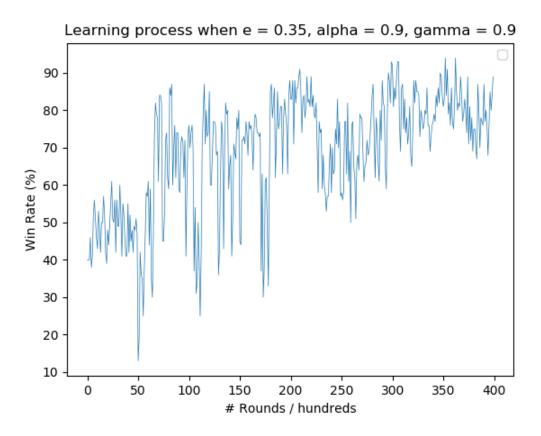
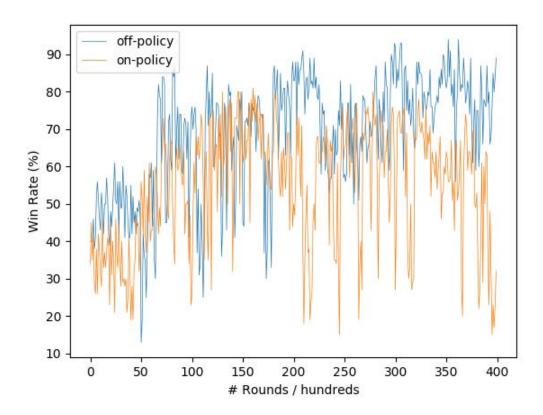
## Assignment2 – Reinforcement learning (Look Up Table) Runze Wang 99829855

- (2) Once you have your robot working, measure its learning performance as follows:
- a) Draw a graph of a parameter that reflects a measure of progress of learning and comment on the convergence of learning of your robot.



This graph shows the learning process of my robot converging over time when e = 0.35, alpha =0.9, gamma =0.9. Initially the robot remains in the win rate of 50%, after 5000 rounds it starts to reach a win rate of 80% highest but can still goes down to 20% lowest. After 25000 rounds, the learning of the robot converges to around 80% and win rate fluctuation remains within 10%.

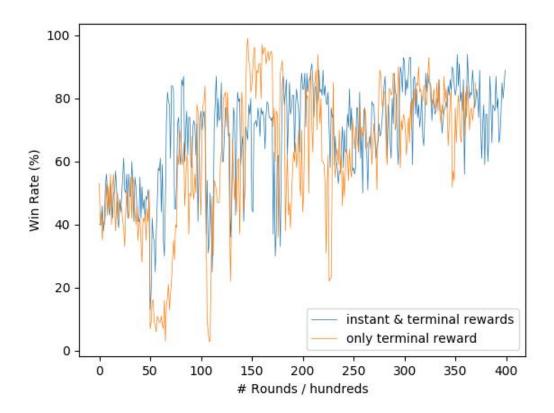
b) Using your robot, show a graph comparing the performance of your robot using on-policy learning vs off-policy learning.



This graph compares the learning efficiency of off-policy and on-policy, in which we can infer that on-policy learning has varying win rate and cannot converge even after 40000 rounds while off-policy learning coverges after 30000 rounds.

The reason is on-policy learning uses the same policy that is improved to select next actions, while off-policy learning uses an independent one. In this way, off-policy learning explores more than on-policy one so the learning outcome is more universal to more battle scenarios.

c) Implement a version of your robot that assumes only terminal rewards and show & compare its behaviour with one having intermediate rewards.

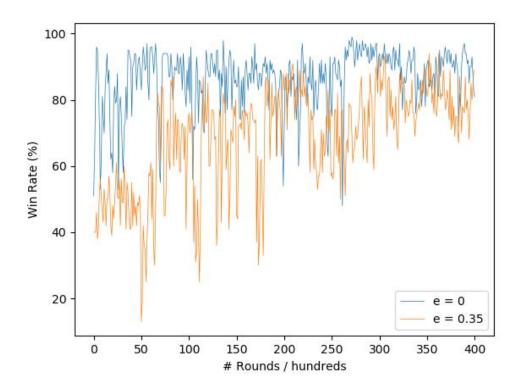


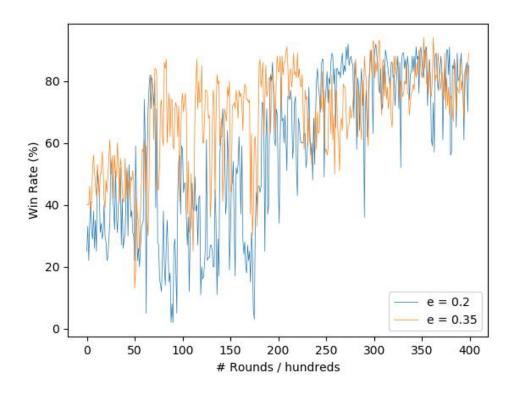
This graph shows the difference between two reward-giving strategies. The blue line indicates the scenario where intermediate rewards are given to the robot instantly if it hits or is hit by its opponent tank, while the yellow line indicates that the reward is given only when the robot wins or loses the battle.

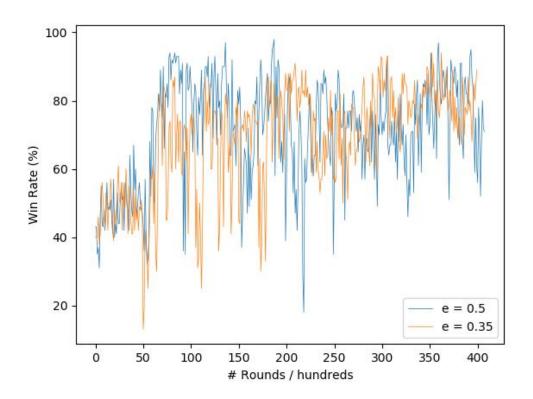
From the graph we can see that when only terminal rewards are given, the win rate fluctuates more dramatically which means the performance of the robot is not stable. One of the possible reason of this behavior is that without intermediate rewards, the robot cannot learn more detailed information within the battle: winning(losing) a battle does not necessarily mean **every** 

action taken in this battle is correct(wrong), thus the convergence rate is slower than that of the learning method with intermediate rewards as the former takes more rounds to learn the same amount of knowledge than the latter.

(3) This part is about exploration. While training via RL, the next move is selected randomly with probability e and greedily with probability 1—e a) Compare training performance using different values of e including no exploration at all. Provide graphs of the measured performance of your tank vs e.







The three graphs above shows the differences between probabilities e used to select random action.

When e = 0, there's no exploration at all, which means every action is greedy, this can be good for **this** battle but may not be useful to others if we change the opponent type and it's easy to come up with a local optimal solution.

When e = 0.2, the win rate remains at a lower level and still has a possibility of going down to 40% occasionally even after it converges; this happens when a certain but insufficient exploration rate is provided.

When e = 0.5, exploration rate goes higher than needed, which causes the learning process still cannot converge after 40000 rounds and the win rate varies dramatically over time.

Overall speaking, e = 0.35 is the rate that leads to the best learning performance.

## Appendix

## RLRobotLUT.java

```
import java.io.*;
import java.io.File;
import java.util.Arrays;
import java.util.Scanner;

public class RLRobotLUT implements LUTInterface {
    private int level1;
    private int level2;
    private int level3;
    private int level4;
    private int level5;
    private double[][][][] lut;

    public RLRobotLUT(int level1, int level2, int level3, int level4,
int level5) {
        this.level1 = level1;
        this.level2 = level2;
        this.level3 = level3;
        this.level4 = level4;
        this.level5 = level5;
        lut = new double[level1][level2][level3][level4][level5];
    }
}
```

```
public double outputFor(double[] x){
        if(!argFile.exists()){
           argFile.createNewFile();
       FileWriter myWriter = new
FileWriter(argFile.getAbsolutePath());
       myWriter.write(jsonModel);
       modelReader.close();
       this.lut = loadedLUT.getLUT();
```

```
this.level1 = loadedLUT.getLevel1();
    this.level2 = loadedLUT.getLevel2();
    this.level3 = loadedLUT.getLevel3();
    this.level4 = loadedLUT.getLevel4();
    this.level5 = loadedLUT.getLevel5();
    return;
}

public double[][][][][] getLut() {
    return lut;
}

public int getLevel1() {
    return level1;
}

public int getLevel2() {
    return level2;
}

public int getLevel3() {
    return level3;
}

public int getLevel4() {
    return level4;
}

public int getLevel5() {
    return level5;
}
```

## RLRobot.java

```
import robocode.*;
import java.awt.*;
import java.util.Random;
import static robocode.util.Utils.normalRelativeAngleDegrees;
enum Energy {empty, almostEmpty, medium, half, high}
enum Action {retreat, advance, leaveCorner, fire, spin}
enum Distance {veryClose, close, middle, far, veryFar}

public class RLRobotCantWork extends AdvancedRobot {
    private final Energy energies[] = new Energy[] {
        Energy.empty,
        Energy.almostEmpty,
        Energy.medium,
        Energy.half,
        Energy.high
    };

    private final Distance distances[] = new Distance[] {
```

```
Energy.values().length,
        Distance.values().length,
        Distance. values().length,
        Action. values().length
RLLUT.initialise();
```

```
private void robotMovement() {
           curAction = selectBestAction(
                turnGunRight(normalRelativeAngleDegrees(getHeading() -
                setFire(3);
xMid, yMid, getHeadingRadians());
               setTurnRight(bearing);
   private void radarMovement() {
        double Q = computeQ(curReward);
```

```
robotMovement();
        radarMovement();
            execute();
       execute();
   enemyBearing = e.getBearing();
   curMyEnergy = EnergyOf(getEnergy());
public void onBulletHit(BulletHitEvent e) {
public void onHitByBullet(HitByBulletEvent e) {
private void updateBattleStats(){
```

```
trainLUT();
   execute();
public void onWin(WinEvent e) {
   updateBattleStats();
public double computeQ(double r) {
```

```
Action candidateAction;
        curAction = selectBestAction(
double curQ = RLLUT.outputFor(curStateAction);
int energy = EnergyOf(e).ordinal();
int distanceleaveCorner = DistanceOf(e2).ordinal();
```