Continuous_Control

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1 Continuous Control

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]: %%capture
        !pip install numpy --upgrade;
        !pip install --upgrade ipython;
        !pip -q install ./python;
```

The environments corresponding to both versions of the environment are already saved in the Workspace and can be accessed at the file paths provided below.

Please select one of the two options below for loading the environment.

```
In [2]: from unityagents import UnityEnvironment
        import numpy as np

        # select this option to load version 1 (with a single agent) of the environment
        #env = UnityEnvironment(file_name='/data/Reacher_One_Linux_NoVis/Reacher_One_Linux_NoVis

        # select this option to load version 2 (with 20 agents) of the environment
        env = UnityEnvironment(file_name='/data/Reacher_Linux_NoVis/Reacher.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 :
                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]
```

1.0.2 2. Examine the State and Action Spaces

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

```
Number of agents: 20
Size of each action: 4
There are 20 agents. Each observes a state with length: 33
The state for the first agent looks like: [ 0.00000000e+00 -4.00000000e+00  0.00000000e+00  1.00
 -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
```

```
 5.55726624e+00  0.00000000e+00  1.00000000e+00  0.00000000e+00
-1.68164849e-01]
```

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 agents while they are 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
        states = env_info.vector_observations                  # get the current state (for each
        scores = np.zeros(num_agents)                          # initialize the score (for each
        while True:
            actions = np.random.randn(num_agents, action_size) # select an action (for each agen
            actions = np.clip(actions, -1, 1)                  # all actions between -1 and 1
            env_info = env.step(actions)[brain_name]           # send all actions to tne environ
            next_states = env_info.vector_observations         # get next state (for each agent)
            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 agen
            states = next_states                               # roll over states to next time s
            if np.any(dones):                                  # exit loop if episode finished
                break
        print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

```
Total score (averaged over agents) this episode: 0.07599999830126762
```

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 agents while they are training. However, ***after training the agents***, you can download the saved model weights to watch the agents on your own machine!

1.0.5 5. Train the Agent with DDPG

5.1. Set up

```
In [6]: import gym
        import random
        import torch
        #import numpy as np
        from collections import deque
        import matplotlib.pyplot as plt
        %matplotlib inline

        from ddpg_agent import Agent
```

5.2. Initialize the agent

```
In [7]: agent = Agent(state_size, action_size, random_seed=3)
```

5.3. Define the DDPG Main definitions for DDPG algorithm:

- **Deep Deterministic Policy Gradient(DDPG):**

There are two main components, the actor and the critic. The actor produces a deterministic policy and the critic evaluates it. The critic uses the TD error to update itself and the actor uses the deterministic gradient policy to train itself.

- **Architecture of Actor Network**
  - Input: 33
  - output: 4
  - Number of layers: 2
    - layer 1:
      - number of neurons: 256
      - activation function: ReLU
    - layer 2:
      - number of neurons: 128
      - activation function: ReLU
- **Architecture of Critic Network**
  - Input: 33
  - output: 1
  - Number of layers: 3
    - layer 1:
      - number of neurons: 256
      - activation function: ReLU
    - layer 2:
      - number of neurons: 256
      - activation function: ReLU
    - layer 3:
      - number of neurons: 128

· activation function: ReLU

- **Hyperparameters:**

```
BUFFER_SIZE = int(1e6)  # replay buffer size
BATCH_SIZE = 256        # minibatch size
GAMMA = 0.99            # discount factor
TAU = 1e-3              # 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
EPSILON = 1.0           # epsilon noise parameter
EPSILON_DECAY = 1e-6    # decay parameter of epsilon
# Suggested modifications in the benchmark implementation
LEARNING_PERIOD = 20
UPDATE_FACTOR   = 10
```

```
In [8]: def ddpg(n_episodes, max_t, print_every):
            scores_deque = deque(maxlen=100)
            global_score = []

            for i_episode in range(1, n_episodes+1):
                env_info = env.reset(train_mode=True)[brain_name]
                states = env_info.vector_observations
                scores = np.zeros(num_agents)
                agent.reset()
                average_score = 0

                for t in range(max_t):
                    actions = agent.act(states)
                    env_info = env.step(actions)[brain_name]
                    next_states = env_info.vector_observations
                    rewards = env_info.rewards
                    dones = env_info.local_done
                    agent.step(states, actions, rewards, next_states, dones, t)
                    states = next_states
                    scores += rewards
                    if np.any(dones):
                        break

                score = np.mean(scores)
                scores_deque.append(score)
                average_score = np.mean(scores_deque)
                global_score.append(score)

                print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_deq
                torch.save(agent.actor_local.state_dict(), 'checkpoint_actor.pth')
                torch.save(agent.critic_local.state_dict(), 'checkpoint_critic.pth')
```

