Navigation

June 22, 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.
```

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 [9]: 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 [10]: # 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 [11]: # 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 [12]: 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 environme
             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
             if done:                                       # exit loop if episode finished
                 break

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

```
Score: 0.0
```

When finished, you can close the environment.

```
In [23]: 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 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 [ ]: '''
        Note to the reviewer 18-Jun-21
        This project used a double deep-Q network modifying the code provided in the lessons.
        Alterations to the code were in the double_dqn, the agent, and the class as per the file
        submitted.  I used Batch Normaliztion to accelerates learning on layers one and two, alt
        the fcx_unit sizes which did very little to improve performance so I stuck with 64 as th
        fc1 and fc2.
```

```
The final saved trained model used a three layer neural network where the batchsize was
Hyper-parameters: (1) LR-learning-rate; (2) Espsilon-Decay value and; (3) Gamma we adjus
realize the best results. The best hyper-parameter adjustments were LR changed to 5e-55
and Epsion-Decay lowered down to 0.9645. Dropping Gamma to around0.95 helped realize the
faster, but not as much as the other two.

Within this notebook you will also see runs using a four layer neural net altering the
hyper-parameters. Results were roughly the same so I chose the final two layer model.

Thank you.
Kim

'''
```

In [2]:
```
#
#. Import the Necessary Packages
#
#
import random
import torch
import numpy as np
from collections import deque
import matplotlib.pyplot as plt
%matplotlib inline

!python -m pip install pyvirtualdisplay
from pyvirtualdisplay import Display
display = Display(visible=0, size=(1400, 900))
display.start()

is_ipython = 'inline' in plt.get_backend()
if is_ipython:
    from IPython import display

plt.ion()
```

```
Collecting pyvirtualdisplay
  Downloading https://files.pythonhosted.org/packages/79/30/e99e0c480a858410757e7516958e149285ea
Collecting EasyProcess (from pyvirtualdisplay)
  Downloading https://files.pythonhosted.org/packages/48/3c/75573613641c90c6d094059ac28adb748560
Installing collected packages: EasyProcess, pyvirtualdisplay
Successfully installed EasyProcess-0.3 pyvirtualdisplay-2.2
```

In [5]:
```
print(torch.__version__)
```

```
0.4.0
```

```
In [7]: #
        #  Re the Environment and Agent
        #
        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: [ 0.          0.          1.          0.          0.16101955  1.          0.
  0.          0.          0.04571758  1.          0.          0.          0.
  0.2937662   0.          0.          1.          0.          0.14386636
  0.          0.          1.          0.          0.16776823  1.          0.
  0.          0.          0.04420976  1.          0.          0.          0.
  0.05423063  0.          0.        ]
States have length: 37
```

```
In [14]: #
         #  Establish path to files
         #
         import os
         dir = os.getcwd()
         print(dir)

         from pathlib import Path  #/home/workspace/ etc
         print(*Path(dir).iterdir(), sep="\n") # print files in the directory
         #
         # set the trained file name
         #
         file_name = dir + '/trained_model.pt'
         file_name
```

```
/home/workspace
/home/workspace/dqn_agent_prj1.py
/home/workspace/model_prj1.py
/home/workspace/python
```

```
/home/workspace/__pycache__
/home/workspace/unity-environment.log
/home/workspace/checkpoint.pth
/home/workspace/.ipynb_checkpoints
/home/workspace/Navigation.ipynb
```

```
Out[14]: '/home/workspace/trained_model.pt'
```

```
In [15]: def get_ns_rewrd_done(env_info):
             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]            # get done-status
             return next_state, reward, done
```

```
In [16]: #nxt,rr,dd = get_ns_rewrd_done(env_info)
         nxt,_,_ = get_ns_rewrd_done(env_info)
         print(nxt,len(nxt))
         #print(rr)
         #print(dd)
```

```
[ 1.          0.          0.          0.          0.43962687  1.          0.
  0.          0.          0.19398789  1.          0.          0.          0.
  0.48112735  0.          0.          1.          0.          0.52109712
  0.          0.          1.          0.          0.38285938  1.          0.
  0.          0.          0.10405888  1.          0.          0.          0.
  0.37148571  0.          0.        ] 37
```

```
In [17]: from dqn_agent_prj1 import Agent
         agent = Agent(state_size=37, action_size=4, seed=42)
```

