Team 4 MCTS Report

Our project is a maven project

MCTS

We made the following key improvements to the MCTS algorithm:

1. Changed the data type of the `wins` variable from integer to double to support a more complex scoring system for wins and losses.
2. For backpropagation, we chose to use the parent node (parentNode) instead of the default `backPropagate` function.
3. Added a new function `double reward()` in State.java to allow different states to have different reward values. This enables us to customize a more precise scoring system for complex games like Othello, rather than just having binary win/loss outcomes.

TicTacToe

MCTS

select

1. Starting Point

   The selection begins at the root node of the tree, which represents the current game state.

2. Tree Traversal

   The algorithm traverses down the tree by selecting child nodes according to a selection policy until it reaches a leaf node or a node with unexplored children.

3. Prioritizing Unexplored Paths

   The selection algorithm first checks if the current node has any children that have never been visited (playouts = 0). If such children exist, one of these is immediately selected to ensure all options are eventually explored.

4. Balancing Exploration and Exploitation

   When all children have been visited at least once, the selection policy (typically using the UCT formula) guides the algorithm to choose the most promising node, balancing between exploring new possibilities and exploiting known promising paths.

5. Terminal Condition

   The selection process stops when it reaches either:

   - A leaf node (representing a terminal game state)
   - A node that has children in the game tree but not all possible children have been added to the search tree

expand

1. Node Evaluation:

   First, the algorithm checks if the selected node is a leaf node (representing a terminal game state). If it is, no expansion is possible, and the node is returned as is.

2. Child Node Generation

   If the selected node has no children yet (i.e., it's an unexplored non-terminal node), the algorithm generates all possible child nodes representing all legal moves from the current game state.

3. Child Selection

   After generating all possible children, the algorithm randomly selects one of these newly created child nodes to proceed with the simulation phase. This random selection ensures diversity in the exploration process.

4. Tree Growth

   By adding these new nodes to the tree, the algorithm gradually expands the search space, allowing for more informed decision-making in future iterations.

simulate

1. Initialize the simulation state:

   Obtain the board state (simState) corresponding to the current node. Record the player number (currentPlayer) of the current action for determining the win-loss relationship.

2. Playout whole game

   ```
   while (!simState.isTerminal()) {
      Move<TicTacToe> move = simState.chooseMove(simState.player());
      simState = simState.next(move);
   }
   ```

   Repeat until the game ends (isTerminal()). The current player selects a legal random action using chooseMove() and performs this action to obtain a new state.

3. Evaluate the final score (Reward)

   ```
   Optional<Integer> winner = simState.winner();
   int reward = 2;
   if (winner.isEmpty()) {
       return 1;  // Draw
   } else {
       if (winner.get() == currentPlayer) {
           return 2 - reward;  // Current player wins (returns 0)
       } else {
           return reward;  // Current player loses (returns 2)
       }
   }
   ```

   - If no one wins (a draw): Return 1.

- If someone wins:
  - If the initial currentPlayer wins: Return 0 (lower reward)
  - Otherwise (currentPlayer loses): Return 2 (higher reward)

  This reward structure incentivizes moves that lead to opponent losses and penalizes moves that lead to the current player losing.

backpropagate

`backPropagate(Node<TicTacToe> node, int reward):`

This function propagates the simulation result (reward) upwards and updates the simulation counts and victory scores of all nodes along the path.

```java
while (node != null) {
   if (node instanceof TicTacToeNode ticNode) {
      int curPlayer = ticNode.state().player();
      ticNode.incrementPlayouts();    // Total number of games played +1
      ticNode.addWins(curPlayer == player ? reward : 2 - reward);  // Adjust reward based
on player perspective
      node = ticNode.getParent();     // Propagate upwards to the parent node
   } else {
      throw new RuntimeException("Node is not a TicTacToeNode");
   }
}
```

1. Why do we adjust the reward based on player perspective?

   MCTS involves top-down search and bottom-up propagation. In games where players take turns, the perspectives alternate at each level of the tree.

   By adjusting the reward based on the current node's player (`curPlayer == player ? reward : 2 - reward`), we ensure that wins are correctly attributed to the player who made the move at that level. This adjustment transforms a win for one player into a loss for the opponent, correctly updating the win rate estimation at each level.

