Set 4: Game-Playing

ICS 271 Fall 2014

Kalev Kask

Overview

- **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; replace terminal leaf utility fn with eval fn
  - alpha-beta-pruning
  - heuristic techniques
  - games with chance

- **Status of Game-Playing Systems**
  - in chess, checkers, backgammon, Othello, etc, computers routinely defeat leading world players

- **Motivation: multiagent competitive environments**
  - think of “nature” as an opponent
  - economics, war-gaming, medical drug treatment

Types of games

	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon monopoly
imperfect information		bridge, poker, scrabble nuclear war

Not Considered: Physical games like tennis, croquet, ice hockey, etc.
(but see “robot soccer” http://www.robocup.org/)

Search versus Games

- **Search – no adversary**
  - Solution is a part from start to goal, or a series of actions from start to goal
  - Heuristics and search techniques can find *optimal* solution
  - Evaluation function: estimate of cost from start to goal through given node
  - Actions have cost
  - Examples: path planning, scheduling activities

- **Games – adversary**
  - Solution is strategy
    - strategy specifies move for every possible opponent reply.
  - Time limits force an *approximate* solution
  - Evaluation function: evaluate “goodness” of game position
  - Board configurations have utility
  - Examples: chess, checkers, Othello, backgammon

Solving 2-player Games

- **Two players, fully observable environments, deterministic, turn-taking, zero-sum games of perfect information**
- **Examples: e.g., chess, checkers, tic-tac-toe**
- **Configuration of the board = unique arrangement of "pieces"**
- **Statement of Game as a Search Problem:**
  - **States** = board configurations
  - **Operators** = legal moves. The transition model
  - **Initial State** = current configuration
  - **Goal** = winning configuration
  - **payoff function (utility)**= gives numerical value of outcome of the game
- **Two players, MIN and MAX taking turns. MIN/MAX will use search tree to find next move**
- **A working example: Grundy's game**
  - Given a set of coins, a player takes a set and divides it into two unequal sets. The player who cannot do uneven split, looses.
  - What is a state? Moves? Goal?

Grundy's game - special case of nim

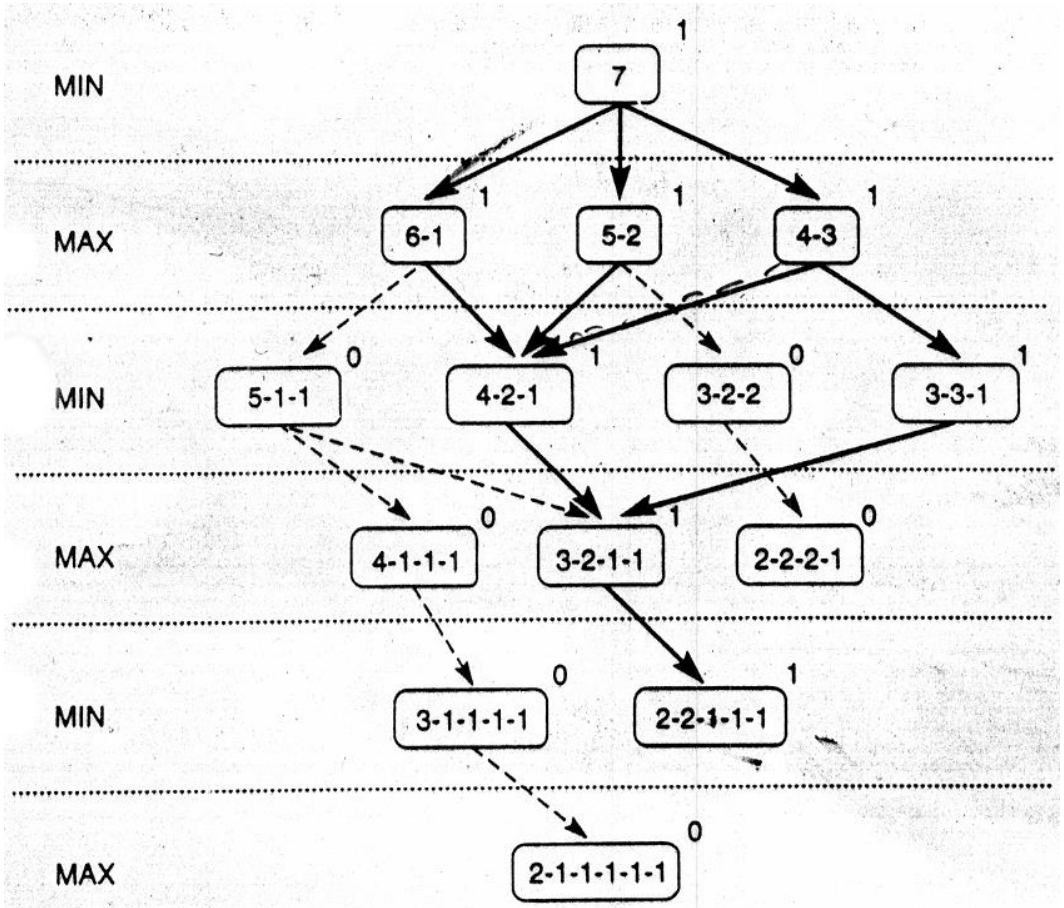


Figure 4.14 Exhaustive minimax for the game of nim. Bold lines indicate forced win for MAX. Each node is marked with its derived value (0 or 1) under minimax.

Game Trees: Tic-tac-toe

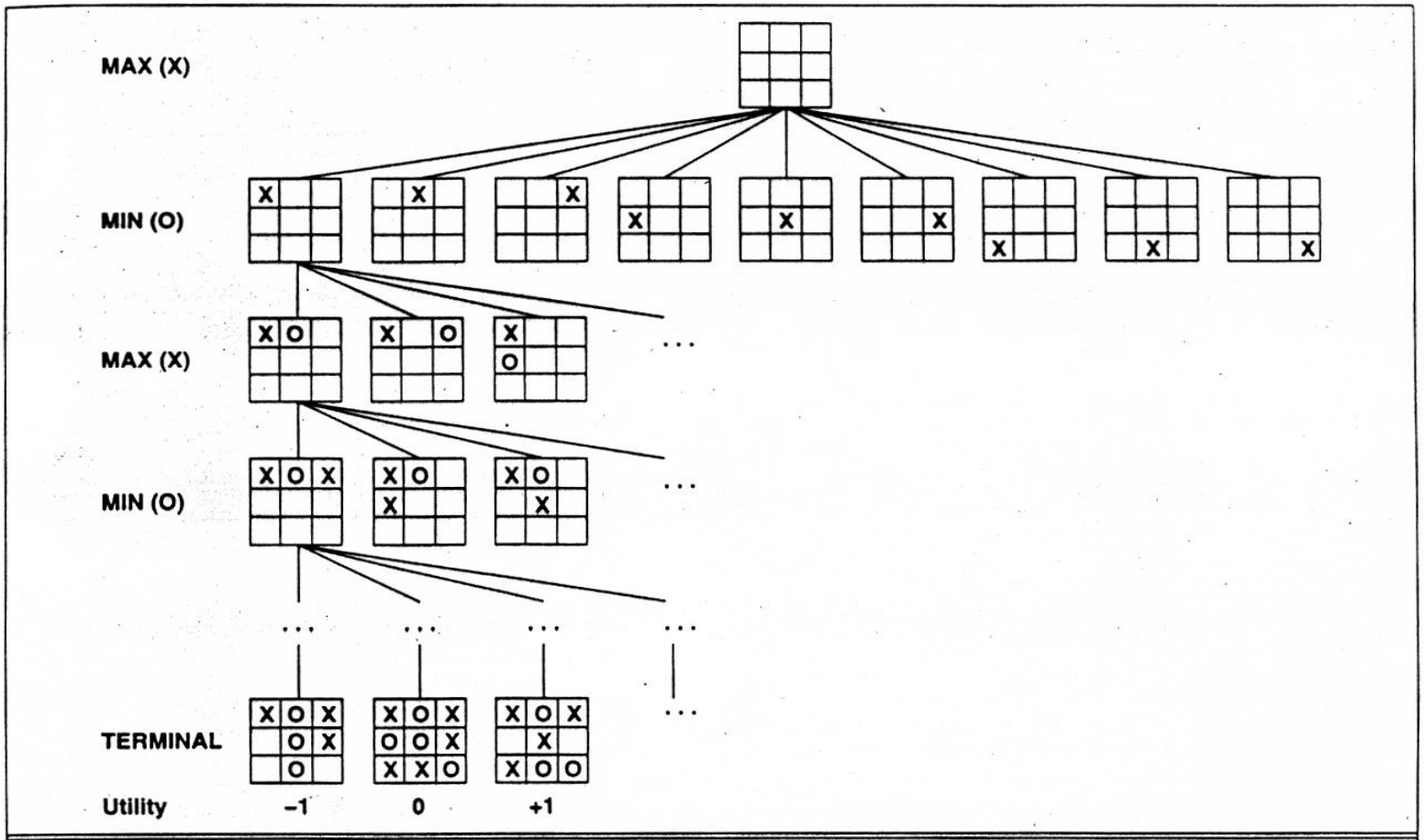


Figure 5.1 A (partial) search tree for the game of Tic-Tac-Toe. The top node is the initial state, and MAX moves first, placing an X in some square. We show part of the search tree, giving alternating moves by MIN (O) and MAX, until we eventually reach terminal states, which can be assigned utilities according to the rules of the game.

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

The Minimax Algorithm

- Designed to find the optimal strategy or just best first 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. When value reaches the root: choose max value and the corresponding move.

Minimax:

Search the game-tree in a DFS manner to find the value of the root.

Game Trees

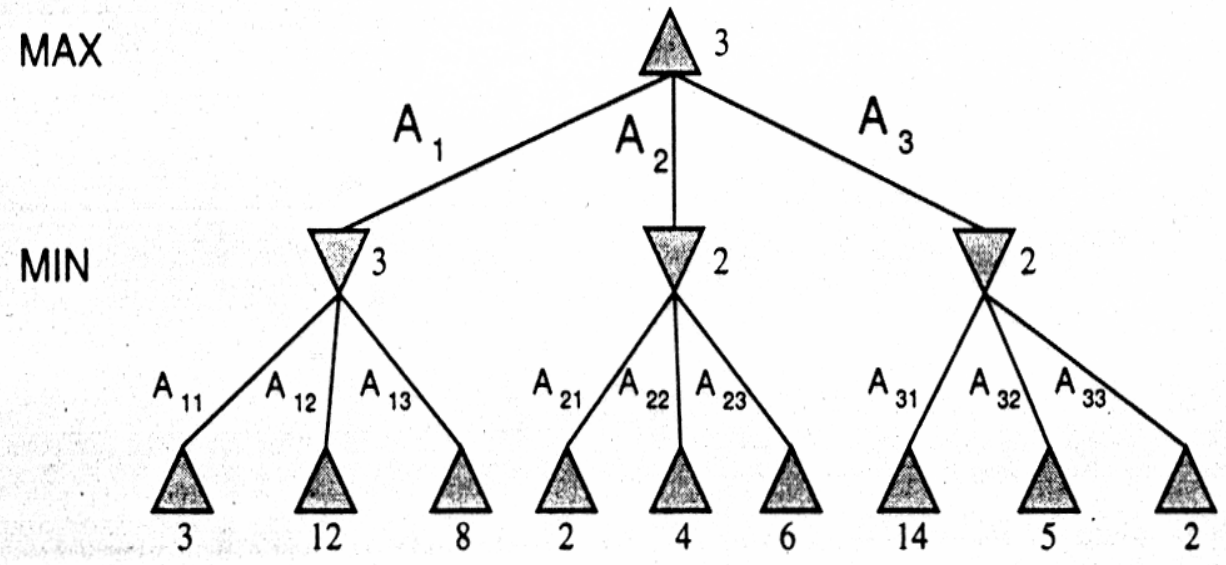
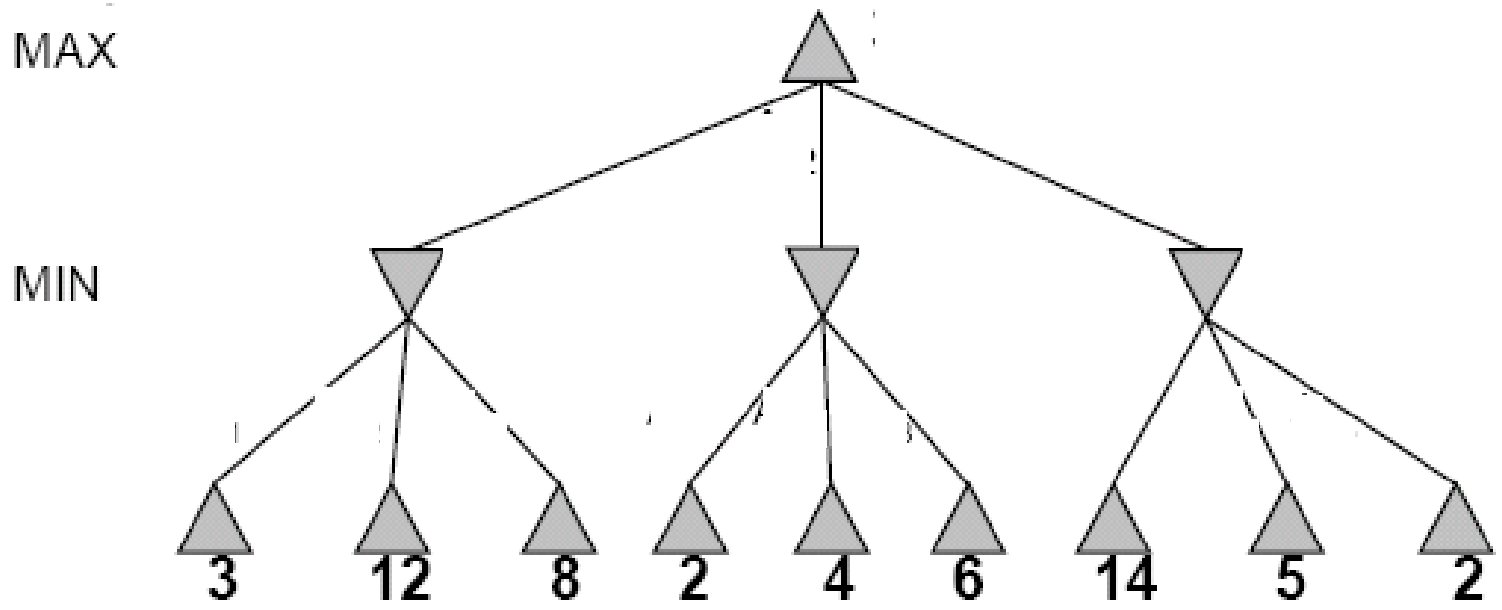
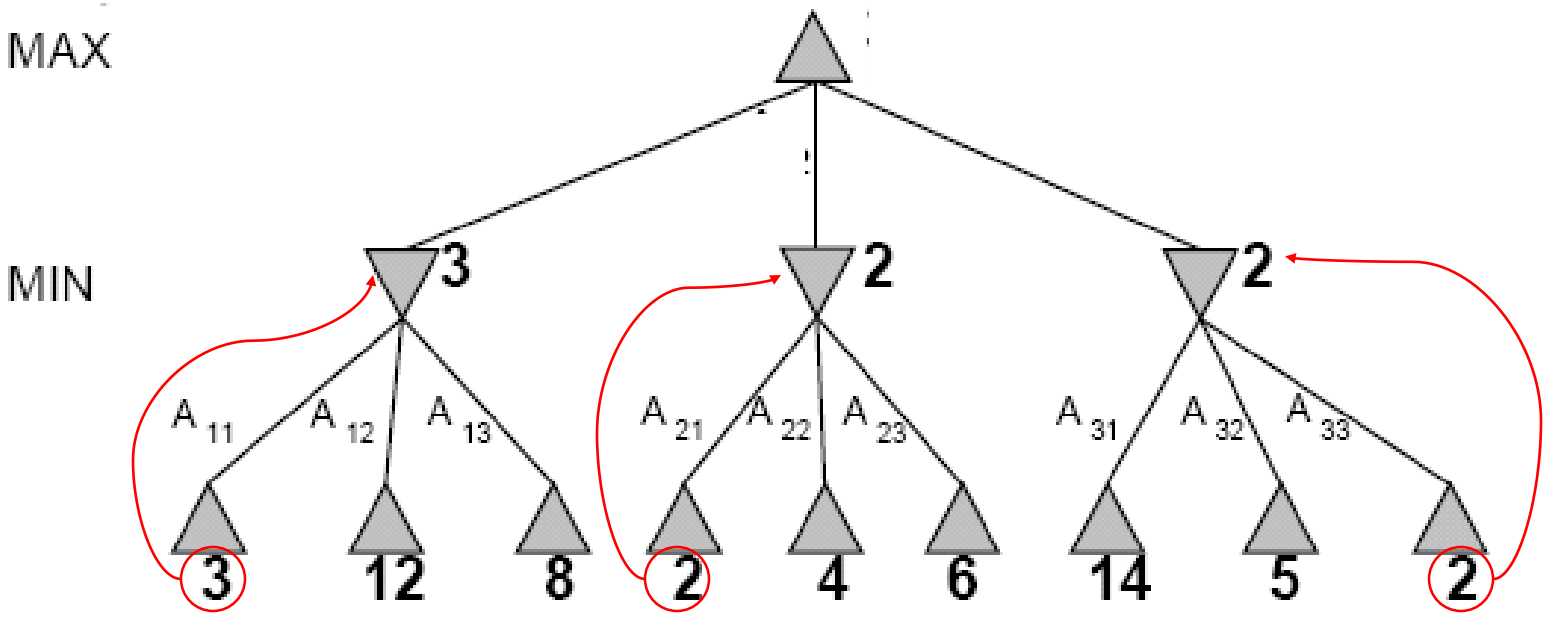


Figure 5.2 A two-ply game tree as generated by the minimax algorithm. The △ nodes are moves by MAX and the ▽ nodes are moves by MIN. The terminal nodes show the utility value for MAX computed by the utility function (i.e., by the rules of the game), whereas the utilities of the other nodes are computed by the minimax algorithm from the utilities of their successors. MAX's best move is A_1, and MIN's best reply is A_{11}.

Two-Ply Game Tree

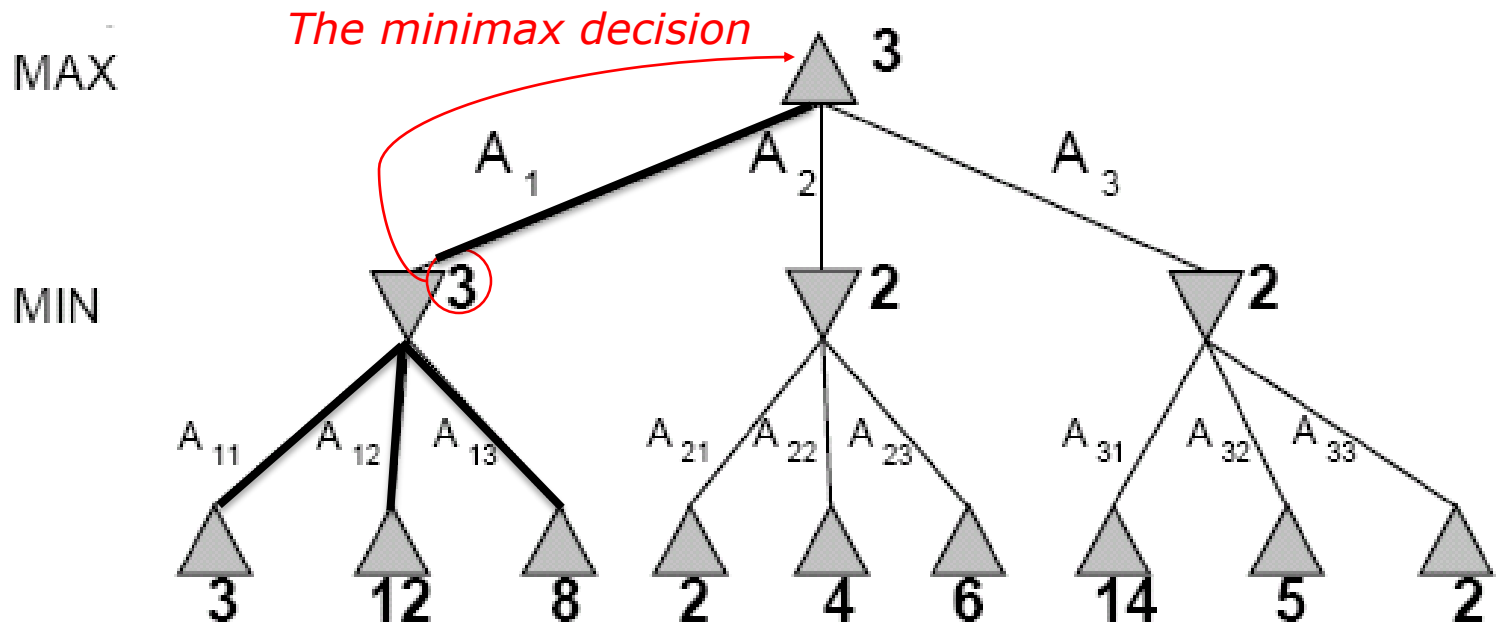


Two-Ply Game Tree



Two-Ply Game Tree

Minimax maximizes the utility for the worst-case outcome for max



A solution tree is highlighted

Properties of minimax

- **Complete?**
  - Yes (if tree is finite).
- **Optimal?**
  - Yes (against an optimal opponent).
  - Can it be beaten by an opponent playing sub-optimally?
    - No. (Why not?)
- **Time complexity?**
  - $O(b^m)$
- **Space complexity?**
  - 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 ≈ 5 legal actions per state on average, total of 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 quite reasonable**

- **Chess**
  - b ≈ 35 (approximate average branching factor)
  - d ≈ 100 (depth of game tree for "typical" game)
  - $b^d \approx 35^{100} \approx 10^{154}$ nodes!!
  - → **exact solution completely infeasible**

- **It is usually impossible to develop the whole search tree. Instead develop part of the tree up to some depth and evaluate leaves using an evaluation fn**
- **Optimal strategy (solution tree) too large to store.**

Static (Heuristic) Evaluation Functions

- **An Evaluation Function:**
  - Estimates how good the current board configuration is for a player.
  - Typically, one figures how good it is for the player, and how good it is for the opponent, and subtracts the opponents score from the player.
  - Othello: Number of white pieces - Number of black pieces
  - Chess: Value of all white pieces - Value of all black pieces
- **Typical values from -infinity (loss) to +infinity (win) or [-1, +1].**
- **If the board evaluation is X for a player, it's -X for the opponent**
- **Example:**
  - Evaluating chess boards,
  - Checkers
  - Tic-tac-toe

Applying MiniMax to tic-tac-toe

- **The static evaluation function heuristic**

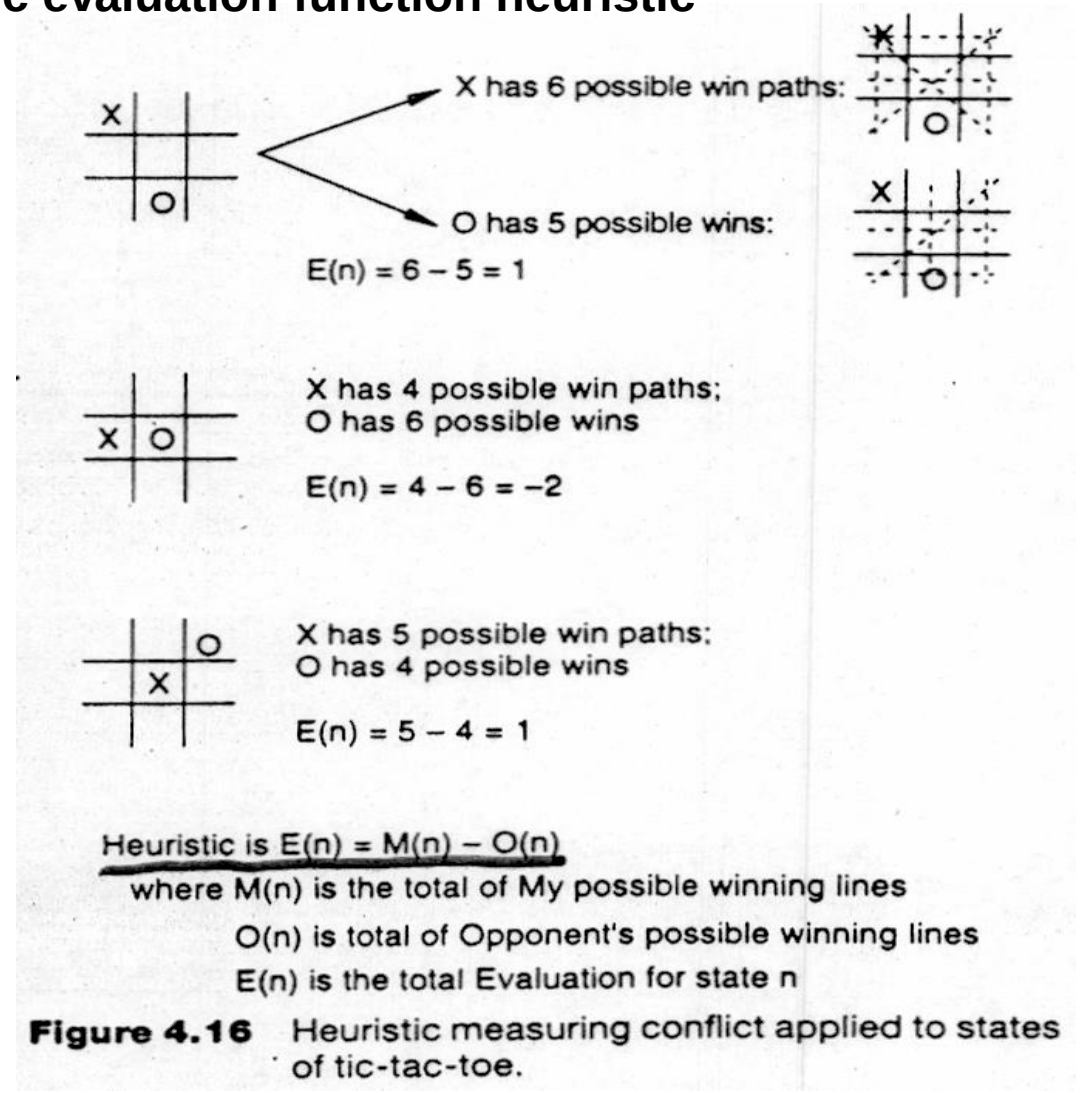


Figure 4.16 Heuristic measuring conflict applied to states of tic-tac-toe.

Backup Values

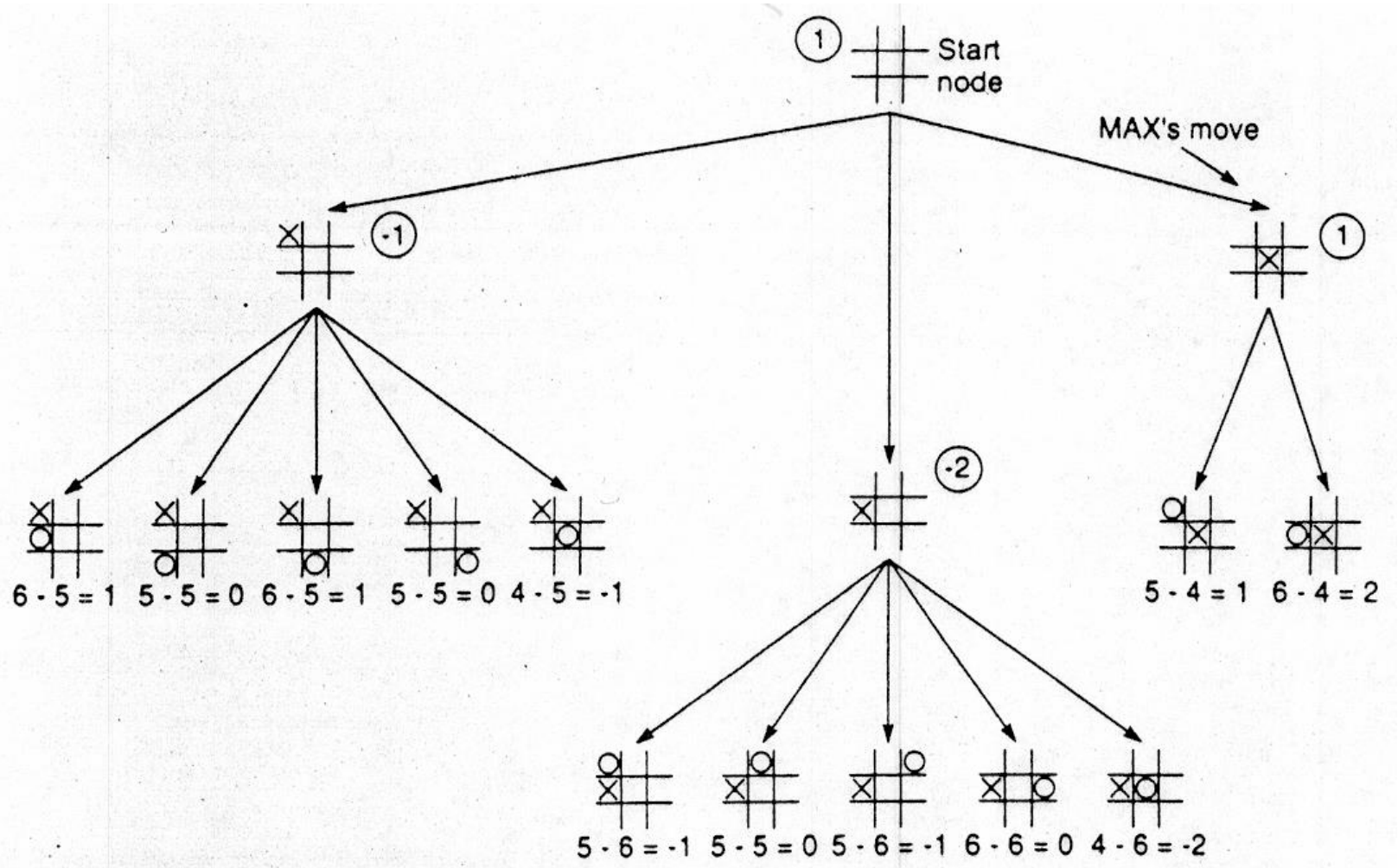


Figure 4.17 Two-ply minimax applied to the opening move of tic-tac-toe.

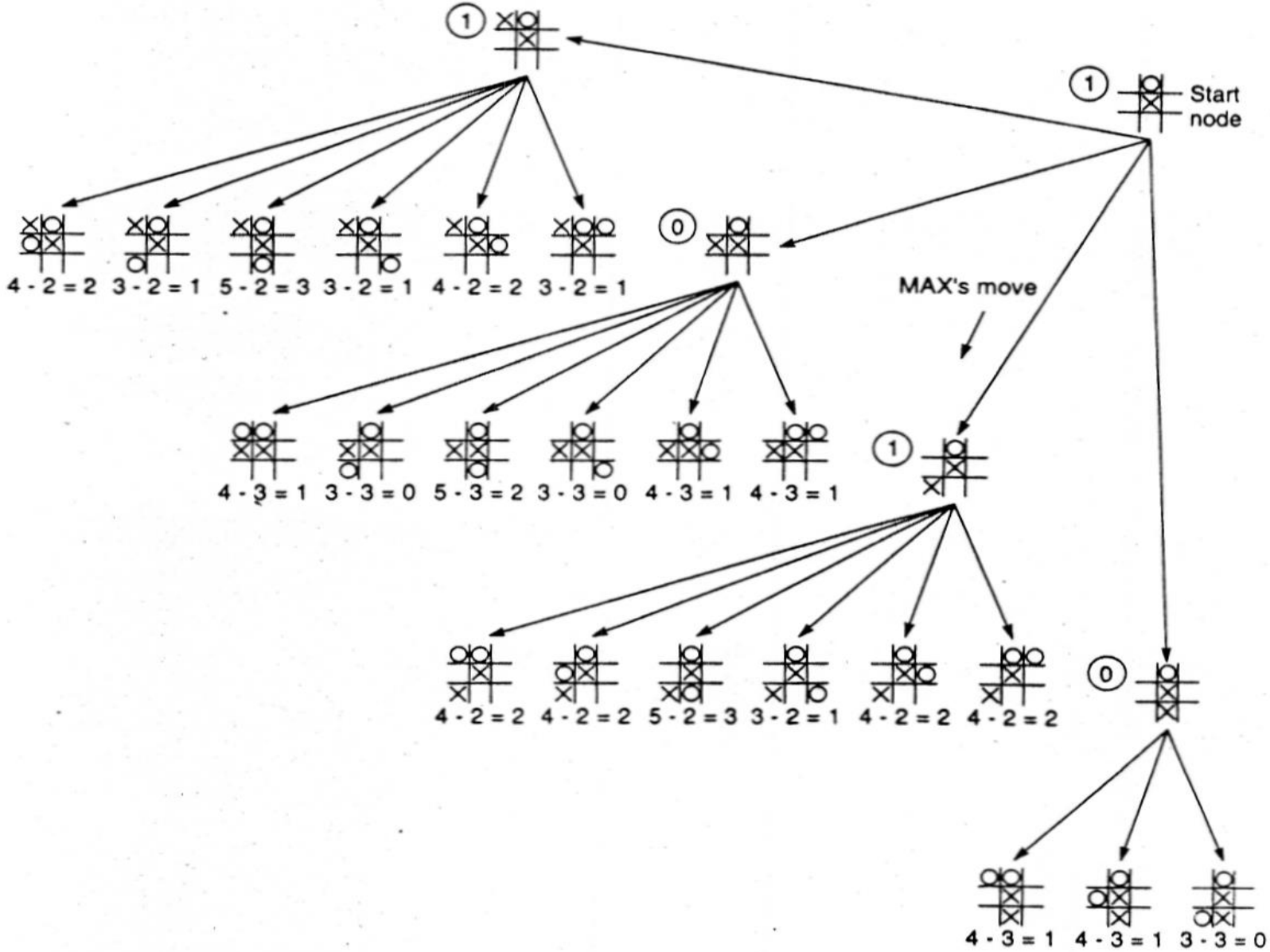


Figure 4.18 Two-ply minimax applied to X's second move of tic-tac-toe.

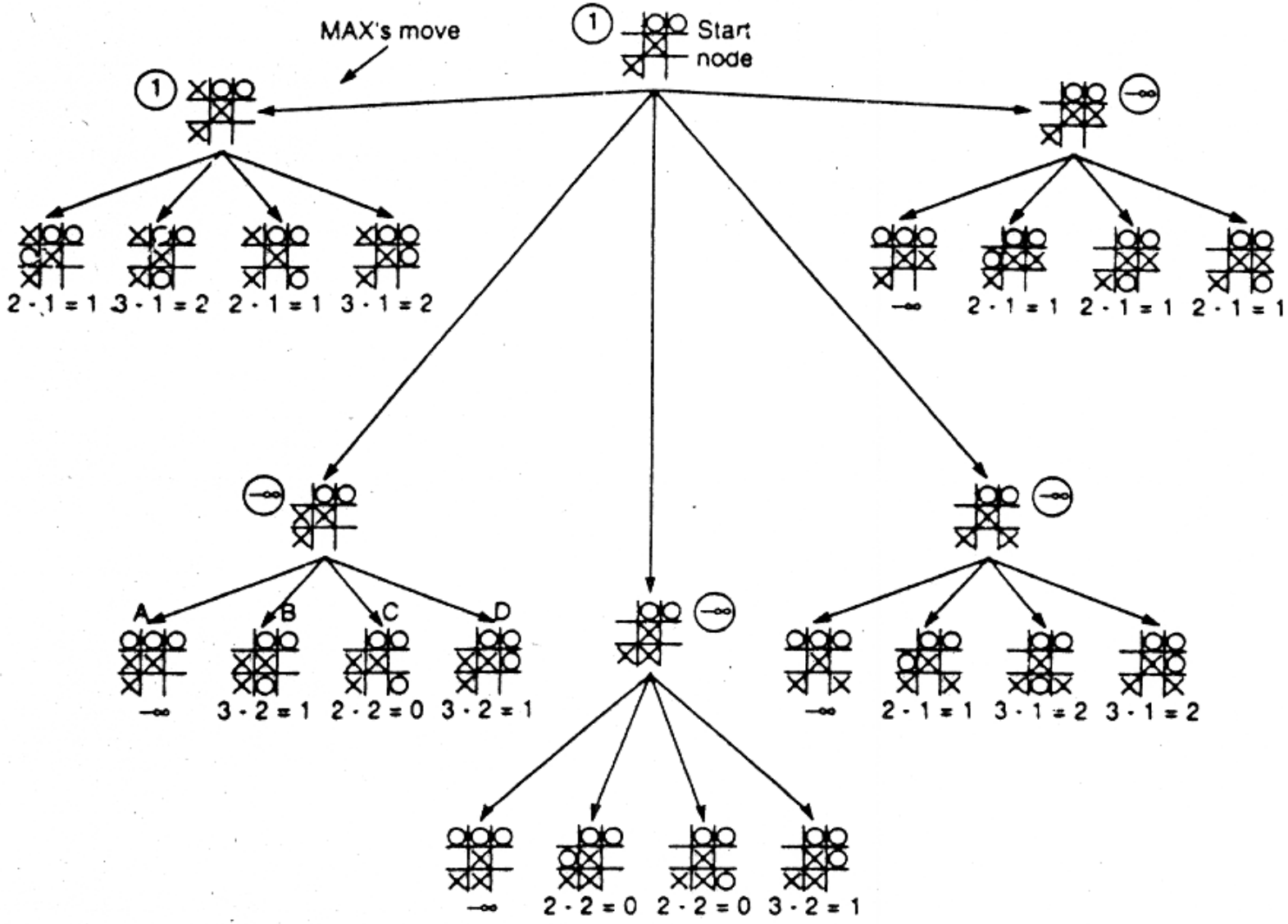
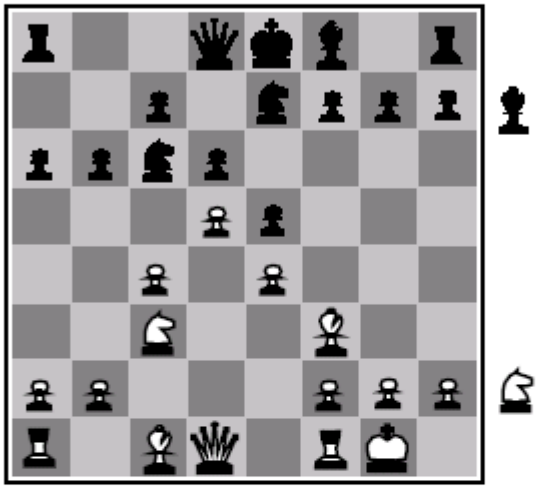


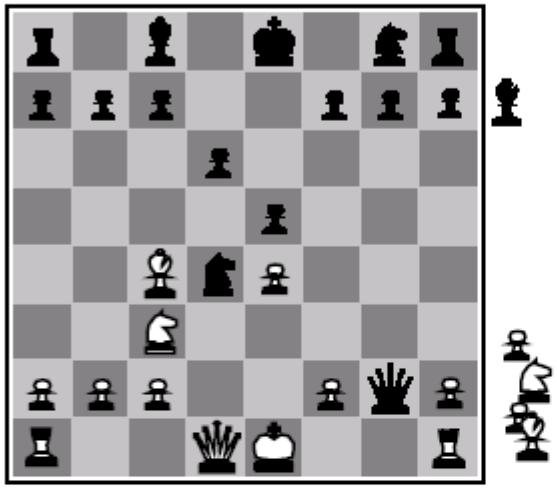
Figure 4.19 Two-ply minimax applied to **X**'s move near end game.

Evaluation functions



Black to move

White slightly better



White to move

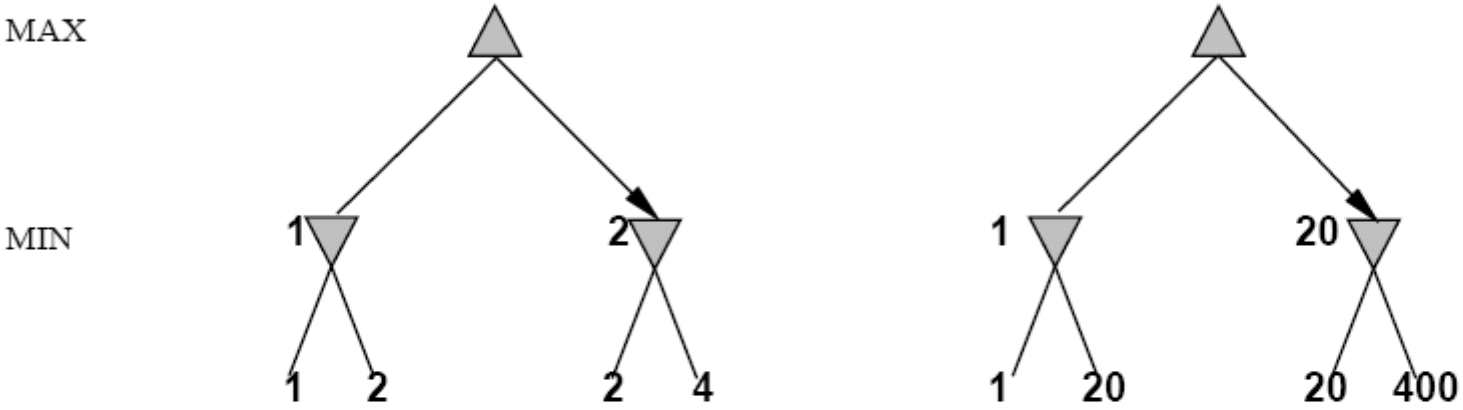
Black winning

For chess, typically *linear* weighted sum of features

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

e.g., $w_1 = 9$ with
$f_1(s) =$ (number of white queens) – (number of black queens), etc.

