```
import torch
import torch.nn as nn

import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import gym
from collections import namedtuple
import random
import matplotlib.pyplot as plt
```

```
!pip install selenium
!apt-get update # to update ubuntu to correctly run apt i
!apt install chromium-chromedriver
!cp /usr/lib/chromium-browser/chromedriver /usr/bin
```

```
pip install gym-chrome-dino
```

```
device = torch.device('cuda' if torch.cuda.is_available()
```

Abstract

I wrote this double deep q algoritham to train an RL agent to play the chrome dino game. I was initially using the normal DQN algorithm , but the training was very unstable , SO later I switched to Double Deep q networks. The entire pipeline is I have an image encoder which is a basic cnn, where I bundle 4 frames 1 current and 3 previous and encode it using CNN , after encoding the vector will be fed into the q network as a state , and the network assigns q values, for each state action pairs. The algorithms uses replay buffer to store the experience/episodes , state, action , reward and next state values. I have then random sampled experiences and trained the network again so that the agent doesn't forget past experiences, there's also priority replay buffers where episodes which have high q values - reward differences will be sampled first. As I am using double deep q networks, I am using 2 networks policy and a target network.

I am also using epsilon - greedy strategy which is mostly common for RL algorithms which pushed the agents to explore more increasing the randomness in taking actions, once it's trained on all possibilties , we make the model exploit more with occasional exploration.

Training :

For each experience in the batch, the target Q-value is computed using the Double Q-Learning approach:

The policy network is used to determine the action taking the argmax Q-value for the next state.

The target network then evaluates the Q-value for that action to compute the target.

The Q-Network is updated by minimizing the difference between the predicted Q-values and the computed target Q-values.

The target network updates periodically using soft update, this is the main advantage which keeps the target stable.

This is the demo that i got: https://www.youtube.com/watch?v=3nfH1JJUL0g

```
#Install the chrome dino packages for running the gym simu
import gym_chrome_dino
from gym_chrome_dino.utils.wrappers import make_dino
import cv2

num_epochs=4
alpha=1e-4
batch_size=512

#Creating a named tuple for storing the experience

Experience = namedtuple('Experience',('state','action','n


#This is the class that I am using for replaymemory, whic
#batches to train later on, This is fine as the q learnin
#are enough experiences.

class replaymemory():
  def __init__(self,capacity):
    self.capacity=capacity
```

```
    self.memory=[]
    self.push_count=0

  def push(self,experience):
    if(self.push_count>self.capacity):
      self.memory[self.push_count%self.capacity]=experien
    else:
      self.memory.append(experience)
    self.push_count+=1



  def sample(self,batch_size):
    e=random.sample(self.memory,batch_size)
    #print(type(e1.state))
    states=torch.tensor([e1.state for e1 in e]).to(device
    actions=torch.tensor([e1.action for e1 in e]).to(devi
    next=torch.tensor([e1.next_state for e1 in e]).to(dev
    rewards = torch.tensor(([e1.reward for e1 in e])).to(
    dones = torch.tensor([e1.done for e1 in e])

    #states=states.view(64,1,80,160)
    return states.float(),actions,next,rewards,dones

  def can_provide(self,batch_size):
    return len(self.memory)>=batch_size


#I am just using this to create a 4 framed array, so that

class cstate():
  def __init__(self,size):
    self.size=size
    self.states=[]
    self.push_count=0
  def push(self,state):
    if self.push_count<self.size:
      self.states.append(state)
      self.push_count=self.push_count+1
    else:
```

```
      self.states.pop(0)
      self.states.append(state)
```

```
#This is the class for epsilon strategy , where with gree
# with the highest q value, where as for get_action depen
# in the inital phases it favours more of exploration and

class eps_strat():
  def __init__(self,num_actions,start,decay,end,device):
    self.cur_step=0
    self.num=num_actions
    self.device=device
    self.start=start
    self.decay=decay
    self.end=end
  def get_action(self,policy,state,step):
    self.cur_step=step
    ep=self.end+(self.start-self.end) * np.exp(-1*self.cu
    #self.cur_step=self.cur_step+1
    #print(ep,self.cur_step)
    if ep>random.random():
      #print("NO")
      action=random.randrange(self.num)
      return action
    else:
      policy.eval()
      with torch.no_grad():
        #print("yes")
        return torch.argmax(policy.forward(state)).item()
  def get_value(self,step):
    self.cur_step=step
    ep=self.end+(self.start-self.end) * np.exp(-1*self.cu
    return ep
  def greedy(self,policy,state):
```

```
    policy.eval()
    with torch.no_grad():
      return torch.argmax(policy.forward(state)).item()




#This is my convolutional network architecture

class convnet(nn.Module):
  def __init__(self):
    super(convnet,self).__init__()
    self.conv1= nn.Conv2d(4,32,8)
    self.conv2 = nn.Conv2d(32,64,4)
    self.conv3=nn.Conv2d(64,64,3)
    self.fc1=nn.Linear(64*68*68,512)
    self.fc2=nn.Linear(512,64)
    self.fc3=nn.Linear(64,2)

  def forward(self,x):
    out=F.relu(self.conv1(x))
    out=F.relu(self.conv2(out))
    out=F.relu(self.conv3(out))
    out = out.view(-1,64*68*68)
    out=F.relu(self.fc1(out))
    out=F.relu(self.fc2(out))
    out=self.fc3(out)
    return out


class lin(nn.Module):
  def __init__(self):
    super(lin,self).__init__()
    self.fc1=nn.Linear(2,128)
    self.fc2=nn.Linear(128,64)
