

# Game Playing

## *Alpha–Beta Pruning*

# Minimax: Properties

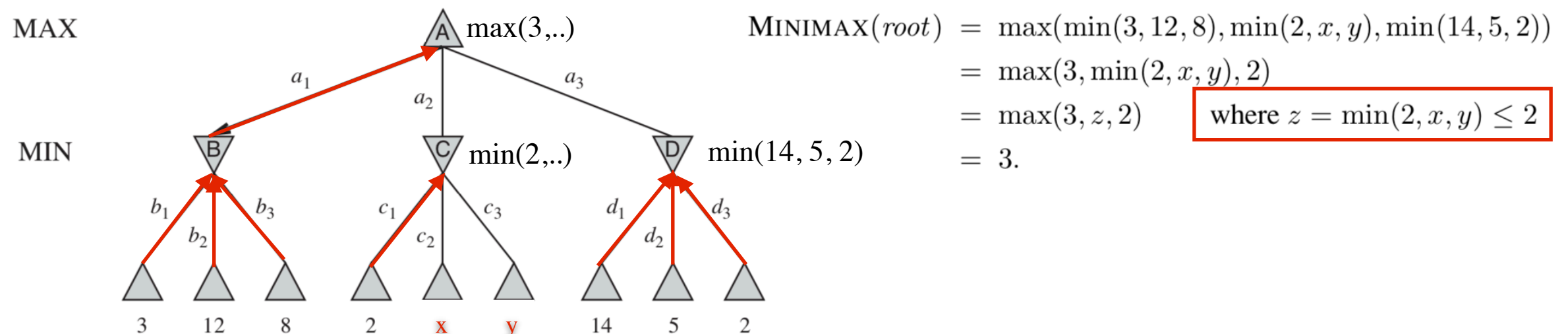
- Depth-first traversal (branching factor  $b$ , depth  $m$ )
- **Complete?** Yes if tree is finite
- **Optimal?** Yes against an optimal opponent
- **Time complexity?**  $O(b^m)$
- **Space complexity?**  $O(bm)$
- Time cost is not practical for real games (Chess:  
 $m \approx 100, b \approx 35$ )

# Minimax Problems

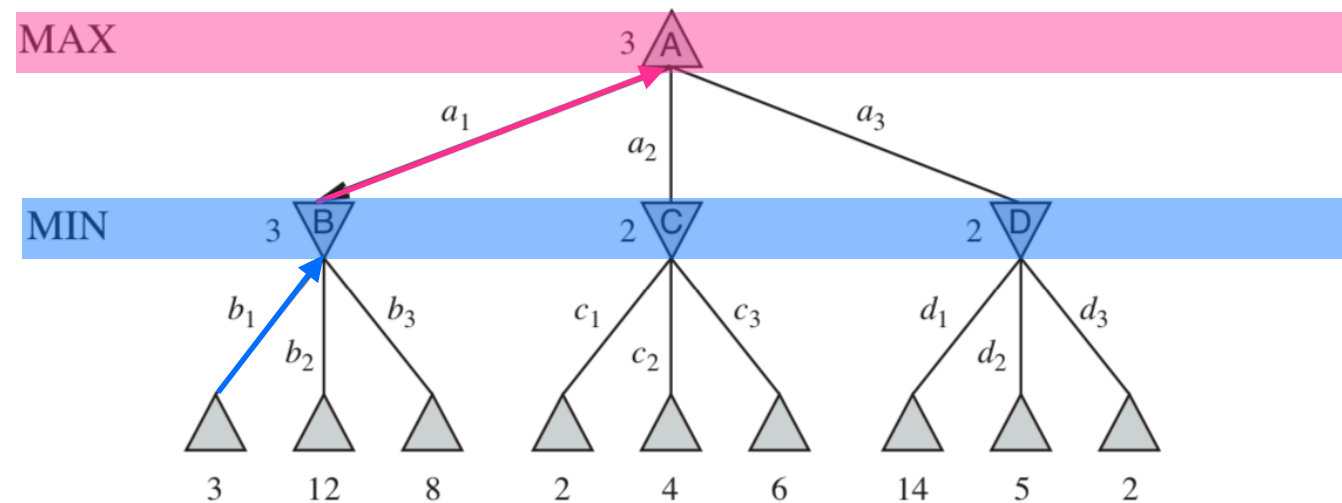
- The number of game states it has to examine is exponential in the depth of the tree
- Can we ignore some nodes?
- Can eliminate large parts of the tree using **pruning**
  - eliminating possibilities from consideration without having to examine them
  - allows us to ignore portions of the search tree that make no difference to the final choice

# Minimax: Are There Shortcuts?

- **Minimax problem:** Number of game states it has to examine is exponential in the depth of the tree
- We can cut it in half by **pruning**, i.e. ignore portions of the search tree that makes ***no difference*** to the final choice (reduce the number of evaluations and branching)
- Calculation of optimal decision by considering what we **already know** at each point in the process could lead to minimax decision without evaluating some nodes
- Remove the nodes that don't have to be evaluated – removing redundancy



# Node Evaluation



- $B \leq 3$  MIN – the biggest value that I can have is 3
- $A \geq 3$  MAX – the smallest value that I can have is 3

# 8. Alpha-Beta Pruning

- Main idea: If Player has a choice to move to node  $n$  for consideration, and if there is already a **better choice** of value for Player from previously processed nodes, then  $n$  can be **ignored**
- Alpha ( $\alpha$ ) is concerning what is the **minimum**,  $\geq$  that I can take (worst-case scenario), i.e. the first player who is trying to maximise the score
- Beta ( $\beta$ ) is concerning what is the **maximum**,  $\leq$  that I have to give (worst-case scenario), i.e. the second player who is trying to minimise the score
- Pruning (termination of the recursive call) happens when the value of the current node is **worse than** the current alpha (Max) or beta (Min)

# Alpha-Beta: Pseudocode

**function** ALPHA-BETA-SEARCH(*state*) **returns** an action  
 $v \leftarrow \text{MAX-VALUE}(\text{state}, -\infty, +\infty)$   
**return** the *action* in ACTIONS(*state*) with value *v*

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**function** MAX-VALUE(*state*,  $\alpha$ ,  $\beta$ ) **returns** a utility value  
**if** TERMINAL-TEST(*state*) **then return** UTILITY(*state*)  
 $v \leftarrow -\infty$   
**for each** *a* **in** ACTIONS(*state*) **do**  
 $v \leftarrow \text{MAX}(v, \text{MIN-VALUE}(\text{RESULT}(s, a), \alpha, \beta))$   
**if**  $v \geq \beta$  **then return** *v*  
 $\alpha \leftarrow \text{MAX}(\alpha, v)$   
**return** *v*

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**function** MIN-VALUE(*state*,  $\alpha$ ,  $\beta$ ) **returns** a utility value  
**if** TERMINAL-TEST(*state*) **then return** UTILITY(*state*)  
 $v \leftarrow +\infty$   
**for each** *a* **in** ACTIONS(*state*) **do**  
 $v \leftarrow \text{MIN}(v, \text{MAX-VALUE}(\text{RESULT}(s, a), \alpha, \beta))$   
**if**  $v \leq \alpha$  **then return** *v*  
 $\beta \leftarrow \text{MIN}(\beta, v)$   
**return** *v*

- 2 main functions with 3 parameters –  
 $s$  (current state),  $\alpha$  (best explored option for Max from root to  $s$ ) and  $\beta$  (best explored option for Min from root to  $s$ ) and an output value,  $v$
- At the start node:
  - **Smallest** value that I can have,  
 $\alpha = -\infty$
  - **Biggest** value that I can have,  
 $\beta = +\infty$
- Keep track of alpha & beta globally and locally (lower and upper bounds)
- $v$  is the value used to manipulate  $\alpha$  and  $\beta$  and it is passed back from the function

