## **Stock Trading Using Deep Q-Learning**

## **Problem Statement**

Prepare an agent by implementing Deep Q-Learning that can perform unsupervised trading in stock trade. The aim of this project is to train an agent that uses Q-learning and neural networks to predict the profit or loss by building a model and implementing it on a dataset that is available for evaluation. The stock trading index environment provides the agent with a set of actions:

Buy

Sell

• Sit This project has following sections:

Import libraries

Create a DQN agent

· Preprocess the data · Train and build the model

Steps to perform

· Evaluate the model and agent In the section create a DQN agent, create a class called agent where: Action size is defined as 3 • Experience replay memory to deque is 1000

· Empty list for stocks that has already been bought The agent must possess the following hyperparameters: ■ gamma= 0.95 epsilon = 1.0 epsilon final = 0.01

epsilon\_decay = 0.995

Note: It is advised to compare the results using different values in hyperparameters. Neural network has 3 hidden layers · Action and experience replay are defined **Solution** 

Import the libraries import keras from keras.models import Sequential from keras.models import load\_model from keras.layers import Dense

from keras.optimizers import Adam import numpy as np import random from collections import deque **Create a DQN agent** In [ ]: class Agent():

Use the instruction below to prepare an agent

# Action space include 3 actions: Buy, Sell, and Sit def \_\_init\_\_(self, state\_size, is\_eval=False, model\_name=""): #normalize the previous days #sit, buy, sell self.action\_size = 3

self.state\_size = state\_size #Setting up the experience replay memory to deque with 1000 elements inside it self.memory = deque(maxlen=1000) #Empty list with inventory is created that contains the stocks that were already bought self.inventory=[] self.model\_name = model\_name self.is\_eval = is\_eval self.gamma = 0.95

#Setting up gamma to 0.95, that helps to maximize the current reward over the long-term #Epsilon parameter determines whether to use a random action or to use the model for the action. #In the beginning random actions are encouraged, hence epsilon is set up to 1.0 when the model is not trained. #And over time the epsilon is reduced to 0.01 in order to decrease the random actions and use the trained model #We're then set the speed of decreasing epsililon in the epsilon\_decay parameter self.epsilon = 1.0self.epsilon\_min = 0.01  $self.epsilon_decay = 0.995$ self.model = load\_model(""+model\_name) if is\_eval else self.\_model() #Defining our neural network #Define the neural network function called \_model and it just takes the keyword self #Define the model with Sequential() #Define states i.e. the previous n days and stock prices of the days #Defining 3 hidden layers in this network

#Changing the activation function to relu because mean-squared error is used for the loss def \_model(self): model = Sequential() model.add(Dense(units=64, input\_dim = self.state\_size, activation='relu')) model.add(Dense(units=32, activation='relu')) model.add(Dense(units=8, activation='relu')) model.add(Dense(self.action\_size, activation='linear')) model.compile(loss = 'mse', optimizer=Adam(lr=0.001)) return model def act(self, state): if not self.is\_eval and np.random.rand() <= self.epsilon:</pre> return random.randrange(self.action\_size) options = self.model.predict(state) return np.argmax(options[0])

for i in range(l-batch\_size + 1, 1): mini\_batch.append(self.memory[i]) for state, action, reward, next\_state, done in mini\_batch: target = reward if not done: #amax = return the maximum of an array or maximum along an axis target = reward + self.gamma\*np.argmax(self.model.predict(next\_state[0])) target\_f = self.model.predict(state) target\_f[0][action] = target self.model.fit(state, target\_f, epochs=1, verbose=0) if self.epsilon > self.epsilon\_min: self.epsilon \*= self.epsilon\_decay

