Report
On
EE4483/IM4483
Artificial Intelligence and Data Mining
Continuous Assessment
BY FP growth

Xiong ChenYu
U1521516C
EEE

Oct. 20, 2017

Contents

1 Abstract **2**

2 Question 1 (How many frequent itemsets have the minimum support of 20%, 10%, 5%, and 3% respectively?) **3**

3 Question 2 (What are the respective percentages of frequent 3-itemsets, and 2-itemsets, with respect to all possible itemsets, which have a minimum support of 3%?) **5**

4 Question 3 (How many association rules have a minimum confidence of 50% and a minimum support of 5% and 10%, respectively? Briefly explain how the minimum support affects the strong rules generated.) **6**

5 Question 4 (List three association rules that have the highest support with 100% confidence?) **7**

6 Question 5 (Do you find any "interesting" rules? What are they? Briefly explain why.) **7**

7 REFERENCE **7**

8 APPENDIX A **7**

List of Tables

List of Figures

1 heuristics estimate 3

2 "Skip" every 2 level 5

1 Abstract

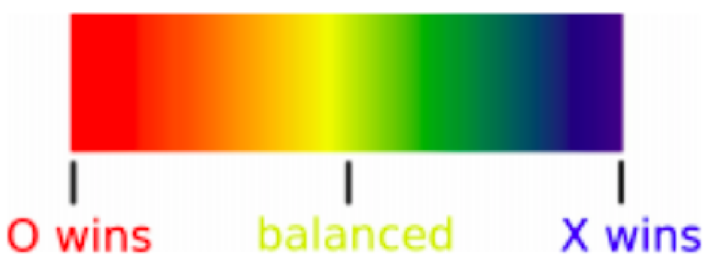
This report answer questions of the research and study on the continues assessment.

2 Question 1 (How many frequent itemsets have the minimum support of 20%, 10%, 5%, and 3% respectively?)

In John Hughes's model, their are 4 distinguishable steps to constructing and evaluating the game tree: defining the representation, generating the game tree, applying and evaluating heuristics, and applying lazy evaluation to the game tree generator. He defines these functions as prototypes to illustrate how easy it is to compose higher-order functions to form more powerful functions but does not explicitly define the function.

I skip the game definition and leave the code in appendix. I will explain the heuristic measure below.

Figure 1: heuristics estimate



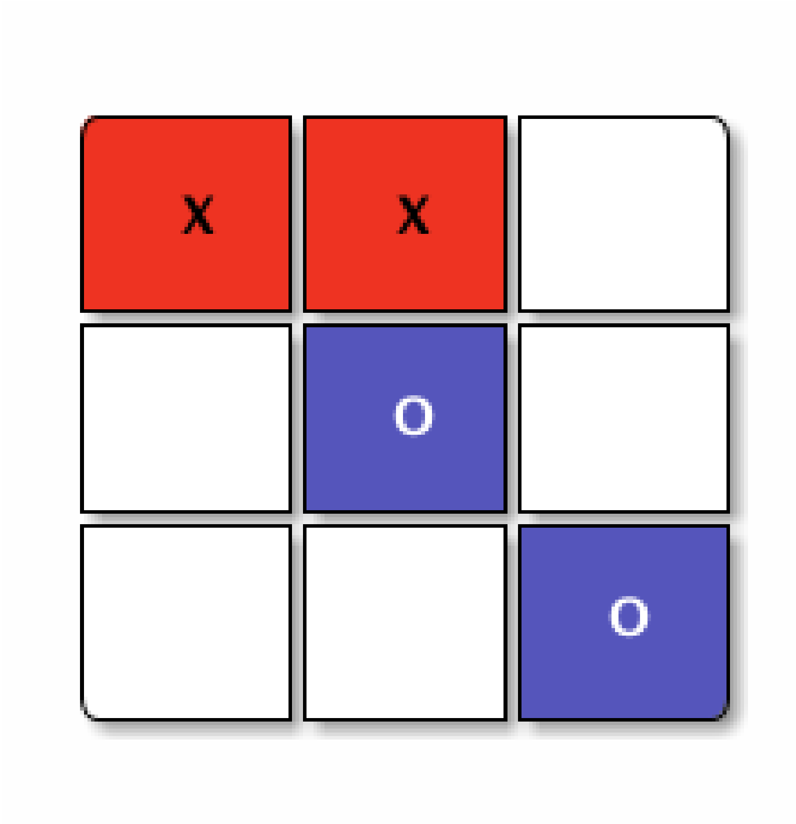
The heuristic rely heavily on game-specific knowledge. Finding good evaluation heuristics is difficult.The heuristic measure I use for tic tac toe is like blow.

1. In this adversarial game. I define that the X will go for the maximum marks. While O will go for the minimum marks.
2. I calculate the single mark for rows columns diagonal and anti-diagonal.
3. The single mark is define by the count difference of X pieces and O pieces
    - If the count of X pieces minus the count of O pieces is 3, that means X wins, then get 1000.
    - If the count of X pieces minus the count of O pieces is 2, that means X have 2 pieces while O have 0 in a line, then get 50.
    - If the count of X pieces minus the count of O pieces is -3, that means O wins, then get -1000.
    - If the count of X pieces minus the count of O pieces is -2, that means O have 2 pieces while X have 0 in a line, then get -50.

- otherwise 0 marks will be given.

4. Then add the single marks rows by rows, columns by columns, and the 2 diagonal together to get the final marks

This evaluation heuristic can be applied to non-final positions of game state, which can be future apply to the minimax search algorithm.



For example this is a random game State. The total score is

$$\begin{aligned} TotalScore = row1 + row2 + row3 + column1 + column2 + column3 + diagonal + anti - diagonal \\ = 50 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 50 \end{aligned} \tag{1}$$

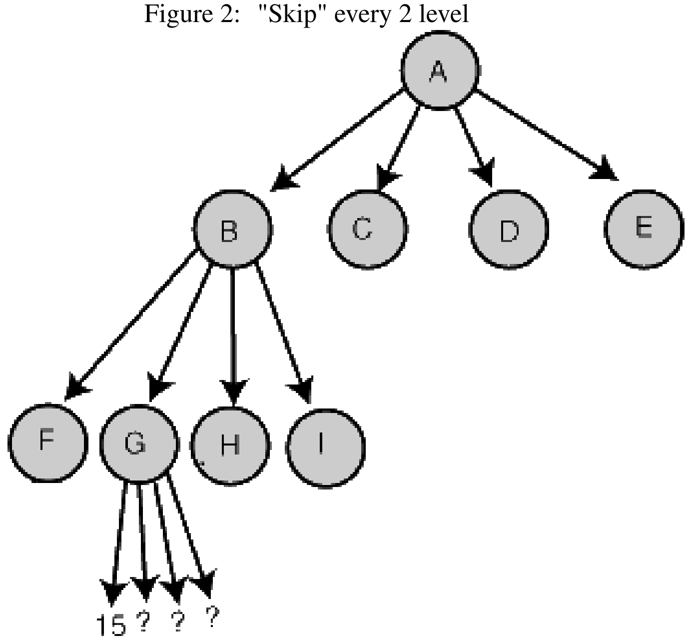
3 Question 2 (What are the respective percentages of frequent 3-itemsets, and 2-itemsets, with respect to all possible itemsets, which have a minimum support of 3%?)

The search strategy is minimax algorithm with Alpha-beta pruning to decrease the number of nodes that are evaluated by the minimax algorithm in its search tree.

With an (average or constant) branching factor of b, and a search depth of n plies, the maximum number of leaf node positions evaluated (when the move ordering is pessimal) is $O(bb... * b) = O(b^n)$ – the same as a simple minimax search. If the move ordering for the search is optimal (meaning the best moves are always searched first), the number of leaf node positions evaluated is about $O(b * 1 * b * 1 * ... * b)$ for odd depth and $O(b * 1 * b * 1 * ... * 1)$ for even depth, or $O(b^{\frac{n}{2}})$. In the latter case, where the ply of a search is even, the effective branching factor is reduced to its square root, or, equivalently, the search can go twice as deep with the same amount of computation.

The explanation of $b * 1 * b * 1 * \ldots$ is that all the first player's moves must be studied to find the best one, but for each, only the best second player's move is needed to refute all but the first (and best) first player move – alpha–beta ensures no other second player moves need be considered.

Figure 2: "Skip" every 2 level



The best case time complexity of Alpha-beta pruning is $O(b^{\frac{n}{2}})$. And the space complexity is the b*n.

4 Question 3 (How many association rules have a minimum confidence of 50% and a minimum support of 5% and 10%, respectively? Briefly explain how the minimum support affects the strong rules generated.)

By compare to other heuristic search algorithm. The Alpha-beta pruning is a best choice balance between a greedy search algorithm and brute forth search algorithm.

The greedy search algorithm runs fast compare to Alpha-beta pruning. The time complexity is O(1) compare to Alpha-beta pruning which is $O(b^{\frac{n}{2}})$. But it have it's own shortage. The evaluation function for greedy search algorithm is very hard to write. And if the evaluation function does not describe the game model well. The greedy algorithm AI will easily get the local maximum rather than global and lose the game.

And compare to another extreme, the brute forth search, which is very easy to write the evaluation function, just 3 case win, lose or draw. And the program will always get the global maximum and take the best strategy. But for the simple game like Tic Tac Toe, the brute forth search is possible cause the solution space is only 9! = 362880. But for other games like chess. It is impossible. Actually, the chess computer Deep Blue (the first one to beat a reigning world champion, Garry Kasparov at that time) looked ahead at least 12 plies, then applied a heuristic evaluation function. The searching function it used is the Alpha-beta pruning.

By compare to the 2 extreme one is the fast but hard to write evaluation function and easily get local maximum by using the greedy searching algorithm. Another is the easiest evaluation but time consuming. The advantages of minimax Alpha-beta pruning searching algorithm balance perfect between the time consuming of running code and the time consuming of witting the evaluation functions.

The limitations of using the minimum Alpha-beta pruning is that this searching algorithm can only be use in the 2 person zero-sum adversarial game.

5 Question 4 (List three association rules that have the highest support with 100% confidence?)

If the pruning level is more then 5, then my program will always make the best move, so if I make one single mistake the program can win the game.

6 Question 5 (Do you find any "interesting" rules? What are they? Briefly explain why.)

If the pruning level is more then 5, then my program will always make the best move, so if I make one single mistake the program can win the game.

7 REFERENCE

[1] J. Hughes. Why functional programming matters. The Computer Journal, 32(2):98–107, 1989.
https://en.wikipedia.org/wiki/Minimax#Minimax_algorithm_with_alternate_moves
https://en.wikipedia.org/wiki/Alpha%E2%80%93beta_pruning
http://perugini.cps.udayton.edu/teaching/courses/Spring2016/cps499/projects/korenewychs1/korenewychs1-paper.pdf

8 APPENDIX A

```
import Data.Array
import Data.List (intercalate, intersperse,elemIndex)
import Data.Tree

data Cell = B | X | O
  deriving (Enum, Read, Eq, Ord)

instance Show Cell where
  show B = "."
  show X    = "X"
  show O    = "O"

opposite :: Cell -> Cell
```

```haskell
opposite B = B
opposite X = O
opposite O = X

type Position = (Int, Int)
type State = Array Position Cell

newGame :: State
newGame = listArray boardInds $ repeat B
        where boardInds = ((0,0), (2,2))

update :: State -> (Position, Cell) -> State
update st pc = st // [pc]

getTurn :: State -> Cell
getTurn st
  | pieceDiff == 0    = X
  | pieceDiff == 1    = O
  | otherwise = error "encountered invalid board state"
  where pieceDiff = (count X st) - (count O st)
        count cell state = length . filter (==cell) $ elems state

lookupCell :: State -> Position -> Cell
lookupCell = (!)

getRow, getCol :: State -> Int -> [Cell]
getRow s i = [ lookupCell s (i,j) | j <- [0,1,2] ]
getCol s i = [ lookupCell s (j,i) | j <- [0,1,2] ]

getDiag, getAntiDiag :: State -> [Cell]
getDiag s = [ lookupCell s (i,j) | (i,j) <- [(0,0), (1,1), (2,2)] ]
getAntiDiag s = [ lookupCell s (i,j) | (i,j) <- [(2,0), (1,1), (0,2)] ]

win :: Cell -> State -> Bool
win piece state = checkRows || checkCols || checkDiag || checkAntiDiag
  where checkWin piece list = all (==piece) list
        checkRows = any (==True) [checkWin piece $ getRow state i | i <- [0,1,2]]
        checkCols = any (==True) [checkWin piece $ getCol state i | i <- [0,1,2]]
        checkDiag = checkWin piece $ getDiag state
        checkAntiDiag = checkWin piece $ getAntiDiag state

draw :: State -> Bool
draw st = (length . filter (/=B) $ elems st) == 9

moves :: State -> [State]
moves st
```

```haskell
  | win X st || win O st = []
  | otherwise = map (\p -> update st (p, getTurn st)) (freePositions st)
  where freePositions st = filter (\p -> st ! p == B) $ indices newGame


pprint :: State -> IO ()
pprint st = putStrLn $ pretty
         where chars = concat $ map show $ elems st
               rows = [0..2] >>= \i -> return $ take 3 (drop (3*i) chars)
               pretty = intercalate "\n" rows


generate :: State -> Tree State
generate = unfoldTree (\s -> (s, moves s))

prune :: Int -> Tree a -> Tree a
prune 0 t = Node (rootLabel t) []
prune n t = Node (rootLabel t) (map (prune (n-1)) (subForest t))

staticVal :: State -> Int
staticVal = marks

marks :: State -> Int
marks state = checkRows + checkCols + checkDiag + checkAntiDiag
  where getMarks list = case (count X list) - (count O list) of
                          3 -> 1000
                          2 -> 5
                          -2 -> -5
                          -3 -> -1000
                          _ -> 0
        checkRows = sum [getMarks $ getRow state i | i <- [0,1,2]]
        checkCols = sum [getMarks $ getCol state i | i <- [0,1,2]]
        checkDiag = getMarks $ getDiag state
        checkAntiDiag = getMarks $ getAntiDiag state
        count cell list = length . filter (==cell) $ list

mapmin :: Ord a => [[a]] -> [a]
mapmin [] = []
mapmin (xs:rest) = (omit n rest)
  where n = minimum xs
        omit n [] = [n]
        omit n (xs:rest) | minleq n xs = omit n rest
                         | otherwise   = omit k rest
                            where k = minimum xs
        minleq _ [] = False
        minleq n (y:ys) | y <= n = True
```

```
                        | otherwise = minleq n ys

mapmax :: Ord t => [[t]] -> [t]
mapmax [] = []
mapmax (xs:rest) = (omit n rest)
  where n = maximum xs
        omit n [] = [n]
        omit n (xs:rest) | maxleq n xs = omit n rest
                         | otherwise   = omit k rest
                             where k = maximum xs
        maxleq _ [] = False
        maxleq n (y:ys) | y >= n = True
                        | otherwise = maxleq n ys

abMaxList :: (Ord a) => Tree a -> [a]
abMaxList (Node x []) = [x]
abMaxList (Node x subs) = mapmin . map abMinList $ subs

abMinList :: (Ord a) => Tree a -> [a]
abMinList (Node x []) = [x]
abMinList (Node x subs) = mapmax . map abMaxList $ subs

minIndex :: Ord a => [a] -> Int
minIndex xs = head $ filter ((== minimum xs) . (xs !!)) [0..]

maxIndex :: Ord a => [a] -> Int
maxIndex xs = head $ filter ((== maximum xs) . (xs !!)) [0..]

abmax :: State -> Int
abmax = maximum .
        abMaxList .
        fmap staticVal .
        prune 4 .
        generate

abmin :: State -> Int
abmin = minimum .
           abMinList .
           fmap staticVal .
           prune 4 .
          generate

playX :: State -> State
playX s = moves s !! (maxIndex . fmap abmin $ moves s)

playO :: State -> State
```

```
playO s = moves s !! (minIndex . fmap abmax $ moves s)

playAi :: State -> State
playAi s = case getTurn s of
           X -> playX s
           _ -> playO s

playHuman :: State -> Position -> State
playHuman s p = update s (p,(getTurn s))

main :: IO ()
main = putStrLn "Welcome to the Heuristic Tic Tac Toe" >>
       putStrLn "Below show the board, the up left is the root" >>
       putStrLn "Please decide you want to play first or second (X or O)" >>
       fmap (read::String -> Cell) getLine >>= loop newGame

loop:: State -> Cell -> IO()
loop s c
    | c == X =
        if win O s then
            pprint s >>
            putStrLn "Owin"
          else
            if win X s then
                  pprint s >>
                  putStrLn "Xwin"
              else
                if draw s then
                    pprint s >>
                    putStrLn "Draw"
                else
                    pprint s >>
                    putStrLn "Please input as (x,y) such as (0,0) 0<=x<=2, 0<=y<=2" >>
                    fmap (read::String -> Position) getLine >>=
                    \p -> loop  (playHuman s p) (opposite  c)
    | otherwise =
        if win O s then
            pprint s >>
            putStrLn "Owin"
          else
            if win X s then
                  pprint s >>
                  putStrLn "Xwin"
              else
                if draw s then
                    pprint s >>
```

```haskell
    putStrLn "Draw"
else
  pprint s >>
  putStrLn "Now please wait AI to calculate" >>
  loop (playAi s) (opposite c)
```