Tennis

June 29, 2020

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 3.0.
```

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 [6]: for i in range(5):
            env_info = env.reset(train_mode=False)[brain_name]
            states = env_info.vector_observations
            scores = np.zeros(num_agents)
            counter = 0
            while True:
                counter += 1
                actions = np.random.randn(num_agents, action_size)
                actions = np.clip(actions, -1, 1)
                env_info = env.step(actions)[brain_name]
                next_states = env_info.vector_observations
                rewards = env_info.rewards
                dones = env_info.local_done

                scores += env_info.rewards
                states = next_states
                if np.any(dones):
                    break
            print('Total score (averaged over agents) this episode: {} {}'.format(np.mean(scores
```

```
Total score (averaged over agents) this episode: -0.004999999888241291 15
Total score (averaged over agents) this episode: -0.004999999888241291 16
Total score (averaged over agents) this episode: -0.004999999888241291 14
Total score (averaged over agents) this episode: -0.004999999888241291 13
Total score (averaged over agents) this episode: -0.004999999888241291 21
```

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!

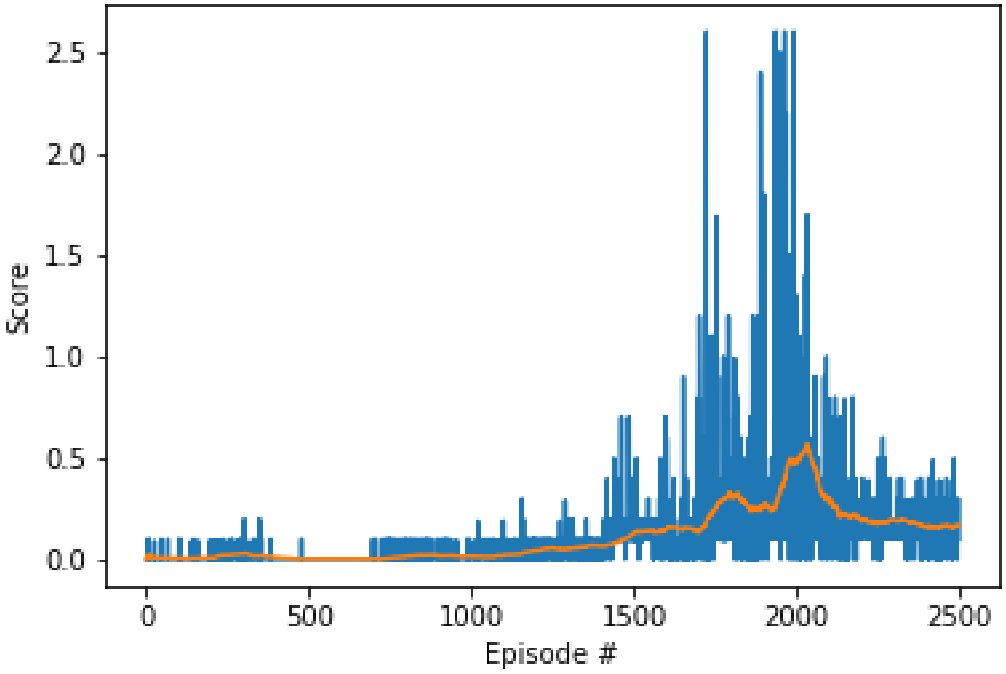
```
In [6]: from maddpg import MADDPGAgent
        from collections import deque
        import matplotlib.pyplot as plt
        import torch

        o_dim = 24
        a_dim = 2
```

```
x_dim = num_agents * o_dim

LR_ACTOR = 1e-2
LR_CRITIC = 1e-4
LEARN_NUM = 1
BATCH_SIZE = 128
GAMMA = .99
TAU = 0.001
BUFFER_SIZE = int(1e6)

eps_start = 1.0
eps_end = 0.01
eps_decay = 0.99

maddpg = MADDPGAgent(num_agents, x_dim, o_dim, a_dim,
                     lr_actor = LR_ACTOR, lr_critic = LR_CRITIC, learn_num = LEARN_NUM,
                     batch_size = BATCH_SIZE, gamma = GAMMA, tau = TAU,
                     buffer_size = BUFFER_SIZE, seed = 1234)

NUM_EPISODES = 2500
PRINT_EVERY = 100
```

```
In [7]: # train agents

        score_list = []
        score_window = deque(maxlen = PRINT_EVERY)


        eps = eps_start
        best_score = 0.5
        for e in range(1, NUM_EPISODES+1):
            env_info = env.reset(train_mode=True)[brain_name]   # reset environment
            states = env_info.vector_observations
            scores = np.zeros(num_agents)
            while True:
                actions = maddpg.get_actions(states, eps)

                env_info = env.step(actions)[brain_name]
                next_states = env_info.vector_observations
                dones = env_info.local_done
                rewards = env_info.rewards

                maddpg.step(states, actions, rewards, next_states, dones )

                states = next_states
                scores += rewards
                if np.any(dones):
                    break
        eps = max(eps_end, eps_decay*eps) # decrease exploartion
        max_score = np.max(scores) # max score among the agents

        score_window.append(max_score)
        mean_score = np.mean(score_window)
        score_list.append([max_score, mean_score])

        maddpg.lr_scheduler()

        print('\rEpisode {}\t score {:8.2f}\t mean score {:8.2f}'.format(e, max_score, mean_
        if e % PRINT_EVERY == 0:
            print('\rEpisode {}\t score {:8.2f}\t mean score {:8.2f}'.format(e, max_score, m

        if mean_score>= best_score:
            print('\rEpisode {}\t score {:8.2f}\t mean score {:8.2f}\t saved!'.format(e, max
            best_score = mean_score
            for i, agent in enumerate(maddpg.agents):
                torch.save(agent.actor.state_dict(), 'checkpoint_actor'+str(i)+'.pth')
                torch.save(agent.critic.state_dict(), 'checkpoint_critic'+str(i)+'.pth')
```

```
Episode 100         score     0.00         mean score     0.00
Episode 200         score     0.00         mean score     0.01
Episode 300         score     0.10         mean score     0.03
Episode 400         score     0.00         mean score     0.01
Episode 500         score     0.00         mean score     0.00
Episode 600         score     0.00         mean score     0.00
Episode 700         score     0.00         mean score     0.00
Episode 800         score     0.00         mean score     0.01
Episode 900         score     0.00         mean score     0.02
Episode 1000         score     0.00         mean score     0.02
Episode 1100         score     0.09         mean score     0.02
Episode 1200         score     0.10         mean score     0.04
Episode 1300         score     0.10         mean score     0.05
Episode 1400         score     0.09         mean score     0.07
Episode 1500         score     0.40         mean score     0.13
Episode 1600         score     0.70         mean score     0.15
Episode 1700         score     0.80         mean score     0.14
Episode 1800         score     0.20         mean score     0.32
Episode 1900         score     0.10         mean score     0.26
Episode 2000         score     0.10         mean score     0.49
Episode 2010         score     0.70         mean score     0.50         saved!
Episode 2012         score     1.00         mean score     0.51         saved!
Episode 2016         score     0.90         mean score     0.52         saved!
Episode 2018         score     0.60         mean score     0.52         saved!
Episode 2019         score     0.20         mean score     0.52         saved!
Episode 2020         score     0.10         mean score     0.52         saved!
Episode 2021         score     0.20         mean score     0.52         saved!
Episode 2022        score    0.30        mean score     0.52         saved!
Episode 2023        score    0.20        mean score     0.53         saved!
Episode 2024        score    0.50        mean score     0.53         saved!
Episode 2025        score    0.50        mean score     0.53         saved!
Episode 2026        score    0.50        mean score     0.53         saved!
Episode 2027        score    0.50        mean score     0.54         saved!
Episode 2028        score    1.40        mean score     0.54         saved!
Episode 2029        score    0.60        mean score     0.55         saved!
Episode 2030        score    0.40        mean score     0.55         saved!
Episode 2032        score    1.20        mean score     0.56         saved!
Episode 2034        score    1.70        mean score     0.57         saved!
Episode 2035        score    0.20        mean score     0.57         saved!
Episode 2100        score    0.20        mean score     0.30
Episode 2200        score    0.10        mean score     0.20
Episode 2300        score    0.20        mean score     0.20
Episode 2400        score    0.10        mean score     0.16
Episode 2500        score    0.10        mean score     0.17
```

```
In [8]: fig = plt.figure()
        ax = fig.add_subplot(111)
        plt.plot(np.arange(len(score_list)), score_list)
        plt.ylabel('Score')
        plt.xlabel('Episode #')
        plt.show()
```



```
In [10]: # watch trained agents
         for i, agent in enumerate(maddpg.agents):
             agent.actor.load_state_dict(torch.load('checkpoint_actor'+str(i)+'.pth'))

         for i in range(5):
             env_info = env.reset(train_mode=False)[brain_name]
             states = env_info.vector_observations
             scores = np.zeros(num_agents)
             while True:
                 actions = maddpg.get_actions(states, eps)
                 env_info = env.step(actions)[brain_name]
                 next_states = env_info.vector_observations
                 rewards = env_info.rewards
                 dones = env_info.local_done

                 scores += env_info.rewards
                 states = next_states
                 if np.any(dones):
                     break
             print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores))
```

```
Total score (averaged over agents) this episode: 0.7950000120326877
Total score (averaged over agents) this episode: 0.04500000085681677
Total score (averaged over agents) this episode: 0.44500000681728125
Total score (averaged over agents) this episode: 0.04000000096857548
Total score (averaged over agents) this episode: 0.1450000023469329
```

When finished, you can close the environment.

```
In [11]: env.close()
```

```
In [ ]:
```