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
```

1.0.2 2. 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 [2]: #import the right packages
        from unityagents import UnityEnvironment
        import torch
        import numpy as np
        import matplotlib.pyplot as plt
        from agent import DQH2Agent, DDQH2Agent, DQH3Agent, DDQH3Agent
        from collections import deque
        %matplotlib inline

        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: , , ,
```

1.0.3 3. 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.

In [3]:
```
# get the default brain
brain_name = env.brain_names[0]
brain = env.brains[brain_name]

# Reset the Unity 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)
print(type(state))
state_size = len(state)
print('action_size = ', action_size, '  state_size = ', 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.        ]
<class 'numpy.ndarray'>
action_size =  4   state_size =  37
```

1.0.4 4. Define the training function

Pass the agent and the training parameters. - I have noticed a faster convergence with epsilon decay set at 0.99

```
In [4]: def train(name, agent, n_episodes=2000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_dec
            """Deep Q-Learning.

            Args
                name (string) use for saving the model
                agent to be used for the training
                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 selectic
                eps_end (float): minimum value of epsilon
                eps_decay (float): multiplicative factor (per episode) for decreasing epsilon
                train (bool): flag deciding if the agent will train or just play through the epi
            """
            # scores from each episode
            scores = []
            # scores from last 100 scores
            scores_window = deque(maxlen=100)

            # initialize epsilon
            eps = eps_start

            for i_episode in range(1, n_episodes+1):
                env_info = env.reset(train_mode=train)[brain_name]
                state = env_info.vector_observations[0]
                score = 0
                for t in range(max_t):
                    action = agent.act(state, eps if train else 0.0)
                    env_info = env.step(action)[brain_name]

                    # get the next state
                    next_state = env_info.vector_observations[0]
```

```
                # get the reward
                reward = env_info.rewards[0]

                # see if episode has finished
                done = env_info.local_done[0]

                # go to next state
                agent.step(state, action, reward, next_state, done)
                # update the score
                score += reward
                # roll over the state to next time step
                state = next_state

                # exit loop if episode finished
                if done:
                    break

            # save most recent score
            scores_window.append(score)
            scores.append(score)
            # decrease epsilon
            eps = max(eps_end, eps_decay*eps)

            print('\rEpisode {}\tMean Score: {:.2f}'.format(i_episode, np.mean(scores_window
            if i_episode % 100 == 0:
                print('\rEpisode {}\tMean Score: {:.2f}'.format(i_episode, np.mean(scores_wi
            if np.mean(scores_window)>=13.0 and train:
                print('\nBanana Environment solved in {:d} episodes!\tScore: {:.2f}'.format(
                torch.save(agent.dqnetwork_local.state_dict(), name)
                break
        return scores
```

1.0.5 5. First Trial

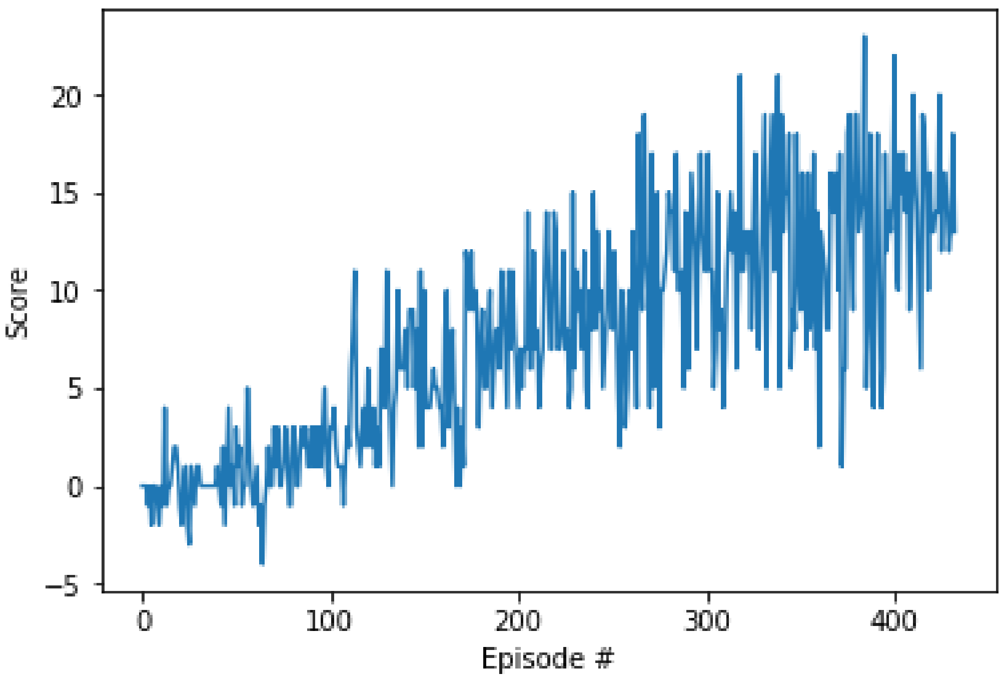
Deep Q Network with a 2 hidden layers neural network - I've changed the default value to 128 nodes at the first hidden layer and 64 nodes at the second hidden layer

```
In [5]: print('Deep Q-Network with 2 hiden layers using ', brain_name)
        # Execute the deep-q learning process
        agent = DQH2Agent(state_size=state_size, action_size=action_size, seed=0)
        scores = train("model_DQH2.pth",agent)

        # 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()
```

```
Deep Q-Network with 2 hiden layers using  BananaBrain
Episode 100        Mean Score: 0.58
Episode 200        Mean Score: 5.48
Episode 300        Mean Score: 9.48
Episode 400        Mean Score: 12.00
Episode 433        Mean Score: 13.04
Banana Environment solved in 433 episodes!        Score: 13.04
```



1.0.6 6. Second Trial

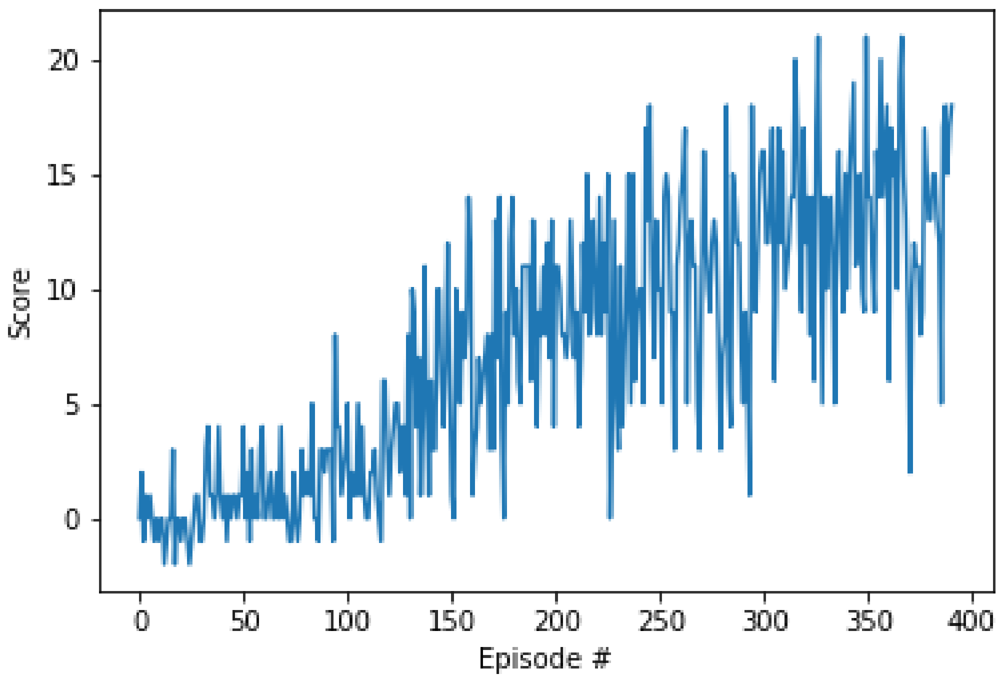
Double Deep Q Network with a 2 hidden layers neural network - I've also changed the default value to 128 nodes at the first hidden layer and 64 nodes at the second hidden layer

```
In [6]: print('Double Deep Q-Network with 2 hiden layers using ', brain_name)
        # Execute the deep-q learning process
        agent = DDQH2Agent(state_size=state_size, action_size=action_size, seed=0)
        scores = train("model_DDQH2.pth",agent)

        # 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()
```

```
Double Deep Q-Network with 2 hiden layers using  BananaBrain
Episode 100        Mean Score: 0.90
Episode 200        Mean Score: 5.83
Episode 300        Mean Score: 9.96
Episode 391        Mean Score: 13.01
Banana Environment solved in 391 episodes!        Score: 13.01
```



