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
```

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
        import numpy as np

        # 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 [3]: # 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 [4]: #### Do not run this again
        # 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 [5]: 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.

```
In [6]: 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!

1.0.5 Let's define the Agent class now alongwith the Q Network that we will use.

```
In [13]: import numpy as np
         import random
         import torch
         import torch.nn as nn
         import torch.nn.functional as F
         import torch.optim as optim
         from collections import namedtuple,deque

         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 network

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")



class Agent():


    def __init__(self, state_size, action_size, seed):
        """Initialize an Agent object.

        Params
        ======
            state_size (int): dimension of each state
            action_size (int): dimension of each action
            seed (int): random seed
        """
        # the state size and action size will be used to generate the Q Network
        self.state_size = state_size
        self.action_size = action_size
        ### random.seed(seed) generates sequence of random numbers by performing some o
        #If same initial value is used, it will generate the same sequence of random nu
        self.seed = random.seed(seed)

        # Q-Network
        self.qnetwork_local = QNetwork(state_size, action_size, seed).to(device)
        self.qnetwork_target = QNetwork(state_size, action_size, seed).to(device)
        self.optimizer = optim.Adam(self.qnetwork_local.parameters(), lr=LR)

        # Replay memory
        self.memory = Replay_Buffer(action_size, Buffer_Size, Batch_Size, seed)
        # Initialize time step (for updating every UPDATE_EVERY steps)
        self.t_step = 0

    def select_act(self, state, eps=0.):

        " selects action based on state and epsilon"

        # get the state array from env, convert to tensor

        state = torch.from_numpy(state).float().unsqueeze(0).to(device)

        # unsqueeze(0) adds a singleton dimension at 0 positon
        # useful because the states are in batches
        # to(device) moves the tensor to the device memory, cpu or cuda
```

```
        ## put network in eval mode
        self.qnetwork_local.eval()

        #get last_layer of the network to retrive index of the max reward
        with torch.no_grad(): # torch.no_grad() prevents calculating gradients in the f
            action_values = self.qnetwork_local(state)

        self.qnetwork_local.train()

        if random.random() > eps:
            return np.argmax(action_values.cpu().data.numpy())
        else:
            return np.random.randint(self.action_size)        # select an action
        #random.choice(np.arange(self.action_size))

    def learn(self,experiences,gamma):

        states, actions, rewards, next_states, dones = experiences

        # Get max predicted Q values (for next states) from target model
        Q_next_states = self.qnetwork_target(next_states).detach().max(1)[0].unsqueeze(

        # detach returns a new tensor detachd from the current graph
        # final layer is (batch_size ,action_size)i.e. (64,4), max(1), will find max in
        # the new tensor is (64,), we then add a singleton dimensin to it with unsqueez
        # Q_targets_next is the max reward of the four actons for each of the 64 states

        Q_target = rewards + (gamma*Q_next_states*(1-dones))


        Q_expected = self.qnetwork_local(states).gather(1,actions)

        #gather rearranges values in the dimension (1 here) of the input tensor (64,4),
        #as per the indices in the index tensor provided, actions here...actions carrie
        # given the state in states. SO only one value will be provided..it coud be eit
        #therefore output is 64,1.with reward corresponding to only that action chosen

        # the rewars generated by q_network local is used for comparison with Q_targets
        #then we update parametrs to min loss


        loss = F.mse_loss(Q_expected,Q_target)
        self.optimizer.zero_grad()
        loss.backward()
        self.optimizer.step()

        self.soft_update(self.qnetwork_local, self.qnetwork_target, TAU)
```

```
    def step(self,state,action,reward,next_state,done):

        self.memory.add(state,action,reward,next_state,done)

        self.t_step = (self.t_step+1) % UPDATE_EVERY # self.t_step will increase by 1 a
                                                    # that means every time step
        if self.t_step == 0:
            if len(self.memory) > Batch_Size:
                experiences = self.memory.sample()
                self.learn(experiences, gamma)

    def soft_update(self, local_model, target_model, TAU):
        """Soft update model parameters.
        _target = *_local + (1 - )*_target
        Params
        ======
            local_model (PyTorch model): weights will be copied from
            target_model (PyTorch model): weights will be copied to
            tau (float): interpolation parameter
        """
        for target_param, local_param in zip(target_model.parameters(), local_model.par
            target_param.data.copy_(TAU*local_param.data + (1.0-TAU)*target_param.data)



class Replay_Buffer:

    def __init__(self, action_size, Buffer_Size, Batch_Size,seed):

        self.action_size = action_size
        self.memory = deque(maxlen=Buffer_Size)
        self.Batch_Size = Batch_Size
        self.experience = namedtuple("Experience", field_names=["state", "action", "rew
        self.seed = random.seed(seed)

    def add(self, state,action,reward,next_state,done):

        e = self.experience(state,action,reward,next_state,done)
        # add state,action... values to the named tuple self.experience

        return self.memory.append(e)

    def sample(self):

        experiences = random.sample(self.memory, k = self.Batch_Size)
```

```
            states = torch.from_numpy(np.vstack([e.state for e in experiences if e is not N
            actions = torch.from_numpy(np.vstack([e.action for e in experiences if e is not
            rewards = torch.from_numpy(np.vstack([e.reward for e in experiences if e is not
            next_states = torch.from_numpy(np.vstack([e.next_state for e in experiences if
            dones = torch.from_numpy(np.vstack([e.done for e in experiences if e is not Non

            return (states,actions,rewards,next_states,dones)

        def __len__(self):
            return len(self.memory)


    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)
```

