#**Tutorial 5 - 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
!pip install gym[classic_control]
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: setuptools in
/usr/local/lib/python3.8/dist-packages (67.4.0)
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: gym[classic_control] in
/usr/local/lib/python3.8/dist-packages (0.25.2)
Requirement already satisfied: numpy>=1.18.0 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control])
(1.22.4)
Requirement already satisfied: gym-notices>=0.0.4 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control])
(0.0.8)
Requirement already satisfied: cloudpickle>=1.2.0 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control])
(2.2.1)
Requirement already satisfied: importlib-metadata>=4.8.0 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control])
(6.0.0)
Requirement already satisfied: pygame==2.1.0 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control])
(2.1.0)
```

```
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.8/dist-packages (from importlib-
metadata>=4.8.0->gym[classic_control]) (3.15.0)
```

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

import numpy as np
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.record_video import RecordVideo
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
```

```
/usr/local/lib/python3.8/dist-packages/tensorflow_probability/python/
__init__.py:57: DeprecationWarning: distutils Version classes are
deprecated. Use packaging.version instead.
  if (distutils.version.LooseVersion(tf.__version__) <
```

```python
'''
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-v1'
'MountainCar-v0'
'''
```

```
env = gym.make('CartPole-v1')
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
```

```
----
[ 0.01369617 -0.02302133 -0.04590265 -0.04834723]
----
0
----
[ 0.01323574 -0.21745604 -0.04686959  0.22950698]
1.0
False
{}
----

/usr/local/lib/python3.8/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.8/dist-packages/gym/wrappers/step_api_compatibi
lity.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.8/dist-packages/gym/core.py:256:
DeprecationWarning: WARN: Function `env.seed(seed)` is marked as
deprecated and will be removed in the future. Please use
`env.reset(seed=seed)` instead.
  deprecation(
```

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
```

```python
'''

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)  # replay buffer size
BATCH_SIZE = 64         # minibatch size
GAMMA = 0.99            # discount factor
LR = 5e-4               # learning rate
UPDATE_EVERY = 20       # how often to update the network (When Q
target is present)


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.

```python
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 '''

begin_time = datetime.datetime.now()
agent = TutorialAgent(state_size=state_shape,action_size =
action_shape,seed = 0)


scores_eg = dqn()


time_taken = datetime.datetime.now() - begin_time

print(time_taken)
```

```
Episode 100	Average Score: 38.24
Episode 200	Average Score: 144.32
Episode 231	Average Score: 195.80
Environment solved in 131 episodes!	Average Score: 195.80
0:02:11.880334
```

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-v1 defines "solving" as getting average reward of 195.0 over 100 consecutive trials)

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.

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-1 environment and add a new text cell below it with your inferences.

Task 1a:

The exploration strategy used in the above implementation of the agent is *ϵ-greedy*. As the explorative actions are taken with probability ϵ.

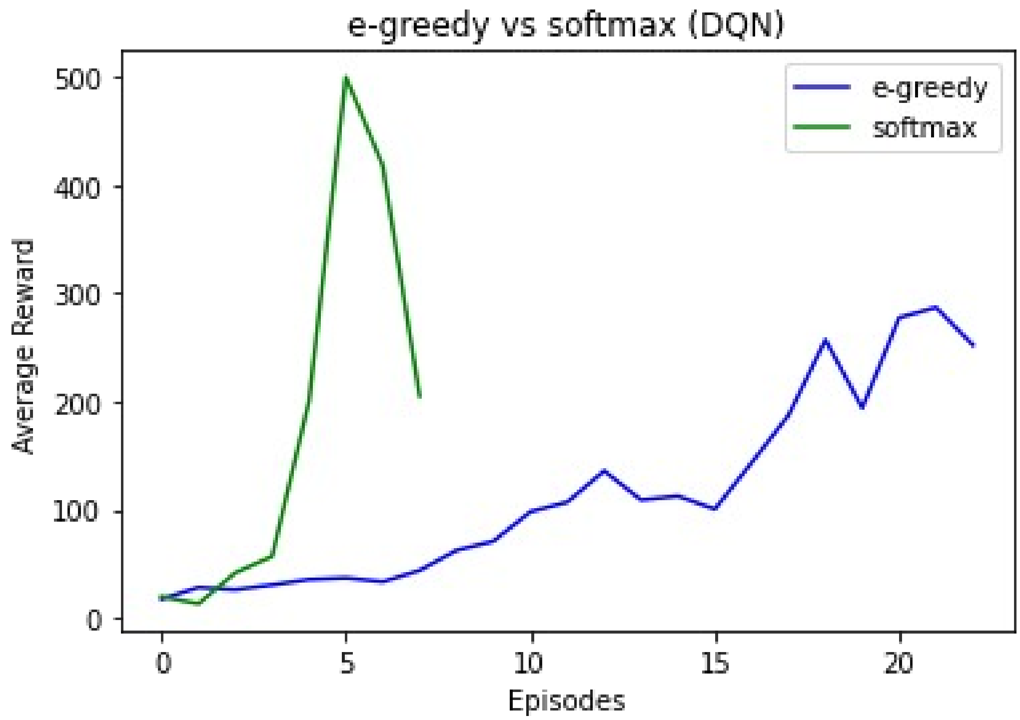
```
# Task 1B
# Softmax implementation for Agent
from scipy.special import softmax

class TutorialAgent_Softmax(TutorialAgent):
  def act(self, state, tau = .001):
    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 implementation '''
    return np.random.choice(np.arange(self.action_size), p =
softmax(action_values.cpu().data.numpy()).reshape(action_values.shape[
1]))
```

```
# Task 1C

agent = TutorialAgent_Softmax(state_size=state_shape,action_size =
action_shape,seed = 0)
scores_softmax = dqn()
time_taken = datetime.datetime.now() - begin_time
print(time_taken)
```

```
Episode 89 Average Score: 196.02
Environment solved in -11 episodes!   Average Score: 196.02
0:04:07.829770
```

```
plt.plot(range(scores_eg[0].shape[0]), scores_eg[0], color='blue',
label='e-greedy')
plt.plot(range(scores_softmax[0].shape[0]), scores_softmax[0],
color='green', label = 'softmax')
plt.xlabel('Episodes')
```

```
plt.ylabel('Average Reward')
plt.title('e-greedy vs softmax (DQN)')
plt.legend()
plt.show()
```



Task 1 C

Inference:

Reward plot: From the reward plot it is clear that the agent with softmax (τ = 0.001)exploration strategy reaches the average reward of 195 in 93 episodes while the ϵ-greedy(ϵ = 0.) exploration requires 231 episodes. From this we can infer that agent with softmax learns faster than the ϵ -greedy version.

Compute time: Softmax exploration has much more compute time than its ϵ-greedy version (roughly 2x higher), which shows that softmax computation is more expensive than the ϵ-greedy exploration.

Conclusion: Softmax learns muuch faster in lesser number of episodes than ϵ-greedy version but it is computationally more expensive than the ϵ-greedy version.

Part 2: One-Step Actor-Critic Algorithm

Actor-Critic methods learn both a policy $\pi(a \vee s;\theta)$ 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 $\pi(a \vee s;\theta) \forall a$
- 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,
$$L_{actor}^{(t)} = -\log \pi(a_t \vee s_t;\theta)\delta_t$$
$$L_{critic}^{(t)} = \delta_t^2$$
- **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 = 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 - V_s## Complete
this
            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-v1')

#Initializing Agent
agent = Agent(lr=1e-4, action_size=env.action_space.n)
#Number of episodes
episodes = 1800
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:])
        average_reward_list.append(avg_100)
        if avg_100 > 195.0:
            print('Stopped at Episode ',ep-100)
            break

