Continuous Control

In this notebook, you will learn how to use the Unity ML-Agents environment for the second project of the Deep Reinforcement Learning Nanodegree program.

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 and NumPy.

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/Reacher.app"`
- **Windows** (x86): `"path/to/Reacher_Windows_x86/Reacher.exe"`
- **Windows** (x86_64): `"path/to/Reacher_Windows_x86_64/Reacher.exe"`
- **Linux** (x86): `"path/to/Reacher_Linux/Reacher.x86"`
- **Linux** (x86_64): `"path/to/Reacher_Linux/Reacher.x86_64"`
- **Linux** (x86, headless): `"path/to/Reacher_Linux_NoVis/Reacher.x86"`
- **Linux** (x86_64, headless): `"path/to/Reacher_Linux_NoVis/Reacher.x86_64"`

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

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

In [2]:

```
env = UnityEnvironment(file_name='V1/Reacher.exe')
```

```
INFO:unityagents:
'Academy' started successfully!
Unity Academy name: Academy
        Number of Brains: 1
        Number of External Brains : 1
        Lesson number : 0
        Reset Parameters :
                goal_speed -> 1.0
                goal_size -> 5.0
Unity brain name: ReacherBrain
        Number of Visual Observations (per agent): 0
        Vector Observation space type: continuous
        Vector Observation space size (per agent): 33
        Number of stacked Vector Observation: 1
        Vector Action space type: continuous
```

```
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]
```

2. Examine the State and Action Spaces

In this environment, a double-jointed arm can move to target locations. A reward of `+0.1` is provided for each step that the agent's hand is in the goal location. Thus, the goal of your agent is to maintain its position at the target location for as many time steps as possible.

The observation space consists of `33` variables corresponding to position, rotation, velocity, and angular velocities of the arm. Each action is a vector with four numbers, corresponding to torque applicable to two joints. Every entry in the action vector must be a number between `-1` and `1`.

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.shap
print('The state for the first agent looks like:', states[0])
```

```
Number of agents: 1
Size of each action: 4
There are 1 agents. Each observes a state with length: 33
The state for the first agent looks like: [ 0.00000000e+00 -4.00000000e+00  0.0000000
0e+00  1.00000000e+00
 -0.00000000e+00 -0.00000000e+00 -4.37113883e-08  0.00000000e+00
  0.00000000e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
  0.00000000e+00  0.00000000e+00 -1.00000000e+01  0.00000000e+00
  1.00000000e+00 -0.00000000e+00 -0.00000000e+00 -4.37113883e-08
  0.00000000e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
  0.00000000e+00  0.00000000e+00  5.75471878e+00 -1.00000000e+00
  5.55726671e+00  0.00000000e+00  1.00000000e+00  0.00000000e+00
 -1.68164849e-01]
```

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.

Once this cell is executed, you will watch the agent's performance, if it selects an action at random with each time step. A window should pop up that allows you to observe the agent, as it moves through the environment.

Of course, as part of the project, you'll have to change the code so that the agent is able to use its experience to gradually choose better actions when interacting with the environment!

In [15]:

```
#env_info = env.reset(train_mode=False)[brain_name]     # reset the environment
#states = env_info.vector_observations                  # get the current state (for
#scores = np.zeros(num_agents)                          # initialize the score (for e
#while True:
#    actions = np.random.randn(num_agents, action_size) # select an action (for each
#    actions = np.clip(actions, -1, 1)                  # all actions between -1 and
#    env_info = env.step(actions)[brain_name]           # send all actions to tne env
#    next_states = env_info.vector_observations         # get next state (for each ag
#    rewards = env_info.rewards                         # get reward (for each agent)
#    dones = env_info.local_done                        # see if episode finished
#    scores += env_info.rewards                         # update the score (for each
#    states = next_states                               # roll over states to next ti
#    if np.any(dones):                                  # exit loop if episode finish
#        break
#print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

When finished, you can close the environment.

