

# Part II

## Foundations

# Vocabularies

$a \cdot b$  “ $a$  times  $b$ ”

“ $a$  multiplied by  $b$ ”

“ $a$  into  $b$ ”

$\frac{a}{b}$  “ $a$  divided by  $b$ ”

“ $a$  by  $b$ ”

“ $a$  over  $b$ ”

( $a$ : numerator (Zähler),  $b$ : denominator (Nenner))

$a^b$  “ $a$  raised to the  $b$ -th power”

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$$f : X \rightarrow Y, x \mapsto x^2$$

$f$  is a function that maps from **domain** (Definitionsbereich)  $X$  to **codomain** (Zielmenge)  $Y$ . The set  $\{y \in Y \mid \exists x \in X : f(x) = y\}$  is the **image** or the **range** of the function (Bildbereich/Wertebereich).

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## 3 Goals

- ▶ Gain knowledge about efficient algorithms for important problems, i.e., learn how to solve certain types of problems efficiently.
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## 1 What do you measure?

- ▶ **Memory requirement**
- ▶ Running time
- ▶ Number of comparisons
- ▶ Number of multiplications
- ▶ Number of hard-disc accesses
- ▶ Program size
- ▶ Power consumption
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# 4 Modelling Issues

## How do you measure?

- ▶ Implementing and testing on representative inputs
  - ▶ How do you choose your inputs?
  - ▶ May be very time-consuming.
  - ▶ Very reliable results if done correctly.
  - ▶ Results only hold for a specific machine and for a specific set of inputs.

- ▶ Theoretical analysis in a specific **model of computation**.

Ques: How many comparisons does this algorithm always take?

Ans:  $n^2 - n + 1$  comparisons. (This is a worst case analysis.)

Typically focuses on the

Can this lower bound also be comparison-based sorting algorithm needs at least  $\frac{n \log n}{2}$  comparisons in the worst case.

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Ques: How many comparisons does this algorithm always take?

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Can this lower bound be any comparison-based sorting algorithm needs at least  $\log_2(n!)$  comparisons in the worst case.

What's next?

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Ques: How long will the Tims algorithm always run in the worst case?

Typical answer:  $O(n^2)$

Can this lower bound be very computer-implementation dependent?  
Algorithm needs at least  $n$  comparisons in the worst case.

Wrong case!

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Quick question: How many times does this algorithm always run in  $\Theta(n^2)$ ?

Typical answer:  $\Theta(n^2)$ .

Can this lower bound be improved by using a more sophisticated sorting algorithm such as merge sort? What happens if the input is sorted?

Wrong again!



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### Input length

The theoretical bounds are usually given by a function  $f: \mathbb{N} \rightarrow \mathbb{N}$  that maps the **input length** to the running time (or storage space, comparisons, multiplications, program size etc.).

The **input length** may e.g. be

the size of the input (number of bits)

the number of arguments

the number of nodes in the input tree

the number of nodes in the input graph

the number of nodes in the input DAG

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### Example 1

Suppose  $n$  numbers from the interval  $\{1, \dots, N\}$  have to be sorted. In this case we usually say that the input length is  $n$  instead of e.g.  $n \log N$ , which would be the number of bits required to encode the input.



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## How to measure performance

1. Calculate running time and storage space etc. on a simplified, idealized model of computation, e.g. Random Access Machine (RAM), Turing Machine (TM), . . .
2. Calculate number of certain basic operations: comparisons, multiplications, harddisc accesses, . . .

Version 2. is often easier, but focusing on one type of operation makes it more difficult to obtain meaningful results.

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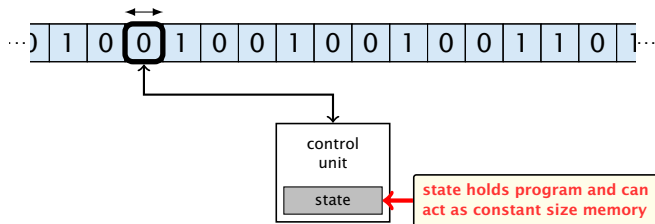
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# Turing Machine

- ▶ Very simple model of computation.
- ▶ Only the “current” memory location can be altered.
- ▶ Very good model for discussing computability, or polynomial vs. exponential time.
- ▶ Some simple problems like recognizing whether input is of the form  $x^x$ , where  $x$  is a string, have quadratic lower bound.

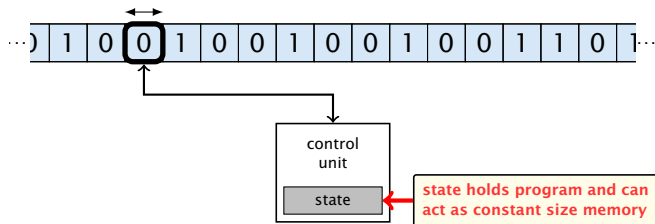
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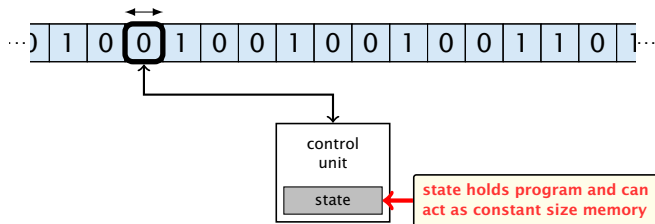




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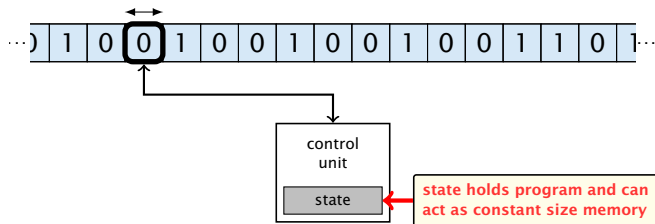
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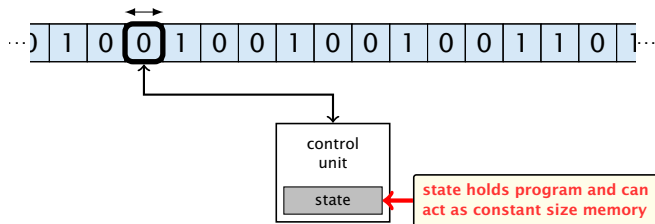
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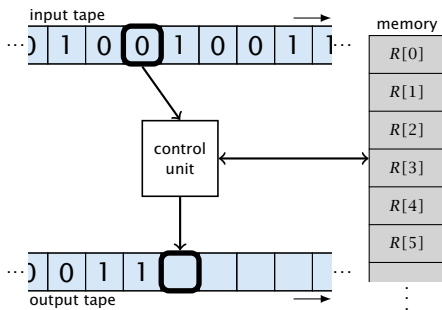
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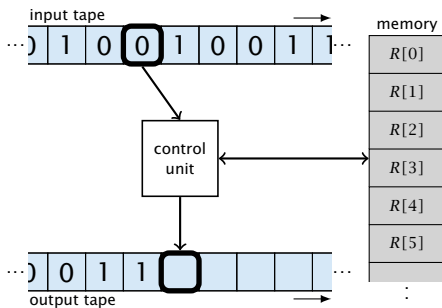
# Random Access Machine (RAM)

- ▶ Input tape and output tape (sequences of zeros and ones; unbounded length).
- ▶ Memory unit: infinite but countable number of registers  $R[0], R[1], R[2], \dots$
- ▶ Registers hold integers.
- ▶ Indirect addressing.



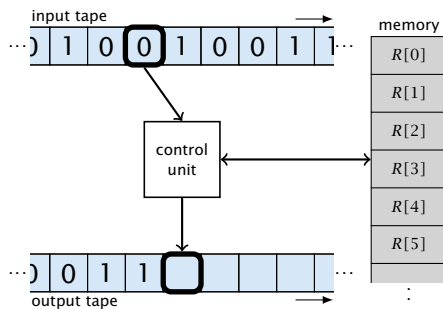
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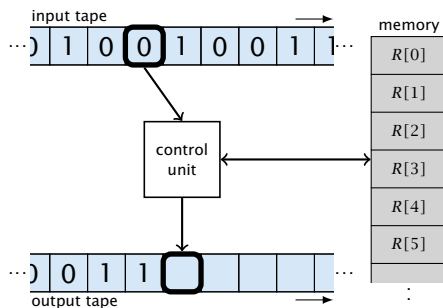
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- ▶ register-register transfers
  - ▶  $R[j] := R[i]$
  - ▶  $R[j] := 4$
- ▶ **indirect** addressing
  - ▶  $R[j] := R[R[i]]$   
loads the content of the  $R[i]$ -th register into the  $j$ -th register
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Every operation takes time 1.

- ▶ **logarithmic** cost model

The cost depends on the content of memory cells:

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**Bounded word RAM model:** cost is uniform but the largest value stored in a register may not exceed  $2^w$ , where usually  $w = \log_2 n$ .



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3. People write e.g.  $h(n) = f(n) + o(g(n))$  when they mean that there exists a function  $z: \mathbb{N} \rightarrow \mathbb{R}^+, n \mapsto z(n), z \in o(g)$  such that  $h(n) = f(n) + z(n)$ .
4. People write  $\mathcal{O}(f(n)) = \mathcal{O}(g(n))$ , when they mean  $\mathcal{O}(f(n)) \subseteq \mathcal{O}(g(n))$ . Again this is not an equality.

# Asymptotic Notation in Equations

How do we interpret an expression like:

$$2n^2 + 3n + 1 = 2n^2 + \Theta(n)$$

Here,  $\Theta(n)$  stands for an **anonymous function** in the set  $\Theta(n)$  that makes the expression true.

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How do we interpret an expression like:

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How do we interpret an expression like:

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Careful!

“It is understood” that every occurrence of an  $\Theta$ -symbol (or  $\Theta, \Omega, o, \omega$ ) on the left represents *one anonymous function*.

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# Asymptotic Notation in Equations

We can view an expression containing asymptotic notation as generating a set:

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n)$$

represents

$$\left\{ f : \mathbb{N} \rightarrow \mathbb{R}^+ \mid f(n) = n^2 \cdot g(n) + h(n) \right. \\ \left. \text{with } g(n) \in \mathcal{O}(n) \text{ and } h(n) \in \mathcal{O}(\log n) \right\}$$

# Asymptotic Notation in Equations

Then an asymptotic equation can be interpreted as containment btw. two sets:

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n) = \Theta(n^2)$$

represents

$$n^2 \cdot \mathcal{O}(n) + \mathcal{O}(\log n) \subseteq \Theta(n^2)$$

# Asymptotic Notation

## Lemma 3

Let  $f, g$  be functions with the property

$\exists n_0 > 0 \forall n \geq n_0 : f(n) > 0$  (the same for  $g$ ). Then

- ▶  $c \cdot f(n) \in \Theta(f(n))$  for any constant  $c$
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- ▶ Do not use asymptotic notation within induction proofs.
- ▶ For any constants  $a, b$  we have  $\log_a n = \Theta(\log_b n)$ .  
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- ▶ If the running time analysis is tight and actually occurs in practise (i.e., the asymptotic bound is not a purely theoretical worst-case bound), then the algorithm that has better asymptotic running time will always outperform a weaker algorithm for large enough values of  $n$ .
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## 6 Recurrences

### Algorithm 2 mergesort(list $L$ )

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1:  $n \leftarrow \text{size}(L)$ 
2: if  $n \leq 1$  return  $L$ 
3:  $L_1 \leftarrow L[1 \cdots \lfloor \frac{n}{2} \rfloor]$ 
4:  $L_2 \leftarrow L[\lfloor \frac{n}{2} \rfloor + 1 \cdots n]$ 
5: mergesort( $L_1$ )
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7:  $L \leftarrow \text{merge}(L_1, L_2)$ 
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This algorithm requires

$$T(n) = T\left(\left\lceil \frac{n}{2} \right\rceil\right) + T\left(\left\lfloor \frac{n}{2} \right\rfloor\right) + \mathcal{O}(n) \leq 2T\left(\left\lceil \frac{n}{2} \right\rceil\right) + \mathcal{O}(n)$$

comparisons when  $n > 1$  and 0 comparisons when  $n \leq 1$ .

# Recurrences

How do we bring the expression for the number of comparisons ( $\approx$  running time) into a **closed form**?

For this we need to **solve** the recurrence.

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# Methods for Solving Recurrences

## 1. Guessing+Induction

Guess the right solution and prove that it is correct via induction. It needs experience to make the right guess.

## 2. Master Theorem

For a lot of recurrences that appear in the analysis of algorithms this theorem can be used to obtain tight asymptotic bounds. It does not provide exact solutions.

## 3. Characteristic Polynomial

Linear homogenous recurrences can be solved via this method.



## 4. Generating Functions

A more general technique that allows to solve certain types of linear inhomogenous relations and also sometimes non-linear recurrence relations.

## 5. Transformation of the Recurrence

Sometimes one can transform the given recurrence relations so that it e.g. becomes linear and can therefore be solved with one of the other techniques.

## 6.1 Guessing+Induction

First we need to get rid of the  $\mathcal{O}$ -notation in our recurrence:

$$T(n) \leq \begin{cases} 2T(\lceil \frac{n}{2} \rceil) + cn & n \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

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One way of solving such a recurrence is to **guess** a solution, and check that it is correct by plugging it in.

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Formally one would make an induction proof, where the above is the induction step. The base case is usually trivial.

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$$\begin{aligned} T(n) &\leq 2T\left(\frac{n}{2}\right) + cn \\ &\leq 2\left(d\frac{n}{2} \log \frac{n}{2}\right) + cn \\ &= dn(\log n - 1) + cn \\ &= dn \log n + (c - d)n \\ &\leq dn \log n \end{aligned}$$

Hence, statement is **true** if we choose  $d \geq c$ .



## 6.1 Guessing+Induction

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If we do not do this we instead consider the following recurrence:

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Note that we can do this as for constant-sized inputs the running time is always some constant ( $b$  in the above case).

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We also make a guess of  $T(n) \leq dn \log n$  and get

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$$\boxed{\left\lceil \frac{n}{2} \right\rceil \leq \frac{n}{2} + 1} \leq 2(d(n/2 + 1) \log(n/2 + 1)) + cn$$



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$$\boxed{\left\lceil \frac{n}{2} \right\rceil \leq \frac{n}{2} + 1} \leq 2\left(d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right)\right) + cn$$

$$\boxed{\frac{n}{2} + 1 \leq \frac{9}{16}n} \leq dn \log\left(\frac{9}{16}n\right) + 2d \log n + cn$$

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$$\frac{n}{2} + 1 \leq \frac{9}{16}n$$

$$\leq dn \log\left(\frac{9}{16}n\right) + 2d \log n + cn$$

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$$= dn \log n + (\log 9 - 4)dn + 2d \log n + cn$$

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$$\frac{n}{2} + 1 \leq \frac{9}{16}n$$

$$\log \frac{9}{16}n = \log n + (\log 9 - 4)$$

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$$\left\lceil \frac{n}{2} \right\rceil \leq \frac{n}{2} + 1$$

$$\leq 2\left(d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right)\right) + cn$$

$$\frac{n}{2} + 1 \leq \frac{9}{16}n$$

$$\leq dn \log\left(\frac{9}{16}n\right) + 2d \log n + cn$$

$$\log \frac{9}{16}n = \log n + (\log 9 - 4)$$

$$= dn \log n + (\log 9 - 4)dn + 2d \log n + cn$$

$$\log n \leq \frac{n}{4}$$

$$\leq dn \log n + (\log 9 - 3.5)dn + cn$$

## 6.1 Guessing+Induction

We also make a guess of  $T(n) \leq dn \log n$  and get

$$T(n) \leq 2T\left(\left\lceil \frac{n}{2} \right\rceil\right) + cn$$

$$\leq 2\left(d\left\lceil \frac{n}{2} \right\rceil \log \left\lceil \frac{n}{2} \right\rceil\right) + cn$$

$$\left\lceil \frac{n}{2} \right\rceil \leq \frac{n}{2} + 1$$

$$\leq 2\left(d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right)\right) + cn$$

$$\frac{n}{2} + 1 \leq \frac{9}{16}n$$

$$\leq dn \log\left(\frac{9}{16}n\right) + 2d \log n + cn$$

$$\log \frac{9}{16}n = \log n + (\log 9 - 4)$$

$$= dn \log n + (\log 9 - 4)dn + 2d \log n + cn$$

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$$\leq dn \log n - 0.33dn + cn$$

## 6.1 Guessing+Induction

We also make a guess of  $T(n) \leq dn \log n$  and get

$$\begin{aligned}T(n) &\leq 2T\left(\left\lceil \frac{n}{2} \right\rceil\right) + cn \\&\leq 2\left(d\left\lceil \frac{n}{2} \right\rceil \log \left\lceil \frac{n}{2} \right\rceil\right) + cn \\&\leq 2\left(d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right)\right) + cn \\&\leq dn \log\left(\frac{9}{16}n\right) + 2d \log n + cn \\&= dn \log n + (\log 9 - 4)dn + 2d \log n + cn \\&\leq dn \log n + (\log 9 - 3.5)dn + cn \\&\leq dn \log n - 0.33dn + cn \\&\leq dn \log n\end{aligned}$$

for a suitable choice of  $d$ .



## 6.2 Master Theorem

### Lemma 4

Let  $a \geq 1$ ,  $b \geq 1$  and  $\epsilon > 0$  denote constants. Consider the recurrence

$$T(n) = aT\left(\frac{n}{b}\right) + f(n) .$$

#### Case 1.

If  $f(n) = \mathcal{O}(n^{\log_b(a)-\epsilon})$  then  $T(n) = \Theta(n^{\log_b a})$ .

#### Case 2.

If  $f(n) = \Theta(n^{\log_b(a)} \log^k n)$  then  $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$ ,  
 $k \geq 0$ .

#### Case 3.

If  $f(n) = \Omega(n^{\log_b(a)+\epsilon})$  and for sufficiently large  $n$   
 $af\left(\frac{n}{b}\right) \leq cf(n)$  for some constant  $c < 1$  then  $T(n) = \Theta(f(n))$ .

## 6.2 Master Theorem

We prove the Master Theorem for the case that  $n$  is of the form  $b^{\ell}$ , and we assume that the non-recursive case occurs for problem size 1 and incurs cost 1.

# The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:

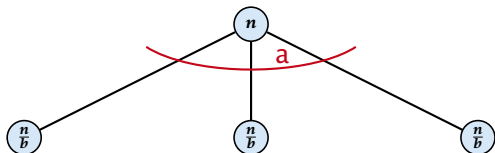
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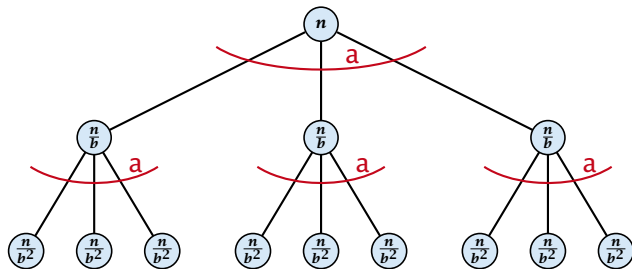
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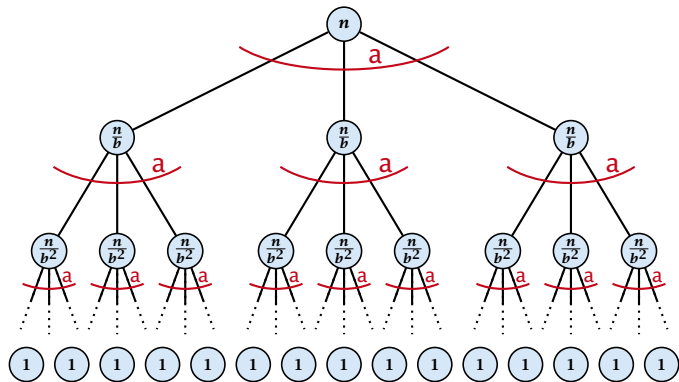
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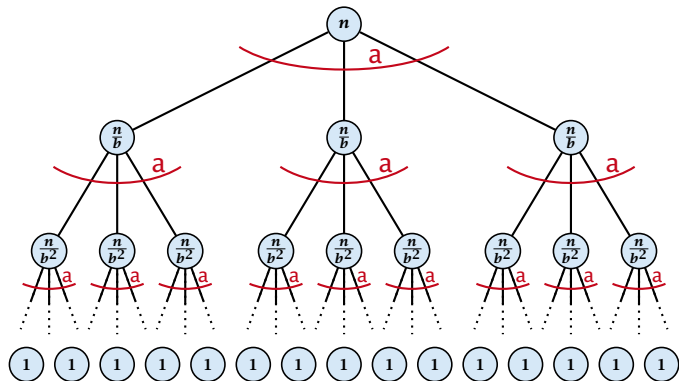
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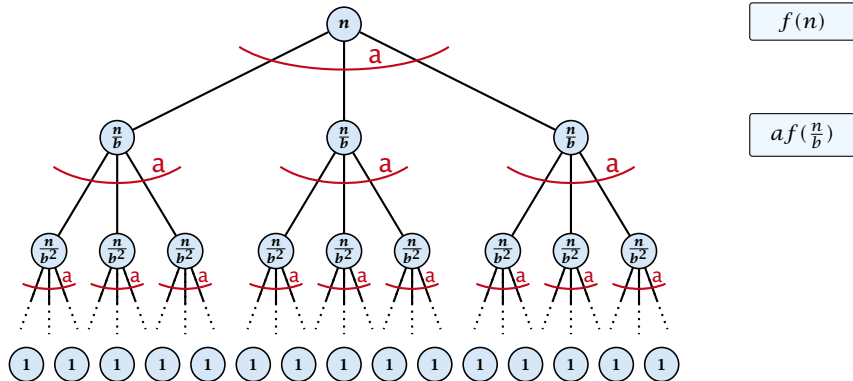
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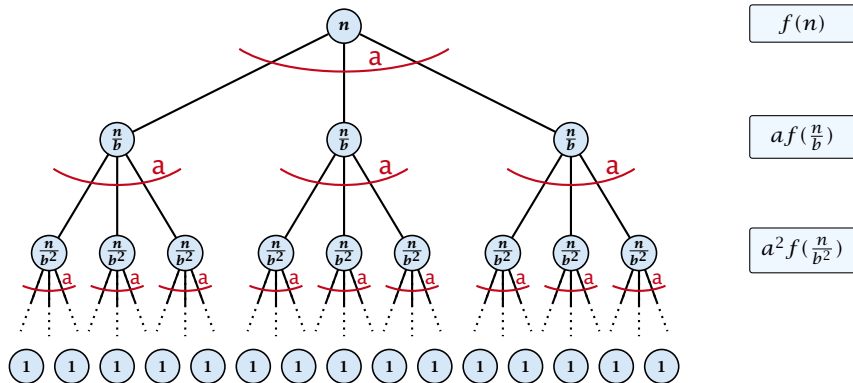
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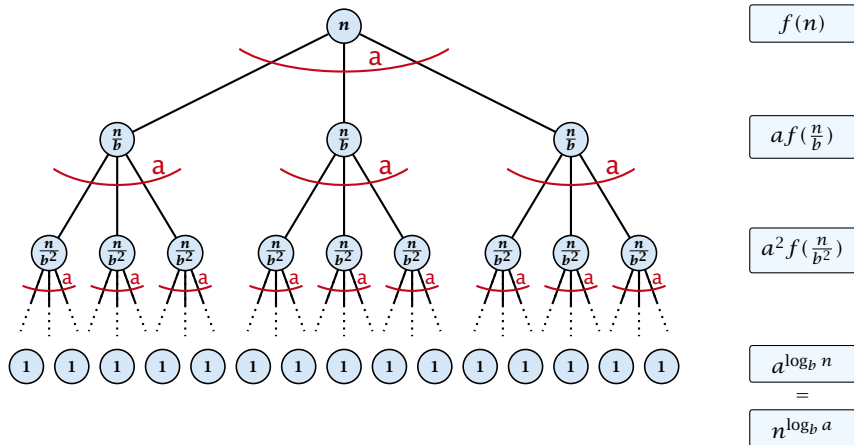
The running time of a recursive algorithm can be visualized by a recursion tree:





# The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:



## 6.2 Master Theorem

This gives

$$T(n) = n^{\log_b a} + \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right).$$

Case 1. Now suppose that  $f(n) \leq cn^{\log_b a - \epsilon}$ .

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$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$



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$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \end{aligned}$$

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$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}$$

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$$\boxed{b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}} = cn^{\log_b a - \epsilon} \sum_{i=0}^{\log_b n - 1} (b^{\epsilon})^i$$

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$$\boxed{\sum_{i=0}^k q^i = \frac{q^{k+1} - 1}{q - 1}}$$

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$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i} \quad = cn^{\log_b a - \epsilon} \sum_{i=0}^{\log_b n - 1} (b^{\epsilon})^i$$

$$\sum_{i=0}^k q^i = \frac{q^{k+1} - 1}{q - 1} \quad = cn^{\log_b a - \epsilon} (b^{\epsilon \log_b n} - 1) / (b^{\epsilon} - 1)$$

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$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \end{aligned}$$

$$\begin{aligned} \boxed{b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}} &= cn^{\log_b a - \epsilon} \sum_{i=0}^{\log_b n - 1} (b^{\epsilon})^i \\ \boxed{\sum_{i=0}^k q^i = \frac{q^{k+1} - 1}{q - 1}} &= cn^{\log_b a - \epsilon} (b^{\epsilon \log_b n} - 1) / (b^{\epsilon} - 1) \\ &= cn^{\log_b a - \epsilon} (n^{\epsilon} - 1) / (b^{\epsilon} - 1) \end{aligned}$$

Case 1. Now suppose that  $f(n) \leq cn^{\log_b a - \epsilon}$ .

$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \end{aligned}$$

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Case 1. Now suppose that  $f(n) \leq cn^{\log_b a - \epsilon}$ .

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Hence,

$$T(n) \leq \left( \frac{c}{b^{\epsilon} - 1} + 1 \right) n^{\log_b(a)}$$



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$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \end{aligned}$$

$$\begin{aligned} b^{-i(\log_b a - \epsilon)} &= b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i} \\ &= cn^{\log_b a - \epsilon} \sum_{i=0}^{\log_b n - 1} (b^\epsilon)^i \\ \sum_{i=0}^k q^i &= \frac{q^{k+1} - 1}{q - 1} \\ &= cn^{\log_b a - \epsilon} (b^{\epsilon \log_b n} - 1) / (b^\epsilon - 1) \\ &= cn^{\log_b a - \epsilon} (n^\epsilon - 1) / (b^\epsilon - 1) \\ &= \frac{c}{b^\epsilon - 1} n^{\log_b a} (n^\epsilon - 1) / (n^\epsilon) \end{aligned}$$

Hence,

$$T(n) \leq \left( \frac{c}{b^\epsilon - 1} + 1 \right) n^{\log_b a} \quad \Rightarrow T(n) = \mathcal{O}(n^{\log_b a}).$$

Case 2. Now suppose that  $f(n) \leq cn^{\log_b a}$ .

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Hence,

$$T(n) = \mathcal{O}(n^{\log_b a} \log_b n)$$



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Hence,

$$T(n) = \mathcal{O}(n^{\log_b a} \log_b n)$$

$$\Rightarrow T(n) = \mathcal{O}(n^{\log_b a} \log n).$$

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Hence,

$$T(n) = \Omega(n^{\log_b a} \log_b n)$$



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Hence,

$$T(n) = \Omega(n^{\log_b a} \log_b n) \quad \Rightarrow T(n) = \Omega(n^{\log_b a} \log n).$$

Case 2. Now suppose that  $f(n) \leq cn^{\log_b a} (\log_b(n))^k$ .

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

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$$\begin{aligned} T(n) - n^{\log_b a} &= \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\ &\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b\left(\frac{n}{b^i}\right)\right)^k \end{aligned}$$

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$n = b^\ell \Rightarrow \ell = \log_b n$
--

$$= cn^{\log_b a} \sum_{i=0}^{\ell-1} \left(\log_b\left(\frac{b^\ell}{b^i}\right)\right)^k$$

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$$n = b^\ell \Rightarrow \ell = \log_b n$$

$$\begin{aligned} &= cn^{\log_b a} \sum_{i=0}^{\ell-1} \left(\log_b\left(\frac{b^\ell}{b^i}\right)\right)^k \\ &= cn^{\log_b a} \sum_{i=0}^{\ell-1} (\ell - i)^k \end{aligned}$$



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$$= cn^{\log_b a} \sum_{i=0}^{\ell-1} (\ell - i)^k$$

$$= cn^{\log_b a} \sum_{i=1}^{\ell} i^k \approx \frac{1}{k} \ell^{k+1}$$

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$$= cn^{\log_b a} \sum_{i=1}^{\ell} i^k$$

$$\approx \frac{c}{k} n^{\log_b a} \ell^{k+1}$$

$$\Rightarrow T(n) = \mathcal{O}(n^{\log_b a} \log^{k+1} n).$$

Case 3. Now suppose that  $f(n) \geq dn^{\log_b a + \epsilon}$ , and that for sufficiently large  $n$ :  $af(n/b) \leq cf(n)$ , for  $c < 1$ .

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$$q < 1 : \sum_{i=0}^n q^i = \frac{1 - q^{n+1}}{1 - q} \leq \frac{1}{1 - q}$$

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$$q < 1 : \sum_{i=0}^n q^i = \frac{1-q^{n+1}}{1-q} \leq \frac{1}{1-q}$$

Hence,

$$T(n) \leq \mathcal{O}(f(n))$$

$$\Rightarrow T(n) = \Theta(f(n)).$$

## Example: Multiplying Two Integers

Suppose we want to multiply two  $n$ -bit Integers, but our registers can only perform operations on integers of constant size.

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$$\begin{array}{r} 1\ 1\ 0\ 1\ 1\ 0\ 1\ 0\ 1\ A \\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1\ B \\ \hline \end{array}$$

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<hr/>									



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<hr/>									
								0	

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$$\begin{array}{rcccccccc} 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\ \hline & & & & & & & 1 & & \\ & & & & & & & & 0 & \end{array}$$

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							1	1	
							0	0	

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<hr/>									
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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
<hr/>						0	0	0	

The diagram illustrates the addition of two 9-bit integers, A and B. The bits of A are 1 1 0 1 1 0 1 0 1 and the bits of B are 1 0 0 0 1 0 0 1 1. A horizontal line is drawn under the bits of B. The result of the addition is shown below the line, with the bits 0 0 0. The bit 1 in the 7th position of the result is highlighted with a light blue box, and the bit 1 in the 8th position of the result is also highlighted with a light blue box. The bit 1 in the 8th position of the result is also highlighted with a light blue box.

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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
<hr/>									
					1	1	1		
						0	0	0	

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1	0	0	0	1	0	0	1	1	B
					0				
					1	0	0	0	

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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
<hr/>									
					1	0	0	0	

The diagram illustrates the addition of two 9-bit integers, A and B. The bits of A are 1 1 0 1 1 0 1 0 1 and the bits of B are 1 0 0 0 1 0 0 1 1. A vertical box highlights the 5th bit (from the left) of both numbers, which is 1. Below the horizontal line, the result of the addition is shown as 1 0 0 0, with the 1 being the carry from the 5th bit. Small subscripts '0', '1', '1', '1' are placed below the 6th, 7th, 8th, and 9th bits of the result, indicating carry propagation.



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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
				1	0	1	1	1	
-----				0	1	0	0	0	

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				1	0	1	1	1	
				0	1	0	0	0	

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1	0	0	0	1	0	0	1	1		$B$
			1	1	0	1	1	1		
			0	0	1	0	0	0		

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1	1	0	1	1	0	1	0	1	$A$
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<hr/>									
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			0	0	1	0	0	0	

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1	0	0	0	1	0	0	1	1		$B$
		1	0	0	1	0	0	0		

0 1 1 0 1 1 1

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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
<hr/>									
		1	0	0	1	0	0	0	

*Note: In the original image, a vertical box highlights the first two bits of A and B (1 and 1), and a horizontal line is drawn below the second bit of B. Small subscripts are present below the bits of B: 0, 1, 1, 0, 1, 1, 1.*



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1	1	0	1	1	0	1	0	1	$A$
1	0	0	0	1	0	0	1	1	$B$
<hr/>									
	1	1	0	0	1	0	0	0	

The diagram shows the addition of two 9-bit integers, A and B. The result of the addition is shown below a horizontal line. The first bit of the result is 0, which is highlighted in a light blue box. The bits of A are 1 1 0 1 1 0 1 0 1 and the bits of B are 1 0 0 0 1 0 0 1 1. The result bits are 1 1 0 0 1 0 0 0.



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Suppose we want to multiply two  $n$ -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers  $A$  and  $B$ :

	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	$A$
	<b>1</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>1</b>	$B$
1	0	0	1	1	0	1	1	1		
<hr/>										
	<b>0</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>0</b>	

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	1	1	0	1	1	0	1	0	1	$A$
	1	0	0	0	1	0	0	1	1	$B$
	<hr/>									
	0	1	1	0	0	1	0	0	0	

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For this we first need to be able to add two integers  $A$  and  $B$ :

	1	1	0	1	1	0	1	0	1	$A$
	1	0	0	0	1	0	0	1	1	$B$
	<hr/>									
1	0	1	1	0	0	1	0	0	0	

## Example: Multiplying Two Integers

Suppose we want to multiply two  $n$ -bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers  $A$  and  $B$ :

$$\begin{array}{r} 1\ 1\ 0\ 1\ 1\ 0\ 1\ 0\ 1\ A \\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1\ B \\ \hline 1\ 0\ 1\ 1\ 0\ 0\ 1\ 0\ 0\ 0 \end{array}$$

This gives that two  $n$ -bit integers can be added in time  $\mathcal{O}(n)$ .

## Example: Multiplying Two Integers

Suppose that we want to multiply an  $n$ -bit integer  $A$  and an  $m$ -bit integer  $B$  ( $m \leq n$ ).

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Suppose that we want to multiply an  $n$ -bit integer  $A$  and an  $m$ -bit integer  $B$  ( $m \leq n$ ).

$$\begin{array}{r} 1\ 0\ 0\ 0\ 1 \times 1\ 0\ 1\ \boxed{1} \\ \hline \phantom{1\ 0\ 0\ 0\ 1} 1\ 0\ 0\ 0\ 1 \end{array}$$



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**Time requirement:**

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**Time requirement:**

- ▶ Computing intermediate results:  $\mathcal{O}(nm)$ .

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**Time requirement:**

- ▶ Computing intermediate results:  $\mathcal{O}(nm)$ .
- ▶ Adding  $m$  numbers of length  $\leq 2n$ :  
 $\mathcal{O}((m+n)m) = \mathcal{O}(nm)$ .

## Example: Multiplying Two Integers

**A recursive approach:**

Suppose that integers  $A$  and  $B$  are of length  $n = 2^k$ , for some  $k$ .

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$$\boxed{b_n \quad \dots \quad b_0} \times \boxed{a_n \quad \dots \quad a_0}$$

## Example: Multiplying Two Integers

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Suppose that integers  $A$  and  $B$  are of length  $n = 2^k$ , for some  $k$ .

$$\boxed{b_n \quad \cdots \quad b_{\frac{n}{2}} \quad b_{\frac{n}{2}-1} \quad \cdots \quad b_0} \times \boxed{a_n \quad \cdots \quad a_{\frac{n}{2}} \quad a_{\frac{n}{2}-1} \quad \cdots \quad a_0}$$

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**A recursive approach:**

Suppose that integers  $A$  and  $B$  are of length  $n = 2^k$ , for some  $k$ .

$$\begin{array}{|c|c|} \hline B_1 & B_0 \\ \hline \end{array} \times \begin{array}{|c|c|} \hline A_1 & A_0 \\ \hline \end{array}$$

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Suppose that integers  $A$  and  $B$  are of length  $n = 2^k$ , for some  $k$ .



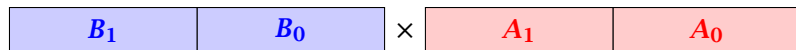
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$$A = A_1 \cdot 2^{\frac{n}{2}} + A_0 \text{ and } B = B_1 \cdot 2^{\frac{n}{2}} + B_0$$

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Then it holds that

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Hence,

$$A \cdot B = A_1 B_1 \cdot 2^n + (A_1 B_0 + A_0 B_1) \cdot 2^{\frac{n}{2}} + A_0 \cdot B_0$$

## Example: Multiplying Two Integers

### Algorithm 3 $\text{mult}(A, B)$

```
1: if  $|A| = |B| = 1$  then  
2:   return  $a_0 \cdot b_0$   
3: split  $A$  into  $A_0$  and  $A_1$   
4: split  $B$  into  $B_0$  and  $B_1$   
5:  $Z_2 \leftarrow \text{mult}(A_1, B_1)$   
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$\mathcal{O}(1)$

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$T\left(\frac{n}{2}\right)$

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We get the following recurrence:

$$T(n) = 4T\left(\frac{n}{2}\right) + \mathcal{O}(n) .$$

# Example: Multiplying Two Integers

**Master Theorem:** Recurrence:  $T[n] = aT(\frac{n}{b}) + f(n)$ .

- ▶ Case 1:  $f(n) = \mathcal{O}(n^{\log_b a - \epsilon})$        $T(n) = \Theta(n^{\log_b a})$
- ▶ Case 2:  $f(n) = \Theta(n^{\log_b a} \log^k n)$        $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$
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In our case  $a = 4$ ,  $b = 2$ , and  $f(n) = \Theta(n)$ . Hence, we are in Case 1, since  $n = \mathcal{O}(n^{2-\epsilon}) = \mathcal{O}(n^{\log_b a - \epsilon})$ .

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We get a running time of  $\mathcal{O}(n^2)$  for our algorithm.

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⇒ Not better than the “school method”.

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Hence,



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We get the following recurrence:

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Master Theorem: Recurrence:  $T[n] = aT\left(\frac{n}{b}\right) + f(n)$ .

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Again we are in Case 1. We get a running time of  $\Theta(n^{\log_2 3}) \approx \Theta(n^{1.59})$ .

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Consider the recurrence relation:

$$c_0T(n) + c_1T(n-1) + c_2T(n-2) + \dots + c_kT(n-k) = f(n)$$

This is the general form of a **linear** recurrence relation of **order  $k$**  with constant coefficients ( $c_0, c_k \neq 0$ ).

The recurrence depends on the preceding values. This means that the recurrence relation is of **order  $k$** .

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- ▶ The solution  $T[1], T[2], T[3], \dots$  is completely determined by a set of **boundary conditions** that specify values for  $T[1], \dots, T[k]$ .
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- ▶  $k$  non-consecutive values might not be an appropriate set of boundary conditions (depends on the problem).

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# The Homogenous Case

The solution space

$$S = \left\{ \mathcal{T} = T[1], T[2], T[3], \dots \mid \mathcal{T} \text{ fulfills recurrence relation} \right\}$$

is a **vector space**. This means that if  $\mathcal{T}_1, \mathcal{T}_2 \in S$ , then also  $\alpha\mathcal{T}_1 + \beta\mathcal{T}_2 \in S$ , for arbitrary constants  $\alpha, \beta$ .

How do we find a non-trivial solution?

We guess that the solution is of the form  $\lambda^n$ ,  $\lambda \neq 0$ , and see what happens. In order for this guess to fulfill the recurrence we need

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We guess that the solution is of the form  $\lambda^n$ ,  $\lambda \neq 0$ , and see what happens. In order for this guess to fulfill the recurrence we need

$$c_0\lambda^n + c_1\lambda^{n-1} + c_2 \cdot \lambda^{n-2} + \dots + c_k \cdot \lambda^{n-k} = 0$$

for all  $n \geq k$ .

# The Homogenous Case

The solution space

$$S = \{ \mathcal{T} = T[1], T[2], T[3], \dots \mid \mathcal{T} \text{ fulfills recurrence relation} \}$$

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# The Homogenous Case

Dividing by  $\lambda^{n-k}$  gives that all these constraints are identical to

$$c_0\lambda^k + c_1\lambda^{k-1} + c_2 \cdot \lambda^{k-2} + \dots + c_k = 0$$

This means that if  $\lambda_i$  is a root (Nullstelle) of  $P[\lambda]$  then  $T[n] = \lambda_i^n$  is a solution to the recurrence relation.

Let  $\lambda_1, \dots, \lambda_k$  be the  $k$  (complex) roots of  $P[\lambda]$ . Then, because of the vector space property

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Assume that the characteristic polynomial has  $k$  *distinct* roots  $\lambda_1, \dots, \lambda_k$ . Then *all* solutions to the recurrence relation are of the form

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## Proof.

There is one solution for every possible choice of boundary conditions for  $T[1], \dots, T[k]$ .

We show that the above set of solutions contains one solution for every choice of boundary conditions.

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Suppose I am given boundary conditions  $T[i]$  and I want to see whether I can choose the  $\alpha'_i$ s such that these conditions are met:

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We show that the column vectors are linearly independent. Then the above equation has a solution.

# Computing the Determinant

$$\begin{vmatrix} \lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\ \lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\ \vdots & \vdots & & \vdots & \vdots \\ \lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \end{vmatrix} =$$

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$$= \prod_{i=1}^k \lambda_i \cdot \begin{vmatrix} 1 & \lambda_1 & \cdots & \lambda_1^{k-2} & \lambda_1^{k-1} \\ 1 & \lambda_2 & \cdots & \lambda_2^{k-2} & \lambda_2^{k-1} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & \lambda_k & \cdots & \lambda_k^{k-2} & \lambda_k^{k-1} \end{vmatrix}$$

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$$\begin{vmatrix} 1 & \lambda_1 - \lambda_1 \cdot 1 & \cdots & \lambda_1^{k-2} - \lambda_1 \cdot \lambda_1^{k-3} & \lambda_1^{k-1} - \lambda_1 \cdot \lambda_1^{k-2} \\ 1 & \lambda_2 - \lambda_1 \cdot 1 & \cdots & \lambda_2^{k-2} - \lambda_1 \cdot \lambda_2^{k-3} & \lambda_2^{k-1} - \lambda_1 \cdot \lambda_2^{k-2} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & \lambda_k - \lambda_1 \cdot 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2} \end{vmatrix}$$

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$$\begin{vmatrix} 1 & 0 & \cdots & 0 & 0 \\ 1 & (\lambda_2 - \lambda_1) \cdot 1 & \cdots & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-3} & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-2} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & (\lambda_k - \lambda_1) \cdot 1 & \cdots & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-3} & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-2} \end{vmatrix}$$

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$$\prod_{i=2}^k (\lambda_i - \lambda_1) \cdot \begin{vmatrix} 1 & \lambda_2 & \cdots & \lambda_2^{k-3} & \lambda_2^{k-2} \\ \vdots & \vdots & & \vdots & \vdots \\ 1 & \lambda_k & \cdots & \lambda_k^{k-3} & \lambda_k^{k-2} \end{vmatrix}$$

# Computing the Determinant

Repeating the above steps gives:

$$\begin{vmatrix} \lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\ \lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\ \vdots & \vdots & & \vdots & \vdots \\ \lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \end{vmatrix} = \prod_{i=1}^k \lambda_i \cdot \prod_{i>\ell} (\lambda_i - \lambda_\ell)$$

Hence, if all  $\lambda_i$ 's are different, then the determinant is non-zero.



# The Homogeneous Case

## What happens if the roots are not all distinct?

Suppose we have a root  $\lambda_i$  with multiplicity (Vielfachheit) at least 2. Then not only is  $\lambda_i^n$  a solution to the recurrence but also  $n\lambda_i^{n-1}$ .

To see this consider the polynomial

$$P[\lambda] \cdot \lambda^{n-k} = c_0\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \dots + c_k\lambda^{n-k}$$

Since  $\lambda_i$  is a root we can write this as  $Q[\lambda] \cdot (\lambda - \lambda_i)^2$ .

Calculating the derivative gives a polynomial that still has root  $\lambda_i$ .

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Hence,

$$\underbrace{c_0 n \lambda_i^n}_{T[n]} + \underbrace{c_1 (n-1) \lambda_i^{n-1}}_{T[n-1]} + \dots + \underbrace{c_k (n-k) \lambda_i^{n-k}}_{T[n-k]} = 0$$

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(after taking the derivative; multiplying with  $\lambda$ ; plugging in  $\lambda_i$ )

Doing this again gives

$$c_0 n^2 \lambda_i^n + c_1 (n-1)^2 \lambda_i^{n-1} + \dots + c_k (n-k)^2 \lambda_i^{n-k} = 0$$

We can continue  $j-1$  times.

Hence,  $n^\ell \lambda_i^n$  is a solution for  $\ell \in 0, \dots, j-1$ .



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We can continue  $j-1$  times.

Hence,  $n^\ell \lambda_i^n$  is a solution for  $\ell \in 0, \dots, j-1$ .

# The Homogeneous Case

## Lemma 6

Let  $P[\lambda]$  denote the characteristic polynomial to the recurrence

$$c_0T[n] + c_1T[n-1] + \dots + c_kT[n-k] = 0$$

Let  $\lambda_i, i = 1, \dots, m$  be the (complex) roots of  $P[\lambda]$  with multiplicities  $\ell_i$ . Then the general solution to the recurrence is given by

$$T[n] = \sum_{i=1}^m \sum_{j=0}^{\ell_i-1} \alpha_{ij} \cdot (n^j \lambda_i^n) .$$

The full proof is omitted. We have only shown that any choice of  $\alpha_{ij}$ 's is a solution to the recurrence.

## Example: Fibonacci Sequence

$$T[0] = 0$$

$$T[1] = 1$$

$$T[n] = T[n - 1] + T[n - 2] \text{ for } n \geq 2$$

The characteristic polynomial is

$$\lambda^2 - \lambda - 1$$

Finding the roots, gives

$$\lambda_{1/2} = \frac{1}{2} \pm \sqrt{\frac{1}{4} + 1} = \frac{1}{2} (1 \pm \sqrt{5})$$

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$$T[n] = T[n - 1] + T[n - 2] \text{ for } n \geq 2$$

The characteristic polynomial is

$$\lambda^2 - \lambda - 1$$

Finding the roots, gives

$$\lambda_{1/2} = \frac{1}{2} \pm \sqrt{\frac{1}{4} + 1} = \frac{1}{2} (1 \pm \sqrt{5})$$

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## Example: Fibonacci Sequence

Hence, the solution is

$$\frac{1}{\sqrt{5}} \left[ \left( \frac{1 + \sqrt{5}}{2} \right)^n - \left( \frac{1 - \sqrt{5}}{2} \right)^n \right]$$

# The Inhomogeneous Case

Consider the recurrence relation:

$$c_0T(n) + c_1T(n-1) + c_2T(n-2) + \cdots + c_kT(n-k) = f(n)$$

with  $f(n) \neq 0$ .

While we have a fairly general technique for solving **homogeneous**, linear recurrence relations the inhomogeneous case is different.

# The Inhomogeneous Case

The general solution of the recurrence relation is

$$T(n) = T_h(n) + T_p(n) ,$$

where  $T_h$  is **any** solution to the homogeneous equation, and  $T_p$  is **one** particular solution to the inhomogeneous equation.

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# The Inhomogeneous Case

Example:

$$T[n] = T[n - 1] + 1 \quad T[0] = 1$$

Then,

$$T[n - 1] = T[n - 2] + 1 \quad (n \geq 2)$$

Subtracting the first from the second equation gives,

$$T[n] - T[n - 1] = T[n - 1] - T[n - 2] \quad (n \geq 2)$$

or

$$T[n] = 2T[n - 1] - T[n - 2] \quad (n \geq 2)$$

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If  $f(n)$  is a polynomial of degree  $r$  this method can be applied  $r + 1$  times to obtain a homogeneous equation:

$$T[n] = T[n - 1] + n^2$$

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Difference:

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Shift:

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and so on...

## 6.4 Generating Functions

### Definition 7 (Generating Function)

Let  $(a_n)_{n \geq 0}$  be a sequence. The corresponding

- ▶ **generating function** (Erzeugendenfunktion) is

$$F(z) := \sum_{n \geq 0} a_n z^n;$$

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## 6.4 Generating Functions

There are two different views:

A generating function is a **formal power series** (formale Potenzreihe).

Then the generating function is an **algebraic object**.

Let  $f = \sum_{n \geq 0} a_n z^n$  and  $g = \sum_{n \geq 0} b_n z^n$ .

- ▶ **Equality:**  $f$  and  $g$  are equal if  $a_n = b_n$  for all  $n$ .
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The arithmetic view:

We view a power series as a function  $f : \mathbb{C} \rightarrow \mathbb{C}$ .

Then, it is important to think about convergence/convergence radius etc.

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What does  $\sum_{n \geq 0} z^n = \frac{1}{1-z}$  mean in the algebraic view?

It means that the power series  $1 - z$  and the power series  $\sum_{n \geq 0} z^n$  are invers, i.e.,

$$(1 - z) \cdot \left( \sum_{n \geq 0} z^n \right) = 1 .$$

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Hence, the generating function of the sequence  $a_n = n + 1$  is  $1/(1-z)^2$ .

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Hence:

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The generating function of the sequence  $a_n = \binom{n+k}{k}$  is  $\frac{1}{(1-z)^{k+1}}$ .

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We know

$$\sum_{n \geq 0} y^n = \frac{1}{1-y}$$

Hence,

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Hence,  $a_n = n + 1$ .

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$\frac{1}{n!}$	$e^z$

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$$A(z) = \frac{(1-z)^2 + z}{(1-3z)(1-z)^2}$$





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5. Write  $f(z)$  as a formal power series:

We use partial fraction decomposition:

$$\frac{z^2 - z + 1}{(1 - 3z)(1 - z)^2} \stackrel{!}{=} \frac{A}{1 - 3z} + \frac{B}{1 - z} + \frac{C}{(1 - z)^2}$$

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which gives

$$A = \frac{7}{4} \quad B = -\frac{1}{4} \quad C = -\frac{1}{2}$$



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6. This means  $a_n = \frac{7}{4}3^n - \frac{1}{2}n - \frac{3}{4}$ .

## 6.5 Transformation of the Recurrence

### Example 9

$$f_0 = 1$$

$$f_1 = 2$$

$$f_n = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2 .$$

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Let  $n = 2^k$ :

$$g_k = 3^{k+1} - 2^{k+1}, \text{ hence}$$

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