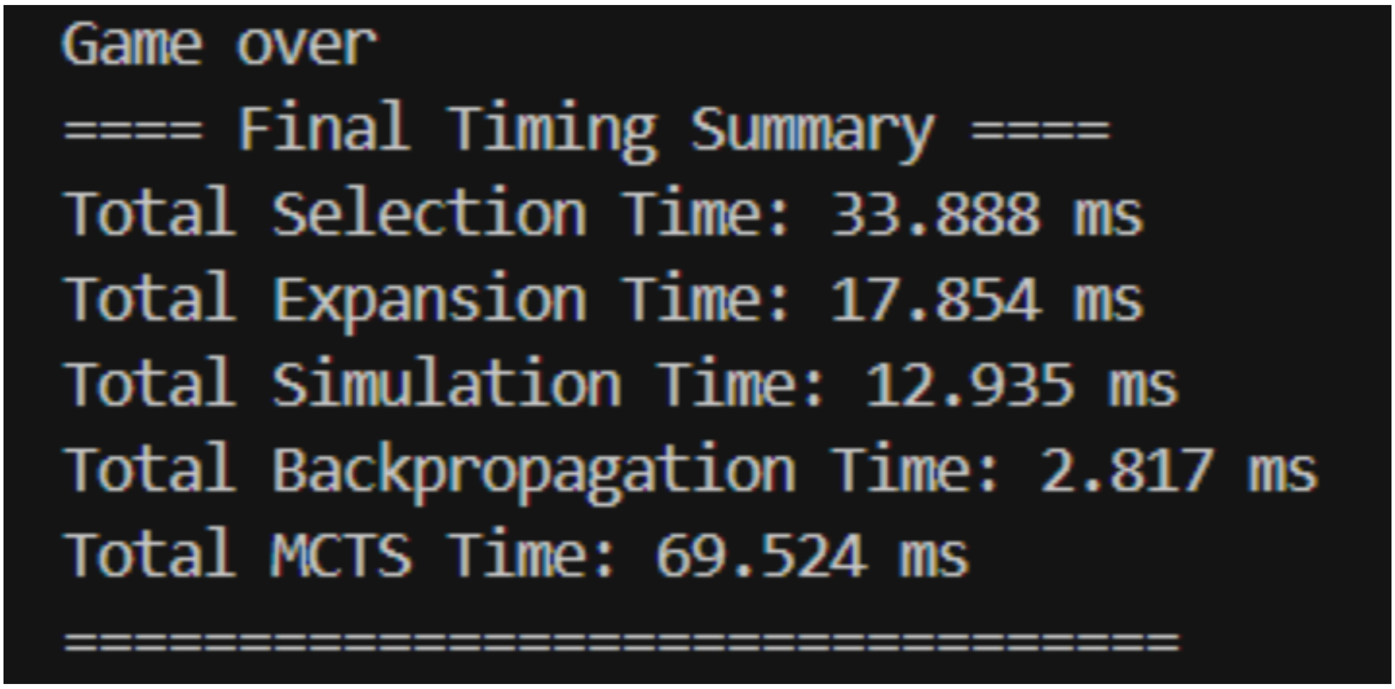
2. Why incrementPlayouts() and addWins(reward)?

   incrementPlayouts() records how many times this node has been visited (simulated).

   addWins(reward) accumulates the reward value, which is used to calculate the UCT score for evaluating the node's potential.