1.0.7 7. Third Trial

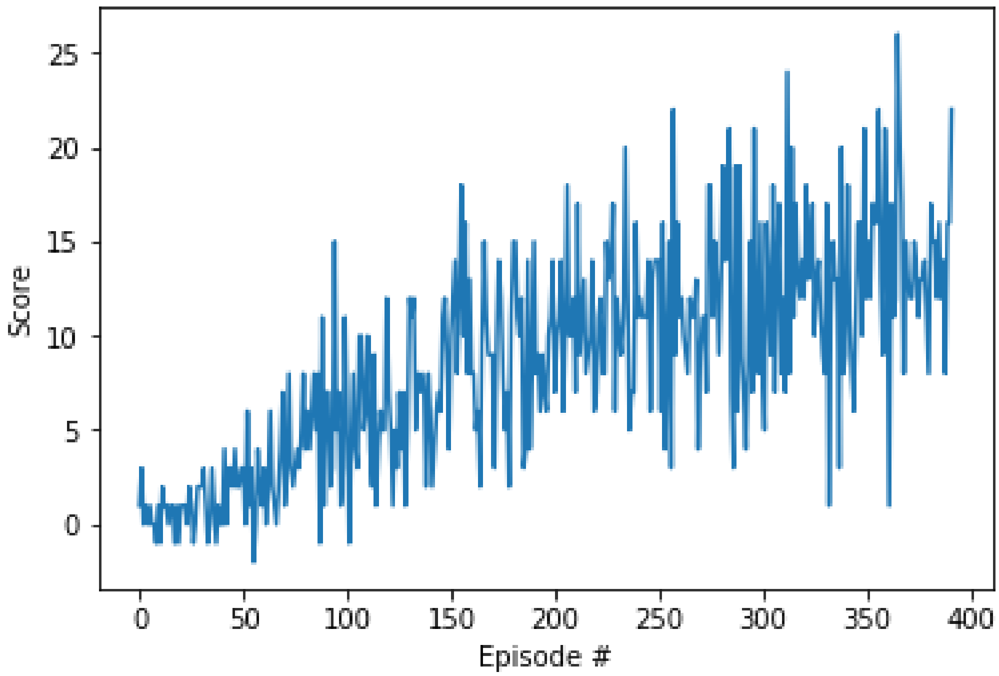
Deep Q Network with a 3 hidden layers neural network - I've used 64 nodes at the first hidden layer, 128 nodes at the second hidden layer and 64 nodes at the third hidden layer

```
In [7]: print('Deep Q-Network with 3 hiden layers using ', brain_name)
        # Execute the deep-q learning process
        agent = DQH3Agent(state_size=state_size, action_size=action_size, seed=0)
        scores = train("model_DQH3.pth",agent)

        # 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()
```

```
Deep Q-Network with 3 hiden layers using  BananaBrain
Episode 100        Mean Score: 2.49
Episode 200        Mean Score: 7.81
Episode 300        Mean Score: 11.30
Episode 392        Mean Score: 13.05
Banana Environment solved in 392 episodes!        Score: 13.05
```



