Tutorial 4 - DQN and Actor-Critic

Please follow this tutorial to understand the structure (code) of DQNs & get familiar with Actor Critic methods.

References:

Please follow [Human-level control through deep reinforcement learning](#) for the original publication as well as the psuedocode. Watch Prof. Ravi's lectures on moodle or nptel for further understanding the core concepts. Contact the TAs for further resources if needed.

Part 1: DQN

```
'''
Installing packages for rendering the game on Colab
'''

!pip install gym pyvirtualdisplay > /dev/null 2>&1
!apt-get install -y xvfb python-opengl ffmpeg > /dev/null 2>&1
!apt-get update > /dev/null 2>&1
!apt-get install cmake > /dev/null 2>&1
!pip install --upgrade setuptools 2>&1
!pip install ez_setup > /dev/null 2>&1
!pip install gym[atari] > /dev/null 2>&1
!pip install git+https://github.com/tensorflow/docs > /dev/null 2>&1
```

```
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (60.9.3)
```

```
!pip install tensorflow-gpu
```

```
'''
A bunch of imports, you don't have to worry about these
'''

import numpy as np
from scipy.special import softmax
import random
import torch
import torch.nn as nn
import torch.nn.functional as F
from collections import namedtuple, deque
import torch.optim as optim
import datetime
import gym
from gym.wrappers import Monitor
import glob
import io
import base64
import matplotlib.pyplot as plt
from IPython.display import HTML
from pyvirtualdisplay import Display
import tensorflow as tf
from IPython import display as ipythondisplay
from PIL import Image
import tensorflow_probability as tfp
```

```
'''
Please refer to the first tutorial for more details on the specifics of environments
We've only added important commands you might find useful for experiments.
'''

'''
List of example environments
(Source - https://gym.openai.com/envs/#classic_control)

'Acrobot-v1'
'CartPole-v0'
'MountainCar-v0'
'''

env = gym.make('CartPole-v0')
env.seed(0)

state_shape = env.observation_space.shape[0]
```

```
no_of_actions = env.action_space.n

print(state_shape)
print(no_of_actions)
print(env.action_space.sample())
print("----")

'''
# Understanding State, Action, Reward Dynamics

The agent decides an action to take depending on the state.

The Environment keeps a variable specifically for the current state.
- Everytime an action is passed to the environment, it calculates the new state and updates the current state variable.
- It returns the new current state and reward for the agent to take the next action

'''

state = env.reset()
''' This returns the initial state (when environment is reset) '''

print(state)
print("----")

action = env.action_space.sample()
''' We take a random action now '''

print(action)
print("----")

next_state, reward, done, info = env.step(action)
''' env.step is used to calculate new state and obtain reward based on old state and action taken  '''

print(next_state)
print(reward)
print(done)
print(info)
print("----")
```

```
4
2
0
----
[-0.04456399  0.04653909  0.01326909 -0.02099827]
----
1
----
[-0.04363321  0.24146826  0.01284913 -0.30946528]
1.0
False
{}
----
```

DQN

Using NNs as substitutes isn't something new. It has been tried earlier, but the 'human control' paper really popularised using NNs by providing a few stability ideas (Q-Targets, Experience Replay & Truncation). The 'Deep-Q Network' (DQN) Algorithm can be broken down into having the following components.

Q-Network:

The neural network used as a function approximator is defined below

```
'''
### Q Network & Some 'hyperparameters'

QNetwork1:
Input Layer - 4 nodes (State Shape) \
Hidden Layer 1 - 64 nodes \
Hidden Layer 2 - 64 nodes \
Output Layer - 2 nodes (Action Space) \
Optimizer - zero_grad()

QNetwork2: Feel free to experiment more
'''
```

```
import torch
import torch.nn as nn
import torch.nn.functional as F


'''
Bunch of Hyper parameters (Which you might have to tune later **wink wink**)
'''
BUFFER_SIZE = int(1e5)
BATCH_SIZE = 64
GAMMA = 0.99
LR = 5e-4
UPDATE_EVERY = 20


class QNetwork1(nn.Module):

    def __init__(self, state_size, action_size, seed, fc1_units=128, fc2_units=64):
        """Initialize parameters and build model.
        Params
        ======
            state_size (int): Dimension of each state
            action_size (int): Dimension of each action
            seed (int): Random seed
            fc1_units (int): Number of nodes in first hidden layer
            fc2_units (int): Number of nodes in second hidden layer
        """
        super(QNetwork1, self).__init__()
        self.seed = torch.manual_seed(seed)
        self.fc1 = nn.Linear(state_size, fc1_units)
        self.fc2 = nn.Linear(fc1_units, fc2_units)
        self.fc3 = nn.Linear(fc2_units, action_size)

    def forward(self, state):
        """Build a network that maps state -> action values."""
        x = F.relu(self.fc1(state))
        x = F.relu(self.fc2(x))
        return self.fc3(x)
```

Replay Buffer:

This is a 'deque' that helps us store experiences. Recall why we use such a technique.

```
import random
import torch
import numpy as np
from collections import deque, namedtuple

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

class ReplayBuffer:
    """Fixed-size buffer to store experience tuples."""

    def __init__(self, action_size, buffer_size, batch_size, seed):
        """Initialize a ReplayBuffer object.

        Params
        ======
            action_size (int): dimension of each action
            buffer_size (int): maximum size of buffer
            batch_size (int): size of each training batch
            seed (int): random seed
        """
        self.action_size = action_size
        self.memory = deque(maxlen=buffer_size)
        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):
        """Add a new experience to memory."""
        e = self.experience(state, action, reward, next_state, done)
        self.memory.append(e)

    def sample(self):
        """Randomly sample a batch of experiences from memory."""
        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])).long().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)

    def __len__(self):
        """Return the current size of internal memory."""
        return len(self.memory)
```

Truncation:

We add a line (optionally) in the code to truncate the gradient in hopes that it would help with the stability of the learning process.

Tutorial Agent Code:

```
class TutorialAgent():

    def __init__(self, state_size, action_size, seed):

        ''' Agent Environment Interaction '''
        self.state_size = state_size
        self.action_size = action_size
        self.seed = random.seed(seed)

        ''' Q-Network '''
        self.qnetwork_local = QNetwork1(state_size, action_size, seed).to(device)
        self.qnetwork_target = QNetwork1(state_size, action_size, seed).to(device)
        self.optimizer = optim.Adam(self.qnetwork_local.parameters(), lr=LR)

        ''' Replay memory '''
        self.memory = ReplayBuffer(action_size, BUFFER_SIZE, BATCH_SIZE, seed)

        ''' Initialize time step (for updating every UPDATE_EVERY steps)           -Needed for Q Targets '''
        self.t_step = 0

    def step(self, state, action, reward, next_state, done):

        ''' Save experience in replay memory '''
        self.memory.add(state, action, reward, next_state, done)

        ''' If enough samples are available in memory, get random subset and learn '''
        if len(self.memory) >= BATCH_SIZE:
            experiences = self.memory.sample()
            self.learn(experiences, GAMMA)

        """ +Q TARGETS PRESENT """
        ''' Updating the Network every 'UPDATE_EVERY' steps taken '''
        self.t_step = (self.t_step + 1) % UPDATE_EVERY
        if self.t_step == 0:

            self.qnetwork_target.load_state_dict(self.qnetwork_local.state_dict())

    def act(self, state, eps=0.):

        state = torch.from_numpy(state).float().unsqueeze(0).to(device)
        self.qnetwork_local.eval()
        with torch.no_grad():
            action_values = self.qnetwork_local(state)
        self.qnetwork_local.train()

        ''' Epsilon-greedy action selection (Already Present) '''
        if random.random() > eps:
            return np.argmax(action_values.cpu().data.numpy())
        else:
            return random.choice(np.arange(self.action_size))

    def learn(self, experiences, gamma):
        """ +E EXPERIENCE REPLAY PRESENT """
        states, actions, rewards, next_states, dones = experiences

        ''' Get max predicted Q values (for next states) from target model'''
        Q_targets_next = self.qnetwork_target(next_states).detach().max(1)[0].unsqueeze(1)
```

```
        ''' Compute Q targets for current states '''
        Q_targets = rewards + (gamma * Q_targets_next * (1 - dones))

        ''' Get expected Q values from local model '''
        Q_expected = self.qnetwork_local(states).gather(1, actions)

        ''' Compute loss '''
        loss = F.mse_loss(Q_expected, Q_targets)

        ''' Minimize the loss '''
        self.optimizer.zero_grad()
        loss.backward()

        ''' Gradiant Clipping '''
        """ +T TRUNCATION PRESENT """
        for param in self.qnetwork_local.parameters():
            param.grad.data.clamp_(-1, 1)

        self.optimizer.step()
```

Here, we present the DQN algorithm code.

```
''' Defining DQN Algorithm '''

state_shape = env.observation_space.shape[0]
action_shape = env.action_space.n

def dqn(n_episodes=10000, max_t=1000, eps_start=1.0, eps_end=0.01, eps_decay=0.995):

    scores = []
    ''' list containing scores from each episode '''

    scores_window_printing = deque(maxlen=10)
    ''' For printing in the graph '''

    scores_window= deque(maxlen=100)
    ''' last 100 scores for checking if the avg is more than 195 '''

    eps = eps_start
    ''' initialize epsilon '''

    for i_episode in range(1, n_episodes+1):
        state = env.reset()
        score = 0
        for t in range(max_t):
            action = agent.act(state, eps)
            next_state, reward, done, _ = env.step(action)
            agent.step(state, action, reward, next_state, done)
            state = next_state
            score += reward
            if done:
                break

        scores_window.append(score)
        scores_window_printing.append(score)
        ''' save most recent score '''

        eps = max(eps_end, eps_decay*eps)
        ''' decrease epsilon '''

        print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_window)), end="")
        if i_episode % 10 == 0:
            scores.append(np.mean(scores_window_printing))
        if i_episode % 100 == 0:
           print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_window)))
        if np.mean(scores_window)>=195.0:
           print('\nEnvironment solved in {:d} episodes!\tAverage Score: {:.2f}'.format(i_episode-100, np.mean(scores_window)))
           break
    return [np.array(scores),i_episode-100]

''' Trial run to check if algorithm runs and saves the data '''
```

```
     ' Trial run to check if algorithm runs and saves the data '
```

Task 1a

Understand the core of the algorithm, follow the flow of data. Identify the exploration strategy used.

Task 1b

Out of the two exploration strategies discussed in class (ϵ-greedy & Softmax). Implement the strategy that's not used here.

Task 1c

How fast does the agent 'solve' the environment in terms of the number of episodes? (CartPole-v0 defines "solving" as getting average reward of 195.0 over 100 consecutive trials. SOURCE - https://gym.openai.com/envs/CartPole-v0/)

How 'well' does the agent learn? (reward plot?) The above two are some 'evaluation metrics' you can use to comment on the performance of an algorithm.

Please compare DQN (using ϵ-greedy) with DQN (using softmax). Think along the lines of 'no. of episodes', 'reward plots', 'compute time', etc. and add a few comments.

Task 1d (Optional)

Take a look at the official submissions page on [OpenAI gym's CartPole v-0 evaluations]()

Submission Steps

Task 1: Add a text cell with the answer.

Task 2: Add a code cell below task 1 solution and use 'Tutorial Agent Code' to build your new agent (with a different exploration strategy).

Task 3: Add a code cell below task 2 solution running both the agents to solve the CartPole v-0 environment and add a new text cell below it with your inferences.

