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- Running time should be expressed by simple functions.



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### **Formal Definition**

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

•  $\mathcal{O}(f) = \{g \mid \exists c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \leq c \cdot f(n)] \}$  (set of functions that asymptotically grow not faster than f)

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- There also exist versions for arbitrary functions, and for the case that the limes is not infinity.

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$$g \in \Omega(f)$$
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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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1. People write  $f = \mathcal{O}(g)$ , when they mean  $f \in \mathcal{O}(g)$ . This is **not** an equality (how could a function be equal to a set of functions).

- **2.** In this context f(n) does **not** mean the function f evaluated at n, but instead it is a shorthand for the function itself (leaving out domain and codomain and only giving the rule of correspondence of the function).
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- 3. People write e.g. h(n) = f(n) + o(g(n)) when they mean that there exists a function  $z: \mathbb{N} \to \mathbb{R}^+, n \mapsto z(n), z \in o(g)$ such that h(n) = f(n) + z(n).

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- **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.

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Note that  $\Theta(n)$  is on the right hand side, otw. this interpretation is wrong.

How do we interpret an expression like:

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Regardless of how we choose the anonymous function  $f(n) \in \mathcal{O}(n)$  there is an anonymous function  $g(n) \in \Theta(n^2)$  that makes the expression true.

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How do we interpret an expression like:

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

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Careful!

The  $\Theta(i)$ -symbol on the left represents one anonymous function  $f: \mathbb{N} \to \mathbb{R}^+$ , and then  $\sum_i f(i)$  is computed.

How do we interpret an expression like:

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### Careful!

"It is understood" that every occurrence of an  $\mathcal{O}$ -symbol (or  $\Theta, \Omega, \rho, \omega$ ) on the left represents one anonymous function.

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

$$\Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n)$$

 $\Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n)$  does not really have a reasonable interpreta-

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

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

### represents

$$\left\{ f: \mathbb{N} \to \mathbb{R}^+ \mid f(n) = n^2 \cdot g(n) + h(n) \right.$$
 with  $g(n) \in \mathcal{O}(n)$  and  $h(n) \in \mathcal{O}(\log n) \right\}$  Recall that according to the previous slide e.g. the expressions  $\sum_{i=1}^n \mathcal{O}(i)$  and  $\sum_{i=1}^{n/2} \mathcal{O}(i) + \sum_{i=n/2+1}^n \mathcal{O}(i)$  generate different sets

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

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

represents

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

Note that the equation does not hold.

#### Lemma 1

Let f, g be functions with the property

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

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

### **Comments**

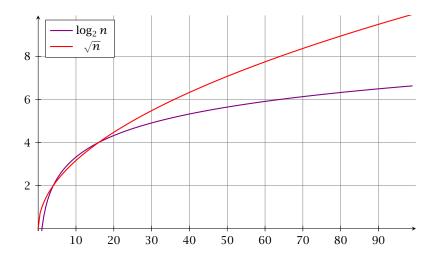
Do not use asymptotic notation within induction proofs.

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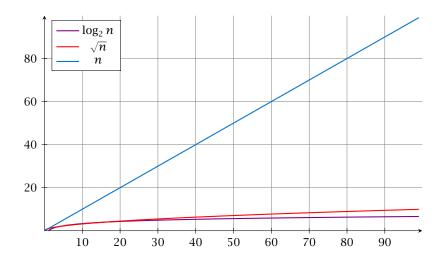
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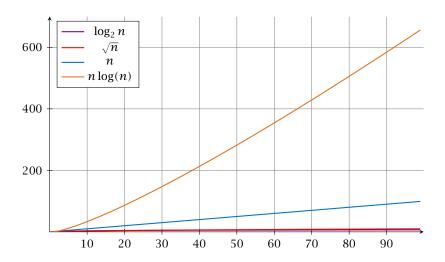
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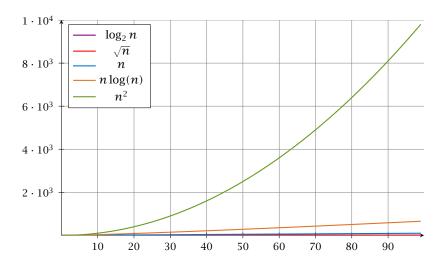
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- For any constants a, b we have  $\log_a n = \Theta(\log_b n)$ . Therefore, we will usually ignore the base of a logarithm within asymptotic notation.
- In general  $\log n = \log_2 n$ , i.e., we use 2 as the default base for the logarithm.



