

02393 Programming in C++



Before and after teaching:



**If you feel ill,
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**Keep your
distance to
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**Disinfect
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**Respect the
marking/do not
move furniture**



**Do not
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equipment
with others**



**If in doubt,
please ask**

02393 Programming in C++

Module 10: Recursion

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(Slides based on previous versions by Andrea Vandin, Alberto Lluch Lafuente, Sebastian Mödersheim)

3 November 2020

Lecture Plan

#	Date	Topic	Book chapter *
1	01.09	Introduction	
2	08.09	Basic C++	1
3	15.09	Data Types Libraries and Interfaces	2
4	22.09		
5	29.09		3
6	06.10	Classes and Objects	4.1, 4.2 and 9.1, 9.2
<i>Autumn break</i>			
7	20.10	Templates	4.1, 11.1
8	27.10	LAB DAY	Old exams
9	03.11	Inheritance	14.3, 14.4, 14.5
10	10.11	Recursive Programming	5
11	17.11	Linked Lists	10.5
12	24.11	Trees	13
13	01.12	Summary & Exam Preparation	
	07.12	Exam	

* Recall that the book uses sometimes ad-hoc libraries that are slightly different with respect to the standard libraries (e.g., strings and vectors).

Recursion

What is Recursion?

- Solution technique that **solves large problems** by **reducing them to smaller problems of the same form**
- It is crucial that the smaller problem has the same form
- This means we can use the same technique for the big and the small problem!

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Why might recursion seem... weird?

- It requires a form of mathematical *inductive* reasoning
- Other programming concepts have a clearer real-life intuition
 - ★ *loop*: repeat an action several times, on different objects
 - ★ *if then else*: making decisions

Examples

Mathematical definitions often use recursion:

$$n! = \begin{cases} 1 & \text{if } n = 0 \\ n \cdot ((n-1)!) & \text{otherwise} \end{cases}$$

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int factorial = 1;
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    factorial = factorial * i;
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A possible *recursive* implementation in C++:

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int Fact(unsigned int n) {
    if (n == 0) return 1;
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Examples

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$$\text{Fact}(n) = \begin{cases} 1 & \text{if } n = 0 \\ n \cdot (\text{Fact}(n-1)) & \text{otherwise} \end{cases}$$

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Executing the factorial

main

Fact

n

4

```
→ if (n == 0) {  
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} else {  
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}
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Executing the factorial (continued)

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↑ ?

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`n`

`2`

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Executing the factorial (continued)

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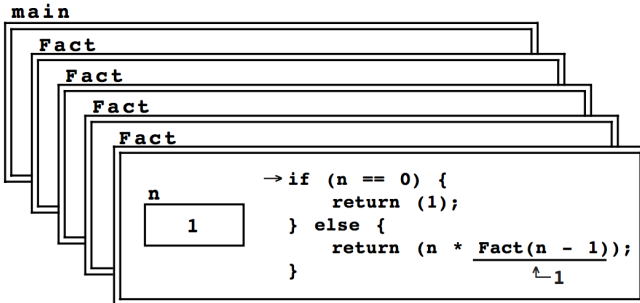
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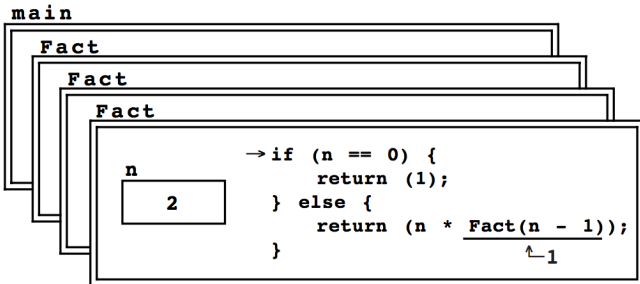
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↑₂

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↑ 6

Recursion

When using recursion we must ensure:

- ① Every recursion step reduces to a **smaller** problem
- ② There is a **smallest** problem (or a set of smallest problems) that can be handled directly, without recursion
- ③ Every sequence of recursion steps eventually **reaches** one of such smallest problems

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Otherwise?

- Risk of **non-termination** or **crash** (stack overflow)!

Recursive Leap of Faith

When writing a recursive function, we need to assume that each recursive call (with a smaller argument) computes the correct solution

- Example: to write $\text{Fact}(n)$, we need $\text{Fact}(n-1)$ to be correct

Assuming that a recursive call works correctly is called the *Recursive Leap of Faith*

Recursion: Rules of Thumb

- 1 Identify the smallest cases before decomposition
- 2 Solve the smallest cases
- 3 Check that decomposition makes the problem simpler
- 4 Ensure that decomposition eventually reaches one of the smallest cases
- 5 Ensure that the arguments to the recursive calls are smaller versions of the original arguments
- 6 When you take the recursive leap of faith, ensure that recursive calls yield a correct solution to all smaller problems

Live coding

Another simple example: sum of n consecutive integers

On Complexity

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Notes:

- Some problems are not computable! (no algorithm exists)
- Sometimes trade-off between time and space
- For many problems, the precise complexity is not known:
 - ★ We have a best known algorithm
 - ★ We can give a lower bound

Asymptotic Complexity

Big-O notation and Big-Ω notation

We often focus on the worst-case time / space requirements of an algorithm, for input size N . We use **Big-O notation**. E.g.:

$$2N^2 + 17N + 53 \text{ operations} \implies O(N^2) \text{ time complexity}$$

We only consider dominant terms because, as N grows,

- larger exponents have more impact
- constant factors and minor terms tend to become irrelevant

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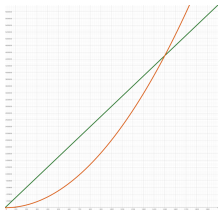
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For example, if we have:

- ① a good algorithm, time: $3000N \implies O(N)$
- ② a bad algorithm, time: $2N^2 \implies O(N^2)$

Above some N , algorithm (1) performs better

Asymptotic Complexity

Big-O notation and Big-Ω notation

Definition (Big-O Notation)

$O(f)$: the class of functions that asymptotically grow no faster than f

$$O(f) = \{g : \mathbb{N} \rightarrow \mathbb{R}^+ \mid \exists c \in \mathbb{R}^+ : \exists N_0 \in \mathbb{N} : \forall N \geq N_0 : g(N) \leq c f(N)\}$$

For instance:

$$2N^2 + 17N + 53 < 73N^2$$

For $c = \frac{1}{73}$ and $N_0 = 1$, we obtain:

$$2N^2 + 17N + 53 \in O(N^2)$$

Dually, for giving lower-bounds on complexity, one uses $\Omega(f)$, which is the class of functions that grow at least as fast as f

More Examples of Recursion (see lecture code)

- Efficient search: **binary search**
 - ★ Naive search (linear search) of an element in a set takes $O(n)$
 - ★ Binary search is a divide-and-conquer $O(\log n)$ solution
- Efficient sorting: **merge sort**
 - ★ The recursion paradigm directly triggers an efficient solution!
 - ★ Naive bubble sort: $O(n^2)$ for array of size n
 - ★ Merge sort: $O(n \log n)$ (theoretical optimum)
- **Efficient exponentiation** in cryptography ($a^n \bmod p$)
 - ★ Naive exponentiation: $O(n)$
 - ★ Efficient exponentiation: $O(\log n)$
 - ★ Efficient solution is hard to program without recursion!

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