Running Time

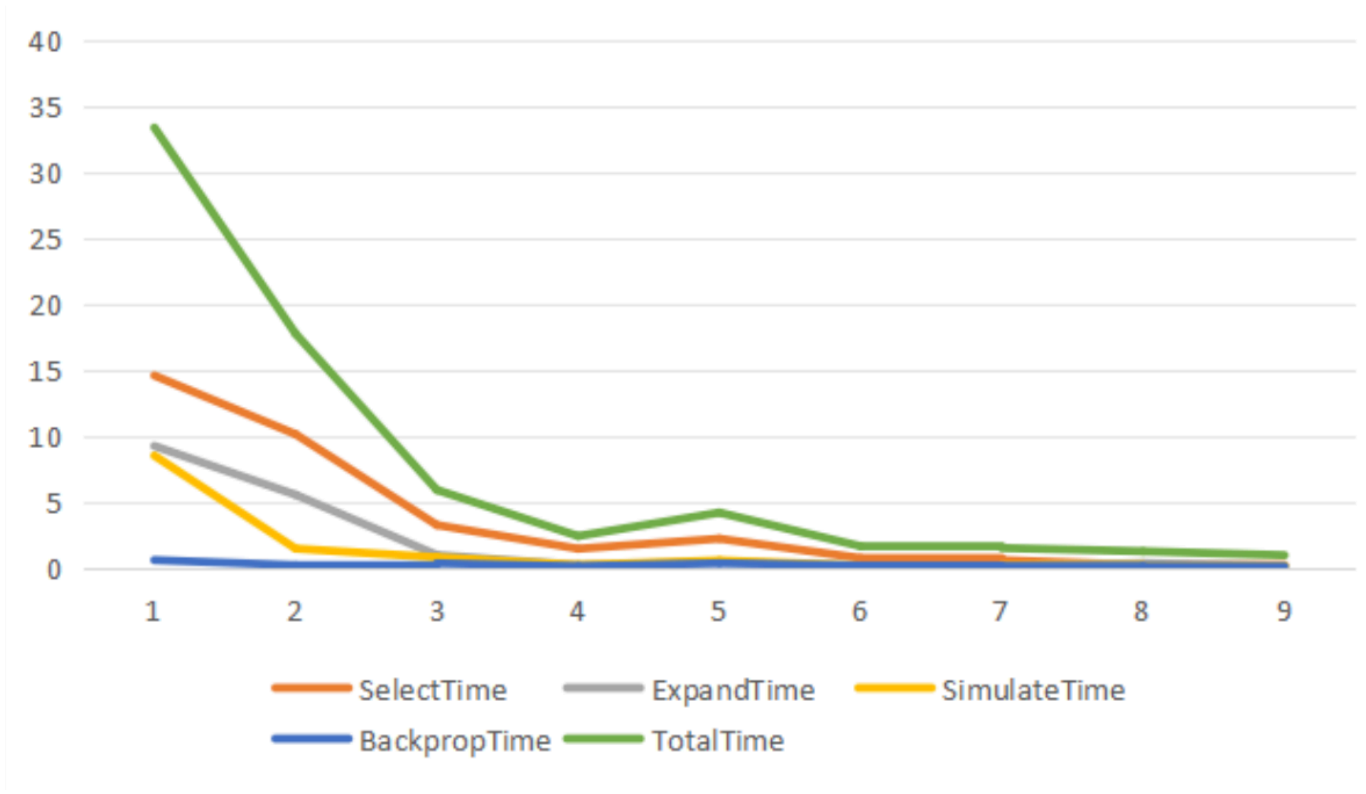
We use System.nanoTime() to obtain the running times of the four stages.



```
Game over
==== Final Timing Summary ====
Total Selection Time: 33.888 ms
Total Expansion Time: 17.854 ms
Total Simulation Time: 12.935 ms
Total Backpropagation Time: 2.817 ms
Total MCTS Time: 69.524 ms
================================
```

operations results

Step	SelectTime	ExpandTime	SimulateTime	BackpropTime	TotalTime
1	14.627	9.293	8.568	0.663	33.386
2	10.184	5.605	1.528	0.276	17.787
3	3.315	1.046	0.871	0.418	5.972
4	1.521	0.297	0.298	0.192	2.481
5	2.283	0.534	0.643	0.422	4.254
6	0.814	0.209	0.252	0.249	1.711
7	0.654	0.214	0.294	0.213	1.575
8	0.3	0.436	0.239	0.188	1.327
9	0.19	0.221	0.244	0.196	1.031



Here are some observations and related consumption

- The time for step 1 is significantly higher

  SelectTime (selection) and ExpandTime (expansion) are particularly time-consuming in the first step, approximately 14ms and 9ms respectively, which might be due to the first initialization or the deeper nodes in the tree.

  The SimulateTime is also relatively high (8.5ms), which is in line with expectations.

- Rapid downward trend

  Starting from step 2, the time consumption of each stage decreases rapidly and tends to be stable.

  The total time of the subsequent steps drops to the range of 1 to 5ms, and the system performance enters a steady state.

- Backpropagation always has a very small overhead:

  It remains almost at 0.2-0.4ms in all steps, with extremely low overhead and almost negligible.

Conclusion

In our practical tests, we found that if playouts are used as the criterion for selecting the next move, MCTS does not choose the center as the first move. Although this may seem counterintuitive at first, in the case of Tic-Tac-Toe, if both players play optimally, the game will always end in a draw—so the choice of the first move doesn't actually matter. However, if we use win rate as the selection criterion, MCTS tends to choose the center as the first move.

Othello

Othello rules for wikipedia: https://en.wikipedia.org/wiki/Reversi

We choose otheloo instead of reversi, because it is a much cooler name.

java file explanation

1. NextStep.java

   The `NextStep.java` file defines a crucial data structure for the Othello game implementation. This class represents a potential move that a player can make during their turn.

