

DESIGN AND ANALYSIS OF ALGORITHMS

BSE: 5th SEMESTER
(After Mid)

21/11/24

→ Insertion Sort : $O(n^2)$

→ Merge Sort : $\Theta(n \log n)$

Θ Space Complexity:

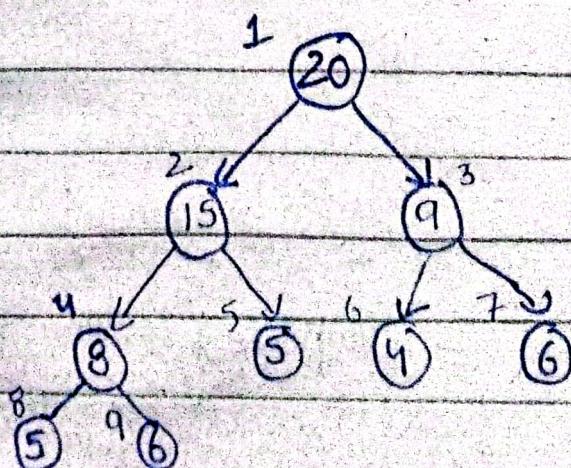
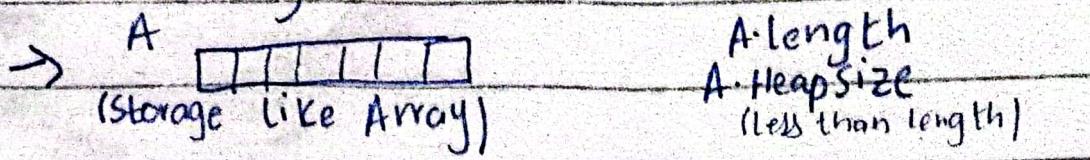
(i) Inplace Sorting Algorithm (use that space of specific Data structure)
(Do sorting within that structure)
(Insertion sort)

(ii) Not in Place sorting Algorithm (Merge sort)

Θ Heap:

→ Tree Data Structure - Heap

→ Binary Tree Visualization



: left child - 2i
(Greater)
Right child - 2i + 1
(Less)

: Complete Binary Tree
(Either 2 child or leaf node)

$$\rightarrow A[\text{parent}(i)] \geq A[i]$$

$\therefore \text{Parent}(i) = \lfloor \frac{i}{2} \rfloor$

$\text{Left}(i) = 2i$

$\text{Right}(i) = 2i+1$

$\rightarrow \text{MaxHeapify } (A, i)$

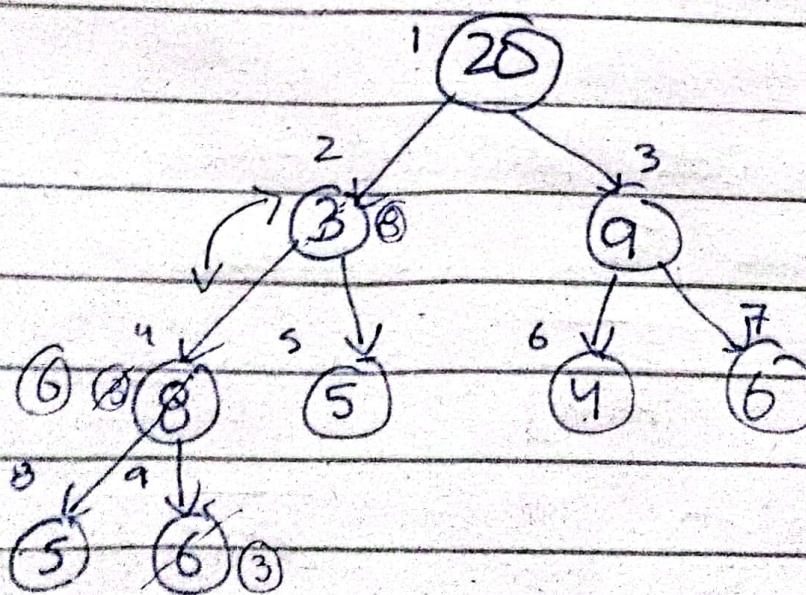
(array) (node)

Max or
Min Heap

A

20	15	9	8	5	4	6	5	6
1	2	3	4	5	6	7	8	9

$\text{MaxHeapify } (A, 2)$



: Root Node
should
be greater
than other
two.

: Write
algorithm.

$\rightarrow \text{MaxHeapify } (A[n], i)$

{ while ($i < \text{heapsz}$) }

: Find
Time
complexity

→ Max_Heapify(A, i)

{

- : Two comparison
- : One swapping

Max_Heapify();

$$Tn = aT\left(\frac{n}{b}\right) + C$$

$$Tn = 1 T\left(\frac{n}{2}\right) + \Theta(1)$$

$$O(\log n)$$

: Not Specified
that tree
is equally
divided

$$\log_b^n$$

$$: n^{\log_b^n} = n^0 = 1$$

: 1. $\log n$

① Build Heap :

→ Random Array is given

and Max_Heapify on each element.

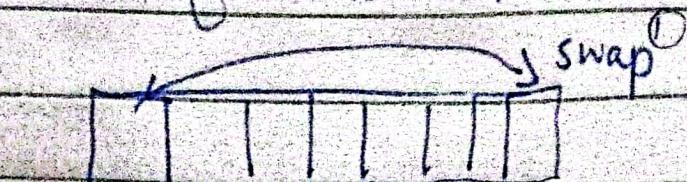
" → Where leaf nodes are present?

Not call Max_Heapify on leaf nodes.

② Heapsort :

($n \log n$)

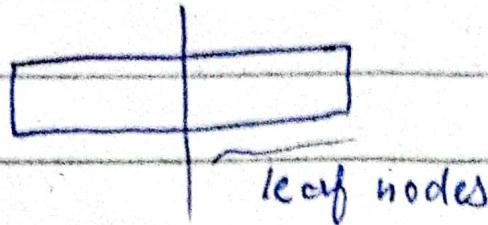
→ Ascending Order (Large value at end) (Swap Root with last value and call max_Heapify for now Root value)



: Overall
Heapsort cost
 $(n \log n)$
 $O(n \log n)$

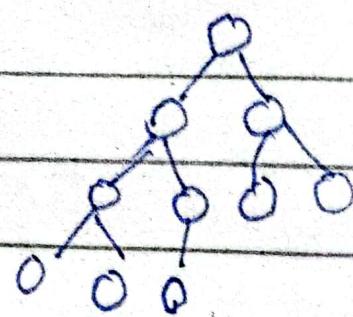
② call max_Heapify
for it

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* It can further be made better from $n \log n$:

: Suppose:

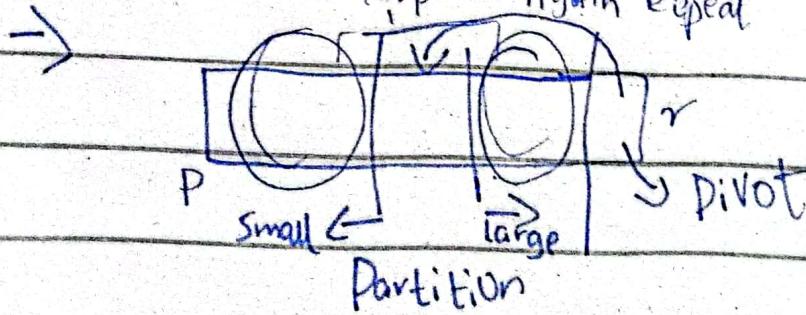


Quick Sort:

→ Sorting Algorithm

→ Divide and Conquer Rule

→ Two part Again repeat



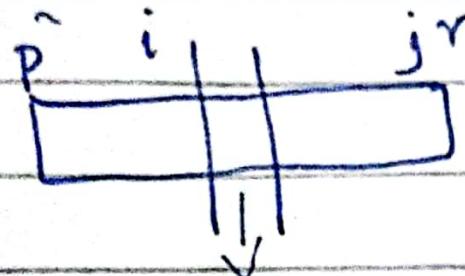
→ Main is Partition Algorithm

{ → $q = \text{Partition}(A, p, r)$

Quicksort($A, p, q - 1$)

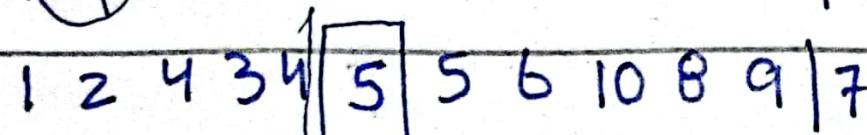
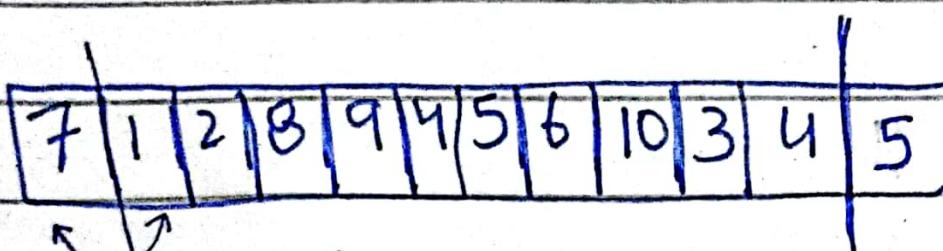
Quicksort($A, q + 1, r$)

↓ Main algorithm Pseudo code



q

$i \ j$
p



i
pivot
(i+1)

: compare
with

: If greater
than keep
there

: If less
than

swap
and i float
next

: j float
continuously

* Strict Bounds: $\Theta(n)$

* Quick sort (Complete Read it).

(Ex: 7.1 - 7.4) (Do it hand-written)

5 | 12 | 24

○ Performance Analysis of Quick-Sort:

→ Worst-Case Partitioning:

- All problems shift on one side. Suppose on right there is no problem but maximum weight of problem is on left.

$$\begin{aligned}
 T(n) &= T(0) + T(n-1) + \Theta(n) \\
 &= T(n-1) + \Theta(n) \\
 &\Theta(n^2)
 \end{aligned}$$

① Best-Case Scenario Partitioning:

→ When problems is divided into equal problem size two parts.

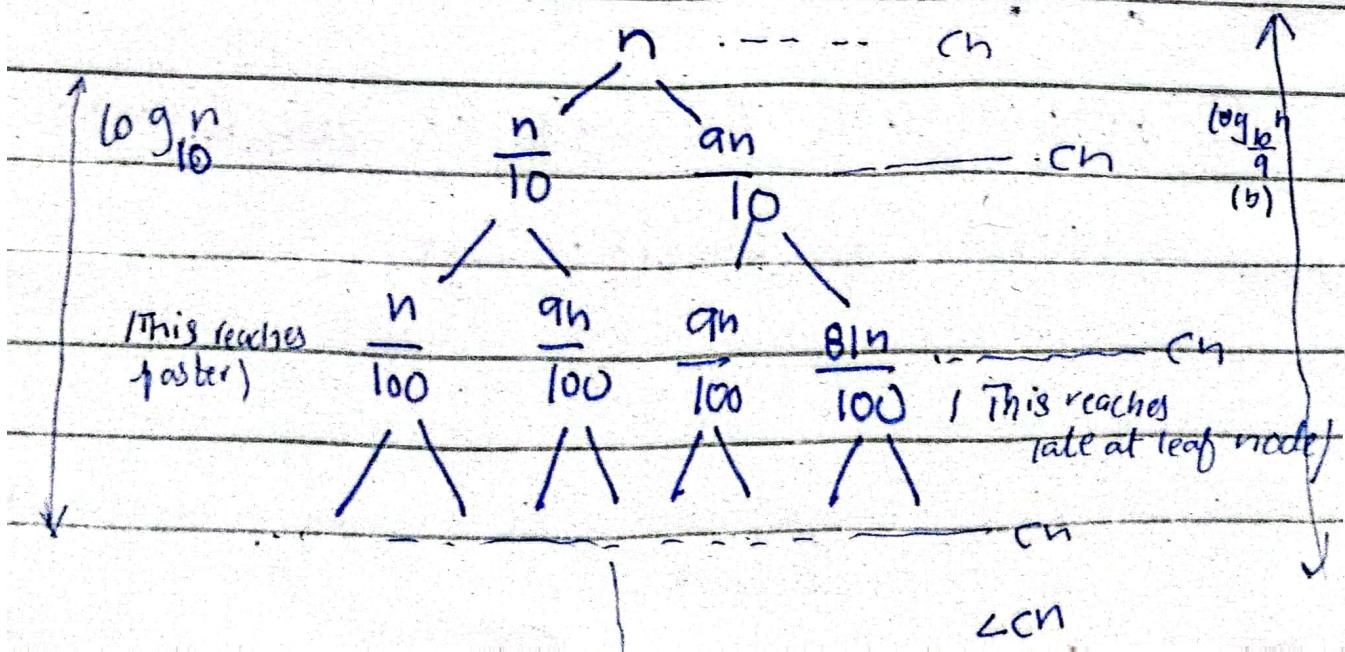
$$\begin{aligned}
 \rightarrow T(n) &= 2T\left(\frac{n}{2}\right) + \Theta(n) \\
 &\Theta(n \log n)
 \end{aligned}$$

② Balance Scenario:

→ E.g there is ratio of 1:9 (10%, 90%)

We are more concerned about worst-case

$$T(n) = T\left(\frac{n}{10}\right) + T\left(\frac{9n}{10}\right) + \Theta(n)$$



$\Theta(n \log n)$

: $\leq cn \log_{\frac{10}{9}} n$
(Big O)

$\Theta(n \log n)$

(\log Base 2)

: $\log_{10} n$

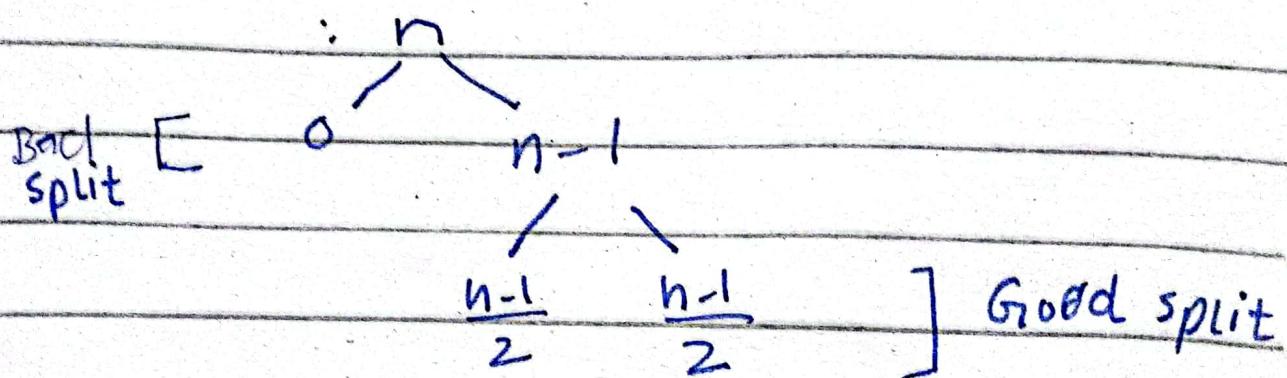
: $\log_{\frac{10}{9}} n$

* : But Asymptotic
ally

it is $n \log_2 n$
(why base 2)
(so prove it)

For Average Case:

→ It is mix of good and bad split



→ Bad split followed by good split

: $\Theta(n) + 0 + \Theta(n-1)$

: choose random number (pivot)
then swap it.

: we finally
intuite
that $\log n$

→ Worst case Analysis:

$$T(n) = \max T(q) + T(n-q-1)$$

$$0 \leq q \leq n-1$$

(By Substitution)

(It's guess would be worst-case (n^2))

$$\leq \max_{0 \leq q \leq n-1} \{ cq^2 + c(n-q-1)^2 \}$$

$$= c \cdot \max_{q} (q^2 + (n-q-1)^2) + O(n)$$

maxima (First Derivative \rightarrow Equal to zero)

Second Derivative (\leftarrow Stationary point)

\checkmark It is positive or negative }
(max) (min)

$$\rightarrow c(n-1)^2 + O(n)$$

$$\rightarrow cn^2 - 2n + c + O(n)$$

$$\rightarrow cn^2 - c(2n-1) + O(n)$$

(Big) - small \uparrow = smaller value

$$< cn^2$$

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

: Precise
Average
Case Analysis
(Random)

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$O(n \log n)$

1:1

(Perfect
Bal)

$O(n \log n)$

1:99

(Different)
(Bad Balance)

(But performance is same)

→ Big O is upper bound so 1:1 and 1:99 will be below constant factor $n \log n$ but not similar. according to performance and can be similar (growth rate) ^{as} belong to similar family.

: $T(n)$

$$0 \leq f_a(n) \leq c_1 n \log n$$

$$0 \leq f_b(n) \leq c_2 n \log n$$

① Average Case / Expected Case:

→ Under all circumstances how average Case / Expected Case works.

