Navigation

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1 Navigation

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.
```

```
In [2]: print('Start')
```

```
Start
```

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 [3]: # from unityagents import UnityEnvironment
        # import numpy as np

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

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)
```

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 environmen
#     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
#     if done:                                       # exit loop if episode finished
#         break

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

When finished, you can close the environment.

In [7]:
```
# env.close()
```

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!

In [8]:
```
###########################################



import random
from collections import deque
import matplotlib.pyplot as plt
from unityagents import UnityEnvironment
import numpy as np
import torch

from dqn_agent import Agent


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

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


# 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)
```

```
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: , , ,


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
```

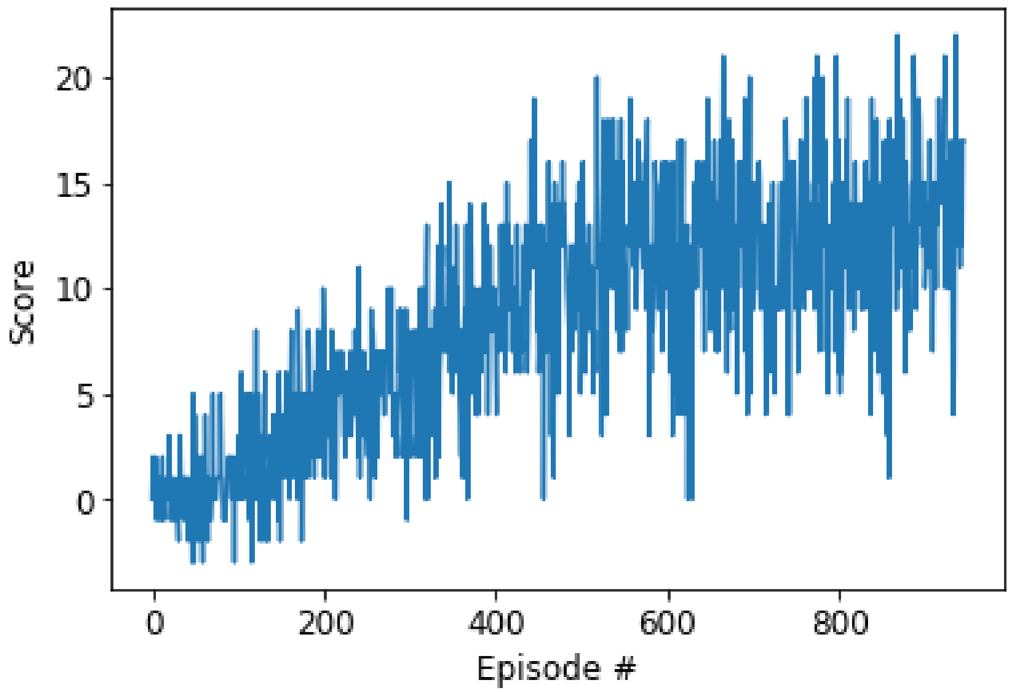
In [9]:
```
n_episodes = 2000

        max_t=1000
        eps_start=1.0
        eps_end=0.01
        eps_decay=0.995
        env=env
        brain=brain

        """Deep Q-Learning.

        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 selection
    eps_end (float): minimum value of epsilon
    eps_decay (float): multiplicative factor (per episode) for decreasing epsilon
    """
    agent = Agent(state_size=state_size, action_size=action_size, seed=0)

    env_info = env.reset(train_mode=True)[brain_name] # reset the environment

    state = env_info.vector_observations[0]

    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):
        count_timesteps = 0
        state = env_info.vector_observations[0]
        score = 0
        for t in range(max_t):

            action = agent.act(state, eps)
            #step
            env_info = env.step(action)[brain_name]
            # get next state
            next_state = env_info.vector_observations[0]
            # reward
            reward = env_info.rewards[0]
            #done
            done = env_info.local_done[0]
            #print(f'Done is : {done}')

            agent.step(state, action, reward, next_state, done)
            state = next_state
            score += reward

            #print(count_timesteps)
            count_timesteps +=1

            #print(f'The score is {score}, the action is {action}')
            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
```

