Navigation

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1 Navigation - Using Double-DQN With Dueling Network

You are welcome to use this coding environment to train your agent for the project. Follow the instructions below to get started!

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 3.0.
```

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]: # Imports.
        import matplotlib.pyplot as plt
        %matplotlib inline

        # High-resolution plots for retina displays.
        %config InlineBackend.figure_format = 'retina'

        import os
        import torch
        import numpy as np
        import time
        import random

        # Hide any deprecate warnings.
        import warnings
        warnings.filterwarnings("ignore")

        # Utility imports.
```

```
        from collections import deque
        from unityagents import UnityEnvironment

        # Agents interact with, and learns from environments.
        from agent import Agent

        # Please do not modify the line below.
        env_path = "/data/Banana_Linux_NoVis/Banana.x86_64"
        env = UnityEnvironment(file_name=env_path)
```

```
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: , , ,
```

Obtain NVidia GPU information

```
In [3]: # Set the working device on the NVIDIA Tesla K80 accelerator GPU (depending on availabil
        # Otherwise we use the CPU.
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
        print('Using device:', str(device).upper())
        print()

        # Log additional info (when using the NVIDIA Tesla K80 accelerator).
        # See <https://www.nvidia.com/en-gb/data-center/tesla-k80/>.
        if device.type == 'cuda':
            print(torch.cuda.get_device_name(0))
            print('Memory Usage:')
            print('Allocated:', round(torch.cuda.memory_allocated(0)/1024**3,1), 'GB')
            print('Cached:   ', round(torch.cuda.memory_cached(0)/1024**3,1), 'GB')
```

```
Using device: CUDA

Tesla K80
Memory Usage:
```

```
Allocated: 0.0 GB
Cached:    0.0 GB
```

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. 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.

Note that **in this coding environment, you will not be able to watch the agent while it is training**, and you should set `train_mode=True` to restart the environment.

```
In [6]: 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 = 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
```

1.0.4 4. It's Your Turn!

Now it's your turn to train your own agent to solve the environment! A few **important notes**: - 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]
```

- To structure your work, you're welcome to work directly in this Jupyter notebook, or you might like to start over with a new file! You can see the list of files in the workspace by clicking on ***Jupyter*** in the top left corner of the notebook.
- In this coding environment, you will not be able to watch the agent while it is training. However, ***after training the agent***, you can download the saved model weights to watch the agent on your own machine!

Define the Training Function

```
In [7]: """ Global configuration.
        """
        TOGGLE_DOUBLE_DQN = True              # True for the Double-DQN method. False for the fixe
        TOGGLE_DUELING_NETWORK = True         # True for the Dueling Network (DN) method.
        TOGGLE_PRIORITIZED_REPLAY = False     # True for the Prioritized Replay memory buffer.
```

```
In [8]: def dqn(n_episodes=int(2e3), max_t=int(1e3), eps_start=1., eps_end=1e-2, eps_decay=995e-
            """ Implementation of the Deep Q-Network (DQN) algorithm.

            Params
            ======
                n_episodes (int): Maximum number of training episodes
                max_t (int): Maximum number of timesteps per episode
```

```python
        eps_start (float): Starting value of epsilon (), for epsilon-greedy action selec
        eps_end (float): Minimum value of epsilon ()
        eps_decay (float): Multiplicative factor (per episode, ) for decreasing epsilon
    """

    # List containing scores from each episode.
    scores = []

    # List the mean of the window scores.
    scores_mean = []

    # Last 100 scores.
    scores_window = deque(maxlen=100)

    # Initialize epsilon ().
    eps = eps_start

    for i_episode in range(1, n_episodes+1):
        state = env.reset(train_mode=True)[brain_name].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 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]                  # Gee if episode has finished
            agent.step(state, action, reward, next_state, done)
            state = next_state
            score += reward
            if done:
                break

        # Save most recent score.
        scores.append(score)

        # Save most recent score.
        scores_window.append(score)
        scores_mean.append(np.mean(scores_window))

        # Log the scores.
        print('\rEPISODE {}\tAVG SCORE: {:.4f}\tEPS: {:.4f}\tLEARNING RATE: {}'
              .format(i_episode, scores_mean[-1], eps, agent.lr_scheduler.get_lr()), end

        # Decrease epsilon.
        eps = max(eps_end, eps_decay*eps)

        if i_episode % 100 == 0:
            print('\rEPISODE {}\tAVG SCORE: {:.4f}\tEPS: {:.4f}\tLEARNING RATE: {}'.form
```

```
                        i_episode, scores_mean[-1], eps, agent.lr_scheduler.get_lr()))

                if np.mean(scores_window) >= 13.:
                    print('\n\nEnvironment solved in {:d} episodes.\nAverage score: {}.'.format(
                        i_episode-100, np.mean(scores_window)))
                    torch.save(agent.qnetwork_local.state_dict(), 'models/checkpoint_double_dqn_
                    print("Model saved successfully.")
                    break

