МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ им. Н.Э. Баумана

Факультет «Информатика и системы управления» Кафедра «Систем обработки информации и управления»

ОТЧЕТ

Лабораторная работа №__7_ по дисциплине «Методы машинного обучения»

Тема: «Алгоритмы Actor-Critic»

ИСПОЛНИТЕЛІ группа ИУ5-24	*	Подопригорова С.С.	
	""	2023 г.	
ПРЕПОДАВАТЕЛЬ:			
	" "	2023 г.	

Задание:

Реализуйте любой алгоритм семейства Actor-Critic для произвольной среды.

Текст программы. import gym import random from collections import deque import matplotlib.pyplot as plt import numpy as np import random import copy from collections import namedtuple, deque import torch import torch.nn as nn import torch.nn.functional as F import torch.optim as optim BUFFER_SIZE = int(1e6) # replay buffer size $\#BATCH_SIZE = 128$ # minibatch size $BATCH_{\overline{S}IZE} = 500$ # minibatch size GAMMA = 0.99# discount factor # for soft update of target parameters TAU = 1e-4 $LR_ACTOR = 1e-4$ # learning rate of the actor LR CRITIC = 3e-4 # learning rate of the critic WEIGHT DECAY = 0.0001 # L2 weight decay device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu") def hidden_init(layer): fan_in = layer.weight.data.size()[0] lim = 1. / np.sqrt(fan_in) return (-lim, lim) class Actor(nn.Module): """Actor (Policy) Model.""" def __init__(self, state_size, action_size, seed, fc_units=256): super(Actor, self).__init__() self.seed = torch.manual_seed(seed) 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): """Critic (Value) Model.""" def __init__(self, state_size, action_size, seed, fcs1_units=256, fc2_units=256, fc3_units=128): super(Critic, self).__init__() self.seed = torch.manual seed(seed)

self.fcs1 = nn.Linear(state_size, fcs1_units)

self.fc3 = nn.Linear(fc2_units, fc3_units)

self.fc2 = nn.Linear(fcs1 units+action size, fc2 units)

