me19b190-tutorial-5

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#Tutorial 5 - DQN and Actor-Critic

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

0.0.1 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

[1]:
```
'''
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 (57.4.0)
Collecting setuptools
  Downloading setuptools-67.4.0-py3-none-any.whl (1.1 MB)
                             1.1/1.1 MB
21.1 MB/s eta 0:00:00
Installing collected packages: setuptools
  Attempting uninstall: setuptools
    Found existing installation: setuptools 57.4.0
    Uninstalling setuptools-57.4.0:
      Successfully uninstalled setuptools-57.4.0
```

```
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
ipython 7.9.0 requires jedi>=0.10, which is not installed.
cvxpy 1.2.3 requires setuptools<=64.0.2, but you have setuptools 67.4.0 which is
incompatible.
Successfully installed setuptools-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: 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: gym-notices>=0.0.4 in
/usr/local/lib/python3.8/dist-packages (from gym[classic_control]) (0.0.8)
Collecting pygame==2.1.0
  Downloading
pygame-2.1.0-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (18.3 MB)
                           18.3/18.3 MB
61.8 MB/s eta 0:00:00
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)
Installing collected packages: pygame
Successfully installed pygame-2.1.0
```

[2]:
```
'''
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
```

[ ]:
```
'''
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_compatibility.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(
```

0.1 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.

0.1.1 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)  # 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)
```

0.1.2 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)
```

0.2 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.

0.3 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()
```

0.3.1 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)


reward_eps_greedy, episodes_eps_greedy = 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
0:01:48.460789
```

0.3.2 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. ##**Answers:**

Task 1a: Understand the core of the algorithm, follow the flow of data. Identify the exploration strategy used.

Answer: The exploration strategy used in the code is epsilon greedy. The value of epsilon is decayed from 1 to 0.01, with a decay factor of 0.995. Initially we make the agent to be more exploratory in nature so we don't miss out on potential strategies and we then gradually decrease the epsilon to exploit the learnt poilicy.

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).

Softmax exploration strategy has been implemented with beta decay. Beta has been started with a very high value of 100 and has been gradually decayed to 0.01. Thus, during the initial phase of training we are making the agent more exploratory in nature, so we don't miss out on potential strategies and in due course we are exploiting the learnt policy. This, performs better in practice compared to beta =1 as we are explicity stating that the agent should explore more in the initial stages of training and exploit the learnt strategy(i.e greedy with respect to the learnt policy) during the later stages .The code has been implemented below.

[ ]:
```
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, beta=100.):

        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 exploration '''

        probab = torch.nn.functional.softmax(action_values/beta, dim = 1)
        return np.random.choice(np.arange(self.action_size), p = probab.cpu().
↪data.numpy().flatten())

    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()
```

[ ]:
```
''' Defining DQN Algorithm '''

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

def dqn_softmax(n_episodes=10000, max_t=1000, beta_start=100, beta_end=0.01,␣
 ↪beta_decay=0.99):

    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 '''

    beta = beta_start
    ''' initialize beta '''

    for i_episode in range(1, n_episodes+1):
        state = env.reset()
        score = 0
        for t in range(max_t):
            action = agent.act(state, beta)
            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 '''

        beta = max(beta_end, beta_decay*beta)
        ''' decrease beta '''

        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_softmax(state_size=state_shape,action_size =␣
 ↪action_shape,seed = 0)


reward_softmax, episodes_softmax = dqn_softmax()


time_taken = datetime.datetime.now() - begin_time

print(time_taken)
```

```
Episode 100     Average Score: 24.74
Episode 200     Average Score: 46.45
Episode 300     Average Score: 189.73
Episode 400     Average Score: 11.21
Episode 500     Average Score: 24.60
Episode 600     Average Score: 56.56
Episode 700     Average Score: 166.47
Episode 706     Average Score: 195.90
Environment solved in 606 episodes!     Average Score: 195.90
0:03:27.386258
```

[ ]:
```
#comparing exploration strategies...

timetaken_epsilon_greedy = []
timetaken_softmax = []
rewards_eps, rewards_soft = [],[]
num_expts = 2
plt.figure(figsize = (10,10))
plt.title("Reward curves")
plt.xlabel("Number of Episodes")
plt.ylabel("reward")
for i in range(num_expts):
```

