

# 1. What is Algorithm?

An algorithm is a sequence of unambiguous instructions for solving a problem i.e. for obtaining a required o/p for any legitimate input in finite amount of time.

## 2) Euclid's algorithm for computing gcd (m, n)

1) Compute gcd (m, n)

// I/P:- 2 non -ve, not both zero integer m & n

// O/P:- Greatest common divisor of m & n

when while  $n \neq 0$  do

$r \leftarrow m \bmod n$

$m \leftarrow n$

$n \leftarrow r$

return m

$r \leftarrow m \bmod n$

$m \leftarrow n$

$n \leftarrow r$

return m

Step 1:- If  $m=0$ , return n

Step 2:-  $m \leftarrow n$ ,  $n \leftarrow m \bmod n$

Step 3:- Assign value of n to m,  $n \leftarrow n$  return m

## 3) Consecutive Integer checking for gcd (m, n)

Step 1:- Assign value of min {m, n} to t

Step 2:- divide m by t, if  $r=0$  goto step 3 or else goto step 4.

Step 3:-  $m \leftarrow t$ ,  $n \leftarrow 0$  return t

Step 4:- decrease value of t by 1. goto step 2

1)  $t \leftarrow \min(m, n)$

2) if  $n \% t = 0$  goto 3  
else goto 4

3) if  $m \% t = 0$  return t  
else goto 4

4)  $t \leftarrow t - 1$

5) goto 2

## 4) Middle School procedure:-

→ 1) Find prime factor of m

2) Find prime factor of n

3) Identify all the common factor in two prime expansion in ① & ②

4) Compute the product of all common factors & return it.

Ex:- 60, 24

$60 = 2 \times 2 \times 3 \times 5$

$24 = 2 \times 2 \times 2 \times 3$

$2 \times 2 \times 3 = 12$

$60 = 2 \times 30$

$2 \times 3 \times 10$

$2 \times 2 \times 5 \times 5$

## 5) sieve(n)

# Implements the sieve of Eratosthenes

// I/P:- A prime number n

// O/P:- Array L of all prime number less than / equal to n

for  $p \leftarrow 2$  to  $n$  do  $A[p] \leftarrow p$

for  $p \leftarrow 2$  to  $\lfloor \sqrt{n} \rfloor$  do

if  $A[p] \neq 0$

$j \leftarrow p \times p$

while  $j \leq n$  do

$A[j] \leftarrow 0$

$j \leftarrow j + p$

$i \leftarrow 0$

for  $p \leftarrow 2$  to  $n$  do

if  $A[p] \neq 0$

$L[i] \leftarrow A[p]$

$p \leftarrow p + 1$

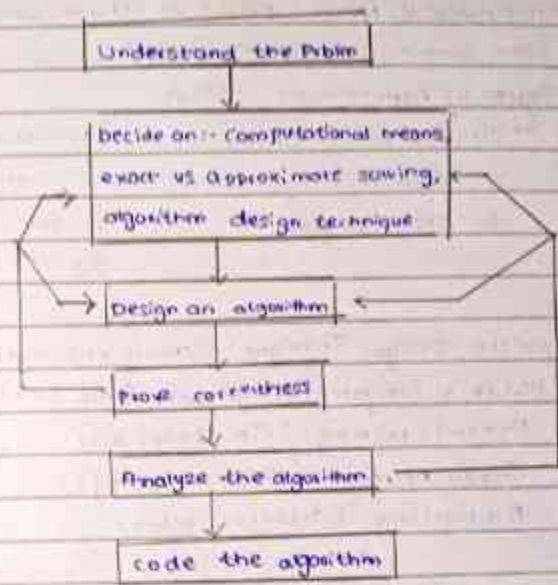
return  $L$

Ex: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,

2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15

2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,

c) Algorithm design & Analysis process.



① understanding the problem.

→ Before designing an algorithm, it's essential to understand the problem clearly.

→ This includes identifying the I/O, ops constraints & expected behavior of the soln.

→ It helps in selecting an efficient approach.



## ② Decide on Computational Means & Design Techniques.

- Computational Means: determine the resources available (CPU, memory, parallel computing)
- Exact vs Approximate Solving
  - ↳ give the precise ans
  - ↳ provide near-optimal soln when exact soln is too slow.
  - Ex: Dijkstra's algorithm for shortest path
  - Eg: NP-hard probm.
- Algorithm Design Technique: choose the right method.
  - Divide & Conquer (Merge sort, Quick sort)
  - Dynamic programming (Fib, knapsack)
  - Greedy Approach (Huffman coding)
  - Backtracking (Sudoku solver)

## ③ Design & Algorithm

- Develop a Step-by-Step procedure to solve the probm
- Consider factor like efficiency, simplicity & feasibility
- Represent algorithm using pseudocode / flowchart before implementation

## ④ Prove Correctness.

- Ensure that the algorithm always produce the correct output
- Common technique for correctness proof:
  - Mathematical Induction
  - Loop Invariant
  - Contradiction method

### 5) Analyse the Algorithm

→ Time Complexity :- Measure how the running time varies with I/p Size (Big O notation)

Ex :-  $O(1) \rightarrow$  constant time

$O(\log n) \rightarrow$  logarithmic (Binary Search)

$O(n) \rightarrow$  linear (Linear sort)

$O(n^2) \rightarrow$  Quadratic (Bubble sort)

$O(2^n) \rightarrow$  Exponential (Brute-force Soln)

→ Space Complexity :- Evaluate how many memory the algorithm uses.

### 6) Code the Algorithm

→ Convert the designed algorithm into an actual program (C, Python, Java, etc...)

→ Optimize for better readability, maintainability & efficiency

→ Perform testing using sample I/p

### 7) Sequential Search

Search for the given value in a given array by SS.

I/P :-  $A[0..n-1]$  an array & search key  $K$

O/P :- The index of element in  $A$  that matches  $K$

If  $n = 0$  no matching elements

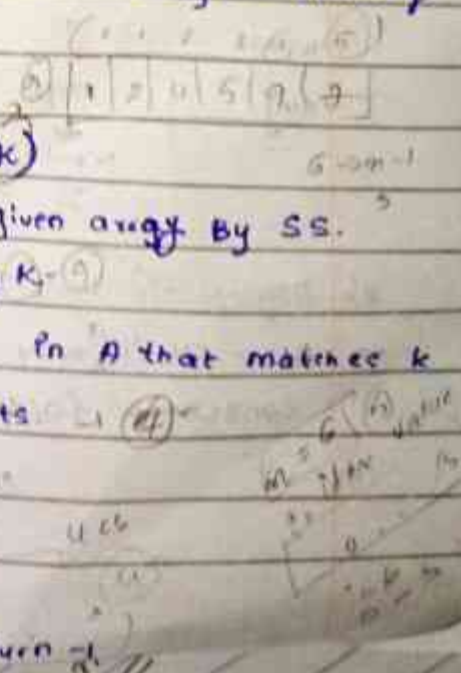
$e \neq 0$

while  $e < n$  and  $A[e] \neq K$  do

$e \leftarrow e + 1$

(if  $e < n$  return  $e$ )

else return -1





worst case:-

→ It happens when the element is at the best position / not in the list at all.

→ Time Complexity  $C_{\text{worst}}(n) = n$

Best case

→ when found at the 1<sup>st</sup> position

→  $C(n) = 1$

Average case

→ found somewhere in middle.

$$C_{\text{avg}}(n) = \frac{P(n-1) + n(1-P)}{2}$$

Case	no. of comparisons	Time Complexity
Best	1	$O(1)$
worst	$n$	$O(n)$
Avg	$n/2$ ↓ $\frac{P(n-1) + n(1-P)}{2}$	$O(n)$

8) Asymptotic Notation & Basic Efficiency classes.

→ Ans:- It is a way of comparing func that ignores constants factors & small p/p size.

1)

1) Big Oh Notation ( $O$ ) :-

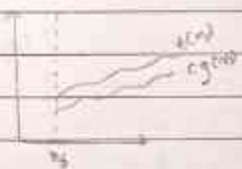
① A function  $t(n)$  is said to be  $O(g(n))$ , denoted  $t(n) \in O(g(n))$ , ② if  $t(n)$  is bounded above by some constant multiple of  $g(n)$   $\forall n$ . ③ i.e. If there exist some +ve constant  $C$  & some non -ve integer  $n_0$  such that  $t(n) \leq C \cdot g(n)$   $\forall n \geq n_0$ .



$$\begin{aligned} t(n) &= 100n + 5 \\ \Rightarrow t(n) &\leq C \cdot g(n) \quad \forall n \geq n_0 \\ 100n + 5 &\leq 101n \quad \forall n \geq 5 \\ \Rightarrow C &= 101, \quad g(n) = n, \quad n_0 = 5 \\ \therefore t(n) &\in O(g(n)) \end{aligned}$$

2) Big Omega Notation ( $\Omega$ ) :-

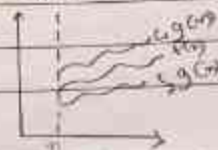
① A function  $t(n)$  is said to be  $\Omega(g(n))$ , denoted  $t(n) \in \Omega(g(n))$ , ② if  $t(n)$  is bounded below by some constant multiple of  $g(n)$   $\forall n$ .



$$\begin{aligned} t(n) &= 10n^3 + 5 \\ \Rightarrow t(n) &\geq C \cdot g(n) \quad \forall n \geq n_0 \\ 10n^3 + 5 &\geq 10n^3 \quad \forall n \geq 0 \\ \Rightarrow C &= 10, \quad g(n) = n^3, \quad n_0 = 0 \\ \therefore t(n) &\in \Omega(g(n)) \end{aligned}$$

3) Big Theta Notation ( $\Theta$ )

① A function  $t(n)$  is said to be  $\Theta(g(n))$ , denoted  $t(n) \in \Theta(g(n))$ , ② if  $t(n)$  is bounded both above and below by some constant multiple of  $g(n)$   $\forall n$ .



return n

9) P.S.M

a) Compare order of growth of  $\frac{1}{2}n(n-1)$  &  $n^2$

$$\lim_{n \rightarrow \infty} \frac{\frac{1}{2}n(n-1)}{n^2} = \frac{1}{2} \lim_{n \rightarrow \infty} \frac{n^2 - n}{n^2}$$

$$= \frac{1}{2} \lim_{n \rightarrow \infty} \frac{n^2 - n}{n^2} = \frac{1}{2}$$

$$= \frac{1}{2} \lim_{n \rightarrow \infty} \left(1 - \frac{1}{n}\right)$$

$$= \frac{1}{2} \left(1 - \frac{1}{\infty}\right)$$

$$= \frac{1}{2} (1 - 0)$$

$$= \frac{1}{2}$$

two order have same growth

$$= \frac{1}{2} n(n-1) \in \Theta(n^2)$$

b)  $\log n$  &  $n$

$$\lim_{n \rightarrow \infty} \frac{\log n}{n} = \lim_{n \rightarrow \infty} \frac{\ln n}{n} = 0$$

$$\log n = \ln n$$

10)  $m$  &  $n^m$

$$\lim_{n \rightarrow \infty} \frac{m}{n^m} = 0$$

10) General plan for analysis of Non-Recursive Algorithms.

a) Divide on a parameter indicating on tip size.

b) Identify the algorithm's basic operation

c) Check whether the number of times the basic operation executed depends only on size of tip

If it also depends on some additional property, worse.

best, any case & if necessary a better case has to be investigated separately.

d) Set up sum expressing the sum of times the algorithm's basic operation is executed.

e) Using standard formula & rule of sum manipulation, either find a closed form formula

for count / at very least, establish its order of growth.



(i) largest element in a list / MaxElement  $A[0 \dots n-1]$

→ // Determines the value of the largest element in array

// I/P :-  $A[0 \dots n-1]$  of real num

// O/P :- value of largest element

maxval  $\leftarrow A[0]$

for  $i \leftarrow 1$  to  $n-1$  do

if  $A[i] \geq \text{maxval}$  ✓

maxval  $\leftarrow A[i]$

return maxval

Step 1: I/P Size  $n$

2: Basic Operation :- Comparison

$$C(n) = \sum_{i=1}^{n-1} 1$$

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

$$= n-1 \in \Theta(n)$$

(ii) Element Uniqueness problem

// all element distinct

// I/P :-  $A[0 \dots n-1]$

// O/P :- Return true if all elements in  $A$  distinct else false

for  $i \leftarrow 0$  to  $n-2$  do

for  $j \leftarrow i+1$  to  $n-1$  do

if  $A[i] = A[j]$  return false

return true

Step 1:- P/p size  $= n$

2:- B.O  $\rightarrow$  Composition.

$$(6) = \sum_{l=0}^{n-2} \sum_{j=l+1}^{n-1} 1 = \sum_{l=0}^{n-2} (n-1-l) = \frac{n(n-1)}{2}$$

$$\frac{(n-2-0+1)(n-1-l+1)}{(n-1)(n-0)} = \frac{(n-2)-1-l}{n-2} \quad \text{for } l < n-1$$

(iii) Matrix Multiplication.

// Multiplies 2 square matrices of order  $n$  by

// P/p :-  $n \times n$

//  $C = AB \rightarrow$  O/p

$$\begin{bmatrix} A \end{bmatrix}_{2 \times 3} \begin{bmatrix} B \end{bmatrix}_{3 \times 4} = \begin{bmatrix} C \end{bmatrix}_{2 \times 4}$$

for  $l \leftarrow 0$  to  $n-1$  do

for  $j \leftarrow 0$  to  $n-1$  do

$C[l, j] \leftarrow 0.0$

for  $k \leftarrow 0$  to  $n-1$  do

$$C[l, j] \leftarrow C[l, j] + A[l, k] * B[k, j]$$

return  $C$

$$2, 3 \times 1 (3, 4)$$

(2, 4)

Step 1 :- P/p size  $= n$

2:- B.O. multiplication

$$M(n) = \sum_{l=0}^{n-1} \sum_{j=0}^{n-1} \sum_{k=0}^{n-1} 1 = \sum_{l=0}^{n-1} \sum_{j=0}^{n-1} n = n^3$$

$$= \frac{n^3}{3} \in \Theta(n^3)$$



(9v) find the numb of binary digits.

// I/P  $\rightarrow$  +ve decimal no.  $n$

// O/P  $\rightarrow$  binary numb

count  $\leftarrow 1$

while  $n > 1$  do

count  $\leftarrow$  count + 1

$n \leftarrow \lfloor n/2 \rfloor$

return count

step 1: I/P size =  $n$

B.O - addition

$(n) =$

ii)

a)

b)

c) check whether the no. of times the basic operation is executed can vary on different I/P of same size

d) set up a recurrence relation, with an appropriate initial condition, for the number of time the basic operation is executed

e) Solve the recurrence / at least, ascertain the order of growth of its term

(i) factorial function  $F(n) = n!$  for non -ve integer  $n$ .

if  $n=0$  return 1

else return  $F(n-1) * n$

$M(n) = ?$  p size =  $n$

B.O = Multiplication

$$M(n) = M(n-1) + 1 \quad \checkmark \quad \text{for } n > 0$$

$$M(0) = 0 \quad \checkmark \quad \text{for } n = 0$$

$$M(n) = M(n-1) + 1$$

$$= [M(n-2) + 1] + 1$$

$$= M(n-2) + 2$$

$$M(n) = M(n-3) + 3$$

$$M(n) = M(n-p) + p \quad \checkmark$$

Substitute  $p=n$

$$M(n) = m(n-n) + n$$

$$= M(0) + n$$

$$= \underline{\underline{n}} \in \theta(n)$$

(ii) TOH

Step 1:- p size =  $n$

2:- B.O :- no. of moves

$$M(n) = M(n-1) + 1 + m(n-1)$$

$$= 2M(n-1) + 1 \quad \text{for } n > 1$$



$$M(1) = 1 \quad \text{for } n=1$$

$$\Rightarrow M(n) = 2[M(n-2) + 1] + 1$$

$$2 \cdot M(n-1) + 1$$

$$= 2[2M(n-2) + 1] + 1$$

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

$$= 2^3 [M(n-3) + 2^2 + 2 + 1]$$

$$= 2^4 [M(n-4) + 2^3 + 2^2 + 2 + 1]$$

$$= 2^p M(n-p) + 2^{p-1} + 2^{p-2} + \dots + 2 + 1$$

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

$$= 2^{n-1} M(n(n-1)) - 1$$

$$= 2^{n-1} M(1) + 2^{n-1} - 1$$

$$= 2^n - 1 \in \theta(2^n)$$

$$\sum_{i=0}^{n-1} 2^i = 2^n - 1$$

$$\sum_{i=0}^{p-1} 2^{i-1+1} = 2^p - 1$$

(iii) BinRec (n)

If  $n=1$  return 1

else  
~~if~~ return  $(\lfloor n/2 \rfloor) + 1$

Step 1:- If size  $n$

Step 2:- B.O :- Additim

$$A(n) = A(\lfloor n/2 \rfloor) + 1$$

$$A(1) = 0$$

$$n = 2^k$$

$$A(2^k) = A\left(\frac{2^k}{2}\right) + 1$$

$$= A(2^{k-1}) + 1$$

$$\theta(2^k) = \theta(2^{k-1})$$

$$\begin{aligned}
 A(2^k) &= A(2^{k-1}) + 1 \\
 &= A(2^{k-2}) + 2 \\
 &= A(2^{k-3}) + 3 \\
 &= A(2^{k-e}) + e
 \end{aligned}$$

Substitute  $e = k$

$$= A(2^{k-k}) + k$$

$$= k$$

$$n = 2^k$$

$$k = \log_2 n$$

$$\underline{\underline{A(n) = \log_2 n \in (\log n)}}$$

Brute force is a straight-forward approach to solving a problem, usually directly based on the problem statement & definition of the concepts involved.

(v) Selection Sort

for  $i \leftarrow 0$  to  $n-2$  do

    find  $\min \leftarrow i$

    for  $j \leftarrow i+1$  to  $n-1$  do

        if  $A[j] < A[\min]$   $\min \leftarrow j$

    Swap  $A[i]$  and  $A[\min]$

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



89 45 68 90 29 34 17  
 17 | 45 68 90 29 30 89  
 17 29 | 68 90 85 89  
 17 29 30 | 90 45 68 89  
 17 29 30 45 | 90 68 89  
 17 29 30 45 68 | 90 89  
 17 29 30 45 68 89 | 90

$S(n) = \text{key swap}$

$$\begin{aligned}
 S(n) &= \sum_{i=0}^{n-2} 1 = n-2+1 \\
 &= n-1 \in \underline{\underline{O(n)}}
 \end{aligned}$$

(2c) Bubble sort

for  $i \leftarrow 0$  to  $n-2$  do

for  $j \leftarrow 0$  to  $n-2-i$  do

if  $A[j+1] < A[j]$  swap  $A[j]$  and  $A[j+1]$

$$\begin{aligned}
 CC(n) &= \sum_{i=0}^{n-2} \sum_{j=0}^{n-2-i} 1 = \sum_{i=0}^{n-2} n-2-i+1 \\
 &= \sum_{i=0}^{n-2} (n-1-i) \\
 &= \underline{\underline{(n-1)n \in O(n^2)}}
 \end{aligned}$$

$$\begin{aligned}
 S(n) &= \sum_{i=0}^{n-2} \sum_{j=0}^{n-2-i} 2 \\
 &= \underline{\underline{n^2}}
 \end{aligned}$$

# Sequential Search and Brute-Force String Matching

**ALGORITHM** *SequentialSearch2*( $A[0..n]$ ,  $K$ )

//Implements sequential search with a search key as a sentinel

//Input: An array  $A$  of  $n$  elements and a search key  $K$

//Output: The index of the first element in  $A[0..n - 1]$  whose value is

// equal to  $K$  or  $-1$  if no such element is found

$A[n] \leftarrow K$

$i \leftarrow 0$

**while**  $A[i] \neq K$  **do**

$i \leftarrow i + 1$

**if**  $i < n$  **return**  $i$

**else return**  $-1$



**ALGORITHM** *BruteForceStringMatch*( $T[0..n-1]$ ,  $P[0..m-1]$ )

//Implements brute-force string matching

//Input: An array  $T[0..n-1]$  of  $n$  characters representing a text and

// an array  $P[0..m-1]$  of  $m$  characters representing a pattern

//Output: The index of the first character in the text that starts a

// matching substring or  $-1$  if the search is unsuccessful

**for**  $i \leftarrow 0$  **to**  $n - m$  **do**

$j \leftarrow 0$

**while**  $j < m$  **and**  $P[j] = T[i + j]$  **do**

$j \leftarrow j + 1$

**if**  $j = m$  **return**  $i$

**return**  $-1$

N O B O D Y \_ N O T I C E D \_ H I M  
N O N T O N T O N T O N T O N T O N T O N  
T O T

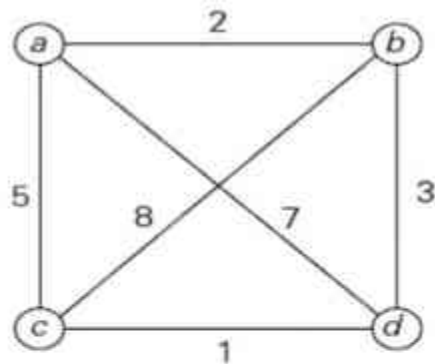


- Exhaustive search is simply a brute-force approach to combinatorial problems
- It suggests generating each and every element of the problem domain, selecting those of them that satisfy all the constraints, and then finding a desired element

# Traveling Salesman Problem

- The problem asks to find the shortest tour through a given set of  $n$  cities that visits each city exactly once before returning to the city where it started
- The problem can be conveniently modeled by a weighted graph, with the graph's vertices representing the cities and the edge weights specifying the distances
- Then the problem can be stated as the problem of finding the shortest Hamiltonian circuit of the graph





Tour

Length

$a \rightarrow b \rightarrow c \rightarrow d \rightarrow a$

$$l = 2 + 8 + 1 + 7 = 18$$

$a \rightarrow b \rightarrow d \rightarrow c \rightarrow a$

$$l = 2 + 3 + 1 + 5 = 11$$

optimal

$a \rightarrow c \rightarrow b \rightarrow d \rightarrow a$

$$l = 5 + 8 + 3 + 7 = 23$$

$a \rightarrow c \rightarrow d \rightarrow b \rightarrow a$

$$l = 5 + 1 + 3 + 2 = 11$$

optimal

$a \rightarrow d \rightarrow b \rightarrow c \rightarrow a$

$$l = 7 + 3 + 8 + 5 = 23$$

$a \rightarrow d \rightarrow c \rightarrow b \rightarrow a$

$$l = 7 + 1 + 8 + 2 = 18$$

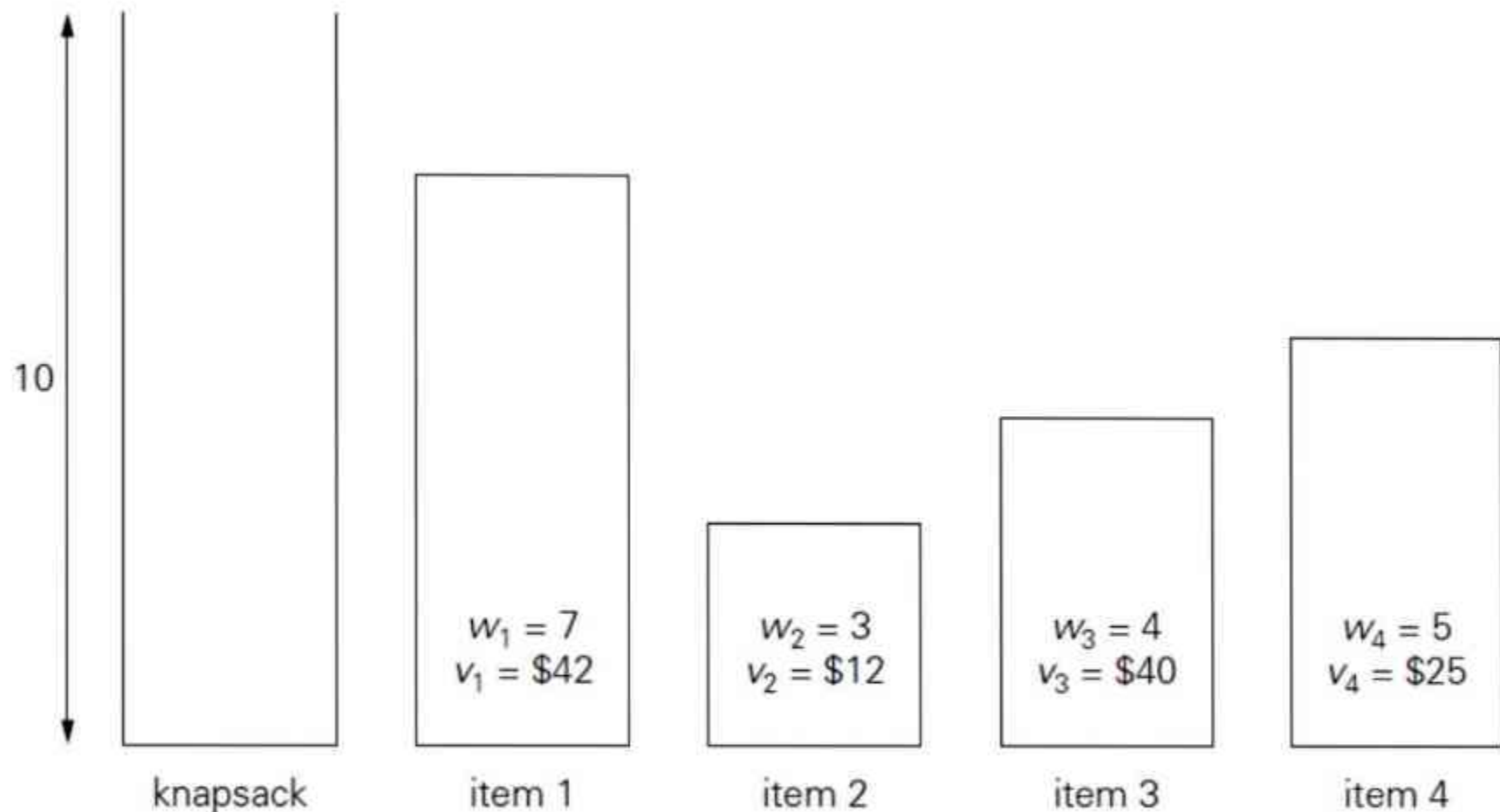
We can get all the tours by generating all the permutations of  $n - 1$  intermediate cities, compute the tour lengths, and find the shortest among them



Given  $n$  items of known weights  $w_1, w_2, \dots, w_n$  and values  $v_1, v_2, \dots, v_n$  and a knapsack of capacity  $W$ , find the most valuable subset of the items that fit into the knapsack

Since the number of subsets of an  $n$ -element set is  $2^n$ , the exhaustive search leads to a  $O(2^n)$  algorithm, no matter how efficiently individual subsets are generated





Subset	Total weight	Total value
$\emptyset$	0	\$ 0
{1}	7	\$42
{2}	3	\$12
{3}	4	\$40
{4}	5	\$25
{1, 2}	10	\$54
{1, 3}	11	not feasible
{1, 4}	12	not feasible
{2, 3}	7	\$52
{2, 4}	8	\$37
<b>{3, 4}</b>	<b>9</b>	<b>\$65</b>
{1, 2, 3}	14	not feasible
{1, 2, 4}	15	not feasible
{1, 3, 4}	16	not feasible
{2, 3, 4}	12	not feasible
{1, 2, 3, 4}	19	not feasible

# Assignment Problem

- There are  $n$  people who need to be assigned to execute  $n$  jobs, one person per job.
- That is, each person is assigned to exactly one job and each job is assigned to exactly one person
- The cost that would accrue if the  $i$ th person is assigned to the  $j$ th job is a known quantity  $C[i, j]$  for each pair  $i, j = 1, 2, \dots, n$
- The problem is to find an assignment with the minimum total cost



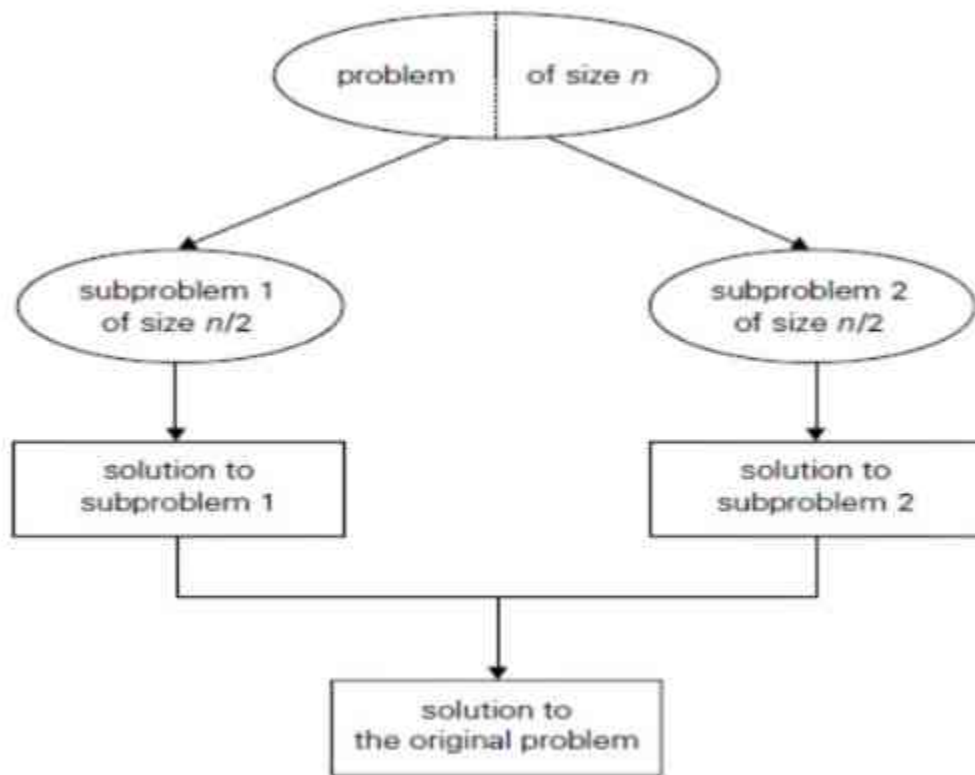
	<b>Job 1</b>	<b>Job 2</b>	<b>Job 3</b>	<b>Job 4</b>
<b>Person 1</b>	9	2	7	8
<b>Person 2</b>	6	4	3	7
<b>Person 3</b>	5	8	1	8
<b>Person 4</b>	7	6	9	4

$C = \begin{bmatrix} 9 & 2 & 7 & 8 \\ 6 & 4 & 3 & 7 \\ 5 & 8 & 1 & 8 \\ 7 & 6 & 9 & 4 \end{bmatrix}$	$\langle 1, 2, 3, 4 \rangle$	cost = $9 + 4 + 1 + 4 = 18$	etc.
	$\langle 1, 2, 4, 3 \rangle$	cost = $9 + 4 + 8 + 9 = 30$	
	$\langle 1, 3, 2, 4 \rangle$	cost = $9 + 3 + 8 + 4 = 24$	
	$\langle 1, 3, 4, 2 \rangle$	cost = $9 + 3 + 8 + 6 = 26$	
	$\langle 1, 4, 2, 3 \rangle$	cost = $9 + 7 + 8 + 9 = 33$	
	$\langle 1, 4, 3, 2 \rangle$	cost = $9 + 7 + 1 + 6 = 23$	

**FIGURE 3.9** First few iterations of solving a small instance of the assignment problem by exhaustive search.

- Divide-and-conquer algorithms work according to the following general plan:
  - A problem is divided into several subproblems of the same type, ideally of about equal size
  - The subproblems are solved (typically recursively, though sometimes a different algorithm is employed, especially when subproblems become small enough)
  - If necessary, the solutions to the subproblems are combined to get a solution to the original problem.





**FIGURE 5.1** Divide-and-conquer technique (typical case).

$$T(n) = aT(n/b) + f(n), \quad (5.1)$$

**Master Theorem** If  $f(n) \in \Theta(n^d)$  where  $d \geq 0$  in recurrence (5.1), then

$$T(n) \in \begin{cases} \Theta(n^d) & \text{if } a < b^d, \\ \Theta(n^d \log n) & \text{if } a = b^d, \\ \Theta(n^{\log_b a}) & \text{if } a > b^d. \end{cases}$$

Analogous results hold for the  $O$  and  $\Omega$  notations, too.

- Mergesort is a perfect example of a successful application of the divide-and conquer technique
- It sorts a given array  $A[0..n - 1]$  by dividing it into two halves  $A[0..n/2 - 1]$  and  $A[n/2..n - 1]$ , sorting each of them recursively, and then merging the two smaller sorted arrays into a single sorted one



**ALGORITHM** *Mergesort*( $A[0..n - 1]$ )

//Sorts array  $A[0..n - 1]$  by recursive mergesort

//Input: An array  $A[0..n - 1]$  of orderable elements

//Output: Array  $A[0..n - 1]$  sorted in nondecreasing order

**if**  $n > 1$

    copy  $A[0..\lfloor n/2 \rfloor - 1]$  to  $B[0..\lfloor n/2 \rfloor - 1]$

    copy  $A[\lfloor n/2 \rfloor..n - 1]$  to  $C[0..\lceil n/2 \rceil - 1]$

*Mergesort*( $B[0..\lfloor n/2 \rfloor - 1]$ )

*Mergesort*( $C[0..\lceil n/2 \rceil - 1]$ )

*Merge*( $B, C, A$ ) //see below

**ALGORITHM** *Merge*( $B[0..p-1]$ ,  $C[0..q-1]$ ,  $A[0..p+q-1]$ )

//Merges two sorted arrays into one sorted array

//Input: Arrays  $B[0..p-1]$  and  $C[0..q-1]$  both sorted

//Output: Sorted array  $A[0..p+q-1]$  of the elements of  $B$  and  $C$

$i \leftarrow 0$ ;  $j \leftarrow 0$ ;  $k \leftarrow 0$

**while**  $i < p$  **and**  $j < q$  **do**

**if**  $B[i] \leq C[j]$

$A[k] \leftarrow B[i]$ ;  $i \leftarrow i + 1$

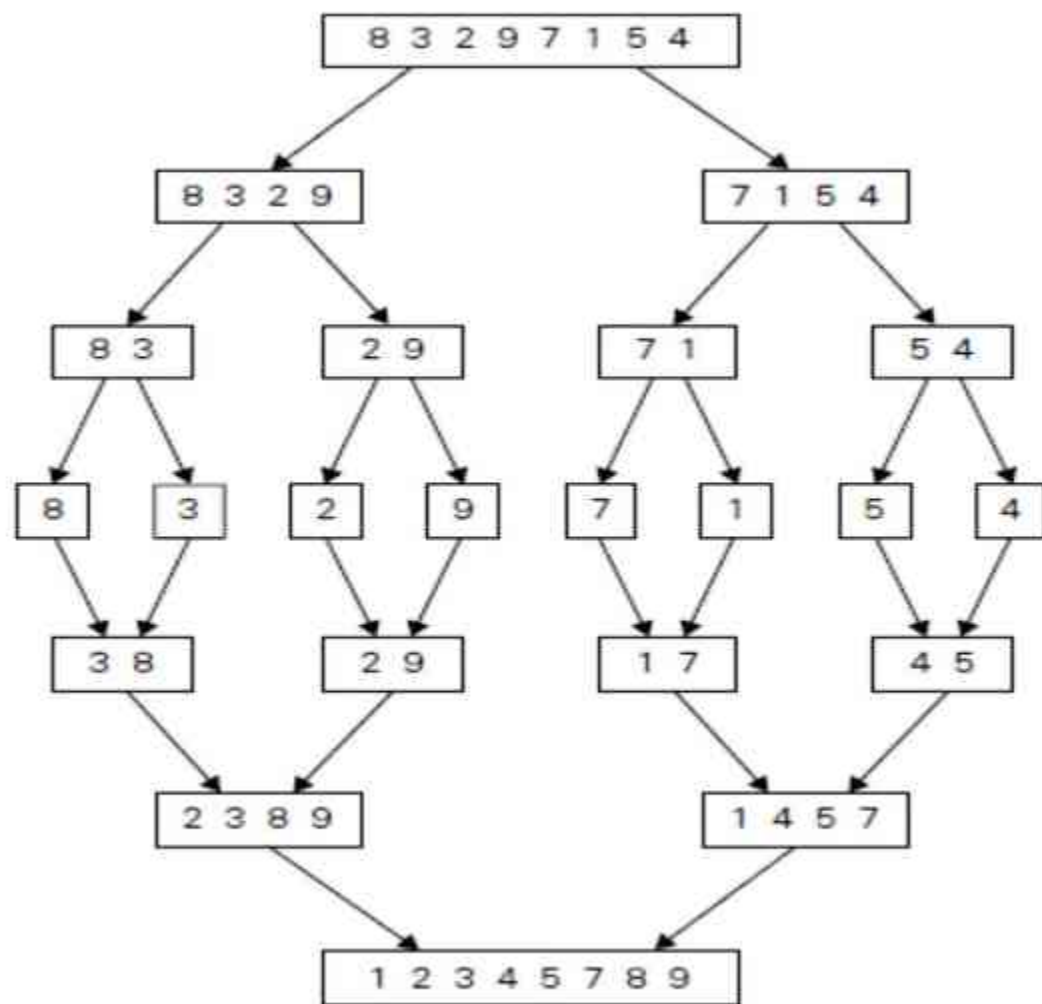
**else**  $A[k] \leftarrow C[j]$ ;  $j \leftarrow j + 1$

$k \leftarrow k + 1$

**if**  $i = p$

    copy  $C[j..q-1]$  to  $A[k..p+q-1]$

**else** copy  $B[i..p-1]$  to  $A[k..p+q-1]$



**FIGURE 5.2** Example of mergesort operation.



- Hence, according to the Master Theorem

$$C_{worst}(n) \in \Theta(n \log n)$$

- Unlike mergesort, which divides its input elements according to their position in the array, quicksort divides them according to their value
- A partition is an arrangement of the array's elements so that all the elements to the left of some element  $A[s]$  are less than or equal to  $A[s]$ , and all the elements to the right of  $A[s]$  are greater than or equal to it:

$$\underbrace{A[0] \dots A[s-1]}_{\text{all are } \leq A[s]} \quad A[s] \quad \underbrace{A[s+1] \dots A[n-1]}_{\text{all are } \geq A[s]}$$

**ALGORITHM**    *Quicksort*( $A[l..r]$ )

//Sorts a subarray by quicksort

//Input: Subarray of array  $A[0..n - 1]$ , defined by its left and right

//        indices  $l$  and  $r$

//Output: Subarray  $A[l..r]$  sorted in nondecreasing order

**if**  $l < r$

$s \leftarrow \text{Partition}(A[l..r])$  //  $s$  is a split position

*Quicksort*( $A[l..s - 1]$ )

*Quicksort*( $A[s + 1..r]$ )

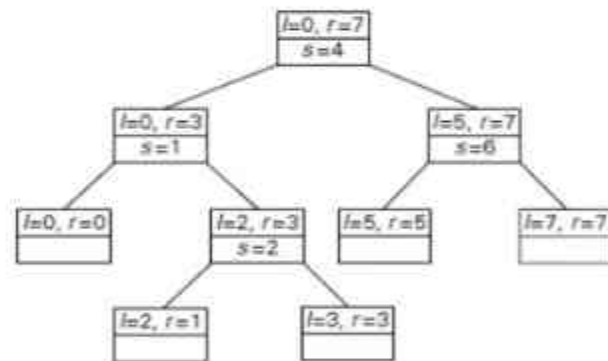
- As before, we start by selecting a pivot—an element with respect to whose value we are going to divide the subarray
- There are several different strategies for selecting a pivot
- We use the simplest strategy of selecting the subarray's first element:  $p = A[l]$



**ALGORITHM** *HoarePartition*( $A[l..r]$ )

```
//Partitions a subarray by Hoare's algorithm, using the first element
//      as a pivot
//Input: Subarray of array  $A[0..n - 1]$ , defined by its left and right
//      indices  $l$  and  $r$  ( $l < r$ )
//Output: Partition of  $A[l..r]$ , with the split position returned as
//      this function's value
 $p \leftarrow A[l]$ 
 $i \leftarrow l; j \leftarrow r + 1$ 
repeat
    repeat  $i \leftarrow i + 1$  until  $A[i] \geq p$ 
    repeat  $j \leftarrow j - 1$  until  $A[j] \leq p$ 
    swap( $A[i], A[j]$ )
until  $i \geq j$ 
swap( $A[i], A[j]$ ) //undo last swap when  $i \geq j$ 
swap( $A[l], A[j]$ )
return  $j$ 
```

0	1	2	3	4	5	6	7
5	3	1	9	8	2	4	7
5	3	1	9	8	2	4	7
5	3	1	4	8	2	9	7
5	3	1	4	8	2	9	7
5	3	1	4	2	8	9	7
5	3	1	4	2	8	9	7
2	3	1	4	5	8	9	7
2	3	1	4				
2	3	1	4				
2	1	3	4				
2	1	3	4				
1	2	3	4				
1			4				
		3	4				
		3	4				
			4				
				8	9	7	
				8	7	9	
				8	7	9	
				7	8	9	
				7			9

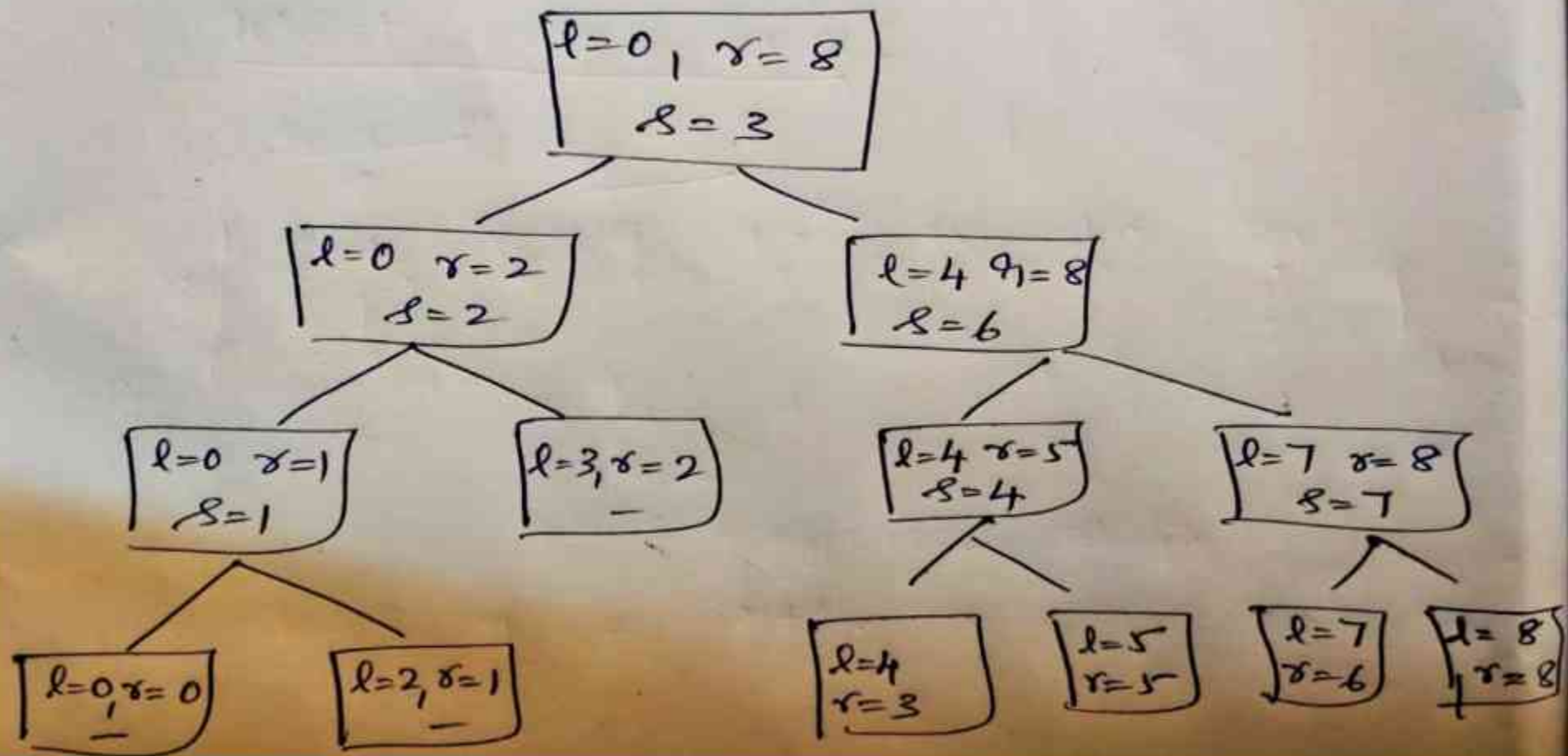


(b)

- The total number of key comparisons made will be equal to

$$C_{\text{worst}}(n) = (n+1) + n + \dots + 3 = \frac{(n+1)(n+2)}{2} - 3 \in \Theta(n^2).$$

m, E, R, G, E, S, O, R, T





- Binary search is a remarkably efficient algorithm for searching in a sorted array
- It works by comparing a search key  $K$  with the array's middle element  $A[m]$
- If they match, the algorithm stops; otherwise, the same operation is repeated recursively for the first half of the array if  $K < A[m]$ , and for the second half if  $K > A[m]$

$$\begin{array}{c}
 K \\
 \updownarrow \\
 \underbrace{A[0] \dots A[m-1]}_{\text{search here if } K < A[m]} \quad A[m] \quad \underbrace{A[m+1] \dots A[n-1]}_{\text{search here if } K > A[m]}
 \end{array}$$

As an example, let us apply binary search to searching for  $K = 70$  in the array

3	14	27	31	39	42	55	70	74	81	85	93	98
---	----	----	----	----	----	----	----	----	----	----	----	----

The iterations of the algorithm are given in the following table:

index	0	1	2	3	4	5	6	7	8	9	10	11	12
value	3	14	27	31	39	42	55	70	74	81	85	93	98
iteration 1	$l$						$m$						$r$
iteration 2								$l$		$m$			$r$
iteration 3								$l, m$	$r$				

**ALGORITHM** *BinarySearch*( $A[0..n - 1]$ ,  $K$ )

//Implements nonrecursive binary search

//Input: An array  $A[0..n - 1]$  sorted in ascending order and

//        a search key  $K$

//Output: An index of the array's element that is equal to  $K$

//        or  $-1$  if there is no such element

$l \leftarrow 0$ ;    $r \leftarrow n - 1$

**while**  $l \leq r$  **do**

$m \leftarrow \lfloor (l + r)/2 \rfloor$

**if**  $K = A[m]$  **return**  $m$

**else if**  $K < A[m]$   $r \leftarrow m - 1$

**else**  $l \leftarrow m + 1$

**return**  $-1$

- The worst-case time efficiency of binary search is  $\Theta(\log n)$

*Refer BinarySearch.c*



**EXAMPLE 2** Compare the orders of growth of  $\log_2 n$  and  $\sqrt{n}$ . (Unlike Example 1, the answer here is not immediately obvious.)

$$\lim_{n \rightarrow \infty} \frac{\log_2 n}{\sqrt{n}} = \lim_{n \rightarrow \infty} \frac{(\log_2 n)'}{(\sqrt{n})'} = \lim_{n \rightarrow \infty} \frac{(\log_2 e) \frac{1}{n}}{\frac{1}{2\sqrt{n}}} = 2 \log_2 e \lim_{n \rightarrow \infty} \frac{1}{\sqrt{n}} = 0.$$

Since the limit is equal to zero,  $\log_2 n$  has a smaller order of growth than  $\sqrt{n}$ . (Since  $\lim_{n \rightarrow \infty} \frac{\log_2 n}{\sqrt{n}} = 0$ , we can use the so-called *little-oh notation*:  $\log_2 n \in o(\sqrt{n})$ . Unlike the big-Oh, the little-oh notation is rarely used in analysis of algorithms.) ■

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**EXAMPLE 3** Compare the orders of growth of  $n!$  and  $2^n$ . (We discussed this informally in Section 2.1.) Taking advantage of Stirling's formula, we get

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

Thus, though  $2^n$  grows very fast,  $n!$  grows still faster. We can write symbolically that  $n! \in \Omega(2^n)$ ; note, however, that while the big-Omega notation does not preclude the possibility that  $n!$  and  $2^n$  have the same order of growth, the limit computed here certainly does. ■

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**THEOREM** If  $t_1(n) \in O(g_1(n))$  and  $t_2(n) \in O(g_2(n))$ , then

$$t_1(n) + t_2(n) \in O(\max\{g_1(n), g_2(n)\}).$$

(The analogous assertions are true for the  $\Omega$  and  $\Theta$  notations as well.)

**PROOF** The proof extends to orders of growth the following simple fact about four arbitrary real numbers  $a_1, b_1, a_2, b_2$ : if  $a_1 \leq b_1$  and  $a_2 \leq b_2$ , then  $a_1 + a_2 \leq 2 \max\{b_1, b_2\}$ .

Since  $t_1(n) \in O(g_1(n))$ , there exist some positive constant  $c_1$  and some non-negative integer  $n_1$  such that

$$t_1(n) \leq c_1 g_1(n) \quad \text{for all } n \geq n_1.$$

Similarly, since  $t_2(n) \in O(g_2(n))$ ,

$$t_2(n) \leq c_2 g_2(n) \quad \text{for all } n \geq n_2.$$

Let us denote  $c_3 = \max\{c_1, c_2\}$  and consider  $n \geq \max\{n_1, n_2\}$  so that we can use both inequalities. Adding them yields the following:

$$\begin{aligned} t_1(n) + t_2(n) &\leq c_1 g_1(n) + c_2 g_2(n) \\ &\leq c_3 g_1(n) + c_3 g_2(n) = c_3 [g_1(n) + g_2(n)] \\ &\leq c_3 2 \max\{g_1(n), g_2(n)\}. \end{aligned}$$

Hence,  $t_1(n) + t_2(n) \in O(\max\{g_1(n), g_2(n)\})$ , with the constants  $c$  and  $n_0$  required by the  $O$  definition being  $2c_3 = 2 \max\{c_1, c_2\}$  and  $\max\{n_1, n_2\}$ , respectively. ■