# Read Me for Al Project 1

I have used the AI-Gym environment provided by OpenAI to test 2 learning and control algorithms.

### Method 1 (DQN):

The first method uses q learning to compute loss on the basis of reward gained. A neural network is used to make the prediction and it is updated using Markov decision process (MDP). The neural network improves by training on the replays of previous experiences over time.

### Method 2 (ANN with GA):

The second method uses genetic algorithms to optimize the weights of a neural network over multiple generations. It starts by creating a random population. Each individual is then given a fitness score which the time for which they have survived in the game. Then the most fit individuals are chosen to create off springs for the next generation. This process is then continued over several generations until the desired score is achieved.

# Method 1 Using DQN

### **Imports**

```
import os
import random
import gym
import numpy as np
from collections import deque
from keras.models import Model, load_model
from keras.layers import Input, Dense
from keras.optimizers import Adam, RMSprop
```

### **Defining Parameters**

```
#Training parameters
   n episodes = 300
 3
   n_{win_{ticks}} = 200
 5 gamma = 1.0 # Discount Factor
 6 epsilon = 1.0 # Exploration Factor
 7 epsilon_decay = 0.99
8 \text{ epsilon_min} = 0.01
9 | lr = 0.01 #learning rate
10 lr_decay = 0.01
11
12 batch_size = 64 # how may samples to train on from memmory
13
   monitor = False
14 quiet = False
15
16
```

## Setting up the Cart Pole environment

```
# Environment Parameter
memory = deque(maxlen=10000)
env = gym.make('CartPole-v0')
env.max_episode_steps = 500
input_shape = 4
action_space = 2
```

#### **Neural Network Architechture**

```
1 def OurModel(input_shape, action_space):
     # Input Layer of state size(4)
       X_input = Input(input_shape)
       # Hidden Layer with 512 nodes
      X = Dense(512, input_shape=input_shape, activation="relu")(X_input)
# Hidden Layer with 256 nodes
      X = Dense(256, activation="relu")(X)
       # Hidden layer with 64 nodes
      X = Dense(64, activation="relu")(X)
# Output Layer with # of actions: 2 nodes (left, right)
      X = Dense(action_space, activation="linear")(X)
11
       model = Model(inputs = X_input, outputs = X, name='CartPole_DQN_model')
      model.compile(loss="mse", optimizer=RMSprop(lr=0.00025, rho=0.95, epsilon=0.01), metrics=["accuracy"])
13
14
       model.summary()
15
       return model
```

#### Agent

```
1 class DONAgent:
       def __init__(self):
           #Setting Up environment and initialising parameters
 3
 4
           self.env = gym.make('CartPole-v1')
 5
           self.state_size = self.env.observation_space.shape[0]
           self.action_size = self.env.action_space.n
 6
 7
           self.EPISODES = 1000
 8
           self.memory = deque(maxlen=2000)
 9
           self.gamma = 0.95
                             # discount rate
10
           self.epsilon = 1.0 # exploration rate
11
           self.epsilon min = 0.001
12
           self.epsilon_decay = 0.999
13
           self.batch size = 64
14
           self.train_start = 1000
15
           # creating main model
           self.model = OurModel(input_shape=(self.state_size,), action_space = self.action_size)
16
18
         def remember(self, state, action, reward, next_state, done):
19
              self.memory.append((state, action, reward, next state, done))
20
              if len(self.memory) > self.train start:
21
                  if self.epsilon > self.epsilon min:
22
                       self.epsilon *= self.epsilon decay
23
24
         def select_action(self, state):
25
              if np.random.random() <= self.epsilon:</pre>
26
                  return random.randrange(self.action size)
27
28
                  return np.argmax(self.model.predict(state))
```

```
30
       def replay(self):
31
            if len(self.memory) < self.train_start:</pre>
32
                return
            # Randomly sample minibatch from the memory and then taining neural network on the experience
33
34
           minibatch = random.sample(self.memory, min(len(self.memory), self.batch_size))
35
            state = np.zeros((self.batch_size, self.state_size))
36
            next_state = np.zeros((self.batch_size, self.state_size))
37
            action, reward, done = [], [], []
38
            for i in range(self.batch_size):
39
                state[i] = minibatch[i][0]
40
                action.append(minibatch[i][1])
41
                reward.append(minibatch[i][2])
42
                next_state[i] = minibatch[i][3]
43
                done.append(minibatch[i][4])
44
            target = self.model.predict(state)
45
            target_next = self.model.predict(next_state)
46
47
            for i in range(self.batch_size):
48
                # Updating Q value for the action
49
                if done[i]:
50
                   target[i][action[i]] = reward[i]
51
52
                    target[i][action[i]] = reward[i] + self.gamma * (np.amax(target_next[i]))
53
54
            # Train the Neural Network with batches
55
            self.model.fit(state, target, batch_size=self.batch_size, verbose=0)
```

```
def run(self):
58
           flag = 0
59
           for e in range(self.EPISODES):
              state = self.env.reset()
60
               state = np.reshape(state, [1, self.state_size])
61
62
               done = False
63
               i = 0
               while not done:
64
65
                   #self.env.render()
                   action = self.select_action(state)
66
67
                   next_state, reward, done, _ = self.env.step(action)
                   next_state = np.reshape(next_state, [1, self.state_size])
if not done or i == self.env._max_episode_steps-1:
68
69
70
                       self.remember(state, action, reward, next_state, done)
71
72
                       self.remember(state, action, -100, next_state, done)
73
74
                   state = next_state
75
                   i += reward
                   if done:
76
77
78
                       print(f"episode: {e}/{self.EPISODES}, score: {i}, e: {self.epsilon}")
79
80
                           print("|-----Solved-----
                           print(f"episode: {e}/{self.EPISODES}, score: {i}, e: {self.epsilon}")
81
82
                           flag = 1
83
                           break
                       if flag == 1:
84
85
                         break
86
                   if flag == 1:
87
                        break
88
                   self.replay()
               if flag == 1:
89
90
                   break
```

### **Executing Model**

```
1 print("------Method 1 Using DQN-----")
2 agent = DQNAgent()
3 agent.run()
```

-----Method 1 Using DQN-----Model: "CartPole\_DQN\_model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 4)]	0
dense (Dense)	(None, 512)	2560
dense_1 (Dense)	(None, 256)	131328
dense_2 (Dense)	(None, 64)	16448
dense_3 (Dense)	(None, 2)	130

Total params: 150,466 Trainable params: 150,466 Non-trainable params: 0

\_\_\_\_\_

episode: 0/1000, score: 52.0, e: 1.0 episode: 1/1000, score: 28.0, e: 1.0

```
episoue. 04/1000, score. 10.0, e. 0.014000/0000/141/
episode: 55/1000, score: 19.0, e: 0.7992255563671304
episode: 56/1000, score: 40.0, e: 0.7678721062162944
episode: 57/1000, score: 14.0, e: 0.7571914943525904
episode: 58/1000, score: 44.0, e: 0.724581445483085
episode: 59/1000, score: 32.0, e: 0.7017506636113059
episode: 60/1000, score: 56.0, e: 0.6635141250307047
episode: 61/1000, score: 20.0, e: 0.6503691570122084
episode: 62/1000, score: 84.0, e: 0.5979446000009478
episode: 63/1000, score: 81.0, e: 0.5513983909676525
episode: 64/1000, score: 72.0, e: 0.5130747553488376
episode: 65/1000, score: 30.0, e: 0.4979036311114436
episode: 66/1000, score: 82.0, e: 0.4586858344239834
episode: 67/1000, score: 119.0, e: 0.4072006165777428
episode: 68/1000, score: 101.0, e: 0.36806348825922275
episode: 69/1000, score: 131.0, e: 0.32285067248442284
episode: 70/1000, score: 168.0, e: 0.27290011414765825
episode: 71/1000, score: 132.0, e: 0.23913776344553783
episode: 72/1000, score: 127.0, e: 0.21060329799922556
episode: 73/1000, score: 332.0, e: 0.15108009835289823
|-----|
```

episode: 73/1000, score: 332.0, e: 0.15108009835289823

# Method 2: Using NN with Genetic Algorithm

# Imports ¶

```
import gym
import numpy as np
import math
from matplotlib import pyplot as plt
from random import randint
from statistics import median, mean
np.random.seed(seed=20)
```

### **Settingup Initial Parameters**

```
1  award_set =[]
2  test_run = 15
3  best_gen =[]
4  n_of_generations = 1000
```

# Setting Up Environment

```
]: 1 env = gym.make('CartPole-v1')
2 
3 ind = env.observation_space.shape[0]
4 adim = env.action_space.n #discrete
```

### **Creating Neural Network**

```
def softmax(x):
 2
       x = np.exp(x)/np.sum(np.exp(x))
 3
       return x
 4
 5 def lreLu(x):
 6
       alpha=0.2
       return tf.nn.relu(x)-alpha*tf.nn.relu(-x)
 7
8
9 def sigmoid(x):
10
       return 1/(1+np.exp(-x))
11
12 def reLu(x):
       return np.maximum(0,x)
13
14
15 def nn(obs,in_w,in_b,hid_w,out_w):
16
       obs = obs/max(np.max(np.linalg.norm(obs)),1)
17
18
19
       Ain = reLu(np.dot(obs,in_w)+in_b.T)
20
       Ahid = reLu(np.dot(Ain,hid_w))
21
22
       lhid = np.dot(Ahid,out_w)
23
24
       out_put = reLu(lhid)
25
       out_put = softmax(out_put)
       out_put = out_put.argsort().reshape(1,adim)
26
27
       act = out_put[0][0] #index of discrete action
28
29
       return act
```

### Generate initial set of weights and bias

```
1
   def intial_gen(test_run):
 2
        input_weight = []
 3
        input bias = []
 4
 5
        hidden_weight = []
        out_weight = []
 6
 8
        in_node = 4
9
        hid node = 2
10
11
        for i in range(test run):
12
            in_w = np.random.rand(ind,in_node)
13
            input weight.append(in w)
14
15
            in_b = np.random.rand((in_node))
16
            input_bias.append(in_b)
17
            hid_w = np.random.rand(in_node,hid_node)
18
19
            hidden_weight.append(hid_w)
20
21
22
            out_w = np.random.rand(hid_node, adim)
23
            out_weight.append(out_w)
24
25
        generation = [input_weight, input_bias, hidden_weight, out_weight]
26
        return generation
```

### Run environment randomly

```
1
 2
   def rand run(env,test run):
       award_set = []
4
       generations = intial_gen(test_run)
 5
 6
       for episode in range(test run):# run env 10 time
 7
            in_w = generations[0][episode]
8
            in_b = generations[1][episode]
9
           hid_w = generations[2][episode]
            out_w = generations[3][episode]
10
11
            award = run_env(env,in_w,in_b,hid_w,out_w)
12
            award_set = np.append(award_set,award)
13
        gen_award = [generations, award_set]
14
        return gen award
```

