13강.Actor-Critic:
DDPG,SAC

Contents

- Deep Deterministic Policy Gradient(DDPG)
- Code Ex.1
- Soft Actor Critic(SAC)
- Code Ex.2

DDPG

- Designed specifically for continuous action spaces
- Instead of a discrete action set: $a \in \{a_0, a_1, a_2, a_3, \ldots\}$, the number of valid actions is infinite

- Example of a continuous action a = [0.2, 1.5, 0.1]

DDPG

- If Q*(s, a) is the optimal Q-value function, Q*(s, a) then the optimal actions are given by:

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

- But how do we find the action with the highest value among infinite possible actions?

DDPG

- In order to solve control tasks,
  DDPG assume that Q(s, a(s)), is differentiable w.r.t a(s)
  - Q(s, a(s)) change very smoothly as the values of actions change
  - gradient ascent to get max. Q

- Similar actions should have similar values:
  - E.g., action [1, -1], action[1.0001, -1] will have very similar Q values.
  - E.g., In practice, setting steering boat wheel at 15 is very similar to the setting 15.01

DDPG

- DDPG updates θ of π (s|θ) via gradient ascent in the direction of maximum Q(s, π_θ(s)) increase, so that it produces the highest Q-value action

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta \underline{Q(s, \pi_\theta(s))}$$

Q(s, π_θ(s)) is differentiable w.r.t θ)

- Recall PG optimize policy π (s|θ) via gradient ascent so that it produces the most valuable actions:

$$\theta_{t+1} = \theta_t + \alpha \gamma^t G_t \nabla \ln \pi(A_t | S_t, \theta_t)$$ REINFORCE

$$\theta_{t+1} = \theta_t + \alpha \gamma^t \widehat{\mathrm{Adv}}_t \nabla \ln \pi(A_t | S_t, \theta_t)$$ A2C

DDPG

- Updates the policy through the Q-network:

  Compute Q values by policy's chosen action

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta Q(s, \underline{\pi_\theta(s)})$$

Deterministic policy
(argmax policy)

Find derivative w.r.t the neural net. parameters of the policy (without involving the Q network)

Perform stochastic gradient ascent to improve the policy

DDPG

- DDPG belongs to Actor-Critic method:
  - Learn a policy and a value function at the same time

- While we update the policy to make better decision, we also train the Q-network to estimate the action values better

$$\mathrm{L}(\theta) = (Q_\theta(s, a) - \hat{y})$$

$$,\text{where } \hat{y} = r + \gamma Q(s', a'))$$

DDPG

- Problem: If we push our policy to take the actions we think are best (deterministic), how do we explore?

- DDPG Adds Gaussian noise:

$$\mu'(s) = \mu(s) + \varepsilon \qquad \varepsilon \sim N(0, \sigma)$$

e.g., $\mu(s) = [0.5, 2]$ $\varepsilon = [0.02, -0.3]$

DDPG

Behavior policy is stochastic due to the added noise for exploration

Target policy is deterministic (a_{t+1} = argmax policy)

$\nabla_\theta Q(s, \mu_\theta(s)) = \nabla_a Q(s, a)\ \nabla_\theta \mu(s)$

Recall:
h(x) = (g·f)(x)
h′(x)=g′(f(x))f′(x)

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \underline{\mathcal{N}_t}$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \underline{\mu'(s_{i+1}|\theta^{\mu'})}|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q)^2)$
    Update the actor policy using the sampled gradient:

$$\nabla_{\theta^\mu} \mu|_{s_i} \approx \frac{1}{N} \sum_i \underline{\nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)}}\, \underline{\nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$

$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Let’s play with the code

1. Install Anaconda
2. Make a virtual environment:
   - conda create –n ‘your_name’ python=3.8
3. Pytorch Install:
   - go https://pytorch.kr/get-started/locally/ , and copy the command line depending on your computer OS
4. Gym Package Install:
   - pip install gym<0.25.0
   - pip install gym[box2d]
   - Pip install numpy==1.23.1
   - Pip install matplotlib

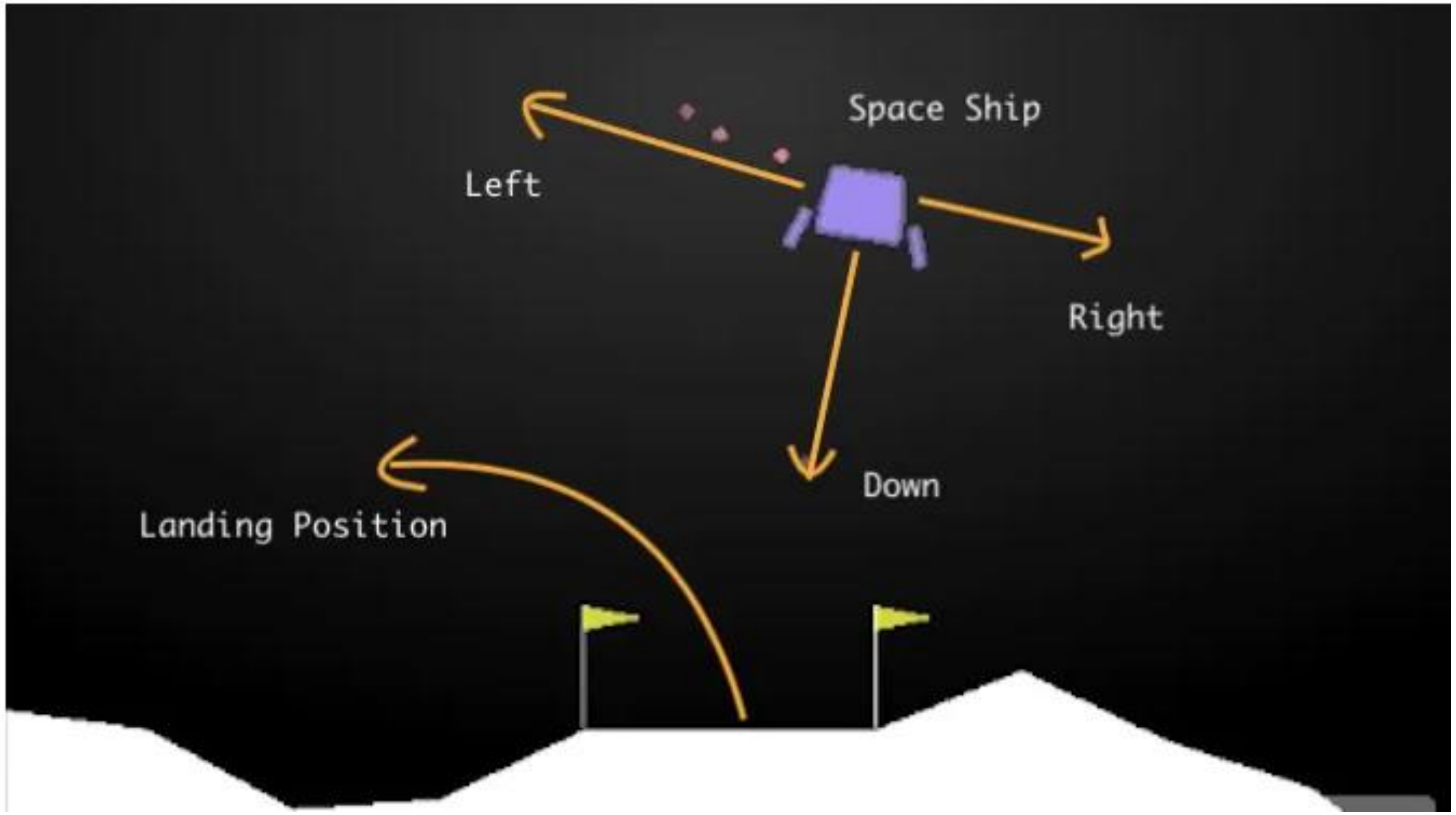
Let’s play with the code

- In /DDPG
  - main_ddpg.py # main loop interacting the env., agent learning
  - ddpg_torch.py # defines agent obj.
  - networks.py # defines actor and critic network
  - buffer.py # defines replay buffer
  - noise.py # generates OU action noise
  - utils.py # plotting function
  - /temp # store parameters
  - /plots # store the score that agent get while training

Let’s play with the code

Let’s play with the code

- LunarLanderContinuous-v2



Let's play with the code

- $a \sim [-1,1]x[-1,1]$
- a is np.array([main, lateral])
- the main engine will be turned off completely if main < 0 and the throttle scales affinely from 50% to 100% for 0 <= main <= 1
- -0.5 < lateral < 0.5, no lateral boosters fire
- lateral < -0.5, the left booster fire
- lateral > 0.5, the right booster fire

Action Space	`Box(-1, +1, (2,), dtype=np.float32)`
Observation Space	`Box([-1.5 -1.5 -5. -5. -3.1415927 -5. -0. -0. ], [1.5 1.5 5. 5. 3.1415927 5. 1. 1. ], (8,), float32)`
import	`gymnasium.make("LunarLander-v2")`

11강.Soft Actor-Critic(SAC)

Problem with Deterministic Policy

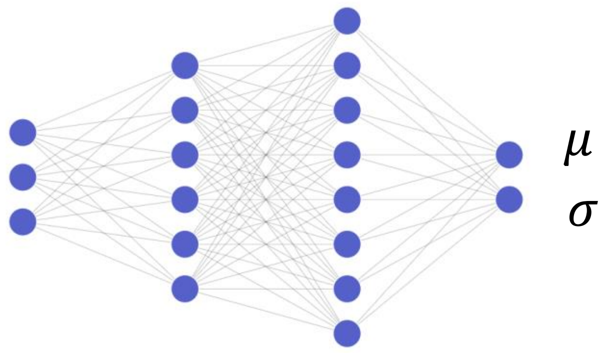
- Deterministic policy:
  - always takes same action for a specific state s. It means that we need extra “tricks” to explore
  - (e.g., ϵ-greedy policy, target policy smoothing, adding random noise)

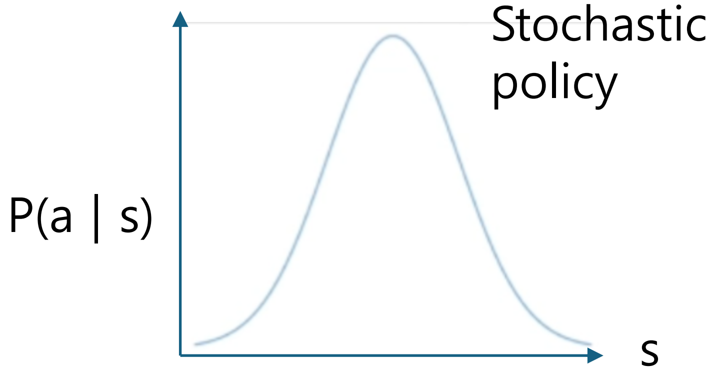
- Stochastic policy:
  - doesn’t need to apply any of these tricks
  - it doesn’t always choose the same action in the same state
  - Assigns a probability to each action and extract samples

Stochastic policies

- If we make the policy follow a normal distribution, then we just need to compute the mean and standard deviation

$$\mathrm{N}(\mu,\sigma)$$





Entropy

- We want to maintain the agent's exploration but we do not have mechanisms such as ε -greedy policies
- Now the neural net. is our policy. How to incorporate an exploration mechanism into our neural network?
- We will incentivize the agent to keep the entropy of its policy as high as possible

$$H(X) = -\sum_{x \in X} p(x) \cdot \ln p(x)$$

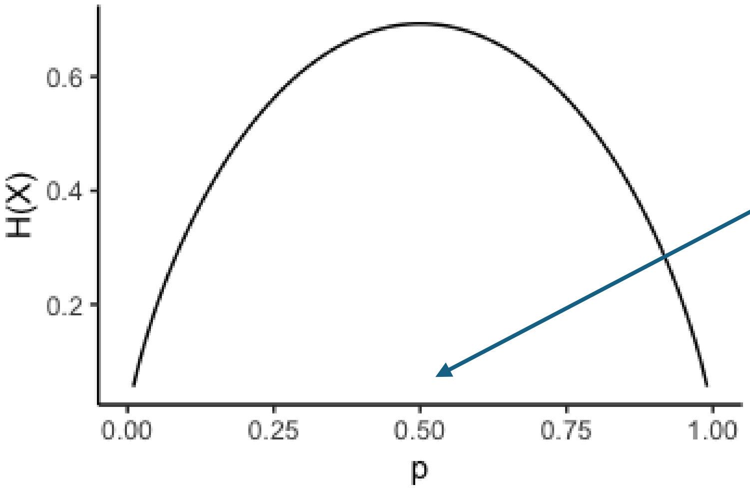
Entropy

- What is Entropy? the level of uncertainty of a random variable

e,g.,

if $p(X = x_1) = 1, p(X = x_2) = 0$, $H(X) = -[1 \cdot \ln(1) + 0 \cdot \ln(0)] = 0$

if $p(X = x_1) = 0.5, p(X = x_2) = 0.5$, $H(X) = -[0.5 \cdot \ln(0.5) + 0.5 \cdot \ln(0.5)] \approx 0.6931$



- Max. point where our confidence in our predictions will go down.
- Max. point where it surprises us

Entropy

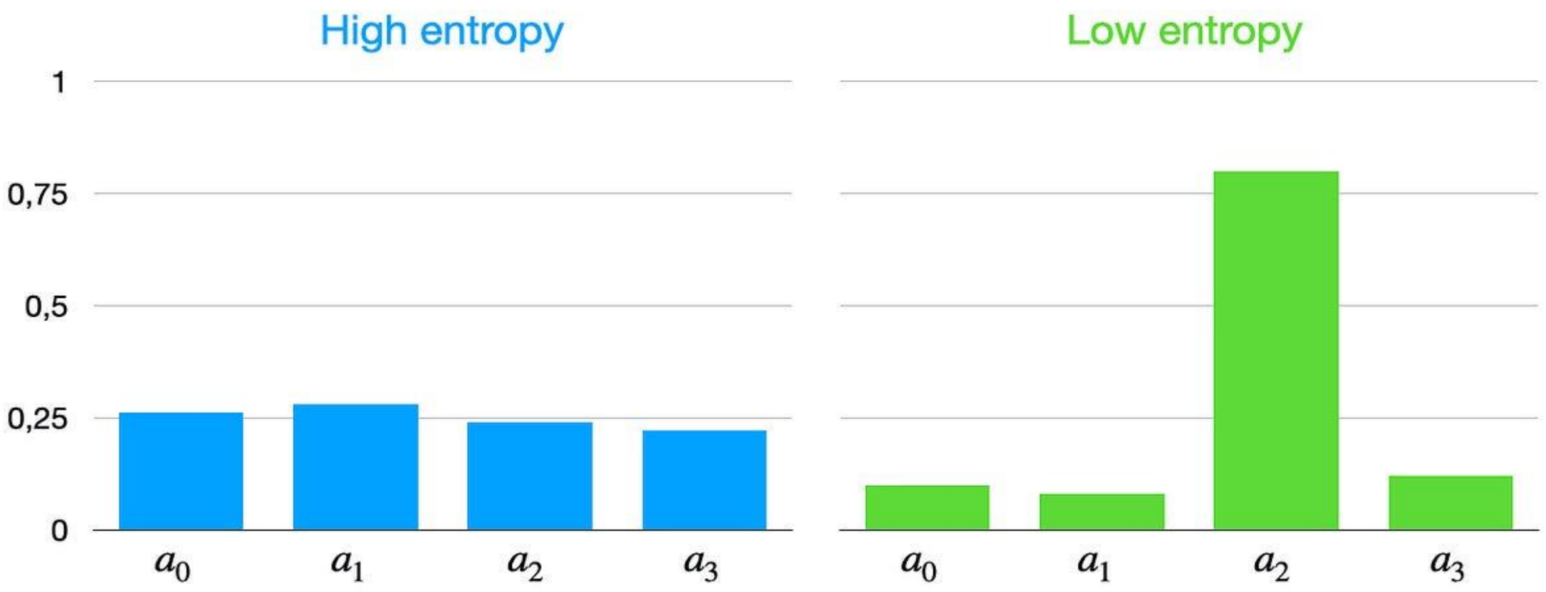
- What is the entropy of a policy?
- Uncertainty in the action to be selected in a state:

