Navigation

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1 Navigation

In this notebook, you will learn how to use the Unity ML-Agents environment for the first project of the Deep Reinforcement Learning Nanodegree.

1.0.1 1. Start the Environment

We begin by importing some necessary packages. If the code cell below returns an error, please revisit the project instructions to double-check that you have installed Unity ML-Agents and NumPy.

```
In [1]: from unityagents import UnityEnvironment
        import numpy as np
```

Next, we will start the environment! ***Before running the code cell below***, change the `file_name` parameter to match the location of the Unity environment that you downloaded.

- **Mac**: `"path/to/Banana.app"`
- **Windows** (x86): `"path/to/Banana_Windows_x86/Banana.exe"`
- **Windows** (x86_64): `"path/to/Banana_Windows_x86_64/Banana.exe"`
- **Linux** (x86): `"path/to/Banana_Linux/Banana.x86"`
- **Linux** (x86_64): `"path/to/Banana_Linux/Banana.x86_64"`
- **Linux** (x86, headless): `"path/to/Banana_Linux_NoVis/Banana.x86"`
- **Linux** (x86_64, headless): `"path/to/Banana_Linux_NoVis/Banana.x86_64"`

For instance, if you are using a Mac, then you downloaded `Banana.app`. If this file is in the same folder as the notebook, then the line below should appear as follows:

```
env = UnityEnvironment(file_name="Banana.app")
```

```
In [2]: env = UnityEnvironment(file_name="/media/flash/DATA/RL/Banana_Linux/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]
        print(brain)

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: , , ,
```

1.0.2 2. Examine the State and Action Spaces

The simulation contains a single agent that navigates a large environment. At each time step, it has four actions at its disposal: - `0` - walk forward - `1` - walk backward - `2` - turn left - `3` - turn right

The state space has `37` dimensions and contains the agent's velocity, along with ray-based perception of objects around agent's forward direction. A reward of `+1` is provided for collecting a yellow banana, and a reward of `-1` is provided for collecting a blue banana.

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: [0.         1.         0.         0.         0.16895212 0.
 1.         0.         0.         0.20073597 1.         0.
 0.         0.         0.12865657 0.         1.         0.
 0.         0.14938059 1.         0.         0.         0.
 0.58185619 0.         1.         0.         0.         0.16089135
 0.         1.         0.         0.         0.31775284 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.

Once this cell is executed, you will watch the agent's performance, if it selects an action (uniformly) at random with each time step. A window should pop up that allows you to observe the agent, as it moves through the environment.

Of course, as part of the project, you'll have to change the code so that the agent is able to use its experience to gradually choose better actions when interacting with the environment!

```
In [5]: env_info = env.reset(train_mode=False)[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!

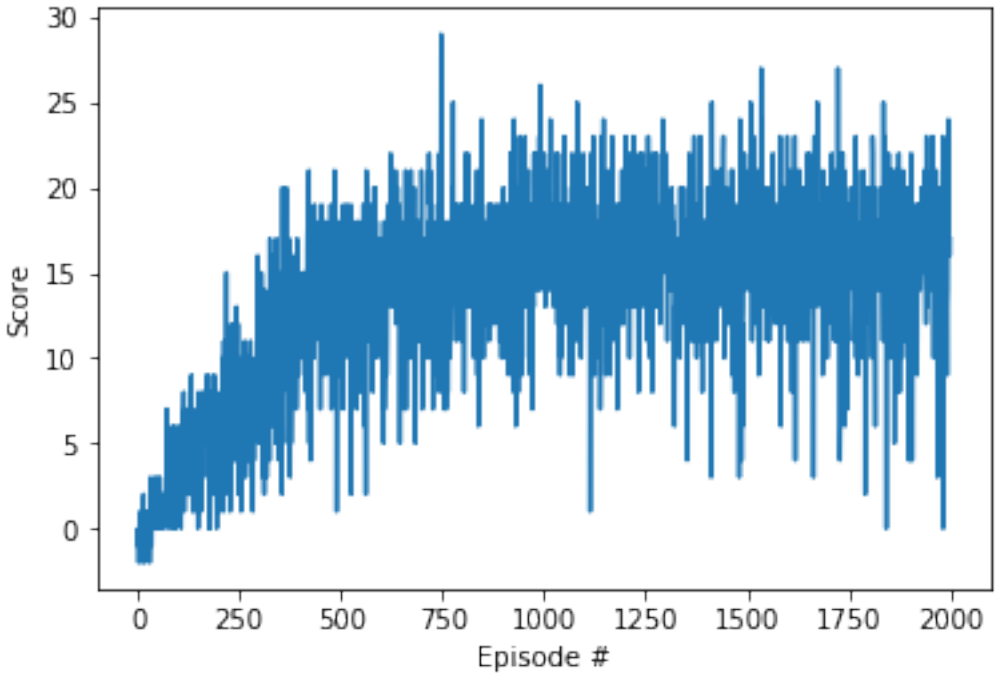
Now it's your turn to train your own agent to solve the environment! When training the environment, set `train_mode=True`, so that the line for resetting the environment looks like the following:

```
env_info = env.reset(train_mode=True)[brain_name]
```

```
In [6]: from dqn import Agent
        from collections import namedtuple, deque

        agent = Agent(state_size= len(state), action_size=4, seed=0)
        def dqn(n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995):
            """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 selectio
                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

            # get the default brain
            brain_name = env.brain_names[0]
            for i_episode in range(1, n_episodes+1):
                env_info = env.reset(train_mode=True)[brain_name]
                state = env_info.vector_observations[0]            # get the current state
                score = 0
                for t in range(max_t):


                    action = agent.act(state, eps)

                    env_info = env.step(action)[brain_name]        # send the action to the envi
                    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]

                    #next_state, reward, done, _ = env.step(action)
                    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_win
            if i_episode % 100 == 0:
                print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores
            if np.mean(scores_window)>=200.0:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                break
        return scores

scores = dqn()
import matplotlib.pyplot as plt
%matplotlib inline
# plot the scores
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: 0.92
Episode 200        Average Score: 4.33
Episode 300        Average Score: 7.11
Episode 400        Average Score: 10.44
Episode 500        Average Score: 13.43
Episode 600        Average Score: 13.89
Episode 700        Average Score: 14.88
Episode 800        Average Score: 14.94
Episode 900        Average Score: 15.24
Episode 1000        Average Score: 16.14
Episode 1100        Average Score: 16.32
Episode 1200        Average Score: 15.46
Episode 1300        Average Score: 16.88
Episode 1400        Average Score: 15.47
Episode 1500        Average Score: 15.92
Episode 1600        Average Score: 16.32
Episode 1700        Average Score: 16.23
Episode 1800        Average Score: 15.50
Episode 1900        Average Score: 16.09
Episode 2000        Average Score: 15.48
```


Score
Episode #
0
5
10
15
20
25
30
0
250
500
750
1000
1250
1500
1750
2000

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