1.0.8 8. Fouth Trial

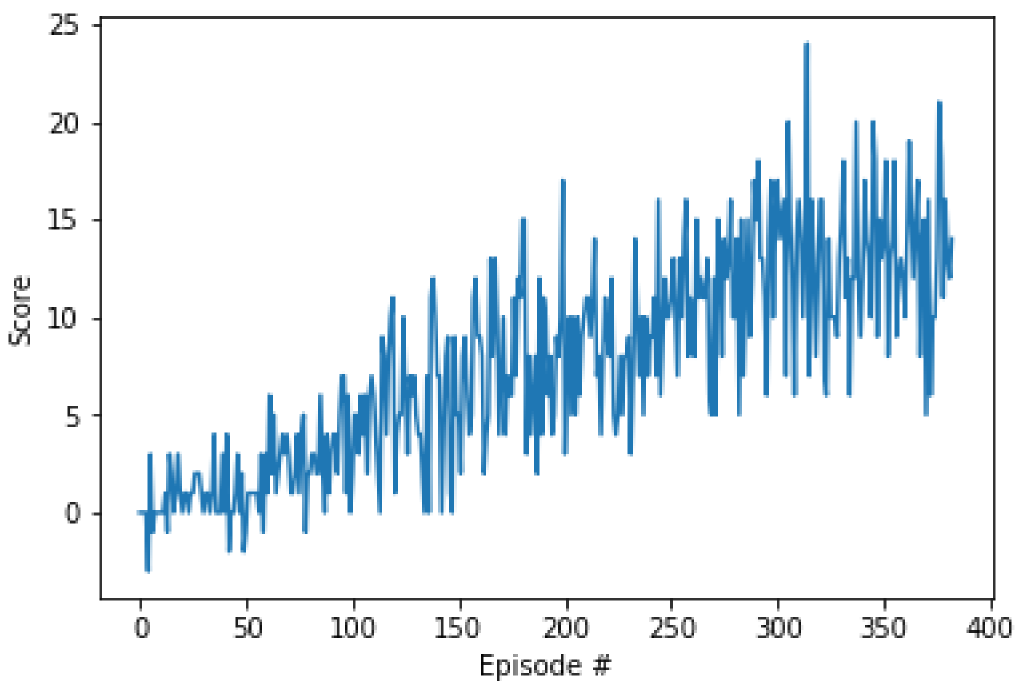
Double Deep Q Network with a 3 hidden layers neural network - I've used 64 nodes at the first hidden layer, 128 nodes at the second hidden layer and 64 nodes at the third hidden layer

```
In [5]: print('Double Deep Q-Network with 3 hiden layers using ', brain_name)
        # Execute the deep-q learning process
        agent = DDQH3Agent(state_size=state_size, action_size=action_size, seed=0)
        scores = train("model_DDQH3.pth",agent)

        # 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()
```

```
Double Deep Q-Network with 3 hiden layers using  BananaBrain
Episode 100        Mean Score: 1.62
Episode 200        Mean Score: 6.60
Episode 300        Mean Score: 10.02
Episode 383        Mean Score: 13.03
Banana Environment solved in 383 episodes!        Score: 13.03
```



1.0.9 9. conclusion

- Faster convergence has been observed when setting epsilon decay to 0.99 instead of 0.995
- Faster convergence has been observed when using more neurons at the first hidden layer (128) than at the second hidden layer (64)
- Faster convergence has been observed when using Double Deep Q Network
- Faster convergence has been observed when using a 3 hidden layer for the Deep Q implementation
- Best result has been obtained when using Double Deep Q Network with 3 hidden layers !
- No GPU required for getting this result

In [ ]: