# Tennis

November 30, 2019

## 1 Collaboration and Competition

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You are welcome to use this coding environment to train your agent for the project. Follow the instructions below to get started!

#### 1.0.1 1. Start the Environment

Run the next code cell to install a few packages. This line will take a few minutes to run!

```
In [1]: !pip -q install ./python
```

```
tensorflow 1.7.1 has requirement numpy>=1.13.3, but you'll have numpy 1.12.1 which is incompatib
ipython 6.5.0 has requirement prompt-toolkit<2.0.0,>=1.0.15, but you'll have prompt-toolkit 2.0.
```

The environment is already saved in the Workspace and can be accessed at the file path provided below.

```
In [2]: from unityagents import UnityEnvironment
        import numpy as np

        env = UnityEnvironment(file_name="/data/Tennis_Linux_NoVis/Tennis")
```

```
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: ,
```

Environments contain ***brains*** which are responsible for deciding the actions of their associated agents. Here we check for the first brain available, and set it as the default brain we will be controlling from Python.

```
In [3]: # get the default brain
        brain_name = env.brain_names[0]
        brain = env.brains[brain_name]
```

### 1.0.2 2. Examine the State and Action Spaces

Run the code cell below to print some information about the environment.

```
In [4]: # reset the environment
        env_info = env.reset(train_mode=True)[brain_name]

        # number of agents
        num_agents = len(env_info.agents)
        print('Number of agents:', num_agents)

        # size of each action
        action_size = brain.vector_action_space_size
        print('Size of each action:', action_size)

        # examine the state space
        states = env_info.vector_observations
        state_size = states.shape[1]
        print('There are {} agents. Each observes a state with length: {}'.format(states.shape[0
        print('The state for the first agent looks like:', states[0])
```

```
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.         -6.65278625 -1.5        -0.          0.
  6.83172083  6.         -0.          0.        ]
```

### 1.0.3 3. Take Random Actions in the Environment

In the next code cell, you will learn how to use the Python API to control the agent and receive feedback from the environment.

Note that **in this coding environment, you will not be able to watch the agents while they are training**, and you should set `train_mode=True` to restart the environment.

```
In [5]: for i in range(5):                                         # play game for 5 episodes
            env_info = env.reset(train_mode=False)[brain_name]     # reset the environment
            states = env_info.vector_observations                  # get the current state (for
            scores = np.zeros(num_agents)                          # initialize the score (for e
            while True:
                actions = np.random.randn(num_agents, action_size) # select an action (for each
                actions = np.clip(actions, -1, 1)                  # all actions between -1 and
                env_info = env.step(actions)[brain_name]           # send all actions to tne env
                next_states = env_info.vector_observations         # get next state (for each ag
                rewards = env_info.rewards                         # get reward (for each agent)
                dones = env_info.local_done                        # see if episode finished
                scores += env_info.rewards                         # update the score (for each
                states = next_states                               # roll over states to next ti
                if np.any(dones):                                  # exit loop if episode finish
                    break
            print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

```
Total score (averaged over agents) this episode: -0.004999999888241291
Total score (averaged over agents) this episode: -0.004999999888241291
Total score (averaged over agents) this episode: 0.09500000160187483
Total score (averaged over agents) this episode: 0.04500000085681677
Total score (averaged over agents) this episode: -0.004999999888241291
```

When finished, you can close the environment.

```
In [6]: #env.close()
```

#### 1.0.4 4. It's Your Turn!

Now it's your turn to train your own agent to solve the environment! A few **important notes**: - When training the environment, set `train_mode=True`, so that the line for resetting the environment looks like the following:

```
env_info = env.reset(train_mode=True)[brain_name]
```

- To structure your work, you're welcome to work directly in this Jupyter notebook, or you might like to start over with a new file! You can see the list of files in the workspace by clicking on ***Jupyter*** in the top left corner of the notebook.
- In this coding environment, you will not be able to watch the agents while they are training. However, ***after training the agents***, you can download the saved model weights to watch the agents on your own machine!

#### 1.0.5 4.1 Importing libraries

```
In [7]: import matplotlib.pyplot as plt
        %matplotlib inline

        import numpy as np
```

```python
import random
import time
import torch
# import utilities to keep workspaces alive during model training
from workspace_utils import active_session
from collections import deque
from ddpg_agent import Agent
from unityagents import UnityEnvironment
```

#### 1.0.6 4.2 Setting parameters

# 2 The chosen hyperparameters Hyperparameters

BUFFER_SIZE = int(4e5) # Replay buffer size
BATCH_SIZE = 256 # Minibatch size
GAMMA = 0.99 # Discount factor
TAU = 2e-3 # For soft update of target parameters
LR_ACTOR = 2e-4 # Learning rate of the actor
LR_CRITIC = 6e-4 # Learning rate of the critic
WEIGHT_DECAY = 0 # L2 weight decay
OU_SIGMA = 0.01 # Ornstein-Uhlenbeck noise parameter, volatility
OU_THETA = 0.15 # Ornstein_Uhlenbeck noise parameter, speed of mean reversion
Suggested on slack:
LEARN_EVERY = 20 # learning timestep interval
LEARN_NUM = 10 # number of learning passes
GRAD_CLIPPING = 1.0 # Gradient Clipping
EPSILON = 1.0 # for epsilon in the noise process (act step)
EPSILON_DECAY = 1e-6

#### 2.0.1 4.3 Training loop

# 3 Model architecture

Similar to single-agent Actor Critic architecture, each agent has it's own actor and critic network. The actor network takes in the current state of agent and output a recommended action for that agent. However the critic part is slightly different from ordinary single-agent DDPG. Here the critic network of each agent has full visibility on the environment. It not only takes in the observation and action of that particular agent, but also observations and actions of all other agents as well. Critic network has much higher visibility on what is happening while actor network can only access to the observation information of the respective agent. The output of the critic network is, nevertheless, still the Q value estimated given a full observation input(all agents) and a full action input(all agents). The output of the actor network is a recommended action for that particular agent.

# 4 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.bn1 = nn.BatchNorm1d(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))

# 5 class Critic(nn.Module): """Critic (Value) 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 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.fc1 = nn.Linear(state_size, fc1_units) self.bn1 = nn.BatchNorm1d(fc1_units) self.fc2 = nn.Linear(fc1_units+action_size, fc2_units) self.fc3 = nn.Linear(fc2_units, 1) 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, action): """Build a critic (value) network that maps (state, action) pairs -> Q-values.""" xs = F.relu(self.bn1(self.fc1(state))) x = torch.cat((xs, action), dim=1) x = F.relu(self.fc2(x)) return self.fc3(x)

In [ ]:

### 5.0.1 4.4 Train the Agent with MADDPG

In [8]:
```
agent = Agent(state_size=state_size, action_size=action_size, random_seed=9)
```

In [9]:
```
def ddpg(n_episodes=2500, max_t=1000, print_every=10):
    """Deep Deterministic Policy Gradient (DDPG)

    Params
    ======
        n_episodes  (int)   : maximum number of training episodes
        max_t       (int)   : maximum number of timesteps per episode
        print_every (int)   : interval to display results

    """
    mean_scores = []                               # list of mean scores from each episo
    moving_avgs = []                               # list of moving averages
    best_score  = -np.inf
```

```
        scores_window = deque(maxlen=100)            # mean scores from most recent 100 ep

        for i_episode in range(1, n_episodes+1):
            env_info = env.reset(train_mode=True)[brain_name]       # reset environment
            states = env_info.vector_observations                   # get current state for
            scores = np.zeros(num_agents)                           # initialize score for e
            agent.reset()
            start_time = time.time()
            for t in range(max_t):
                actions = agent.act(states, add_noise=True)         # select an action
                env_info = env.step(actions)[brain_name]            # send actions to enviro
                next_states = env_info.vector_observations          # get next state
                rewards = env_info.rewards                          # get reward
                dones = env_info.local_done                         # see if episode has fin
                # save experience to replay buffer, perform learning step at defined interva
                for state, action, reward, next_state, done in zip(states, actions, rewards,
                    agent.step(state, action, reward, next_state, done, t)
                states = next_states
                scores += rewards
                if np.any(dones):                                   # exit loop when episode
                    break

            duration = time.time() - start_time
            mean_scores.append(np.mean(scores))           # save mean score for the episode
            scores_window.append(mean_scores[-1])         # save mean score to window
            moving_avgs.append(np.mean(scores_window))    # save moving average

            if i_episode % print_every == 0:
                print('\rEpisode {} ({}s)\tMean: {:.1f}\tMoving Avg: {:.1f}'.format(\
                      i_episode, round(duration), mean_scores[-1], moving_avgs[-1]))

            if moving_avgs[-1] >= 0.5:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format
                torch.save(agent.actor_local.state_dict(), 'checkpoint_actor.pth')
                torch.save(agent.critic_local.state_dict(), 'checkpoint_critic.pth')
                break

        return mean_scores, moving_avgs
```

In [10]:
```
with active_session():
    scores, avgs = ddpg()
```

```
Episode 10 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 20 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 30 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 40 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 50 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 60 (1s)        Mean: -0.0        Moving Avg: -0.0
```

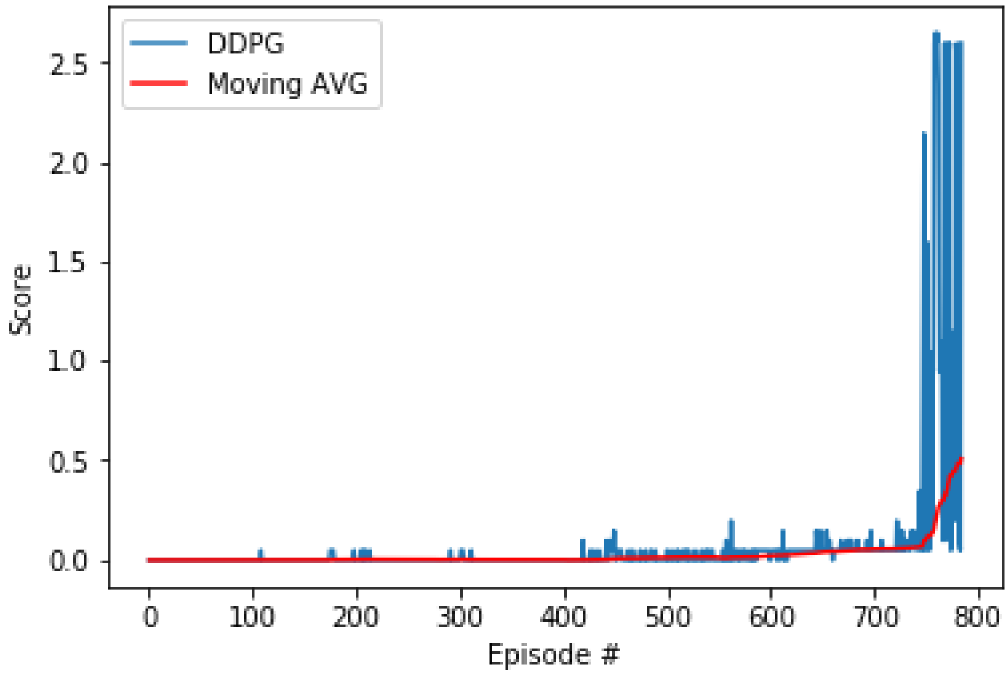
```
Episode 70 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 80 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 90 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 100 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 110 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 120 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 130 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 140 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 150 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 160 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 170 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 180 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 190 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 200 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 210 (1s)        Mean: 0.0        Moving Avg: -0.0
Episode 220 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 230 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 240 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 250 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 260 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 270 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 280 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 290 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 300 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 310 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 320 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 330 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 340 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 350 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 360 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 370 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 380 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 390 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 400 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 410 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 420 (2s)        Mean: 0.1        Moving Avg: -0.0
Episode 430 (1s)        Mean: 0.0        Moving Avg: -0.0
Episode 440 (1s)        Mean: -0.0        Moving Avg: -0.0
Episode 450 (3s)        Mean: 0.1        Moving Avg: 0.0
Episode 460 (1s)        Mean: -0.0        Moving Avg: 0.0
Episode 470 (1s)        Mean: -0.0        Moving Avg: 0.0
Episode 480 (1s)        Mean: 0.0        Moving Avg: 0.0
Episode 490 (1s)        Mean: 0.0        Moving Avg: 0.0
Episode 500 (1s)        Mean: -0.0        Moving Avg: 0.0
Episode 510 (1s)        Mean: 0.0        Moving Avg: 0.0
Episode 520 (1s)        Mean: 0.0        Moving Avg: 0.0
Episode 530 (1s)        Mean: -0.0        Moving Avg: 0.0
Episode 540 (1s)        Mean: 0.0        Moving Avg: 0.0
```

```
Episode 550 (1s)        Mean: -0.0       Moving Avg: 0.0
Episode 560 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 570 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 580 (1s)        Mean: -0.0       Moving Avg: 0.0
Episode 590 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 600 (1s)        Mean: -0.0       Moving Avg: 0.0
Episode 610 (1s)        Mean: -0.0       Moving Avg: 0.0
Episode 620 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 630 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 640 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 650 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 660 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 670 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 680 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 690 (1s)        Mean: 0.0       Moving Avg: 0.0
Episode 700 (1s)        Mean: 0.0       Moving Avg: 0.1
Episode 710 (1s)        Mean: 0.0       Moving Avg: 0.1
Episode 720 (1s)        Mean: 0.0       Moving Avg: 0.1
Episode 730 (2s)        Mean: 0.1       Moving Avg: 0.1
Episode 740 (2s)        Mean: 0.1       Moving Avg: 0.1
Episode 750 (1s)        Mean: 0.0       Moving Avg: 0.1
Episode 760 (32s)        Mean: 2.7       Moving Avg: 0.2
Episode 770 (2s)        Mean: 0.1       Moving Avg: 0.3
Episode 780 (6s)        Mean: 0.4       Moving Avg: 0.5

Environment solved in 685 episodes!        Average Score: 0.51
```

### 5.0.2 4.4 Reward Plot

In [11]:
```python
# plot the scores
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores, label='DDPG')
plt.plot(np.arange(len(scores)), avgs, c='r', label='Moving AVG')
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.legend(loc='upper left');
plt.show()
```




When finished, you can close the environment.

```
In [12]: env.close()
```

#### 5.0.3 4.5 Ideas for improving the agent's performance

Batch Normalization Neural network enhancement for a better performance.

```
In [ ]:
```