In [6]:

```
#env.close()
```

4. It's Your Turn!

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]
```

In [7]:

```
import torch
from ddpg_agent import Agent
from ddpg_result_visualization import plot_scores, format_episode_score
from ddpg_gridsearch import DDPGGridsearch
from ddpg_hyperparameters import DDPGHyperparameters
from collections import deque
from numpy import random
```

In [8]:

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda
```

In [9]:

```
moving_avg_size = 100
min_moving_avg_score = 30
print(f"Moving average size: {moving_avg_size}")
print(f"Minimum moving average score: {min_moving_avg_score}")
```

```
Moving average size: 100
Minimum moving average score: 30
```

4.1 Train the Agent with DDPG

In [10]:

```
def ddpg(agent, n_episodes=1000, max_t=1000, print_every=100, moving_avg_size=100, mi
         min_skip_episodes = 70, skip_score = 2.0):

    scores = []
    scores_window = deque(maxlen=moving_avg_size)
    needed_episodes = 0
    best_moving_avg_score = 0
    solved = False

    for i_episode in range(1, n_episodes+1):
        env_info = env.reset(train_mode=True)[brain_name]
        episode_score = 0                                    # initialize the scor
        agent.reset()                                        # reset the OUNoise o
        state = env_info.vector_observations[0]

        for t in range(max_t):
            action =  agent.act(state)
            env_info = env.step(action)[brain_name]          # send action to the
            next_state = env_info.vector_observations[0]     # get next state
            reward = env_info.rewards[0]                     # get reward
            done = env_info.local_done[0]                    # see if episode fini
            agent.step(state, action, reward, next_state, done)

            episode_score += reward                          # update the score
            state = next_state                               # roll over state to
            if done:
                break


        scores.append(episode_score)
        scores_window.append(episode_score)
        moving_avg_score = np.mean(scores_window)

        if moving_avg_score > best_moving_avg_score:
            best_moving_avg_score = moving_avg_score

        if (i_episode == min_skip_episodes) and moving_avg_score < skip_score: # skip
            print(format_episode_score(i_episode, episode_score, moving_avg_score))
            print(f"Episodes skipped\tEnvironment not solved!")
            break

        if i_episode % print_every == 0:
            print(format_episode_score(i_episode, episode_score, moving_avg_score))
        if (i_episode >= moving_avg_size) and (moving_avg_score >= min_moving_avg_sco
            print(format_episode_score(i_episode, episode_score, moving_avg_score))
            print(f"Environment solved!")
            needed_episodes = i_episode - moving_avg_size
            solved = True
            break
        if (i_episode+1 == n_episodes+1) and (moving_avg_score < min_moving_avg_score
            print(format_episode_score(i_episode, episode_score, moving_avg_score))
            print(f"Environment not solved!")

    return scores, best_moving_avg_score, needed_episodes, solved
```

