

# Algorithms and Datastructures

## Runtime analysis Minsort / Heapsort, Induction

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Algorithms and Datastructures, October 2017

## Runtime Example

Minsort

## Basic Operations

## Runtime analysis

Minsort

Heapsort

Introduction to Induction

## Logarithms

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Minsort

## Basic Operations

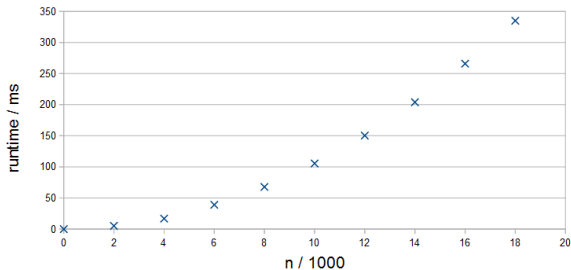
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  - What is running in the background
  - Which compiler is used to compile the code



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- **Problem:** The runtime is also depending on many other influences, especially:
  - Which kind of computer is the code executed on
  - What is running in the background
  - Which compiler is used to compile the code
- **Abstraction 1:** Analyze the number of basic operations, rather than analyzing the runtime

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## Incomplete list of basic operations:

- Arithmetic operation, for example:  $a + b$
- Assignment of variables, for example:  $x = y$
- Function call, for example: *minsort(lst)*

## Intuitive:

lines of code

## Better:

lines of machine  
code

## Best:

process cycles

## Important:

The actual runtime has to be roughly proportional to the number of operations.

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- **Abstraction 2:** We calculate the upper (lower) bound, rather than counting the operations exactly

**Reason:** Runtime is approximated by number of basic operations, but we can still infer:

- Upper bound
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**Reason:** Runtime is approximated by number of basic operations, but we can still infer:

- Upper bound
  - Lower bound
- **Basic Assumption:**
  - $n$  is size of the input data (i.e. array)
  - $T(n)$  number of operations for input  $n$

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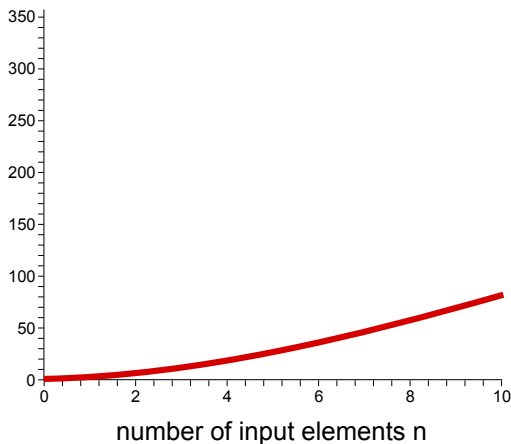
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- **Claim:** There are constants  $C_1$  and  $C_2$  such that:

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- This is called “quadratic runtime” (due to  $n^2$ )

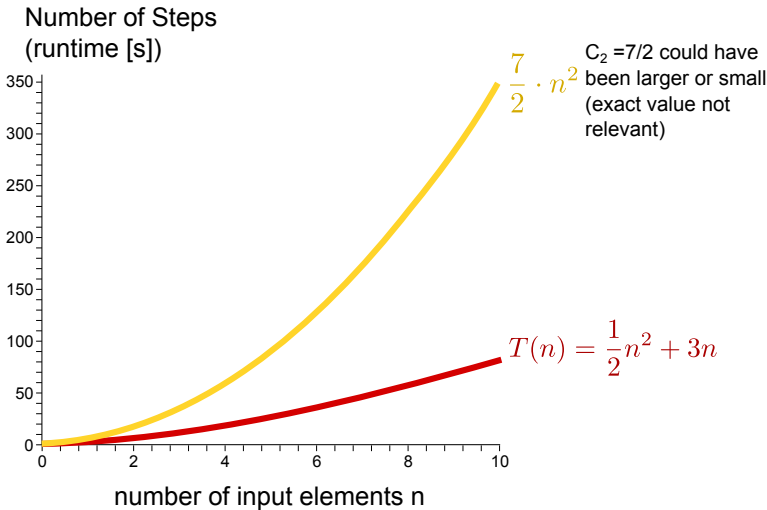
# Runtime Example

Number of Steps  
(runtime [s])

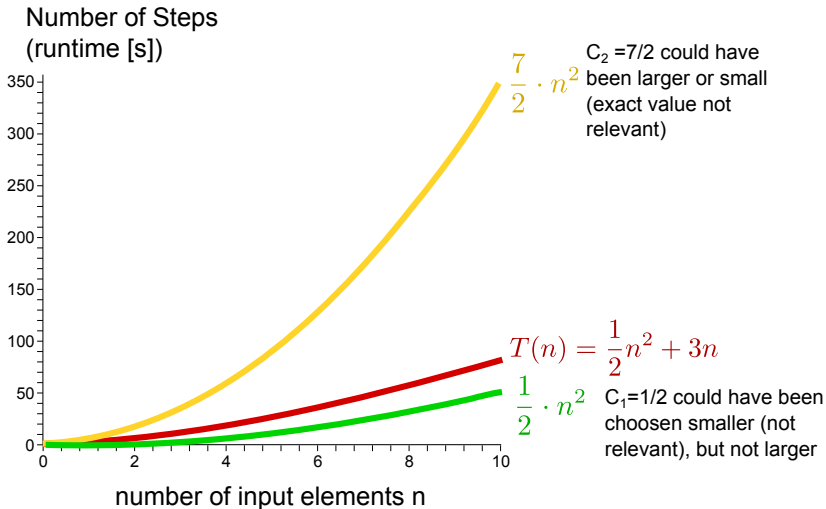


$$T(n) = \frac{1}{2}n^2 + 3n$$

# Runtime Example



# Runtime Example



## We declare:

- Runtime of operations:  $T(n)$
- Number of Elements:  $n$
- Constants:  $C_1$  (lower bound),  $C_2$  (upper bound)  
$$C_1 \cdot n^2 \leq T(n) \leq C_2 \cdot n^2$$
- Number of operations in round  $i$ :  $T_i$



**Figure:** *Minsort* at the iteration  $i = 4$ . We have to check  $n - 3$  elements

Compares at each  
iteration:

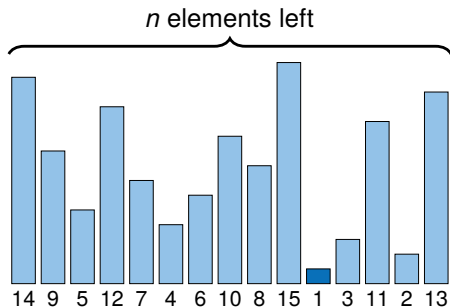


Figure: *Minsort* with start data

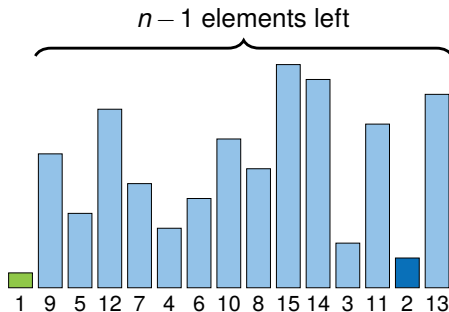
Compares at each iteration:

$$T_1 \leq C'_2 \cdot (n - 0)$$



Figure: *Minsort* at iteration  $i = 1$





Compares at each iteration:

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$$T_2 \leq C'_2 \cdot (n - 1)$$

Figure: *Minsort* at iteration  $i = 2$



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Figure: *Minsort* at iteration  $i = 3$



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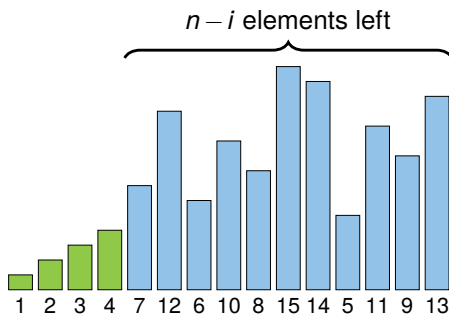


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$\vdots$

$$T_{n-1} \leq C'_2 \cdot 2$$

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$$T(n) = C'_2 \cdot (T_1 + \dots + T_n) \leq \sum_{i=1}^n (C'_2 \cdot i)$$

## Alternative: Analyse the Code:

```
def minsort(elements):  
    for i in range(0, len(elements)-1):  
        minimum = i  
  
        for j in range(i+1, len(elements)):  
            if elements[j] < elements[minimum]:  
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        if minimum != i:  
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Diagram illustrating the runtime analysis of the Minsort algorithm:

- The inner loop (for j in range(i+1, len(elements))) is labeled "const. runtime".
- The inner loop is repeated  $n-i-1$  times for each iteration of the outer loop.
- The outer loop (for i in range(0, len(elements)-1)) is repeated  $n-1$  times.

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**Remark:**  $C'_2$  is cost of comparison  $\Rightarrow$  assumed constant

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# Excursion - Small Gauss Formula

**Proof of lower bound:**  $C_1 \cdot n^2 \leq T(n)$

Like for the upper boundary there exists a  $C_1$ . Summation analysis is the same

$$T(n) \geq \sum_{i=1}^{n-1} C'_1 \cdot (n-i)$$

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## Summarized:

$$\frac{C'_1}{4} \cdot n^2 \leq T(n) \leq C'_2 \cdot n^2$$

## Quadratic runtime proven:

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- **Quadratic runtime = “big” problems unsolvable**

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## Formal:

- Let  $T(n)$  be the runtime for the *Heapsort* algorithm with  $n$  elements
- On the next pages we will proof  $T(n) \leq C \cdot n \log_2 n$

## Depth of a binary tree:

- **Depth  $d$ :** longest path through the tree
- Complete binary tree has  $n = 2^d - 1$  nodes
- Example:  $d = 4$   
 $\Rightarrow n = 2^4 - 1 = 15$

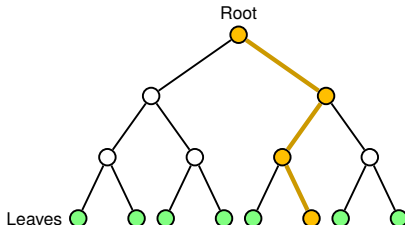


Figure: Binary tree with 15 nodes

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  - 1 **Induction basis:** we show that our assumption is valid at one point (for example:  $n = 1, A(1)$ ).
  - 2 **Induction step:** we show that the assumption is valid for all  $n$  (normally one step forward:  $n = n + 1, A(1), \dots, A(n)$ ).

## Basics:

- You want to show assumption  $A(n)$  is valid  $\forall n \in \mathbb{N}$
- We show induction in two steps:
  - 1 **Induction basis:** we show that our assumption is valid at one point (for example:  $n = 1, A(1)$ ).
  - 2 **Induction step:** we show that the assumption is valid for all  $n$  (normally one step forward:  $n = n + 1, A(1), \dots, A(n)$ ).
- If both has been proven, then  $A(n)$  holds for all natural numbers  $n$  by **induction**

Claim:

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Figure: Tree of depth 1 has 1 node

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$\Rightarrow$  correct ✓

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# Induction - Example 1



Number of nodes  $n(d)$  in a binary tree with depth  $d$ :

- **Induction assumption:**  $n(d) = 2^d - 1$



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Figure: Binary tree with subtrees

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$$n(d+1) = 2 \cdot n(d) + 1$$

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$$\begin{aligned} n(d+1) &= 2 \cdot n(d) + 1 \\ &= 2 \cdot (2^d - 1) + 1 \end{aligned}$$

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⇒ **By induction:**  $n(d) = 2^d - 1 \quad \forall n \in \mathbb{N} \quad \square$

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## Heapsort has the following steps:

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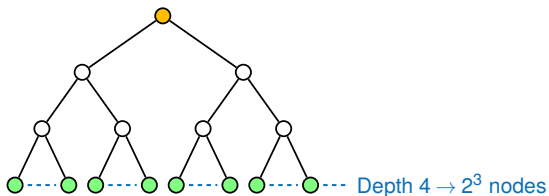
## Heapsort has the following steps:

- **Initially:** heapify list of  $n$  elements
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  - Remove root as minimal element
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  - Repair heap by sifting

Runtime of heapify depends on depth  $d$ :



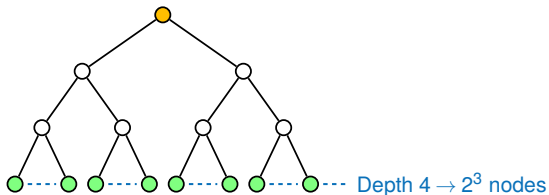
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Runtime of heapify with depth of  $d$ :

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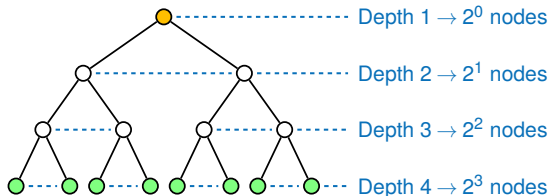


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- No costs at depth  $d$  with  $2^{d-1}$  (or less) nodes
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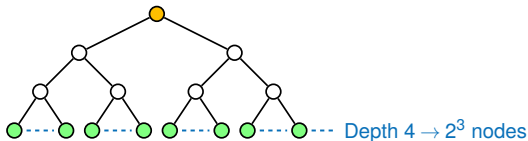
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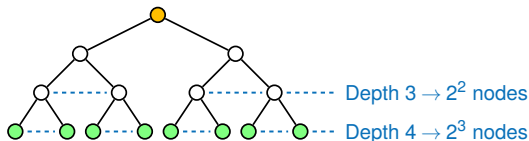
- No costs at depth  $d$  with  $2^{d-1}$  (or less) nodes
- The cost for sifting with depth 1 is at most  $1C$  per node
- In general: Sifting costs are linear with path length **and** number of nodes

Heapify total runtime:



Depth	Nodes	Path length	Costs per node
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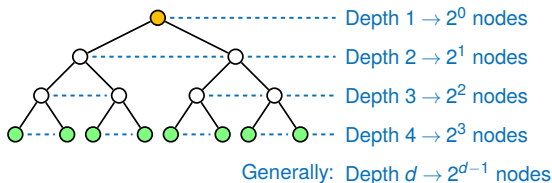
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**In total:** 
$$T(d) \leq \sum_{i=1}^d (C \cdot (i-1) \cdot 2^{d-i})$$

Heapify total runtime:



Depth	Nodes	Path length	Costs per node	Upper bound
$d$	$2^{d-1}$	0	$\leq C \cdot 0$	Standard Equation
$d-1$	$2^{d-2}$	1	$\leq C \cdot 1$	
$d-2$	$2^{d-3}$	2	$\leq C \cdot 2$	
$d-3$	$2^{d-4}$	3	$\leq C \cdot 3$	

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$d-2$	$2^{d-3}$	2	$\leq C \cdot 2$	$\leq C \cdot 3$
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- **However:** We want costs in relation to  $n$



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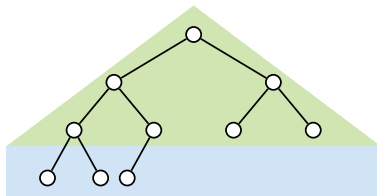


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■ Equation multiplied by  $2^2$   
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■ Cost for heapify:  
 $\Rightarrow T(n) \leq C \cdot 4 \cdot n$

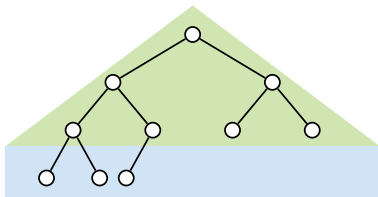


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- We want to proof (induction assumption):

$$\underbrace{\sum_{i=1}^d (i \cdot 2^{d-i})}_{A(d)} \leq \underbrace{2^{d+1}}_{B(d)}$$

- We denote the left side with  $A$ , the right side with  $B$

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$$2^0 \leq 2^2 \quad \checkmark$$

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- **Idea:** Write down right hand formula and try to get  $A(d)$  and  $B(d)$  out of it

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$$2 \cdot \sum_{i=1}^{d+1} (i \cdot 2^{d-i}) \leq 2 \cdot 2^{d+1}$$

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■ **Problem:** Does not work but claim still holds

## Working proof:

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- **Advantage:** Results in a stronger induction assumption  
 $\Rightarrow$  **exercise**

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- **Recall:** The depth and number of elements is decreasing
  - **Hence:**  $T(n) \leq n \cdot (1 + \log_2 n) \cdot C$
  - We can reduce this to:

$$T(n) \leq 2 \cdot n \log_2 n \cdot C \quad (\text{holds for } n > 2)$$

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  - Upper bound:  $C_2 \cdot n \log_2 n \geq T(n)$  (for  $n \geq 2$ )
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  - $\Rightarrow C_1$  and  $C_2$  are constant



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## Logarithm to different bases:

$$\log_a n = \frac{\log_b n}{\log_b a} = \log_b n \cdot \frac{1}{\log_b a}$$

The only difference is a constant coefficient  $\frac{1}{\log_b a}$

### Examples:

- $\log_2 4 = \log_{10} 4 \cdot \frac{1}{\log_2 10} = 0.602 \dots \cdot 3.322 \dots = 2 \checkmark$
- $\log_{10} 1000 = \log_e 1000 \cdot \frac{1}{\log_e 10} = \ln 1000 \cdot \frac{1}{\ln 10} = 3 \checkmark$

## Runtime of $n \log_2 n$ :

- Assume we have constants  $C_1$  and  $C_2$  with

$$C_1 \cdot n \cdot \log_2 n \leq T(n) \leq C_2 \cdot n \cdot \log_2 n \quad \text{for } n \geq 2$$

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- $2 \times$  elements  $\Rightarrow$  only slightly larger than  $2 \times$  runtime
  - $C = 1$  ns (1 simple instruction  $\approx 1$  ns)
  - $n = 2^{20}$  (1 million numbers = 4 MB with 4 B/number)
    - $C \cdot n \cdot \log_2 n = 10^{-9} \text{ s} \cdot 2^{20} \cdot 20 = 21.0 \text{ ms}$

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  - $C = 1$  ns (1 simple instruction  $\approx 1$  ns)
  - $n = 2^{20}$  (1 million numbers = 4 MB with 4 B/number)
    - $C \cdot n \cdot \log_2 n = 10^{-9} \text{ s} \cdot 2^{20} \cdot 20 = 21.0 \text{ ms}$
  - $n = 2^{30}$  (1 billion numbers = 4 GB)
    - $C \cdot n \cdot \log_2 n = 10^{-9} \text{ s} \cdot 2^{30} \cdot 30 = 32 \text{ s}$

## Runtime of $n \log_2 n$ :

- Assume we have constants  $C_1$  and  $C_2$  with

$$C_1 \cdot n \cdot \log_2 n \leq T(n) \leq C_2 \cdot n \cdot \log_2 n \quad \text{for } n \geq 2$$

- $2 \times$  elements  $\Rightarrow$  only slightly larger than  $2 \times$  runtime
  - $C = 1$  ns (1 simple instruction  $\approx 1$  ns)
  - $n = 2^{20}$  (1 million numbers = 4 MB with 4 B/number)
    - $C \cdot n \cdot \log_2 n = 10^{-9} \text{ s} \cdot 2^{20} \cdot 20 = 21.0 \text{ ms}$
  - $n = 2^{30}$  (1 billion numbers = 4 GB)
    - $C \cdot n \cdot \log_2 n = 10^{-9} \text{ s} \cdot 2^{30} \cdot 30 = 32 \text{ s}$
- **Runtime  $n \log_2 n$  is nearly as good as linear!**



## ■ General for this Lecture

[CRL01] Thomas H. Cormen, Ronald L. Rivest, and Charles E. Leiserson.

**Introduction to Algorithms.**

MIT Press, Cambridge, Mass, 2001.

[MS08] Kurt Mehlhorn and Peter Sanders.

Algorithms and data structures, 2008.

<https://people.mpi-inf.mpg.de/~mehlhorn/ftp/Mehlhorn-Sanders-Toolbox.pdf>.

## ■ Mathematical Induction

[Wik] [Mathematical induction](https://en.wikipedia.org/wiki/Mathematical_induction)

`https://en.wikipedia.org/wiki/Mathematical\_induction`