

## TENNIS ENVIRONMENT

In the Tennis 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. 2 continuous actions are available, corresponding to movement toward (or away from) the net, and jumping.

- 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

The task is episodic, and in order to solve the environment, 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.

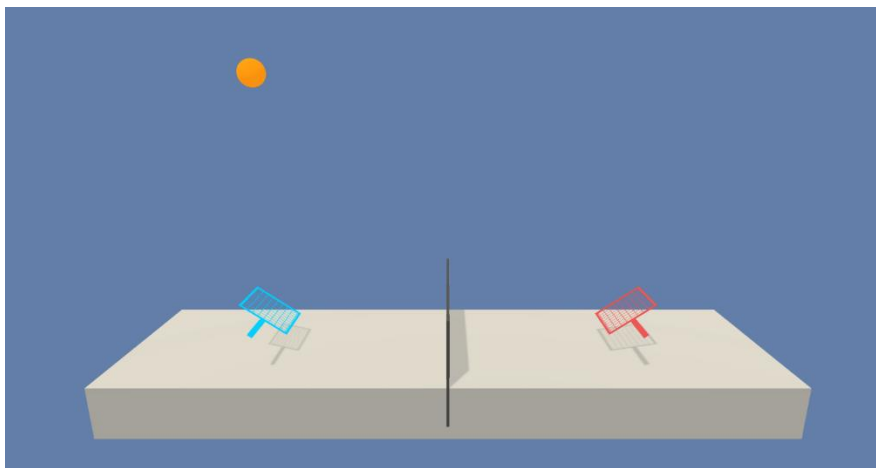


Figure 1: Unity ML-Agents Tennis Environment

## DEEP DETERMINISTIC POLICY GRADIENTS FOR MULTI-AGENT ENVIRONMENTS

Deep deterministic policy gradients (DDPG) is a combination of deterministic policy gradients with ideas from deep Q-learning. It is under the umbrella of [actor-critic algorithms](#). DDPG uses a critic network that learns a Q-function and an actor network that learns a policy. The critic can be thought of as a generalization of the DQN to continuous action spaces. DQN estimates the Q function and computes the max over actions,  $\max_a Q(s, a)$ ,

to select a policy. Computing max over actions for a continuous action space, requires iterative optimization and is expensive. Therefore, critic approximates it by  $\max_a Q(s, a) \approx Q(s, \mu(s))$ . The loss function for the critic is mean-squared Bellman error (MSBE), same as DQN. The actor network then performs policy gradient using  $Q(s, \mu(s))$  as a loss function (step 14 in Figure 2).

### DDPG Algorithm:

DDPG implementation is described [here](#) in detail. The pseudo code of the algorithm is below and follows the [OpenAI baseline](#).

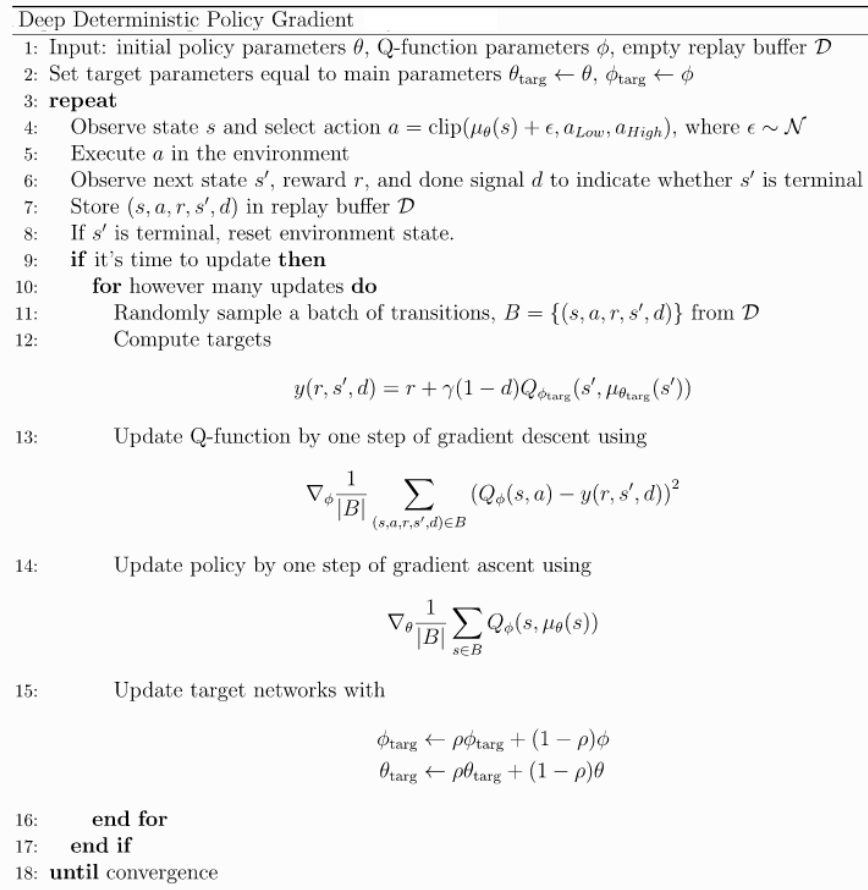


Figure 2: Pseudocode of DDPG

To summarize the key components:

- **Replay buffer:** State transitions and corresponding rewards are saved in a buffer and sampled randomly in batches during training (step 11). Therefore, DDPG is an off-policy method. Since MSBE is used as a loss function and the off-policy samples can be used.

- **Soft parameter update:** Just like DQN, DDPG uses target networks for both the actor and the critic to decorrelate target and predicted Q values, which in turn improves the stability of learning algorithm and convergence. The online network weights are slowly blended into the target network (step 15)
- **Exploration:** DDPG uses a deterministic policy which can hinder exploration. In discrete action spaces, exploration is encouraged by using an epsilon-greedy policy. In DDPG, Ornstein-Uhlenbeck noise is added during training to encourage exploration over a continuous action space (step 4). The state value is also clipped to the min and max allowable range. In the OpenAI implementation, the agent also takes uniformly sampled random actions for a fixed number of steps at the beginning before starting training.

### **Extension to Multi-Agent Systems:**

There are several challenges in applying Q-learning and policy gradient methods to multi-agent settings. As the paper below summarizes, in a multi-agent setting, since all agents take actions, the environment is non-stationary from the perspective of an individual agent. This prevents the use of experience replay which is crucial to use for stability of Q-learning. Policy gradient methods experience high variance when multiple agents are used. The paper by Lowe *et. al* presents a framework that uses centralized training and decentralized execution.

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Lowe, R., Wu, Y., Tamar, A., Harb, J., Abbeel, O. P., & Mordatch, I. (2017). Multi-agent actor-critic for mixed cooperative-competitive environments. In *Advances in neural information processing systems* (pp. 6379-6390).

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The critic is augmented with extra information about the policies of other agents, while the actor only has access to local information. After training is completed, only the local actors are used at execution phase, acting in a decentralized manner.

**Algorithm 1:** Multi-Agent Deep Deterministic Policy Gradient for  $N$  agents

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for episode = 1 to  $M$  do
  Initialize a random process  $\mathcal{N}$  for action exploration
  Receive initial state  $\mathbf{x}$ 
  for  $t = 1$  to max-episode-length do
    for each agent  $i$ , select action  $a_i = \mu_{\theta_i}(o_i) + \mathcal{N}_t$  w.r.t. the current policy and exploration
    Execute actions  $a = (a_1, \dots, a_N)$  and observe reward  $r$  and new state  $\mathbf{x}'$ 
    Store  $(\mathbf{x}, a, r, \mathbf{x}')$  in replay buffer  $\mathcal{D}$ 
     $\mathbf{x} \leftarrow \mathbf{x}'$ 
    for agent  $i = 1$  to  $N$  do
      Sample a random minibatch of  $S$  samples  $(\mathbf{x}^j, a^j, r^j, \mathbf{x}^{tj})$  from  $\mathcal{D}$ 
      Set  $y^j = r_i^j + \gamma Q_i^{\mu'}(\mathbf{x}^{tj}, a_1^j, \dots, a_N^j)|_{a_k^j = \mu_k'(o_k^j)}$ 
      Update critic by minimizing the loss  $\mathcal{L}(\theta_i) = \frac{1}{S} \sum_j (y^j - Q_i^{\mu}(\mathbf{x}^j, a_1^j, \dots, a_N^j))^2$ 
      Update actor using the sampled policy gradient:
        
$$\nabla_{\theta_i} J \approx \frac{1}{S} \sum_j \nabla_{\theta_i} \mu_i(o_i^j) \nabla_{a_i} Q_i^{\mu}(\mathbf{x}^j, a_1^j, \dots, a_N^j)|_{a_i = \mu_i(o_i^j)}$$

    end for
    Update target network parameters for each agent  $i$ :
      
$$\theta'_i \leftarrow \tau \theta_i + (1 - \tau) \theta'_i$$

  end for
end for

```

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Figure 3: Pseudocode of MDDPG

**IMPLEMENTATION**

Figure 4 show the architecture for multi-agent DDPG (MADDPG). The critic is a centralized action-value function and uses the actions and observations (states) of all agents. Since the critic has access to actions taken by all agents, the environment is stationary even as the policies change. The experience of all agents are added in the replay buffer such that the input to the critic is : (states\*number of agents, actions\*number of agents)=52 and the output is the mean action-value (same as DDPG). **There are two main pitfalls during implementation.** First, if you use the ReplayBuffer class from DDPG project, you need to keep track of which state and action pair belongs to which agent during training. You can either decode observations from OpenAI environment as they come and put them in different ReplayBuffers or you can use one ReplayBuffer but decode the observations during training. I did the latter. I used encode and decode functions provided in [fdalisva59@github](#) to add data to and grab data from the replay buffer. Second, note than during training (backprop step) of an agent's actor network, the other agent's actions should be detached from the network. Most implementations I came across get this part wrong. They essentially create two instances of DDPG, stack each agent's experience as if they are coming from the same source. They essentially create two copies of the same critic since they treat agent states/actions as if they are coming from identical sources. The schematic in the paper looks trivial, but the devil is in the detail.

## Architecture:

### Actor:

- (fc1) : Linear (in\_features=24, out\_features=400, bias)
- (bn1): BatchNorm1d(400, eps=1e-05, momentum=0.1)
- (fc2) : Linear(in\_features=400, out\_features=300)
- (fc3) : Linear(in\_features=300, out\_features=2)
- tanh activation

### Critic:

- (fc1): Linear(in\_features=52, out\_features=400)
- (bn1): BatchNorm1d(400, eps=1e-05, momentum=0.1)
- (fc2) : Linear(in\_features=400, out\_features=300)
- (fc3) : Linear(in\_features=300, out\_features=1)
- no activation

Detach other agents' actions during backprop

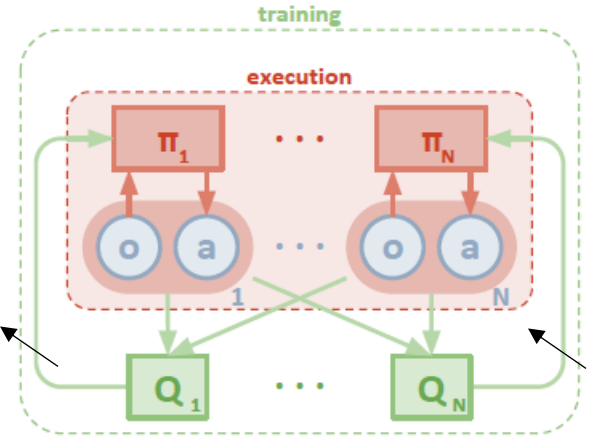


Figure 4: MADDPG architecture

## Hyper-parameters:

```
#Parameters from OpenAI Baselines
BUFFER_SIZE = int(1e5) # replay buffer size
BATCH_SIZE = 200 # minibatch size
UPDATE_EVERY = 4 # Number of episodes that should elapse between gradient descent updates
GAMMA = 0.995 # discount factor
TAU = 1e-3 # for soft update of target parameters
LR_ACTOR = 1e-4 # learning rate of the actor
LR_CRITIC = 5e-3 # learning rate of the critic
WEIGHT_DECAY = 0 # L2 weight decay
EPSILON = 1.0 # Exploration noise coefficient
EPSILON_DECAY = 0 # Decay rate for exploration noise
LEARN_TIMES= 3 # Number of times to backprop with the batch
WARM_UP= 0 # Number of steps for uniform-random action selection, before running real policy. Helps exploration.
CLIP_NORM=False
```

## RESULTS

I had trouble connecting and maintaining connection to the Udacity GPU server, so I had to train the network locally which took on average **4 hours on a CPU**.

## IMPROVEMENTS

- **Prioritized replay:** Sampling of the replay buffer can be prioritized based on each sample's TD error, thereby biasing sampling to samples with higher TD error or rare samples of the state space.
- **Hyperparameter selection:** More systematic way of selecting optimal hyperparameters using Bayesian optimization or starting with grid search. Not being able to connect to a GPU restricted this option for me.
- **Other algorithms:** DDPG requires a lot of tweaking. The next step is to try the algorithms in OpenAI [benchmarks](#) such as Proximal Policy Optimization ([PPO](#)), Distributed Distributional Deep Deterministic Policy Gradient ([D4PG](#)), and twin-delayed DDPG ([TD3](#)).