2. PositionState.java

   ```
   public enum PositionState {
      BLACK_WIN,
      WHITE_WIN,
      DRAW,
      IN_PEOGRESS,
   }
   ```

   The `PositionState` enum serves to classify the current state of an Othello game, providing a clear way to determine if the game has ended and, if so, who the winner is. This is crucial for both the game logic and the MCTS algorithm implementation.

3. other files

   the purposes of other files are same as those of tictactoe

Othello Analysis

In implementing the Monte Carlo Tree Search algorithm for Othello, we encountered several challenges and made improvements:

Initial Attempts and Challenges

Initially, we attempted to apply the same MCTS logic used for TicTacToe to the Othello game. However, we quickly discovered that this simple adaptation resulted in an AI with poor playing skills. Through deep analysis using DFS, we found that Othello has an enormous number of possible board states, far exceeding TicTacToe. This meant that purely random simulations had little practical value in such a large state space and couldn't effectively explore valuable game paths.

Game Characteristic Analysis

We observed that Othello games typically conclude within 27-31 moves, indicating that despite the large state space, the game depth is not particularly high. Based on this observation, we decided to run each simulation in the MCTS simulation phase until the game's conclusion, rather than simulating only a fixed number of moves. This approach allowed us to obtain more accurate endgame evaluations, leading to more effective decision-making.

Improvement Strategies

To enhance MCTS performance in Othello, we implemented the following improvements:

1. **Complete Game Simulation**: Each simulation runs until the game reaches its conclusion, providing a definitive win/loss result

2. **Heuristic Evaluation Function**: When selecting nodes for expansion, we incorporate position weights, prioritizing corners and edge positions
3. **Dynamic Exploration Parameter Adjustment**: We adjust the exploration constant in the UCT formula based on the progression of the game
4. **Position Value Matrix**: We implemented a position value matrix to evaluate board positions when a simulation reaches its conclusion. This matrix assigns different weights to different positions on the board:
    - Corners are assigned the highest values as they cannot be flipped once captured
    - Edge positions have higher values than center positions
    - Positions adjacent to corners are assigned negative values as they can give the opponent access to corners

    The value matrix is used during the backpropagation phase to provide a more nuanced evaluation than simple win/loss outcomes. This helps the algorithm make better decisions by considering the strategic value of different board positions, especially in the early and middle game phases where the final outcome is still uncertain.

These improvements enabled our MCTS algorithm to search more effectively within Othello's large state space, resulting in stronger game strategies.

Othello MCTS

select

same logic as TicTacToe

expand

The Othello expansion phase differs from the standard MCTS implementation by incorporating a heuristic scoring function to prioritize strategically valuable moves, sorting possible moves based on position values, and always selecting the highest-rated move for simulation, rather than using the purely random selection approach found in traditional MCTS.

simulate

The simulate method is used to perform a playout, starting from a given node, randomly or nearly randomly playing the game until the end, and returning the reward value of the simulation result. Here, we will focus on the differences from TicTacToe.

Obtain all the legal actions of the current player.

```
ArrayList<Move<Othello>> moves = new ArrayList<>(state.moves(state.player()));
```

If there is no action to take, suspend the simulation.

Prematurely ending without a legal action (representing one party skipping. Othello is different from TicTactToe. When one party has no place to play, the other party can play twice or more in a row. Therefore, we need to make additional judgments on this situation.)

Action selection Strategy (Heuristic Scoring Top-K)

```
int topK = Math.min(3, moves.size());
PriorityQueue<Move<Othello>> heap = new PriorityQueue<>(topK, ...);
```

Construct the maximum heap and select the top-K actions with high scores from all the actions. The score is given by getMoveScore(), which is based on the positional weights matrix (POSITION_WEIGHTS[x][y]) on the chessboard.

Select one from the Top-K actions for execution.

```
Move<Othello> selected = topMoves.get(state.random().nextInt(topMoves.size()));
state = state.next(selected);
```

Finally calculate the reward value

```
Optional<Integer> winner = state.winner();
if (winner.isEmpty()) return 1.0;
return winner.get() == currentPlayer ? state.reward() : 2.0 - state.reward();
```

In case of a draw, return the neutral reward 1.0
If the current player wins, return reward() (such as 1.0)
If the current player fails, return 2.0 - reward() (such as 0.0)

The role of the weight matrix POSITION_WEIGHTS

```
public static final int[][] POSITION_WEIGHTS = {
        { 100, -25,  10,   5,   5,  10, -25, 100 },
        { -25, -50,  -2,  -2,  -2,  -2, -50, -25 },
        {  10,  -2,   5,   1,   1,   5,  -2,  10 },
        {   5,  -2,   1,   0,   0,   1,  -2,   5 },
        {   5,  -2,   1,   0,   0,   1,  -2,   5 },
        {  10,  -2,   5,   1,   1,   5,  -2,  10 },
        { -25, -50,  -2,  -2,  -2,  -2, -50, -25 },
        { 100, -25,  10,   5,   5,  10, -25, 100 }
    };
```

During the simulation process, generate all possible moves from the current state.

