Continuous_Control

May 26, 2020

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]: !pip -q install ./python
```

```
tensorflow 1.7.1 has requirement numpy>=1.13.3, but you'll have numpy 1.12.1 which is incompatib
ipython 6.5.0 has requirement prompt-toolkit<2.0.0,>=1.0.15, but you'll have prompt-toolkit 3.0.
```

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
        import matplotlib.pyplot as plt

        import gym
        import random
        import torch
        import numpy as np
        from collections import namedtuple, deque
        import copy

        import torch
        import torch.nn as nn
        import torch.nn.functional as F
        import torch.optim as optim
        from torch.distributions import Categorical

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

```
In [3]: # 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 [4]: # get the default brain
        brain_name = 'ReacherBrain'
        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 [5]: # 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
  -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 [6]: #buffer = ReplayBuffer(300)

        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
        counter = 0
        while True:
            counter += 1
            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
        #    buffer.push(states, actions, rewards, next_states, dones)
            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)))
        counter
```

```
Total score (averaged over agents) this episode: 0.1304999970830977
```

```
Out[6]: 1001
```

When finished, you can close the environment.

1.0.4 4.1 DDPG (actor-critic)

This notebook implement DDPG algotithm to solve this continuous control problem. Two networks are utilized: one for actor and one for critic. The uniform weights inilization helps the training to converge faster.

```
In [ ]: def hidden_init(layer):
            fan_in = layer.weight.data.size()[0]
            lim = 1. / np.sqrt(fan_in)
            return (-lim, lim)

        class Actor(nn.Module):
            def __init__(self, state_size, action_size, fc_units=256):
                super(Actor, self).__init__()
                self.fc1 = nn.Linear(state_size, fc_units)
                self.fc2 = nn.Linear(fc_units, action_size)
                self.reset_parameters()

            def reset_parameters(self):
                self.fc1.weight.data.uniform_(*hidden_init(self.fc1))
                self.fc2.weight.data.uniform_(-3e-3, 3e-3)

            def forward(self, state):
                x = F.relu(self.fc1(state))
                return F.tanh(self.fc2(x))


        class Critic(nn.Module):
            def __init__(self, state_size, action_size, fcs1_units=256, fc2_units=256, fc3_units
                super(Critic, self).__init__()
                self.fcs1 = nn.Linear(state_size, fcs1_units)
                self.fc2 = nn.Linear(fcs1_units+action_size, fc2_units)
                self.fc3 = nn.Linear(fc2_units, fc3_units)
                self.fc4 = nn.Linear(fc3_units, 1)
                self.reset_parameters()

            def reset_parameters(self):
                self.fcs1.weight.data.uniform_(*hidden_init(self.fcs1))
                self.fc2.weight.data.uniform_(*hidden_init(self.fc2))
                self.fc3.weight.data.uniform_(*hidden_init(self.fc3))
                self.fc4.weight.data.uniform_(-3e-3, 3e-3)
```

```
    def forward(self, state, action):
        xs = F.leaky_relu(self.fcs1(state))
        x = torch.cat((xs, action), dim=1)
        x = F.leaky_relu(self.fc2(x))
        x = F.leaky_relu(self.fc3(x))
        return self.fc4(x)
```

1.0.5 4.2 add noise

Because the actor (policy) network is deterministic. To consider exploitation in the training Ornstein-Uhlenbeck process is used for adding noise

```
In [ ]: class OUNoise:
            """Ornstein-Uhlenbeck process."""

            def __init__(self, size, mu=0., theta=0.15, sigma=0.2):
                """Initialize parameters and noise process."""
                self.size = size
                self.mu = mu * np.ones(size)
                self.theta = theta
                self.sigma = sigma
                self.reset()

            def reset(self):
                """Reset the internal state (= noise) to mean (mu)."""
                self.state = copy.copy(self.mu)

            def sample(self):
                """Update internal state and return it as a noise sample."""
                x = self.state
                dx = self.theta * (self.mu - x) + self.sigma * np.random.standard_normal(self.si
                self.state = x + dx
                return self.state
```

1.0.6 4.3 replay buffer

This algorith is off policy. So we initialize a replay buffer to store the tuples collected at each step and reuse them for training.

