P3 competition and collaboration

Yifan Tian

1. Learning Algorithm

In this project, the algorithm is the multi-agent DPG algorithm. Compared with the single agent version of the DPG algorithm. The difference of the multi-agent algorithm is that the actor and critic network is shared by the two multi-agents or two agents here. And the same for the memory.

The DPG algorithm maintains a parameterized actor function μ(s|θμ) which specifies the current policy by deterministically mapping states to a specific action. The critic Q(s, a) is learned using the Bellman equation as in Q-learning. The actor is updated by following the applying the chain rule to the expected return from the start distribution J with respect to the actor parameters.
Below shows the pseudocode

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

The replay buffer is a finite sized cache R. Transitions were sampled from the environment according to the exploration policy and the tuple (st, at, rt, st+1) was stored in the replay buffer. When the replay buffer was full the oldest samples were discarded. At each timestep the actor and critic are updated by sampling a minibatch uniformly from

the buffer. Because DDPG is an off-policy algorithm, the replay buffer can be large, allowing the algorithm to benefit from learning across a set of uncorrelated transitions.

A replay buffer of size 100000 was used from which was drawn random batches of 128 experiences during training. Soft updates between both actor and critic's local and target networks both mixed in a fraction $\tau=0.001$ of the local network.

In each episodes, there are max_t = 500 steps to be played. The episode will end when the 500 steps finished instead of one game is done.

HyperParameter

batch_size = 128
buffer_size = int(1e5)
gamma = 0.99
lr_actor = 1e-3
lr_critic = 1e-3
tau = 1e-3
noise_decay = 0.999
max_t = 500

Model architecture

The architecture of the network is following

Actor network layers:

```
ModuleList(
  (0): Linear(in_features=33, out_features=256, bias=True)
  (1): Linear(in_features=256, out_features=256, bias=True)
  (2): Linear(in_features=256, out_features=4, bias=True)
)
```

2 hidden layers with relu activation function

Critic network layers:

```
ModuleList(
  (0): Linear(in_features=33, out_features=256, bias=True)
  (1): Linear(in_features=260, out_features=256, bias=True)
  (2): Linear(in_features=256, out_features=1, bias=True)
)
```

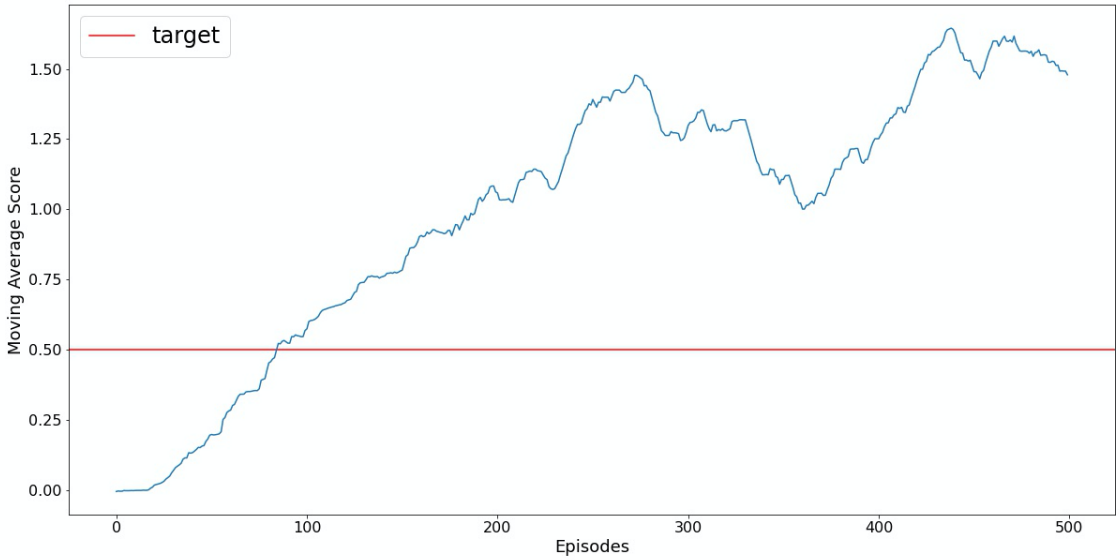
Also 2 hidden layers with relu activation function

In the implementation, there are two networks, local and target.
We update the local network by the following equation:
θ_target = τ*θ_local + (1 - τ)*θ_target

We train and optimize the local network, we update the target network from the above soft update scheme. There are two networks because we want to slowly train the target network. Rather than update the network completely after each step.

1. Plot of Rewards

The following figure shows the Average score versus the number of episodes. The average score is done by the accumulated reward of 1000 steps of an episode divided by the total number of games of this episode. Since in most of the steps, the ball is flying and only when the ball crosses the net, there is reward. So the total reward divided by the number of games makes sense. Which is how much score one game can obtain.



So after how many episodes the agent can solve the environment? From the above figure, we can see that the score is improving steadily overy the 300 hundreds episodes. And the score of one game passes the 1.0 after about 300 episodes.

2. Ideas for Future Work

- Current training takes a long time. So Prioritized Experience Replay can be used to speed up the training. The learning rate and the use of decay noise term can also be used to speed up the training.
- By tuning the network architecture, we can improve the score. So I think there is space for improvement in model architecture.