Minimax Mancala

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Parallel Functional Programming

Fall 2022

Dec 21, 2022

I. The Game

Mancala is a two-player game with the goal to capture as many marbles as possible. A wooden board contains two rows of six holes each and two pockets on either side called mandalas that are used to store the marbles for each player as shown in Figure 1. The game starts with 6 marbles in each of the six holes. Players take turns choosing a hole on their side and distributing the marbles to the holes in a counter-clockwise direction, making sure to drop a marble in their designated mancala as they pass it. If the last marble lands on the opposing player's side, their turn ends. If it lands in an empty pocket on their own side and there is at least one marble in the hole directly across from it, the player gets to capture both holes' marbles. If the last marble lands in their store, they get to choose another hole. The game ends when either player has an empty row. Any marbles that are not captured at this time, go to the player whose side they were left on.



Figure 1. Diagram of Mancala game board

II. Minimax

Minimax is a search algorithm usually used in game-solving to find the best next move. The algorithm works by using a minimizer and a maximizer where the player tries to minimize and maximize their score respectively [1]. This score is calculated by evaluating the current game state and determining which new game state will minimize/maximize the score based on possible moves.

A tree with nodes of next possible games states and evaluates those nodes to see which move has the highest evaluation score (Figure 2). Because there are so many possible moves, a depth limit is passed in to indicate how far down the tree we want to search [1].



Figure 2. Steps in example minimax tree

III. Alphabeta Pruning

The alphabeta technique is used to optimize the Minimax algorithm. Using this technique, minimax is able to search the nodes of the tree faster. The algorithm will know not to search certain branches of the tree because it will not hold the minimal or maximum value [2]. It works by passing in alpha and beta values to the Minimax algorithm. Alpha is the maximized value and beta is the minimized value. The maximizer updates the alpha value to the maximum value found so far while the minimizer updates the beta value to the minimum value found [3].

IV. Implementation and Parallelism

Below is a snippet of the sequential minimax implementation. The function takes in the current game state, a boolean indicating whether or not we want to minimize or maximize the score, a starting depth, and the depth limit of the tree. It then returns a tuple of the score which is a result of the game board evaluation and the best move to get that score (which is represented by a number on the board).

```
minimax :: (GameState a) => a -> Bool -> Int -> Int -> (Int, Maybe
Int)
minimax gs _ depth depthlimit | depth == depthlimit || gameOver gs =
(evaluate gs, Nothing)
minimax gs minimize depth depthlimit =
    let minOrMax = (if minimize then minimumBy else maximumBy) (comparing
fst)
possibilities = (possibleMoves gs)
scores = map fst $ map (\poss -> (minimax (makePossibility gs
poss) (not minimize) (depth+1) depthlimit)) possibilities
wrappedPossibilities = map Just possibilities
scorePossPairs = zip scores wrappedPossibilities in
minOrMax scorePossPairs
```

The parallelized minimax algorithm is similar to the sequential, except that it implements parList from the Control.Parallel.Strategies library to evaluate each list element in parallel based on a given strategy. A strategy takes a data structure as input and parallelizes it using rpar and rseq to then return the original value [4]. In this case, the strategy is rseq which evaluates an argument to its Weak Head Normal Form (WHNF) [4]. WHNF is defined as when the outermost part has been evaluated to the lambda abstraction [5].

```
minimaxPar :: (GameState a) => a -> Bool -> Int -> Int -> (Int, Maybe
Int)
minimaxPar gs _ depth depthlimit | depth == depthlimit || gameOver gs =
(evaluate gs, Nothing)
minimaxPar gs minimize depth depthlimit =
let minOrMax = (if minimize then minimumBy else maximumBy) (comparing
fst)
possibilities = (possibleMoves gs)
scores = (map fst $ map (\poss -> (minimaxPar (makePossibility gs
poss) (not minimize) (depth+1) depthlimit)) possibilities) `using` parList rseq
wrappedPossibilities = map Just possibilities
scorePossPairs = zip scores wrappedPossibilities in
minOrMax scorePossPairs
```

V. Results and Conclusion

In order to test the results, two boards were tested with a depth limit that was kept constant across all functions in order to accurately compare the data. It is expected that the results will vary when tested with "harder" or more complicated boards. Tests were conducted with the starting mancala board defined as

```
let board = Board $ V.fromList [6,6,6,6,6,6,6,6,6,6,6,6,6,0]
```

and a fixed depth limit of 8.

	Avg. Running Time (s)		
Minimax	4.249		
AlphaBeta Pruning	0.764		

Figure 3. Average running times of minimax and alphabeta pruning algorithms on starting board

The average running times of the sequential minimax and alphabeta pruning implementations are shown in Figure 3. The alpha beta pruning algorithm, even without parallelism, was 3.485 seconds faster than the standard minimax. This is equivalent to a 82.02% decrease in time.

Parallel Minimax						
Cores	1	2	4	6	8	10
Total Running Time (s)	4.456	2.438	1.344	1.916	2.173	2.073

Figure 4. Parallel Minimax running on increasing cores on starting board

Figure 4 displays the results of the parallel minimax algorithm using different amounts of cores. The largest difference in time is seen with 4 cores at 1.344 seconds which is 68.37% faster than the sequential minimax. There is an increase in the total time at 6, 8, and 10 cores which contradicts the idea that parallelism is used to increase performance. However, with the increase in new threads also comes an increase in the time needed to create all those threads. This starts to outweigh the benefits of parallelism especially since the algorithm was already running pretty quickly to begin with. This can also be the result of hardware limitations when it comes to how many threads the computer can make. With these results it can be inferred that alphabeta is the most optimized when it comes to the starting game board and an alphabeta parallel

could possibly be even faster.

Parallel Minimax Threadscope and Runtime Data



Figure 5. Performance data of parallel minimax on 1 core



Figure 6. Parallel minimax on 1 core



Figure 7. Performance data of parallel minimax on 2 cores



Figure 8. Parallel minimax on 2 cores



Figure 9. Performance data of parallel minimax on 4 cores



Figure 10. Parallel minimax on 4 cores



Figure 11. Performance data of parallel minimax on 6 cores



Figure 12. Parallel minimax on 6 cores



Figure 13. Performance data of parallel minimax on 8 cores



Figure 14. Parallel minimax on 8 cores

```
(base) chanceonyiorah@Chances-MBP src % time ./Minimax +RTS -N10 -ls -s
(1,Just 3)
12,826,186,136 bytes allocated in the heap
      100,957,624 bytes copied during GC
        1,056,192 bytes maximum residency (44 sample(s))
          132,896 bytes maximum slop
               13 MiB total memory in use (0 MB lost due to fragmentation)
                                       Tot time (elapsed) Avg pause Max pause
               2495 colls, 2495 par
                                         2.292s
                                                  0.421s
                                                             0.0002s
                                                                        0.0012s
   Gen 0
   Gen
                 44 colls,
                              43 par
                                         0.055s
                                                  0.011s
                                                             0.0003s
                                                                         0.0007s
   Parallel GC work balance: 62.82% (serial 0%, perfect 100%)
   TASKS: 22 (1 bound, 21 peak workers (21 total), using -N10)
   SPARKS: 1179436 (2923 converted, 0 overflowed, 0 dud, 1075211 GC'd, 101302 fizzled)
   INIT
           time
                   0.001s
                            (
                               0.010s elapsed)
                               1.627s elapsed)
   MUT
           time
                   4.806s
   GC
           time
                   2.347s
                               0.432s elapsed)
   EXIT
           time
                   0.000s
                              0.004s elapsed)
   Total
           time
                   7.154s
                              2.073s elapsed)
   Alloc rate
                 2,668,991,606 bytes per MUT second
   Productivity 67.2% of total user, 78.5% of total elapsed
 ./Minimax +RTS -N10 -ls -s 7.16s user 0.37s system 359% cpu 2.091 total
```

Figure 15. Performance data of parallel minimax on 10 cores



Figure 16. Parallel minimax on 10 cores

From these Threadscope graphs, we can see that the effects of parallelism on the load balancing between cores tapers off after 4 cores are used.

Board 2

let board = Board \$ V.fromList [1,2,7,4,0,1,32,1,0,2,1,1,2,18]

	Avg. Running Time (s)		
Minimax	3.707		
AlphaBeta Pruning	1.823		

Figure 17. Average running times of minimax and alphabeta pruning algorithms on

Board 2

Parallel Minimax						
Cores	1	2	4	6	8	10
Total Running Time (s)	3.840	1.822	1.217	1.660	1.620	1.797

Figure 18. Parallel Minimax running on increasing cores on Board 2

In Figure 17 we can see that the alphabeta function again ran faster than the minimax algorithm, but with a significantly less speedup of 50.82%. Figure 18 also displays the results of the parallel minimax algorithm on Board 2 with the increasing number of cores. Again we see the least amount of time taken with 4 cores at 1.217 seconds which is 67.17% faster than the sequential minimax. In this case, the speedup was more consistent in comparison to the results with the starting board. This can lead us to think that the alphabeta function's optimization is dependent on the board and the

efficiency of the original sequential minimax algorithm which already ran quickly to begin with.

VI. Code

Play.hs

module Main where		
import		
import qualified		
import		
getComputerMove :	:: String -> Int	
getComputerMove '		
getComputerMove '	'q" = 13quit	
getComputerMove '	'Q" = 13quit	
getComputerMove _		
valid player mo		

```
retPlayerMove :: String -> Int
getPlayerMove "A" = 12
getPlayerMove "B" = 11
getPlayerMove "C" = 10
getPlayerMove "D" = 9
getPlayerMove "E" = 8
getPlayerMove "F" = 7
getPlayerMove "q" = 13 --quit
getPlayerMove "Q" = 13 --quit
getPlayerMove _ = 14 --invalid inpuy
getComputerLetter :: Int -> String
getComputerLetter 0 = "L"
getComputerLetter 1 = "K"
getComputerLetter 2 = "J"
getComputerLetter 3 = "I"
getComputerLetter 4 = "H"
getComputerLetter <mark>5 = "G"</mark>
getComputerLetter _ = error "Invalid move"
getMove :: Player -> Board -> IO Int
getMove p (Board b) = do
printPlayer :: Player -> IO ()
```

```
printPlayer Player2 = putStrLn "You:
printMarbles :: Board -> [Int] -> IO String
printTopRow :: Board -> IO ()
printTopRow b = do
orintBottomRow :: Board -> IO ()
printBottomRow b = do
orintStores :: Board -> IO ()
printStores (<mark>Board</mark> b) =
6)
printBoard :: Board -> IO ()
printBoard b = do
orintGameState :: MancalaGameState -> IO ()
printGameState (MancalaGameState b p ) = do
```

```
applyMove :: MancalaGameState -> Int -> IO ()
applyMove gs move = return (distributeMarbles gs move) >>= playGame
numanMoveGS :: MancalaGameState -> IO Int
humanMoveGS (MancalaGameState board player ) = do
nakeMoveGS :: MancalaGameState -> IO Int
playGame :: MancalaGameState -> IO()
rowEmpty board Player2 = do
playGame (MancalaGameState board Computer Computer) = do
```

```
playGame (MancalaGameState board Player2 x) = do
  printGameState (MancalaGameState board Player2 x)
  putStr "Enter move: "
  hFlush stdout
  move <- humanMoveGS (MancalaGameState board Player2 x)
  applyMove (MancalaGameState board Player2 x) move
startGameState = MancalaGameState initialBoard Computer Computer
main = do
  startGS <- return startGameState
  playGame startGS</pre>
```

Mancala.hs

```
nodule Mancala where
lass GameState a where
  gameOver :: a -> Bool
  isMaximizing :: a -> Bool
data Player = Computer | Player2
  deriving (Eq, Show)
data Board = Board (V.Vector Int)
  deriving (Show)
initialBoard = Board $ V.fromList [6,6,6,6,6,6,6,6,6,6,6,6,6,0]
data MancalaGameState = MancalaGameState Board Player Player
  deriving Show
instance GameState MancalaGameState where
```

```
rowEmpty :: Board -> Player -> Bool
board V.! 3 + board V.! 4 + board V.! 5
nancalaTotal :: Board -> Player -> Int
mancalaTotal (Board board) player = board V.! (storePos player)
isGameOver :: Board -> Bool
isGameOver board
storePos :: Player -> Int
storePos p | p == Computer = 6
getScore :: Board -> Player -> Int
getScore board player = (if (rowEmpty board Computer || rowEmpty board Player2) then
100 else 1) * (mancalaTotal board player - mancalaTotal board otherPlayer)
getPossibleMoves :: Board -> Player -> [Int]
getPossibleMoves (<mark>Board</mark> board) player =
```

distributeMarbles :: MancalaGameState -> Int -> MancalaGameState

```
endGameMove newBoard
endGameMove :: Board -> Board
nextPos :: Player -> Int -> Int
nextPos player pos | (player == Computer && pos == 12) = 0
placeLastStone :: Board -> Player -> Int -> (Board, Player)
placeLastStone (Board board) player pos
```

Minimax.hs

module	
where	
import	qualified Data.Vector as V
import	
{ -	
Test	
main :	
main =	
let	
let	
p1	

```
-print (minimaxPar gs False 0 8)
minimax
         :: (GameState a) => a -> Bool -> Int -> Int -> (Int, Maybe Int)
minimax gs   depth depthlimit | depth == depthlimit || gameOver gs = (evaluate gs,
minimax gs minimize depth depthlimit =
minimize) (depth+1) depthlimit)) possibilities
ninimaxPar :: (GameState a) => a -> Bool -> Int -> Int -> (Int, Maybe Int)
minimaxPar gs minimize depth depthlimit =
minimize) (depth+1) depthlimit)) possibilities) `using` parList rseq
```

References

[1] https://www.baeldung.com/java-minimax-algorithm

[2] https://www.geeksforgeeks.org/minimax-algorithm-in-game-theory-set-4-alpha-beta-pruning/amp/

[3] https://www.cs.cornell.edu/courses/cs312/2002sp/lectures/rec21.htm

[4] https://www.oreilly.com/library/view/parallel-and-concurrent/9781449335939/ch03.html

[5]

https://medium.com/@aleksandrasays/brief-normal-forms-explanation-with-haskell-cd5dfa94a157#:~:text

=An%20expression%20is%20in%20weak,would%20be%20in%20normal%20form.

[6] <u>https://github.com/vagueanxiety/mancala</u> (Referenced for code)

[7] https://gitlab.haskell.org/Abhiroop/nofib/-/blob/master/parallel/minimax/Game.hs (Referenced for code)