Report for Project 3 - Collaboration and Competition Udacity Deep Learning Nanodegree

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This notebook uses the Unity ML-Agents environment for the third project of the [Deep Reinforcement Learning Nanodegree (https://www.udacity.com/course/deep-reinforcement-learning-nanodegree--nd893)](https://www.udacity.com/course/deep-reinforcement-learning-nanodegree--nd893) program.

This notebook is run in a PC with NVidia GTX 1050 Ti, 16GB RAM, i7-7700 CPU.

1. Start the Environment

We begin by importing the necessary packages. If the code cell below returns an error, please revisit the project instructions to double-check that you have installed [Unity ML-Agents (https://github.com/Unity-Technologies/ml-agents/blob/master/docs/Installation.md)](https://github.com/Unity-Technologies/ml-agents/blob/master/docs/Installation.md) and [NumPy (http://www.numpy.org/)](http://www.numpy.org/).

In [1]:
```
from unityagents import UnityEnvironment
import numpy as np
```

Next, we will start the environment! ***Before running the code cell below***, change the `file_name` parameter to match the location of the Unity environment that you downloaded.

- **Mac**: `"path/to/Tennis.app"`
- **Windows** (x86): `"path/to/Tennis_Windows_x86/Tennis.exe"`
- **Windows** (x86_64): `"path/to/Tennis_Windows_x86_64/Tennis.exe"`
- **Linux** (x86): `"path/to/Tennis_Linux/Tennis.x86"`
- **Linux** (x86_64): `"path/to/Tennis_Linux/Tennis.x86_64"`
- **Linux** (x86, headless): `"path/to/Tennis_Linux_NoVis/Tennis.x86"`
- **Linux** (x86_64, headless): `"path/to/Tennis_Linux_NoVis/Tennis.x86_64"`

For instance, if you are using a Mac, then you downloaded `Tennis.app`. If this file is in the same folder as the notebook, then the line below should appear as follows:

```
env = UnityEnvironment(file_name="Tennis.app")
```

In [2]:
```
env = UnityEnvironment(file_name="Tennis_Windows_x86_64/Tennis.exe")
```

```
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: TennisBrain
        Number of Visual Observations (per agent): 0
        Vector Observation space type: continuous
        Vector Observation space size (per agent): 8
        Number of stacked Vector Observation: 3
        Vector Action space type: continuous
        Vector Action space size (per agent): 2
        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]
```

2. Examine the State and Action Spaces

In this environment, two agents control rackets to bounce a ball over a net. If an agent hits the ball over the net, it receives a reward of +0.1. If an agent lets a ball hit the ground or hits the ball out of bounds, it receives a reward of -0.01. Thus, the goal of each agent is to keep the ball in play.

The observation space consists of 8 variables corresponding to the position and velocity of the ball and racket. Two continuous actions are available, corresponding to movement toward (or away from) the net, and jumping.

Run the code cell below to print some information about the environment.

In [4]:
```
# reset the environment
env_info = env.reset(train_mode=True)[brain_name]

# number of agents
num_agents = len(env_info.agents)
print('Number of agents:', num_agents)

# size of each action
action_size = brain.vector_action_space_size
print('Size of each action:', action_size)

# examine the state space
states = env_info.vector_observations
state_size = states.shape[1]
print('There are {} agents. Each observes a state with length: {}'.format(states
print('The state for the first agent looks like:', states[0])
```

```
Number of agents: 2
Size of each action: 2
There are 2 agents. Each observes a state with length: 24
The state for the first agent looks like: [ 0.          0.          0.
0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.         -6.65278625 -1.5
 -0.          0.          6.83172083  6.         -0.          0.        ]
```

3. Take Random Actions in the Environment

In the next code cell, you will learn how to use the Python API to control the agents and receive feedback from the environment.

Once this cell is executed, you will watch the agents' performance, if they select actions at random with each time step. A window should pop up that allows you to observe the agents.

Of course, as part of the project, you'll have to change the code so that the agents are able to use their experiences to gradually choose better actions when interacting with the environment!

