Search

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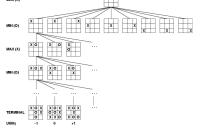
Games vs. search problems

- "Unpredictable" opponent → specifying a move for every possible opponent reply
- Time limits → unlikely to find goal, must approximate

Game as Search Problem

- Initial State
 - Board position and player to move
- Successor Function
 - Returns list of (state, move) pairs
 - Legal moves and resulting states
- Terminal (Goal) Test
 - When game is over
- · Utility (Objective) Function
 - Assigns numeric outcome to terminal states
 - E.g. +1, -1, 0 for win, lose, draw

Game tree (2-player, deterministic, turns)

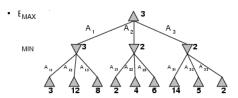


Optimal Strategy

- Leads to outcomes as good as any other strategy when playing an infallible opponent
- Tree where max takes a turn and min takes a turn is ONE MOVE DEEP made up two halfmoves - each half move is called a ply

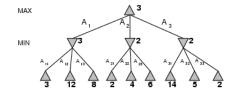
Minimax

- Perfect play for deterministic games
- Idea: choose move to position with highest minimax value = best achievable payoff against best play



Minimax

- Minimax(node) is utility for max of being in corresponding
- · Max prefers a state with maximum value
- · Min prefers a state with minimum value



Minimax algorithm

function Minimax-Decision(state) returns an action

 $v \leftarrow \text{Max-Value}(state)$ return the action in Successors(state) with value v

function Max-Value(state) returns a utility value if Terminal-Test(state) then return Utility(state)

 $v \leftarrow -\infty$ for a, s in Successors(state) do $v \leftarrow \text{Max}(v, \text{Min-Value}(s))$ return v

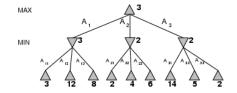
function Min-Value(state) returns a utility value

if Terminal-Test(state) then return Utility(state)

 $v \leftarrow \infty$ for a, s in Successors(state) do $v \leftarrow \text{Min}(v, \text{Max-Value}(s))$

Minimax

 Recursion proceeds to leaves and based on utility function assigns minimax values at the level above and so on



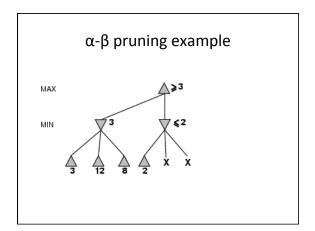
Properties of minimax

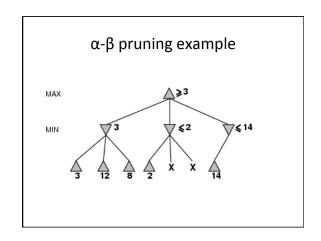
- Complete? Yes (if tree is finite)
- Optimal? Yes (against an optimal opponent)
- Time complexity? O(bm)
- Space complexity? O(bm) (depth-first exploration)
- For chess, b ≈ 35, m ≈100 for "reasonable" games → exact solution completely infeasible

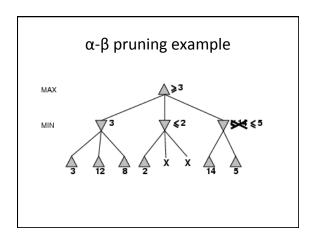
Problem

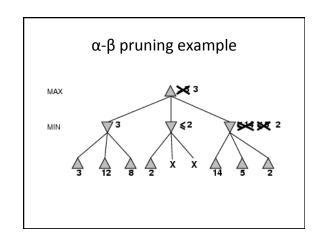
- Number of game states exponential in number of moves
- · Can cut in half with pruning
 - Still exponential
 - Get rid of braches that can't influence final decision

α - β pruning example <u></u>≱3 MAX MIN









Properties of α - β

- Pruning does not affect final result
- Good move ordering improves effectiveness of pruning
- With "perfect ordering," time complexity = O(b^{m/2})
 → doubles depth of search
- A simple example of the value of reasoning about which computations are relevant (a form of metareasoning)

Why is it called α-β? • α is the value of the best (i.e., highest-value) choice found so far at any choice point along the path for max • If v is worse than α, max will avoid it • prune that branch • Define β similarly for min MIN

The $\alpha\text{-}\beta$ algorithm

The α - β algorithm

function Min-Value(state, α, β) returns a utility value inputs: state, current state in game $\alpha, \text{ the value of the best alternative for } \text{ Max along the path to } \text{ state}$ $\beta, \text{ the value of the best alternative for } \text{ Min along the path to } \text{ state}$ if Terminal-Test(state) then return Utility(state) $v \leftarrow +\infty$ for a, s in Successors(state) do $v \leftarrow \text{Min}(v, \text{Max-Value}(s, \alpha, \beta))$ if $v \leq \alpha$ then return v $\beta \leftarrow \text{Min}(\beta, v)$

Resource limits

Suppose we have 100 secs, explore 10⁴ nodes/sec

→ 10⁴ nodes per move

Standard approach:

- · cutoff test:
 - e.g., depth limit
- evaluation function
 - = estimated desirability of position

Usually a heuristic function

Resource limits

Standard approach:

- \bullet Use Cutoff-Test instead of Terminal-Test e.g., depth limit (perhaps add quiescence search)
- Use EVAL instead of UTILITY
 - i.e., evaluation function that estimates desirability of position

Suppose we have 100 seconds, explore 10^4 nodes/second

 $\Rightarrow 10^6$ nodes per move $\approx 35^{8/2}$

 $\Rightarrow \alpha\!\!-\!\!\beta$ reaches depth 8 \Rightarrow pretty good chess program

Evaluation Functions



White slightly better

tly better

For chess, typically linear weighted sum of features

 $Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s)$

e.g., w₁ = 9 with

 $f_{4}(s) = \text{(number of white queens)} - \text{(number of black queens), etc.}$

Deterministic games in practice

- Checkers: Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used an endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 443,748,401,247 positions.
- **Othello:** human champions refuse to compete against computers, who are too good.

Deterministic games in practice

- Chess: Deep Blue defeated human world champion Gary Kasparov in a six- game match in 1997. Deep Blue searches 200 million positions per second, uses very sophisticated evaluation, and undisclosed methods for extending some lines of search up to 40 ply.
- Go: human champions refuse to compete against computers, who are too bad. In go, b > 300, so most programs use pattern knowledge bases to suggest plausible moves.

Getting Better

- http://en.wikipedia.org/wiki/Computer Go
- http://en.wikipedia.org/wiki/English draughts
- http://en.wikipedia.org/wiki/Computer chess
- http://en.wikipedia.org/wiki/ Computer Othello