Adversarial Search

Chapter 5

Mausam

(Based on slides of Stuart Russell, Henry Kautz, Linda Shapiro & UW AI Faculty)

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?

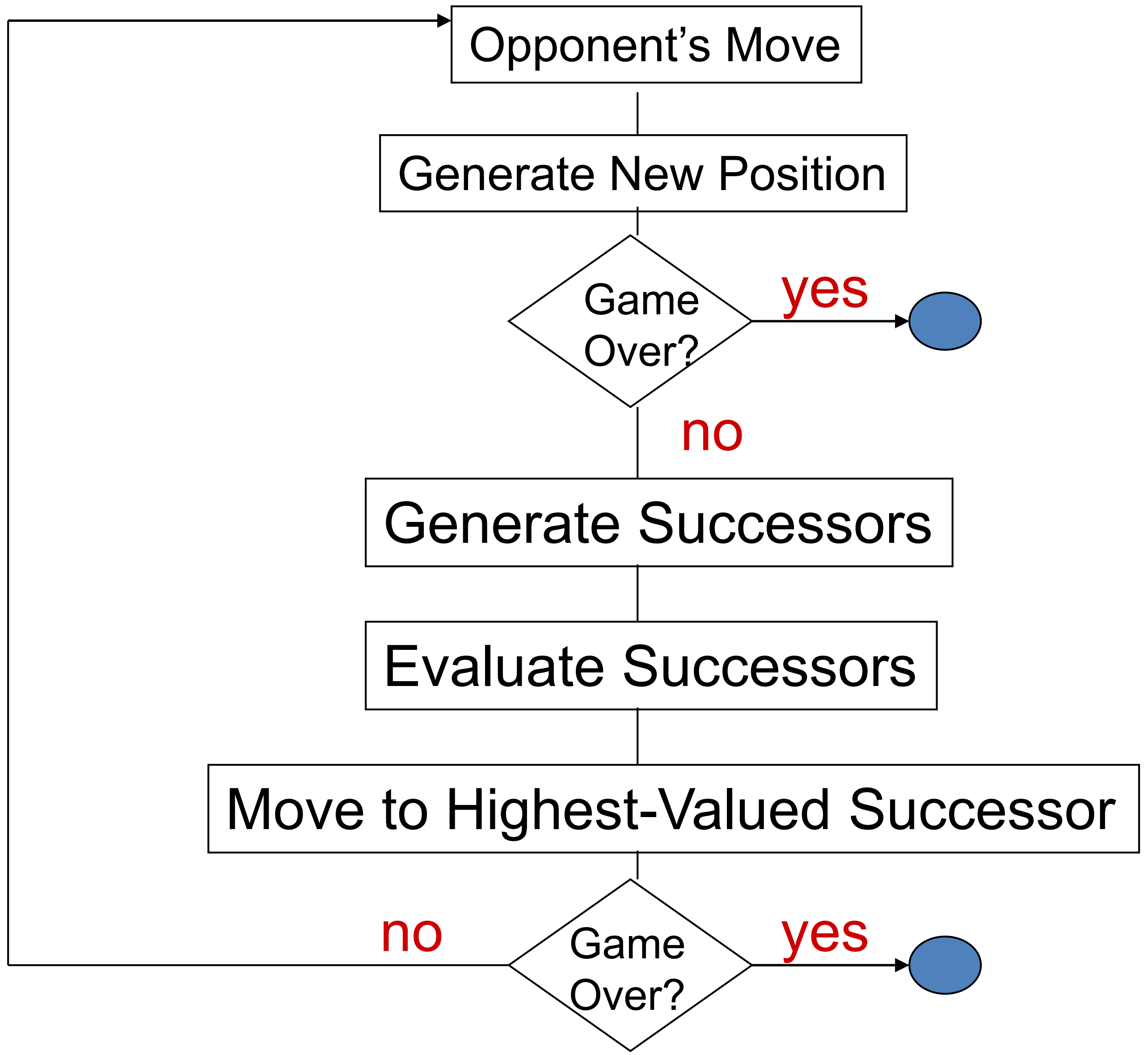
Mainly games of strategy with the following characteristics:

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)

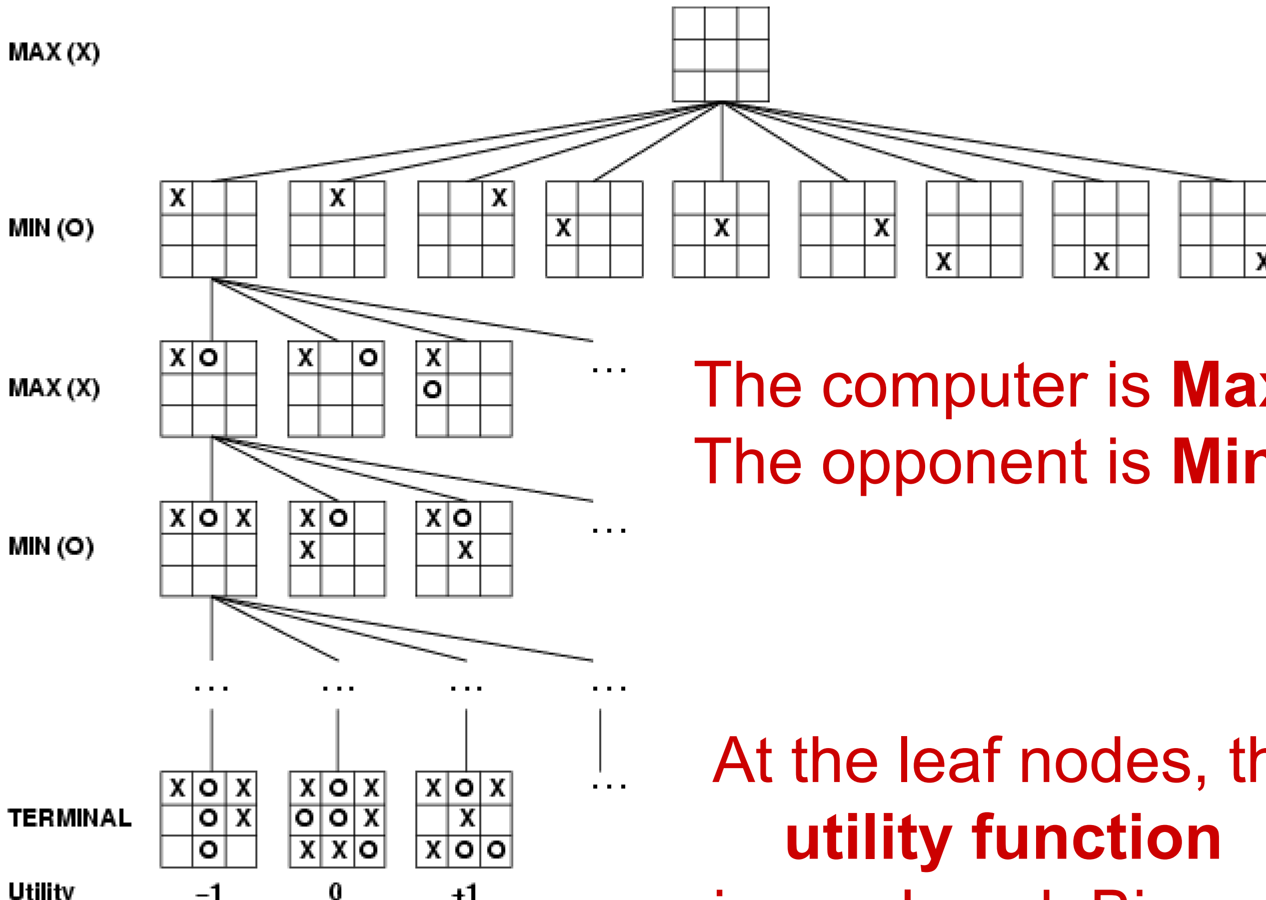
computer's turn

opponent's turn

computer's turn

opponent's turn

leaf nodes are evaluated



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

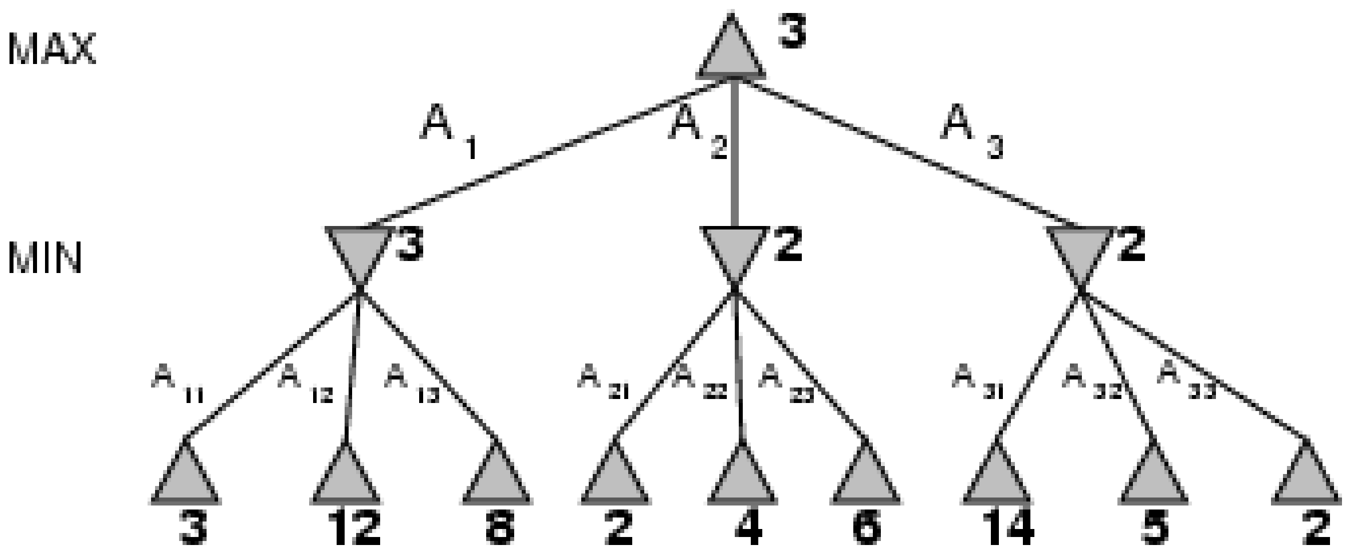
At the leaf nodes, the **utility function** is employed. Big value means good, small is bad.

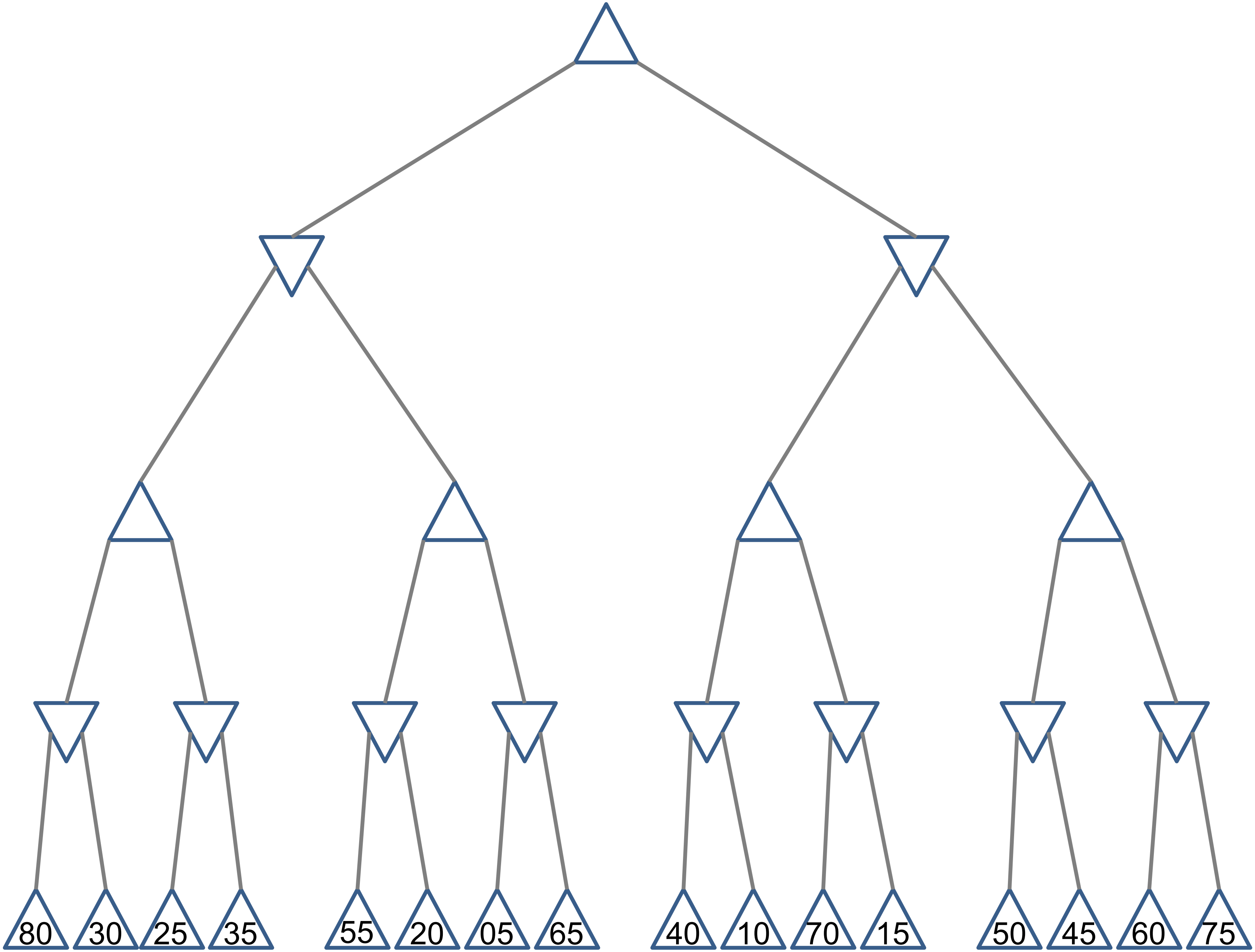
Mini-Max Terminology

- 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:

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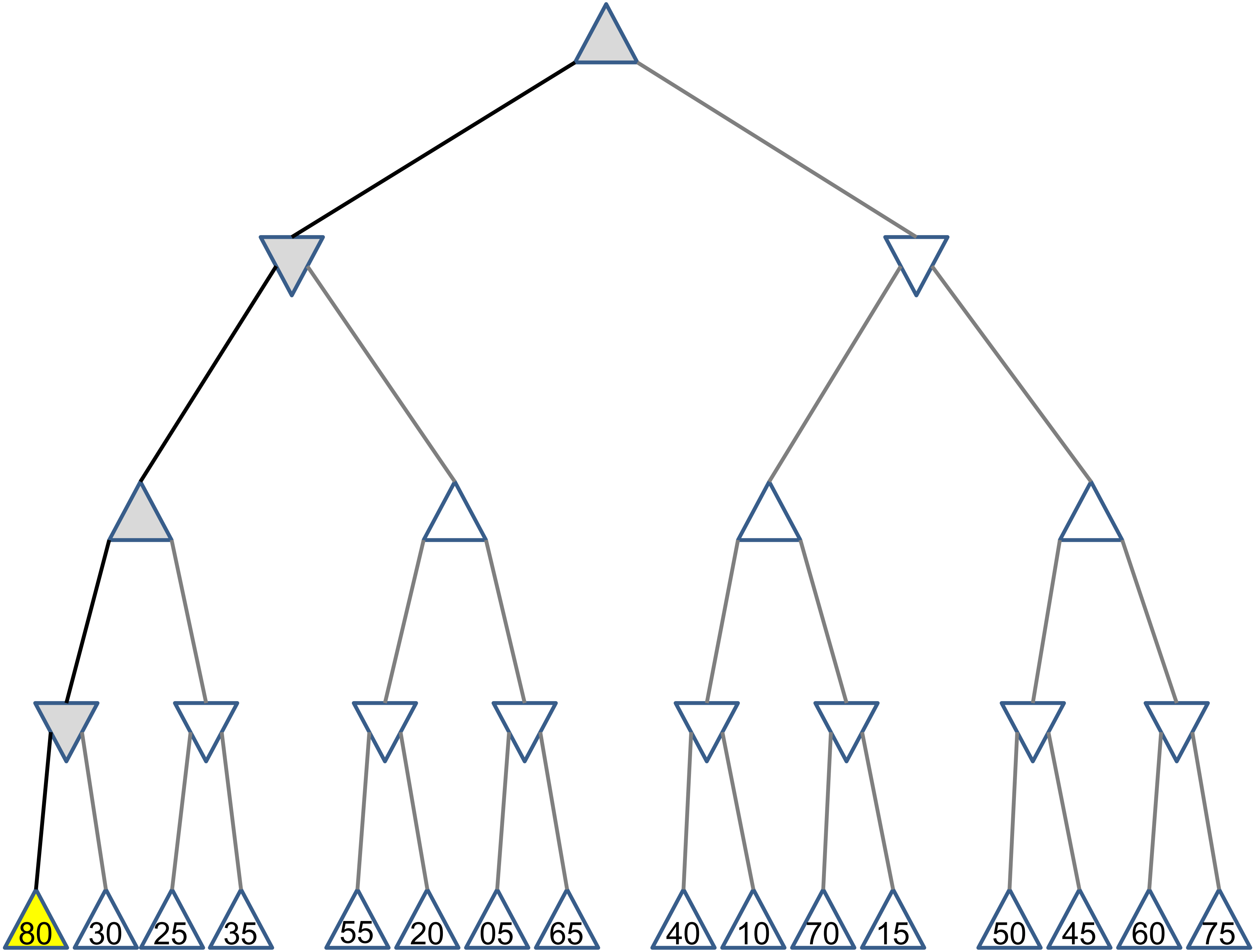
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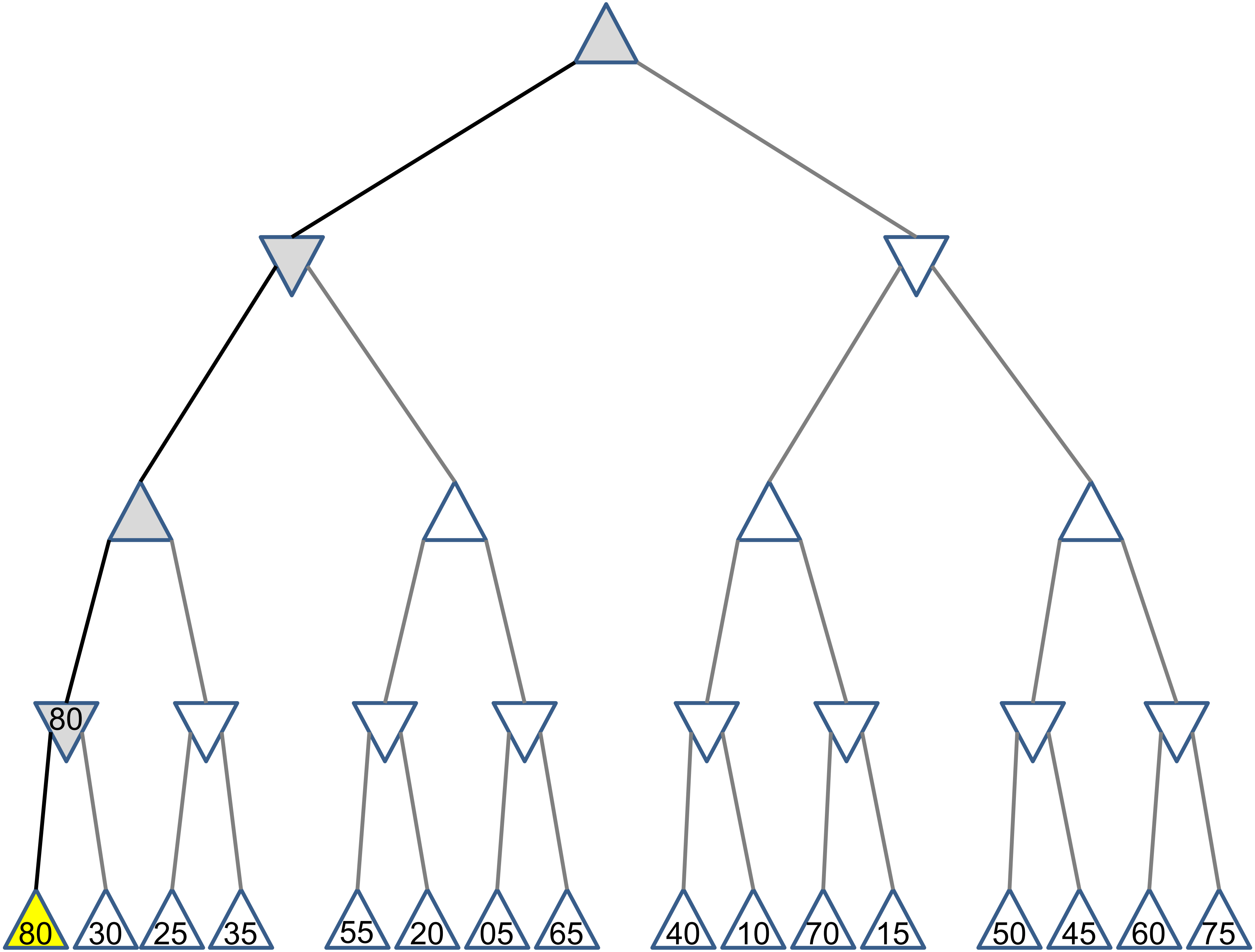
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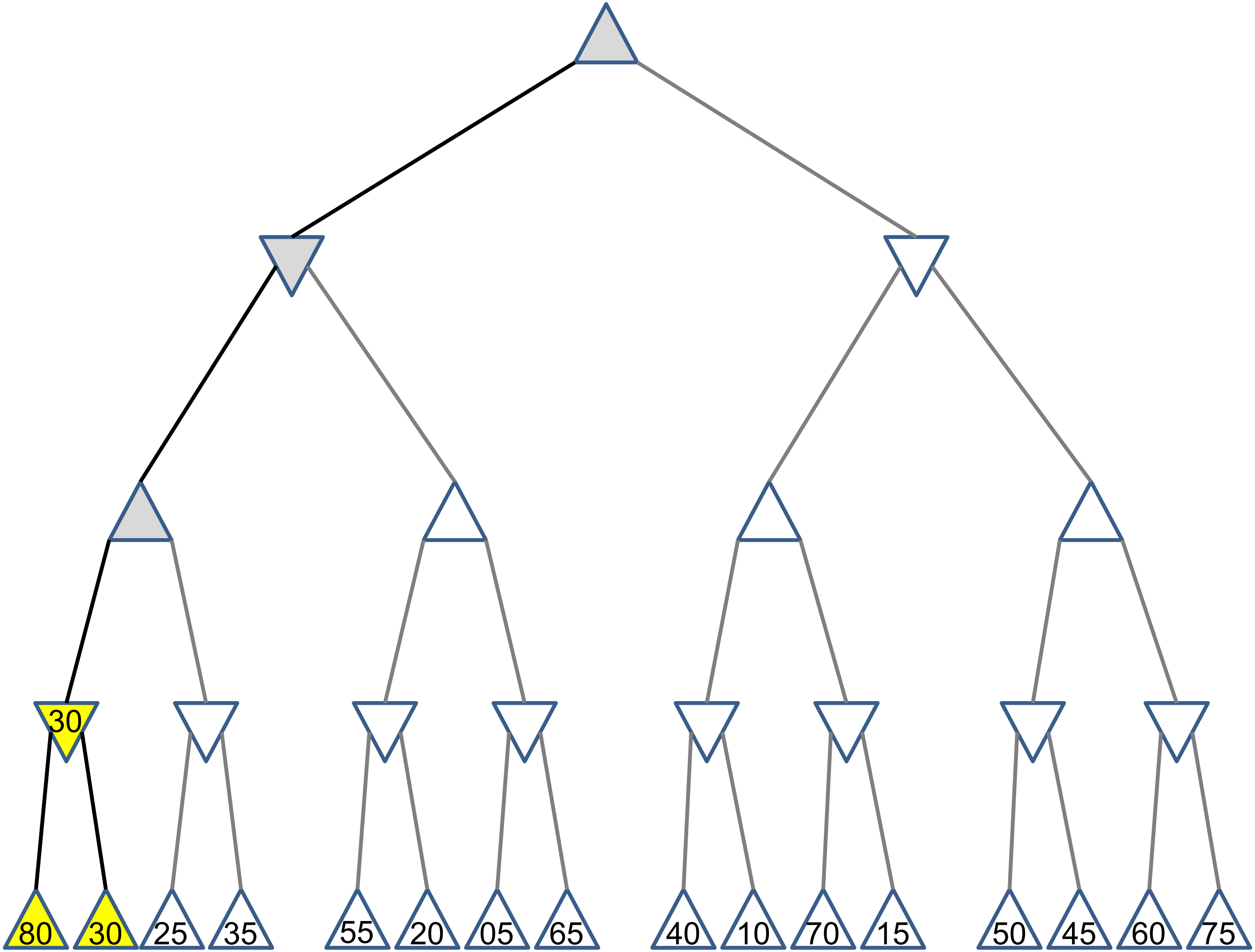
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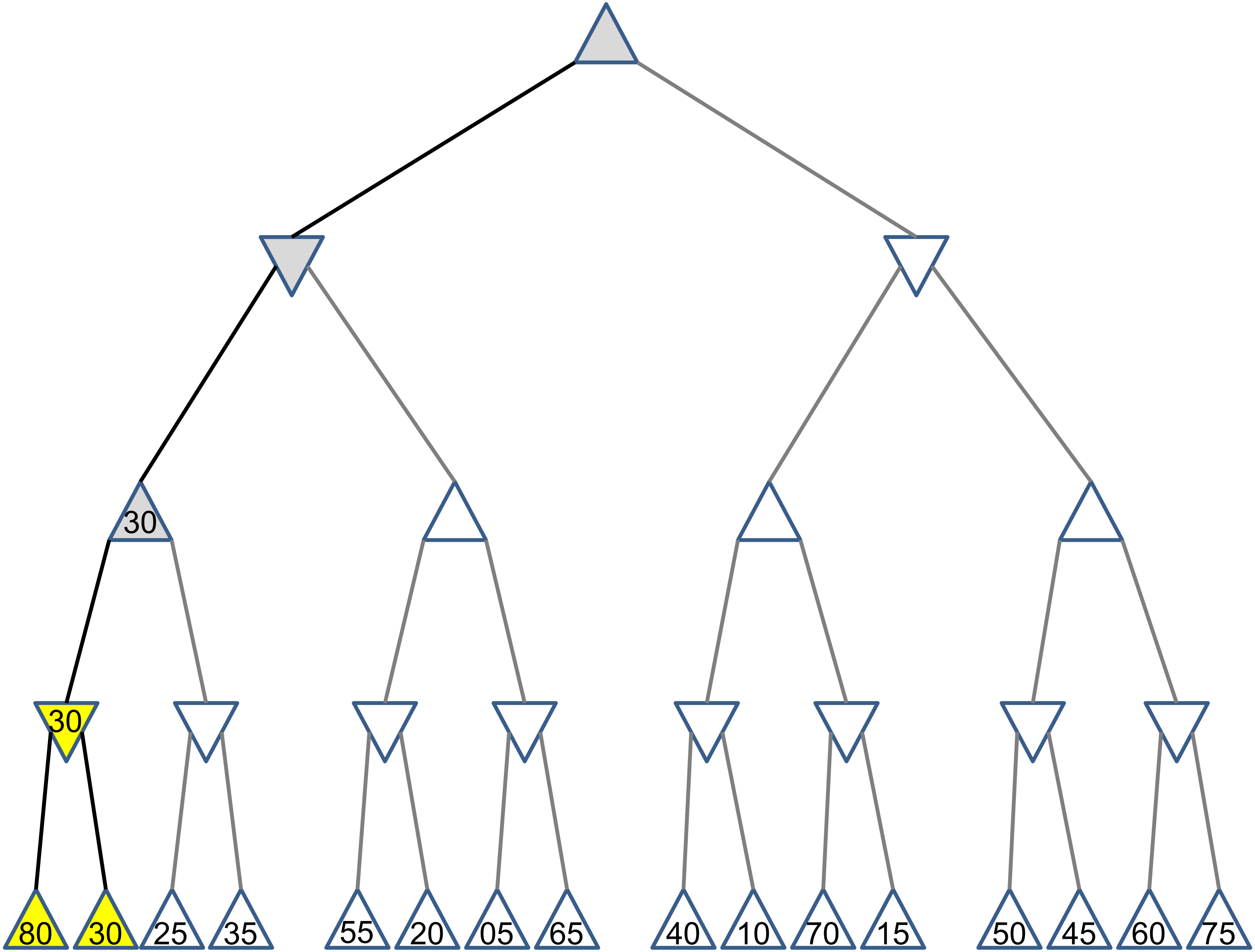
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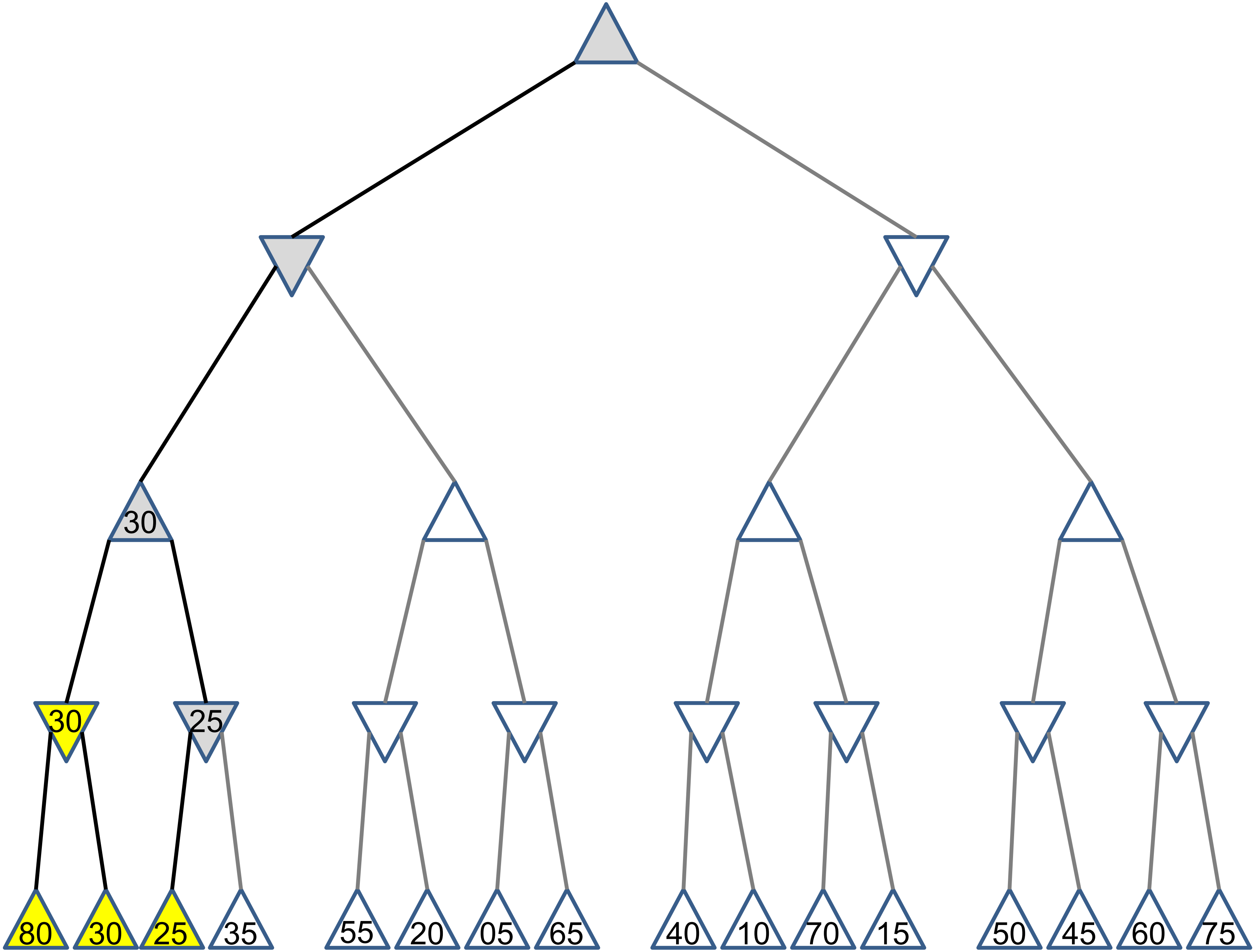
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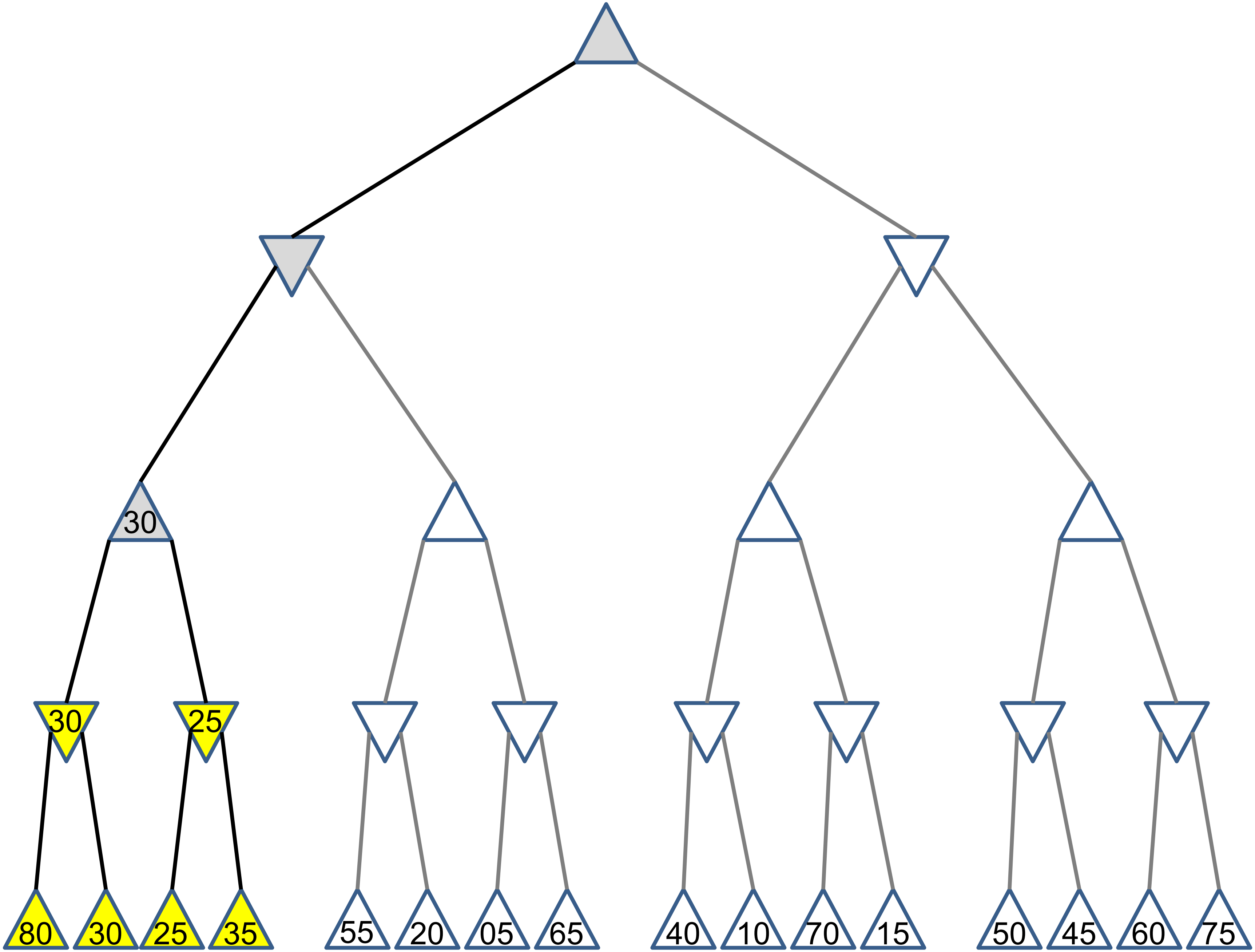
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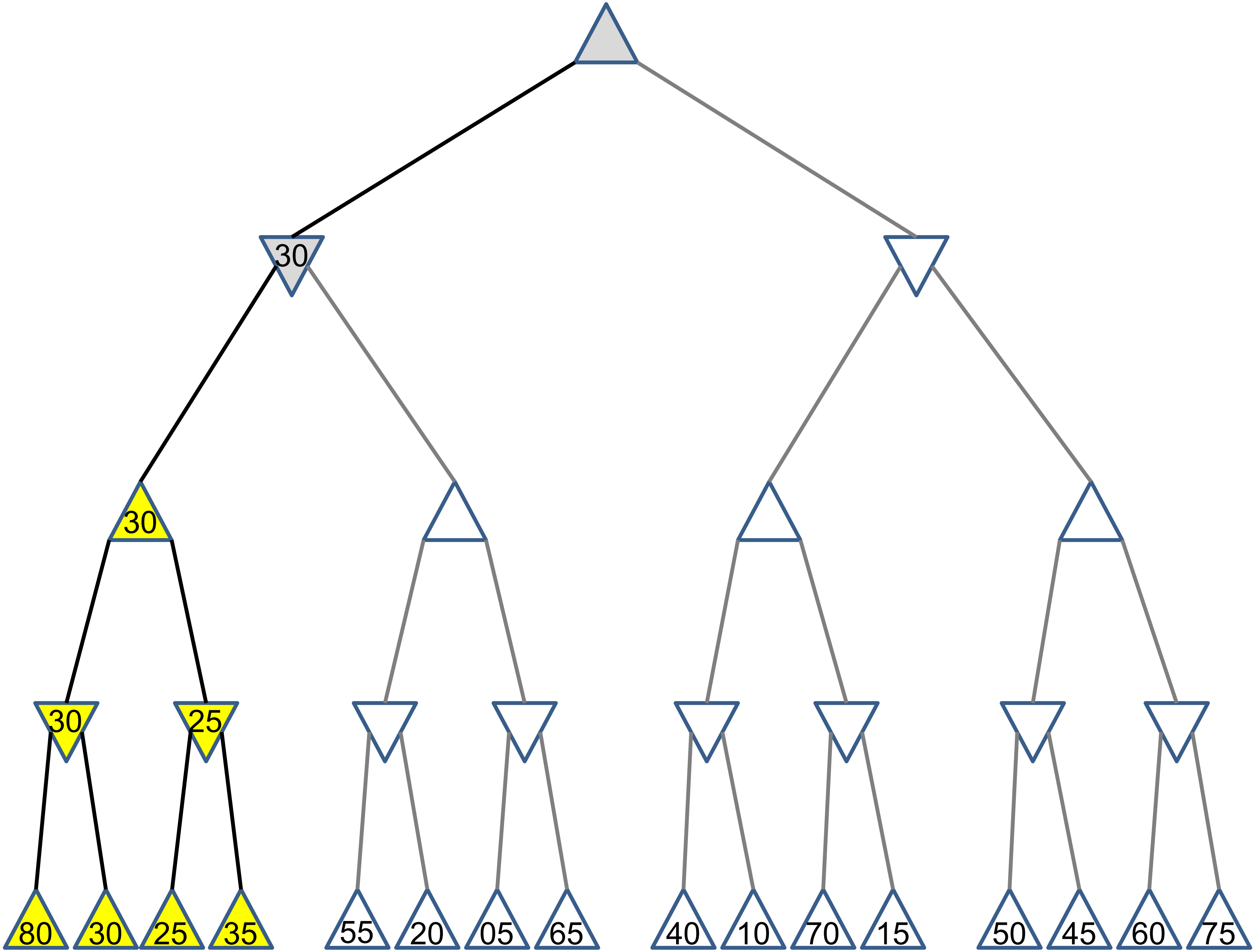
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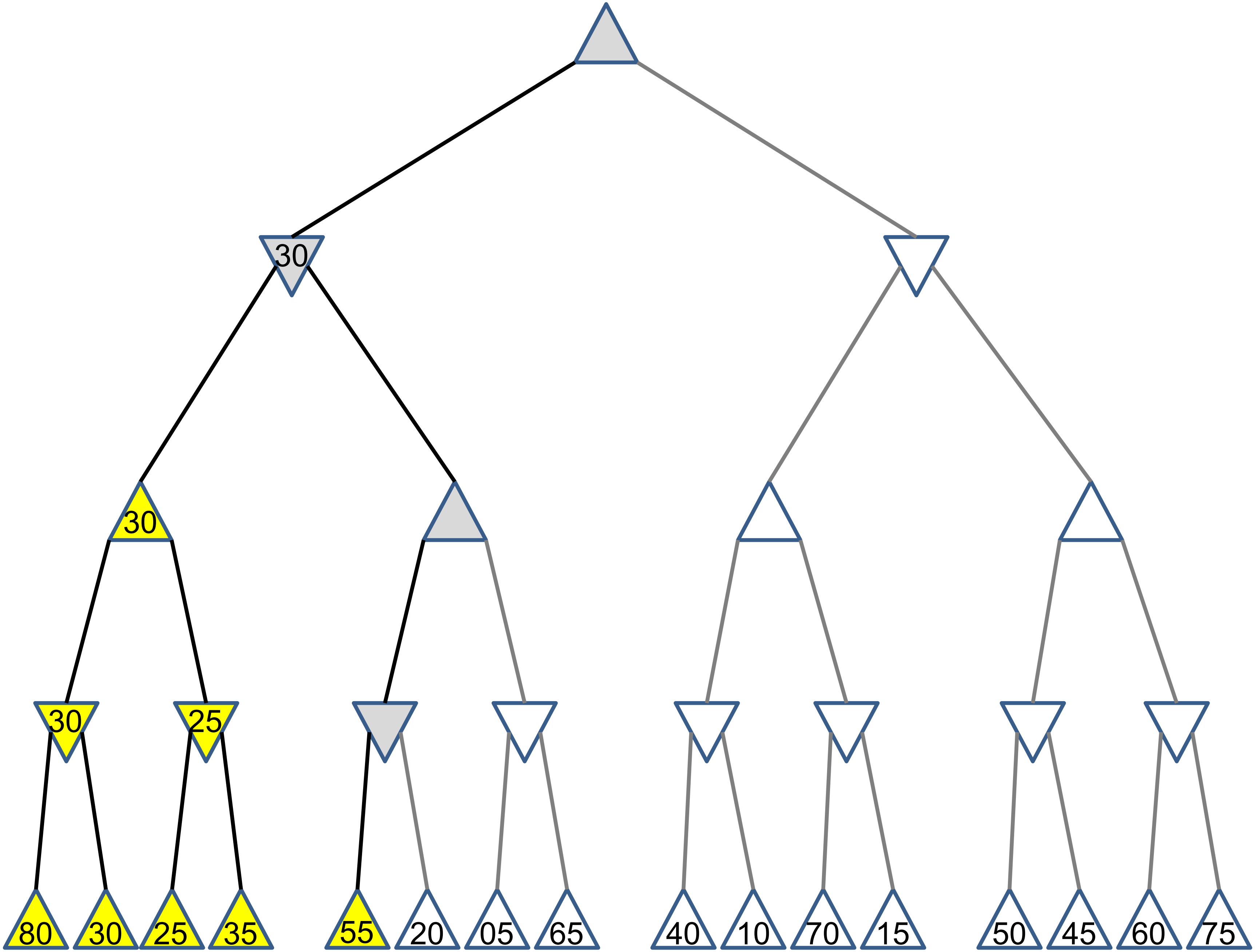
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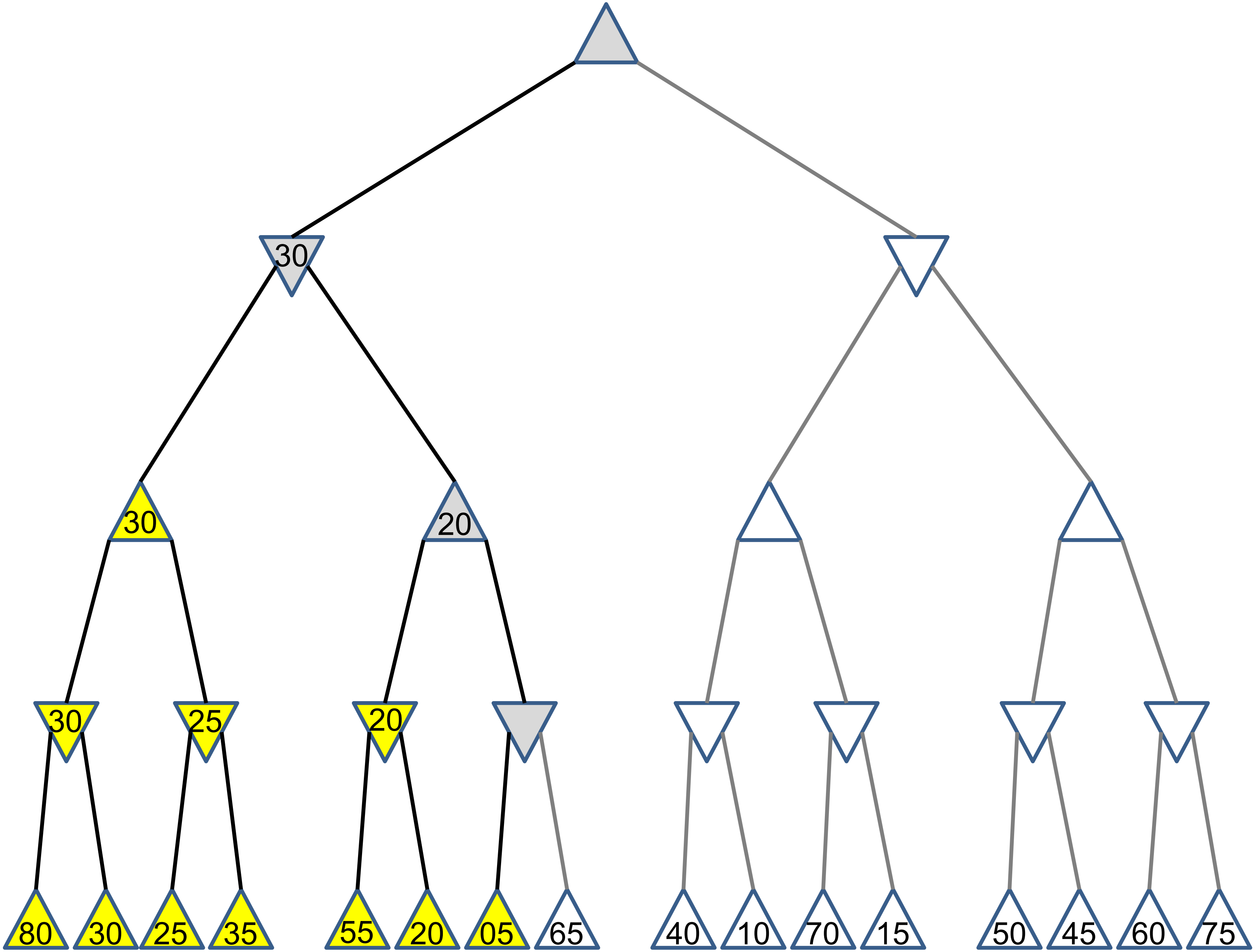
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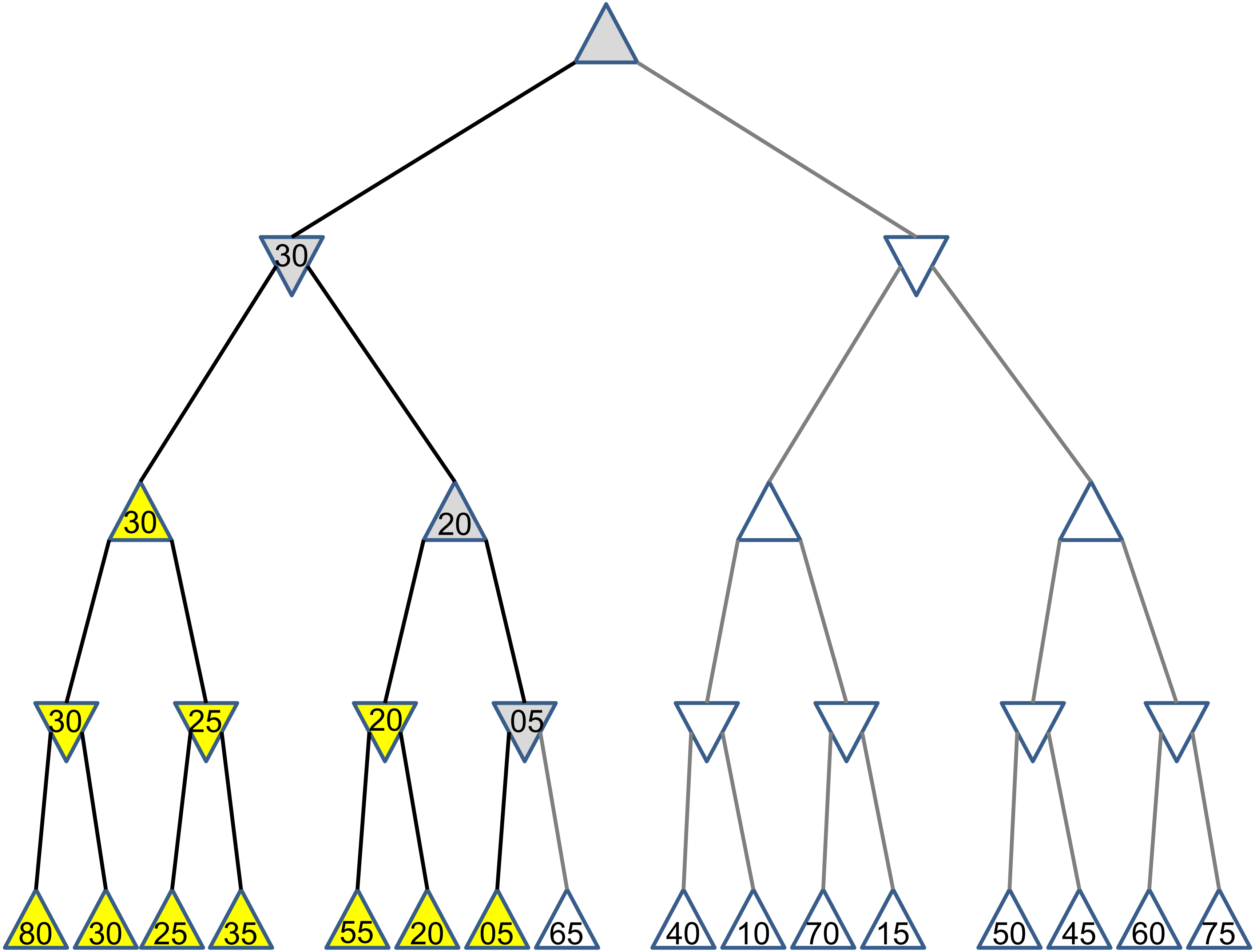
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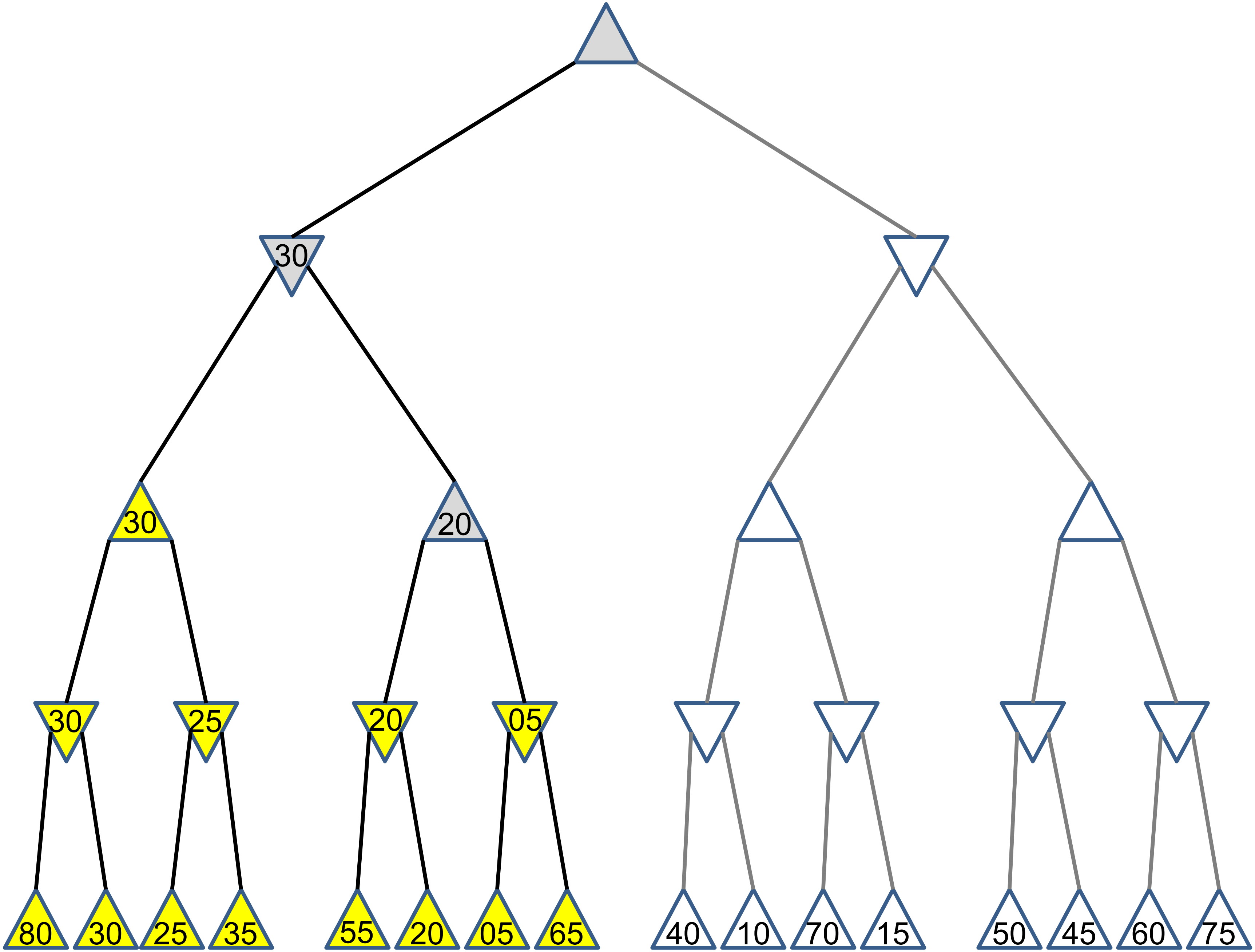
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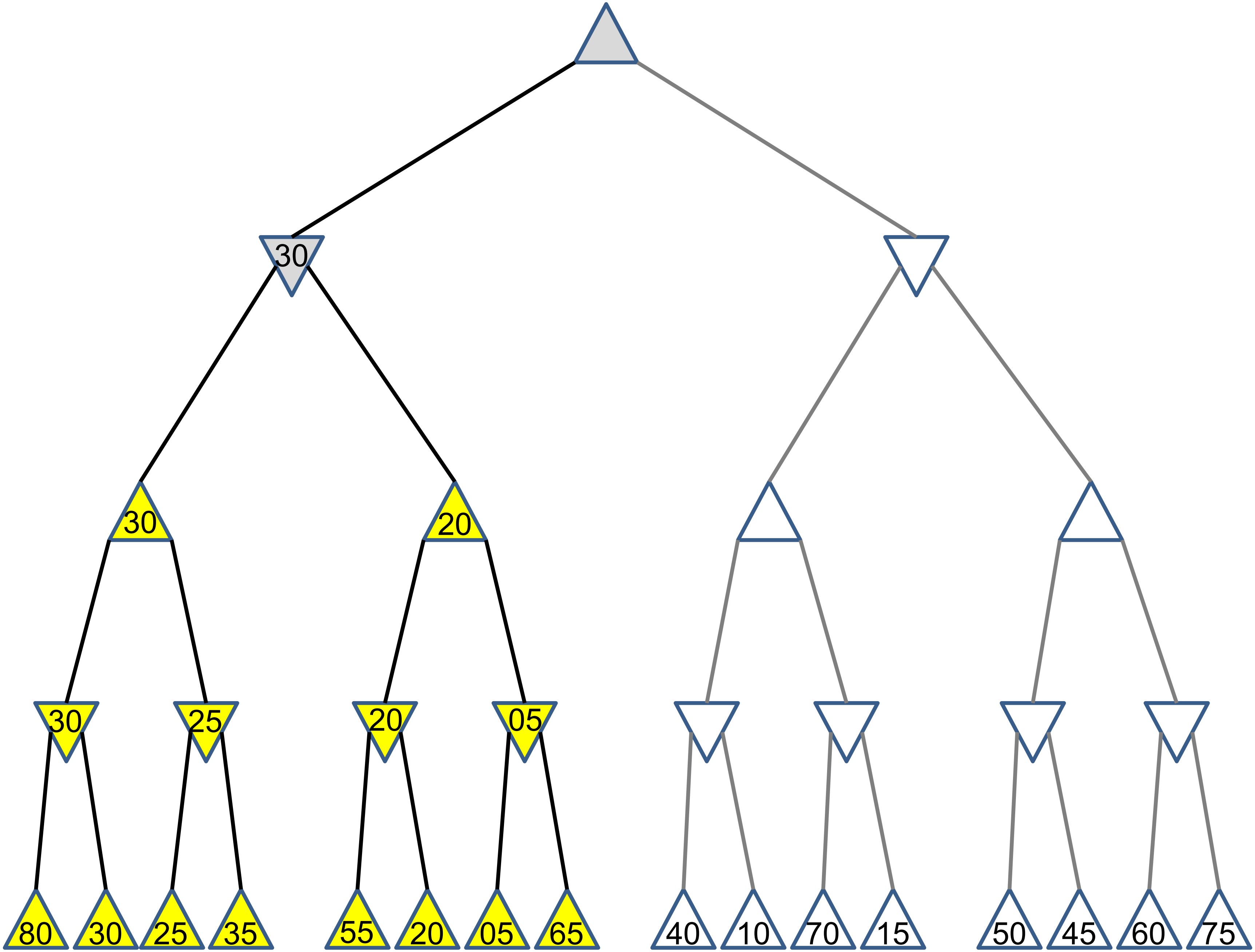
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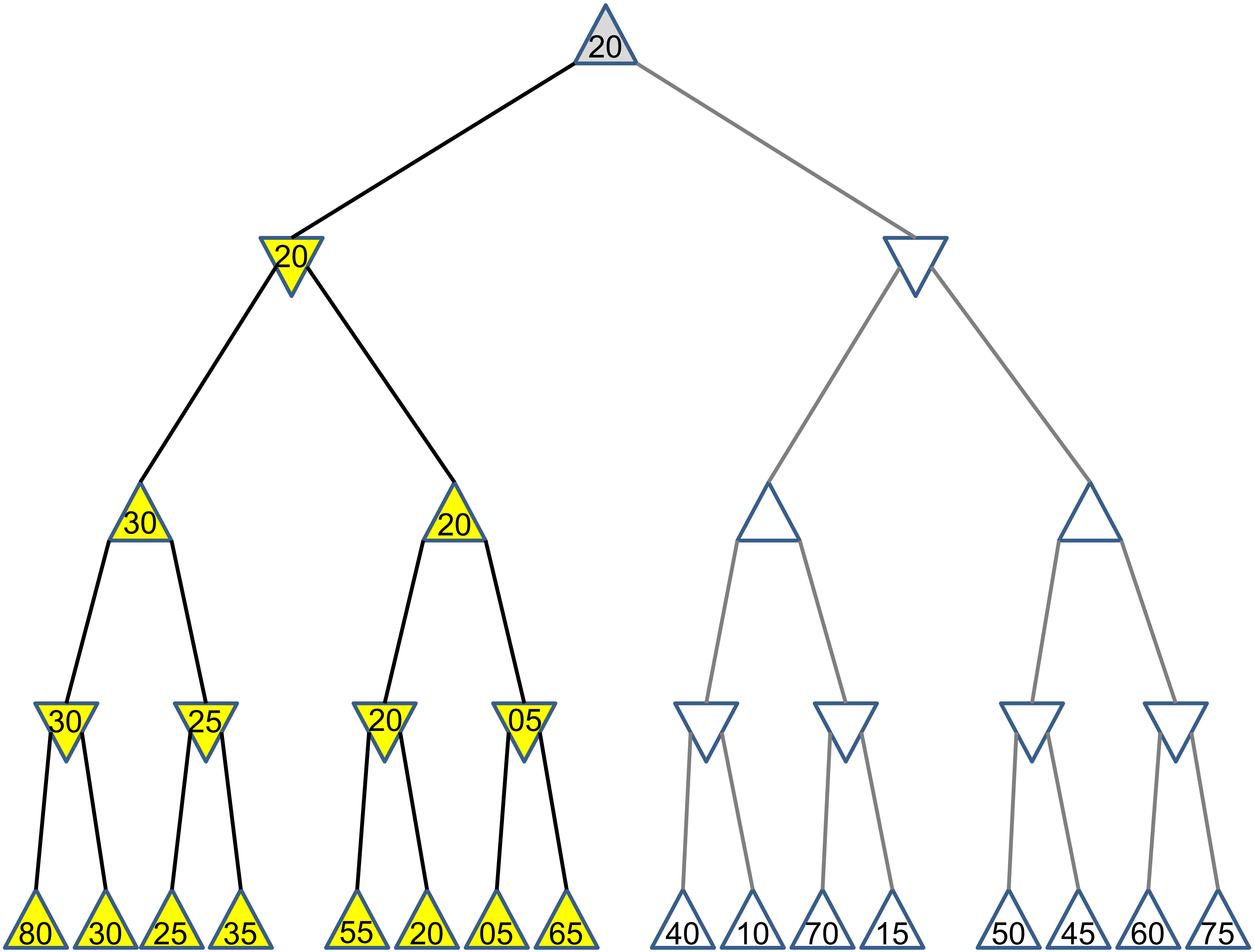
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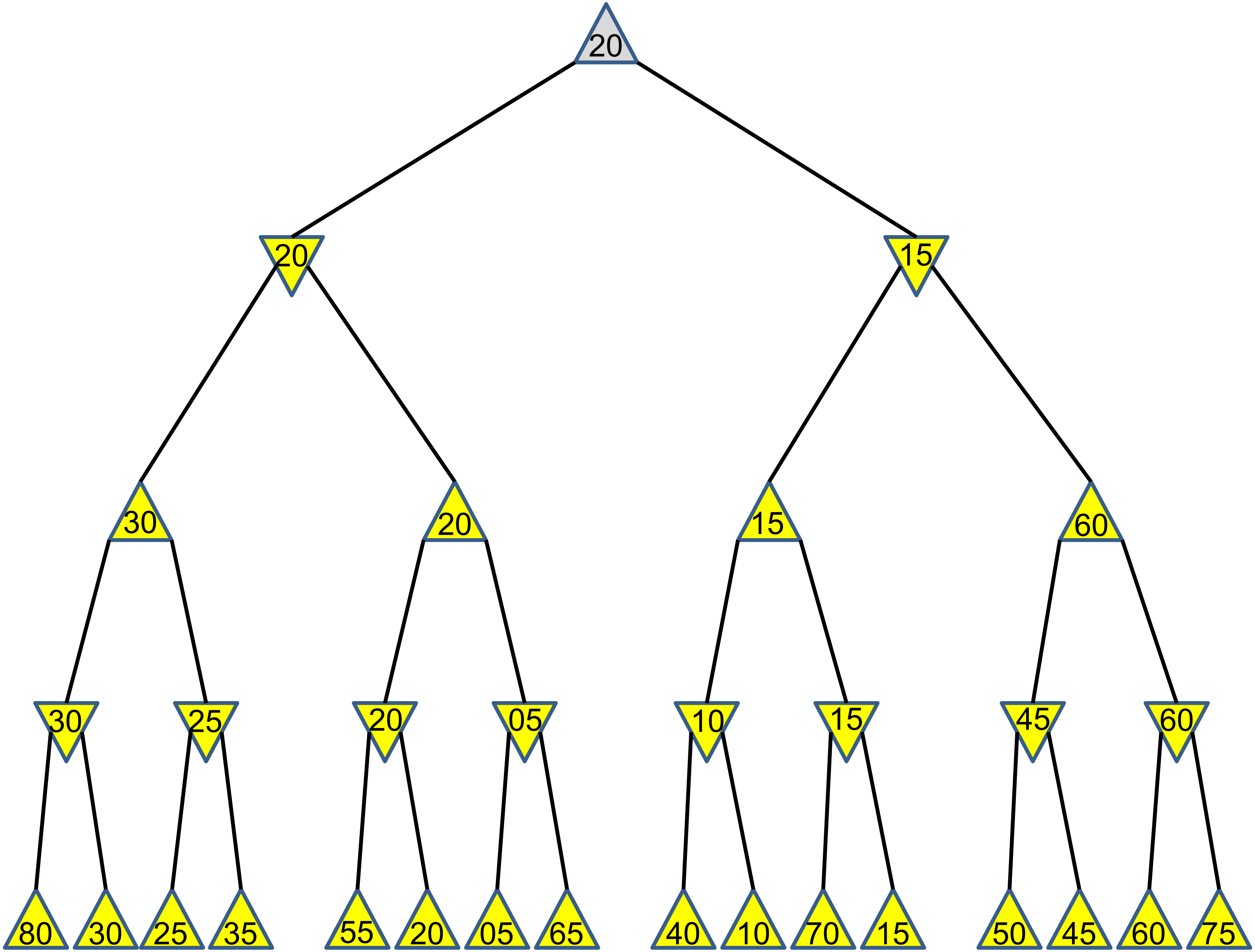
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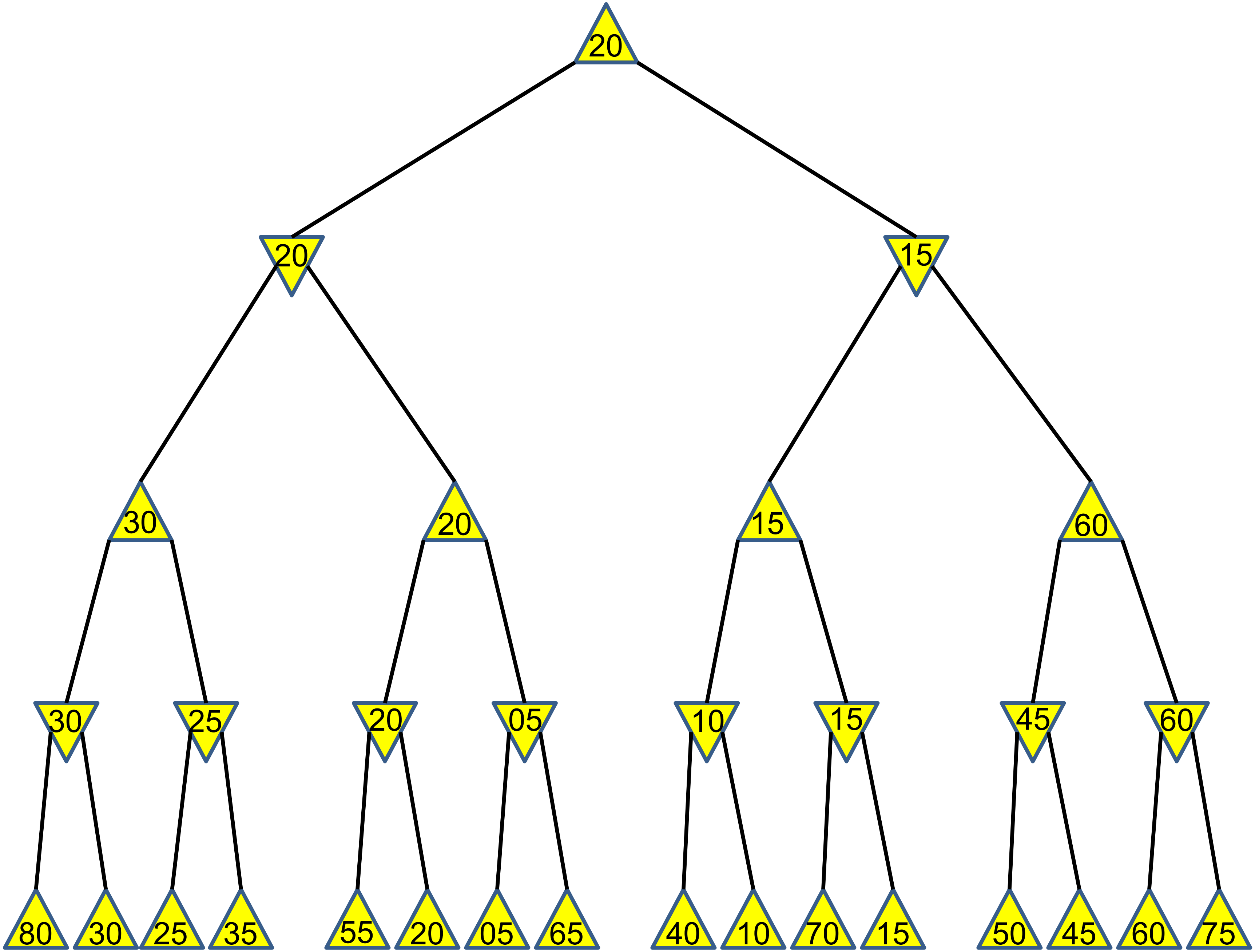
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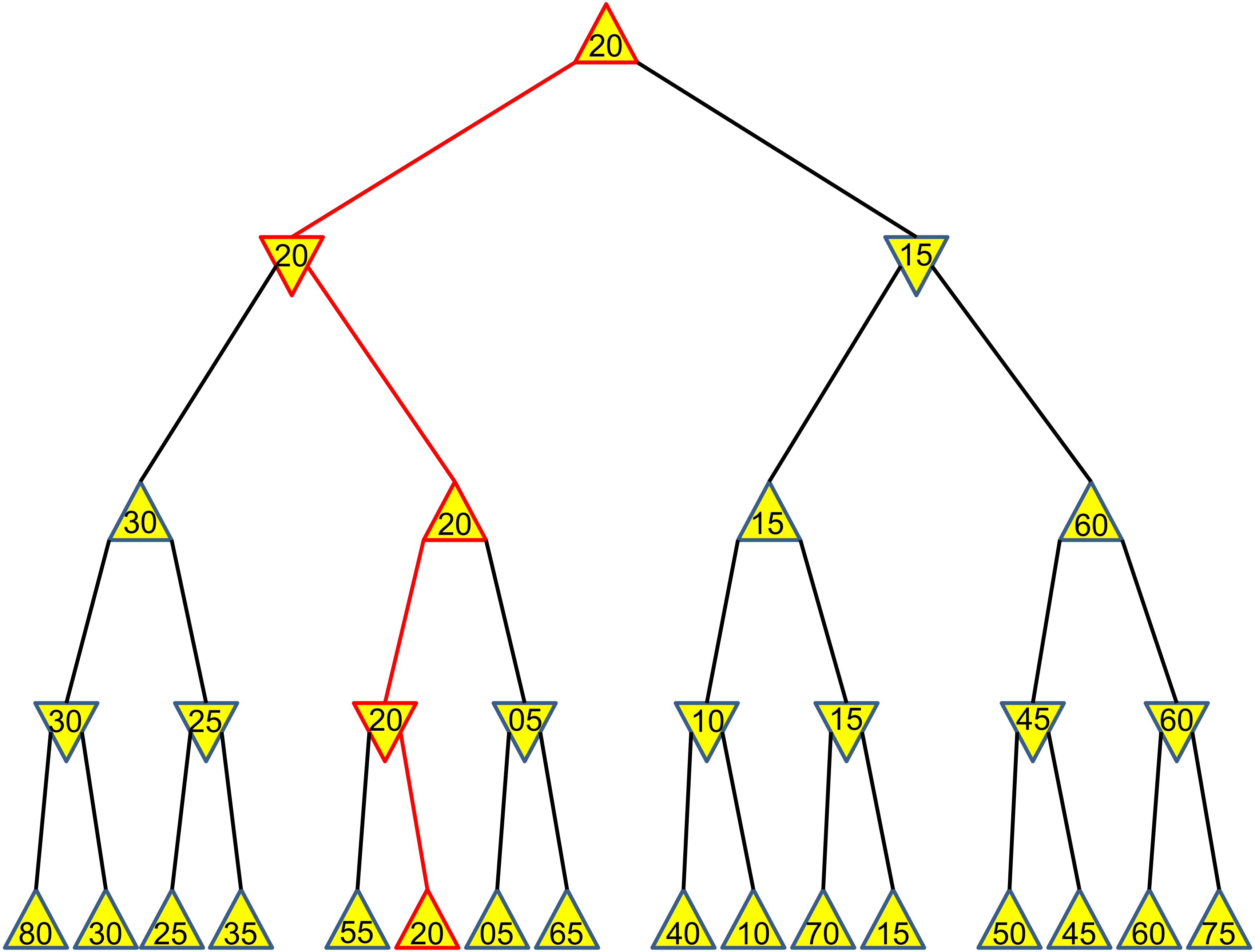
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Minimax Strategy

- 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 ← 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 ← −∞
    for a, s in SUCCESSORS(state) do
        v ← MAX(v, MIN-VALUE(s))
    return v
```

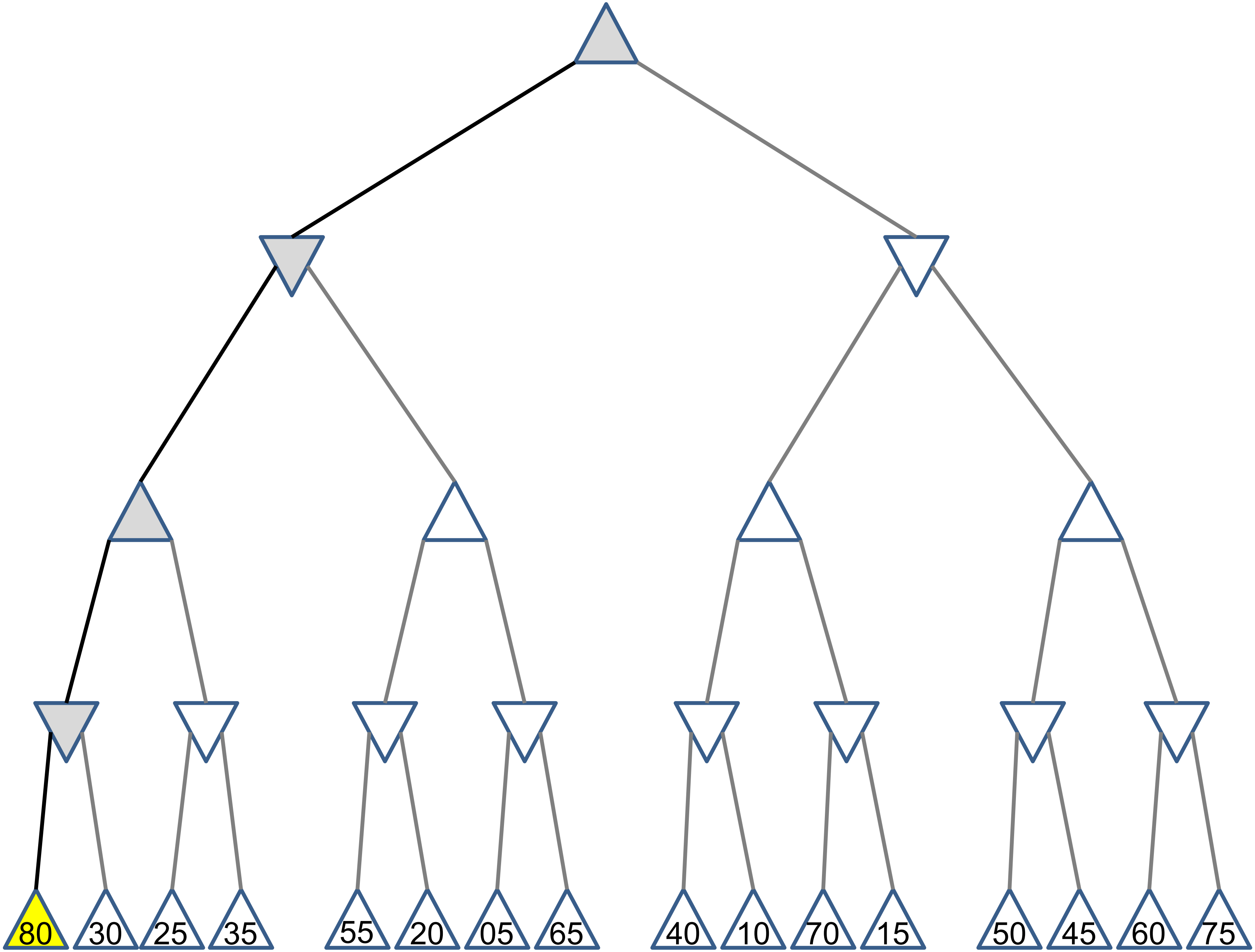
```
function MIN-VALUE(state) returns a utility value
    if TERMINAL-TEST(state) then return UTILITY(state)
    v ← ∞
    for a, s in SUCCESSORS(state) do
        v ← MIN(v, MAX-VALUE(s))
    return v
```

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 moves/sec x 10^{78} x $10^{18} = 10^{104}$
- Exact solution completely infeasible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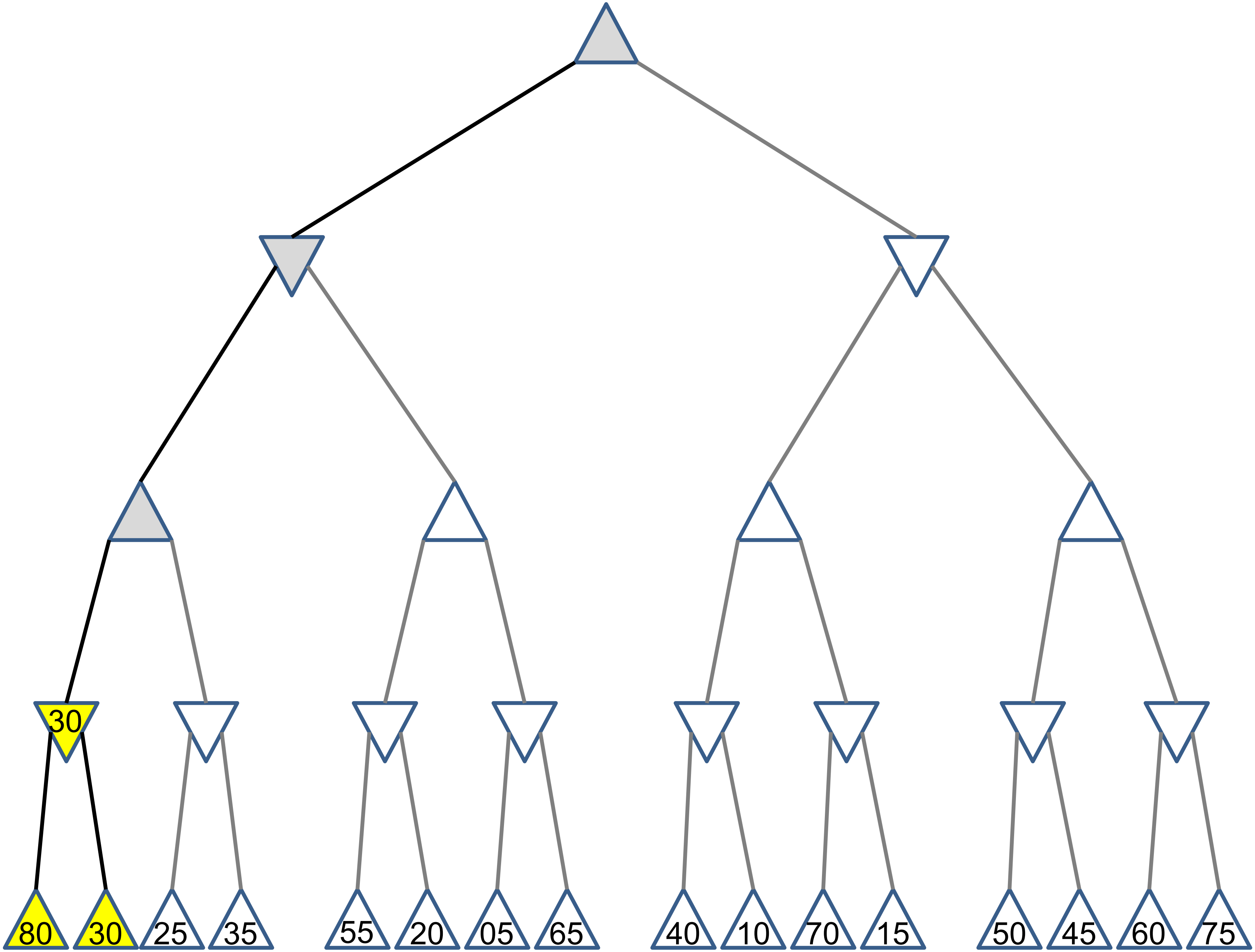
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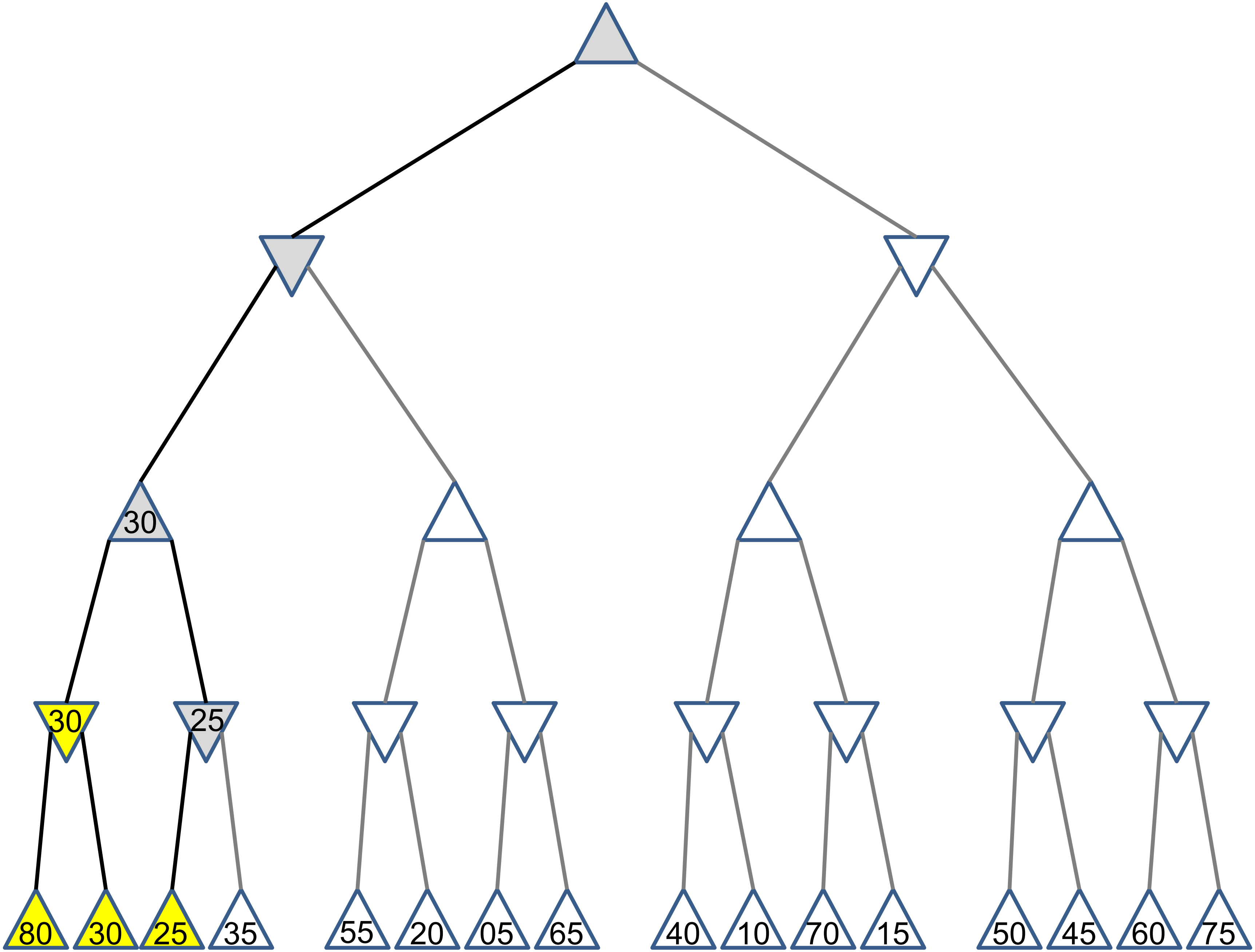
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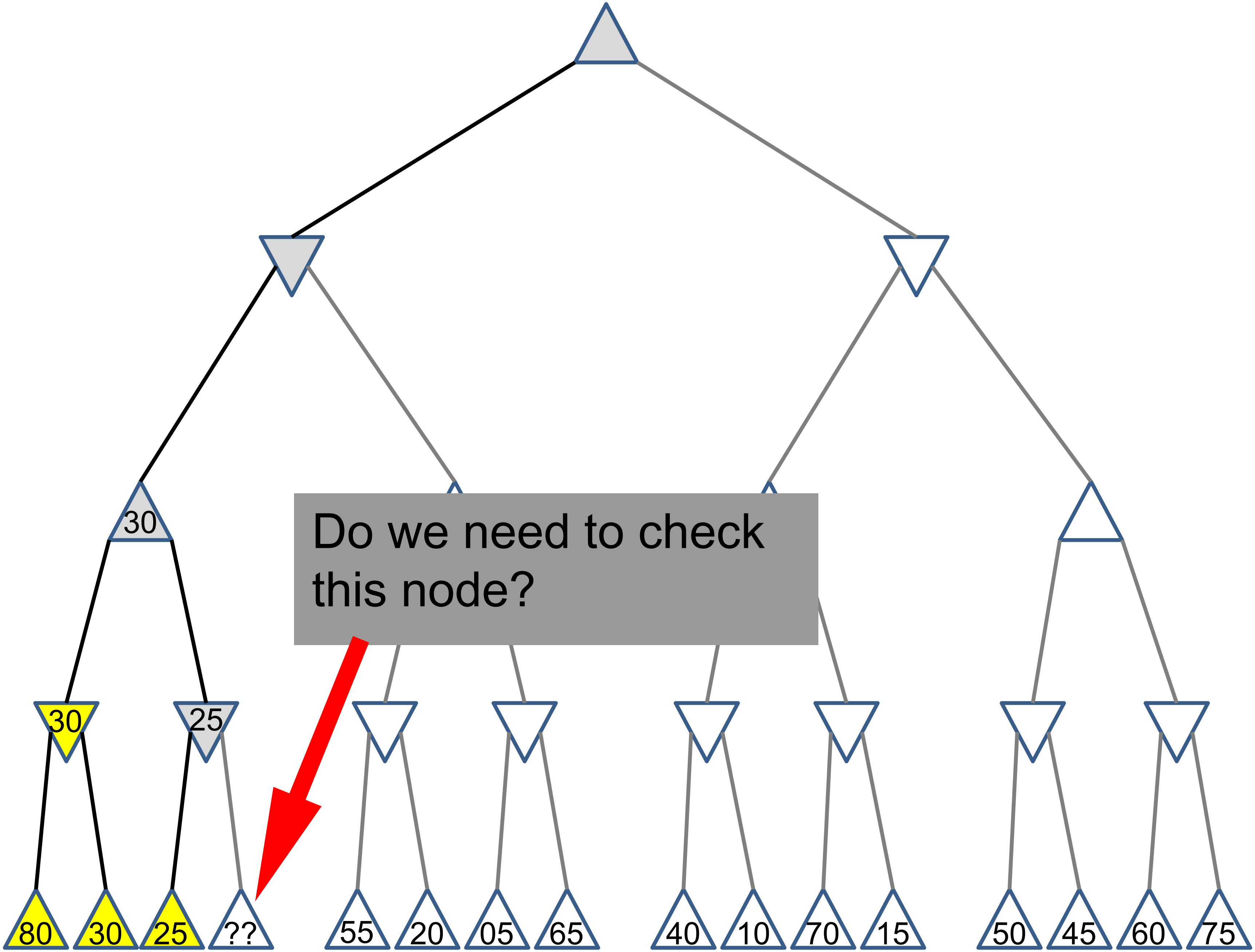
Do we need to check
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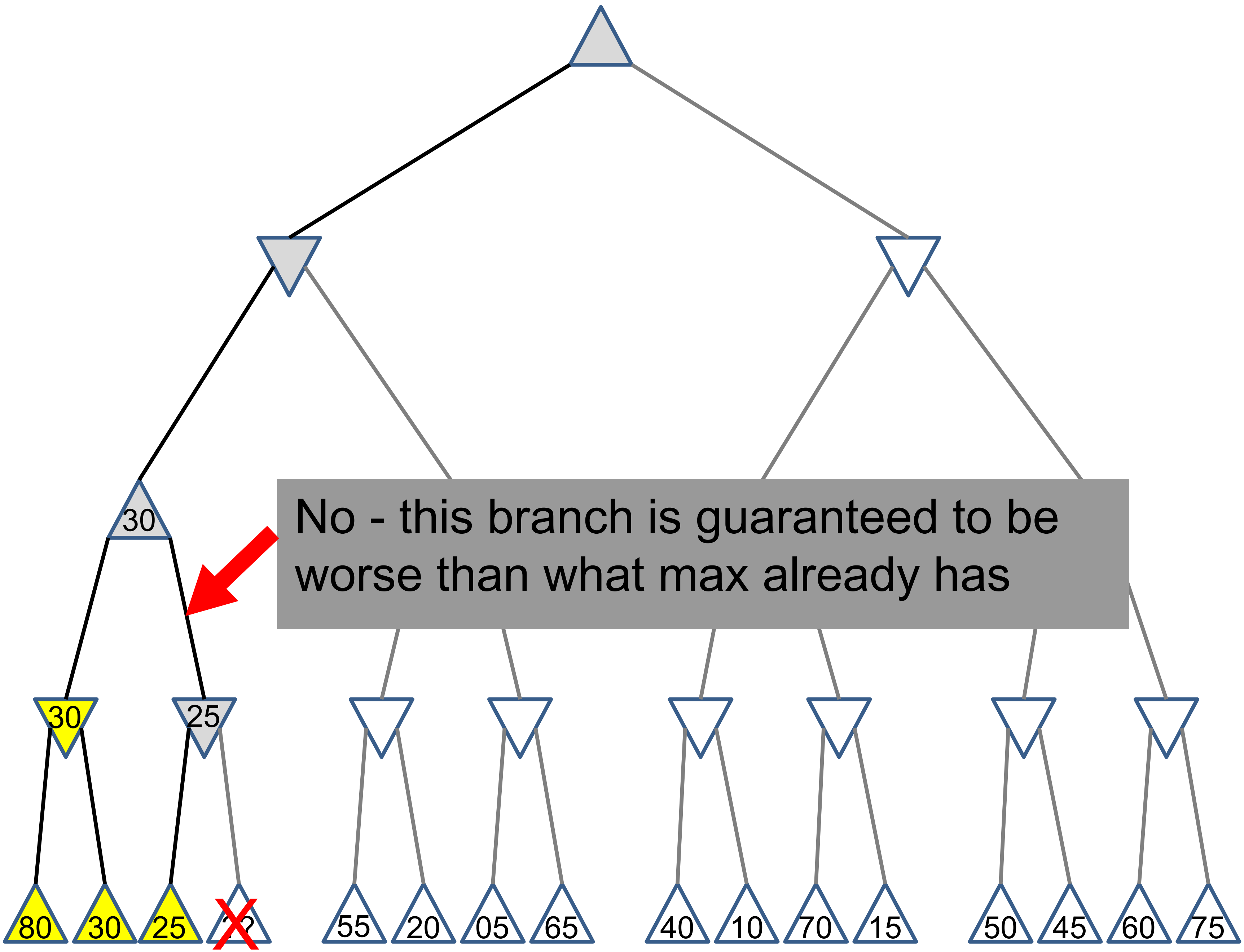
No - this branch is guaranteed to be worse than what max already has
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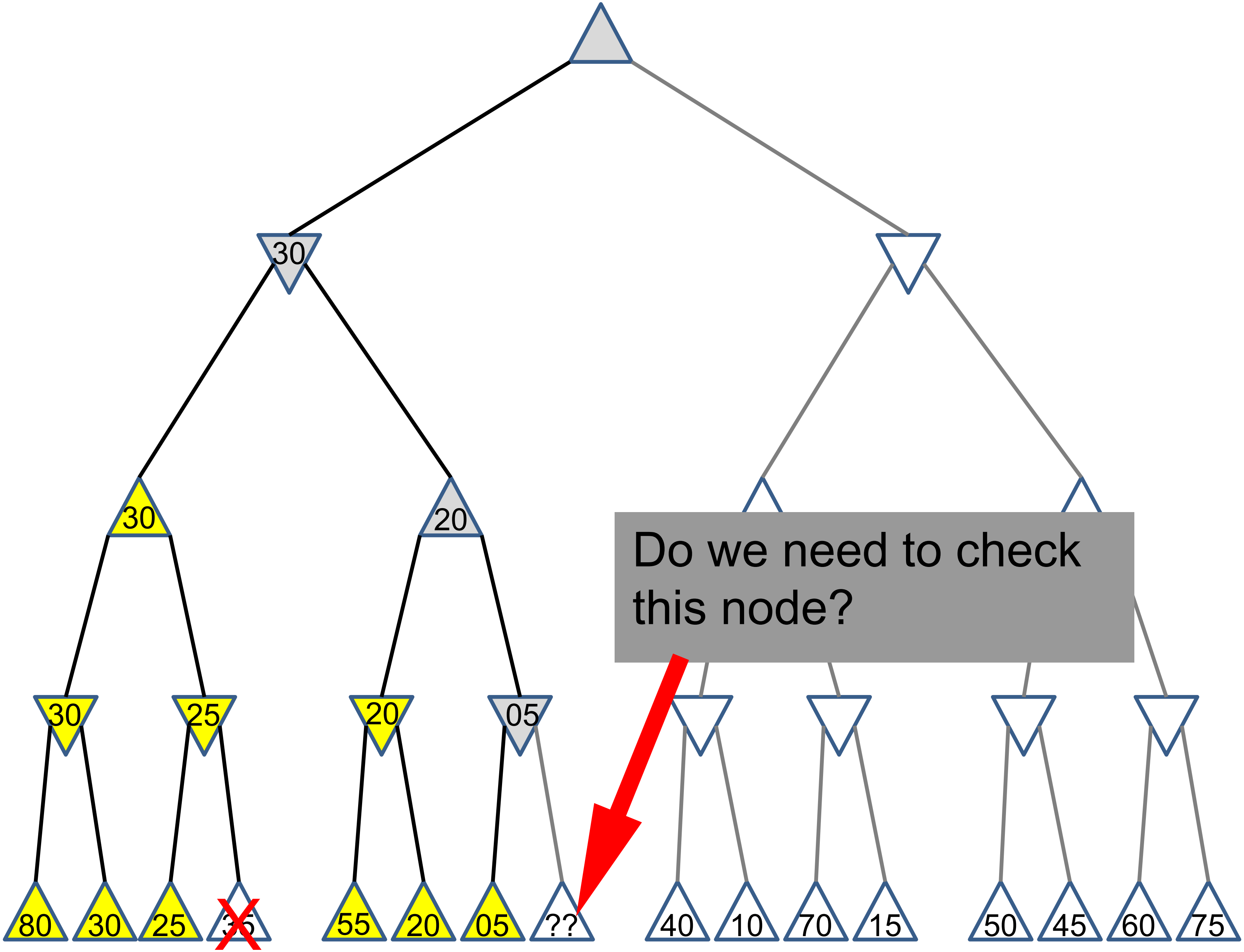
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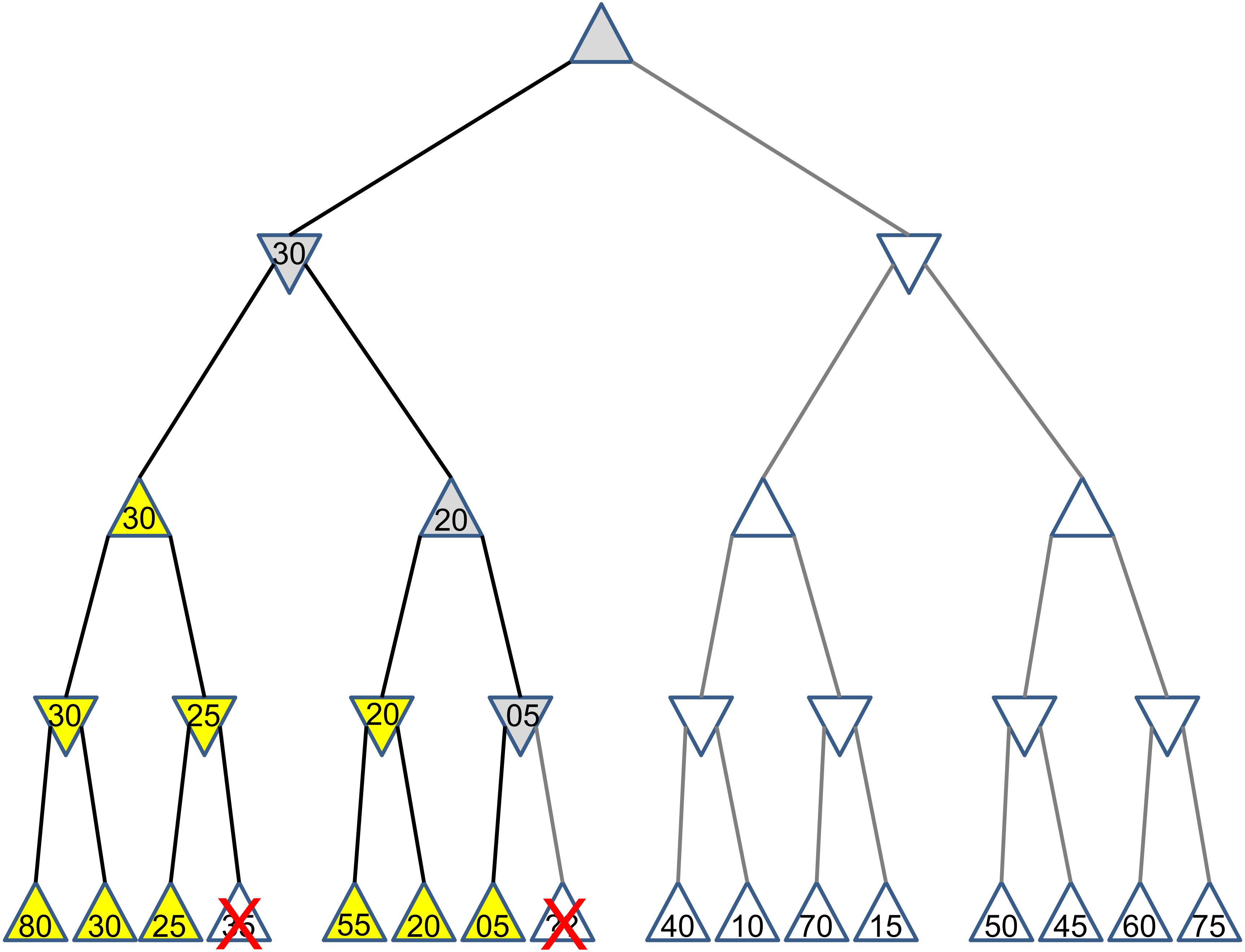
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Alpha-Beta

- 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 best child (min); }
```

alpha = the **highest** value for **MAX** along the path

beta = the **lowest** value for **MIN** along the path

Alpha-Beta

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MaxVal(state, alpha, beta){
  if (terminal(state))
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  }
  return best child (max); }
```

alpha = the **highest** value for **MAX** along the path

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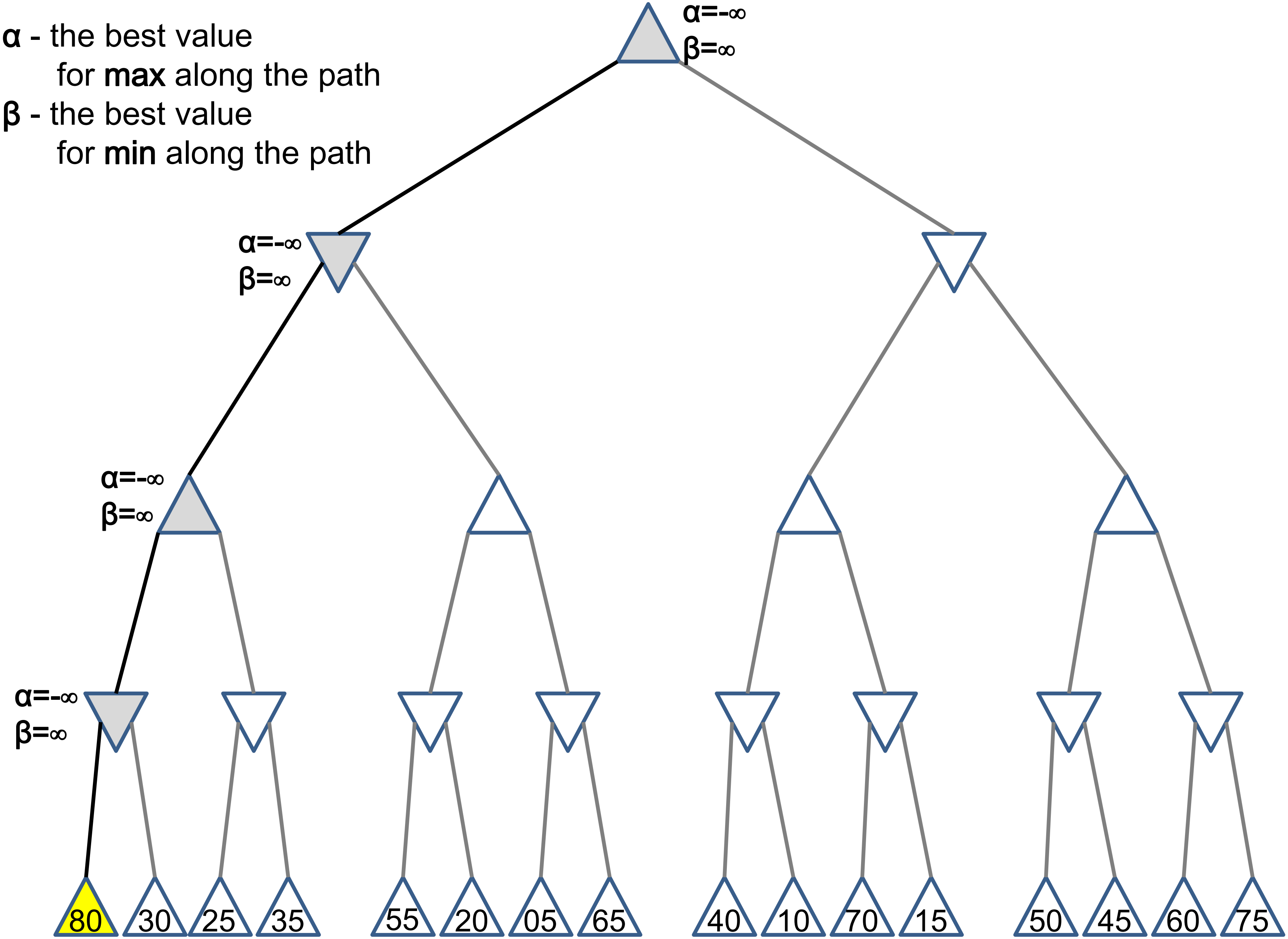

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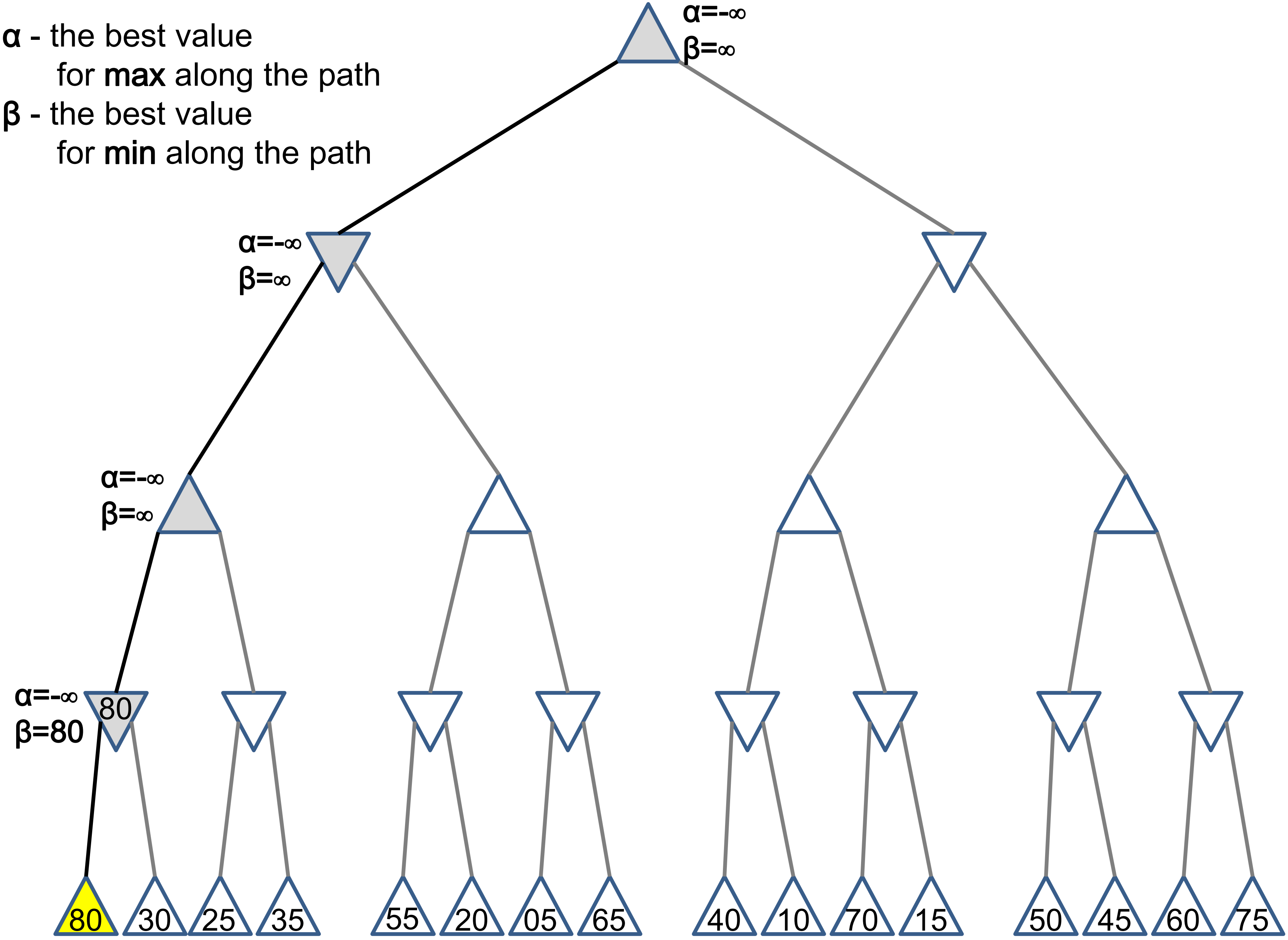

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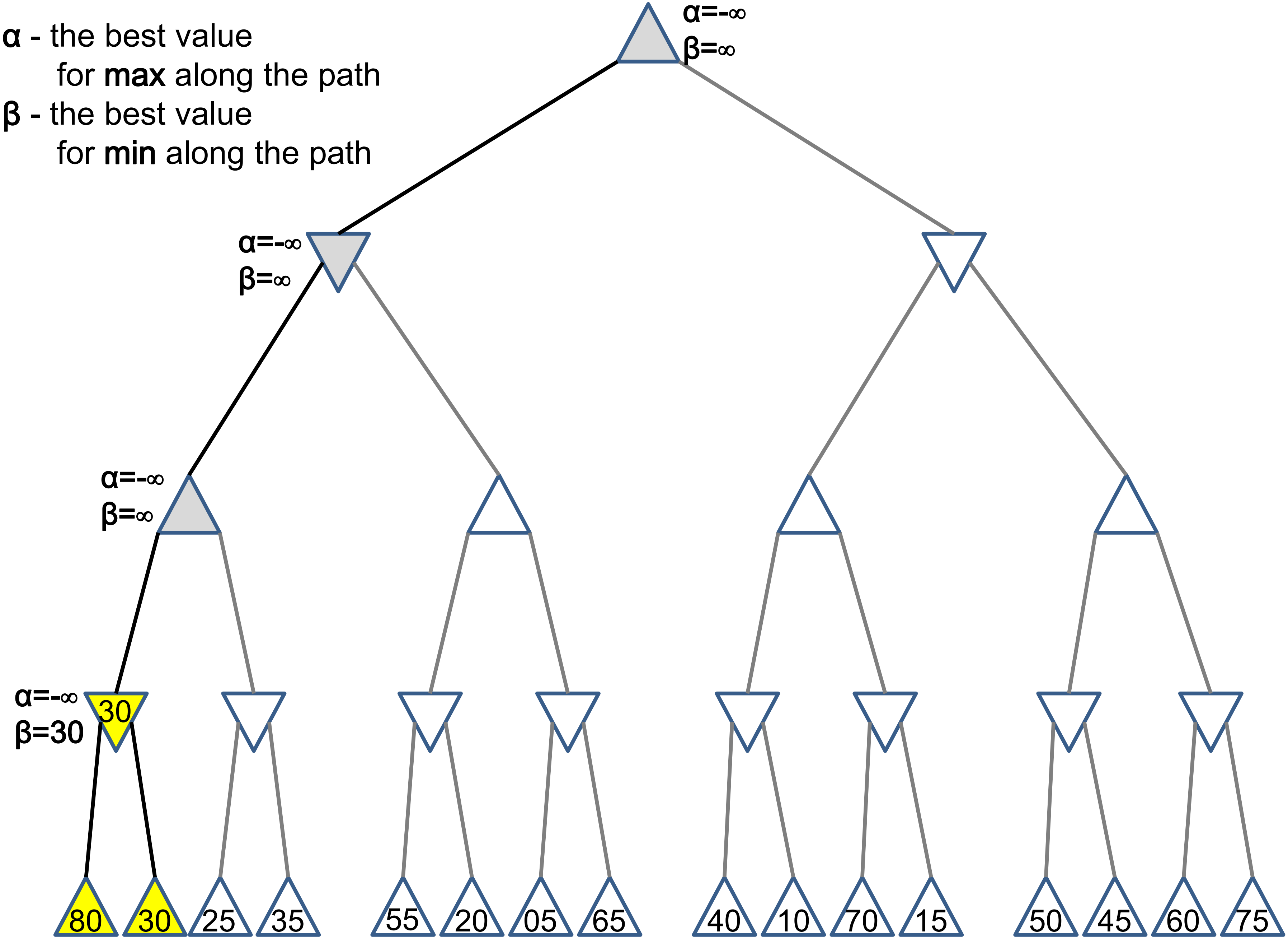

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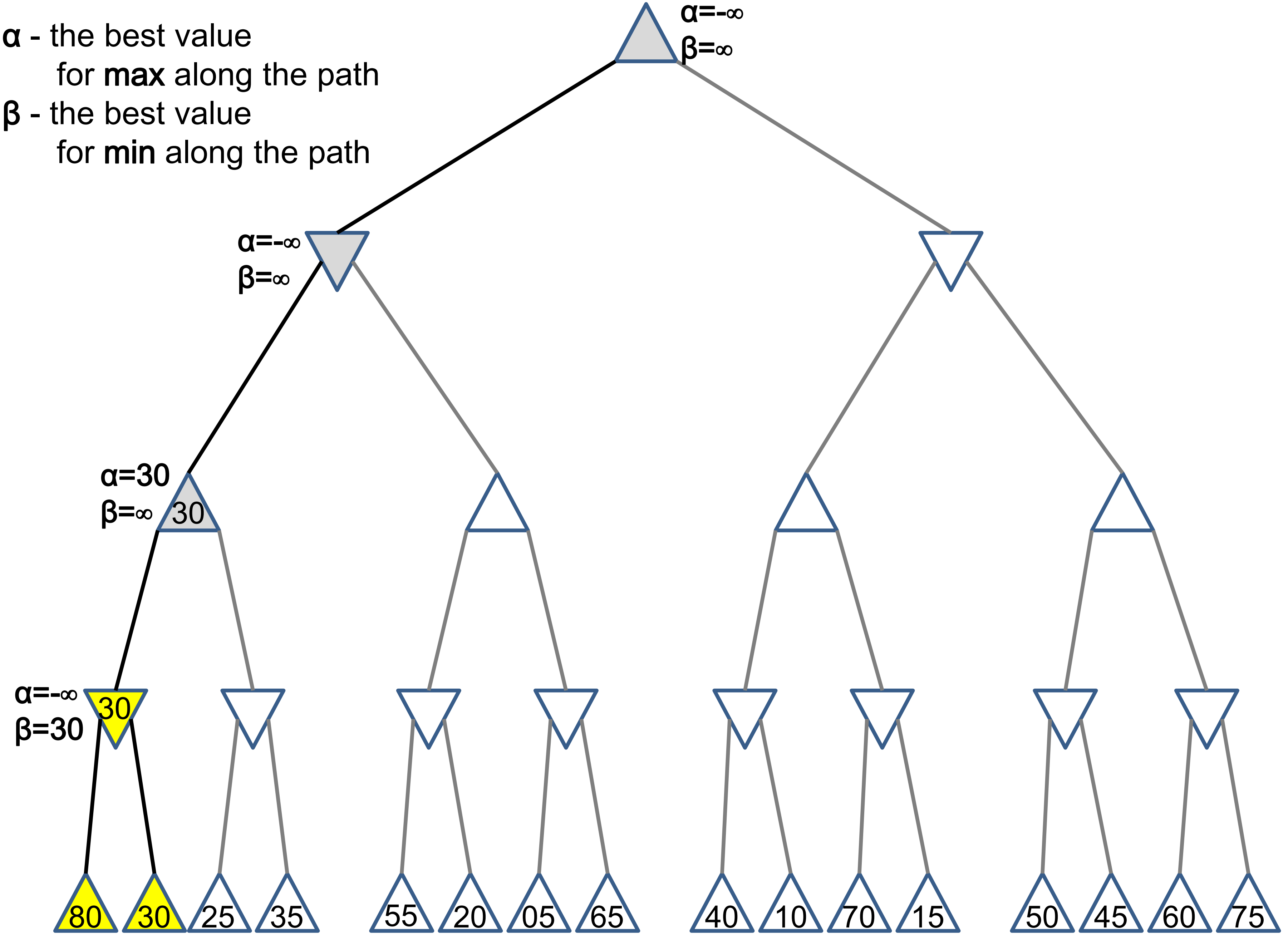

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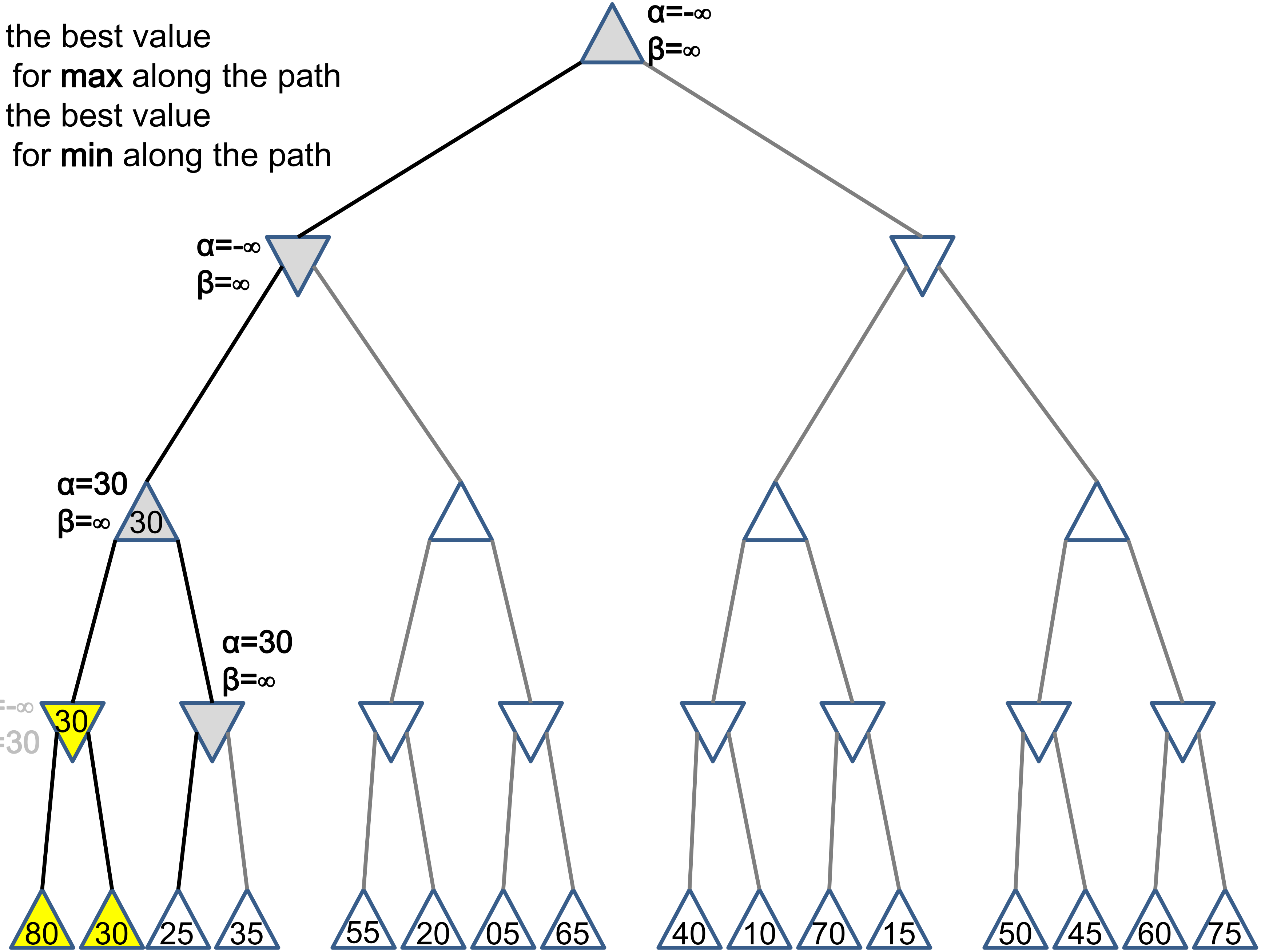

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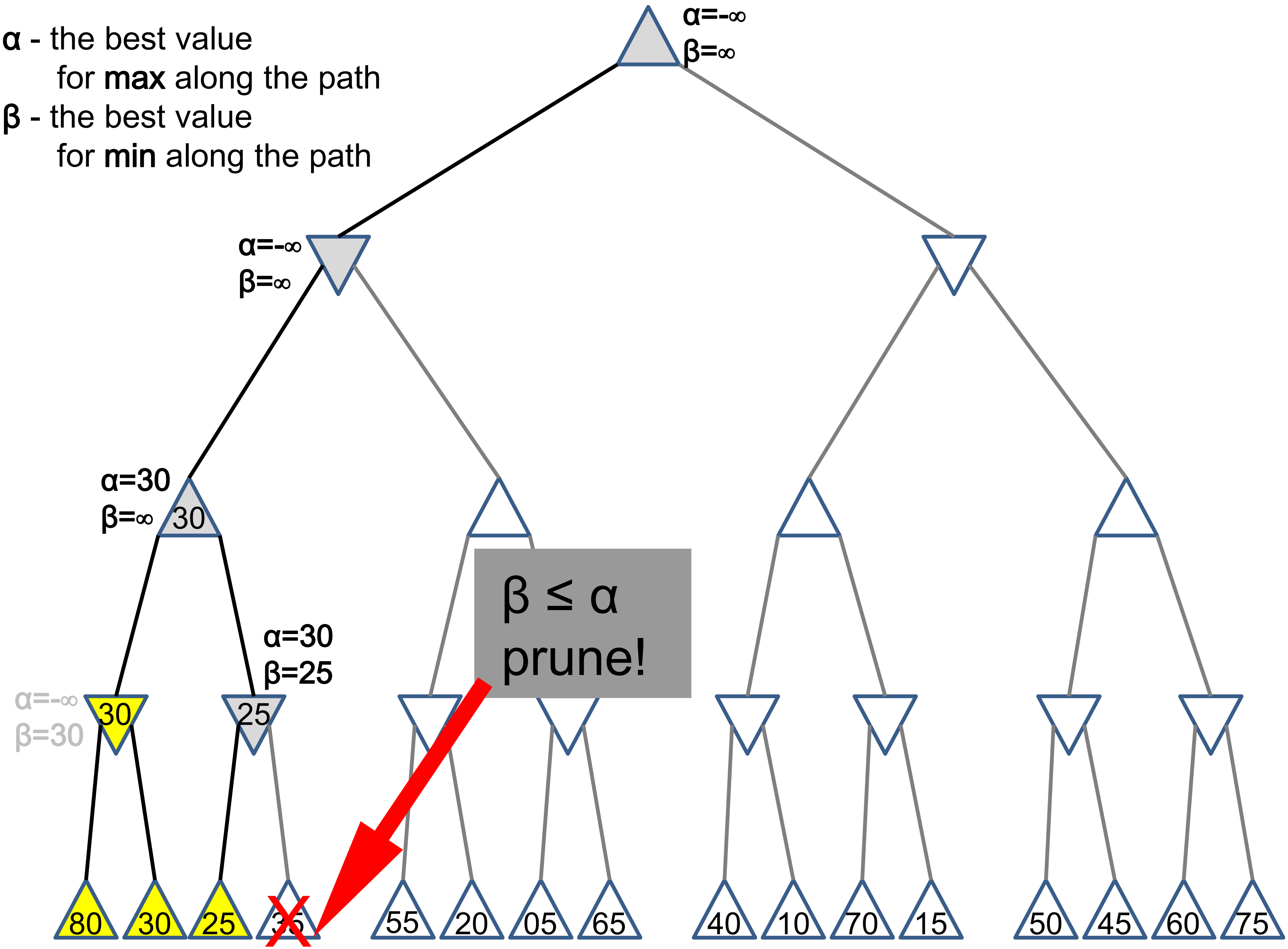

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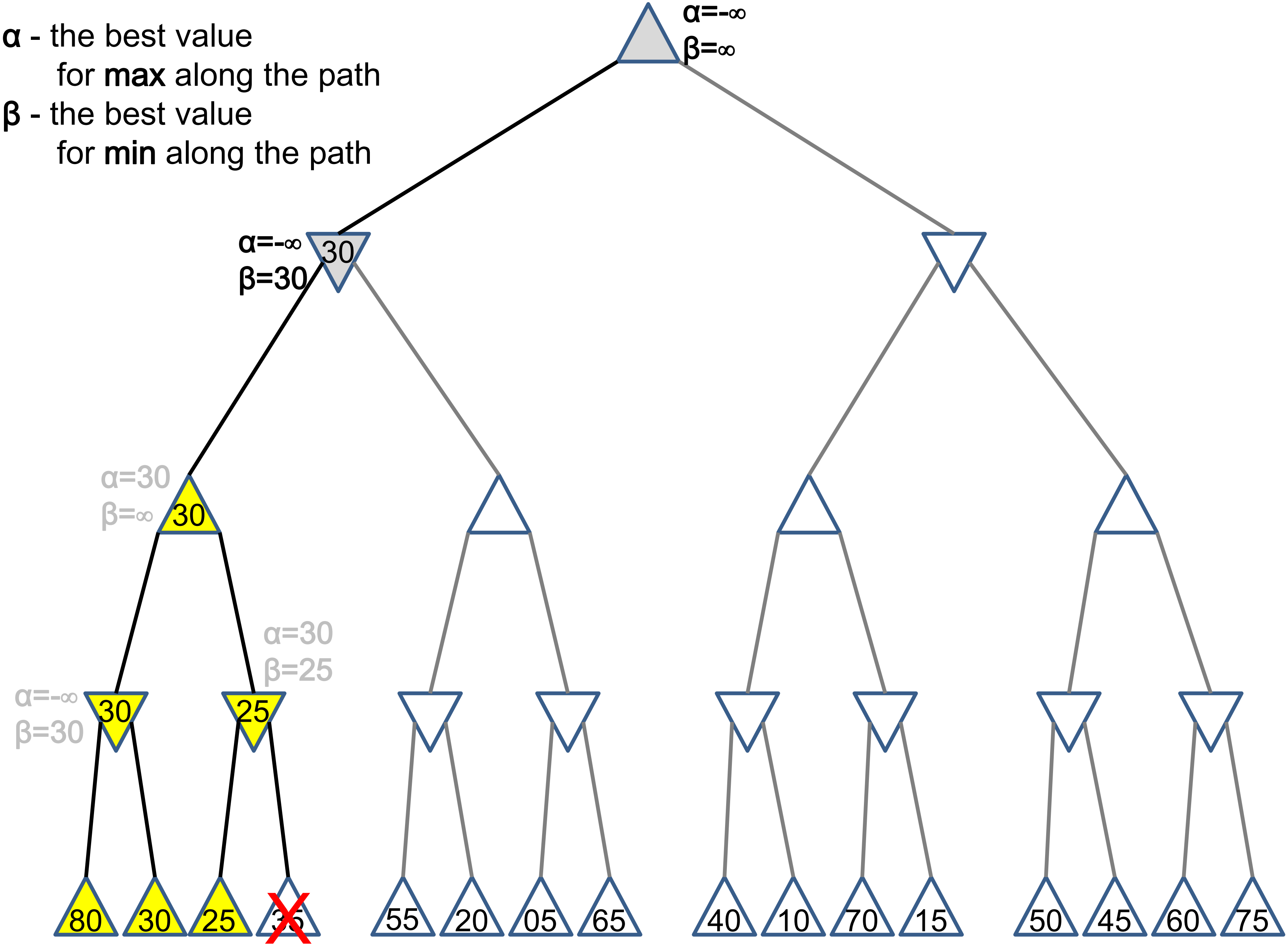

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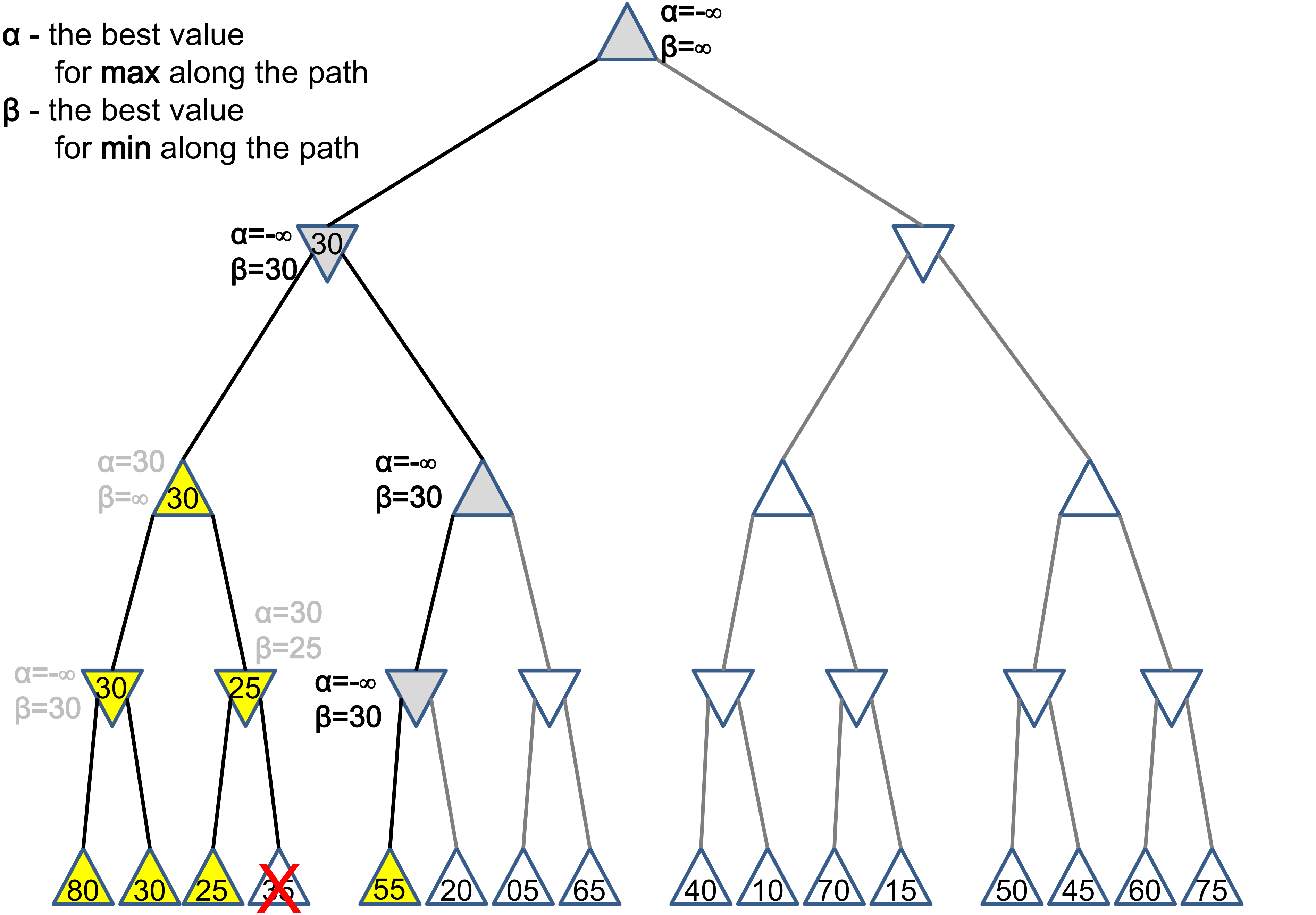

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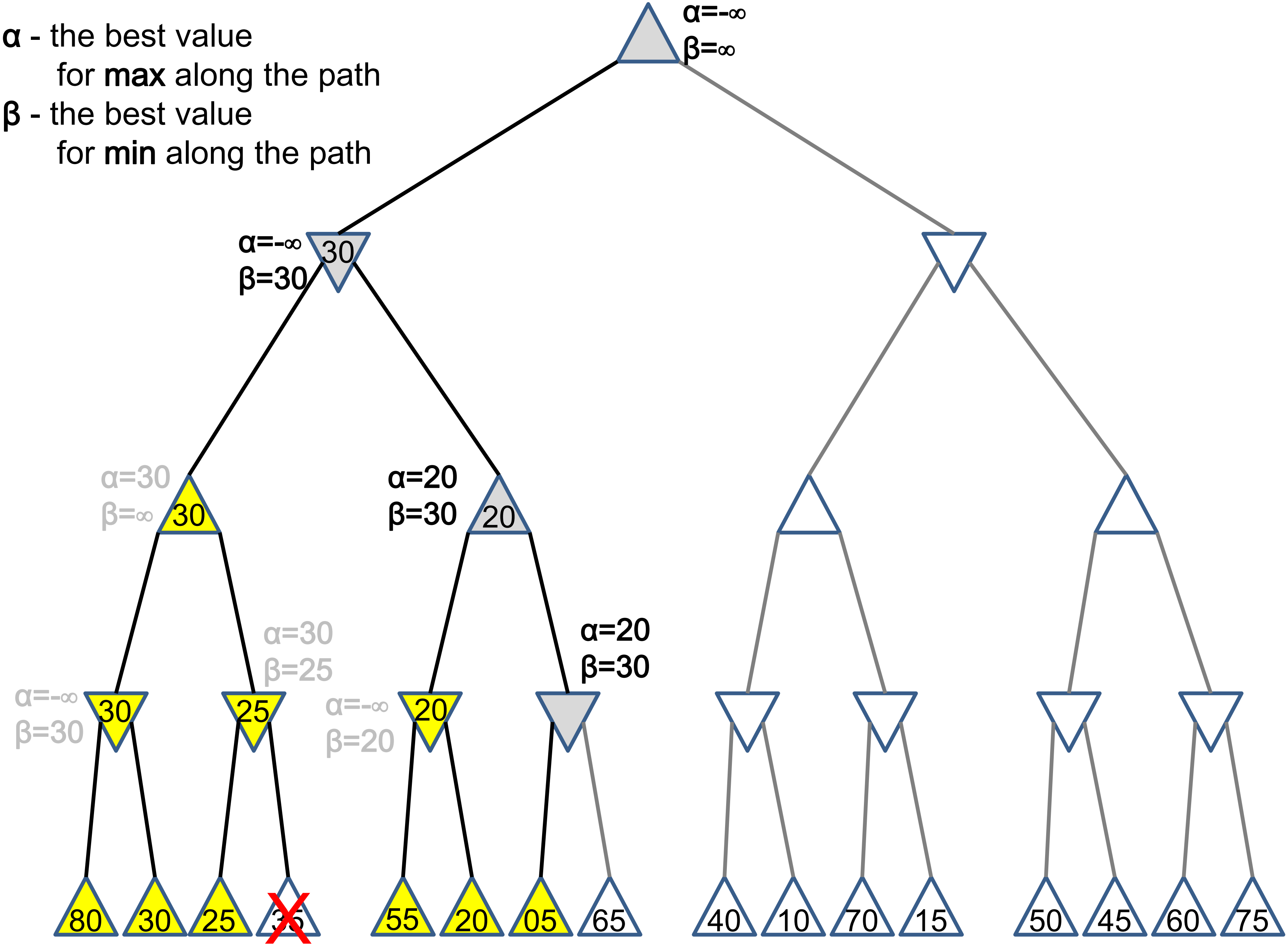

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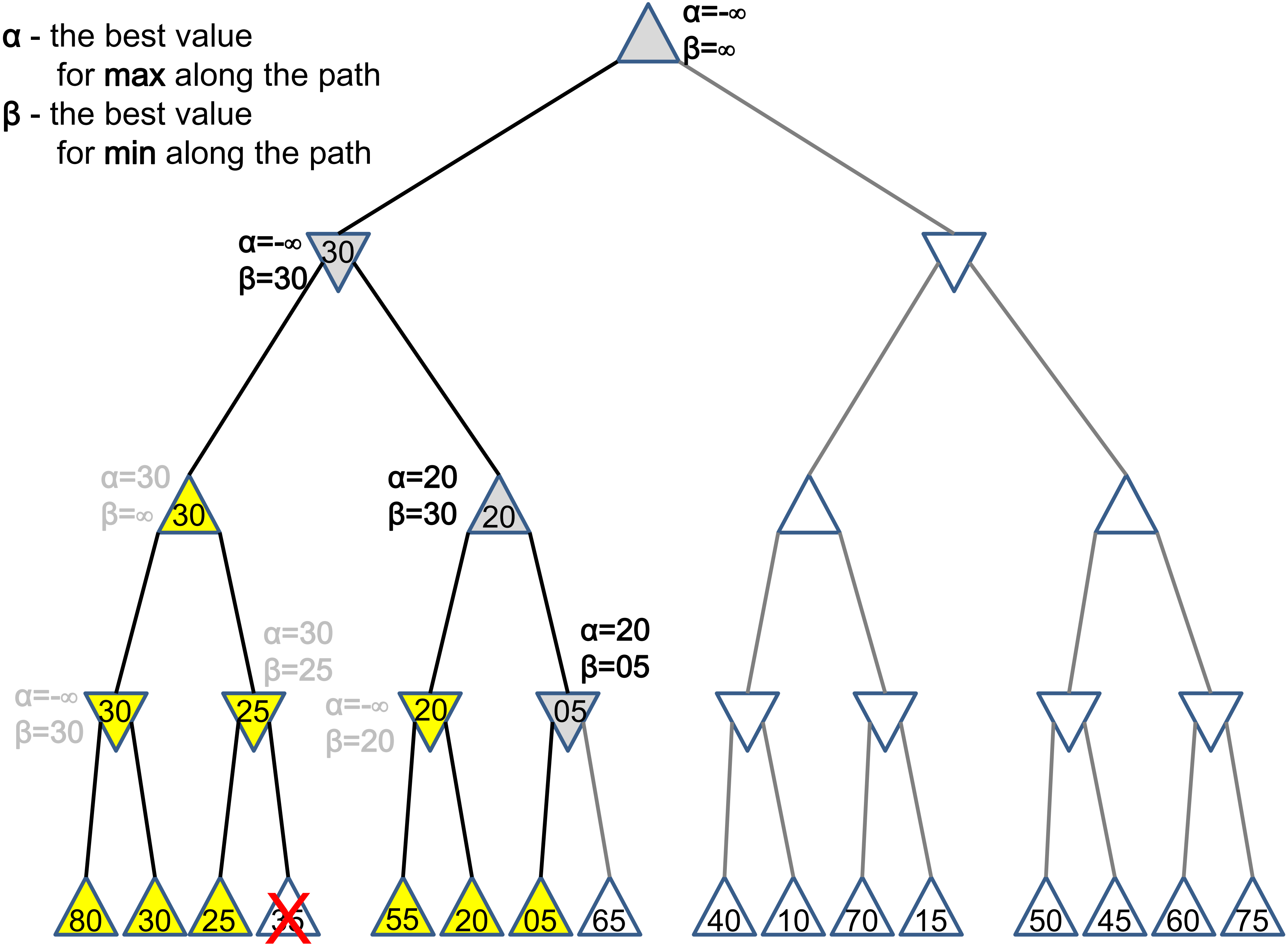

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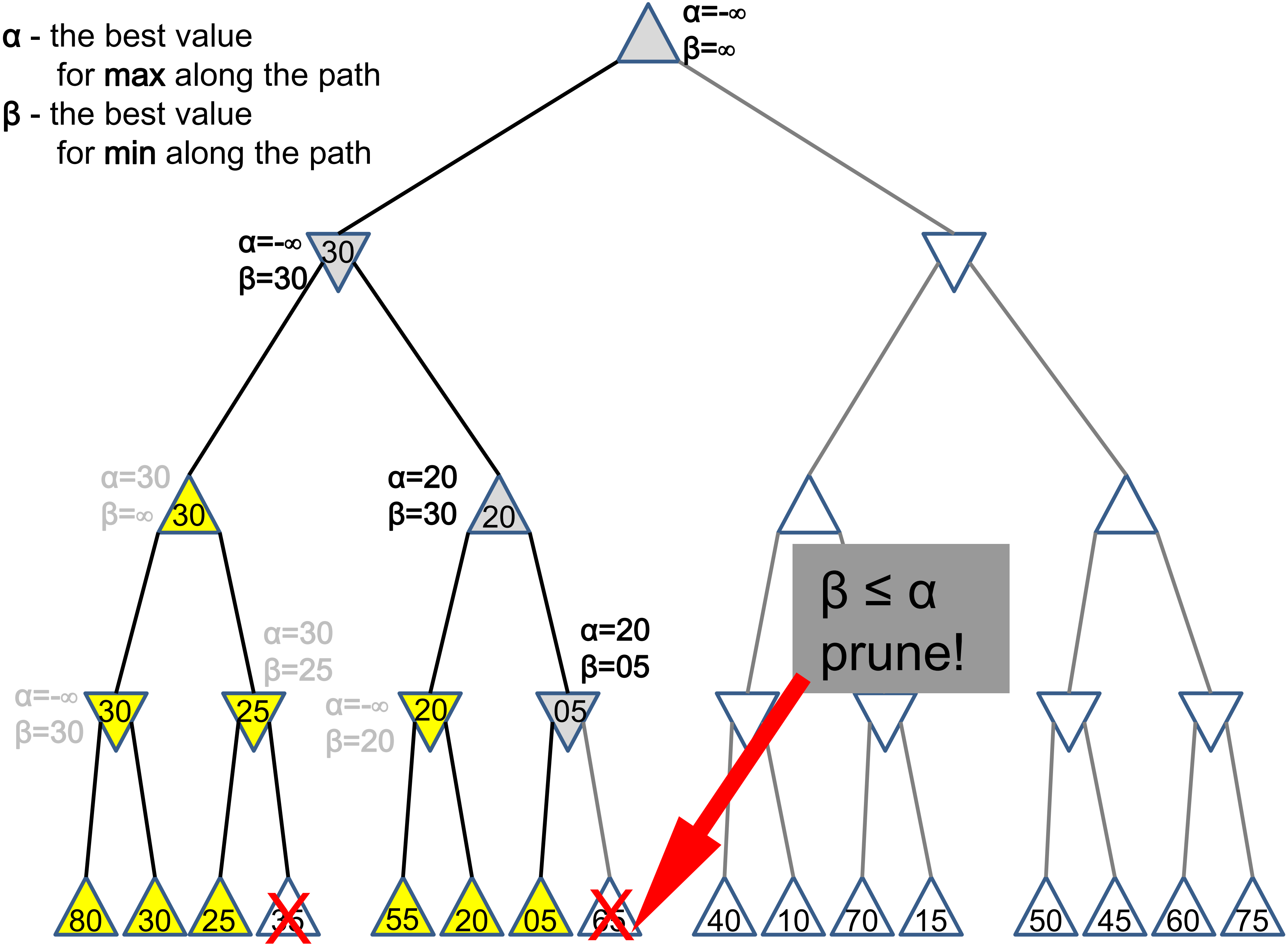

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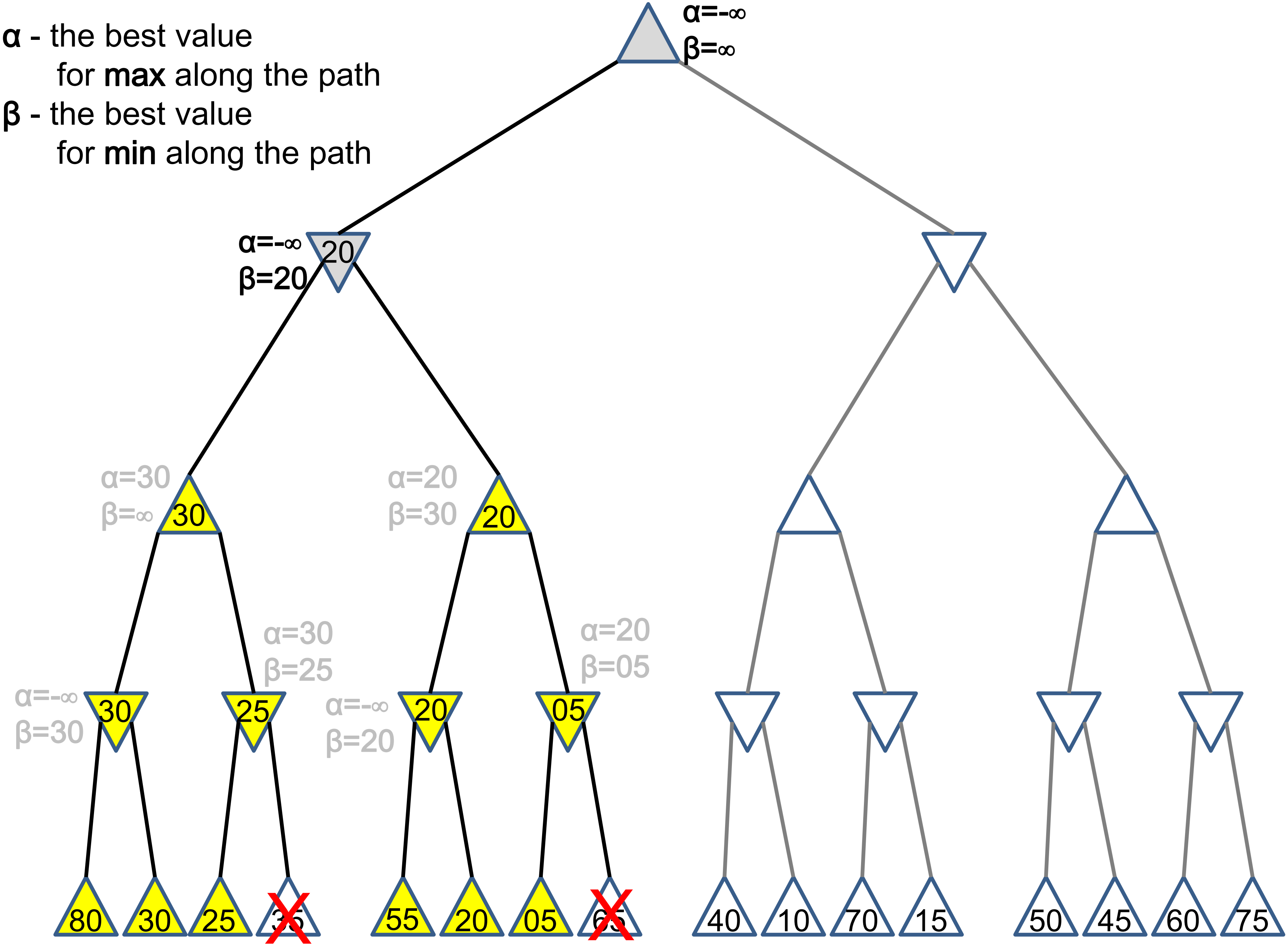

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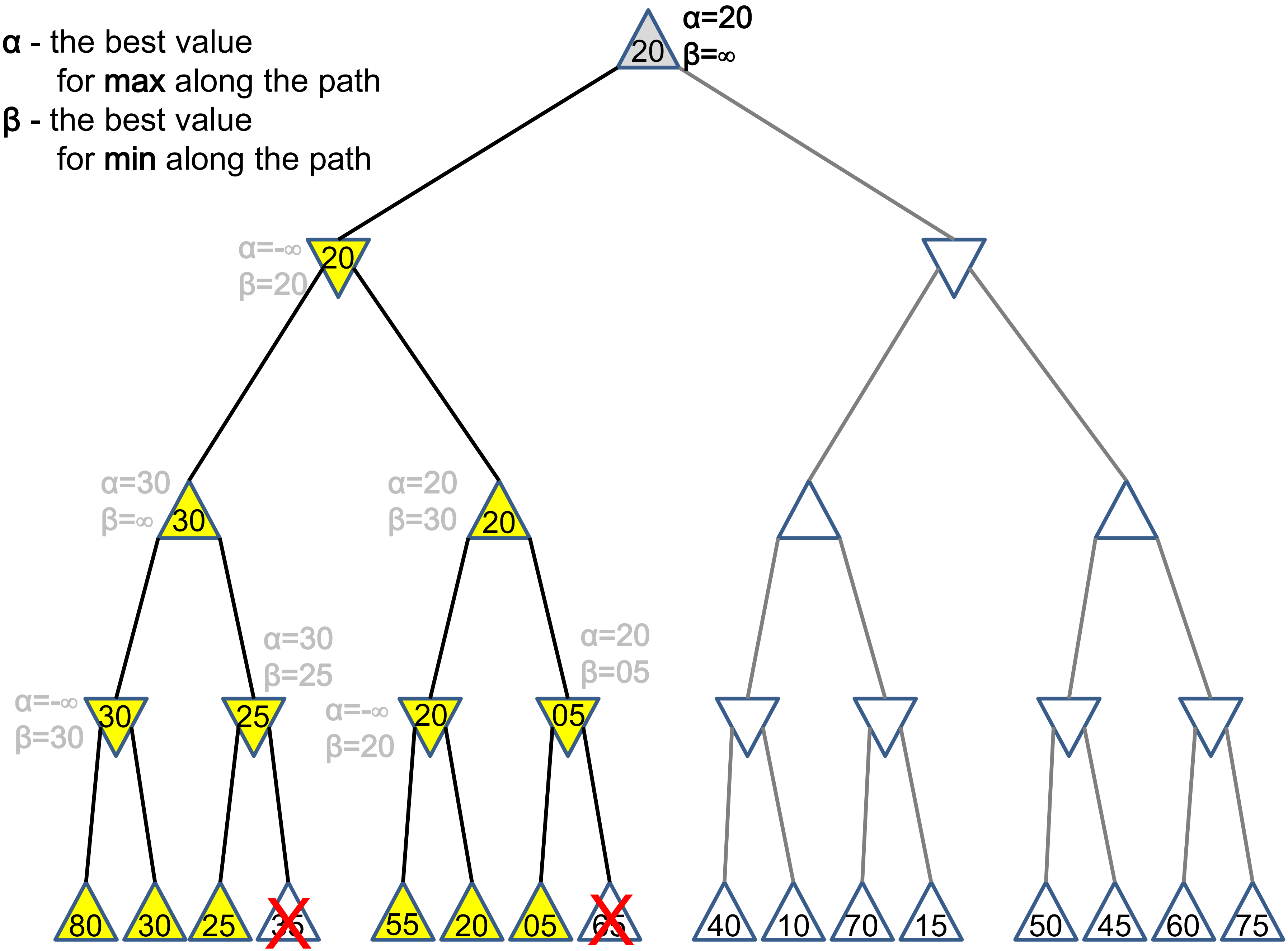

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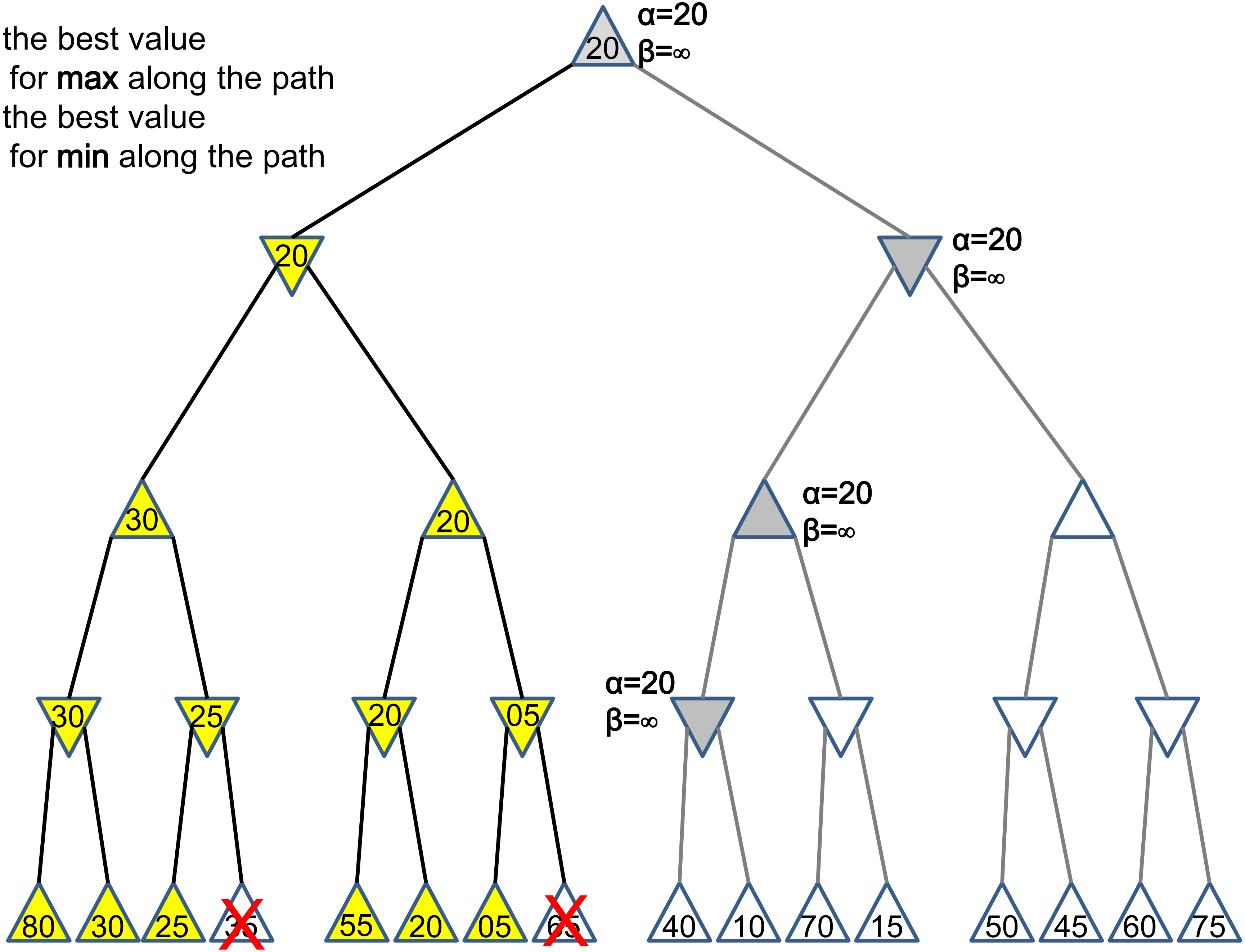

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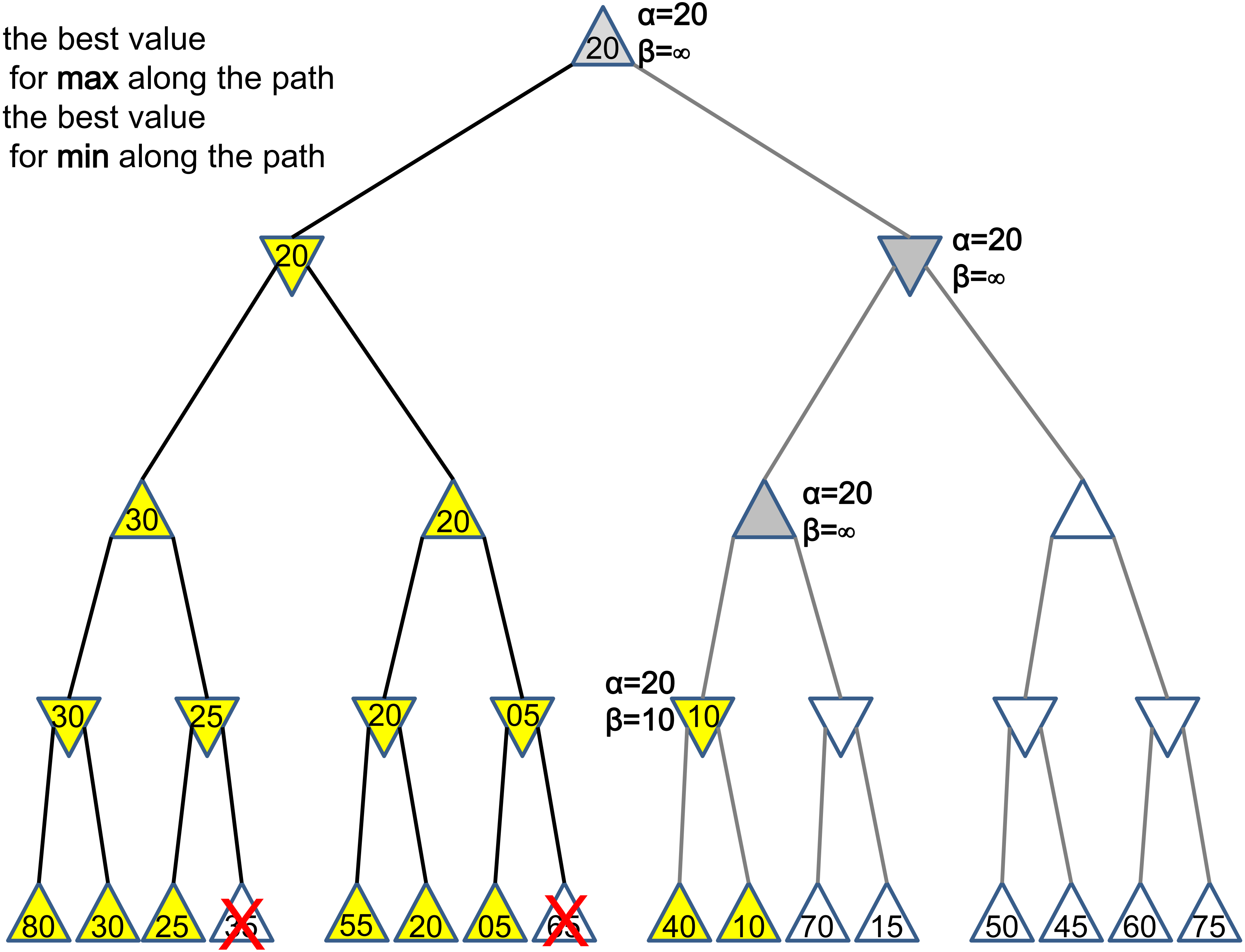

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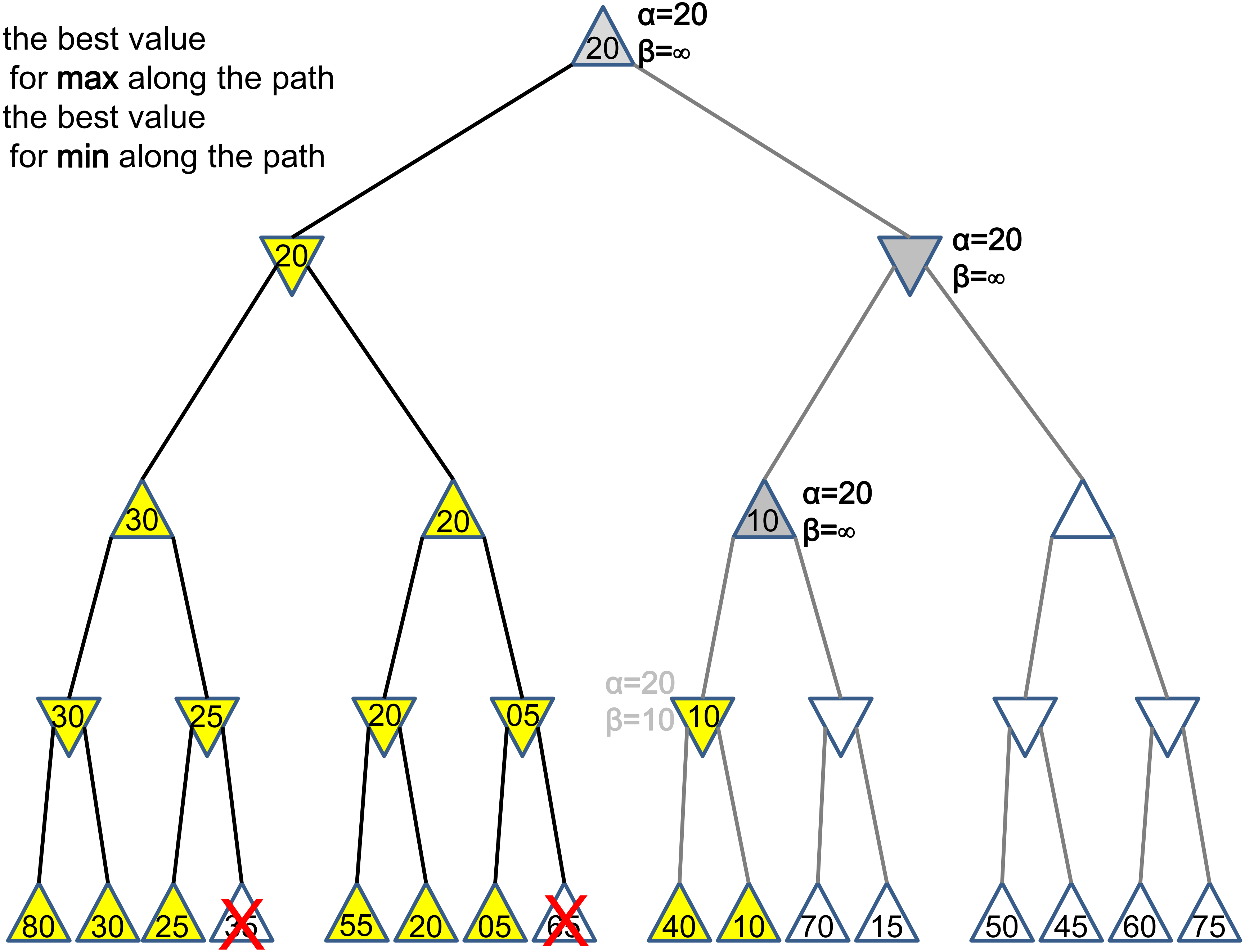

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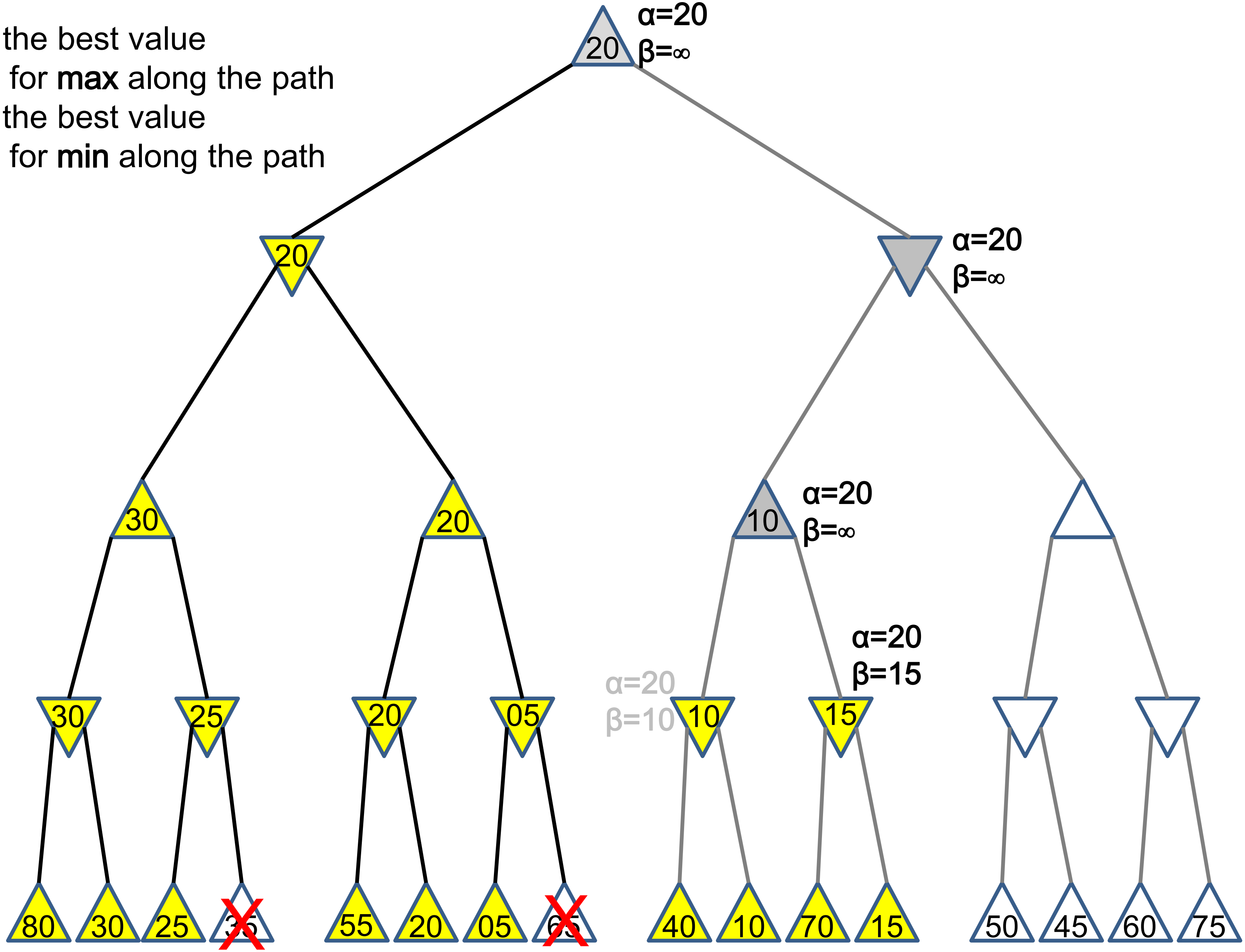

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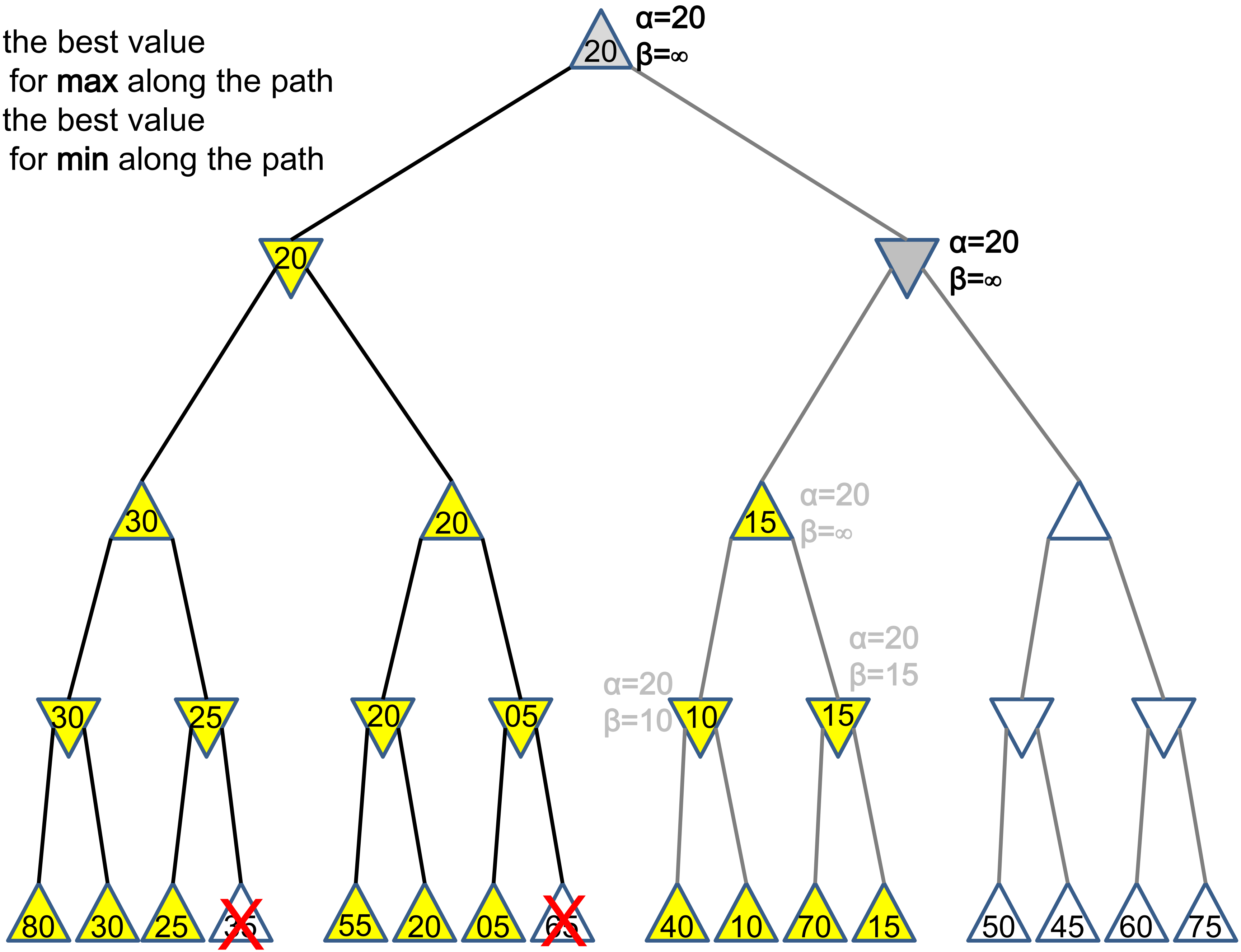
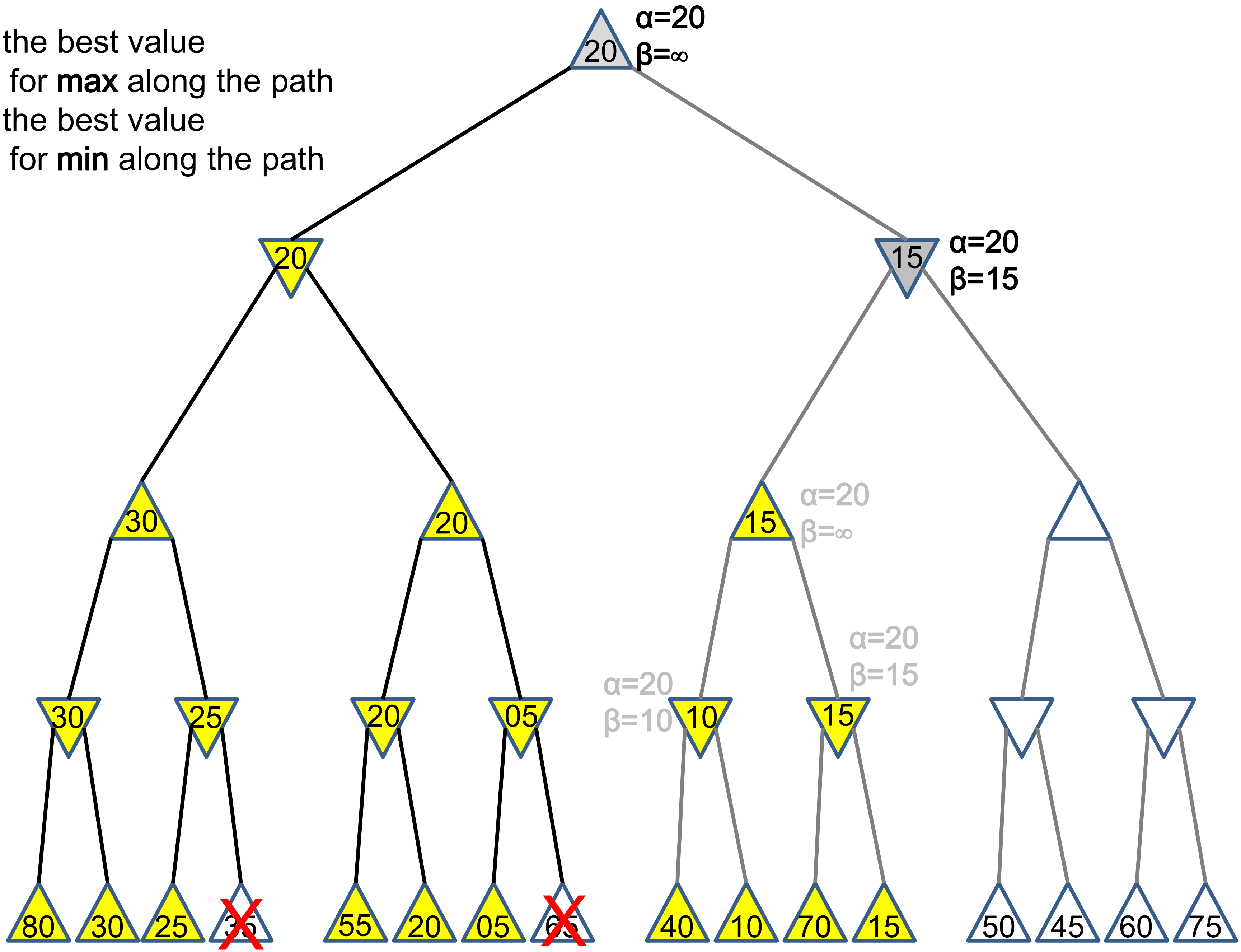
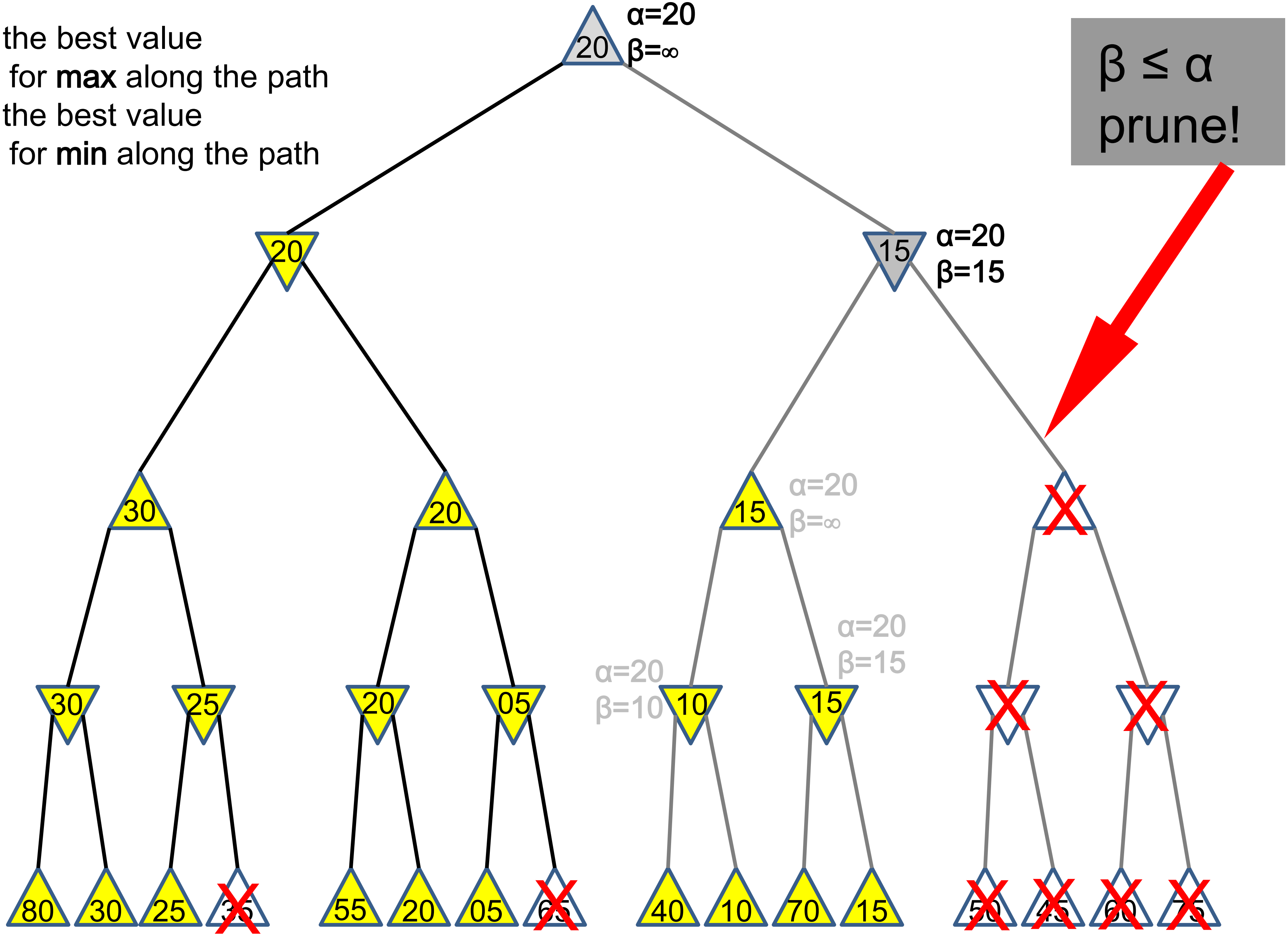


α - the best value
for **max** along the path

β - the best value
for **min** along the path



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



Bad and Good Cases for Alpha-Beta Pruning

- Bad: Worst moves encountered first

```
                          4                    MAX
           +--------------+--------------+
           2              3              4          MIN
      +----+----+     +----+----+     +----+----+
      6    4    2     7    5    3     8    6    4       MAX
    +--+  +--+  +--+ +-+-+ +--+ +--+ +--+  +--+ +--+--+
    6  5  4  3  2  1 1 3 7  4  5  2  3  8  2  1  6 1  2  4
```

- Good: Good moves ordered first

```
                          4                    MAX
           +--------------+--------------+
           4              3              2          MIN
       +----+----+    +----+----+    +----+----+
       4    6    8    3    x    x    2    x    x       MAX
     +--+  +--+  +--+ +--+           +-+-+
     4  2  6  x  8  x 3  2           1 2 1
```

- If we can order moves, we can get more benefit from alpha-beta pruning

Properties of α-β

- 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)

Why $O(b^{m/2})$?

Let $T(m)$ be time complexity of search for depth m

Normally:

$T(m) = b.T(m-1) + c \Rightarrow T(m) = O(b^m)$

With ideal α-β pruning:

$T(m) = T(m-1) + (b-1)T(m-2) + c \Rightarrow T(m) = O(b^{m/2})$

Node Ordering

Iterative deepening search

Use evaluations of the previous search for order

Also helps in returning a move in given time

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 moves/sec x 10^{78} x 10^{18} = 10^{104}

The universe can play chess - can we?

Cutting off Search

MinimaxCutoff is identical to *MinimaxValue* except

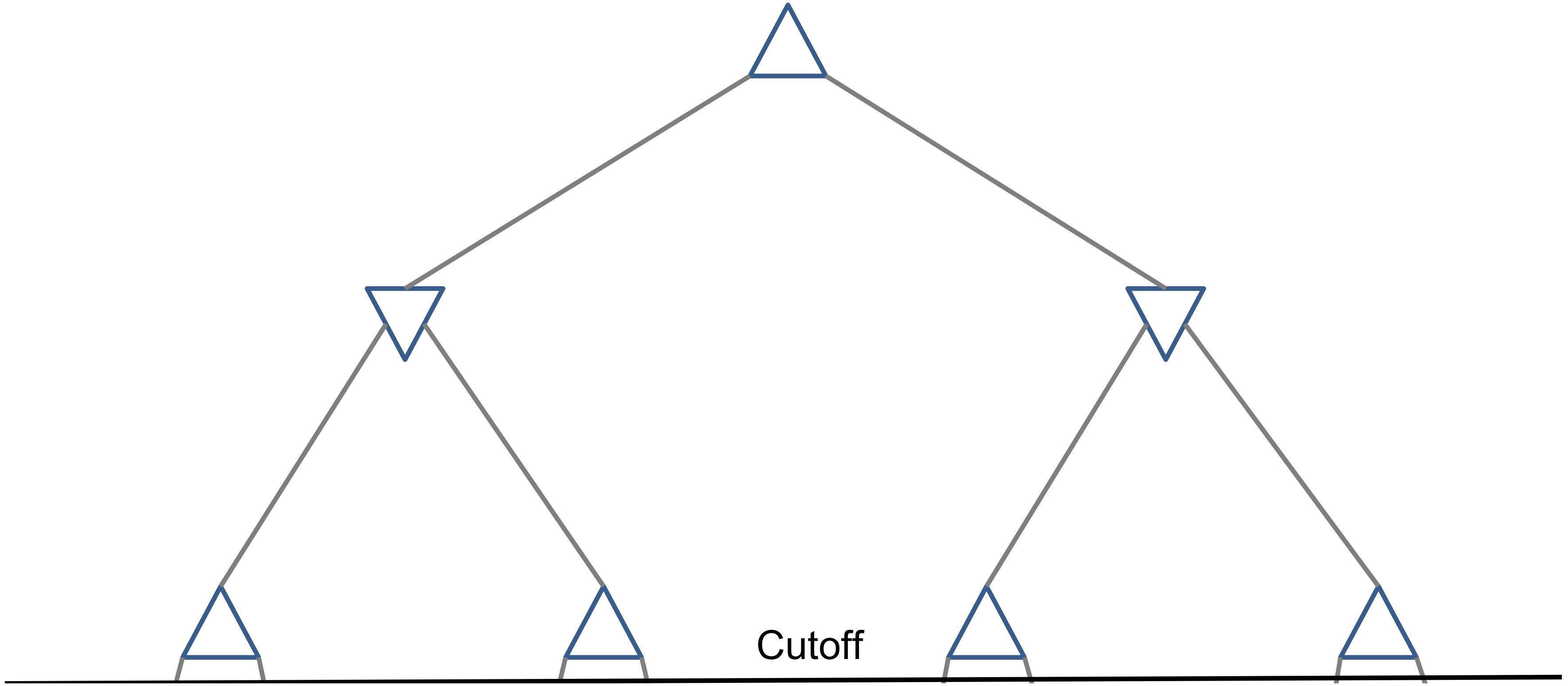
1. *Terminal?* is replaced by *Cutoff?*
2. *Utility* is replaced by *Eval*

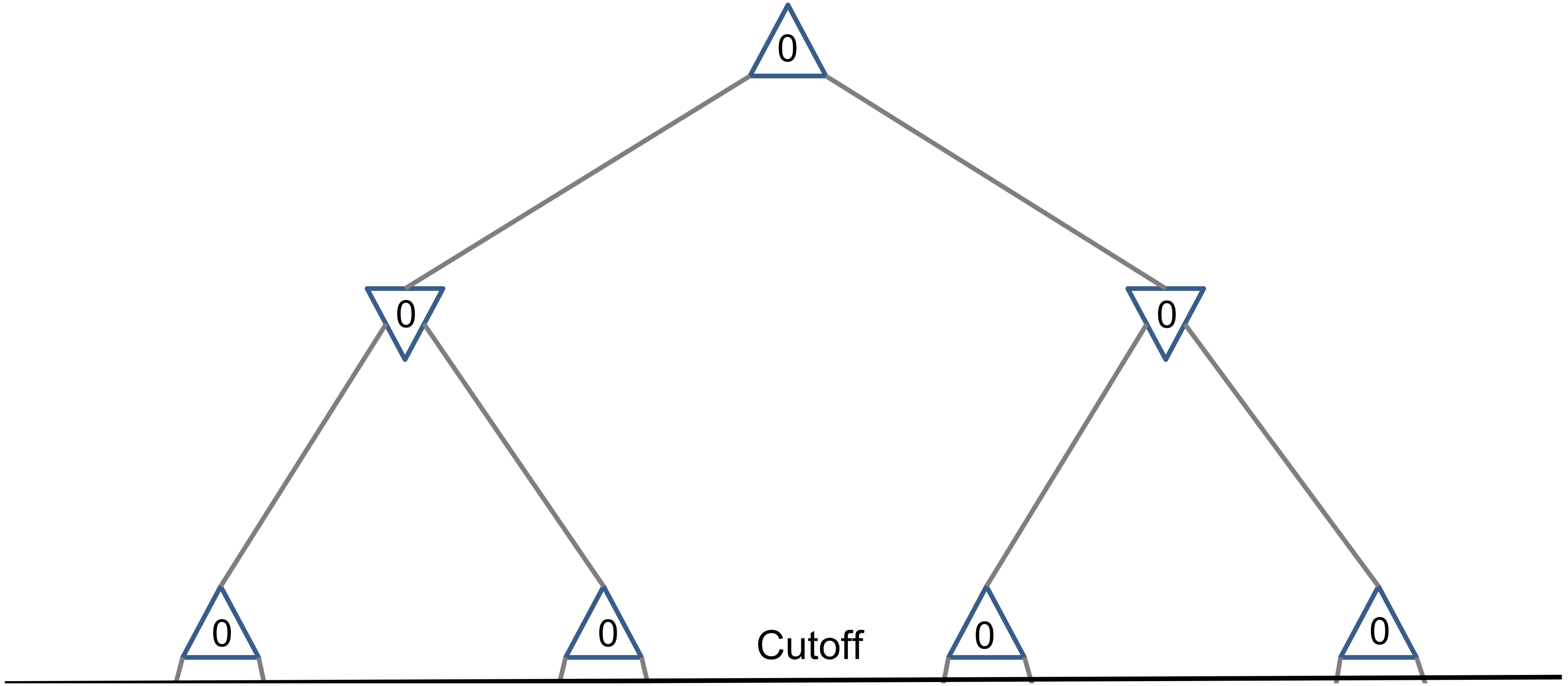
Does it work in practice?

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

4-ply lookahead is a hopeless chess player!

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


Cutoff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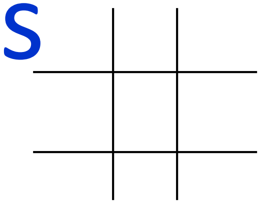
Evaluation Functions
Tic Tac Toe



- 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

	O	
	X	

O	O	X
X	X	

	X	O
rows		
cols		
diags		

	X	O
rows		
cols		
diags		

Evaluation functions

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

$$Eval(s) = w_1\, f_1(s) + w_2\, f_2(s) + \ldots + w_m\, f_m(s)$$

e.g., $w_1 = 9$ with

$f_1(s)$ = (number of white queens) – (number of black queens), etc.

Example: Samuel's Checker-Playing Program

- It uses a linear evaluation function

  $f(n) = w_1f_1(n) + w_2f_2(n) + ... + w_mf_m(n)$

  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?

Coefficent replacement

$\triangle$(node) = backed-up value(node) – initial value(node)

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

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