
CS 471/571 (Fall 2023): Introduction to Artificial Intelligence

Lecture 8: Adversarial Search

Thanh H. Nguyen

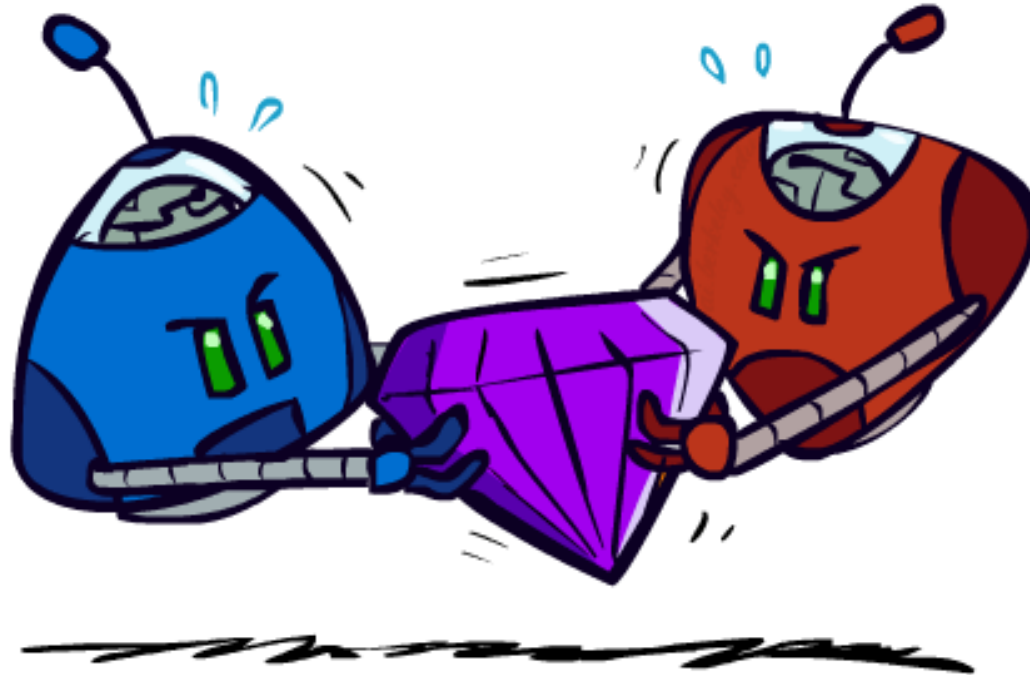
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Announcement and Reminder

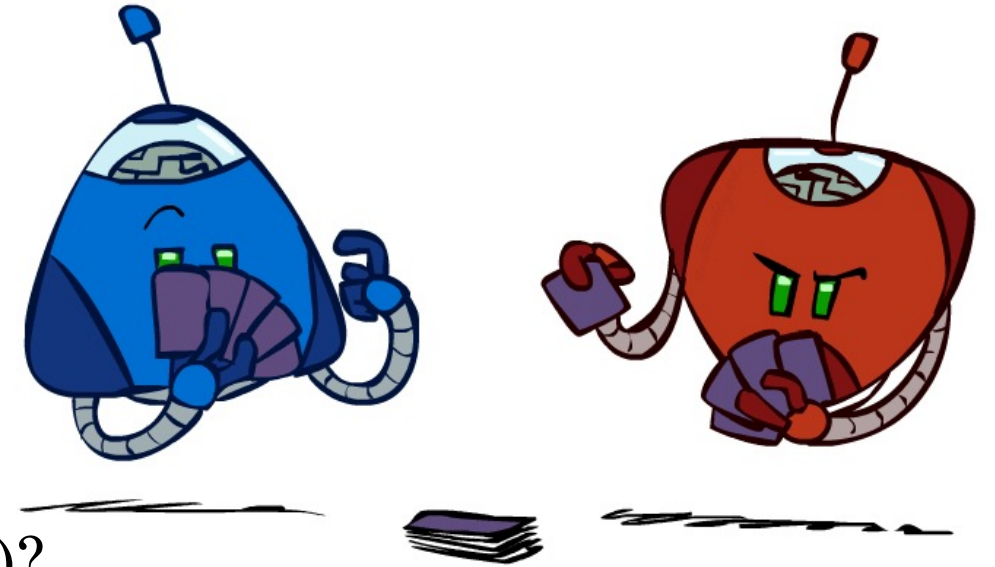
- Programming project 1:
 - Deadline: Oct 16th, 2023
- Written assignment 2:
 - Will be posted tomorrow
 - Deadline: Oct 25th, 2023
- No office hour today
 - Make-up office hour on Monday (Oct 16th), 1:30 pm – 3:30 pm.

Adversarial Games



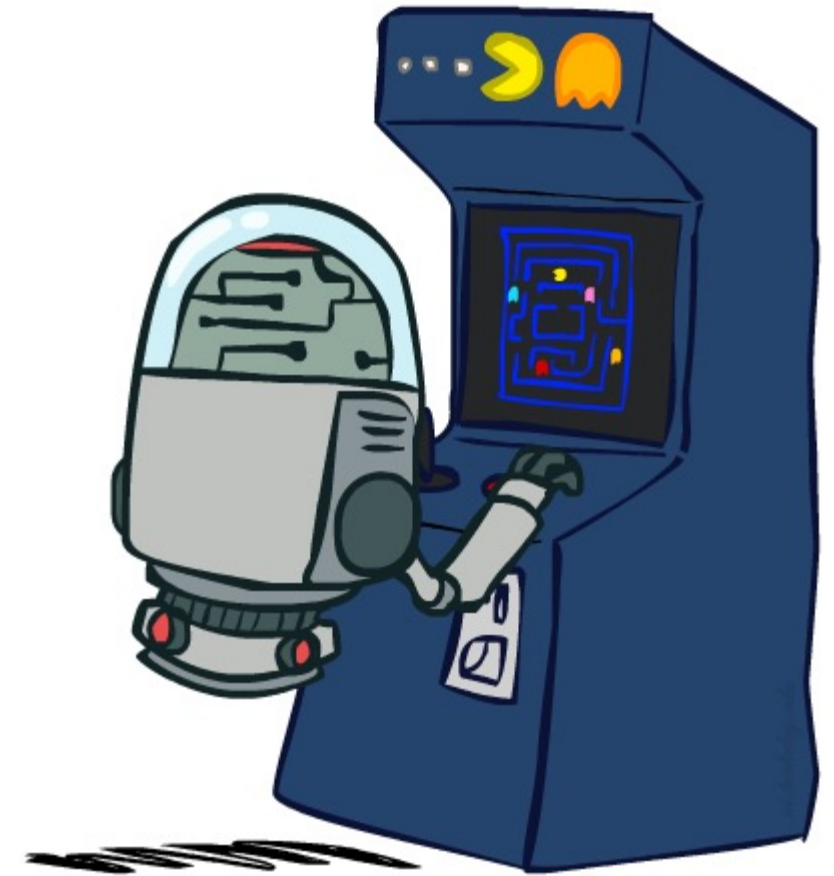
Types of Games

- Many different kinds of games!
- Axes:
 - Deterministic or stochastic?
 - One, two, or more players?
 - Zero sum?
 - Perfect information (can you see the state)?
- Want algorithms for calculating a **strategy (policy)** which recommends a move from each state

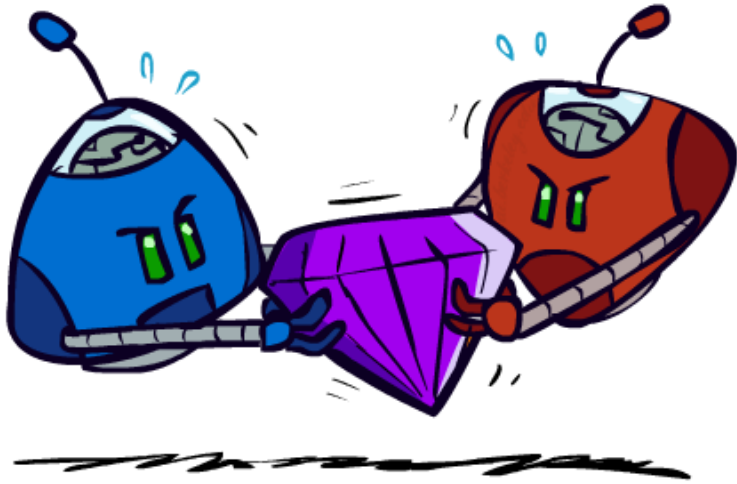


Deterministic Games

- 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: $S \times A \rightarrow S$
 - Terminal Test: $S \rightarrow \{t, f\}$
 - Terminal Utilities: $S \times P \rightarrow R$
- Solution for a player is a **policy**: $S \rightarrow A$



Zero-Sum Games



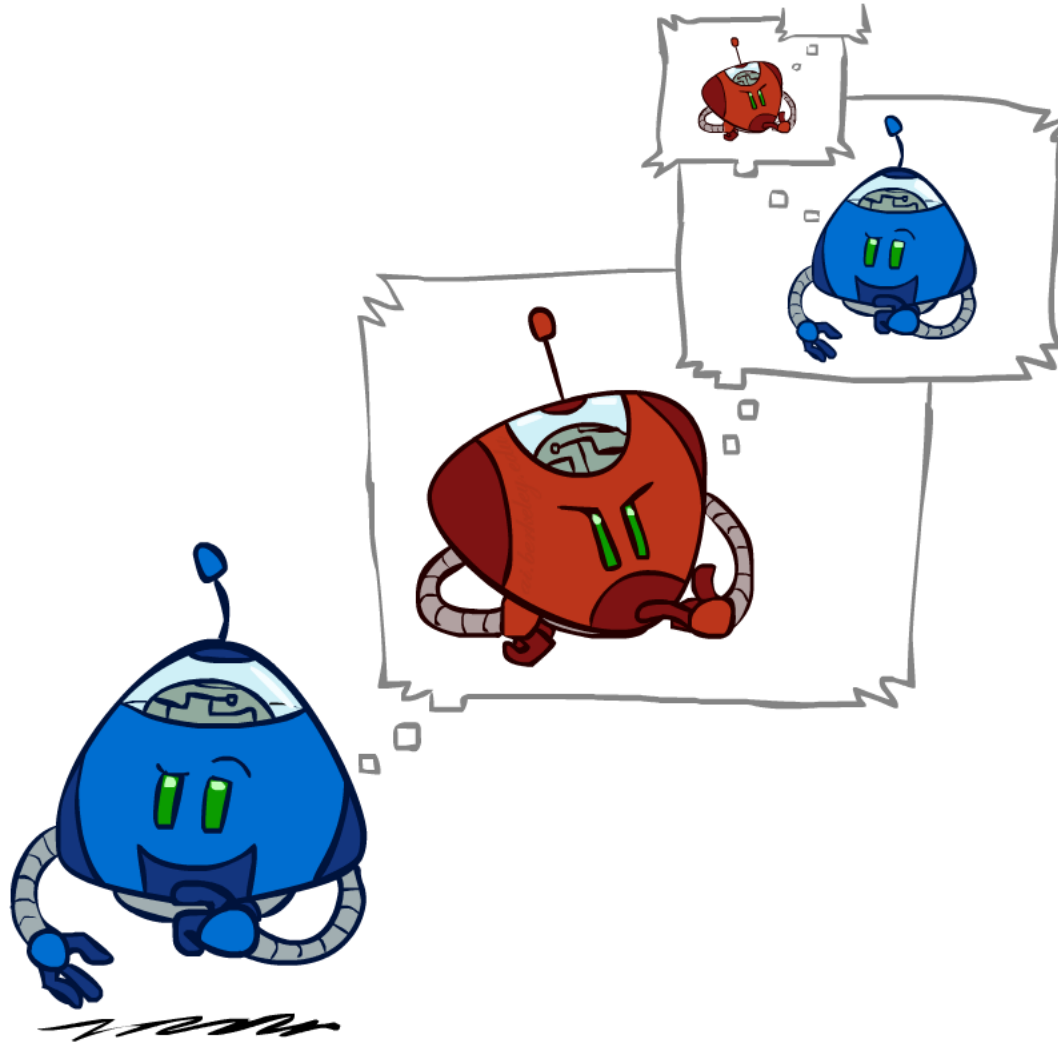
- Zero-Sum Games

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

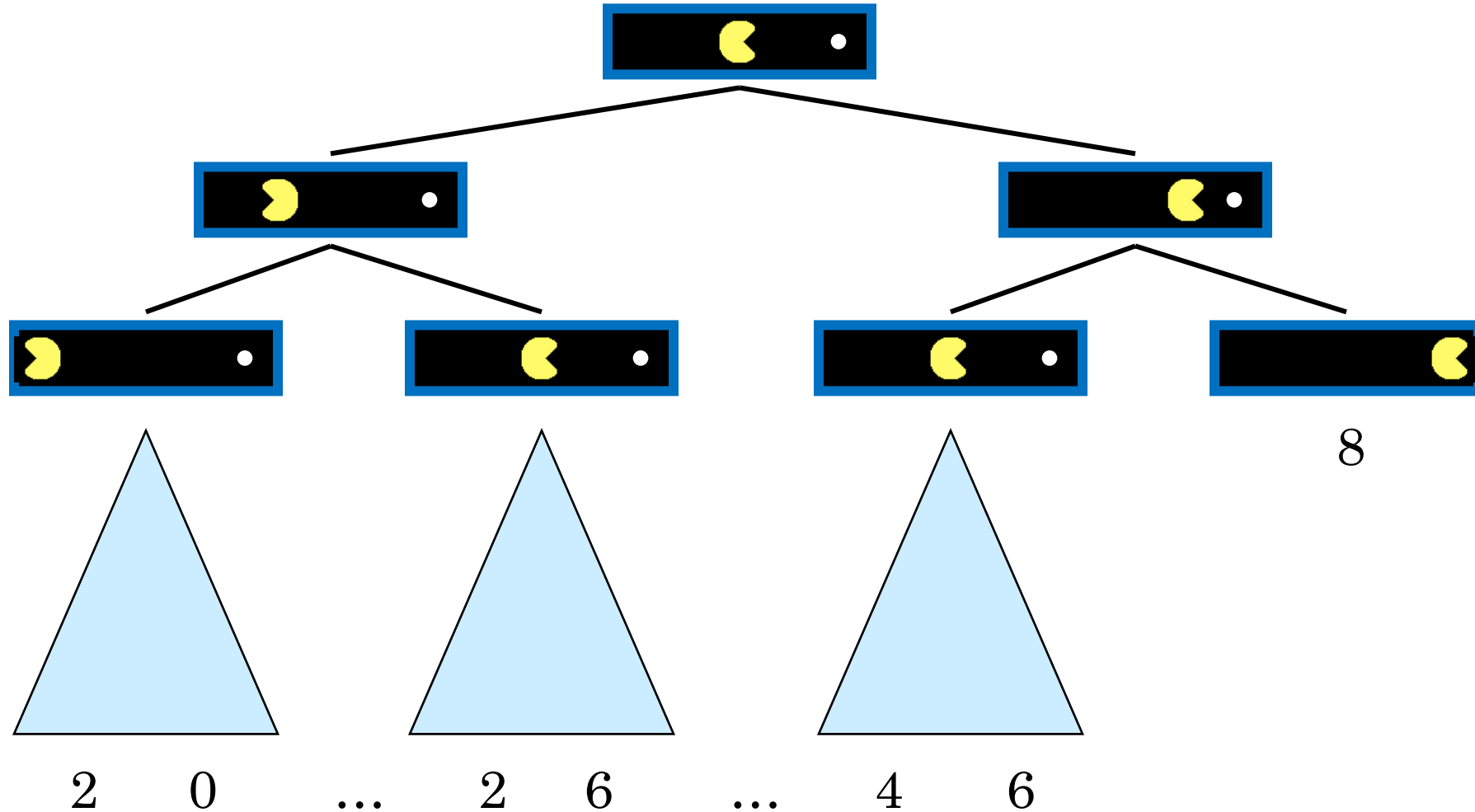
- General Games

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

Adversarial Search

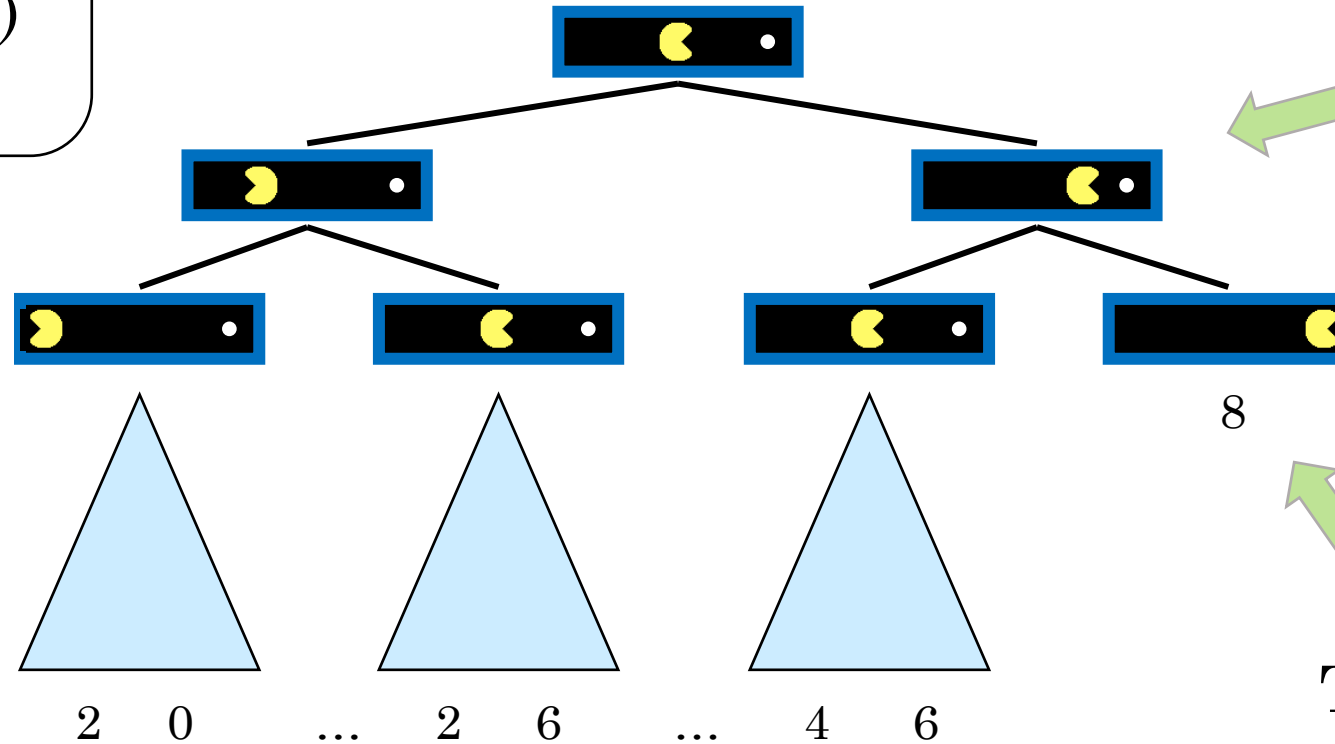


Single-Agent Trees



Value of a State

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



Non-Terminal States:

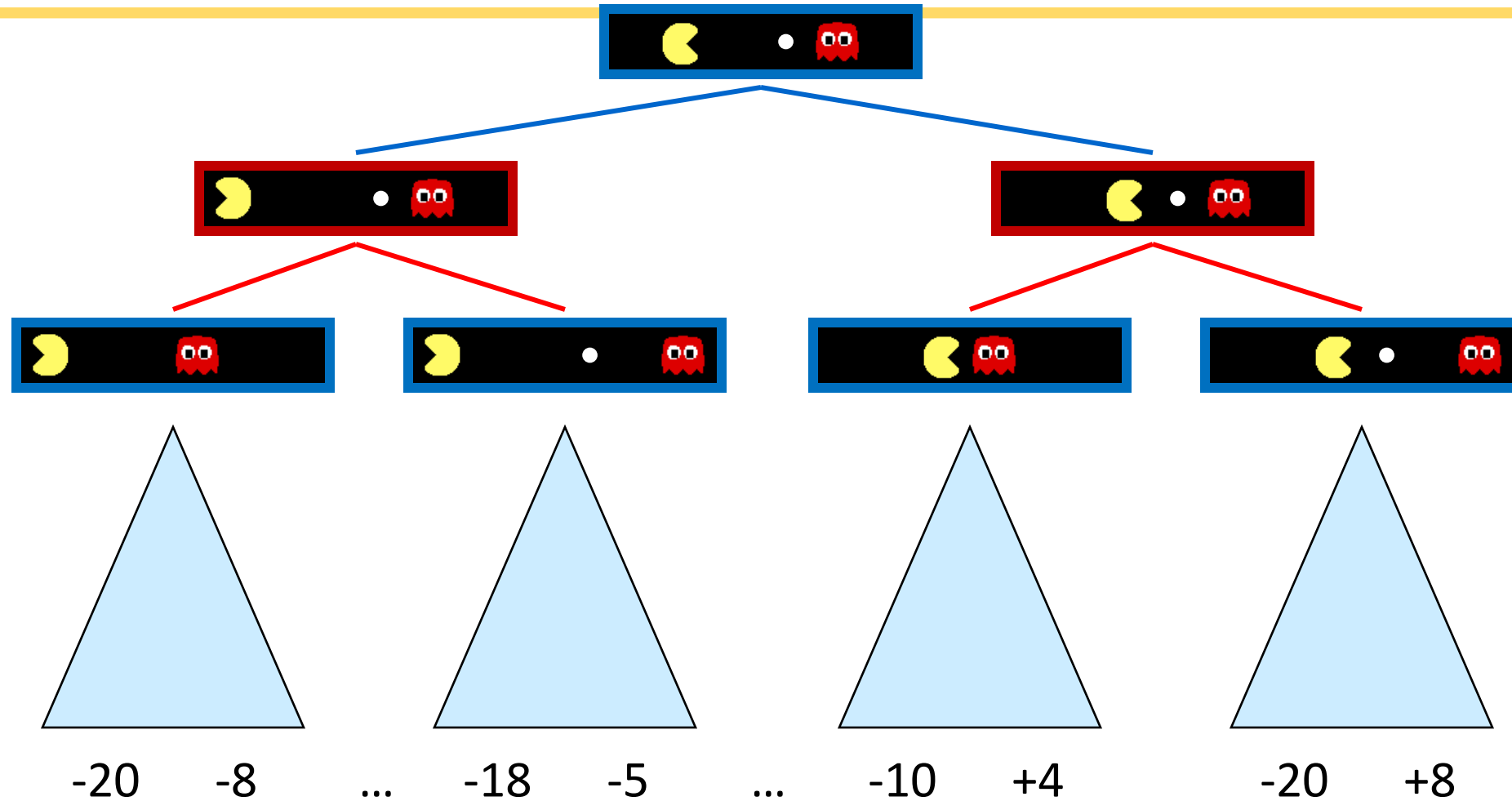
$$V(s) = \max_{s' \in \text{children}(s)} V(s')$$

Terminal States:

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



Adversarial Game Trees



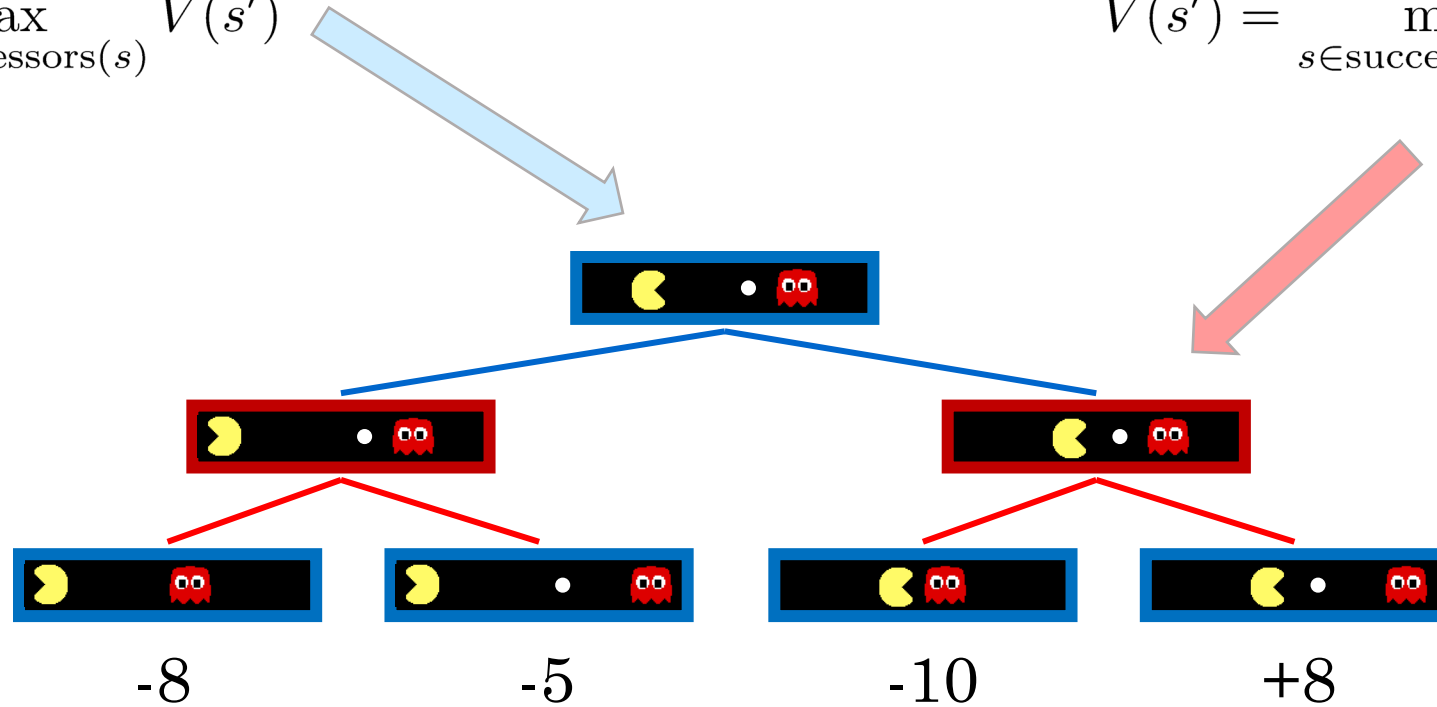
Minimax Values

States Under Agent's Control:

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

States Under Opponent's Control:

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



Terminal States:

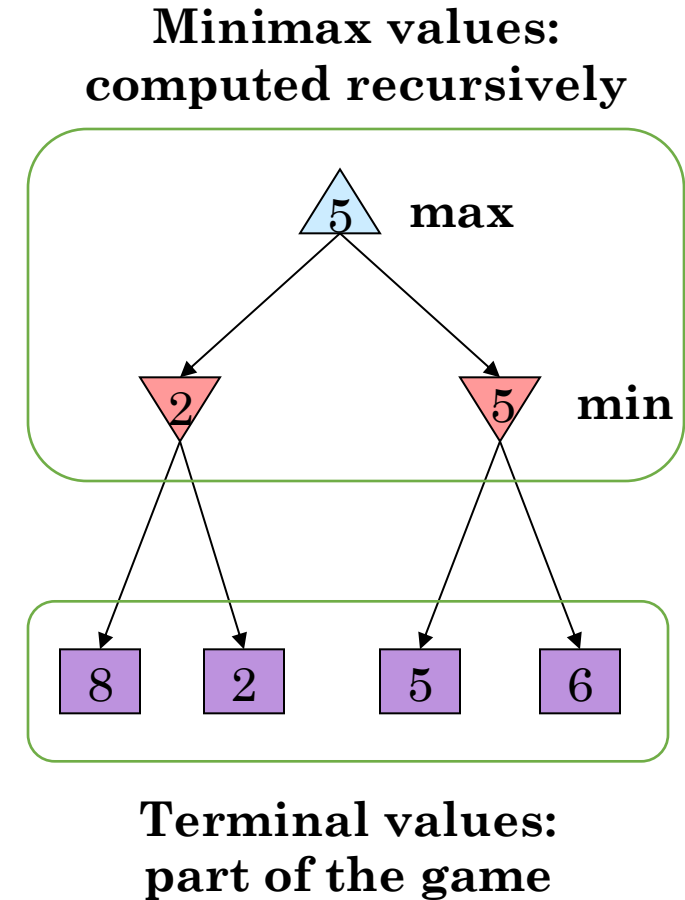
$$V(s) = \text{known}$$





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
 - Compute each node's **minimax value**: the best achievable utility against a rational (optimal) adversary



Minimax Implementation

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)

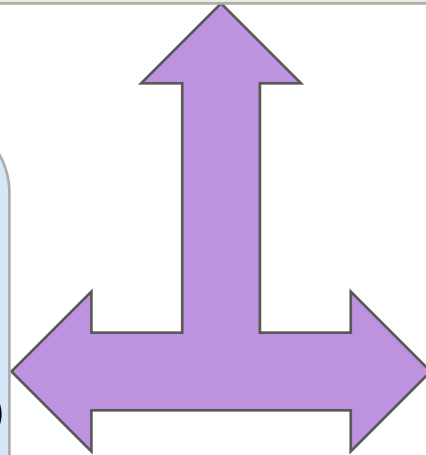
def max-value(state):

initialize $v = -\infty$

for each successor of state:

$v = \max(v, \text{value}(\text{successor}))$

return v



def min-value(state):

initialize $v = +\infty$

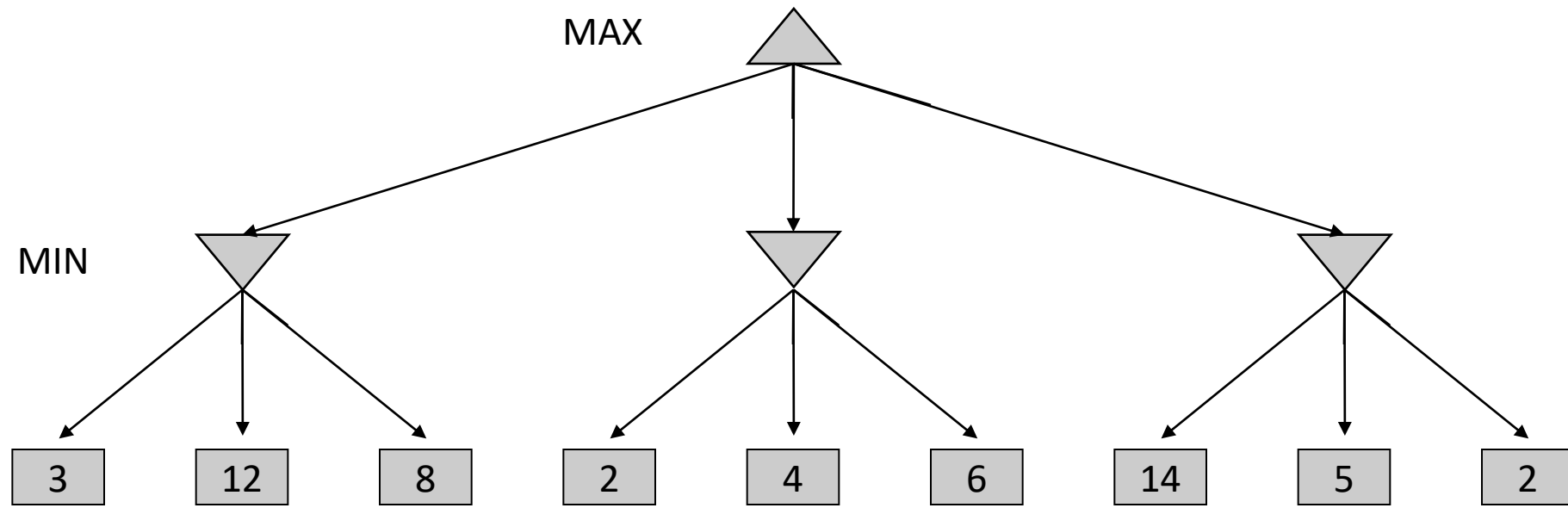
for each successor of state:

$v = \min(v, \text{value}(\text{successor}))$

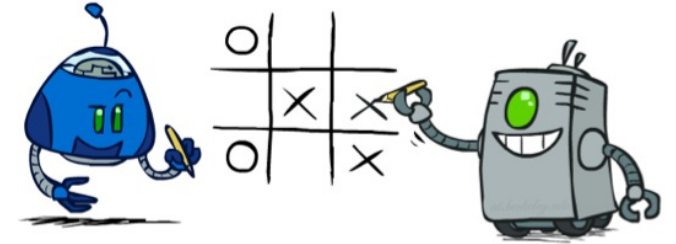
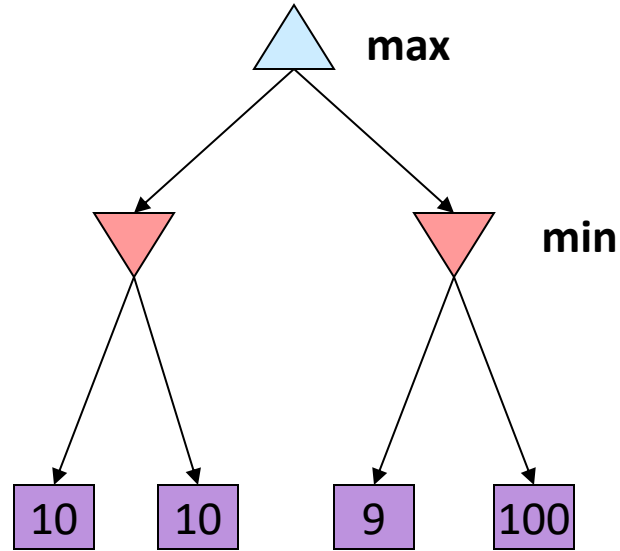
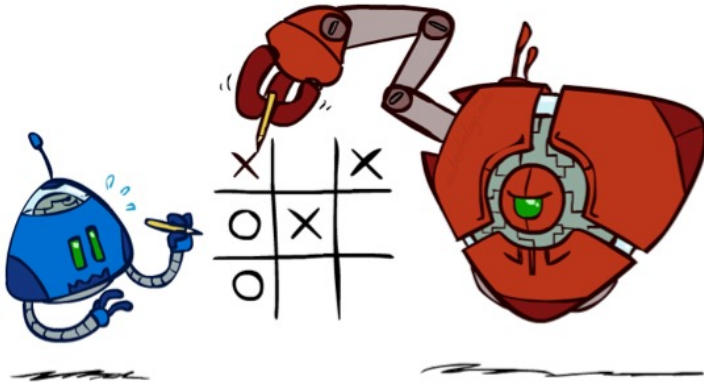
return v



Minimax Example



Minimax Properties

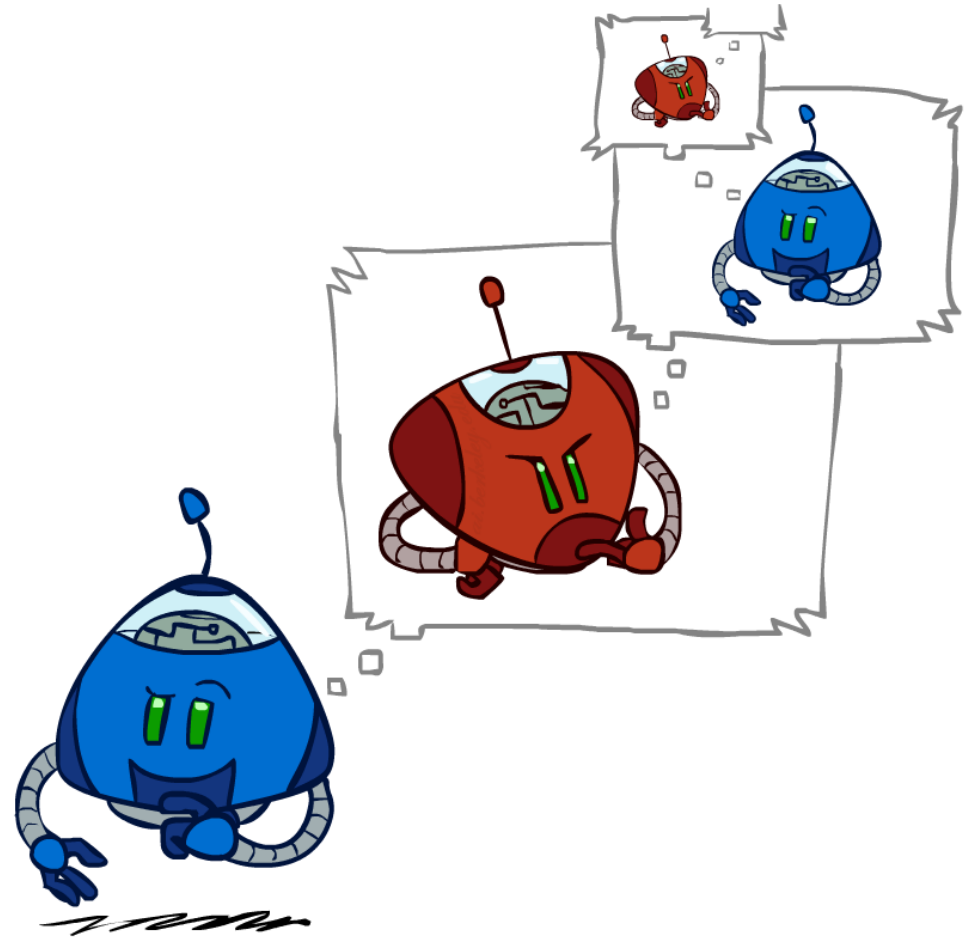


Optimal against a perfect player. Otherwise?



