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 [5]: !pip -q install ./python
```

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 [6]: 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!

```
In [7]: import torch
        import numpy as np
        from collections import deque
        import matplotlib.pyplot as plt
        %matplotlib inline
        #from unityagents import UnityEnvironment

        #
        from dqn_agent import Agent
```

```
In [31]: def dqn(env, n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995)
             """Deep Q-Learning.

             Params
```

```
    ======
        env (Unity Environment): environment
        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 episode
    scores_window = deque(maxlen=100)  # last 100 scores
    eps = eps_start                    # initialize epsilon
    solved = False
    for i_episode in range(1, n_episodes+1):
        # reset env
        env_info = env.reset(train_mode=True)[brain_name]
        state =  env_info.vector_observations[0]
        score = 0
        for t in range(max_t):
            action = agent.act(state, eps)
            env_info = env.step(action)[brain_name]
            next_state = env_info.vector_observations[0]
            reward = env_info.rewards[0]
            done = env_info.local_done[0]

            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


        # Log progress
        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 and not solved:
            solved = True
            print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.forma
            torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
    return scores
```

In [32]:
```
brain_name = env.brain_names[0]
brain = env.brains[brain_name]
env_info = env.reset(train_mode=True)[brain_name]
action_size = brain.vector_action_space_size
```

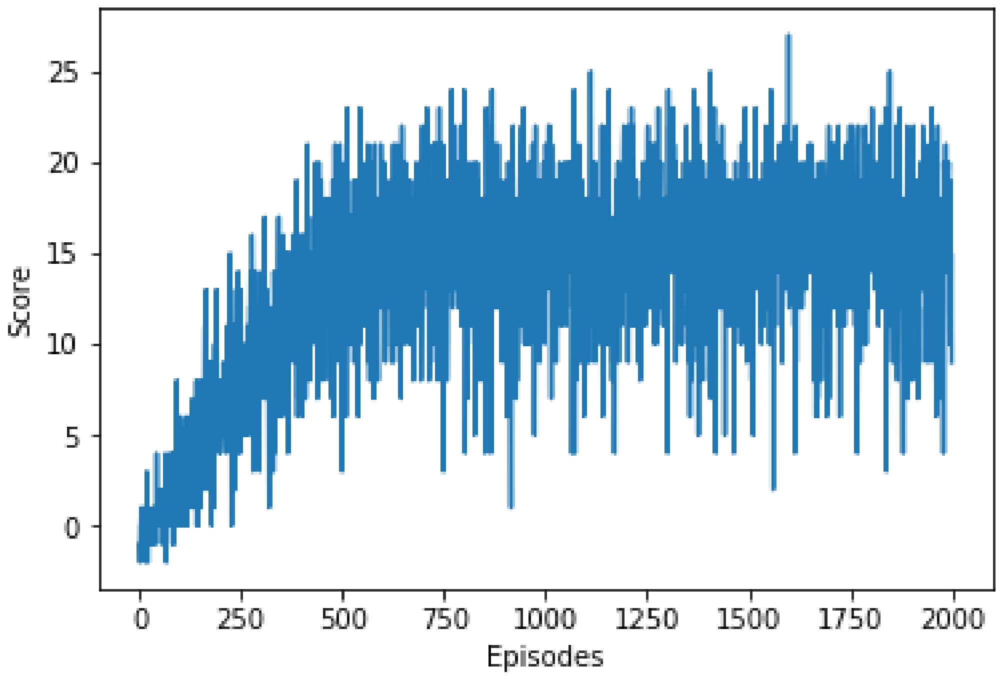
```
        state = env_info.vector_observations[0]
        state_size = len(state)
```

In [33]:
```
agent = Agent(state_size=state_size, action_size=action_size, seed=0)
```

In [34]:
```
scores = dqn(env)
```

```
Episode 100        Average Score: 0.71
Episode 200        Average Score: 4.81
Episode 300        Average Score: 8.07
Episode 400        Average Score: 10.72
Episode 463        Average Score: 13.01
Environment solved in 363 episodes!        Average Score: 13.01
Episode 500        Average Score: 13.57
Episode 600        Average Score: 14.41
Episode 700        Average Score: 14.92
Episode 800        Average Score: 15.86
Episode 900        Average Score: 14.99
Episode 1000        Average Score: 14.53
Episode 1100        Average Score: 15.57
Episode 1200        Average Score: 15.32
Episode 1300        Average Score: 15.82
Episode 1400        Average Score: 15.31
Episode 1500        Average Score: 15.37
Episode 1600        Average Score: 15.95
Episode 1700        Average Score: 15.87
Episode 1800        Average Score: 16.14
Episode 1900        Average Score: 15.73
Episode 2000        Average Score: 15.14
```

In [35]:
```
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores)
plt.xlabel('Episodes')
plt.ylabel('Score')
plt.show()
```



25
20
15
10
5
0
Score
0
250
500
750
1000
1250
1500
1750
2000
Episodes


```
In [ ]:
```