→ On average it should be mix of good split and bad split but not exact clear.

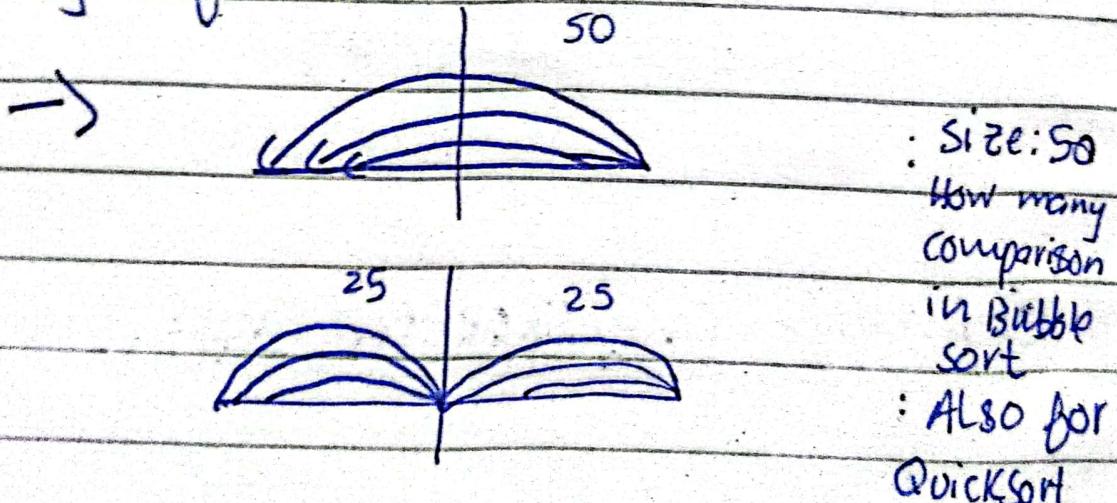
→ Random variable possible

outcomes:
(1 of 6 dice)
rolled

$$\sum(x) = \sum x P(x)$$

- On average partition would be prediction.
- Partition would be better if we got median in less than $(n/\log n)$.
- Arrangement possible would be found by permutation.
- In ^{Algorithm} computational steps are:
 - (i) Comparison of values
(More comparison, more computational steps)

④ In Bubble Sort, comparison are easily found



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No. of elements

Composition

100

99

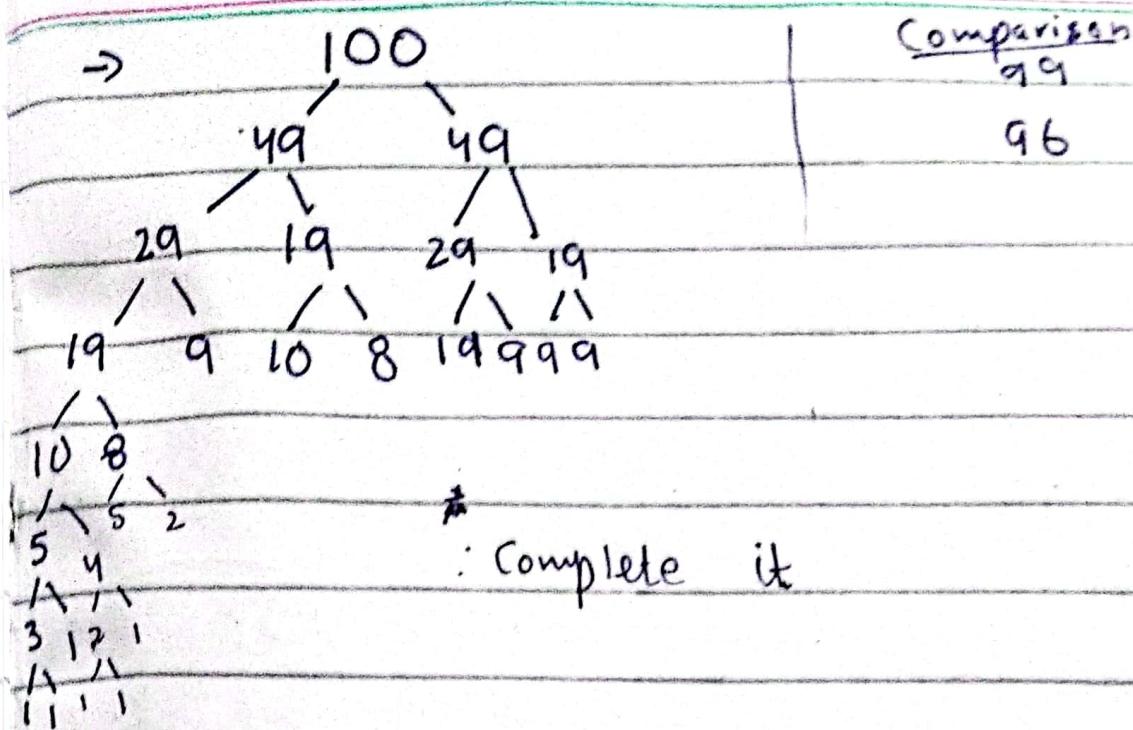
(77) 78 (21)

