A5_Q4_Deshmane_Aakash

April 27, 2023

AAKASH DESHMANE UIN : 133008022 ECEN 743 ASSIGNMENT 5 POLICY GRADIENT IMPLEMENTATION OF MOUNTAIN CAR CONTINUOUS

[ ]:
```
import gymnasium as gym
import random
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import argparse
import numpy as np
import math
from collections import deque
import matplotlib.pyplot as plt
```

VALUE NETWORK

[ ]:
```
class value_network(nn.Module):
        '''
        Value Network: Designed to take in state as input and give value as␣
 ↪output
        Used as a baseline in Policy Gradient (PG) algorithms
        '''
        def __init__(self,state_dim):
                '''
                        state_dim (int): state dimenssion
                '''
                super(value_network, self).__init__()
                self.l1 = nn.Linear(state_dim, 128)
                self.l2 = nn.Linear(128, 64)
                self.l3 = nn.Linear(64, 1)

        def forward(self,state):
                '''
                Input: State
                Output: Value of state
                '''
                v = F.tanh(self.l1(state))
```

```python
        v = F.tanh(self.l2(v))
        return self.l3(v)
```

POLICY NETWORK

```python
class policy_network(nn.Module):
    '''
    Policy Network: Designed for continous action space, where given a
    state, the network outputs the mean and standard deviation of the action
    '''
    def __init__(self,state_dim,action_dim,log_std = 0.0):
        """
                state_dim (int): state dimenssion
                action_dim (int): action dimenssion
                log_std (float): log of standard deviation (std)
        """
        super(policy_network, self).__init__()
        self.state_dim = state_dim
        self.action_dim = action_dim
        self.l1 = nn.Linear(state_dim,64)
        self.l2 = nn.Linear(64,64)
        #self.l3 = nn.Linear(64,64)
        #self.l4 = nn.Linear(64,64)
        self.mean = nn.Linear(64,action_dim)
        self.log_std = nn.Parameter(torch.ones(1, action_dim) * log_std)


    def forward(self,state):
        '''
        Input: State
        Output: Mean, log_std and std of action
        '''
        a = F.tanh(self.l1(state))
        a = F.tanh(self.l2(a))
        a_mean = self.mean(a)
        a_log_std = self.log_std.expand_as(a_mean)
        a_std = torch.exp(a_log_std)
        return a_mean, a_log_std, a_std

    def select_action(self, state):
        '''
        Input: State
        Output: Sample drawn from a normal disribution with mean and std
        '''



        a_mean, _, a_std = self.forward(state)
```

```
                action = torch.normal(a_mean)
                return action

        def get_log_prob(self, state, action):
                '''
                Input: State, Action
                Output: log probabilities
                '''
                mean, log_std, std = self.forward(state)
                var = std.pow(2)
                log_density = -(action - mean).pow(2) / (2 * var) - 0.5 * math.
↪log(2 * math.pi) - log_std
                return log_density.sum(1, keepdim=True)
```

[ ]:
```
class PGAgent():
        '''
        An agent that performs different variants of the PG algorithm
        '''
        def __init__(self,
         state_dim,
         action_dim,
         discount=0.99,
         lr=1e-3,
         gpu_index=0,
         seed=0,
         env="LunarLander-v2"
         ):
                """
                        state_size (int): dimension of each state
                        action_size (int): dimension of each action
                        discount (float): discount factor
                        lr (float): learning rate
                        gpu_index (int): GPU used for training
                        seed (int): Seed of simulation
                        env (str): Name of environment
                """
                self.state_dim = state_dim
                self.action_dim = action_dim
                self.discount = discount
                self.lr = lr
                self.device = torch.device('cuda', index=gpu_index) if torch.
↪cuda.is_available() else torch.device('cpu')
                self.env_name = env
                self.seed = seed
                self.policy = policy_network(state_dim,action_dim)
                self.value = value_network(state_dim)
```

```
        self.optimizer_policy = torch.optim.Adam(self.policy.
↪parameters(), lr=self.lr)
        self.optimizer_value = torch.optim.Adam(self.value.
↪parameters(), lr=self.lr)

    def sample_traj(self,batch_size=4000,evaluate = False):
        '''
        Input:
            batch_size: minimum batch size needed for update
            evaluate: flag to be set during evaluation
        Output:
            states, actions, rewards,not_dones, episodic reward␣
↪
        '''
        self.policy.to("cpu") #Move network to CPU for sampling
        env = gym.make(self.env_name)
        states = []
        actions = []
        rewards = []
        n_dones = []
        curr_reward_list = []
        while len(states) < batch_size:
            state, _ = env.reset(seed=self.seed)
            curr_reward = 0
            for t in range(1000):
                state_ten = torch.from_numpy(state).float().
↪unsqueeze(0)
                with torch.no_grad():
                    if evaluate:
                        action = self.
↪policy(state_ten)[0][0].numpy() # Take mean action during evaluation
                    else:
                        action = self.policy.
↪select_action(state_ten)[0].numpy() # Sample from distribution during␣
↪training
                action = action.astype(np.float32)
                n_state,reward,terminated,truncated,_ = env.
↪step(action) # Execute action in the environment
                done = terminated or truncated
                states.append(state)
                actions.append(action)
                rewards.append(reward)
                n_done = 0 if done else 1
                n_dones.append(n_done)
                state = n_state
                curr_reward += reward
```

```
                        if done:
                                break
                curr_reward_list.append(curr_reward)
        if evaluate:
                return np.mean(curr_reward_list)
        return states,actions,rewards,n_dones, np.mean(curr_reward_list)




def update(self,states,actions,rewards,n_dones,update_type='Baseline'):

        self.policy.to(self.device) #Move policy to GPU
        if update_type == "Baseline":
                self.value.to(self.device)        #Move value to GPU
        states_ten = torch.from_numpy(np.stack(states)).to(self.device)␣
↪  #Convert to tensor and move to GPU
        action_ten = torch.from_numpy(np.stack(actions)).to(self.
↪device)  #Convert to tensor and move to GPU
        rewards_ten = torch.from_numpy(np.stack(rewards)).to(self.
↪device) #Convert to tensor and move to GPU
        n_dones_ten = torch.from_numpy(np.stack(n_dones)).to(self.
↪device) #Convert to tensor and move to GPU



        if update_type == "Rt":

                rt = torch.zeros(rewards_ten.shape[0],1).to(self.device)
                rt_accum = 0
                for t in reversed(range(rewards_ten.shape[0])):
                                rt_accum = rewards_ten[t] + rt_accum *␣
↪self.discount *n_dones_ten[t]
                                rt[t] = rt_accum

                log_prob = self.policy.get_log_prob(states_ten,␣
↪action_ten)
                policy_loss = -(log_prob * rt.detach()).mean()

                self.optimizer_policy.zero_grad()
                policy_loss.backward()
                self.optimizer_policy.step()

        if update_type == 'Gt':
                gt = torch.zeros(rewards_ten.shape[0],1).to(self.device)
                g = 0
                for i in reversed(range(rewards_ten.size(0))):
```

```
                                g = rewards_ten[i] + self.discount * g␣
↪*(n_dones_ten[i])
                                gt[i] = g

                        gt = (gt - gt.mean()) / gt.std() #Helps with learning␣
↪stablity
                        log_prob = self.policy.get_log_prob(states_ten,␣
↪action_ten)
                        policy_loss = -(log_prob * gt.detach()).mean()

                        self.optimizer_policy.zero_grad()
                        policy_loss.backward()
                        self.optimizer_policy.step()

                if update_type == 'Gt_with_Baseline':
                        '''
                        TODO: Peform PG using reward_to_go and baseline
                        1. Compute values of states, this will be used as the␣
↪baseline
                        2. Compute reward_to_go (gt) using rewards_ten and␣
↪n_dones_ten
                        3. gt should be of the same length as rewards_ten
                        4. Compute advantages
                        5. Update the value network to predict gt for each␣
↪state (L2 norm)
                        6. Compute log probabilities using states_ten and␣
↪action_ten
                        7. Compute policy loss (using advantages) and update␣
↪the policy
                        '''
                        state_t = torch.FloatTensor(states).to(self.device)

                        # STEP 1 CALCULATE VALUES
                        with torch.no_grad():
                                self.value.to(self.device)
                                val = self.value(states_ten).to(self.
↪device)

                        # gt SHOULD HAVE THE SAME LENGTH AS rewards_ten
                        gt = torch.zeros(rewards_ten.shape[0],1).to(self.device)

                        g=0

                        # STEP 2 : COMPUTE REWARD-TO-GO (gt) and ADVANTAGES
                        returns = torch.zeros((rewards_ten.shape[0], 1)).
↪to(self.device)
```

```
                        advantages = torch.zeros((rewards_ten.shape[0], 1)).
↪to(self.device)
                        s = rewards_ten.size(0)
                        for i in reversed(range(s)):
                                g = rewards_ten[i] + self.discount * g *␣
↪n_dones_ten[i]
                                gt[i] = g

                        # STEP 4 : COMPUTE ADVANTAGES
                        advantages = gt - val


                        # Normalize advantages
                        advantages = (advantages - advantages.mean()) /␣
↪advantages.std()


                        # STEP 5 : UPDATE VALUE NETWORK TO PREDICT gt FOR EACH␣
↪STATE (L2 NORM)
                        loss = torch.nn.MSELoss()
                        value_loss = loss(self.value(states_ten), gt)
                        self.optimizer_value.zero_grad()
                        value_loss.backward()
                        self.optimizer_value.step()

                        # STEP 6 : COMPUTE LOG PROBABILITIES USING states_ten␣
↪and Compute log probabilities using states_ten and action_ten
                        log_probs = self.policy.get_log_prob(states_ten,␣
↪action_ten)

                        # STEP 7 : COMPUTE POLICY LOSS AND UPDATE POLICY
                        self.optimizer_policy.zero_grad()
                        l = log_probs * advantages.detach()
                        loss = -(l).mean()
                        loss.backward()
                        self.optimizer_policy.step()
            #␣
↪------------------------------------------------------------------------
```

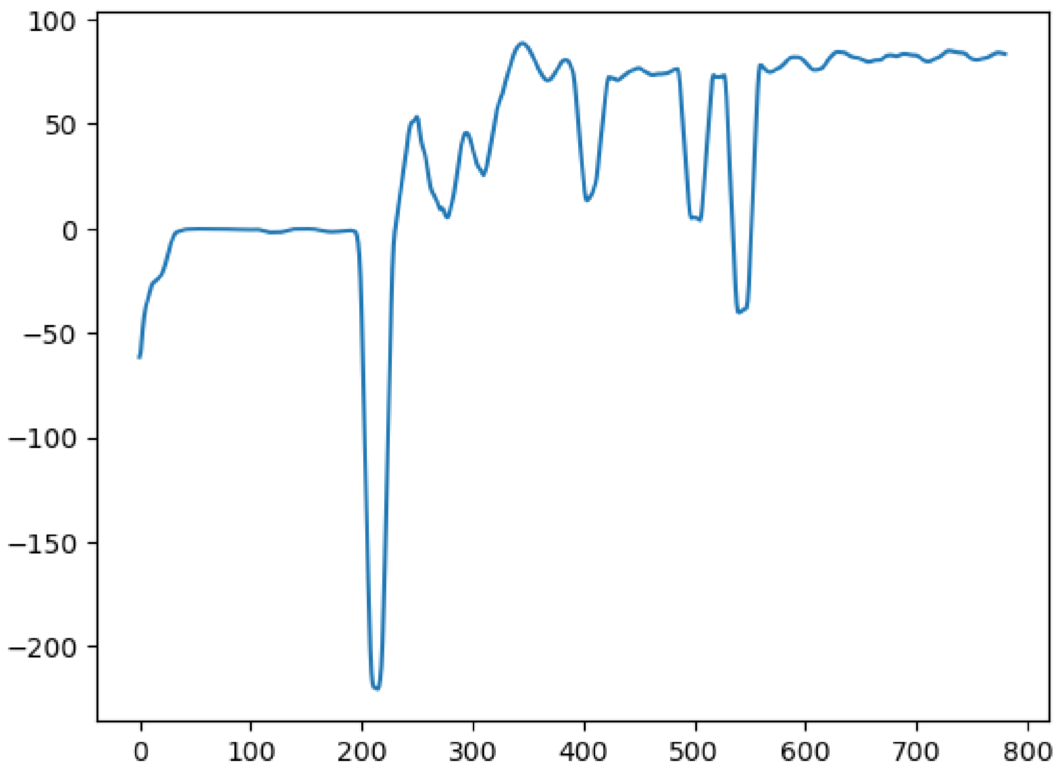
RUNNIN MOUNTAIN CAR FOR MORE NUMBER OF ITERATIONS TO ACHIEVE CONVERGENCE HYPERPARAMETERS TUNED TO: * ITERATIONS : 800 * DISCOUNT : 0.99 * BATCH SIZE : 4000 * LEARNING RATE : 8e-4

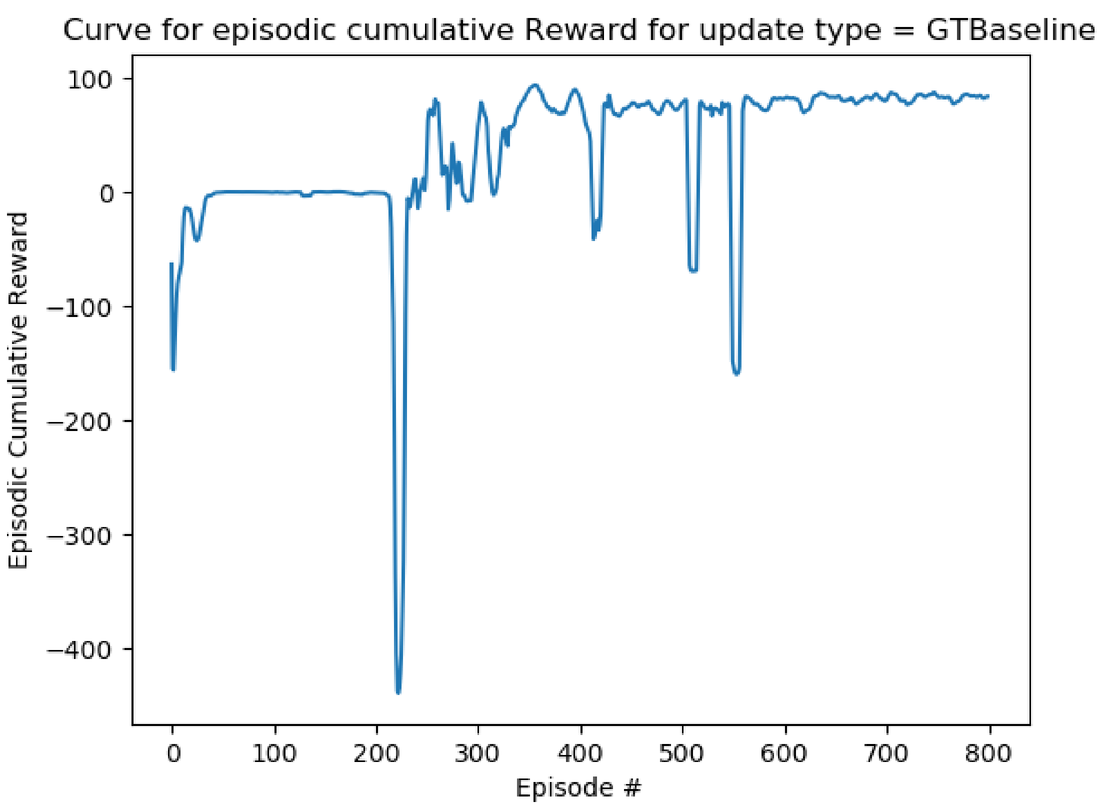
[ ]:
```
env_type = "MountainCarContinuous-v0" # Gymnasium environment name
seed=0          # Sets Gym, PyTorch and Numpy seeds
n_iter = 800      # Maximum number of training iterations
discount = 0.99   # Discount factor
batch_size = 4000 # Training samples in each batch of training
```

```
lr = 8e-3        # Learning rate
gpu_index = 0                 # GPU index
algo = "Gt_ with_Baseline"                    # PG algorithm type.␣
 ↪Baseline_with_Gt/Gt/Rt


# Making the environment
env = gym.make(env_type)

# Setting seeds
torch.manual_seed(seed)
np.random.seed(seed)
random.seed(seed)

state_dim = env.observation_space.shape[0]
print(state_dim)
action_dim = env.action_space.shape[0]

kwargs = {
        "state_dim":state_dim,
        "action_dim":action_dim,
        "discount":discount,
        "lr":lr,
        "gpu_index":gpu_index,
        "seed":seed,
        "env":env_type
}
learner = PGAgent(**kwargs) # Creating the PG learning agent
average_rewards=[]
moving_window = deque(maxlen=10)
old_reward=-1
for e in range(n_iter):
        states,actions,rewards,n_dones,train_reward = learner.
 ↪sample_traj(batch_size=batch_size)
        learner.update(states,actions,rewards,n_dones,algo)
        eval_reward= learner.sample_traj(evaluate=True)
        moving_window.append(eval_reward)
        if not e%100: print('Training Iteration {} Training Reward: {:.2f}␣
 ↪Evaluation Reward: {:.2f} \
        Average Evaluation Reward: {:.2f}'.format(e,train_reward,eval_reward,np.
 ↪mean(moving_window)))

        average_rewards.append(np.mean(moving_window))

        if np.mean(moving_window) > old_reward:
                old_reward = np.mean(moving_window)
```

```
                torch.save(learner.policy.state_dict(), (algo + '_checkpoint1.
↪pth'))

window_size = 20
averages = []
fig1=plt.figure()
for i in range(len(average_rewards)-window_size + 1):
        window = average_rewards[i:i+window_size]
        average = sum(window)/window_size
        averages.append(average)
plt.plot(averages)
plt.show()
fig2=plt.figure()

plt.plot(average_rewards)
plt.ylabel('Episodic Cumulative Reward')
plt.xlabel('Episode #')
plt.title('Curve for Episodic Cumulative Reward for algorithm = {}'.
↪format(algo))
plt.show()
```

```
2

/tmp/ipykernel_16353/4280312714.py:122: UserWarning: Creating a tensor from a
list of numpy.ndarrays is extremely slow. Please consider converting the list to
a single numpy.ndarray with numpy.array() before converting to a tensor.
(Triggered internally at ../torch/csrc/utils/tensor_new.cpp:245.)
  state_t = torch.FloatTensor(states).to(self.device)

Training Iteration 0 Training Reward: -102.77 Evaluation Reward: -63.52
Average Evaluation Reward: -63.52
Training Iteration 100 Training Reward: -94.95 Evaluation Reward: -0.19
Average Evaluation Reward: -0.61
Training Iteration 200 Training Reward: -101.77 Evaluation Reward: -1.52
Average Evaluation Reward: -0.89
Training Iteration 300 Training Reward: 53.55 Evaluation Reward: 75.41  Average
Evaluation Reward: 57.69
Training Iteration 400 Training Reward: 55.07 Evaluation Reward: 67.36  Average
Evaluation Reward: 81.26
Training Iteration 500 Training Reward: 75.35 Evaluation Reward: 82.92  Average
Evaluation Reward: 78.08
Training Iteration 600 Training Reward: 70.57 Evaluation Reward: 78.63  Average
Evaluation Reward: 81.68
Training Iteration 700 Training Reward: 72.33 Evaluation Reward: 91.86  Average
Evaluation Reward: 80.78
```


100
50
0
−50
−100
−150
−200
0
100
200
300
400
500
600
700
800


Curve for episodic cumulative Reward for update type = GTBaseline
Episodic Cumulative Reward
100
0
−100
−200
−300
−400
0
100
200
300
400
500
600
700
800
Episode #

[ ]:
```

```

THE CODE BELOW IS JUST TO EXPORT THE VIDEO AND DOES NOT TAKE PART IN THE ALGORITHM

[ ]:
```
 #For visualization
import gymnasium as gym
from gym.wrappers.monitoring import video_recorder
from IPython.display import HTML
from IPython import display
import glob
import cv2
```

VIDEO FUNCTION

[ ]:
```
def video_fn(agent, env_name, algo):
    env = gym.make(env_name, render_mode="rgb_array")
    fourcc = cv2.VideoWriter_fourcc(*'mp4v')
    video = cv2.VideoWriter(algo+'_video.mp4', fourcc, 30, (600, 400))
    agent.policy.load_state_dict(torch.load(algo+"_checkpoint.pth"))
    agent.policy.eval()
    state, _= env.reset()
    done = False
    while not done:
        frame = env.render()
        video.write(frame)
        state_ten = torch.from_numpy(state).float().unsqueeze(0)
        action = agent.policy.select_action(state_ten)[0].detach().numpy()
        action = action.astype(np.float64)
        n_state, reward, terminated, truncated, _ = env.step(action)
        done = terminated or truncated
        state = n_state
    env.close()
    video.release()
```

EXPORTING VIDEO

[ ]:
```
env_type = "MountainCarContinuous"
env = gym.make(env_type)
state_dim = env.observation_space.shape[0]
action_dim = env.action_space.shape[0]
plotter_agent = PGAgent(state_dim,action_dim)
#video_fn(plotter_agent, "MountainCarContinuous", "Rt")
#video_fn(plotter_agent, "MountainCarContinuous", "Gt")
video_fn(plotter_agent, "MountainCarContinuous", "Gt_with_Baseline")
```