# 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 three tasks:

(1) Solve LunarLander-v2 using deep Q-network (DQN)

(2) Solve LunarLanderContinuous-v2 using deep deterministic policy gradient (DDPG).

(3) Solve BreakoutNoFrameskip-v4 using deep Q-network (DQN)

## Important Date:

Experiment report submission deadline: 05/30 (Tue) 12:00 (No demo)

## Turn in:

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

Notice: zip all files with name "DL_LAB6_StudentId_Name.zip",

e.g.: 「DL_LAB6_311551059_陳昱丞.zip」

```
DL_LAB6_311551059_陳昱丞
├── dqn.py
├── ddpg.py
├── dqn_breakout.py
├── ddqn.py (bonus)
├── td3.py (bonus)
└── report.pdf
```

(Wrong format deduction: -5pts; Multiple deductions may apply.)

## 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 – LunarLander-v2:

- Introduction: Rocket trajectory optimization is a classic topic in optimal control. Coordinates are the first two numbers in state vector, where landing pad is always at coordinates (0,0). Reward for moving from the top of the screen to landing pad and zero speed is about 100 to 140 points. If lander moves away from landing pad it loses reward back. Episode finishes if the lander crashes or comes to rest, receiving additional -100 or +100 points. Each leg ground contact is +10. Firing main engine is -0.3 points each frame. Landing outside landing pad is possible. Fuel is infinite, so an agent can learn to fly and then land on its first attempt. Four discrete actions available: do nothing, fire left orientation engine, fire main engine, fire right orientation engine.
- Observation [8]:
  - Horizontal Coordinate
  - Vertical Coordinate
  - Horizontal Speed
  - Vertical Speed
  - Angle
  - Angle Speed
  - If first leg has contact
  - If second leg has contact

- Action [4]: 0 (No-op), 1 (Fire left engine), 2 (Fire main engine), 3 (Fire right engine)

## Game Environment – LunarLanderContinuous-v2:

- Introduction: same as LunarLander-v2.
- Observation [8]: same as LunarLander-v2.
- Action [2]:
  - Main engine: -1 to 0 off, 0 to +1 throttle from 50% to 100% power. Engine can't work with less than 50% power.
  - Left-right: -1.0 to -0.5 fire left engine, +0.5 to +1.0 fire right engine, -0.5 to 0.5 off

## Game Environment – BreakoutNoFrameskip-v4:

- Introduction: Another famous Atari game. The dynamics are similar to pong: You move a paddle and hit the ball in a brick wall at the top of the screen. Your goal is to destroy the brick wall. You can try to break through the wall and let the ball wreak havoc on the other side, all on its own! You have five lives. Detailed documentation can be found on the AtariAge page.
- Observation: By default, the environment returns the RGB image that is displayed to human players as an observation.
- Action [4]: 0 (No-op), 1 (Fire), 2 (Right), 3 (Left)

## Implementation Details – LunarLander-v2:

**Network Architecture**

- Input: an 8-dimension observation (not an image)
- First layer: fully connected layer (ReLU)
  - input: 8, output: 32
- Second layer: fully connected layer (ReLU)
  - input: 32, output: 32
- Third layer: fully connected layer
  - input: 32, output: 4

**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 every 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 $\theta$
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 $\varepsilon$ 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 $\theta$
    Every $C$ steps reset $\hat{Q} = Q$
  **End For**
**End For**

## Implementation Details – LunarLanderContinuous-v2:

**Network Architecture**

- Please refer to the sample code for details.

**Training Hyper-Parameters**

- Memory capacity (experience buffer size): 500000
- Batch size: 64
- Warmup step: 10000
- Optimizer: Adam
- Learning rate (actor): 0.001
- Learning rate (critic): 0.001
- Gamma (discount factor): 0.99
- Tau: 0.005

## Algorithm – DDPG algorithm:

Randomly initialize critic network $Q(s,a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights $\theta^Q$ and $\theta^\mu$

Initialize target network $Q'$ and $\mu'$ 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 $y_i = r_i + \gamma Q'\left(s_{t+1}, \mu'\left(s_{t+1}|\theta^{\mu'}\right)|\theta^{Q'}\right)$

    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i \left(y_i - Q(s_i, a_i|\theta^Q)\right)^2$

    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**

## Implementation Details – BreakoutNoFrameskip-v4:

**Network Architecture**

- Deepmind DQN network. Please refer to the sample code for details.