In [5]:
```
for i in range(1, 6):                                      # play game for 5 epi
    env_info = env.reset(train_mode=False)[brain_name]     # reset the environme
    states = env_info.vector_observations                  # get the current sta
    scores = np.zeros(num_agents)                          # initialize the scor
    while True:
        actions = np.random.randn(num_agents, action_size) # select an action (f
        actions = np.clip(actions, -1, 1)                  # all actions between
        env_info = env.step(actions)[brain_name]           # send all actions to
        next_states = env_info.vector_observations         # get next state (for
        rewards = env_info.rewards                         # get reward (for eac
        dones = env_info.local_done                        # see if episode fini
        scores += env_info.rewards                         # update the score (f
        states = next_states                               # roll over states to
        if np.any(dones):                                  # exit loop if episod
            break
    print('Score (max over agents) from episode {}: {}'.format(i, np.max(scores)
```

```
Score (max over agents) from episode 1: 0.0
Score (max over agents) from episode 2: 0.09000000171363354
Score (max over agents) from episode 3: 0.0
Score (max over agents) from episode 4: 0.0
Score (max over agents) from episode 5: 0.0
```

When finished, you can close the environment.

In [6]:
```
#env.close()
```

4. The experiments

Now it's your turn to train your own agent to solve the environment! 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]
```

Importing the necessary libraries to train the agent

Please refer to `agent.py` and `model.py` for the agent and model implementation in this notebook.

In [7]:
```
from collections import deque
import matplotlib.pyplot as plt
from agent import Agent
import torch
from replay_buffer import ReplayBuffer
import random

%matplotlib inline
```

Setting up the hyperparameters

In [8]:
```
BUFFER_SIZE=int(1e5)  # replay buffer size (1e6 in the original paper)
BATCH_SIZE=256   #minibatch size (64 in the original paper)
GAMMA=0.99     #discount factor
TAU=1e-2        #for soft update of target parameters
LR_ACTOR=1e-3     #learning rate of the actor
LR_CRITIC=1e-3   # learning rate of the critic
WEIGHT_DECAY=0   #L2 weight decay (1e-2 in original paper)
RANDOM_SEED=0

agent1 = Agent(
    state_size=state_size,
    action_size=action_size,
    buffer_size=BUFFER_SIZE,
    batch_size=BATCH_SIZE,
    gamma=GAMMA,
    tau=TAU,
    lr_actor=LR_ACTOR,
    lr_critic=LR_CRITIC,
    weight_decay=WEIGHT_DECAY,
    random_seed=RANDOM_SEED
)