### Genetic Algorithm

```
def run_env(env,in_w,in_b,hid_w,out_w):
 2
       obs = env.reset()
 3
       award = 0
4
       for t in range(300):
5
           #env.render() this slows the process theredore commented
           action = nn(obs,in_w,in_b,hid_w,out_w)
7
           obs, reward, done, info = env.step(action)
8
           award += reward
9
           if done:
               break
10
       return award
11
12
13 def mutation(new_dna):
14
       j = np.random.randint(0,len(new_dna))
15
16
       if ( 0 < j < 10): # controlling rate for amount of mutation
17
           for ix in range(j):
               n = np.random.randint(0,len(new_dna)) #random postion for mutation
18
19
               new_dna[n] = new_dna[n] + np.random.rand()
20
21
       mut_dna = new_dna
22
23
       return mut_dna
```

```
24
25 def crossover(Dna_list):
26
      newDNA list = []
27
       newDNA list.append(Dna list[0])
       newDNA_list.append(Dna_list[1])
28
29
30
       for 1 in range(10): # generation after crassover
           j = np.random.randint(0,len(Dna_list[0]))
31
32
           new_dna = np.append(Dna_list[0][:j], Dna_list[1][j:])
33
           mut dna = mutation(new dna)
34
35
           newDNA_list.append(mut_dna)
36
37
       return newDNA list
38
39 #Generate new set of weights and bias from the best previous weights and bias
```

```
40
41
   def reproduce(award set, generations):
42
       good award idx = award set.argsort()[-2:][::-1] # here only best 2 are selected
43
       good_generation = []
44
45
       DNA list = []
46
       new input weight = []
47
48
       new_input_bias = []
49
       new_hidden_weight = []
50
51
52
       new_output_weight =[]
53
54
       new_award_set = []
55
56
57
       #Extraction of all weight info into a single sequence
58
       for index in good award idx:
59
60
           w1 = generations[0][index]
           dna_in_w = w1.reshape(w1.shape[1],-1)
61
62
63
           b1 = generations[1][index]
64
           dna_b1 = np.append(dna_in_w, b1)
65
           w2 = generations[2][index]
66
67
           dna whid = w2.reshape(w2.shape[1],-1)
68
           dna_w2 = np.append(dna_b1,dna_whid)
69
70
           wh = generations[3][index]
71
           dna = np.append(dna w2, wh)
72
73
```

```
73
74
            DNA_list.append(dna) # make 2 dna for good gerneration
75
76
        newDNA_list = crossover(DNA_list)
77
78
        for newdna in newDNA list: # collection of weights from dna info
79
            newdna_in_w1 = np.array(newdna[:generations[0][0].size])
80
81
            new_in_w = np.reshape(newdna_in_w1, (-1,generations[0][0].shape[1]))
            new_input_weight.append(new_in_w)
82
83
84
            new_in_b = np.array([newdna[newdna_in_w1.size:newdna_in_w1.size+generations[1][0].size]]).T #bias
85
            new_input_bias.append(new_in_b)
86
87
            sh = newdna_in_w1.size + new_in_b.size
88
            newdna_in_w2 = np.array([newdna[sh:sh+generations[2][0].size]])
            new_hid_w = np.reshape(newdna_in_w2, (-1,generations[2][0].shape[1]))
89
            new_hidden_weight.append(new_hid_w)
90
91
92
            sl = newdna_in_w1.size + new_in_b.size + newdna_in_w2.size
            new_out_w = np.array([newdna[sl:]]).T
93
            new_out_w = np.reshape(new_out_w, (-1,generations[3][0].shape[1]))
94
95
            new_output_weight.append(new_out_w)
96
97
            new_award = run_env(env, new_in_w, new_in_b, new_hid_w, new_out_w) #bias
98
            new_award_set = np.append(new_award_set,new_award)
99
100
        new_generation = [new_input_weight,new_input_bias,new_hidden_weight,new_output_weight]
101
102
        return new_generation, new_award_set
```

```
105 def evolution(env,test_run,n_of_generations):
        gen_award = rand_run(env, test_run)
106
        current_gens = gen_award[0]
107
108
       current_award_set = gen_award[1]
109
       best_gen =[]
110
        A =[]
       for n in range(n_of_generations):
111
           new_generation, new_award_set = reproduce(current_award_set, current_gens)
112
113
           current_gens = new_generation
114
           current award set = new award set
115
           avg = np.average(current_award_set)
116
           a = np.amax(current_award_set)
117
           print(f"generation: {n+1}, score: {a}")
118
           if np.amax(current_award_set) >= 200:
119
               print("|-----|")
120
               print(f"generation: {n}/{n_of_generations}, score: {np.amax(current_award_set)}")
121
122
123
           A = np.append(A, a)
124
125
       Best_award = np.amax(A)
126
```

### **Executing Model**

```
1 print("------Method 2: Using NN with Genetic Algorithm-----")
 3 evolution(env, test_run, n of generations)
-----Method 2 Using NN with Genetic Algorithm------
generation: 1, score: 10.0
generation: 2, score: 27.0
generation: 3, score: 37.0
generation: 4, score: 110.0
generation: 5, score: 109.0
generation: 6, score: 107.0
generation: 7, score: 160.0
generation: 8, score: 144.0
generation: 9, score: 158.0
generation: 10, score: 150.0
generation: 11, score: 177.0
generation: 12, score: 176.0
generation: 13, score: 300.0
-----Solved-------
generation: 12/1000, score: 300.0
```