$$H_\pi(A_t) = -\sum_{a \in At} \pi(a|St) \cdot \ln \pi(a|St)$$

- Random variable(A_t) is the action the policy will choose in a state.
- The entropy is computed by multiplying the probability of choosing each action by its logarithm and adding up the results

Entropy

- What is the entropy of a policy?
- Imagine that we have 4 actions available



Entropy-regularized RL

- Maximize the cumulative sum of rewards while keeping the entropy of the policy as high as possible

- The entropy measures "how random" is our policy is

$$H(\pi) = E[-\ln \pi]$$

- Soft MDPs :

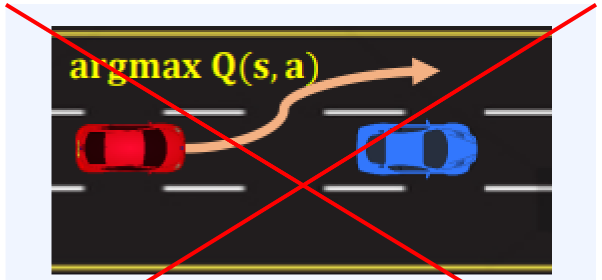
$$\max_{\pi} E[\sum_{t=0}^{\infty} \gamma^t r(st, at)] + \underline{\alpha H(\pi)}$$

Entropy Regularization:
Entropy of policy distribution

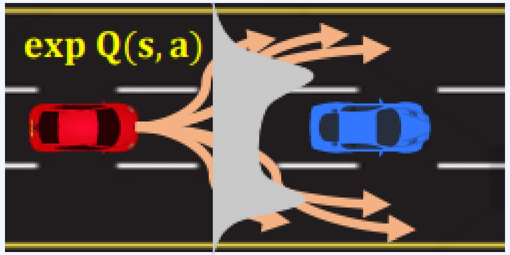
Softmax Policy

- A stochastic policy can provide multiple action choices
- Softmax dist. is the optimal solution of soft MDP (Max. Ent RL)
- Probability is exponentially proportional to the state action value Q(s, a)

$$\pi(a|s) = \frac{\exp Q(s,\ a)}{\sum_{a'} \exp Q(s, a')}$$



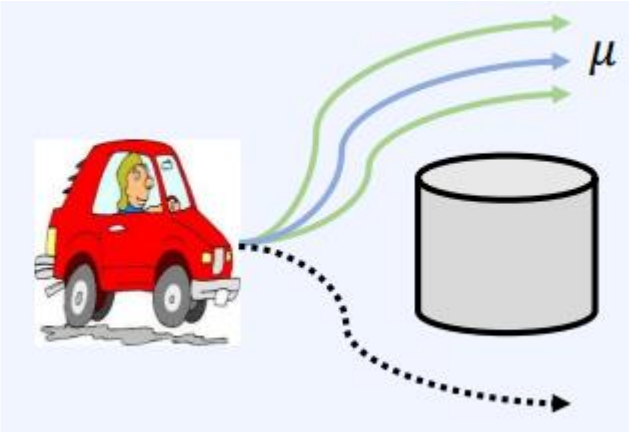
Original MDP (Deterministic)



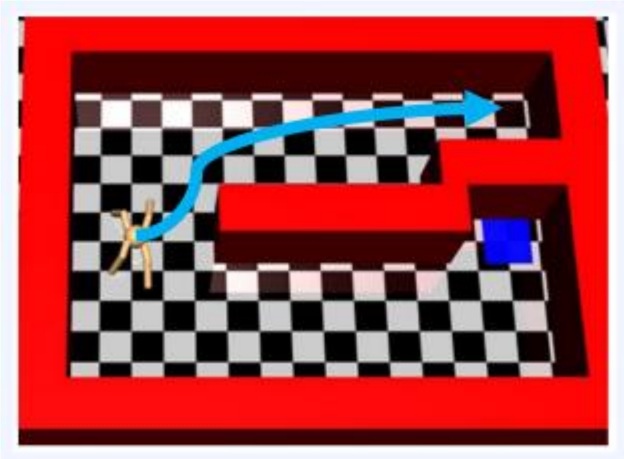
Soft MDP (Stochastic)

Softmax Policy

- Robustness
  - By finding multiple near optimal actions
- Avoid mode collapsing

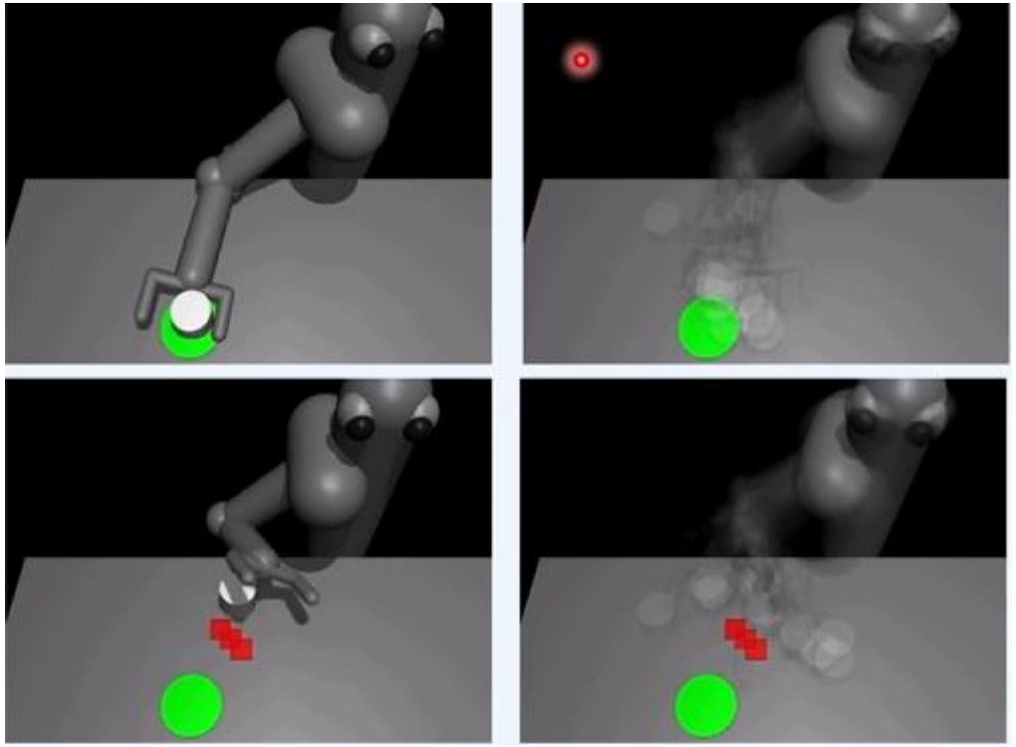


- Efficient exploration
  - Policy represents multiple promising actions till the end of learning
- Escape from local optima

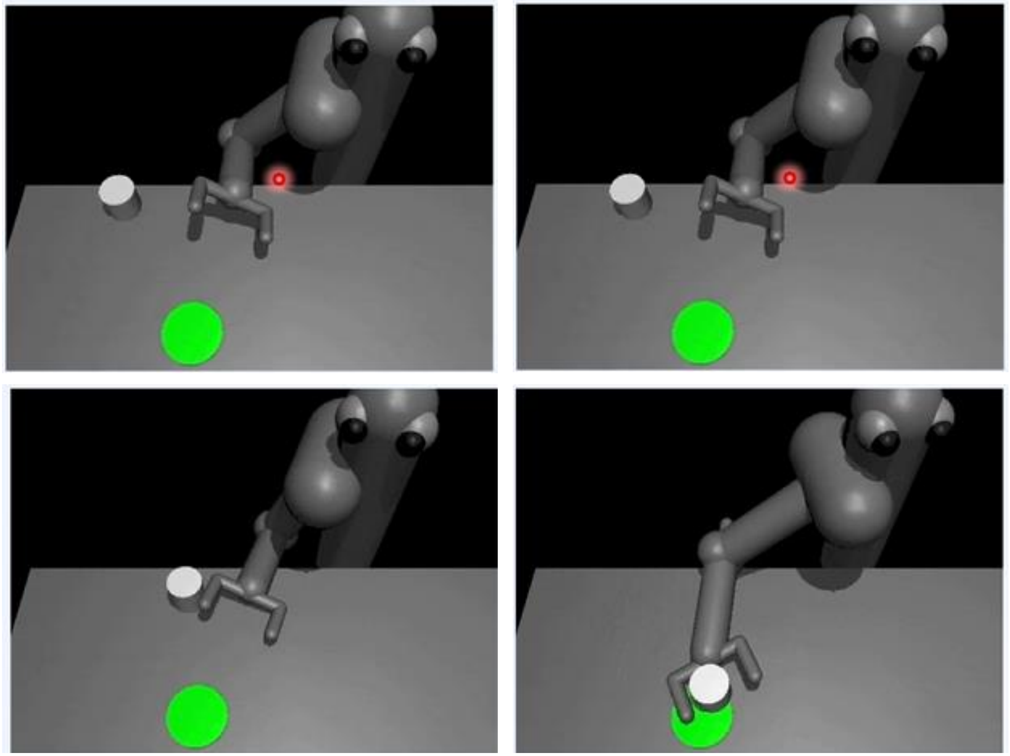


Softmax Policy

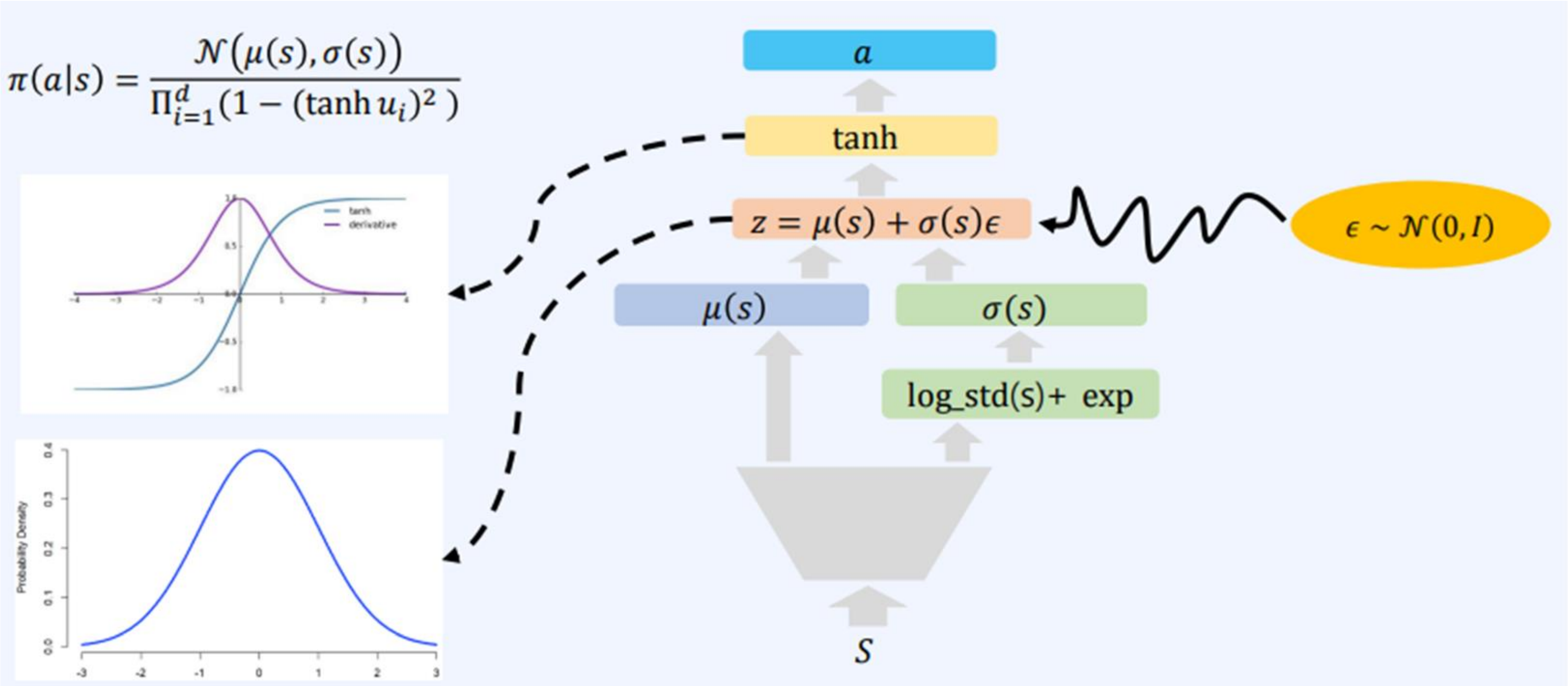
Std. RL vs. Max. Ent. RL



Std. RL vs. Max. Ent. RL



Soft Actor



$\pi(a|s) = \frac{\mathcal{N}(\mu(s), \sigma(s))}{\Pi_{i=1}^{d}(1 - (\tanh u_i)^2)}$
tanh
derivative
Probability Density
a
tanh
$z = \mu(s) + \sigma(s)\epsilon$
$\epsilon \sim \mathcal{N}(0, I)$
$\mu(s)$
$\sigma(s)$
log_std(s)+ exp
s

Soft Actor

- $DKL(\pi(\cdot|s) \,||\, \pi'(\cdot|s)) = \int \pi(a|s)\log(\frac{\pi(a|s)}{\pi'(a|s)})da$

$$\pi'(a|s) = \frac{\exp\left(\frac{1}{\alpha}Q(s,a)\right)}{Z^{\pi old}Q(st)},\ \pi(a|s) = \frac{N(\mu(s),\sigma(s))}{\prod_{i=1}^{d}(1-(\tanh ui)2)}$$

- Soft Actor Objective:여기에 수식을 입력하십시오.

$$\arg\min_{\varphi} E_{a\sim\pi}[\log(\frac{\pi(a|s)}{\pi'(a|s)})]$$

$$= E_{s\sim D}\left[E_{a\sim\pi}\left[\log\pi(a|s) - \left(\log\exp\left(\frac{1}{\alpha}Q(s,\ a)\right) - \cancel{\log Z(st)}\right)\right]\right]$$

Can be ignored with no impact on the policy parameter differentiation

$$= E_{s\sim D}[E_{a\sim\pi}[\alpha\underline{\log\pi(a|s)} - Q(s,a)]]$$

decreasing $\log\pi(a|s)$ = increasing entropy($-\log\pi(a|s)$)

Double Q trick

- Recall the maximization bias in double Q-learning

- Use two independent Q-networks to estimate target values, and select most conservative target values.

$$\hat{y} = r + \gamma \max_{i=1,2} Q_i(s', a')$$

- Q1 and Q2 will be updated independently (each has its own target network):

$$L(\theta_i) = (Q_i(s, a) - \hat{y})$$

Double Q trick

- We must change the update rule of the Q-network:

$$L(\theta) = (Q_\theta(s, a) - \hat{y})$$

- Entropy of the policy:

$$H(\pi) = E[-\ln \pi]$$

- Now the target $\hat{y}$ is:

$$\hat{y} = r + \gamma(\min_{i=1,2} Q_{i(}s', a'_{)} - \alpha \ln \pi(a' \mid s'))$$

$$a' \sim \pi(s)$$

SAC

Q target uses double-Q trick
Q target has policy entropy bonus
a′ ~ the softmax policy

