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PAPER TITLE : ANALYSIS & DESIGN OF
ALGORITHMS

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Q 1 b (i) $T(n) = 3T(n/4) + n^2$

$T(n) = aT(n/b) + f(n)$. using Master Method

$a = 3, b = 4, f(n) = n^2$.

$n^{\log_b a} = n^{\log_4 3} \approx n^{0.792}$

$\therefore f(n) = \Theta(n^{\log_b a + \epsilon})$

$n^2 = \Theta(n^{0.792 + \epsilon}) \Rightarrow \epsilon > 0$.

case 3

$a f(n/b) \leq c f(n)$

$3 f(n/4) \leq c \cdot n^2$

$3 \times \frac{n^2}{16} \leq c \cdot n^2$

$c \geq 3/16 \Rightarrow c < 1 \checkmark$

$\therefore T(n) = \Theta(f(n)) = \underline{\underline{\Theta(n^2)}}$

(ii) $T(n) = 2T(\sqrt{n}) + 1$

using change of variables.

$m = \log n \Rightarrow n = 2^m$

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

Let $T(2^m) = S(m)$

$S(m) = 2T(m/2) + 1$

using Master's method,

$T(n) = aT(n/b) + f(n)$

$a = 2, b = 2, f(n) = n^0$

$n^{\log_b a} = n^{\log_2 2} = n^1$

$f(n) = \Theta(n^{\log_b a - \epsilon})$

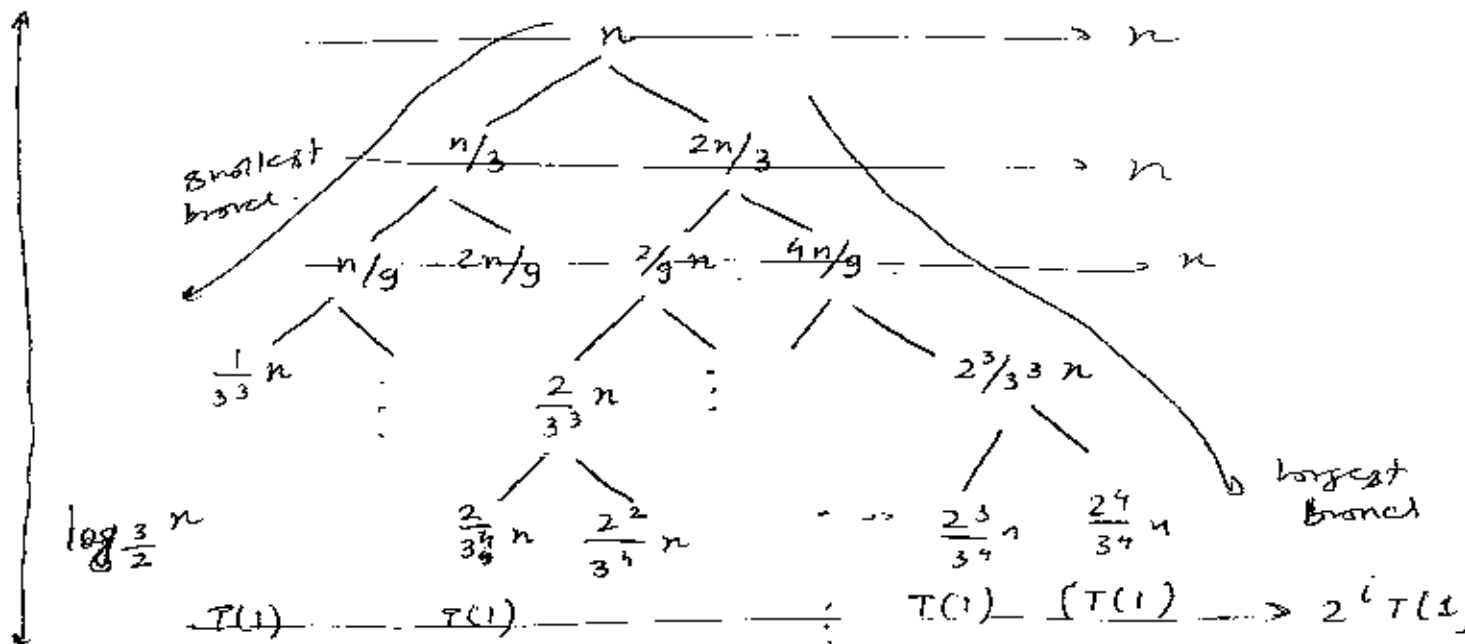
$n^0 = \Theta(n^{1 - \epsilon}) \quad \epsilon > 0$

case 1

$T(n) = \Theta(n^{\log_b a}) = \boxed{\Theta(n^1)}$

Q (b) (ii) $T(n) = T(n/3) + T(2n/3) + n$

using recursion tree method



$T(n/3^i) = 1$ ← Termination point.

$T(2^i n / 3^i) = 1$ ← Largest branch.

ht of tree = $\log_{3/2} n$.

$T(n) = n + n + n + \dots \log_{3/2} \text{ times} + (2^i T(1))$

$= n \log_{3/2} n + 2^{\log_{3/2} n}$

$= n \log_{3/2} n + n^{\log_{3/2} 2} \text{ const.}$

$T(n) = O(n \log n)$



Q 1 c) (i) RAM (random access Model) of computation and reference model for Algorithm analysis:

→ instructions executed serially, no concurrency

→ Each

Aithmetic (+, -, *, /, %, <, >, ...)

Data movement (load, store, copy)

control (conditional, unconditional branch, subroutine call & return)

Instructions take a constant amount of time

→ Datatypes are integer & floating point.

word size \sim clogn bits ($c \geq 1$) for inputs of size n .

→ other instructions such as exponentiation, shift left etc in RAM gray area.

→ memory hierarchy is not considered.

array Function (A, n)

i/p: Array A of integers

o/p: A.

1. $a = 0$.
2. for $i = 0$ to $n - 1$ do.
3. $a = a + A[i]$.
4. $A[i] = a / (i + 1)$.
5. return A.

primitive operations.

1. control loop
3. ($=$, $++$) $\times n$
3. ($+$, $=$, $[i]$) $\times n$
4. ($+$, $=$, $/$, $[i]$) $\times n$
- 1.

Total primitive operations.

$$= 1 + 3n + 7(n-1) + 1$$

$$= \boxed{10n - 5}$$

Q1 (ii) Binary Search Recurrence equation.

```

BinSea (A, l, r, key) {
    if (l > r) return;
    mid = l+r/2
    if (A[mid] == key)
        return mid;
    if (A[mid] < key)
        return BinSea (A, l, mid, key);
    return BinSea (A, mid+1, r, key);
}
    
```

- we match the key with middle element of sorted array A, if it matches → we found the key → return mid index
- If $key < A[mid]$ → the key shall exist in first half of array, otherwise in second half of array
- with each recursive call, we reduce the search space by half.

- ∴ Divide : To compare $A[mid]$ with key → $O(1)$
- Conquer : In each iteration, search space halves → $T(n/2)$
- Combine : No combination → $O(\text{cost})$.

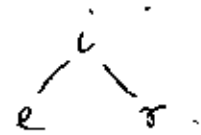
∴ recurrence relⁿ for binary search is.

$$T(n) = \begin{cases} O(1) & \text{if } n \leq 1 \\ T(n/2) + O(1) & \text{otherwise} \end{cases}$$

$$\Rightarrow \boxed{T(n) = O(\log n)}$$

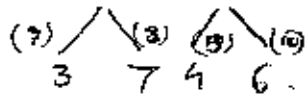
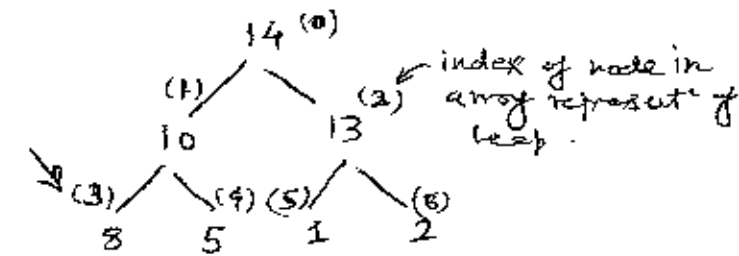
- The best case complexity of binary search is $\boxed{\Omega(1)}$ when mid of array matches with the key in first step
- The worst case complexity occurs when either the key is not found or found at the last recursion. Ht of recursion tree in binary search in $\log n$ in worst case → $\boxed{T(n) = O(\log n)}$

- Q2 a) (i) MAX-HEAPIFY (A, i)
1. $l = \text{LEFT}(i)$. // return index of left child of i
 2. $r = \text{RIGHT}(i)$
 3. if $l \leq A.\text{heapsize} \ \& \ A[l] > A[i]$
 4. $\text{largest} = l$
 5. else $\text{largest} = i$
 6. if $r \leq A.\text{heapsize} \ \& \ A[r] > A[\text{largest}]$.
 7. $\text{largest} = r$.
 8. if $\text{largest} \neq i$
 9. exchange $A[i]$ with $A[\text{largest}]$.
 10. MAX-HEAPIFY $A[\text{largest}]$



find largest of i, l, r
 if $\text{largest} \neq i \rightarrow$ heap property
 violated \rightarrow exchange i with largest
 of its children & max-heapify
 subtree rooted at new root

Step 1



$i = 3$

$l = \text{left}(3) = 7 \quad (2i+1)$

$r = \text{right}(3) = 8 \quad (2i+2)$

$A[7] = 3 > A[3] = 8$ No \rightarrow $\text{largest} = 3$.

$A[8] = 7 > A[\text{largest}] = A[3] = 8$ No \rightarrow $\text{largest} = 3$.

$\text{largest} = i = 3 \rightarrow$ No swap required.

\rightarrow The Algorithm terminates
 after step 1 bec
 subtree rooted at
 index 3 is already
 a max heap.

Apply MAX-HEAPIFY
 in bottom up way for all
 internal nodes.

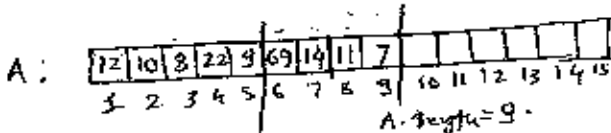
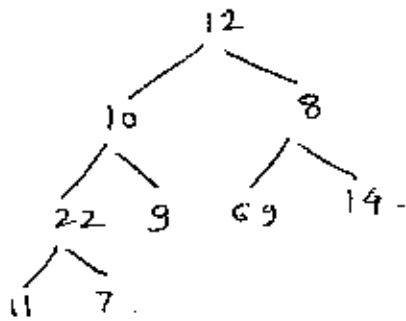
2a (ii)

BUILD-MAX-HEAP(A)

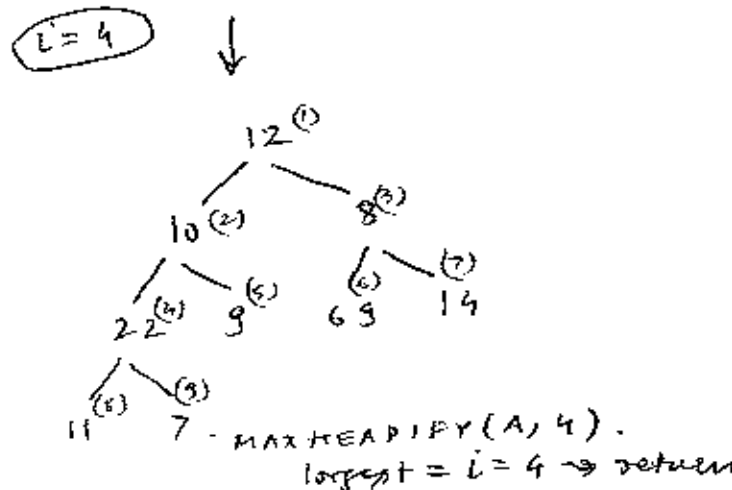
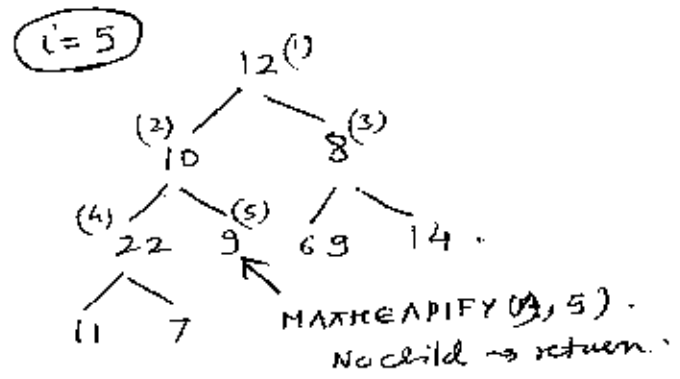
1. A.heapsize = A.length.
2. for $i = \lfloor A.length / 2 \rfloor$ down to 1.
3. MAX-HEAPIFY(A, i)

Analysis

$$\begin{aligned}
 T(n) &= \sum_{h=0}^{\lfloor \log n \rfloor} \left[\frac{n}{2^{h+1}} \right] O(h) \\
 &= O\left(n \sum_{h=0}^{\lfloor \log n \rfloor} \frac{h}{2^h} \right) \quad \text{removes const factor} \\
 &\leq O\left(n \sum_{h=0}^{\infty} h \left(\frac{1}{2}\right)^h \right) \quad \sum_{k=0}^{\infty} kx^k = \frac{x}{(1-x)^2} \\
 &= O\left(n \frac{1/2}{(1-1/2)^2} \right) = \boxed{O(n)}
 \end{aligned}$$

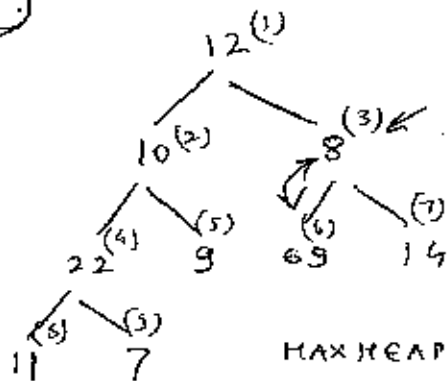


$\lfloor 9/2 \rfloor = \lfloor 4.5 \rfloor = 5$





$L=3$



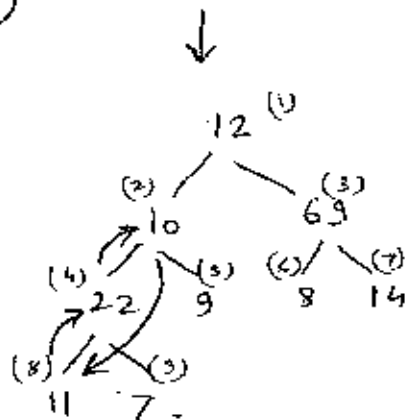
MAXHEAPIFY(A, 3)

$\log_{2} 8 = 3 \neq 3 \rightarrow \text{swap } A[3], A[6]$

MAXHEAPIFY(A, 6)

$\log_{2} 8 = 3 = L \rightarrow \text{return}$

$L=2$



MAXHEAPIFY(A, 2)

