

CPEN 502

Assignment 3 Report

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Question 4

(4) The use of a neural network to replace the look-up table and approximate the Q -function has some disadvantages and advantages.

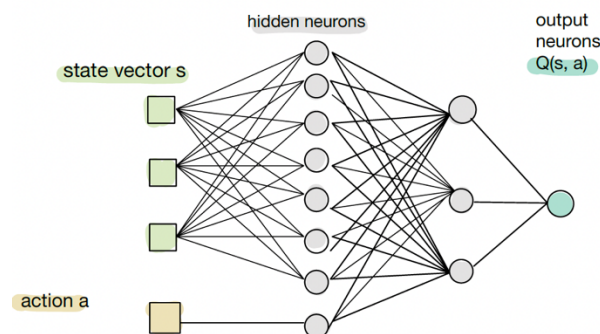
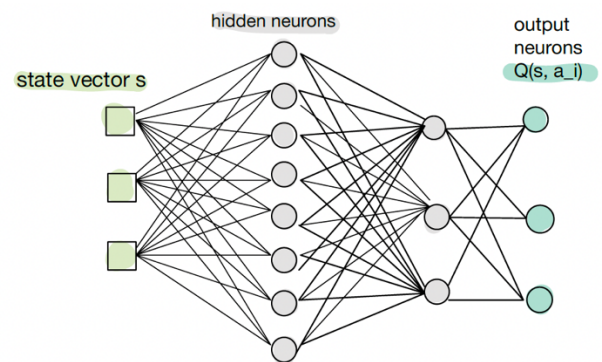
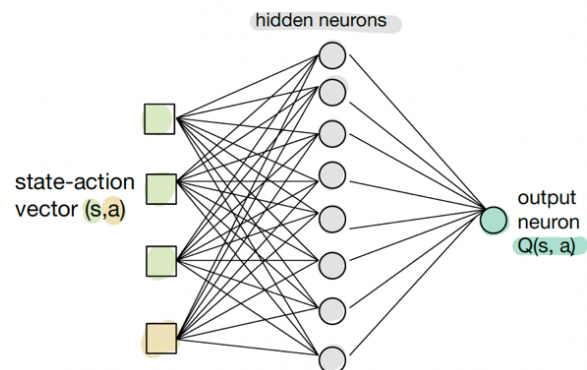
Question 4a

a) There are 3 options for the architecture of your neural network. Describe and draw all three options and state which you selected and why. (3pts)

- 1) Inputs: a vector of the state and action (s, a), output: $Q(s, a)$, single layer
- 2) Inputs: a vector of state s , outputs: $Q(s, a_1), Q(s, a_2) \dots$ for all actions, multiple layers
- 3) Inputs: two vectors (s is for state and a is for action) which are not fully connected to the first hidden layer, output: $Q(s, a)$, multiple layers

Note that all of three options could potentially use single layer or multiple layers.

I selected option 1, because it aligns with the structure of the neural network that we wrote in assignment 1. It also aligns the structure of the look up table that we used where Q values are stored in assignment 2. **In summary, I chose option 1 because of the compatibility of the previous structure and I believe it is sufficient for this relatively small state-action space.**



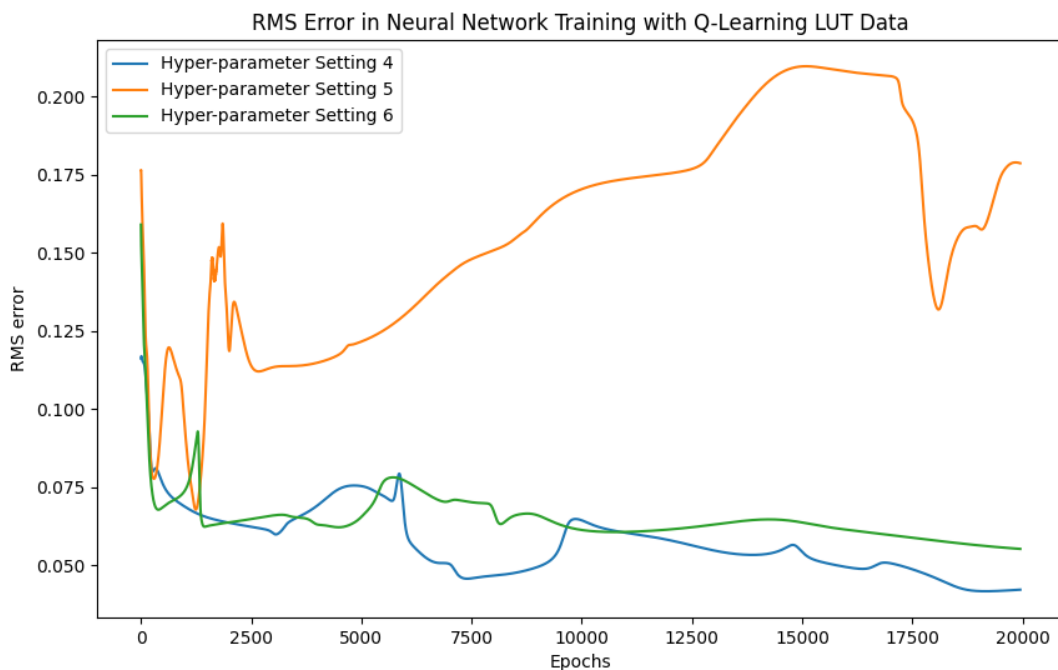
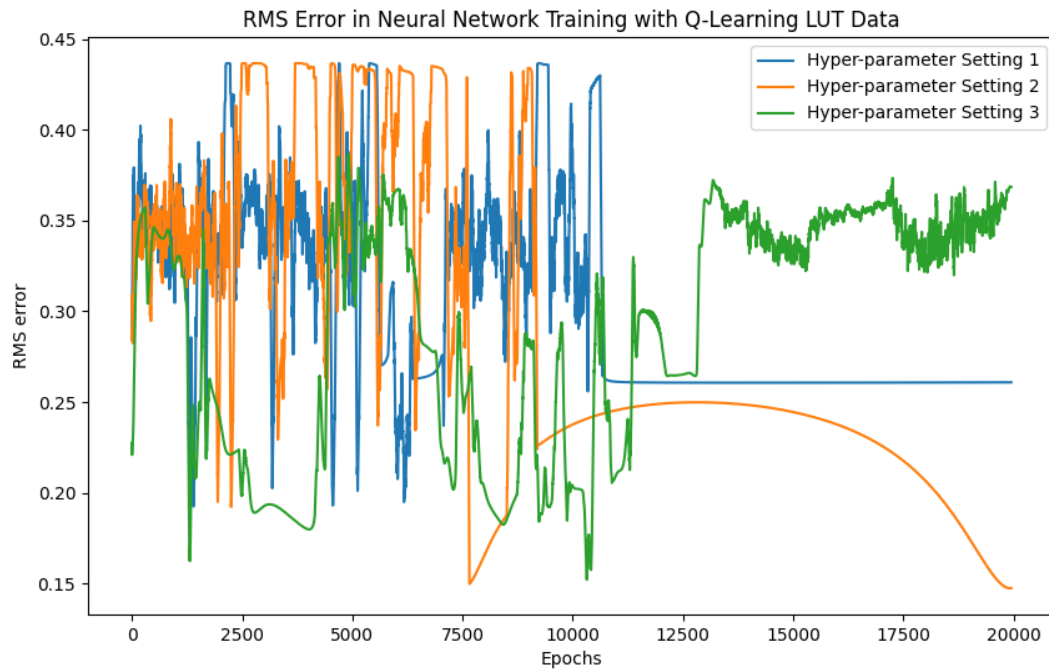
Question 4b

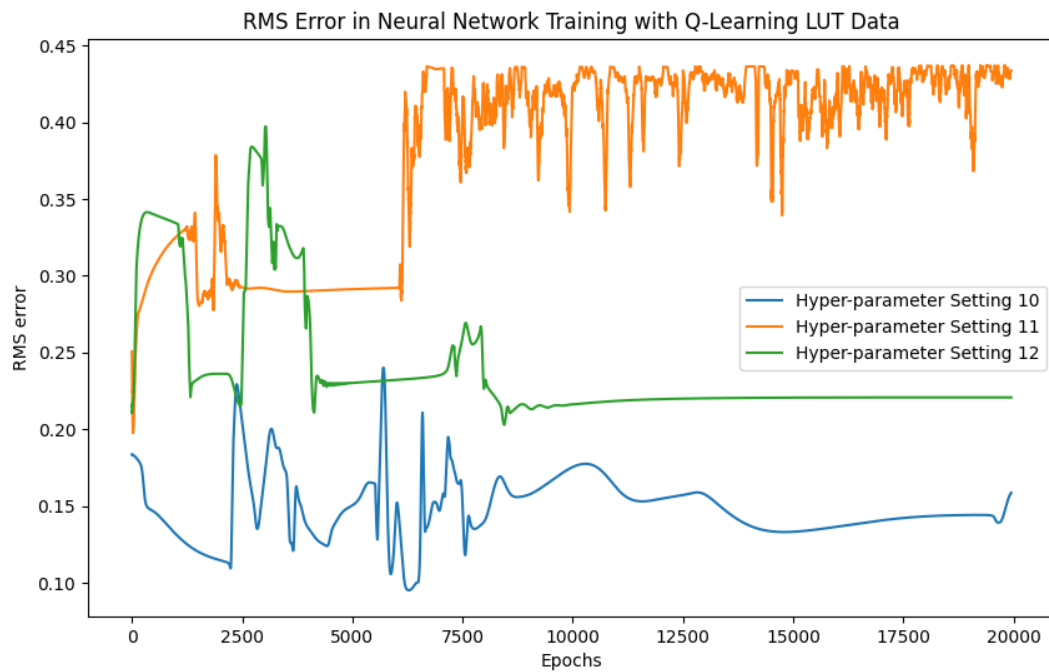
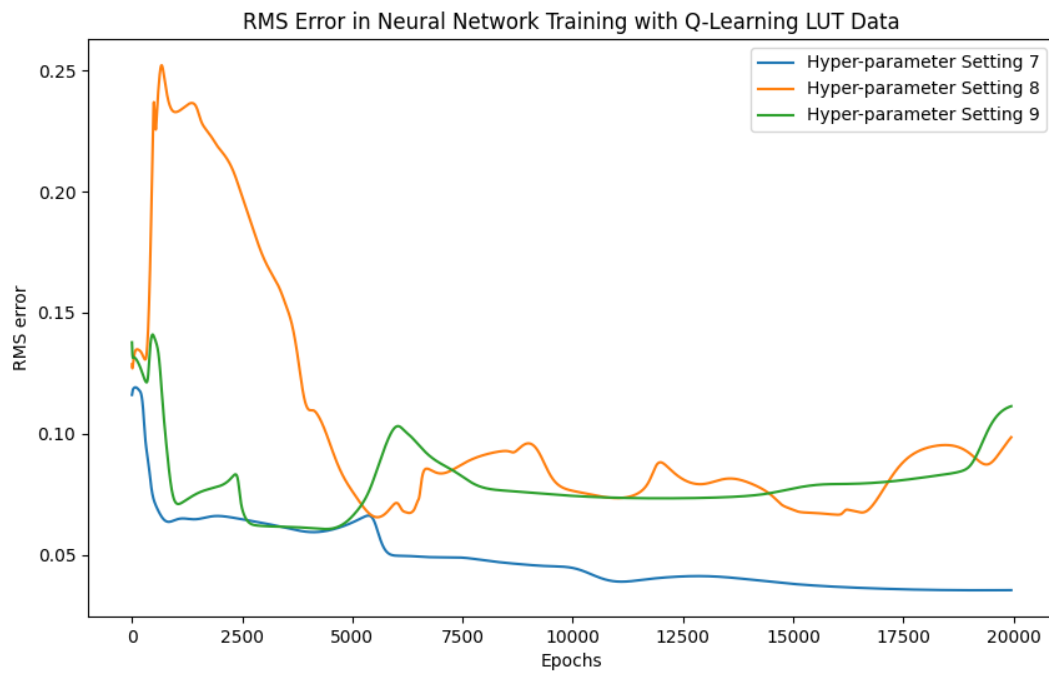
b) Show (as a graph) the results of training your neural network using the contents of the LUT from Part 2. Your answer should describe how you found the hyper-parameters which worked best for you (i.e. momentum, learning rate, number of hidden neurons). Provide graphs to backup your selection process. Compute the RMS error for your best results. (5 pts)

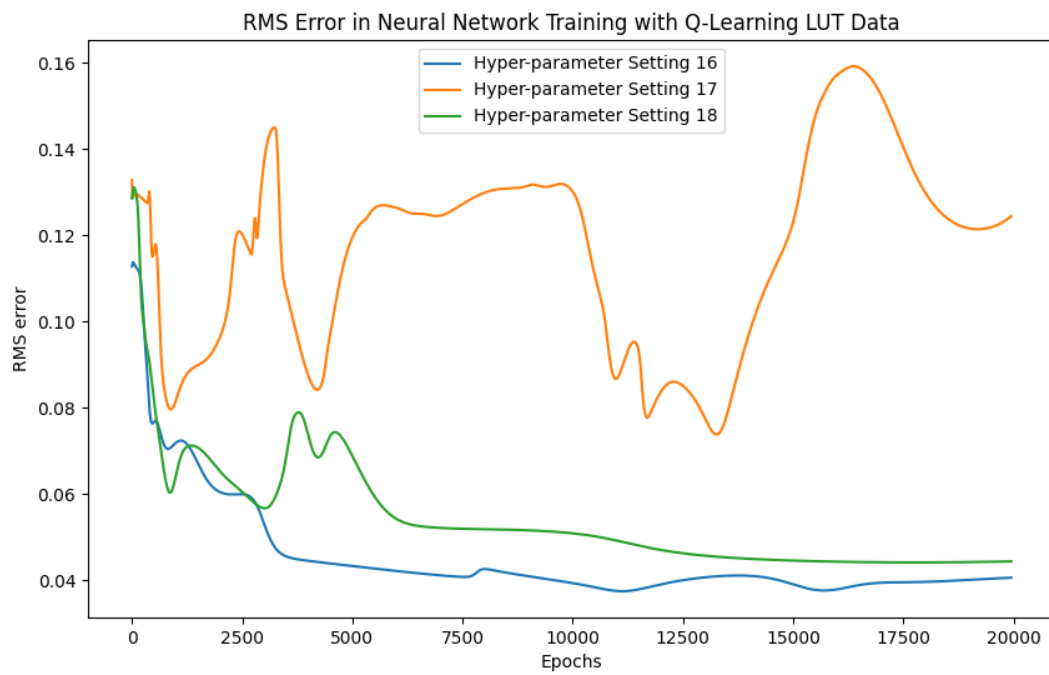
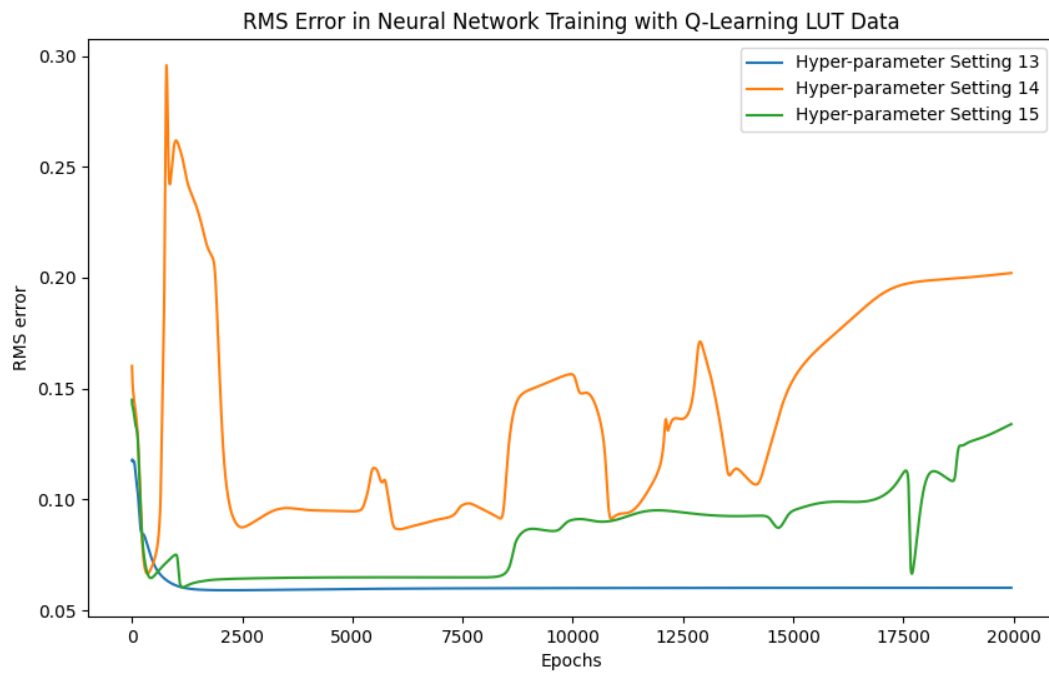
I trained the neural network with 18 different settings of the hyper-parameters (number of hidden neurons: 8, 10, learning rate: 0.2, 0.4, 0.6, momentum:0.4, 0.6, 0.8), 20000 epochs for each setting.

Hyper-parameter Setting Number	number of hidden neurons	learning rate	momentum	Hyper-parameter Setting Number	number of hidden neurons	learning rate	momentum
1	8	0.2	0.8	10	10	0.2	0.8
2	8	0.6	0.8	11	10	0.6	0.8
3	8	0.4	0.8	12	10	0.4	0.8
4	8	0.2	0.6	13	10	0.2	0.6
5	8	0.6	0.6	14	10	0.6	0.6
6	8	0.4	0.6	15	10	0.4	0.6
7	8	0.2	0.4	16	10	0.2	0.4
8	8	0.6	0.4	17	10	0.6	0.4
9	8	0.4	0.4	18	10	0.4	0.4

By analysing the graphs of the errors for all 18 settings, many settings are eliminated because of weird behavior of RMS such as noisy (e.g., setting 1), multiple peaks (e.g., setting 5), and not converging (e.g., 15). Among all settings, I finally choose the hyper-parameters setting 16 (**10 hidden neurons, learning rate = 0.2, momentum = 0.4**), because this setting seems to converge fast with a reasonably RMS pattern, as well as achieving a best RMS error around **0.04**.







Question 4c

c) Comment on why theoretically a neural network (or any other approach to Q-function approximation) would not necessarily need the same level of state space reduction as a look up table. (2 pts)

When applying Q-learning using a look up table, state space reduction is necessary because a look up table stores the state-action and the Q values accordingly, but it is impossible to store all possible states, especially if there are continuous variables.

However, Q-function approximation tries to find out the **relationship** between the input and output, which are the state-action pair and the Q value. It is trying to find a relationship or a function, so it is **generalizable**. It needs to learn the pattern from the inputs and outputs, but it does **not need to store** all the inputs, thus it does not necessarily need the same level of state space reduction.

Question 5

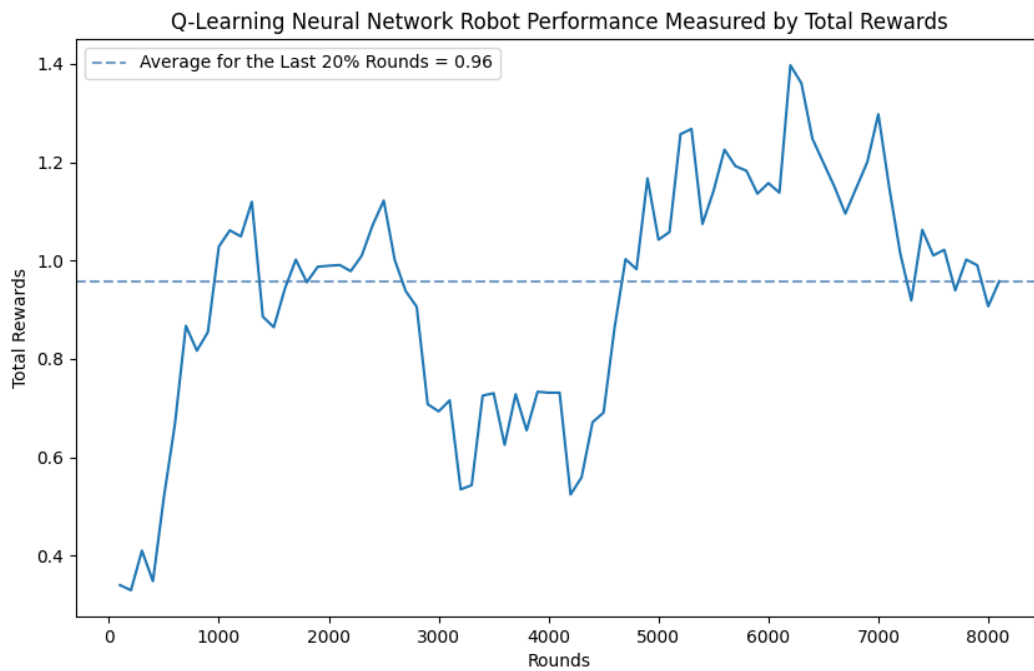
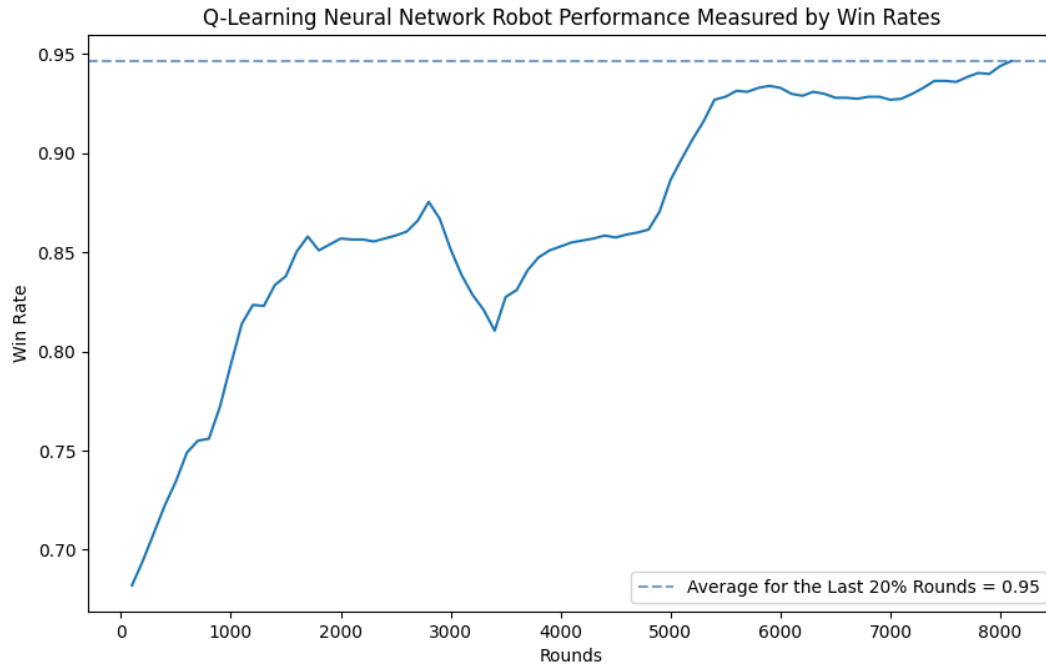
(5) Hopefully you were able to train your robot to find at least one movement pattern that results in defeat of your chosen enemy tank, most of the time.

Question 5a

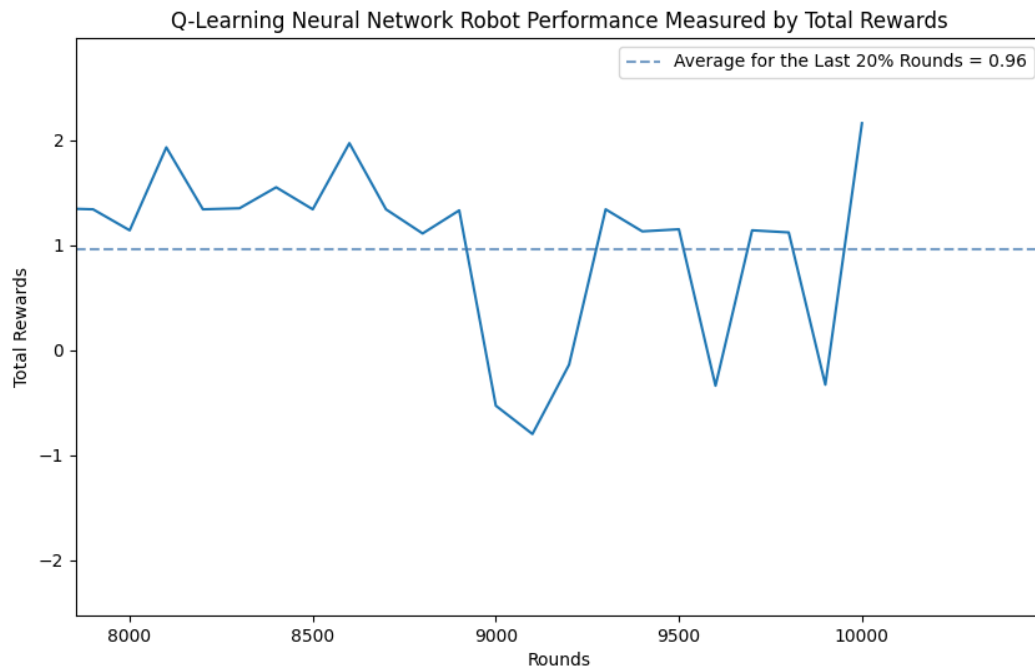
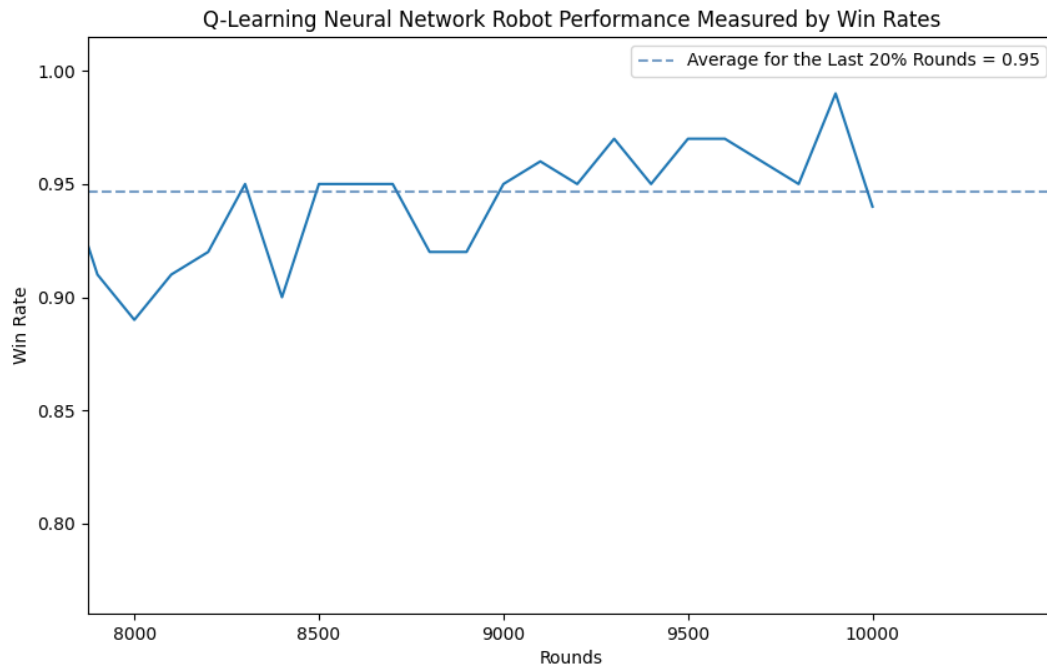
a) Identify two metrics and use them to measure the performance of your robot with online training. I.e. during battle. Describe how the results were obtained, particularly with regard to exploration? Your answer should provide graphs to support your results. (5 pts)

I am using two metrics (1) win rates in every 100 rounds and (2) total rewards in every 100 rounds to measure the performance of my robot. In the total 10000 rounds, exploration decay is used in the first 80% rounds, the true performance after learning is measure in the last 2000 rounds with $\epsilon=0$. By calculating the average of the last 20% rounds (performance measurement state), we conclude that our robot achieves a **win rate 0.95**, and **total rewards 0.96** after learning. **The graphs are in the next page.**

Performance measured by win rate and total rewards in 10000 rounds. Note: In order to better show the trend, moving average is used to smooth out fluctuations in data, which is the reason why the x slightly shifted.



Zoomed-In version: Performance measured by win rate and total rewards in the last 20% rounds.



Question 5b

b) The discount factor can be used to modify influence of future reward. Measure the performance of your robot for different values of γ and plot your results. Would you expect higher or lower values to be better and why? (3 pts)

Setting of the experiment:

I tested four different discount factors (1, 0.9, 0.4, 0.1) in neural network training. In the total 10000 rounds, exploration decay is used in the first 80% rounds, the true performance after learning is measure in the last 2000 rounds with $\epsilon=0$. Robot performance is measured by (1) win rate in every 100 rounds and (2) total rewards in every 100 rounds.

Findings: (Please find the graphs in the next two pages)

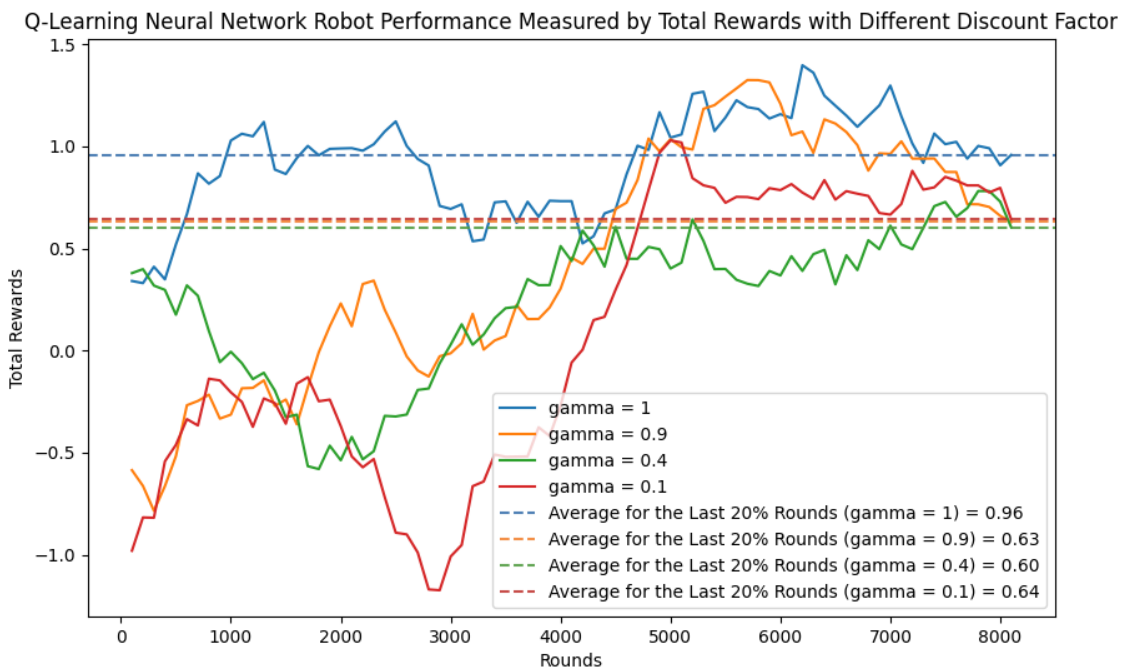
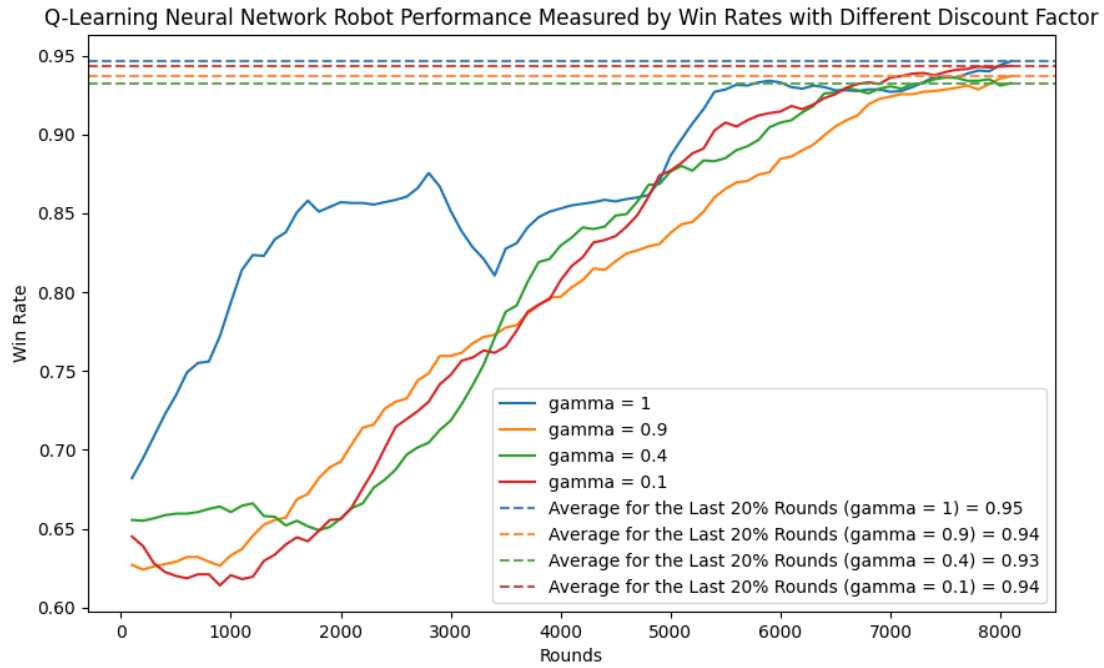
By analyzing the data, we found that different gammas have different effects in the performance when using different measurement. If we measure the performance of the robot by win rate, we notice that all different gammas reach a similar win rate 0.94 eventually. However, if we measure the performance of the robot by total rewards, the neural network with $\gamma=1$ reaches the highest total rewards 0.96, while the lower gammas 0.9, 0.4, 0.1 all give total rewards around 0.62.

