Recursion and Backtracking

02393 - Programming in C++
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Lecture Plan

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

Definition

Recursion (lat.): see Recursion ... or Google 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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- This means we can use the same technique for the big and the small problem!

Why is Recursion... weird for some people?

- ▶ Some people are not used to inductive reasoning/abstraction...
- Other programming concepts are common in normal life:
 - repeat an action several times, on different objects (loops);
 - making decisions (if then else);
 - etc.

When using recursion we must ensure:

- Every recursion step reduces to a smaller problem.
- ► There is a smallest problem (or a set of smallest problems) that can be handled directly, without recursion.
- Every chain of recursion steps eventually reaches one of these smallest problems.

Otherwise?

Risk of non-termination!

Recursive Leap of Faith

- When writing a recursive function, we believe that the recursive call computes the right solution, if the argument to the recursive call is smaller.
- ▶ Assuming that any recursive call works correctly is called the *Recursive Leap of Faith*.

Rules of thumb

- ► Checking if you have a simple problem before decomposition.
- Solve the simple cases correctly!
- Check that decomposition makes the problem simpler!
- Ensure that decomposition eventually reaches one of the simple cases.
- ► The arguments to the recursive calls must be simpler versions of the original argument!
- When you take the recursive leap of faith, do the recursive calls provide with a correct solution to all simpler problems possible?

Examples

Mathematical definitions often use recusion:

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

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And can be easily transformed into a C++ program:

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Note the similarity of recursion with induction proofs.

Example Theorem and Inductive Proof

n! > 0 for all natural numbers n.

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Proof: trivial.

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 - (*) Suppose for some number n-1 we have proved that (n-1)! > 0.
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 - ▶ Thus n! > 0.

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 - ▶ We have that n > 0 (since $n 1 \ge 0$) and fact(n 1) > 0 (by \star). It then trivially follows that $n \cdot fact(n 1) > 0$.
 - Thus n! > 0.
 - ► Thus fact(n) > 0.

Examples/Live programming

- ► Toy examples: factorial, sum.
- 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 $(a^n \mod p)$
 - Naive exponentiation: O(n)
 - ► Efficient exponentiation: $O(\log n)$
 - Efficient solution is hard to program without recursion!

On Complexity

Resources needed by an algorithm:

- ► Time: number of operations
- Space: amount of memory/disk
- Depends on the size N of the problem.
- ▶ Usually working with asymptotic complexity, e.g. O(N)

Complexity of a Problem:

- Given a concrete problem (e.g. sorting a list of numbers)
- What is the best algorithm in terms of time and/or space?

Notes:

- Sometimes trade-off between time and space
- ► For many problems, the precise complexity is not known:
 - We have a best known algorithm (e.g. $O(2^N)$)
 - ▶ We can give a lower bound (e.g. $\Omega(N^5)$)
- Some problems are not computable at all.

 $\mathsf{Big}\text{-}\mathsf{O}$ notation and $\mathsf{Big}\text{-}\Omega$ notation

▶ Abstract from constant factors (and minor terms):

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

Big-O notation and Big- Ω notation

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- Intuition:
 - constant factors can be "made up" by faster hardware
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- ► Example: race between—
 - 1. slow hardware running a good algorithm, say time: 3000 N
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- ► Example: race between—
 - 1. slow hardware running a good algorithm, say time: 3000 N
 - 2. fast hardware running a bad algorithm, say time: $2N^2$
 - (1.) wins for N > 1500.

Big-O notation and Big- Ω notation

Definition (Big-O Notation)

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

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

For instance:

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

so for $c=\frac{1}{73}$ and $N_0=1$, we can see

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

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.