Reinforcement Learning

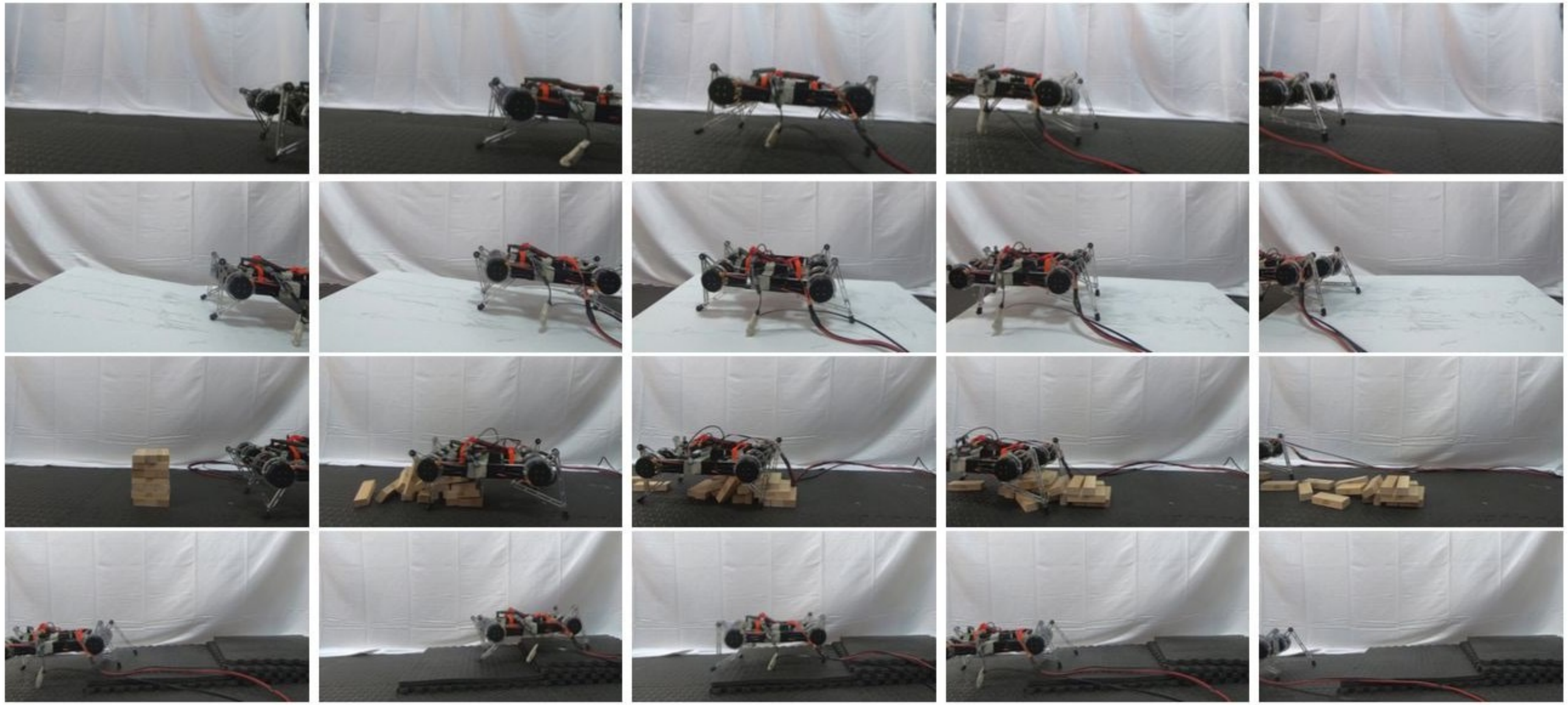
Naeemullah Khan

naeemullah.khan@kaust.edu.sa

جامعة الملك عبدالله للعلوم والتقنية
King Abdullah University of Science and Technology

KAUST Academy
King Abdullah University of Science and Technology

Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement



Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, Sergey Levine

Main Problem: Sample Inefficiency

- Number of times the agent must interact with the environment in order to learn a task

- Good sample complexity is the first prerequisite for successful skill acquisition.

- Learning skills in the real world can take a substantial amount of time
  - can get damaged through trial and error

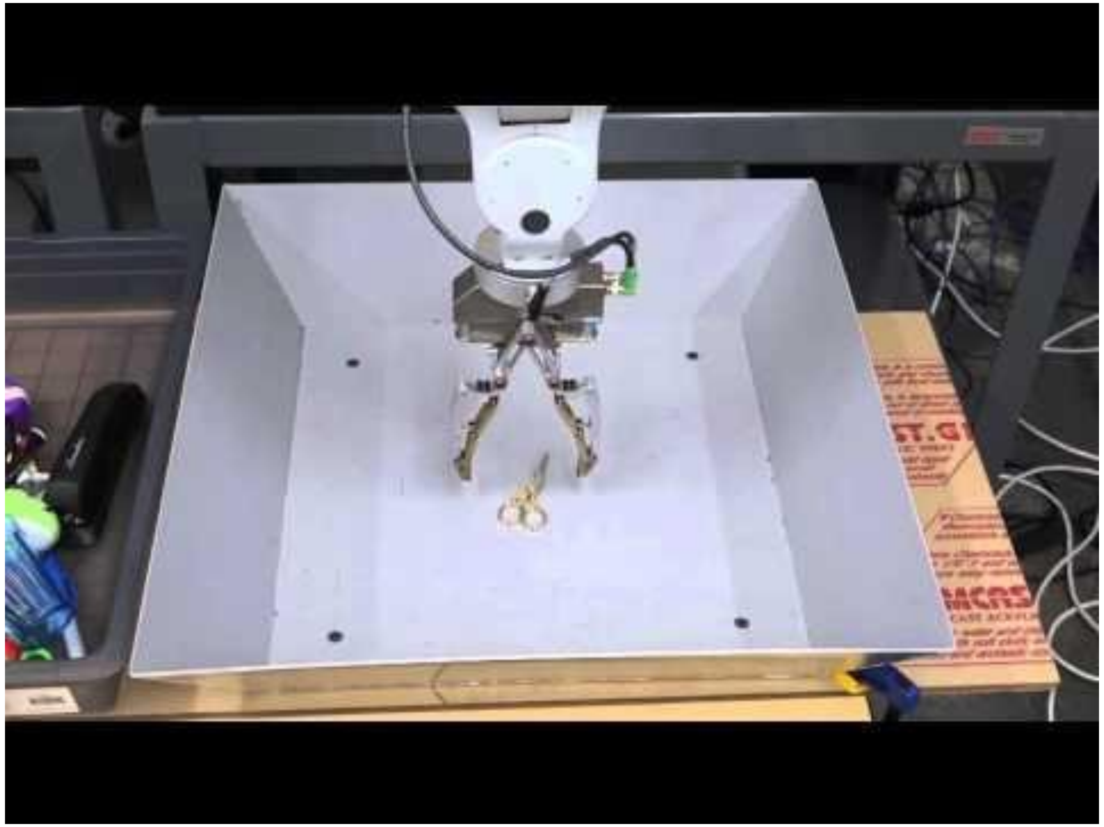
Main Problem: Sample Inefficiency

- "Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection", Levine et al., 2016
    - 14 robot arms learning to grasp in parallel
    - objects started being picked up at around 20,000 grasps

https://spectrum.ieee.org/automaton/robotics/artificial-intelligence/google-large-scale-robotic-grasping-project

Main Problem: Sample Inefficiency

> *Observing the behavior of the robot after over 800,000 grasp attempts, which is equivalent to about 3000 robot-hours of practice, we can see the beginnings of intelligent reactive behaviors*



https://www.youtube.com/watch?v=cXaic_k80uM

Main Problem: Sample Inefficiency

- Solution?

- Off-Policy Learning!

Background: On-Policy vs. Off-Policy

أكاديمية كاوست
KAUST ACADEMY

- On-policy learning: use the deterministic outcomes or samples from the target policy to train the algorithm
  - has low sample efficiency (TRPO, PPO, A3C)
  - require new samples to be collected for nearly every update to the policy
  - becomes extremely expensive when the task is complex

- Off-policy methods: training on a distribution of transitions or episodes produced by a different behavior policy rather than that produced by the target policy
  - Does not require full trajectories and can reuse any past episodes (experience replay) for much better sample efficiency
  - relatively straightforward for Q-learning based methods

Background: Bellman Equation

- Value Function: How good is a state?

$$
\begin{aligned}
V(s) &= \mathbb{E}[G_t | S_t = s] \\
&= \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots | S_t = s] \\
&= \mathbb{E}[R_{t+1} + \gamma (R_{t+2} + \gamma R_{t+3} + \dots) | S_t = s] \\
&= \mathbb{E}[R_{t+1} + \gamma G_{t+1} | S_t = s] \\
&= \mathbb{E}[\underline{R_{t+1} + \gamma V(S_{t+1})} | S_t = s]
\end{aligned}
$$

temporal difference target

- Similarly, for Q-Function: How good is a state-action pair?

$$
\begin{aligned}
Q(s, a) &= \mathbb{E}[R_{t+1} + \gamma V(S_{t+1}) \mid S_t = s, A_t = a] \\
&= \mathbb{E}[R_{t+1} + \gamma \mathbb{E}_{a \sim \pi} Q(S_{t+1}, a) \mid S_t = s, A_t = a]
\end{aligned}
$$

Background: Value-Based Method

- $\ldots, S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1}, \ldots$ (on-policy):

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t))$$

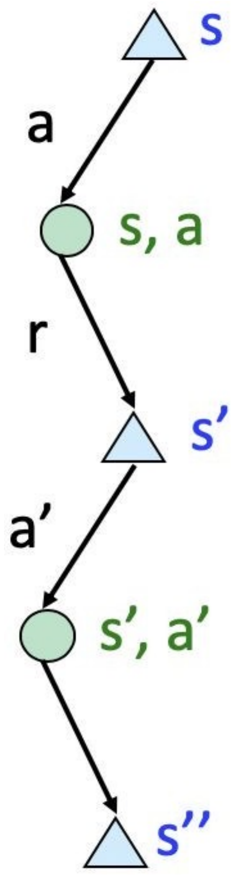
- Q-Learning (off-policy)

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_{a \in \mathcal{A}} Q(S_{t+1}, a) - Q(S_t, A_t))$$

- DQN, Minh et al., 2015

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s') \sim U(D)} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta) \right)^2 \right]$$

  - Function Approximation
  - Experience Replay: samples randomly drawn from replay memory
  - Doesn’t scale to continuous action space



Background: Policy-Based Method (Actor-Critic)

أكاديمية كاوست
KAUST ACADEMY

- **Critic**: updates value function parameters w and depending on the algorithm it could be action-value $Q(a|s; w)$ or state-value $V(s; w)$.
- **Actor**: updates policy parameters θ, in the direction suggested by the critic, $\pi(a|s; \theta)$.

$$\nabla \mathcal{J}(\theta) = \mathbb{E}_{\pi_\theta}[\nabla \ln \pi(a|s, \theta) Q_\pi(s, a)]$$ policy gradient

$$\theta \leftarrow \theta + \alpha_\theta Q(s, a; w) \nabla_\theta \ln \pi(a|s; \theta)$$ update actor

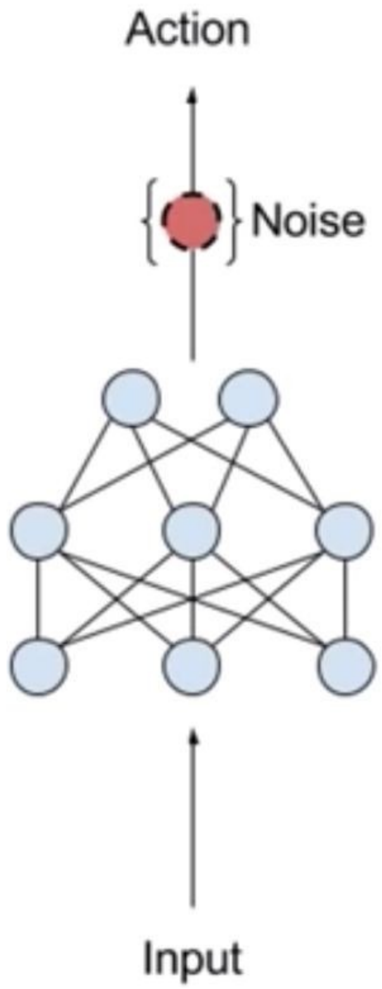
$$G_{t:t+1} = r_t + \gamma Q(s', a'; w) - Q(s, a; w)$$ correction for action-value

$$w \leftarrow w + \alpha_w G_{t:t+1} \nabla_w Q(s, a; w).$$ update critic

https://lilianweng.github.io/lil-log/2018/02/19/a-long-peek-into-reinforcement-learning.html#actor-critic

Prior Work: DDPG

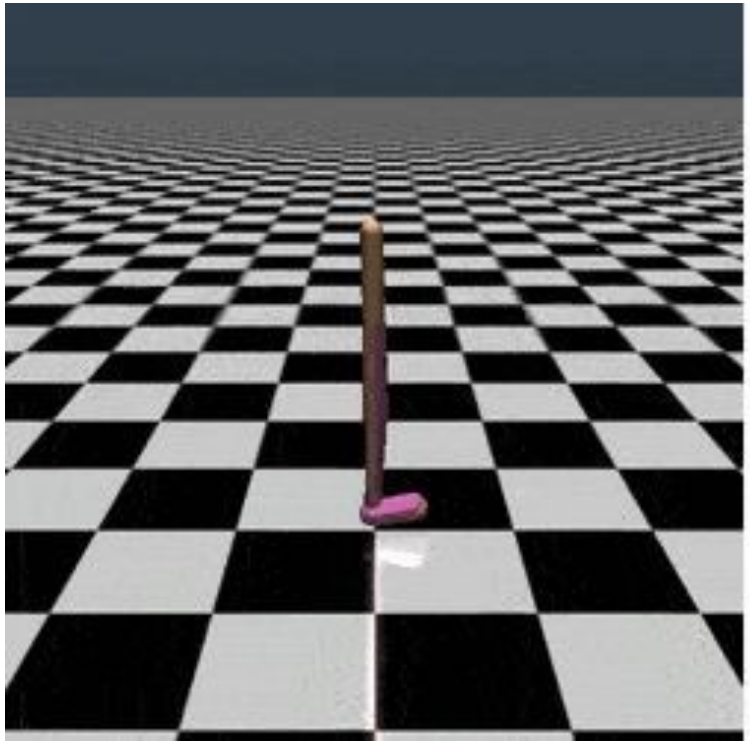
- DDPG = DQN + DPG (Lillicrap et al., 2015)
  - off-policy actor-critic method that learns a deterministic policy in continuous domain
  - exploration noise added to the deterministic policy when select action
  - difficult to stabilize and brittle to hyperparameters (Duan et al., 2016, Henderson et al., 2017)
  - unscalable to complex tasks with high dimensions (Gu et al., 2017)

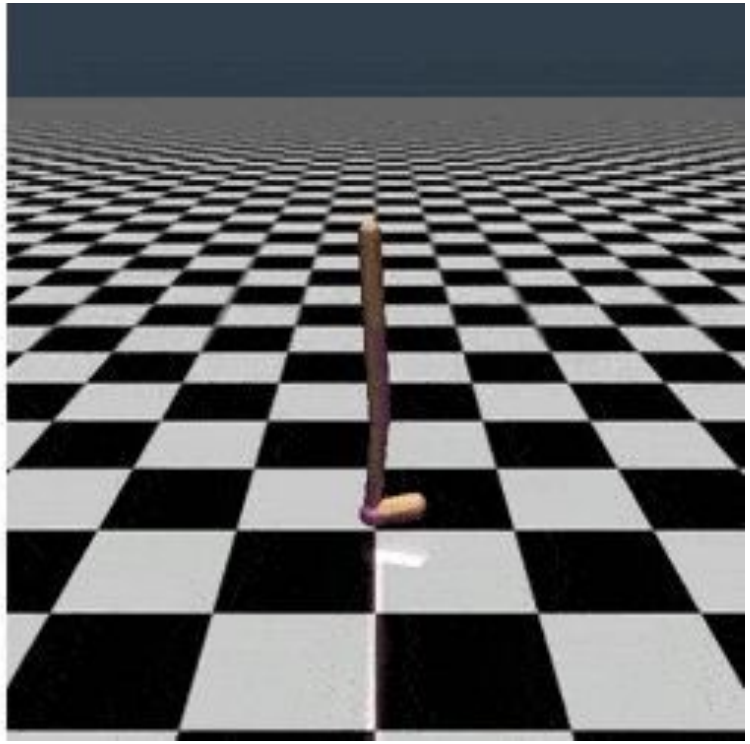


https://www.youtube.com/watch?v=zR11FLZ-O9M&t=2145s

Main Problems: Robustness

- Training is sensitive to randomness in the environment, initialization of the policy and the algorithm implementation

