Udacity

Deep Reinforcement Learning Nanodegree

<u>Project 3- Collaboration and Competition</u>

Algorithm

In this project, we use the DDPG algorithm (Deep Deterministic Policy Gradient) and the MADDPG algorithm, a wrapper for DDPG. MADDPG stands for Multi-Agent DDPG.

DDPG is an algorithm which concurrently learns a Q-function and a policy. It uses off-policy data and the Bellman equation to learn the Q-function, and uses the Q-function to learn the policy. This dual mechanism is the actor-critic method. The DDPG algorithm uses two additional mechanisms: Replay Buffer and Soft Updates.

In MADDPG, we train two separate agents, and the agents need to collaborate (like don’t let the ball hit the ground) and compete (like gather as many points as possible). Just doing a simple extension of single agent RL by independently training the two agents does not work very well because the agents are independently updating their policies as learning progresses. And this causes the environment to appear non-stationary from the viewpoint of any one agent. In MADDPG, each agent’s critic is trained using the observations and actions from both agents , whereas each agent’s actor is trained using just its own observations.

DDPG is used because in this algorithm, Actor directly maps states to actions (the output of the network directly the output) instead of outputting the probability distribution across a discrete action space. The target networks are time-delayed copies of their original networks that slowly track the learned networks. Using these target value networks greatly improve stability in learning.

In the finction step() of the class madppg___agent_, we collect all current info for both agents into the common variable_memory of the type ReplayBuffer. The main reason is that the agent may get caught in a tight loop of specific states that loop back through one another and detract from the agent exploring the full environment ”equally”. By sharing a common replay buffer, we ensure that we explore all the environment. Note that the agents still have their own actor and critic networks to train.

Then we get the random sample from memory into the variable experience. This experience together with the current number of agent (0 or 1) go to the function learn(). We get the corresponding agent (of type _ddpg___agent_):

agent = self.agents[agent_number]

and experience is transferred to function learn() of the class ddpg___agent. There, the actor and the critic are handled by different ways.

Goal

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.

Hyperparameters

Please note that following parameters were used after experimentation with different values.

From ddpg_agent.py

```
GAMMA = 0.99
TAU = 5e-2
LR_ACTOR = 5e-4
LR_CRITIC = 5e-4
WEIGHT_DECAY = 0.0
NOISE_AMPLIFICATION = 1
NOISE_AMPLIFICATION_DECAY = 1
```

From maddpg_agent.py

```
BUFFER_SIZE = int(1e6)
BATCH_SIZE = 512
LEARNING_PERIOD = 2
```

Neural Networks

In this project, there are 8 *neural networks*. For the training, we create one *maddpg agent*.

```
maddpg = maddpg_agent()
```

In turn, *maddpg agent* creates 2 _ddpg agents_:

```
self.agents = [ddpg_agent(state_size, action_size, i+1, random_seed=0)
```

Each of two agents (red and blue) create 4 neural networks:

```
self.actor_local = Actor(state_size, action_size).to(device)

self.actor_target = Actor(state_size, action_size).to(device)
self.critic_local = Critic(state_size, action_size).to(device)

self.critic_target = Critic(state_size, action_size).to(device)
```

Classes Actor and Critic are provided by **model.py**. Please note that this architecture is chosen for Actor/Critic it optimizes the learning rate of the agent but in our project noise is not added to the agent. The typical behavior of the actor

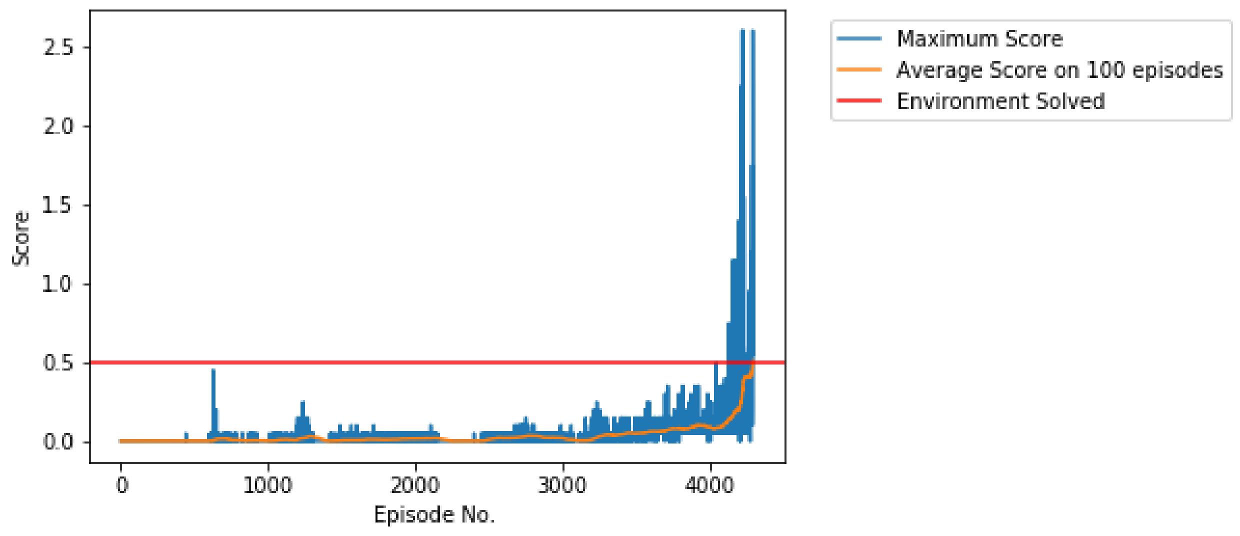
```
actor_target(state) -> next_actions

actor_local(states) -> actions_pred
```

Both the actor and critic classes implement the neural network with 3 fully-connected layers and 2 re ctified nonlinear layers. These networks are realized in the framework of package PyTorch. Such a network is used in Udacity model.py code for the Pendulum model using DDPG.

Results of Training

While using Udacity Workspace with GPU enable, the desired average reward **+0.5** was achiev ed in **4291** episodes in **00h:45m:33s**. Complete output is too large and can be seen in the Ten nis Notebook. Below is just summary of the result

Plot



Ideas for Future Work

1. Tuning hyperparameters value for better result.
2. Continue training the model rather than breaking the loop when goal achieved initially.