```
            if i_episode % print_every == 0:
                print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores
            if np.mean(scores_deque) >=30.0:
                print('\nEnvironment solved in {:d} Episodes \tAverage Score: {:.2f}'.format
                break

        return global_score
```

5.4. Set variables

```
In [9]: n_episodes=500
        max_t=2000
        print_every=50
```

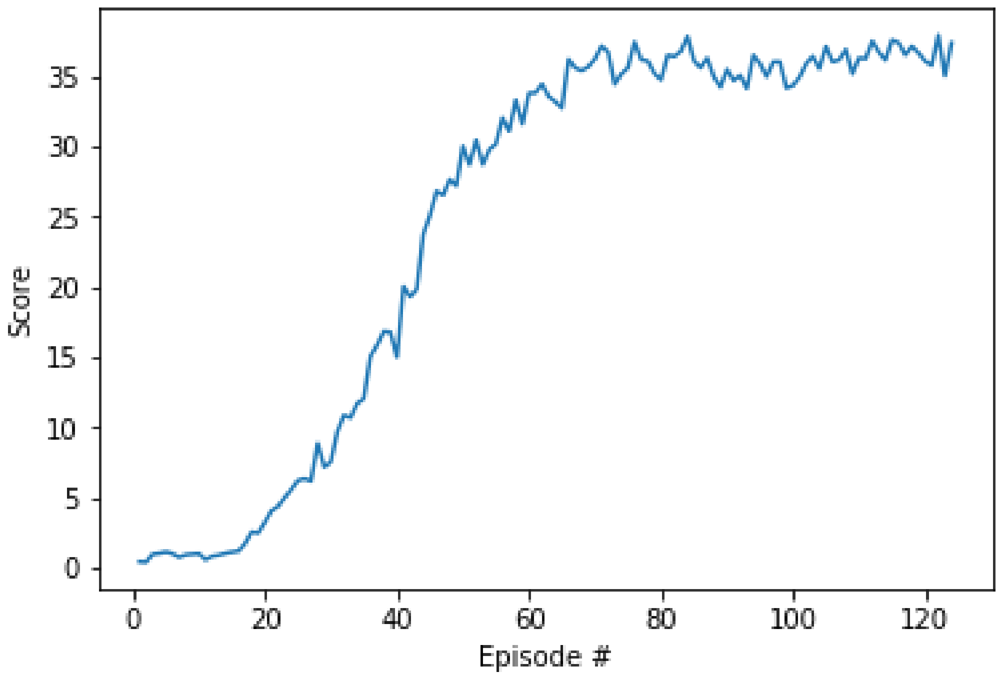
5.5. Train

```
In [10]: scores = ddpg(n_episodes, max_t,print_every)
```

```
Episode 50        Average Score: 9.35
Episode 100        Average Score: 21.96
Episode 124        Average Score: 30.27
Environment solved in 124 Episodes         Average Score: 30.27
```

5.6. Show results

```
In [11]: 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()
```



1.0.6 6. Run Trained agent

In [12]:
```
agent.actor_local.load_state_dict(torch.load('checkpoint_actor.pth'))
agent.critic_local.load_state_dict(torch.load('checkpoint_critic.pth'))

env_info = env.reset(train_mode=True)[brain_name]
states = env_info.vector_observations
scores = np.zeros(num_agents)
while True:
    actions = agent.act(states)
    env_info = env.step(actions)[brain_name]
    next_states = env_info.vector_observations
    rewards = env_info.rewards
    dones = env_info.local_done
    scores += env_info.rewards
    states = next_states
    if np.any(dones):
        break
print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

```
Total score (averaged over agents) this episode: 32.23049927959219
```

In [13]:
```
env.close()
```

1.0.7 7. Ideas for future work

There are other two possible improvements to the results:

1. Implement normalizations.
2. Use a A3C algorithm.