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]: import time
        from collections import deque
        import numpy as np
        import matplotlib.pyplot as plt
        import torch
        from unityagents import UnityEnvironment
```

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="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

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 [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.

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 [ ]: 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))
```

When finished, you can close the environment.

```
In [ ]: 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 [5]: from dqn_agent import Agent

        agent = Agent(state_size=state_size, action_size=action_size, seed=0)
```

Run the next cell if you would like to load in previously trained weights.

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

```
In [6]: 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
            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
                t_step = 0
                while True:
                    action = agent.act(state, eps) # based on the current state get 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
                    agent.step(state, action, reward, next_state, done) # agent executes a step
                    score += reward # update the score
                    state = next_state # roll over the state to next time step
                    t_step += 1 # increment the number of steps seen this episode.
                    if done or t_step >= max_t: # exit loop if episode finished
                        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) >= 13.0:
                    print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format
```

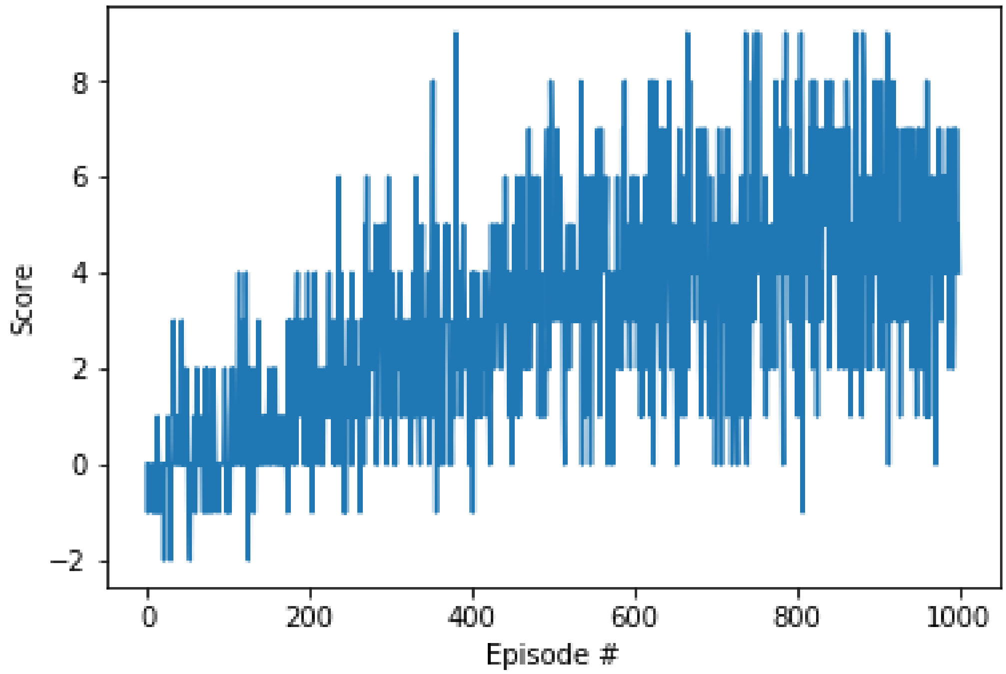
```
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                break
        return scores
```

Note that the Banana Sim is hard coded to run a maximum of 300 steps per episode. If we set a `max_t` value to be some number of steps less than this maximum, then we can train much faster. However, in doing so it is unlikely that we will hit our target score of 13 because we won't be giving the agent enough time to accumulate the required reward. Therefore we will need to save the agent by hand once training is complete. Alternatively, you could stop training once the average over 100 episodes goes above $13 * \frac{max\_t}{300}$

```
In [7]: t0 = time.time()
        scores = dqn(n_episodes=1000, max_t=100)
        print(time.time() - t0, 'seconds')

        # 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: 0.17
Episode 200	Average Score: 0.94
Episode 300	Average Score: 1.98
Episode 400	Average Score: 2.57
Episode 500	Average Score: 3.12
Episode 600	Average Score: 3.74
Episode 700	Average Score: 4.18
Episode 800	Average Score: 4.25
Episode 900	Average Score: 4.88
Episode 1000	Average Score: 4.58
563.3376793861389
```



Run the next cell a few times to make sure your getting scores >= 13.

```
In [9]: 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)
            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
            agent.step(state, action, reward, next_state, done)
            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: 20.0
```

Run the next cell to save a copy of your agent.

```
In [10]: torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
```

```
In [11]: env.close()
```

1.1 Ideas for future work

- Implement a double DQN, a dueling DQN, and/or prioritized experience replay
- Try to training an agent from raw pixels. (See Navigation_Pixels.ipynb)

```
In [ ]:
```