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

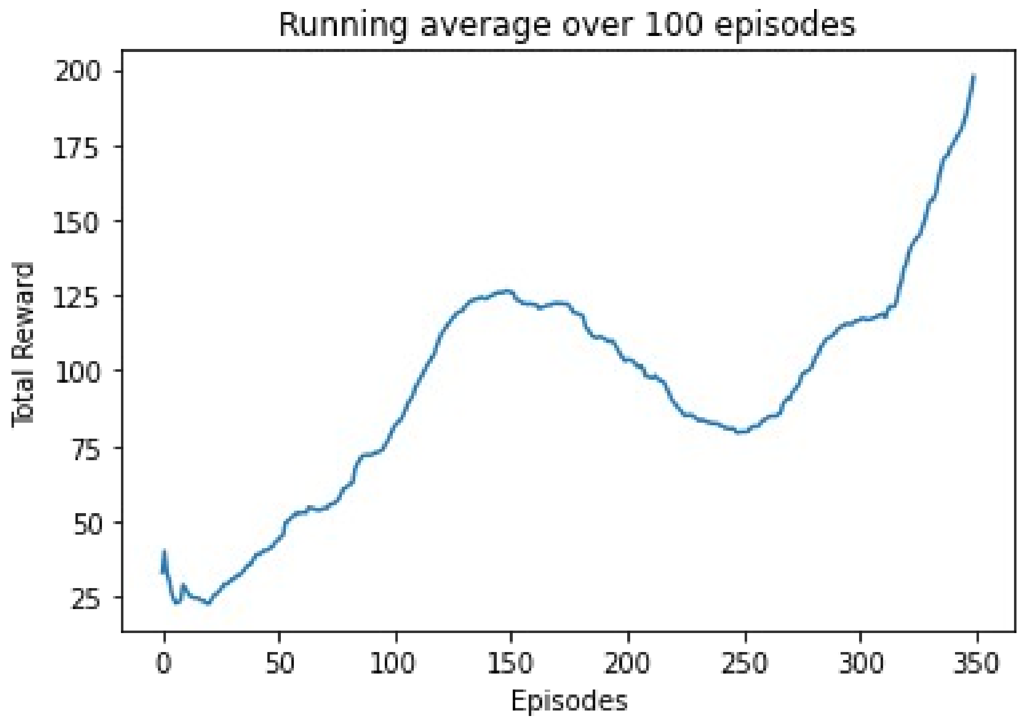
```
/usr/local/lib/python3.8/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.8/dist-packages/gym/wrappers/step_api_compatibi
lity.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(

Episode  10 Reward 75.000000 Average Reward 28.700000
Episode  20 Reward 9.000000 Average Reward 16.900000
Episode  30 Reward 56.000000 Average Reward 44.100000
Episode  40 Reward 95.000000 Average Reward 58.100000
Episode  50 Reward 108.000000 Average Reward 68.900000
Episode  60 Reward 40.000000 Average Reward 99.000000
Episode  70 Reward 78.000000 Average Reward 62.700000
Episode  80 Reward 79.000000 Average Reward 109.700000
Episode  90 Reward 79.000000 Average Reward 159.200000
Episode  100 Reward 184.000000 Average Reward 145.600000
Episode  110 Reward 219.000000 Average Reward 155.400000
Episode  120 Reward 283.000000 Average Reward 177.300000
Episode  130 Reward 84.000000 Average Reward 159.900000
Episode  140 Reward 66.000000 Average Reward 103.600000
Episode  150 Reward 158.000000 Average Reward 92.900000
Episode  160 Reward 66.000000 Average Reward 56.200000
Episode  170 Reward 139.000000 Average Reward 63.300000
Episode  180 Reward 62.000000 Average Reward 77.400000
Episode  190 Reward 120.000000 Average Reward 80.800000
Episode  200 Reward 97.000000 Average Reward 78.100000
Episode  210 Reward 75.000000 Average Reward 113.100000
```

```
Episode  220 Reward 89.000000 Average Reward 114.700000
Episode  230 Reward 96.000000 Average Reward 72.400000
Episode  240 Reward 71.000000 Average Reward 76.000000
Episode  250 Reward 50.000000 Average Reward 62.000000
Episode  260 Reward 135.000000 Average Reward 82.500000
Episode  270 Reward 421.000000 Average Reward 131.900000
Episode  280 Reward 118.000000 Average Reward 185.500000
Episode  290 Reward 150.000000 Average Reward 193.300000
Episode  300 Reward 85.000000 Average Reward 121.600000
Episode  310 Reward 99.000000 Average Reward 134.200000
Episode  320 Reward 305.000000 Average Reward 175.500000
Episode  330 Reward 172.000000 Average Reward 289.000000
Episode  340 Reward 374.000000 Average Reward 326.000000
Episode  350 Reward 284.000000 Average Reward 215.400000
Stopped at Episode  253
0:07:53.996745
```

Task 2b: Plot total reward curve

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

```python
### Plot of total reward vs episode
## Write Code Below
plt.plot(range(len(average_reward_list)), average_reward_list)
plt.xlabel('Episodes')
plt.ylabel('Total Reward')
plt.title('Running average over 100 episodes')
plt.show()
```



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-v1.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)
```

```
/usr/local/lib/python3.8/dist-packages/gym/core.py:43:
DeprecationWarning: WARN: The argument mode in render method is
deprecated; use render_mode during environment initialization instead.
See here for more information: https://www.gymlibrary.ml/content/api/
  deprecation(
```

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

```
<IPython.core.display.HTML object>
```