



خوارزميات

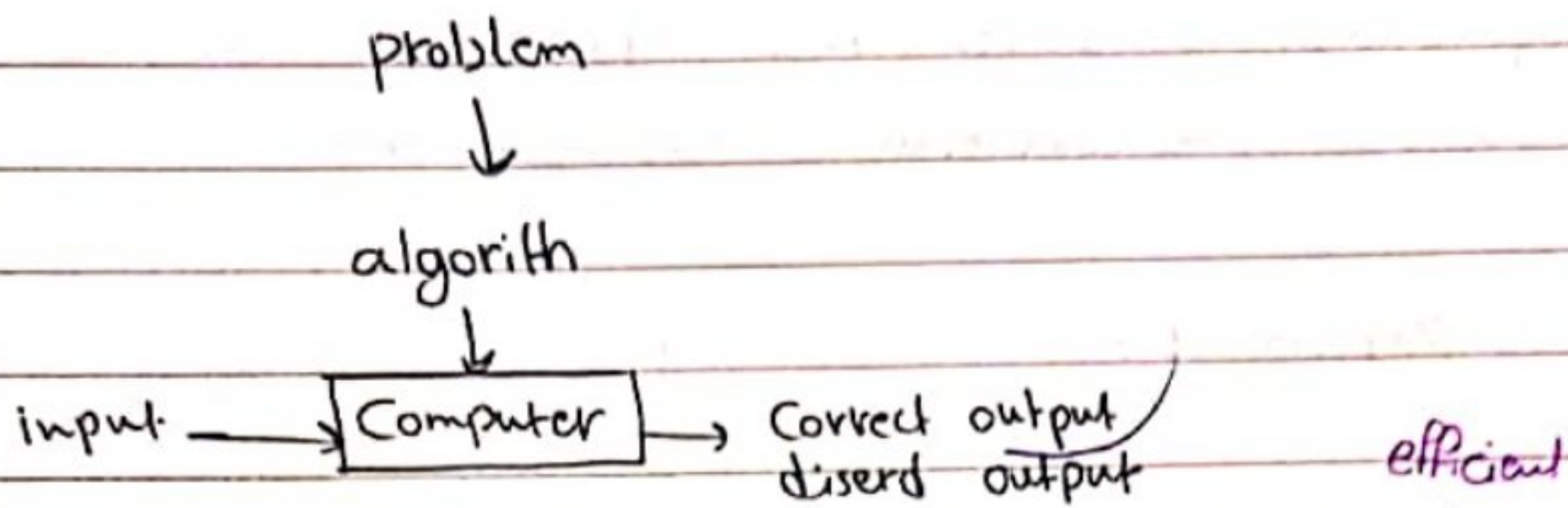
د. خليل يوسف

للطالبان المبدعتان
فلسطين حمدان
فيحاء الحديدي

إرادة - ثقة - تغيير

Algorithm

Algorithm: is a sequence of unambiguous instructions for solving a problem



other defined: a precisely defined sequence of (computational) steps that transfer a given input into a desired output. [Sequence of precise and clear steps to solve a problem]

a method for solving problem: ① Correctness the method
② performance the method

* Not all problems can be defined by an algorithm, Ex: halting problem the computer can't take the program is solve or not
* A problem is said to be solvable \Rightarrow IF a computer program can be written to produce the correct output for any input.

\rightarrow what is an algorithm?

The way to write an algorithm \rightarrow ALGORITHM NAME {
input(s)
output(s)
steps
}

\rightarrow Title of the course \rightarrow Design and analysis of Algorithms

↳ Time efficiency of complexity } Approaches
- Space " " } ① Theoretical analysis
② Empirical

\rightarrow Does there exist a better algorithm? lower bounds, optimality

analyzing Algorithms → To asymptotically compare the performance of multiple algorithms used to solve the same problem.

How to compare with one is better (Time complexity, Space complexity)

Comparison based on Time complexity (basic operation)

* Asymptotic performance Analysis: [For the n is size of the input]

$f(n) = n^3$ ③, $f(n) = n^2$ ④ $O(1) < O(\log n) < O(n) < O(n^2)$

$f(n) = \log n$ ②, $f(n) = n^3$ growth \uparrow n كبر

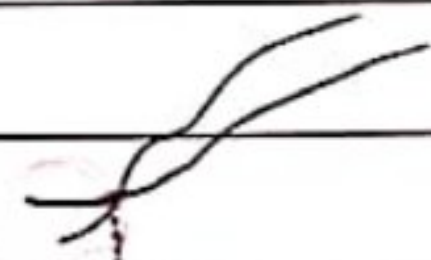
$f(n) = n \log n$, $f(n) = 2^n$

$f(n) = 1$ ①

to finding order of Growth

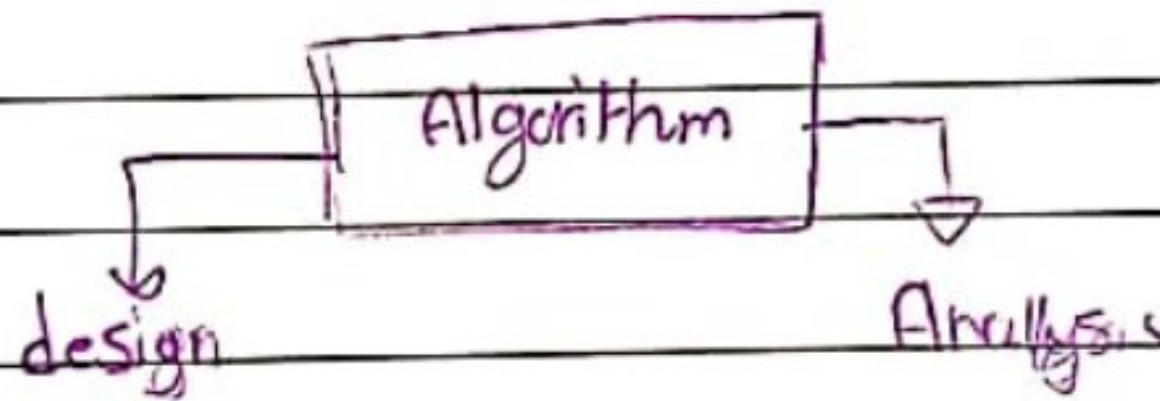
Count # of basic operations as a function of the size of the input

Top perf. Time Complexity Function



minimum value of n_0

$n > n_0$
↳ known



English statement to express the code

pseudocode

syntax is not important

programming languages independent

must written in one of the programming languages → syntax

problem

Code

Computer

we desired to solve this problem using computer

⇒ we need to write a code or program.

problem

we can have multiple Algorithms to solve the same problem

but we desire the algorithms that provides the best performance

but what do we mean by the word performance?

↳ we will quantify this word

time complexity
space complexity

time ↑ speed ↓ time needed to split the input and get correct and desired output

Asymptotic performance → order of growth notation

Big-oh $O()$

Big-Theta $\Theta()$

Big-omega $\Omega()$

little-oh $o()$

little-omega $\omega()$

lowest growth \rightarrow # of Basic operations \downarrow \rightarrow least of time \downarrow \rightarrow performance or speed \uparrow

of Basic operations \downarrow time \downarrow performance or speed \uparrow
 (lowest growth)

Design techniques: ① Brute Force ② Divide and...

Sorting problem

lets assume each Algorithm step will take one clock cycle

Example: lets consider an Algorithm for searching a list of element for a particular one (key)

Linear search

input: linear list of element A, $A = \{a_1, a_2, \dots, a_n\}$
 Input: (A, n, k)
 array size of array particular key that we are looking for

output: return the index of the found key otherwise, return "-1" or "null"

Linear Search (A, n, k)

$A = \{5, 10, 3, 4, 20\}$

$n =$ size of input

```

{
  for i=1 to n (int i=1, i<=n; i++)
  {
    if (k == A[i])  $\rightarrow$  Basic operation
      return i;
  }
}

```

of comparison
 $k=30 \rightarrow$ worst case $O(n)$
 $k=5 \rightarrow$ Best case $O(1)$

return -1

small order terms and constants are ignored

$2n \rightarrow O(n)$

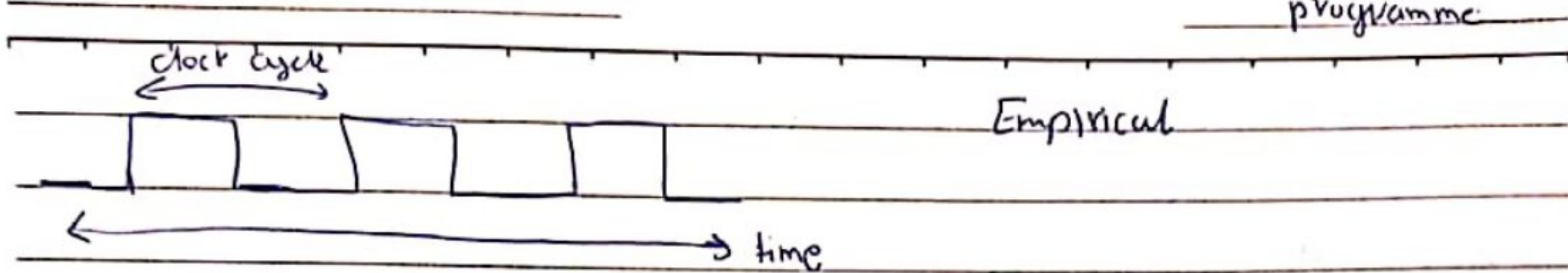
$3n + 1000000 \rightarrow O(n)$

$n \rightarrow O(n)$

CR = 2GHz

clock cycle time = $\frac{1}{CR}$
 $= \frac{1}{2 \times 10^9 \text{ Hz}} = 0.5 \text{ nsec}$

Independently from hardware and programme



clock Rate = $\frac{\# \text{ of clock cycle}}{1 \text{ sec}} = \# \text{ of clock cycle Hz}$, $\text{Hz} = \frac{1}{\text{sec}}$

4 GHz $\rightarrow 4 \times 10^9 \text{ Hz}$

clock cycle Time = $\frac{1}{\text{CR}} = \frac{1}{4 \times 10^9} \text{ sec} = 0.25 \text{ nsec}$

Array of n element \leftarrow key to be searched for
 Linear search (A, k)
 input

```

For i = 1 : n
  if (A[i] == k)
    return i;
  
```

basic operation
[ajla] steps

return -1;

we count the basic operation [best case, worst case]

problem 2:

$T(n) = \sum_{i=1}^{n-1} 1 = n-1$
 one unit of time
 For j

MAXVAL \leftarrow A[0]
 For i \leftarrow 1

problem 3:

two For loop
 $T(n) = \sum_{i=1}^{n-1} i = (n-1)(n-2) + \dots + 1$
 $\rightarrow \frac{(n-1)(n-1+1)}{2} = \frac{(n-1)(n)}{2} = \frac{n^2-n}{2}$
 $\Theta(n^2)$

$\# \text{ of } n \rightarrow \text{last index} - \text{first index} + 1$
 $n-1 - 1 + 1 \rightarrow n-1$

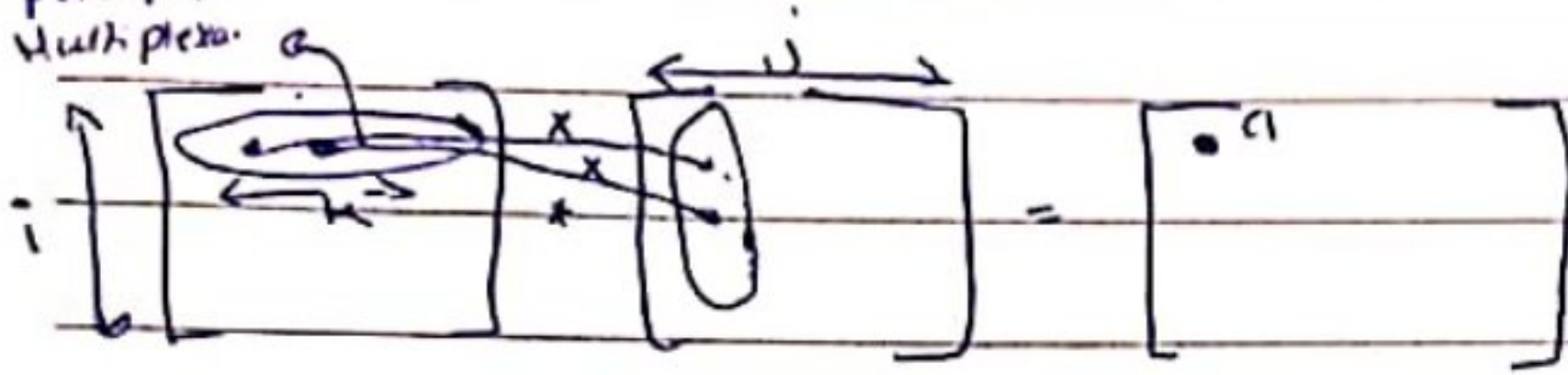
* Arithmetic Series = $\sum_{i=1}^n i = \frac{n(n+1)}{2}$

$\sum_{i=1}^n i = 1+2+3+4+5+\dots+n$
 $\sum_{i=1}^n = n+n-1+n-2+n-3+\dots+1$

$2 \sum_{i=1}^n i = (n+1) + (n+1) + (n+1) + \dots$
 $\rightarrow \frac{2 \sum_{i=1}^n i}{2} = \frac{n(n+1)}{2}$

$$A_{n \times m} \times B_{m \times l} = C_{n \times l}$$

pairwise
multiplication



$$c_i = a_{i1}b_{1i} + a_{i2}b_{2i} + \dots$$

pairwise Mult.

* online Lec.

Sorting problem

↳ Insertion Algorithm [Design analysis]

↳ input: array and n element $A = \{a_1, \dots, a_n\}$

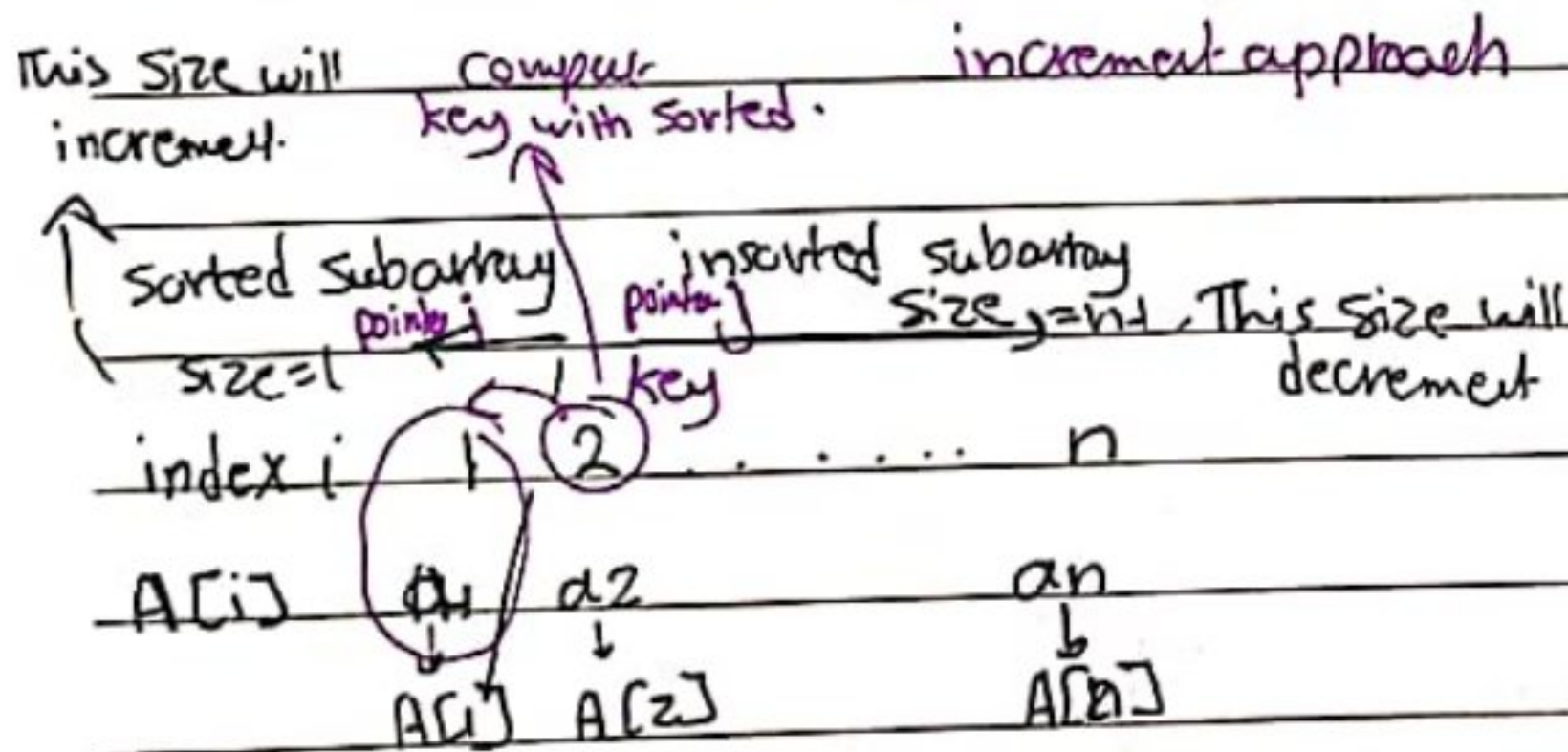
output: sorted array \rightarrow ascending / st $a_1 \leq a_2 \leq \dots \leq a_n$ when $\{a_1, \dots, a_n\} \in A$
 \rightarrow descending x

How \rightarrow need to write the set of steps that will take input to a desired output

↳ Design strategy: Decrease and conquer

- ① Reduce problem instance to small inst. of the same problems
- ② Solve small instance
- ③ Extend solution of smaller instance to obtain solution to original //.

implementation
 Top-down or Bottom-up
 another name: to obtain solution to original //.



Let's assume the first element is already sorted.

Insertion Sort (A, n)

{ for (i = 2 to n)

{ key = A[i]

j = i - 1

while $j > 0$ & $A[j] > key$

{ $A[j+1] = A[j]$

$j = j - 1;$

Insertion Sort -

→ Consider as one example of the sorting problem when we have a list of numbers $A = \{a_1, \dots, a_n\}$ of a goal to find the correct permutation $\{\bar{a}_1, \bar{a}_2, \dots, \bar{a}_n\}$ of the list A s.t.:

$a_1 \leq a_2 \leq \dots \leq a_n$ (ascending order)

ex) $A = \{3, 2, 1\} = \{a_1, a_2, a_3\}, n = 3$

soln: $\{1, 2, 3\} = \{a_1, a_2, a_3\}$

Insertion sort analysis:

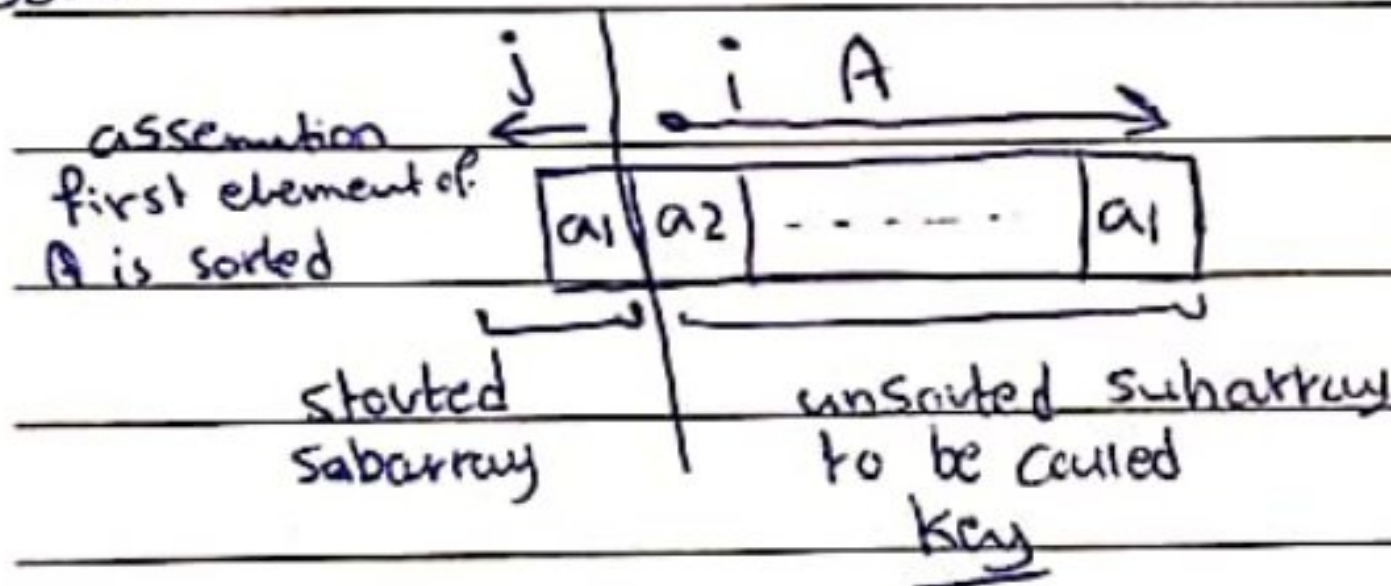
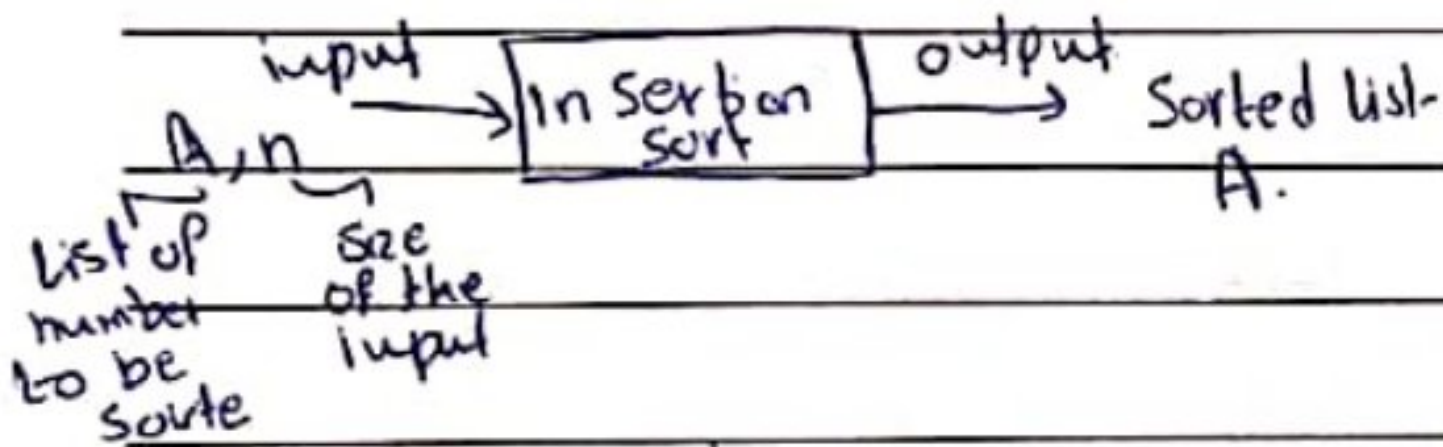
① Time complexity: count the basic operation as of a function the size of the input. $[T(n)]$

↳ Best case:

↳ Worst case:

↳ Average case: usually requires probabilistic analysis (not focus)

② Space complexity:



Insertion sort ($A[n]$)

1. for $i = 2$ to n /

2. $key = A[i];$

3. $j = i - 1;$

4. while $j > 0$ & $A[j] > key$ Basic operation.

5. $A[j+1] = A[j];$

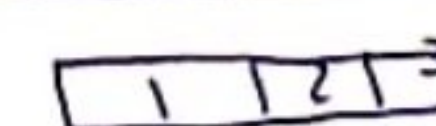
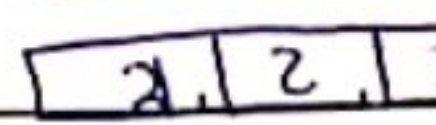
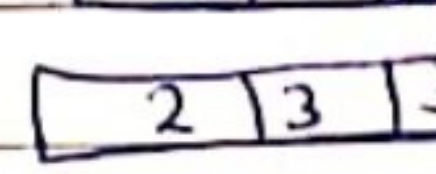
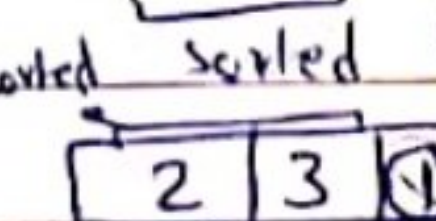
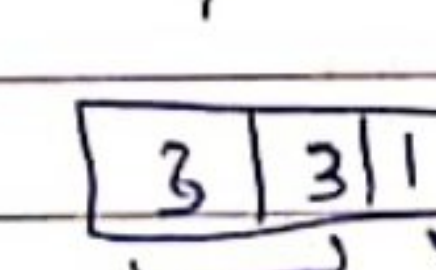
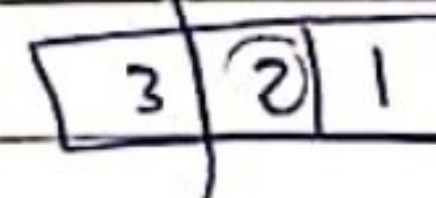
6. $j = j - 1;$

7. $A[j+1] = key;$

$t_i = 5$

worst case
 $2 + 3$

sorted | unsorted



دفعه $A[j] > key$

دفعه $A[j] > key$

of compared index for key

دفعه $A[j] > key$ (3) دفعه

Time complexity function: $T(n)$ lets assume $t_j = \#$ of time the inner loop while is executed for the best ith For loop (outer loop) $t_j = \begin{cases} 1, \text{ Best case} \\ i, \text{ worst case} \end{cases}$

index of array: 1 2 3 4 5 sum 15

i =	1	2	3	4	5
sorted	6	5	3	2	1
# of comparison		2	3	4	5

$\sum_{i=2}^n i = \frac{n(n+1)}{2}$ [let $j=i-1$ when $i=2, j=1$ $i=n, j=n-1$] remaining

2+3+4+5 = 14 only valid in the (worst case) scenario when the input is reverse sorted

1	2	3	5	6
1	1	1	1	1

$T_i = 4 = 1+1+1+1$

$T(n) = n-1$ Input is already sorted (Best case)
 $t_i = 1$ linear $O(n)$

$\sum_{i=2}^n i = \sum_{j=1}^{n-1} j+1 = \sum_{j=1}^{n-1} j + \sum_{j=1}^{n-1} 1 = \frac{(n-1)(n-1+1)}{2} + n-1$

$= \frac{(n-1)(n)}{2} + 2n-2 = \frac{n^2+n-2}{2} = \frac{25+30-2}{2} = 29$ (14)

closed Form Solution

order of Basic Asymptotic

line	time	count
1	C_1	n
2	C_2	$n-1$
3	C_3	$n-1$
4	C_4	$m = \sum_{i=2}^n t_i$
5	C_5	$m-1$
6	C_6	$m-1$
7	C_7	$n-1$

of times to execute this line (while) at the iteration [sufficient times]

This is Design: Design Decrease & Conquer or incremental Conquer Approach

Ex: A: { 7, 6, 1, 6, 4 }

7	6	1	6	4
7	6	1	6	4
2	7	6	4	
2	7	7	6	4
2	2	7	6	4
3	2	7	6	4

efficient for this algorithm \rightarrow n small or n in Best case

oil storage, limited space, ul, lol, Time ul, sic, line *

Best case \rightarrow # of Comparison (basic operation) $\rightarrow n-1$, $O(n)$

The inner loop "while" is only executed once

Worst case \rightarrow when the input is reverse sorted (in this case) the inner-loop "while" is only executed number of time = the index value of outer loop For

i k
 4 (3) 2 1 key 3

امثلة من عندي

4 4 2 1
 3 4 2 1 key 2

3 4 4 1

3 3 4 1

2 3 4 1 key 1

2 3 4 4

2 3 3 4

$2 + 3 + 4 = 9$

2 2 3 4

1 2 3 4

i k

7 2 1 6 4 key 2

30 10 40 20

7 7 1 6 4

2 30 30 40 20

2 7 1 6 4 key 1

10 30 40 20

1 10 30 40 20

2 7 7 6 4

10 30 40 40

3 10 30 30 40

2 2 7 6 4

10 20 30 40

1 2 7 6 4 key 6

6 → average

1 2 7 7 4

1 2 6 7 4 key

Best- worst

1 2 6 7 7

3 9

1 2 6 6 7

1 2 4 6 7

non-stable (نموذج غير مستقر)

stability: For duplicates $A = \{x_1, x_1, x_1, \dots, x_n\}$

① nc

change of variable

$$\sum_{k=1}^n k + \sum_{k=1}^n 1$$

② $\sum_{k=1}^{n-1} k+1$

let $k=j-1$ so $j=2 \rightarrow k=1$ $j=n \rightarrow k=n-1$

$$= \frac{(n-1)(n-1+1)}{2} = \frac{(n-1)n}{2} + \frac{(n-1+1)n}{2} = \frac{(n)(n-1) + (n-1)n}{2}$$

③ $\sum_{j=2}^n j - \sum_{j=2}^n 1 = (n-1)n$ $\rightarrow j=k+1$

Best Case \rightarrow The input is already sorted or we have array of duplicates
 worst case \rightarrow when the input is reverse sorted

$\sum_{k=0}^{10} 2^k = \frac{2^{10+1} - 1}{2-1}$

closed form solution (صيغة مغلقة)

$\sum_{k=0}^{\infty} \frac{d}{dx} [x^k] = \frac{d}{dx} \left(\frac{1}{1-x} \right)$

derivative of sum (مشتق المجموع)

$$= \sum_{k=0}^{\infty} k x^{k-1} = \frac{-1 \cdot x^{-1}}{(1-x)^2}$$

$x \left[\sum_{k=0}^{\infty} k x^{k-1} = \frac{1}{(1-x)^2} \right]$

$$\sum_{k=0}^{\infty} k x^k = \frac{x}{(1-x)^2}$$

$+ O(1)$ constant

Ex 1 For nested loop do for do

$$T(n) = \sum_{i=1}^n \left[\sum_{j=1}^n 2 \cdot 1 \right] = \sum_{i=1}^n 2(n-i+1) = 2 \sum_{i=1}^n n - 2 \sum_{i=1}^n i + 2 \sum_{i=1}^n 1$$

$$= 2n^2 - 2 \left(\frac{n(n+1)}{2} \right) + 2n$$

$$= 2n^2 - n^2 - n + 2n$$

$$= n^2 + n$$

$O(n^2)$ Closed Form solution

Ex 2:

ال Σ لل nested loop (أكبر من) ليست

$$\sum_{i=1}^n \sum_{j=1}^i \sum_{k=1}^j 2 = \sum_{i=1}^n \sum_{j=1}^i 2(j-1+1) = \sum_{i=1}^n \sum_{j=1}^i 2j = \sum_{i=1}^n 2 \frac{(i)(i+1)}{2}$$

$$= \sum_{i=1}^n (i^2 + i)$$

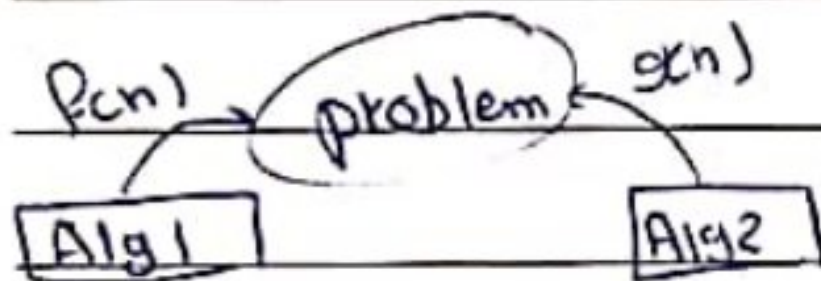
$$= \sum_{i=1}^n i^2 + \sum_{i=1}^n i$$

$$= \frac{n(n+1)(2n+1)}{2} + \frac{n(n+1)}{2}$$

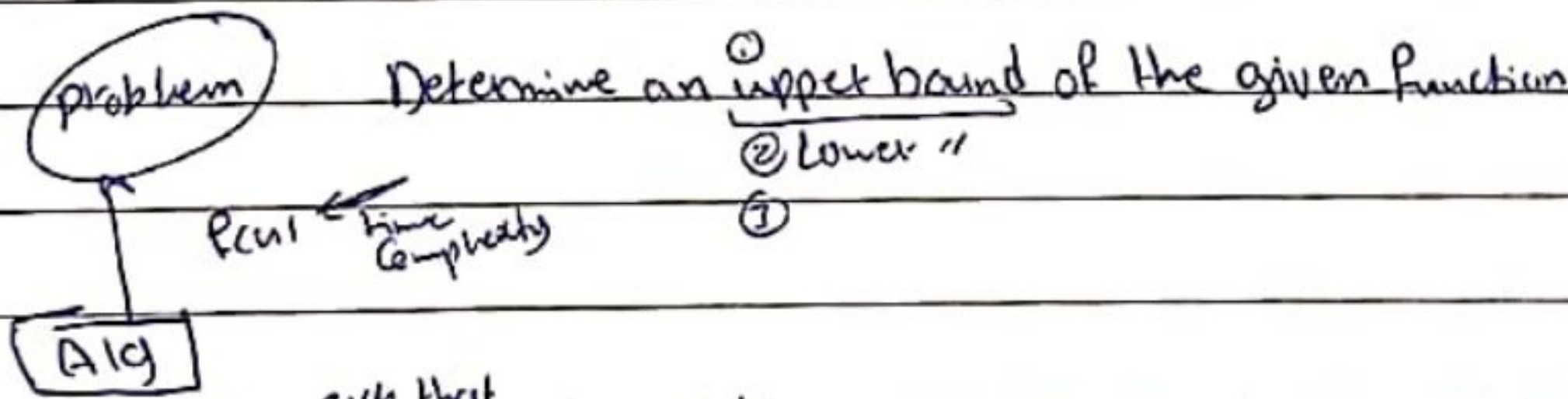
Lect 2:

order of growth in relation

$$f(n) = \boxed{\quad} (g(n))$$



$f(n)$ and $g(n)$ are time complexity functions



Determine an ^① upper bound of the given function
② lower "
③

such that there exists
All $f(n)$'s s.t. \exists constants

$c, n_0 > 0$, where

$$0 < f(n) \leq c g(n)$$

prove that $f(n) = O(g(n))$, when $f(n) = n^3 + 8n^2 - 4$

$$g(n) = n^3$$

\rightarrow Find $c, n_0 > 0$ s.t. $\frac{n^3 + 8n^2 - 4}{n^3} < \frac{cn^3}{n^3} \quad \forall n > n_0$

$$1 + \frac{8}{n} - \frac{4}{n^3} < C$$

g(n) كذا
n³ n³

↳ let n₀ = 2

$$1 + \frac{8}{2} - \frac{4}{8} < C$$

4.5 < C then chose $C = 5$

analysis

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

prove that: $f(n) = \Omega(g(n))$

$$\text{when } f(n) = n^3 + 8n^2 - 4$$

$$g(n) = n^3$$

$$cn^3 < n^3 + 8n^2 - 4$$

$$c < 1 + \frac{8}{n} - \frac{4}{n^3}$$

$$c < 1 + \frac{8}{2} - \frac{4}{8} \rightarrow c < 4.5$$

$c = 4$

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

All $f(n)$'s st $c_1, c_2, n_0 > 0$

when

$$0 < c_2 g(n) < f(n) < c_1 g(n) \quad \forall n > n_0$$

Little
O

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \text{constant} \quad \Omega$$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0 \quad O$$

inverse
 $\omega \leftrightarrow O$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty \quad \omega$$

another program is the list

denied

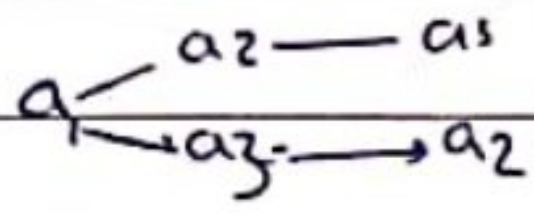
another installation is already in progress

concept to find the first bootstrap

6x10000
subig ul

Ex: a_1, a_2, a_3 $n=3$

$3! = 3 \times 2 \times 1 = 6$



For sure one of these

permutation will be our desired

solution

① list of the permutation as shown above for an input for size n } Brute Force
 } Naive
 } sortkey

② check the condition

$O(n!)$ time complexity

permutation tree

while

space (whenever)

for

Useful Summation Formulas

- **Arithmetic Series:** Constant differences $a_k - a_{k-1}$.

$$\sum_{k=1}^n k = \frac{n(n+1)}{2} = \Theta(n^2)$$

$$\sum_{k=1}^n k^2 = \frac{n(2n+1)(n+1)}{6}$$

- **Geometric Series:** Constant ratio $\frac{a_k}{a_{k-1}}$. For real $x \neq 1$,

$$\sum_{k=0}^n x^k = \frac{x^{n+1} - 1}{x - 1}$$

Infinite decreasing geometric series if $|x| < 1$:

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}$$

- **Harmonic Series:** For positive integers n ,

$$H_n = \sum_{k=1}^n \frac{1}{k} = \ln n + O(1)$$

- **Integration and Differentiation of Series:** By differentiating both sides of the infinite geometric series formula and multiplying by x , we get:

$$\sum_{k=0}^{\infty} k \cdot x^{k-1} \cdot x = \sum_{k=0}^{\infty} k \cdot x^k = \frac{x}{(1-x)^2}$$

51

Analyzing Code: Example 1

Analyze the running time of the following code segment, assuming that the time to perform the assignment on line 3 is 2 units of time. Provide a summation and solve it in closed form.

1. for $i \leftarrow 1$ to n
2. do for $j \leftarrow i$ to n
3. do $k \leftarrow k + j$

Analyzing Code: Example 2

Analyze the running time of the following code segment, assuming that the time to perform the assignment on line 4 is 2 units of time. Provide a summation and solve it in closed form.

```

1. for i ← 1 to n
2.   do for j ← 1 to i
3.     do for k ← 1 to j
4.       do x ← x + 1
    
```

$$\sum_{i=1}^n \sum_{j=1}^i \sum_{k=1}^j 2$$

$$\sum_{i=1}^n \sum_{j=1}^i 2(j-1+1)$$

$$\sum_{i=1}^n \frac{2i(i+1)}{2}$$

$$\sum_{i=1}^n i^2 + i$$

$$\sum_{i=1}^n i^2 + \sum_{i=1}^n i$$

$$\frac{n(n+1)(2n+1)}{6} + \frac{n(n+1)}{2}$$

53

Discussion of the INSERTION-SORT Analysis

- What is the best-case running time for insertion sort? When does it occur?
 - Best case -- inner loop body never executed
 - The input array is already sorted
 - T(n) is a linear function

$$T(n) = c_1n + c_2(n-1) + c_4(n-1) + c_5 \sum_{j=2}^n c_j + c_6 \sum_{j=2}^n c_j + c_7 \sum_{j=2}^n c_j - 1 + c_8(n-1)$$

$$T(n) = c_9n + c_{10}$$

Discussion of the INSERTION-SORT Analysis continued

- What is the worst-case running time for insertion sort? When does it occur?
 - Worst case -- inner loop body executed for all previous elements
 - $T(n)$ is a quadratic function

$$\begin{aligned}
 T(n) &= c_1n + c_2(n-1) + c_4(n-1) + c_5\left(\frac{n(n+1)}{2} - 1\right) \\
 &\quad + c_6\left(\frac{n(n-1)}{2}\right) + c_7\left(\frac{n(n-1)}{2}\right) + c_8(n-1) \\
 &= \left(\frac{c_5}{2} + \frac{c_6}{2} + \frac{c_7}{2}\right)n^2 + \left(c_1 + c_2 + c_4 + \frac{c_5}{2} - \frac{c_6}{2} - \frac{c_7}{2} + c_8\right)n \\
 &\quad - (c_2 + c_4 + c_5 + c_8)
 \end{aligned}$$

$$T(n) = c_9n^2 + c_{10}n + c_{11}$$

$$\sum_{j=2}^n j = \frac{n(n+1)}{2} - 1$$

Discussion of the INSERTION-SORT Analysis continued

- What is the average-case running time for insertion sort? (Refer to the book)
 - The “average case” is often roughly as bad as the worst case.
 - Suppose that we randomly choose n numbers and apply insertion sort. How long does it take to determine where in subarray $A[1 .. j-1]$ to insert element $A[j]$
 - On average, half the elements in $A[1 .. j-1]$ are less than $A[j]$, and half the elements are greater.
 - On average, therefore, we check half of the subarray $A[1 .. j-1]$, and so t_j is about $j/2$. The resulting average-case running time turns out to be a quadratic function of the input size, just like the worst-case running time.
 - It should be mentioned that the average-case running time of an algorithm is usually being computed by applying the technique of probabilistic analysis (See Chapter 5)
- How much space is needed in (best-case, average-case, worst-case)?
- Is Insertion sort considered as a stable algorithm?

Algorithms

Dr. Khalil Yousef

Lecture 2:

Reading Assignment:
Read Chapter 3 of the book

1

Course Learning Outcomes

Analyze numerical computations algorithms

(e.g. matrix multiplication).

order of growth function and notation → it is an important tool to compare the performance of several algorithms that solve a certain problem.

Time Complexity
Space Comp.

→ we will use five order of growth functions notation.

order of growth function expression

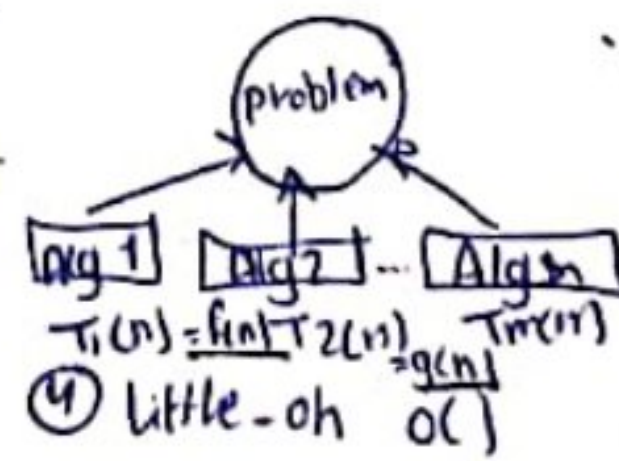
- ① Big-oh $O()$ ② Big-omega $\Omega()$ ③ Big-theta $\Theta()$

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

this operator isn't intended to reflect an assignment relationship, but we use it for simplicity to mean ∈ (belong to)

In other words, $O(g(n))$ is a class of functions, it isn't a single function

⇒ by writing the above expression we mean



Outline

- Big-Oh and Other Notations in Algorithm Analysis
 - Classifying Functions by Their Asymptotic Growth
 - Theta, Little oh, Little omega
 - Big Oh, Big Omega
 - Rules to manipulate Big-Oh expressions
 - Typical Growth Rates

constant $O(1)$ → top performance
linear $O(n)$
quadratic $O(n^2)$
:
exponential $O(2^n)$
:
→ worst performance 3

Classifying Functions by Their Asymptotic Growth

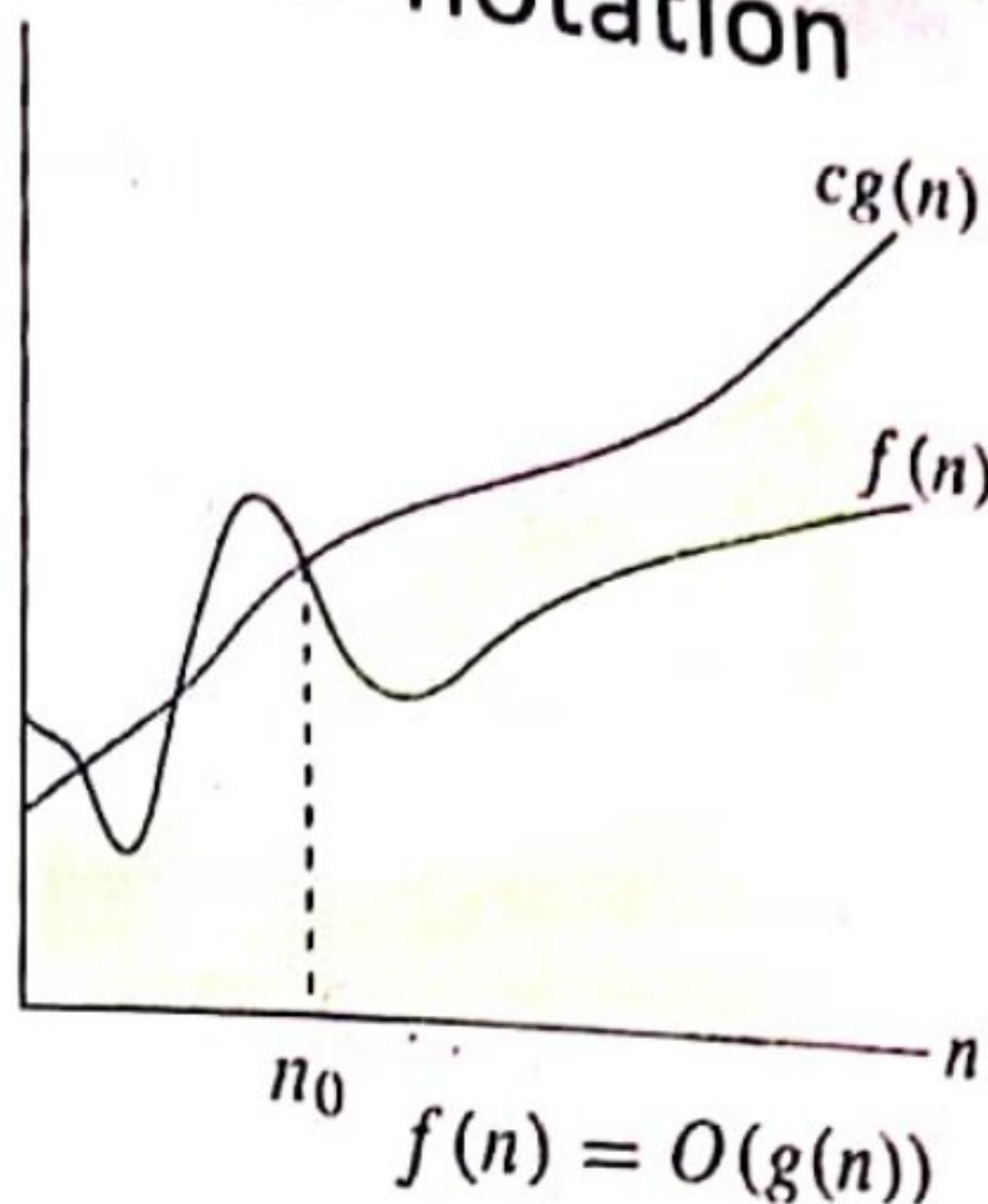
- Asymptotic growth:
 - The rate of growth of a function as a size of input [term of n]
- Given a particular differentiable function $f(n)$, all other differentiable functions fall into three classes:
 - Growing with the same rate $\Theta()$
 - Growing faster $\Omega()$ or $\omega()$
 - Growing slower $O()$ or $o()$

The Big-Oh Notation: O-notation

- For a given function $g(n)$, we denote by $O(g(n))$ the set of functions
- $O(g(n)) = \{f(n) : \text{there exist positive constants } c \text{ and } n_0 \text{ such that}$

$$0 \leq f(n) \leq cg(n),$$

for all $n \geq n_0$



We say $g(n)$ is an *asymptotic upper bound* for $f(n)$
Or we say $f(n)$ grows with same rate or slower than $g(n)$.

Important Notes

- A very useful aspect of this asymptotic notation (*Big-Oh* and others) is that constants and lower-order terms can be ignored.
 - Example
 - $5n^2 + 100n + 22 = O(n^2)$ and $n = O(n^2)$
- The worst-case running time of INSERTION-SORT is $O(n^2)$, but this does not imply that there is a $O(n^2)$ bound on every input. For example, on sorted input INSERTION-SORT runs in linear time.
- Though we write $f(n) = O(g(n))$, technically this means $f(n) \in O(g(n))$.

Asymptotic Notation in Equations

- When asymptotic notation appears alone on the right-hand side of an equation, as in $f(n) \in O(n^2)$, we are indicating that $f(n) \in O(n^2)$.

- When it appears in a formula, we interpret it as standing for *some anonymous function that shall remain nameless*.

- For example, $2n^2 + 3n + 1 \stackrel{\text{equal operator}}{=} 2n^2 + \Theta(n)$ means: $2n^2 + 3n + 1 = 2n^2 + \underbrace{f(n)}_{\substack{\text{any function from} \\ \text{the linear class [highest order n]}}}$ where $f(n)$ is some function in the set $\Theta(n)$.
 $\frac{n+3}{5} - 1000 \dots$

- By using this mechanism, we can eliminate clutter in equations.

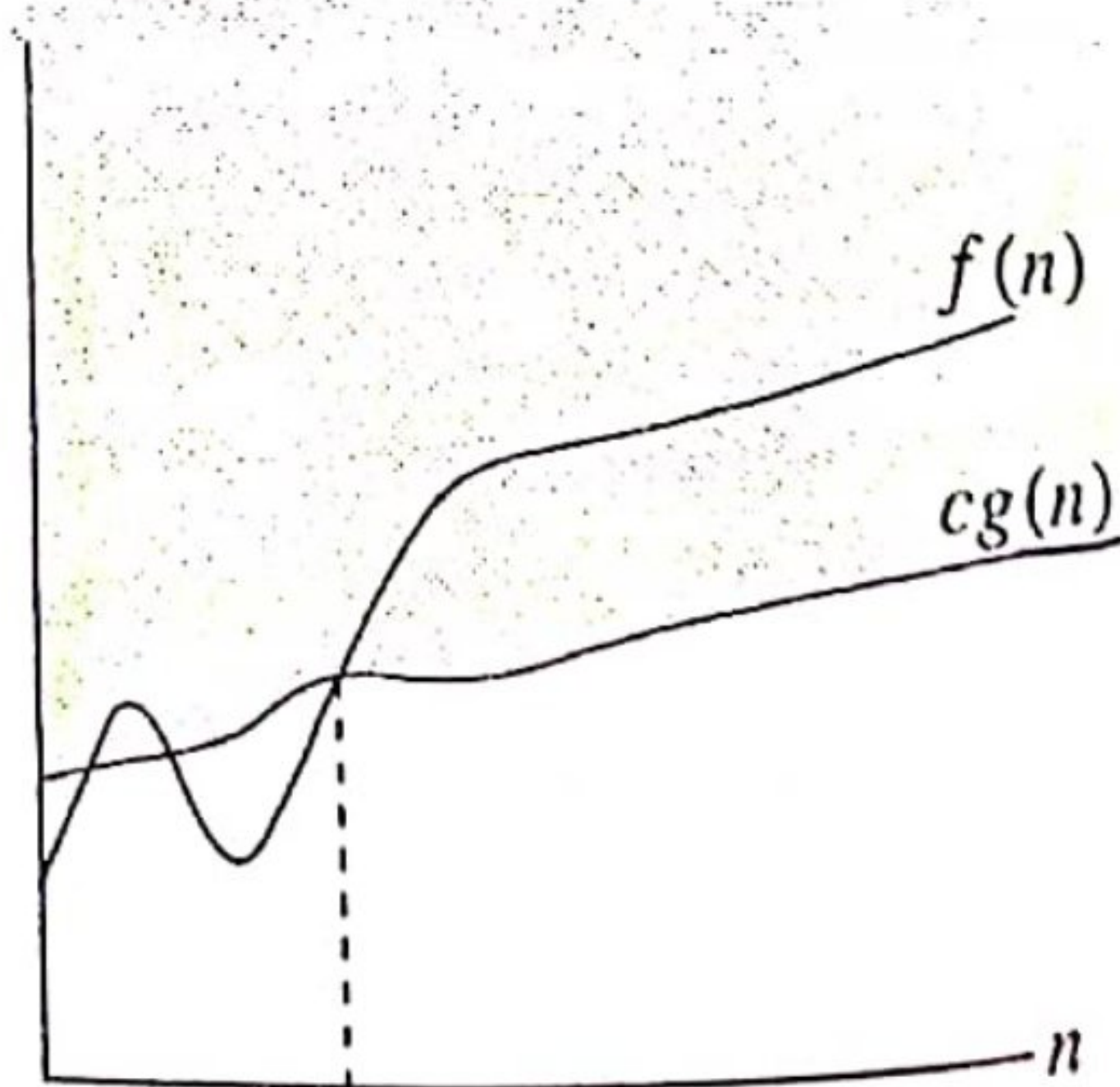
- What if it occurs on both sides? As in $2n^2 + 3n + \underbrace{\Theta(1)}_{\text{constant}} = 2n^2 + \underbrace{\Theta(n)}_{\text{linear}}$. We take this to mean for any $f(n) \in \Theta(1)$ there is some $g(n) \in \Theta(n)$ such that $2n^2 + 3n + f(n) = 2n^2 + g(n)$.

The Big-Omega Notation: Ω -notation

- For a given function $g(n)$, we denote by $\Omega(g(n))$ the set of functions
- $\Omega(g(n)) = \{f(n): \text{there exist positive constants } c \text{ and } n_0 \text{ such that}$

$$0 \leq cg(n) \leq f(n)$$

for all $n \geq n_0\}$



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

We say $g(n)$ is an asymptotic lower bound for $f(n)$

Or we say $f(n)$ grows with **same rate or faster** than $g(n)$.

The Big-Omega Notation: Ω -notation

- Example:

- $5n^2 + 100n + 22 = \Omega(n^2)$ and $n^2 = \Omega(n)$.

Θ notation (Theta) (Tight Bound)

- In some cases,

- If $f(n) = O(g(n))$ and $f(n) = \Omega(g(n))$

- This means, that the worst and best cases require the same amount of time t within a constant factor

- In this case we use a new notation called "theta Θ "

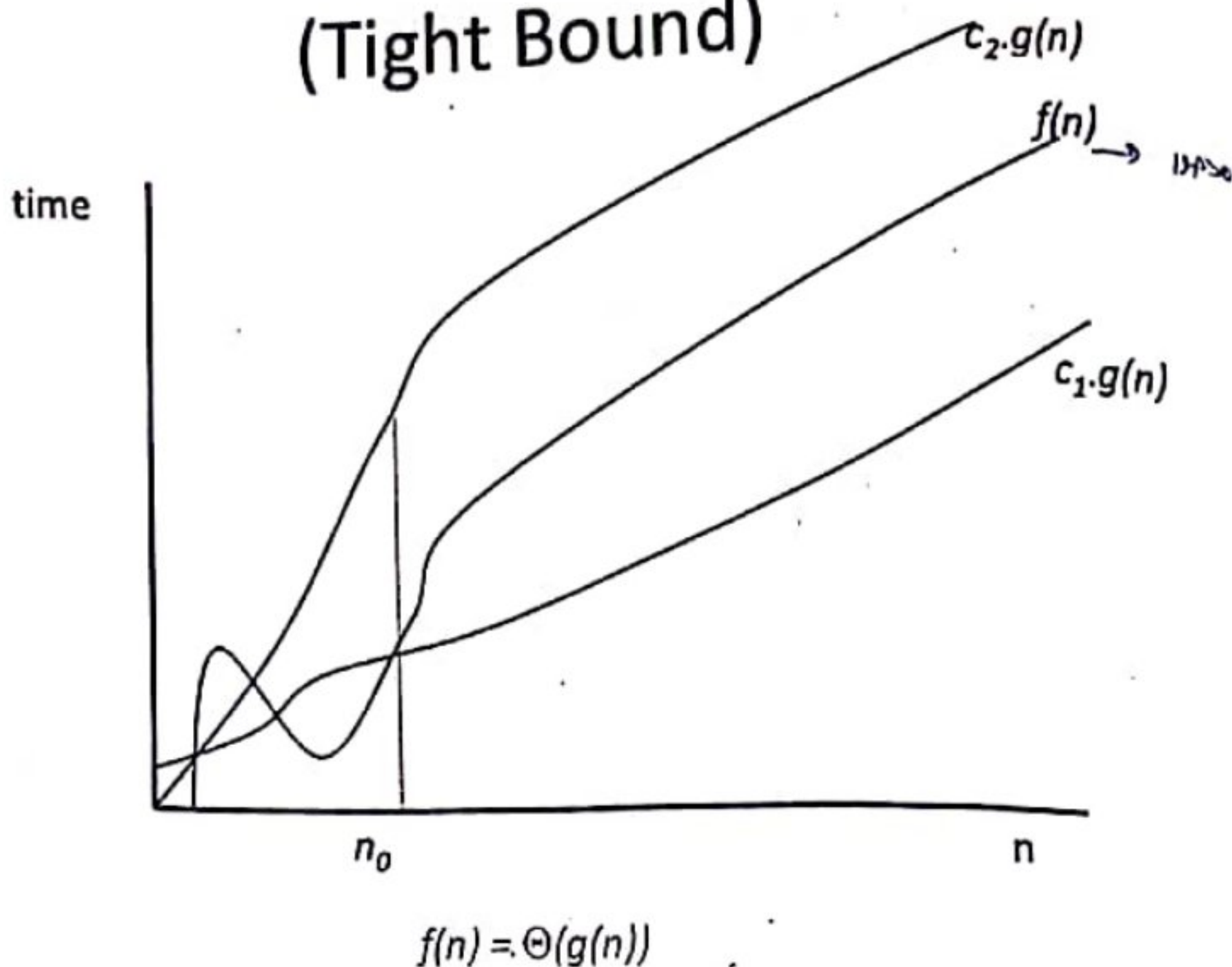
- "theta Θ " represents an asymptotically tight bound

- For a given function $g(n)$, we denote by $\Theta(g(n))$ the set of functions

- $\Theta(g(n)) = \{f(n) : \text{there exist positive constants } c_1 > 0, c_2 > 0 \text{ and } n_0 > 0 \text{ such that}$

- $c_1 g(n) \leq f(n) \leq c_2 g(n) \forall n \geq n_0$

Θ notation (Theta) (Tight Bound)



11

Discussion of the Asymptotic Notation

- Example 1: prove that $6n^3 \neq \Theta(n^2)$.

Proof by contradiction: i.e., assume $6n^3 = \Theta(n^2)$. $\Rightarrow c_1, c_2, n_0$
تعريف الـ Theta

$$0 \leq \frac{c_1 n^2}{n^2} \leq \frac{6n^3}{n^2} \leq \frac{c_2 n^2}{n^2}, \forall n \geq n_0 \rightarrow \cancel{n^2}$$

$$0 \leq c_1 \leq \frac{6n}{1} \leq c_2, \forall n \geq n_0$$

Linear const

This implies that $n \leq \frac{c_2}{6}, \forall n \geq n_0$, a contradiction.

Linear faster than constant for no...

if $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \text{constant} \neq 0$, then $f(n) = \Theta(g(n))$
 = 0, then $f(n) = o(g(n))$
 = ∞ ; then $f(n) = \omega(g(n))$

$$\lim_{n \rightarrow \infty} \frac{6n^3}{n^2} = \lim_{n \rightarrow \infty} 6n = \infty$$

بنتقل مع الـ def الـ Theta

Discussion of the Asymptotic Notation

• Example 2:

$$f(n) = 5n^2 + 1000n$$

✓ Claim: $f(n) = \Theta(n^2)$

Needed: c_1, c_2 , and n_0 , such that:

no \downarrow c_1, c_2 \uparrow
 c_1, c_2 \uparrow n_0 \downarrow

$$0 \leq \underbrace{c_1}_{\frac{c_1 n^2}{n^2}} n^2 \leq \underbrace{5n^2 + 1000n}_{\frac{f(n)}{n^2}} \leq \underbrace{c_2}_{\frac{c_2 n^2}{n^2}} n^2$$

$$0 \leq c_1 \leq 5 + \frac{1000}{n} \leq c_2$$

not unique

$$c_1, c_2, n_0 > 0$$

$c_1 \leq 6 \leq c_2$
 $5 + \frac{1000}{1000} \leq c_2$
 $c_2 = 6$
 we need to pick n_0

One choice: $n_0 = 1000, c_1 = 5, c_2 = 6$
 then set compute value for c_1 and c_2
 we assume n_0

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \frac{5n^2 + 1000n}{n^2}$$

$\lim_{n \rightarrow \infty} 5 + \frac{1000}{n} \rightarrow 5$
 Constant
 So it's Theta

Discussion of the Asymptotic Notation

• Example 3: Let us try to prove that $n \neq \Theta(n^2)$.

Proof by contradiction: i.e., assume $n = \Theta(n^2)$.
 افرض انه العكس صحیحاً و طبق الحدیث

$$0 \leq c_1 \frac{n^2}{n^2} \leq \frac{n}{n^2} \leq \frac{c_2 n^2}{n^2}, \forall n \geq n_0$$

growth rate constant $\frac{1}{n}$ is linear inverse

$$0 \leq c_1 \leq \frac{1}{n} \leq c_2, \forall n \geq n_0$$

invers linear



This implies that $n \leq \frac{1}{c_1}, \forall n \geq n_0$, a contradiction.

Little oh Notation: o-notation

← نفس ال () ولكن بدون المساواة

- o-notation denotes an upper bound that is not asymptotically tight (it is certain to grow faster). In contrast, O may or may not be asymptotically tight.
- For a given function $g(n)$, we denote by $o(g(n))$ the set of functions:
- $o(g(n)) = \{f(n): \text{for any positive constant } c > 0, \text{ there exists a constant } n_0 > 0 \text{ such that } 0 < f(n) < cg(n) \text{ for all } n \geq n_0\}$
- $f(n)$ becomes insignificant relative to $g(n)$ as n approaches infinity: i.e. $f(n) = o(g(n))$ iff $\lim_{n \rightarrow \infty} [f(n) / g(n)] = 0$
- We say $g(n)$ is an upper bound for $f(n)$ that is not asymptotically tight.
 - For example, $2n = o(n^2)$, but $2n^2 \neq o(n^2)$.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \lim_{n \rightarrow \infty} \frac{2n}{n^2} = \lim_{n \rightarrow \infty} \frac{2}{n} = \frac{2}{\infty} = 0 \checkmark$$

slower than n^2

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \lim_{n \rightarrow \infty} \frac{2n^2}{n^2} = \lim_{n \rightarrow \infty} 2 = 2 \times$$

↳ constant = Θ theta

15

$O(*)$ versus $o(*)$

$O(g(n)) = \{f(n): \text{there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \leq f(n) \leq cg(n), \text{ for all } n \geq n_0\}$.

$o(g(n)) = \{f(n): \text{for any positive constant } c > 0, \text{ there exists a constant } n_0 > 0 \text{ such that } 0 \leq f(n) < cg(n) \text{ for all } n \geq n_0\}$.

Thus $o(f(n))$ is a weakened $O(f(n))$.

For example: $n^2 = O(n^2)$

$$n^2 \neq o(n^2) \checkmark$$

$$n^2 = O(n^3) \checkmark$$

$$n^2 = o(n^3) \checkmark$$

little o subset of little omega

o little هو

big O هو

big omega هو

little omega هو

big omega هو little o هو

16

Little omega Notation: ω -notation

it is the inverse of little O

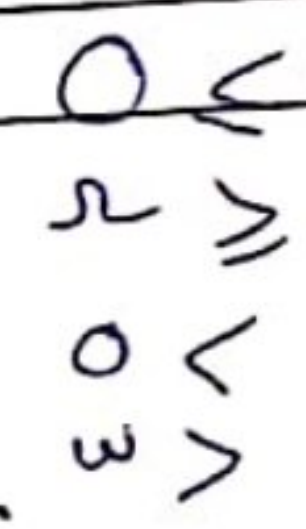
- For a given function $g(n)$, we denote by $w(g(n))$ the set of functions:
- $\omega(g(n)) = \{f(n) : \text{for any positive constant } c > 0, \text{ there exists a constant } n_0 > 0 \text{ such that } 0 \leq cg(n) \leq f(n) \text{ for all } n \geq n_0\}$
- $f(n)$ becomes insignificant relative to $g(n)$ as n approaches infinity: $f(n) = \omega(g(n))$ iff $\lim_{n \rightarrow \infty} [f(n) / g(n)] = \infty$
- We say $g(n)$ is an lower bound for $f(n)$ that is not asymptotically tight.

For example, $\frac{n^2}{2} = \omega(n)$, but $\frac{n^2}{2} \neq \omega(n^2)$

$\lim_{n \rightarrow \infty} \frac{n^2}{2} = \lim_{n \rightarrow \infty} \frac{n}{2} = \frac{\infty}{2} = \infty$

same rate
 \rightarrow ∞ constant

$f(n) = \boxed{17} g(n)$
 $\Theta =$



Comparison of Asymptotic Functions

Transitivity:

Conjunction Means AND

$f(n) = \Theta(g(n)) \wedge g(n) = \Theta(h(n)) \rightarrow f(n) = \Theta(h(n)) \rightarrow$ apply rule

and
 Common Function

$f(n) = O(g(n)) \wedge g(n) = O(h(n)) \rightarrow f(n) = O(h(n))$

$f(n) = \Omega(g(n)) \wedge g(n) = \Omega(h(n)) \rightarrow f(n) = \Omega(h(n))$

$f(n) = o(g(n)) \wedge g(n) = o(h(n)) \rightarrow f(n) = o(h(n))$

$f(n) = \omega(g(n)) \wedge g(n) = \omega(h(n)) \rightarrow f(n) = \omega(h(n))$

Reflexivity:

نفسه

$f(n) = \Theta(f(n))$
 $f(n) = O(f(n))$
 $f(n) = \Omega(f(n))$

Symmetry:

$f(n) = \Theta(g(n))$ iff $g(n) = \Theta(f(n))$

تبدیل ال
 ال ال

Comparison of Asymptotic Functions (Cont...)

Transpose Symmetry:

O inverse Ω
 o inverse ω

إذا قلبت لعكست
بإذن ال inverse

$$f(n) = O(g(n)) \text{ iff } g(n) = \Omega(f(n))$$

$$f(n) = o(g(n)) \text{ iff } g(n) = \omega(f(n))$$

These properties allow us to draw an analogy between the asymptotic comparison of functions f and g and the comparison of real numbers a and b :

$$f(n) = O(g(n)) \approx a \leq b$$

$$f(n) = \Omega(g(n)) \approx a \geq b$$

$$f(n) = \Theta(g(n)) \approx a = b$$

$$f(n) = o(g(n)) \approx a < b$$

$$f(n) = \omega(g(n)) \approx a > b$$

Although two real numbers can be compared (using $<$, $=$, or $>$), not all functions are asymptotically comparable (e.g., n and $n^{1+\sin n}$ cannot be compared; the exponent of the second oscillates between 0 and 2).

static $\frac{n}{n^{1+\sin n}}$ 15
مذبذب
oscillate between 1 and -1

we can't compare
-1 } $n^{1+0} = n$
 $n^{1+1} = n^2$
 $n^{1-1} = n^0 = 1$ } تجربت

SUMMARY

The Big-Oh Notation

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

if $f(n)$ grows with same rate or slower than $g(n)$. or asymptotic bound

Means $f(n) = \Theta(g(n))$ or
 $f(n) = o(g(n))$

21

The Big-Omega Notation

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

if $f(n)$ grows with same rate or faster than $g(n)$.

Means $f(n) = \Theta(g(n))$ or
 $f(n) = \omega(g(n))$

The Big-Omega Notation

- The inverse of Big-Oh is Ω
- If $g(n) = O(f(n))$,
- then $f(n) = \Omega(g(n))$

23

Theta Θ

- $f(n)$ and $g(n)$ have same rate of growth, if

$$\lim_{n \rightarrow \infty} (f(n) / g(n)) = c, \quad \text{constant}$$

$$-\infty < c < \infty, \quad n \rightarrow \infty$$

$c \neq 0$

- Notation: $f(n) = \Theta(g(n))$
- Pronounced "theta"

Theta: Relation of Equivalence

- Θ : "having the same rate of growth":
 - Relation of equivalence
 - Gives a partition over the set of all differentiable functions - classes of equivalence.
class of functions, not one function...
- Functions in one and the same class are equivalent with respect to their growth.

25

Little oh

$f(n)$ grows slower than $g(n)$
(or $g(n)$ grows faster than $f(n)$)

if

$$\lim(f(n) / g(n)) = \underline{0}, \quad n \rightarrow \infty$$

Notation: $f(n) = o(g(n))$ pronounced "little oh"

Little omega

$f(n)$ grows faster than $g(n)$
(or $g(n)$ grows slower than $f(n)$)
if

$$\lim (f(n) / g(n)) = \infty, \quad n \rightarrow \infty$$

Notation: $f(n) = \omega(g(n))$ pronounced "little omega"

27

inverse: Little omega and Little oh

- if $g(n) = o(f(n))$
- then $f(n) = \omega(g(n))$

- **Examples:** Compare n and n^2

$$- \lim (n/n^2) = 0, \quad n \rightarrow \infty, \quad n = o(n^2)_{n \rightarrow \infty}$$

$$- \lim (n^2/n) = \infty, \quad n \rightarrow \infty, \quad n^2 = \omega(n)_{n \rightarrow \infty}$$

28

Examples

29

Recall: Algorithms with Same Complexity

- Two algorithms have same complexity, if the functions representing the number of basic operations have same rate of growth.
- Among all functions with same rate of growth we choose the simplest one to represent the complexity.

30

$$a^{\log_b n} = n$$

$$x \cdot 2^{\log_2 n} = n = n' = \lfloor n \rfloor$$

Example

$$\log_2 n = \lg n$$

$$x \cdot 8^{\log_8 n} = n = n^3$$

- Compare n and $(n+1)/2$

– $\lim(n / ((n+1)/2)) = 2,$

– same rate of growth

- $(n+1)/2 = \Theta(n)$

– Rate of growth of a linear function

اليمين

Right side

B function

Left side

A function

	n^2	n	$2^{\log n}$	$8^{\log n}$
n^2	Θ	Θ	Θ	Θ

$$A = \boxed{} B$$

Example

- Compare n^2 and $n^2 + 6n$

– $\lim(n^2 / (n^2 + 6n)) = 1$

– same rate of growth.

– $n^2 + 6n = \Theta(n^2)$

– Rate of growth of a quadratic function

اليمين
لايف
 Θ

Example

- Compare $\log n$ and $\log n^2$

- $\lim(\log n / \log n^2) = \frac{1}{2}$

- Same rate of growth.

- $\log n^2 = \Theta(\log n)$

- logarithmic rate of growth

نفس الشيء اذا كان \log
 $\log n^2 = \frac{2 \log n}{\text{Ignored}} = \log n$

اذا القوى تغيرت او اذا ال base تغير

بغير نفس class \log

$\log_a n^b$ $\log_a n^b$

يفضل Θ $\left. \begin{matrix} b \neq b \\ a \neq a \end{matrix} \right\}$

Example

$\Theta(n^3)$: n^3
 $5n^3 + 4n$
 $105n^3 + 4n^2 + 6n$

$\Theta(n^2)$: n^2
 $5n^2 + 4n + 6$
 $n^2 + 5$

$\Theta(\log n)$: $\log n$
 $\log n^2$
 $\log(n + n^3)$

ان \log كله صروفه لقون
 $(\log n)^3 \neq \log n^3$
 $m^3 \neq m$

$\log n^3 \rightarrow \boxed{3 \log n}$
 $\log n^2 \rightarrow \boxed{2 \log n}$

Example

$$n+5 = \Theta(n) = O(n) = O(n^2) \\ = O(n^3) = O(n^5) = O(1) = O\left(\frac{1}{n}\right)$$

The closest estimation: $n+5 = \Theta(n)$

The general practice is to use

The Big-Oh notation:

$$n+5 = O(n)$$

will pick the
tightest bound

Techniques to show that $f(n)$ is (not) $\Theta(n)$, $O(n)$, or $\Omega(n)$

to prove:

1. Use the definition. For example, to show $f(n) = O(n)$, find positive constants c, n_0 to solve $0 \leq f(n) \leq cn$.

Content Valid ←

2. Proof by contradiction (e.g., to show $f(n) \neq O(n)$).

3a. If $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$ and $f(n), g(n)$ are asymptotically non-negative (≥ 0 for large n), then $f(n) = o(g(n))$. This is a special case for o : $g(n)$ is growing much faster than $f(n)$.

3b. If $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = c, c \neq 0$ and $f(n), g(n)$ are asymptotically non-negative (≥ 0 for large n), then $f(n) = \Theta(g(n))$.

Techniques to show that $f(n)$ is (not) $\Theta(n)$, $O(n)$, or $\Omega(n)$

3c. If $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$ and $f(n), g(n)$ are asymptotically non-negative (≥ 0 for large n), then $f(n) = \omega(g(n))$. This is a special case for ω : $f(n)$ is growing much faster than $g(n)$.

4. L'Hôpital's Rule: If $\lim_{n \rightarrow \infty} f(n) = \lim_{n \rightarrow \infty} g(n) = \infty$, then $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \lim_{n \rightarrow \infty} \frac{f'(n)}{g'(n)}$.
 مخرج أكبر / مخرج أصغر

Rules to manipulate Big-Oh expressions

Rule 1:

a. If

$$T_1(N) = O(f(N))$$

$$\rightarrow n^2 + n = O(n^2)$$

and

$$T_2(N) = O(g(N))$$

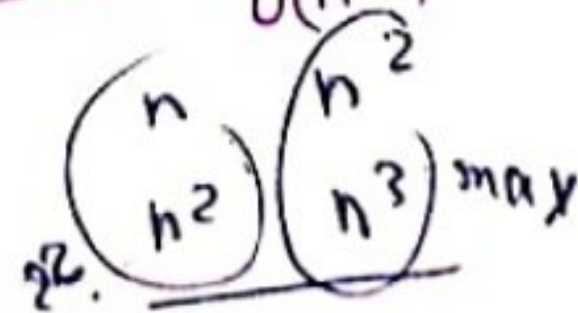
$$\rightarrow \frac{n^3 + n^2 = O(n^3)}{O(n^3)} +$$

then

$$T_1(N) \oplus T_2(N) =$$

$$\max(O(f(N)), O(g(N)))$$

بما حالة الجمع بأحد الأكبر لك big oh



Rules to manipulate Big-Oh expressions

b. $f(n) + g(n) \neq \Theta(\min(f(n), g(n)))$
 $n^4 + n^2 \neq \Theta(n^2)$ *

$f(n) \neq O((f(n))^2)$ → *لا في سالكون*
positiv f(n) 222
 $f(n) = \frac{1}{n^2} \neq O\left(\frac{1}{n^4}\right)$ → *grows in negative y*
decreasing

$f(n) \neq \Theta(f(n/2))$ *decreases the size of input*
 $f(n) = 4^n \neq \Theta(4^{n/2})$ *exponential*

4^n $(4^{1/2})^n = 2^n$
different orders

39

Rules to manipulate Big-Oh expressions

c. If

$$T_1(N) = O(f(N))$$

and

$$T_2(N) = O(g(N))$$

then

$$T_1(N) * T_2(N) = O(f(N) * g(N))$$

اذا بدى افرد بفرق
 ال

Rules to manipulate Big-Oh expressions

Rule 2:

If $T(N)$ is a polynomial of degree k , then

$$T(N) = \Theta(N^k)$$

الـ poly يكون
highest order term Θ

Rule 3:

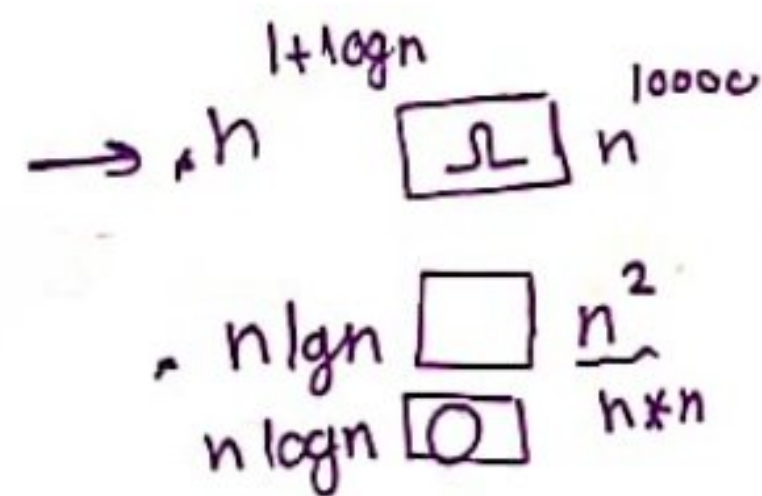
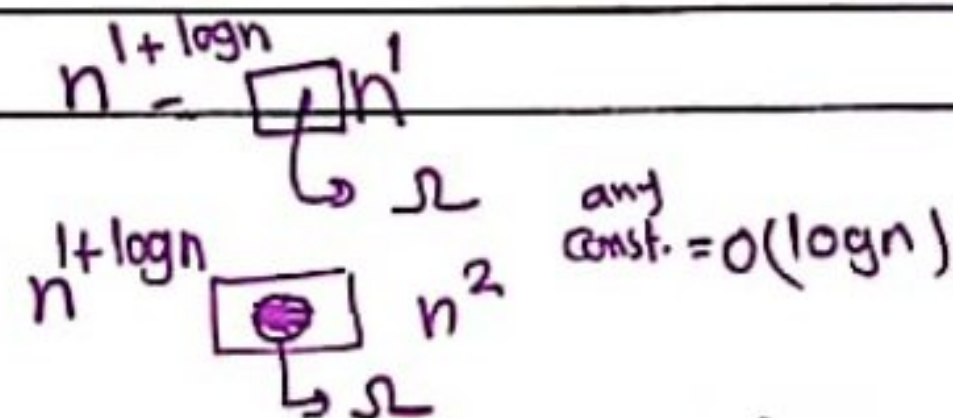
the power k less than or same rate the linear growth of a log function tends to

$$\log^k N = O(N) \text{ for any constant } k: = (\log N)^k \ll \text{Linear}$$

الـ log الرفع لغوة يكون slower than linear

$$(\log n)^{1000} = \log^{1000} n = O(n)$$

41



Examples

$\log n < n$

- $n^2 + n = O(n^2)$
– we disregard any lower-order term

- $\underline{n \log(n)} = O(n \log(n))$ and Θ

- $\underline{n^2} + n \log(n) = O(n^2)$ and Θ
Linear order الـ $n \log(n)$

42

Standard Notations: Monotonicity

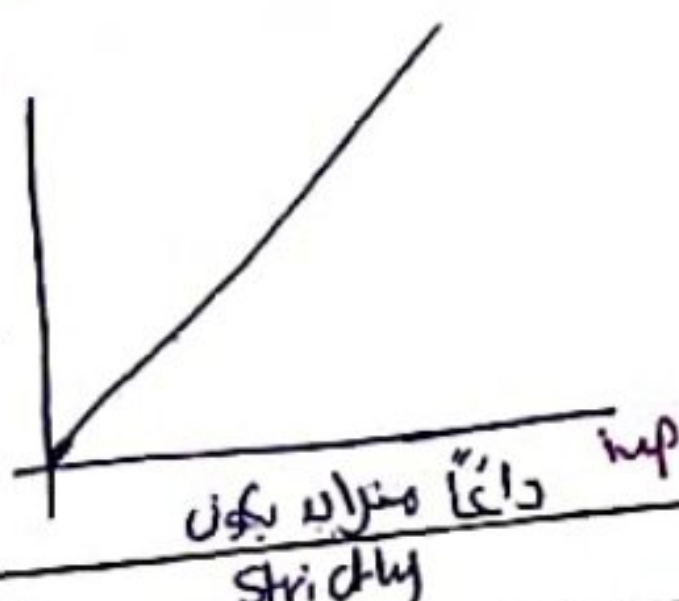
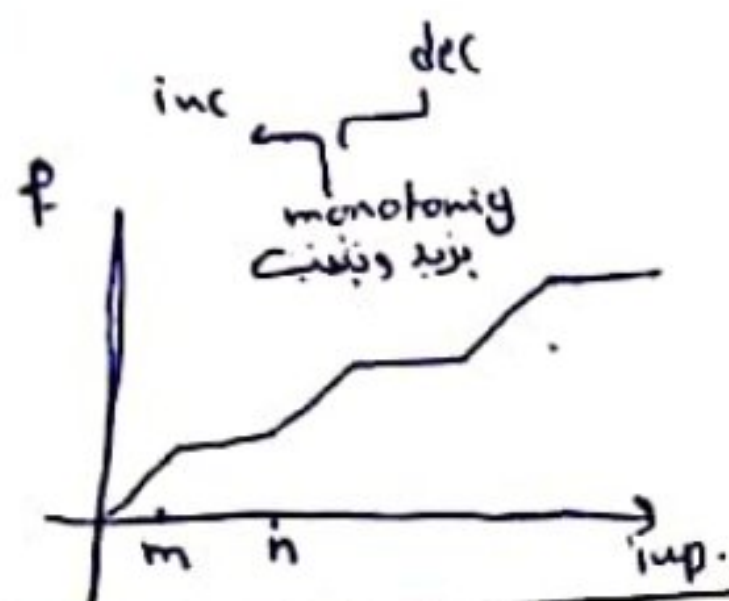
Monotonicity of a function:

A function is monotonically increasing if $m \leq n \rightarrow f(m) \leq f(n)$.

A function is monotonically decreasing if $m \leq n \rightarrow f(m) \geq f(n)$.

A function is strictly increasing if $m < n \rightarrow f(m) < f(n)$.

A function is strictly decreasing if $m < n \rightarrow f(m) > f(n)$.



$m < n \rightarrow$ Function \leq Function

Strictly
dec inc

decreasing
> < < <

Standard Notations: Floors and Ceilings

For any real number x , the greatest integer less than or equal to x is called the floor of x , denoted $\lfloor x \rfloor$.

For any real number x , the least integer greater than or equal to x is called the ceiling of x , denoted $\lceil x \rceil$.

For all real x , $x - 1 < \lfloor x \rfloor \leq x \leq \lceil x \rceil < x + 1$.

For any integer n , $\lfloor \frac{n}{2} \rfloor + \lceil \frac{n}{2} \rceil = n$.

For any integer n and integers $a \neq 0, b \neq 0$:

ceiling
Floor و Floor
Floor و Floor

$$\lceil \frac{\lceil n \rceil}{a} \rceil = \lceil \frac{n}{ab} \rceil$$

$$\lfloor \frac{\lfloor n \rfloor}{b} \rfloor = \lfloor \frac{n}{ab} \rfloor$$

Polynomials

Given a positive integer d , a polynomial in n of degree d is a function $p(n)$ in the form:

$$p(n) = \sum_{i=0}^d a_i n^i$$

\leftarrow *المرتبة* \leftarrow *Factor* \leftarrow $a_0 n^0 + a_1 n^1 + \dots + a_d n^d$
 $O(n^d)$ *مرتبة أعلى* \leftarrow *order*

where a_0, a_1, \dots, a_n are called coefficients, and $a_d \neq 0$. (n^d)

For an asymptotically positive polynomial of degree d (i.e., $a_d > 0$), $p(n) = \Theta(n^d)$.

We say that $f(n)$ is polynomially bounded if $f(n) = n^{O(1)}$, which is equivalent to $f(n) = O(n^k)$ for constant k .

Exponentials

$$\begin{aligned}
 a^0 &= 1 \\
 a^1 &= a \\
 a^{-1} &= \frac{1}{a} \\
 (a^m)^n &= a^{mn} \\
 (a^m)^n &= (a^n)^m \\
 a^m a^n &= a^{m+n}
 \end{aligned}$$

It is useful to know some properties of the special exponential e^x .

For example, for all real x , $e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots = \sum_{i=0}^{\infty} \frac{x^i}{i!}$ *Opt:*

For all real x , $e^x \geq 1 + x$, where equality holds only if $x = 0$.

لا تخف لتتحقق لكل اعداد حقيقي الطريقة
 When $|x| \leq 1$, $1 + x \leq e^x \leq 1 + x + x^2$ *From series*

$\forall x, \lim_{n \rightarrow \infty} (1 + \frac{x}{n})^n = e^x$

e^x faster than $1+x$ and $O(1+x+x^2)$

Logarithms

بديف شي بكون في دنا

$$\lg n = \log_2 n \text{ (binary logarithm)}$$

$$\ln n = \log_e n \text{ (natural logarithm)}$$

$$\lg^k n = (\lg n)^k \text{ (exponentiation)}$$

$$\lg \lg n = \lg(\lg n) \text{ (composition)}$$

For all real $a > 0, b > 0, c > 0$:

لغ

$$a = b^{\log_b a} \quad \text{exp + log}$$

$$\log_c(ab) = \log_c a + \log_c b$$

$$a^{\log_b a} = a^{\log_b a}$$

$$\log_b a^n = n \log_b a$$

$$\log_b a = \frac{\log_c a}{\log_c b}$$

$$\log_b \left(\frac{1}{a}\right) = -\log_b a$$

$$\log_b a = \frac{1}{\log_a b}$$

$$a^{\log_b n} = n^{\log_b a}$$

$$n^{\log_b a} = \log_b a$$

$$4^{\lg n^2} = 4^{2 \lg n} = 4^2 \times 4^{\lg n} = 16 \times n^{\lg 4} = 16n^2$$

quadratic function

$$8^{\lg n} = n^3$$

Logarithms

• Show that $a^{\log_b n} = n^{\log_b a}$

let $a = b^{\log_b a}$

$$\therefore a^{\log_b n} = (b^{\log_b a})^{\log_b n} = b^{(\log_b a)(\log_b n)} = b^{(\log_b n)(\log_b a)} = a^{\log_b n} = (b^{\log_b n})^{\log_b a} = n^{\log_b a}$$

Logarithms (Cont...)

Note that $\lg n + k = (\lg n) + k$.

Since changing a log base only changes a value by a constant factor, we will usually use $\lg n$ when we don't care about constant factors.

Note, when $|x| < 1$:

series for \ln

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \dots$$

bound for \ln

For $x > -1$, $\frac{x}{1+x} \leq \ln(1+x) \leq x$, where the equality holds if $x = 0$.

A function is polylogarithmically bounded if $f(n) = \lg^{O(1)} n$.

Rates of Growth

The rates of growth of any positive exponential function is faster than any polynomial function, as the following shows.

For all real constants a, b , where $a > 1$, $\lim_{n \rightarrow \infty} \frac{n^b}{a^n} = 0$, hence we can conclude

grow slower exp.

polynomial for b degree $n^b = o(a^n)$ little oh exponent ($a > b$)

The rates of growth of any polynomial function is faster than any polylogarithmic function, as the following shows.

By substituting $\lg n$ for n and 2^a for a in the above, we get:

$$\lim_{n \rightarrow \infty} \frac{\lg^b n}{(2^a)^{\lg n}} = \lim_{n \rightarrow \infty} \frac{\lg^b n}{n^a} = 0$$

grow slower

Hence, we can conclude $\lg^b n = o(n^a)$, for any $a > 0$.

logarithmic power is

polynomial little-oh

Factorials

$f(n) = \log n!$, $g(n) = (\log n)!$

$$n! = \begin{cases} 1 & \text{if } n = 0, \\ n(n-1)! & n > 0. \end{cases}$$

$$n! = \prod_{i=1}^n i$$

Intuition: $n!$ is the number possible permutations of a given input set with n members. This is fast-growing!

A weak upper bound on the factorial function is $n! \leq n^n$.

Stirling's Approximation provides us with tighter upper and lower bounds.

ignore linear

$$n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n \left(1 + \Theta\left(\frac{1}{n}\right)\right) = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

lower bound

$$\sqrt{2\pi n} \left(\frac{n}{e}\right)^n \leq n! \leq \sqrt{2\pi n} \left(\frac{n}{e}\right)^n e^{\frac{1}{2n}}, n \geq 8$$

$$n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

$f(n) \mid \log(n!) = \log \left[\sqrt{2\pi n} \left(\frac{n}{e}\right)^n \right] = \frac{1}{2} \log(2\pi n) + n \log\left(\frac{n}{e}\right)$

$g(n) \mid = (\log n)!$

$$= \sqrt{2\pi \log n} \left(\frac{\log n}{e}\right)^{\log n}$$

$$= \sqrt{2\pi} (\log n)^{\frac{1}{2}} \left(\frac{\log n}{e}\right)^{\log n}$$

$$= \frac{1}{2} \left[\underbrace{\log 2 + \log \pi}_{\text{const}} + \underbrace{\log n}_{\log} \right] + \underbrace{n \log n}_{\text{highest}} - \underbrace{n \log e}_{\text{const } n(\text{const})}$$

highest order

$$\log \log n = n$$

$O(n^{\log \log n})$

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

$f(n) \leq g(n)$

The Iterated Logarithm Function

تعريف دالة اللوغاريتم المتكرر

and recursive (تكرارية)

The notation $\lg^* n$ is used to represent the iterated logarithm, which is an extremely slow growing function defined in terms of $\lg^{(i)} n$, which is a function defined on non-negative integers that applies the logarithm function i times in succession.

$$\lg^{(i)} n = \begin{cases} n & \text{if } i = 0, \\ \lg(\lg^{(i-1)} n) & \text{if } i > 0 \text{ and } \lg^{(i-1)} n > 0 \\ \text{undefined} & \text{if } i > 0 \text{ and } \lg^{(i-1)} n \leq 0 \text{ or } \lg^{(i-1)} \text{ is undefined} \end{cases}$$

$\log 4 = 2$
 $\log 2 = 1$
 $\lfloor 2 \rfloor$

$\log 16 = \log 4$
 $\log 2 = 1$
 $\lfloor 3 \rfloor$

Then:

$$\lg^* n = \min\{i \geq 0 : \lg^{(i)} n \leq 1\}$$

For example:

$\lg^* n$, $\lg^k(\lg n)$

$\lg^* 2 = 1$
 $\lg^* 4 = 2$
 $\lg^* 16 = 3$
 $\lg^* 65536 = 4$, etc.

$2^{16} = 16 = 4 = 2 = 1$

Rank Ordering Functions by Order or Growth

To rank order a list of functions into an arrangement f_1, f_2, \dots, f_n and $f_1 = \Omega(f_2), f_2 = \Omega(f_3), \dots, f_{n-1} = \Omega(f_n)$ (as well as identify those functions that belong to the same equivalence class, where $f_1(n)$ and $f_2(n)$ belong in the same equivalence class if and only if (iff) $f_1(n) = \Theta(f_2(n))$), we can use what we know about the functions themselves and asymptotic notation. Much of the ranking is based on:

- Exponential functions grow faster than polynomial functions, which grow faster than polylogarithmic functions.
- The base of a logarithm does not matter asymptotically (recall $\log_b a = \frac{\log_c a}{\log_c b}$), but the base of an exponential and the degree of a polynomial do matter.
- Identities can help, as can working with approximation formulas such as Stirling's approximation.

53

Rank Ordering Functions by Order or Growth: Useful Identities

1. $2^{\lg n} = n^{\lg 2} = n$

2. $4^{\lg n} = n^{\lg 4} = n^2$

3. $(\lg n)^{\lg n} = n^{\lg \lg n}$

4. $2 = n^{\frac{1}{\lg n}}$ (raising identity 1 to the power $\frac{1}{\lg n}$)

5. $(\sqrt{2})^{\lg n} = 2^{\frac{1}{2} \lg n} = 2^{\lg \sqrt{n}} = \sqrt{n}$

$n^{\lg \sqrt{2}} = \log_2 2^{\frac{1}{2}} = \frac{1}{2} \lg n$

$[2^{\lg n}] = [n]$
 $2 = n^{\frac{1}{\lg n}}$

* rank the following for $\lg n \in \Omega(1)$
 $1000 \gg n$
 $1000 = \Theta(n^{\lg n})$
 $1000 \in \Theta(2)$ [constant]

* $n^3, n^{\lg n}$
 \downarrow
 0

54

Rank Ordering Functions by Order or Growth: More Useful Identities

1. $n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n (1 + \Theta(\frac{1}{n}))$

2. $n! = \Theta(n^{n+\frac{1}{2}} e^{-n})$ (drop constants and low order term)

3. $(\lg n)! = \Theta((\lg n)^{\lg n + \frac{1}{2}} e^{-\lg n}) = \Theta((\lg n)^{\lg n + \frac{1}{2}} n^{-\lg e})$ (substitute $\lg n$ for n in 2)
 ↳ $O(n^{\lg \lg n})$

4. $\lg(n!) = \Theta(n \lg n)$

5. $n! = o(n^n)$ $n(n-1)(n-2)\dots 1$
 $n \times n \times n \dots \times n$

6. $n! = \omega(2^n)$
 أكبر

CLR 3-3: Rank Ordering Functions by Order or Growth: Examples

Ranking by asymptotic growth rate, equivalent classes are enclosed by '[]'.
 ↓ Top Performance

Const. $[1, n^{1/\lg n}] \Theta(1)$
 $\lg(\lg^* n)$
 $[\lg^*(\lg n), \lg^*(n)] \Theta$
 $2^{\lg^* n}$

$\ln \ln n$
 $\sqrt{\lg n}$

$[\ln n, \log n]$

$\lg^2 n$

$2^{\sqrt{2 \lg n}}$

$(\sqrt{2})^{\lg n}$

Linear $\rightarrow 2^{\lg n}$

$[n \lg n, \lg(n!)] \Theta$

$[4^{\lg n}, n^2]$

n^3

$[(\lg n)!, n^{\lg \lg n}, (\lg n)^{\lg n}] \Theta$

$(3/2)^n$

2^n

$n 2^n$

... e^n

$n!$

$(n+1)!$

2^{2^n}

$2^{2^{n+1}}$

slowest performance

Base exponential growth

Term $n! = O((n+1)!)$

From slowest to the fastest.

exp faster poly.

$\log n$
 \downarrow
 m
 $m = O(m^2)$

$\log n^2$
 \downarrow
 m^2

Rank Ordering Functions by Order or Growth: Examples

$n^{\log \log n}$
قريب من $n \log n$

Order the following functions:

1. $(\lg n)^{\lg n}$ and n^3

$n^{\log \log n} = \Omega(n^3)$

prove \lim def.

2. $n^{\frac{1}{\lg n}}$ and n

$n = O(n)$

3. 2^n and $(\frac{3}{2})^n$

$2^n = \Omega(\frac{3}{2})^n$

4. $\lg^2 n$ and $\ln n$

$(\lg n)^2 \sim \lg n$

5. $4^{\lg n}$ and $8^{\lg n}$

$n^2 \sim n^3$

6. $(\lg n)!$ and $\lg(n!)$

Typical Growth Rates

C	constant, we write $O(1)$	order
$\log N$	logarithmic	
$\log^2 N$	log-squared	
N	linear	
$N \log N$		
N^2	quadratic	
N^3	cubic	
2^N	exponential	
$N!$	factorial	$2^N \sim O(\frac{n^n}{n!})$

Problems

- $N^2 = O(N^2)$
- true
- $2N = O(N^2)$
- true
- $N = O(N^2)$
- true

- Σ
- $N^2 = O(N)$
- false
 - $2N = O(N)$
- true
 - $N = O(N)$
- true

Problems

- $N^2 = \Theta(N^2)$
- true
- $2N = \Theta(N^2)$
- false
- $N = \Theta(N^2)$
○ - false

- Σ
- $N^2 = \Theta(N)$
- false
 - $2N = \Theta(N)$
- true
 - $N = \Theta(N)$
- true

Course Learning Outcomes

Analyze numerical computations algorithms
(e.g. **matrix multiplication**).

stop when size of 2x2

$\begin{matrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{matrix}$

$\begin{matrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{matrix}$

=

$\begin{matrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{matrix}$

(recursion divide and conquer) and the same size $\leftarrow n^2$ by n^2 sub \rightarrow 8 divisions

$T(n) = 8T(\frac{n}{2}) + \Theta(n^2)$
 $= \Theta(n^3)$

Matrix Multiplication

Design methodology **Brute Force Alg.**

Counting Scalar Multiplications in Matrix Multiplication

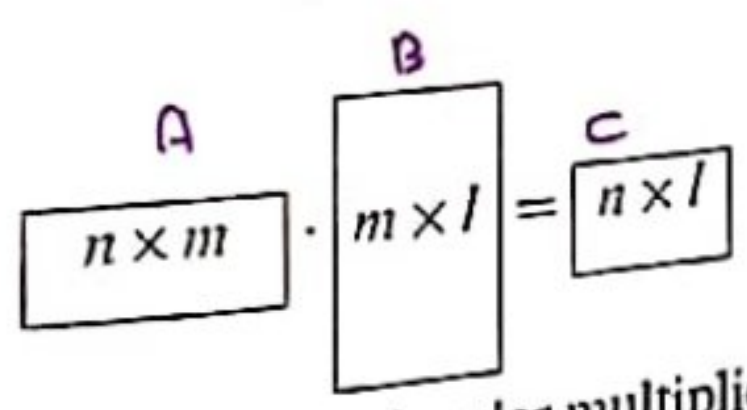
```

MATRIX-MULTIPLY(A, B)
1. if columns[A] ≠ rows[B]
2. then error "incompatible dimensions"
3. else for i ← 1 to rows[A]
4.     do for j ← 1 to columns[B]
5.         do C[i, j] ← 0
6.         for k ← 1 to columns[A]
7.             do C[i, j] = C[i, j] + A[i, k] · B[k, j]
8.     return C
    
```

For simplicity let $n=m=1$
we have same matrix

$\Theta(n^3)$

Basic operation \neq of basic operation



The number of scalar multiplications is: $n \times m \times 1$

$(x-y)^2 = x^2 - 2xy + y^2$
 $x \cdot x = 2xy + y \cdot y$ (3 mult)
 $(x-y)(x-y)$ (1 mult)

$A \times B = \begin{matrix} \downarrow \\ \downarrow \\ \downarrow \end{matrix} \begin{matrix} \downarrow \\ \downarrow \\ \downarrow \end{matrix}$ 8 multiplication

$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \cdot \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$

$C_{11} = a_{11} \cdot b_{11} + a_{12} \cdot b_{21}$ 8 multiplication
 $C_{12} = a_{11} \cdot b_{12} + a_{12} \cdot b_{22}$
 $C_{21} = a_{21} \cdot b_{11} + a_{22} \cdot b_{21}$
 $C_{22} = a_{21} \cdot b_{12} + a_{22} \cdot b_{22}$

Matrix Multiplication Brute Force Alg.

- If $m=l=n$
– Then Time complexity is n^3

63

بفكر انزل better

Strassen's Matrix Multiplication

Strassen observed [1969] that the product of two matrices can be computed as follows:

$$\begin{pmatrix} C_{00} & C_{01} \\ C_{10} & C_{11} \end{pmatrix}_{2 \times 2} = \begin{pmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{pmatrix}_{2 \times 2} * \begin{pmatrix} B_{00} & B_{01} \\ B_{10} & B_{11} \end{pmatrix}_{2 \times 2}$$

$$\begin{aligned}
 C_{00} &= A_{00} * B_{00} + A_{01} * B_{10} \\
 C_{10} &= A_{10} * B_{00} + A_{11} * B_{10} \\
 C_{01} &= A_{00} * B_{01} + A_{01} * B_{11} \\
 C_{11} &= A_{10} * B_{01} + A_{11} * B_{11}
 \end{aligned}$$

(8) عمليات ضرب

$2 \times 2 \times 2 = 8$

تقلل عملية الضرب

7 ←

مفاتيح

$$= \begin{pmatrix} M_1 + M_4 - M_5 + M_7 & M_3 + M_5 \\ M_2 + M_4 & M_1 + M_3 - M_2 + M_6 \end{pmatrix}$$

64

Formulas for Strassen's Algorithm

$$M_1 = (A_{00} + A_{11}) * (B_{00} + B_{11})$$

$$M_2 = (A_{10} + A_{11}) * B_{00}$$

$$M_3 = A_{00} * (B_{01} - B_{11})$$

$$M_4 = A_{11} * (B_{10} - B_{00})$$

$$M_5 = (A_{00} + A_{01}) * B_{11}$$

$$M_6 = (A_{10} - A_{00}) * (B_{00} + B_{01})$$

$$M_7 = (A_{01} - A_{11}) * (B_{10} + B_{11})$$

$$\begin{pmatrix} C_{00} & C_{01} \\ C_{10} & C_{11} \end{pmatrix} = \begin{pmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{pmatrix} * \begin{pmatrix} B_{00} & B_{01} \\ B_{10} & B_{11} \end{pmatrix}$$

$$\begin{pmatrix} M_1 + M_4 - M_5 + M_7 & M_3 + M_5 \\ M_2 + M_4 & M_1 + M_3 - M_2 + M_6 \end{pmatrix}$$

قل على باب ال ضرب

Time Complexity
= $n^{2.807}$ 65

$$T(n) = 7T(n/2) + \Theta(n^2)$$

$$\Theta(n^{\log_2 7}) = \Theta(n^3)$$

guesses for time complexity

قل ال because multiplication

Analysis of Strassen's Algorithm

- If n is not a power of 2, matrices can be padded with zeros.
 في حال ما كان ليس ال size ← zeros

- Number of multiplications:

$$M(n) = 7M(n/2), \quad M(1) = 1$$

- Solution: $M(n) = 7^{\log_2 n} = n^{\log_2 7} \approx n^{2.807}$ vs. n^3 of brute-force alg.
 guesses
 perf افضل

- Algorithms with better asymptotic efficiency are known but they are even more complex.
 ❗

Course Learning Outcomes

- Use algorithm design methods, such as exhaustive search, divide-and-conquer and dynamic programming, to develop efficient algorithms.

2

Designing Algorithms: Techniques/Strategies

- Brute force
- **Divide and conquer**
- Decrease and conquer
- Transform and conquer
- Space and time tradeoffs
- Greedy approach
- Dynamic programming
- Iterative improvement
- Backtracking
- Branch and bound

3



Divide-and-Conquer

The most-well known algorithm design strategy:

1. Divide instance of problem into two or more smaller instances
2. Solve smaller instances recursively
3. Obtain solution to original (larger) instance by combining these solutions

Insertion sort $O(n^2)$ worst-case

merge sort $O(n \log n)$ up

$n \log n < n^2$

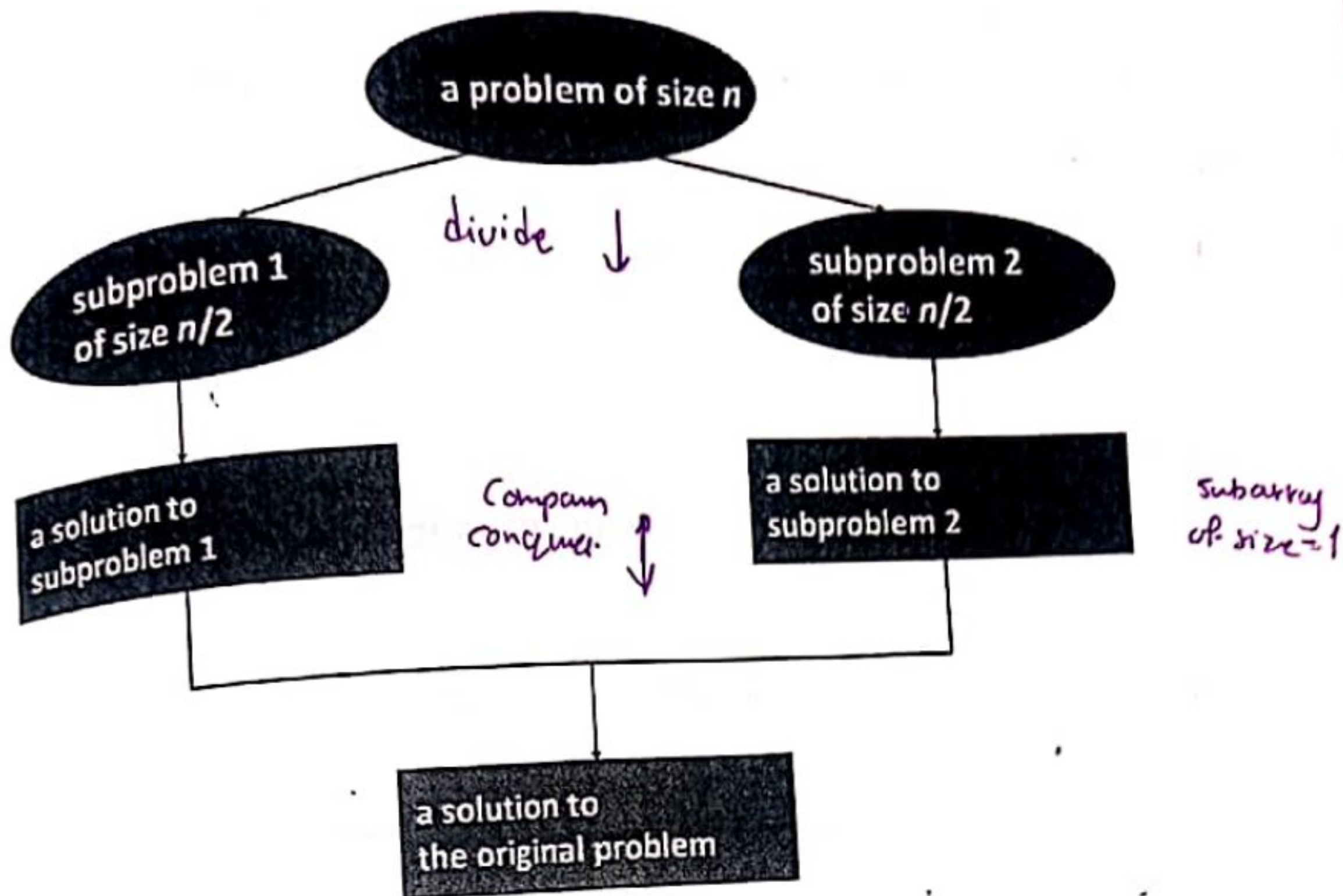
perf. جيد



Divide-and-Conquer Examples

- Sorting: mergesort and quicksort
- Binary tree traversals
- Multiplication of large integers
- Matrix multiplication: Strassen's algorithm
- Closest-pair and convex-hull algorithms
- Binary search: decrease-by-half (or degenerate divide&conq.)

Divide-and-Conquer Technique (cont.)



6

MERGE-SORT

- **MERGE-SORT** is an example of a divide-and-conquer algorithm.

Mergesort

- Split array $A[0..n-1]$ in two about equal halves and make copies of each half in arrays L and R
- Sort arrays L and R recursively
- Merge sorted arrays L and R into array A as follows:
 - Repeat the following until no elements remain in one of the arrays:
 - compare the first elements in the remaining unprocessed portions of the arrays
 - copy the smaller of the two into A , while incrementing the index indicating the unprocessed portion of that array
 - Once all elements in one of the arrays are processed, copy the remaining unprocessed elements from the other array into A .

index of first element in subarray \rightarrow p index of last element \rightarrow r

can be any numbers. $p=1, r=10$

input a array of n element $A[p..r]$

stop condition \rightarrow $p \geq r$

$q = \lfloor \frac{p+r}{2} \rfloor$ \rightarrow middle point

$n = r - p + 1$ [may be even or odd]

$q = \lfloor \frac{p+r}{2} \rfloor$

MERGE-SORT $\lfloor \frac{1+10}{2} \rfloor = 5$

1. if $p < r$

2. then $q \leftarrow \lfloor \frac{p+r}{2} \rfloor$

3. MERGE-SORT(A, p, q)

4. MERGE-SORT($A, q+1, r$)

5. MERGE(A, p, q, r)

assume the right already sorted and left

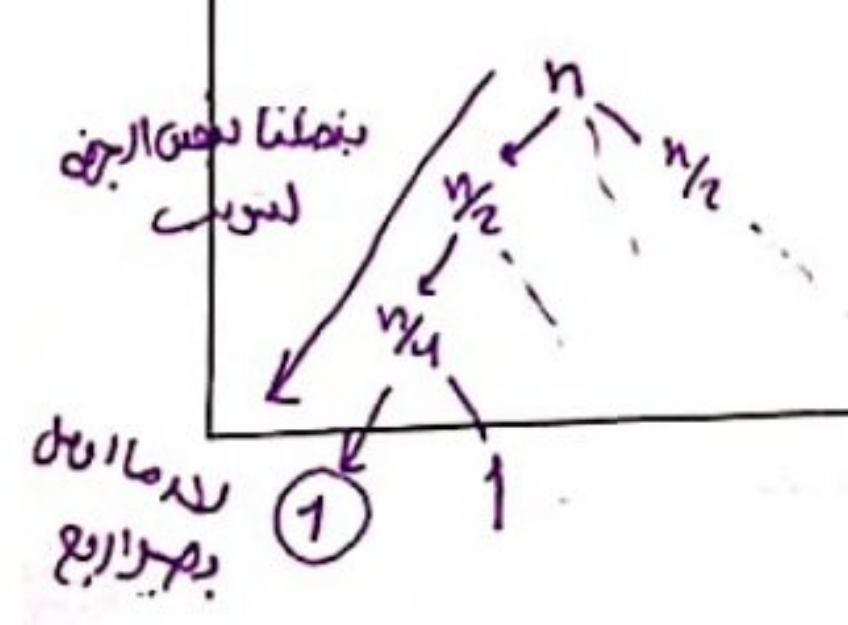
index \rightarrow $p, q, q+1, r$

First element and last element p, q

same size

odd \rightarrow n even \rightarrow n

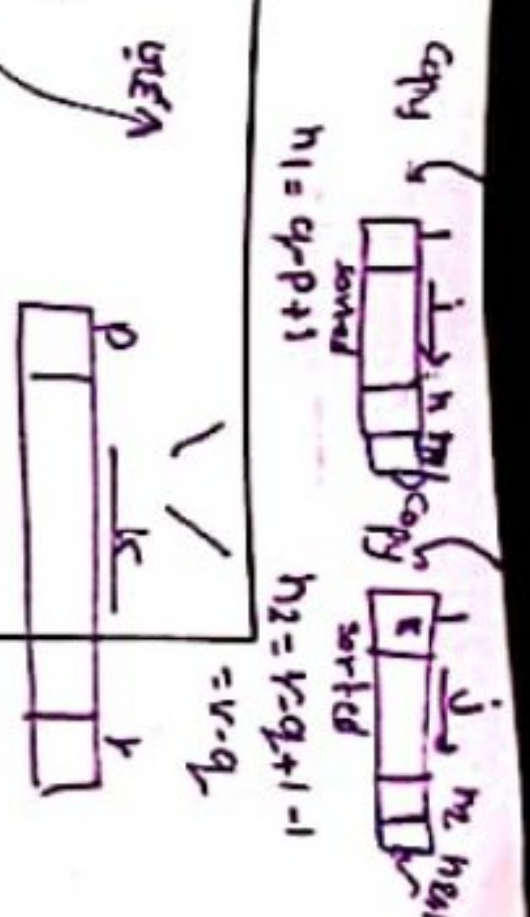
- **Divide:** Break the problem in half $D(n) = \theta(1)$.
- **Conquer:** Recursively solve two problems of size $n/2$ in $2T(n/2)$. (Keep dividing until length 1, which is sorted.)
- **Combine:** Merge two sorted arrays into one in $C(n) = \theta(n)$. (Keep moving the smallest element of the two arrays into the result array.)



MERGE-SORT

```

MERGE(A, p, q, r)
1  n1 ← q - p + 1
2  n2 ← r - q
3  create arrays L[1..n1 + 1] and R[1..n2 + 1]
4  for i ← 1 to n1
5    do L[i] ← A[p + i - 1]
6  for j ← 1 to n2
7    do R[j] ← A[q + j]
8  L[n1 + 1] ← ∞
9  R[n2 + 1] ← ∞
10 i ← 1
11 j ← 1
12 for k ← p to r
13   do if L[i] ≤ R[j]
14     then A[k] ← L[i]
15        i ← i + 1
16     else A[k] ← R[j]
17        j ← j + 1
    
```



```

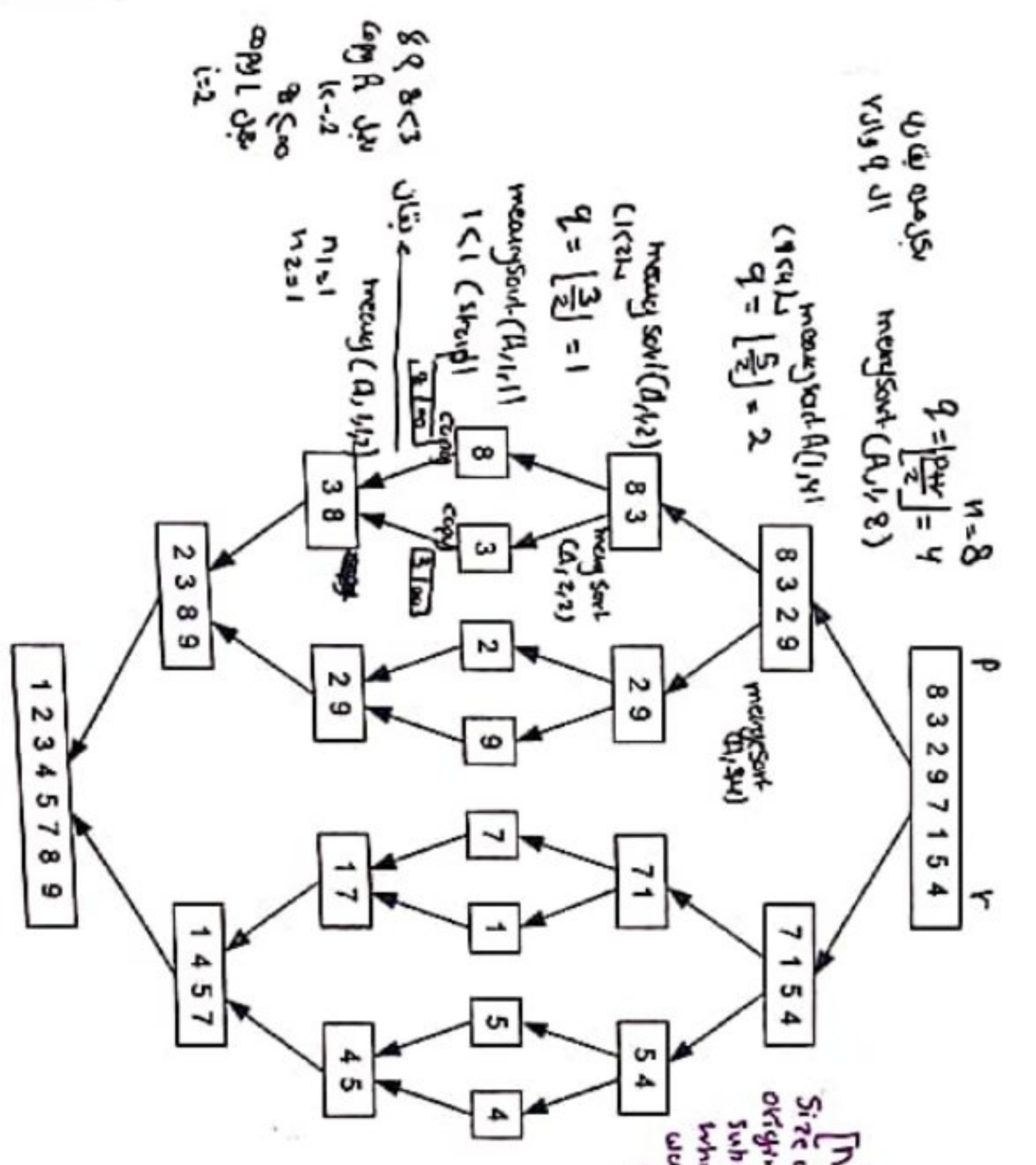
merge(A, p, q, r)
{
  i = 1
  j = 1
  n1 = q - p + 1
  n2 = r - q
  L[i] = A[p + i - 1]
  R[j] = A[q + j]
  }
    
```

(Small) R
 First in job till us li copy
 element

one element
 For $i=1$ to n_1
 $L[i] = A[p+i-1]$
 For $j=1$ to n_2
 $R[j] = A[q+j]$

// copy left
 // i=1, p+1 to p
 // j=1, q-p+1 to
 // q+r-q = r

Mergesort Example 1



For $k=p$ to r
 if $L[i] \leq R[j]$
 $A[k] = L[i]$
 $i = i + 1$
 else
 $A[k] = R[j]$
 $j = j + 1$

Size of subproblem
 original when many
 way carried if it

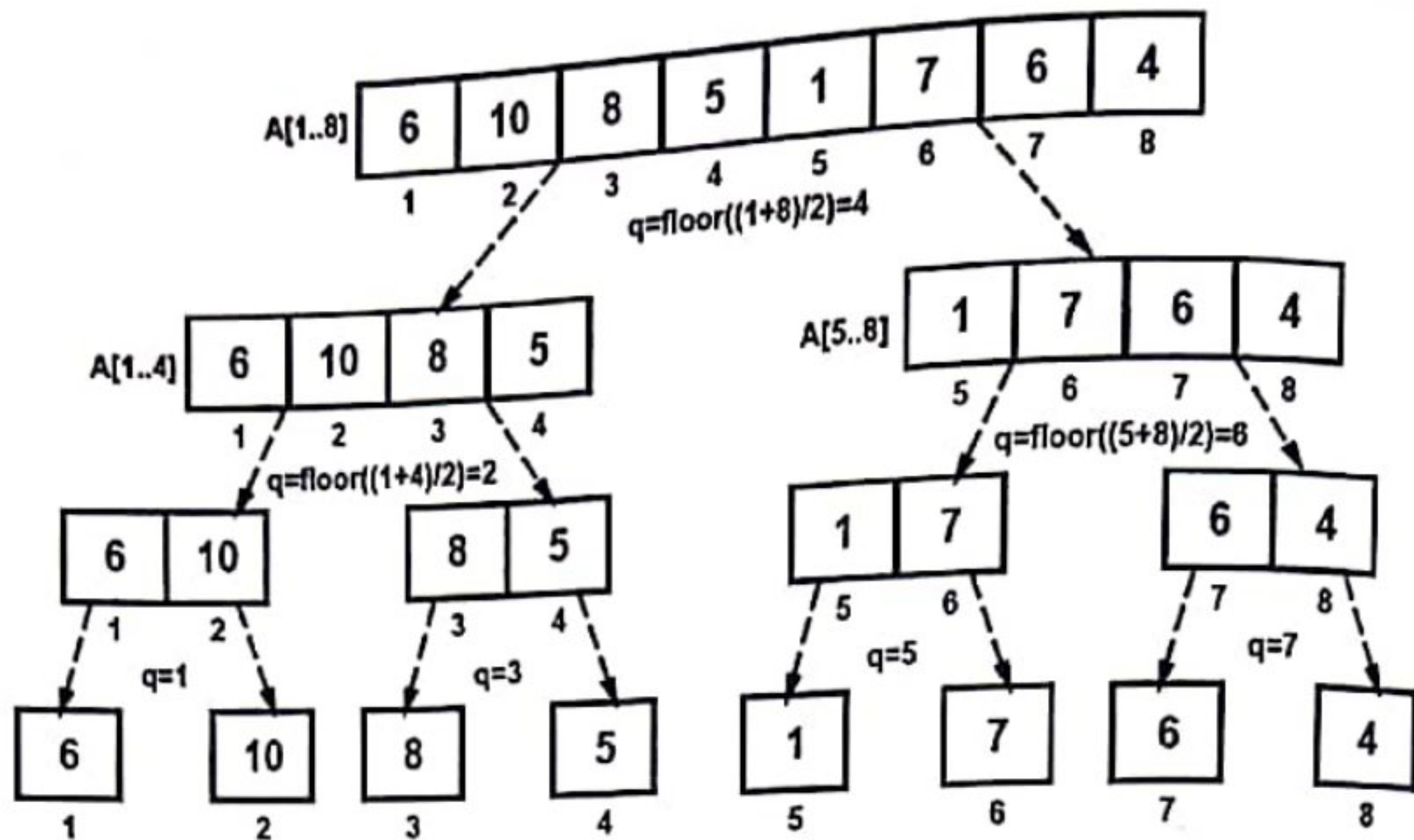
For $k=p$ to r
 if $L[i] \leq R[j]$
 $A[k] = L[i]$
 $i = i + 1$
 else
 $A[k] = R[j]$
 $j = j + 1$

// copy left
 // i=1, p+1 to p
 // j=1, q-p+1 to
 // q+r-q = r

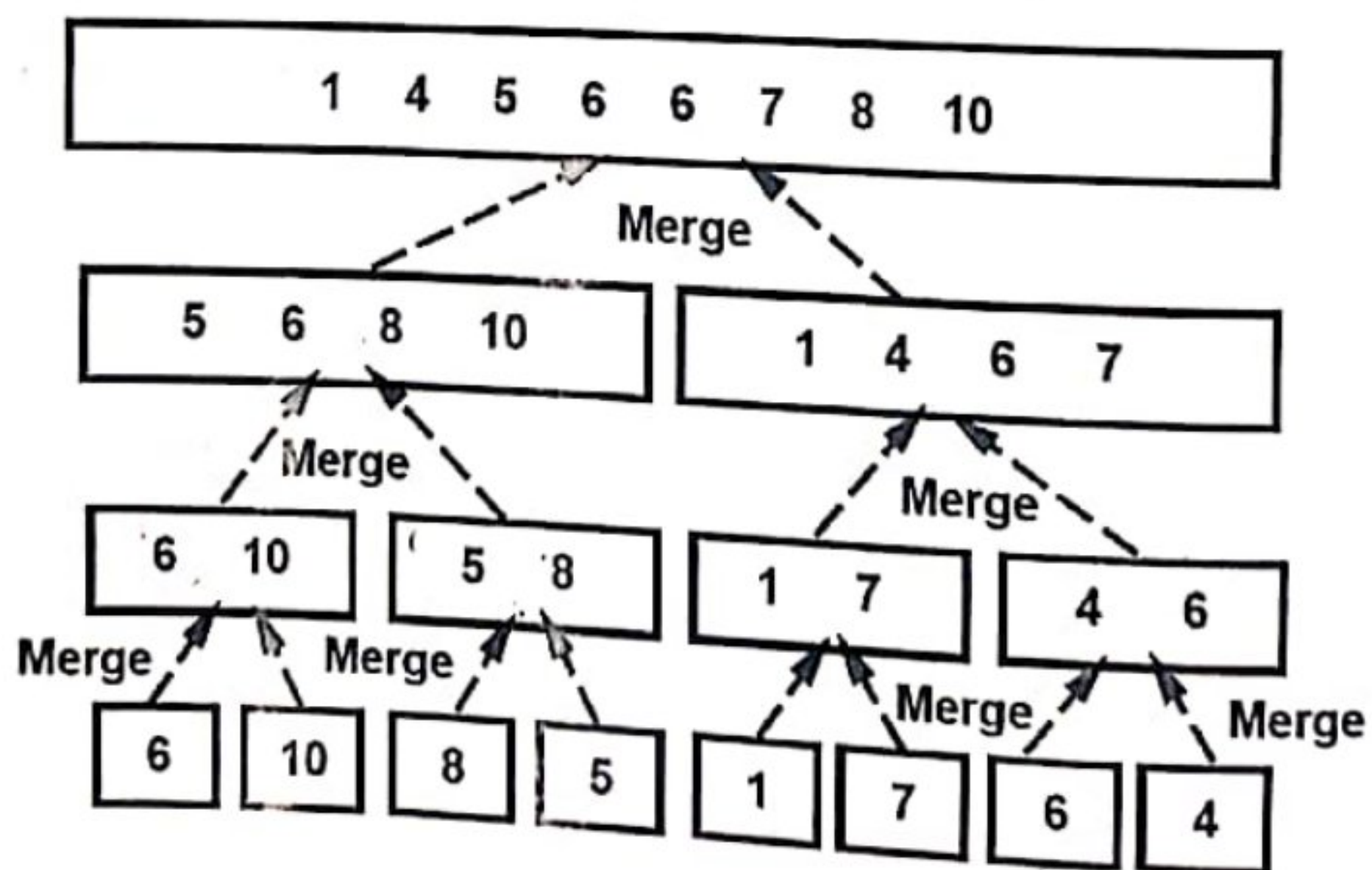
merge sort	insertion sort
best case $\Theta(n)$	best case $\Theta(n^2)$
avg case $\Theta(n \log n)$	avg case $\Theta(n^2)$
worst case $\Theta(n \log n)$	worst case $\Theta(n^2)$
space $\Theta(1)$	space $\Theta(n)$

in all cases $\Theta(n \log n)$
 best and worst and average
 how many levels = $\log n$
 a for time complexity
 = # of division level work down at
 each level
 = $\log n \times \Theta(n)$

MERGE-SORT: Example 2: <6, 10, 8, 5, 1, 7, 6, 4>



MERGE-SORT: Example 2: <6, 10, 8, 5, 1, 7, 6, 4>



Plan for Analysis of Recursive Algorithms

- Decide on a parameter indicating an input's size.
- Identify the algorithm's basic operation.
- Check whether the number of times the basic op. is executed may vary on different inputs of the same size. (If it may, the worst, average, and best cases must be investigated separately.)
- Set up a recurrence relation with an appropriate initial condition expressing the number of times the basic op. is executed.
- Solve the recurrence (or, at the very least, establish its solution's order of growth) by backward substitutions or another method.

14

Running Time of Divide and Conquer Algorithms

- We use recurrence equations to analyze the running time of a recursive algorithm.
- Let $T(n)$ be the running time.
 - Divide into a subproblems of size $n/b \rightarrow$ the running time of the subproblems is $aT(n/b)$.
 - Division takes $D(n)$ time.
 - Combining takes $C(n)$ time.

$$T(n) = \begin{cases} \Theta(1) & \text{divide} \quad \text{combine} \quad \text{if } n \leq c, \\ aT(\frac{n}{b}) + D(n) + C(n) & \text{otherwise.} \end{cases} \quad \text{Base: } \Theta(1)$$

15

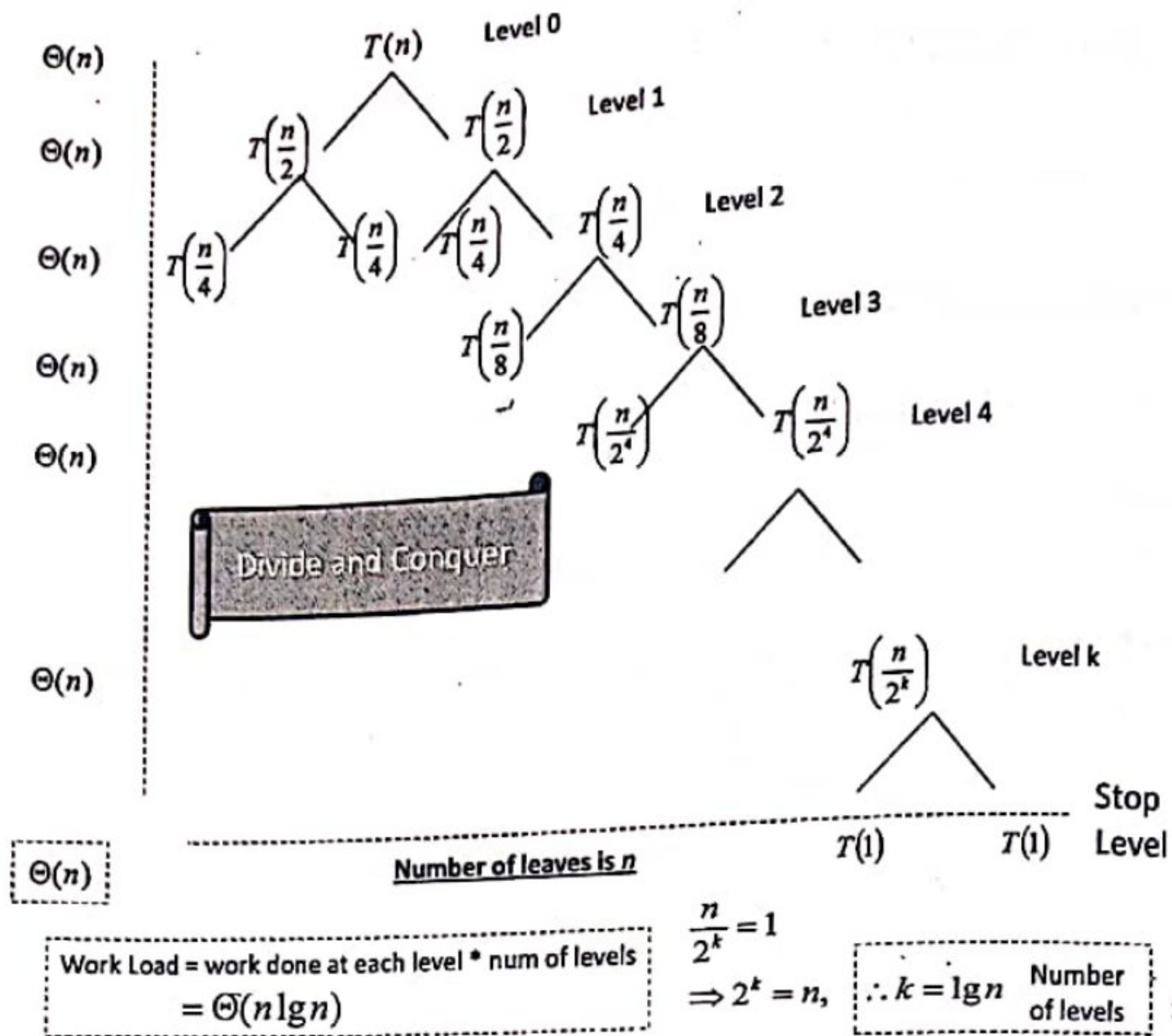
$$2T(\frac{n}{2}) = T(\lfloor \frac{n}{2} \rfloor) + T(\lceil \frac{n}{2} \rceil)$$

Plan 93 Celling

$$\frac{11}{2} = 5.5$$

$$\lfloor 5.5 \rfloor = 5$$

$$\lceil 5.5 \rceil = 6$$



MERGE-SORT Analysis

For Merge-Sort, the running time is described by the following:

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ 2T(\frac{n}{2}) + \Theta(n) & n > 1. \end{cases}$$

We will show that $T(n)$ is $\Theta(n \lg n)$, and so it is asymptotically faster than INSERTION-SORT.

$$T(n) = T(\frac{n}{3}) + T(\frac{2n}{3}) + \Theta(n)$$

$\frac{1}{3}n$ subproblem $\frac{2}{3}n$ subproblem

How to Generate a Tight Bound Guess For Certain Recursion equation

① Substitution method
 ② Provide a guess and prove it using mathematical induction

Lecture 4: Recurrences and Master Theorem

Try to manipulate the current recursion equation to look similar to well known recursion equation for which are already know their Time Complexity Function in order of growth notation

$$T(n) = 2T(n/2) + n \quad \Theta(n \lg n)$$

$$S(m) = 2S(m/2) + m$$

where both $T(n)$ and $S(m)$ are time compl. function
 let $m = \lg n$

$$n = 2^m$$

$$T(2^m) = 2T(2^{m-1}) + m$$

$$T(2^m) = 2T(2^{m/2}) + m \quad \text{let } S(m) = T(2^m)$$

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

$$S(m) = 2S(m/2) + m$$

so $= \Theta(m \lg m)$, now we can substitute back the original value of m

$$\Theta(\lg n \lg \lg n)$$

Read Chapter 4 of Introduction to Algorithms

Ex: we know that recursion equation for merge sort

$$T(n) = 2T(n/2) + \Theta(n), \quad T(1) = 1, \text{ has order of growth notation } \Theta(n \lg n)$$

know let's see how we can write, provide a tight bound guess for the following recursion equation

$$T(n) = 2T(\sqrt{n}) + \lg n$$

Recurrences

A recurrence is an equation or inequality that describes a function in terms of its value(s) on smaller inputs. For example, the following recurrence describes the worst-case running time of MERGE-SORT:

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ 2T(n/2) + \Theta(n) & n > 1. \end{cases}$$

The solution to this equation is $\Theta(n \lg n)$. An important question is how can we find such a closed-form expression (exact or asymptotic) for recurrences?

We will discuss 3 methods:

- **Substitution method:** Guess the bound and prove by induction.
- **Iteration method:** Treat it as summation. ^{Mathematical} construct a recursion tree [iteratively] unravel the recursion equation until we see a pattern and we solve it provide a guess
- **Master method:** A "cookbook" method for solving $T(n) = aT(n/b) + f(n)$, $a \geq 1, b > 1$, and $f(n)$ is a given function.
 بقدر زرع الحل الاخراج

Recurrences *continued*

In practice, we often neglect certain details when we state and solve recurrences. Sometimes we gloss over the assumption that the functions take integer arguments. For example, the MERGE-SORT worst-case running time is really:

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ T(\lceil \frac{n}{2} \rceil) + T(\lfloor \frac{n}{2} \rfloor) + \Theta(n) & n > 1. \end{cases}$$

$c_1 n \leq T(n) \leq c_2 n$ (n متغير)

We also typically don't state the boundary conditions. For sufficiently small n , generally $T(n) = \Theta(1)$. Hence, we often report the recurrence simply as:

$$T(n) = 2T(\frac{n}{2}) + \Theta(n)$$

We omit floors, ceilings, and boundary conditions when they don't matter. We also often solve for powers of 2 rather than all n (and in that case, we really haven't shown the bound for all n).

The Substitution Method

guess for time complexity

Example: Solve the recurrence: $T(n) = 4T(\frac{n}{2}) + n, T(1) = 1.$

Base case
قبل ما اطي
Base case
يعني اول

Guess to Verify by Induction: $T(n) = O(n^3)$, i.e., $T(n) \leq cn^3$.

دعنا نفرض
ان الفرضية

1) **Base Case:** $T(1) = 1 \leq c1^3 = c$, if $c \geq 1$.

2) **Inductive hypothesis**
Assume: $T(k) \leq ck^3$, for $k \leq n$. $T(k) \leq \frac{1}{2}n^3$
let $c=1$

بصحت الـ Const. الـ
تطبق الـ Base case

3) **Inductive Step:**

show that $T(k) \leq ck^3$
when $k=n$

$T(n) = 4T(\frac{n}{2}) + n$

$$\leq 4c(\frac{n}{2})^3 + n$$

$$= \frac{c}{2}n^3 + n$$

$$\frac{c}{2}k^3 = \frac{2}{2}ck^3 - \frac{c}{2}k^3$$

$$= ck^3 - \frac{c}{2}k^3 + k$$

$$\leq cn^3, \text{ if } c \geq 2, n \geq 1$$

على الـ k اقدر كان متغير منها
نظن ان
بجد ان (n^2)

← $T(k)$
Reason الـ الـ
الـ

$$T(k) = 4T(\frac{k}{2}) + k$$

use the inductive hypothesis use $c=1$

$$\leq 4c(\frac{k}{2})^3 + k$$

$$\leq 4c \frac{k^3}{8} + k$$

$$\leq \frac{c}{2}k^3 + k \leq ck^3 ?$$

اصغر كان متغير منها
على الـ k اقدر كان متغير منها

The Substitution Method continued

How to make a good guess:

- Similarity to known function, e.g., $T(n) = 2T(n/2) + n$
- Start with a loose upper and lower bound and try to narrow it down.

Example on Renaming Variable

There are times when you can guess a bound but the math doesn't work out in the induction. Sometimes the inductive assumption isn't strong enough to prove a detailed bound; try subtracting a lower-order term. We will next show an example where this technique will help.

The Substitution Method continued

$O(n^3)$ is **not** a tight bound for $T(n) = 4T(n/2) + n$; we can show that $T(n) = O(n^2)$.

Check previous lecture (lecture 3).

$$T(n) = O(n^2), \quad T(n) \leq cn^2$$
$$T(k) \leq ck^2, \quad 1 \leq c(1)^2 \rightarrow \boxed{c=1}$$

$$T(n) = 4T(n/2) + n$$
$$T(k) = 4T(k/2) + n$$
$$T(k) = 4c \frac{k^2}{4} + n$$
$$T(k) = ck^2 + n$$

$$ck^2 = \frac{2c}{2}k^2 - \frac{c}{2}k^2$$

$$ck^2 + n \leq ck^2$$
$$O(n^2)$$

The Substitution Method continued

Sometimes a little algebraic manipulation can make an unknown recurrence into one we have seen before. For example,

$$T(n) = 2T(\lfloor \sqrt{n} \rfloor) + \lg n$$

Renaming $n = 2^m$ (so $m = \lg n$) yields:

$$T(2^m) = 2T(2^{\frac{m}{2}}) + m$$

Now we can rename $S(m) = T(2^m)$:

$$S(m) = 2S(\frac{m}{2}) + m$$

We know $S(m) = O(m \lg m)$. Changing back from $S(m)$ to $T(n)$ yields:

$$T(n) = T(2^m) = S(m) = O(m \lg m) = O(\lg n \lg \lg n)$$

$$T(n) = 2T(n^{1/2}) + \lg n$$

$$\text{let } \lg n = m,$$

6

$T(\frac{n}{2}) = S(m)$ تعريف
نقطة انكسار التكرار

The Iteration Method

Recursion tree

unroll the recursion equation several times until we see a pattern (mathematical series)

The idea is to expand the recurrence and express the recurrence as a summation dependent only on n and the initial conditions. Then techniques for evaluating summations can be used to provide a bound on the solution. For example, recall the recurrence equation: $T(n) = 4T(\frac{n}{2}) + n$. Let us expand $T(n)$ a few times looking for patterns:

$$T(1) = 1 \text{ Base case}$$

Iteration method

$$T(n) = 4T(\frac{n}{2}) + n$$

$$= n + 4T(\frac{n}{2})$$

$$= n + 4[4T(\frac{n}{2^2}) + \frac{n}{2}]$$

$$= n + \frac{4n}{2} + 4^2 T(\frac{n}{2^2})$$

$$= n + \frac{4}{2}n + 4^2 [4T(\frac{n}{2^2}) + \frac{n}{2^2}]$$

$$= n + \frac{4}{2}n + \frac{4^2}{2^2}n + 4^3 T(\frac{n}{2^3})$$

$$= (\frac{4}{2})^0 n + (\frac{4}{2})^1 n + (\frac{4}{2})^2 n + (\frac{4}{2})^3 n + \dots + 4^k T(\frac{n}{2^k})$$

stop when $\frac{n}{2^k} = 1 \rightarrow k = \lg n$

$$T(n) = \sum_{k=0}^{\lg n - 1} (\frac{4}{2})^k n + 4^{\lg n} T(1)$$

$$T(n) = n + 4T(\frac{n}{2})$$

$$= n + 4(\frac{n}{2} + 4T(\frac{n}{4}))$$

$$= n + 4(\frac{n}{2} + 4(\frac{n}{4} + 4T(\frac{n}{8}))) = n + 4\frac{n}{2} + 4^2\frac{n}{4} + 4^3 T(\frac{n}{8})$$

$$\vdots$$

$$= n + 4\frac{n}{2} + 4^2\frac{n}{4} + 4^3\frac{n}{8} + \dots + 4^k T(\frac{n}{2^k})$$

$$\vdash \text{Iterate until } \frac{n}{2^k} = 1 \text{ or } \lg n \text{ times.}$$

$$= n + 4\frac{n}{2} + 4^2\frac{n}{4} + 4^3\frac{n}{8} + \dots + 4^{\lg n} T(1), \text{ where } 4^{\lg n} = n^2$$

$$= \sum_{i=0}^{\lg n - 1} 4^i \frac{n}{2^i} + \Theta(n^2)$$

$$= n(\sum_{i=0}^{\lg n - 1} 2^i) + \Theta(n^2) = n(\frac{2^{\lg n} - 1}{2 - 1}) + \Theta(n^2)$$

$$= (\frac{4}{2})^0 n + (\frac{4}{2})^1 n + (\frac{4}{2})^2 n + (\frac{4}{2})^3 n + \dots + 4^k T(\frac{n}{2^k}) = \Theta(n^2) + \Theta(n^2) = \Theta(n^2)$$

$$T(n) = \sum_{k=0}^{\lg n - 1} 2^k n + n^2$$

$$= n \left[\frac{2^{\lg n} - 1}{2 - 1} \right] + n^2$$

$$= n[2^{\lg n} - 1] + n^2$$

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

$$= n^2 - n + n^2$$

$$= 2n^2 - n$$

$$= \Theta(n^2)$$

الفرق مع

The Iteration Method continued

Let's obtain an exact solution for: $T(n) = 2T(\frac{n}{2}) + 2$. Assume that n is a power of 2 and $T(2) = 1$.

Min / Max
بداية / خاتمة

$$\begin{aligned}
 T(n) &= 2 + 2T(\frac{n}{2}) \\
 &= 2 + 2(2 + 2T(\frac{n}{4})) = 2 + 4 + 4T(\frac{n}{4}) \\
 &= 2 + 4 + 4(2 + 2T(\frac{n}{8})) = 2 + 4 + 8 + 8T(\frac{n}{8}) \\
 &\vdots \\
 &= 2 + 4 + 8 + 16 + \dots + 2^k + 2^k T(\frac{n}{2^k}) \\
 \therefore T(2) \text{ is the base case, so solve } \frac{n}{2^k} &= 2.
 \end{aligned}$$

$$2^1 + 2^2 + 2^3 + \dots + 2^k = 2^k + 2^k T(\frac{n}{2^k})$$

$$\frac{n}{2^k} = 2$$

$$n = 2^{k+1}$$

$$k+1 = \lg n$$

$$k = \lg n - 1$$

$$T(2) = 1$$

substituted in $2^k T(\frac{n}{2^k})$

$$\begin{aligned}
 T(\frac{n}{2^k}) &= 1 \\
 \frac{n}{2^k} &= 2 \\
 2^k &= \frac{n}{2} \\
 2^{k+1} &= n \\
 k+1 &= \lg n \\
 k &= \lg n - 1
 \end{aligned}$$

$$k \leftarrow \lg n - 1$$

$$= \sum_{i=1}^{\lg n - 1} 2^i + 2^{\lg n - 1} T(\frac{n}{2^{\lg n - 1}})$$

$$= \sum_{i=0}^{\lg n - 1} 2^i - 1 + \frac{n}{2} T(\frac{n}{2})$$

$$= \frac{2^{\lg n} - 1}{2 - 1} - 1 + \frac{n}{2} T(2) = n - 2 + \frac{n}{2}$$

$\Theta(n)$

$$2^{\lg n - 1} = 2^{\lg n} \cdot 2^{-1} = \frac{2^{\lg n}}{2} = \frac{n}{2}$$

$$\sum_{k=1}^{\lg n} 2^k$$

$$= \sum_{k=0}^{\lg n - 1} 2^k - 2^0 \rightarrow \frac{2^{\lg n} - 1}{2 - 1} - 1 = n - 2$$

$$n - 2 + \frac{n}{2} \rightarrow \frac{3}{2}n - 2 = \Theta(n)$$

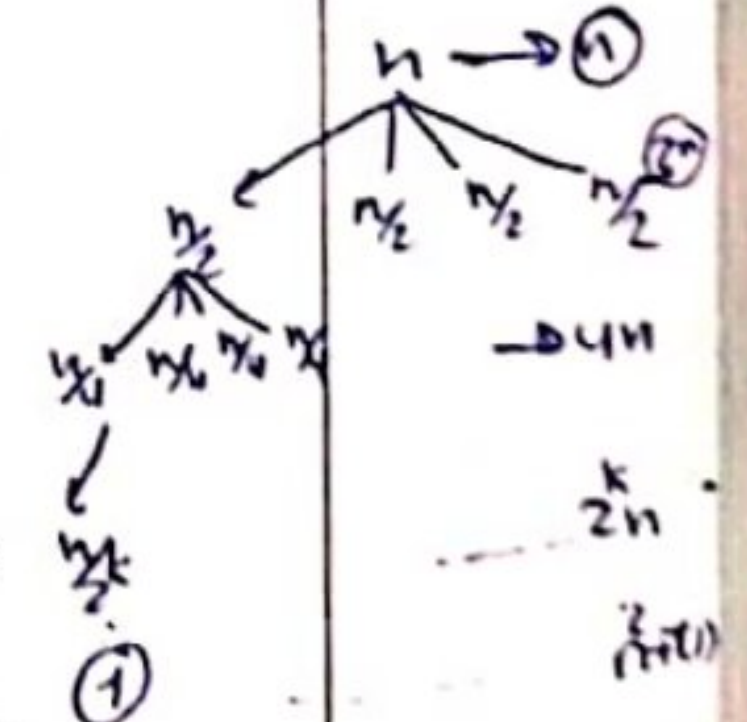
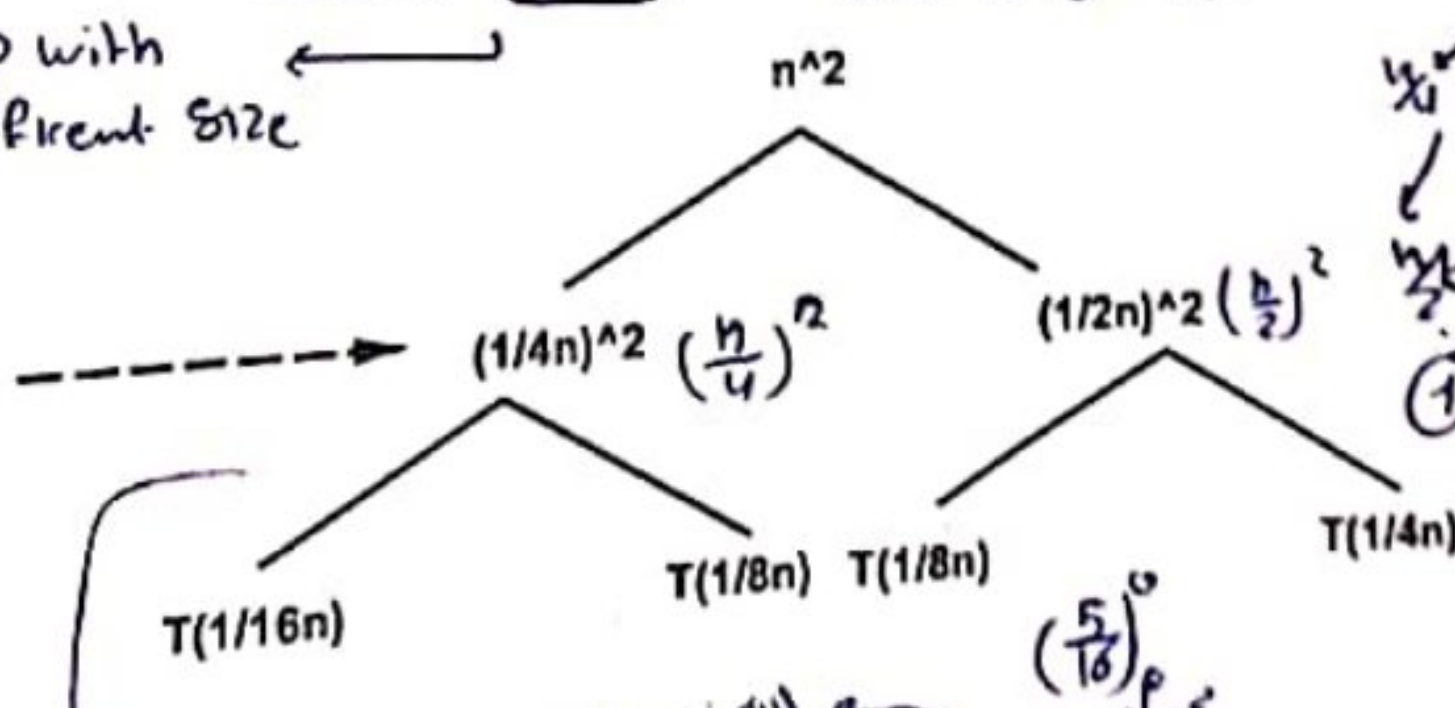
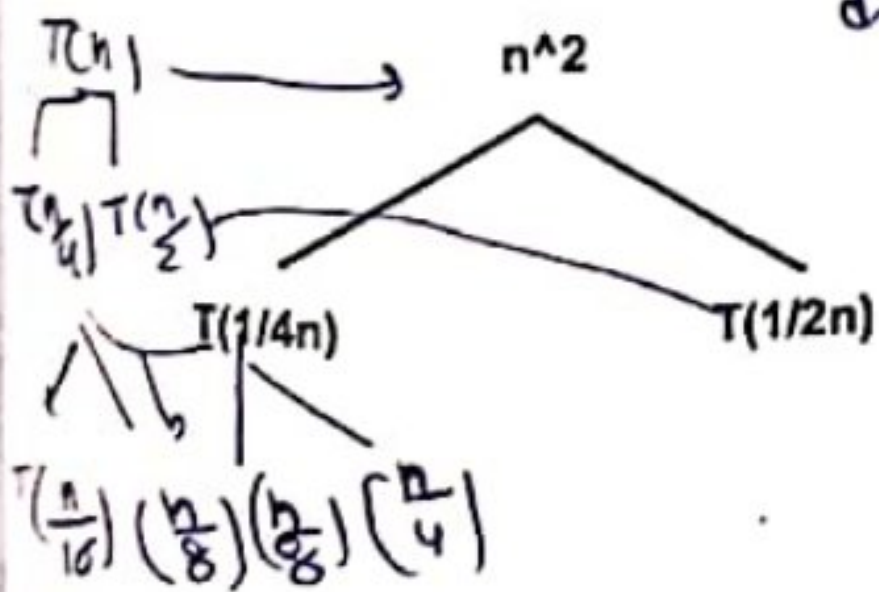
Recursion Trees

For certain forms of recursions a graphical representation is convenient for visualizing the iteration of a recurrence. For example:

$$T(n) = T(\frac{n}{4}) + T(\frac{n}{2}) + n^2$$

Sup with different size

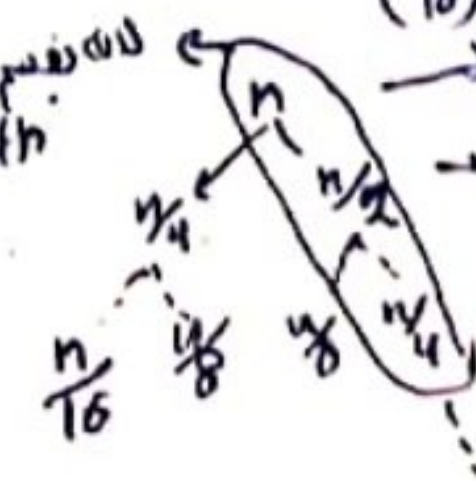
Level



$$(\frac{n}{2})^2 + (\frac{n}{8})^2 = \frac{5}{16}n^2$$

$$(\frac{n}{16})^2 + (\frac{n}{8})^2 + (\frac{n}{8})^2 + (\frac{n}{4})^2 = \frac{25}{256}n^2$$

longest path



$$\begin{aligned}
 (\frac{n}{4})^2 + (\frac{n}{8})^2 &= \frac{n^2}{16} + \frac{n^2}{64} = \frac{5n^2}{16} \\
 (\frac{n}{16})^2 + (\frac{n}{8})^2 + (\frac{n}{8})^2 + (\frac{n}{4})^2 &= (\frac{5}{16})n^2
 \end{aligned}$$

$$105 T(n) \leq \sum_{k=0}^{\lg n} (\frac{5}{16})^k n^2 \rightarrow \sum_{k=0}^{\infty} (\frac{5}{16})^k n^2 = \frac{16}{1-5/16} n^2 = \frac{16}{11} n^2 = \Theta(n^2)$$

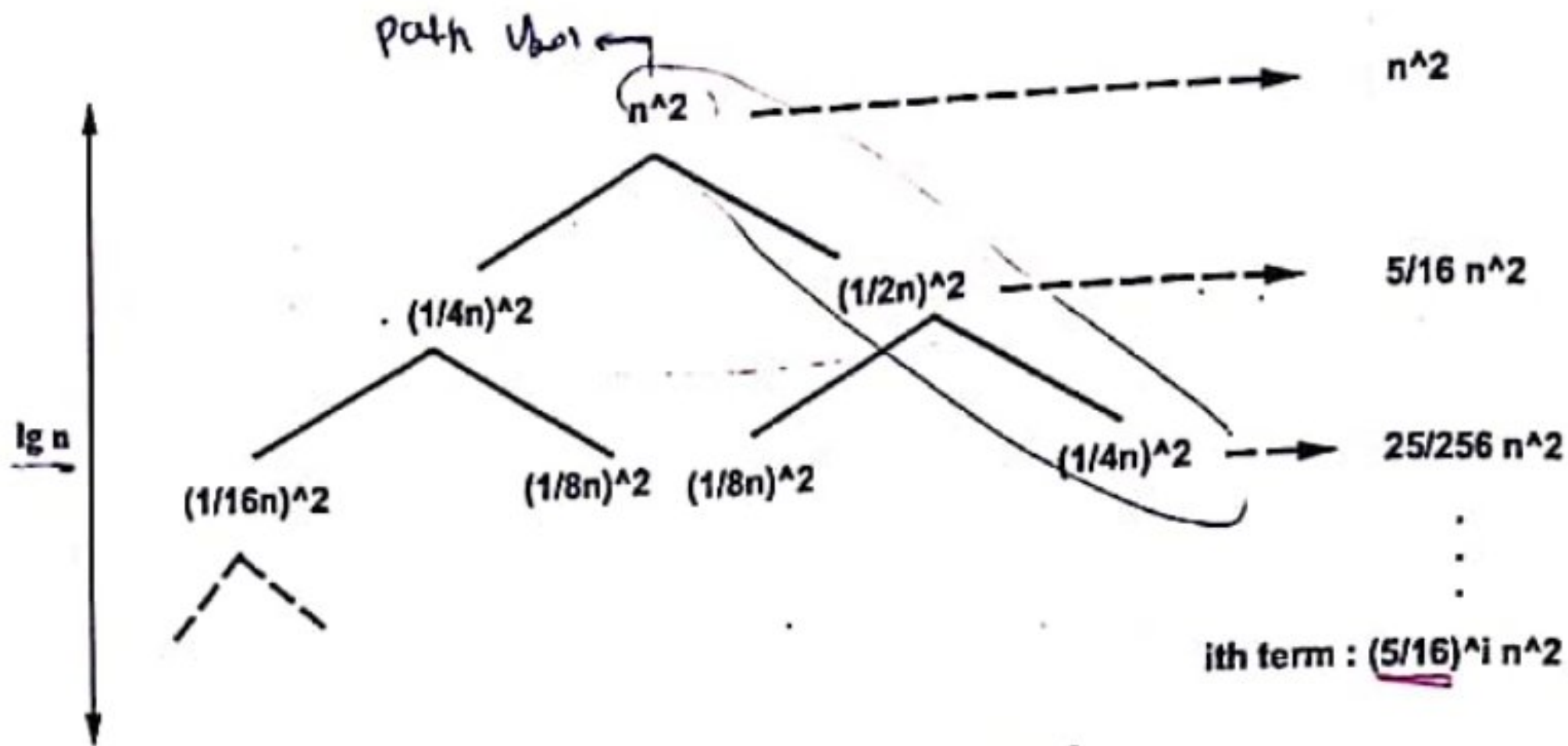
إذا تعمقنا أكثر انوقفنا
إذا تعمقنا أكثر انوقفنا

$T(1) = 1$

$\frac{n}{2^k} = 1 \rightarrow k = \log_2 n$

Recursion trees *continued*

Recursion Tree for $T(n) = T(n/4) + T(n/2) + n^2$



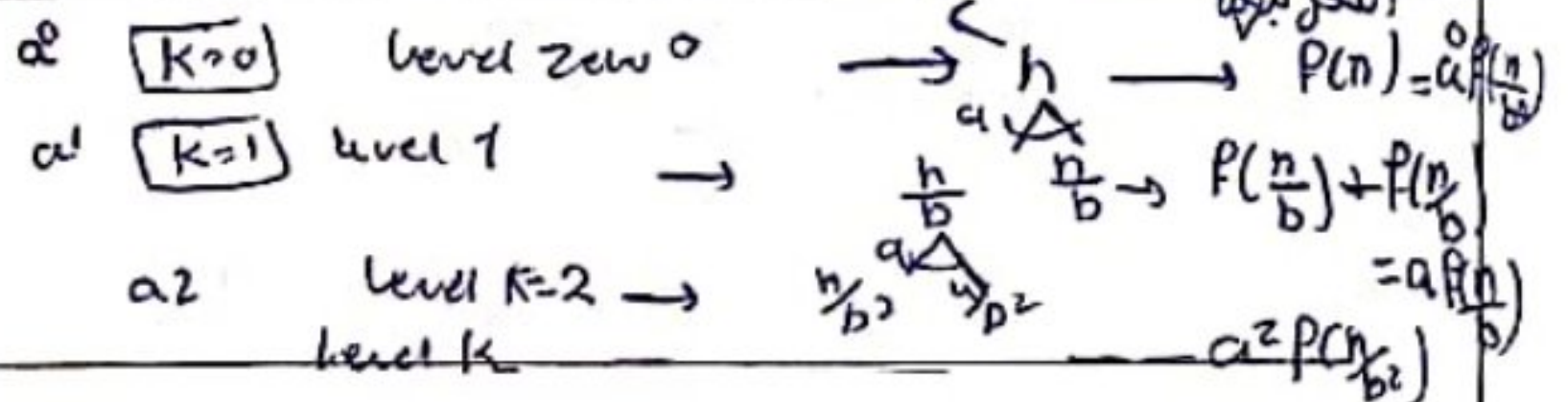
Summing over levels gives a decreasing geometric series:

$\sum_{i=0}^{\lg n - 1} \left(\frac{5}{16}\right)^i n^2 \leq n^2 \sum_{i=0}^{\infty} \left(\frac{5}{16}\right)^i = n^2 \frac{1}{1 - \frac{5}{16}} = O(n^2)$

$\frac{1}{1-x} = \left(\frac{1}{1-\frac{5}{16}}\right) n^2$

10

The Master Method



"Cookbook method" for solving recurrences of the type:

$T(n) = aT\left(\frac{n}{b}\right) + f(n)$

where $a \geq 1, b > 1$, and f is asymptotically positive.

- Divide the problem of size n into a subproblems of size $\frac{n}{b}$.
- Solve them recursively.
- Cost to divide the original problem and recombine the results is $f(n)$, which is asymptotically positive.

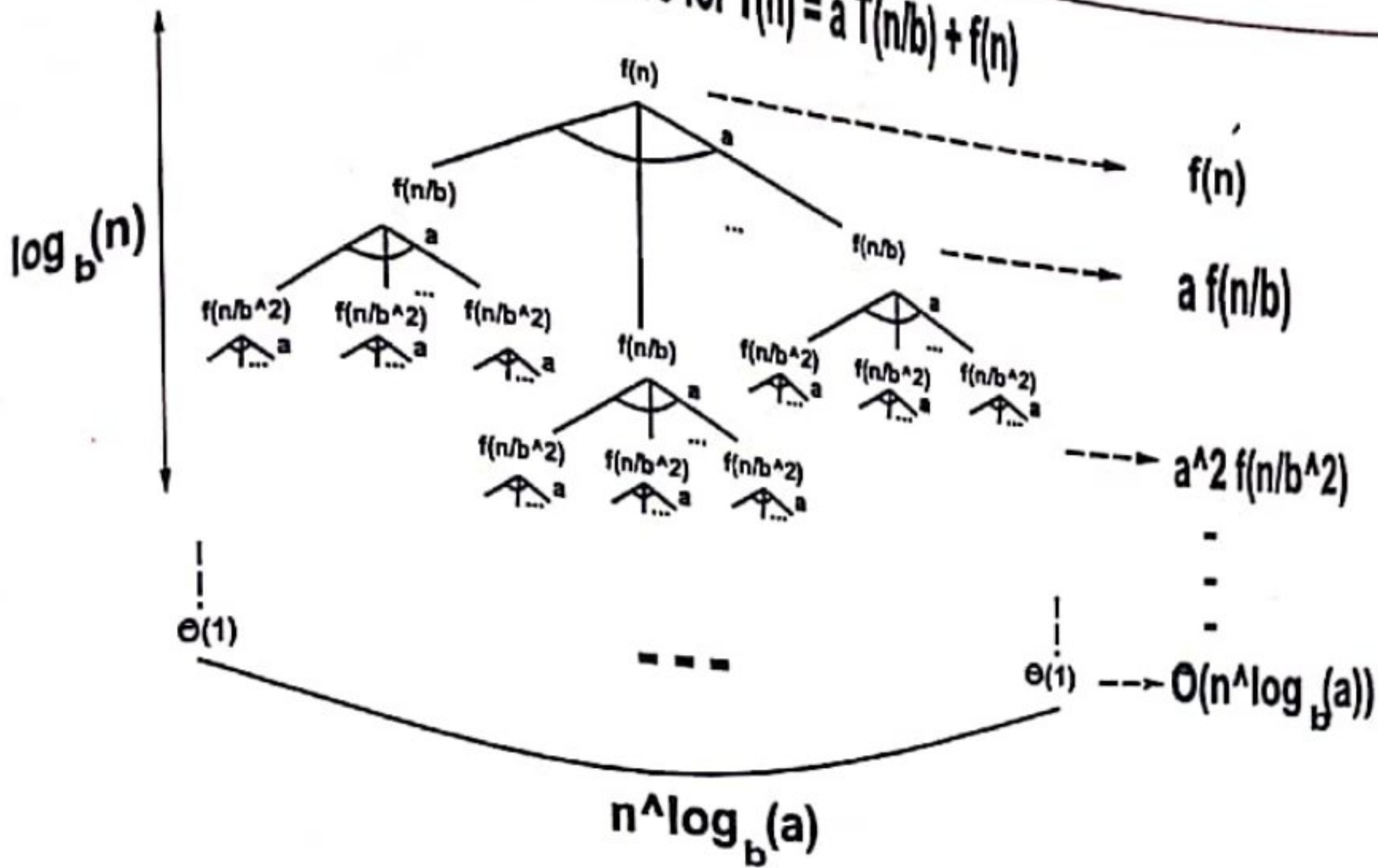
3 cases

$T(n) = \sum_{i=0}^{(\log_b n) - 1} a^i P\left(\frac{n}{b^i}\right) + \Theta(n^{\log_b a})$

Let this be B
dominant of the root work $P(n)$

$A > B \rightarrow T(n)$ Case 1
 $B > A \rightarrow T(B)$ Case 2
 $B = A \rightarrow$ Case 3 up to log

Recursion Tree for $T(n) = aT(n/b) + f(n)$



The Master Theorem

Theorem 4.1 The Master Theorem

Let $a \geq 1$ and $b > 1$ be constants, $f(n)$ be a function, and $T(n)$ be defined on the nonnegative integers by the recurrence:

$$T(n) = aT\left(\frac{n}{b}\right) + f(n), T(1) = \Theta(1)$$

where we interpret $\frac{n}{b}$ to mean either $\lfloor \frac{n}{b} \rfloor$ or $\lceil \frac{n}{b} \rceil$. Then $T(n)$ can be bounded asymptotically as follows:

1. If $f(n) = O(n^{\log_b a - \epsilon})$ for some constant $\epsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$. Or alternatively, $\frac{n^{\log_b a}}{f(n)} = \Omega(n^\epsilon), \epsilon > 0$ (equivalently, $\frac{f(n)}{n^{\log_b a}} = O(n^{-\epsilon}), \epsilon > 0$). In other words, $n^{\log_b a}$ is polynomially larger than $f(n)$. The running time is dominated by the costs in the leaves.
poly work
 $n^{\log_b a}$ leaves work

The Master Theorem *continued*

2. If $f(n) = \Theta(n^{\log_b a} \lg^k n)$, for $k \geq 0$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$ (as in Exercise 4.4-2). Or alternatively, $\frac{f(n)}{n^{\log_b a}} = \Theta(\lg^k n)$ for some constant $k \geq 0$. In other words, $f(n)$ and $n^{\log_b a}$ are within a polylogarithmic factor. The cost is evenly distributed across levels.

3. If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for some constant $\epsilon > 0$, and if $a f(\frac{n}{b}) \leq c f(n)$ for some constant $c < 1$ and all sufficiently large n , then $T(n) = \Theta(f(n))$. Or alternatively, $\frac{f(n)}{n^{\log_b a}} = \Omega(n^\epsilon)$, $\epsilon > 0$ and $a f(\frac{n}{b}) \leq c f(n)$ for some constant $c < 1$ and all sufficiently large n . In other words, $f(n)$ is polynomially larger than $n^{\log_b a}$. Hence, the time is dominated by the cost of the root.

The Master Theorem *continued*

The following equation represents the running time for the class of problems for which the Master Method applies:

$$T(n) = \Theta(n^{\log_b a}) + \sum_{j=0}^{\log_b n - 1} a^j f\left(\frac{n}{b^j}\right)$$

Note that the number of small problems to solve (leaves in the tree) is $a^{\log_b n} = n^{\log_b a}$.

$$\begin{aligned} a^{\log_b n} &= (b^{\log_b a})^{\log_b n} \\ &= b^{\log_b a \log_b n} \\ &= b^{\log_b n \log_b a} \\ &= (b^{\log_b n})^{\log_b a} \\ &= n^{\log_b a} \end{aligned}$$

Applying the Master Method

Example 1: $T(n) = 9T(\frac{n}{3}) + n$

Test: $a = 9, b = 3, f(n) = n$ ^{leave work} so $n^{\log_b a} = n^{\log_3 9} = n^2 - \epsilon$

Because $f(n) = n = O(n^{2-\epsilon})$ for $0 < \epsilon \leq 1$ (or $\frac{n^2}{n} = \Omega(n^\epsilon)$ for $\epsilon > 0$) case 1 applies
 and so $T(n) = \Theta(n^2)$ Confirm by induction: $T(n) \leq cn^2$.

Base Case: Assuming $T(1) = \Theta(1) \leq c1^2 = c$, if $c > 1$.

Assume: $T(k) = ck^2 - k$ for $k < n$

Inductive Step:

$$\begin{aligned} T(n) &= 9T(\frac{n}{3}) + n \leq 9(c(\frac{n}{3})^2 - \frac{n}{3}) + n \\ &= cn^2 - 3n + n = cn^2 - 2n \\ &\leq cn^2 - n \end{aligned}$$

16

Applying the Master Method *continued*

Example 2: $T(n) = 2T(\frac{n}{2}) + 2$

Test: $a = 2, b = 2, f(n) = 2$ so $n^{\log_b a} = n^{\log_2 2} = n$.

Because $f(n) = \Theta(1) = O(n^{1-\epsilon})$ for $0 < \epsilon \leq 1$ (or $\frac{n}{2} = \Omega(n^\epsilon), 0 < \epsilon \leq 1$), case 1 applies and so $T(n) = \Theta(n)$ $T(n) \leq O(n)$

Example 3: $T(n) = 2T(\frac{n}{2}) + n \rightarrow n \log^2 \sim n \log^3$

Test: $a = 2, b = 2, f(n) = n$ so $n^{\log_b a} = n^{\log_2 2} = n$.

Because $f(n) = \Theta(n^{\log_b a} \lg^k n)$ (or $\frac{n}{n} = \Theta(1) = \Theta(\lg^0 n)$), case 2 applies; hence,
 $T(n) = \Theta(n \lg n)$.
 $\frac{1}{n} \log_2 n \rightarrow n \log n$

17

Applying the Master Method *continued*

Example 4: $T(n) = 4T(\frac{n}{2}) + n^3$

Test: $a = 4, b = 2, f(n) = \boxed{n^3}$ so $n^{\log_b a} = n^{\log_2 4} = \boxed{n^2}$

Because $f(n) = n^3 = \Omega(n^{\log_b a + \epsilon}) = \Omega(n^{2+\epsilon})$ (or $\frac{n^3}{n^{\log_2 4}} = n = \Omega(n^\epsilon)$) for $0 < \epsilon \leq 1$, and $4f(\frac{n}{2}) \leq c f(n)$ for $c < 1$ (say $c = \frac{1}{2}$); hence case 3 applies and $T(n) = \Theta(n^3)$.

$a f(\frac{n}{b}) \leq c f(n)$

$4f(\frac{n}{2}) \leq c f(n) \rightarrow$

$4(\frac{n}{2})^3 \leq c n^3$

$\frac{4}{8} n^3 \leq c n^3 \rightarrow$

$\boxed{\frac{1}{2} \leq c}$

$\boxed{c \leq \frac{1}{2}}$

∇

Example 5: $T(n) = 4T(\frac{n}{2}) + \frac{n^2}{\lg n}$

Test: $a = 4, b = 2, f(n) = \boxed{\frac{n^2}{\lg n}}$ so $n^{\log_b a} = n^{\log_2 4} = \boxed{n^2}$

Because $\frac{n^2}{\lg n} = \frac{1}{\lg n}$, which is not $O(n^{-\epsilon})$, $\epsilon > 0$ (i.e., $\lg n \neq \Omega(n^\epsilon)$), $\Theta(\lg^k n)$, $k \geq 0$, or $\Omega(n^\epsilon)$, $\epsilon > 0$, no case applies (must use another method).

Recall the sorting Algorithms we seen:

- ① selection sort.
- ② insertion sort
- ③ Merge sort.

Lecture 5: Heap Sort

dynamic allocated memory at run time
 ديناميكي مخصص في وقت التشغيل

space complexity
 تعقيد المساحة
 merge sort

with special probability and characteristic and operation)

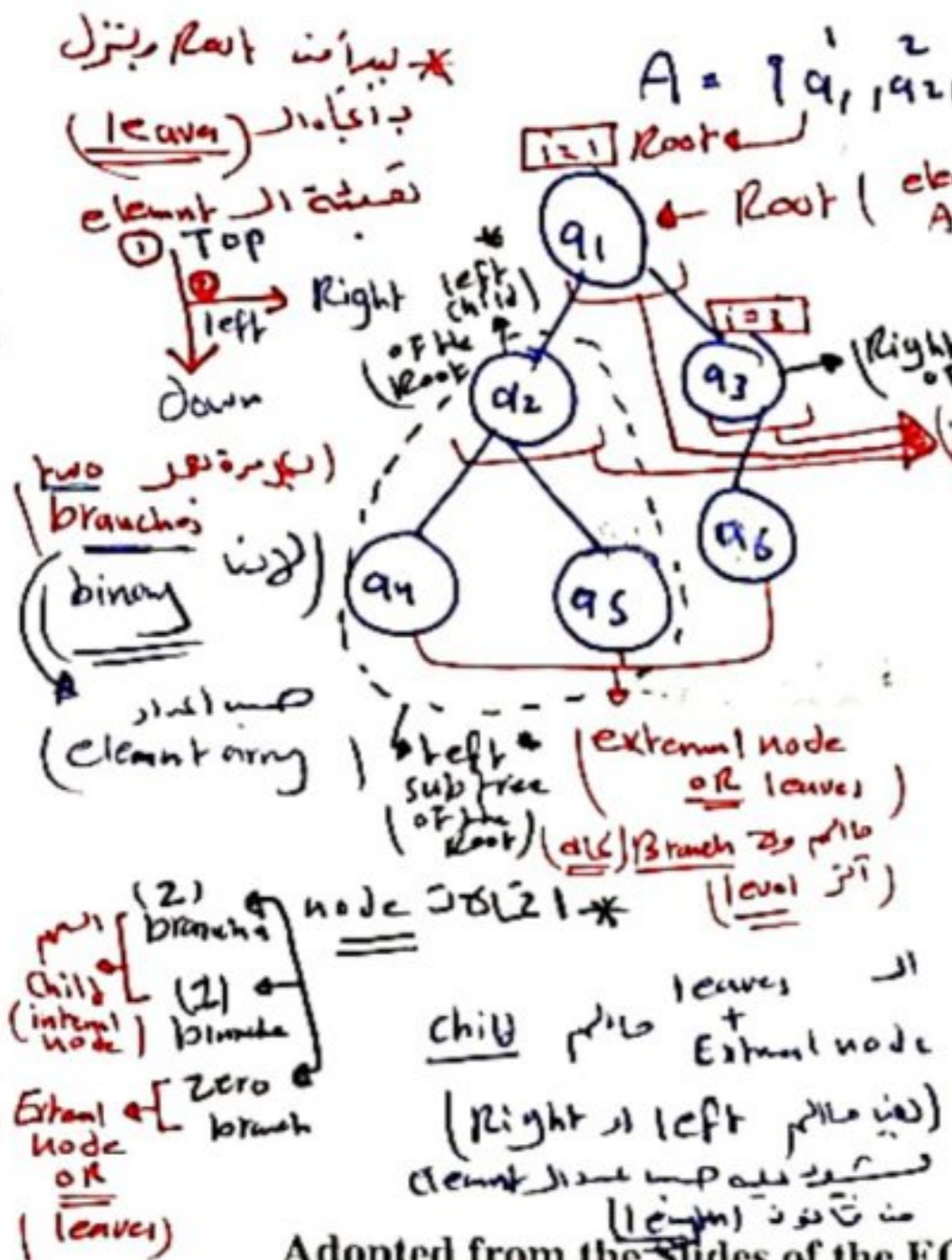
Algorithm design	time complexity			space complexity	stability
	Best	Avg.	worst		
Brut force	n^3	n^3	n^3	1	✓
decrease and conquer	n	n^2	n^2	1	✓
divide and conquer	$n \log n$	$n \log n$	$n \log n$	n	✓

Dr. Khalil Yousef

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

Read Chapter 6 of *Introduction to Algorithms*

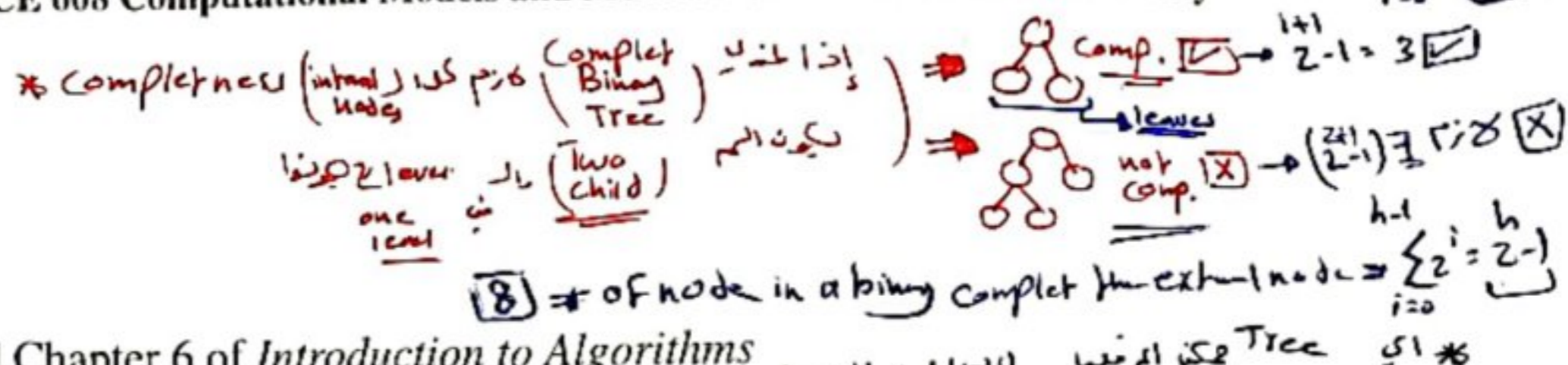
Lecture 5: Heap Sort



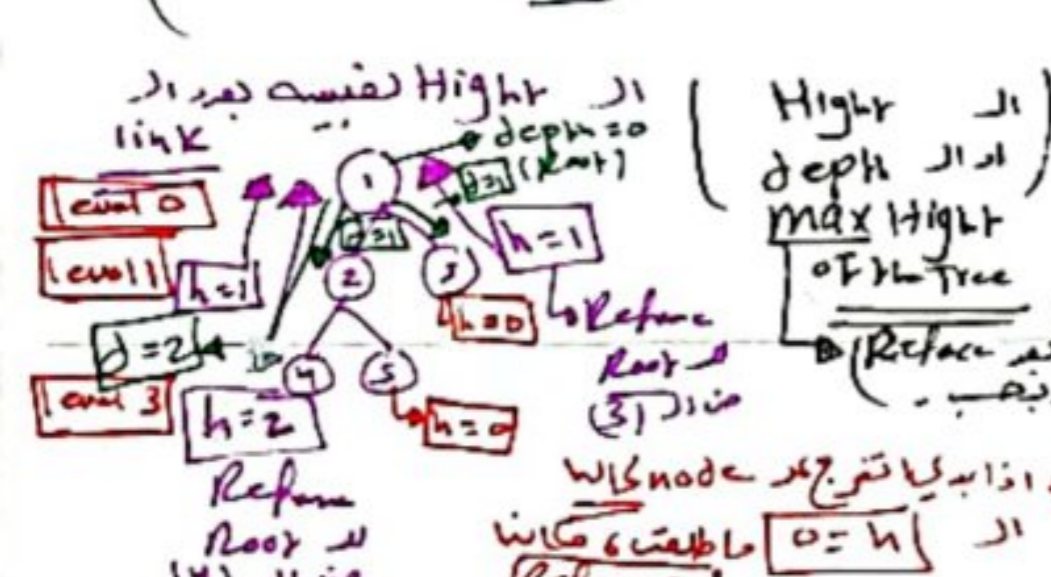
- (1) Parent (i) = $\lfloor \frac{i}{2} \rfloor$
- (2) left (i) = 2i
- (3) Right (i) = 2i + 1
- (4) length (A) = n
- (5) indices of the internal nodes = $\{1, 2, \dots, \lfloor \frac{n}{2} \rfloor\}$
- (6) indices of the External nodes = $\{\lfloor \frac{n}{2} \rfloor + 1, \dots, n\}$
- (7) # of node in a complete binary tree = $\sum_{i=0}^{h-1} 2^i = 2^h - 1$
- (8) # of node in a binary complete tree = $\sum_{i=0}^{h-1} 2^i = 2^h - 1$

Dr. Khalil Yousef

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University



Read Chapter 6 of Introduction to Algorithms



The Sorting Problem

max height of this = 2
max depth of this = 2

The Sorting Problem (non-decreasing):

Input: a sequence of n numbers $\langle a_1, a_2, \dots, a_n \rangle$

Output: a permutation of the input sequence $\langle a'_1, a'_2, \dots, a'_n \rangle$ such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$

Sorting algorithms:
 * Heap data instr. it's Complete (any internal node have two child) OR nearly complete binary tree \Rightarrow heap property
 Binary tree
 value of parent \geq children
 Complete or nearly
 (Parent (value) \geq children)
 * From a Root to a leaf
 (max) Root \geq (max) child
 (min) heap / (min) child
 (max) heap / (max) child
 (min) heap / (min) child
 (max) heap / (max) child

Insertion Sort: $\Theta(n^2)$

Merge Sort: $\Theta(n \lg n)$

Heap Sort: $\Theta(n \lg n)$ (large constant factor)

Quick Sort: It has a worst case running time of $\Theta(n^2)$, but an average case running time of $\Theta(n \lg n)$ (small constant factor).

Linear sort algorithms will also be discussed which are not comparison sorts.

Linear sort algorithms will also be discussed which are not comparison sorts.
 * بين منبه صفة انه دال على ان Root هو الحد max
 عدد من element مع تقويمه (Array)
 دجته مكانه (heap)
 (Heap size = length(A))
 (Best + Avg)
 (Heap size = length(A))
 (Best + Avg)

Some Sorting Terminology

A list or array of elements that is to be sorted often consists of elements that are records. Each record is sorted with respect to its **key**, which is some ordinal type. The record will also typically contain **satellite data**. The book does not focus on the satellite data.

(basic operation Computer)
Comparison Sort: Uses comparisons between elements in the input array (or list) of elements to produce a sorted output.

In-place Sort: Uses only a constant amount of storage in addition to the input data structure.

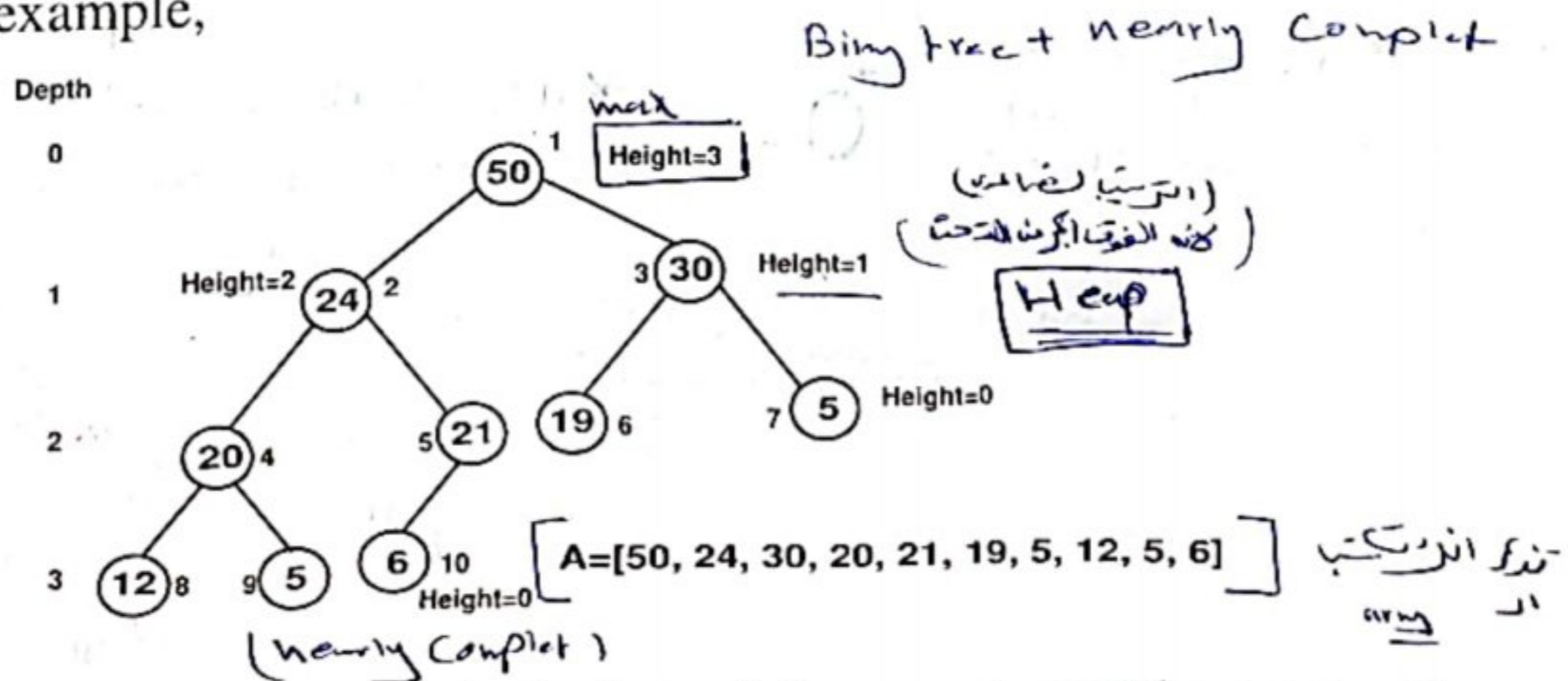
(insertion)
heap (not stable)
Stable Sort: Maintains the same relative ordering of elements with the same key in the sorted output as in the input.

2

The Heap Data Structure

We first define heaps and the various operations on them.

Definition: A (binary) **heap** is a nearly complete binary tree that satisfies the heap property. For example,

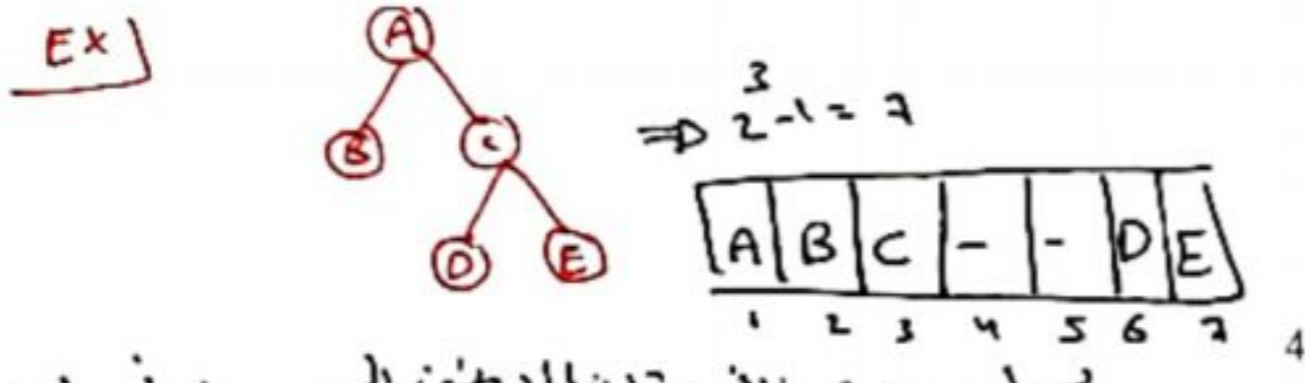
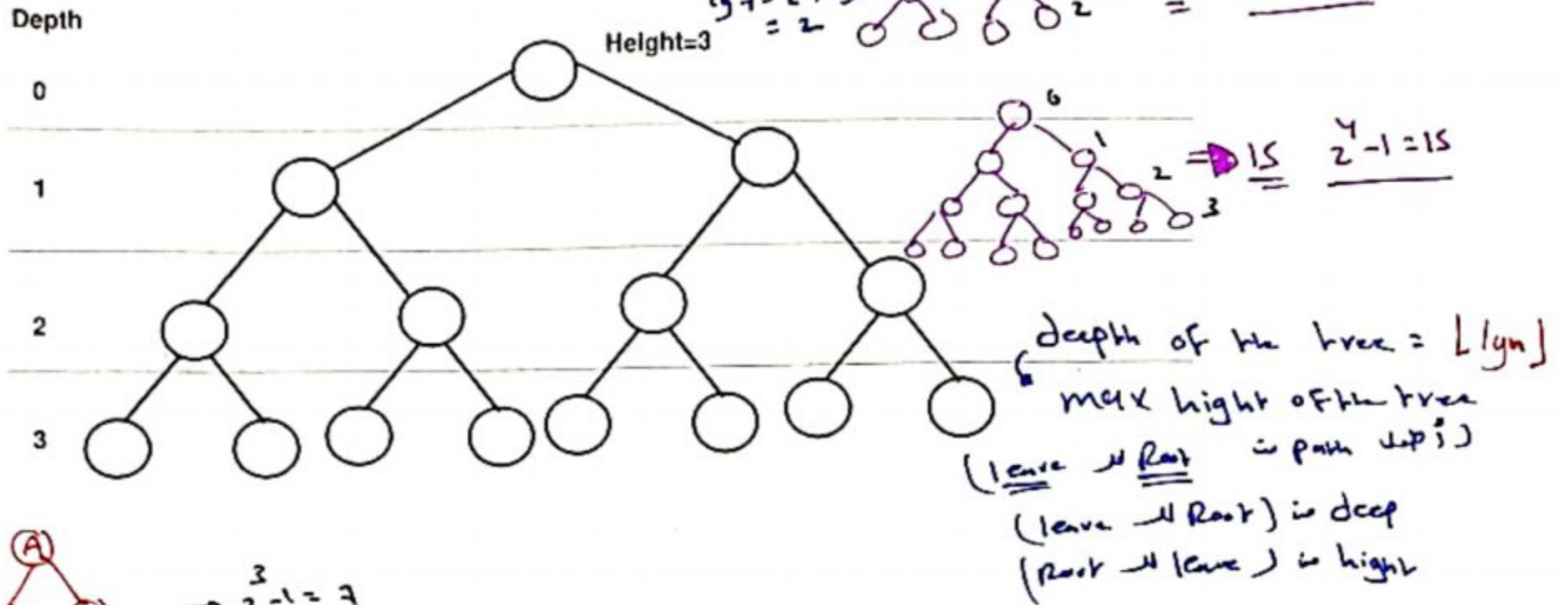
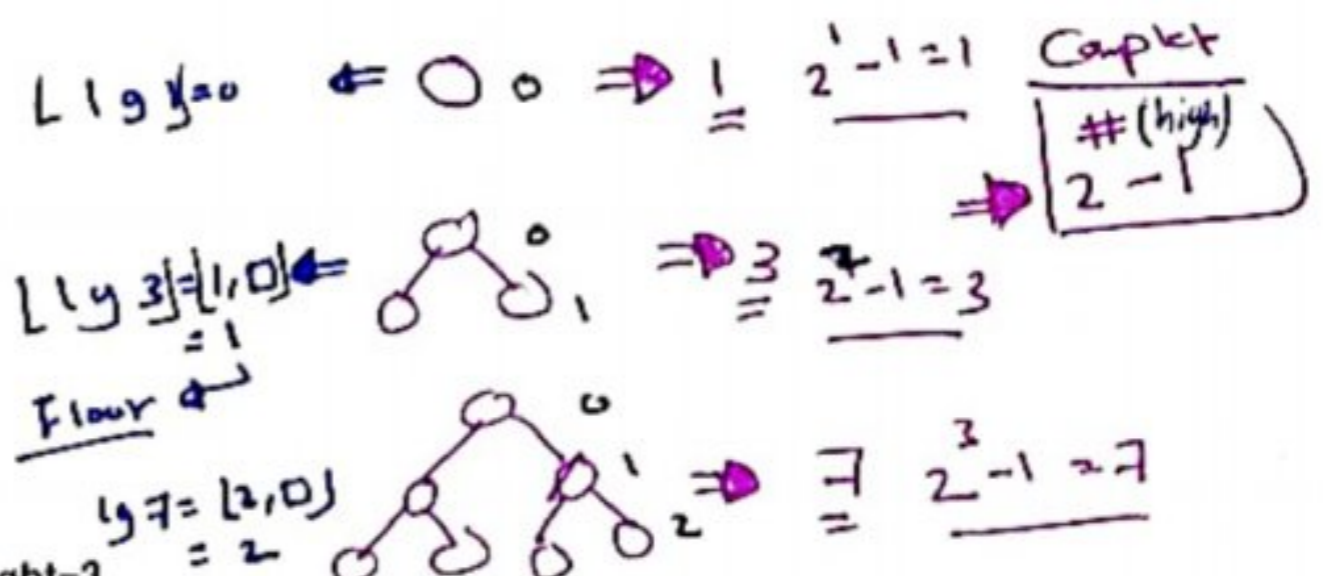


Definition: The **heap property** is the key of the parent must be greater than or equal to the key of the child, i.e., $A[\text{PARENT}(i)] \geq A[i]$. $A[1]$ is the root of the heap.

Binary Tree Terminology

A binary tree T either contains no nodes or is comprised of three disjoint sets:

- the root node,
- the left subtree, which is a binary tree,
- the right subtree, which is a binary tree.



نصف حطين من الخ صتان لما صطين الـ
 دطخ الاحوية رصخ $2^3 = 8$ مار 3 ابوال كالت
 $2^2 = 4$ مار 2 ابوال كالت

Binary Tree Terminology *continued*

The number of children that a node x can have in a tree T is called its **degree**. The nodes in a binary tree can have at most a degree of 2. (عدد اول child) max binary = 2

The length of the longest path from root r to a node x in T defines the **depth** of x . Note that a root has depth 0. The **height** of a tree T is the largest depth of any node in T . The height of a node in a tree is the length of the longest simple path to a leaf node.

A **complete** binary tree contains only nodes that are leaf nodes or have a degree of 2, and all leaf nodes have the same depth. The number of nodes in a complete

binary tree of height h is $\sum_{i=0}^h 2^i = \frac{2^{h+1}-1}{2-1} = 2^{h+1} - 1$.

Nodes that are leaf nodes are often called **external nodes**. Nodes that have at least one child are called **internal nodes**. The number of internal nodes in a complete

binary tree of height h is $\sum_{i=0}^{h-1} 2^i = \frac{2^h-1}{2-1} = 2^h - 1$.

The Heap Data Structure *continued*

Note that we number the nodes in the heap from top to bottom, left to right. Then we can store the heap in an array, A , where the number associated with a node is its array index. The array A has two attributes:

1. $length[A]$ indicates the number of elements in the array; this stays constant throughout HEAPSORT.
2. $heap-size[A]$ indicates the number of elements in the heap. $heap-size[A] \leq length[A]$. This value will decrease during the iterations in HEAPSORT.

We define three access functions:

1. $PARENT(i)$ return $\lfloor i/2 \rfloor$
2. $LEFT(i)$ return $2i$
3. $RIGHT(i)$ return $2i + 1$

6

The Heap Data Structure *continued*

Properties of a heap:

1. The root of a heap is the largest element.
2. Any path from leaf to root has values in ascending order.
3. The assignment of keys to a node in a heap structure is not unique, though the structure (i.e., shape) of the heap with a certain number of elements is unique.
4. All leaves are at depth $d - 1$ or d , where d is the maximum depth.
5. All non-leaf vertices, except for possibly one, have two children. If a non-leaf vertex has only one child (which must be a left child), it is the right-most vertex at that depth with children.

Heap Operations

There are several heap operations that we will discuss:

- HEAPIFY: $\Theta(\lg n)$ (if parent is larger than child)
- BUILD-HEAP: $\Theta(n)$ (start from root and move down)
- HEAPSORT: $\Theta(n \lg n)$ (repeatedly extract max)
- HEAP-EXTRACT-MAX: $\Theta(\lg n)$ (swap root with last element)
- HEAP-INSERT: $\Theta(\lg n)$ (insert new element and bubble up)

A heap with n elements has height $\Theta(\lg n)$; hence, many of the basic operations on a heap run in time proportional to $\Theta(\lg n)$.

#min heap property \Rightarrow $Key_{parent} < Key_{child}$

The HEAPIFY Algorithm (Bottom up approach) \Rightarrow (leaf nodes to root)

HEAPIFY takes two parameters, an array A and an index i into the array. It is assumed that the binary trees rooted at $LEFT(i)$ and $RIGHT(i)$ are heaps, but the element at position i may be out of place. This routine moves the i th element into its proper place, so that the subtree rooted at i becomes a heap.

```

HEAPIFY(A, i)
1. l ← LEFT(i)
2. r ← RIGHT(i)
3. if l ≤ heap-size[A] and A[l] > A[i]
4.   then largest ← l
5.   else largest ← i
6. if r ≤ heap-size[A] and A[r] > A[largest]
7.   then largest ← r
8. if largest ≠ i
9.   then exchange A[i] ↔ A[largest]
10.  HEAPIFY(A, largest)
    
```

Handwritten notes for HEAPIFY algorithm:

- 1. $l \leftarrow LEFT(i)$: left child index
- 2. $r \leftarrow RIGHT(i)$: right child index
- 3. $if\ l \leq heap\ size[A]\ and\ A[l] > A[i]$: if left child is larger than parent
- 4. $then\ largest \leftarrow l$: set largest to left child
- 5. $else\ largest \leftarrow i$: parent is largest
- 6. $if\ r \leq heap\ size[A]\ and\ A[r] > A[largest]$: if right child is larger than current largest
- 7. $then\ largest \leftarrow r$: set largest to right child
- 8. $if\ largest \neq i$: if largest is not the parent
- 9. $then\ exchange\ A[i] \leftrightarrow A[largest]$: swap parent with largest child
- 10. $HEAPIFY(A, largest)$: recursively heapify the subtree

The HEAPIFY Algorithm

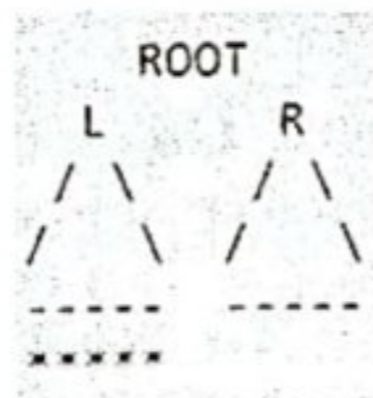
The way HEAPIFY works:

- Compare $A[i]$, $A[LEFT(i)]$, and $A[RIGHT(i)]$.
- If necessary, swap $A[i]$ with the larger of the two children to preserve heap property.
- Continue this process of comparing and swapping down the heap, until subtree rooted at i is max-heap. If we hit a leaf, then the subtree rooted at the leaf is trivially a max-heap.

Worst-case Analysis of HEAPIFY

(Sub problem)
 (element)
 $\frac{2n}{3}$

Assertion: A child of node i can have a tree of size at most $\frac{2n}{3}$.



$$T(n) \leq T\left(\frac{n}{\frac{3}{2}}\right) + \Theta(1)$$

$\frac{1}{a=1} \quad \frac{1}{b=\frac{3}{2}}$

$$n^{\frac{1}{b}} = \frac{n^{\frac{1}{2}}}{2} = n^0 = 1$$

Case 2

$$T(n) = \Theta(\lg n)$$

For a complete binary tree of height h , the number of nodes is $f(h) = 2^{h+1} - 1$. In above case we have nearly complete binary tree with the bottom half full. We can visualize this as collection of ROOT + LEFT complete tree (L) + RIGHT complete tree (R). If height of original tree is h , then the height of left is $h - 1$ and right is $h - 2$. So the total number of nodes in the tree (without the * nodes) can be expressed using the following equations:

$$n = 1 + f(h - 1) + f(h - 2) \dots (1)$$

We want to solve above for $f(h - 1)$ expressed as in terms of n

$$f(h - 2) = 2^{(h-1)} - 1 = (2^h - 1 + 1)/2 - 1 = (f(h - 1) - 1)/2 \dots (2)$$

Using above in (1) we have

$$n = 1 + f(h - 1) + (f(h - 1) - 1)/2 = 1/2 + 3 * f(h - 1)/2$$

$$\Rightarrow f(h - 1) = 2 * (n - 1/2)/3 \Rightarrow \text{Hence } O(2n/3)$$

Worst-case Analysis of HEAPIFY *continued*

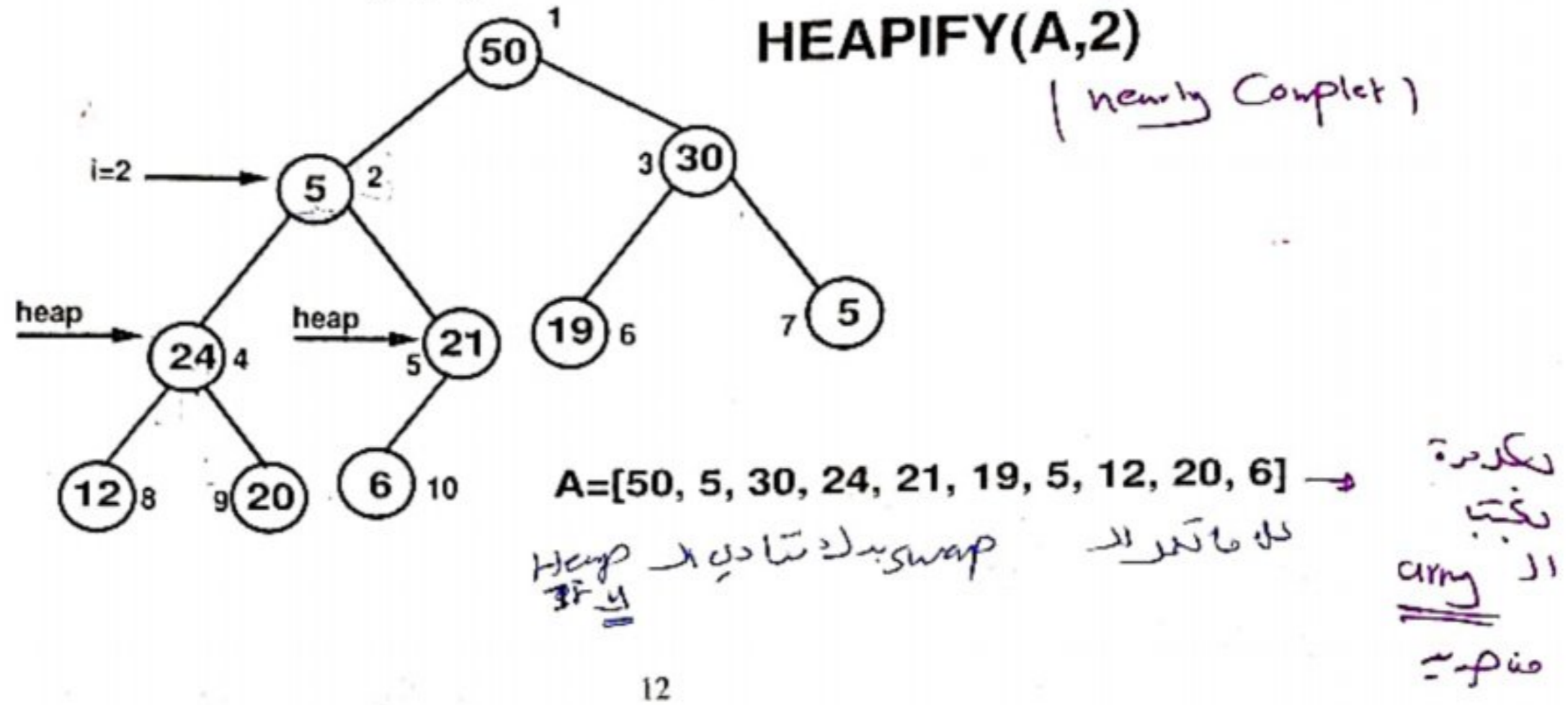
Complexity: Because the child of node i can have a tree of size at most $\frac{2n}{3}$,

$$T(n) \leq T\left(\frac{2n}{3}\right) + \Theta(1)$$

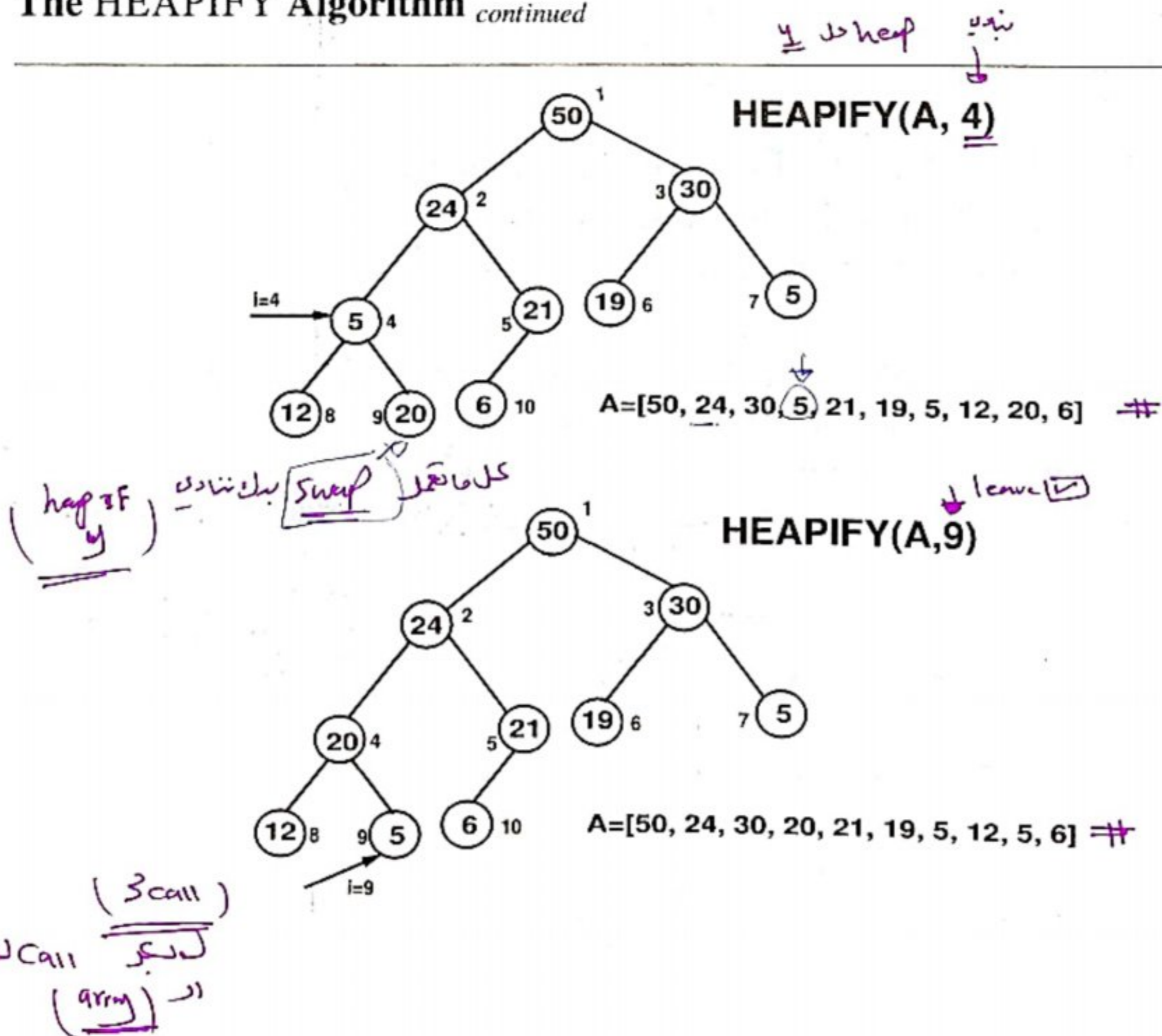
By case 2 of the Master Theorem, $a = 1$, $b = \frac{3}{2}$, so $n^{\log_b a} = \Theta(1)$, and $f(n) = \Theta(1)$, so:

$$T(n) = O(\lg n) = O(h), \text{ where } h \text{ is the height of the heap.}$$

Example: Run HEAPIFY(A, 2) on the following:



The HEAPIFY Algorithm *continued*



Building a Heap

We can use HEAPIFY in a bottom-up way to convert $A[1..n]$, $n = \text{length}[A]$ into a heap. Since $A[(\lfloor \frac{n}{2} \rfloor + 1)..n]$ are leaves, they are already heaps; hence, BUILD-HEAP works bottom-up with the remaining nodes of A.

BUILD-HEAP(A)

1. $\text{heap-size}[A] \leftarrow \text{length}[A]$
2. for $i \leftarrow \lfloor \frac{\text{length}[A]}{2} \rfloor$ downto 1
3. do HEAPIFY(A, i)

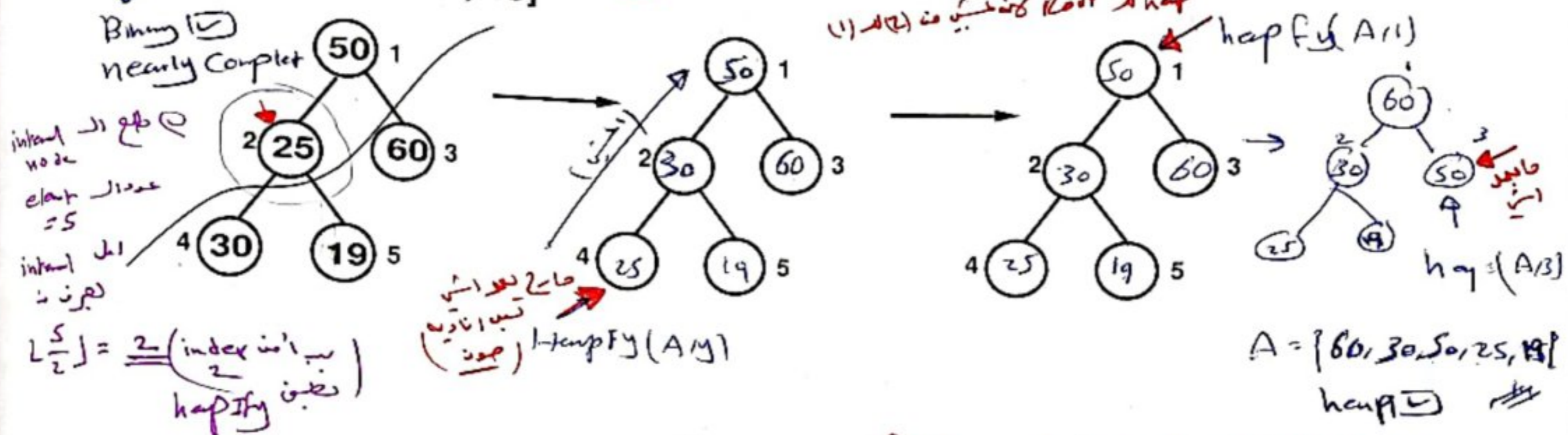
$T(n) = \lg n \Rightarrow$ Root (أول عنصر في المقارنات) Root (يؤخذ الـ Root)

(bottom of Top) (من أسفل إلى أعلى) (تبدأ من أسفل ثم تتحرك للأعلى)

heap (أول عنصر في المقارنات) (bottom of Top) (من أسفل إلى أعلى) (تبدأ من أسفل ثم تتحرك للأعلى) (out of the index) (خارج الـ index) (left, Right)

Example:

A = [50, 25, 60, 30, 19]



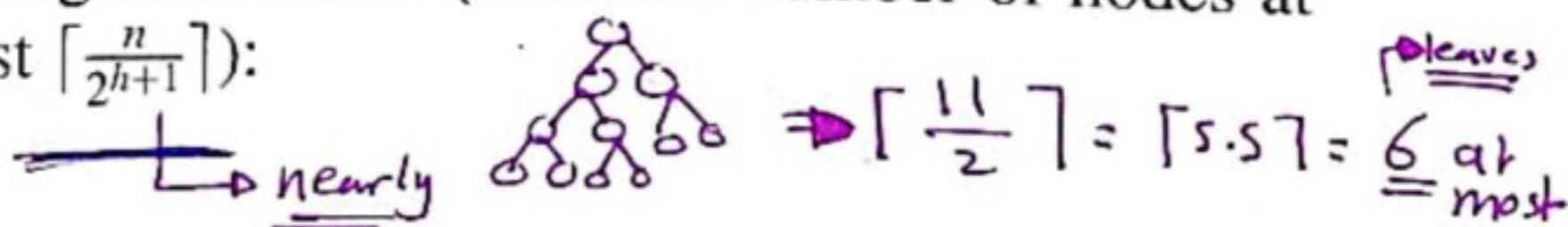
Build (إذا قدرت البنية في المرة الأولى) (max) (أول عنصر في المقارنات) (Root) (يؤخذ الـ Root) (من أسفل إلى أعلى) (تبدأ من أسفل ثم تتحرك للأعلى)

Building a Heap continued

Complexity:

A simple upper bound for BUILD-HEAP can be determined: each call to HEAPIFY is $O(\lg n)$ and there can be n such calls, giving an $O(n \lg n)$ worst-case running time. However, this is not asymptotically tight.

The time to HEAPIFY a node at height h is $O(h)$, so we can express the cost of BUILD-HEAP with the following summation (since the number of nodes at height h in an n node heap is at most $\lceil \frac{n}{2^{h+1}} \rceil$):



$$\sum_{h=0}^{\lfloor \lg n \rfloor} \lceil \frac{n}{2^{h+1}} \rceil O(h) = O\left(\frac{n}{2} \sum_{h=0}^{\lfloor \lg n \rfloor} \frac{h}{2^h}\right) = O\left(\frac{n}{2} \sum_{h=0}^{\lfloor \lg n \rfloor} h \left(\frac{1}{2}\right)^h\right) =$$

Because $\sum_{k=0}^{\infty} kx^k = \frac{x}{(1-x)^2}$, $\sum_{h=0}^{\infty} \frac{h}{2^h} = \frac{\frac{1}{2}}{(1-\frac{1}{2})^2} = 2$. Hence,

$$T(n) = O\left(n \sum_{h=0}^{\lfloor \lg n \rfloor} \frac{h}{2^h}\right) = O\left(n \sum_{h=0}^{\infty} \frac{h}{2^h}\right) = O(n)$$

Heapsort

(not stable) Alg.

$[T(n) = n \lg n]$

كيفية بناء Root

HEAPSORT(A)

1. BUILD-HEAP(A)

2. for $i \leftarrow \text{length}[A]$ downto 2

3. do exchange $A[1] \leftrightarrow A[i]$

4. $\text{heap-size}[A] = \text{heap-size}[A] - 1$

5. HEAPIFY(A, 1)

لبس البنيان heap انما Extract
 لا max (طول max وشبه
 من heap كمتى Array
 انما بعد ربطت البنيان max
 عند ان heap
 على السته فرع آخر leave طوله كان
 Root او heap تقرب الادرطه
 heap size
 heap اخره انما heap مرة ثالثة

(سبح او قضا كذا)
 ما ادره لا عدو
 وحيه

ممازة من
 heap index
 الى

اد
 بانه بدلته انشاء
 ()

عبر مرات انادي العليه
 (element - 1)
 لانها منو داعيا انادي العليه على (node وحيه)

من آخر index

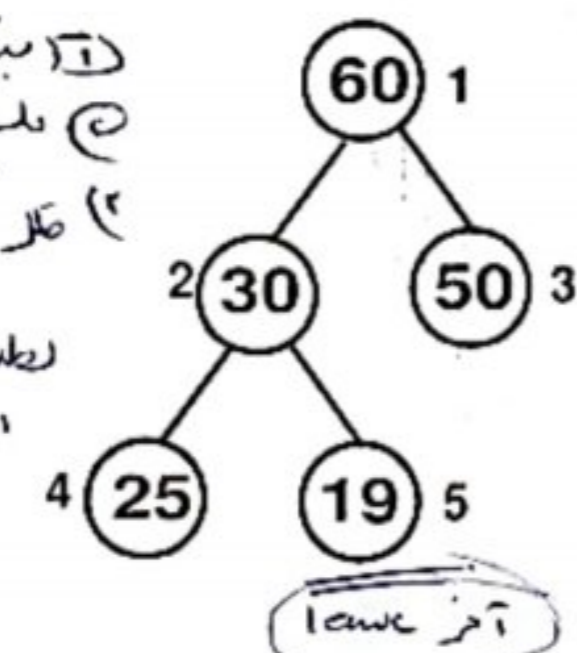
Complexity:

The $O(n)$ time to do BUILD-HEAP together with n calls to HEAPIFY gives HEAPSORT a worst-case running time of $O(n \lg n)$.

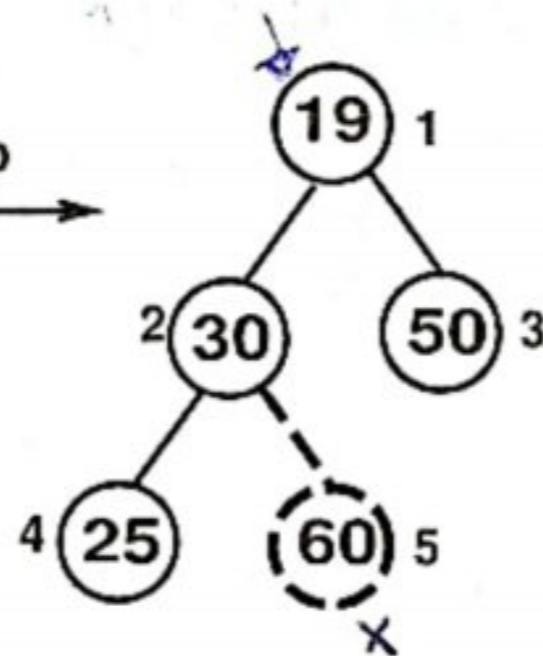
Heapsort Example

A=[60, 30, 50, 25, 19]

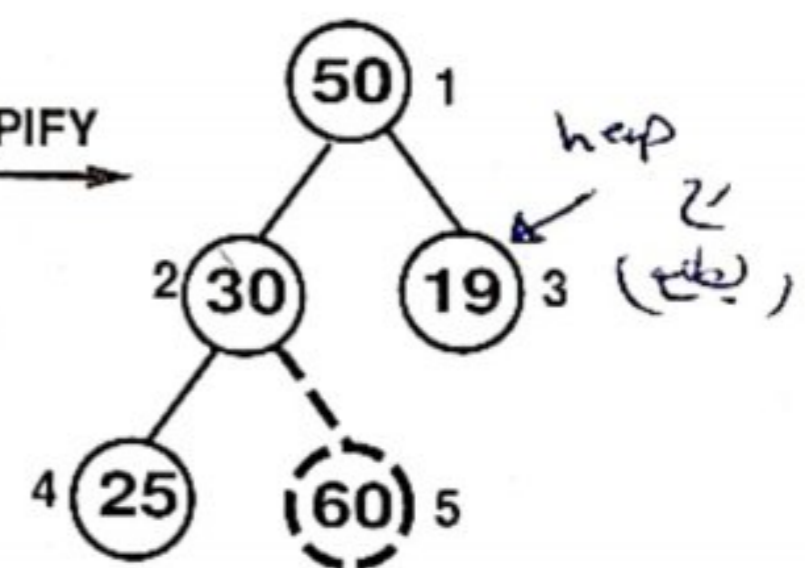
heap بنيان
 @ بلش من آخر leave
 كل (heap size) بفض
 لقطه عند ان heap
 او leave



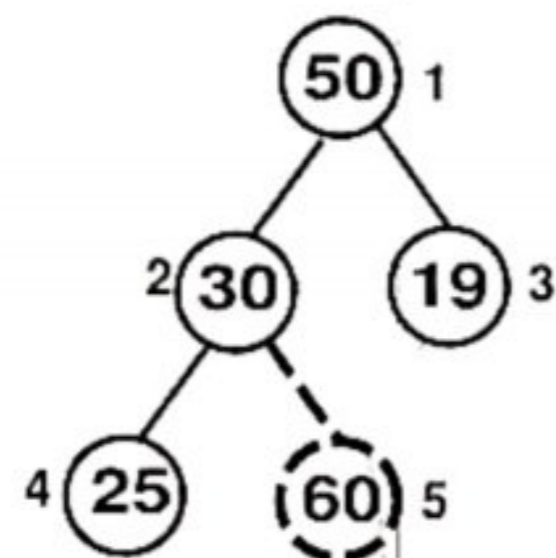
swap



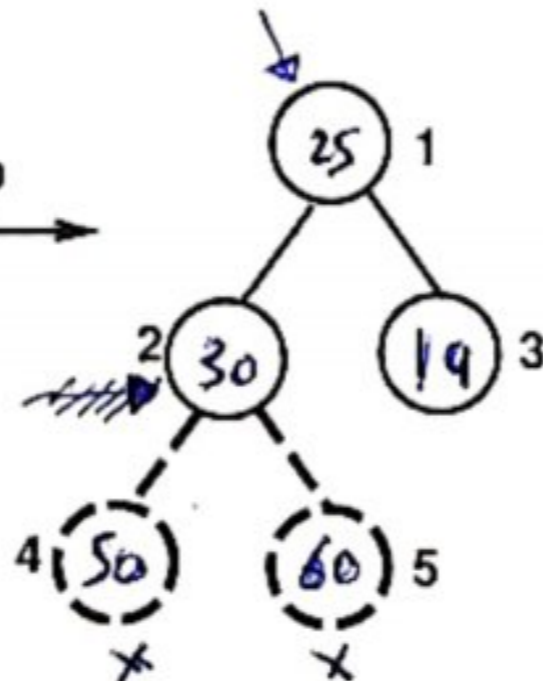
HEAPIFY



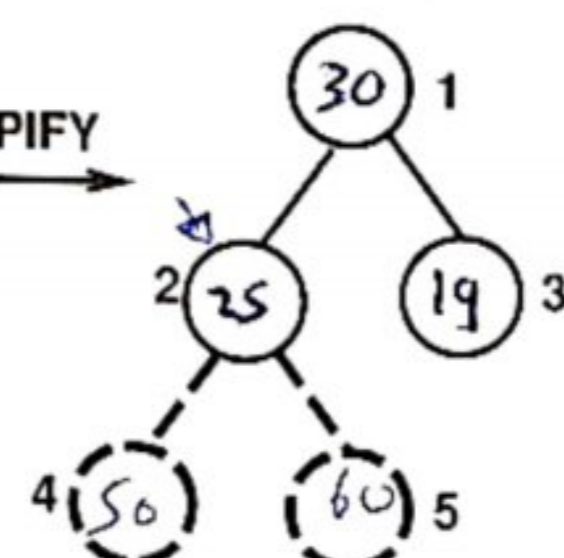
A=[50, 30, 19, 25, 60]



swap

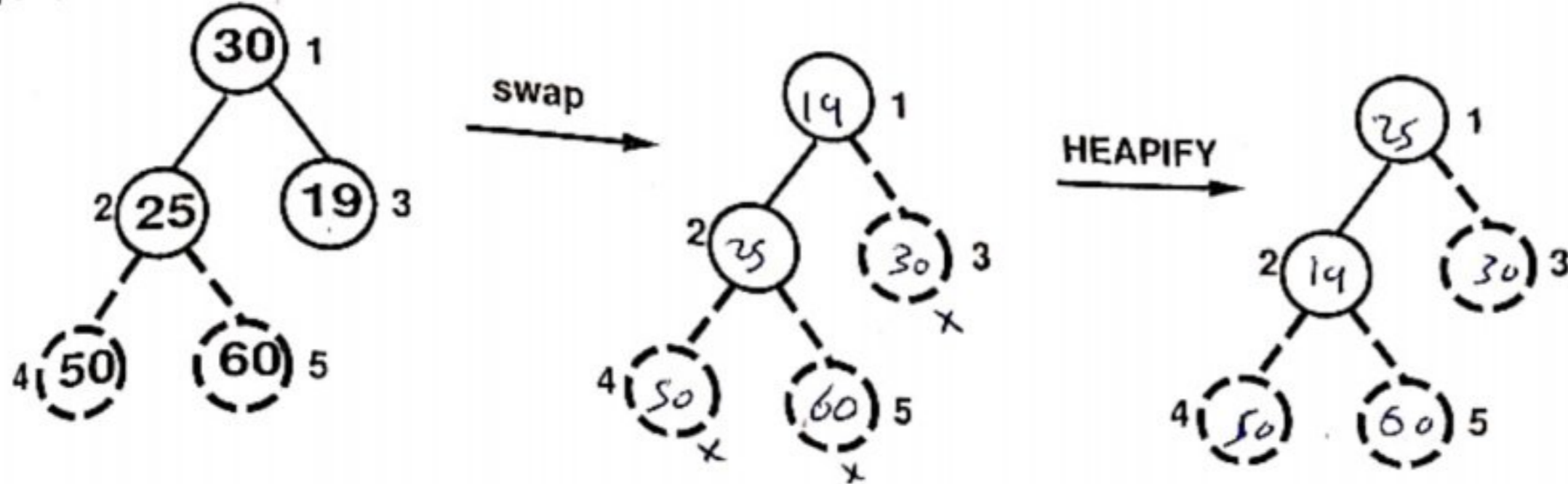


HEAPIFY

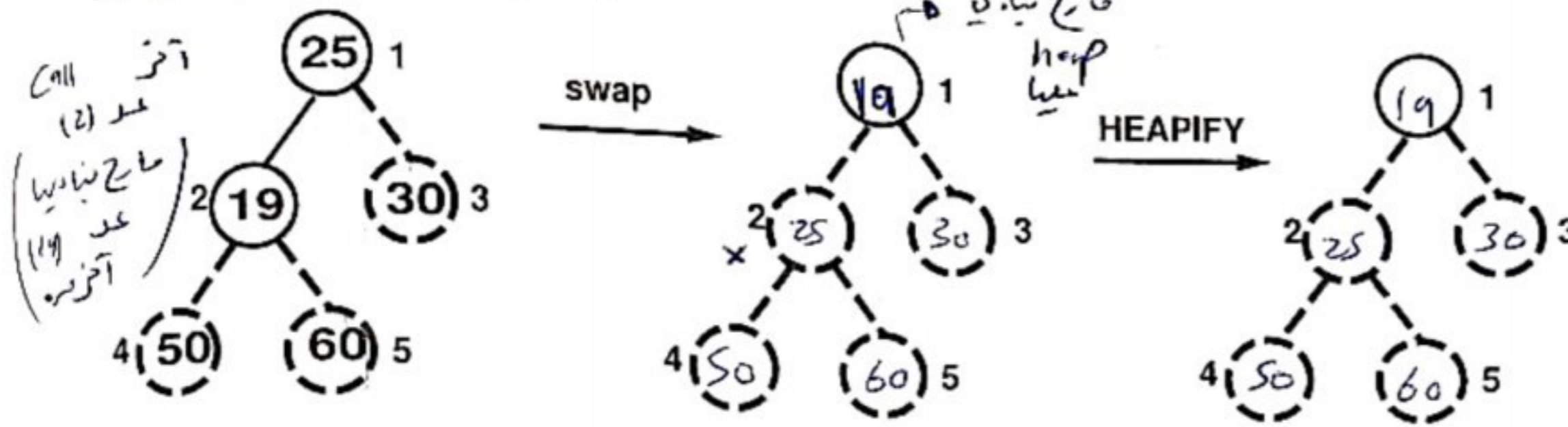


Heapsort Example *continued*

A=[30, 25, 19, 50, 60]



A=[25, 19, 30, 50, 60]



{ 19, 25, 30, 50, 60 }

Priority Queues

A **priority queue** is a data structure for maintaining a set of elements, S , which supports the following operations:

- **INSERT**(S, x): insert element x into the set S .
- **MAXIMUM**(S): returns element with the largest key from the set S .
- **EXTRACT-MAX**(S): removes and returns the element with the largest key from the set S .
- **INCREASE-KEY**(S, x, k): increases the value of element x 's key to the new value k , which is assumed to be at least as large as x 's current key value.

For example, a priority queue can be used in scheduling jobs with priorities on a computer system.

A heap is a good data structure for implementing a priority queue. We will examine the routines **HEAP-EXTRACT-MAX**, **HEAP-INSERT** and **HEAP-INCREASE-KEY**. The worst-case running time of these algorithms is related to the height of the heap, $O(\lg n)$.

The way HEAP-INSERT Algorithm work

Say that we want to insert element x into a heap with $(n - 1)$ elements .

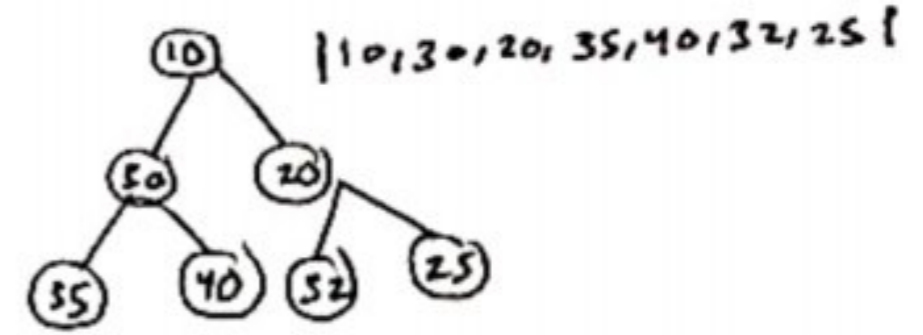
- Add x at the highest number level leaf.
- Increase heap size.
- Restore Heap property.
 - Repeat:
 - Compare x to its parent
 - If x is larger than its parent, then swap x with its parent until no swap is needed or x is at the root.

The way HEAP-EXTRACT-MAX Algorithm work

We want to delete the max element from the (n) elements heap .

- Delete the root (We need to restore Heap property).
- Decrease heap size.
- Put the right most element in the last level of the heap tree in the root position.
- Restore Heap property.

min heap



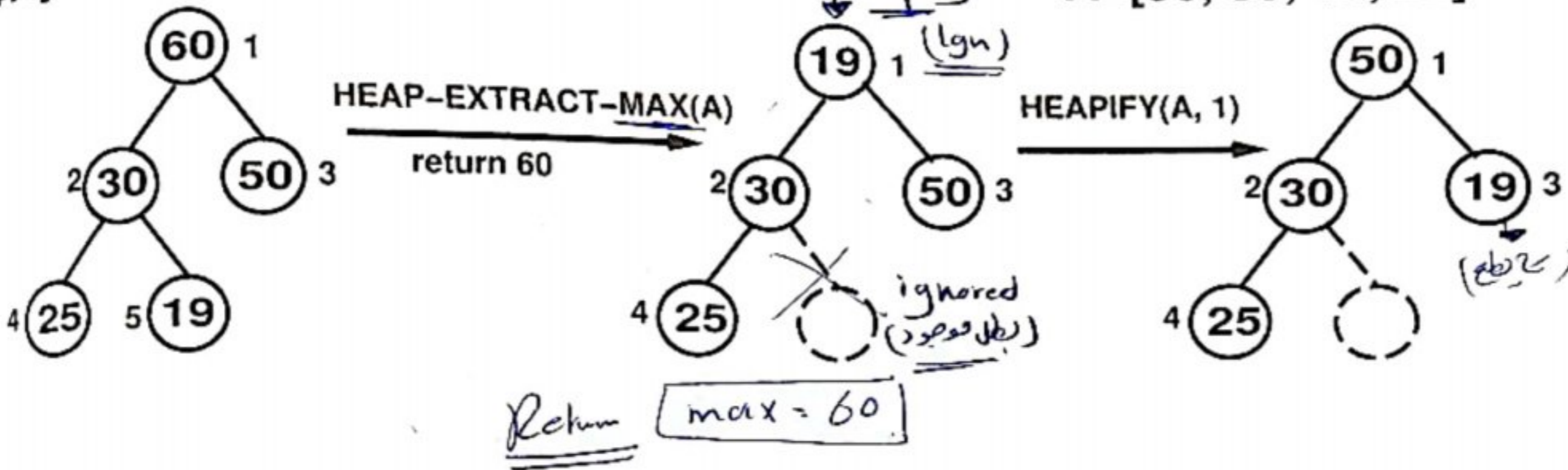
min
HEAP-EXTRACT-MAX(A)

1. if heap-size[A] < 1
2. then error "heap underflow"
3. max ← A[1]
4. A[1] ← A[heap-size[A]]
5. heap-size[A] = heap-size[A] - 1
6. HEAPIFY(A, 1)
7. return max min

(largest) - smallest? min max

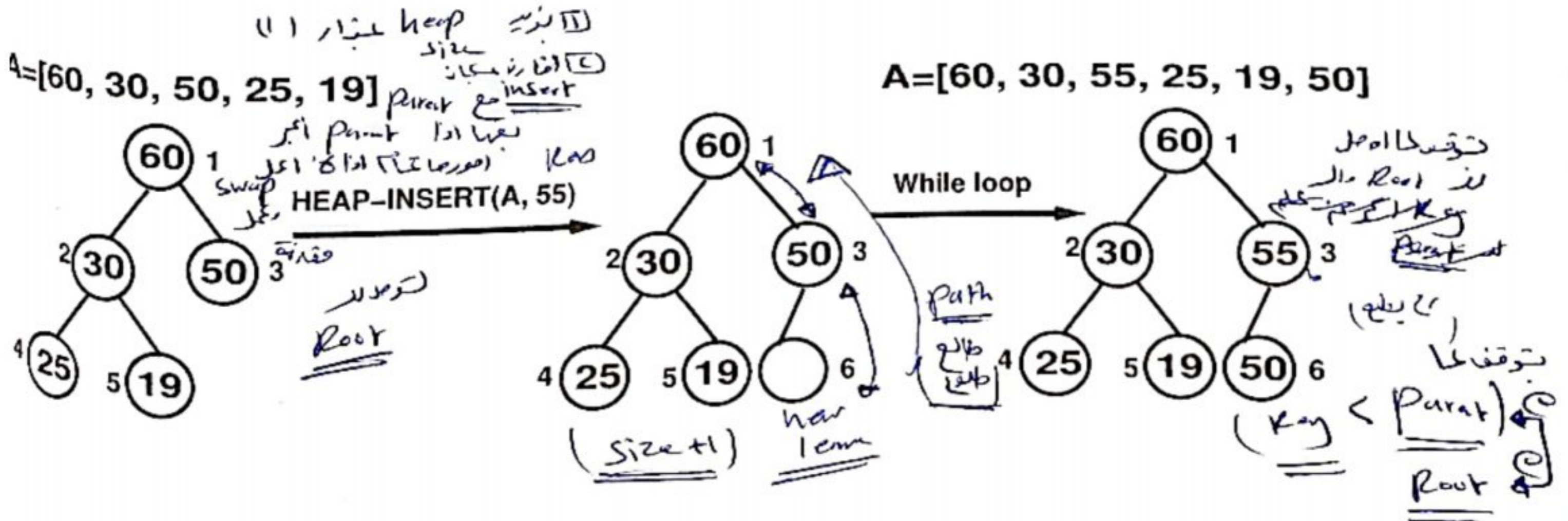
A = [60, 30, 50, 25, 19]

A = [50, 30, 19, 25]



Insert
HEAP-INSERT(A, key)

1. heap-size[A] = heap-size[A] + 1
2. i ← heap-size[A]
3. while i > 1 and A[PARENT(i)] < key
4. do A[i] ← A[PARENT(i)]
5. i ← [PARENT(i)]
6. A[i] ← key



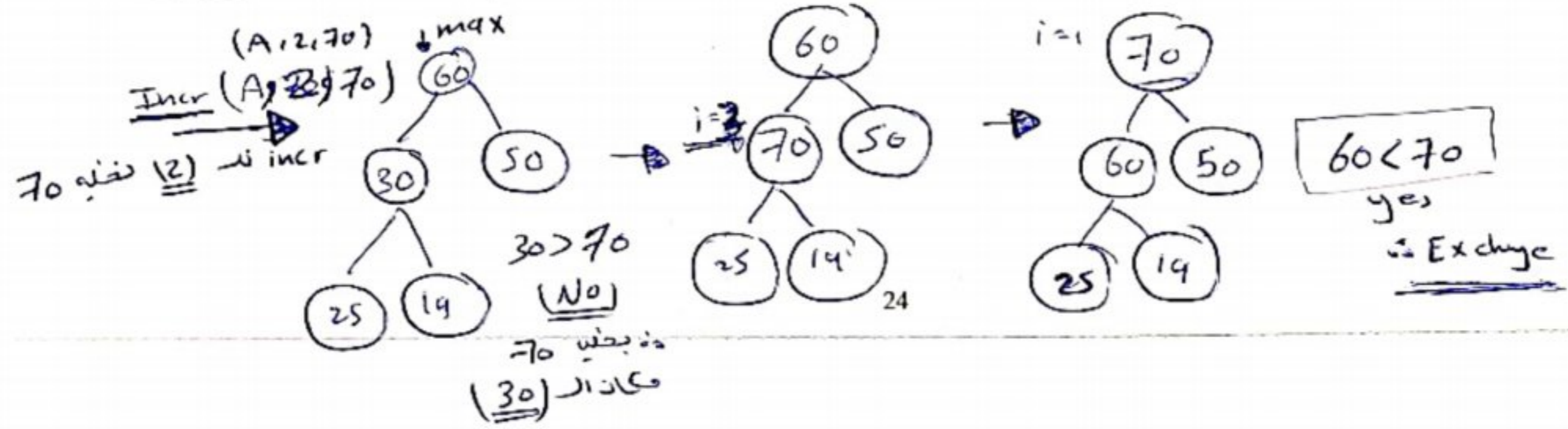
Priority Queues *continued*

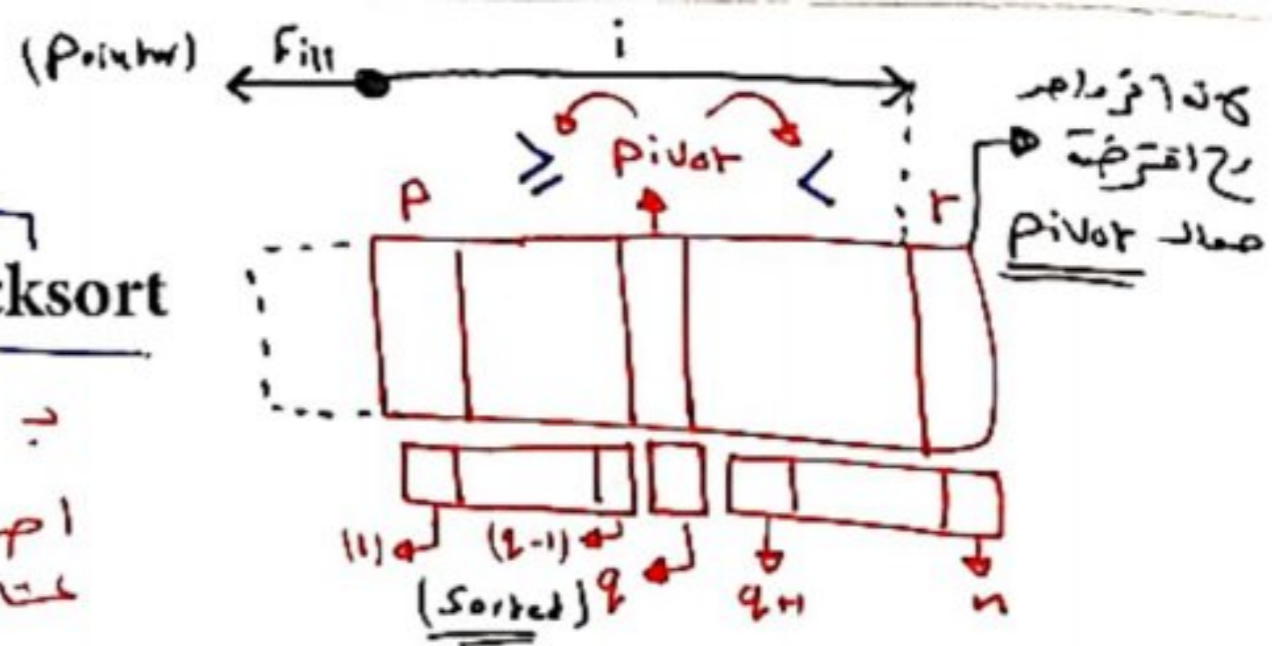
node
صفحة
استبدال
Current val
استبد
Condition
original val
أذا
صفحة
increas

HEAP-INCREASE-KEY (A, i, key)

1. if $key < A[i]$
2. then error / "new key is smaller than current key"
3. $A[i] \leftarrow key$ (غير تقارن مع)
4. while $i > 1$ and $A[PARENT(i)] < A[i]$
5. exchange $A[i]$ with $A[PARENT(i)]$
6. $i \leftarrow [PARENT(i)]$

Exercise: Modify the above routines to design a min-priority queue that supports the following operations INSERT, MINIMUM, EXTRACT-MIN, and DECREASE-KEY.





Lecture 6: Quicksort

Merge Sort (Merge Sort) - Merge Sort (Merge Sort) - Merge Sort (Merge Sort)

in place (in place) - in place (in place) - in place (in place)

auxiliary storage (auxiliary storage) - auxiliary storage (auxiliary storage) - auxiliary storage (auxiliary storage)

one element (one element) - one element (one element) - one element (one element)

merge (merge) - merge (merge) - merge (merge)

base case (base case) - base case (base case) - base case (base case)

array (array) - array (array) - array (array)

extra storage (extra storage) - extra storage (extra storage) - extra storage (extra storage)

sorted element (sorted element) - sorted element (sorted element) - sorted element (sorted element)

original array (original array) - original array (original array) - original array (original array)

Quick Sort (Quick Sort) - Quick Sort (Quick Sort) - Quick Sort (Quick Sort)

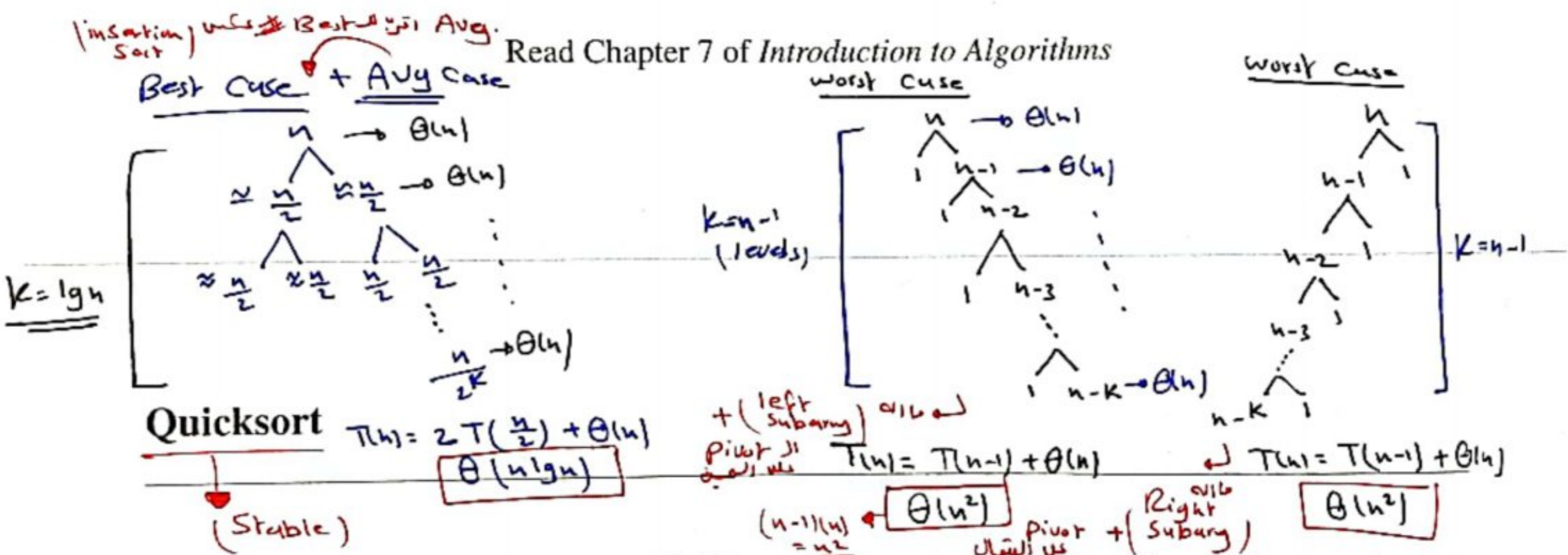
partition (partition) - partition (partition) - partition (partition)

Dr. Khalil Yousef (Dr. Khalil Yousef) - Dr. Khalil Yousef (Dr. Khalil Yousef) - Dr. Khalil Yousef (Dr. Khalil Yousef)

partition work at this division point (partition work at this division point) - partition work at this division point (partition work at this division point) - partition work at this division point (partition work at this division point)

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

* على سبب تعقيد كازال Pivot بد Best او ال Worst ؟! على input حسب شو بجدك



Quicksort, like merge sort, is a divide-and-conquer algorithm for sorting a subarray $A[p..r]$.

Divide: Partition the subarray $A[l..r]$ into two subarrays: $A[l..q-1]$ and $A[(q+1)..r]$ so that all the elements in the first subarray are less than or equal to $A[q]$, and all of the elements in the second are greater than $A[q]$. The value q is computed during the partition process.

Conquer: Recursively sort the two subarrays.

Combine: No work required as the subarrays are sorted in-place.

The Quicksort Algorithm

$\overline{\text{QUICKSORT}}(A, p, r)$ ← array element ← array element
1. if $p < r$ ← (pivot)
2. then $q \leftarrow \text{PARTITION}(A, p, r)$ ← (pivot element)
3. QUICKSORT(A, p, q-1)
4. QUICKSORT(A, q+1, r)

The initial call is $\text{QUICKSORT}(A, 1, \text{length}[A])$.

2

The Partition Algorithm

The Partition Algorithm (in English):

- Pick a **pivot** element (we'll use the element at the right end).
- Pass over elements from left to right, swapping any element \leq the pivot to a growing region at the left end. Left end gets filled with the "small" elements.
- After the pass, the pivot gets swapped to the place just after the "small element" region.
- Return the final index of the pivot.

The Partition Algorithm *continued*

Time Complexity = $n-1$

PARTITION(A, p, r)

1. $pivot \leftarrow A[r]$
2. $fill \leftarrow p-1$ ($fill = p-1$)
3. for $j \leftarrow p$ to $r-1$ (for $i = p$ to $r-1$)
4. [do if $A[j] \leq pivot$] then exchange $A[++fill] \leftrightarrow A[j]$
5. then exchange $A[++fill] \leftrightarrow A[r]$ place pivot element
6. return $fill$

(pointer) \leftarrow Fill ليبتنر
opposite direction
Concept: Value اذا ار (value)
Pivot قيمة
Right Side
Value من طرف (incr. Fill)
Value اترت Pivot
Fill ما عمل

Exchge Fill ما عمل
Fill
Basic (n-1) of parti
Fill = Fill + 1
place pivot element
or pivot (pivot = A[r])

قطع او شق
لما قطع راصد ال
element عد القال
ايمت Pivot
(ما بيزيد ال Fill)
ديجر skip بيمين ليعبر اذا بلي
وراه الامل بيزيد ال Fill

The running time of PARTITION is $\Theta(n)$, where $n = r - l + 1$.

Exchge
Pivot اترت
Fill ما عمل

Fill في ابدية مع اخله ليايد
zero index بجزوار zero ل Fill
one index بجزوار 2 = p و ال 1 = fill

المخلص (افترضنا اننا اوجدنا pivot عبي افر كلال element من (p) الى (r-1))
بيدي انا كمل كذا بلي عد تمامه انكره ساري ال pivot كذا ما نلوش element اترت
اعمل swap كذا اذا الصير ال element اترت ما نقل swap ال الطريقة بتضمن

Right Subarray
Left Subarray
Pivot ايمت
ال Fill ما عمل مكان انت عملته swap

Partition Example: $A = \langle 7, 8, 2, 6, 5, 1, 3, 4 \rangle$

Draw behavior of fill, pivot, and j during PARTITION(A, 1, 8) on overhead.

Sol $A = \langle 7, 8, 2, 6, 5, 1, 3, 4 \rangle$ (نادي ال Partition) $1 < 8$
 $p = 1, r = 8$
 (A, 1, 8) \Rightarrow $(2, 8, 7, 6, 5, 1, 3, 4)$
 $7 < 4 \otimes, 8 < 4 \otimes, 2 < 4 \checkmark$
 $6 < 4 \otimes, 5 < 4 \otimes, 1 < 4 \checkmark$
 $3 < 4 \checkmark$
 $(2, 1, 7, 6, 5, 8, 3, 4)$
 $(2, 1, 3, 6, 5, 8, 7, 4)$
 $(2, 1, 3, 4, 5, 8, 7, 6)$
 return 4 (index)
 Value ليع

Fill بيزيد (Fill = 1)
 i = 3
 Exchge i = 3, Fill
 Fill بيزيد (Fill = 2)
 i = 6
 Exchge i = 6, Fill
 Fill بيزيد (Fill = 3)
 i = 7
 Exchge i = 7, Fill

Partition (A, 1, 3)
 Pivot (3)
 Fill (2, 1, 3)
 2 < 3 \checkmark , 1 < 3 \checkmark
 1 < 3 \checkmark
 return = 3 (index)

Partition (A, 5, 8)
 Pivot (6)
 Fill (5, 8, 7, 6)
 5 < 6 \checkmark , 8 < 6 \otimes , 7 < 6 \otimes
 (5, 6, 7, 8)

The Partition Algorithm *continued*

The correctness of this algorithm can be shown using a loop invariant:

At the beginning of each iteration of the **for** loop, $A[l..r]$ contains the same elements it started with, possibly rearranged, and, for any array index k ,

1. If $l \leq k \leq i$, then $A[k] \leq pivot$.

2. If $i < k < j$, then $A[k] > pivot$.

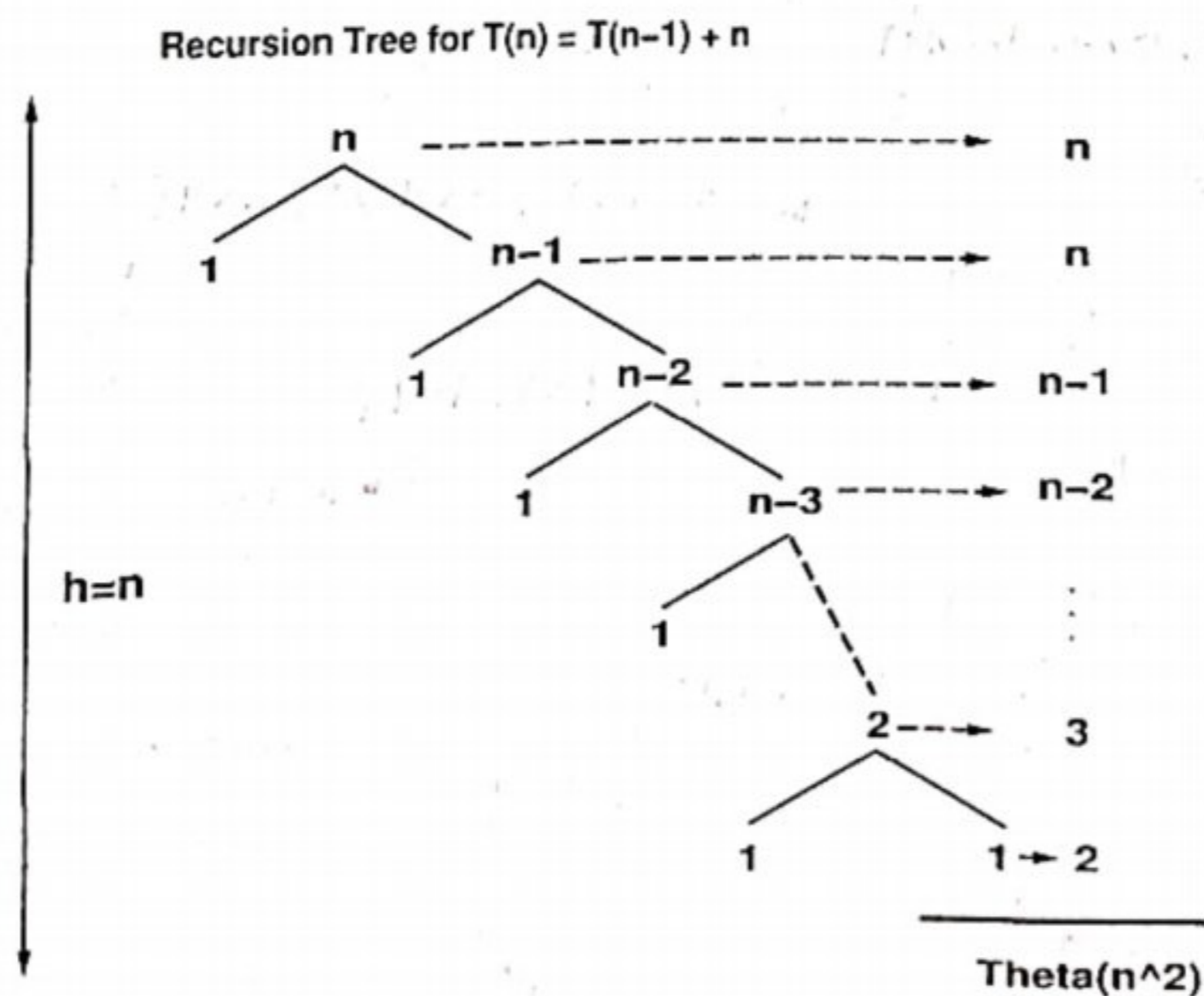
3. If $k = r$, then $A[k] = pivot$.

The running time of QUICKSORT depends on the sizes of the left and right partitions (which are affected by the choice of the pivot).

6

Worst Case Performance of Quicksort

Worst Case: The left or right partition has size of one element.



Worst Case Performance of Quicksort *continued*

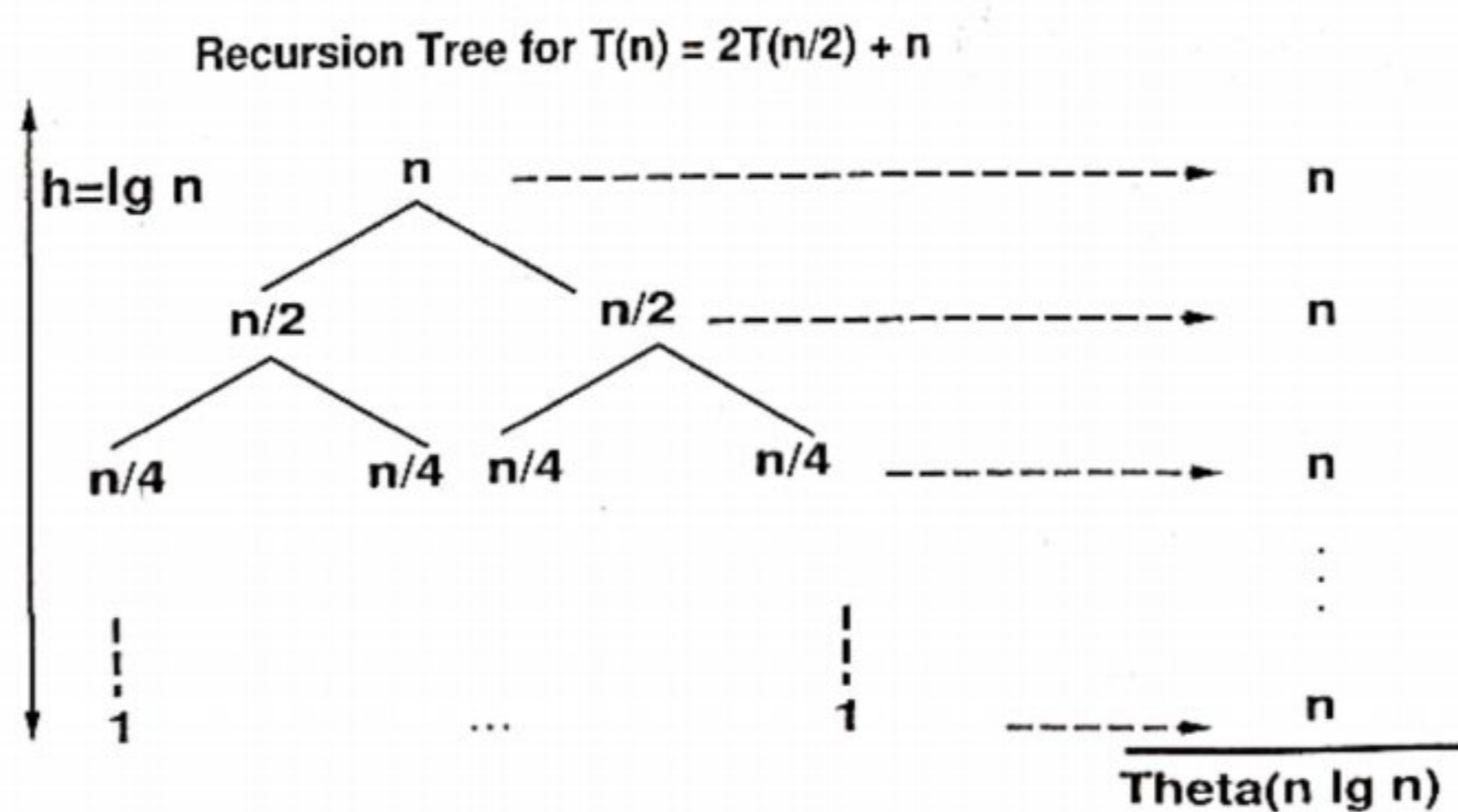
$$\begin{aligned} T(n) &= T(n-1) + \Theta(n) \\ &= T(n-2) + \Theta(n-1) + \Theta(n) \\ &= T(n-3) + \Theta(n-2) + \Theta(n-1) + \Theta(n) \\ &\vdots \\ &= \sum_{k=1}^n \Theta(k) \\ &= \Theta\left(\sum_{k=1}^n k\right) \\ &= \Theta(n^2) \end{aligned}$$

When does the worst case occur?

8

Best Case Performance of Quicksort

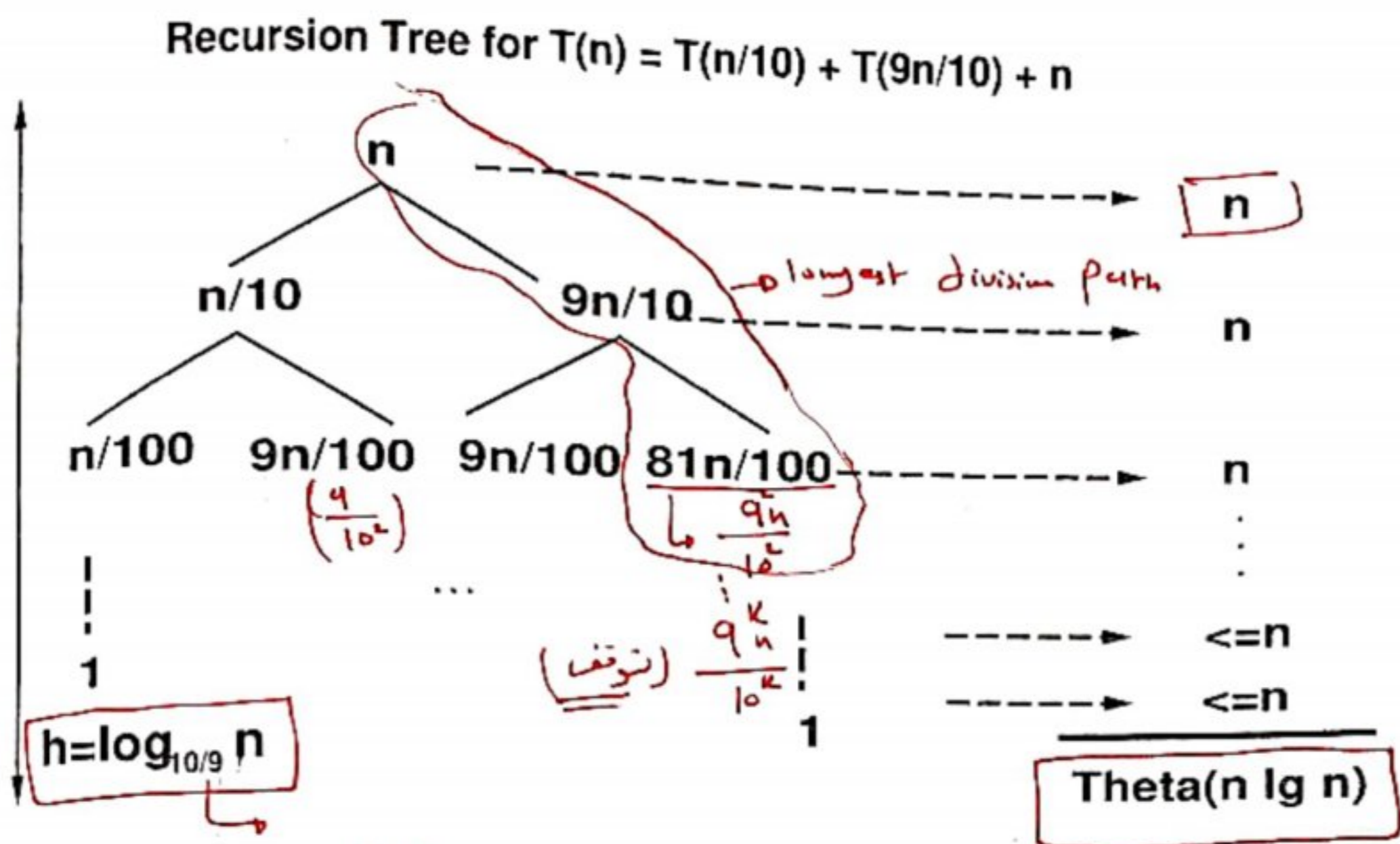
The best case occurs when the sizes of the left and right partitions are equal sized.



$$\begin{aligned} T(n) &= 2T(n/2) + \Theta(n) \\ &= \Theta(n \lg n) \end{aligned}$$

Balanced Partition Case

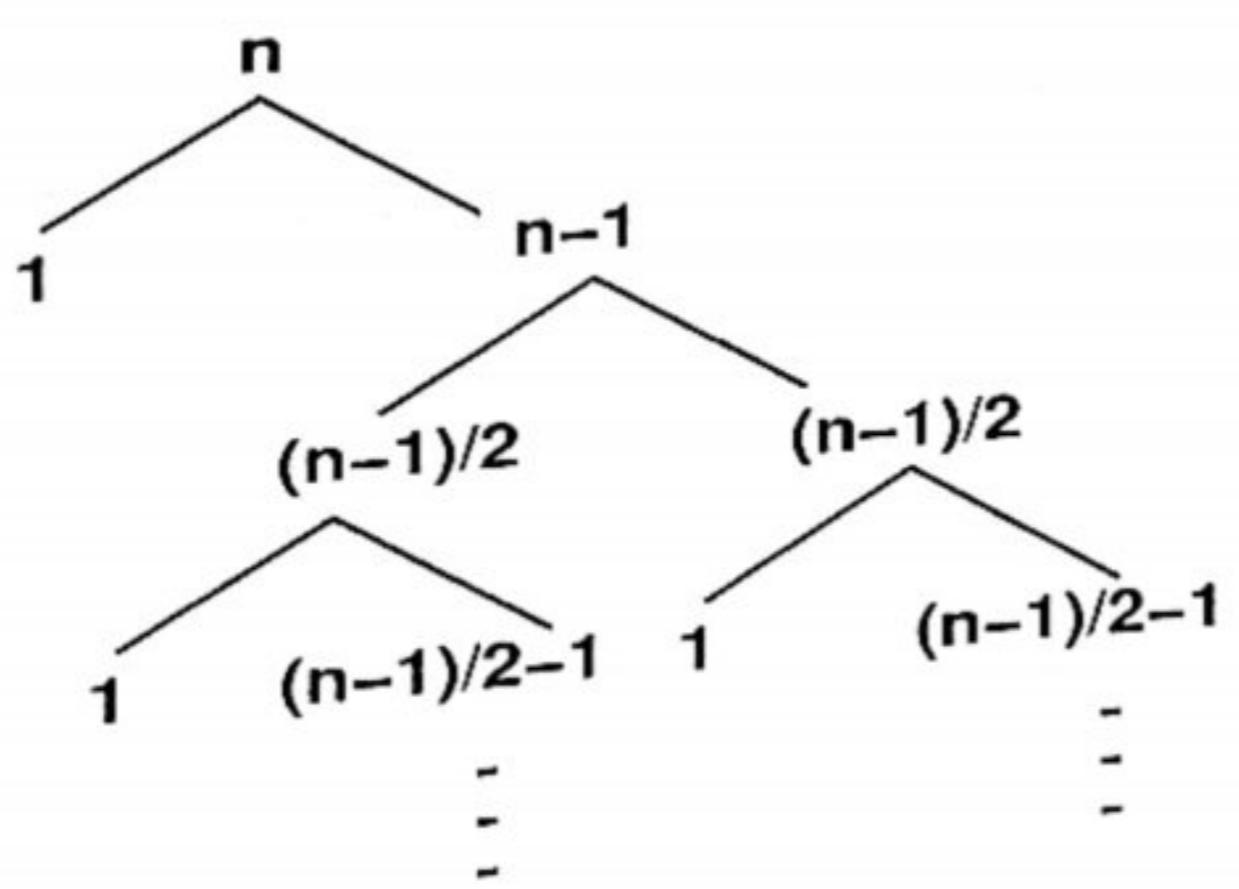
The average case running time of QUICKSORT is closer to the best case than the worst case. Even if there is an imbalance in the partitions of 9-to-1 (or 99-to-1 for that matter), we obtain a running time of $\Theta(n \lg n)$:



Avg Case Best Case (Average case is very similar to the best case) $\Theta(n \lg n)$

Intuition for the Average Case

When we run QUICKSORT, it is unlikely that the partition occurs in the same way at every level; some will be balanced and some won't be. In the average case, PARTITION produces a random mix of "good" and "bad" splits. If the good and bad splits alternate over the levels, we end up with a nearly balanced partition which is better than the 9-to-1 case:



Average Case will be $O(n \lg n)$

Randomized Quicksort

QUICKSORT's performance depends on the distribution of the input data. If we create a randomized version of QUICKSORT, the worst case behavior will rely on the random number generator hitting an unlucky and unlikely partition, again and again.

One possible implementation of RANDOMIZED-QUICKSORT is to randomize PARTITION by picking the pivot element at random from the range $l..r$, exchange $A[r]$ with that element, and run PARTITION as before.

(صدا المآ باضداد Pivot آخر راضی) و شکر مشا ایشا کین
← ممکن سبطل تکیون (Stable)
RANDOMIZED-PARTITION(A, l, r)
1. $i \leftarrow \text{RANDOM}(l, r)$
2. $\text{exchange } A[r] \leftrightarrow A[i]$
3. $\text{return PARTITION}(A, l, r)$

Worst Case
input ریا تبودنید لدر
(worst case)

12

Randomized Quicksort *continued*

RANDOMIZED-QUICKSORT(A, l, r)

1. **if** $l < r$
2. **then** $q \leftarrow \text{RANDOMIZED-PARTITION}(A, l, r)$
3. RANDOMIZED-QUICKSORT($A, l, q - 1$)
4. RANDOMIZED-QUICKSORT($A, q + 1, r$)

Note: This does not improve the worst case running time of the algorithm, but it does prevent particular input cases from causing the worst-case behavior.

Thus the worst case running time is still $O(n^2)$.

proof of this was done through what is known as Decision trees

it was show no such Alga in the worst case could achieve better than $\Theta(n \lg n)$

Selection Sort, Insertion Sort, Merge Sort, Heap Sort, Quick Sort
Comparison Based Sorting Algo

Lecture 7: Linear Sorts

النتائج بتكفي إذا برك تحصل Performance أفضل من $n \lg n$ بتكيد (for getting to sorting) \Rightarrow (linear sorting)
Course Learning Outcome :

Show how time and space complexities can be traded-off (e.g. distribution counting sort, hashing)

Dr. Khalil Yousef

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

*Linear Sorting Algorithms

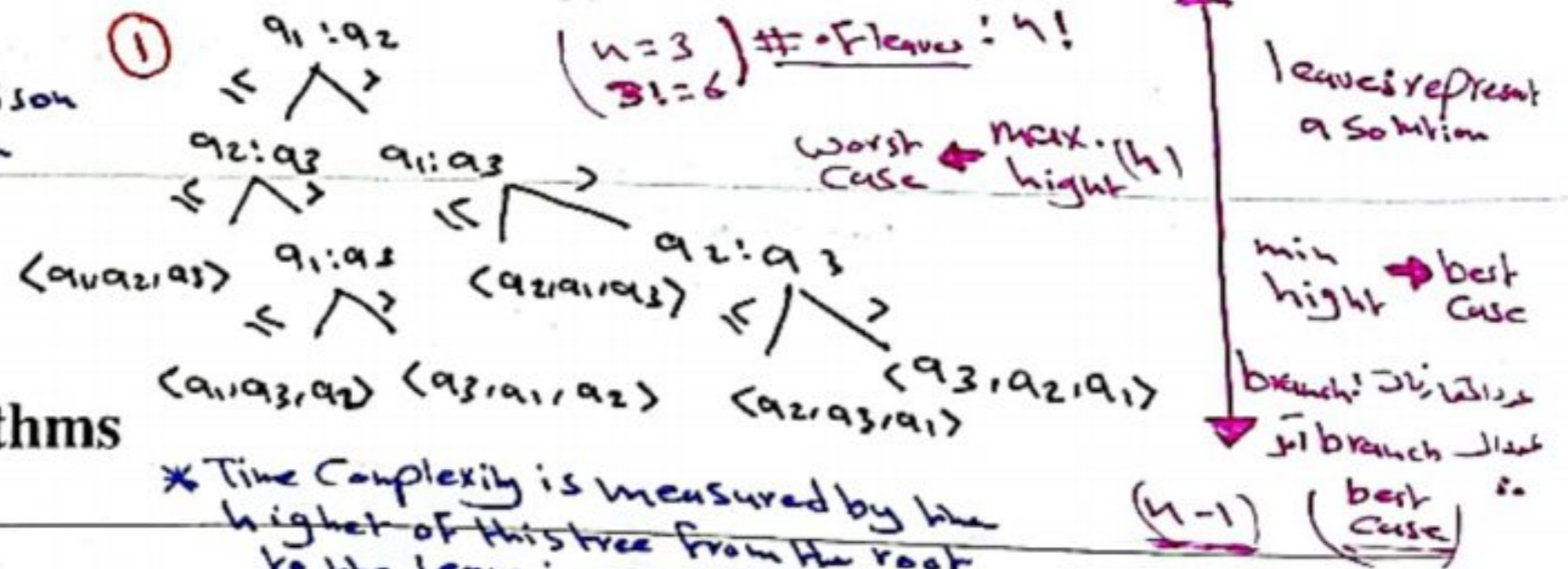
- 1) Counting Sort
- 2) Radix Sort
- 3) Bucket Sort

*Theorem: we can't achieve better than $n \lg n$ (i.e. $\Omega(n \lg n)$) for any Comparison Based Sorting Algorithm in the worst case

Read Chapter 8 of Introduction to Algorithms

*let's consider three elements in an array $A = \langle a_1, a_2, a_3 \rangle$

Decision Tree: (present or show all possible comparison that has comparison as its basic operation)



Comparison Sort Algorithms

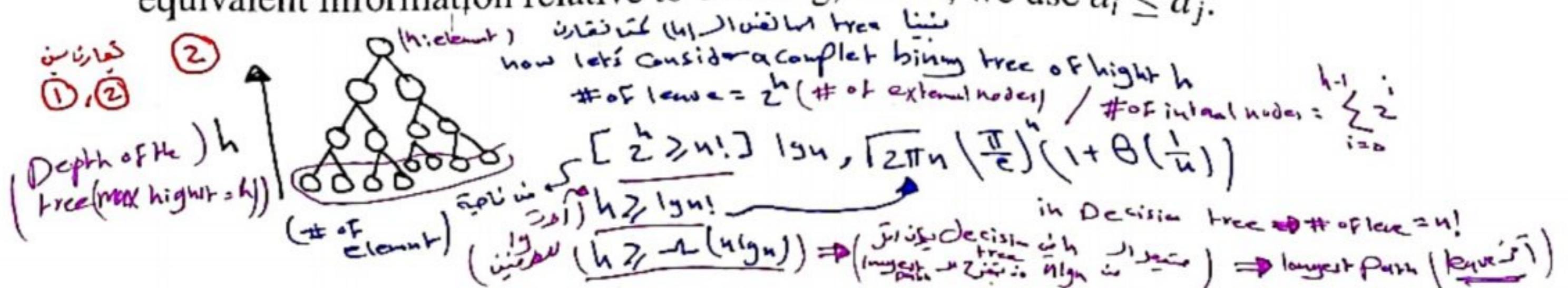
*Time Complexity is measured by the height of this tree from the root to the leaf in solution

How fast can we sort? Much depends on the assumptions one makes about how the sorting is accomplished.

So far we have considered only algorithms that sort by comparing pairs of elements (i.e., INSERTION-SORT, MERGE-SORT, HEAPSORT, and QUICKSORT). They are called comparison sorts.

Any sort requires at least $n - 1$ comparisons, or it won't have examined the input. However, all comparison sorts require $\Omega(n \lg n)$ comparisons to sort in the worst case. Can we achieve a sort that is faster than $\Omega(n \lg n)$? yes, linear sorting

We assume that all elements are distinct while we are discussing the lower bound on comparison sorts. In this case, $a_i < a_j$, $a_i > a_j$, $a_i \leq a_j$, $a_i \geq a_j$ provide equivalent information relative to ordering; hence, we use $a_i \leq a_j$.

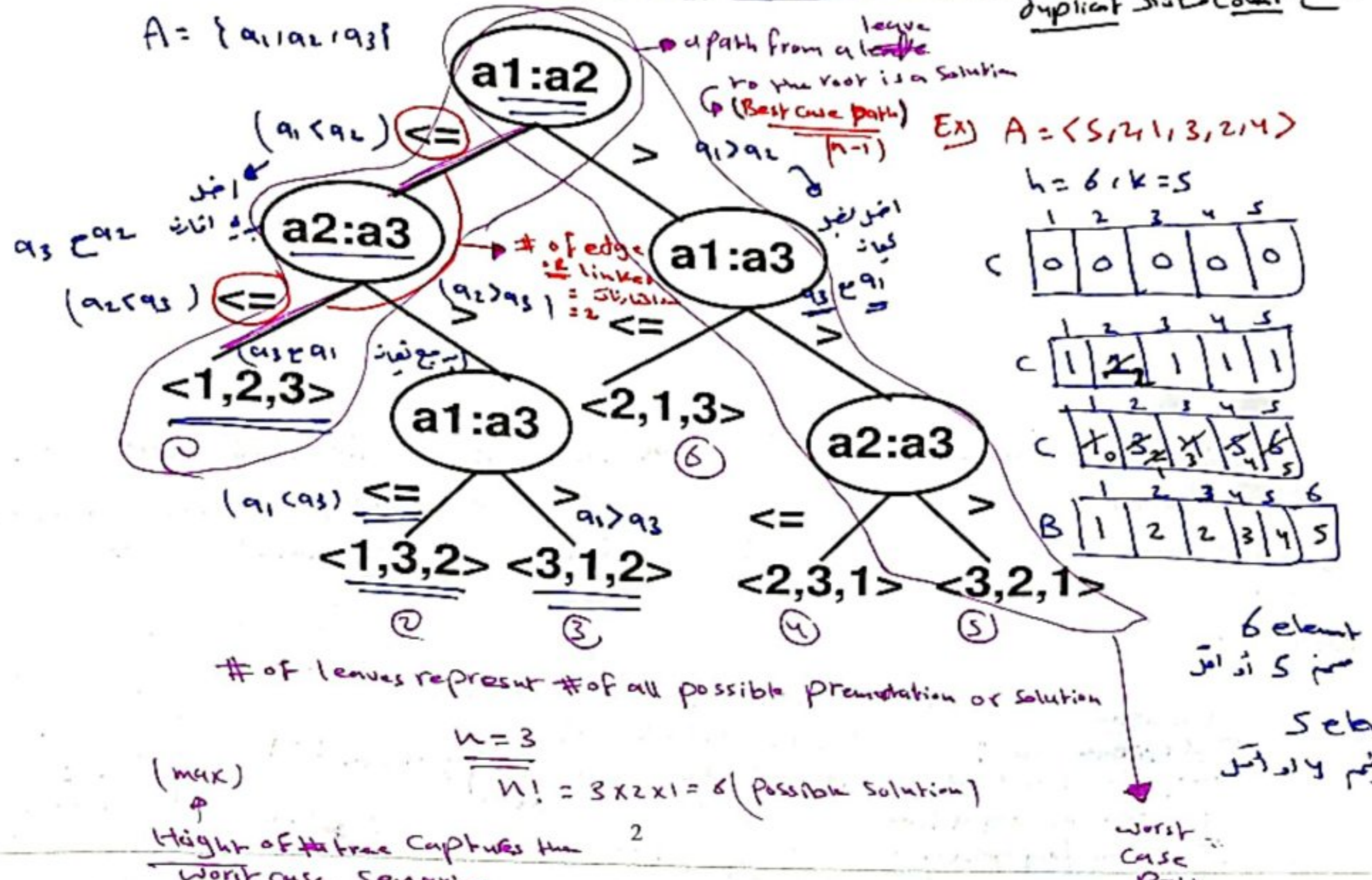


Decision Trees

* Counting Sort: Assume the input array A is a set of n integers in the range linear $1:k$

Counting Sort (A, n, k)
 For $i=1$ to k
 $C[i] = 0$
 For $j=1$ to n
 $C[A[j]] = C[A[j]] + 1$
 For $i=2$ to k
 $C[i] = C[i] + C[i-1]$
 For $j=n$ to 2
 $B[j] = A[j]$
 $C[A[j]] = C[A[j]] - 1$
 $\theta(n+k)$
 لا تكون k تربية من n linear

A comparison sort can be viewed in terms of a decision tree, which represents the comparisons performed by the algorithm operating on an input of a certain size.



Decision Trees continued

of leaves in binary tree > # of leaves in the Decision tree

$$\frac{k}{2} > n!$$

- There is a comparison tree for each input of size n .
- The leaves represent all possible permutations of the input array; hence, there are $n!$ leaves in the tree.
- Internal nodes represent comparisons between pairs of elements.
- The path from the root to a leaf shows the comparisons for arriving at the leaf's permutation (an execution trace).
- The length of the longest path in the tree indicates its worst-case running time.
 length shortest path = Best Case

Theorem 9.1: Any decision tree that sorts n elements has height $\Omega(n \lg n)$, (i.e., at least one path is that length).

Complexity of Comparison Sorts

Proof: (We ignore data movement, bookkeeping operations, etc.)

The number of leaves in the decision tree is at least $n!$, or two permutations go to the same leaf.

The number of leaves in a binary tree is $\leq 2^h$, and:

$$2^h \geq n!$$

$$h \geq \lg(n!)$$

Recall **Stirling's approximation**: $n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n (1 + \Theta(1/n)) > \left(\frac{n}{e}\right)^n$, hence:

$$h \geq \lg\left(\frac{n}{e}\right)^n = n \lg n - n \lg e$$

$$h = \Omega(n \lg n)$$

better than $n \lg n$ in the worst case

longest path ←

من تقريباتنا نحتاج اجابت $n \lg n$ ؟! انتقل الى linear sorting

Decision Tree Questions

1. In a comparison sort decision tree, what do the leaves of the tree represent? How many leaves must there be in a decision tree sorting n elements? $n!$
2. In a comparison sort decision tree, what do the non-leaf nodes of the tree represent?
3. In a comparison sort decision tree, what do the edges of the tree represent?
4. What is the length of the longest possible path in any comparison sort decision tree for an input of size n such that comparisons are not duplicated? Why?
5. What is the length of the shortest possible path in any comparison sort decision tree? Why? $(n-1)$ Best case OK اذا اتت (n-1) العنصر

ما هي المسألة (input)

Distribution Counting Sort or simply Counting Sort

Sorting process is based on a counting principle

so, then is no single comparison being made by this algo.

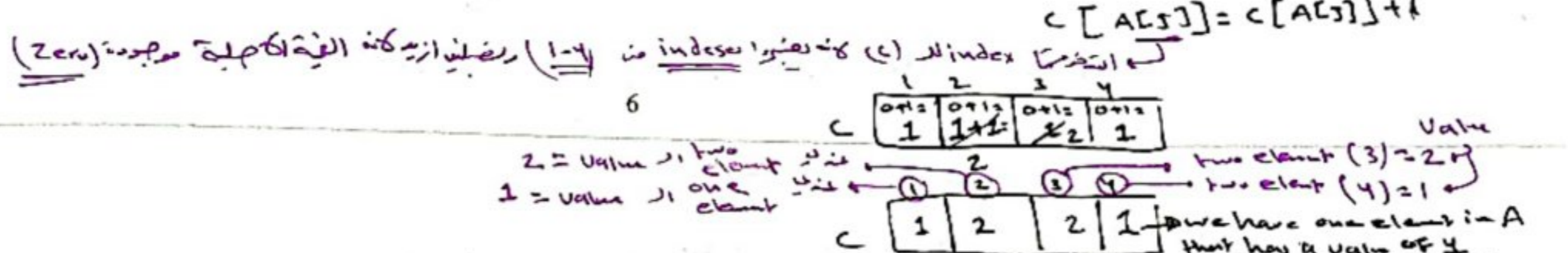
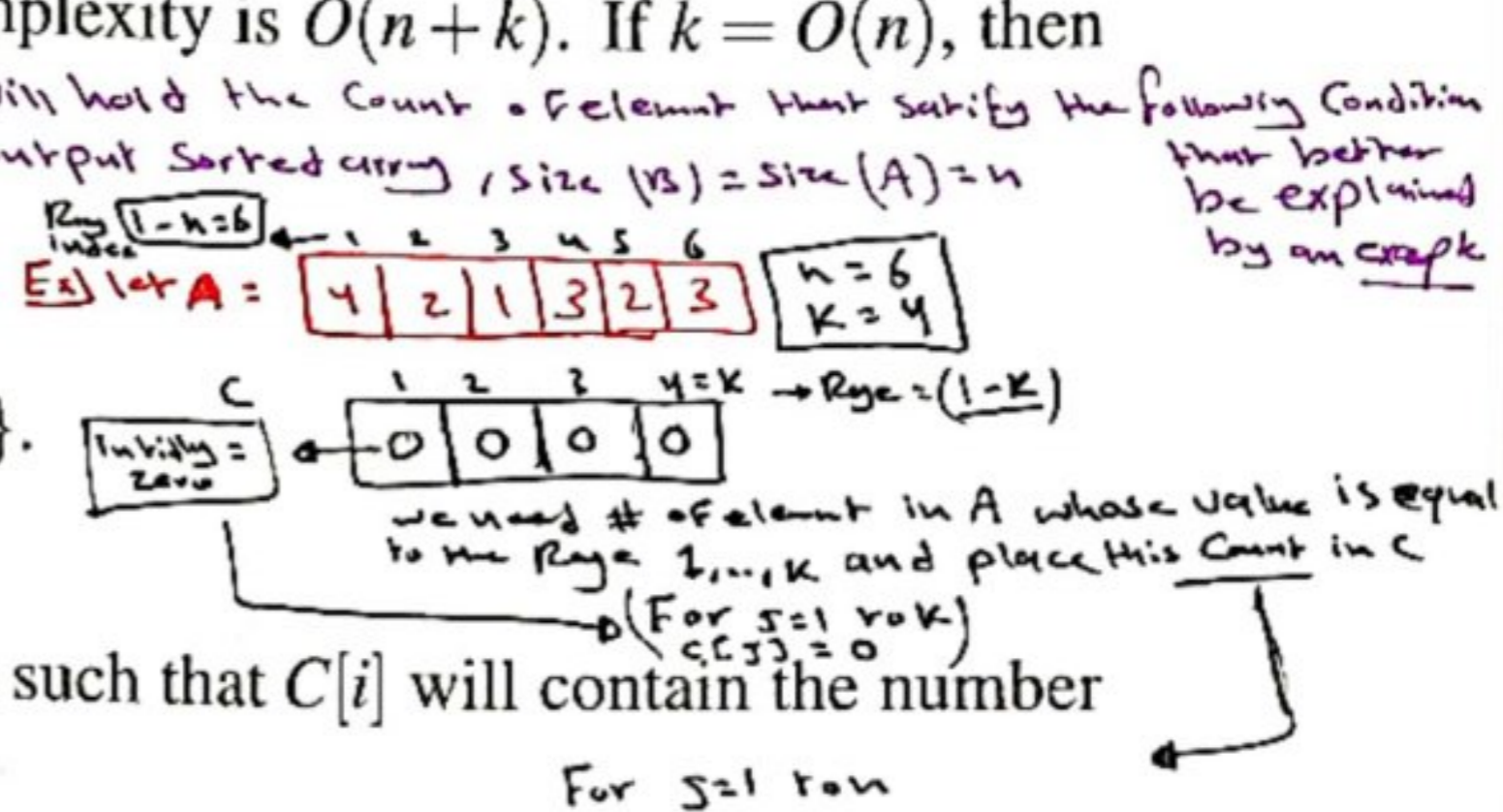
Assumption: input elements are integers in the range 1 to k , where k can be different than n . Duplicates are allowed.

Abstract: The basic idea is to count, for each element x , the number of elements less than that element so that we can determine the index of placement for x . If 10 elements are less than x , then x goes into the 11th position. (The algorithm is slightly more complex than this because it handles duplicates.)

We will show that COUNTING-SORT's complexity is $O(n+k)$. If $k = O(n)$, then the complexity is $O(n)$.

Data structures used:

- Input:** $A[1..n]$ where $A[j] \in \{1, 2, \dots, k\}$.
- Output:** $B[1..n]$, which is sorted.
- Auxiliary:** $C[1..k]$ is temporary storage such that $C[i]$ will contain the number of elements less than or equal to key i .

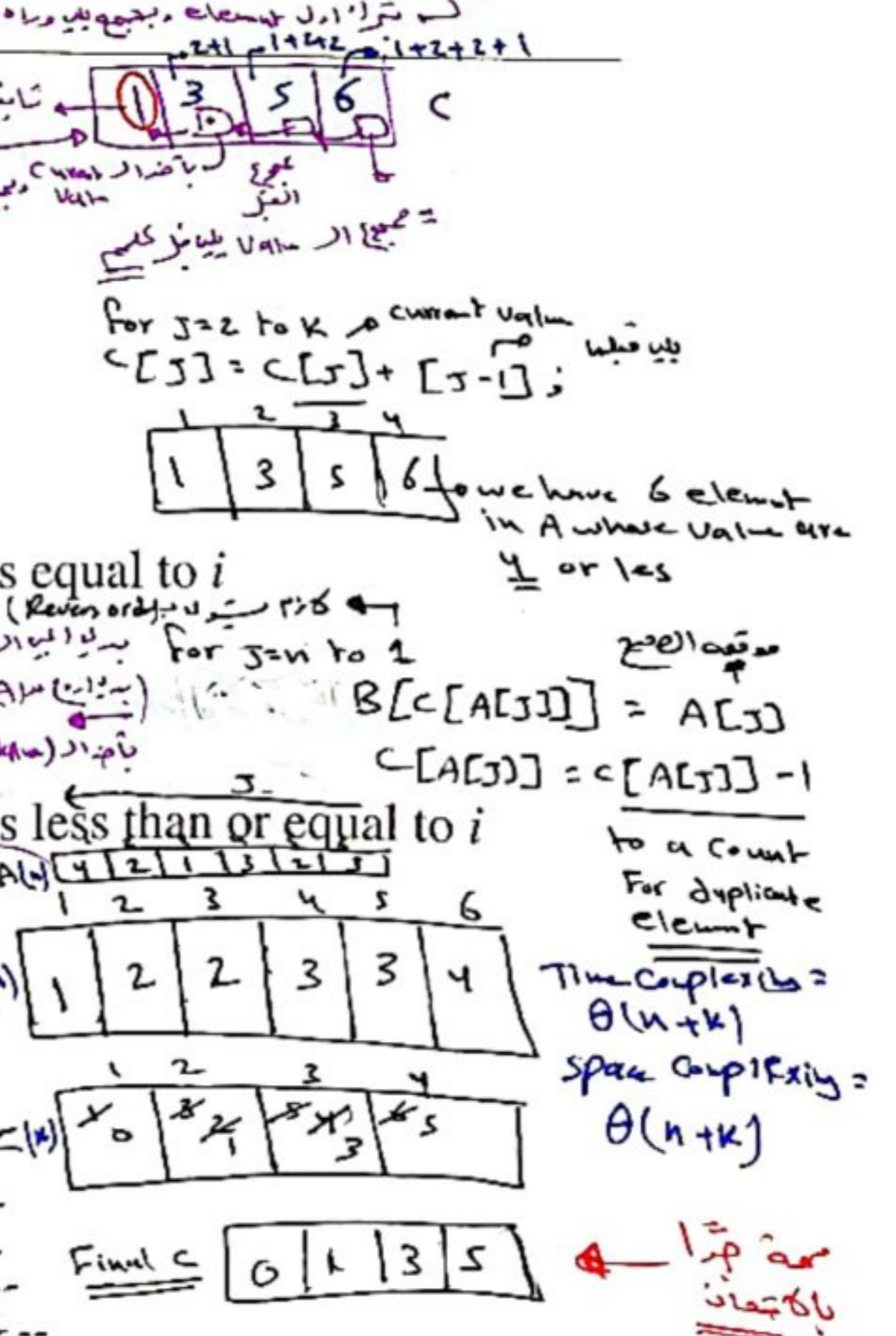


The COUNTING-SORT Algorithm

- for $i \leftarrow 1$ to k
- do $C[i] \leftarrow 0$
- for $j \leftarrow 1$ to $\text{length}[A]$
- do $C[A[j]] \leftarrow C[A[j]] + 1$

- $\triangleright C[i]$ now contains the number of elements equal to i
- for $i \leftarrow 2$ to k
- do $C[i] \leftarrow C[i] + C[i-1]$
- $\triangleright C[i]$ now contains the number of elements less than or equal to i

- for $j \leftarrow \text{length}[A]$ downto 1
- do $B[C[A[j]]] \leftarrow A[j]$
- $C[A[j]] \leftarrow C[A[j]] - 1$



Time Complexity = $\theta(n+k)$
Space Complexity = $\theta(n+k)$

ما استعملت ابي عملية المقارنة
اعتماد على الـ A و B
لما عملت مع الـ A و B مرة واحدة
فصاحبها عنك (Duplicity) نفس الـ A و B

$A[2] \Rightarrow C[2] = 3 \Rightarrow B[3] = 2, c = \dots$
 $A[3] \Rightarrow C[3] = 4 \Rightarrow B[4] = 3, c = \dots$
 $A[1] \Rightarrow C[1] = 1 \Rightarrow B[1] = 1, c = \dots$
 $A[2] \Rightarrow C[2] = 2 \Rightarrow B[2] = 2, c = \dots$
 $A[4] \Rightarrow C[4] = 6 \Rightarrow B[6] = 4, c = \dots$

COUNTING-SORT Example: $A = \langle 4, 2, 1, 3, 2, 3 \rangle$ (stable)

Initially A is:

1	2	3	4	5	6
4	2	1	3	2	3

 $n=6$
 $k=4$

After executing lines 1 through 4, C is:

1	2	3	4
1	2	2	1

After executing lines 6 through 7, C is:

1	3	5	6
---	---	---	---

Now we begin iterating over the loop in lines 9 through 11.

$C = 0, 1, 3, 5$ (المجموع)

Iteration 1: $j = 6$, so place $A[6]$ into the correct position in B given C : $B[C[A[6]]] = B[5] = A[6] = 3$ and $C[A[6]] = C[A[6]] - 1 = 5 - 1 = 4$, so:

B is:

				3	
--	--	--	--	---	--

 C is:

1	3	4	6
---	---	---	---

Time complexity = $\Theta(n+k)$

Can we get rid of k in terms of A ?
 Sol: Yes, but through Best case: $k \leq n \rightarrow k = O(n) \rightarrow T(n) = \Theta(n)$
 Avg case: $k \in \Theta(n)$
 Worst case: $k \gg n \rightarrow T(n) = \Theta(k)$
 Consider when $A = \langle 5, 7, 10000 \rangle$ $n=3, k=10000$ (much larger than n)

(linear) $A \rightarrow$ Best
 • Worst في الحالة في

Radix Sort
 That means we must improve this Algo.

COUNTING-SORT Example: $A = \langle 4, 2, 1, 3, 2, 3 \rangle$ continued

Iteration 2: $j = 5$, so place $A[5]$ into the correct position in B given C : $B[C[A[5]]] = B[3] = A[5] = 2$ and $C[A[5]] = C[A[5]] - 1 = 3 - 1 = 2$, so:

B is:

				3	
--	--	--	--	---	--

 C is:

1	2	4	6
---	---	---	---

Iteration 3: $j = 4$, so place $A[4]$ into the correct position in B given C : $B[C[A[4]]] = B[4] = A[4] = 3$ and $C[A[4]] = C[A[4]] - 1 = 4 - 1 = 3$, so:

B is:

		2	3	3	
--	--	---	---	---	--

 C is:

1	2	3	6
---	---	---	---

Iteration 4: $j = 3$, so place $A[3]$ into the correct position in B given C : $B[C[A[3]]] = B[1] = A[3] = 1$ and $C[A[3]] = C[A[3]] - 1 = 1 - 1 = 0$, so:

B is:

1	2	3	3		
---	---	---	---	--	--

 C is:

0	2	3	6
---	---	---	---

COUNTING-SORT Example: $A = \langle 4, 2, 1, 3, 2, 3 \rangle$ continued

Iteration 5: $j = 2$, so place $A[2]$ into the correct position in B given C : $B[C[A[2]]] = B[2] = A[2] = 2$ and $C[A[2]] = C[A[2]] - 1 = 2 - 1 = 1$, so:

B is:

1	2	2	3	3	
---	---	---	---	---	--

 C is:

0	1	3	6
---	---	---	---

Iteration 6: $j = 1$, so place $A[1]$ into the correct position in B given C : $B[C[A[1]]] = B[6] = A[1] = 4$ and $C[A[1]] = C[A[1]] - 1 = 6 - 1 = 5$, so:

B is:

1	2	2	3	3	4
---	---	---	---	---	---

 C is:

0	1	3	5
---	---	---	---

The COUNTING-SORT Algorithm *continued*

If the elements of A are distinct, then $C[A[j]]$ contains the correct final position for $A[j]$ in B ; however, if there are duplicates, then $C[A[j]]$ is decremented each time we move $A[j]$ into B , so that subsequent duplicates of $A[j]$ can be correctly placed in B .

COUNTING-SORT is stable. A sort is stable if equal keys remain in the same relative order in the sorted sequence as in the original input sequence. For example,

4	2 ₁	3	2 ₂
---	----------------	---	----------------

 \rightarrow

2 ₁	2 ₂	3	4
----------------	----------------	---	---

$k \gg n$ الترتيب الواسع
Radix Sort الترتيب

Complexity: COUNTING-SORT runs in $\Theta(n + k)$ time. Hence, it is not bounded by $\Omega(n \lg n)$. Note that it is not a comparison sort, so there is no contradiction.

Counting Sort: Assumption: Input are integer in the Range $1, \dots, K$
 ↳ This Algo. because problematic when of size n when $K \gg n$ (must be known)
 $T(n) = \theta(k)$

Radix Sort

If k is very large, it may dominate the function $O(n+k)$. k can be reduced by combining COUNTING-SORT with RADIX-SORT.

The basic idea is to sort n d -digit numbers from the least significant digit to the most significant digit (where digit 1 is the lowest-order digit and d is the highest-order digit). This requires d passes with a stable sort; hence, COUNTING-SORT is an excellent choice.

$\theta(n \log n)$ Merge Sort
 $\theta(n^2)$ Insertion Sort
 $\theta(n+k)$ Counting Sort
 Total $\rightarrow \theta(d(n+k))$
 $\theta(d(n^2))$
 $\theta(d(n \log n))$

1. for $i \leftarrow 1$ to d
 2. do (use a stable sort to sort array A on digit i)

Counting Sort on digit d

A = [5 | 1000 | 2 | $n=3$]
 C = [] $K=1000$
 B = [2 | 5 | 1000]

Decimal: The max possible $K=9$

RADIX-SORT Example

$\theta(n+k) \times 3 \rightarrow \theta(n+k) = 3(n+k) \Rightarrow$ linear performance

$n=5, d=3$
 $n=5, K=729$

Initial array: 729, 321, 119, 021, 728
 Pass 1 ($i=1$): 321, 021, 728, 729, 119
 Pass 2 ($i=2$): 119, 021, 728, 729, 321
 Pass 3 ($i=3$): 021, 119, 321, 728, 729

Sorted array: 021, 119, 321, 728, 729

$\theta(d(n+k))$ Count Sort for decimal number $K=9$

The correctness of RADIX-SORT follows by induction on the digit being sorted.

Why do we work from the lowest order digit to the highest? What would be required to work from high to low?

may digit
 insert d^2

Correctness of RADIX-SORT

Base Case: If $d = 1$, there's only one digit, so sorting on that digit sorts the array.

Assume: The sort on the low-order $d - 1$ digits correctly sorts the array if we ignore the higher order digits.

Inductive step: The sort on the d th digit will order the elements by their d th digit. Consider two elements, a and b , with d th digits a_d and b_d , respectively. There are three cases to consider:

1. If $a_d < b_d$, the sort will put a before b which is correct regardless of the lower order digits.
2. If $a_d > b_d$, the sort will put b before a which is correct regardless of the lower order digits.
3. If $a_d = b_d$, the sort will leave a and b in the same relative order because the sort is stable. Because the order was correct based on the $d - 1$ lower-order digits, a and b are in the correct order.

14

Complexity of RADIX-SORT

COUNTING-SORT is an excellent choice for the stable sorting algorithm used by RADIX-SORT. In that case, $T(n) = \Theta(d(n+k))$. If $k = O(n)$, then the running time is $O(dn)$ for d passes of COUNTING-SORT.

Example 1: If we sort binary numbers in the range of 1 to n , $k = 2$ and $d = \lg n$, then $T(n) = O(n \lg n)$.

Example 2: Same scenario, except that we increase k and decrease d by grouping the bits into groups of r bits, so that $k = 2^r$ and $d = \lg n / r$. Then $T(n) = O(\frac{\lg n}{r}(n + 2^r))$.

Example 3: Taking $r = \lg n$ we would get $T(n) = O(n)$ and $d = 1$; we are just doing COUNTING-SORT.

RADIX-SORT is also useful for sorting on multiple keys, where we treat each key as a "digit".

Bucket Sort

BUCKET-SORT sorts in linear time on the average by making a different kind of assumption than COUNTING-SORT.

Assumption: A (uniformly distributed) B $***$ over the range $[0, 1)$.

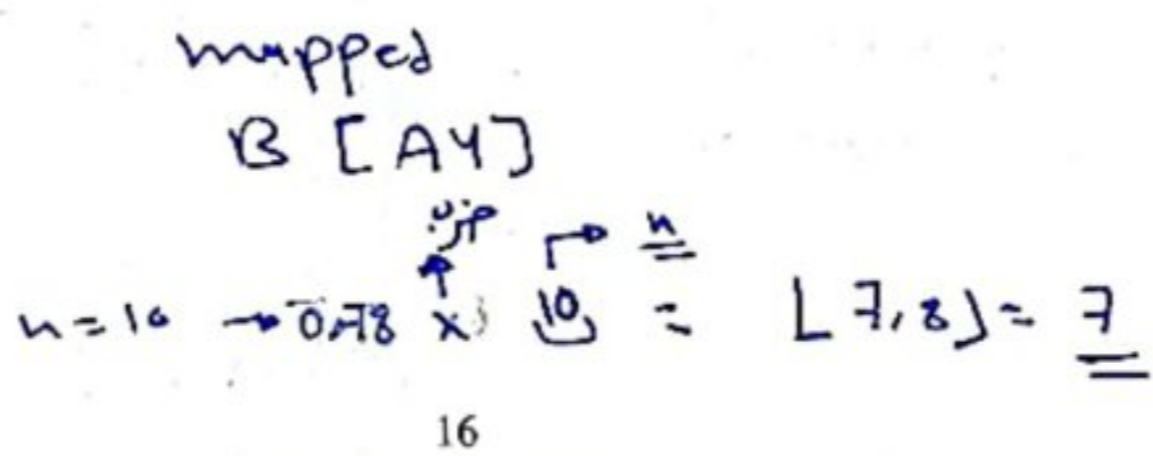
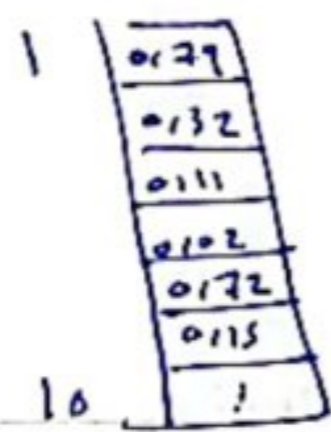
Data structures used:

1. **Input:** $A[1..n]$ where $0 \leq A[j] < 1$.

2. **Auxiliary:** $B[0..n-1]$ is a set of buckets corresponding to subintervals of $[0, 1)$ with which to classify and sort the elements of A . Each $B[i]$ is a pointer to a sorted list of $A[j]$'s that fall into bucket i . We place $A[j]$ into bucket $B[\lfloor nA[j] \rfloor]$, and bucket $B[i]$ holds $[\frac{i}{n}, \frac{i+1}{n})$.

$i=0 \rightarrow i=n-1$
bucket (i)
by holds values to A

Given that the elements in A are evenly distributed over interval $[0, 1)$, the $B[i]$ lists should be short.



BUCKET-SORT Algorithm

BUCKET-SORT(A)

1. $n \leftarrow \text{length}[A]$

2. **for** $i \leftarrow 1$ **to** n go over elements in A (2, ..., n)

3. **do** insert $A[i]$ into list $B[\lfloor nA[i] \rfloor]$ linear time

(linear time)

4. **for** $i \leftarrow 0$ **to** $n-1$ go over the bucket (0, ..., n-1)

5. **do** sort list $B[i]$ with **INSERTION-SORT**

(linear time)

(provided the condition)

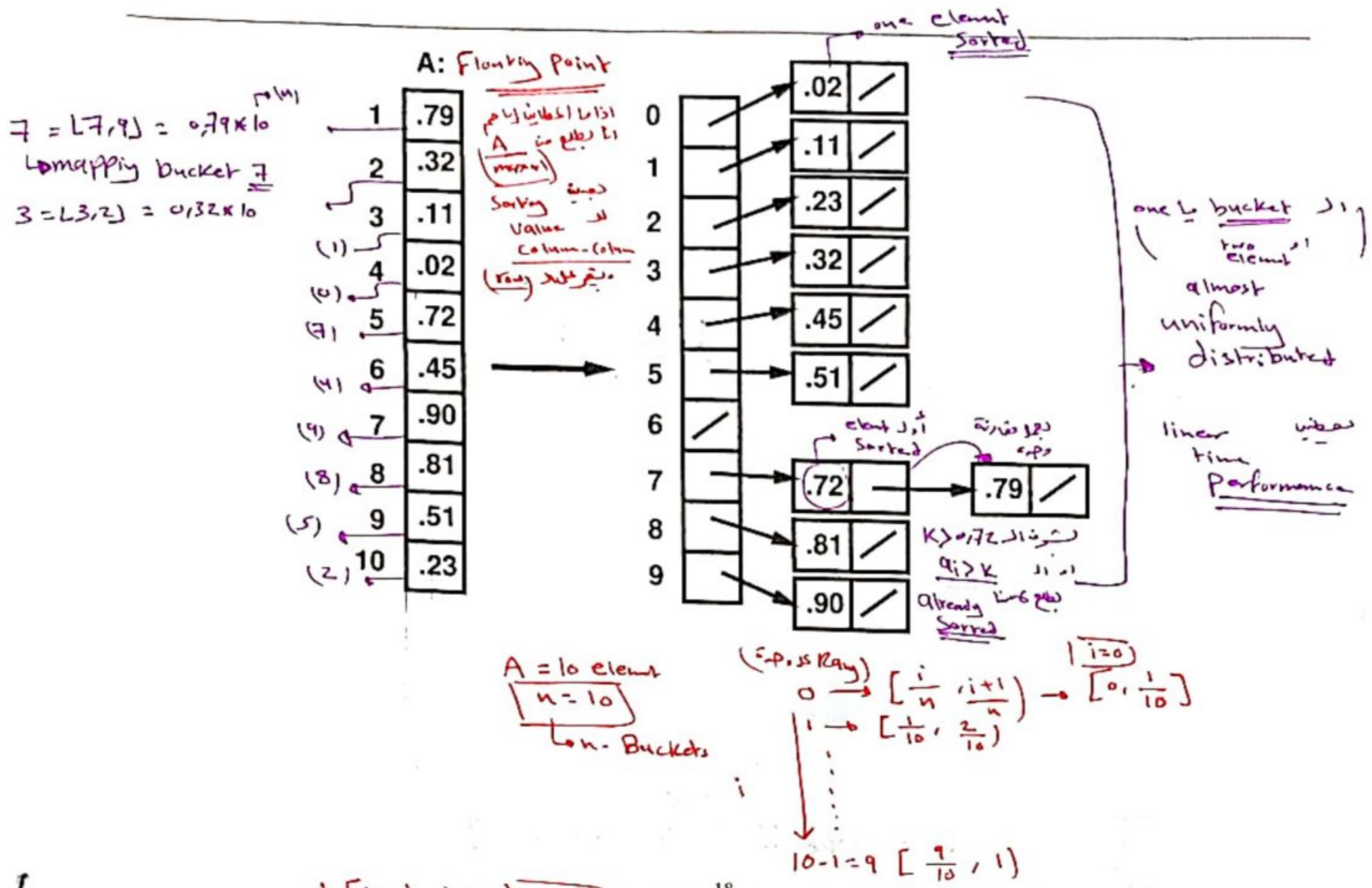
6. concatenate the lists $B[0], B[1], \dots, B[n-1]$ together in order consider the uniformly distributed condition

(Total linear time)
Performance

the insertion sort work in constant

linear $\leftarrow \text{Const} \times n \leftarrow$ one element per bucket or two element

BUCKET-SORT Example



كيفية mapping!؟ ضد كل k من عندك ما جزء $\lfloor \frac{n}{k} \rfloor$ و $\lfloor \text{Floor} \rfloor$ $n=10$

BUCKET-SORT Complexity

To analyze the running time, we observe that all steps except the INSERTION-SORT require $O(n)$ time. The question is how much time do the INSERTION-SORT calls require?

Bucket sort runs in expected time $O(n)$. The worst case is $O(n^2)$ however, as all numbers could conceivably land in the same bucket.

Handwritten notes:
 on AV + Best case
 one bucket
 element

motivation we need to have a support to perform Query and modification in constant time on AV

Lecture 8: Search and Hash Tables

(data structure) عبارة
dynamic data structure الدائرية

- 1) Modification
- 2) Querying

Course Learning Outcomes (CLOs):

- Use advanced searching techniques, such as hashing and 2-3 trees.
- Show how time and space complexities can be traded-off (e.g. distribution counting sort, hashing).

n : worst case
1 : Best case

Dr. Khalil Yousef

* لو امكننا عملية Search لوال element موجودة في
(Search في Hash في وقت ثابت اي ان Search Constant بدل linear في AV)

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

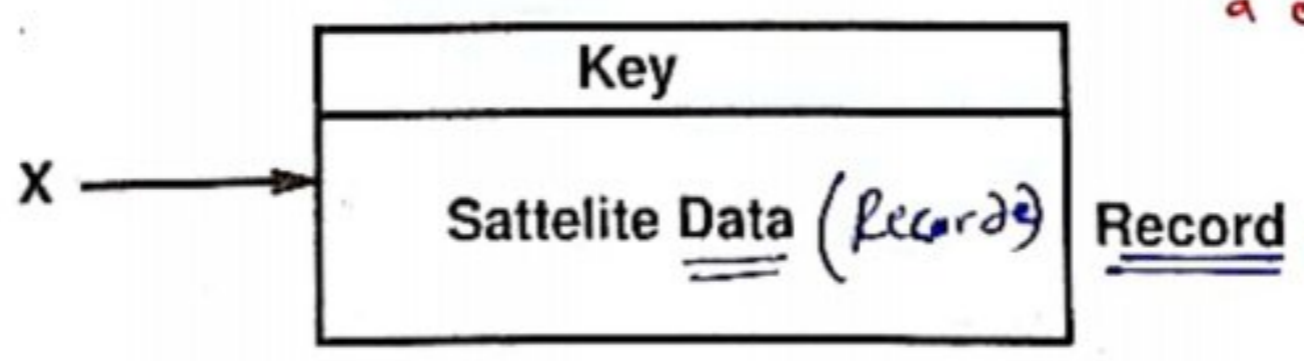
Review Chapter 10 and Read Chapter 11 of *Introduction to Algorithms*

Sets

set of element
 - static - we can't Add, remove element to the set.
 - dynamic - the size of the set can change due to insertion and deletion.

A fundamental concept in computer science is the (dynamic set) which can grow and shrink over time. For example, a dictionary is a dynamic set that supports the insertion and deletion of elements, as well as a membership test.

Each element in a dynamic set is represented as an object whose fields can be examined or modified if we have a pointer to the object. Elements often have a key field as well as satellite data. For example:



Ex. of a dynamic set:
 Consider a set of User names to login to a certain machine.
 Each user name must contain 8 small alphabetic letters.
 Consider the size of the set to be 100.
 4

The best way to implement a set depends on the operations that are supported on the set. It is also important to consider the number of elements that will be stored in the set S , $|S|$, and compare it to the size of the universe U , $|U|$ (the set of elements that could conceivably be in S).

بنفسه

Operations on Sets

Operations on sets are either queries or modifying operations. The running time of these operations is reported in terms of the size of the set.

- SEARCH(S, k): a query that returns a pointer x to an element in S such that $key[x] = k$ or NIL if there is no such element in S .
(المكانات Records)
 (ادوات صمم)
- INSERT(S, x): a modifying operation such that $S \leftarrow S \cup \{x\}$.
- DELETE(S, x): a modifying operation such that $S \leftarrow S - \{x\}$.
- MINIMUM(S): a query on a totally ordered set S such that a pointer to the element with the smallest key in S is returned.
(الترتيب مرتبة)

2

Operations on Sets *continued*

- MAXIMUM(S): a query on a totally ordered set S such that a pointer to the element with the largest key in S is returned.
(الترتيب مرتبة) (اضاعدي)
- SUCCESSOR(S, x): a query on a totally ordered set S such that a pointer to the smallest element in S greater than x is returned, unless x is the maximum, in which case NIL is returned. This can easily be extended to sets with duplicate keys.
(مرتبة)
 ترتيب عدد (بما يتبع المجموعة)
 لا يوجد $e < k_x$
 (د)
- PREDECESSOR(S, x): a query on a totally ordered set S such that a pointer to the largest element in S less than x is returned, unless x is the minimum, in which case NIL is returned. This can easily be extended to sets with duplicate keys.
(مرتبة Sorted)

Set Examples

- The login table for a computer system with 100 users where logins are of length 10 and consist of lower case alphabetic characters; $|U| = 26^{10}$, $|S| = 10^2$. Support INSERT, DELETE, and SEARCH.

↳ Subset
100

$|U| \gg |S|$
 26^{10} (lower case letters) (Size) 100
 ال (100) جاينين 26¹⁰
 * لا ما بركتار 14: راجع بديتيا اجز
 ↳ small + cap ⇒ 26+26 = 52
 ↳ numerical ⇒ 10
 ↳ special char. ⇒ 10
 minimal length is 14
 $52 + 10 + 10 = 72$
 $|U| = 72^{14}$

4

Implementation Issues for Dictionaries

One way to implement a dictionary is as a linear list. In this case, SEARCH can take $\Theta(n)$ time in the worst case, and at least one of the INSERT or DELETE operations can take $\Theta(n)$ time in the worst case.

One way to implement a dictionary is as a heap. In this case, the INSERT and DELETE operations can take $\Theta(\lg n)$ time in the worst case. What about the running time of SEARCH?

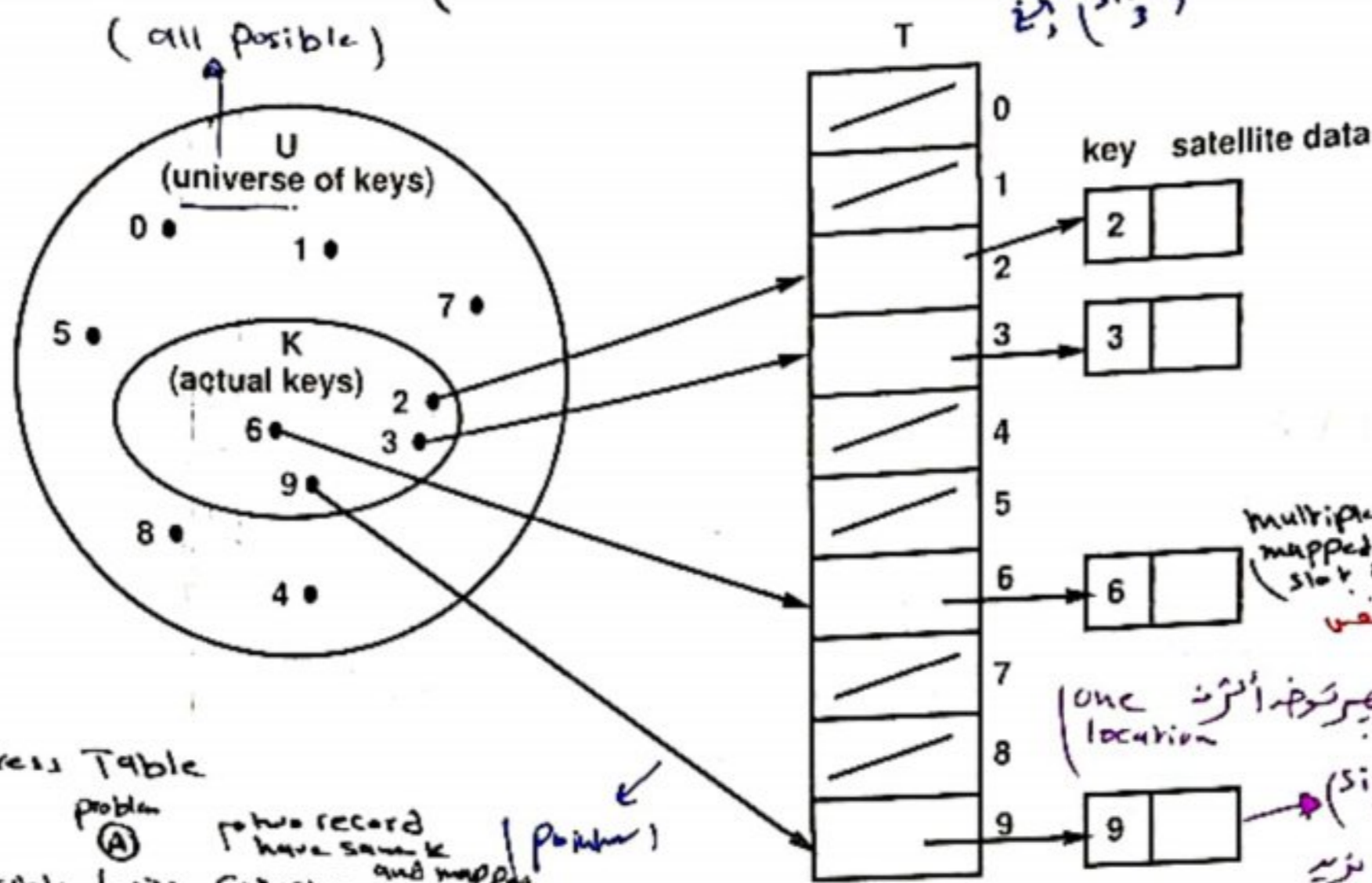
We would like to use a datastructure that supports efficient dynamic set operations. In particular, we would like the INSERT, SEARCH, DELETE operations to take $O(1)$ time.

The Direct-Address Table

To represent a dynamic set, we can use a direct-address table $T[0..m-1]$ where each slot corresponds to a key in the universe and:

$$T[i] = \begin{cases} x & \text{if } x \in S \text{ and } \text{key}[x] = i, \\ \text{NIL} & \text{otherwise.} \end{cases}$$

Size of the Table = m
 Size of the Key = n
 $\alpha = \frac{n}{m}$ (load factor)
 $n > m, \alpha > 1$ (overflow)



Direct Address Table
 Hash Table (with Collision and mapping Avoidance strategies)
 (1) chaining
 (2) open Addressing

Multiple keys mapped same slot in table (Duplicate records)
 one location
 Size of the Table
 Element
 Overflow
 Size Table

The Direct-Address Table continued

All of the following operations on a direct-address table are $O(1)$:

1. DIRECT-ADDRESS-SEARCH(T, k)

return $T[k]$ → constant

2. DIRECT-ADDRESS-INSERT(T, x)

$T[\text{key}[x]] \leftarrow x$

3. DIRECT-ADDRESS-DELETE(T, x)

$T[\text{key}[x]] \leftarrow \text{NIL}$

Direct Addressing is a simple technique that works well if the universe of keys, $U = \{0, 1, 2, \dots, m-1\}$, is relatively small and no two elements have the same key.

Hash Tables

Problem: usually the range of keys is much larger than the desired table size m (e.g., ASCII strings).
 (over Flow + Duplicate) \Rightarrow collision (Problem)
 from 0 to $m-1$

A **hash table** is a generalization of an ordinary array which supports the direct addressing of an element in the table in $O(1)$ average case time, although the worst case time is $\Theta(n)$.
 (دالة التجزئة) \Rightarrow mapping $\{0, \dots, m-1\}$ Table Slots
 (مجموعه المفاتيح) \Rightarrow universe of keys U
 (مجموعة المفاتيح الفعلية) \Rightarrow actual keys K
 (مؤشر) \Rightarrow index
 (تكرار) \Rightarrow duplicate
 (مجموعه المفاتيح) \Rightarrow set of keys
 (مجموعه المفاتيح) \Rightarrow set of keys
 (مجموعه المفاتيح) \Rightarrow set of keys

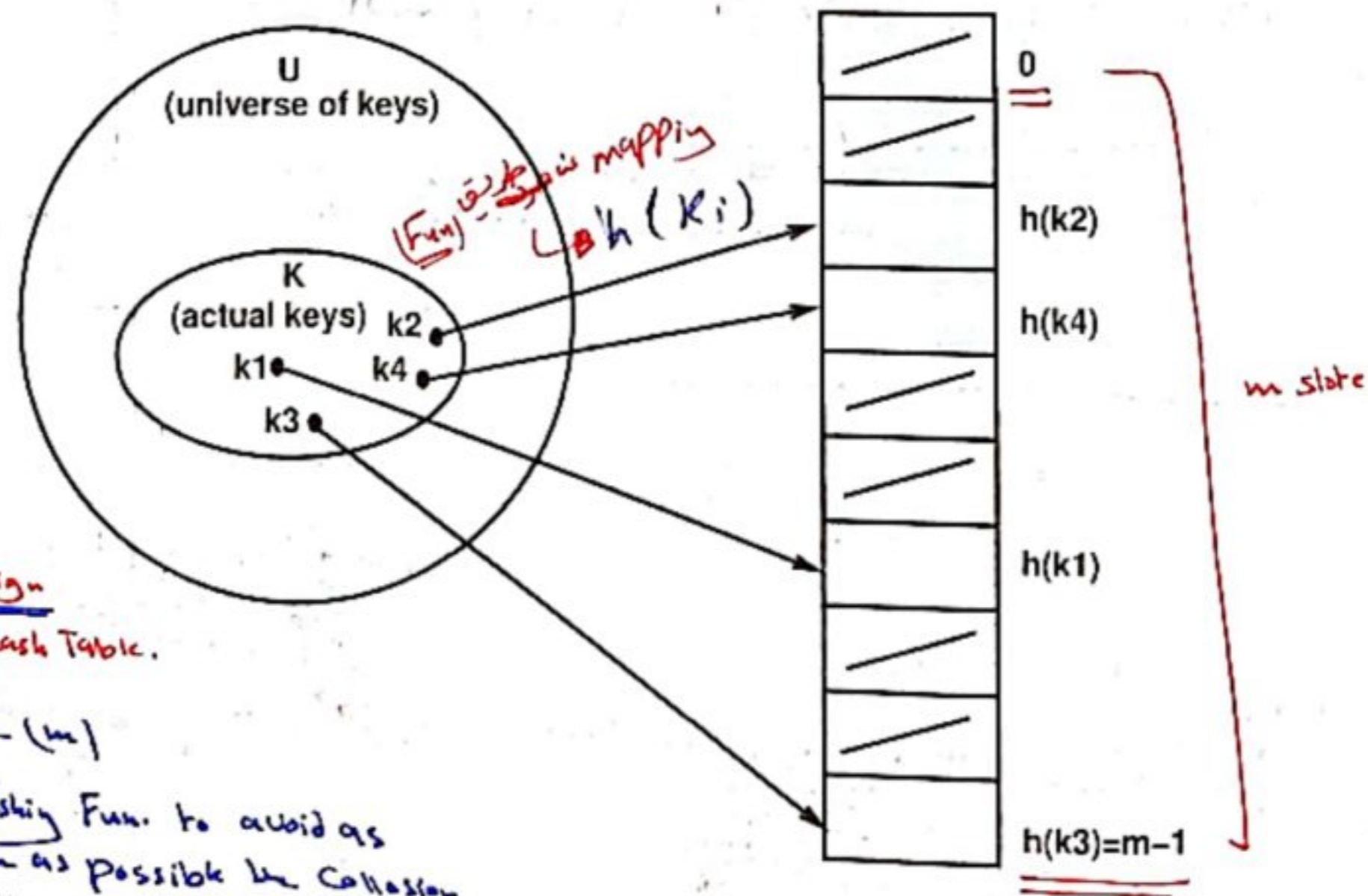
The idea is to store keys in a large hash table of size m (say $n \leq m \leq 2n$, where n is the number of keys to store) such that the data is scattered across the table uniformly.
 (Bucket Sort)
 (توزيع المفاتيح على الخانات) \Rightarrow scatter data across the table

The INSERT, SEARCH, DELETE operations on a hash table take $O(1)$ average case time, as we shall see.

Example: A symbol table in a compiler is often represented using a hash table, where each element key consists of the string of characters to store in the table.

Hash Tables continued

The element with key k is stored in slot $h(k)$ given that h is a function which maps a key $k \in U$ to an index of hash table $T[0..m-1]$. Note that $h : U \rightarrow \{0, 1, \dots, m-1\}$ given that m is the size of the hash table. h should be computable in $O(1)$ time.



- two important design parameters to the hash table.
- 1) Hash Table size (m)
 - 2) choice of the hashing Fun. to avoid as reduce as much as possible the collision of multiple keys.

Hash Tables continued

If K represents the set of keys to store and $|K| \ll |U|$, then, by using a hash table, we can reduce the storage space for T to $\Theta(|K|)$ and still access the elements in $O(1)$ average case time.

(مستند الـ Password)
 حجم الـ Table
 بجدول الـ Hash

Hashing schemes perform very well in practice when the maximum number of keys is known in advance and can be implemented in fewer than 200 lines of C or C++ code!

Problem: A collision occurs if $h(k_1) = h(k_2)$.

Two keys same hash value
 نفس الـ hash
 طرفة متساوية

It is best to avoid collisions altogether by obtaining a suitable hash function that minimizes the number of collisions. However, if $|K| > m$, there will be keys that hash to the same index; hence, collision avoidance is not possible.

ما ينفرد
 Collision

Fortunately, there are effective techniques for resolving the conflicts created by collisions.

Collision Resolution Methods

إذا الـ index
 إذا الـ index
 Lots of Deletion
 Deletion عند الـ index
 open addressing

There are two methods for resolving collisions:

linked:
 Pointer

1. **Chaining:** Keep a linked list of the elements that hash to the same index. This method is simple to implement and degrades gracefully when the number of keys n exceeds (the table size m). It uses dynamic memory allocation.

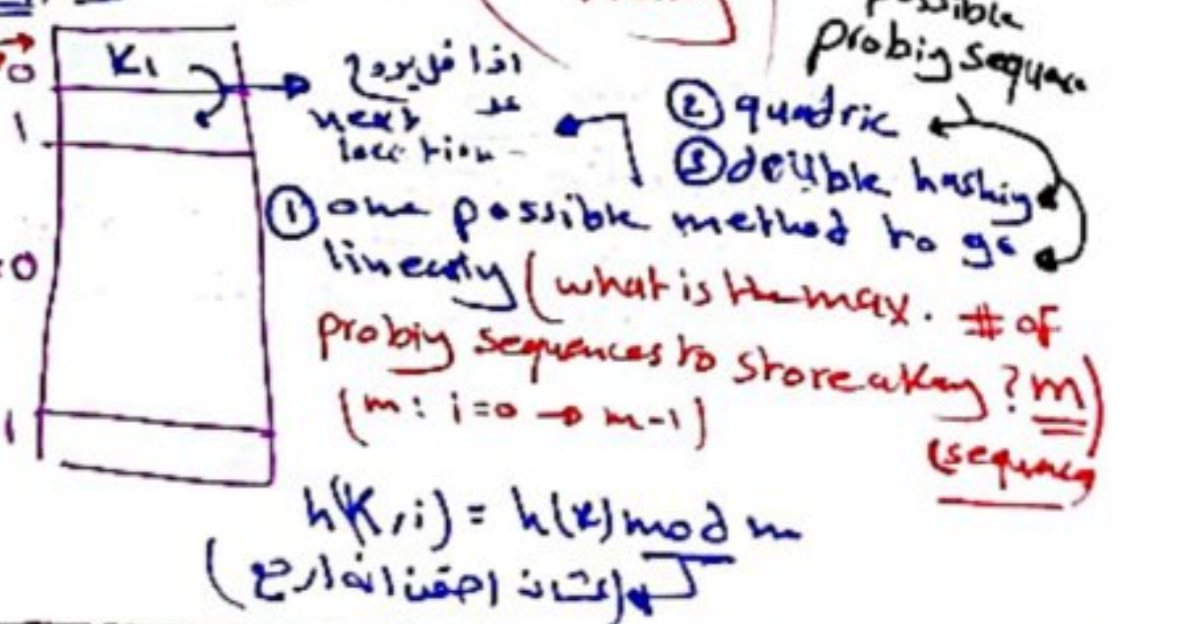
شأن تضمن يكون
 on AV we have Constant Performance
 worst case
 mapped الـ
 بالـ index
 one linked list

2. **Open Addressing:** Store all keys in the table itself, and if a collision occurs, then use some method to obtain another location to place the item in the table.

This is easy to implement and no dynamic memory allocation is used; however, n must be less than or equal to m , performance degrades as $n \rightarrow m$, and deletion operations are difficult to support, as we shall see.

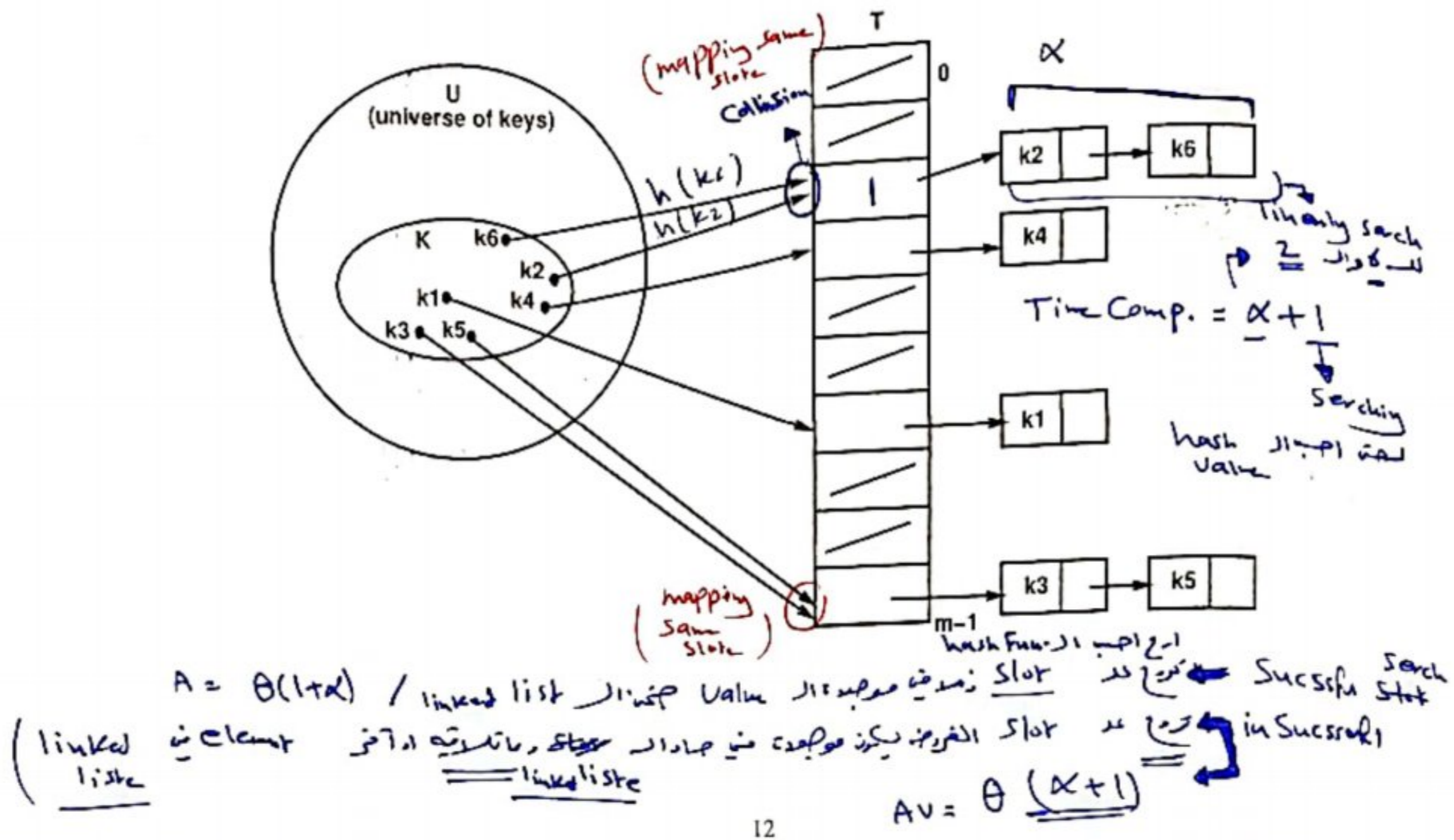
Search عملية
 linear timing
 possible Probig Sequence
 quadratic
 double hashing
 one possible method to go linearly (what is the max. # of Probig sequences to store a key? m)
 ($m: i=0 \rightarrow m-1$)
 ($h(k, i) = h(k) \bmod m$)

use a Probig method to find an empty location for k_2 star in next best Probig and $h(k_1) = h(k_2) = 0$
 $\alpha = \text{load factor} = \frac{n}{m}$ at least larger or equal to 1
 α in open addressing must be ≤ 1 or less
 element



Collision Resolution by Chaining

The simplest collision resolution technique is called chaining. The basic idea is that all items that hash to the same index are stored in a linked list pointed at by that table entry.



Collision Resolution by Chaining *continued*

The operations on the chained hash table are defined below:

- 1. CHAINED-HASH-SEARCH(T, k)**
 search for an element with key k in $T[h(k)]$

The worst case running time is proportional to the length of the list. (α)

- 2. CHAINED-HASH-INSERT(T, x)**
 insert x at the head of the list $T[h(key[x])]$

The worst case running time is $O(1)$.

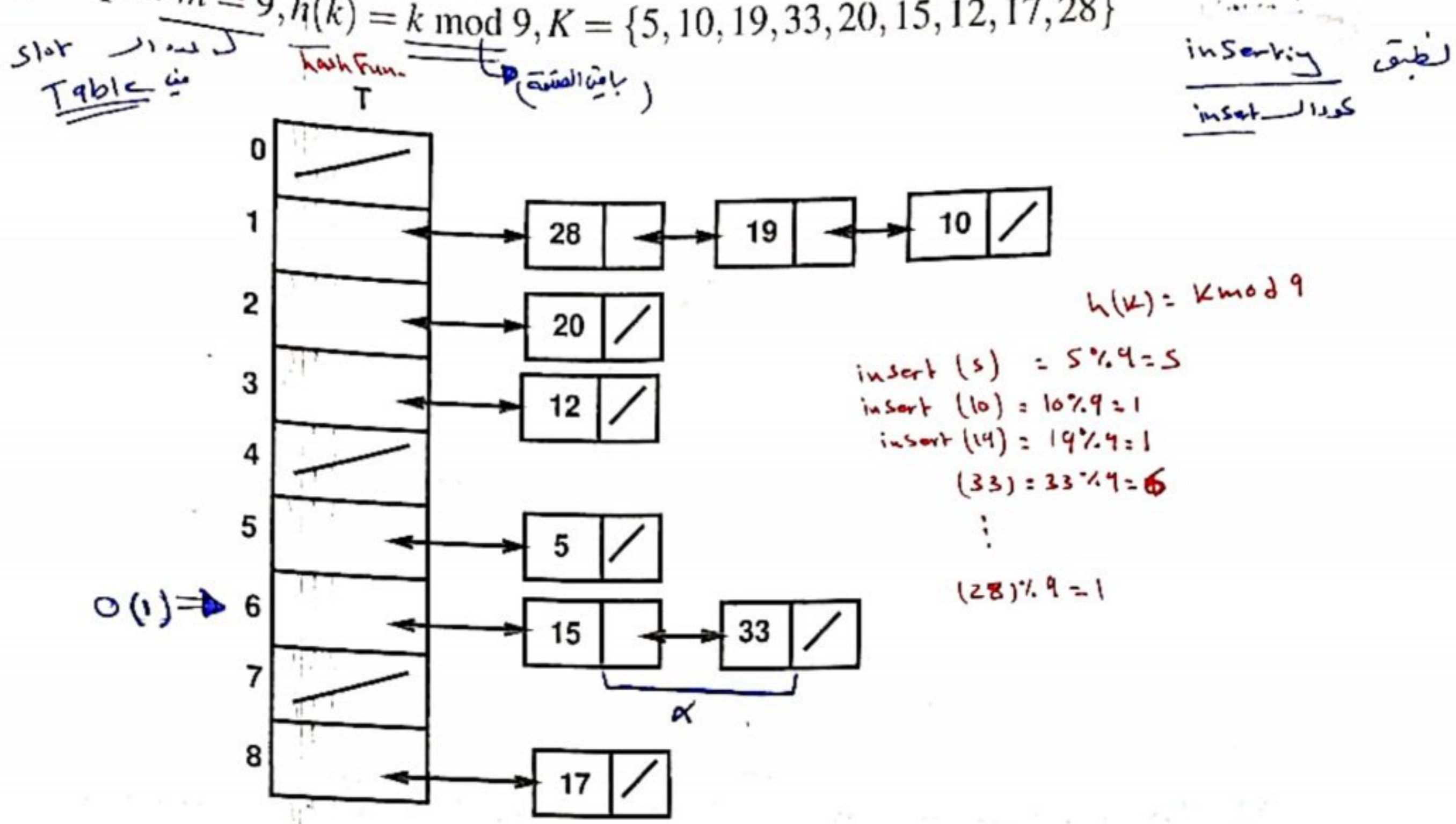
- 3. CHAINED-HASH-DELETE(T, x)**
 delete x from list $T[h(key[x])]$

The worst case running time is $O(1)$ if the list is doubly linked. If singly linked, it must search for x 's predecessor to perform the operation.

$(1 + \alpha)$
 double pointer
 لغيره + العنصر

An Example of Hashing with Chaining

Example: $m = 9, h(k) = k \bmod 9, K = \{5, 10, 19, 33, 20, 15, 12, 17, 28\}$



Analysis of Hashing with Chaining

The worst case running time to search for an element in hashing with chaining is $\Theta(n)$, when all keys hash to the same slot.

The average case depends on how well the n keys are distributed among the m slots.
 simple uniform hashing, $\alpha = \frac{n}{m}$, size of each linked list = α (load factor), $\Theta(1 + \alpha)$

Given a hash table of size m and n elements to store in the table, we define **load factor** as $\alpha = \frac{n}{m}$. Our analysis will be in terms of α .

For analysis, we will make the assumption of **simple uniform hashing**, which means that any given element is equally likely to hash into any of the hash table slots, independently of the other elements.
 simple uniform hashing, any key is equally likely to hash any of the m slots of the hash table.

prob. [1 key mapped to 1 one of m the n slots] = $\frac{1}{m}$

Compare with (uniform hashing assumption)

open addressing

Analysis of Hashing with Chaining *continued*

Theorem: In a hash table in which collisions are resolved by chaining, an unsuccessful search takes time $\Theta(1 + \alpha)$, on average, under the assumption of simple uniform hashing.

Proof:

- The assumption of simple uniform hashing implies that any key k is equally likely to hash to any of the m slots. ($\frac{1}{m}$)
- The average time to search unsuccessfully for key k is the average time to search one of the m lists.
- Given that the average length of a list is $\alpha = \frac{n}{m}$, the expected number of elements to examine in an unsuccessful search is α .
- Hence, the total time required is $\Theta(1 + \alpha)$ (including the time to compute $h(k)$).
Chaining

Analysis of Hashing with Chaining *continued*

Theorem: In a hash table in which collisions are resolved by chaining, a successful search takes time $\Theta(1 + \alpha)$, on average, under the assumption of simple uniform hashing.

Proof: See the textbook.

Hash Table Size

The following are guidelines on the selection of hash table size, m : ^{more using}

- Select m as a prime number or power of two. In theory the prime is slightly better (more choice when picking a hash function and universal hashing can be used more easily), but in practice we tend to choose $m = 2^k$ (eliminates the need to do modulo operations).

- If using chaining, use $n \leq m \leq 2n_{max}$, where n_{max} is the maximum number of keys to be stored in the table at one time. Nothing hinges on a particular choice.

- For open addressing with double hashing, use $\frac{3}{2}n_{max} \leq m \leq 2n_{max}$. Larger values result in better performance.

two design any $n \leq m \leq 2n$
 $\frac{3}{2}n \leq m \leq 2n$

Hash Functions

Often keys are similar or clustered, but we do not want this regularity of key distribution to affect uniformity of the hash function. $h(x)$ and $h(x + \epsilon)$ should differ, where ϵ represents some small change (e.g., integer, real, or string).

A good hash function should come close to satisfying the assumption of simple uniform hashing. More formally, assume that each key is drawn independently from U according to the probability distribution P , where $P(k)$ is the probability that key k is drawn, then:

$$\sum_{k:h(k)=j} P(k) = \frac{1}{m} \quad j = 0, 1, \dots, m-1$$

Unfortunately, P is generally unknown (though sometimes it is, for example, random reals in the range $[0..1)$).

Usually heuristic techniques are used to create hash functions that perform fairly well. Sometimes stronger assumptions are required than simple uniform hashing.

Most hash functions assume that the universe of keys is the set of natural numbers (or that they can be mapped to natural numbers).

Hash Functions *continued*

① **Division method:** $h(k) = k \bmod m$

Example: If $m = 52$ and $k = 235$, then $h(k) = 27$.

Rules of thumb:

- Avoid powers of 2 as the value of m ; otherwise, not all bits of the key will be used by the function. If $m = 2^p$, then only the lowest order p bits will be used!
- Avoid powers of 10 when decimal numbers are used as keys.
- If $m = 2^p - 1$ and k is a character string interpreted in radix 2^p , then keys that are permutations of the same digits hash to the same slot! For example, 51 in radix 2^4 ($5 \times 16^1 + 1 \times 16^0 \bmod 15 = 6$) collides with 15 in radix 2^4 ($1 \times 16^1 + 5 \times 16^0 \bmod 15 = 6$) when $m = 15$. (See 11.3-3.)
- Good values of m are primes not too close to a power of 2.

Example: If $n = 2000$, and we are willing to examine 4 elements on average during search, then $h(k) = k \bmod 491$ is a good choice (512 is the power of 2).

Hash Functions *continued*

Multiplication method:

Refer to the book for further details on this method.

Open Addressing

Open Addressing: All elements are stored directly in the hash table (i.e., there are no pointers); hence, either there is an element or NIL in a table entry.

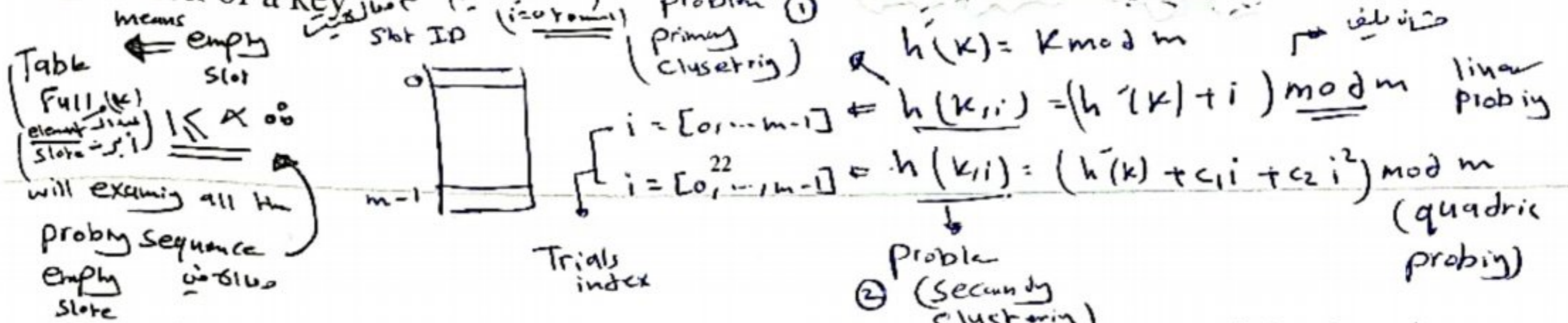
The hash table is now a static entity that can fill up, so $\alpha \leq 1$. This method trades pointers for table size.

To perform a table insertion, we now **probe** the hash table for an empty slot in some (systematic) way. Instead of using a fixed order; however, the sequence of positions probed depends on the key to be inserted.

The hash function is redefined as:

$$h: U \times \{0, 1, \dots, m-1\} \rightarrow \{0, 1, \dots, m-1\}$$

For every key k , the **probe sequence** $\langle h(k, 0), h(k, 1), \dots, h(k, m-1) \rangle$ is considered. As the table fills up, every position in the table is a possible option for the insertion of a key.

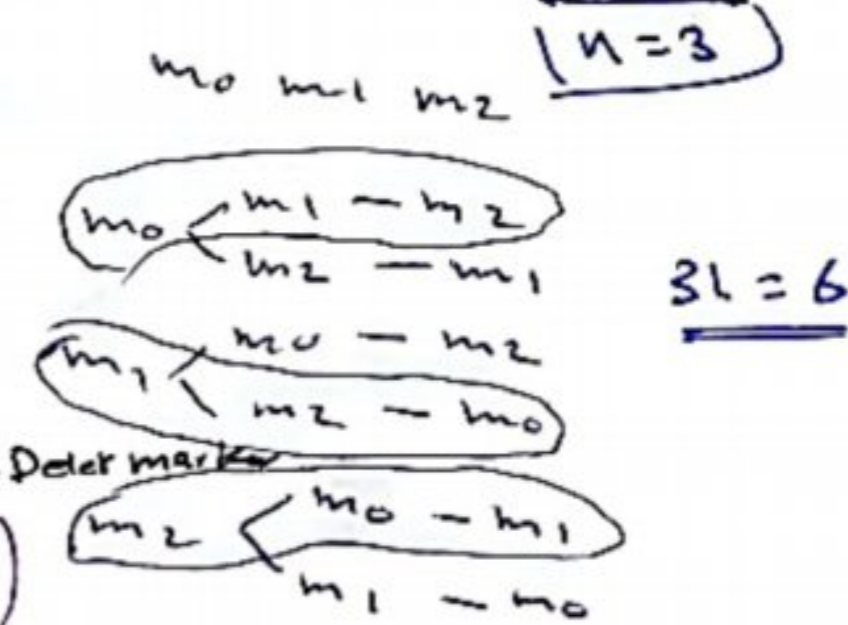


Open Addressing continued

We assume that we are storing only keys in the table; there is no satellite data; hence, a table slot either contains a key k or NIL.

HASH-INSERT(T, k)

1. $i \leftarrow 0$
2. **repeat** $j \leftarrow h(k, i)$
3. **if** $T[j] = NIL$ **then** $T[j] \leftarrow k$ **insert**
4. **return** j
5. **else** $i \leftarrow i + 1$
6. **until** $i = m$
7. **error** "hash table overflow"



of possible permutations of the m slot = $m!$ possible probing seq.

Linear $\frac{1}{m}$

Quadratic $\frac{1}{m^2}$

Double $\frac{1}{m^2}$

prob[] = $\frac{1}{(m-1)!}$

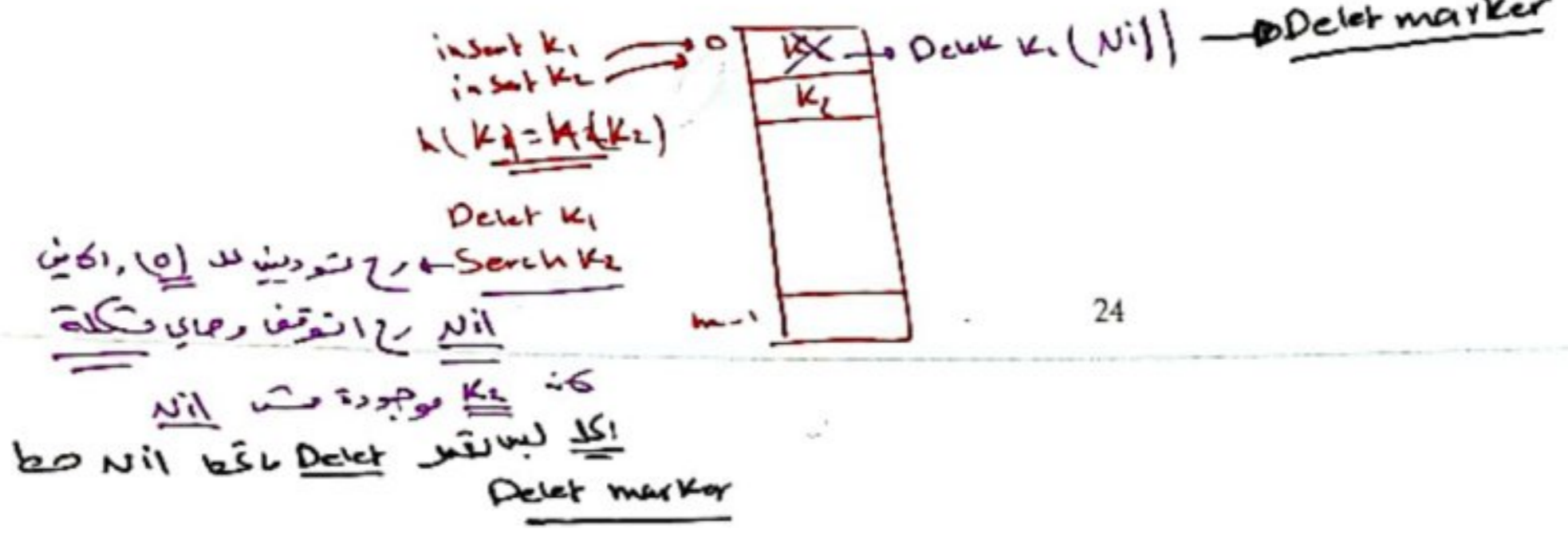
Open Addressing *continued*

HASH-SEARCH uses the hash function to search for key k , and it will terminate if it finds k in the slot, returning the index where the item is found. It also terminates with NIL if it finds NIL in a probed slot or if it searches the entire table without success.

HASH-SEARCH(T, k)

1. $i \leftarrow 0$
2. **repeat** $j \leftarrow h(k, i)$
3. **if** $T[j] = k$
4. **then return** j (index)
5. $i \leftarrow i + 1$
6. **until** $T[j] = \text{NIL}$ or $i = m$
7. **return** NIL

Handwritten notes:
 - Insertion: $insert$ (تدبير) / $insert$ (تدبير) / $insert$ (تدبير)
 - Hash value: $hash$ (قيمة)
 - Table slot: $Table$ slot (موقع في الجدول)
 - Deletion: $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف)
 - Search: $Search$ (تفتيش) / $Search$ (تفتيش) / $Search$ (تفتيش)
 - Stop: $stop$ (توقف) / $stop$ (توقف) / $stop$ (توقف)
 - Probe seq.: $probe$ seq. (تسلسل التفتيش)
 - Deletion marker: $Deletion$ marker (علامة الحذف)
 - If $T[j] = k$ then return j (index) (إذا $T[j] = k$ فارجع j (القيمة))
 - If $T[j] = \text{NIL}$ or $i = m$ then return NIL (إذا $T[j] = \text{NIL}$ أو $i = m$ فارجع NIL)
 - $i \leftarrow i + 1$ (إذا $i < m$ فزد i بـ 1)



Deleting in an Open-address Table

We cannot simply delete an element in a table by inserting a NIL; it could break the probe sequence for other elements in the table.

It is possible to get around this by using pointers, which goes against the spirit of open addressing.

We could also use a special purpose delete marker instead of NIL when an element is removed.

Then HASH-SEARCH will automatically search further when looking for other elements when encountering the delete marker. HASH-INSERT can be modified to treat the delete marker as NIL. However, using this approach, the search time is no longer dependent only on the load factor α .

Because deletion in open-address hash tables is difficult, usually open-address hashing is not done when delete operations are required.

Handwritten notes: $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف) / $Deletion$ (حذف)

Probe Sequences

In the analysis of open addressing, we make the assumption of uniform hashing, which requires that each key considered is equally likely to have any of the $m!$ permutations of $\{0, 1, \dots, m-1\}$ as its probe sequence. $prob. [j] = \frac{1}{m!}$

Three techniques are commonly used to compute probe sequences for open addressing:

1. linear probing m out of $m!$
2. quadratic probing m out of $m!$
3. double hashing m^2 out of $m!$

$\frac{1}{m!} \neq \frac{m}{m!}$ (not equal)

اضربوا m في m (المربع)

These techniques guarantee that $\langle h(k, 0), h(k, 1), \dots, h(k, m-1) \rangle$ is a permutation of $\langle 0, 1, \dots, m-1 \rangle$ for each key k , but none fulfills the assumption of uniform hashing since none can generate more than m^2 sequences.

Linear Probing

Given $h' : U \rightarrow \{0, 1, \dots, m-1\}$, linear probing uses the hash function: $h(k, i) = (h'(k) + i) \bmod m$ for $i = 0, 1, \dots, m-1$.

Given key k , the first slot probed is $T[h'(k)]$, then $T[h'(k) + 1]$, $T[h'(k) + 2]$, etc. Hence, the first probe determines the remaining probe sequence.

Example: $h'(k_1) = h'(k_2) = j$, $h'(k_3) = j+1$, $h'(k_4) = j$, and the keys are entered in the order: k_1, k_2, k_3, k_4 , giving the following table:

hash table (open addressing)

1	2	3	4	5	6	7	8
k_1	k_2	k_3	k_4				

$m = 8$

insert 4 keys

k_1	$i=0$
k_2	$i=1$
k_3	$i=1$
k_4	$i=3$

Collision

no other collision

(Problem)

$h(k_1) = j / h(k_2) = j / h(k_3) = j+1 / h(k_4) = j$

$h(k, i) = [h(k) + i] \bmod m$

$k_1 = h(k_1) + 0 \rightarrow k_1 \rightarrow 0$ empty

$k_2 = h(k_2) + 0 \rightarrow k_2 \rightarrow 0$ not empty

$i=1$ not empty

$k_3 = h(k_3) + 0 = j+1$

$i=1$ Collision $i=1 \rightarrow i++$

$i=2$

$k_4 = h(k_4) + 0 = j$

Collision $i=1$

$i++$ Collision $i=2$

$i++$ Collision $i=3$

$i++$ empty \therefore insert

This method is easy to implement, but suffers from primary clustering, that is, two keys that hash to different locations compete with each other for successive rehashes. Hence, long runs of occupied slots build up, increasing search times.

ردائي بعد نفس المكان اضطررت ان ادره بعد ان اتقن للبايعه مع بعدي حائل

Quadratic probing

Solved the Primary clustering problem but faced another problem secondary clustering.

Quadratic hashing uses a hash function of the form:

الخطوة الأولى Linear Hashing (Primary)

$$h(k, i) = (h'(k) + c_1 i + c_2 i^2) \text{ mod } m$$

where h' is an auxiliary hash function, $c_1, c_2 \neq 0$ are auxiliary constants, and $i = 0, 1, \dots, m-1$. Note that m, c_1 , and c_2 must be selected carefully.

The initial probe position is $T[h'(k)]$, with subsequent positions depending on a quadratic function of the probe number i .

Example: probe sequence given $c_1 = c_2 = 1 \rightarrow i + i^2$

J	J+1	J+2	J+3	J+4	J+5	J+6	J+7	J+8	J+9	J+10	J+11	J+12	J+13
P1		P2				P3							P4

Quadratic probing is better than linear probing because it spreads subsequent probes out from the initial probe position. However, when two keys have the same initial probe position, their probe sequences are the same, a phenomenon known as secondary clustering.

secondary clustering

Solving this problem Double Hashing

4 keys to be inserted in an open addressing hash table in which collisions are sorted by resolved

let $h'(p_1) = h'(p_2) = h'(p_3) = h'(p_4) = J$ for all keys.

Assum $h'(k) = J$

$h(k, i) = h(k) + i + i^2$

$P_1 \Rightarrow h(P_1) + 0 + 0 = J$
 $P_2 \Rightarrow h(P_2) + 0 + 0 = J$ (Collision), $i+1$
 $P_3 \Rightarrow h(P_3) + 1 + 1 = J+2$ empty
 $P_4 \Rightarrow h(P_4) + 0 + 0 = J$ Collision, $i+1$
 $h(P_4) + 1 + 1 = J+2$ Collision, $i+1$

$h(P_1) + 2 + 4 = J+6$
 $h(P_2) + 3 + 9 = J+12$
 $h(P_3) + 4 + 16 = J+20$
 $h(P_4) + 5 + 25 = J+30$

Table in which collisions are sorted by resolved
 J P1 (i=0)
 J+1 P2 (i=1)
 J+2 P2 (i=1)
 J+3
 J+4
 J+5
 J+6 P3 (i=2)
 J+7
 J+8
 J+9
 J+10
 J+11
 J+12 P4 (i=3)
 J+13

Double hashing is one of the best open addressing methods available because the permutations produced have many of the characteristics of randomly chosen permutations. It uses a hash function of the form:

Secondary & Primary

$$h(k, i) = (h_1(k) + i \cdot h_2(k)) \text{ mod } m$$

where h_1 and h_2 are auxiliary hash functions.

The initial position probed is $T[h_1(k)]$, with successive positions offset by the amount $(i h_2(k)) \text{ modulo } m$.

Now, keys with the same initial probe position can have different probe sequences.

Note that $h_2(k)$ must be relatively prime to m for the entire hash table to be accessible for insertion and search. If $d = \text{GCD}(h_2(k), m) > 1$ for some key k , then search for key k would only access $\frac{1}{d}$ th of the table. (See Chapter 33.)

Double Hashing *continued*

A convenient way to ensure that $h_2(k)$ is relatively prime of m is to select m as a power of 2 and design h_2 to produce an odd positive integer. Or, select a prime m and h_2 to produce a positive integer less than m .

Example: $h_1(k) = k \bmod m$, $h_2(k) = \underline{1} + (k \bmod m')$, where m' is slightly less than m .

Double hashing is an improvement over linear and quadratic probing in that $\Theta(m^2)$ sequences are used rather than $\Theta(m)$, since every $(h_1(k), h_2(k))$ pair yields a distinct probe sequence, and the initial probe position, $h_1(k)$, and offset, $h_2(k)$, vary independently.

Double Hashing *continued*

Example: Use double hashing to store the keys 10, 18, and 34 in a hash table of size $m = 8$, using:

$$h_1(k) = k \bmod 8, h_2(k) = 1 + (k \bmod 6)$$

0	1	2	3	4	5	6	7
		10	18				34
		↓ $i=0$	↓ $i=1$				↓ $i=1$

$$h(k, i) = (h_1(k) + i h_2(k)) \bmod 8$$

Handwritten calculations:

Insert $k=10, i=0$
 $10 \% 8 = 2 + 0(1 + 10 \% 6) = 2$ ✓ Slot insertion

Insert $k=18, i=0$
 $18 \% 8 = 2 + 0(1 + 18 \% 6) = 2$ Collision
 $i++$, $i=1$
 $h(18, 1) = 2 + 1(1 + 0) = 3$ ✓ Slot insertion

Insert $k=34, i=0$
 $34 \% 8 = 2 + 0(1 + 34 \% 6) = 2$ Collision
 $i++$, $i=1$
 $h(34, 1) = 2 + 1(1 + 4) = 7$ ✓ Slot insertion

Analysis of Open-Address Hashing

Theorem: Given an open-address hash table with load factor $\alpha = \frac{n}{m} < 1$ the expected number of probes in an unsuccessful search is at most $\frac{1}{1-\alpha}$, assuming uniform hashing.

عزم حرة
رج تنظر
نحوه (نا)
كدرما نعمل

Proof:

• Refer to the book for the proof.

(Theoretically assumption) لتبين

ازمانه و ال...
بجفتال
uniform hashing
ازمانه و ال...
بجفتال

Table size
عدد العنصر

let $n=20, m=40$ Find α ?
② expected # of probe.

Sol

① $\alpha = \frac{n}{m} = \frac{20}{40} = 0.5$

② expected = $\frac{1}{1-\alpha} = \frac{1}{1-0.5} = 2$

Analysis of Open-Address Hashing *continued*

Corollary 12.6. Inserting an element into an open-address hash table with load factor α requires at most $\frac{1}{1-\alpha}$ probes on average, assuming uniform hashing.

Proof:

Insertion of a key requires an unsuccessful search followed by the placement of the key in the first empty slot found. Thus the expected number of probes is at most $\frac{1}{1-\alpha}$.

let $n=20, m=40$, Find α , Considering in sorting an element in open address hash table with load factor it computed above, what is the expected # of probe in AV to perform insertion?

① $\alpha = 0.5$

② $\frac{1}{1-\alpha} = 2$

Analysis of Open-Address Hashing *continued*

Theorem: Given an open-address hash table with load factor $\alpha < 1$, the expected number of probes in a successful search is at most $\frac{1}{\alpha} \ln \frac{1}{1-\alpha}$, assuming uniform hashing and assuming that each key in the table is equally likely to be searched for.

Proof: Refer to the book for the proof.

let $n = 10, m = 20$ Successful Search

Sol | $\alpha = 0.5$ \rightarrow (تونسلا) $(0.693) \times 2$

$$\frac{1}{0.5} \ln \frac{1}{1-0.5} = 2 \ln 2 = 1.39$$

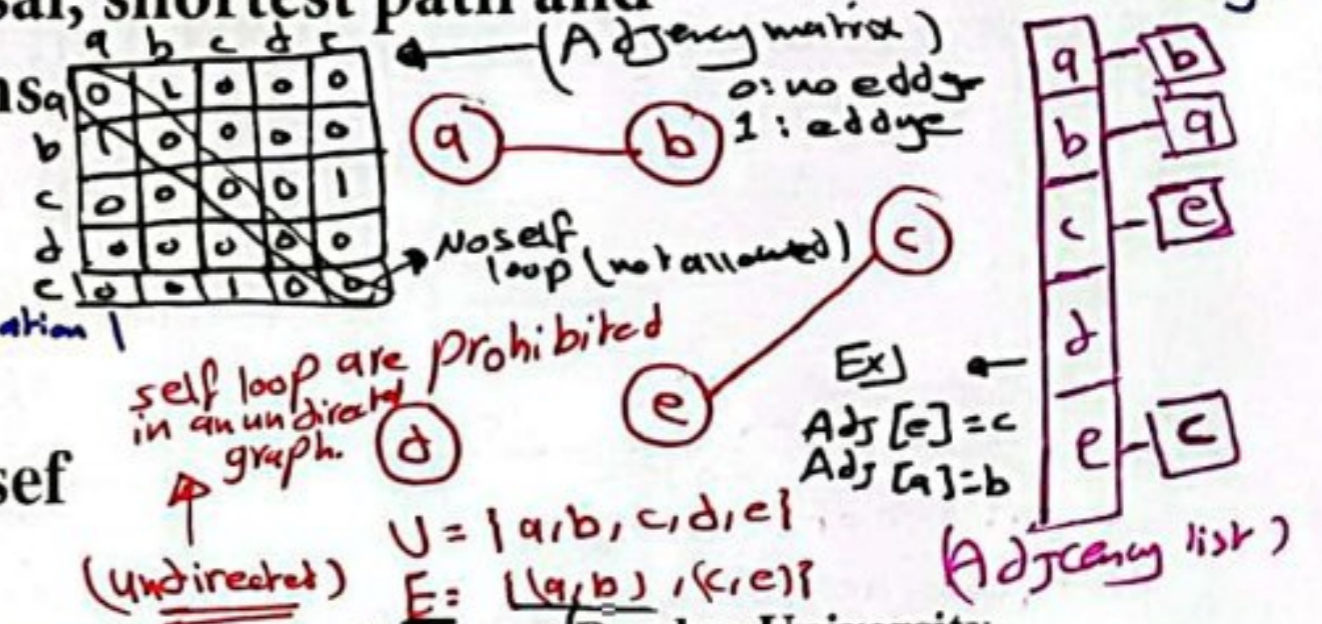
behavior (Constant timing in AVG) (Search + Deletion + Insertion)

Lecture 10: Graphs, BFS, DFS, and Topological Sort

Graph: usually denoted by the letter $G(V, E)$ and it is composed from two sets $S = \{a, b, c, d, e\}$, $|S| = 5$.
 Graph could be given or written using alphabet letters or numerical numbers.
 Graph is usually captured by circles.

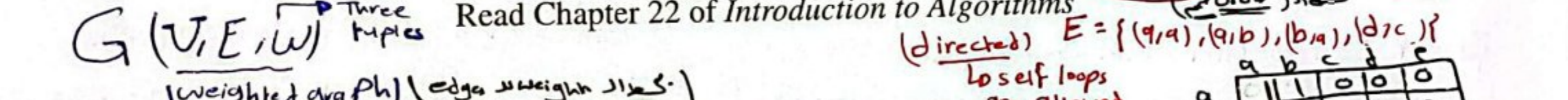
Course Learning Outcome
 Use fundamental graph algorithms, like traversal, shortest path and spanning tree in the solution of real-life problems.

eg: Consider two nodes or vertices from V i.e. $v, u \in V$.
 Then an example of: (source) (v, u) or (destination) (u, v) .
 (A) Directed edge: (v, u) or (u, v) (self loop are allowed) Two tuple.
 (B) Undirected: $(v, u) = (u, v)$ (self loop not allowed).
 self loop are prohibited in an undirected graph.



Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University.
 Dr. Khalil Yousef

(3) Set of weights: W when $w_i \in \mathbb{R}$.
 Captured by inserting the value of w_i on top bottom of every edge (directed or undirected) but then our graph would be given as:



- * Classification of the graphs
- 1- Based on the edges (e.g. (1) Directed graph, (2) undirected graph)
 - 2- Based on the existence of the weight (e.g. (1) weighted graph, (2) unweighted graph)
 - 3- Based on the density of the edges (e.g. (1) Dense graph: $|E| \approx |V|^2$, (2) Sparse graph: $|E| \ll |V|^2$ in a directed graph)
 - 4- Based on the connectivity of the graph (e.g. Fully Connected graph)

Graphs
 Graph representations of data structures are very useful in a variety of disciplines.
 Examples of graph applications:

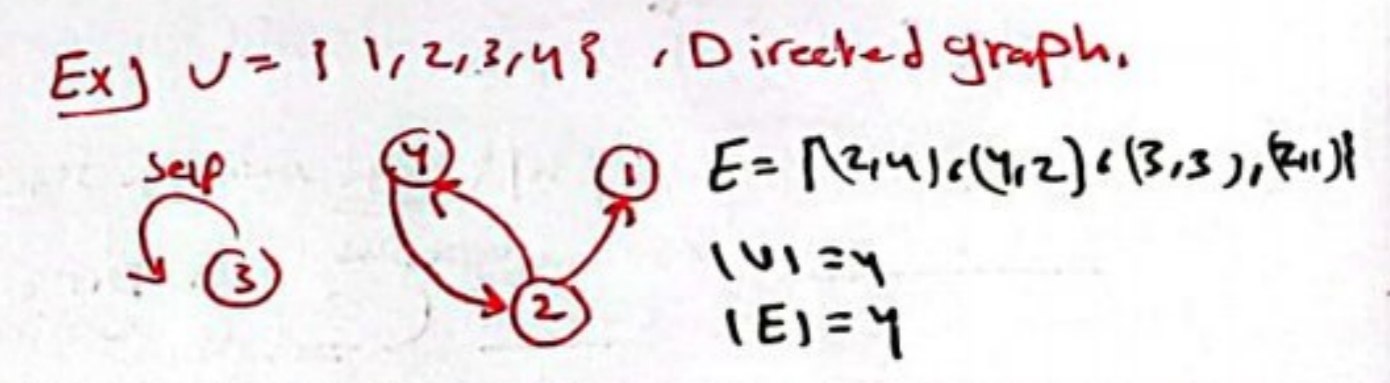
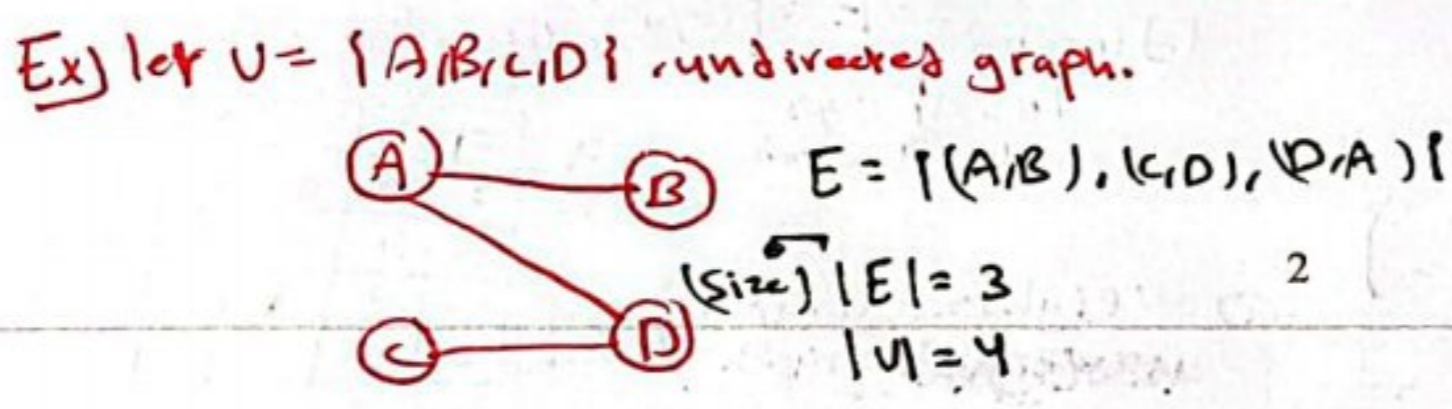
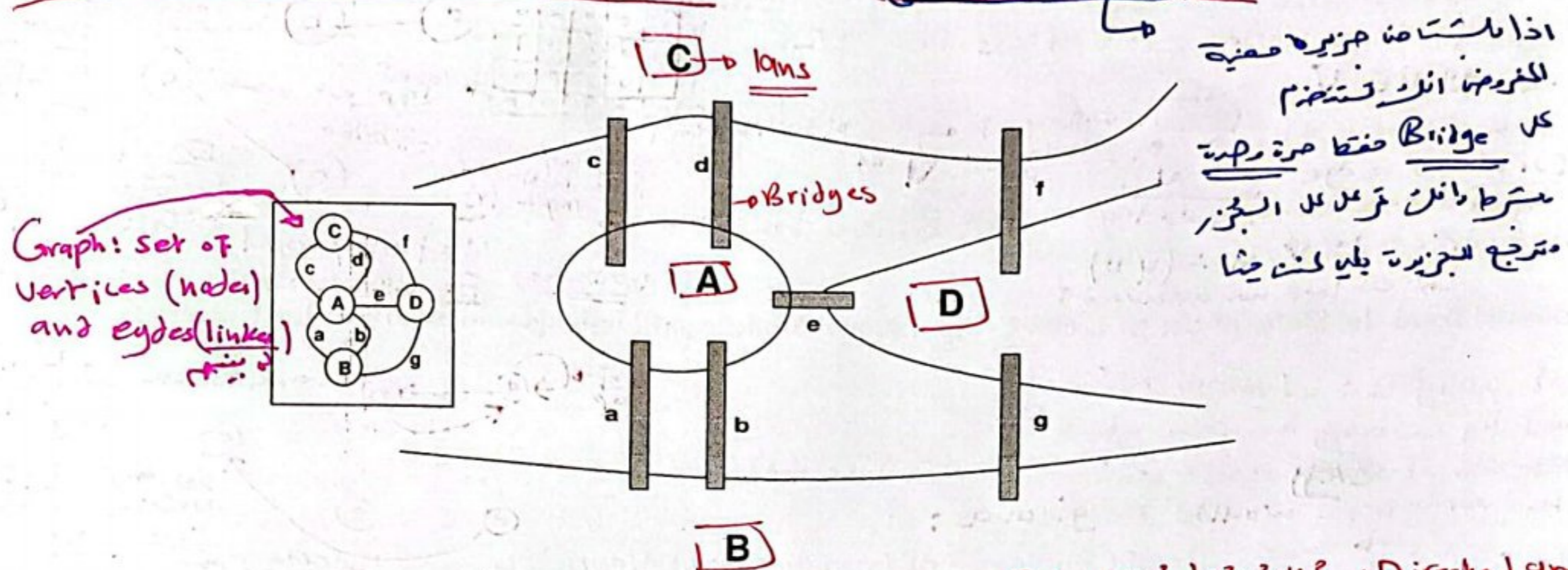
- Network Analysis
- Project Planning (PERT charts)
- Shortest Route Planning
- Compilers: Data-Dependency Graphs, Control-Flow Graphs
- VLSI
- Natural Language Processing

How to represent a graph in a memory of a computer?
 (1) Adjacency list: $Storage = \Theta(|V| + 2|E|) = \Theta(|V| + E)$
 (2) Adjacency matrix: "No pointers" $size = |V|^2, storage = \Theta(|V|^2)$

We will discuss techniques for representing graphs and perform some basic operations on them (e.g., breadth-first search, depth-first search, topological sort).
 (1) degree of a node: in degree, out degree in directed graph.
 (2) Adjacency principle: The nodes u, v are to be called adjacent iff there exist a link of edge between them.

The First Use of Graphs

Graphs were first used by Euler in 1736, when he worked on the **Königsberg Bridge Problem**. There are four land areas (or vertices): A, B, C, D and seven bridges (or edges): a, b, c, d, e, f, g . The problem is to determine whether there is a way to start out from one land area and walk across each of the bridges exactly once and return to the original land area (i.e., Is there a Eulerian walk?).



Definition of a Graph

A graph G consists of a finite, non-empty vertex (or node) set V and an edge set E (possibly empty), i.e., $G = (V, E)$. Note that $E \subseteq V \times V$; hence $|E| = O(V^2)$.

If $u, v \in V$ and there is an edge between those vertices, we can represent this by storing an ordered pair (u, v) in E . Normally, (u, v) appears in E only once (unless you are working with a **multigraph**, which allows multiple edges between vertices).

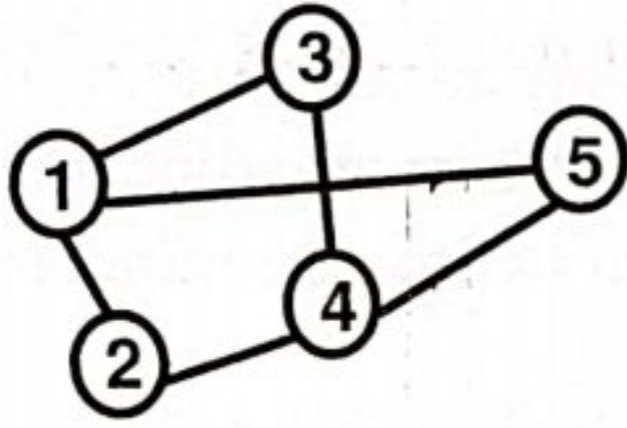
اتجاه الحواف

If an edge between two vertices is **directed** from one vertex to the other, $u \rightarrow v$, it is represented as a tuple $(u, v) \in E$. Note that (v, v) represents a self-looping directed edge.

If an edge between two vertices is **undirected**, then for $(i, j) \in E$, $(i, j) = (j, i)$. There are no self-loops allowed, i.e., $(v, v) \notin E$.

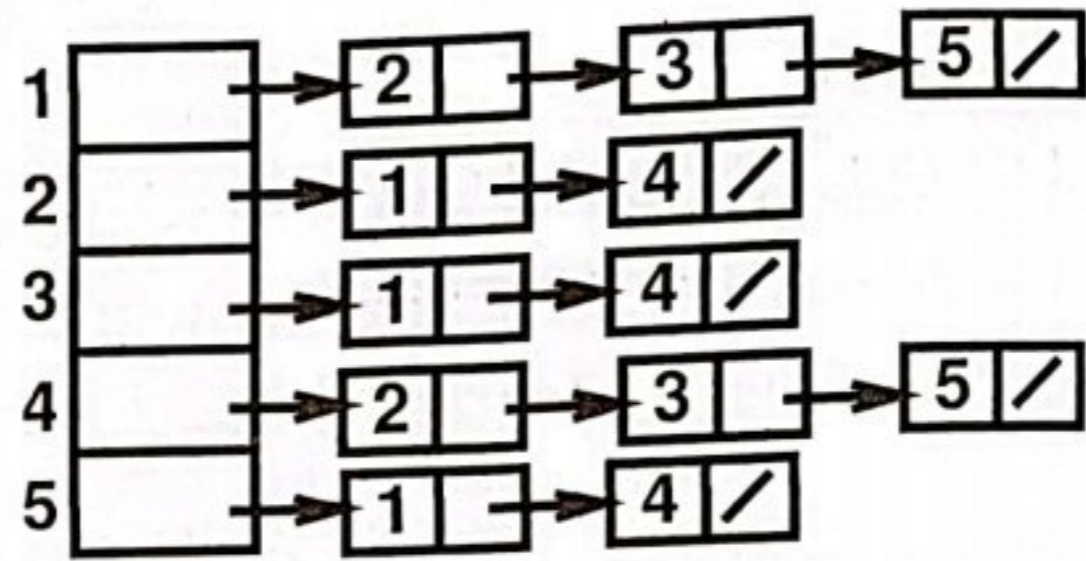
Example of an Undirected Graph

Undirected Graph, G



$G = (V, E)$
 $V = \{1, 2, 3, 4, 5\}$
 $E = \{(1,2), (1,3), (1,5), (2,4), (3,4), (4,5)\}$

* Adjacency List for G



* Adjacency Matrix for G

	1	2	3	4	5
1	0	1	1	0	1
2	1	0	0	1	0
3	1	0	0	1	0
4	0	1	1	0	1
5	1	0	0	1	0

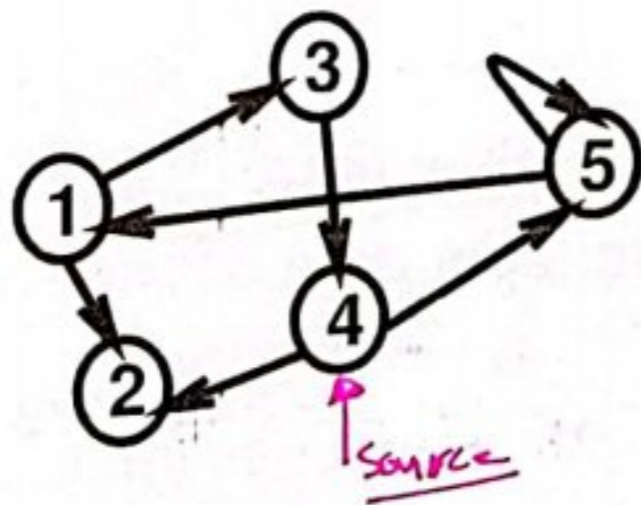
وزن
 * إذا كان وزن = 0, 1
 إذا كان weight كجانب

no self loop
undirected

Example of a Directed Graph (or Digraph)

هذا السؤال عن (BFS)

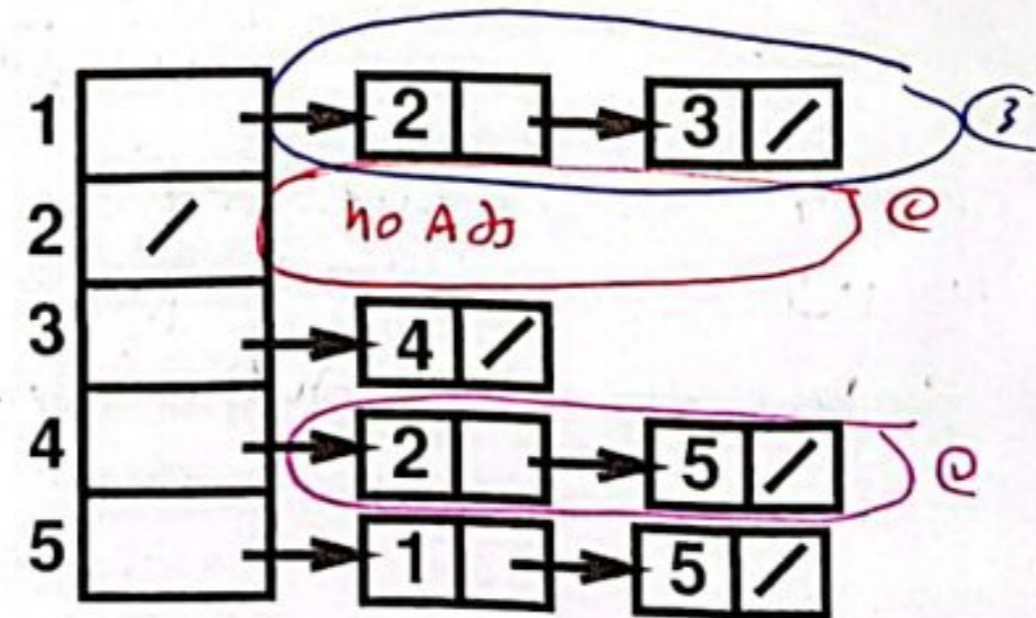
Directed Graph, G



$G = (V, E)$
 $V = \{1, 2, 3, 4, 5\}$
 $E = \{(1,2), (1,3), (3,4), (4,2), (4,5), (5,1), (5,5)\}$

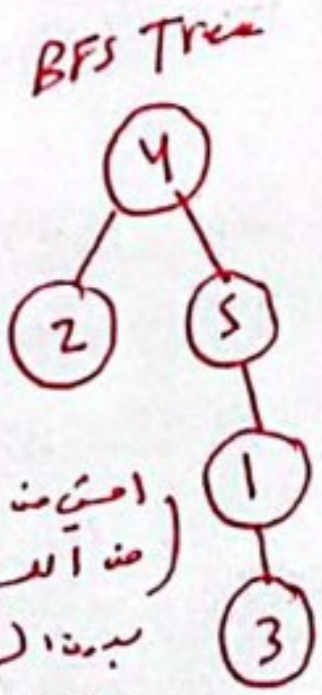
Node	1	2	3	4	5
CC	✓ B	✓ B	✓ B	✓ B	✓ G
D	∞	∞	∞	0	∞
Parent	∞	1	3	∞	4

Adjacency List for G



Adjacency Matrix for G

	1	2	3	4	5
1	0	1	1	0	0
2	0	0	0	0	0
3	0	0	0	1	0
4	0	1	0	0	1
5	1	0	0	0	1



استخدمت هذه الخوارزمية
 هذا الخوارزمية في الكود الذي كتبته في الوب
 بدون (Parent)
 فانقيار رسم
BFS Tree

1. Graph Representation: Adjacency Lists

For graph $G = (V, E)$, an adjacency list representation consists of an array of length $|V|$, Adj , such that for each vertex $v \in V$, $Adj[v]$ keeps a list of those vertices adjacent to v .

Given that the **degree** of a vertex v is the number of incident edges to v in an undirected graph $G = (V, E)$, we know that the number of items in an adjacency list representing G is $\sum_{v \in V} degree(v) = 2|E|$. Hence, the amount of storage required to represent G is $\Theta(V + E) = \Theta(\max(V, E))$.

A directed graph's vertices have both **in-degree** and **out-degree**. The number of items stored in an adjacency list for a directed graph $G = (V, E)$ is $\sum_{v \in V} out-degree(v) = |E|$, resulting in storage requirements of $\Theta(V + E) = \Theta(\max(V, E))$.

Adjacency lists are good representations for sparse graphs $|E| \ll |V|^2$ however, there is no quick way to determine whether a given edge (u, v) is present in the graph without searching the list associated with $Adj[u]$.

6

2. Graph Representation: Adjacency Matrix

For graph $G = (V, E)$, an adjacency matrix consists of a $|V| \times |V|$ matrix A , such that:

$$A[i, j] = \begin{cases} 1 & \text{if } (i, j) \in E, \\ 0 & \text{if } (i, j) \notin E. \end{cases}$$

Using this method, we can determine very quickly whether there is an edge between two vertices; however, it uses $\Theta(V^2)$ memory, independent of the size of E .

Note that for an undirected graph G represented with an adjacency matrix A that $A = A^T$, i.e., $A[i, j] = A[j, i]$, which can be used to cut the memory requirements in half. We can further reduce space by using a bit matrix representation.

This is a good representation for dense graphs, i.e., $|E| \approx |V|^2$ or for small graphs. Usually this method requires too much storage for large graphs, especially since many graphs are sparse (e.g., planar graphs).

Weighted Graphs

In a **weighted graph** G , weights can be associated with the edges or the vertices of the graph.

If each edge has an associated **weight** given by a weight function $w : E \rightarrow \mathbf{R}$, adjacency-list and adjacency-matrix representations must be modified to represent this additional information.

The adjacency list for G can be easily adapted to represent this weight information. For each edge $(u, v) \in E$, store the weight $w(u, v)$ with vertex v in u 's adjacency list.

Adjacency matrices can also be easily adapted to represent a weighted graph, G . For each edge $(u, v) \in E$, store the weight $w(u, v)$ in $A[u, v]$ (NIL if no edge). Note that no bit-matrix representation is possible in this case.

- ① distance function $d[]$: Initially all vertices in the graph except for the source node will be initialized to a very large value (∞). Means all vertices are assumed initially unreachable from the source.
 - ② distance all the source is zero (0 = initial value)
 - ③ Parent function $\pi[]$: maintain the parent relationship of nodes. help in constructing the BFS tree.
 - ④ Color function: 3 colors will be used.
 - (W) white: see the slide
 - (G) Gray: see the slide
 - (B) Black: see the slide
- Function: $d[]$: distance function, $\pi[]$: parent function (source is 1), $c[]$: color function, $adj[]$: adjacency list.

Breadth-First Search (BFS)

- ③ Defined set of functions to manage the information about traversal of the source vertex.
- ② use FIFO Queue to manage the traversal of the nodes from the source vertex.
- ① Assumption: The graph will be represented using Adjacency List.

Input Graph Given a directed or undirected graph $G = (V, E)$ and a distinguished source vertex s , the breadth-first search algorithm systematically explores the edges of G to discover whether every vertex is reachable from s . It does this by visiting all vertices at distance k before vertices at distance $k + 1$. The algorithm:

- computes the distance (fewest number of edges) from the source vertex to every other vertex,

- creates a breadth-first tree with root s to all reachable vertices such that the path from s to v represents the shortest path between those two nodes.

Ancestors and descendants in the breadth-first tree are defined with respect to the shortest path from the source to each vertex.

Breadth-First Search Algorithm: BFS

BFS:

- assumes that $G = (V, E)$ is represented using an adjacency list.
- uses a first-in-first-out (FIFO) queue, Q , to manage the traversal of vertices.
 operation (Head, Enqueue (insert), Dequeue (remove))
- keeps track of the color of a vertex $u \in V$ using $color[u]$. If u is WHITE, it has not been discovered; if GRAY, it has been put on Q ; if BLACK, its successors have been added to Q .
 initially all vertices is white source
- keeps track of the distance between the source vertex s and $u \in V$ in $d[u]$.
 (Q) سلسله
- uses $\pi[u]$ to store the predecessor of u in order to construct a BFS-Tree. If there is no predecessor, the value of $\pi[u]$ is NIL.
 Parent of source

BFS(G, s)

1. **for** each vertex $u \in V[G] - \{s\}$
 except the source
2. **do** $color[u] \leftarrow$ WHITE
3. $d[u] \leftarrow \infty$
 unreachable
4. $\pi[u] \leftarrow$ NIL

10

Breadth-First Search Algorithm: BFS continued

5. $color[s] \leftarrow$ GRAY
 مطابقه دایره اول (Q)
 6. $d[s] \leftarrow 0$
 7. $\pi[s] \leftarrow$ NIL
 8. $Q \leftarrow \{s\}$
 in Q (s) → (Q) دایره اول
 9. **while** $Q \neq \emptyset$
 (Q not empty) (از node نی) (Q)
 10. **do** $u \leftarrow$ head[Q]
 از node نی (Q)
 11. **for** each $v \in Adj[u]$
 12. **do if** $color[v] =$ WHITE
 دایره اول (Q)
 13. **then** $color[v] \leftarrow$ GRAY
 دایره اول (Q)
 14. $d[v] \leftarrow d[u] + 1$
 15. $\pi[v] \leftarrow u$
 16. ENQUEUE(Q, v)
 براد node بلین کنت تبادلده و سیمیه (u)
 17. DEQUEUE(Q)
 Remove
 18. $color[u] \leftarrow$ BLACK
 color
- دایره اول (Q) + طبعه اول (u)*

Example: BFS(G, a)

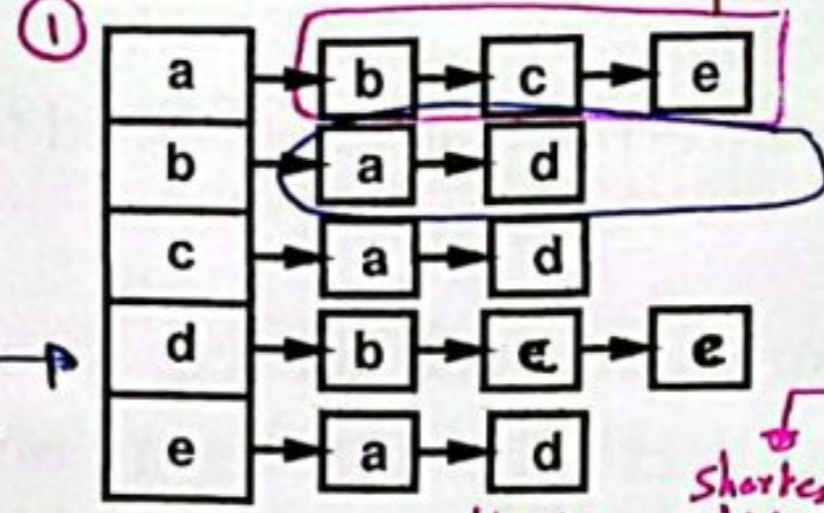
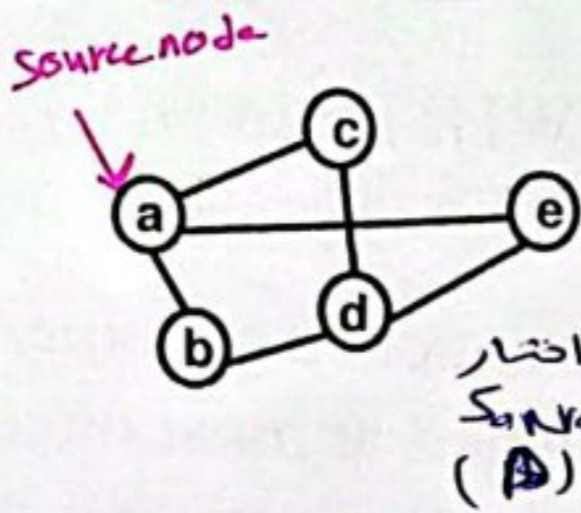
Shortest distance

- dist of a = 0
- dist of b = 1
- dist of c = 1
- dist of d = 2
- dist of e = 1

Table

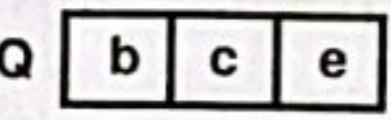
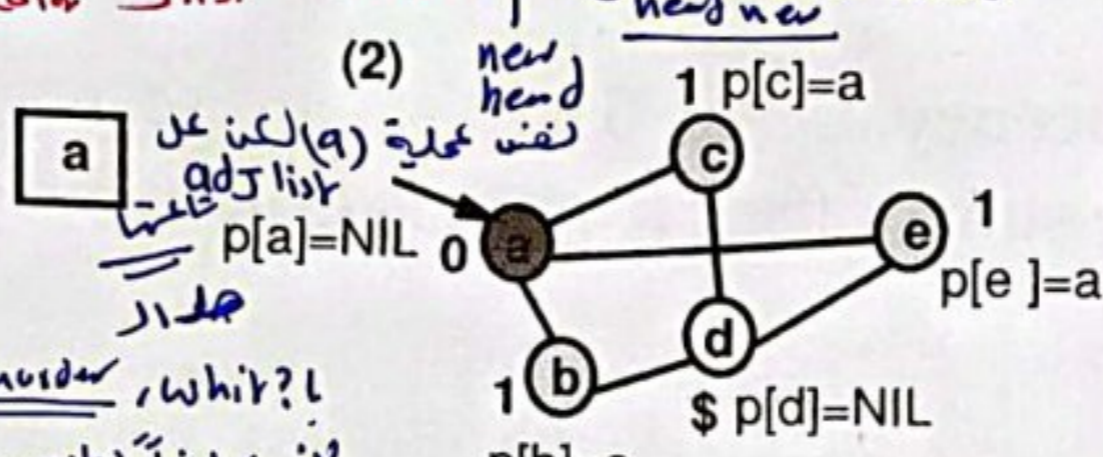
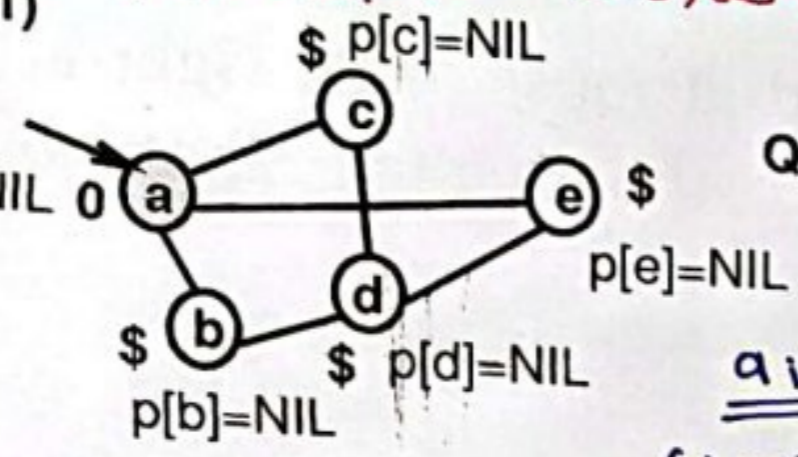
Node	a	b	c	d	e
c[]					
b[]					
a[]					
d[]					
e[]					

$V = \{a, b, c, d, e\}$
 $E = \{(a, b), (a, c), (a, e), (c, d), (c, e), (b, a), (b, d), (d, e), (d, b)\}$

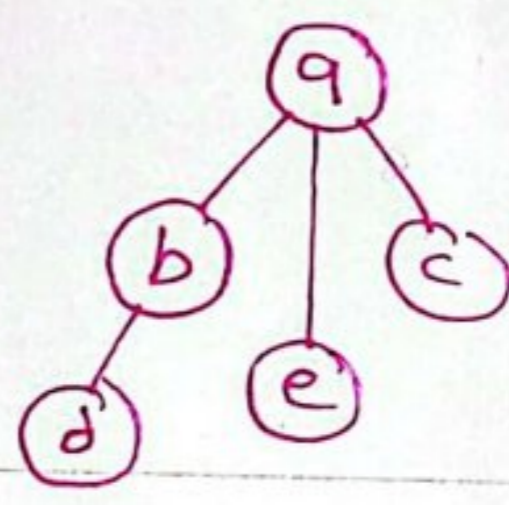


order
 head
 tail
 new head
 new tail

parent
 list
 dep(a)
 parent, distance

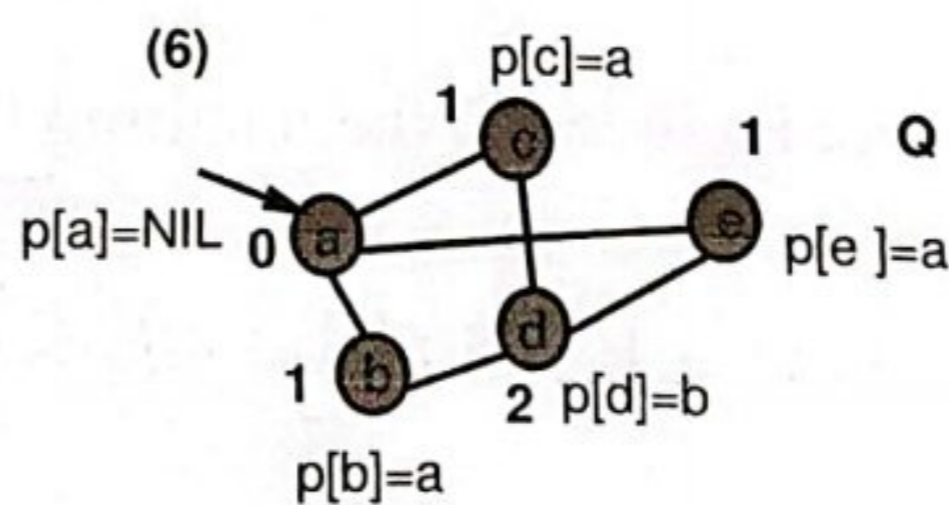
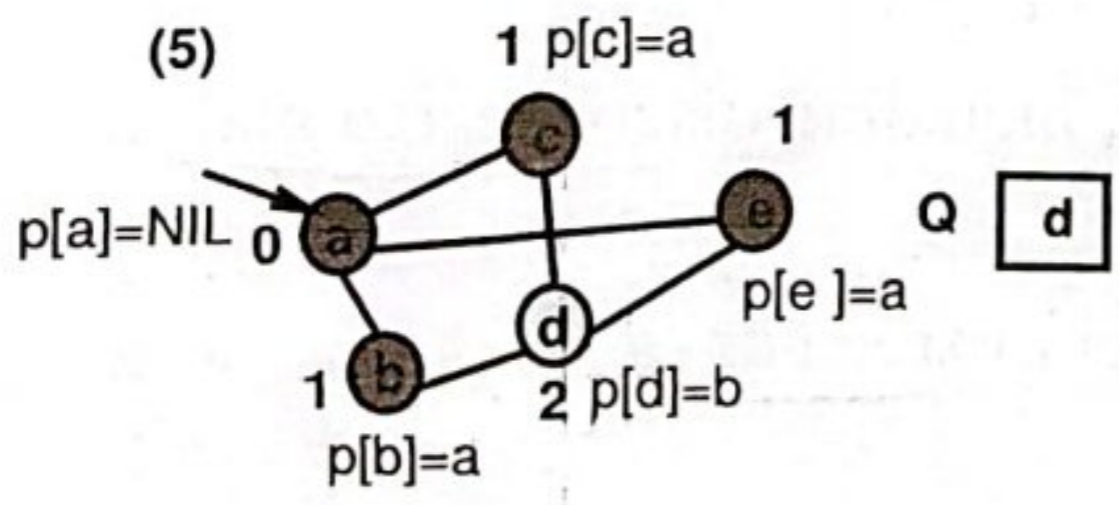
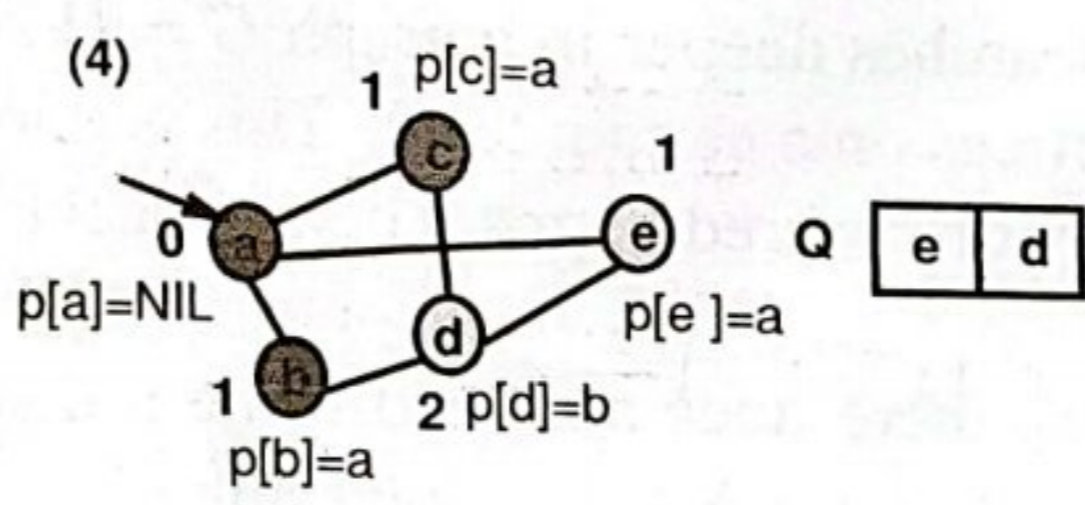
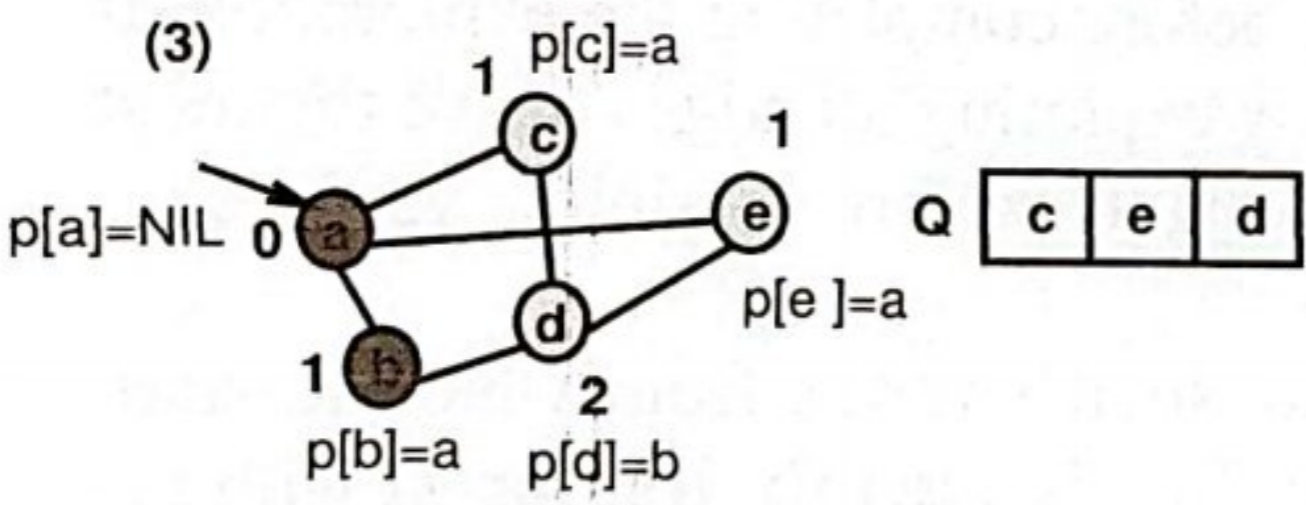


BFS Tree



Branch
 one edge
 two edges
 one edge + (9) = (10)

Example: BFS(G, a) continued



Complexity of BFS

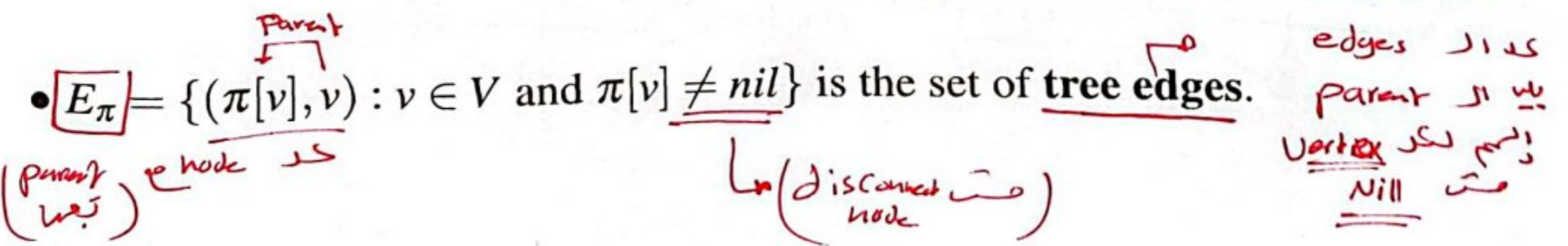
- **Initialize:** $|V| - 1$ vertices are initialized to WHITE in $\Theta(V)$.
- **Queue Operations:** Because vertices when enqueued become GRAY and they are never reset to WHITE, vertices are enqueued at most once. Each enqueue and dequeue operation uses $O(1)$ time; hence, all queue operations take $O(V)$ time.
- **Scanning Adjacency Lists:** The lists are scanned at most once, right after dequeuing. The sum of their lengths is $\Theta(E)$. Hence, the time to scan the lists is $O(E)$.
- **Resulting Complexity:** $O(V + E)$

The Depth-First Search Algorithm: DFS (طابع كنفذ Φ من BFS) \rightarrow إذا تمّت (علاوة) خارج استن \rightarrow إذا تمّت (علاوة) خارج استن (سطحياً) \rightarrow إذا تمّت (علاوة) خارج استن (سطحياً) \rightarrow إذا تمّت (علاوة) خارج استن (سطحياً)

DFS searches deeper in a graph $G = (V, E)$ before completing the exploration of the vertices on a certain level. This is done by exploring all edges out of the most recently discovered vertex v before backtracking to explore v 's sibling vertices.

In **DFS**, there does not need to be a distinct source vertex from which to start. The resulting predecessor subgraph $G_\pi = (V_\pi, E_\pi)$ is a **depth-first forest** with the following properties:

- All vertices are included in the resulting **forest**, including disconnected nodes.
- $E_\pi = \{(\pi[v], v) : v \in V \text{ and } \pi[v] \neq \text{nil}\}$ is the set of **tree edges**.



The Depth-First Search Algorithm: DFS *continued*

DFS:

- assumes that $G = (V, E)$ is represented using an adjacency list.
- uses backtracking to manage the traversal of vertices.
- keeps track of the color of a vertex $u \in V$ using $color[u]$. If u is WHITE, it has not been discovered; if GRAY, it has been discovered; if BLACK, its adjacency list has been completely explored. (مررتنا عليه مش انه طيبه) (Finish)
- uses $\pi[u]$ to store the predecessor of u in order to construct a DFS-Forest. If there is no predecessor, the value of $\pi[u]$ is NIL. (Parent)
- keeps track of two timestamps for each vertex $v \in V$; $d[v]$ records when v is first discovered and grayed; $f[v]$ records when v 's adjacency list has been completely examined, at which point v is made BLACK. Note that $d[v] < f[v]$ and both timestamps are integers in the range $[1, 2|V|]$. Each time stamp will be set only one time for each vertex v . (مررتنا وقت فقط ما فيه update)

16

DFS(G)

DFS(G) (تسجل الـ order)

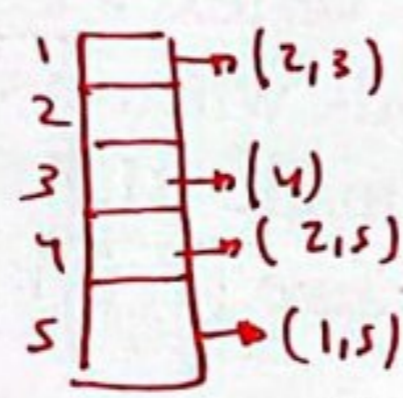
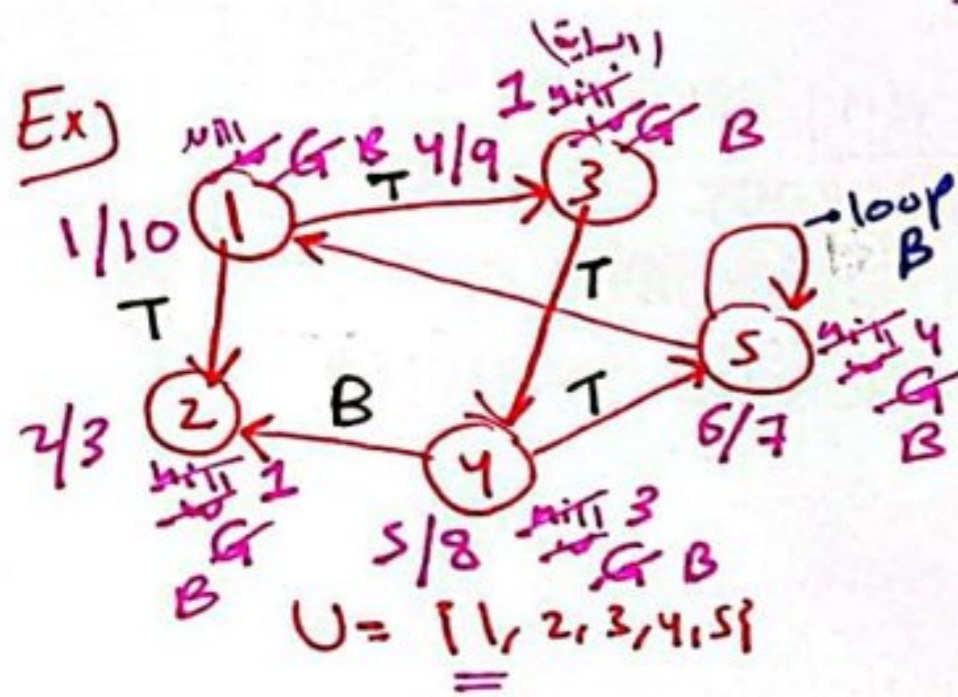
1. for each vertex $u \in V[G]$
2. do $color[u] \leftarrow WHITE$
3. $\pi[u] \leftarrow NIL$ (parent)
4. $time \leftarrow 0$ \triangleright global timestamp
5. for each vertex $u \in V[G]$
6. do if $color[u] = WHITE$
7. then **DFS-VISIT(u)**

رطل استنادك على node
while

DFS-VISIT(u)

DFS-VISIT(u)

1. $color[u] \leftarrow \text{GRAY}$
2. $d[u] \leftarrow time \leftarrow time + 1$
3. **for** each vertex $v \in Adj[u]$
4. **do if** $color[v] = \text{WHITE}$
5. **then** $\pi[v] \leftarrow u$ (بجداد)
6. DFS-VISIT(v) (مليحاً از درون)
7. $color[u] \leftarrow \text{BLACK}$
8. $f[u] \leftarrow time \leftarrow time + 1$



node	1	2	3	4	5
C[]	B	B	B	B	B
π []	nil	1	1	3	4
d[]	1	2	4	5	6
f[]	10	3	9	8	7

(الأمم ابي)

Final Table (Tree) السجبي حد

Classification

Tree edge: T (أول مرة بزور node و كانت white)

Back edge: B (أول مرة بزور node و كانت white (loop))

Complexity of DFS

- **Initialize:** $|V|$ vertices are initialized to WHITE in $\Theta(V)$.
- **DFS-VISIT:** is called once for each vertex $v \in V$ because vertices are never reset to WHITE. During the execution of DFS-VISIT(v), the loop at lines 3-6 is executed $|Adj[v]|$ times. Because $\sum_{v \in V} |Adj[v]| = \Theta(E)$, the total cost to execute the loop over all vertices is $\Theta(E)$.
- **Resulting Complexity:** $O(V + E)$

Example: DFS(G)

برج من 6 في 6! white?!

order of visit
 $V = \{a, b, c, d, e\}$

ب ا ب (9) حد white!؟ يعني
 اذا نجحنا visit بجراد Color (G)
 بجزء ال Time (زمن)

Exp ماين
 برجع ب (B) وبعده Finish
 برجع ب (B) وبعده Finish
 متي اذ انجزها (B)
 كله (B) ماين (B)
 :ظرفها

node	a	b	c	d	e
Color	0	0	0	0	0
Parent	NIL	a	b	a	b
Order	1	2	6	3	4
Finish	10	9	7	8	5

(1) $p[a] = \text{NIL}$

(2) $p[b] = a$

(3) $p[d] = b$

(4) $p[e] = d$

(5)

(6)

Example: DFS(G) continued

(7) $p[c] = d$

(8)

(9)

(10)

(11)

(12) $p[a] = \text{NIL}$, $p[c] = d$, $p[e] = d$, $p[b] = a$, $p[d] = b$

DFS(G) Edge Classification

The edges in directed G can be classified as follows by $DFS(G)$:

1. **Tree Edge:** an edge (u, v) in a DFS-Forest G_π resulting from the discovery of a vertex v from a GRAY vertex u ($d[u] < d[v] < f[v] < f[u]$). When the edge (u, v) is first explored v is WHITE.
 (إذا زرت node وكانت white)

2. **Back Edge:** an edge (u, v) connecting vertex u to an ancestor v (or u itself) ($d[v] < d[u] < f[u] < f[v]$). When the edge (u, v) is first explored v is GRAY.
 (لو (loop) edge بعد hp بعد edge)
 (لو (loop) edge بعد hp بعد edge)

3. **Forward Edge:** a non-tree edge (u, v) connecting u to a descendent v in a DFS-Tree ($d[u] < d[v] < f[v] < f[u]$). When the edge (u, v) is first explored v is BLACK.
 (لو (loop) edge بعد hp بعد edge)
 (لو (loop) edge بعد hp بعد edge)

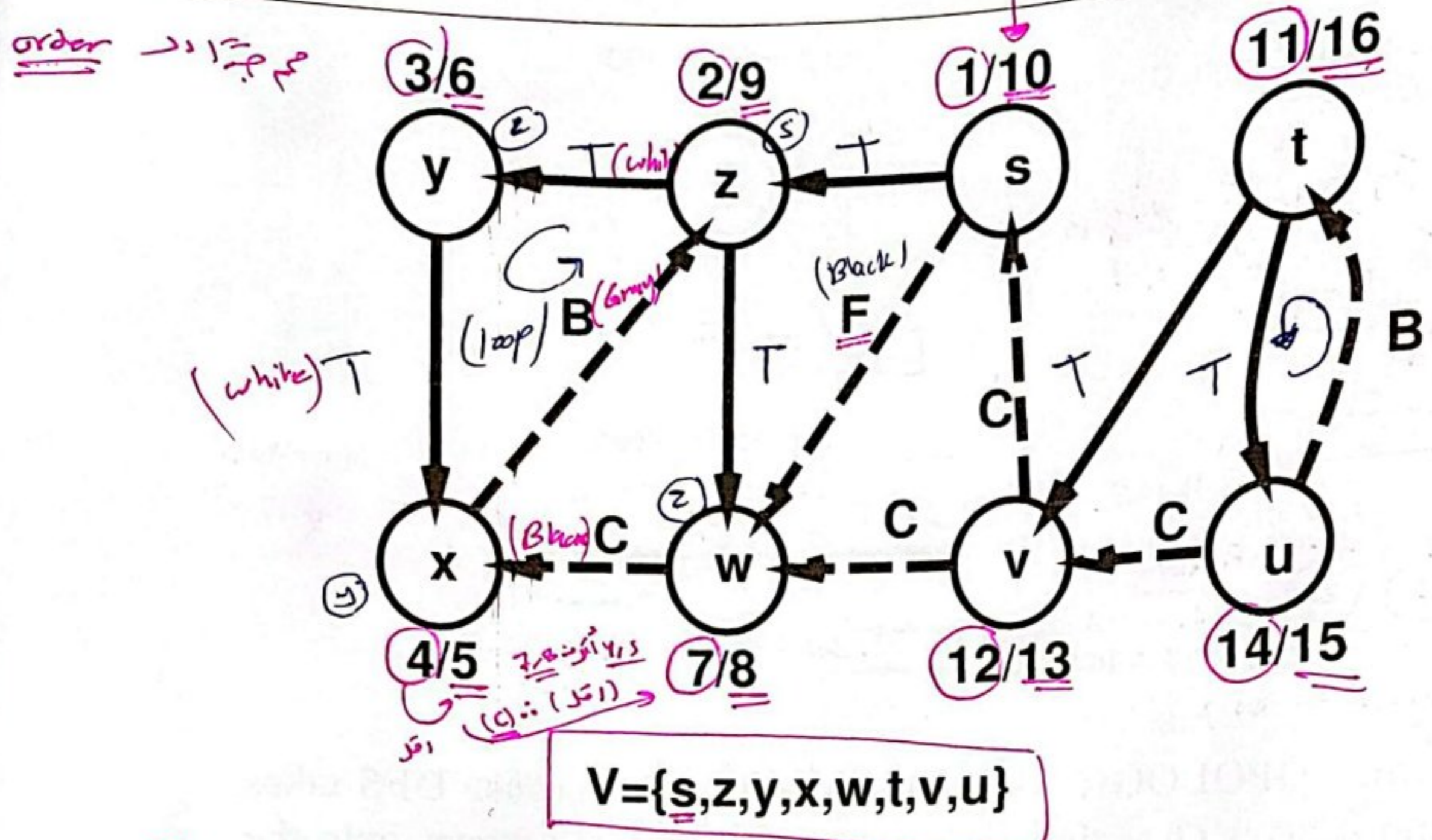
4. **Cross Edge:** all remaining edges; either within a single tree where there is no ancestor relationship between the vertices or edges between two different trees in the forest ($d[v] < f[v] < d[u] < f[u]$). When the edge (u, v) is first explored v is BLACK.
 (لو (loop) edge بعد hp بعد edge)
 (لو (loop) edge بعد hp بعد edge)

DFS(G) Edge Classification

More about the Forward and Cross Edges.

- Forward Edge:** Forward edges are those non-tree edges (u, v) connecting a vertex u to a descendant v in a depth-first tree. Forward edges describe **ancestor-to-descendant relations**, as they lead from **low to high nodes**.
- Cross Edge:** Cross edges are all other edges. They can go between vertices in the same depth-first tree as long as one vertex is not an ancestor of the other, or they can go between vertices in different depth-first trees. Cross edges link nodes with **no ancestor-descendant relation** and point from **high to low nodes**.

DFS(G) Edge Classification Example



Q: Design Question

Design an Algorithm to discover if a given directed graph contains a loop(s) or Not?!

- Run DFS on the directed graph.
- classify the edges in the graph.
- check if there are any Back edges.
- if Yes, Return yes the graph contains a loop otherwise, Return No.

The Complexity $\Rightarrow \Theta(V + E)$

Topological Sort

A topological sort of a directed acyclic graph (or DAG), $G = (V, E)$ is a linear ordering of all of its vertices such that if $(u, v) \in E$, then u appears before v in the ordering.

A DAG expresses a partial order on its vertices; a topological sort generates a linear ordering of the vertices such that the partial order relations are preserved.

Basic Idea: The finish times produced by DFS form a total order needed to produce a topological sort of a DAG.

TOPOLOGICAL-SORT(G)

1. call $DFS(G)$ to compute finish times $f[v]$ for each $v \in V$.
2. as each vertex is finished, insert it into the front of a linked list.
3. return the linked list of vertices.

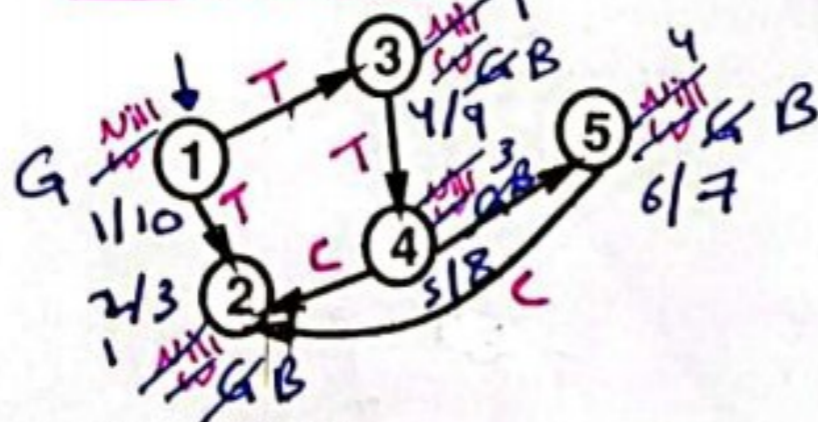
الترتيب حسب
Finish Time

السبب Time Complexity = $V + E$

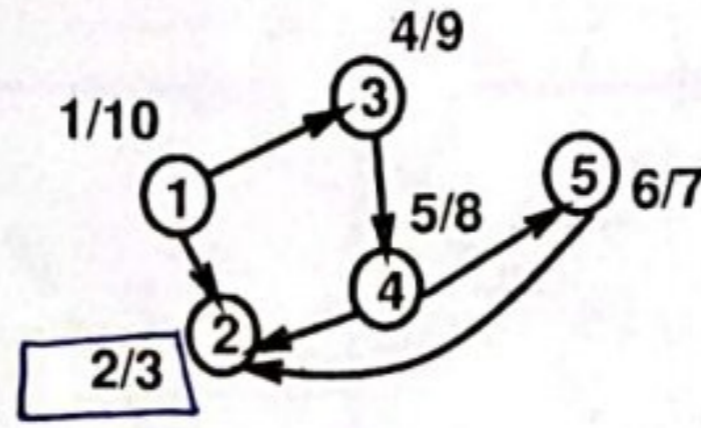
TOPOLOGICAL-SORT Example

Directed Acyclic Graph, G

Run DFS (G)



Labels after DFS

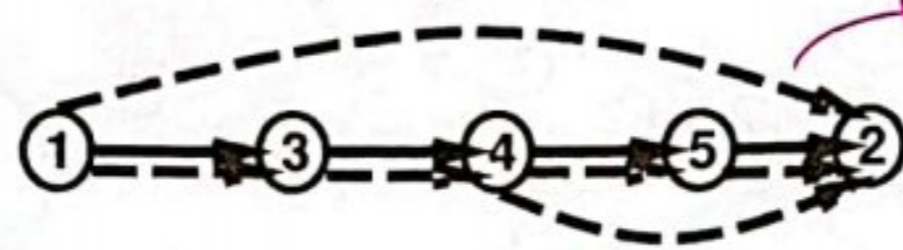


$G = (V, E)$

$V = \{1, 2, 3, 4, 5\}$

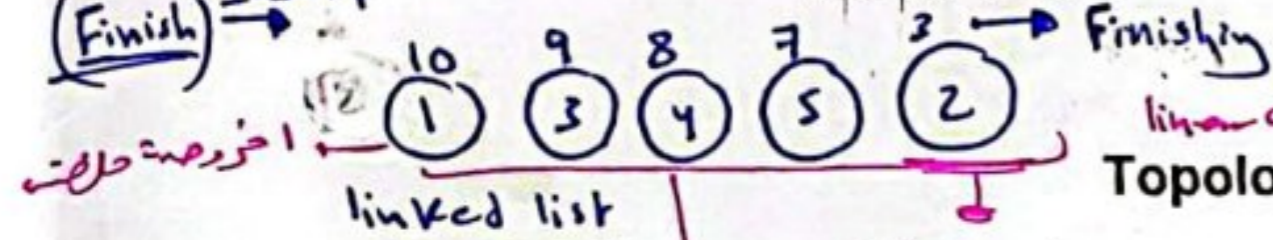
$E = \{(1,2), (1,3), (3,4), (4,2), (4,5), (5,2)\}$

Topological Sort



رسم (graph) د

(Finish) Insert



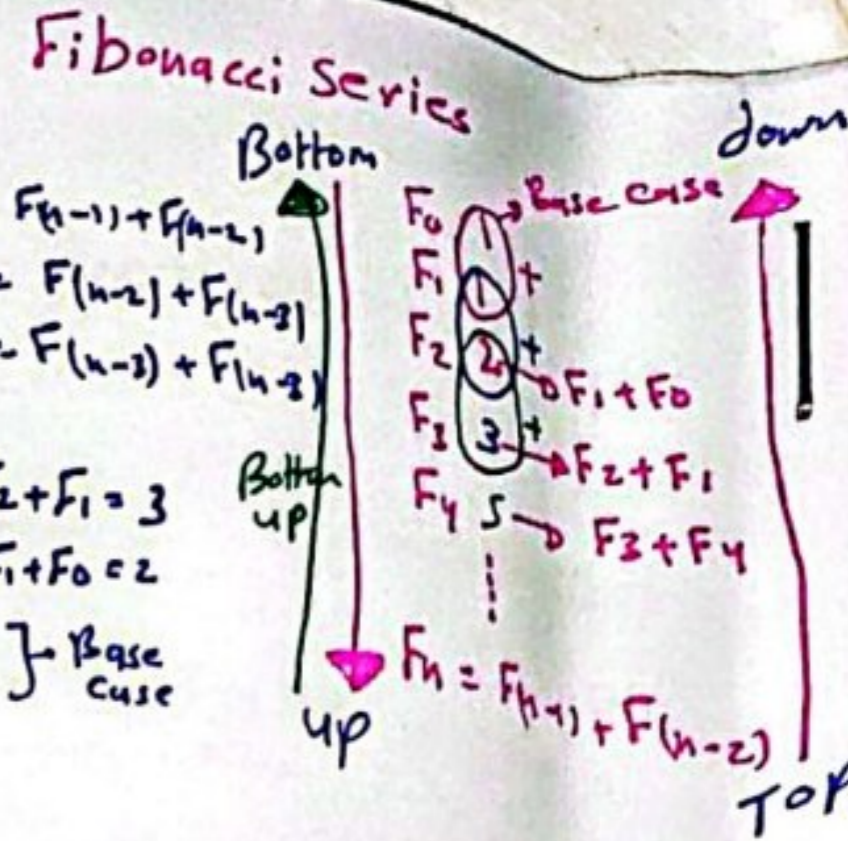
linear order of vertices based on the finishing Time
Topological Sort $\Theta(V+E)$

Topological sort in the graph

The time to perform TOPOLOGICAL-SORT is $\Theta(V + E)$ because DFS takes $\Theta(V + E)$ time and it takes $O(1)$ time to insert each of the $|V|$ vertices onto the front of a linked list.

Lecture 11: Dynamic Programming Matrix-chain Multiplication Problem

Course Learning Outcome

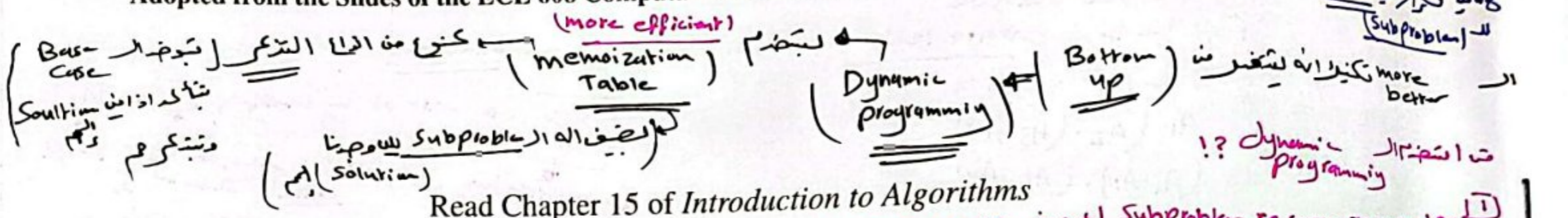


- Use algorithm design methods, such as exhaustive search, divide-and-conquer and dynamic programming, to develop efficient algorithms.

Dr. Khalil Yousef

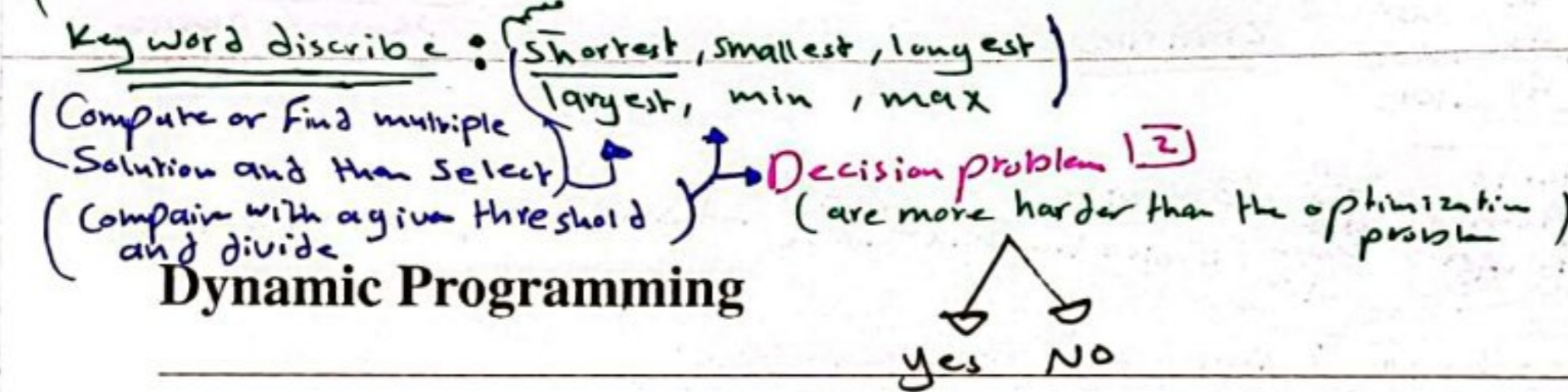
Solution: use dynamic prog. (not efficient when subproblem recur over and over)

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University



Read Chapter 15 of Introduction to Algorithms

هو انك لا تبني مسار dynamic programming!
 optimization problems (تكوننا كرمنا على ما قاتر اضروا)
 Key word describe: Shortest, smallest, longest, largest, min, max
 Decision problem (are more harder than the optimization problem)
 # of distinct or unique subproba $O(n^2)$ (عدد جوار (Table) mem.)



* dynamic programming Techniques, Consider the matrix chain multiplication optimization problem.

Dynamic programming is a metatechnique (not an algorithm) like the divide-and-conquer method. It is used to create algorithms for problems that can be solved by combining solutions to smaller subproblems.

However, it is a method that is most effective when a subproblems recur again and again in other subproblems.

In such a case, the divide-and-conquer techniques would redo the subproblems each time, resulting in much unnecessary work.

Dynamic programming is often used for solving optimization problems, in which a set of choices must be made to arrive at an optimal solution to a problem (minimizing or maximizing some value associated with the problem). Note that there may be more than one optimal solution to a problem.

- Optimization problems: e.g find the shortest path
- Decision problems (YES/NO): e.g is there is a path of k (threshold or less) ...

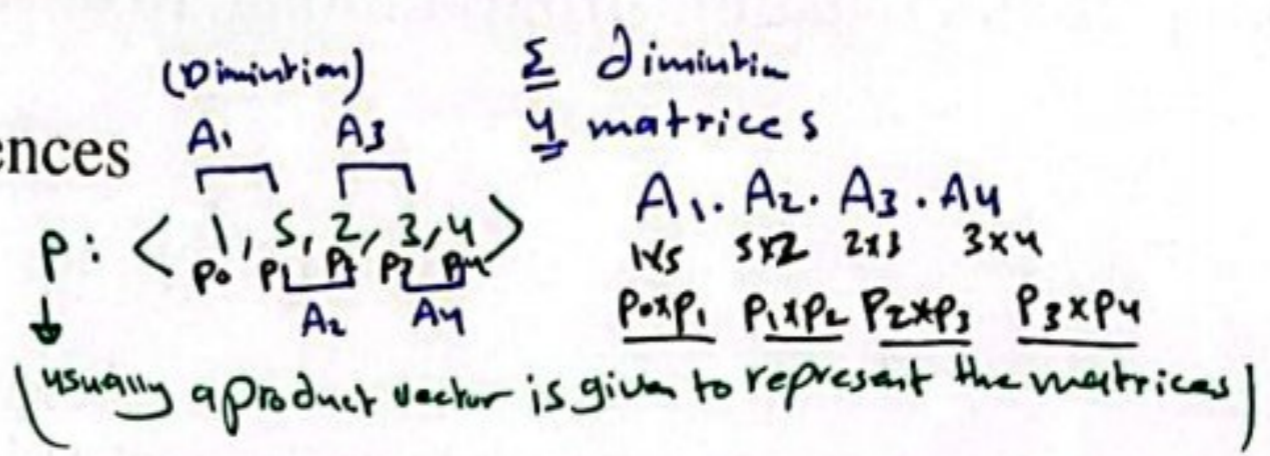
Dynamic Programming *continued*

Examples:

- Minimizing scalar multiplications in a chain of matrix multiplications
- Scheduling problems

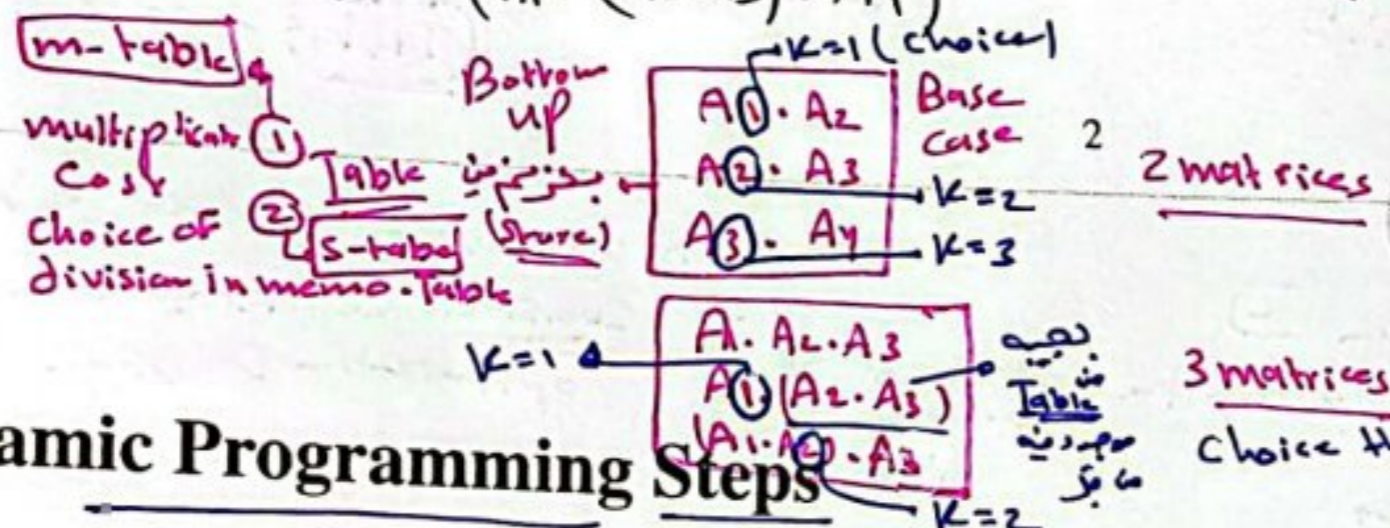
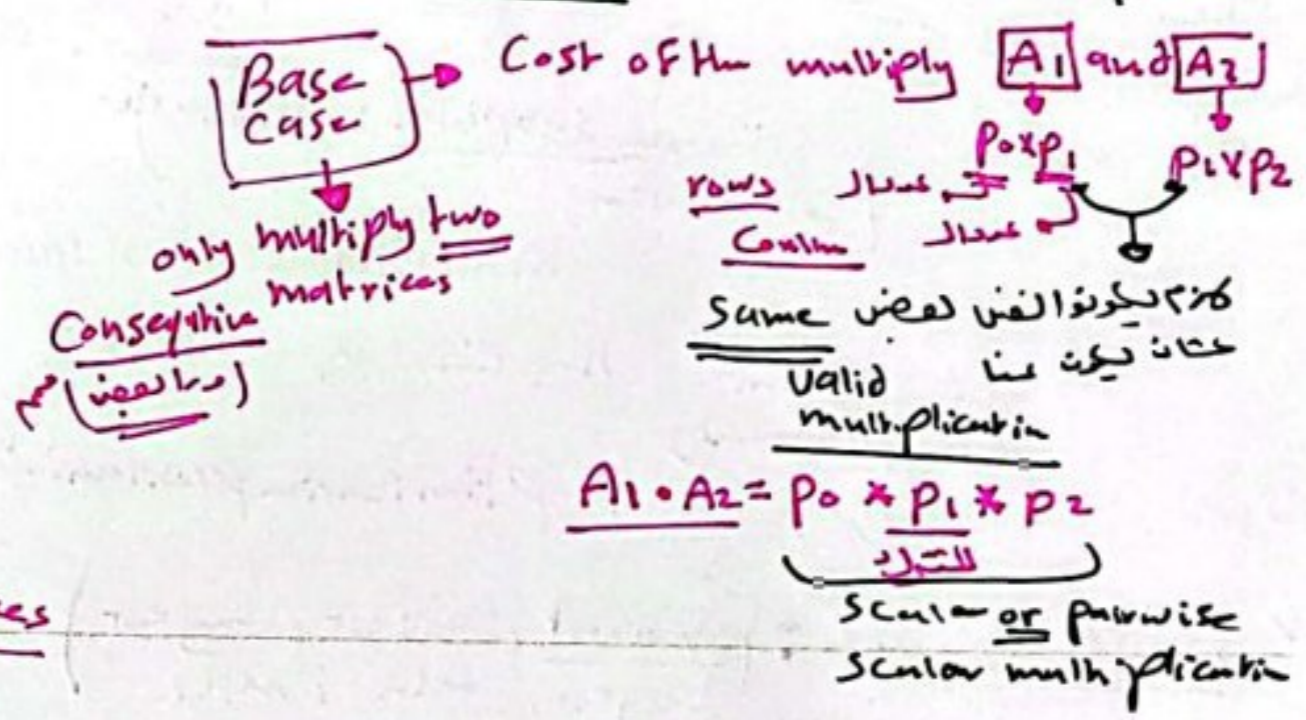
Longest common subsequence in two sequences

Example Dynamic programming :-
Matrix chain multiplication



minimization: optimization problem
 Consider four matrices
 Find the best parameterization that will result in the minimum # of scalar multiplication

- matrices
- $A_1 (A_2 \cdot (A_3 \cdot A_4))$
 - $(A_1 \cdot A_2) \cdot (A_3 \cdot A_4)$
 - $((A_1 \cdot A_2) \cdot A_3) \cdot A_4$
 - $A_1 \cdot (A_2 \cdot A_3) \cdot A_4$



Dynamic Programming Steps

The development of a dynamic programming algorithm is characterized by four steps:

1. Characterize the structure of an optimal solution.
 - Example: Fibonacci series
 $F_0 = 1, F_1 = 1, F_2 = F_1 + F_0$
 Store in memoization table
 Restore from the table = $1 + 1 = 2$
2. Recursively define the value of an optimal solution.
 - Step of Recursive P
 Perform Renaming of the indices of the matrices to allow expression all possible subproblems
 Consider $[A_i \dots A_k \dots A_j]$
 division
3. Compute the value of an optimal solution in a bottom-up fashion.
 - (Extra step usually)
4. Compute an optimal solution from the computed information.
 - Solution to this subproblem must be recovered from the memo-table except for the base cases.
 - Choice of division of K
 where $m(i,j)$ is a function that would compute and store the min. # of scalar multiplication for multiply sequence $A_i \dots A_j$
 Goal: Compute $m(1,n) = p_{i-1} \times p_k \times p_j$

The first three steps form the basis of dynamic programming, and the last is needed only if we want to report an optimal solution, not just return its value.

possible of (optimal) solution
 Sub-problem
 Recursion equation
 most important step in any dynamic programming problem (check all possible k-choices)

$$m(i,j) = \min (m(i,k) + m(k+1,j) + p_{i-1} \times p_k \times p_j)$$

$i \leq k \leq j$

Example: Matrix-chain Multiplication

We will first discuss the dynamic programming method in terms of a chain of n matrices to be multiplied. For example, the following chain

$$A_1 \cdot A_2 \cdot A_3 \cdot A_4$$

can be computed in the following ways:

$$\underline{(A_1 \cdot (A_2 \cdot (A_3 \cdot A_4)))} \text{ or}$$

$$\underline{(A_1 \cdot ((A_2 \cdot A_3) \cdot A_4))} \text{ or}$$

$$\underline{((A_1 \cdot A_2) \cdot (A_3 \cdot A_4))} \text{ or}$$

$$\underline{((A_1 \cdot (A_2 \cdot A_3)) \cdot A_4)} \text{ or}$$

$$\underline{(((A_1 \cdot A_2) \cdot A_3) \cdot A_4)}$$

This parenthesization can have a dramatic impact on the cost of evaluating the product.

Two important properties to consider dynamic programming method:

- 1) Overlapping Subproblem: Distinct subproblem = $O(n^2)$
- 2) Optimal Substructure: The optimal solution to the general problem contains optimal solution to the subproblem.

Example: Matrix-chain Multiplication

The main idea of this dynamic programming example is to answer the following question: Which parenthesization will give the best (the cheapest cost) i.e. How many basic operations at minimum will it take under the best parenthesization to multiply the sequence A_1, A_2, \dots, A_n .

Thus we have two questions to answer: (1) what does it cost to get the best parenthesization and (2) How to get it.

→ m-table + m-Recursive equation

- Natural way: try all possible parenthesization
- So, for each parenthesize (division point), make a recursive call on the left side of the division point and another recursive call on the right side. Then compute the combined cost remembering (memoization) if this division point is the best so far (the cheapest).
- A recursion call is terminated if the problem is small enough and give the trivial answer (optimal solution).
- Return the best cost found

تكرارية

Example: Matrix-chain Multiplication

Note that: The idea in dynamic programming is different than quick sort (i.e. divide and conquer)

- In quick sort, we only look at the location of one pivot.
- In dynamic programming, we look at all of the pivot's possible locations to answer the question of what is the best pivot placement in the quick sort algorithm.

Note that, as we will see in this example

Dynamic programming = optimal division point + overlapping subproblems.

The above in red defines the Elements of Dynamic Programming

6

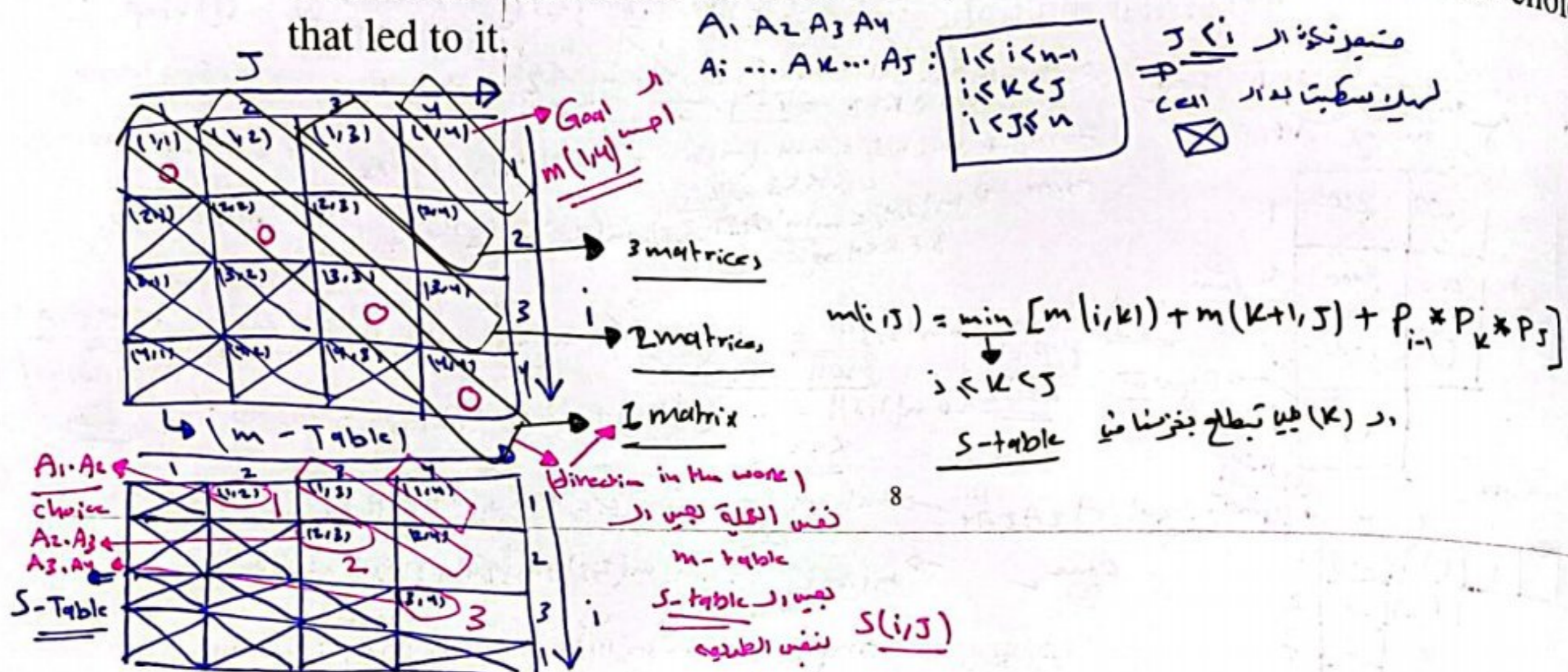
Elements of Dynamic Programming

- **Optimal Substructure:** The optimal solution is built from optimal solutions to subproblems. In the case of the matrix-chain algorithm, if $A_1 \cdot A_2 \cdot \dots \cdot A_k$ is a prefix subchain of an optimal parenthesization of $A_1 \cdot A_2 \cdot \dots \cdot A_n$, then $A_1 \cdot A_2 \cdot \dots \cdot A_k$ and $A_{k+1} \cdot A_{k+2} \cdot \dots \cdot A_n$ must be optimally parenthesized. (This allows using divide and conquer approach i.e. when independent smaller optimization problem of the same form contribute to the solution of the original problem)
- **Overlapping Subproblems:** The space of subproblems must be small (in the sense that the recursive algorithm solves many of the subproblems over and over again) for this method to be useful. The number of distinct problems should be polynomial. In the case of the matrix-chain algorithm, the number of subproblems as we will see, is $\Theta(n^2)$.

Example: Matrix-chain Multiplication

The general approach of Dynamic programming (Top down approach) can be summarized as follows:

- **Memoization:** Check if the subproblem was already solved (trivial solution)
 - For each parenthesize (choice or division point)
 - * Divide and Conquer: make a recursive call on the left side of the division point and another recursive call on the right side.
 - * Compute the combined cost checking if this division point (choice) was the best so far (the cheapest).
 - Return and remember the best cost (solution value) found and the choice that led to it.



Counting Scalar Multiplications in Matrix Multiplication

MATRIX-MULTIPLY(A, B)

1. if $columns[A] \neq rows[B]$
2. then error "incompatible dimensions"
3. else for $i \leftarrow 1$ to $rows[A]$
4. do for $j \leftarrow 1$ to $columns[B]$
5. do $C[i, j] \leftarrow 0$
6. for $k \leftarrow 1$ to $columns[A]$
7. do $C[i, j] = C[i, j] + A[i, k] \cdot B[k, j]$
8. return C

$$\boxed{n \times m} \cdot \boxed{m \times l} = \boxed{n \times l}$$

The number of scalar multiplications is: $n \times m \times l$

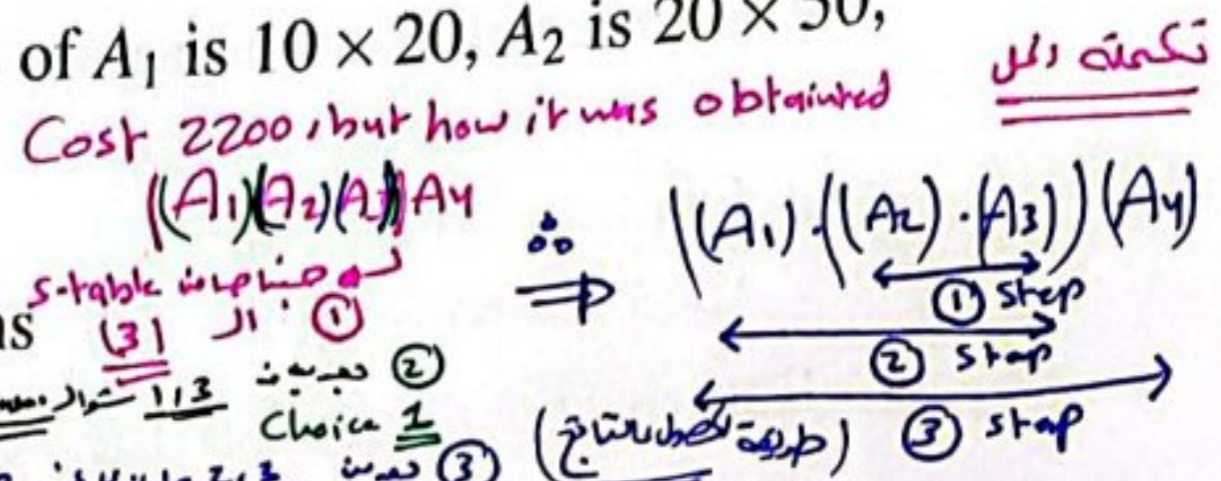
The Matrix-Chain Multiplication Problem

The matrix-chain multiplication problem: given a chain $\langle A_1, A_2, \dots, A_n \rangle$ of n matrices, such that for $i = 1, 2, \dots, n$, matrix A_i has dimensions $p_{i-1} \times p_i$, fully parenthesize the product $A_1 \cdot A_2 \cdot \dots \cdot A_n$ in a way to minimize the number of scalar multiplications.

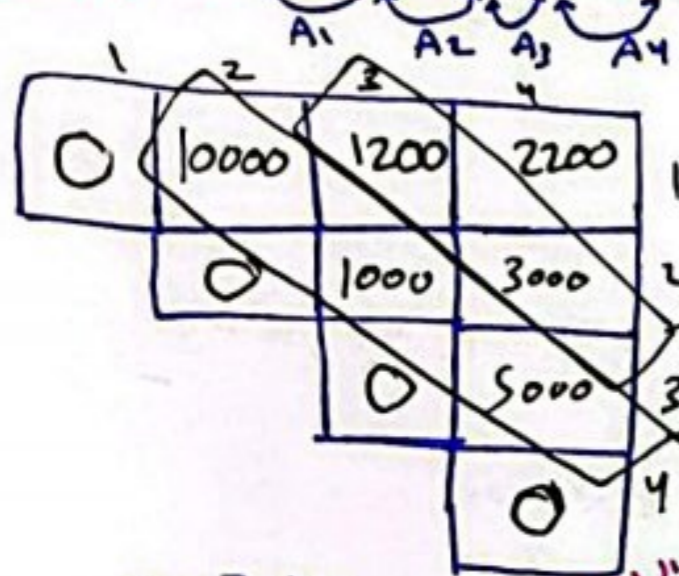
Example: $A_1 \cdot A_2 \cdot A_3 \cdot A_4$ such that the dimensions of A_1 is 10×20 , A_2 is 20×50 , A_3 is 50×1 , and A_4 is 1×100 .

$A_1 \cdot (A_2 \cdot (A_3 \cdot A_4)) \rightarrow 125,000$ scalar multiplications

$(A_1 \cdot (A_2 \cdot A_3)) \cdot A_4 \rightarrow 2,200$ scalar multiplications



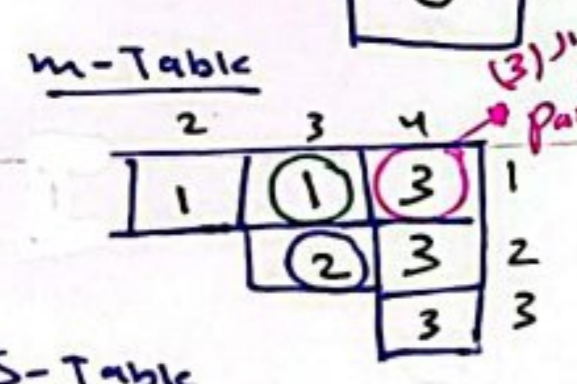
Ex) $P = [10, 20, 50, 1, 100]$



$A_1 A_2 \rightarrow m(1,2) = \min_{1 \leq k < 2} [m(1,k) + m(k,2) + p_0 p_k p_2] = 10 \times 20 \times 50 = 10000$
 $A_2 A_3 \rightarrow m(2,3) = \min_{2 \leq k < 3} [m(2,k) + m(k,3) + p_1 p_k p_3] = 20 \times 50 \times 1 = 1000$
 $A_3 A_4 \rightarrow m(3,4) = \min_{3 \leq k < 4} [m(3,k) + m(k,4) + p_2 p_k p_4] = 50 \times 1 \times 100 = 5000$

$A_1 A_2 A_3 \rightarrow m(1,3) = \min_{k=1,2} [m(1,k) + m(k,3) + p_0 p_k p_3]$
 $k=1: m(1,1) + m(1,3) + p_0 p_1 p_3 = 0 + 1200 + 10 \times 20 \times 1 = 1200$
 $k=2: m(1,2) + m(2,3) + p_0 p_2 p_3 = 10000 + 1000 + 10 \times 50 \times 1 = 10500$
Choice: $k=1$

$A_2 A_3 A_4 \rightarrow m(2,4) = \min_{k=3} [m(2,3) + m(3,4) + p_1 p_3 p_4] = 1000 + 5000 + 20 \times 50 \times 100 = 105000$
 $A_1 A_2 A_3 A_4 \rightarrow m(1,4) = \min_{k=2,3} [m(1,k) + m(k,4) + p_0 p_k p_4]$
 $k=2: m(1,2) + m(2,4) + p_0 p_2 p_4 = 10000 + 105000 + 10 \times 50 \times 100 = 23000$
 $k=3: m(1,3) + m(3,4) + p_0 p_3 p_4 = 1200 + 5000 + 10 \times 50 \times 100 = 65000$
Choice: $k=2$



How to Choose the Best Parenthesization

Exhaustive checking will not provide an efficient algorithm because this would result in an exponential running time algorithm. To see this let's devise a recurrence:

Let $P(n)$ be the number of alternative parenthesizations for an n matrix chain. We can split the sequence between the k th and $(k+1)$ st matrix for any $k = 1, 2, \dots, (n-1)$, and then parenthesize the remaining subsequences, giving the recurrence:

$$P(n) = \begin{cases} 1 & \text{if } n = 1, \\ \sum_{k=1}^{n-1} P(k)P(n-k) & \text{if } n \geq 2. \end{cases}$$

Note that this recurrence has a closed form solution of $P(n) = C(n-1)$, where $C(n)$ is the n th Catalan number, and $C(n) = \frac{1}{n+1} \binom{2n}{n} = \Omega(\frac{4^n}{n^{3/2}})$.

1. Characterizing the Structure of an Optimal Parenthesization

To characterize the structure of an optimal solution for the matrix-chain multiplication problem, we must split the product $A_1 \cdot A_2 \cdot \dots \cdot A_n$ between A_k and A_{k+1} for some integer $1 \leq k < n$.

$A_{i..j}$ denotes the matrix resulting from multiplying $A_i \cdot A_{i+1} \cdot \dots \cdot A_j$.

Using this notation, the cost of the optimal parenthesization is the cost of computing $A_{1..k}$ and $A_{(k+1)..n}$ along with the cost of multiplying the two matrices together.

Note that if $A_1 \cdot A_2 \cdot \dots \cdot A_k$ is a prefix subchain of an optimal parenthesization of $A_1 \cdot A_2 \cdot \dots \cdot A_n$, then $A_1 \cdot A_2 \cdot \dots \cdot A_k$ must be optimally parenthesized. If not, then we could provide a lower cost alternative. An optimal solution to the matrix-chain multiplication problem must contain optimal solutions to subproblems.

2. Defining the Value of an Optimal Solution Recursively

Let $m[i, j]$ denote the minimum number of scalar multiplications to compute $A_{i..j}$; hence, $m[1, n]$ is the minimum number to compute $A_{1..n}$. Note that $A_{i..i} = A_i$ requires no scalar multiplications; hence, $m[i, i] = 0$ for $i = 1, 2, \dots, n$.

Assuming that the optimal parenthesization splits the product $A_i \cdot A_{i+1} \cdot \dots \cdot A_j$ between k and $k+1$ where $i \leq k < j$, then $m[i, j]$ is the minimum cost of computing the subproducts $A_{i..k}$ and $A_{(k+1)..j}$ plus the cost of multiplying them together, $p_{i-1}p_kp_j$:

$$m[i, j] = m[i, k] + m[k+1, j] + p_{i-1}p_kp_j$$

Note that there are $j - 1 - i + 1 = j - i$ possible values of k to check for a given i and j . Below is the recursive definition for the minimum cost of parenthesizing the product $A_i \cdot A_{i+1} \cdot \dots \cdot A_j$:

$$m[i, j] = \begin{cases} 0 & \text{if } i = j, \\ \min_{i \leq k < j} \{m[i, k] + m[k+1, j] + p_{i-1}p_kp_j\} & \text{if } i < j. \end{cases}$$

3. Compute the Optimal Solution Bottom-Up

MATRIX-CHAIN-ORDER is a bottom-up algorithm for computing the optimal solution, which takes a single argument $p = \langle p_0, p_1, \dots, p_n \rangle$, where the dimension of A_i is $p_{i-1} \times p_i$, for $i = 1, 2, \dots, n$.

It uses an auxiliary table $m[1..n, 1..n]$ to store the $m[i, j]$ costs and $s[1..n, 1..n]$ to record the index of k that achieves the optimal cost in computing $m[i, j]$.

MATRIX-CHAIN-ORDER(p)

1. $n \leftarrow \text{length}[p] - 1$
2. **for** $i \leftarrow 1$ to n
3. **do** $m[i, i] \leftarrow 0$ *

14

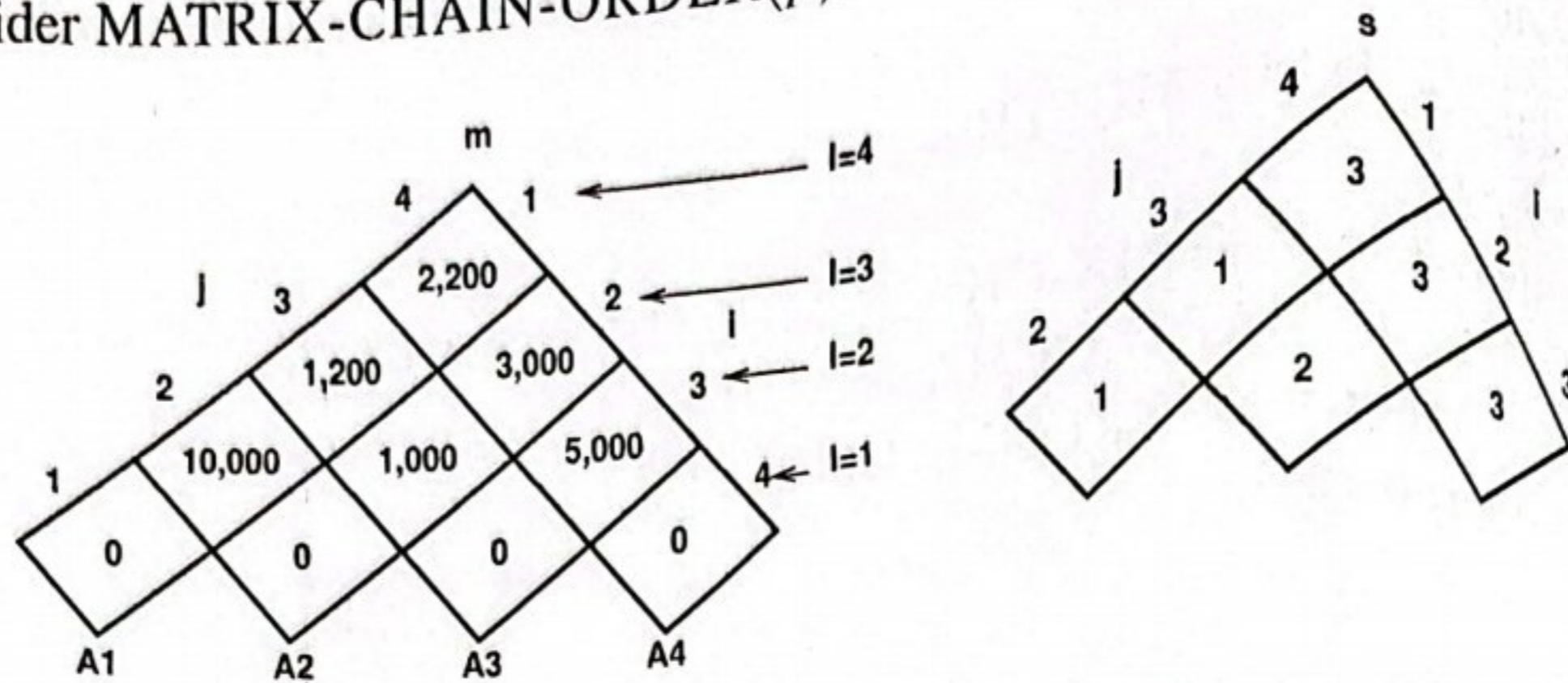
3. Compute the Optimal Solution Bottom-Up *continued*

4. **for** $l \leftarrow 2$ to n
5. **do for** $i \leftarrow 1$ to $n - l + 1$
6. **do** $j \leftarrow i + l - 1$
7. ** $m[i, j] \leftarrow \infty$
8. * **for** $k \leftarrow i$ to $j - 1$
9. * **do** $q \leftarrow m[i, k] + m[k + 1, j] + p_{i-1}p_kp_j$
10. **if** $q < m[i, j]$
11. **then** $m[i, j] \leftarrow q$
12. $s[i, j] \leftarrow k$
13. **return** m and s

At each step, the $m[i, j]$ computed in lines 9-12 depends only on the table entries $m[i, k]$ and $m[k + 1, j]$ already computed.

MATRIX-CHAIN-ORDER Example

Consider MATRIX-CHAIN-ORDER(p), where $p = \langle 10, 20, 50, 1, 100 \rangle$.



16

MATRIX-CHAIN-ORDER Example *continued*

The computations are provided below:

$$m[1, 2] = \min_{1 \leq k < 2} \{m[1, 1] + m[2, 2] + p_0 p_1 p_2\} = 10,000$$

$$m[2, 3] = \min_{2 \leq k < 3} \{m[2, 2] + m[3, 3] + p_1 p_2 p_3\} = 1,000$$

$$m[3, 4] = \min_{3 \leq k < 4} \{m[3, 3] + m[4, 4] + p_2 p_3 p_4\} = 5,000$$

$$m[1, 3] = \min_{1 \leq k < 3} \{m[1, 1] + m[2, 3] + p_0 p_1 p_3 = 1,200, \\ m[1, 2] + m[3, 3] + p_0 p_2 p_3 = 10,500\} = 1,200$$

$$m[2, 4] = \min_{2 \leq k < 4} \{m[2, 2] + m[3, 4] + p_1 p_2 p_4 = 105,000, \\ m[2, 3] + m[4, 4] + p_1 p_3 p_4 = 3,000\} = 3,000$$

$$m[1, 4] = \min_{1 \leq k < 4} \{m[1, 1] + m[2, 4] + p_0 p_1 p_4 = 23,000, \\ m[1, 2] + m[3, 4] + p_0 p_2 p_4 = 65,000, \\ m[1, 3] + m[4, 4] + p_0 p_3 p_4 = 2,200\} = 2,200$$

4. Constructing the Optimal Solution

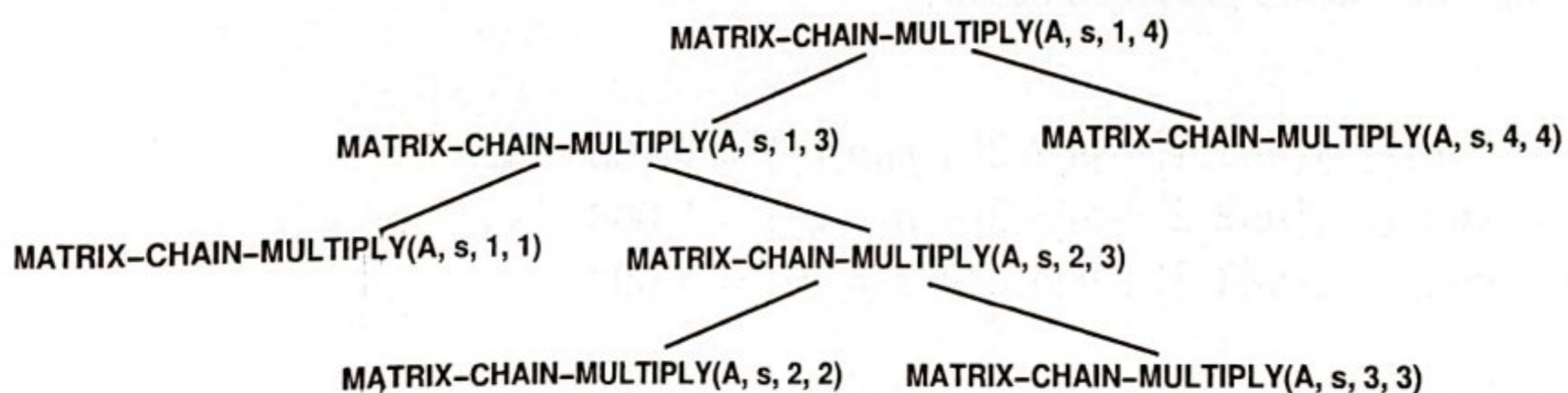
The following algorithm uses the table $s[1..n, 1..n]$ to determine the best way to multiply the matrices.

```
MATRIX-CHAIN-MULTIPLY(A, s, i, j)
1. if  $j > i$ 
2.   then  $X \leftarrow$  MATRIX-CHAIN-MULTIPLY(A, s, i, s[i, j])
3.        $Y \leftarrow$  MATRIX-CHAIN-MULTIPLY(A, s, s[i, j] + 1, j)
4.       return MATRIX-MULTIPLY(X, Y)
5. else return  $A_i$ 
```

For our example, this computes the matrix multiplication as $((A_1 \cdot (A_2 \cdot A_3)) \cdot A_4)$.

18

Constructing the Optimal Solution for the Example



Complexity of MATRIX-CHAIN-ORDER

The complexity of the algorithm for $2 \leq l < n$ is computed as follows:

$$T(n) = \sum_{l=2}^n \sum_{i=1}^{n-l+1} \sum_{k=i}^{j-1} 1 \quad (1)$$

$$= \sum_{l=2}^n \sum_{i=1}^{n-l+1} (j-i) \quad (2)$$

$$= \sum_{l=2}^n \sum_{i=1}^{n-l+1} (i+l-1-i) \quad (3)$$

$$= \sum_{l=2}^n \sum_{i=1}^{n-l+1} (l-1) \quad (4)$$

$$= \sum_{l=2}^n (l-1)(n-l+1) \quad (5)$$

$$= \sum_{l=1}^{n-1} (n-l) \cdot l = n \sum_{l=1}^{n-1} l - \sum_{l=1}^{n-1} l^2 \quad (6)$$

$$= \frac{n^2(n-1)}{2} - \frac{n(n-1)(2n-1)}{6} \quad (7)$$

$$= \frac{n^3 - n}{6} = O(n^3) \quad (8)$$

n = loop لكل l For loop
20

let $p(n)$: number of all possible n -matrixes parantization of the sequence $A_1 \dots A_n$

$$p(n) = \sum_{k=1}^{n-1} p(k) * p(n-k) \quad \begin{matrix} (A_1 \dots A_k) & (A_{k+1} \dots A_n) \\ \underbrace{\hspace{2cm}}_k & \underbrace{\hspace{2cm}}_{n-k} \end{matrix}$$

$$= \sim \left(\frac{4^n}{n^{3/2}} \right) \text{ exponential}$$

Lecture 12: Greedy Algorithms

Fractional Knapsack Problem

→ Greedy Algorithms have with Dynamic programming. Similarities → optimal substructure + Applied to optimization problem. Differences → there is (greedy) no assumption of having pre-computed solution to the subproblem. } one of the advantages of the greedy over the dynamic programming. (أيضا في المسألة Storage)

There is a guarantee to achieve or reach to the optimal solution ← dynamic programming disadvantage ← [① there is no guarantee to achieve or reach to the optimal solution of the underlying problem.]

Dr. Khalil Yousef

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

→ uniqu property (Dynamic programming): Greedy choice → make locally optimal choices in the hope to reach an optimal solution.
 Ex) Computing the shortest path from a single source in a graph.

Read Chapter 16 of Introduction to Algorithms

different example → Knapsack problem → Integer Fraction } work in the graph problem
 → minimum-spanning-tree algorithms
 → Single source shortest path

فكرة ال Knapsack Solution

Example: item (n=3), W=50, b=23 kg
 Solution 1 (binary) → Dynamic programming
 ① $w_1=10, b=7, v=70$
 ② $w_2=20, b=12, v=120$
 ③ $w_3=20, b=9, v=90$

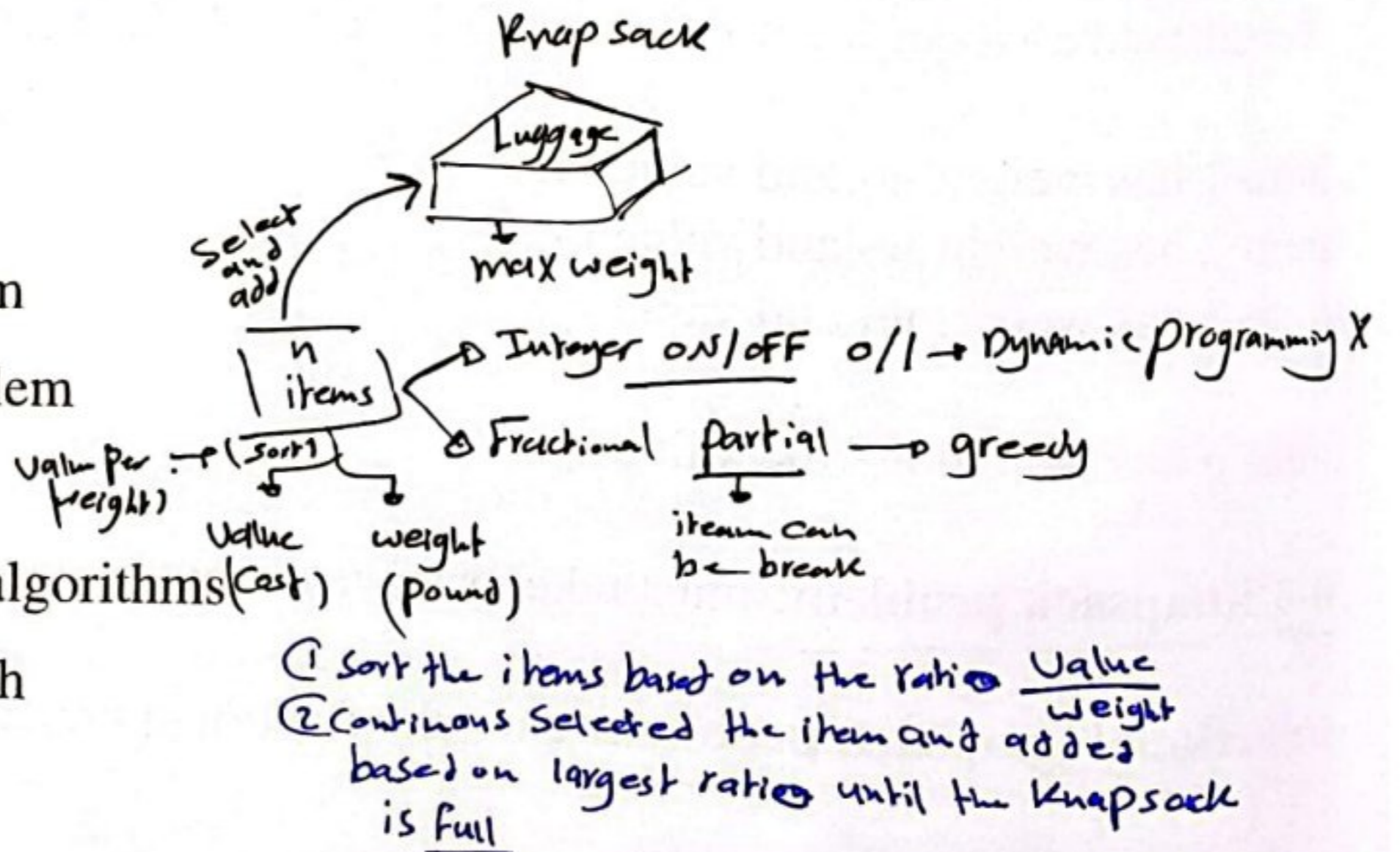
Greedy Algorithms: value per weight (value / weight) → greedy
 ① $w_1 + w_2$
 ② $w_2 + w_3$
 ③ $w_1 + w_2 + \frac{2}{3}w_3$ (Fractional Knapsack)

A greedy algorithm makes the choice that looks best at the moment, i.e., it makes a locally optimal choice in hopes of achieving a globally optimal solution.

Dis It is a powerful and widely applicable method, but it may not always lead to the optimal solution.

Examples:

- Activity-selection problem
- Fractional knapsack problem
- Huffman coding
- Minimum-spanning-tree algorithms (Cost)
- Single-source shortest path



Complexity: $O(n \log n)$

When is a Greedy Algorithm Applicable?

A greedy algorithm obtains an optimal solution by making a sequence of choices that seem best at the moment they are chosen. This heuristic strategy; however, does not always produce an optimal solution for all problems.

There are two properties that are exhibited by most of the problems that lend themselves to a greedy strategy:

- ① **Greedy-choice property:** It is possible to make locally-optimal choices in order to arrive at a globally optimal solution. Note that greedy choices are made without relying on having solutions to subproblems first. This is an important difference from the dynamic programming method
- ② **Optimal substructure:** The optimal solution contains subproblems which are optimal solutions to subproblems. This property is important for the dynamic programming method as well.

2

Greedy Strategy versus Dynamic Programming

To illustrate how to choose between dynamic programming and a greedy approach, we will consider two variants of a classical optimization problem, **the knapsack problem**. The basic idea is to maximize the value of goods in a knapsack, which can only hold W pounds. Note that each item to consider for packing has both a weight and a value:

item 1 has weight w_1 and value v_1 .
item 2 has weight w_2 and value v_2 .
item 3 has weight w_3 and value v_3 .
:
item n has weight w_n and value v_n .

0-1 knapsack problem: must take or leave the entire item.

Fractional knapsack problem: can take fractional items.

Greedy Strategy versus Dynamic Programming *continued*

Both knapsack problems exhibit the optimal-substructure property:

- **0-1 knapsack problem:** consider the most valuable load weighing W pounds. If we remove j , the remaining load must be the most valuable load weighing $W - w_j$ using the $n - 1$ items excluding j .
- **fractional knapsack problem:** consider removing a weight w of one item j from an optimal load weighing W pounds. The remaining load must be the most valuable load weighing $W - w$ given the $n - 1$ items and $w_j - w$ pounds of j .

Even though the fractional knapsack problem can be solved with a greedy approach, the 0-1 knapsack problem cannot be.

4

Greedy Strategy for the Fractional Knapsack Problem

- First, for each item i , compute the value per pound $\frac{v_i}{w_i}$ and sort the items by this value in $O(n \lg n)$ time.
- Obeying a greedy strategy, take as much of the item with the **greatest value per pound**.
- If there is still capacity, continue with the next most valuable item, taking as much as possible.
- Continue with the next most valuable item until the knapsack is full.
- This greedy algorithm runs in $O(n \lg n)$ time.

↳ Surviving

Greedy Strategy for the 0-1 Knapsack Problem

Consider the packings for a 0-1 knapsack problem with the following items and a knapsack with capacity, $W = 50$ pounds.

item 1: $w_1 = 10, v_1 = \$70, \frac{v_1}{w_1} = \7 (ratio)

item 2: $w_2 = 20, v_2 = \$120, \frac{v_2}{w_2} = \6 (ratio)

item 3: $w_3 = 30, v_3 = \$135, \frac{v_3}{w_3} = \4.5 (ratio)

1. **The greedy packing:** pick item 1 and then item 2, leaving a capacity too small for item 3. The weight is 30 pounds, the value is \$190. \rightarrow this is optimal?! No (عكس رطل انظر)
2. **A better non-greedy packing:** pick items 1 and 3, leaving a capacity too small for item 2. The weight is 40 pounds, the value is \$205. (better) \rightarrow this is optimal?! Fraction: No (بصرا انظر)
3. **An optimal non-greedy packing:** pick items 2 and 3, leaving a capacity too small for item 1. The weight is 50 pounds, the value is \$255.

This problem can be solved using dynamic programming because of the overlapping subproblems and optimal-substructure property.

Lecture 13: (Minimal) Spanning Trees

Course Learning Outcome

- Use fundamental graph algorithms, like traversal, shortest path and spanning tree in the solution of real-life problems

Dr. Khalil Yousef

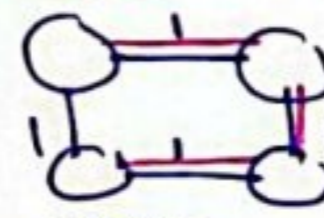
Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

Read Sections 21.1-21.3 and Chapter 23 of *Introduction to Algorithms*

MST = Φ : Is it ^{min. spanning tree} unique? and if it is not, when this can happen

optimal solution "MST" is unique iff the graph contains distinct weight (weight duplicate = لا يوجد)

$|V|$ vertices
 $|V|-1$ MST = edge

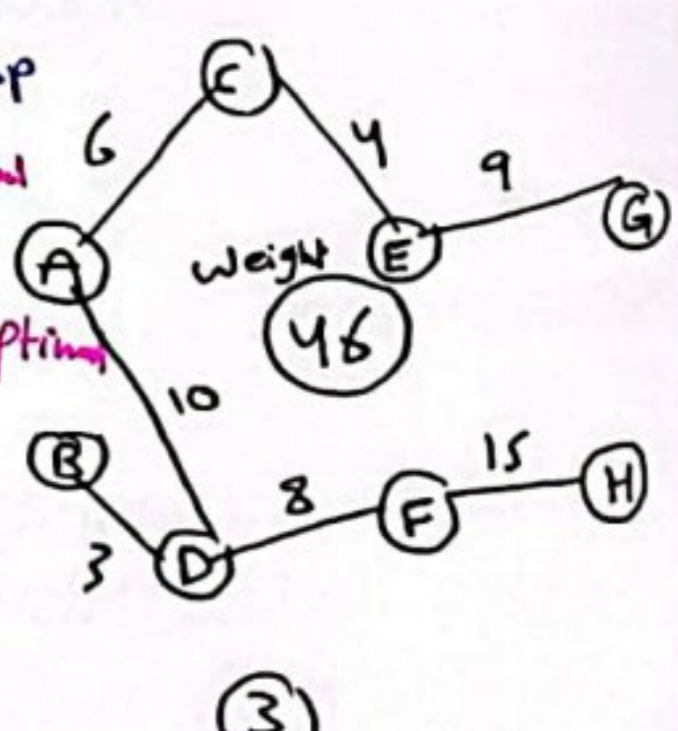
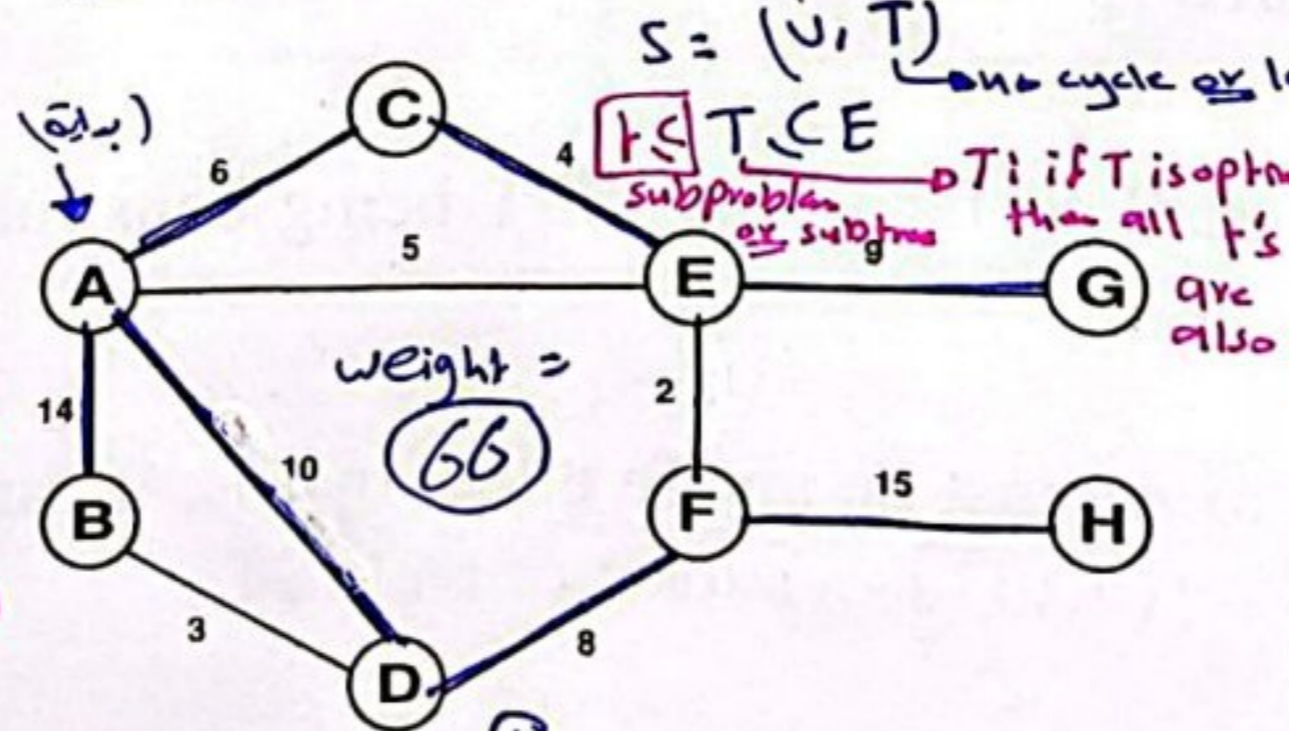
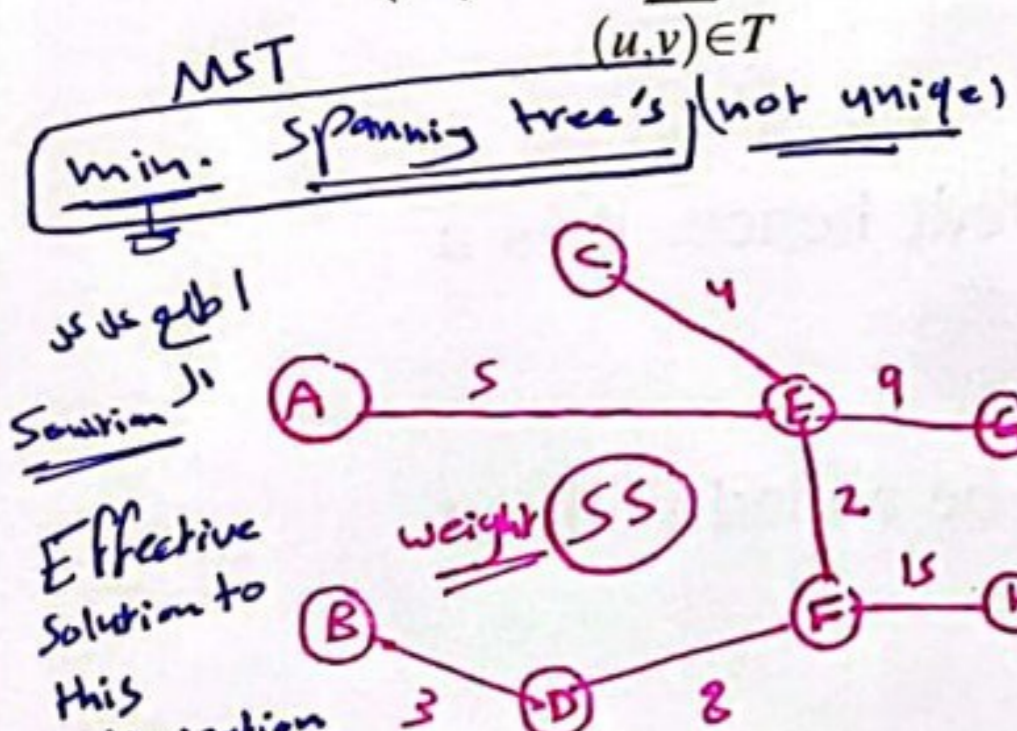


Cost = 3
 MST in this example is not unique, in fact every spanning tree has a MST

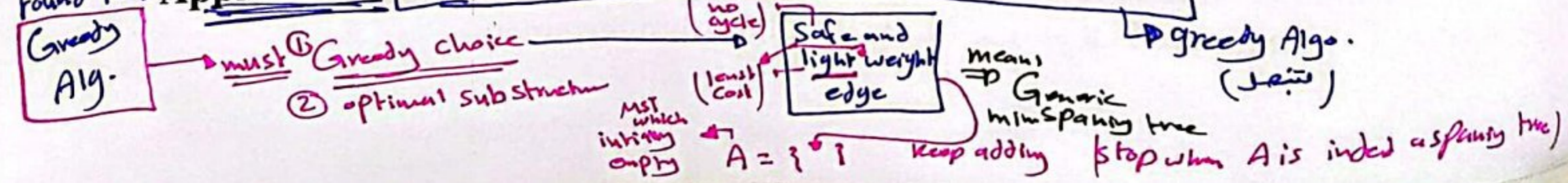
Spanning Trees

A **spanning tree** $S = (V, T)$, for a connected undirected graph $G = (V, E)$ is an undirected tree (i.e., connected and acyclic) that connects all vertices V with $T \subseteq E$.

A **minimum spanning tree** (or MST) for a connected undirected graph $G = (V, E)$, given a weight function $w : E \rightarrow R$, is the spanning tree $S = (V, T)$ for which $w(T) = \sum_{(u,v) \in T} w(u,v)$ is minimized. For example:



Applications: Minimize the cost of wiring electronic circuits.



Optimal Substructure Property of MST

An MST has the optimal substructure property in that an optimal MST contains optimal subtrees.

- To demonstrate this, consider an MST for the connected undirected graph $G = (V, E)$, T , containing an edge (u, v) .
- If we remove the edge, T is partitioned into two subtrees T_1 and T_2 .
- T_1 must be an MST of $G_1 = (V_1, E_1)$, the subgraph of G induced by the vertices of T_1 (i.e., V_1 are the vertices of T_1 and $E_1 = \{(x, y) \in E : x, y \in V_1\}$).
- Similarly, T_2 must be an MST of G_2 .
- Because $w(T) = w(u, v) + w(T_1) + w(T_2)$, there cannot be a more optimal tree than T_1 or T_2 ; otherwise, T would be suboptimal.

2

GENERIC-MST

GENERIC-MST(G, w)

1. $A \leftarrow \emptyset$ (empty) initial
2. while A does not form a spanning tree $\Rightarrow A = \{\emptyset\}$ empty \rightarrow تبدأ
3. do find an edge (u, v) that is safe for A
4. $A \leftarrow A \cup \{(u, v)\}$ \rightarrow no cycle + least weight (cost)
5. return A

A is the set of edges added so far to the MST being constructed; hence, it is a subgraph of an MST.

Each edge (u, v) added to A must be a safe edge, that is, it can be added without violating the fact that $A \cup \{(u, v)\}$ is a subset of an MST.

The loop in lines 2-4 is executed $|V| - 1$ times as each of the $|V| - 1$ edges of the MST is determined. Initially, there are $|V|$ trees, with each iteration reducing the number by 1. When there is a single MST, the algorithm terminates.

Terminology for Safe Edge Selection

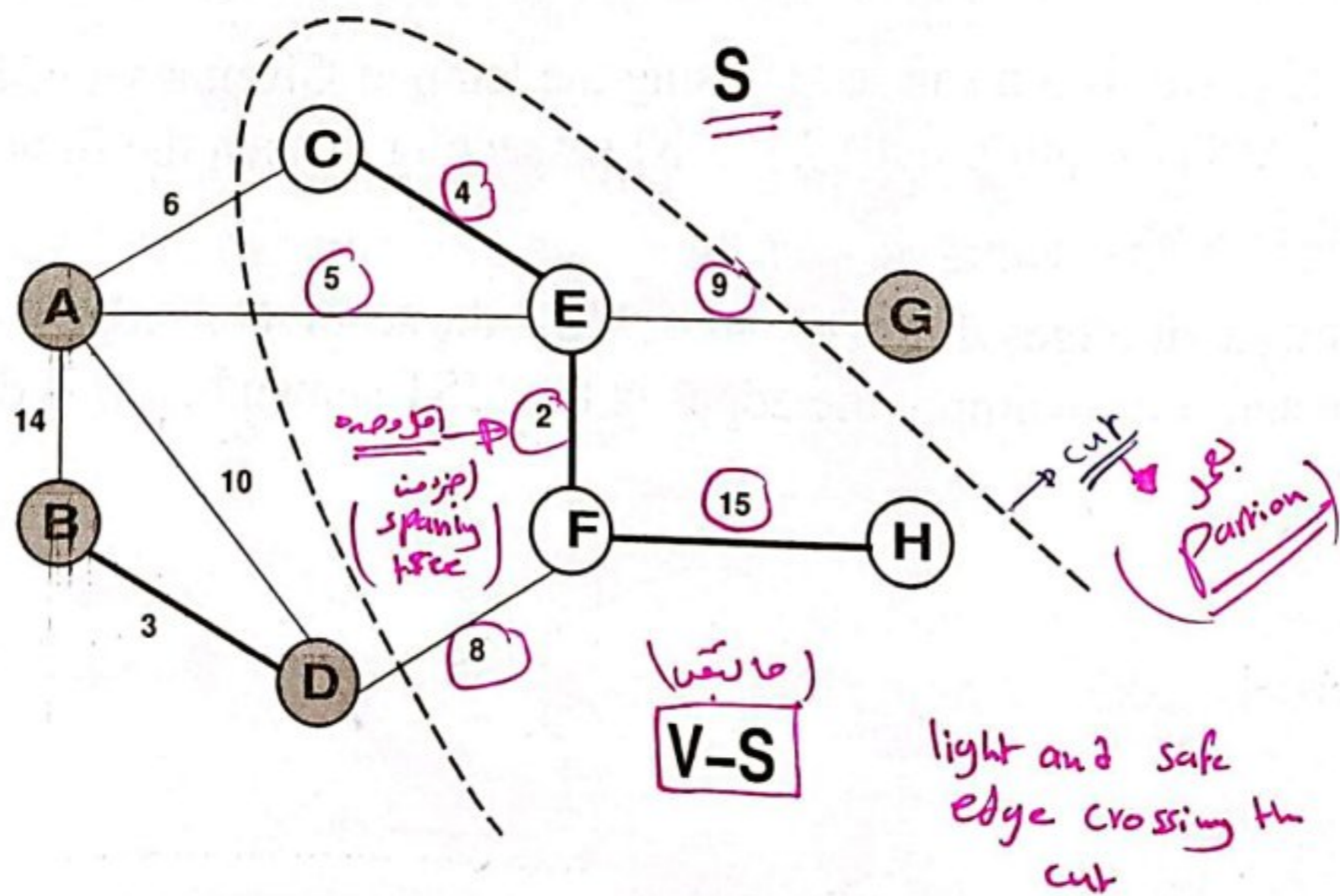
We need some definitions to help us to understand GENERIC-MST:

فكرت ان
في البداية
الشيء

- A **cut** $(S, V - S)$ of an undirected graph $G = (V, E)$ is a partition of V .
- An edge $(u, v) \in E$ **crosses** the cut $(S, V - S)$ if one endpoint is in S and the other is in $V - S$.
- A cut **respects** the set A if no edge in A crosses the cut.
- A **light edge** is the the minimum-weight edge crossing the cut.
- A **safe edge** is an edge that can be added to A , a subset of the MST, so that is still a subset of the MST.

4

Example Illustrating Terminology



$$A = \{(B,D), (C,E), (E,F), (F,H)\}$$

بختار الحواف الآمنة أو (ج) ، لأنها تكون جزء من spanning tree بحيث لا يعبر القطع (أي لا يتركز في باقي) cut
 $S = \{E, F\}$ (أي الحواف الآمنة)

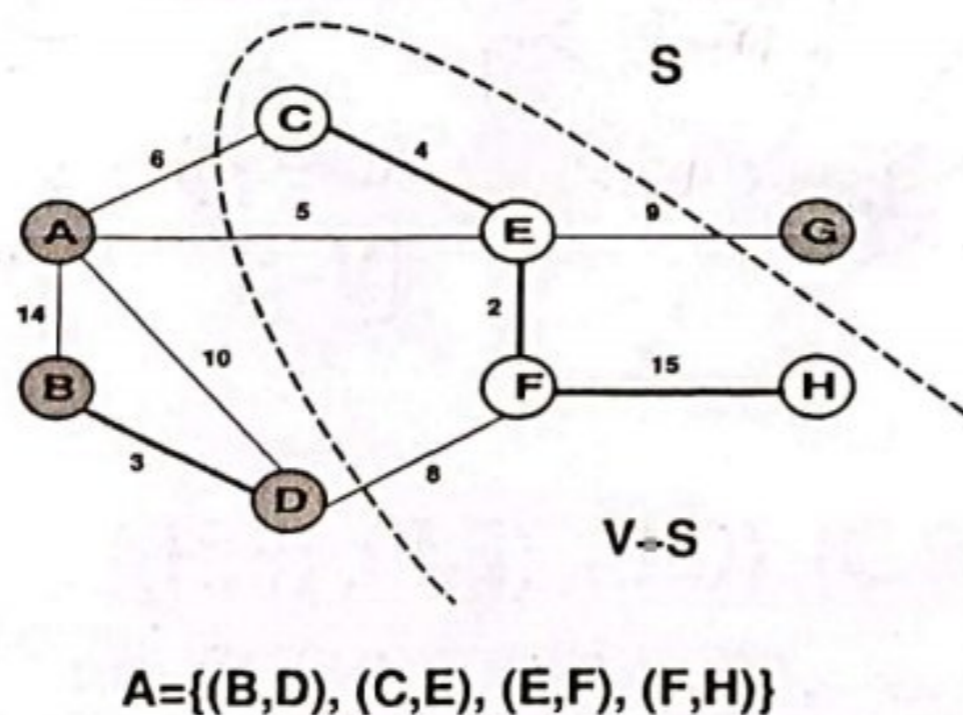
MST: Important Notes:

Distinct weights in the a graph guarantee that the minimum spanning tree of the graph is unique. Without this condition, there may be several different minimum spanning trees. For example, if all the edges have weight 1, then every spanning tree is a minimum spanning tree with weight $V - 1$.

8

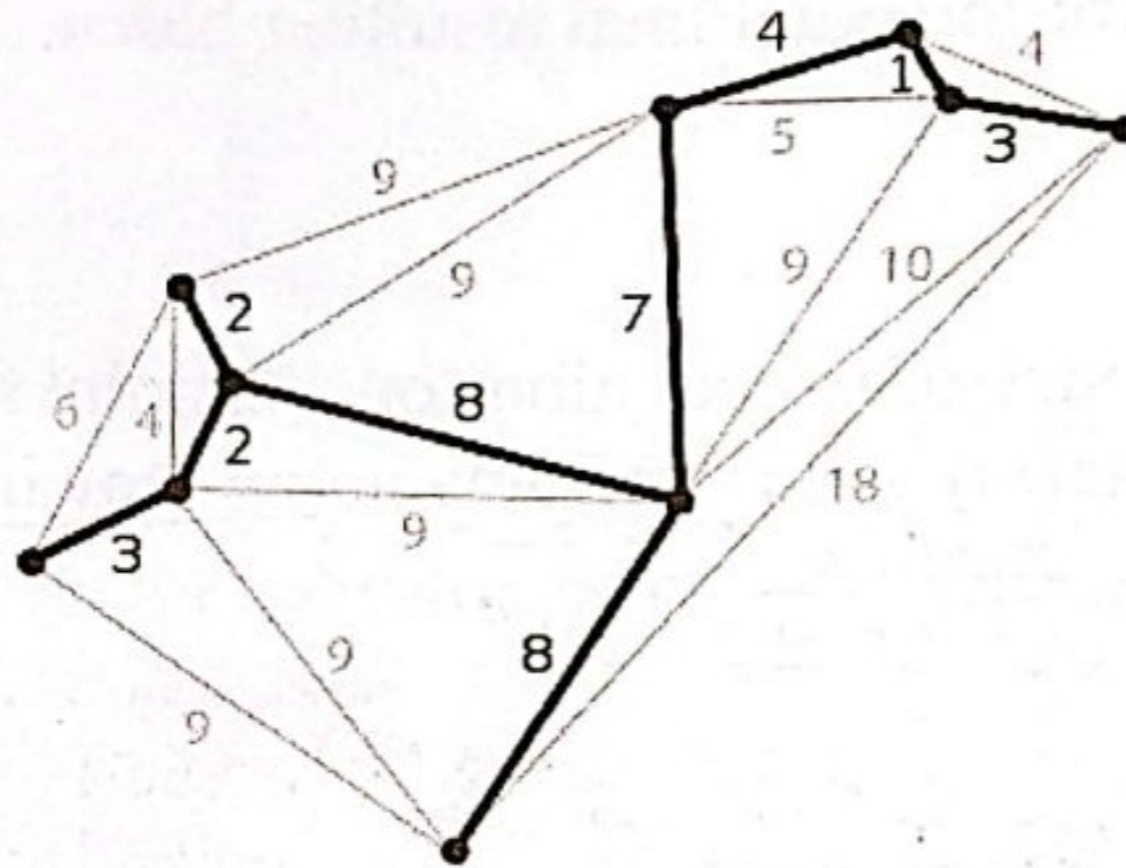
MST: Important Notes:

- For Greedy algorithms, there are efficient means to identify safe choices of the edges; Prim and Kruskal Algorithms.
- For MST, we find a safe edge using the lemma: Given a set of edges A that is part of MST A and a cut $(S, V - S)$ respecting A , then the light edge crossing the cut is safe.
- Given a set of edges A that is part of MST, the set of these edges is not necessary connected. For example the edges in the MST shown below is disconnected.



MST: Important Notes:

- The MST actual algorithm doesn't developed yet; because how to find a cut and how to find a lightest edge. The following algorithms describe the safe edge but use the same Generic MST.
 - Kruskal's MST Algorithm
 - Prim's MST Algorithm



10

Requires using special disjoint set operation

make-set
FIND-SET
Union

are associated with low order Time complexity

Kruskal's MST Algorithm

these operation will be used in away to sure that we add to A a light and safe edge

Repeatidly:

Add (Update partition (tree) by UNION (u, v) i.e. $A = A \cup \{(u, v)\}$)

the lightest (lowest weight edge)

legal edge to A (doesn't cause a cycle to A; Question: how to find this edge; This edge should join two different blocks of the partitions (trees) satisfying the condition that FIND-SET(u) \neq FIND-SET(v)).

ما تجوزك لاس

Note that UNION (u, v) , FIND-SET(u), FIND-SET(v), and others are operations on a disjoint data structure. We will now describe some of these operations.

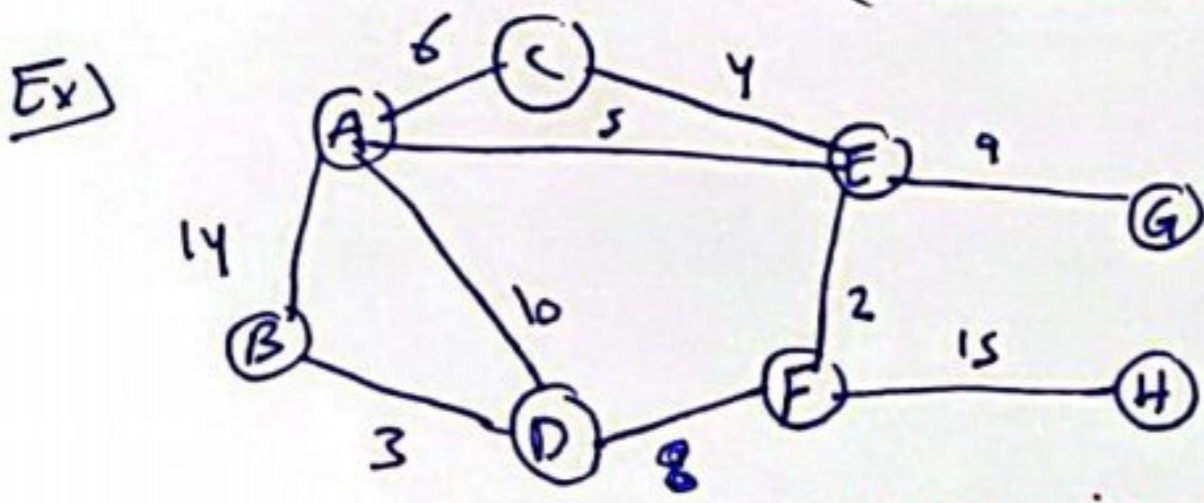
Kruskal's MST Algorithm

Disjoint Set Data structure operations:

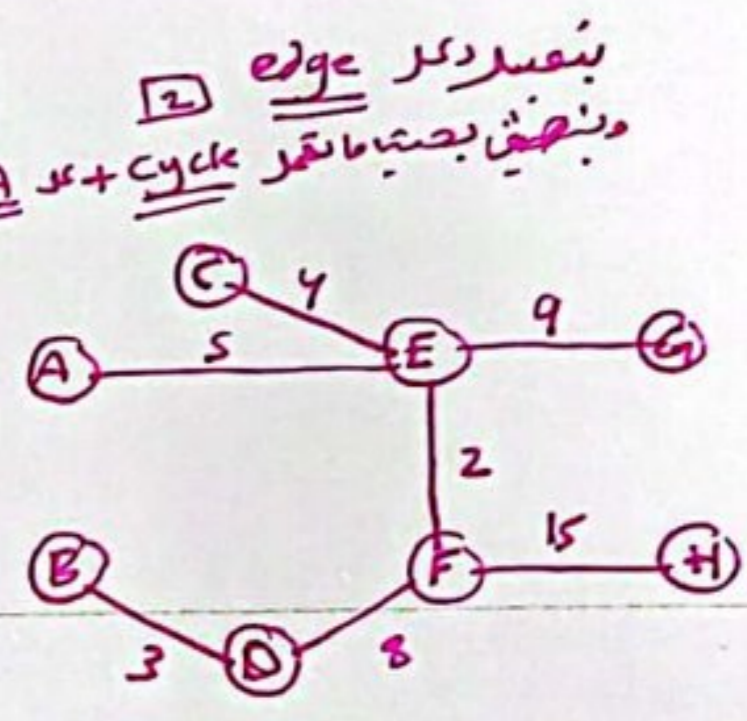
- **MAKE-SET**(x): adds x to the partition, extending the domain. (دفع الى set مجموعة)
- **FIND-SET**(x): returns the representative element (name of the set) of the partition block containing x.
- **UNION**(x, y): combine the partition blocks for x and y and choose a new representative element for the combined resulting block. (مجموع)

Running time cost: A sequence of m operations on a disjoint set data structure runs in $O(m\alpha(m))$ time, where $\alpha(m) \leq 4$ (extremely a low growing function)

(Constant time)



- Step 1: Sorting edges by weight
- ✓ (E,F) 2
 - ✓ (B,D) 3
 - ✓ (C,E) 4
 - ✓ (A,E) 5
 - ✗ (A,C) 6 (cycle)
 - ✓ (D,F) 8
 - ✓ (E,G) 9
 - ✗ (A,D) 10 (cycle)
 - ✗ (A,B) 14 (cycle)
 - ✓ (F,H) 15



$A = \{(E,F), (B,D), (C,E), (A,E), (D,F), (E,G)\}$

Kruskal's MST Algorithm (Ex)

(Cost MST) $46 = 2+3+4+5+8+9+15 = \text{weight} \neq (F,H)$

This algorithm finds a safe edge to add to the growing forest by finding, of all the edges that connect any two trees, the edge (u, v) of least weight. Let T_1 and T_2 denote two trees connected by edge (u, v) . Since (u, v) must be a light edge connecting T_1 to another tree, Corollary 24.2 implies that (u, v) is a safe edge.

MST-KRUSKAL(G, w)

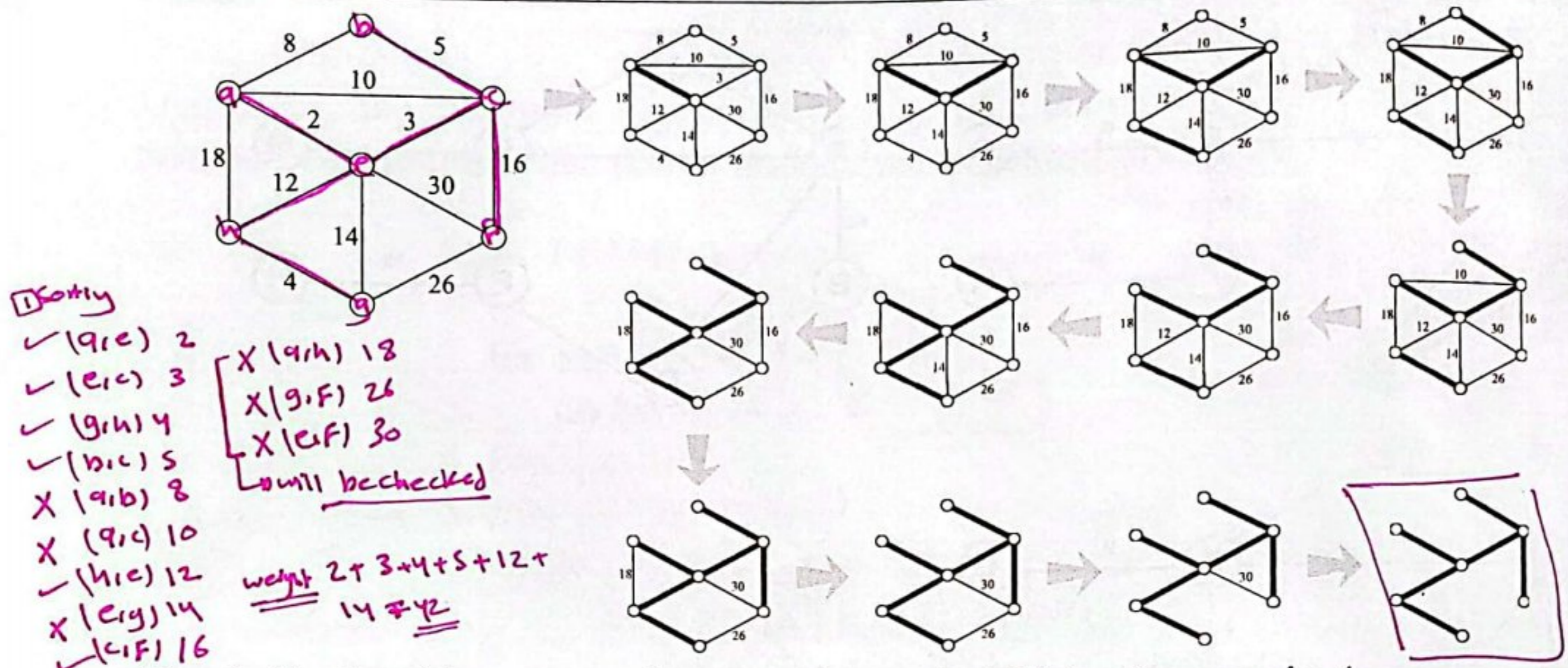
1. $A \leftarrow \emptyset$
2. for each vertex $v \in V[G]$
3. do **MAKE-SET**(v) (isolated node)
4. sort the edges of E by non-decreasing weight w
5. for each edge $(u, v) \in E$, in order of w
6. do if **FIND-SET**(u) \neq **FIND-SET**(v)
7. then $A \leftarrow A \cup \{(u, v)\}$
8. **UNION**(u, v) (not belong same path (no have) loop)
9. return A

Time Complexity $\Rightarrow O(|E| \lg |E|)$

أهم خطوة في هذا الـ algo

ترتيب edge في graph weight $\in (E \lg E)$

MST-KRUSKAL Example



Sort by

- ✓ (a,c) 2
- ✓ (b,c) 3
- ✓ (d,h) 4
- ✓ (b,c) 5
- X (a,b) 8
- X (a,d) 10
- ✓ (h,c) 12
- X (c,g) 14
- ✓ (c,f) 16

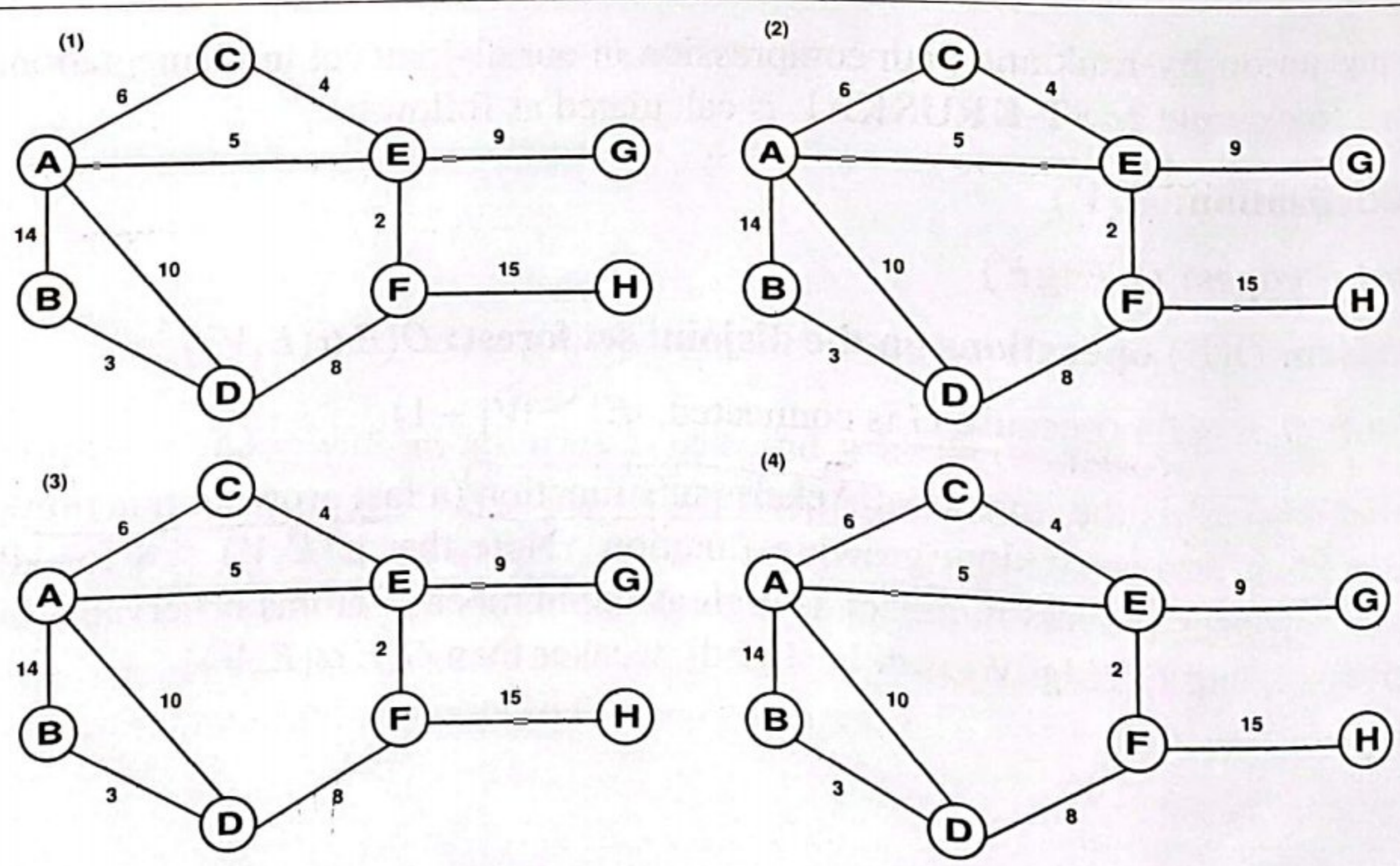
X (a,h) 18
X (g,f) 26
X (c,f) 30
Low will be checked

weight $2+3+4+5+12+14+16 = 42$

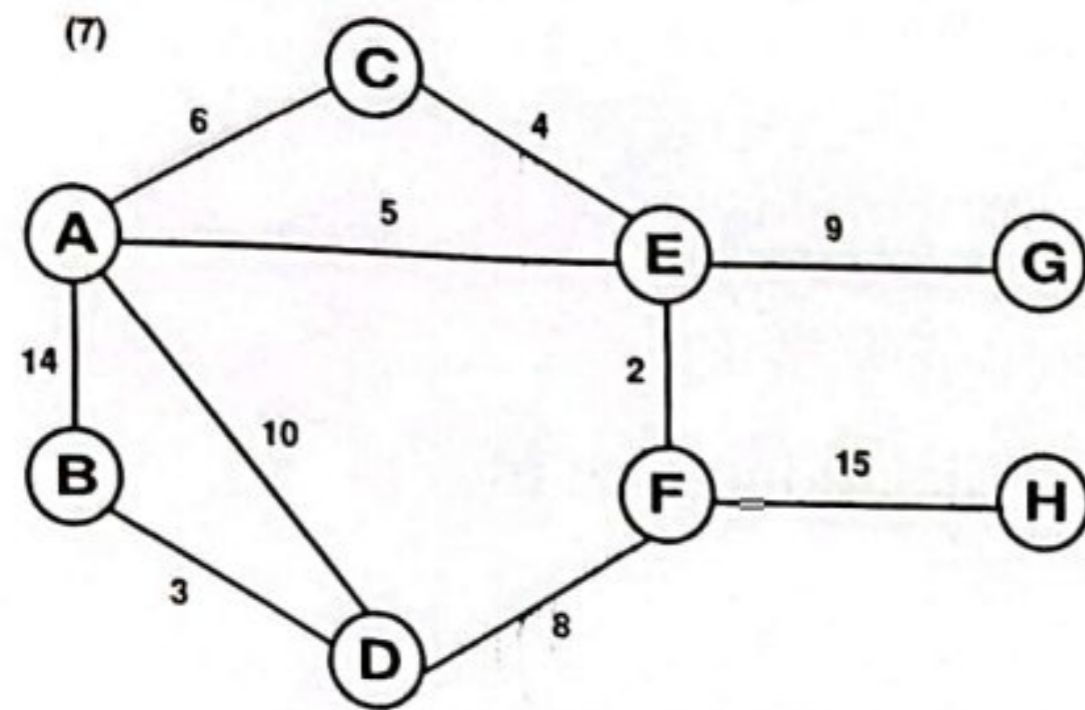
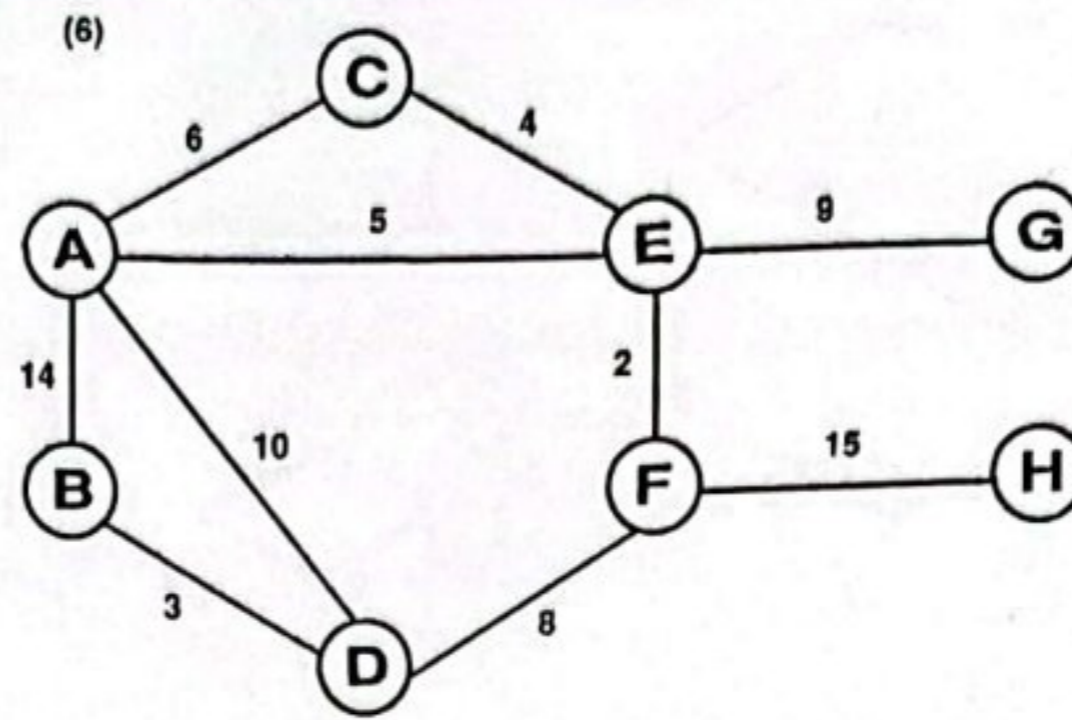
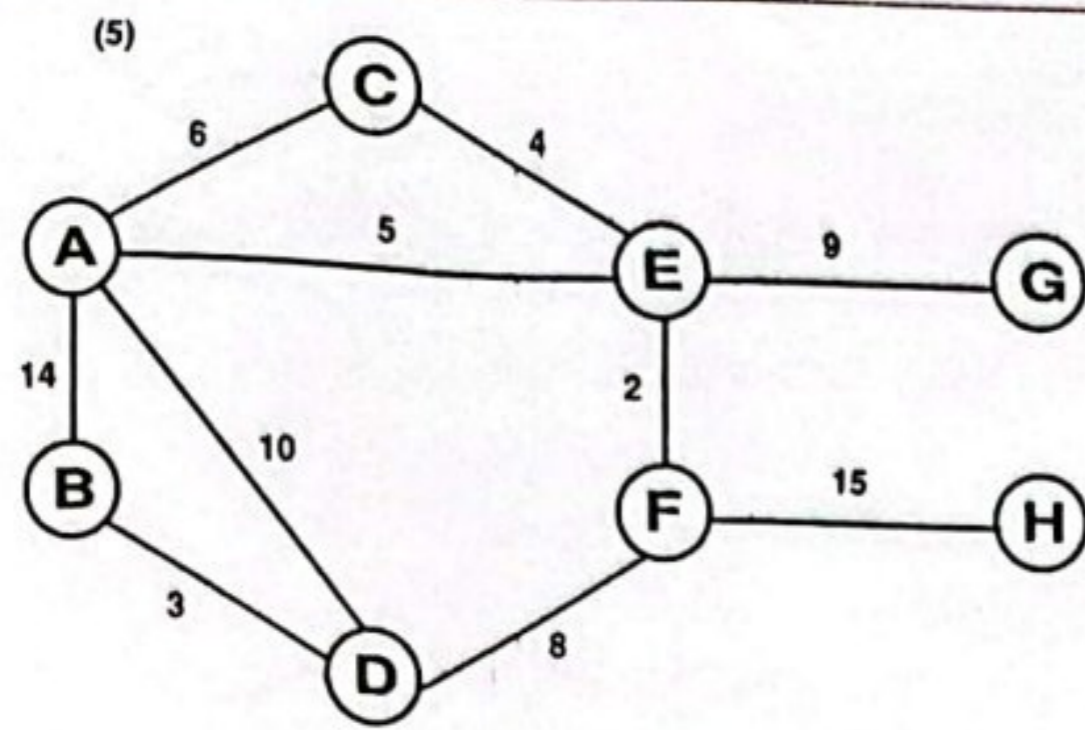
Kruskal's algorithm run on the example graph. Thick edges are in A.

<http://www.cs.uinc.edu/~jeffe/teaching/373/notes/13-mst.pdf>

MST-KRUSKAL Example



MST-KRUSKAL Example *continued*



16

MST-KRUSKAL Running Time

If we use union-by-rank and path compression in our disjoint set implementation, the time to execute MST-KRUSKAL is calculated as follows:

- **Initialization:** $\Theta(V)$
- **Sort E edges:** $O(E \lg E)$
- **Perform $O(E)$ operations on the disjoint set forest:** $O(E \alpha(E, V))$
- **Total:** $O(E \lg E)$ (because G is connected, $|E| \geq |V| - 1$)

Note that $\alpha(m, n)$ is the inverse of Ackerman's function (a fast growing function), and as such it is a very slow growing function. Note that $\alpha(E, V) \leq 4$ for all practical purposes (covers numbers as high as the number of atoms observable in the universe), and $O(E \lg^* V)$ is only slightly weaker than $O(E \alpha(E, V))$.

① Very Similar to BFS (will use a Queue + will use what we call Keys of the vertices to help us pick the light weight and safe edge)

Prim's MST Algorithm

(Priority Queue = min heap)

② Uses Key[v] Function for all the vertices to keep the min. weight of any edge connecting to v from vertices in the tree → (MST)

The algorithm uses a queue, Q, to select an edge to add to A. For each vertex v, key[v] keeps the minimum weight of any edge connecting to v from vertices in the tree, and π[v] points to the parent node in the tree. Initially, key[v] = ∞.

③ uses π[v] parent function to point to the parent node in the Tree MST

④ Input to the Algorithm * undirected graph * unique source node

```

MST-PRIM(G, w, r)
1. Q ← V[G] (min heap)
2. for each vertex u ∈ Q
3.   do key[u] ← ∞ (Source node)
4. key[r] ← 0
5. π[r] ← NIL (Source)
6. while Q ≠ ∅
7.   do u ← EXTRACT-MIN(Q)
8.   for each v ∈ Adj[u]
9.     do if v ∈ Q and w(u, v) < key[v]
10.      then π[v] ← u
11.      key[v] ← w(u, v)
  
```

لعمري زي BFS
Source node
adj.
BFS
unit distance
parent
بجمله امانه
MST
من قدامه
من Key
على weight
Edges
ال weight
edge
vertices
Extract min

BFS

u, v

heap Dec. Key
α(1) α(lg v)
Fibonacci binning

Time Complexity (Finally heap)
Total = $\Theta(V \lg V + E \lg V)$
 $= \Theta((V+E) \lg V)$

Time Complexity
Fibonacci heap
= $V \lg V + E$

node	a	b	...			
Key[]	0	∞	∞	∞	∞	∞
π[]	NIL	NIL	NIL	NIL	NIL	NIL

MST-PRIM Discussion

During the course of the algorithm:

$$A = \{(v, \pi[v]) : v \in V - \{r\} - Q\}$$

At the end:

$$A = \{(v, \pi[v]) : v \in V - \{r\}\}$$

MST-PRIM starts with an arbitrary root r and it loops until it constructs a tree spanning the vertices of V. At each step, a light edge connecting a vertex in A to a vertex in V - A is added to the tree. By corollary 24.2, the algorithm will add only edges that are safe for A, so the resulting tree will be an MST. The strategy is clearly a greedy one, since at each step, the tree is augmented with an edge that contributes a minimum amount to the tree's weight.

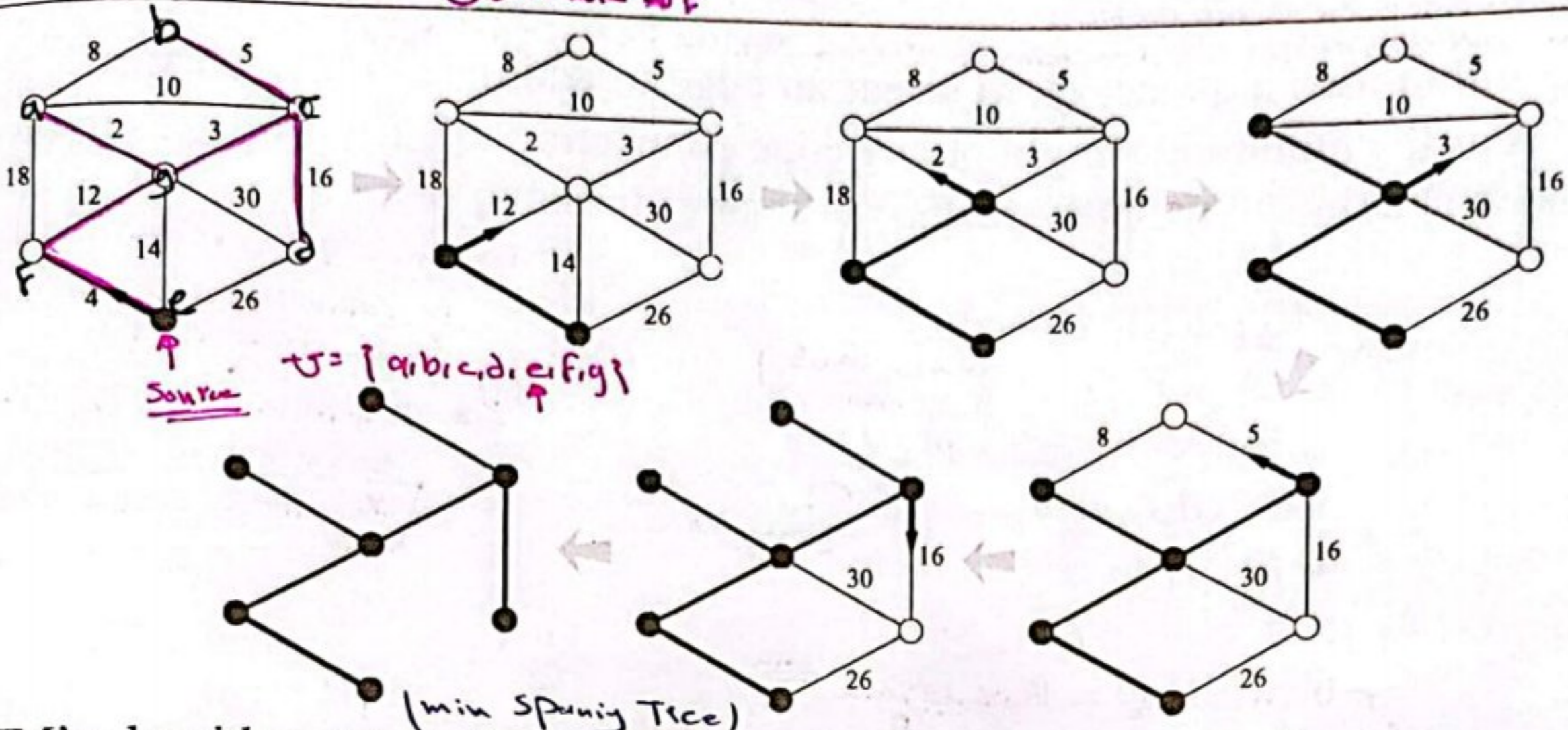
18 Recall the operation on the min heap Q
|Q| = |V|
consider Binary heap
use other kind of heap ⇒ Fibonacci heap

Extract-min() = $O(\lg V)$
Decrease-Key() = $O(\lg V)$
Extract-min() = $O(\lg V)$
Decrease-Key() = $O(1)$
as a fact ← Key()

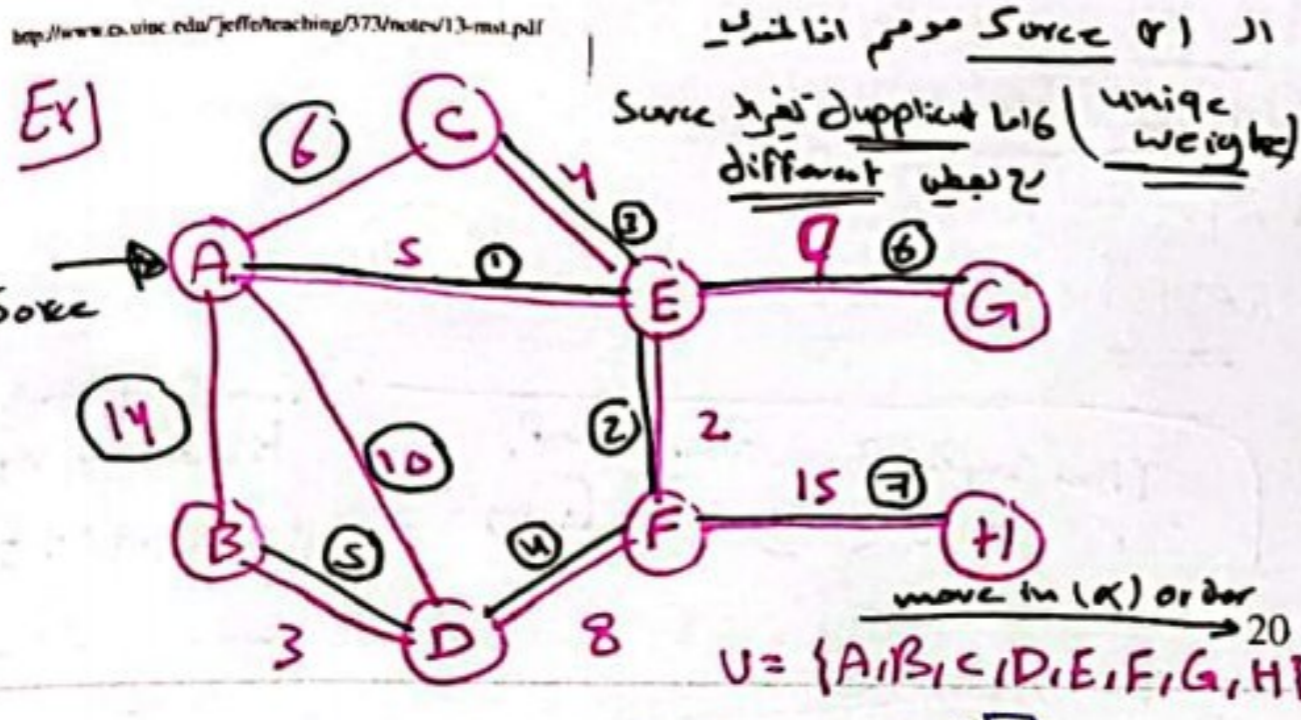
MST-PRIM Example

node	x	x	x	x	x	x	x
key[]	9	8	3	25	50	4	12
π[]	nil	a	g	e	nil	e	e

Cost $\Rightarrow 2+5+3+16+0+4+12 = 42$



PRIM's algorithm run on the example graph. Thick edges are in A.

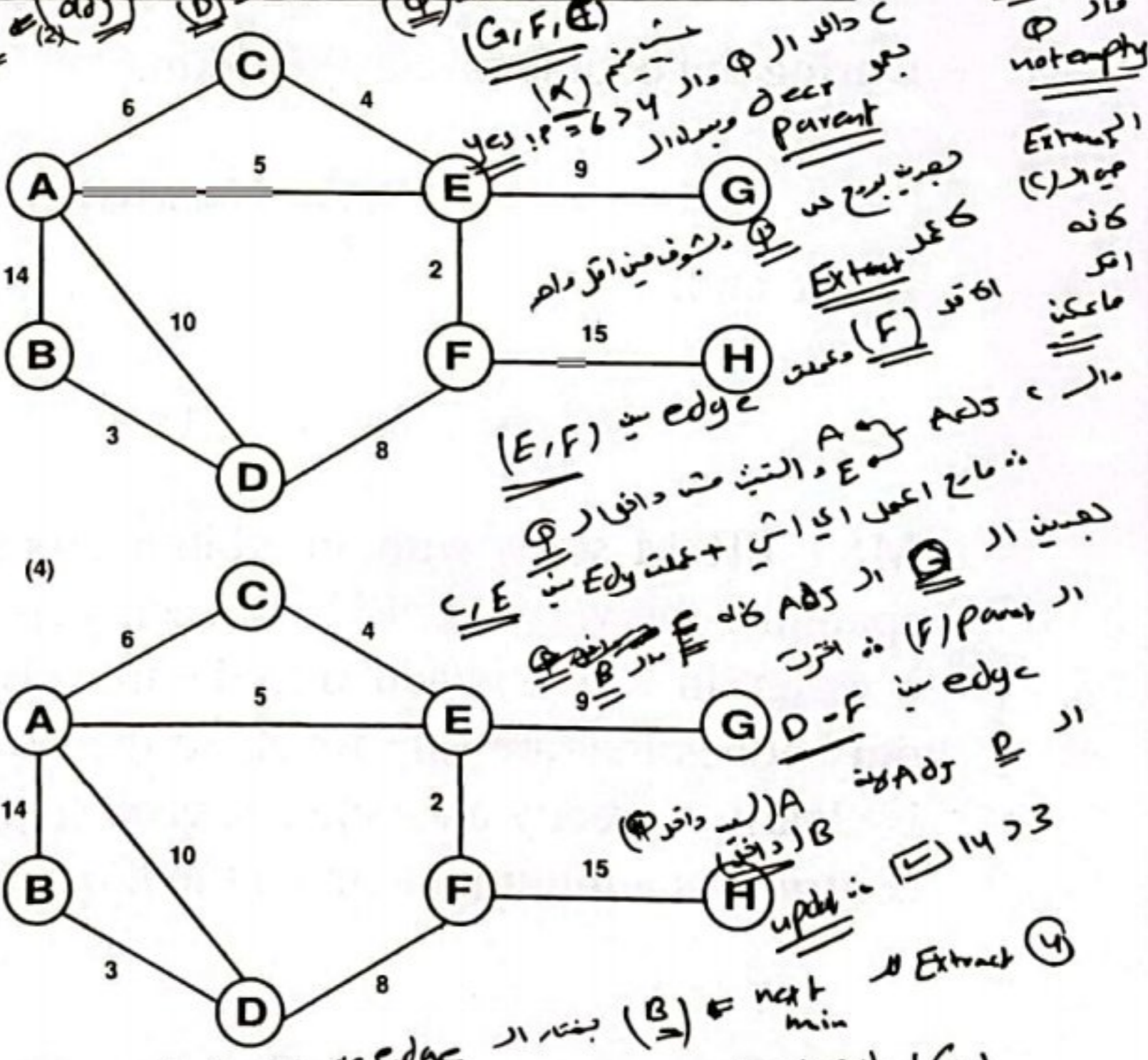
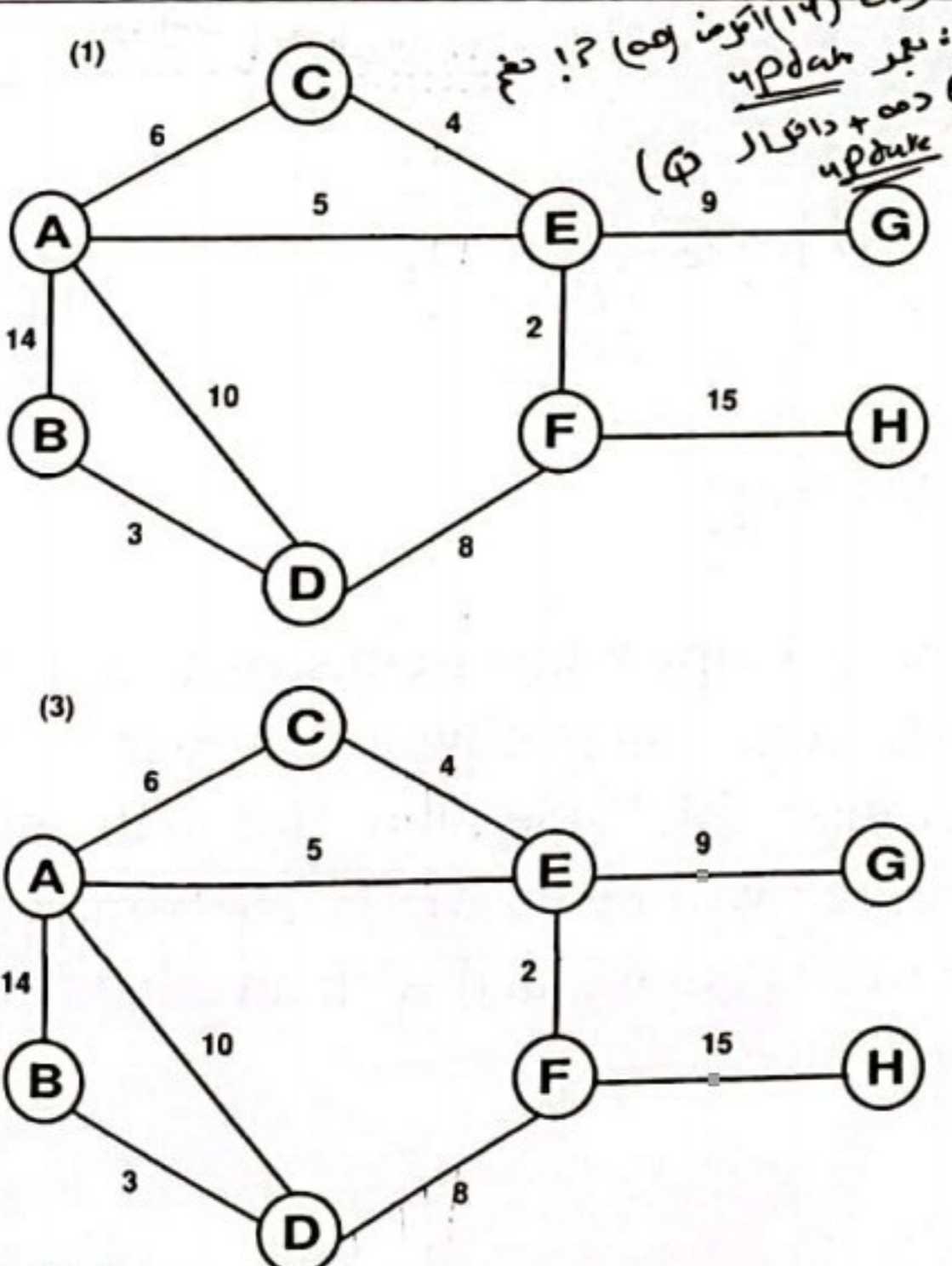


node	A	B	C	D	E	F	G	H
key[]	0	14	6	3	5	2	9	15
π[]	nil	A	A	A	A	E	E	F

Priority Queue (min heap)

node	A	B	C	D	E	F	G	H
key	0	14	6	3	5	2	9	15

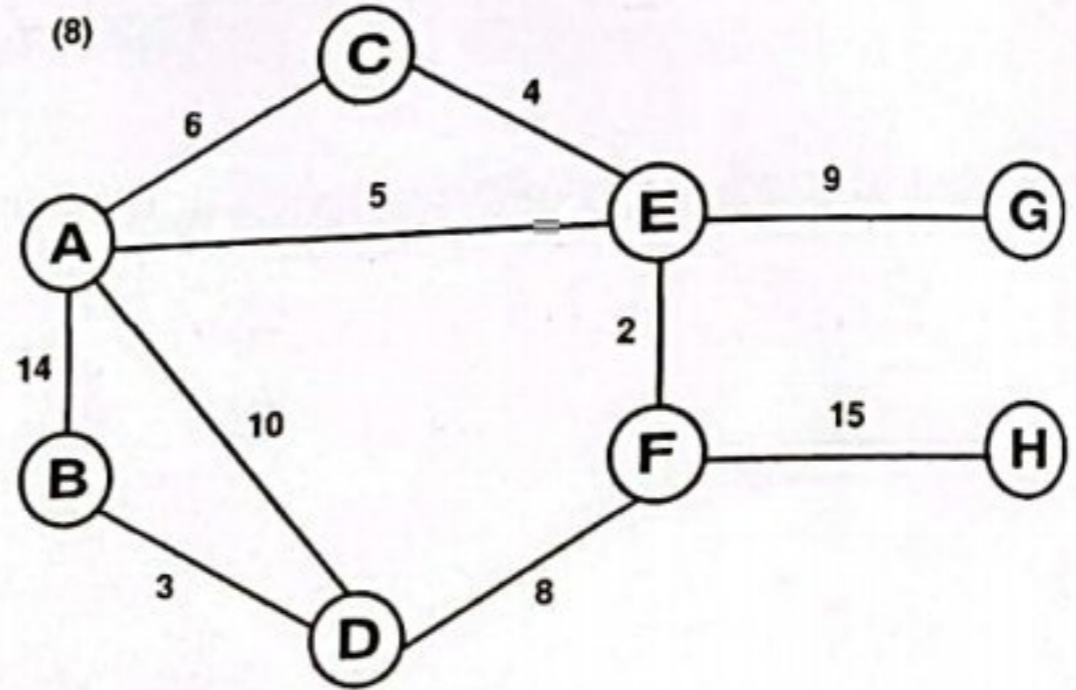
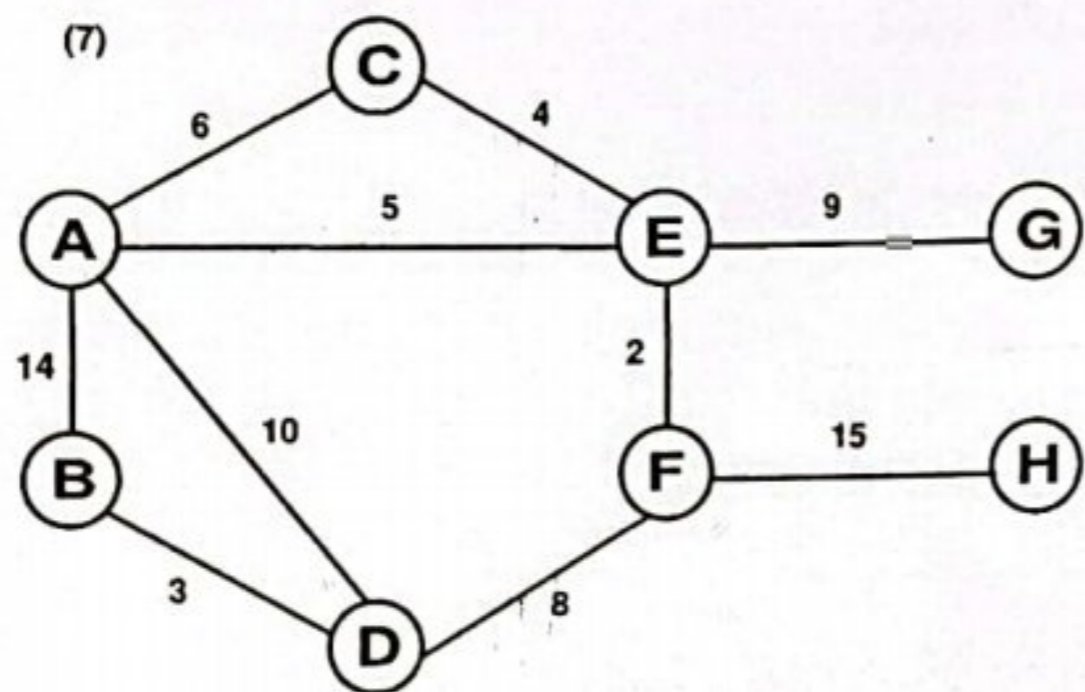
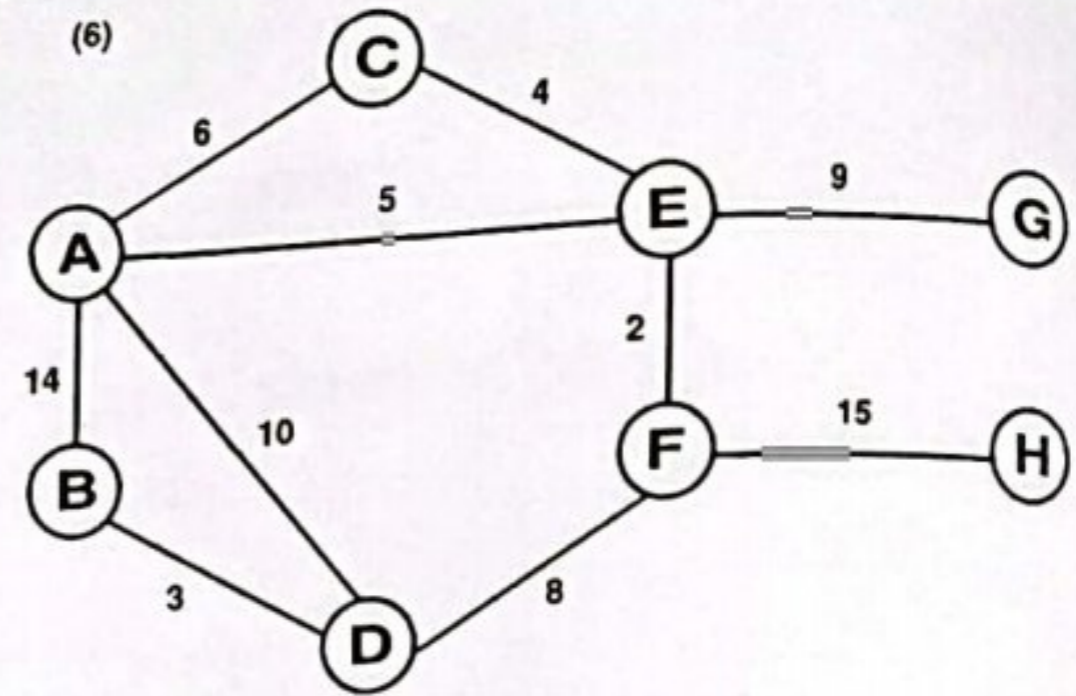
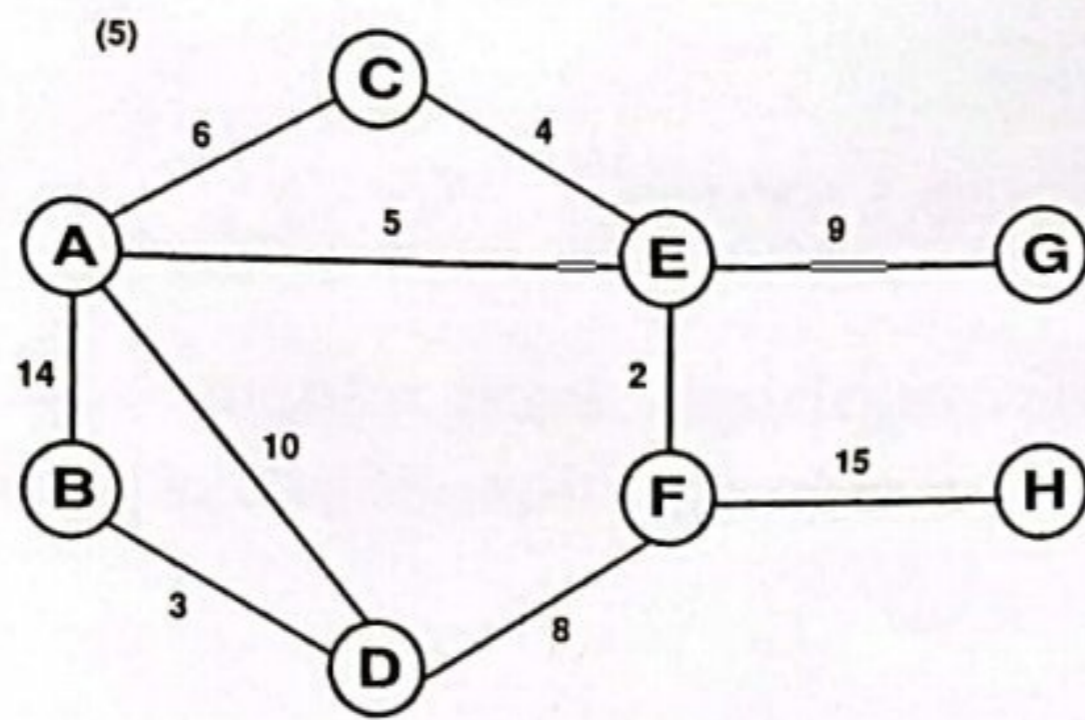
MST-PRIM Example



ان edge سبيل استخريم لنبطع
 حسابار (MST) Cost
 $6+3+4+8+5+2+9+15 = 46$

ان edge من (B-D) مينه رد ادر B صوار A (متداف) مانعد اسين
 (E-G) edge مانع العمل سبب + بعد edge (E-G)
 F = A رد ادر (متداف) + بعد edge (F-H) مانعد اسين لبطع
 (G) = next min ادر
 H = next min ادر
 (B) = next min ادر

MST-PRIM Example *continued*



22

MST-PRIM Complexity

The running time of MST-PRIM depends on the implementation of the priority queue selected.

(٤) **Heap:** DECREASE-KEY runs in $O(\lg n)$ time.

- Initialization: $O(V)$
- EXTRACT-MIN Operations: $O(V \lg V)$
- DECREASE-KEY Operations: $O(E \lg V)$
- Total: $O((V + E) \lg V)$

(٥) **Fibonacci Heap** (see Chapter 21): DECREASE-KEY runs in $O(1)$ time.

- Initialization: $O(V)$
- EXTRACT-MIN Operations: $O(V \lg V)$
- DECREASE-KEY Operations: $O(E)$
- Total: $O(E + V \lg V)$

Lecture 14: Single-Source Shortest Path Algorithms

Course Learning Outcome

- Use fundamental graph algorithms, like traversal, shortest path and spanning tree in the solution of real-life problems

Dr. Khalil Yousef

Adopted from the Slides of the ECE 608 Computational Models and Methods Course at Purdue University

Read Chapter 25 of *Introduction to Algorithms*

The Shortest-Paths Problem

A shortest-paths problem, given a weighted, directed graph $G = (V, E)$ with weight function $w : E \rightarrow \mathbf{R}$, is to find the shortest path between two arbitrary vertices, u and v .

Examples:

Determine the shortest route from Aqaba to Irbid.

Determine the shortest distance between two intersections from a street map.

This problem is a generalization of breadth-first search to handle weighted graphs. In BFS, the weight of each edge is 1.

Edge weights can be interpreted, instead of as distances, as time, cost, penalties, etc.

Shortest-Path Terminology

The **weight** of a path $p = \langle v_0, v_1, \dots, v_k \rangle$ is the sum of the weights of the member edges:

$$w(p) = \sum_{i=1}^k w(v_{i-1}, v_i)$$
 (طوع او path يلا انا المجموع weight)

The **shortest-path weight** from u to v is defined as:

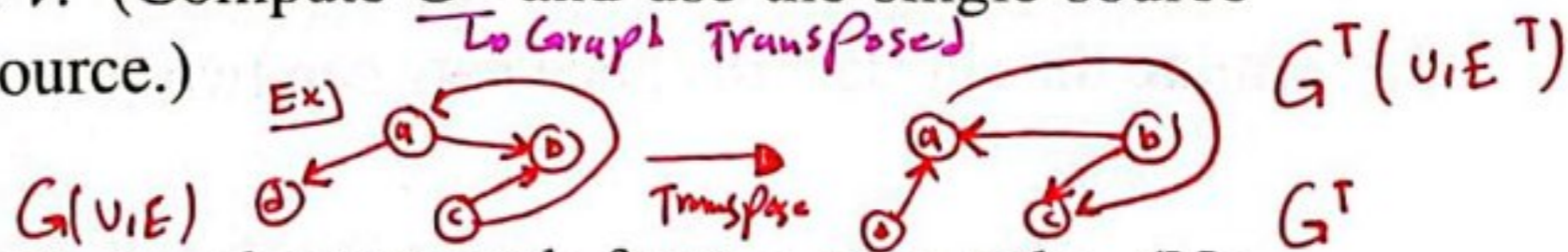
$$\delta(u, v) = \begin{cases} \min\{w(p) : u \xrightarrow{p} v\} & \text{if there is a path from } u \text{ to } v \\ \infty & \text{otherwise. (path غير موجود)} \end{cases}$$
 (shortest path) (unreachable)

A **shortest path** from u to v is any path p with $w(p) = \delta(u, v)$.

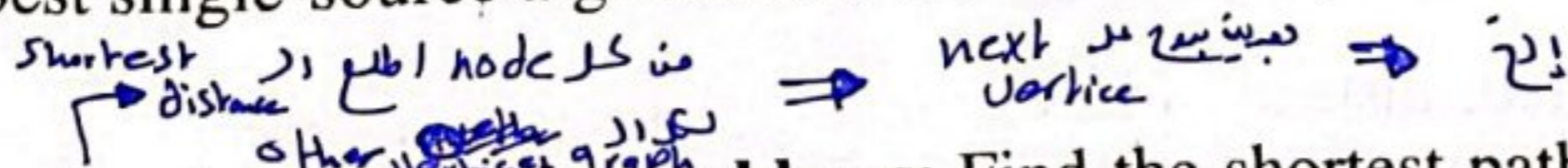
The Single-Source Shortest-Paths Problem and Variations

This lecture focuses on the **single-source shortest-paths problem**: given a graph $G = (V, E)$, find the shortest path from a given **source vertex** $s \in V$ to every other vertex, $v \in V$. There are many variations that can be solved with the algorithm for this problem:

Single-destination shortest-paths problem: Find the shortest path to a given **destination vertex** t from any vertex v . (Compute G^T and use the single-source shortest path algorithm with t as source.)

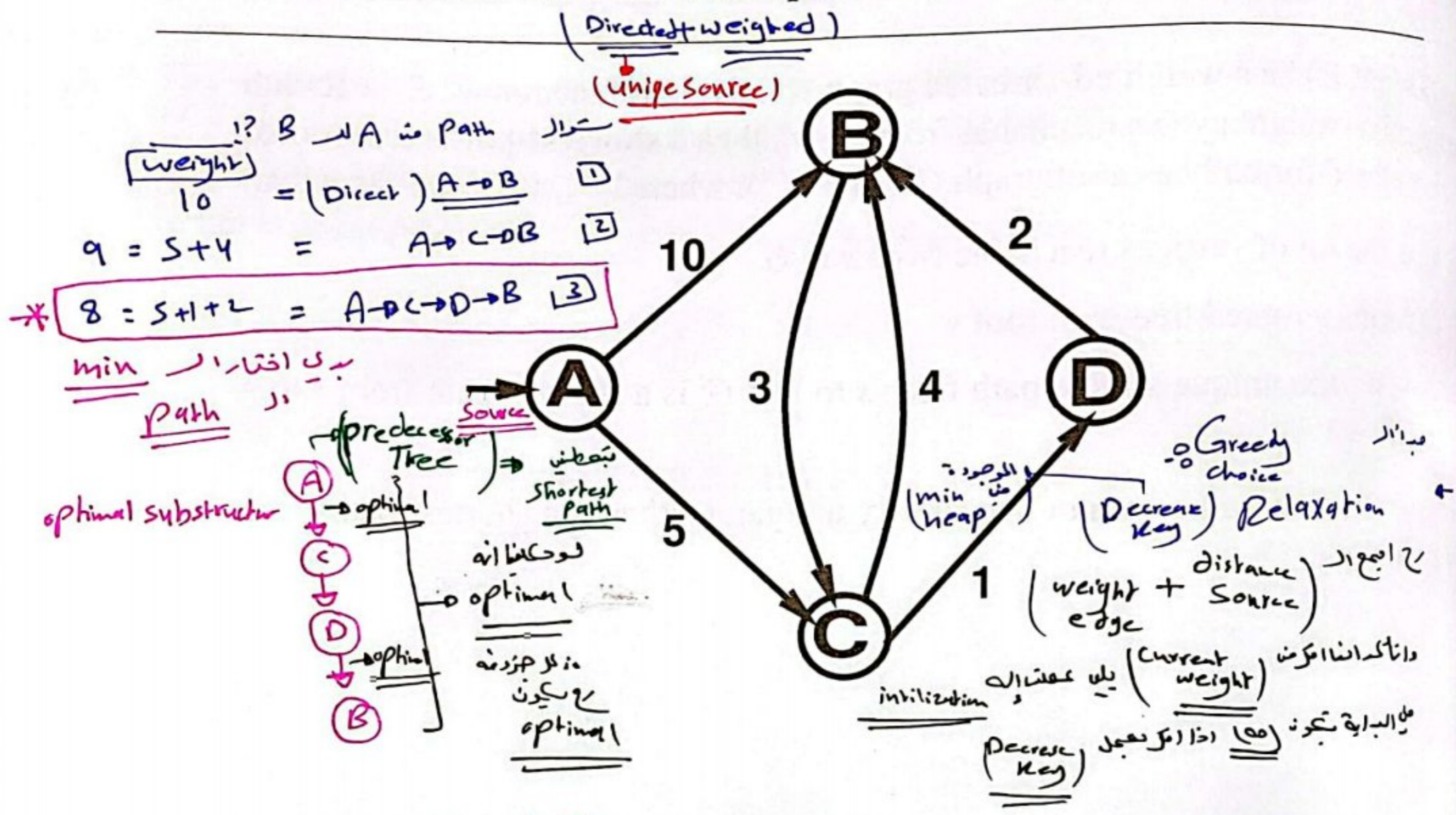


Single-pair shortest-path problem: Find a shortest path from u to v only. (No algorithms for this problem are known that run asymptotically faster than the best single-source algorithm in the worst case.)



All-pairs shortest-paths problems: Find the shortest path from u to v for every pair of vertices u and v . (Can use the single-source algorithm for each vertex, but it is best handled as an all-pairs problem.)

A Single-Source Shortest-Paths Example



Greedy Algo. (Problem is Greedy)

- 1 optimization problem
 - 2 optimal substructure
 - 3 Greedy choice
- Dijkstra's Algo. → it has very similar implementation to Both Prim's MST and BFS Algo.
 → Bellman Ford Algo. (Distance Table in Key)

A Representation for the Shortest Paths

We typically want to compute, not only the weight of each shortest path, but also the vertices in each shortest path.

As in the BFS algorithm, the shortest-paths algorithms will, for a given graph $G = (V, E)$, maintain for each vertex $v \in V$, a predecessor, $\pi[v]$ (has a value of some $u \in V$ or NIL), so that PRINT-PATH(G, s, v) can be used to print the shortest path from s to v .

The shortest-paths algorithm will use a predecessor subgraph, $G_\pi = (V_\pi, E_\pi)$, induced by the π values, such that:

$$V_\pi = \{v \in V : \pi[v] \neq NIL\} \cup \{s\}$$

$$E_\pi = \{(\pi[v], v) \in E : v \in V_\pi - \{s\}\}$$

We shall prove that the π values produced by the shortest-paths algorithms when they terminate have the property that G_π is a **shortest-paths tree**, a tree rooted at s containing a shortest path from s to each vertex $v \in V$ reachable from s .

Shortest-Paths Tree

Let $G = (V, E)$ be a weighted, directed graph with weight function $w : E \rightarrow \mathbf{R}$ with no negative-weight cycles reachable from $s \in V$, then a **shortest-paths tree** rooted at s is defined formally as a subgraph $G' = (V', E')$, where $V' \subseteq V, E' \subseteq E$ such that:

1. V' is the set of vertices reachable from s in G .
2. G' forms a rooted tree with root s .
3. $\forall v \in V'$, the unique simple path from s to v in G' is a shortest path from s to v in G .

Because shortest paths are not necessarily unique, neither is a shortest-paths tree always unique.

Optimal Substructure of a Shortest Path

The shortest-paths algorithms exploit the property that subpaths of a shortest path are shortest paths.

Lemma 25.1. (Subpaths of shortest paths are shortest paths)

The proof is provided in the book

Shortest-Paths Algorithms: Initialization

The single-source shortest-paths algorithms operate on a weighted, directed graph $G = (V, E)$ and use two arrays, π and d , to calculate the shortest paths from s to each $v \in V$. When the algorithms terminate, for $v \in V$, $\pi[v]$ is the predecessor of v in the shortest path from s to v and $d[v]$ is the weight of that path.

The following routine is used by the single-source shortest-paths algorithms to initialize the arrays:

INITIALIZE-SINGLE-SOURCE(G, s)

1. **for** each vertex $v \in V[G]$
2. **do** $d[v] \leftarrow \infty$
3. $\pi[v] \leftarrow \text{NIL}$
4. $d[s] \leftarrow 0$

8

Shortest-Paths Algorithms: Relaxation

The shortest-paths algorithms use a technique called **relaxation**. The basic idea is that $d[v]$ is an upper bound on the weight of a shortest path from source s to v , and as such is called a **shortest-path estimate**, which is reduced from ∞ until it finally reaches the shortest-path weight value $\delta(s, u)$.

RELAX(u, v, w) updates $d[v]$ (and $\pi[v]$) by examining the impact of the weight of edge (u, v) .

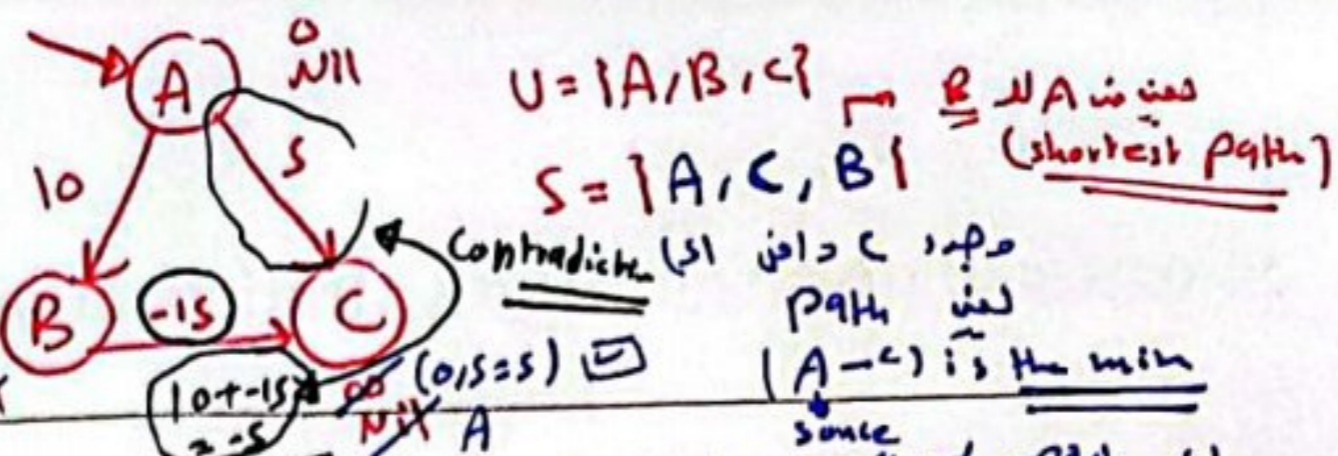
RELAX(u, v, w)

1. **if** $d[v] > d[u] + w(u, v)$
2. **then** $d[v] \leftarrow d[u] + w(u, v)$ (Relaxation)
3. $\pi[v] \leftarrow u$ (update parent)

Handwritten notes:
 - $d[s] = \delta(s, s)$
 - $d[s, u] = \delta(s, u)$
 - $d[s, v] = \delta(s, v)$
 - $w(u, v)$ weight
 - Source node
 - $d[s, u] = d[s, v]$
 - Upper Bound on the distance from s to v , so it is not a Tight Bound $\delta(s, v)$
 - This is what we desired Tight bound
 - $d[v] > d[u] + w(u, v)$ update parent + distance
 - $d[s, v] > d[s, u] + w(u, v)$ اذا اكثر بعض
 - $d[s, v] > d[s, u] + w(u, v)$ update parent

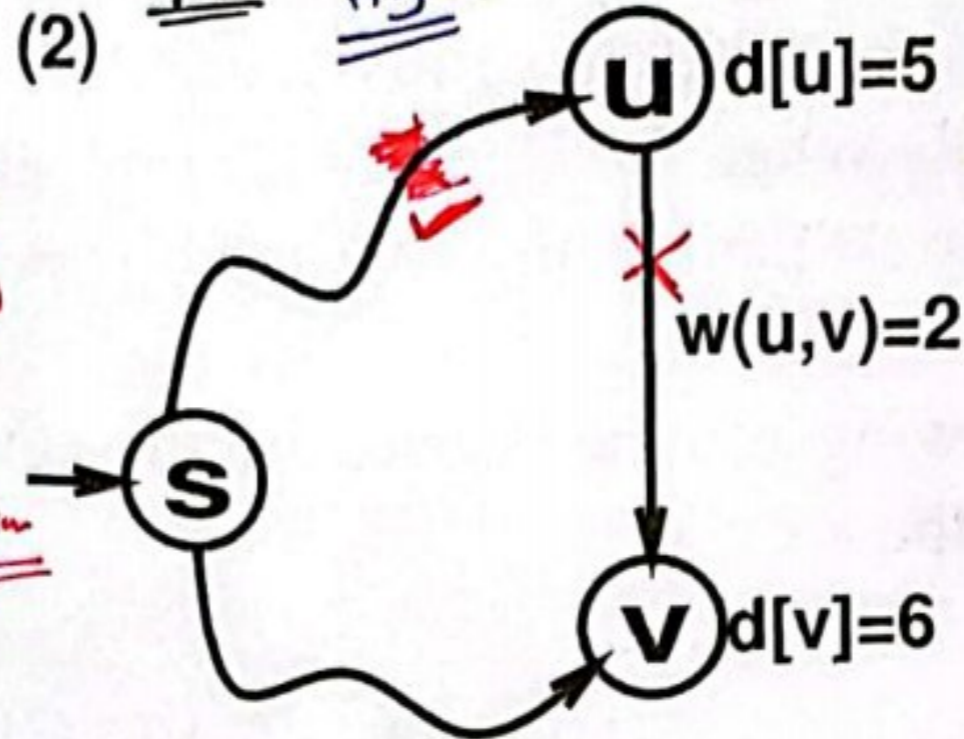
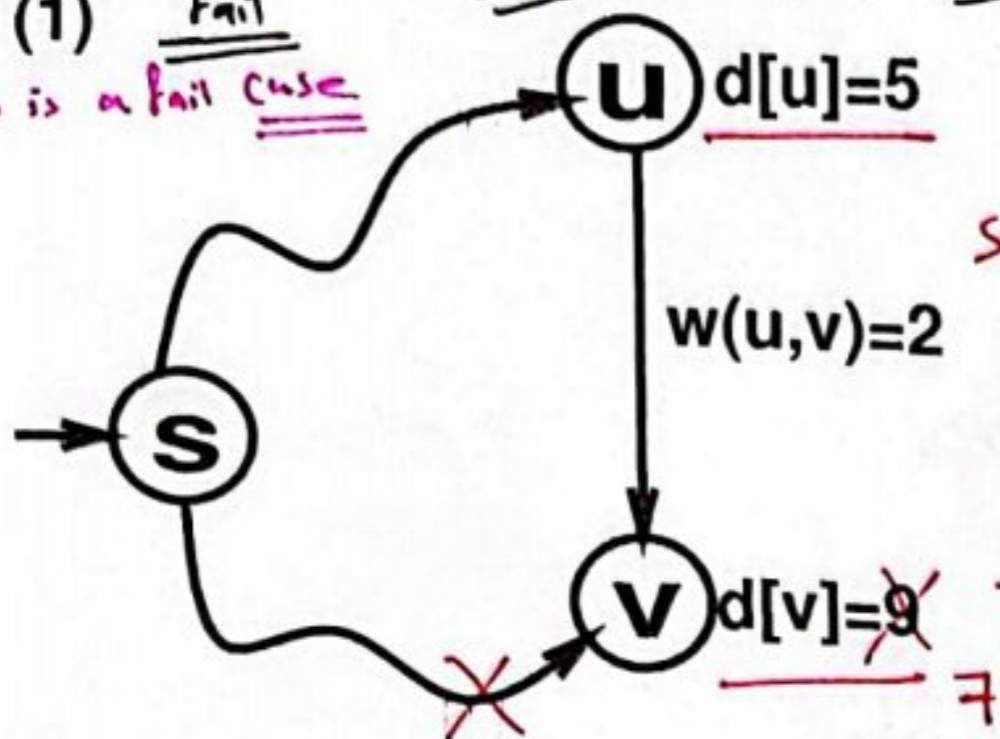
Relaxation is the only means by which shortest-path estimates and predecessors change once they are initialized in all of the single-source shortest-path algorithms.

Ex) Dijkstra Algo
negative weight



Shortest-Paths Algorithms: Relaxation

(1) Contradiction
Fail
this is a fail case



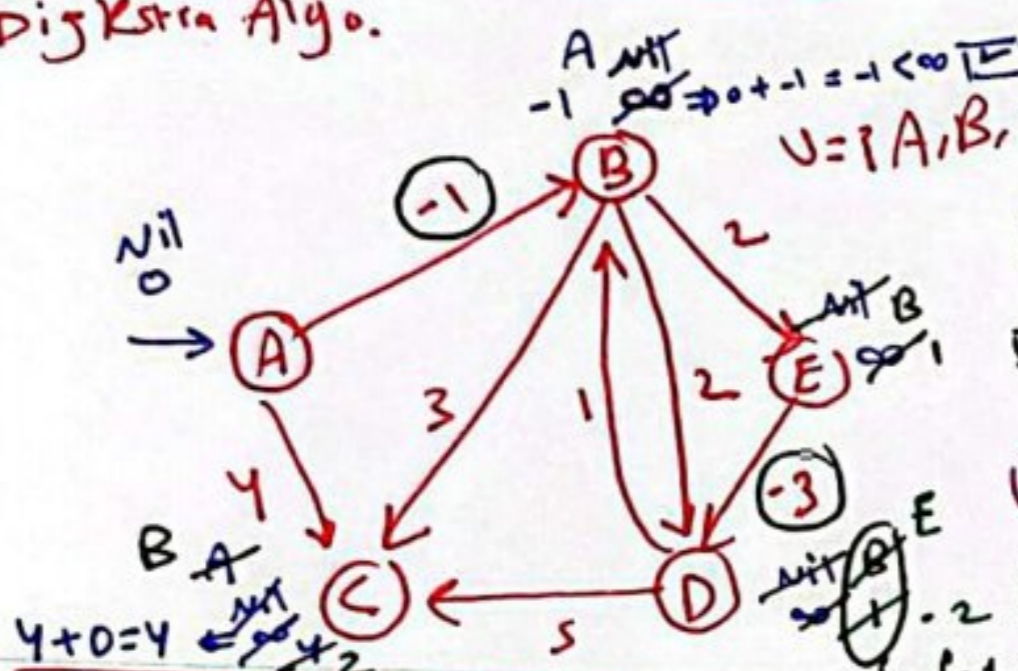
$5+2 < 9$
yes
Relaxation

Extract shortest path
 $5+2 < 6$
No
No Relaxation

update path + weight
Puray

update path + weight
Puray

Ex) Dijkstra Algo.



- 1) Extract min A → B
- 2) Extract B → D
- 3) Extract D → E
- 4) Extract E → C

node	A	B	C	D	E
Q	0	∞	∞	∞	∞
π	nil	A	B	B	B

Final Table
Fail Case
S = {A, B, D, E} (Fail Case)

negative weight edges
this is a problem
this example

Properties of Relaxation

Lemma 25.4. Let $G = (V, E)$ be a weighted, directed graph with weight function $w : E \rightarrow \mathbf{R}$, and let $(u, v) \in E$. Then, immediately after relaxing (u, v) using $\text{RELAX}(u, v, w)$, $d[v] \leq d[u] + w(u, v)$.

Proof:

If $d[v] > d[u] + w(u, v)$ just prior to the call $\text{RELAX}(u, v, w)$, then $d[v] = d[u] + w(u, v)$ afterward. On the other hand, if $d[v] \leq d[u] + w(u, v)$ just prior to the call, then nothing changes.

Lemma 25.5. Let $G = (V, E)$ be a weighted, directed graph with weight function $w : E \rightarrow \mathbf{R}$, let s be the source vertex, and let the graph be initialized using $\text{INITIALIZE-SINGLE-SOURCE}(G, s)$, then $d[v] \geq \delta(s, v)$ for all $v \in V$, and this invariant is maintained over any sequence of relaxation steps on E . Once $d[v]$ achieves its lower bound $\delta(s, v)$, it never changes.

Dijkstra's Algorithm

- Dijkstra's Algorithm uses a greedy strategy together with the assumption of no negative edge weights to determine the shortest paths from a source vertex s in a weighted, directed graph $G = (V, E)$, represented using adjacency lists, to all $v \in V$.

من S إلى u في graph

- The algorithm creates a set S of vertices whose shortest-path weights from s have been determined.

vertices ليعتد بها

Shortest Path من S إلى u

- The algorithm repeatedly selects the minimum vertex from a priority queue Q , containing vertices in $V - S$ keyed by their d values.

Shortest path من ال Source

- It is like BFS except that it uses a priority queue, keyed on d . It is also similar to MST-PRIM.

S → initially empty except for the source node
 $V - S$ → initially inserted in a priority queue (min heap)

DIJKSTRA(G, w, s)

DIJKSTRA(G, w, s)

- INITIALIZE-SINGLE-SOURCE(G, s) Distance = ∞
parent = Nil
- $S \leftarrow \emptyset$ (initially empty)
- $Q \leftarrow V[G]$ (vertices في queue)
- while $Q \neq \emptyset$ (not empty)
 - do $u \leftarrow \text{EXTRACT-MIN}(Q)$ node من queue
 - $S \leftarrow S \cup \{u\}$ كطه من S
 - for each vertex $v \in \text{Adj}[u]$
 - RELAX(u, v, w) Relax بعد Adj

$u|v$
 $u|v + w$
 (binay)
 (Fibonacci) $u|v + w$
 OR $u|v + w$

ليس شرطاً العملية كما في قرار (\emptyset)

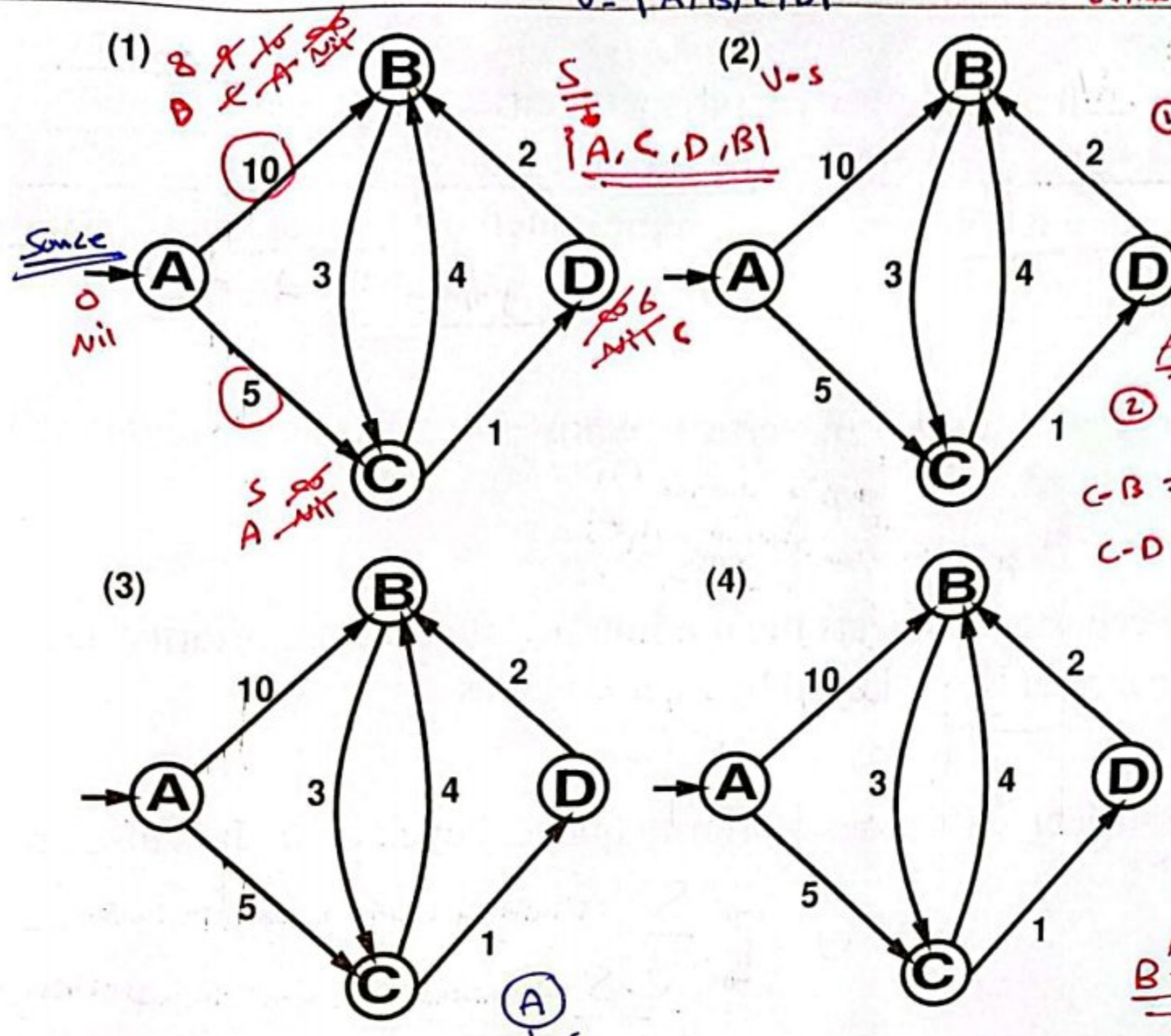
Time complexity = $\begin{cases} u|v + E|v \\ u|v + E \end{cases}$

DIJKSTRA Example

Ex →

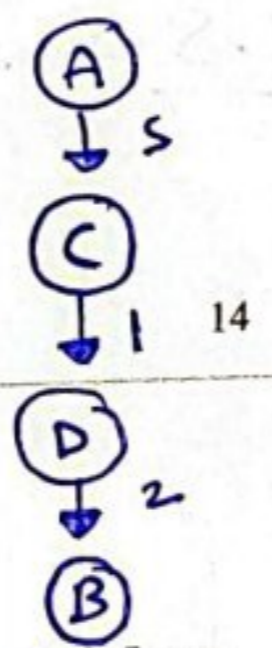
node	A	B	C	D
$\delta[]$	∞	∞	∞	∞
$\pi[]$	Nil	A	A	C

Initialization
 [2] Source ($\delta=0$)
 2 vertices (all are initially inserted into a Priority Queue (min heap))
 Extract min(A) → Adj A → B (Relax)



(1) $\delta[A]=0$, $\delta[B]=\infty$, $\delta[C]=\infty$, $\delta[D]=\infty$
 A-B $\Rightarrow 10 < \infty$, yes is Relax + update parent
 A-C $\Rightarrow 5 < \infty$, yes is Relax
 Extract min (A) → Adj A → B (Relax)
 Extract min (C) → Adj C → D (Relax)
 (2) $U = S$
 A-B $\Rightarrow 10 < \infty$, yes is Relax + update parent
 A-C $\Rightarrow 5 < \infty$, yes is Relax
 Extract min (C) → Adj C → D (Relax)
 (3) $U = S$
 C-B $\Rightarrow 4 + 5 < 10$, yes is Relax
 C-D $\Rightarrow 1 + 5 < \infty$, yes is Relax
 Extract min (D) → Adj D → B (Relax)
 (4) $U = S$
 D-B $\Rightarrow 6 + 2 < 9$, yes is Relax
 Extract min (B) → Adj B → C (Relax)
 B-C $\Rightarrow 8 + 3 < 5$, No (ما بعد الاستغناء)
 Queue is empty → Finish Algo

(برسم الشجرة من معرفتي للـ Parent)



order $S \Rightarrow \{A, C, D, B\}$
 $U-S \Rightarrow \emptyset$

Running Time of Dijkstra's Algorithm

EXTRACT-MIN: $|V|$ times.

DECREASE-KEY: $|E|$ times.

Hence, the worst case running time of DIJKSTRA can be characterized by the equation $|V|T_{\text{EXTRACT-MIN}} + |E|T_{\text{DECREASE-KEY}}$.

Q	$T_{\text{EXTRACT-MIN}}$	$T_{\text{DECREASE-KEY}}$	Total
Array	$O(V)$	$O(1)$	$O(V^2)$
Binary Heap	$O(\lg V)$	$O(\lg V)$	$O((E+V) \lg V)$
Fibonacci Heap	$O(\lg V)$	$O(1)$	$O(V \lg V + E)$

(افضل خيار)

The Bellman-Ford Algorithm

BELLMAN-FORD(G, w, s) is a single-source shortest-paths algorithm that supports negative edge weights. Given a weighted, directed graph $G = (V, E)$ with source s and weight function $w : E \rightarrow \mathbf{R}$, (it returns a solution if and only if there is no negative-weight cycle reachable from s (a boolean value of FALSE indicates that no solution exists because there is a negative-weight cycle).

BELLMAN-FORD(G, w, s)

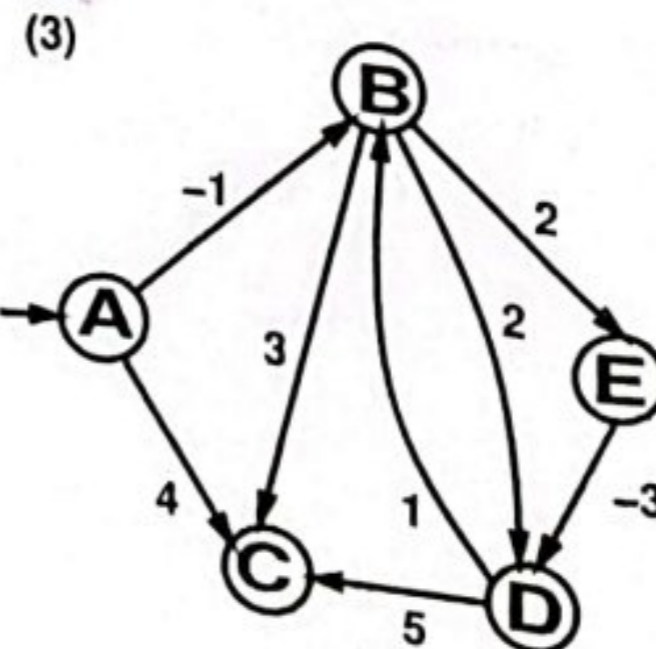
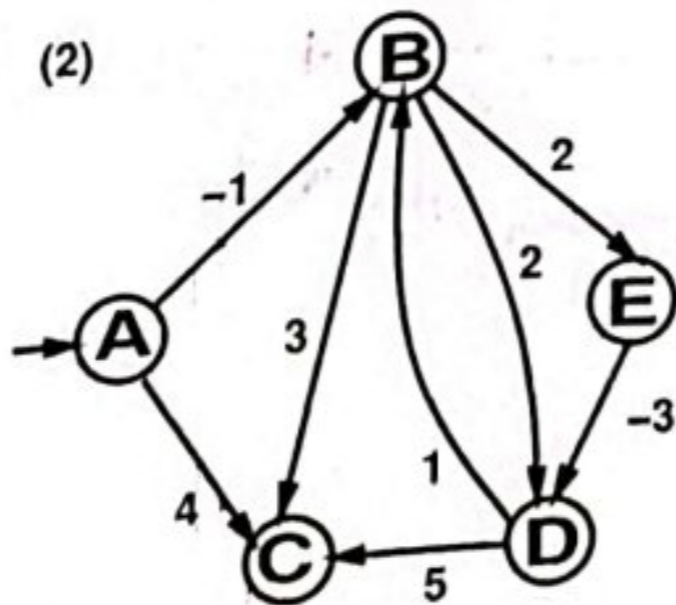
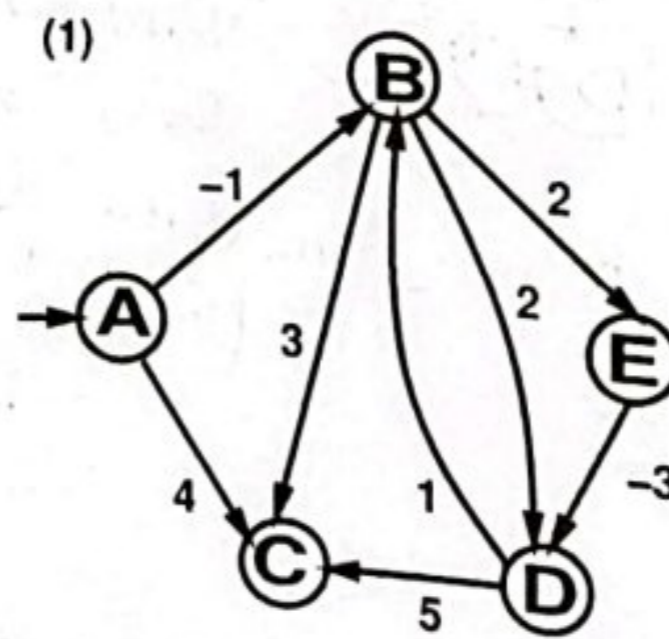
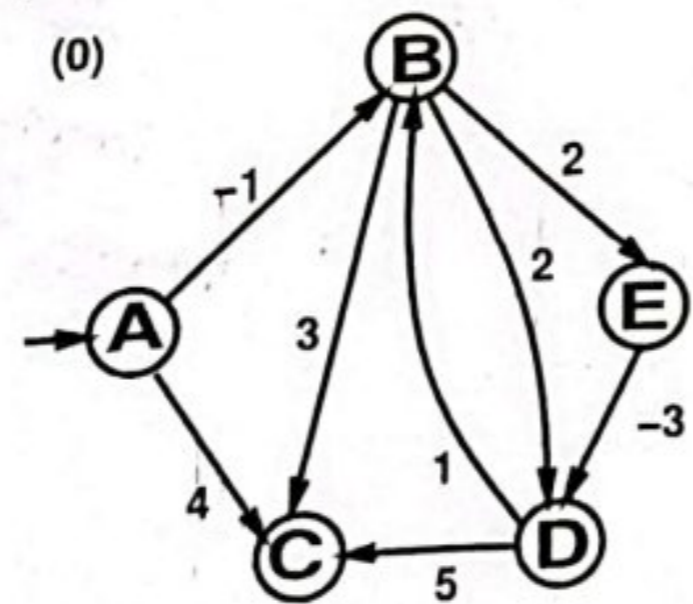
1. INITIALIZE-SINGLE-SOURCE(G, s) $\Rightarrow U$ *initialization*
2. for $i \leftarrow 1$ to $|V[G]| - 1$ $\Rightarrow U$ *iteration*
3. do for each edge $(u, v) \in E[G]$ $\Rightarrow UE$
4. do RELAX(u, v, w)
5. for each edge $(u, v) \in E[G]$ *If we were able to perform one more relaxation*
6. do if $d[v] > d[u] + w(u, v)$
7. then return **FALSE** *negative weight cycle*
8. return **TRUE** *must return False*

Time Complexity = $O(VE)$

True) False

BELLMAN-FORD Example

Consider the edges in the following order: (A, B) , (A, C) , (B, C) , (B, D) , (D, B) , (D, C) , (E, D) , (B, E) .



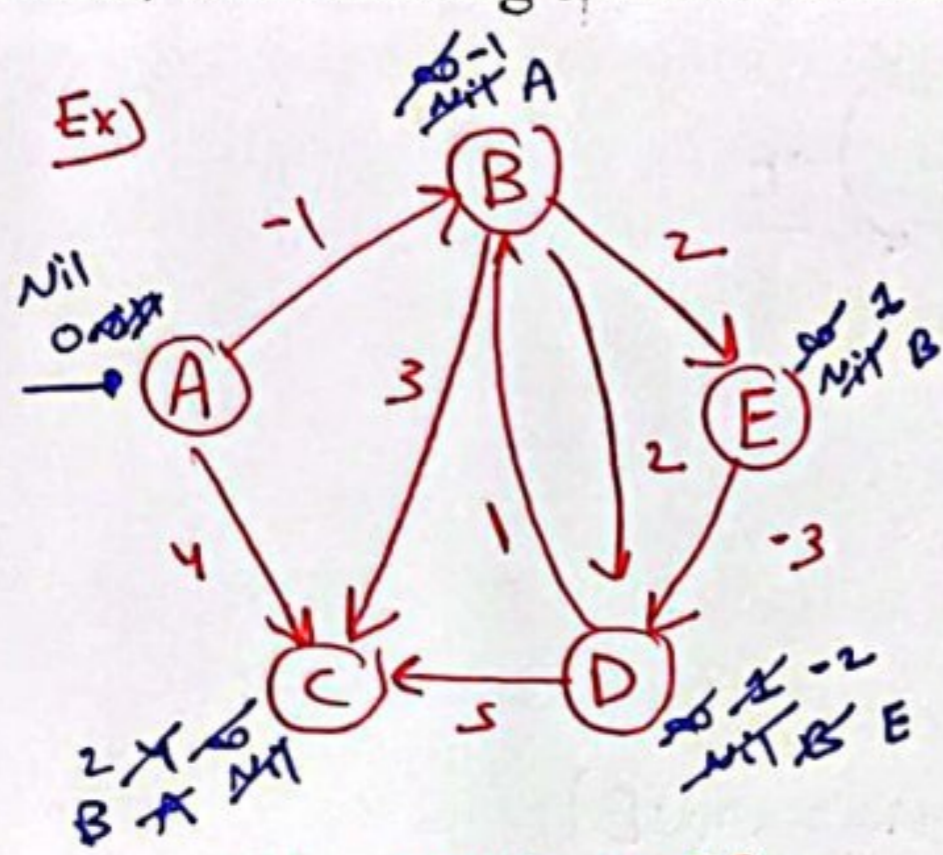
The Running Time of BELLMAN-FORD

INITIALIZE-SINGLE-SOURCE takes $\Theta(V)$ time.

In lines 2-4, there are $|V| - 1$ passes over E edges, which takes $O(VE)$ time.

Lines 5-7 takes $O(E)$ time.

Hence, the running time of BELLMAN-FORD is $O(VE)$.



$U = \{A, B, C, D, E\}$

$|U| = 5$ (size) so For loop = 4

order	i=1	i=2	i=3	i=4 relax
(A,B)	✓	×		
(A,C)	✓	×		
(B,C)	✓	×		
(B,D)	✓	×		
(B,E)	✓	×		
(D,B)	×	×	Will be the same	
(D,C)	×	×	Will be the same	
(E,D)	✓	×		

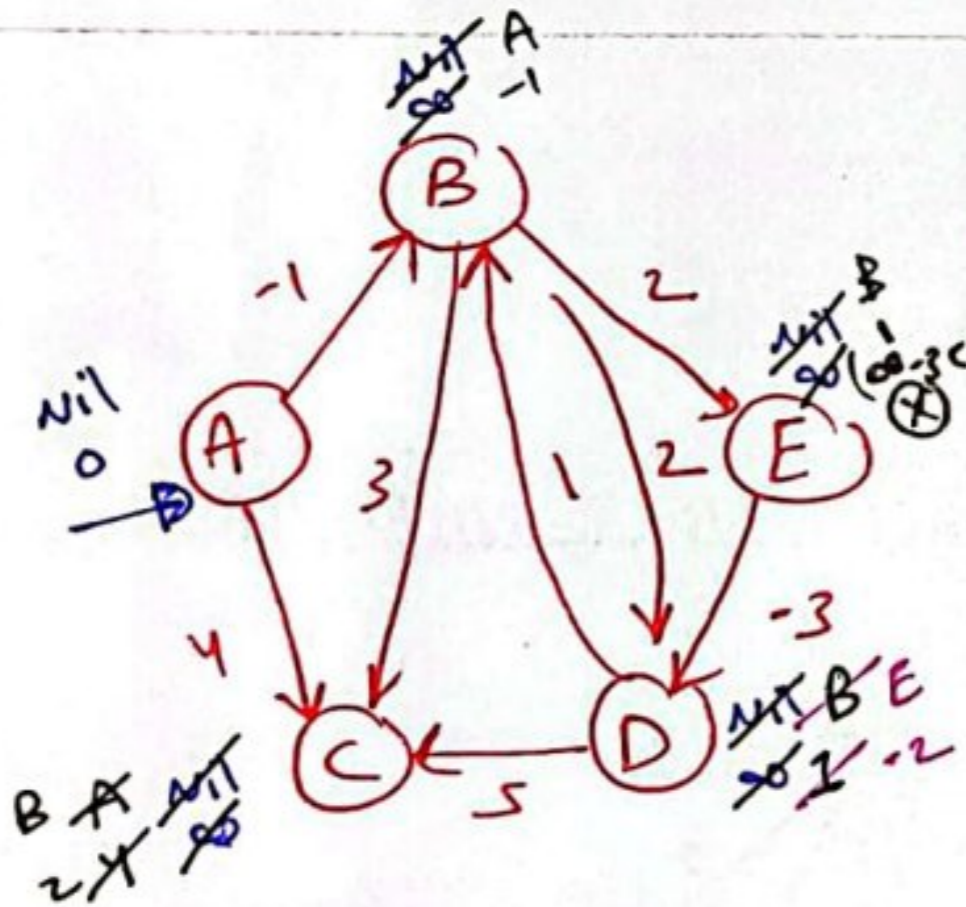
✓: update (relax)
x: no update (no relax)

ما في update
منه لو جيتي لا
نفس الجواب مع قطع

Alg. return True
Final Table

Result is True

node	A	B	C	D	E
$d[u]$	0	-1	2	-2	1
$\pi[u]$	Nil	A	B	E	B



order	i=1	i=2	i=3
(A,B)	✓	×	
(A,C)	✓	×	
(B,C)	✓	×	
(B,D)	✓	×	
(D,B)	×	×	Will be the same
(D,C)	×	×	
(E,D)	⊗	✓	
(B,E)	✓	✓	

Final ANS
Final ANS
Final ANS
بليج يا ترشدو ال intention
Relaxation في كل iteration

تشان بيكتشف ال (negative weight cycle) (Bellman Ford)

جيتي

negative weight edges

graph اذا في

Note

Bellman Ford Alg.

Dijkstra Alg.

اذا ما في انا