

Gekitai: Adversarial Search

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Problem Formalization

State Representation

- ▶ The game state represents a specific state of the game.
- ▶ It holds information about the board, the current player and the number of markers each player has left to play.
 - ▶ Board's size and the number of markers can be customized too.
- ▶ The initial state is represented by an empty board (a matrix full of 0's) and each player marker is represented by a number - either 1 or 2.

Objective Test

- ▶ In Gekitai, there are 2 possible ways to win the game:
 1. A player lines up 3 pieces in a row at the end of their turn (after pushing).
 2. A player places all of their markers in the board (after pushing).

Operators

`move(game, position)`

► Preconditions:

1. `game.board[position] == 0`

► Effects:

1. `game.board[position] = game.current_player`
2. The neighbour markers might:
 - 2.1 Be pushed away by 1 space from the new marker if the destination is empty
 - 2.2 Otherwise they stay in the same place
 - 2.3 Fall out of the board and be returned to their respective player
3. `swap(game.previous_player, game.current_player)`

Game Implementation

Libraries Used

The project uses python¹ inside a conda env. Both built-in and external libraries were used.

- ▶ Numpy

- ▶ Fast array manipulation proved to be crucial for the intensive computations made on the board's game (in particular with minimax).

- ▶ SciPy

- ▶ The main propose of this library was the use of `convolve2d` - a powerful routine used in the implemented evaluation functions.

- ▶ PyGame

- ▶ Used in for the graphical interface and for hadndle input events from the user.

¹The setup guide can be found in the README file.

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Algorithms Implemented

For this game we found appropriate to implement the following algorithms:

- ▶ Minimax with alpha-beta cuts (together with several evaluation functions)
- ▶ Monte Carlo Search Tree

`minimax(game, ev, depth, is_max, alpha, beta)`

- ▶ The minimax algorithm was the one that generated better moves overall.
- ▶ However, it takes a significantly long time when the depth value increases, due to its exponential time complexity² - $O(b^{\text{depth}})$
 - ▶ The value b represents the branching factor, which on average for a board of 6 by 6 and 8 markers for each player is 30!
- ▶ The pruning of the tree, with alpha-beta cuts, helps reducing the time it takes to generate the move, yet far from optimal since it is very difficult to order the nodes of the tree in a consistent way, e.g. many moves have the same evaluation values.

²Time taken to generate a move

Evaluation functions

- ▶ Evaluation functions are the key for the success of the minimax.
- ▶ Since this a zero-sum based game, positive values shows that player 1 is in front whereas negative values show the opposite.
- ▶ In the project we developed 3 different functions. Since we have 2 different ways of winning, 2 of those functions focus on 1 of the criterion over the other.
 - ▶ `markers_evaluator(game)`
 - ▶ Benefits the player with more markers placed in the board.
 - ▶ Uses $f(m,p) = -m / (m-p)$ where m is the initial number of markers and p is the number of markers already placed³.
 - ▶ `combination_evaluator(game)`
 - ▶ Benefit the player that is close to win by having 2 markers together.
 - ▶ It uses `convolve2d` provided by the SciPy library.
 - ▶ `mix_evaluator(game)`
 - ▶ Combines, as the name suggests, both functions described above.

³View the graph

`mcts(game, iterations, ci)`

- ▶ The Monte Carlo Tree Search algorithm, generates worst moves when compared against minimax, since it does not perform a full search.
- ▶ Increasing the number of iterations, the allows MCTS to produce better moves at the expense of taking more time⁴. However, the time increase does not have the same impact as changing the depth in minimax.
- ▶ One big advantage of MCTS is the fact that an evaluation function is not required.
- ▶ In our implementation, we select our nodes based on the UCB1 formula, hence the `ci` parameter. It is also important to point out how we deal with backpropagation after a simulation:
 - ▶ If win Then reward = 1
 - ▶ If lose Then reward = -1

⁴Time taken to generate a move

Extras

Features

Below are some of the features implemented:

- ▶ Customizable board sizes and number of markers at the beginning of each game.
- ▶ Various game mode, i.e. Human vs. Human, Human vs. PC and PC vs. PC.
- ▶ Algorithm fine tuning.
- ▶ Possibility of requesting an hint based in minimax or MCTS.

References

- ▶ Gekitai Rules
- ▶ IA Course's Moodle
- ▶ Artificial Intelligence - A Modern Approach (3rd Edition) by Stuart Russel & Peter Norvig
- ▶ Minimax
- ▶ Minimax by Sebastian Lague
- ▶ MCTS
- ▶ MCTS by Jonh Levine