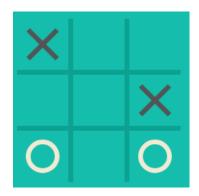
AI Player

Finally we turn our attention to creating the AIPlayer class. The goal of this class is to create a computer controlled "player" that will learn to play the game of Tic-Tac-Toe perfectly (i.e. choose moves to play in a game in such way that it will the game if possible, or tie the game.)

To make the program "learn" to play Tic-Tac-Toe, we are going to use a strategy called Reinforcement Learning, or "Q-Learning". The "Q" stands for Quality - that is the program will learn to assign a particular Quality to each possible move, and will choose the move with the best quality each time.

Q-Learning depends on the computer developing a memory of the **STATE** of Tic-Tac-Toe game, and which move (or **ACTION**) it choose when the game was in that state. For every "STATE-ACTION" pair, the algorithm will assign a **QUALITY** to that choice, based on the reward for making that decision.

The **state** of the game will be given as a String representing the game board at a given moment. For example the board:



Would be represented "x....xo.o"

The chosen action for a given state will be given by a number representing the square the computer chooses to play in. Each possible square will be numbered using the values 0 through 8.

So the **STATE-ACTION** pair " $x \dots x_0.0-7$ " in this case, could represent placing the token ("O") in the second column of the third row of the board.

This should be seen as a high quality move (because it wins the game!). A double value will be used to represent the quality of a given move. A move that wins the game may have a quality of 10.0.

Creating and Storing the AI Player's Memory

```
2⊖ import java.util.HashMap;
 3 import java.util.List;
 4 import java.util.Map;
 5 import java.util.Map.Entry;
 6 import java.util.Random;
8 public class AI {
9
10
       private final Random RNG = new Random();
11
       private final double LEARNING RATE = 0.75;
12
       private final double DISCOUNT_FACTOR = 0.5;
13
14⊖
       /* As it plays, the AI generates a memory of State-Action pairs
          The state represents the current look of the board
15
16
          The action is the move the computer chooses in that state
17
          Each state—action pair is mapped to a double representing the quality of that move
          Over time, the quality of moves is adjusted up or down as the computer learns
18
19
          E.g. "X....X0.0-7" -> 5.75
               -the board state is "X....XO.O" and the chosen move is 7.
20
21
               -the quality of this move is rated 5.75 */
22
       HashMap<String, Double> memory = new HashMap<>();
```

Within the code, we will use an object called a HashMap to create this memory.

A HashMap creates a table of values that matches one object (In this case a String representing a STATE-ACTION pair) with a second object (in this case a Double value representing the quality of that action choice).

The computer learns to play to Tic-Tac-Toe by finding and saving around 16,000 different state-action Strings, rating the quality of each, and storing them in this table of values. It takes somewhere around 30,000-50,000 games for the AI to develop an optimal strategy

Choosing a Move

How does the computer decide what move it should choose?

The AI Player needs to look into it's memory to see if it has ever encountered a game board matching the current game before.

If it has never seen a match before, the computer will randomly choose a possible move.

If it has seen a match before, the computer should choose the highest quality move out of all the known moves matching this board.

We also want a certain amount of chance that the computer will EXPLORE new moves rather choosing the best known move. This way the algorithm does not get stuck on choosing a known move when a move it has never tried before might actually be better.

In code, that looks like:

```
24⊜
       public int chooseMove(Game game, double exploreProbability) {
25
           //first make sure that the game is still going
26
           if (game.getStatus() != Game.GAME_CONTINUES) return -1;
27
28
           //get a string representing the current board state
29
           String state = game.getState();
30
           //Check the memory to see if we have ever encountered this state before
31
32
           List<Entry<String, Double>> previousActions = memory.entrySet().stream()
33
                    .filter(entry -> entry.getKey().startsWith(state))
34
                    .toList();
35
36
37
           //choose a random move if we have never seen this state before,
38
           // or randomly choose to explore
           if (previousActions.isEmpty() || RNG.nextDouble() < exploreProbability) {</pre>
39
40
               List<Integer> moves = game.availableMoves();
41
               return moves.get(RNG.nextInt(moves.size()));
42
           }
43
           //if we have seen this state before, look for the best known action
44
45
           double maxQuality = previousActions.stream()
46
                    .map(Map.Entry::getValue)
47
                    .max(Double::compare)
48
                    .orElse(0.0);
49
50
           //create a list of all previous actions tied for the highest quality
51
           List<String> tiedActions = previousActions.stream()
52
                    .filter(entry -> entry.getValue().equals(maxQuality))
53
                    .map(Map.Entry::getKey)
54
                    .toList();
55
           //Choose an action off this list
56
57
           String chosenAction = tiedActions.get(RNG.nextInt(tiedActions.size()));
58
59
           //Chosen action will be the last digit of the chosenAction, converted to int
60
           return Integer.parseInt(chosenAction.substring(chosenAction.length()-1));
61
       }
```

