

Lecture 1: Introduction and asymptotic complexity

BE5B33ALG — Algorithms

Ing. Robert Pěnička, Ph.D.
doc. RNDr. Daniel Průša, Ph.D.

Faculty of Electrical Engineering
Czech Technical University in Prague



FACULTY
OF ELECTRICAL
ENGINEERING
CTU IN PRAGUE



MULTI-ROBOT
SYSTEMS
GROUP

- **Course page**

<https://cw.fel.cvut.cz/b251/courses/be5b33alg/start>

- **Credits**

6 credits = 10 hours per week! (in 14 weeks + 5-week exam period)

- **Goals**

Teach efficient solutions of various problems arising from elementary computer science. The main topics include algorithmic complexity, sorting and searching algorithms,

- **Prerequisites**

Expected capability of proficient programming in either C, C++, Java or Python. Integral and mandatory part are practical programming homeworks. Attendants are expected to be familiar with basic data structures such as arrays, lists, files etc.

- **Literature**

Cormen TH, Leiserson CE, Rivest RL, Stein C. *Introduction to algorithms*. MIT press; 2022 Apr 5.

- **Timetable**

1.5h Lecture + 1.5h Practices <https://intranet.fel.cvut.cz/en/education/rozvrhynng.B251/public/html/predmety/43/56/p4356206.html>

- **Brute system**

Upload system for homeworks and exams <https://cw.felk.cvut.cz/brute/>

- **Plan of the semester**

week #	Topic
1	Order of growth of functions, asymptotic complexity
2	Trees, binary trees, recursion
3	More recursion and backtrack examples
4	Graph, graph representation, basic graph processing
5	Queue, Stack, Breadth/Depth First Search
6	Array search, Binary search tree
7	AVL and B- trees
8	Sorting algorithms I
9	Sorting algorithms II
10	Dynamic programming I
11	Dynamic programming II
12	Complexity of recursive algorithms, Master theorem
13	Hashing I & II
14	Individual repetitions and exam preparation

• Points

- Points gained by solving **homeworks** (max 36 points).
- Points gained by solving the **midterm test** (max 12 points).
Acceptable minimum from homeworks and the test is 24 points (out of 48 points).
- Points gained by solving the **programming part** (max 20 points).
Acceptable minimum is 10 points. Each correctly processed input file of total 10 files is worth 2 points.
- Points gained by solving the **theoretical part** (max 32 points).
Acceptable minimum is 16 points. The amount of points gained is decided by the examiner.

• Grading

Points total	Grade
< 50	F
50 – 59.99	E
60 – 69.99	D
70 – 79.99	C
80 – 89.99	B
90 – 100	A

- **Computational problem P**

The task of transforming an input IN into an output data OUT such that some prescribed conditions are satisfied.

- **Algorithm A**

- Computational process that reflects the progress of solution of problem P .
- Exact and unambiguous description of the sequence of computational steps which transforms input data IN step by step into the output data OUT satisfying the conditions of problem P .

- **Problem instance I**

Problem P taken together with one set of particular input data.

- **Correctness**

Property of algorithm A that guarantees that for **each** problem instance I the algorithm produces **appropriate** output in **finite time**.

How to compare algorithms?

Empirically?

- Based on the algorithm we can write a program which implements it and run it on a computer on some set of instances
- We can compare the speed and memory demands of each implementation.
- However, is this a good way how to compare algorithms?
 - What if the computer is different? What if the OS is different?
 - What if the programming language is different? What if the compiler is different?
 - What if the instances are different?



- A more fair comparison of particular algorithms is needed for independent comparison...

How to compare algorithms?

Lecture 1:
Introduction and
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complexity

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations



<https://www.youtube.com/watch?v=ZZuD6iUe3Pc>

Computing the complexity

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- **Elementary operation:** an operation that takes a constant amount of time, e.g., arithmetic operations, comparisons, assignments, memory moves.
- **Complexity:** the number of elementary operations performed by an algorithm (with respect to input size).
- **Worst case:** when all conditions are unfavorable w.r.t. the complexity (e.g., searching for an element in an unsorted list).
- **Best case:** when all conditions are favorable w.r.t. the complexity (e.g., searching for an element in a sorted list).

Computing the complexity - Examples

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Find minimum $\min$ and maximum $\max$ value in an array a .
- Standard variant iterate index i from 1 to $n - 1$ by one.

$a =$

3	2	7	10	0	5	-10	4	6
---	---	---	----	---	---	-----	---	---

- Result is $\min = -10, \max = 10$

```
1  $\min = a[0], \max = a[0]$ 
2 for  $i \leftarrow 1$  to  $n - 1$  do
3   if  $a[i] < \min$  then
4      $\min = a[i]$ 
5   if  $a[i] > \max$  then
6      $\max = a[i]$ 
```

Computing the complexity – example

- Find minimum $\min$ and maximum $\max$ value in an array a .
- Faster variant: iterate index i from 1 to $n - 1$ by two.

$a =$

3	2	7	10	0	5	-10	4	6
---	---	---	----	---	---	-----	---	---

```
1   $\min = a[0], \max = a[0]$ 
2  for  $i$  to  $n - 1$  with  $i = i + 2$  do
3      if  $a[i] < a[i + 1]$  then
4          if  $a[i] < \min$  then
5               $\min = a[i]$ 
6          if  $a[i + 1] > \max$  then
7               $\max = a[i + 1]$ 
8      else
9          if  $a[i] > \max$  then
10              $\max = a[i]$ 
11          if  $a[i + 1] < \min$  then
12              $\min = a[i + 1]$ 
```

Computing the complexity – example

- Assume N is the size of the input array a .
- **Complexity:** the number of elementary operations performed.
- Can be **simplified** to number of elementary operations on the data (e.g. on our array a).
- **Most commonly simplified to the number of comparisons made on the data.**

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n-1}^{N-1}$  do
3      if  $\overbrace{a[i] < min}^{N-1}$  then
4           $\overbrace{min = a[i]}^{0 \dots N-1}$ 
5      if  $\overbrace{a[i] > max}^{N-1}$  then
6           $\overbrace{max = a[i]}^{0 \dots N-1}$ 
```

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n-1}^{(N-1)/2}$  with  $i = i + 2$  do
3      if  $\overbrace{a[i] < a[i+1]}^{N-1}$  then }  $\frac{N-1}{2}$ 
4          if  $\overbrace{a[i] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
5               $\overbrace{min = a[i]}^{0 \dots (N-1)/2}$ 
6          if  $\overbrace{a[i+1] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
7               $\overbrace{max = a[i+1]}^{0 \dots (N-1)/2}$ 
8      else
9          if  $\overbrace{a[i] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
10              $\overbrace{max = a[i]}^{0 \dots (N-1)/2}$ 
11         if  $\overbrace{a[i+1] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
12              $\overbrace{min = a[i+1]}^{0 \dots (N-1)/2}$ 
```

Computing the complexity – example

- Assume N is the size of the input array a .
- What is the number of **elementary operations** of the standard algorithm?
- What is the number of **elementary operations on the data** (array a ?) of the standard algorithm?
- What is the number of **comparisons made on the data** (array a ?) of both algorithms?

