

# ALGORITHMS AND DATA STRUCTURES I

Course 3

# Previous Course



**Some simple examples**



**Subalgorithms**

Specification

Usage

# Course content



**WHAT IS THE ANALYSIS OF  
THE EFFICIENCY OF  
ALGORITHMS?**



**HOW CAN THE EFFICIENCY  
OF ALGORITHMS BE  
MEASURED?**



**EXAMPLES**



**MOST FAVORABLE, WORST  
CASE AND MEDIUM CASE  
ANALYSIS**

# What is the analysis of the efficiency of algorithms?

- Analysis of the **efficiency** of **algorithms** means:
  - estimating the **amount** of computing **resources** needed to execute algorithms
- Note: the term **complexity** analysis is sometimes used
- Utility
  - efficiency analysis is useful to **compare algorithms** with each other and obtain information on the computing resources needed to execute algorithms

# What is the analysis of the efficiency of algorithms? Resources

- Computing resources
  - Memory space
    - space required to store data processed by the algorithm
  - Execution time
    - time required for the execution of processing within the algorithm
- Efficient algorithm
  - algorithm that requires a reasonable amount of computing resources
- If one algorithm uses fewer computing resources than another algorithm, then it is considered more efficient

# What is the analysis of the efficiency of algorithms?

- Efficiency types
  - Efficiency in relation to **memory space**
    - refers to the memory space required to store all data processed by the algorithm
  - Efficiency in relation to **execution time**
    - refers to the time required to execute the processing in the algorithm
- Both types of algorithm efficiency analysis are based on the following assumption:
  - The amount of computing resources required depends on the **volume and/or characteristics** of the **input data**  
=> the **size of the problem**
- The purpose of efficiency analysis is to answer the question:
  - **How does the amount of resources needed depend on the size of the problem?**

# How to determine the size of the problem?

- ... usually very simple, starting from the problem statement and the properties of the input data;
- Problem size = amount of memory required to store all problem input data
- The size of the problem is expressed in one of the following:
  - Number of components (real values, integer values, characters, etc.) of the input data
  - The number of bits (internal representation of the data type) needed to store input data
- The choice is made depending on the level at which the processing is done ...

# How to determine the size of the problem?

- Examples:
  - Determining the **minimum** value stored into an **array  $x[1..n]$** 
    - Problem size:  **$n$**
    - Note: the number of elements of the array
  - Calculation of the value of a **polynomial of order  $n$** 
    - Problem size:  **$n$**
    - Note: the number of coefficients is actually  $n+1$
  - Calculation of the sum of two **matrices** with  **$m$  lines**, and  **$n$  columns**
    - Problem size:  **$(m,n)$  or  $m \cdot n$**
    - Note: the number of elements of the matrix
  - Check the **primality** of a number,  **$n$** 
    - Problem size:  **$n$  or  $\log_2 n$**
    - Note: the number of bits required to store the value of  $n$  is actually  $\lfloor \log_2 n \rfloor + 1$  ( $\lfloor \dots \rfloor$  represents the lower integer part of a real number)

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# How can the efficiency of algorithms be measured?

- Next we will refer only to the analysis of efficiency in terms of **execution time**.
- For the (theoretical) estimation of the execution time it is necessary to establish:
  - A **calculation model**
  - A **unit of measurement** of execution time

# How can the efficiency of algorithms be measured?

- Calculation model: **random access machine** (Random Access Machine = RAM)
- Features (simplifying assumptions):
  - All processing is carried out **sequentially** (there is no parallelism in the execution of the algorithm)
  - The **execution time** of an elementary processing **does not depend on** the values of the **operands** (the execution time required to calculate  $1+2$  does not differ from the execution time required for  $12433+4567$ )
  - The time required to **access** the data **does not depend on** the **location** of the data in **memory** (there is no difference between the time required to process the first element of an array and that of processing the last element) – we will return to this restriction when we discuss the analysis of the processing performed on different data structures (in context of amortized analysis)

# Way simplifying assumptions?

- Execution time can depend also on
  - Speed of the computer on which the program will run (e.g., a smartphone vs. a Google server)
  - The programming language used to implement the algorithm (e.g., C vs. Python)
    - Different optimizations of the programming languages
    - Interpreter, garbage collector
  - The efficiency of the implementation, for the specific machine

```
dim = 50000
x = [0] * dim
y = [0] * dim
for i in range(dim):
    y[i] = i * 1.0
for i in range(dim):
    for j in range(dim):
        x[i] += y[j]
```

Python code

Is the same algorithm implemented in both languages?

Is the running time the same?

C code

```
int main() {
    int dim = 50000;
    float x[dim], y[dim];
    int i;
    for (i = 0; i < dim; i++) {
        y[i] = i * 1.0;
    }
    for (i = 1; i < dim; i++) {
        for (int j = 1; j < dim; j++) {
            x[i] += y[j];
        }
    }
}
```

# How can the efficiency of algorithms be measured?

- Unit of measurement = time required to carry out basic processing (basic operation)
- Basic operations
  - Assign
  - Arithmetic operations (addition, subtraction, multiplication, division)
  - Comparisons
  - Logical operations
- Algorithm execution time = number of elementary operations executed
- Remark: The execution time estimate is aimed at determining the dependence between the number of elementary operations executed and the problem size

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# Example. Sum of the elements of an array

Input data:  $x[1..n]$ ,  $n \geq 1$

Output:  $S = x[1] + x[2] + \dots + x[n]$

Problem size:  $n$

Algorithm

Sum( $x[1..n]$ )

1:  $S \leftarrow 0$

2:  $i \leftarrow 0$

3: WHILE  $i < n$  DO

4:      $i \leftarrow i + 1$

5:      $S \leftarrow S + x[i]$

6: ENDWHILE

7: RETURN  $S$

Cost table

Operation	Cost	Times
1	$c_1$	1
2	$c_2$	1
3	$c_3$	$n+1$
4	$c_4$	$n$
5	$c_5$	$n$

Execution time:

$$T(n) = (c_3 + c_4 + c_5)n + (c_1 + c_2 + c_3) = a * n + b$$

Remark: Some of the costs are identical ( $C_1 = C_2$ ) and others can be considered different ( $C_5 > C_1$ ). It is necessary such a detailed analyses – in general case no, use the simplifying assumptions.

# Example. Sum of the elements of an array

- Remarks
  - The simplest option is to consider all **basic processing** as having the **same cost**
    - If in the previous example it is considered that all elementary operations have unit cost, then the following estimate for execution time is obtained:  $T(n)=3(n+1)$
  - The **constants** that intervene in the expression of execution time are **not very important**. The important element is that the **execution time depends linearly on the size of the problem**.

- The previous algorithm is equivalent to:

```
S ← 0  
FOR i ← 1,n DO S ← S + x[i] ENDFOR
```

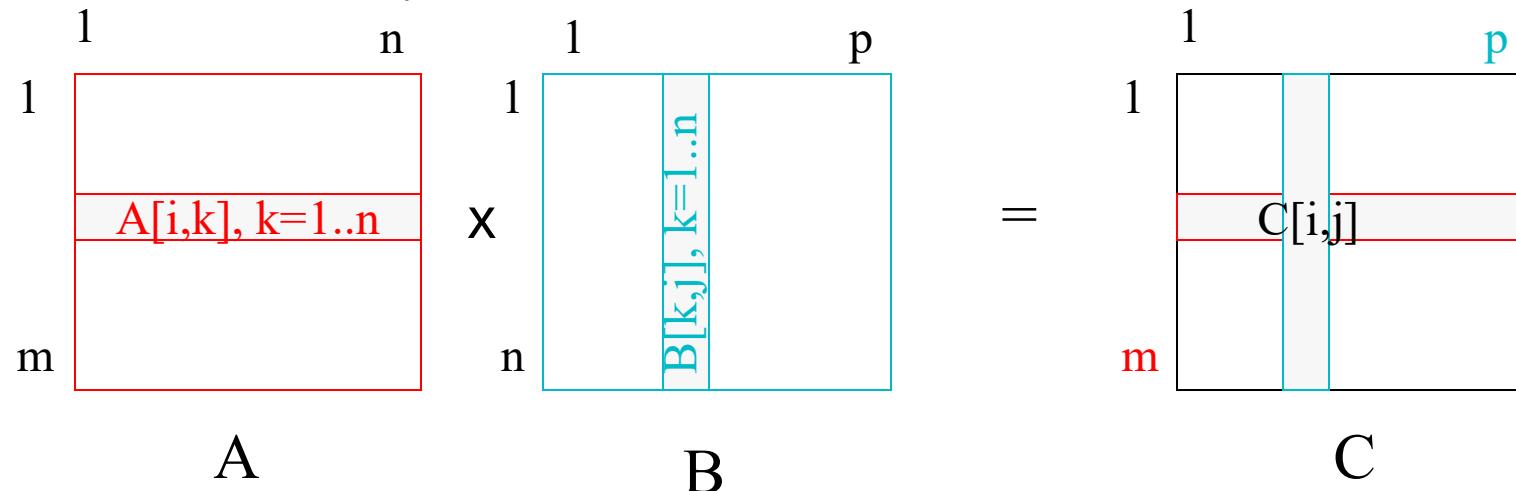
- Note that the management of the FOR cycle counter involves the execution of  $2(n+1)$  operations; the other  $(n+1)$  operations correspond to the calculation of the sum (initialization of S and update from each repetition of the cycle body)

# Example. Matrix multiplication

Input data:  $A_{m \times n}, B_{n \times p}$

Output:  $C = A * B$

Problem size:  $(m, n, p)$



$$C_{ij} = \sum_{k=1}^n A_{ik} B_{kj}$$

$$C[i,j] = A[i,1]*B[1,j] + A[i,2]*B[2,j] + \dots + A[i,n]*B[n,j], \\ i=1..m, \quad j=1..p$$

# Example. Matrix multiplication

Basic idea: for each  $i=1..m$  and  $j=1..p$  calculate the sum after  $k$

## Algorithm

```
Product(A[1..m,1..n],B[1..n,1..p])  
1: FOR i ← 1,m DO  
2:   FOR j ← 1,p DO  
3:     C[i,j] ← 0  
4:     FOR k ← 1,n DO  
5:       C[i,j] ← C[i,j]+A[i,k]*B[k,j]  
6:     ENDFOR  
7:   ENDFOR  
8: ENDFOR  
9: RETURN C[1..m,1..p]
```

## Cost table

Operation	Cost	Times.	Total
1	$2(m+1)$	1	$2(m+1)$
2	$2(p+1)$	$m$	$2m(p+1)$
3	1	$mp$	$mp$
4	$2(n+1)$	$mp$	$2mp(n+1)$
5	2	$mpn$	$2mpn$

$$T(m,n,p)=4mnp+5mp+4m+2$$

# Example. Matrix multiplication

## Algorithm

```
Product(A[1..m,1..n],B[1..n,1..p])  
1: FOR i ← 1,m DO  
2:   FOR j ← 1,p DO  
3:     C[i,j] ← 0  
4:     FOR k ← 1,n DO  
5:       C[i,j] ← C[i,j]+A[i,k]*B[k,j]  
6:     ENDFOR  
7:   ENDFOR  
8: ENDFOR  
9: RETURN C[1..m,1..p]
```

**Note:** As a rule, it is not necessary to fill in the entire cost table, but it is enough to count only the dominant operation

**Dominant operation:** the most common (expensive) operation

**Execution time**  
estimated: $T(m,n,p)=mnp$

# Example. Minimum element of an array

Input data:  $x[1..n]$ ,  $n \geq 1$

Output:  $m = \min(x[1..n])$

Problem size:  $n$

## Algorithm:

Minimum( $x[1..n]$ )

```
1: m ← x[1]
2: FOR i ← 2, n DO
3:   IF x[i] < m THEN
4:     m ← x[i]
5:   ENDIF
6: ENDFOR
7: RETURN m
```

## Cost table:

Operation	Cost	Times	Total
1	1	1	1
2	$2n$	1	$2n$
3	1	$n-1$	$n-1$
4	1	$t(n)$	$t(n)$

$$T(n) = 3n + t(n)$$

$t(n)$  = number of changes of variable  $m$   
(depends on how the elements of the array are arranged)

Remark: The execution time depends not only on the size of problem but also the properties of input data

# Example. Minimum element of an array

- If the execution time depends on the properties of the input data, then at least the extreme cases should be analyzed:

- Most favorable case:

$$x[1] \leq x[i], i=1..n \Rightarrow t(n)=0 \Rightarrow T(n)=3n$$

- Worst-case scenario:

$$x[1] > x[2] > \dots > x[n] \Rightarrow t(n)=n-1 \Rightarrow T(n)=4n-1$$

It results that:  $3n \leq T(n) \leq 4n-1$

- Both the lower limit and the superior limit linearly depend on the size of the problem
- The variant of analysis that takes into account only the dominant operation, the comparison ( $x[i] < m$ ), leads to  $T(n) = n-1$  (regardless of the position of the minimum value, all elements of  $x$  must be analyzed)

## Algorithm

Minimum( $x[1..n]$ )

```
1: m ← x[1]
2: FOR i ← 2,n DO
3:   IF x[i]<m THEN
4:     m ← x[i]
5:   ENDIF
6: ENDFOR
7: RETURN m
```

# Example. Search an element in an array

Input data:  $x[1..n]$ ,  $n \geq 1$

Output: "the value is found" or "the value is not found"

Result: the logical variable "found" contains the truth value of the statement "the value  $v$  is in array  $x[1..n]$ "

Problem size:  $n$

Algorithm (sequential search):

```
search( $x[1..n], v$ )
1: found  $\leftarrow$  False
2:  $i \leftarrow 1$ 
3: WHILE (found==False) AND ( $i \leq n$ ) DO
4:   IF  $x[i]==v$                                 // $t_1(n)$ 
5:     THEN found  $\leftarrow$  True    // $t_2(n)$ 
6:     ELSE  $i \leftarrow i+1$       // $t_3(n)$ 
7:   ENDIF
8: ENDWHILE
9: RETURN found
```

Cost table:

Operation	Times
1	1
2	1
3	$t_1(n)+1$
4	$t_2(n)$
5	$t_3(n)$

# **Example. Search an element in an array**

The execution time depends on the properties of array  $x[1..n]$ .

**Case 1:** the value  $v$  belongs to the array (consider  $k$  the smallest index with the property that  $x[k] = v$  )

**Case 2:** value v is not in the array

$$t1(n) = \begin{cases} k & \text{if } v \text{ in } x[1..n] \\ n & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

$$t2(n) = \begin{cases} 1 & \text{if } v \text{ is in } x[1..n] \\ 0 & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

$$t3(n) = \begin{cases} k-1 & \text{if } v \text{ is in } x[1..n] \\ n & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

## Algorithm (sequential search):

search(x[1..n],v)

1:  $\text{found} \leftarrow \text{False}$

2:  $i \leftarrow 1$

3: WHILE (found==False) AND (i<=n) DO

5:            THEN found  $\leftarrow$  True    //t2(n)

6: ELSE  $i \leftarrow i+1$  //t3(n)

7: ENDIF

## 8. FNDWHII F

## 9: RETURN found

# Example. Search an element in an array

Best-case scenario:  $x[1]=v$

$$t_1(n)=1, t_2(n)=1, t_3(n)=0$$

$$T(n)=6$$

Worst-case scenario:  $v$  is not in  $x[1..n]$

$$t_1(n)=n, t_2(n)=0, t_3(n)=n$$

$$T(n)=3n+3$$

The edges (lower and upper) of execution time are:

$$6 \leq T(n) \leq 3(n+1)$$

Note: the lower limit is constant and the upper limit depends linearly on the problem size

$$t_1(n)= \begin{cases} k & \text{if } v \text{ in } x[1..n] \\ n & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

$$t_2(n)= \begin{cases} 1 & \text{if } v \text{ is in } x[1..n] \\ 0 & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

$$t_3(n)= \begin{cases} k-1 & \text{if } v \text{ is in } x[1..n] \\ n & \text{if } v \text{ is not in } x[1..n] \end{cases}$$

# Example. Search an element in an array – other variant

Algorithm (sequential search):

```
search2(x[1..n],v)
1: i ← 1
2: WHILE i<n AND x[i]≠v DO
3:   i ← i+1
4: ENDWHILE
5: IF x[i]≠v THEN found ← False
6:   ELSE found ← True
7: ENDIF
8: RETURN found
```

The most favorable case (v - value is in first position):

$$T(n)=5$$

Worst case scenario (v - value is in last position or not in the array):

$$T(n)=1+n+(n-1)+2=2n+2$$

If the comparison  $x[i] \neq v$  is considered as the dominant operation, then:

- Best-case scenario:  $T(n)=2$
- Worst-case scenario:  $T(n)=n+1$

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# Best case and worst case analysis

## *Best-case analysis (most favorable)*

- Provides a **lower margin** for execution time
- It allows to identify inefficient algorithms (if an algorithm has a high cost, even in the most favorable case, then it is not an acceptable solution)

## *Worst case analysys (most unfavorable )*

- Provides the highest execution time relative to all input data dimensions (represents **an upper margin** of execution time)
- The upper margin of execution time is more important than the lower margin

# Analysis of the medium case

For certain problems, the most favorable and unfavorable cases are rare cases (exceptions)

Thus... the best and worst case execution time does **not provide sufficient information**

In these cases, another analysis is carried out... **Medium case analysis**

The purpose of this analysis is to provide information on the behavior of the algorithm in the case of **arbitrary input data** (which does not necessarily correspond to either the most favorable or the worst case)

# Analysis of the medium case

This analysis is based on knowledge of the **probability distribution of input data**

This means knowing (estimating) the **probability of occurrence of each** of the possible instances of the input data (how frequently each of the possible values of the input data occurs)

The **average execution time** is the average value (in the statistical sense) of the execution times corresponding to the different instances of the input data

# Analysis of the medium case

- Assumptions. We assume that the following assumptions are satisfied:
  - Input data can be grouped into classes so that the execution time corresponding to data of the same class is the same
  - are  $m=M(n)$  classes with input data
  - The probability of occurrence of a  $k$ -class data is  $P_k$
  - The execution time of the algorithm for input data belonging to class  $k$  is  $T_k(n)$
- In these assumptions the average execution time is:
$$T_{\text{average}}(n) = P_1 T_1(n) + P_2 T_2(n) + \dots + P_m T_m(n)$$
- Remark: if all data classes have the same probability then the average execution time is:

$$T_{\text{average}}(n) = (T_1(n) + T_2(n) + \dots + T_m(n)) / m$$

# Analysis of the medium case

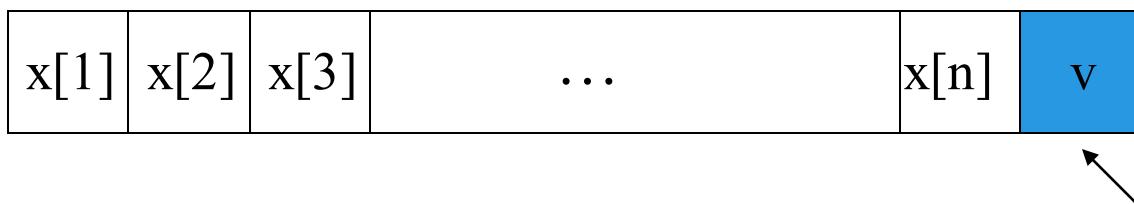
- Example: sequential search (dominant operation: comparison)
- Assumptions about the probability distribution of input data:
  - Probability that the value  $v$  is in the array:  $p$ 
    - The value  $v$  appears with the **same probability on each of the positions** in the table
    - The probability that the value  $v$  is at position  $k$  is  $1/n$
  - Probability that  $v$  is not in the array:  $1-p$   
(in the case of alg search2 if the searched value is at position  $k$  then the number of comparisons performed is  $(k+1)$ )  
$$T_{\text{average}}(n) = p(2+3+\dots+(n+1))/n + (1-p)(n+1) = p(n+1)/2 + (1-p)n = (1-p/2)n + p/2 + p/(2n)$$
- If  $p=0.5$  we get  $T_{\text{average}}(n)=3/4 n+1/4+1/4n$
- Conclusion: The average execution time of the sequential search algorithm is **linearly dependent** on the size of the input data

# Analysis of the medium case

**Example:** Sequential search (sentinel or pennant)

**Basic idea:**

- The table is extended by an **additional element** (position  $n+1$ ) whose value is  $v$
- The table is completed until the value  $v$  is reached (the value will be found in the worst case at position  $n+1$  – corresponds to the situation when the table  $x[1..n]$  does not contain the value  $v$ )



**Sentinel value  
(fanion)**

# Analysis of the medium case

Algorithm:

Search\_sentinel(x[1..n],v)

$i \leftarrow 1$

WHILE  $x[i] \neq v$  DO

$i \leftarrow i+1$

ENDWHILE

RETURN i

Dominant operation: comparison

Hypothesis: The probability that the value v is at position k in  $\{1, 2, \dots, n+1\}$  is  $1/(n+1)$

Average execution time:

$$T_{\text{average}}(n) = (1+2+\dots+(n+1))/(n+1) = (n+2)/2$$

Remark:

Changing the assumption about the distribution of input data, the mean time value changes (in the case of sequential search, the dependence on the size of the problem remains linear);

Remark. The average execution time is NOT necessarily the arithmetic average between execution times corresponding to extreme cases (most favorable and unfavorable).

# Abstract: stages of efficiency analysis

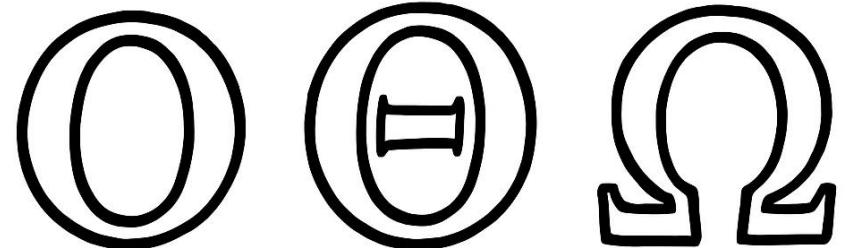
- Step 1: Identify the size of the problem
- Step 2: Establish the dominant operation
- Step 3: Determine the number of executions of the dominant operation
- Step 4. If the number of executions of the dominant operation depends on the properties of the input data, then it is analyzed:
  - The most favorable case
  - Worst-case scenario
  - Medium case
- Step 5. The order (class) of complexity is established (see next course)

# Next course

.. All about analyzing the efficiency of algorithms.

More specifically, the following will be presented:

- Growth order
- Asymptotic notations (O, Theta, Omega)
- Complexity classes



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# Q&A