In [11]:

```python
gridsearch = DDPGGridsearch()
hyperparameters = gridsearch.create_gridsearch_params() #create a grid search hyperpa

print("DDPGGridsearch hyperparameters:")
print(gridsearch)
print()
params_len = len(hyperparameters)

n_episodes = 1000
print_every = 10
max_t = 1000
best_scores = []
best_avg_score = 0
best_needed_episodes = 0
best_params = None
moving_avg_scores = []

for idx, params in enumerate(hyperparameters): #for every DDPQHyperparameters object
    print(f"DQNHyperparameters: {idx+1}/{params_len}")
    print(params)
    agent = Agent(device, params, state_size, action_size)

    scores, moving_avg_score, needed_episodes, solved = ddpg(agent=agent, n_episodes=
                                                     max_t=max_t, print_every=print_e
                                                     moving_avg_size=moving_avg_size,
                                                     min_moving_avg_score=min_moving_

    if (moving_avg_score >= best_avg_score): # find the best moving average score
        best_scores = scores
        best_needed_episodes = needed_episodes
        best_avg_score = moving_avg_score
        best_params = params
        score_v = int(best_avg_score)
        print(f"New best moving average score: {best_avg_score:.2f}")
        actor_cp = f"checkpoint_actor_{score_v}.pth"
        critic_cp = f"checkpoint_critic_{score_v}.pth"
        print(f"Save checkpoint {actor_cp}")
        print(f"Save checkpoint {critic_cp}")
        torch.save(agent.actor_local.state_dict(), actor_cp)   # save the best model
        torch.save(agent.critic_local.state_dict(), critic_cp) # save the best model

    if solved:
        break

    print()

print()
print("Best DDPGHyperparameters:")
print(best_params)
print(f"Solved in {best_needed_episodes} episodes.")
```

```
DDPGGridsearch hyperparameters:
lr_actor: [0.00015]
lr critic: [0.00015]
gamma: [0.99]
buffer size: [100000]
batch size: [128]
weight decay: [0.0001]
```

```
random seed: [4]
fc1 units actor: [600]
fc2 units actor: [400]
fc3 units actor: [200]

DQNHyperparameters: 1/1
lr_actor: 0.00015
lr_critic: 0.00015
gamma: 0.99
buffer_size: 100000
batch_size: 128
tau: 0.001
weight_decay: 0.0001
random_seed: 4
fc1_units actor: 600
fc2_units actor: 400
fc3_units actor: 200
fc1_units critic: 400
fc2_units critic: 300
Episode: 10     Episode average score: 0.44     Moving average score: 0.99
Episode: 20     Episode average score: 1.46     Moving average score: 1.02
Episode: 30     Episode average score: 0.06     Moving average score: 1.08
Episode: 40     Episode average score: 2.51     Moving average score: 1.21
Episode: 50     Episode average score: 2.29     Moving average score: 1.42
Episode: 60     Episode average score: 2.52     Moving average score: 1.73
Episode: 70     Episode average score: 6.82     Moving average score: 2.01
Episode: 80     Episode average score: 4.68     Moving average score: 2.33
Episode: 90     Episode average score: 3.38     Moving average score: 2.52
Episode: 100    Episode average score: 5.27     Moving average score: 2.77
Episode: 110    Episode average score: 9.00     Moving average score: 3.21
Episode: 120    Episode average score: 7.81     Moving average score: 3.82
Episode: 130    Episode average score: 6.43     Moving average score: 4.38
Episode: 140    Episode average score: 12.53    Moving average score: 5.02
Episode: 150    Episode average score: 13.77    Moving average score: 5.82
Episode: 160    Episode average score: 6.73     Moving average score: 6.45
Episode: 170    Episode average score: 9.24     Moving average score: 7.24
Episode: 180    Episode average score: 2.85     Moving average score: 7.71
Episode: 190    Episode average score: 13.19    Moving average score: 8.57
Episode: 200    Episode average score: 17.35    Moving average score: 9.34
Episode: 210    Episode average score: 8.05     Moving average score: 10.03
Episode: 220    Episode average score: 10.86    Moving average score: 10.55
Episode: 230    Episode average score: 11.69    Moving average score: 10.90
Episode: 240    Episode average score: 9.12     Moving average score: 11.18
Episode: 250    Episode average score: 13.37    Moving average score: 11.35
Episode: 260    Episode average score: 16.68    Moving average score: 11.56
Episode: 270    Episode average score: 13.32    Moving average score: 11.46
Episode: 280    Episode average score: 17.20    Moving average score: 12.12
Episode: 290    Episode average score: 10.01    Moving average score: 12.46
Episode: 300    Episode average score: 21.31    Moving average score: 12.72
Episode: 310    Episode average score: 14.74    Moving average score: 13.16
Episode: 320    Episode average score: 18.57    Moving average score: 13.60
Episode: 330    Episode average score: 12.81    Moving average score: 14.28
Episode: 340    Episode average score: 19.23    Moving average score: 14.93
Episode: 350    Episode average score: 8.84     Moving average score: 15.24
Episode: 360    Episode average score: 9.43     Moving average score: 15.73
Episode: 370    Episode average score: 19.24    Moving average score: 16.21
Episode: 380    Episode average score: 15.09    Moving average score: 16.41
Episode: 390    Episode average score: 11.55    Moving average score: 16.33
Episode: 400    Episode average score: 17.67    Moving average score: 16.78
Episode: 410    Episode average score: 24.00    Moving average score: 17.11
Episode: 420    Episode average score: 37.84    Moving average score: 17.84
Episode: 430    Episode average score: 29.40    Moving average score: 18.16
```