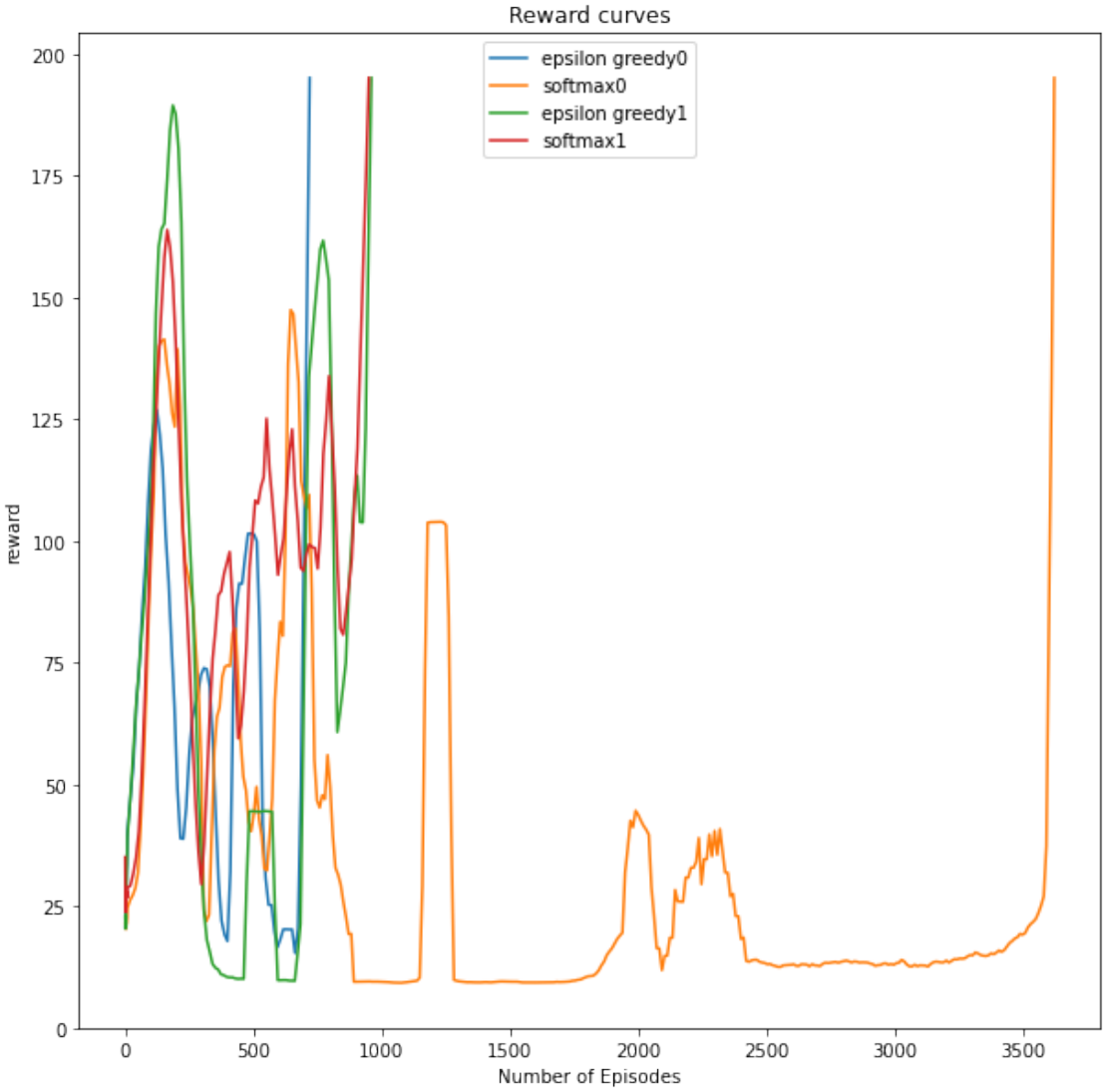
```
␣
↪print("================================================================================")
print('Experiment number: ',i+1)
begin_time = datetime.datetime.now()
agent = TutorialAgent(state_size=state_shape,action_size = action_shape,seed␣
↪= 0)
print('Exploration strategy: Epsilon greedy')
reward_eps_greedy, episodes_eps_greedy = dqn()
time_taken_eps = datetime.datetime.now() - begin_time
print('Time taken: ', time_taken_eps)


begin_time = datetime.datetime.now()
agent = TutorialAgent_softmax(state_size=state_shape,action_size =␣
↪action_shape,seed = 0)
print('Exploration strategy: softmax')
reward_softmax, episodes_softmax = dqn_softmax()
time_taken_soft = datetime.datetime.now() - begin_time
print('Time taken: ', time_taken_soft)

rewards_eps.append(reward_eps_greedy)
rewards_soft.append(reward_softmax)
timetaken_epsilon_greedy.append(time_taken_eps.total_seconds())
timetaken_softmax.append(time_taken_soft.total_seconds())

episodes_eps = np.
↪linspace(1,(10*len(reward_eps_greedy)),len(reward_eps_greedy))
episodes_soft = np.linspace(1,(10*len(reward_softmax)),len(reward_softmax))

reward_per_100 = []

k = 0

while k < (len(rewards_eps[i])):

  if k<10:
    reward_per_100.append(np.mean(rewards_eps[i][:k]))
    k += 1
  else:
    reward_per_100.append(np.mean(rewards_eps[i][k-10:k]))
    k+=1
reward_per_100.append(195)
episodes_1 = np.arange(10)
episodes_2 = np.
↪linspace(10,(10*len(reward_eps_greedy)),len(reward_eps_greedy)-9)
episodes_eps = np.concatenate((episodes_1,episodes_2))
```

