Q-Learning Agent Report

Question 5 – Write *a* Q-Learning agent in QLearningAgent.java by implementing the train() & extractPolicy()methods. Your agent should follow an ε-greedy policy during training (and only during training – during testing it should follow the extracted policy). Your agent will need to train for many episodes before the q-values converge. Although default values have been set/given in the code, you are strongly encouraged to play round with the hyperparameters of q-learning: the learning rate (α), number of episodes to train, as well as the epsilon in the ε-greedy policy followed during training. **(6 points)**

Answer 5 –

Summary for Q-Learning Agent Implementation

1) **Functions Modified:**
    a) **train()**
    b) **extractPolicy()**
    c) Several helper methods for **strategic move selection**
2) **Detailed Implementation Analysis:**
    a) **Training Method train() -** The training method implements a focused Q-learning algorithm with several features:
        (a) The agent uses an epsilon-greedy policy during training:
            1. With probability epsilon, the agent explores (tries random moves)
            2. With probability 1 - epsilon, the agent exploits (chooses best-known move)
            3. Epsilon decays over time to reduce random exploration as learning progresses
        (b) Episode-Based Learning
            1. Plays multiple episodes (games) to learn
            2. Resets environment at the start of each episode
            3. Continue until a terminal game state is reached
        (c) Move Selection Strategy - Two main selection approaches:
            1. Exploration:
                a. Randomly selects moves while prioritizing defensive moves when exploring
                b. Uses helper methods to find strategic moves
            2. Exploitation:
                a. Selects moves with highest Q-values
                b. Considers multiple strategic elements
        (d) Reward Shaping
            (i) Assigns different rewards based on game outcomes
            (ii) Defensive moves: Small bonus (+5)
        (e) Q-Value Update Uses the Q-learning update rule:

$$Q(s,a) = (1 - \alpha) * Q(s,a) + \alpha * (reward + \gamma * \max(Q(s',a')))$$

This calculates expected future rewards

b) Strategic Helper Methods - The implementation includes several sophisticated helper methods:

(i) findDefensiveMoves() - Identifies moves that:

a. Block opponent's potential wins

b. Prevent fork opportunities

c. Block two-in-a-row threats

(ii) pickBestMove() - Selects moves considering:

a. Q-values

b. Strategic board positions

c. Immediate win detection

d. Blocking critical moves

(iii) wouldBlockTwoInARow() and wouldBlockForkOpportunity()

a. Advanced defensive strategies to prevent opponent's winning moves

b. Analyzes board configurations to detect potential threats

c) Policy Extraction: extractPolicy()

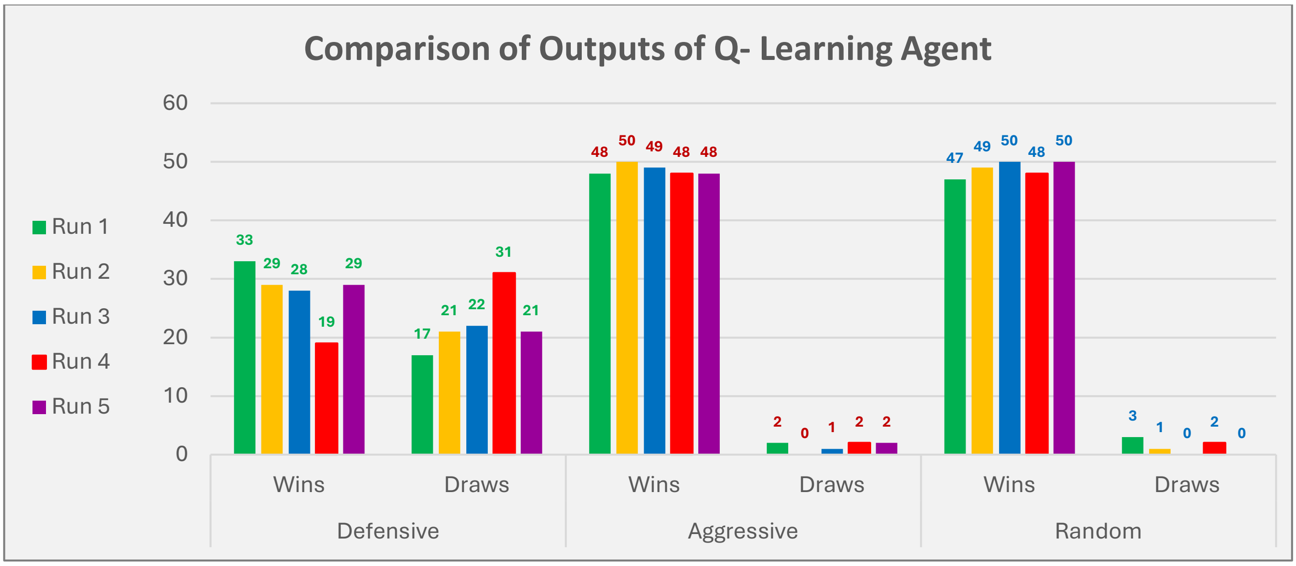
i) Converts learned Q-values into a deterministic policy

ii) For each game state, selects the move with the highest Q-value

Question 6 – Test your Value Iteration Agent against each of the provided agents 50 times and report on the results – how many games they won, lost & drew against each of the other rule-based agents. The rule-based agents are random, aggressive, defensive. (1 point)

Answer 6 –

Iteration/ Agent	Defensive			Aggressive			Random		
	Wins	Losses	Draws	Wins	Losses	Draws	Wins	Losses	Draws
Run 1	33	0	17	48	0	2	47	0	3
Run 2	29	0	21	50	0	0	49	0	1
Run 3	28	0	22	49	0	1	50	0	0
Run 4	19	0	31	48	0	2	48	0	2
Run 5	29	0	21	48	0	2	50	0	0



The program was run for a total of 250 iterations split into 5 runs of 50 iterations each. As we can see from the tabular column, we obtain the best result during iteration 1 of the Value-Iteration Agent.