$\log_{2} 4 = 2 \neq 2 \rightarrow \text{swap } A[2], A[4]$

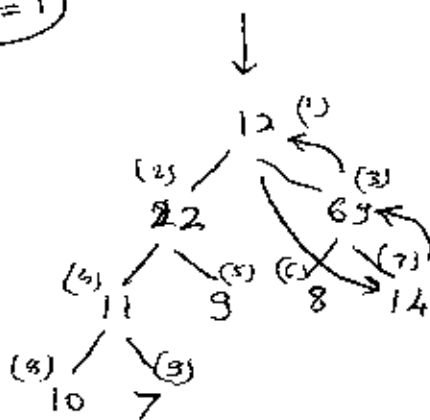
MAXHEAPIFY(A, 4)

$\log_{2} 4 = 2 \neq 4 \rightarrow \text{swap } A[4], A[8]$

MAXHEAPIFY(A, 8)

No children \rightarrow return

$L=1$



MAXHEAPIFY(A, 1)

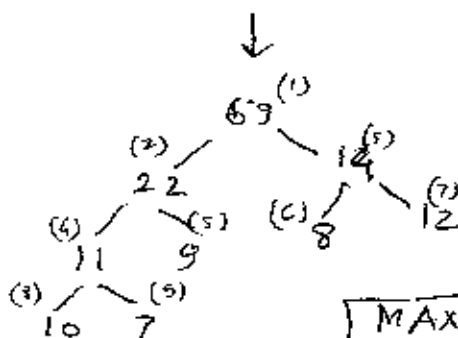
$\log_{2} 3 = 1 \neq 1 \rightarrow \text{swap } A[1], A[3]$

MAXHEAPIFY(A, 3)

$\log_{2} 7 = 2 \neq 3 \rightarrow \text{swap } A[3], A[7]$

MAXHEAPIFY(A, 7)

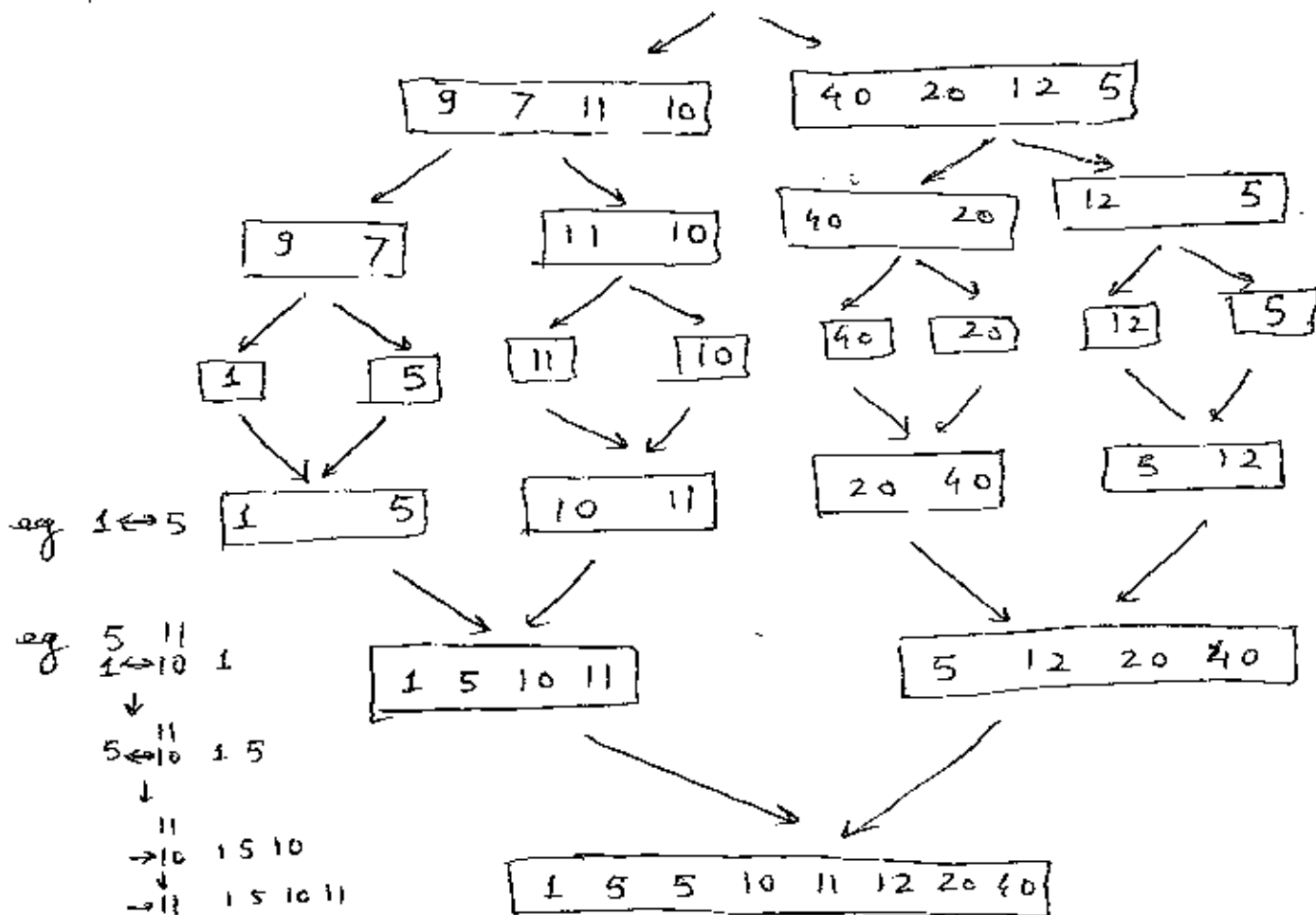
No children \rightarrow return



MAXHEAP obtained

Q2 b (i)

9 7 11 10 40 20 12 5



eg 1 ↔ 5

eg 5 11
1 ↔ 10 1
↓
5 11 1 5
↓
11 15 10
→ 10 15 10
→ 11 15 10 11

eg . 1 ↔ 5
5 12
10 20
11 40 1

5 12
10 20 1 5
11 40

5 12
10 20 1 5 5
11 40

12
10 20 1 5 5 10
11 40

12
10 20 1 5 5 10 11
11 40

12
20
40
1 5 5 10 11 12 20 40

Best case complexity of Merge Sort .

$T(n) = 2T(n/2) + \underbrace{n}_{n \text{ no of comparisons}} + m$ instead of $n+m$

$T(n) = aT(n/b) + 1$

$a=2, b=2, f(n) = n^d$

$n \log_a n = n^1, \epsilon = 0$

∴ case 2

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



Q2 b) (ii)

QUICKSORT (A, l, r).

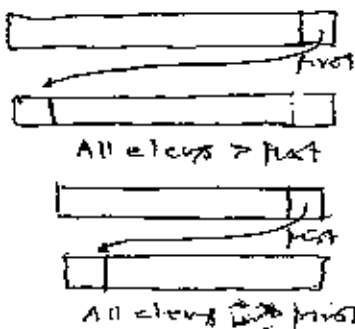
1. if $l < r$
2. $q = \text{PARTITION}(A, l, r)$
3. QUICKSORT (A, l, q-1)
4. QUICKSORT (A, q+1, r).

PARTITION (A, l, r).

1. $x = A[r]$
2. $i = l - 1$
3. for $j = l$ to $r - 1$.
4. if $A[j] \leq x$.
5. $i = i + 1$.
6. exchange $A[i]$ with $A[j]$
7. exchange $A[i+1]$ with $A[r]$
8. return $i + 1$

worst case complexity of quicksort .

worst case partitioning : unbalanced partitioning at each recursive call .



ie Array is reverse sorted.

$$T(n) = T(n-1) + T(0) + \theta(n)$$

divide *conquer* *combine*

$$= T(n-1) + \theta(n)$$

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

$$= T(n-3) + n - 2 + n - 1 + n$$

⋮

$$= T(k) + \theta(n-k+1) + \dots + n - 2 + n - 1 + n$$

$k=1$

$$= T(1) + 1 + 3 + \dots + n - 2 + n - 1 + n$$

$$= 1 + 2 + 3 + \dots + n$$

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

$$= \boxed{O(n^2)}$$

(using iterative method)

DESIGN OF ALGORITHM .

↑
Pivot

↓ PARTITIONING about D .

A

D

 E S I G N O F A L G O R I T H M
1 2 3 4 5 6 7 8 9 10 11 15

∴ Position of D after applying quicksort in 1 indexed array will be

2



Q 3 a) (i)

DFS (depth first search) is a graph traversal algorithm, which starting from a source vertex s , penetrates the graph as deep as possible until a dead end emerges due to No more further choices to expand, which can occur if either the degree of current vertex is 1 or all its neighbours are visited. Once a dead end emerges, the DFS backtracks the path it has traced until further choices to expand appear. This process is repeated until all vertices are ~~visited~~ discovered.

The predecessor subgraph of a DFS forms a depth first forest.

DFS colors vertices during the search to indicate their state and also timestamps each vertex.

v .color = white (initially)
grey (when discovered)
black (when finishes its adjacency list is examined completely)

v .d = time when v is first discovered.
 v .f = time when v is completely examined.

DFS has several applications

- Finding connected components.
- Topological sort on DAGs.
- Finding strongly connected components.
- Finding Articulation pts in a graph
- Find bridges in a graph, etc
- ⋮

DFS classifies the edges of a graph in 3 categories.

DFS (G)

1. for each vertex $u \in G.V.$
2. $u.color = white.$
3. $u.\pi = NIL$
4. $time = 0.$
5. for each vertex $u \in G.V.$
6. if $color == WHITE$
7. DFS-VISIT(G, u).

DFS-VISIT(G, u).

1. $time = time + 1.$
2. $u.d = time.$
3. $u.color = grey.$
4. for each $v \in G-Adj[u].$
5. if $v.color = WHITE.$
6. $v.\pi = u.$
7. DFS-VISIT(G, v).
8. $u.color = BLACK$
9. $time = time + 1.$
10. $u.f = time$

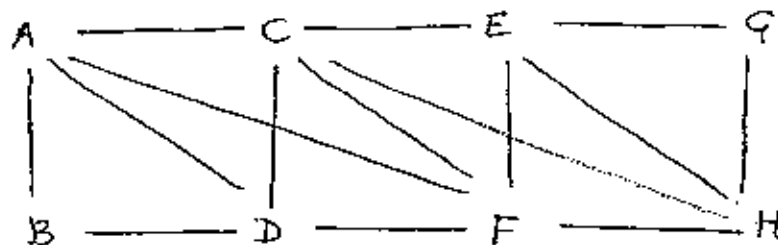
Analysis

$$T = O(V + E).$$

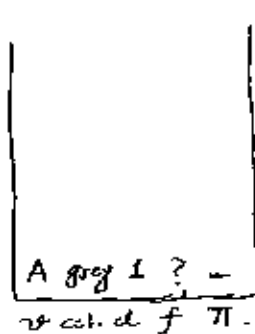
$$S = O(V)$$

At max V vertices
can be stack
(if graph contains
hamiltonian path)

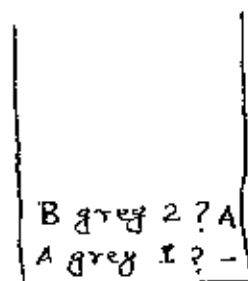
This is the recursive version of DFS, we can show its implementation by using an implicit stack



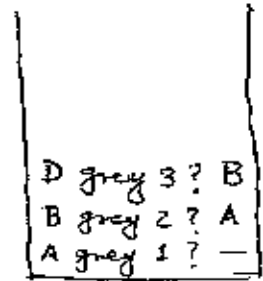
stack.



→



→



→



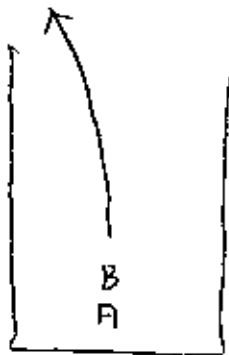
C	grey	4	? D
D	grey	3	? B
B	grey	2	? A
A	grey	1	? -

→ . . . →

G	grey	8	? H
H	grey	7	? F
F	grey	6	? E
E	grey	5	? C
C	grey	4	? D
D	grey	3	? B
B	grey	2	? A
A	grey	1	? -

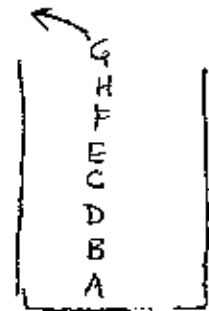
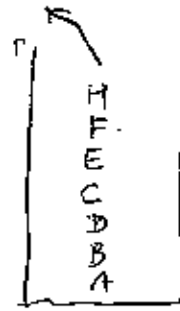
No unvisited
 neighbour
 of G.
 ∴ backtrack
 i.e. pop G.

B black 2 15 A



H black 7 10 F

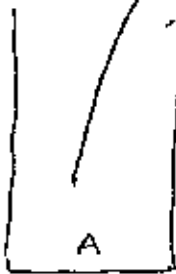
G black 8 9 H



. . .

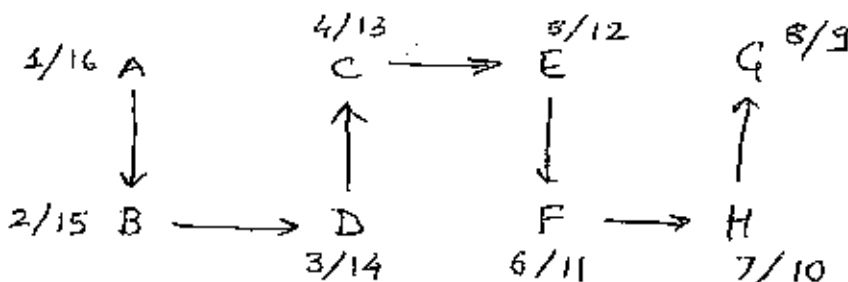
↓

A black 1 16 -



stack empty
 ∴ return

The depth first tree obtained is .



Q3 a (ii)

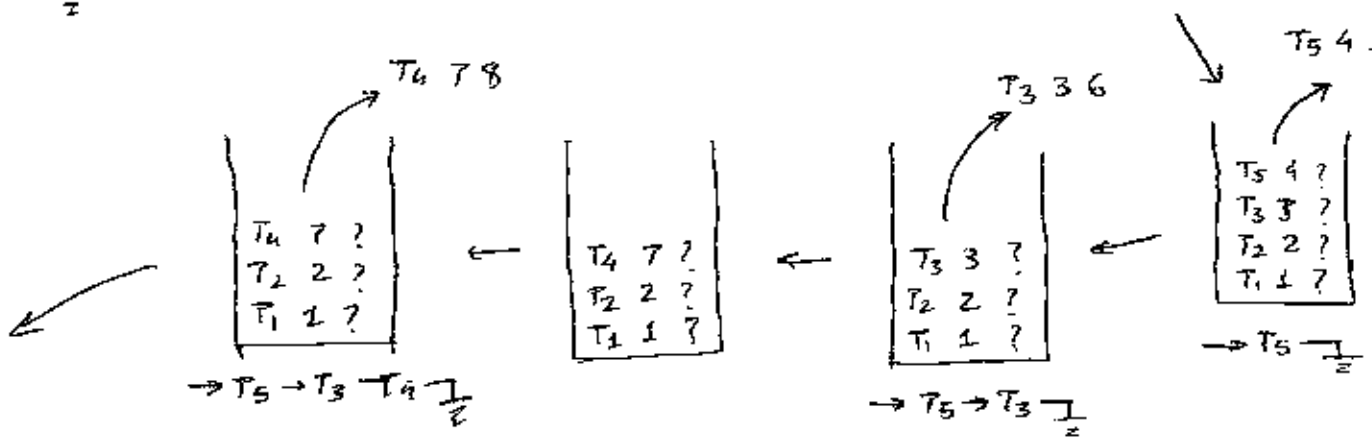
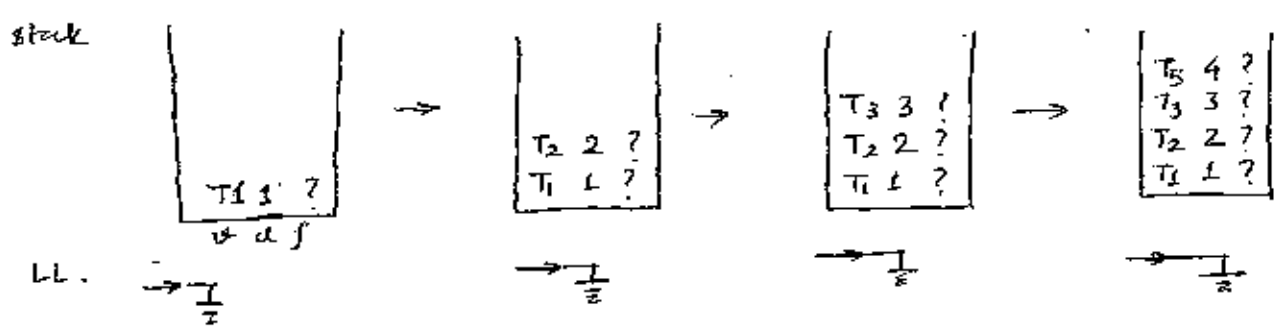
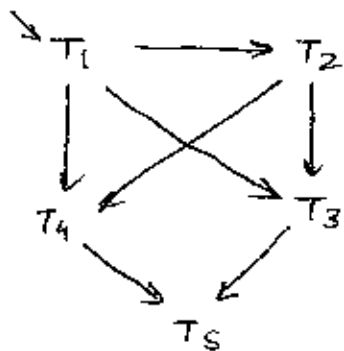
TOPOLOGICAL-SORT(G).

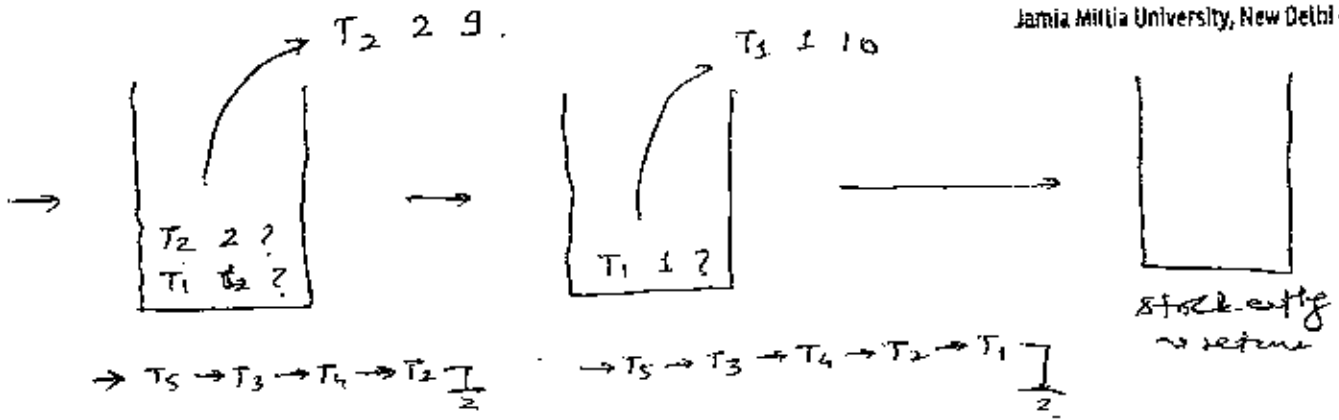
1. call DFS(G) to compute finishing times v.f for each vertex v.
2. as each vertex is finished, insert it in front of a linked list.
3. return the LL of vertices.

Topologically sort vertices after in reverse order in LL.

$T = O(V + E)$

[$O(V + E)$ for DFS & $O(V)$ insertions in LL of cost $O(1)$ each]





∴ One of the Topological sorts of given DAG is ,

$$T_1 \rightarrow T_2 \rightarrow T_4 \rightarrow T_3 \rightarrow T_5$$



Q 3 c)

MST-PRIM (G, ω, s)

1. for each $u \in G.V$
2. $u.key = \infty$
3. $u.\pi = NIL$
4. $s.key = 0.$
5. $\Phi = G.V$
6. while $\Phi \neq \emptyset.$
7. $u = \text{EXTRACT-MIN}(\Phi)$
8. for each $v \in G.adj[u]$
9. if $v \in \Phi$ & $\omega(u, v) < v.key.$
10. $v.\pi = u$
11. $v.key = \omega(u, v).$

s : arbitrary source vertex.

G : graph $G = (V, E)$
 \uparrow set of edges
 \downarrow set of vertices
 $E \subseteq V^2$

u, v : vertex - has two attributes

1. value key
2. parent vertex π .

Φ : minimum priority queue (implemented using min-heap)

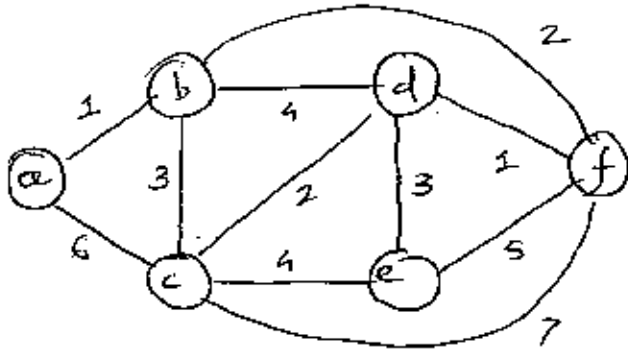
ω : weight function $\omega : V \times V \rightarrow \mathbb{R}$ or $E \rightarrow \mathbb{R}$.

Analysis .

1. line 1 to 3 initializes each vertex $O(V)$
2. line 4 is single assignment $O(1)$
3. line 5 is implemented using $BUILD-MIN-HEAP()$ funcn $O(V)$.
4. line 7 runs $\text{EXTRACT-MIN}()$ funcn $V \times O(\log V)$
on heap which is logarithmic in size of heap & since while loop runs (V) no. of times
5. line 8 runs in total for $\sum_{u=0}^{V-1} |adj[u]| = O(E)$ $O(E)$.
6. line 11 is implemented using $DECREASE-KEY()$ this log time & it runs in total $O(E)$ times as in for loop on line 8. $E \times O(\log V)$

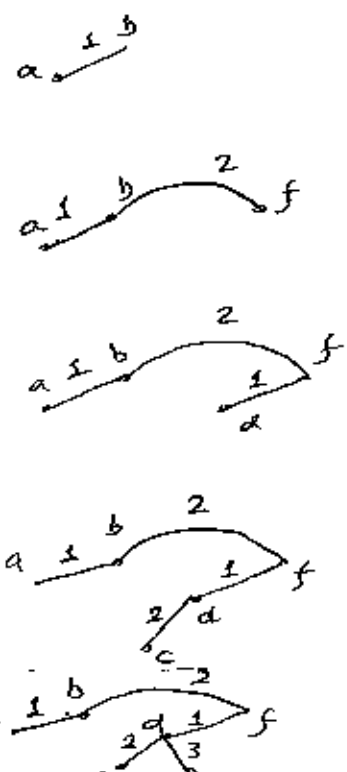
∴ Total time = $O(V \log V + E \log V) = O(E \log V)$
 Assuming $E = O(V^2)$ in worst case (for complete graph)

$$T(n) = O(E \log V) = O(V^2 \log V)$$



Minimum spanning tree

	a	b	c	d	e	f
key	∞	∞	∞	∞	∞	∞
π	-	-	-	-	-	-
key	0	∞	∞	∞	∞	∞
π	-	-	-	-	-	-
key	1	6	∞	∞	∞	∞
π	a	a	-	-	-	-
key	4	4	∞	2	∞	∞
π	b	b	-	b	-	-
key	4	1	5	∞	∞	∞
π	b	f	f	-	-	-
key	2	3	∞	∞	∞	∞
π	d	d	-	-	-	-
key	3	3	∞	∞	∞	∞
π	d	d	-	-	-	-
key	3	3	3	∞	∞	∞
π	d	d	d	-	-	-



Q empty.

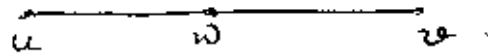
$u = \min(a, b, c, d, e, f) = a$
 $u = \min(a, b, c, d, e, f) = b$
 $u = \min(a, b, c, d, e, f) = f$
 $u = \min(a, b, c, d, e, f) = d$
 $u = \min(a, b, c, d, e, f) = c$
 $u = \min(a, b, c, d, e, f) = e$

Q 4) a) (i) Characteristics of Dynamic programming.

1. Optimal Substructure.

A problem exhibits optimal substructure if optimal solution to the problem consists within it the optimal solutions to subproblems.

eg. in a graph, shortest path between nodes exhibits optimal substructure.

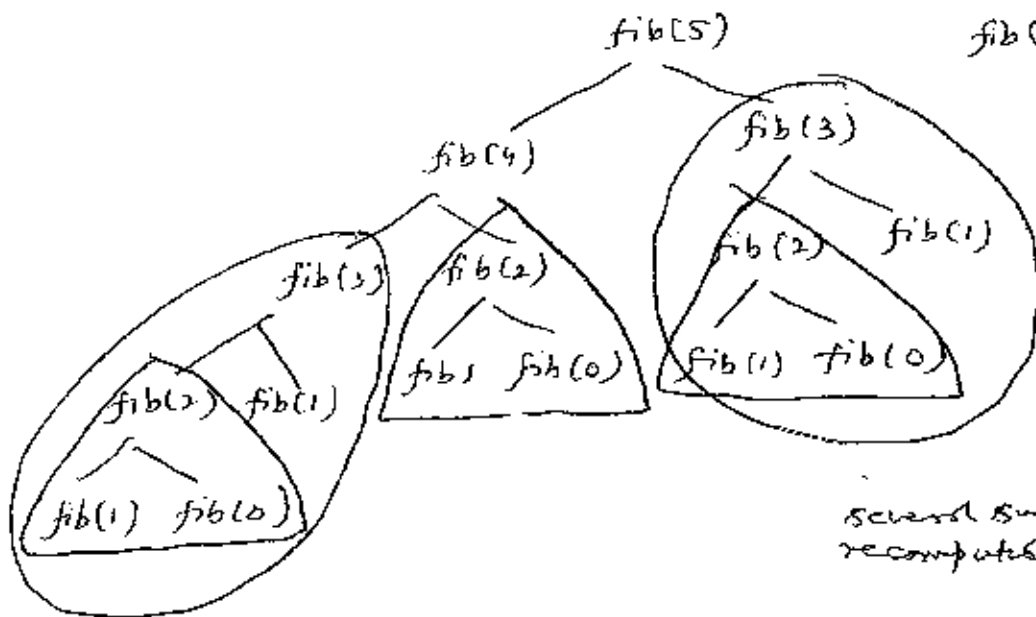


if $P^*(u, v)$ is shortest path from u, v & $w \in P^*(u, v)$ then $P(u, w)$ & $P(w, v)$ are shortest paths from u, w & w, v as well.

2. overlapping subproblems

The space of subproblems must be small in the sense that a recursive algorithm for problem solves the same subproblems over & over rather than always generating new subproblems.

eg. recursive generation of fibonacci nos



$$fib(n) = \begin{cases} 1 & \text{if } n=0 \\ fib(n-1) + fib(n-2) & \text{otherwise} \end{cases}$$

several subproblems are recomputed eg fib(3) 2 times, fib(2) 3 times

Limitations of Dynamic programming

→ In combinatorial problems which do not obey optimal substructure like longest path problem, dynamic programming cannot yield a polynomial time solution.

4a)(ii)

Fibonacci series using bottom up DP (Tabulation)
(1 dimensional DP)

```
int fib(int n) {  
    int dp[n+1];  
    dp[0] = 0;  
    dp[1] = 1;  
    for (int i = 2; i ≤ n; i++)  
        dp[i] = dp[i-1] + dp[i-2];  
    return dp[n];  
}
```

$T = O(n)$ for loop runs $n-1$ times, body is $O(1)$
 $S = O(n)$ for dp array.



Q 4 c)

Problem stmt

LCS problem: Given two sequences $X = \langle x_1, x_2, \dots, x_m \rangle$ and $Y = \langle y_1, y_2, \dots, y_n \rangle$, find the maximum length subsequence of X & Y .

Problem characteristics

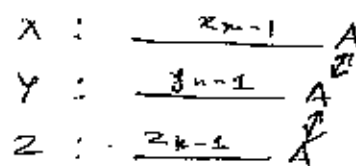
① LCS has optimal substructure property.

Let $X = \langle x_1, x_2, \dots, x_m \rangle$

$Y = \langle y_1, y_2, \dots, y_n \rangle$ be sequences.

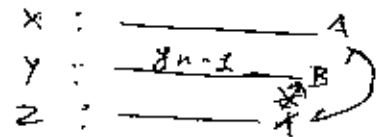
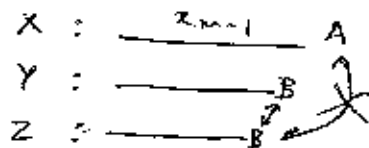
& $Z = \langle z_1, z_2, \dots, z_k \rangle$ be LCS of X, Y .

1. if $x_m = y_n$, then $z_k = x_m = y_n$ & z_{k-1} is LCS of x_{m-1} & y_{n-1} .



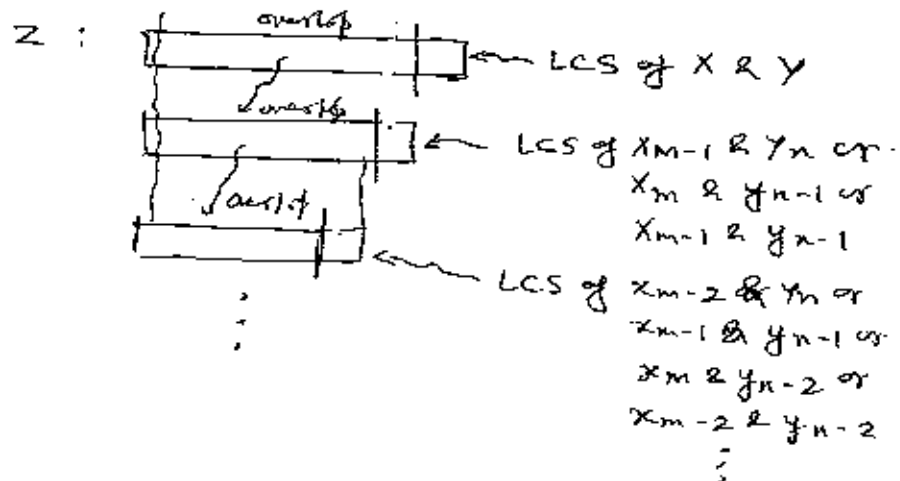
2. if $x_m \neq y_n$, then $z_k \neq x_m \Rightarrow z$ is LCS of x_{m-1} & y

3. if $x_m \neq y_n$, then $z_k \neq y_n \Rightarrow z$ is LCS of x & y_{n-1} .



② LCS has overlapping subproblems property.

LCS of two sequences contains within it the LCS prefixes of the two sequences.



length of X
length of Y

③ LCS has only $O(mn)$ distinct subproblems
hence we can apply 2 dimensional bottom up DP to solve the problem efficiently.

Dynamic programming algorithm for LCS

```

LCS-LENGTH(X, Y)
1. m = X.length
2. n = Y.length
3. let b[1..m, 1..n] & c[0..m, 0..n] be new tables
4. for i = 1 to m
5.     c[i, 0] = 0
6. for j = 0 to n
7.     c[0, j] = 0
8. for i = 1 to m                               = O(m)
9.     for j = 1 to n                             = mO(n)
10.        if x_i == y_j
11.            c[i, j] = c[i-1, j-1] + 1
12.            b[i, j] = "\
13.        else if c[i-1, j] >= c[i, j-1]
14.            c[i, j] = c[i-1, j]
15.            b[i, j] = "\
16.        else c[i, j] = c[i, j-1]
17.            b[i, j] = "\
18. return c, b
    
```

T(n) = O(mxn)
S(n) = O(mn)

to print LCS

```

PRINT-LCS(b, X, i, j)
1. if i == 0 or j == 0
2.     return
3. if b[i, j] == "\
4.     PRINT-LCS(b, X, i-1, j-1)
5.     print x_i
6. else if b[i, j] == "\
7.     PRINT-LCS(b, X, i-1, j)
8. else PRINT-LCS(b, X, i, j-1)
    
```

initial call to print LCS is PRINT-LCS(b, X, X.length, Y.length)



X = NOWADAYS

Y = CONGRATS

	j	0	1	2	3	4	5	6	7	8	
			C O N G R A T S								
i	x _i	0	0	0	0	0	0	0	0	0	
1	N	0	N=C	N=O	N=N	N=G	N=R	N=A	N=T	N=S	
2	O	0	O=C	O=O	O=N	O=G	O=R	O=A	O=T	O=S	
3	W	0	W=C	W=O	W=N	W=G	W=R	W=A	W=T	W=S	
4	A	0	A=C	A=O	A=N	A=G	A=R	A=A	A=T	A=S	
5	D	0	D=C	D=O	D=N	D=G	D=R	D=A	D=T	D=S	
6	A	0	A=C	A=O	A=N	A=G	A=R	A=A	A=T	A=S	
7	Y	0	Y=C	Y=O	Y=N	Y=G	Y=R	Y=A	Y=T	Y=S	
8	S	0	S=C	S=O	S=N	S=G	S=R	S=A	S=T	S=S	

c

		1	2	3	4	5	6	7	8	
		C O N G R A T S								
1	(N)	↓	↓	↘	↘	↘	→	→	→	
2	O	↓	↘	↓	↓	↘	↓	↓	↓	
3	W	↓	↓	↓	↓	↘	↓	↓	↓	
4	(A)	↓	↓	↓	↓	↓	↘	→	→	
5	D	↓	↓	↓	↓	↓	↓	↘	↓	
6	A	↓	↓	↓	↓	↓	↘	↓	↓	
7	Y	↓	↓	↓	↓	↓	↓	↘	↓	
8	(S)	↓	↓	↓	↓	↓	↓	↓	↘	

b

X : N O W A D A Y S
 Y : C O N G R A T S

LCS : N A S

There can be other LCSs as well if other paths are followed.

PL(b, X, 8, 8)
 ↓
 PL(b, X, 7, 7) → X₈ = 'S'
 ↓
 PL(b, X, 6, 7)
 ↓
 PL(b, X, 5, 7)
 ↓
 PL(b, X, 4, 7)
 ↓
 PL(b, X, 4, 6) → X₄ = 'A'
 ↓
 PL(b, X, 3, 5)
 ↓
 PL(b, X, 2, 5)
 ↓
 PL(b, X, 1, 5)
 PL(b, X, 1, 4) → X₁ = 'N'
 ↓
 PL(b, X, 0, 3) → other

Analysis of Algorithm.

There are nested loops of m within m & each inner loop costing $O(1)$ therefore,

$$T(n) = O(m^2)$$

length of x length of y .

Since we are allocating two tables of size $m \times n$ & $(m+1) \times (n+1)$, the space complexity is

$$S(n) = O(mn).$$

We can use space optimization to store only 3 entries to calculate current entry, but we cannot avoid building

Q5 a) string matching Algorithm with finite Automata

- we preprocess the pattern to build
 - we run the text through this finite automata character by character, whenever few reaches final state, we detect the pattern P at location $i - m$ pattern length
- current character pos^*

COMPUTE-TRANSITION-FUNC (P, Σ)

1. $m = P.length$
2. for $q = 0$ to m
3. for each character $a \in \Sigma$
4. $k = \min(m+1, q+2)$
5. repeat $k = k-1$ until $P_k \neq P_{q+1}$
6. $\delta(q, a) = k$
7. return δ

$T(n) = O(m^3 |\Sigma|)$
 $S(n) = O(m^2)$
 pattern length

FINITE-AUTOMATON-MATCHER

1. $n = T.length$
2. $q = 0$
3. for $i = 1$ to n
4. $q = \delta(q, T[i])$
5. if ($q == m$)
6. print "pattern found at shift $i - m$."

$T(n) = O(n)$

Transition function δ for FSM of given pattern $P = "a c"$
 No of states = pattern size + 1 = 3 + 1 = 4 [0..3]

$\Sigma = \{a, b, c\}$

state	a	c	b	pattern
→ 0	1	0	0	a
1	1	2	0	c
2	2	3	0	c
③	1	0	0	

$a|a$
 match for len = 1
 $\overline{a}ca$
 match for len = 2

$a|b$
 $\overline{a}cca$
 $\overline{a}cb$
 $\overline{a}ccc$
 $\overline{a}ccb$
 match for len = 1
 match for len = 2

Q 5 (i) NP-class

Set of all decision problems solved by a non deterministic machine in polynomial time
or.

It is a complexity class that represents set of all decision problems where the answer is 'yes' have proofs that can be verified in polynomial time.

This means, if someone gives us an instance of the problem and a certificate (sometimes called witness) to the answer being yes, we can check that it is correct in polynomial time.

eg. INTEGER FACTORIZATION.

pbm: given integers n & m , is there an integer f with $1 < f < m$ such that f divides n ?

This is a decision pbm bco answers are yes or no. If someone hands us an instance of the pbm (n, m & f) and an integer f s.t. $1 < f < m$, and claim that f is a factor of n (the certificate), we can check the answer in polynomial time by performing the division n/f .

NP-complete

NPC is a complexity class which represents the set of all problems X in NP for which it is possible to reduce any other NP pbm Y to X in polynomial time.

This means that we can solve Y quickly if we know how to solve X quickly. Y is reducible to X , if there is a polynomial time algorithm f to transform instances y of Y to instances $x = f(y)$ of X in polynomial time, with the property that the answer to y is yes, iff the answer to $f(y)$ is yes.

eg. 3 SAT (a Boolean satisfiability problem)

problem: given a conjunction (ANDs) of 3-clause disjunctions (ORs), i.e. strings of form

$$\begin{aligned} & (v_{11} \text{ OR } v_{21} \text{ OR } v_{31}) \text{ AND} \\ & (v_{12} \text{ OR } v_{22} \text{ OR } v_{32}) \text{ AND} \\ & \dots \text{ AND} \\ & (v_{1n} \text{ OR } v_{2n} \text{ OR } v_{3n}) \end{aligned}$$

where v_{ij} is a boolean variable or negation of a variable from a finite predefined list (x_1, x_2, \dots, x_n)

It can be shown that every NP problem can be reduced to 3SAT: Cook's theorem.

NP problems are important because if a deterministic polynomial time algorithm is found to solve any one of them, then every NP problem is solvable in polynomial time.

NP-HARD

These are the problems which are at least as hard as the NP-complete problems. All NPH problems do not have to be NP, and they do not have to be decision problems.

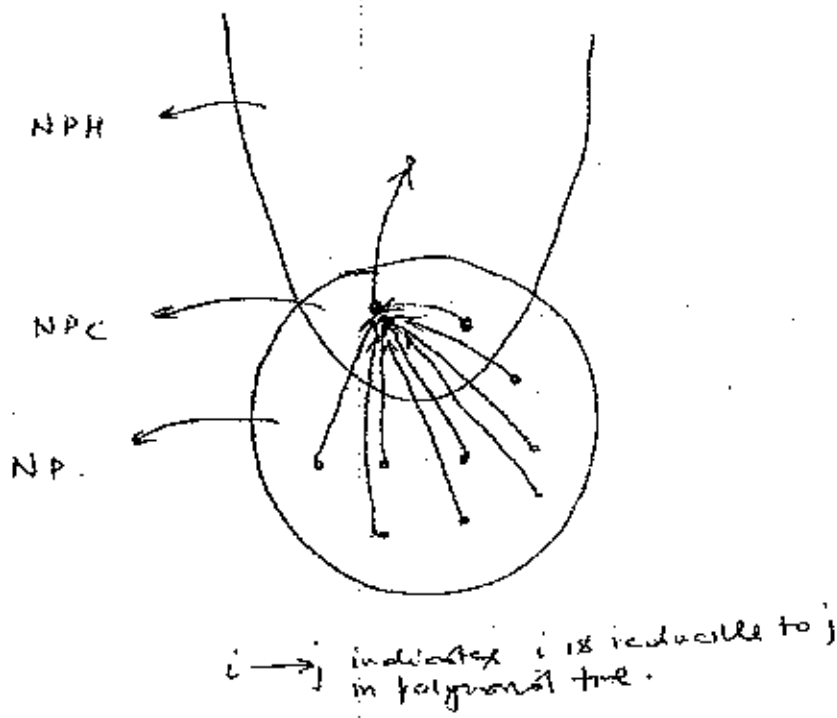
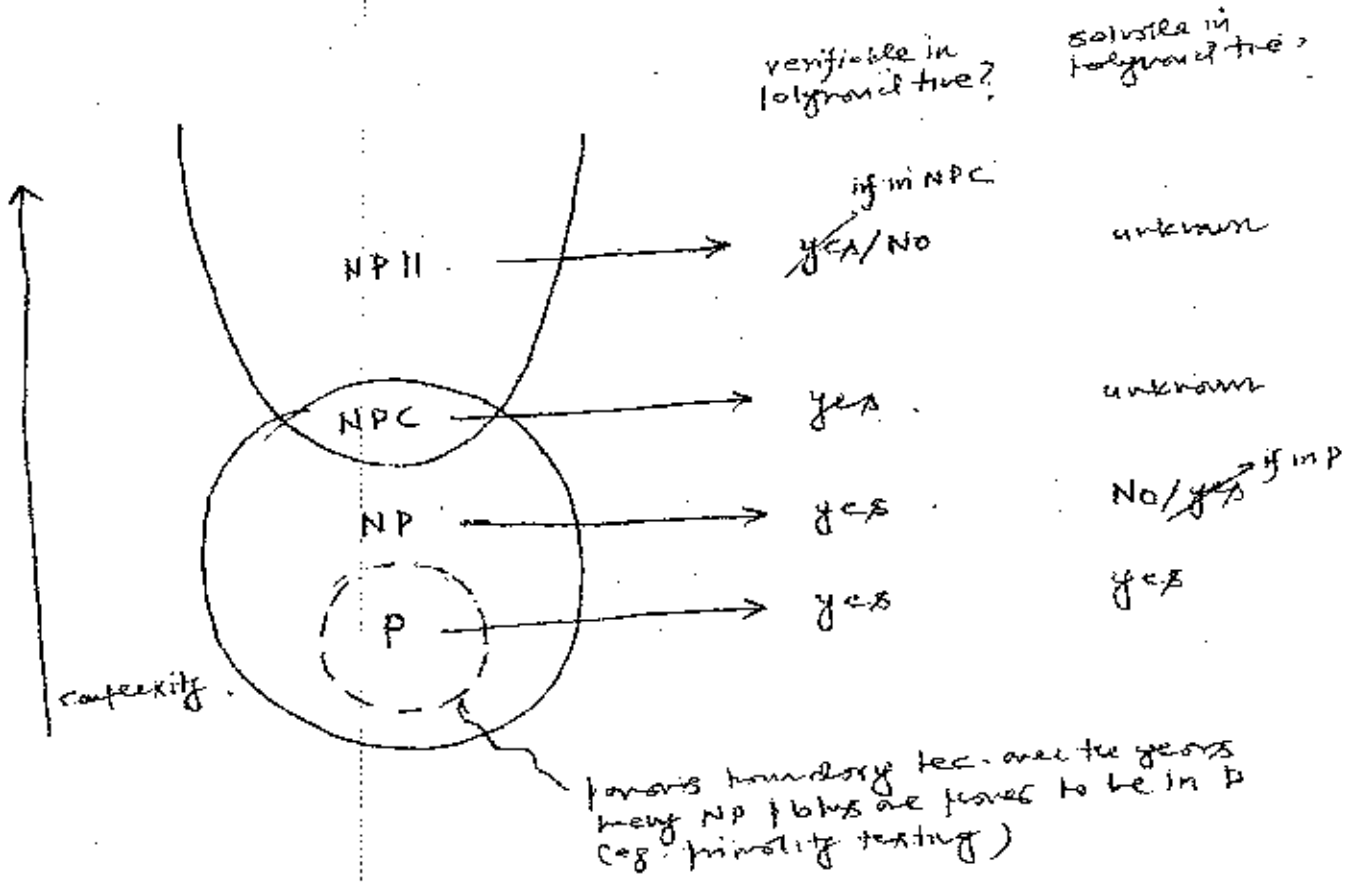
~~The precise definition is as follows:~~

A problem X is NP-hard, if there is an NP-complete problem Y , such that Y is reducible to X in polynomial time.

But since any NPC problem can be reduced to any other NPC in polynomial time, all NPC problems can be reduced to any NPH problem in polynomial time. Then, if there is a solution to one NPH problem in polynomial time, there is a solution to all NP problems in polynomial time.

eg. HALTING PROBLEM

problem: given a program P and input I , will it halt?



Q5c) (ii) Naive Algorithm for string matching.

NAIVE - STRING - MATCHER (T, P).

1. $n = T.length()$.
2. $m = P.length()$.
3. for $s = 0$ to $n - m$
4. if $P[1..m] == T[s+1..s+m]$
5. print "pattern occurs at shift s ".

explanation:

The algorithm works by matching pattern with constantly window of text by shifting window one character at a time.

Analysis.

$$T(n) = O((n-m+1)m).$$

$$S(n) = O(1).$$

This is an inefficient algorithm as it recomputes information which can be used to foster further operations.