Discussion:

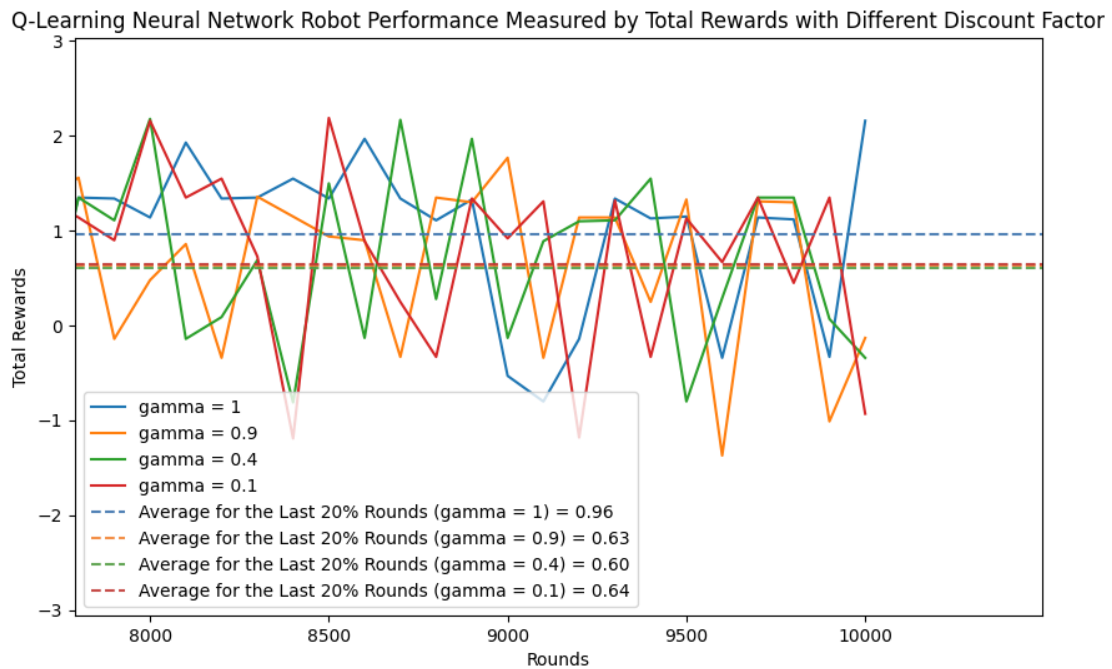
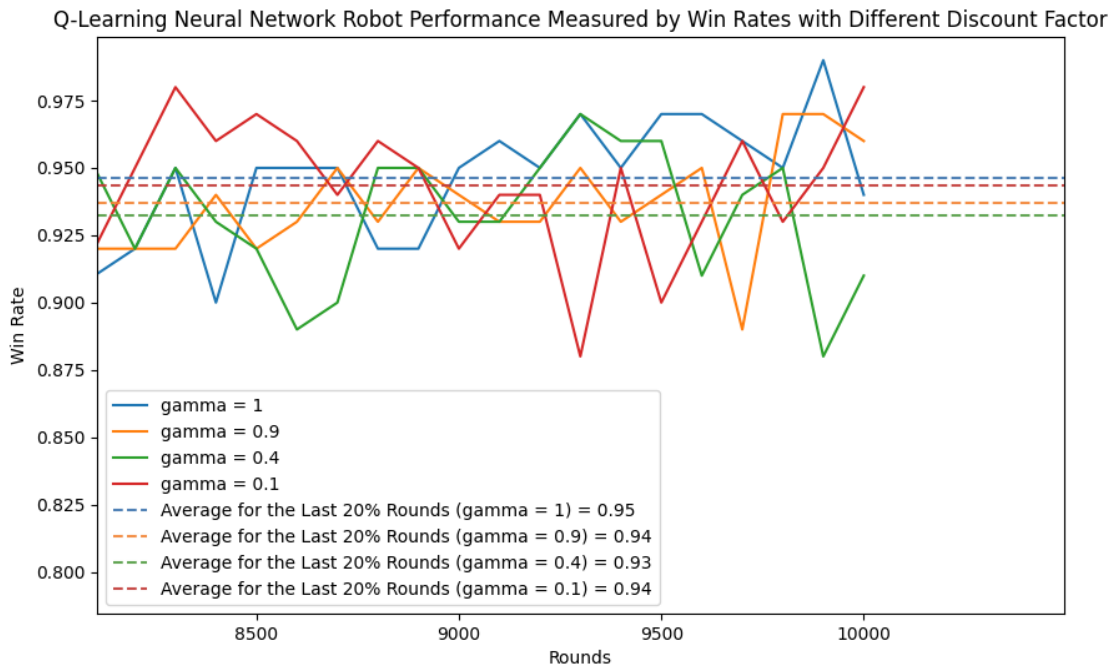
The **Initially expectation** was that the higher discount factor would give higher win rate and higher total rewards. The rational was that prioritize the future rewards would, to some extent, mean that it prioritizes the terminal rewards more. To reach the terminal rewards, we need to win the game (and the strategy that the robot discovered is to fire, not to hide) by accumulate immediate rewards, consequently both the win rate and the total rewards would go high.

After examining the results, I found that the effect is could be more complex because of the complex nature of the robot. We found that the discount factors would reach a high win rate after sufficient training, but it does not necessarily guarantee the similar total rewards because they may have different decision-making. Only the $\gamma=1$ shows a significantly high total rewards, which is a possible indicator of better optimized resource utilization. It is interesting to notice that $\gamma=0.9$ and $\gamma=0.1$ have similar low total rewards 0.62, this could be just because in our specific dynamics of the robocode setting (the nature of the battle, the opponent, the way that we set up the terminal and immediate rewards), an extreme high discount factor would be significantly better, and any deviation ones could result similar low total rewards.

Performance measured by win rate and total rewards in 10000 rounds, with 4 different gammas. Note: In order to better show the trend, moving average is used to smooth out fluctuations in data, which is the reason why the x slightly shifted.



Zoomed-In version: Performance measured by win rate and total rewards in the last 20% rounds, with 4 different gammas.



Question 5c

c) Theory question: With a look-up table, the TD learning algorithm is proven to converge – i.e. will arrive at a stable set of -values for all visited states. This is not so when the Q-function is approximated. Explain this convergence in terms of the Bellman equation and also why when using approximation, convergence is no longer guaranteed. (3 pts)

From the Bellman equation $V(s_t) = r_t + \gamma * V(s_{t'})$, we can derive that error $e(s_t) = \gamma * e(s_{t'})$. The reward at the terminal is known as zero, therefore after enough learning, we will have $e(s_t) = 0$ for all t , which leads to an optimal value function $V(s_t) = r_t + \gamma * V'(s_t)$. $V(s_t)$ approaches $V'(s_t)$, the optimal value.

When using neural network to do Q function approximation, convergence is not guaranteed because ultimately it is an approximation of the value function. In more details, a possible reason is that when we use iteration in a look up table, other unrelated states' value does not get influenced by the update of a specific state. However, in function approximation through neural network, we approximate value function by updating all the weights, which will indeed influence all states' values to minimize the error.

Question 5d

d) When using a neural network for supervised learning, performance of training is typically measured by computing a total error over the training set. When using the NN for online learning of the Q -function in robocode this is not possible since there is no a -priori training set to work with. Suggest how you might monitor learning performance of the neural net now. (3 pts)

We can monitor the learning performance by the **performance of the robot**, such as win rate, total rewards, etc. We can also monitor it by evaluate the actions or **observe the behaviours** of the robot before and after training, and try to interpret if the decision-making process reflects some learning. What's more, we can have a **baseline** where we evaluate the performance of the robot using the same weights of the neural network (usually generated randomly) before any backpropagation or learning.

What's more, we can compare the speed or the efficiency of learning performance by the **convergence speed** of the matrices mentioned above (such as win rate, total rewards, action choices), or the **convergence speed** of the weights of the neural network.

Question 5e

e) At each time step, the neural net in your robot performs a back propagation using a single training vector provided by the RL agent. Modify your code so that it keeps an array of the last say n training vectors and at each time step performs n back propagations. Using graphs compare the performance of your robot for different values of n. (4 pts)

Setting of the experiment:

I tested four different replay memory size (3, 8, 10, 15, 20) in neural network training. In the total 15000 rounds, exploration decay is used in the first 80% rounds, the true performance after learning is measure in the last 2000 rounds with $\epsilon=0$. Robot performance is measured by (1) win rate in every 100 rounds and (2) total rewards in every 100 rounds.

Findings: (Please find the graphs in the next two pages)

By analyzing the data, we found that different replay memory sizes have different effects in the performance when using different measurement.

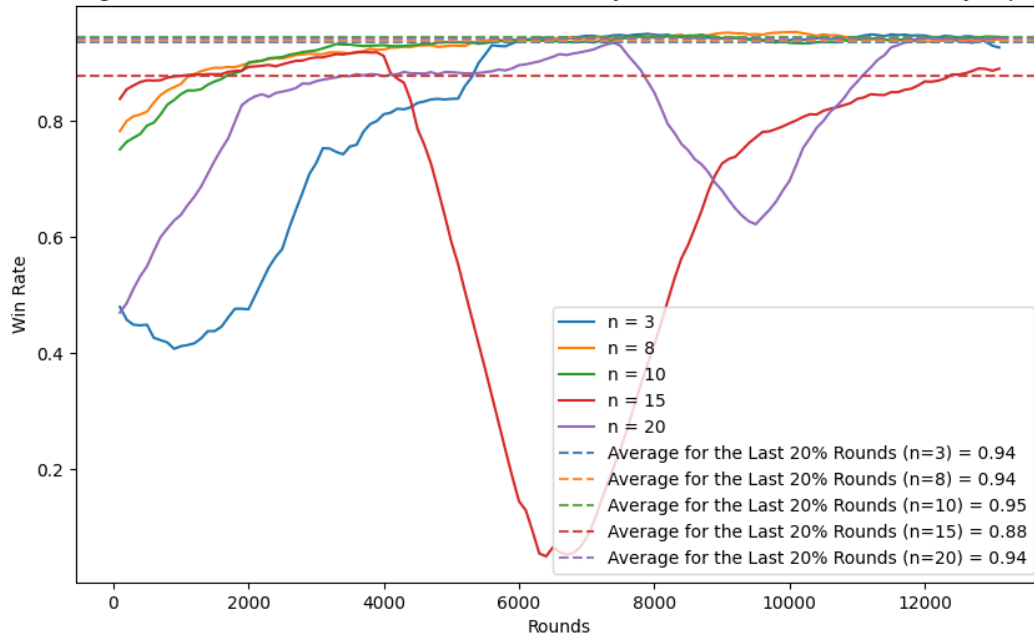
If we measure the performance of the robot by **win rate**, we notice that $n=15$ reaches a win rate 0.88, while all other sizes $n=3, 8, 10, 20$ reach a higher win rate 0.94 eventually.

If we measure the performance of the robot by **total rewards**, the neural network with $n=3$ reaches a total rewards 0.82, $n=8$ reaches a total rewards 0.56, while all higher sizes $n=10, 15, 20$ give total rewards around 1.03.

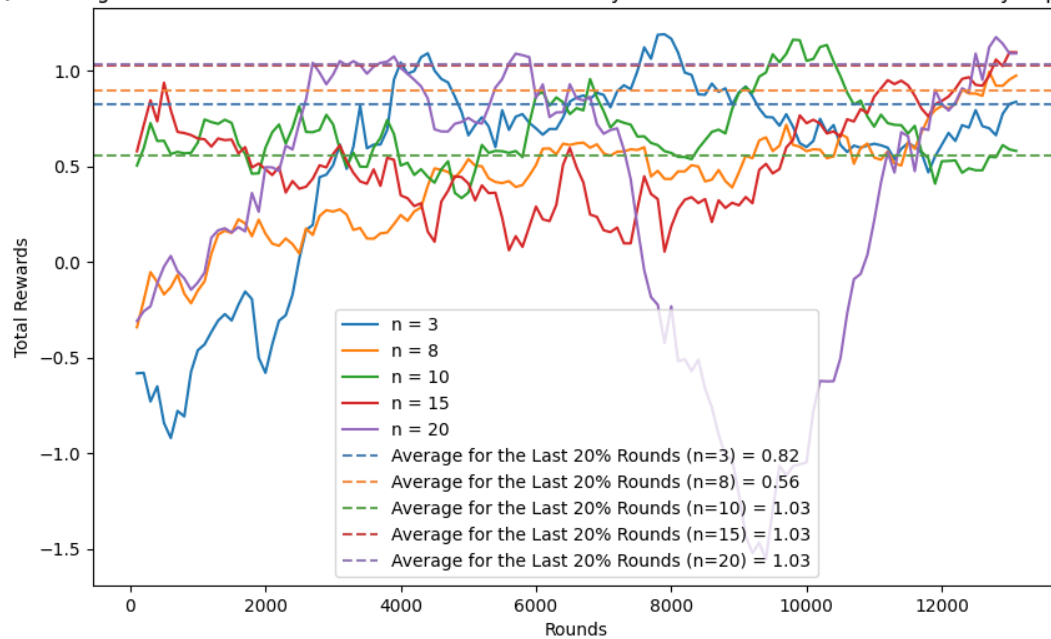
In summary, I found that larger replay memory sizes generally tend to lead better performance of the robot. This seems make sense because one major advantage of reply memory is that it can break the correlation between consecutive samples thus lead to faster and better learning. However, the replay memory size takes extra memory to store the experiences, so there is a trade-off in application. What's more, I notice that $n=15$ and $n=20$ have some sudden drop of performance during training process, which could be because the time span among the experiences is too extensive so it causes significant changes in the environment.

Performance measured by win rate and total rewards in the last 20% rounds, with 5 different replay memory size. Note: In order to better show the trend, moving average is used to smooth out fluctuations in data, which is the reason why the x slightly shifted.

