LAB 6

TA 陳昱丞

yucheng.cs11@nycu.edu.tw

Deadline: 2023/5/30(Tue) 12:00

No Demo

In this lab,

Must use sample code, otherwise no credit.

Outline

Part 1: High-Level Observation

- Solve LunarLander-v2 using DQN (30%)
- Solve LunarLanderContinuous-v2 using DDPG (30%)
- Bonus: Implement DDQN (5%)
- Bonus: Implement TD3 (10%)

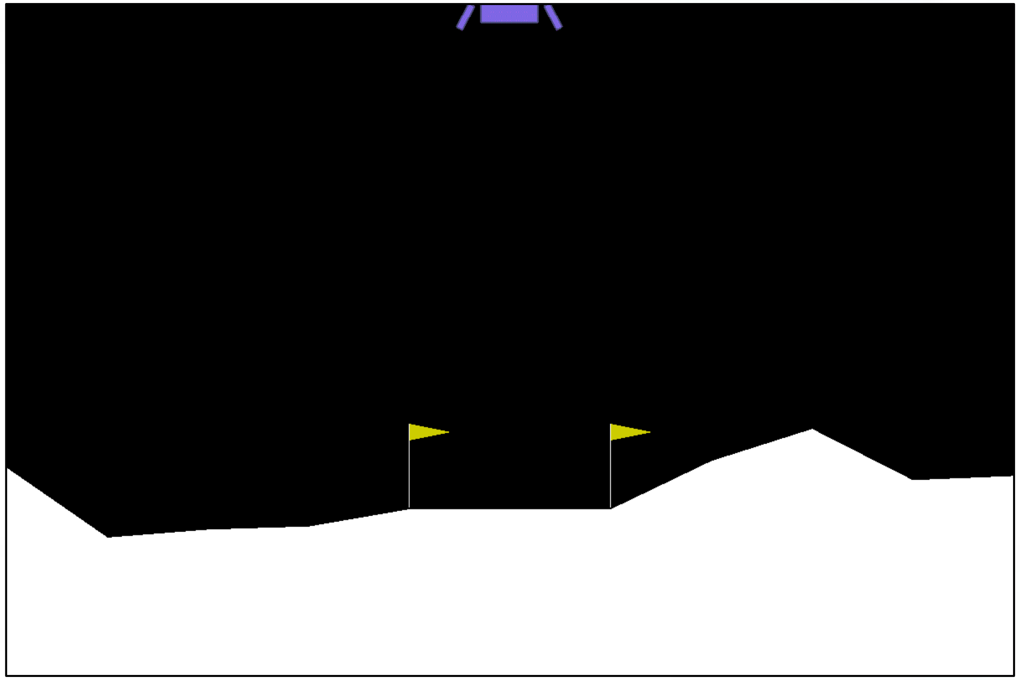
Part 2: Low-Level Observation

- Solve BreakoutNoFrameskip-v4 using DQN (40%)

Report:

- Result (0% but necessary)
- Bonus: Questions (10%)

LunarLander-v2



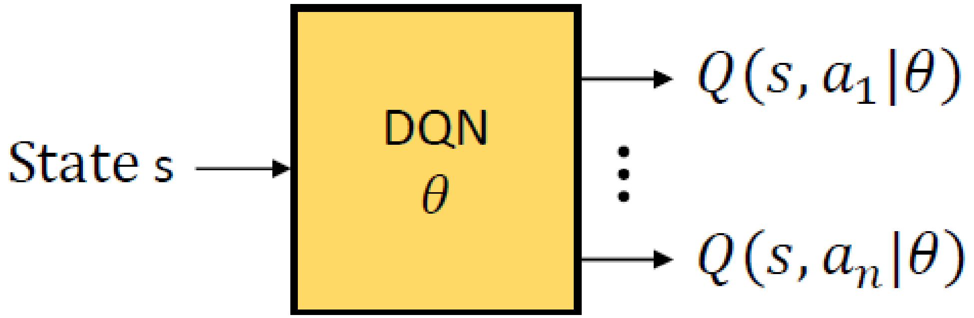
- Observation [8]
  1. Horizontal Coordinate
  2. Vertical Coordinate
  3. Horizontal Speed
  4. Vertical Speed
  5. Angle
  6. Angle Speed
  7. If first leg has contact
  8. If second leg has contact
- Action [4]
  1. No-op
  2. Fire left engine
  3. Fire main engine
  4. Fire right engine

- Action [2] (Continuous)
  - 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

Deep Q-Network (DQN)

Target Q:

$$Y_t^Q = r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a' | \theta)$$



Loss function:

$$L_Q(s_t, a_t|\theta) = (Y_t^Q - Q(s_t, a_t|\theta))^2$$

Gradient descent:

$$\nabla_\theta L_Q(s_t, a_t|\theta) = (Y_t^Q - Q(s_t, a_t|\theta))\nabla_\theta Q(s_t, a_t|\theta)$$

Deep Q-Network (DQN)

Algorithm 1 – 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 $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^-\right) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

Behavior and target network

ϵ-greedy based on behavior network

Experience replay

Update behavior and target network

Deep Deterministic Policy Gradient (DDPG)

Consider continuous actions and deterministic policy: $a = \pi_\theta(s)$

Deterministic Policy Gradient Theorem:

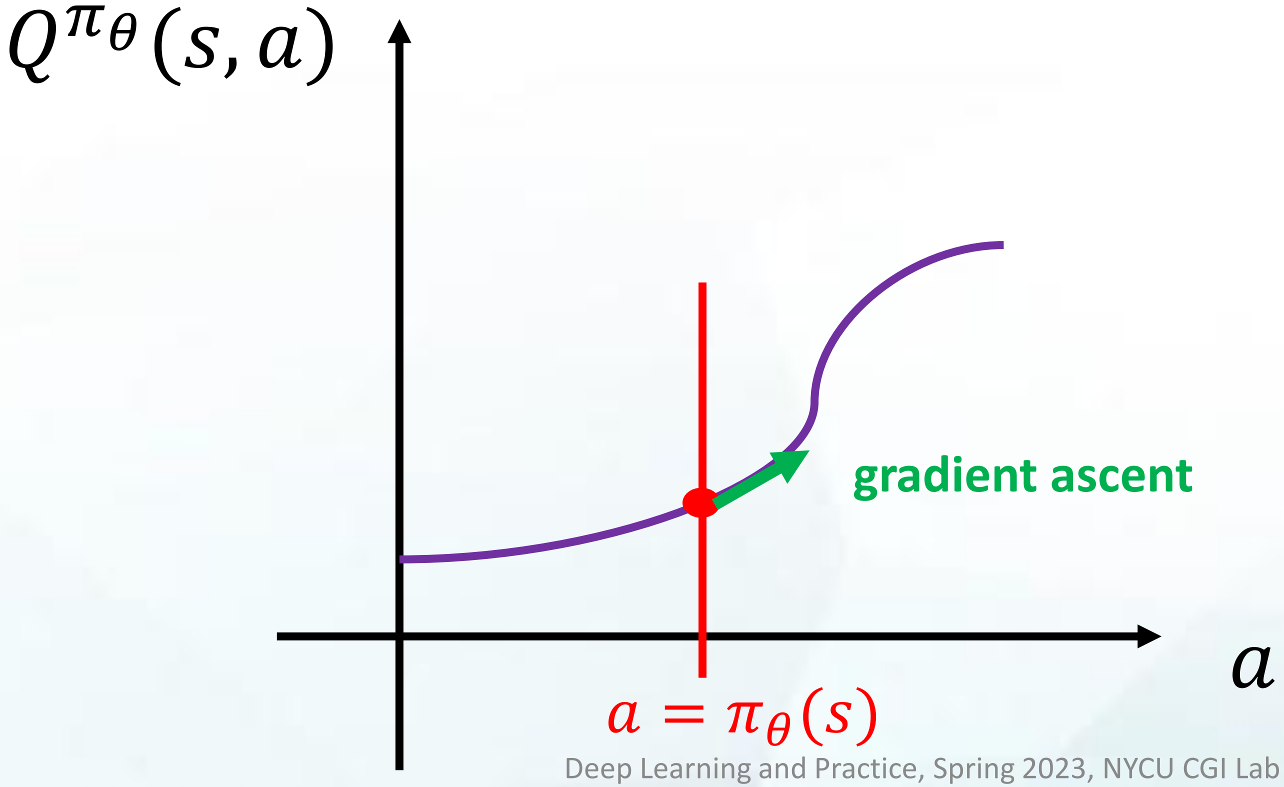
$$\nabla_\theta V^{\pi_\theta}(\mu) = \frac{1}{1-\gamma} E_{s\sim d_\mu^{\pi_\theta}}[\nabla_\theta \pi_\theta(s) \nabla_a Q^{\pi_\theta}(s,a)|_{a=\pi_\theta(s)}]$$

