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 (57.4.0)
Collecting setuptools
  Downloading setuptools-67.4.0-py3-none-any.whl (1.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.1/1.1 MB 37.5 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 so
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: gym-notices>=0.0.4 in /usr/local/lib/python3.8/dist-packages (from gym[classic_control]) (0.0.8)
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: importlib-metadata>=4.8.0 in /usr/local/lib/python3.8/dist-packages (from gym[classic_control]) (6.0
Requirement already satisfied: cloudpickle>=1.2.0 in /usr/local/lib/python3.8/dist-packages (from gym[classic_control]) (2.2.1)
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 74.4 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_con
Installing collected packages: pygame
Successfully installed pygame-2.1.0
```

```
'''
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]
----
1
----
[ 0.01323574  0.17272775 -0.04686959 -0.3551522 ]
1.0
False
{}
----
/usr/local/lib/python3.8/dist-packages/gym/core.py:317: DeprecationWarning: WARN: Initializing wrapper in old step API which return
  deprecation(
/usr/local/lib/python3.8/dist-packages/gym/wrappers/step_api_compatibility.py:39: DeprecationWarning: WARN: Initializing environmen
  deprecation(
/usr/local/lib/python3.8/dist-packages/gym/core.py:256: DeprecationWarning: WARN: Function `env.seed(seed)` is marked as deprecated
  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
'''

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.

```
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)


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
0:01:57.681861
```

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

Epsilon Greedy exploration strategy was used.

Task 1b

Out of the two exploration strategies discussed in class (ϵ -greedy & Softmax), ϵ -greedy was implemented already. Implemented the strategy that's not used here i.e Softmax Policy.

```
from scipy.special import softmax
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, temp = 1):

        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 '''
        prob = np.nan_to_num(softmax(action_values.cpu().data.numpy()[0]/temp))
        prob /= prob.sum()
        return np.random.choice(self.action_size, p = prob)

    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, temp_start= 10000, temp_end=1, temp_decay=0.995):

    scores_softmax = []
    ''' 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 '''

    temp = temp_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, temp)
            #print(action)
            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 '''

        temp = temp*temp_decay
        ''' decrease temperature '''

        print('\rEpisode {}\tAverage Score: {:.2f}'.format(i_episode, np.mean(scores_window)), end="")

        scores_softmax.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_softmax),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)


dqn_softmax()


time_taken = datetime.datetime.now() - begin_time

print(time_taken)
```

```
Episode 100     Average Score: 24.19
Episode 200     Average Score: 20.25
Episode 300     Average Score: 23.88
Episode 400     Average Score: 24.72
Episode 500     Average Score: 28.62
Episode 600     Average Score: 35.70
Episode 700     Average Score: 100.10
Episode 787     Average Score: 195.21
Environment solved in 687 episodes!     Average Score: 195.21
0:02:53.279581
```

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.

Computation Time => ϵ-greedy = 01:54 , softmax = 02:43

No. of episodes till convergence => ϵ-greedy = 131 , softmax = 658

Softmax is slower than ϵ-greedy in terms of "compute time" and takes more "number of episodes" to converge.

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

```
4
5   [y_axis, x_axis] = dqn()
6
7   time_taken = datetime.datetime.now() - begin_time
8
9   print("Computation Time =" , time_taken)
```

```
    Episode 100     Average Score: 42.36
    Episode 200     Average Score: 125.91
    Episode 236     Average Score: 196.09
    Environment solved in 136 episodes!     Average Score: 196.09
    Computation Time = 0:01:38.273009
```

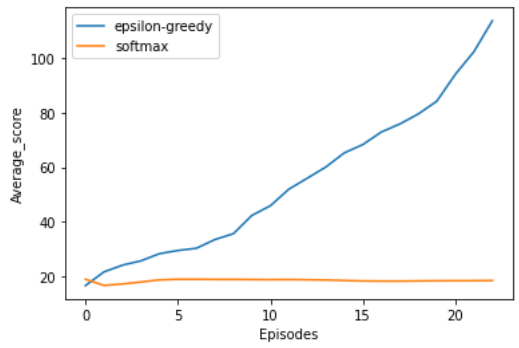
```
1 scores_eps_greedy = []
2 N_ep = len(y_axis)
3 for i in range(N_ep):
4   idx = min(99,i)
5   scores_eps_greedy.append(np.mean(y_axis[i-idx:i+1]))
```

```
1 begin_time = datetime.datetime.now()
2 agent = TutorialAgent_Softmax(state_size=state_shape,action_size = action_shape,seed = 0)
3
4 [y_axis_softmax ,x_axis_softmax] = dqn_softmax()
5
6 time_taken_softmax = datetime.datetime.now() - begin_time
7
8 print(time_taken_softmax)
```

```
    Episode 100     Average Score: 22.55
    Episode 200     Average Score: 22.96
    Episode 300     Average Score: 20.76
    Episode 400     Average Score: 21.48
    Episode 500     Average Score: 23.51
    Episode 600     Average Score: 28.74
    Episode 700     Average Score: 40.66
    Episode 800     Average Score: 135.12
    Episode 900     Average Score: 184.15
    Episode 1000    Average Score: 171.38
    Episode 1100    Average Score: 155.53
    Episode 1200    Average Score: 104.70
    Episode 1300    Average Score: 56.85
    Episode 1400    Average Score: 34.08
    Episode 1500    Average Score: 22.37
    Episode 1600    Average Score: 42.32
    Episode 1700    Average Score: 39.83
    Episode 1800    Average Score: 158.11
    Episode 1900    Average Score: 34.87
    Episode 1987    Average Score: 195.24
    Environment solved in 1887 episodes!    Average Score: 195.24
    0:10:15.072345
```

```
1 scores_softmax = []
2 N_ep = len(y_axis)
3 for i in range(N_ep):
4   idx = min(99,i)
5   scores_softmax.append(np.mean(y_axis_softmax[i-idx:i+1]))
```

```
1 ### Plot of total reward vs episode
2 ## Write Code Below
3
4 plt.xlabel('Episodes')
5 plt.ylabel('Average_score')
6 plt.plot(np.arange(len(scores_eps_greedy)) ,scores_eps_greedy)
7 plt.plot(np.arange(len(scores_softmax)) ,scores_softmax)
8 plt.legend(['epsilon-greedy','softmax'])
9 plt.show()
```



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 = 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 = delta = reward + self.gamma * V_s_next * (1 - done) - 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:])
        if avg_100 > 195.0:
            print('Stopped at Episode ',ep-100)
            break

```

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

```
Episode  10 Reward 19.000000 Average Reward 17.200000
Episode  20 Reward 13.000000 Average Reward 30.800000
Episode  30 Reward 14.000000 Average Reward 24.700000
Episode  40 Reward 11.000000 Average Reward 21.700000
Episode  50 Reward 12.000000 Average Reward 17.400000
Episode  60 Reward 9.000000 Average Reward 14.900000
Episode  70 Reward 19.000000 Average Reward 13.200000
Episode  80 Reward 11.000000 Average Reward 13.400000
Episode  90 Reward 16.000000 Average Reward 27.600000
Episode  100 Reward 18.000000 Average Reward 30.700000
Episode  110 Reward 31.000000 Average Reward 43.500000
Episode  120 Reward 127.000000 Average Reward 54.100000
Episode  130 Reward 46.000000 Average Reward 70.700000
Episode  140 Reward 51.000000 Average Reward 61.500000
Episode  150 Reward 46.000000 Average Reward 70.900000
Episode  160 Reward 103.000000 Average Reward 110.300000
Episode  170 Reward 111.000000 Average Reward 102.700000
Episode  180 Reward 121.000000 Average Reward 116.500000
Episode  190 Reward 136.000000 Average Reward 117.400000
Episode  200 Reward 107.000000 Average Reward 111.600000
Episode  210 Reward 102.000000 Average Reward 99.100000
Episode  220 Reward 121.000000 Average Reward 114.200000
Episode  230 Reward 126.000000 Average Reward 90.700000
Episode  240 Reward 103.000000 Average Reward 107.800000
Episode  250 Reward 111.000000 Average Reward 112.500000
Episode  260 Reward 128.000000 Average Reward 112.100000
Episode  270 Reward 109.000000 Average Reward 116.300000
Episode  280 Reward 58.000000 Average Reward 106.400000
Episode  290 Reward 108.000000 Average Reward 107.000000
Episode  300 Reward 123.000000 Average Reward 106.200000
Episode  310 Reward 106.000000 Average Reward 119.600000
Episode  320 Reward 107.000000 Average Reward 101.400000
Episode  330 Reward 114.000000 Average Reward 103.500000
Episode  340 Reward 134.000000 Average Reward 120.700000
Episode  350 Reward 75.000000 Average Reward 59.000000
Episode  360 Reward 119.000000 Average Reward 86.200000
Episode  370 Reward 128.000000 Average Reward 113.800000
Episode  380 Reward 120.000000 Average Reward 126.900000
Episode  390 Reward 143.000000 Average Reward 116.800000
Episode  400 Reward 159.000000 Average Reward 134.900000
Episode  410 Reward 102.000000 Average Reward 151.400000
Episode  420 Reward 248.000000 Average Reward 152.400000
Episode  430 Reward 204.000000 Average Reward 214.500000
Episode  440 Reward 138.000000 Average Reward 137.800000
Episode  450 Reward 113.000000 Average Reward 130.300000
Episode  460 Reward 123.000000 Average Reward 168.700000
Episode  470 Reward 101.000000 Average Reward 109.600000
Episode  480 Reward 122.000000 Average Reward 119.000000
Episode  490 Reward 125.000000 Average Reward 116.400000
Episode  500 Reward 123.000000 Average Reward 136.400000
Episode  510 Reward 432.000000 Average Reward 141.000000
Episode  520 Reward 293.000000 Average Reward 160.800000
Episode  530 Reward 112.000000 Average Reward 119.100000
Episode  540 Reward 160.000000 Average Reward 125.100000
Episode  550 Reward 161.000000 Average Reward 148.400000
Episode  560 Reward 110.000000 Average Reward 125.900000
Episode  570 Reward 122.000000 Average Reward 125.600000
Episode  580 Reward 93.000000 Average Reward 99.500000
```

Task 2b: Plot total reward curve

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

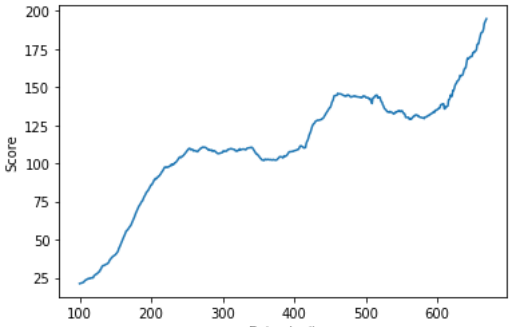
```
### Plot of total reward vs episode
## Write Code Below

def plot_scores(scores):
    # calculate moving average over 100 episodes
    ma_scores = [np.mean(scores[i:i+100]) for i in range(len(scores)-100)]

    # plot scores and moving average
    fig = plt.figure()
    ax = fig.add_subplot(111)
    #plt.plot(np.arange(len(scores)), scores)
    plt.plot(np.arange(100, len(scores)), ma_scores)
    plt.ylabel('Score')
    plt.xlabel('Episode #')
    plt.show()

plot_scores(reward_list)

```



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

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

1

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