```
In [ ]: class ReplayBuffer(object):
            def __init__(self, buffer_size) :
                self.memory = deque(maxlen = buffer_size)
                self.experience = namedtuple("Experience", field_names=["state", "action", "rewa

            def push(self, states, actions, rewards, next_states, dones):
                for state, action, reward, next_state, done in zip(states, actions, rewards, nex
                    self.memory.append(self.experience(state, action, reward, next_state, done))

            def sample(self, batch_size):
```

```
        samples = random.sample(self.memory, k = batch_size)
        batch = self.experience(*zip(*samples))
        states = torch.from_numpy(np.asarray(batch.state)).float().to(device)
        actions = torch.from_numpy(np.asarray(batch.action)).float().to(device) # discre
        rewards = torch.from_numpy(np.asarray(batch.reward)).float().view(-1,1).to(devic
        next_states = torch.tensor(np.asarray(batch.next_state)).float().to(device)
        # 0 for note finished, 1 for terminated
        dones = torch.tensor([1 if done else 0 for done in batch.done]).float().view(-1,
        return states, actions, rewards, next_states, dones

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

1.0.7 4.4 agent

The agent class stores two set of networks: critic and actor networks for training; a copy of them (actor_target, critic_target) to compute the loss (avoid the moving target). The weights of target networks are soft updated at every step.

```
In [7]: class Agent():
            def __init__(self, state_size, action_size, num_agents):
                self.state_size = state_size
                self.action_size = action_size
                self.epsilon = EPSILON
                self.t_step = 0
                # Actor Network (w/ Target Network)
                self.actor = Actor(state_size, action_size).to(device)
                self.actor_target = Actor(state_size, action_size).to(device)
                self.actor_optimizer = optim.Adam(self.actor.parameters(), lr = LR_ACTOR)
                # Critic Network (w/ Target Network)
                self.critic = Critic(state_size, action_size).to(device)
                self.critic_target = Critic(state_size, action_size).to(device)
                self.critic_optimizer = optim.Adam(self.critic.parameters(), lr = LR_CRITIC, wei
                # Noise process
                self.noise = OUNoise((num_agents, action_size))
                # Replay memory
                self.buffer = ReplayBuffer(buffer_size = BUFFER_SIZE)

            def get_action(self, state, add_noise = True):
                state_tensor = torch.from_numpy(state).float().to(device)

                self.actor.eval()
                with torch.no_grad():
                    action = self.actor(state_tensor).detach().cpu().numpy()
                self.actor.train()

                if add_noise:
                    action += self.epsilon * self.noise.sample()
```

```python
        return np.clip(action, -1, 1)

    def learn(self, experiences, gamma):
        states, actions, rewards, next_states, dones = experiences
        # ---------------------------- update critic ---------------------------- #
        actions_next = self.actor_target(next_states)
        Q_targets_next = self.critic_target(next_states, actions_next)
        Q_targets = rewards + (gamma * Q_targets_next * (1 - dones))

        Q_expected = self.critic(states, actions)

        loss_fn = nn.MSELoss()
        critic_loss = loss_fn(Q_expected, Q_targets.detach())

        self.critic_optimizer.zero_grad()
        critic_loss.backward()
        self.critic_optimizer.step()
        # ---------------------------- update actor ---------------------------- #
        actions_pred = self.actor(states)
        actor_loss = -self.critic(states, actions_pred).mean()

        self.actor_optimizer.zero_grad()
        actor_loss.backward()
        self.actor_optimizer.step()

    def soft_update(self, model, target_model, tau):
        for target_param, param in zip(target_model.parameters(), model.parameters()):
            target_param.data.copy_(tau*target_param.data + (1.0-tau)*param.data)


    def step(self, state, action, reward, next_state, done):
        self.buffer.push(state, action, reward, next_state, done)

        if len(self.buffer)> BATCH_SIZE:
            self.t_step = self.t_step + 1
            for _ in range(LEARN_NUM):
                experiences = self.buffer.sample(BATCH_SIZE)
                self.learn(experiences, GAMMA)

            if (self.t_step % UPDATE_EVERY) == 0:
                self.soft_update(self.critic, self.critic_target, TAU)
                self.soft_update(self.actor, self.actor_target, TAU)
                self.t_step = 0

    def reset(self):
        self.noise.reset()
        self.epsilon = self.epsilon * EPSILON_DECAY
```

1.0.8 4.5 train agent

start training

```
In [ ]: BUFFER_SIZE = int(1e5)  # replay buffer size
        BATCH_SIZE = 128        # minibatch size
        GAMMA = 0.99            # discount factor
        TAU = 0.999             # for soft update of target parameters
        LR_ACTOR = 5e-4         # learning rate of the actor
        LR_CRITIC = 5e-4        # learning rate of the critic
        WEIGHT_DECAY = 0.0      # L2 weight decay
        EPSILON = 1.0           # explore->exploit noise process added to act step
        EPSILON_DECAY = 0.99    # decay rate for noise process
        UPDATE_EVERY = 1        # how often to update the target network
        LEARN_NUM = 1

        agent = Agent(state_size, action_size, num_agents)
```