Off-policy Deterministic Policy Gradient:

$$\nabla_\theta J_\beta^{\pi_\theta} \approx E_{\underline{s\sim d_\mu^{\beta}}}[\nabla_\theta \pi_\theta(s) \nabla_a Q^{\pi_\theta}(s,a)|_{a=\pi_\theta(s)}]$$

Deep Deterministic Policy Gradient (DDPG)

$$\nabla_\theta J_\beta^{\pi_\theta} \approx E_{s\sim d_\mu^\beta}[\nabla_\theta \pi_\theta(s) \nabla_a Q^{\pi_\theta}(s,a)|_{a=\pi_\theta(s)}]$$



Deep Deterministic Policy Gradient (DDPG)

Algorithm 1 – DDPG:

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

2 Behavior and 2 target networks

Action drawn from deterministic policy with exploration

Experience replay

Update actor and critic

Update target networks (soft update)

TODO

- Solve LunarLander-v2 using DQN.
- Solve LunarLanderContinuous-v2 using DDPG.
- Find the #TODO comments and hints, remove the raise NotImplementedError.
- Screenshot your tensorboard and testing results and put it on the report.

TODO

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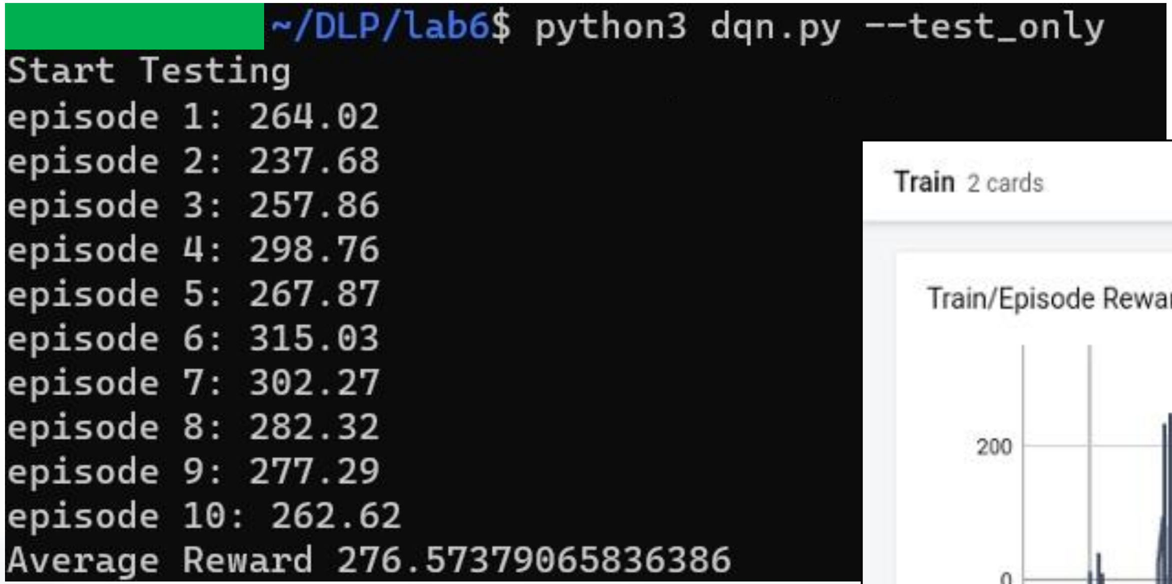
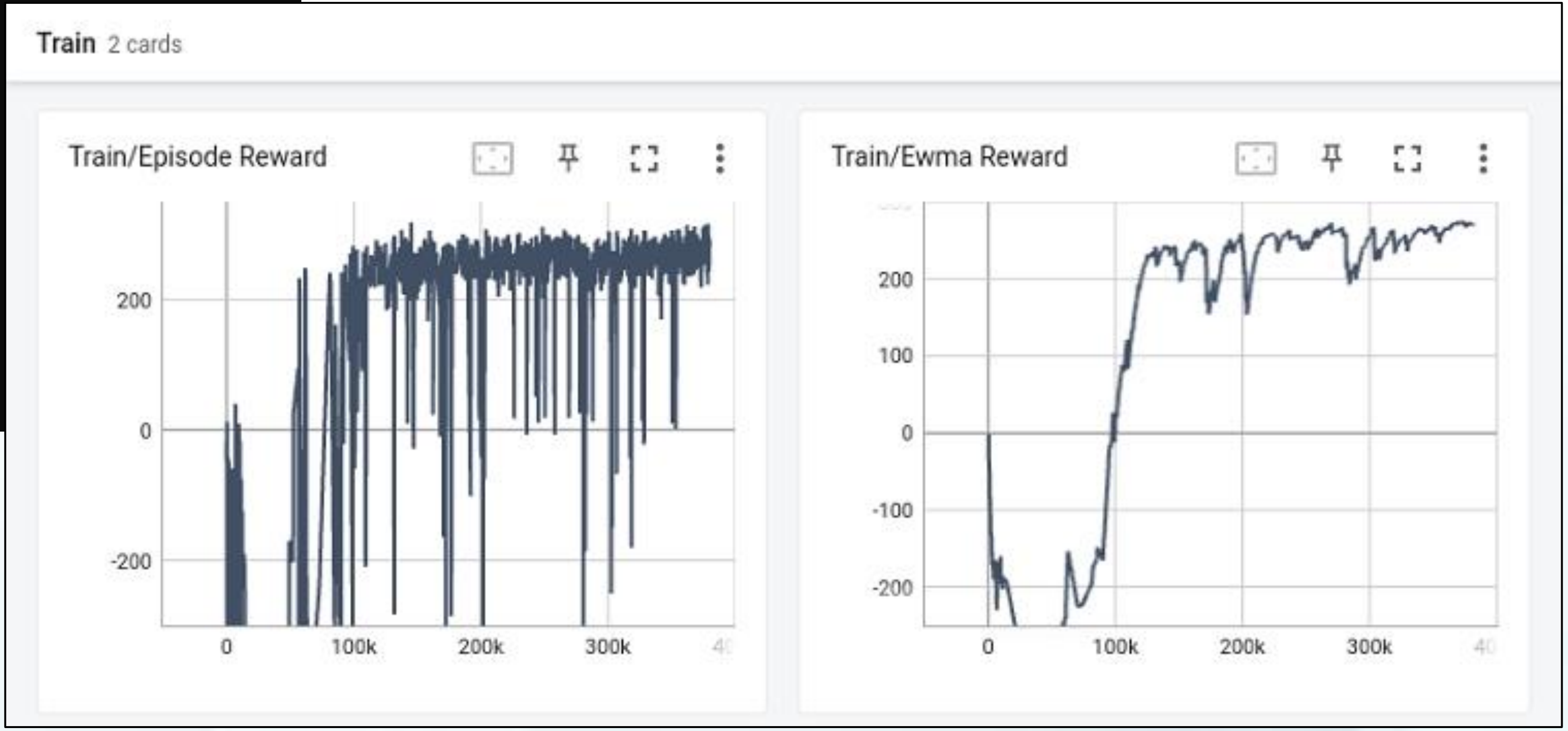




Scoring Criteria

- DQN performance (30%)
  - Bonus: implement DDQN (5%)
- DDPG performance (30%)
  - Bonus: implement TD3 (10%)
- Run test 10 times, average score:

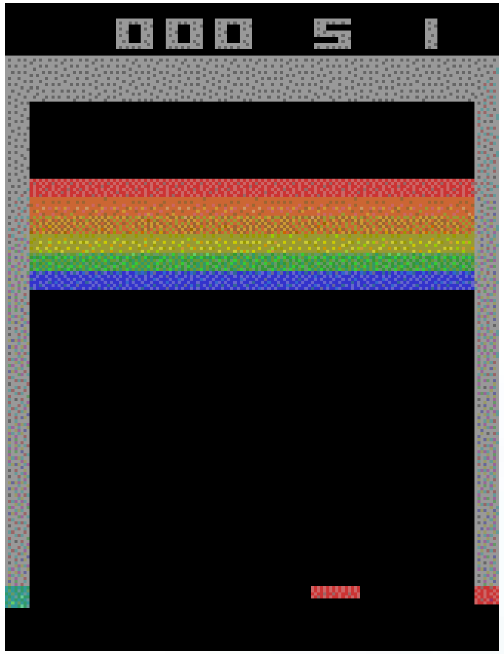
```
~/DLP/lab6$ python3 dqn.py --test_only
Start Testing
episode 1: 264.02
episode 2: 237.68
episode 3: 257.86
episode 4: 298.76
episode 5: 267.87
episode 6: 315.03
episode 7: 302.27
episode 8: 282.32
episode 9: 277.29
episode 10: 262.62
Average Reward 276.57379065836386
```

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

BreakoutNoFrameskip-v4

- Observation space:
  - The whole image
- Action space:

Num	Action
0	NOOP
1	FIRE
2	RIGHT
3	LEFT

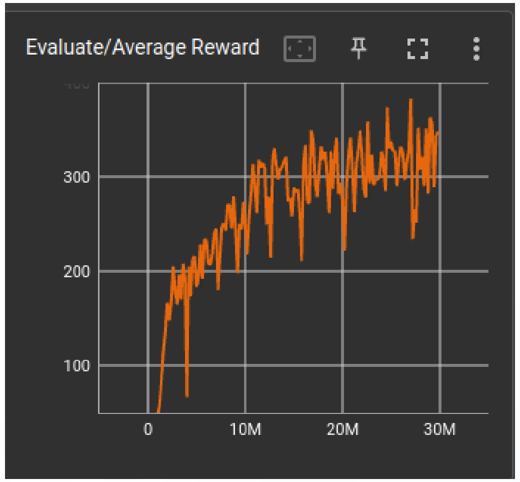


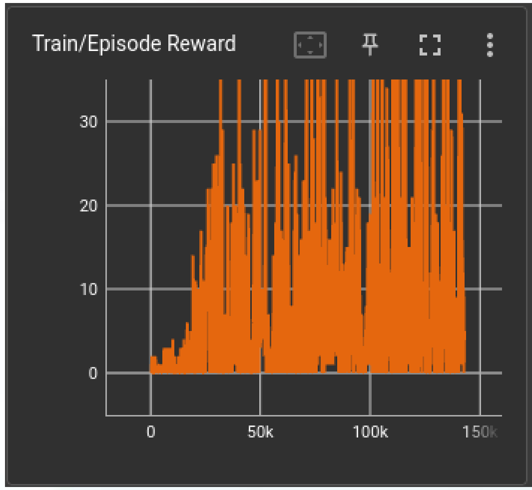
TODO

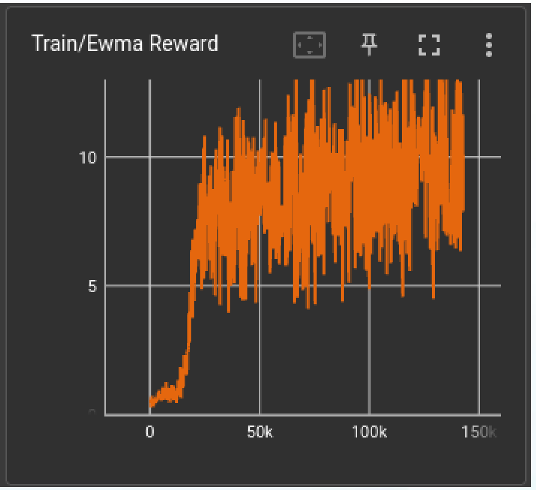
- Solve BreakoutNoFrameskip-v4 using DQN.
- You can use any trick you want.
- Screenshot your tensorboard and testing results and put it on the report.

TODO

- Screenshot your tensorboard and testing results and put it on the report.








```
Start Testing
episode 1: 421.00
episode 2: 414.00
episode 3: 828.00
episode 4: 427.00
episode 5: 396.00
episode 6: 430.00
episode 7: 424.00
episode 8: 798.00
episode 9: 433.00
episode 10: 427.00
Average Reward: 499.80
```

Hint: Trick 1

- Use make_Atari() and wrap_deepmind() provided by OpenAI baselines.
  - atari_wrappers.py

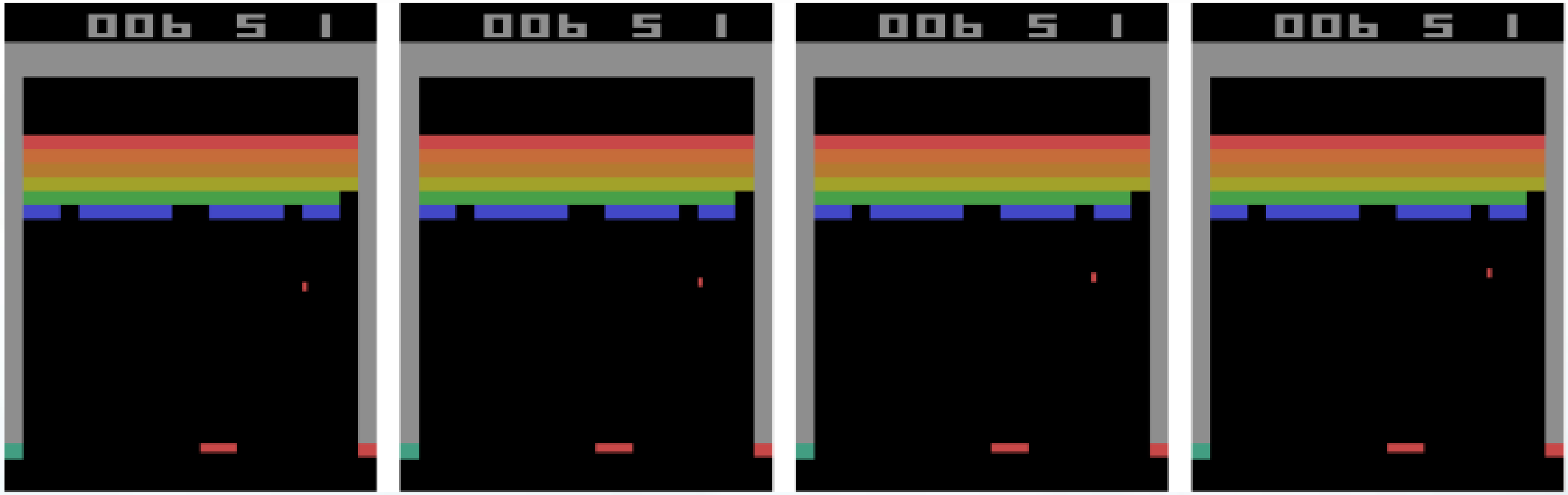
- Remember to set episode_life=False, clip_rewards=False while testing.

Hint: Trick 2

- Stack a sequence of four frames together.

state

frame 1: frame 2: frame 3: frame 4:



Scoring Criteria

- Performance (40%)
- Run test 10 times, min(5 * sqrt(average score), 100).
- For example:

```
Start Testing
episode 1: 421.00
episode 2: 414.00
episode 3: 828.00
episode 4: 427.00
episode 5: 396.00
episode 6: 430.00
episode 7: 424.00
episode 8: 798.00
episode 9: 433.00
episode 10: 427.00
Average Reward: 499.80
```

sqrt(499.8) = 22.35
5 * 22.35 = 111.75
min(111.75, 100) = 100
40 * 100% = 40 points you get

Tensorboard Remote Server

- ssh -p [your port] -L 6006:localhost:6006 pp037@140.113.215.196
- tensorboard --logdir log/dqn
- Open your browser locally and input 127.0.0.1:6006

Package Version

• gym	0.15.7
• numpy	1.22.3
• pytorch	1.7.1
• tensorboard	2.10.0

Reminders

- Your network architecture and hyper-parameters can differ from the defaults.
- Ensure the shape of tensors all the time especially when calculating the loss.
- with no_grad() : scope is the same as xxx.detach()
- Be aware of the indentation of hints.
- When testing DDPG, action selection need NOT include the noise.

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 DoubleQ-Learning.” AAAI. 2016.
4. Lillicrap, Timothy P. et al. “Continuous control with deep reinforcement learning.” CoRRabs/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 .