

COMP526 (Fall 2023) University of Liverpool version 2023-09-30 16:40

# **Learning Outcomes**

- 1. Understand the difference between empirical *running time* and algorithm *analysis*.
- 2. Understand *worst/best/average case* models for input data.
- 3. Know the *RAM machine* model.
- **4.** Know the definitions of *asymptotic notation* (Big-Oh classes and relatives).
- 5. Understand the reasons to make *asymptotic approximations*.
- 6. Be able to *analyze* simple *algorithms*.

#### Unit 1: Machines & Models



#### Outline

# **1** Machines & Models

- 1.1 Algorithm analysis
- 1.2 The RAM Model
- 1.3 Asymptotics & Big-Oh

# What is an algorithm?

An algorithm is a sequence of instructions.  $\chi_{\text{think: recipe}}$ 

More precisely:

e.g. Python script

- **1**. mechanically executable
  - $\rightsquigarrow$  no "common sense" needed
- **2.** finite description *≠* finite computation!
- 3. solves a *problem*, i. e., a class of problem instances x + y, not only 17 + 4
- input-processing-output abstraction





#### Typical example: bubblesort

→ not a specific program but the underlying idea

#### What is a data structure?

A data structure is

- 1. a rule for encoding data (in computer memory), plus
- 2. algorithms to work with it (queries, updates, etc.)

typical example: binary search tree



1.1 Algorithm analysis

# **Good algorithms**

Our goal: Find good (best?) algorithms and data structures for a task.

Good "usually" means can be complicated in distributed systems

- fast running time
- moderate memory *space* usage

Algorithm analysis is a way to

- compare different algorithms,
- predict their performance in an application

# **Running time experiments**

Why not simply run and time it?

- results only apply to
  - ▶ single *test* machine
  - tested inputs
  - tested implementation
  - ► ...
  - $\neq$  universal truths



- instead: consider and analyze algorithms on an abstract machine
  - $\rightsquigarrow\,$  provable statements for model

survives Pentium 4

- $\rightsquigarrow$  testable model hypotheses
- → Need precise model of machine (costs), input data and algorithms.

### **Data Models**

Algorithm analysis typically uses one of the following simple data models:

worst-case performance: consider the *worst* of all inputs as our cost metric

#### **best-case performance:**

consider the best of all inputs as our cost metric

#### average-case performance:

consider the average/expectation of a random input as our cost metric

Usually, we apply the above for *inputs of same size n*.

 $\rightsquigarrow$  performance is only a **function of** *n*.

# **1.2 The RAM Model**









#### Machine models

The machine model decides

- what algorithms are possible
- how they are described (= programming language)

what an execution costs

**Goal:** Machine model should be

detailed and powerful enough to reflect actual machines, abstract enough to unify architectures, simple enough to analyze.

## Machine models

The machine model decides

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detailed and powerful enough to reflect actual machines, abstract enough to unify architectures, simple enough to analyze.

→ usually some compromise is needed



#### **Random Access Machines**

#### Random access machine (RAM)

- ▶ unlimited *memory* MEM[0], MEM[1], MEM[2], ...
- fixed number of *registers*  $R_1, \ldots, R_r$  (say r = 100)
- ▶ memory cells MEM[*i*] and registers  $R_i$  store *w*-bit integers, i. e., numbers in  $[0..2^w 1]$ *w* is the word width/size; typically  $w \propto \lg n \rightarrow 2^w \approx n$

/ we will see further models later

Instructions:

- ▶ load & store: R<sub>i</sub> := MEM[R<sub>j</sub>] MEM[R<sub>j</sub>] := R<sub>i</sub>
   ▶ operations on registers: R<sub>k</sub> := R<sub>i</sub> + R<sub>j</sub> (arithmetic is modulo 2<sup>w</sup>!) also R<sub>i</sub> - R<sub>j</sub>, R<sub>i</sub> · R<sub>j</sub>, R<sub>i</sub> div R<sub>j</sub>, R<sub>i</sub> mod R<sub>j</sub> C-style operations (bitwise and/or/xor, left/right shift)
- conditional and unconditional jumps
- cost: number of executed instructions

---- The RAM is the standard model for sequential computation.

more detail in §2.2 of Sequential and Parallel Algorithms and Data Structures by Sanders, Mehlhorn, Dietzfelbinger, Dementiev

#### Pseudocode

- ▶ Programs for the random-access machine are very low level and detailed
- $\approx$  assembly/machine language

Typical simplifications when describing and analyzing algorithms:

code that humans understand (easily)

- more abstract pseudocode\*
  - control flow using if, for, while, etc.
  - variable names instead of fixed registers and memory cells
  - memory management (next slide)
- count *dominant operations* (e.g. memory accesses) instead of all RAM instructions

In both cases: We can go to full detail where needed.



## Memory management & Pointers

- A random-access machine is a bit like a bare CPU . . . without any operating system
  ~ cumbersome to use
- ▶ All high-level programming languages add *memory management* to that:
  - ▶ Instruction to *allocate* a contiguous piece of memory of a given size (like malloc).
    - used to allocate a new array (of a fixed size) or
    - a new object/record (with a known list of instance variables)
    - There's a similar instruction to free allocated memory again.
  - ► A *pointer* is a memory address (i. e., the *i* of MEM[*i*]).
  - Support for procedures (a.k.a. functions, methods) calls including recursive calls
    - (this internally requires maintaining call stack)



We will mostly ignore *how* all this works in COMP526.

# 1.3 Asymptotics & Big-Oh









## Why asymptotics?

Algorithm analysis focuses on (the limiting behavior for infinitely) large inputs.

- abstracts from unnecessary detail
- simplifies analysis
- often necessary for sensible comparison

Asymptotics = approximation around  $\infty$ 

**Example:** Consider a function f(n) given by  $2n^2 - 3n\lfloor \log_2(n+1) \rfloor + 7n - 3\lfloor \log_2(n+1) \rfloor + 120$ 





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**Example:** Consider a function f(n) given by  $2n^2 - 3n \lfloor \log_2(n+1) \rfloor + 7n - 3 \lfloor \log_2(n+1) \rfloor + 120 \sim 2n^2$ 





#### Asymptotic tools – Formal & definitive definition

► "Tilde Notation":  $f(n) \sim g(n)$  iff  $\lim_{n \to \infty} \frac{f(n)}{g(n)} = 1$ "f and g are asymptotically equivalent" Asymptotic tools – Formal & definitive definition if, and only if ▶ "Tilde Notation":  $f(n) \sim g(n)$  iff  $\lim_{n \to \infty} \frac{f(n)}{g(n)} = 1$ "f and g are asymptotically equivalent" **"Big-Oh Notation":**  $f(n) \in O(g(n))$  iff  $\left| \frac{f(n)}{g(n)} \right|$  is bounded for  $n \ge n_0$ need supremum since limit might not exist!  $\inf \lim_{n \to \infty} \sup_{n \to \infty} \left| \frac{f(n)}{g(n)} \right| < \infty$ **riants:** "Big-Omega" •  $f(n) \in \Omega(g(n))$  iff  $g(n) \in O(f(n))$ •  $f(n) \in \Theta(g(n))$  iff  $f(n) \in O(g(n))$  and  $f(n) \in \Omega(g(n))$ Variants:

Asymptotic tools – Formal & definitive definition if, and only if ▶ "Tilde Notation":  $f(n) \sim g(n)$  iff  $\lim_{n \to \infty} \frac{f(n)}{\sigma(n)} = 1$ "f and g are asymptotically equivalent" **"Big-Oh Notation":**  $f(n) \in O(g(n))$  iff  $\left| \frac{f(n)}{g(n)} \right|$  is bounded for  $n \ge n_0$ need supremum since limit might not exist!  $\inf \lim_{n \to \infty} \sup_{n \to \infty} \left| \frac{f(n)}{g(n)} \right| < \infty$ **Variants:** "Big-Omega"  $f(n) \in \Omega(g(n))$  iff  $g(n) \in O(f(n))$ ►  $f(n) \in \Theta(g(n))$  iff  $f(n) \in O(g(n))$  and  $f(n) \in \Omega(g(n))$ "Big-Theta" <sup>"Big-Theta"</sup>  $f(n) \in o(g(n))$  iff  $\lim_{n \to \infty} \left| \frac{f(n)}{g(n)} \right| = 0$ "Little-Oh Notation":  $f(n) \in \omega(g(n))$  if  $\lim \infty$ 

# Asymptotic tools – Intuition

► f(n) = O(g(n)): f(n) is at most g(n)up to constant factors and for sufficiently large n



►  $f(n) = \Theta(g(n))$ : f(n) is equal to g(n)up to constant factors and  $f'(a) \neq g(a)$  for sufficiently large n

Example 🗗

Plots can be misleading!







$$f(u) \leq g(u) \leq (-) \int (u) \geq f(u)$$

Assume  $f(n) \in O(g(n))$ . What can we say about g(n)? A g(n) = O(f(n))B  $g(n) = \Omega(f(n)) \checkmark$ C  $g(n) = \Theta(f(n))$ D Nothing (it depends on f and g)









Use *wolframalpha* to compute/check limits.







#### Asymptotics – Frequently used facts

► Rules:

- $c \cdot f(n) = \Theta(f(n))$  for constant  $c \neq 0$
- $\Theta(f + g) = \Theta(\max\{f, g\})$  largest summand determines  $\Theta$ -class
- Frequently used orders of growth:
  - ► logarithmic  $\Theta(\log n)$  Note: a, b > 0 constants  $\rightsquigarrow \Theta(\log_a(n)) = \Theta(\log_b(n))$
  - linear  $\Theta(n)$
  - linearithmic  $\Theta(n \log n)$
  - quadratic  $\Theta(n^2)$
  - polynomial  $O(n^c)$  for constant c
  - exponential  $O(c^n)$  for constant c Note: a > b > 0 constants  $\rightsquigarrow b^n = o(a^n)$

# **Asymptotics – Example 2**

Square-and-multiply algorithm for computing  $x^m$  with  $m \in \mathbb{N}$ 

Inputs:

- *m* as binary number (array of bits)
- n =#bits in m
- ► *x* a floating-point number

1 def pow(x, m):
2 # compute binary representation of exponent
3 exponent\_bits = bin(m)[2:]
4 result = 1
5 for bit in exponent\_bits:
6 result \*= result
7 if bit == '1':
8 result \*= x
9 return result

Cost: C = # multiplications

• C = n (line 4) + #one-bits binary representation of *m* (line 5)  $\sim n \le C \le 2n$ 



We showed  $n \le C(n) \le 2n$ ; what is the most precise asymptotic approximation for C(n) that we can make?

Write e.g.  $O(n^2)$  for  $O(n^2)$  or Theta(sqrt(n)) for  $\Theta(\sqrt{n})$ .



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- Cost: C = # multiplications
- C = n (line 4) + #one-bits binary representation of *m* (line 5)

$$\rightsquigarrow n \le C \le 2n$$

 $\rightsquigarrow C = \Theta(n) = \Theta(\log m)$ 

**Note:** Often, you can pretend  $\Theta$  is "like ~ with an unknown constant" *but in this case, no such constant exists*!