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

Alpha-Beta Pruning
Exploiting the Fact of an Adversary

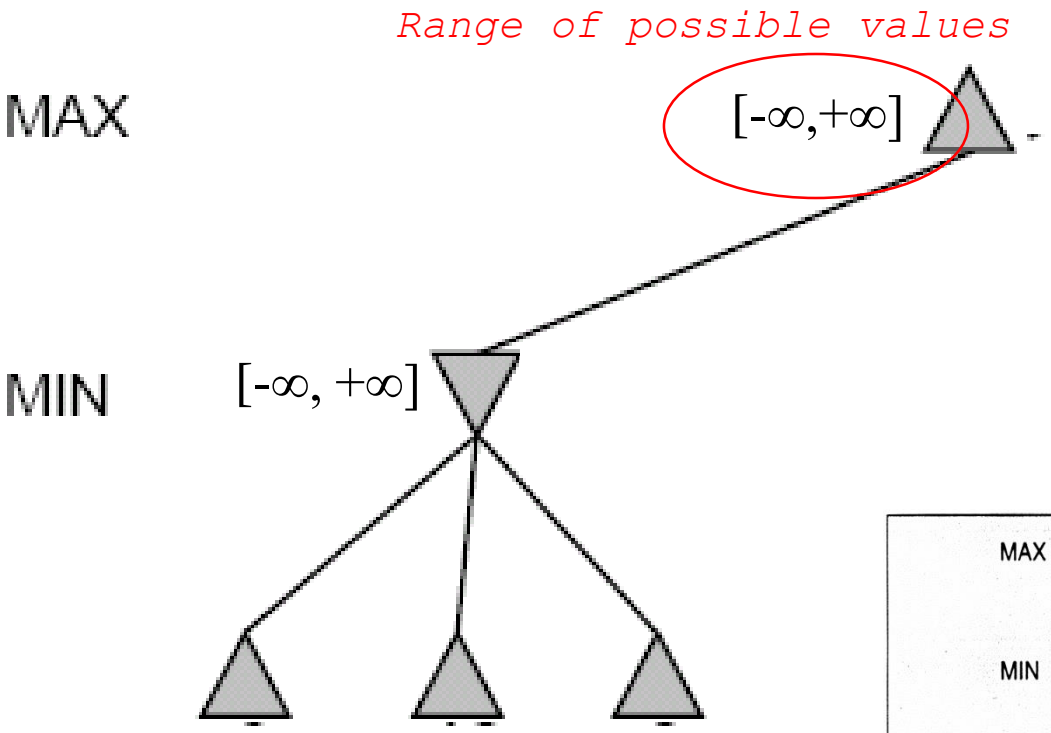
- **If a position is provably bad:**
  - It is NO USE expending search time to find out exactly how bad, if you have a better alternative
- **If the adversary can force a bad position:**
  - It is NO USE expending search time to find out the good positions that the adversary won't let you achieve anyway
- **Bad = not better than we already know we can achieve elsewhere.**
- **Contrast normal search:**
  - ANY node might be a winner.
  - ALL nodes must be considered.
  - (A* avoids this through knowledge, i.e., heuristics)

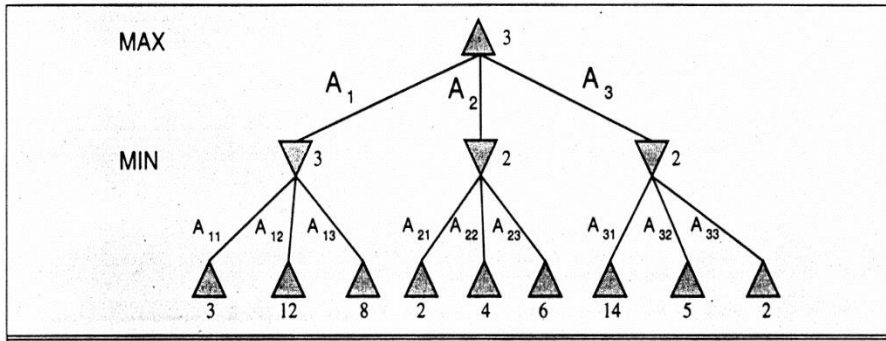
Alpha Beta Procedure

- **Idea:**
  - Do depth first search to generate partial game tree,
  - Give static evaluation function to leaves,
  - Compute bound on internal nodes.
- **α, β bounds:**
  - α value for max node means that max real value is at least α.
  - β for min node means that min can guarantee a value no more than β.
- **Computation:**
  - α of MAX node is the max of children seen.
  - β of MIN node is the min of children seen.
  - Update α/β when backup values are propagated.

Alpha-Beta Example

Do DF-search until first leaf





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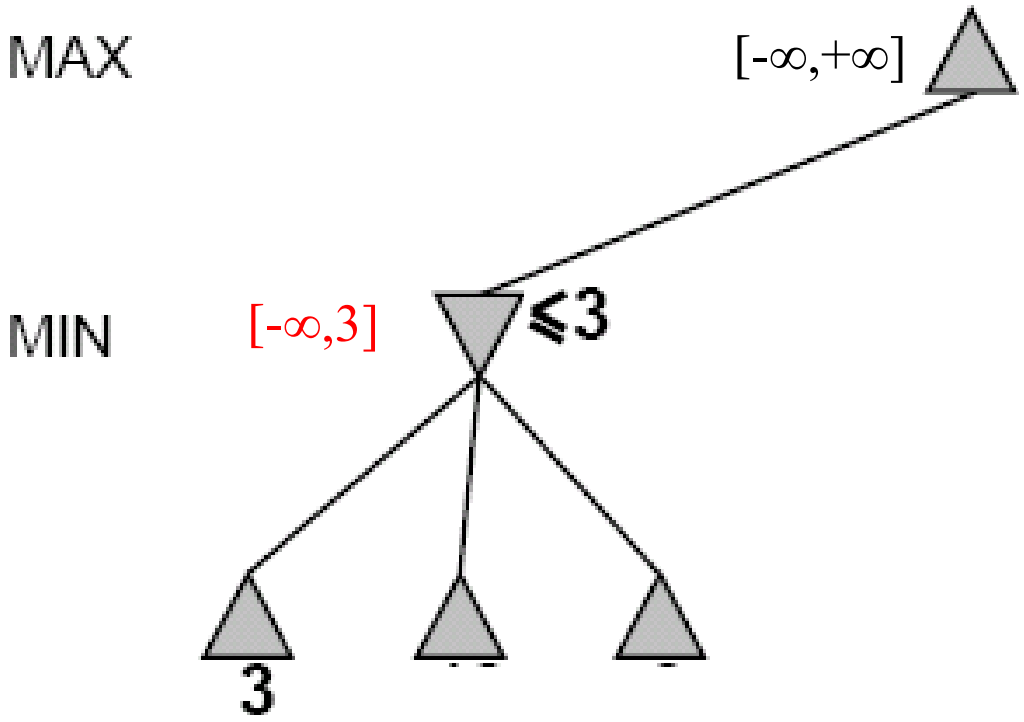
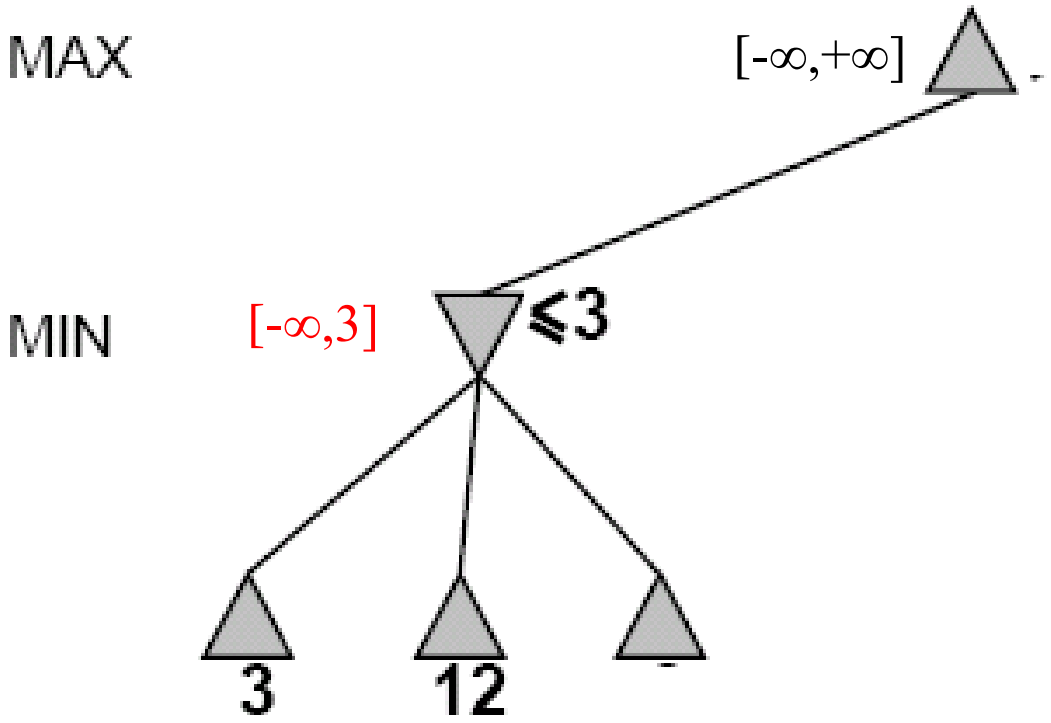
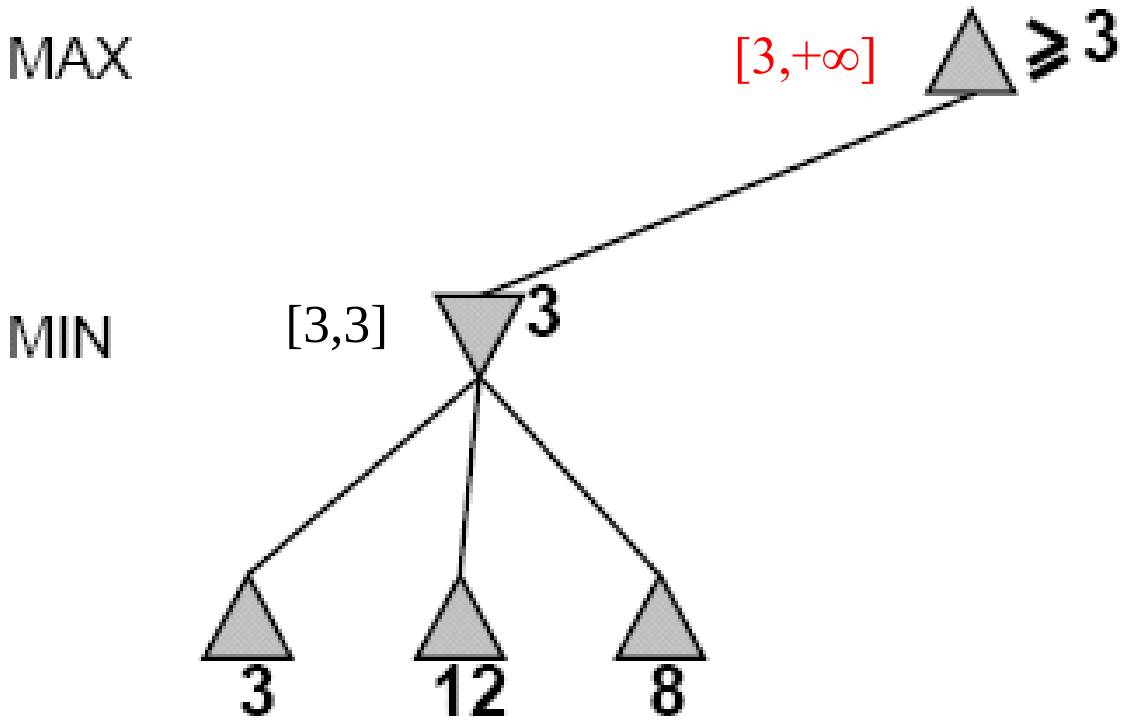


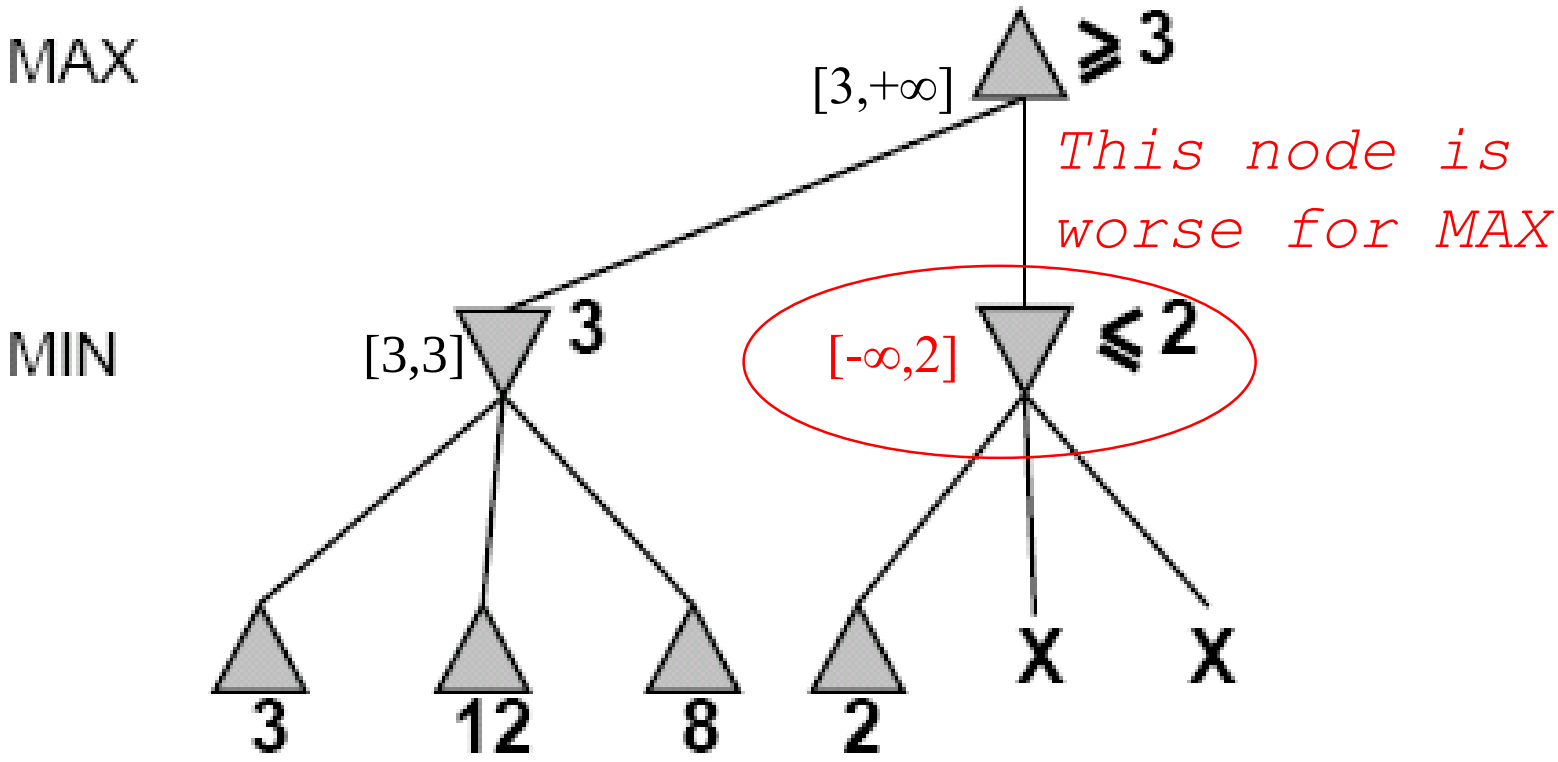
Alpha-Beta Example (continued)



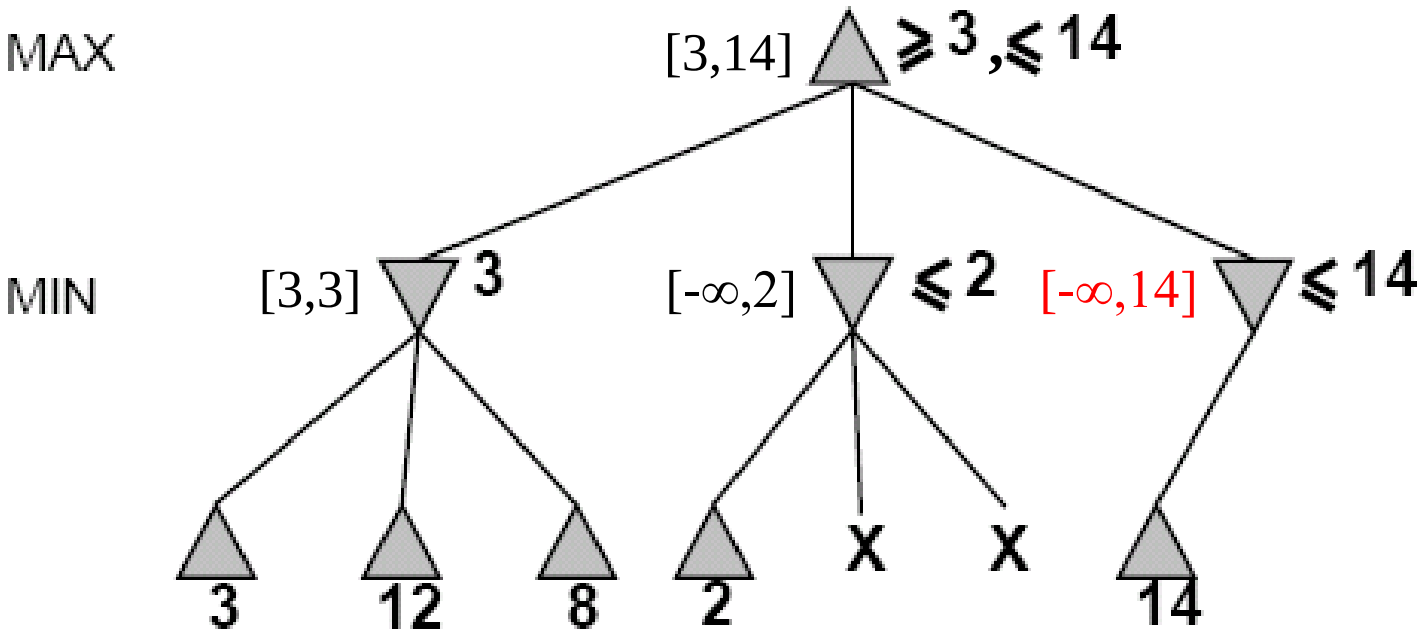
Alpha-Beta Example (continued)



