Udacity Deep Reinforcement Learning Nanodegree
Collaboration and Competition Project

1. Learning algorithm
    - Use the algorithm below

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 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 $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    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:

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

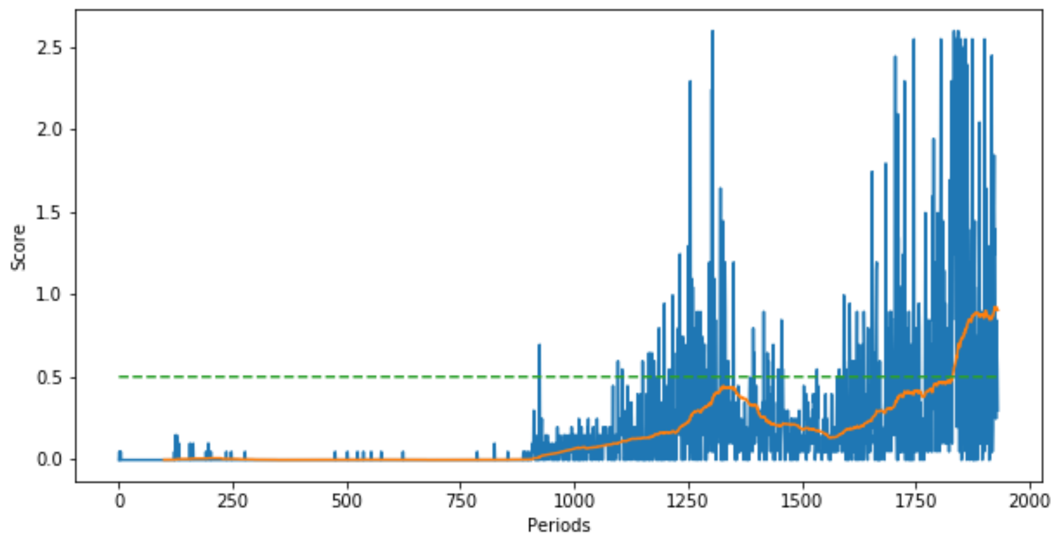
    Update the target networks:

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

  end for
end for

- Neural network:
    - Actor
        - Two hidden layers
        - First layer with 128 nodes; relu activation
        - Second layer with 64 nodes; relu activation
        - Tanh activation for last layer (4 actions)
    - Critic
        - Two hidden layers
        - First layer with 128 nodes; relu activation
        - Second layer with 128 nodes; concatenated with 4 actions; relu activation
        - Linear for last layer (one value)

2. Plot of scores



The environment is solved in 1931 periods. The criteria is that the average scores (with each score equal to average over the 2 agents in one period) over the previous 100 periods are greater than 0.5 for a consecutive 100 periods.

3. Future work:
    - I tried a few versions of MADDPG, but the result is not as good as DDPG reported here. I plan to further experiment with network structures in MADDPG and see whether MADDPG can beat DDPG for this case.
    - Use batch normalization to improve performance
    - Adding prioritized experience replay