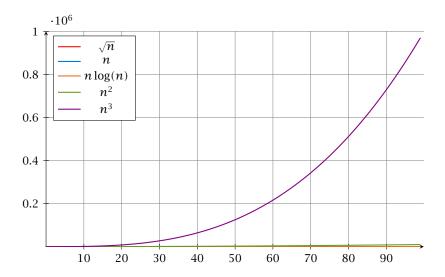




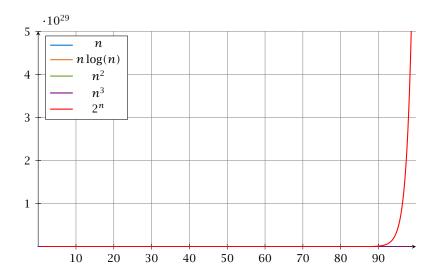












### Laufzeiten

Funktion	Eingabelänge n							
f(n)	10	$10^{2}$	$10^{3}$	$10^{4}$	$10^{5}$	$10^{6}$	10 <sup>7</sup>	$10^{8}$
$\log n$	33 <b>ns</b>	66ns	0.1µs	0.1µs	0.2µs	0.2µs	0.2µs	0.3µs
$\sqrt{n}$	32ns	$0.1 \mu s$	0.3µs	1µs	3.1 <b>µs</b>	10 <b>µs</b>	31 <b>µs</b>	$0.1  \mathrm{ms}$
n	100ns	1µs	10 <b>µs</b>	$0.1 \mathrm{ms}$	1ms	10ms	0.1s	1s
$n \log n$	0.3µs	6.6µs	0.1ms	1.3ms	16ms	0.2s	2.3s	27s
$n^{3/2}$	0.3µs	10µs	0.3ms	10ms	0.3s	10s	5.2min	2.7h
$n^2$	1µs	$0.1 \mathrm{ms}$	10ms	1s	1.7min	2.8h	11 <b>d</b>	3.2 <b>y</b>
$n^3$	10µs	10ms	10s	2.8h	115 <b>d</b>	317 <b>y</b>	3.2·10 <sup>5</sup> y	
$1.1^{n}$	26ns	0.1 ms	$7.8 \cdot 10^{25}$ y					
$2^n$	10µs	$4\cdot 10^{14}$ y						
n!	36ms	$3 \cdot 10^{142}$ y						

1 Operation = 10ns; 100MHz

Alter des Universums: ca.  $13.8 \cdot 10^9 \mathrm{y}$ 

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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Clearly f = o(g). However, as long as  $\log n \le 1000$  Algorithm B will be more efficient.



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#### **Formal Definition**

Let f, g denote functions from  $\mathbb{N}^d$  to  $\mathbb{R}_0^+$ .

 $\mathcal{O}(f) = \{g \mid \exists c > 0 \ \exists N \in \mathbb{N}_0 \ \forall \vec{n} \ \text{with} \ n_i \geq N \ \text{for some} \ i : \\ [g(\vec{n}) \leq c \cdot f(\vec{n})] \}$ 

(set of functions that asymptotically grow not faster than f)

#### Example 2

 $f: \mathbb{N} \to \mathbb{R}_0^+, f(n,m) = 1 \text{ und } g: \mathbb{N} \to \mathbb{R}_0^+, g(n,m) = n-1$ 

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