Q-Learning Neural Network Robot Performance Measured by Win Rates with Different Memory Replay Size n

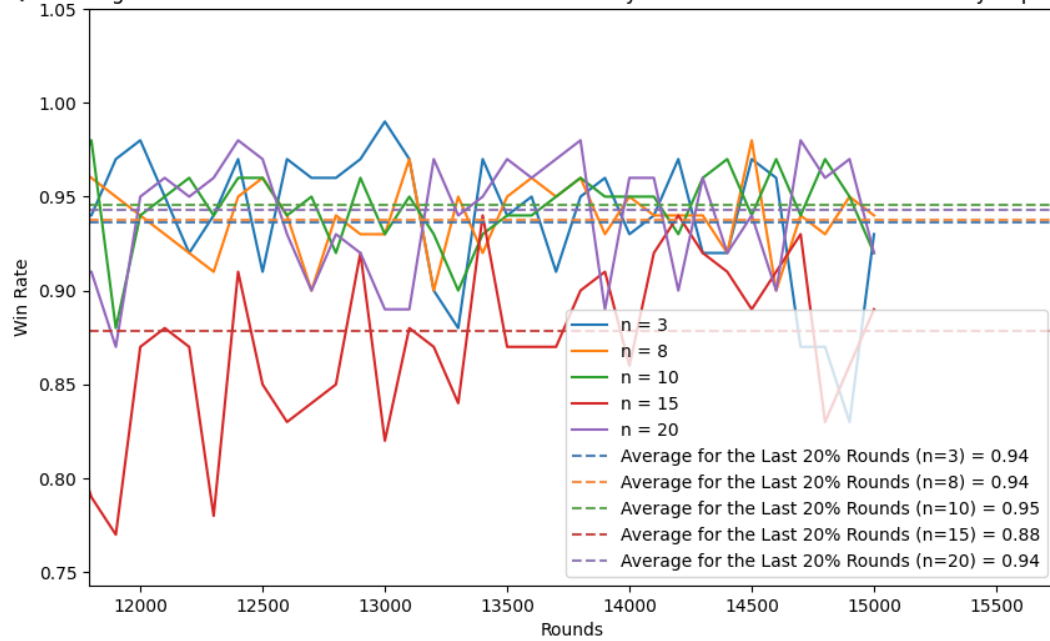


Q-Learning Neural Network Robot Performance Measured by Total Rewards with Different Memory Replay Size n

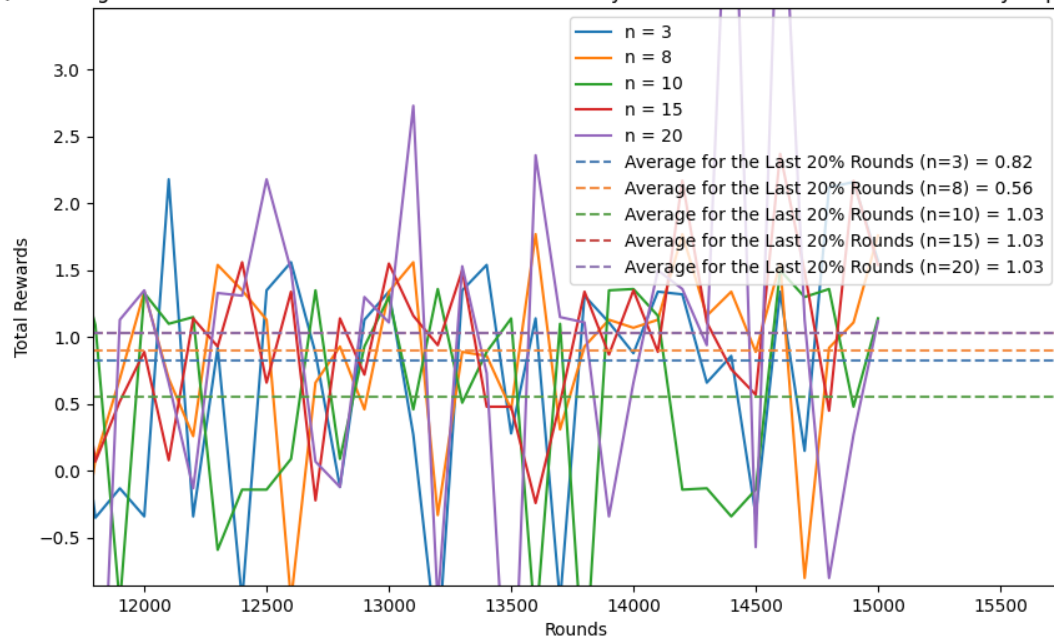


Zoomed-In version: Performance measured by win rate and total rewards in the last 20% rounds, with 5 different replay memory size.

Q-Learning Neural Network Robot Performance Measured by Win Rates with Different Memory Replay Size n



Q-Learning Neural Network Robot Performance Measured by Total Rewards with Different Memory Replay Size n



Question 6

(6) Overall Conclusions

Question 6a

a) This question is open-ended and offers you an opportunity to reflect on what you have learned overall through this project. For example, what insights are you able to offer with regard to the practical issues surrounding the application of RL & BP to your problem? E.g. What could you do to improve the performance of your robot? How would you suggest convergence problems be addressed? What advice would you give when applying RL with neural network based function approximation to other practical applications? (4 pts)

From the project, one of the things that I learned is that **hyper-parameter tuning** is crucial yet challenging. I had 3 main hyper-parameter (learning rate, number of hidden neurons, momentum) in this assignment, and there are potentially more to consider, such as discount factor, number of hidden layers. I learned that the hyper-parameter has strong and somewhat unpredictable effect on the performance of learning, thus careful tuning process is important. Specifically for this project, I think using other architecture such as **multiple hidden layers** may help improve the performance too.

One thing I would improve is to adjust **exploration control** more in order to gain insights how it affects the performance of learning and the robot. I tried exploration decay (decay from initial exploration rate to 0 in the first 80% rounds and stay 0 in the last 20% rounds to measure the performance) and exploration windows (initial exploration rate for 10% rounds and no exploration for the next 10% rounds, and repeat). However, I did not have the chance to carefully compare the results in these two different or possibly more ways of controlling exploration rate (also possibly for more choices of exploration rates), and measure the performance. I expect that using the exploration window method could help evaluate the **convergence speed** better in order to measure the actual **performance of the learning**.

Another thing that I reflect on is about **generalization**. Using different opponents could be a good idea to generalize the overall performance of the robot. Although I expect it could be hard and require lots of more training and hyper-parameter tuning.

Question 6b

b) Theory question: Imagine a closed-loop control system for automatically delivering anesthetic to a patient under going surgery. You intend to train the controller using the approach used in this project. Discuss any concerns with this and identify one potential variation that could alleviate those concerns. (3 pts)

Concerns:

- My first concern would be **safety**. In the robot project we did, it is fine to experience bad performance even after hyper-parameter training. However, it would be damaging if our controller delivering anesthetic does not perform well in practice.
- Another concern is that it could be hard to have enough high-quality **training data**, because the controller is designed to perform a sensitive task. Furthermore, how to perform **exploration** will be a problem.

Variations:

- A possible way to handle safety concern is to use **pre-defined rules** as well in the system. Besides reinforcement learning and neural network function approximation, we can combine experts' knowledge with the model to better ensure the safety.
- In terms of lack of training data, **synthetic data** in simulated training environments could be helpful.

Appendix for source code

MyNNRobot.java

```

1 package Robot.My502Robot;
2
3 import NN.NeuralNet;
4 import ReplayMemory.ReplayMemory;
5 import Robot.Action;
6 import Robot.Experience;
7 import Robot.StateNN;
8 import robocode.*;
9
10 import java.awt.*;
11 import java.io.IOException;
12 import java.io.PrintStream;
13 import java.util.Arrays;
14 import java.util.Date;
15
16 import static robocode.util.Utils.normalRelativeAngleDegrees;
17
18
19 public class MyNNRobot extends AdvancedRobot {
20     // static double alpha = 0.2;
21     // private String weightsFileName = getClass().getSimpleName() + "-weights.txt";
22     static final int MAX_SAMPLE_SIZE = 15;
23     static ReplayMemory<Experience> replayMemory = new ReplayMemory<Experience>(MAX_SAMPLE_SIZE);
24     static double gamma = 1;
25     static int totalNumRounds = 0;
26     static int numRoundTo100 = 0;
27     static int numWins = 0;
28     // for question2(a), used 15000, other times used 10000
29     static int desiredTotalRounds = 15000;
30     static double[] winRatePer100 = new double[desiredTotalRounds / 100];
31     static double[] epsilonList = new double[winRatePer100.length];
32     static double[] totalRewardsPer100 = new double[desiredTotalRounds / 100];
33     // for question3(a), try e = 0, 0.2, 0.4, 0.6 and 0.8(default)
34     static double epsilon = 0.8;
35     static double epsilon_init = 0.8;
36     static double[][] actionCountsPer100 = new double[desiredTotalRounds / 100][3];
37     // static ArrayList<Integer> actionList = new ArrayList<>();
38     static int numOfRoundsToDecayE = (int) (desiredTotalRounds * 0.8);
39     static double decayEStepSize = epsilon_init / numOfRoundsToDecayE;
40     // static private LUT lut = new LUT();
41     static private int argA = -1;
42     static private int argB = 1;
43     static private NeuralNet NN = new NeuralNet(4, 8, 0.2, 0.4, argA, argB, 2);
44     private enumOperationalMode operationalMode = enumOperationalMode.scan;
45     private String logFileName = getClass().getSimpleName() + "-" + "qValues" + new Date().toString() + ".dat";
46     private String logFileName1 = getClass().getSimpleName() + "-" + "qValuesBeforeTurningOffE" + new Date().toString() + ".dat";
47     private String logFileNameWinRate = getClass().getSimpleName() + "-" + "winRate" + new Date().toString() + ".dat";
48     private String logFileNameTotalRewards = getClass().getSimpleName() + "-" + "totalRewards" + new Date().toString() + ".dat";
49     private String logFileNameEpsilonList = getClass().getSimpleName() + "-" + "epsilonList" + new Date().toString() + ".dat";
50     private String logFileNameActions = getClass().getSimpleName() + "-" + "actionList" + new Date().toString() + ".dat";
51     // private String[] outputLog;
52     private double curR;
53     private double goodTerminalReward = 1;
54     private double badTerminalReward = -1;
55     // private double[] totalR = new double[100];
56     private double totalR = 0;
57     private double oE;
58
59     ;
60     private double oD;
61     private double oV;
62     private double oB;
63     private double eH;
64     private StateNN curS, preS;
65     private Action curA, preA;
66
67     public void run() {
68         initialize();
69         setColor();
70
71         for(int i = 0; i < NN.hiddenNeurons.length; i++){
72             System.out.println("weights for : " + i + "neuron");
73             printArrayCheck(NN.hiddenNeurons[i].getWeights());
74         }
75         System.out.println("weights for : " + "output neuron");
76         printArrayCheck(NN.outputNeuron.getWeights());
77
78         while (true) {
79             switch (operationalMode) {
80                 case scan: {
81                     turnRadarLeft(360);
82                     curR = 0; // reset curR to 0 when scan again
83                     break;
84                 }
85                 case performAction: {
86                     if (Math.random() <= epsilon) {
87                         curA = selectRandomAction();
88                     } else {
89                         curA = bestAction(curS);
90                     }
91                 }
92             }
93             // actionList.add(curA.ordinal());
94             actionCountsPer100[totalNumRounds/100][curA.ordinal()] = actionCountsPer100[totalNumRounds/100][curA.ordinal()] + 1;

```

```

95
96         switch (curA) {
97             case ATTACK: {
98                 turnGunRight(normalRelativeAngleDegrees(getHeading() - getGunHeading() + oB));
99                 fire(3);
100                 execute();
101                 break;
102             }
103             case ATTACK_MINOR: {
104                 turnGunRight(normalRelativeAngleDegrees(getHeading() - getGunHeading() + oB));
105                 fire(1);
106                 execute();
107                 break;
108             }
109             // case RUN_AWAY: {
110             //     turnRight(normalRelativeAngleDegrees(90 - (getHeading() - eH)));
111             //     ahead(30);
112             //     execute();
113             //     break;
114             // }
115             // deleted this action because it does not seem to be useful
116             case MOVE_LEFT: {
117                 turnLeft(90);
118                 ahead(15);
119                 execute();
120                 break;
121             }
122             // case MOVE_RIGHT: {
123             //     setTurnRight(90);
124             //     setVelocityRate(3);
125             //     setAhead(50);
126             //     execute();
127             //     break;
128             // }
129         }
130     }
131
132     // update Q value for (s,a)
133     lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
134     NN.train(preS.transformToX(preA), computeQ(preS, curS, curR));
135     NN.train(preS.transformToX(preA), computeTargetForNN(preS, curS, curR));
136     System.out.println("training done");
137     System.out.println("cur A is " + curA.name());
138     // for(int i = 0; i < NN.hiddenNeurons.length; i++){
139     //     System.out.println("weights for : " + i + "neuron");
140     //     printArrayCheck(NN.hiddenNeurons[i].getWeights());
141     // }
142     // System.out.println("weights for : " + "output neuron");
143     // printArrayCheck(NN.outputNeuron.getWeights());
144
145     replayMemory.add(new Experience(preS, preA, curR, curS));
146     replayExperience(replayMemory);
147
148     this.operationalMode = enumOperationalMode.scan;
149 }
150 }
151 }
152 }
153 }
154
155 private void setColor() {
156     setBodyColor(Color.yellow);
157     setGunColor(Color.black);
158     setRadarColor(Color.red);
159     setBulletColor(Color.white);
160     setScanColor(Color.white);
161 }
162
163 private void initialize() {
164     curS = new StateNN(getEnergy(), 100, 100);
165     curA = Action.values()[0];
166
167     preS = curS;
168     preA = curA;
169 }
170
171 private Action bestAction(StateNN curS) {
172     double bestQ = -Double.MAX_VALUE;
173     int bestAindex = 0;
174     double[] X = curS.transformToX();
175     double[] newX = Arrays.copyOf(X, X.length + 1);
176     for (int i = 0; i < Action.values().length; i++) {
177         System.out.println(Action.values().length);
178         switch (i){
179             case 0: newX[X.length]=-1;
180                 break;
181             case 1: newX[X.length]=0;
182                 break;
183             case 2: newX[X.length]=1;
184                 break;
185         }
186         //newX[X.length] = i;
187         double q = lut.outputFor(newX);
188         // double q = NN.outputFor(newX);
189         System.out.println("newX is: ");

```

```

192         printArrayCheck(newX);
193         System.out.println("NN.outputFor(newX) is: ");
194         System.out.println(q);
195
196         if (q > bestQ) {
197             bestQ = q;
198             bestAindex = i;
199         }
200     }
201     Action bestA = Action.values()[bestAindex];
202     return bestA;
203 }
204
205 private void printArrayCheck(double[] newX) {
206     for( double x : newX){
207         System.out.println(x);
208     }
209 }
210
211 private double bestActionQ(StateNN curS) {
212     double bestQ = -Double.MAX_VALUE;
213     int bestAindex = 0;
214     double[] X = curS.transformToX();
215     double[] newX = Arrays.copyOf(X, X.length + 1);
216     for (int i = 0; i < Action.values().length; i++) {
217         switch (i){
218             case 0: newX[X.length]=-1;
219                     break;
220             case 1: newX[X.length]=0;
221                     break;
222             case 2: newX[X.length]=1;
223                     break;
224         }
225         // newX[X.length] = i;
226         // double q = lut.outputFor(newX);
227         double q = NN.outputFor(newX);
228         if (q > bestQ) {
229             bestQ = q;
230             bestAindex = i;
231         }
232     }
233     Action bestA = Action.values()[bestAindex];
234     return bestQ;
235 }
236
237 // private double computeQ(State preS, State curS, double r) {
238 //     // off-policy, q learning
239 //     // take action, observe r, s' (find the best a' and update Q(s,a))
240 //     //  $Q(s,a) = Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$ 
241 //     double oldQ = lut.outputFor(preS.transformToX(preA));
242 //     double oldQ = NN.outputFor(preS.transformToX(preA));
243 //     double maxNextQ = bestActionQ(curS);
244 //     return oldQ + alpha * (r + gamma * maxNextQ - oldQ);
245 //
246 //     // on-policy
247 //     double oldQ = lut.outputFor(preS.transformToX(preA));
248 //     double curQ = lut.outputFor(curS.transformToX(curA));
249 //     return oldQ + alpha * (r + gamma * curQ - oldQ);
250 // }
251
252 private double computeTargetForNN(StateNN preS, StateNN curS, double r) {
253     // off-policy, q learning
254     // take action, observe r, s' (find the best a' and update Q(s,a))
255     //  $Q(s,a) = Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$ 
256     // double oldQ = lut.outputFor(preS.transformToX(preA));
257     // double oldQ = NN.outputFor(preS.transformToX(preA));
258     double maxNextQ = bestActionQ(curS);
259     return (r + gamma * maxNextQ);
260
261     // on-policy
262     double oldQ = lut.outputFor(preS.transformToX(preA));
263     double curQ = lut.outputFor(curS.transformToX(curA));
264     return oldQ + alpha * (r + gamma * curQ - oldQ);
265 }
266
267 private Action selectRandomAction() {
268     int numOfChoice = Action.values().length;
269     return Action.values()[((int) (Math.random() * numOfChoice))];
270 }
271
272 public void onScannedRobot(ScannedRobotEvent e) {
273     // update preS, preA; update curS
274     preS = curS;
275     preA = curA;
276     curS = new StateNN(getEnergy(), e.getEnergy(), e.getDistance());
277     oB = e.getBearing();
278     eH = e.getHeading();
279
280     this.operationalMode = enumOperationalMode.performAction;
281 }
282
283 public void replayExperience(ReplayMemory rm){
284     int memorySize = rm.sizeOf();
285     int requestedSampleSize = (memorySize < MAX_SAMPLE_SIZE) ? memorySize : MAX_SAMPLE_SIZE;
286 }
287
288

