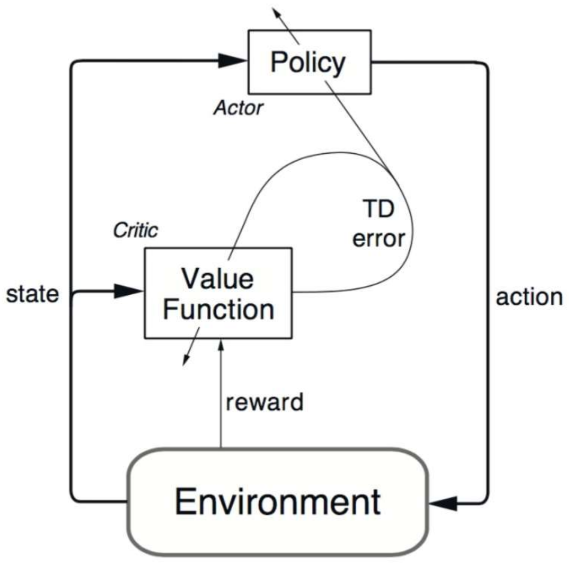
Report

The solution is based on DDPG (Deep Deterministic Policy Gradient) arch itecture.

The DDPG approach is an actor-critic policy gradient algorithm. In this case two neural networks are used. The first network is called the ‘act or’ and approximates the optimal policy. The optimal policy is the poli cy that maximizes the reward of an agent when it is followed. In this c ase the agent performs the action in any given state, which provide the highest reward for this state.
The second neural network is called the ‘critic’, it evaluates the poli cy by estimating the reward following that approximately optimal policy given by the actor. To improve, actor and critic network update through their loss functions. Actor and critic perform in a loop to improve by comparing the estimated reward to the actual reward and the actor there for gets closer to the true optimal policy. The following image describ es the architecture (source: https://arxiv.org/abs/1509.02971)

