# Analysis of Algorithms Script of Lecture 2

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## **Contents**

- Quick reminder on asymptotic notations  $\mathcal{O}$ ,  $\Omega$ ,  $\Theta$ .
- Rules to calculate the cost of iterative algorithms.
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# **Analysis of Iterative Algorithms**

- The cost of elementary operations (see previous class) is  $\Theta(1)$ .
- Sequential composition: Given two fragments of code  $s_1$ ,  $s_2$  with cost  $f_1$  and  $f_2$  respectively, the cost of the fragment:

is 
$$f_1 + f_2$$

• Conditional composition: Let A be an expression with cost to evaluate  $f_a$ , and  $s_1$  and  $s_2$  two fragments of code with cost  $f_1$  and  $f_2$  respectively, the cost, in worst case, of the fragment:

is:  $f_a + \max\{f_1, f_2\}$ 

• Iterative Composition: Let A be an expression with cost to evaluate it at the i-th iteration  $g_i$ , and it is a code fragment with cost to the i-th iteration  $f_i$ , the cost, if not worse, of the fragment:

if n iterations are performed is:  $\sum_{i=1}^{n} (f_i + g_i) = O(n(f+g))$  with  $f = \max\{f_i\}$  and  $g = \max\{g_i\}$ .

### **Examples**

Calculation of the cost of different loops.

### **Analysis of recursive algorithms**

The cost (in worst case, average, ...) of a recursive algorithm T(n) satisfies a recurrent equation: this is, T(n) will depend on the value of T for smaller values of n. Frequently, the recurrence has one of the following forms:

$$T(n) = a \cdot T(n-c) + g(n),$$
  

$$T(n) = a \cdot T(n/b) + g(n).$$

The first one corresponds to algorithms that have a non recursive part with cost g(n) and do a recursive calls with subproblems of size n-c, with c a constant.

The second one corresponds to algorithms with a non recursive part of cost g(n) that do a recursive calls with subproblems of size (approximately) n/b, with b>1.

**Theorem 1.** Let T(n) be the cost (worst case, average case, ...) of a recursive algorithm that satisfies the recurrence:

$$T(n) = \begin{cases} f(n) & \text{if } 0 \le n < n_0 \\ a \cdot T(n-c) + g(n) & \text{if } n \ge n_0, \end{cases}$$

where  $n_0$  is a constant,  $c \ge 1$ , f(n) is an arbitrary function and  $g(n) = \Theta(n^k)$  for a constant  $k \ge 0$ .

Then

$$T(n) = \begin{cases} \Theta(n^k) & \text{if } a < 1\\ \Theta(n^{k+1}) & \text{if } a = 1\\ \Theta(a^{n/c}) & \text{if } a > 1. \end{cases}$$

**Theorem 2.** Let T(n) be the cost (worst case, average case, ...) of a recursive algorithm that satisfies the recurrence:

$$T(n) = \begin{cases} f(n) & \text{if } 0 \le n < n_0 \\ a \cdot T(n/b) + g(n) & \text{if } n \ge n_0, \end{cases}$$

where  $n_0$  is a constant, b > 1, f(n) is an arbitrary function and  $g(n) = \Theta(n^k)$  for a constant  $k \ge 0$ .

Let  $\alpha = \log_b a$ . Then

$$T(n) = \begin{cases} \Theta(n^k) & \text{if } \alpha < k \\ \Theta(n^k \log n) & \text{if } \alpha = k \\ \Theta(n^{\alpha}) & \text{if } \alpha > k. \end{cases}$$

# **Examples**

- Binary search:  $\Theta(\log(n))$  in the worst case.
- Fast exponentiation:  $\Theta(\log(n))$ .
- Fibonacci numbers:  $\mathcal{O}(2^n)$  and  $\Omega(2^{(n/2)})$ .