

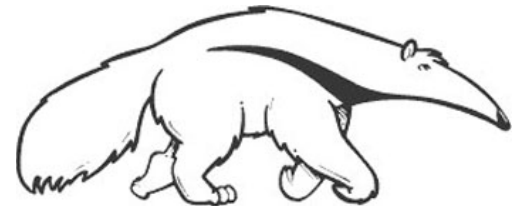
Games and Adversarial Search A: Mini-max, Cutting Off Search

CS171, Summer 1 Quarter, 2019

Introduction to Artificial Intelligence

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Read Beforehand: R&N 5.1, 5.2, 5.4



Outline

- **Computer programs that play 2-player games**
 - game-playing as search with the complication of an opponent
- **General principles of game-playing and search**
 - game tree
 - minimax principle; impractical, but theoretical basis for analysis
 - evaluation functions; cutting off search; static heuristic functions
 - alpha-beta-pruning
 - heuristic techniques
 - games with chance
 - Monte-Carlo ree search
- **Status of Game-Playing Systems**
 - in chess, checkers, backgammon, Othello, Go, etc., computers routinely defeat leading world players.

Types of games

Deterministic:

Chance:

Perfect
Information:

chess, checkers, go,
othello

backgammon,
monopoly

Imperfect
Information:

battleship, Kriegspiel

Bridge, poker,
scrabble, ...

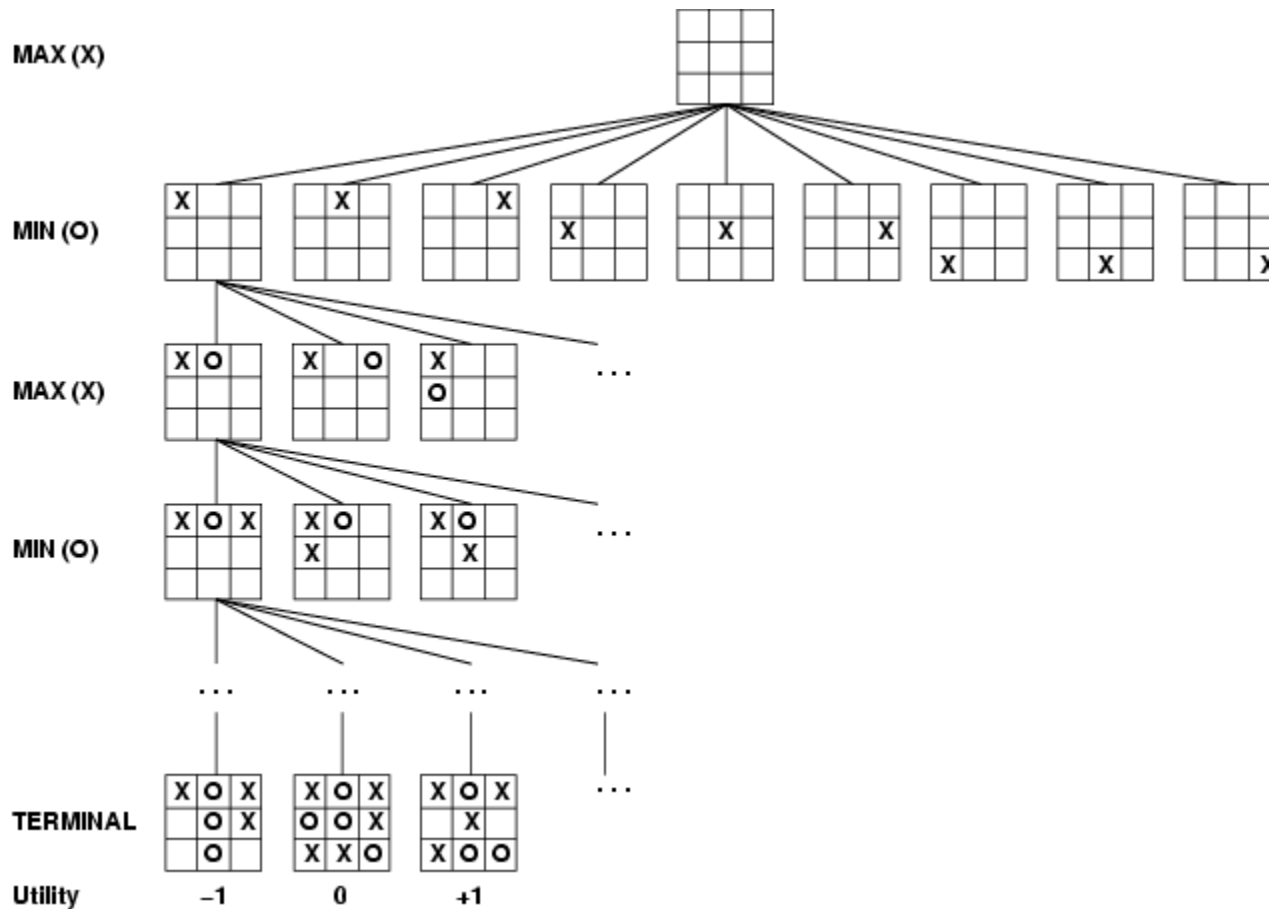
- Start with deterministic, perfect information games (easiest)
- Not considered:
 - Physical games like tennis, ice hockey, etc.
 - But, see “robot soccer,” <http://www.robocup.org/>

Typical assumptions

- Two agents, whose actions alternate
- Utility values for each agent are the opposite of the other
 - “Zero-sum” game; this creates adversarial situation
- Fully observable environments
- In game theory terms:
 - Deterministic, turn-taking, zero-sum, perfect information
- Generalizes: stochastic, multiplayer, non zero-sum, etc.
- Compare to e.g., Prisoner’s Dilemma” (R&N pp. 666-668)
 - Non-turn-taking, Non-zero-sum, Imperfect information

Game Tree (tic-tac-toe)

- All possible moves at each step



- How do we search this tree to find the optimal move?

Search versus Games

- **Search:** no adversary
 - Solution is a path from start to goal, or a series of actions from start to goal
 - Search, Heuristics, and constraint techniques can find optimal solution
 - Evaluation function: estimate cost from start to goal through a given node
 - Actions have costs (sum of step costs = path cost)
 - Examples: path planning, scheduling activities, ...
- **Games:** adversary
 - Solution is a strategy
 - Specifies move for every possible opponent reply
 - Time limits force an approximate solution
 - Evaluation function: evaluate “goodness” of game position
 - Examples: chess, checkers, Othello, backgammon, Go

Games as search

- Two players, “MAX” and “MIN”
- MAX moves first, and they take turns until game is over
 - Winner gets reward, loser gets penalty
 - “Zero sum”: sum of reward and penalty is constant
- Formal definition as a search problem:
 - **Initial state**: set-up defined by rules, e.g., initial board for chess
 - **Player(s)**: which player has the move in state s
 - **Actions(s)**: set of legal moves in a state
 - **Result(s,a)**: transition model defines result of a move
 - **Terminal-Test(s)**: true if the game is finished; false otherwise
 - **Utility(s,p)**: the numerical value of terminal state s for player p
 - E.g., win (+1), lose (-1), and draw (0) in tic-tac-toe
 - E.g., win (+1), lose (0), and draw (1/2) in chess
- MAX uses search tree to determine “best” next move

Min-Max: an optimal procedure

- Finds the optimal strategy or next best move for MAX:
 - Optimal strategy is a solution tree

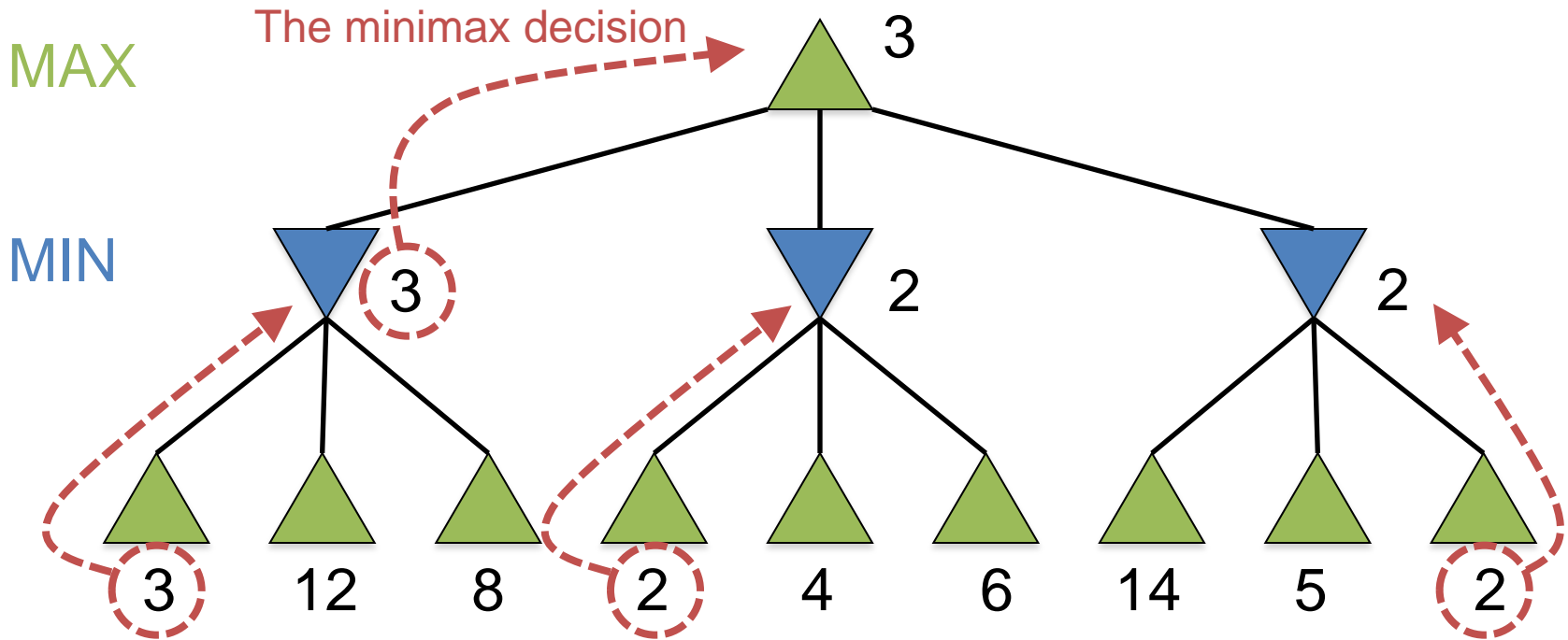
Brute Force:

1. Generate the whole game tree to leaves
2. Apply utility (payoff) function to leaves
3. Back-up values from leaves toward the root:
 - a Max node computes the max of its child values
 - a Min node computes the min of its child values
4. At root: choose move leading to the child of highest value

Minimax:

Search the game tree using DFS to find the value (= best move) at the root

Two-ply Game Tree



Minimax maximizes the utility of the worst-case outcome for MAX

Recursive min-max search

minMaxSearch(state)

return argmax([minValue(apply(state,a)) for each action a])

Simple stub to call recursion f' ns

maxValue(state)

if (terminal(state)) return utility(state);

v = -infty

for each action a:

v = max(v, minValue(apply(state,a)))

return v

If recursion limit reached, eval position

Otherwise, find our best child:

minValue(state)

if (terminal(state)) return utility(state);

v = infty

for each action a:

v = min(v, maxValue(apply(state,a)))

return v

If recursion limit reached, eval position

Otherwise, find the worst child:

Properties of minimax

- **Complete?** Yes (if tree is finite)
- **Optimal?**
 - Yes (against an optimal opponent)
 - Can it be beaten by a suboptimal opponent? (No – why?)
- **Time?** $O(b^m)$
- **Space?**
 - $O(bm)$ (depth-first search, generate all actions at once)
 - $O(m)$ (backtracking search, generate actions one at a time)

Game tree size

- Tic-tac-toe

- $B \approx 5$ legal actions per state on average; total 9 plies in game
 - “ply” = one action by one player; “move” = two plies
- $5^9 = 1,953,125$
- $9! = 362,880$ (computer goes first)
- $8! = 40,320$ (computer goes second)
- Exact solution is quite reasonable

- Chess

- $b \approx 35$ (approximate average branching factor)
- $d \approx 100$ (depth of game tree for “typical” game)
- $b^d = 35^{100} \approx 10^{154}$ nodes!!!
- Exact solution completely infeasible

It is usually impossible to develop the whole search tree.

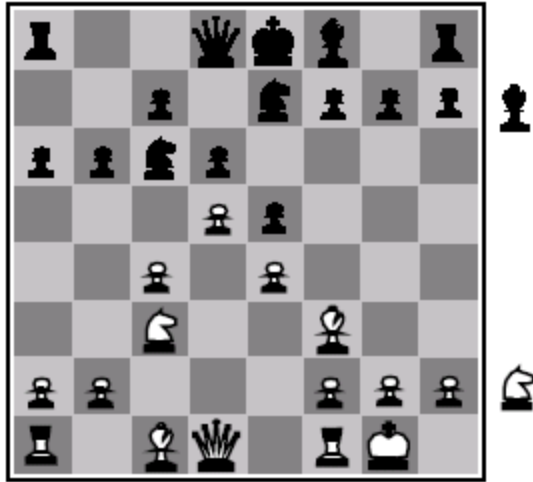
Cutting off search

- One solution: cut off tree before game ends
- Replace
 - Terminal(s) with Cutoff(s) – e.g., stop at some max depth
 - Utility(s,p) with Eval(s,p) – estimate position quality
- Does it work in practice?
 - $b^m \approx 10^6$, $b \approx 35 \rightarrow m \approx 4$
 - 4-ply look-ahead is a poor chess player
 - 4-ply \approx human novice
 - 8-ply \approx typical PC, human master
 - 12-ply \approx Deep Blue, human grand champion Kasparov
 - $35^{12} \approx 10^{18}$ (Yikes! but possible, with other clever methods)

Static (Heuristic) Evaluation Functions

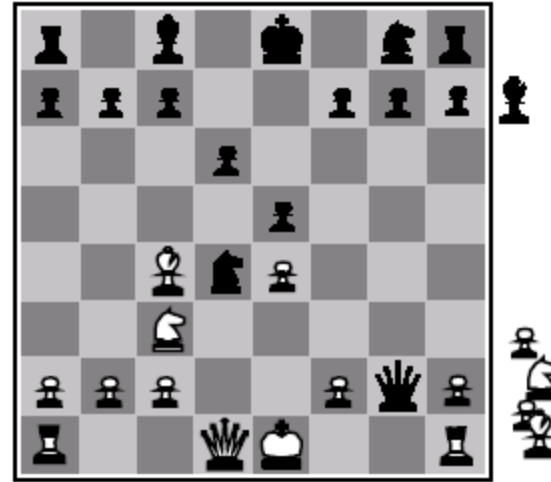
- **An Evaluation Function:**
 - Estimate how good the current board configuration is for a player.
 - Typically, evaluate how good it is for the player, and how good it is for the opponent, and subtract the opponent's score from the player's.
 - Often called “static” because it is called on a static board position
 - Ex: Othello: Number of white pieces - Number of black pieces
 - Ex: Chess: Value of all white pieces - Value of all black pieces
- Typical value ranges:
[-1, 1] (loss/win) or [-1 , +1] or [0 , 1]
- Board evaluation: X for one player => -X for opponent
 - Zero-sum game: scores sum to a constant

Evaluation functions



Black to move

White slightly better



White to move

Black winning

For chess, typically *linear* weighted sum of *features*

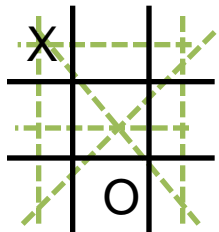
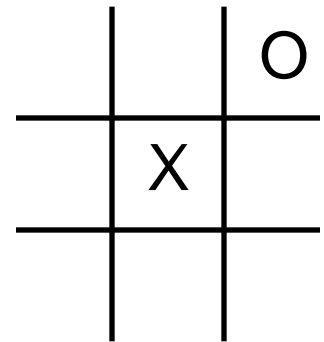
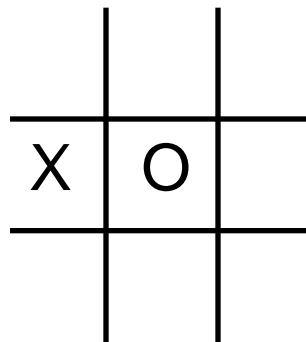
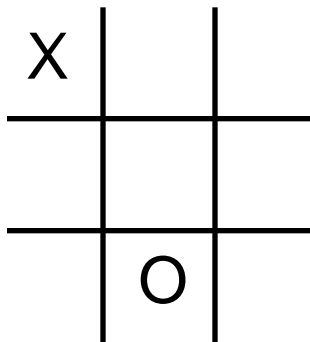
$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$

e.g., $w_1 = 9$ with

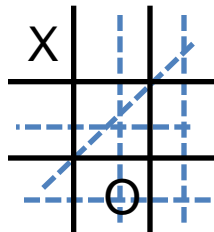
$f_1(s) = (\text{number of white queens}) - (\text{number of black queens}),$ etc.

Applying minimax to tic-tac-toe

- The static heuristic evaluation function:
 - Count the number of possible win lines



X has 6 possible win paths



O has 5 possible win paths

$$E(s) = 6 - 5 = 1$$

X has 4 possible wins
O has 6 possible wins

$$E(n) = 4 - 6 = -2$$

X has 5 possible wins
O has 4 possible wins

$$E(n) = 5 - 4 = 1$$

Minimax values (two ply)

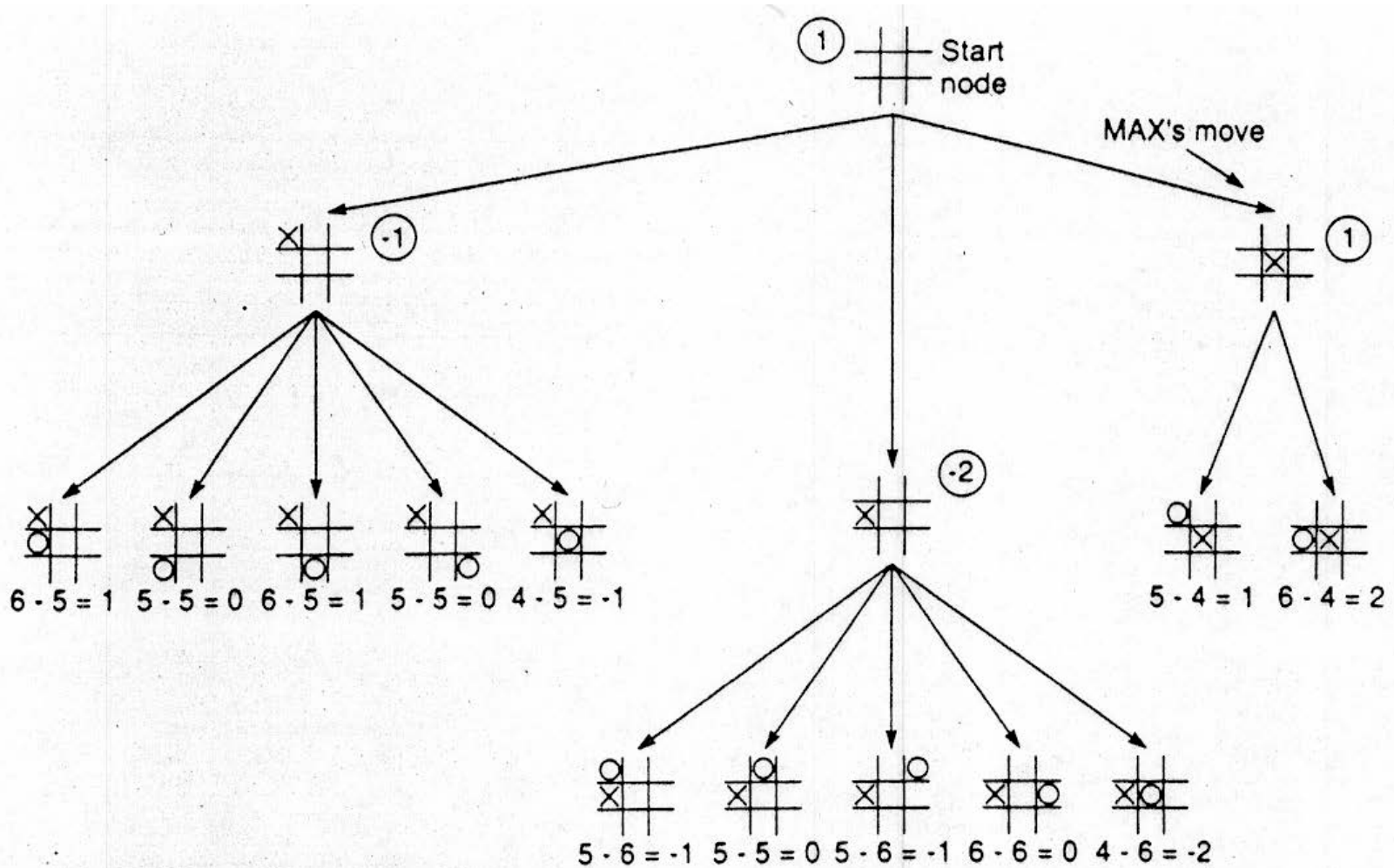
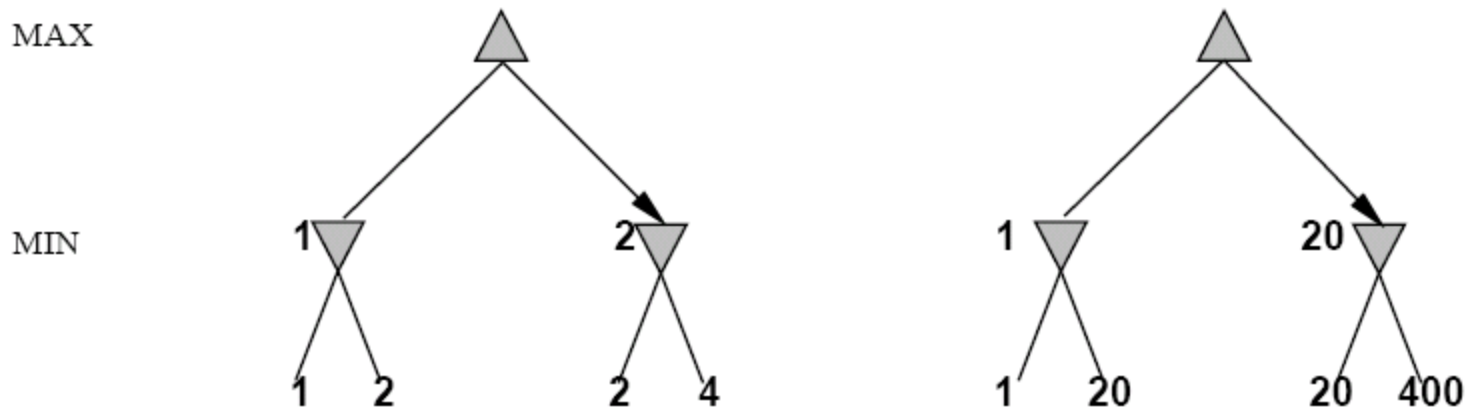


Figure 4.17 Two-ply minimax applied to the opening move of tic-tac-toe.

Digression: Exact values don't matter



Behaviour is preserved under any *monotonic* transformation of EVAL

Only the order matters:

payoff in deterministic games acts as an *ordinal utility* function

Iterative deepening

- In real games, there is usually a time limit T to make a move
- How do we take this into account?
- Minimax cannot use “partial” results with any confidence, unless the full tree has been searched
 - Conservative: set small depth limit to guarantee finding a move in time $< T$
 - But, we may finish early – could do more search!
- In practice, iterative deepening search (IDS) is used
 - IDS: depth-first search with increasing depth limit
 - When time runs out, use the solution from previous depth
 - With alpha-beta pruning (next), we can sort the nodes based on values from the previous depth limit in order to maximize pruning during the next depth limit => search deeper!

Limited horizon effects

- The Horizon Effect
 - Sometimes there's a major "effect" (such as a piece being captured) which is just "below" the depth to which the tree has been expanded.
 - The computer cannot see that this major event could happen because it has a "limited horizon".
 - There are heuristics to try to follow certain branches more deeply to detect such important events
 - This helps to avoid catastrophic losses due to "short-sightedness"
- Heuristics for Tree Exploration
 - Often better to explore some branches more deeply in the allotted time
 - Various heuristics exist to identify "promising" branches
 - Stop at "quiescent" positions – all battles are over, things are quiet
 - Continue when things are in violent flux – the middle of a battle

Selectively deeper game trees

MAX

(Computer's move)