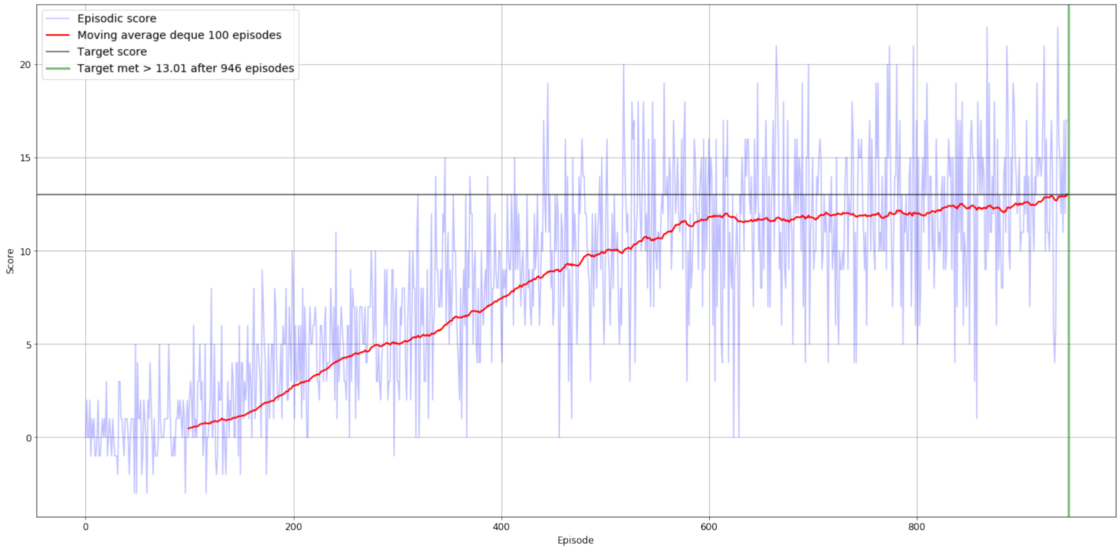
```
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_window)
            
            if i_episode % 100 == 0:
                print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_win
            
            if np.mean(scores_window)>=13.01:
                print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format(i_e
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                break
            env_info = env.reset(train_mode=True)[brain_name]
```

```
Episode 100	Average Score: 0.48
Episode 200	Average Score: 2.72
Episode 300	Average Score: 5.06
Episode 400	Average Score: 7.42
Episode 500	Average Score: 9.88
Episode 600	Average Score: 11.75
Episode 700	Average Score: 11.80
Episode 800	Average Score: 12.00
Episode 900	Average Score: 12.55
Episode 946	Average Score: 13.04
Environment solved in 846 episodes!	Average Score: 13.04
```

In [29]:
```
# 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()
```



In [33]:
```
import pandas as pd


fig, ax = plt.subplots(1, 1, figsize=[20, 10])
plt.rcParams.update({'font.size': 14})

scores_rolling = pd.Series(scores).rolling(100).mean()
ax.plot(scores, "-", c="blue", alpha=0.25)
ax.plot(scores_rolling, "-", c="red", linewidth=2)
ax.set_xlabel("Episode")
ax.set_ylabel("Score")
ax.grid(which="major")
ax.axhline(13.01, c="black", linewidth=2, alpha=0.5)
ax.axvline(i_episode, c="green", linewidth=3, alpha=0.5)
ax.legend(["Episodic score", "Moving average deque 100 episodes", "Target score", f'Tar

fig.tight_layout()
fig.savefig("Result_episodic_scores.jpg")
```



In [15]:
```
#state = env_info.vector_observations[0]
#print(state)

torch.save(agent.qnetwork_local.state_dict(), 'checkpoint_OPTIMAL.pth')
```

In [12]:
```
# with open("Output.txt", "w") as text_file:
#     print(f"Score: {scores}", file=text_file)
```

In [ ]: