

CSE202

Design and Analysis of Algorithms

Constantin Enea

Week 1: Overview & Basics

I. Overview of the Course

Summary of Last Year

CSE 101/102: Computer programming.
Data structures and algorithms.
Basic graph/tree algorithms.

CSE 103: Introduction to algorithms.
Divide and conquer. Sorting. Searching
Dynamic programming. Greedy algorithms.
Graph algorithms.

Plan for this Course

Introduction

Divide & Conquer

Randomization

Amortization, balancing

String Algorithms

P vs NP - Approximation algorithms

Basic principles through many examples
data-structures along the way

Organization

Lectures: Wednesdays 10:15—11:45
amphi Cauchy

Tutorials
in Python

Thursdays 13:15—15:15
rooms 33 & 35 & 36

Antoine Lavignotte
Martin Krejka
Simon Bliudze

Material: see Moodle

Questions: constantin.enea@polytechnique.edu

Assessment

	Week	Ratio
Homework assignments	1—14	10 %
Weekly tutorials	1—14	10 %
Midterm	7	40 %
Final	15	40 %

Midterm: programming
Final: written exam

Exam rules:
No collaboration,
no laptop,
no internet.

II. Algorithms

*An algorithm is a finite answer to an
infinite number of questions.*

Stephen Kleene

Example of Algorithm: Binary Powering

1. A well-specified problem:

Input: $(x, n) \in \mathbb{A} \times \mathbb{N}$

Output: $y \in \mathbb{N}$ such that $y = x^n$

2. A method to solve it:

$$\text{Idea. } x^n = \begin{cases} (x^{n/2})^2, & \text{for even } n \\ (x^{(n-1)/2})^2 x, & \text{otherwise} \end{cases}$$

Binary-Powering(x,n)

if $n = 0$ then return 1

tmp \leftarrow **Binary-Powering**(x,n/2)

tmp \leftarrow tmp * tmp

if (n is even) return tmp

return tmp * x

Pseudocode.

Example of Algorithm: Binary Powering

Algorithm:

Binary-Powering(x,n)

if $n = 0$ then return 1

tmp \leftarrow **Binary-Powering**(x,n/2)

tmp \leftarrow tmp * tmp

if (n is even) return tmp

return tmp * x

Implemented in programs:

```
pow(int, int):  
    mov     eax, 1  
    test    esi, esi  
    jne     .L8  
    ret  
  
.L8:  
    push    rbp  
    push    rbx  
    sub     rsp, 8  
    mov     ebp, edi  
    mov     ebx, esi  
    shr     esi, 31  
    add     esi, ebx  
    sar     esi  
    call    pow(int, int)  
    imul    eax, eax  
    test    bl, 1  
    je      .L1  
    imul    eax, ebp  
  
.L1:  
    add     rsp, 8  
    pop     rbx  
    pop     rbp  
    ret
```

Example of Algorithm: Binary Powering

Algorithm:

Binary-Powering(x,n)

if $n = 0$ then return 1
tmp \leftarrow **Binary-Powering**(x,n/2)
tmp \leftarrow tmp * tmp
if (n is even) return tmp
return tmp * x

Implemented in programs:

```
def binpow(x,n):  
    if n==0: return 1  
    tmp=binpow(x,n//2)  
    tmp=tmp*tmp  
    if n%2==0: return tmp  
    return tmp*x
```

Paying attention to details in the programming language semantics,
e.g., integer precision

- C/C++, Java have fixed integer precision => overflow

Correctness

Def. An algorithm is *correct* if

1. it terminates;
2. it computes what its specification claims.

A useful proof technique: look for **variants** and **invariants**.

```
# Input:  x that can be multiplied
#         n nonnegative integer
# Output: x^n
def bincpow(x,n):
    if n==0: return 1
    # n>0
    tmp=bincpow(x,n//2) # n//2 < n
    # tmp = x^(n//2)
    tmp=tmp*tmp # tmp = x^(2*(n//2))
    if n%2==0: return tmp
    return tmp*x
```

} Specification

$n > 0 \Rightarrow n//2 < n$
proves termination

Correctness by
induction

(Obvious)
invariants

Correctness: a less obvious example

```
# Input:  x that can be multiplied
#         n nonnegative integer
# Output: x^n
def binpow2(x,n): # let n_0=n, x_0=x
    if n==0: return 1
    y = 1
    while n>1: # y*(x^n)=x_0^{n_0}
        if n%2==1: y *= x
        x *= x
        n //= 2
    return y*x
```

Termination:
same argument

Correctness:
invariant



Proof. In one iteration of the loop, $y * (x^n)$ becomes

$$y * (x^2)^{(n//2)} = y * (x^n) \quad \text{for even } n$$

$$y * x * (x^2)^{(n//2)} = y * (x^n) \quad \text{for odd } n$$

Termination is a very hard problem

The general problem is **undecidable**. (See CSE 203)

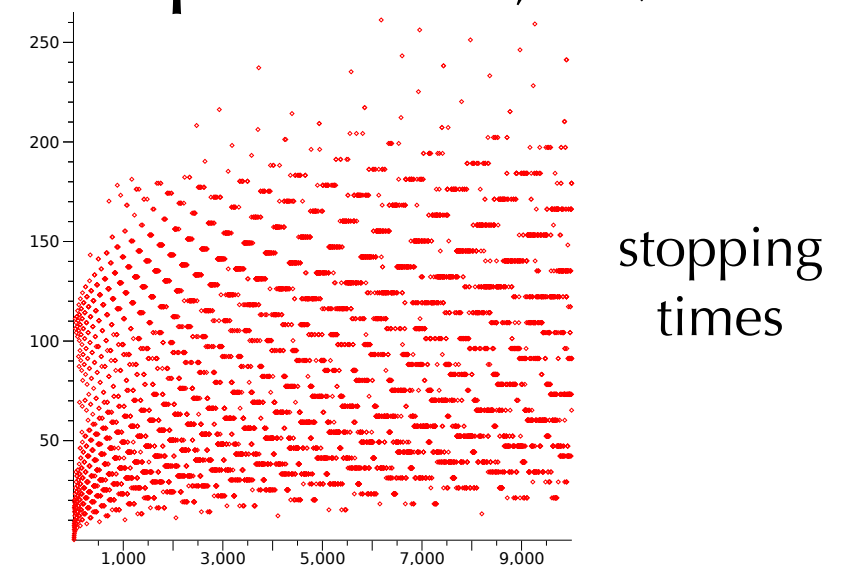
Already hard for seemingly simple programs:

```
def syracuse(n):  
    if n==1: return  
    if n%2==0: return syracuse(n//2)  
    return syracuse(3*n+1)
```

Conjecture. ($3n+1$ conjecture, Syracuse problem,...)

This program terminates.

Open since 1937!



III. Complexity

Complexity

*How long will my program take?
Do I have enough memory?*

The scientific approach:

1. Experiment for various sizes;
2. Model;
3. Analyse the model;
4. Validate with experiments;
5. If necessary, go to 2.

Experimental Determination of (Polynomial) Complexity

If the time for a computation grows like $C(n) \sim Kn^\alpha \log^p n$

then **doubling** n should take time $C(2n) \sim K2^\alpha n^\alpha \log^p n$

so that

$$\alpha \approx \log_2 \frac{C(2n)}{C(n)}.$$

Example: matrix product

n	10	20	40	80
time (s)	0,023	0,158	1,159	9,075
ln2(ratio)		2.78	2.88	2.97

```
from sympy.matrices import randMatrix
import timeit

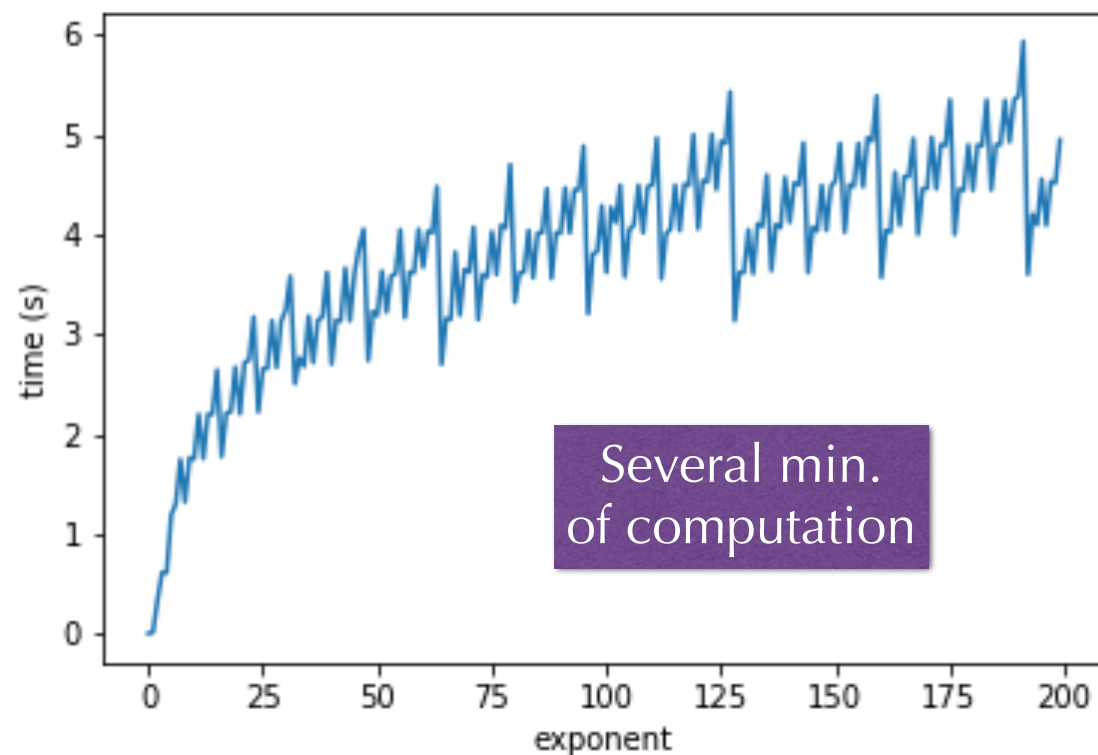
def testMatrixMul(size,nbtests):
    total = 0
    for i in range(nbtests):
        A = randMatrix(size)*1.
        B = randMatrix(size)*1.
        def doit():
            return A*B
        total += timeit.timeit(doit,number=1)
    return total/nbtests
```

suggests **cubic** complexity.

Blackboard:
3 is expected

Binary Powering 1. Model

1. Experiment



```
from sympy.matrices import randMatrix
import timeit

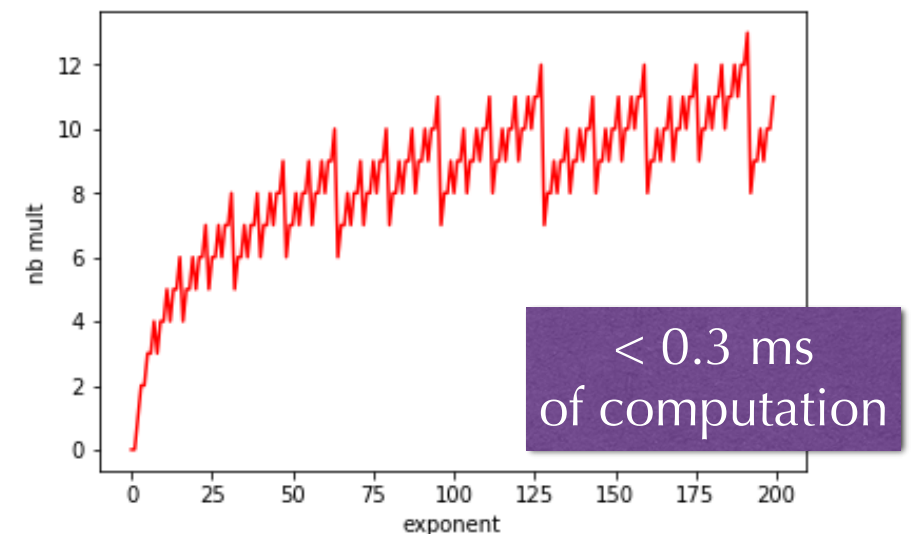
def test(size,maxpow):
    A = randMatrix(size)*1.
    val = [0 for i in range(maxpow)]
    for i in range(maxpow):
        def doit():
            return binpow(A,i)
        val[i] = timeit.timeit(doit,number=3)
    return val
```

x is a 20x20
matrix of floats

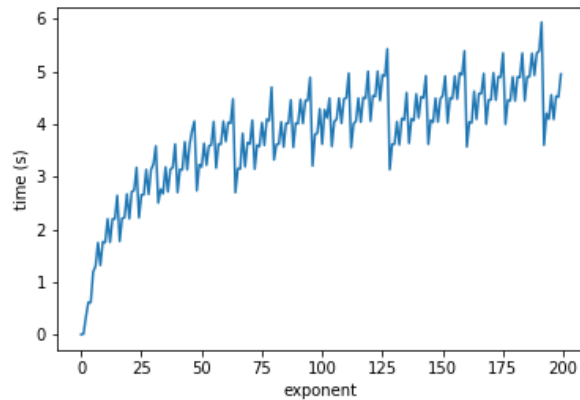
```
def binpow(x,n):
    if n==0: return 1
    if n==1: return x
    tmp=binpow(x,n//2)
    tmp=tmp*tmp
    if n%2==0: return tmp
    return tmp*x
```

2. Model: count multiplications only

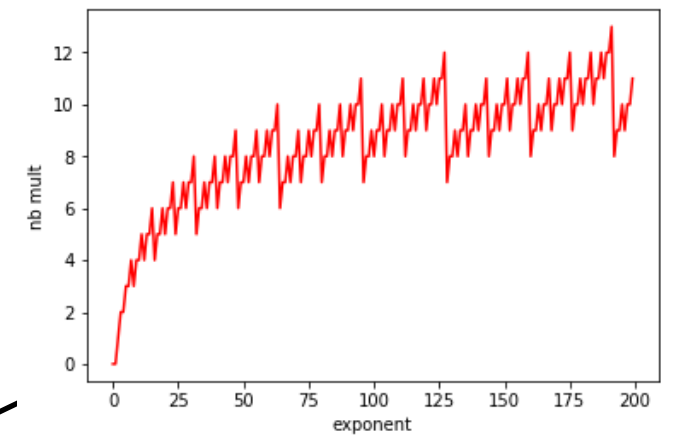
$$C(n) = \begin{cases} C(n/2) + 1, & \text{for even } n > 0 \\ C((n-1)/2) + 2, & \text{for odd } n > 1 \end{cases}$$
$$C(0) = C(1) = 0.$$



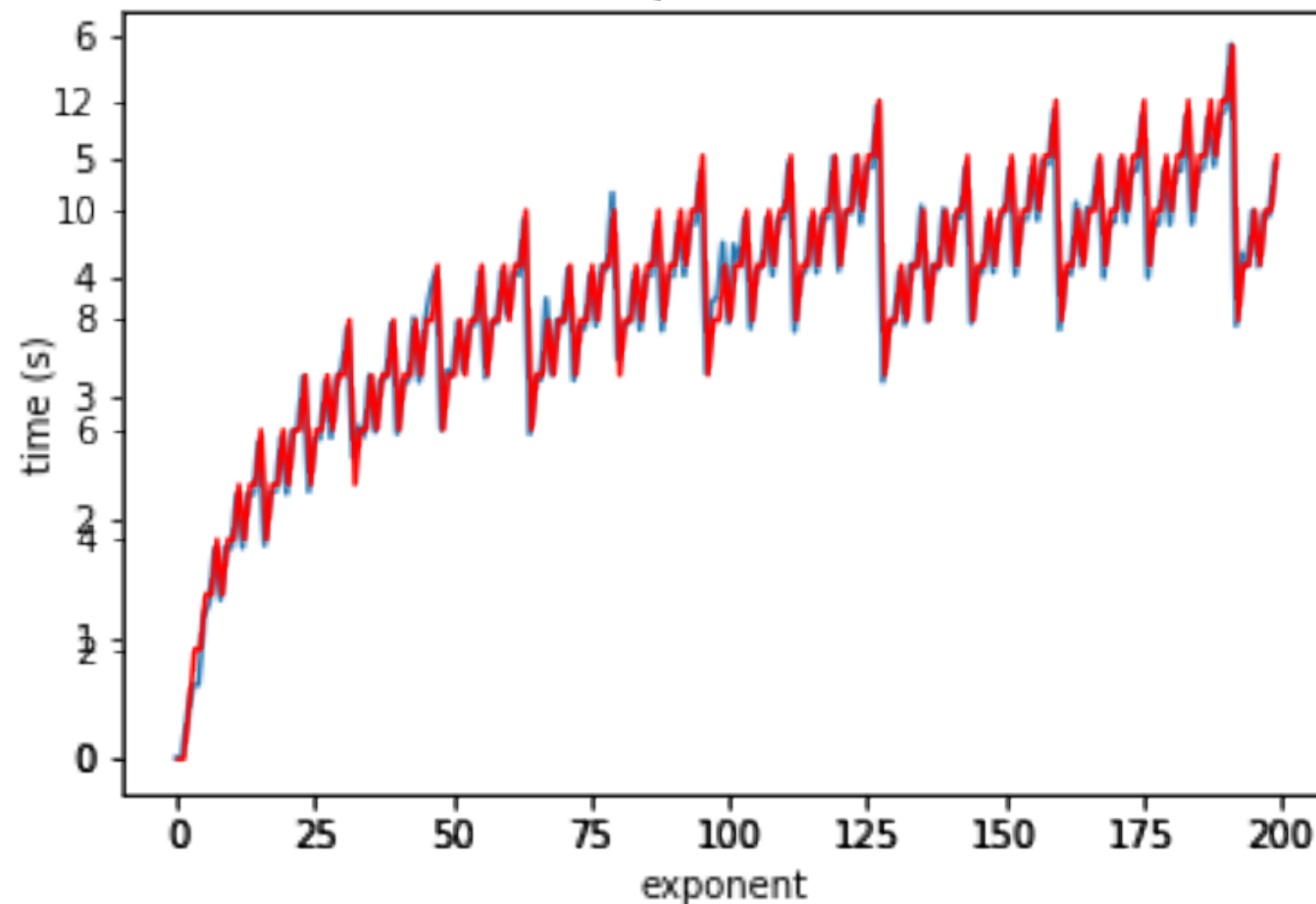
Binary Powering 2. Comparison



time



nb mult



Asymptotically,
the cost of
multiplications
dominates

Binary Powering 3. Analysis

$$C(n) = 1 + \begin{cases} C(n/2), & \text{for even } n > 0 \\ C((n-1)/2) + 1, & \text{for odd } n > 1 \end{cases} \quad \text{with } C(0) = C(1) = 0$$

Lemma. For $n \geq 1$, $C(n) = \lfloor \log_2 n \rfloor - 1 + \lambda(n)$,
where $\lambda(n)$ is the number of 1's in the binary expansion of n .

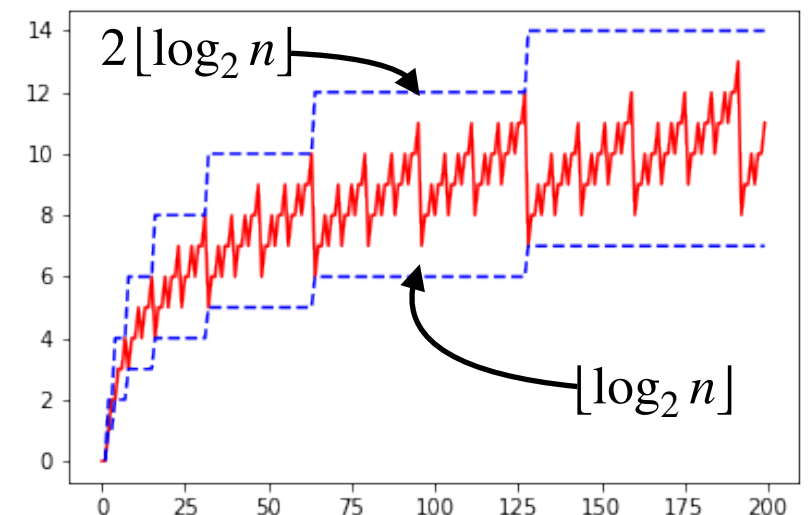
Blackboard
proof

Ex. $82 = 64 + 16 + 2 = \overline{1010010}^2 \rightarrow 6-1+3=8$ mult.

Consequence:

$$\lfloor \log_2 n \rfloor \leq C(n) \leq 2 \lfloor \log_2 n \rfloor$$

$$C(n) = O(\log n)$$



Notation

$$f(n) \sim g(n) \quad \text{means} \quad \lim_{n \rightarrow \infty} f(n)/g(n) = 1$$

Recall: $f(n) = O(g(n))$ means $\exists K \exists M \forall n \geq M, |f(n)| \leq Kg(n)$

$$f(n) = \Theta(g(n)) \quad \text{means} \quad f(n) = O(g(n)) \text{ and } g(n) = O(f(n))$$

Exs.: $\log(2n) = O(\log n)$

$$10^{10^{10}} n = O(n)$$

$$10^{10^{10}} n + n^2 = O(n^2)$$

$$n + n^2 = O(n^{20})$$

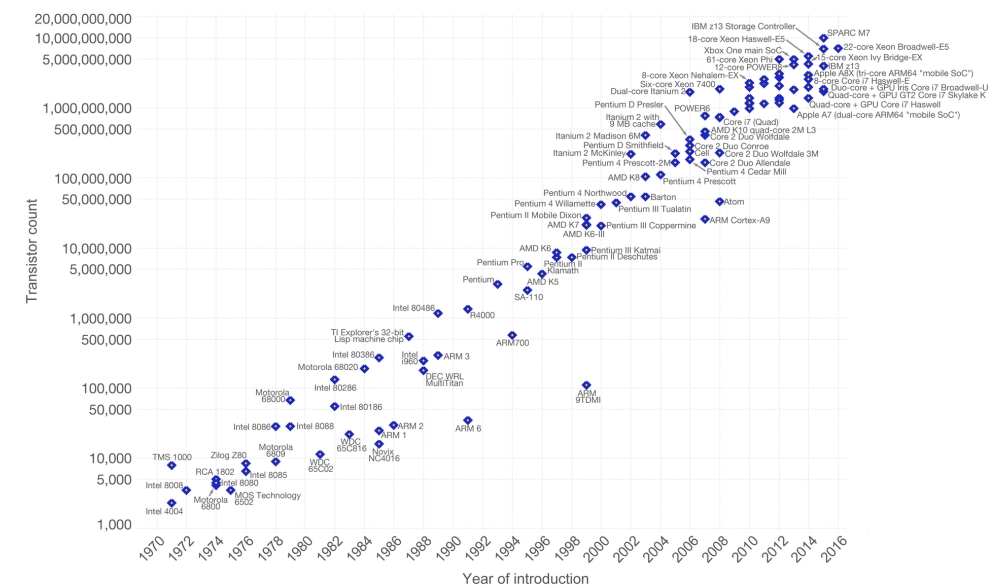
Moore's "law"

Gordon Moore, co-founder of Intel, predicted in 1965 that the number of transistors on integrated circuits would double every year for 10 years.

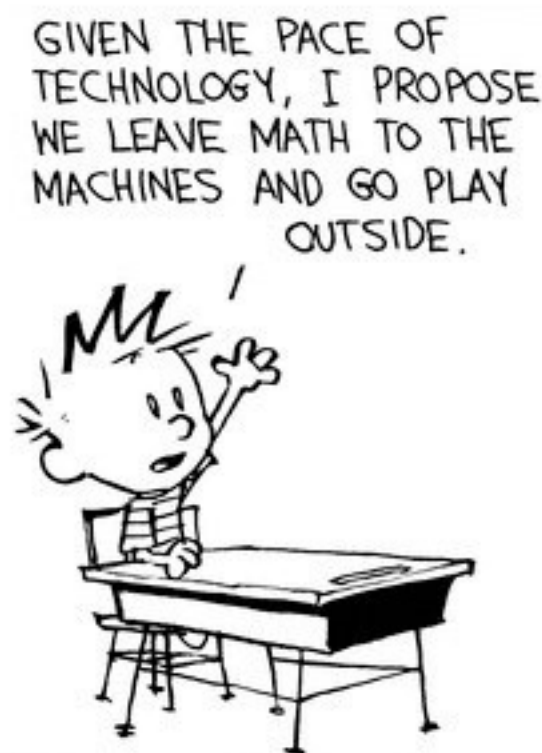
Moore's Law – The number of transistors on integrated circuit chips (1971-2016)

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important as other aspects of technological progress – such as processing speed or the price of electronic products – are strongly linked to Moore's law.



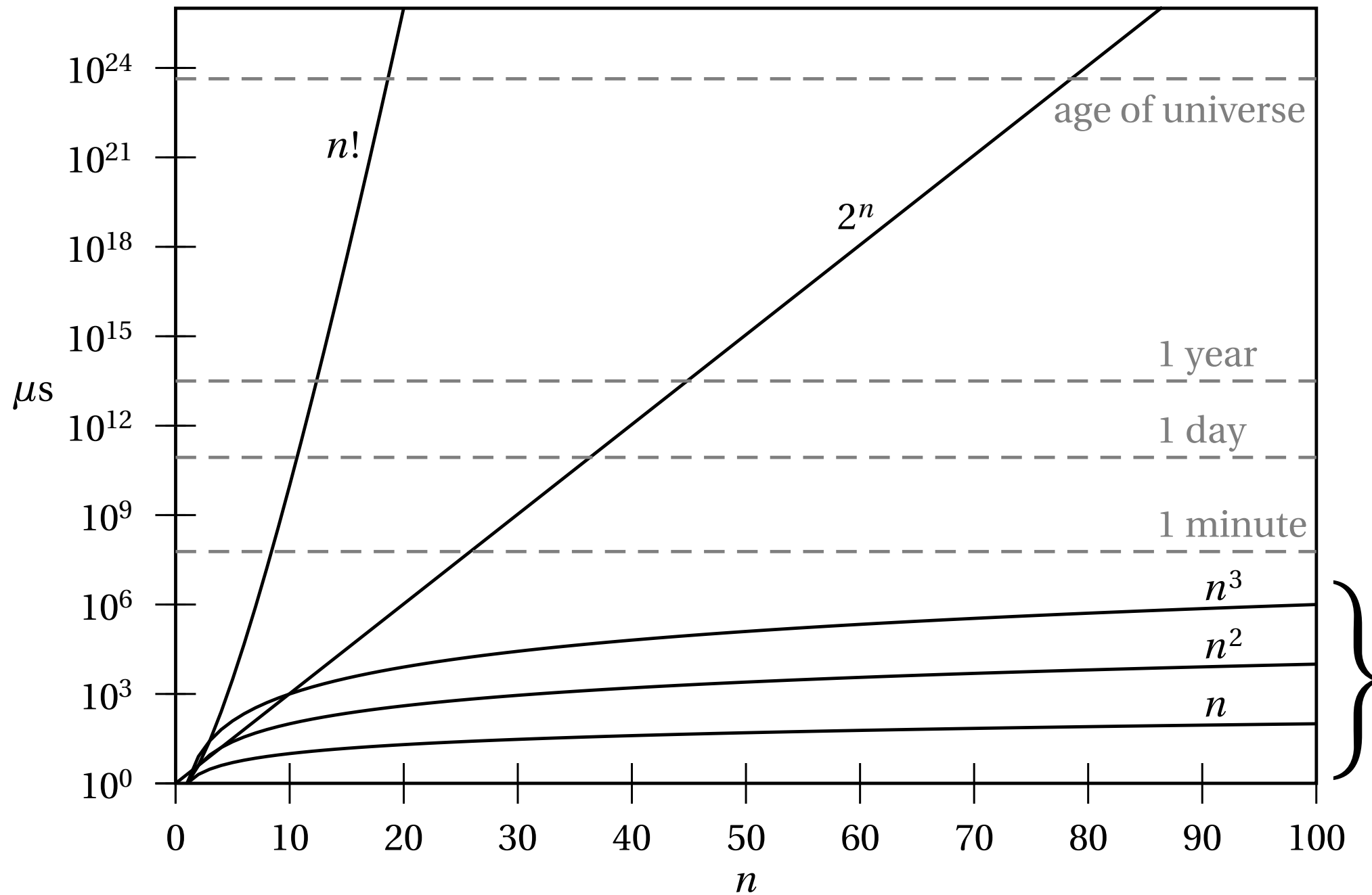


Data source: Wikipedia (https://en.wikipedia.org/wiki/Transistor_count)
The data visualization is available at [OurWorldinData.org](https://ourworldindata.org). There you find more visualizations and research on this topic.



The expression Moore's "law" is commonly used to mean that the speed and memory of computers is expected to **double every 18 months**.

Orders of Growth



This is
where we
want to be

Moore's "law" means a small vertical shift from one machine to the next

Picture due to Moore & Mertens (2011).

IV. Lower Bounds

Complexity of a Problem

Def. The *complexity of a problem* is that of the most efficient (possibly unknown) algorithm that solves it.

Ex. **Sorting** n elements has complexity $O(n \log n)$ comparisons.

Proof. Mergesort (CSE103) reaches the bound.

```
def mergesort(l):  
    if len(l) <= 1:  
        return l  
    else:  
        l1 = first half of l  
        l2 = second half of l  
        return merge(mergesort(l1), mergesort(l2))
```

Ex. **Sorting** n elements has complexity $\Theta(n \log n)$ comparisons.

Proof. k comparisons cannot distinguish more than 2^k permutations and $\log_2 n! \sim n \log_2 n$.

Complexity of Powering

$$(x, n) \in \mathbb{A} \times \mathbb{N} \mapsto x^n \in \mathbb{A}$$

We already know it is $O(\log n)$ multiplications in \mathbb{A} .

Can this be improved?

Lower bounds on the complexity require a precise definition (a **model**) of what operations the “most efficient” algorithm can perform.

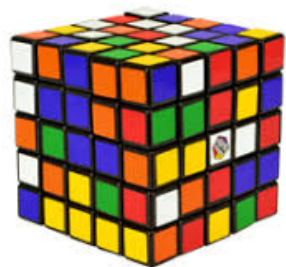
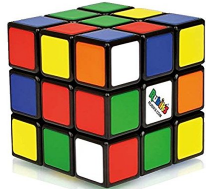
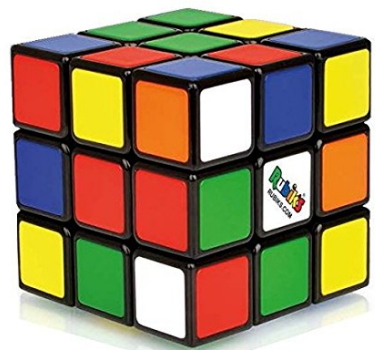
Ex. If the only available operation in \mathbb{A} is multiplication, x^{2^k} requires k multiplications, so that $\log_2 n$ is a lower bound.

Ex. In floating point arithmetic, $x^n = \exp(n \log x)$ and the complexity hardly depends on n .

Complexity of a Problem

Ex. Rubik's 3x3x3 cube has complexity $O(1)$.

Proof. Store the solutions of each of the *finitely* many configurations, and look them up.



... would be a better problem.

Simple Lower Bounds

In most useful models, reading the input and writing the output take time. Then,

$$\text{size(Input)} + \text{size(Output)} \leq \text{complexity.}$$

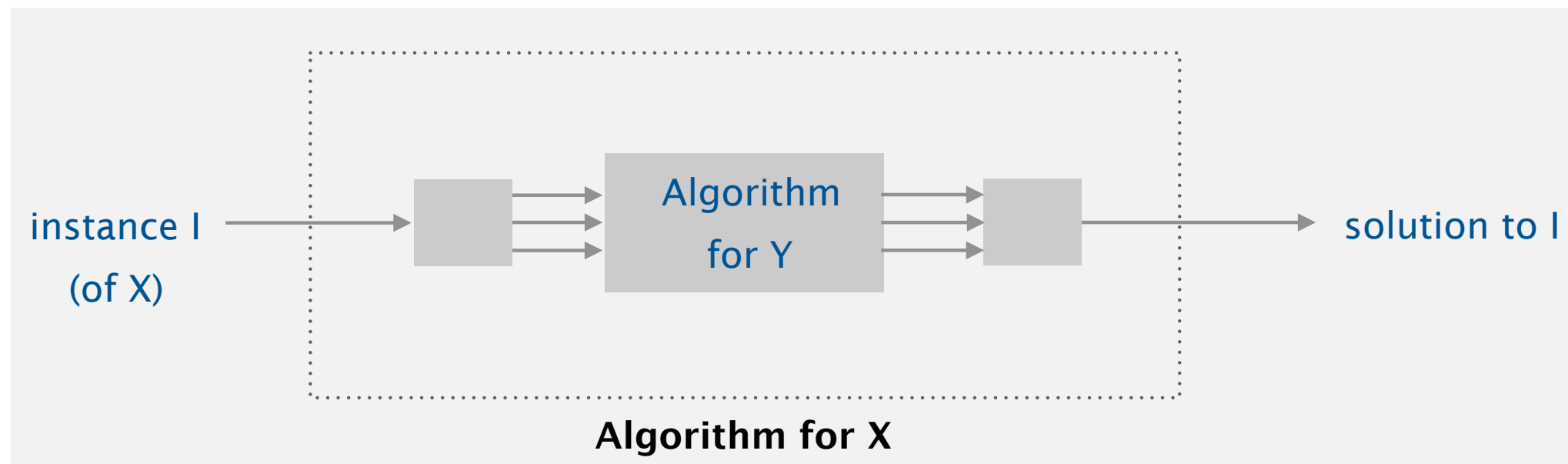
Examples:

Problem	Input	Simple Lower Bound	Best known algorithm	Measure
Sorting	n elts	n	$O(n \log n)$	comparisons
Polynomial multiplication	degree n	n	$O(n \log n)$	ops on coeffs
Matrix multiplication	size n x n	n^2	$O(n^{2.373})$	ops on coeffs
Subset sum	n integers	n	$2^{O(n)}$	time

V. Reductions

Reduction

Problem X **reduces to** problem Y if you can use an algorithm that solves Y to help solve X



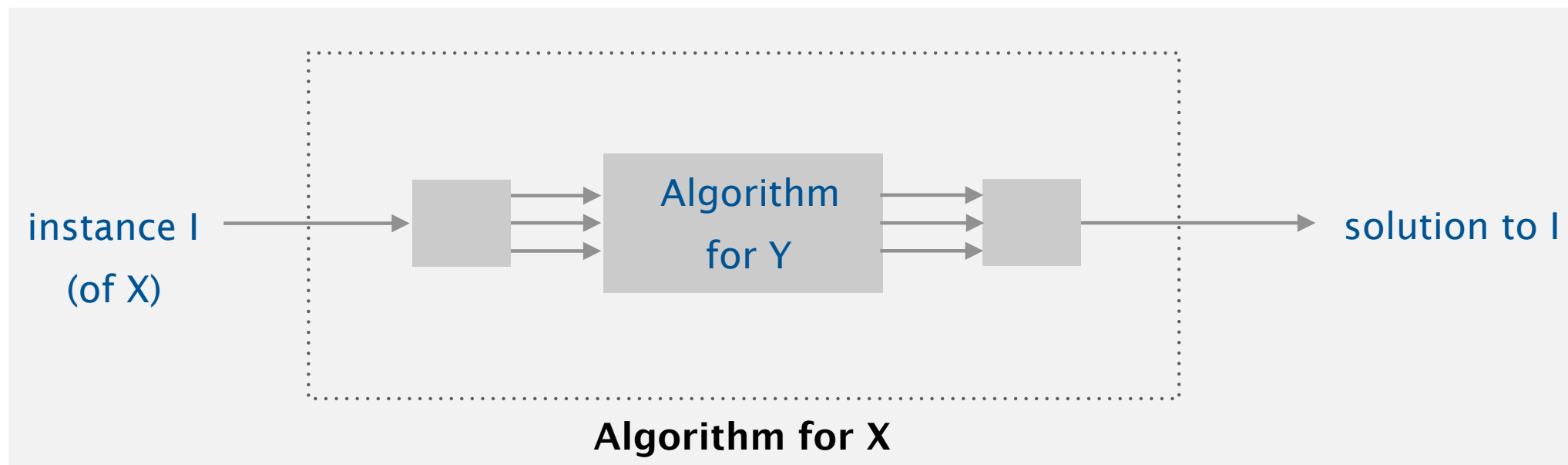
Complexity of solving X = complexity of solving Y + cost of the reduction

↑
perhaps many calls to Y on instances of
different sizes (typically, only one call)

↑
preprocessing and postprocessing
(typically, less than the cost of solving Y)

Reduction

Problem X **reduces to** problem Y if you can use an algorithm that solves Y to help solve X



Ex. [powering x^n reduces to multiplication]

Binary Powering algorithm

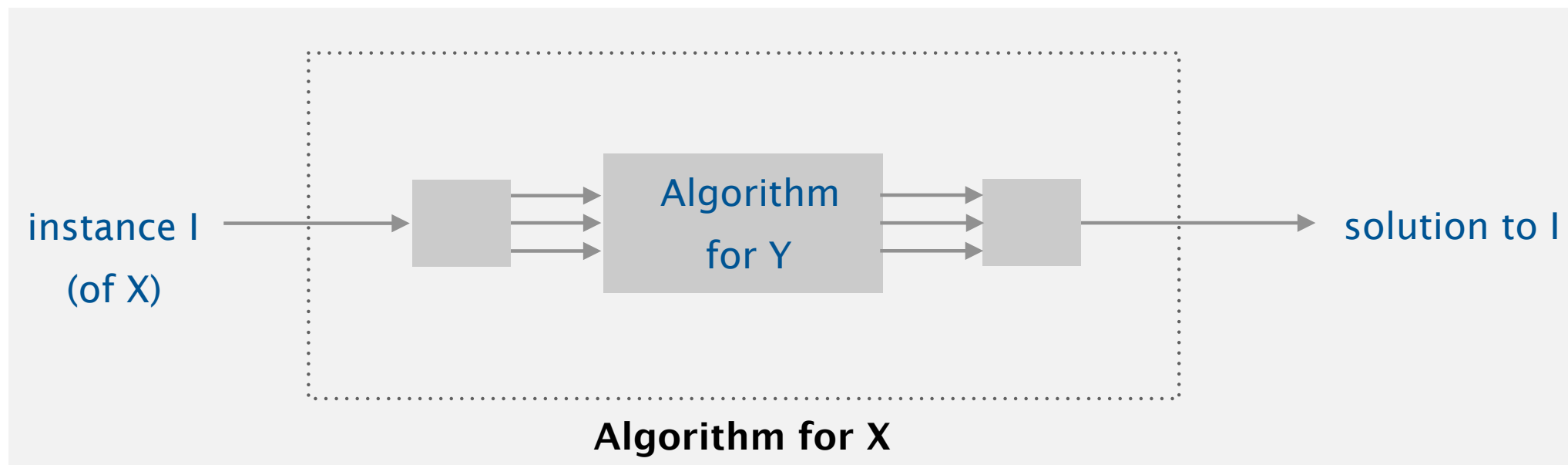
Complexity: $O(\log n)$ * complexity of multiplication



discussed next week

Reduction

Problem X **reduces to** problem Y if you can use an algorithm that solves Y to help solve X



Ex. [finding the median of N items (the value separating the higher half from the lower half) reduces to sorting]

To find the median of N items:

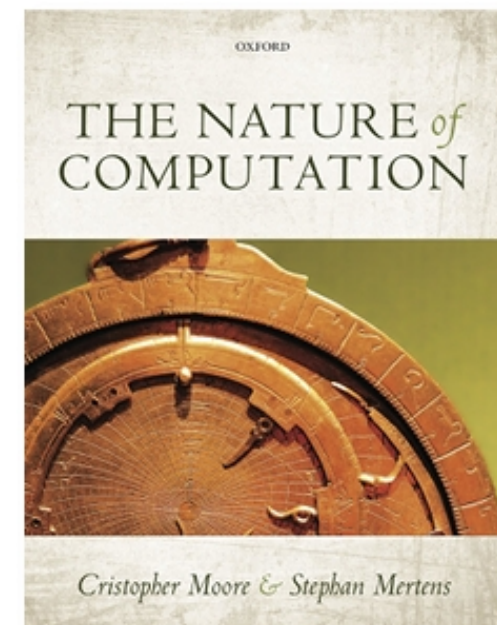
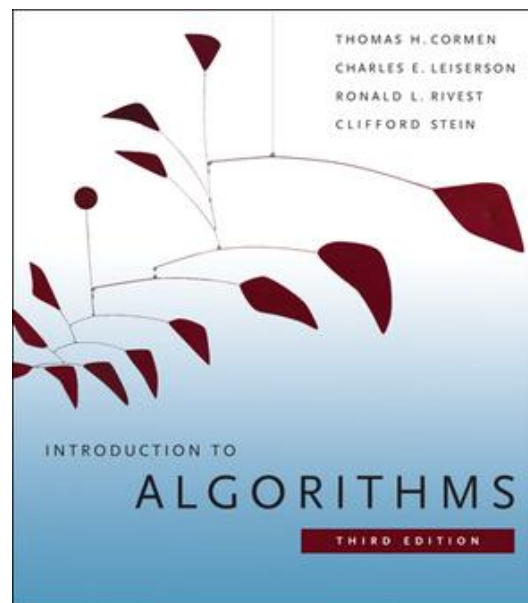
- Sort N items
- Return item in the middle

Complexity: $N \log N + 1$ (cost of sorting + cost of reduction)

References

The slides are designed to be self-contained.

They were prepared using the following books that I recommend if you want to learn more:



Next

Assignment this week: optimal powering

Next tutorial: fast powering via addition chains

Next week: fast multiplication

Feedback

Moodle

Questions: constantin.enea@polytechnique.edu