# $\alpha - \beta$ Pruning Walkthrough

function **Alpha-Beta-Search**( $s$ ) returns an action  
 $s \leftarrow \text{root}$  # start from root  
 $v \leftarrow \text{Minimax-ab}(s, -\infty, +\infty)$  # initialise alpha and beta  
 return the action in Actions( $s$ ) with value  $v$

function **Minimax-ab**( $s, \alpha, \beta$ ) returns a value  $v$   
 if Terminal-test( $s$ ) then **return** Utility( $s$ ) # base case

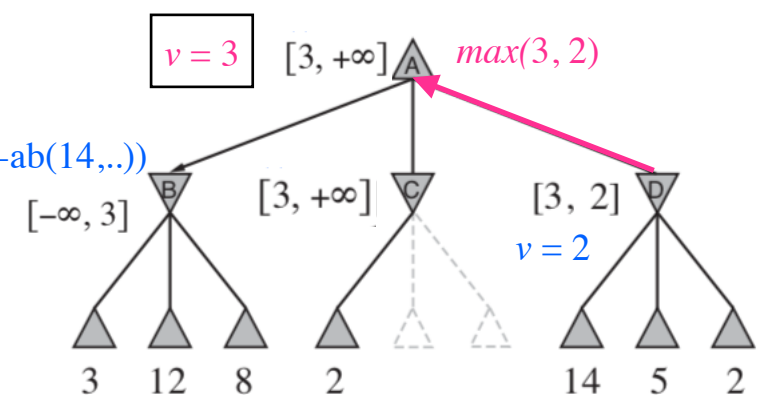
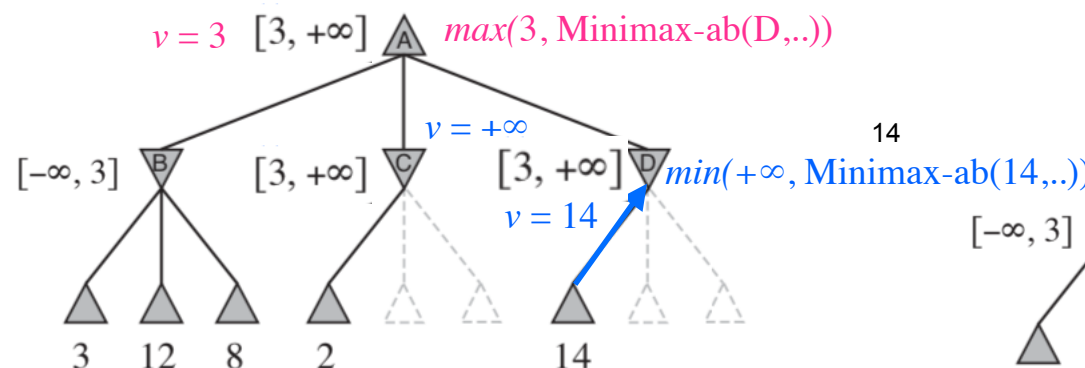
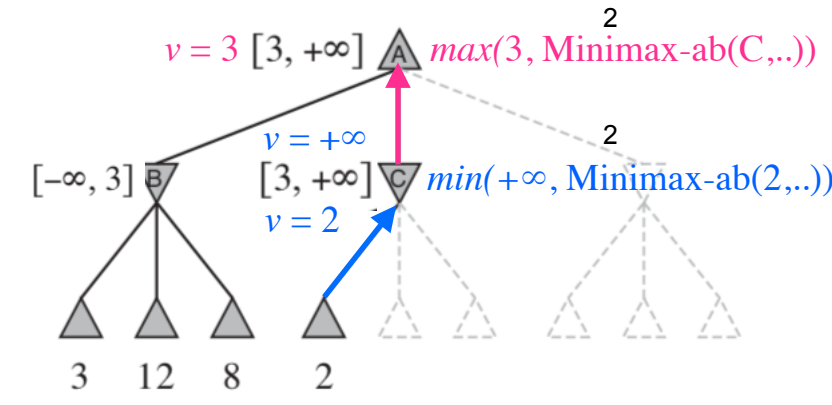
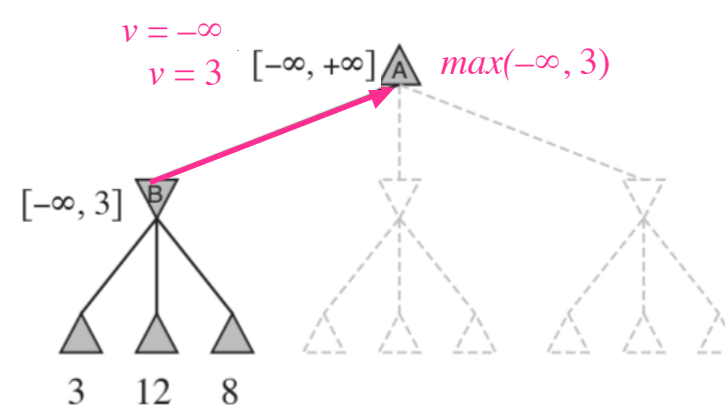
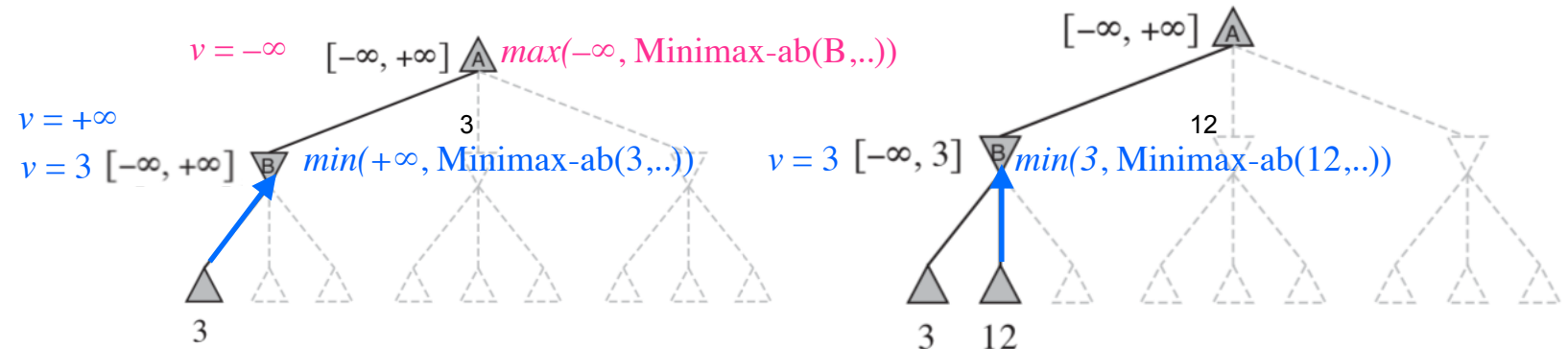
**else if (Player == Max)**

$v \leftarrow -\infty$  # reset  $v$  to  $-\infty$  at every Max Player node  
 for each child,  $c$  of  $s$   
 $v \leftarrow \max(v, \text{Minimax-ab}(c, \alpha, \beta))$   
 if  $v \geq \beta$  then **return**  $v$  # Pruning  
 else  $\alpha \leftarrow \max(\alpha, v)$

**else if (Player == Min)**

$v \leftarrow +\infty$  # reset  $v$  to  $+\infty$  at every Min Player node  
 for each child,  $c$  of  $s$   
 $v \leftarrow \min(v, \text{Minimax-ab}(c, \alpha, \beta))$   
 if  $v \leq \alpha$  then **return**  $v$  # Pruning  
 else  $\beta \leftarrow \min(\beta, v)$

**return**  $v$





# Alpha-beta Pruning Points

- $\alpha$  and  $\beta$  are **inherited** from the parent and they are manipulated locally at the current node for its own use
  - but they are not passed back up. Only  $v$  is passed back up (via return)
- At every node,  $v$  is **reset** to  $-\infty$  if it is the node is a Max player or  $+\infty$  if it is a Min Player
- At **Max**, **pruning** happens when  $v$  is **bigger than  $\beta$**  – Min Player above will ignore this path because it is worse (bigger) than the best that they have so far,  $\beta$
- At **Min**, **pruning** happens when  $v$  is **smaller than  $\alpha$**  – Max Player above will ignore this path because it is worse (smaller) than the best they have so far,  $\alpha$

# Alpha–Beta: Properties

- Pruning does not affect final result
- Good move ordering improves effectiveness of pruning
- With perfect ordering, time complexity =  $O(b^{\frac{m}{2}})$ 
  - ➔ doubles solvable depth
  - ➔ can easily reach depth 8 and play good chess

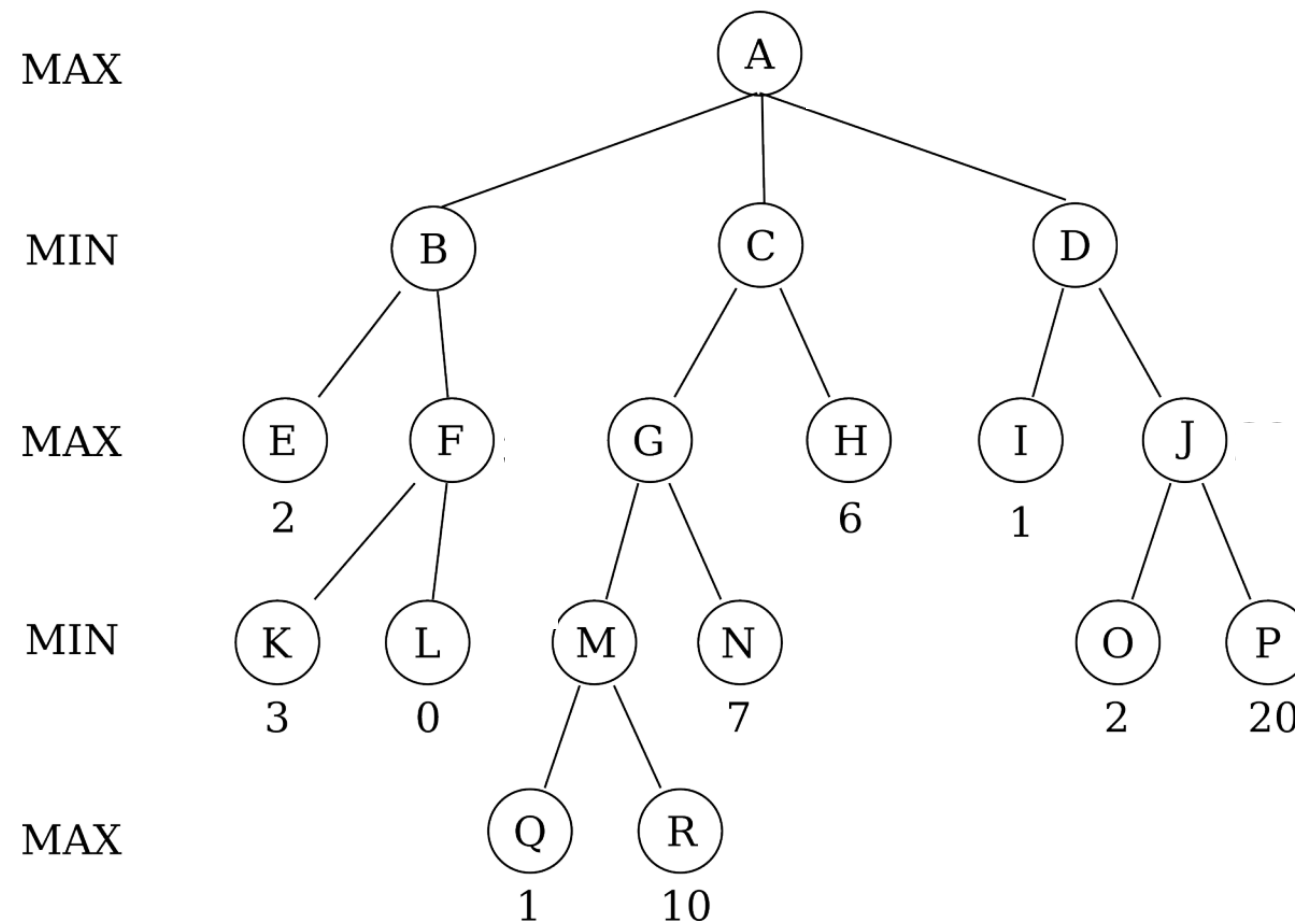
# Summary

- Game playing as adversarial search
  - zero-sum games
  - utility values
- Search in games with perfect information:
  - Minimax
  - Alpha-beta pruning
    - ➔ Alpha-Beta has been used by popular programs like Deep Blue to efficiently play against Chess Grandmasters

# References

- Russel and Norvig, Chapter 5, until 5.3
- J. Schrum, Alpha-beta pruning intuition [[Video](#)]
- S. Kambhapati, Alpha-beta intuition [[Video](#)]
- Historical reading:
  - Computer considers possible lines of play (Babbage, 1846)
  - Algorithm for perfect play (Zermelo, 1912; Von Neumann 1944)
  - Finite horizon, approximate evaluation (Zuse, 1945; Wiener, 1948; Shannon 1950)
  - First chess program (Turing, 1950)
  - Machine learning to improve evaluation accuracy (Samuel, 1952–57)
  - Pruning to allow deeper search (McCarthy, 1956)

# Exercise: $\alpha - \beta$ Pruning



- Order the evaluations by nodes and  $\alpha$ ,  $\beta$  and  $v$  values
- First step:
  1.  $A : \alpha = -\infty, \beta = +\infty, v = -\infty$

function **Alpha-Beta-Search**( $s$ ) returns an action  
 $s \leftarrow \text{root}$  # start from root  
 $v \leftarrow \text{Minimax-ab}(s, -\infty, +\infty)$  # initialise alpha and beta  
 return the action in  $\text{Actions}(s)$  with value  $v$

function **Minimax-ab**( $s, \alpha, \beta$ ) returns a value  $v$   
 if  $\text{Terminal-test}(s)$  then **return**  $\text{Utility}(s)$  # base case

**else if** ( $\text{Player} == \text{Max}$ )

$v \leftarrow -\infty$  # reset  $v$  to  $-\infty$  at every Max Player node

for each child,  $c$  of  $s$

$v \leftarrow \max(v, \text{Minimax-ab}(c, \alpha, \beta))$

if  $v \geq \beta$  then **return**  $v$  # Pruning

else  $\alpha \leftarrow \max(\alpha, v)$

**else if** ( $\text{Player} == \text{Min}$ )

$v \leftarrow +\infty$  # reset  $v$  to  $+\infty$  at every Min Player node

for each child,  $c$  of  $s$

$v \leftarrow \min(v, \text{Minimax-ab}(c, \alpha, \beta))$

if  $v \leq \alpha$  then **return**  $v$  # Pruning

else  $\beta \leftarrow \min(\beta, v)$

**return**  $v$