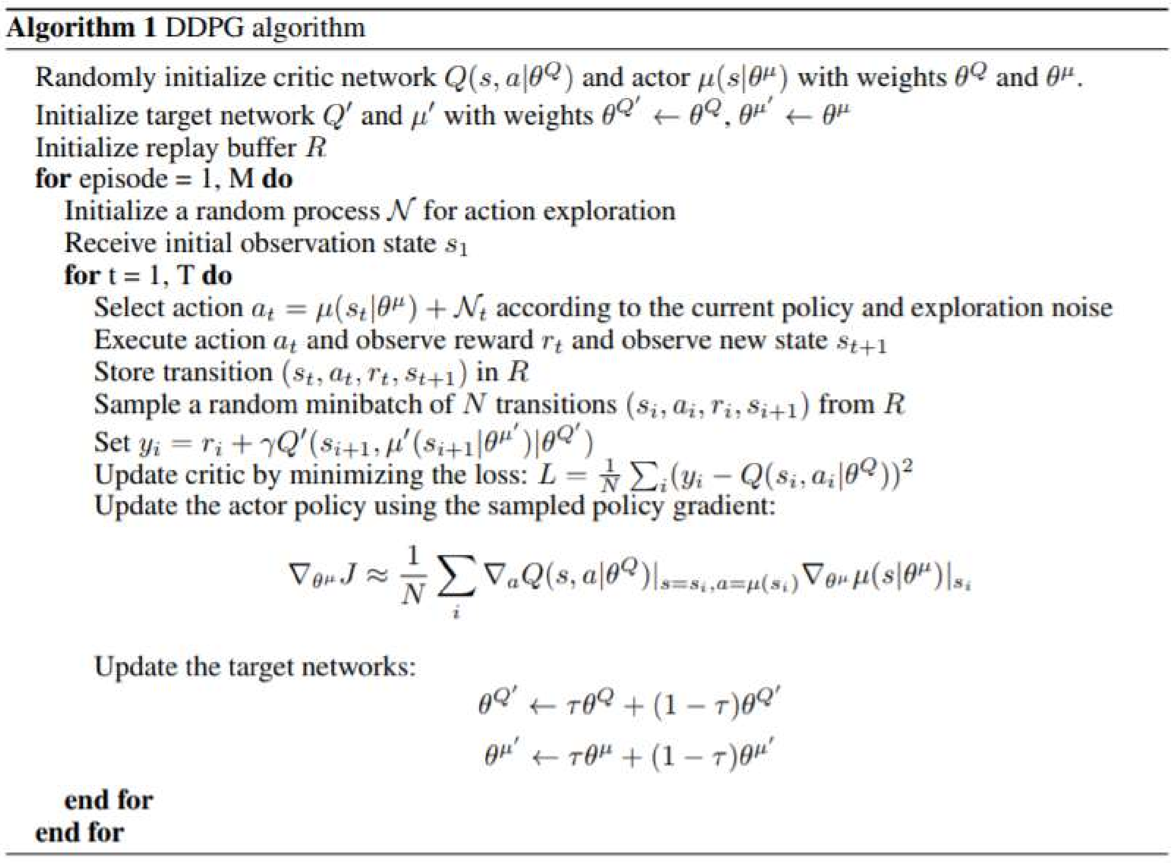


One of the challenges of the DDPG approach, is that it is not really pe rforming exploration for the action. An approach to overcome this is to add noise to the parameter or action space. In this case the Ornstein-U hlenbeck Random process is used to introduce noise to select a specific action in a timestep.

So what happens, when the training starts?

In the beginning the networks for actor and critic are initialized with random values. The actor then gets the state of the environment and the actor returns an action based on the policy. Noise (Ornstein-Uhlenbeck) is added and the action on the step is determined. The action taken lea ds to a new state of the environment and a reward is given to the actor . This happens for every time step t in an episode. Information on stat e, taken action, reward, next state is stored in the replay buffer. Thi s holds an amount of these tuples and randomly gives a sample to the cr itic network. The critic network approximates the expected Q value. Bas ed on the mean squared value between the expected and the actual Q valu e, both networks are updated. The actor network is updated towards a be tter policy using gradient ascent.

Below is a description of the algorithm (source: https://arxiv.org/abs/1509.02971)



```
Algorithm 1 DDPG algorithm
  Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights $\theta^Q$ and $\theta^\mu$.
  Initialize target network $Q'$ and $\mu'$ 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
```

For more details see the following paper on DDPG(https://arxiv.org/abs/1509.02971)

For the implementation, the foundation for the solution was provided in the Udacity repository for the Deep Reinforcement Learning Nanodegree (https://github.com/udacity/deep-reinforcement-learning)

While the training approach is based on the agent.py in the repository folder ddpg-pendulum, the model.py file is based on the model definition provided in the ddpg-bipedal folder of the same repository. Agent.py has been modified to accommodate for multiple agents in the environment, while model.py has not been changed from its original version (except of the fc_unit settings). The key in this case is that the agents use the same replay buffer and share experiences.

1. Environment Description

```
INFO:unityagents:
'Academy' started successfully!
Unity Academy name: Academy
        Number of Brains: 1
        Number of External Brains : 1
        Lesson number : 0
        Reset Parameters :

Unity brain name: TennisBrain
        Number of Visual Observations (per agent): 0
        Vector Observation space type: continuous
        Vector Observation space size (per agent): 8
        Number of stacked Vector Observation: 3
        Vector Action space type: continuous
        Vector Action space size (per agent): 2
        Vector Action descriptions: ,
```

2. State and action spaces

```
Number of agents: 2
Size of each action: 2
There are 2 agents. Each observes a state with length: 24
The state for the first agent looks like: [ 0.          0.          0.
0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
0.
  0.          0.         -6.65278625 -1.5        -0.          0.
  6.83172083  6.         -0.          0.        ]
```

3. Model Description (actor_target, critic_target):

```
Actor(
  (fc1): Linear(in_features=24, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=2, bias=True)
)
Critic(
  (fcs1): Linear(in_features=24, out_features=256, bias=True)
  (fc2): Linear(in_features=258, out_features=256, bias=True)
  (fc3): Linear(in_features=256, out_features=128, bias=True)
  (fc4): Linear(in_features=128, out_features=1, bias=True)
)
```

The summary above provides the description of the underlying deep neural networks used in the approach as part of this solution. The solution uses two networks, one for actor and one for the critic.