    self.fc3=nn.Linear(64,2)
  def forward(self,x):
    out=F.relu(self.fc1(x))
    out=F.relu(self.fc2(out))
    out=self.fc3(out)
```

```
    return out

# This is the duelling netowork that I wanted to try out,
class duelling(nn.Module):
  def __init__(self,num_actions):
    super(duelling,self).__init__()
    self.a = num_actions
    self.conv1 = nn.Conv2d(4,32,8)
    self.conv2 =nn.Conv2d(32,64,4)
    self.conv3 = nn.Conv2d(64,64,3)
    self.fc1_value = nn.Linear(64*68*68,512)
    self.fc2_value = nn.Linear(512,64)
    self.fc3_value = nn.Linear(64,1)
    self.fc1_adv = nn.Linear(64*68*68,512)
    self.fc2_adv = nn.Linear(512,64)
    self.fc3_adv = nn.Linear(64,self.x)
  def forward(self,x):
    out=F.relu(self.conv1(x))
    out = F.relu(self.conv2(out))
    out = F.relu(self.conv3(out))
    out = out.view(-1,64*68*68)
    state_value = F.relu(self.fc1_value(out))
    state_value = F.relu(self.fc2_value(state_value))
    state_value = self.fc3_value(state_value)
    advantage = F.relu(self.fc1_adv(out))
    advantage = F.relu(self.fc2_adv(advantage))
    advantage = self.fc3_adv(advantage)

    return state_value+advantage-torch.mean(advantage)




#This is the function that I am using to update the targe

def soft_update(local,target,t):
  for target_param,local_param in zip(target.parameters()
    target_param.data.copy_(t*local_param.data+(1-t)*targ
```

```
#Initialising the target net and policy network and makin

target_net = convnet().to(device)
policy=convnet().to(device)
soft_update(policy,target_net,1)
```

```
num_episodes=1000000
from PIL import Image


#converting the image frames by doing pre processing.

def convert1(observation):
  cv2_imshow(np.array(observation))
  ob=torch.tensor(observation)
  ob=ob.view(4,80,160)
  ob=ob.numpy()

  f_ob=[]
  for i in range(4):
    l=ob[i]
    cv2_imshow(l)
    print("wtf")
    im = Image.fromarray(l)

    f_ob.append(np.asarray(im.resize((80,80))))

  f_ob=np.array(f_ob)

  ob=torch.tensor([f_ob]).to(torch.float)
  ob=ob.view(-1,4,80,80)
  return ob

#initialising memory replay with 10000 capacity
```

```
mem=replaymemory(10000)

from PIL import Image
def convert(observation):
  ob=np.array(observation,dtype="float32")
  #print(ob.shape)

  ob=cv2.cvtColor(ob,cv2.COLOR_BGR2GRAY)
  im = Image.fromarray(ob)
  ob = np.asarray(im.resize((80,80)))


  return ob

#Creating and intialising the gym environment and pushing
env = gym.make('ChromeDino-v0')
from google.colab.patches import cv2_imshow

ob=env.reset()
done_1=False
ob=convert(ob)

print(ob.shape)
stack=cstate(4)

stack.push(ob)
stack.push(ob)
stack.push(ob)
stack.push(ob)

a2=torch.tensor([stack.states])

a= nn.Conv2d(4,32,8)
b = nn.Conv2d(32,64,4)
c=nn.Conv2d(64,64,3)
out=a(a2)
out=b(torch.tensor(out))
out=c(torch.tensor(out))
```

```
print(out.shape)
#env=env.unwrapped
state=env.reset()
reward_sum=0
gamma=torch.tensor(0.999)

start=1
end=0.00001
decay=0.1
#decay=0.1

#tau for soft update

tau=0.89

t_decay=eps_strat(2,0.9,0.01,0.001,device)
print(tau)
```

```
(80, 80)
torch.Size([1, 64, 68, 68])
0.89
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:24: UserWarning:
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:25: UserWarning:
```

```
FILE='/content/drive/MyDrive/chrome_dino/target_net_dino_
File='/content/drive/MyDrive/chrome_dino/model_dino_3.pth
from IPython.display import clear_output
#model.load_state_dict(torch.load(file_path))
target_net.load_state_dict(torch.load(FILE))
policy.load_state_dict(torch.load(File))
```

```
<All keys matched successfully>
```

Double-click (or enter) to edit

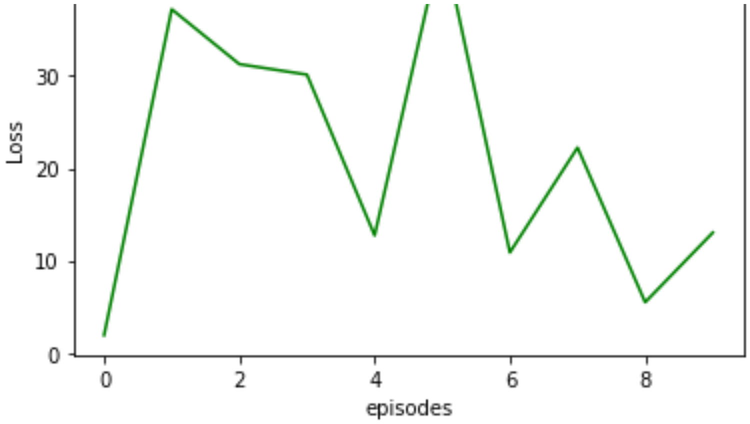
```
import cv2
height=720
width=1200
fps=10
fourcc = cv2.VideoWriter_fourcc(*'mp4v')  # setting up vid
```

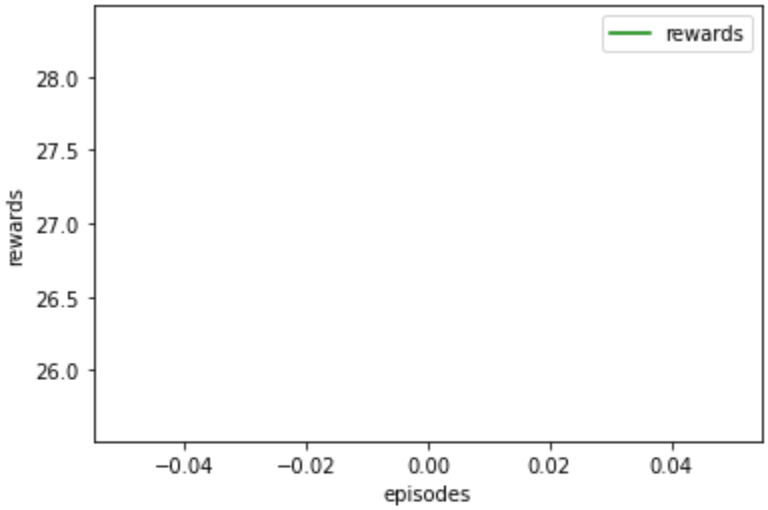
```
FILE='/content/drive/MyDrive/chrome_dino/target_net_dino_5
File='/content/drive/MyDrive/chrome_dino/model_dino_5.pth'
step=0
step_1=0
eps=0
lo=[]  # list to store loss values for plotting
re=[]  # list to store rewards for plotting
video=[]
video_ep=[]  # List to store video frames for the current
max_rew=0  # keeping track track of the max reward

for eps in range(num_episodes):  # Training loop over a gi

    reward_sum=0  # initi total reward for the current epi
    state=env.reset()  # Reseteting the environment
    state=convert(state)

    done_1=False  # flag to check if the current episode i
    video_ep=[]
    while not done_1:  # Loop until the episode ends
        step=step+1
        ep=eps_strat(2, start, decay, end, device)  # Crea

        # Get the current state stack and reshape it for t
        a2=torch.tensor(stack.states)
        a2=a2.view(1,4,80,80)
        action= ep.get_action(policy, a2.float().to(device

        next_state, reward, done_1, info = env.step(action
        video_ep.append(next_state)  # Add frame to curren

        next_state=convert(next_state)
        stack.push(next_state)  # Push the new state onto
        a3=torch.tensor(stack.states)
        a3=a3.view(1,4,80,80)

        reward = 1
```

```
        if done_1:
            reward = -10  # Setting reward to -10 for game

        # storing the experience in the replay memory
        e1 = Experience(a2.numpy(), action, a3.numpy(), re
        mem.push(e1)

        reward_sum += reward  # accumulate the rewards for
        state = next_state  #update to nest state

    if max_rew < reward_sum:
        max_rew = reward_sum
        video = video_ep.copy()

    re.append(reward_sum)  # Track rewards for plotting
    print(eps, reward_sum)

    if mem.can_provide(64):  # If enough experiences are i
        epochs = 10
        for i in range(epochs):
            states_1, actions, next_states, rewards, done

            # Reshape the sampled states for the network
            states_1 = states_1.view(64, 4, 80, 80)
            next_states = next_states.view(64, 4, 80, 80)

            # Calculate the expected Q values using the po
            ex = policy.forward(next_states.float()).detac
            target_q = target_net.forward(next_states.floa
            j = [t.index(max(t)) for t in ex]  # Get the a

            # Select the target Q-values corresponding to
            target_q = torch.tensor([target_q[i][j[i]] for

            done = done.int().to(device)
            q = (rewards + gamma * (target_q * (1 - done))
            q = q.unsqueeze(1)
            l = torch.tensor([actions[i] for i in range(64
```

```
        l = l.unsqueeze(1)

        # Calculate the loss between the predicted Q-v
        exp_q = policy.forward(states_1.float()).gathe
        loss = nn.MSELoss()
        tr = loss(exp_q, q)
        lo.append(tr)  # Track loss for plotting

        # Perform a gradient descent step
        optimizer = torch.optim.Adam(policy.parameters
        optimizer.zero_grad()
        tr.backward()
        optimizer.step()

if eps % 100 == 0:  # Every 100 episodes, update the t
    soft_update(policy, target_net, 1)
    episodes = range(len(lo))
    epi = range(len(re))
    plt.plot(episodes, lo, 'g', label='loss')
    plt.xlabel('episodes')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
    plt.plot(epi, re, 'g', label='rewards')
    plt.xlabel('episodes')
    plt.ylabel('rewards')
    plt.legend()
    plt.show()

if eps % 50 == 0:  # Save the model weights and best v
    torch.save(target_net.state_dict(), FILE)
    torch.save(policy.state_dict(), File)
    print("Weights saved")
    np.save('dino', np.array(video))
```

```
0 27
```






```
Weights saved
1 3115
2 319
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-115-ae600cf9c877> in <module>()
     37     #print(action)
     38 
---> 39     next_state,reward,done_1,info=env.step(action)
     40     #cv2_imshow(next_state)
     41     #time.sleep(0.5)

5 frames

/usr/local/lib/python3.7/dist-packages/PIL/PngImagePlugin.py in
load_end(self)
    890                 logger.debug("%r %s %s (unknown)", cid, pos, length)
    891                 ImageFile._safe_read(self.fp, length)
--> 892         self._text = self.png.im_text
    893         if not self.is_animated:
    894             self.png.close()

KeyboardInterrupt:
```

```
for i in video:
  cv2_imshow(i)
  time.sleep(0.07)
```

```
    time.sleep(0.07)
    clear_output()
```