Minimax Efficiency

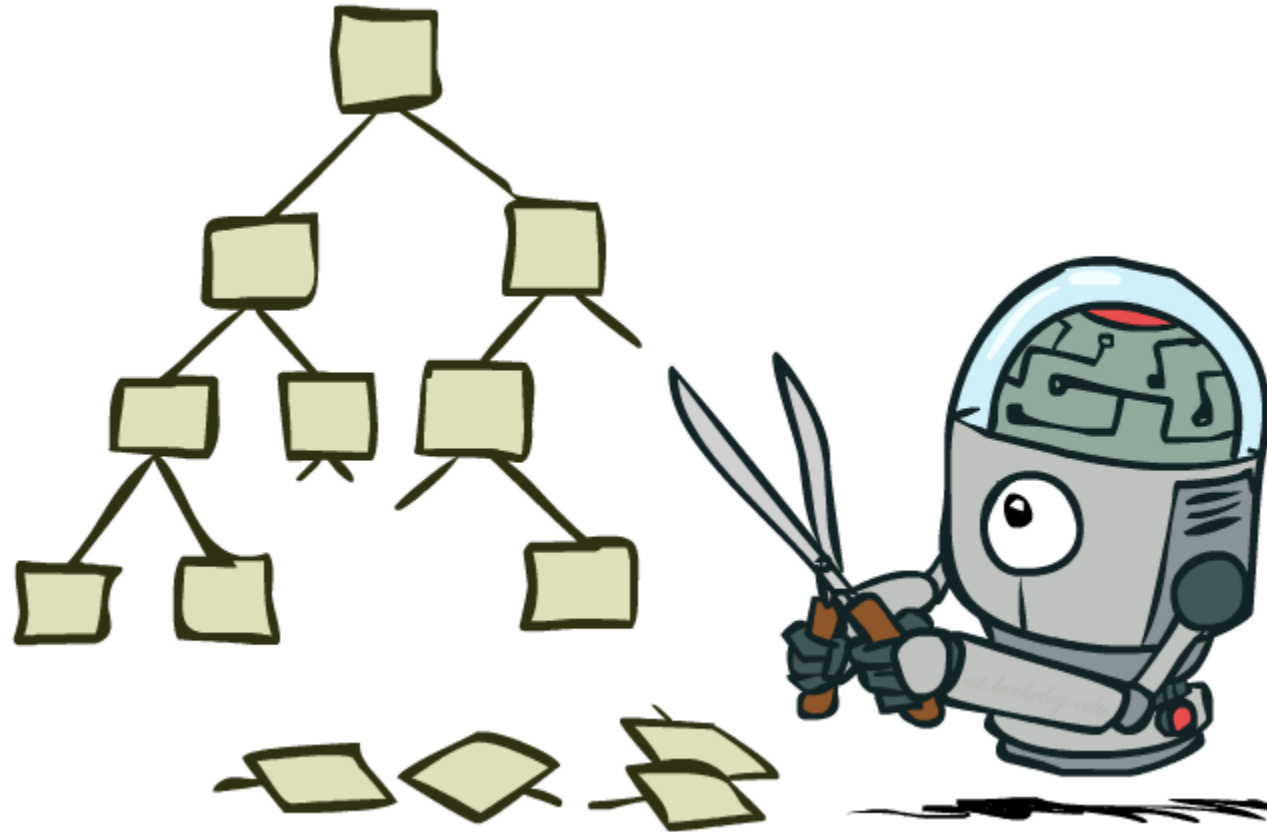
- How efficient is minimax?
 - Just like (exhaustive) DFS
 - Time: $O(b^m)$
 - Space: $O(bm)$
- Example: For chess, $b \approx 35$, $m \approx 100$
 - Exact solution is completely infeasible
 - But, do we need to explore the whole tree?



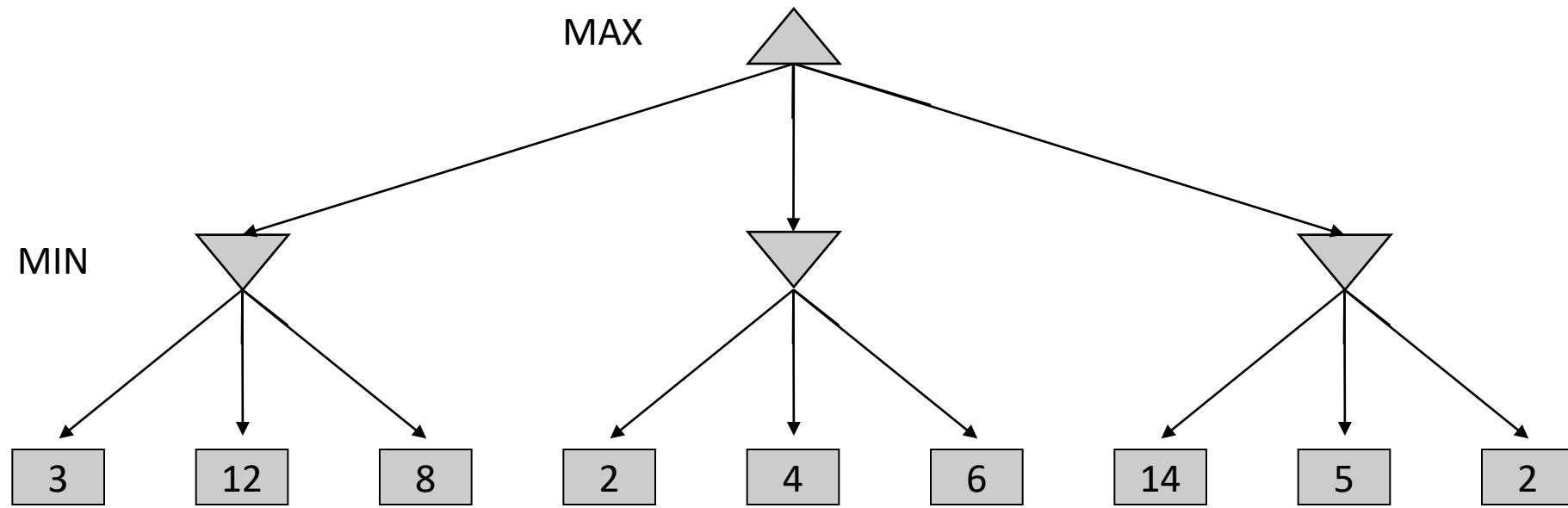
Resource Limits



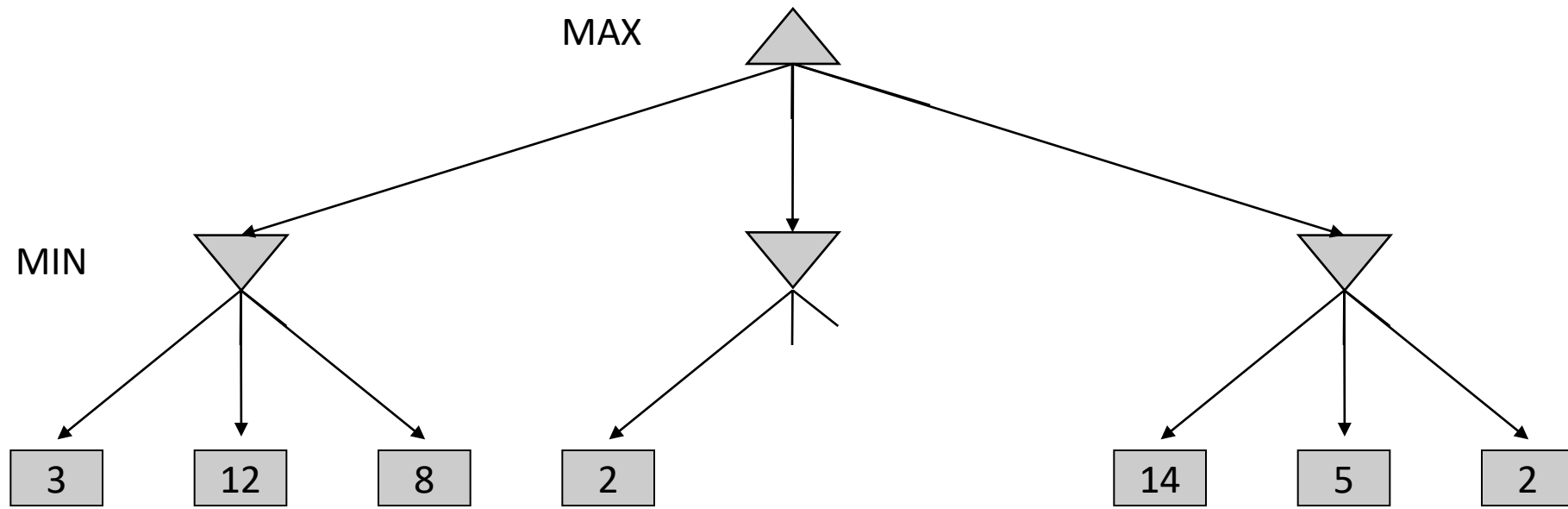
Game Tree Pruning



Minimax Example



Minimax Pruning



Alpha-Beta Pruning

- **Alpha α** : value of the best choice so far for MAX (lower bound of Max utility)
- **Beta β** : value of the best choice so far for MIN (upper bound of Min utility)
- Expanding at MAX node **n**: update α
 - If a child of **n** has value greater than β , stop expanding the MAX node **n**
 - Reason: MIN parent of **n** would not choose the action which leads to **n**
- At MIN node **n**: update β
 - If a child of **n** has value less than α , stop expanding the MIN node **n**
 - Reason: MAX parent of **n** would not choose the action which leads to **n**

Alpha-Beta Implementation

def value(state, α , β):

if the state is a terminal state: return the state's utility

if the next agent is MAX: return max-value(state, α , β)

if the next agent is MIN: return min-value(state, α , β)

def max-value(state, α , β):

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, α , β):

initialize $v = +\infty$

for each successor of state:

$v = \min(v, \text{value}(\text{successor}, \alpha, \beta))$

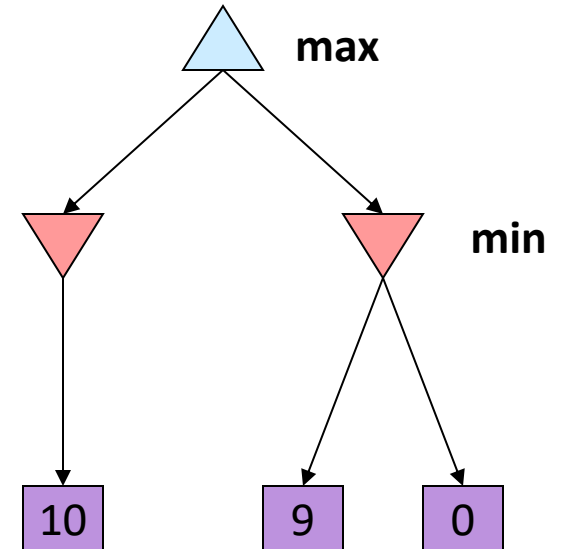
if $v \leq \alpha$ return v

$\beta = \min(\beta, v)$

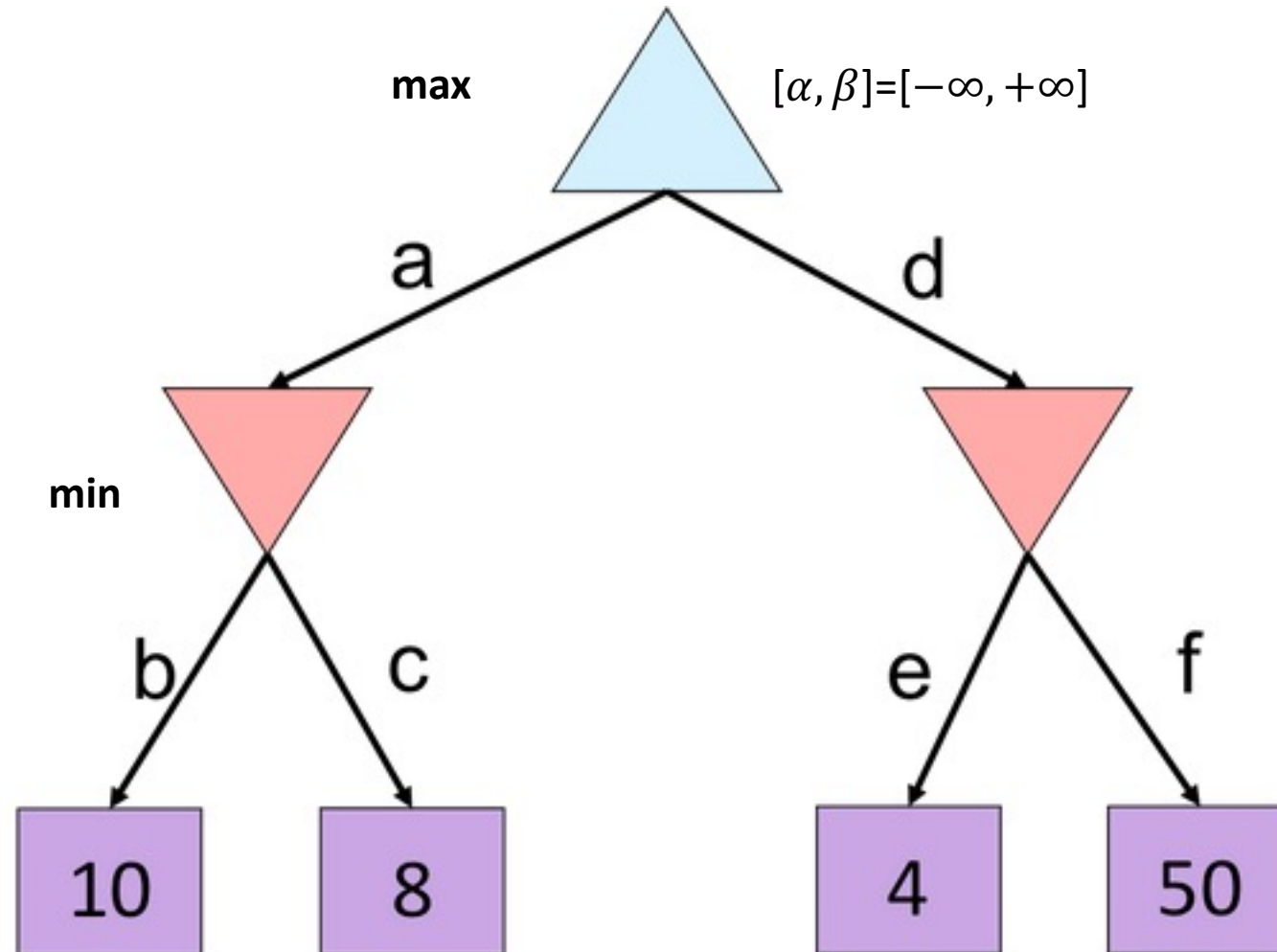
return v

Alpha-Beta Pruning Properties

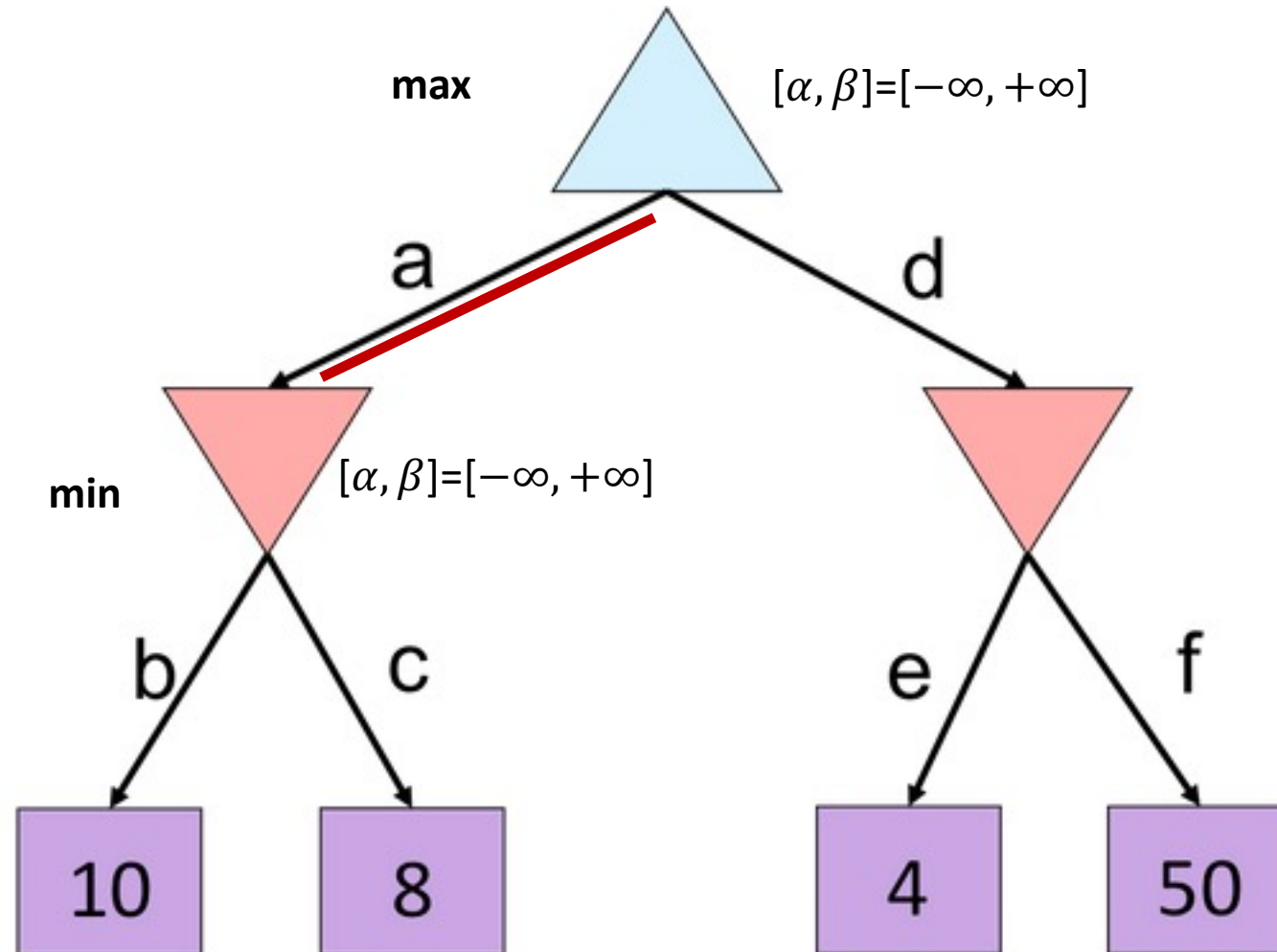
- This pruning has **no effect** on minimax value computed for the root!
- Values of intermediate nodes might be wrong
 - Important: children of the root may have the wrong value
 - So the most naïve version won't let you do action selection
- Good child ordering improves effectiveness of pruning