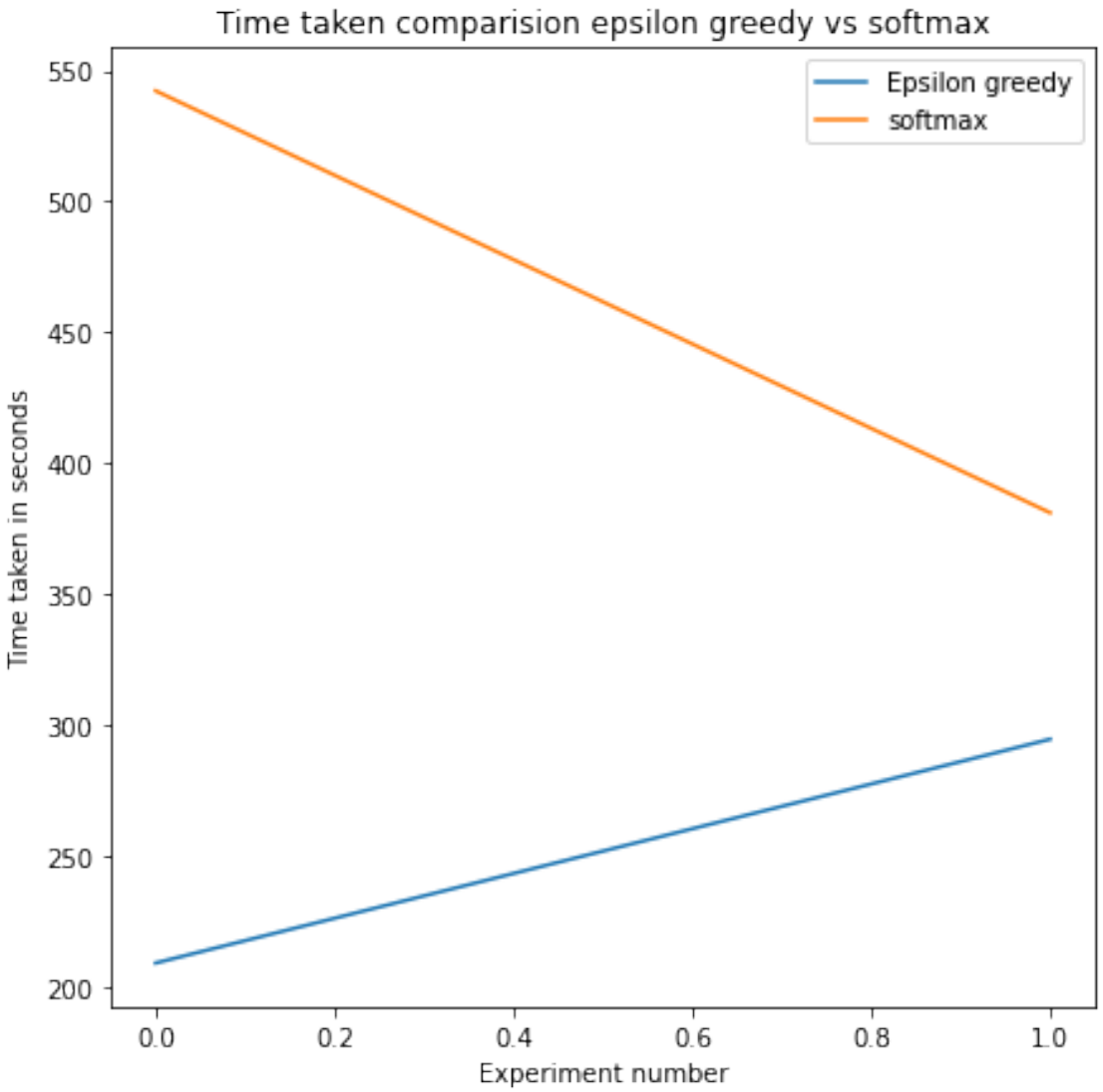
```
  reward_per_100_soft = []

  k = 0

  while k < (len(rewards_soft[i])):

    if k<10:
      reward_per_100_soft.append(np.mean(rewards_soft[i][:k]))
      k += 1
    else:
      reward_per_100_soft.append(np.mean(rewards_soft[i][k-10:k]))
      k+=1
  reward_per_100_soft.append(195)
  episodes_1 = np.arange(10)
  episodes_2 = np.linspace(10,(10*len(reward_softmax)),len(reward_softmax)-9)
  episodes_soft = np.concatenate((episodes_1,episodes_2))

  plt.plot(episodes_eps,reward_per_100,label = 'epsilon greedy'+str(i))
  plt.plot(episodes_soft,reward_per_100_soft,label = 'softmax'+str(i))


plt.legend()
plt.show()

#plotting the avergae time of epsilon greedy and softmax
plt.figure(figsize = (7,7))
plt.title("Time taken comparision epsilon greedy vs softmax")
plt.plot(np.arange(num_expts),timetaken_epsilon_greedy,label = 'Epsilon greedy')
plt.plot(np.arange(num_expts),timetaken_softmax, label = 'softmax')
plt.xlabel('Experiment number')
plt.ylabel('Time taken in seconds')
plt.legend()
plt.show()
print("Average time taken for epsilon greedy exploration: ", np.
 ↪array(timetaken_epsilon_greedy).mean())
print("Average time taken for softmax exploration: ", np.
 ↪array(timetaken_softmax).mean())
```

```
================================================================================
Experiment number:  1
Exploration strategy: Epsilon greedy
Episode 100     Average Score: 40.20
Episode 200     Average Score: 126.86
Episode 300     Average Score: 45.28
Episode 400     Average Score: 44.02
Episode 500     Average Score: 96.53
Episode 600     Average Score: 19.79
```

```
Episode 700     Average Score: 98.75
Episode 721     Average Score: 198.31
Environment solved in 621 episodes!     Average Score: 198.31
Time taken:  0:03:28.816420
Exploration strategy: softmax
Episode 100     Average Score: 24.58
Episode 200     Average Score: 109.90
Episode 300     Average Score: 127.51
Episode 400     Average Score: 21.86
Episode 500     Average Score: 81.08
Episode 600     Average Score: 42.70
Episode 700     Average Score: 100.32
Episode 800     Average Score: 89.72
Episode 900     Average Score: 31.41
Episode 1000    Average Score: 9.44
Episode 1100    Average Score: 9.28
Episode 1200    Average Score: 9.64
Episode 1300    Average Score: 103.75
Episode 1400    Average Score: 9.34
Episode 1500    Average Score: 9.43
Episode 1600    Average Score: 9.28
Episode 1700    Average Score: 9.31
Episode 1800    Average Score: 9.65
Episode 1900    Average Score: 12.77
Episode 2000    Average Score: 36.84
Episode 2100    Average Score: 22.91
Episode 2200    Average Score: 25.90
Episode 2300    Average Score: 34.58
Episode 2400    Average Score: 27.50
Episode 2500    Average Score: 13.55
Episode 2600    Average Score: 12.83
Episode 2700    Average Score: 13.02
Episode 2800    Average Score: 13.32
Episode 2900    Average Score: 13.37
Episode 3000    Average Score: 13.06
Episode 3100    Average Score: 12.61
Episode 3200    Average Score: 13.41
Episode 3300    Average Score: 14.89
Episode 3400    Average Score: 15.40
Episode 3500    Average Score: 19.07
Episode 3600    Average Score: 85.61
Episode 3628    Average Score: 199.05
Environment solved in 3528 episodes!    Average Score: 199.05
Time taken:  0:09:02.244935
================================================================================
Experiment number:  2
Exploration strategy: Epsilon greedy
Episode 100     Average Score: 39.35
```

```
Episode 200     Average Score: 146.51
Episode 300     Average Score: 134.25
Episode 400     Average Score: 13.07
Episode 500     Average Score: 10.05
Episode 600     Average Score: 44.38
Episode 700     Average Score: 15.11
Episode 800     Average Score: 157.79
Episode 900     Average Score: 108.80
Episode 960     Average Score: 198.34
Environment solved in 860 episodes!     Average Score: 198.34
Time taken:  0:04:54.386086
Exploration strategy: softmax
Episode 100     Average Score: 28.76
Episode 200     Average Score: 125.14
Episode 300     Average Score: 96.26
Episode 400     Average Score: 75.73
Episode 500     Average Score: 62.12
Episode 600     Average Score: 114.84
Episode 700     Average Score: 104.07
Episode 800     Average Score: 124.76
Episode 900     Average Score: 108.69
Episode 952     Average Score: 195.89
Environment solved in 852 episodes!     Average Score: 195.89
Time taken:  0:06:20.953535
```