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n-1}^{N-1}$  do
3      if  $\overbrace{a[i] < min}^{N-1}$  then
4           $\overbrace{min = a[i]}^{0 \dots N-1}$ 
5      if  $\overbrace{a[i] > max}^{N-1}$  then
6           $\overbrace{max = a[i]}^{0 \dots N-1}$ 
```

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n-1}^{(N-1)/2}$  with  $i = i + 2$  do
3      if  $\overbrace{a[i] < a[i+1]}^{N-1}$  then }  $\frac{N-1}{2}$ 
4          if  $\overbrace{a[i] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
5               $\overbrace{min = a[i]}^{0 \dots (N-1)/2}$ 
6          if  $\overbrace{a[i+1] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
7               $\overbrace{max = a[i+1]}^{0 \dots (N-1)/2}$ 
8      else
9          if  $\overbrace{a[i] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
10              $\overbrace{max = a[i]}^{0 \dots (N-1)/2}$ 
11         if  $\overbrace{a[i+1] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
12              $\overbrace{min = a[i+1]}^{0 \dots (N-1)/2}$ 
```

Computing the complexity – example

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Total operations: $3N$ best case and $5N - 2$ worst case (includes also blue and green).
- Operations on data: $2N$ best case and $4N - 2$ worst case (includes also green).
- Comparisons on data: always $2N - 2$ for standard and always $3(N - 1)/2$ for faster variant.

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n - 1}^{N-1}$  do
3      if  $\overbrace{a[i] < min}^{N-1}$  then
4           $\overbrace{min = a[i]}^{0 \dots N-1}$ 
5      if  $\overbrace{a[i] > max}^{N-1}$  then
6           $\overbrace{max = a[i]}^{0 \dots N-1}$ 
```

```
1   $\overbrace{min = a[0]}^1, \overbrace{max = a[0]}^1$ 
2  for  $\overbrace{i \leftarrow 1}^1$  to  $\overbrace{n - 1}^{(N-1)/2}$  with  $i = i + 2$  do
3      if  $\overbrace{a[i] < a[i + 1]}^{N-1}$  then }  $\frac{N-1}{2}$ 
4          if  $\overbrace{a[i] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
5               $\overbrace{min = a[i]}^{0 \dots (N-1)/2}$ 
6          if  $\overbrace{a[i + 1] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
7               $\overbrace{max = a[i + 1]}^{0 \dots (N-1)/2}$ 
8      else
9          if  $\overbrace{a[i] > max}^{N-1}$  then }  $\frac{N-1}{2}$ 
10              $\overbrace{max = a[i]}^{0 \dots (N-1)/2}$ 
11         if  $\overbrace{a[i + 1] < min}^{N-1}$  then }  $\frac{N-1}{2}$ 
12              $\overbrace{min = a[i + 1]}^{0 \dots (N-1)/2}$ 
```

Rate of growth of functions

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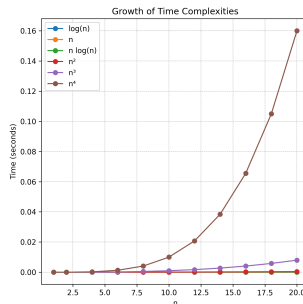
- n number of the data items (size of the data)
- Assumes one operation takes exactly 1μ
- $T(n)$ time needed to process n data items

Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations



$n/T(n)$	20	40	60	80	100
$\log(n)$	4.3 μ s	5.3 μ s	5.9 μ s	6.3 μ s	6.6 μ s
n	20 μ s	40 μ s	60 μ s	80 μ s	0.1 ms
$n \log(n)$	86 μ s	0.2 ms	0.35 ms	0.5 ms	0.7 ms
n^2	0.4 ms	1.6 ms	3.6 ms	6.4 ms	10 ms
n^3	8 ms	64 ms	0.22 sec	0.5 sec	1 sec
n^4	0.16 sec	2.56 sec	13 sec	41 sec	100 sec
2^n	1 sec	12.7 days	36600 yrs	10^{11} yrs	10^{16} yrs
$n!$	77100 yrs	10^{34} yrs	10^{68} yrs	10^{105} yrs	10^{144} yrs

- Upper asymptotic estimate (big-O (omicron) notation)

$$f(n) \in O(g(n))$$

- **Meaning:**

function f is asymptotically upper-bounded (from above) by a function g disregarding the additive and multiplicative constants.

- **Definition:**

$$(\exists c > 0)(\exists n_0)(\forall n > n_0) : f(n) \leq c \cdot g(n)$$

where: $c \in \mathbb{R}^{>0}$, $n_0, n \in \mathbb{N}$, $f, g \in \mathbb{N} \rightarrow \mathbb{R}^{\geq 0}$

Asymptotic estimations – examples

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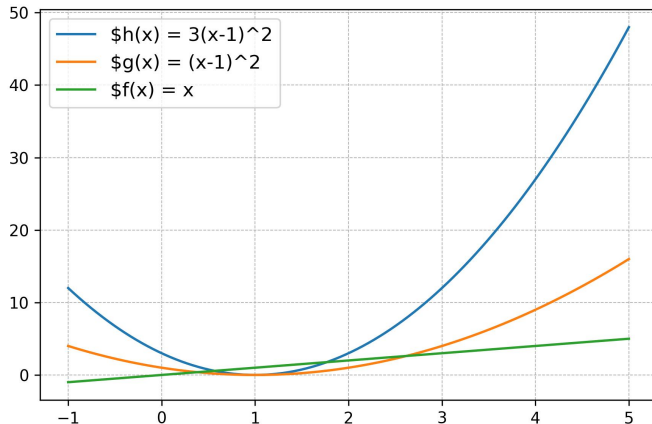
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Is it true that $f(n) \in O(g(n))$ and that $h(n) \in O(g(n))$?
- What are the values of c and n_0 ? ($f(n) \in O$ if $f(n) \leq c \cdot g(n)$)



Asymptotic estimations – examples

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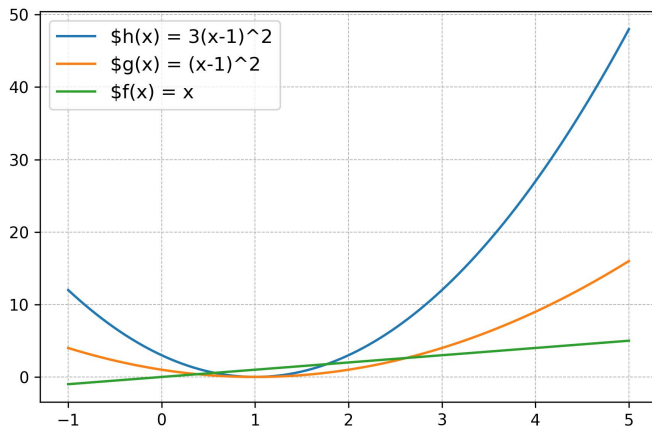
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Is it true that $f(n) \in O(g(n))$ YES and that $h(n) \in O(g(n))$ YES?
- What are the values of c and n_0 ? ($f(n) \in O$ if $f(n) \leq c \cdot g(n)$)



Asymptotic estimations – Lower asymptotic estimate Ω

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Lower asymptotic estimate (big-Omega notation)

$$f(n) \in \Omega(g(n))$$

- **Meaning:**

function f is asymptotically lower-bounded (bounded from below) by a function g disregarding the additive and multiplicative constants.

- **Definition:**

$$(\exists c > 0)(\exists n_0)(\forall n > n_0) : c \cdot g(n) \leq f(n)$$

where: $c \in \mathbb{R}^{>0}$, $n_0, n \in \mathbb{N}$, $f, g \in \mathbb{N} \rightarrow \mathbb{R}^{\geq 0}$

Asymptotic estimations for functions of more variables

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Upper asymptotic estimate (big-O (omicron) notation)

$$f(n_1, \dots, n_k) \in O(g(n_1, \dots, n_k))$$

- **Definition:**

$$(\exists c > 0)(\exists n_0)(\forall n_1 > n_0) \cdots (\forall n_k > n_0) : f(n_1, \dots, n_k) \leq c \cdot g(n_1, \dots, n_k)$$

$$\text{where: } c \in \mathbb{R}^{>0} \quad n_0, n_1, \dots, n_k \in \mathbb{N} \quad f, g \in \mathbb{N} \rightarrow \mathbb{R}^{\geq 0}$$

- Lower asymptotic estimate (big-Omega notation) can be defined similarly for functions of more variables as the for the single-variable functions.

- Optimal asymptotic estimate (capital Theta notation)

$$f(n) \in \Theta(g(n))$$

- **Meaning:**

function f is asymptotically bounded from above and from below by a function g disregarding the additive and multiplicative constants.

- **Definition:**

$$\Theta(g(n)) := O(g(n)) \cap \Omega(g(n))$$

$$\text{i.e. } (\exists c_1, c_2 > 0)(\exists n_0)(\forall n > n_0) : c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)$$

$$\text{where: } c_1, c_2 \in \mathbb{R}^{>0} \quad n_0, n \in \mathbb{N} \quad f, g \in \mathbb{N} \rightarrow \mathbb{R}^{\geq 0}$$

Asymptotic estimations – examples

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Introduction and
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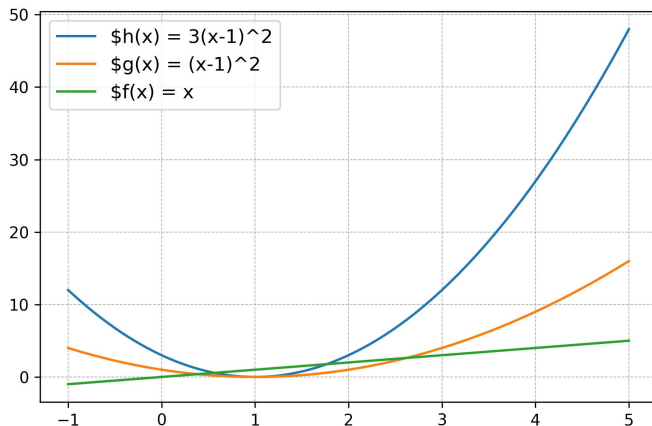
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Is it true that $f(n) \in \Theta(g(n))$ and that $h(n) \in \Theta(g(n))$?
- What are the values of c_1, c_2 and n_0 ? ($\Theta(g(n)) : c_1 \cdot g(n) \leq h(n) \leq c_2 \cdot g(n)$)



Asymptotic estimations – examples

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Introduction and
asymptotic
complexity

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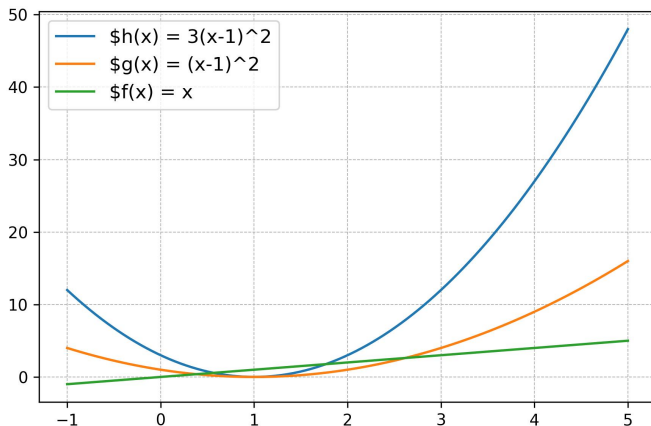
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Is it true that $f(n) \in \Theta(g(n))$ **NO** and that $h(n) \in \Theta(g(n))$ **YES** ?
- What are the values of c_1, c_2 and n_0 ? ($\Theta(g(n)) : c_1 \cdot g(n) \leq h(n) \leq c_2 \cdot g(n)$)



- Example: What is the asymptotic complexity of finding maximum value in 2D array with $M \times N$ numbers?

Which are upper bounds?

- $O((M + N)^2)$
- $O(\max(M, N)^2)$
- $O(N^2)$
- $O(M \cdot N)$

Which is the optimal asymptotic complexity of finding maximum value in 2D array with $M \times N$ numbers?

Which are lower bounds?

- $\Omega(1)$
- $\Omega(M)$
- $\Omega(M \cdot N)$

- Example: What is the asymptotic complexity of finding maximum value in 2D array with $M \times N$ numbers?

Which are upper bounds?

- $O((M + N)^2)$ YES
- $O(\max(M, N)^2)$ YES
- $O(N^2)$ NO
- $O(M \cdot N)$ YES

Which is the optimal asymptotic complexity of finding maximum value in 2D array with $M \times N$ numbers? $\Theta(M \cdot N)$

Which are lower bounds?

- $\Omega(1)$ YES
- $\Omega(M)$ YES
- $\Omega(M \cdot N)$ YES

An algorithm with complexity $f(n)$ is said to be:

- **logarithmic**, if $f(n) \in \Theta(\log(n))$
 - **linear**, if $f(n) \in \Theta(n)$
 - **quadratic**, if $f(n) \in \Theta(n^2)$
 - **cubic**, if $f(n) \in \Theta(n^3)$
 - **polynomial**, if $f(n) \in \Theta(n^k)$ for some $k \in \mathbb{N}$
 - **exponential**, if $f(n) \in \Theta(2^n)$ for some $k \in \mathbb{N}$
- Note that logarithmic complexities do not require to include the base of the logarithm, as for any base a, b it holds that $\log_a(n) = \Theta(\log_b(n))$.

An algorithm with complexity $f(n)$ is said to be:

- Why exactly this holds $\log_a(n) = \Theta(\log_b(n))$?
- Using formula for change of base of logarithm:

$$\log_a(n) = \frac{\log_b(n)}{\log_b(a)} = \underbrace{\frac{1}{\log_b(a)}}_{\text{constant}} \cdot \log_b(n)$$

- We can show that there exists c_1, c_2 such that for all $n > n_0$ it holds that

$$c_1 \cdot \log_b(n) \leq \log_a(n) \leq c_2 \cdot \log_b(n)$$

where $c_1 \leq \frac{1}{\log_b(a)} \leq c_2$ and $n_0 = 1$.

- Properties of the asymptotic complexity:

$$n^m \in O(n^{m'}) \quad \text{if } m \leq m'$$

$$f(n) \in O(f(n))$$

$$c \cdot O(f(n)) = O(c \cdot f(n)) = O(f(n))$$

$$O(O(f(n))) = O(f(n))$$

$$O(f(n)) + O(g(n)) = O(\max\{f(n), g(n)\})$$

$$O(f(n)) \cdot O(g(n)) = O(f(n) \cdot g(n))$$

$$O(f(n) \cdot g(n)) = f(n) \cdot O(g(n))$$

- The class of the complexity of a polynomial is given by the term with the highest exponent:
$$\sum_{i=0}^k a_i \cdot n^{k-i} \in \sum_{i=0}^k O(n^k) = k \cdot O(n^k) = O(k \cdot n^k) = O(n^k)$$

Properties of asymptotic estimations

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Introduction and
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complexity

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Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- Theorem: If functions $f(n), g(n)$ are always positive, then for the limit at infinity:

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0 \Rightarrow f(n) \in O(g(n)), \text{ but not } f(n) \in \Theta(g(n))$$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = a, \quad 0 < a < \infty \Rightarrow f(n) \in \Theta(g(n))$$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty \Rightarrow g(n) \in O(f(n)), \text{ but not } g(n) \in \Theta(f(n))$$

- Corollary: Let $i \in \mathbb{N}$ be a fixed integer. Then

$$(\log n)^i \in O(n)$$

You may use L'Hôpital's rule to prove the corollary.

Why complexity is important?

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Introduction and
asymptotic
complexity

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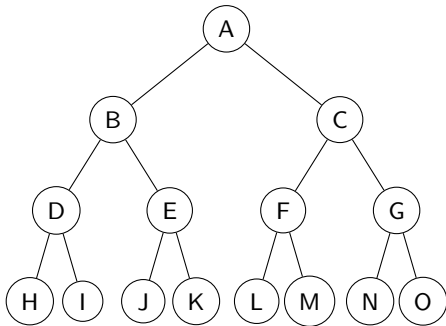
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

- What is better complexity, $\log(n)$, n or n^2 ?
- what is the $\log(n)$ complexity associated with and why? what about the n and n^2 ?



	A	B	C	D	E	F
	0	1	2	3	4	5
0						
1						
2						
3						
4						
5						

Why complexity is important?

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Introduction and
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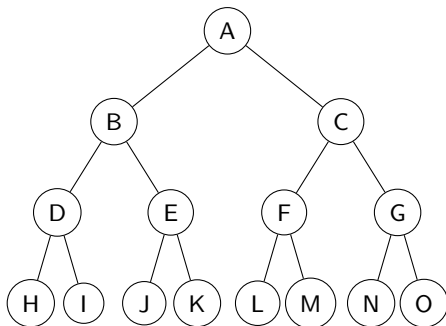
Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

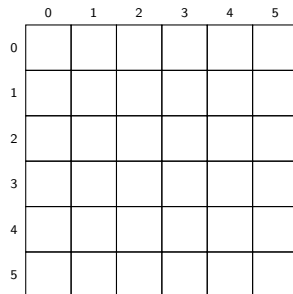
- What is better complexity, $\log(n)$, n or n^2 ?
- what is the $\log(n)$ complexity associated with and why? what about the n and n^2 ?



Tree: often logarithmic (search), or linear (traversal)



1D Array: linear



2D Array: quadratic (full scan), linear (row/col scan)

Homework: Orchard Division

Lecture 1:
Introduction and
asymptotic
complexity

Robert
Pěnička,
Daniel
Průša

Introduction

Computing
the
complexity

Rate of
growth of
functions

Asymptotic
estimations

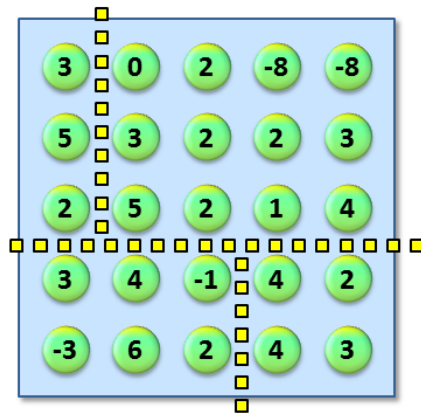
Problem setup:

- Orchard is an $N \times N$ grid of trees.
- Each tree has an integer **quality index**.
- Divide into **4 rectangular parts** using:
 - One horizontal cut (East–West).
 - One vertical cut in the North.
 - One vertical cut in the South.

Goal: Minimize the difference between the **max** and **min** part quality. (Part quality = sum of tree values)

Input: N , then N rows of N integers. **Output:** Minimum possible difference.

Maybe some hint?



Example division of the orchard.

Prefix sums

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Let:

- $A \dots$ array of numbers indexed from 1 to N
- $P \dots$ array of prefix sums (same length as A), indexed from 0 to N

Definition:

$$P[i] = A[1] + A[2] + \dots + A[i], \quad P[0] = 0$$

Example:

$$A = \{1, -2, 4, 5, -1, -5, 2, 7\}$$

$$P = \{0, 1, -1, 3, 8, 7, 2, 4, 11\}$$

Any subarray sum can be computed in constant time:

$$A[i] + A[i+1] + \dots + A[j] = P[j] - P[i-1]$$

See more: https://en.wikipedia.org/wiki/Prefix_sum