Tennis

April 20, 2021

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]: %%capture
        !pip install numpy --upgrade;
        !pip install --upgrade ipython;
        !pip -q install ./python;
```

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.          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 the 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
```

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 5. Train the Agent with MADDPG

5.1. Set up

```
In [6]: import gym
        import random
        import torch
        #import numpy as np
        from collections import deque
        import matplotlib.pyplot as plt
```

```
%matplotlib inline

from maddpg_agent import Agent, OUNoise
```

5.2. Initialize the agent

```
In [7]: agent = Agent(state_size=state_size, action_size=action_size, num_agents=num_agents, ran
```

Main definitions for MADDPG algorithm:

- **Multy Agent Deep Deterministic Policy Gradient(MADDPG):**

"Extends DDPG into a multi-agent policy gradient algorithm where decentralized agents learn a centralized critic based on the observations and actions of all agents. It leads to learned policies that only use local information (i.e. their own observations) at execution time, does not assume a differentiable model of the environment dynamics or any particular structure on the communication method between agents, and is applicable not only to cooperative interaction but to competitive or mixed interaction involving both physical and communicative behavior. 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"
Took from: https://paperswithcode.com/method/maddpg

- **Architecture of Actor Network**
  - Input: 24
  - output: 2
  - Number of layers: 3
    - layer 1:
      - number of neurons: 128
      - activation function: ReLU
    - layer 2:
      - number of neurons: 64
      - activation function: ReLU
    - layer 3:
      - number of neurons: 64
      - activation function: ReLU
  - Batch normalization: yes
- **Architecture of Critic Network**
  - Batch normalization: yes
  - Input: 24
  - output: 1
  - Number of layers: 2
    - layer 1:
      - number of neurons: 64

· activation function: ReLU

* layer 2:
  · number of neurons: 64
  · activation function: ReLU
- Batch normalization: yes

- **Hyperparameters:**

```
BUFFER_SIZE = int(1e6)  # replay buffer size
BATCH_SIZE = 512        # minibatch size
GAMMA = 0.99            # discount factor
TAU = 5e-2              # for soft update of target parameters
LR_ACTOR = 5e-4         # learning rate of the actor
LR_CRITIC = 5e-4        # learning rate of the critic
WEIGHT_DECAY = 0        # L2 weight decay
```

```
In [8]: def maddpg(n_episodes, max_t, print_every):
            scores_deque = deque(maxlen=print_every)
            scores = []
            avg_scores = []

            for i_episode in range(1, n_episodes+1):
                env_info = env.reset(train_mode=True)[brain_name]
                state = env_info.vector_observations
                agent.reset()
                score = np.zeros(num_agents)

                for t in range(max_t):
                    action1 = agent.act(state[0])
                    action2 = agent.act(state[1])
                    actions = np.concatenate((action1, action2), axis=0)
                    actions = np.clip(actions, -1, 1)
                    env_info = env.step(actions)[brain_name]
                    next_state = env_info.vector_observations
                    reward = env_info.rewards
                    done = env_info.local_done
                    agent.step(state, actions, reward, next_state, done)
                    state = next_state
                    score += reward
                    if np.any(done):
                        break

                scores_deque.append(np.max(score))
                scores.append(np.max(score))
                avg_scores.append(np.mean(scores_deque))

                print('\rEpisode {}\tAverage Score: {:.4f}'.format(i_episode, np.mean(scores_deq
                torch.save(agent.actor_local.state_dict(), 'checkpoint_actor.pth')
```

```
            torch.save(agent.critic_local.state_dict(), 'checkpoint_critic.pth')
            if i_episode % print_every == 0:
                print('\rEpisode {}\tAverage Score: {:.4f}'.format(i_episode, np.mean(scores
            if np.mean(scores_deque) > 0.5:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.4f}'.format
                break

        return scores, avg_scores
```

5.4. Set variables

```
In [9]: n_episodes=2500
        max_t=300
        print_every=100
```

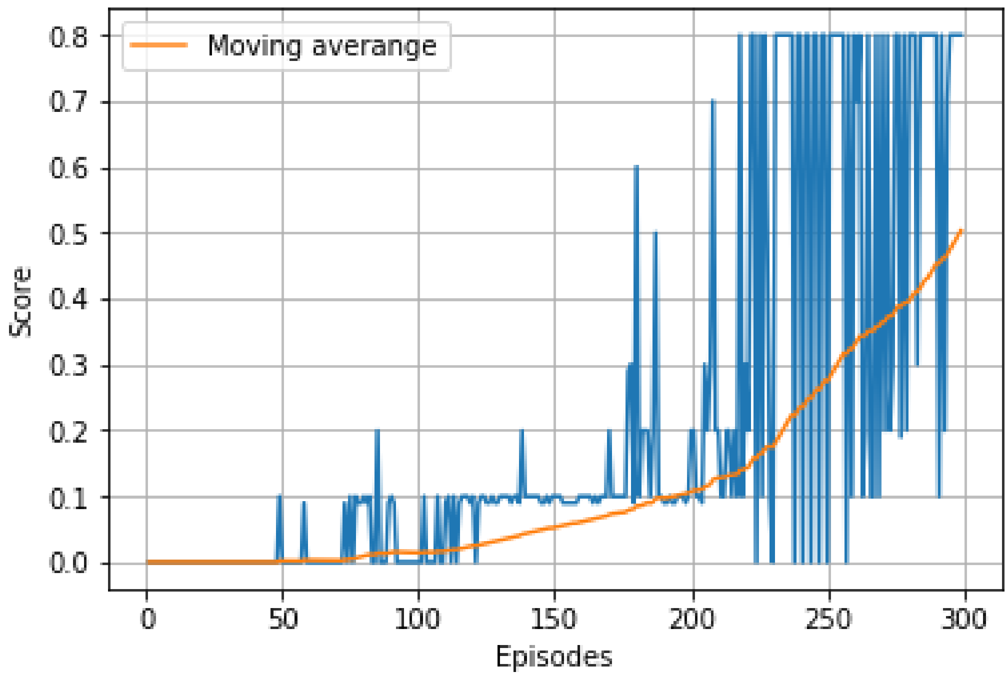
5.5. Train

```
In [10]: scores, avg_scores = maddpg(n_episodes, max_t, print_every)
```

```
Episode 100        Average Score: 0.0143
Episode 200        Average Score: 0.1072
Episode 299        Average Score: 0.5028
Environment solved in 299 episodes!        Average Score: 0.5028
```

5.6. Show results

```
In [11]: fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(1, len(scores)+1), scores)
         plt.plot(np.arange(1, len(avg_scores)+1), avg_scores, label='Moving averange')
         plt.ylabel('Score')
         plt.xlabel('Episodes')
         plt.legend(loc='upper left')
         plt.grid()
         plt.show()
```



1.0.6 6. Run Trained agent

```
In [12]: agent.actor_local.load_state_dict(torch.load('checkpoint_actor.pth'))
         agent.critic_local.load_state_dict(torch.load('checkpoint_critic.pth'))

         env_info = env.reset(train_mode=False)[brain_name]     # reset the environment
         states = env_info.vector_observations                  # get the current state (for eac
         scores = np.zeros(num_agents)                          # initialize the score (for each
         while True:
             action1 = agent.act(states[0])
             action2 = agent.act(states[1])
             actions = np.concatenate((action1, action2), axis=0)
             actions = np.clip(actions, -1, 1)                  # all actions between -1 and 1
             env_info = env.step(actions)[brain_name]           # send all actions to tne envir
             next_states = env_info.vector_observations         # get next state (for each agen
             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 ag
             states = next_states                               # roll over states to next time
             if np.any(dones):                                  # exit loop if episode finished
                 break
         print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

```
Total score (averaged over agents) this episode: 0.1450000023469329
```

```
In [13]: env.close()
```

1.0.7 7. Ideas for future work

There are other two possible improvements to the results:

1. Try adding other layer to the critic network.
2. Use a MAPPO algorithm