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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)
class Agent():
    def __init__(self, state_size, action_size, random_seed):
        self.state_size = state_size
        self.action_size = action_size
        self.seed = random.seed(random_seed)
        # Actor Network
        self.actor_local = Actor(state_size, action_size,
random_seed).to(device)
        self.actor_target = Actor(state_size, action_size,
random_seed).to(device)
        self.actor_optimizer = optim.Adam(self.actor_local.parameters(),
lr=LR ACTOR)
        # Critic Network
        self.critic_local = Critic(state_size, action_size,
random_seed).to(device)
        self.critic_target = Critic(state_size, action_size,
random_seed).to(device)
        self.critic_optimizer = optim.Adam(self.critic_local.parameters(),
lr=LR_CRITIC, weight_decay=WEIGHT_DECAY)
        self.noise = OUNoise(action_size, random_seed)
        self.memory = ReplayBuffer(action size, BUFFER SIZE, BATCH SIZE,
random_seed)
    def step(self, state, action, reward, next_state, done):
        self.memory.add(state, action, reward, next_state, done)
        if len(self.memory) > BATCH_SIZE:
            experiences = self.memory.sample()
            self.learn(experiences, GAMMA)
   def act(self, state, add_noise=True):
        state = torch.from_numpy(state).float().to(device)
        self.actor_local.eval()
        with torch.no_grad():
            action = self.actor_local(state).cpu().data.numpy()
        self.actor_local.train()
        if add noise:
            action += self.noise.sample()
        return np.clip(action, -1, 1)
   def reset(self):
        self.noise.reset()
    def learn(self, experiences, gamma):
        states, actions, rewards, next_states, dones = experiences
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# ----- update critic
           ----- #
        # Get predicted next-state actions and Q values from target models
        actions_next = self.actor_target(next_states)
        Q_targets_next = self.critic_target(next_states, actions_next)
        # Compute Q targets for current states (y_i)
Q_targets = rewards + (gamma * Q_targets_next * (1 - dones))
        # Compute critic loss
        Q_expected = self.critic_local(states, actions)
        critic_loss = F.mse_loss(Q_expected, Q_targets)
        # Minimize the loss
        self.critic_optimizer.zero_grad()
        critic loss.backward()
        self.critic optimizer.step()
        # ------ update actor ------
        # Compute actor loss
        actions_pred = self.actor_local(states)
        actor_loss = -self.critic_local(states, actions_pred).mean()
        # Minimize the loss
        self.actor_optimizer.zero_grad()
        actor_loss_backward()
        self.actor_optimizer.step()
        #
        self.soft_update(self.critic_local, self.critic_target, TAU)
self.soft_update(self.actor_local, self.actor_target, TAU)
    def soft_update(self, local_model, target_model, tau):
    for target_param, local_param in zip(target_model.parameters(),
local_model.parameters()):
             target_param.data.copy_(tau*local_param.data + (1.0-
tau)*target_param.data)
class OUNoise:
        __init__(self, size, seed, mu=0., theta=0.15, sigma=0.2):
"""Initialize parameters and noise process."""
        self.mu = mu * np.ones(size)
        self.theta = theta
        self.sigma = sigma
        self.seed = random.seed(seed)
        self.reset()
    def reset(self):
        self.state = copy.copy(self.mu)
    def sample(self):
        x = self.state
        dx = self.theta * (self.mu - x) + self.sigma * np.array([random.random()])
for i in range(len(x))])
        self.state = x + dx
        return self.state
class ReplayBuffer:
    def __init__(self, action_size, buffer_size, batch_size, seed):
        self.action_size = action_size
        self.memory = deque(maxlen=buffer_size) # internal memory (deque)
        self.batch_size = batch_size
        self.experience = namedTuple("Experience", field_names=["state",
"action", "reward", "next_state", "done"])
self.seed = random.seed(seed)
    def add(self, state, action, reward, next_state, done):
        e = self.experience(state, action, reward, next_state, done)
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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 None])).float().to(device)
         actions = torch.from_numpy(np.vstack([e.action for e in experiences if e
is not None])).float().to(device)
         rewards = torch.from_numpy(np.vstack([e.reward for e in experiences if e
is not None])).float().to(device)
         next_states = torch.from_numpy(np.vstack([e.next_state for e in
experiences if e is not None])).float().to(device)
         dones = torch.from numpy(np.vstack([e.done for e in experiences if e is
not None]).astype(np.uint8)).float().to(device)
         return (states, actions, rewards, next states, dones)
          _len__(self):
    def
         return len(self.memory)
def ddpg(n_episodes=1500, max_t=700):
    scores_deque = deque(maxlen=100)
    scores = []
    max_score = -np.Inf
    for i_episode in range(1, n_episodes+1):
         state, info = env.reset()
         agent.reset()
         score = 0
         for t in range(max_t):
             action = agent.act(state)
             next_state, reward, terminate, truncated, _ = env.step(action)
done = terminate or truncated
             agent.step(state, action, reward, next_state, done)
             state = next_state
             score += reward
             if done:
                 break
         scores_deque.append(score)
         scores.append(score)
        print('\rEpisode {}\tAverage Score: {:.2f}\tScore:
{:.2f}'.format(i_episode, np.mean(scores_deque), score), end="")
         if i_episode % 100 == 0:
             torch.save(agent.actor_local.state_dict(), 'checkpoint_actor.pth')
torch.save(agent.critic_local.state_dict(), 'checkpoint_critic.pth')
print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode,
np.mean(scores_deque)))
    return scores
if __name__ == "__main__":
    env = gym.make('BipedalWalker-v3')
    agent = Agent(state_size=env.observation_space.shape[0],
action_size=env.action_space.shape[0], random_seed=100)
    scores = ddpq()
    print(scores)
    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()
    # watch
    env = gym.make('BipedalWalker-v3', render mode="human")
```

Экранные формы с примерами выполнения программы



