Deep Reinforcement Learning Nanodegree

Project 3 Report - Collaboration and Competition

Introduction

This project is the third and final in Udacity's Deep Reinforcement Learning Nanodegree. In this project, the goal is to implement multiagent model/s based on [Deep Deterministic Policy Gradient (DDPG)] to play Tennis with each other in a Unity ML-Agents environment.

Environment description

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 8 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.

Task description

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.

Learning Algorithm

Deep Deterministic Policy Gradient (DDPG) is an algorithm which concurrently learns a Q-function and a policy using two networks in an (Actor-Critic) approach. It's also worth noting that each of these two networks contain two separate networks in its own, just as DQN where there is a local and a target network together making the DQN network. At each learning step, the Actor network is used to estimate the best action given the current state, and the Critic uses the current state and best action as in a DDQN to evaluate the optimal action value function which will be used back to tarin the Actor network.

Hyperparameters Tuning:

After careful monitoring of the training process using multiple sets of hyperparameters. The best set that was found was as follows:

Variable Name	Hyperparameters Description	Chosen Value
n_episodes	how many episodes to train for	300
BUFFER_SIZE	replay buffer size	1e5
BATCH_SIZE	sampling size from buffer	128
GAMMA	discount factor	0.99
TAU	Target networks soft update factor	1e-3
LR_ACTOR	Actor local network learning rate	1e-4
LR_CRITIC	Critic local network learning rate	1e-4
learn_every	time steps to update Actor and Critic networks	20

As each agent receives its own local observation. It was decided to simultaneously train both agents using the same networks through self-play. Each agent uses the same actor network to select actions, and the experience was added to a shared replay buffer.

Network Architecture

For the Actor network, both the main and target networks were composed of 3 fully connected (dense) layers as follows:

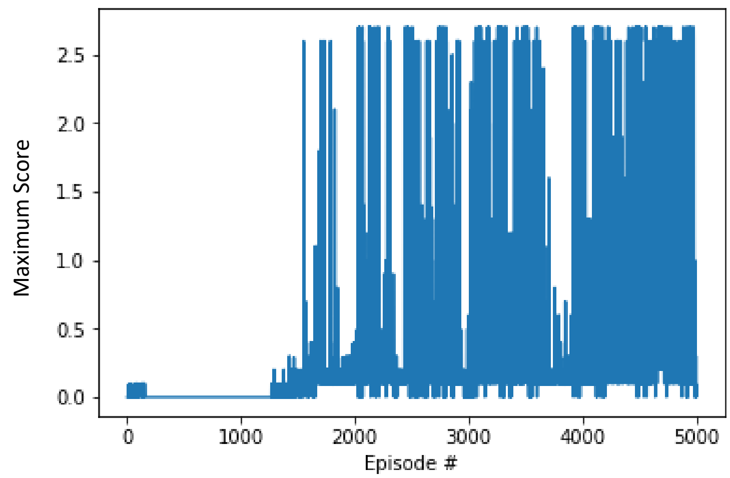
```
class Actor(nn.Module):
    """Actor (Policy) Model."""

    def __init__(self, state_size, action_size, seed, fc1_units=400, fc2_units=300):
        """Initialize parameters and build model.
        Params
        ======
            state_size (int): Dimension of each state
            action_size (int): Dimension of each action
            seed (int): Random seed
            fc1_units (int): Number of nodes in first hidden layer
            fc2_units (int): Number of nodes in second hidden layer
        """
        super(Actor, self).__init__()
        self.seed = torch.manual_seed(seed)
        self.fc1 = nn.Linear(state_size, fc1_units)
        self.fc2 = nn.Linear(fc1_units, fc2_units)
        self.fc3 = nn.Linear(fc2_units, action_size)
        self.reset_parameters()

    def reset_parameters(self):
        self.fc1.weight.data.uniform_(*hidden_init(self.fc1))
        self.fc2.weight.data.uniform_(*hidden_init(self.fc2))
        self.fc3.weight.data.uniform_(-3e-3, 3e-3)

    def forward(self, state):
        """Build an actor (policy) network that maps states -> actions."""
        x = F.relu(self.fc1(state))
        x = F.relu(self.fc2(x))
        return torch.tanh(self.fc3(x))
```

For the Critic network, both the main and target networks were composed of 3 fully connected (dense) layers as follows:

```
class Critic(nn.Module):
    """Critic (Value) Model."""

    def __init__(self, state_size, action_size, seed, fcs1_units=400, fc2_units=300):
        """Initialize parameters and build model.
        Params
        ======
            state_size (int): Dimension of each state
            action_size (int): Dimension of each action
            seed (int): Random seed
            fcs1_units (int): Number of nodes in the first hidden layer
            fc2_units (int): Number of nodes in the second hidden layer
        """
        super(Critic, self).__init__()
        self.seed = torch.manual_seed(seed)
        self.fcs1 = nn.Linear(state_size, fcs1_units)
        self.fc2 = nn.Linear(fcs1_units+action_size, fc2_units)
        self.fc3 = nn.Linear(fc2_units, 1)
        self.reset_parameters()

    def reset_parameters(self):
        self.fcs1.weight.data.uniform_(*hidden_init(self.fcs1))
        self.fc2.weight.data.uniform_(*hidden_init(self.fc2))
        self.fc3.weight.data.uniform_(-3e-3, 3e-3)

    def forward(self, state, action):
        """Build a critic (value) network that maps (state, action) pairs -> Q-values."""
        xs = F.relu(self.fcs1(state))
        x = torch.cat((xs, action), dim=1)
        x = F.relu(self.fc2(x))
        return self.fc3(x)
```

Results

The training process lasted for 5000 episodes (although it could have been done within 2500). There was a steady increase in the score from around episode 1500 to episode 1800, then the scores started slowly oscillating back and forth between 2.5 and 0.1.



The maximum score of the two agents has been recorded at the end of each episode and is shown in the figure below:

The maximum average score over 100 consecutive episodes was recorded as 1.99 and the environment has been solved from episode number 1939 : 2039 with an average score of 0.54

The models weights of both Actor and Critic local networks at the max score achieved have been saved in the *checkpoint_critic.pth* and *checkpoint_actor.pth* files in the root of the GitHub repository so it can be retrieved again after the end of training.

Future work to consider:

To improve on the current implementation, it is recommended to add following features to the above learning algorithm :

- More tuning of hyperparameters and model architecture
- Other model such as PPO, A3C or D4PG could also achieve better results than DDPG.