4. Hyperparameter:

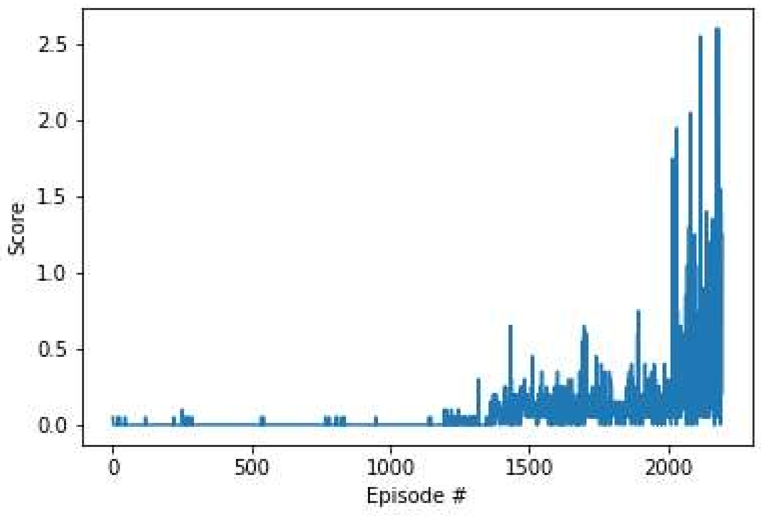
Parameter	Value
n_episodes (int): maximum number of training episodes	**10000**
max_t (int): maximum number of timesteps per episode	**1000**
num_agents : amount of agents in the environment	**2**
DDPG Agent HyperParameters	
BUFFER_SIZE: replay buffer size	**int(1e6)**
BATCH_SIZE: minibatch size	**512**
GAMMA: discount factor	**0.99**
TAU: for soft update of target parameters	**1e-3**
LR_ACTOR: learning rate for actor	**1e-4**

LR_CRITIC: learning rate for criti c	**1e-4**
WEIGHT_DECAY: L2 weigth decay	**0**

5. Training Summary:

```
…
Episode 2185   Mean score (last 100 episodes): 0.45
Episode 2186   Mean score (last 100 episodes): 0.45
Episode 2187   Mean score (last 100 episodes): 0.46
Episode 2188   Mean score (last 100 episodes): 0.45
Episode 2189   Mean score (last 100 episodes): 0.47
Episode 2190   Mean score (last 100 episodes): 0.48
Episode 2191   Mean score (last 100 episodes): 0.49
Episode 2192   Mean score (last 100 episodes): 0.49
Episode 2193   Mean score (last 100 episodes): 0.49
Episode 2194   Mean score (last 100 episodes): 0.50

Environment solved in 2194 episodes!Mean score(last 100 episodes): 0.50
```



The plot above shows the agents score achieved during the training episodes. the agent can receive an average reward (over 100 episodes, and over all 20 agents) of >= 0.50 after 2194 episodes.

6. Ideas for optimizing the solution:

- **Optimizing hyperparamters:** During the development of the exercise I experimented with the hyperparameters (especially with the fc_units, learning rates, tau and batch size) I strongly believe that there is plenty of room of further optimization here with automating the experimentation efforts. Creating a script that changes parameters based on statistical methods (grid search) and combining it with an automated AWS script to spin up multiple environments, can give a good solution to scale experimentation efforts.
- **Changing the Algorithm:** As an option Proximal Policy Optimization (PPO) and Distributed Distributional Deterministic Policy Gradients (D4PG) methods could be explored.