We are usually not interested in exact running times, but only in an asymptotic classification of the running time, that ignores constant factors and constant additive offsets.

- **▶ We are usually interested in the running times for large** values of *n*. Then constant additive terms do not play an important role.
- **►** An exact analysis (e.g. *exactly* counting the number of operations in a RAM) may be hard, but wouldn't lead to more precise results as the computational model is already quite a distance from reality.
- ▶ A linear speed-up (i.e., by a constant factor) is always possible by e.g. implementing the algorithm on a faster machine.
- \triangleright Running time should be expressed by simple functions.

Formal Definition

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

- \rightarrow *O*(*f*) = {*g* | ∃*c* > 0 ∃*n*₀ ∈ N₀ ∀*n* ≥ *n*₀ : [*g*(*n*) ≤ *c* · *f*(*n*)]} (set of functions that asymptotically grow not faster than *f*)
- \rightarrow Ω(f) = {*g* | ∃*c* > 0 ∃*n*₀ ∈ N₀ ∀*n* ≥ *n*₀ : [*g*(*n*) ≥ *c* · *f*(*n*)]} (set of functions that asymptotically grow not slower than *f*)
- \blacktriangleright $\Theta(f) = \Omega(f) \cap \mathcal{O}(f)$ (functions that asymptotically have the same growth as *f*)
- \rightarrow *o*(*f*) = {*g* | ∀*c* > 0 ∃*n*₀ ∈ N₀ ∀*n* ≥ *n*₀ : [*g*(*n*) ≤ *c* · *f*(*n*)]} (set of functions that asymptotically grow slower than *f*)
- \triangleright *ω*(*f*) = { $g | \forall c > 0$ ∃ $n_0 \in \mathbb{N}_0$ ∀ $n \ge n_0$: [$g(n) \ge c \cdot f(n)$]} (set of functions that asymptotically grow faster than *f*)

There is an equivalent definition using limes notation (assuming that the respective limes exists). *f* and *g* are functions from \aleph_0 to \mathbb{R}^+_0 .

\n- ▶
$$
g \in \mathcal{O}(f)
$$
: $0 \leq \lim_{n \to \infty} \frac{g(n)}{f(n)} < \infty$
\n- ▶ $g \in \Omega(f)$: $0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} \leq \infty$
\n- ▶ $g \in \Theta(f)$: $0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} < \infty$
\n- ▶ $g \in o(f)$: $\lim_{n \to \infty} \frac{g(n)}{f(n)} = 0$
\n- ▶ $g \in \omega(f)$: $\lim_{n \to \infty} \frac{g(n)}{f(n)} = \infty$
\n

• Note that for the version of the Landau notation defined here, we assume that *f* and *g* are positive functions. • There also exist versions for arbitrary functions, and for the case that the

limes is not infinity.

5 Asymptotic Notation

Abuse of notation

- 1. People write $f = O(g)$, when they mean $f \in O(g)$. This is not an equality (how could a function be equal to a set of functions).
- 2. People write $f(n) = O(g(n))$, when they mean $f \in O(g)$, with $f : \mathbb{N} \to \mathbb{R}^+, n \mapsto f(n)$, and $g : \mathbb{N} \to \mathbb{R}^+, n \mapsto g(n)$.
- **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 $h(n) = f(n) + z(n)$.

Abuse of notation

4. People write $O(f(n)) = O(g(n))$, when they mean $O(f(n)) \subseteq O(g(n))$. Again this is not an equality.

How do we interpret an expression like:

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

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

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

How do we interpret an expression like:

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

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.

How do we interpret an expression like:

```
\sum_{i=1}^{n} \Theta(i) = \Theta(n^2)i=1
```
Careful!

"It is understood" that every occurence of an $\mathcal O$ -symbol (or Θ*,* Ω*, o, ω*) on the left represents one anonymous function.

Hence, the left side is not equal to

 $\Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n)$ $\frac{1}{\Theta(1)}$ + $\Theta(2)$ +···+ $\Theta(n-1)$ + $\Theta(n)$ does I not really have a reasonable interpretation.

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.

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

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

represents

n *f* : N → R⁺ | *f (n)* = *n* 2 · *g(n)* + *h(n)* with *g(n)* ∈ O*(n)* and *h(n)* ∈ O*(*log *n)*o Recall that according to the previous slide e.g. the expressions P*ⁿ ⁱ*=¹ O*(i)* and P*n/*² *ⁱ*=¹ O*(i)* + P*ⁿ ⁱ*=*n/*2+¹ O*(i)* generate different sets.

5 Asymptotic Notation

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.

5 Asymptotic Notation

Lemma 1

Let f , g be functions with the property

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

- \blacktriangleright *c* · *f*(*n*) $\in \Theta(f(n))$ *for any constant c*
- \rightarrow $\mathcal{O}(f(n)) + \mathcal{O}(g(n)) = \mathcal{O}(f(n) + g(n))$
- \rightarrow $\mathcal{O}(f(n)) \cdot \mathcal{O}(q(n)) = \mathcal{O}(f(n) \cdot g(n))$
- \rightarrow $\mathcal{O}(f(n)) + \mathcal{O}(g(n)) = \mathcal{O}(\max\{f(n), g(n)\})$

The expressions also hold for Ω*. 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.
- **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.
- \triangleright In general $\log n = \log_2 n$, i.e., we use 2 as the default base for the logarithm.

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

- **Follo** 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*.
- **However, suppose that I have two algorithms:**
	- Algorithm A. Running time $f(n) = 1000 \log n = O(\log n)$.
	- Algorithm B. Running time $g(n) = \log^2 n$.

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

Bibliography

- [MS08] Kurt Mehlhorn, Peter Sanders: *Algorithms and Data Structures — The Basic Toolbox*, Springer, 2008
- [CLRS90] Thomas H. Cormen, Charles E. Leiserson, Ron L. Rivest, Clifford Stein: *Introduction to algorithms (3rd ed.)*, McGraw-Hill, 2009

Mainly Chapter 3 of [CLRS90]. [MS08] covers this topic in chapter 2.1 but not very detailed.