In [ ]:

1.1 Let's run the cell below and printout some information about the environment.

In [5]:
```
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(state.shape)
        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.        ]
(37,)
States have length: 37
```

```
In [8]: agent = Agent(state_size = 37, action_size = 4, seed = 0)
```

```
In [9]: def dqn_unity(num_episodes = 2000,  eps_start = 1, eps_decay=0.995, eps_end = 0.01):

            scores = [] # list of scores from each episode
            score_window = deque(maxlen = 100) # a deque of 100 episode scores to average
            eps = eps_start

            for i_episode in range(1,num_episodes+1):
                env_info = env.reset(train_mode=True)[brain_name] # reset the environment
                state = env_info.vector_observations[0]            # get the current state

                score = 0
                while True:


                    action = agent.select_act(state,eps)            # select an action
                    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]                   # see if episode has finished
                    agent.step(state,action,reward,next_state,done)
                    score += reward
                    state = next_state
```

```
            if done:
                break

        scores.append(score)
        score_window.append(score)
        eps = max(eps_end, eps_decay*eps) # decrease epsilon
        print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(score_wind
        if i_episode % 100 == 0:
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(score_
        if np.mean(score_window)>=13:
            print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format
            torch.save(agent.qnetwork_local.state_dict(), 'Banana_saved_model.pth')
            break

    return scores
```

1.2 Let's train our agent to solve the environment

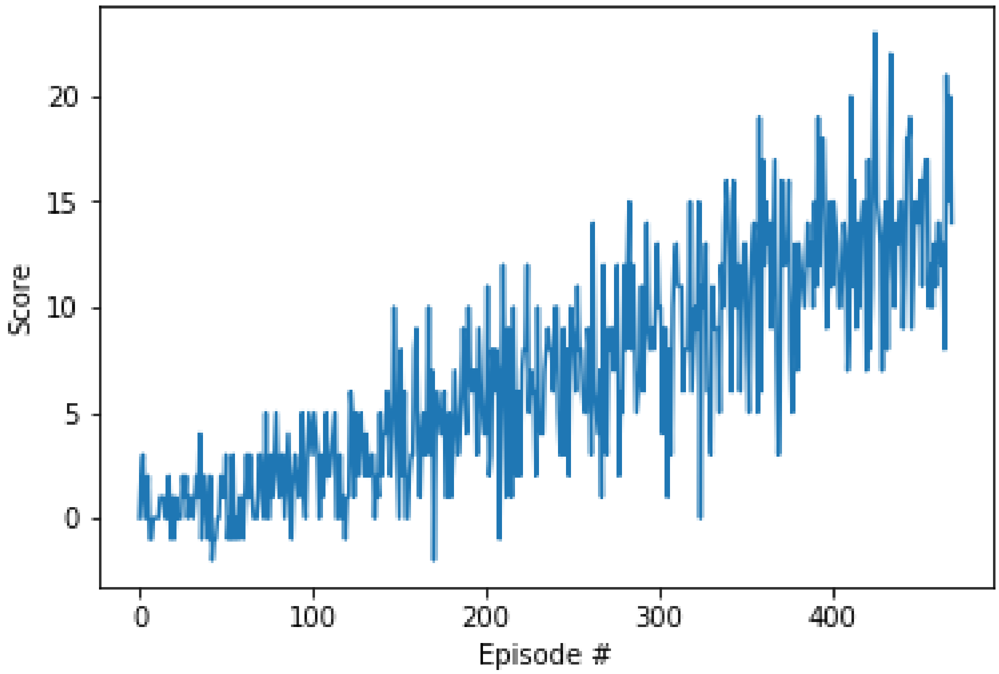
In [ ]:

In [10]:
```
import matplotlib.pyplot as plt
import numpy as np

scores = dqn_unity()


fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(len(scores)), scores)
plt.ylabel('Score')
plt.xlabel('Episode #')
plt.show()
#fig
```

```
Episode 100	Average Score: 1.08
Episode 200	Average Score: 3.77
Episode 300	Average Score: 7.10
Episode 400	Average Score: 10.63
Episode 470	Average Score: 13.10
Environment solved in 370 episodes!	Average Score: 13.10
```



1.3 Let's evaluate our model

```
In [29]: agent.qnetwork_local.load_state_dict(torch.load('Banana_saved_model.pth'))

In [30]: eps = 0.
         scores = []
         for i in range(5):

             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.select_act(state,eps)           # select an action

                 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]                  # see if episode has finished
                 score += reward                                # update the score
                 state = next_state                             # roll over the state to next ti
                 if done:                                       # exit loop if episode finished
                     break
             scores.append(score)
             #print("Score: {}".format(score))
         print('Avg score:',np.mean(scores))
```

```
Avg score: 14.2
```

As the average score over just 5 episodes is also over 13, i.e 14.2, we can say that we have solved the environment successfully using the DQN network.

```
In [ ]:
```