Task 1a: The exploration strategy used is an epsilon-greedy policy

Task 1b

```
class TutorialAgent_softmax():

    def __init__(self, state_size, action_size, seed):

        ''' Agent Environment Interaction '''
        self.state_size = state_size
        self.action_size = action_size
        self.seed = random.seed(seed)

        ''' Q-Network '''
        self.qnetwork_local = QNetwork1(state_size, action_size, seed).to(device)
        self.qnetwork_target = QNetwork1(state_size, action_size, seed).to(device)
        self.optimizer = optim.Adam(self.qnetwork_local.parameters(), lr=LR)

        ''' Replay memory '''
        self.memory = ReplayBuffer(action_size, BUFFER_SIZE, BATCH_SIZE, seed)

        ''' Initialize time step (for updating every UPDATE_EVERY steps)           -Needed for Q Targets '''
        self.t_step = 0

    def step(self, state, action, reward, next_state, done):

        ''' Save experience in replay memory '''
        self.memory.add(state, action, reward, next_state, done)

        ''' If enough samples are available in memory, get random subset and learn '''
        if len(self.memory) >= BATCH_SIZE:
            experiences = self.memory.sample()
            self.learn(experiences, GAMMA)

        """ +Q TARGETS PRESENT """
        ''' Updating the Network every 'UPDATE_EVERY' steps taken '''
        self.t_step = (self.t_step + 1) % UPDATE_EVERY
        if self.t_step == 0:

            self.qnetwork_target.load_state_dict(self.qnetwork_local.state_dict())
```

```
    def act(self, state, eps=0.):

        state = torch.from_numpy(state).float().unsqueeze(0).to(device)
        self.qnetwork_local.eval()
        with torch.no_grad():
            action_values = self.qnetwork_local(state)
        self.qnetwork_local.train()

        ''' Softmax action selection (Already Present) '''
        return random.choices(np.arange(self.action_size), weights = softmax(action_values.cpu().data.numpy()).ravel())[-1]

    def learn(self, experiences, gamma):
        """ +E EXPERIENCE REPLAY PRESENT """
        states, actions, rewards, next_states, dones = experiences

        ''' Get max predicted Q values (for next states) from target model'''
        Q_targets_next = self.qnetwork_target(next_states).detach().max(1)[0].unsqueeze(1)

        ''' Compute Q targets for current states '''
        Q_targets = rewards + (gamma * Q_targets_next * (1 - dones))

        ''' Get expected Q values from local model '''
        Q_expected = self.qnetwork_local(states).gather(1, actions)

        ''' Compute loss '''
        loss = F.mse_loss(Q_expected, Q_targets)

        ''' Minimize the loss '''
        self.optimizer.zero_grad()
        loss.backward()

        ''' Gradiant Clipping '''
        """ +T TRUNCATION PRESENT """
        for param in self.qnetwork_local.parameters():
            param.grad.data.clamp_(-1, 1)

        self.optimizer.step()
```

Task 1c

```
# Epsilon-greedy
begin_time = datetime.datetime.now()
agent = TutorialAgent(state_size=state_shape,action_size = action_shape,seed = 0)


dqn()


time_taken = datetime.datetime.now() - begin_time

print(time_taken)

# Softmax
begin_time = datetime.datetime.now()
agent = TutorialAgent_softmax(state_size=state_shape,action_size = action_shape,seed = 0)


dqn()


time_taken = datetime.datetime.now() - begin_time

print(time_taken)
```

```
Episode 2000    Average Score: 19.06
Episode 2100    Average Score: 26.55
Episode 2200    Average Score: 9.39
Episode 2300    Average Score: 9.25
Episode 2400    Average Score: 9.53
Episode 2500    Average Score: 13.22
Episode 2600    Average Score: 9.46
Episode 2700    Average Score: 9.38
Episode 2800    Average Score: 9.39
Episode 2900    Average Score: 9.23
Episode 3000    Average Score: 9.32
Episode 3100    Average Score: 9.41
Episode 3200    Average Score: 9.44
Episode 3300    Average Score: 9.60
```

```
Episode 3400	Average Score: 10.12
Episode 3500	Average Score: 10.75
Episode 3600	Average Score: 11.48
Episode 3700	Average Score: 13.94
Episode 3800	Average Score: 35.62
Episode 3900	Average Score: 20.62
Episode 4000	Average Score: 22.22
Episode 4100	Average Score: 25.44
Episode 4200	Average Score: 43.87
Episode 4300	Average Score: 75.55
Episode 4400	Average Score: 104.66
Episode 4500	Average Score: 36.79
Episode 4600	Average Score: 27.65
Episode 4700	Average Score: 20.72
Episode 4800	Average Score: 16.03
Episode 4900	Average Score: 13.17
Episode 5000	Average Score: 11.74
Episode 5100	Average Score: 10.97
Episode 5200	Average Score: 10.37
Episode 5300	Average Score: 10.30
Episode 5400	Average Score: 10.06
Episode 5500	Average Score: 10.02
Episode 5600	Average Score: 10.14
Episode 5700	Average Score: 10.18
Episode 5800	Average Score: 10.24
Episode 5900	Average Score: 10.49
Episode 6000	Average Score: 10.61
Episode 6100	Average Score: 10.81
Episode 6200	Average Score: 11.21
Episode 6300	Average Score: 11.64
Episode 6400	Average Score: 12.19
Episode 6500	Average Score: 13.32
Episode 6600	Average Score: 14.23
Episode 6700	Average Score: 15.97
Episode 6800	Average Score: 17.27
Episode 6900	Average Score: 19.39
Episode 7000	Average Score: 20.79
Episode 7100	Average Score: 22.41
Episode 7200	Average Score: 26.74
Episode 7300	Average Score: 70.06
Episode 7400	Average Score: 175.22
Episode 7426	Average Score: 195.27
Environment solved in 7326 episodes!	Average Score: 195.27
0:12:05.590909
```

Inference:

The agent reaches the target (average reward of 195) much quicker (1815 episodes) when trained with an epsilon-greedy policy than when trained with a softmax behavorial policy (7326 episodes). In both the training phases, the average reward increases and then decreases, showing signs of instability.

Part 2: One-Step Actor-Critic Algorithm

Actor-Critic methods learn both a policy $\pi(a|s;\theta)$ and a state-value function $v(s;w)$ simultaneously. The policy is referred to as the actor that suggests actions given a state. The estimated value function is referred to as the critic. It evaluates actions taken by the actor based on the given policy. In this exercise, both functions are approximated by feedforward neural networks.

- The policy network is parametrized by θ - it takes a state s as input and outputs the probabilities $\pi(a|s;\theta)\ \forall\ a$
- The value network is parametrized by w - it takes a state s as input and outputs a scalar value associated with the state, i.e., $v(s;w)$
- The single step TD error can be defined as follows:
$$\delta_t = R_{t+1} + \gamma v(s_{t+1};w) - v(s_t;w)$$
- The loss function to be minimized at every step ($L_{tot}^{(t)}$) is a summation of two terms, as follows:
$$L_{tot}^{(t)} = L_{actor}^{(t)} + L_{critic}^{(t)}$$
where,
$$L_{actor}^{(t)} = -\log \pi(a_t|s_t;\theta)\delta_t$$
$$L_{critic}^{(t)} = \delta_t^2$$
- **NOTE: Here, weights of the first two hidden layers are shared by the policy and the value network**
    - First two hidden layer sizes: [1024, 512]
    - Output size of policy network: 2 (Softmax activation)
    - Output size of value network: 1 (Linear activation)

Initializing Actor-Critic Network

```
class ActorCriticModel(tf.keras.Model):
    """
    Defining policy and value networkss
    """
    def __init__(self, action_size, n_hidden1=1024, n_hidden2=512):
        super(ActorCriticModel, self).__init__()

        #Hidden Layer 1
        self.fc1 = tf.keras.layers.Dense(n_hidden1, activation='relu')
        #Hidden Layer 2
        self.fc2 = tf.keras.layers.Dense(n_hidden2, activation='relu')

        #Output Layer for policy
        self.pi_out = tf.keras.layers.Dense(action_size, activation='softmax')
        #Output Layer for state-value
        self.v_out = tf.keras.layers.Dense(1)

    def call(self, state):
        """
        Computes policy distribution and state-value for a given state
        """
        layer1 = self.fc1(state)
        layer2 = self.fc2(layer1)

        pi = self.pi_out(layer2)
        v = self.v_out(layer2)

        return pi, v
```

Agent Class

Task 2a: Write code to compute δ_t inside the Agent.learn() function

```
class Agent:
    """
    Agent class
    """
    def __init__(self, action_size, lr=0.001, gamma=0.99, seed = 85):
        self.gamma = gamma
        self.ac_model = ActorCriticModel(action_size=action_size)
        self.ac_model.compile(tf.keras.optimizers.Adam(learning_rate=lr))
        np.random.seed(seed)

    def sample_action(self, state):
        """
        Given a state, compute the policy distribution over all actions and sample one action
        """
        pi,_ = self.ac_model(state)

        action_probabilities = tfp.distributions.Categorical(probs=pi)
        sample = action_probabilities.sample()

        return int(sample.numpy()[0])

    def actor_loss(self, action, pi, delta):
        """
        Compute Actor Loss
        """
        return -tf.math.log(pi[0,action]) * delta

    def critic_loss(self,delta):
        """
        Critic loss aims to minimize TD error
        """
        return delta**2

    @tf.function
    def learn(self, state, action, reward, next_state, done):
        """
        For a given transition (s,a,s',r) update the paramters by computing the
        gradient of the total loss
        """
        with tf.GradientTape(persistent=True) as tape:
```

```
            pi, V_s = self.ac_model(state)
            _, V_s_next = self.ac_model(next_state)

            V_s_next = tf.stop_gradient(V_s_next)

            V_s = tf.squeeze(V_s)
            V_s_next = tf.squeeze(V_s_next)


            #### TO DO: Write the equation for delta (TD error)
            ## Write code below
            delta = reward + (self.gamma * V_s_next * (1 - done)) - V_s

            loss_a = self.actor_loss(action, pi, delta)
            loss_c =self.critic_loss(delta)
            loss_total = loss_a + loss_c

        gradient = tape.gradient(loss_total, self.ac_model.trainable_variables)
        self.ac_model.optimizer.apply_gradients(zip(gradient, self.ac_model.trainable_variables))
```

Train the Network

```
env = gym.make('CartPole-v0')

#Initializing Agent
agent = Agent(lr=1e-4, action_size=env.action_space.n)
#Number of episodes
episodes = 1000
tf.compat.v1.reset_default_graph()

reward_list = []
average_reward_list = []
begin_time = datetime.datetime.now()

for ep in range(1, episodes + 1):
    state = env.reset().reshape(1,-1)
    done = False
    ep_rew = 0
    while not done:
        action = agent.sample_action(state) ##Sample Action
        next_state, reward, done, info = env.step(action) ##Take action
        next_state = next_state.reshape(1,-1)
        ep_rew += reward  ##Updating episode reward
        agent.learn(state, action, reward, next_state, done) ##Update Parameters
        state = next_state ##Updating State
    reward_list.append(ep_rew)

    if ep % 10 == 0:
        avg_rew = np.mean(reward_list[-10:])
        print('Episode ', ep, 'Reward %f' % ep_rew, 'Average Reward %f' % avg_rew)

    if ep % 100:
        avg_100 =  np.mean(reward_list[-100:])
        if avg_100 > 195.0:
            print('Stopped at Episode ',ep-100)
            break

time_taken = datetime.datetime.now() - begin_time
print(time_taken)
```

```
Episode  350 Reward 41.000000 Average Reward 74.100000
Episode  360 Reward 200.000000 Average Reward 87.500000
Episode  370 Reward 126.000000 Average Reward 44.200000
Episode  380 Reward 11.000000 Average Reward 75.100000
Episode  390 Reward 43.000000 Average Reward 35.900000
Episode  400 Reward 31.000000 Average Reward 72.700000
Episode  410 Reward 200.000000 Average Reward 131.300000
Episode  420 Reward 52.000000 Average Reward 73.800000
Episode  430 Reward 183.000000 Average Reward 123.600000
Episode  440 Reward 25.000000 Average Reward 98.800000
Episode  450 Reward 171.000000 Average Reward 154.800000
Episode  460 Reward 200.000000 Average Reward 136.500000
Episode  470 Reward 200.000000 Average Reward 173.100000
Episode  480 Reward 150.000000 Average Reward 103.500000
Episode  490 Reward 33.000000 Average Reward 131.300000
Episode  500 Reward 200.000000 Average Reward 127.000000
Episode  510 Reward 129.000000 Average Reward 173.300000
Episode  520 Reward 110.000000 Average Reward 114.700000
Episode  530 Reward 135.000000 Average Reward 146.100000
Episode  540 Reward 132.000000 Average Reward 145.400000
```

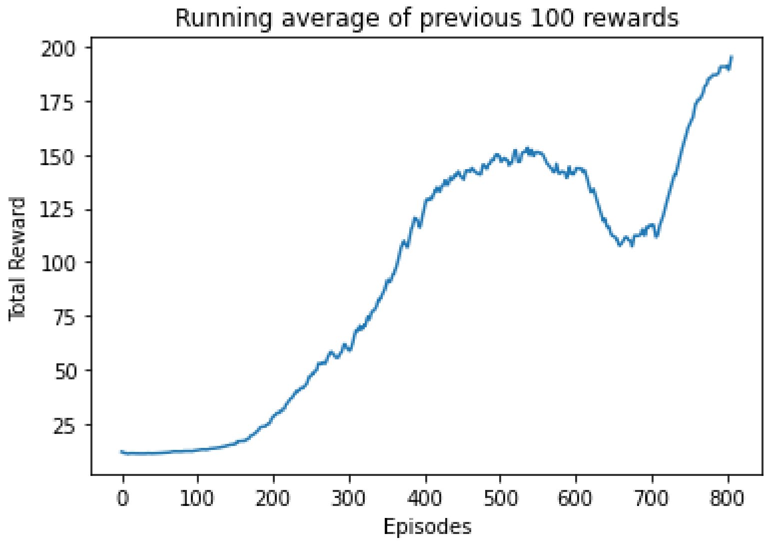
```
Episode  540 Reward 152.000000 Average Reward 145.400000
Episode  550 Reward 147.000000 Average Reward 143.300000
Episode  560 Reward 180.000000 Average Reward 164.900000
Episode  570 Reward 200.000000 Average Reward 164.800000
Episode  580 Reward 134.000000 Average Reward 136.000000
Episode  590 Reward 18.000000 Average Reward 160.200000
Episode  600 Reward 132.000000 Average Reward 139.300000
Episode  610 Reward 131.000000 Average Reward 160.000000
Episode  620 Reward 197.000000 Average Reward 159.500000
Episode  630 Reward 182.000000 Average Reward 136.100000
Episode  640 Reward 200.000000 Average Reward 140.800000
Episode  650 Reward 142.000000 Average Reward 150.500000
Episode  660 Reward 117.000000 Average Reward 132.800000
Episode  670 Reward 97.000000 Average Reward 107.900000
Episode  680 Reward 153.000000 Average Reward 126.700000
Episode  690 Reward 200.000000 Average Reward 157.700000
Episode  700 Reward 200.000000 Average Reward 151.700000
Episode  710 Reward 26.000000 Average Reward 155.400000
Episode  720 Reward 76.000000 Average Reward 72.800000
Episode  730 Reward 66.000000 Average Reward 74.300000
Episode  740 Reward 60.000000 Average Reward 59.100000
Episode  750 Reward 140.000000 Average Reward 84.400000
Episode  760 Reward 188.000000 Average Reward 93.800000
Episode  770 Reward 18.000000 Average Reward 129.600000
Episode  780 Reward 149.000000 Average Reward 145.400000
Episode  790 Reward 126.000000 Average Reward 178.400000
Episode  800 Reward 171.000000 Average Reward 174.400000
Episode  810 Reward 200.000000 Average Reward 139.400000
Episode  820 Reward 200.000000 Average Reward 195.600000
Episode  830 Reward 200.000000 Average Reward 200.000000
Episode  840 Reward 200.000000 Average Reward 175.600000
Episode  850 Reward 200.000000 Average Reward 200.000000
Episode  860 Reward 200.000000 Average Reward 199.400000
Episode  870 Reward 200.000000 Average Reward 200.000000
Episode  880 Reward 200.000000 Average Reward 200.000000
Episode  890 Reward 200.000000 Average Reward 200.000000
Episode  900 Reward 200.000000 Average Reward 200.000000
Stopped at Episode  806
0:09:34.114683
```

Task 2b: Plot total reward curve

In the cell below, write code to plot the total reward averaged over 100 episodes (moving average)

```
avg_reward_list = []
for i in range(len(reward_list) - 99):
  avg_reward_list.append(np.mean(reward_list[i:i + 100]))


### Plot of total reward vs episode
## Write Code Below

plt.plot(avg_reward_list)
plt.xlabel('Episodes')
plt.ylabel('Total Reward')
plt.title('Running average of previous 100 rewards')
```

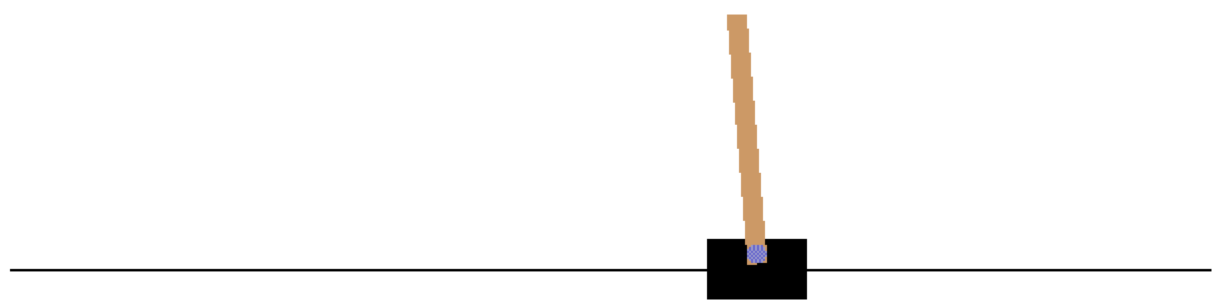
```
Text(0.5, 1.0, 'Running average of previous 100 rewards')
```



Code for rendering (source)

```
# Render an episode and save as a GIF file
```

```
display = Display(visible=0, size=(400, 300))
display.start()


def render_episode(env: gym.Env, model: tf.keras.Model, max_steps: int):
  screen = env.render(mode='rgb_array')
  im = Image.fromarray(screen)

  images = [im]

  state = tf.constant(env.reset(), dtype=tf.float32)
  for i in range(1, max_steps + 1):
    state = tf.expand_dims(state, 0)
    action_probs, _ = model(state)
    action = np.argmax(np.squeeze(action_probs))
    state, _, done, _ = env.step(action)
    state = tf.constant(state, dtype=tf.float32)

    # Render screen every 10 steps
    if i % 10 == 0:
      screen = env.render(mode='rgb_array')
      images.append(Image.fromarray(screen))

    if done:
      break

  return images


# Save GIF image
images = render_episode(env, agent.ac_model, 200)
image_file = 'cartpole-v0.gif'
# loop=0: loop forever, duration=1: play each frame for 1ms
images[0].save(
    image_file, save_all=True, append_images=images[1:], loop=0, duration=1)


import tensorflow_docs.vis.embed as embed
embed.embed_file(image_file)
```



0s completed at 12:56 PM