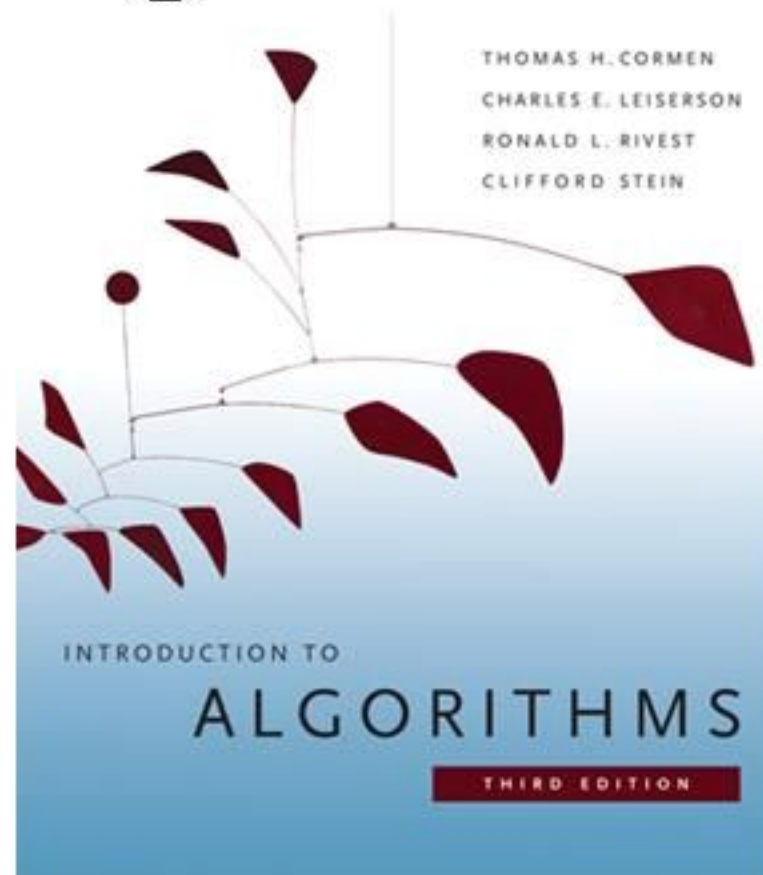


# 6.006- *Introduction to Algorithms*



## *Lecture 8*

**Prof. Constantinos Daskalakis**

**CLRS: chapter 4.**

# Menu

- Sorting!
  - Insertion Sort
  - Merge Sort
- Recurrences
  - Master theorem

# The problem of sorting

**Input:** array  $A[1 \dots n]$  of numbers.

**Output:** permutation  $B[1 \dots n]$  of  $A$  such that  $B[1] \leq B[2] \leq \dots \leq B[n]$ .

e.g.  $A = [7, 2, 5, 5, 9.6] \rightarrow B = [2, 5, 5, 7, 9.6]$

How can we do it efficiently ?

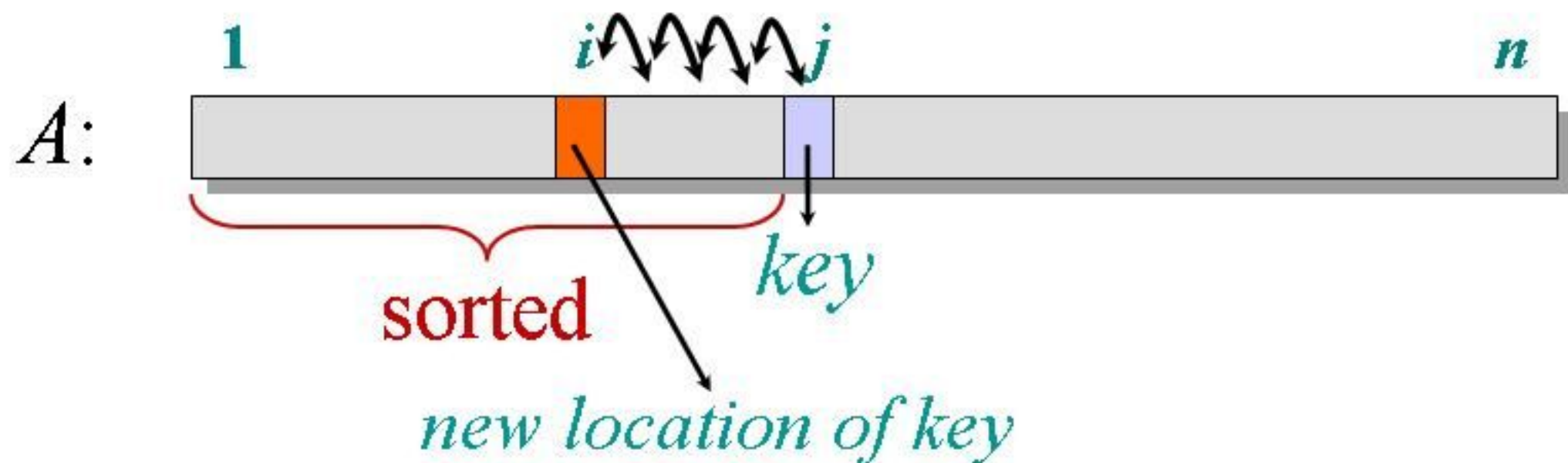
# Insertion sort

INSERTION-SORT ( $A, n$ )  $\triangleright A[1 \dots n]$

**for**  $j \leftarrow 2$  **to**  $n$

    insert key  $A[j]$  into the (already sorted) sub-array  $A[1 \dots j-1]$ .  
    by pairwise key-swaps down to its right position

**Illustration of iteration  $j$**



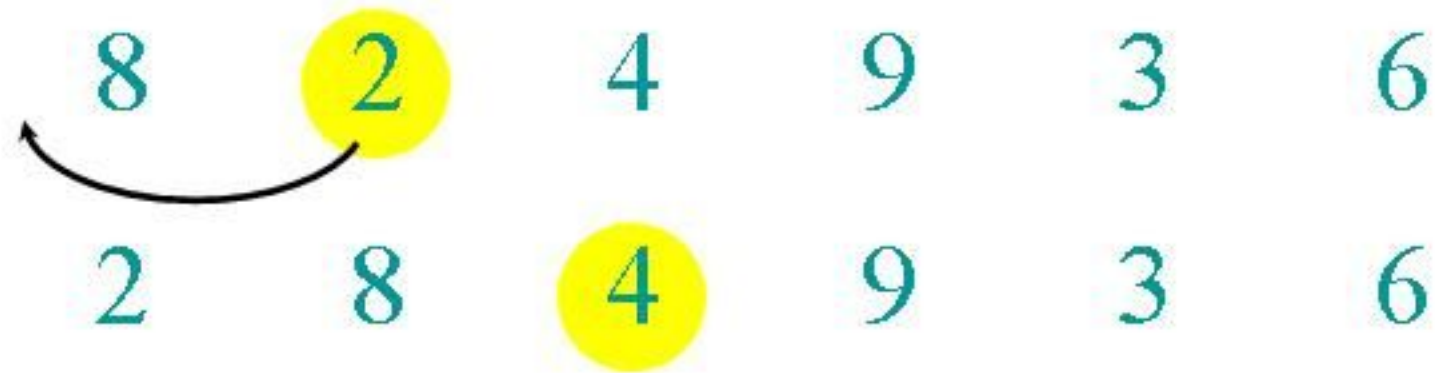
# Example of insertion sort

8 2 4 9 3 6

# Example of insertion sort



# Example of insertion sort

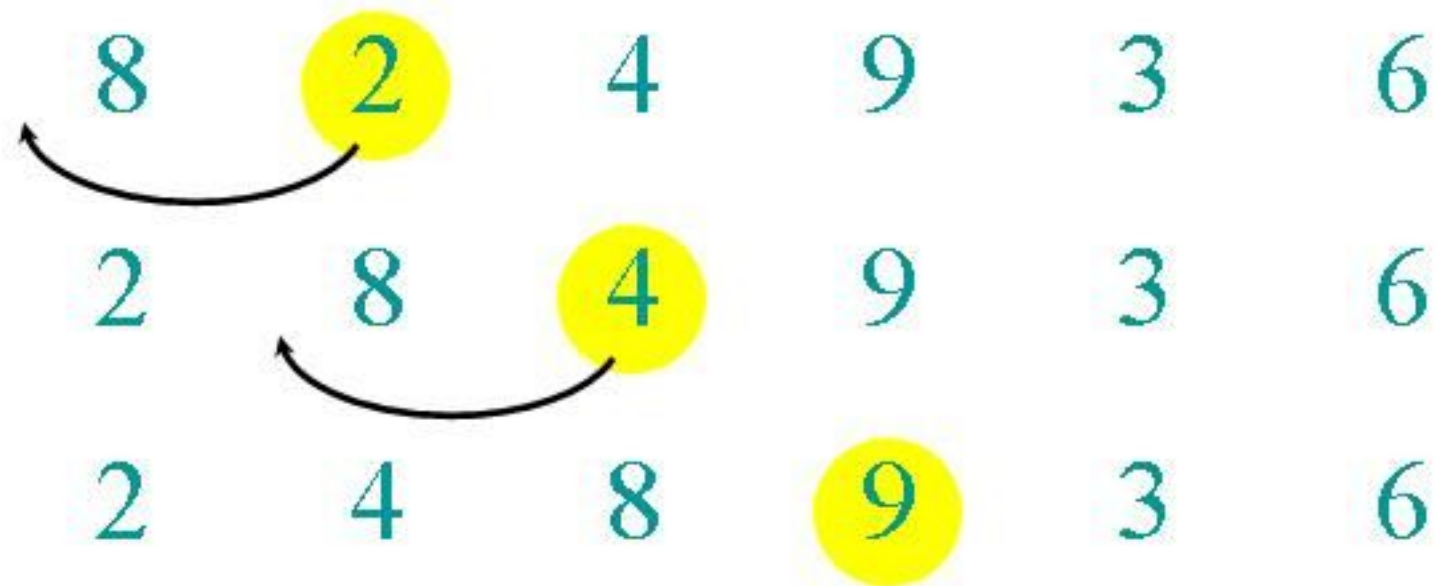


# Example of insertion sort

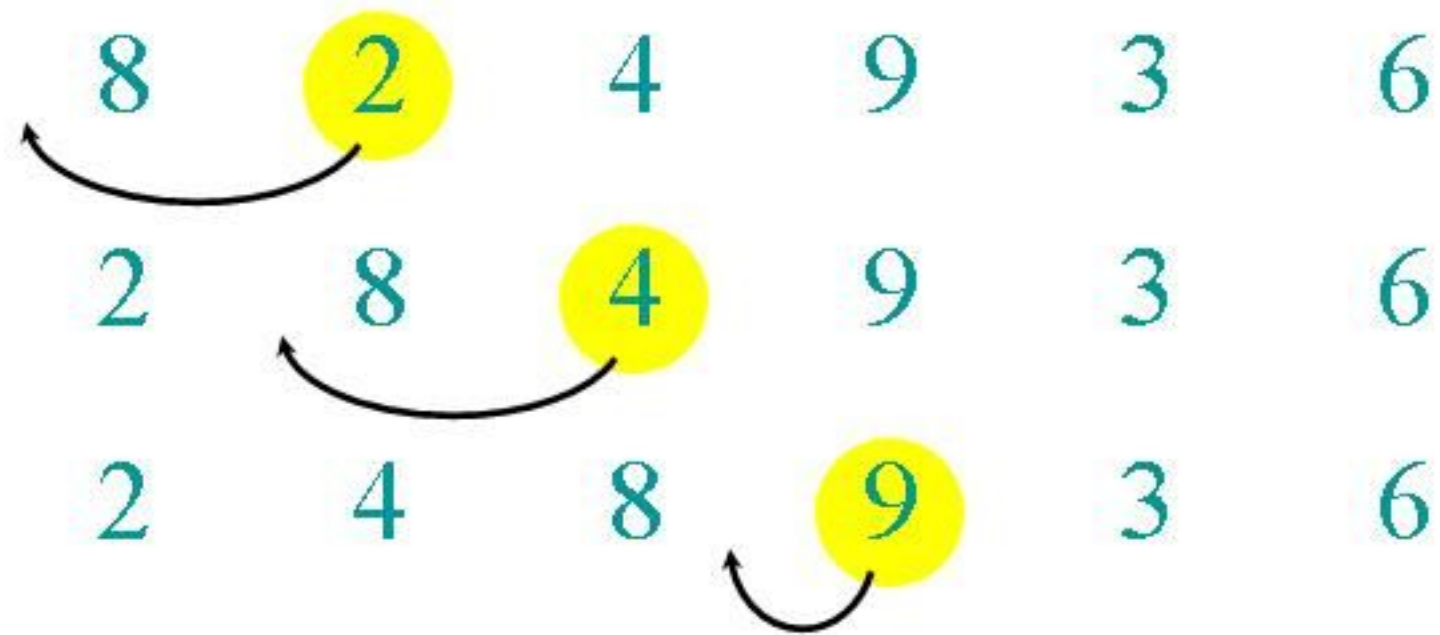




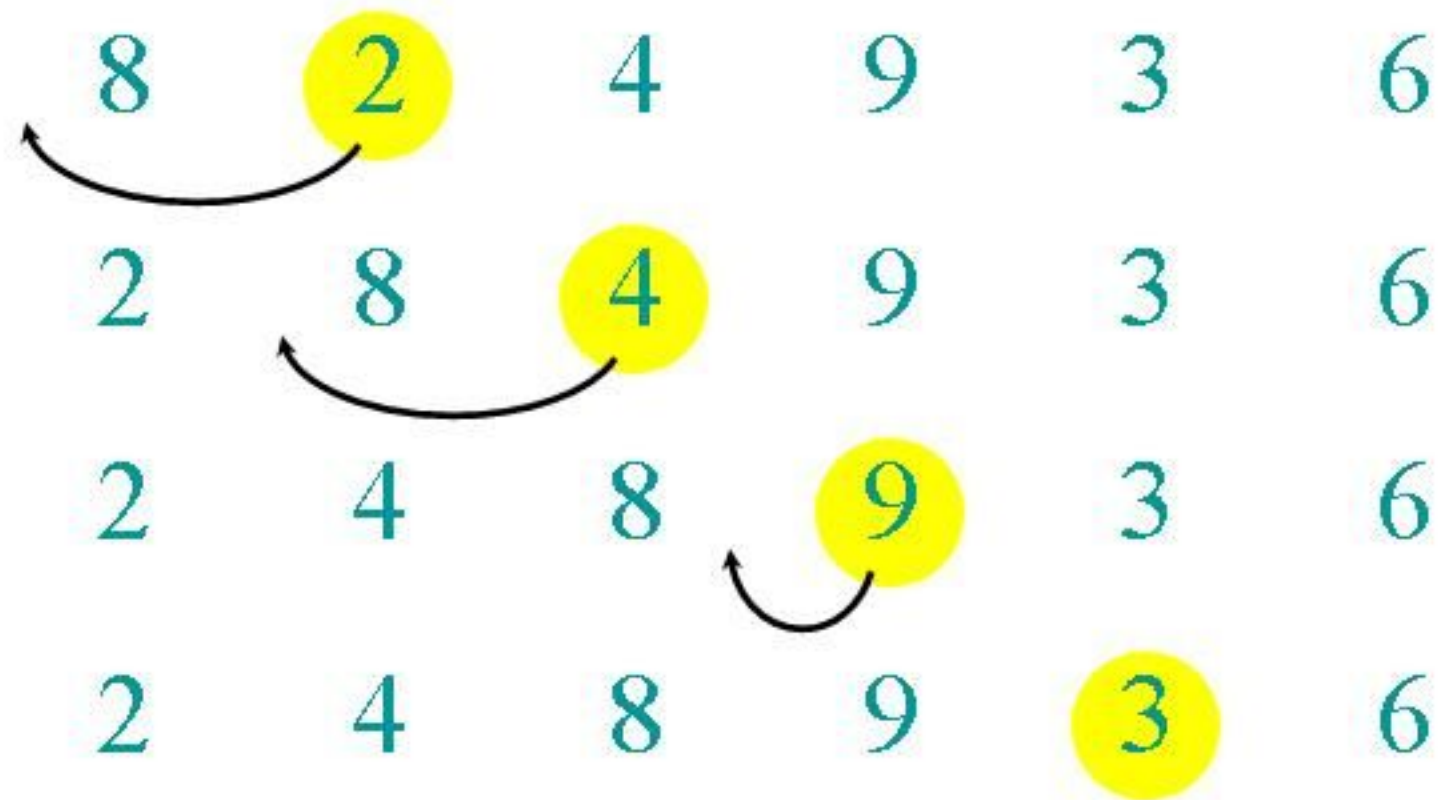
# Example of insertion sort



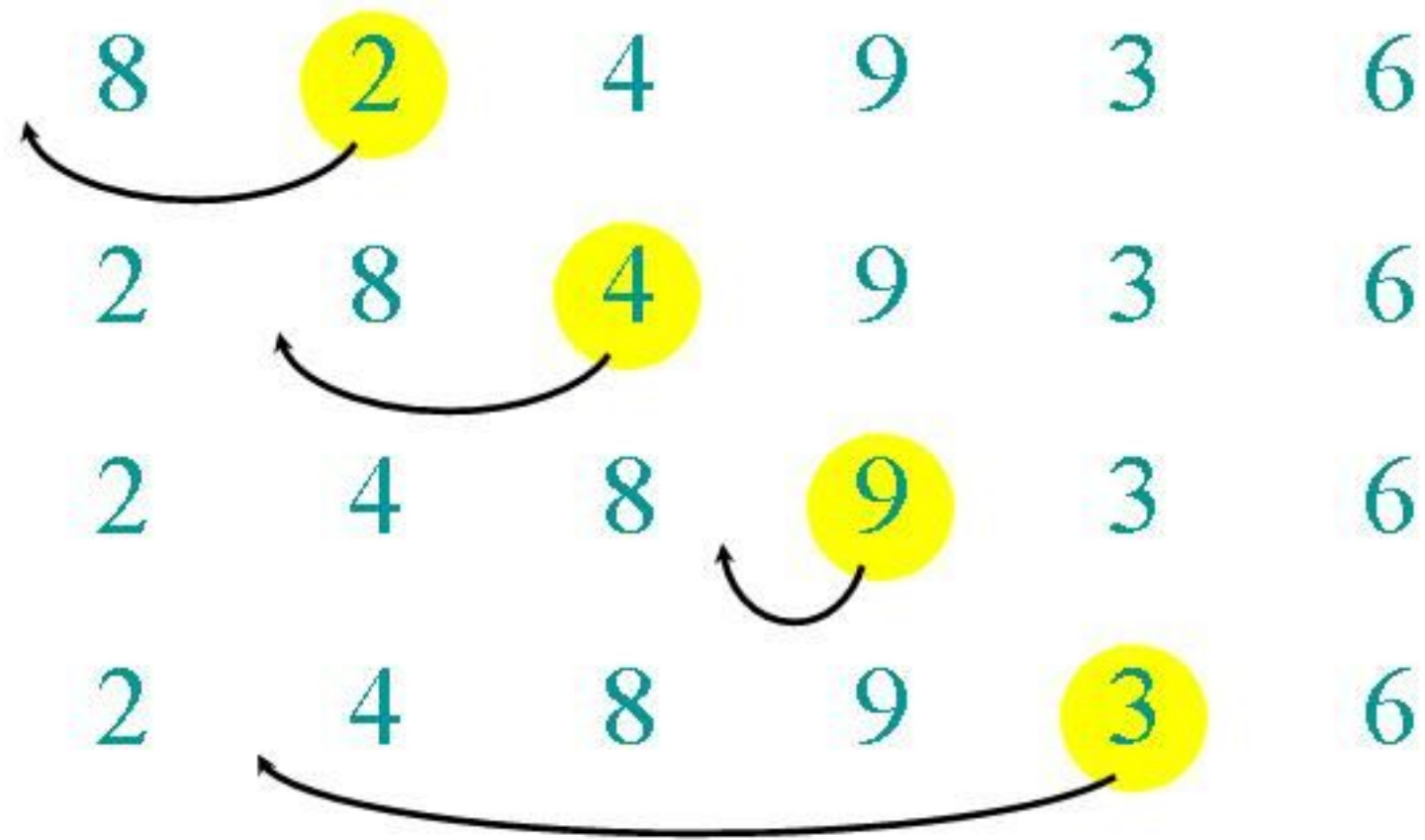
# Example of insertion sort



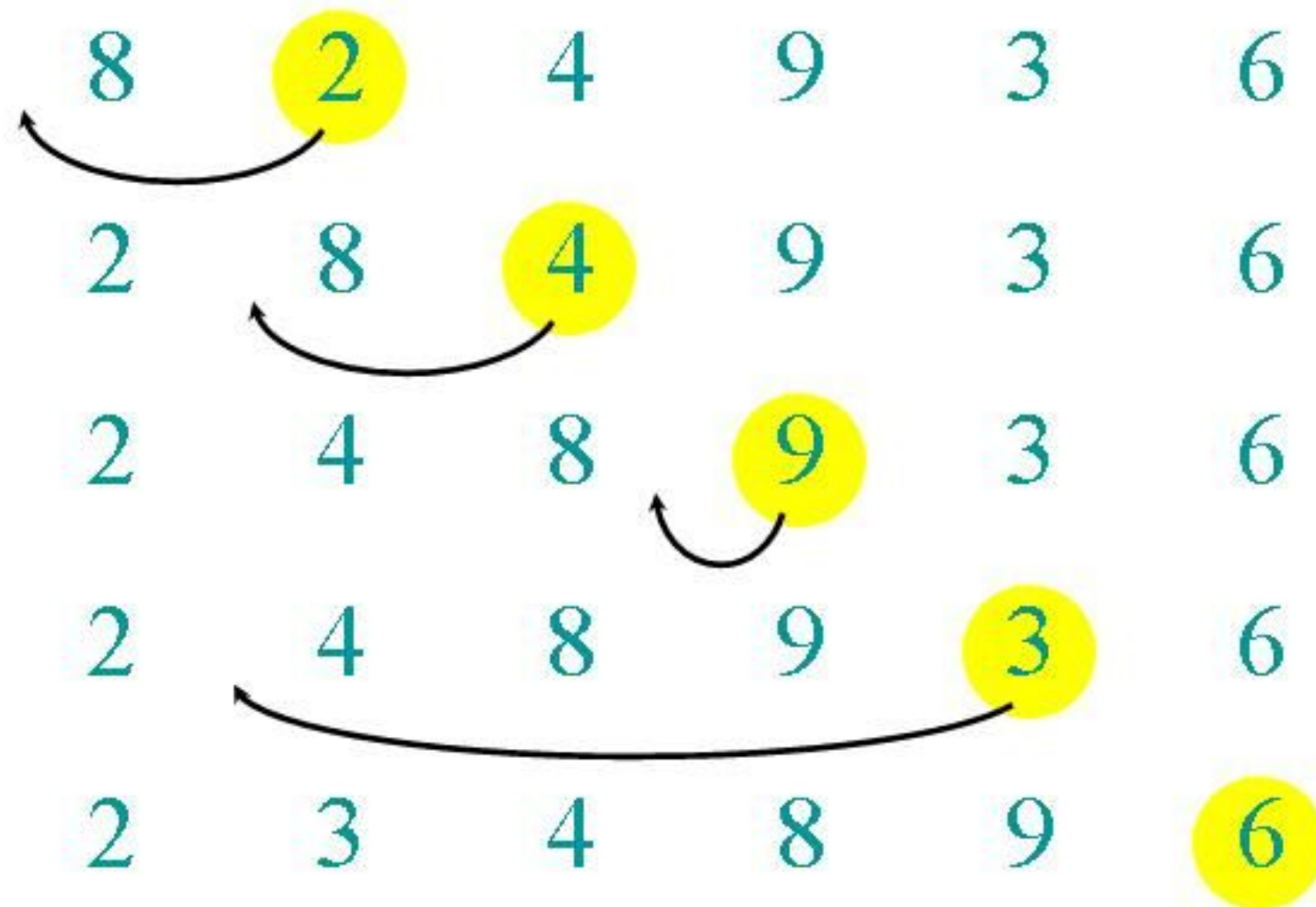
