Navigation

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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 2.0.
```

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 [2]: 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 [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 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 [5]: 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: 0.0
```

When finished, you can close the environment.

```
In [6]: # 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!

1.0.5 My Implementation

```
In [7]: import random
        import torch
        from collections import deque
        import time
        import matplotlib.pyplot as plt
        %matplotlib inline
```

First, import your DQN Agent

```
In [8]: from dqn_agent import Agent

        # lets set the states and action for the agent (Information is printed above)
        agent = Agent(state_size=37, action_size=4, seed=50)
```

Deep Q-Learning. Parameter definitions

- 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 selection
- eps_end (float): minimum value of epsilon
- eps_decay (float): multiplicative factor (per episode) for decreasing epsilon

Parameters	Values
n_episodes	2000
max_t	1000
eps_start	1
eps_end	0.01
eps_decay	0.0995

Parameter Values Chosen

Learning Algorithim - Deep Q-Learning Algorithim Start with an initial action-value $Q_0(s,a)$ for all states and action s, a. `Q(terminal state) = 0`

for $episode = 1, 2, ...$ until number of episodes: - Get initial state s fron the environment - for $n = 1, 2, ...$ until convergence: - - sample probabilities of actions a - - execute action in the environment at state s, get reward and next state $s^{'}$ - - if $s\prime$ is terminal: - - - target = $R(s,a,s^{'})$ - - - sample new initial state $s^{'}$ - - else: - - - target = $R(s,a,s^{'}) + \gamma max Q_k(s^{'}, a^{'})$ - - $Q_{k+1}(s,a)(1-\alpha)Q_k(s,a) + [target]$ - - $ss^{'}$

Model Architectures - A neural network which consists of two fully connected layers with 64 units each together with an output layer

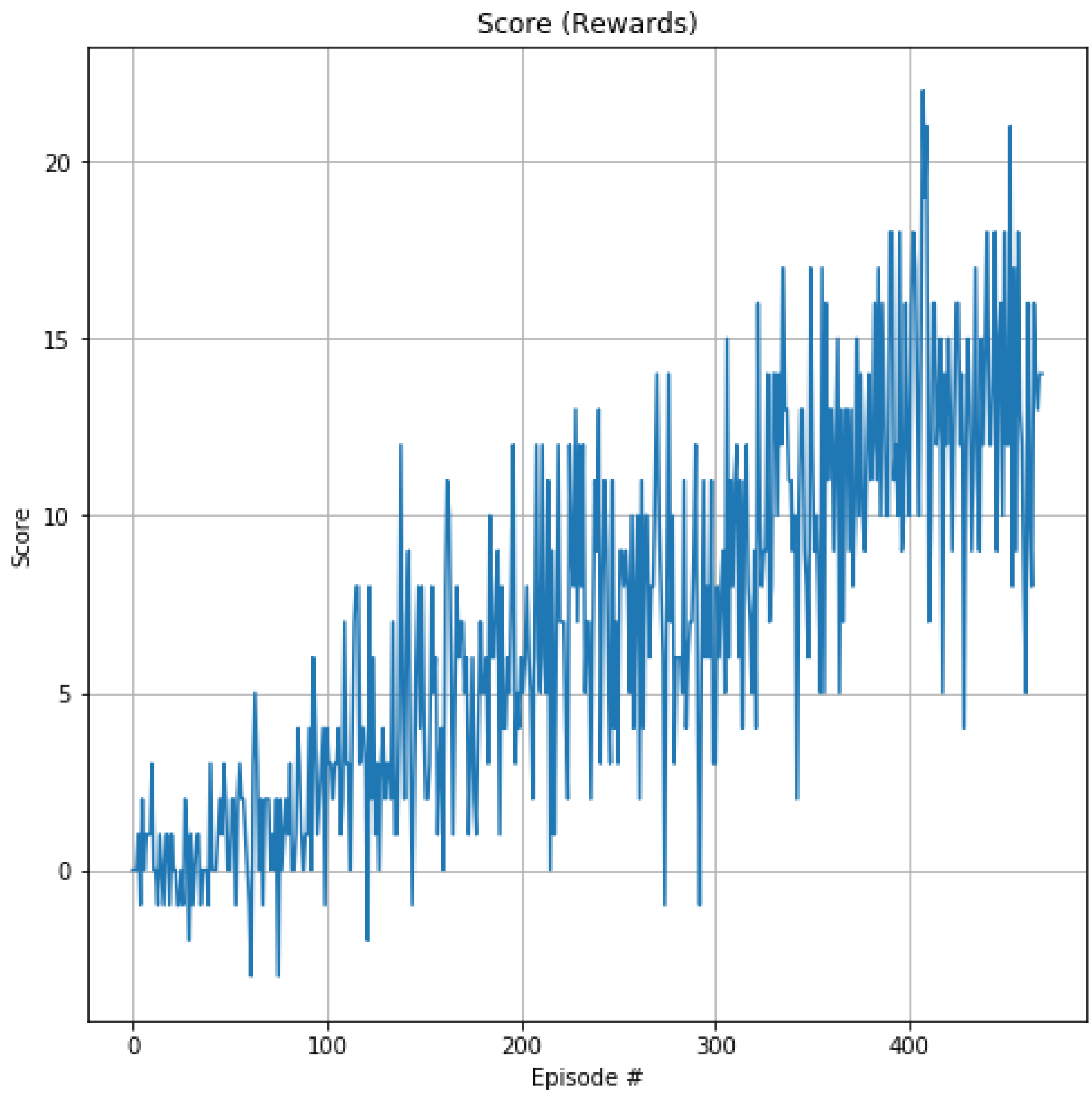
```
In [9]: def dqn(n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995):

            scores = []                        # Initialize list to save 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):
                env_space = env.reset(train_mode=True)[brain_name]     # reset the state environm
                state = env_space.vector_observations[0]            # get the current state

                score = 0
```

```
            for t in range( max_t):
                action = agent.act(state, eps)   # get a probability of states
                env_space = env.step(action)[brain_name]   # take action in the environment
                reward = env_space.rewards[0]     # get reward
                next_state = env_space.vector_observations[0]  # get next state
                done = env_space.local_done[0]    # check to see if current episode has fini
                agent.step(state, action, reward, next_state, done)
                score += reward     #update score
                state = next_state
                if done:
                    break

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

In [10]:
```
# Train the agent
start_time = time.time() # Monitor Training Time
scores = dqn()
print("\nTotal Training time = {:.1f} min".format((time.time()-start_time)/60))
```

```
Episode 100       Average Score: 0.89
Episode 200       Average Score: 4.53
Episode 300       Average Score: 7.25
Episode 400       Average Score: 10.75
Episode 469       Average Score: 13.00
Environment solved in 369 episodes!       Average Score: 13.00

Total Training time = 9.8 min
```

In [11]:
```
# plot the scores
fig = plt.figure(figsize=(8,8))
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores)
plt.title('Score (Rewards)')
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.grid(True)
plt.show()
```



1.0.6 Near Future Improvement and Exploration to Tryout

- Train the agent using raw screen pixels as input Link to Implementation
- Improve performance using Prioritized Experience Replay. Prioritized Experience Replay using a special data structure Sum Tree
- Other Improvements in Deep Q Learning Link to Implementation

```
In [ ]:
```