**Training Hyper-Parameters**

- Memory capacity (experience buffer size): 100000
- Batch size: 32
- Warmup steps: 20000
- Optimizer: Adam
- Learning rate: 0.0000625
- Epsilon: 1 → 0.1

- Gamma (discount factor): 0.99
- Update network every 4 steps
- Update target network every 10000 steps

**You can tune the hyperparameter yourself.**

## Scoring Criteria:

**Show your results, otherwise no credit will be granted.**

- **Report contains three parts:**
  - **(1) Experimental Results (100%)**
  - **(2) Experimental Results of bonus parts (DDQN, TD3) (bonus) (15%)**
  - **(3) Questions (bonus) (10%)**
- **Score you get on part 1 and part 2 will based on your testing performance.**
  - LunarLander:

| average score | points |
|---|---|
| <= 0 | 0 |
| 0 ~ 100 | 5 |
| 100 ~ 150 | 10 |
| 150 ~ 200 | 20 |
| >= 200 | 30 |

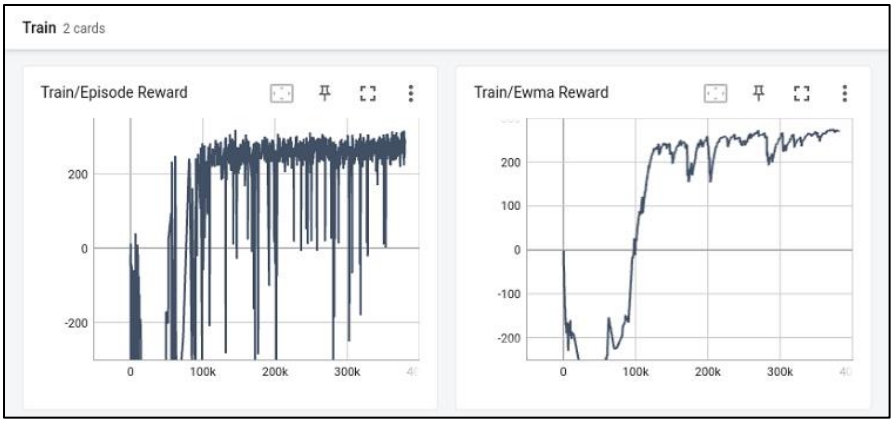
  - Breakout: min(5 * sqrt(average testing score), 100) * 0.4.

- Experimental Results (100%)
  - Your screenshot of tensorboard and testing results on LunarLander-v2. The format of your screenshots should look like this: (30%)

    **(1)** Testing results:

```
~/DLP/lab6$ python3 dqn.py --test_only
Start Testing
episode 1: 264.02
episode 2: 237.68
episode 3: 257.86
episode 4: 298.76
episode 5: 267.87
episode 6: 315.03
episode 7: 302.27
episode 8: 282.32
episode 9: 277.29
episode 10: 262.62
Average Reward 276.57379065836386
```

**(2)** Tensorboard:




- Your screenshot of tensorboard and testing results on LunarLanderContinuous-v2. The format of your screenshots should look like the picture above. (30%)
- Your screenshot of tensorboard and testing results on BreakoutNoFrameskip-v4. The format of your screenshots should look like the picture above. (40%)

- Experimental Results of bonus parts (DDQN, TD3) (15%)
  - Your screenshot of tensorboard and testing results on LunarLander-v2 using DDQN. The format of your screenshots should look like the picture above.
  - Your screenshot of tensorboard and testing results on LunarLanderContinuous-v2 using TD3. The format of your screenshots should look like the picture above.

- Questions (10%)
  - (5%) Describe your major implementation of both DQN and DDPG in detail. Your description should at least contain three parts:
    **(1)** Your implementation of Q network updating in DQN.
    **(2)** Your implementation and the gradient of actor updating in DDPG.
    **(3)** Your implementation and the gradient of critic updating in DDPG.
  - (1%) Explain effects of the discount factor.
  - (1%) Explain benefits of epsilon-greedy in comparison to greedy action selection.
  - (1%) Explain the necessity of the target network.
  - (2%) Describe the tricks you used in Breakout and their effects, and how they differ from those used in LunarLander.

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