REPORT OF IMPLEMENTATION

Learning Algorithm

In this project was used Actor-Critic method, through the DDPG algorithm. DDPG means Deep Deterministic Policy Gradient and extend policy-based reinforcement learning methods to complex problems using deep neural networks.
DDPG is very similar to DQN method, using ReplayBuffer. A big difference is that DQN is used to discrete action spaces and DDPG is used to continuous action spaces.
In algorithms like DDPG that implement actor-critic method we have two neural networks, one is the actor and another is the critic.
Also, was used Experience Replay and Fixed Q-Targets methods to improve the agent's performance.
OUNoise Class is used to add noise to actions to promote exploration. It uses the Ornstein-Uhlenback process to achieve this.

CODE

1- model.py
In this file was created the actor and critic classes, each one with your own neural network.
The neural network was created using PyTorch.

2- ddpg_agent.py
In this file was created the Agent class.
Looking for learning and improving the results, the agent implements the Experience Replay and Fixed Q-Targets methods.
Was created the ReplayBuffer class to implement the Experience Replay method

4- Training the agent
The agent was trained in 2.000 episodes and epsilon decay = 0.995
The environment is considered solved when the agent achieve the mean score >= 13.0, but the train continues until finish the 2.000 episodes.

ATTEMPT 1

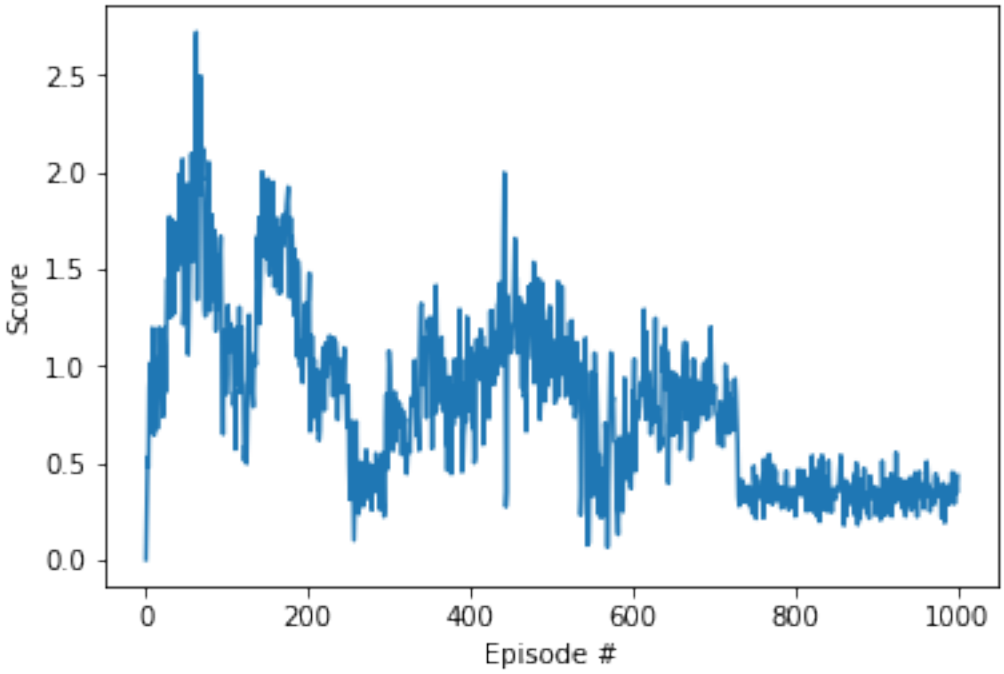
Model.py
Actor model architecture:
- three fully connected layers, receiving the state as input and actions as output.
- 33(Input-state_size) x 400(hidden_layer) x 300(hidden_layer) x 4(output - action_size)
- Was applied ReLu activation at hidden layers and Tanh activation at output layer.

Critic model architecture:
- three fully connected layers, receiving the state as input and return as output only one unit, the Q-values.
- 33(Input-state_size) x 404(hidden_layer+action_size) x 300(hidden_layer) x 1(output - Q-values)
- Was applied ReLu activation at hidden layers.

Hyperparameters used to train the agent:
```
BUFFER_SIZE = int(1e5)  # 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-3 # learning rate of the critic
WEIGHT_DECAY = 0 # L2 weight decay
UPDATE_EVERY = 1 # how often to update the network
N_EPISODES = 1000 # number of episodes

The result of the first attempt was really bad. The max scored achieved was around 2.5



ATTEMPT 2

To second attempt I did some changes:

- Neural network architecture of the Actor
- Neural network architecture of the Critic
- Hyperparameters
- UoNoise

Model.py

Actor model architecture:

- three fully connected layers, receiving the state as input and actions as output.
- 33(Input-state_size) x 256(hidden_layer) x 128(hidden_layer) x 4(output - action_size)
- Was applied ReLu activation at hidden layers and Tanh activation at output layer.

Critic model architecture:

- four fully connected layers, receiving the state as input and return as output only one unit, the Q-values.
- 33(Input-state_size) x
  132(hidden_layer+action_size) x
  64(hidden_layer) x
  32(hidden_layer) x
  1(output - Q-values)

- Was applied ReLu activation at hidden layers.

Hyperparameters used to train the agent (Only modified hyperparameters):

```
BUFFER_SIZE = int(1e6)  # replay buffer size
BATCH_SIZE = 1024       # minibatch size
```

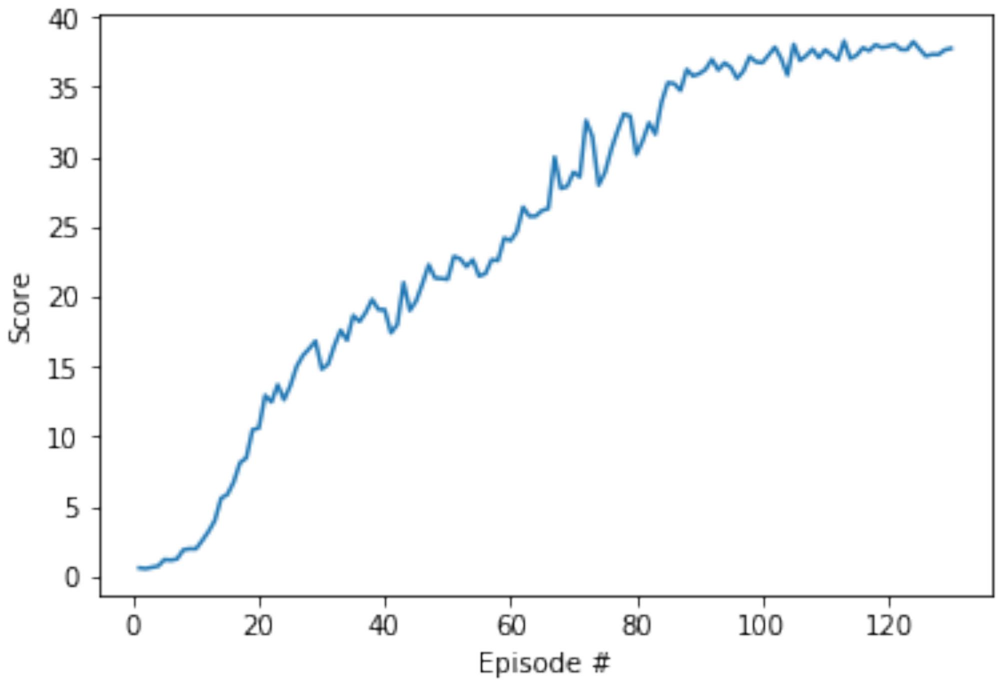
"""Ornstein-Uhlenbeck process.”""
Was necessary to change the noise process. Below the old and new version of code.

```
#dx = self.theta * (self.mu - x) + self.sigma * np.array([random.random() for i in range(len(x))])
  dx = self.theta * (self.mu - x) + self.sigma * np.random.standard_normal(self.size)
```

RESULT

With those architecture and hyper parameters was possible achieve the Average Score of the 30.19 in only 130 episodes.
Below the progress of the agent’s learning.

```
Episode 10   Average Score: 1.19   Episode Score: 1.96
Episode 20   Average Score: 3.87   Episode Score: 10.60
Episode 30   Average Score: 7.39   Episode Score: 14.82
Episode 40   Average Score: 10.04  Episode Score: 19.07
Episode 50   Average Score: 12.07  Episode Score: 21.24
Episode 60   Average Score: 13.84  Episode Score: 24.01
Episode 70   Average Score: 15.72  Episode Score: 28.91
Episode 80   Average Score: 17.60  Episode Score: 30.17
Episode 90   Average Score: 19.45  Episode Score: 35.95
Episode 100  Average Score: 21.16  Episode Score: 36.73
Episode 110  Average Score: 24.76  Episode Score: 37.66
Episode 120  Average Score: 27.87  Episode Score: 37.90
Episode 130  Average Score: 30.19  Episode Score: 37.76
Environment solved in 130 episodes
```



Future ideas for improving agent’s performance

Looking for improving the agent’s performance we suggest to try the following actions:

- Modifying the hyper parameters, looking for speed up training or increase the final score.
- Implement a differente algorithm like PPO or D4PG.
- Modifying the model architecture by changing the number of layers or neurons.
- Change the update frequency of the networks in the step function.