

Princess Nora University  
Faculty of Computer & Information Systems



جامعة الأميرة نورة بنت عبد الرحمن  
Princess Nora Bint Abdul Rahman University

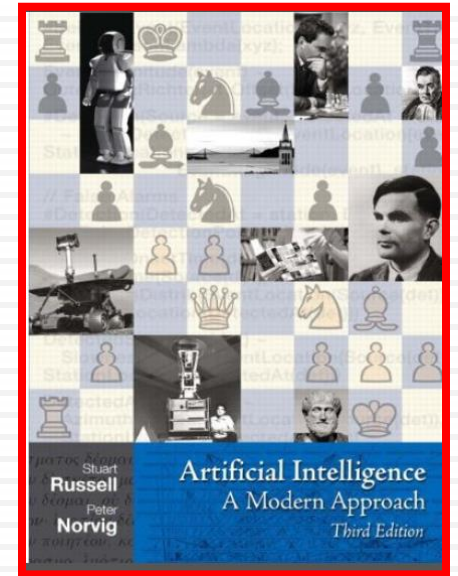


# ARTIFICIAL INTELLIGENCE

## (CS 370D)



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## (CHAPTER-5) ADVERSARIAL SEARCH



# ADVERSARIAL SEARCH

- Optimal decisions
- MinMax algorithm
- $\alpha$ - $\beta$  pruning
- Imperfect, real-time decisions





# ADVERSARIAL SEARCH



## ➤ Search problems seen so far:

- ✓ Single agent.
- ✓ No interference from other agents and no competition.

## ➤ Game playing:

- ✓ Multi-agent environment.
- ✓ Cooperative games.
- ✓ Competitive games → **adversarial search**

## ➤ Specifics of adversarial search:

- ✓ Sequences of player's decisions we control.
- ✓ Decisions of other players we do not control.





# Games vs. search problems

- "Unpredictable" opponent → specifying a move for every possible opponent reply
- Time limits → unlikely to find goal, must approximate





# Game as Search Problem

## MinMax Algorithm





# Game setup

- Consider a game with Two players: **(Max)** and **(Min)**
- **Max** moves first and they take turns until the game is over. Winner gets award, loser gets penalty.
- **Games as search:**
  - **Initial state:** e.g. board configuration of chess
  - **Successor function:** list of (move, state) pairs specifying legal moves.
  - **Goal test:** Is the game finished?
  - **Utility function:** Gives numerical value of terminal states. E.g. win (+1), lose (-1) and draw (0) in tic-tac-toe



**Max** uses **search tree** to determine next move.





# Example of an ADVERSARIAL two player Game

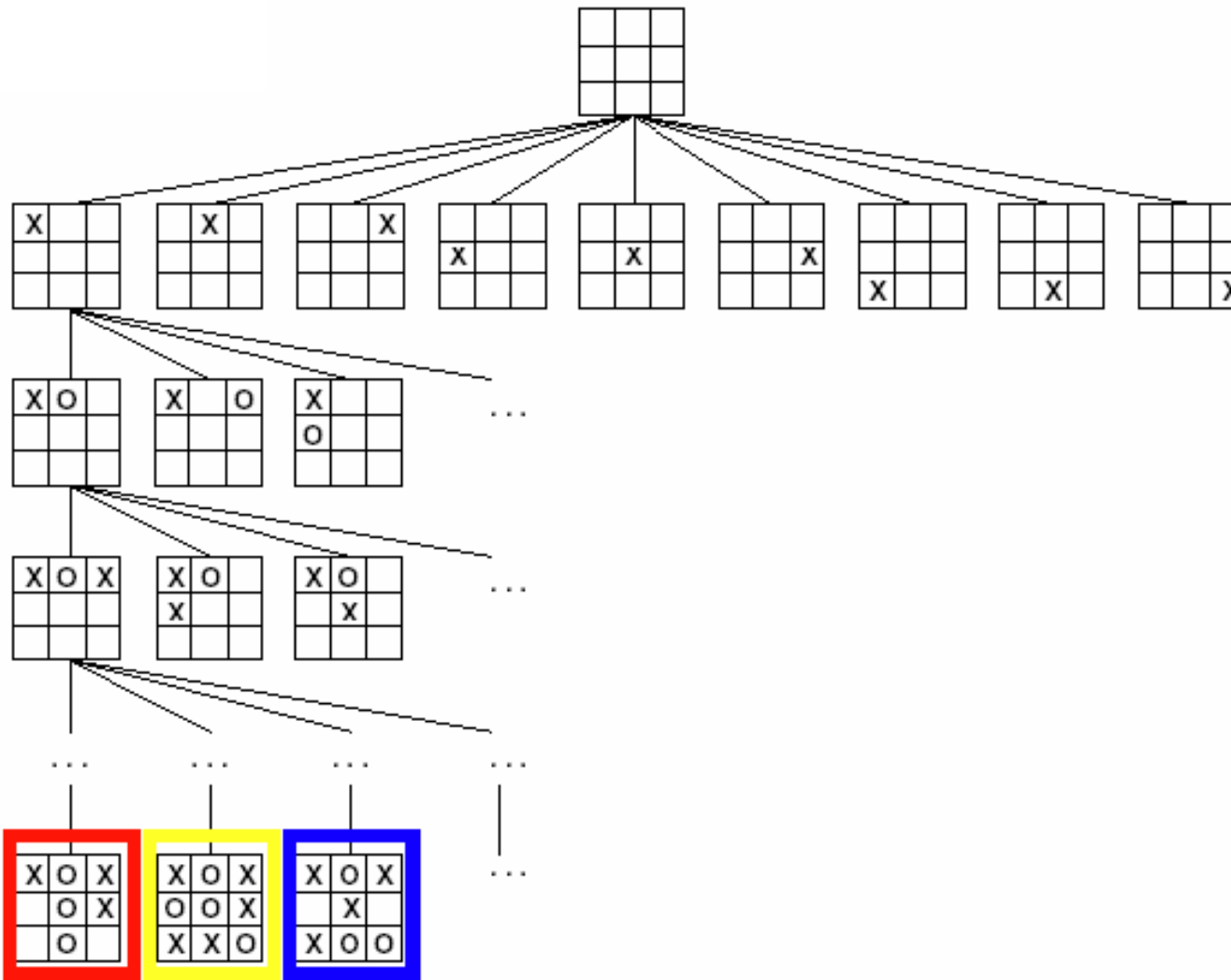
## Tic-Tac-Toe (TTT)

- MAX has 9 possible first moves, etc.
- Utility value is always from the point of view of MAX.
- High values good for MAX and bad for MIN.





# Example of an adversarial 2 person game: Tic-tac-toe



**Loss**   **Draw**   **Win**





# How to Play a Game by Searching

## □ General Scheme

- Consider all legal moves, each of which will lead to some new state of the environment ('board position')
- **Evaluate** each possible resulting board position
- Pick the move which leads to the best board position.
- Wait for your opponent's move, then **repeat**.

## □ Key problems

- Representing the 'board'
- Representing legal next boards
- Evaluating positions
- Looking ahead



# Game Trees



- Represent the problem space for a game by a tree
  - ❖ **Nodes** represent 'board positions' (state)
  - ❖ **edges** represent legal moves.
  
- **Root node** is the position in which a decision must be made.
  
- **Evaluation function  $f$**  assigns real-number scores to 'board positions.'



**Terminal nodes (leaf)** represent ways the game could end, labeled with the desirability of that ending (e.g. win/lose/draw or a numerical score)





## MAX & MIN Nodes

- When **I** move, I attempt to **MAXimize** my performance.
- When my opponent moves, he attempts to **MINimize** my performance.

### TO REPRESENT THIS:

- If we move first, label the root **MAX**; if our opponent does, label it **MIN**.
- **Alternate** labels for each successive tree level.
  - if the root (level 0) is our turn (**MAX**), all even levels will represent turns for us (**MAX**), and all odd ones turns for our opponent (**MIN**).





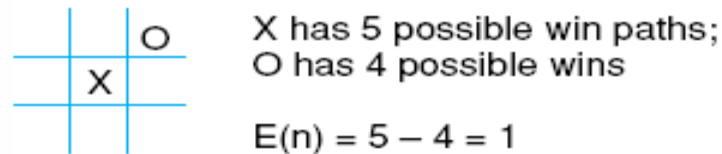
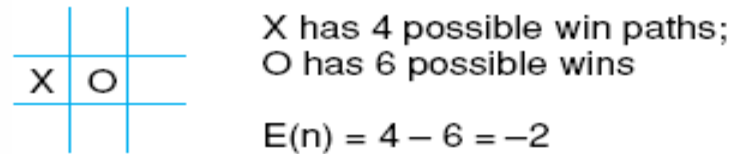
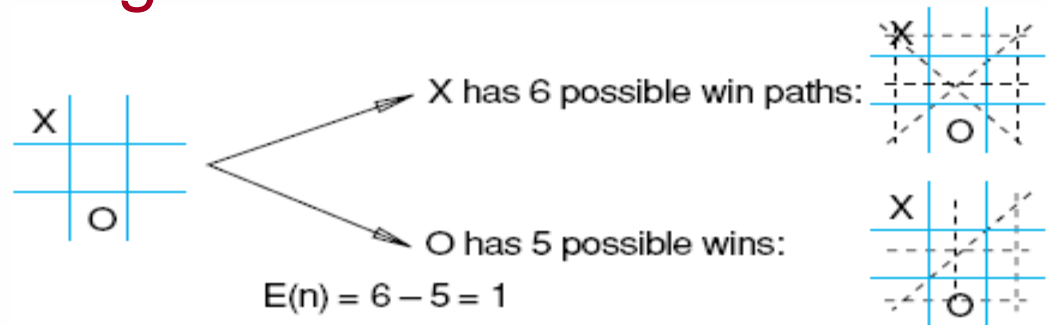
# Evaluation functions

- Evaluations how good a ‘board position’ is
  - ▣ Based on **static features** of that board alone
- **Zero-sum** assumption lets us use **one function** to describe goodness for both players.
  - ▣  $f(n) > 0$  if we are winning in position  $n$
  - ▣  $f(n) = 0$  if position  $n$  is tied
  - ▣  $f(n) < 0$  if our opponent is winning in position  $n$
- Build using expert knowledge (**Heuristic**),
  - ▣ Tic-tac-toe:  $f(n) = (\# \text{ of } 3 \text{ lengths possible for me}) - (\# \text{ } 3 \text{ lengths possible for you})$





# Heuristic measuring for adversarial tic-tac-toe



Heuristic is  $E(n) = M(n) - O(n)$

where  $M(n)$  is the total of My possible winning lines

$O(n)$  is total of Opponent's possible winning lines

$E(n)$  is the total Evaluation for state  $n$

$E(n) = 0$  when my opponent and I have equal number of possibilities.

Maximize  $E(n)$





# MinMax Algorithm

- **Main idea:** choose move to position with highest minimax value. = best achievable payoff against best play.
- E.g., 2-ply game:





# MinMax Algorithm

**function** MINIMAX-DECISION(*state*) *returns an action*

$v \leftarrow \text{MAX-VALUE}(\textit{state})$

**return** the *action* in SUCCESSORS(*state*) with value *v*

---

**function** MAX-VALUE(*state*) *returns a utility value*

**if** TERMINAL-TEST(*state*) **then return** UTILITY(*state*)

$v \leftarrow -\infty$

**for** *a, s* in SUCCESSORS(*state*) **do**

$v \leftarrow \text{MAX}(v, \text{MIN-VALUE}(s))$

**return** *v*

---

**function** MIN-VALUE(*state*) *returns a utility value*

**if** TERMINAL-TEST(*state*) **then return** UTILITY(*state*)

$v \leftarrow \infty$

**for** *a, s* in SUCCESSORS(*state*) **do**

$v \leftarrow \text{MIN}(v, \text{MAX-VALUE}(s))$

**return** *v*





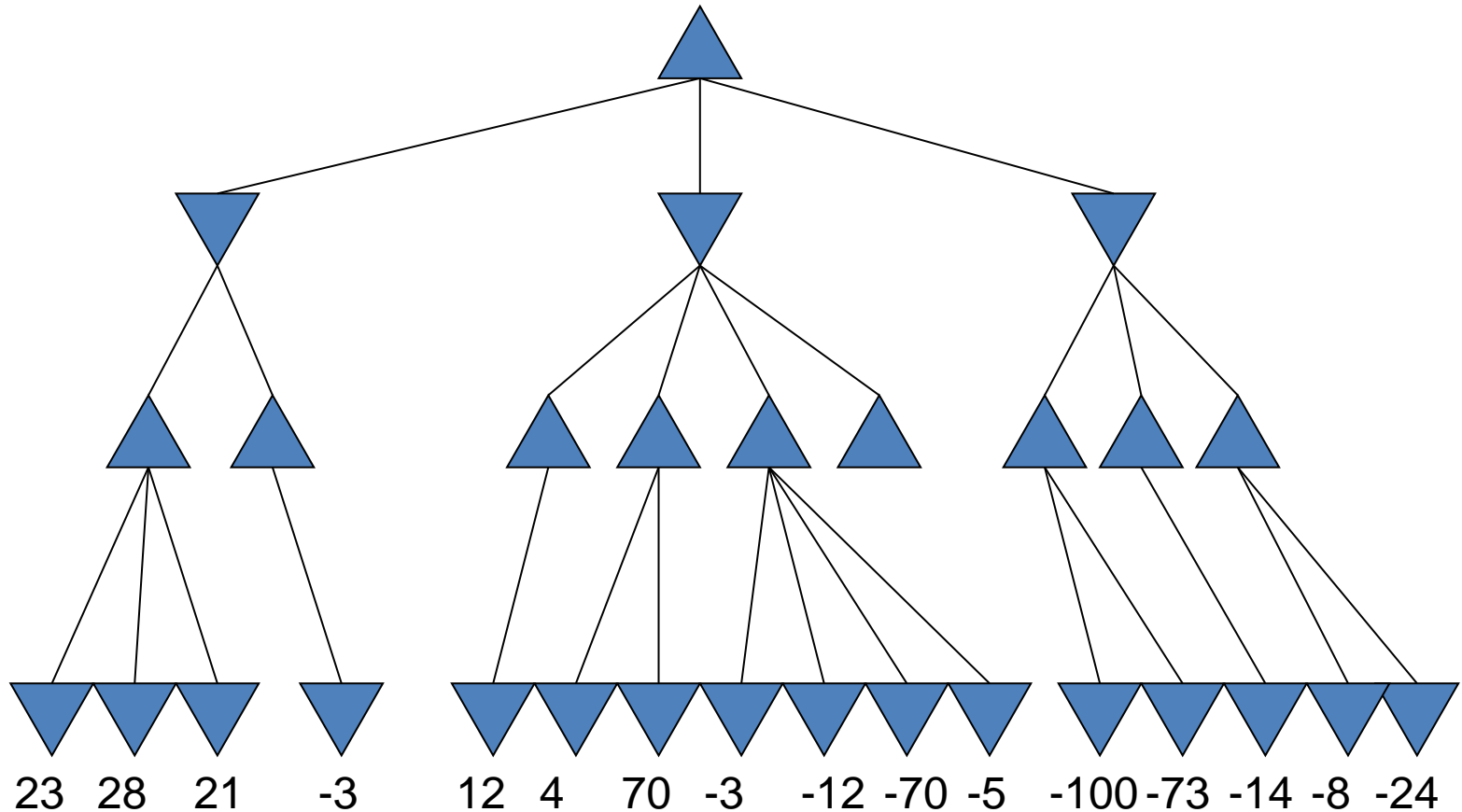
# Minimax tree

Max

Min

Max

Min





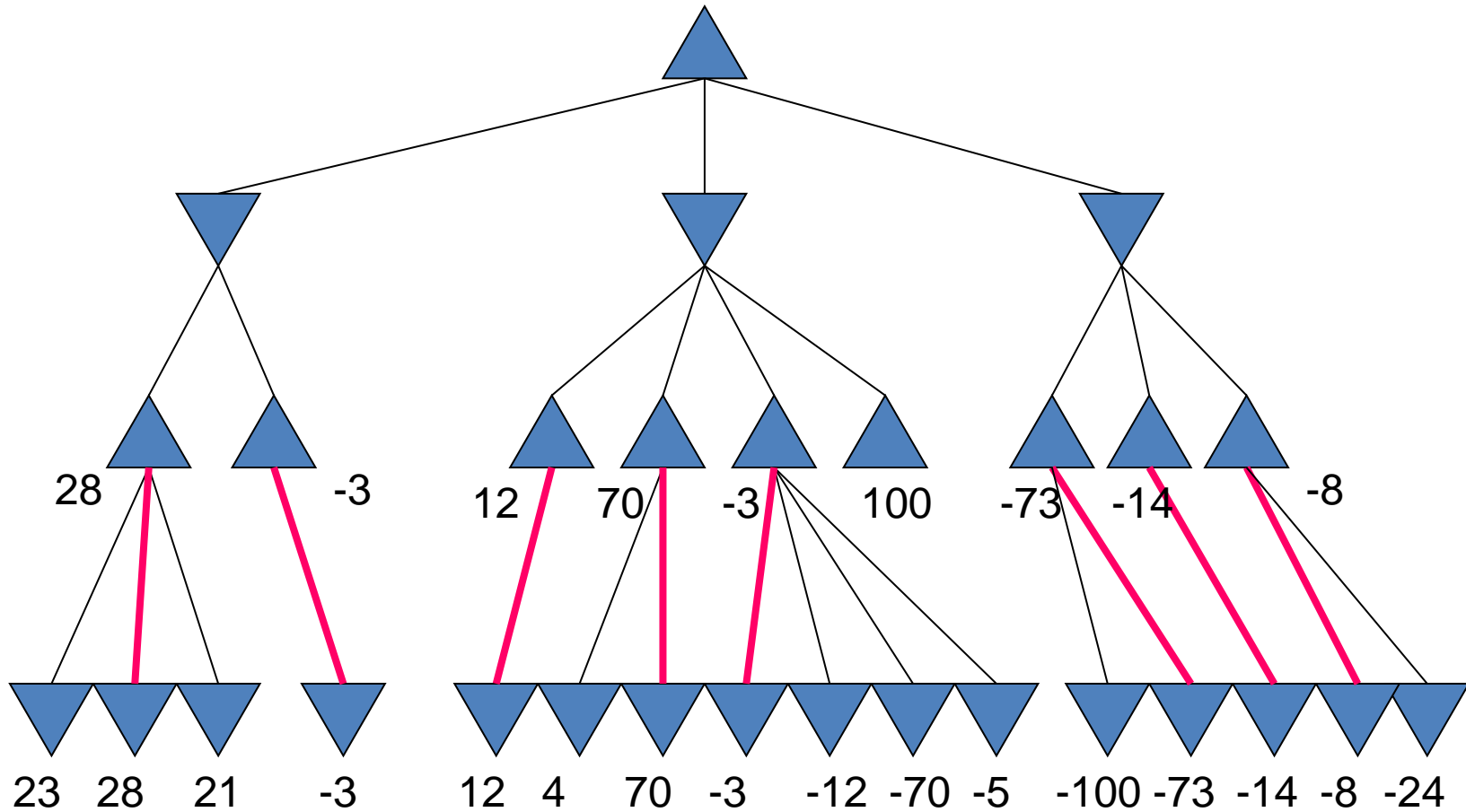
# Minimax tree

Max

Min

Max

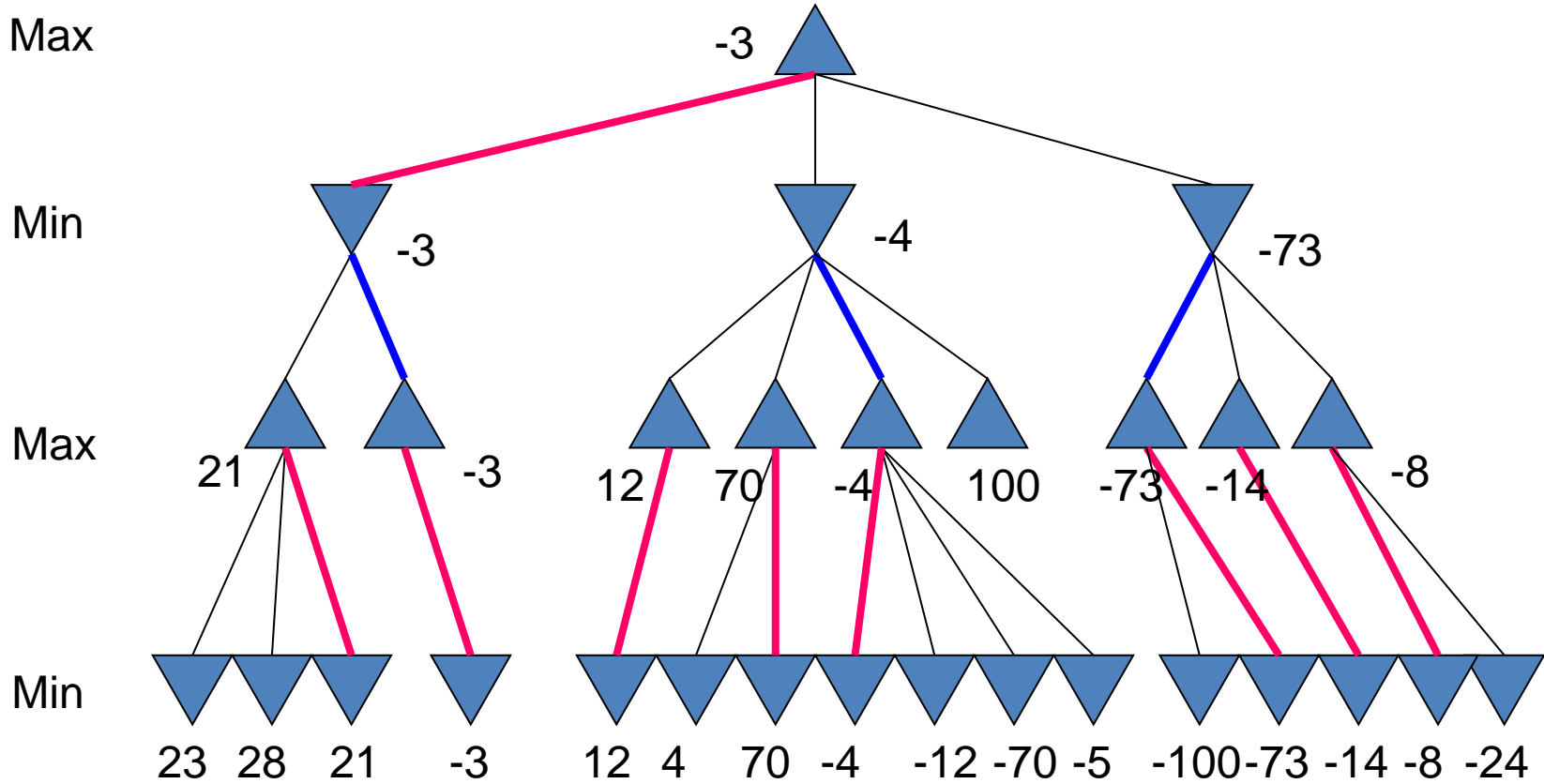
Min





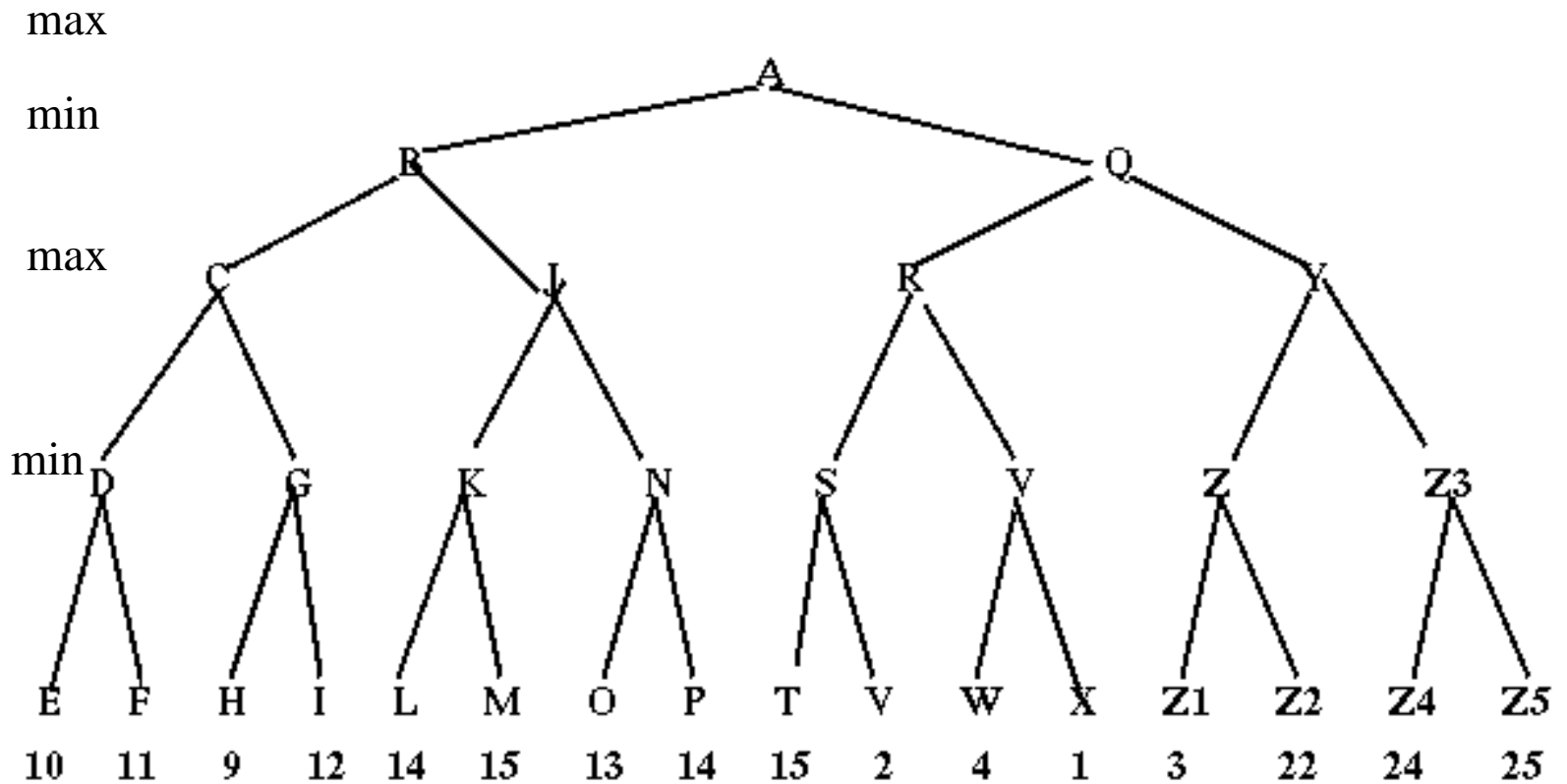


# Minimax tree



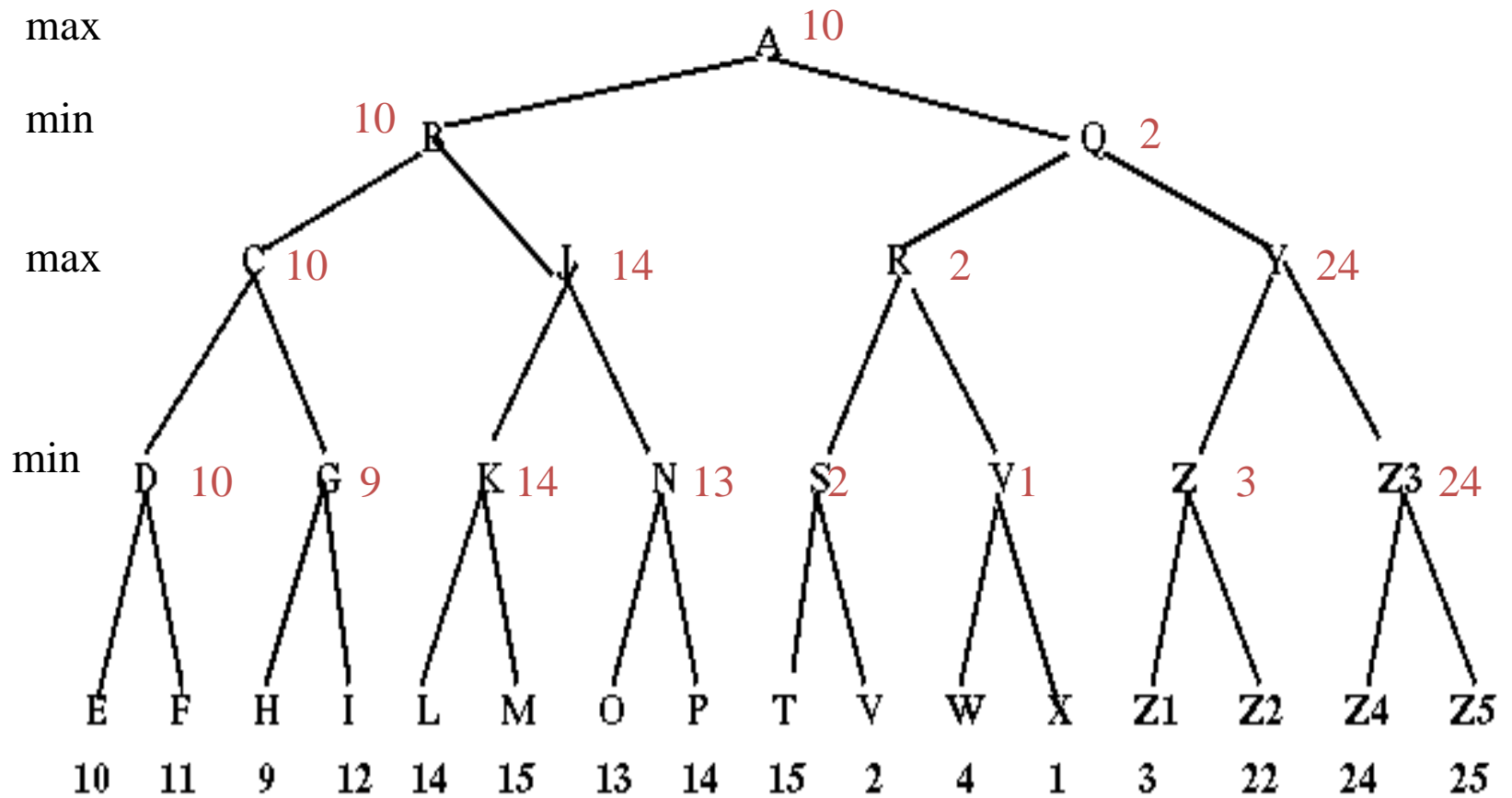


# Minimax





# Minimax





# MinMax Analysis

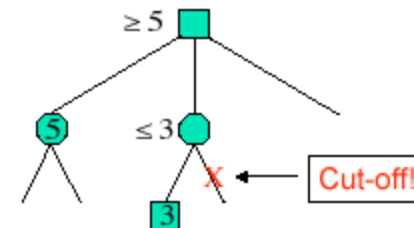
- Time Complexity:  $O(b^d)$
- Space Complexity:  $O(b*d)$
- Optimality: Yes

**Problem: Game  $\rightarrow$  Resources Limited!**

□ Time to make an action is limited

Some nodes in the search can be *proven* to be irrelevant to the outcome of the search

- Can we do better ? Yes !
- How ? Cutting useless branches !





# $\alpha$ Cuts

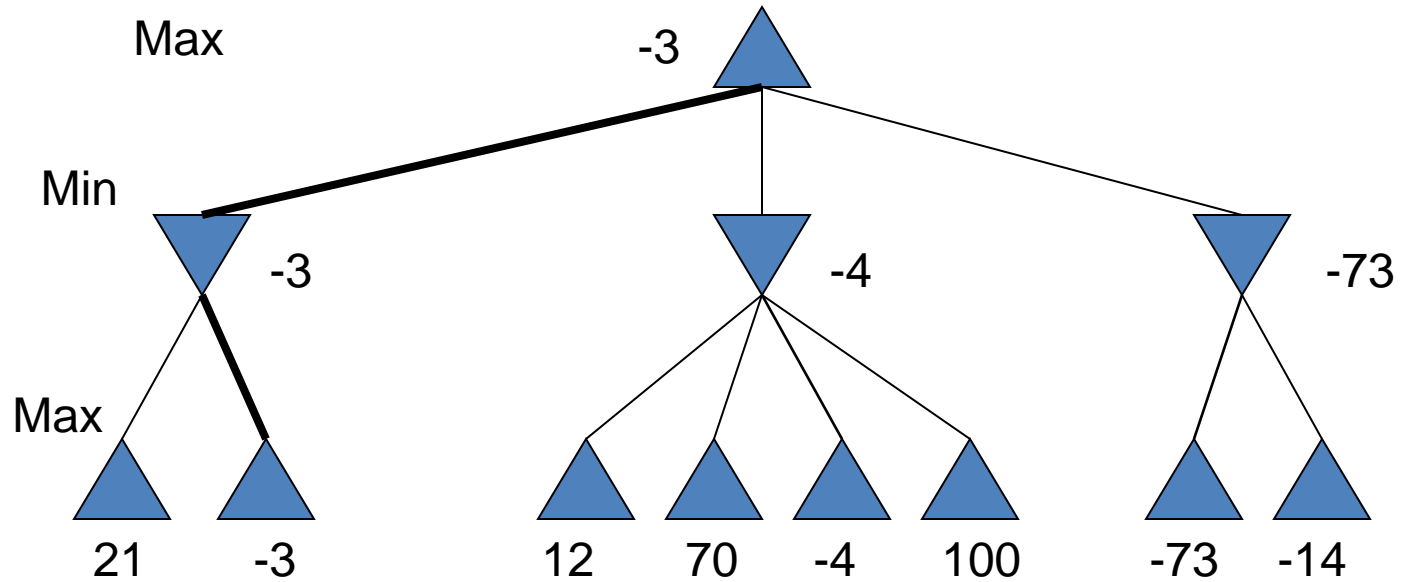
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- If the **current max** value is greater than the successor's min value, **don't** explore that min subtree any more



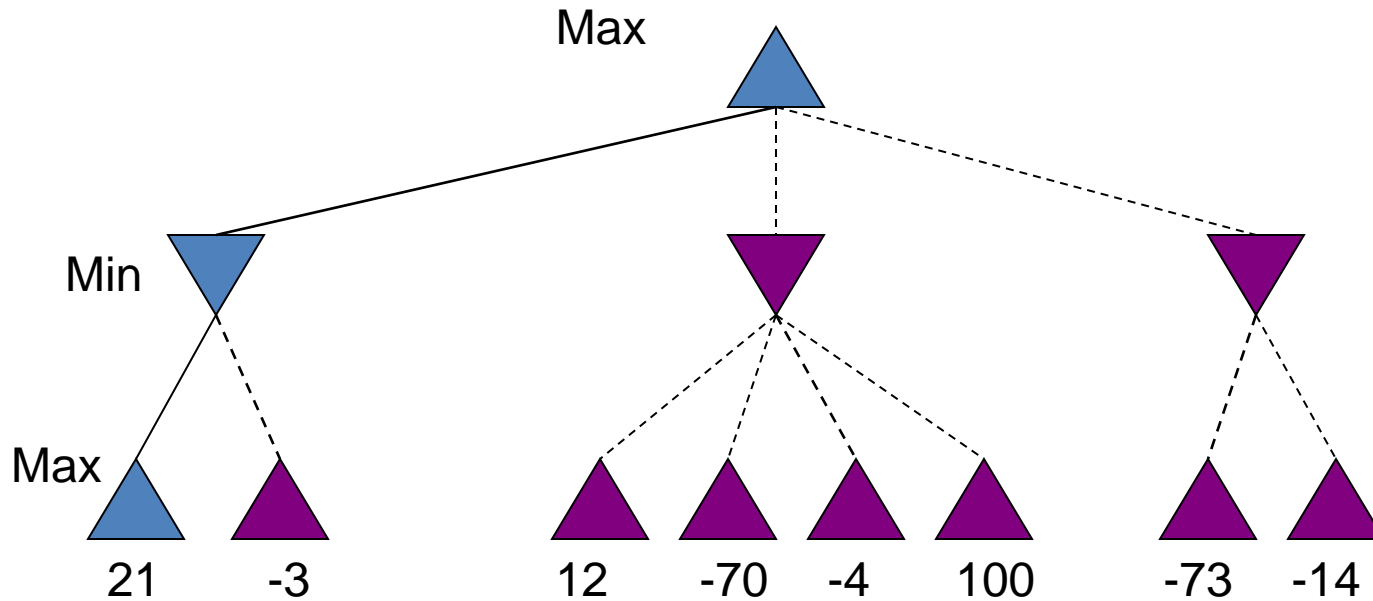


# $\alpha$ Cut example





# $\alpha$ Cut example

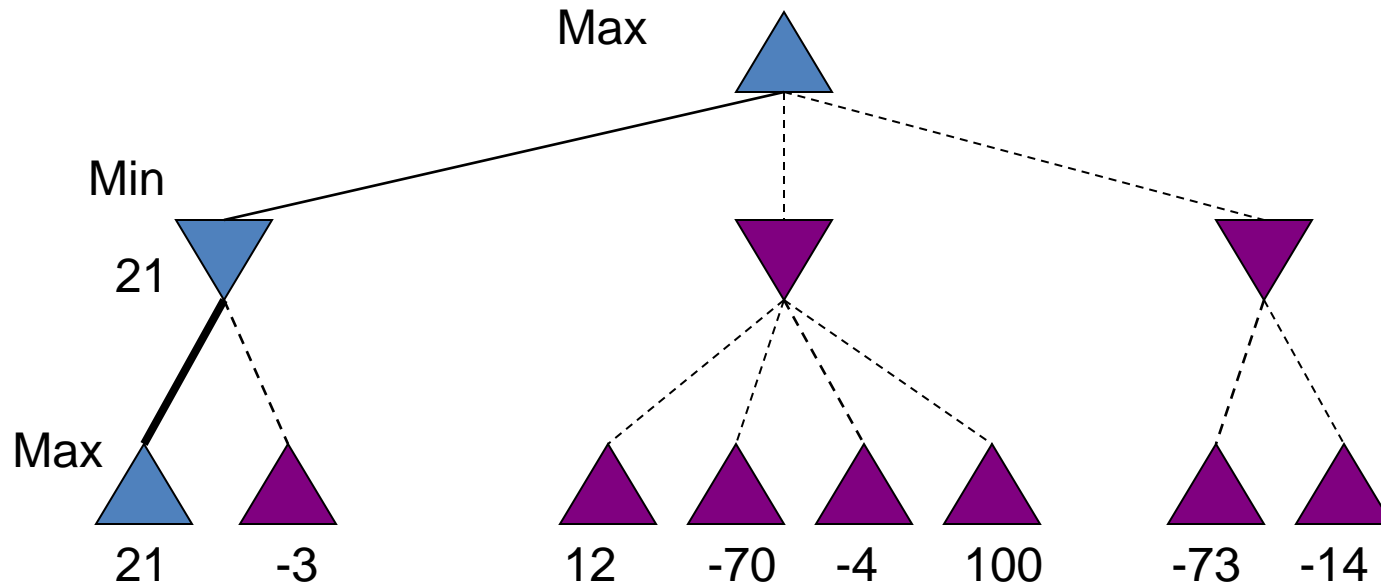


- Depth first search along path 1





# $\alpha$ Cut example



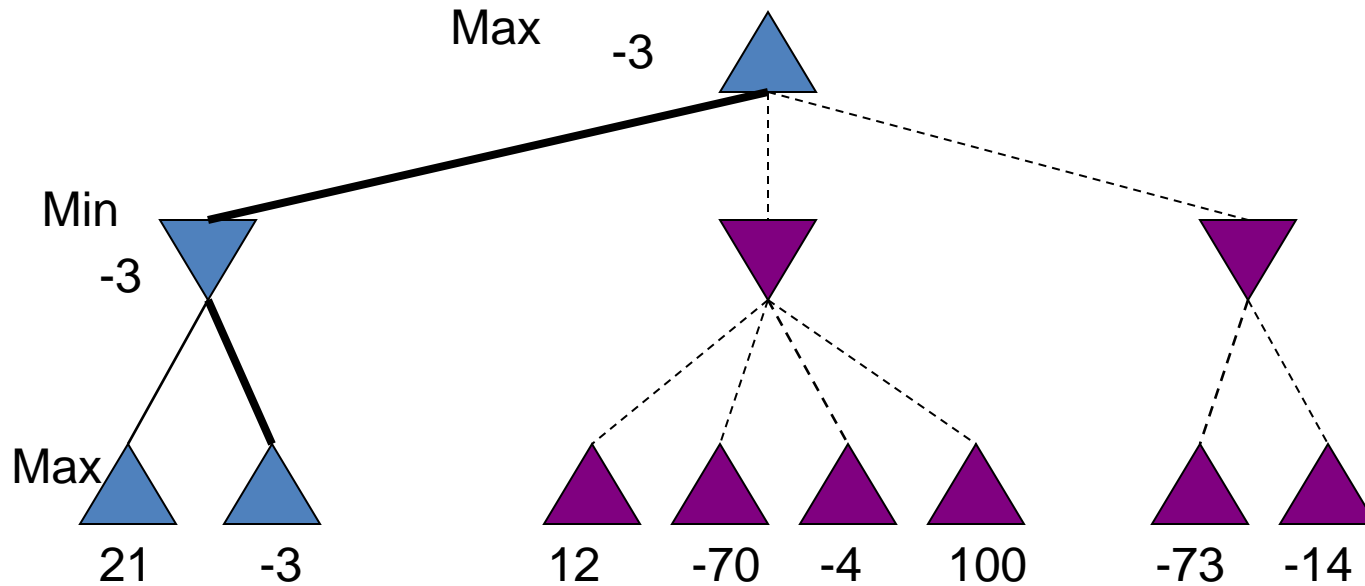
- 21 is minimum so far (second level)
- Can't evaluate yet at top level





# $\alpha$ Cut example

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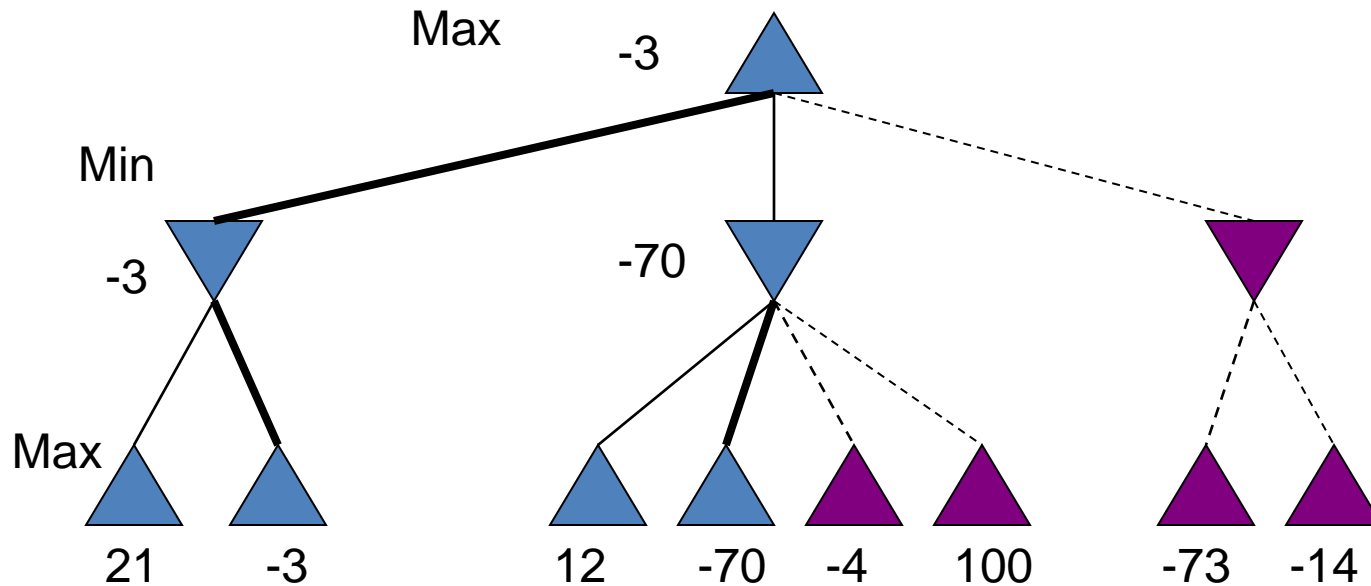


- -3 is minimum so far (second level)
- -3 is maximum so far (top level)





# $\alpha$ Cut example

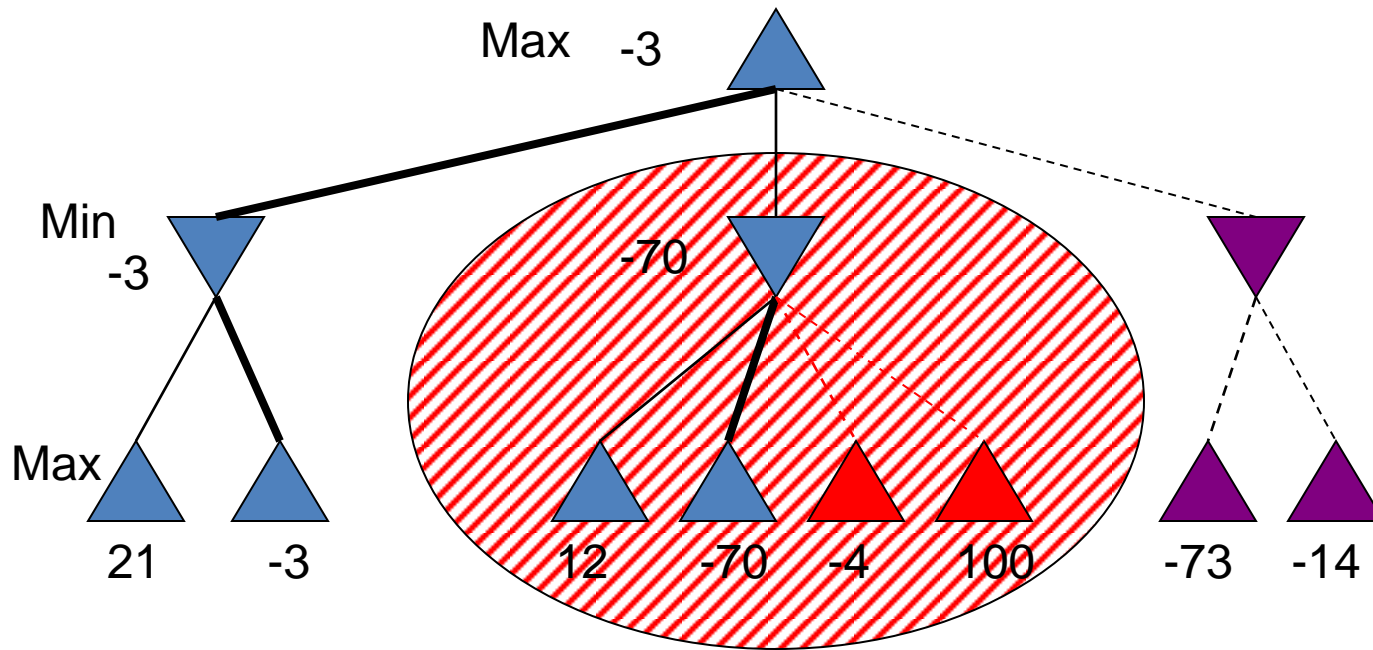


- -70 is now minimum so far (second level)
- -3 is still maximum (can't use second node yet)





# $\alpha$ Cut example

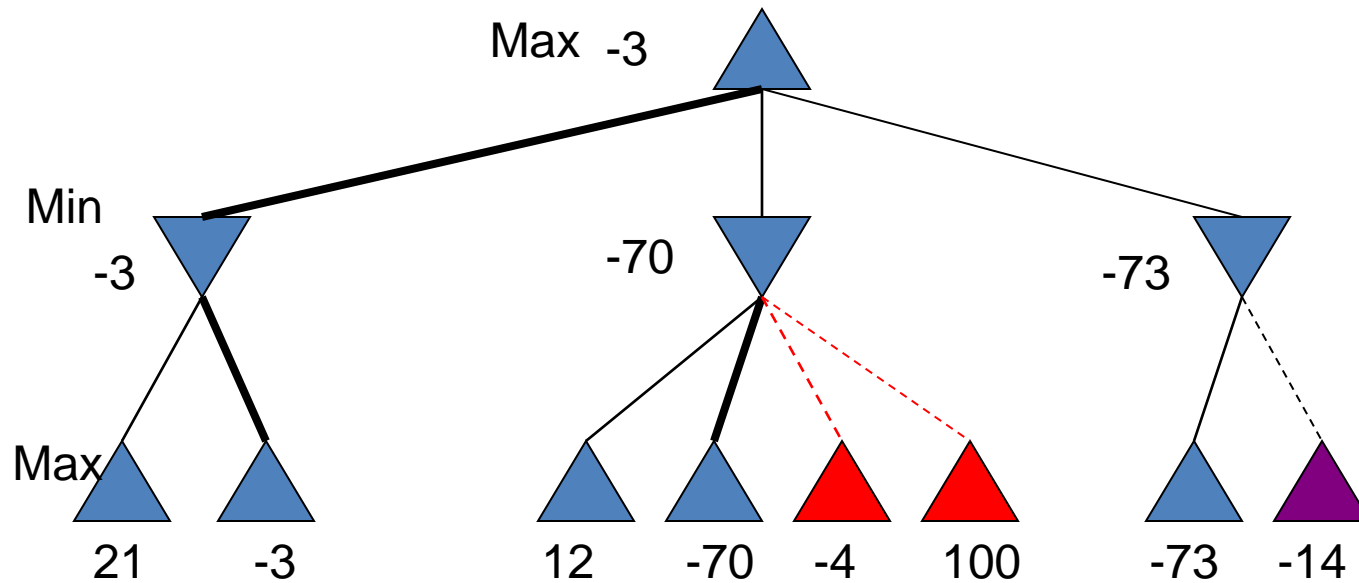


- Since second level node will never be  $> -70$ , it will never be chosen by the previous level
- We can stop exploring that node





# $\alpha$ Cut example

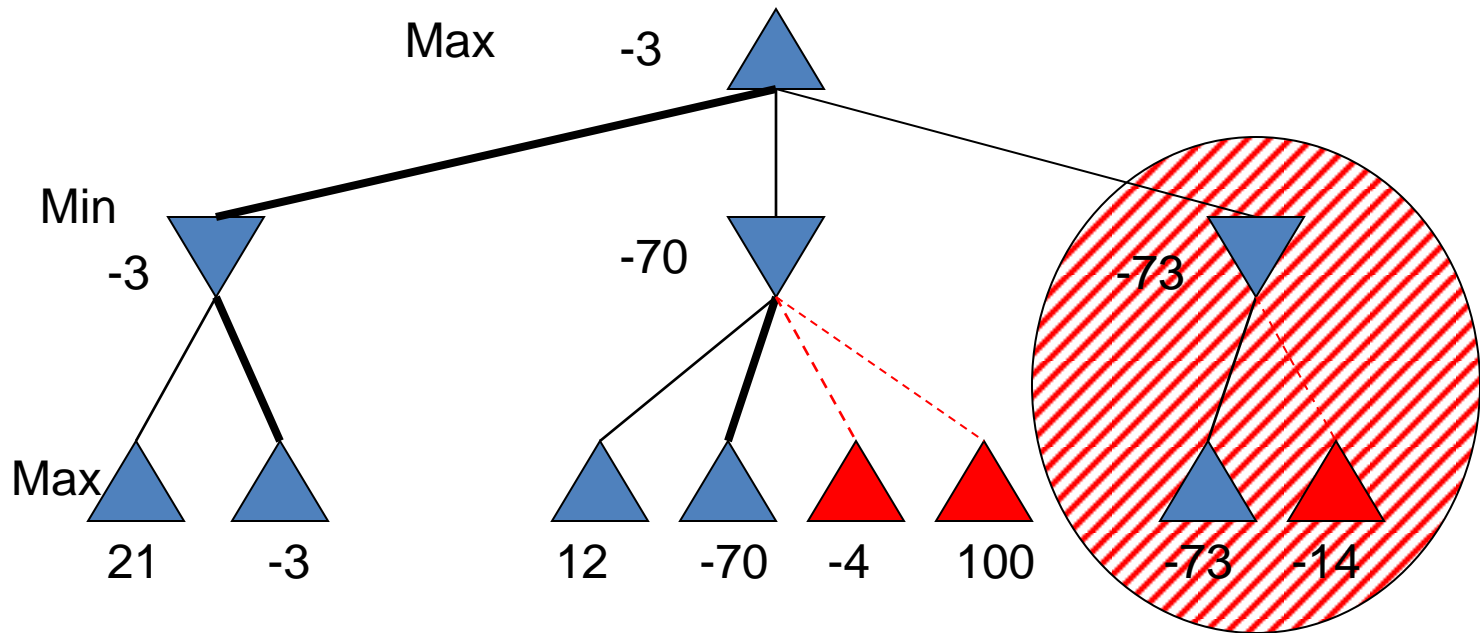


- Evaluation at second level is -73





# $\alpha$ Cut example

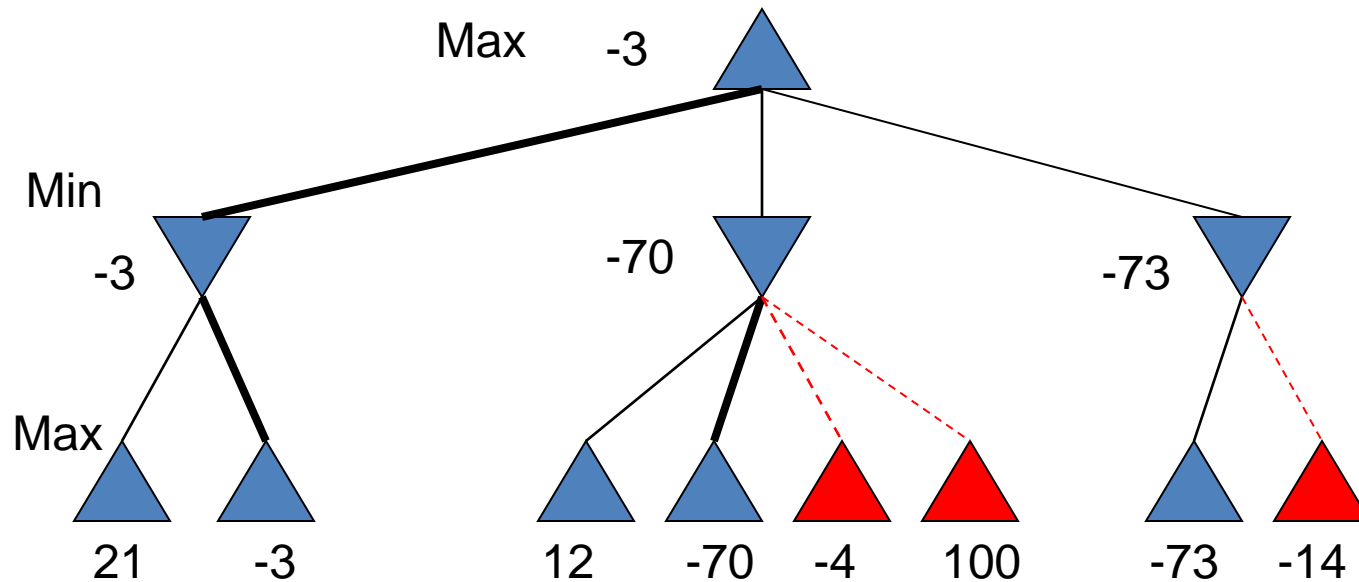


- Again, can apply  $\alpha$  cut since the second level node will never be  $> -73$ , and thus will never be chosen by the previous level





# $\alpha$ Cut example



- As a result, we evaluated the Max node without evaluating several of the possible paths





# $\beta$ cuts

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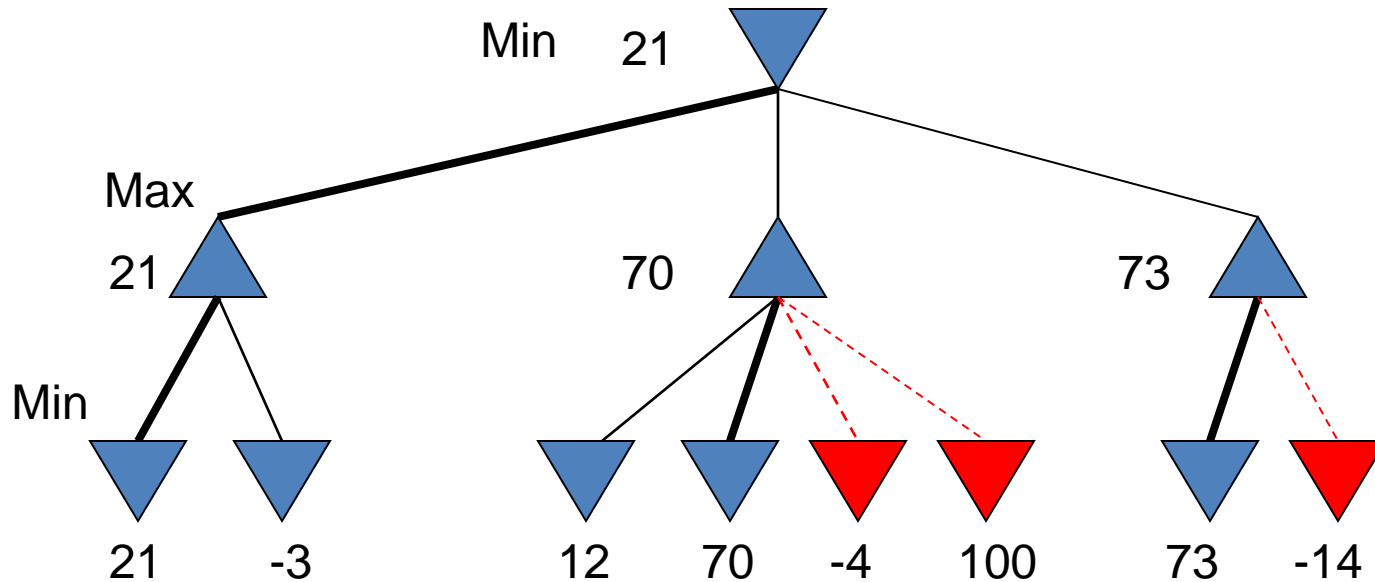
- Similar idea to  $\alpha$  cuts, but the other way around
- If the current minimum is less than the successor's max value, don't look down that max tree any more





# $\beta$ Cut example

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- Some subtrees at second level already have values  $>$  min from previous, so we can stop evaluating them.





# $\alpha$ - $\beta$ Pruning

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- Pruning by these cuts does not affect final result
  - ▣ May allow you to go much deeper in tree
- “Good” ordering of moves can make this pruning much more efficient
  - ▣ Evaluating “best” branch first yields better likelihood of pruning later branches
  - ▣ Perfect ordering reduces time to  $b^{m/2}$
  - ▣ i.e. doubles the depth you can search to!





# $\alpha$ - $\beta$ Pruning

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- Can store information along an entire *path*, not just at most recent levels!
- Keep along the path:
  - ▣  $\alpha$ : **best MAX** value found on this path  
(initialize to most negative utility value)
  - ▣  $\beta$ : **best MIN** value found on this path  
(initialize to most positive utility value)





# The Alpha and the Beta

- For a leaf,  $\alpha = \beta = \text{utility}$
- At a max node:
  - ▣  $\alpha =$  largest child utility found so far
  - ▣  $\beta = \beta$  of parent
- At a min node:
  - ▣  $\alpha = \alpha$  of parent
  - ▣  $\beta =$  smallest child utility found so far
- For any node:
  - ▣  $\alpha \leq \text{utility} \leq \beta$
  - ▣ “If I had to decide now, it would be...”





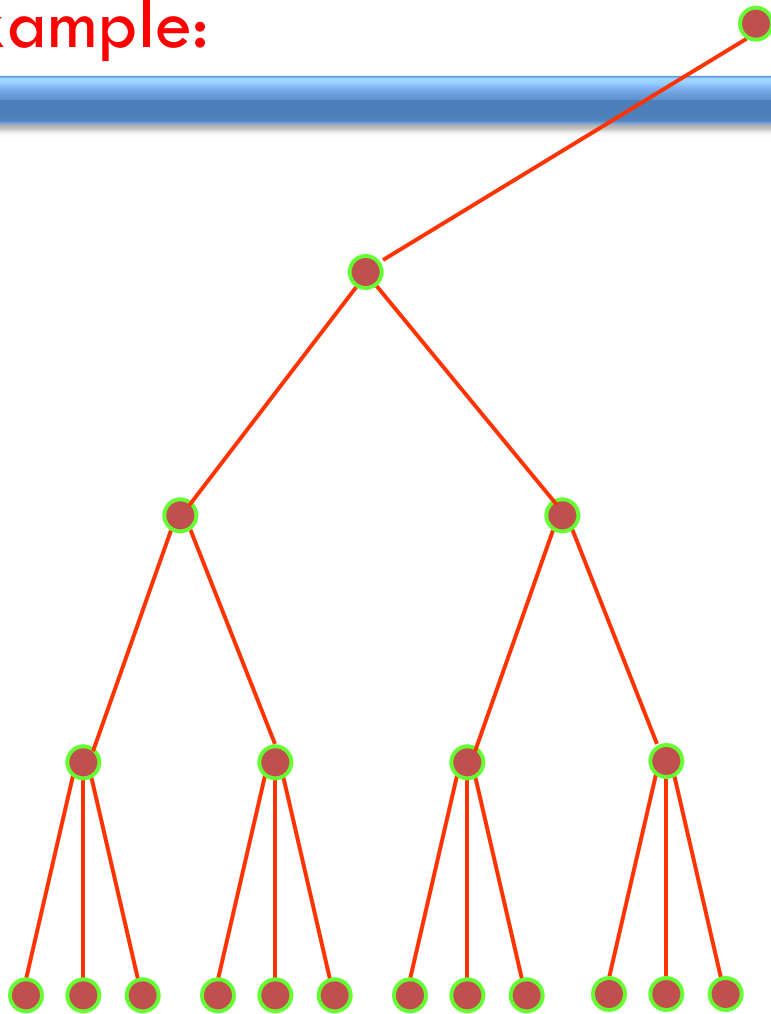
# Alpha-Beta example



# The Alpha-Beta Procedure



Example:



max

min

max

min



# The Alpha-Beta Procedure



Example:

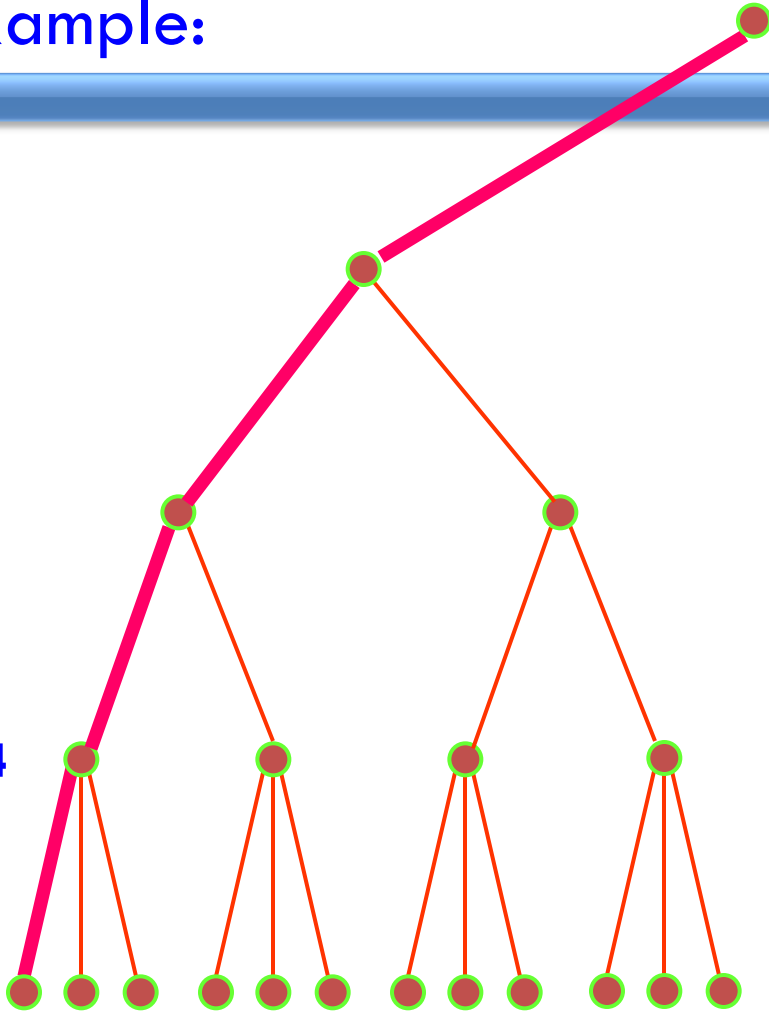
max

min

max

min

$\beta = 4$



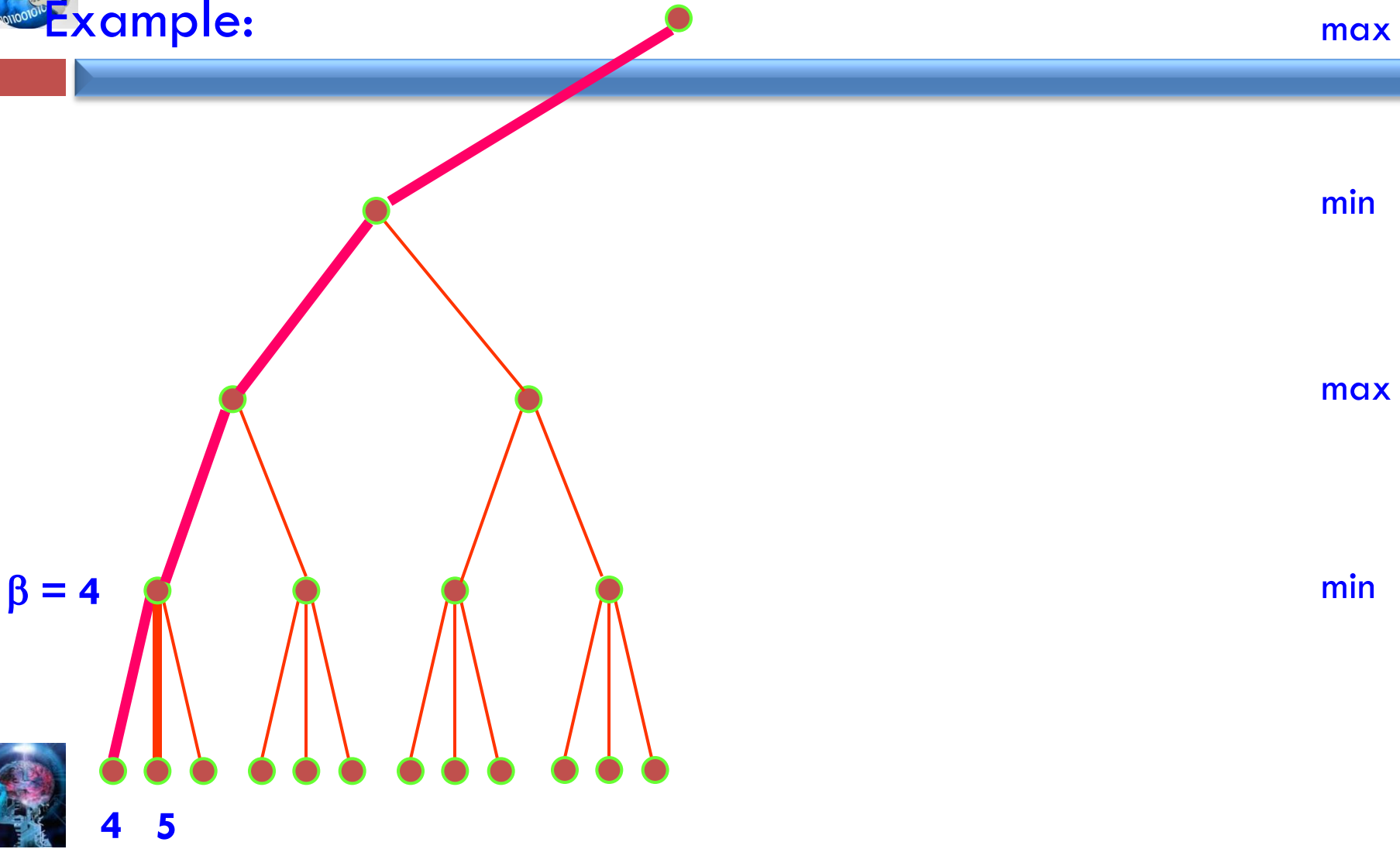
4



# The Alpha-Beta Procedure



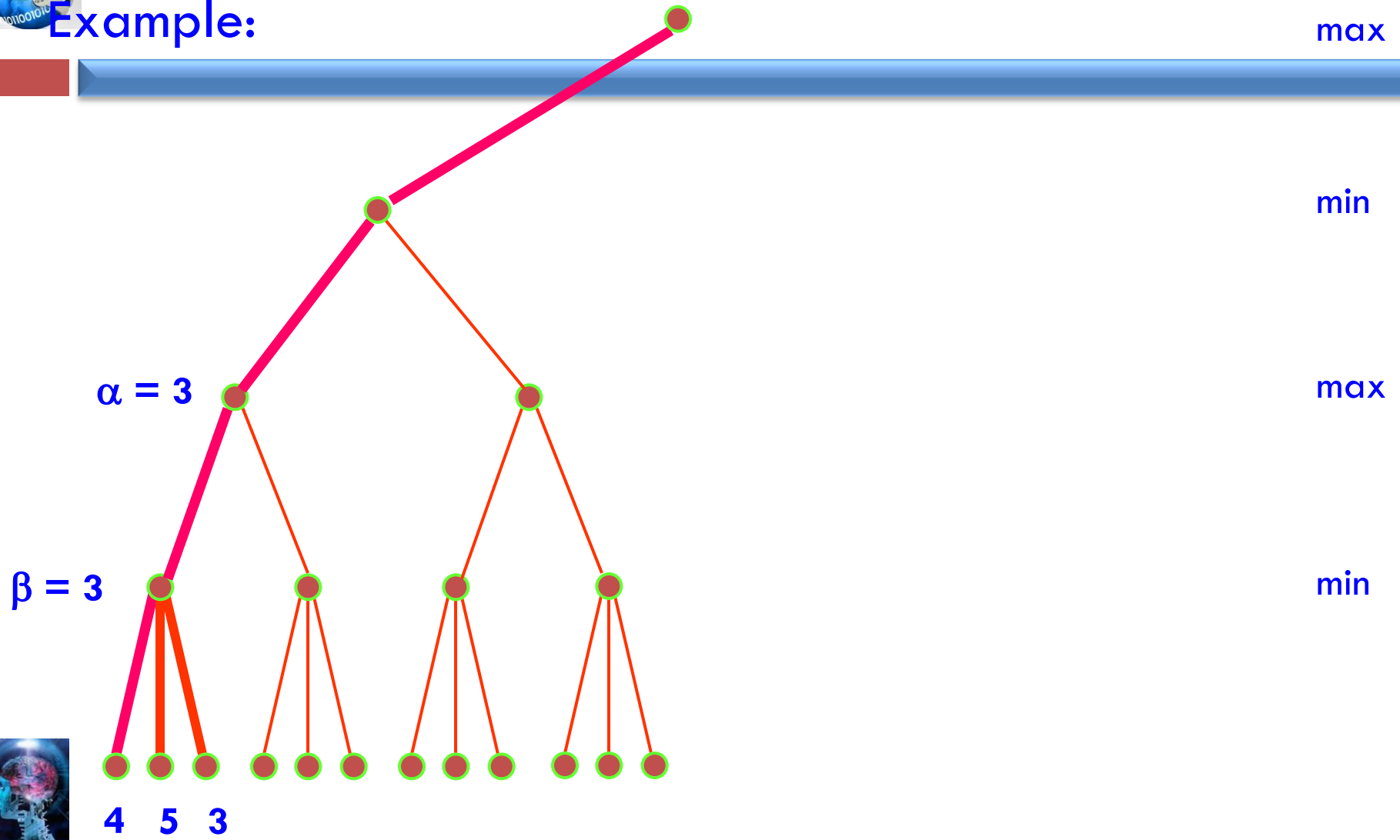
Example:



# The Alpha-Beta Procedure



Example:

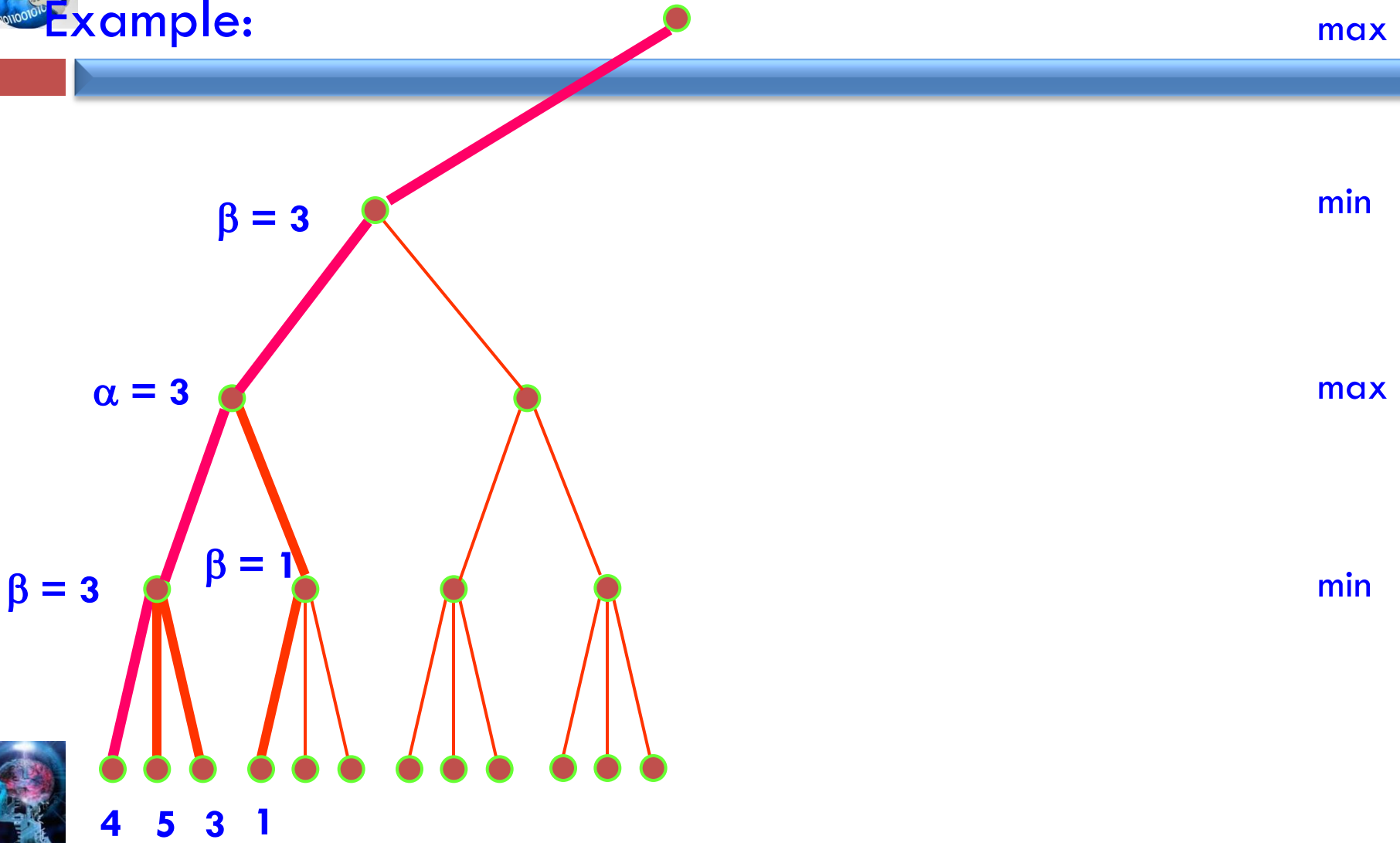




# The Alpha-Beta Procedure



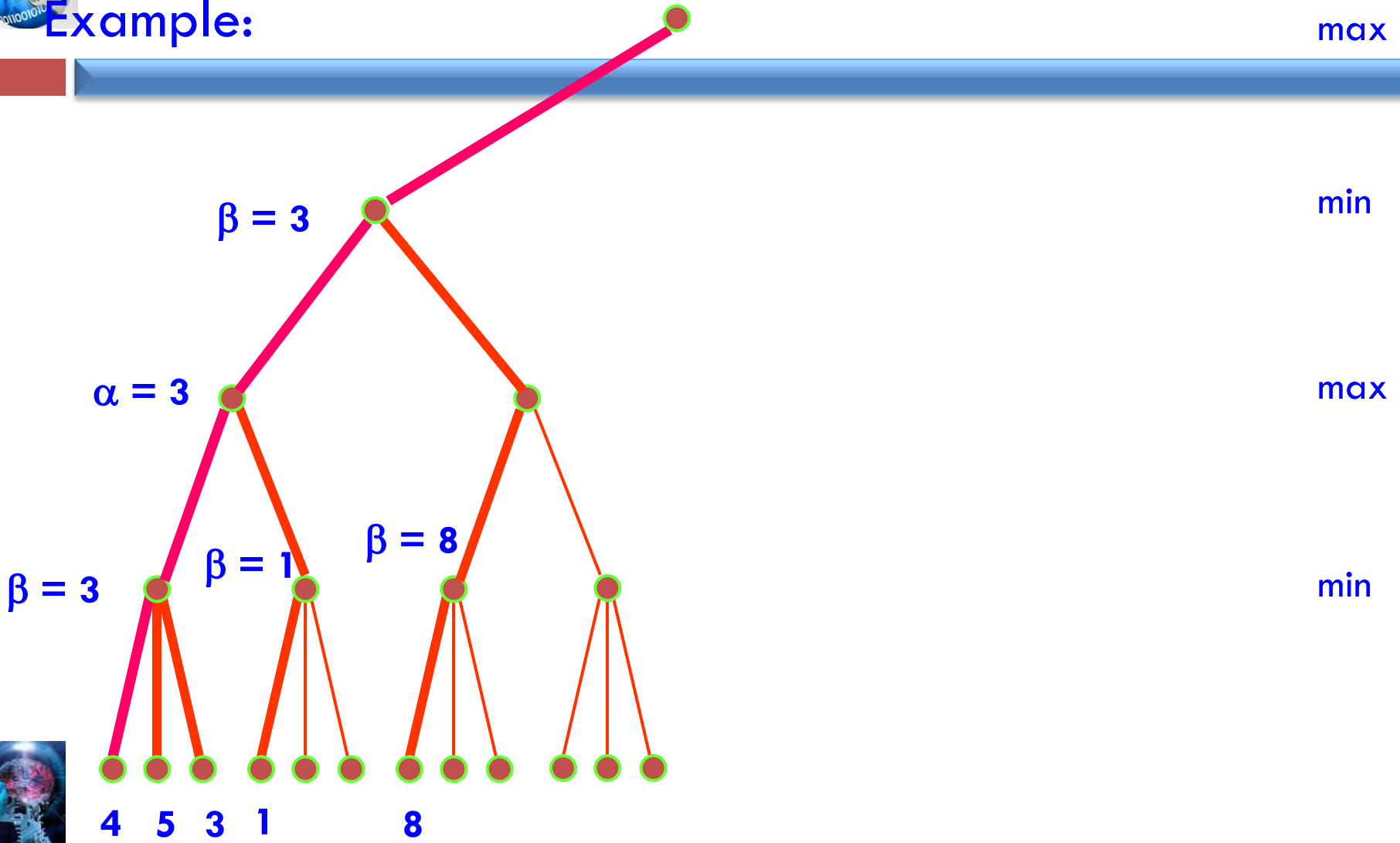
Example:



# The Alpha-Beta Procedure



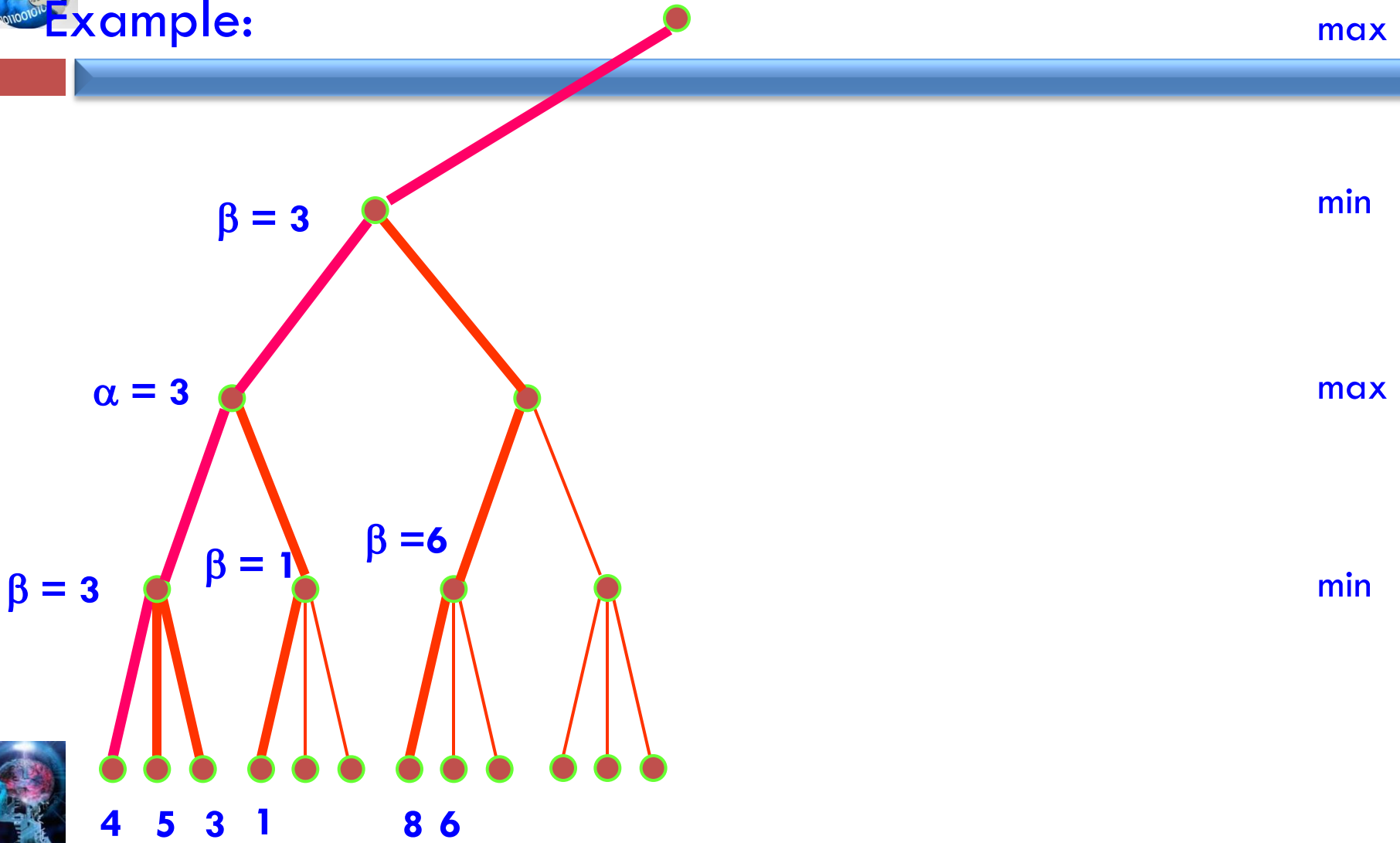
Example:



# The Alpha-Beta Procedure



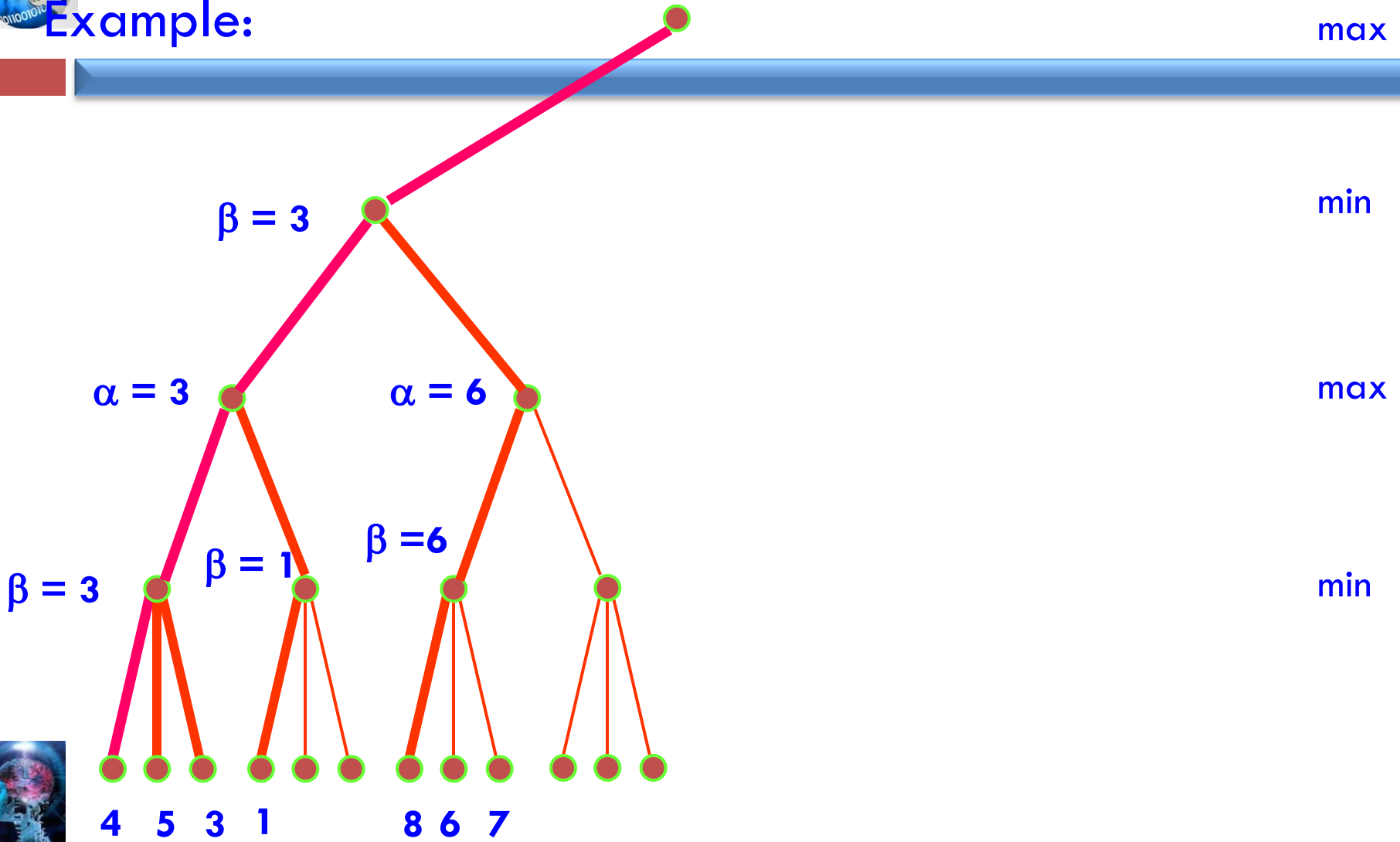
Example:



# The Alpha-Beta Procedure



Example:





# Thank you



## End of Chapter 5