# Example of insertion sort



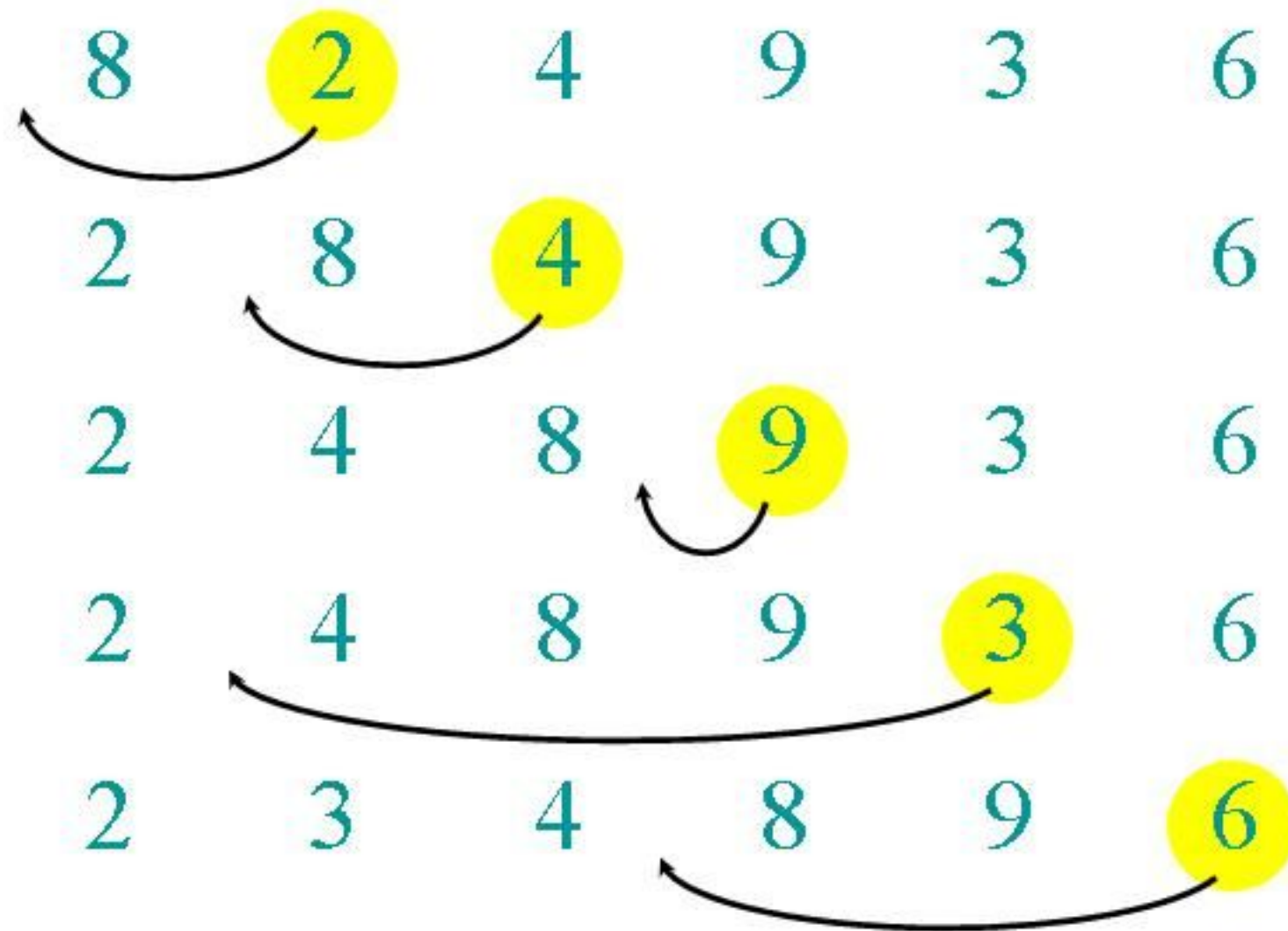
# Example of insertion sort



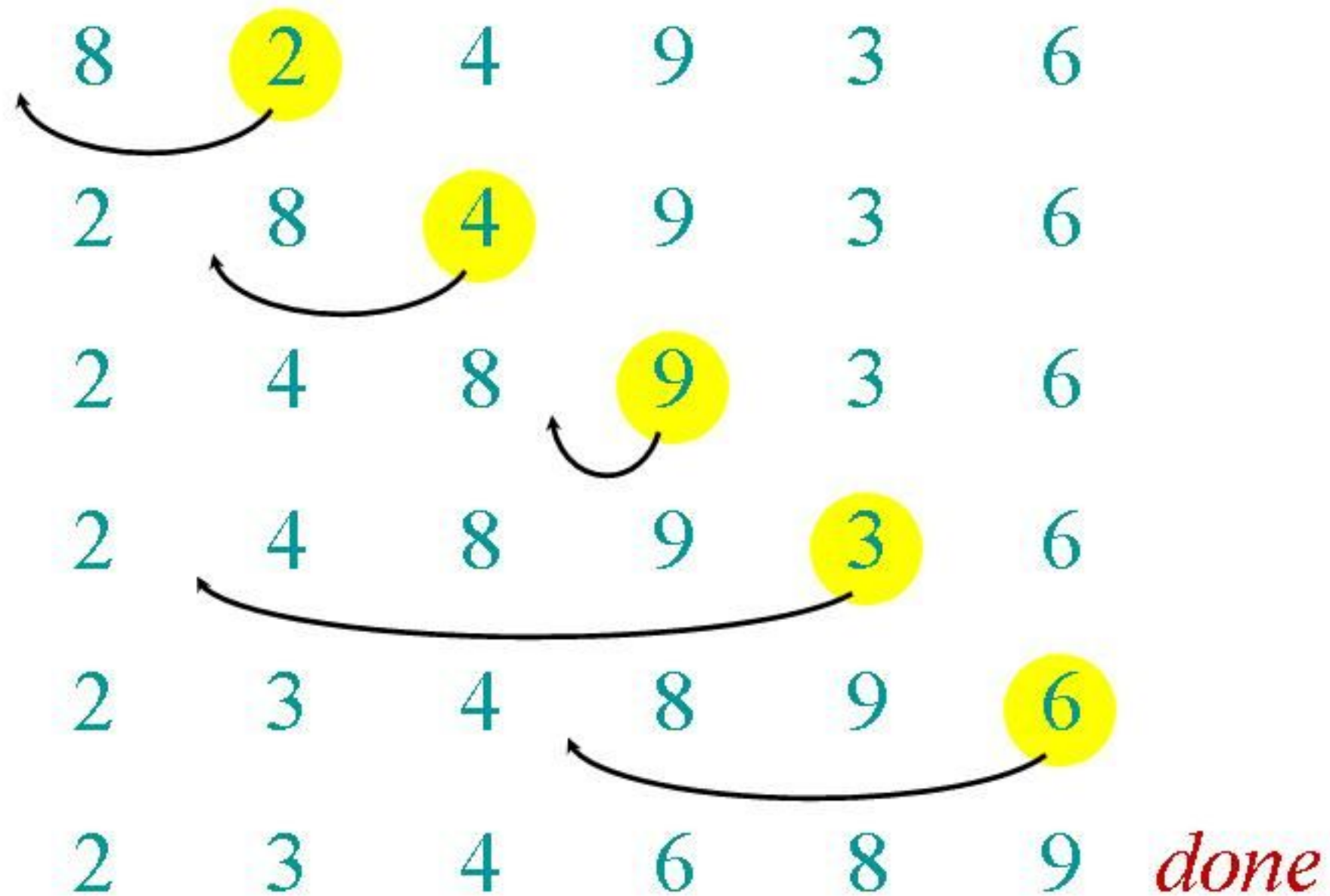
# Example of insertion sort



# Example of insertion sort



# Example of insertion sort



Running time?

$O(n^2)$

e.g. when input is  $A = [n, n - 1, n - 2, \dots, 2, 1]$



# Meet Merge Sort

divide and  
conquer

**MERGE-SORT**  $A[1 \dots n]$

1. If  $n = 1$ , done (nothing to sort).
2. Otherwise, recursively sort  $A[1 \dots n/2]$  and  $A[n/2+1 \dots n]$ .
3. “*Merge*” the two sorted sub-arrays.

***Key subroutine:*** **MERGE**



# Merging two sorted arrays

20 12

13 11

7 9

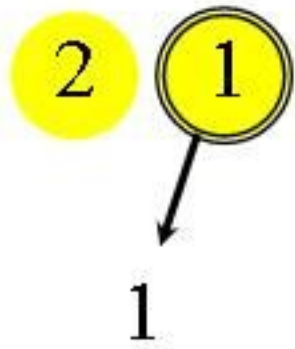
2 1

# Merging two sorted arrays

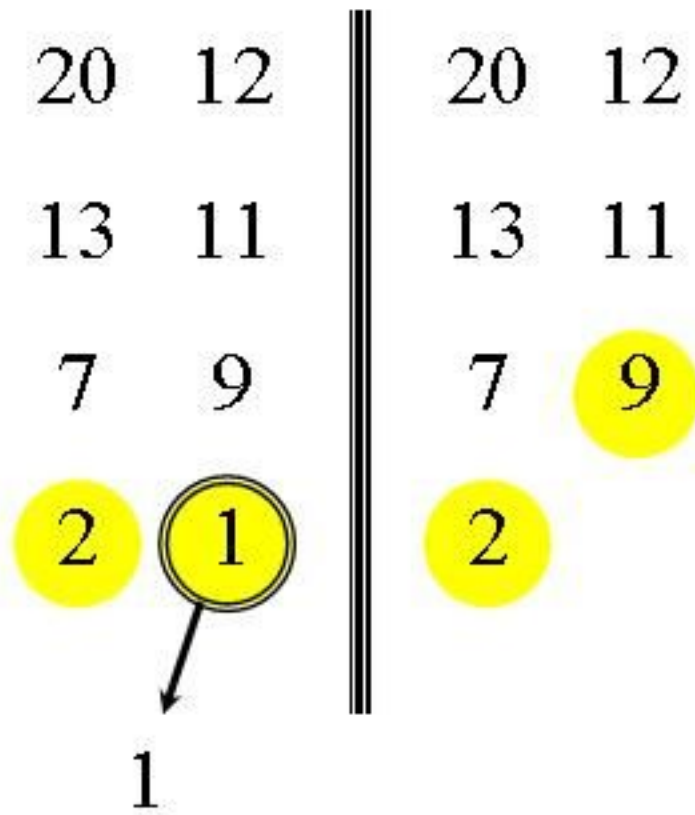
20 12

13 11

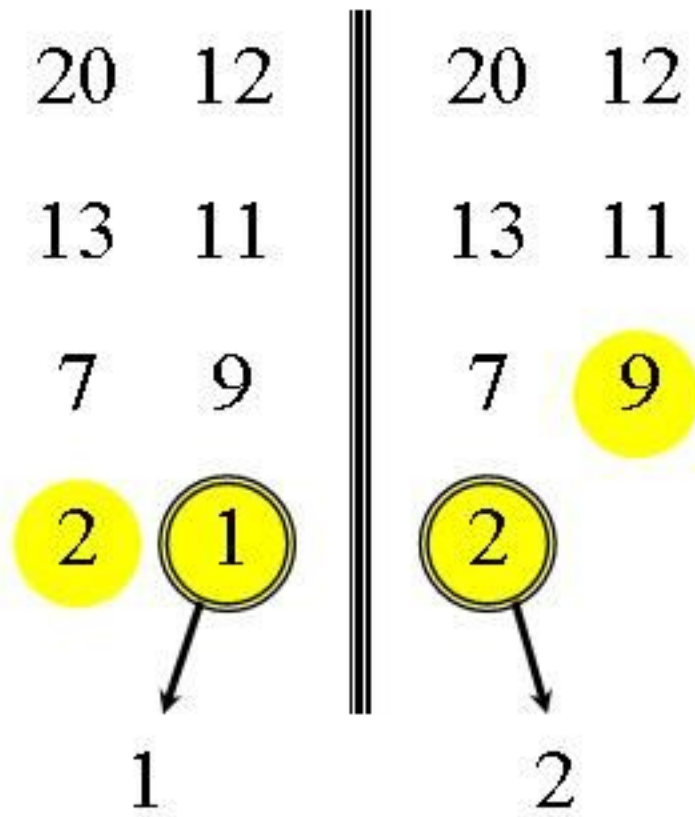
7 9



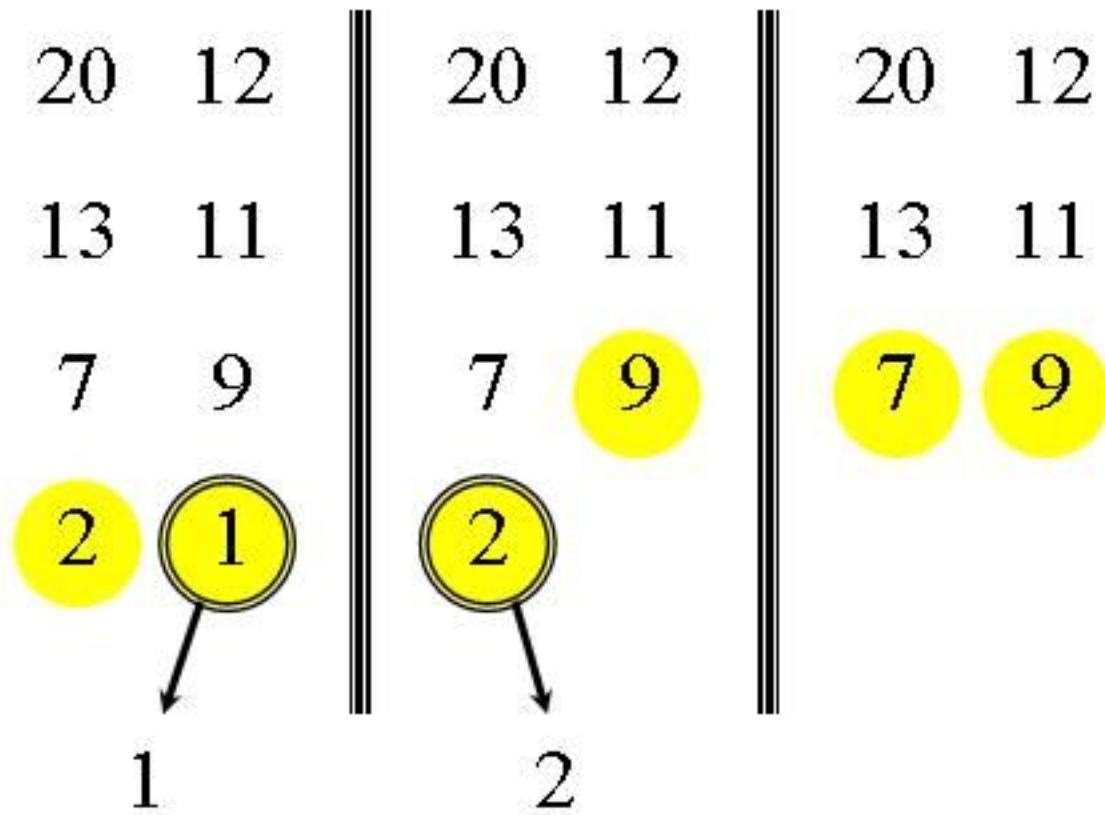
# Merging two sorted arrays



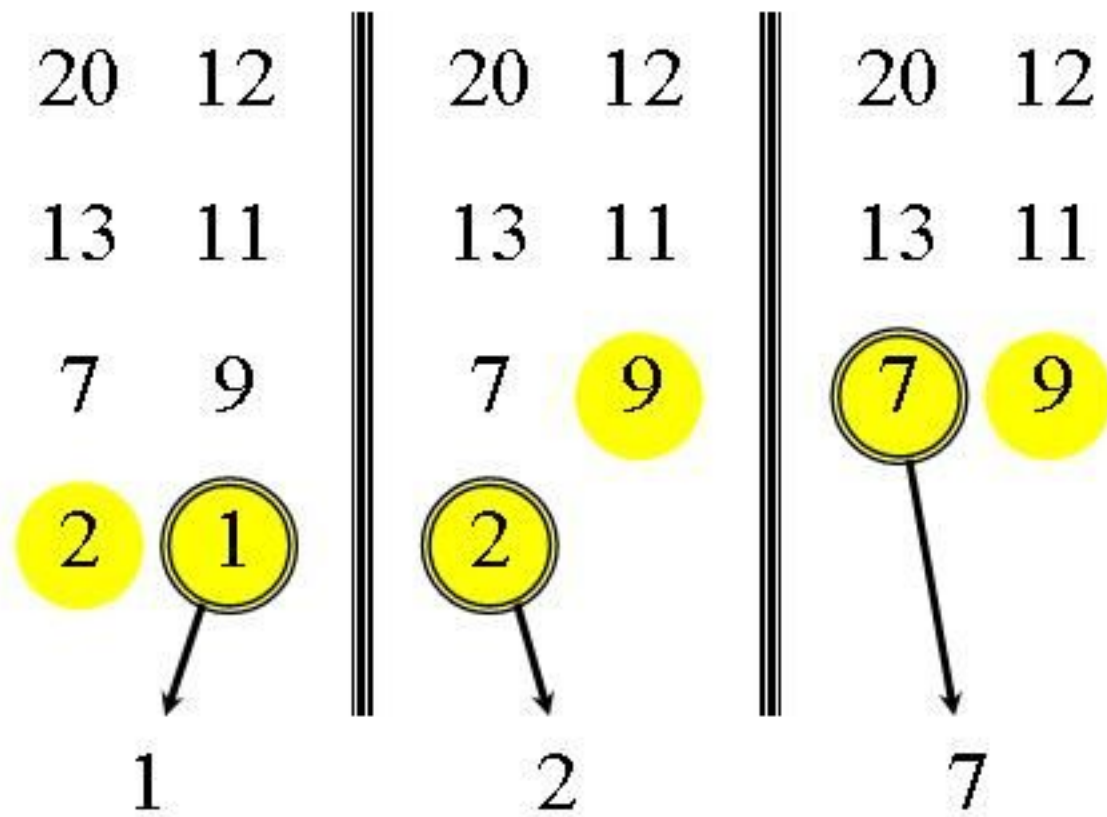
# Merging two sorted arrays



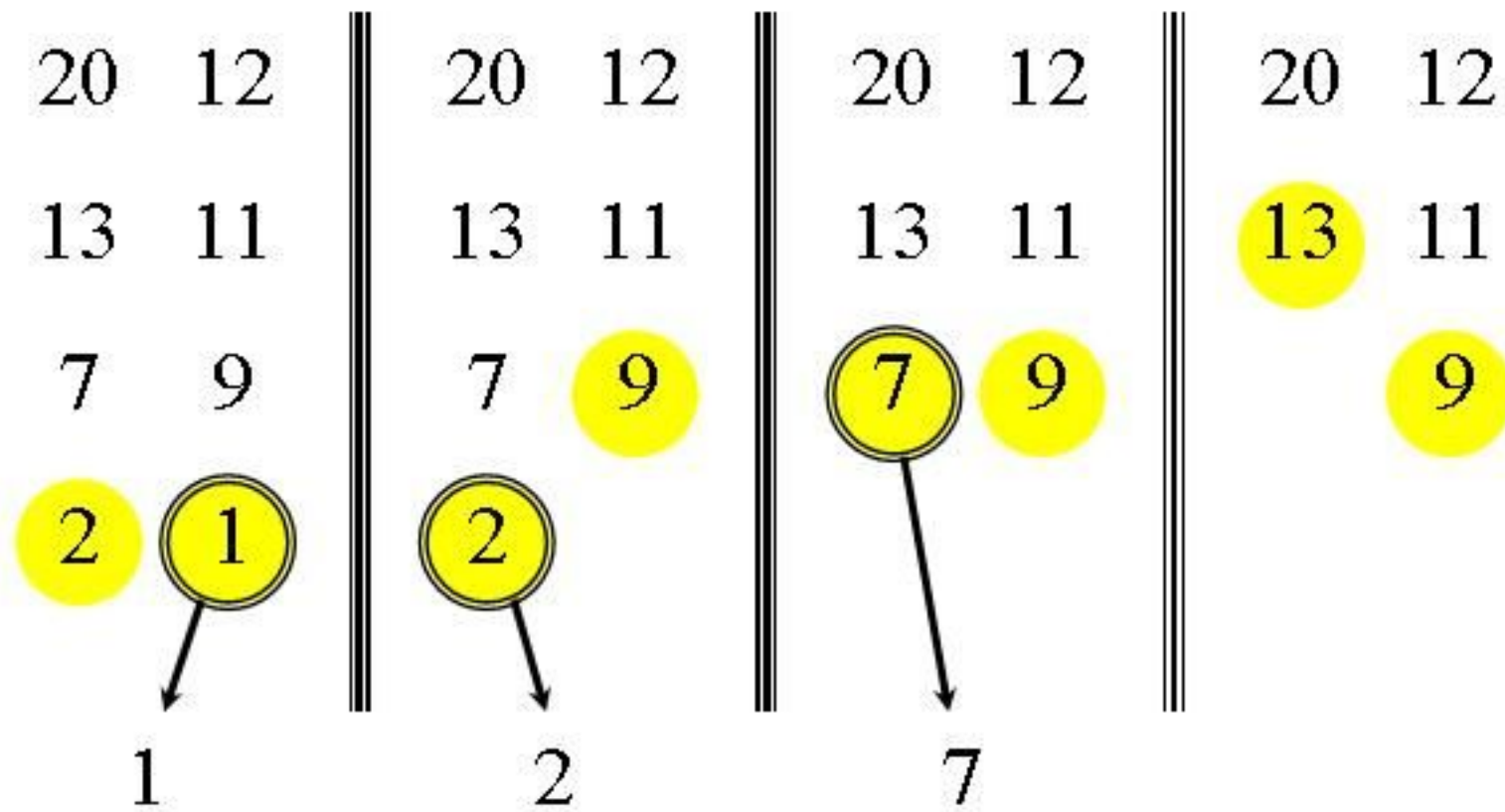
# Merging two sorted arrays



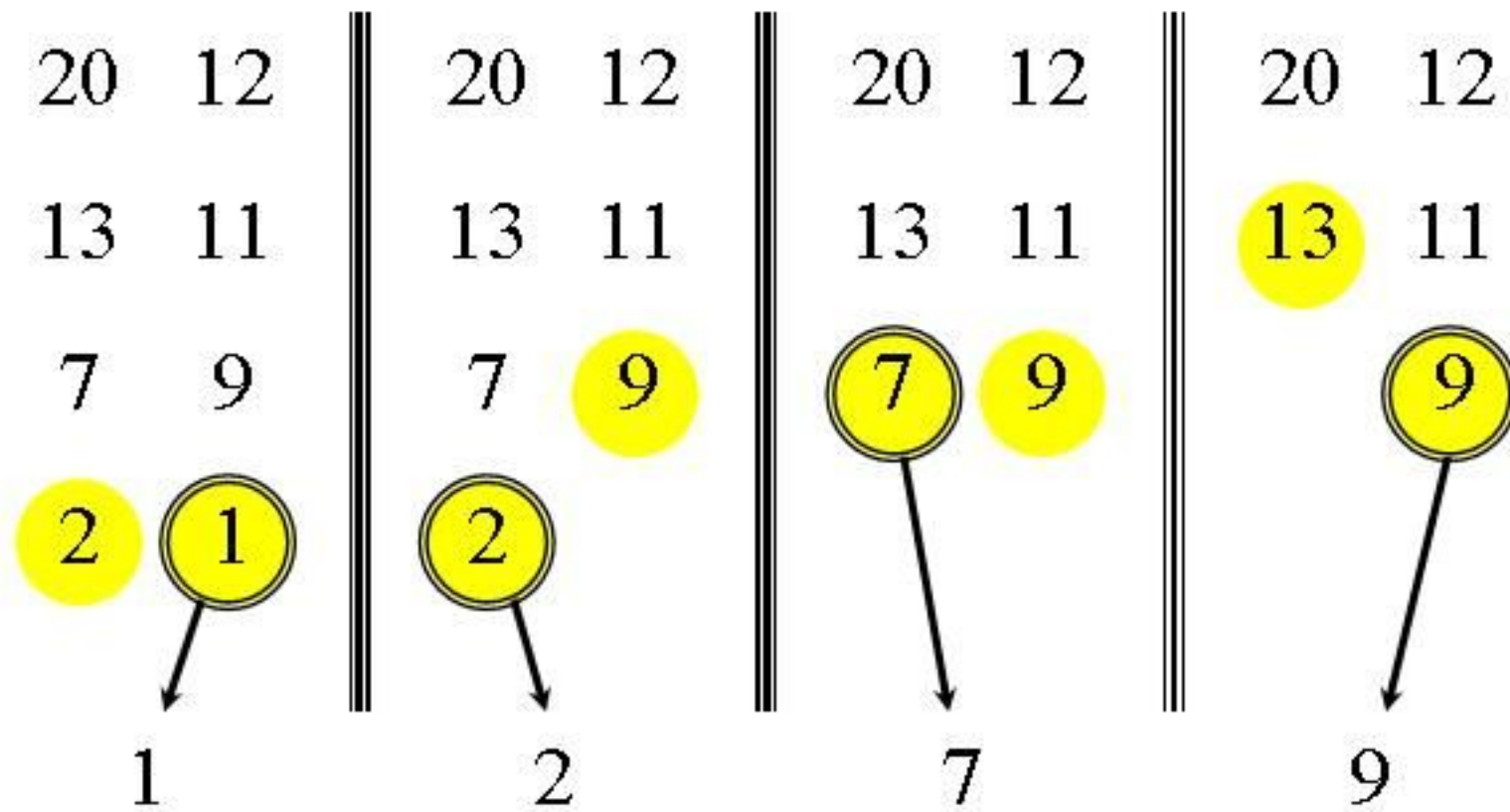
# Merging two sorted arrays



# Merging two sorted arrays

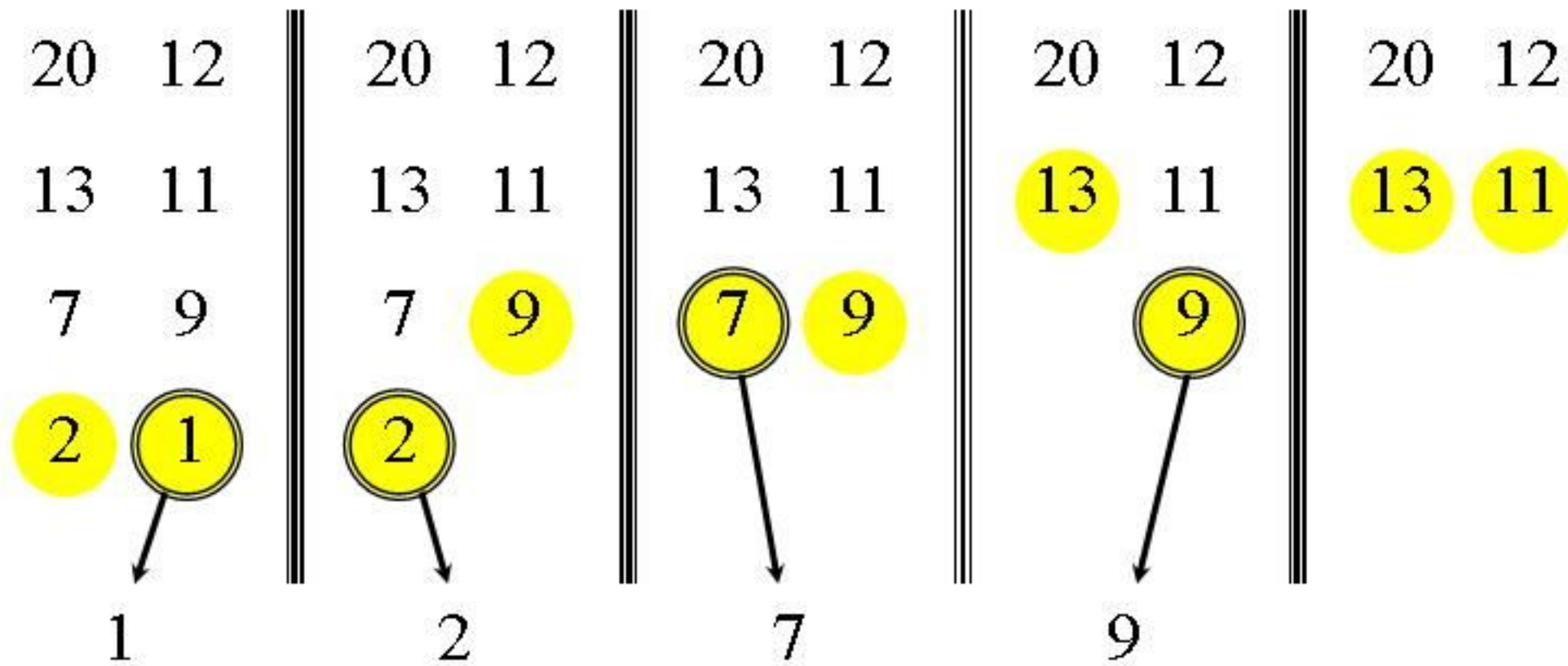


# Merging two sorted arrays

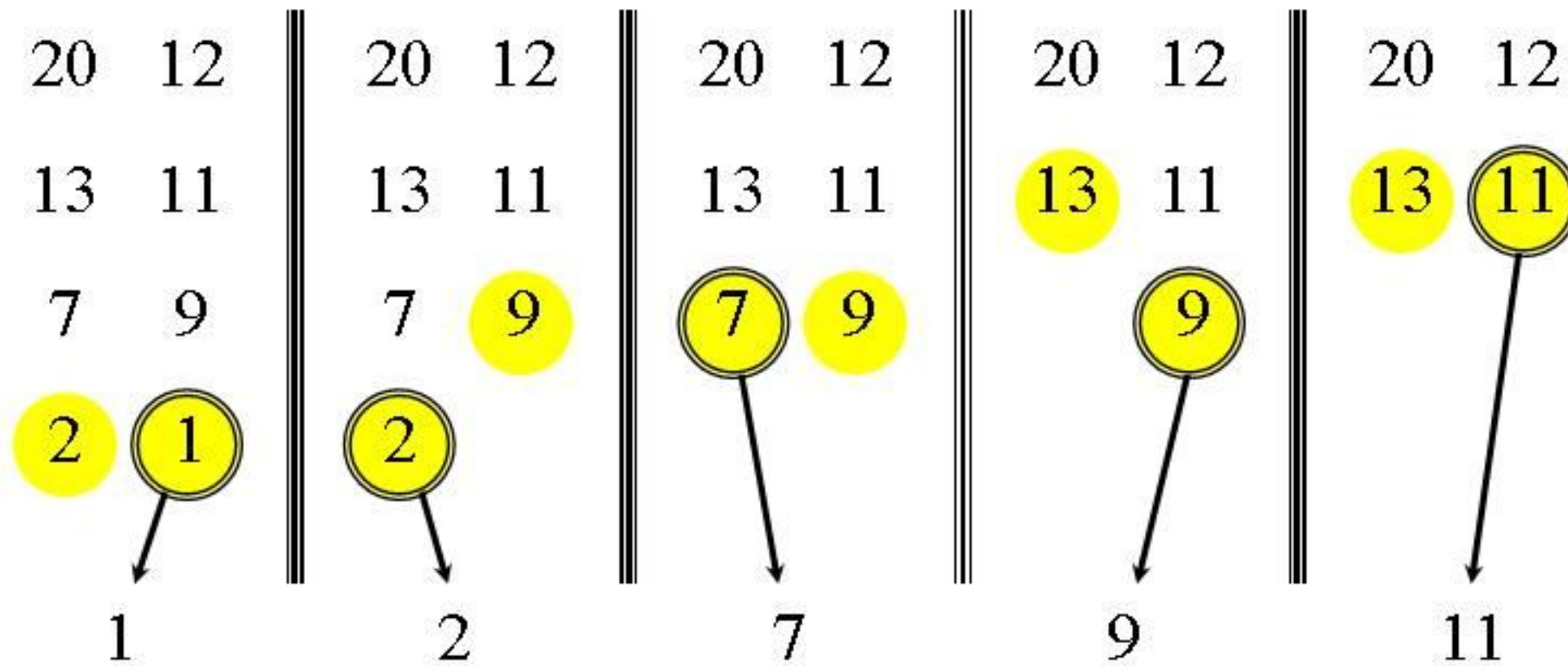




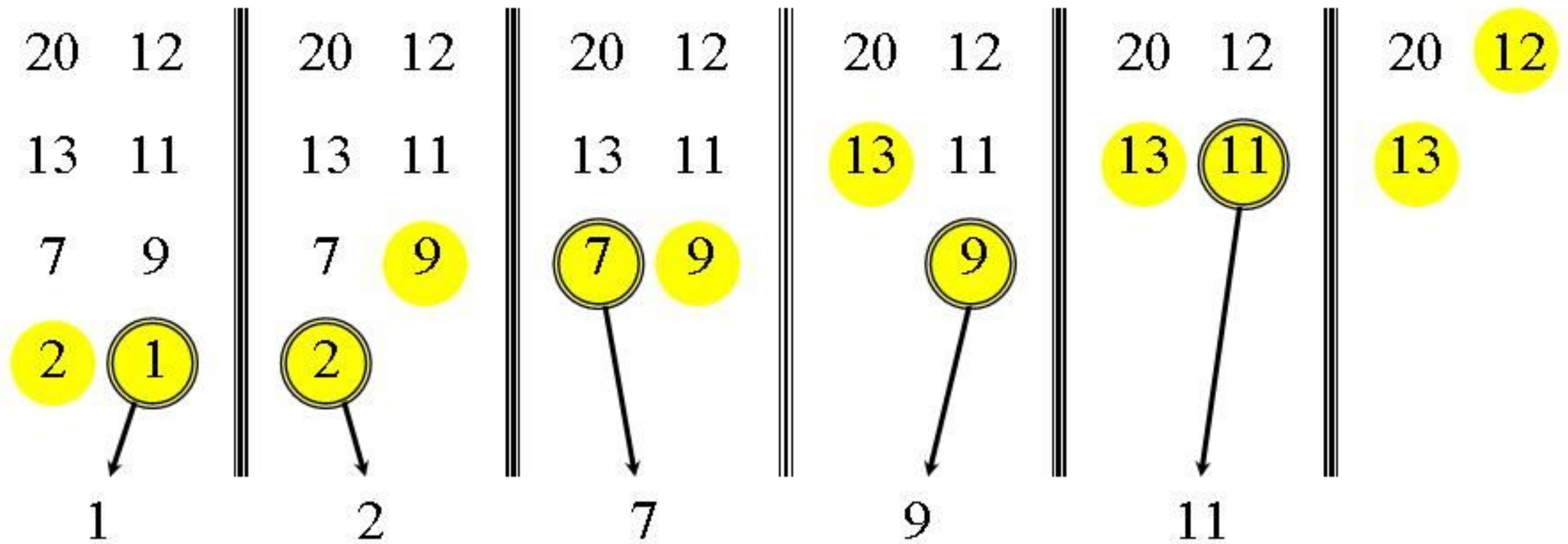
# Merging two sorted arrays



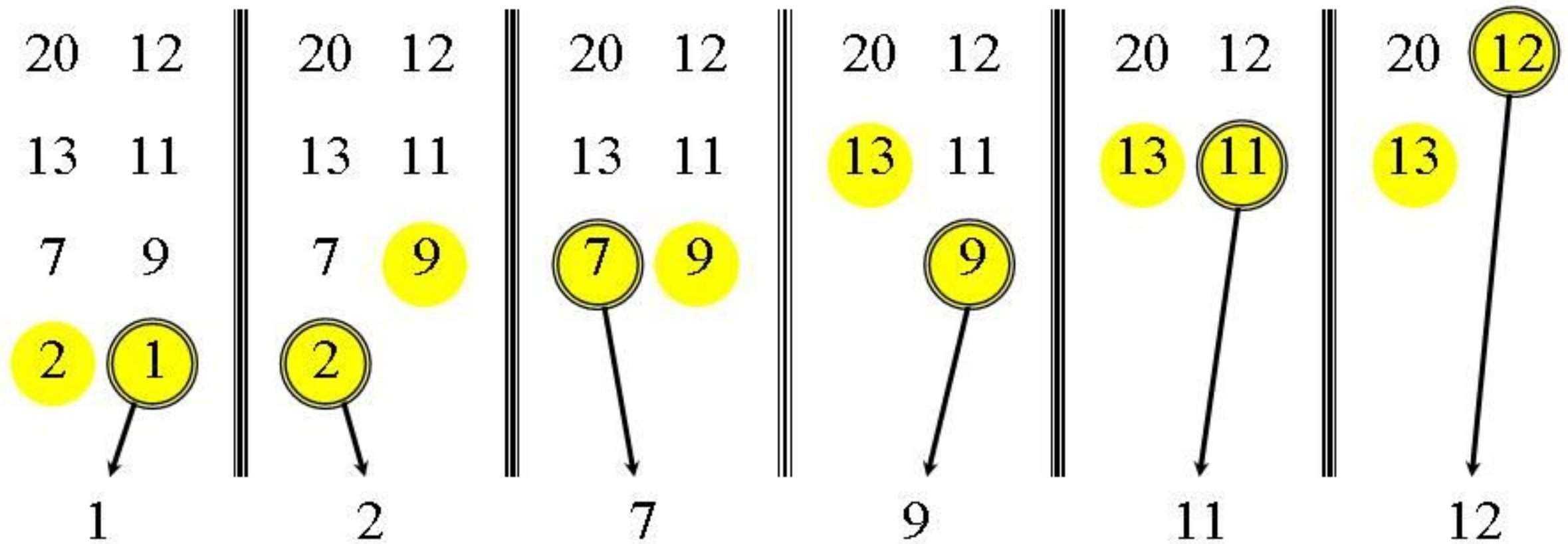
# Merging two sorted arrays



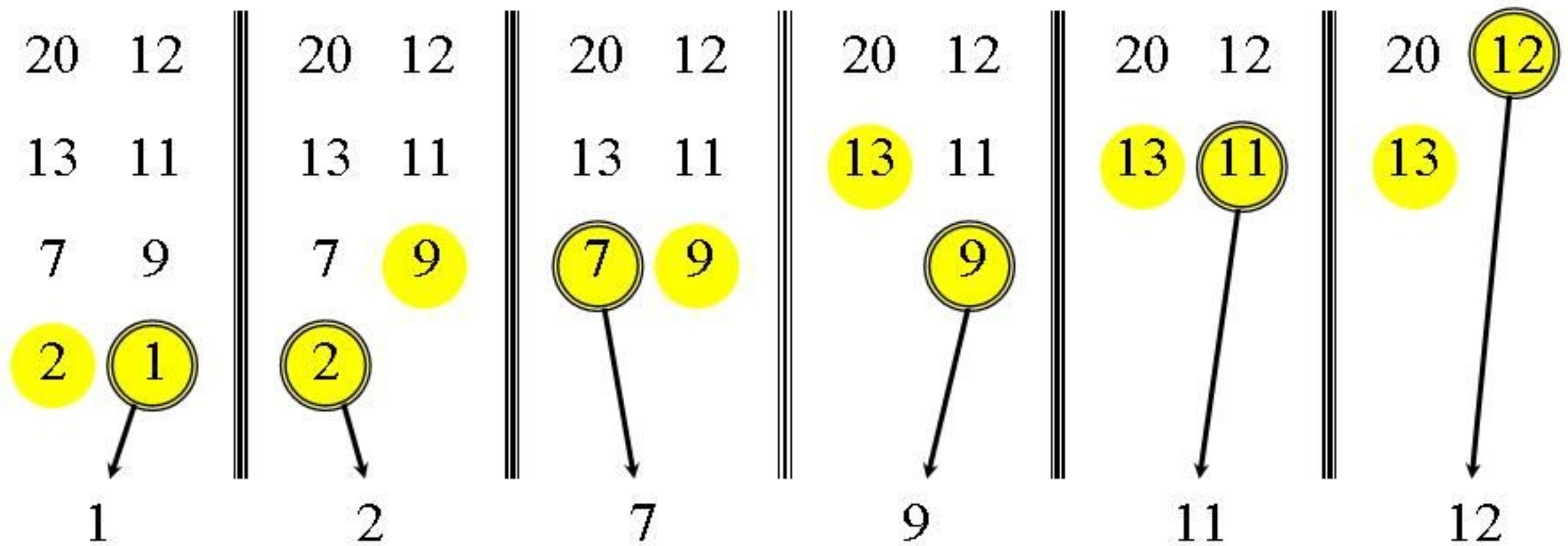