            # Return the scores.
            return scores, scores_mean
```

Create and Train the Agent

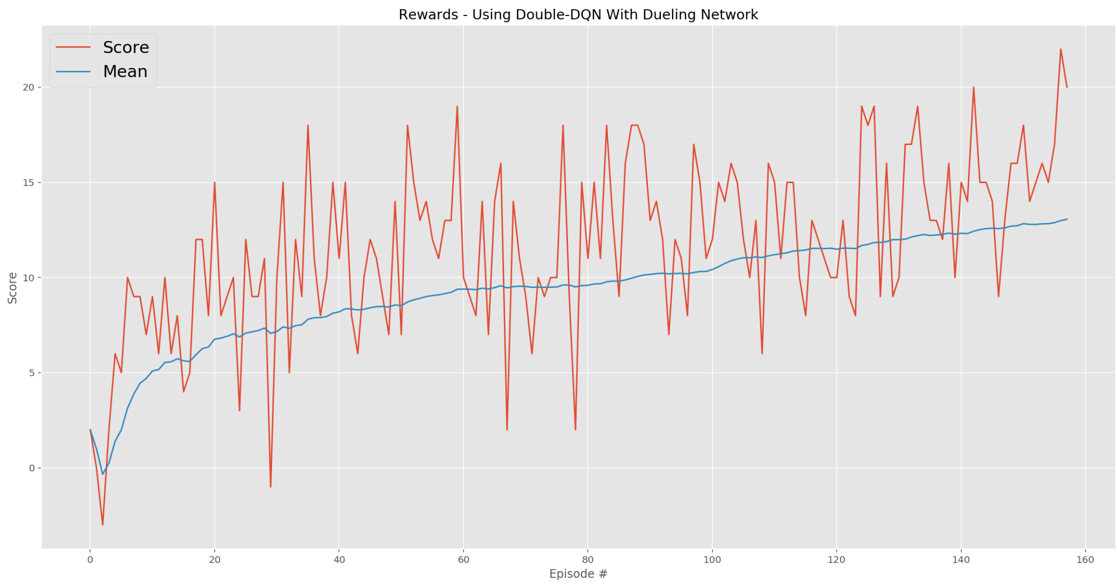
```
In [9]: # Initialize a DQN agent instance.
        agent = Agent(
            state_size=state_size, action_size=action_size, seed=0,
            double_dqn=TOGGLE_DOUBLE_DQN,
            dueling_network=TOGGLE_DUELING_NETWORK,
            prioritized_replay=TOGGLE_PRIORITIZED_REPLAY)

        # Monitor training time (start time).
        start_time = time.time()

        # Now, we train the agent.
        scores, mean = dqn(n_episodes=int(2e3), max_t=int(3e2), eps_start=1e-1, eps_end=1e-2, ep

        # Monitor training time (end time).
        end_time = (time.time()-start_time)/6e1

        # Log the runtime.
        print("\nSolved in {:.2f} minutes.".format(end_time))
```

```
EPISODE 100        AVG SCORE: 10.3200        EPS: 0.0270        LEARNING RATE: [0.00022711322607
EPISODE 158        AVG SCORE: 13.0600        EPS: 0.0128        LEARNING RATE: [0.00014699916918

Environment solved in 58 episodes.
Average score: 13.06.
Model saved successfully.

Solved in 4.06 minutes.
```

Plot the Results

```
In [10]: # Plot the scores using matplotlib.
         plt.style.use('ggplot')
```

```
fig = plt.figure(figsize=(20,10))
ax = fig.add_subplot(111)
plt.title('Rewards - Using Double-DQN With Dueling Network')
plt.plot(np.arange(len(scores)), scores)
plt.plot(np.arange(len(mean)), mean)
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.legend(('Score', 'Mean'), fontsize='xx-large')

# Reveal the plot.
plt.show()
```



Reset the Environment Now, we reset the environment and load the saved model (checkpoint) for further training.

```
In [11]: try:
             env
         except:
             env = UnityEnvironment(env_path) # Should be "/data/Banana_Linux_NoVis/Banana.x86_6

             # Get the default brain.
             brain_name = env.brain_names[0]
             brain = env.brains[brain_name]

             # Get the environment info (reusing code from above).
             env_info = env.reset(train_mode=False)[brain_name]

             # Number of actions.
```

```
    action_size = brain.vector_action_space_size

    # Examine the state space.
    state = env_info.vector_observations[0]
    state_size = len(state)

    # Initialize a DQN agent instanceins.
    agent = Agent(
        state_size=state_size, action_size=action_size, seed=0, lr_decay=9999e-4,
        double_dqn=TOGGLE_DOUBLE_DQN,
        dueling_network=TOGGLE_DUELING_NETWORK,
        prioritized_replay=TOGGLE_PRIORITIZED_REPLAY)

# Load the saved model (checkpoint).
state_dict = torch.load('models/checkpoint_double_dqn_dn.pth')
agent.qnetwork_local.load_state_dict(state_dict)
agent.qnetwork_local.eval()

# Try different parameters.
max_t = int(3e2)
n_episodes = 5 # 10.

# Monitor training time (start time).
start_time = time.time()

# List containing scores from each episode.
scores = []

# List the mean of the window scores.
scores_mean = []

for i_episode in range(1, n_episodes+1):
    state = env.reset(train_mode=False)[brain_name].vector_observations[0]
    score = 0
    for t in range(max_t):
        action = agent.act(state)
        env_info = env.step(action)[brain_name]        # Send the action to the environ
        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]                  # Gee if episode has finished.
        state = next_state
        score += reward
        print('\rEPISODE {}\tSCORE: {:.2f}'.format(i_episode, score), end="")
        if done:
            break

    # Save most recent score.
    scores.append(score)
```

```
            # Save most recent score.
            scores_mean.append(np.mean(scores))

            # Log the current episode.
            print('\rEPISODE {}\tSCORE: {:.2f}'.format(i_episode, scores[-1]))

        # Monitor training time (end time).
        end_time = (time.time()-start_time)/6e1

        # Log the runtime.
        print("\nRuntime: {:.2f} minutes.".format(end_time))
```

```
EPISODE 1        SCORE: 18.00
EPISODE 2        SCORE: 18.00
EPISODE 3        SCORE: 9.00
EPISODE 4        SCORE: 13.00
EPISODE 5        SCORE: 9.00

Runtime: 2.49 minutes.
```

We're Finished! When finished, you can close the environment.

```
In [12]: env.close()
```