Assignment 4 : Fapprox and SARSA control

Name: Vijaykumar Maraviya
Student Number: 1006040320

In this assignment, I attempted the **cart pole problem** and solved it using function approximation and on-policy control (SARSA n-step).

1. **Code:**
   please find code in the attached file 'solver.py' or in the appendix of this document.

2. **NN structure:**
   After manually trying several values for number of layers and neuron in each layer, I choose the network with **2 hidden layers with 32 and 16 neurons, respectively**. A **ReLU** is used for activation for both the layers. Input layer has 5 neurons (corresponding to 4 for state values and 1 for action) and output has 1 neuron (for value of state-action pair). Adam optimizer is used to update the parameters of the network.

3. **Algorithm:**
   Episodic semi-gradient n-step SARSA (textbook section 10.2, page number 247) is implemented. Update rule for weight vector **w** is as follows:

$$\boldsymbol{w} \leftarrow \boldsymbol{w} + \alpha[G - \hat{q}(S_\tau, A_\tau, \boldsymbol{w})]\, \nabla\hat{q}(S_\tau, A_\tau, \boldsymbol{w})$$

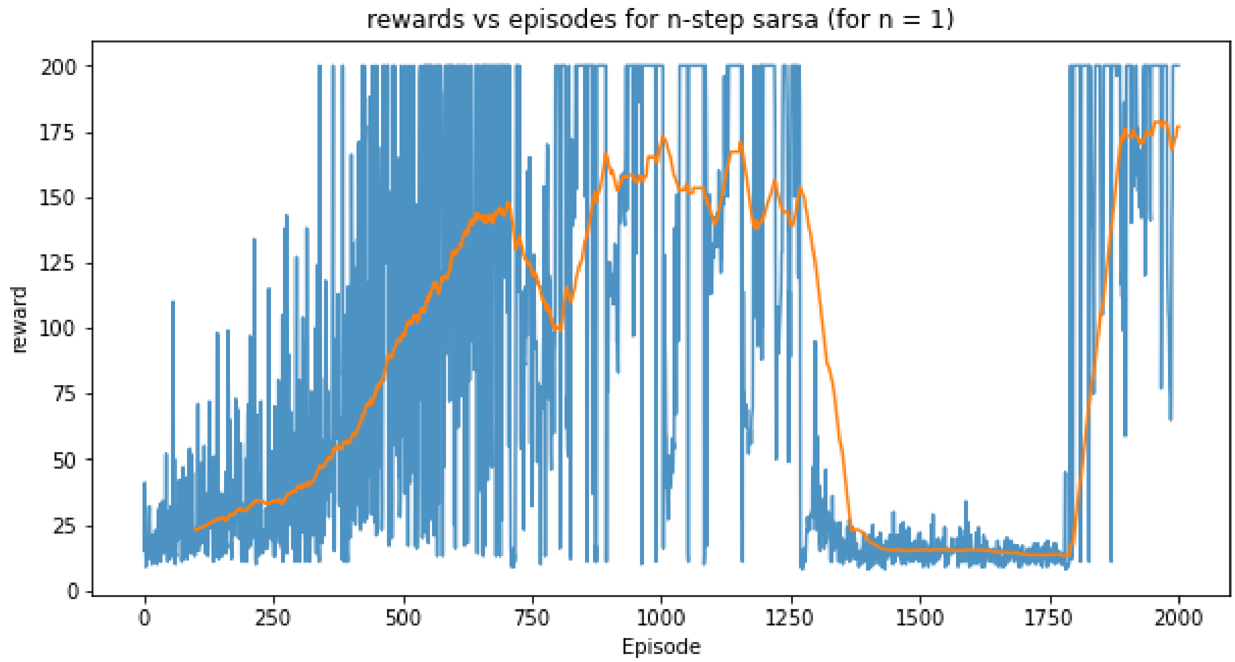
   Where G is the n-step return. The G is calculated using n-step return using bootstrap. Due to bootstrapping, it depends on the action-value function being approximated, and hence, consequently also depends on **w.** However, during update of **w,** we treat the G as a true target and do not calculate the gradient of G, as reflected by 'semi-gradient' in the name of the algorithm. To ensure this, the tensor for G is detached from the computation graph that computes the gradients and the attribute 'requires_grad' set to False.

   The algorithm is trained for 2,000 episodes. To facilitate the fast training, the epsilon is set to high value of 1 for initial episodes and gradually decreased with each episode up to 0.05 by the 2,000th episode.

   The slow learning rate of 0.005 is selected and kept constant throughout the training. With tuning of this hyperparameters, even faster training could be achieved.

4. **Training characteristics:**
   The network learns relatively fast after very high exploration initially. The training is faster in comparison to what I achieved with tabular methods. In fact, the approximate action-value function learned in less than 2000 episodes achieves the 100% success (reward of 200 in 100 continuous episodes). However, it is also observed that the learned function has a very high variance. That is, after achieving the very high average reward for multiple episodes, it starts

to do worst for several consecutive episodes before improving again. This can be seen in the plot shown in the figure below.



Some of the techniques used in supervised training of neural network can be tried to reduce the variance such as early stopping, dropout, etc.

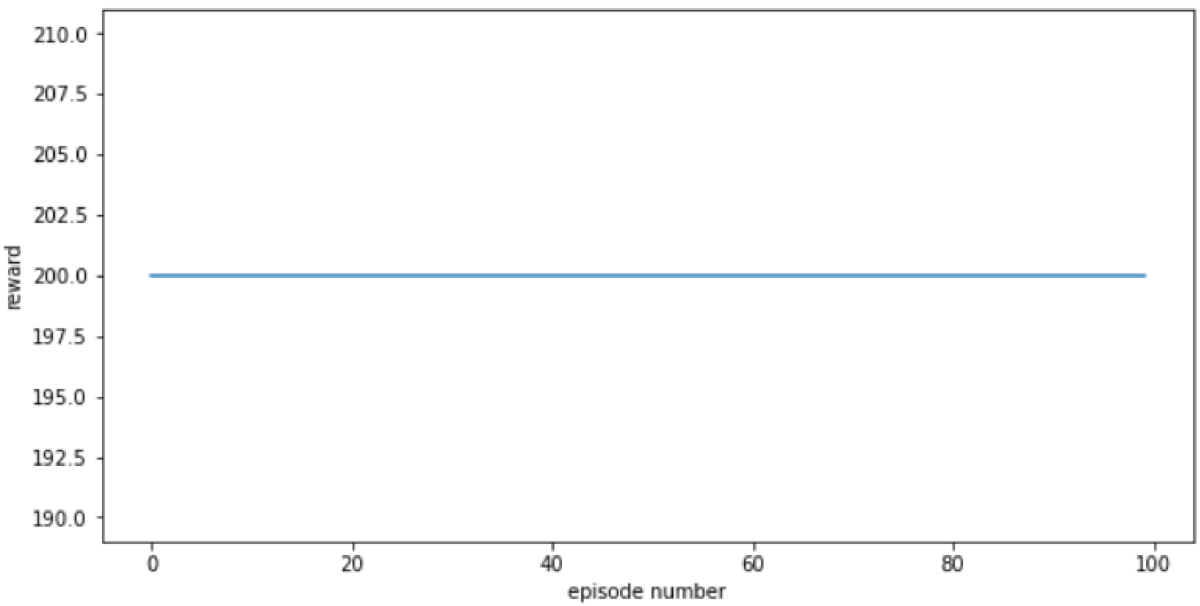
Here is the output of training performance, reported after every 100 episodes:

```
episode: 100 | avg_reward for last 100 episodes: 23.1
episode: 200 | avg_reward for last 100 episodes: 30.9
episode: 300 | avg_reward for last 100 episodes: 40.1
episode: 400 | avg_reward for last 100 episodes: 56.7
episode: 500 | avg_reward for last 100 episodes: 97.9
episode: 600 | avg_reward for last 100 episodes: 128.6
episode: 700 | avg_reward for last 100 episodes: 145.3
episode: 800 | avg_reward for last 100 episodes: 100.0
episode: 900 | avg_reward for last 100 episodes: 160.9
episode: 1000 | avg_reward for last 100 episodes: 170.7
episode: 1100 | avg_reward for last 100 episodes: 141.2
episode: 1200 | avg_reward for last 100 episodes: 144.0
episode: 1300 | avg_reward for last 100 episodes: 121.0
episode: 1400 | avg_reward for last 100 episodes: 19.3
episode: 1500 | avg_reward for last 100 episodes: 15.4
episode: 1600 | avg_reward for last 100 episodes: 15.4
episode: 1700 | avg_reward for last 100 episodes: 13.6
episode: 1800 | avg_reward for last 100 episodes: 25.1
episode: 1900 | avg_reward for last 100 episodes: 173.2
```

5. **Performance:**

The learned approximated action-value function achieved excellent performance in 100 test episodes and achieved 100% reward (maximum reward of 200) in each. The plot in the figure shows this graphically.

```
Average reward over 100 episodes: 200.00
```



In terms of robustness, speed of training, and compute used for training, we could do better by tuning parameters. Other concern with this method is that it doesn't provide the convergence guarantee and weights may blow-up in many problems. Nevertheless, this method performed better than all the tabular methods I have tried before for cart-pole problem.

Appendix

Code:

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:


import gym
import numpy as np
import pandas as pd
```

```
from math import inf
import math
import matplotlib.pyplot as plt
from IPython import display as ipythondisplay


# In[2]:


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


# In[3]:


# create the device object
dev = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")


# ### Cart Pole environment

# In[4]:


# cart pole environment
cp_env = gym.make('CartPole-v0')
cp_env.reset()

# action_space
cp_action_space = [0,1]


# ## Implementation

# This function selects an action using e-greedy policy for a given q_hat

# In[5]:


# action selection with epsilon greed policy
def e_greedy(q_hat, eps, S, action_space):
    # random action with probability eps
    if np.random.random() < eps:
```

```
        return np.random.choice(action_space)

    # greedy action otherwise
    act_vals = np.array([q_hat(feature(S,a)).cpu().detach().numpy() for a in acti
on_space])

    return np.random.choice(np.where(act_vals == act_vals.max())[0])


# In[6]:


# decay function for epsilon
def decay_eps(current_eps, eps_min, eps_dec):
    new_eps = current_eps - eps_dec
    return max(new_eps, eps_min)


# In[7]:


# create input feature from state and action
def feature(s,a):
    np_feature = np.append(s,a)
    return torch.from_numpy(np_feature).float().to(dev)


# ### Neural Network model to represent the action-value function

# In[8]:


class NeuralNet(nn.Module):
    '''
    input layer: no of nueron = input size (length of state space + 1 (action))
    hidden layers: 2 layers 32 and 16 neurons respectively with ReLU activation
    output layer: 1 neuron (representing the value of state-action pair)
    '''
    def __init__(self, input_size, hidden_size_1 = 32, hidden_size_2 = 16):
        super().__init__()
        self.l1 = nn.Linear(input_size, hidden_size_1)
        self.activation1 = nn.ReLU()
        self.l2 = nn.Linear(hidden_size_1, hidden_size_2)
        self.activation2 = nn.ReLU()
        self.l3 = nn.Linear(hidden_size_2, 1)
```

```python
    def forward(self, X):
        pred = self.l1(X)
        pred = self.activation1(pred)
        pred = self.l2(pred)
        pred = self.activation2(pred)
        pred = self.l3(pred)
        return pred


# In[9]:


# size of input layer
cp_input_size  = cp_env.observation_space.shape[0] + 1

# Neural net as a paramatric function to approximate action-value function Q
cp_q_hat = NeuralNet(cp_input_size, hidden_size_1 = 32, hidden_size_2 = 16)
cp_q_hat.to(dev)

# adam optimiser with learning rate of 0.005
optimiser = optim.Adam(cp_q_hat.parameters(), lr = 0.005)


# ### Episodic semi-gradient n-step SARSA

# In[10]:


def n_step_sarsa(env, action_space, q_hat, opt,
                 max_episodes = 50000, GAMMA = 1.0,
                 EPS_MAX = 1.0, EPS_MIN = 0.05, n=1,
                 loss_fn = nn.MSELoss()):

    # set seed for reproducible results
    env.seed(0)
    np.random.seed(0)

    # epsilon decay per episode
    eps_dec = (EPS_MAX - EPS_MIN)*2/max_episodes
    eps = EPS_MAX

    scores = []

    for episode in range(max_episodes):
        T = inf
        t = 0
```

```
        # storage
        states = [0]*(n+1)
        actions = [0]*(n+1)
        rewards = [0]*(n+1)

        # initialize S and store
        S = env.reset()
        states[t % (n+1)] = S

        # choose A and store
        A = e_greedy(q_hat, eps, S, action_space)
        actions[t % (n+1)] = A

        score = 0
        while True:
            if t < T:
                # take action A, observe R and S_next
                S, R, done, _ = env.step(A)

                score += R

                # store R and S_next
                rewards[(t+1) % (n+1)] = R
                states[(t+1) % (n+1)] = S

                if done:
                    T = t + 1
                else:
                    # choose and store A_next
                    A = e_greedy(q_hat, eps, S, action_space)
                    actions[(t+1) % (n+1)] = A

            tau = t - n + 1
            if tau >= 0:
                # compute the target G
                G = [GAMMA**(i-tau-1)*rewards[i % (n+1)]
                      for i in range(tau+1, min(tau+n, T) + 1)]
                G = [np.sum(G)]
                if tau + n < T:
                    s = states[(tau+n) % (n+1)]
                    a = actions[(tau+n) % (n+1)]
                    G += (GAMMA**n) * (q_hat(feature(s,a)).cpu().detach().numpy()
)

                G = torch.tensor(G).float().to(dev)
```

```
                s = states[tau % (n+1)]
                a = actions[tau % (n+1)]
                # predict the value
                pred = q_hat(feature(s,a))
                # compute gradient
                loss = loss_fn(pred, G)
                loss.backward()
                # update the params
                opt.step()
                opt.zero_grad()

            t += 1
            if tau == T - 1:
                break

        # decay the epsilon
        eps = decay_eps(eps, EPS_MIN, eps_dec)

        scores.append(score)
        avg_score = np.mean(scores[-100:])

        if episode % 100 == 0:
            print('episode:', episode, '| avg_reward for last 100 episodes: %.1f'
 % avg_score)

    return q_hat, scores


# In[11]:


q_hat_1_step_sarsa, rewards_1_step_sarsa = n_step_sarsa(env = cp_env,
                                                        action_space = cp_action_
space,
                                                        q_hat = cp_q_hat, opt = o
ptimiser,
                                                        max_episodes = 2000,
                                                        n=1)


# In[12]:


# plot rewards to assess the training performance
plt.figure(2, figsize=[10,5])
```

```
rewards = pd.Series(rewards_1_step_sarsa)
rm_r = rewards.rolling(100).mean()
plt.plot(rewards, alpha=0.8)
plt.plot(rm_r)
plt.xlabel('Episode')
plt.ylabel('reward')
plt.title('rewards vs episodes for n-step sarsa (for n = 1)')
plt.show()


# ### performance test

# In[13]:


def test(q_hat, eps, action_space, num_episodes = 1000):
    rewards = np.zeros(num_episodes)
    for i in range(num_episodes):
        totalReward = 0
        observation  = cp_env.reset()
        done = False
        while not done:
            action =  e_greedy(q_hat, eps, observation, action_space)
            observation, reward, done, info = cp_env.step(action)
            totalReward += reward
        rewards[i] = totalReward

    print(f"Average reward over {num_episodes} episodes: {np.average(rewards):.2f
}")

    plt.figure(2, figsize=[10,5])
    plt.plot(rewards)
    plt.xlabel('episode number')
    plt.ylabel('reward')
    plt.show()


# In[14]:


# test the learned policy
test(q_hat_1_step_sarsa, 0, cp_action_space, 100 )
```