```



```

289     Object [] sample = rm.randomSample(requestedSampleSize);
290     for(Object item: sample){
291         Experience exp = (Experience) item;
292
293         //         double[] x = new double[] {
294         //             exp.preS.myEl,
295         //             exp.preS.oEl,
296         //             exp.preS.disL,
297         //             exp.
298         //         }
299         NN.train(exp.preS.transformToX(exp.preA), computeTargetForNN(exp.preS, exp.curS, exp.curR));
300     }
301 }
302
303 public void onWin(WinEvent e) {
304     System.out.println("I win!!!!!!!!!!!!!!");
305     numWins++;
306
307     curR = goodTerminalReward;
308     totalR += curR;
309
310     //         lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
311     //         NN.train(preS.transformToX(preA), computeQ(preS, curS, curR));
312     NN.train(preS.transformToX(preA), computeTargetForNN(preS, curS, curR));
313     //TODO: can add stat
314     System.out.println("totalR =" + totalR);
315 }
316
317 public void onDeath(DeathEvent e) {
318     System.out.println("I lose.");
319     curR = badTerminalReward;
320     totalR += curR;
321
322     //         lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
323     //         NN.train(preS.transformToX(preA), computeQ(preS, curS, curR));
324     NN.train(preS.transformToX(preA), computeTargetForNN(preS, curS, curR));
325
326     System.out.println("totalR =" + totalR);
327 }
328
329 //////////////////////////////////////////////////intermediate rewards start////////////////////////////////////
330 public void onBulletHit(BulletHitEvent e) {
331     curR = +0.4;
332     totalR += curR;
333 }
334
335
336 public void onBulletMissed(BulletMissedEvent e) {
337     curR = -0.01;
338     totalR += curR;
339 }
340
341 public void onHitByBullet(HitByBulletEvent event) {
342     curR = -0.2;
343     totalR += curR;
344 }
345
346 public void onHitWall(HitWallEvent event) {
347     curR = -0.01;
348     totalR += curR;
349 }
350
351 //////////////////////////////////////////////////intermediate rewards end////////////////////////////////////
352 public void onRoundEnded(RoundEndedEvent event) {
353
354     //         actionList.add(99);
355     if (totalNumRounds == numOfRoundsToDecayE) {
356         //WriteQ();
357     }
358     //         method 1: decay E to 0 in the first 80% rounds, stay 0 in the last 20% rounds
359     if (totalNumRounds < numOfRoundsToDecayE) {
360         if(epsilon > 0 & epsilon > decayEStepSize){
361             epsilon -= decayEStepSize; // so e decaying to 0 in the first 80% round
362         }
363     } else {
364         epsilon = 0;
365     }
366
367     // method 2: constant E for 10% rounds, stay 0 for 10% rounds, repeat 5 times
368     if (totalNumRounds > (0.1 * desiredTotalRounds) && totalNumRounds < (0.2 * desiredTotalRounds)) {
369         //
370         //
371         //         epsilon = 0;
372         //     }else if(totalNumRounds > (0.3 * desiredTotalRounds) && totalNumRounds < (0.4 * desiredTotalRounds)){
373         //         epsilon = 0;
374         //     }else if(totalNumRounds > (0.5 * desiredTotalRounds) && totalNumRounds < (0.6 * desiredTotalRounds)){
375         //         epsilon = 0;
376         //     }else if(totalNumRounds > (0.7 * desiredTotalRounds) && totalNumRounds < (0.8 * desiredTotalRounds)){
377         //         epsilon = 0;
378         //     }else if(totalNumRounds > (0.9 * desiredTotalRounds) && totalNumRounds < (1 * desiredTotalRounds)){
379         //         epsilon = 0;
380         //     }else{
381         //         epsilon=epsilon_init;
382         //     }
383
384     totalNumRounds++;
385     if (totalNumRounds % 100 == 0) {

```

```

386         int index = totalNumRounds / 100 - 1;
387         winRatePer100[index] = numWins;
388         totalRewardsPer100[index] = totalR;
389         epsilonList[index] = epsilon;
390
391         out.println("The round has ended and the winRatePer100[] updated");
392         out.println("totalNumRounds" + totalNumRounds);
393         out.println("winRatePer100" + winRatePer100[index]);
394         out.println("totalRewardsPer100" + totalRewardsPer100[index]);
395         out.println("numWins" + numWins);
396         numWins = 0; // reset
397         totalR = 0;
398         out.println("numWins set to 0 again");
399
400     }
401     System.out.println("round ended");
402
403 }
404
405 public void onBattleEnded(BattleEndedEvent e) {
406     //finalWrite0();
407     finalWriteWins();
408     finalWriteEpsilonList();
409     //    finalWriteActionList();
410     finalWriteRewardss();
411     finalWriteActionList();
412 }
413
414
415 private void finalWriteEpsilonList() {
416     PrintStream w = null;
417     try {
418         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameEpsilonList)));
419
420         for (double e : epsilonList) {
421             w.println(e);
422         }
423
424         if (w.checkError()) {
425             out.println("I could not write the finalWriteEpsilonList!");
426         }
427     } catch (IOException e) {
428         out.println("IOException trying to write: ");
429         e.printStackTrace(out);
430     } finally {
431         if (w != null) {
432             w.close();
433         }
434     }
435 }
436
437 private void finalWriteWins() {
438     PrintStream w = null;
439     try {
440         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameWinRate)));
441
442         for (double winR : winRatePer100) {
443             w.println(winR);
444         }
445
446         if (w.checkError()) {
447             out.println("I could not write the winRatePer100!");
448         }
449     } catch (IOException e) {
450         out.println("IOException trying to write: ");
451         e.printStackTrace(out);
452     } finally {
453         if (w != null) {
454             w.close();
455         }
456     }
457 }
458
459 private void finalWriteRewardss() {
460     PrintStream w = null;
461     try {
462         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameTotalRewards)));
463
464         for (double R : totalRewardsPer100) {
465             w.println(R);
466         }
467
468         if (w.checkError()) {
469             out.println("I could not write the winRatePer100!");
470         }
471     } catch (IOException e) {
472         out.println("IOException trying to write: ");
473         e.printStackTrace(out);
474     } finally {
475         if (w != null) {
476             w.close();
477         }
478     }
479 }
480
481 private void finalWriteActionList() {
482     PrintStream w = null;

```

```

483     try {
484         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameActions)));
485
486         for (double[] row : actionCountsPer100) {
487             for(double actionCount: row) {
488                 w.println(actionCount);
489             }
490         }
491
492         if (w.checkError()) {
493             out.println("I could not write the actionList!");
494         }
495     } catch (IOException e) {
496         out.println("IOException trying to write: ");
497         e.printStackTrace(out);
498     } finally {
499         if (w != null) {
500             w.close();
501         }
502     }
503 }
504
505
506
507 public enum enumOperationalMode {scan, performAction}
508 }
509

```

StateNN.java

```

1  package Robot;
2  // this class is different from State in minor way:
3  // StateNN is state that we use for NN, with argA, argB be the domain of the data
4  // this is different than quantized data used in LUT
5  public class StateNN {
6      static final int argA = -1;
7      static final int argB = 1;
8      // static final int numOfLevelForDistance = 5;
9      // static final int disForTooCloseToWall = 100;
10     static final int numOfLevelForEnergy = 5;
11
12     // public static final int possibleStates = numOfLevelForDistance * numOfLevelForEnergy * numOfLevelForEnergy * 2 * 2;
13     // public static final int possibleStates = numOfLevelForDistance * numOfLevelForEnergy * numOfLevelForEnergy;
14     private double disL;
15     // private int isCloseToW;
16     private double myEL;
17     private double oEL;
18
19     // private int isFaster;
20     public StateNN(double myE, double oE,
21                   //double myX, double myY,
22                   double oD
23                   // double myV, double oV
24     ) {
25         // disL: distance level between the enemy and our robot: low(1), high(numOfLevelForDistance)
26         // closeToW: if it is too close to wall: yes(1), no(-1)
27         // elMy: my energy level: low(1), high(numOfLevelForEnergy)
28         // el0: enemy's energy level: low(1), high(numOfLevelForEnergy)
29         // total possible state: numOfLevelForDistance * numOfLevelForEnergy * numOfLevelForEnergy * 2 * 2
30         this.myEL = convertEnergyLevel(myE);
31         this.oEL = convertEnergyLevel(oE);
32         this.disL = convertDistance(oD);
33         // this.isCloseToW = computeTooCloseToWall(myX, myY);
34         // this.isFaster = computeIsFaster(oV, myV);
35     }
36
37     // public StateNN(int myE, int oEL, int disL
38     // // // , int isCloseToW, int isFaster
39     // // // ) {
40     // // //     this.myEL = myE;
41     // // //     this.oEL = oEL;
42     // // //     this.disL = disL;
43     // // //     this.isCloseToW = isCloseToW;
44     // // //     this.isFaster = isFaster;
45     // // // }
46     // // // }
47     // // //
48
49     /*
50     return the index for this state (among all possible states)
51     */
52     // public int getIndex(int actionIndex) {
53     // // // int tempForisCloseToW = 0;
54     // // // int tempForisFaster = 0;
55     // // // if(this.isCloseToW == -1){
56     // // //     tempForisCloseToW = 1;
57     // // // }else{
58     // // //     tempForisCloseToW = 2;
59     // // // }
60     // // //
61     // // // if(this.isFaster == -1){
62     // // //     tempForisFaster = 1;
63     // // // }else{
64     // // //     tempForisFaster = 2;
65     // // // }
66     // // //
67     // // // //int actionIndex = a.ordinal();
68     // // // int numOfActions = Action.values().length;
69     // // // return this.myEL*this.oEL*this.disL*tempForisCloseToW*tempForisFaster*numOfActions + actionIndex;
70     // // //
71     // // // int NUM_ACTIONS = Action.values().length;
72     // // // return (myEL - 1) * (numOfLevelForEnergy * numOfLevelForDistance * NUM_ACTIONS)
73     // // // + (oEL - 1) * (numOfLevelForDistance * NUM_ACTIONS)
74     // // // + (disL - 1) * (NUM_ACTIONS)
75     // // // + (tempForisCloseToW-1) * (2 * NUM_ACTIONS)
76     // // // + (tempForisFaster-1) * NUM_ACTIONS
77     // // // + actionIndex;
78     // // // }
79
80     public double[] transformToX() {
81     // double[] X = new double[5];
82     double[] X = new double[3];
83     X[0] = this.myEL;
84     X[1] = this.oEL;
85     X[2] = this.disL;
86     // X[3] = this.isCloseToW;
87     // X[4] = this.isFaster;
88     return X;
89     }
90
91     public double[] transformToX(Action a) {
92     double[] X = new double[4];
93     X[0] = this.myEL;
94     X[1] = this.oEL;

```

```

95         X[2] = this.disl;
96         //     X[3] = this.isCloseToW;
97         //     X[4] = this.isFaster;
98         switch (a.ordinal()){
99             case 0: X[3]=-1;
100                 break;
101             case 1: X[3]=0;
102                 break;
103             case 2: X[3]=1;
104                 break;
105         }
106
107         //     X[3] = a.ordinal();
108         //     X[5] = a.ordinal();
109         return X;
110     }
111
112     // private int computeIsFaster(double oV, double myV) {
113     //     if (oV < myV){
114     //         return 1; // faster than the opponent
115     //     }else{
116     //         return -1;
117     //     }
118     // }
119
120     // convert energy (around 0 to 105) to argA and argB
121     private double convertEnergyLevel(double e) {
122         double scaledValue = scaleValue(e, 0, 110, argA, argB);
123         return scaledValue;
124     }
125
126     private double convertDistance(double oD) {
127         double scaledValue = scaleValue(oD, 0, 1000, argA, argB);
128         return scaledValue;
129     }
130     public static double scaleValue(double originalValue, double minOriginal, double maxOriginal, double minTarget, double maxTarget) {
131         // Linear scaling formula
132         return minTarget + (originalValue - minOriginal) * (maxTarget - minTarget) / (maxOriginal - minOriginal);
133     }
134 }
135 }
136

```

Action.java

```
1  package Robot;
2
3  public enum Action {
4      MOVE_LEFT,
5
6      ATTACK_MINOR,
7
8      ATTACK;
9      //      RUN_AWAY;
10     //      CHASE;
11 }
12
13
```

Main.java

```

1  import NN.NeuralNet;
2
3  import java.io.*;
4  import java.util.ArrayList;
5  import java.util.Scanner;
6
7  public class Main {
8
9      static ArrayList<Double> printValues = new ArrayList<>();
10     static final double[][] XORInputBinary = {{0.0, 0.0}, {0.0, 1.0}, {1.0, 0.0}, {1.0, 1.0}};
11     static final double[] XOROutputBinary = {0.0, 1.0, 1.0, 0.0};
12
13     static final double[][] XORInputBipolar = {{-1.0, -1.0}, {-1.0, 1.0}, {1.0, -1.0}, {1.0, 1.0}};
14     static final double[] XOROutputBipolar = {-1.0, 1.0, 1.0, -1.0};
15
16     public static void main(String[] args) {
17         // Q1a();
18         // Q1b();
19         // Q1c();
20         Q4();
21     }
22
23     public static void Q1a() {
24         int totalTrials = 1000;
25         int numOfConverge = 0, numOfFail = 0;
26         int totalEpochsToConverge = 0;
27
28         for (int trial = 0; trial < totalTrials; trial++) {
29             NeuralNet XORNNBinary = new NeuralNet(2, 4, 0.2, 0.0, 0, 1, 2);
30
31             double errs[] = new double[4];
32             int numEpoch = 0;
33             double totalErr;
34             do {
35                 totalErr = 0;
36                 // train all pattern once
37                 for (int i = 0; i < 4; i++) {
38                     errs[i] = XORNNBinary.train(XORInputBinary[i], XOROutputBinary[i]);
39                     // totalErr += errs[i];
40                 }
41
42                 //after one epoch, calculate the total error
43                 for (int i = 0; i < 4; i++) {
44                     double output = XORNNBinary.outputFor(XORInputBinary[i]);
45                     totalErr += Math.pow((output - XOROutputBinary[i]), 2);
46                 }
47                 totalErr *= 0.5;
48                 System.out.println("Total error " + totalErr + " at " + numEpoch + " epochs.");
49                 numEpoch++;
50
51                 if (totalErr < 0.05) {
52                     numOfConverge++;
53                     totalEpochsToConverge += numEpoch;
54                     System.out.println("Desired error reached at " + numEpoch + " epochs.");
55                     break;
56                 }
57             } while (numEpoch < 10000);
58
59             if (numEpoch >= 10000) {
60                 System.out.println("Fail within " + numEpoch + " epochs.");
61                 numOfFail++;
62             }
63         }
64         System.out.println("=====SUMMARY=====");
65         System.out.println("Total trials: " + totalTrials);
66         System.out.println("Success to reach desired error " + numOfConverge + " times");
67         System.out.println("Fail to reach desired error (within 10000 epochs) " + numOfFail + " times");
68         System.out.println("Average epochs to reach desired error: " + totalEpochsToConverge / numOfConverge);
69
70     }
71
72     public static void Q1b() {
73         int totalTrials = 1000;
74         int numOfConverge = 0, numOfFail = 0;
75         int totalEpochsToConverge = 0;
76
77         for (int trial = 0; trial < totalTrials; trial++) {
78             NeuralNet XORNNBinary = new NeuralNet(2, 4, 0.2, 0.0, -1, 1, 2);
79
80             double errs[] = new double[4];

```

```

82     int numEpoch = 0;
83     double totalErr;
84     do {
85         totalErr = 0;
86         // train all pattern once
87         for (int i = 0; i < 4; i++) {
88             errs[i] = XORNNBinary.train(XORInputBipolar[i], XOROutputBipolar[i]);
89             totalErr += errs[i];
90         }
91
92         //after one epoch, calculate the total error
93         for (int i = 0; i < 4; i++) {
94             double output = XORNNBinary.outputFor(XORInputBipolar[i]);
95             totalErr += Math.pow((output - XOROutputBipolar[i]), 2);
96         }
97         totalErr *= 0.5;
98         // System.out.println("Total error " + totalErr + " at " + numEpoch + " epochs.");
99         numEpoch++;
100
101         if (totalErr < 0.05) {
102             numOfConverge++;
103             totalEpochsToConverge += numEpoch;
104             System.out.println("Desired error reached at " + numEpoch + " epochs.");
105             break;
106         }
107     } while (numEpoch < 10000);
108
109     if (numEpoch >= 10000) {
110         System.out.println("Fail within " + numEpoch + " epochs.");
111         numOfFail++;
112     }
113 }
114
115 System.out.println("=====SUMMARY=====");
116 System.out.println("Total trials: " + totalTrials);
117 System.out.println("Success to reach desired error " + numOfConverge + " times");
118 System.out.println("Fail to reach desired error (within 10000 epochs) " + numOfFail + " times");
119 System.out.println("Average epochs to reach desired error: " + totalEpochsToConverge / numOfConverge);
120
121 }
122
123 public static void Q1c() {
124     int totalTrials = 1000;
125     int numOfConverge = 0, numOfFail = 0;
126     int totalEpochsToConverge = 0;
127
128     for (int trial = 0; trial < totalTrials; trial++) {
129         NeuralNet XORNNBinary = new NeuralNet(2, 4, 0.2, 0.9, -1, 1, 2);
130
131         double errs[] = new double[4];
132         int numEpoch = 0;
133         double totalErr;
134         do {
135             totalErr = 0;
136             // train all pattern once
137             for (int i = 0; i < 4; i++) {
138                 errs[i] = XORNNBinary.train(XORInputBipolar[i], XOROutputBipolar[i]);
139                 totalErr += errs[i];
140             }
141
142             //after one epoch, calculate the total error
143             for (int i = 0; i < 4; i++) {
144                 double output = XORNNBinary.outputFor(XORInputBipolar[i]);
145                 totalErr += Math.pow((output - XOROutputBipolar[i]), 2);
146             }
147             totalErr *= 0.5;
148             // System.out.println("Total error " + totalErr + " at " + numEpoch + " epochs.");
149             numEpoch++;
150
151             if (totalErr < 0.05) {
152                 numOfConverge++;
153                 totalEpochsToConverge += numEpoch;
154                 System.out.println("Desired error reached at " + numEpoch + " epochs.");
155                 break;
156             }
157         } while (numEpoch < 10000);
158
159         if (numEpoch >= 10000) {
160             System.out.println("Fail within " + numEpoch + " epochs.");
161             numOfFail++;
162         }
163     }
164 }
165 System.out.println("=====SUMMARY=====");

```



```

166     System.out.println("Total trials: " + totalTrials);
167     System.out.println("Success to reach desired error " + numOfConverge + " times");
168     System.out.println("Fail to reach desired error (within 10000 epochs) " + numOfFail + " times");
169     System.out.println("Average epochs to reach desired error: " + totalEpochsToConverge / numOfConverge);
170 }
171
172
173 // use LUT from Q2 to train NN, to pick up hyper-parameter:
174 // numhidden, learningrate, momentum
175 public static void Q4() {
176     // double[][] LUTInputBipolar = {{20,20,200,1},{20,20,200,2},{20,20,200,3}};
177     double[][] input = generateLUTInputBipolar();
178     // double[][] LUTInputBipolar = transformToBipolar(input);
179     double[][] LUTInputBipolar = input;
180     printArray(LUTInputBipolar);
181
182     double[] q = loadQfromLUT();
183     // double[] LUTOutputBipolar = transformQtoBipolar(q);
184     // double[] LUTOutputBipolar = bipolarTransform(q);
185     double[] LUTOutputBipolar = transformToRange(q);
186     // double[] LUTOutputBipolar=q;
187     // Assertions.assertEquals(LUTOutputBipolar.length, LUTInputBipolar.length, "Arrays have different lengths");
188
189     if (LUTOutputBipolar.length == LUTInputBipolar.length) {
190         System.out.println("Arrays have the same length");
191     } else {
192         System.out.println("!!!!Arrays have different lengths!!!!");
193     }
194     for (double v : LUTOutputBipolar) {
195         System.out.println(v);
196     }
197     //writeQ(LUTOutputBipolar);
198
199
200     int totalTrials = 1;
201     int numOfConverge = 0, numOfFail = 0;
202     int totalEpochsToConverge = 0;
203
204
205     int argA = 1;
206     int argB = 2;
207
208     System.out.println(argA);
209     System.out.println(argB);
210     for (int trial = 0; trial < totalTrials; trial++) {
211         NeuralNet LUTNNBipolar = new NeuralNet(4, 8, 0.2, 0.4, argA, argB, 2);
212
213         // num of patterns (inputs): 5*5*5*numofaction(3)=375
214         int numOfPatterns = 375;
215         double errs[] = new double[numOfPatterns];
216         int numEpoch = 0;
217         double totalErr;
218         do {
219             totalErr = 0;
220             // train all pattern once
221             for (int i = 0; i < numOfPatterns; i++) {
222                 errs[i] = LUTNNBipolar.train(LUTInputBipolar[i], LUTOutputBipolar[i]);
223             }
224             // totalErr += errs[i];
225
226             //after one epoch, calculate the total error
227             for (int i = 0; i < numOfPatterns; i++) {
228                 double output = LUTNNBipolar.outputFor(LUTInputBipolar[i]);
229                 System.out.println(output);
230                 System.out.println(LUTOutputBipolar[i]);
231                 totalErr += Math.pow((output - LUTOutputBipolar[i]), 2);
232             }
233             // totalErr *= 0.5;
234             // System.out.println(totalErr);
235             // totalErr = totalErr*(1/numOfPatterns);
236             // System.out.println(totalErr);
237             // totalErr = Math.pow(totalErr, 0.5);
238             // System.out.println(totalErr);
239             System.out.println(totalErr);
240             printValues.add(totalErr);
241
242             System.out.println("Total error " + totalErr + " at " + numEpoch + " epochs.");
243             numEpoch++;
244
245             if (totalErr < 0.05) {
246                 numOfConverge++;
247                 totalEpochsToConverge += numEpoch;
248                 System.out.println("Desired error reached at " + numEpoch + " epochs.");
249                 break;

```

```

250 //      }
251
252      } while (numEpoch < 20000);
253      String filePath = "output.txt";
254      saveArrayListToTxt(printValues, filePath);
255      System.out.println("Array saved to: " + filePath);
256
257      if (numEpoch >= 20000) {
258          System.out.println("Fail within " + numEpoch + " epochs.");
259          numOfFail++;
260      }
261  }
262  System.out.println("=====SUMMARY=====");
263  System.out.println("Total trials: " + totalTrials);
264  System.out.println("Success to reach desired error " + numOfConverge + " times");
265  System.out.println("Fail to reach desired error (within 10000 epochs) " + numOfFail + " times");
266  System.out.println("Average epochs to reach desired error: " + totalEpochsToConverge / numOfConverge);
267  }
268
269  private static void saveArrayListToTxt(ArrayList<Double> arrayList, String filePath) {
270      try (PrintWriter writer = new PrintWriter(new FileWriter(new File(filePath)))) {
271          for (Double value : arrayList) {
272              writer.println(value);
273          }
274      } catch (IOException e) {
275          e.printStackTrace();
276      }
277  }
278
279  private static void printArray(double[][] array) {
280      for (double[] row : array) {
281          for (double value : row) {
282              System.out.print(value + "\t");
283          }
284          System.out.println();
285      }
286  }
287
288  private static double[] transformToRange(double[] originalArray) {
289      double[] transformedArray = new double[originalArray.length];
290
291      // Find the maximum absolute value in the original array
292      double maxAbsValue = 0;
293      for (double value : originalArray) {
294          maxAbsValue = Math.max(maxAbsValue, Math.abs(value));
295      }
296
297      // Define the target range [1, 2] and the center (1.5)
298      double targetMin = 1.0;
299      double targetMax = 2.0;
300      double center = 1.5;
301
302      // Perform the transformation
303      for (int i = 0; i < originalArray.length; i++) {
304          if (originalArray[i] > 0) {
305              transformedArray[i] = ((originalArray[i] / maxAbsValue) * (targetMax - center)) + center;
306          } else {
307              transformedArray[i] = ((originalArray[i] / maxAbsValue) * (center - targetMin)) + center;
308          }
309      }
310
311      return transformedArray;
312  }
313
314  private static double[] bipolarTransform(double[] originalArray) {
315      double minValue = findMinValue(originalArray);
316      double maxValue = findMaxValue(originalArray);
317
318      double[] bipolarArray = new double[originalArray.length];
319
320      for (int i = 0; i < originalArray.length; i++) {
321          bipolarArray[i] = ((originalArray[i] - minValue) / (maxValue - minValue)) * 2 - 1;
322      }
323
324      return bipolarArray;
325  }
326
327  private static double findMinValue(double[] array) {
328      double minValue = Double.MAX_VALUE;
329      for (double value : array) {
330          minValue = Math.min(minValue, value);
331      }
332      return minValue;
333  }

```

```

334
335 private static double findMaxValue(double[] array) {
336     double maxValue = Double.MIN_VALUE;
337     for (double value : array) {
338         maxValue = Math.max(maxValue, value);
339     }
340     return maxValue;
341 }
342
343 private static double[][] generateLUTInputBipolar() {
344     // Define the ranges for each dimension
345     // int[] xValues = {20, 40, 60, 80, 100};
346     // int[] yValues = {20, 40, 60, 80, 100};
347     // int[] zValues = {20, 40, 60, 80, 100};
348     // int[] aValues = {10, 20, 30};
349
350     double[] xValues = {1, 1.25, 1.5, 1.75, 2};
351     double[] yValues = {1, 1.25, 1.5, 1.75, 2};
352     double[] zValues = {1, 1.25, 1.5, 1.75, 2};
353     double[] aValues = {1, 1.5, 2};
354     // Calculate the total number of combinations
355     int totalCombinations = xValues.length * yValues.length * zValues.length * aValues.length;
356
357     // Create the LUTInputBipolar array
358     double[][] LUTInputBipolar = new double[totalCombinations][4];
359     int index = 0;
360
361     // Generate all combinations
362     for (double x : xValues) {
363         for (double y : yValues) {
364             for (double z : zValues) {
365                 for (double a : aValues) {
366                     LUTInputBipolar[index][0] = x;
367                     LUTInputBipolar[index][1] = y;
368                     LUTInputBipolar[index][2] = z;
369                     LUTInputBipolar[index][3] = a;
370                     index++;
371                 }
372             }
373         }
374     }
375     return LUTInputBipolar;
376 }
377
378
379
380 public static double[] loadQfromLUT() {
381     // Provide the path to your text file
382     String filePath = "Users/zhangxiyu/IdeaProjects/MyRobot/src/q.txt";
383     // Create an ArrayList to store the values
384     ArrayList<Double> values = new ArrayList<>();
385     try {
386         // Create a File object representing the text file
387         File file = new File(filePath);
388
389         // Create a Scanner to read from the file
390         Scanner scanner = new Scanner(file);
391
392         // Read values from the file and add them to the ArrayList
393         while (scanner.hasNextDouble()) {
394             double value = scanner.nextDouble();
395             values.add(value);
396         }
397
398         // Close the scanner
399         scanner.close();
400
401     } catch (FileNotFoundException e) {
402         // Handle file not found exception
403         e.printStackTrace();
404     }
405     // Convert the ArrayList to an array if needed
406     double[] valuesArray = new double[values.size()];
407     for (int i = 0; i < values.size(); i++) {
408         valuesArray[i] = values.get(i);
409     }
410
411     // Now you can use the valuesArray as an array in your code
412     return valuesArray;
413 }
414
415
416
417

```

418 }
419

CircularQueue.java

```
1  package ReplayMemory;
2  import java.util.LinkedList;
3
4  public class CircularQueue<T> extends LinkedList<T> {
5      private int capacity = 10;
6
7      public CircularQueue(int capacity){
8          this.capacity = capacity;
9      }
10
11     public boolean add(T e) {
12         if(size() >= capacity)
13             removeFirst();
14         return super.add(e);
15     }
16
17     public Object [] toArray() {
18         return super.toArray();
19     }
20 }
21
22
```

Experience.java

```
1  package Robot;
2
3  public class Experience {
4      public StateNN preS;
5      public Action preA;
6      public double curR;
7      public StateNN curS;
8
9      public Experience(StateNN preS, Action preA, double curR, StateNN curS){
10         this.preS = preS;
11         this.preA = preA;
12         this.curR = curR;
13         this.curS = curS;
14     }
15 }
16
17
```

ReplayMemory.java

```

1 package ReplayMemory;
2 import java.util.Arrays;
3 import java.util.Collections;
4
5 /**
6  * Author: Sarbjit Sarkaria
7  * Date : 07th January 2021
8  * This class implements a replay memory for any type T.
9  * The capacity of the memory must be specified upon construction.
10 * The memory will discard the oldest items that do not fit.
11 * @param <T> Type to be managed by the ReplayMemory
12 */
13
14 public class ReplayMemory<T> {
15
16     private CircularQueue<T> memory;
17     private Object[] EMPTYARRAY = {};
18
19     // Constructor
20     public ReplayMemory(int size) {
21         memory = new CircularQueue<T>(size);
22     }
23
24     // Add an item to the memory
25     public void add(T experience) {
26         memory.add(experience);
27     }
28
29     // Retrieve a sample of n most recently added items from the memory and return it as an array
30     public Object[] sample(int n) {
31         if (memory.isEmpty())
32             return EMPTYARRAY;
33         else {
34             // I don't have a way of returning T[], so instead I return Object[]
35             // See the unit tests to see how to use this tyle - no additional effort necessary
36             // .... see here for more : https://stackoverflow.com/questions/1115230/casting-object-array-to-integer-array-error
37             int size = memory.size();
38             Object[] objectArray = memory.toArray();
39             Object[] sampleObjectArray = Arrays.copyOfRange(objectArray, size-n, size);
40             return sampleObjectArray;
41         }
42     }
43
44     // Retrieve a random sample of n items from the memory and return it as an array
45     public Object[] randomSample(int n) {
46         if (memory.isEmpty())
47             return EMPTYARRAY;
48         else {
49             // I don't have a way of returning T[], so instead I return Object[]
50             // See the unit tests to see how to use this tyle - no additional effort necessary
51             // .... see here for more : https://stackoverflow.com/questions/1115230/casting-object-array-to-integer-array-error
52             int size = memory.size();
53             CircularQueue shuffledMemory = new CircularQueue<T>(size);
54             shuffledMemory.addAll(memory); // This does a deep copy
55             Collections.shuffle(shuffledMemory);
56             Object[] objectArray = shuffledMemory.toArray();
57             Object[] sampleObjectArray = Arrays.copyOfRange(objectArray, size-n, size);
58             return sampleObjectArray;
59         }
60     }
61
62     // Returns the current size of the replay memory. Use for test/debug purposes
63     public int sizeOf() {
64         if (memory.isEmpty())
65             return 0;
66         else
67             return memory.size();
68     }
69 }
70