```
In [18]: def double_dqn(n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.99
             """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
             """
             scores        = []                        # list containing scores from each episod
             scores_window = deque(maxlen=100)  # last 100 scores
             eps           = eps_start                      # initialize epsilon

             for i_episode in range(1, n_episodes+1):
                 #state = env.reset()
```

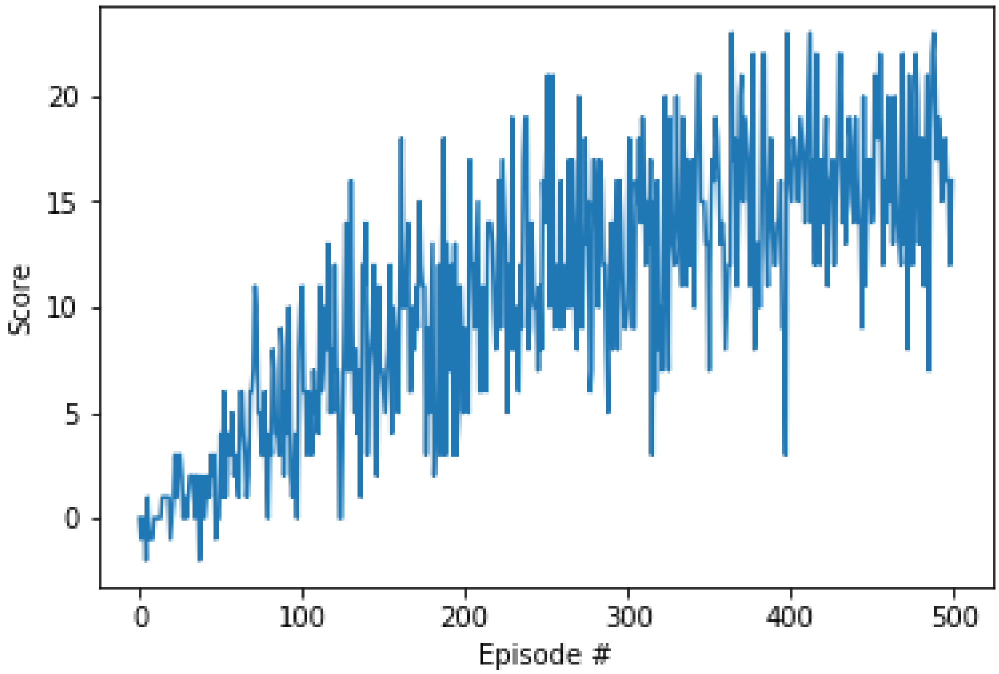
```
            env_info  = env.reset(train_mode=True)[brain_name] # reset the environment
            state,_,_ = get_ns_rewrd_done(env_info)            # get the current state
            score     = 0

            for t in range(max_t):
                action   = agent.act(state, eps)          # Get action(s) for current state
                env_info = env.step(action)[brain_name]  # Take action w/in the environment
                next_state, reward, done = get_ns_rewrd_done(env_info) # get next state & r

                agent.step(state, action, reward, next_state, done)
                state = next_state
                score += reward
                if done:
                    break
            scores_window.append(score)       # save most recent score
            scores.append(score)              # save most recent score
            eps = max(eps_end, eps_decay*eps) # decrease epsilon
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_wi
            if i_episode % 100 == 0:
                print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(score
            if np.mean(scores_window)>13.0:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.forma
                #torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                torch.save(agent.qnetwork_local.state_dict(), file_name)
                break
        return scores
```

In [4]:
```
#
#  Set directory for saving model
#
```

In [11]:
```
#***KEEP***
# New 4-layer model 10-Jun-2021
#
BATCH_SIZE  = 64
LR          = 5e-55
GAMMA       = 0.95
agent       = Agent(state_size=37, action_size=4, seed=42)
scores      = 0
scores = dqn(n_episodes=500, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.9865)
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores)
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.show()
```

```
Episode 100	Average Score: 2.57
Episode 200	Average Score: 7.95
```

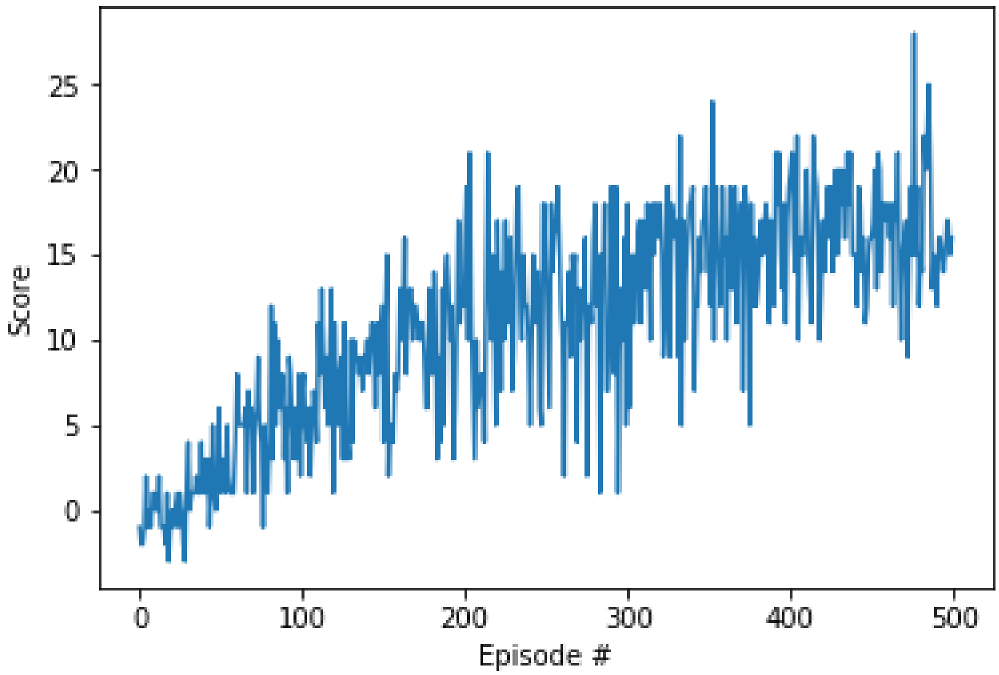
```
Episode 300        Average Score: 11.82
Episode 400        Average Score: 14.28
Episode 500        Average Score: 16.38
```




```
In [21]: #***KEEP
         # New 4-layer model 10-Jun-2021 3:10pm
         #
         #  esp decay =0.9845;  GAMMA 0.05; batchsize =32
         #
         BATCH_SIZE  = 32
         LR          = 5e-55
         GAMMA       = 0.95
         agent       = Agent(state_size=37, action_size=4, seed=42)
         scores      = 0
         scores = dqn(n_episodes=500, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.9845)
         fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(len(scores)), scores)
         plt.ylabel('Score')
         plt.xlabel('Episode #')
         plt.show()
```

```
Episode 100        Average Score: 2.55
Episode 200        Average Score: 8.72
```

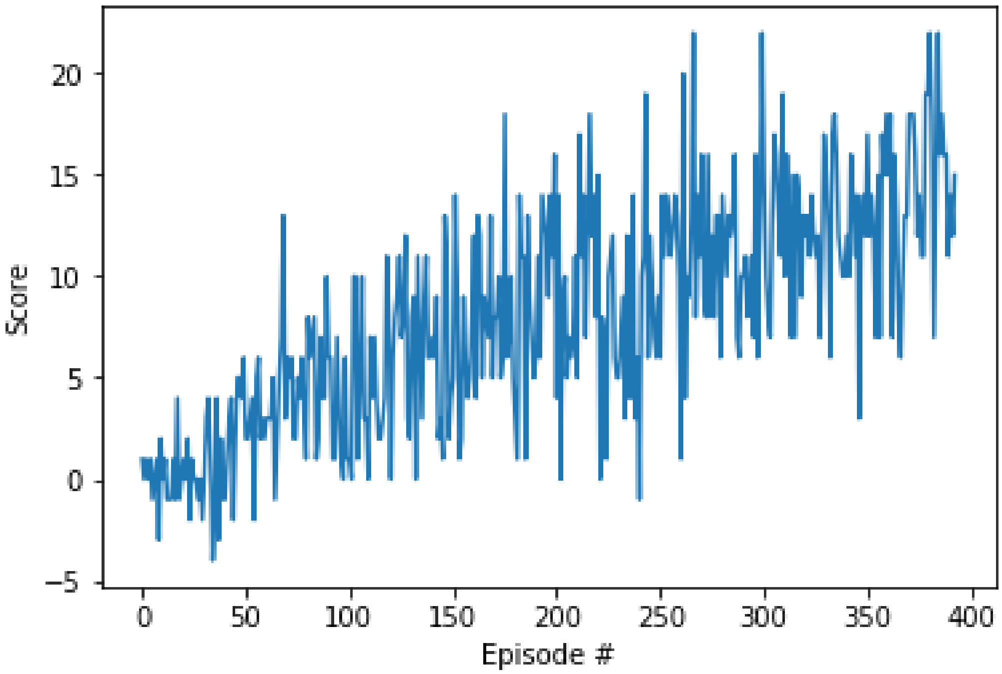
```
Episode 300	Average Score: 11.83
Episode 400	Average Score: 15.03
Episode 500	Average Score: 16.55
```




```
In [22]: #***BEST RUN ***
         # 13-Jun-2021 3-layer model 9:20 AM
         #
         #  esp decay =0.9645;  GAMMA 0.95; batchsize =32
         #
         BATCH_SIZE  = 32
         LR          = 5e-55
         GAMMA       = 0.95
         agent       = Agent(state_size=37, action_size=4, seed=42)
         scores      = 0
         print('BATCH_SIZE',BATCH_SIZE )
         scores = double_dqn(n_episodes=700, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=
         fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(len(scores)), scores)
         plt.ylabel('Score')
         plt.xlabel('Episode #')
         plt.show()
```

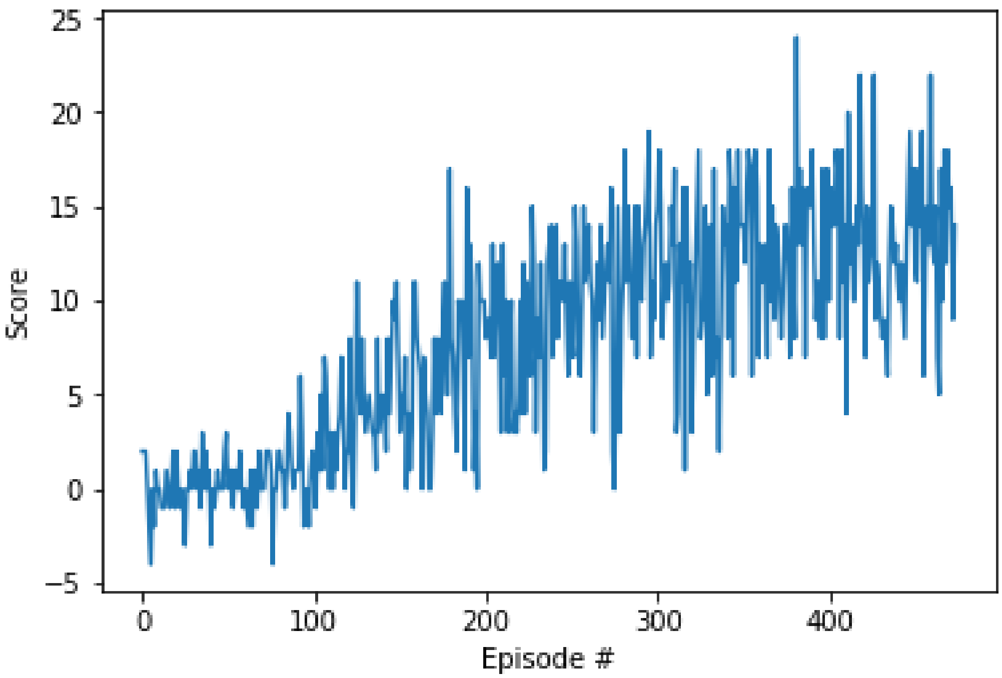
```
BATCH_SIZE 32
Episode 100	Average Score: 2.33
```

```
Episode 200        Average Score: 7.11
Episode 300        Average Score: 9.86
Episode 393        Average Score: 13.07
Environment solved in 293 episodes!        Average Score: 13.07
```



In [13]:
```
#
# 13-Jun-2021 3-layer model 9:20 AM
#
#  esp decay =0.9845;  GAMMA 0.05; batchsize =32
#
#
BATCH_SIZE  = 64
LR          = 5e-55
GAMMA       = 0.95
agent       = Agent(state_size=37, action_size=4, seed=42)
scores      = 0
print('BATCH_SIZE',BATCH_SIZE )
scores = double_dqn(n_episodes=700, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores)
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.show()
```

```
BATCH_SIZE 64
Episode 100	Average Score: 0.38
Episode 200	Average Score: 5.22
Episode 300	Average Score: 9.63
Episode 400	Average Score: 12.16
Episode 474	Average Score: 13.03
Environment solved in 374 episodes!	Average Score: 13.03
```




```
In [25]: env.close()
```

```
In [24]: #
         # check that model is saved
         #
         print(*Path(dir).iterdir(), sep="\n")#"/home/workspace/dog_project/images/"
```

```
/home/workspace/dqn_agent_prj1.py
/home/workspace/model_prj1.py
/home/workspace/python
/home/workspace/__pycache__
/home/workspace/unity-environment.log
/home/workspace/checkpoint.pth
/home/workspace/.ipynb_checkpoints
/home/workspace/Navigation.ipynb
/home/workspace/trained_model.pt
```

In [3]:
```
#
#    Improving Performance
#
'''
To improve performance I would change the architecture back to a 4-layer neural network
Batch Normaliztion to accelerates learning on just two layers one and three; see the tou
results using a four-layer network. I would  altered the fc3_unit size to 32 versus 64 a
reapply these same hyperparameters:
   BATCH_SIZE  = 32 #
   LR          = 5e-65  # Speed up learning a little more
   GAMMA       = 0.95
   agent       = Agent(state_size=37, action_size=4, seed=42)
I would also try the memory prioritization algotithm to determine if there is an increas
attainment.
'''
```

Out[3]:
```
'\nTo improve performance I would change the architecture back to a 4-layer neural netwo
```

In [ ]: