# Project 3: Collaboration and Competition

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This is a report to describe the implementation of the Actor-Critic algorithm to solve the Collaboration and Competition project.

## 1 The project introduction

The environment of the project is created using the Unity Machine Learning Agents v0.4. To create the environment on the local machine, we can follow the instruction on the following link .

In this environment, two agents control rackets to bounce a ball over a net. If an agent hits the ball over the net, it receives a reward of +0.1. If an agent lets a ball hit the ground or hits the ball out of bounds, it receives a reward of -0.01. Thus, the goal of each agent is to keep the ball in play.

The observation space consists of 24 variables corresponding to the position and velocity of the ball and racket. Each agent receives its own, local observation. Two continuous actions are available, corresponding to movement toward (or away from) the net, and jumping.

The task is episodic, and in order to solve the environment, your agents must get an average score of +0.5 (over 100 consecutive episodes, after taking the maximum over both agents). Specifically,

- After each episode, we add up the rewards that each agent received (without discounting), to get a score for each agent. This yields 2 (potentially different) scores. We then take the maximum of these 2 scores.
- This yields a single score for each episode.

The environment is considered solved, when the average (over 100 episodes) of those scores is at least +0.5.

## 2 Algorithm

The algorithm used in this project is Deep Deterministic Policy Gradients (DDPG) agent. The algorithm is as following:

```
Algorithm 1: DDPG
Initialization:;
Create target actor $A_t(S)$ and local actor $A_l(S)$ with weights $\theta_t$ and $\theta_l$ , respectively. The input $S$ represents
  the state at any time step. Both models output a vector with size same as the dimension of the action space;
Create target critic $C_t(S, A)$ and local critic $C_l(S, A)$ with weights $\eta_t$ and $\eta_l$ , respectively. The input $S$
  represents the state at any time step, while the input $A$ represents the action at any time step. Both models
  output a one dimensional vector representing the value of the state action pair;
Let $T$ be the maximum number of time steps each work can play in one episode;
Let $E$ be the number of episodes each work can play;
while $t < T$ do
    Reset environment;
    while $t < T$ do
        Let each worker interact with the environment N time steps using target actor $A_t(S)$ and random
          noise generated from a Ornstein-Uhlenbeck process. Collect all the tuples $(S_{i,j}, A_{i,j}, R_{i,j}, S'_{i,j})$ for
          the i$-th$ worker and j$-th$ time step;
        Define $y^c_{i,j} = R_{i,j} + \gamma C_l(S'_{i,j}, A'_{i,j})$ as the observation and $\hat{y}^c_{i,j} = C_l(S_{i,j}, A_{i,j})$ as the fitted value.
          Define loss $L_c = \sqrt{\sum_{i,j}(y^c_{i,j} - \hat{y}^c_{i,j})^2}$;
        Define the loss for actor $L_a = -\mathrm{E}\left[y^c_{i,j}\right]$;
        Update the local critic $C_l(S, A)$ with the above defined loss $L_c$. Soft update the target critic $C_t(S, A)$;
        Update the local actor $A_l(S)$ with the above defined loss $L_a$. Soft update the target actor $A_t(S)$;
    end
end
```

### 2.1 The architecture of the neural networks

All the models used in the algorithm $A_t(S)$, $A_l(S)$, $C_t(S)$, $C_l(S)$ are feed forward neural network with two hidden layers. Each hidden layer has 256 and 128 units, respectively.

### 2.2 The choice of hyper-parameters

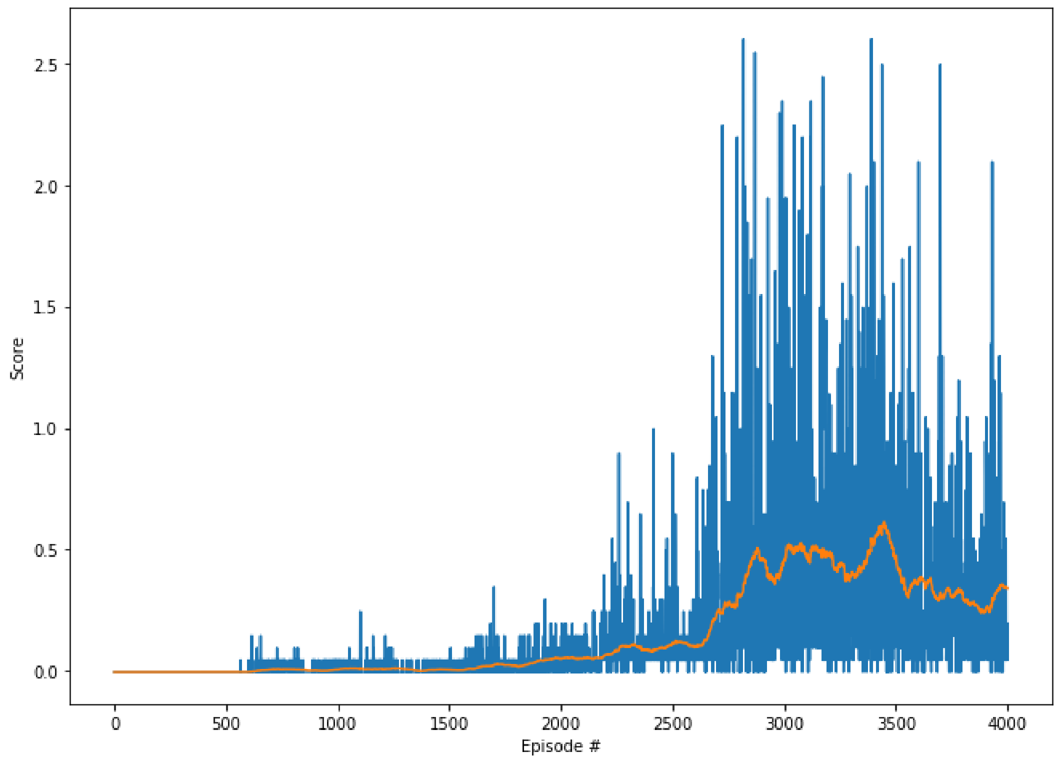
The hyperparameters used in the algorithm are listed in the following table:

| argument | value | explanation |
|---|---|---|
| n_episodes | 80 | |
| tau | 0.001 | update rate? |
| actor_LR | 0.0001 | learning rate for actor |
| critic_LR | 0.0003 | learning rate for critic |
| gamma | 0.99 | decay rate for future return |
| max_t | 2000 | maximum number of steps in one episode |
| actor_hiden_layer_size | [256,128] | neural network hidden layer and cells in each layer for actor |
| critic_hiden_layer_size | [256,128] | neural network hidden layer and cells in each layer for critic |
| actor_hiden_layer_act | [nn.ReLU(),nn.ReLU()] | neural network activation function in each hidden layer for actor |
| critic_hiden_layer_act | [nn.ReLU(),nn.ReLU()] | neural network activation function in each hidden layer for critic |
| buffer_size | int(1e5) | replay buffer size |
| batch_size | 128 | batch size |
| update_every | 1 | update frequency |

Based on my testing, smaller neural network does not work very well. High updating frequency really help speed up the training. It seems this project requires more of exploration than some other environments. A small batch size of 128 can speed up the model training, increase variance of the models and thus more likely to find the direction to improve.

## 3 Outcome

The plot of the average score is shown as following:



In the problem description, maximum score is required. Compare to average maximum score from 100 consecutive episodes higher than 0.5, the metric plotted here is more strict.

## 4 Conclusion and future work

The performance of the agent quickly declines after reaching the project requirement. My hypothesis is that the critic is getting too good compare to the actor and starts penalizing the actor after about 3500 episodes. I think one way to test this is to reduce the $\tau$ used to update the models in the later period of the learning. It would also be very interesting to see whether updating the actors in turn for each agent would make a difference.