CSCI 3202 Course Project Report - Chenghao Xiong

Mancala AI: Minimax and Alpha-Beta Search with Utility Function Comparison

1. Algorithms Implemented

1.1 Random Player (Baseline)

The random player simply selects a non-empty pit from its side during its turn.

1.2 Minimax AI

- Explores all possible move sequences up to a predefined depth.
- Alternates between maximizing (AI) and minimizing (opponent) utility values.
- Uses recursive tree traversal and deepcopy() for state simulation.

1.3 Alpha-Beta AI

- Builds upon Minimax with alpha-beta pruning to eliminate irrelevant branches.
- Preserves optimality while significantly reducing the search space.
- Results in improved performance and shorter runtime, especially at higher depths.

2. Code Structure and Implementation Details

This project is implemented in Python 3, using a modular, object-oriented structure and common data science libraries.

Libraries Used:

- random: Generate legal random moves
- copy.deepcopy: Simulate board states in tree traversal
- multiprocessing: Run batch simulations in parallel
- datetime: Track runtime per game
- pandas: Store and export statistics
- matplotlib.pyplot: Plot win-rate comparisons
- tqdm: Display progress bars

Main Code Components:

1. Mancala Class

- Represents the board state and rules.
- Tracks player turns, captures, and winning conditions.

2. MinimaxPlayer Class

- Implements Minimax search to optimal depth.
- Tracks game tree nodes and transition states.

3. AlphaBetaPlayer Class

- Enhances Minimax with alpha-beta pruning.

4. Utility Functions

- utility: Default version uses Mancala score difference.
- utility_v2: Enhanced version with weighted pit stone control.

5. Game Simulations

- do_one_minimax_game() / do_one_alphabeta_game(): simulate one full game.
- run_xxx_games_parallel(): performs bulk evaluation.

6. Main Runner Script

- Uses asyncio.run(main()) to execute experiments.
- Exports results to .csv and generates win-rate plots.

3. Experiment Design

Each AI played 100 games against a random player.

Tested depths: 1 to 5

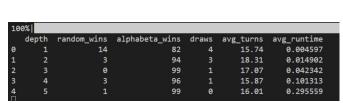
Metrics collected:

- Win counts per player
- Draws
- Average number of turns per game
- Average runtime per game (in seconds)

Both utility and utility_v2 were tested separately.

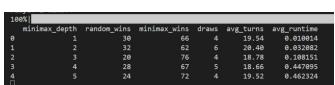
4. Results and Analysis

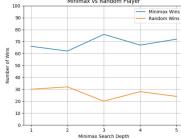
4.1 Alpha-Beta vs Random (utility_v2)



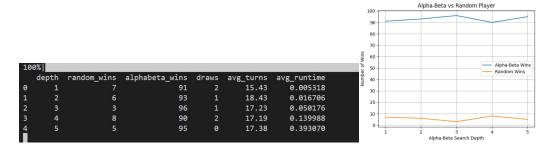


4.2 Minimax vs Random (utility_v2)

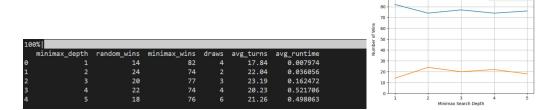




4.3 Alpha-Beta vs Random (utility)



4.4 Minimax vs Random (utility)



5. Utility Function Comparison

Minimax: utility vs utility_v2

Depth | Wins (original) | Wins (v2)

 1
 |82
 |66

 3
 |77
 |76

 5
 |76
 |72

Alpha-Beta: utility vs utility_v2

Depth | Wins (original) | Wins (v2)

1 | 91 | 82 3 | 96 | 99 5 | 95 | 99

6. Conclusion

This project demonstrates the successful implementation and evaluation of AI players for Mancala using Minimax and Alpha-Beta search. Alpha-Beta clearly offers improved performance over Minimax by reducing unnecessary evaluations, especially when paired with an enhanced utility function.

The extended utility function (utility_v2) enables more nuanced play, taking into account both immediate score and future potential. Its effectiveness becomes more visible at higher depths, where long-term planning is more relevant.