Lab 6: Deep Q-Network and Deep Deterministic Policy Gradient

Lab Objective:

In this lab, you will learn and implement two deep reinforcement algorithms by completing the following two tasks: (1) solve CartPole-v1 using deep Q-network (DQN), and (2) solve Pendulum-v0 using deep deterministic policy gradient (DDPG).

Important Date:

1. Experiment report submission deadline: 08/29 (Thu) 12:00

Turn in:

1. Experiment report (.pdf)
2. Source code [NOT including model weights]

Notice: zip all files with name "DLP_LAB6_StudentId_Name.zip",
e.g.: 「DLP_LAB6_0856032_鄭余玄.zip」

Lab Description:

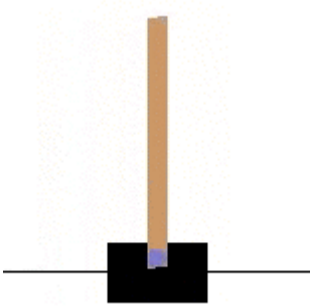
- Understand the mechanism of both behavior network and target network.
- Understand the mechanism of experience replay buffer.
- Learn to construct and design neural networks.
- Understand "soft" target updates.
- Understand the difference between DQN and DDPG.

Requirements:

- Implement DQN
  - Construct the neural network
  - Select action according to epsilon-greedy
  - Construct Q-values and target Q-values
  - Calculate loss function
  - Update behavior and target network
  - Understand deep Q-learning mechanisms
- Implement DDPG
  - Construct neural networks of both actor and critic
  - Select action according to the actor and the exploration noise
  - Update critic by minimizing the loss
  - Update actor using the sampled policy gradient
  - Update target network softly
  - Understand the mechanism of actor-critic

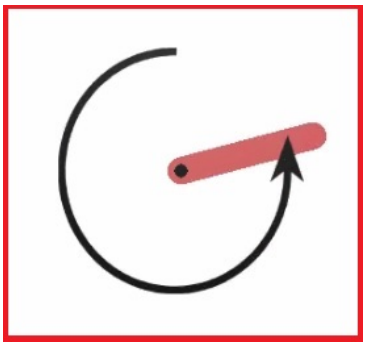
Game Environment – CartPole-v1:

- Introduction: A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The system is controlled by applying a force of +1 or -1 to the cart. The pendulum starts upright, and the goal is to prevent it from falling over. A reward of +1 is provided for every time step that the pole remains upright. The episode ends when the pole is more than 15 degrees from vertical, or the cart moves more than 2.4 units from the center.
- Observation [4]:
  - Cart Position min: -4.8 max:4.8
  - Cart Velocity min: -Inf max: Inf
  - Pole Angle: min: -24° max: 24°
  - Pole Velocity at Tip: min: -Inf max: Inf
- Action [2]: 0 (Left), 1 (Right)
- Reward: +1 for every step including the termination step



Game Environment – Pendulum-v0:

- Introduction: The pendulum starts in a random position, and the goal is to swing it up so it stays upright.
- Observation [3]:
  - cos(theta) min: -1.0 max: 1.0
  - sin(theta) min: -1.0 max: 1.0
  - theta dot min: -8.0 max: 8.0
- Action [1]:
  - Joint effort min: -2.0 max:2.0
- Reward: -(theta^2 + 0.1*theta_dt^2 + 0.001*action^2)



Implementation Details – CartPole-v1:

Network Architecture

- Input: a 4-dimension observation (not an image)
- First layer: fully connected layer (ReLU)
  - input: 4, output: 24
- Second layer: fully connected layer (ReLU)
  - input: 24, output: 24
- Third layer: fully connected layer
  - input: 24, output: 2

Training Hyper-Parameters

- Memory capacity (experience buffer size): 10000
- Batch size: 128
- Warmup steps: 10000
- Optimizer: Adam
- Learning rate: 0. 0005
- Epsilon: 1 → 0.1 or 1 → 0.01
- Gamma (discount factor): 0.99
- Update network evert 4 iterations
- Update target network every 100 iterations

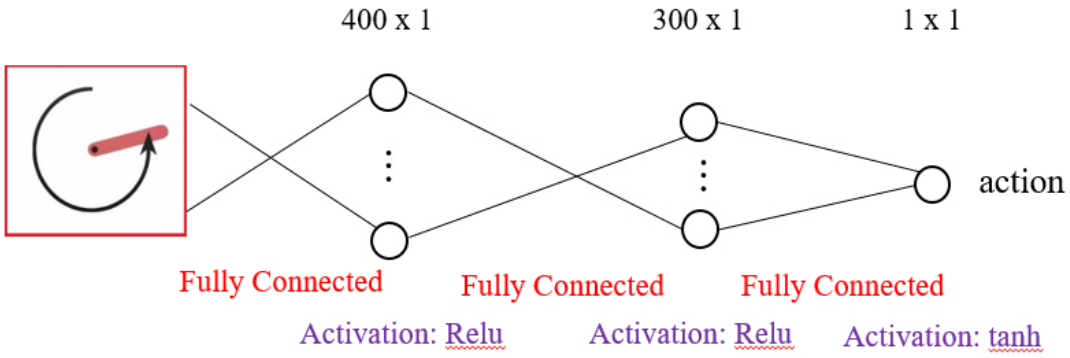
Algorithm – Deep Q-learning with experience replay:

Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$
For episode = 1, M **do**
  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  For t = 1,T **do**
    With probability ε select a random action a_t
    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

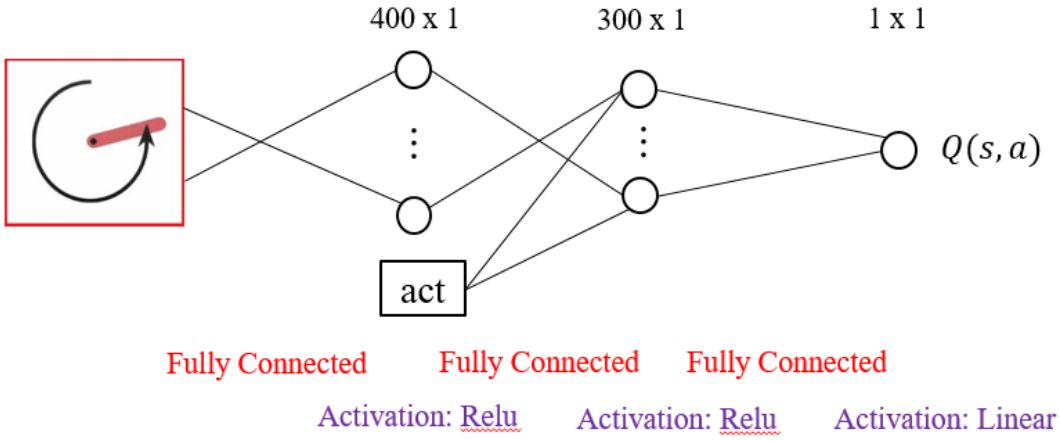
Implementation Details – Pendulum-v0:

Network Architecture

- Actor



- Critic



Training Hyper-Parameters

- Memory capacity (experience buffer size): 10000
- Batch size: 64
- Warmup step: 10000
- Optimizer: Adam
- Learning rate (actor): 0.0001
- Learning rate (critic): 0.001
- Gamma (discount factor): 0.99
- Tau: 0.001

Algorithm – 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 N for action exploration

  Receive initial observation state s_1

  for $t = 1, T$ **do**

    Select action $a_t = \mu(s_t|\theta^\mu) + N_t$ 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 random minibatch of N transitions (s_j, a_j, r_j, s_{j+1}) from R

    Set $y_i = r_i + \gamma Q'(s_{t+1}, \mu'(s_{t+1}|\theta^{\mu'})|\theta^{Q'})$

    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:

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

    Update the target networks:

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

  end for

end for

Scoring Criteria:

Show your work, otherwise no credit will be granted.

- Report (80%)
  - A plot shows episode rewards of at least 1000 training episodes in CartPole-v1 (5%)
  - A plot shows episode rewards of at least 1000 training episodes in Pendulum-v0 (5%)
  - Describe your major implementation of both algorithms in detail. (20%)
  - Describe differences between your implementation and algorithms. (10%)
  - Describe your implementation and the gradient of actor updating. (10%)
  - Describe your implementation and the gradient of critic updating. (10%)

- Explain effects of the discount factor. (5%)
- Explain benefits of epsilon-greedy in comparison to greedy action selection. (5%)
- Explain the necessity of the target network. (5%)
- Explain the effect of replay buffer size in case of too large or too small. (5%)

- Report Bonus (10%)
  - Explain the choice of the random process rather than normal distribution. (5%)
  - Implement and experiment on Double-DQN (5%)
- Performance (20%)
  - [CartPole-v1] Average reward of 10 testing episodes: Average ÷ 5
  - [Pendulum-v0] Average reward of 10 testing episodes: (Average + 700) ÷ 5

References:

[1] Mnih, Volodymyr et al. “Playing Atari with Deep Reinforcement Learning.” ArXiv abs/1312.5602 (2013).

[2] Mnih, Volodymyr et al. “Human-level control through deep reinforcement learning.” Nature 518 (2015): 529-533.

[3] Van Hasselt, Hado, Arthur Guez, and David Silver. “Deep Reinforcement Learning with Double Q-Learning.” AAAI. 2016.

[4] Lillicrap, Timothy P. et al. “Continuous control with deep reinforcement learning.” CoRR abs/1509.02971 (2015).

[5] Silver, David et al. “Deterministic Policy Gradient Algorithms.” ICML (2014).

[6] OpenAI. “OpenAI Gym Documentation.” Retrieved from Getting Started with Gym: https://gym.openai.com/docs/.

[7] OpenAI. “OpenAI Wiki for Pendulum v0.” Retrieved from Github: https://github.com/openai/gym/wiki/Pendulum-v0.

[8] PyTorch. “Reinforcement Learning (DQN) Tutorial.” Retrieved from PyTorch Tutorials: https://pytorch.org/tutorials/intermediate/reinforcement_q_learning.html.