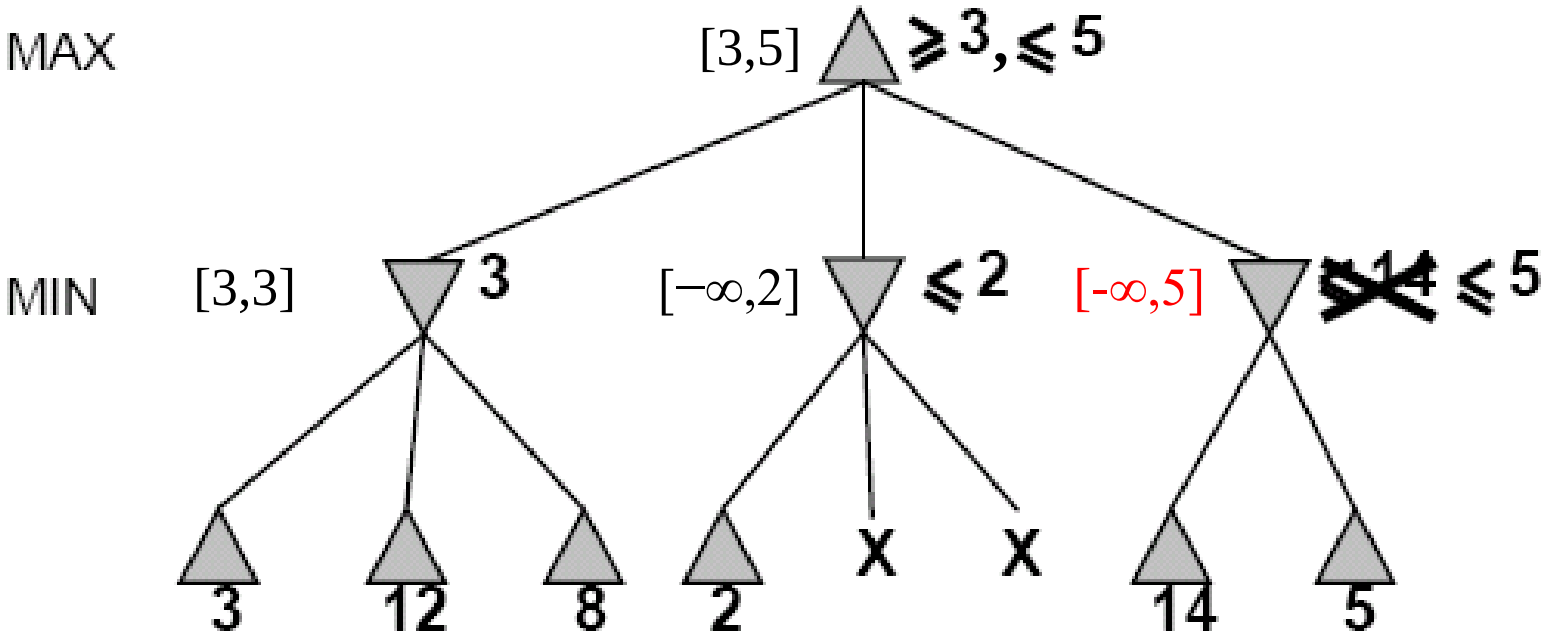
Alpha-Beta Example (continued)



Alpha-Beta Example (continued)



Alpha-Beta Example (continued)



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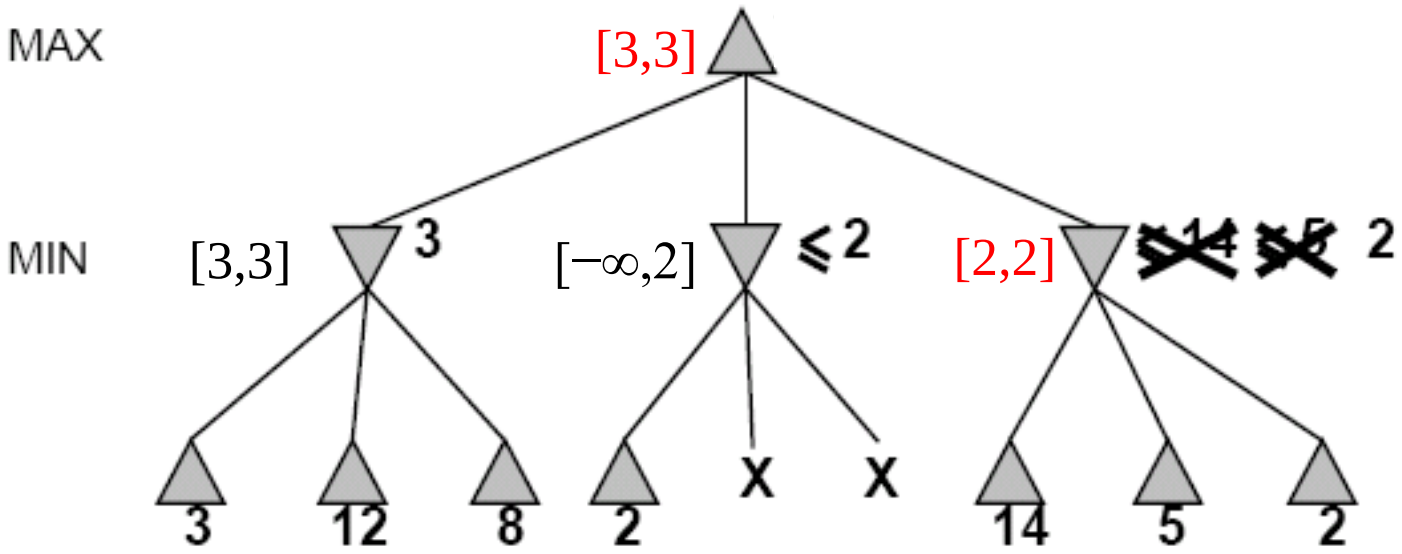

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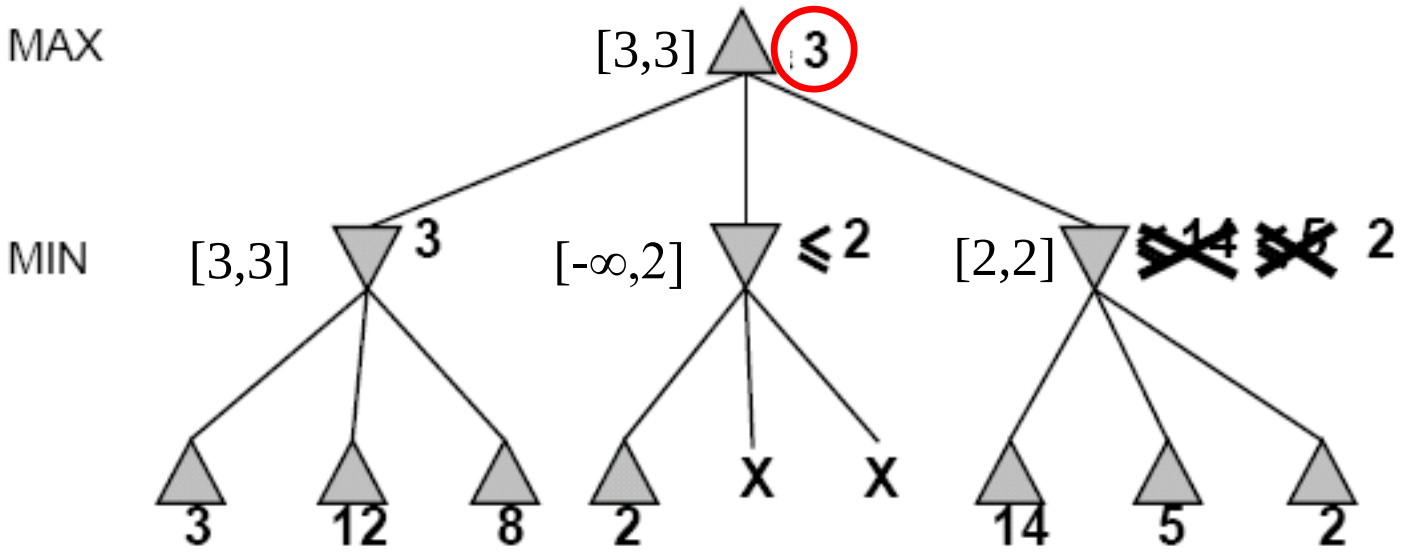


Tic-Tac-Toe Example with Alpha-Beta Pruning

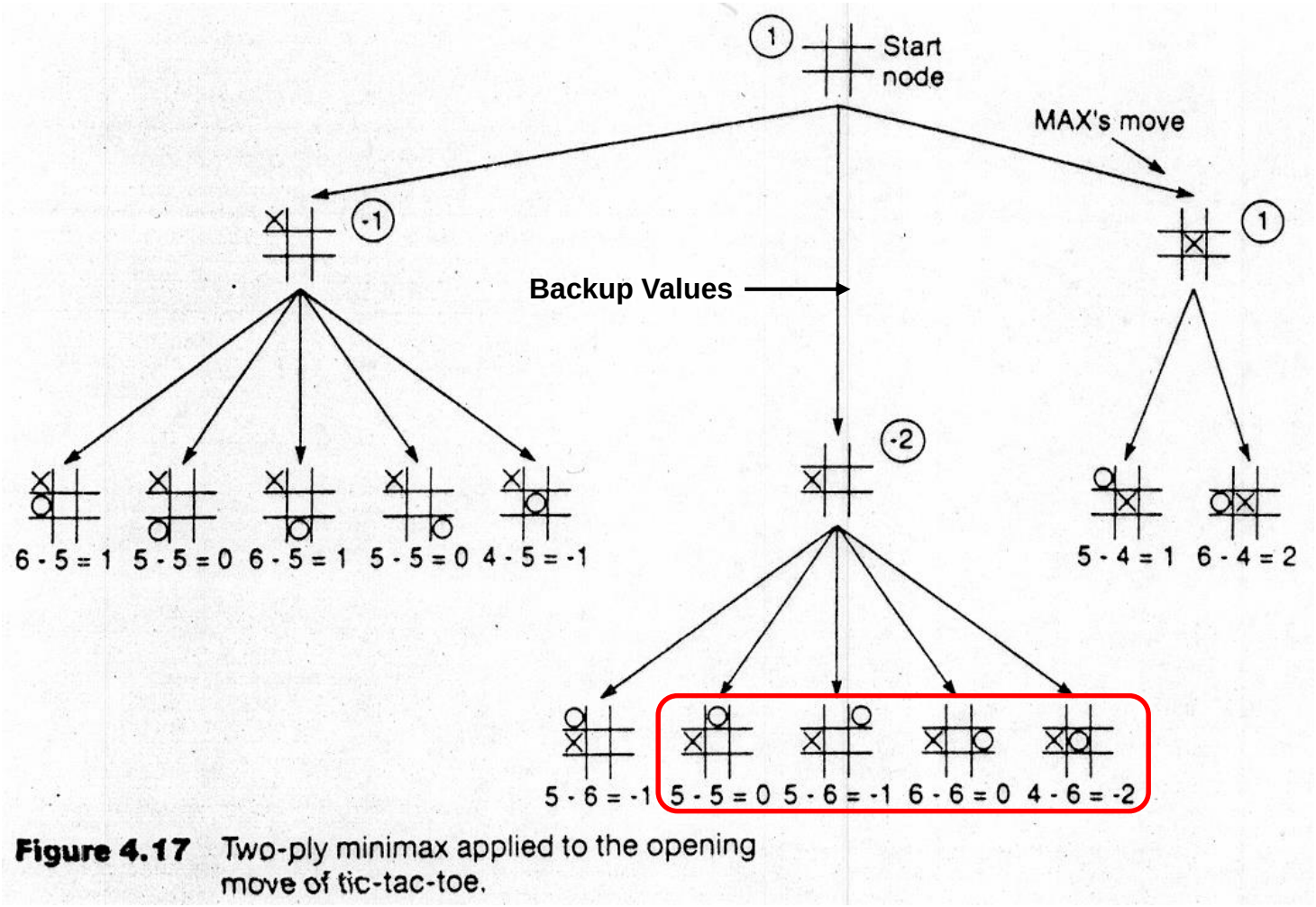


Figure 4.17 Two-ply minimax applied to the opening move of tic-tac-toe.

Alpha-beta Algorithm

- **Depth first search**
  - only considers nodes along a single path from root at any time

α = highest-value choice found at any choice point of path for MAX
(initially, α = −infinity)

β = lowest-value choice found at any choice point of path for MIN
(initially, β = +infinity)

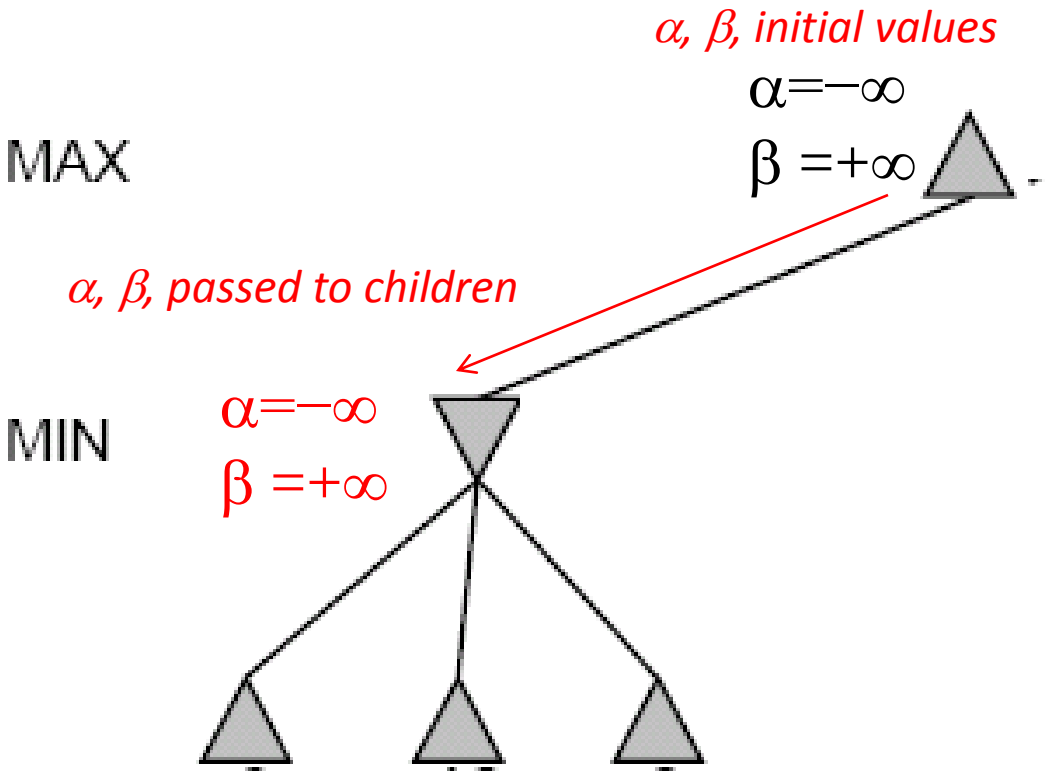
- **Pass current values of α and β down to child nodes during search.**
- **Update values of α and β during search:**
  - MAX updates α at MAX nodes
  - MIN updates β at MIN nodes
- **Prune remaining branches at a node when $\alpha \geq \beta$**

When to Prune

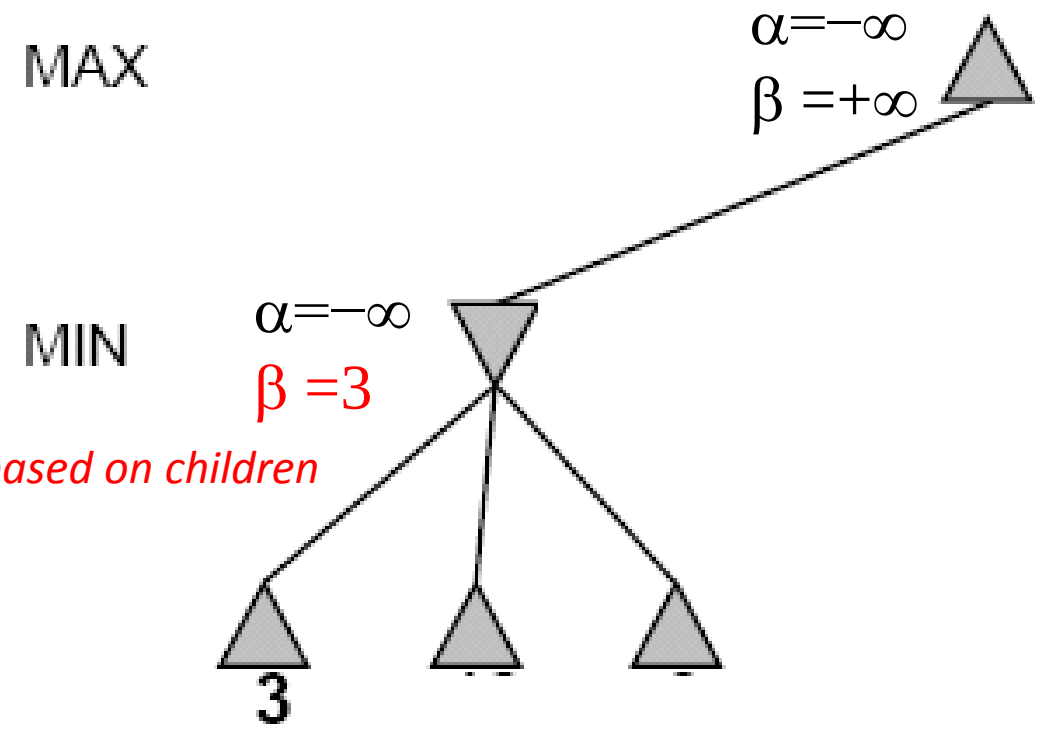
- **Prune whenever $\alpha \geq \beta$.**
  - Prune below a Max node whose alpha value becomes greater than or equal to the beta value of its ancestors.
    - **Max nodes update alpha** based on children's returned values.
  - Prune below a Min node whose beta value becomes less than or equal to the alpha value of its ancestors.
    - **Min nodes update beta** based on children's returned values.

Alpha-Beta Example Revisited

Do DF-search until first leaf

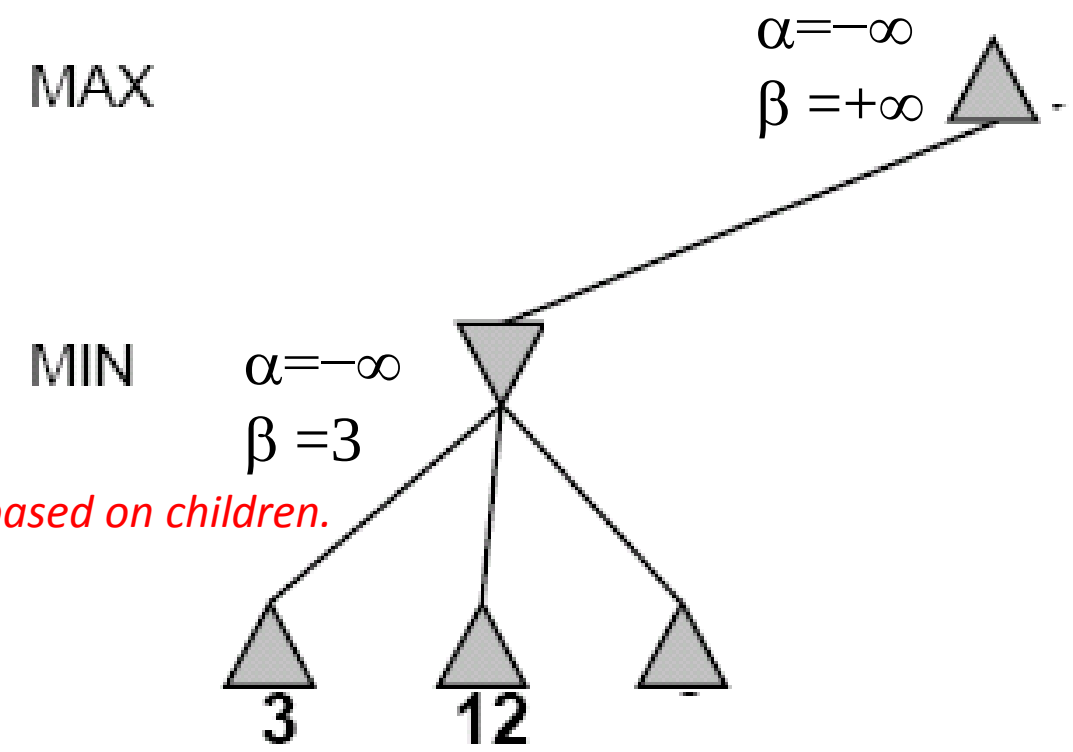


Alpha-Beta Example (continued)



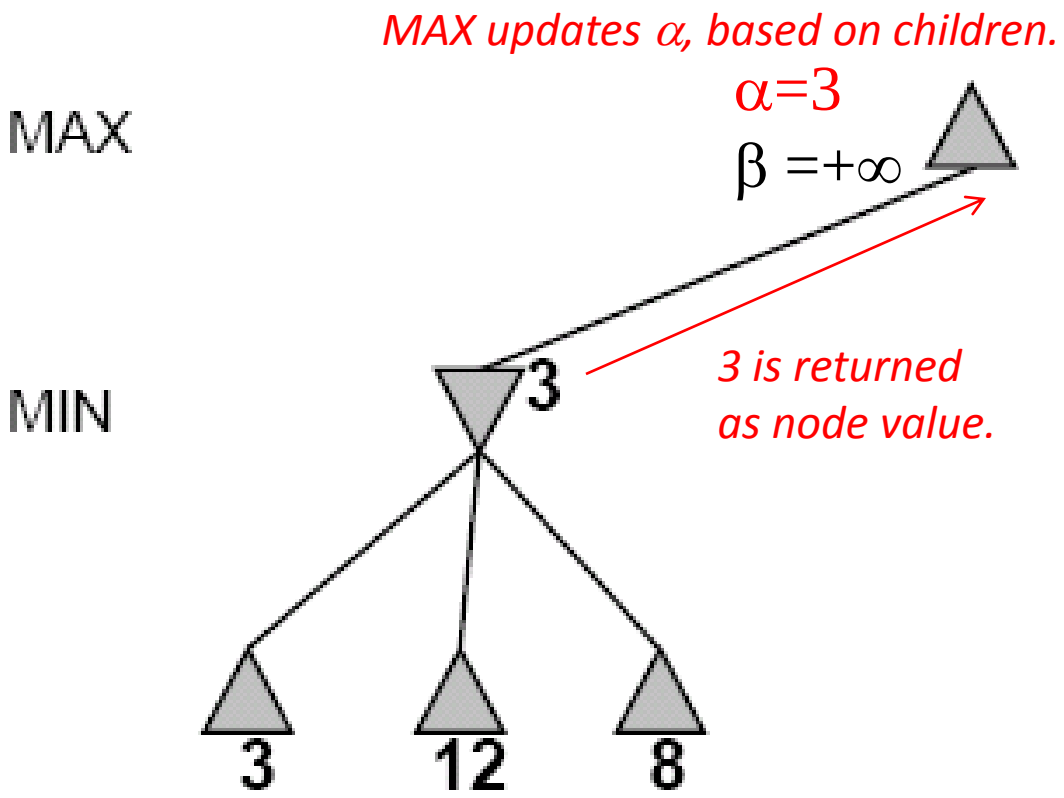
MIN updates β, based on children

Alpha-Beta Example (continued)



MIN updates β, based on children.
No change.

Alpha-Beta Example (continued)



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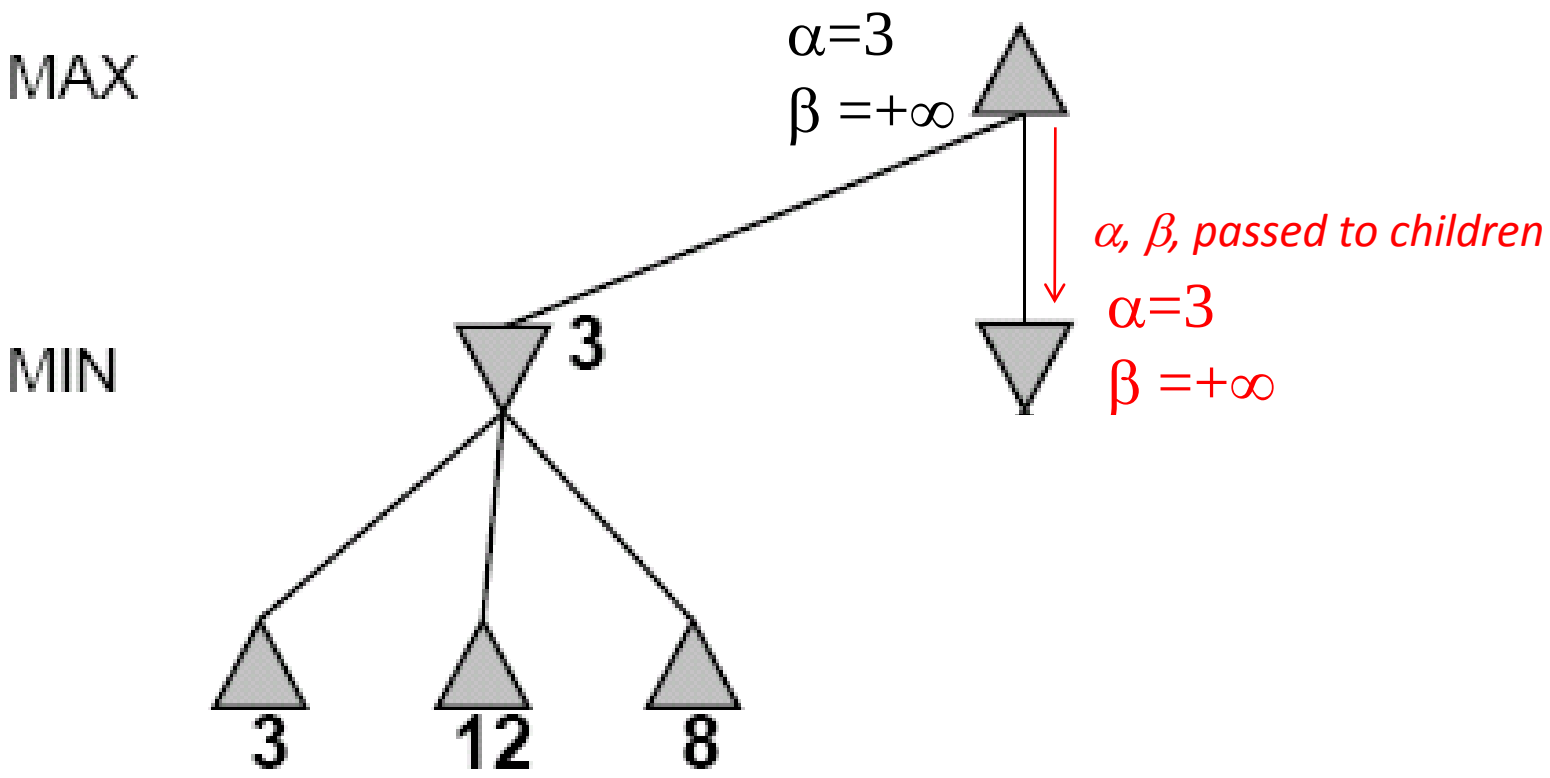

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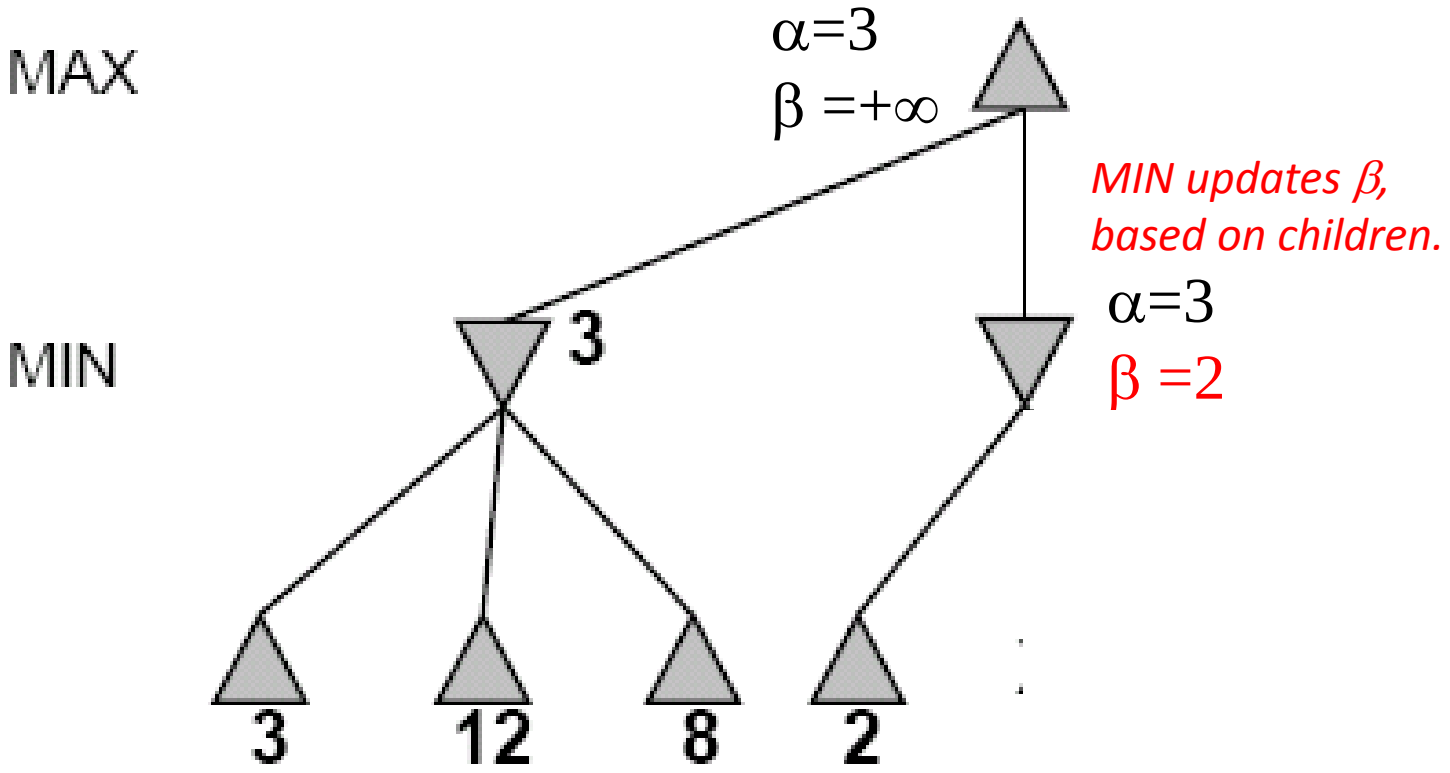

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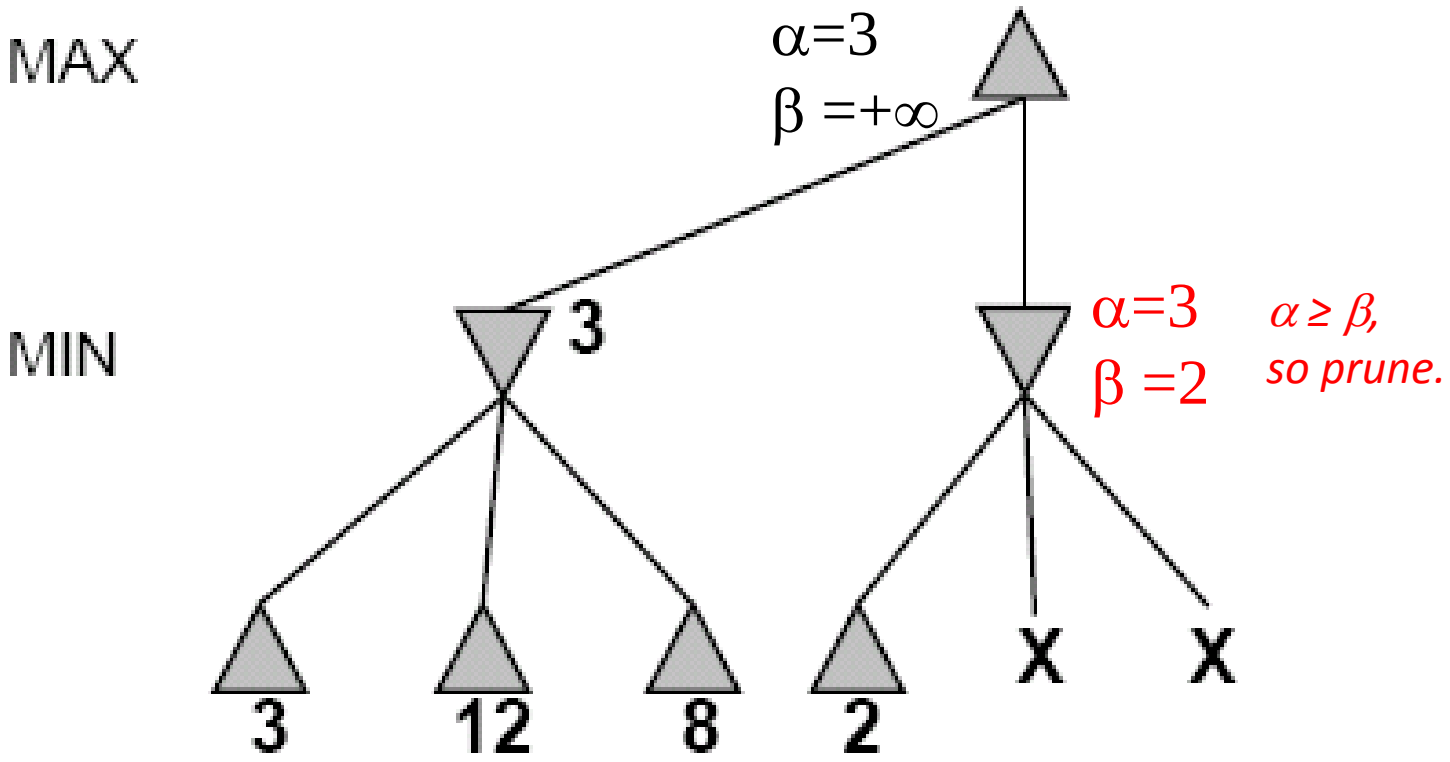

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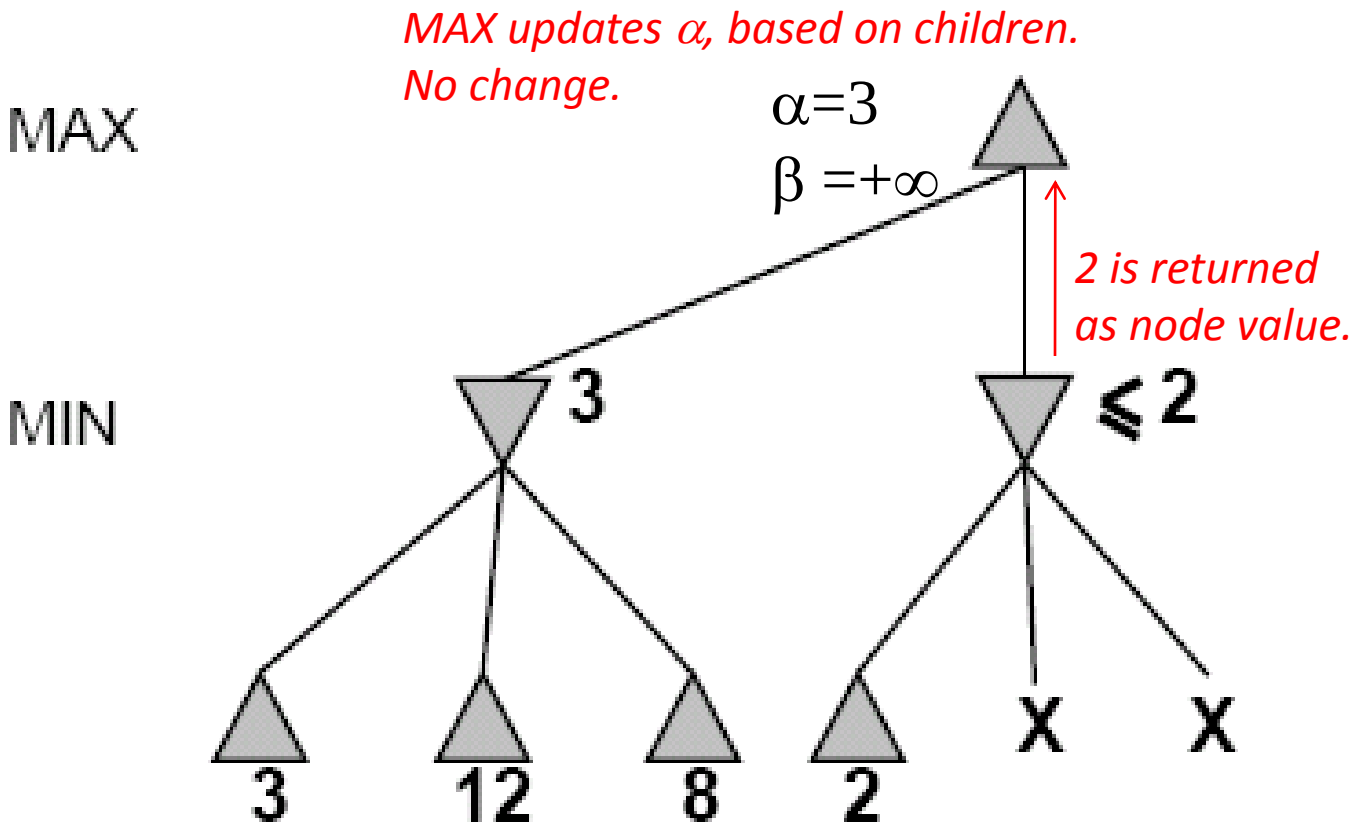

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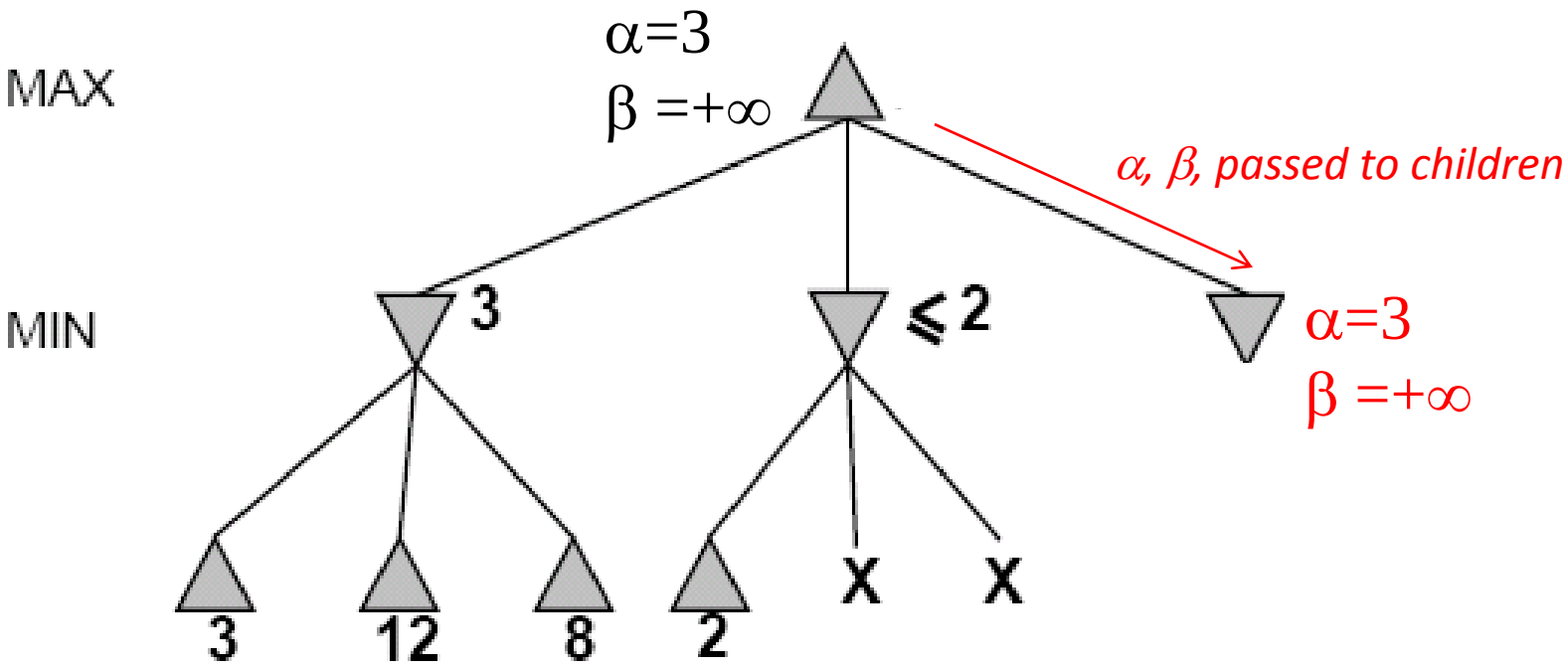

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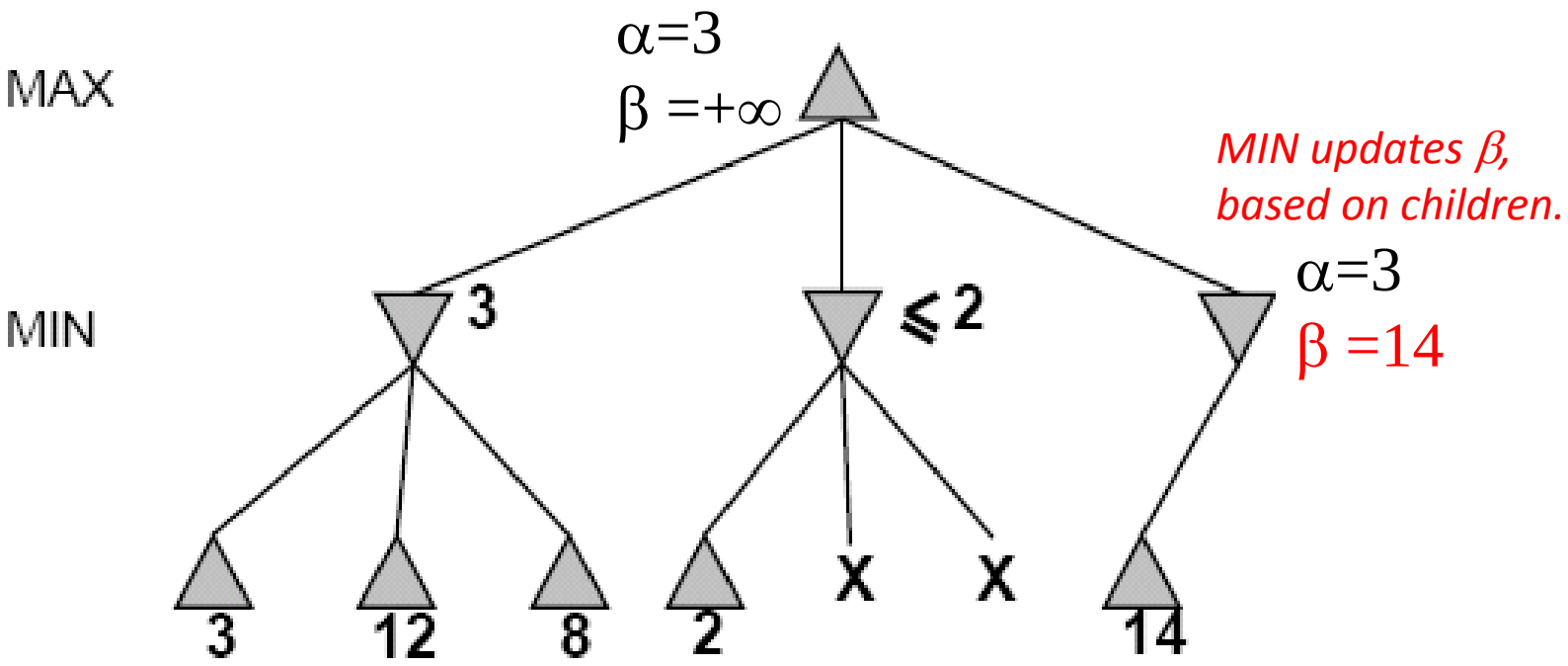

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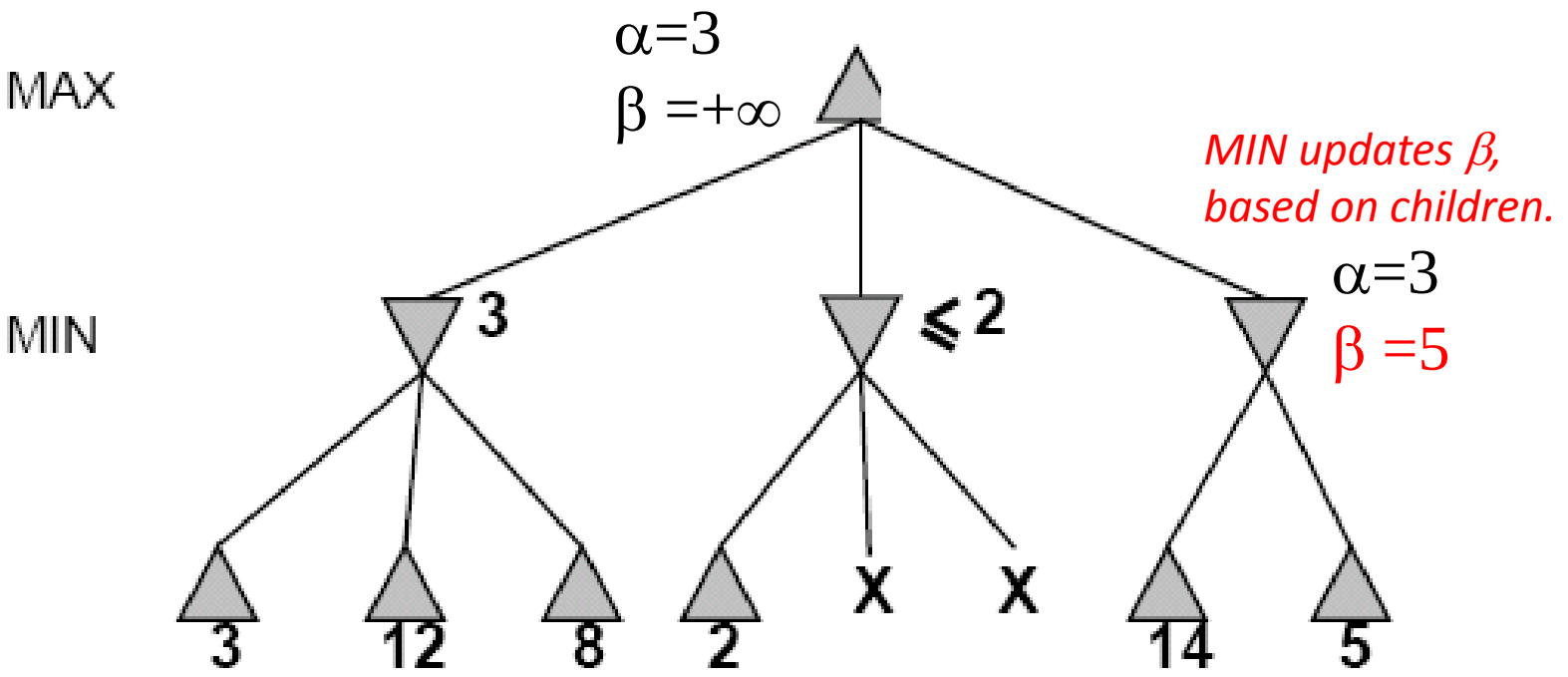

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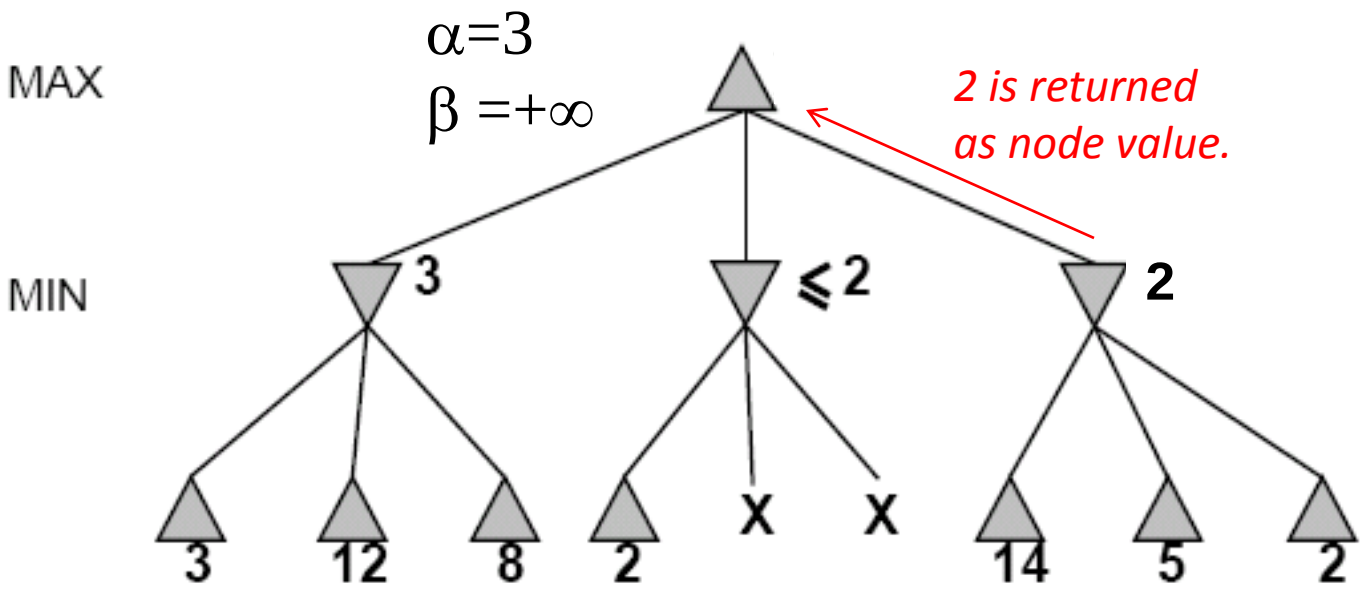
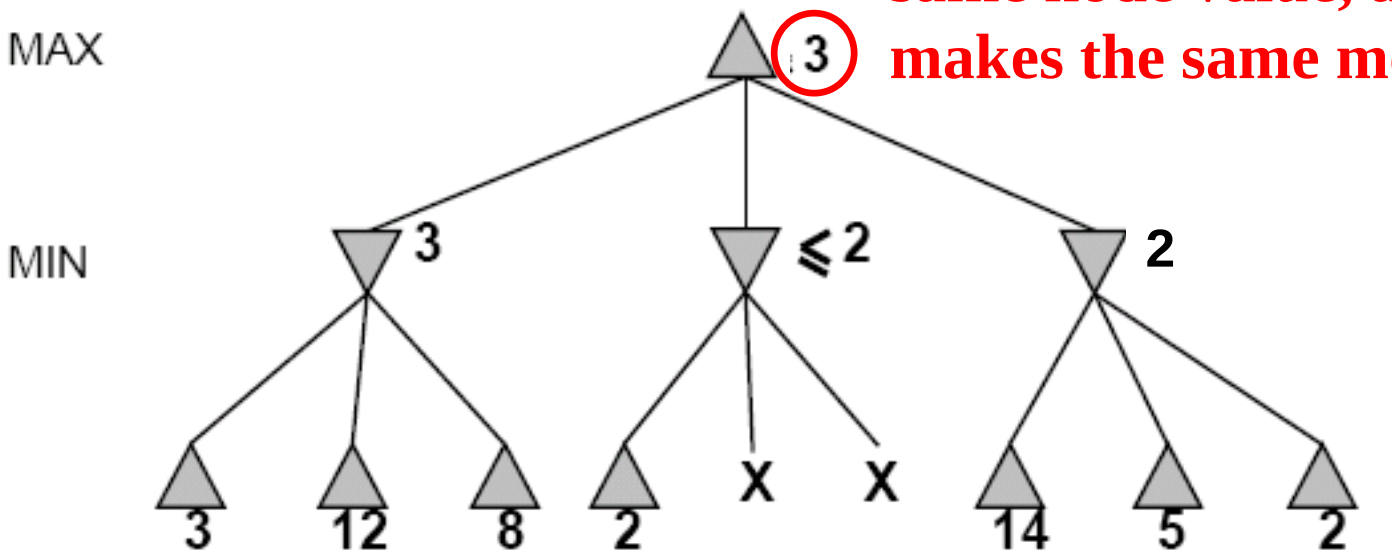


Alpha-Beta Example (continued)



Max calculates the same node value, and makes the same move!

Alpha Beta Practical Implementation

- **Idea:**
  - Do depth first search to generate partial game tree
  - Cutoff test :
    - Depth limit
    - Iterative deepening
    - Cutoff when no big changes (quiescent search)
  - When cutoff, apply static evaluation function to leaves
  - Compute bound on internal nodes.
  - Run α-β pruning using estimated values

Effectiveness of Alpha-Beta Search

- **Worst-Case**
  - Branches are ordered so that no pruning takes place. In this case alpha-beta gives no improvement over exhaustive search

- **Best-Case**
  - Each player's best move is the left-most alternative (i.e., evaluated first)
  - In practice, performance is closer to best rather than worst-case
    - E.g., sort moves by the remembered move values found last time.
    - E.g., expand captures first, then threats, then forward moves, etc.
    - E.g., run Iterative Deepening search, sort by value last iteration.

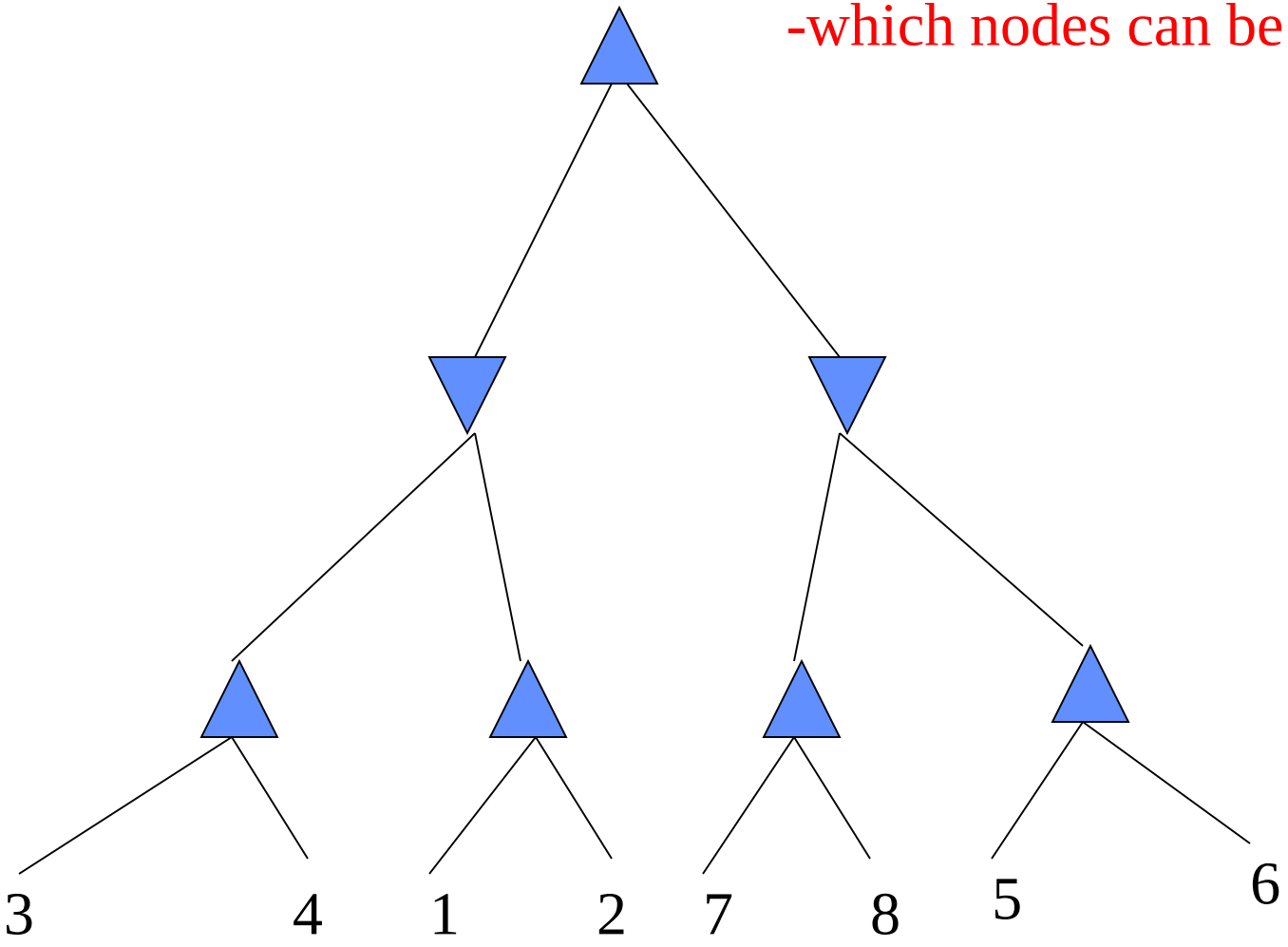
- **Alpha/beta best case is $O(b^{(d/2)})$ rather than $O(b^d)$**
  - This is the same as having a branching factor of sqrt(b),
    - $(\text{sqrt}(b))^d = b^{(d/2)}$ (i.e., we have effectively gone from b to square root of b)
  - In chess go from b ~ 35 to b ~ 6
    - permitting much deeper search in the same amount of time
  - In practice it is often $b^{(2d/3)}$

Final Comments about Alpha-Beta Pruning

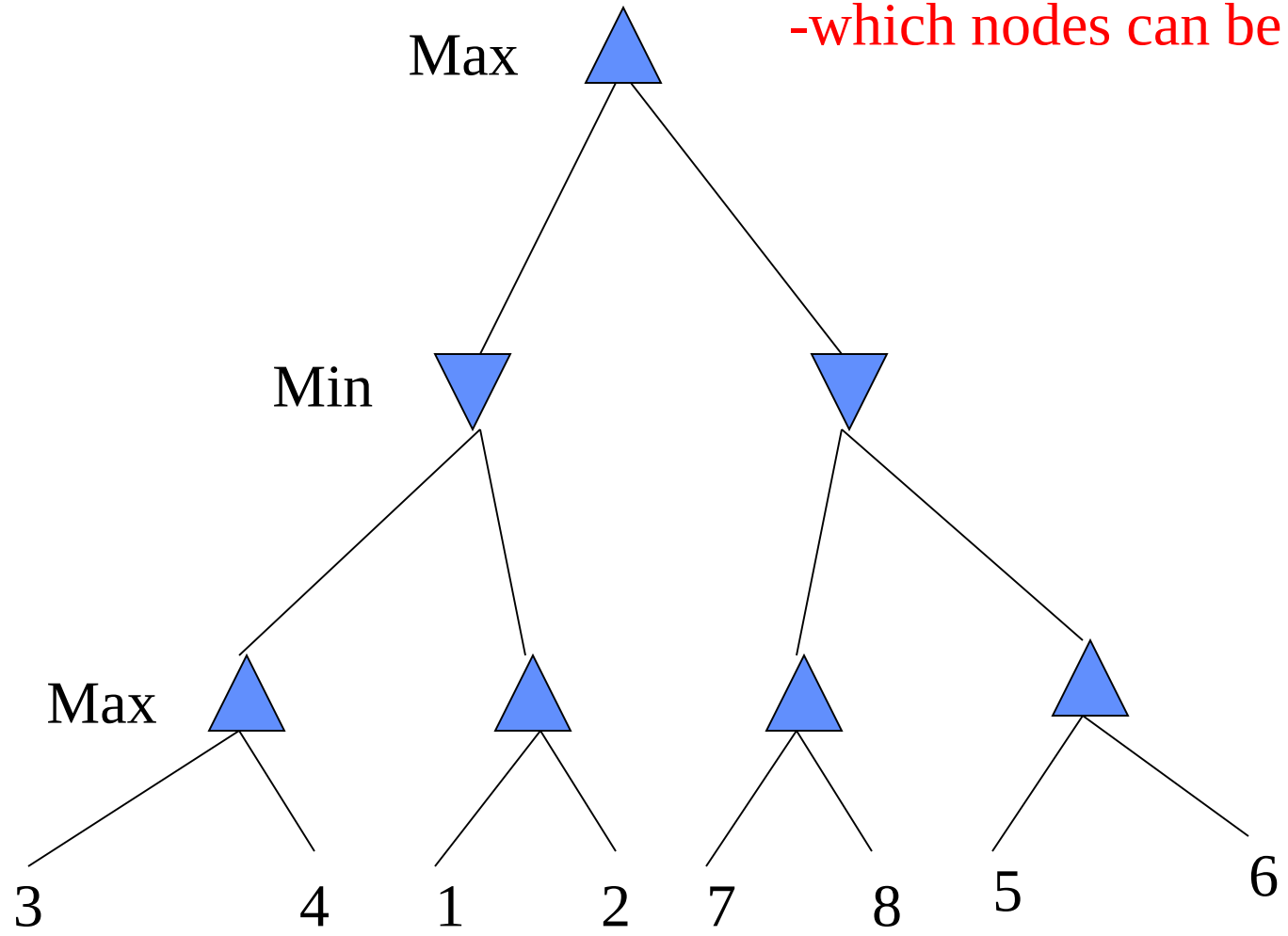
- **Pruning does not affect final results**
- **Entire subtrees can be pruned.**
- **Good move *ordering* improves effectiveness of pruning**
- **Repeated states are again possible.**
  - Store them in memory = transposition table
  - Even in depth-first search we can store the result of an evaluation in a hash table of previously seen positions. Like the notion of "explored" list in graph-search

Example

-which nodes can be pruned?



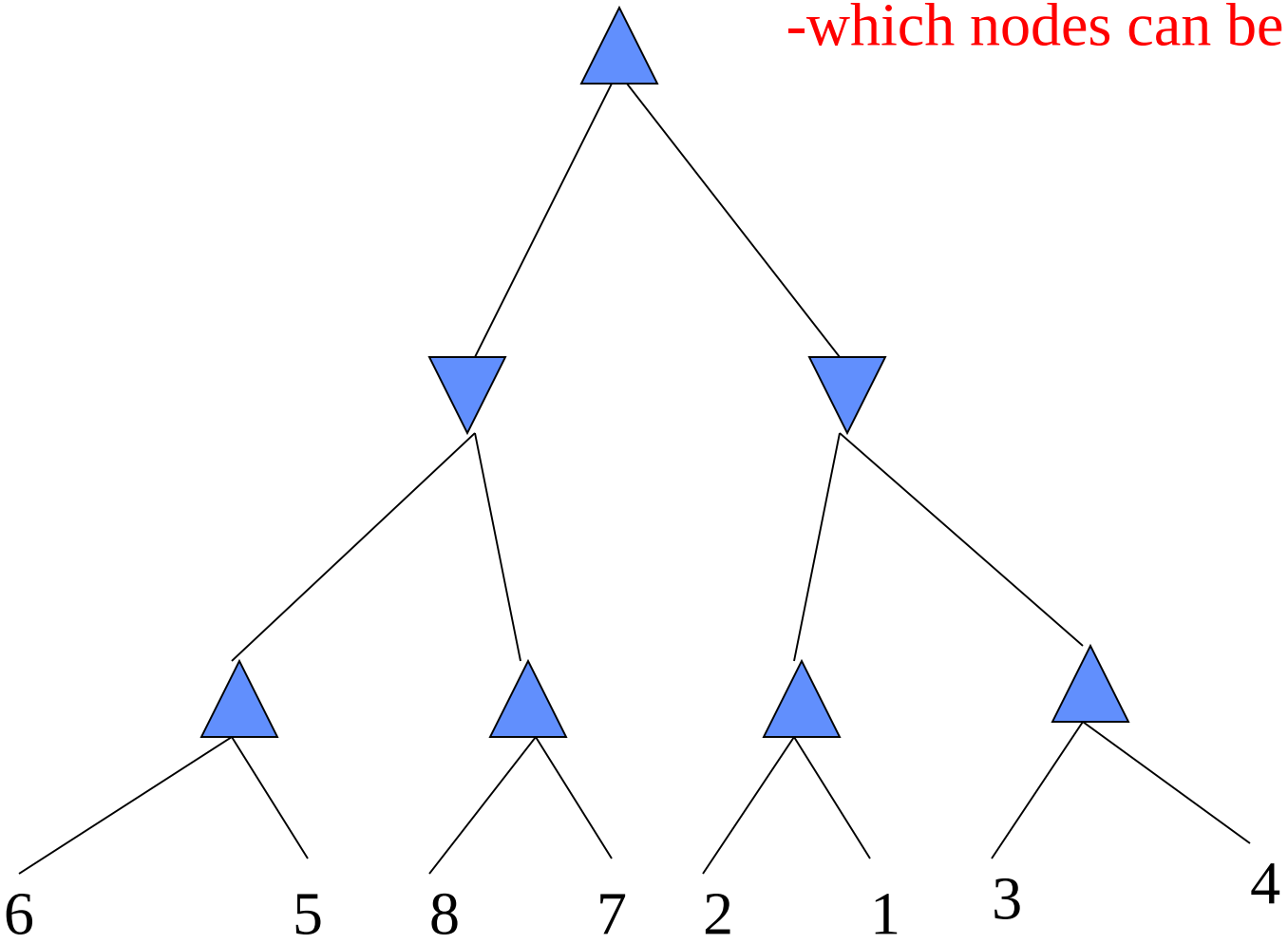
Answer to Example



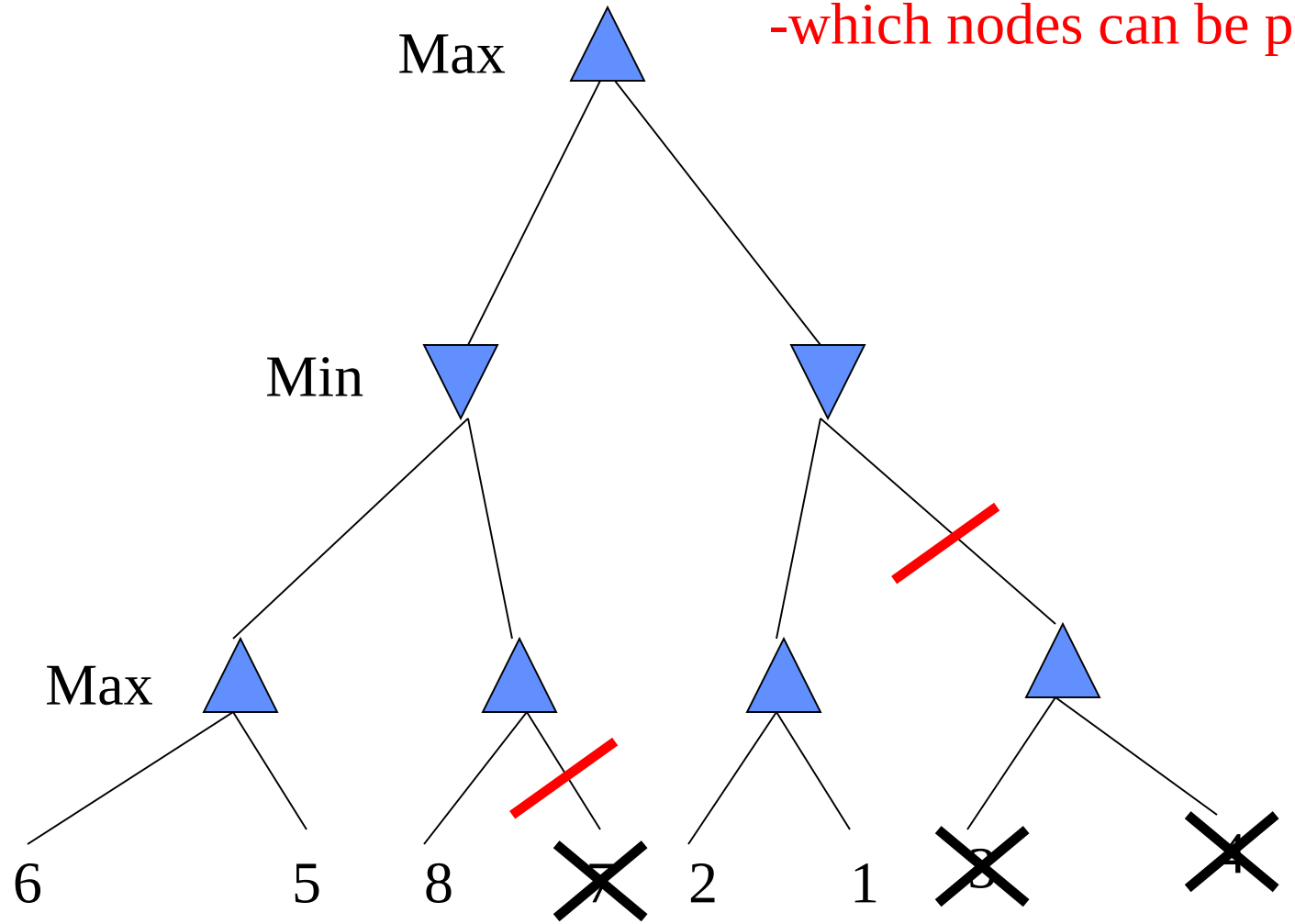
Answer: NONE! Because the most favorable nodes for both are explored last (i.e., in the diagram, are on the right-hand side).

Second Example
(the exact mirror image of the first example)

-which nodes can be pruned?



Answer to Second Example
(the exact mirror image of the first example)



Answer: LOTS! Because the most favorable nodes for both are explored first (i.e., in the diagram, are on the left-hand side).

Heuristics and Game Tree Search: limited horizon

- **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"
  - push unavoidable large neg events "over" the horizon at additional cost

- **Heuristics for Tree Exploration**
  - it may be better to explore some branches more deeply in the allotted time
  - various heuristics exist to identify "promising" branches
- **Search versus lookup tables**
  - (e.g., chess endgames)

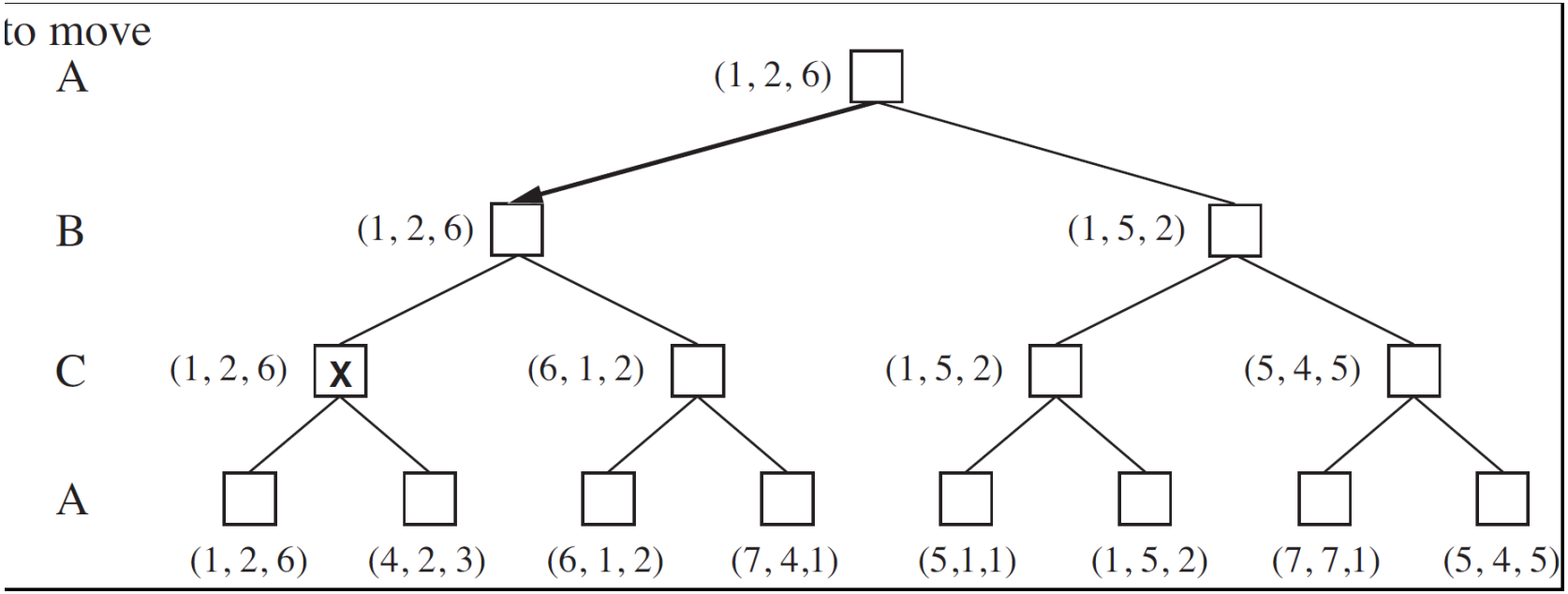
Iterative (Progressive) Deepening

- **In real games, there is usually a time limit T on making a move**

- **How do we take this into account?**
- **Using alpha-beta we cannot use "partial" results with any confidence unless the full breadth of the tree has been searched**
  - So, we could be conservative and set a conservative depth-limit which guarantees that we will find a move in time < T
    - disadvantage is that we may finish early, could do more search

- **In practice, iterative deepening search (IDS) is used**
  - IDS runs depth-first search with an increasing depth-limit
  - when the clock runs out we use the solution found at the previous depth limit

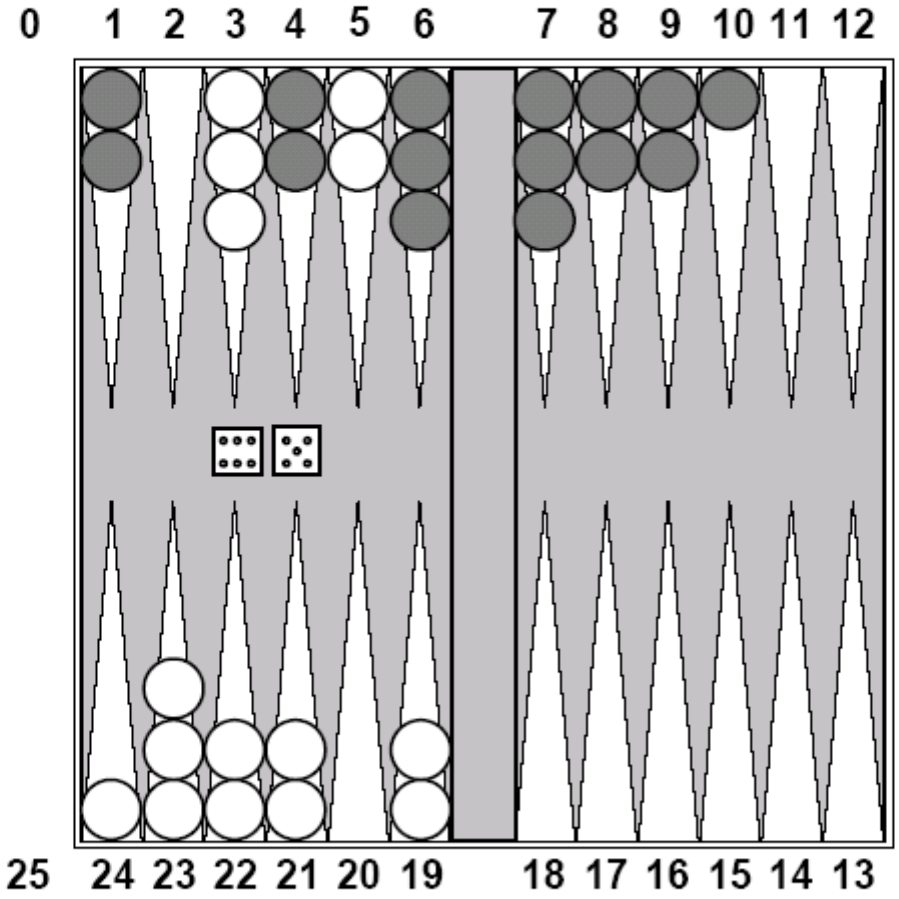
Multiplayer Games



- Multiplayer games often involve alliances: If A and B are in a weak position they can collaborate and act against C

- If games are not zero-sum, collaboration can also occur in two-game plays: if (1000,1000_ Is a best payoff for both, then they will cooperate towards getting there and not towards minimax value.

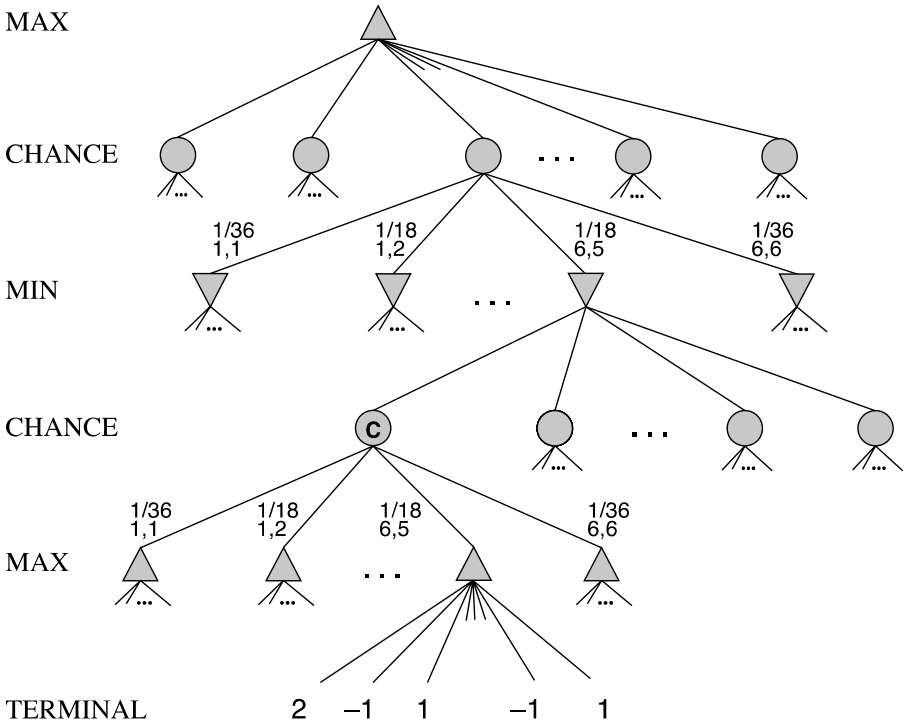
Nondeterministic games: backgammon



In real life there are many unpredictable external events

A game tree in Backgammon must include chance nodes

Schematic Game Tree for Backgammon Position



- How do we evaluate good move?
- By expected utility leading to expected minimax
- Utility for max is highest expected value of child nodes
- Utility of min-nodes is the lowest expected value of child nodes
- Chance node take the expected value of their child nodes.

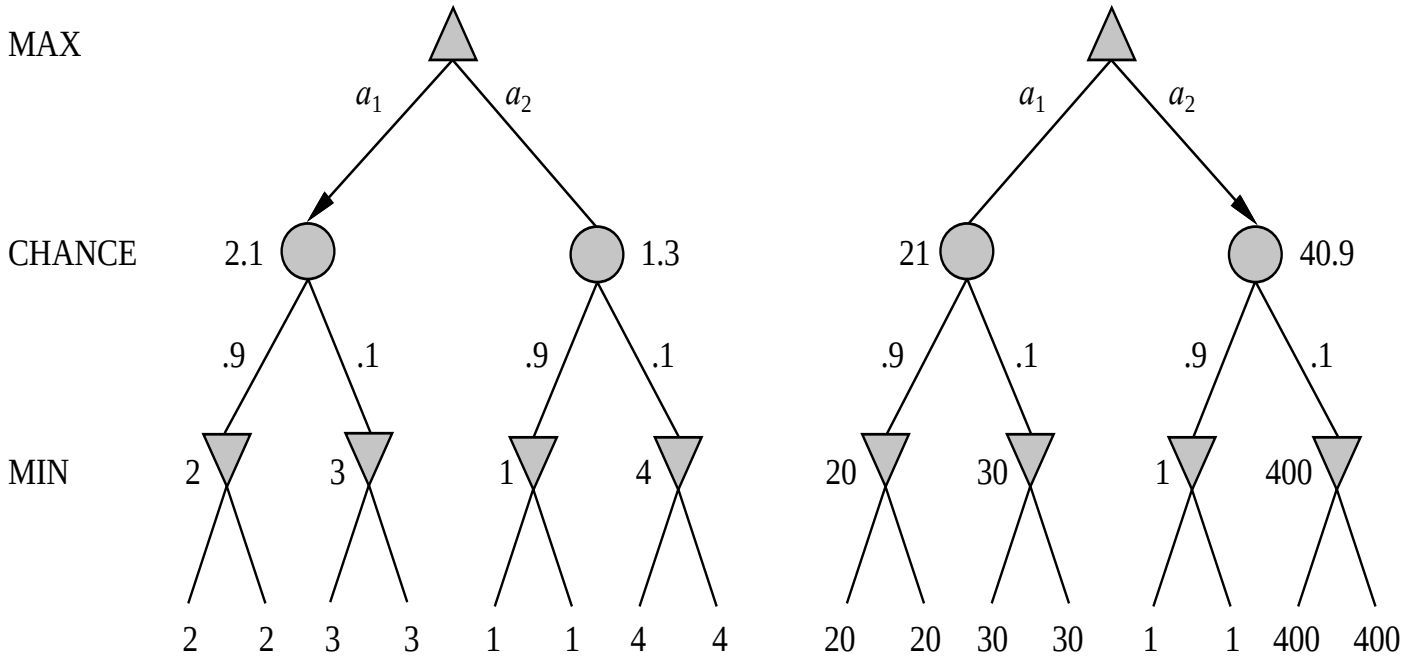
Algorithm for nondeterministic games

EXPECTIMINIMAX gives perfect play

Just like MINIMAX, except we must also handle chance nodes:

```
...
if state is a MAX node then
        return the highest EXPECTIMINIMAX-VALUE of SUCCESSORS(state)
if state is a MIN node then
        return the lowest EXPECTIMINIMAX-VALUE of SUCCESSORS(state)
if state is a chance node then
        return average of EXPECTIMINIMAX-VALUE of SUCCESSORS(state)
...
```

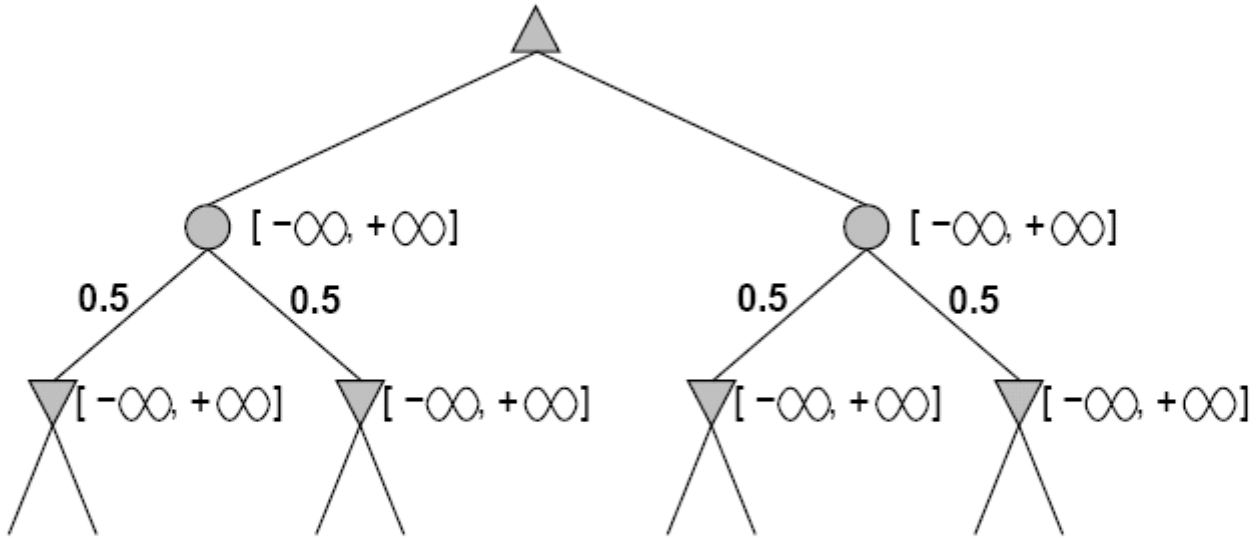
Evaluation functions for stochastic games



- Sensitivity to the absolute values
- The evaluation function should related to the probability of winning from a position, or to the expected utility from the position
- Complexity: O((bn)^m) where m is the depth and n is branching of chance nodes

Pruning in nondeterministic game trees

A version of α-β pruning is possible:



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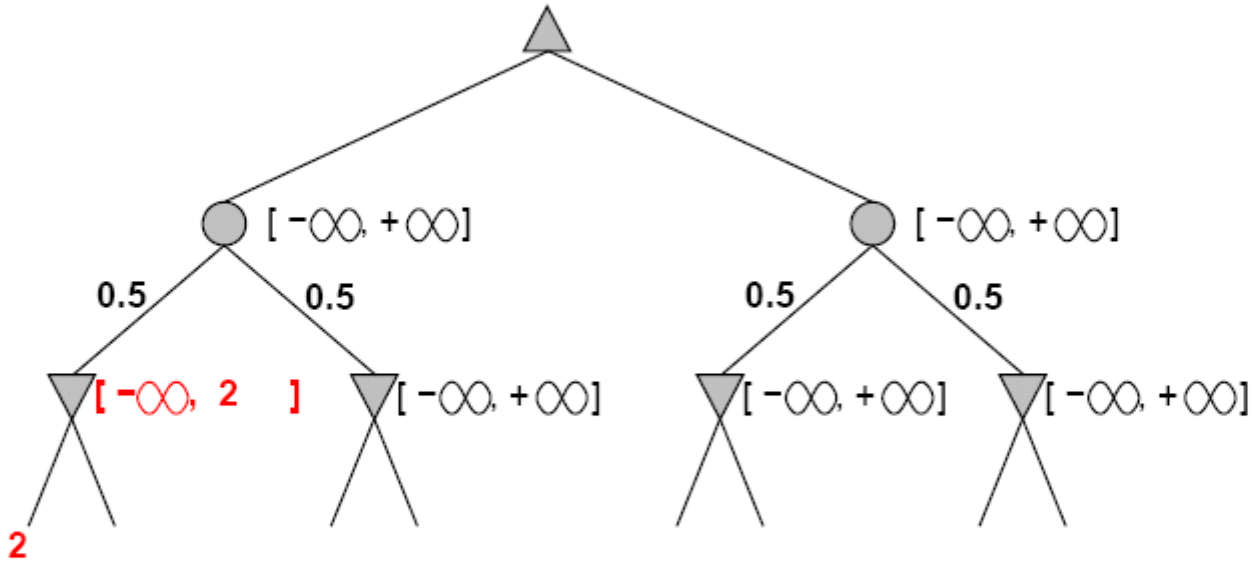

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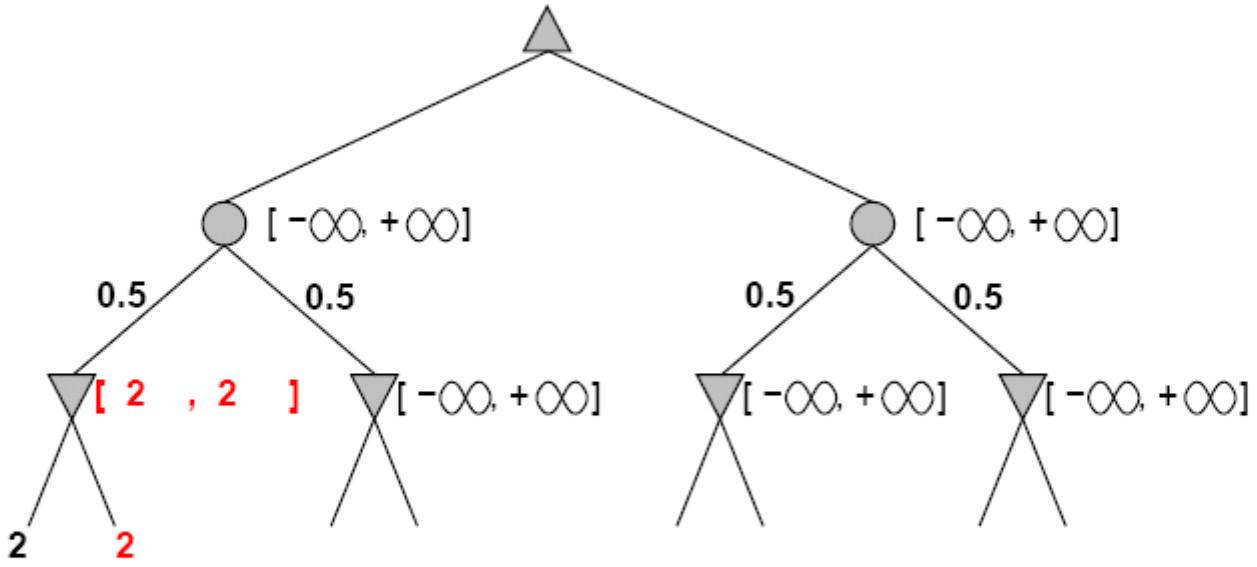

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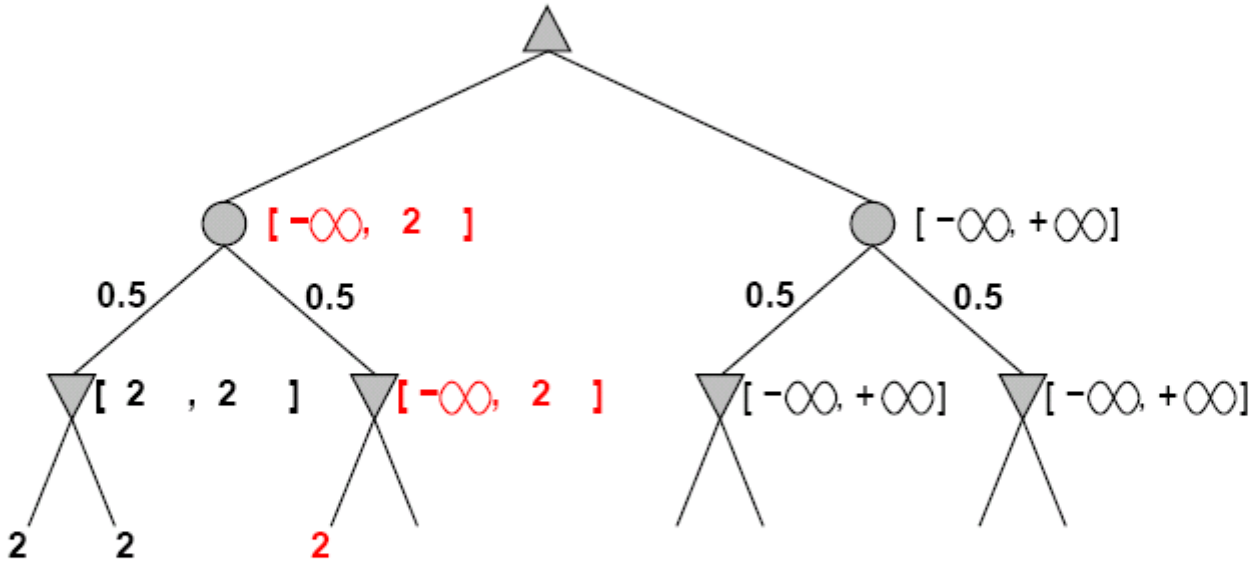

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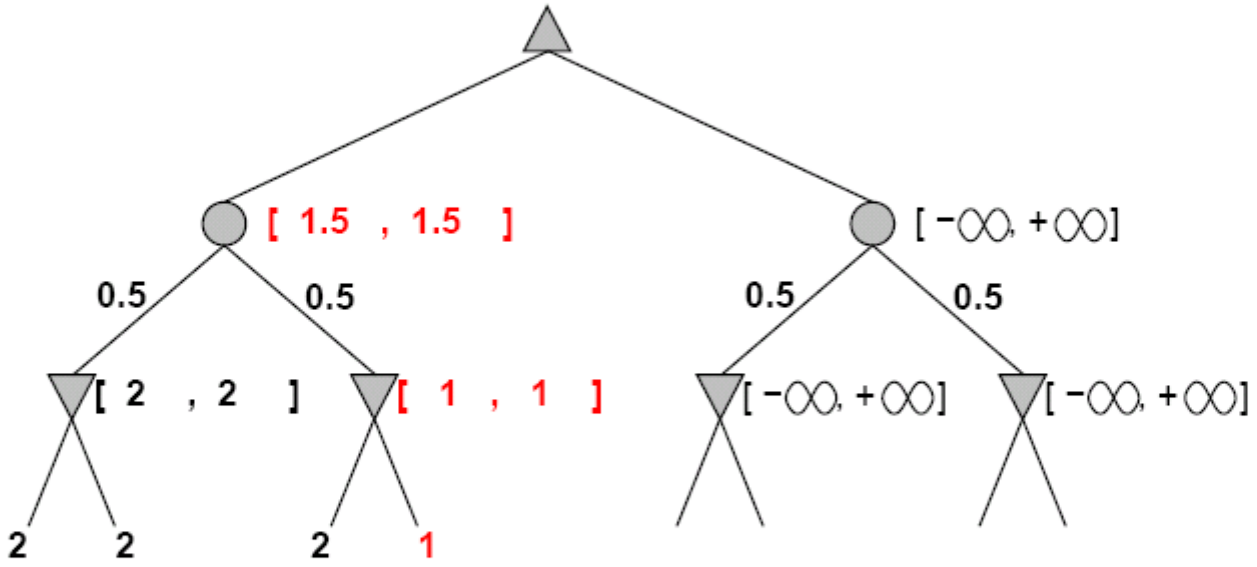

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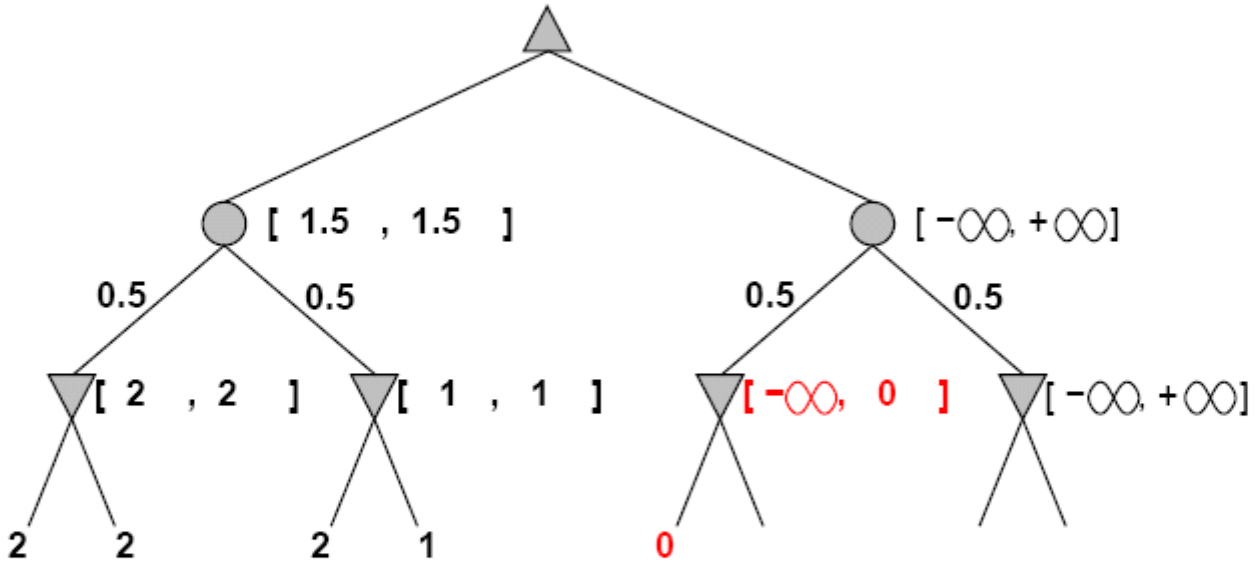

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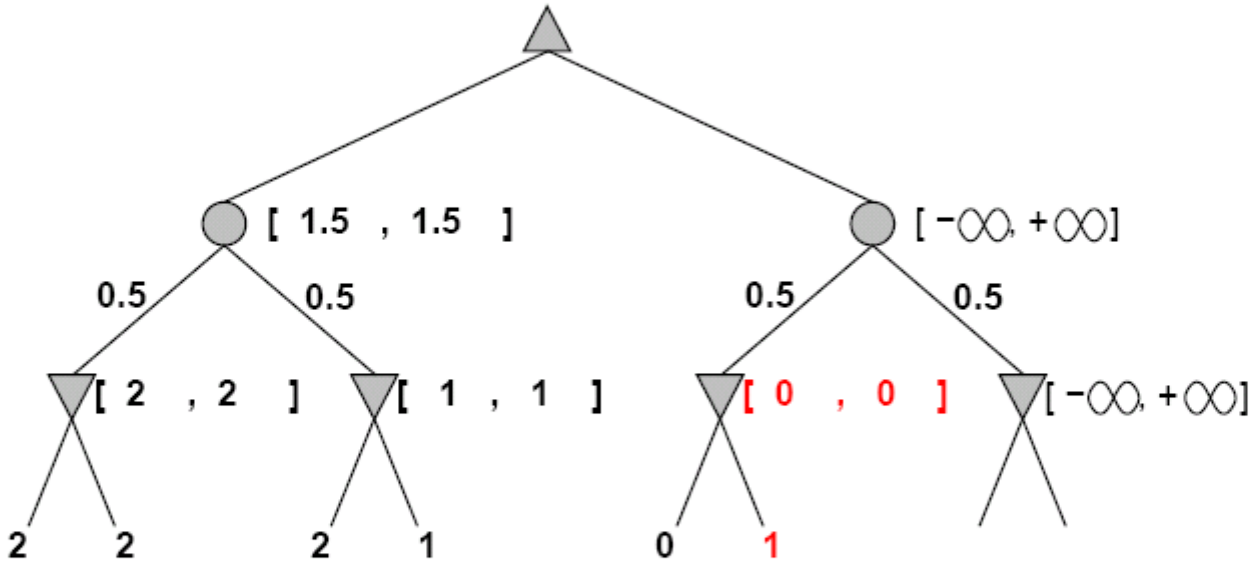

Pruning in nondeterministic game trees

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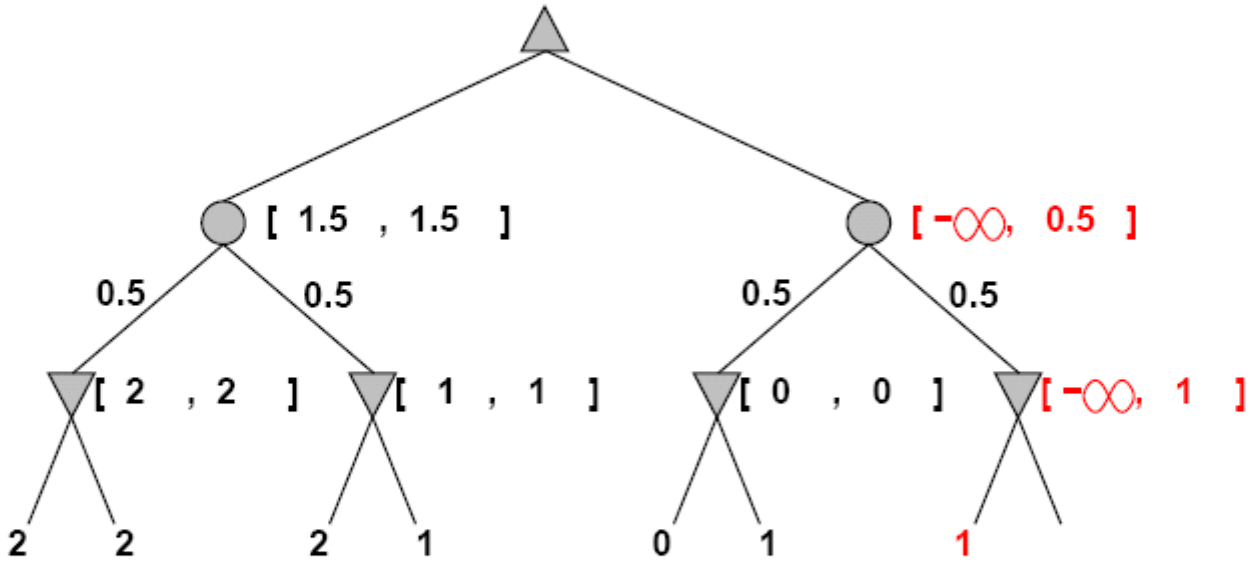
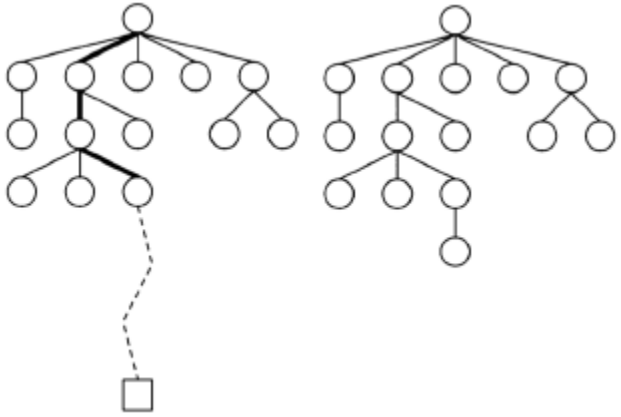


An alternative: Monte Carlo simulations:
Play thousands of games of the program against itself
Using random dice rolls. Record the percentage of win
From a position.

Monte Carlo Tree Search (MCTS)

- Game tree very large, accurate eval fn not available. Example GO
- MC simulation/sampling
  - Many thousands of random self-play games
  - At the end of each simulation, update node/edge values
- Build a tree
  - incrementally : each simulation add highest non-tree node to tree
  - asymmetrically: pursue promising moves



- At each node, solve n-armed bandit problem
  - exploitation vs exploration
  - minimize regret
- Tree policy : select child/action using edge values $X_i + C*\text{sqrt}(\ln(N)/N_i)$
  - X_i = exploitation term, $C*\text{sqrt}(\ln(N)/N_i)$ = exploration term
- Default policy : MC simulation
- winrate values of nodes will converge to minmax values, as $N \rightarrow \infty$
- When time is up, use a move with highest winrate
- Advantage – don't need any heuristic fn

Summary

- Game playing is best modeled as a search problem
- Game trees represent alternate computer/opponent moves
- Evaluation functions estimate the quality of a given board configuration for the Max player.
- Minimax is a procedure which chooses moves by assuming that the opponent will always choose the move which is best for them
- Alpha-Beta is a procedure which can prune large parts of the search tree and allow search to go deeper
- For many well-known games, computer algorithms based on heuristic search match or out-perform human world experts.
- Stochastic games
- Partially observable games
- Reading:R&N Chapter 5.

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.

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.

Othello: human champions refuse to compete against computers, who are too good.

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.