# CMSC 471: Games

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Slides courtesy Tim Finin and Frank Ferarro. Some material adopted from notes by Andreas Geyer-Schulz and Chuck Dyer,
Some materials adopted from slides by Dan Klein and Pieter Abbeel at UC Berkeley [http://ai.berkeley.edu]

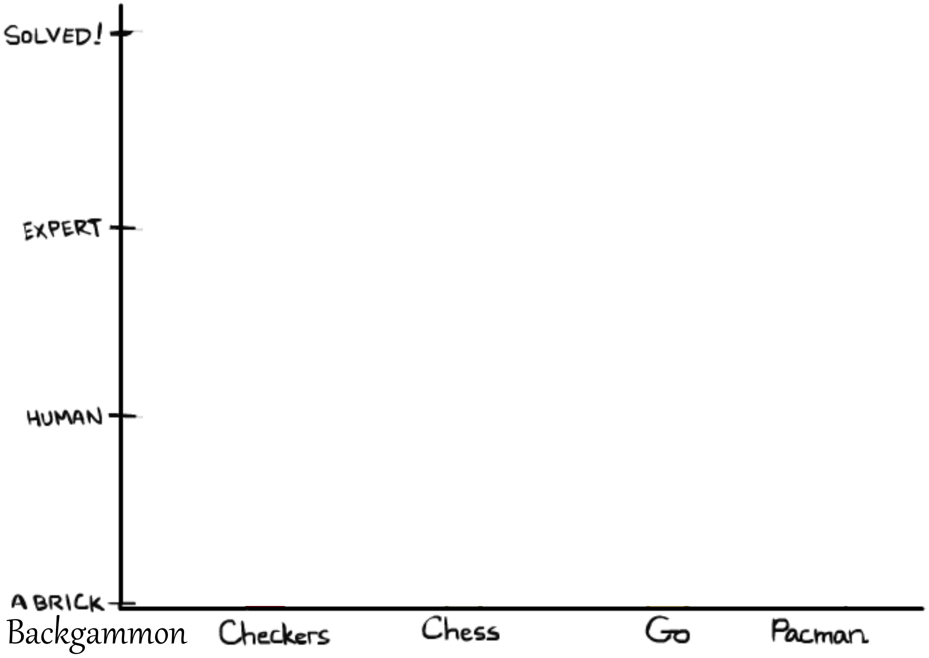
# Overview

- Game playing
  - State of the art and resources
  - Framework
- Game trees
  - Minimax
  - Alpha-beta pruning
  - Adding randomness

# Why study games?

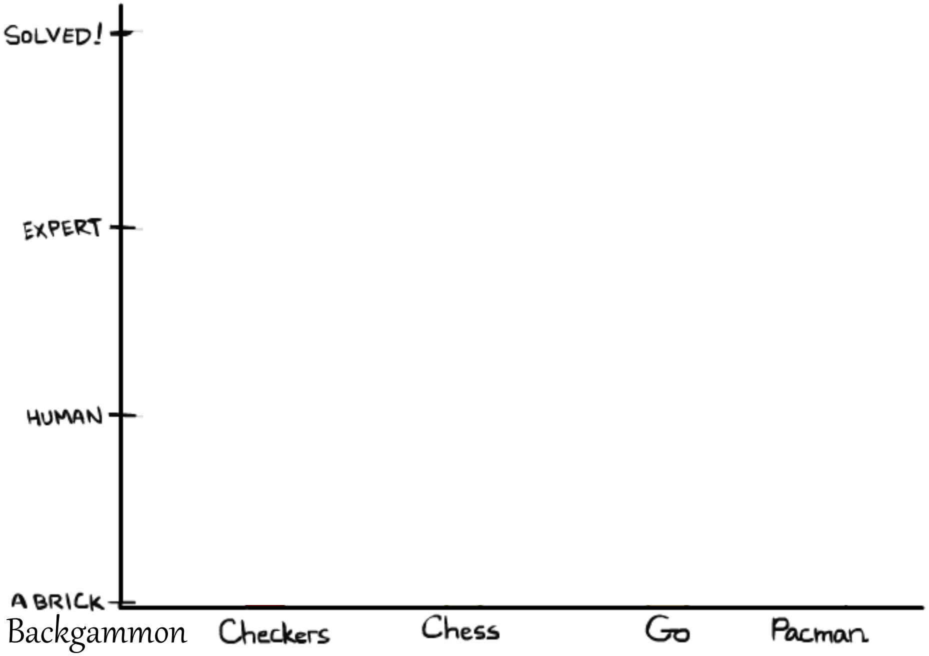
- Interesting, hard problems requiring minimal "initial structure"
- Clear criteria for success
- Study problems involving {hostile, adversarial, competing} agents and uncertainty of interacting with the natural world
- People have used them to assess their intelligence
- Fun, good, easy to understand, PR potential
- Games often define very large search spaces, e.g. chess $35^{100}$ nodes in search tree, $10^{40}$ legal states

# Game Playing State-of-the-Art



# Game Playing State-of-the-Art

- **Checkers:** 1950: First computer player. 1994: First computer champion: Chinook ended 40-year-reign of human champion Marion Tinsley using complete 8-piece endgame. 2007: Checkers solved!



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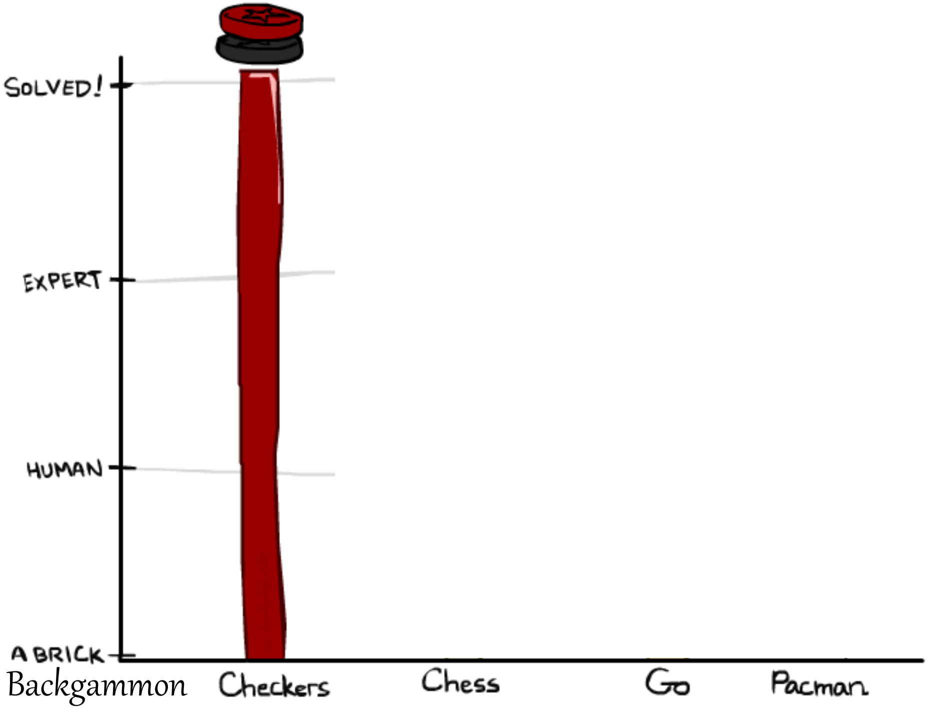

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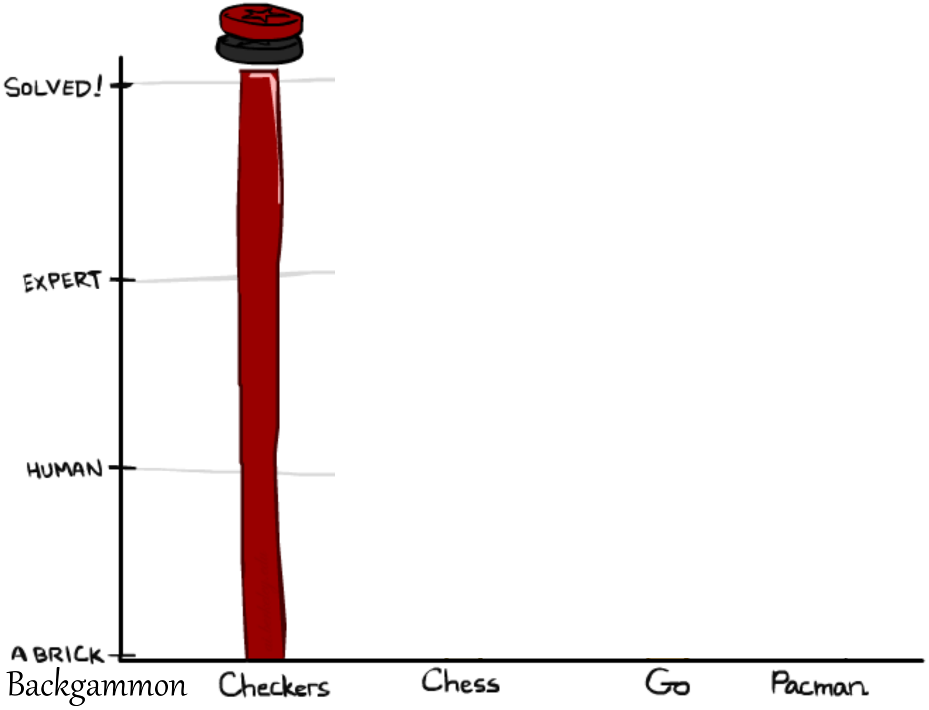

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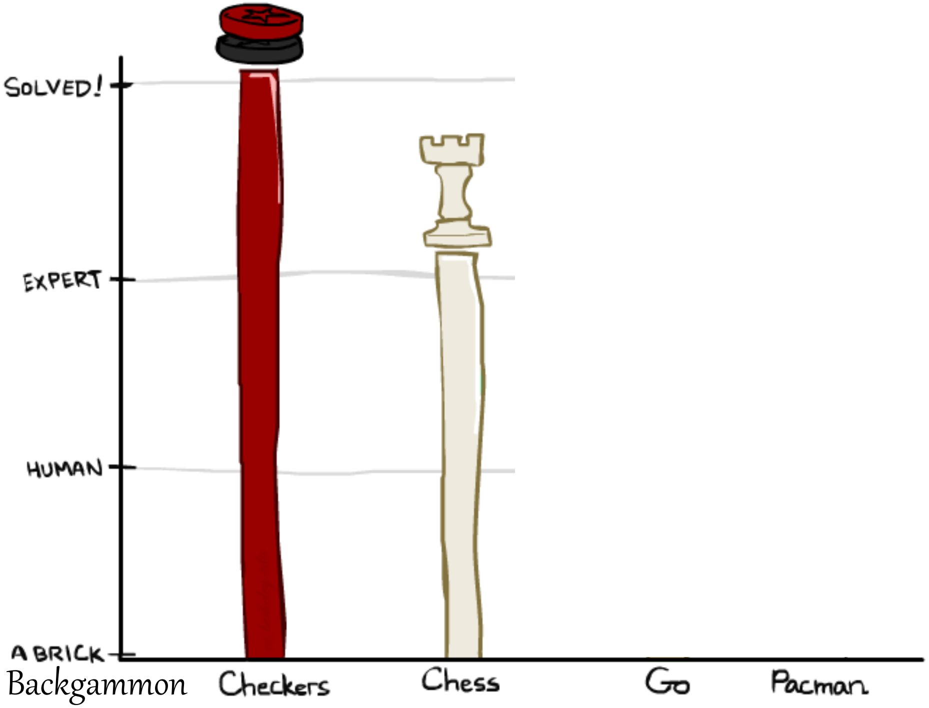

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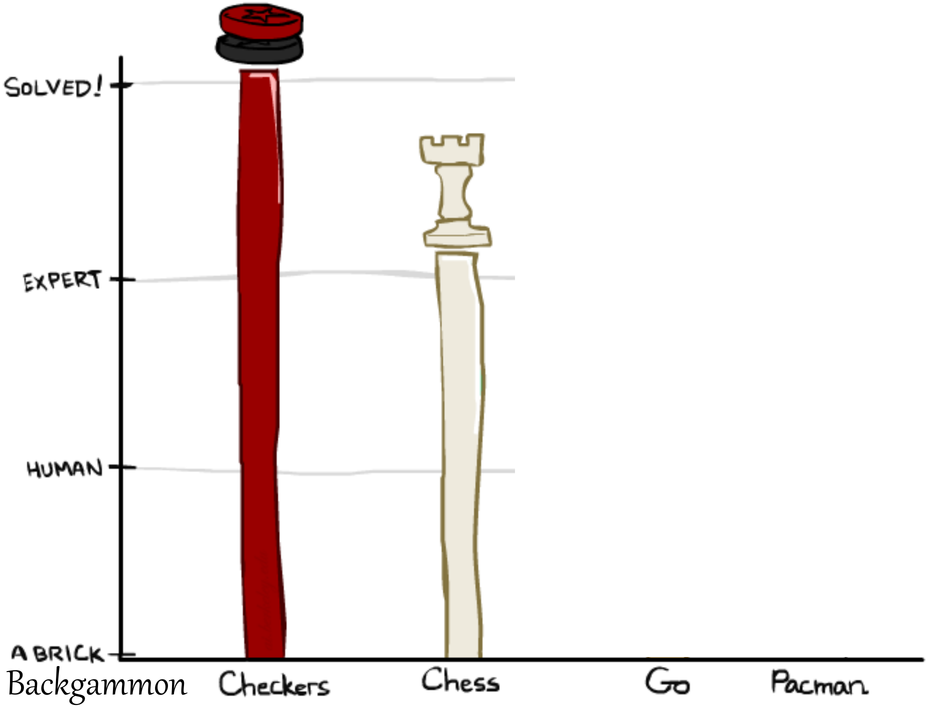
- **Go:** Human champions are now starting to be challenged by machines, though the best humans still beat the best machines. In go, b > 300! Classic programs use pattern knowledge bases, but big recent advances use Monte Carlo (randomized) expansion methods.



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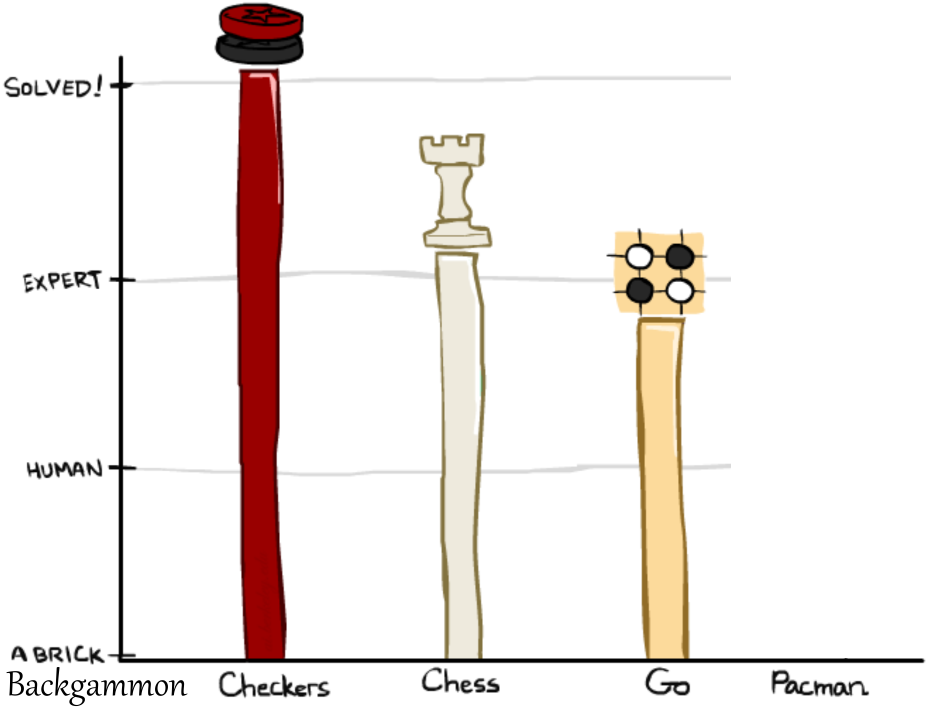

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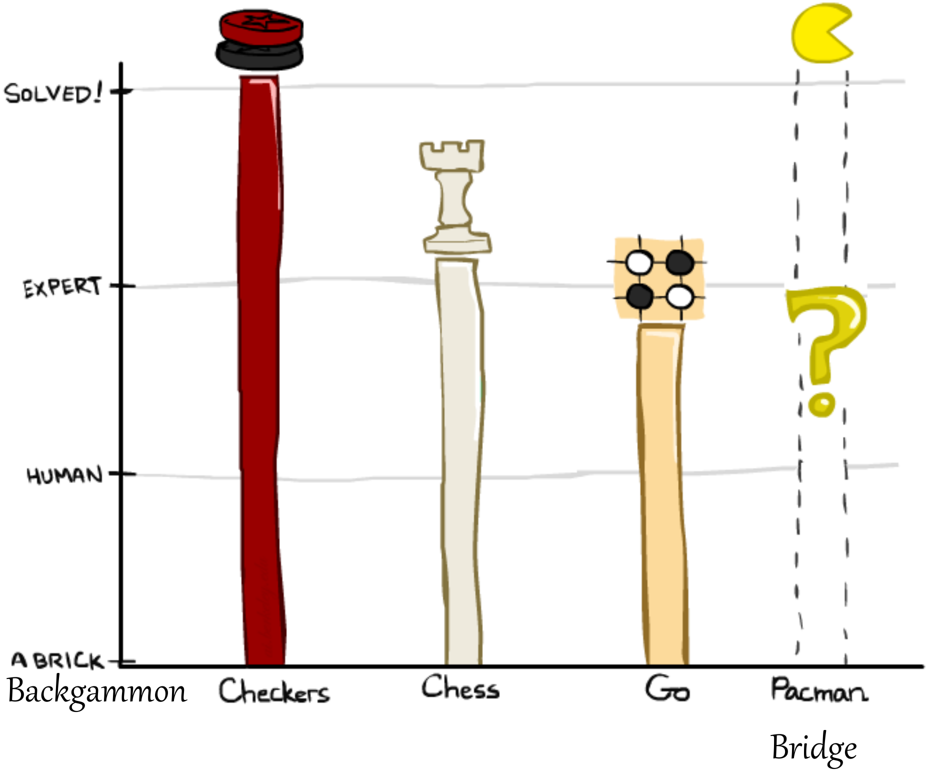


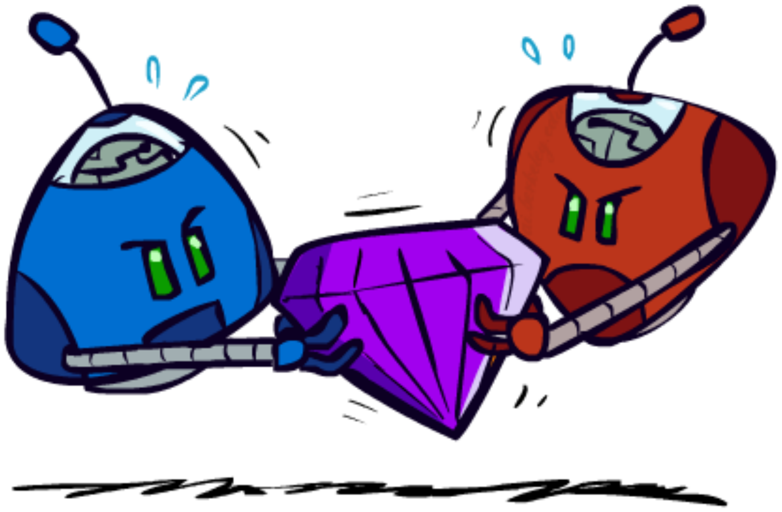
# Classical vs. Statistical/Neural Approaches

- We’ll look first at the classical approach used from the 1940s to 2010

- Then at newer statistical approached of which AlphaGo is an example

- These share some techniques

# Adversarial Games



# Types of Games

- **1-person, 2-person** game, with **alternating moves, or more players**
- **Zero-sum**: one player's loss is the other's gain **/ not**
- **Perfect information**: both players have access to complete information about state of game.  No information hidden from either player.
- **Chance** (e.g., using dice) **vs No chance** involved

# Types of Games

- **2-person** game, with **alternating moves**
- **Zero-sum**: one player's loss is the other's gain
  - A **zero-sum game** is defined as one where the total payoff to all players is the same for every instance of the game.
  - Chess is zero-sum because every game has payoff 0+1, 1+0, or 1⁄2 + 1⁄2.
- **Perfect information**: both players've access to complete information about state of game (chess, checkers). No information hidden from either player (poker).
- **No chance** involved
- Examples: Tic-Tac-Toe, Checkers, Chess, Go, Nim, Othello
- But not: Bridge, Solitaire, Backgammon, Poker, Rock-Paper-Scissors, ...

# Can we use …

Want algorithms for calculating **a strategy (policy)** which recommends a move from each state

- Uninformed search?
- Heuristic search?
- Local search?
- Constraint based search?

None of these model the fact that we have an **adversary** …

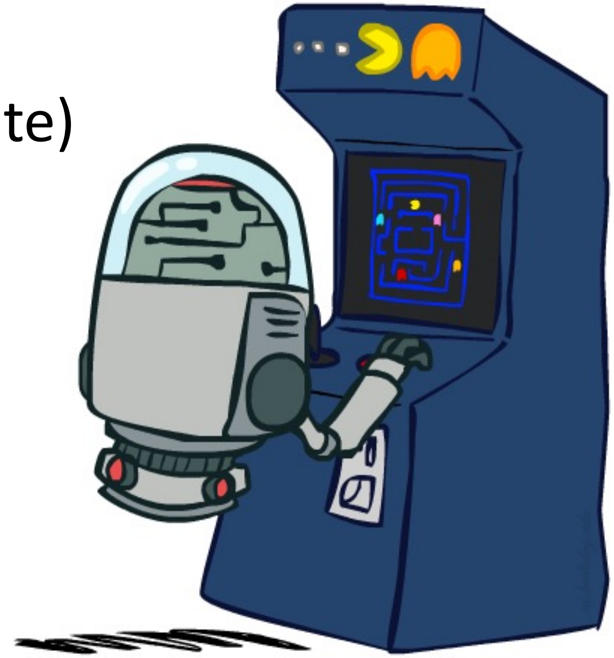
# How to play a game

- A way to play such a game is to:
  - Consider all the legal moves you can make
  - Compute new position resulting from each move
  - Evaluate each to determine which is best
  - Make that move
  - Wait for your opponent to move and repeat
- Key problems are:
  - Representing the "board" (i.e., game state)
  - Generating all legal next boards
  - Evaluating a position

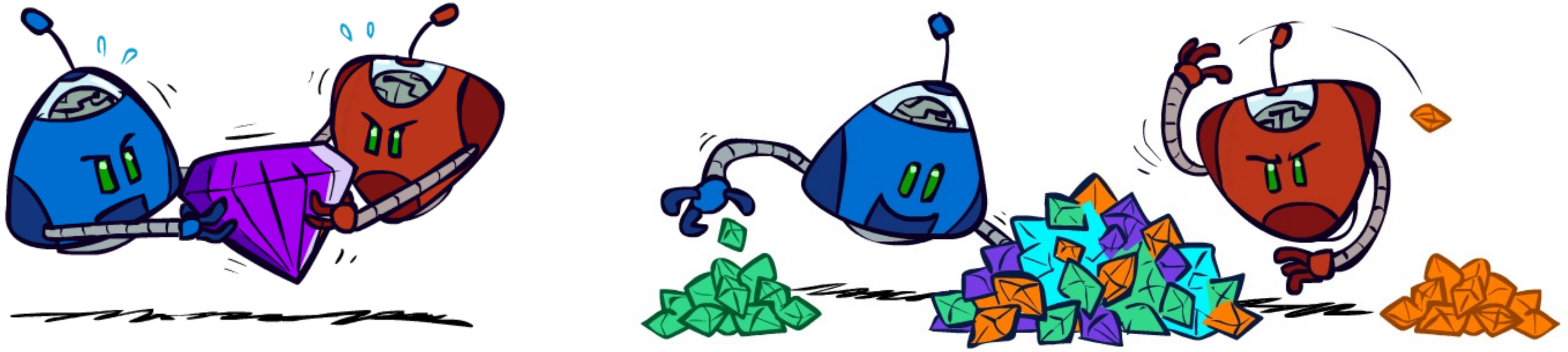
# Deterministic Games

- Many possible formalizations, one is:
  - States: S (start at $s_0$)
  - Players: P={1...N} (usually take turns)
  - Actions: A (may depend on player / state)
  - Transition Function: SxA $\rightarrow$ S
  - Terminal Test: S $\rightarrow$ {t,f}
  - Terminal Utilities: SxP $\rightarrow$ R

- Solution for a player is a policy: S $\rightarrow$ A



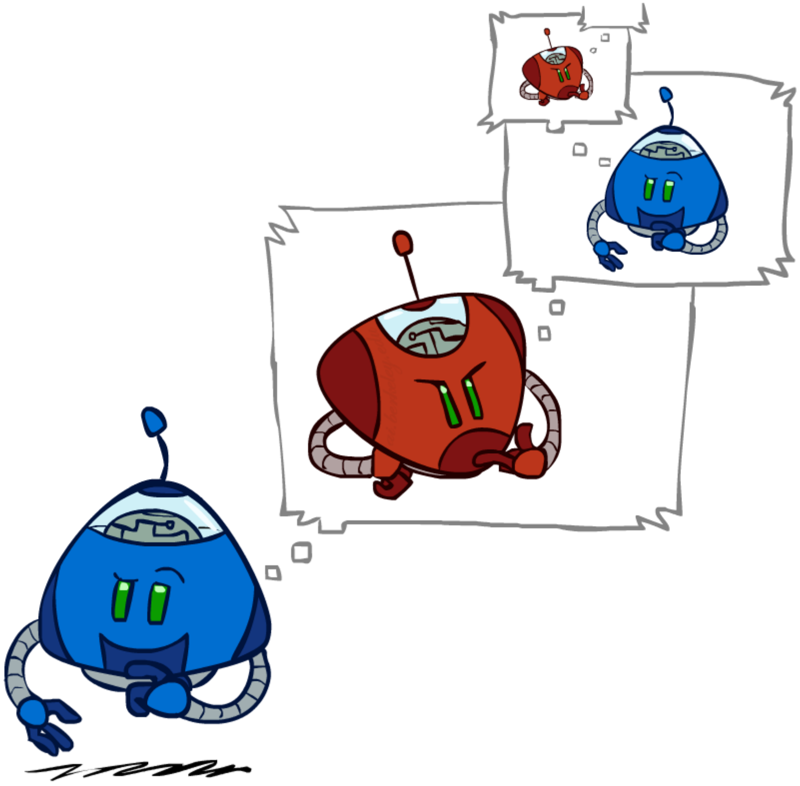
# Zero-Sum Games

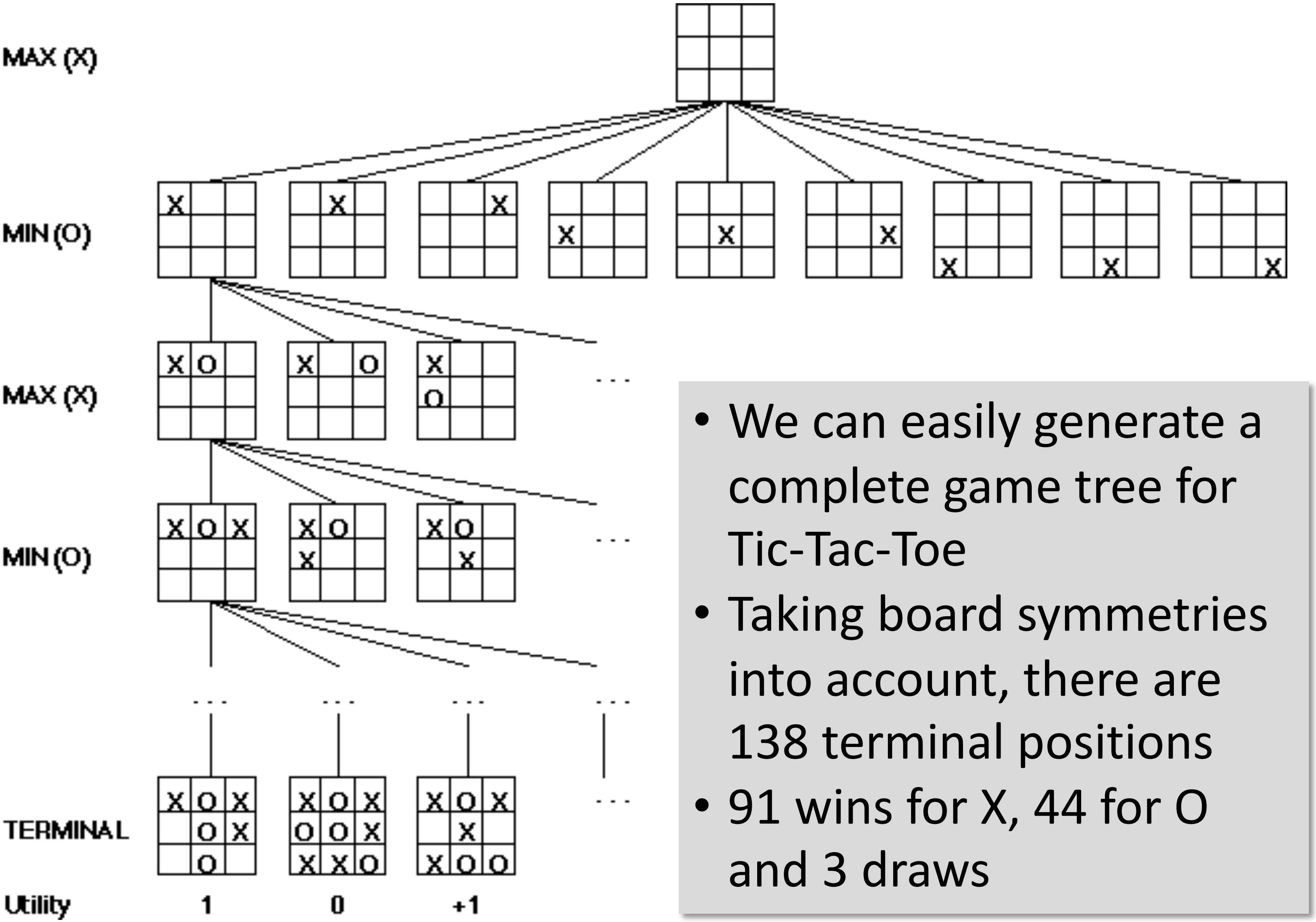


- Zero-Sum Games
  - Agents have opposite utilities (values on outcomes)
  - **Lets us think of a single value that one maximizes and the other minimizes**
  - Adversarial, pure competition

- General Games
  - Agents have independent utilities (values on outcomes)
  - Cooperation, indifference, competition, and more are all possible
  - More later on non-zero-sum games

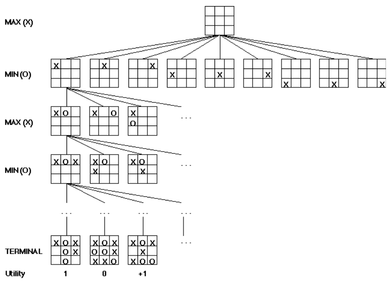
# Adversarial Search





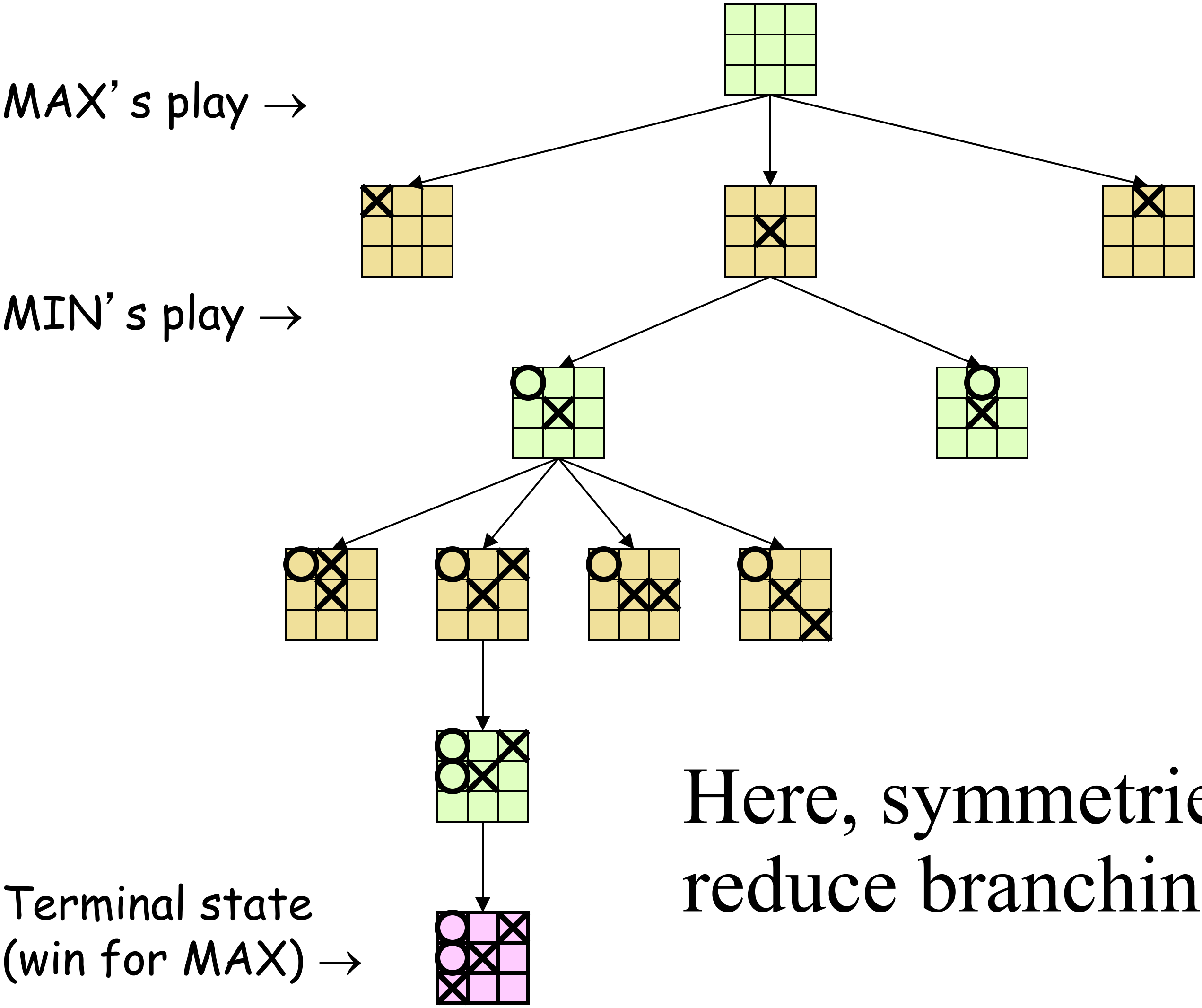
- We can easily generate a complete game tree for Tic-Tac-Toe
- Taking board symmetries into account, there are 138 terminal positions
- 91 wins for X, 44 for O and 3 draws

# Game trees



- Problem spaces for typical games are trees
- Root node is current board configuration; player must decide best single move to make next
- **Static evaluator function** rates board position **f(board):**real, > 0 for me; < 0 for opponent
- Arcs represent possible legal moves for a player
- If **my turn** to move, then root is labeled a "**MAX**" node; otherwise it's a "**MIN**" node
- Each tree level's nodes are all MAX or all MIN; nodes at level i are of opposite kind from those at level i+1

# Game Tree for Tic-Tac-Toe



Here, symmetries are used to reduce branching factor

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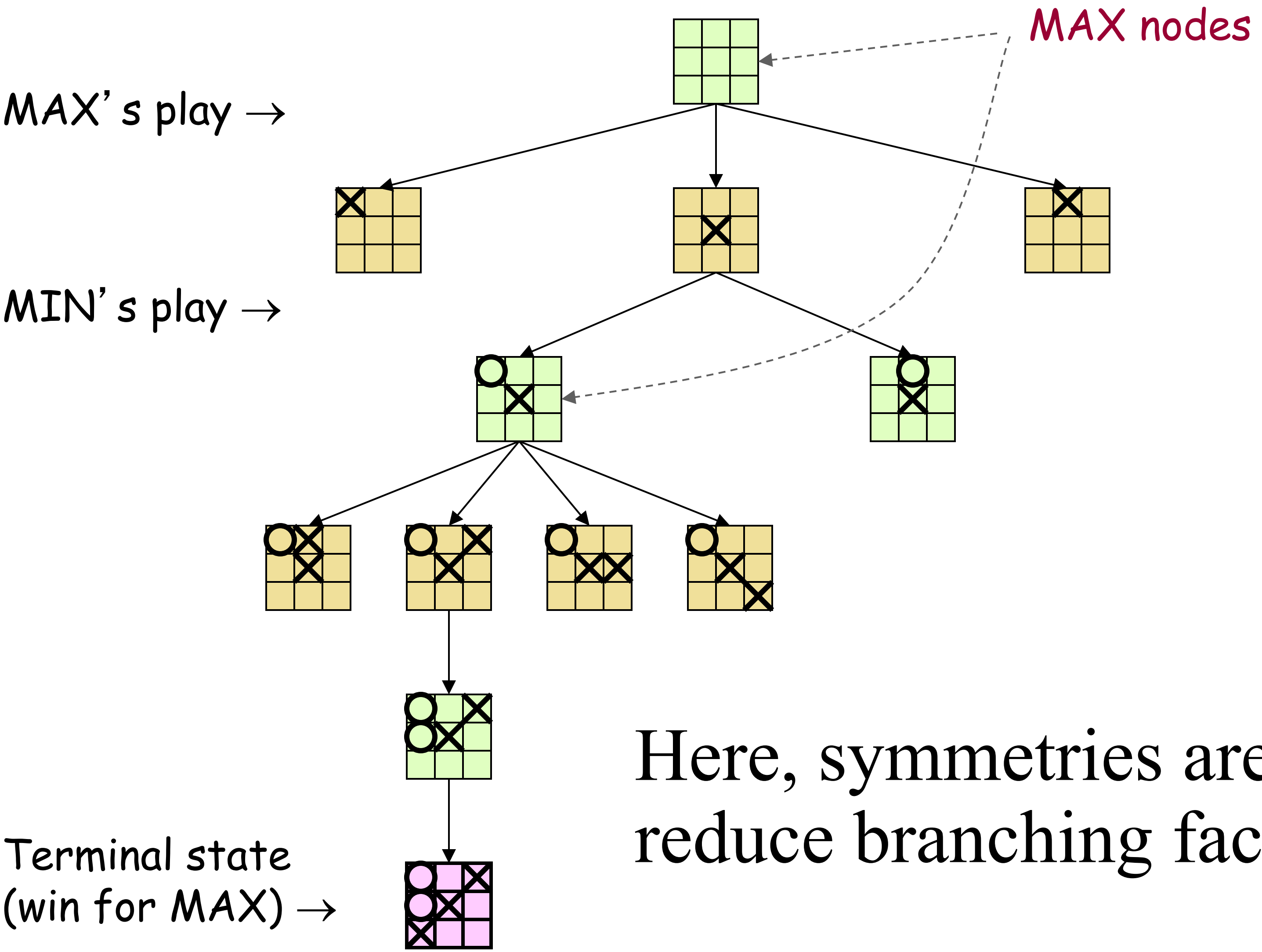

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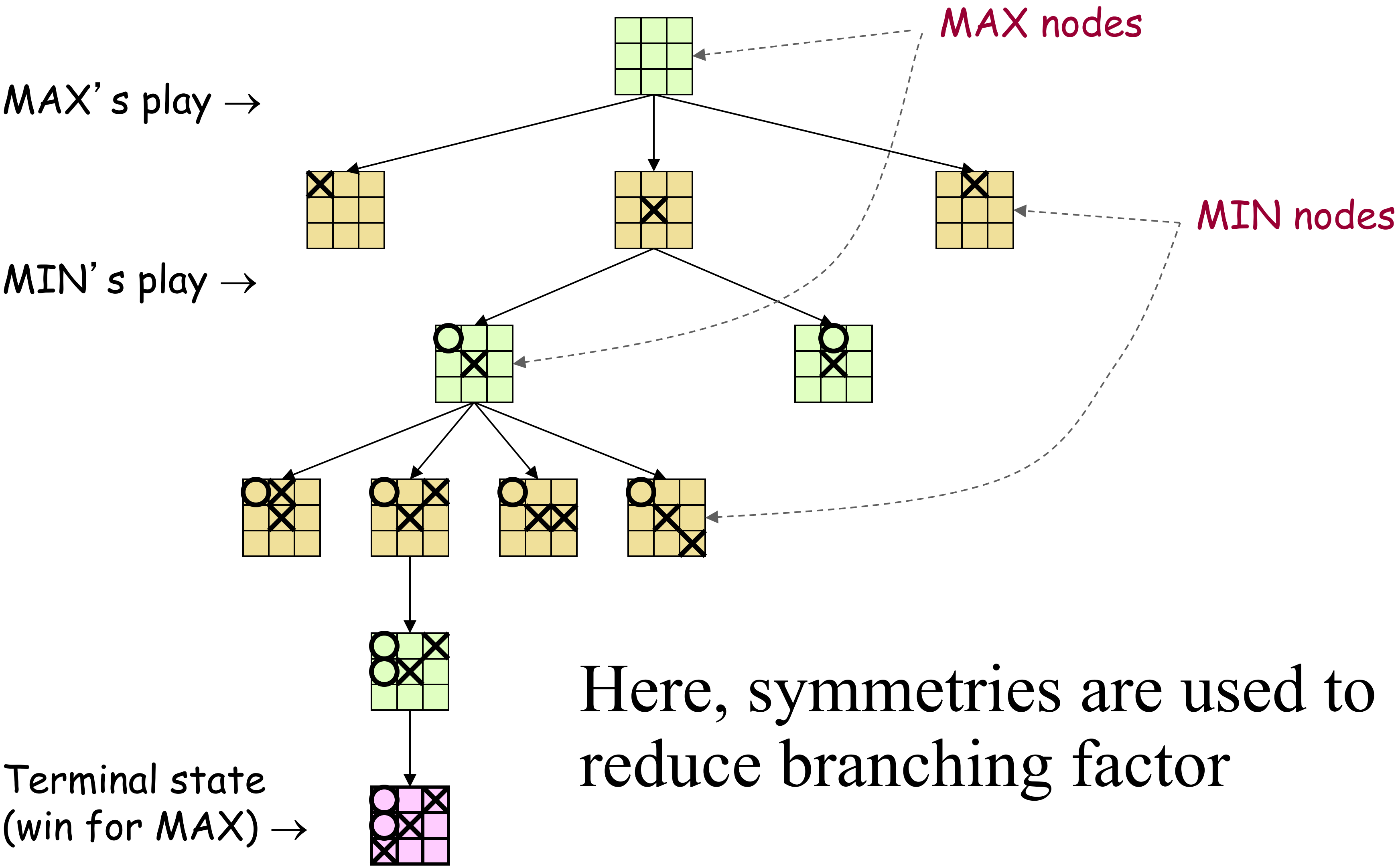

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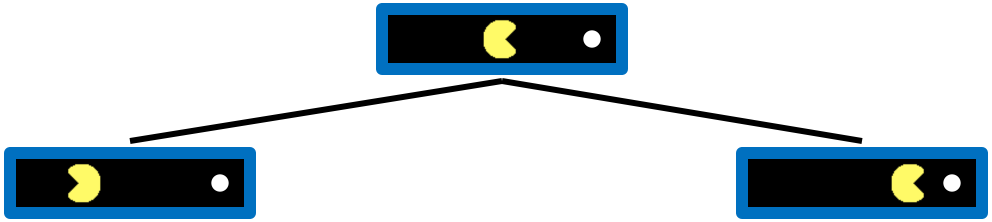

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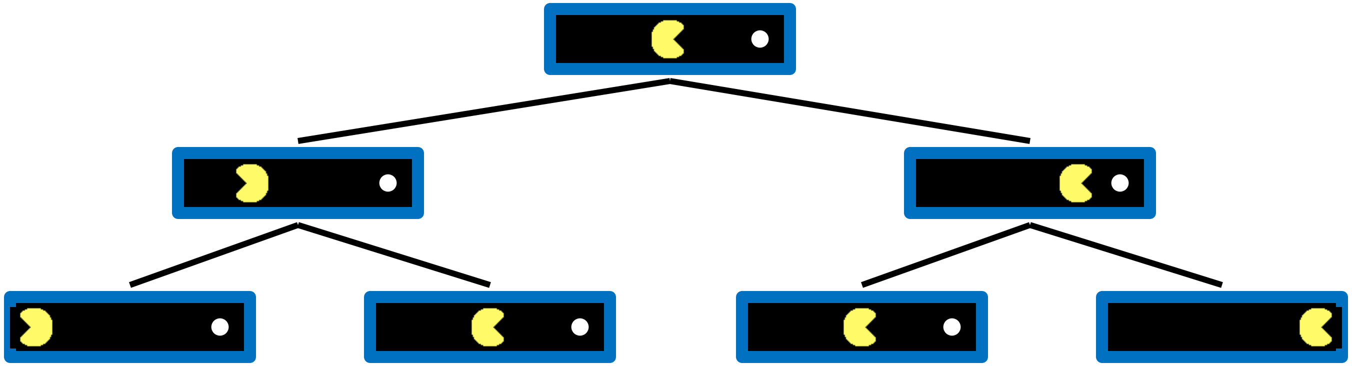

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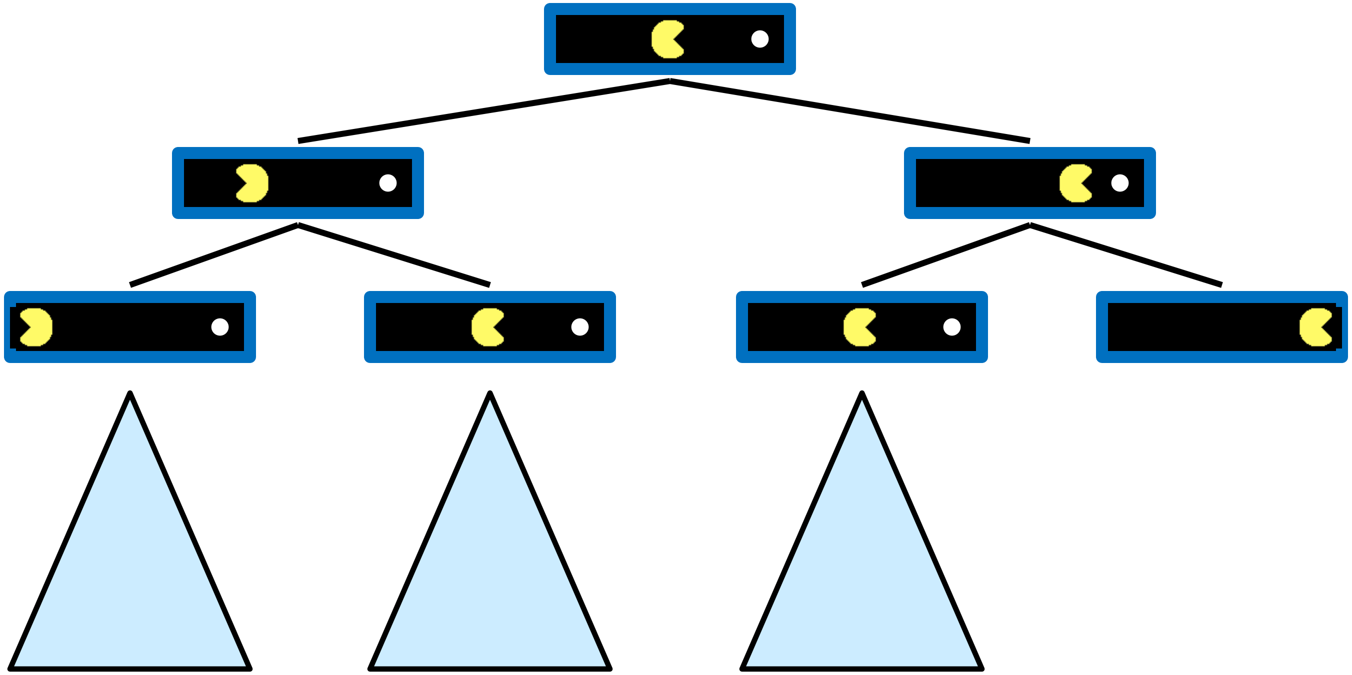

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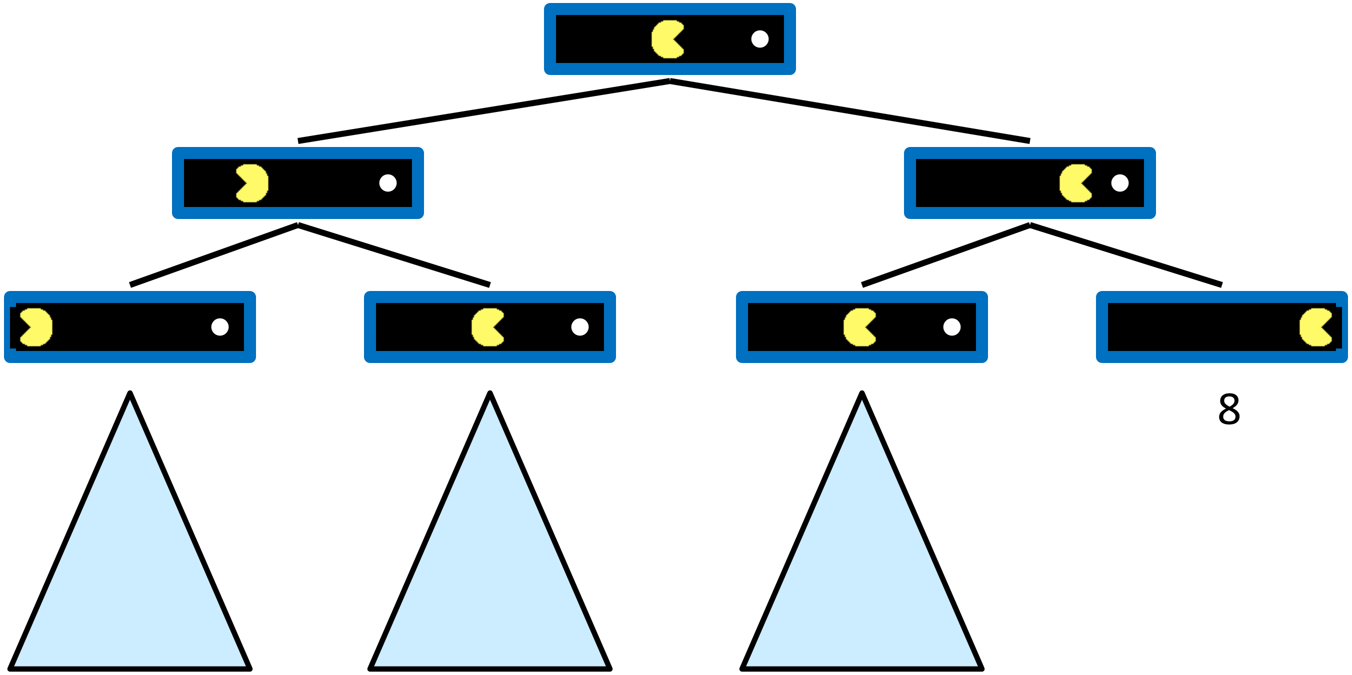

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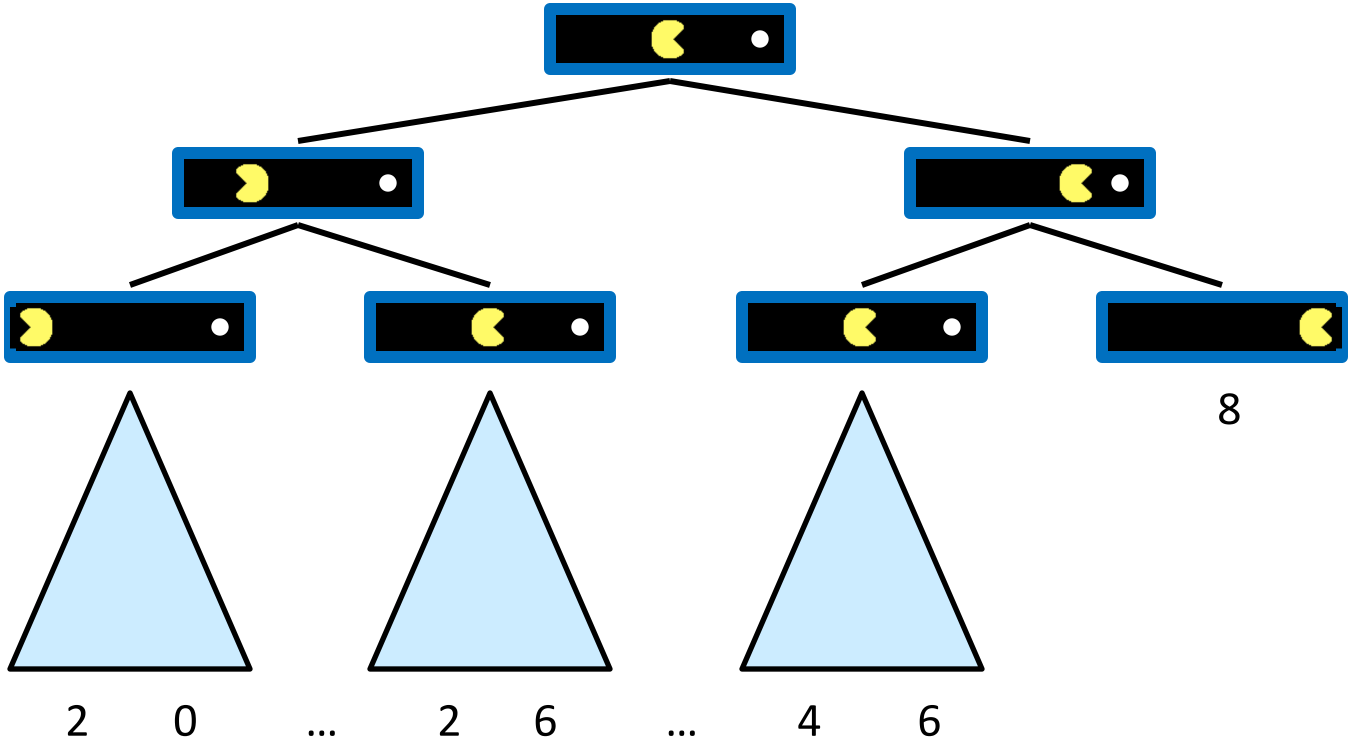
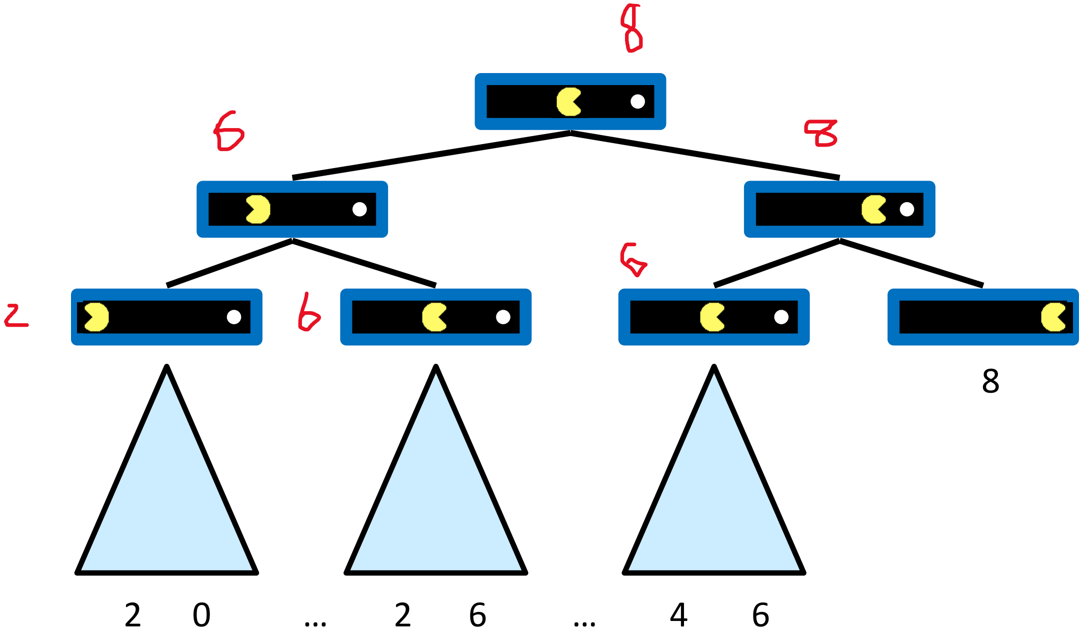
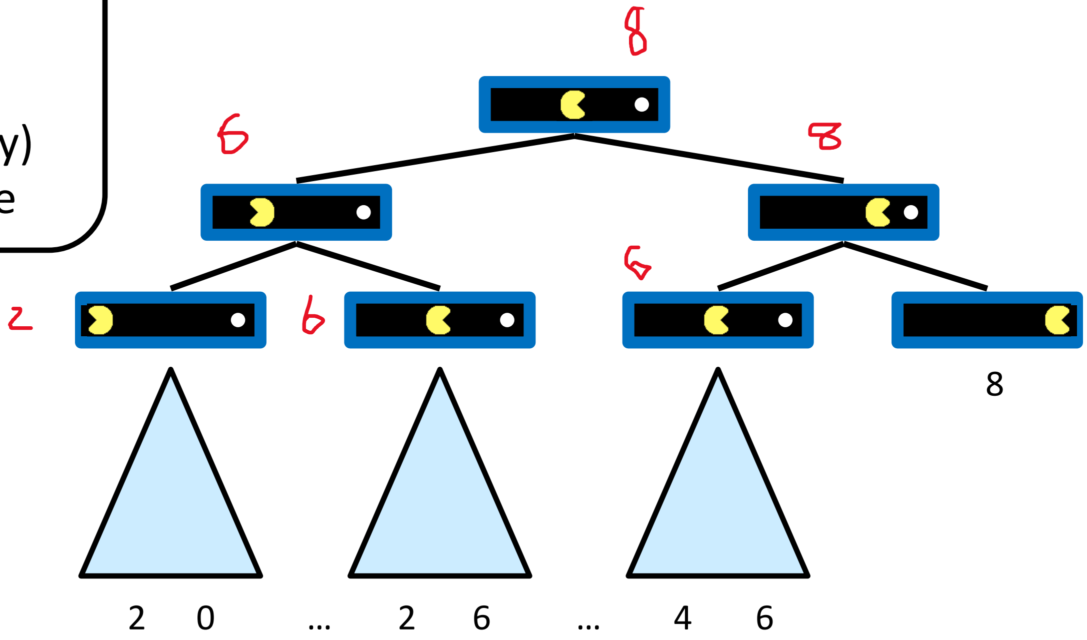


# Value of a State



# Value of a State

Value of a state:
The best achievable outcome (utility) from that state



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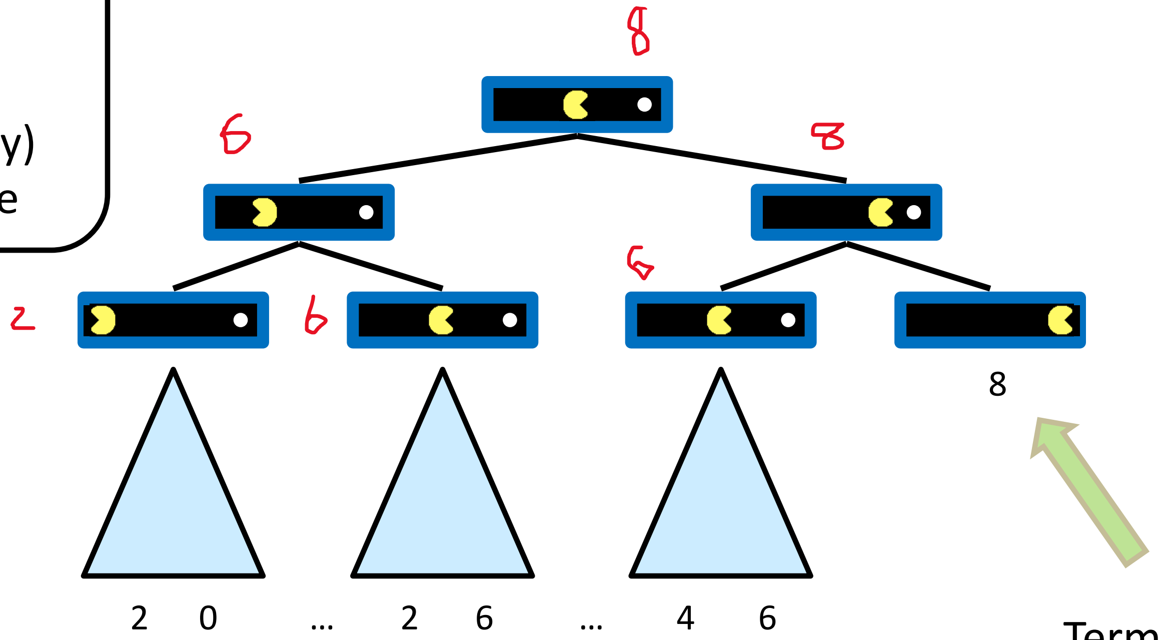

Terminal States:

$V(s) = \text{known}$

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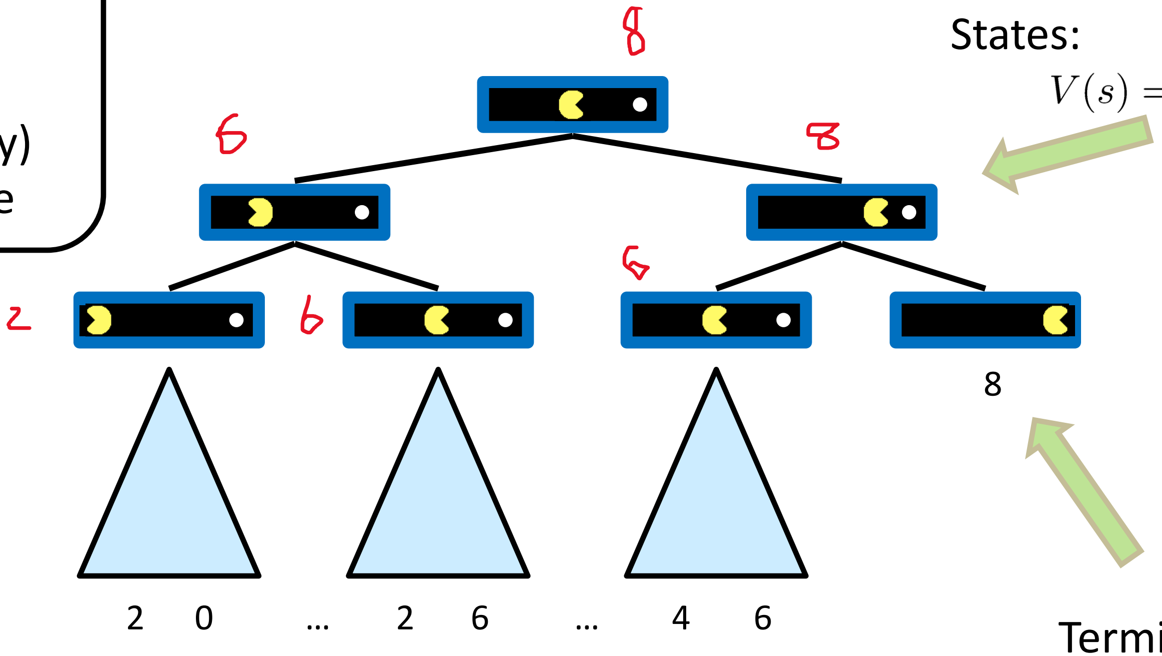

Non-Terminal
States:

$$V(s) = \max_{s' \in \text{children}(s)} V(s')$$

Terminal States:

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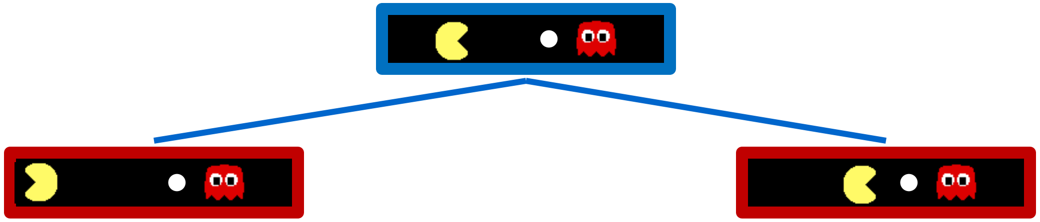

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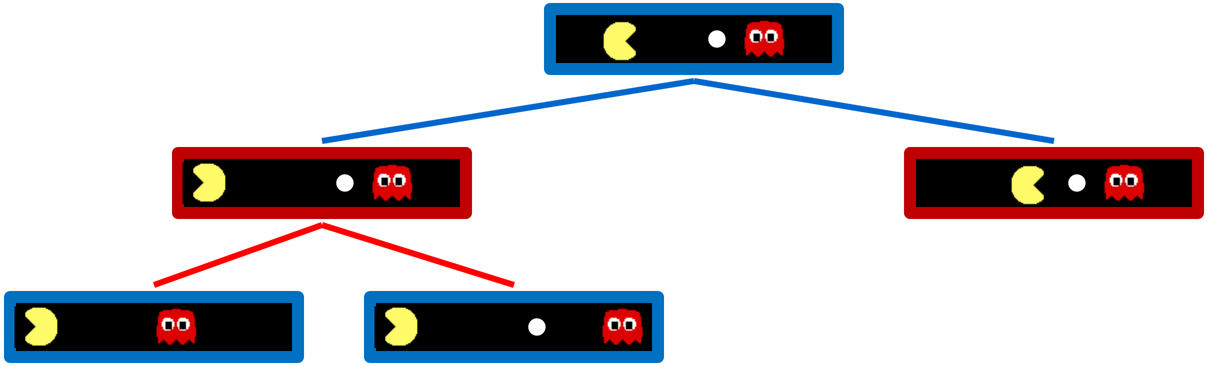

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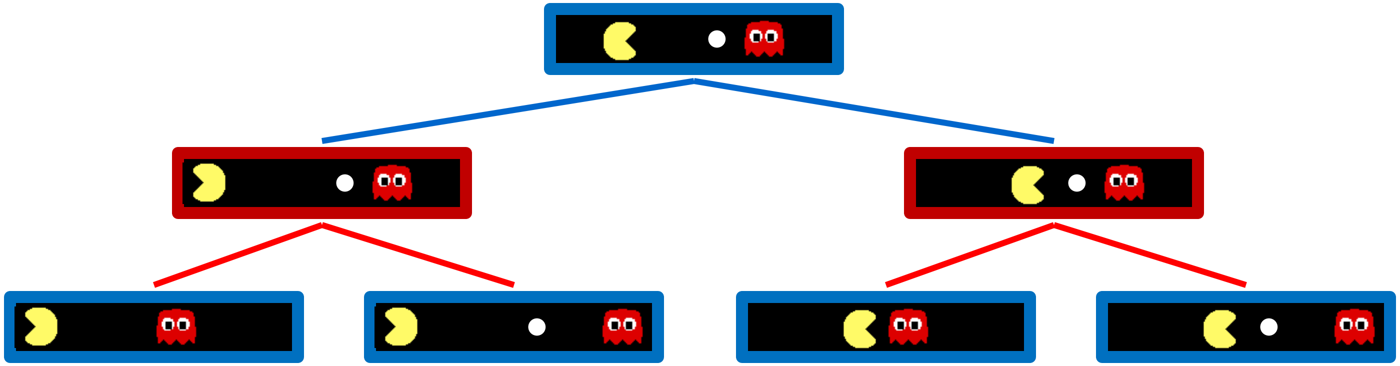

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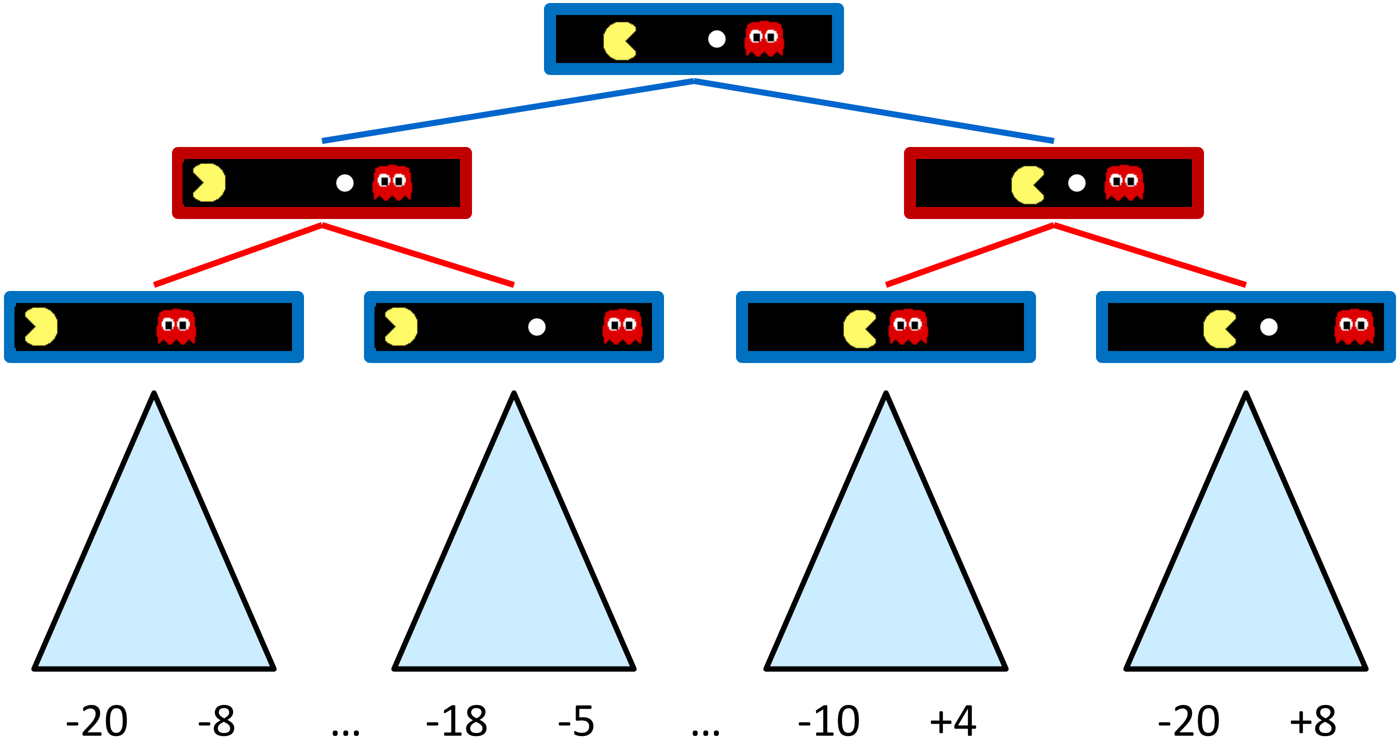
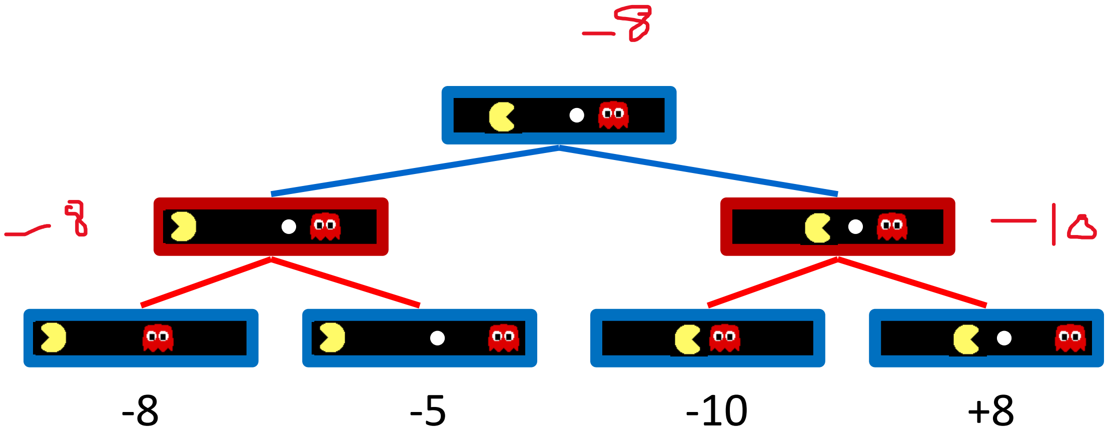


# Minimax Values



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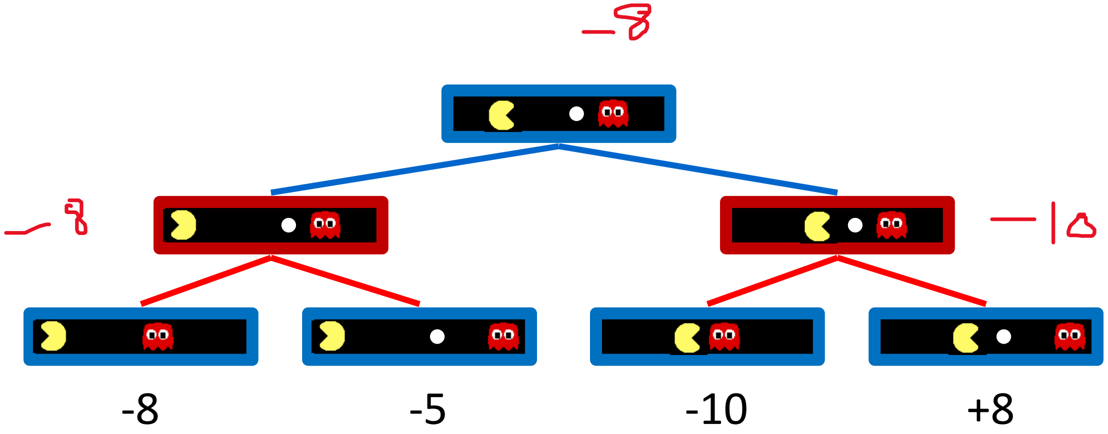

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States Under Opponent's Control:

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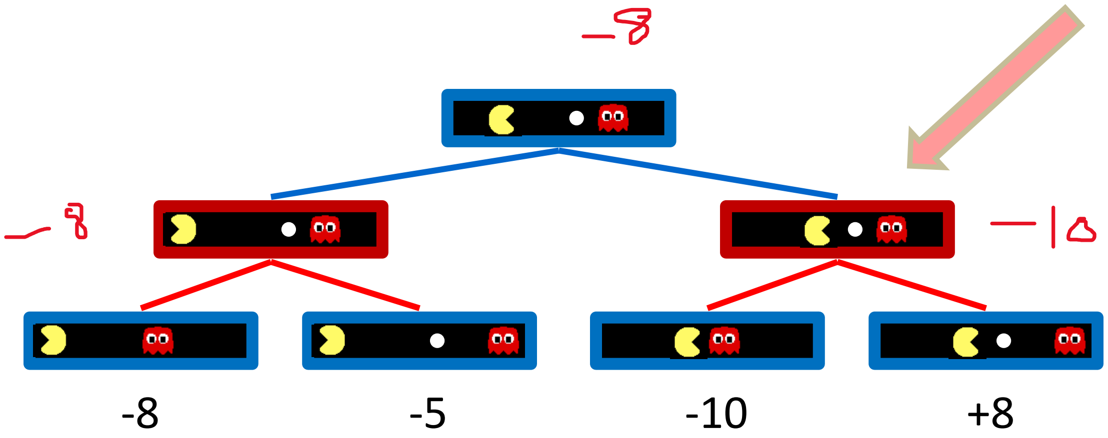

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States Under Agent's Control:

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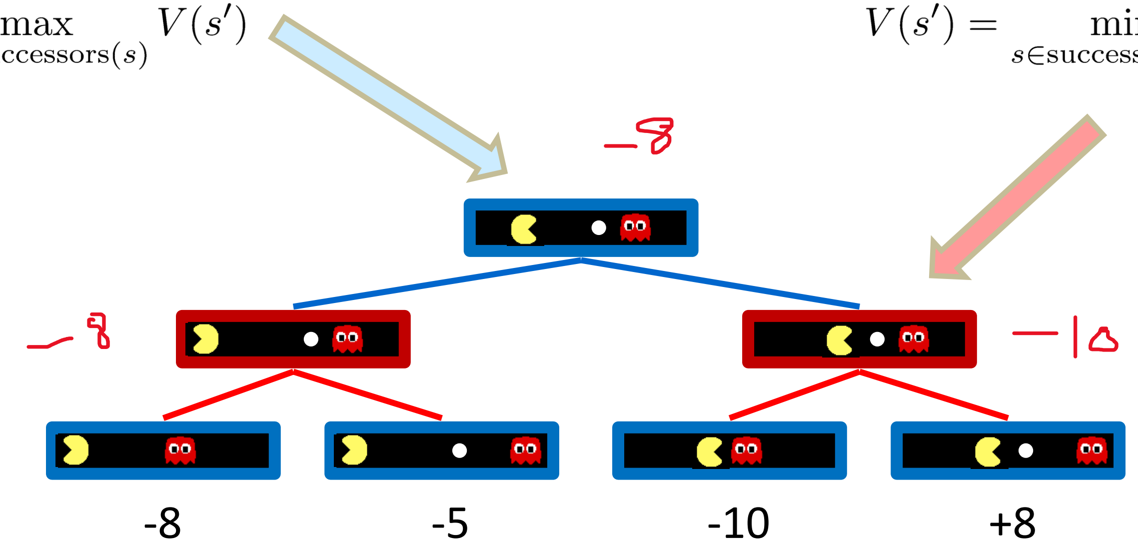

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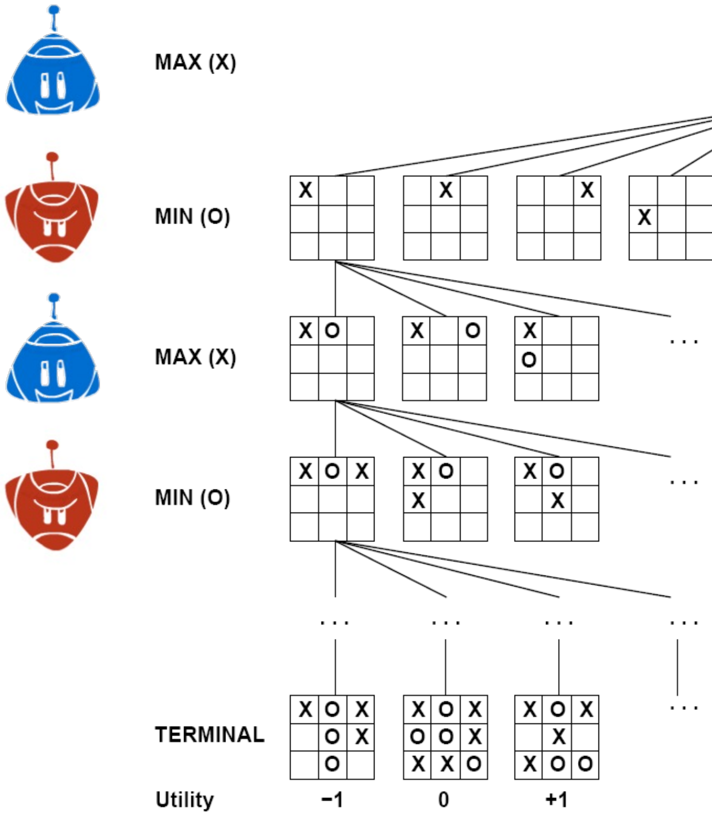
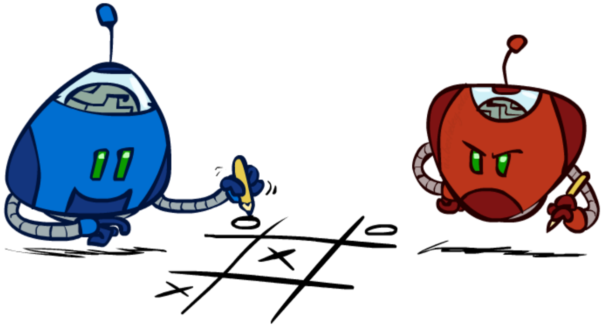
# Tic-Tac-Toe Game Tree

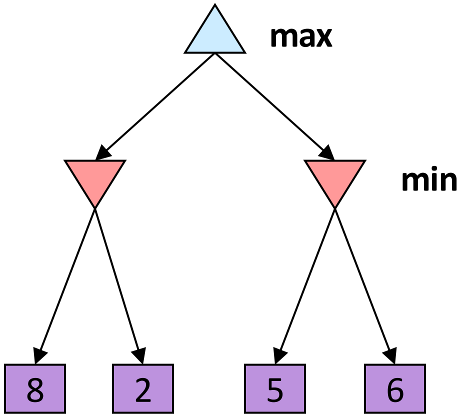




# Adversarial Search (Minimax)

- Deterministic, zero-sum games:
  - Tic-tac-toe, chess, checkers
  - One player maximizes result
  - The other minimizes result

- Minimax search:
  - A state-space search tree
  - Players alternate turns
  - Compute each node's minimax value: the best achievable utility against a rational (optimal) adversary



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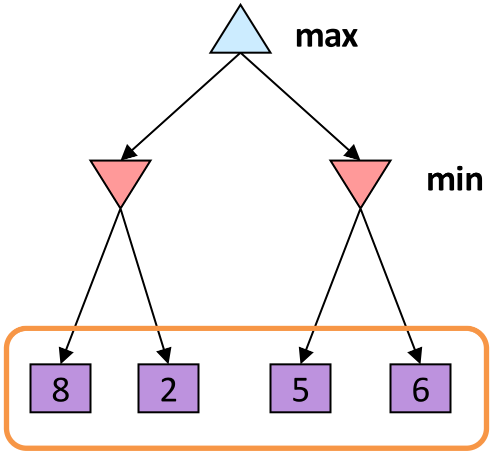

**Terminal values: part of the game**

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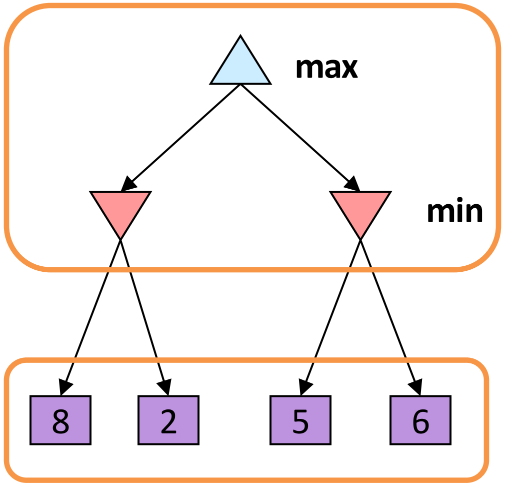
**Minimax values: computed recursively**



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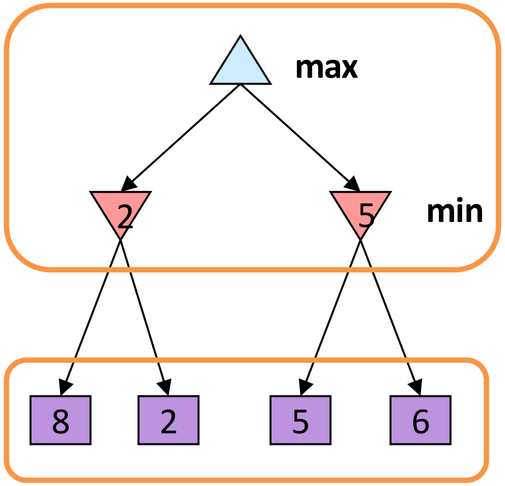

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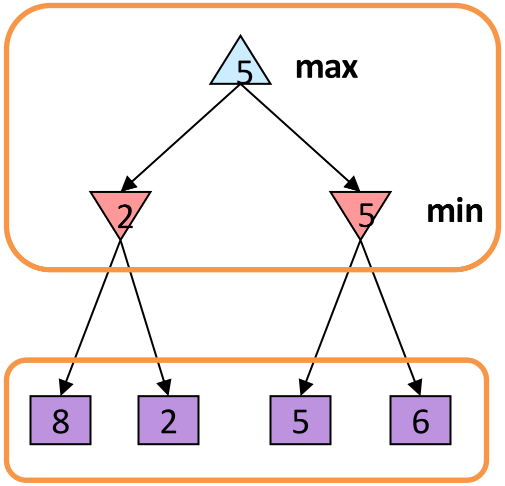

**Terminal values: part of the game**

# Minimax Algorithm

1. Create MAX node with current board configuration
2. *Expand nodes to some **depth** (a.k.a. **plys**) of **lookahead** in game*
3. Apply evaluation function at each **leaf** node
4. ***Back up*** values for each non-leaf node until value is computed for the root node
   - At MIN nodes: value is **minimum** of children's values
   - At MAX nodes: value is **maximum** of children's values
5. Choose move to child node whose backed-up value determined value at root

# Minimax Implementation

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def max-value(state):
    initialize v = -∞
    for each successor of state:
        v = max(v, min-value(successor))
    return v
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        v = min(v, max-value(successor))
    return v
```

$$V(s) = \max_{s' \in \text{successors}(s)} V(s')$$

$$V(s') = \min_{s \in \text{successors}(s')} V(s)$$

# Minimax Implementation (Dispatch)

```
def value(state):
    if the state is a terminal state: return the state's utility
    if the next agent is MAX: return max-value(state)
    if the next agent is MIN: return min-value(state)
```

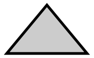
# Minimax Implementation (Dispatch)

```
def value(state):
    if the state is a terminal state: return the state's utility
    if the next agent is MAX: return max-value(state)
    if the next agent is MIN: return min-value(state)
```

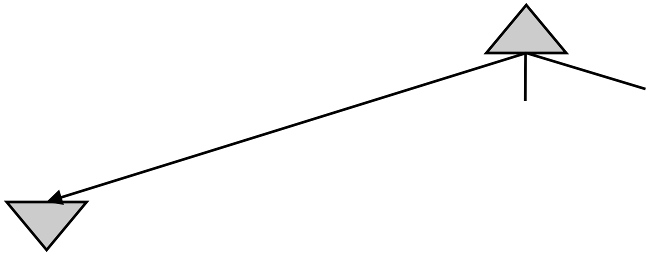
```
def max-value(state):
    initialize v = -∞
    for each successor of state:
        v = max(v, value(successor))
    return v
```

```
def min-value(state):
    initialize v = +∞
    for each successor of state:
        v = min(v, value(successor))
    return v
```

# Minimax Example



# Minimax Example



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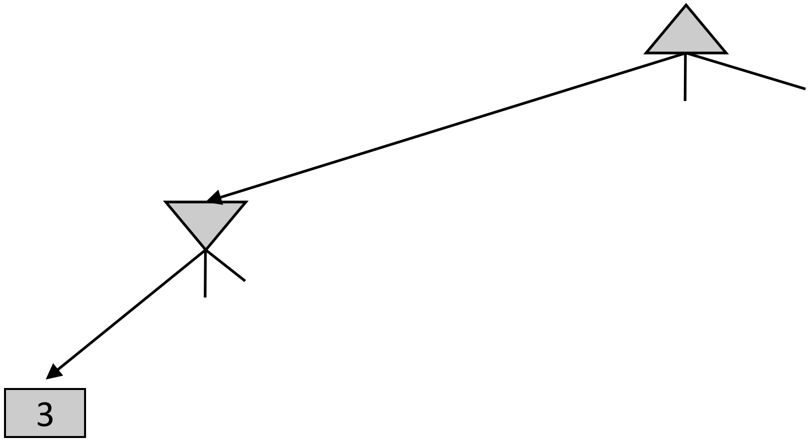

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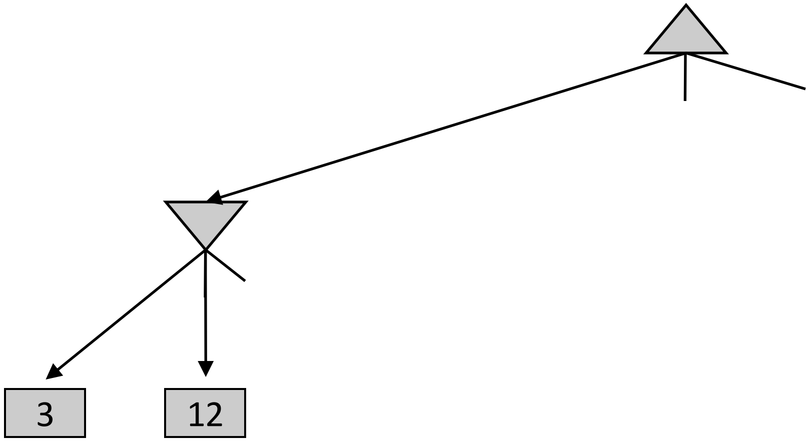

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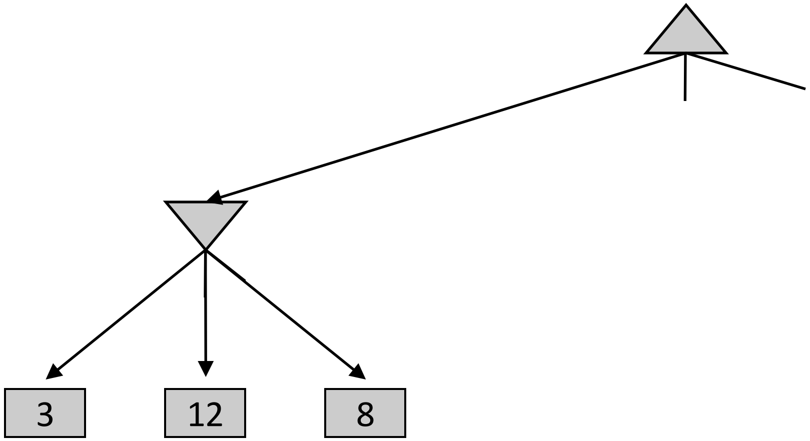

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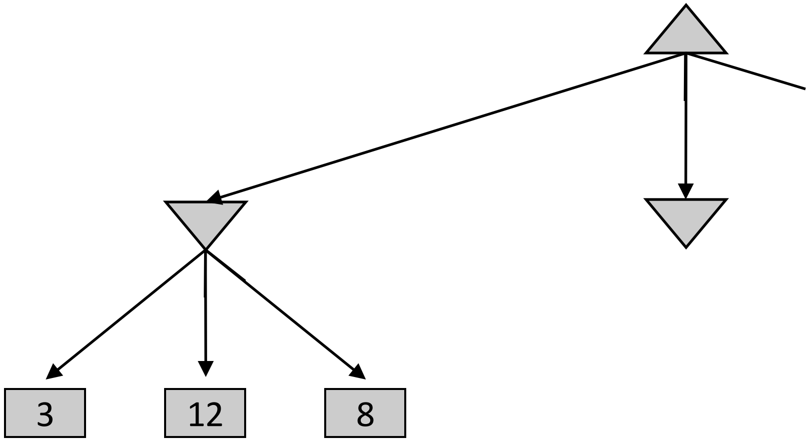

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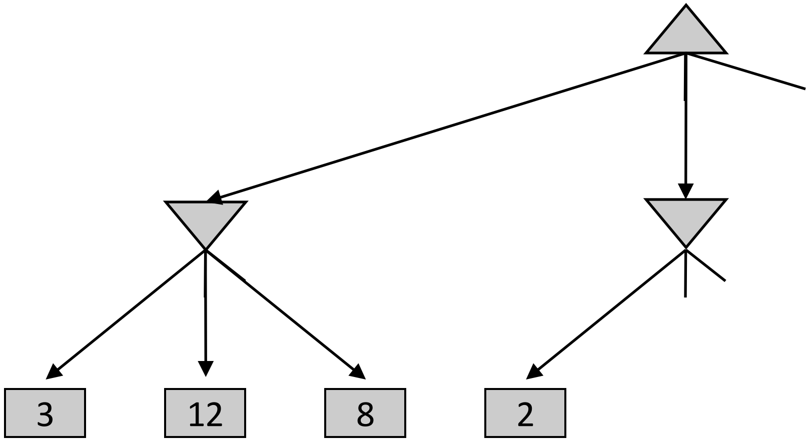

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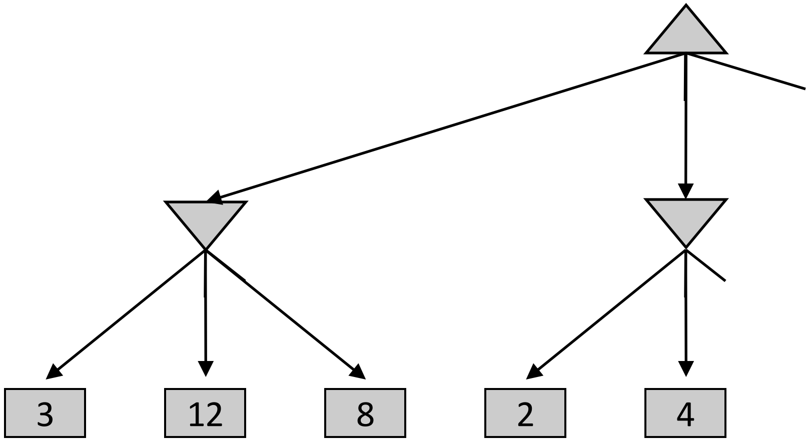

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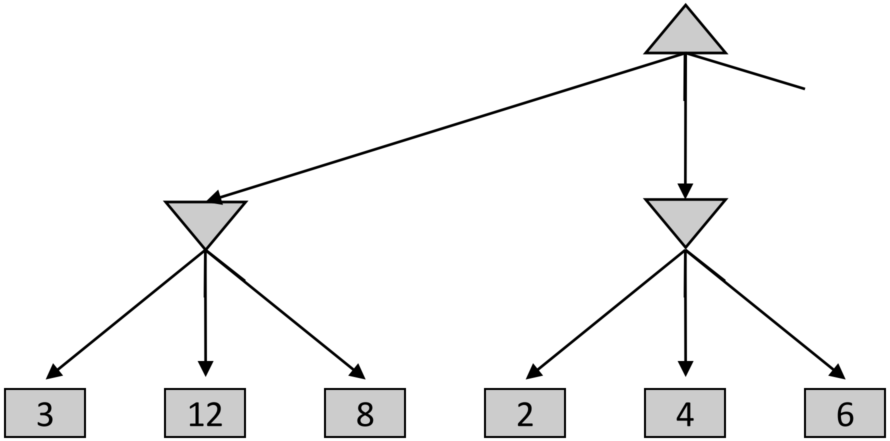

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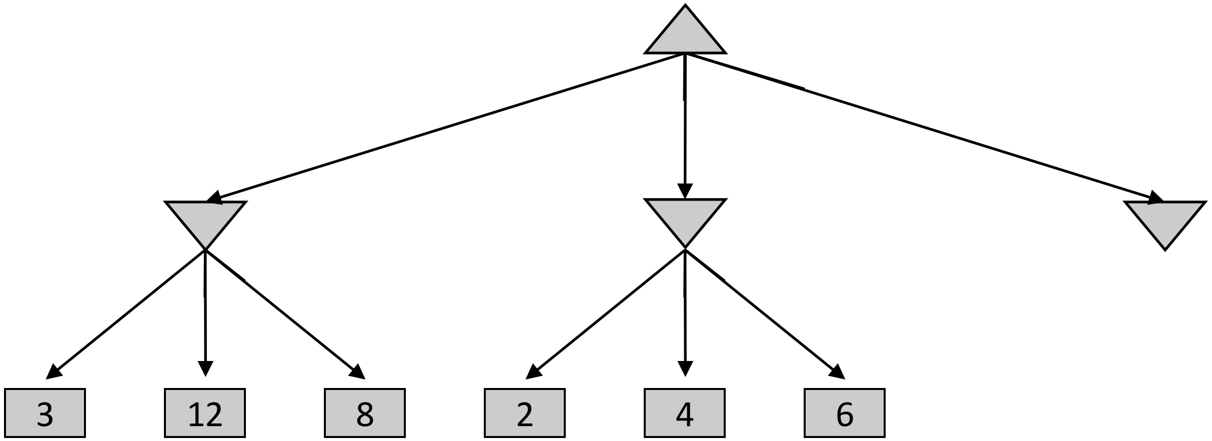

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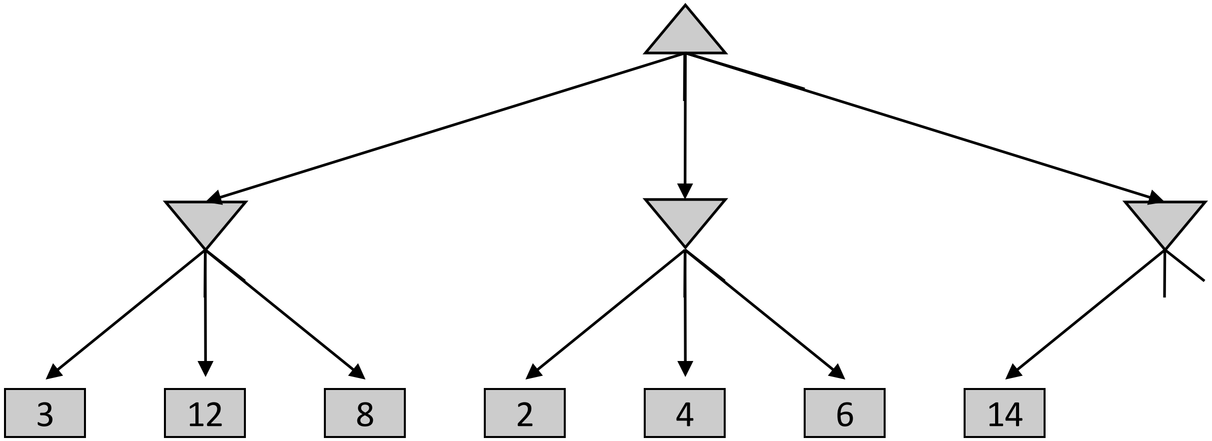

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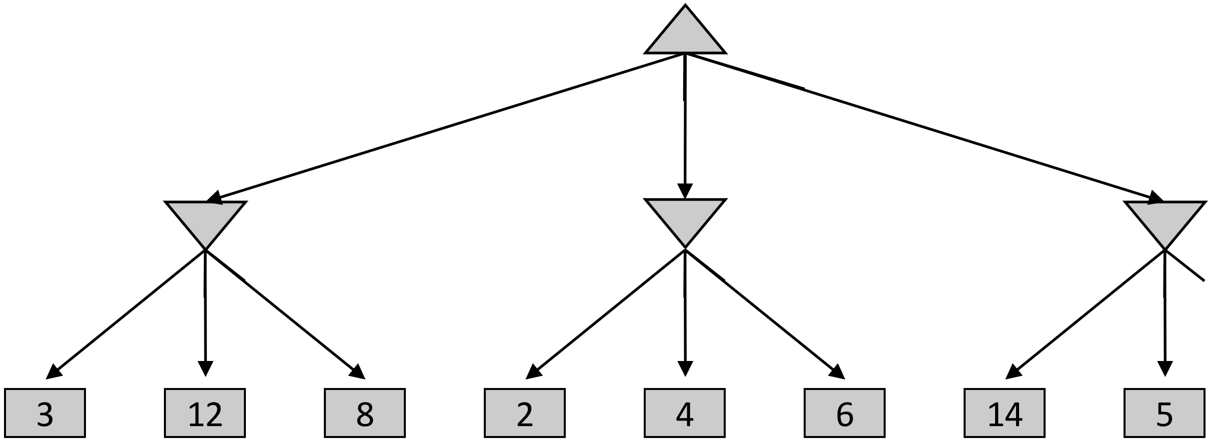

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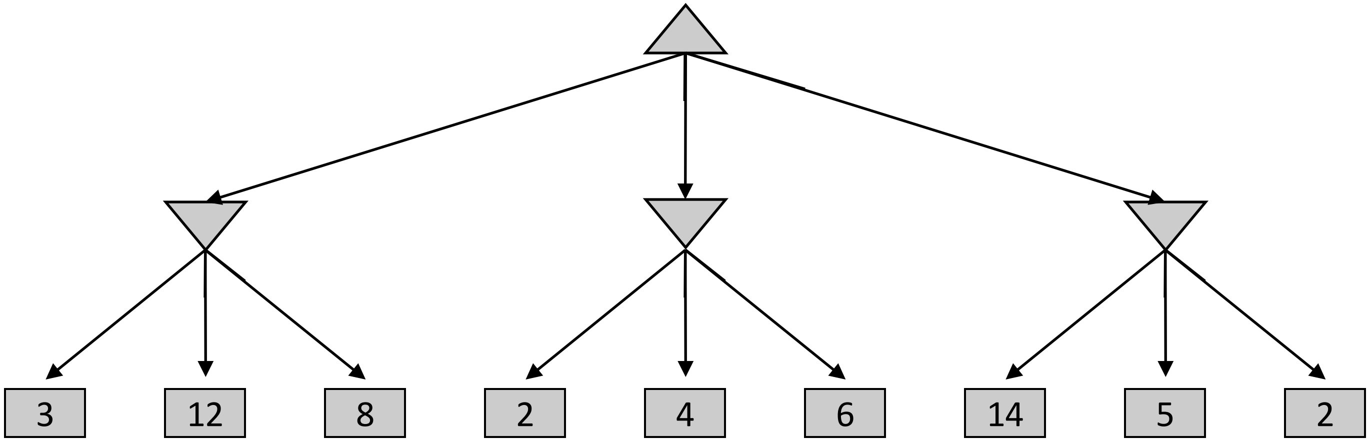
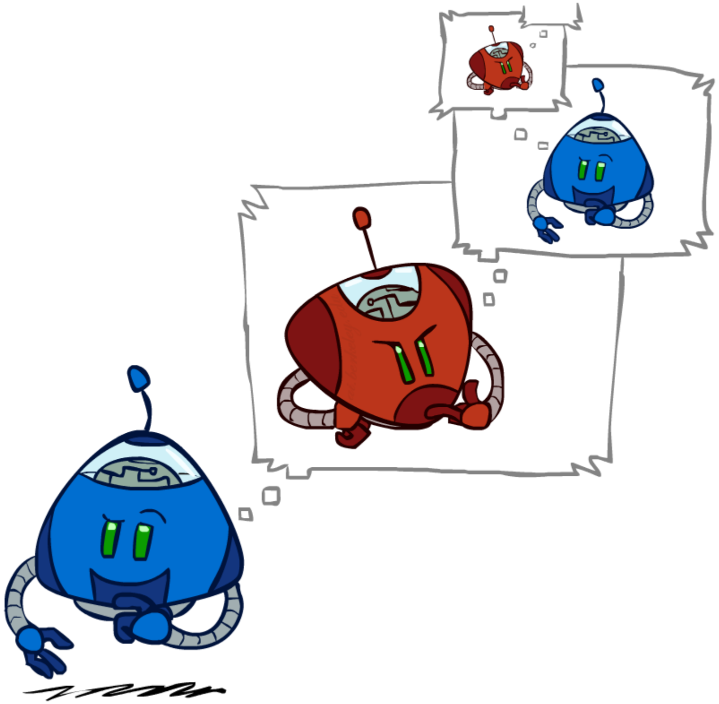
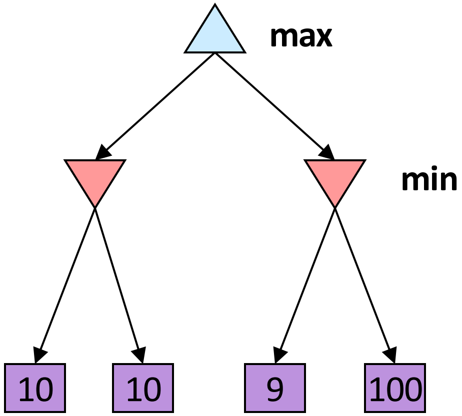


# Minimax Efficiency

- How efficient is minimax?
  - Just like (exhaustive) DFS
  - Time: $O(b^m)$
  - Space: $O(bm)$
- Example: For chess, $b \approx 35$, $m \approx 100$
  - Exact solution is completely infeasible
  - But, do we need to explore the whole tree?



# Minimax Properties



Optimal against a perfect player. Otherwise?

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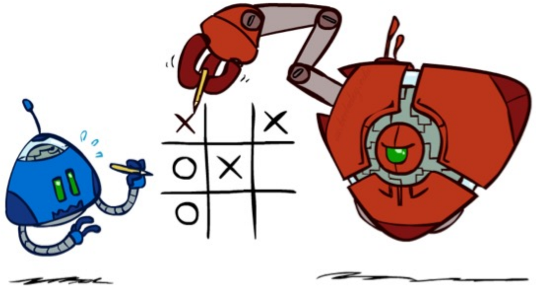

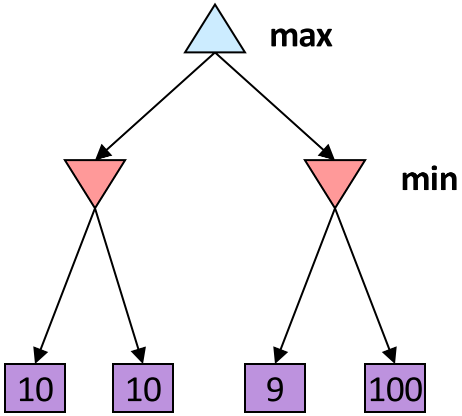

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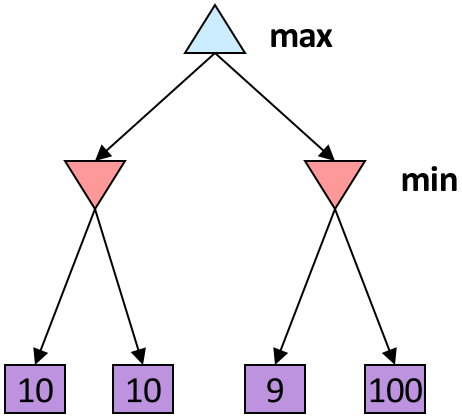

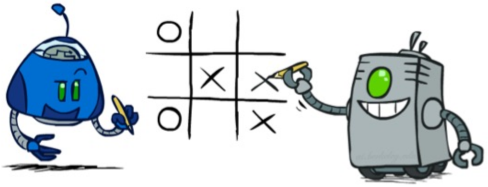

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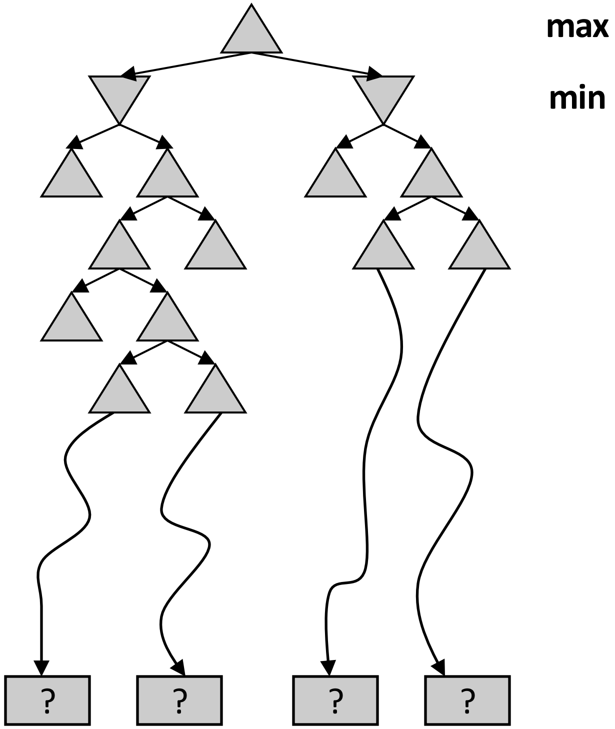
# Resource Limits

# Resource Limits

- Problem: In realistic games, cannot search to leaves!



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- Problem: In realistic games, cannot search to leaves!
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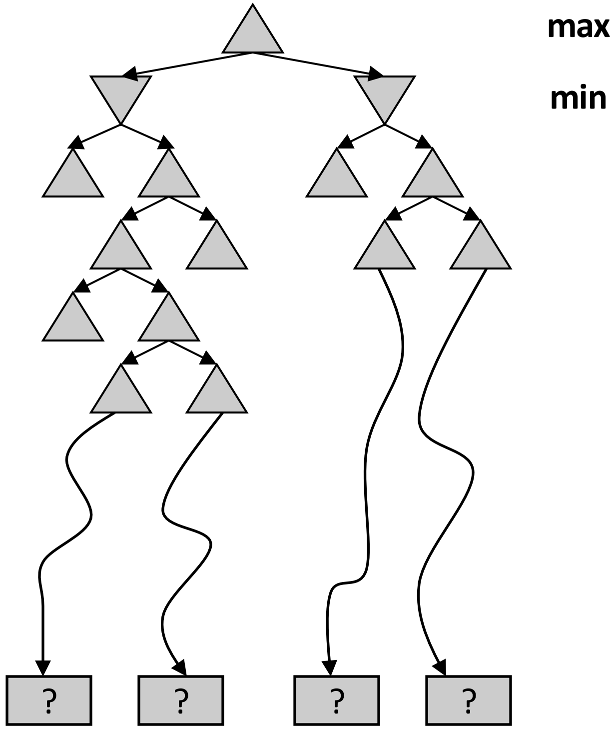
  - Instead, search only to a limited depth in the tree
  - Replace terminal utilities with an evaluation function for non-terminal positions



# Evaluation function

- **Evaluation function** or **static evaluator** used to evaluate the "goodness" of a game position

  Contrast with heuristic search, where evaluation function estimates **cost** from start node to goal passing through given node

- Zero-sum assumption permits **single function to describe goodness of board for both players**
  - **f(n) >> 0**: position n good for me; bad for you
  - **f(n) << 0**: position n bad for me; good for you
  - **f(n) near 0**: position n is a neutral position
  - **f(n) = +infinity**: win for me
  - **f(n) = -infinity**: win for you

# Evaluation function examples

- **For Tic-Tac-Toe**

  f(n) = [# my open 3lengths] - [# your open 3lengths]

  Where 3length is complete row, column or diagonal that has no opponent marks

- **Alan Turing's function for chess**
  - **f(n) = w(n)/b(n)** where w(n) = sum of point value of white's pieces and b(n) = sum of black's
  - Traditional piece values: pawn:1; knight:3; bishop:3; rook:5; queen:9

# Evaluation function examples

- Most evaluation functions specified as a weighted sum of positive features

$$f(n) = w_1 * feat_1(n) + w_2 * feat_2(n) + ... + w_n * feat_k(n)$$

- Example chess features are piece count, piece values, piece placement, squares controlled, etc.
- IBM's chess program Deep Blue (circa 1996) had **>8K features** in its evaluation function

# But, that’s not how people play

- People also use *look ahead*

  i.e., enumerate actions, consider opponent’s possible responses, REPEAT
- Producing a *complete* **game tree** is only possible for simple games
- So, generate a partial game tree for some number of plys
  - Move = each player takes a turn
  - Ply = one player’s turn
- What do we do with the game tree?

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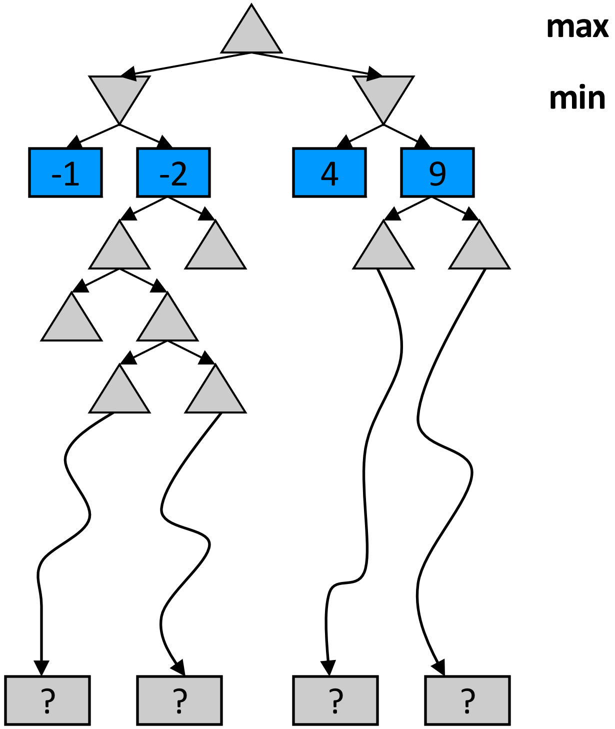

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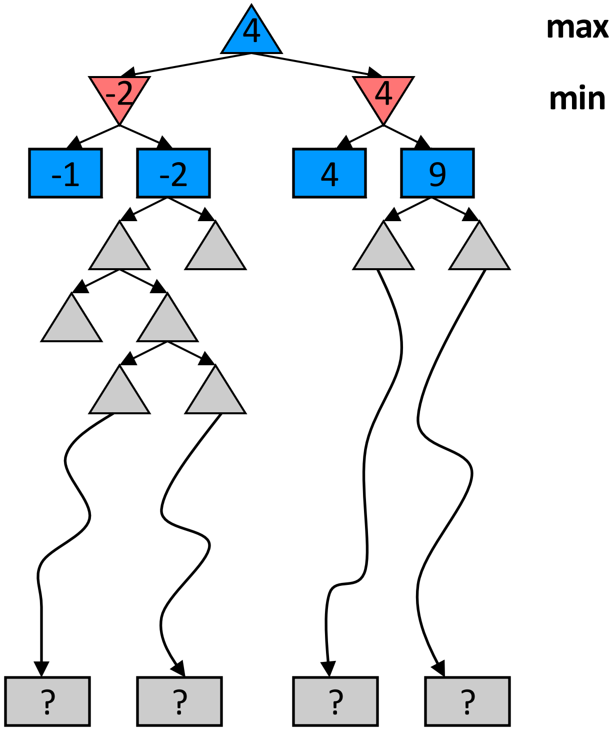

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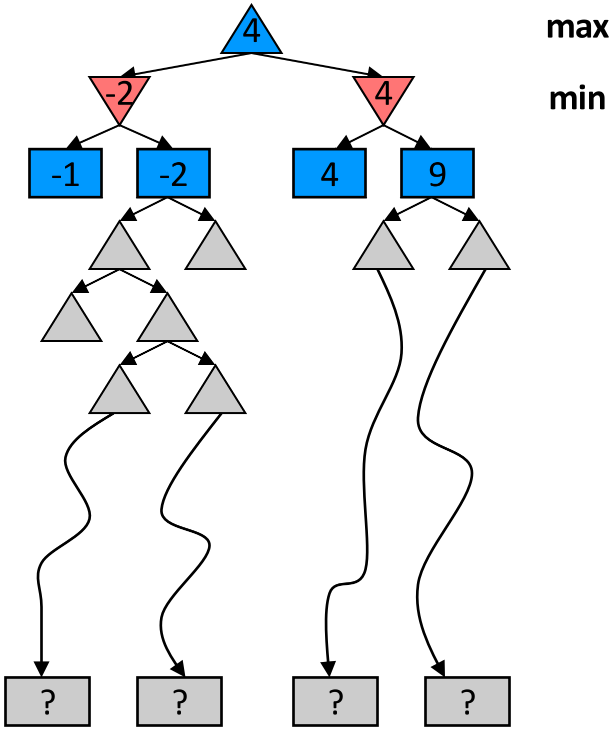
- Example:
  - Suppose we have 100 seconds, can explore 10K nodes / sec
  - So can check 1M nodes per move
  - $\alpha$-$\beta$ reaches about depth 8 – decent chess program



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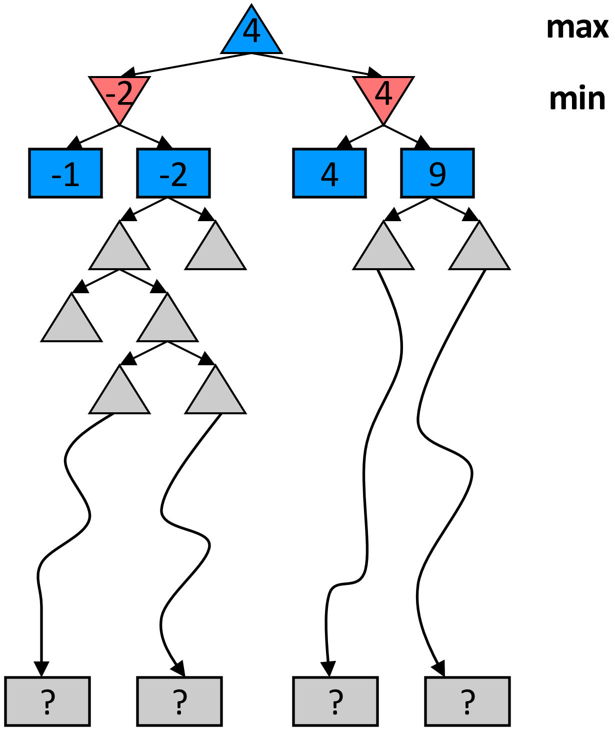
- Guarantee of optimal play is gone
- More plies makes a BIG difference
- Use iterative deepening for an anytime algorithm



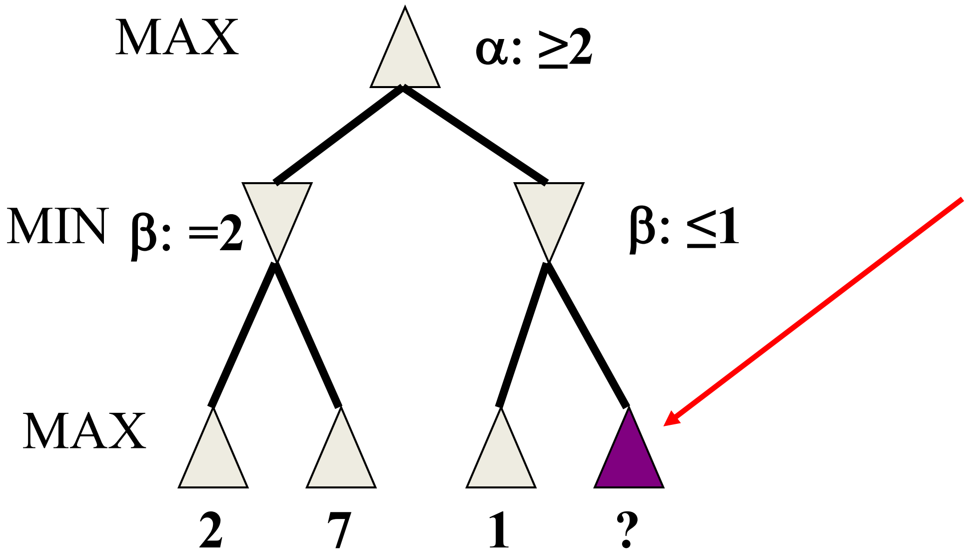
# Depth Matters

- Evaluation functions are always imperfect
- The deeper in the tree the evaluation function is buried, the less the quality of the evaluation function matters
- An important example of the tradeoff between complexity of features and complexity of computation

# Is that all there is to simple games?

# Alpha-beta pruning

- Improve performance of the minimax algorithm through **alpha-beta pruning**
- *"If you have an idea that is surely bad, don't take the time to see how truly awful it is"* -Pat Winston (MIT)

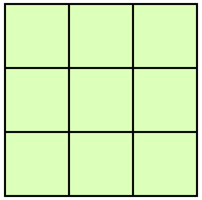


- We don't need to compute the value at this node
- No matter what it is, it can't affect value of the root node

# Alpha-beta pruning

- Traverse search tree in depth-first order
- At **MAX** node n, **alpha(n)** = max value found so far
  Alpha values start at -∞ and only increase
- At **MIN** node n, **beta(n)** = min value found so far
  Beta values start at +∞ and only decrease
- **Beta cutoff**: stop search below MAX node N (i.e., don't examine more descendants) if alpha(N) >= beta(i) for some MIN node ancestor i of N
- **Alpha cutoff:** stop search below MIN node N if beta(N)<=alpha(i) for a MAX node anceastor i of N

# Alpha-Beta Tic-Tac-Toe Example



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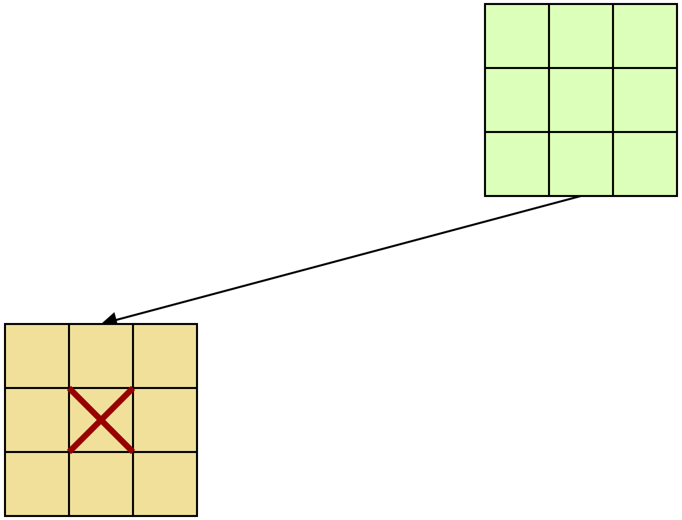

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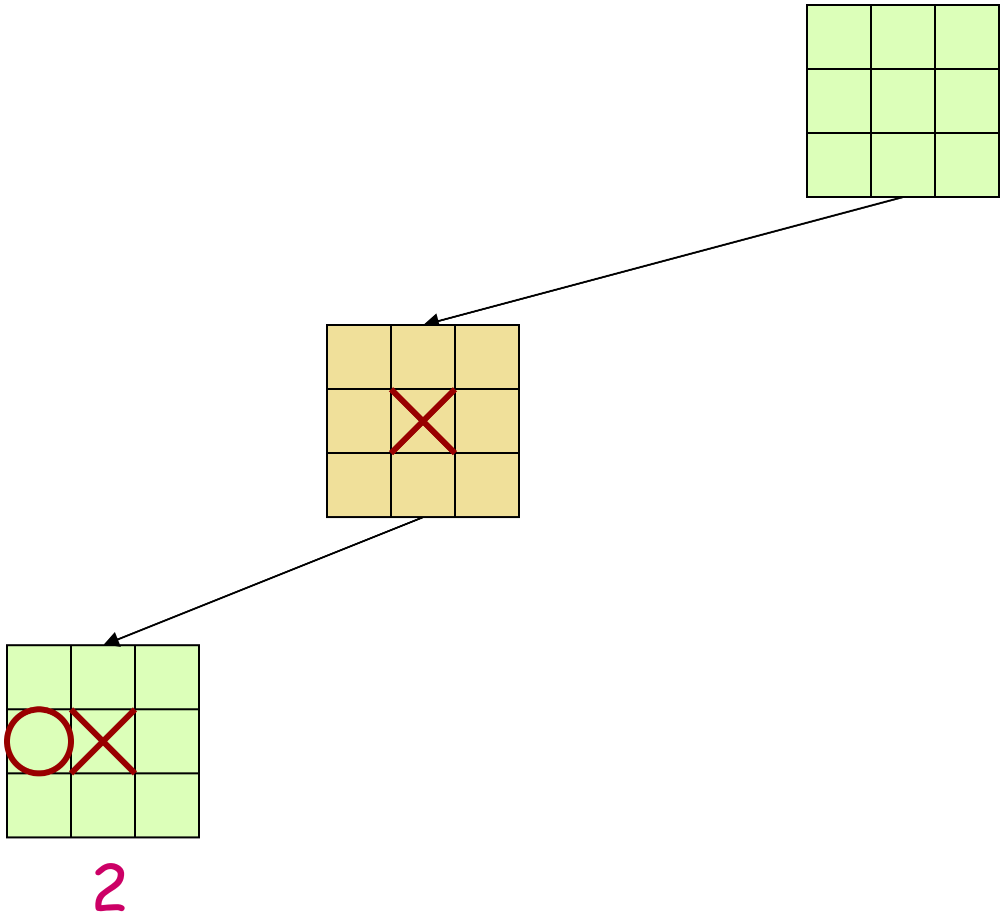

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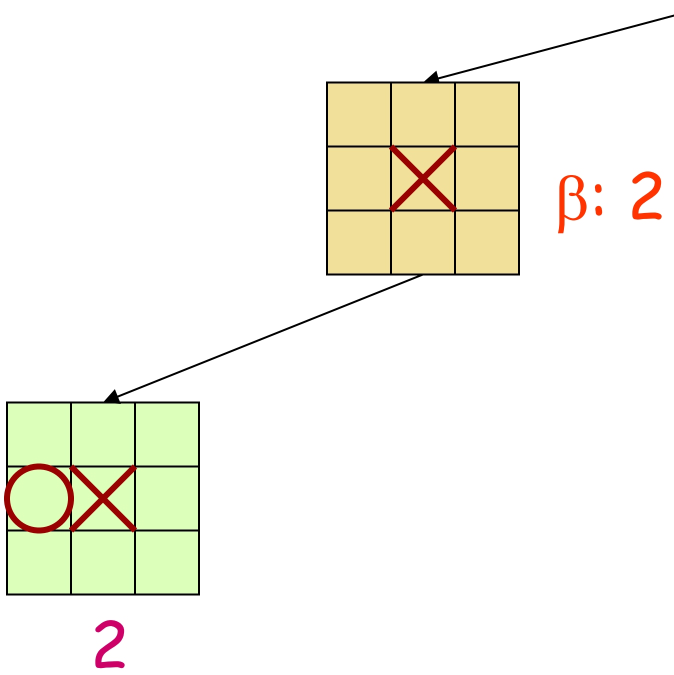

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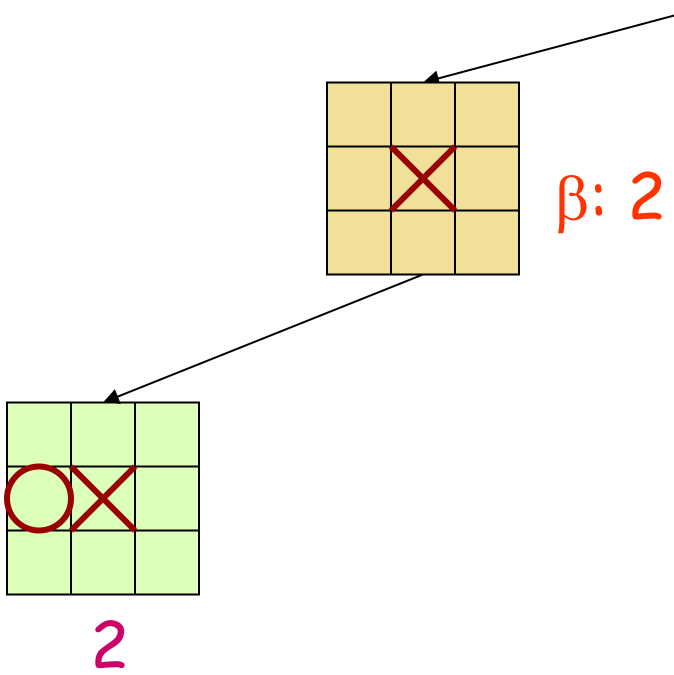

Beta value of a MIN node is **upper** bound on final backed-up value; it can never increase

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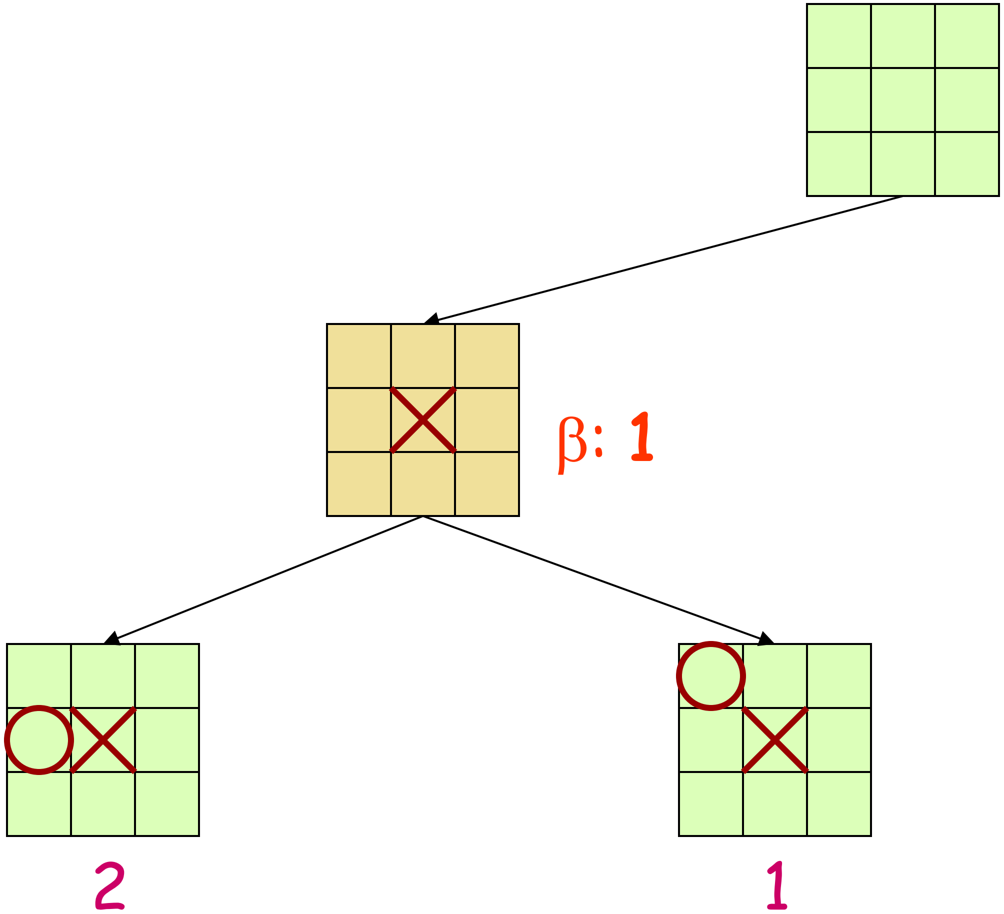

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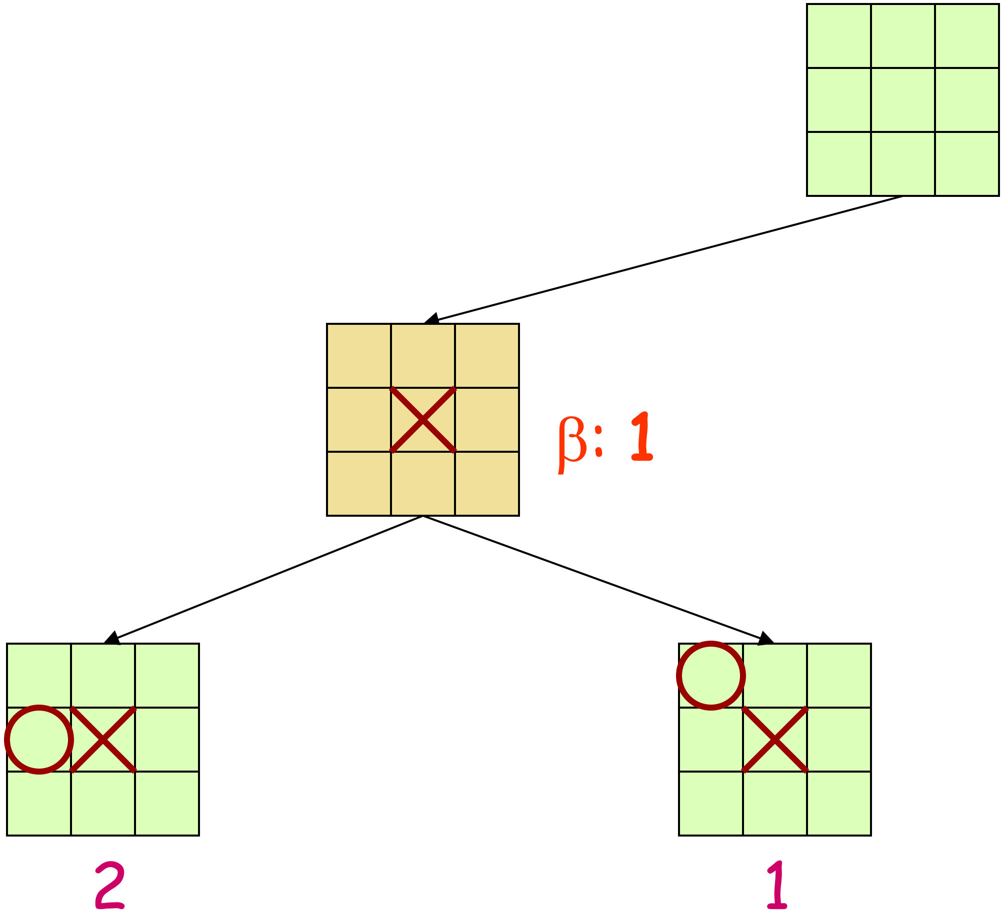

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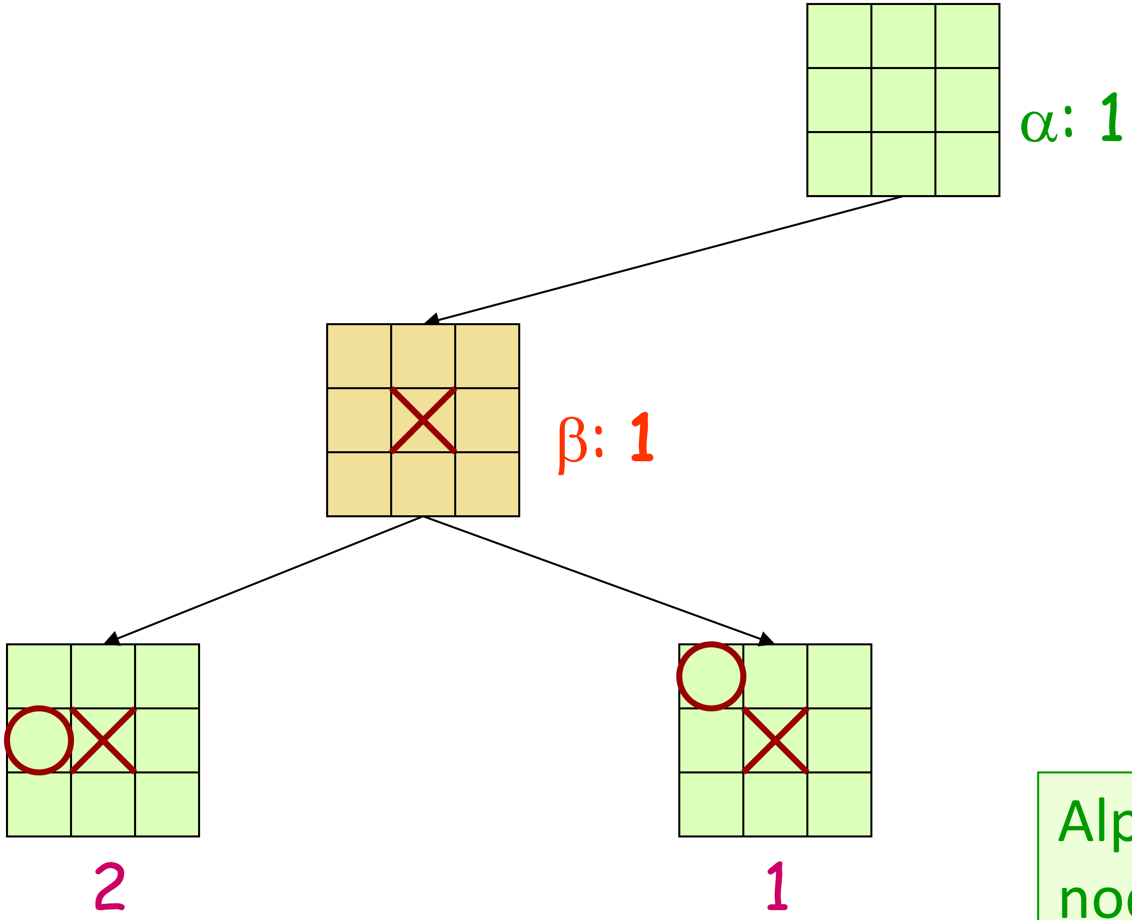
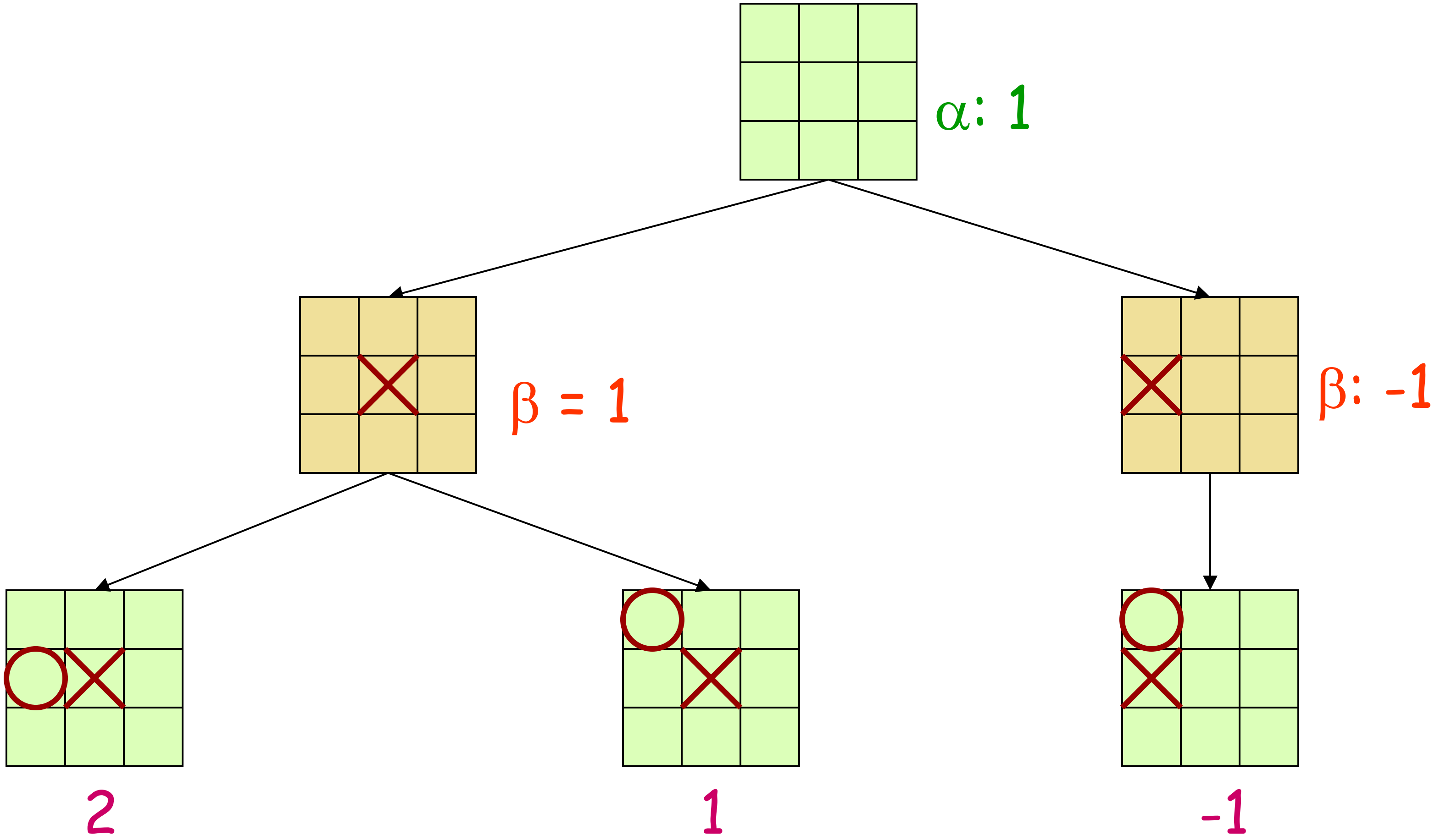


Alpha value of MAX node is **lower** bound on final backed-up value; it can never decrease

# Alpha-Beta Tic-Tac-Toe Example



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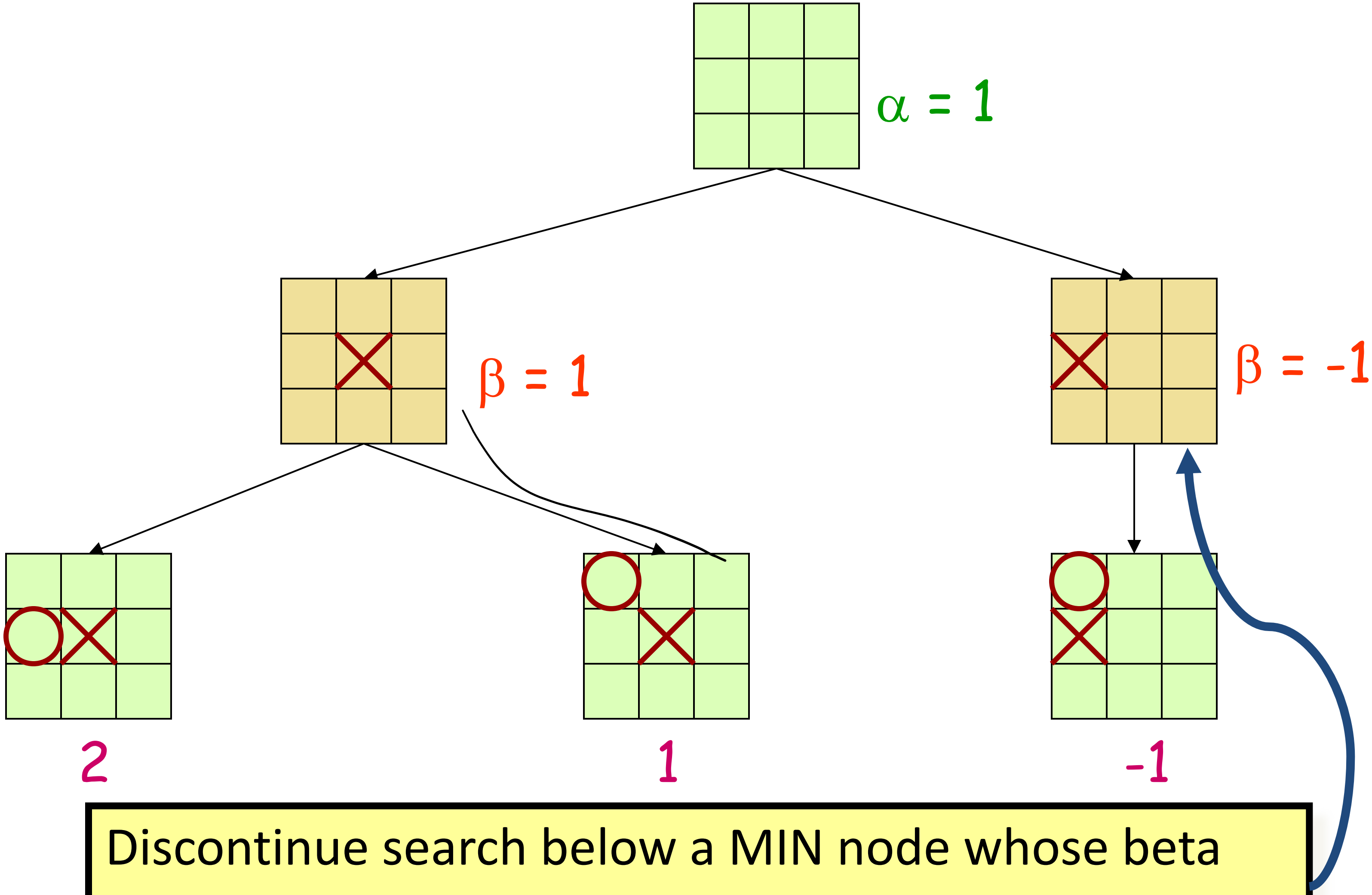


Discontinue search below a MIN node whose beta value ≤ alpha value of one of its MAX ancestors

# Alpha-Beta Implementation

$\alpha$: MAX’s best option on path to root

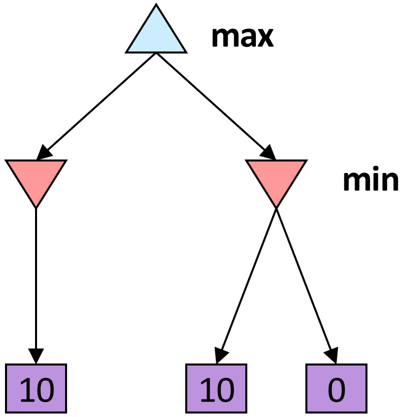
$\beta$: MIN’s best option on path to root

```
def max-value(state, $\alpha$, $\beta$):
    initialize v = $-\infty$
    for each successor of state:
        v = max(v, value(successor, $\alpha$, $\beta$))
        if v $\geq \beta$ return v
        $\alpha$ = max($\alpha$, v)
    return v
```

