```
pip install gym==0.25.2
```

```
Requirement already satisfied: gym==0.25.2 in /usr/local/lib/python3.10/dist-pac Requirement already satisfied: numpy>=1.18.0 in /usr/local/lib/python3.10/dist-p Requirement already satisfied: cloudpickle>=1.2.0 in /usr/local/lib/python3.10/d Requirement already satisfied: gym-notices>=0.0.4 in /usr/local/lib/python3.10/d
```

Cart Pole

In this assignment we implement DQN method for the cart pole problem.

Problem Description

This environment corresponds to the version of the cart-pole problem described by Barto, Sutton, and Anderson in "Neuronlike Adaptive Elements That Can Solve Difficult Learning Control Problem". A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The pendulum is placed upright on the cart and the goal is to balance the pole by applying forces in the left and right direction on the cart. For more information please visit https://www.gymlibrary.dev/environments/classic_control/cart_pole/.

Your Job

- 1. Read https://www.gymlibrary.dev/environments/classic_control/cart_pole/ to understand the environment, states, reward function, etc.
- 2. Implement the DQN method.
- 3. Answer the questions in a pdf.
- 4. Some helpful API documentation can be found here: https://www.gymlibrary.dev/api/core/.

```
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                                       Computational Assignment 3. ipynb - Colaboratory
   from __future__ import print_function
   from future import division
   import numpy as np
   import gym
   from gym import wrappers
   import time
   import random
   import torch
   import torch.nn as nn
   import torch.optim as optim
   import torch.nn.functional as F
   import pandas as pd
   import seaborn as sns; sns.set()
   import matplotlib.pyplot as plt
   We use environment 'CartPole-v1'. Run the following cell to test the environment.
   ## A demo of operating in this environment with a random policy
   def run random policy(env, gamma, render = False):
       Run 15 episodes by taking random actions.
       env: gym environment.
       gamma: discount factor.
       render: boolean to turn rendering on/off.
       obs = env.reset()
       for i in range(15):
           step idx = 0
           total reward = 0
           env.reset()
           while True:
               if render:
                   env.render()
               #choose an action randomly.
               #env.step() returns a tuple (state, reward, done) where done is a booler
               obs, reward, done , _ ,_= env.step(env.action_space.sample())
                total reward += (gamma ** step idx * reward)
               step idx += 1
               if done:
                    break
   env name = 'CartPole-v1'
   env = gym.make(env name).unwrapped
   run random policy(env, gamma=0.99, render = True)
   env.close()
        /usr/local/lib/python3.10/dist-packages/gym/core.py:49: DeprecationWarning: WARN
        If you want to render in human mode, initialize the environment in this way: gym
```

See here for more information: https://www.gymlibrary.ml/content/api/deprecation(

```
class DoubleDQN(nn.Module):
   #Input: state
   #0utput: vector corresponding to state-action values for actions, i.e. Q(s,a).
  def init (self):
     super(DoubleDQN, self). init ()
     'Define a neural network that takes state as an input and outputs Q(s,a) for
      'You should use ONLY 1 hidden layer with say 50 hidden nodes and ReLU activa
     n observation = 4
     n action = 2
     self.layer1 = nn.Linear(n_observation,50)
     self.layer2 = nn.Linear(50,n action)
     def forward(self, x):
     'Define the forward method to get output from your neural network for a give
     x= torch.as tensor(x).float()
     # print(x, "before Relu")
     x= F.relu(self.layer1(x))
     # print(x,"After Relu")
     return self.layer2(x)
     def choose action(model, state, EPSILON = 0.9):
  This is the epsilon-greedy strategy.
  # print("In Choose Action")
   'Write an epsilon greedy strategy to choose action based upon Q(s,a) calculated
   'Return the action'
   if np.random.rand() > EPSILON:
    # print("if here")
    return env.action space.sample()
    # print("if there")
    with torch.no grad():
     return np.argmax(model(state).numpy(), axis=0)
  def copy parameters(local model, target model):
```

```
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    Update model parameters.
    local model (PyTorch model): weights will be copied from.
    target model (PyTorch model): weights will be copied to.
    for target param, local param in zip(target model.parameters(), local model.para
        target param.data.copy (local param.data)
def plot returns(returns, x, title):
    Returns (iterable): list of returns over time
    window: window for rolling mean to smooth plotted curve
    plt.figure(figsize=(8, 6)) # Adjust figure size if needed
    sns.lineplot(
        data=pd.DataFrame(returns),color=x
    )
    plt.title(title)
    plt.xlabel('Epoch')
    plt.ylabel('Reward')
    plt.show()
```

```
def DoubleDQN update(model, model ft, gamma, epochs, render = False):
   Use online learning to update DQN.
   model (DQN): DQN model
   model ft (DQN): DQN model for fixed target
    reward history = []
    initial reward= []
    optimizer = torch.optim.Adam(model.parameters(), lr = 0.001) #feel free to tweaters
   #run epoches of episodes
   #stop at done or 10k epochs
    for i in range(epochs):
       # print(i)
       state = env.reset() #reset environment. Get initial state.
       total reward = 0
       total reward1 = 0
       if i%100 == 0: #update the fixed target network parameters every 100 epochs
           copy parameters(model, model ft)
       'Train the DON model'
        'Use SmoothL1Loss() as the loss function'
        'Train it via two methods. '
          a) Use the original reward returned by the environment for training'
          b) Use the following reward shaping:'
           \#x, x dot, theta, theta dot = state
           \#r1 = (env.x threshold - abs(x)) / env.x threshold - 0.8
           #r2 = (env.theta threshold radians - abs(theta)) / env.theta threshold
           \#reward = r1 + r2
        'We will check if there is a difference in convergence rate with and withou
       for t in range (5000):
         action = torch.argmax(model ft(state)).item()
         # print(action)
         next_state, reward, done, _,_ = env.step(action)
         x, x dot, theta, theta dot = next state
         r1 = (env.x threshold - abs(x)) / env.x threshold - 0.8
         r2 = (env.theta threshold radians - abs(theta)) / env.theta threshold radians
         total reward1 +=reward
         reward = r1 + r2
         total reward+=reward
         q ft= reward+gamma*torch.max(model ft(state), dim=0)[0]*(1-done)
         criterion = nn.SmoothL1Loss()(torch.max(model(state), dim=0)[0].unsqueeze
        reward history.append(total reward)
       initial reward.append(total reward1)
```

```
if __name__ == '__main__':
    gamma = 0.99
    np.random.seed(1111)
    env_name = 'CartPole-v1'
    env = gym.make(env_name).unwrapped
    model = DoubleDQN()
    model_ft = DoubleDQN()
    DoubleDQN_update(model, model_ft, gamma = 0.99, epochs = 200, render = True) #Try
    env.close()
```

Write any other lines of code if you need it for plotting and other purposes.

/usr/local/lib/python3.10/dist-packages/gym/core.py:317: DeprecationWarning: WAR
 deprecation(
 /usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatibility.py:3
 deprecation(
 /usr/local/lib/python3.10/dist-packages/gym/envs/classic_control/cartpole.py:179
 logger.warn(