Reward curves
epsilon greedy0
softmax0
epsilon greedy1
softmax1
reward
Number of Episodes
0
25
50
75
100
125
150
175
200
0
500
1000
1500
2000
2500
3000
3500




```
Average time taken for epsilon greedy exploration:  251.60125299999999
Average time taken for softmax exploration:  461.599235
```

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.

Answer: Epsilon greedy policy performed relatively well compared to softmax exploration strategy. Out of 2 experiments that are simulated, epsilon greedy has converged faster than softmax. The time required for computation for epsilon greedy is less than that of softmax for all the experiments. This is because, the softmax function is computationally intensive to calculate. The number of episodes required for epsilon greedy to converge is less than number of episodes for softmax algorithm to converge(In Experiment 1, epsilon greedy converged far ahead of softmax(721 and 3600 episodes respectively) and in Experiment 2, both epsilon greedy and softmax converged at a similar rates(960 and 952 episodes respectively).This is evident from the reward plots. The avergae computation time over several experiments for epsilon greedy(251.6 seconds) which is far

less than softmax exploration(461.6 sec). Thus, we can conclude that epsilon greedy performed better than softmax in all aspects. For better inferences, we can compare both epsilon greedy and softmax exploration strategies by simulating them over various experiments. Here the analysis is done for two experiments. We can conduct the analysis for multiple experiments by increasing the value of num_expts in the code to get an accurate idea on which exploration strategy would be relatively better.

0.4 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)

0.4.1 Initializing Actor-Critic Network

[40]:
```
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
```

0.4.2 Agent Class

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

[41]:
```
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))
```

0.4.3 Train the Network

[42]:
```
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:])
        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_compatibility.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 26.000000 Average Reward 16.800000
Episode  20 Reward 30.000000 Average Reward 28.600000
Episode  30 Reward 53.000000 Average Reward 51.200000
Episode  40 Reward 105.000000 Average Reward 86.400000
Episode  50 Reward 70.000000 Average Reward 59.700000
Episode  60 Reward 86.000000 Average Reward 73.900000
```

```
Episode  70 Reward 52.000000 Average Reward 97.900000
Episode  80 Reward 90.000000 Average Reward 87.000000
Episode  90 Reward 114.000000 Average Reward 92.300000
Episode  100 Reward 77.000000 Average Reward 92.000000
Episode  110 Reward 111.000000 Average Reward 106.500000
Episode  120 Reward 76.000000 Average Reward 125.700000
Episode  130 Reward 67.000000 Average Reward 88.100000
Episode  140 Reward 193.000000 Average Reward 166.600000
Episode  150 Reward 500.000000 Average Reward 375.900000
Episode  160 Reward 500.000000 Average Reward 487.700000
Episode  170 Reward 337.000000 Average Reward 293.600000
Stopped at Episode  71
0:04:07.822923
```

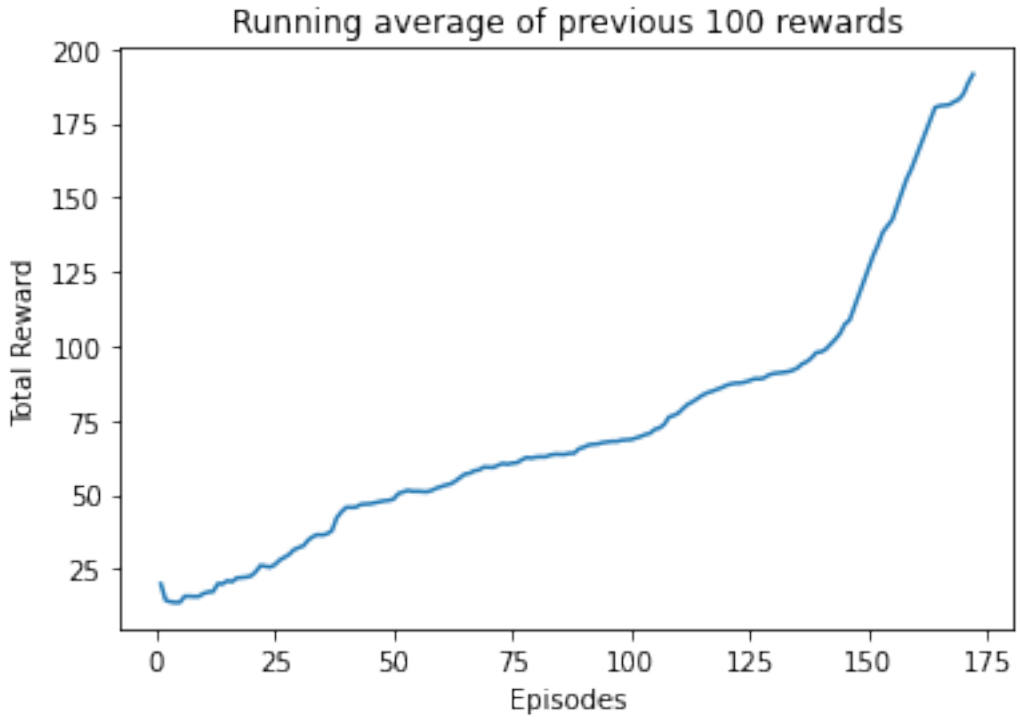
0.4.4 Task 2b: Plot total reward curve

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

[43]:
```
### Plot of total reward vs episode
## Write Code Below
average_reward_list = []
i = 0
while i < (len(reward_list)):

  if i<100:
    average_reward_list.append(np.mean(reward_list[:i]))
    i += 1
  else:
    average_reward_list.append(np.mean(reward_list[i-100:i]))
    i+=1

episodes_1 = np.arange(100)
episodes2 = (np.
 ↪linspace(100,(len(average_reward_list)+1),len(average_reward_list)-100))
episodes_2 = [round(i) for i in episodes2]
episodes = np.concatenate((episodes_1,episodes_2))
plt.figure()
plt.title("Running average of previous 100 rewards")
plt.xlabel("Episodes")
plt.ylabel("Total Reward")
plt.plot(episodes, average_reward_list)
plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/numpy/core/fromnumeric.py:3474:
RuntimeWarning: Mean of empty slice.
  return _methods._mean(a, axis=axis, dtype=dtype,
/usr/local/lib/python3.8/dist-packages/numpy/core/_methods.py:189:
RuntimeWarning: invalid value encountered in double_scalars
```

```
ret = ret.dtype.type(ret / rcount)
```



0.4.5 Code for rendering (source)

[44]:
```
# 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(
```

[45]:
```
import tensorflow_docs.vis.embed as embed
embed.embed_file(image_file)
```

[45]: <IPython.core.display.HTML object>