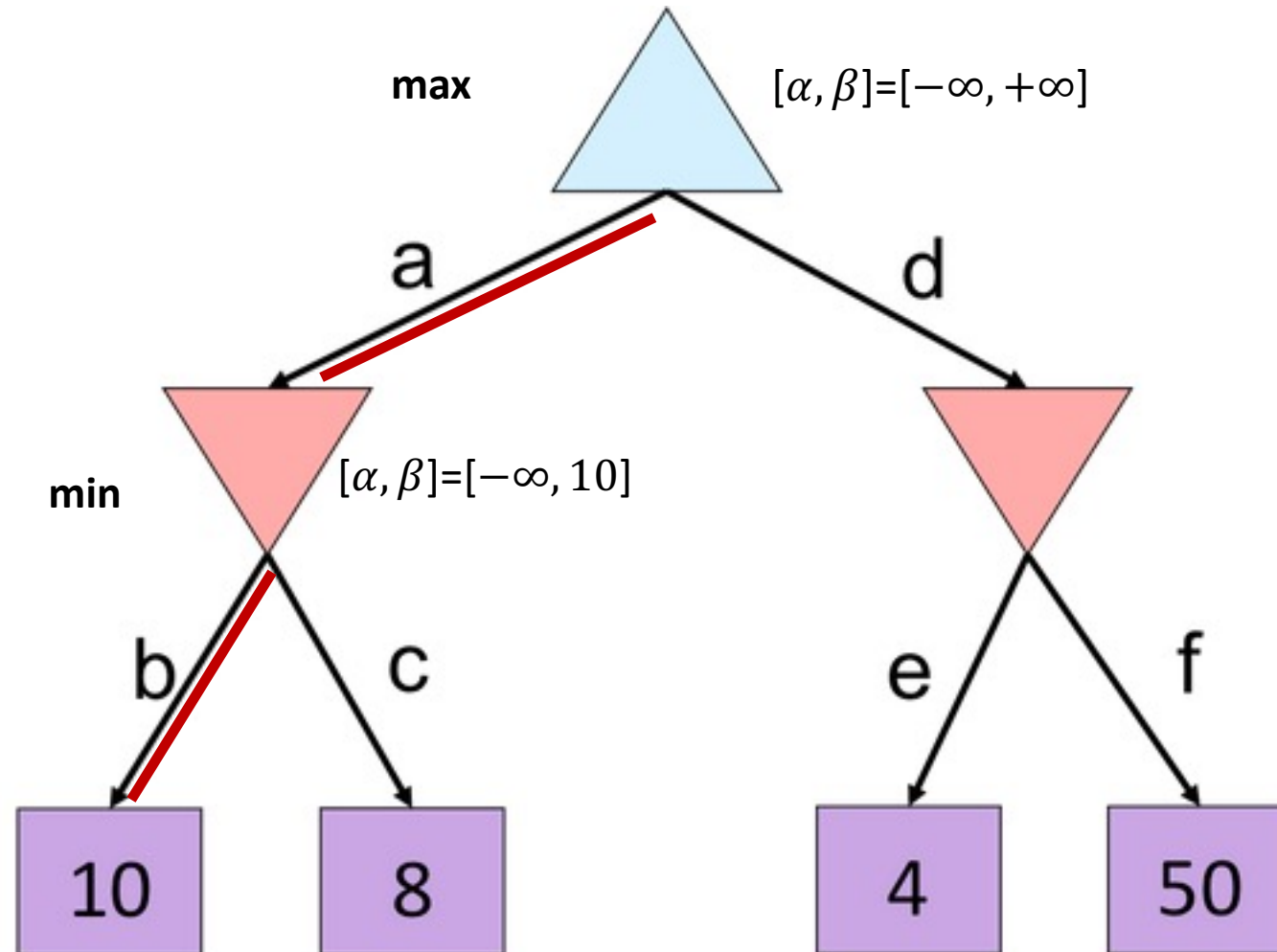
Alpha-Beta Quiz



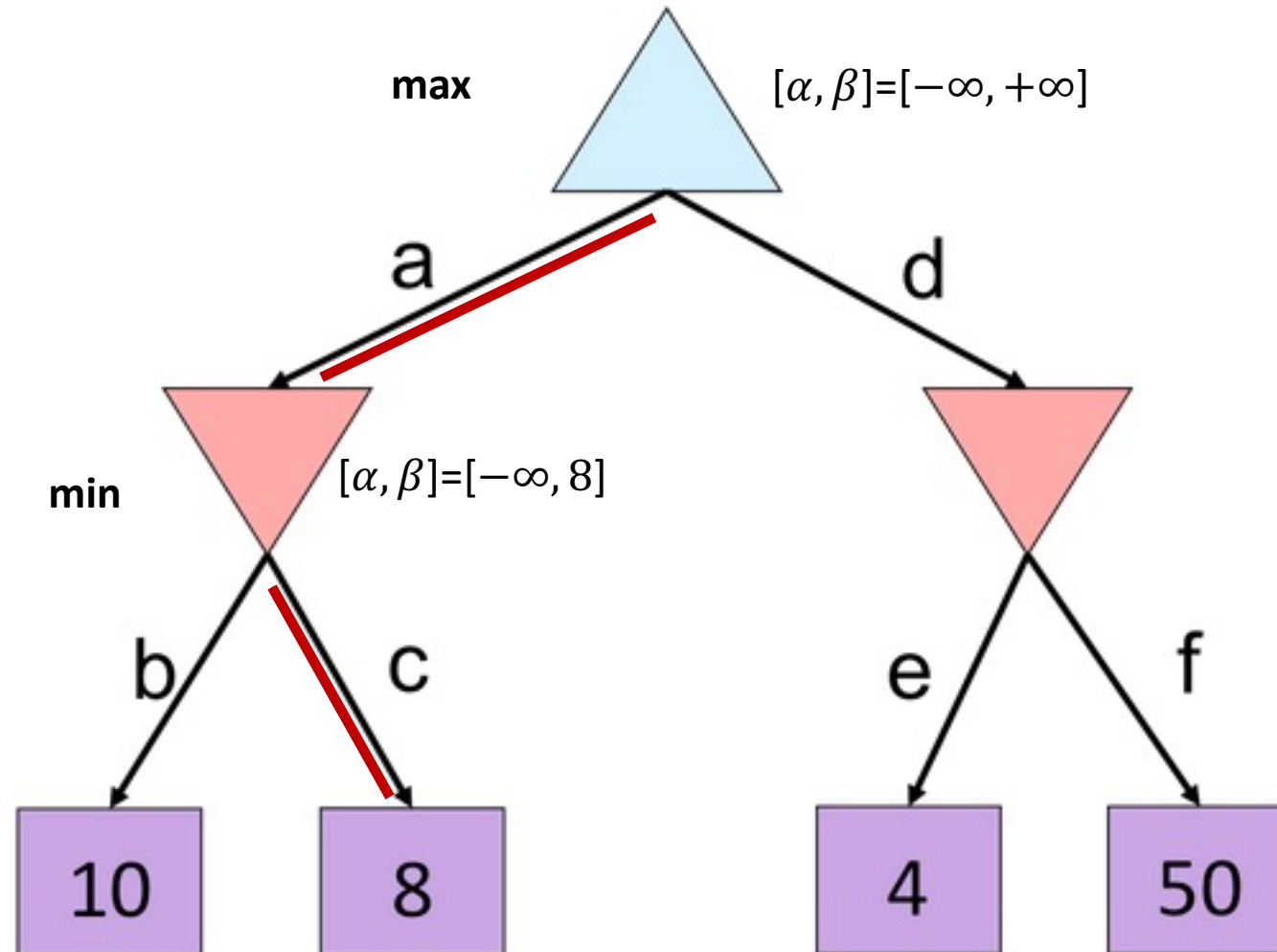
Alpha-Beta Quiz



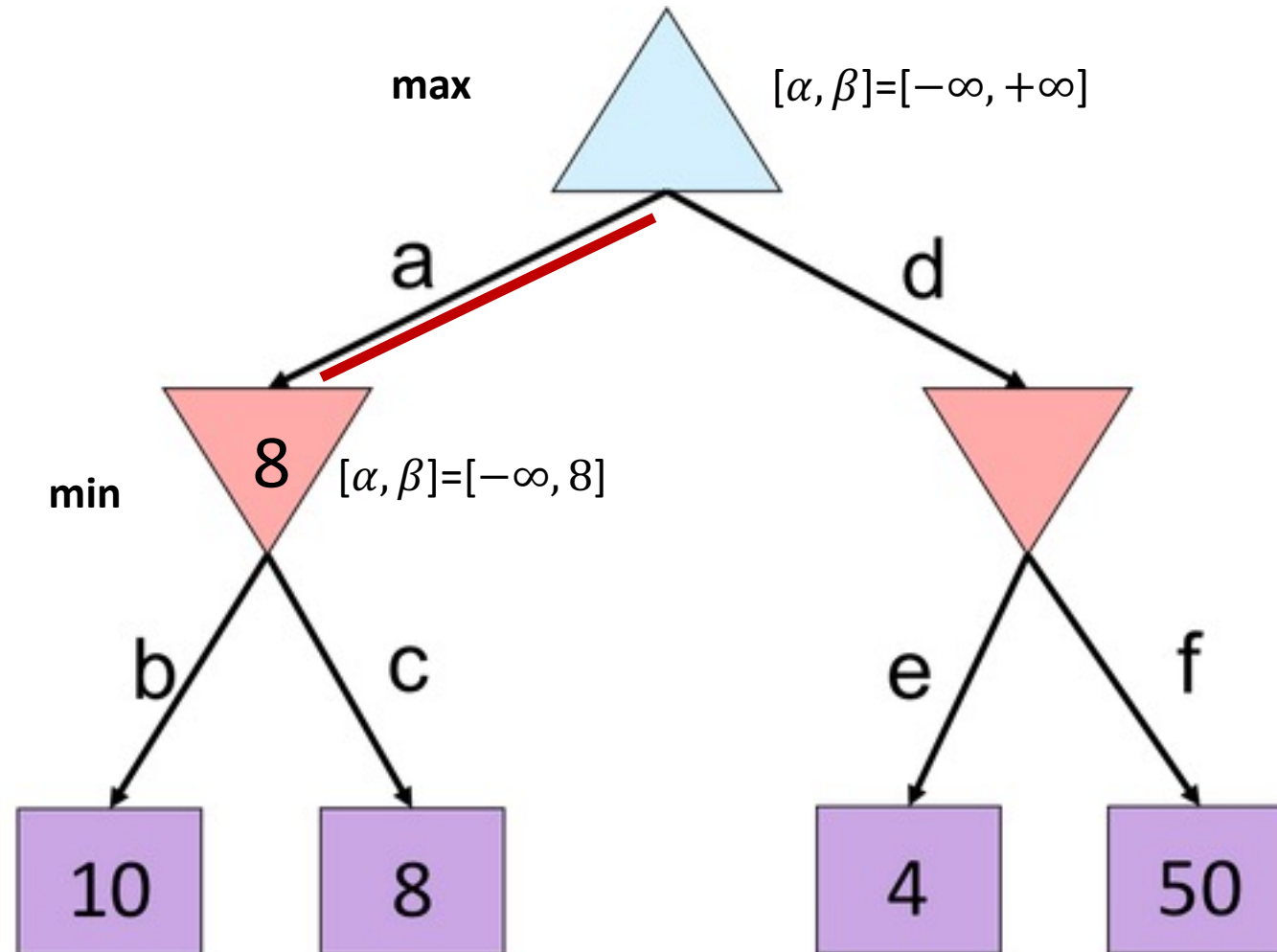
Alpha-Beta Quiz



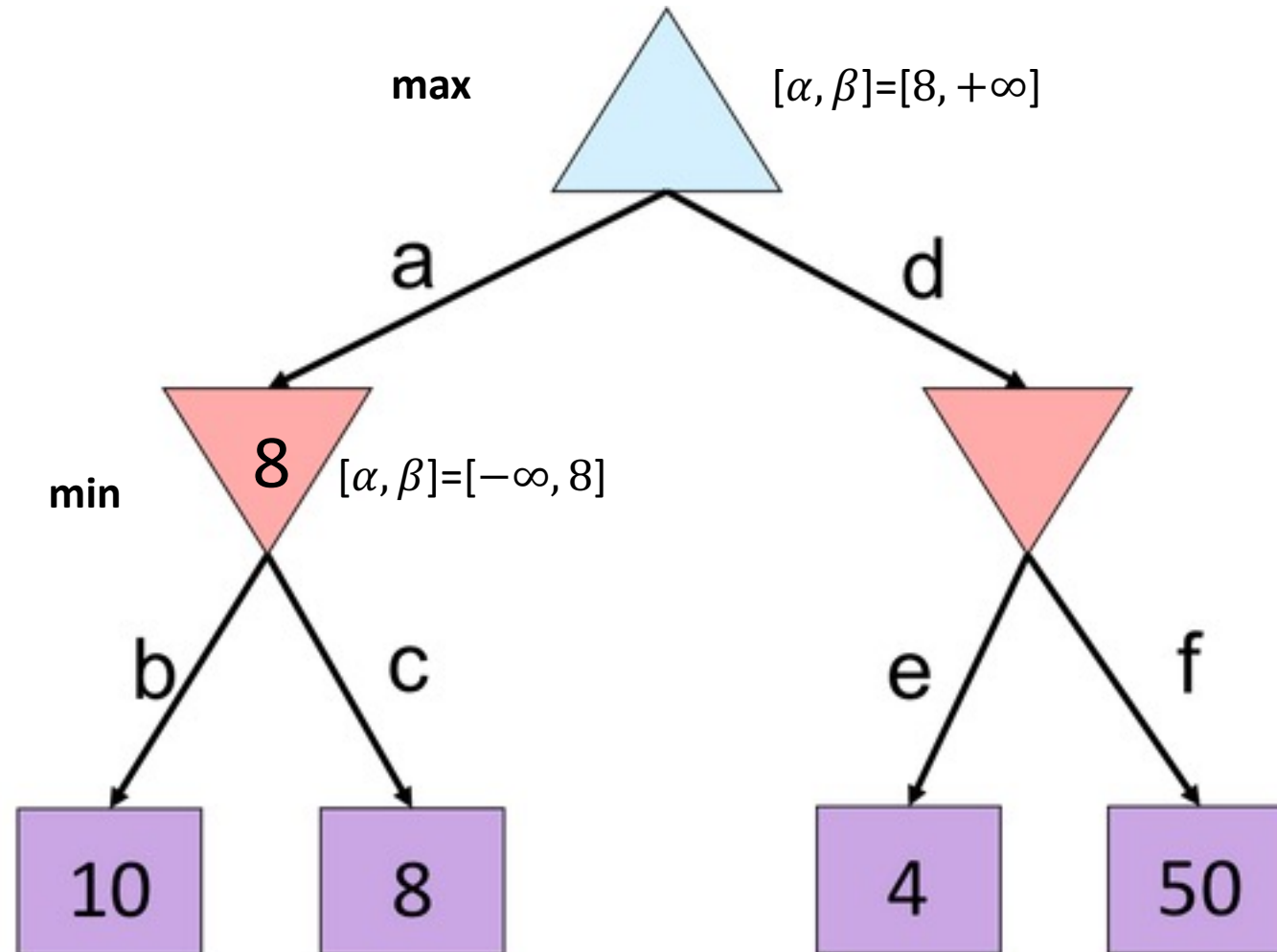
Alpha-Beta Quiz



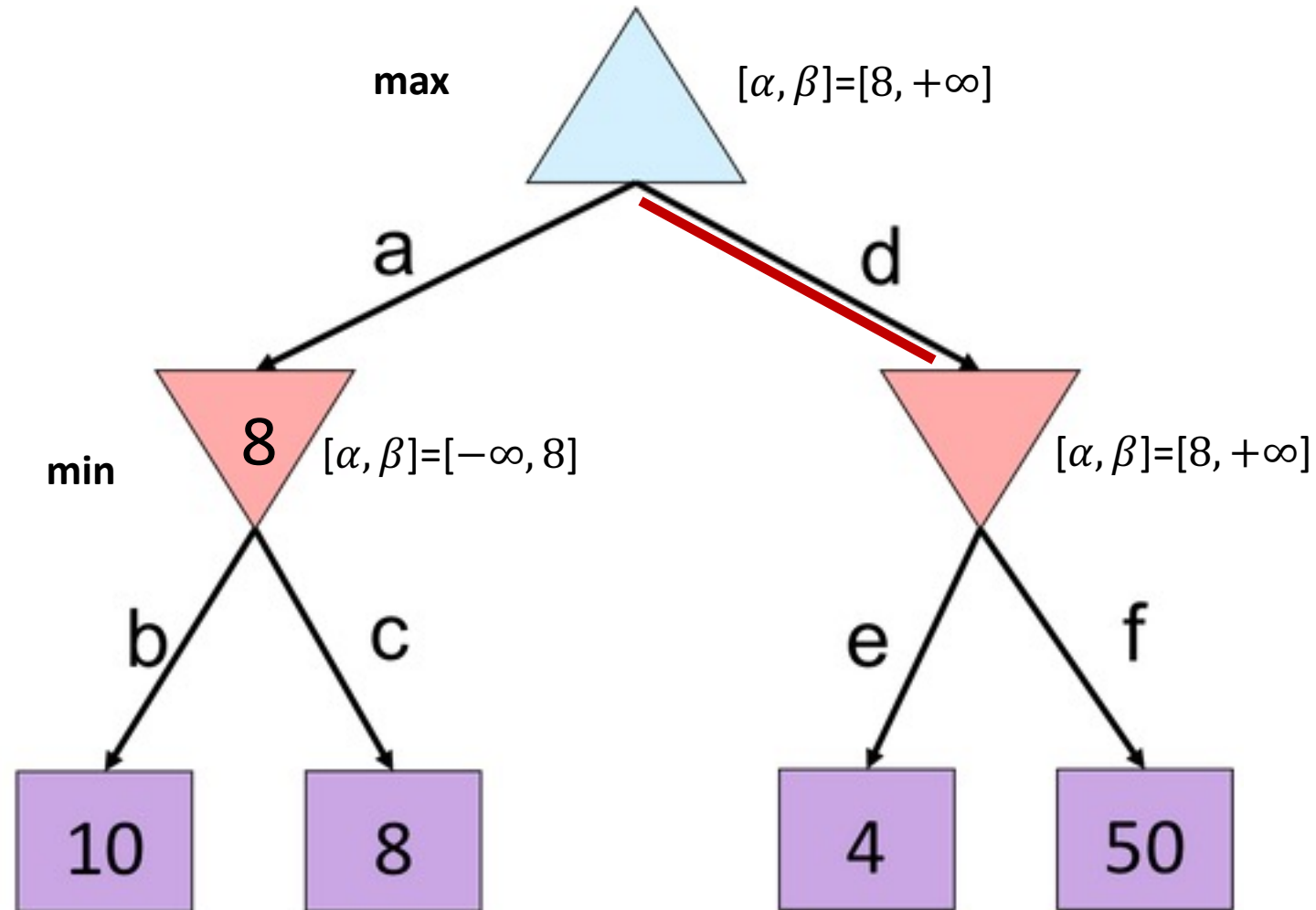
Alpha-Beta Quiz



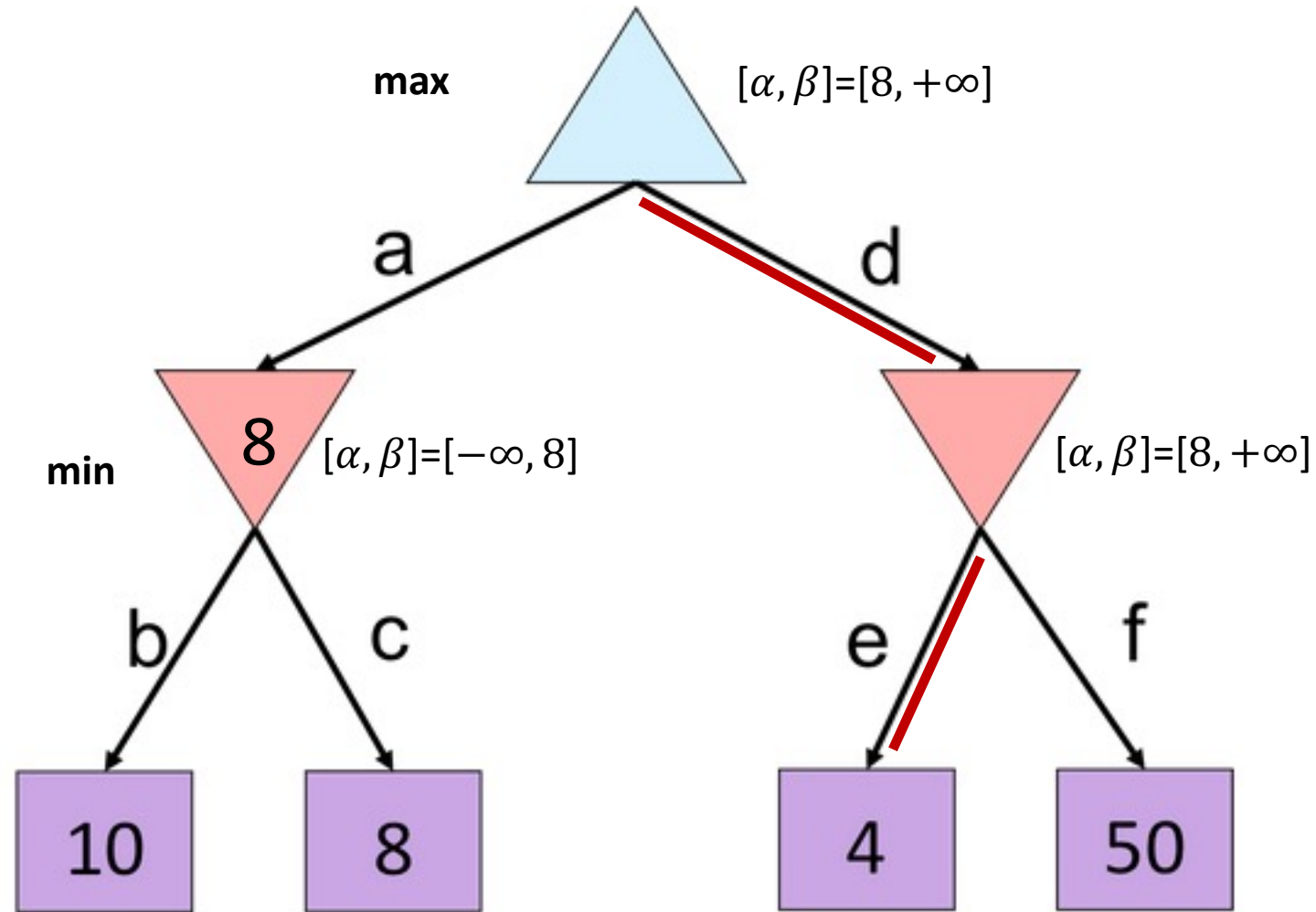
Alpha-Beta Quiz



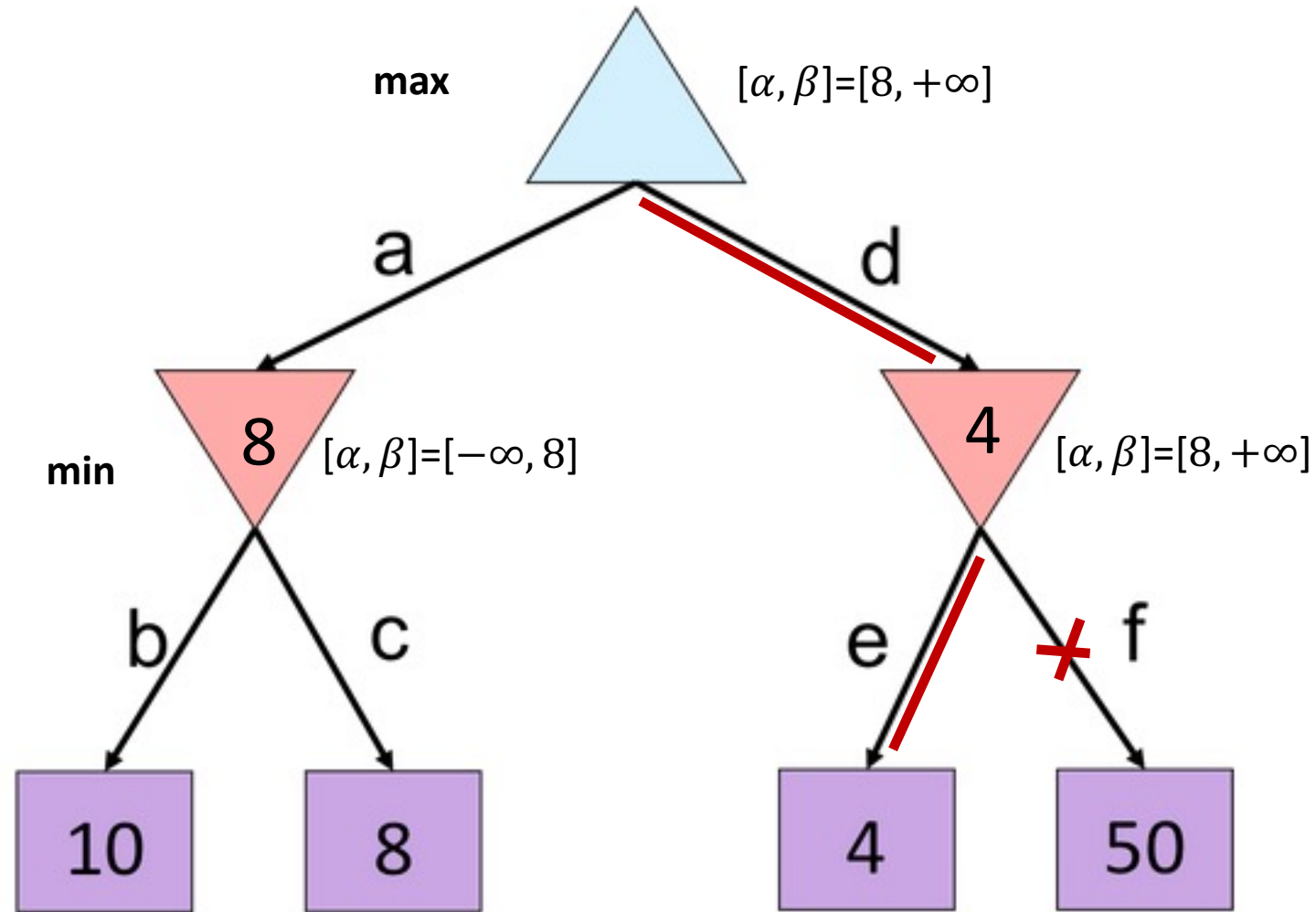
Alpha-Beta Quiz



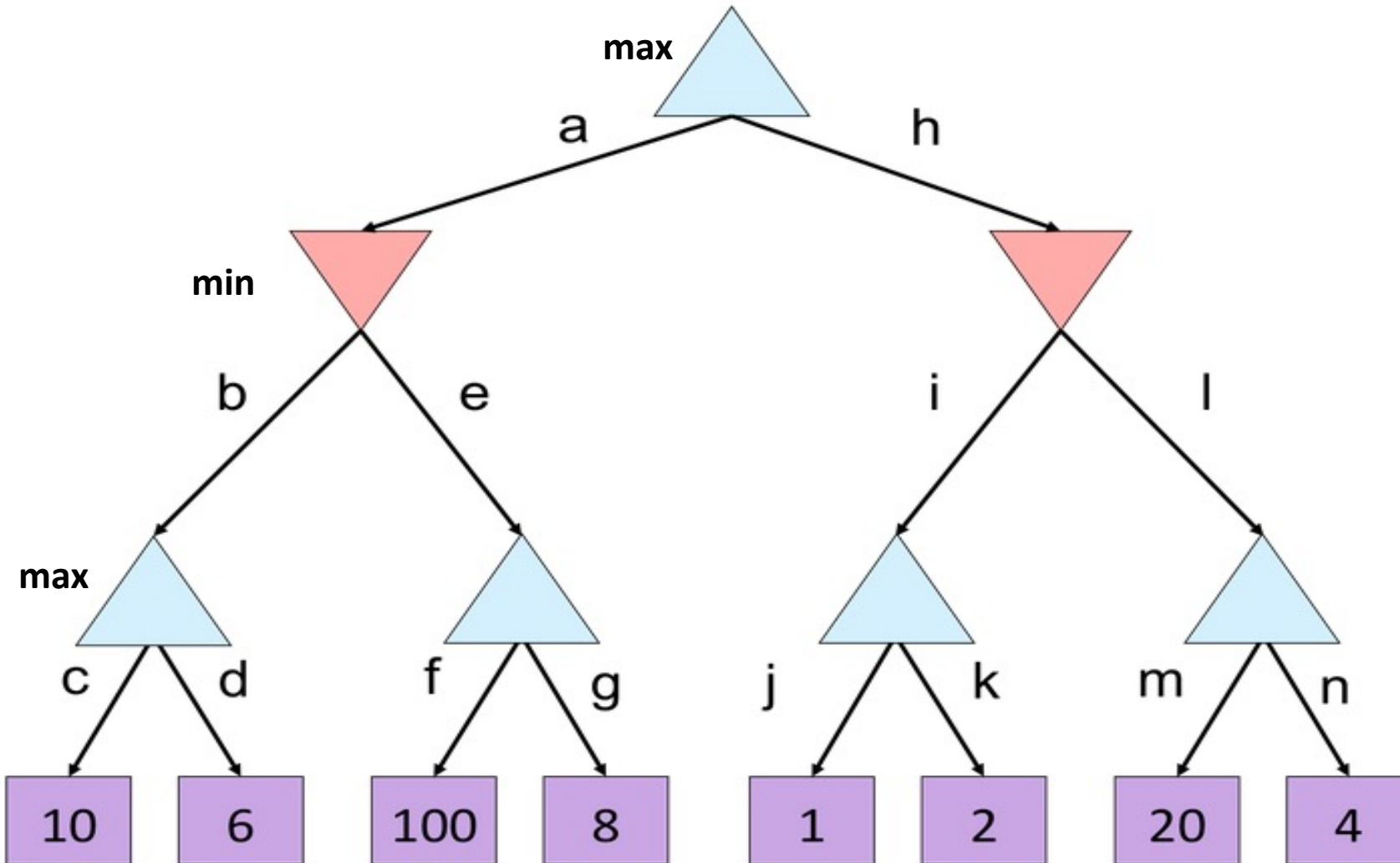
Alpha-Beta Quiz



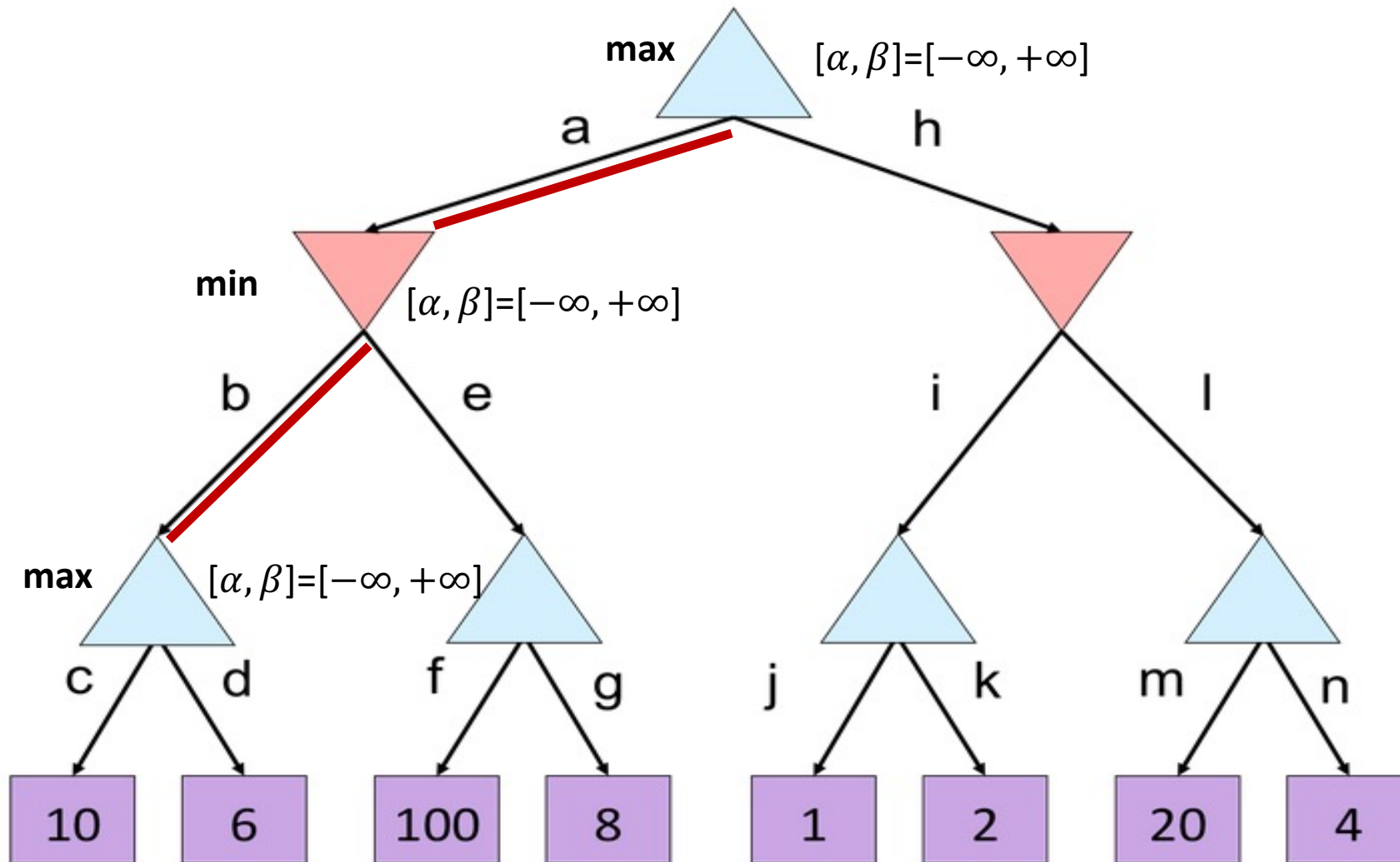
Alpha-Beta Quiz



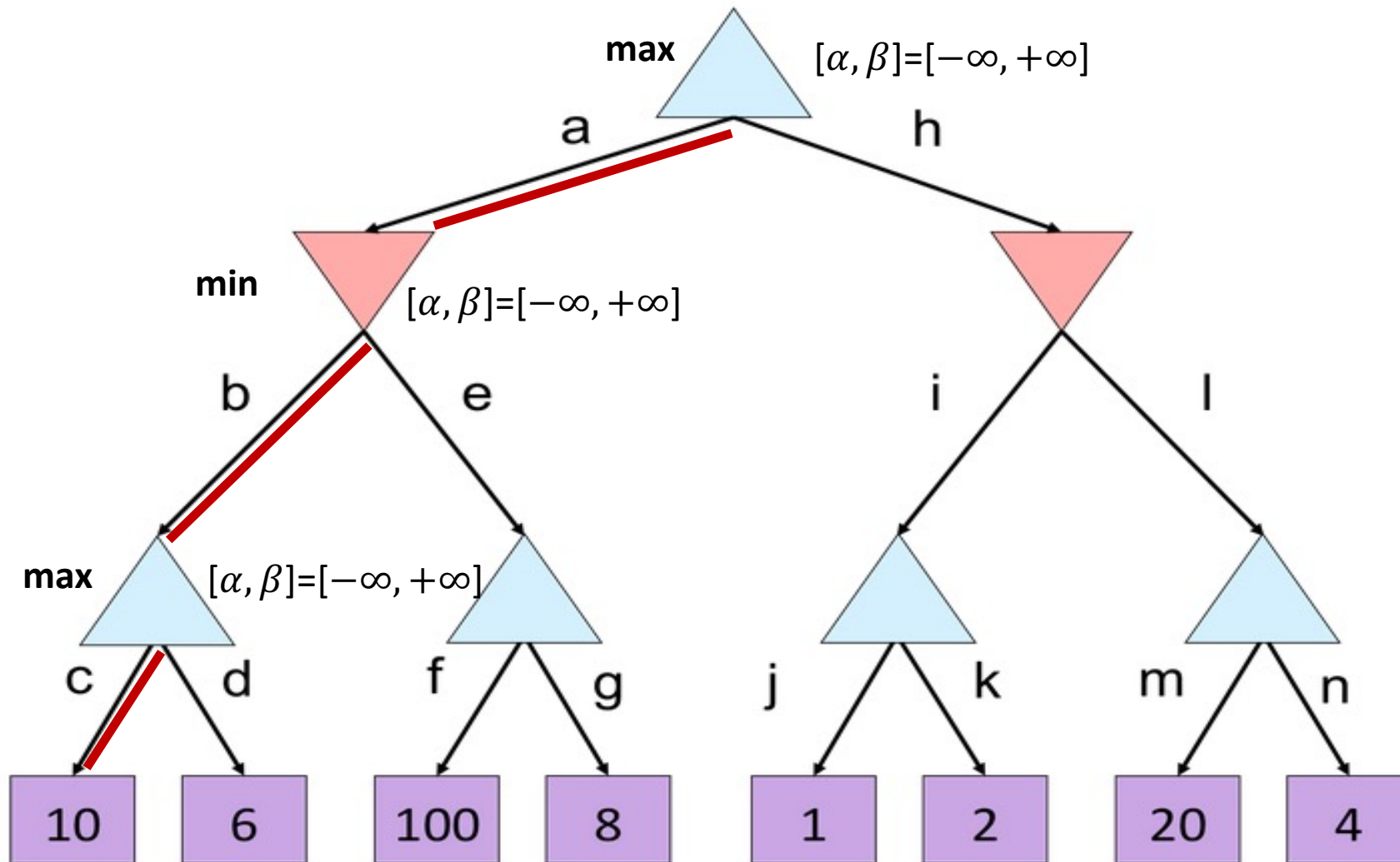
Alpha-Beta Quiz 2



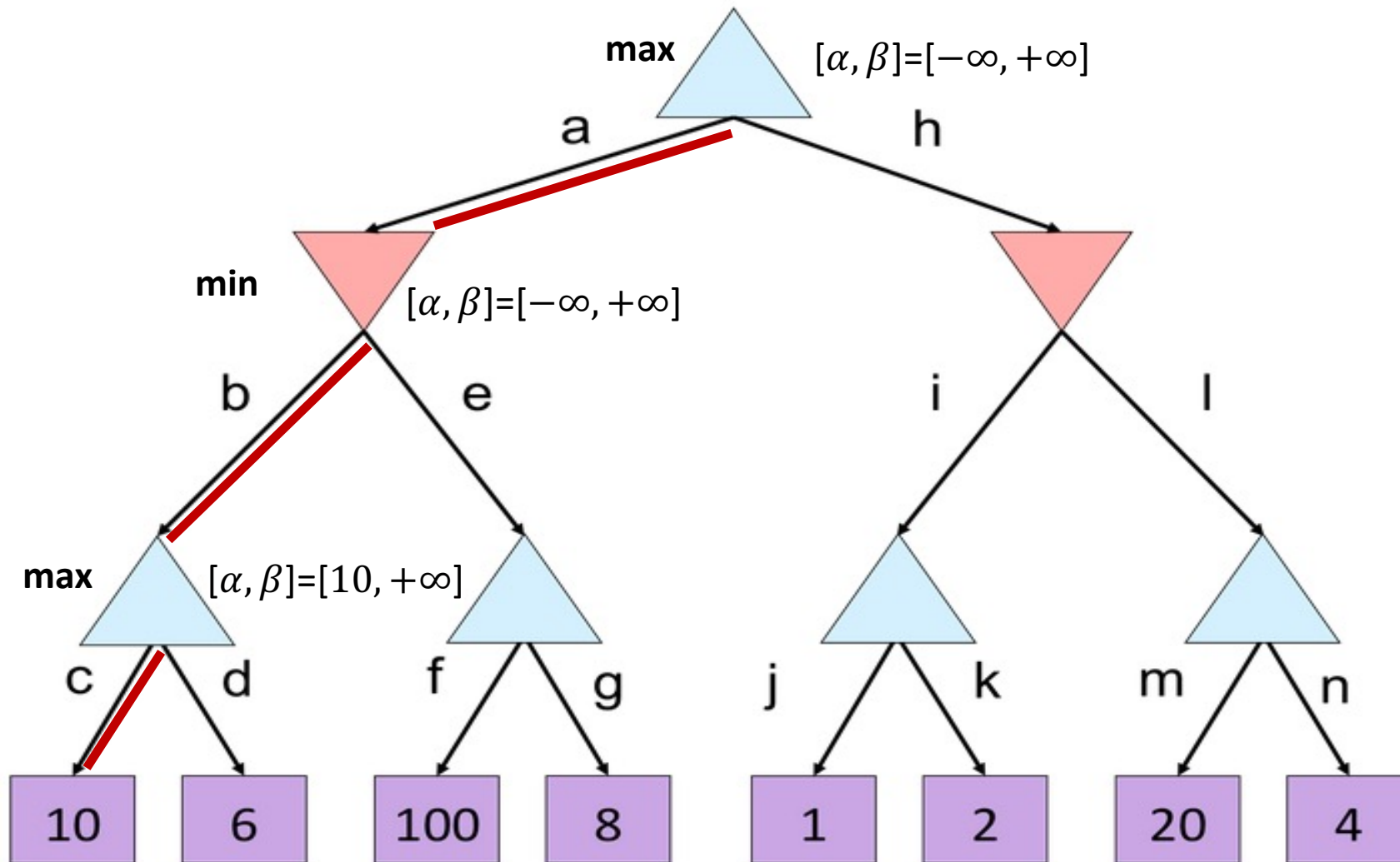
Alpha-Beta Quiz 2



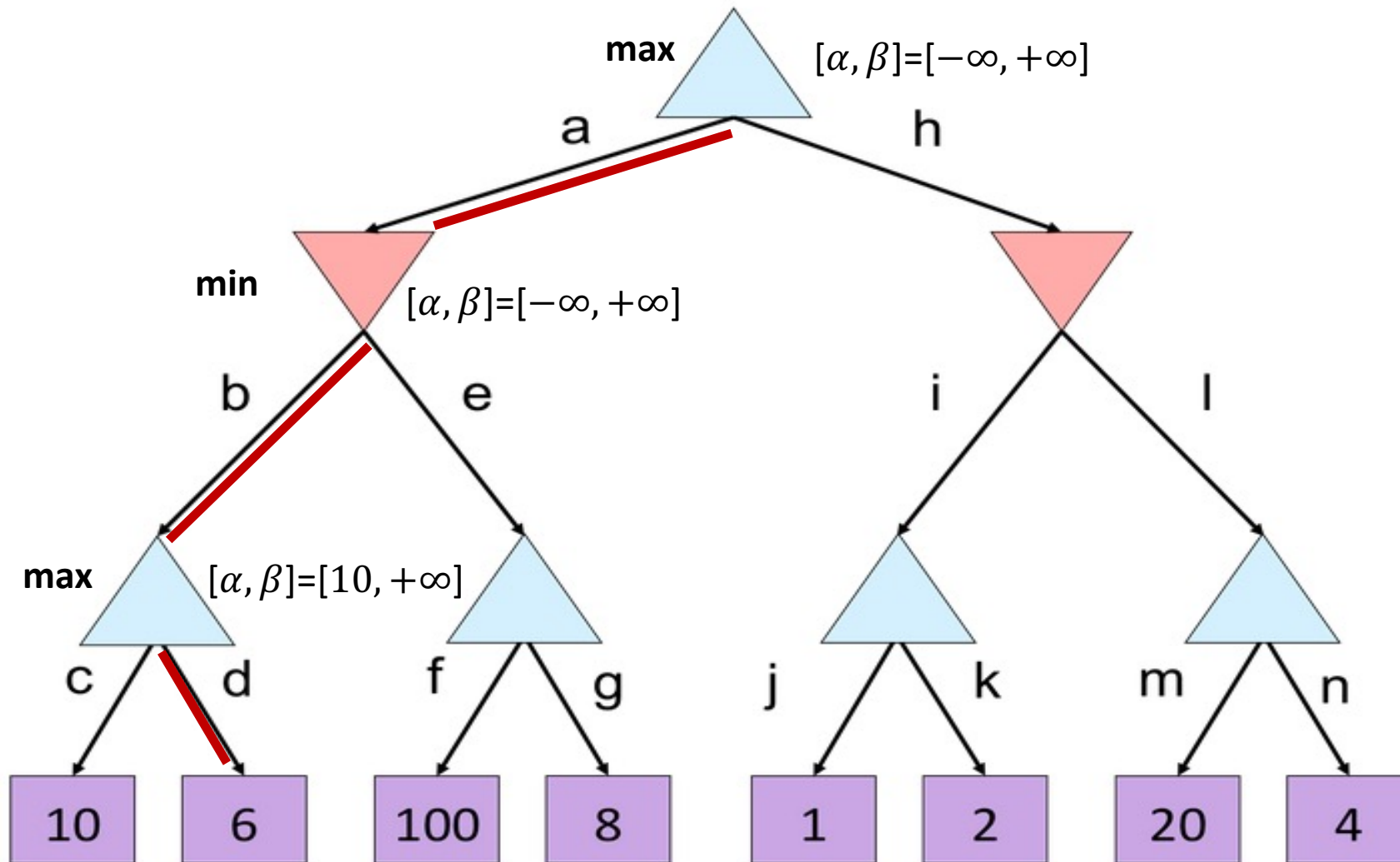
Alpha-Beta Quiz 2



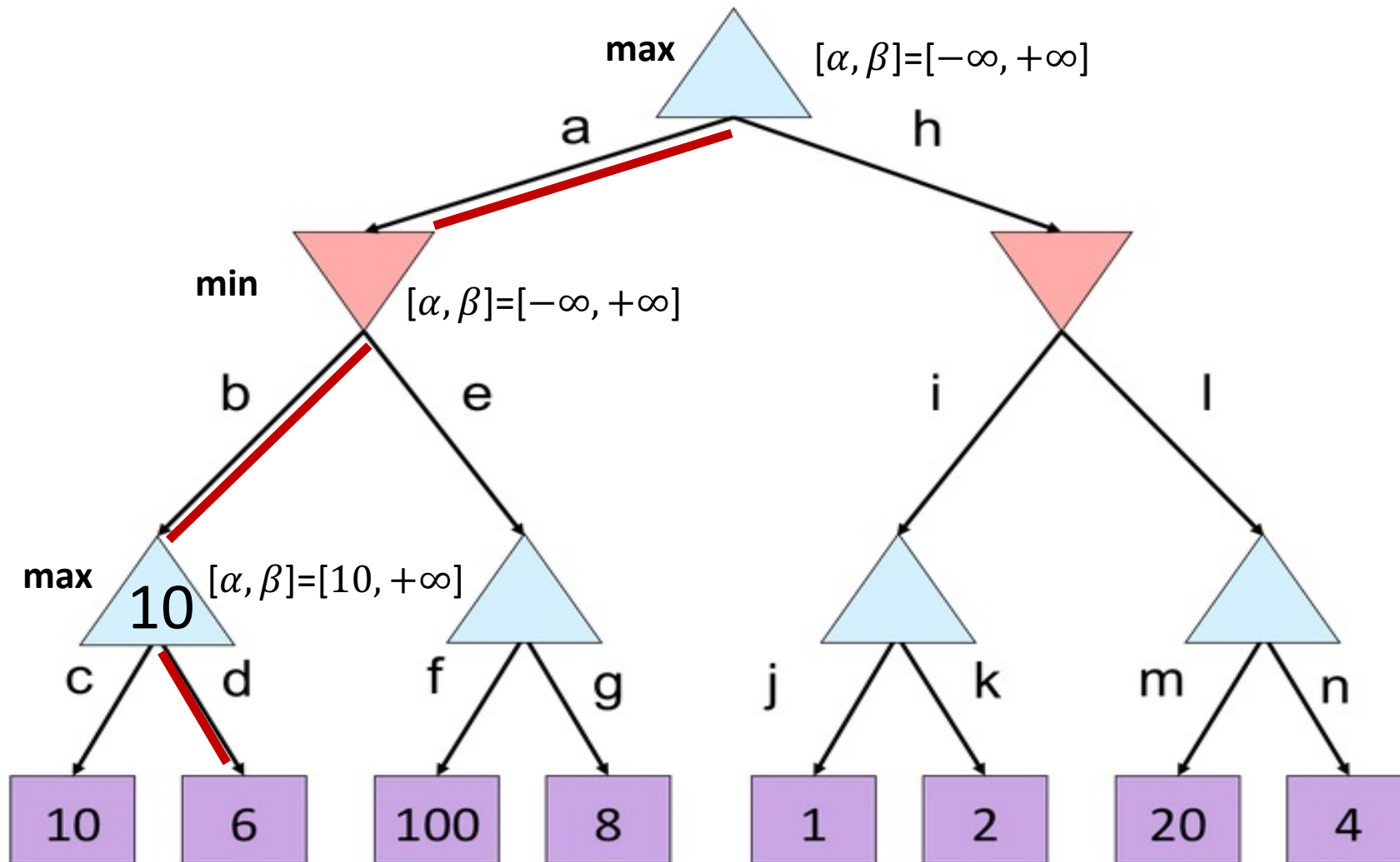
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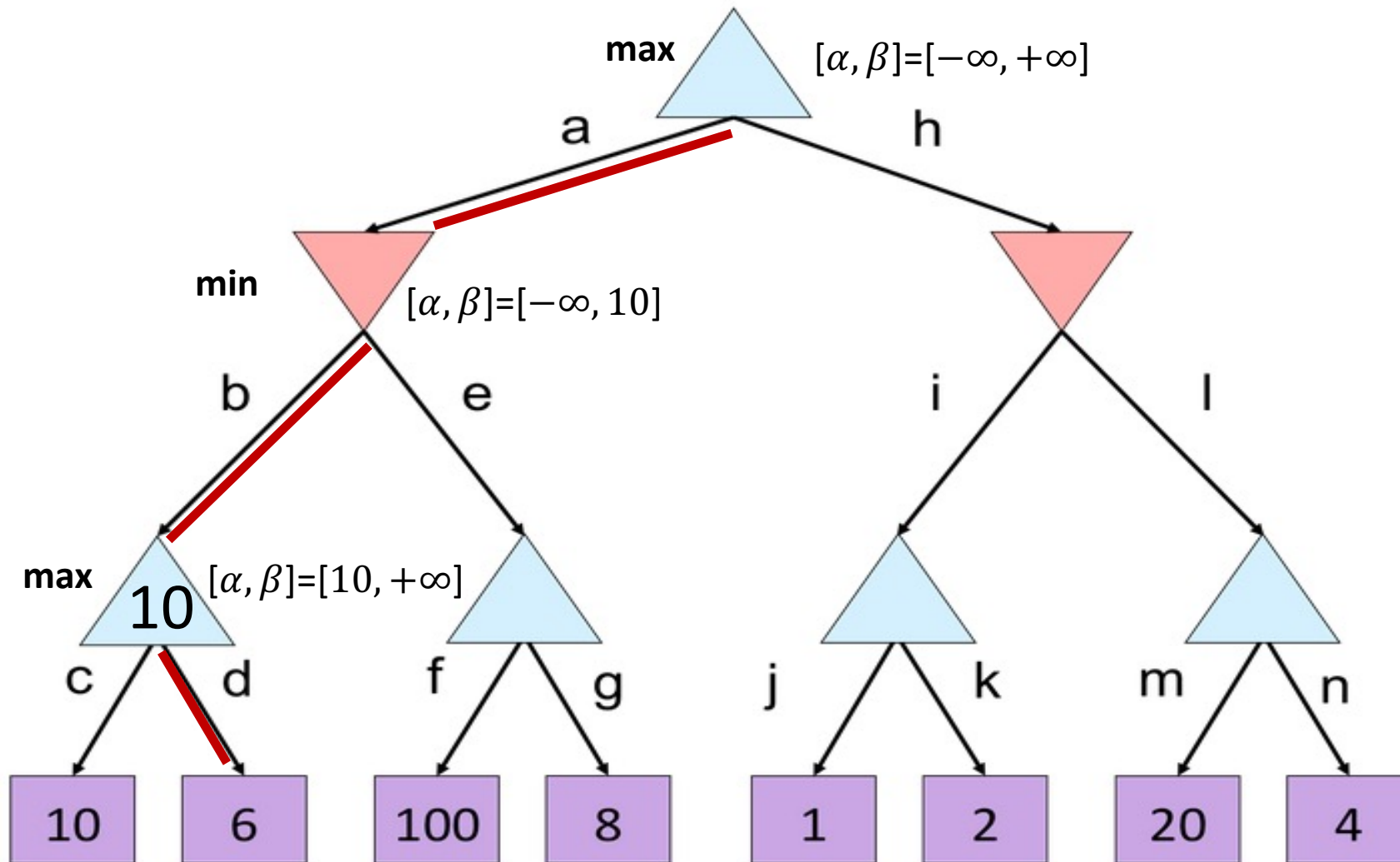
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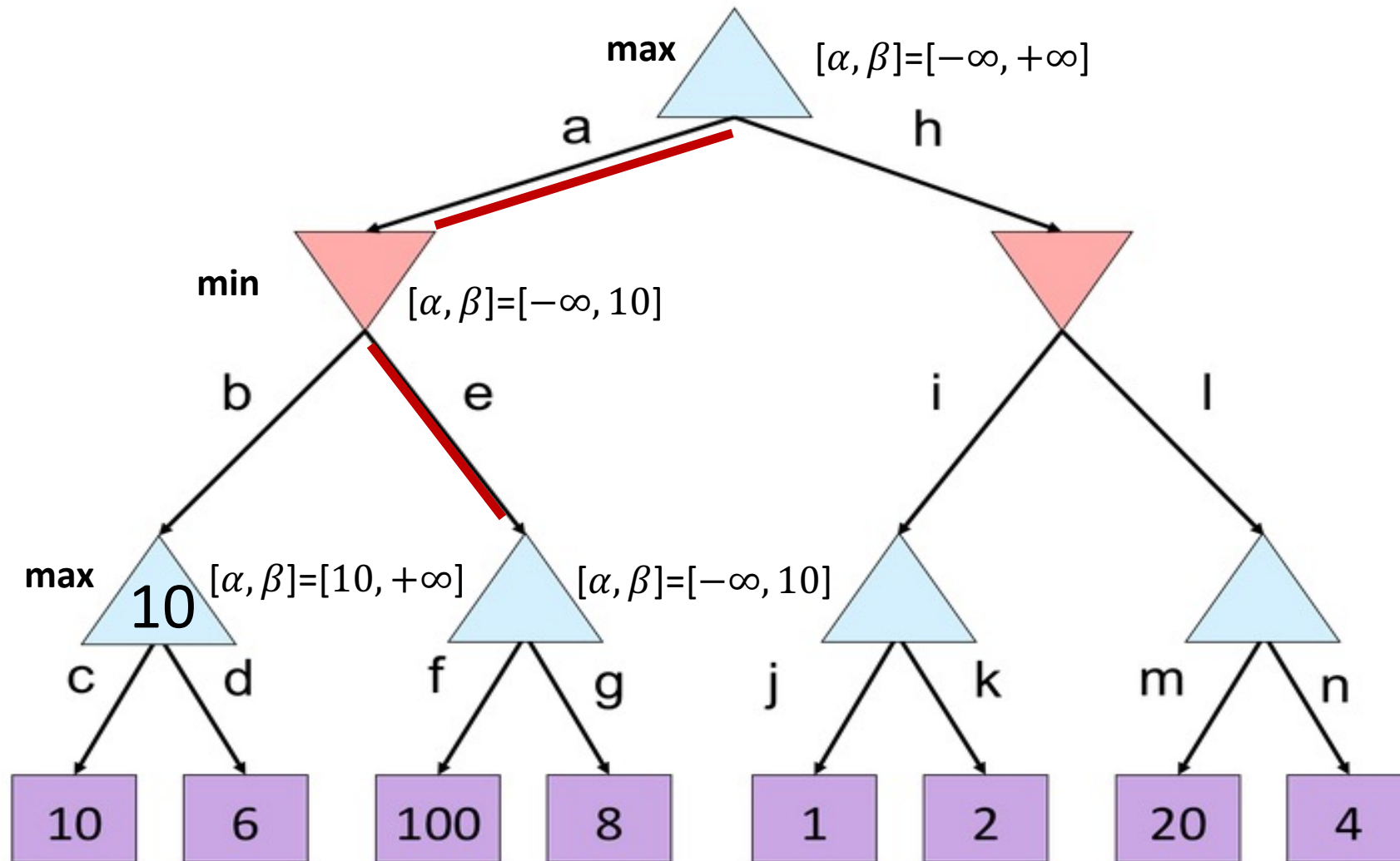
Alpha-Beta Quiz 2



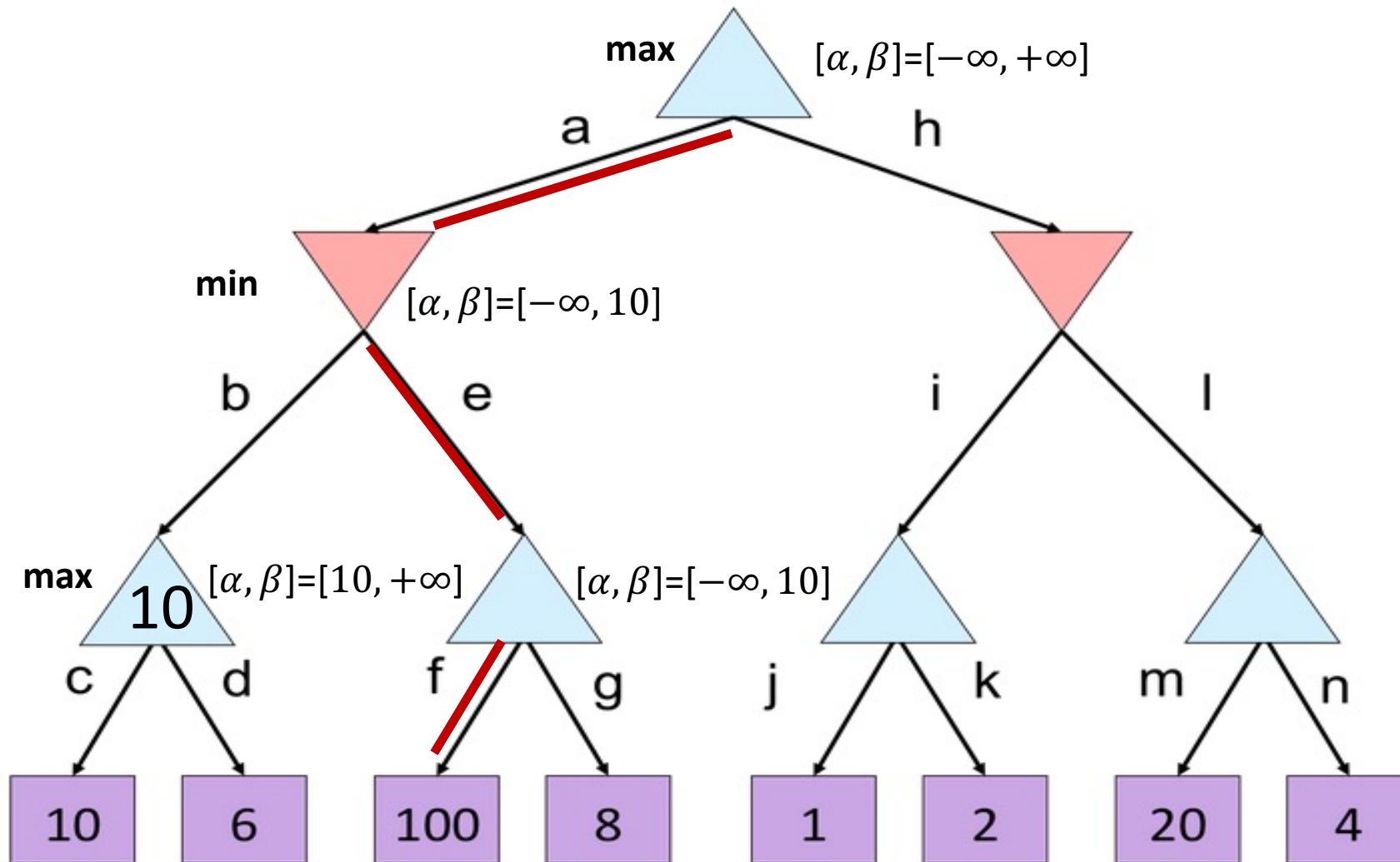
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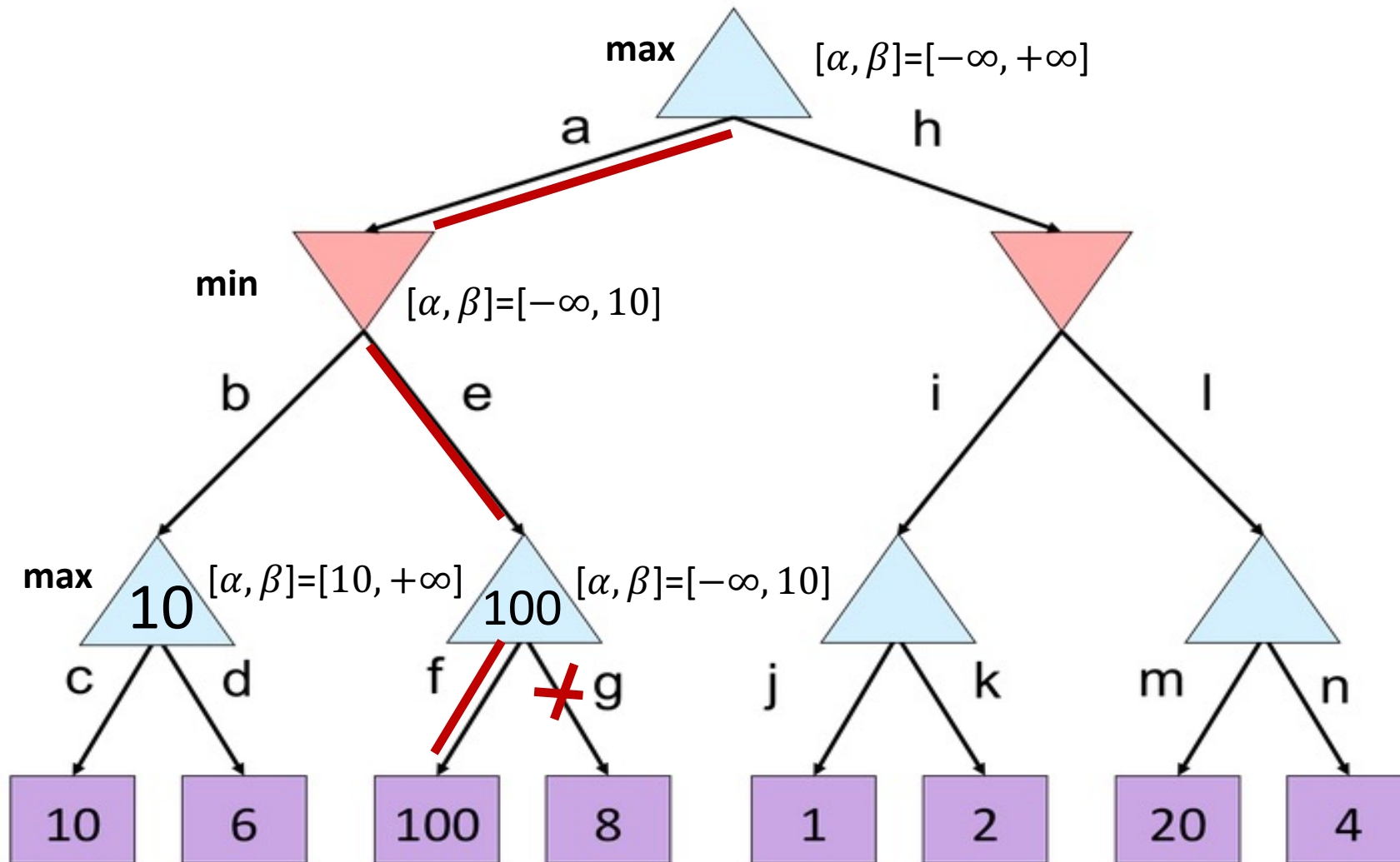
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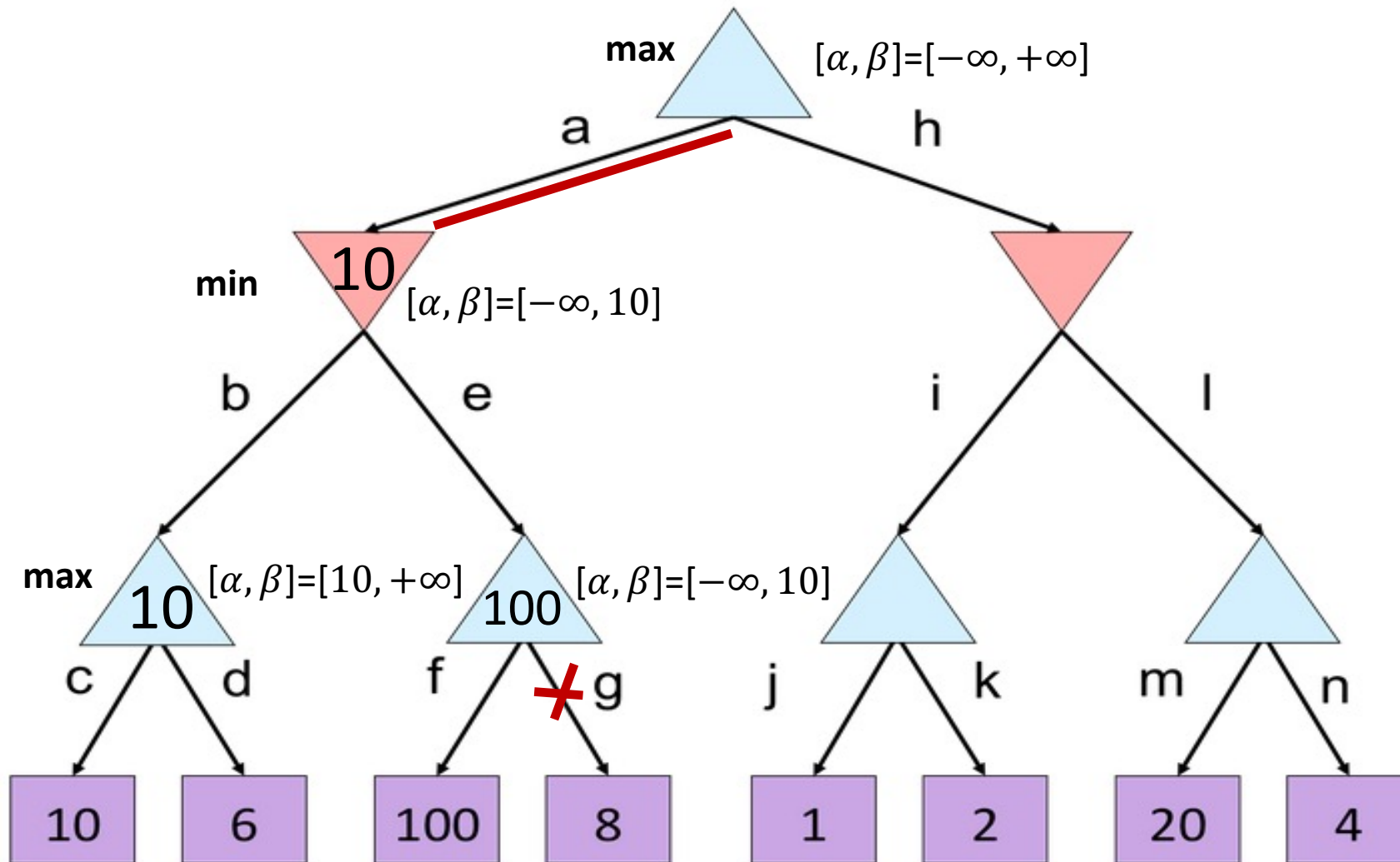
Alpha-Beta Quiz 2



