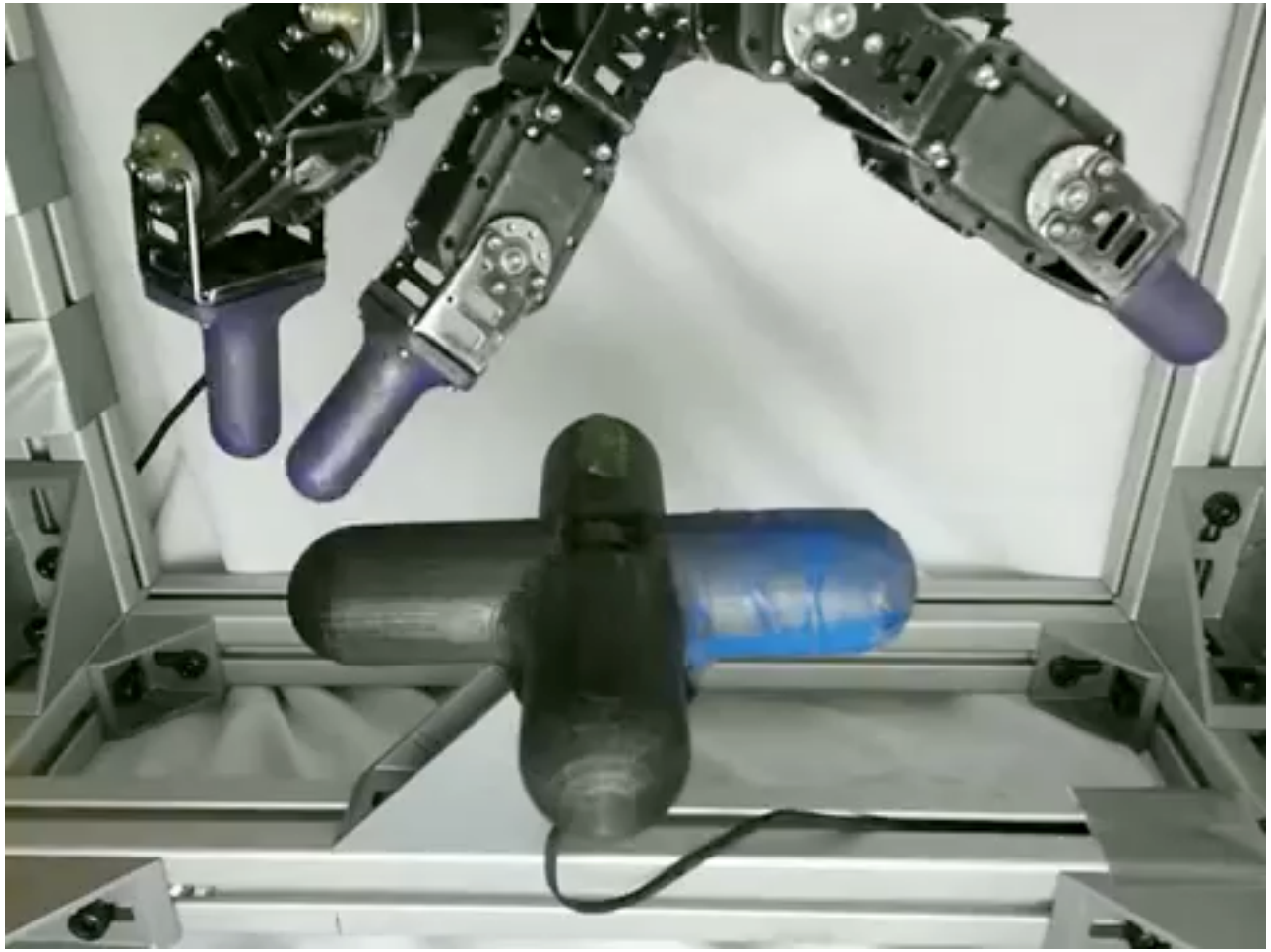
- Soft Actor-Critic on Minitaur - Testing



https://sites.google.com/view/sac-and-applications

Results

- Interfered rollouts from Soft Actor-Critic policy trained for Dynamixel Claw task from vision



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- T. Haarnoja, et, al., “Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor”, ICML 2018
- T. Haarnoja, et, al., “Soft Actor-Critic Algorithms and Applications”, arXiv preprint 2018

Theoretical analysis

- “Induction of Q-learning, Soft Q-learning, and Sparse Q-learning” written by Sungjoon Choi
- “Reinforcement Learning with Deep Energy-Based Policies” reviewed by Kyungjae Lee
- “Entropy Regularization in Reinforcement Learning (Stochastic Policy)” reviewed by Kyungjae Lee
- Reframing Control as an Inference Problem, CS 294-112: Deep Reinforcement Learning
- Constrained optimization problem and dual problem for SAC with automatically adjusted temperature (in Korean)

Thank You!

Any Questions?