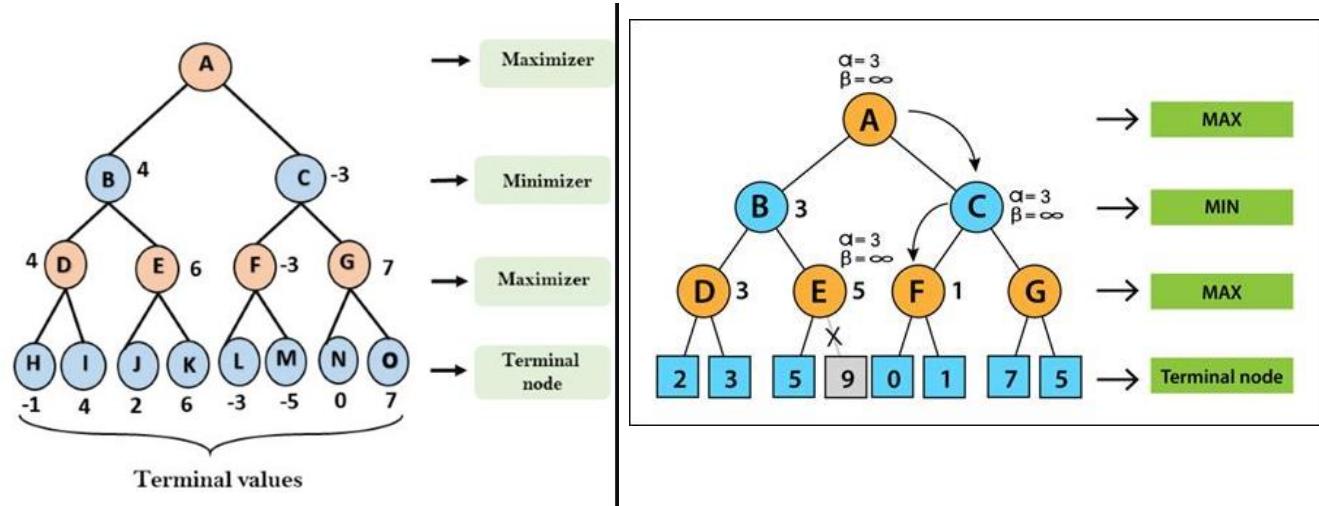
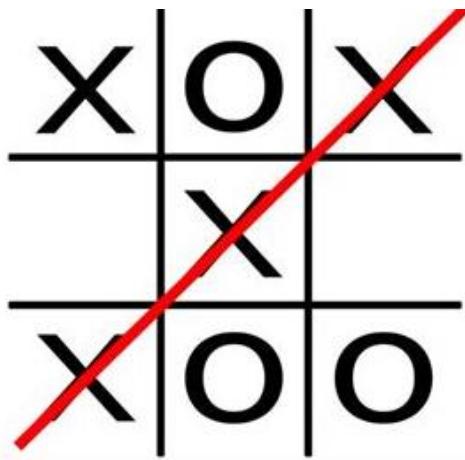


# BCSE306

## Artificial Intelligence

### Module 3: Adversarial Search



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# Lecture Outline

- Adversial Search
  - Search Algorithm and Search Tree
    - Local Search vs Adversial Search
    - Game Tree an Min-max evaluation
      - Initial State, Successor function, Utility function
      - Backed up value for max position
      - Backed up value for min position
      - Ply vs move
    - Elementary two player game: tic-toe

# Game Playing

Why do AI researchers study game playing?

1. It's a good reasoning problem, formal and nontrivial.
2. Direct comparison with humans and other computer programs is easy.

# What Kinds of Games?

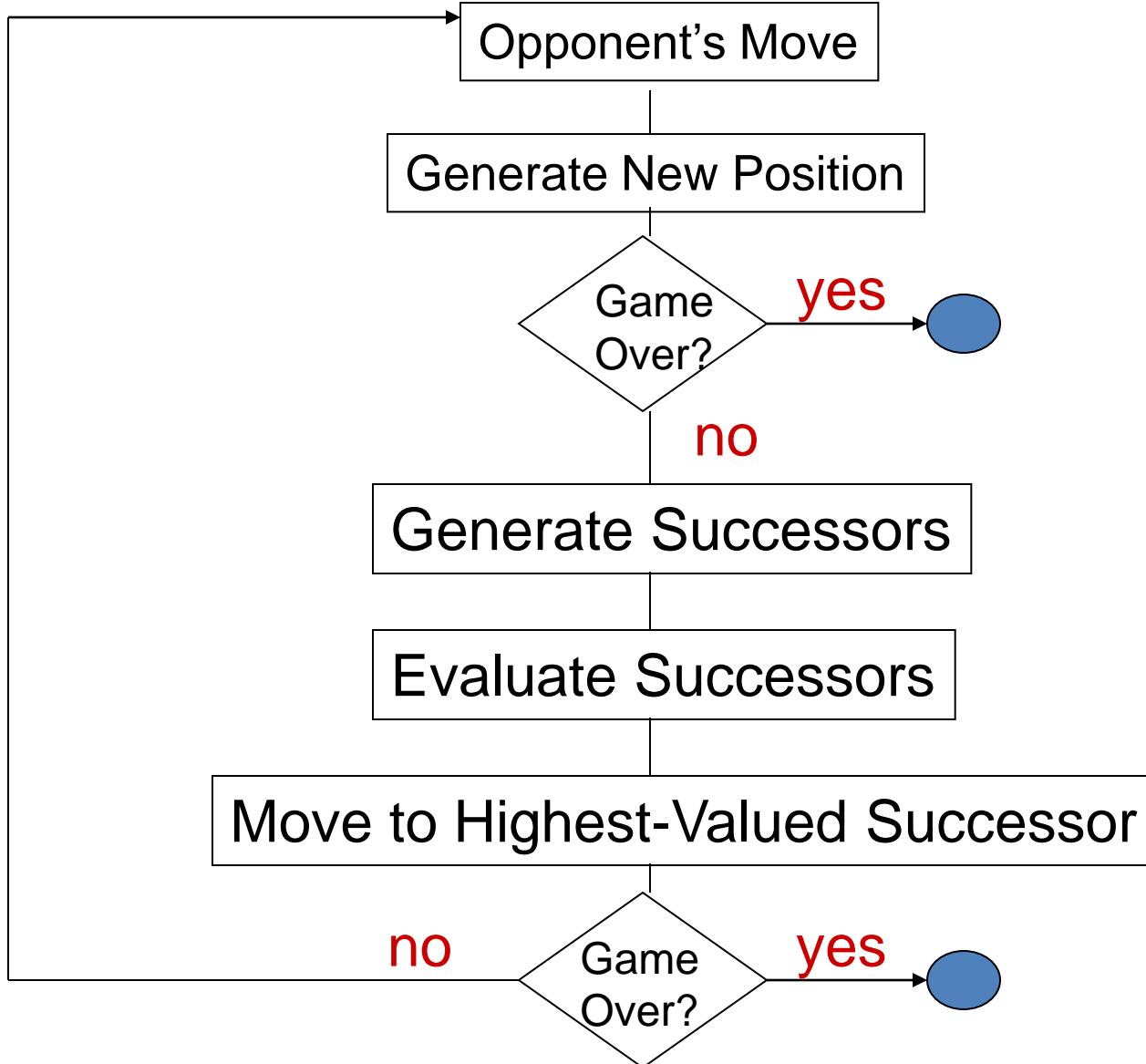
Mainly games of strategy with the following characteristics:

1. Sequence of **moves** to play
2. Rules that specify **possible moves**
3. Rules that specify a **payment** for each move
4. Objective is to **maximize** your payment

# Games vs. Search Problems

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

## Two-Player Game



# Games as Adversarial Search

- States:
  - board configurations
- Initial state:
  - the board position and which player will move
- Successor function:
  - returns list of (move, state) pairs, each indicating a legal move and the resulting state
- Terminal test:
  - determines when the game is over
- Utility function:
  - gives a numeric value in terminal states  
(e.g., -1, 0, +1 for loss, tie, win)

# Game Tree (2-player, Deterministic, Turns)

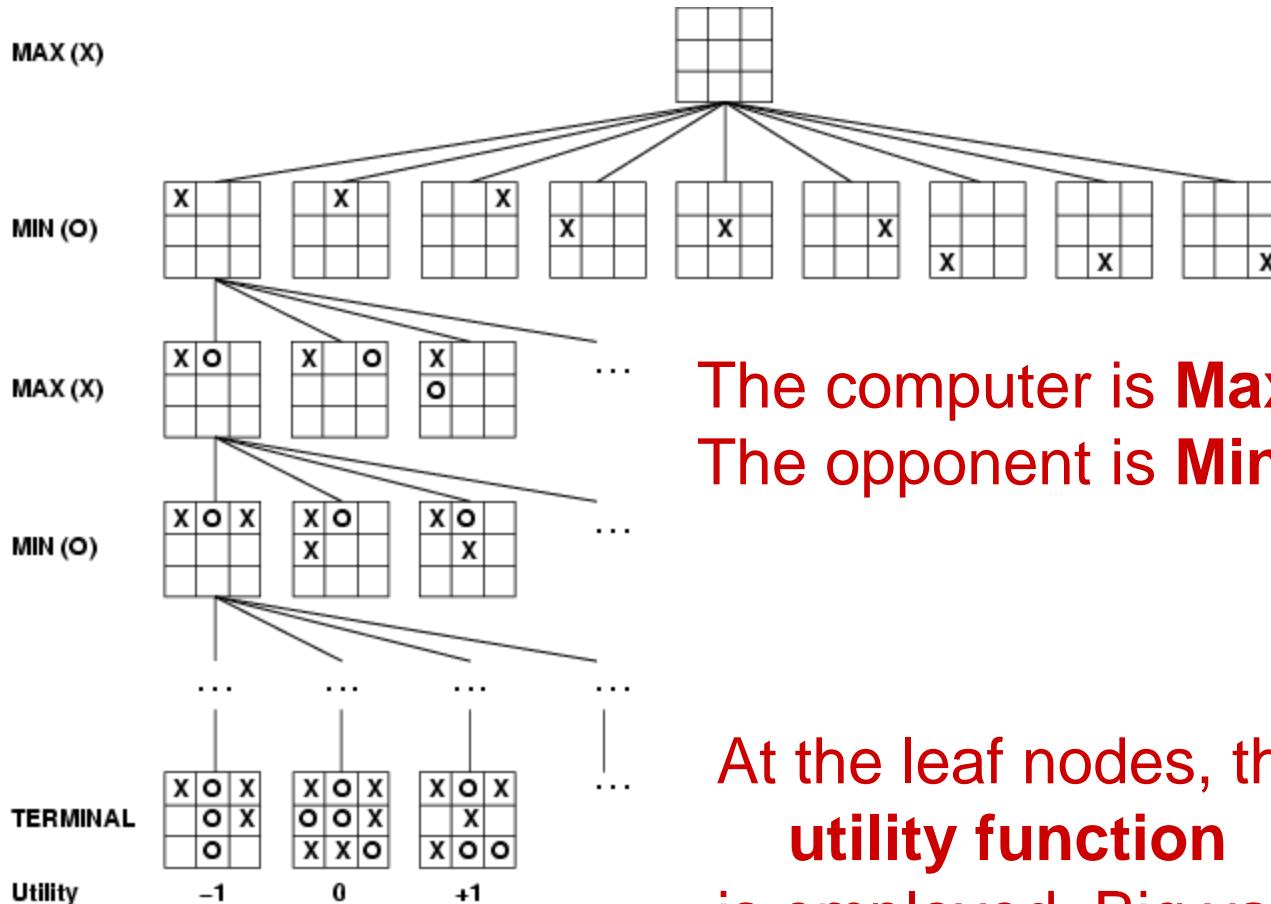
computer's turn

opponent's turn

computer's turn

opponent's turn

leaf nodes are evaluated



The computer is **Max**.  
The opponent is **Min**.

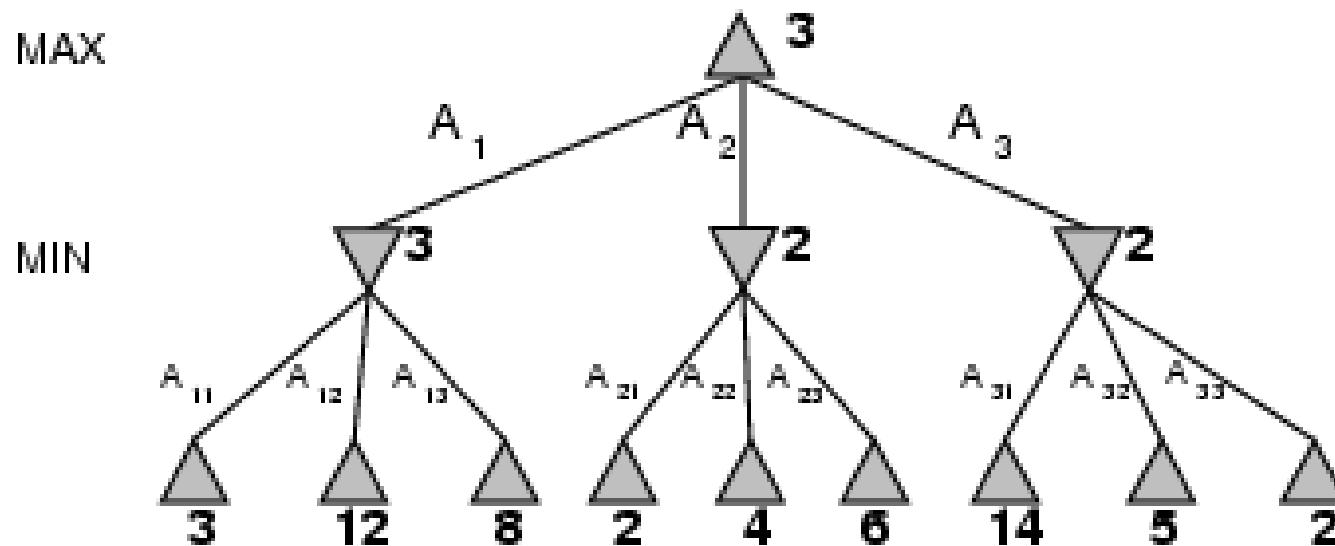
At the leaf nodes, the **utility function** is employed. Big value means good, small is bad.

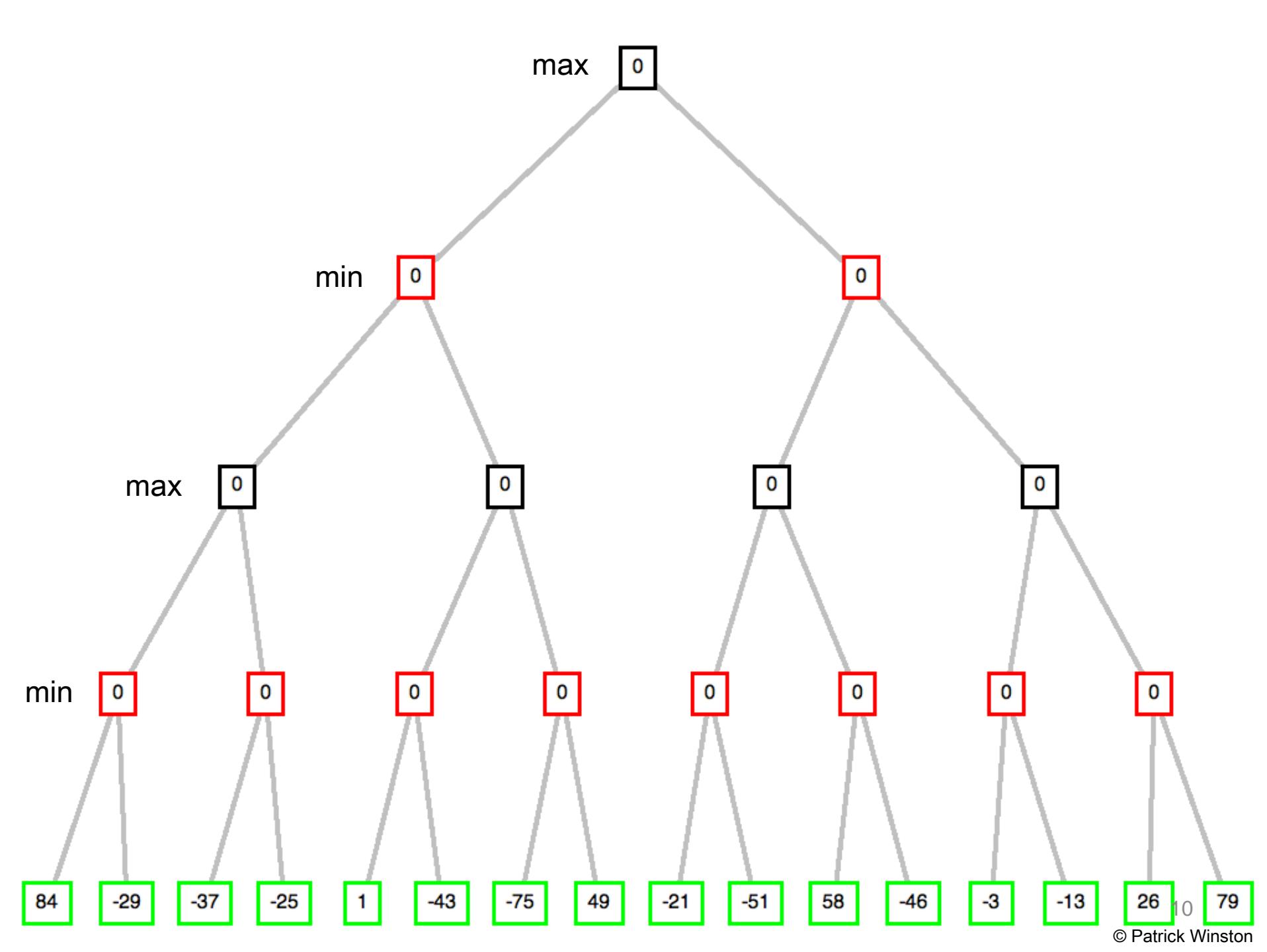
# Mini-Max Terminology

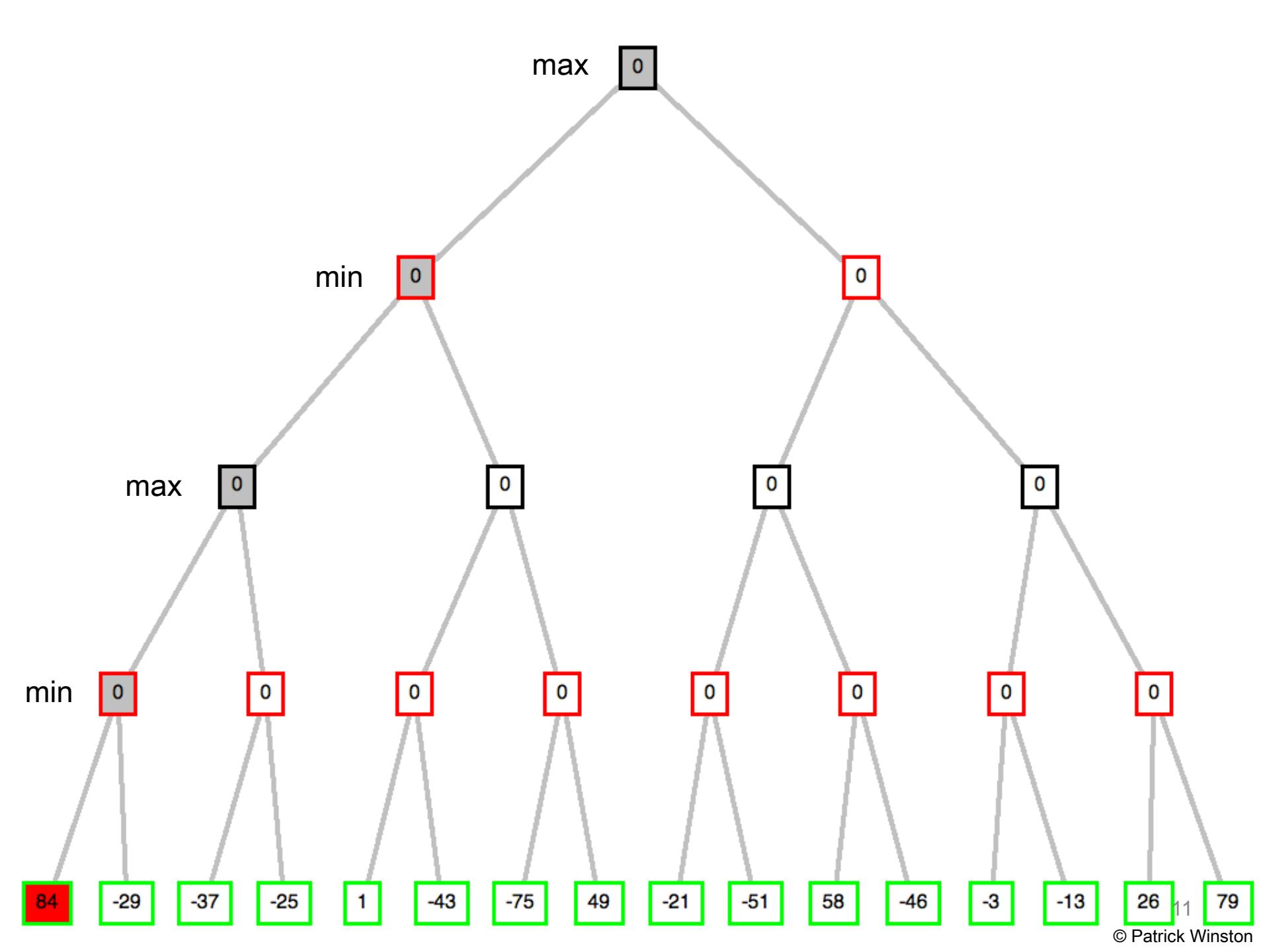
- **move:** a move by both players
- **ply:** a half-move
- **utility function:** the function applied to leaf nodes
- **backed-up value**
  - of a max-position: the value of its largest successor
  - of a min-position: the value of its smallest successor
- **minimax procedure:** search down several levels; at the bottom level apply the utility function, back-up values all the way up to the root node, and that node selects the move.

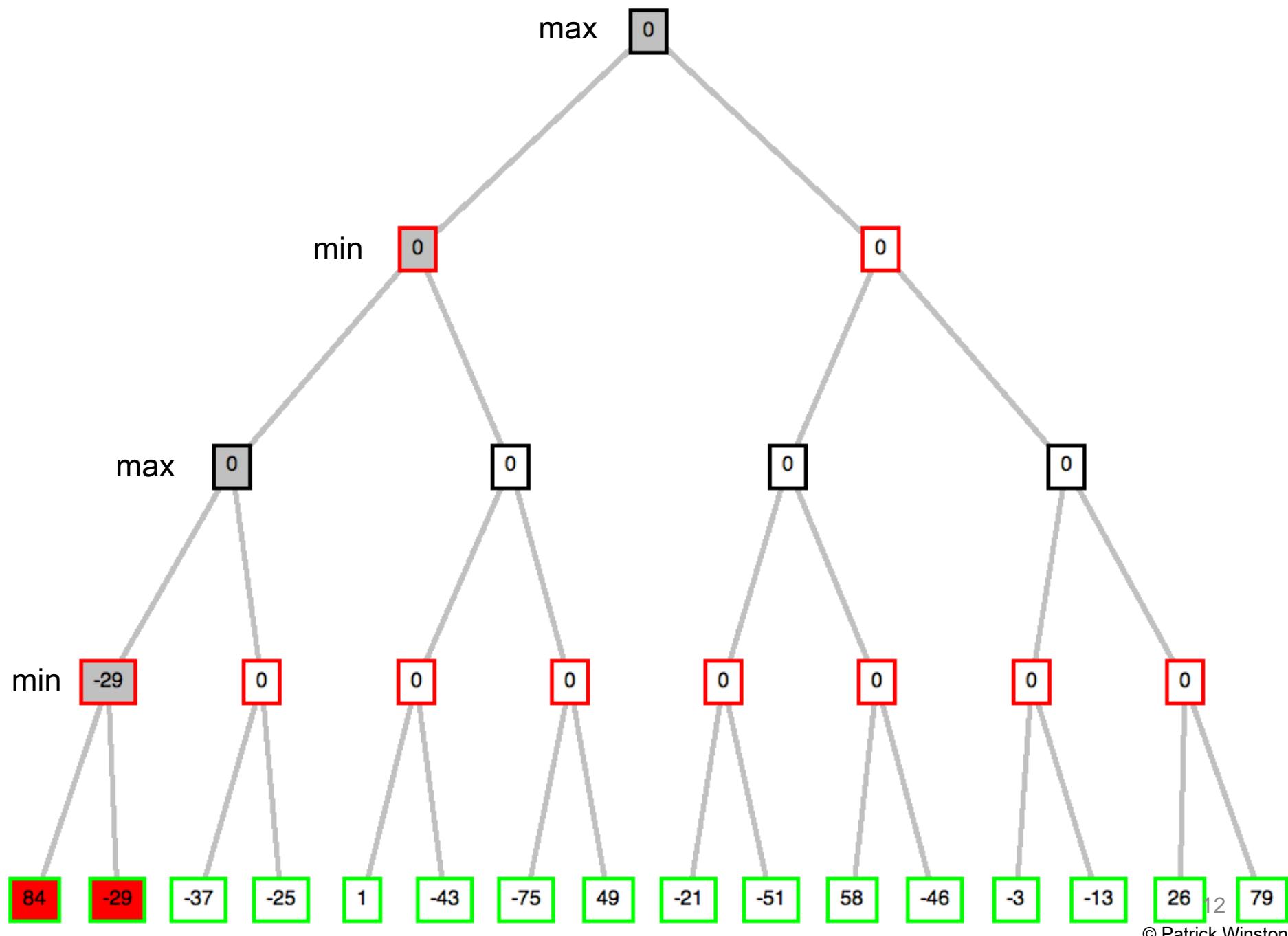
# Minimax

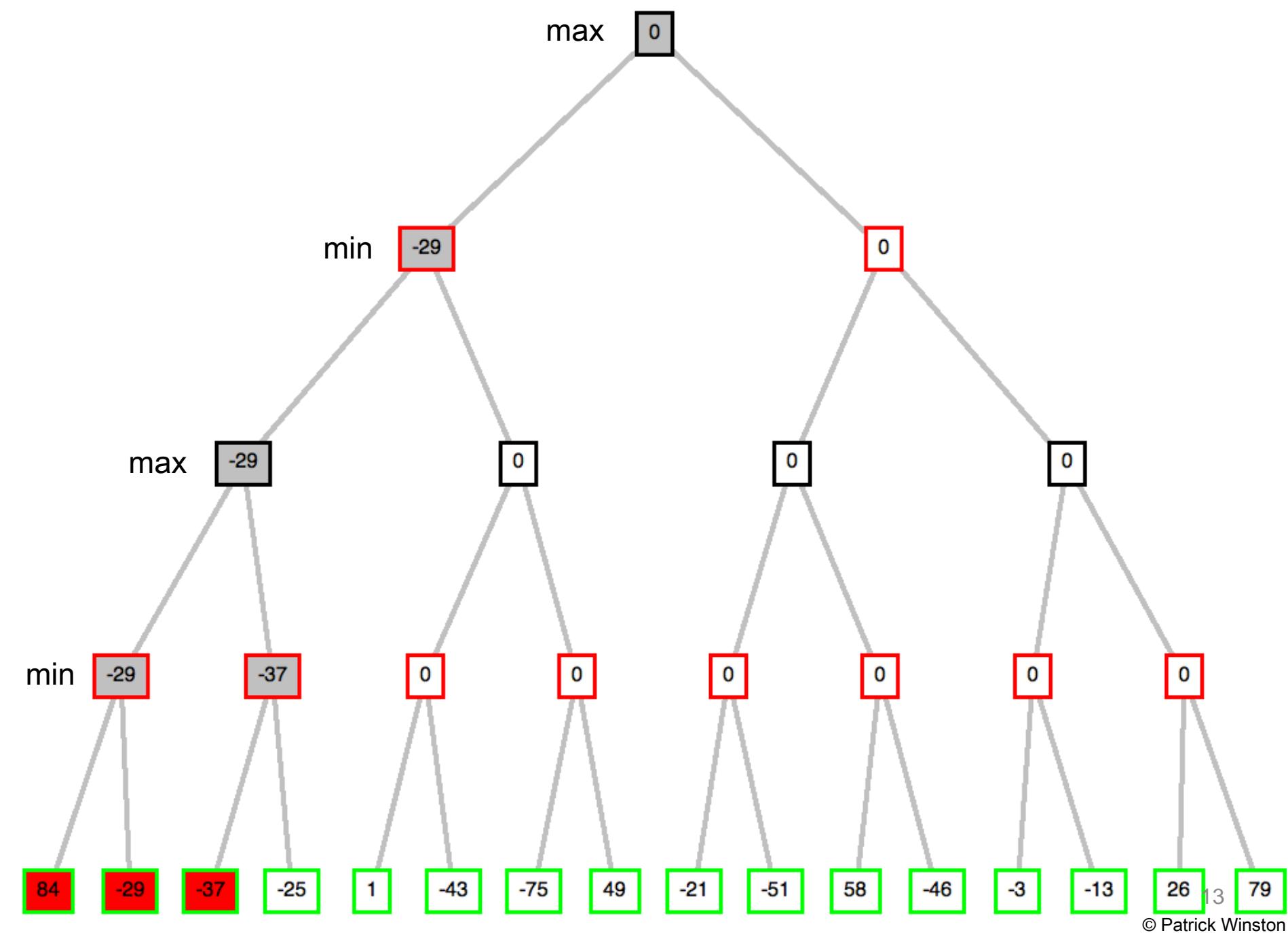
- Perfect play for deterministic games
- Idea: choose move to position with highest **minimax value**  
= best achievable payoff against best play
- E.g., 2-ply game:

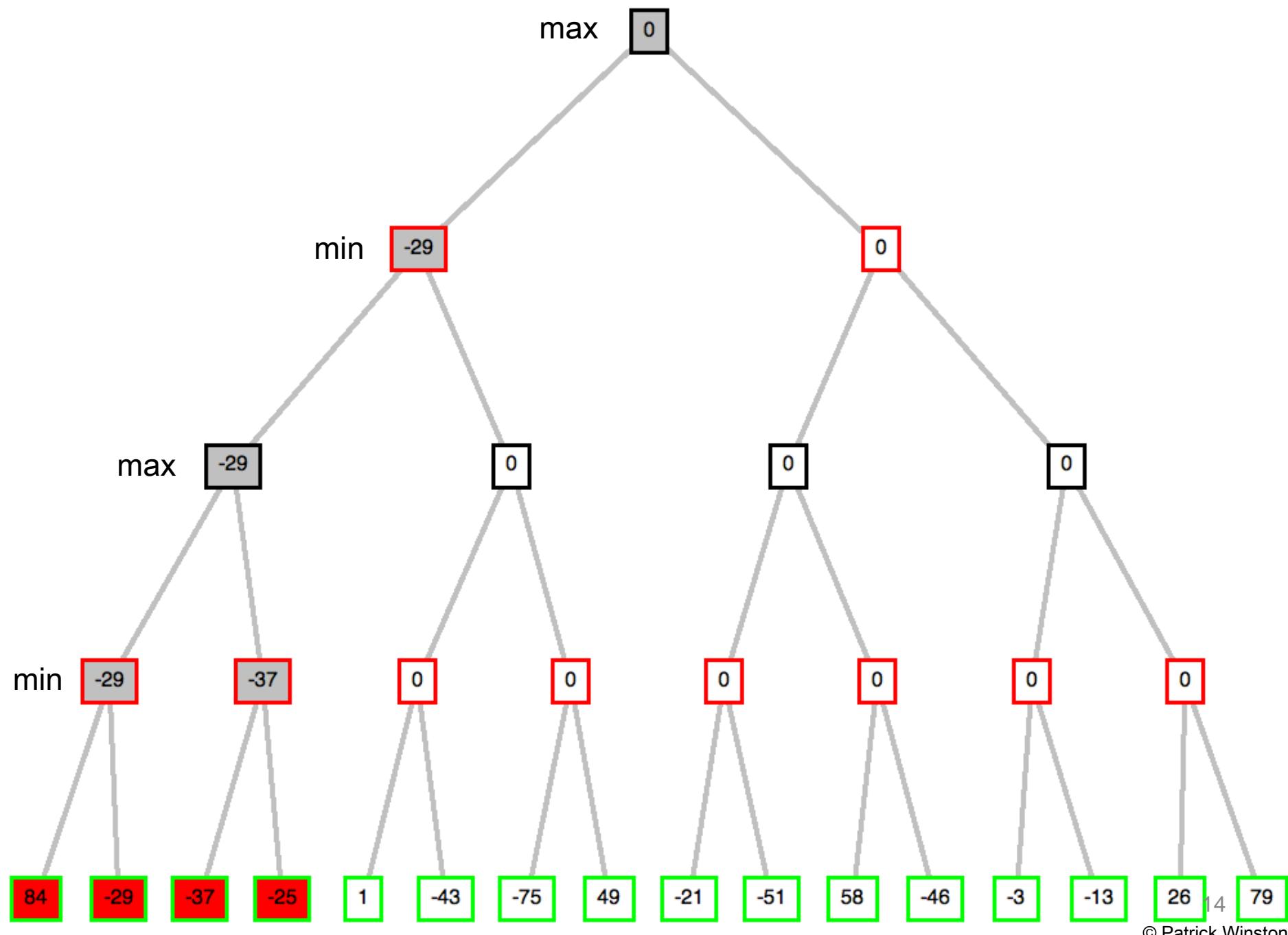


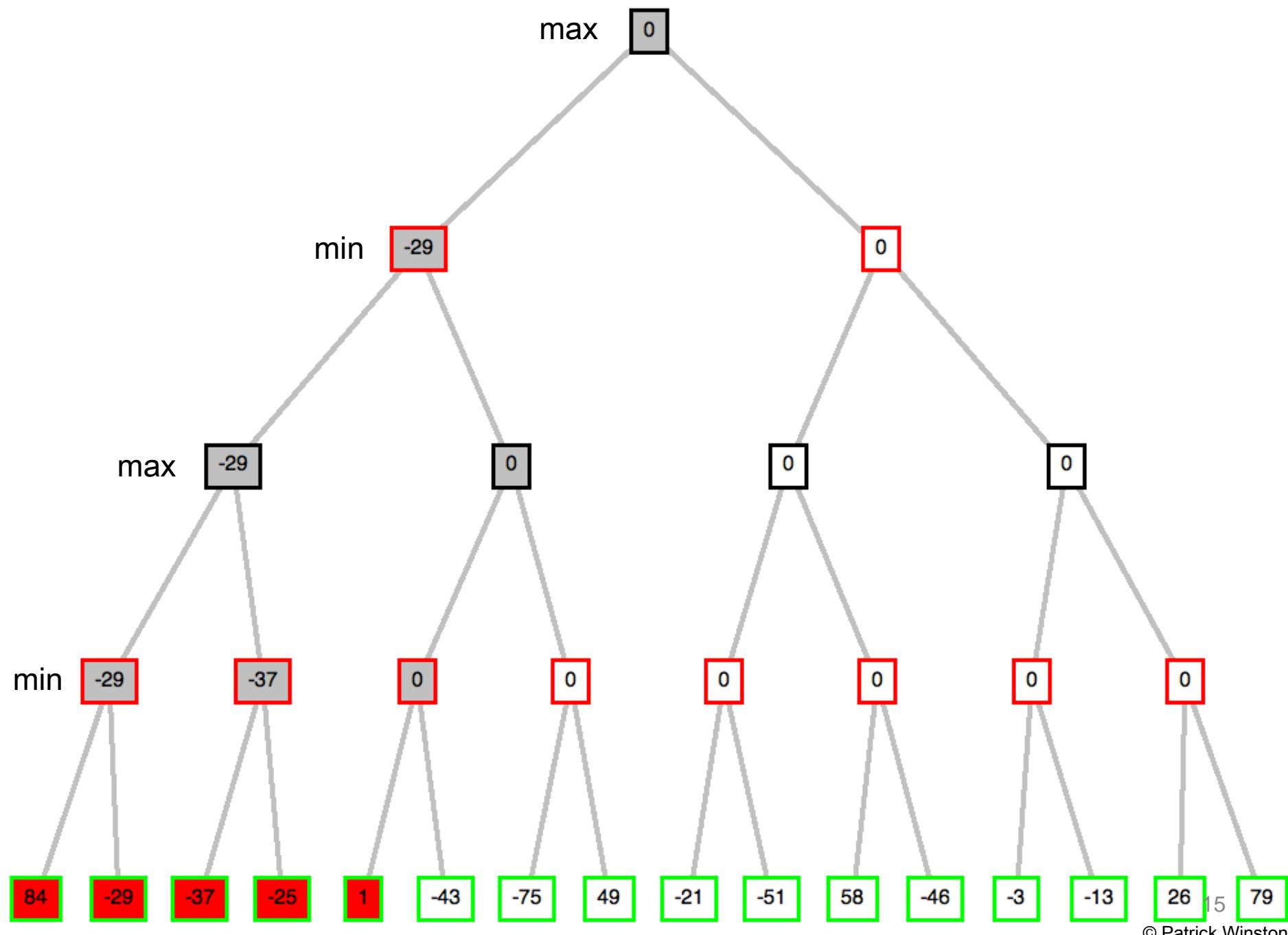


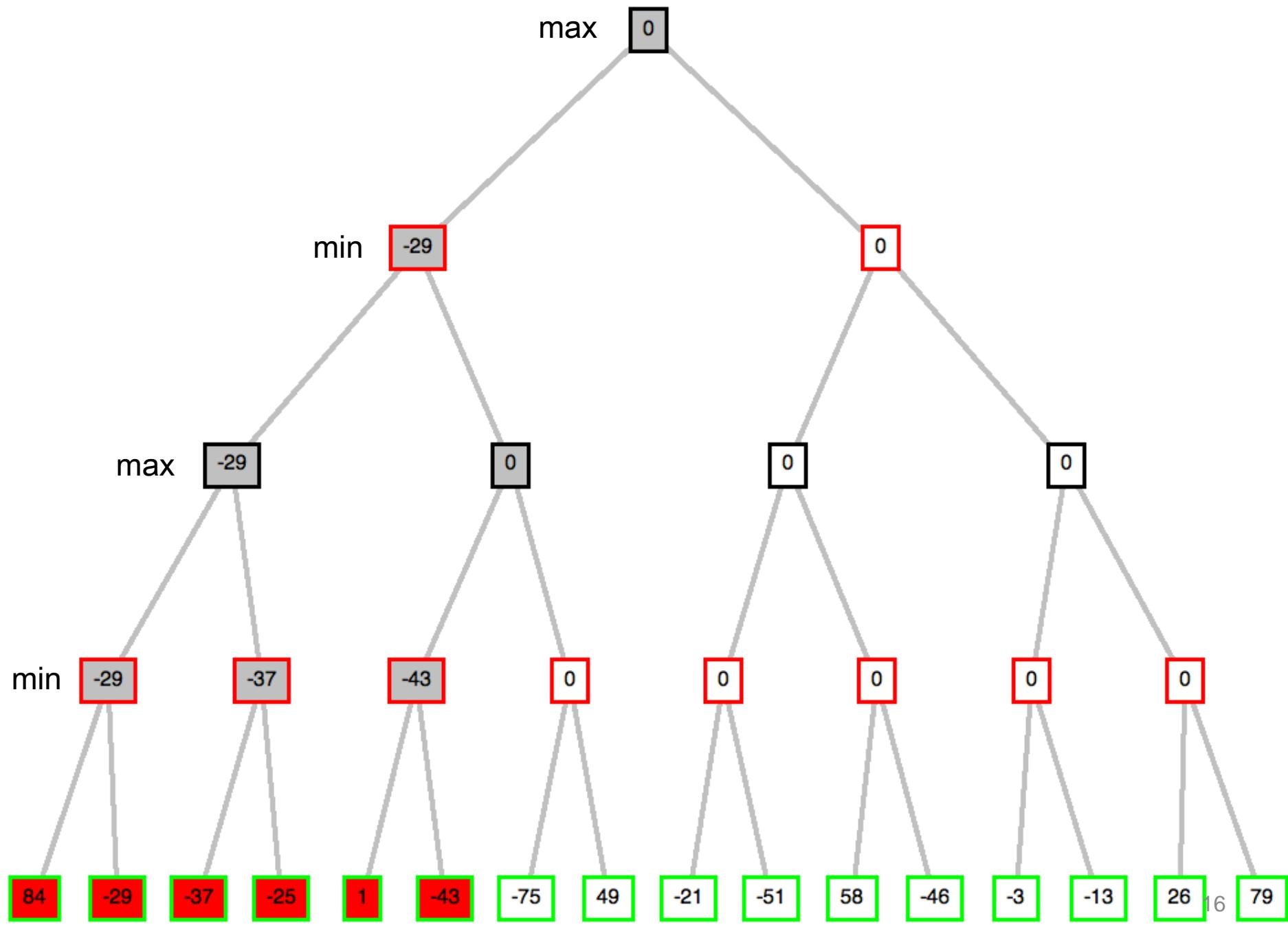


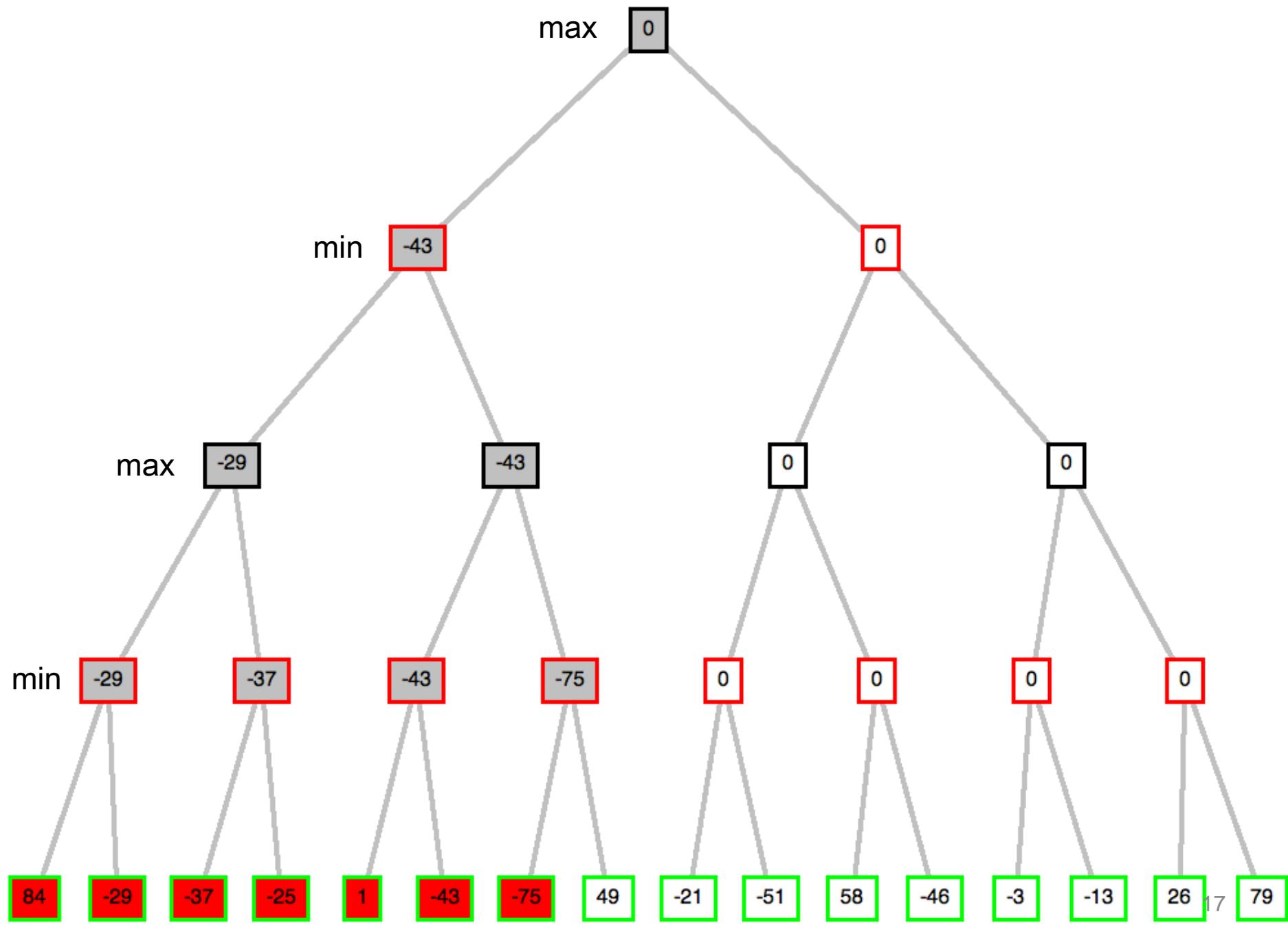


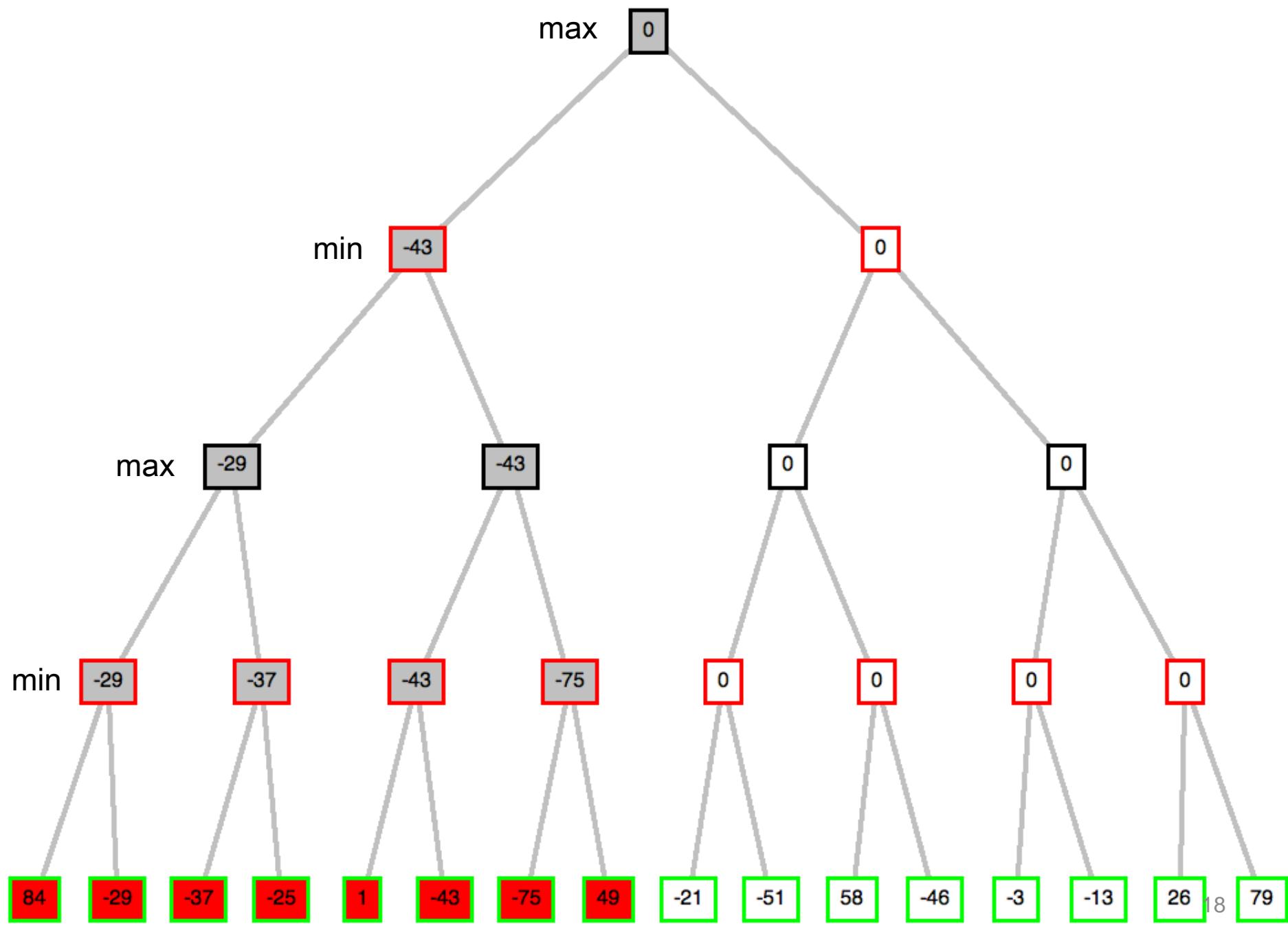


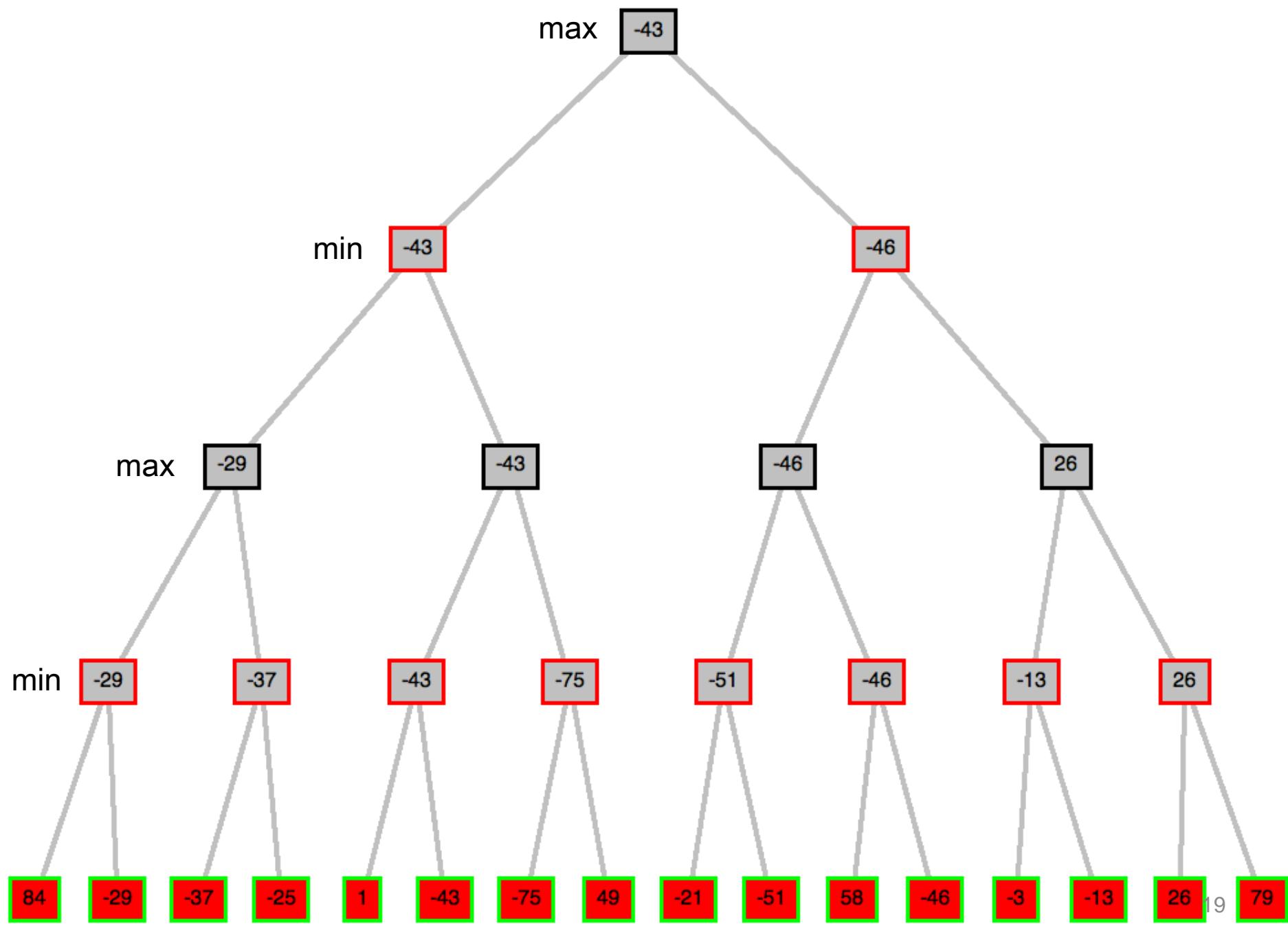


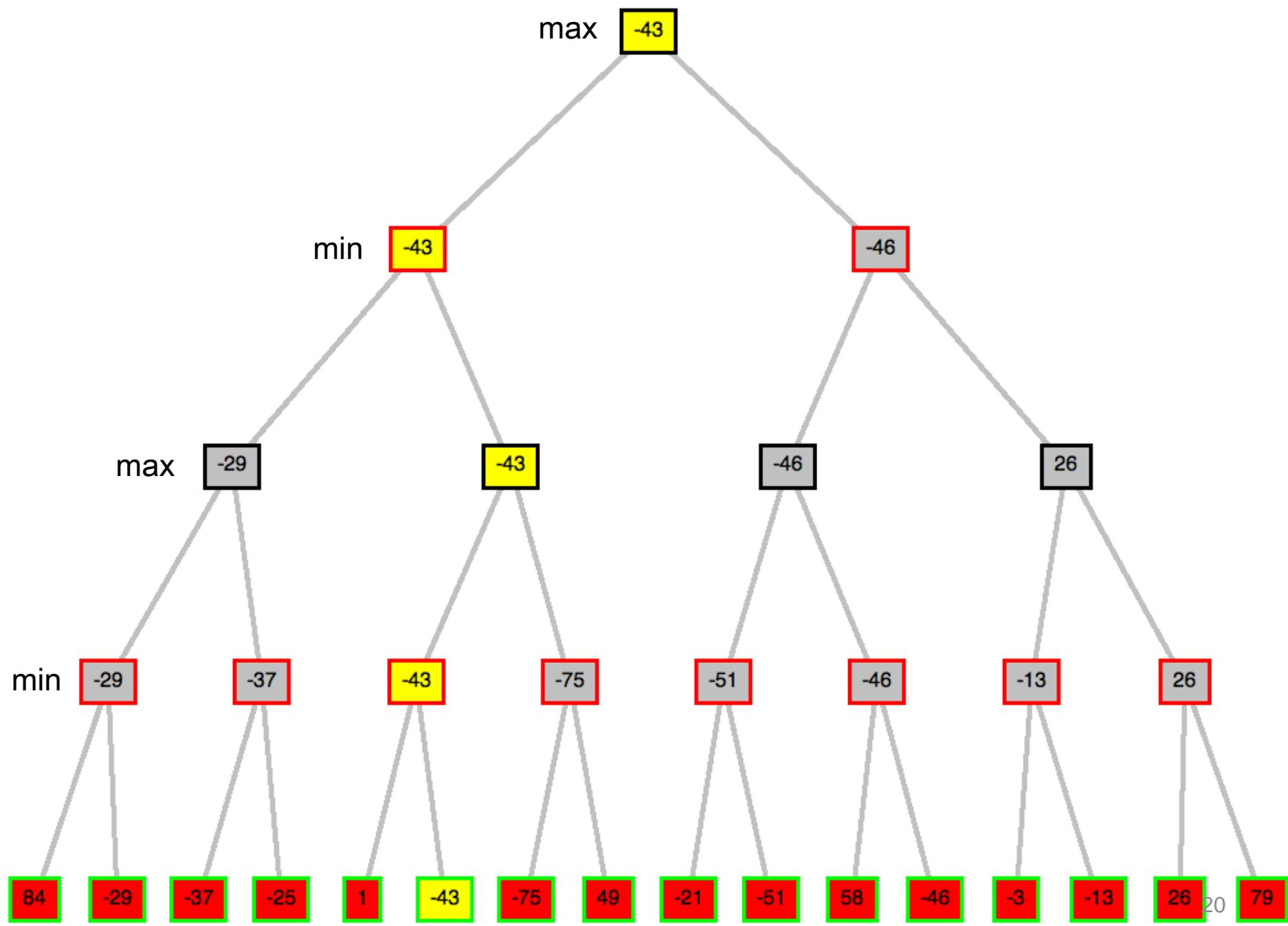












# Minimax Strategy

- Why do we take the **min** value every other level of the tree?
- These nodes represent the **opponent's** choice of move.
- The computer assumes that the human will choose that move that is of **least value** to the computer.

# Minimax algorithm

## Adversarial analogue of DFS

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

```
    v  $\leftarrow$  MAX-VALUE(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
```

# Properties of Minimax

- Complete?
  - Yes (if tree is finite)
- Optimal?
  - Yes (against an optimal opponent)
  - No (does not exploit opponent weakness against suboptimal opponent)
- Time complexity?
  - $O(b^m)$
- Space complexity?
  - $O(bm)$  (depth-first exploration)

# Good Enough?

- Chess:
  - branching factor  $b \approx 35$
  - game length  $m \approx 100$
  - search space  $b^m \approx 35^{100} \approx 10^{154}$
- The Universe:
  - number of atoms  $\approx 10^{78}$
  - age  $\approx 10^{18}$  seconds
  - $10^8 \text{ moves/sec} \times 10^{78} \times 10^{18} = 10^{104}$
- Exact solution completely infeasible

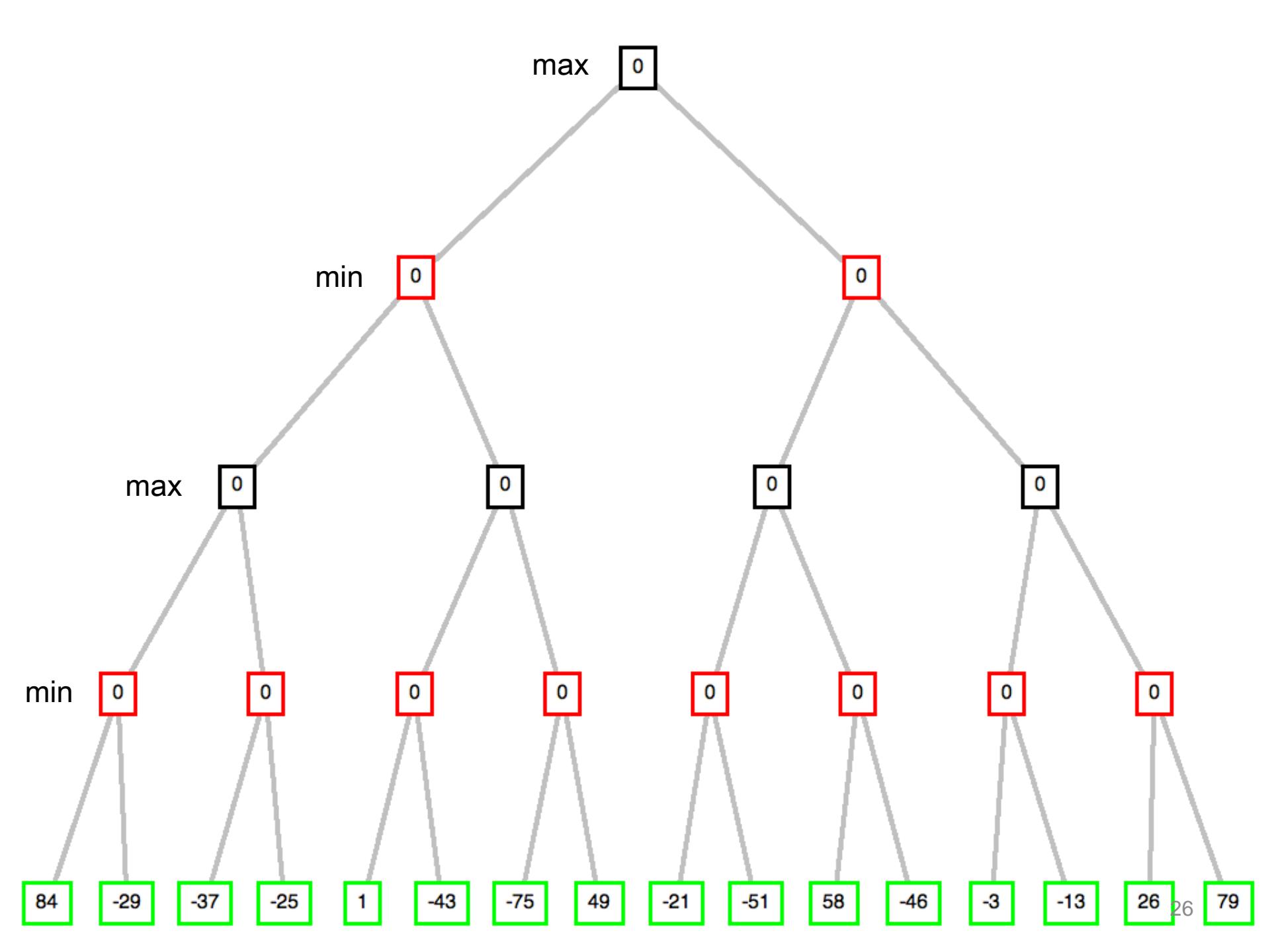
# Alpha-Beta Procedure

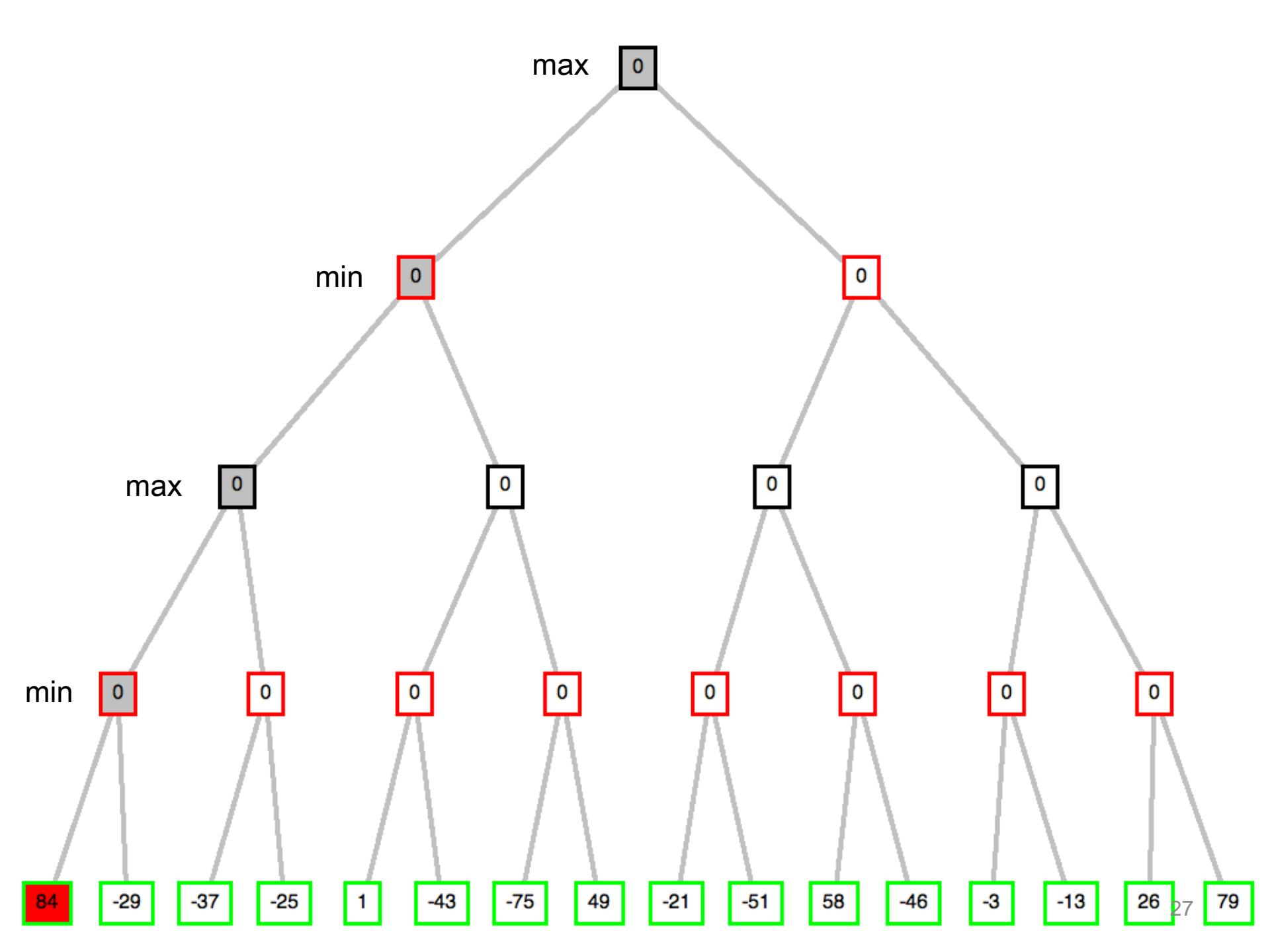
- The alpha-beta procedure can speed up a depth-first minimax search.
- Alpha: a lower bound on the value that a max node may ultimately be assigned

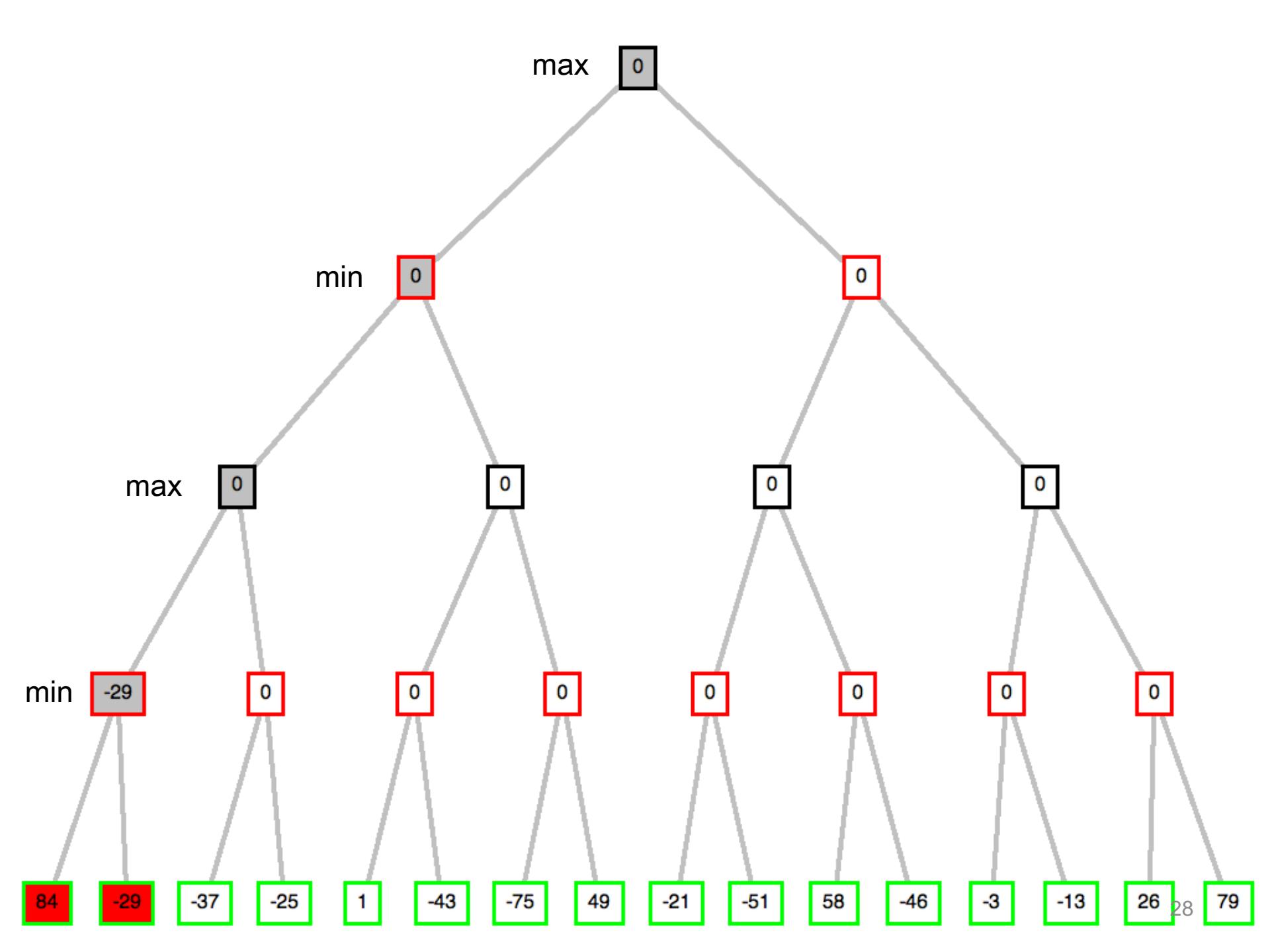
$$v \geq \alpha$$

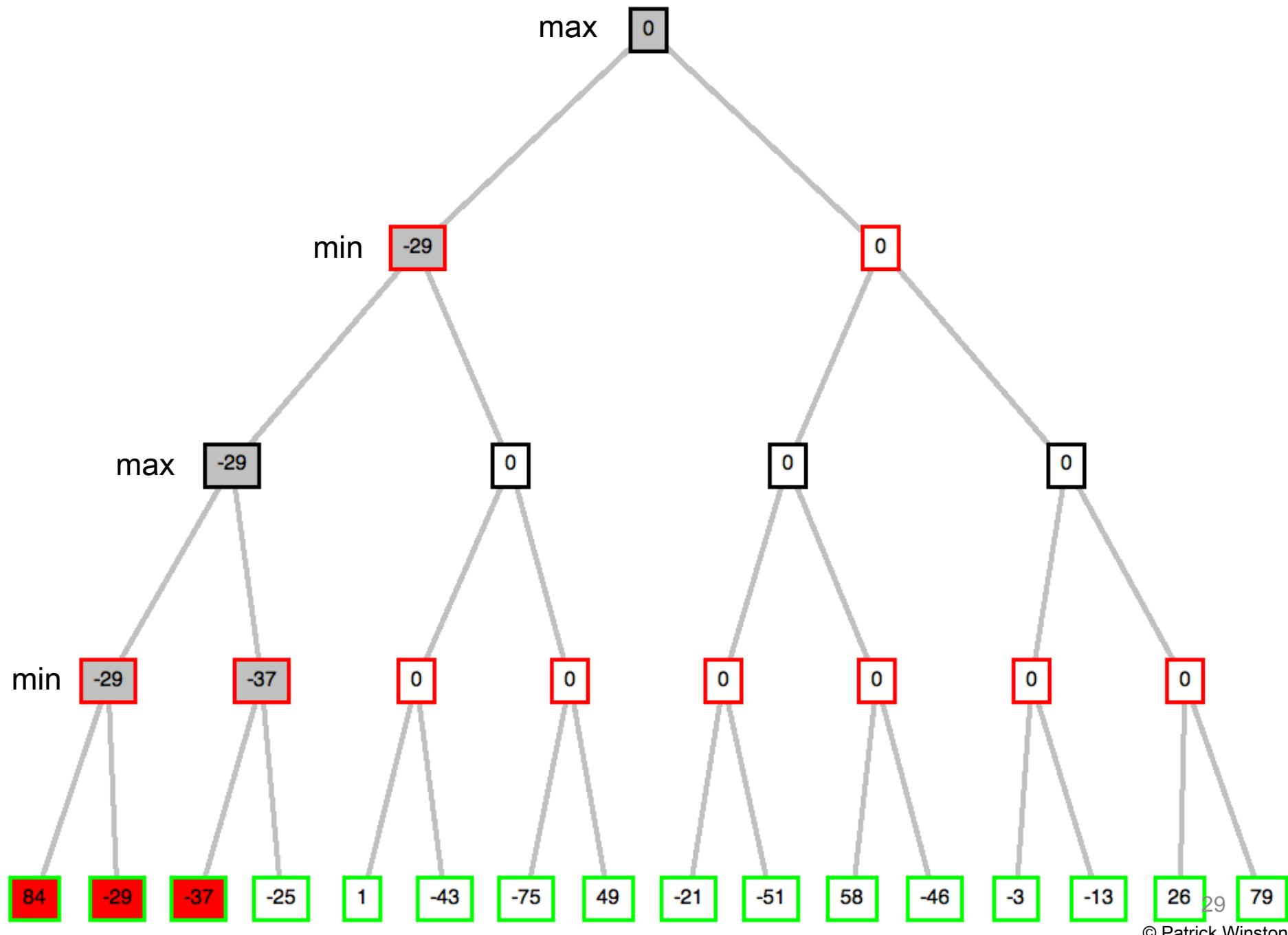
- Beta: an upper bound on the value that a minimizing node may ultimately be assigned

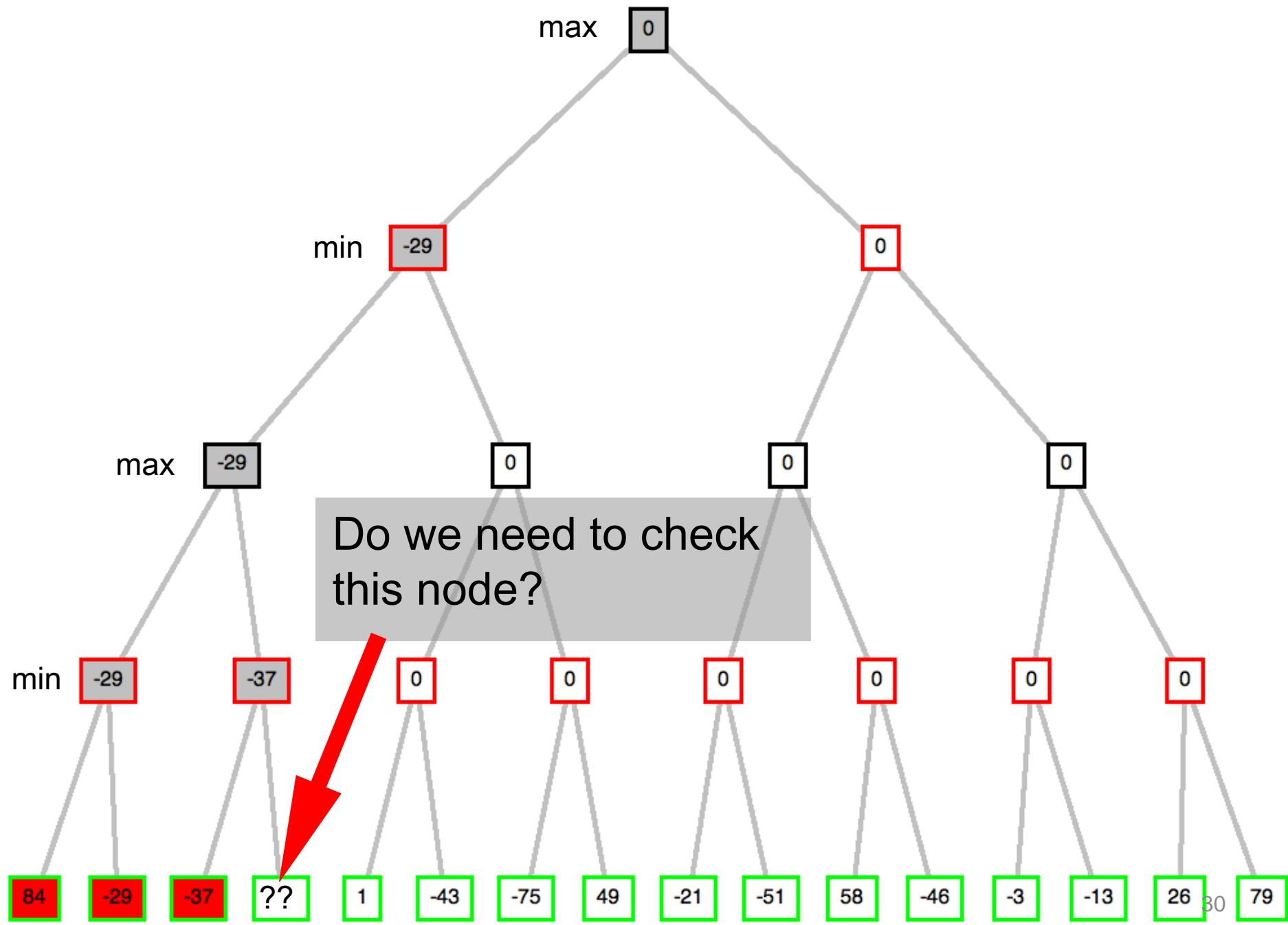
$$v \leq \beta$$

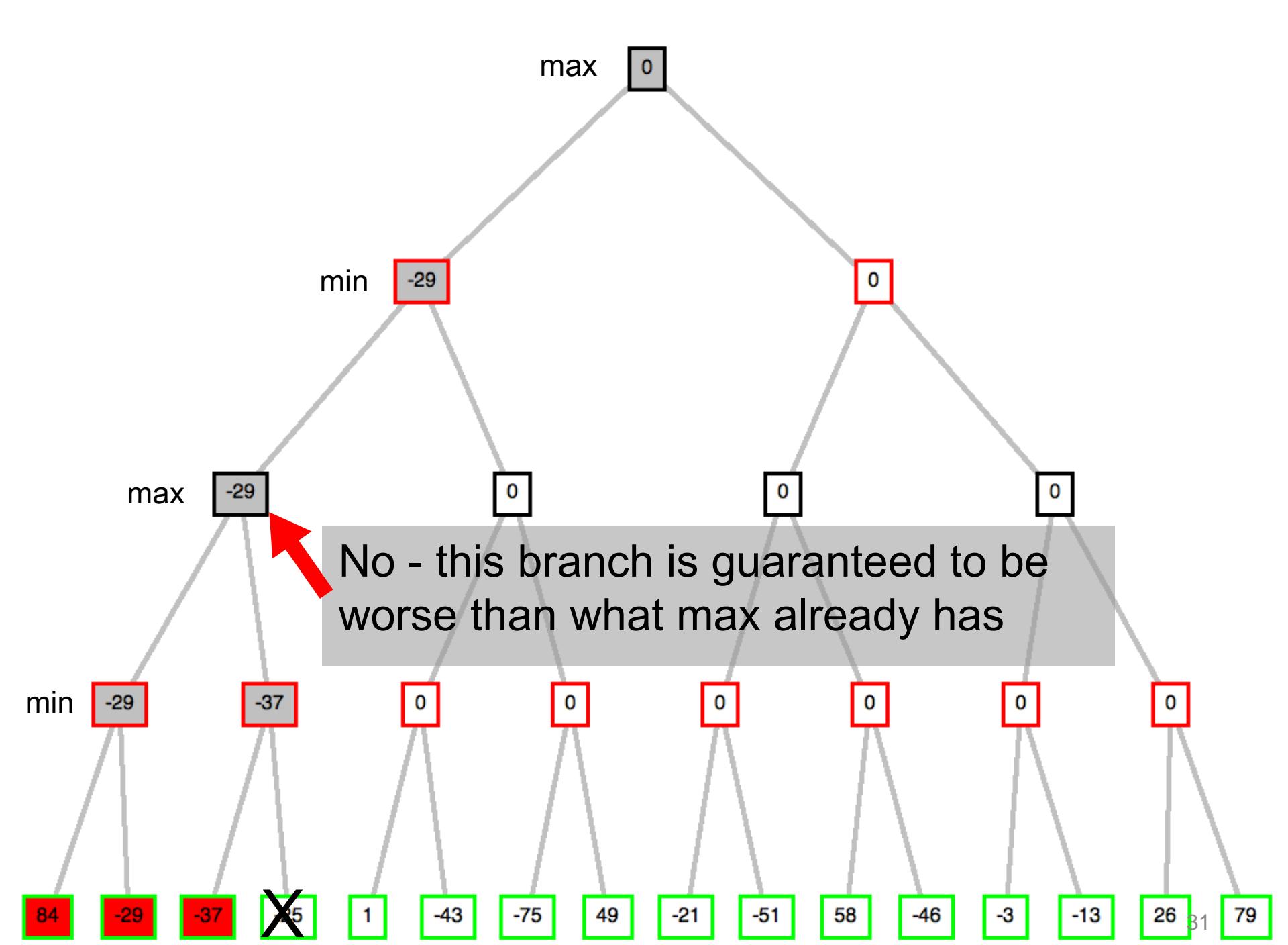












# Alpha-Beta

```
MinVal(state, alpha, beta) {  
    if (terminal(state))  
        return utility(state);  
    for (s in children(state)) {  
        child = MaxVal(s,alpha,beta);  
        beta = min(beta,child);  
        if (alpha>=beta) return child;  
    }  
    return beta; }
```

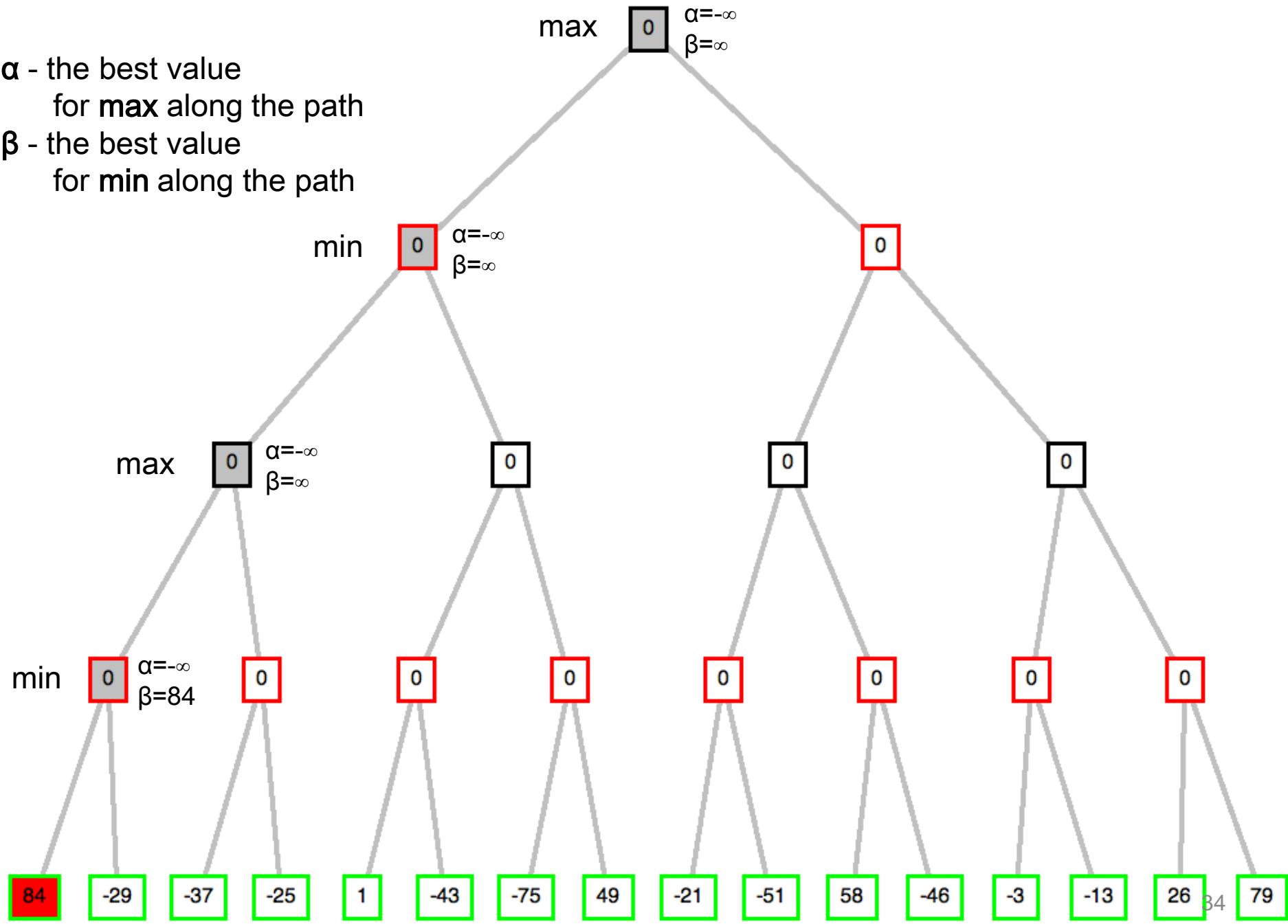
alpha = the highest value for MAX along the path  
beta = the lowest value for MIN along the path

# Alpha-Beta

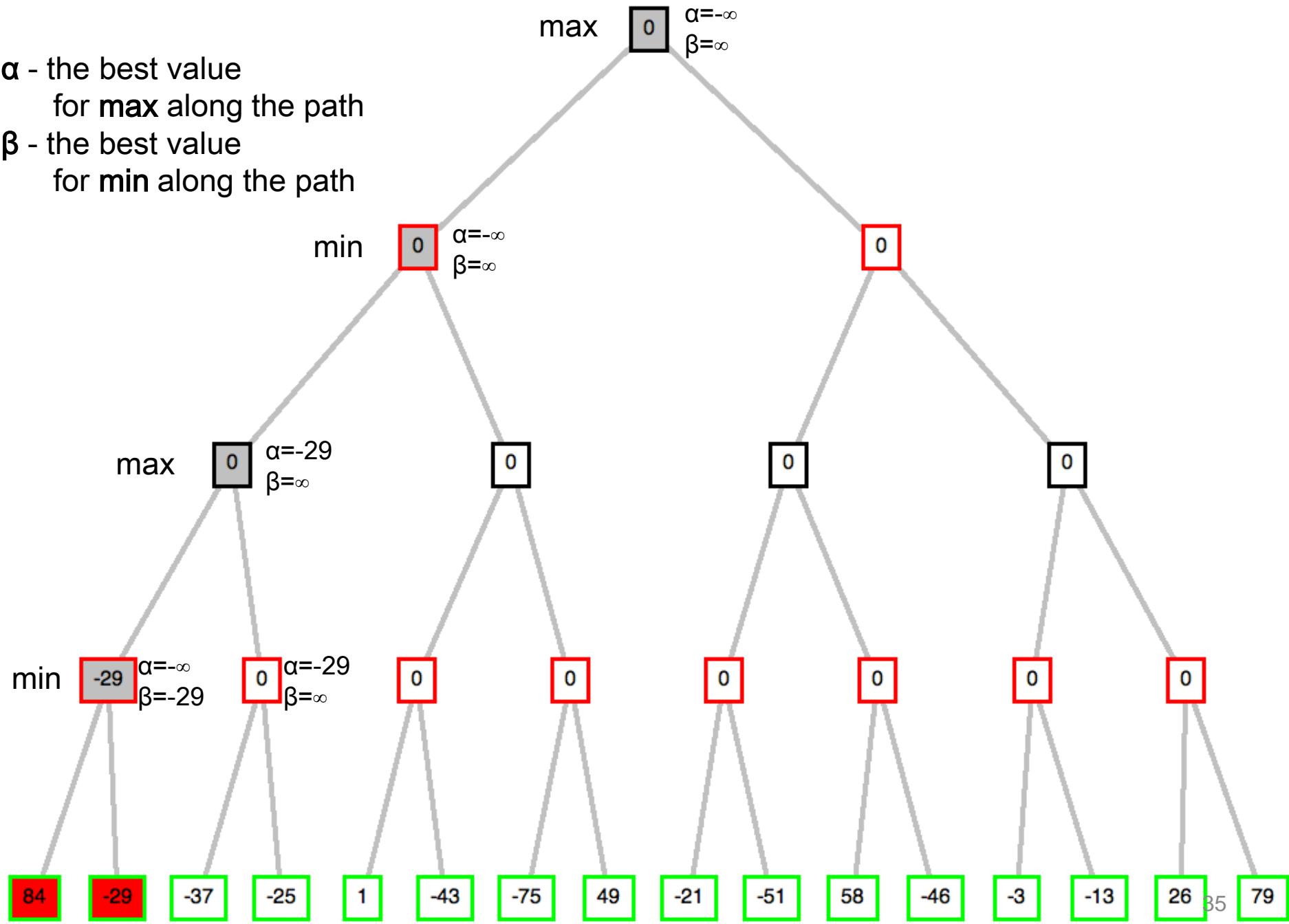
```
MaxVal(state, alpha, beta) {  
    if (terminal(state))  
        return utility(state);  
    for (s in children(state)) {  
        child = MinVal(s,alpha,beta);  
        alpha = max(alpha,child);  
        if (alpha>=beta) return child;  
    }  
    return beta; }
```

alpha = the highest value for MAX along the path  
beta = the lowest value for MIN along the path

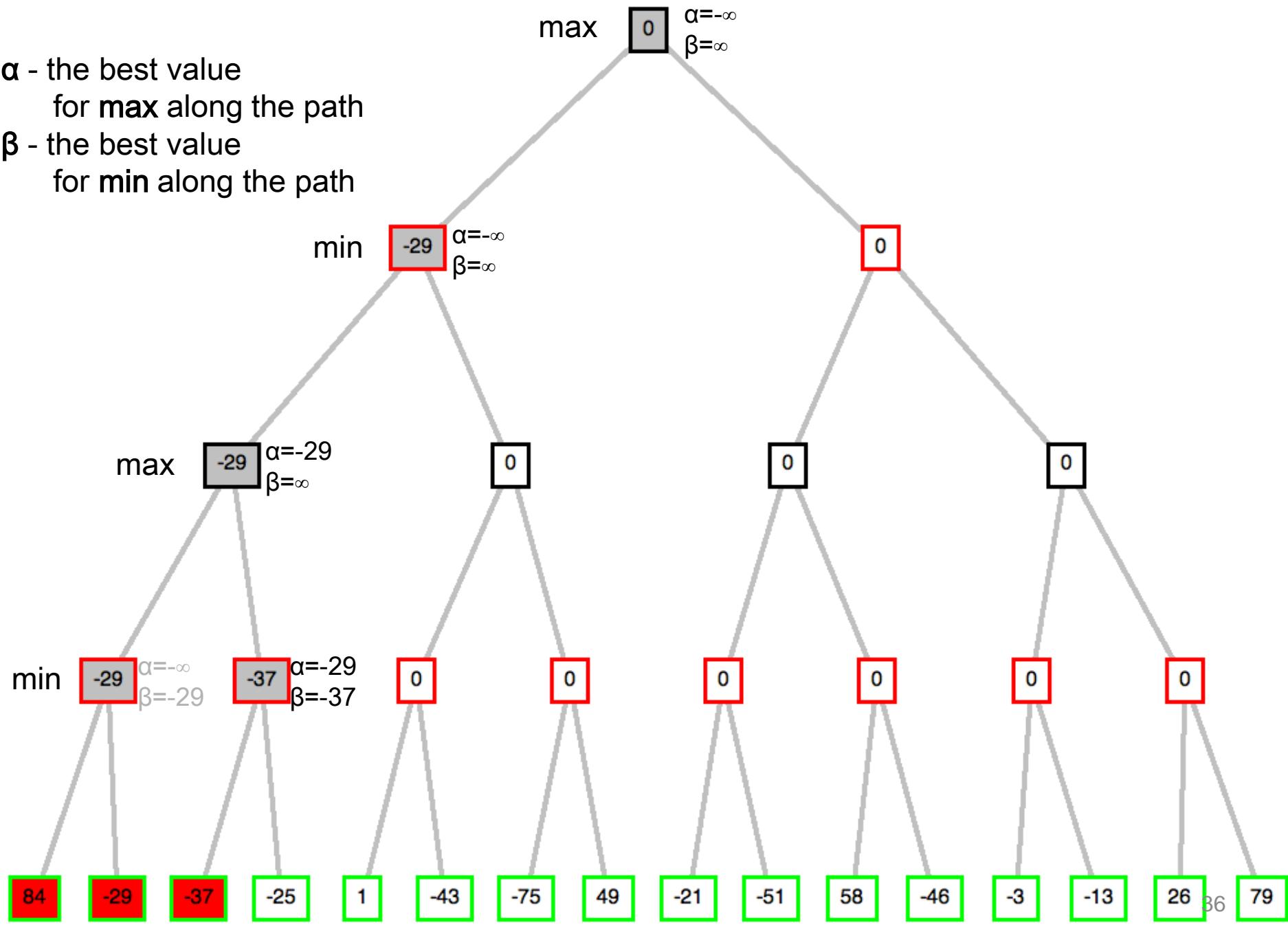
$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
for min along the path



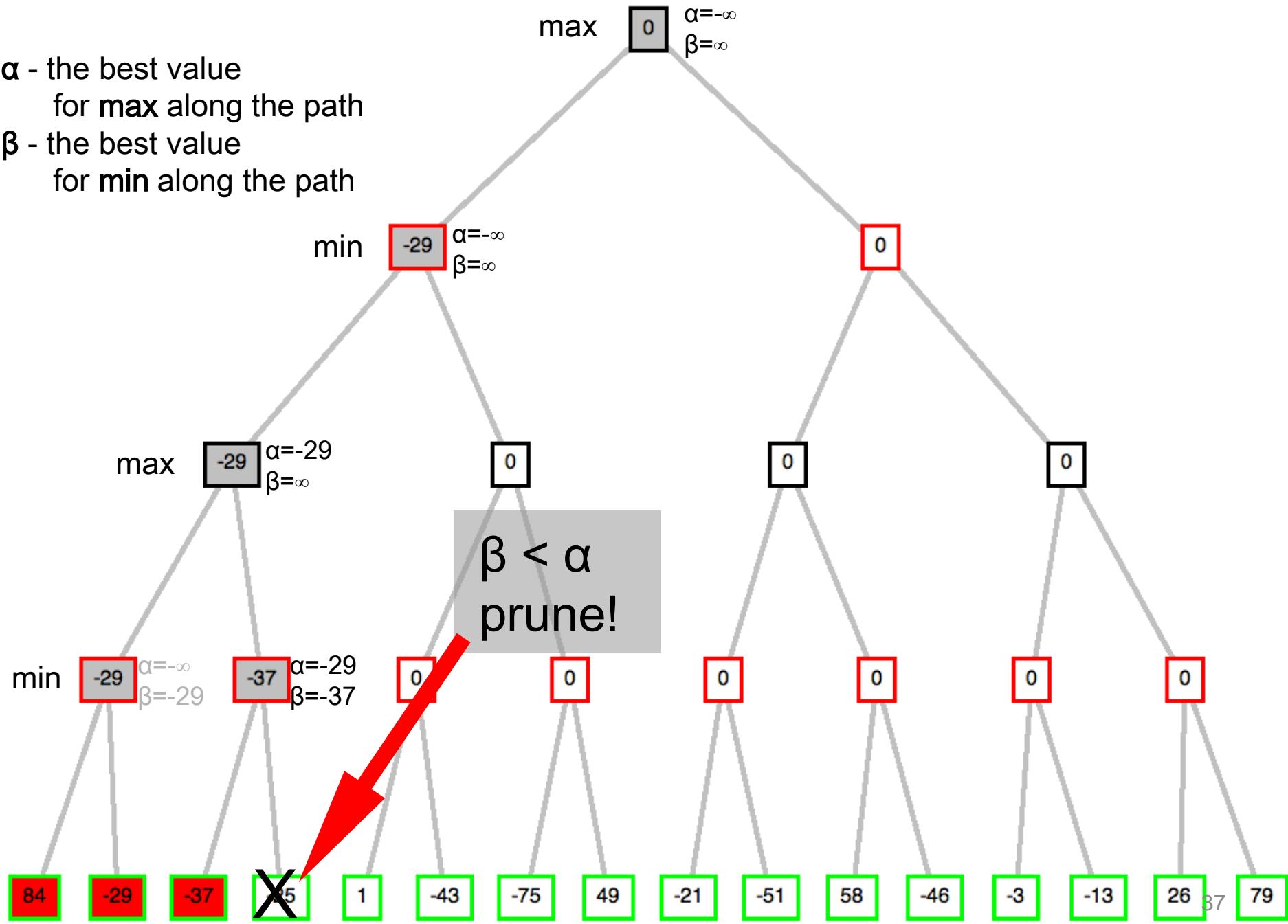
- $\alpha$  - the best value  
for **max** along the path
- $\beta$  - the best value  
for **min** along the path



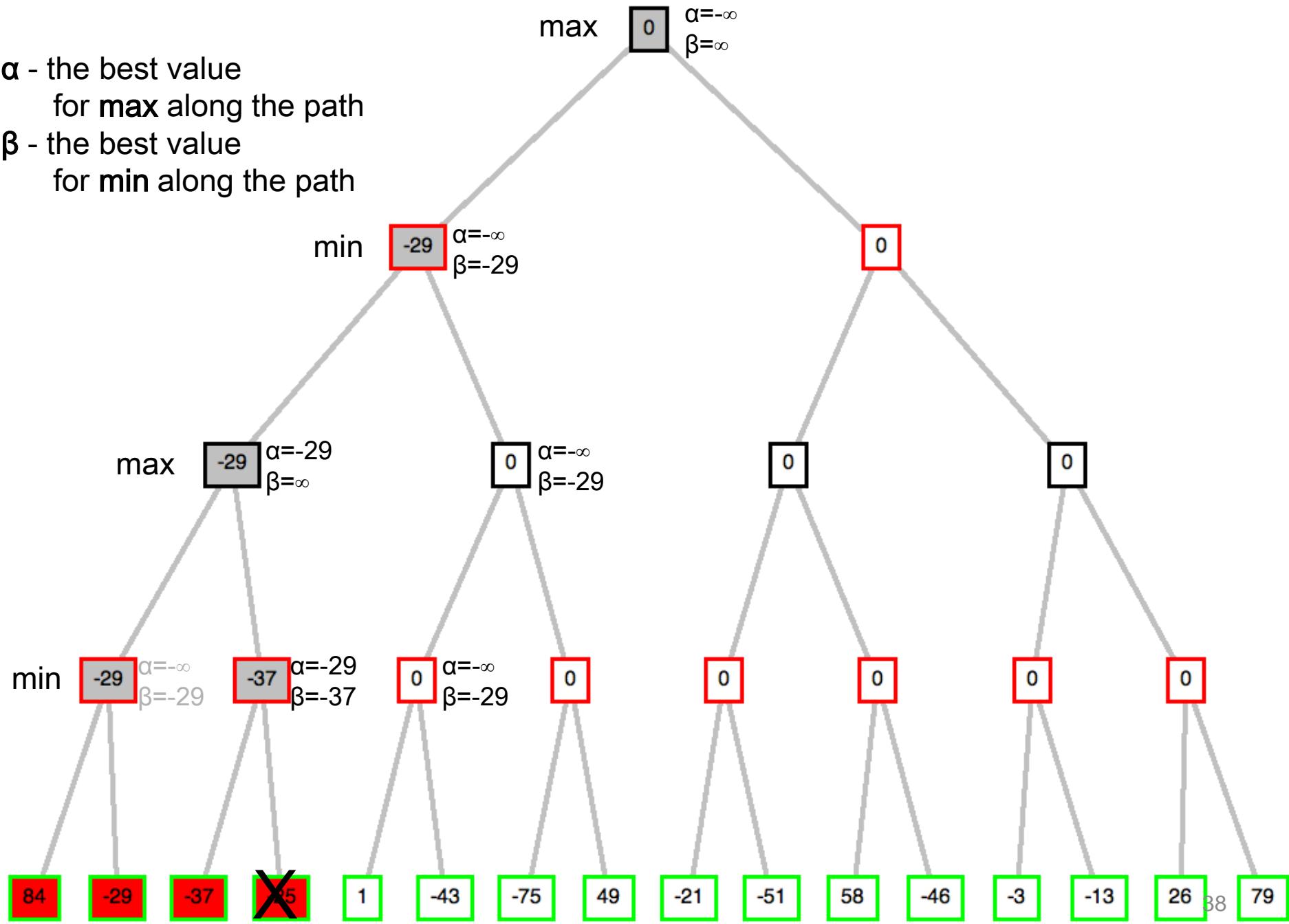
$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
for min along the path



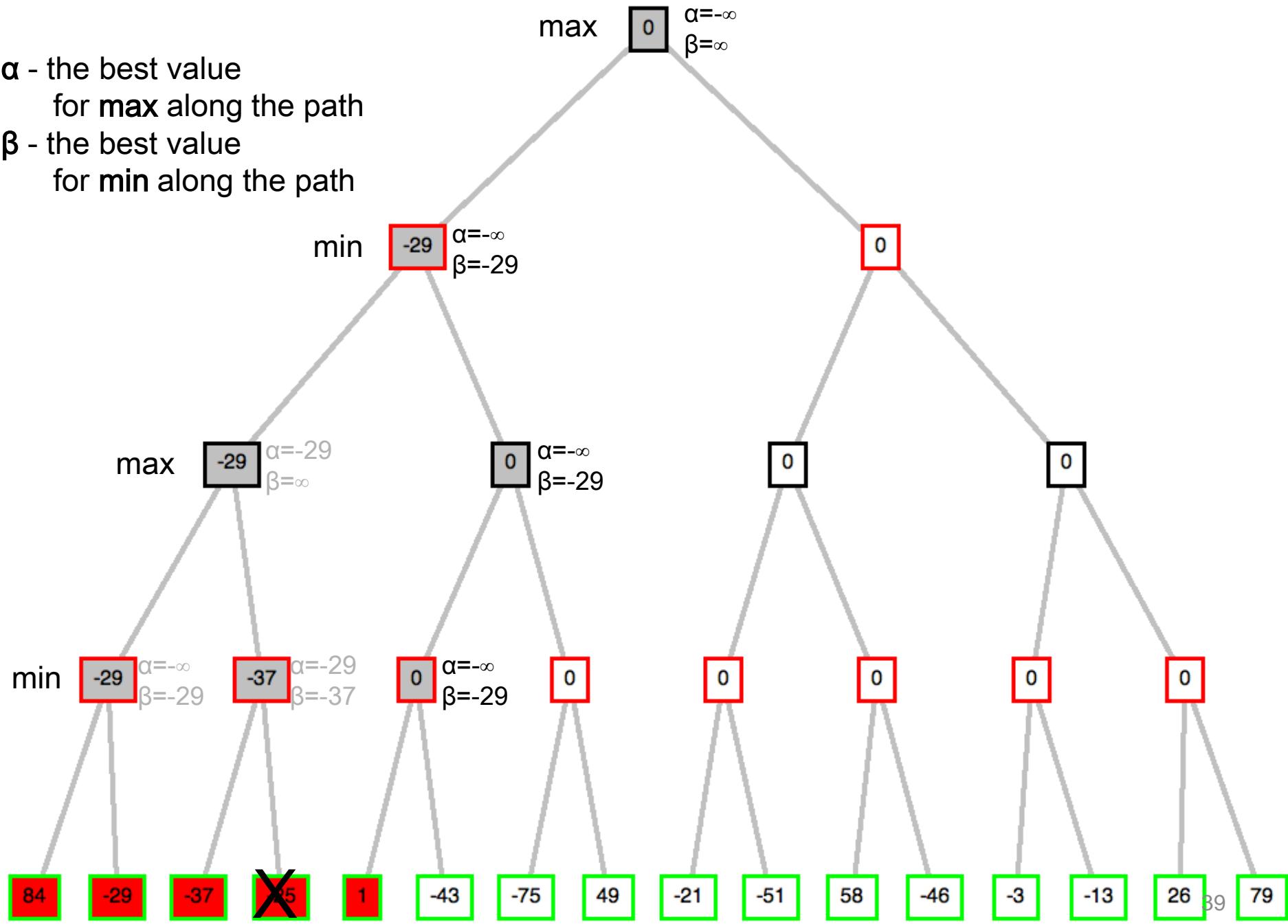
$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
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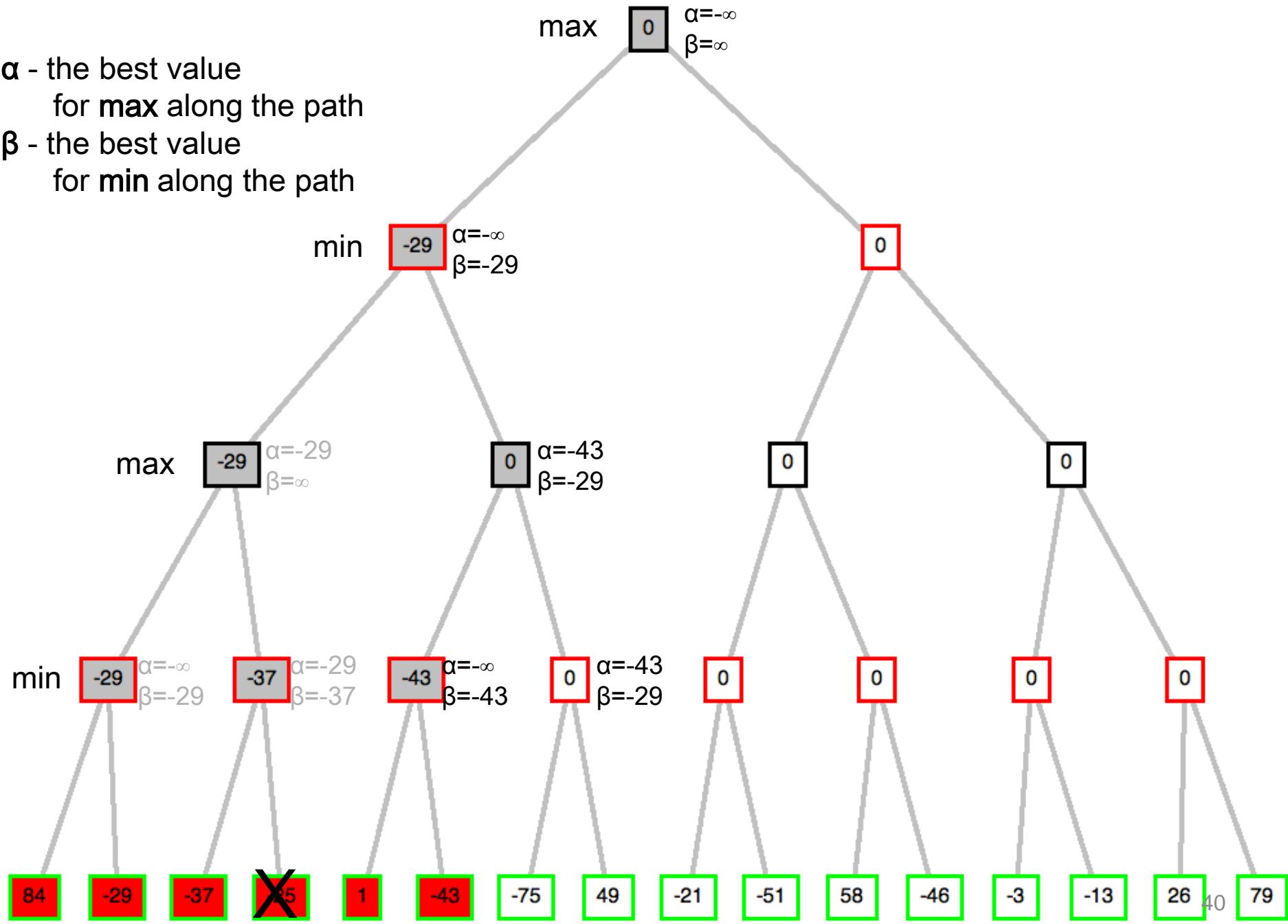
- $\alpha$  - the best value  
for **max** along the path
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for **min** along the path



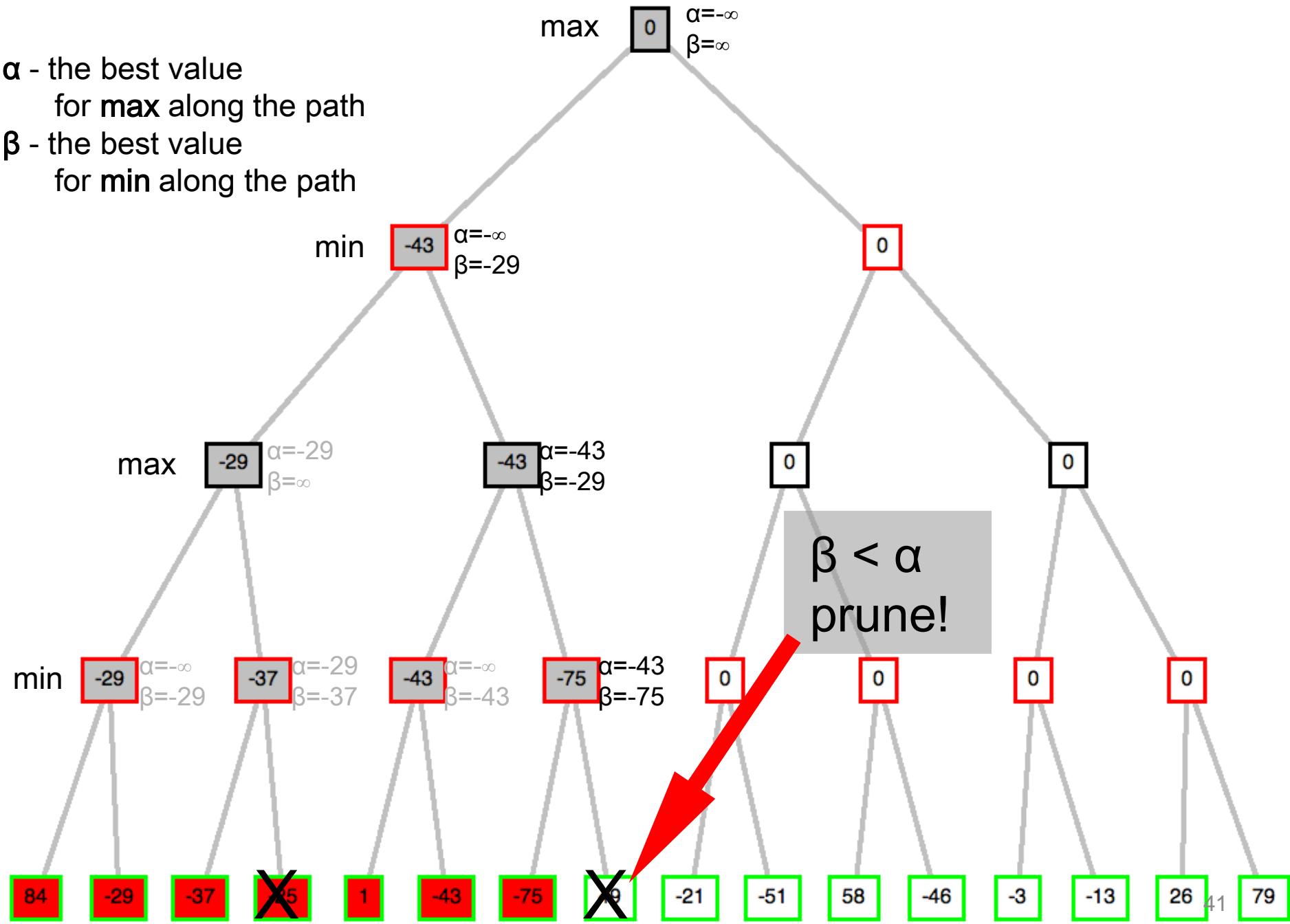
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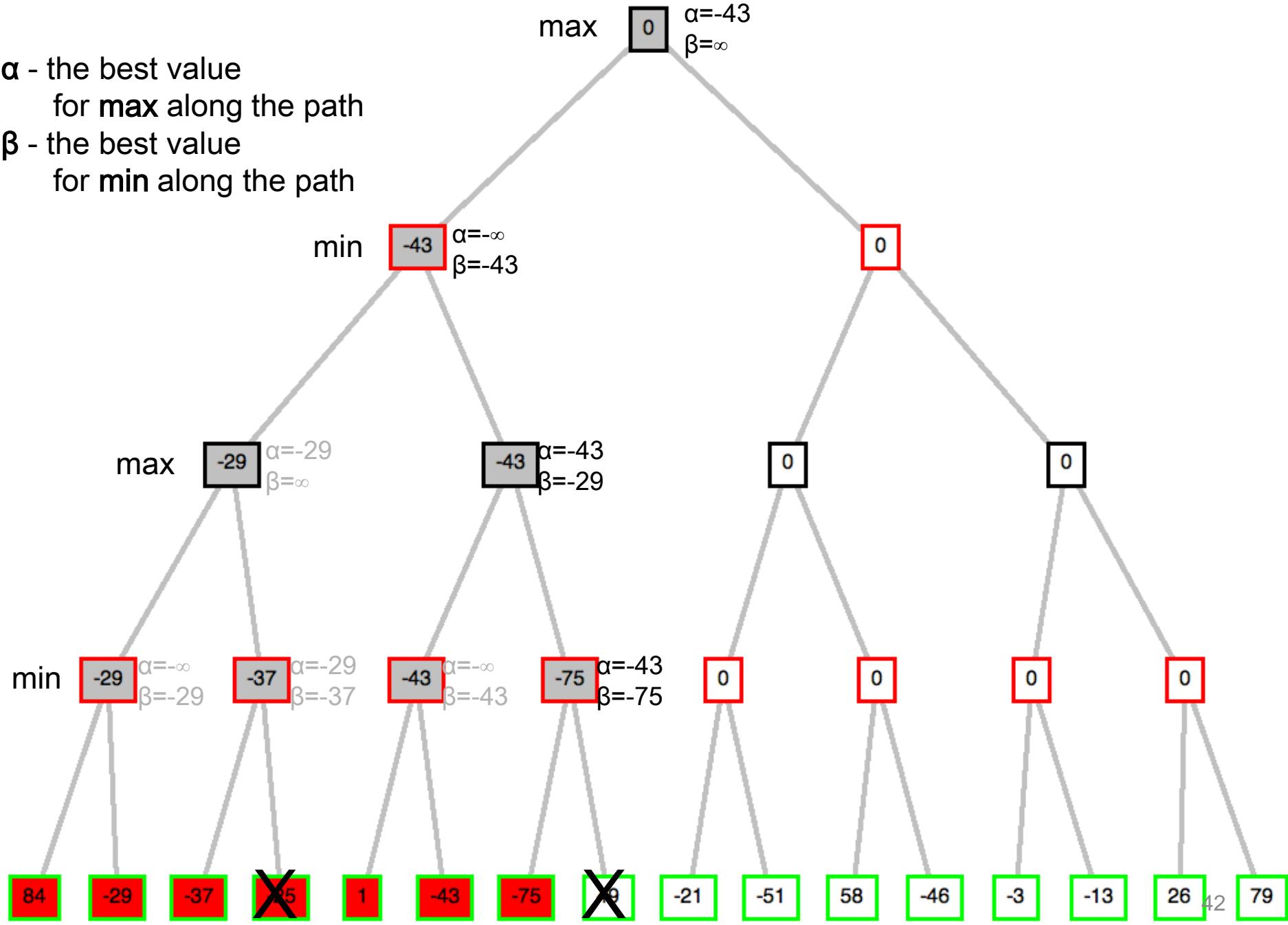
$\alpha$  - the best value  
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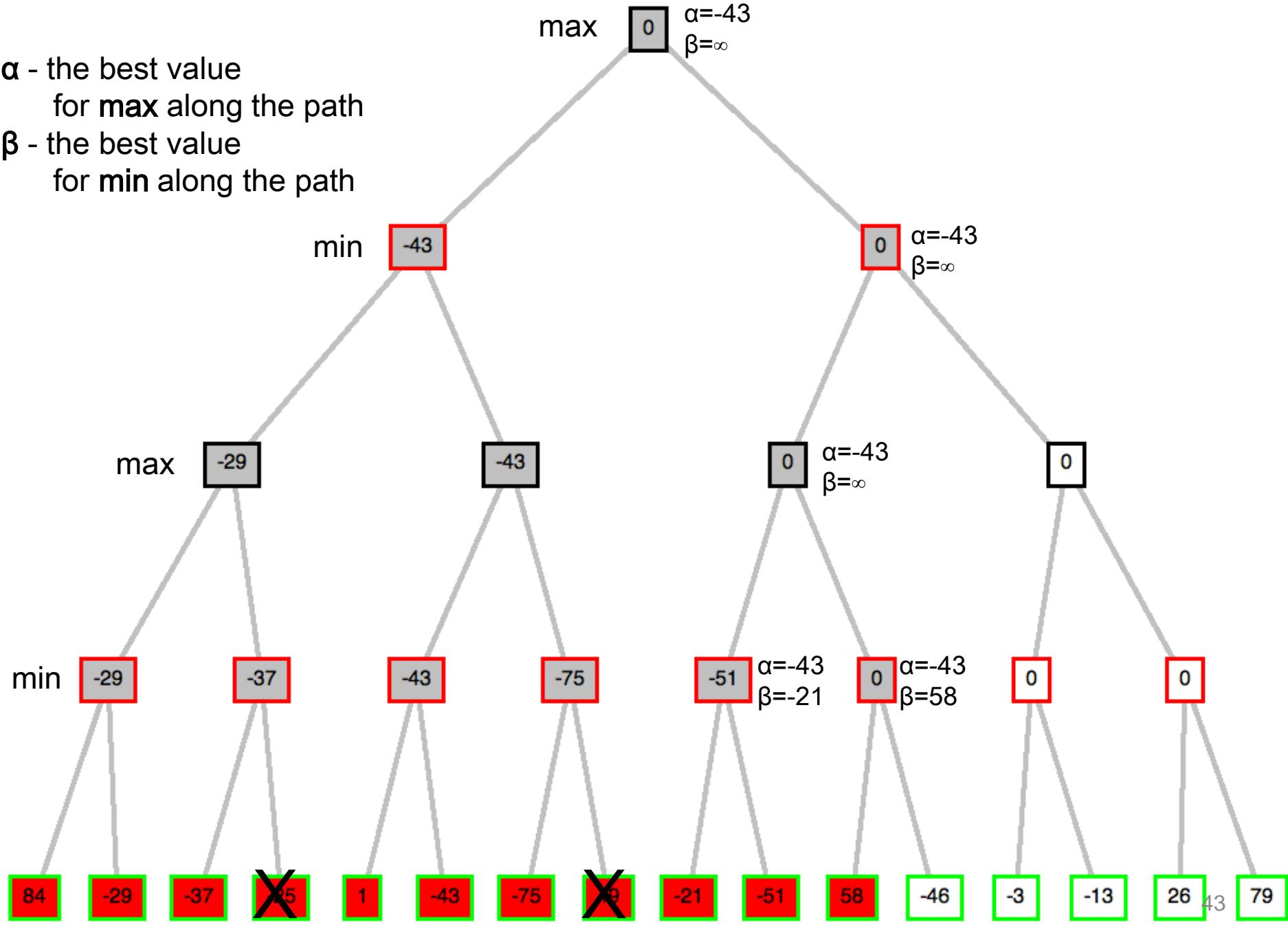
- α - the best value  
for **max** along the path
- β - the best value  
for **min** along the path



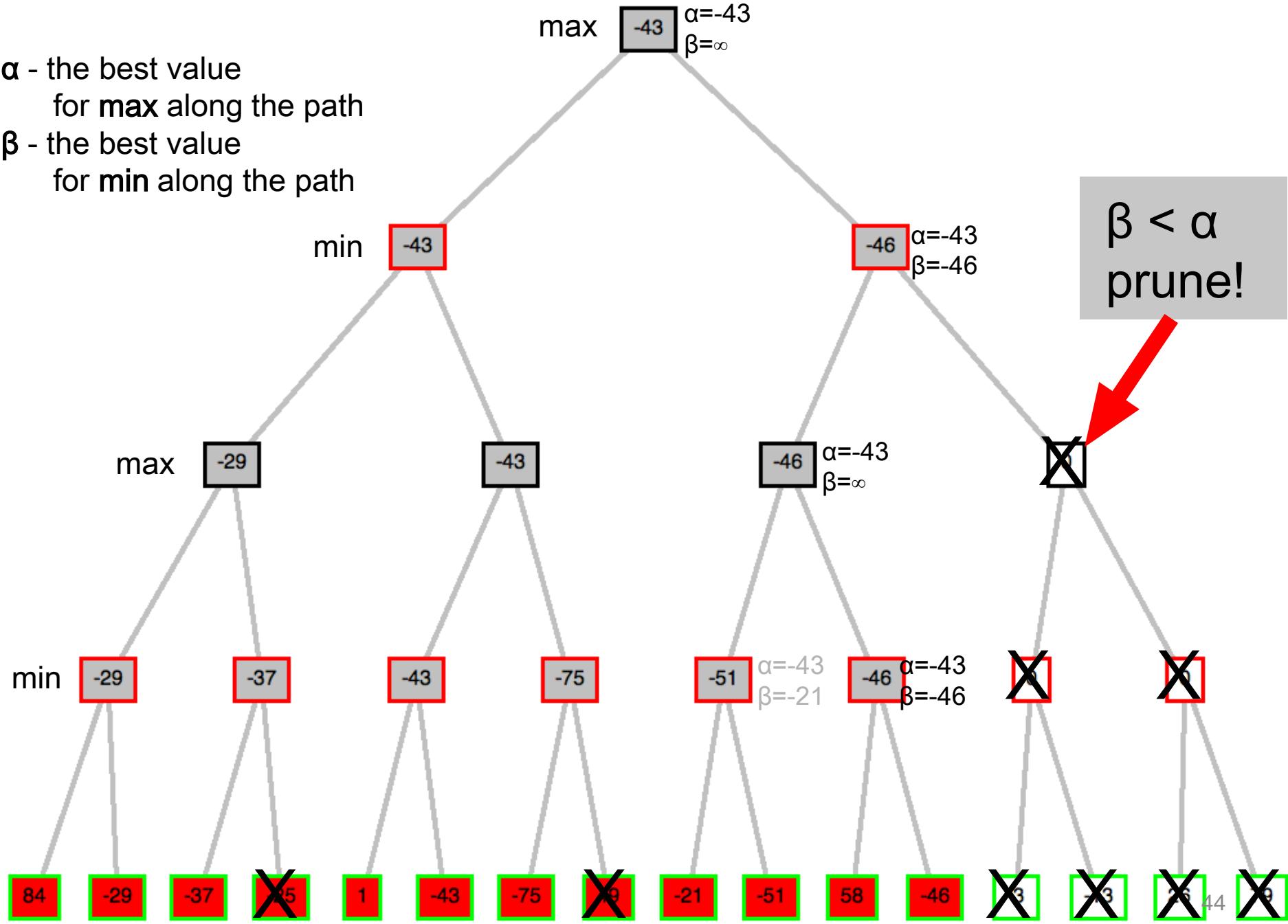
$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
for min along the path



$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
for min along the path



$\alpha$  - the best value  
for max along the path  
 $\beta$  - the best value  
for min along the path



# Properties of $\alpha$ - $\beta$

- Pruning **does not** affect final result. This means that it **gets the exact same result as does full minimax.**
- Good move ordering improves effectiveness of pruning
- With "perfect ordering," time complexity =  $O(b^{m/2})$   
→ **doubles** depth of search
- A simple example of reasoning about 'which computations are relevant' (a form of **metareasoning**)

# Shallow Search Techniques

1. limited search for a few levels
2. reorder the level-1 successors
3. proceed with  $\alpha$ - $\beta$  minimax search

# Good Enough?

- Chess:
    - branching factor  $b \approx 35$
    - game length  $m \approx 100$
    - search space  $b^{m/2} \approx 35^{50} \approx 10^{77}$
  - The Universe:
    - number of atoms  $\approx 10^{78}$
    - age  $\approx 10^{18}$  seconds
    - $10^8 \text{ moves/sec} \times 10^{78} \times 10^{18} = 10^{104}$
- The universe  
can play chess  
- can we?

# Cutting off Search

*MinimaxCutoff* is identical to *MinimaxValue* except

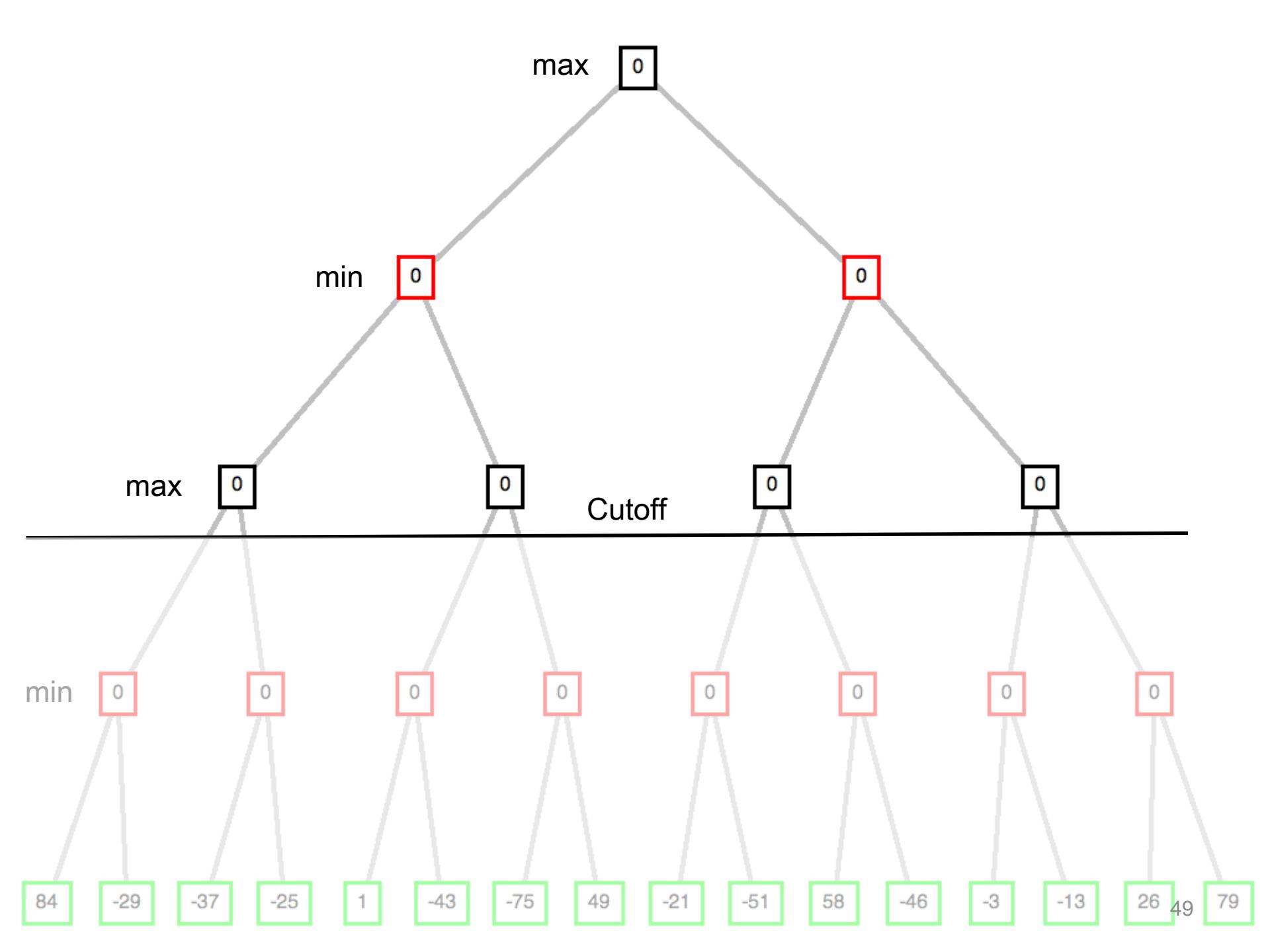
1. *Terminal?* is replaced by *Cutoff?*
2. *Utility* is replaced by *Eval*

Does it work in practice?

$$b^m = 10^6, b=35 \rightarrow m=4$$

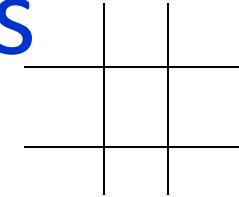
4-ply lookahead is a hopeless chess player!

- 4-ply ≈ human novice
- 8-ply ≈ typical PC, human master
- 12-ply ≈ Deep Blue, Kasparov



# Evaluation Functions

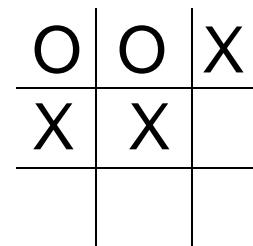
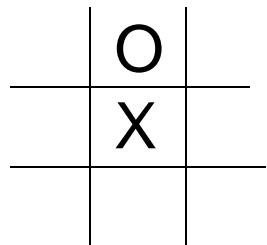
## Tic Tac Toe



- Let  $p$  be a position in the game
- Define the utility function  $f(p)$  by
  - $f(p) =$ 
    - largest positive number if  $p$  is a win for computer
    - smallest negative number if  $p$  is a win for opponent
    - $RCDC - RCDO$
  - where  $RCDC$  is number of rows, columns and diagonals in which computer could still win
  - and  $RCDO$  is number of rows, columns and diagonals in which opponent could still win.

# Sample Evaluations

- X = Computer; O = Opponent



X	O
rows	
cols	
diags	

X	O
rows	
cols	
diags	

# Evaluation functions

- For chess/checkers, typically **linear** weighted sum of **features**

$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$

e.g.,  $w_1 = 9$  with

$f_1(s) = (\text{number of white queens}) - (\text{number of black queens}),$   
etc.

# Example: Samuel's Checker-Playing Program

- It uses a linear evaluation function

$$f(n) = a_1x_1(n) + a_2x_2(n) + \dots + a_mx_m(n)$$

For example:  $f = 6K + 4M + U$

- K = King Advantage
- M = Man Advantage
- U = Undenied Mobility Advantage (number of moves that Max where Min has no jump moves)

# Samuel's Checker Player

- In learning mode
  - Computer acts as 2 players: A and B
  - A adjusts its coefficients after every move
  - B uses the static utility function
  - If A wins, its function is given to B

# Samuel's Checker Player

- How does A change its function?

## 1. Coefficient replacement

$\Delta(\text{node}) = \text{backed-up value}(\text{node}) - \text{initial value}(\text{node})$

if  $\Delta > 0$  then terms that contributed **positively** are given more weight and terms that contributed negatively get less weight

if  $\Delta < 0$  then terms that contributed **negatively** are given more weight and terms that contributed positively get less weight

# Samuel's Checker Player

- How does A change its function?

## 2. Term Replacement

38 terms altogether

16 used in the utility function at any one time

Terms that **consistently correlate low** with the function value are removed and added to the end of the term queue.

They are replaced by terms from the front of the term queue.

# Additional Refinements

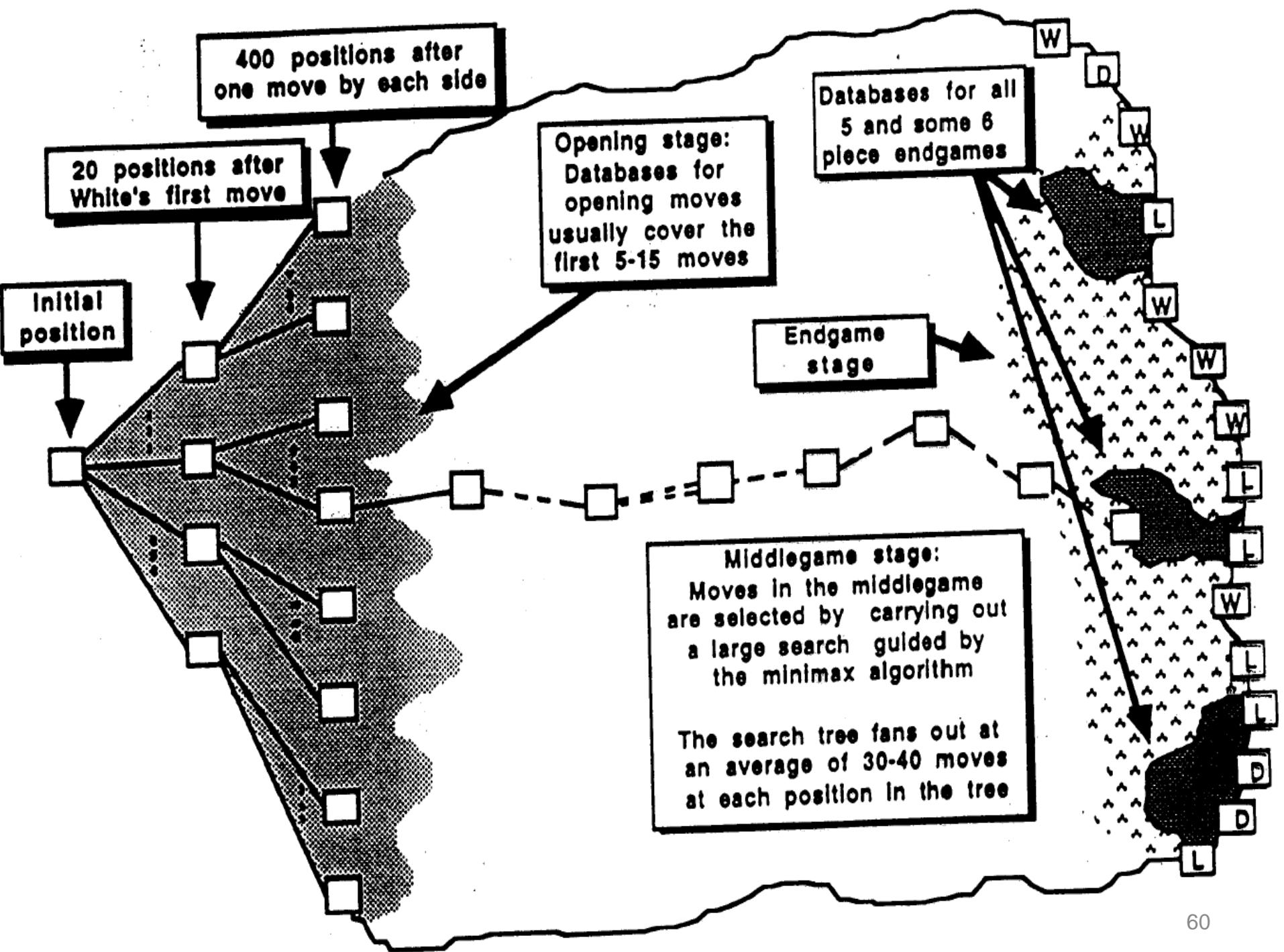
- **Waiting for Quiescence:** continue the search until no drastic change occurs from one level to the next.
- **Secondary Search:** after choosing a move, search a few more levels beneath it to be sure it still looks good.
- **Openings/Endgames:** for some parts of the game (especially initial and end moves), keep a catalog of best moves to make.

# Horizon Effect

The problem with abruptly stopping a search at a fixed depth is called the 'horizon effect'

# Chess: Rich history of cumulative ideas

- Minimax search, evaluation function learning (1950).
- Alpha-Beta search (1966).
- Transposition Tables (1967).
- Iterative deepening DFS (1975).
- End game data bases ,singular extensions(1977, 1980)
- Parallel search and evaluation(1983 ,1985)
- Circuitry (1987)

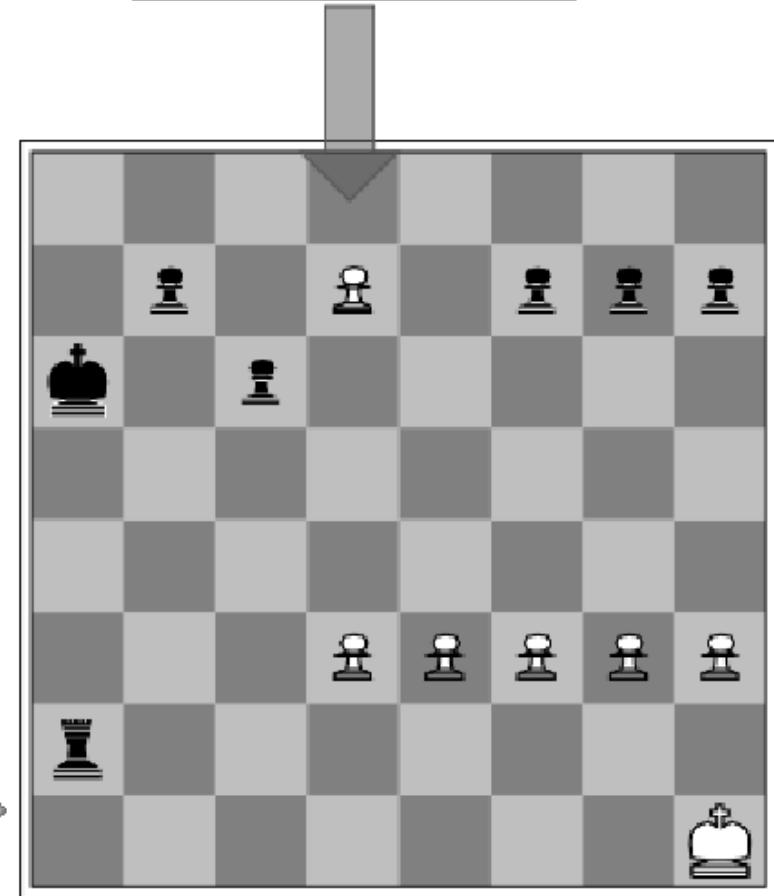


# Problem with fixed depth Searches

if we only search n moves ahead,  
it may be possible that the  
catastrophe can be delayed by a  
sequence of moves that do not  
make any progress

also works in other direction  
(good moves may not be found)

Fixed depth search  
thinks it can avoid  
the queening move



Black can give many  
consecutive checks  
before white escapes



Black to move

# Quiescence Search

This involves searching past the terminal search nodes (depth of 0) and testing all the non-quiescent or 'violent' moves until the situation becomes calm, and only then apply the evaluator.

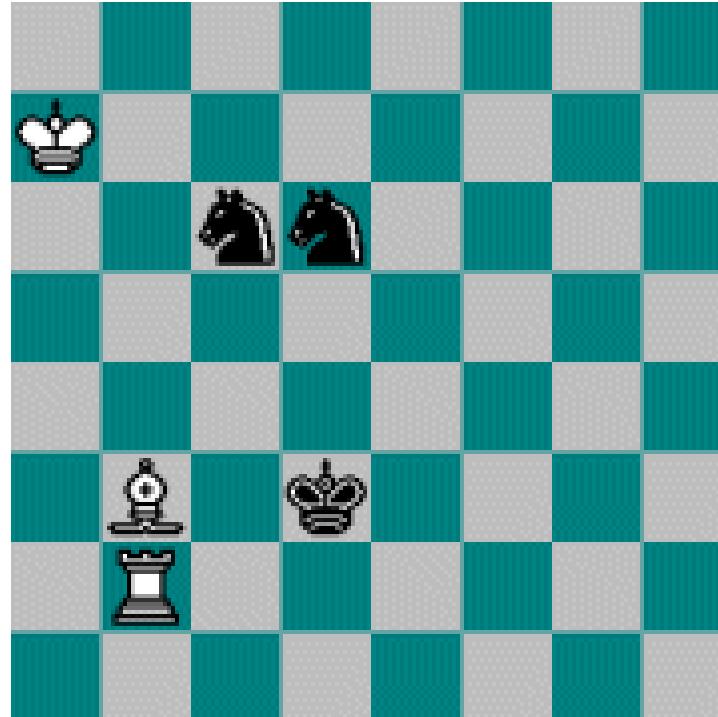
Enables programs to detect long capture sequences and calculate whether or not they are worth initiating.

Expand searches to avoid evaluating a position where tactical disruption is in progress.

# End-Game Databases

- Ken Thompson - all 5 piece end-games
- Lewis Stiller - all 6 piece end-games
  - Refuted common chess wisdom: many positions thought to be ties were really **forced wins -- 90% for white**
  - Is perfect chess a win for white?

# The MONSTER



White wins in 255 moves  
(Stiller, 1991)

# Deterministic Games in Practice

- Checkers: Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used a precomputed endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 444 billion positions. Checkers is now solved!
- Chess: Deep Blue defeated human world champion Garry Kasparov in a six-game match in 1997. Deep Blue searches 200 million positions per second, uses very sophisticated evaluation, and undisclosed methods for extending some lines of search up to 40 ply. Current programs are even better, if less historic!
- Othello: human champions refuse to compete against computers, who are too good.
- Go: human champions refuse to compete against computers, who are too bad. In Go,  $b > 300$ , so most programs use pattern knowledge bases to suggest plausible moves, along with aggressive pruning.

# Game of Go

human champions refuse to compete against computers, because software is too bad.

	Chess	Go
Size of board	8 x 8	19 x 19
Average no. of moves per game	100	300
Avg branching factor per turn	35	235
Additional complexity		Players can pass

# Recent Successes in Go

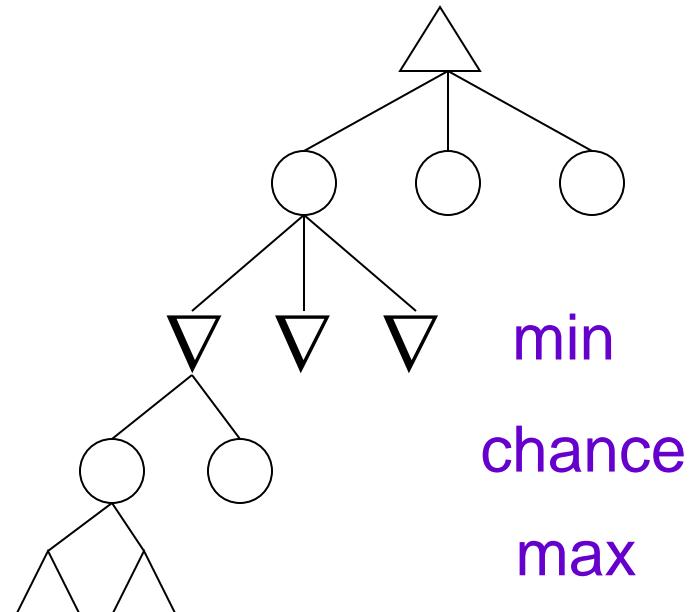
- MoGo defeated a human expert in 9x9 Go
- Still far away from 19x19 Go.
- Hot area of research
- Leading to development of novel techniques
  - Monte Carlo tree search (UCT)

# Other Games

	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon, monopoly
imperfect information	stratego	bridge, poker, scrabble

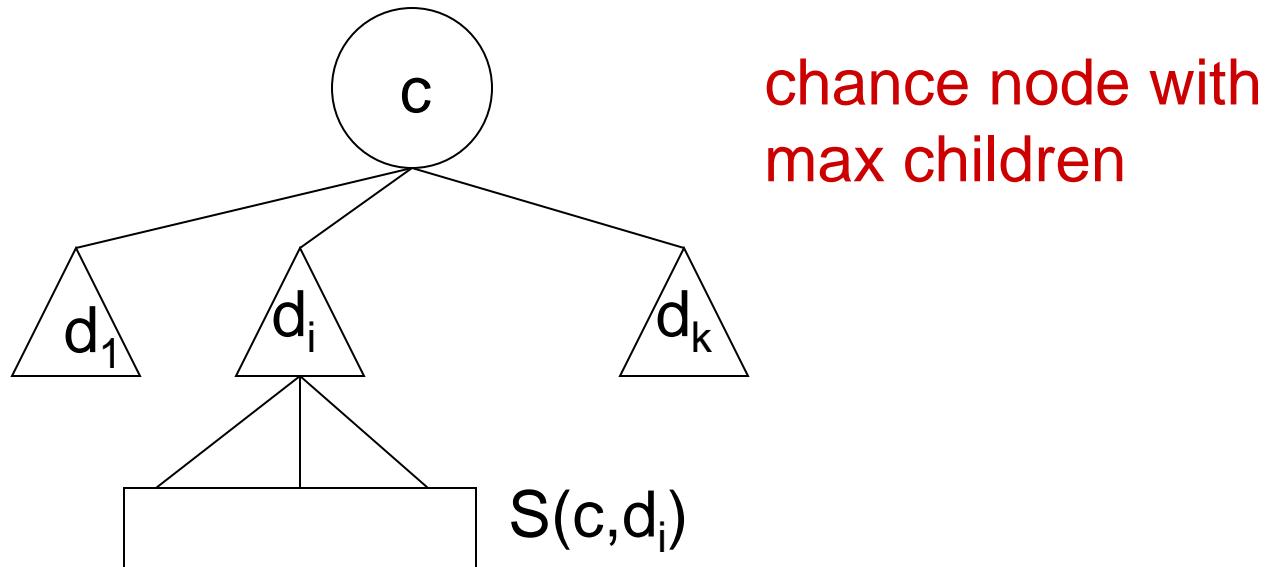
# Games of Chance

- What about games that involve chance, such as
  - rolling dice
  - picking a card
- Use three kinds of nodes:
  - max nodes
  - min nodes
  - chance nodes



# Games of Chance

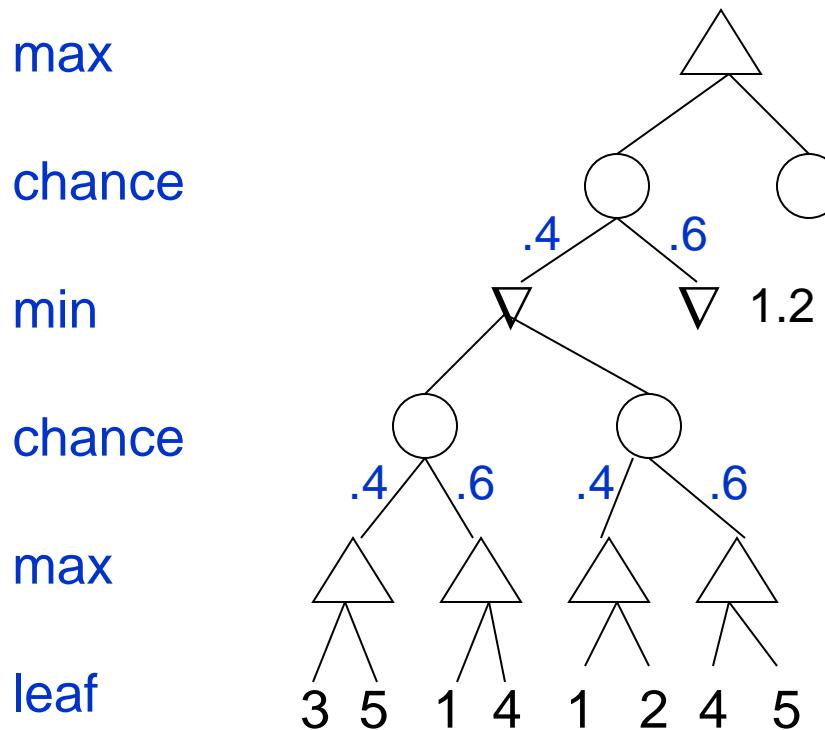
## Expectiminimax



$$\text{expectimax}(c) = \sum_i P(d_i) \max_{s \in S(c, d_i)} \text{backed-up-value}(s)$$

$$\text{expectimin}(c') = \sum_i P(d_i) \min_{s \in S(c, d_i)} \text{backed-up-value}(s)$$

# Example Tree with Chance



# Complexity

- Instead of  $O(b^m)$ , it is  $O(b^m n^m)$  where  $n$  is the number of chance outcomes.
- Since the complexity is higher (both time and space), we cannot search as deeply.
- Pruning algorithms may be applied.

# Imperfect Information

- E.g. card games, where opponents' initial cards unknown
- Idea: For all deals consistent with what you can see
  - compute the minimax value of available actions for each of possible deals
  - compute the expected value over all deals



# Summary

- Games are fun to work on!
- They illustrate several important points about AI.
- Perfection is unattainable → must approximate.
- Game playing programs have shown the world what AI can do.

**Thank You**  
For Your Attention!

Any Questions