MIN

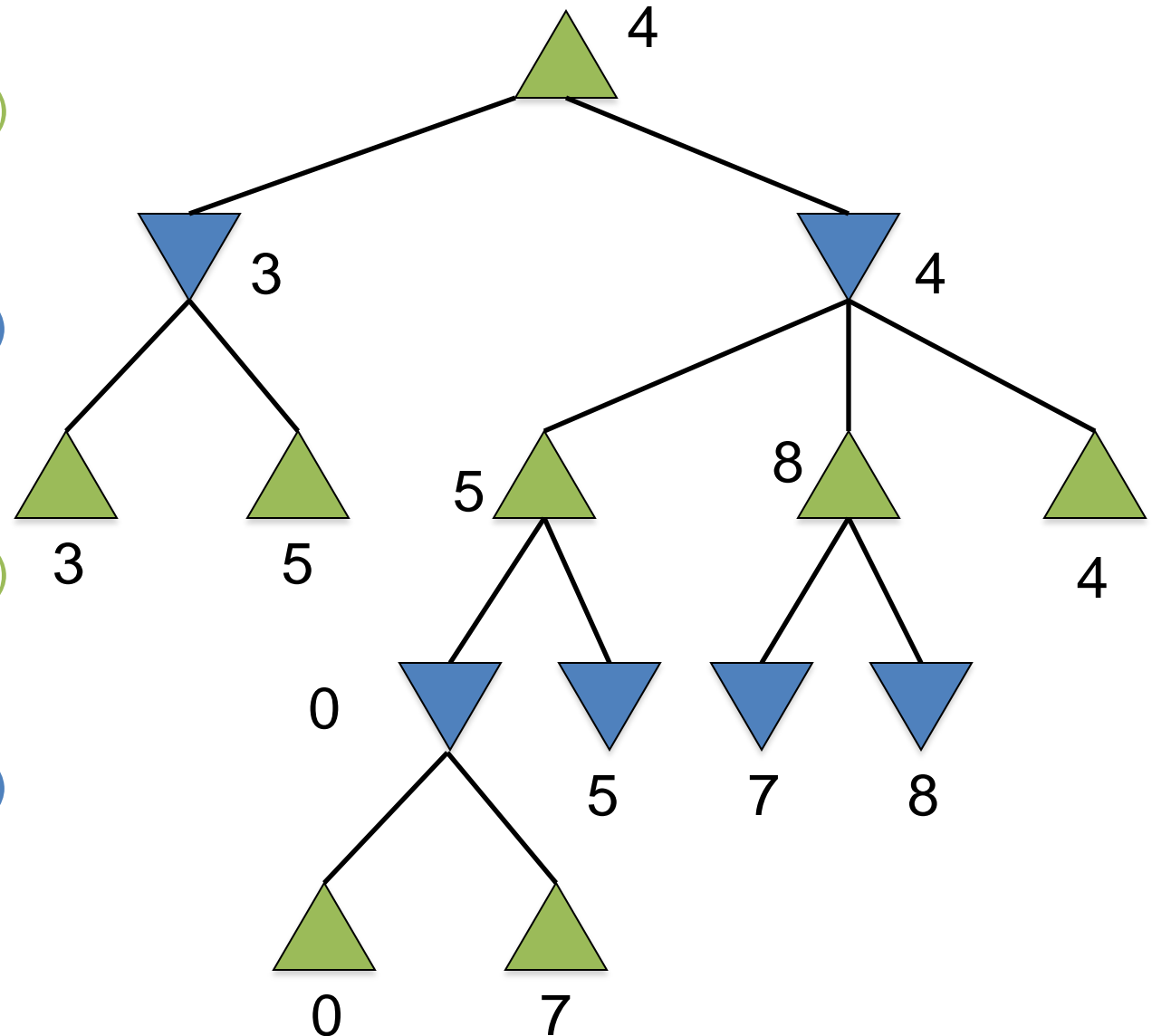
(Opponent's move)

MAX

(Computer's move)

MIN

(Opponent's move)



Eliminate redundant nodes

- On average, each board position appears in the search tree approximately $10^{150} / 10^{40} \approx 10^{100}$ times
 - Vastly redundant search effort
- Can't remember all nodes (too many)
 - Can't eliminate all redundant nodes
- Some short move sequences provably lead to a redundant position
 - These can be deleted dynamically with no memory cost
- Example:
 1. P-QR4 P-QR4; 2. P-KR4 P-KR4leads to the same position as
 1. P-QR4 P-KR4; 2. P-KR4 P-QR4

Summary

- Game playing as a search problem
- Game trees represent alternate computer / opponent moves
- Minimax: choose moves by assuming the opponent will always choose the move that is best for them
 - Avoids all worst-case outcomes for Max, to find the best
 - If opponent makes an error, Minimax will take optimal advantage (after) & make the best possible play that exploits the error
- Cutting off search
 - In general, it's infeasible to search the entire game tree
 - In practice, Cutoff-Test decides when to stop searching
 - Prefer to stop at quiescent positions
 - Prefer to keep searching in positions that are still in flux
- Static heuristic evaluation function
 - Estimate the quality of a given board configuration for MAX player
 - Called when search is cut off, to determine value of position found