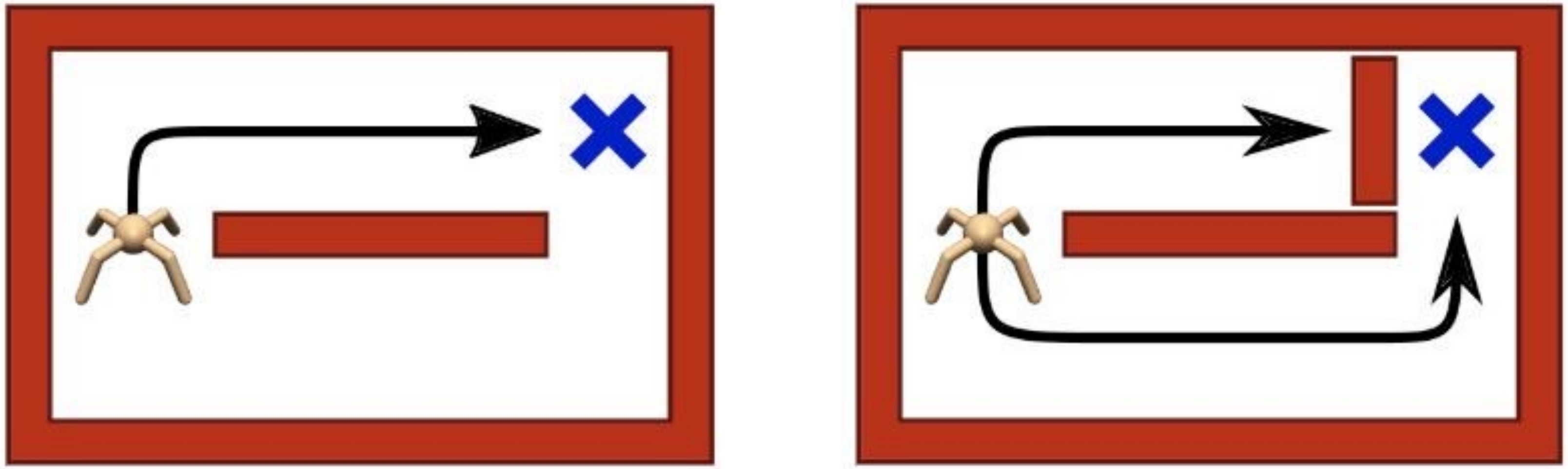




https://gym.openai.com/envs/Walker2d-v2/

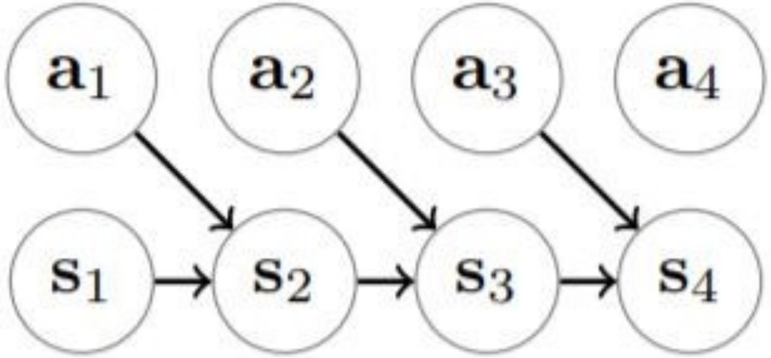
Main Problems: Robustness

- Knowing only one way to act makes agents vulnerable to environmental changes that are common in the real-world

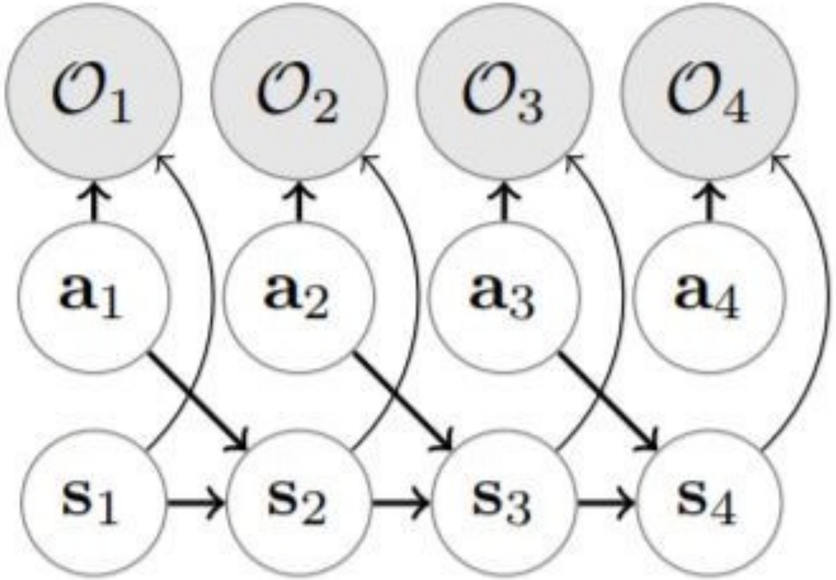


https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/

Background: Control as Inference



Traditional Graph of MDP



Graphical Model with Optimality Variables

Background: Control as Inference

Normal trajectory distribution

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

Posterior trajectory distribution

$$p(\mathcal{O}_t = 1|\mathbf{s}_t, \mathbf{a}_t) = \exp(r(\mathbf{s}_t, \mathbf{a}_t)).$$

$$\begin{aligned}
p(\tau|\mathbf{o}_{1:T}) \propto p(\tau, \mathbf{o}_{1:T}) &= p(\mathbf{s}_1)\prod_{t=1}^{T} p(\mathcal{O}_t = 1|\mathbf{s}_t, \mathbf{a}_t)p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) \\
&= p(\mathbf{s}_1)\prod_{t=1}^{T} \exp(r(\mathbf{s}_t, \mathbf{a}_t))p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) \\
&= \left[p(\mathbf{s}_1)\prod_{t=1}^{T} p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)\right]\exp\left(\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)\right).
\end{aligned}$$

Background: Control as Inference

Variational Inference

$$D_{\mathrm{KL}}(\hat{p}(\tau)\|p(\tau)) = -E_{\tau\sim\hat{p}(\tau)}[\log p(\tau) - \log \hat{p}(\tau)].$$

$$\begin{aligned}
-D_{\mathrm{KL}}(\hat{p}(\tau)\|p(\tau)) = E_{\tau\sim\hat{p}(\tau)} \Bigg[& \log p(\mathbf{s}_1) + \sum_{t=1}^{T} \left(\log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) + r(\mathbf{s}_t, \mathbf{a}_t)\right) - \\
& \log p(\mathbf{s}_1) - \sum_{t=1}^{T} \left(\log p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) + \log \pi(\mathbf{a}_t|\mathbf{s}_t)\right) \Bigg] \\
= E_{\tau\sim\hat{p}(\tau)} & \left[\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t) - \log \pi(\mathbf{a}_t|\mathbf{s}_t) \right] \\
= \sum_{t=1}^{T} & E_{(\mathbf{s}_t,\mathbf{a}_t)\sim\hat{p}(\mathbf{s}_t,\mathbf{a}_t))}[r(\mathbf{s}_t, \mathbf{a}_t) - \log \pi(\mathbf{a}_t|\mathbf{s}_t)] \\
= \sum_{t=1}^{T} & E_{(\mathbf{s}_t,\mathbf{a}_t)\sim\hat{p}(\mathbf{s}_t,\mathbf{a}_t))}[r(\mathbf{s}_t, \mathbf{a}_t)] + E_{\mathbf{s}_t\sim\hat{p}(\mathbf{s}_t)}[\mathcal{H}(\pi(\mathbf{a}_t|\mathbf{s}_t))].
\end{aligned}$$

Background: Max Entropy RL

Conventional RL Objective - Expected Reward

$$\sum_t \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[r(\mathbf{s}_t,\mathbf{a}_t)\right]$$

Maximum Entropy RL Objective - Expected Reward + Entropy of Policy

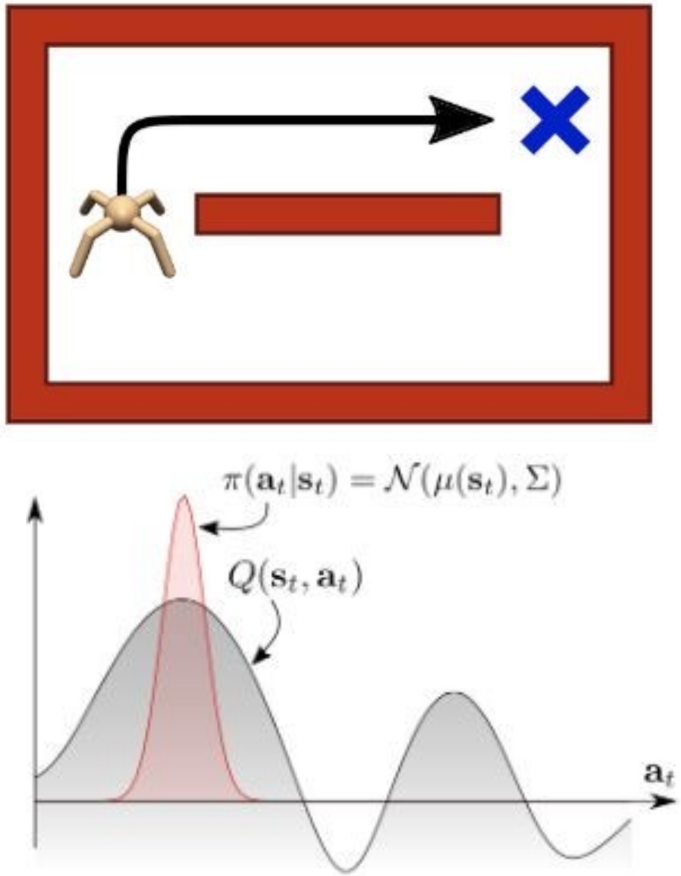
$$\sum_t \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[r(\mathbf{s}_t,\mathbf{a}_t) + \alpha \boxed{\mathcal{H}(\pi(\,\cdot\,|\mathbf{s}_t))}\right]$$

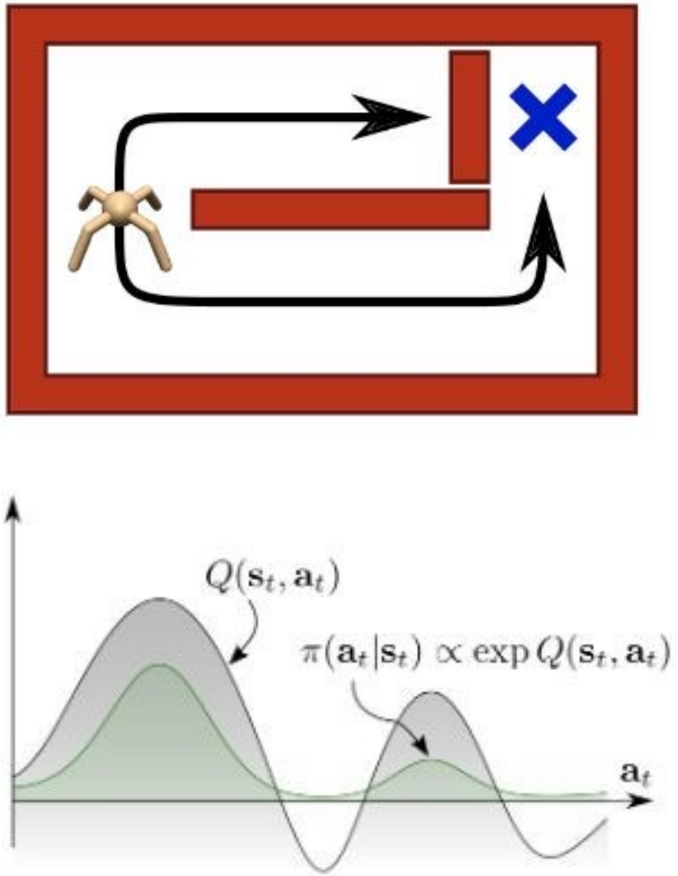
Entropy of a RV x

$$H(P) = \mathop{\mathrm{E}}_{x\sim P}\left[-\log P(x)\right]$$

Max Entropy RL

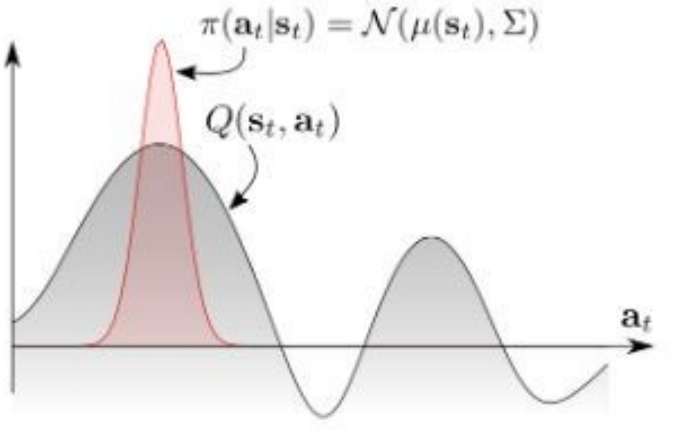
- MaxEnt RL agent can capture different modes of optimality to improve robustness against environmental changes

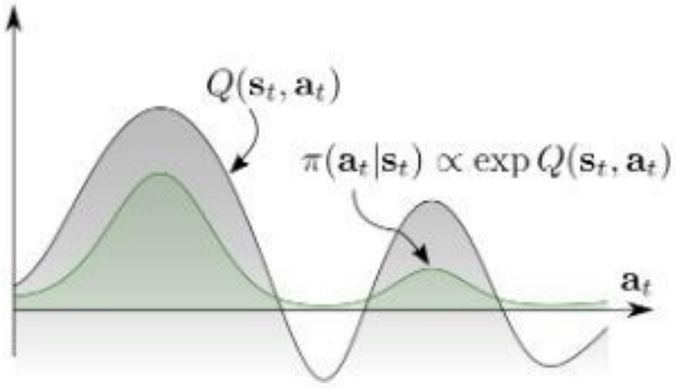




https://bair.berkeley.edu/blog/2017/10/06/soft-q-learning/

Max Entropy RL





$$\min_{\pi} D_{KL}[\pi(\cdot|s_0)||\exp(Q(s_0, \cdot))]$$

$$= \min_{\pi} E_{\pi}[\log \frac{\pi(a_0|s_0)}{\exp(Q(s_0, a_0))}]$$

$$= \max_{\pi} E_{\pi}[Q(s_0, a_0) - \log\pi(a_0|s_0)]$$

$$= \max_{\pi} E_{\pi}[\sum_t r(s_t, a_t) + \mathcal{H}(\pi(\cdot|s_0))|s_0]$$

$$= J_{MaxEnt}(\pi(\cdot|s_0))$$

Prior Work: Soft Q-Learning

- Soft Q-Learning (Haarnoja et al., 2017)
  - off-policy algorithms under MaxEnt RL objective
  - Learns Q* directly
  - Intead of taking max action, sample the action
  - use approximate inference methods to sample
    - Stein variational gradient descent
  - not true actor-critic

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_{a \in \mathcal{A}} Q(S_{t+1}, a) - Q(S_t, A_t))$$

$$Q_{\mathrm{soft}}(\mathbf{s}_t, \mathbf{a}_t) \leftarrow r_t + \gamma \, \mathbb{E}_{\mathbf{s}_{t+1} \sim p_{\mathbf{s}}} \left[V_{\mathrm{soft}}(\mathbf{s}_{t+1}) \right], \; \forall \mathbf{s}_t, \mathbf{a}_t$$

$$V_{\mathrm{soft}}(\mathbf{s}_t) \leftarrow \alpha \log \int_{\mathcal{A}} \exp\left(\frac{1}{\alpha} Q_{\mathrm{soft}}(\mathbf{s}_t, \mathbf{a}') \right) d\mathbf{a}', \; \forall \mathbf{s}_t$$

SAC: Contributions

- One of the most efficient model-free algorithms
  - SOTA off-policy
  - well suited for real world robotics learning
- Can learn stochastic policy on continuous action domain
- Robust to noise

- Ingredients:
  - Actor-critic architecture with seperate policy and value function networks
  - Off-policy formulation to reuse of previously collected data for efficiency
  - Entropy-constrained objective to encourage stability and exploration

Soft Policy Iteration: Policy Evaluation

- policy evaluation: compute value of π according to Max Entropy RL Objective

- modified Bellman backup operator T:

$$\mathcal{T}^\pi Q(\mathbf{s}_t, \mathbf{a}_t) \triangleq r(\mathbf{s}_t, \mathbf{a}_t) + \gamma\, \mathbb{E}_{\mathbf{s}_{t+1} \sim p}\left[\boxed{V(\mathbf{s}_{t+1})}\right]$$

$$V(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t \sim \pi}\left[Q(\mathbf{s}_t, \mathbf{a}_t) - \boxed{\alpha \log \pi(\mathbf{a}_t|\mathbf{s}_t)}\right]$$

- Lemma 1: Contraction Mapping for Soft Bellman Updates

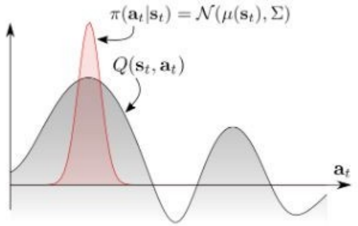
$$Q^{k+1} = \mathcal{T}^\pi Q^k$$ converges to the soft Q-function of π

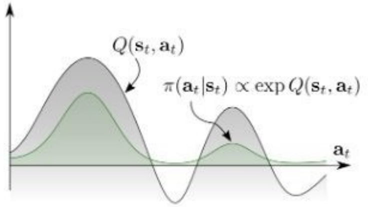
Soft Policy Iteration: Policy Improvement

- policy improvement: update policy towards the exponential of the new soft Q-function

- modified Bellman backup operator T:
  - choose tractable family of distributions big Π
  - choose KL divergence to project the improved policy into big Π

$$\pi_{\mathrm{new}} = \arg\min_{\pi' \in \Pi} \mathrm{D}_{\mathrm{KL}} \left(\pi'(\,\cdot\,|\mathbf{s}_t) \;\middle\|\; \frac{\exp\left(\frac{1}{\alpha} Q^{\pi_{\mathrm{old}}}(\mathbf{s}_t, \,\cdot\,)\right)}{Z^{\pi_{\mathrm{old}}}(\mathbf{s}_t)} \right)$$





- Lemma 2

$$Q^{\pi_{\mathrm{new}}}(\mathbf{s}_t, \mathbf{a}_t) \geq Q^{\pi_{\mathrm{old}}}(\mathbf{s}_t, \mathbf{a}_t)$$ for any state action pair

Soft Policy Iteration

- soft policy iteration: soft policy evaluation <-> soft policy improvement

- Theorem 1: Repeated application of soft policy evaluation and soft policy improvement from any policy $\pi \in \Pi$ converges to the optimal MaxEnt policy among all policies in Π
    - exact form applicable only in discrete case
    - need function approximation to represent Q-values in continuous domains
    - -> Soft Actor-Critic (SAC)!

SAC - Parameterized soft Q-function

$Q_\theta(\mathbf{s}_t, \mathbf{a}_t)$

- e.g.neural network

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

parameterized tractable policy

- e.g. Gaussian with mean and covariances given by neural networks

$J_Q(\theta)$ $\hat{\nabla}_\theta J_Q(\theta)$

soft Q-function objective and its stochastic gradient wrt its parameters

$J_\pi(\phi)$ $\hat{\nabla}_\phi J_\pi(\phi)$

policy objective and stochastic gradient wrt its parameters

SAC: Objectives and Optimization

- Critic - Soft Q-function
  - minimize square error
  - $\bar{\theta}$ exponential moving average of soft Q-function weights to stabilize training (DQN)

$$J_Q(\theta) = \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t)\sim\mathcal{D}}\left[\frac{1}{2}\left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \left(r(\mathbf{s}_t, \mathbf{a}_t) + \gamma\, \mathbb{E}_{\mathbf{s}_{t+1}\sim p}\left[V_{\bar{\theta}}(\mathbf{s}_{t+1})\right]\right)\right)^2\right]$$

$$V(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t\sim\pi}\left[Q(\mathbf{s}_t, \mathbf{a}_t) - \alpha \log \pi(\mathbf{a}_t|\mathbf{s}_t)\right]$$

$$\hat{\nabla}_\theta J_Q(\theta) = \nabla_\theta Q_\theta(\mathbf{a}_t, \mathbf{s}_t)\left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \left(r(\mathbf{s}_t, \mathbf{a}_t) + \gamma\left(Q_{\bar{\theta}}(\mathbf{s}_{t+1}, \mathbf{a}_{t+1}) - \alpha \log\left(\pi_\phi(\mathbf{a}_{t+1}|\mathbf{s}_{t+1})\right)\right)\right)\right)$$

SAC: Objectives and Optimization

- Actor - Policy $\pi_{\text{new}} = \arg\min_{\pi' \in \Pi} \mathrm{D}_{\mathrm{KL}} \left(\pi'(\,\cdot\,|\mathbf{s}_t) \,\middle\|\, \frac{\exp\left(\frac{1}{\alpha} Q^{\pi_{\text{old}}}(\mathbf{s}_t, \cdot)\right)}{Z^{\pi_{\text{old}}}(\mathbf{s}_t)} \right)$

- multiply by alpha and ignoring the normalization Z

$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}} \left[\mathbb{E}_{\mathbf{a}_t \sim \pi_\phi} \left[\alpha \log\left(\pi_\phi(\mathbf{a}_t|\mathbf{s}_t)\right) - Q_\theta(\mathbf{s}_t, \mathbf{s}_t) \right] \right]$$

- reparameterize with neural network f $\mathbf{a}_t = f_\phi(\epsilon_t; \mathbf{s}_t)$
  - epsilon: input noise vector, sampled from a fixed distribution (spherical Gaussian)

$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}, \epsilon_t \sim \mathcal{N}} \left[\alpha \log \pi_\phi(f_\phi(\epsilon_t; \mathbf{s}_t)|\mathbf{s}_t) - Q_\theta(\mathbf{s}_t, f_\phi(\epsilon_t; \mathbf{s}_t)) \right]$$

$$\hat{\nabla}_\phi J_\pi(\phi) = \nabla_\phi \alpha \log\left(\pi_\phi(\mathbf{a}_t|\mathbf{s}_t)\right) + \left(\nabla_{\mathbf{a}_t} \alpha \log\left(\pi_\phi(\mathbf{a}_t|\mathbf{s}_t)\right) - \nabla_{\mathbf{a}_t} Q(\mathbf{s}_t, \mathbf{a}_t)\right) \nabla_\phi f_\phi(\epsilon_t; \mathbf{s}_t)$$

- Unbiased gradient estimator that extends DDPG stype policy gradients to any tractable stochastic policy

SAC: Algorithm

KAUST ACADEMY أكاديمية كاوست

Algorithm 1 Soft Actor-Critic

Input: initial policy parameters θ, Q-function parameters ϕ_1, ϕ_2, empty replay buffer $\mathcal{D}$
Set target parameters equal to main parameters $\phi_{\text{targ},1} \leftarrow \phi_1$, $\phi_{\text{targ},2} \leftarrow \phi_2$
repeat
  Observe state s and select action $a \sim \pi_\theta(\cdot|s)$
  Execute a in the environment
  Observe next state s', reward r, and done signal d to indicate whether s' is terminal
  Store (s, a, r, s', d) in replay buffer $\mathcal{D}$
  If s' is terminal, reset environment state.
  if it's time to update **then**
    for j in range(however many updates) **do**
      Randomly sample a batch of transitions, $B = \{(s, a, r, s', d)\}$ from $\mathcal{D}$
      Compute targets for the Q functions:

$$y(r, s', d) = r + \gamma(1-d)\left(\min_{i=1,2} Q_{\phi_{\text{targ},i}}(s', \tilde{a}') - \alpha \log \pi_\theta(\tilde{a}'|s')\right), \quad \tilde{a}' \sim \pi_\theta(\cdot|s')$$

      Update Q-functions by one step of gradient descent using

$$\nabla_{\phi_i} \frac{1}{|B|} \sum_{(s,a,r,s',d)\in B} \left(Q_{\phi_i}(s,a) - y(r,s',d)\right)^2 \qquad \text{for } i = 1, 2$$

      Update policy by one step of gradient ascent using

$$\nabla_\theta \frac{1}{|B|} \sum_{s \in B} \left(\min_{i=1,2} Q_{\phi_i}(s, \tilde{a}_\theta(s)) - \alpha \log \pi_\theta\left(\tilde{a}_\theta(s)|\, s\right)\right),$$

      where $\tilde{a}_\theta(s)$ is a sample from $\pi_\theta(\cdot|s)$ which is differentiable wrt θ via the reparametrization trick.
      Update target networks with

$$\phi_{\text{targ},i} \leftarrow \rho \phi_{\text{targ},i} + (1-\rho)\phi_i \qquad \text{for } i = 1, 2$$

    end for
  end if
until convergence

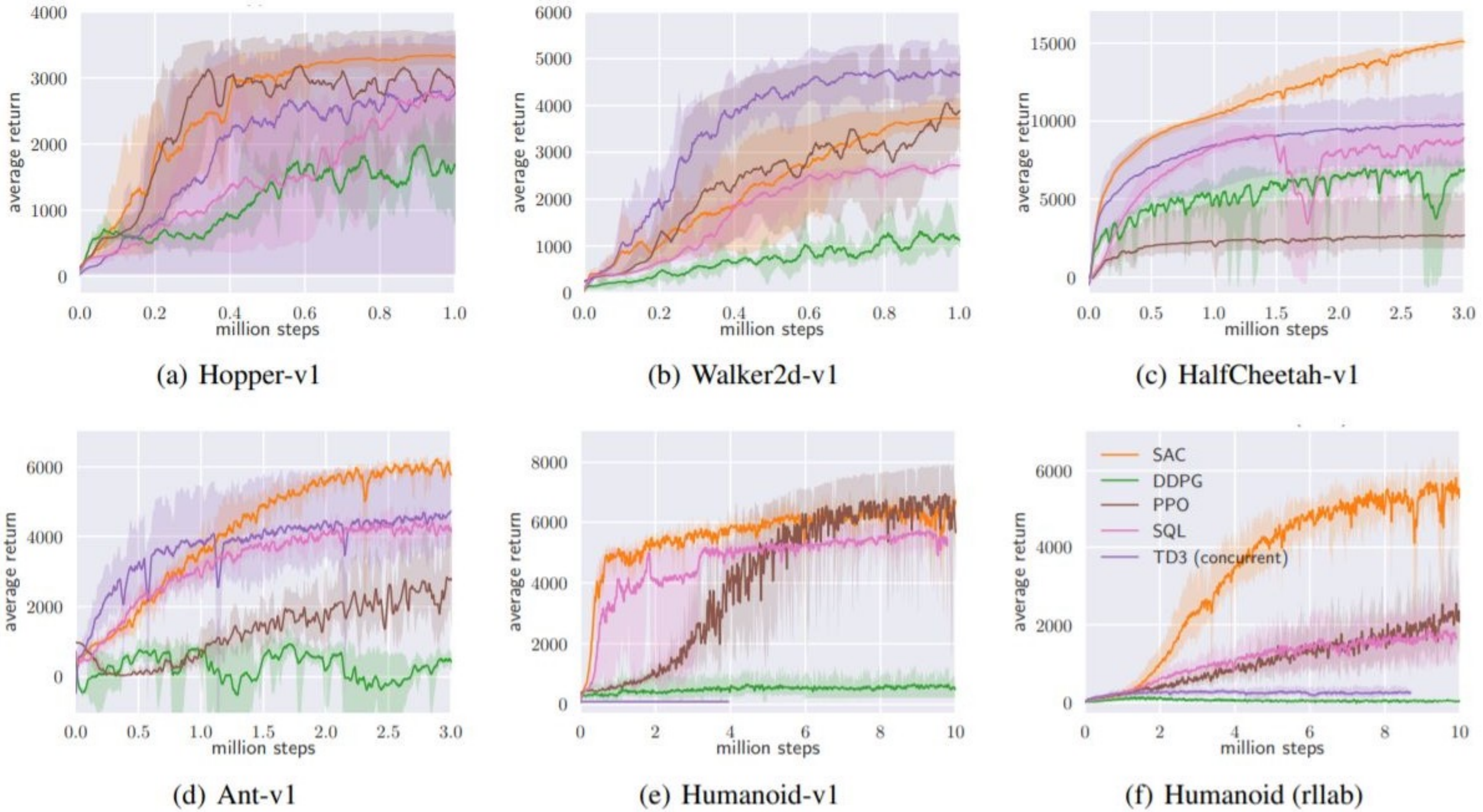
https://spinningup.openai.com/en/latest/algorithms/sac.html

Experimental Results

- Tasks
  - A range of continuous control tasks from the OpenAI gym benchmark suite
  - RL-Lab implementation of the Humanoid task
  - The easier tasks can be solved by a wide range of different algorithms, the more complex benchmarks, such as the 21-dimensional Humanoid (rllab) are exceptionally difficult to solve with off-policy algorithms.
- Baselines:
  - DDPG, SQL, PPO, TD3 (concurrent)
  - TD3 is an extension to DDPG that first applied the double Q-learning trick to continuous control along with other improvements.

https://arxiv.org/abs/1801.01290

SAC: Results

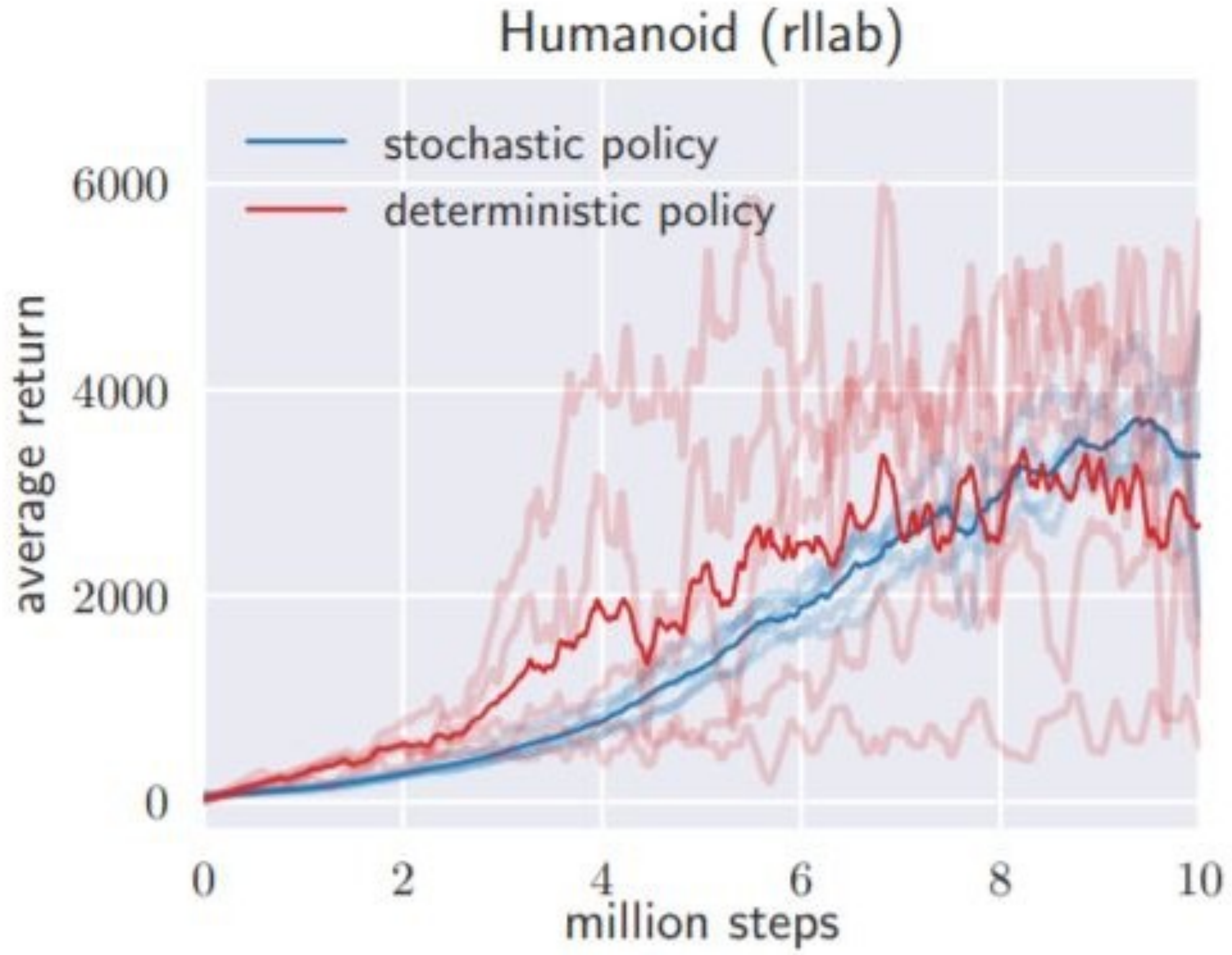


(a) Hopper-v1
(b) Walker2d-v1
(c) HalfCheetah-v1
(d) Ant-v1
(e) Humanoid-v1
(f) Humanoid (rllab)

Experimental Results: Ablation Study

- How does the stochasticity of the policy and entropy maximization affect the performance?

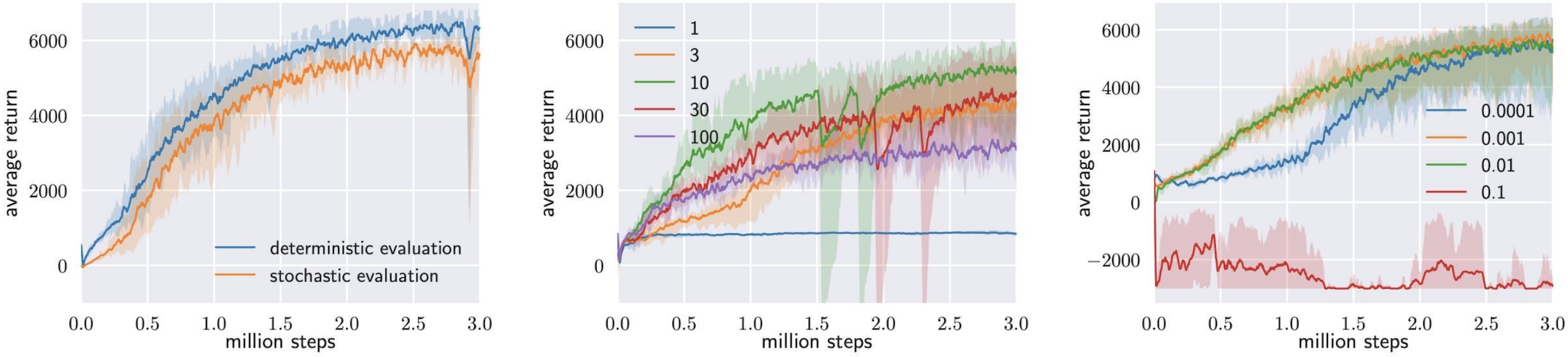
- Comparison with a deterministic variant of SAC that does not maximize the entropy and that closely resembles DDPG



https://arxiv.org/abs/1801.01290

Experimental Results: Hyperparameter Sensitivity

أكاديمية كاوست
KAUST ACADEMY



(a) Evaluation (b) Reward Scale (c) Target Smoothing Coefficient (τ)

https://arxiv.org/abs/1801.01290

Limitation

- Unfortunately, SAC also suffers from brittleness to the alpha temperature hyperparameter that controls exploration
  - -> automatic temperature tuning!

Contributions

- Adaptive temperature coefficient

temperature

$$\sum_t \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[r(\mathbf{s}_t,\mathbf{a}_t) + \alpha\mathcal{H}(\pi(\,\cdot\,|\mathbf{s}_t))\right]$$

- Extend to real-world tasks such as locomotion for a quadrupedal robot and robotic manipulation with a dexterous hand

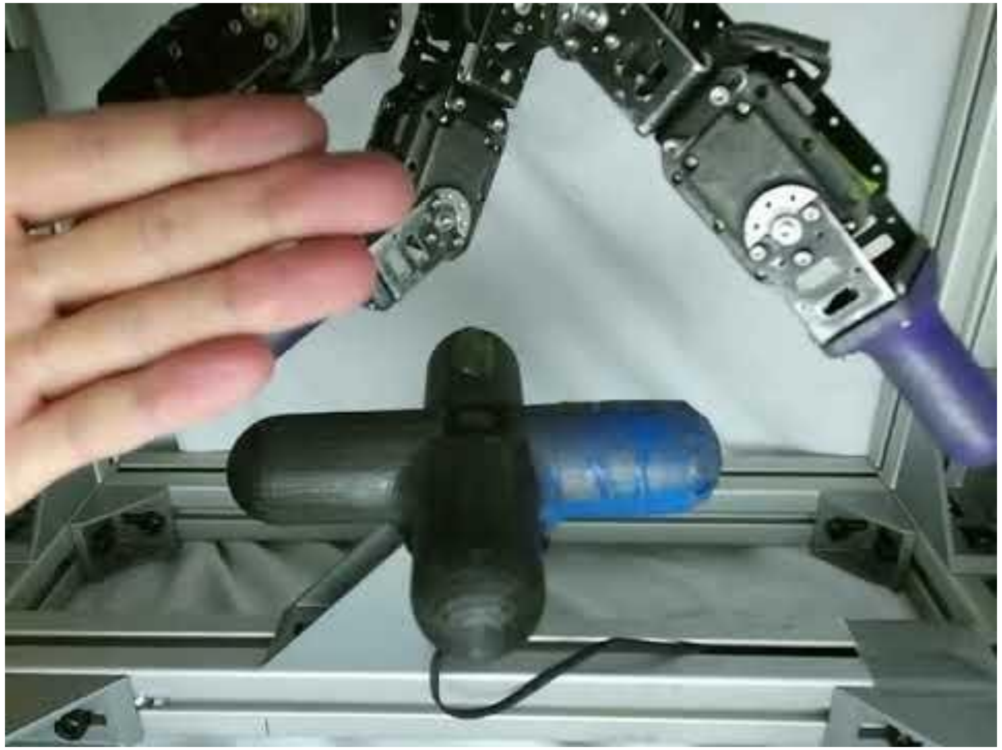
https://arxiv.org/abs/1801.01290

Real World Robots

https://arxiv.org/abs/1801.01290

Real World Robots

- Dexterous Hand Manipulations
- 20 hour end-to-end learning
- valve position as input: SAC 3 hours vs. PPO 7.4 hours



Automatic Temperature Tuning

- Choosing the optimal temperature is non-trivial (tuned for each task)
- Constrained optimization problem:

$$\max \sum_t \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[r(\mathbf{s}_t,\mathbf{a}_t) + \alpha\mathcal{H}(\pi(\,\cdot\,|\mathbf{s}_t))\right]$$

$$\max_{\pi_{0:T}} \mathbb{E}_{\rho_\pi}\left[\sum_{t=0}^{T} r(\mathbf{s}_t,\mathbf{a}_t)\right] \text{ s.t. } \mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[-\log(\pi_t(\mathbf{a}_t|\mathbf{s}_t))\right] \geq \mathcal{H} \;\; \forall t$$

https://arxiv.org/abs/1801.01290

Dual Problem for the Constrained Optimization

Unroll the expectation

$$\max_{\pi_0}\left(\mathbb{E}\left[r(\mathbf{s}_0,\mathbf{a}_0)\right]+\max_{\pi_1}\left(\mathbb{E}\left[\ldots\right]+\boxed{\max_{\pi_T}\mathbb{E}\left[r(\mathbf{s}_T,\mathbf{a}_T)\right]}\right)\right)$$

For the last time step in the trajectory

$$\max_{\pi_T}\mathbb{E}_{(\mathbf{s}_t,\mathbf{a}_t)\sim\rho_\pi}\left[r(\mathbf{s}_T,\mathbf{a}_T)\right]=\min_{\alpha_T\geq 0}\max_{\pi_T}\mathbb{E}\left[r(\mathbf{s}_T,\mathbf{a}_T)-\alpha_T\log\pi(\mathbf{a}_T|\mathbf{s}_T)\right]-\alpha_T\mathcal{H}$$

$$\arg\min_{\alpha_T}\mathbb{E}_{\mathbf{s}_t,\mathbf{a}_t\sim\pi_t^*}\left[-\alpha_T\log\pi_T^*(\mathbf{a}_T|\mathbf{s}_T;\alpha_T)-\alpha_T\mathcal{H}\right].$$

Dual Problem for the Constrained Optimization

Similarly, for the previous time step

$$\max_{\pi_{T-1}} \left(\mathbb{E}\left[r(\mathbf{s}_{T-1}, \mathbf{a}_{T-1})\right] + \max_{\pi_T} \mathbb{E}\left[r(\mathbf{s}_T, \mathbf{a}_T)\right] \right) \tag{16}$$

$$= \max_{\pi_{T-1}} \left(Q^*_{T-1}(\mathbf{s}_{T-1}, \mathbf{a}_{T-1}) - \alpha_T \mathcal{H} \right)$$

$$= \min_{\alpha_{T-1} \geq 0} \max_{\pi_{T-1}} \left(\mathbb{E}\left[Q^*_{T-1}(\mathbf{s}_{T-1}, \mathbf{a}_{T-1})\right] - \mathbb{E}\left[\alpha_{T-1} \log \pi(\mathbf{a}_{T-1}|\mathbf{s}_{T-1})\right] - \alpha_{T-1}\mathcal{H} \right) + \alpha^*_T \mathcal{H}.$$

$$\alpha^*_t = \arg\min_{\alpha_t} \mathbb{E}_{\mathbf{a}_t \sim \pi^*_t}\left[-\alpha_t \log \pi^*_t(\mathbf{a}_t|\mathbf{s}_t; \alpha_t) - \alpha_t \bar{\mathcal{H}}\right]$$

Algorithm 1 Soft Actor-Critic

Input: θ_1, θ_2, ϕ two soft Q-functions ▷ 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 exponential moving average
end for
Output: θ_1, θ_2, ϕ ▷ Optimized parameters

Experimental Results: RL Lab

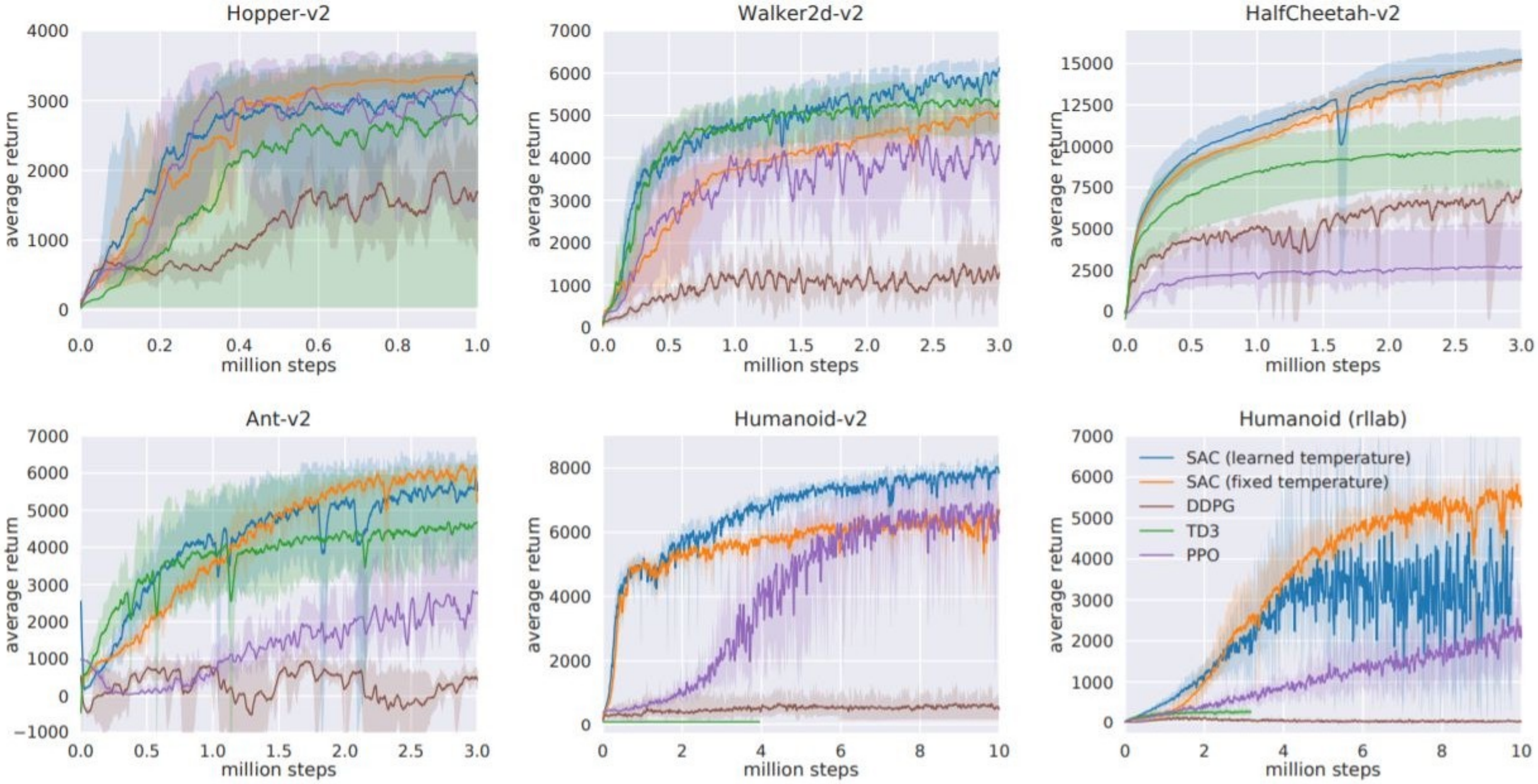
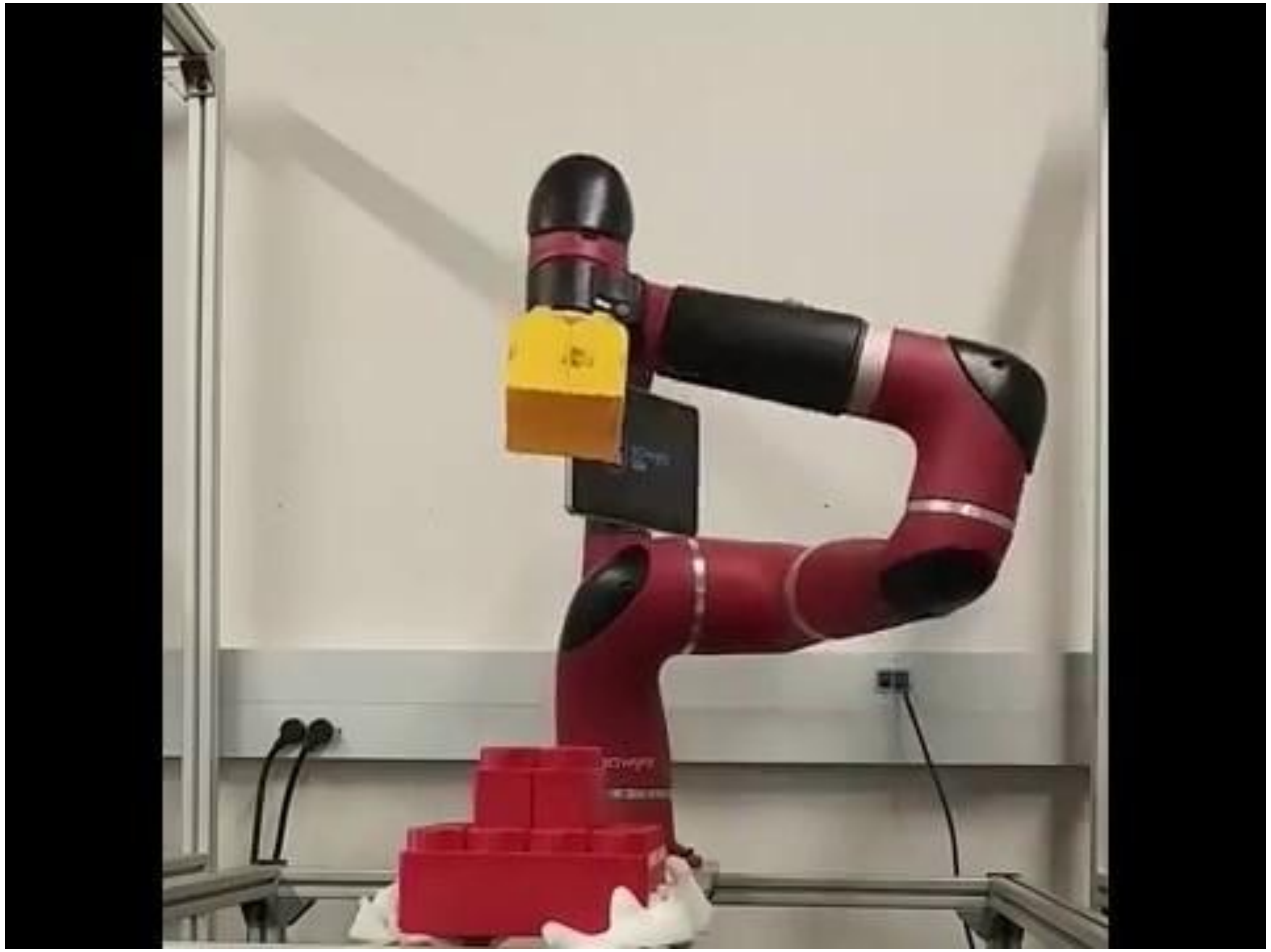