For each valid placement point (x, y), obtain the heuristic score of that point based on POSITION_WEIGHTS[x][y].

Actions with high scores are considered more valuable and are given priority for simulation (Top-K screening).

Objective: To guide the simulation of MCTS to focus more on areas with high strategy value, such as:

Corner (100) : Almost impossible to recapture, of extremely high value.

The sides of the corners (-25 to -50) : They are very easy to be eaten in the opposite direction and have extremely low value.

Central area (0-10) : Neutral or controllable area.

backpropgate

The backPropagate(`Node<Othello>` node, double reward) method is used to perform the backpropagation stage of MCTS, which is similar to the backPropagate of TicTacToe. It propagates the reward value obtained through simulation upwards along the path from the simulation termination node to the root node, updating the number of visits and the victory value of each node.

Othello GUI

run `main()` in OthelloGUI.java for Othello GUI.

1. Chessboard rendering and piece display

Draw black pieces (●), white pieces (○) and empty Spaces in real time according to the game status.

The legal placement positions are indicated by semi-transparent yellow circles.

2. Human-machine chess
   The user clicks on the chessboard to place the pieces:

The GUI automatically identifies the click position and determines whether it is a legal operation.

If it is legal, the system will automatically execute the player's move and call the AI response.

After each move, the chessboard refreshes immediately and updates the player whose turn it is.

3. AI vs. AI
   After the user clicks the "AI vs AI" button, the system automatically controls the AI of both sides to take turns making moves until the end of the game.

There is a 300-millisecond delay between each move, simulating the rhythm of a real game.

Suitable for performance testing and automatic demonstration scenarios.

4. Undo function
   By clicking the "Undo" button, users can undo the previous operation.

The internal state stack is used to store historical states and supports multiple consecutive revocation.

5. Reset the game
   Users can immediately restart a new round of the game by clicking the "Reset" button.

The chessboard status, round information and historical records have all been cleared.

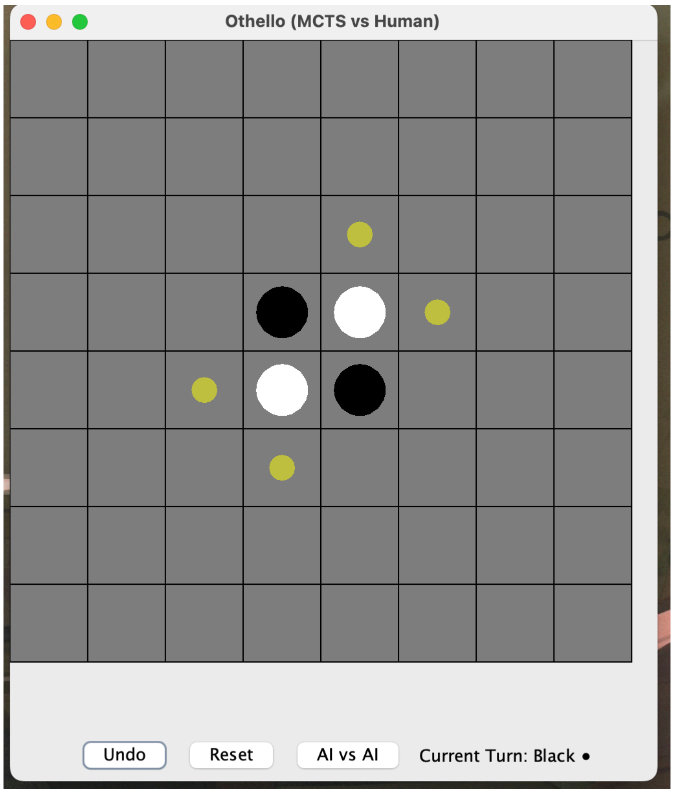
6. Game endgame detection and result display
   When the final game is detected, a dialog box will pop up automatically to prompt:

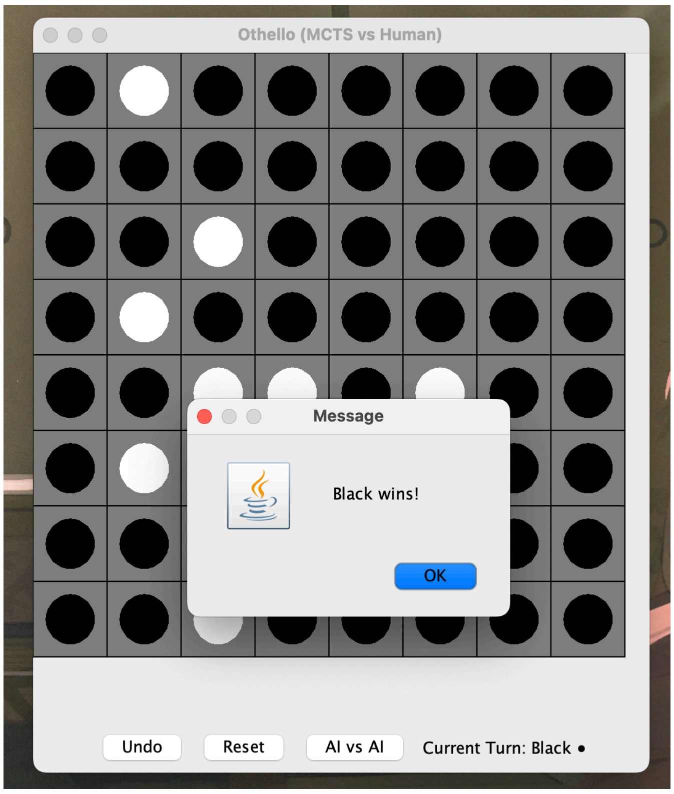
The black side wins/the white side wins/draws.

Visual result feedback is carried out using the JOptionPane component.

7. Status bar information prompt
   The current player's turn (black side/white side) is displayed in real time at the bottom of the interface.

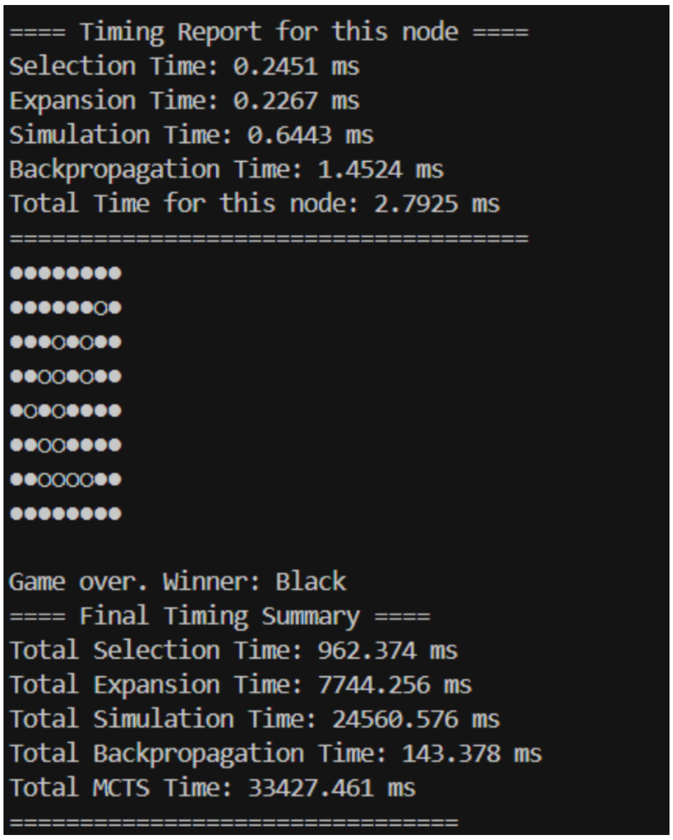
The status bar is updated dynamically according to the game progress without user intervention.





Othello Running Time

We use System.currentTimeMillis() to obtain the running times of the four stages.



```
==== Timing Report for this node ====
Selection Time: 0.2451 ms
Expansion Time: 0.2267 ms
Simulation Time: 0.6443 ms
Backpropagation Time: 1.4524 ms
Total Time for this node: 2.7925 ms
=====================================
●●●●●●●●
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Game over. Winner: Black
==== Final Timing Summary ====
Total Selection Time: 962.374 ms
Total Expansion Time: 7744.256 ms
Total Simulation Time: 24560.576 ms
Total Backpropagation Time: 143.378 ms
Total MCTS Time: 33427.461 ms
================================
```
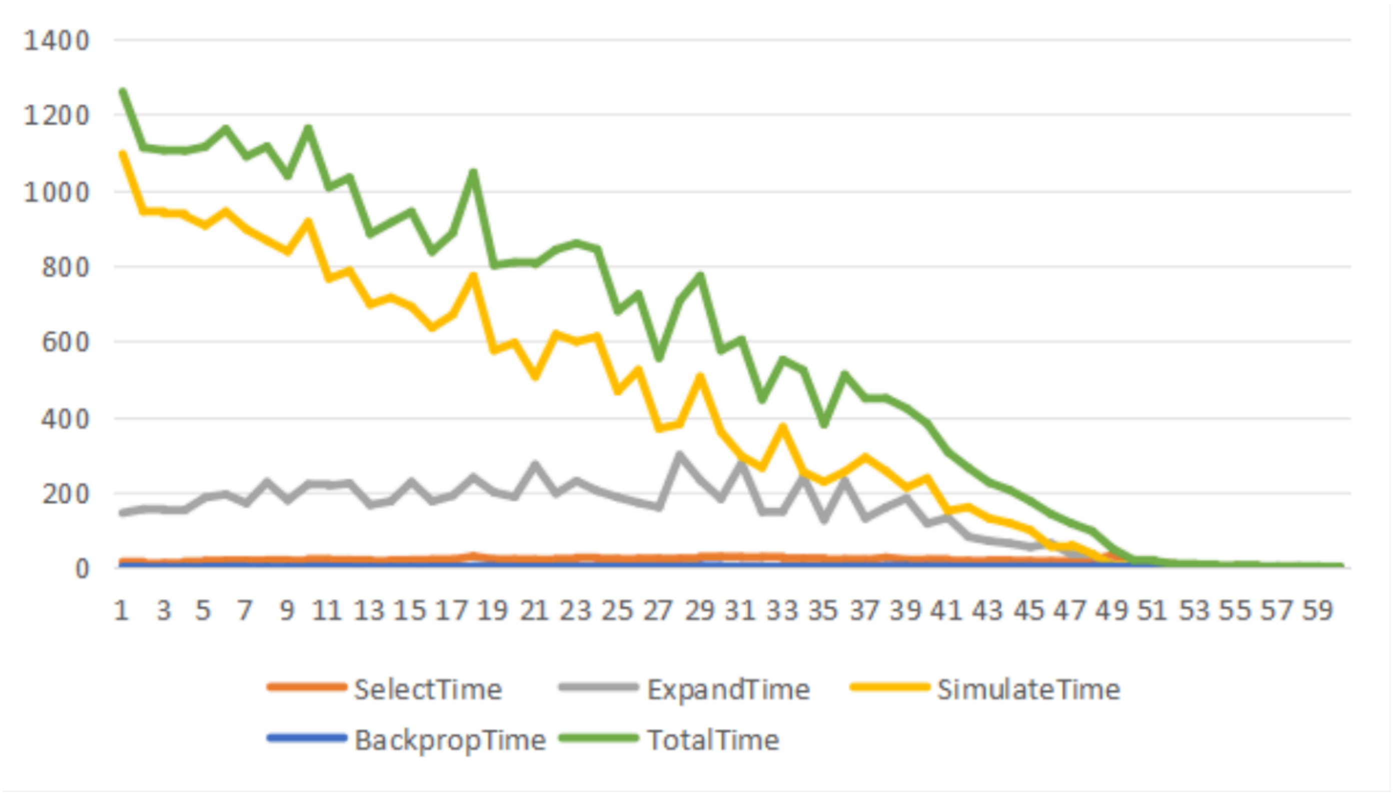

operations result

Step	SelectTime	ExpandTime	SimulateTime	BackpropTime	TotalTime
1	15.738	145.202	1094.965	2.89	1259.794
2	11.577	155.32	943.01	1.632	1112.094
3	12.523	152.516	937.521	1.67	1104.768
4	16.533	152.142	932.177	1.615	1102.962
5	19.086	186.074	905.929	2.616	1114.447
6	19.897	194.198	942.685	3.225	1160.935
7	19.454	170.849	895.724	2.075	1088.499
8	20.413	226.577	865.805	1.798	1114.86
9	19.09	178.816	837.087	1.914	1037.168
10	22.874	221.08	914.892	3.382	1162.548



Here are some observations and related consumption

- Simulation is the most time-consuming stage, averaging 417ms, accounting for more than 70%.
- The second longest Expansion takes an average of 130 milliseconds.
- Backpropagation is almost negligible.
- Some steps take extremely little time (close to zero), which might be due to boundary states or when the game is approaching the end.
- The overall fluctuation is relatively large, and the variance of TotalTime is relatively high (std ≈ 393ms), indicating that the complexity of the tree in some steps has increased sharply.

Conclusion

Despite our use of heuristic functions, the actual effect is still poor because Othello is a game with significant variability. Even if you have secured a good position, it may belong to your opponent in the next move or at the end of the game. Additionally, the POSITION_WEIGHTS are only designed based on our experience. Although we are learning RL in hopes of making our model smarter, due to time constraints, this can only be pursued as a subsequent personal project. Nevertheless, continuously discovering problems, thinking about them, and solving them has been a valuable experience.

During our testing, we encountered memory issues when the simulation count was set too high. This is a common challenge in MCTS implementations, especially for games with high branching factors like Othello. If we had more time, we would implement the following optimizations:

Selective Expansion

Instead of expanding all possible moves, we could implement a selective expansion strategy that only expands the most promising nodes. This approach would:

1. Calculate a heuristic score for each potential move
2. Sort moves based on their scores
3. Only expand the top N moves (e.g., top 5 or 10)

Reference

https://en.wikipedia.org/wiki/Monte_Carlo_tree_search

https://int8.io/monte-carlo-tree-search-beginners-guide/

https://en.wikipedia.org/wiki/Reversi

ChatGPT

Unit Tests

This part explain targets of each unit test

mcts.test.java.edu.info6205.tictactoe.TicTacToeNodeTest

- **winsAndPlayouts**: Test for incrementPlayouts and addWins methods, verifying that wins and playouts are initialized to 0 and can be properly incremented
- **state**: Test for the constructor of TicTacToeNode, ensuring it correctly stores the game state
- **white**: Test for the white() method, confirming it returns the expected boolean value
- **children**: Test for the children() method, checking that a new node starts with 0 children
- **expandAll**: Test for the expandAll() method, verifying it generates all 9 possible moves for an empty TicTacToe board

mcts.test.java.edu.info6205.tictactoe.PositionTest

- **Move tests**: Multiple tests (testMove_2, testMove_1, testMove0, testMove1) to verify that moves are only permitted in valid empty cells and that illegal moves throw exceptions
- **Game state tests**: Tests for winner detection (testWinner0, testWinner1, testWinner2), victory condition checking (testThreeInARow), and board state verification (testFull)
- **Grid projection tests**: Tests for methods that analyze rows, columns, and diagonals (testProjectRow, testProjectCol, testProjectDiag)
- **Parsing and rendering**: Tests for cell parsing (testParseCell) and grid rendering (testRender, testToString)
- **Game mechanics**: Tests for identifying legal moves (testMoves)

mcts.test.java.edu.info6205.tictactoe.TicTacToeTest

- **runGame**: to test whether program can reproduce the same result with same seed

mcts.test.java.edu.info6205.tictactoe.MCTSTest

- **testTerminal**: Verifies the correct identification of terminal states in TicTacToe games
- **testMCTS**: Tests the complete MCTS algorithm flow and verifies the correct reduction of empty spaces after each move
- **testDraw**: Confirms that when both players use MCTS optimally, TicTacToe games consistently end in draws
- **testBenchmark**: Tests the performance measurement functionality for TicTacToe MCTS

mcts.test.java.edu.info6205.othello.OthelloMCTSTest

- **testTerminal**: Verifies the correct identification of terminal states in Othello games
- **testOthelloMCTS**: Tests the complete MCTS algorithm flow for Othello from initial state to game termination
- **testBenchmark**: Tests the performance measurement functionality for Othello MCTS including time metrics for each phase

mcts.test.java.edu.info6205.othello.OthelloNodeTest

- **winsAndPlayouts**: Tests win counter and playout counter incrementation, and leaf node identification
- **state**: Verifies that nodes correctly store and access their game state
- **white**: Tests player identification functionality
- **children**: Confirms that new nodes start with empty children collections
- **expandAll**: Tests that node expansion generates the correct number of child nodes for a given position

mcts.test.java.edu.info6205.othello.OthelloPositionTest

- **Win state tests**: Two tests (testBlackWin1, testBlackWin2) verifying the correct identification of winning states
- **In-progress state tests**: Tests (testInProgress1, testInProgress2) to verify correct identification of ongoing games
- **Move generation**: Tests the move functionality and verifies piece counts after moves are executed

mcts.test.java.edu.info6205.othello.OthelloStateTest

- **Board representation**: Tests the showBoard method to verify correct string representation of game boards
- **Reward calculation**: Tests the reward() method for different game states
- **Legal move generation**: Tests the moves() method to verify correct identification of legal moves
- **State transition**: Tests the next() method for both legal and illegal moves

mcts.test.java.edu.info6205.othello.OthelloTest

- **runGame**: Tests whether the game logic can successfully run a complete game from start to finish