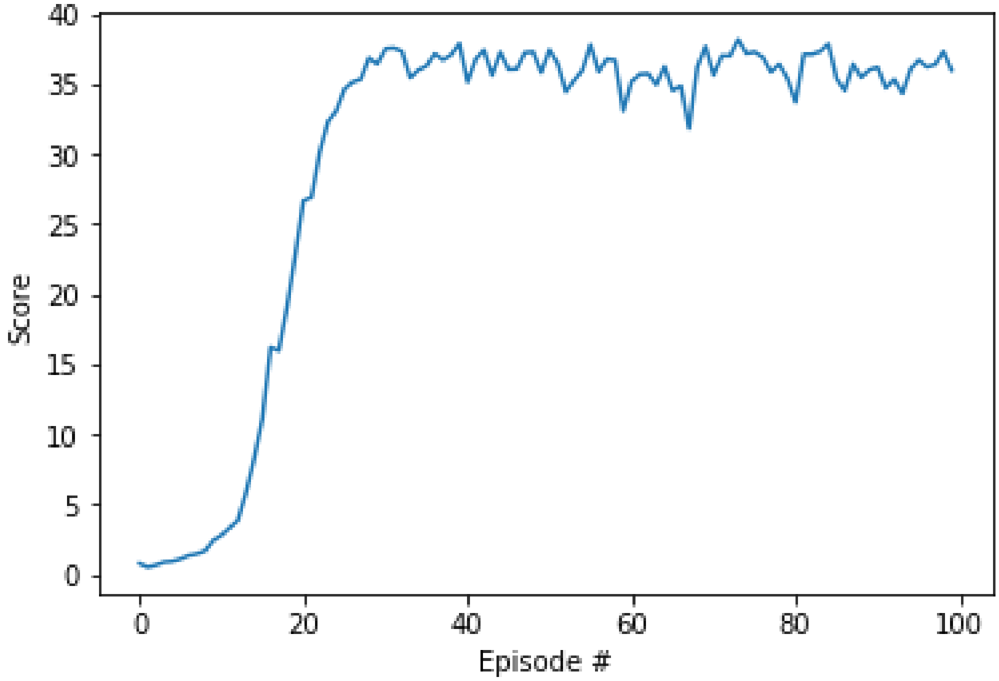
```
In [8]: n_episodes = 100

        score_list = []
        best_score = 30.0
        for i_episode in range(1, n_episodes+1):

            scores = np.zeros(num_agents)
            agent.reset()
            env_info = env.reset(train_mode=True)[brain_name]
            states = env_info.vector_observations

            while True:

                actions = agent.get_action(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)

                states = next_states
                scores += rewards

                if np.any(dones):
                    break
```

```
            print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores)))
            score_list.append(np.mean(scores))

            if np.mean(scores) >= best_score:
                print('\nmodel saved!')
                torch.save(agent.actor.state_dict(), 'checkpoint_actor.pth')
                torch.save(agent.critic.state_dict(), 'checkpoint_critic.pth')
                best_score  = np.mean(scores)

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

```
Episode 1        Average Score: 0.80
Episode 2        Average Score: 0.53
Episode 3        Average Score: 0.67
Episode 4        Average Score: 0.89
Episode 5        Average Score: 0.94
Episode 6        Average Score: 1.11
Episode 7        Average Score: 1.36
Episode 8        Average Score: 1.47
Episode 9        Average Score: 1.68
Episode 10        Average Score: 2.43
Episode 11        Average Score: 2.80
Episode 12        Average Score: 3.33
Episode 13        Average Score: 3.86
Episode 14        Average Score: 5.85
Episode 15        Average Score: 8.28
Episode 16        Average Score: 11.13
Episode 17        Average Score: 16.23
Episode 18        Average Score: 15.98
Episode 19        Average Score: 19.08
Episode 20        Average Score: 22.76
Episode 21        Average Score: 26.67
Episode 22        Average Score: 26.92
Episode 23        Average Score: 30.17

