

# Part II

## Foundations

## 3 Goals

- ▶ Gain knowledge about efficient algorithms for important problems, i.e., learn how to solve certain types of problems efficiently.
- ▶ Learn how to analyze and judge the efficiency of algorithms.
- ▶ Learn how to design efficient algorithms.

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## 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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## 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**.
  - ▶ Gives a **lower bound** like "this algorithm always runs in  $\Omega(n^2)$  time".
  - ▶ Typically focuses on the **number of comparisons**.
  - ▶ Can this lower bound also be **computationally tight** (sorting algorithm needs at least this many comparisons in the worst case)?

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Quick question: How many times does this algorithm always run in  $n$ ?

Answer:  $n^2 + 2n + 1$

Typical question on the

exam: How many comparisons does any comparison-based sorting algorithm need at least? (The answer depends on the input size.)

Answer:  $n \log n$

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- ▶ Theoretical analysis in a specific model of computation.
  - ▶ Question: How fast does this algorithm always run in the worst case?
  - ▶ Typical model: RAM
  - ▶ Can this lower bound be very computer-architecture dependent? (e.g., sorting algorithms need at least  $\log_2 n$  comparisons in the worst case)

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- ▶ Theoretical analysis in a specific model of computation.
  - ▶ Complexity analysis: How fast algorithm always runs in worst case.
  - ▶ Time complexity: How long computation takes in worst case.
  - ▶ Space complexity: How much memory needed for computation.
  - ▶ Lower complexity is better.



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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

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1. Calculate running time and storage space etc. on a simplified, idealized model of computation, e.g. Random Access Machine (RAM), Turing Machine (TM), . . .
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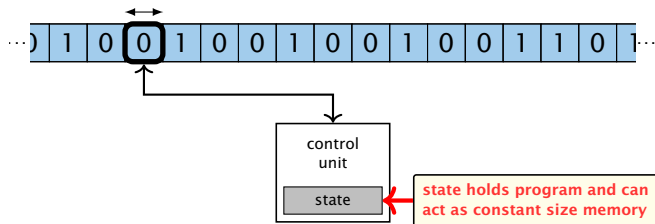
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# Turing Machine

- ▶ 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.

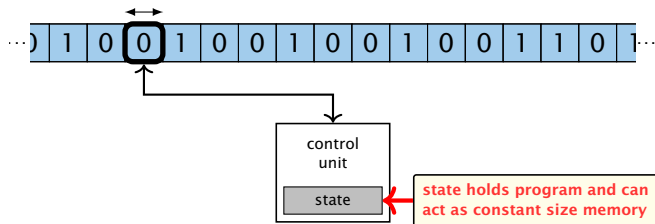
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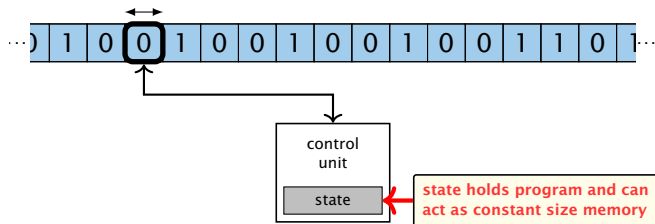




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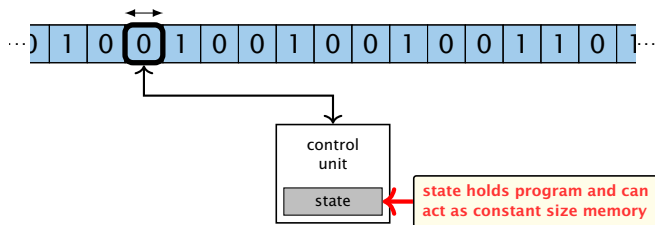
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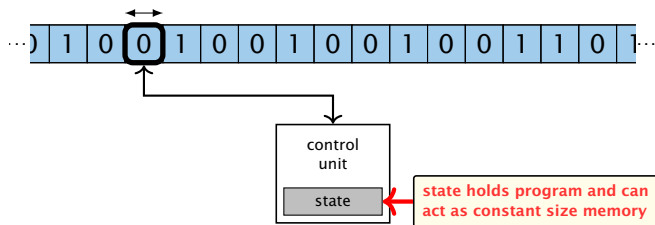
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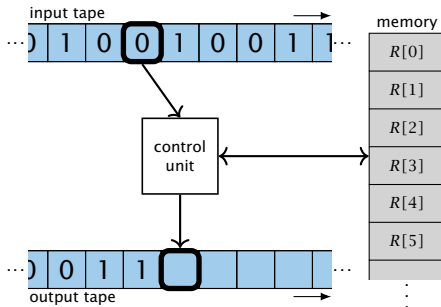
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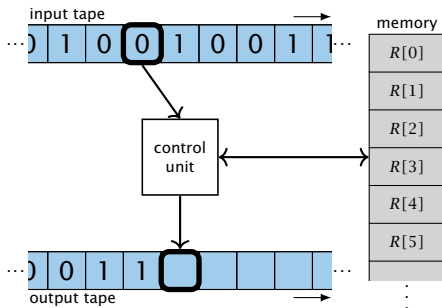
- ▶ Input tape and output tape (sequences of zeros and ones; unbounded length).
- ▶ Memory unit: infinite but countable number of registers  $R[0], R[1], R[2], \dots$
- ▶ Registers hold integers.
- ▶ Indirect addressing.



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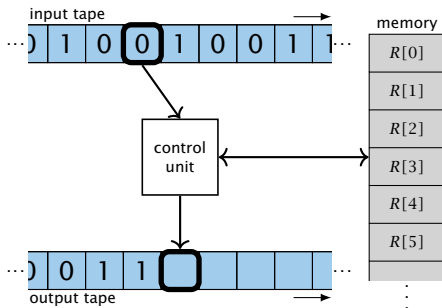
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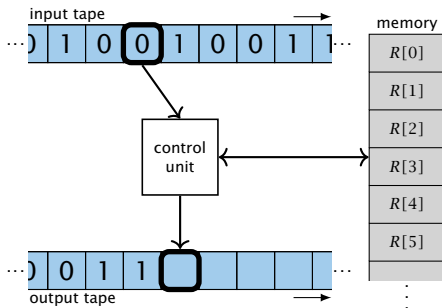
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# Random Access Machine (RAM)

## Operations

- ▶ input operations (input tape  $\rightarrow R[i]$ )
  - ▶ READ  $i$
- ▶ output operations ( $R[i] \rightarrow$  output tape)
- ▶ register-register transfers
- ▶ indirect addressing

Reads the contents of the cell at address  $i$  on the input tape into register  $R[i]$ .

Example:

Reads the contents of the cell at address  $R[i]$  into register  $R[j]$ .

Writes the contents of the cell at address  $i$  into the register  $R[j]$ .



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- ▶ branching (including loops) based on comparisons
  - ▶ `jump  $x$`   
jumps to position  $x$  in the program;  
sets instruction counter to  $x$ ;  
reads the next operation to perform from register  $R[x]$
  - ▶ `jumpz  $x$   $R[i]$`   
jump to  $x$  if  $R[i] = 0$   
if not the instruction counter is increased by 1;
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# Model of Computation

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Every operation takes time 1.

- ▶ **logarithmic** cost model

The cost depends on the content of memory cells:

- ▶ The time for a step is equal to the largest operand involved.

- ▶ The word size of a register is equal to the length (in bits) of the largest value ever stored in it.

- ▶ The time for a step is equal to the word size.

**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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# Model of Computation

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Every operation takes time 1.
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There are **different types of complexity bounds**:

- ▶ **best-case** complexity:

$$C_{bc}(n) := \min\{C(x) \mid |x| = n\}$$

Usually easy to analyze, but not very meaningful.

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## Formal Definition

Let  $f$  denote functions from  $\mathbb{N}$  to  $\mathbb{R}^+$ .

- ▶  $\mathcal{O}(f) = \{g \mid \exists c > 0 \exists n_0 \in \mathbb{N}_0 \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$   
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There is an equivalent definition using limes notation (**assuming that the respective limes exists**).  $f$  and  $g$  are functions from  $\mathbb{N}_0$  to  $\mathbb{R}_0^+$ .

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# 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:

$$\sum_{i=1}^n \Theta(i) = \Theta(n^2)$$

Careful!

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

Hence, the left side is **not** equal to

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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:

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represents

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## 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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- ▶  $\mathcal{O}(f(n)) + \mathcal{O}(g(n)) = \mathcal{O}(\max\{f(n), g(n)\})$

The expressions also hold for  $\Omega$ . Note that this means that  $f(n) + g(n) \in \Theta(\max\{f(n), g(n)\})$ .

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The expressions also hold for  $\Omega$ . Note that this means that  $f(n) + g(n) \in \Theta(\max\{f(n), g(n)\})$ .



# Asymptotic Notation

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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

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## Comments

- ▶ 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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In general asymptotic classification of running times is a good measure for comparing algorithms:

- ▶ 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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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:

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

**Informal way:**

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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, this is not correct if  $n$  is not a power of 2. Also even in this case one would need to do an induction proof.

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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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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:

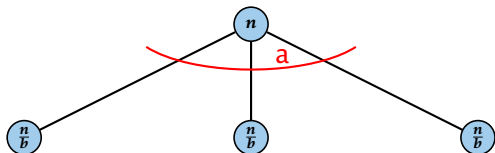
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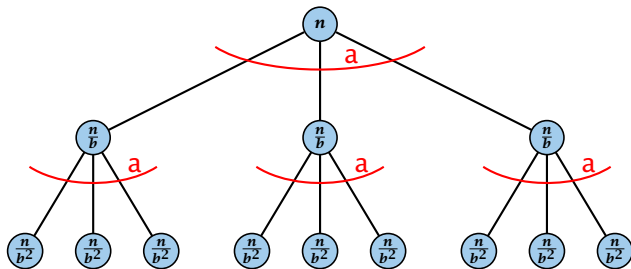
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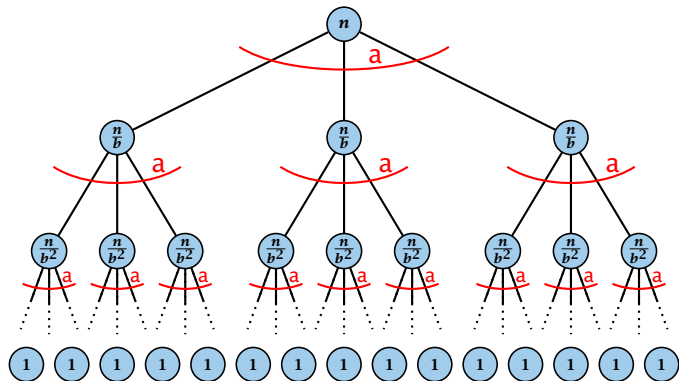
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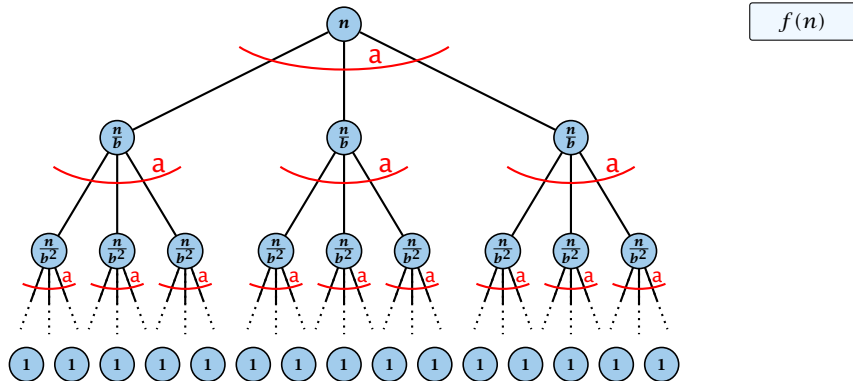
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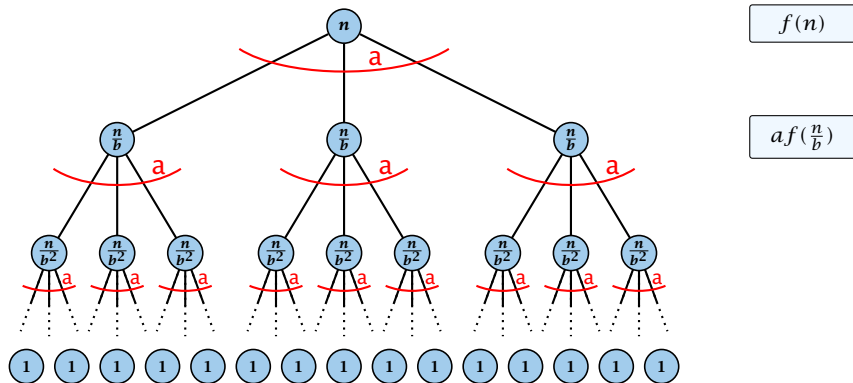
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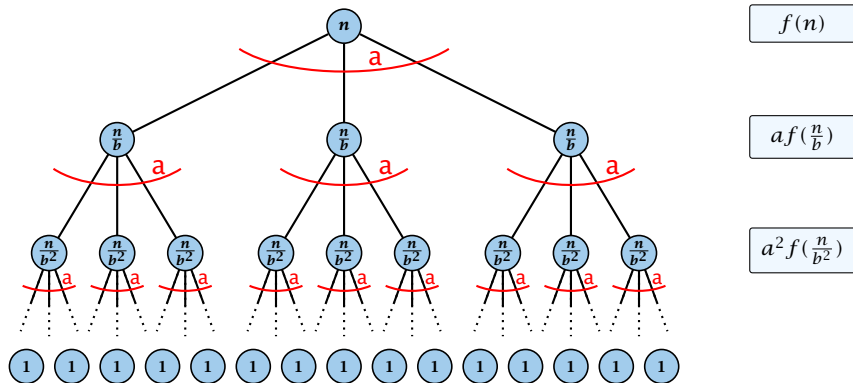
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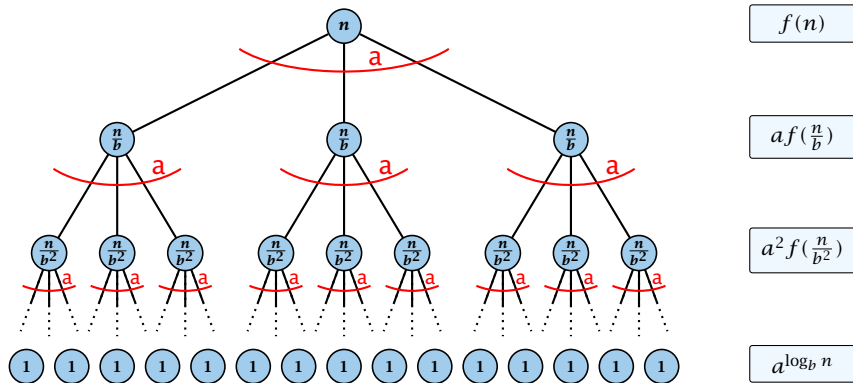
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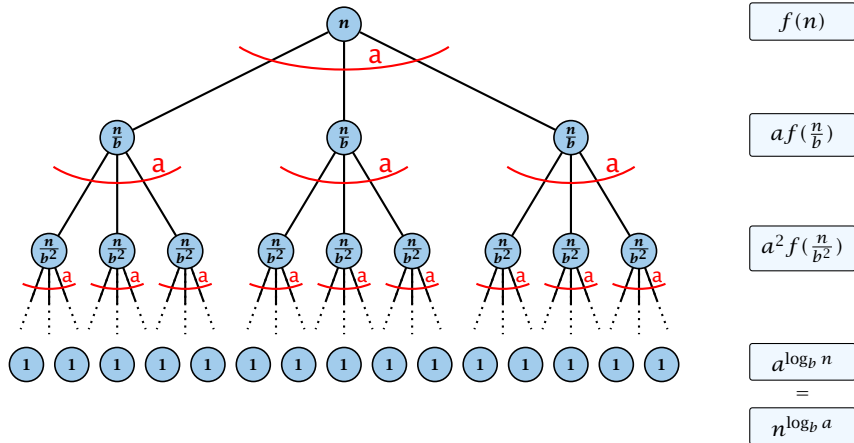
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## 6.2 Master Theorem

This gives

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



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

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



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

Hence,

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

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Hence,

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

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

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Hence,

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

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

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

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

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From this we get  $a^i f(n/b^i) \leq c^i f(n)$ , where we assume that  $n/b^{i-1} \geq n_0$  is still sufficiently large.

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

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

**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  $c < 1$ .

From this we get  $a^i f(n/b^i) \leq c^i f(n)$ , where we assume that  $n/b^{i-1} \geq n_0$  is still sufficiently large.

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

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

Hence,

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

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

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

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.



## 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  $B$ :

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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  $B$ :

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

## Example: Multiplying Two Integers

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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/>									

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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	

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

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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	1	
							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	1		
								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/>						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. The bits of B are 1, 0, 0, 0, 1, 0, 0, 1, 1. A horizontal line is drawn under the 6th bit of B. The result of the addition is shown below the line: 0, 0, 0. The 7th, 8th, and 9th bits of the result are 0, 0, and 0 respectively. The 7th, 8th, and 9th bits of the result are highlighted in a light blue box.



## 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  $B$ :

The diagram shows the binary addition of two integers, A and B. A horizontal line separates the numbers from the result. A light blue vertical box highlights the 6th bit position, which is the 5th bit from the right. The numbers are:

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

Carry bits are indicated by small '1's below the 6th, 7th, and 8th columns. The 6th bit of the result is 0, the 7th is 0, and the 8th is 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  $B$ :

1	1	0	1	1	0	1	0	1		$A$
1	0	0	0	1	0	0	1	1		$B$
					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  $B$ :

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

## Example: Multiplying Two Integers

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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	$B$
				1	0	1	1	1	
-----				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  $B$ :

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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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  $B$ :

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

## Example: Multiplying Two Integers

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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	1	0	1	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  $B$ :

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

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 the carry bit 0 is shown below the first column.*

## 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  $B$ :

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

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 illustrates the addition of two 9-bit integers, A and B. The first column of A (the leftmost '1') is highlighted in a light blue box. Below the horizontal line, the result of the addition is shown as a sequence of bits: 1, 1, 0, 0, 1, 0, 0, 0. Small subscripts are placed below the bits of B: 0, 0, 1, 1, 0, 1, 1, 1.

## 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  $B$ :

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

The diagram illustrates the addition of two 10-bit integers, A and B. The bits of A are 1 1 0 1 1 0 1 0 1 1, and the bits of B are 1 0 0 0 1 0 0 1 1. The result of the addition is 0 1 1 0 0 1 0 0 0. A vertical box highlights the first bit of the result, which is 0, indicating a carry-out from the most significant bit.

## 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  $B$ :

	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	

## 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  $B$ :

	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  $B$  ( $m \leq n$ ).



## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

$$\begin{array}{r} 10001 \times 1011 \\ \hline \end{array}$$

## Example: Multiplying Two Integers

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

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

## 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  $B$  ( $m \leq n$ ).

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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



## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

## Example: Multiplying Two Integers

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

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

**Time requirement:**

## Example: Multiplying Two Integers

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

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

**Time requirement:**

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



## Example: Multiplying Two Integers

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

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

**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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**A recursive approach:**

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

$$\boxed{b_{n-1} \quad \dots \quad b_0} \times \boxed{a_{n-1} \quad \dots \quad a_0}$$

## Example: Multiplying Two Integers

**A recursive approach:**

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

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

## Example: Multiplying Two Integers

**A recursive approach:**

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

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

## Example: Multiplying Two Integers

**A recursive approach:**

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



Then it holds that

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

## Example: Multiplying Two Integers

**A recursive approach:**

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



Then it holds that

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

Hence,

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



## 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:  $Z_2 \leftarrow \text{mult}(A_1, B_1)$   
6:  $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$   
7:  $Z_0 \leftarrow \text{mult}(A_0, B_0)$   
8: return  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$ 
```

## Example: Multiplying Two Integers

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

```
1: if  $|A| = |B| = 1$  then  
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```

$\mathcal{O}(1)$

## Example: Multiplying Two Integers

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

1: **if**  $|A| = |B| = 1$  **then**

$\mathcal{O}(1)$

2:     **return**  $a_0 \cdot b_0$

$\mathcal{O}(1)$

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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## Example: Multiplying Two Integers

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$\mathcal{O}(n)$

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## Example: Multiplying Two Integers

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

$\mathcal{O}(1)$

$\mathcal{O}(n)$

$\mathcal{O}(n)$

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

## Example: Multiplying Two Integers

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

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2:     **return**  $a_0 \cdot b_0$

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

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

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## Example: Multiplying Two Integers

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$\mathcal{O}(1)$

$\mathcal{O}(1)$

$\mathcal{O}(n)$

$\mathcal{O}(n)$

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

$2T(\frac{n}{2}) + \mathcal{O}(n)$

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



## Example: Multiplying Two Integers

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

1: <b>if</b> $ A  =  B  = 1$ <b>then</b>	$\mathcal{O}(1)$
2: <b>return</b> $a_0 \cdot b_0$	$\mathcal{O}(1)$
3: split $A$ into $A_0$ and $A_1$	$\mathcal{O}(n)$
4: split $B$ into $B_0$ and $B_1$	$\mathcal{O}(n)$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$	$T\left(\frac{n}{2}\right)$
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## Example: Multiplying Two Integers

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2: <b>return</b> $a_0 \cdot b_0$	$\mathcal{O}(1)$
3: split $A$ into $A_0$ and $A_1$	$\mathcal{O}(n)$
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8: <b>return</b> $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$	$\mathcal{O}(n)$

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:  $f(n) = \Theta(n^{\log_b a} \log^k n)$        $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$
- ▶ Case 3:  $f(n) = \Omega(n^{\log_b a + \epsilon})$        $T(n) = \Theta(f(n))$

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

## Example: Multiplying Two Integers

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

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

⇒ Not better than the “school method”.

## Example: Multiplying Two Integers

We can use the following identity to compute  $Z_1$ :

## Example: Multiplying Two Integers

We can use the following identity to compute  $Z_1$ :

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## Example: Multiplying Two Integers

We can use the following identity to compute  $Z_1$ :

$$\begin{aligned}Z_1 &= A_1B_0 + A_0B_1 \\ &= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0\end{aligned}$$

## Example: Multiplying Two Integers

We can use the following identity to compute  $Z_1$ :

$$\begin{aligned} Z_1 &= A_1B_0 + A_0B_1 && = Z_2 && = Z_0 \\ &= (A_0 + A_1) \cdot (B_0 + B_1) - \underbrace{A_1B_1} && - \underbrace{A_0B_0} \end{aligned}$$

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Hence,

### Algorithm 4 mult( $A, B$ )

```
1: if  $|A| = |B| = 1$  then
2:   return  $a_0 \cdot b_0$ 
3: split  $A$  into  $A_0$  and  $A_1$ 
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5:  $Z_2 \leftarrow \text{mult}(A_1, B_1)$ 
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8: return  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$ 
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$\mathcal{O}(1)$

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$\mathcal{O}(1)$

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2:     **return**  $a_0 \cdot b_0$

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3: split  $A$  into  $A_0$  and  $A_1$

$\mathcal{O}(n)$

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

### Algorithm 4 mult( $A, B$ )

1: **if**  $|A| = |B| = 1$  **then**

2:     **return**  $a_0 \cdot b_0$

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8: **return**  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

$\mathcal{O}(1)$

$\mathcal{O}(1)$

$\mathcal{O}(n)$

$\mathcal{O}(n)$

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

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Hence,

### Algorithm 4 mult( $A, B$ )

1: **if**  $|A| = |B| = 1$  **then**

2:     **return**  $a_0 \cdot b_0$

3: split  $A$  into  $A_0$  and  $A_1$

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8: **return**  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

$\mathcal{O}(1)$

$\mathcal{O}(1)$

$\mathcal{O}(n)$

$\mathcal{O}(n)$

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

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## Example: Multiplying Two Integers

We can use the following identity to compute  $Z_1$ :

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Hence,

### Algorithm 4 mult( $A, B$ )

1: **if**  $|A| = |B| = 1$  **then**

$\mathcal{O}(1)$

2:     **return**  $a_0 \cdot b_0$

$\mathcal{O}(1)$

3: split  $A$  into  $A_0$  and  $A_1$

$\mathcal{O}(n)$

4: split  $B$  into  $B_0$  and  $B_1$

$\mathcal{O}(n)$

5:  $Z_2 \leftarrow \text{mult}(A_1, B_1)$

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

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7:  $Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$

$T(\frac{n}{2}) + \mathcal{O}(n)$

8: **return**  $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

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We can use the following identity to compute  $Z_1$ :

$$\begin{aligned} Z_1 &= A_1B_0 + A_0B_1 && = Z_2 && = Z_0 \\ &= (A_0 + A_1) \cdot (B_0 + B_1) - \underbrace{A_1B_1} && - \underbrace{A_0B_0} \end{aligned}$$

Hence,

### Algorithm 4 mult( $A, B$ )

1: <b>if</b> $ A  =  B  = 1$ <b>then</b>	$\mathcal{O}(1)$
2: <b>return</b> $a_0 \cdot b_0$	$\mathcal{O}(1)$
3: split $A$ into $A_0$ and $A_1$	$\mathcal{O}(n)$
4: split $B$ into $B_0$ and $B_1$	$\mathcal{O}(n)$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$	$T(\frac{n}{2})$
6: $Z_0 \leftarrow \text{mult}(A_0, B_0)$	$T(\frac{n}{2})$
7: $Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$	$T(\frac{n}{2}) + \mathcal{O}(n)$
8: <b>return</b> $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$	$\mathcal{O}(n)$

## Example: Multiplying Two Integers

We get the following recurrence:

$$T(n) = 3T\left(\frac{n}{2}\right) + \mathcal{O}(n) .$$

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

- ▶ Case 1:  $f(n) = \mathcal{O}(n^{\log_b a - \epsilon})$        $T(n) = \Theta(n^{\log_b a})$
- ▶ Case 2:  $f(n) = \Theta(n^{\log_b a} \log^k n)$        $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$
- ▶ Case 3:  $f(n) = \Omega(n^{\log_b a + \epsilon})$        $T(n) = \Theta(f(n))$

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

A huge improvement over the "school method".

## Example: Multiplying Two Integers

We get the following recurrence:

$$T(n) = 3T\left(\frac{n}{2}\right) + \mathcal{O}(n) .$$

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

- ▶ Case 1:  $f(n) = \mathcal{O}(n^{\log_b a - \epsilon})$        $T(n) = \Theta(n^{\log_b a})$
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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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## 6.3 The Characteristic Polynomial

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 ( $c_0, c_k \neq 0$ ).

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# The Homogenous Case

The solution space

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

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

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

for all  $n \geq k$ .

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

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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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## Lemma 5

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

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



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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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This means

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

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.

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# 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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Hence, the solution is of the form

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

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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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**There is no general method to find a particular solution.**

# 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

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

I get a completely determined recurrence if I add  $T[0] = 1$  and  $T[1] = 2$ .

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$T[1] = 2$  gives  $1 + \beta = 2 \Rightarrow \beta = 1$ .

## The Inhomogeneous Case

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

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

Shift:

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

Difference:

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Shift:

$$T[n - 1] = 2T[n - 2] - T[n - 3] + 2(n - 1) - 1$$

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

Shift:

$$\begin{aligned} T[n - 1] &= 2T[n - 2] - T[n - 3] + 2(n - 1) - 1 \\ &= 2T[n - 2] - T[n - 3] + 2n - 3 \end{aligned}$$

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

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## 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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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  $g = \sum_{n \geq 0} b_n z^n$ .

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

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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.,

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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, the generating function of the sequence

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We know

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

Hence,

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$f_{n-k}$ ( $n \geq k$ ); 0 otw.	$z^k F$
$\sum_{i=0}^n f_i$	$\frac{F(z)}{1-z}$
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# Some Generating Functions

<i>n</i> -th sequence element	generating function
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$c^n f_n$	$F(cz)$

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6. The coefficients of the resulting power series are the  $a_n$ .

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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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## 6 Recurrences

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$$\begin{aligned}g_k &= 3 [g_{k-1}] + 2^k \\&= 3 [3g_{k-2} + 2^{k-1}] + 2^k \\&= 3^2 [g_{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^2 [3g_{k-3} + 2^{k-2}] + 3 \cdot 2^{k-1} + 2^k \\&= 3^3 g_{k-3} + 3^2 2^{k-2} + 3 \cdot 2^{k-1} + 2^k \\&= 2^k \cdot \sum_{i=0}^k \left(\frac{3}{2}\right)^i\end{aligned}$$

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Let  $n = 2^k$ :

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

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