$$76 + 20 = 96$$

(55) 56(26) (12) 13 (7)

$$54 + 19 + 11 + 6 = 90$$

(33) / (20)



④

$z_{ij} \ z_i, z_{i+1}, z_{i+2}, \dots, z_j$

X_{ij} z_i is compared with z_j

$$X = \sum_{i=1}^{n-1} \sum_{j=i+1}^n X_{ij}$$

: Expected $E(X) = E \left[\sum_{i=1}^{n-1} \sum_{j=i+1}^n X_{ij} \right]$

$$= \sum_{i=1}^{n-1} \sum_{j=i+1}^n E(X_{ij})$$

$P_r(z_i \text{ is compared with } z_j)$

(It is chosen as pivot and compared with z_j)

(It is chosen as pivot and compared with z_i)

$$\begin{aligned}
 &= \frac{1}{j-i+1} + \frac{1}{j-i+1} \\
 &= \frac{2}{j-i+1} \quad \cdot (K=j-i)
 \end{aligned}$$

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

$$= \sum_{i=1}^{n-1} \sum_{k=1}^{n-i} \frac{2}{k+1} < \sum_{i=1}^{n-1} \sum_{k=1}^{n-i} \frac{2}{k}$$

$\boxed{\Theta(n \log n)}$

Dynamic Programming

: Bucket sort

→ This technique is also related to Divide and conquer.

: Asymptotic Recurrence Analysis

→ Some unnecessary calculations which increased the Time complexity. (May be Exponential: 2^n)

: Divide & conquer (Design)

→ Dynamic Programming teaches us the repeating thing one time. For the scenario dynamic programming handles better are called optimization (Maximize and Minimize) problem.

Rod cutting:

i	1	2	3	4	5	6	7	8	9	10	Maximize
Pi	1	5	8	9	10	17	17	20	24	30	-1

: More than one optimization solutions.

$$\rightarrow 4 \text{ m} = 9$$

$$1,3 = 9$$

$$\boxed{2,2} = 10$$

Best

$$3,1 = 9$$

$$1,1,2 = 7$$

$$1,2,1 = 7$$

$$1,2,1 = 7$$

$$2,1,1 = 7$$

$$1,1,1,1 = 4$$

: Size $\leq n$

so From

$$(1-n)$$

$\frac{\text{No}}{\text{cut}}$

$$: n = i_1 + i_2 + \dots + i_k$$

$$\gamma_n = P_{i1} + P_{i2} + \dots + P_{ik}$$

$$\gamma_1 = 1 \quad (\text{No cut})$$

$$\gamma_6 = 17 \quad \left(\frac{\text{No cut}}{4,2,3} \right)$$

$$\gamma_2 = 5 \quad ("")$$

$$\gamma_7 = 18 \quad (2,5)$$

$$\gamma_3 = 8 \quad ("")$$

$$\gamma_4 = 10 \quad (2,2)$$

$$\gamma_5 = 13 \quad (2,3)$$

$$\cdot \left(\frac{1-1}{1-1} \right)$$

$$\max(P_4, P_1 + P_3, P_2 + P_2, P_3 + P_1, \dots)$$

$$P_1 + P_2 + P_3 + \dots$$

→ Generalized Expression:

$$r_n = \max_{1 \leq i \leq n} (P_i + r_{n-i})$$

: 15.1

(Pg # 32)

Before

15.2

17/12/24

* Doing unnecessary steps recursively will increase time complexity and for this we use dynamic programming.

