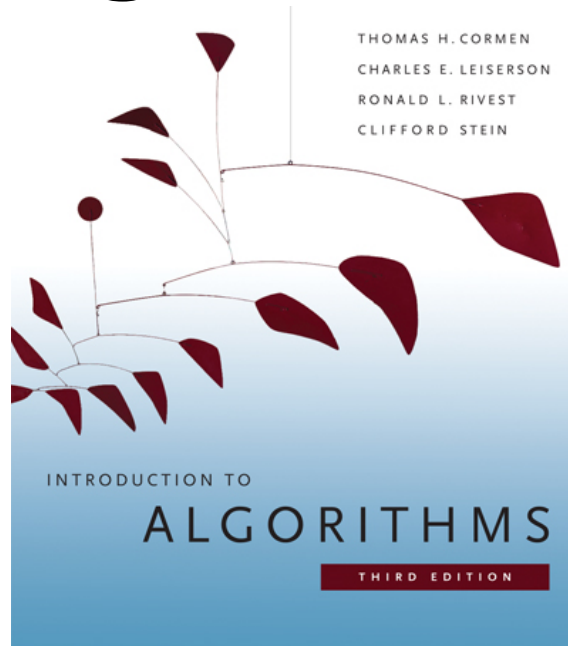


# 6.006- *Introduction to Algorithms*



## *Lecture 8*

**Prof. Silvio Micali**

**CLRS: chapter 4.**

# Menu

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

# The problem of sorting

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

***Output:*** permutation  $B[1..n]$  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 ?

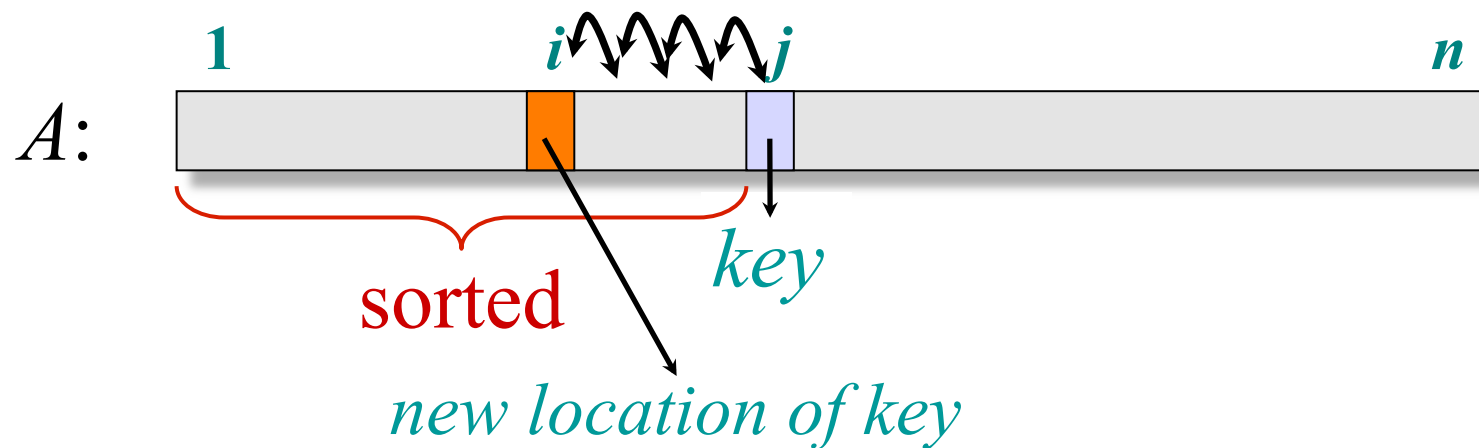
# Insertion sort

**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  $j$**



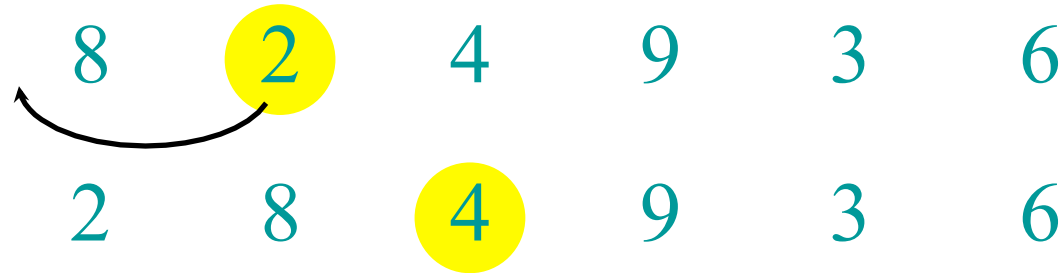
# Example of insertion sort

8   2   4   9   3   6

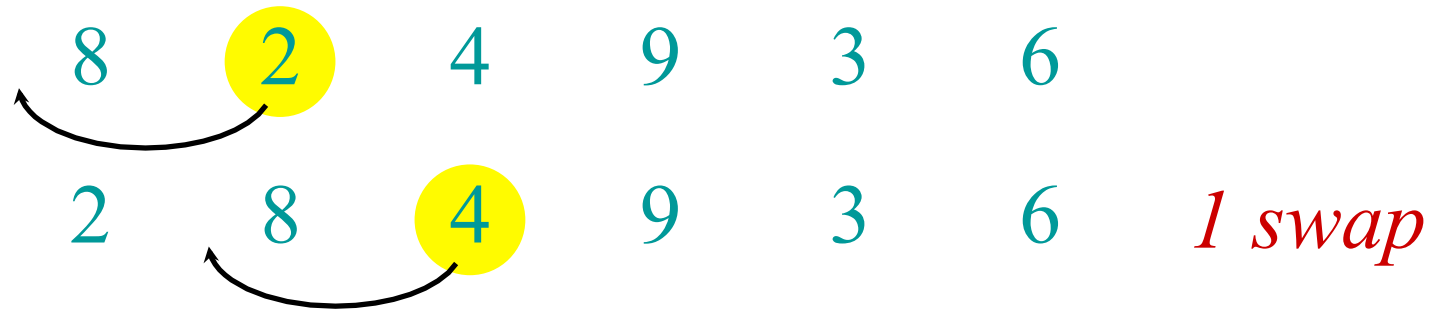
# Example of insertion sort



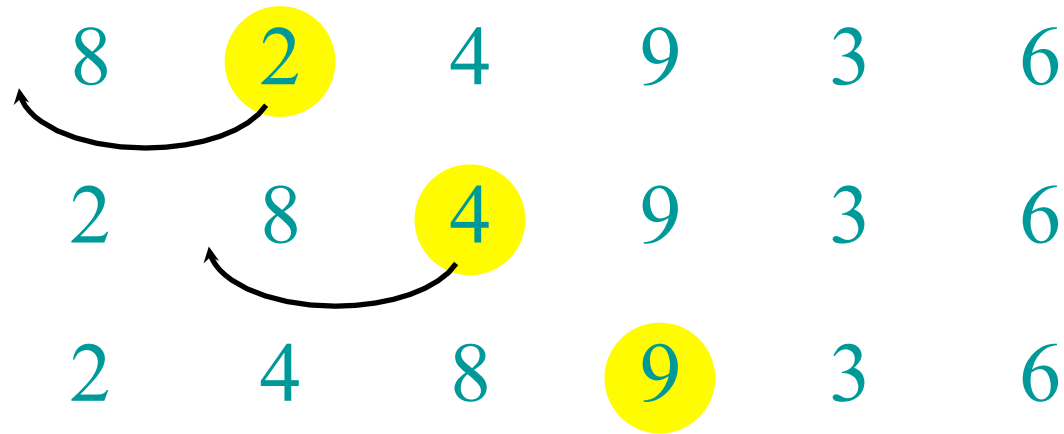
# Example of insertion sort



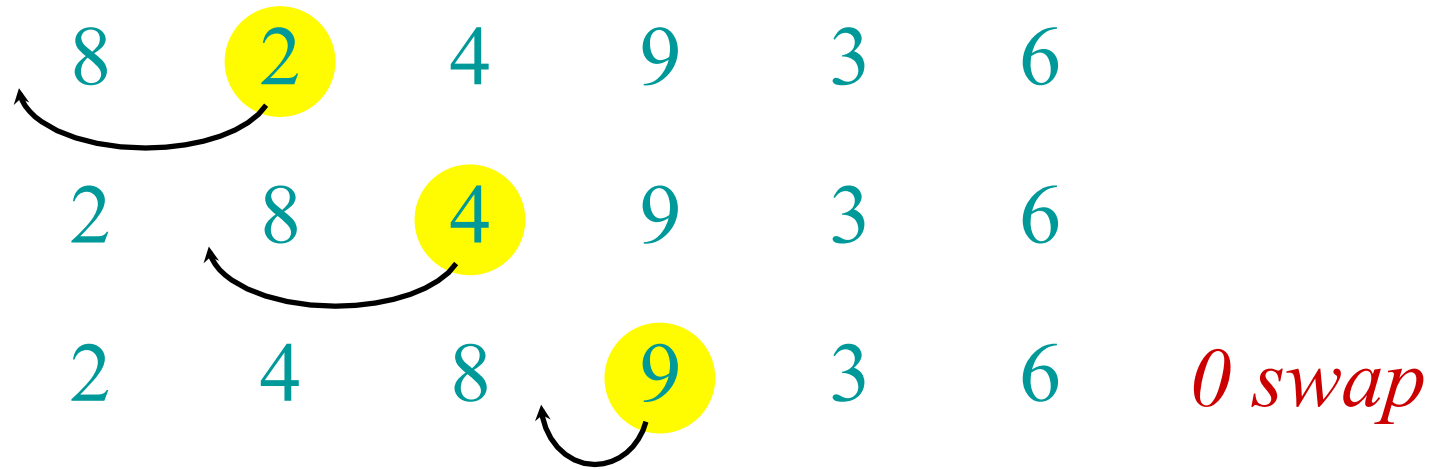
# Example of insertion sort



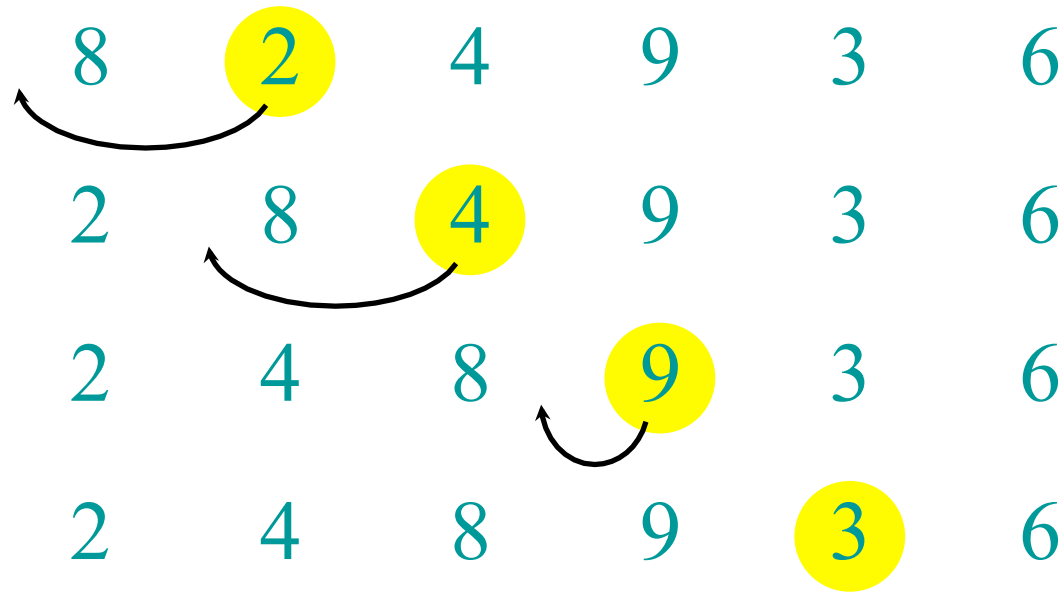
# Example of insertion sort



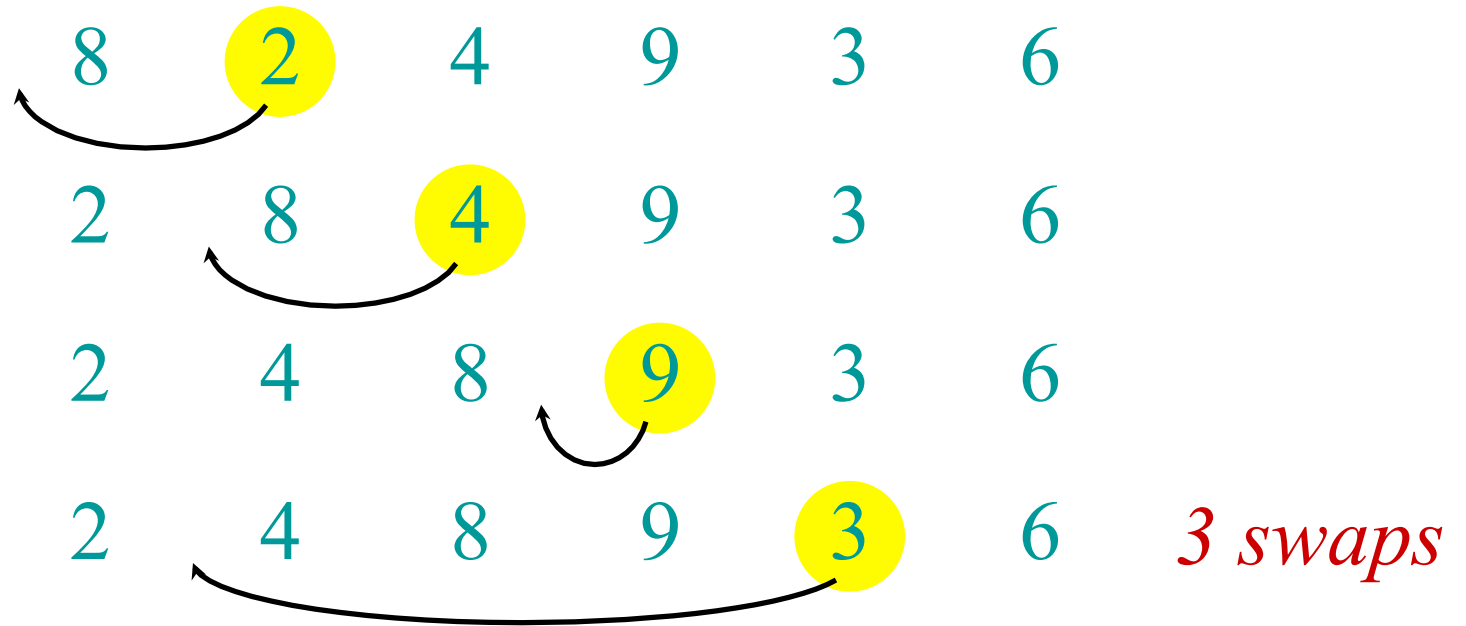
# Example of insertion sort



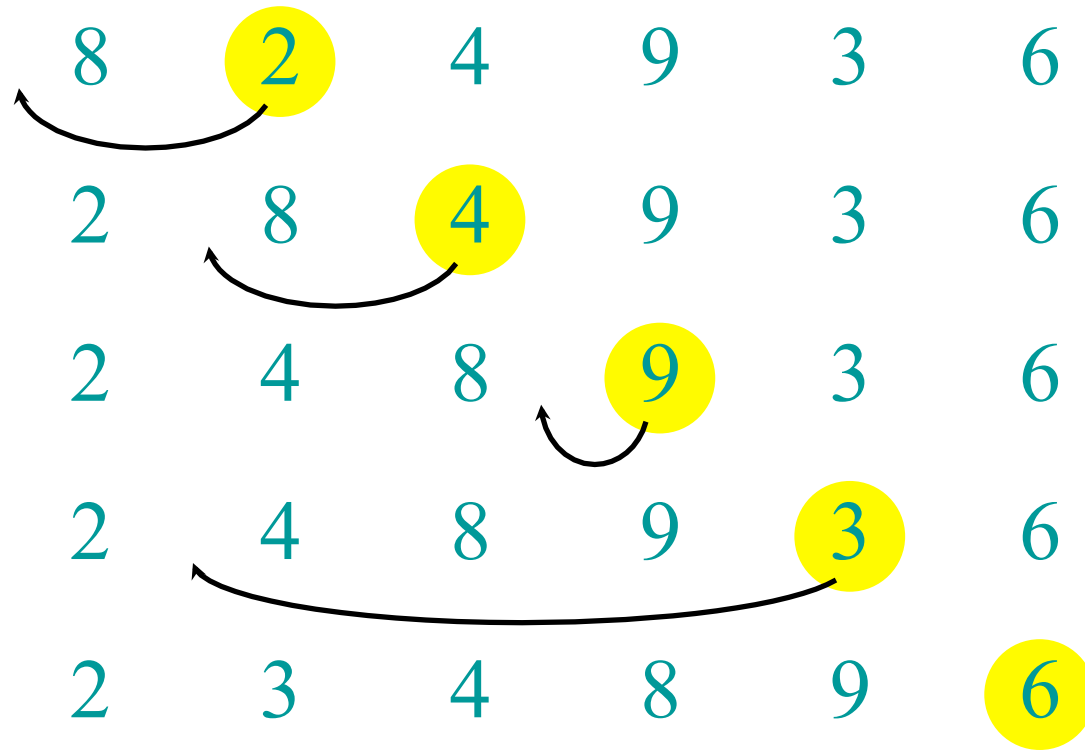
# Example of insertion sort



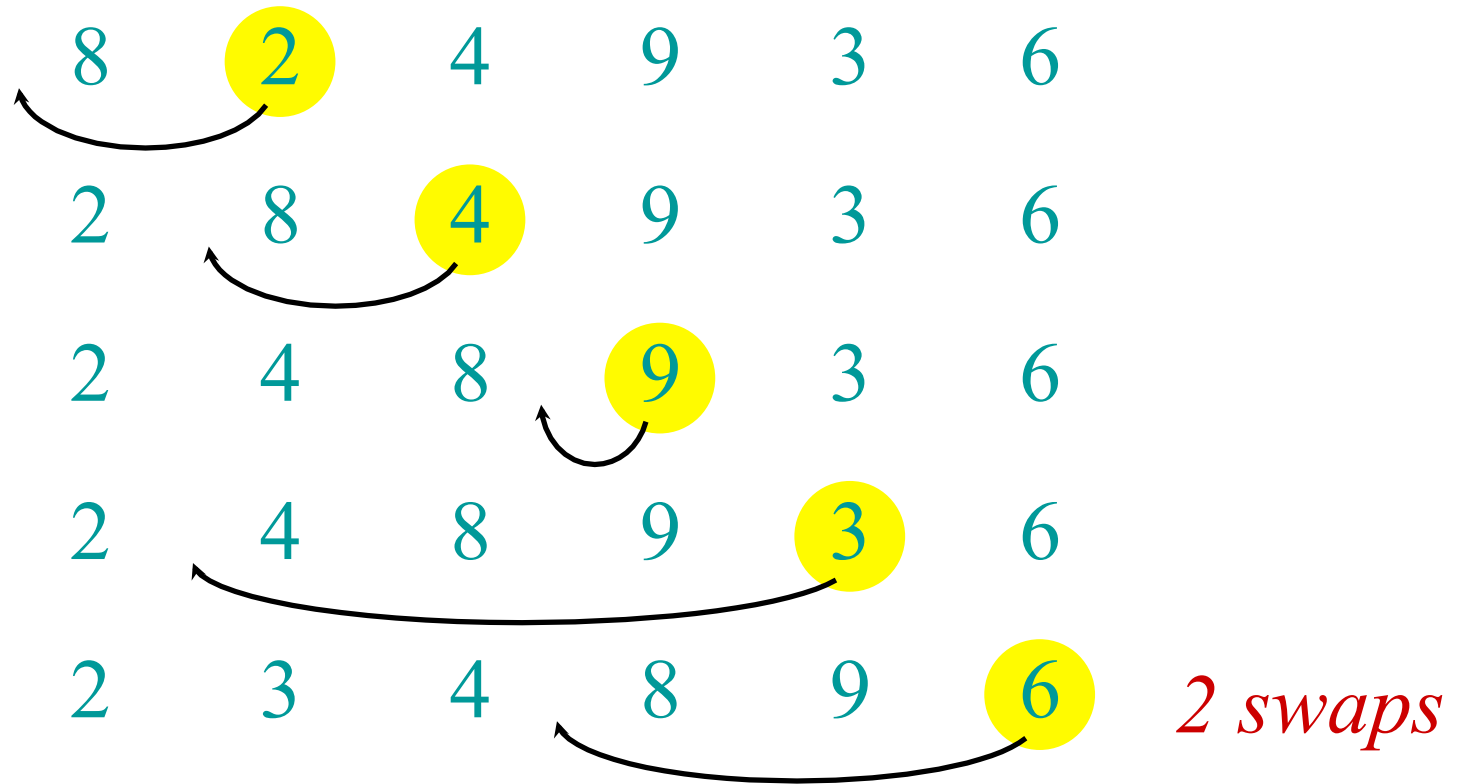
# Example of insertion sort



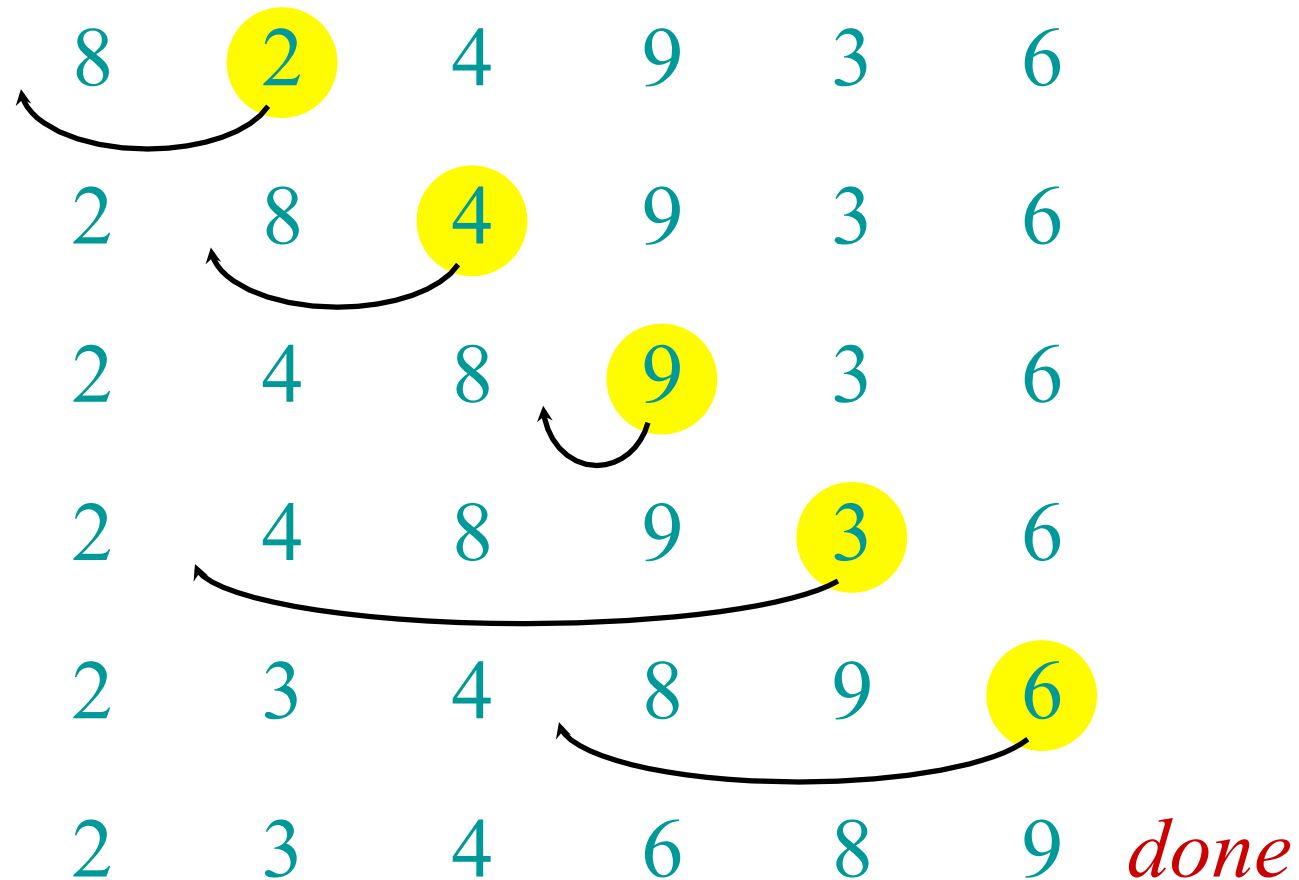
# Example of insertion sort



# 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



...

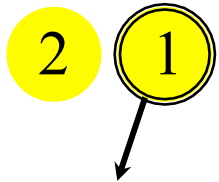
output array

# Merging two sorted arrays

20 12

13 11

7 9



1

⌋

⌋

⌋

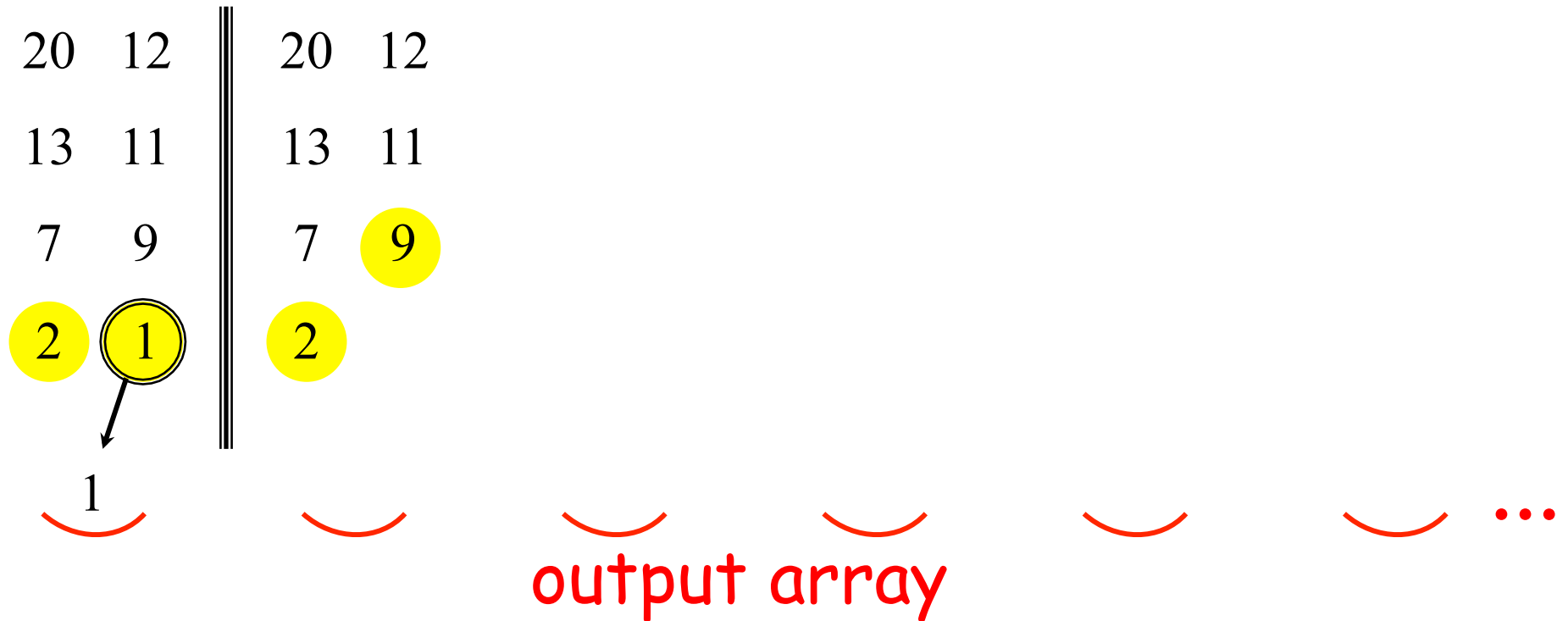
⌋

⌋

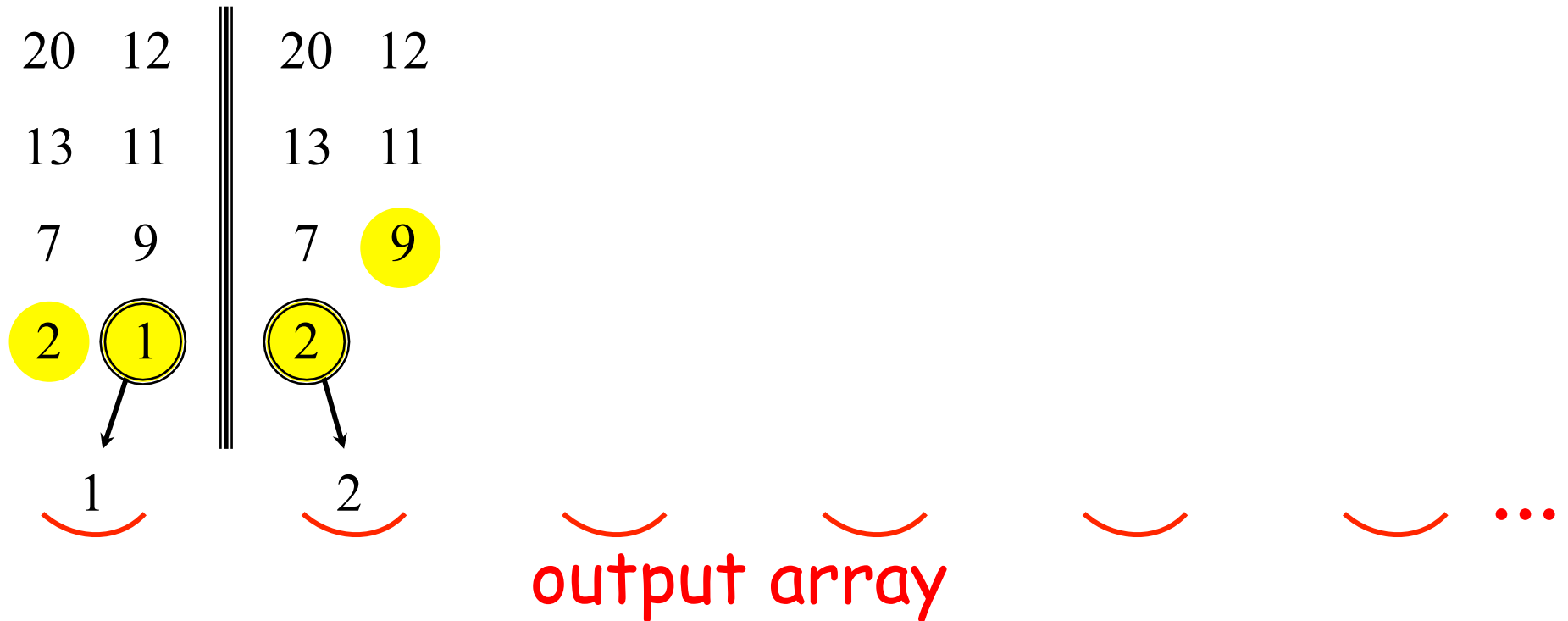
...

output array

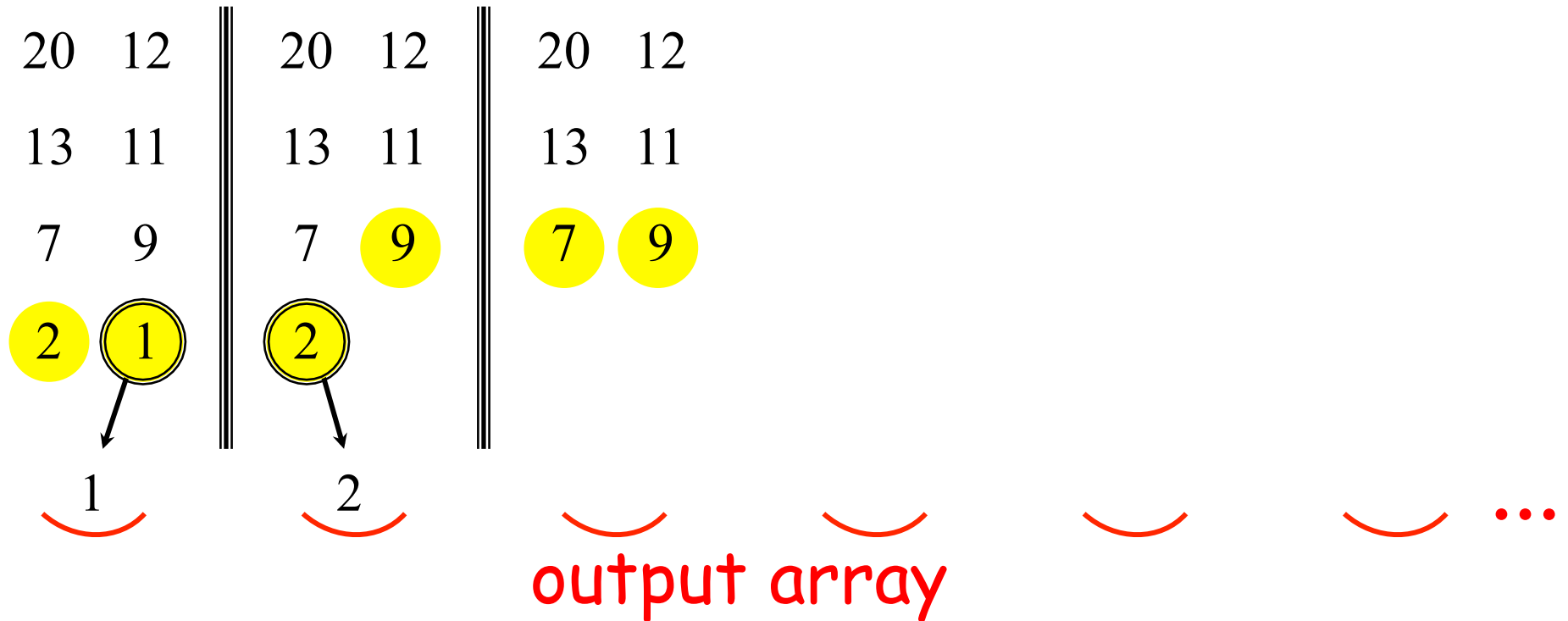
# Merging two sorted arrays



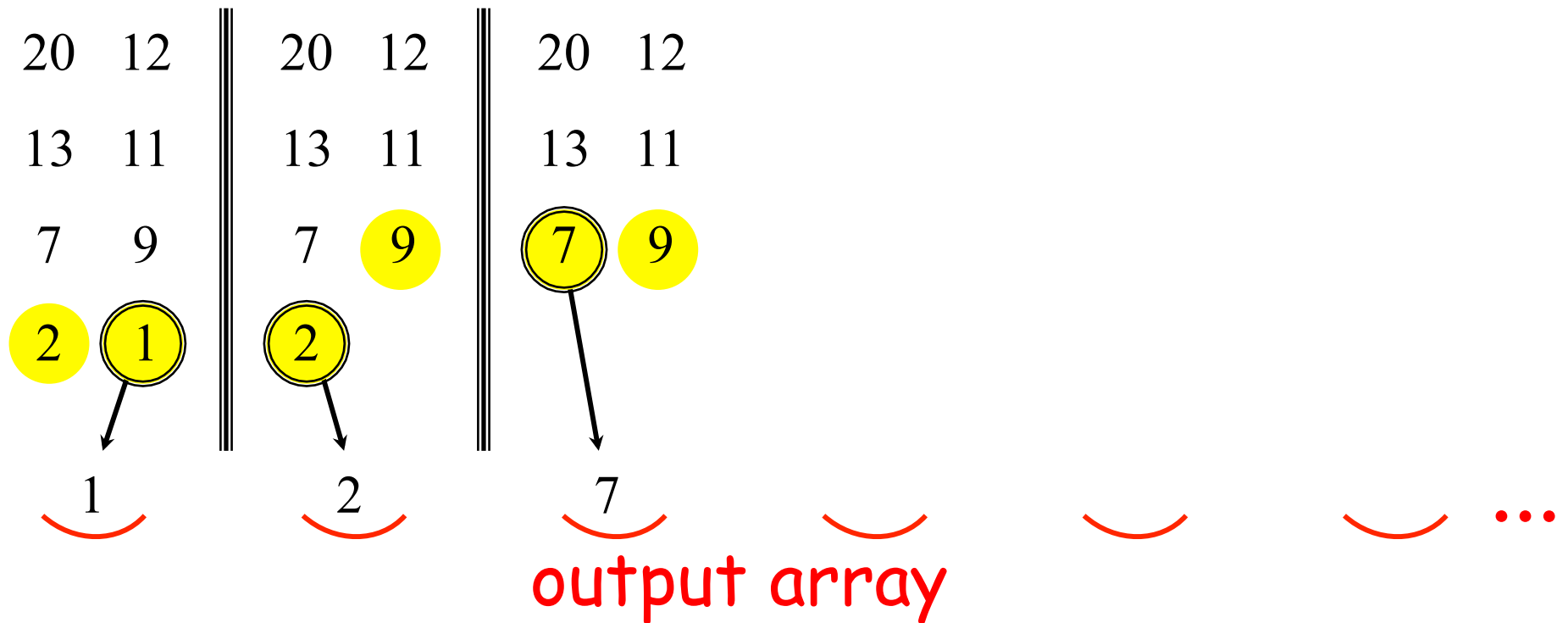
# Merging two sorted arrays



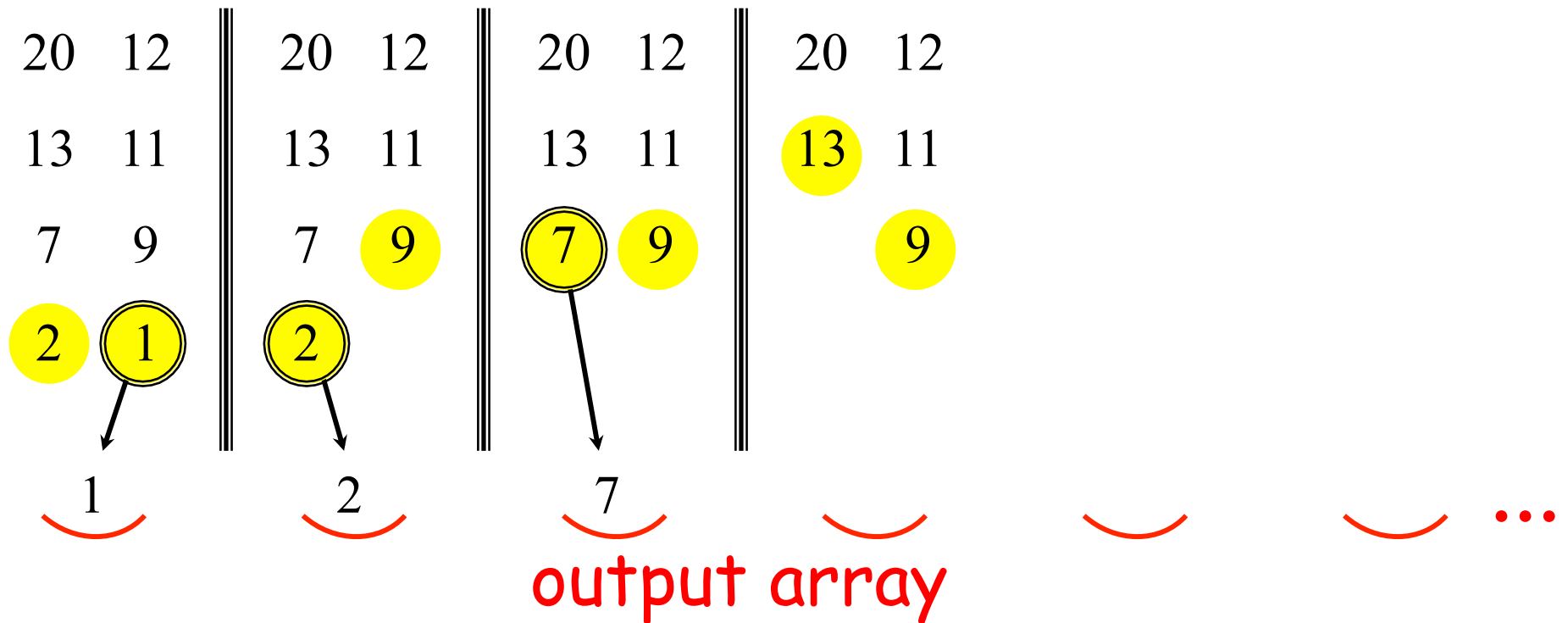
# Merging two sorted arrays



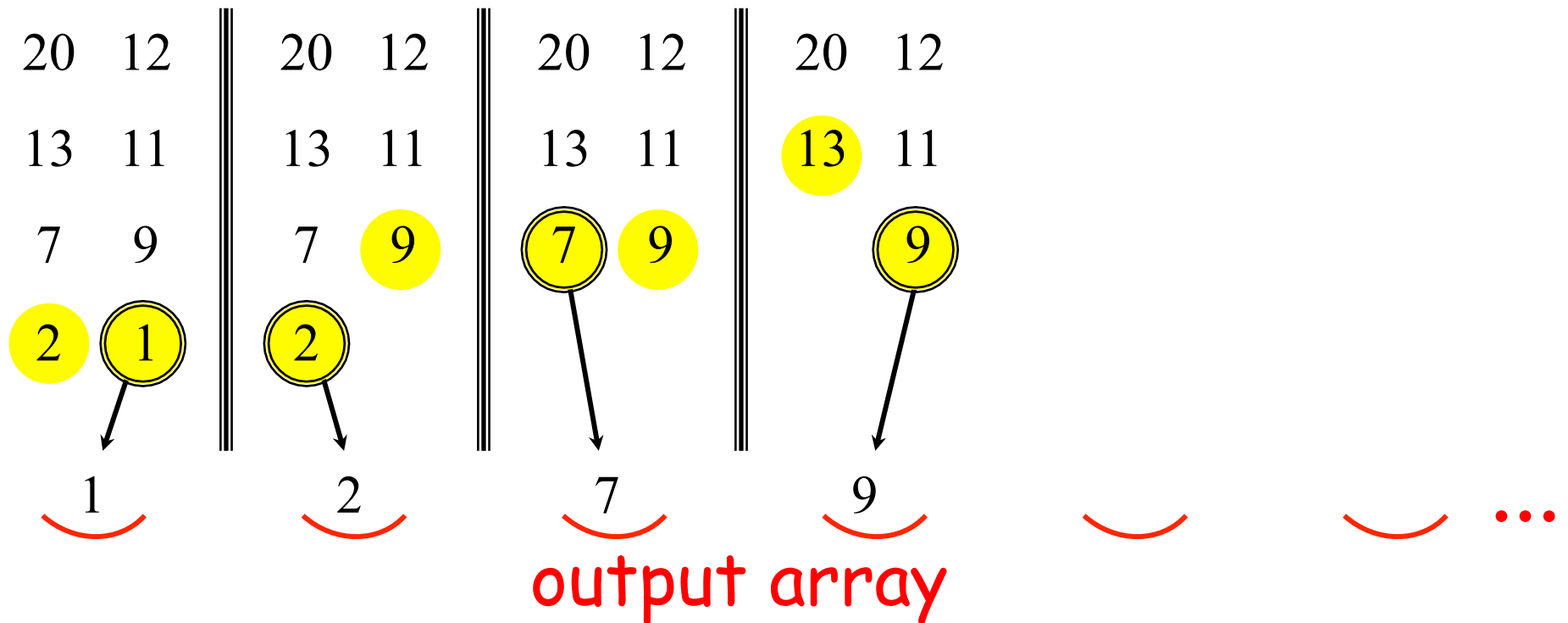
# Merging two sorted arrays



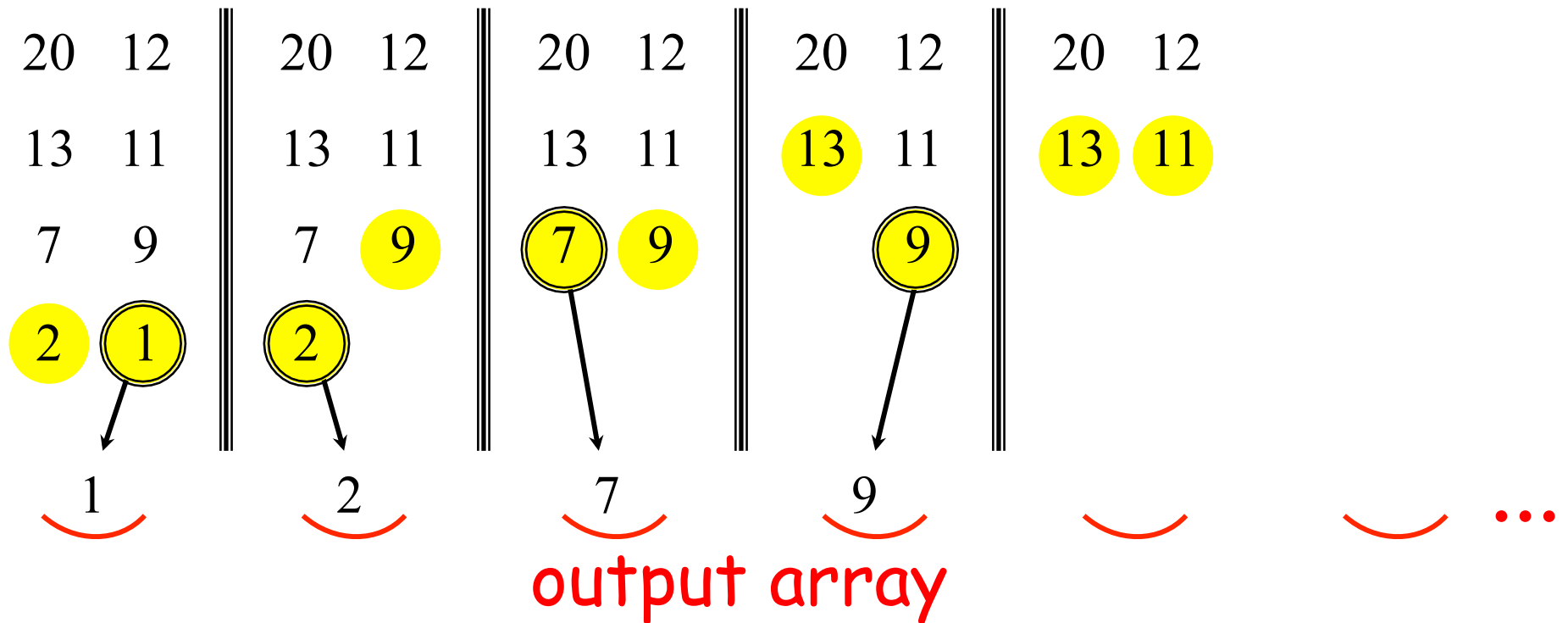
# Merging two sorted arrays



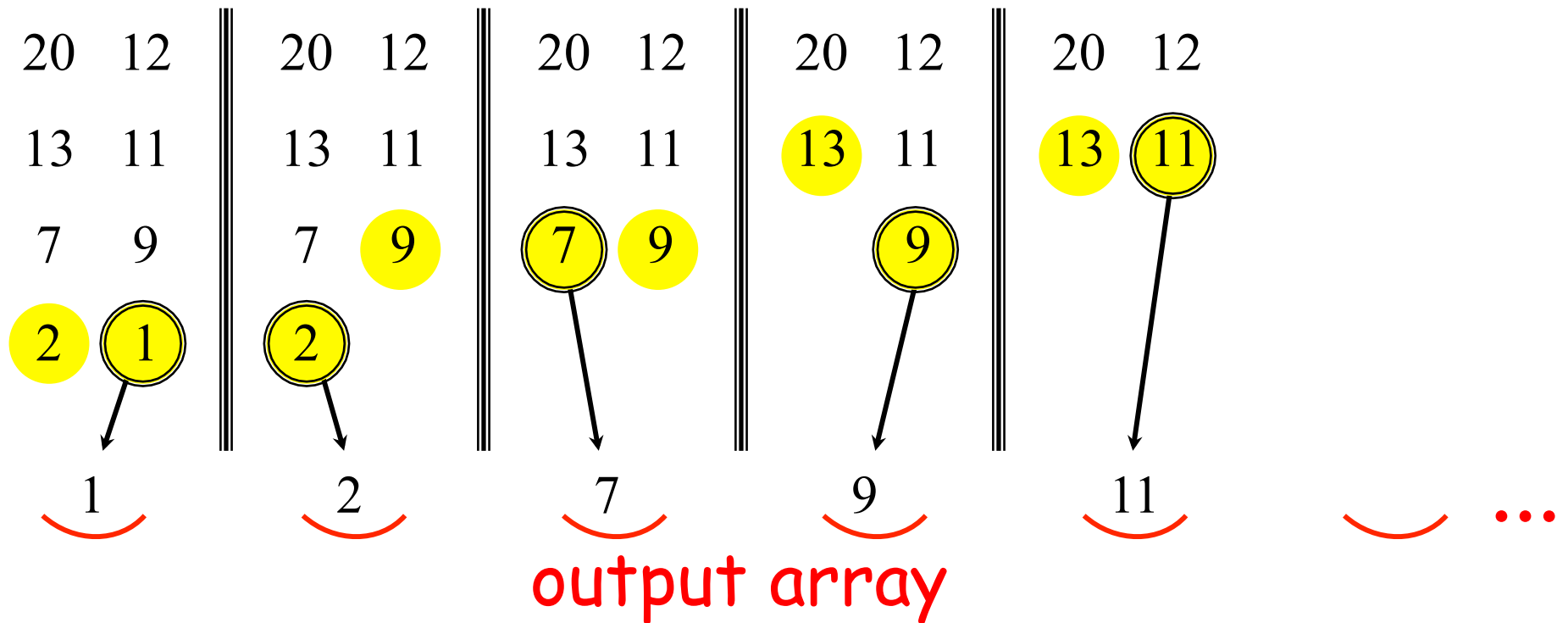
# Merging two sorted arrays



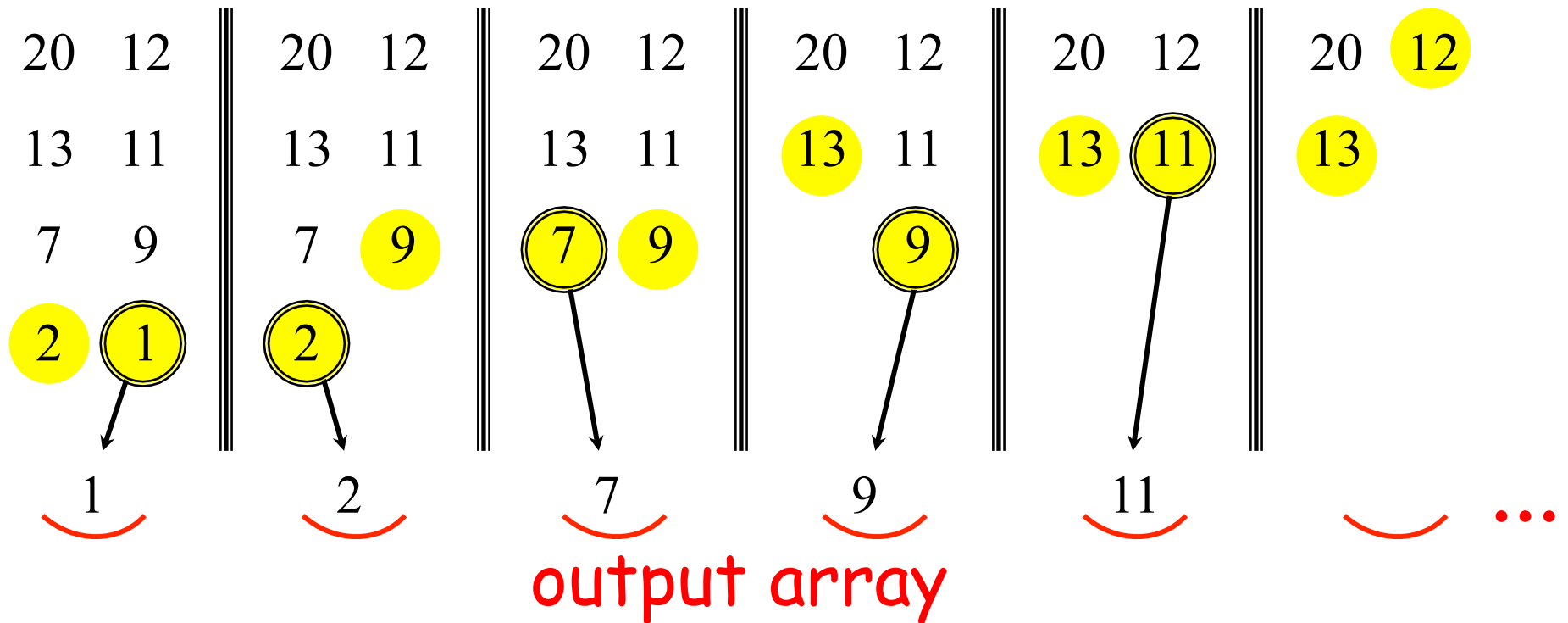
# Merging two sorted arrays



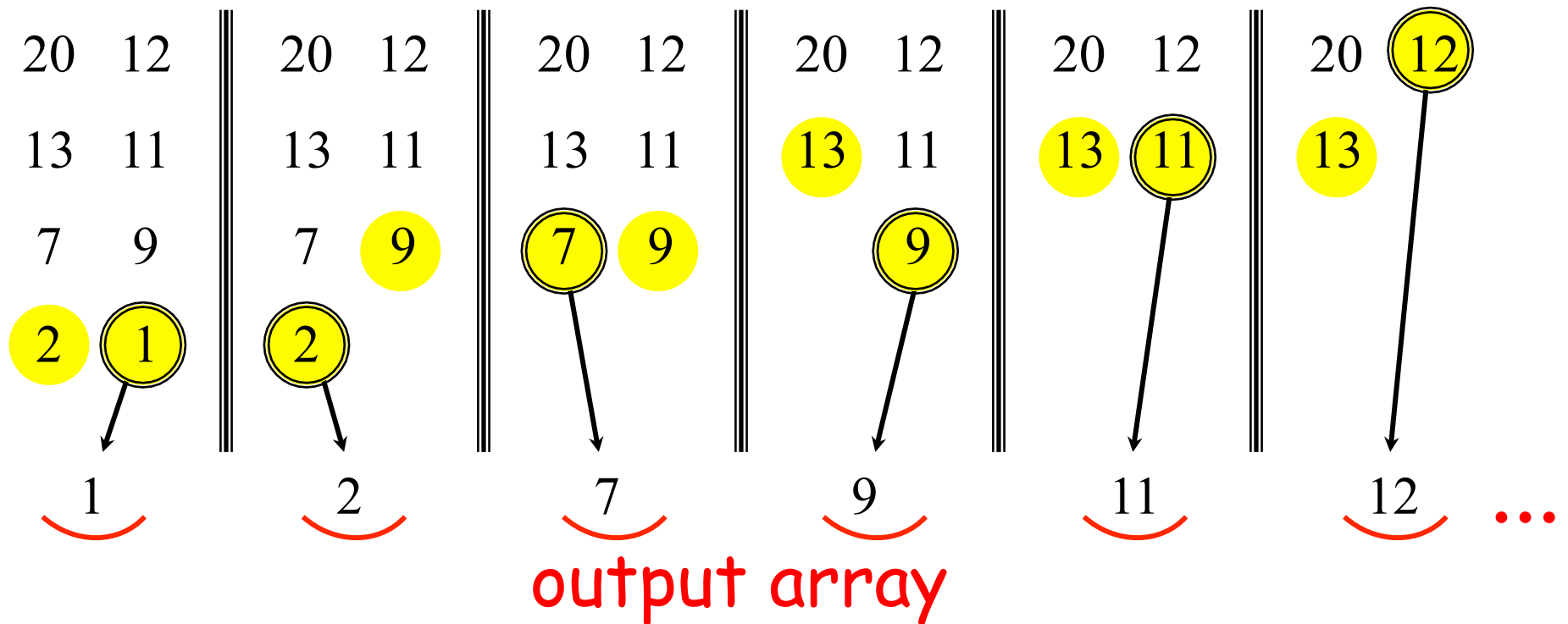
# Merging two sorted arrays



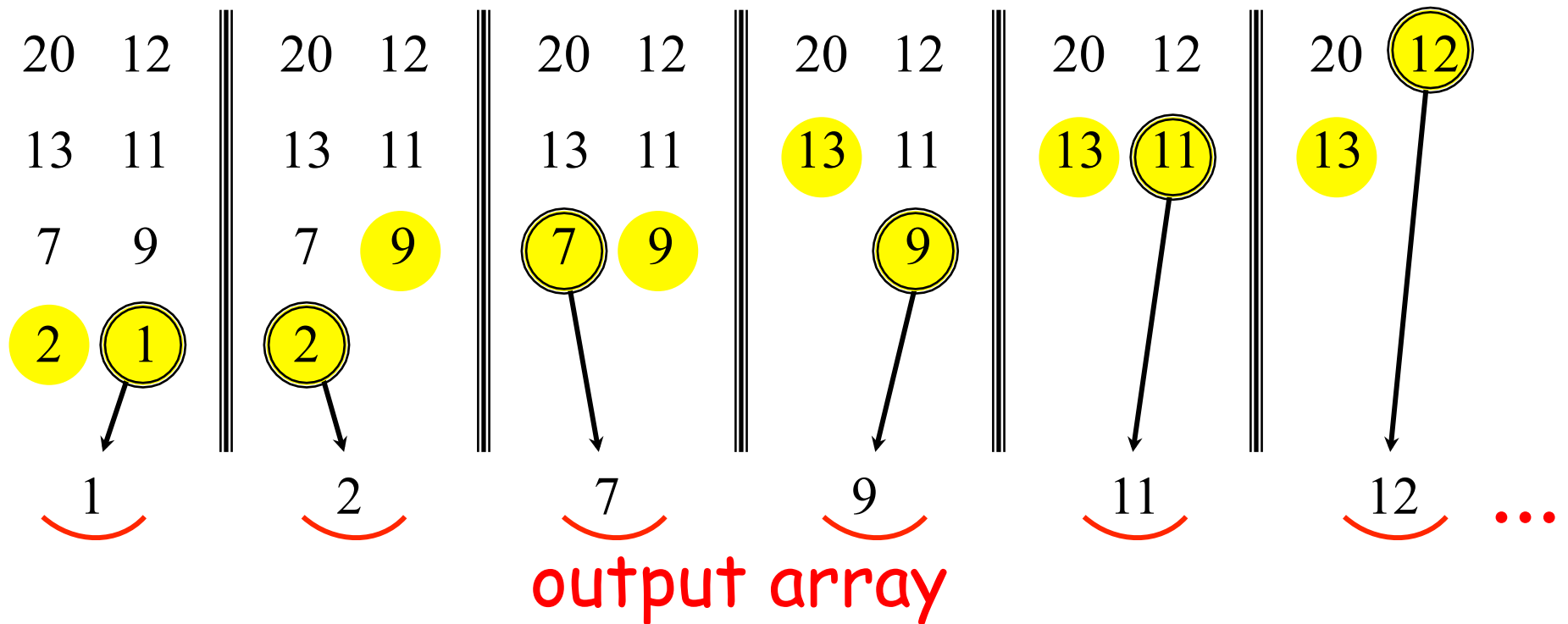
# Merging two sorted arrays



# 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 $A[1 \dots n]$	$T(n)$
1. If $n = 1$ , done	$\Theta(1)$
2. Recursively sort $A[1 \dots \lceil n/2 \rceil]$ and $A[\lceil n/2 \rceil + 1 \dots n]$	$2T(n/2)$
3. “ <i>Merge</i> ” the two sorted lists	$\Theta(n)$

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

# Recurrence solving

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

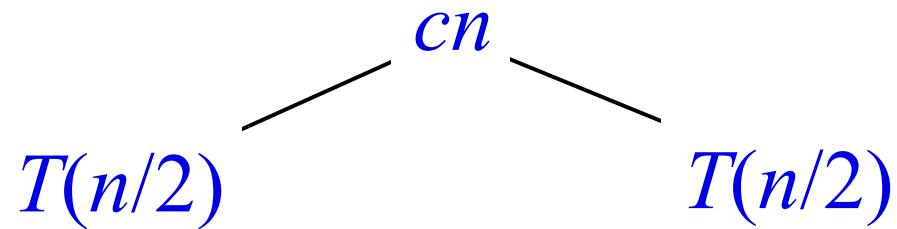
# Recursion tree

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

$$T(n)$$

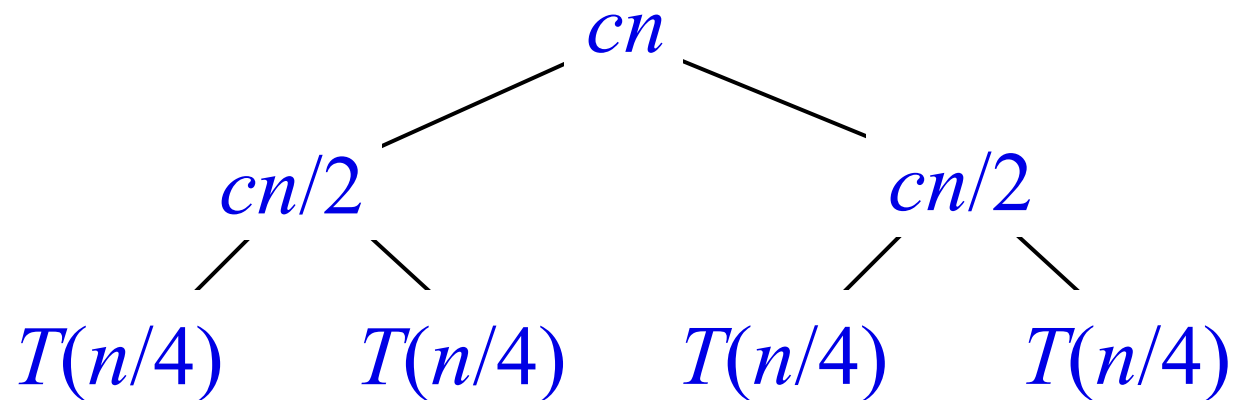
# Recursion tree

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



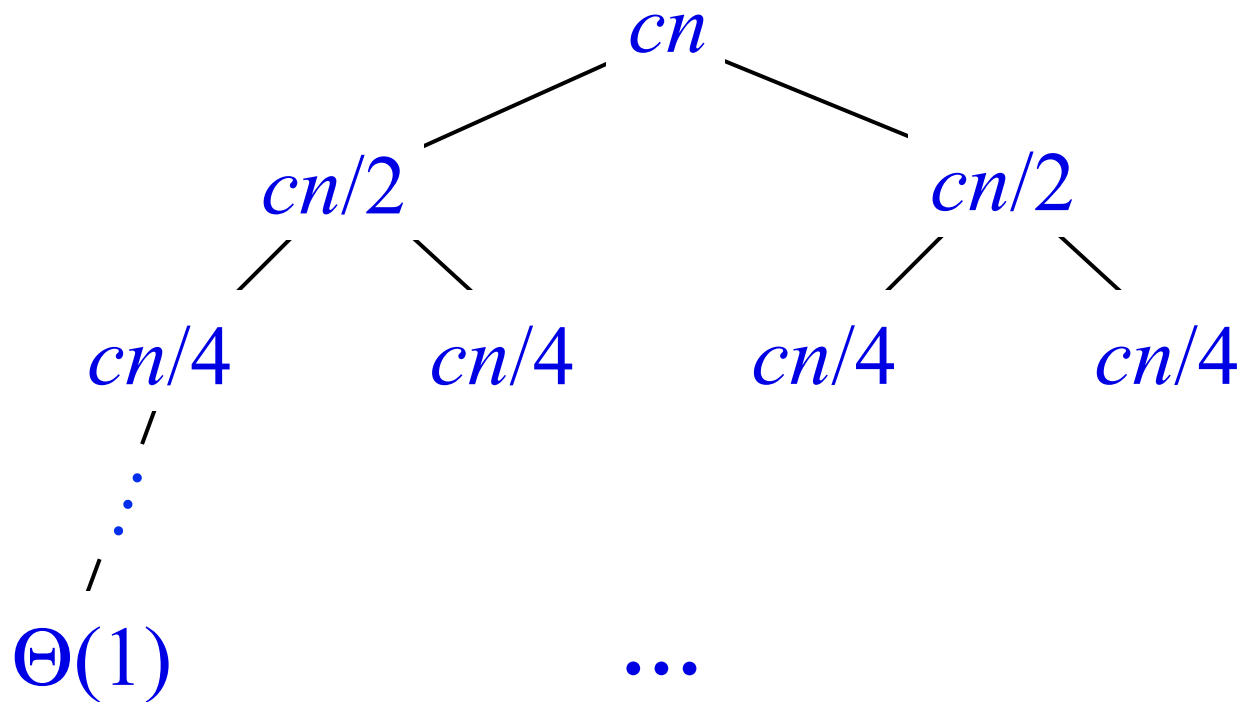
# Recursion tree

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



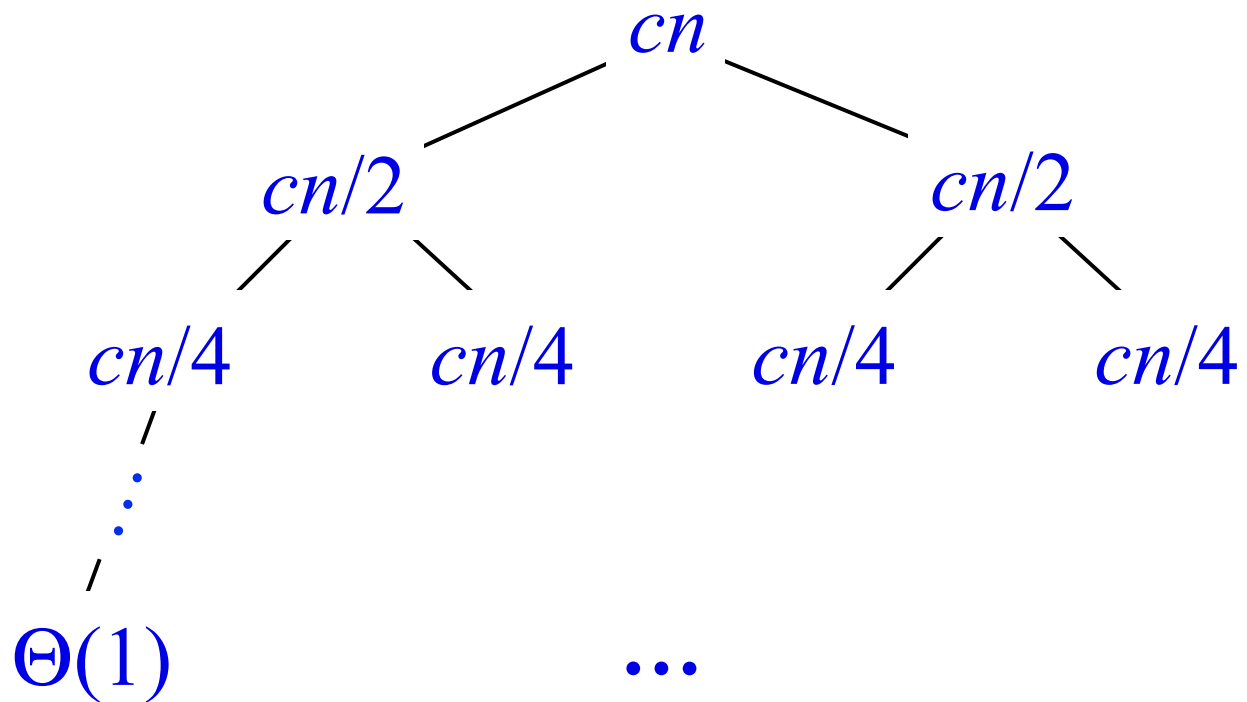
# Recursion tree

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



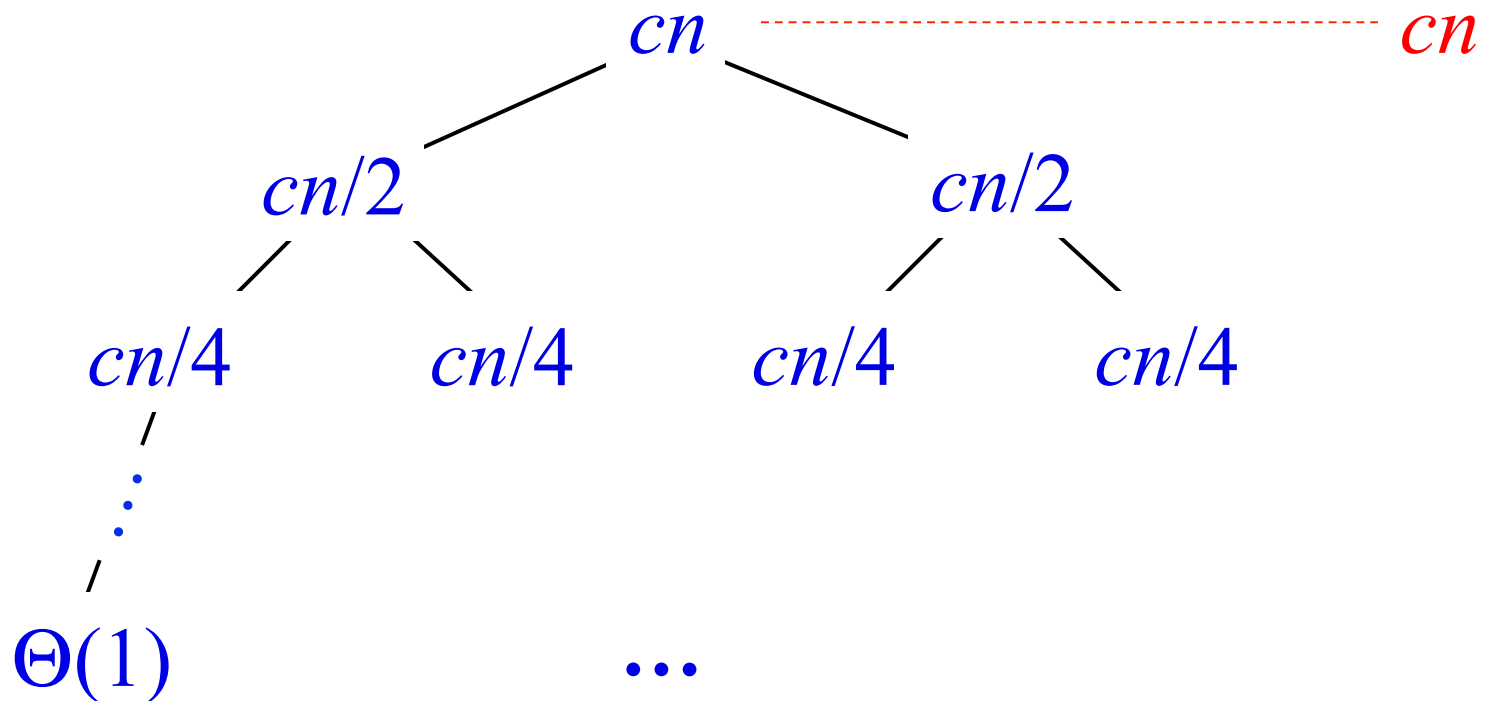
# Recursion tree

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



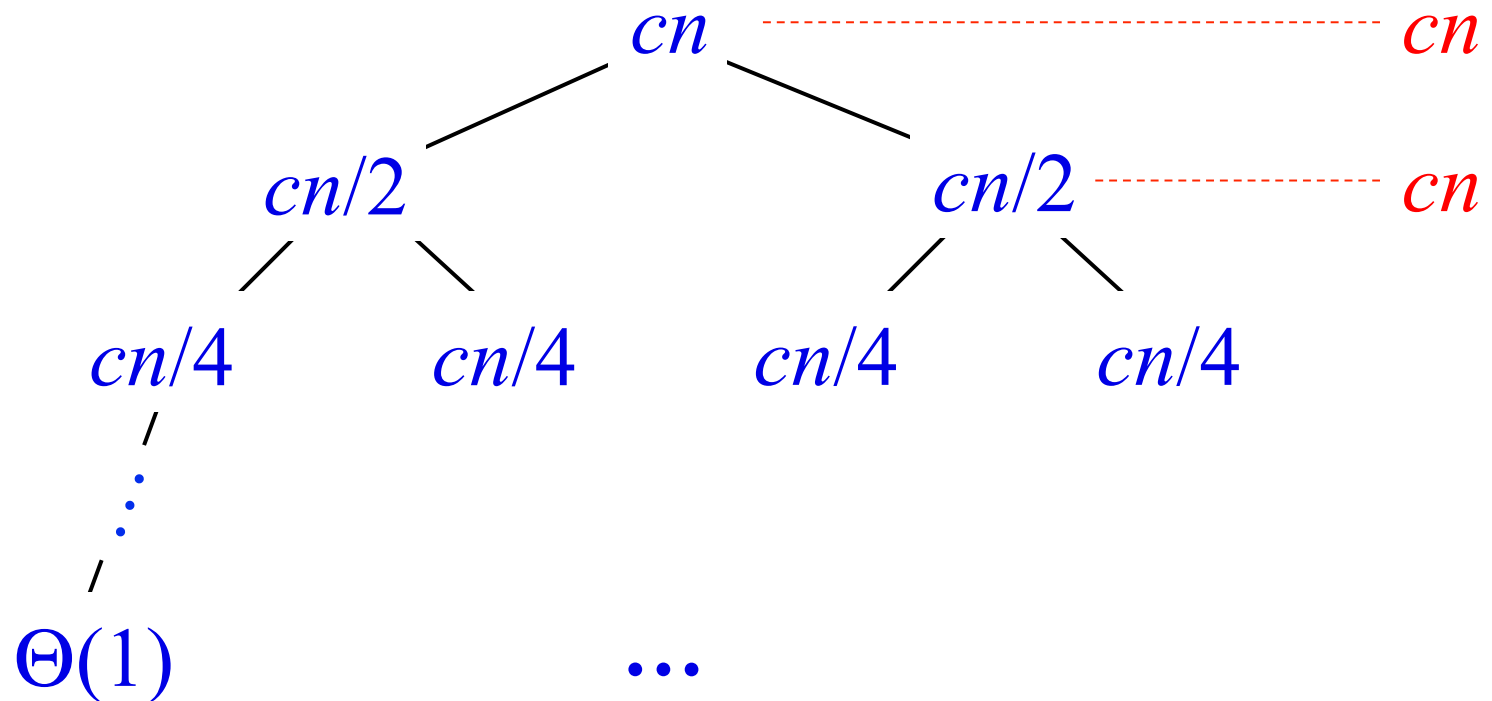
# Recursion tree

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



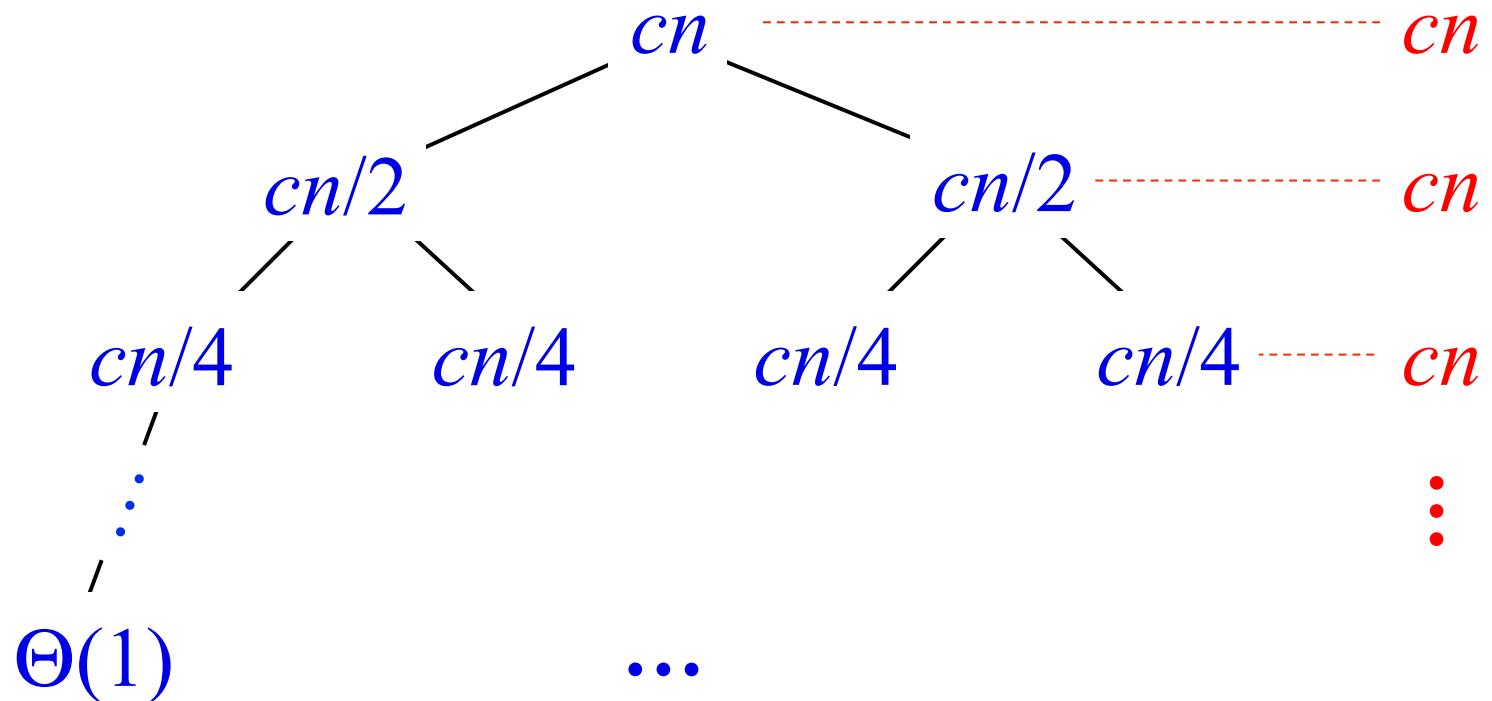
# Recursion tree

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



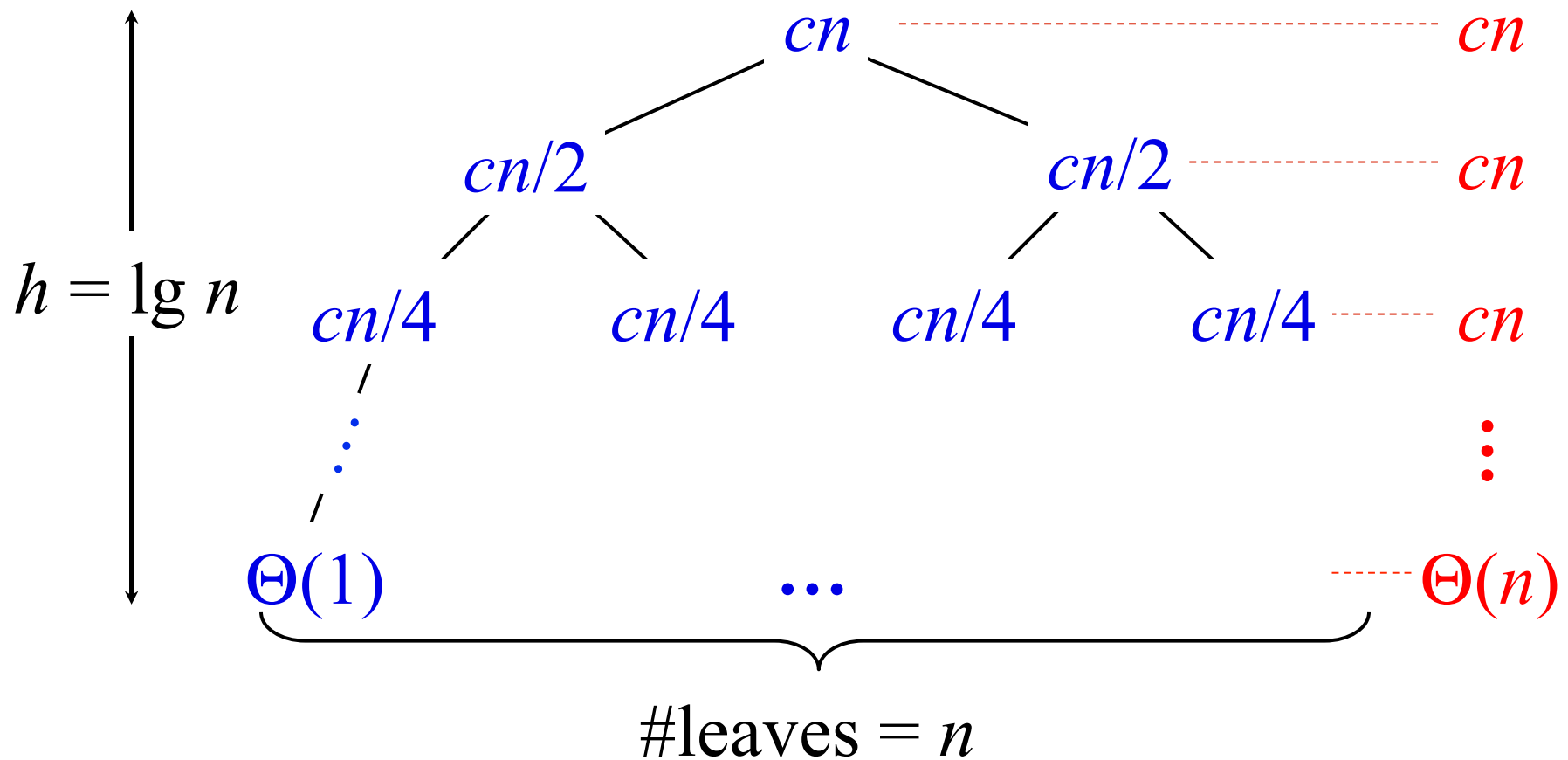
# Recursion tree

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



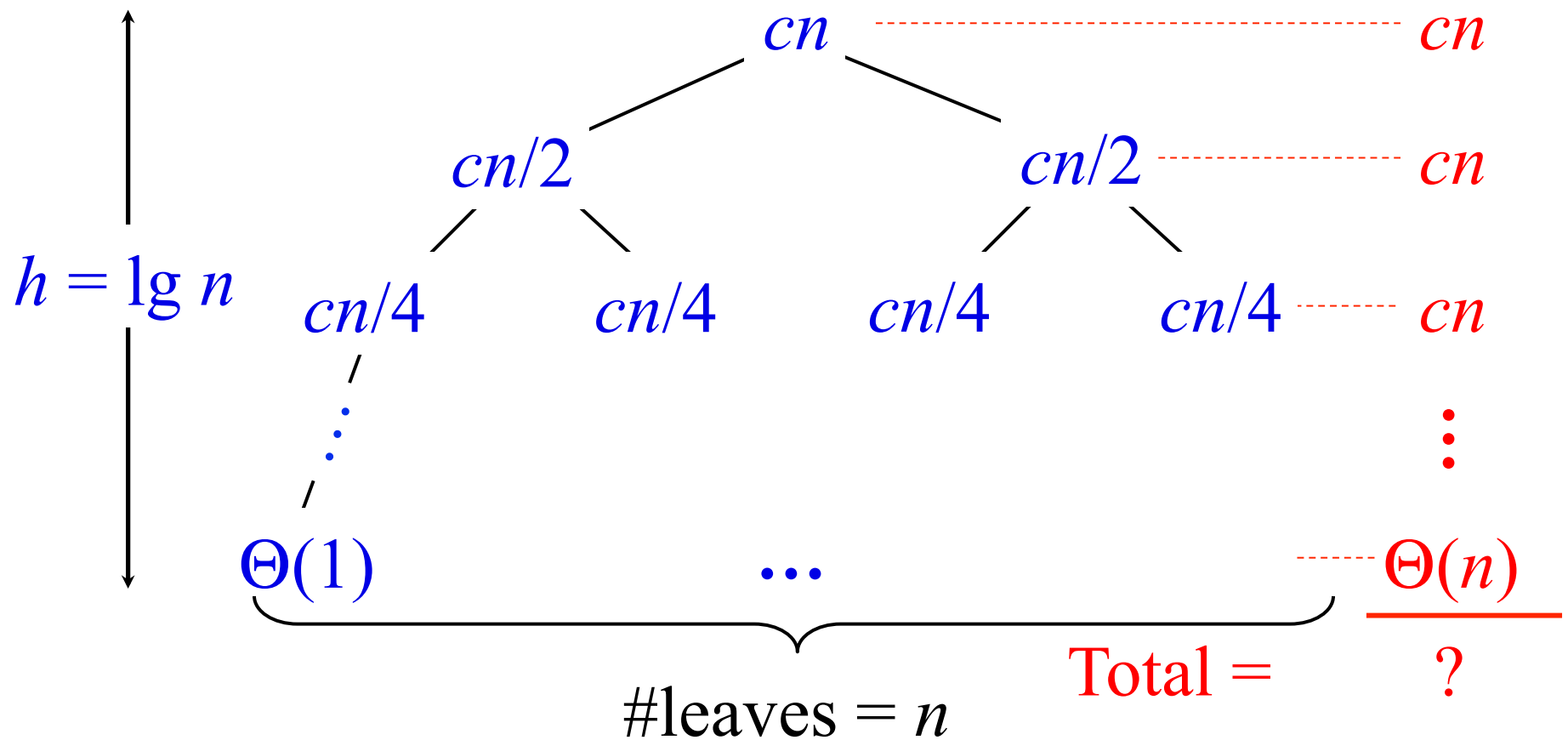
# Recursion tree

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



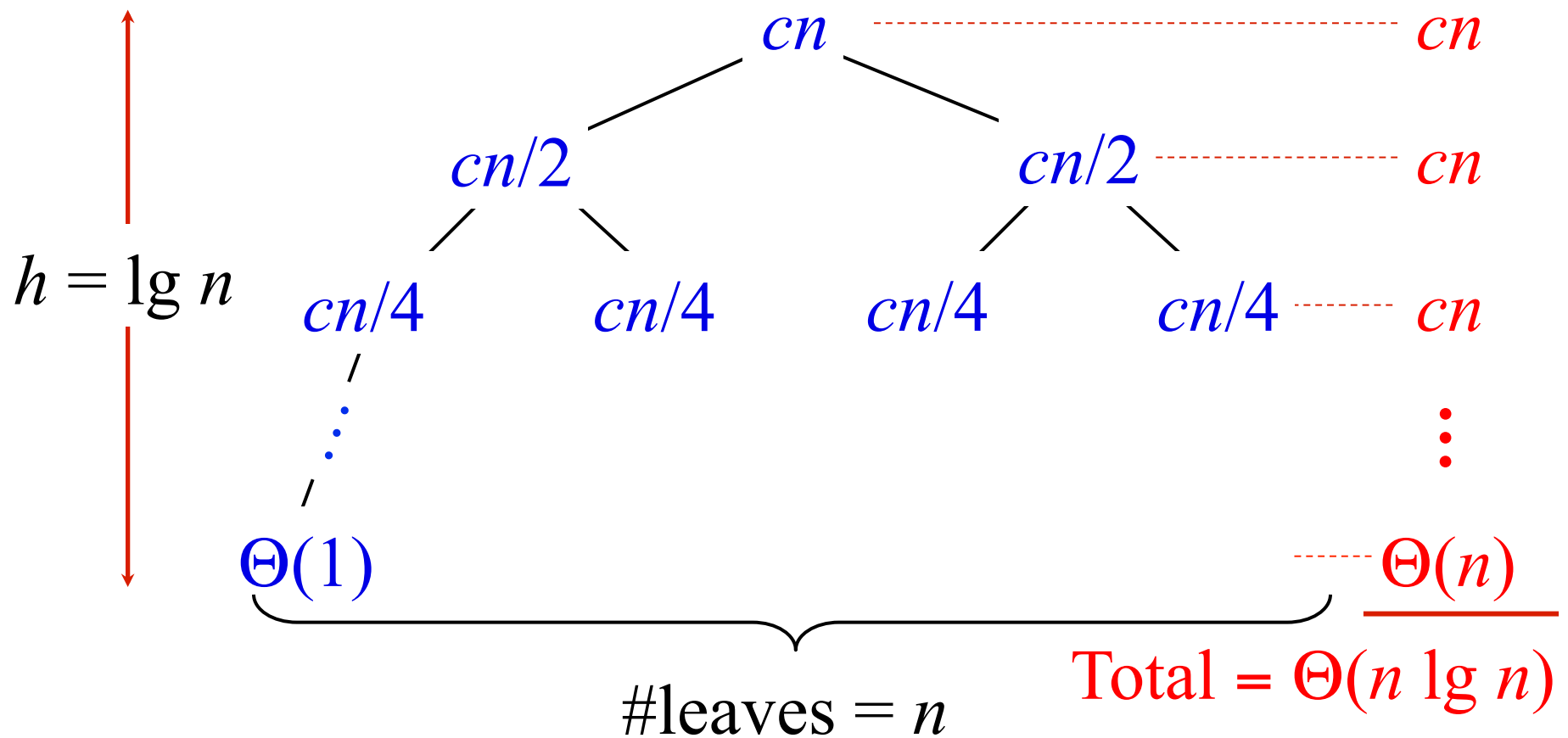
# Recursion tree

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 for all recurrences” (sort of)

It applies to recurrences of the form

$$T(n) = a T(n/b) + f(n),$$

#subproblems      size of each subproblem      time to split into subproblems and combine results

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

e.g. **Mergesort:**  $a=$

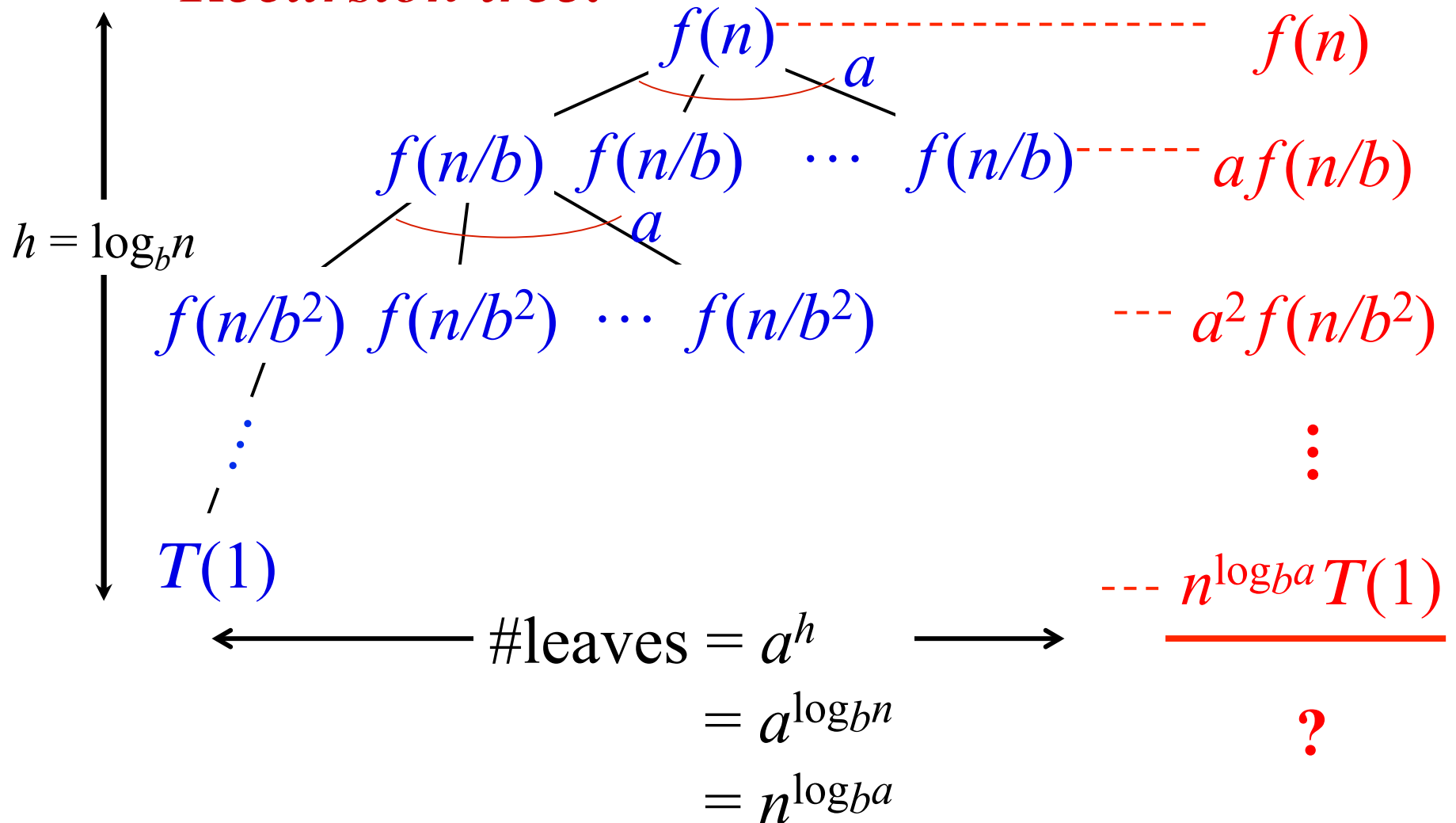
e.g.2 **Binary Search:**  $a=$

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

# Idea of master theorem

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

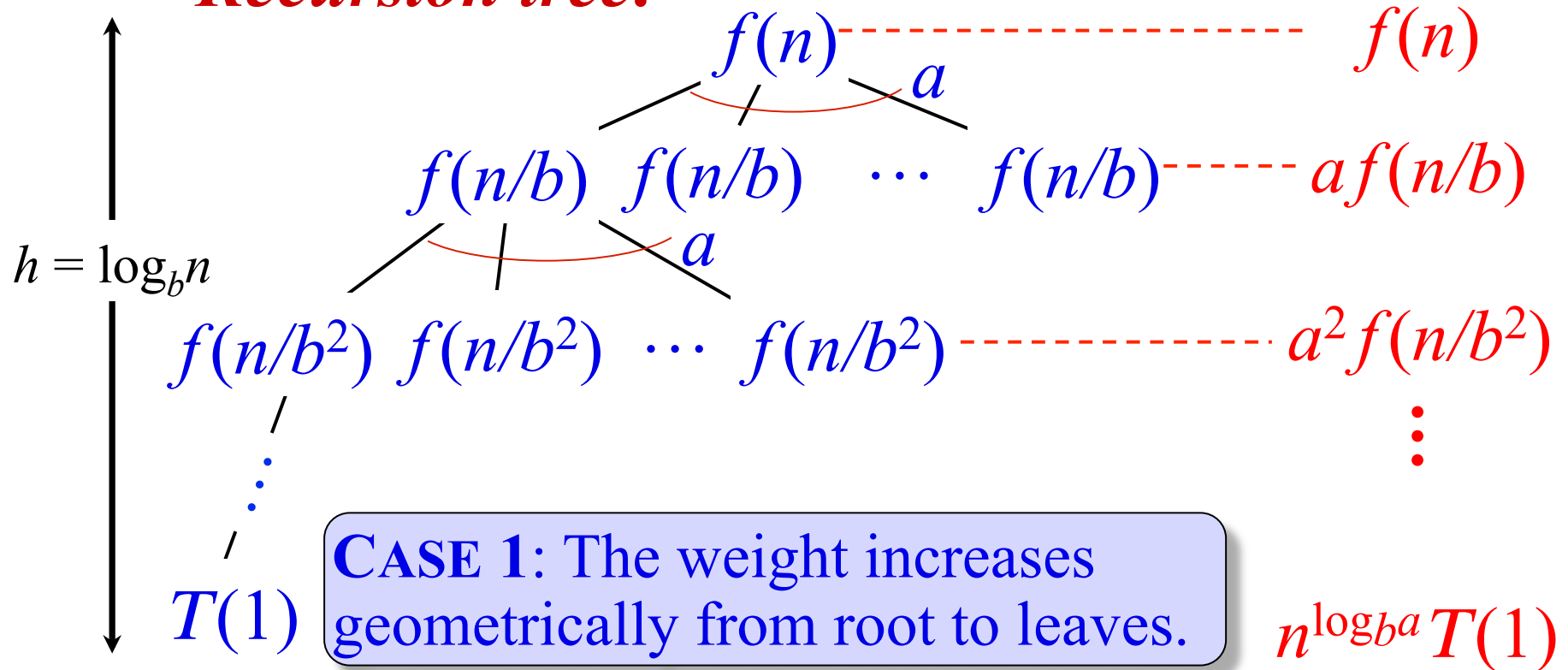
## *Recursion tree:*



# Idea of master theorem

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

*Recursion tree:*



**CASE 1:** The weight increases geometrically from root to leaves.

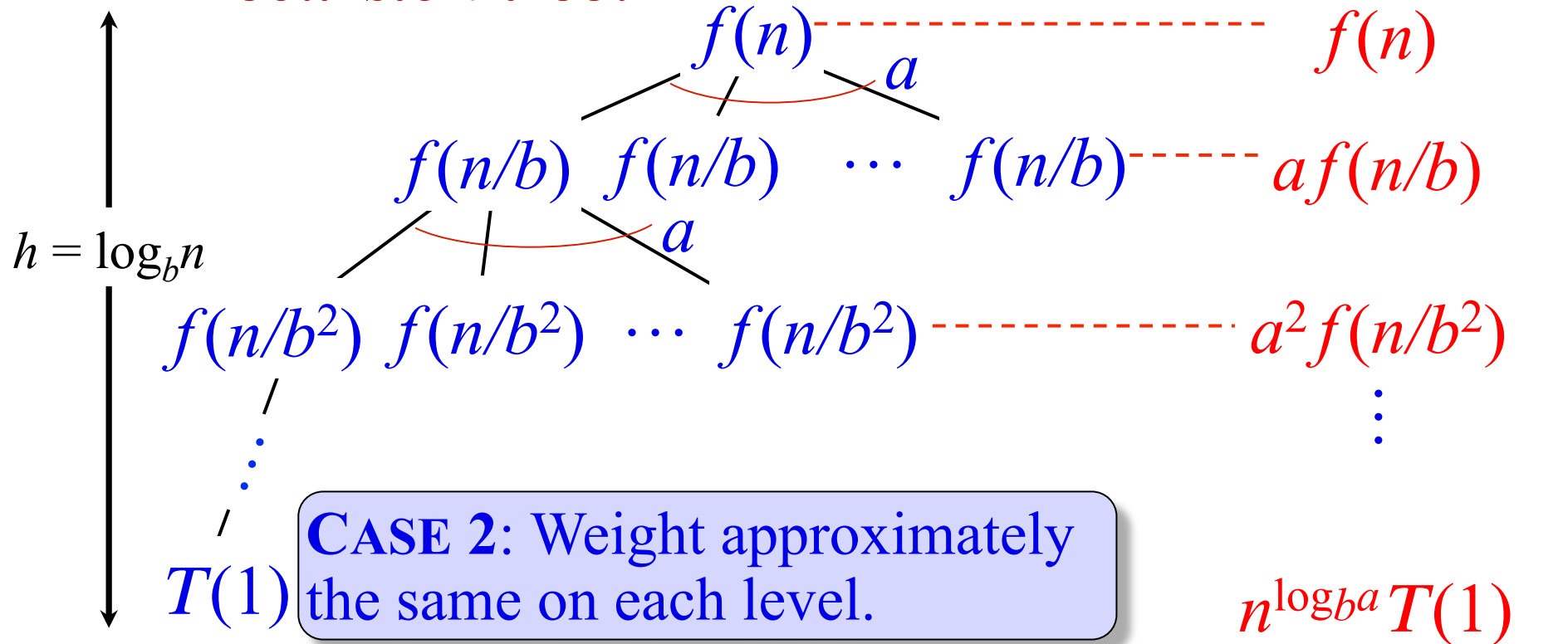
**⇒ Leaves hold a constant fraction of total weight!**

$$\Theta(n^{\log_b a})$$

# Idea of master theorem

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

**Recursion tree:**



**CASE 2:** Weight approximately the same on each level.

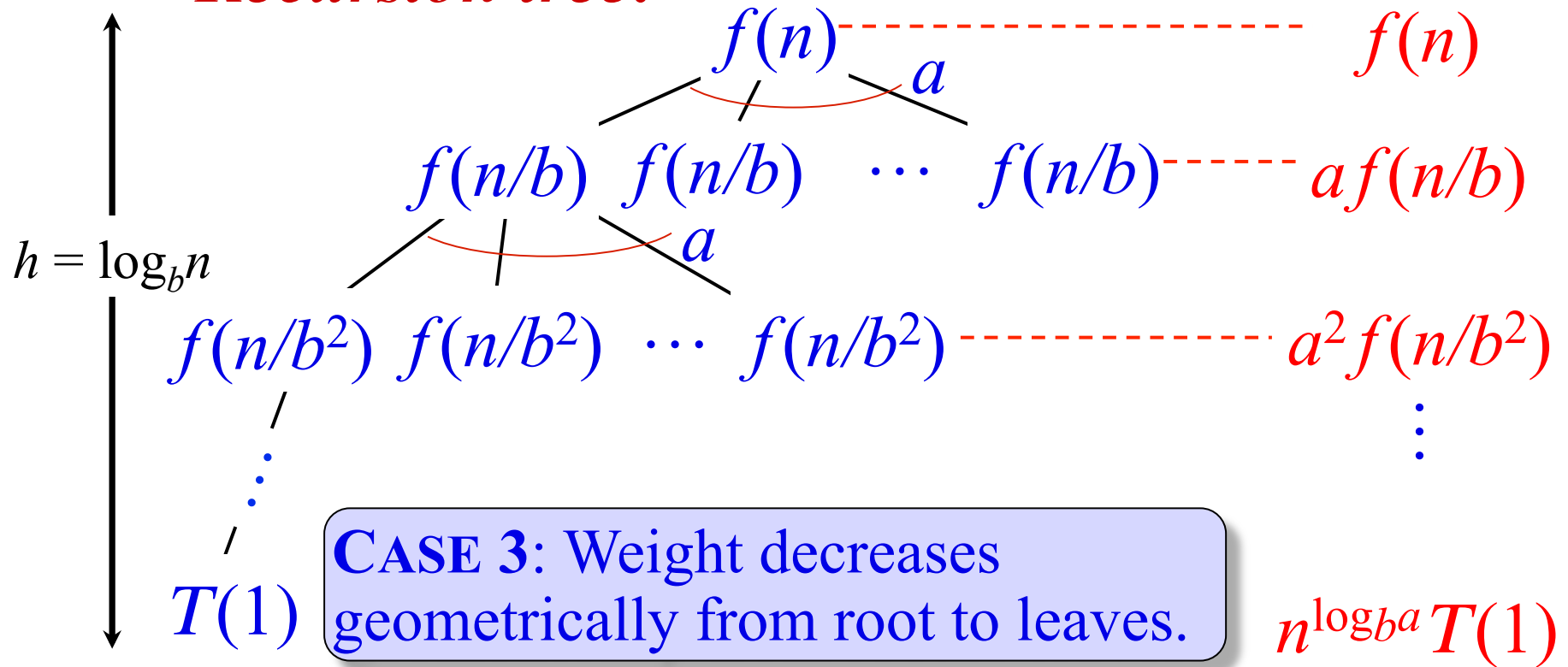
**⇒ Total weight  $\approx$  #levels  $\times$  leaves' weight!**

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

# Idea of master theorem

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

*Recursion tree:*



**CASE 3: Weight decreases geometrically from root to leaves.**

**⇒ Root holds a constant fraction of total weight!**

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

---


$$\Theta(f(n))$$

# Three common cases

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

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

*I.e.*,  $f(n)$  grows polynomially slower than  $n^{\log_b a}$   
(by an  $n^\epsilon$  factor).

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

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

*I.e.*,  $f(n)$  and  $n^{\log_b a}$  grow at similar rates.

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

so all levels have about the same cost

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

## Three common cases (cont.)

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

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

*I.e.*,  $f(n)$  grows polynomially faster 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 decrease of cost as we go deeper in the tree

hence, root cost dominates!

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

# Example 1

$$T(n) = 2T(n/2) + 1$$

Please  
don't!

$a = 2, b = 2$  Use Master Theorem:  $f(n) = 1$

1. Compute  $a$  and  $b$

CASE 1:  $f(n) = O(n^{\log_b a})$  for  $\epsilon(\bar{n})^1$

3. Compare

$\therefore T(n) = \Theta(\bar{n})$ .

## Example 2

$$T(n) = 2T(n/2) + n$$

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

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

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

## Example 3

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

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

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

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

Let's go master the  
rest of the day!