AI Learning

The algorithm is programmed to choose the highest "quality" move, but how will the algorithm determine "quality"? Simple, we award points for making choices that lead to the desired state. In Tic-Tac-Toe the most desirable state is winning the game! The second most desirable state is having a tie game. So we can define a reward method for a game of TicTacToe something like:

```
140⊖
        /**
141
         * Calculate the reward for a move given the status of the game after
142
         * making the move.
143
         * @param status
144
         * @return 10.0 for a win, 5.0 for a draw, 0.0 otherwise
145
         */
146⊖
        private double getReward(int status) {
147
            switch(status) {
148
                 case Game.X_WINS:
149
                 case Game. O_WINS:
150
                     return 10.0;
151
                 case Game. DRAW:
152
                     return 5.0;
153
                 default:
154
                     return 0.0;
            }
155
        }
156
```

In order to learn to choose better moves, each time the computer makes a move, will update the value of the quality of the move it just made according to the formula

```
newQuality = (learningRate) * (reward - discount * bestNextMove) + (1 - learningRate) * (currentQuality)
```

This formula creates (mathematically) a blend between what the currently remembered quality move of taking this move, and the new information learned by taking this move this time (based on any rewards). The formula also provides a certain value for "future" moves. For example, a move that doesn't win on this turn, but sets the AI up to win on it's next turn, will be credited some "future value". The future value is somewhat discounted however, because the AI may or may not receive this future value.

In code we have:

```
11
        private final double LEARNING_RATE = 0.75;
12
        private final double DISCOUNT_FACTOR = 0.5;
639
       /**
64
        * Make an update to the quality stored in the memory table based on the reward for a move
65
        * @param stateAction - starting state and action chosen

    value for making this action

66
        * @param reward
67
                               - state after taking this action
        * @param newState
68
       public void updateQualityValue(String stateAction, double reward, String newState) {
69⊖
70
           //Check the memory for the known quality of the given state/action string (defaulting as 0.0 if it is unknown)
71
           double currentQuality = memory.getOrDefault(stateAction, 0.0);
72
73
           //find out the quality of the best known "next action"
74
           double bestNextMove = memory.entrySet().stream()
75
                   .filter(entry -> entry.getKey().startsWith(newState))
76
                   .map(Map.Entry::getValue)
77
                   .max(Double::compare)
78
                   .orElse(0.0);
79
80
           double newQuality = currentQuality + LEARNING_RATE * (reward - DISCOUNT_FACTOR * bestNextMove - currentQuality);
81
82
           //if there is a change to make, make it
83
           if (currentQuality != newQuality) {
84
               memory.put(stateAction, newQuality);
           }
85
       }
```

(The mathematical formula has be rearranged slightly here, to make a more efficient calculation, but it is algebraically the same).

Training the AI

Finally, now that the AI can choose the best move it knows and can update the value of each move taken, we turn to the task of training the AI to play the game well. The AI will need to learn to play somewhere around 16,000 different moves, and rate the quality of each of these. In order to do that, it will need to play MANY MANY games. Fortunately, we can simply have the AI play against itself!

```
89⊜
        /**
90
         * Trains the AI by playing games against itself
         * @param games number of games to play for training
91
92
93⊜
        public void train(int games) {
            //handy to have some type of progress displayed on screen for this
94
95
            //because it can be lengthy
96
            System.out.printf("Starting training of %d games.\n", games);
            System.out.println("-----3----
97
98
99
            //train for the give number of games
            for (int i = 0; i < games; i++) {</pre>
100
101
                playOneGame();
102
                if ( i % 1000 == 0) System.out.print("*");
            }
103
104
105
            //give some idea of how the memory has changed because of this training
106
            System.out.println();
107
            System.out.println("Training completed.");
            System.out.println("Memory now contains " + memory.size() + " quality values");
108
        }
109
```

To play a single game against itself we have the following code:

```
111⊖
        /**
112
         * play one training game, updating rewards memory when the game finishes
113
114⊖
        private void playOneGame() {
115
            Game game = new Game();
116
117
            //get the initial state of the game (blank board...)
118
            String startingState = game.getState();
119
120
            //play the game until a draw or one player wins
121
            while (game.getStatus() == Game.GAME_CONTINUES) {
                //while training, we give the AI at least some chance to choose
122
                //random moves so that it explores moves it may not have tried
123
124
                int move = chooseMove(game, 0.50);
125
                game.play(move);
126
127
                //calculate a reward for this move
128
                double reward = getReward(game.getStatus());
129
                String newState = game.getState();
130
                //update the Quality table with results of this move
131
132
                updateQualityValue(startingState + ":" + move, reward, newState);
133
134
                //remember this as the starting state for the next move
135
                startingState = newState;
            }
136
137
        }
138
```