agent2 = Agent(
    state_size=state_size,
    action_size=action_size,
    memory=agent1.memory, # Sharing replay memory between ddpg agents.
    batch_size=BATCH_SIZE,
    gamma=GAMMA,
    tau=TAU,
    lr_actor=LR_ACTOR,
    lr_critic=LR_CRITIC,
    weight_decay=WEIGHT_DECAY,
    random_seed=RANDOM_SEED
)
```

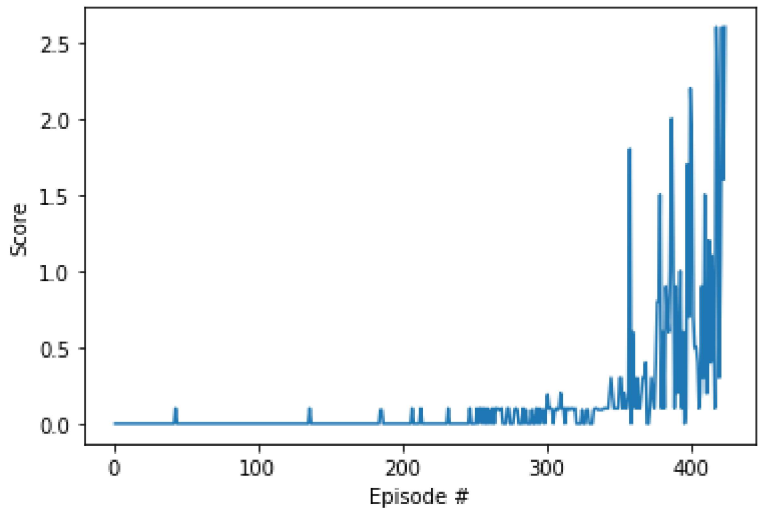
In [9]:
```
STOP_NOISE_AFTER_EP=300
env_info = env.reset(train_mode=True)[brain_name]
def ddpg(n_episodes=1500, print_every=100):
    scores_deque = deque(maxlen=print_every)
    scores = []
    best_score = 0.0
    add_noise = True
    for i_episode in range(1, n_episodes+1):
        if i_episode > STOP_NOISE_AFTER_EP:
            add_noise = False
        env_info = env.reset(train_mode=True)[brain_name]
        states = env_info.vector_observations
        agent1.reset()
        agent2.reset()
        scores_ep = np.zeros(num_agents)
        while True:
            action1 = agent1.act(states[0], add_noise=add_noise).tolist()
            action2 = agent2.act(states[1], add_noise=add_noise).tolist()
            actions = [action1, action2]
            env_info = env.step(actions)[brain_name]
            next_states = env_info.vector_observations
            rewards = env_info.rewards
            dones = env_info.local_done
            agent1.step(states[0], action1, rewards[0], next_states[0], dones[0]
            agent2.step(states[1], action2, rewards[1], next_states[1], dones[1]
            scores_ep += rewards
            states = next_states
            if np.any(dones):
                break
        max_score = np.max(scores_ep)
        scores_deque.append(max_score)
        scores.append(max_score)
        if max_score > best_score:
            best_score = max_score
        print('\rEpisode {}\tAverage Score: {:.2f} best_score {}'.format(i_episo
        torch.save(agent1.actor_local.state_dict(), 'checkpoint_actor1.pth')
        torch.save(agent1.critic_local.state_dict(), 'checkpoint_critic1.pth')
        torch.save(agent2.actor_local.state_dict(), 'checkpoint_actor2.pth')
        torch.save(agent2.critic_local.state_dict(), 'checkpoint_critic2.pth')
        if i_episode % print_every == 0:
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mea
        if np.mean(scores_deque) >= 0.5:
            print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}
            torch.save(agent1.actor_local.state_dict(), 'checkpoint_actor1.pth')
            torch.save(agent1.critic_local.state_dict(), 'checkpoint_critic1.pth
            torch.save(agent2.actor_local.state_dict(), 'checkpoint_actor2.pth')
            torch.save(agent2.critic_local.state_dict(), 'checkpoint_critic2.pth
            break
    return scores

scores = ddpg()

fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot(np.arange(1, len(scores)+1), scores)
plt.ylabel('Score')
```

```
plt.xlabel('Episode #')
plt.show()
```

```
Episode 100     Average Score: 0.00 best_score 0.10000000149011612
Episode 200     Average Score: 0.00 best_score 0.10000000149011612
Episode 300     Average Score: 0.03 best_score 0.10000000149011612
Episode 400     Average Score: 0.30 best_score 2.20000003278255466
Episode 424     Average Score: 0.52 best_score 2.6000000387430196
Environment solved in 424 episodes!     Average Score: 0.52
```



In [10]:
```
for i in range(1, 6):                                      # play game for 5 epi
    env_info = env.reset(train_mode=False)[brain_name]     # reset the environme
    states = env_info.vector_observations                  # get the current sta
    scores = np.zeros(num_agents)                          # initialize the scor
    while True:
        action1 = agent1.act(states[0], add_noise=False).tolist()
        action2 = agent2.act(states[1], add_noise=False).tolist()
        actions = [action1, action2]
        env_info = env.step(actions)[brain_name]           # send all actions to
        next_states = env_info.vector_observations         # get next state (for
        rewards = env_info.rewards                         # get reward (for eac
        dones = env_info.local_done                        # see if episode fini
        scores += env_info.rewards                         # update the score (f
        states = next_states                               # roll over states to
        if np.any(dones):                                  # exit loop if episod
            break
    print('Score (max over agents) from episode {}: {}'.format(i, np.max(scores)
```

```
Score (max over agents) from episode 1: 2.600000038743019
Score (max over agents) from episode 2: 2.7000000402331352
Score (max over agents) from episode 3: 2.600000038743019
Score (max over agents) from episode 4: 2.7000000402331352
Score (max over agents) from episode 5: 2.600000038743019
```

In [11]:
```
env.close()
```

EXPERIMENT 1

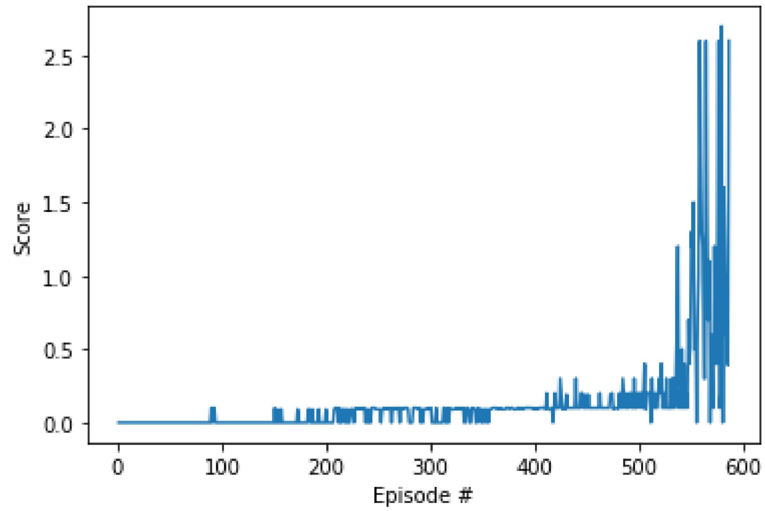
MODEL :
Actor- FC1 units (400), FC2 units (300)
Critic - FC1 units (256), FC2 units (128)
No dropout layer added
Optimizer: Adam

AGENT:
BUFFER_SIZE=int(1e6)
BATCH_SIZE=512

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 587 episodes with average score of 0.51.



EXPERIMENT 2

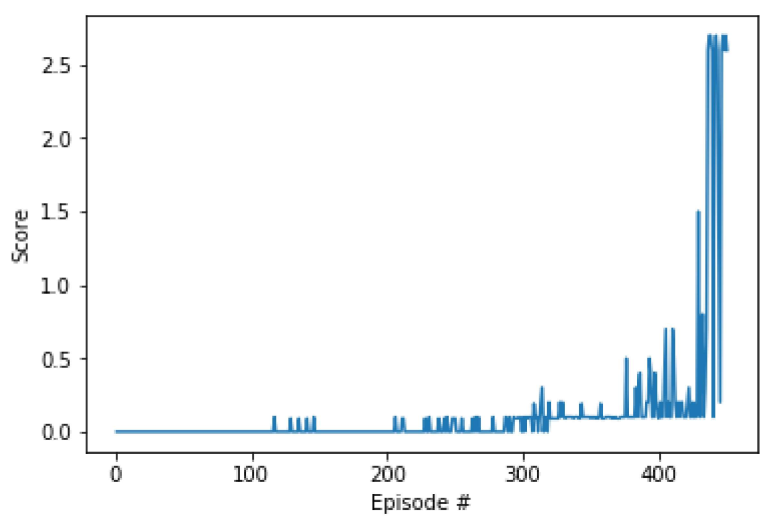
MODEL :
Actor- FC1 units (256), FC2 units (128)
Critic - FC1 units (256), FC2 units (128)
Dropout with probability 0.2 for each layer
Optimizer: Rectified Adam

AGENT:
BUFFER_SIZE=int(1e6)
BATCH_SIZE=256

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 450 episodes with average score of 0.5.