model saved!
Episode 24        Average Score: 32.33

model saved!
Episode 25        Average Score: 33.07

model saved!
Episode 26        Average Score: 34.64
```

```
model saved!
Episode 27	Average Score: 35.14

model saved!
Episode 28	Average Score: 35.34

model saved!
Episode 29	Average Score: 36.87

model saved!
Episode 30	Average Score: 36.43
Episode 31	Average Score: 37.51

model saved!
Episode 32	Average Score: 37.57

model saved!
Episode 33	Average Score: 37.33
Episode 34	Average Score: 35.46
Episode 35	Average Score: 35.99
Episode 36	Average Score: 36.29
Episode 37	Average Score: 37.16
Episode 38	Average Score: 36.72
Episode 39	Average Score: 37.08
Episode 40	Average Score: 37.89

model saved!
Episode 41	Average Score: 35.15
Episode 42	Average Score: 36.77
Episode 43	Average Score: 37.42
Episode 44	Average Score: 35.64
Episode 45	Average Score: 37.26
Episode 46	Average Score: 36.04
Episode 47	Average Score: 36.07
Episode 48	Average Score: 37.24
Episode 49	Average Score: 37.29
Episode 50	Average Score: 35.82
Episode 51	Average Score: 37.44
Episode 52	Average Score: 36.45
Episode 53	Average Score: 34.46
Episode 54	Average Score: 35.26
Episode 55	Average Score: 35.96
Episode 56	Average Score: 37.80
Episode 57	Average Score: 35.87
Episode 58	Average Score: 36.78
Episode 59	Average Score: 36.70
Episode 60	Average Score: 33.08
```

```
Episode 61        Average Score: 35.19
Episode 62        Average Score: 35.70
Episode 63        Average Score: 35.75
Episode 64        Average Score: 34.96
Episode 65        Average Score: 36.24
Episode 66        Average Score: 34.54
Episode 67        Average Score: 34.87
Episode 68        Average Score: 31.83
Episode 69        Average Score: 36.21
Episode 70        Average Score: 37.67
Episode 71        Average Score: 35.65
Episode 72        Average Score: 37.01
Episode 73        Average Score: 37.01
Episode 74        Average Score: 38.17

model saved!
Episode 75        Average Score: 37.18
Episode 76        Average Score: 37.28
Episode 77        Average Score: 36.90
Episode 78        Average Score: 35.85
Episode 79        Average Score: 36.41
Episode 80        Average Score: 35.40
Episode 81        Average Score: 33.71
Episode 82        Average Score: 37.11
Episode 83        Average Score: 37.12
Episode 84        Average Score: 37.32
Episode 85        Average Score: 37.85
Episode 86        Average Score: 35.38
Episode 87        Average Score: 34.54
Episode 88        Average Score: 36.42
Episode 89        Average Score: 35.48
Episode 90        Average Score: 36.00
Episode 91        Average Score: 36.20
Episode 92        Average Score: 34.71
Episode 93        Average Score: 35.34
Episode 94        Average Score: 34.34
Episode 95        Average Score: 36.06
Episode 96        Average Score: 36.69
Episode 97        Average Score: 36.22
Episode 98        Average Score: 36.39
Episode 99        Average Score: 37.31
Episode 100        Average Score: 35.99
```




```
In [19]: env.close()
```

1.0.9 5. Watch trained agent

```
In [3]: env = UnityEnvironment(file_name='/data/Reacher_One_Linux_NoVis/Reacher_One_Linux_NoVis.
        brain_name = 'ReacherBrain'
        brain = env.brains[brain_name]

        env_info = env.reset(train_mode=True)[brain_name]

        num_agents = len(env_info.agents)
        action_size = brain.vector_action_space_size
        states = env_info.vector_observations
        state_size = states.shape[1]
```

```
INFO:unityagents:
'Academy' started successfully!
Unity Academy name: Academy
        Number of Brains: 1
        Number of External Brains : 1
        Lesson number : 0
        Reset Parameters :
                goal_size -> 5.0
                goal_speed -> 1.0
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: , , ,
```

In [13]:
```python
agent = Agent(state_size, action_size, num_agents)

agent.actor.load_state_dict(torch.load('checkpoint_actor.pth'))
agent.critic.load_state_dict(torch.load('checkpoint_critic.pth'))
```

In [15]:
```python
scores = np.zeros(num_agents)                          # initialize the score (for each
env_info = env.reset(train_mode=True)[brain_name]
states = env_info.vector_observations
while True:
    actions = agent.get_action(states, add_noise = False) # select an action (for each
    env_info = env.step(actions)[brain_name]           # send all actions to tne enviro

    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

    states = next_states                               # roll over states to next time
    scores += env_info.rewards                         # update the score (for each age

    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: 37.8899991530925
```

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

1.0.10 6.Ideas for Future Work

- Implement Proximal Policy Optimization (PPO) for better performance
- try prioritized experience replay
- try N-step returns