

Module 10: Recursive Programming

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

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Course plan

Module no.	Date	Topic	Book chapter*
0 and 1	30.08	Welcome & C++ Overview	1
2	06.09	Basic C++ and Data Types	2.1, 2.3 - 2.5, 11.1, 11.3
3	13.09	Enumerations and Structures & LAB DAY	1.5
4	20.09	Memory Management	12.1, 11.2, 11.3
5	27.09	Libraries and Interfaces	2.2, 2.6 - 2.8, 3.1 - 3.3, 4.1 - 4.3
6	04.10	Classes and Objects	5.1, 6.1, 11.2, 12.1, 12.4, 12.7
7	11.10	Templates	5.1, 14.2
Autumn break			
8	25.10	Inheritance	19.1 - 19.3
9	01.11	LAB DAY	Previous exams
10	08.11	Recursive Programming	7
11	15.11	Linked Lists	12.2, 12.3
12	22.11	Trees	16.1 - 16.4
13	29.11	Conclusion & LAB DAY	Exam preparation
	22.12	Exam (held physically, all aids allowed)	

^{*} Recall that the book uses some ad-hoc libraries (e.g., for vectors). We will use standard libraries

Outline

Recursive programming

Recursive programming

Overview

Mathematical recursion, in code

Base cases and termination

The "recursive leap of faith"

Rules of thumb

Live coding

On the complexity of problems and algorithms

Examples on recursive programming and complexity

Lab

What is recursion?

Recursive programming is a solution technique that solves large problems by reducing them to smaller problems of the same form

- ▶ It is crucial that both the large and smaller problems have the same form!
- ▶ So we can use the same technique (and the same code!) to solve both

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Why might recursion seem... weird?

- Recursion requires a form of mathematical inductive reasoning
- ▶ Recursion is more abstract than programming concepts having a mechanical intuition
 - ▶ loop: repeat an action several times
 - if-then-else: check a condition, make a decision
 - recursion: ???

Examples

You may have already seen recursion in mathematical definitions. E.g., the factorial:

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

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A possible **iterative implementation** of the factorial in C++:

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unsigned int factorial = 1;
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Recursive programming

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unsigned int Fact(unsigned int n) {
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Recursive programming

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Example: executing Fact (4)

Recursive programming 0000000

```
main
  Fact
                 if (n == 0) {
     n
                    return (1);
                   else {
                    return (n * Fact(n - 1));
```

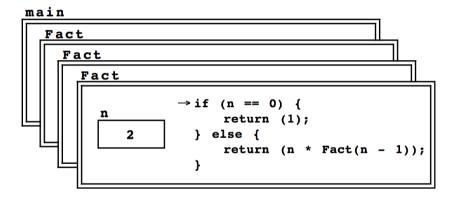
Recursive programming

0000000

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      Fact
                     \rightarrow if (n == 0) {
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Recursive programming

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Recursive programming

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          <u>Fac</u>t
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Using recursion: base cases and termination

When using recursion we must ensure that:

- 1. there are one or more base cases
 - i.e., "smallest" problems for which we return a solution, without recursion
- 2. every recursion step reduces to a smaller problem
- 3. every sequence of recursion steps eventually reaches one of the base cases

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In the Factorial example: the base case is n = 0, we recursively call Fact on smaller and smaller numbers, so we eventually reach the base case n = 0

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If any of the 3 conditions above is not satisfied, recursion may not work properly!

► Risk of non-termination or crashes (stack overflow)

Recursive programming

Using recursion: the "recursive leap of faith"

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

Example: to write Fact(n), we need to assume that Fact(n-1) is correct

```
unsigned int Fact(unsigned int n) {
   if (n == 0) return 1;
   else return n * Fact(n-1):
4 }
```

Assuming that a recursive call works correctly is called the "recursive leap of faith"

Recursion: rules of thumb

- 1. Identify the base cases (i.e., the "smallest" cases whose solution does not need recursion)
- 2. Solve the base cases
- 3. Address the recursive cases (i.e., the non-base cases that need recursive calls)
 - ▶ Ensure that the arguments to the recursive calls are "smaller" than the original arguments
 - ▶ Ensure that recursive calls eventually reach one of the base cases

Live coding

Recursive programming

Another simple example:

sum of n consecutive integers

On the complexity of algorithms and problems

We are often interested in estimating the resources needed by an algorithm:

- **time**: number of operations
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Such resources usually depend on the size of the algorithm inputs (denoted N)

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Notes:

Recursive programming

- ► Some problems are **not computable**! (i.e., no algorithm exists)
- Sometimes we have a trade-off between time and space
- For many problems, the **precise complexity is not known**:
 - we may know some solution algorithms, but we don't know whether a better one exists
 - we can give a **lower bound** to the complexity

Asymptotic complexity: Big-O notation

We are often interested in the worst-case time / space requirements of an algorithm, given an input size N. In such cases, we use **Big-O** notation. E.g.:

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

We **only consider dominant terms**. This is because, as N grows,

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

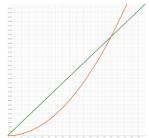
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Recursive programming

For example, if we have:

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

The plot shows N (x-axis) vs. number of operations (y-axis) Above some N, the algorithm (1) performs better (less operations)

Asymptotic complexity: Big-O (cont'd)

Definition (Big-O notation). O(f) is the class of functions that **asymptotically grow no faster** than f. More formally:

$$O(f) = \left\{ g: \mathbb{N} \to \mathbb{R}^+ \mid \exists c \in \mathbb{R}^+ : \exists N_0 \in \mathbb{N} : \forall N \ge N_0 : g(N) \le c f(N) \right\}$$

For instance, we have: $2N^2 + 2N + 1 \in O(N^2)$

This is because taking c=5 and $N_0=1$, we have $2N^2+2N+1 \le cN^2$ for all $N \ge N_0$

Asymptotic complexity: Big-O (cont'd) and Big- Ω notation

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Dually, we are sometimes interested in the **best-case time / space** requirements (i.e., **lower-bound complexity**) of an algorithm, given an input size N

For this we use $\Omega(f)$ which is the class of functions that grow at least as fast as f — and the corresponding $\operatorname{Big-}\Omega$ notation

More examples of recursion (see lecture code)

Efficient search: binary search

Recursive programming

- 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 $(a^n \mod p)$
 - ightharpoonup Naive exponentiation: O(n)
 - **Efficient exponentiation:** $O(\log n)$
 - ▶ Efficient solution is hard to program without recursion!

Lab

Recursive programming

Today's lab begins now. Tasks:

- ▶ make sure C++ works on your computer, request help if it doesn't
- begin working on Assignment 9
- ask questions if something is unclear (including previous assignments)