Preprocess the stock market data

return ("-\$" if n < 0 else "\$") + "{0:.2f}".format(abs(n))</pre>

print ("Usage: python train.py [stock] [window] [episodes]")

print ("Episode " + str(e) + "/" + str(episode\_count))

next\_state = getState(data, t + 1, window\_size + 1)

print ("Buy: " + formatPrice(data[t]))

print ("-----")

agent.inventory.append(data[t])

state = getState(data, 0, window\_size + 1)

action = agent.act(state)

if action == 1: # buy

block = data[d:t + 1] if  $d \ge 0$  else -d \* [data[0]] + data[0:t + 1] # pad with t0

In [ ]:

import math

def sigmoid(x):

# prints formatted price def formatPrice(n):

def expReplay(self, batch\_size):

mini\_batch = [] 1 = len(self.memory)

# returns the vector containing stock data from a fixed file def getStockDataVec(key): vec = [] lines = open("" + key + ".csv", "r").read().splitlines() for line in lines[1:]: vec.append(float(line.split(",")[4])) return vec # returns the sigmoid

return 1 / (1 + math.exp(-x))

# returns an an n-day state representation ending at time t

for i in range(n - 1): res.append(sigmoid(block[i + 1] - block[i])) return np.array([res]) Train and build the model In [ ]: import sys if len(sys.argv) != 4:

def getState(data, t, n): d = t - n + 1

stock\_name = input("Enter stock\_name, window\_size, Episode\_count") #Fill the given information when prompted: #Enter stock\_name = GSPC\_Training\_Dataset #window\_size = 10 #Episode\_count = 100 or it can be 10 or 20 or 30 and so on. window\_size = input() episode\_count = input() stock\_name = str(stock\_name) window\_size = int(window\_size) episode\_count = int(episode\_count)

agent = Agent(window\_size)

l = len(data) - 1batch\_size = 32

data = getStockDataVec(stock\_name)

for e in range(episode\_count + 1):

total\_profit = 0 agent.inventory = []

for t in range(1):

reward = 0

elif action == 2 and len(agent.inventory) > 0: # sell bought\_price = agent.inventory.pop(0) reward = max(data[t] - bought\_price, 0) total\_profit += data[t] - bought\_price print ("Sell: " + formatPrice(data[t]) + " | Profit: " + formatPrice(data[t] - bought\_price)) done = True if t == 1 - 1 else False agent.memory.append((state, action, reward, next\_state, done)) state = next\_state

if done:

if len(sys.argv) != 3: print ("Usage: python evaluate.py [stock] [model]") exit() stock\_name = input("Enter Stock\_name, Model\_name")

model\_name = input()

total\_profit = 0 agent.inventory = []

for t in range(1):

# sit

reward = 0

In [ ]:

import sys

#Fill the given information when prompted: #Enter stock\_name = GSPC\_Evaluation\_Dataset #Model\_name = respective model name model = load\_model("" + model\_name) window\_size = model.layers[0].input.shape.as\_list()[1] agent = Agent(window\_size, True, model\_name) data = getStockDataVec(stock\_name) l = len(data) - 1batch\_size = 32

state = getState(data, 0, window\_size + 1)

agent.inventory.append(data[t]) print ("Buy: " + formatPrice(data[t])) **elif** action == 2 **and** len(agent.inventory) > 0: # *sell* bought\_price = agent.inventory.pop(0) reward = max(data[t] - bought\_price, 0) total\_profit += data[t] - bought\_price print ("Sell: " + formatPrice(data[t]) + " | Profit: " + formatPrice(data[t] - bought\_price)) done = True if t == 1 - 1 else False

if done: print ("----") print (stock\_name + " Total Profit: " + formatPrice(total\_profit)) Note: Run the training section for considerable episodes so that while evaluating the model it can generate significant profit.

print ("Total Profit: " + formatPrice(total\_profit)) if len(agent.memory) > batch\_size: agent.expReplay(batch\_size) #if e % 10 == 0: agent.model.save("model\_ep" + str(e))

**Evaluate the model and agent** from keras.models import load\_model

action = agent.act(state) next\_state = getState(data, t + 1, window\_size + 1) if action == 1: # buy

state = next\_state

agent.memory.append((state, action, reward, next\_state, done))