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 gym
        import random
        import torch
        import numpy as np
        from collections import deque
        import matplotlib.pyplot as plt
        %matplotlib inline
```

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="/home/pedro/deep-reinforcement-learning/p1_navigation/
```

```
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

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 [ ]: # 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)
```

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 [ ]: from dqn_agent import Agent

        agent = Agent(state_size=37, action_size=4, seed=0)
        agent.qnetwork_local.load_state_dict(torch.load('checkpoint.pth'))

        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 = agent.act(state, eps=0.0)             # get action (eps=1 means random acti
            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))
```

1.0.4 4. It's Your Turn!

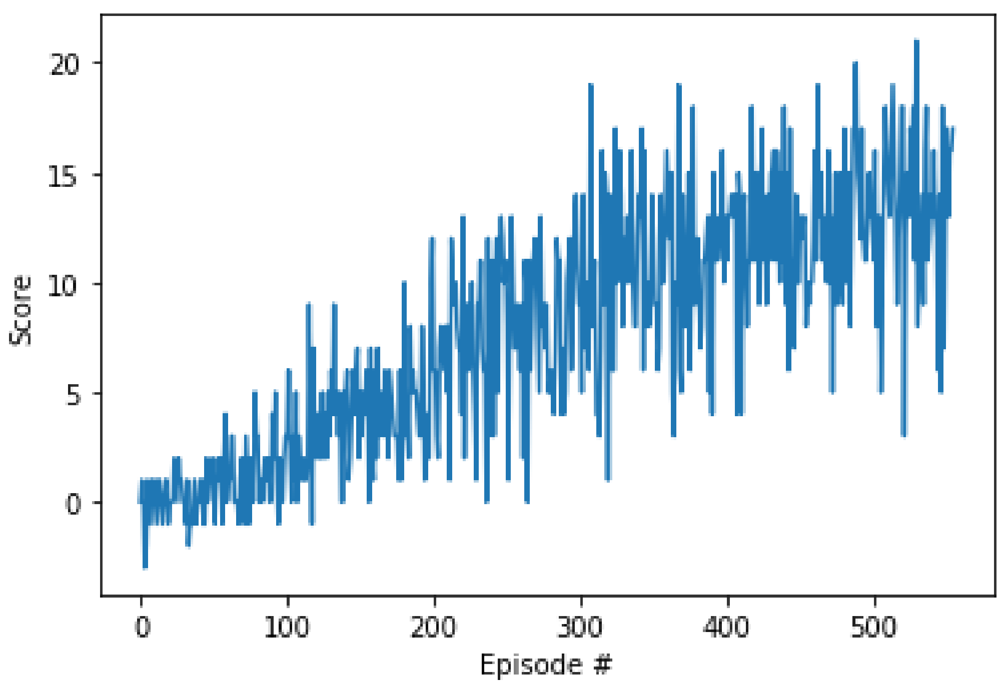
Now it's your turn to train your own agent to solve the environment!

```
In [4]: from dqn_agent import Agent
        agent = Agent(state_size=37, action_size=4, seed=0)
        agent.qnetwork_local.load_state_dict(torch.load('checkpoint.pth'))


        def dqn(n_episodes=2000, eps_start=0.01, eps_end=0.01, eps_decay=0.995):
            """Deep Q-Learning.

            Params
            ======
```

```
            n_episodes (int): maximum number of training episodes
            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
        for i_episode in range(1, n_episodes+1):
            env_info = env.reset(train_mode=True)[brain_name]
            state = env_info.vector_observations[0]
            score = 0
            while True:
                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)
                score += reward
                state = next_state
                if done:
                    break

            scores_window.append(score)
            scores.append(score)
            eps = max(eps_end, eps_decay*eps)
            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
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
            if np.mean(scores_window)>=100.0:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                break
        return scores

    scores = dqn()

    # 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: 2.56
```

```
Episode 200	Average Score: 9.18
Episode 300	Average Score: 10.81
Episode 400	Average Score: 13.66
Episode 500	Average Score: 15.74
Episode 600	Average Score: 16.35
Episode 700	Average Score: 16.16
Episode 800	Average Score: 15.85
Episode 900	Average Score: 16.19
Episode 1000	Average Score: 16.96
Episode 1100	Average Score: 16.40
Episode 1200	Average Score: 16.17
Episode 1300	Average Score: 16.35
Episode 1400	Average Score: 15.63
Episode 1500	Average Score: 15.89
Episode 1600	Average Score: 16.06
Episode 1700	Average Score: 16.38
Episode 1800	Average Score: 15.82
Episode 1900	Average Score: 16.06
Episode 2000	Average Score: 15.99
```



Now watch the result of training

In [ ]:
```
agent.qnetwork_local.load_state_dict(torch.load('checkpoint.pth'))

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 = agent.act(state, eps=0.0)             # get action (eps=0 means trained)
    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))

env.close()
```