Navigation

April 4, 2021

1 Navigation

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.
```

```
In [2]: from collections import deque
        import matplotlib.pyplot as plt
        import numpy as np
        import random
        import torch
        from unityagents import UnityEnvironment

        %matplotlib inline
```

The environment is already saved in the Workspace and can be accessed at the file path provided below. Please run the next code cell without making any changes.

```
In [3]: from unityagents import UnityEnvironment
        import numpy as np

        # please do not modify the line below
        env = UnityEnvironment(file_name="/data/Banana_Linux_NoVis/Banana.x86_64")
```

```
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: BananaBrain
        Number of Visual Observations (per agent): 0
        Vector Observation space type: continuous
        Vector Observation space size (per agent): 37
        Number of stacked Vector Observation: 1
        Vector Action space type: discrete
        Vector Action space size (per agent): 4
        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 [4]: # 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 [5]: # reset the environment
        env_info = env.reset(train_mode=True)[brain_name]

        # number of agents in the environment
        print('Number of agents:', len(env_info.agents))

        # number of actions
        action_size = brain.vector_action_space_size
        print('Number of actions:', action_size)

        # examine the state space
        state = env_info.vector_observations[0]
        print('States look like:', state)
        state_size = len(state)
        print('States have length:', state_size)
```

```
Number of agents: 1
Number of actions: 4
States look like: [ 1.          0.          0.          0.          0.84408134  0.          0.
  1.          0.          0.0748472   0.          1.          0.          0.
  0.25755     1.          0.          0.          0.          0.74177343
  0.          1.          0.          0.          0.25854847  0.          0.
```

```
  1.          0.          0.09355672  0.          1.          0.          0.
  0.31969345  0.          0.        ]
States have length: 37
```

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 agent while it is training**, and you should set `train_mode=True` to restart the environment.

```
In [6]: env_info = env.reset(train_mode=True)[brain_name] # reset the environment
        state = env_info.vector_observations[0]            # get the current state
        score = 0                                          # initialize the score
        while True:
            action = np.random.randint(action_size)        # select an action
            env_info = env.step(action)[brain_name]        # send the action to the environment
            next_state = env_info.vector_observations[0]   # get the next state
            reward = env_info.rewards[0]                   # get the reward
            done = env_info.local_done[0]                  # see if episode has finished
            score += reward                                # update the score
            state = next_state                             # roll over the state to next time st
            if done:                                       # exit loop if episode finished
                break

        print("Score: {}".format(score))
```

```
Score: 1.0
```

When finished, you can close the environment.

```
In [ ]:
```

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]
```

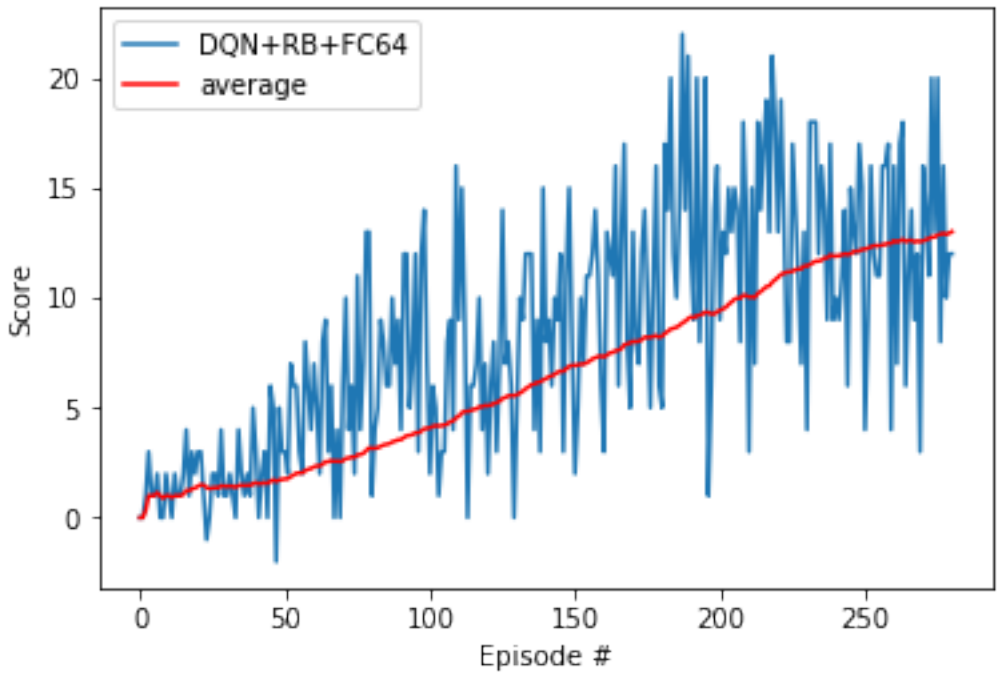
- To structure your work, you're welcome to work directly in this Jupyter notebook, or you might like to start over with a new file! You can see the list of files in the workspace by clicking on ***Jupyter*** in the top left corner of the notebook.
- In this coding environment, you will not be able to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

```
In [17]: from agent import Agent

In [18]: agent = Agent(state_size=state_size, action_size=action_size, seed=0, use_double=False,

In [19]: def dqn(n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995, trai
             ckpt_path='pth_checkpoints/checkpoint.pth'):
         """Deep Q-Learning.

         Params
         ======
             n_episodes (int): maximum number of training episodes
             max_t (int): maximum number of timesteps per episode
             eps_start (float): starting value of epsilon, for epsilon-greedy action selecti
             eps_end (float): minimum value of epsilon
             eps_decay (float): multiplicative factor (per episode) for decreasing epsilon
             train_mode (bool): if 'True' set environment to training mode

         """
         scores = []                        # list containing scores from each episode
         scores_window = deque(maxlen=100)  # last 100 scores
         moving_avgs = []                   # list of moving averages
         eps = eps_start                    # initialize epsilon
         for i_episode in range(1, n_episodes+1):
             env_info = env.reset(train_mode=train_mode)[brain_name] # reset environment
             state = env_info.vector_observations[0]                 # get current state
             score = 0
             for t in range(max_t):
                 action = agent.act(state, eps)                      # select an action
                 env_info = env.step(action)[brain_name]             # send action to enviro
                 next_state = env_info.vector_observations[0]        # get next state
                 reward = env_info.rewards[0]                        # get reward
                 done = env_info.local_done[0]                       # see if episode has fi
                 agent.step(state, action, reward, next_state, done) # learning step
                 state = next_state
                 score += reward
                 if done:
                     break
             scores_window.append(score)          # save most recent score to window
             scores.append(score)                 # save most recent score to total
             moving_avg = np.mean(scores_window)  # calculate moving average
             moving_avgs.append(moving_avg)       # save most recent moving average
             eps = max(eps_end, eps_decay*eps)    # decrease epsilon
             print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, moving_avg), end=
             if i_episode % 100 == 0:
                 print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, moving_avg))
             if moving_avg >= 13.0:
                 print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.forma
                 if train_mode:
```

```
                    torch.save(agent.qnetwork_local.state_dict(), ckpt_path)
                break
        return scores, moving_avgs
```

In [20]:
```
scores, avgs = dqn(n_episodes=600, eps_decay=0.98, eps_end=0.02, ckpt_path='/v28_checkp

# plot the scores
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores, label='DQN+RB+FC64')
plt.plot(np.arange(len(scores)), avgs, c='r', label='average')
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.legend(loc='upper left');
plt.show()
```

```
Episode 100         Average Score: 4.07
Episode 200         Average Score: 9.36
Episode 281         Average Score: 13.01
Environment solved in 181 episodes!         Average Score: 13.01
```



In [21]:
```
env.close()
```

In [ ]: