REPORT OF CS489 FINAL PROJECT

Hongzhou Liu
517030910214
deanlhz@sjtu.edu.cn

1 INTRODUCTION

In this project, I implemented some value-based and policy-based RL algorithm and trained them on different environments based on gym. The key required packages are

- PyTorch
- gym
- mujoco-py (with MuJoCo)

As we learned in the class, value-based RL methods strive to fit action value function or state value function and control agent in off-policy or on-policy ways. Deep Q-Learning is a groudbreaking work that introduces Deep Neural Networks to Q-learning algorithm. However, policy-based method mainly focus on fitting a policy directly. It is achieved by adjusting policy function by policy gradient method. However, the original policy gradient method suffers from high variance, and then Actor-Critic method was proposed. Also, the Actor-Critic method is sample inefficient and it used on-policy. Thus, off-policy algorithm like DDPG is introduced.

2 METHODS

2.1 DEEP Q-LEARNING

The original table-based Q-learning method can be sufficiently applicable to the environment where the all achievable states can be managed and stored in RAM. However, the environment where the number of states overwhelms the capacity of contemporary computers, for example, the Atari games, the original approach is not very applicable. Thus, the Q-table in the original method is replaced by a neural network called Q-network. And such method is called Deep Q-learning, proposed by Mnih et al. (2015).

The two key points in Deep Q-learning is fixed target net and replay buffer. We use the target net to predict target value as label. And we use replay buffer to memorize the history and it can be sampled from when training the actual Q-network. The DQN algorithm is shown in Algorithm 1

The original DQN takes the maximum overestimated values as such is implicitly taking the estimate of the maximum value. This systematic overestimation introduces a maximization bias in learning. And since Q-learning involves bootstrapping learning estimates from estimates such overestimation can be problematic. Thus, Hasselt et al. (2016) proposed Double DQN to tackle this over-estimate problem. The solution involves using two separate Q-value estimators, each of which is used to update the other. Using these independent estimators, we can unbiased Q-value estimates of the actions selected using the opposite estimator. We can thus avoid maximization bias by disentangling our updates from biased estimates. As we can see in DQN, we calculate target value by

$$r_j + \gamma \max_{a'} \hat{Q}\left(s_{j+1}, a'; \hat{\boldsymbol{\theta}}\right)$$

so that the max operator uses the same values to both select and evaluate an action. Thus, it's more likely to select over-estimated values, and results in over-optimistic value estimates. Then, in Double DQN, above problem is solved by changing the evaluation of target value in the algorithm into

$$r_j + \gamma \hat{Q}\left(s_{j+1}, \arg\max_{a'} Q(s_{j+1}, a'; \boldsymbol{\theta}); \hat{\boldsymbol{\theta}}\right)$$

Algorithm 1: DQN

Initialize replay buffer D
Initialize action-value function Q with random weight $\boldsymbol{\theta}$
Initialize target action-value function $\hat{Q}$ with $\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}$
for *episode = 1 to M* **do**
    Initialize the episode and acquire the initial state s_1
    for *t = 1 to T* **do**
        Following ϵ-greedy policy, select action
        $$a_t = \begin{cases} \text{a random action} & \text{with probability } \epsilon \\ \arg\max_a Q\left(s_t, a; \boldsymbol{\theta}\right) & \text{otherwise} \end{cases}$$
        Obtain reward r_t and next state s_{t+1} by executing the action a_t in the environment
        Store transition (s_t, a_t, r_t, s_{t+1}) in the buffer D
        Sample random minibatch of transitions (s_j, a_j, r_j, s_{j+1}) from buffer D
        Calculate target value by
        $$y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}\left(s_{j+1}, a'; \hat{\boldsymbol{\theta}}\right) & \text{otherwise} \end{cases}$$
        Perform a gradient descent on $(y_j - Q(s_j, a_j; \boldsymbol{\theta}))$ w.r.t the network parameter $\boldsymbol{\theta}$
        Every C step reset $\hat{Q} = Q$ by $\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}$

Furthermore, in order to converge faster than original DQN, Wang et al. (2016) proposed the dueling network architecture to estimate state value function $V(s)$ and associated advantage function $A(s, a)$, and then combine them to estimate action value function $Q(s, a)$. In the DQN architecture of Atari tasks, a CNN layer is followed by a fully connected (FC) layer. In dueling architecture, a CNN layer is followed by two streams of FC layers, to estimate value function and advantage function separately; then the two streams are combined to estimate action value function. In this paper, the author proposed the following way to combine $V(s)$ and $A(s, a)$ to obtain $Q(s, a)$:

$$Q(s, a; \boldsymbol{\theta}, \alpha, \beta) = V(s; \boldsymbol{\theta}, \beta) + \left(A(s, a; \boldsymbol{\theta}, \alpha) - \frac{a}{|\mathcal{A}|} A\left(s, a'; \boldsymbol{\theta}, \alpha\right) \right)$$

where α and β are parameters of the two streams of FC layers, $|\mathcal{A}|$ is the size of action space. The architectures of DQN and Dueling DQN are illustrated in Figure 1.

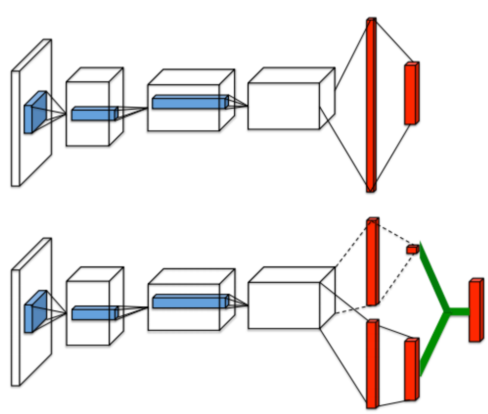


Figure 1: Network Architectures

2.2 Asynchronous Advantage Actor-Critic

A3C is a policy-based RL algorithm proposed by Mnih et al. (2016). We know that a policy maps state to action, and policy optimization is to find an optimal mapping. Compared with original policy gradient method, A3C benefits from Actor-Critic. An actor-critic algorithm learns both a policy and a state-value function, and the value function is used for bootstrapping, i.e., updating a state from subsequent estimates, to reduce variance and accelerate learning. In A3C, parallel actors employ different exploration policies to stabilize training, so that experience replay is not utilized. Different from most deep learning algorithms, asynchronous methods can run on a single multi-core CPU. The algorithm for each actor-learner thread is shown in Algorithm 2.

Algorithm 2: A3C, actor-learner thread

Global shared parameter vectors $\boldsymbol{\theta}$ and $\boldsymbol{\theta}_v$, thread-specific parameter vectors $\boldsymbol{\theta}'$ and $\boldsymbol{\theta}_v'$
Global shared counter $T = 0$, T_{max}
Initialize thread step counter $t \leftarrow 1$
for $T \leq T_{max}$ **do**
    Reset gradients, $d\boldsymbol{\theta} \leftarrow 0$ and $d\boldsymbol{\theta}_v \leftarrow 0$
    Synchronize thread-specific parameters $\boldsymbol{\theta}' = \boldsymbol{\theta}$ and $\boldsymbol{\theta}_v' = \boldsymbol{\theta}_v$
    Set $t_{start} = t$ and get state s_t
    for s_t *not terminal and* $t - t_{start} \leq t_{max}$ **do**
        Perform a_t according to policy $\pi(a_t|s_t;\boldsymbol{\theta}')$
        Receive reward r_t and new state s_{t+1}
        $t \leftarrow t + 1$
        $T \leftarrow T + 1$
    $R = \begin{cases} 0 & \text{for terminal } s_t \\ V\left(s_t, \boldsymbol{\theta}_v'\right) & \text{otherwise} \end{cases}$
    for $i \in \{t-1, \cdots, t_{start}\}$ **do**
        $R \leftarrow r_i + \gamma R$
        Accumulate gradients w.r.t. $\boldsymbol{\theta}'$: $d\boldsymbol{\theta} \leftarrow d\boldsymbol{\theta} + \nabla_{\boldsymbol{\theta}'} \log \pi\left(a_i \mid s_i; \boldsymbol{\theta}'\right)\left(R - V\left(s_i; \boldsymbol{\theta}_v'\right)\right)$
        Accumulate gradients w.r.t. $\boldsymbol{\theta}_v'$: $d\boldsymbol{\theta}_v \leftarrow d\boldsymbol{\theta}_v + \nabla_{\boldsymbol{\theta}_v'}\left(R - V\left(s_i; \boldsymbol{\theta}_v'\right)\right)^2$
    Perform asynchronous update of $\boldsymbol{\theta}$ using $d\boldsymbol{\theta}$, and of $\boldsymbol{\theta}_v$ using $d\boldsymbol{\theta}_v$

As seen above, the A3C maintains a policy $\pi(a_t|s_t;\boldsymbol{\theta})$ and an estimate of the value function $V(s_t;\boldsymbol{\theta}_v)$, being updated with n-step returns in the forward view, after every t_{max} actions or reaching a terminal state, similar to using minibatches. The gradient can be seen as $\nabla_{\boldsymbol{\theta}'} \log \pi\left(a_t \mid s_t; \boldsymbol{\theta}'\right) A\left(s_t, a_t; \boldsymbol{\theta}, \boldsymbol{\theta}_v\right)$, where $A\left(s_t, a_t; \boldsymbol{\theta}, \boldsymbol{\theta}_v\right) = \sum_{i=0}^{k-1} \gamma^i r_{t+i} + \gamma^k V\left(s_{t+k}; \boldsymbol{\theta}_v\right) - V(s_t;\boldsymbol{\theta}_v)$ is an estimate of the advantage function, with k upbounded by t_{max}.

2.3 Deep Deterministic Policy Gradient

Policies are usually stochastic. However, Silver et al. (2014) and Lillicrap et al. (2016) proposed deterministic policy gradient (DPG) for efficient estimation of policy gradients. Silver et al. (2014) introduced the deterministic policy gradient (DPG) algorithm for RL problems with continuous action spaces. The deterministic policy gradient is the expected gradient of the action-value function, which integrates over the state space; whereas in the stochastic case, the policy gradient integrates over both state and action spaces. Consequently, the deterministic policy gradient can be estimated more efficiently than the stochastic policy gradient. The authors introduced an off-policy actor-critic algorithm to learn a deterministic target policy from an exploratory behaviour policy, and to ensure unbiased policy gradient with the compatible function approximation for deterministic policy gradients.

Lillicrap et al. (2016) proposed an actor-critic, model-free, deep deterministic policy gradient (DDPG) algorithm in continuous action spaces, by extending DQN Mnih et al. (2015) and DPG Silver et al. (2014). With actor-critic as in DPG, DDPG avoids the optimization of action at every time step to obtain a greedy policy as in Q-learning, which will make it infeasible in complex action spaces with large, unconstrained function approximators like deep neural networks. To make the learning stable and robust, similar to DQN, DDPQ deploys experience replay and an idea similar to target network, soft target, which, rather than copying the weights directly as in DQN, updates the soft target network weights $\boldsymbol{\theta}'$ slowly to track the learned networks weights $\boldsymbol{\theta}$: $\boldsymbol{\theta}' \leftarrow \tau\boldsymbol{\theta} + (1-\tau)\boldsymbol{\theta}'$ with $\tau \ll 1$. The authors adapted batch normalization to handle the issue that the different components of the observation with different physical units. As an off-policy algorithm, DDPG learns an actor policy from experiences from an exploration policy by adding noise sampled from a noise process to the actor policy. Algorithm 3 shows the detail of DDPG.

Algorithm 3: 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 $\theta^{Q'} \leftarrow \theta^Q$ and $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for *episode = 1 to* M **do**
    Initialize a random process $\mathcal{N}$ for action exploration
    Receive initial observation state s_1
    for t = *1 to* T **do**
        Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ 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 $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
        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 policy gradient:

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

        Update the target networks:

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

To choose a suitable random process $\mathcal{N}$, in Lillicrap et al. (2016), the author utilized Ornstein-Uhlenbeck process proposed by Uhlenbeck & Ornstein (1930) to generate tempoprally correlated exploration for exploration efficiency in physical control problems with inertia. Furthermore, above random process may sometimes lead to local minimum problem. In Plappert et al. (2017), the author proposed parameter space noise for exploration. Such method add noise directly to the agent's parameters, which can lead to more consistent exploration and a richer set of behaviors. The three key points of this method are

- State-dependent exploration: We can still utilize Ornstein-Uhlenbeck process to generate a random process.
- Perturbing deep neural networks: Noise is added to the parameters of neural networks, here in DDPG, we add noise to the actor network.
- Adaptive noise scaling: The parameter noise requires us to pick a suitable scale σ, which is hard to choose. With adaptive noise scaling, such problem will be solved.

3 Experiments

In this part, I trained and tested Dueling Double DQN on the following Atari Games Environment:

- BreakoutNoFrameskip-v4
- PongNoFrameskip-v4

Also, I trained and tested A3C, DDPG and DDPG with parameter space noise on the following MuJoCo Continuous Control Environment:

- Hopper-v2
- HalfCheetah-v2

3.1 Dueling Double DQN

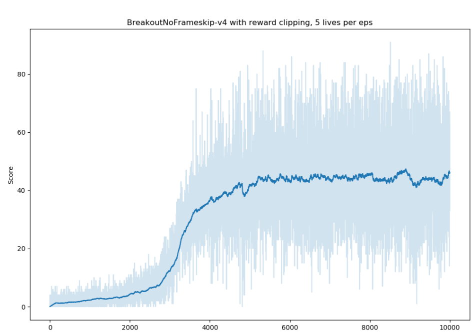
3.1.1 Experiment Setting

I followed the training process in Dhariwal et al. (2017) and Mnih et al. (2015). The observation space of Atari Games Environment is $210 \times 160 \times 3$ here. We need to process the original observations in order to save memory and acquire better performance. First, we need to resize the original input to 84×84 and convert it from the RGB space to grayscale. Also, we have to store the observations into the replay buffer in the type of uint8 to save memory and convert them back to float when sampled from the buffer. Also, similar to Dhariwal et al. (2017), I stacked 4 consecutive frames together as a state in order to encode the movement of the game. I also performed frameskip and reward clipping to stabilize the training process. For BreakoutNoFrameskip-v4, an episode consists of 5 trials, I split it into 5 episodes to keep the same as what Mnih et al. (2015) did in their experiments. The hyper-parameter setting is shown in Table 1. For the detailed implementation and network structure, please refer to the source code. I trained BreakoutNoFrameskip-v4 for 50000 episodes and PongNoFrameskip-v4 for 5000 episodes on a computer with AMD Ryzen 3700X, 128GB Memory and Nvidia GTX 1080Ti. The maximum memory consumption is about 77GB and the training will cost about 10 hours per task.

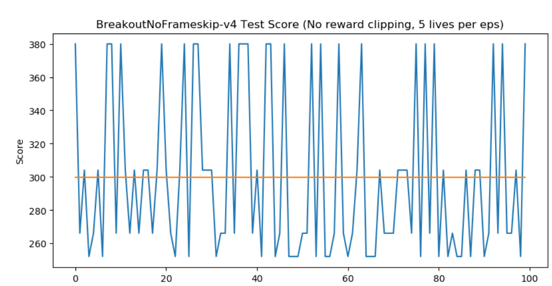
Table 1: Hyper-parameters of Dueling Double DQN

Hyper-parameter	Value
Replay Buffer Size	1000000
γ	0.99
ϵ_0	1.0
ϵ_t	0.1
ϵ decay rate	1000000
Batch Size	32
Learning rate η	0.0002
Stride to perform gradient descent	4
Stride to update target network C	2000

3.1.2 Result

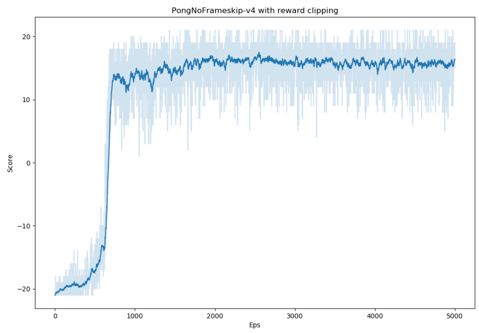


(a) Train

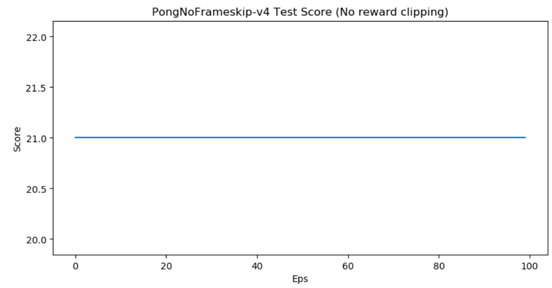


(b) Test

Figure 2: BreakoutNoFrameskip-v4

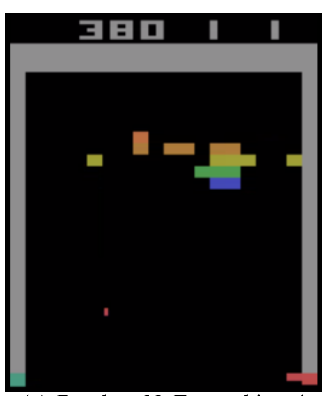


(a) Train

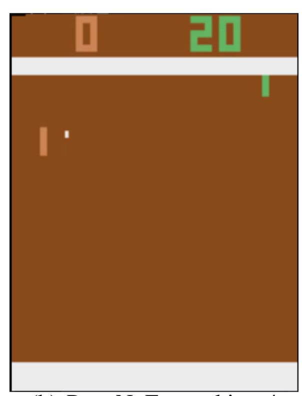


(b) Test

Figure 3: PongNoFrameskip-v4



(a) BreakoutNoFrameskip-v4



(b) PongNoFrameskip-v4

Figure 4: Test

3.2 A3C

3.2.1 Experiment Setting

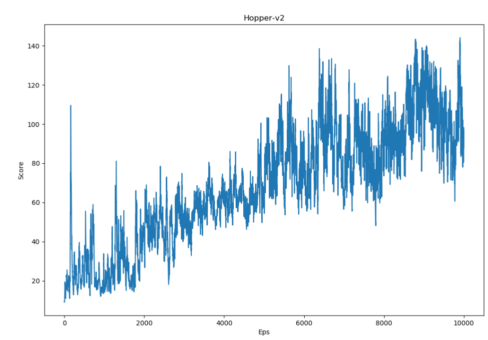
In this part, I trained A3C on two MuJoCo Continuous Control Environments. The hyper-parameter settings is shown in Table 2. I trained both Hopper-v2 and HalfCheetah-v2 for 10000 episodes.

Table 2: Hyper-parameters of A3C

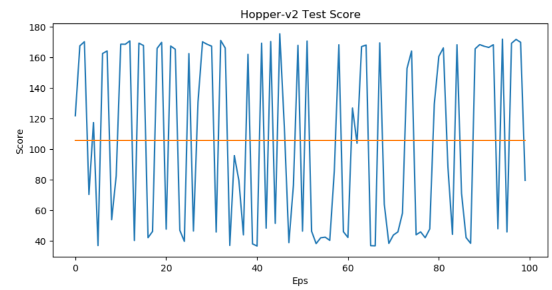
Hyper-parameter	Value
Thread number	8
γ	0.9
Learning rate η	0.00001
Stride to update global network	10

Specially, for HalfCheetah-v2, I set the the number of maximum steps as 1000. For the detailed network architectures, you can refer to the source code. Those tasks are trained on the HPC provided by the course.

3.2.2 Result

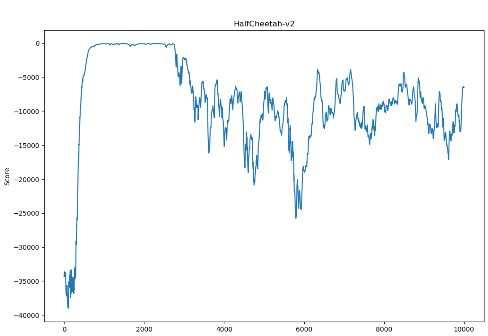


(a) Train

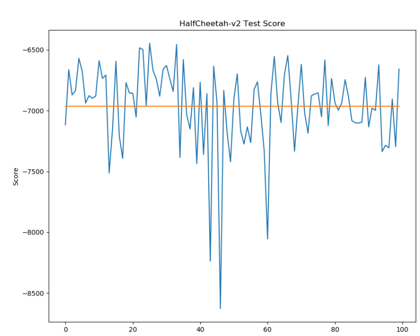


(b) Test

Figure 5: Hopper-v2



(a) Train



(b) Test

Figure 6: HalfCheetah-v2

3.3 DDPG

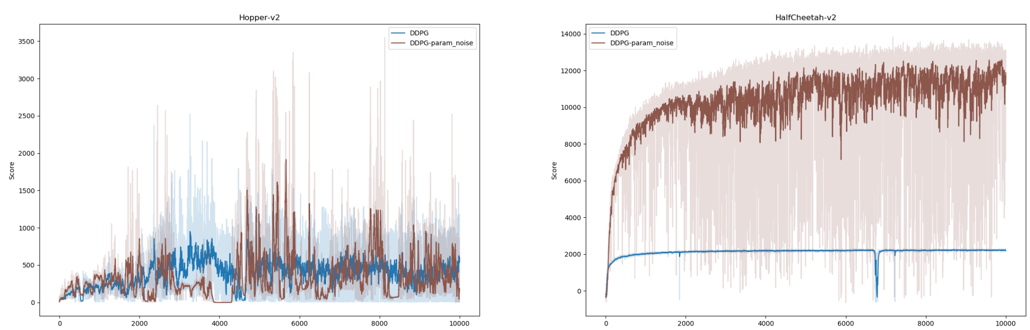
3.3.1 Experiment Setting

In this section, I trained DDPG and it's improvement on Hopper-v2 and HalfCheetah-v2. The settings of hyper-parameter is in 3. Specially, for the parameter space noise method, the adaptation coefficient is set to 1.01. For other details, please refer to the source code. As in A3C, I trained both Hopper-v2 and HalfCheetah-v2 for 10000 episodes. Specially, for HalfCheetah-v2, I set the the number of maximum steps as 1000. Also I trained them on the HPC provided by the course.

Table 3: Hyper-parameters of DDPG

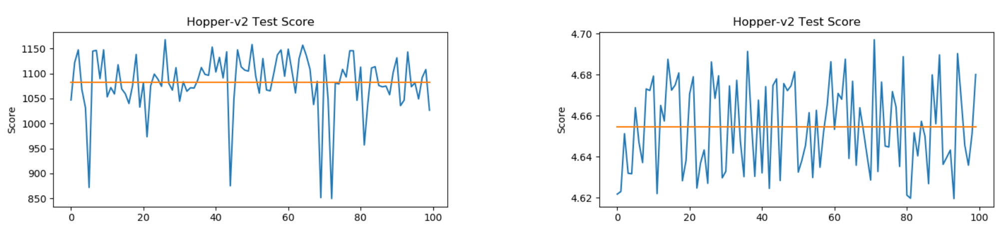
Hyper-parameter	Value
Replay Buffer Size	1000000
γ	0.99
Batch Size	64
Learning rate of actor η_a	0.0001
Learning rate of critic η_c	0.001
Soft update factor τ	0.001
Stride to update target network C	30

3.3.2 Result



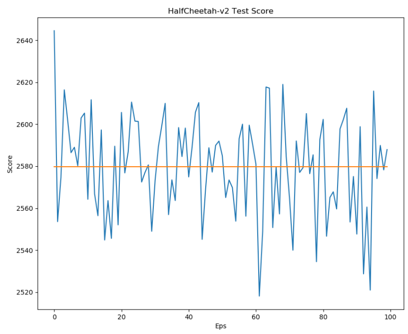
(a) Hopper-v2 (b) HalfCheetah-v2

Figure 7: Train DDPG

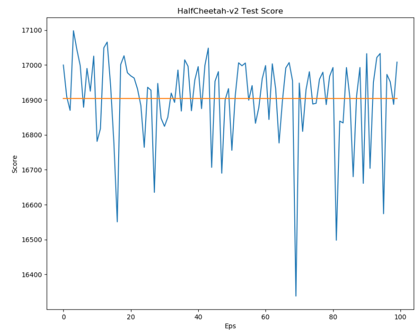


(a) Original DDPG (b) DDPG with Parameter Space Noise

Figure 8: Test Hopper-v2

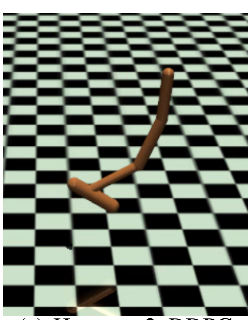


(a) Original DDPG

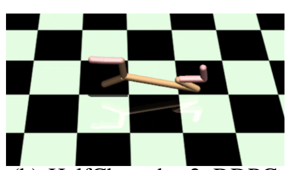


(b) DDPG with Parameter Space Noise

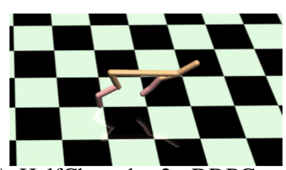
Figure 9: Test HalfCheetah-v2



(a) Hopper-v2, DDPG



(b) HalfCheetah-v2, DDPG



(c) HalfCheetah-v2, DDPG with PSN

Figure 10: Test

4 CONCLUSION

REFERENCES

Prafulla Dhariwal, Christopher Hesse, Oleg Klimov, Alex Nichol, Matthias Plappert, Alec Radford, John Schulman, Szymon Sidor, Yuhuai Wu, and Peter Zhokhov. Openai baselines. `https://github.com/openai/baselines`, 2017.

Hado van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, AAAI16, pp. 20942100. AAAI Press, 2016.

Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. In Yoshua Bengio and Yann LeCun (eds.), *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. *CoRR*, abs/1602.01783, 2016.

Matthias Plappert, Rein Houthooft, Prafulla Dhariwal, Szymon Sidor, Richard Y Chen, Xi Chen, Tamim Asfour, Pieter Abbeel, and Marcin Andrychowicz. Parameter space noise for exploration. *arXiv preprint arXiv:1706.01905*, 2017.

David Silver, Guy Lever, Nicolas Heess, Thomas Degris, Daan Wierstra, and Martin Riedmiller. Deterministic policy gradient algorithms. In *Proceedings of the 31st International Conference on International Conference on Machine Learning - Volume 32*, ICML14, pp. I387I395. JMLR.org, 2014.

George E Uhlenbeck and Leonard S Ornstein. On the theory of the brownian motion. *Physical review*, 36(5):823, 1930.

Ziyu Wang, Tom Schaul, Matteo Hessel, Hado van Hasselt, Marc Lanctot, and Nando de Freitas. Dueling network architectures for deep reinforcement learning. In Maria-Florina Balcan and Kilian Q. Weinberger (eds.), *Proceedings of the 33nd International Conference on Machine Learning, ICML 2016, New York City, NY, USA, June 19-24, 2016*, volume 48 of *JMLR Workshop and Conference Proceedings*, pp. 1995–2003. JMLR.org, 2016.

A APPENDIX

You can pull the whole project from `https://github.com/DeanAlkene/CS489-ReinforcementLearning` which also includes codes and reports of 5 assignments. You can train the models by following command.

`python run.py --env_name` *env* `--method` *method*

All the models in my experiments are saved and can be tested using the command:

`python test.py`

However, you need modify the code of `test.py` to specify the model and environment you want to test.