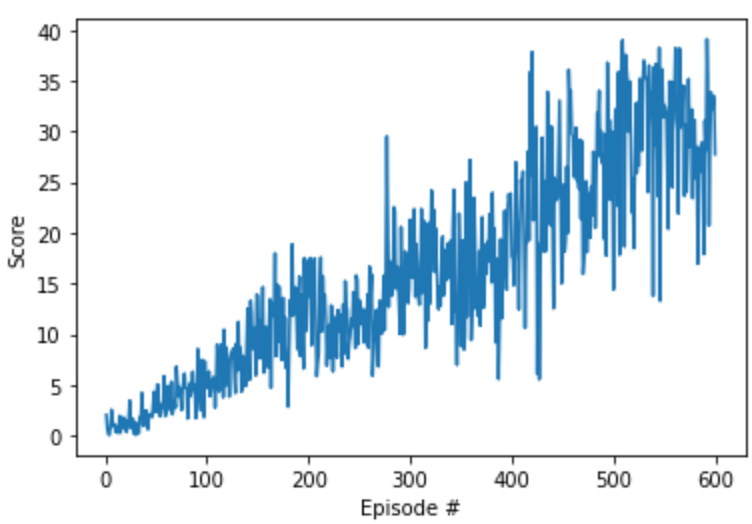
```
Episode: 440    Episode average score: 21.87    Moving average score: 18.91
Episode: 450    Episode average score: 17.64    Moving average score: 19.67
Episode: 460    Episode average score: 29.57    Moving average score: 20.73
Episode: 470    Episode average score: 15.94    Moving average score: 21.74
Episode: 480    Episode average score: 28.00    Moving average score: 22.18
Episode: 490    Episode average score: 27.70    Moving average score: 23.47
Episode: 500    Episode average score: 14.39    Moving average score: 24.05
Episode: 510    Episode average score: 34.09    Moving average score: 25.16
Episode: 520    Episode average score: 18.47    Moving average score: 25.63
Episode: 530    Episode average score: 37.01    Moving average score: 26.72
Episode: 540    Episode average score: 36.32    Moving average score: 27.39
Episode: 550    Episode average score: 32.60    Moving average score: 28.16
Episode: 560    Episode average score: 33.60    Moving average score: 28.49
Episode: 570    Episode average score: 23.62    Moving average score: 29.06
Episode: 580    Episode average score: 31.13    Moving average score: 29.76
Episode: 590    Episode average score: 31.08    Moving average score: 29.47
Episode: 600    Episode average score: 27.75    Moving average score: 30.01
Episode: 600    Episode average score: 27.75    Moving average score: 30.01
Environment solved!
New best moving average score: 30.01
Save checkpoint checkpoint_actor_30.pth
Save checkpoint checkpoint_critic_30.pth

Best DDPGHyperparameters:
lr_actor: 0.00015
lr_critic: 0.00015
gamma: 0.99
buffer_size: 100000
batch_size: 128
tau: 0.001
weight_decay: 0.0001
random_seed: 4
fc1_units actor: 600
fc2_units actor: 400
fc3_units actor: 200
fc1_units critic: 400
fc2_units critic: 300
```

4.2 Solution

In [12]:

```
plot_scores(best_scores)
```



The environment was solved with the DDPG algorithm in 500 episodes.

Model Architecture:
2 Actor Networks with 4 linear layers:
Linear layer 1: 33 x 600
Linear layer 2: 600 x 400
Linear layer 3: 400 x 200
Linear layer 4: 200 x 4

2 Critic Networks with 3 linear layers:
Linear layer 1: 33 x 400
Linear layer 2: (400+4) x 300
Linear layer 3: 300 x 1

Hyperparameters:
Learning rate actor: 0.00015
Learning rate critic: 0.00015
Gamma: 0.99
Buffer size: 100000
Batch size: 128
Tau: 0.001
Weight decay: 0.0001

Improvement
The model performance could possibly improved through batch normalization or dropout layers.

5. Close the environment

In [14]:
```
env.close()
```