SGD for both Q update

Maximize future rewards sum (Q)
Maximize entropy of policy distribution

SGA for policy update

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

Experiments

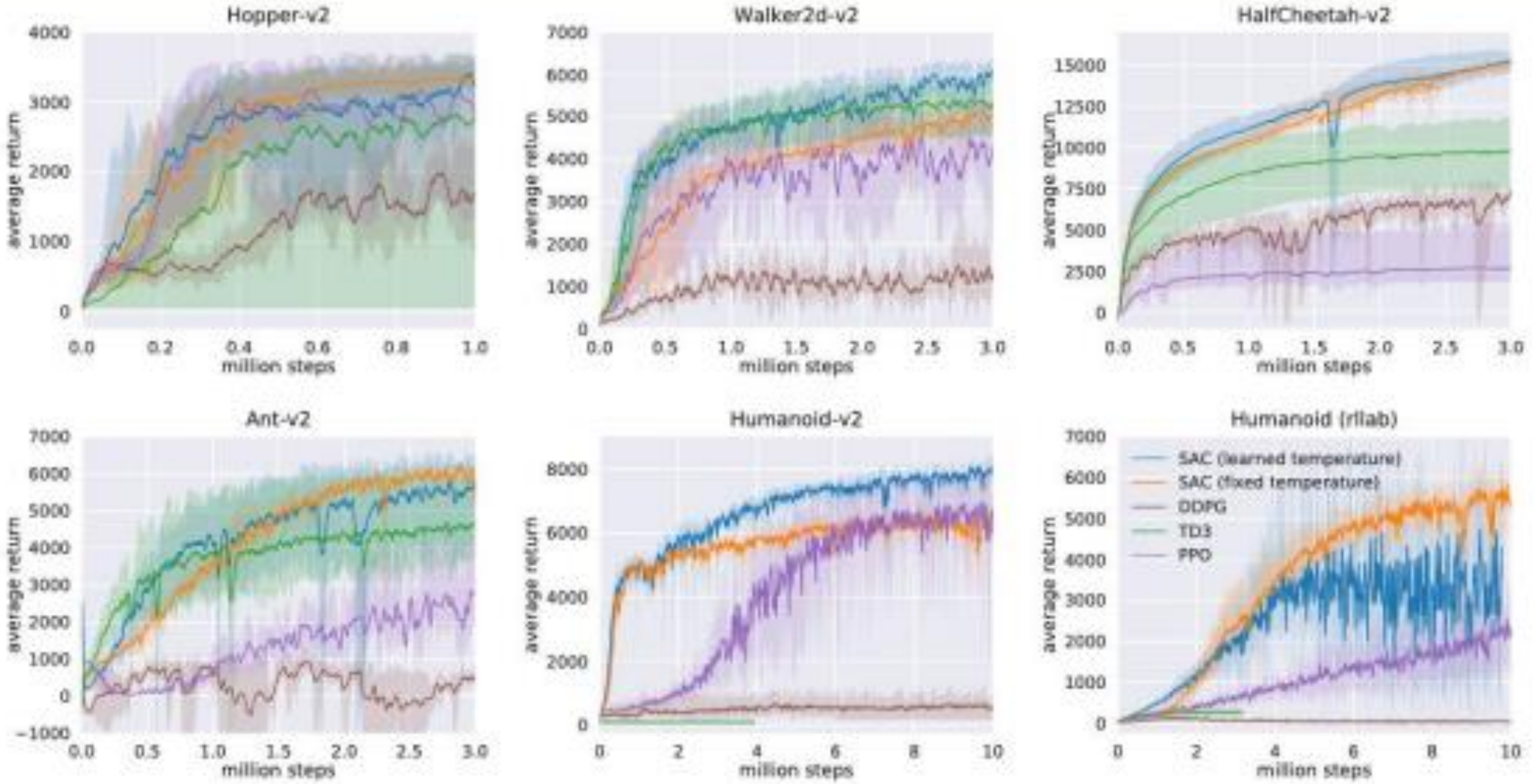
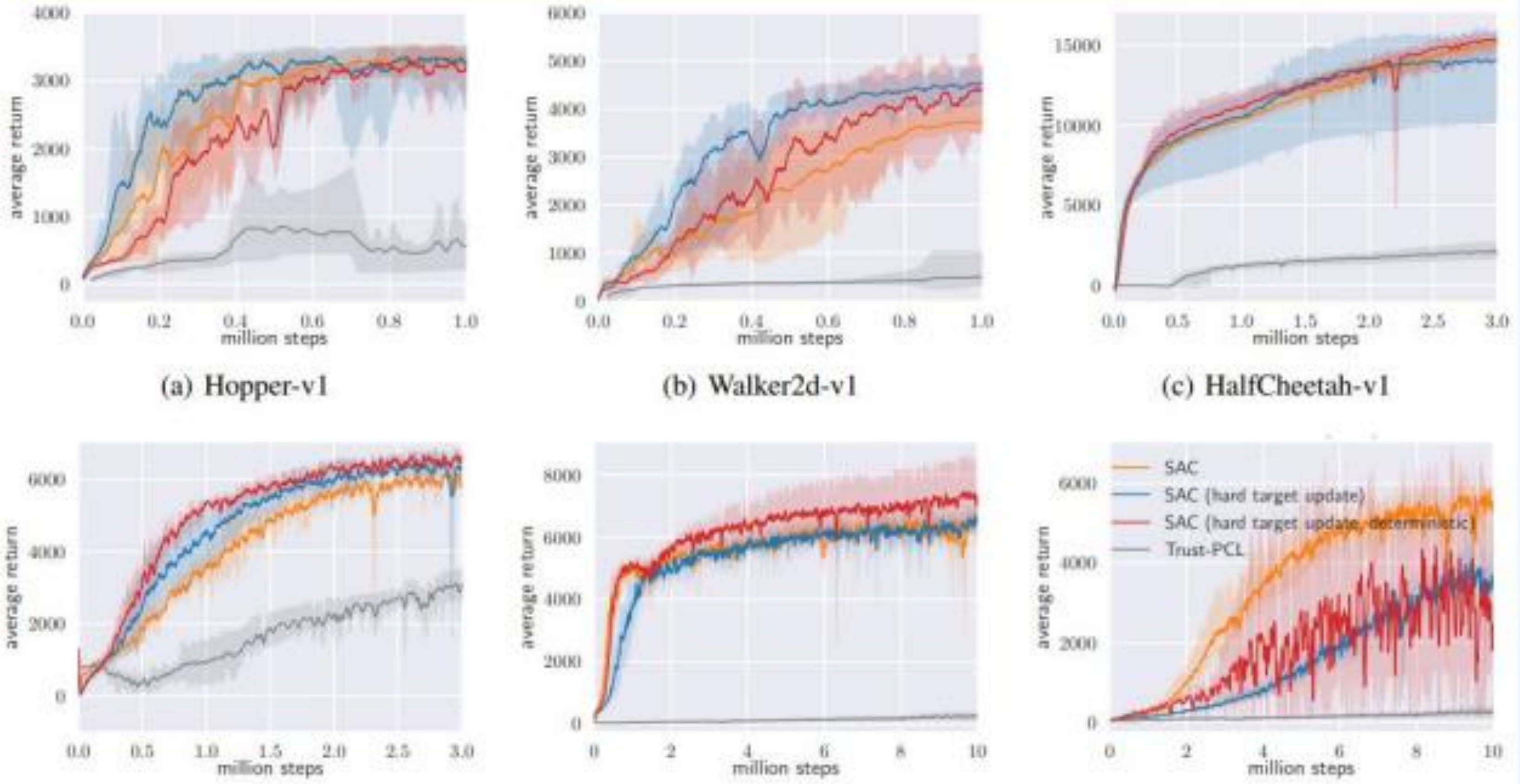


Figure 1: Training curves on continuous control benchmarks. Soft actor-critic (blue and yellow) performs consistently across all tasks and outperforming both on-policy and off-policy methods in the most challenging tasks.

Experiments



(a) Hopper-v1 (b) Walker2d-v1 (c) HalfCheetah-v1

(d) Ant-v1 (e) Humanoid-v1 (f) Humanoid (rllab)

Code Ex.2

- Upload ‘soft_actor_critic.ipynb’ file onto Colab
- The notebook includes ‘Mujoco’ environment, ‘Half Cheetah’
- State(17):
  - (body parts) position,
  - (roter, axis) angle or velocity
- Action(6):
  - Torque on 6 roters (-1~1)
- Reward:
  - Forward_reward: moving-forward reward
  - ctrl_cost: penalty in taking too large action