Project 2 – Report

In this project was used the Deep Deterministic Policy Gradient (DDPG) algorithm to solve the environment with 20 agents (second version). The starting point was the implementation provided by Udacity to solve BipedalWalker environment (ddpg-bipedal).

Learning algorithm description

Deep Deterministic Policy Gradient (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. DDPG can be seen as a Deep Q-Learning algorithm for continuous action domains, since the algorithm combines ideas from DPG (Deterministic Policy Gradient) and DQN (Deep Q-Network), using Experience Replay and slow-learning target networks from DQN, and it is based on DPG, which can operate over continuous action spaces.
Just like Actor-Critic methods, we have two networks (our target networks):

- Actor - It proposes an action given a state
- Critic - It predicts if the action is good (positive value) or bad (negative value) given a state and an action.

The full algorithm is described below:

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

Architectures

The architectures used in the actor and critic can be seen below:

Actor

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

    def __init__(self, state_size, action_size, seed, fc1_units=400, fc2_units=256):
        """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.bn1 = nn.BatchNorm1d(fc1_units)

        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.bn1(self.fc1(state)))
        x = F.relu(self.fc2(x))

        return torch.tanh(self.fc3(x))
```

Critic

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

    def __init__(self, state_size, action_size, seed, fcs1_units=400, fc2_units=256):
        """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.bn1 = nn.BatchNorm1d(fcs1_units)

        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."""
        x = F.relu(self.bn1(self.fcs1(state)))
        x = torch.cat((x, action), dim=1)
        x = F.relu(self.fc2(x))

        return self.fc3(x)
```

These architectures were found through experimentation. Among the modifications made to the original architecture used in the base code, the modification that had the greatest impact was the inclusion of a batch normalization after the first hidden layer.

Hyperparameters

The hyperparameters used can be seen below:

```
BUFFER_SIZE = int(1e6)  # replay buffer size
BATCH_SIZE = 128        # minibatch size
GAMMA = 0.99            # discount factor
TAU = 1e-3              # for soft update of target parameters
LR_ACTOR = 1e-4         # learning rate of the actor
LR_CRITIC = 1e-4        # learning rate of the critic
WEIGHT_DECAY = 0.0001   # L2 weight decay

LEARN_EVERY = 20        # Learning interval
LEARN_TIMES = 10        # Number of times to call learning function
```

Theta and sigma from Ornstein-Uhlenbeck process was also changed to 0.5 and 0.10 respectively.

```
def __init__(self, size, seed, mu=0., theta=0.5, sigma=0.10):
```

LEARN EVERY is used to define the number of time steps required before updating the network weights, once LEARN_EVERY timesteps in the environment have passed, the function to update the network weights (learn) is executed LEARN_TIMES, each time with a different set of experience.

Other Changes

The noise added to the state by Ornstein-Uhlenbeck process was changed, to use random values from a standard normal distribution.

```
dx = self.theta * (self.mu - x) + self.sigma * np.random.standard_normal(self.size)
```

Finally, was implemented a fix to the rewards received by the agent in the environment. As some colleagues pointed out in the peer chat, bugs occasionally occur in the environment and the agent does not correctly receive the reward of 0.1 as it should, but a lower value. To fix this issue, the following line is executed after receiving the rewards.

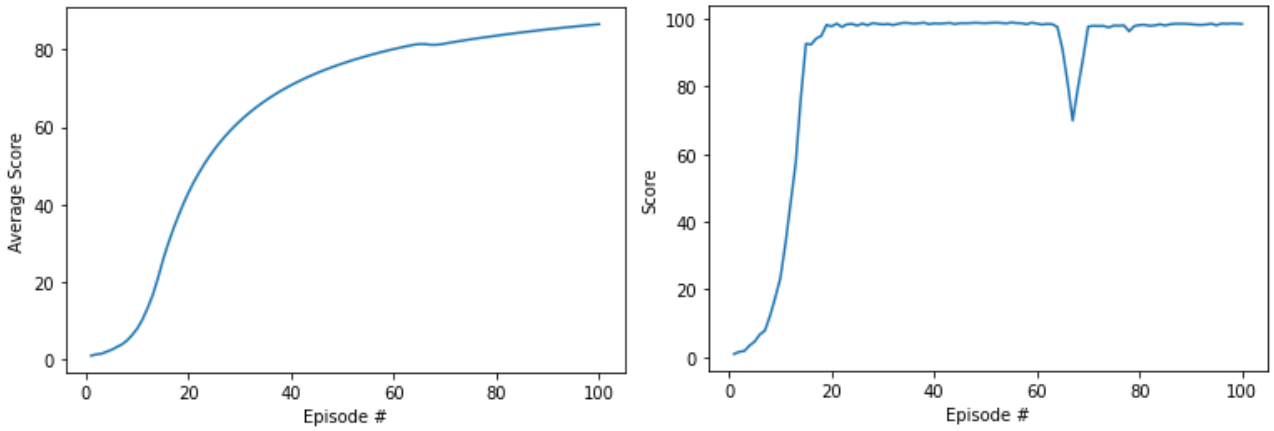
```
rewards = [0.1 if rew > 0 else 0 for rew in rewards]
```

Results

The agent achieved an average score of 30.0 in approximately 20 episodes, but since the environment is considered solved only after 100 episodes with an average score of 30.0, it continued training until episode 100, finishing with an average score of 86.56.

```
Episode 10      Score : 23.23   Average Score: 7.98
Episode 20      Score : 97.82   Average Score: 43.15
Episode 30      Score : 98.39   Average Score: 61.56
Episode 40      Score : 98.70   Average Score: 70.83
Episode 50      Score : 98.75   Average Score: 76.42
Episode 60      Score : 98.64   Average Score: 80.14
Episode 70      Score : 97.77   Average Score: 81.56
Episode 80      Score : 98.22   Average Score: 83.59
Episode 90      Score : 98.47   Average Score: 85.23
Episode 100     Score : 98.53   Average Score: 86.56
Enviroment Solved!
```

Observing the scores of the episodes, 20 onwards, it is possible to observe that the agent obtained an almost perfect score, therefore, if the training continued, the average score would probably increase until almost 100.



Ideas for Future Work

During the development of the project it became clear that the algorithm is very sensitive to the hyperparameters used, so a good starting point for improving the agent would be an optimization of the hyperparameters, which would probably help the agent to solve the environment more quickly (in less episodes). Another improvement would be the implementation of prioritized experience replay, since like DQN, this algorithm used experience replay to learn agents.

Note

The model weights of the actor and critic used to solve the environment is saved respectively with the names best_actor.pth and best_critic.pth in the project root folder.