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 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]: from unityagents import UnityEnvironment
        from dqn_agent import Agent
        import torch
        import numpy as np
        import random
        from collections import deque
        import matplotlib.pyplot as plt
        %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. 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: 1.0
```

When finished, you can close the environment.

1.0.4 4. Train your agent

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]
```

- 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!

4.1 Learning Algorithm - DQN Deep Q-Networks(DQN) was proposed by Mnih et al. (2015). It takes agent's state as input and outputs Q action values. It uses experience replay and target network to stabilize the model training.

```
<img src="images/pseudocode-dqn.png" width="400" height="400">
<br>
<figcaption style = "text-align:center; font-style:italic">Taken from Human-level control throug
```

4.2 Model Architecture The model is made of three fully connected layers. The number of neurons in first two layers is 64 and in the last layer it's equal to action size. Each layer's output except the last layer is transformed using the RelU activation function.

4.3 Hyperparameters

- 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
- n_episodes = 2000 # maximum number of training episodes
- max_t = 1000 # maximum number of time steps per episode
- eps_start = 1.0 # starting value of epsilon, for epsilon-greedy action selection
- eps_end = 0.01 # minimum value of epsilon

- eps_decay = 0.995 # multiplicative factor (per episode) for decreasing epsilon

In [7]:
```
agent = Agent(state_size=37, action_size=4, seed=0)
```

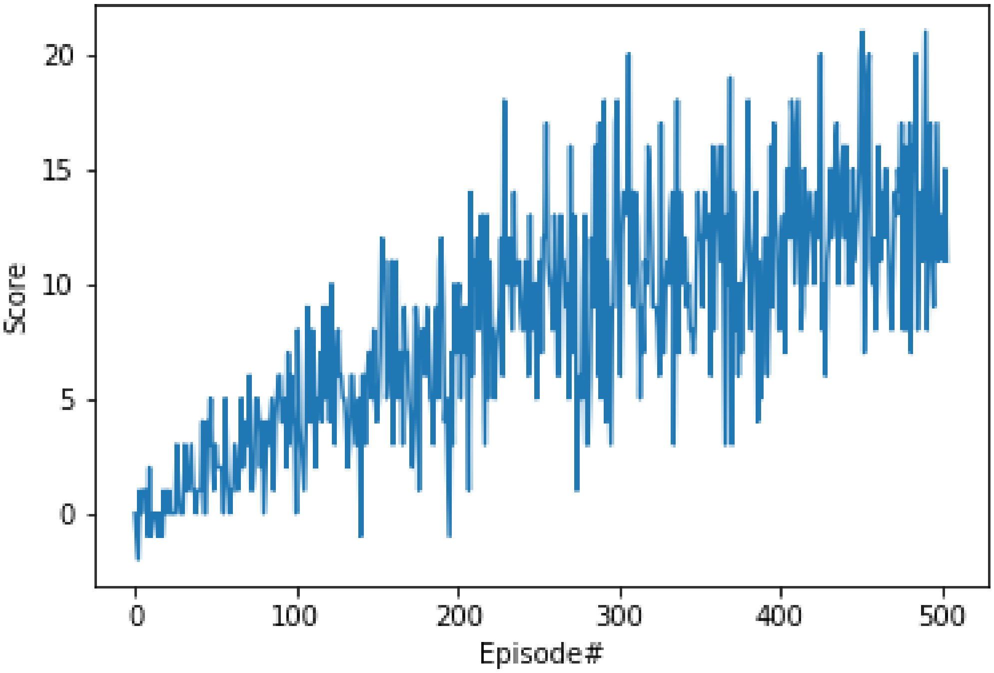
In [10]:
```
def dqn(n_episodes = 2000, max_t = 1000, eps_start = 1.0, eps_end = 0.01, eps_decay = 0
    """Deep Q-Learning.
    Params
    ======
    n_episodes (int): maximum number of training episodes
    max_t (int): maximum number of time steps per episode
    eps_start (float): starting value 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 hundred 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)
        scores.append(score)
        eps = max(eps_end, eps_decay*eps)
        print("\rEpisode {}\tAverage Score: {:.2f}".format(i_episode, np.mean(scores_wi
        if i_episode % 100 == 0:
```

```
                print("\rEpisode {}\tAverage Score: {:.2f}".format(i_episode, np.mean(score
            if np.mean(scores_window) >= 13.0:
                print("\nEnvironment solved in {:d} episodes!\t Average score: {:.2f}".form
                torch.save(agent.qnetwork_local.state_dict(), 'checkpoint.pth')
                break
        return scores
```

```
In [11]: scores = dqn()
```

```
Episode 100        Average Score: 1.93
Episode 200        Average Score: 5.83
Episode 300        Average Score: 9.50
Episode 400        Average Score: 10.81
Episode 500        Average Score: 12.93
Episode 504        Average Score: 13.02
Environment solved in 504 episodes!         Average score: 13.02
```

```
In [12]: fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(len(scores)), scores)
         plt.ylabel("Score")
         plt.xlabel("Episode#")
         plt.show()
```



```
In [18]: #Load a trained agent
         agent.qnetwork_local.load_state_dict(torch.load("checkpoint.pth"))

         for i in range(3):
             env_info = env.reset(train_mode=False)[brain_name]
             state = env_info.vector_observations[0]
             score = 0
             for j in range(1000):
                 action = agent.act(state)
                 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

             print("\rEpisode {}\t Score: {:.2f}".format(i+1, score))
```

```
Episode 1         Score: 17.00
Episode 2         Score: 13.00
Episode 3         Score: 16.00
```

```
In [19]: env.close()
```

1.0.5 5. Future ideas to improve the agent's performance

More experiments can be done to increase the performance of agent by applying different extensions of DQN: * Double DQN (DDQN) * Prioritized experience replay * Dueling DQN * A3C * Distributional DQN * Noisy DQN

We can also apply all the abobe extensions together. This was done by Deepmind's researchers and they have termed it Rainbow. This algorithm has outperformed each of the extension achieved SOTA results on Atari 2600.

```
<img src="images/rainbow.png" width="400" height="400">
<br>
<figcaption style = "text-align:center; font-style:italic">Taken from Rainbow: Combining Improve
```

```
In [ ]:
```