Tennis

June 11, 2019

1 Collaboration and Competition

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

When finished, you can close the environment.

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!

```
In [6]: import matplotlib.pyplot as plt
        import numpy as np
        import random
        import time
        import torch

        from maddpg_agent import Agent
        from collections import deque
```

```
        from unityagents import UnityEnvironment

        %matplotlib inline

In [7]: TARGET_SCORE = 0.51
        EPISODES = 100
        PRINT_EVERY = 10
        ADD_NOISE = True

In [8]: # MADDPG function

        def maddpg(n_episodes=2000, max_t=1000, train_mode=True):
            """Multi-Agent Deep Deterministic Policy Gradient (MADDPG)

            Params
            ======
                n_episodes (int)      : maximum number of training episodes
                max_t (int)           : maximum number of timesteps per episode
                train_mode (bool)     : if 'True' set environment to training mode

            """
            scores_queue = deque(maxlen=EPISODES)
            scores_arr = []
            average_score = []
            best_score = -np.inf
            best_episode = 0
            already_solved = False

            for i_episode in range(1, n_episodes+1):
                env_info = env.reset(train_mode=train_mode)[brain_name]          # reset environm
                states = np.reshape(env_info.vector_observations, (1,48)) # get states
                agent_0.reset()
                agent_1.reset()
                scores = np.zeros(num_agents)
                while True:
                    actions = get_actions(states, ADD_NOISE)           # choose agent actions
                    env_info = env.step(actions)[brain_name]           # send agents' actions to
                    next_states = np.reshape(env_info.vector_observations, (1, 48)) # get agents
                    rewards = env_info.rewards                         # get rewards
                    done = env_info.local_done                         # episode state
                    agent_0.step(states, actions, rewards[0], next_states, done, 0) # learn agen
                    agent_1.step(states, actions, rewards[1], next_states, done, 1) # Learn agen
                    scores += np.max(rewards)                          # add the best score
                    states = next_states                               # roll over states to nex
                    if np.any(done):                                   # exit loop if episode fi
                        break

                episode_best_score = np.max(scores)
```

```
                scores_queue.append(episode_best_score)
                scores_arr.append(episode_best_score)
                average_score.append(np.mean(scores_queue))

                # save best score
                if episode_best_score > best_score:
                    best_score = episode_best_score
                    best_episode = i_episode

                # print results
                if i_episode % PRINT_EVERY == 0:
                    print('Episodes {:0>4d}-{:0>4d}\t Highest Reward: {:.3f}\t Lowest Reward: {:
                        i_episode-PRINT_EVERY, i_episode, np.max(scores_arr[-PRINT_EVERY:]), np.

                # determine if environment is solved and keep best performing models
                if average_score[-1] >= TARGET_SCORE:
                    print('<-- Environment solved in {:d} episodes! \
                        \n<-- Average Score: {:.3f} over past {:d} episodes'.format(
                            i_episode-EPISODES, average_score[-1], EPISODES))
                    already_solved = True
                    # save weights
                    torch.save(agent_0.actor_local.state_dict(), 'checkpoint_actor_0.pth')
                    torch.save(agent_0.critic_local.state_dict(), 'checkpoint_critic_0.pth')
                    torch.save(agent_1.actor_local.state_dict(), 'checkpoint_actor_1.pth')
                    torch.save(agent_1.critic_local.state_dict(), 'checkpoint_critic_1.pth')
                    break


        return scores_arr, average_score
```

```
In [9]: def get_actions(states, add_noise):
            '''gets actions for each agent and a single array with both actions'''
            action_0 = agent_0.act(states, add_noise)    # agent 0 chooses an action
            action_1 = agent_1.act(states, add_noise)    # agent 1 chooses an action
            return np.concatenate((action_0, action_1), axis=0).flatten()
```

```
In [10]: # initialize agents
         agent_0 = Agent(state_size, action_size, num_agents=1, random_seed=0)
         agent_1 = Agent(state_size, action_size, num_agents=1, random_seed=0)
```

```
In [11]: """BUFFER_SIZE = int(1e6)  # replay buffer size
         BATCH_SIZE = 128        # minibatch size
         LR_ACTOR = 1e-3         # learning rate of the actor
         LR_CRITIC = 1e-3        # learning rate of the critic
         WEIGHT_DECAY = 0        # L2 weight decay
         LEARN_EVERY = 5         # learning timestep interval
         LEARN_NUM = 5           # number of learning passes
         GAMMA = 0.99            # discount factor
```

```
        TAU = 7e-2              # for soft update of target parameters
        OU_SIGMA = 0.2          # Ornstein-Uhlenbeck noise parameter, volatility
        OU_THETA = 0.11         # Ornstein-Uhlenbeck noise parameter, speed of mean reversion
        EPS_START = 5.5         # initial value for epsilon in noise decay process in Agent.act
        EPS_EP_END = 250        # episode to end the noise decay process
        EPS_FINAL = 0           # final value for epsilon after decay
        """
```

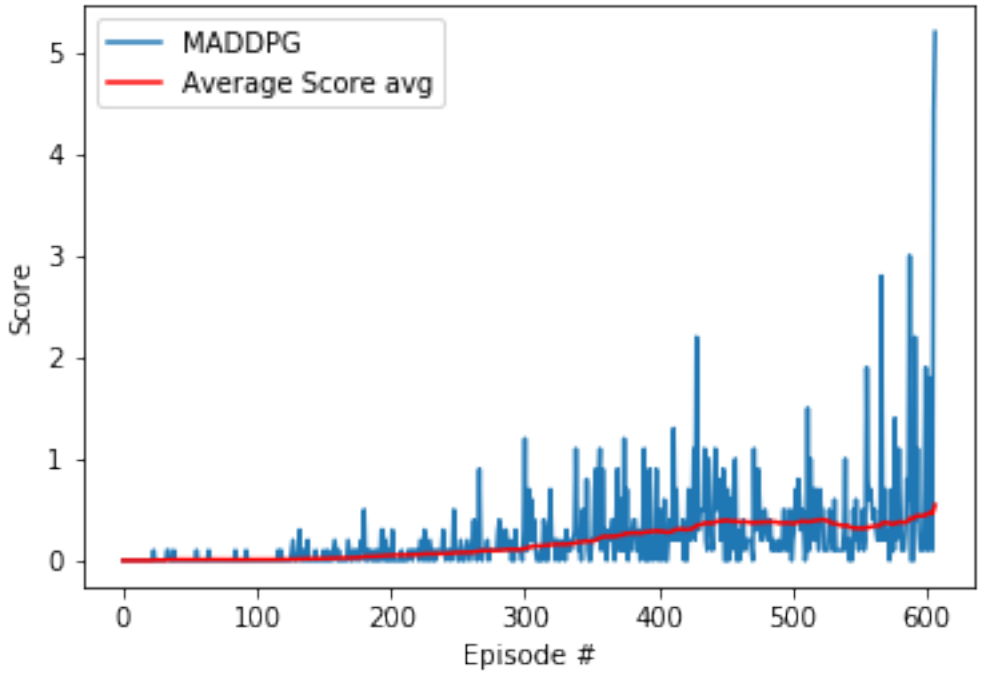
```
Out[11]: 'BUFFER_SIZE = int(1e6)  # replay buffer size\nBATCH_SIZE = 128        # minibatch size
```

```
In [12]: scores, avgs = maddpg()
```

```
Episodes 0000-0010        Highest Reward: 0.000        Lowest Reward: 0.000        Average Sc
Episodes 0010-0020        Highest Reward: 0.000        Lowest Reward: 0.000        Average Sc
Episodes 0020-0030        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0030-0040        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0040-0050        Highest Reward: 0.000        Lowest Reward: 0.000        Average Sc
Episodes 0050-0060        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0060-0070        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0070-0080        Highest Reward: 0.000        Lowest Reward: 0.000        Average Sc
Episodes 0080-0090        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0090-0100        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0100-0110        Highest Reward: 0.000        Lowest Reward: 0.000        Average Sc
Episodes 0110-0120        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0120-0130        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0130-0140        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0140-0150        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0150-0160        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0160-0170        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0170-0180        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0180-0190        Highest Reward: 0.500        Lowest Reward: 0.000        Average Sc
Episodes 0190-0200        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0200-0210        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0210-0220        Highest Reward: 0.100        Lowest Reward: 0.000        Average Sc
Episodes 0220-0230        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0230-0240        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0240-0250        Highest Reward: 0.500        Lowest Reward: 0.000        Average Sc
Episodes 0250-0260        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0260-0270        Highest Reward: 0.900        Lowest Reward: 0.000        Average Sc
Episodes 0270-0280        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0280-0290        Highest Reward: 0.400        Lowest Reward: 0.100        Average Sc
Episodes 0290-0300        Highest Reward: 0.300        Lowest Reward: 0.000        Average Sc
Episodes 0300-0310        Highest Reward: 1.200        Lowest Reward: 0.000        Average Sc
Episodes 0310-0320        Highest Reward: 0.700        Lowest Reward: 0.000        Average Sc
Episodes 0320-0330        Highest Reward: 0.200        Lowest Reward: 0.000        Average Sc
Episodes 0330-0340        Highest Reward: 1.100        Lowest Reward: 0.000        Average Sc
Episodes 0340-0350        Highest Reward: 0.800        Lowest Reward: 0.000        Average Sc
Episodes 0350-0360        Highest Reward: 1.100        Lowest Reward: 0.100        Average Sc
```

```
Episodes 0360-0370        Highest Reward: 0.900        Lowest Reward: 0.000        Average Sc
Episodes 0370-0380        Highest Reward: 1.200        Lowest Reward: 0.000        Average Sc
Episodes 0380-0390        Highest Reward: 1.100        Lowest Reward: 0.000        Average Sc
Episodes 0390-0400        Highest Reward: 0.900        Lowest Reward: 0.000        Average Sc
Episodes 0400-0410        Highest Reward: 0.600        Lowest Reward: 0.000        Average Sc
Episodes 0410-0420        Highest Reward: 1.300        Lowest Reward: 0.000        Average Sc
Episodes 0420-0430        Highest Reward: 2.200        Lowest Reward: 0.000        Average Sc
Episodes 0430-0440        Highest Reward: 1.100        Lowest Reward: 0.100        Average Sc
Episodes 0440-0450        Highest Reward: 1.100        Lowest Reward: 0.000        Average Sc
Episodes 0450-0460        Highest Reward: 1.000        Lowest Reward: 0.000        Average Sc
Episodes 0460-0470        Highest Reward: 0.400        Lowest Reward: 0.000        Average Sc
Episodes 0470-0480        Highest Reward: 1.100        Lowest Reward: 0.000        Average Sc
Episodes 0480-0490        Highest Reward: 0.400        Lowest Reward: 0.100        Average Sc
Episodes 0490-0500        Highest Reward: 0.500        Lowest Reward: 0.000        Average Sc
Episodes 0500-0510        Highest Reward: 0.800        Lowest Reward: 0.000        Average Sc
Episodes 0510-0520        Highest Reward: 1.500        Lowest Reward: 0.100        Average Sc
Episodes 0520-0530        Highest Reward: 0.700        Lowest Reward: 0.100        Average Sc
Episodes 0530-0540        Highest Reward: 1.000        Lowest Reward: 0.100        Average Sc
Episodes 0540-0550        Highest Reward: 0.600        Lowest Reward: 0.000        Average Sc
Episodes 0550-0560        Highest Reward: 1.900        Lowest Reward: 0.100        Average Sc
Episodes 0560-0570        Highest Reward: 2.800        Lowest Reward: 0.200        Average Sc
Episodes 0570-0580        Highest Reward: 1.400        Lowest Reward: 0.000        Average Sc
Episodes 0580-0590        Highest Reward: 3.000        Lowest Reward: 0.000        Average Sc
Episodes 0590-0600        Highest Reward: 2.200        Lowest Reward: 0.000        Average Sc
<-- Environment solved in 507 episodes!
<-- Average Score: 0.547 over past 100 episodes
```

In [13]:
```
# plot the scores
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores, label='MADDPG')
plt.plot(np.arange(len(scores)), avgs, c='r', label='Average Score avg')
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.legend(loc='upper left');
plt.show()
```



In [14]: env.close()

In [ ]:

In [ ]: