

Agents that Search Together: Adversarial Search

Russell and Norvig: Chapter 5

CSE 240: Winter 2023

Lecture 5

Announcements

- Assignment 1 is due WEDNESDAY at 5pm
- Quiz 1 on Thursday: will open at 11:25am (after class on Thursday)
 - Due Friday at 5pm.
 - Open book, open note
 - 30 minutes
 - Time added for DRC.

My Meta-Learning Tips: Quizzes

- Manage stress through relaxation and focus.
 - Relaxation: Take three deep breathes when quiz starts. If you find yourself getting anxious – breathe! It works!!! Be prepared, have notes, review, etc.
 - Focus: Manage time. Be a smart test taker, ALWAYS put down/choose something. Do the easy questions first. Limit distractions.

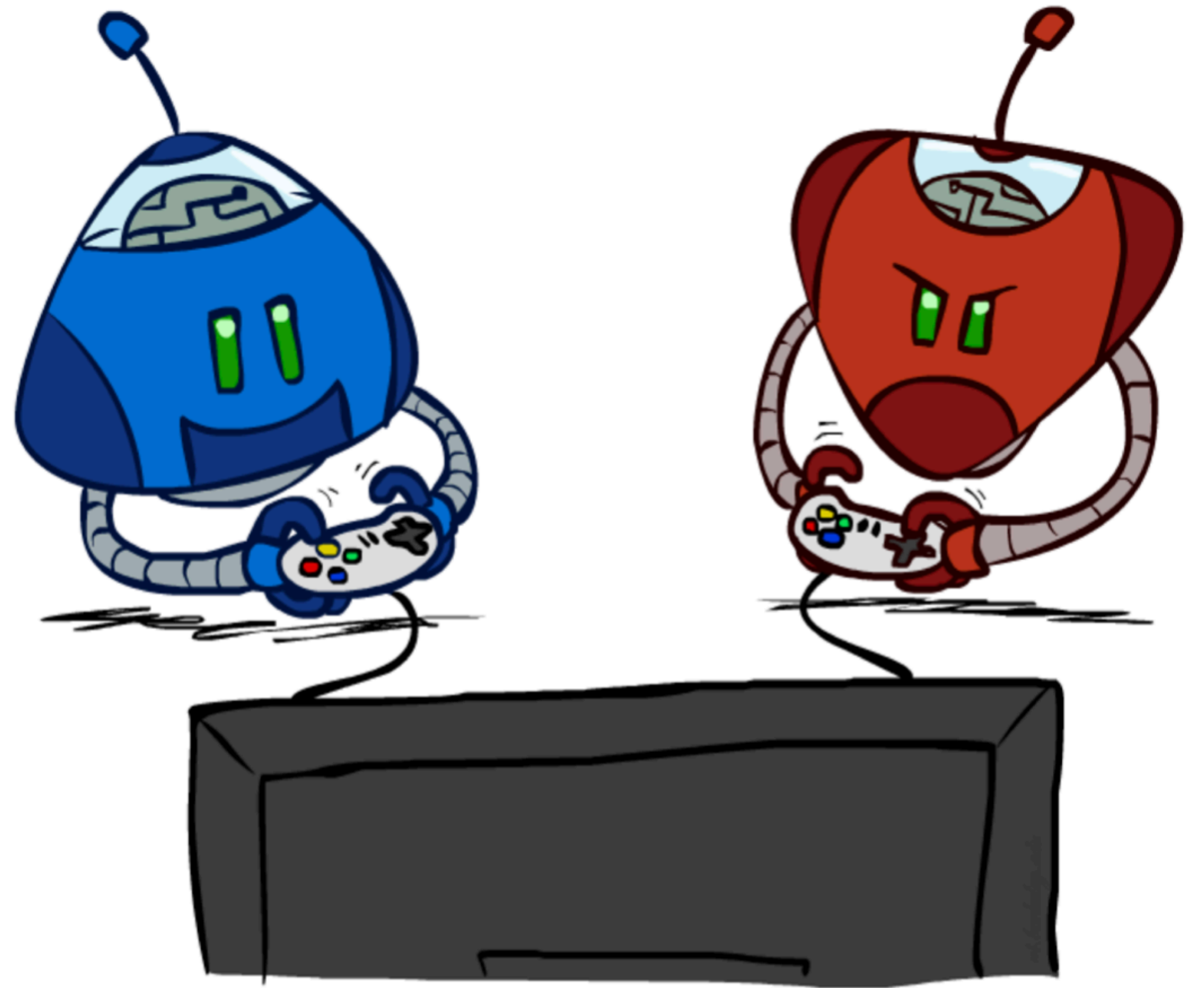
Agenda/Schedule

Week 3

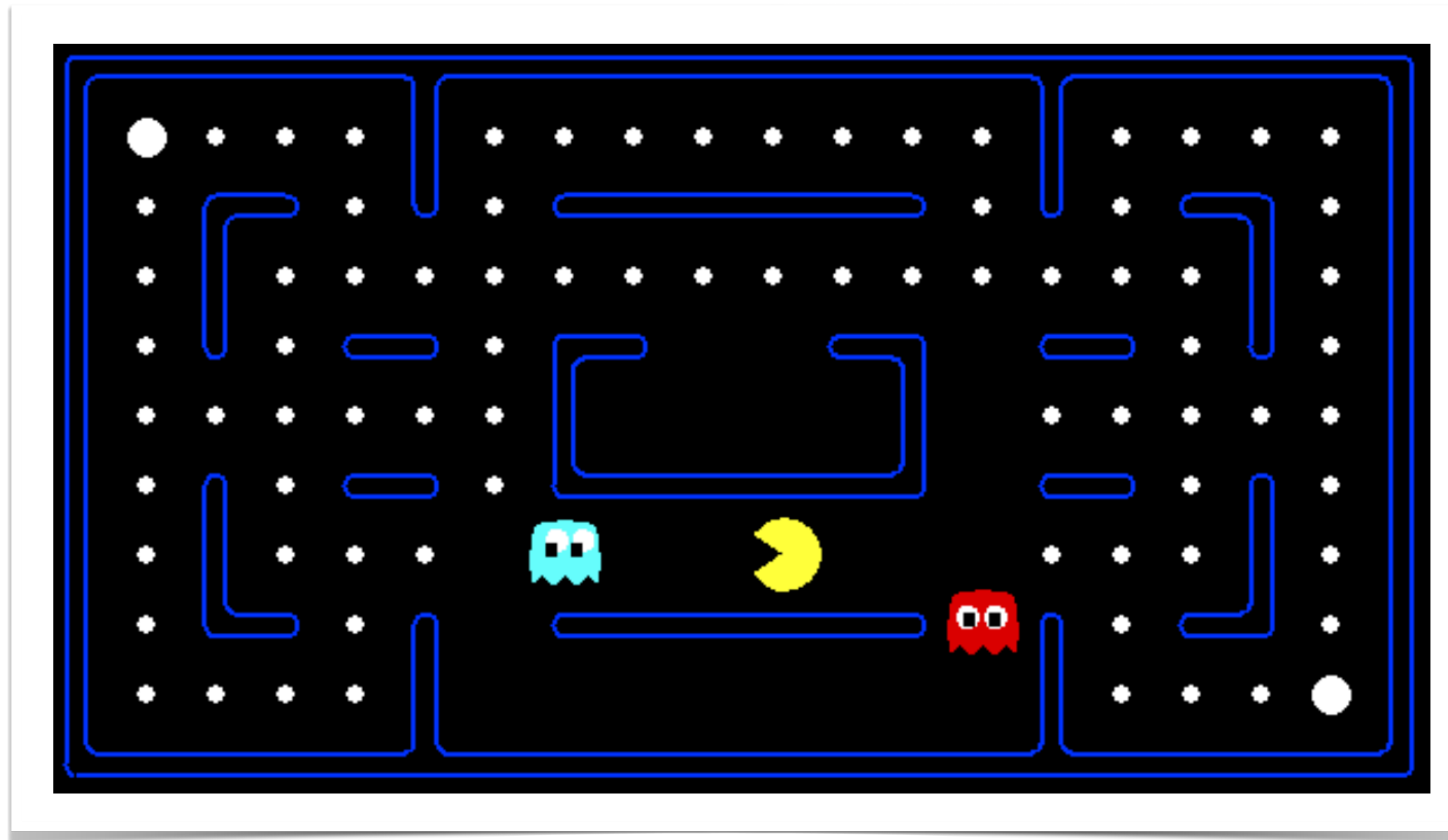
- Game theory
 - Adversarial games
 - Minimax algorithm and alpha-beta pruning
 - Stochastic games
 - Expectimax search algorithm

Today

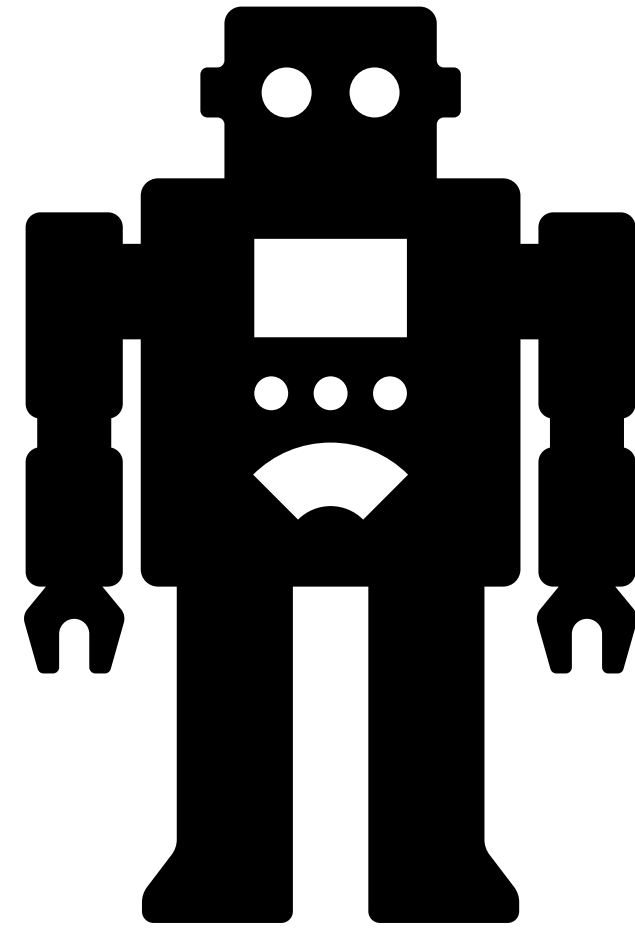
- Adversarial search
 - Or search with other agent



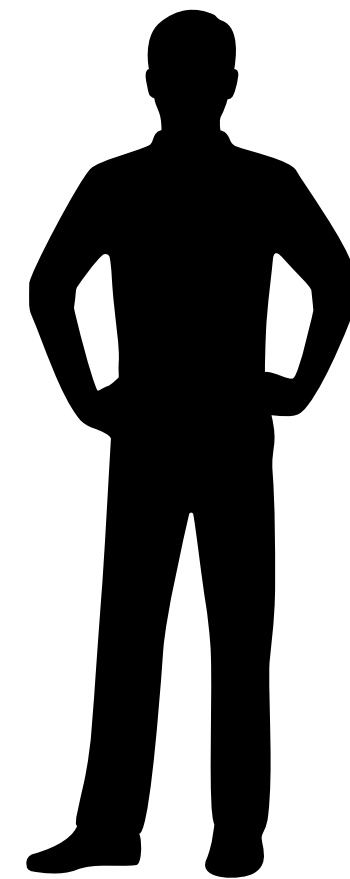
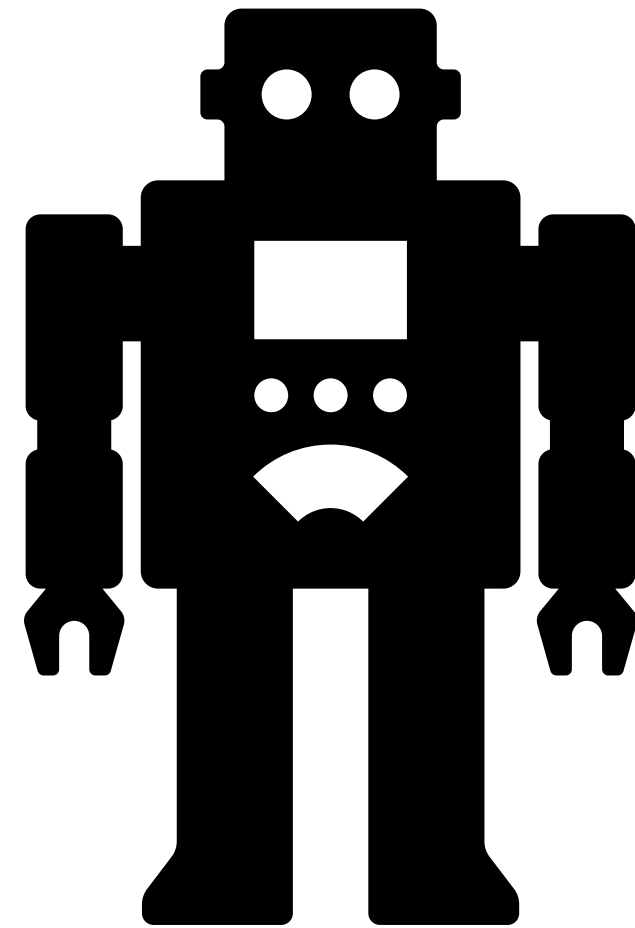
Behavior Based on Computation



Agents Getting Along With Other Agents

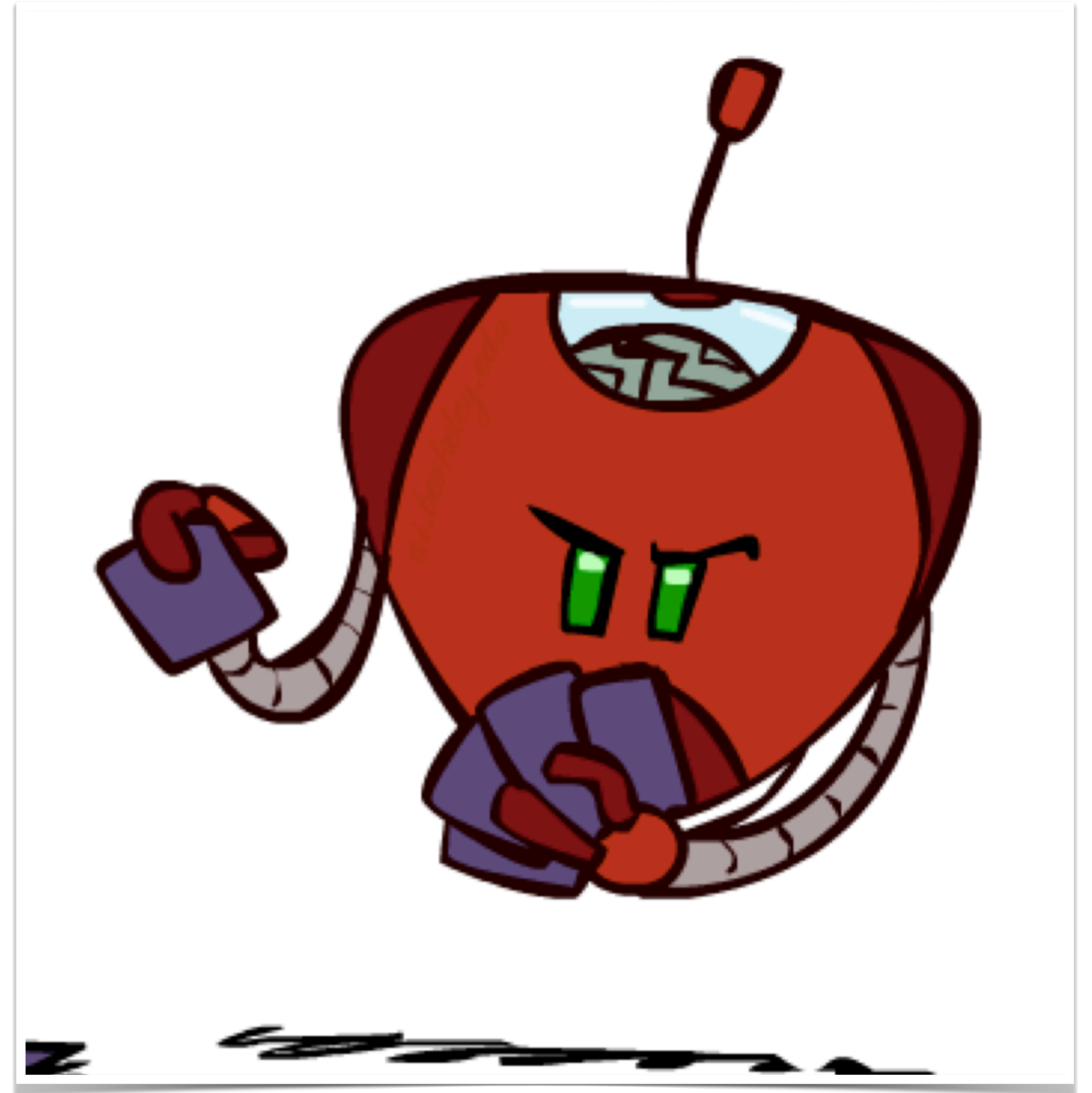


Agents Getting Along With Humans



Types of Game

- Many different kinds of games!
- Types
 - Deterministic or stochastic?
 - One, two or more players?
 - Zero sum?
 - Perfect information (can you see the state)?



Types of Games

- General Games
 - Agents have independent utilities (values on outcomes)
 - Cooperation, indifference, competition, and more are all possible
 - We don't make AI to act in isolation, it should: 1) work around people and 2) help people
 - That means that every AI agents needs to solve a game.
- Zero-Sum Games
 - Agents have opposite utilities (values on outcomes)
 - Think of a single value that one maximizes and the other minimizes
 - Adversarial, pure competition

Primary Assumptions

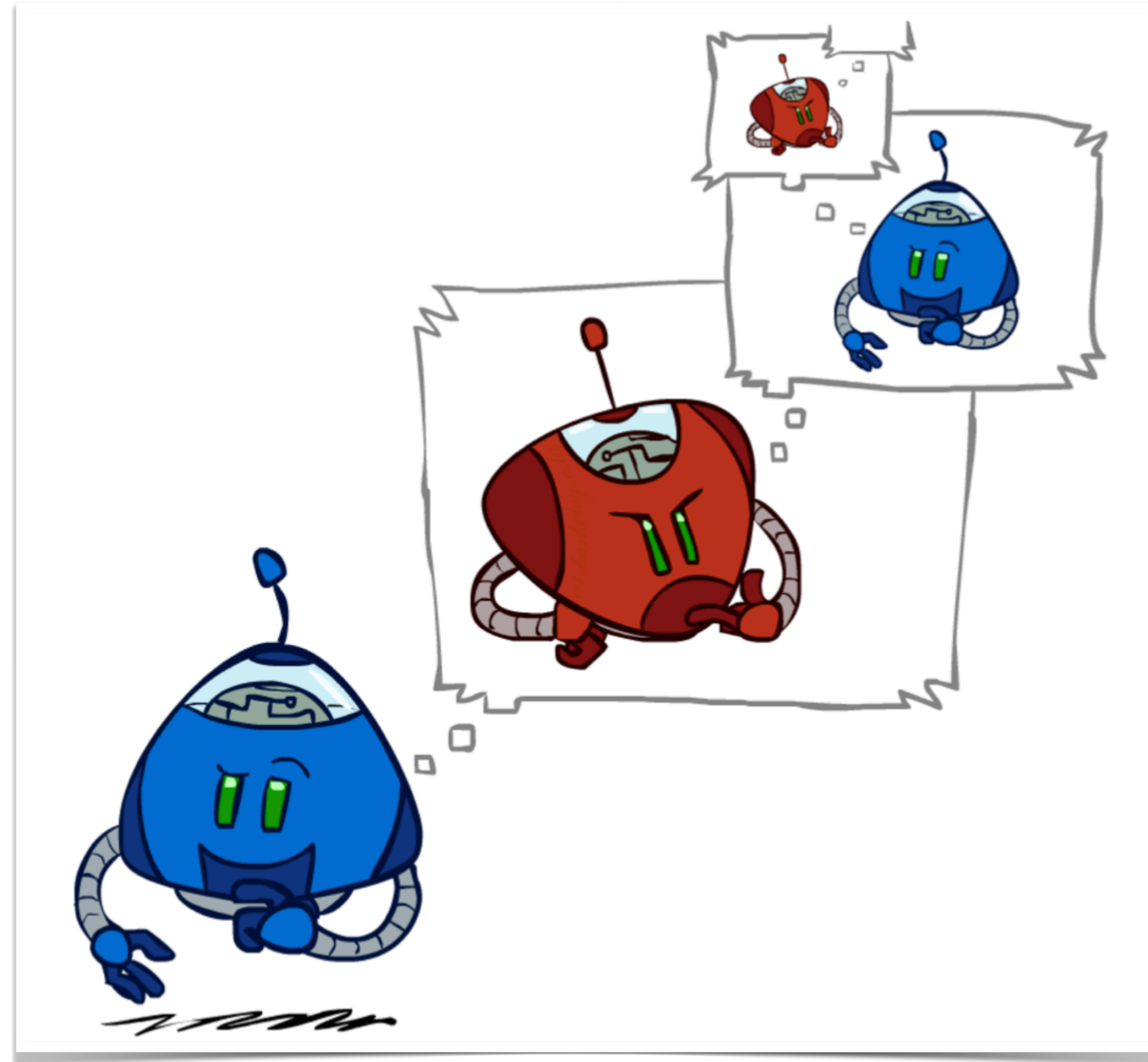
- We start with these games:
 - Two players
 - Turn taking -> agents act alternately
 - Zero sum -> agents' goals are in conflict
 - Deterministic
 - Perfect information -> fully-observable

Deterministic Games with Terminal Utilities

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

Adversarial Games

Adversarial Search



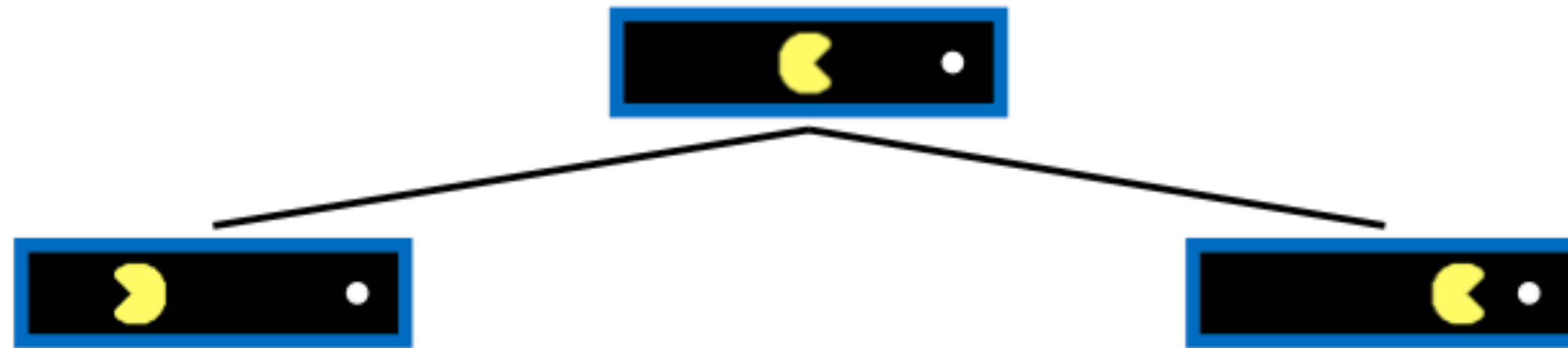
Cost Utility

- No longer minimizing cost!
- Agent now wants to maximize its score/utility!

Single-Agent Trees



Single-Agent Trees



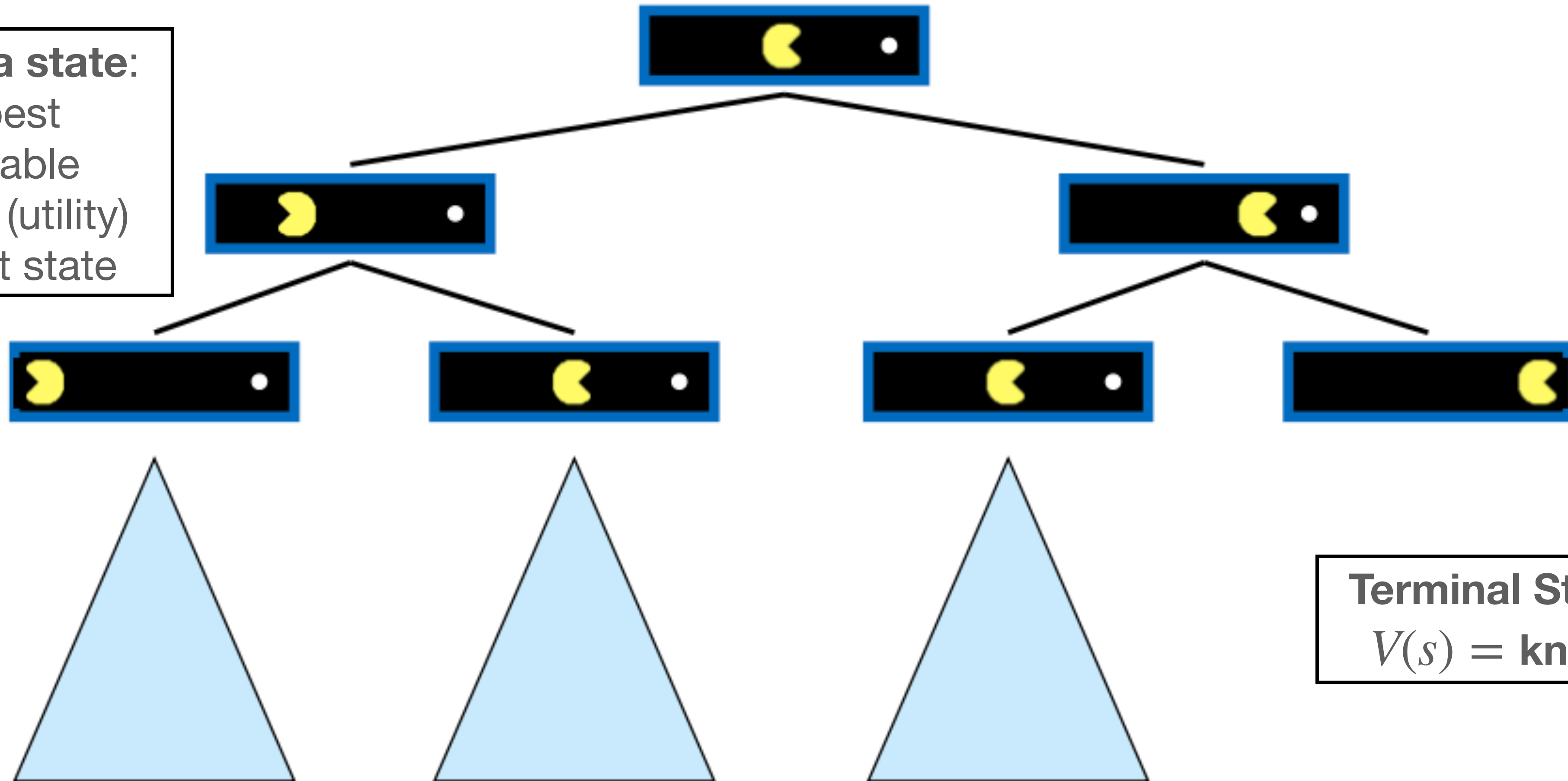
Single-Agent Trees

**Non-terminal
states:**

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

Value of a state:

The best
achievable
outcome (utility)
from that state



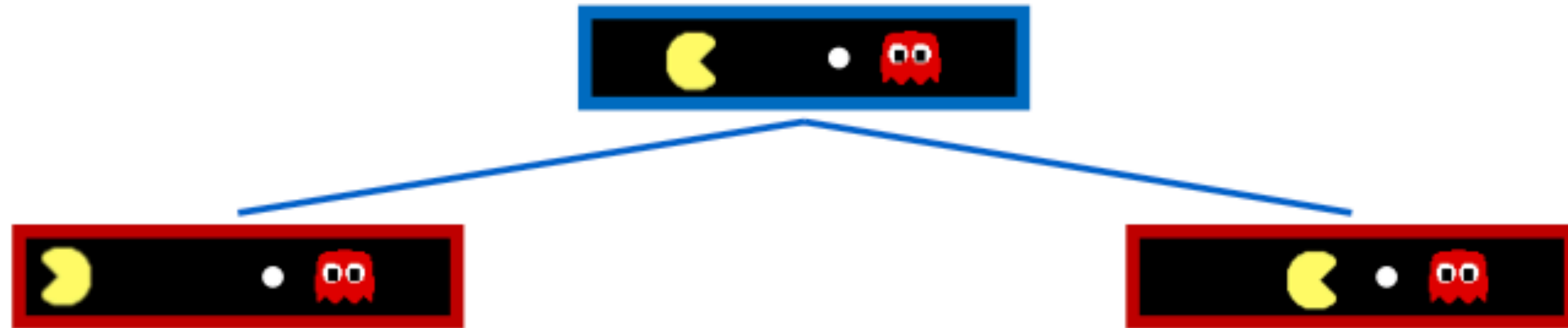
Terminal States:

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

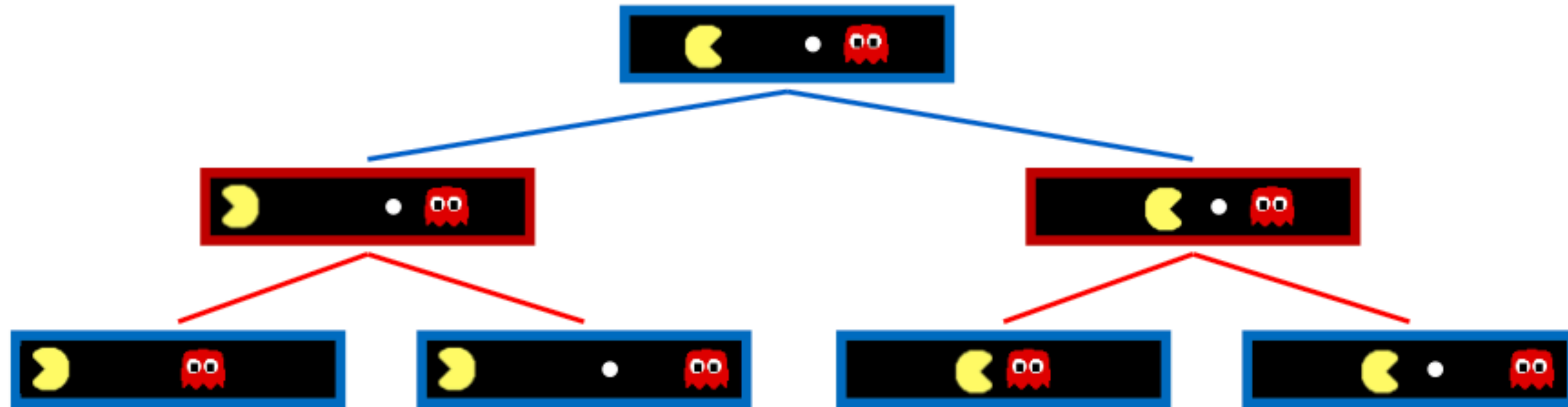
Adversarial Game Trees



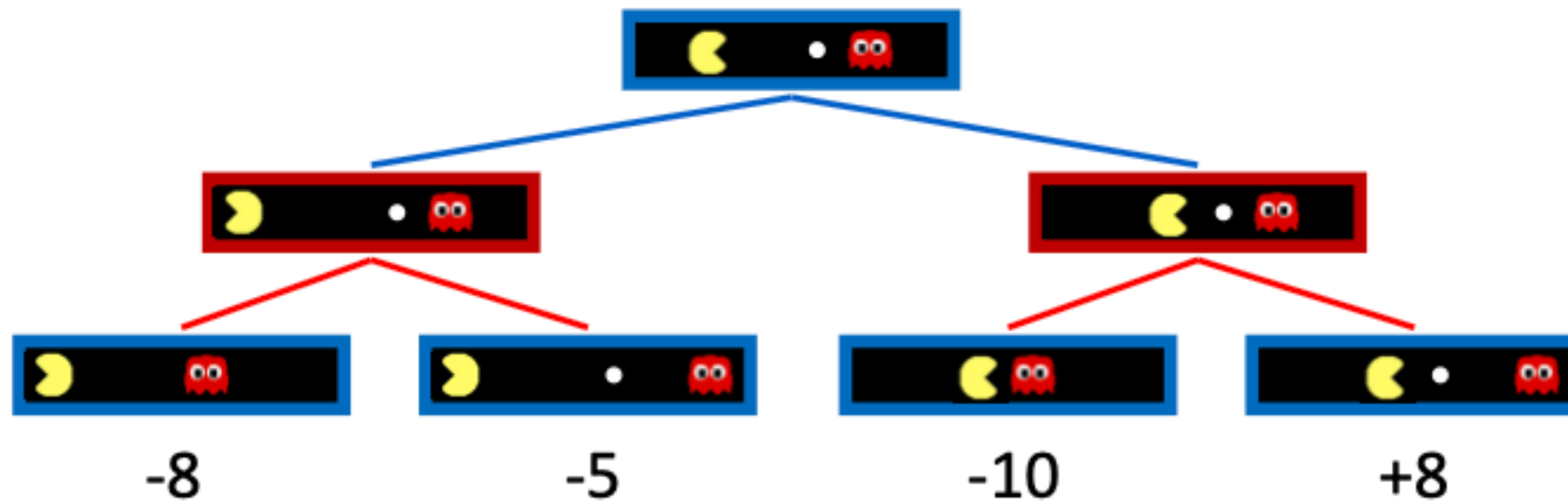
Adversarial Game Trees



Adversarial Game Trees



Minimax Values

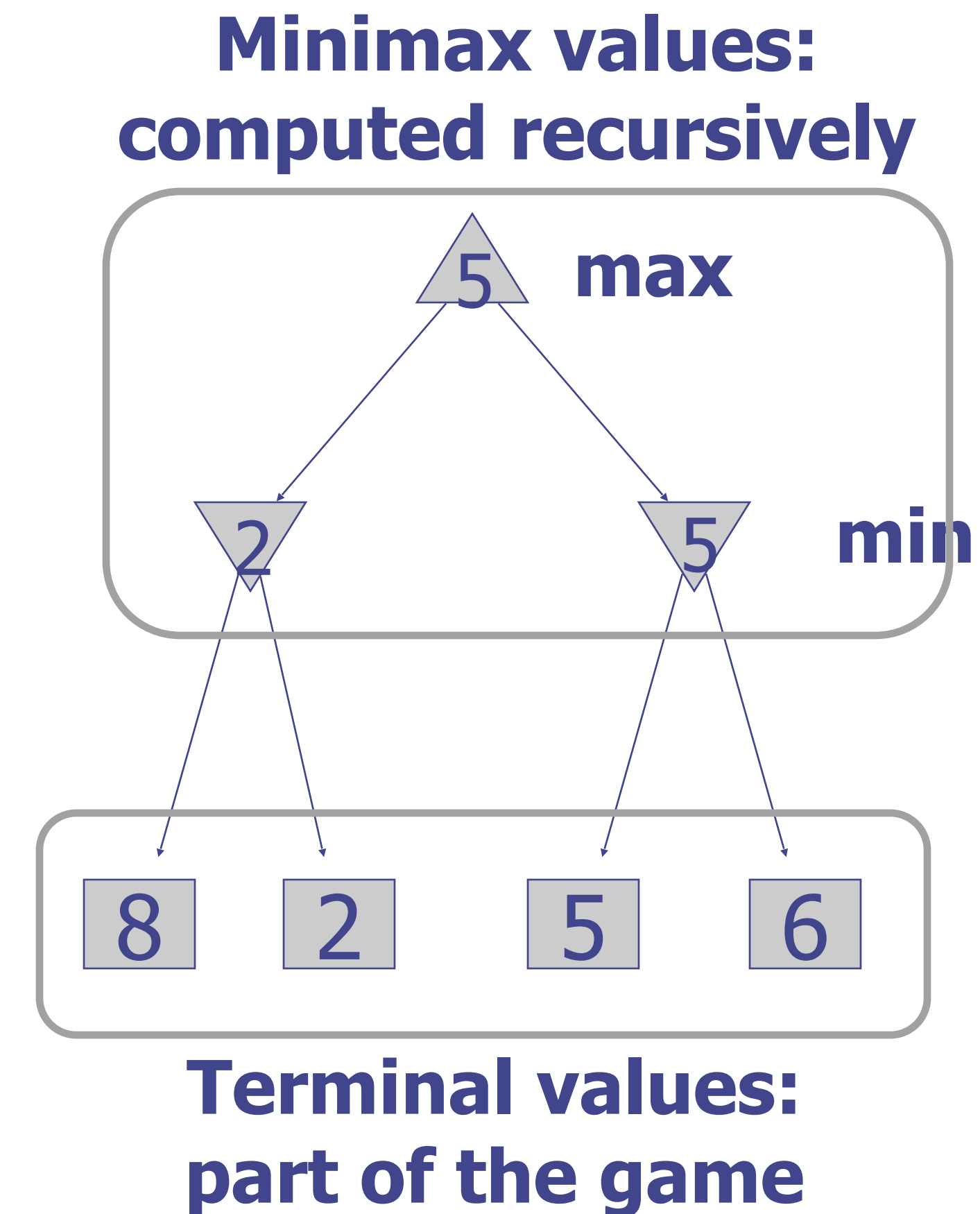


Terminal States:

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

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
 - Each node has a **minimax value**: best achievable utility against a rational adversary



Optimal strategies

- Find the **strategy** for MAX assuming an infallible MIN opponent.
- Assumption: Both players play optimally !!
- Given a game tree, the optimal strategy can be determined by using the minimax value of each node:

MINIMAX-VALUE(n)=

UTILITY(n)

$\max_{s \in \text{successors}(n)} \text{MINIMAX-VALUE}(s)$

$\min_{s \in \text{successors}(n)} \text{MINIMAX-VALUE}(s)$

If n is a terminal

If n is a max node

If n is a min node

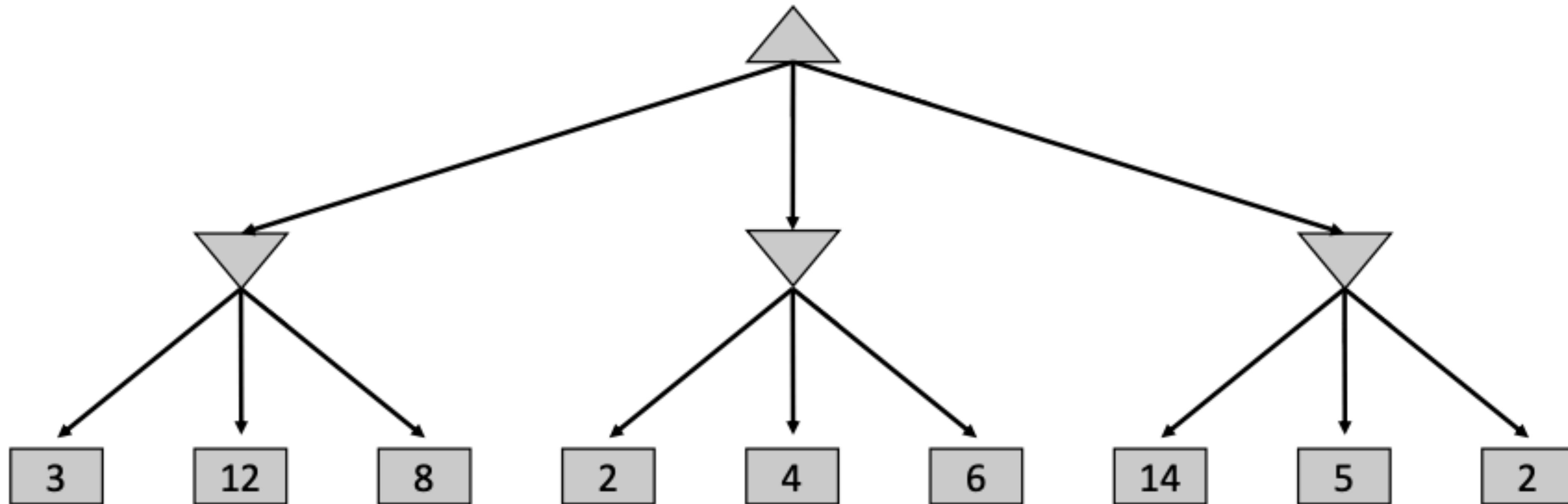
Computing Minimax Values

- Two recursive functions:
 - **max-value** maxes the values of successors
 - **min-value** mins the values of successors
- **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)

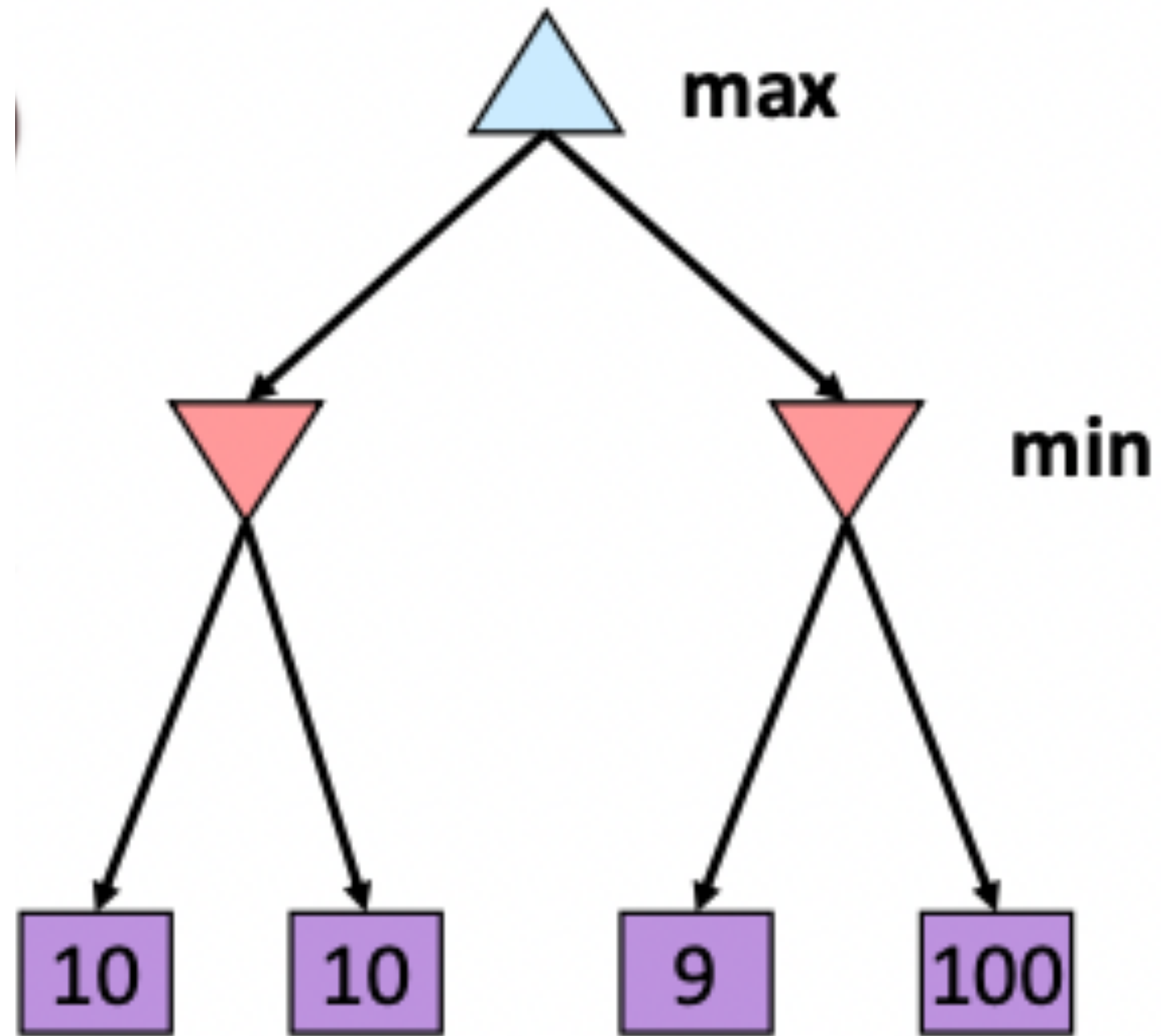
```
def max-value(state):  
    Initialize max =  $-\infty$   
    For each successor of state:  
        Compute value(successor)  
        Update max accordingly  
    Return max
```

```
def min-value(state):  
    Initialize min =  $\infty$   
    For each successor of state:  
        Compute value(successor)  
        Update min accordingly  
    Return min
```

CE 5: Minimax



Minimax Properties



Optimal against a perfect player. Otherwise?

Properties of Minimax

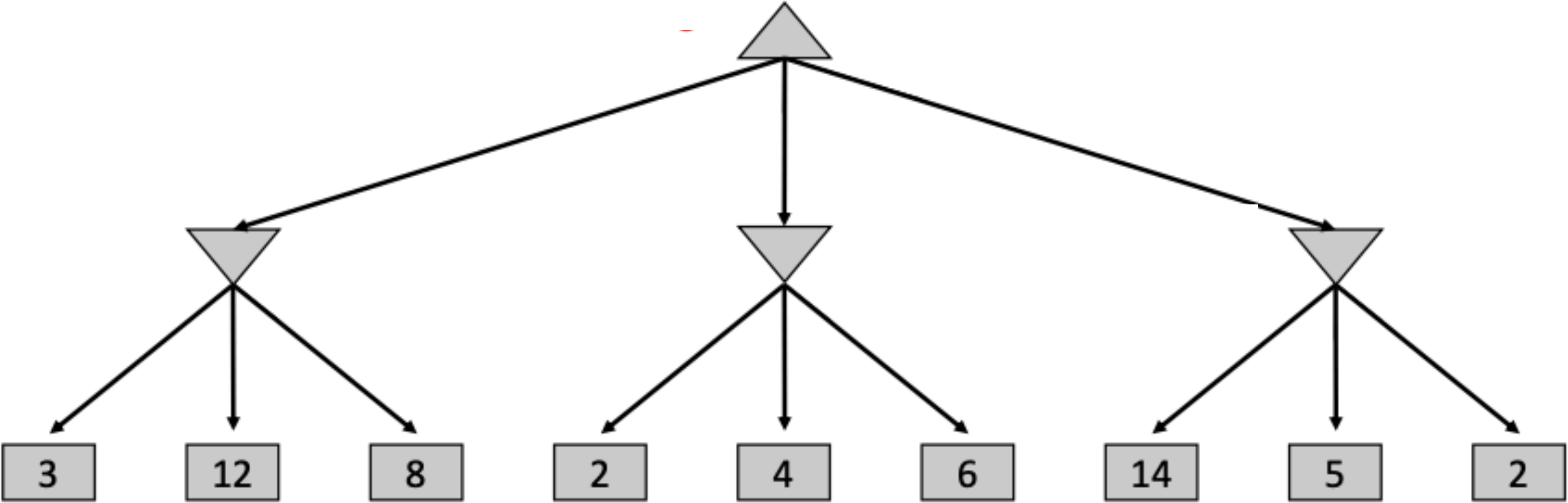
Criterion	Minimax
Complete?	yes, 😊
Optimal?	yes, 😊
Time	$O(b^m)$, 😞
Space	$O(bm)$, 😊

in theory...

For chess, $b \sim 35$, $m \sim 100$, exact solution is completely infeasible

Pruning

Minimax Example

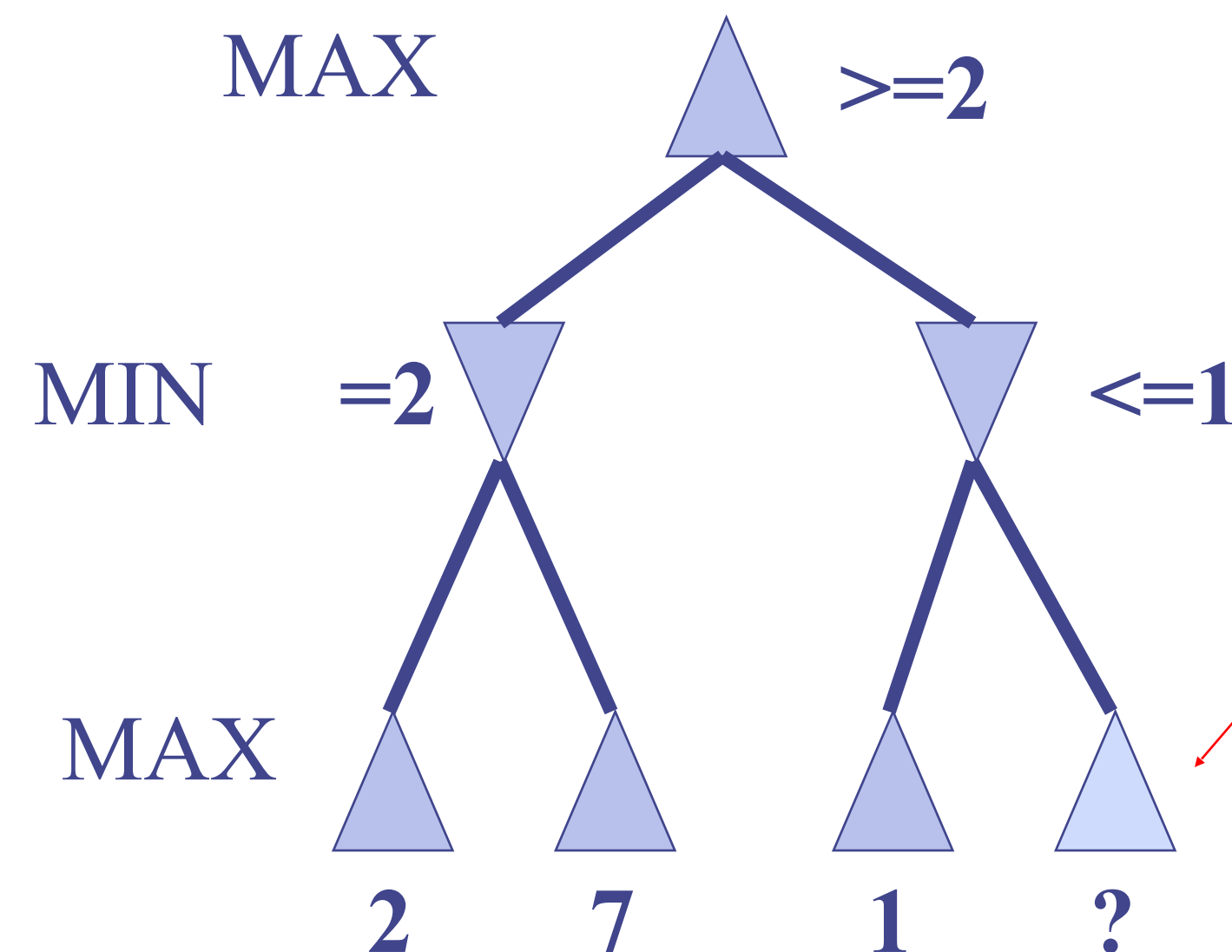


Problem of minimax search

- Number of games states is exponential to the number of moves.
 - Solution: Do not examine every node
 - Alpha-beta pruning
 - Remove branches that do not influence final decision

Alpha-beta pruning

- We can improve on the performance of the minimax algorithm through **alpha-beta pruning**
- Basic idea: “If you have an idea that is surely bad, don't take the time to see how truly awful it is.” -- Patrick Winston



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

Alpha-Beta Pruning

- General configuration
 - We're computing the MIN-VALUE at n
 - We're looping over n 's children
 - n 's value estimate is dropping
 - α is the best value that MAX can get at any choice point along the current path
 - If n becomes worse than α , MAX will avoid it, so can stop considering n 's other children
 - Define β similarly for MIN

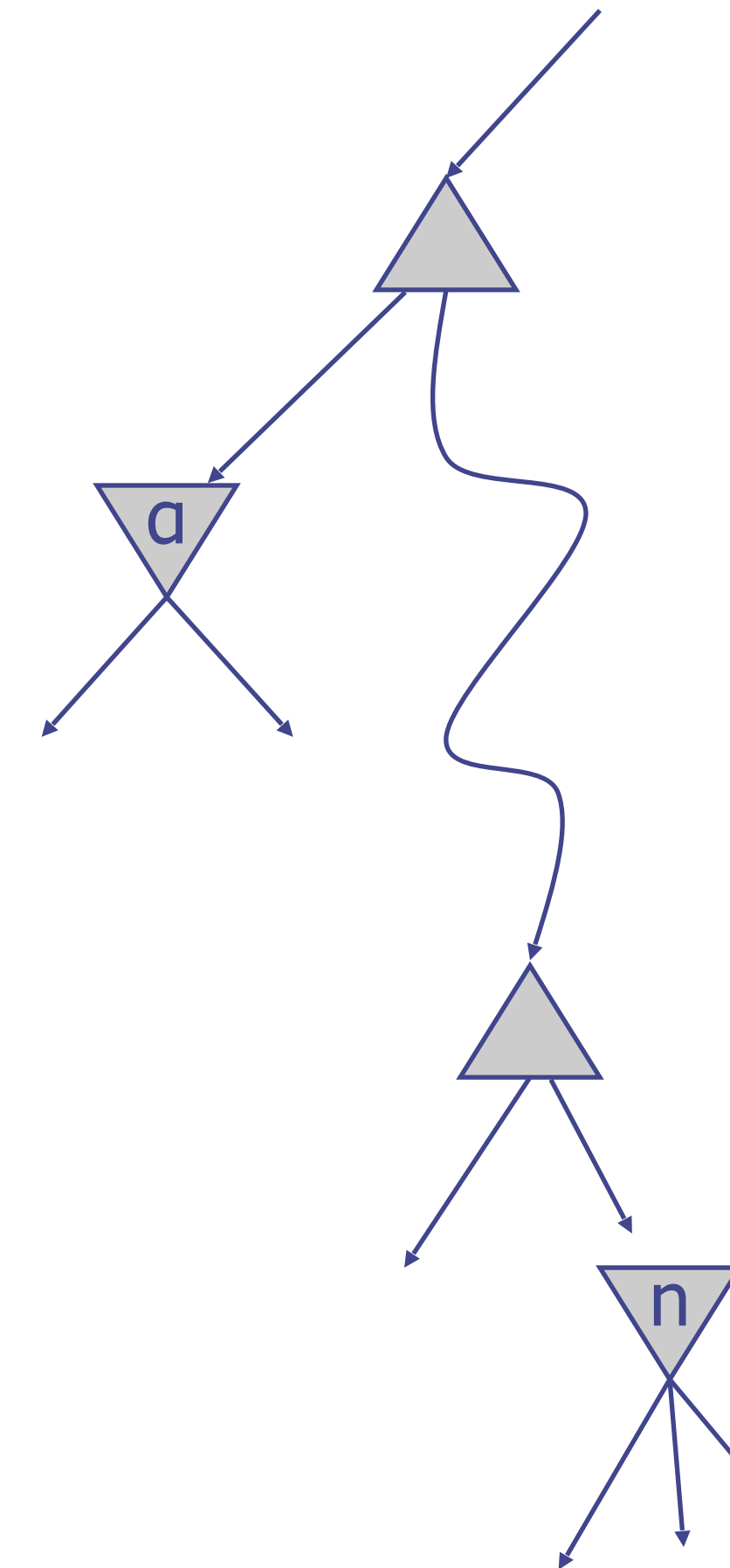
MAX

MIN

⋮

MAX

MIN



Alpha Beta Implementation

α : MAX's best option on path to root
 β : MIN's best option on path to root

```
def max-value(state,  $\alpha$ ,  $\beta$ ):  
    initialize  $v = -\infty$   
    for each successor of state:  
         $v = \max(v, \text{value}(\text{successor}, \alpha, \beta))$   
        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:  
         $v = \min(v, \text{value}(\text{successor}, \alpha, \beta))$   
        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 naive 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

α : best already explored path along path to root for maximizer

β : best already explored path along path to root for minimizer

Alpha-Beta Example

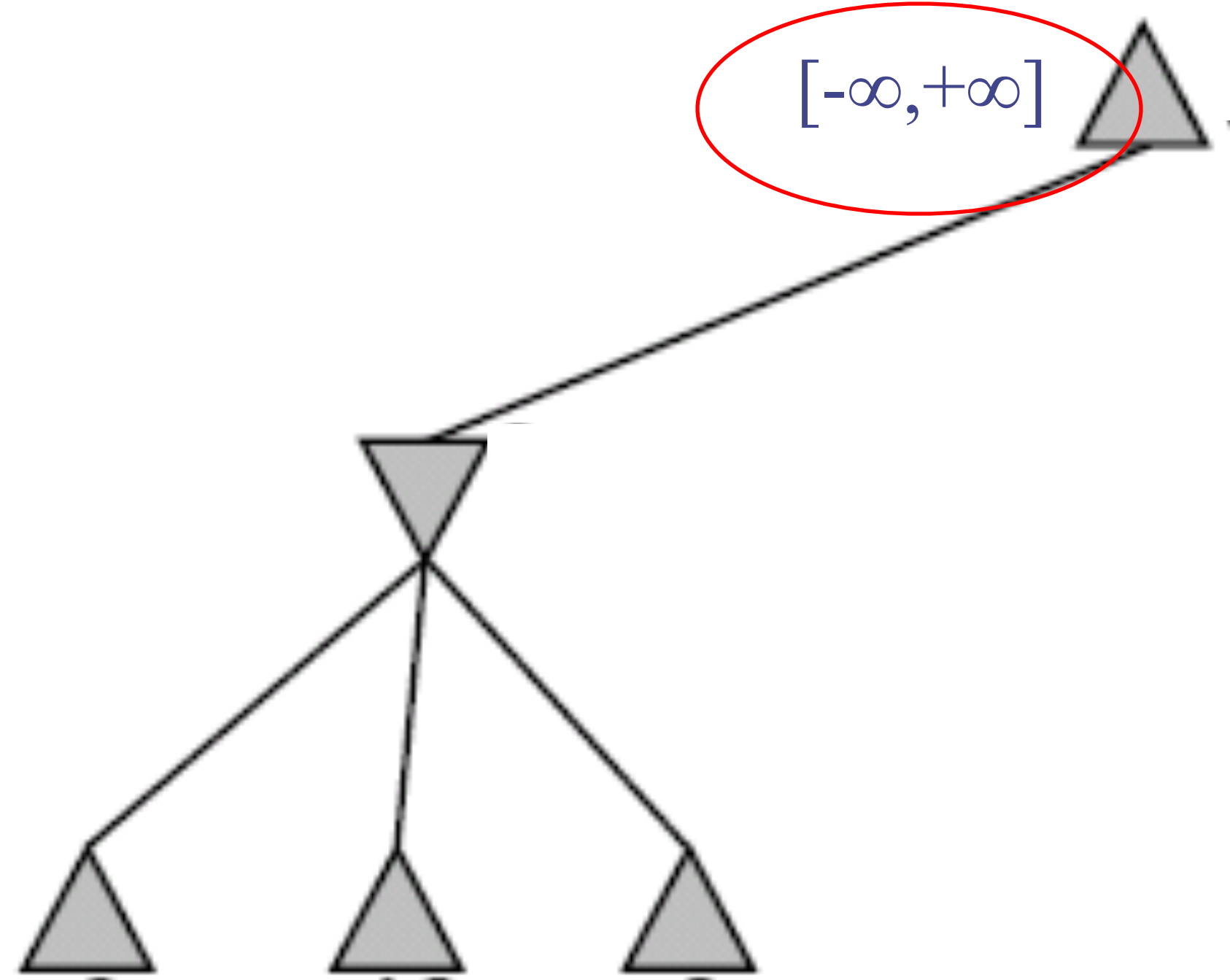
Do DF-search until first leaf

MAX

MIN

Alpha-beta values

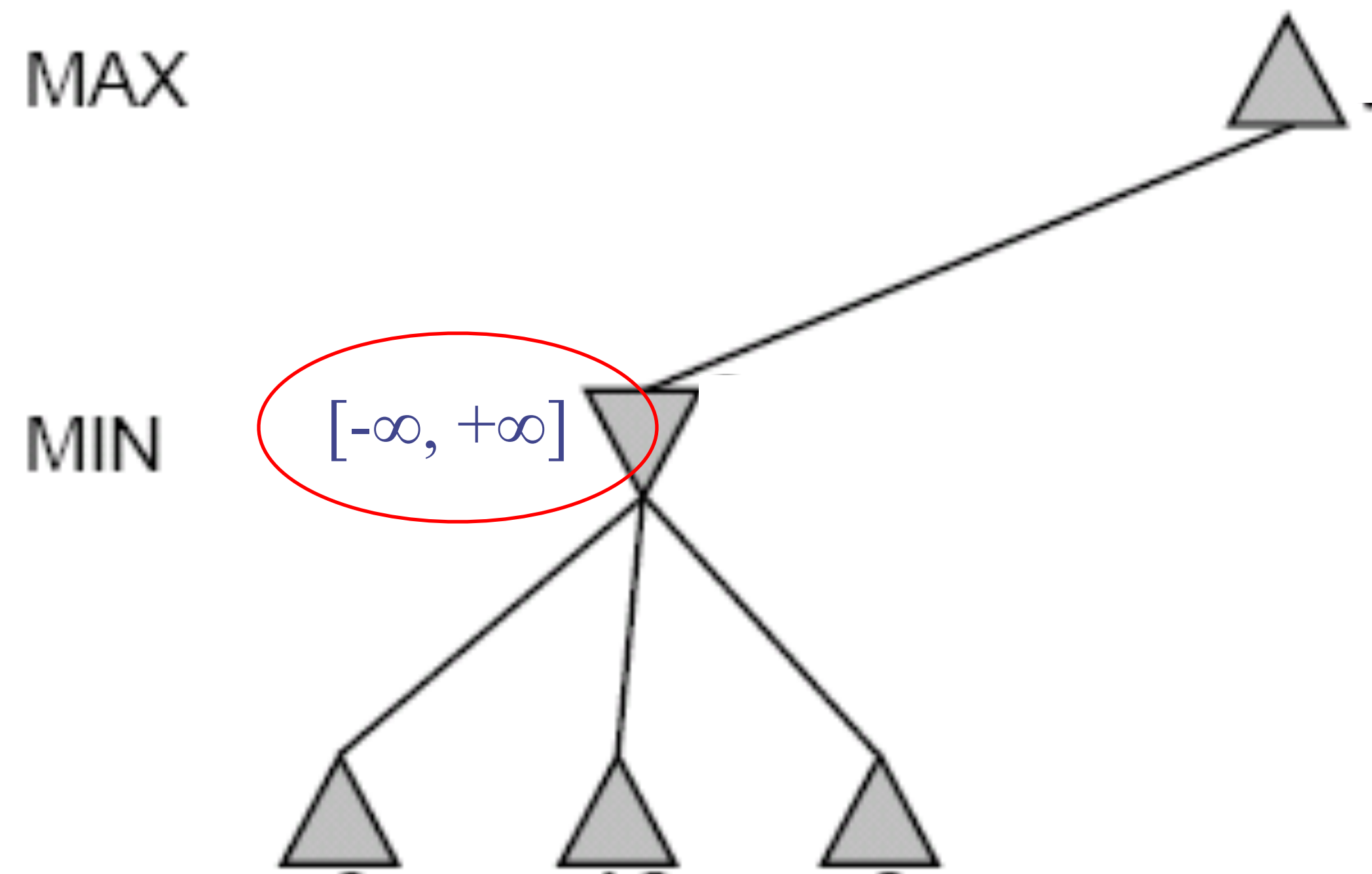
$[-\infty, +\infty]$



α : best already explored path along path to root for maximizer
 β : best already explored path along path to root for minimizer

Alpha-Beta Example

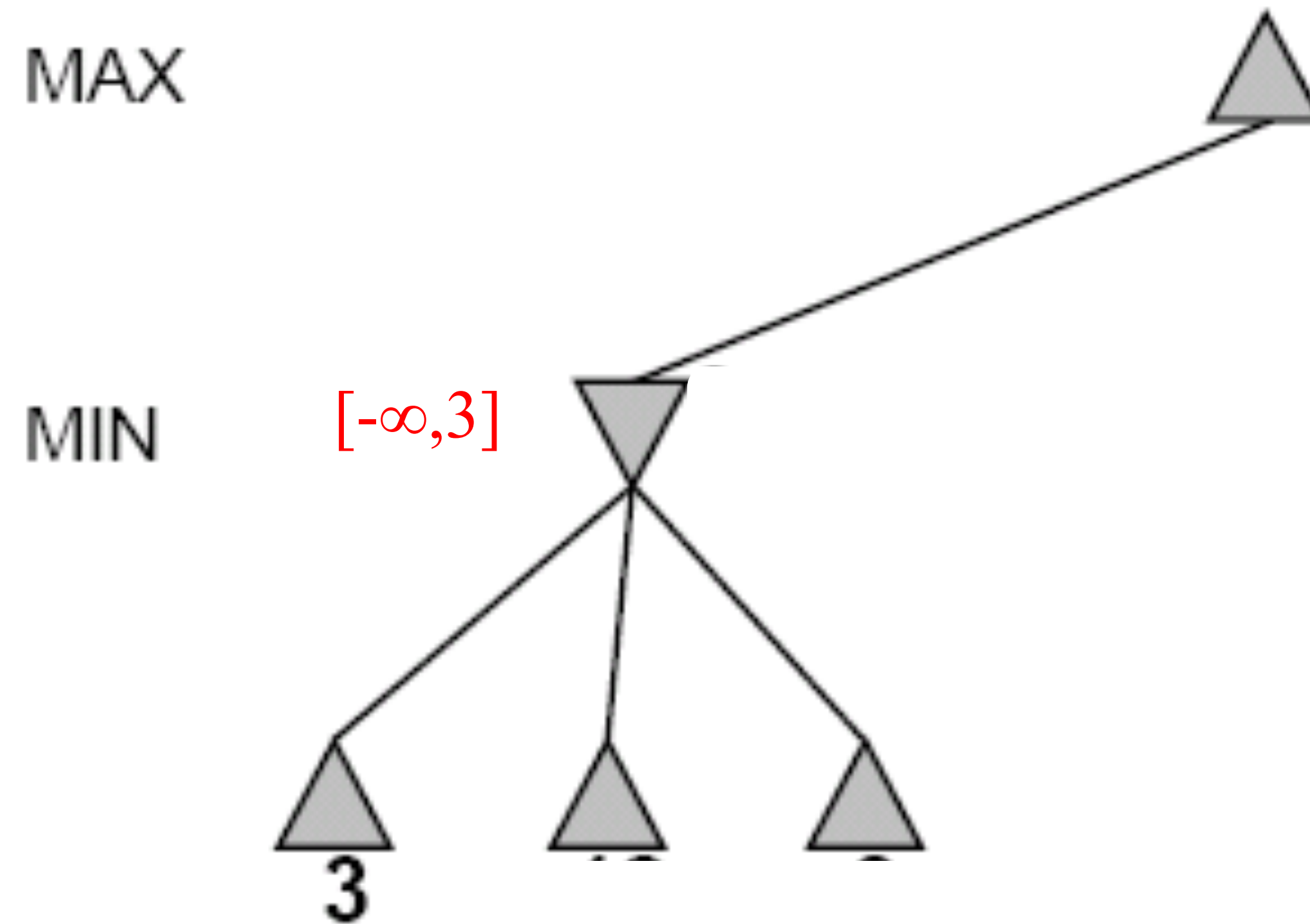
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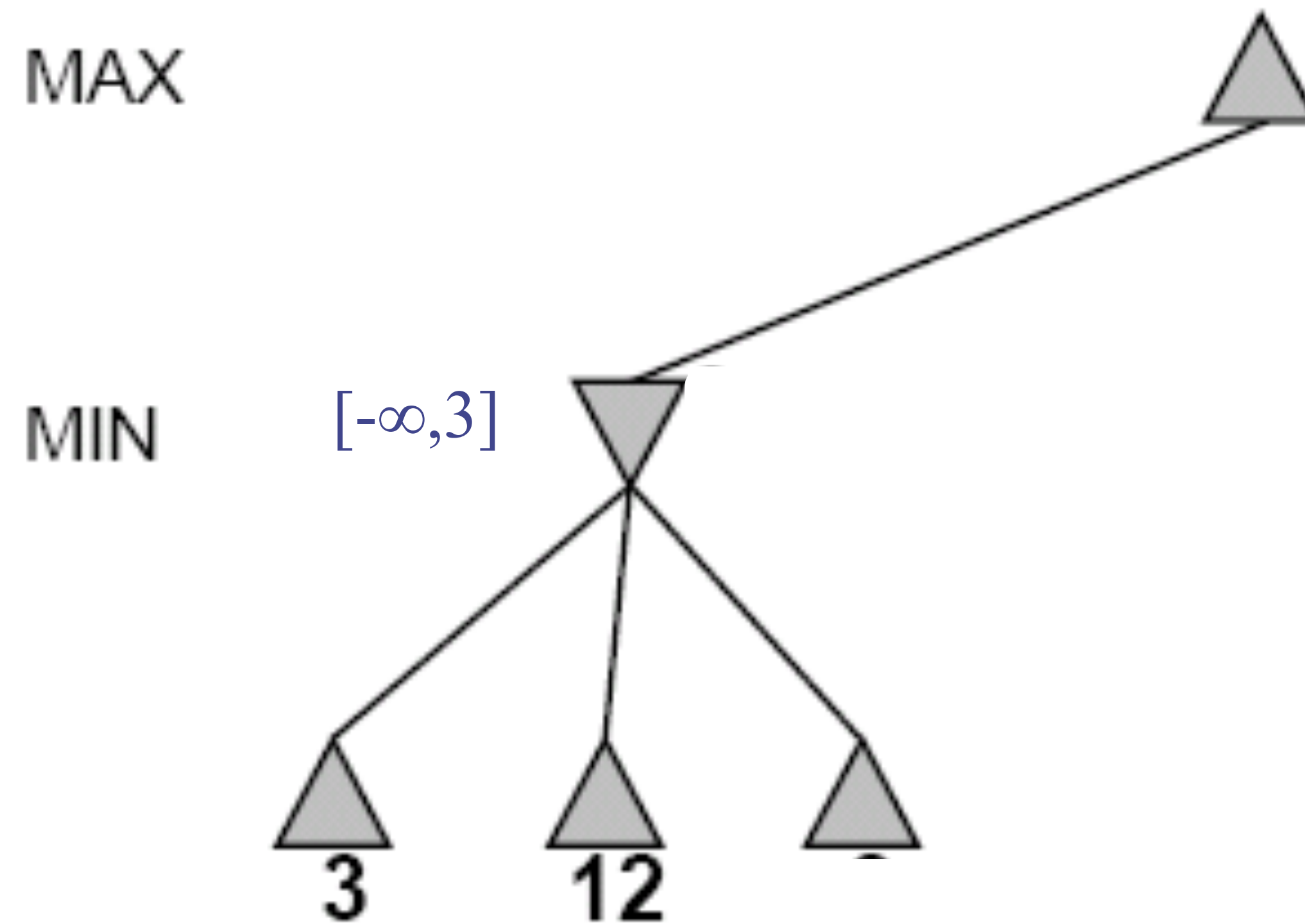
Alpha-Beta Example (continued)



α : best already explored path along path to root for maximizer

β : best already explored path along path to root for minimizer

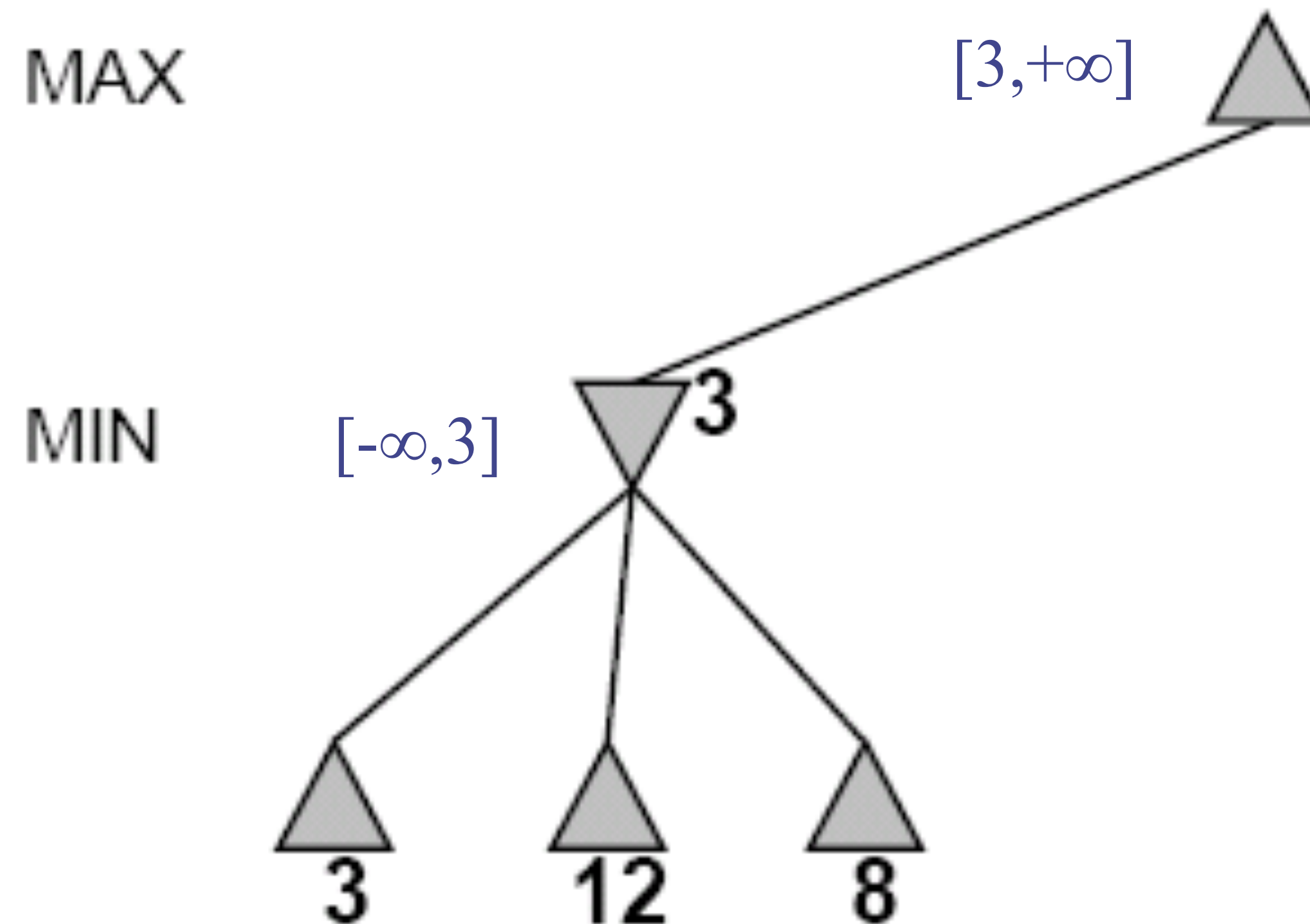
Alpha-Beta Example (continued)



α : best already explored path along path to root for maximizer

β : best already explored path along path to root for minimizer

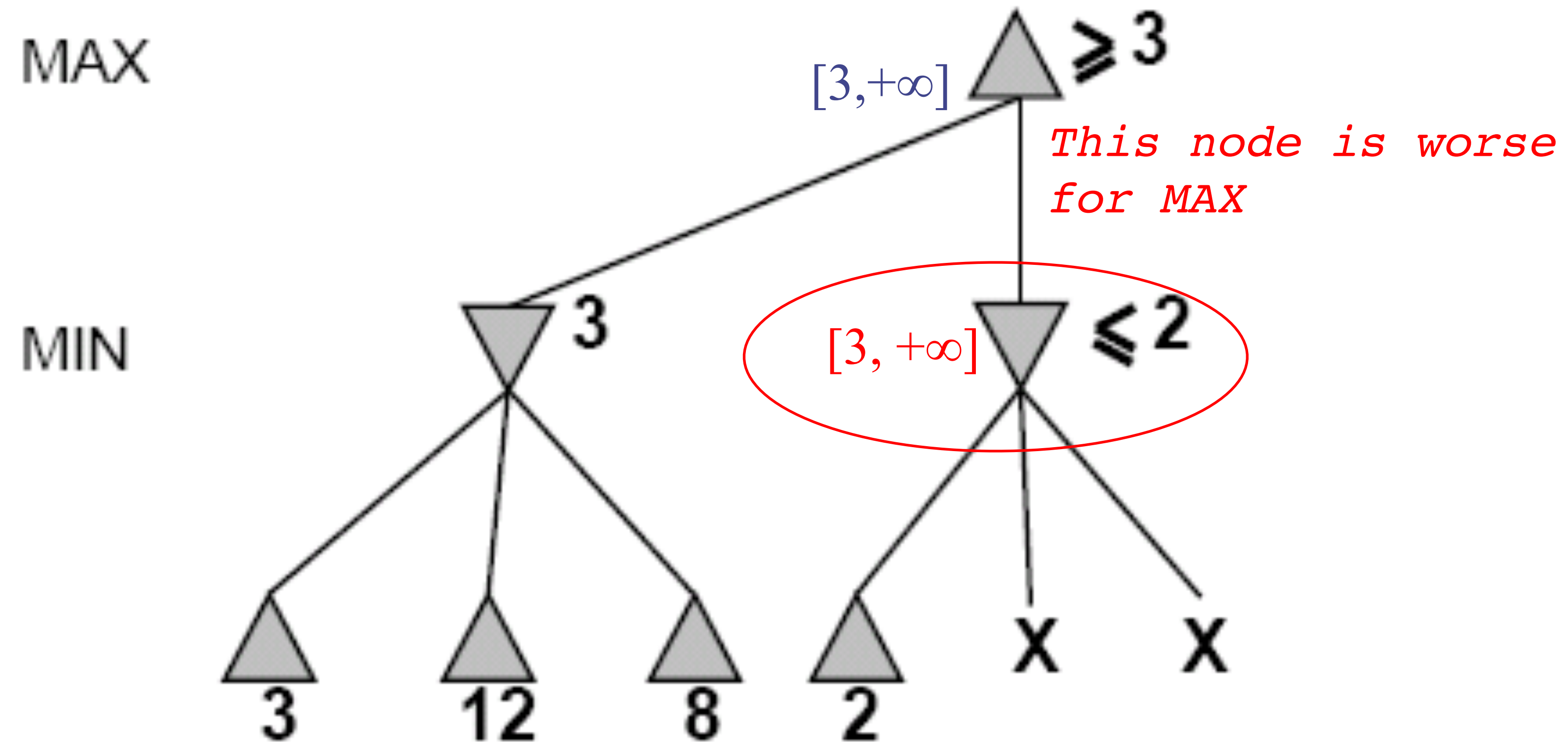
Alpha-Beta Example (continued)



α : best already explored path along path to root for maximizer

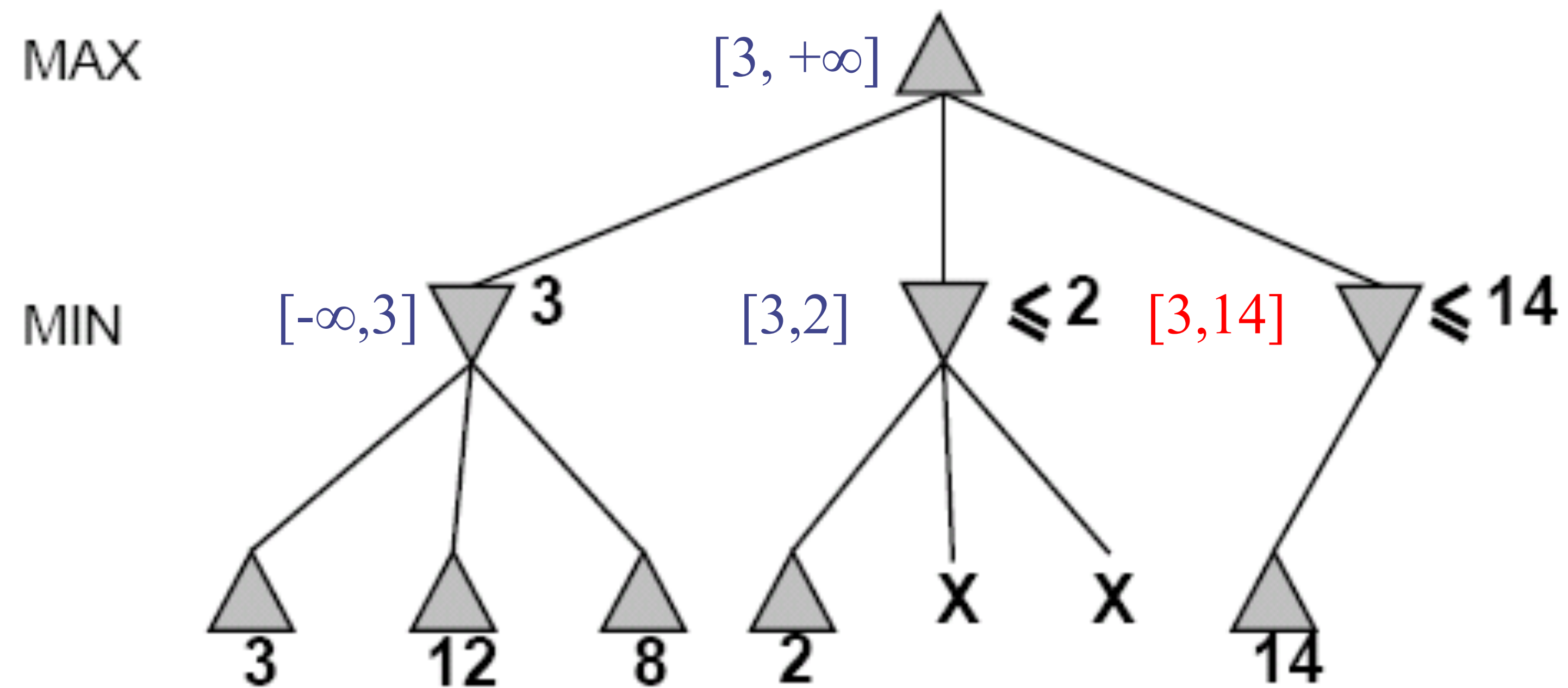
β : best already explored path along path to root for minimizer

Alpha-Beta Example (continued)



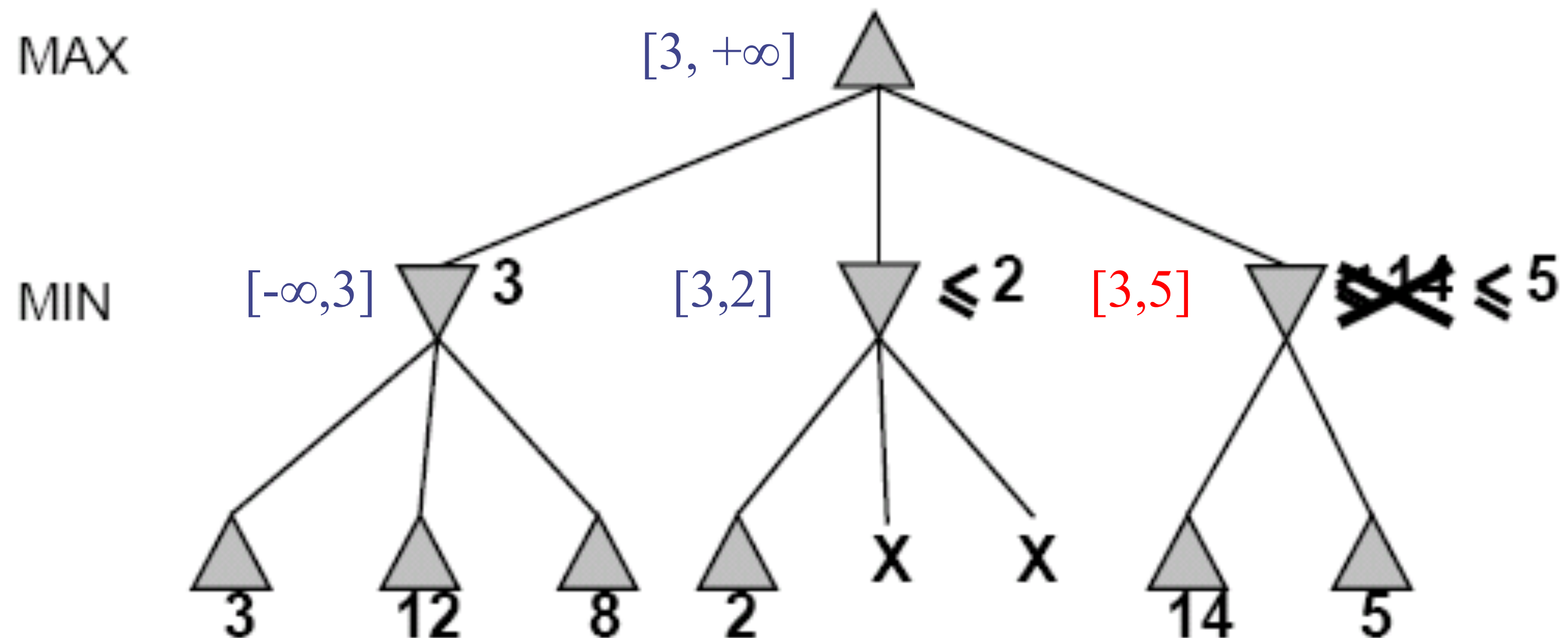
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Alpha-Beta Example (continued)



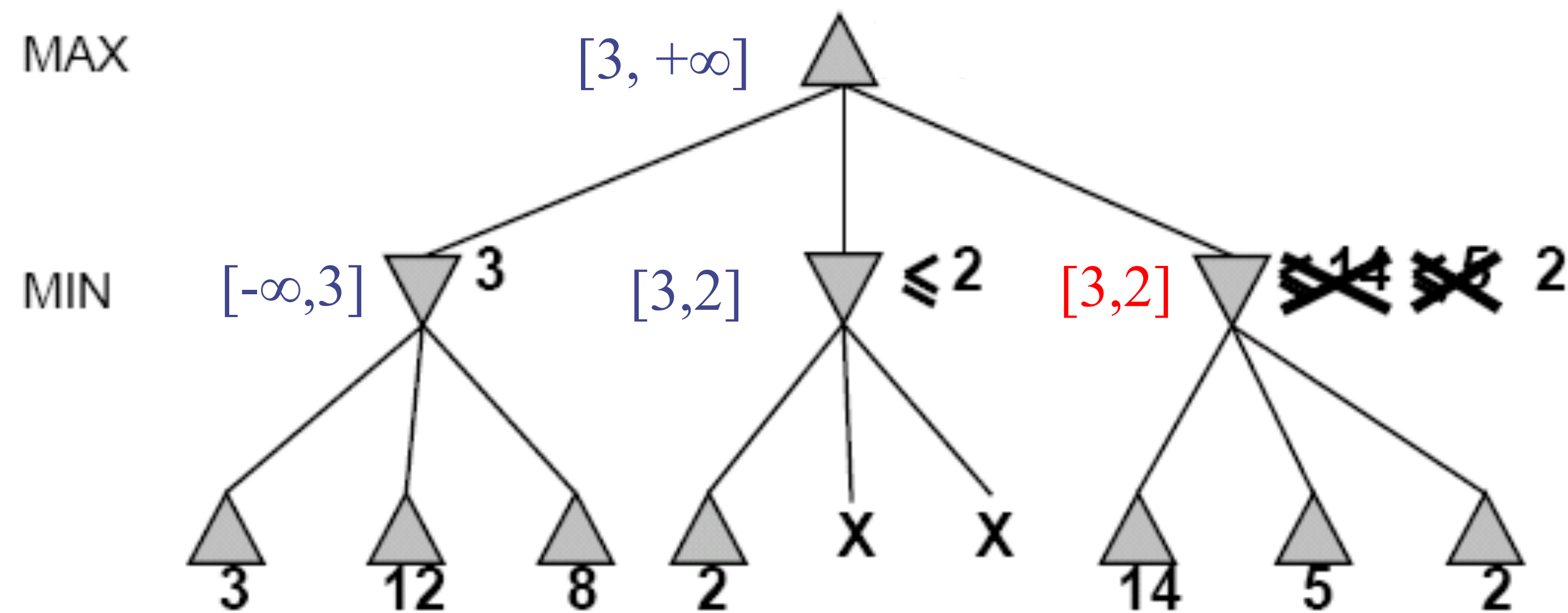
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Alpha-Beta Example (continued)



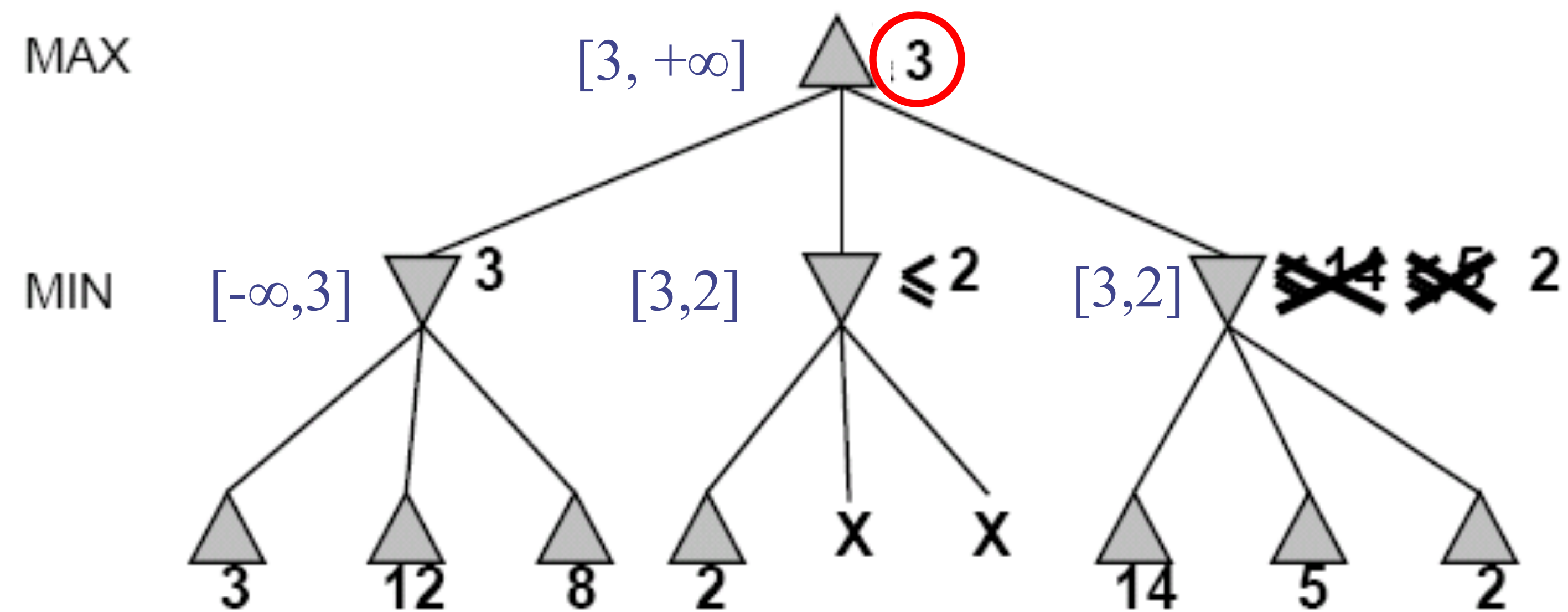
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Alpha-Beta Example (continued)

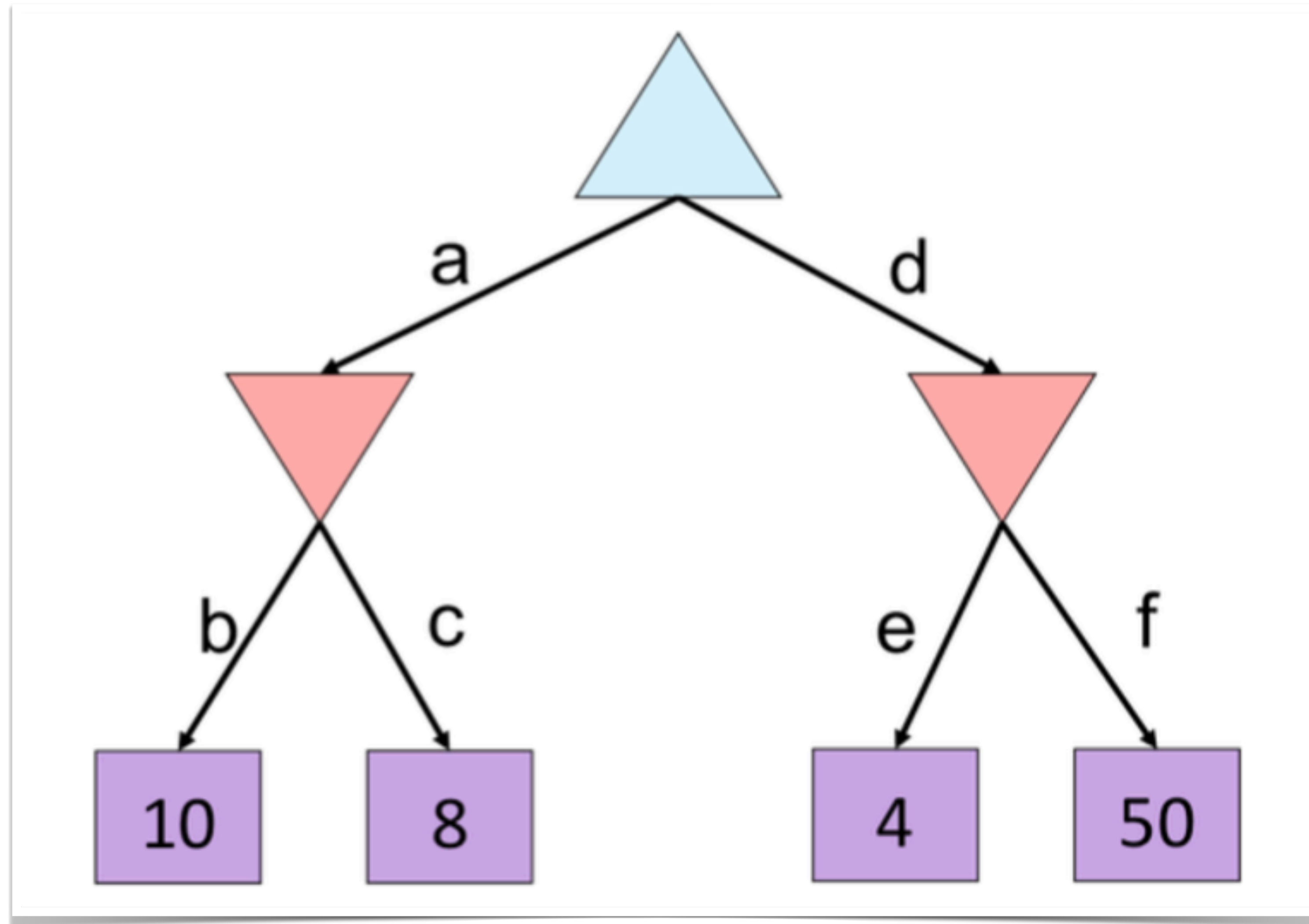


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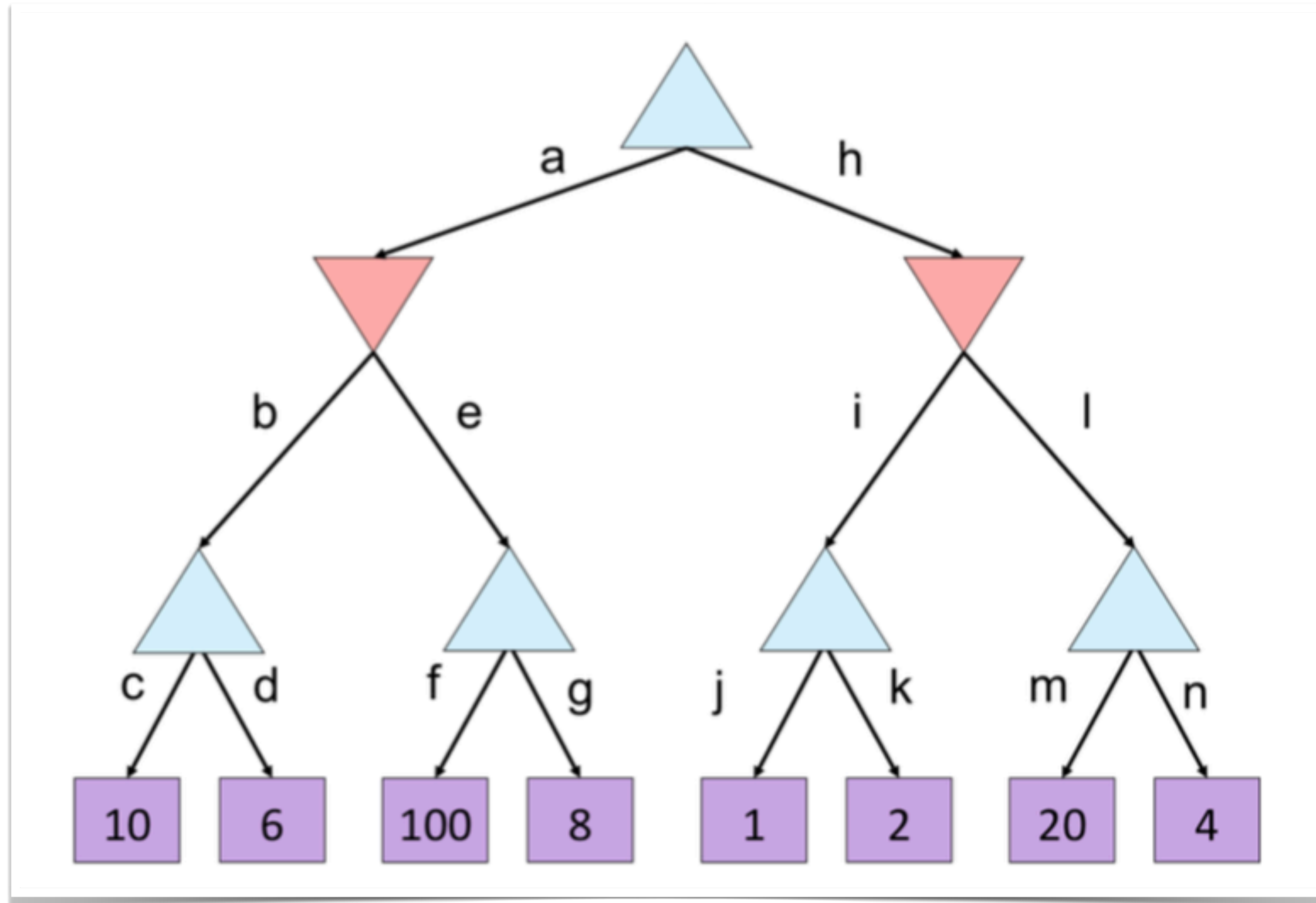
Alpha-Beta Example (continued)



Alpha-Beta Practice 1



Alpha-Beta Practice 2



Recap

- Game theory
 - Adversarial games
 - Minimax algorithm and alpha-beta pruning
- Next lecture
 - Stochastic games
 - Expectimax search algorithm