Navigation-Solution

November 10, 2019

1 Navigation

First project of NANODEGREE PROGRAM Become a Deep Reinforcement Learning Expet Udacity

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

```
tensorflow 1.7.1 has requirement numpy>=1.13.3, but you'll have numpy 1.12.1 which is incompatib
ipython 6.5.0 has requirement prompt-toolkit<2.0.0,>=1.0.15, but you'll have prompt-toolkit 2.0.
```

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 [2]: import torch
        import numpy as np
        from unityagents import UnityEnvironment
        import random
        import matplotlib.pyplot as plt
        from collections import deque
        from dqn_agent import Agent

        %matplotlib inline
```

```
In [3]: # 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 [4]: # 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 [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: [ 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. Initialize the game agent

```
In [6]: agent = Agent(state_size=state_size, action_size=action_size, seed=0)

        output_file_name="double_dueling_agent.pth" # file name under which the weights will be
```

1.0.4 4. Train the Agent with DQN

1.0.5 4.1 Chosen hyperparameters:

Below can be seen the chosen heperparameters used for training the DQN reinforcement learning algorithms in dqn_agent.py file :

BUFFER_SIZE = int(1e5) # replay buffer size BATCH_SIZE = 64 # minibatch size GAMMA = 0.99 # discount factor TAU = 1e-3 # for soft update of target parameters LR = 5e-4 # learning rate UPDATE_EVERY = 4 # how often to update the

1.0.6 4.2 Learning algorithm:

A neural network which consists of 3 Linear layers responsible for an agent behaviour which can be found in model.py file:

class QNetwork(nn.Module): """Actor (Policy) Model."""

```
def __init__(self, state_size, action_size, seed, fc1_units=64, fc2_units=64):
    """Initialize parameters and build model.
    Params
    ======
        state_size (int): Dimension of each state
        action_size (int): Dimension of each action
        seed (int): Random seed
        fc1_units (int): Number of nodes in first hidden layer
        fc2_units (int): Number of nodes in second hidden layer
    """
    super(QNetwork, self).__init__()
    self.seed = torch.manual_seed(seed)
    self.fc1 = nn.Linear(state_size, fc1_units)
    self.fc2 = nn.Linear(fc1_units, fc2_units)
    self.fc3 = nn.Linear(fc2_units, action_size)

def forward(self, state):
    """Build a network that maps state -> action values."""
    x = F.relu(self.fc1(state))
    x = F.relu(self.fc2(x))
    return self.fc3(x)
```

1.0.7 4.3 Deep Q-Learning Algorithm:

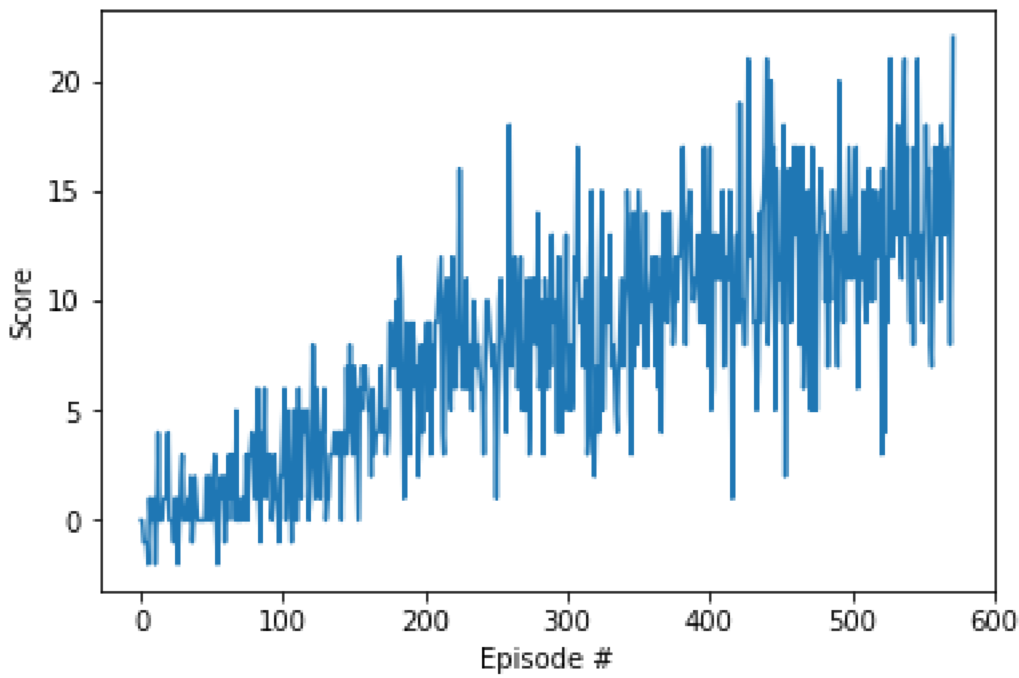
```
In [1]: def dqn(n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995):
            """Deep Q-Learning.

            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
                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
                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:
                    print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'
                          .format(i_episode, np.mean(scores_window)))
                    torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                    break
            return scores
```

1.0.8 4. Start training

```
In [8]: # start training
        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: 1.00
Episode 200	Average Score: 4.52
Episode 300	Average Score: 8.26
Episode 400	Average Score: 9.80
Episode 500	Average Score: 11.98
Episode 572	Average Score: 13.00
Environment solved in 572 episodes!	Average Score: 13.00
```



1.0.9 5. Load the trained network weights

In [9]:
```
# load the trained network weights
agent.qnetwork_local.load_state_dict(torch.load('checkpoint.pth'))

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 = agent.act(state)                      # 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("Single episode agent score after training: {}".format(score))
env.close()
```

```
Single episode agent score after training: 10.0
```

1.0.10 6. Future steps

For improving the agent's performance. There are many possible improvements to this algorithm like:
* Double DQN, * Dueling DQN, * Prioritized Experience Replay, * Rainbow,

```
In [ ]:
```