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Formal Definition

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

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

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- 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 $g: \mathbb{N} \to \mathbb{R}^+, n \mapsto g(n)$.
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"It is understood" that every occurence of an $\mathcal O$ -symbol (or $\Theta,\Omega,\sigma,\omega$) on the left represents one anonymous function

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

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

represents

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

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

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

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

- $ightharpoonup c \cdot f(n) \in \Theta(f(n))$ for any constant c

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

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

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- Do not use asymptotic notation within induction proofs.
- For any constants a, b we have $\log_a n = \Theta(\log_b n)$. Therefore, we will usually ignore the base of a logarithm within asymptotic notation.
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