```

MyLUTRobot.java

```

1  package Robot.My502Robot;
2
3  import LUT.LUT;
4  import Robot.Action;
5  import Robot.State;
6  import robocode.*;
7
8  import java.awt.*;
9  import java.io.IOException;
10 import java.io.PrintStream;
11 import java.util.ArrayList;
12 import java.util.Arrays;
13 import java.util.Date;
14
15 import static robocode.util.Utils.normalRelativeAngleDegrees;
16
17
18 public class MyLUTRobot extends AdvancedRobot {
19     static double alpha = 0.2;
20     static double gamma = 1;
21     static int totalNumRounds = 0;
22     static int numRoundTo100 = 0;
23     static int numWins = 0;
24     // for question2(a), used 15000, other times used 10000
25     static int desiredTotalRounds = 3000;
26     static double[] winRatePer100 = new double[desiredTotalRounds / 100];
27     static double[] epsilonList = new double[winRatePer100.length];
28     // for question3(a), try e = 0, 0.2, 0.4, 0.6 and 0.8(default)
29     static double epsilon = 0.8;
30     static double epsilon_init = 0.8;
31     //static double[] actionList = new double[desiredTotalRounds];
32     static ArrayList<Integer> actionList = new ArrayList<>();
33     static int numOfRoundsToDecayE = (int) (desiredTotalRounds * 0.8);
34     static double decayEStepSize = epsilon_init / numOfRoundsToDecayE;
35     static private LUT lut = new LUT();
36     enumOperationalMode operationalMode = enumOperationalMode.scan;
37     // private String weightsFileName = getClass().getSimpleName() + "-weights.txt";
38     private String logFileName = getClass().getSimpleName() + "-" + "qValues" + new Date().toString() + ".dat";
39     private String logFileName1 = getClass().getSimpleName() + "-" + "qValuesBeforeTurningOffE" + new Date().toString() + ".dat";
40     private String logFileNameWinRate = getClass().getSimpleName() + "-" + "winRate" + new Date().toString() + ".dat";
41     private String logFileNameEpsilonList = getClass().getSimpleName() + "-" + "epsilonList" + new Date().toString() + ".dat";
42     private String logFileNameActions = getClass().getSimpleName() + "-" + "actionList" + new Date().toString() + ".dat";
43     // private String[] outputLog;
44     private double curR;
45     private double goodTerminalReward = 1;
46     private double badTerminalReward = -1;
47     private double totalR = 0;
48     private double oE;
49
50     ;
51     private double oD;
52     private double oV;
53     private double oB;
54     private double eH;
55     private State curS, preS;
56     private Action curA, preA;
57
58     public void run() {
59         initialize();
60         setColor();
61
62         while (true) {
63             switch (operationalMode) {
64                 case scan: {
65                     turnRadarLeft(360);
66                     curR = 0; // reset curR to 0 when scan again
67                     break;
68                 }
69                 case performAction: {
70                     if (Math.random() <= epsilon) {
71                         curA = selectRandomAction();
72                     } else {
73                         curA = bestAction(curS);
74                     }
75
76                     actionList.add(curA.ordinal());
77
78                     switch (curA) {
79                         case ATTACK: {
80                             turnGunRight(normalRelativeAngleDegrees(getHeading() - getGunHeading() + oB));
81                             fire(3);
82                             execute();
83                             break;
84                         }
85                         case ATTACK_MINOR: {
86                             turnGunRight(normalRelativeAngleDegrees(getHeading() - getGunHeading() + oB));
87                             fire(1);
88                             execute();
89                             break;

```



```

90         }
91         //         case RUN_AWAY: {
92         //             turnRight(normalRelativeAngleDegrees(90 - (getHeading() - eH)));
93         //             ahead(30);
94         //             execute();
95         //             break;
96         //         }
97         //         // deleted this action because it does not seem to be useful
98         case MOVE_LEFT: {
99             turnLeft(90);
100            ahead(15);
101            execute();
102            break;
103        }
104        //         case MOVE_RIGHT: {
105        //             setTurnRight(90);
106        //             setVelocityRate(3);
107        //             setAhead(50);
108        //             execute();
109        //             break;
110        //         }
111    }
112
113    // update Q value for (s,a)
114    lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
115
116    // TODO: for assignment 3
117    replayMemory.add(new Experience(pres, preA, curR, curS));
118    replayExperience(replayMemory);
119
120    this.operationalMode = enumOperationalMode.scan;
121
122    }
123
124    }
125
126    }
127
128    private void setColor() {
129        setBodyColor(Color.yellow);
130        setGunColor(Color.black);
131        setRadarColor(Color.red);
132        setBulletColor(Color.white);
133        setScanColor(Color.white);
134    }
135
136    private void initialize() {
137        curS = new State(getEnergy(), 100, 100);
138        curA = Action.values()[0];
139
140        preS = curS;
141        preA = curA;
142    }
143
144    private Action bestAction(State curS) {
145        double bestQ = -Double.MAX_VALUE;
146        int bestAindex = 0;
147        double[] X = curS.transformToX();
148        double[] newX = Arrays.copyOf(X, X.length + 1);
149        for (int i = 0; i < Action.values().length; i++) {
150            newX[X.length] = i;
151            double q = lut.outputFor(newX);
152            if (q > bestQ) {
153                bestQ = q;
154                bestAindex = i;
155            }
156        }
157        Action bestA = Action.values()[bestAindex];
158        return bestA;
159    }
160
161    private double bestActionQ(State curS) {
162        double bestQ = -Double.MAX_VALUE;
163        int bestAindex = 0;
164        double[] X = curS.transformToX();
165        double[] newX = Arrays.copyOf(X, X.length + 1);
166        for (int i = 0; i < Action.values().length; i++) {
167            newX[X.length] = i;
168            double q = lut.outputFor(newX);
169            if (q > bestQ) {
170                bestQ = q;
171                bestAindex = i;
172            }
173        }
174        Action bestA = Action.values()[bestAindex];
175        return bestQ;
176    }
177
178    private double computeQ(State preS, State curS, double r) {
179        // off-policy, q learning
180        // take action, observe r, s' (find the best a' and update Q(s,a))
181        // Q(s,a) = Q(s, a) + alpha(r + gamma * max(Q(s', a')) - Q(s,a))
182        double oldQ = lut.outputFor(preS.transformToX(preA));
183        double maxNextQ = bestActionQ(curS);

```

```

183     return oldQ + alpha * (r + gamma * maxNextQ - oldQ);
184
185     // // on-policy
186     // double oldQ = lut.outputFor(preS.transformToX(preA));
187     // double curQ = lut.outputFor(curS.transformToX(curA));
188     // return oldQ + alpha * (r + gamma * curQ - oldQ);
189 }
190
191 private Action selectRandomAction() {
192     int numOfChoice = Action.values().length;
193     return Action.values()[((int) (Math.random() * numOfChoice))];
194 }
195
196 public void onScannedRobot(ScannedRobotEvent e) {
197     // update preS, preA; update curS
198     preS = curS;
199     preA = curA;
200     curS = new State(getEnergy(), e.getEnergy(), e.getDistance());
201     oB = e.getBearing();
202     eH = e.getHeading();
203
204     this.operationalMode = enumOperationalMode.performAction;
205 }
206
207 // public void replayExperience(ReplayMemory rm){
208 //     int ms = rm.sizeOf();
209 //     int requestedSs = (ms < MAX)
210 // }
211
212 public void onWin(WinEvent e) {
213     System.out.println("I win!!!!!!!!!!!!!!");
214     numWins++;
215
216     curR = goodTerminalReward;
217     totalR += curR;
218
219     lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
220     //TODO: can add stat
221 }
222
223 public void onDeath(DeathEvent e) {
224     System.out.println("I lose.");
225     curR = badTerminalReward;
226     totalR += curR;
227
228     lut.train(preS.transformToX(preA), computeQ(preS, curS, curR));
229     //TODO: can add stat
230 }
231
232 //////////////////////////////////////////////////intermediate rewards start////////////////////////////////
233 public void onBulletHit(BulletHitEvent e) {
234     curR = +0.4;
235     totalR += curR;
236
237     //lut.train(preS.transformToX(), computeQ(preS, curS, curR));
238 }
239
240 public void onBulletMissed(BulletMissedEvent e) {
241     curR = -0.01;
242     totalR += curR;
243 }
244
245 public void onHitByBullet(HitByBulletEvent event) {
246     curR = -0.2;
247     totalR += curR;
248 }
249
250 public void onHitWall(HitWallEvent event) {
251     curR = -0.01;
252     totalR += curR;
253 }
254
255 //////////////////////////////////////////////////intermediate rewards end////////////////////////////////
256 public void onRoundEnded(RoundEndedEvent event) {
257     actionList.add(99);
258     if (totalNumRounds == numOfRoundsToDecayE) {
259         WriteQ();
260     }
261     if (totalNumRounds < numOfRoundsToDecayE) {
262         // if(epsilon > 0 & epsilon > decayEStepSize){
263         //     epsilon -= decayEStepSize; // so e decaying to 0 in the first 80% round
264         // }
265     } else {
266         epsilon = 0;
267     }
268
269     totalNumRounds++;
270     if (totalNumRounds % 100 == 0) {
271         int index = totalNumRounds / 100 - 1;
272         winRatePer100[index] = numWins;
273         epsilonList[index] = epsilon;
274     }
275 }

```

```

276         out.println("The round has ended and the winRatePer100[] updated");
277         out.println("totalNumRounds" + totalNumRounds);
278         out.println("winRatePer100" + winRatePer100[index]);
279         out.println("numWins" + numWins);
280         numWins = 0; // reset
281         out.println("numWins set to 0 again");
282     }
283     System.out.println("round ended");
284 }
285
286 private void WriteQ() {
287     PrintStream w = null;
288     try {
289         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileName1)));
290
291         double[] qs = lut.getQValues();
292         for (double q : qs) {
293             w.println(q);
294             // PrintStreams don't throw IOExceptions during prints, they simply set a flag.... so check it here.
295             if (w.checkError()) {
296                 out.println("I could not finalWriteQ!");
297             }
298         }
299     } catch (IOException e) {
300         out.println("IOException trying to write: ");
301         e.printStackTrace(out);
302     } finally {
303         if (w != null) {
304             w.close();
305         }
306     }
307 }
308
309 public void onBattleEnded(BattleEndedEvent e) {
310     finalWriteQ();
311     finalWriteWins();
312     finalWriteEpsilonList();
313     finalWriteActionList();
314 }
315 //
316
317 private void finalWriteEpsilonList() {
318     PrintStream w = null;
319     try {
320         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameEpsilonList)));
321
322         for (double e : epsilonList) {
323             w.println(e);
324         }
325
326         if (w.checkError()) {
327             out.println("I could not write the finalWriteEpsilonList!");
328         }
329     } catch (IOException e) {
330         out.println("IOException trying to write: ");
331         e.printStackTrace(out);
332     } finally {
333         if (w != null) {
334             w.close();
335         }
336     }
337 }
338
339 private void finalWriteWins() {
340     PrintStream w = null;
341     try {
342         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameWinRate)));
343
344         for (double winR : winRatePer100) {
345             w.println(winR);
346         }
347
348         if (w.checkError()) {
349             out.println("I could not write the winRatePer100!");
350         }
351     } catch (IOException e) {
352         out.println("IOException trying to write: ");
353         e.printStackTrace(out);
354     } finally {
355         if (w != null) {
356             w.close();
357         }
358     }
359 }
360
361 private void finalWriteQ() {
362     PrintStream w = null;
363     try {
364         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileName)));
365
366         double[] qs = lut.getQValues();
367         for (double q : qs) {

```

```

369         w.println(q);
370     } // PrintStreams don't throw IOExceptions during prints, they simply set a flag.... so check it here.
371     if (w.checkError()) {
372         out.println("I could not finalWriteQ!");
373     }
374 } catch (IOException e) {
375     out.println("IOException trying to write: ");
376     e.printStackTrace(out);
377 } finally {
378     if (w != null) {
379         w.close();
380     }
381 }
382 }
383
384 private void finalWriteActionList() {
385     PrintStream w = null;
386     try {
387         w = new PrintStream(new RobocodeFileOutputStream(getDataFile(logFileNameActions)));
388
389         for (int action : actionList) {
390             w.println(action);
391         }
392
393         if (w.checkError()) {
394             out.println("I could not write the actionList!");
395         }
396     } catch (IOException e) {
397         out.println("IOException trying to write: ");
398         e.printStackTrace(out);
399     } finally {
400         if (w != null) {
401             w.close();
402         }
403     }
404 }
405
406 public enum enumOperationalMode {scan, performAction}
407 }
408

```

State.java

```

1  package Robot;
2
3  public class State {
4      static final int numOfLevelForDistance = 5;
5      static final int disForTooCloseToWall = 100;
6      static final int numOfLevelForEnergy = 5;
7
8      public static final int possibleStates = numOfLevelForDistance * numOfLevelForEnergy * numOfLevelForEnergy * 2 * 2;
9      private int disL;
10     private int isCloseToW;
11     private int myEL;
12     private int oEL;
13     private int isFaster;
14     public State(double myE, double oE, double myX, double myY, double oD, double myV, double oV){
15         // disL: distance level between the enemy and our robot: low(1), high(numOfLevelForDistance)
16         // closeToW: if it is too close to wall: yes(1), no(-2)
17         // elMy: my energy level: low(1), high(numOfLevelForEnergy)
18         // elO: enemy's energy level: low(1), high(numOfLevelForEnergy)
19         // total possible state: numOfLevelForDistance * numOfLevelForEnergy * numOfLevelForEnergy * 2 * 2
20         this.myEL = computeEnergyLevel(myE);
21         this.oEL = computeEnergyLevel(oE);
22         this.disL = computeDistanceLevel(oD);
23         this.isCloseToW = computeTooCloseToWall(myX, myY);
24         this.isFaster = computeIsFaster(oV, myV);
25     }
26 }
27
28 public State(int myE, int oEL, int disL, int isCloseToW, int isFaster){
29     this.myEL = myE;
30     this.oEL = oEL;
31     this.disL = disL;
32     this.isCloseToW = isCloseToW;
33     this.isFaster = isFaster;
34 }
35
36
37 /*
38 return the index for this state (among all possible states)
39 */
40 public int getIndex(int actionIndex){
41     int tempForisCloseToW = 0;
42     int tempForisFaster = 0;
43     if(this.isCloseToW == -1){
44         tempForisCloseToW = 1;
45     }else{
46         tempForisCloseToW = 2;
47     }
48
49     if(this.isFaster == -1){
50         tempForisFaster = 1;
51     }else{
52         tempForisFaster = 2;
53     }
54     //int actionIndex = a.ordinal();
55     //int numOfActions = Action.values().length;
56     //return this.myEL*this.oEL*this.disL*tempForisCloseToW*tempForisFaster*numOfActions + actionIndex;
57
58     int NUM_ACTIONS = Action.values().length;
59     return (myEL-1) * (numOfLevelForEnergy * numOfLevelForDistance * 2 * 2 * NUM_ACTIONS)
60         + (oEL-1) * (numOfLevelForDistance * 2 * 2 * NUM_ACTIONS)
61         + (disL-1) * (2 * 2 * NUM_ACTIONS)
62         + (tempForisCloseToW-1) * (2 * NUM_ACTIONS)
63         + (tempForisFaster-1) * NUM_ACTIONS
64         + actionIndex;
65 }
66
67 public double[] transformToX(){
68     double[] X = new double[5];
69     X[0] = this.myEL;
70     X[1] = this.oEL;
71     X[2] = this.disL;
72     X[3] = this.isCloseToW;
73     X[4] = this.isFaster;
74     return X;
75 }
76
77 public double[] transformToX(Action a){
78     double[] X = new double[6];
79     X[0] = this.myEL;
80     X[1] = this.oEL;
81     X[2] = this.disL;

```

```

82     X[3] = this.isCloseToW;
83     X[4] = this.isFaster;
84     X[5] = a.ordinal();
85     return X;
86 }
87
88 private int computeIsFaster(double oV, double myV) {
89     if (oV < myV){
90         return 1; // faster than the opponent
91     }else{
92         return -1;
93     }
94 }
95
96 private int computeEnergyLevel(double e) {
97     double ratio = e / 100.0;
98     int output = (int) Math.ceil(1 + ratio * (numOfLevelForEnergy-1));
99     return output > 5? 5: output; //energy can actually go beyond 100
100    //return (int) Math.ceil(1 + ratio * (numOfLevelForEnergy-1));
101    //return numOfLevelForEnergy - (int) Math.round(myE / numOfLevelForEnergy);
102 }
103
104 private int computeTooCloseToWall(double myX, double myY) {
105     double YtoWall = Math.min(myY, 600-myY);
106     double XtoWall = Math.min(myX, 800-myX);
107     double toWall = Math.min(YtoWall, XtoWall);
108     if (toWall < disForTooCloseToWall){
109         return 1; // to close to wall!
110     }else{
111         return -1;
112     }
113 }
114
115 private int computeDistanceLevel(double oD) {
116     double ratio = oD / 1000.0;
117     return (int) Math.ceil(1 + ratio * (numOfLevelForDistance-1));
118    //return numOfLevelForDistance- (int) Math.round(oD/numOfLevelForDistance);
119 }
120
121 }
122

```

LUT.java

```

1  package LUT;
2
3  import Interface.LUTInterface;
4  import Robot.Action;
5  import Robot.State;
6
7  import java.io.File;
8  import java.io.IOException;
9
10 public class LUT implements LUTInterface {
11     private double[] qValues;
12     private int numOfStates;
13     private int numOfActions;
14     /**
15     * Constructor. (You will need to define one in your implementation)
16     * @param argNumInputs The number of inputs in your input vector
17     * @param argVariableFloor An array specifying the lowest value of each variable in the input vector.
18     * @param argVariableCeiling An array specifying the highest value of each of the variables in the input vector.
19     * The order must match the order as referred to in argVariableFloor. *
20     */
21     /// public LUT( int argNumInputs, int [] argVariableFloor, int [] argVariableCeiling ){
22     public LUT(){
23         numOfStates = State.possibleStates;
24         numOfActions = Action.values().length;
25         int totalStates = 0;
26         for(int i = 0; i < argNumInputs-1; i++){
27             totalStates += (argVariableCeiling[i] - argVariableFloor[i]);
28         }
29         this.numOfStates = totalStates;
30         this.numOfActions = argVariableCeiling[argNumInputs] - argVariableFloor[argNumInputs];
31         initialiseLUT();
32     }
33
34     /**
35     * Initialise the look up table to all zeros.
36     */
37     @Override
38     public void initialiseLUT() {
39         this.qValues = new double[numOfStates * numOfActions];
40     }
41
42     /**
43     * A helper method that translates a vector being used to index the
44     * look up table into an ordinal that can then be used to access
45     * the associated look up table element.
46     * @param X The state action vector used to index the LUT.LUT
47     * @return The index where this vector maps to
48     */
49     @Override
50     public int indexFor(double[] X) {
51         // X = state + action
52         // form the stateVec from copying first n-1 element from X
53         // so that it can be used as a parameter to form a State object
54         // so that we can use getIndex function in State.class to index
55         double[] stateVec = new double[X.length-1];
56         for (int i = 0; i < stateVec.length; i++) {
57             stateVec[i] = X[i];
58         }
59         State state = new State(stateVec[0], stateVec[1], stateVec[2], stateVec[3], stateVec[4], stateVec[5], stateVec[6]);
60         int index = state.getIndex((int) X[X.length]);
61         // we can form the action from X, but it is useless
62         // Action action = Action.values()[X[X.length]];
63         return index;
64     }
65
66     @Override
67     public int indexFor(double[] X) {
68         // X = state(size=5) + action (size=1) -> X length = 6
69         State state = new State((int)X[0], (int)X[1], (int)X[2], (int)X[3], (int)X[4]);
70         int actionIndex = (int) X[5];
71         int index = state.getIndex(actionIndex);
72         return index;
73     }
74
75     @Override
76     public double outputFor(double[] X) {
77         double output = 0.0;
78         try {
79             output = qValues[indexFor(X)];
80         } catch (Exception e) {
81             //return output;
82         }
83     }
84 }

```

```
88     } catch (ArrayIndexOutOfBoundsException e) {
89         System.out.println("Error: " + e.getMessage());
90         for(double x: X){
91             System.out.println(x);
92         }
93     }
94     return output;
95     // return qValues[indexFor(X)];
96 }
97 public double[] getQValues(){
98     return qValues;
99 }
100
101 @Override
102 public double train(double[] X, double argValue) {
103     qValues[indexFor(X)] = argValue;
104     return 0;
105 }
106
107 @Override
108 public void save(File argFile) {
109
110 }
111
112 @Override
113 public void load(String argFileName) throws IOException {
114
115 }
116
117 }
118
```


Neuron.java

```
import java.util.Random;
public class Neuron {
    public double argA;
    public double argB;
    public double[] weights;

    public double[] lastWeightsChanges;
    public double output;

    public double weightedSum;

    // error signal
    public double delta;

    final double bias = 1.0;

    public Neuron(int argNumInputs, double argA, double argB){
        // initialize the weights for the neuron (including the bias)
        this.weights = new double[argNumInputs+1];
        this.lastWeightsChanges = new double[weights.length];
        this.argA = argA;
        this.argB = argB;
    }

    public void initializeWeight(){
        for(int i=0; i< weights.length; i++){
            Random random = new Random();
            weights[i] = -0.5 + random.nextDouble();
        }
    }

    public double[] getLastWeightsChanges(){
        return this.lastWeightsChanges;
    }

    public double[] getWeights(){
        return this.weights;
    }

    public void setWeights(double[] newWeights){
        double[] oldWeights = this.weights;
        double[] changes = new double[oldWeights.length];
        if(newWeights.length != this.weights.length){
            System.out.println("newWeights length does not match the weights for this neuron!");
        }
        for(int i = 0; i < oldWeights.length; i++){
            changes[i] = newWeights[i] - oldWeights[i];
        }
        this.weights = newWeights;
        this.lastWeightsChanges = changes;
    }

    public double getWS(){
        return this.weightedSum;
    }

    public void updateOutput(double[] inputs){
        if(inputs.length != this.weights.length-1){
            System.out.println("inputs length don't match the weights for this neuron!");
            System.out.println("inputs length " + inputs.length + " and weights length " + this.weights.length);
        }
        double sum = bias * weights[weights.length-1];
        for (int i = 0; i < inputs.length; i++) {
            sum += inputs[i] * weights[i];
        }
        this.output = customSigmoid(sum);
        this.weightedSum = sum;
    }

    public double getOutput(){
        return this.output;
    }
}
```

```
}

public double sigmoid(double x) {
    return 2 / (1+Math.exp(-x)) - 1;
}

public double customSigmoid(double x) {
    return (argB-argA) / (1+Math.exp(-x)) + argA;
}
public double getDelta(){
    return this.delta;
}

public void setDelta(double delta){
    this.delta = delta;
}

}
```

NeuralNet.java

```
import java.io.File;
import java.io.IOException;

public class NeuralNet implements NerualNetInterface{
    public double argA;
    public double argB;
    public Neuron[] hiddenNeurons;
    public Neuron outputNeuron;
    public double learningRate;
    public double momentumTerm;
    public int backwardPropagationVersion;

    /**
     * Constructor. (Cannot be declared in an interface, but your implementation will need one)
     *
     * @param argNumInputs    The number of inputs in your input vector
     * @param argNumHidden    The number of hidden neurons in your hidden layer. Only a single hidden layer is supported
     * @param argLearningRate The learning rate coefficient
     * @param argMomentumTerm The momentum coefficient
     * @param argA            Integer lower bound of sigmoid used by the output neuron only.
     * @param argB            Integer upper bound of sigmoid used by the output neuron only.
     */
    public NeuralNet(
        int argNumInputs,
        int argNumHidden,
        double argLearningRate,
        double argMomentumTerm,
        double argA,
        double argB,
        int backwardPropagationVersion){
        // initialize variables for the NN
        this.backwardPropagationVersion = backwardPropagationVersion;
        this.argA=argA;
        this.argB=argB;
        this.learningRate = argLearningRate;
        this.momentumTerm = argMomentumTerm;
        // initialize hidden cells
        this.hiddenNeurons = new Neuron[argNumHidden];
        for(int i = 0; i < hiddenNeurons.length; i++){
            hiddenNeurons[i] = new Neuron(argNumInputs, argA, argB);
        }
        // initialize output cell
        this.outputNeuron = new Neuron(hiddenNeurons.length, argA, argB);

        initializeWeights();
    };

    @Override
    public double sigmoid(double x) {
        return 2 / (1+Math.exp(-x)) - 1;
    }

    @Override
    public double customSigmoid(double x) {
        return (argB-argA) / (1+Math.exp(-x)) + argA;
    }

    public double deri(double x) {
        return (argB-argA) * Math.pow((1+Math.exp(-x)), -2) * Math.exp(-x);
    }

    @Override
    public void initializeWeights() {
        for(int i = 0; i < hiddenNeurons.length; i++){
            hiddenNeurons[i].initializeWeight();
        }
        outputNeuron.initializeWeight();
    }

    @Override
    public void zeroWeights() {
    }

    @Override
    public double outputFor(double[] X) {
        double[] hiddenLayerOutputs = new double[this.hiddenNeurons.length];
        for(int i = 0; i<hiddenLayerOutputs.length; i++){
            hiddenNeurons[i].updateOutput(X);
            hiddenLayerOutputs[i] = hiddenNeurons[i].getOutput();
        }
        outputNeuron.updateOutput(hiddenLayerOutputs);
        return outputNeuron.getOutput();
    }

    /**
     * Given X, update outputs for hidden neurons and output neuron
     * @param X input vector
     */
}
```

```

    */
    public void forward(double[] X){
        double[] hiddenLayerOutputs = new double[this.hiddenNeurons.length];
        for(int i = 0; i<hiddenNeurons.length; i++){
            hiddenNeurons[i].updateOutput(X);
            hiddenLayerOutputs[i] = hiddenNeurons[i].getOutput();
        }
        outputNeuron.updateOutput(hiddenLayerOutputs);
    }

    /**
     * backward propagation: update delta for output neuron and hidden neurons
     * and update weights for output neuron and hidden neurons
     * (also update the lastWeightsChanges)
     *
     * version 1 and version 2 use different orders
     */
    public void backwardPropagationVersion1(double[] X, double argValue){
        updateErrorSignalOutputN(argValue);
        updateErrorSignalHiddenNs();
        updateWeightsOutputN();
        updateWeightsHiddenNs(X);
    }

    /**
     * backward propagation: update delta for output neuron and hidden neurons
     * and update weights for output neuron and hidden neurons
     * (also update the lastWeightsChanges)
     *
     * version 1 and version 2 use different orders
     */
    public void backwardPropagationVersion2(double[] X, double argValue){
        updateErrorSignalOutputN(argValue);
        updateWeightsOutputN();
        updateErrorSignalHiddenNs();
        updateWeightsHiddenNs(X);
    }

    private void updateErrorSignalOutputN(double argValue) {
        // update and set up the delta for output cell
        double y_o = outputNeuron.getOutput();
        double ws_o = outputNeuron.getWS();
        double deri_o = deri(ws_o);
        double δ_o = (argValue-y_o) * (deri_o);
        outputNeuron.setDelta(δ_o);
    }

    private void updateErrorSignalHiddenNs() {
        // update and set up the delta for hidden cells
        for(int i = 0; i < hiddenNeurons.length; i++){
            double y_hi = hiddenNeurons[i].getOutput();
            double ws_hi = hiddenNeurons[i].getWS();
            double deri_hi = deri(ws_hi);
            double δ_hi = outputNeuron.weights[i] * outputNeuron.getDelta() * (deri_hi);
            hiddenNeurons[i].setDelta(δ_hi);
        }
    }

    private void updateWeightsOutputN() {
        double δ_o = outputNeuron.getDelta();
        // update weights for output cell
        //  $w[i] = w[i] + \eta * \delta_o * y_{hi} + a * \Delta w[i]$ 
        double[] oldW_o = outputNeuron.getWeights();
        double[] newW_o = new double[oldW_o.length];
        double[] Δw_o = outputNeuron.getLastWeightsChanges();
        // update everything but the weight for bias
        for(int i = 0; i < newW_o.length-1; i++){
            double y_hi = hiddenNeurons[i].getOutput();
            newW_o[i] = oldW_o[i] + this.learningRate * δ_o * y_hi + this.momentumTerm * Δw_o[i];
        }
        // update weight for bias
        int indexForBias = newW_o.length-1;
        newW_o[indexForBias] = oldW_o[indexForBias] + this.learningRate * δ_o * bias + this.momentumTerm * Δw_o[indexForBias];
        // set up the weights back
        outputNeuron.setWeights(newW_o);
    }

    private void updateWeightsHiddenNs(double[] X) {
        // for each, update weights for hidden cells
        for(int i = 0; i < hiddenNeurons.length; i++){
            double[] oldW_hi = hiddenNeurons[i].getWeights();
            double[] newW_hi = new double[oldW_hi.length];
            double[] Δw_hi = hiddenNeurons[i].getLastWeightsChanges();
            double δ_hi = hiddenNeurons[i].getDelta();
            // update everything but the weight for bias
            for(int j = 0; j < newW_hi.length-1; j++){
                newW_hi[j] = oldW_hi[j] + this.learningRate * δ_hi * X[j] + this.momentumTerm * Δw_hi[j];
            }
            // update weight for bias
            int indexForBias = newW_hi.length-1;
            newW_hi[indexForBias] = oldW_hi[indexForBias] + this.learningRate * δ_hi * bias + this.momentumTerm * Δw_hi[indexForBias];
            // set up the weights back
            hiddenNeurons[i].setWeights(newW_hi);
        }
    }

```

```

    }
}

@Override
public double train(double[] X, double argValue) {
    /*
     * For each pattern:
     *   using train data and weights to do forward calculation
     *   get error signals through backward propagation
     *   update weights for each cell
     *
     * After training all pattern, check if total error is acceptable,
     * if yes, stop
     * otherwise, repeat training
     */
    forward(X);
    switch(this.backwardPropagationVersion){
        case 1:
            backwardPropagationVersion1(X, argValue);
            break;
        case 2:
            backwardPropagationVersion2(X, argValue);
            break;
    }
    return (0.5 * Math.pow((outputFor(X)- argValue), 2));
}

@Override
public void save(File argFile) {
}

@Override
public void load(String argFileName) throws IOException {
}

/**
 * helper function to print the NN
 */
public void printNN(){
    // System.out.println(outputNeuron.getWeights().length); //5
    // System.out.println(hiddenNeurons.length); // 4
    System.out.println("-----print NN-----");
    System.out.println("output Neuron weights:");
    int i = 0;
    while(i < 5){
        System.out.println(outputNeuron.getWeights()[i]);
        i++;
    }

    i = 0;
    while(i < 4){
        System.out.println("hidden Neuron " + i + " weights:");
        int j = 0;
        while(j<3){
            System.out.println(hiddenNeurons[i].getWeights()[j]);
            j++;
        }
        i++;
    }
    System.out.println("-----end-----");
}
}
}

```

CommonInterface.java

```
import java.io.File;
import java.io.IOException;

/**
 * This interface is common to both the Neural Net and LUT interfaces.
 * The idea is that you should be able to easily switch the LUT
 * for the Neural Net since the interfaces are identical
 * @date 20 June 2012
 * @author sarbjit
 */
public interface CommonInterface {
    /**
     * @param X The input vector. An array of doubles.
     * @return The value returned by the LUT or NN for this input vector
     */
    public double outputFor(double [] X);

    /**
     * This method will tell the NN or the LUT the output
     * value that should be mapped to the given input vector. I.E.
     * the desired correct output value for an input
     * @param X The input vector
     * @param argValue The new value to learn
     * @return The error in the output for that input vector
     */
    public double train(double [] X, double argValue);

    /**
     * A method to write either a LUT or weights of a neural net to a File
     * @param argFile of type File
     */
    public void save(File argFile);

    /**
     * Loads the LUT or NN weights from file. The load must of course
     * have knowledge of how the the data was written out by the save method,
     * You should raise an error in the case that an attempt is being made
     * to load data into an LUT or nerual net whose structure does not match
     * the data in the file. (e.g., wrong number of hidden neurons)
     * @param argFileName
     * @throws IOException
     */
    public void load(String argFileName) throws IOException;
}
```

LUTInterface.java

```
1  package Interface;
2
3  public interface LUTInterface extends CommonInterface {
4
5
6      /**
7       * Initialise the look up table to all zeros.
8       */
9      public void initialiseLUT();
10
11
12
13     /**
14      * A helper method that translates a vector being used to index the
15      * look up table into an ordinal that can then be used to access
16      * the associated look up table element.
17      * @param X The state action vector used to index the LUT.LUT
18      * @return The index where this vector maps to
19      */
20     public int indexFor(double [] X);
21 }
22
```

NerualNetInterface.java

```
public interface NerualNetInterface extends CommonInterface{
    final double bias = 1.0; // The input for each neurons bias weight

    /**
     * Return a bipolar sigmoid of the input X
     * @param x The input
     * @return  $f(x) = 2 / (1+e(-x)) - 1$ 
     */
    public double sigmoid(double x);

    /**
     * This method implements a general sigmoid with asymptotes bounded by (a,b)
     * @param x The input
     * @return  $f(x) = b\_minus\_a / (1+e(-x)) - minus\_a$ 
     */
    public double customSigmoid(double x);

    /**
     * Initialize the weights to random values.
     * For say 2 inputs, the input vector is [0] & [1]. We add [2] for the bias.
     * Like wise for hidden units. For say 2 hidden units which are stored in an array.
     * [0] & [1] are the hidden & [2] the bias.
     * We also initialise the last weight change arrays. This is to implement the alpha term.
     */
    public void initializeWeights();

    /**
     * Initialize the weights to 0.
     */
    public void zeroWeights();
}
```