EXPERIMENT 3

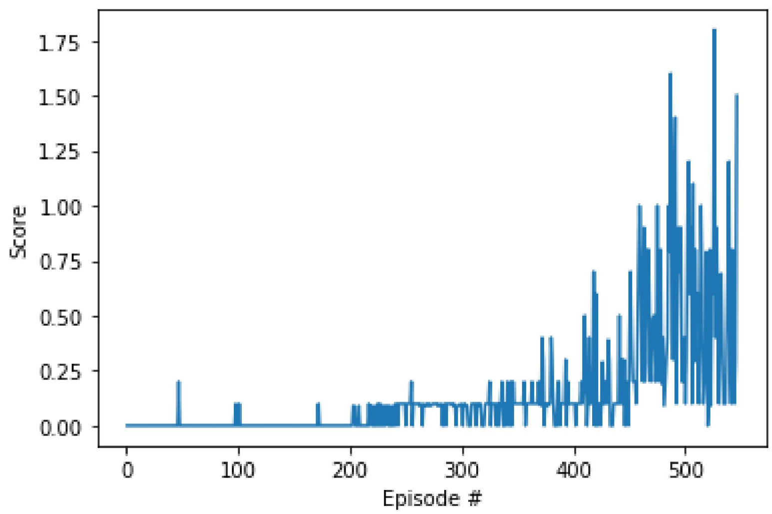
MODEL :
Actor- FC1 units (400), FC2 units (300)
Critic - FC1 units (256), FC2 units (128)
No dropout layer added
Optimizer: Rectified Adam

AGENT:
BUFFER_SIZE=int(1e6)
BATCH_SIZE=512

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 546 episodes with average score of 0.51.



EXPERIMENT 4

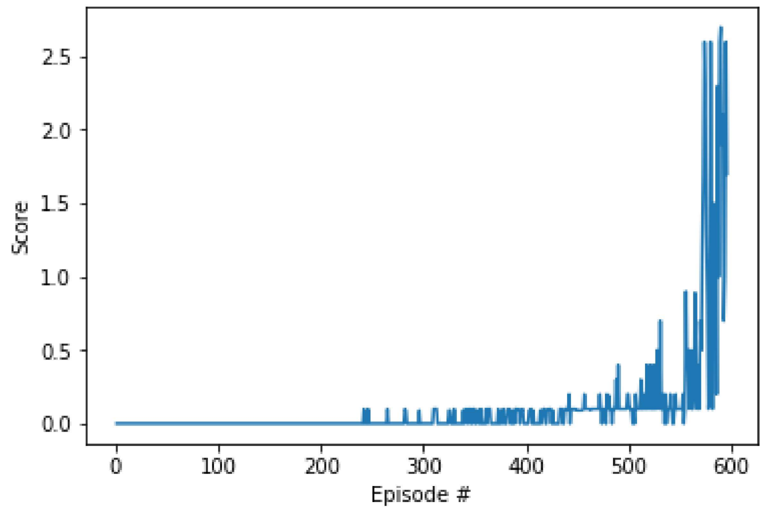
MODEL :
Actor- FC1 units (256), FC2 units (128)
Critic - FC1 units (256), FC2 units (128)
Dropout for each layer with probability of 0.2
Optimizer: Rectified Adam

AGENT:
BUFFER_SIZE=int(1e5)
BATCH_SIZE=256

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 596 episodes with average score of 0.51.



EXPERIMENT 5

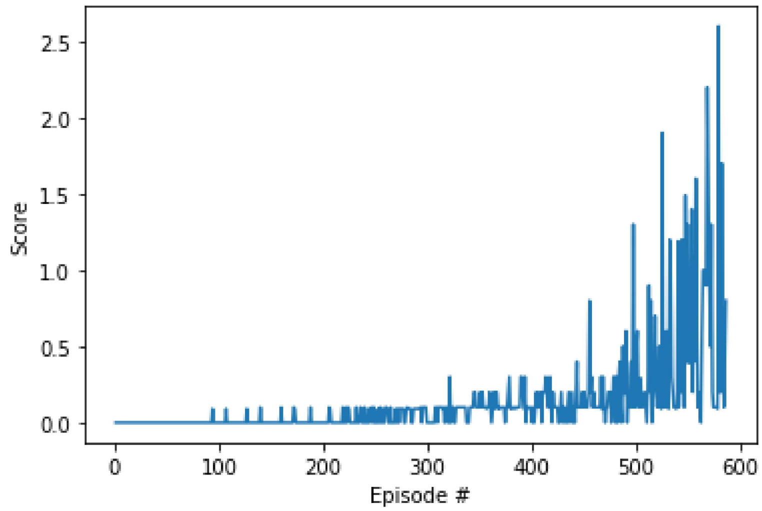
MODEL :
Actor- FC1 units (400), FC2 units (300)
Critic - FC1 units (256), FC2 units (128)
Dropout for each layer with probability of 0.2
Optimizer: Rectified Adam

AGENT:
BUFFER_SIZE=int(1e6)
BATCH_SIZE=512

