Project 3 Collaboration and Competition Report

Udacity Deep Reinforcement Learning NanoDegree

Author: Denis O'Connor

Implementation

The base of this implementation was taken from the Udacity Deep Reinforcement Learning ddpg-pendulum project. I relied heavily on implementation from Project 2. I was surprised that I didn't have to modify more. In addition to the base code used, I had to play around with several other elements. Initially, while trying to train with the original DDPG code I was encountering issues with UnityActionExceptions. I wasn't properly handling the step and act functions in my Agent. After perusing the Udacity Knowledge forum and going through the MADDPG lab closer, I was able to correct this. I updated the Agent constructor to take the number of agents, and then had to update the act function to properly handle and return actions. Additionally, I needed to use a different constructor for the OuNoise object by passing the now available number of agents

Learning Algorithm

Per Medium.com, I used this explanation for the basis of my learning algorithm. I used a Deep Deterministic Policy Gradients approach. Also per Medium.com, "The network architecture is comprised of two fully connected hidden layers of 128 units each with ReLU activations. In order to help speed up learning and avoid getting stuck in a local minimum, batch normalization was introduced to each hidden layer. The hyperbolic tan activation was used on the output layer for the actor-network as it ensures that every entry in the action vector is a number between -1 and 1. Adam was used as an optimizer for both actor and critic networks." However, through my troubleshooting I commented out the batch normalization after the second layer's activation. At the time, I was hitting problems where training was resulting in an average score of 0.0. Although, I did not try uncommenting it out after solving some of my other workspace issues.

Hyperparameters

Batch size: 128

Replay buffer size: 1e6

Gamma (discount factor): 0.99

TAU: 1e-3

Actor learn rate: 1e-3

Critic learn rate: 1e-3

Weight decay: 0

OUNoise theta: 0.15

OUNoise sigma: 0.1

Maximum Timesteps Per Episode: 1000

Results

```
Episode 1510 Average Score: 0.18
           Episode 1520
                               Average Score: 0.29
           Episode 1530
                               Average Score: 0.51
           Environment solved in 1430 episodes
                                                             Average Score: 0.51
In [10]: fig = plt.figure()
ax = fig.add_subplot(111)
           plt.plot(np.arange(len(scores)), scores)
plt.ylabel('Score')
plt.xlabel('Episode #')
            plt.show()
               4
              1
                               400
                                           800
                                                 1000
                                                        1200
                                        Episode #
```

Future Improvements

First improvement I would implement is to reintroduce the batch normalization to the second hidden layer. Although, for once I was fairly pleased with my results, I believe tweaking the hyperparameters could yield better results. Also, it would be a great learning experience to try to apply my implementation to the Soccer Environment.