```
def min-value(state , $\alpha$, $\beta$):
    initialize v = $+\infty$
    for each successor of state:
        v = min(v, value(successor, $\alpha$, $\beta$))
        if v $\leq \alpha$ return v
        $\beta$ = min($\beta$, v)
    return v
```

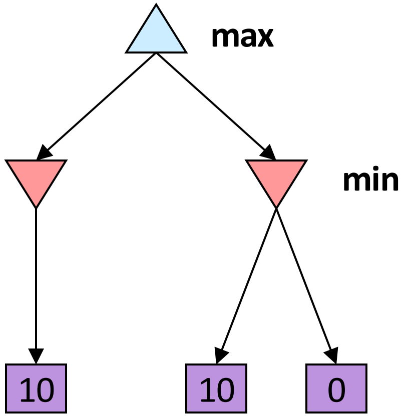
# Alpha-Beta Pruning Properties

- This pruning has no effect on minimax value computed for the root!
- Values of intermediate nodes might be wrong
  - Important: children of the root may have the wrong value
  - So the most naïve version won't let you do action selection

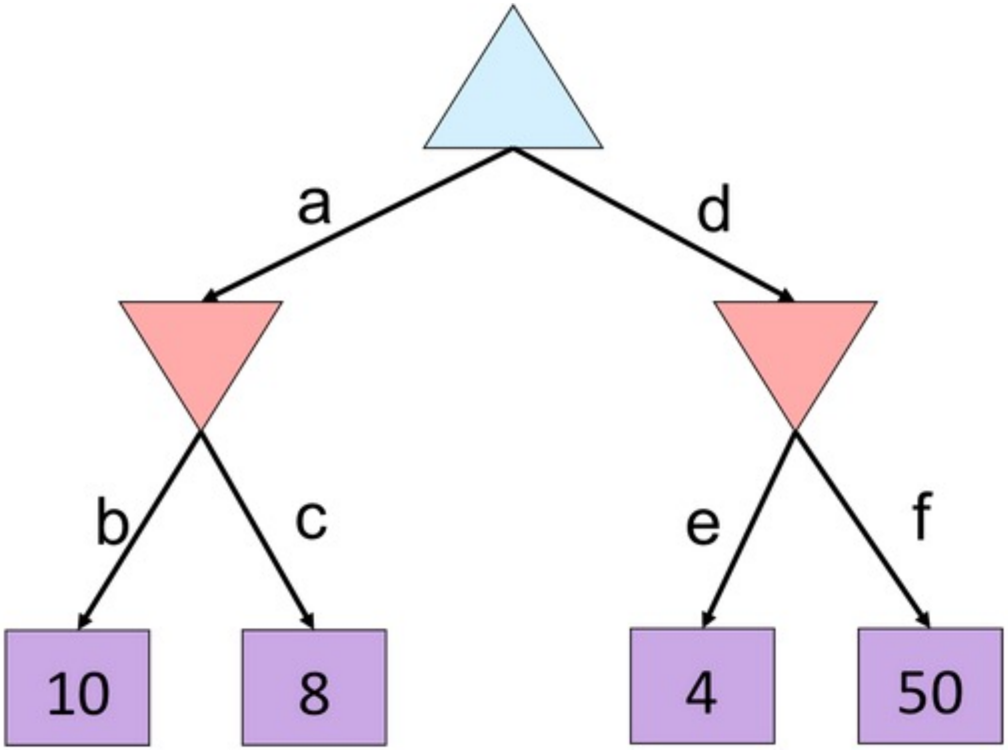


# Alpha-Beta Pruning Properties

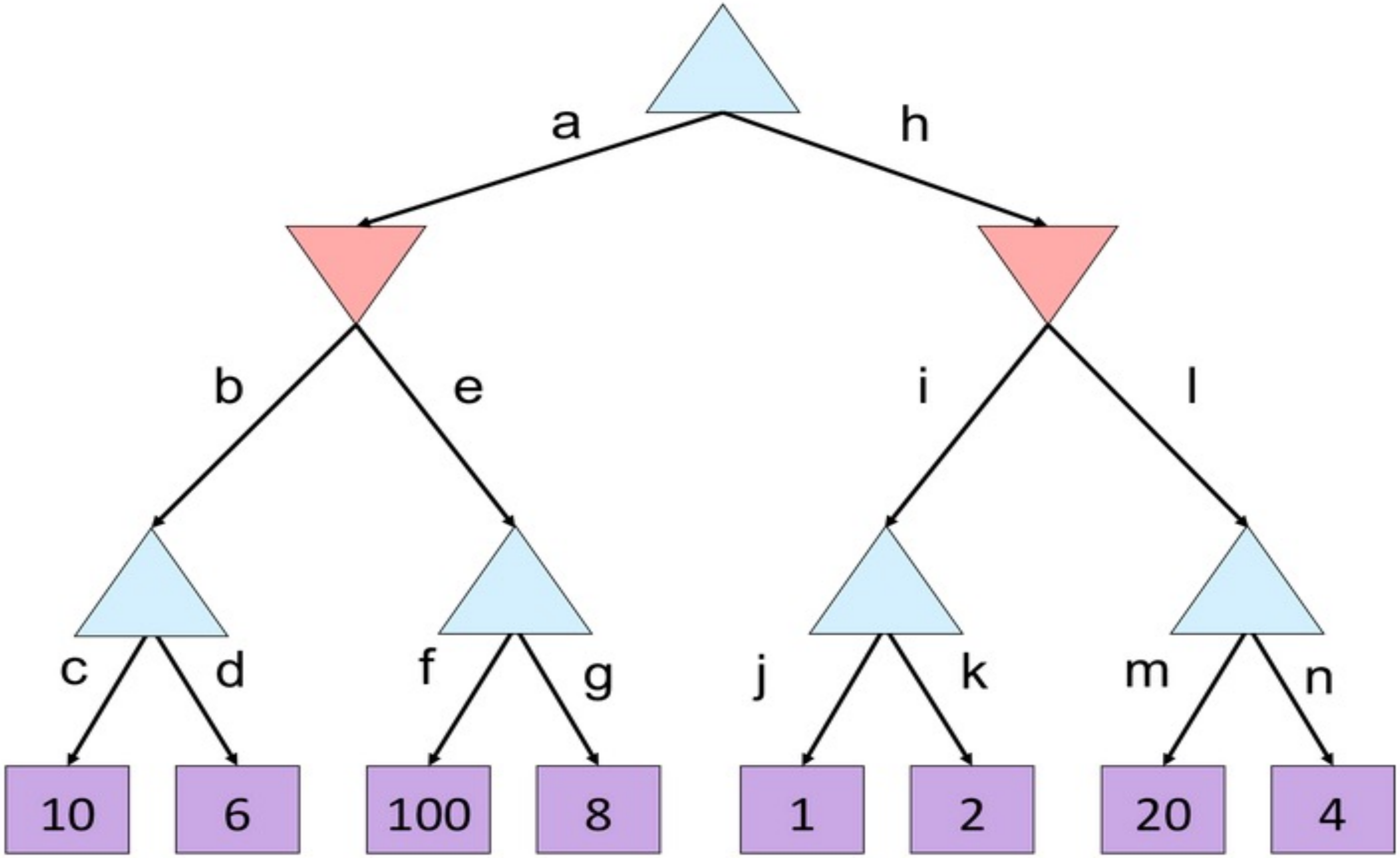
- This pruning has no effect on minimax value computed for the root!
- Values of intermediate nodes might be wrong
  - Important: children of the root may have the wrong value
  - So the most naïve version won't let you do action selection
- Good child ordering improves effectiveness of pruning
- With "perfect ordering":
  - **Time complexity drops to O($b^{m/2}$)**
  - Doubles solvable depth!
  - Full search of, e.g. chess, is still hopeless…
- This is a simple example of metareasoning (computing about what to compute)



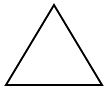
# Alpha-Beta Quiz



# Alpha-Beta Quiz 2



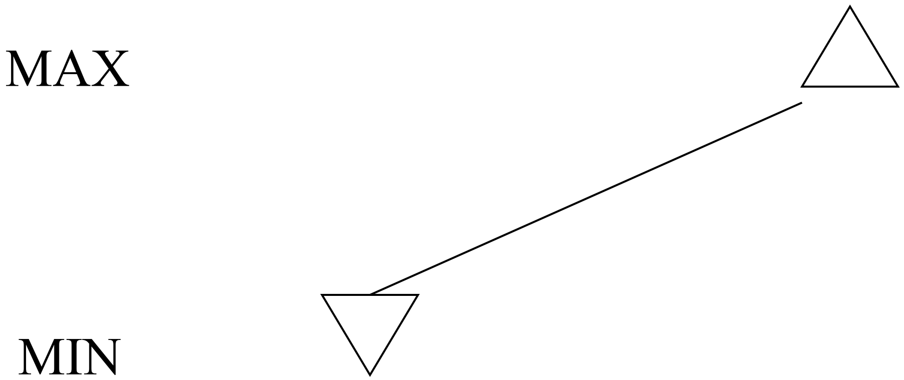
# Another alpha-beta example



MAX

MIN

# Another alpha-beta example



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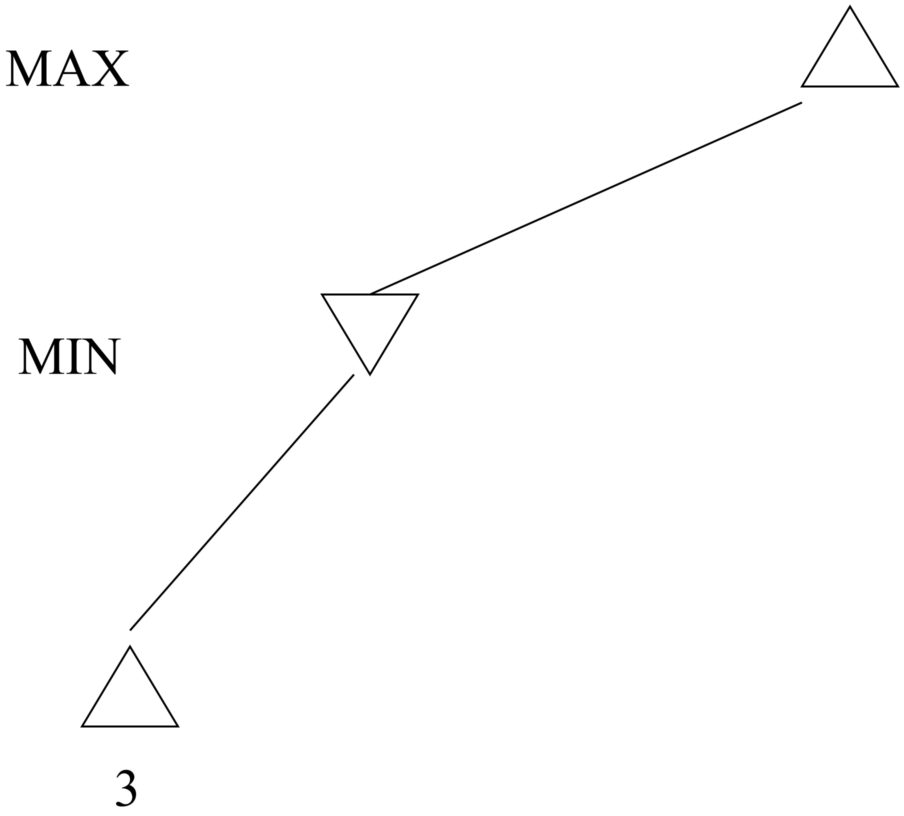

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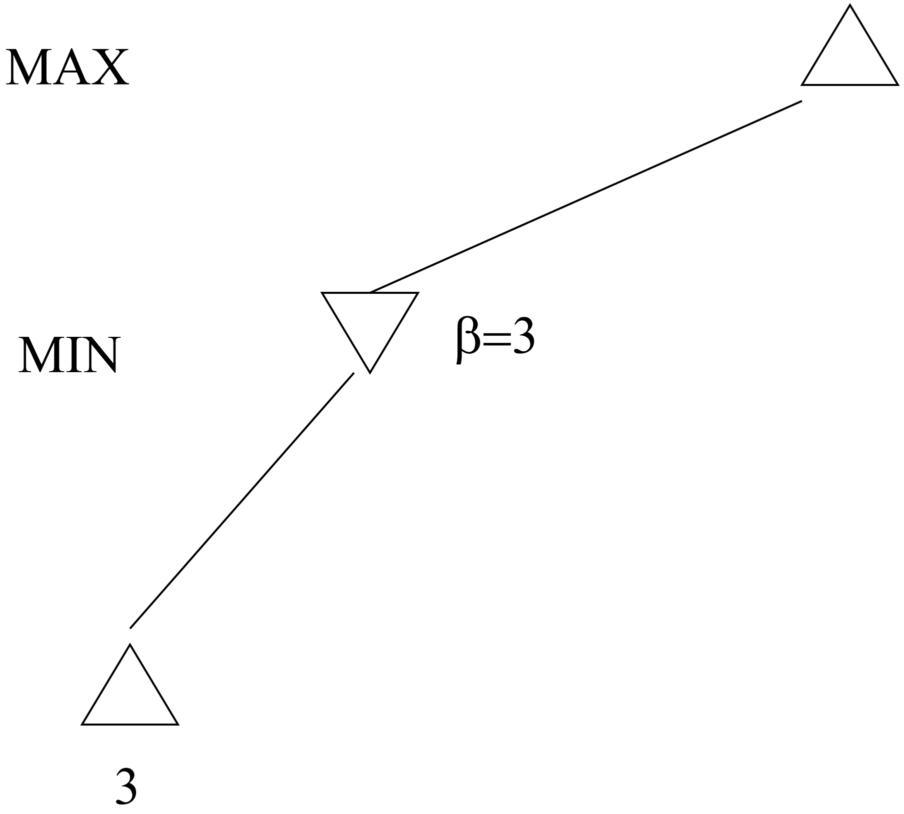

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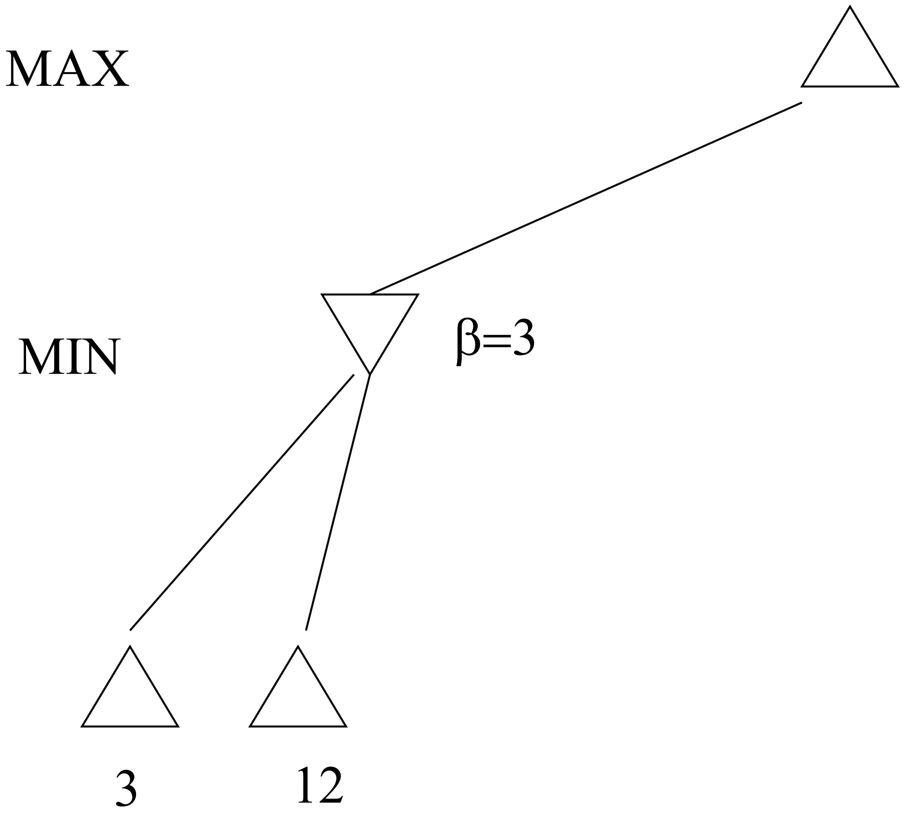

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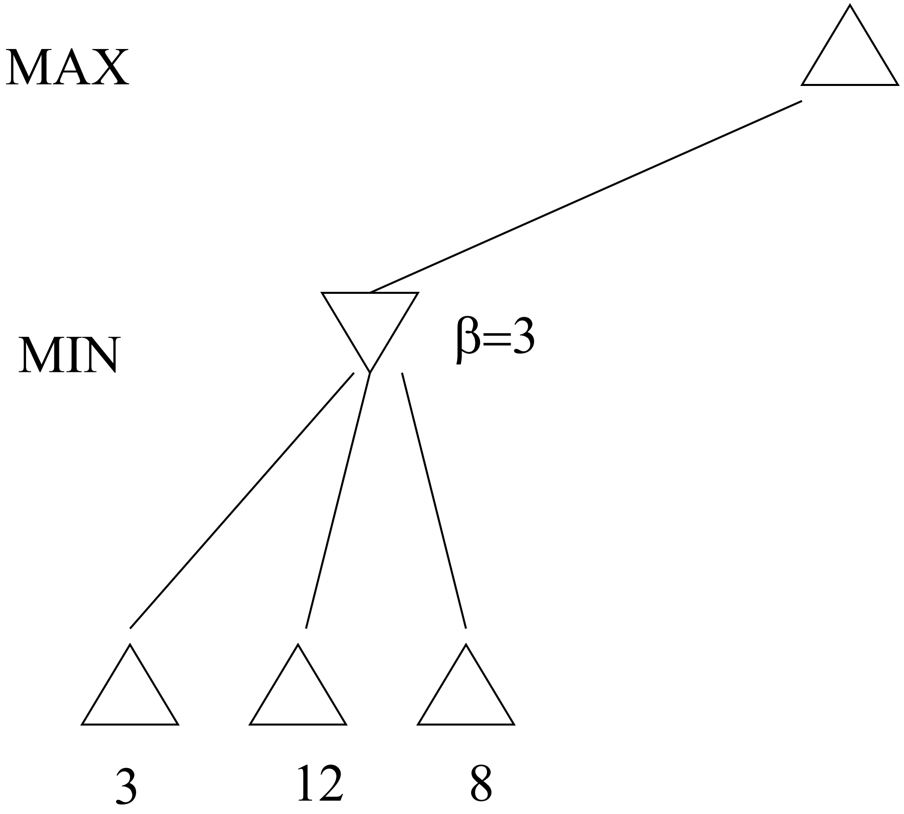

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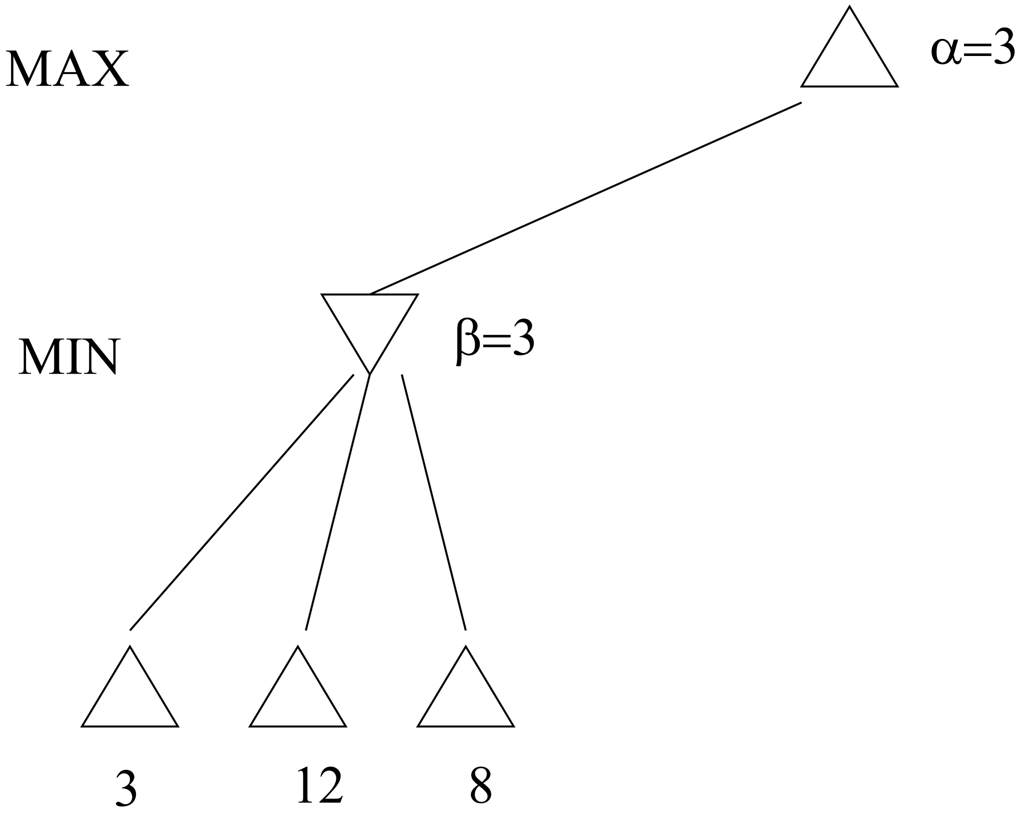

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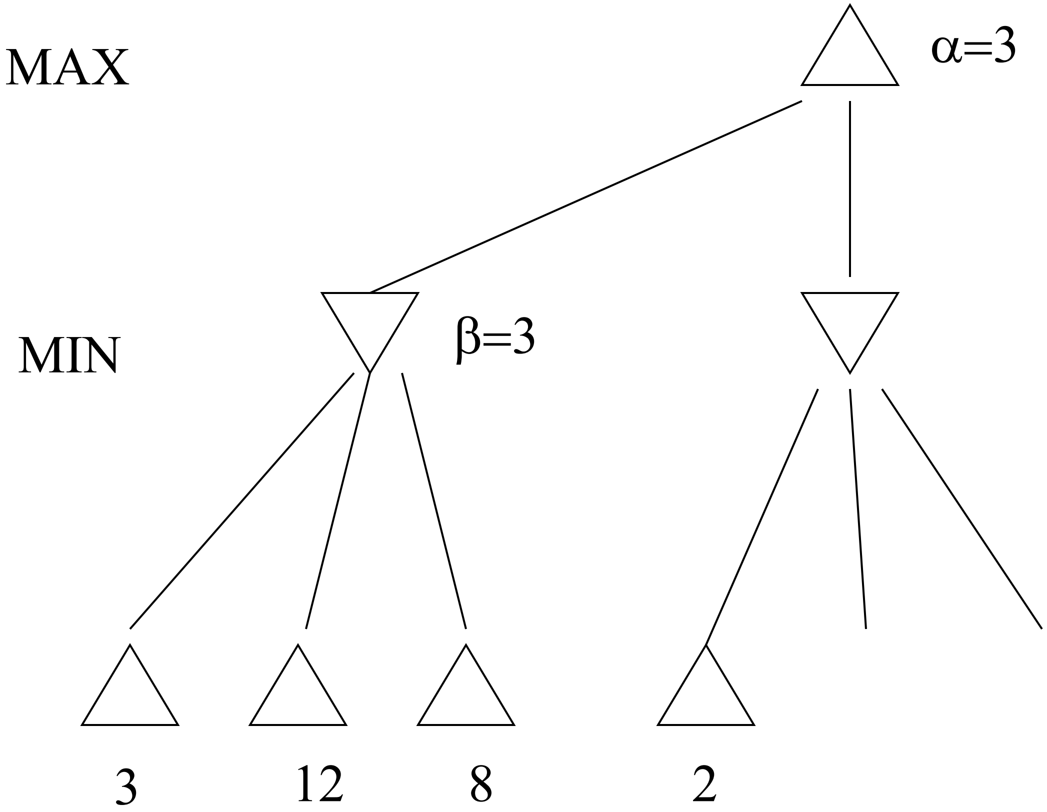

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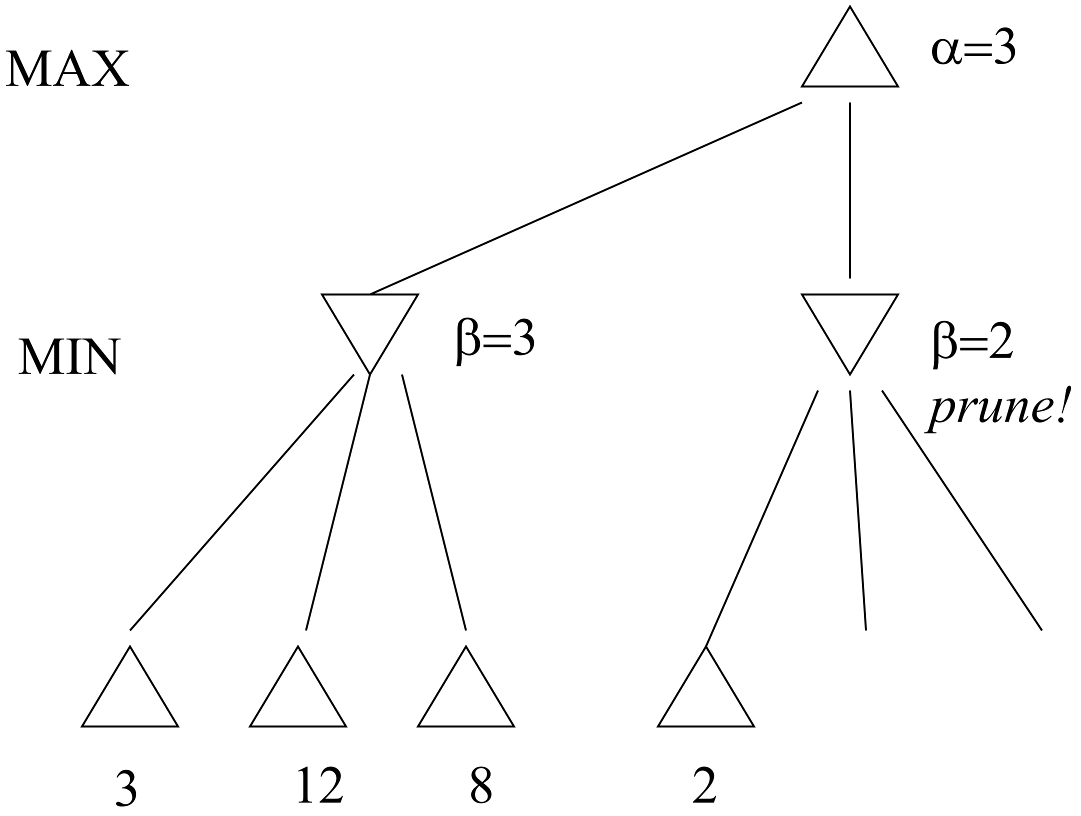

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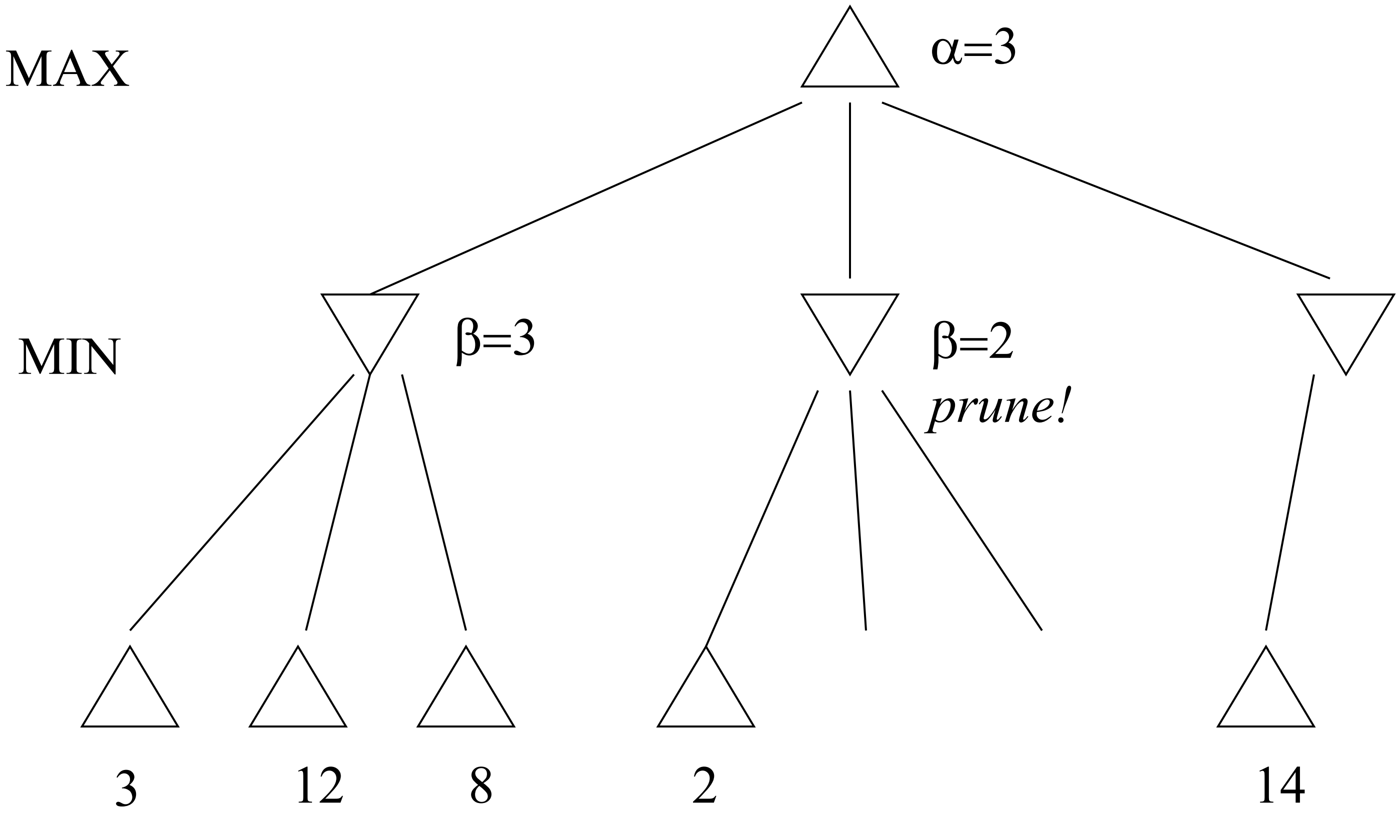

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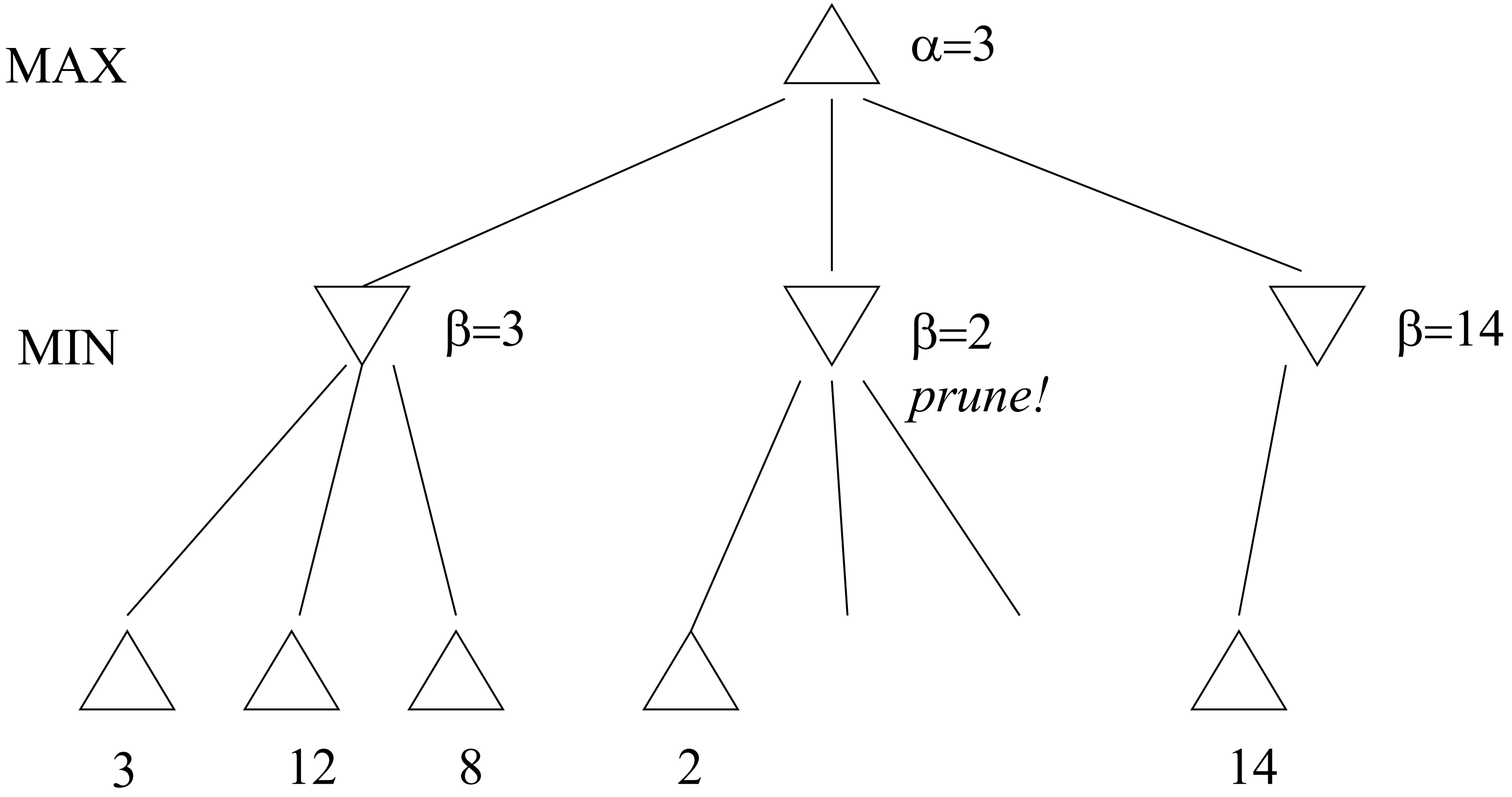
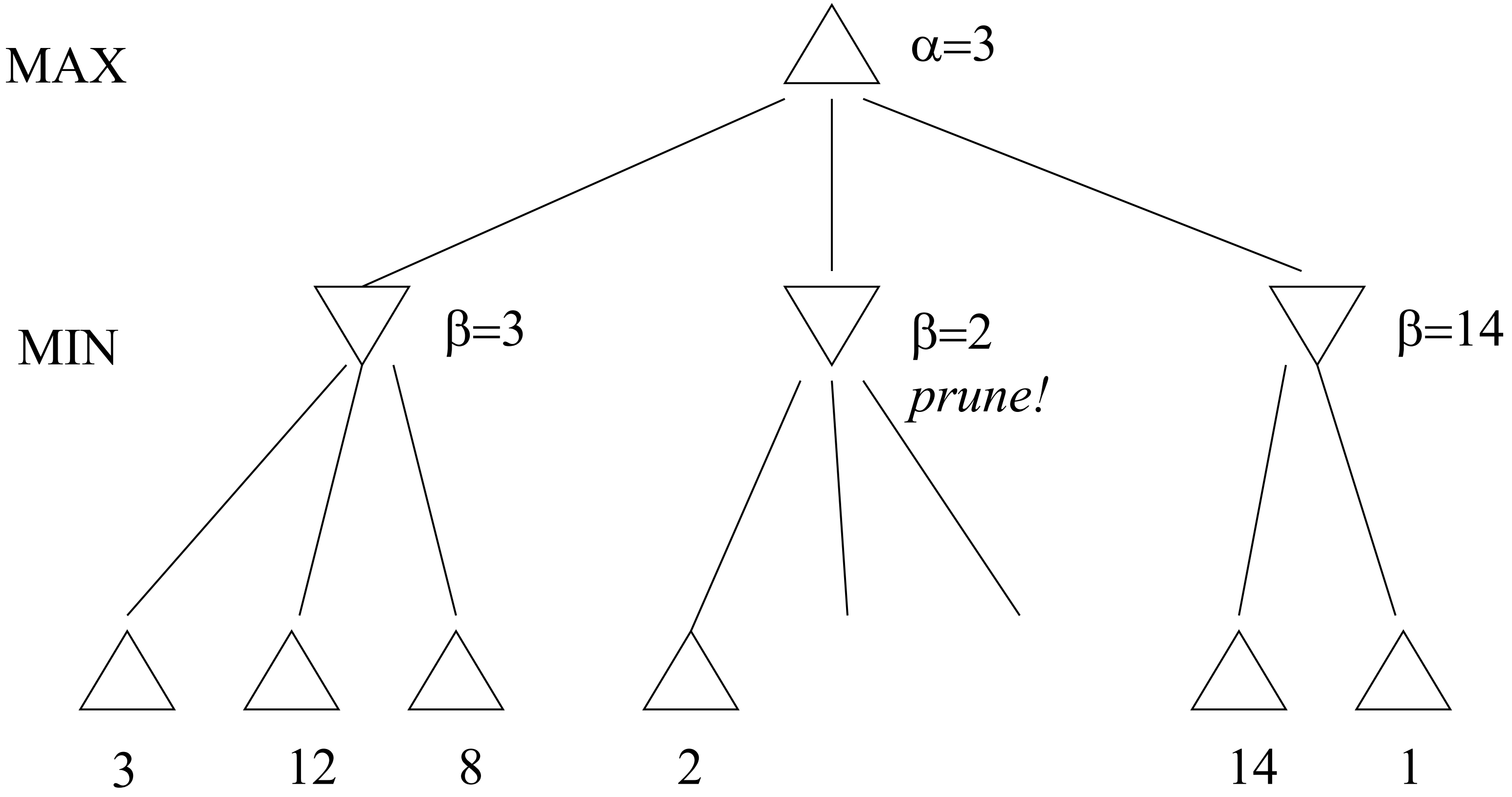


# Another alpha-beta example



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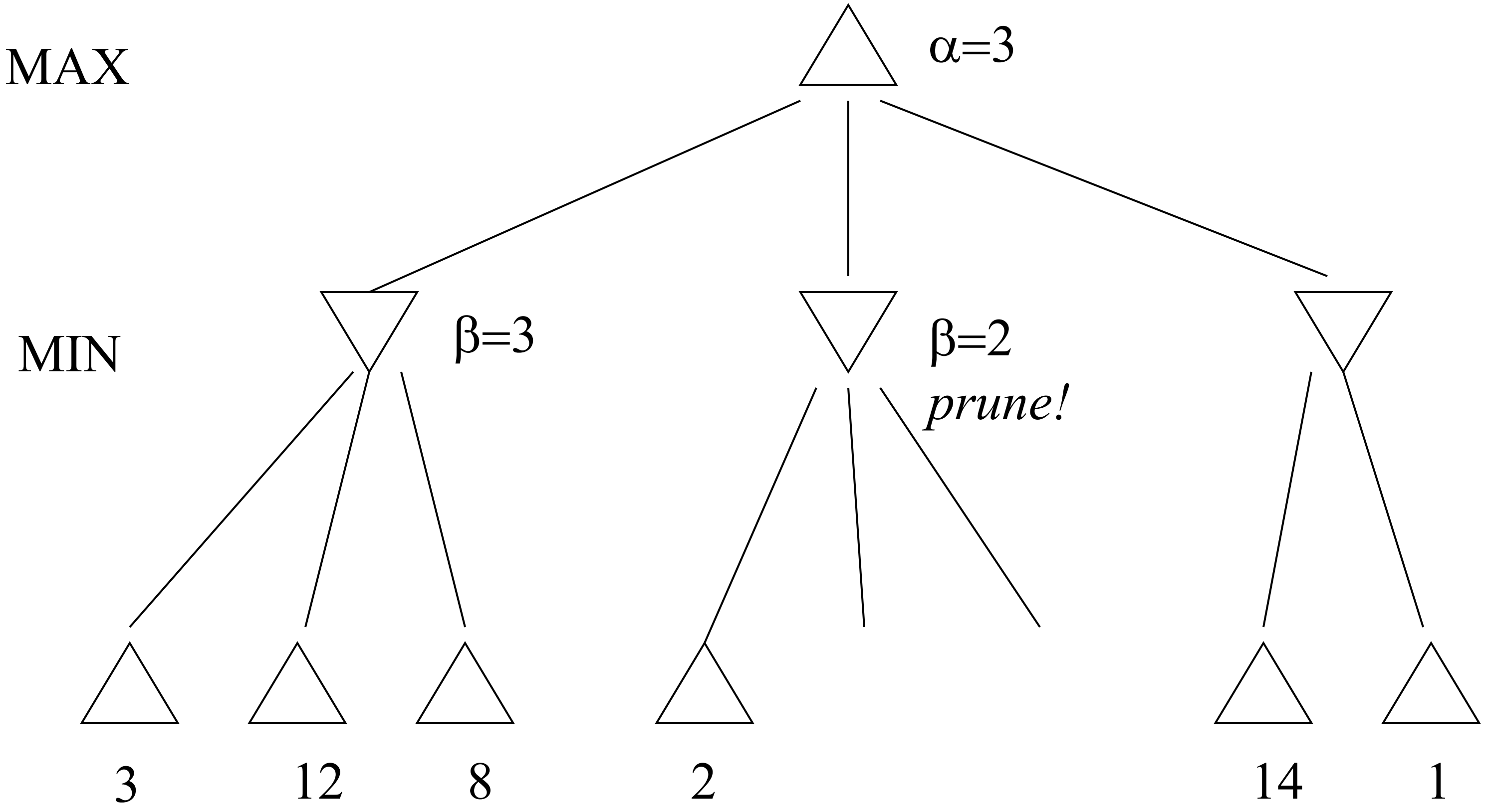

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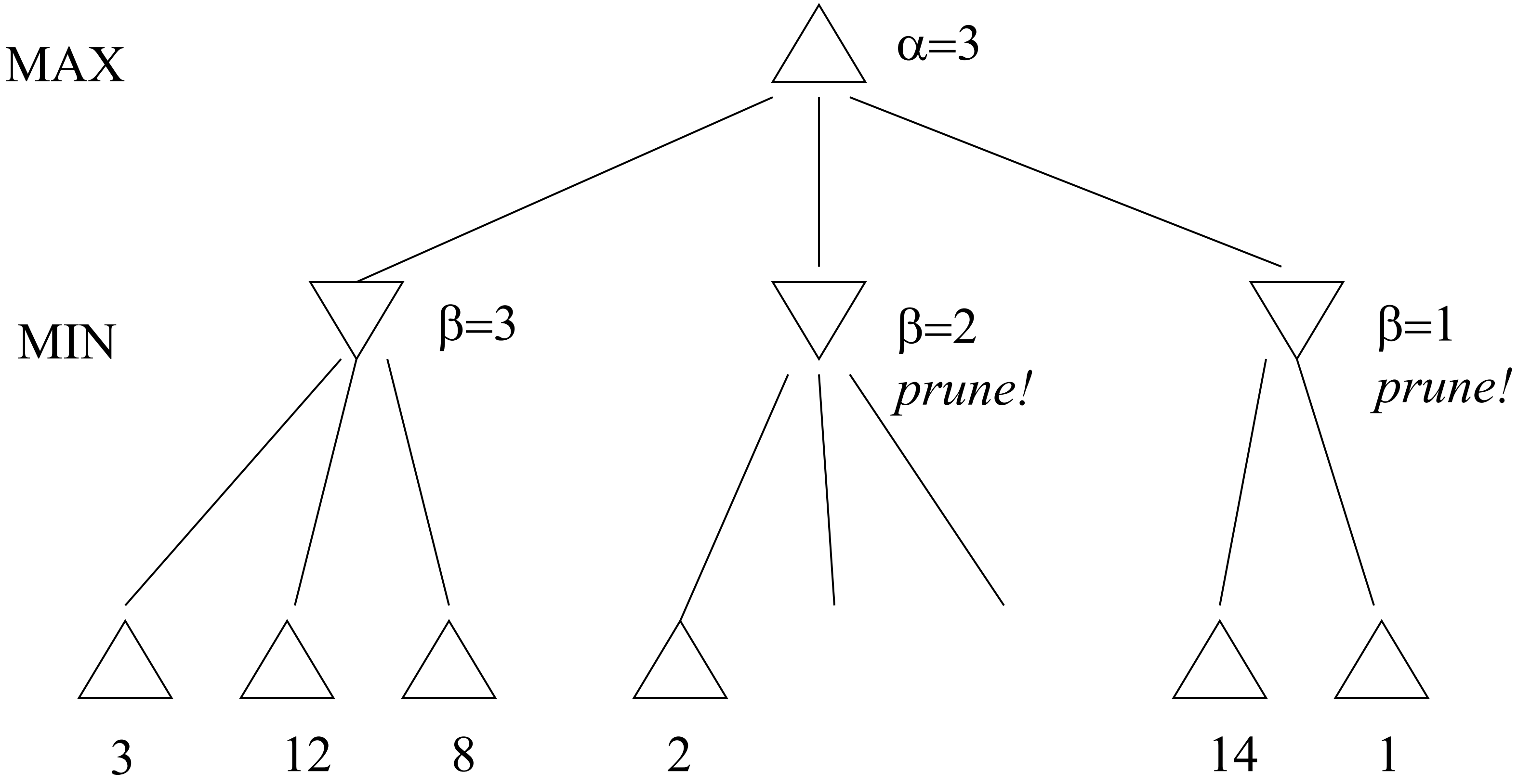

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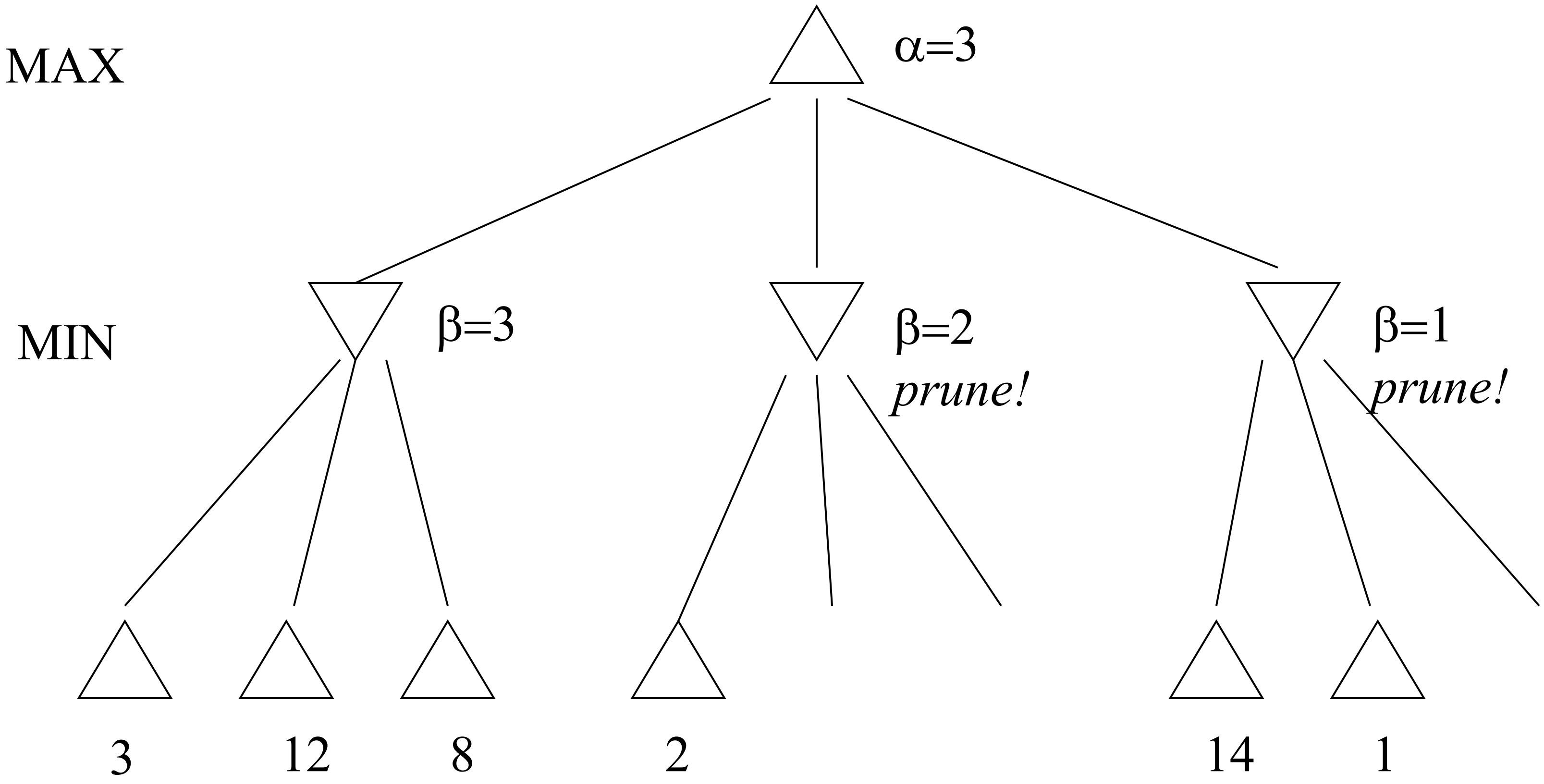

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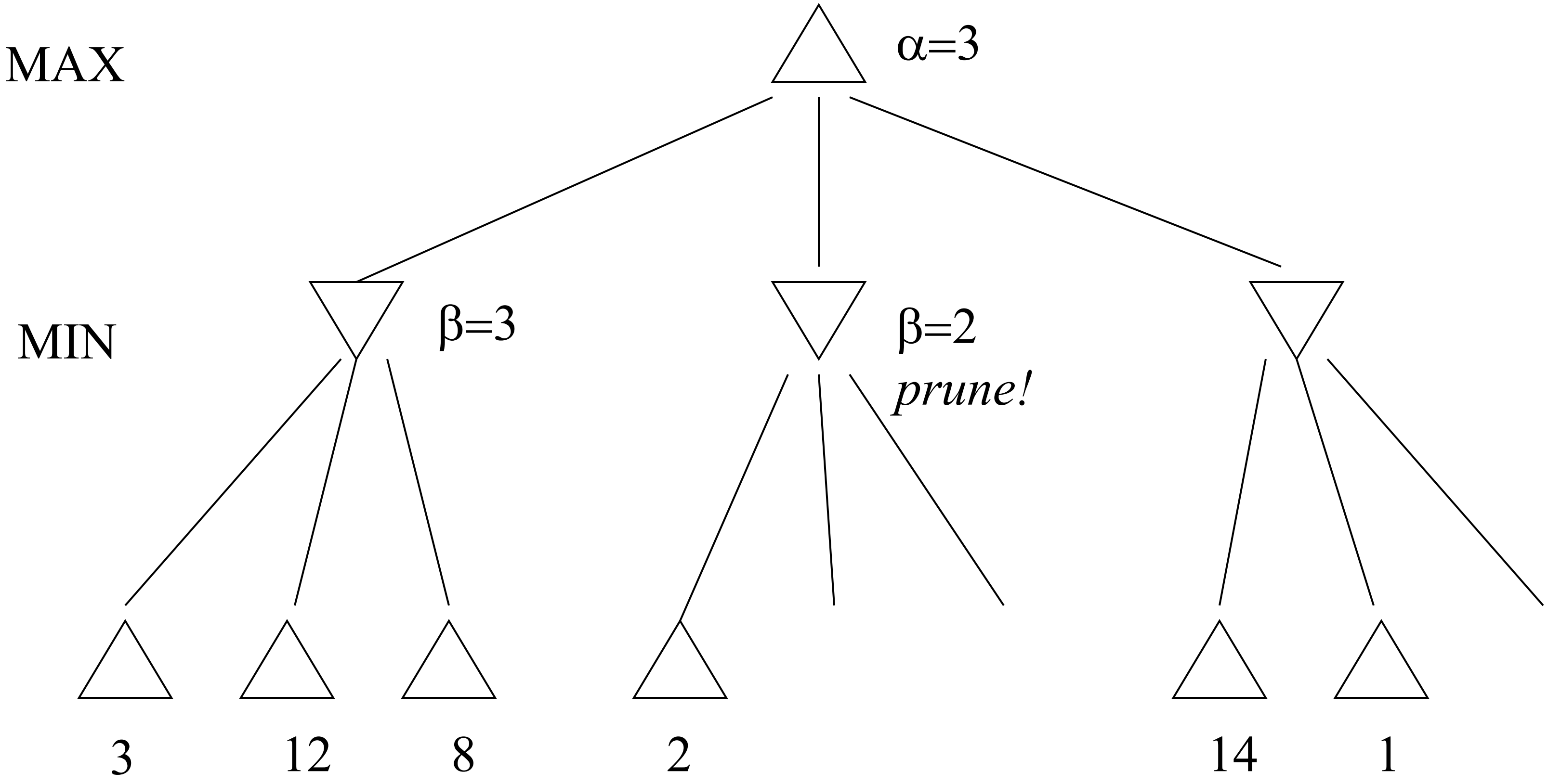
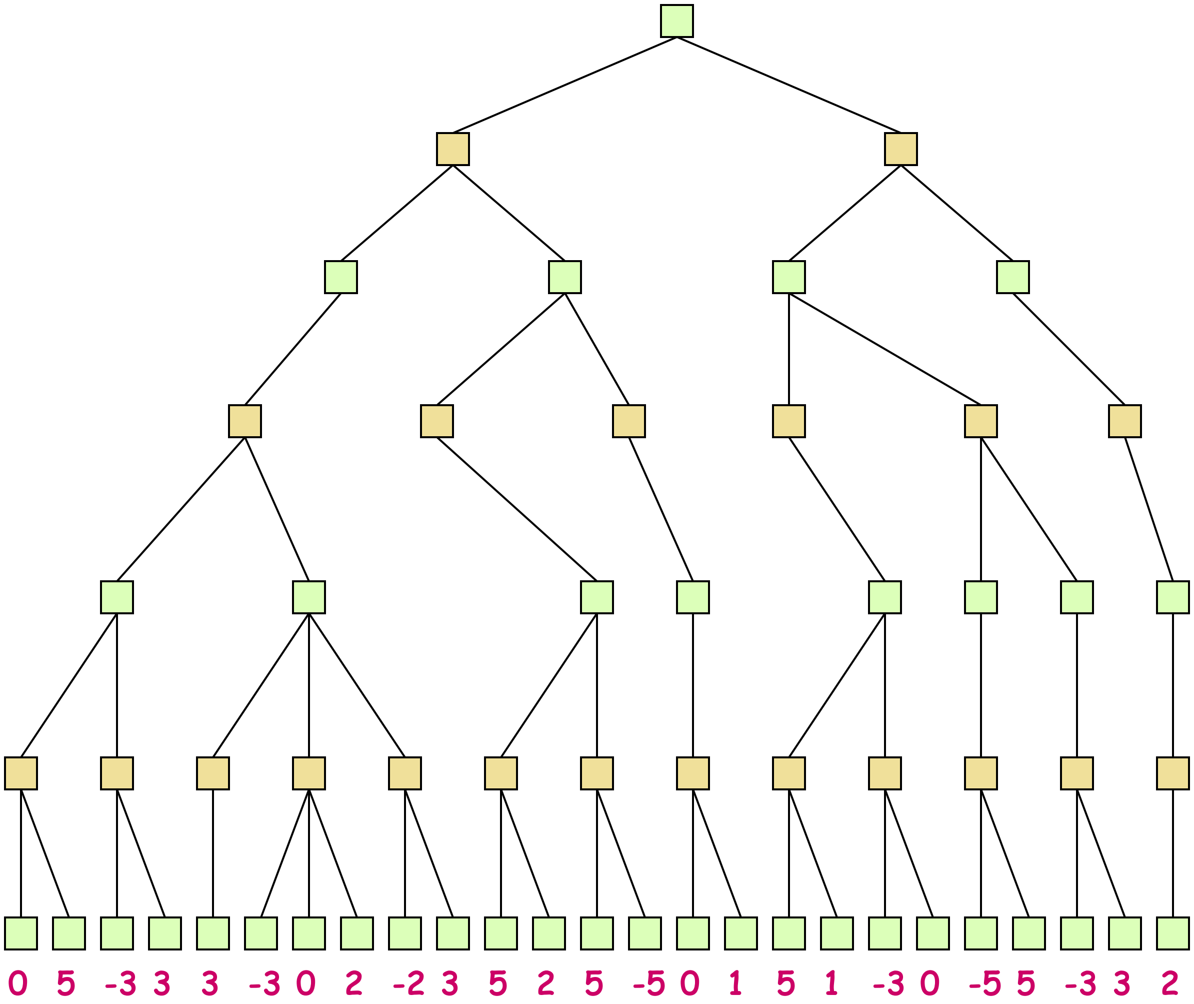
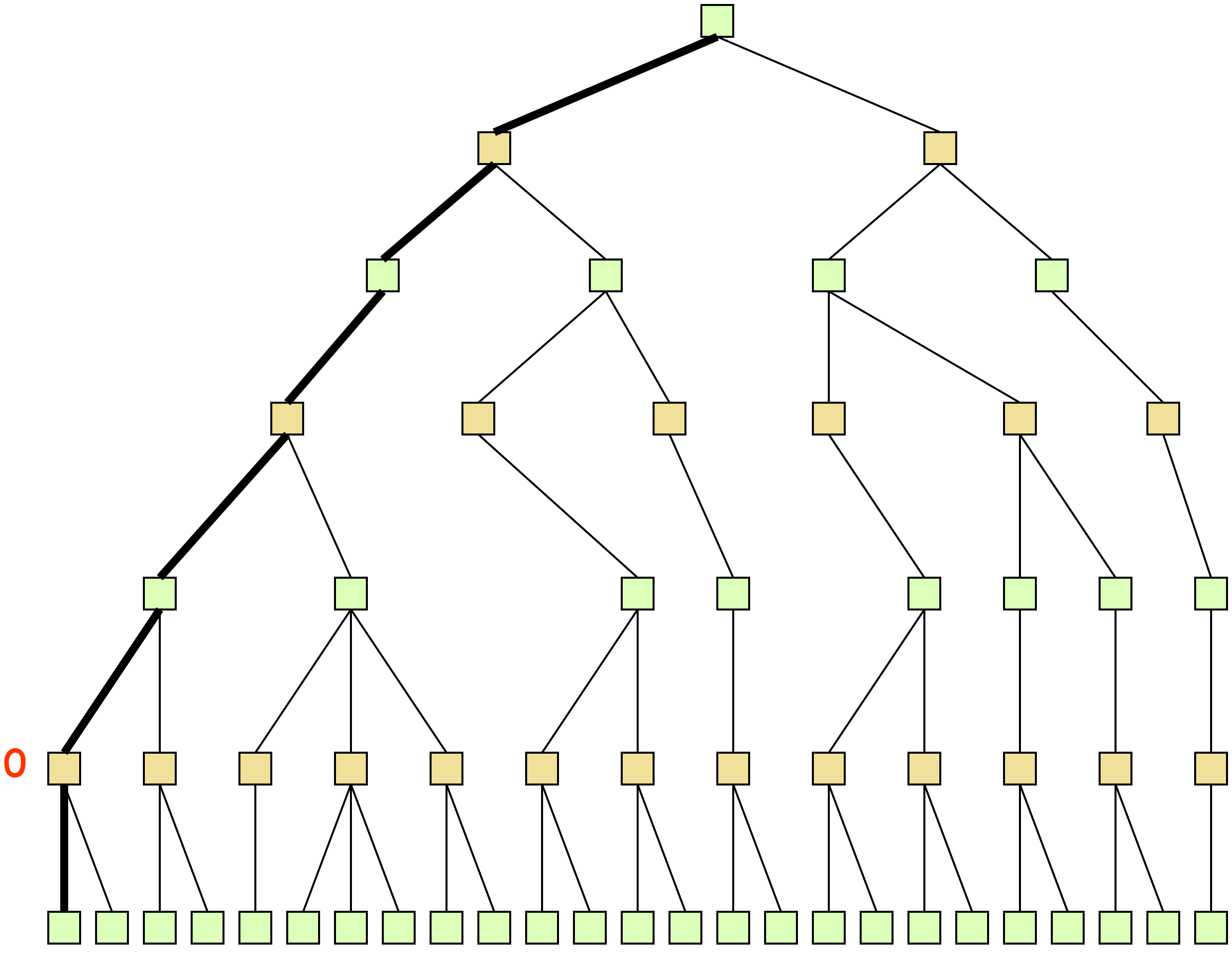


# Alpha-Beta Tic-Tac-Toe Example 2

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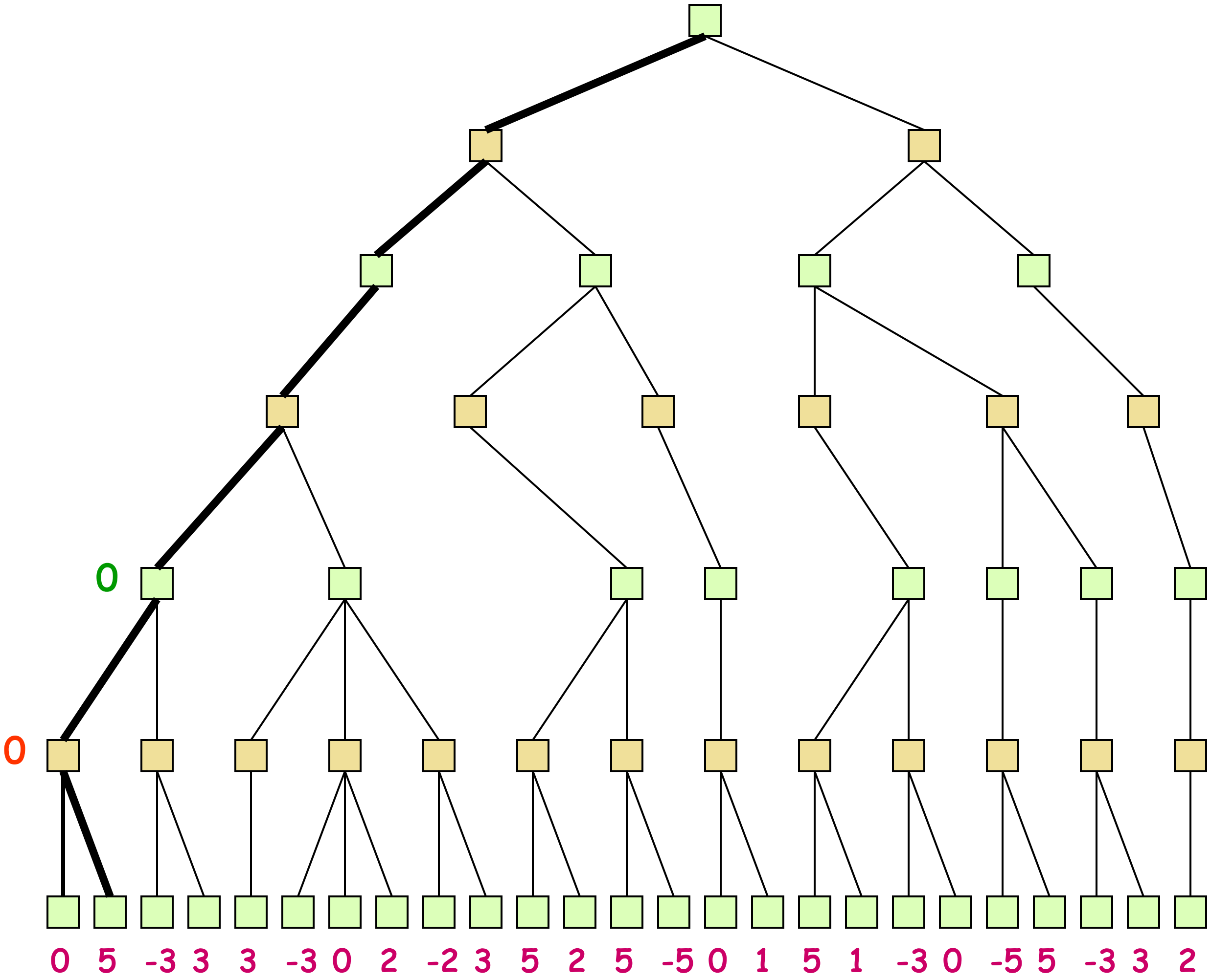
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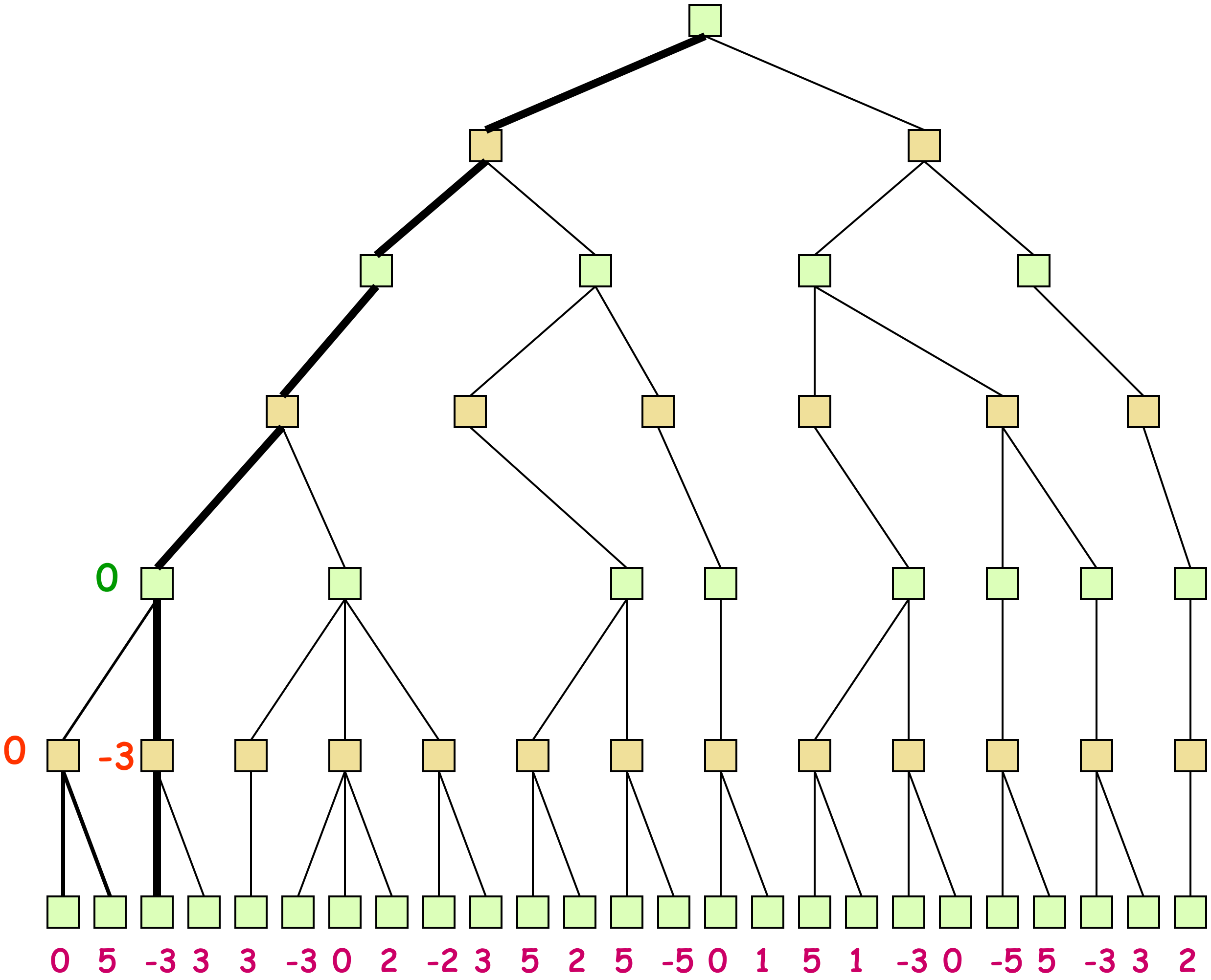
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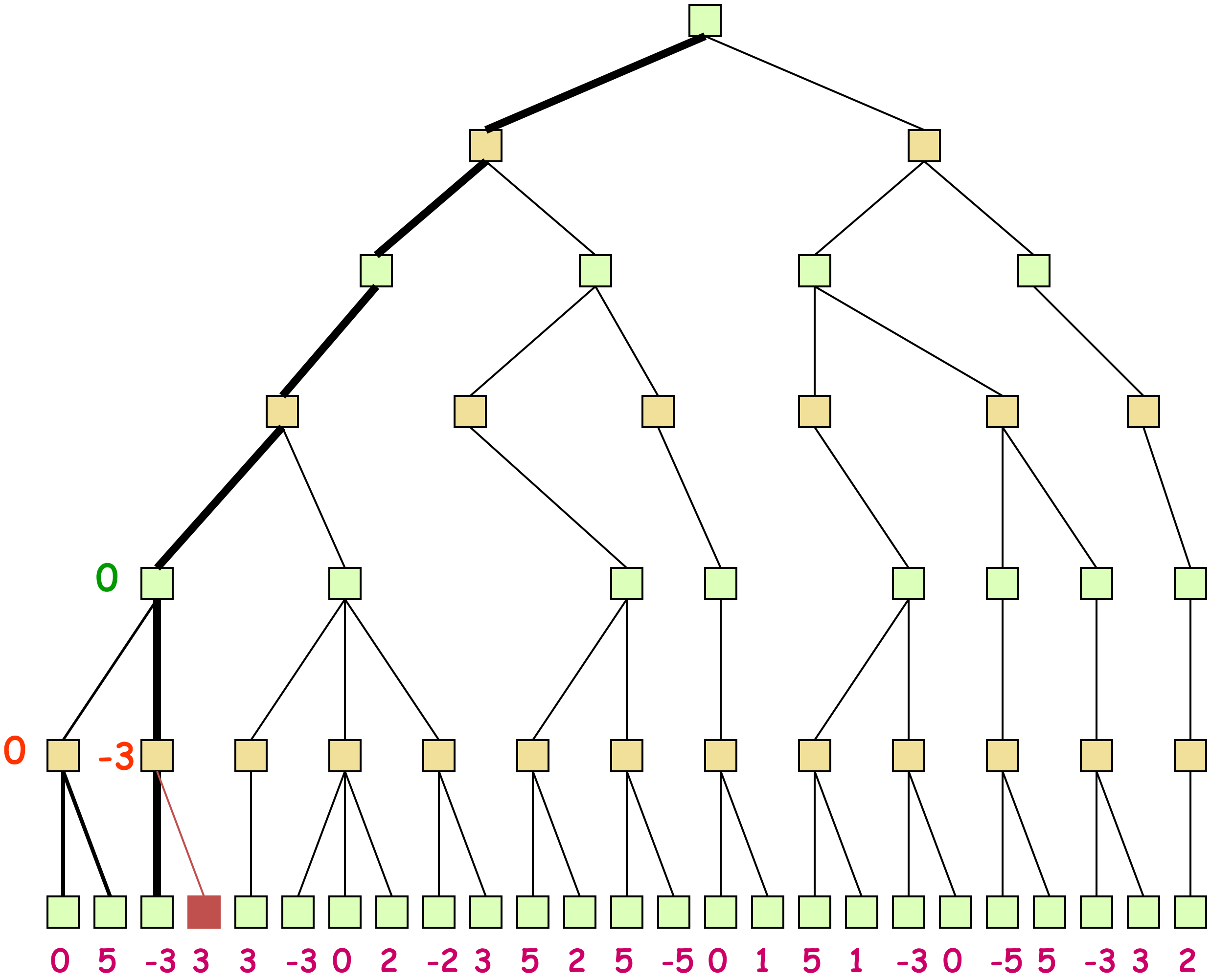
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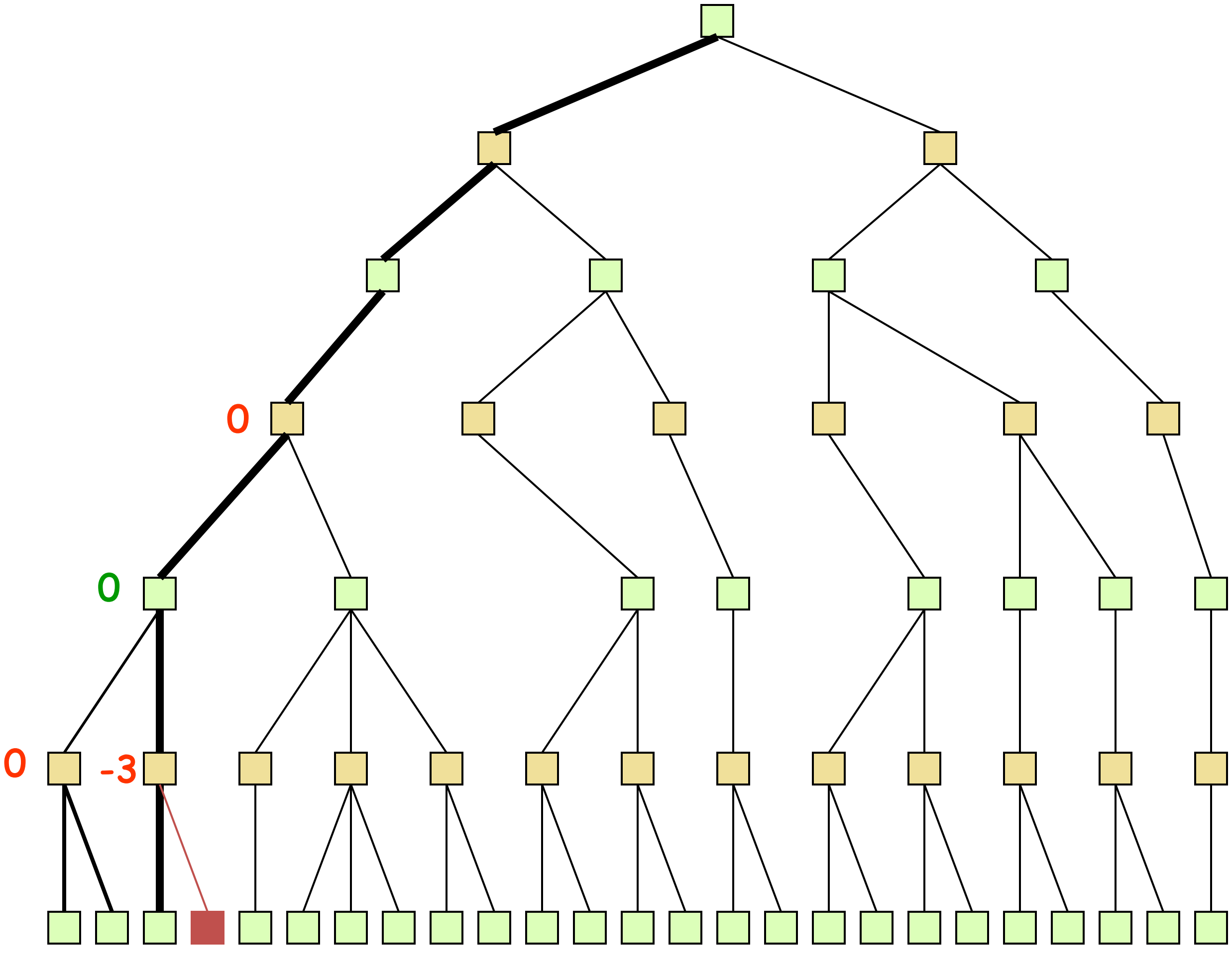
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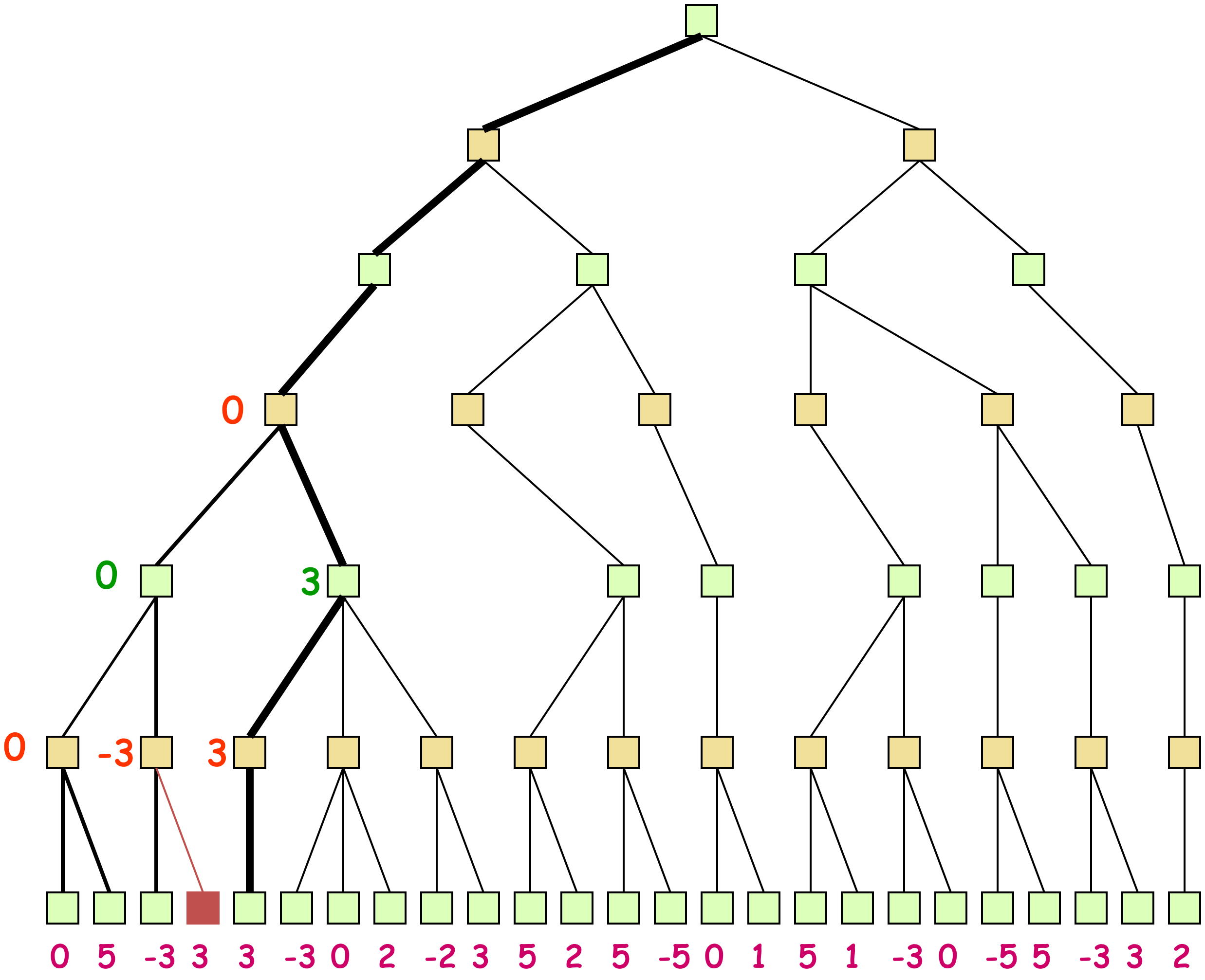
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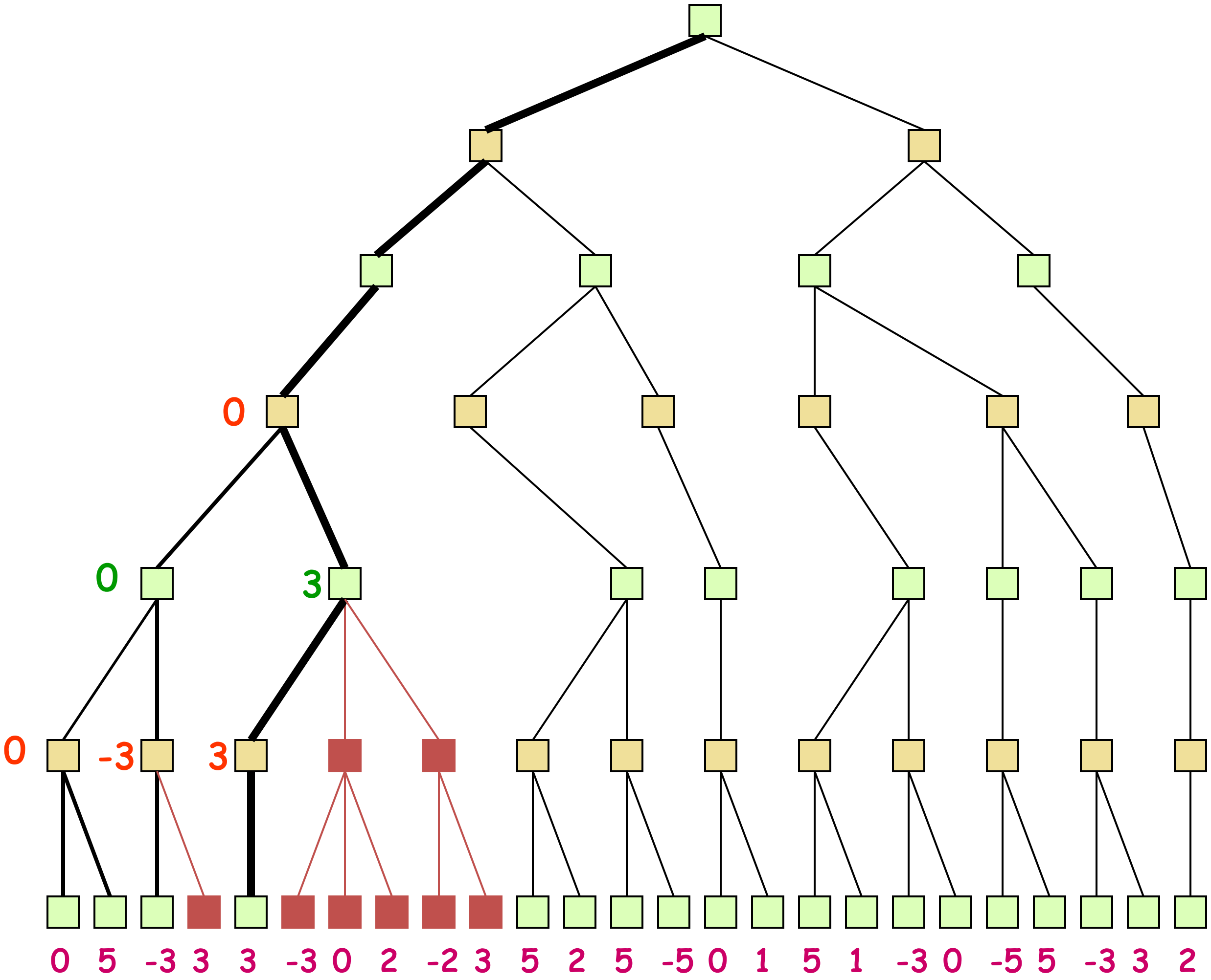
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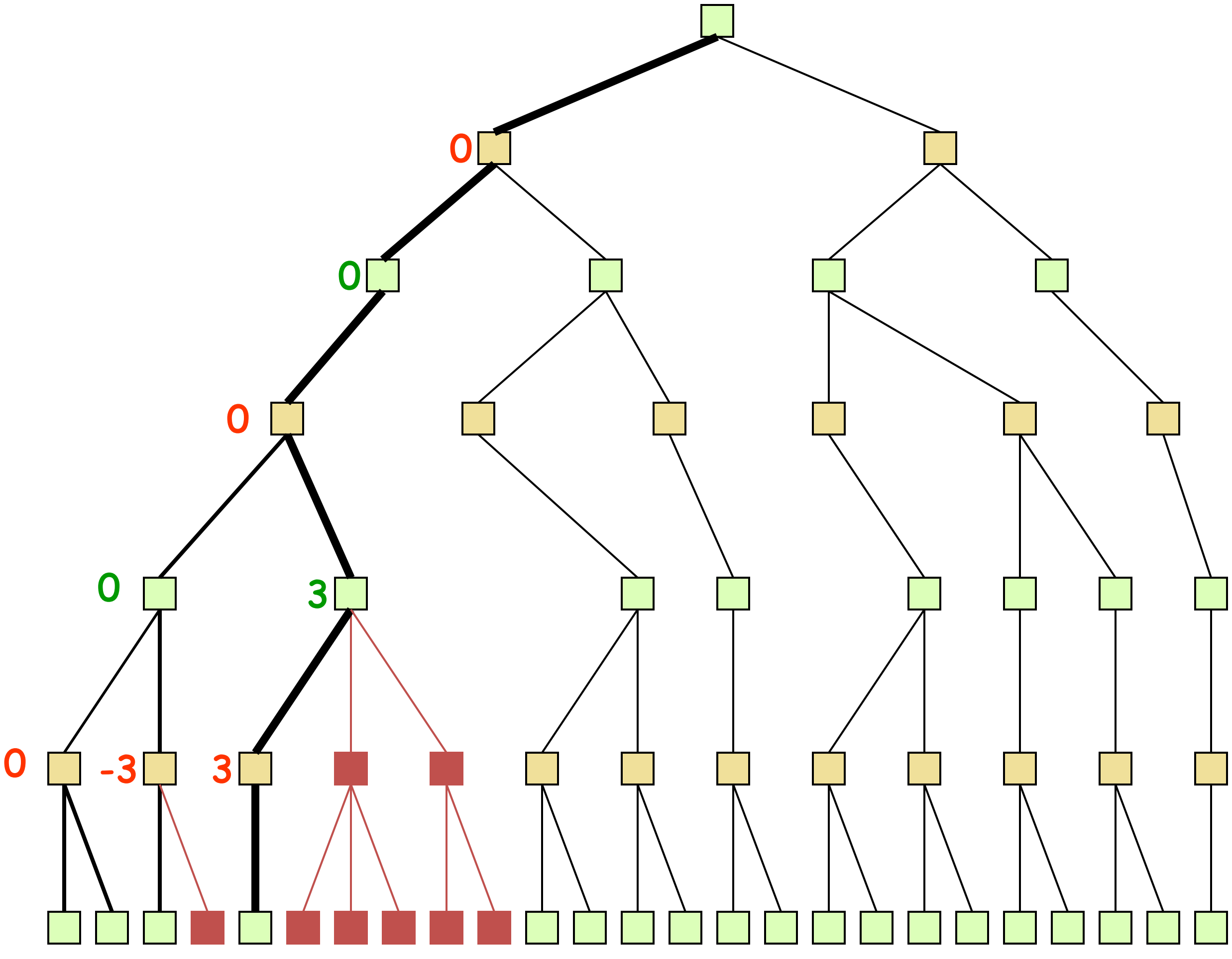
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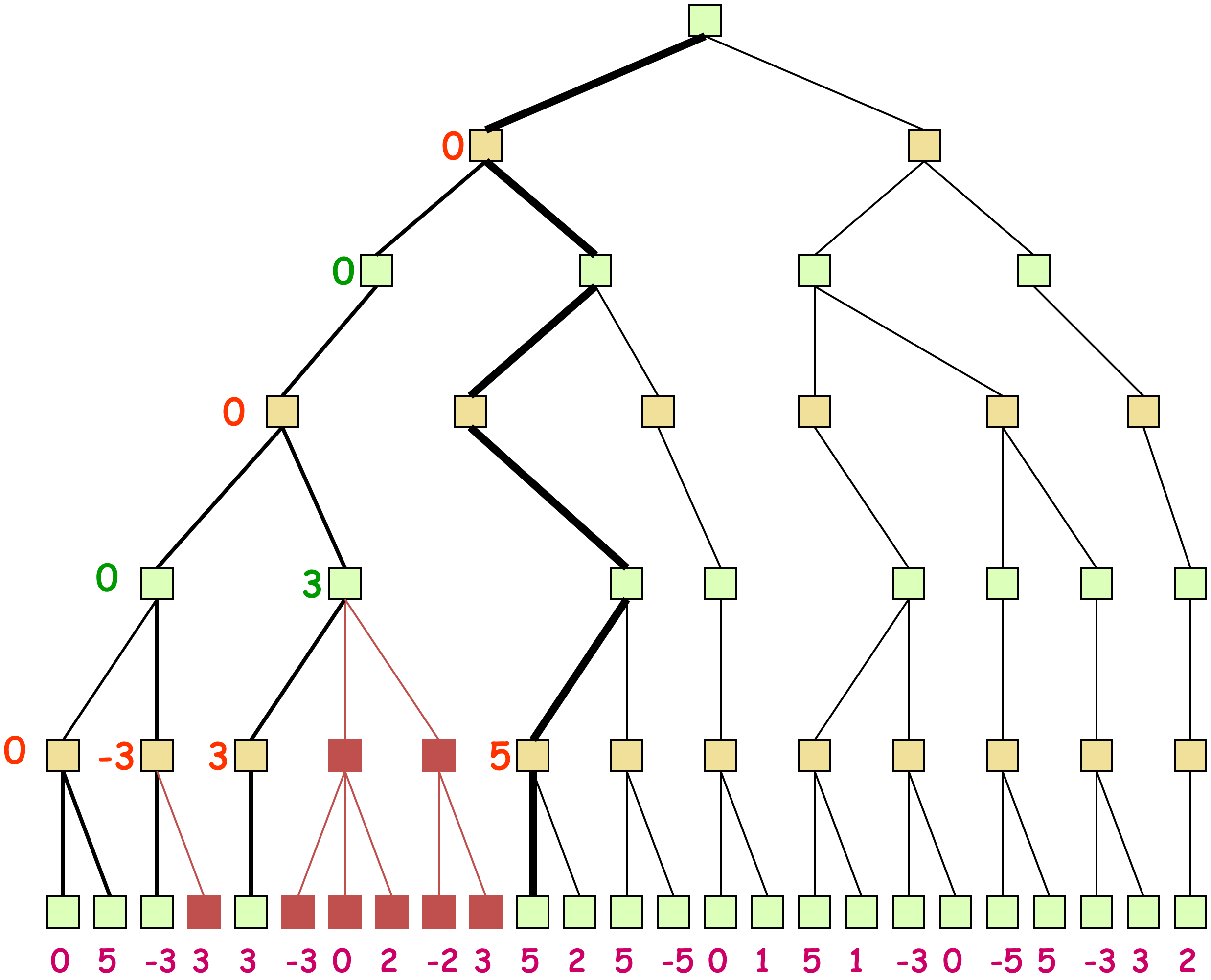
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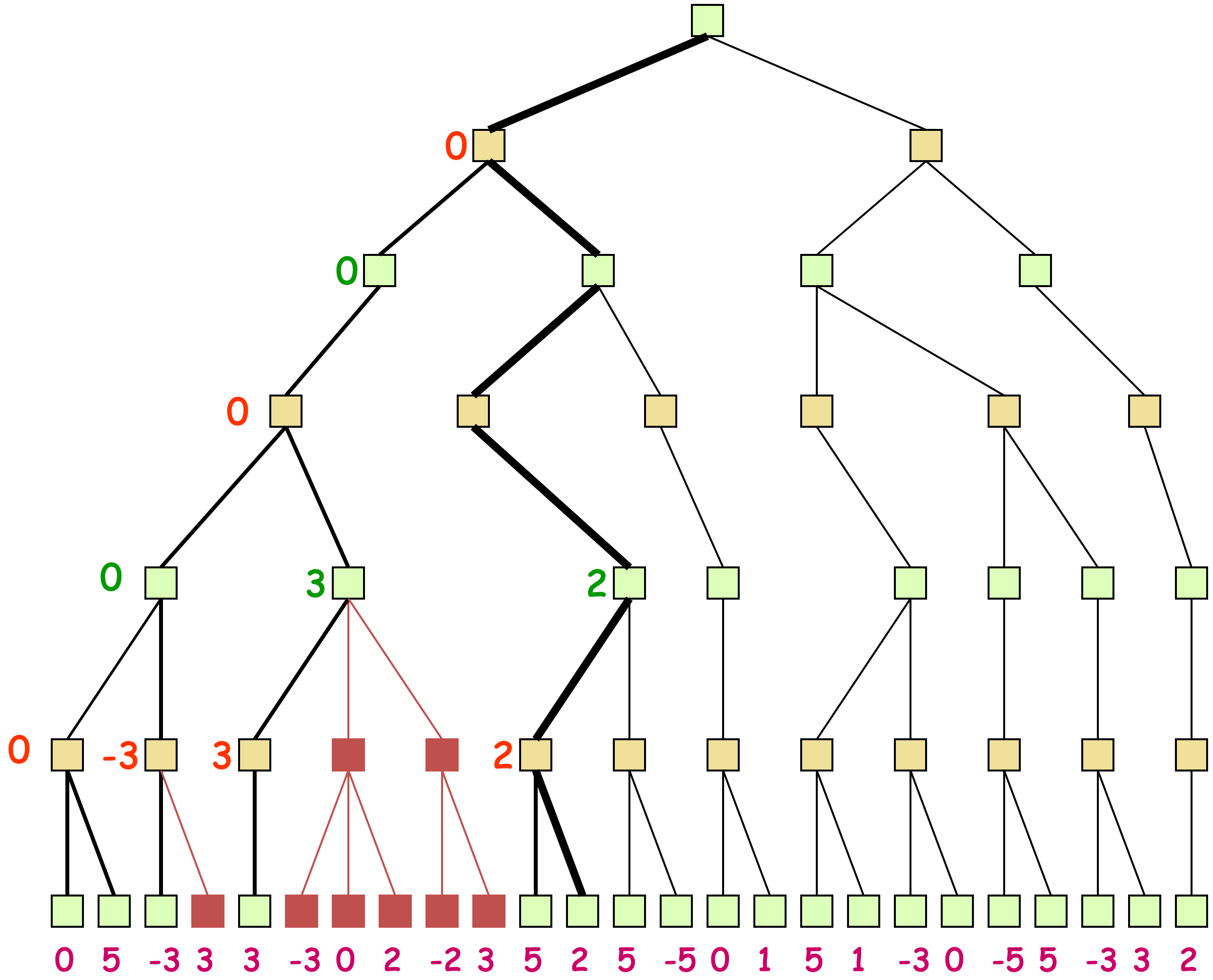
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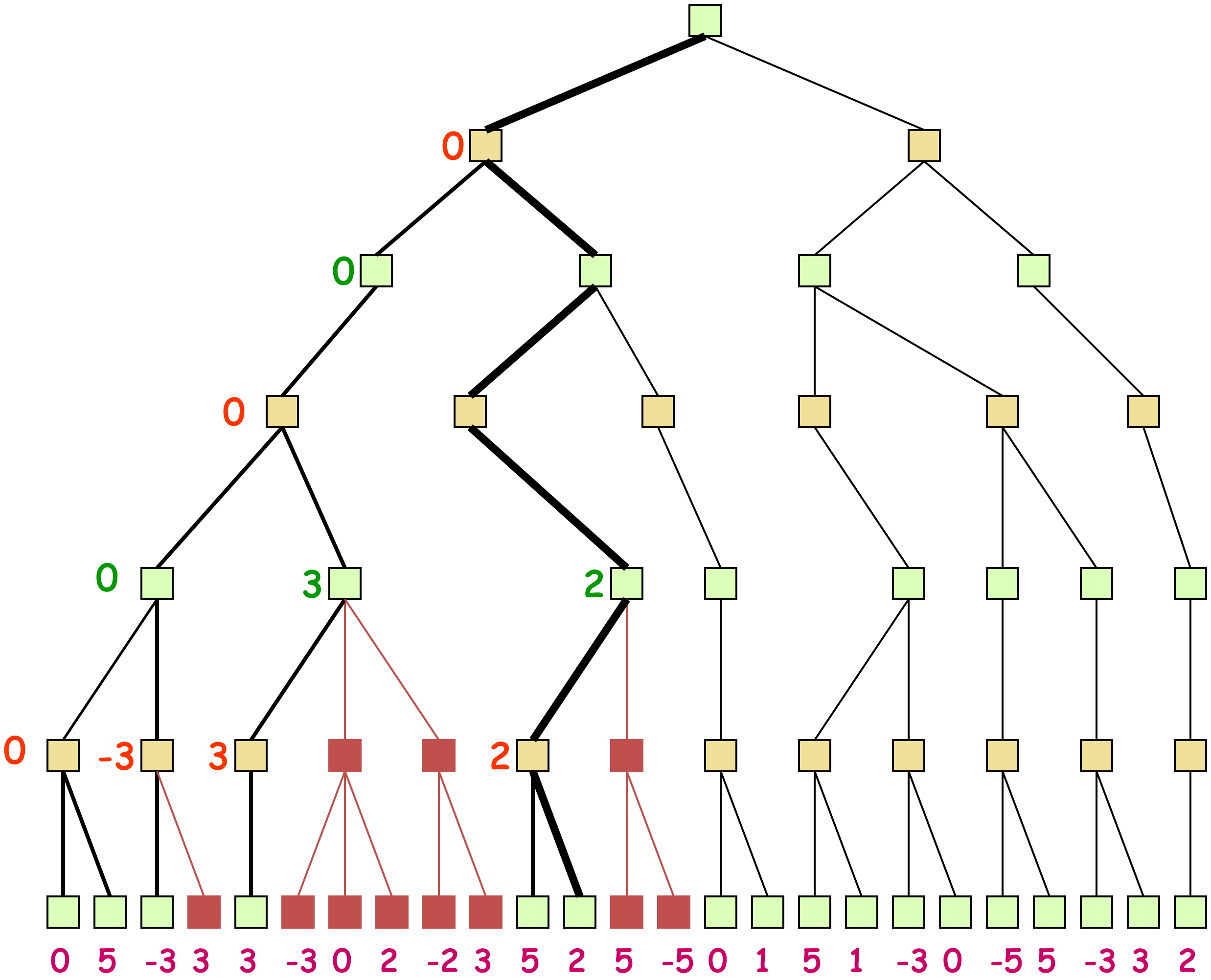
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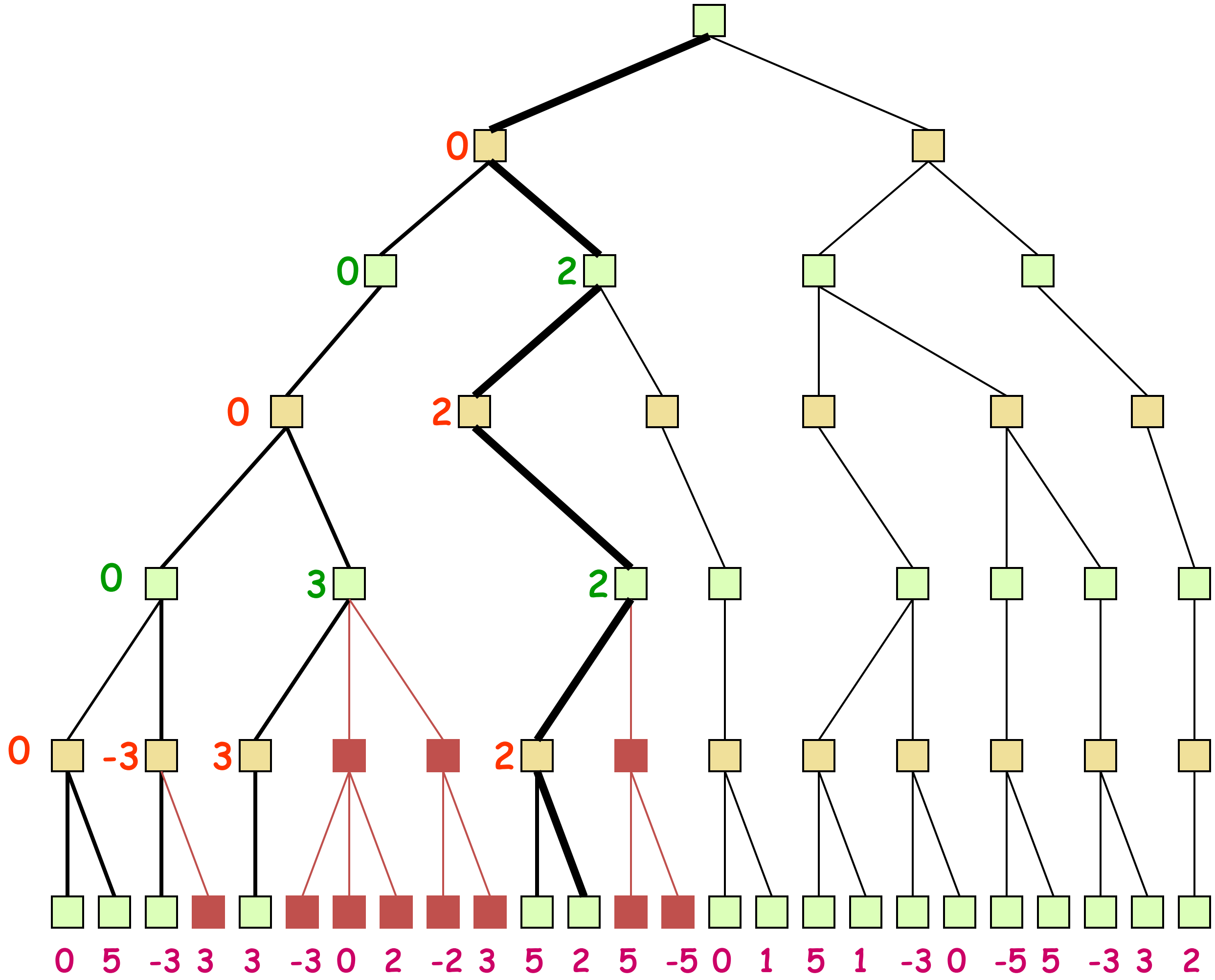
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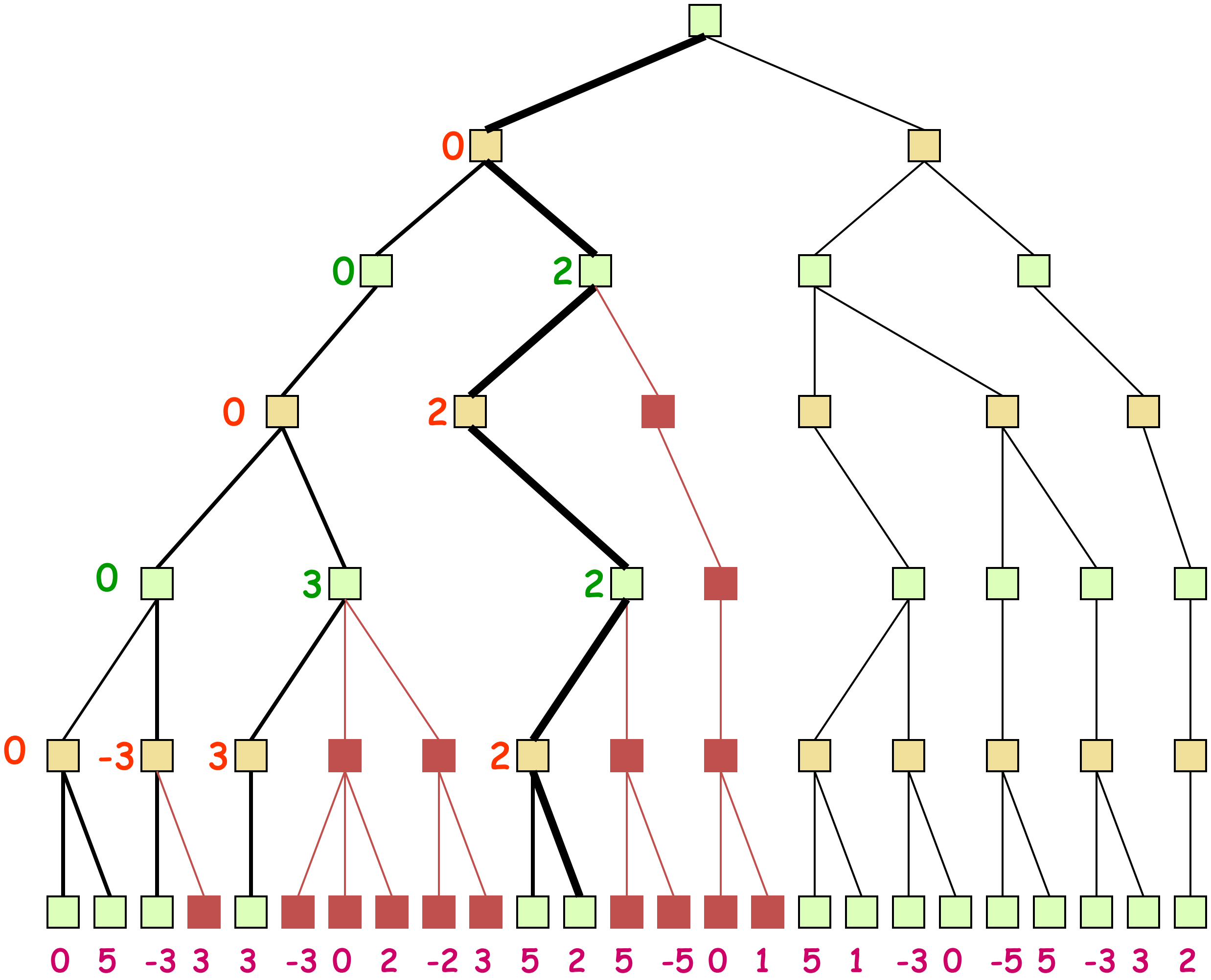
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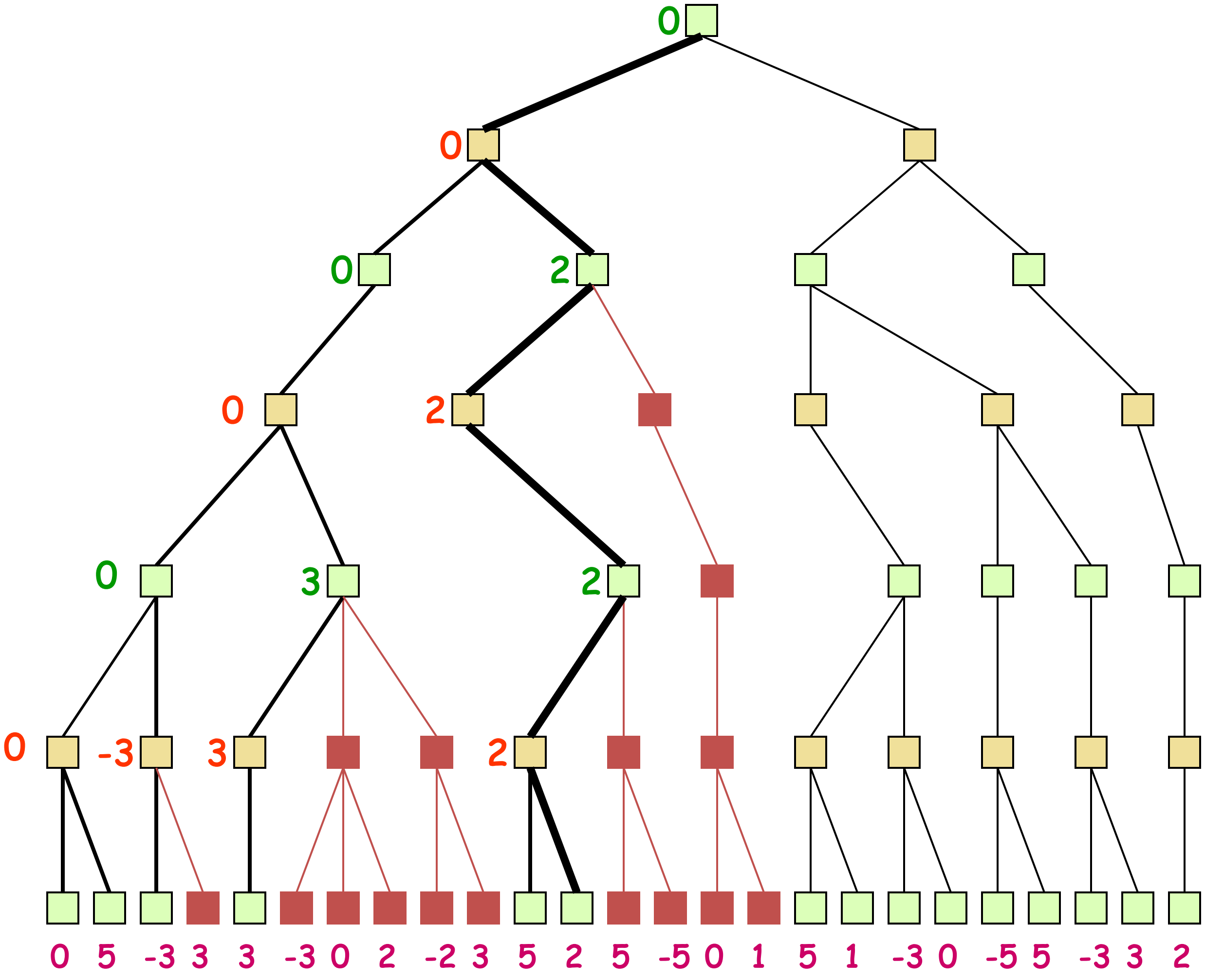
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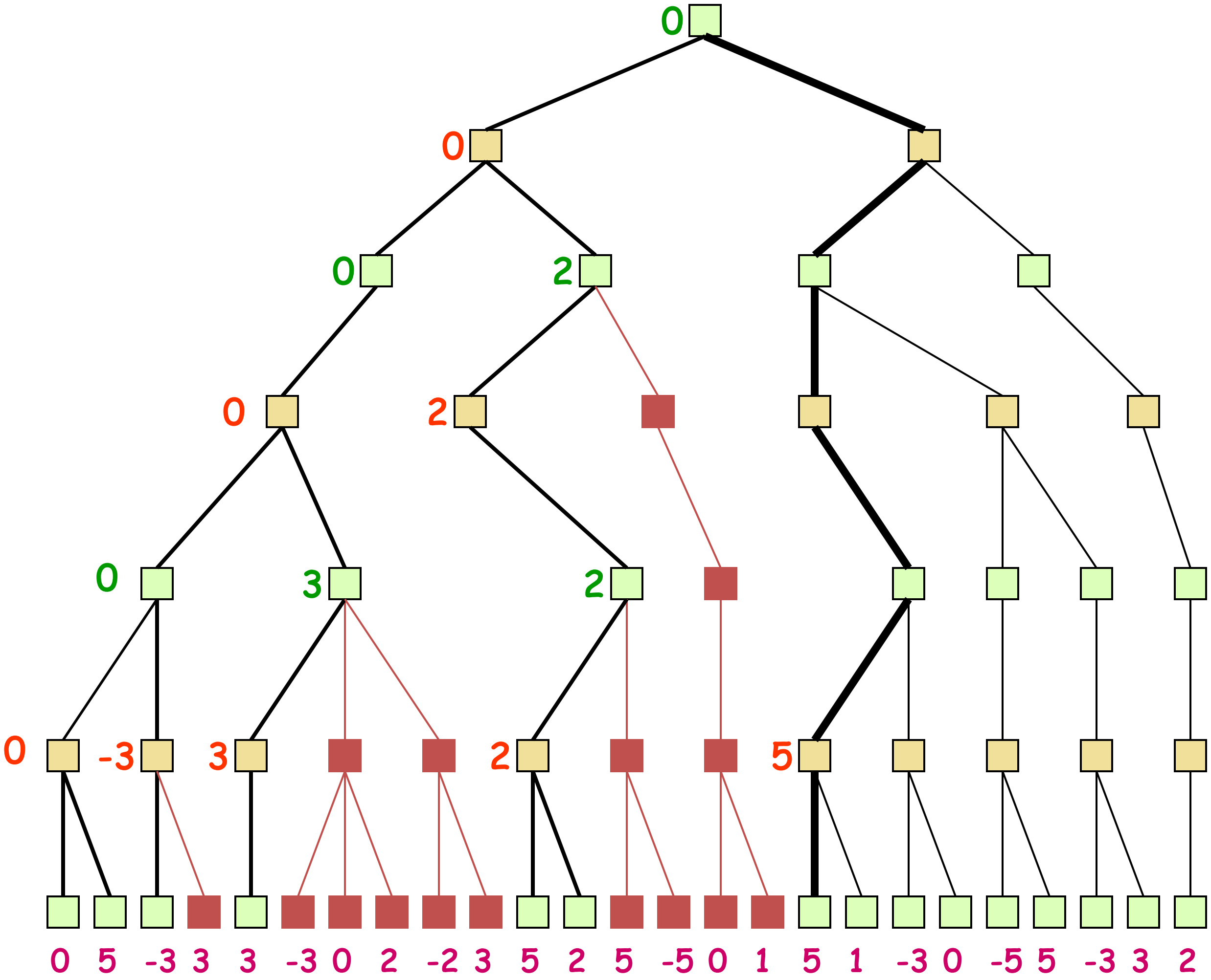
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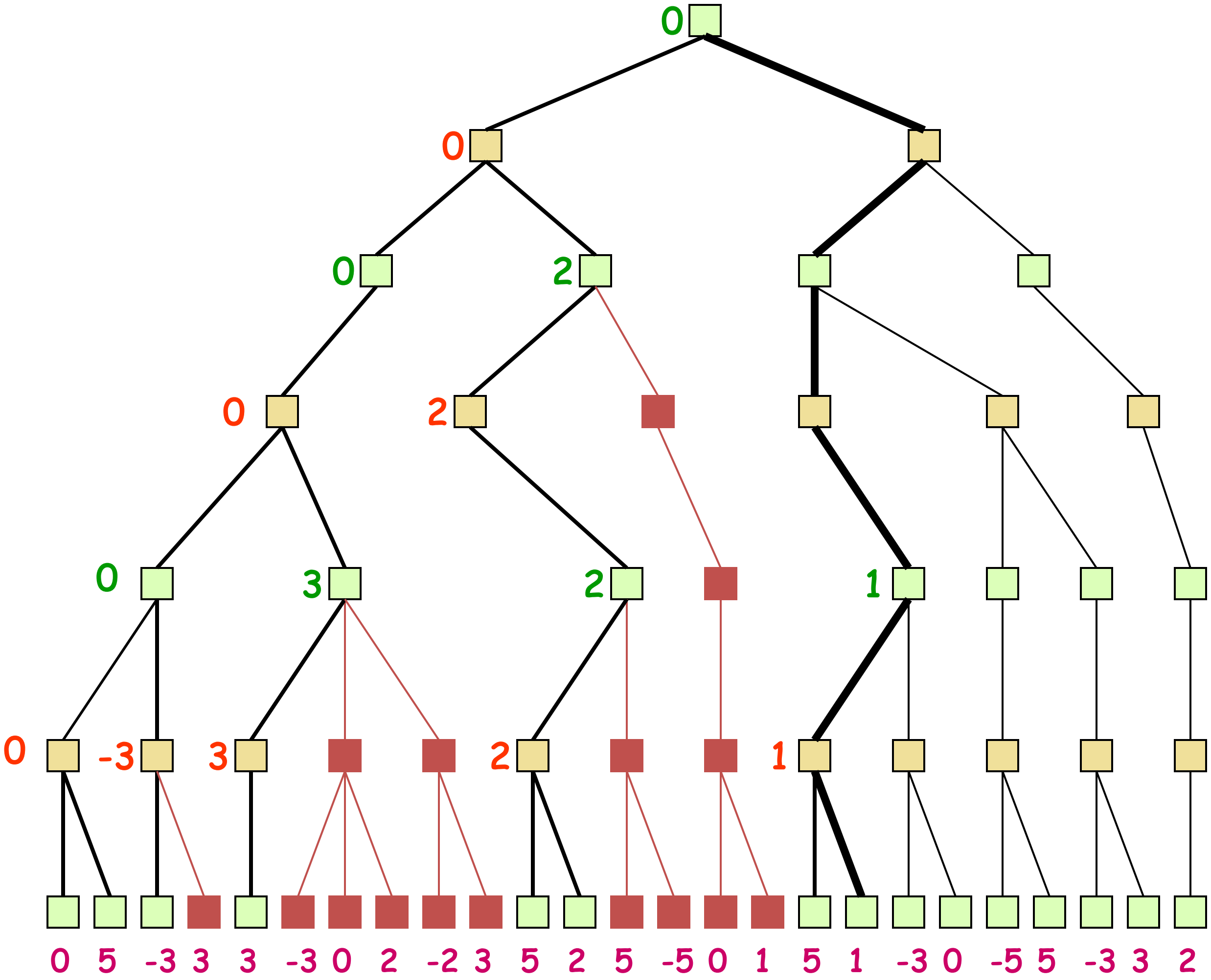
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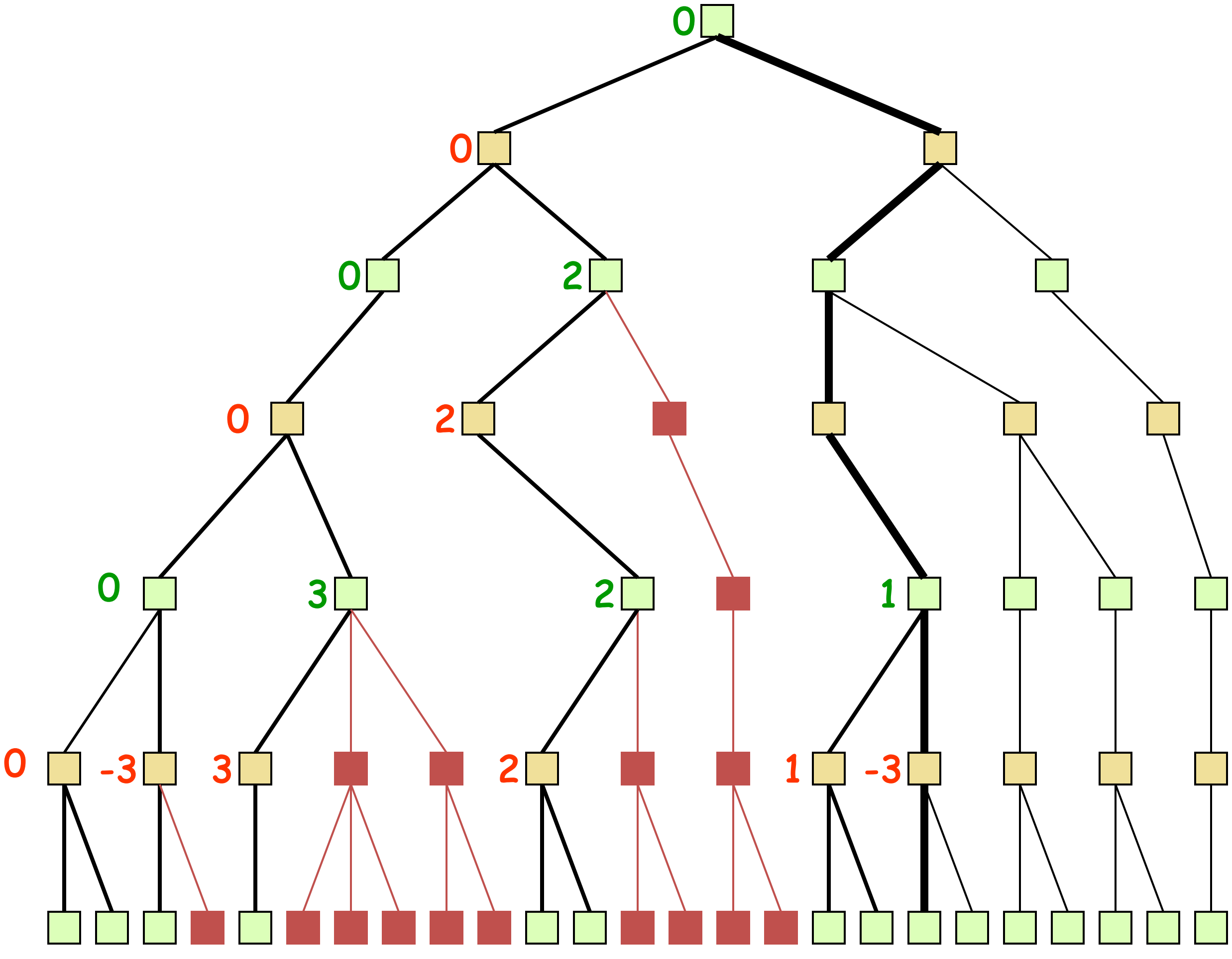
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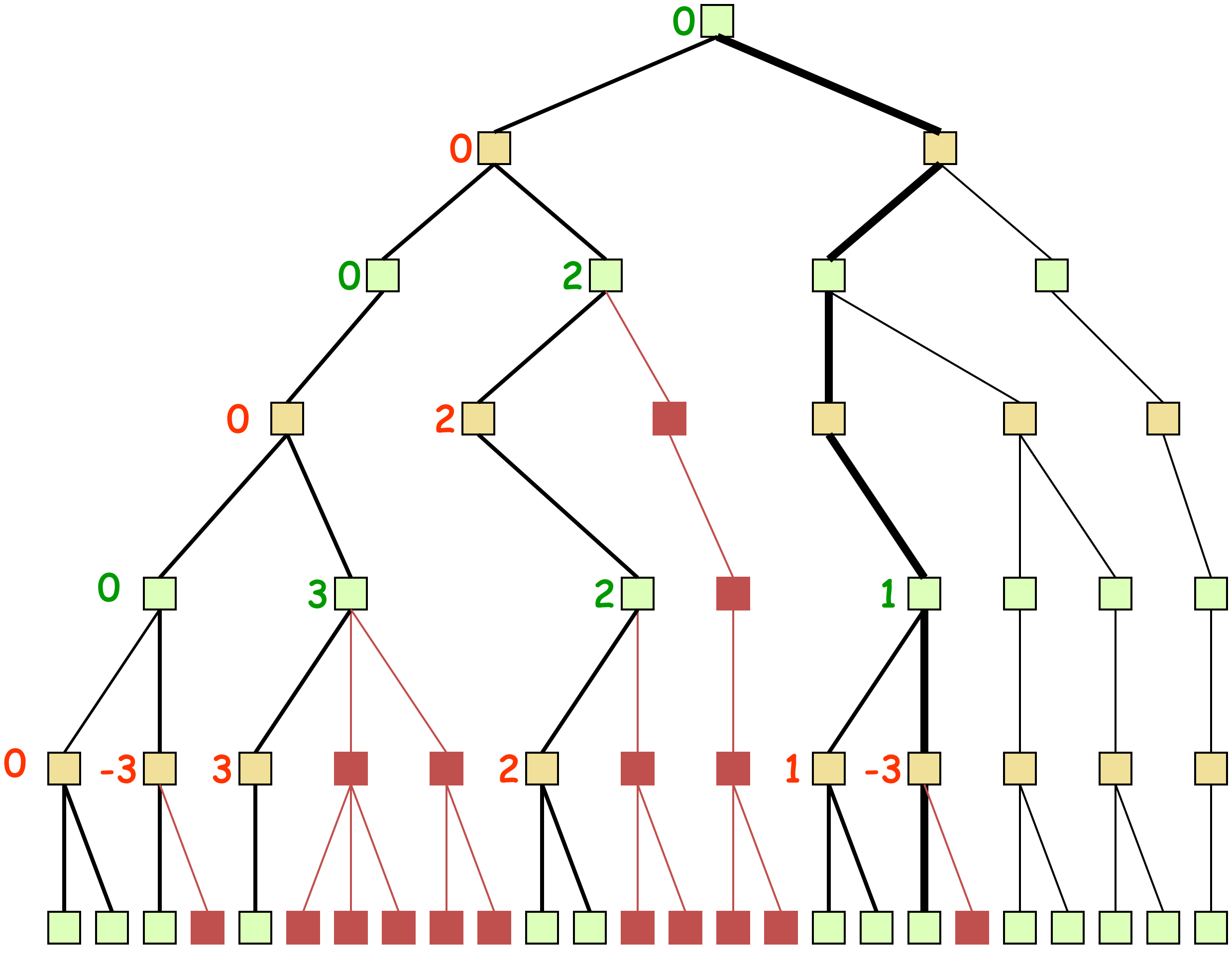
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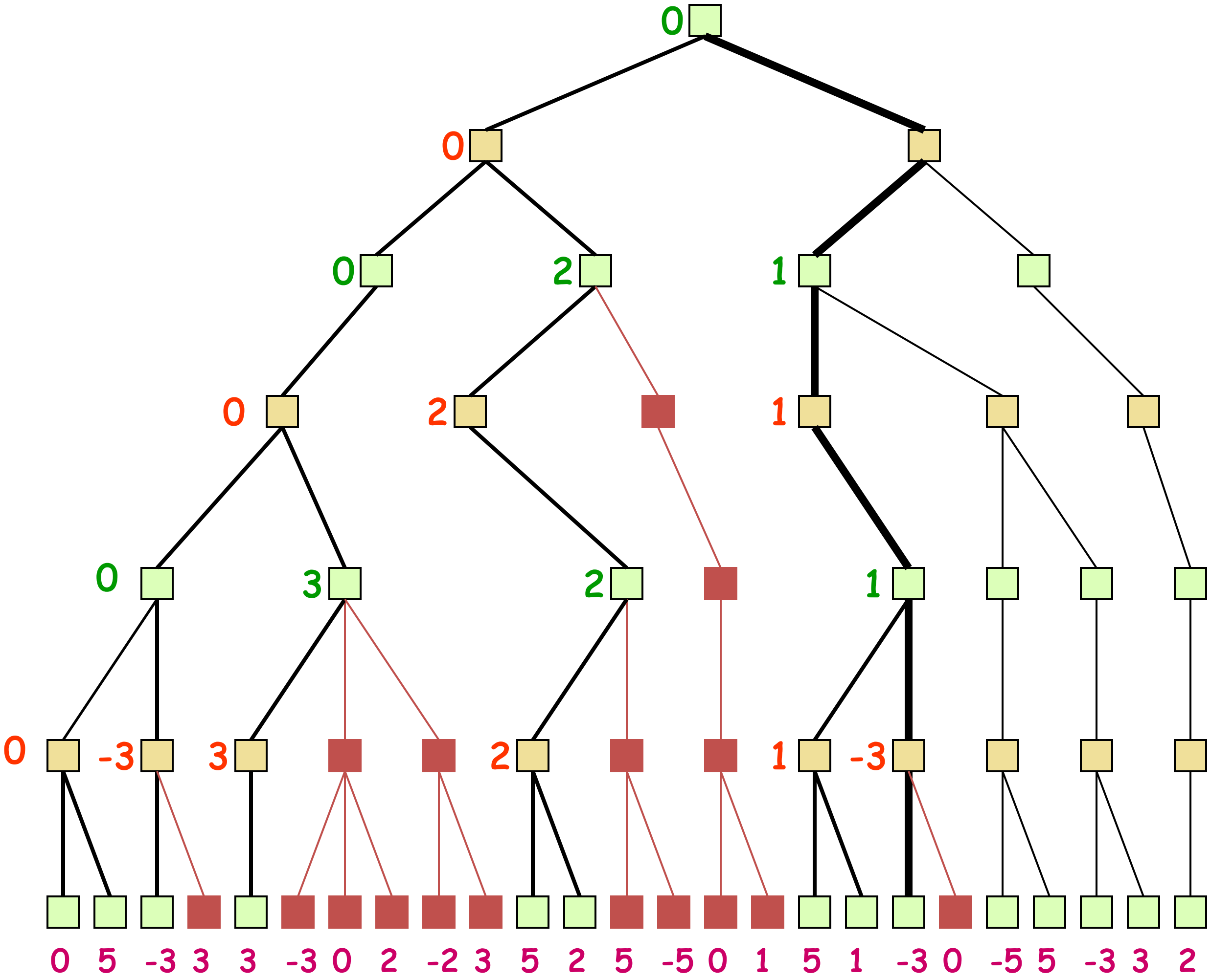
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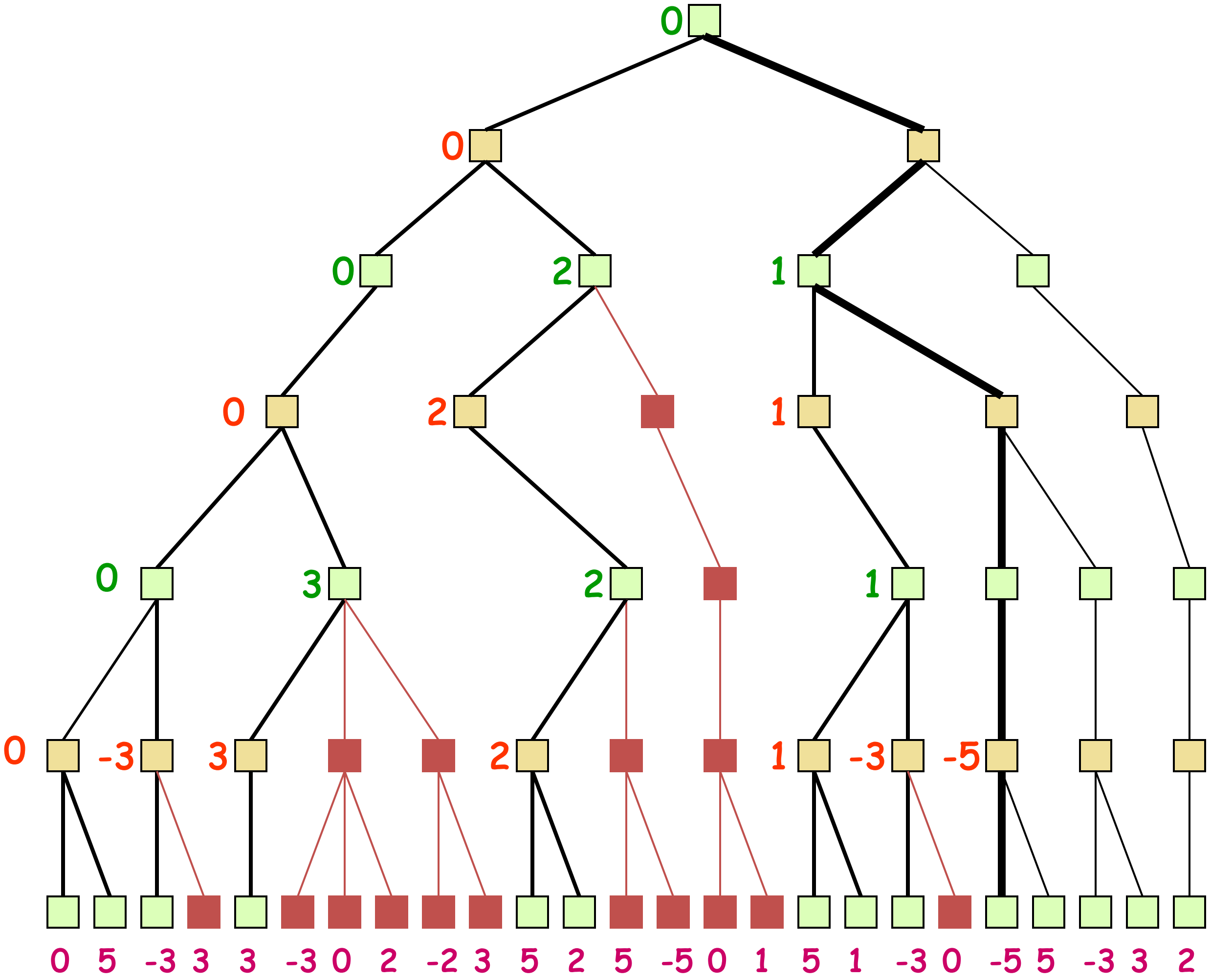
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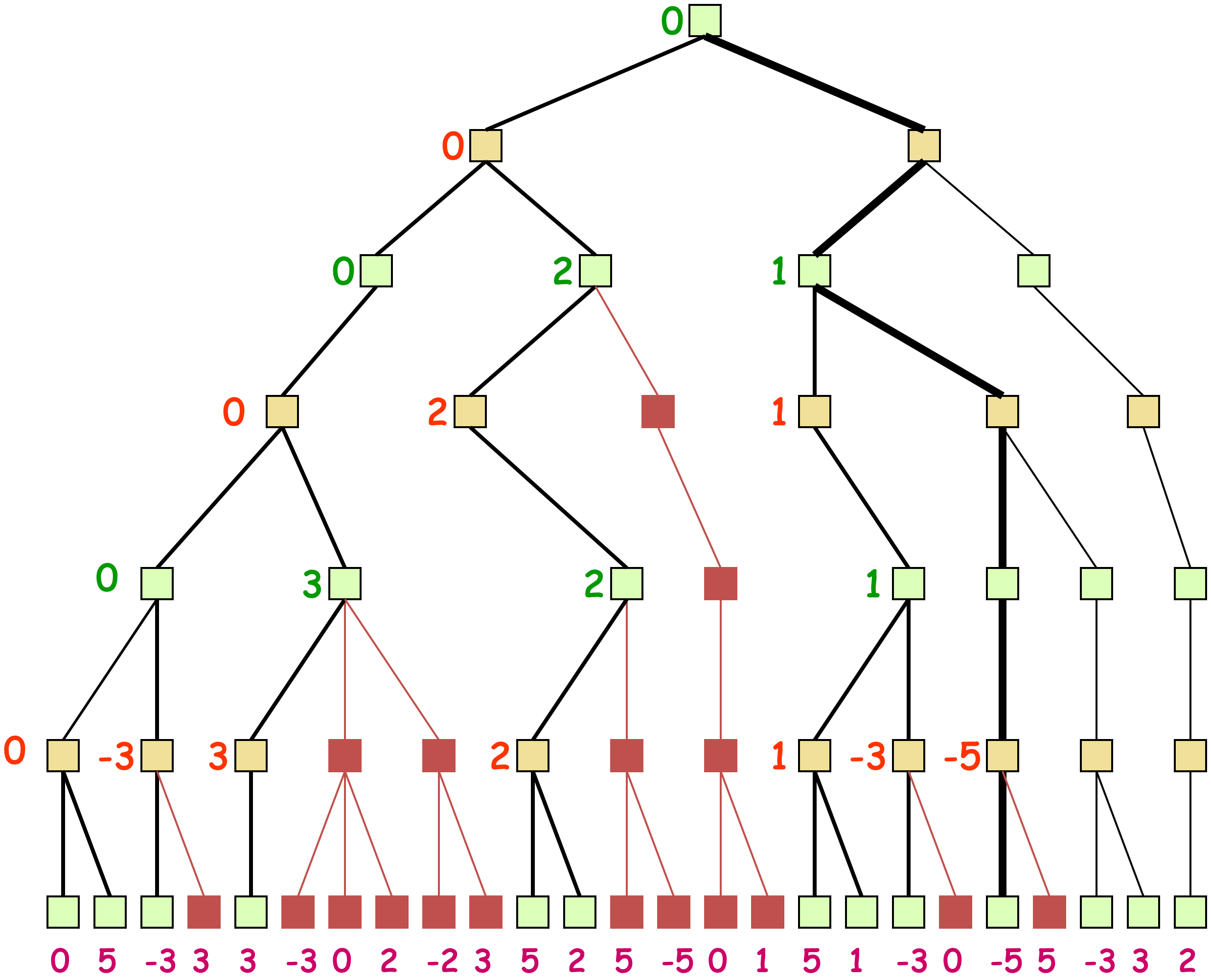
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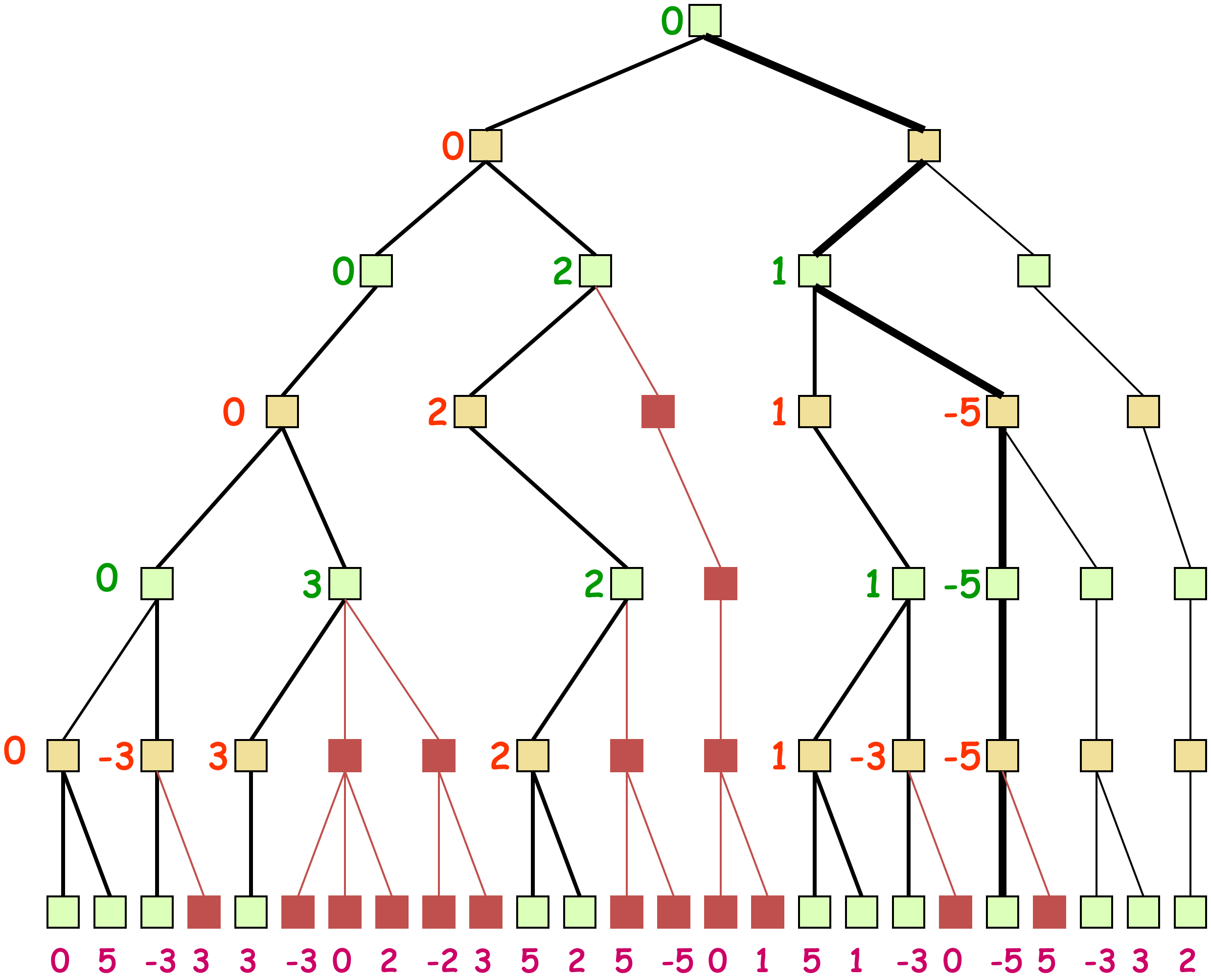
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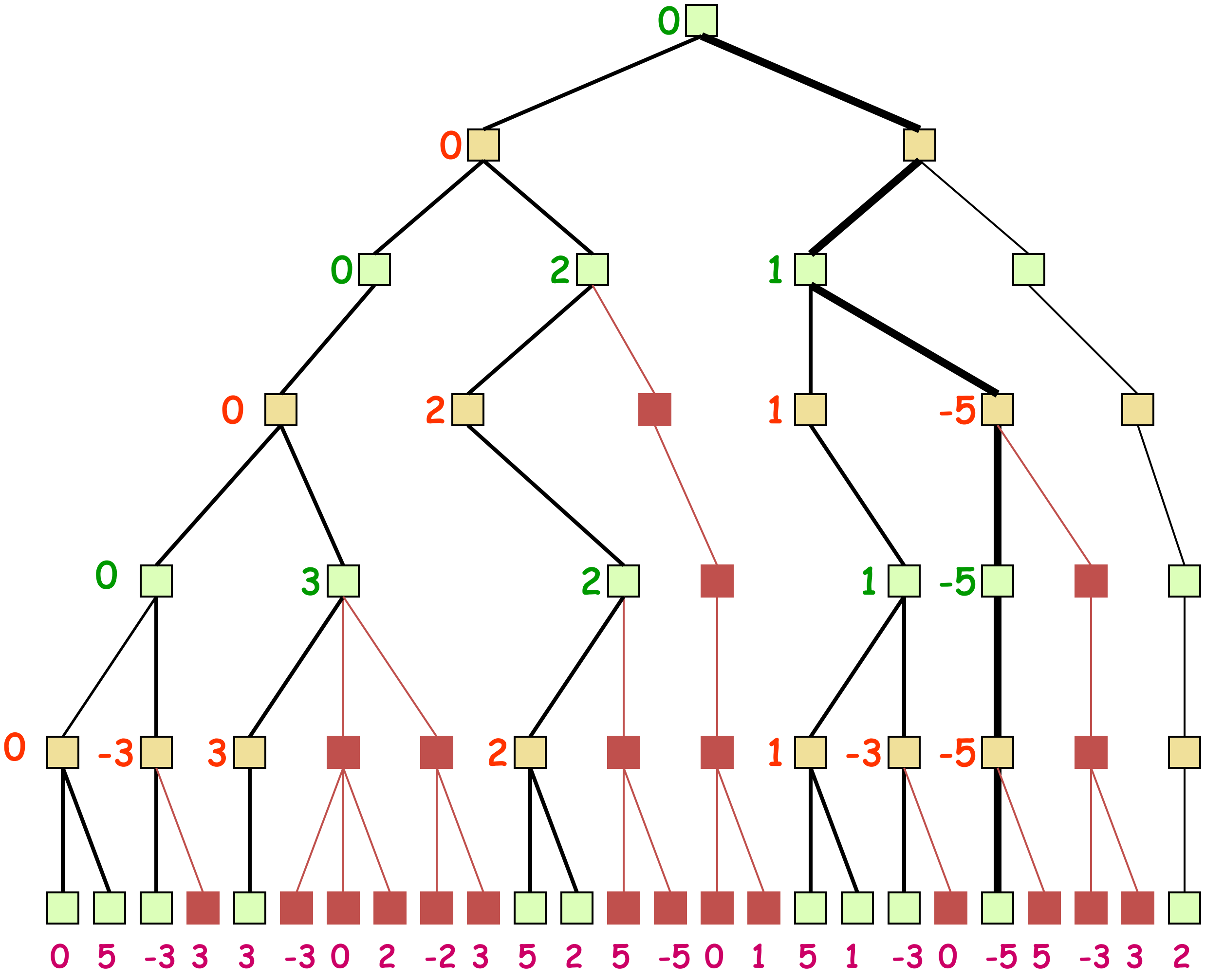
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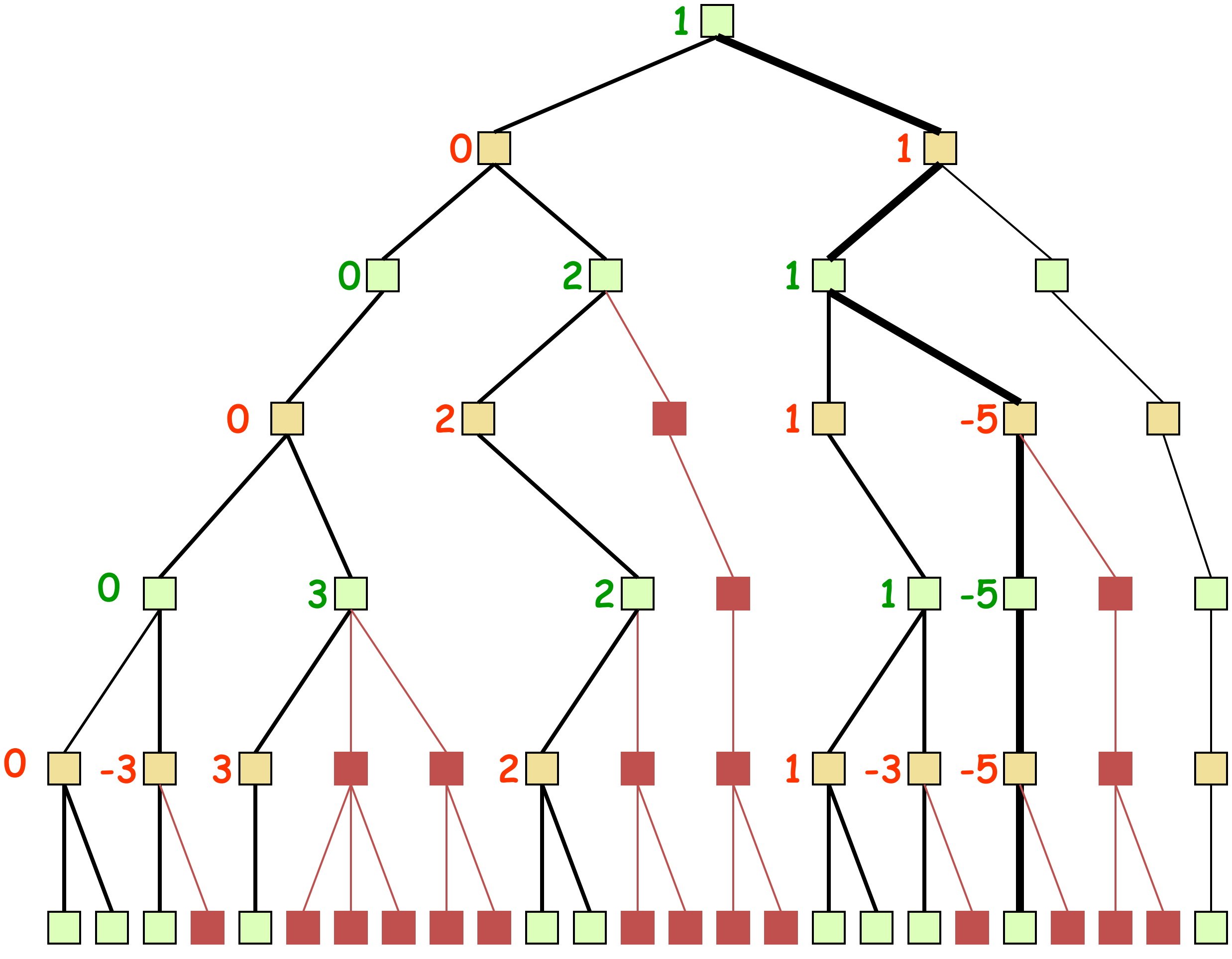
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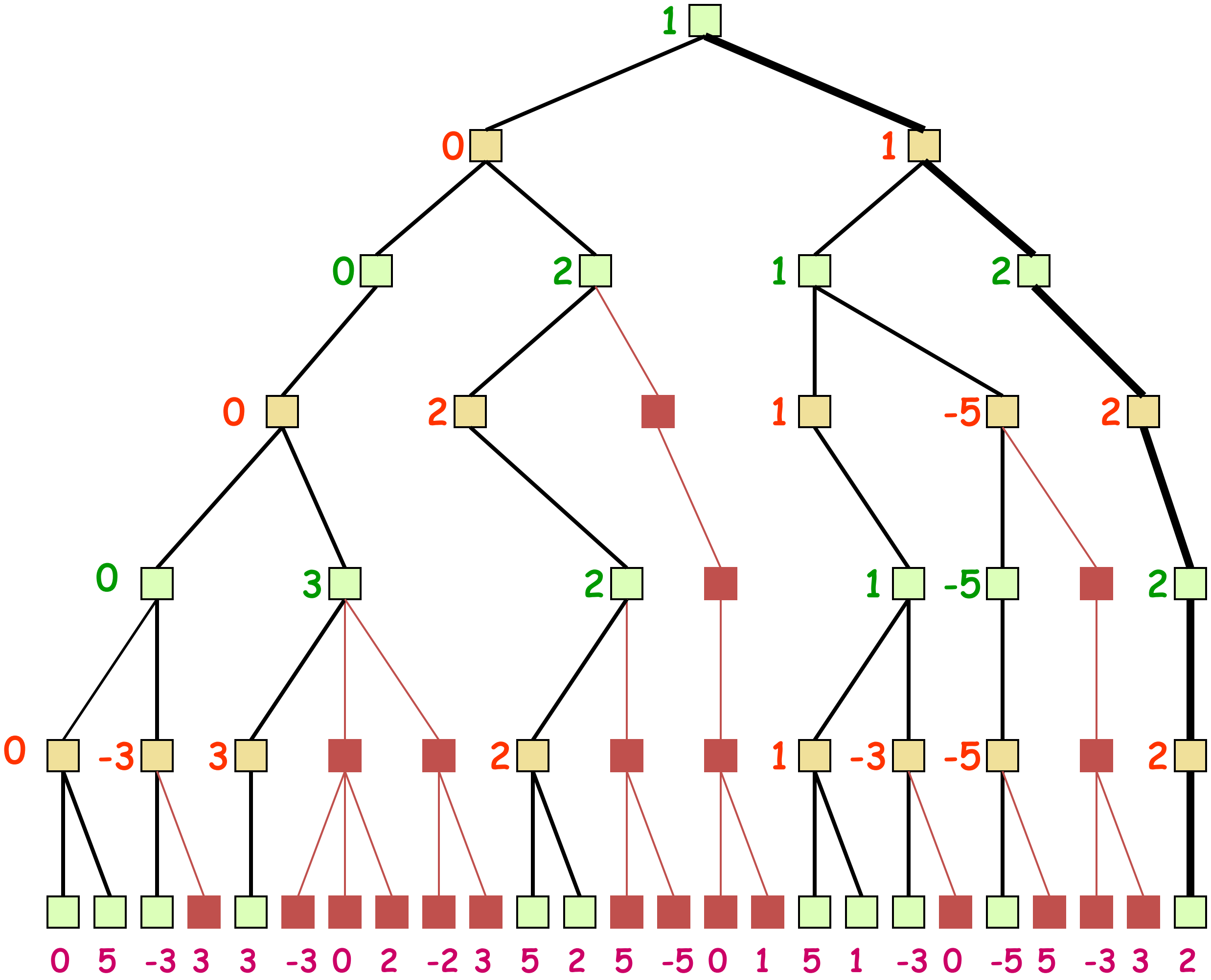
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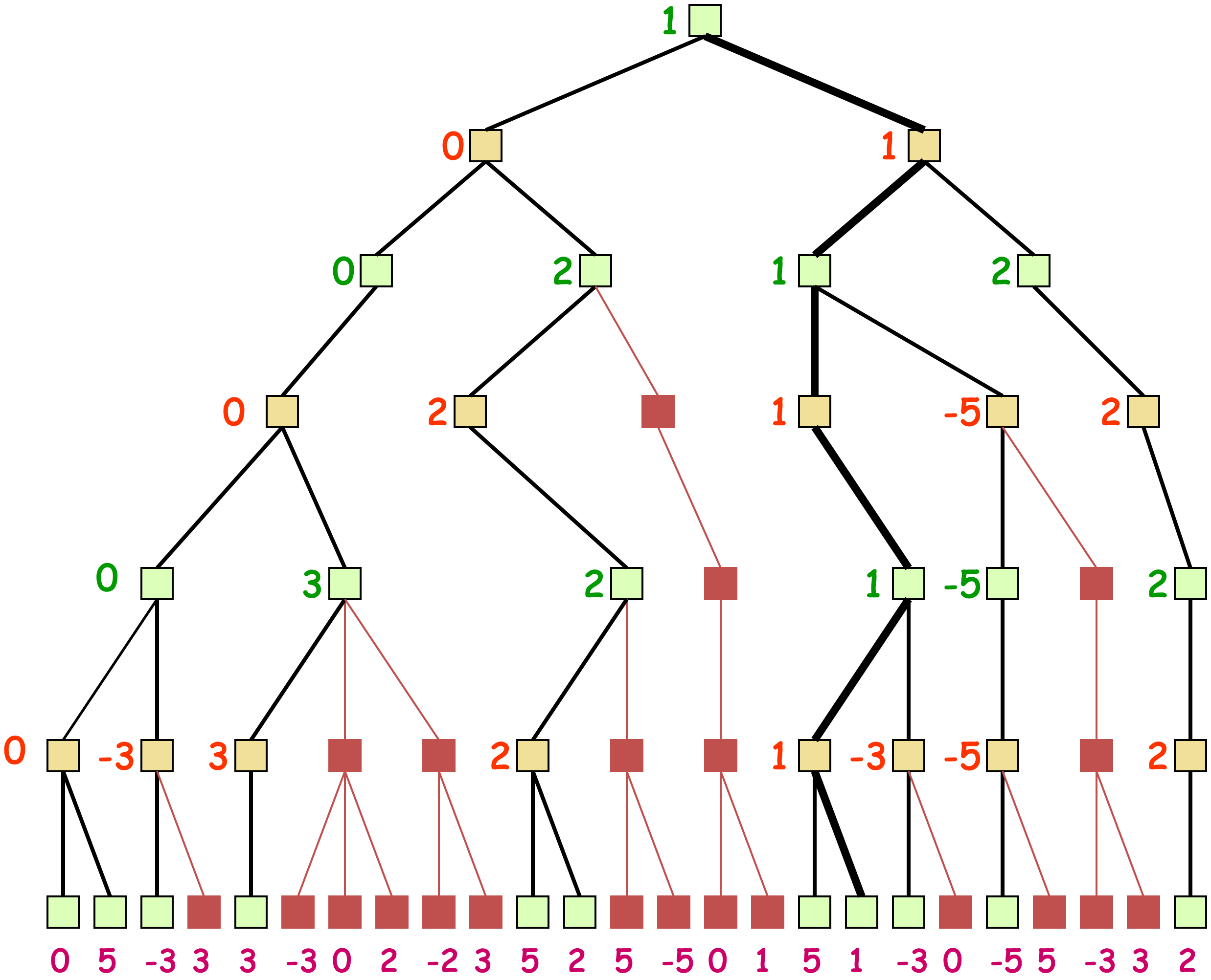
# With alpha-beta we avoided computing a static evaluation metric for 14 of the 25 leaf nodes



# Many other improvements

- **Adaptive horizon + iterative deepening**
- **Extended search**: retain k>1 best paths (not just one) extend tree at greater depth below their leaf nodes to help dealing with "horizon effect"
- **Singular extension**: If move is obviously better than others in node at horizon h, expand it
- Use **transposition tables** to deal with repeated states