Figure 1: Training curves on continuous control benchmarks. Soft actor-critic (blue and yellow) performs consistently across all tasks and outperforming both on-policy and off-policy methods in the most challenging tasks.

https://arxiv.org/abs/1801.01290

Experimental Results: Robustness

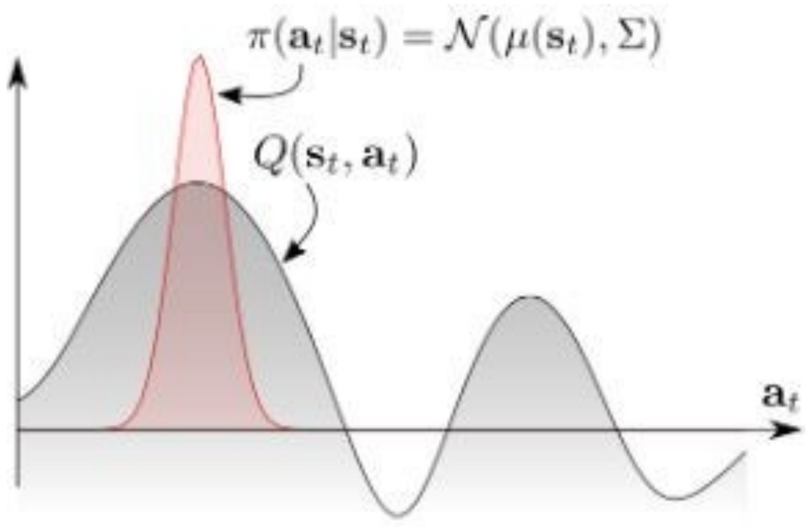


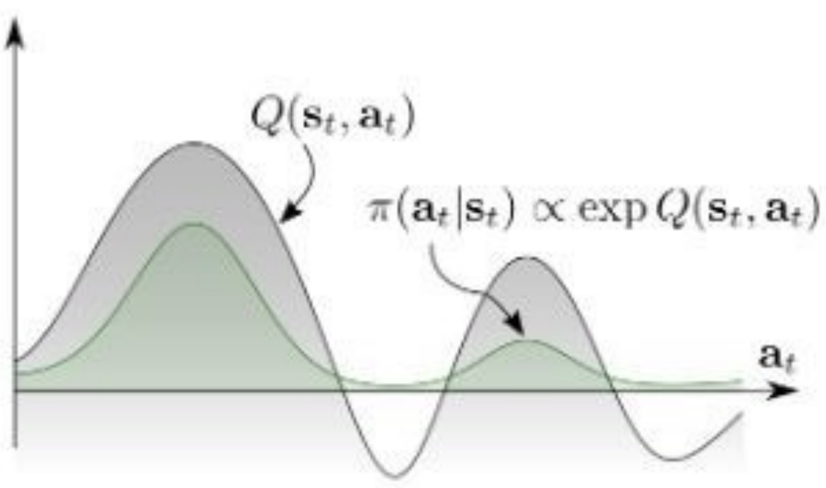
Limitations/Open Issues

- Lack of experiments on hard-exploration problem

Limitations/Open Issues

- Lack of experiments on hard-exploration problem
- Approximating a multi-modal Boltzmann distribution with a unimodal Gaussian



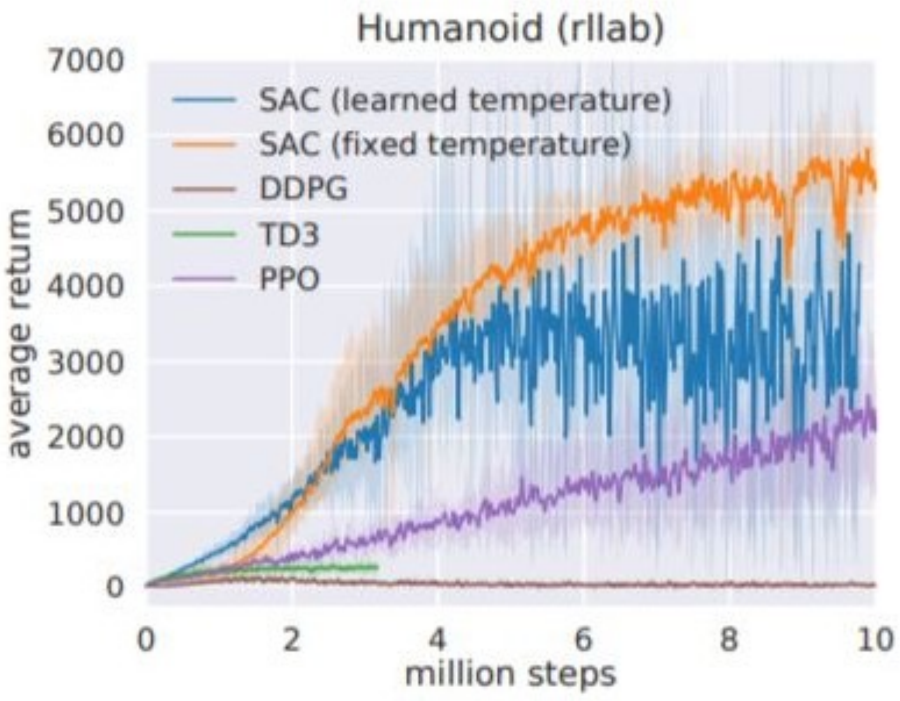


Limitations/Open Issues

- Lack of experiments on hard-exploration problem
- Approximating a multi-modal Boltzmann distribution with a unimodal Gaussian
- High-variance using automatic temperature tuning

Limitations/Open Issues

- Lack of experiments on hard-exploration problem
- Approximating a multi-modal Boltzmann distribution with a unimodal Gaussian
- High-variance using automatic temperature tuning



Recap: SAC

- An off-policy maximum entropy deep reinforcement learning algorithm
  - Sample-efficient
  - Scale to high-dimensional observation/action space
  - Robustness to random seed, noise and etc.
- Theoretical Results
  - Convergence of soft policy iteration
  - Derivation of soft-actor critic algorithm
- Empirical Results
  - SAC outperforms SOTA model-free deep RL methods, including DDPG, PPO and Soft Q-learning, in terms of the policy's optimality, sample complexity and robustness.

References

These slides have been adapted from

- Animesh Garg, CSC2621: Reinforcement Learning in Robotics, University of Toronto