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.

[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")
```

[ ]:
```
env = UnityEnvironment(file_name="Banana.app")
```

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.

[ ]:
```
# 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.

[ ]:
```
# 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!

[ ]:
```
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 step
    if done:                                            # exit loop if episode␣
↪finished
        break

print("Score: {}".format(score))
```

[ ]:
```
When finished, you can close the environment.
```

[5]:
```
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]
```

[1]:
```
from unityagents import UnityEnvironment
import numpy as np
from collections import deque
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
# Setup environment
env = UnityEnvironment(file_name="Banana.app")
# Get the first brain as the one we will control
# get the default brain
brain_name = env.brain_names[0]
brain = env.brains[brain_name]
```

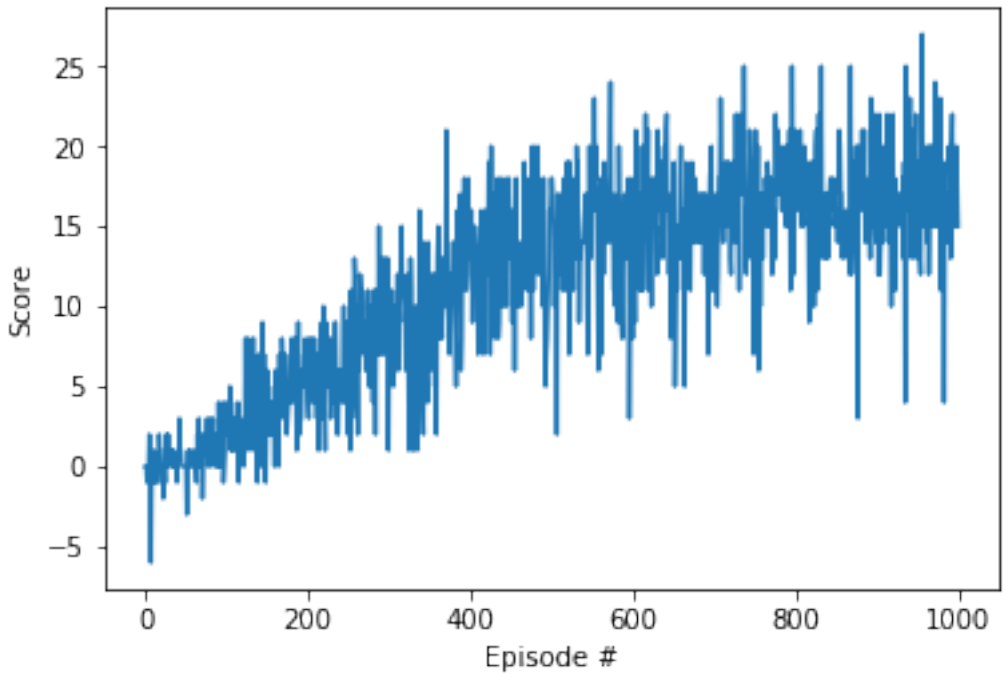
```
INFO:unityagents:
'Academy' started successfully!
Unity Academy name: Academy
        Number of Brains: 1
        Number of External Brains : 1
        Lesson number : 0
        Reset Parameters :

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: , , ,
```

[1]:
```
# Agent

from state_obs.agent import Agent
from state_obs.agent_rainbow import Agent_Rainbow

import torch

state_size = 37
action_size = 4
seed = 0

agent = Agent_Rainbow(state_size=state_size, action_size=action_size,␣
↪seed=seed, ddqn=True)
```

[4]:
```
def dqn(n_episodes=1000, max_t=500, 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␣
↪selection
        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
    first_time = True                  # first time we reach score >= 13.0
    for i_episode in range(1, n_episodes+1):

        # get environment info
        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]        # 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)

            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_window)), end="")
        if i_episode % 100 == 0:
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.
↪mean(scores_window)))
        if np.mean(scores_window)>=13.0:
            if first_time:
                first_time = False
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:
↪.2f}'.format(i_episode, np.mean(scores_window)))
            agent.save()
    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: 0.51
Episode 200     Average Score: 3.85
Episode 300     Average Score: 6.92
Episode 400     Average Score: 9.79
Episode 477     Average Score: 13.07
Environment solved in 477 episodes!     Average Score: 13.07
Episode 500     Average Score: 13.21
Episode 600     Average Score: 14.37
Episode 700     Average Score: 15.23
Episode 800     Average Score: 16.50
Episode 900     Average Score: 16.40
Episode 1000    Average Score: 16.87
```



2 Let's test the agent

[4]:
```
import time
# Run the trained agent

# load the weights from file
agent.qnetwork_local.load_state_dict(torch.load('checkpoint_rainbow.pth'))

for i in range(3):
    env_info = env.reset(train_mode=False)[brain_name]
    state = env_info.vector_observations[0]
    for j in range(2000):
        action = agent.act(state)
        env_info = env.step(action)[brain_name]
        state = env_info.vector_observations[0]
        done = env_info.local_done[0]
        if done:
            break

env.close()
```

[5]:
```
!export PATH=/Library/TeX/texbin:$PATH
```

[ ]: