Intro. to Intelligent Systems

Sem. Ganjil 2023/2024

08–Adversarial Search

Lionov

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Overview

- Game Search
- Minimax & $\alpha - \beta$ Pruning
- Monte Carlo Tree Search
- Stochastic Game
- Partially Observable Games

Background

Adversarial

involving people opposing or disagreeing with each other

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Games are modeled as search problems and use heuristic evaluation functions.

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Consider a **zero-sum game** with an environment that:

- Deterministic
- Perfect information (fully observable)
- Sequential (taking turn)
- Static
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We use term **move** for "action" and **position** for "state"

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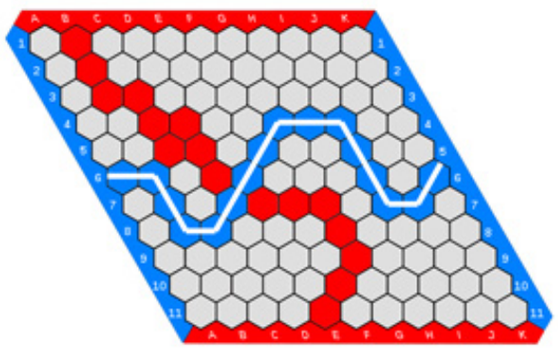

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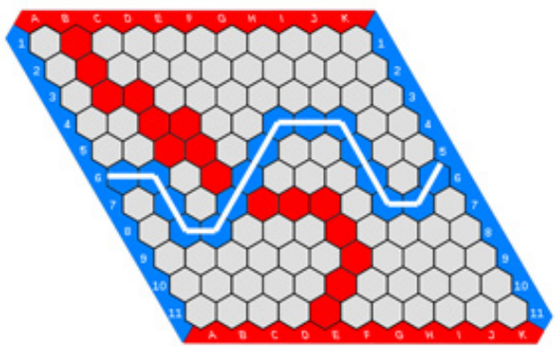

Othello: human champions *refuse* to compete :D

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- **Is-Terminal(s)** : true when the game is over (at terminal states)
- **Utility(s, p)**: A utility function (objective/ payoff function) that defines the final numeric value to players p when the game ends in terminal state s

State-space Graph in a Game

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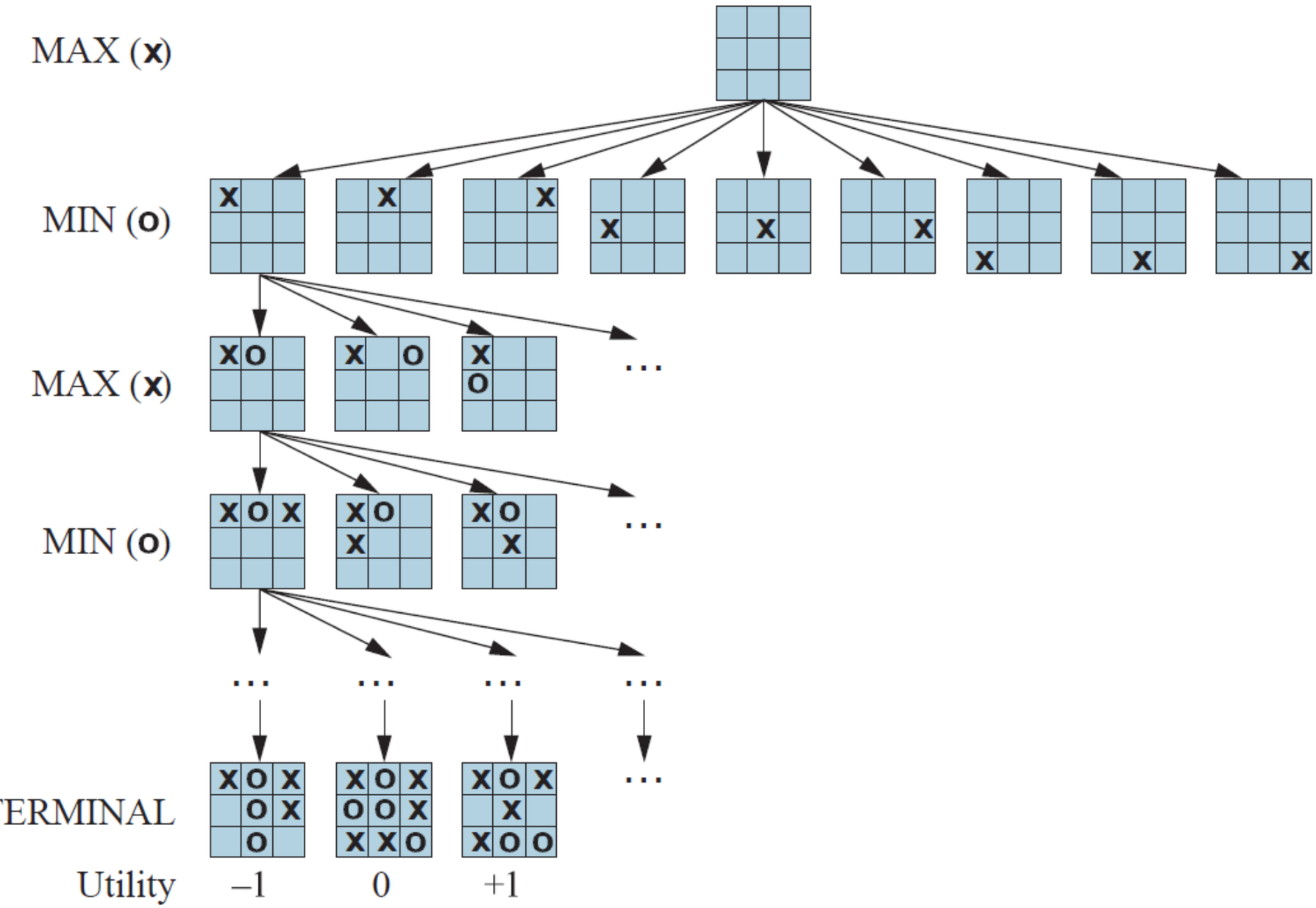

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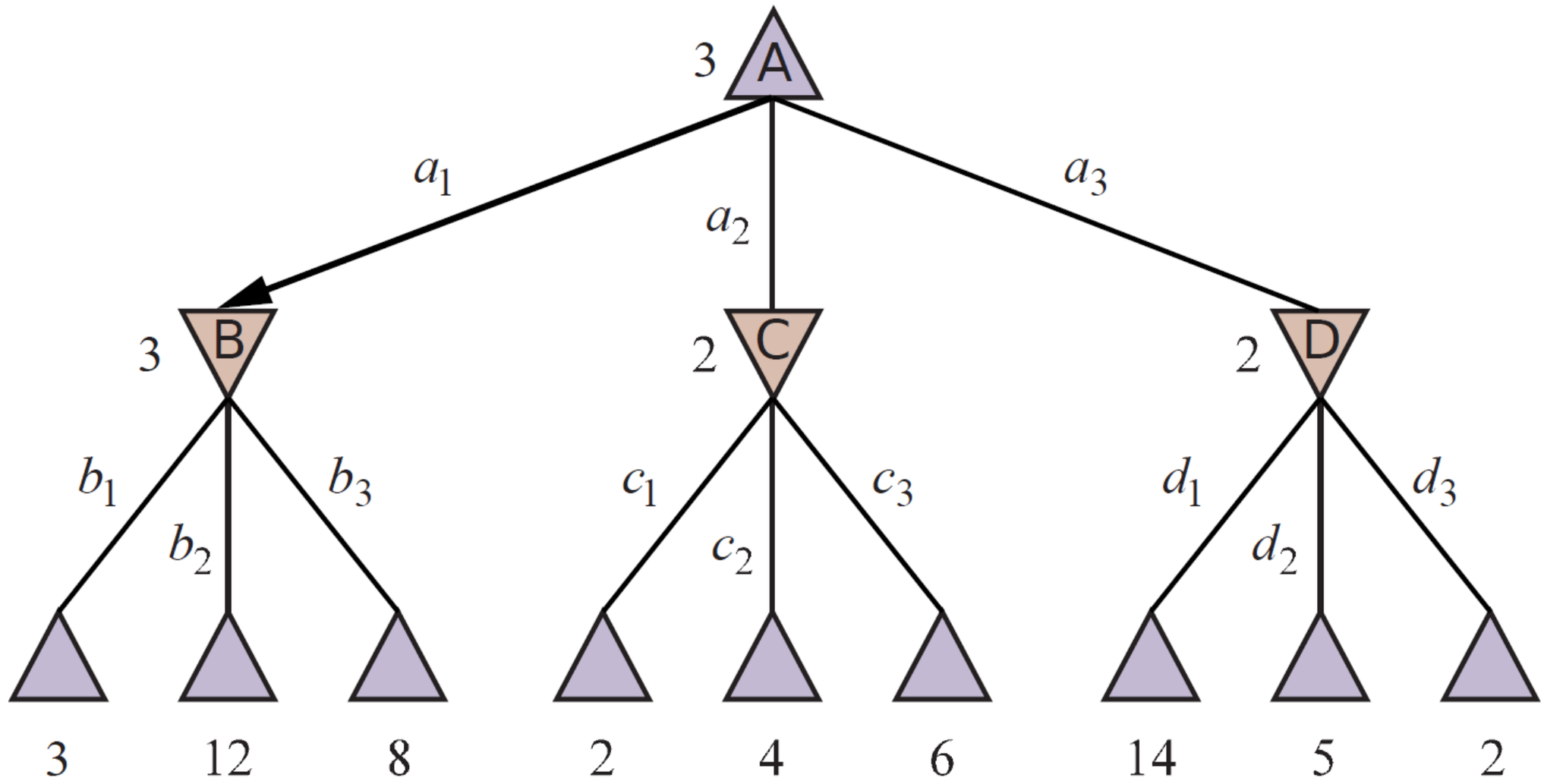

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$$\textsc{Minimax}(s) = \begin{cases} \textsc{Utility}(s, \textsc{max}) & \text{if } \textsc{Is-Terminal}(s) \\ \max_{a \in Actions(s)} \textsc{Minimax}(\textsc{Result}(s, a)) & \text{if } \textsc{To-Move}(s) = \textsc{max} \\ \min_{a \in Actions(s)} \textsc{Minimax}(\textsc{Result}(s, a)) & \text{if } \textsc{To-Move}(s) = \textsc{min} \end{cases}$$

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We can identify the **minimax decision** at the root

Minimax Algorithm

```
function MINIMAX-SEARCH(game, state) returns an action
    player ← game.TO-MOVE(state)
    value, move ← MAX-VALUE(game, state)
    return move

function MAX-VALUE(game, state) returns a (utility, move) pair
    if game.IS-TERMINAL(state) then return game.UTILITY(state, player), null
    v ← −∞
    for each a in game.ACTIONS(state) do
        v2, a2 ← MIN-VALUE(game, game.RESULT(state, a))
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Time complexity is $O(b^m)$ and the space complexity is $O(bm)$

Where m is the maximum depth of the tree and there are b legal moves at each point

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Returns a vector of n values (n = the number of players)

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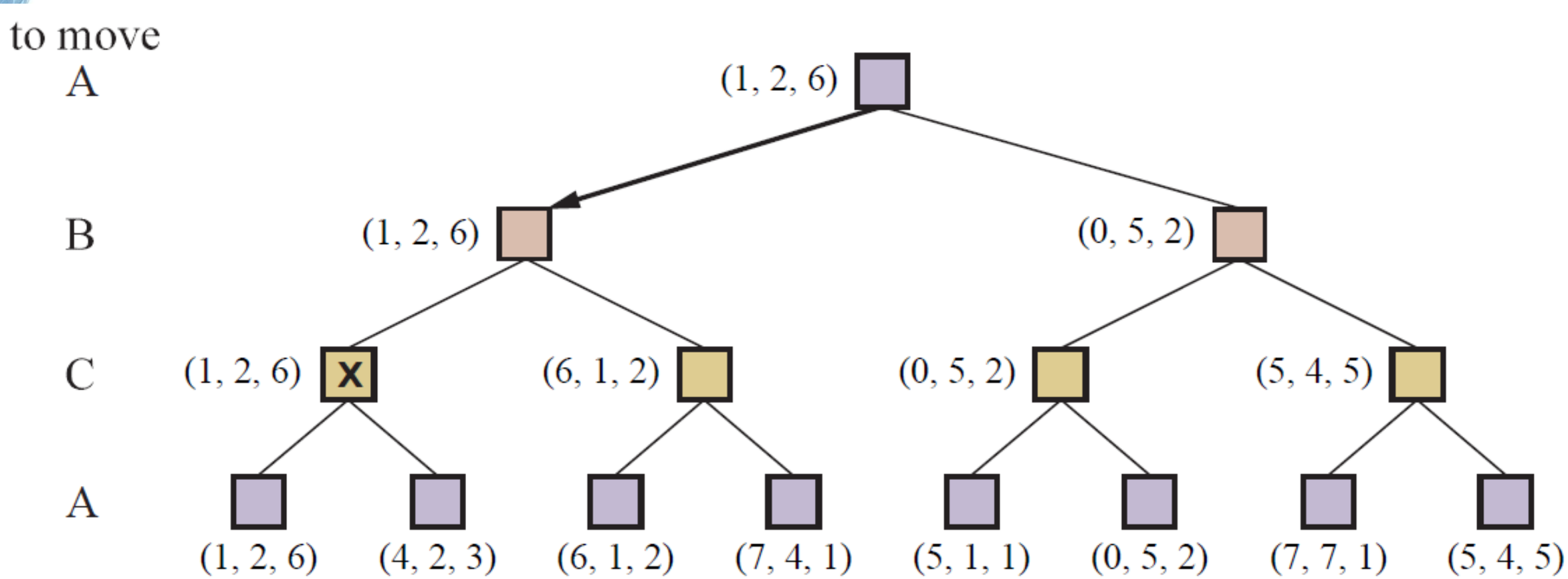

Alpha-Beta Pruning

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α: the value of the best (highest-value) choice found so far for ***MAX***("at least")

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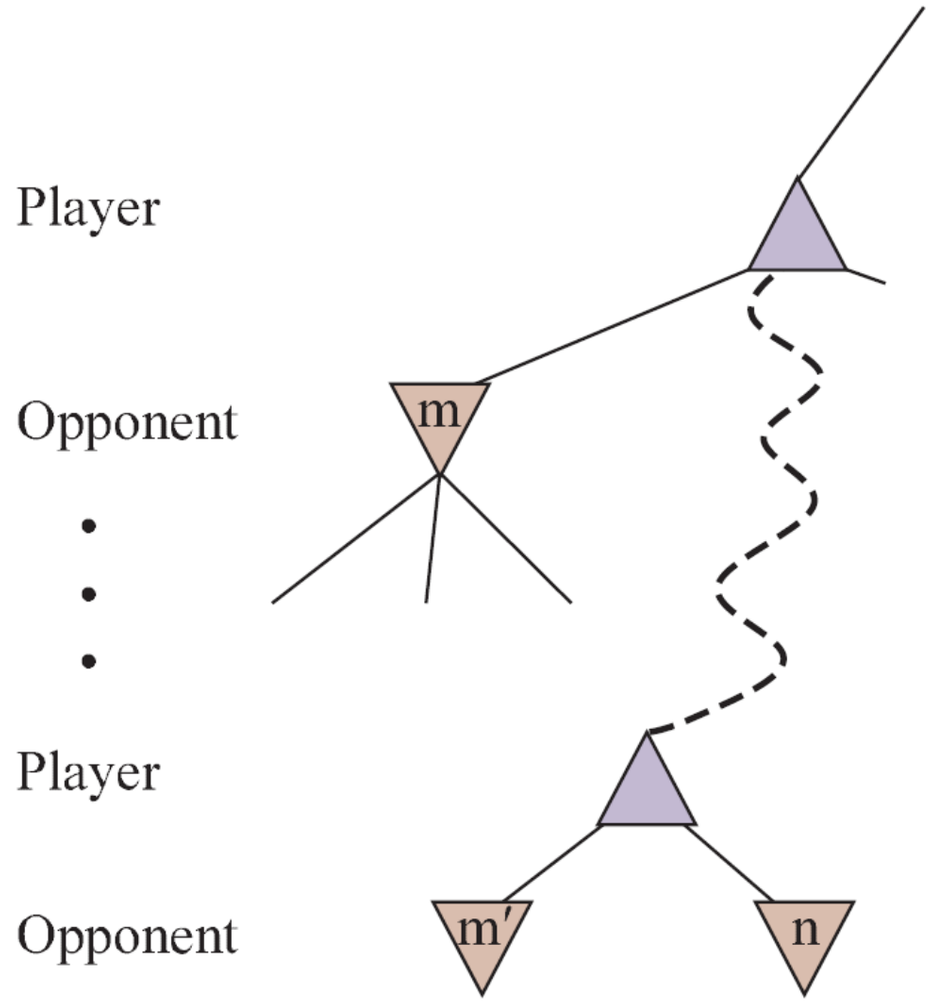
The general principle:
Consider a node n such that a player has a choice of moving to n.

If the player has **a better choice** either at the same level (m') or at any point higher up in the tree (m), then the player will never move to n.

Once we have found out enough about n (by examining some of its descendants) to reach this conclusion, we can prune it.



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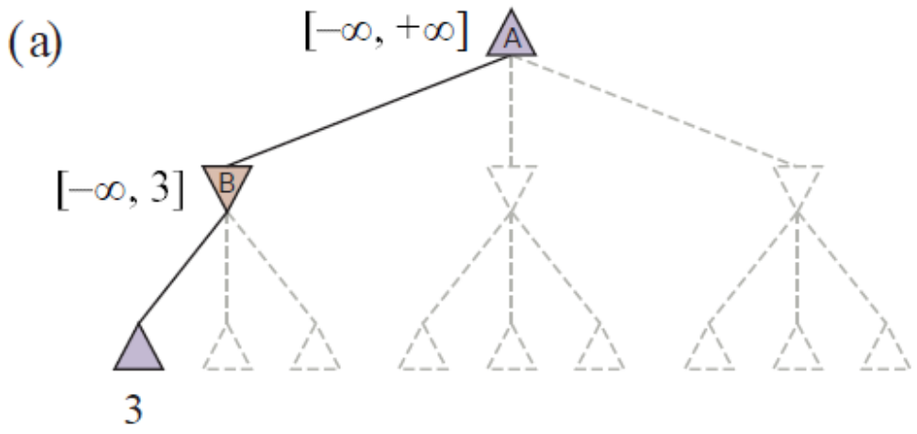

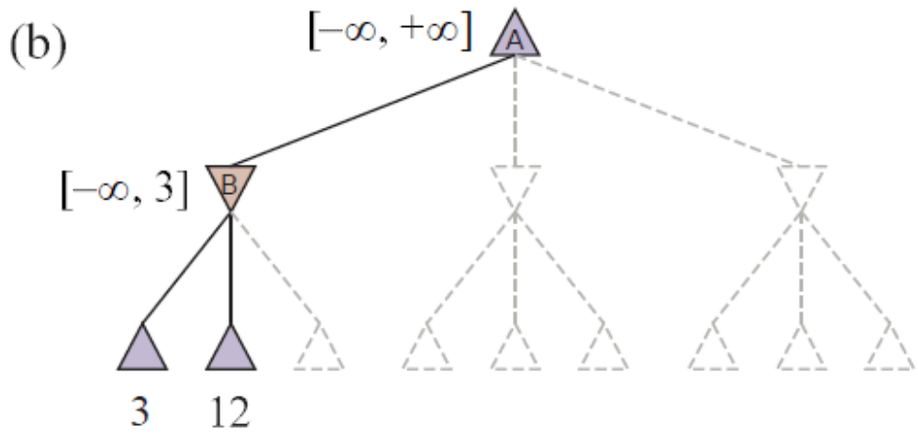

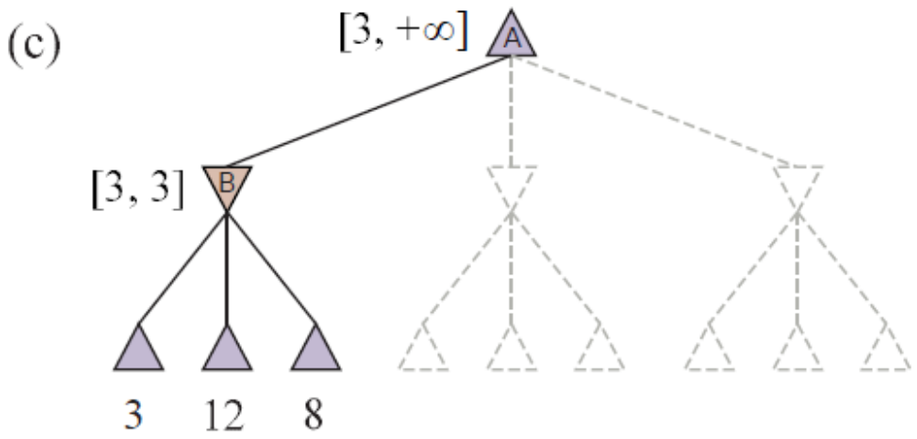

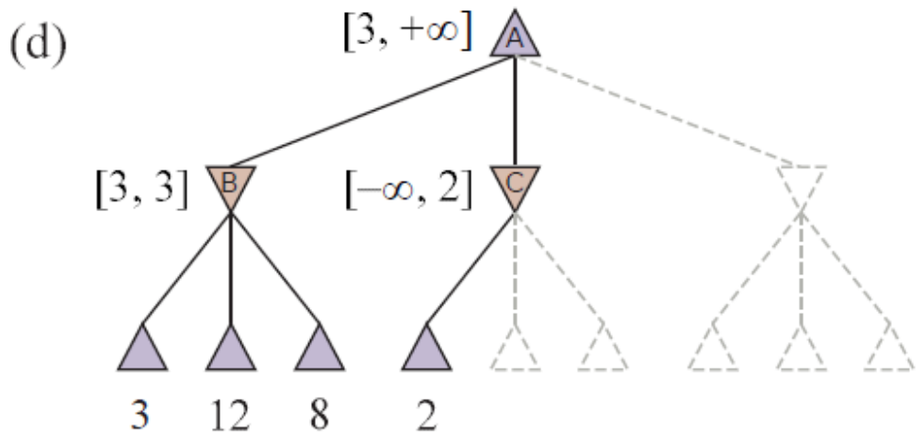

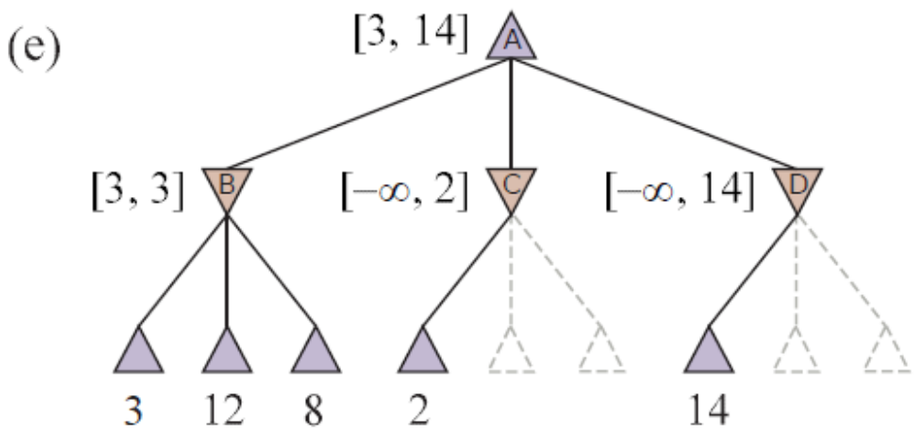

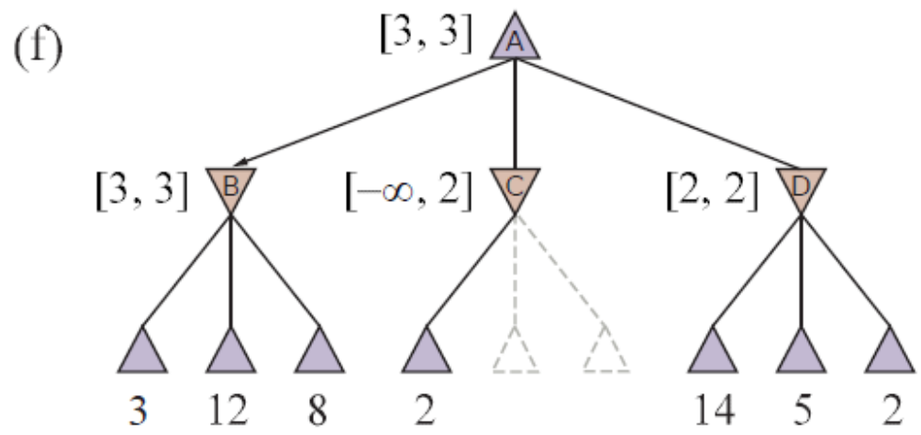

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$\alpha - \beta$ Pruning Algorithm

```
function ALPHA-BETA-SEARCH(game, state) returns an action
    player ← game.TO-MOVE(state)
    value, move ← MAX-VALUE(game, state, −∞, +∞)
    return move

function MAX-VALUE(game, state, α, β) returns a (utility, move) pair
    if game.IS-TERMINAL(state) then return game.UTILITY(state, player), null
    v ← −∞
    for each a in game.ACTIONS(state) do
        v2, a2 ← MIN-VALUE(game, game.RESULT(state, a), α, β)
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            α ← MAX(α, v)
        if v ≥ β then return v, move
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            β ← MIN(β, v)
        if v ≤ α then return v, move
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- **Type A strategy**: considers all possible moves to a certain depth in the search tree, and then uses a heuristic evaluation function to estimate the utility of states at that depth.
- **Type B strategy**: ignores moves that look bad, and follows promising lines "as far as possible".

Heuristic for $\alpha - \beta$ Search

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Most evaluation functions work by calculating various features of the state

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Weighted combination of features of a game state:

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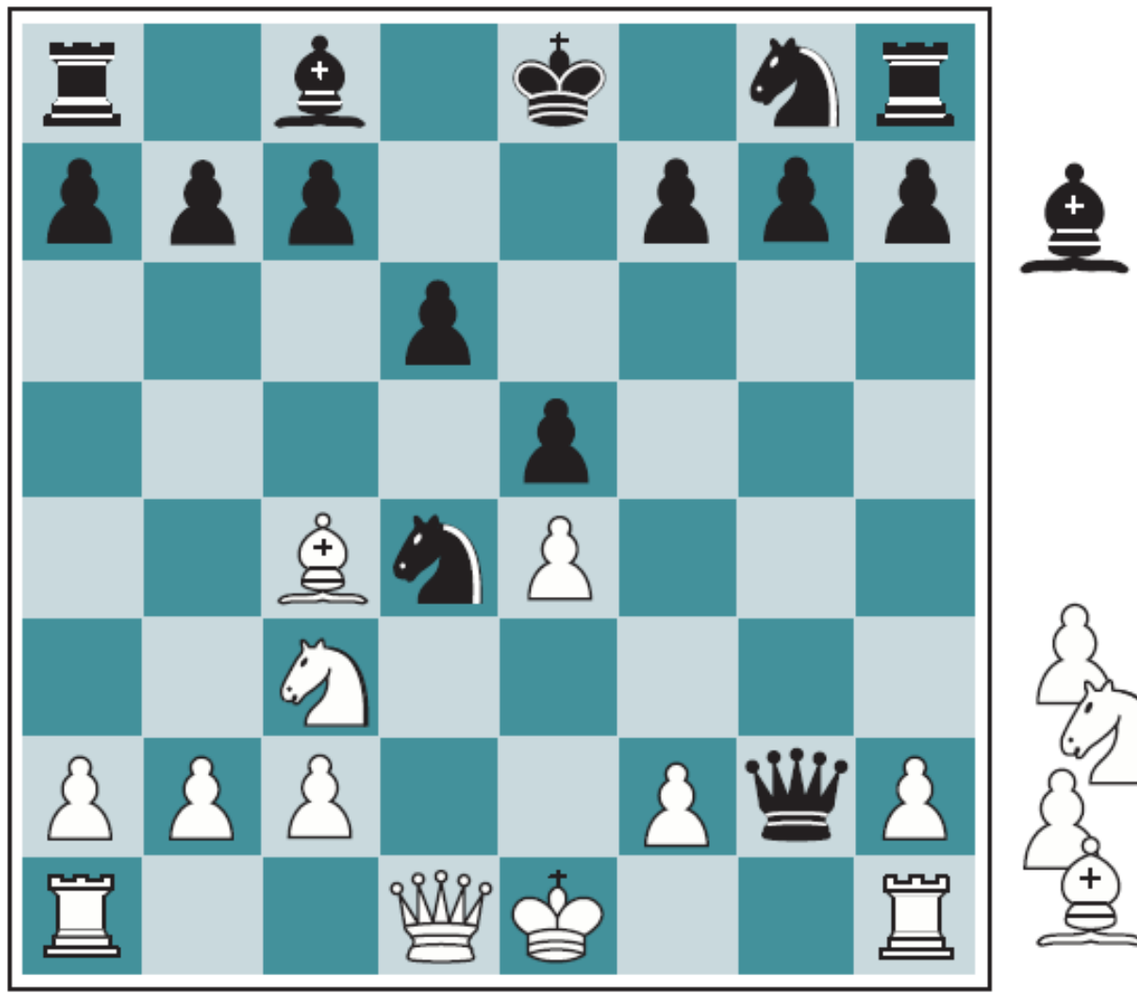

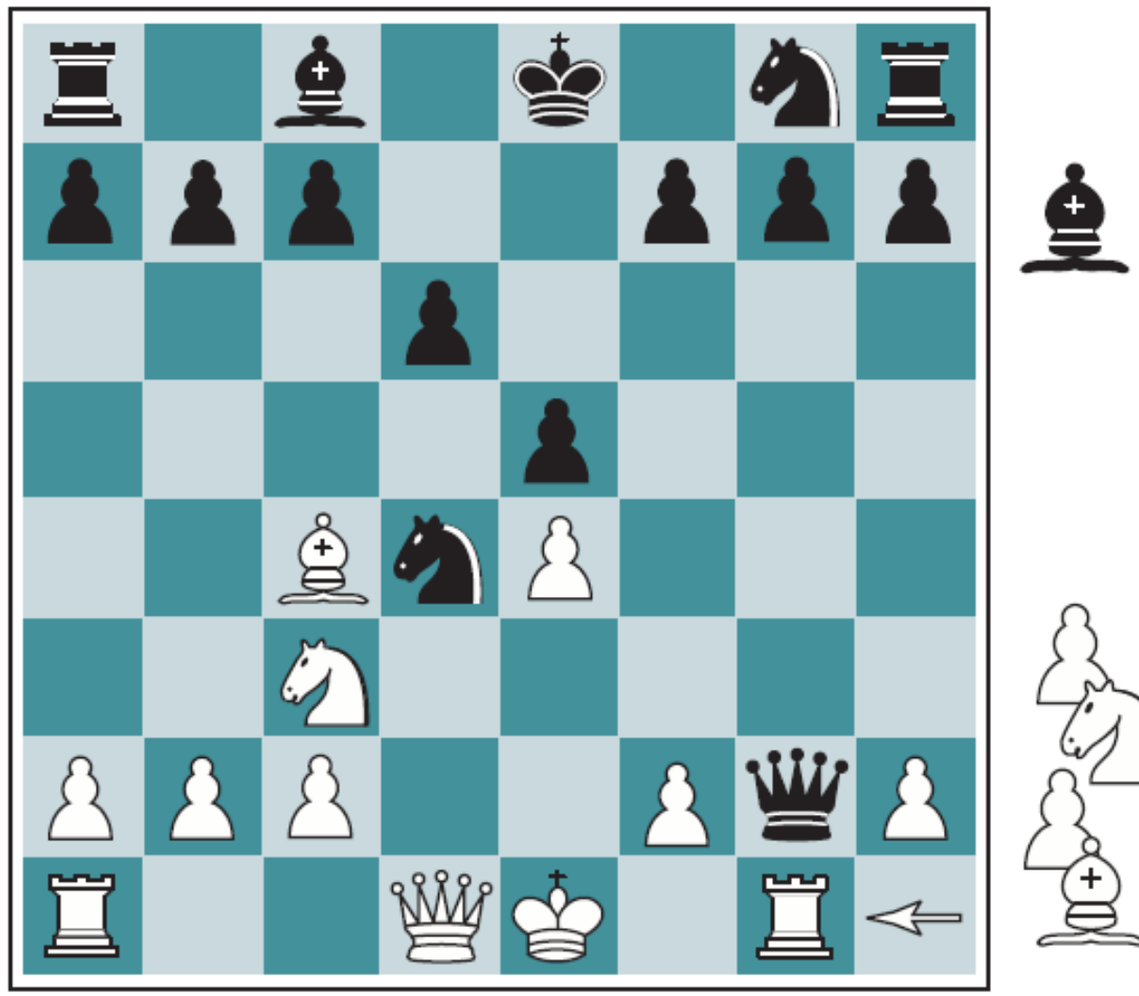

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Modify the ALPHA-BETA-SEARCH: it calls the EVAL function to cut off the search

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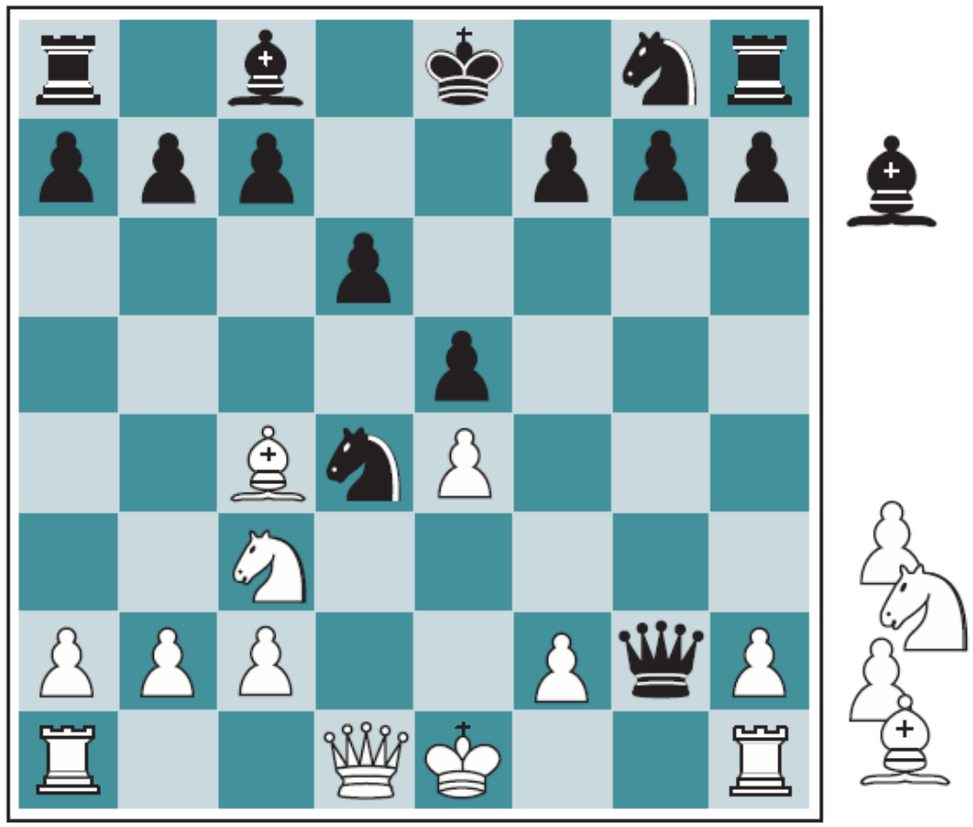
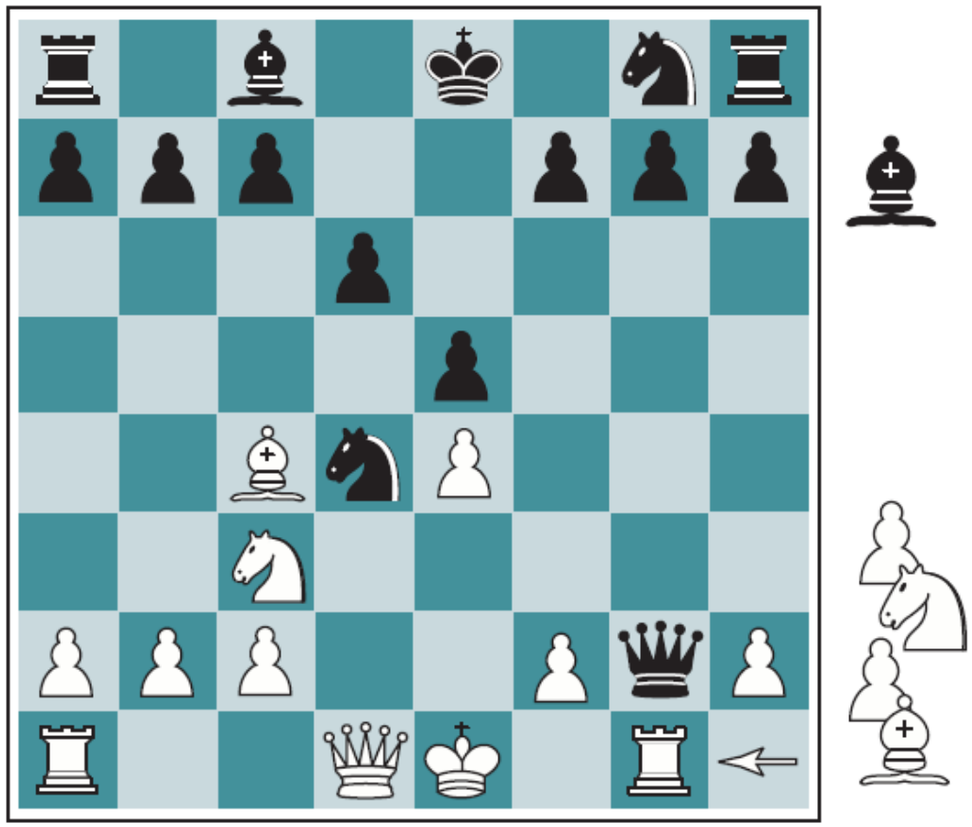
This strategies may lead to error:





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  Map every possible state to the best move in that state. The computer can play perfectly by looking up the right move in this table.

Monte Carlo Tree Search

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Pure Monte Carlo search: do N simulations starting from the current state and track which of the possible moves has the highest win percentage

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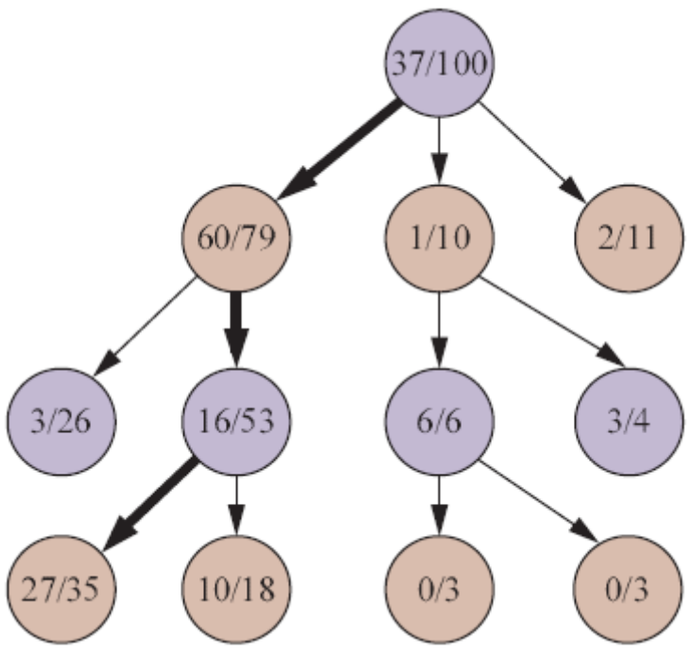
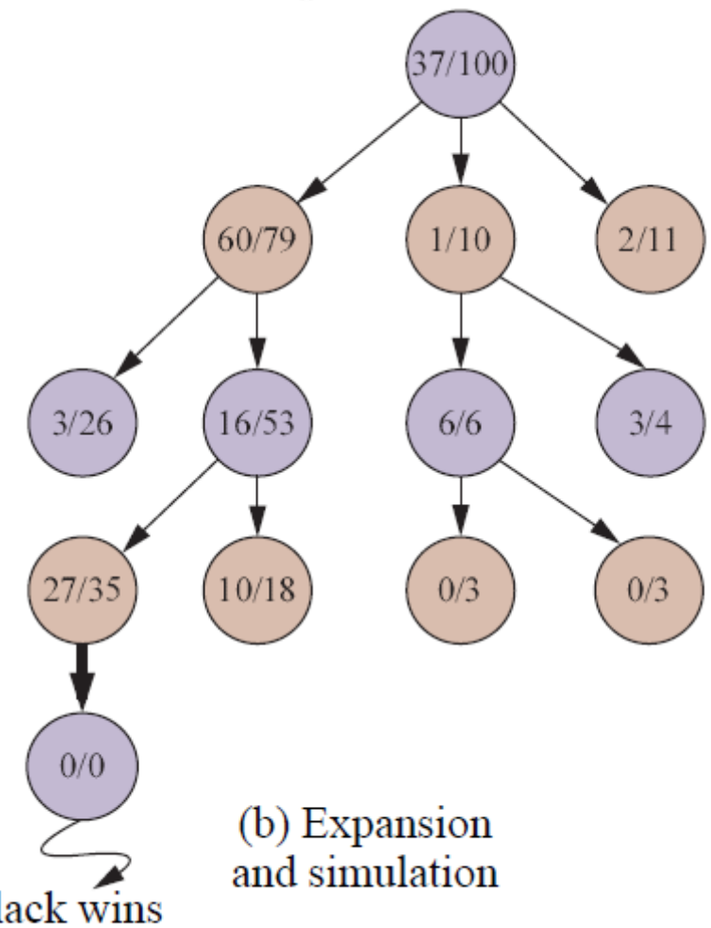
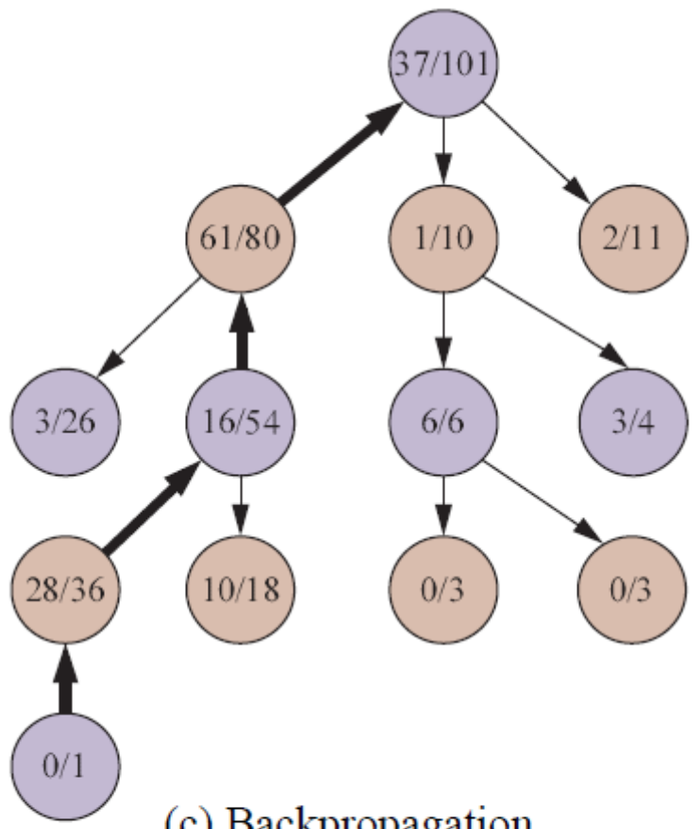


(a) Selection



(b) Expansion and simulation



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Exp. of a selection policy: "upper confidence bounds applied to trees" or **UCT**.
UCT ranks possible move based on an upper confidence bound formula **UCB1**

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function MONTE-CARLO-TREE-SEARCH(*state*) **returns** *an action*
  tree ← NODE(*state*)
  while IS-TIME-REMAINING() **do**
    leaf ← SELECT(*tree*)
    child ← EXPAND(*leaf*)
    result ← SIMULATE(*child*)
    BACK-PROPAGATE(*result*, *child*)
  return the move in ACTIONS(*state*) whose node has highest number of playouts

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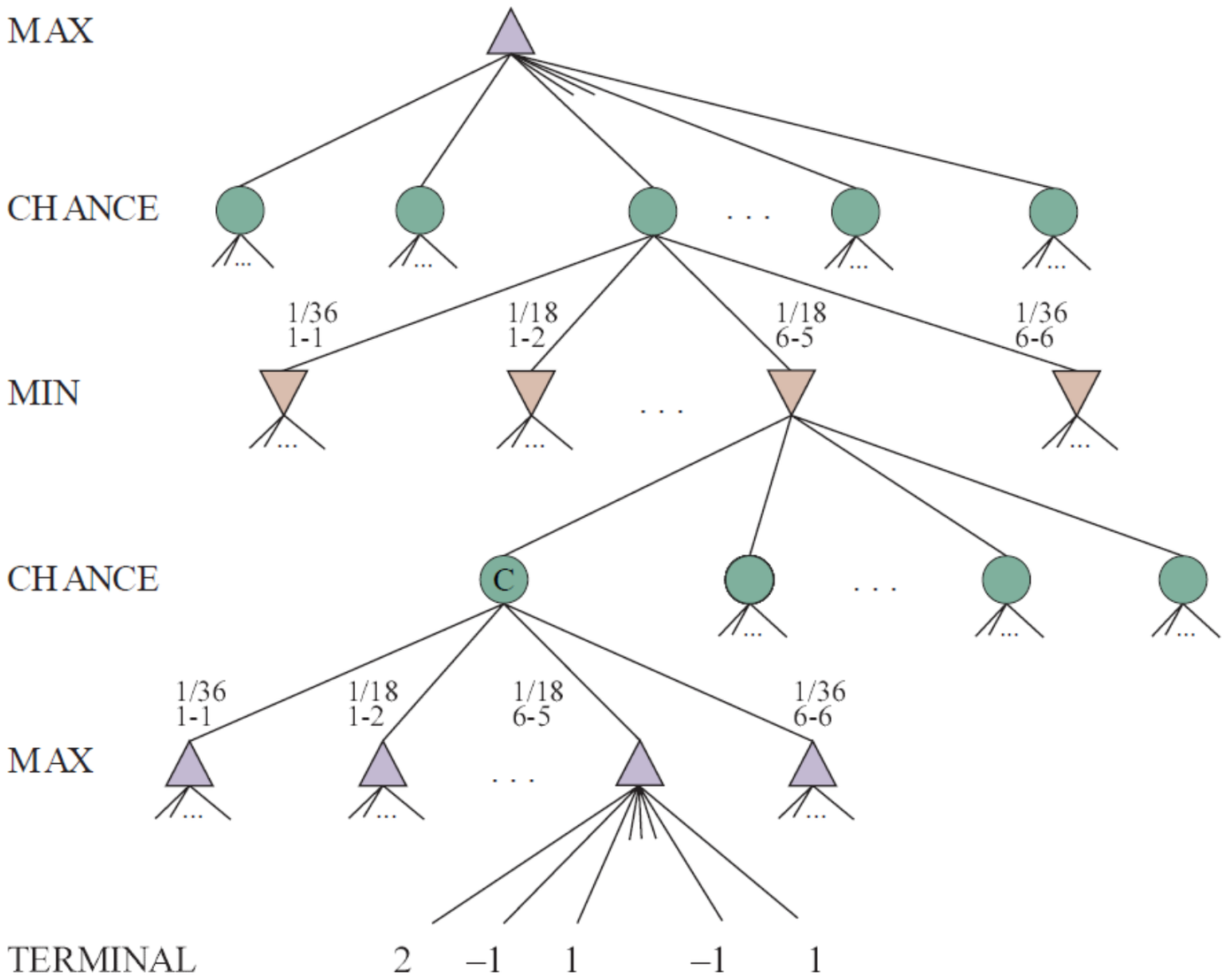

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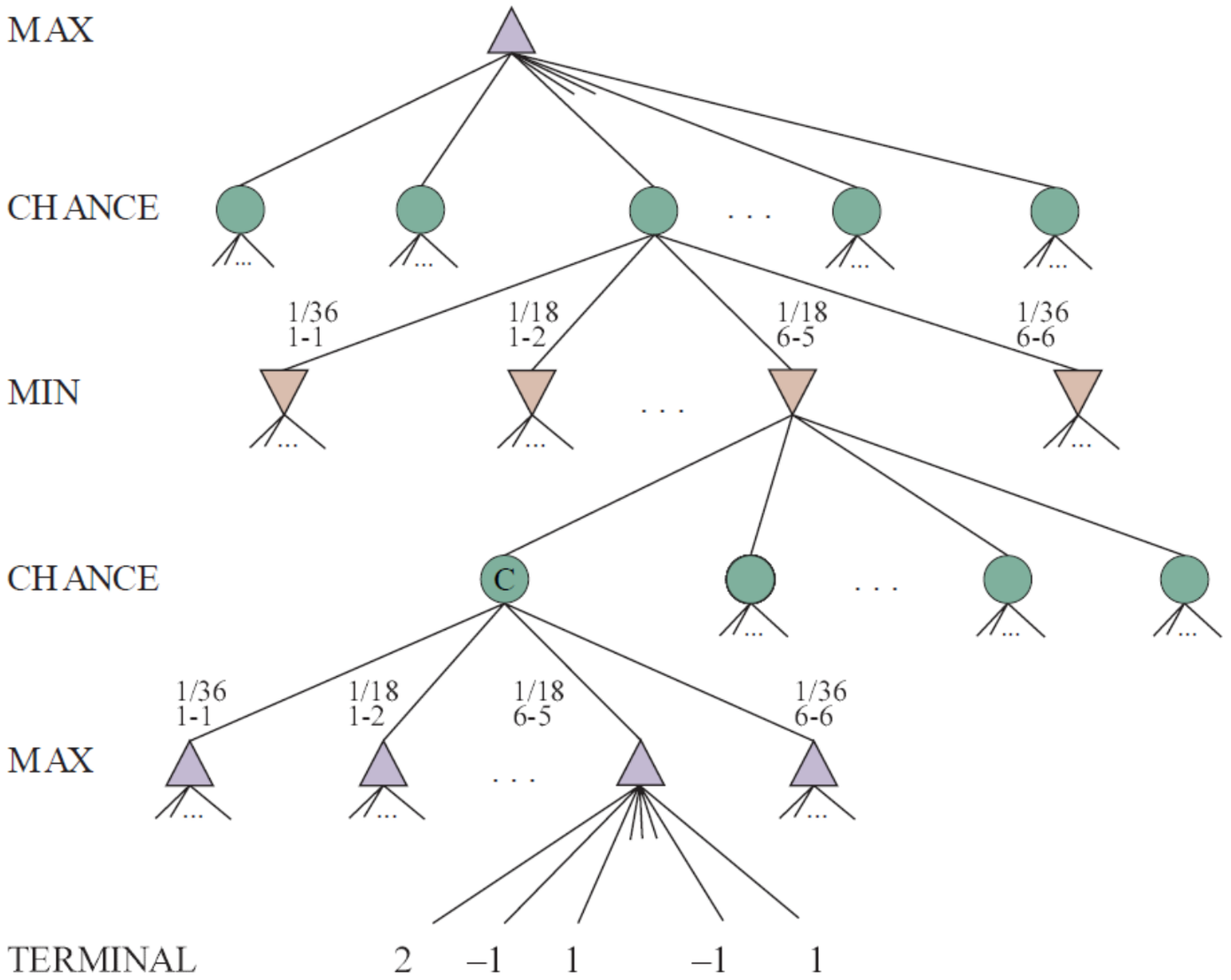

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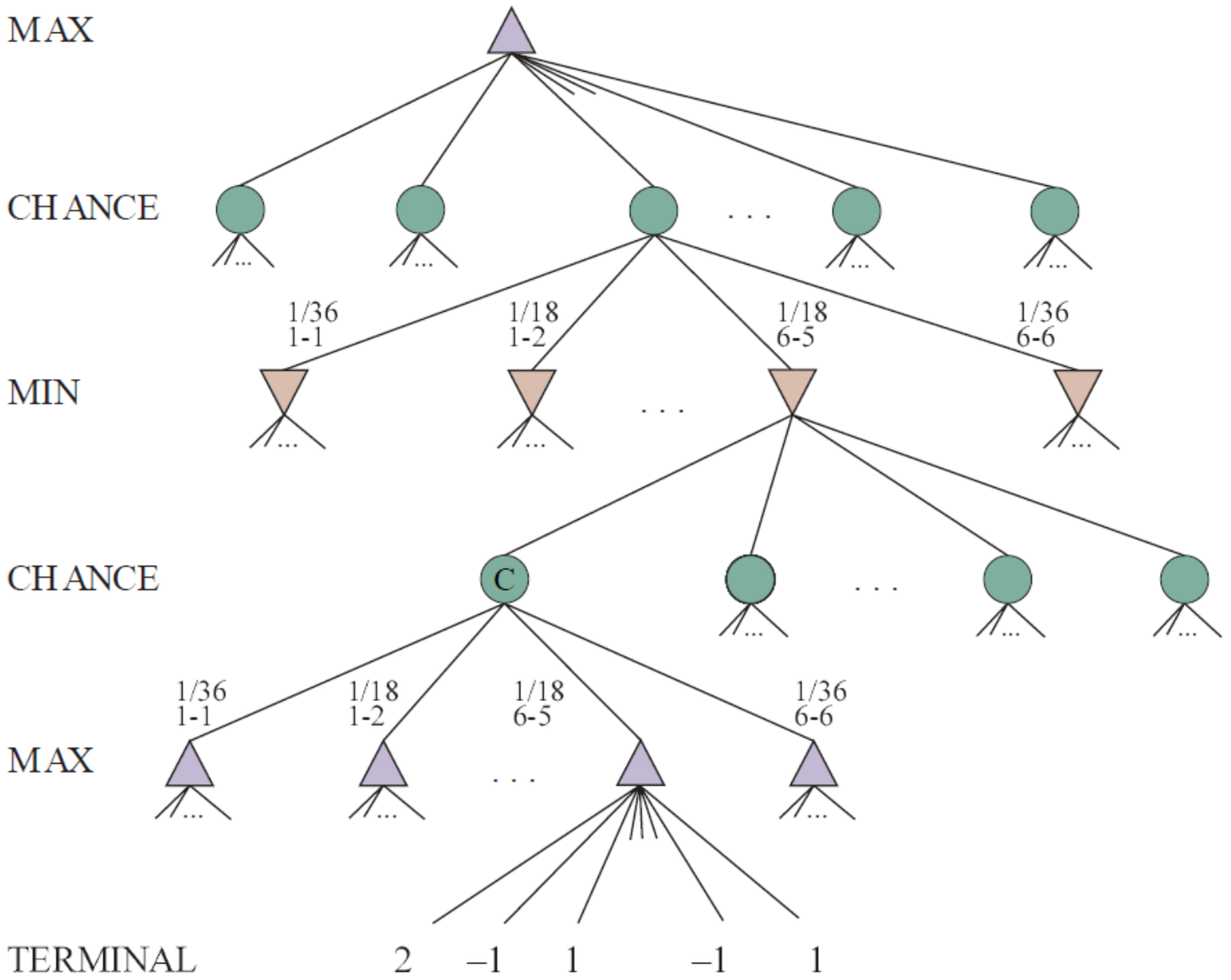
Expectiminimax value for games with chance nodes, a generalization of the minimax value for deterministic games



Partially Observable Games

In games of imperfect information, such as Kriegspiel and poker, optimal play requires reasoning about the current and future belief states of each player. A simple approximation can be obtained by averaging the value of an action over each possible configuration of missing information.

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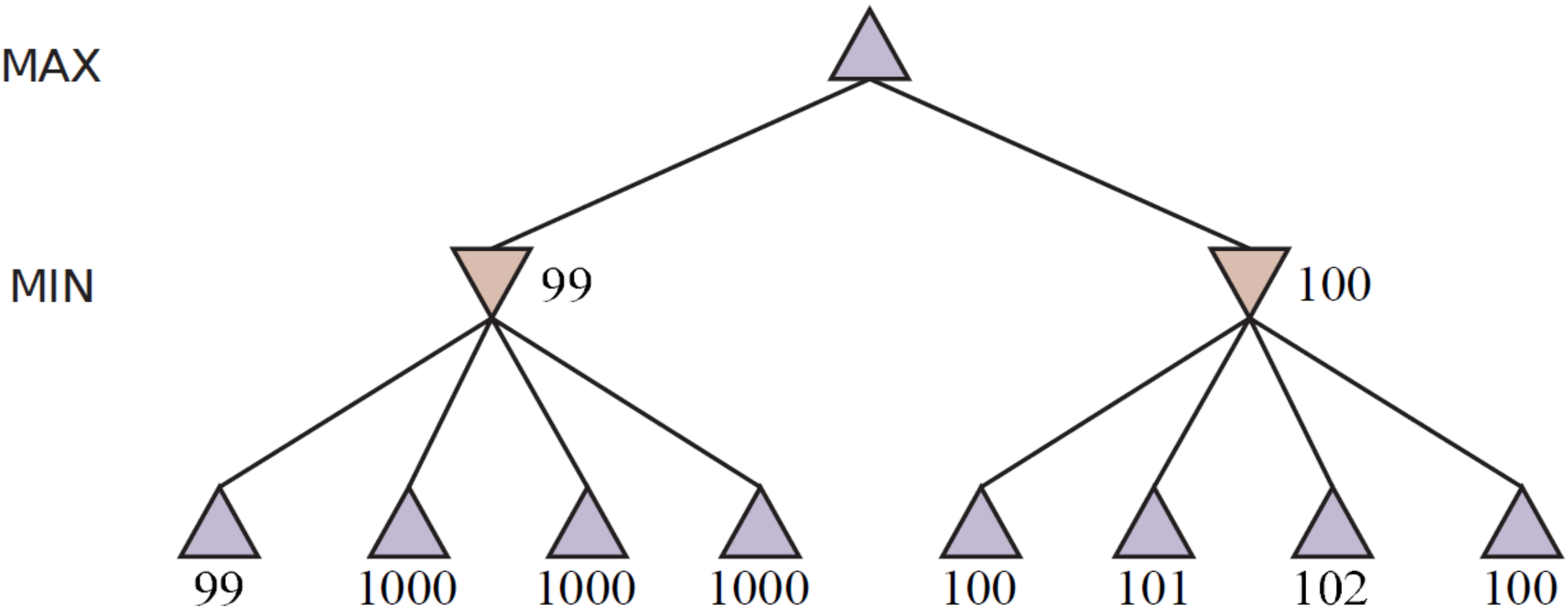

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- Reasoning are done at the level of individual moves. Humans play games differently: reasoning at the abstract level
- No ability to incorporate machine learning into the game search process

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