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.
- Running time should be expressed by simple functions.

Formal Definition

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

- ▶ $\mathcal{O}(f) = \{g \mid \exists c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$ (set of functions that asymptotically grow not faster than f)
- ▶ $\Omega(f) = \{g \mid \exists c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 \colon [g(n) \geq c \cdot f(n)]\}$ (set of functions that asymptotically grow not slower than f)
- $\Theta(f) = \Omega(f) \cap \mathcal{O}(f)$ (functions that asymptotically have the same growth as f)
- ▶ $o(f) = \{g \mid \forall c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$ (set of functions that asymptotically grow slower than f)
- $\omega(f) = \{g \mid \forall c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \geq c \cdot f(n)] \}$ (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 \mathbb{N}_0 to \mathbb{R}_0^+ .

•
$$g \in \Omega(f)$$
: $0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} \le \infty$

$$g \in \Theta(f): \quad 0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} < \infty$$

$$g \in o(f): \lim_{n \to \infty} \frac{g(n)}{f(n)} = 0$$

•
$$g \in \omega(f)$$
: $\lim_{n \to \infty} \frac{g(n)}{f(n)} = \infty$

- 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.

Abuse of notation

- 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.** People write $f(n) = \mathcal{O}(g(n))$, when they mean $f \in \mathcal{O}(g)$, 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).
 - function f evaluated at n, but instead $\frac{1}{n}$ it is a shorthand for the function itself it (leaving out domain and codomain and hi only giving the rule of correspondence of the function).
 - **2.** In this context f(n) does **not** mean the $\frac{1}{n}$ **3.** This is particularly useful if you do not $\frac{1}{n}$ want to ignore constant factors. For ex-! ample the median of n elements can be determined using $\frac{3}{2}n + o(n)$ comparisons.

Abuse of notation

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.

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.

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.

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

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 \mathcal{O} -symbol (or $\Theta, \Omega, o, \omega$) 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

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

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 dif-

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

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

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.
- 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:

- 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

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	Algorithms and Data Structures — The Basic Toolbox,
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[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.