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 587 episodes with average score of 0.50.



EXPERIMENT 6

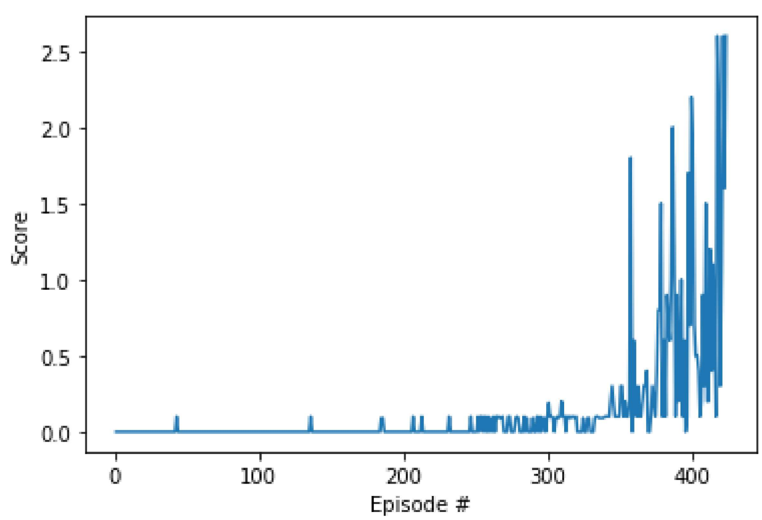
MODEL :
Actor- FC1 units (256), FC2 units (128)
Critic - FC1 units (256), FC2 units (128)
Dropout for each layer with probability of 0.25
Optimizer: Rectified Adam

AGENT:
BUFFER_SIZE=int(1e5)
BATCH_SIZE=256

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 424 episodes with average score of 0.52.



EXPERIMENT 6

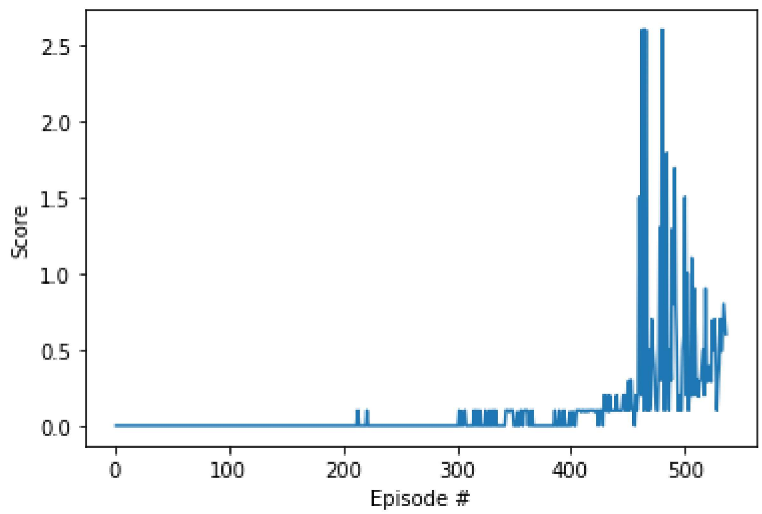
MODEL :
Actor- FC1 units (256), FC2 units (128)
Critic - FC1 units (256), FC2 units (128)
Dropout for each layer with probability of 0.25
Optimizer: Adam

AGENT:
BUFFER_SIZE=int(1e5)
BATCH_SIZE=256

TAU=1e-2
LR_ACTOR=1e-3

LR_CRITIC=1e-3

RESULTS:
Environment solved in 536 episodes with average score of 0.50.



Future Works

Try to implement by using Proximal Policy Optimization (PPO) and Distributed Distributional Deterministic Policy Gradients (D4PG) instead of DDPG.

```
In [ ]:
```