# Merging two sorted arrays



# Merging two sorted arrays



# Merging two sorted arrays



Time =  $\Theta(n)$  to merge a total of  $n$  elements (linear time).



# Analyzing merge sort

**MERGE-SORT**  $A[1 \dots n]$

- |   |             |
|---|-------------|
| 1. If $n = 1$ , done.   | $T(n)$      |
| 2. Recursively sort $A[1 \dots \lfloor n/2 \rfloor]$ and $A[\lfloor n/2 \rfloor + 1 \dots n]$ . | $\Theta(1)$ |
| 3. “Merge” the two sorted lists   | $2T(n/2)$   |
|   | $\Theta(n)$ |

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1; \\ 2T(n/2) + \Theta(n) & \text{if } n > 1. \end{cases}$$

# Recurrence solving

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.

# Recursion tree

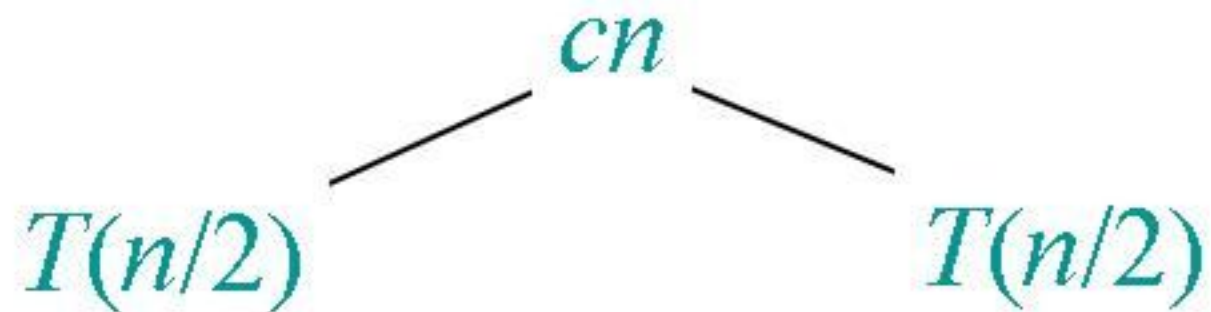
Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.

$$T(n)$$



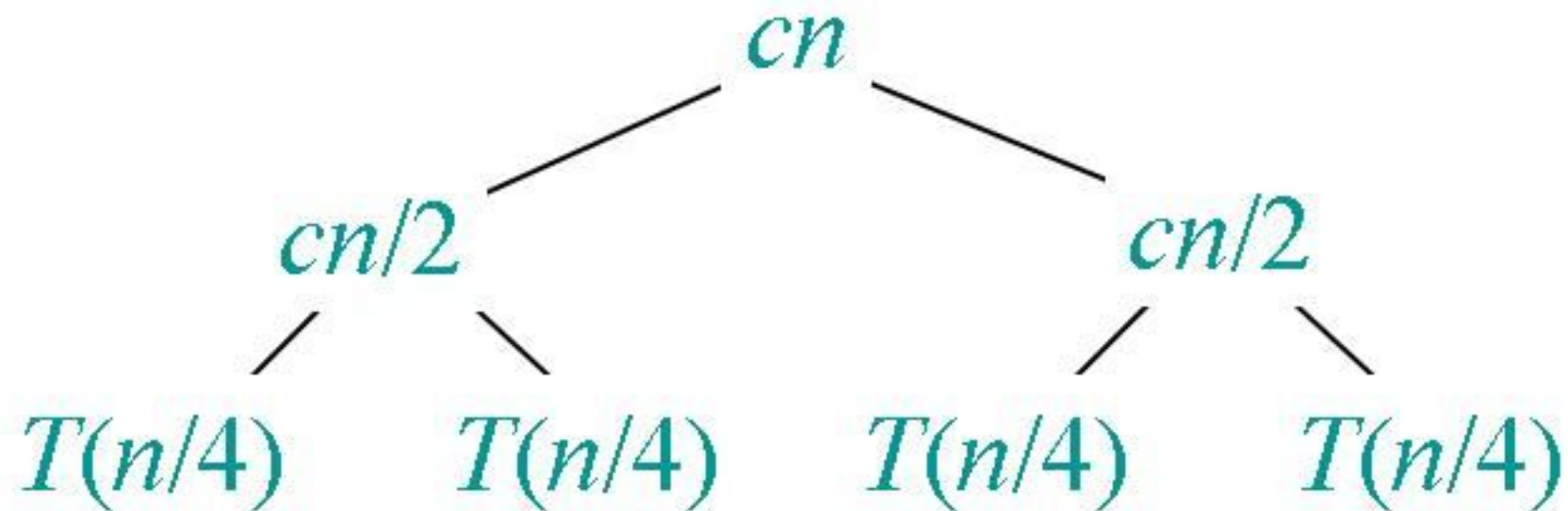
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



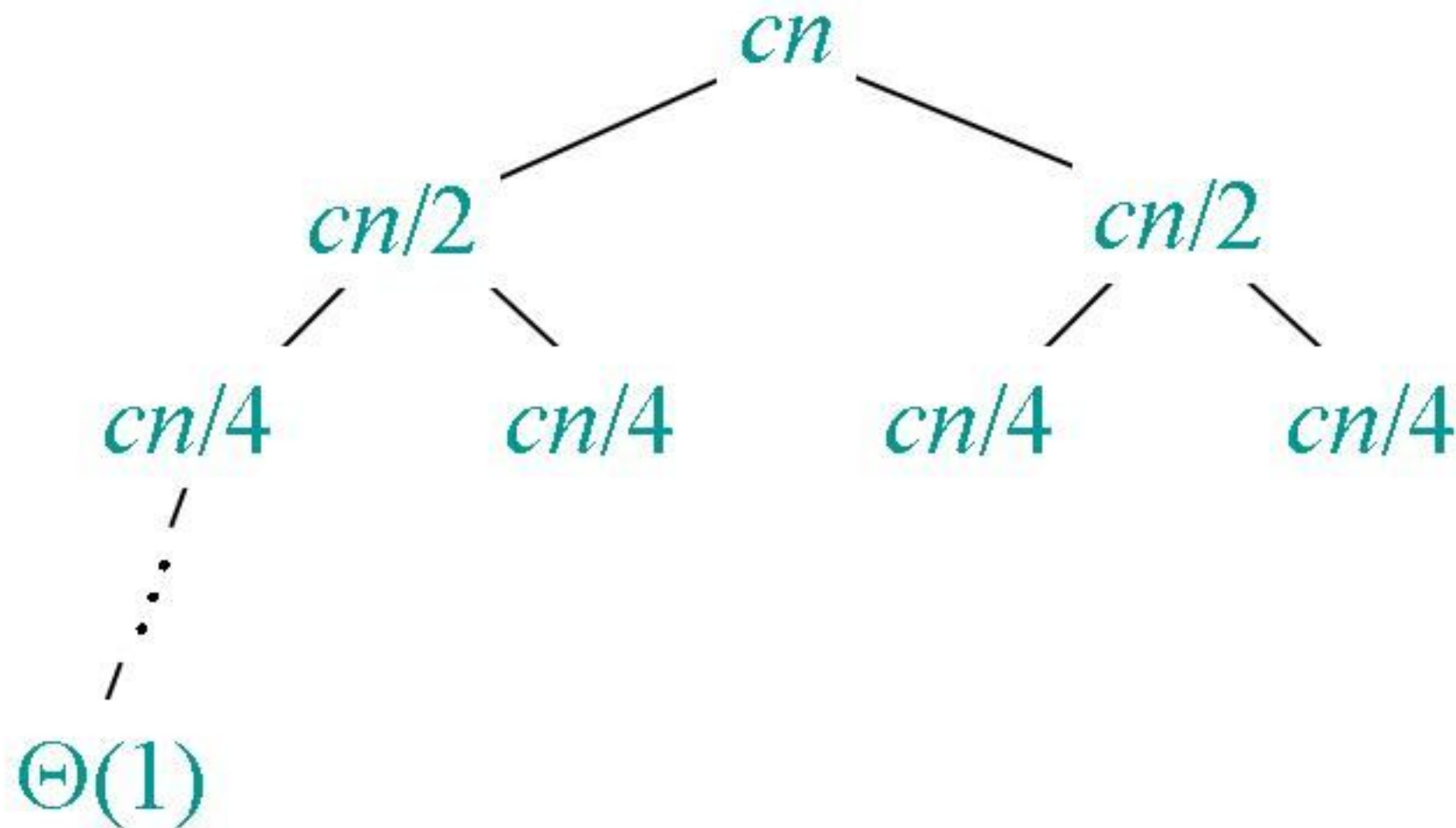
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



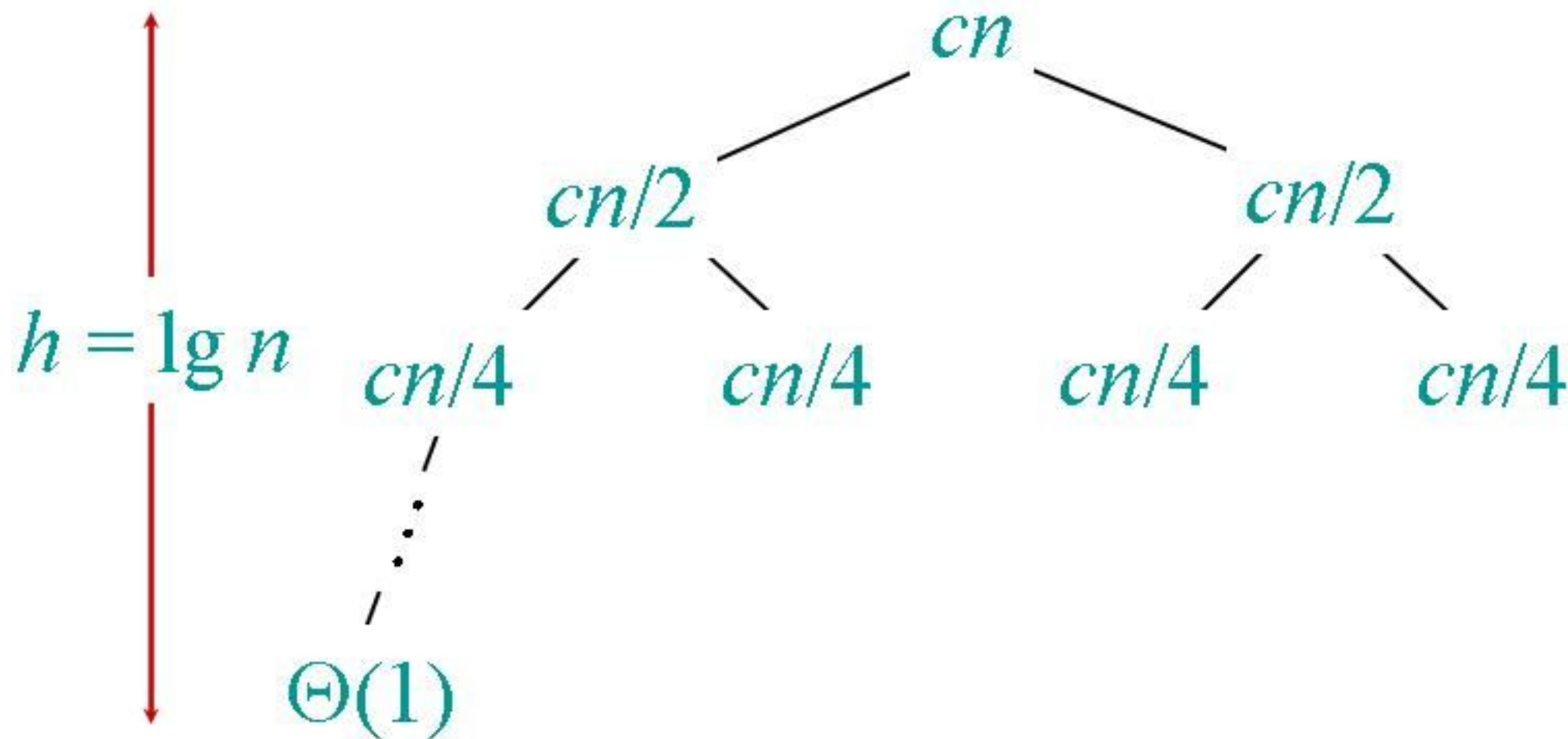
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



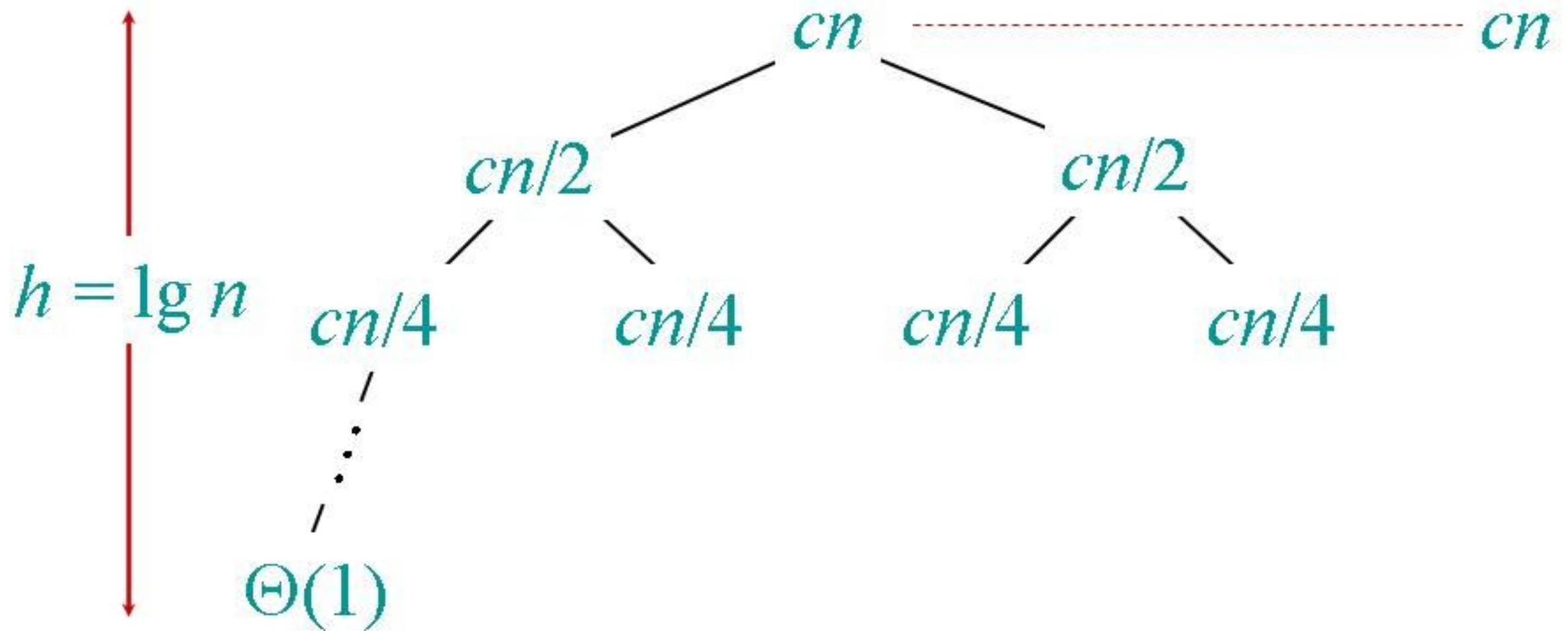
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



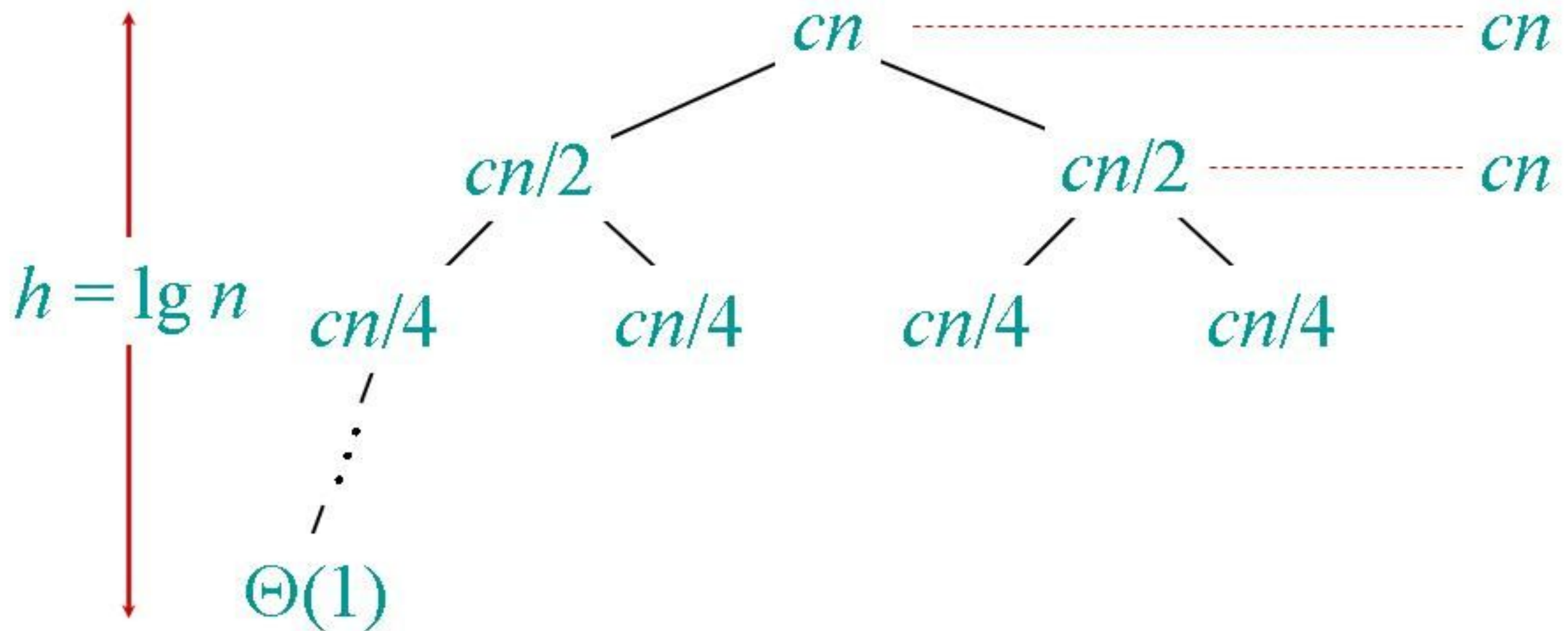
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



# Recursion tree

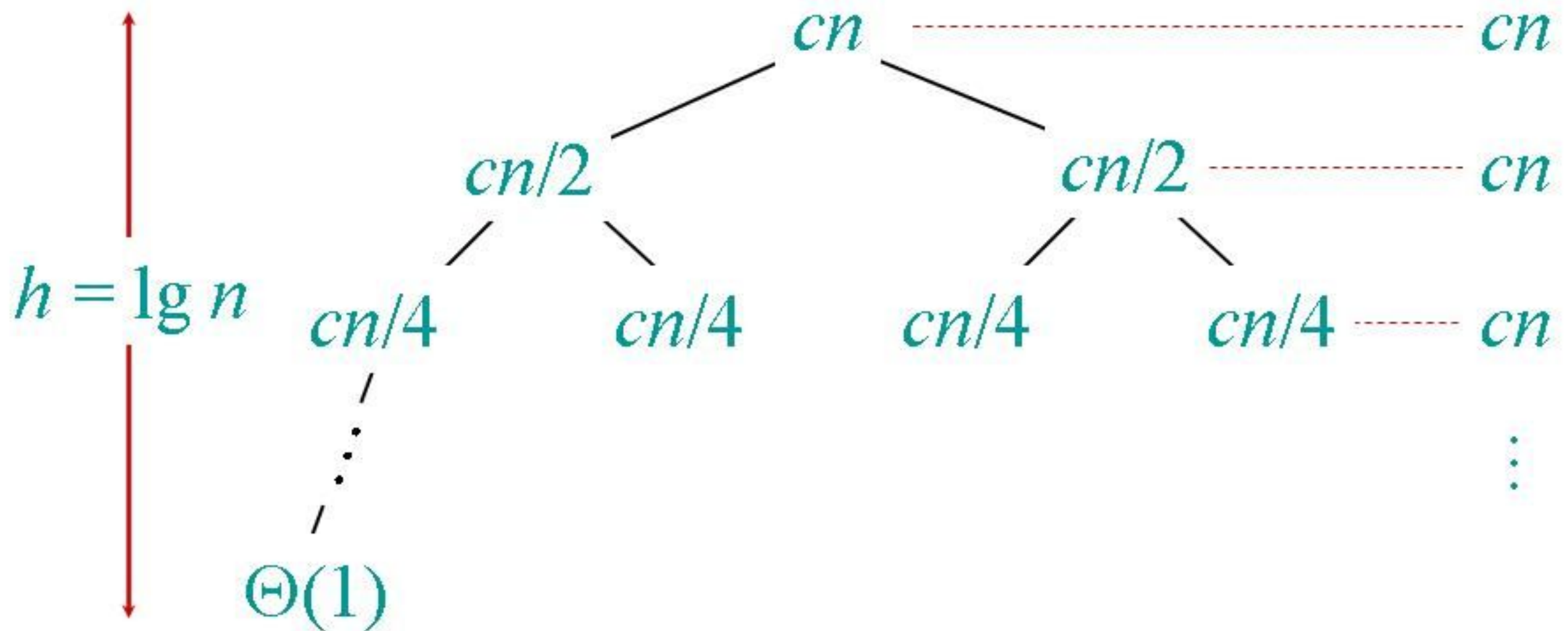
Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.





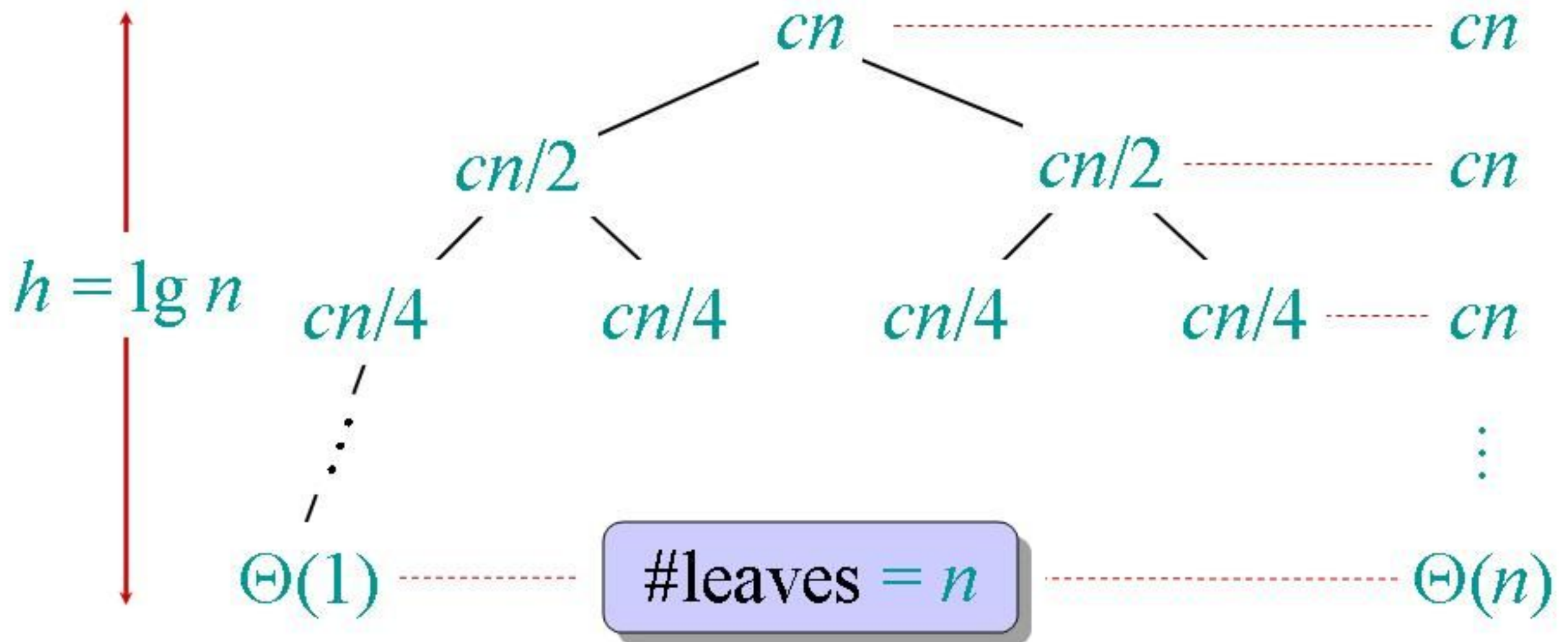
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



# Recursion tree

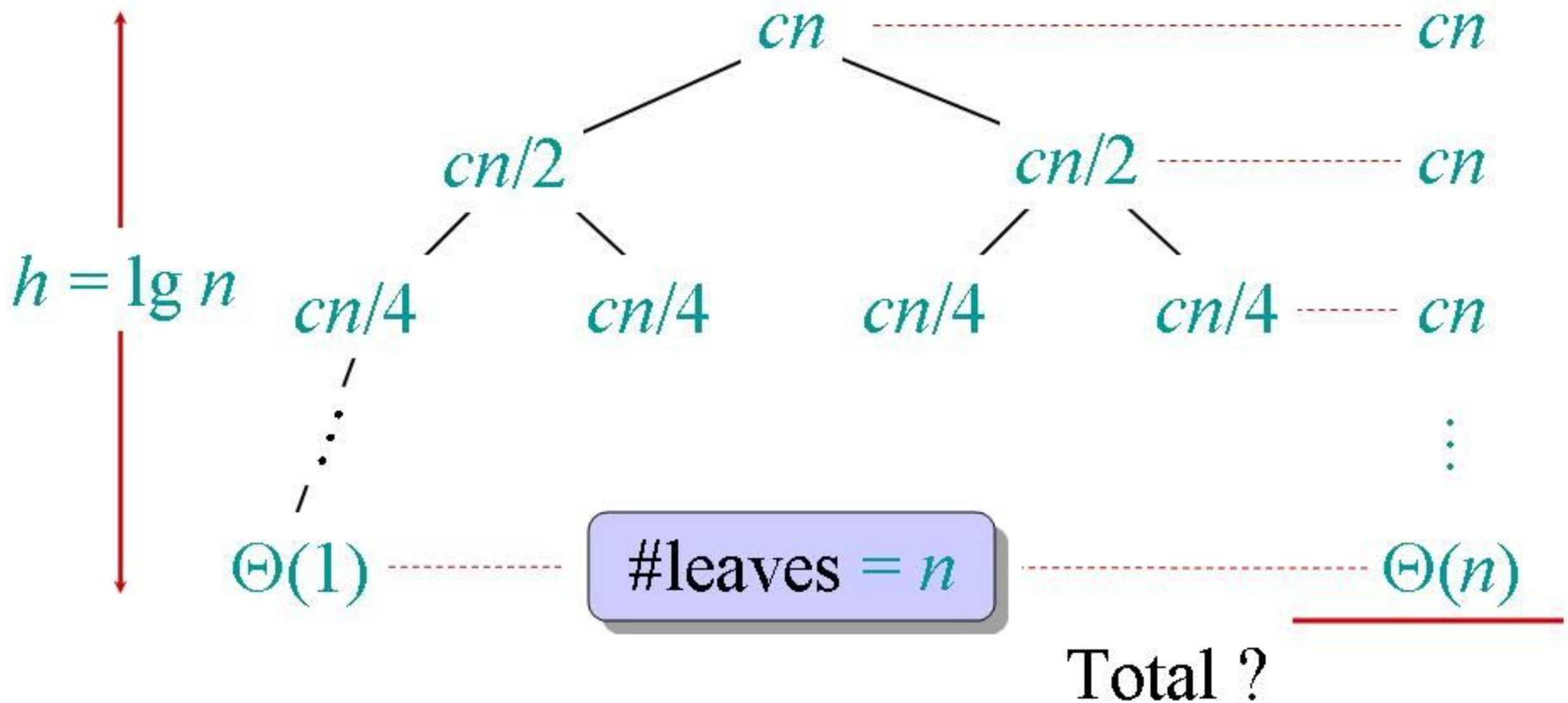
Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.





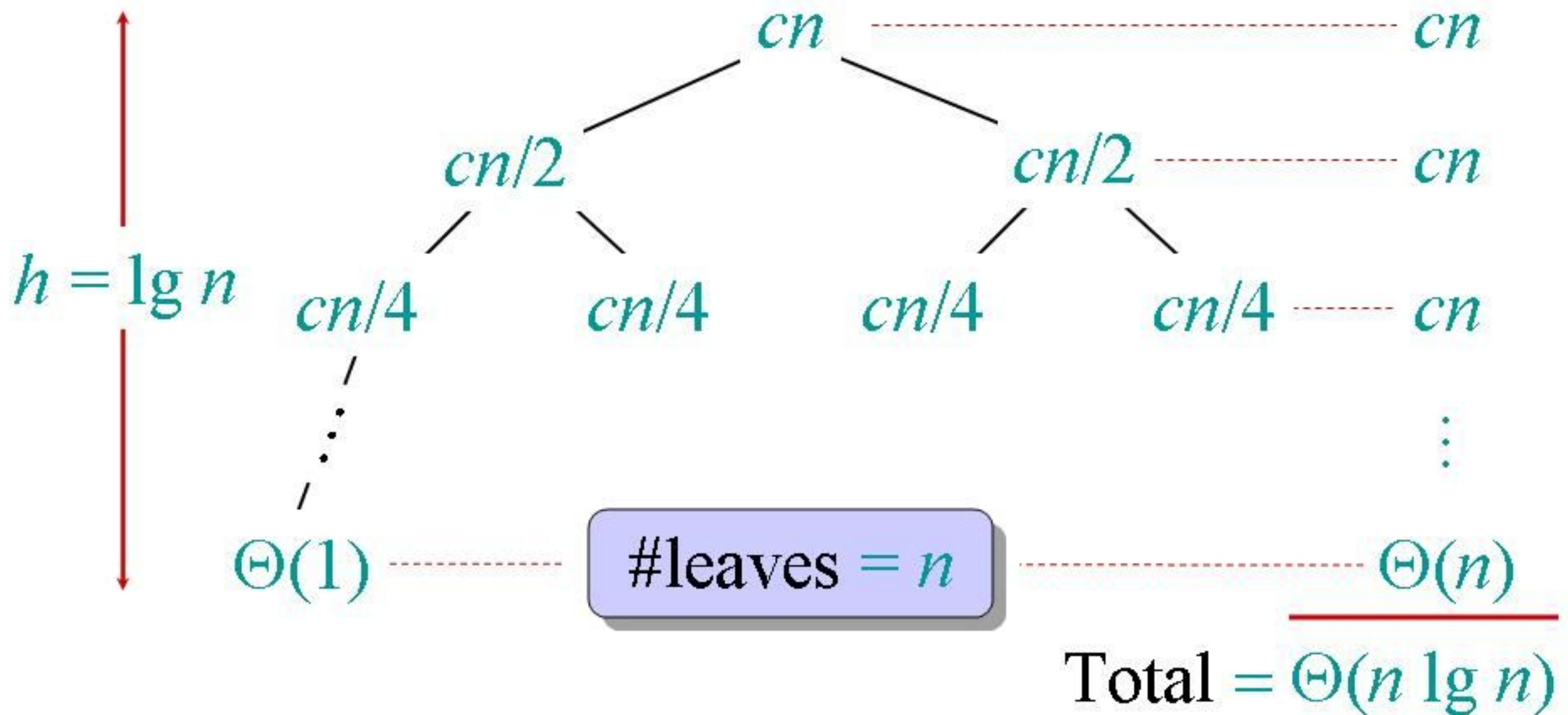
# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



# Recursion tree

Solve  $T(n) = 2T(n/2) + cn$ , where  $c > 0$  is constant.



# The master method

“One theorem to rule them all” (sort of)

The master method applies to recurrences of the form

$$T(n) = \overset{\substack{\text{\#subproblems} \\ \swarrow}}{a} \overset{\substack{\text{size of each} \\ \text{subproblem}}}{T(n/b)} + \overset{\substack{\text{time to split into} \\ \text{subproblems and} \\ \text{combine results}}}{f(n)},$$

where  $a \geq 1$ ,  $b > 1$ , and  $f$  is positive.

e.g. Mergesort:  $a=2$ ,  $b=2$ ,  $f(n)=O(n)$

e.g.2 Binary Search:  $a=1$ ,  $b=2$ ,  $f(n)=O(1)$

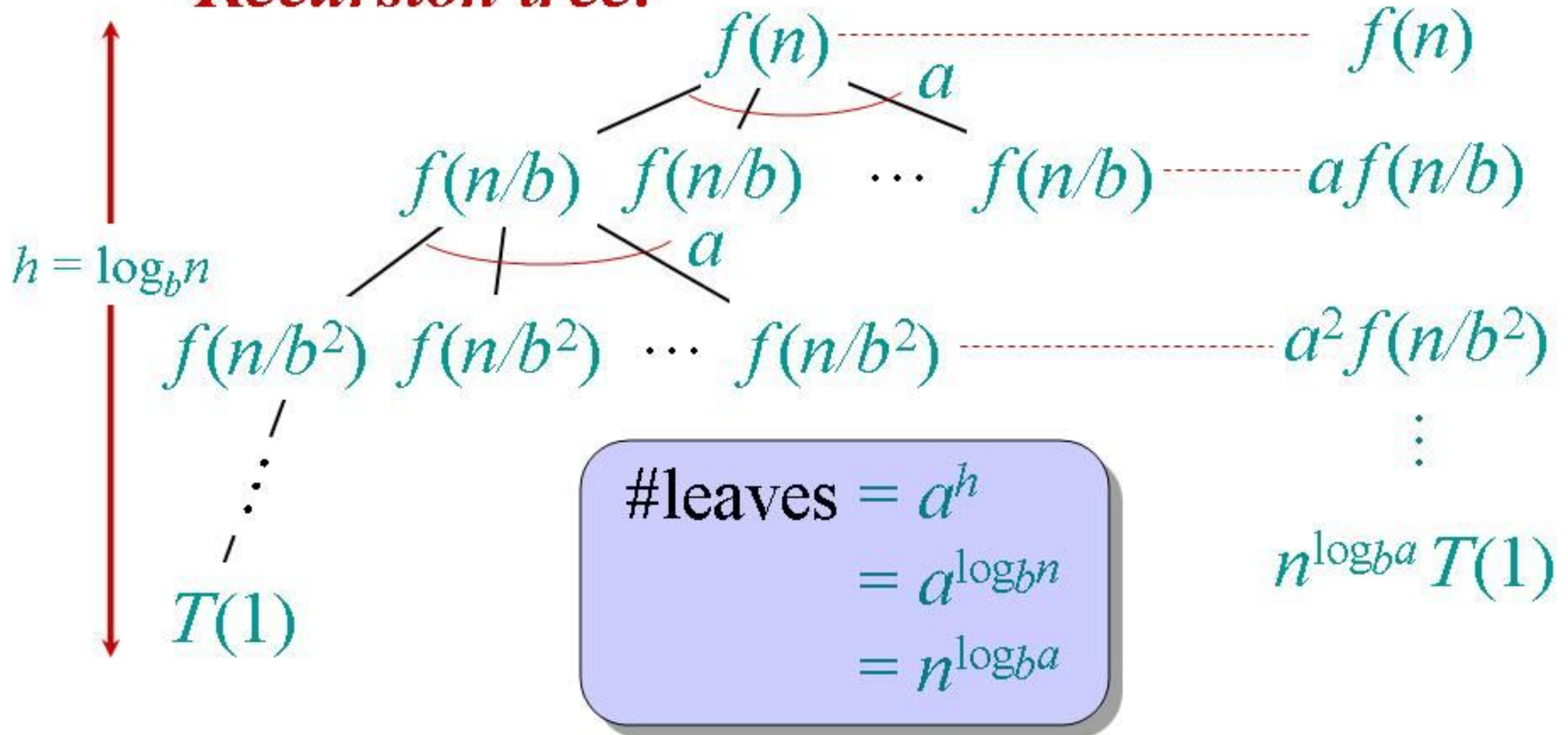
**Basic Idea:** Compare  $f(n)$  with  $n^{\log_b a}$ .



# Idea of master theorem

$$T(n) = aT(n/b) + f(n)$$

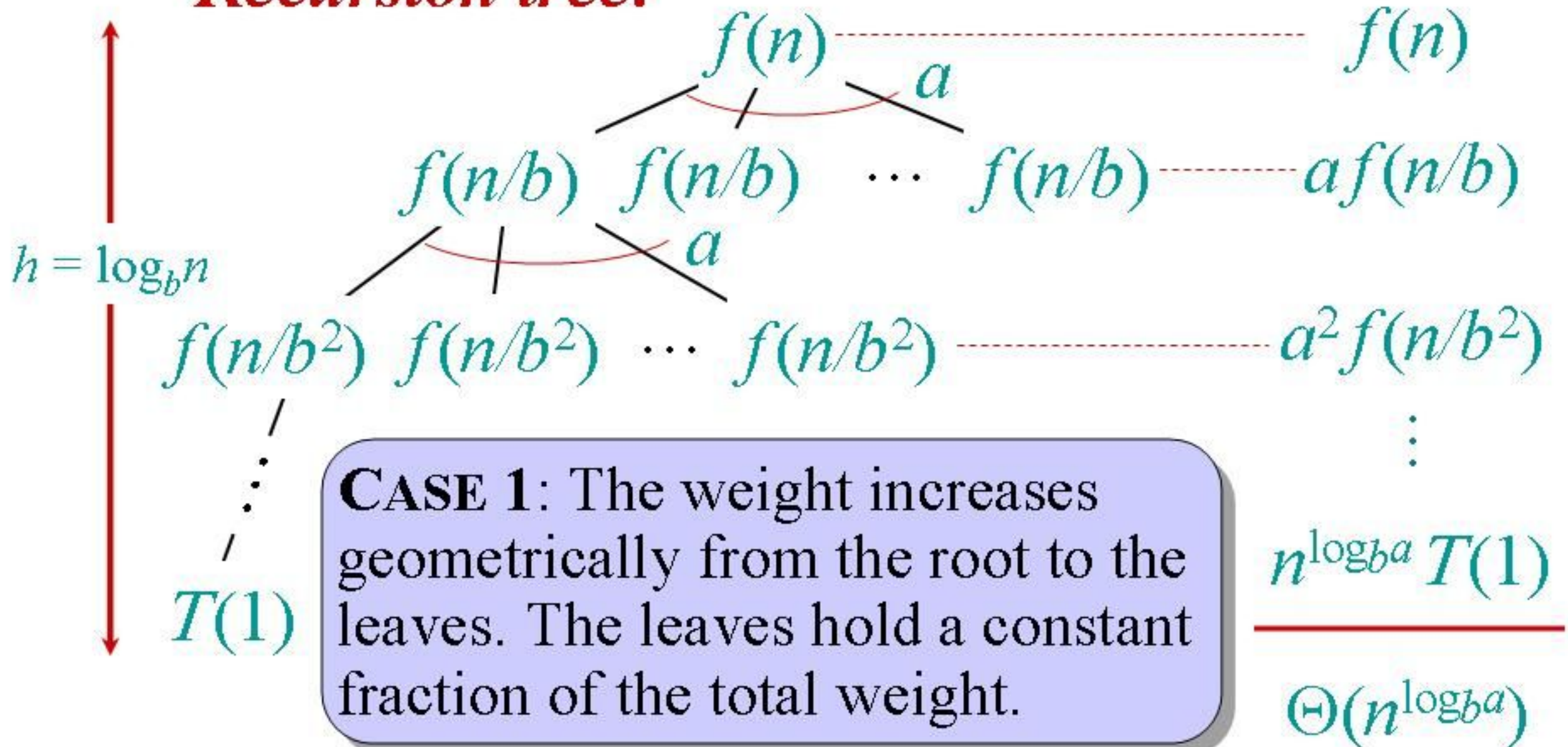
**Recursion tree:**



# Idea of master theorem

$$T(n) = aT(n/b) + f(n)$$

**Recursion tree:**

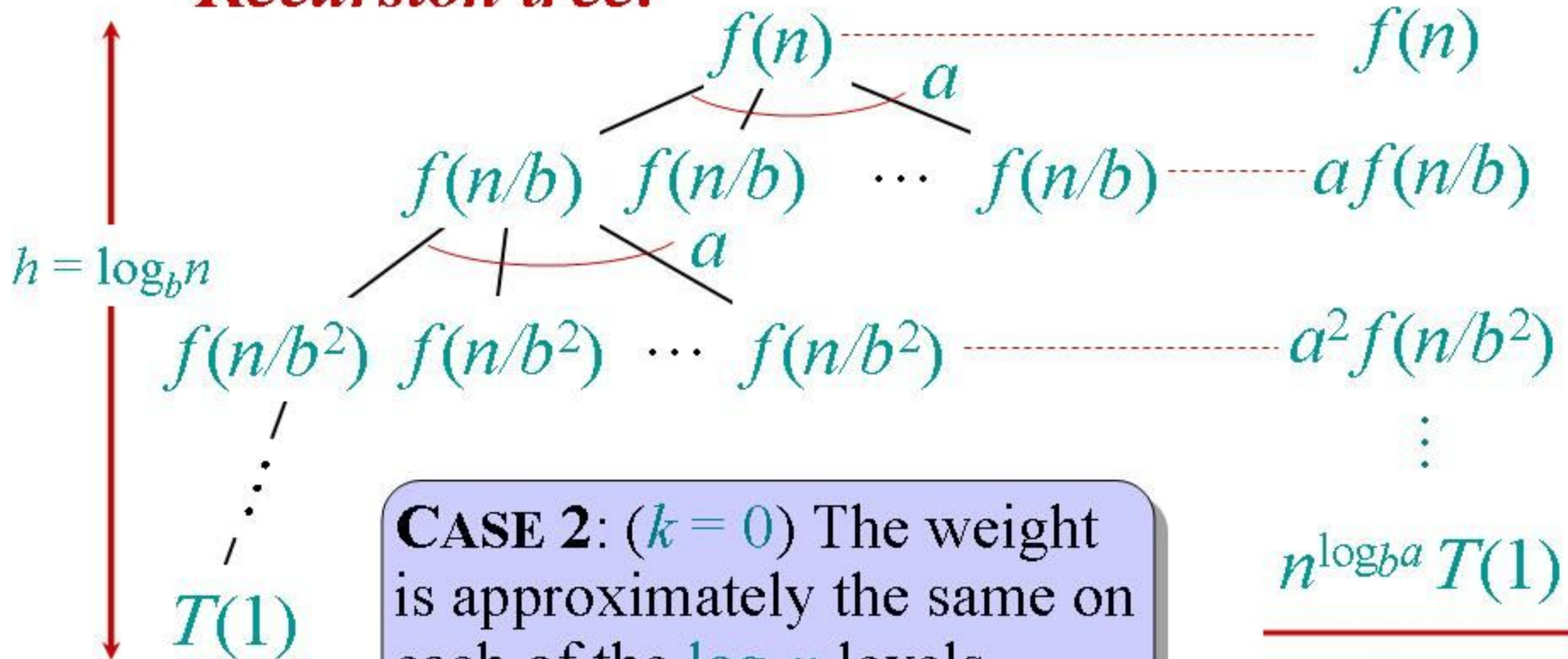




# Idea of master theorem

$$T(n) = aT(n/b) + f(n)$$

**Recursion tree:**



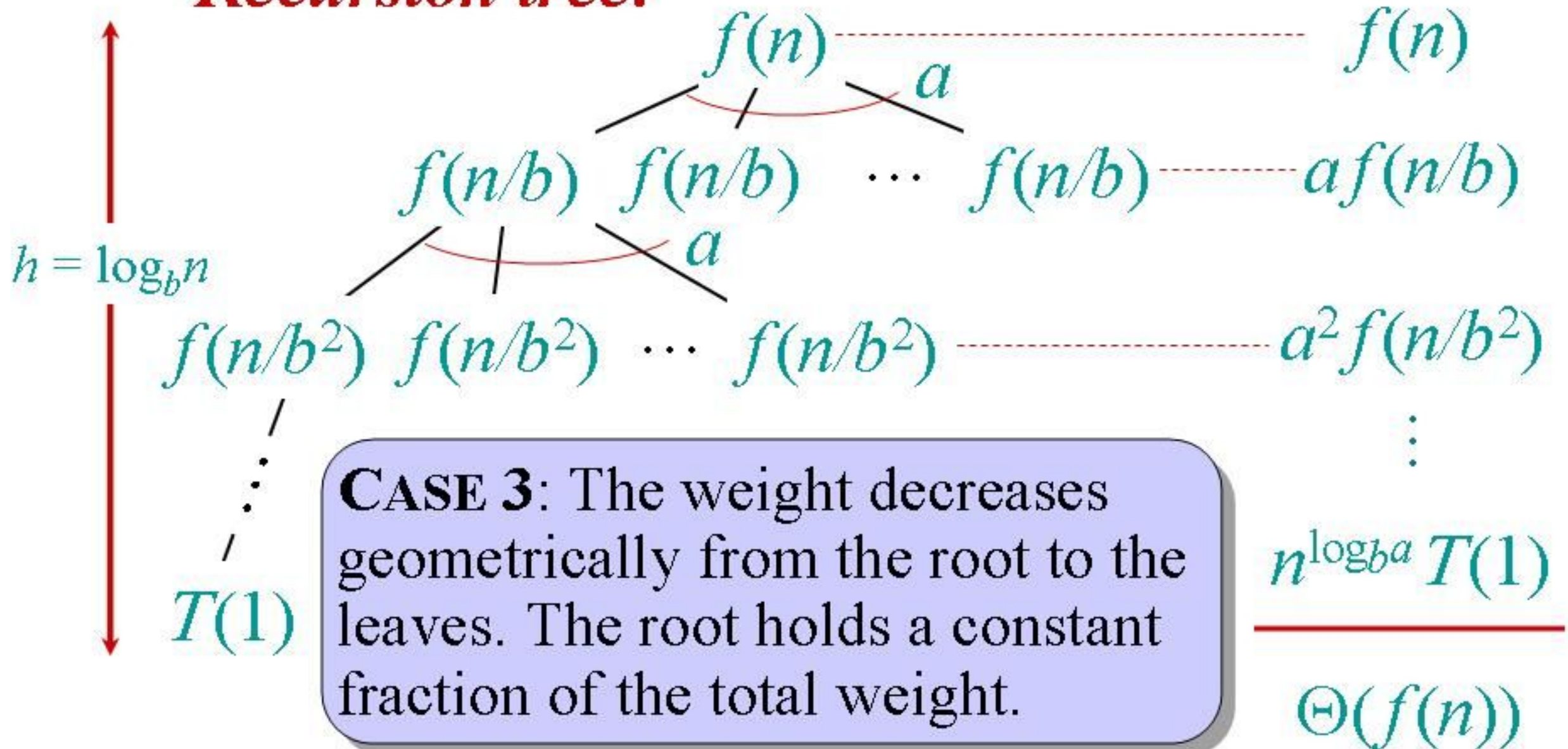
**CASE 2:** ( $k = 0$ ) The weight is approximately the same on each of the  $\log_b n$  levels.

$$\frac{n^{\log_b a} T(1)}{\Theta(n^{\log_b a} \lg n)}$$

# Idea of master theorem

$$T(n) = aT(n/b) + f(n)$$

**Recursion tree:**





# Three common cases

Compare  $f(n)$  with  $n^{\log_b a}$ :

1.  $f(n) = \Theta(n^{\log_b a - \varepsilon})$  for some constant  $\varepsilon > 0$ .

- $f(n)$  grows polynomially slower than  $n^{\log_b a}$  (by an  $n^\varepsilon$  factor).

cost of level  $i = a^i f(n/b^i) = \Theta(n^{\log_b a - \varepsilon} \cdot b^{i \varepsilon})$

so geometric increase of cost as we go deeper in the tree

hence, leaf level cost dominates!

**Solution:**  $T(n) = \Theta(n^{\log_b a})$ .

## Three common cases (cont.)

Compare  $f(n)$  with  $n^{\log_b a}$ :

2.  $f(n) = \Theta(n^{\log_b a} \log^k n)$  for some constant  $k \geq 0$ .

- $f(n)$  and  $n^{\log_b a}$  grow at similar rates.

$$(\text{cost of level } i) = a^i f(n/b^i) = \Theta(n^{\log_b a} \cdot \log^k(n/b^i))$$

so all levels have about the same cost

**Solution:**  $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$ .

# Three common cases (cont.)

Compare  $f(n)$  with  $n^{\log_b a}$ :

3.  $f(n) = \Theta(n^{\log_b a + \varepsilon})$  for some constant  $\varepsilon > 0$ .

- $f(n)$  grows polynomially faster than  $n^{\log_b a}$  (by an  $n^\varepsilon$  factor).

$$(\text{cost of level } i) = a^i f(n/b^i) = \Theta(n^{\log_b a + \varepsilon} \cdot b^{-i \varepsilon})$$

so geometric decrease of cost as we go deeper in the tree  
hence, root cost dominates!

**Solution:**  $T(n) = \Theta(f(n))$ .



# Examples

**Ex.**  $T(n) = 2T(n/2) + 1$

$$a = 2, b = 2 \Rightarrow n^{\log_b a} = n; f(n) = 1.$$

**CASE 1:**  $f(n) = O(n^{1-\varepsilon})$  for  $\varepsilon = 1$ .

$$\therefore T(n) = \Theta(n).$$

**Ex.**  $T(n) = 2T(n/2) + n$

$$a = 2, b = 2 \Rightarrow n^{\log_b a} = n; f(n) = n.$$

**CASE 2:**  $f(n) = \Theta(n \lg^0 n)$ , that is,  $k = 0$ .

$$\therefore T(n) = \Theta(n \lg n).$$

# Examples

**Ex.**  $T(n) = 4T(n/2) + n^3$

$a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^3.$

**CASE 3:**  $f(n) = \Omega(n^{2+\varepsilon})$  for  $\varepsilon = 1$ .

$\therefore T(n) = \Theta(n^3).$