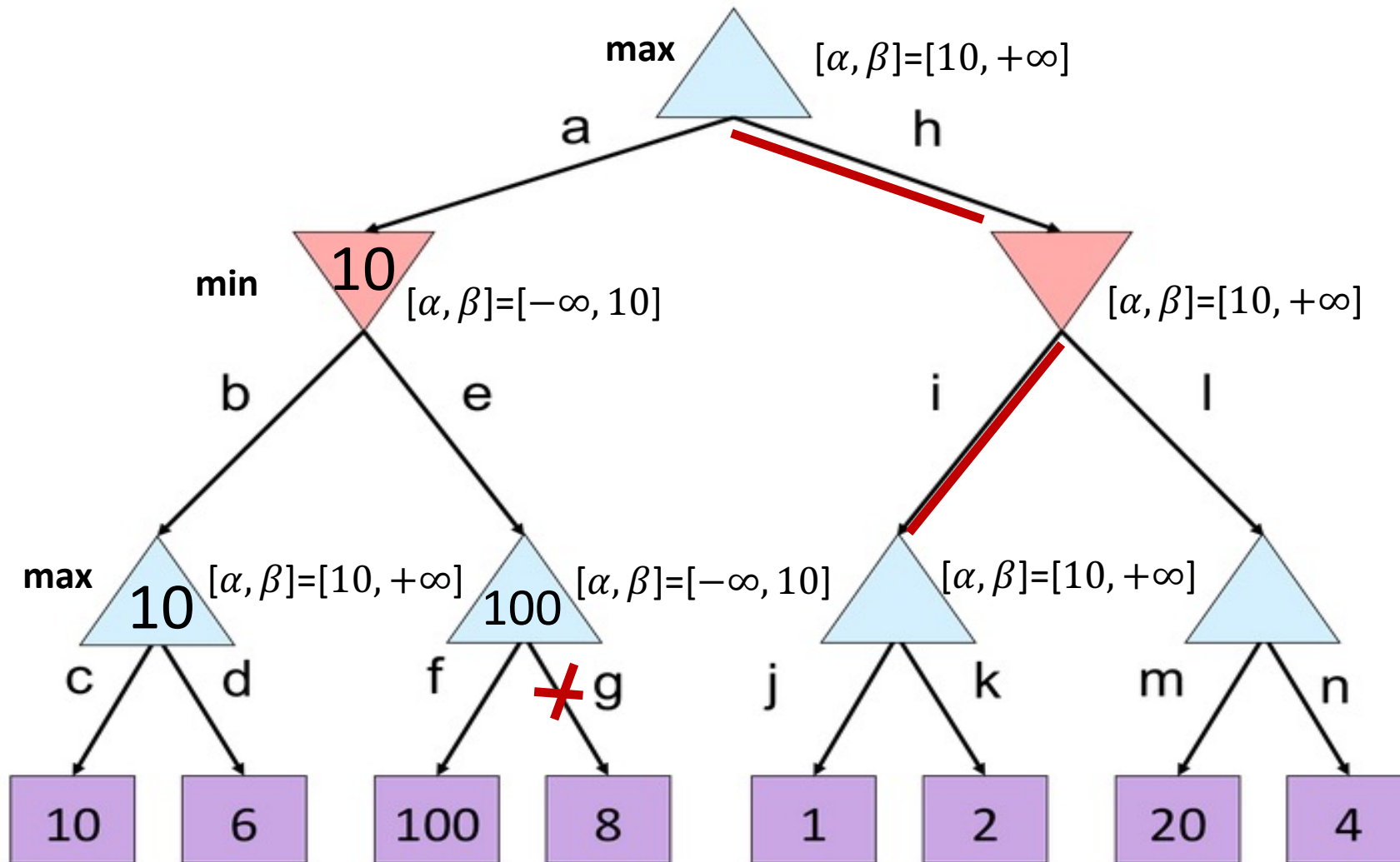
Alpha-Beta Quiz 2



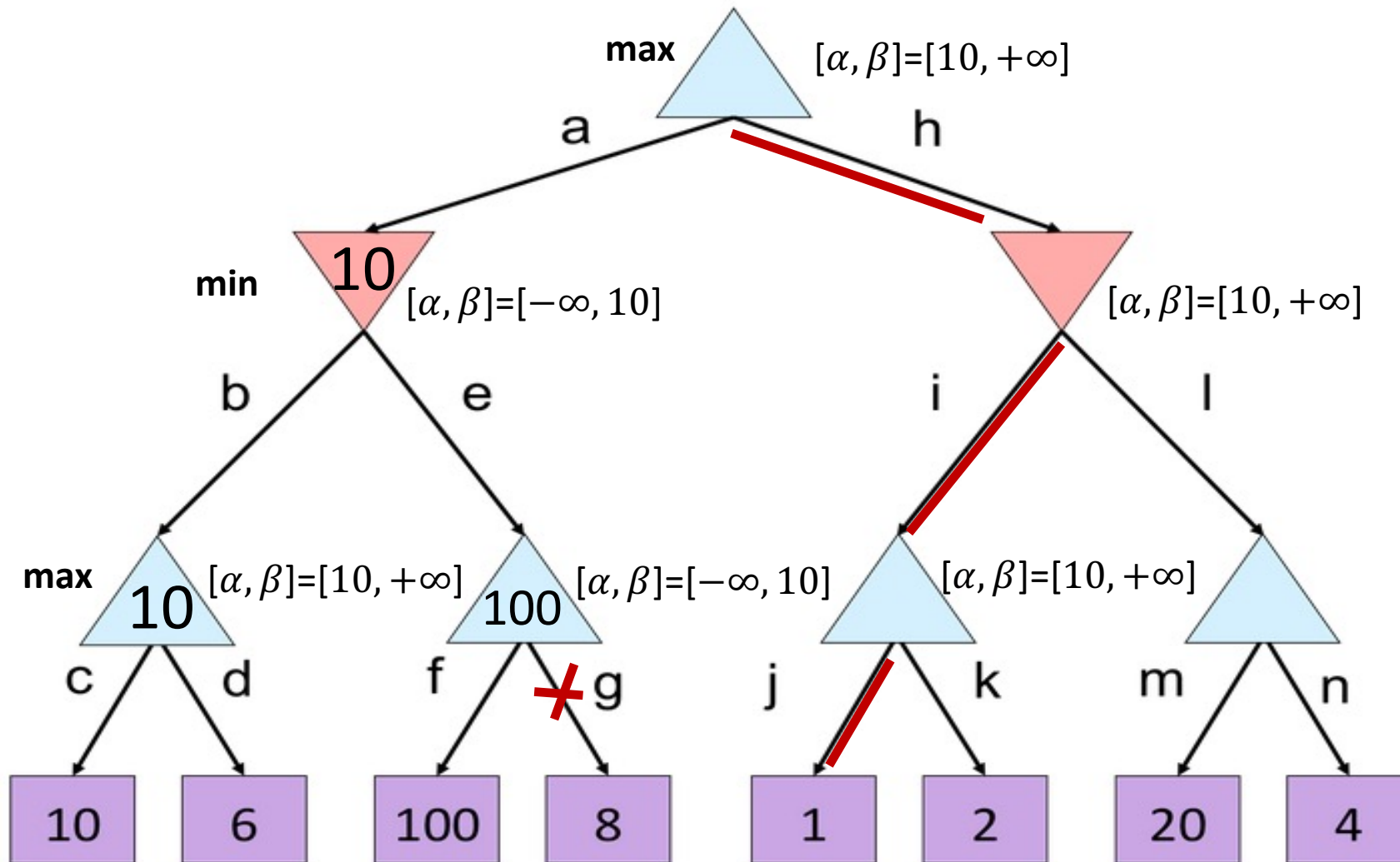
Alpha-Beta Quiz 2



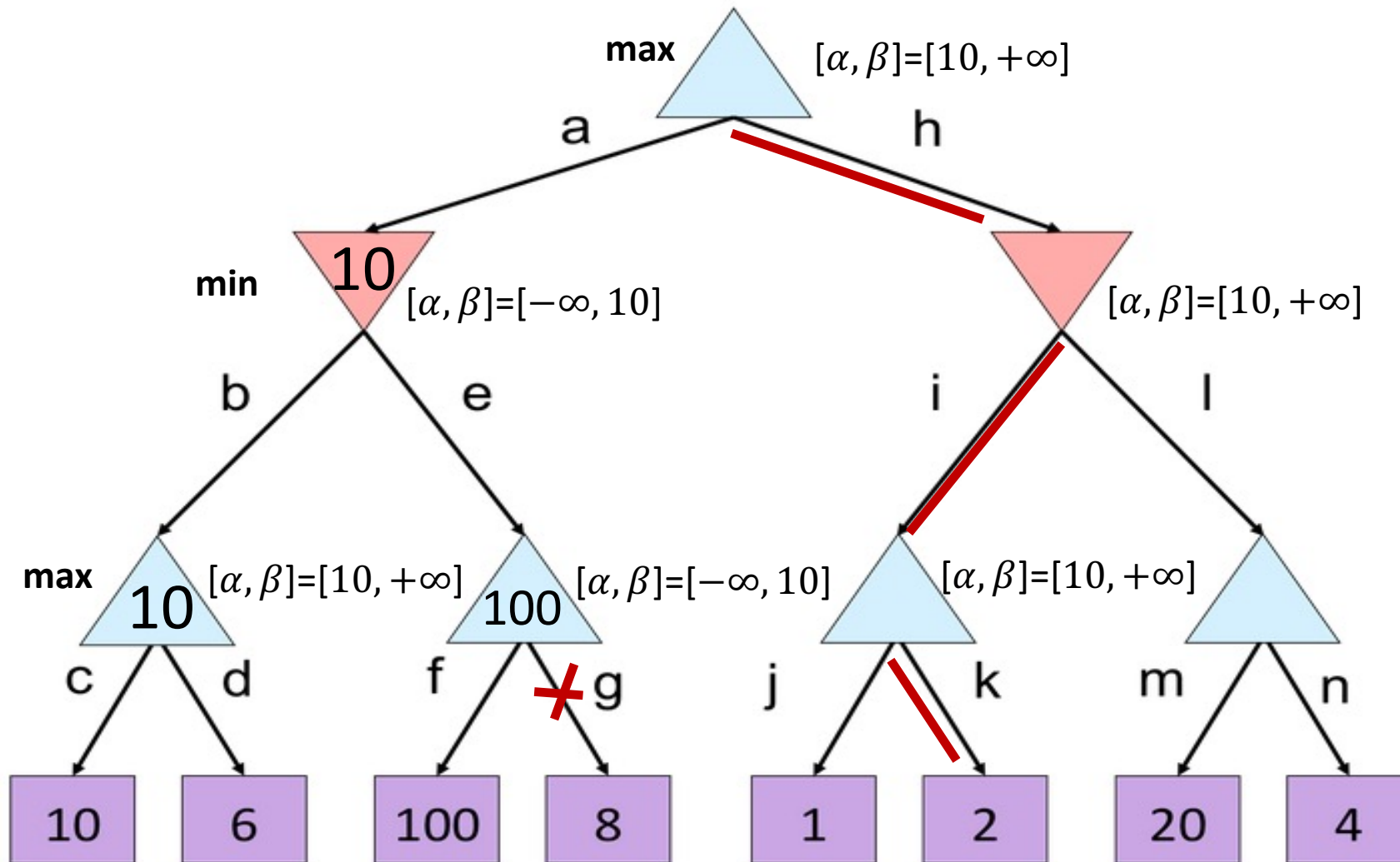
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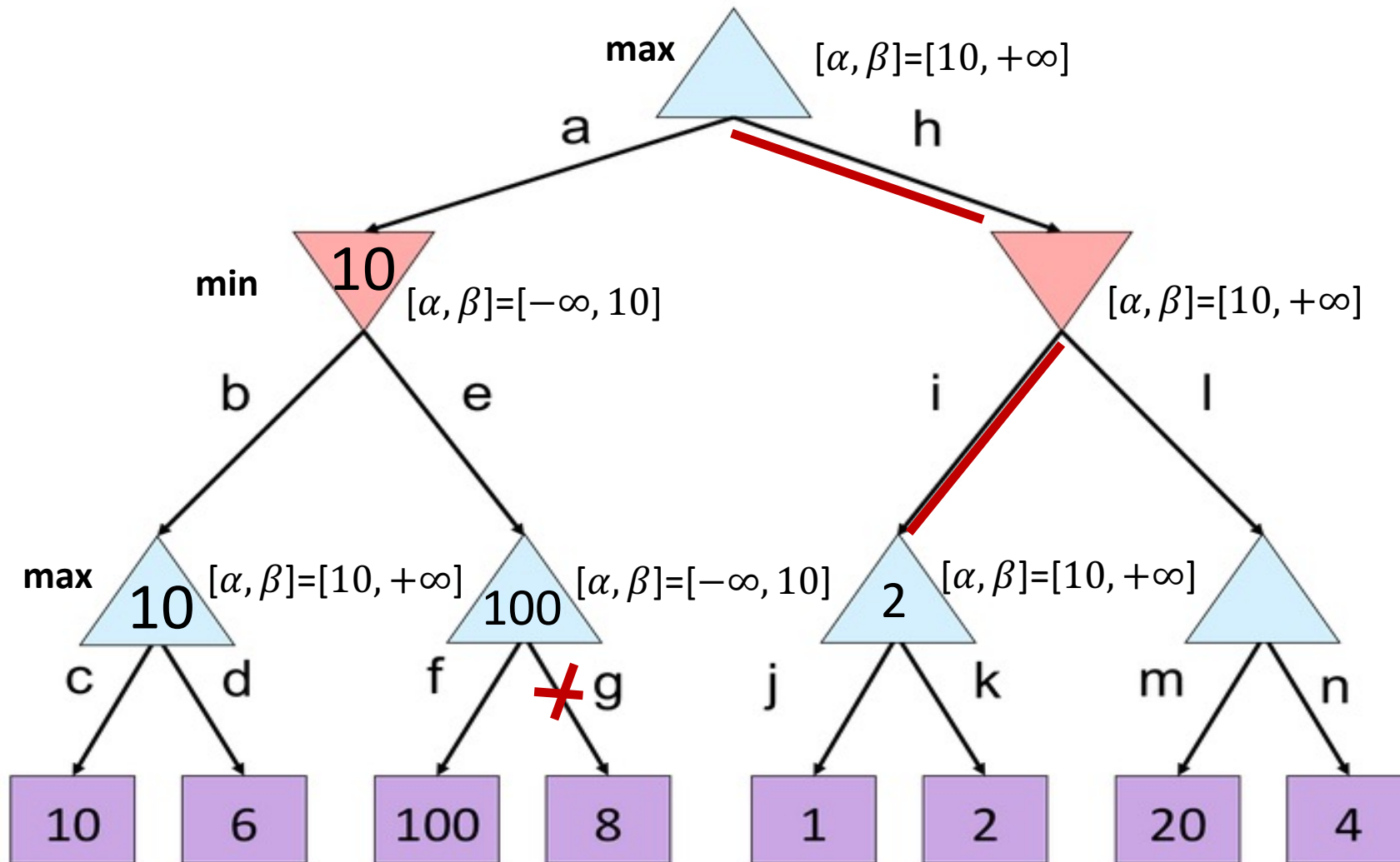
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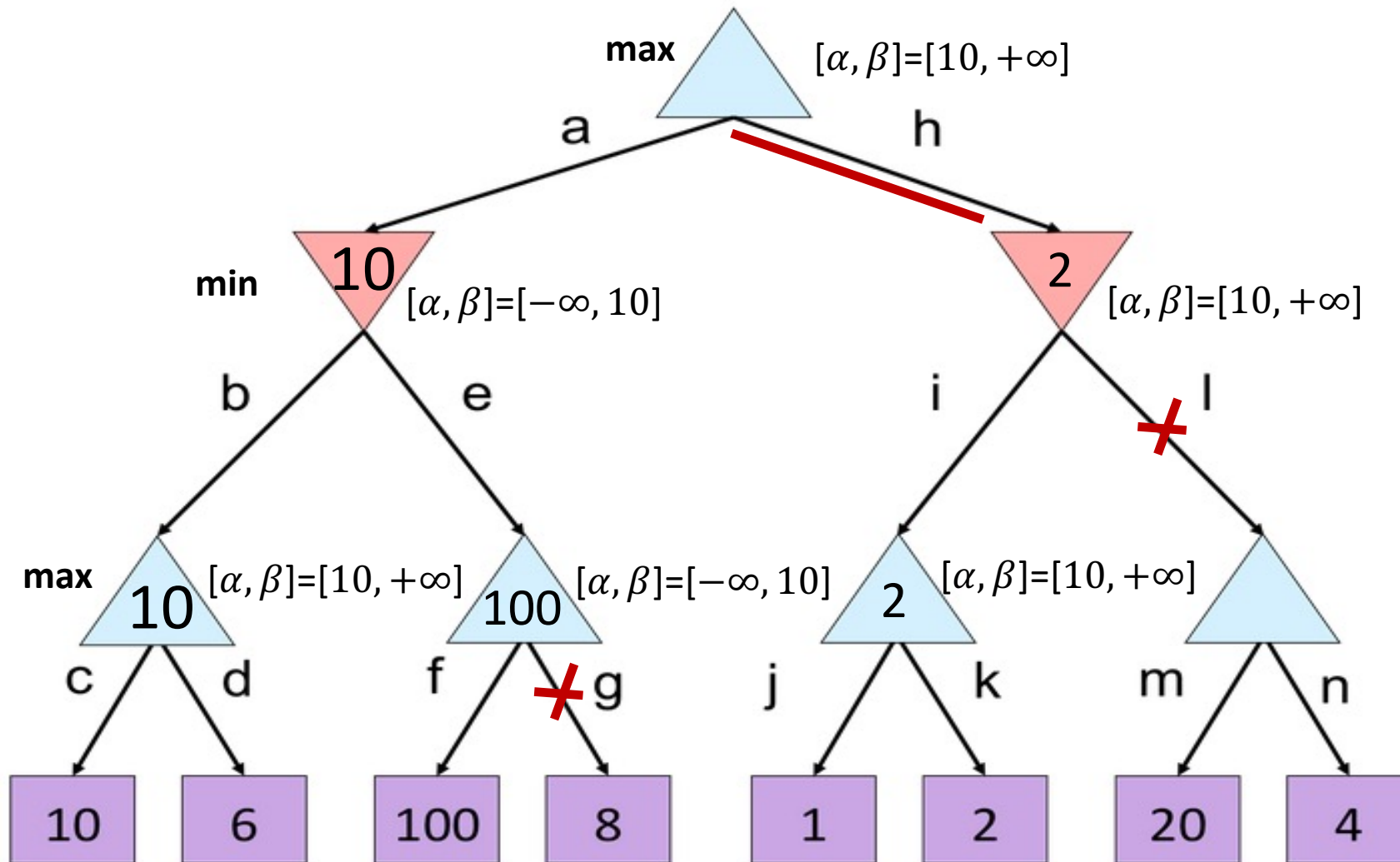
Alpha-Beta Quiz 2



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Alpha-Beta Quiz 2

