1. Learning Architecture

a) Algorithm

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 ${\cal R}$

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 $a_t = \mu(s_t|\theta^{\mu}) + \mathcal{N}_t$ 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
$$y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$$

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:

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

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

end for end for

b) Model Structure

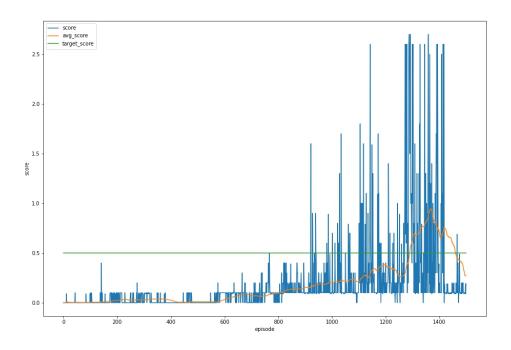
- i. Actor:
 - 1. Input size = State size = 24
 - 2. Hidden layers(2)
 - a) Fully connected with 128 batch-normalized rectifiers
 - b) Fully connected with 256 rectifiers
 - Output size = Action size = 2
- ii. Critic:
 - 1. Input 1 size = State size = 24 at 1st layer
 - 2. Input 2 size = Action size = 2 concat to 2nd layer
 - 3. Hidden layers(2)
 - a) Fully connected with 128 batch-normalized rectifiers
 - b) Fully connected with 256+4 rectifiers
 - Output size = Value function = 1
- c) Hyperparameters(Final)

i.	Batch size	40
ii.	Memory buffer size	1e6
iii.	Number of episodes	1500
iv.	Target score	30.0
V.	Discount factor gamma	1e-3
vi.	Learning rate for Actor	1e-4
vii.	Learning rate for Critic	1e-3

viii. Update Period	
ix. Update Times per update	10
x. Weight Decay	0
xi. Agent number	20
xii. Alpha(prioritized exp replay)	0.7
xiii. Beta(prioritized exp replay)	

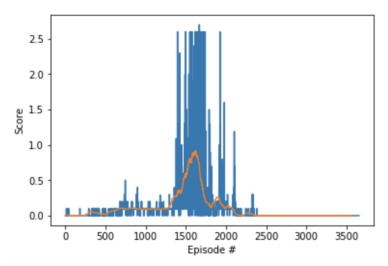
2. Results

- a) DDPG with prioritized experience replay
 - i. Folder: ddpg_result_2023_05_21_22_08_57
 - ii. Result:



3. Conclusions

a) The prioritized exp replay method do have accelerations on training(<1300 episodes), comparing to the original DDPG baseline provided by course instructions below(>1500 episodes).



4. Future Improvements

- a) Will try to implement n-step bootstrapping
- b) Will try to use array to represent replay buffer's binary tree
- c) Will try to implement other algorithms like Reinforce and TRPO