* In general, dynamic problem is best for optimization.

* Revenue compute for 400 m

Long Rod ((1,399), (2,388))



: r: revenue
n: length

$$r_n = \underbrace{\left(P_n, r_{1+n-1}, r_2 + r_{n-2}, \dots, r_{n-1} + r_1 \right)}_{\text{Max}}$$

(Generic Expression)

E.g.: n=2

$$r_2 = \max(P_2, r_2 + r_1)$$

: Considering
root
with
no cut
to
smaller
cut

: $n=3$

$$r_3 = \max(P_3, r_1+r_2, r_2+r_1)$$

\therefore Brute Force
(All combination)

$$\textcircled{A} \quad r_n = \max_{1 \leq i \leq n} (P_i + r_{n-i}) \quad : P_i + r_{n-i}$$

, $P_{n-1} + r_{n-2}$

\textcircled{B} Pseudo code:

$R_n(P, n)$
if $(n=0)$
return 0;

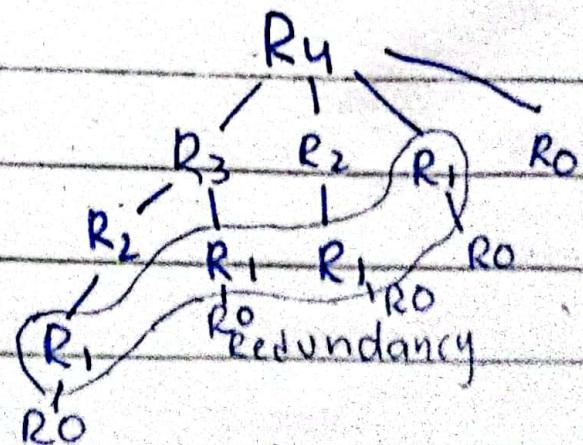
$$q_V = -\infty$$

for $i=1$ to n

$$q_V = \max(q_V, P_i + R_{n-i}) \quad \begin{matrix} \text{Rod-cut} \\ (P_{n-i}) \end{matrix}$$

return q_V

$R_n \left\{ \begin{matrix} R_3 \\ R_2 \\ R_1 \end{matrix} \right.$



$$\rightarrow T(n) = \begin{cases} 1 & T(n) = 1 + \sum_{j=0}^{n-1} T(j) \end{cases}$$

$$T(0) = 1$$

$$T(1) = 2$$

$$T(2) = 4$$

$$T(3) = 8$$

$$T(4) = 16$$

$$T(n) = (2^n) \text{ (complexity)}$$

$$: s_n = a \left(\frac{1-r}{1-r} \right)^n$$

① Two - Approaches

(i) Top- Down

(Memorization) (which is needed to be computed)

(ii) Bottom- Up

(starts from 1) (all are covered in it)

→ We need to store results and need data structure.

→ Space is increasing but Time is decreasing.

$$\rightarrow P = [1 \dots n]$$

$$P_i \rightarrow r = [0 \dots n]$$

r_i

: Top Down : $R_n((P, n), r)$

if $n=0$

$q_1=0$

if $r_n > 0$ else
return $x_n;$

$q_1 = \infty$
for $i=1$ to n

$$q_i = \max(q_i, P_i + R_{n-i})$$

$r_i = q_i;$

: $\Theta(n^2)$

Nesting effect

: Bottom-up:

→ More simpler starts from 0

$T(0)$
 $T(1)$
 $T(2)$ —

: Matrix chain
IS-2 (check for 2 Multiplications)

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① Matrix-Chain Multiplication =

→ Matrix (2-D structure)

$$\begin{bmatrix} M_1 \end{bmatrix}_{(r_1 \times c_1)} \times \begin{bmatrix} M_2 \end{bmatrix}_{(r_2 \times c_2)} = \begin{bmatrix} \end{bmatrix}_{(r_1 \times c_2)}$$

∴ ~~====~~ (Three loops for multiplication)

$$\Theta(n^3)$$

: $r_1 \times c_1 \times c_2$ (cost formula)

→ Associativity:

$$(A_1 A_2) A_3 = A_1 (A_2 A_3)$$

$$\begin{array}{ccc} A_1 & A_2 & A_3 \\ (100 \times 100) & (100 \times 5) & (5 \times 50) \\ r_1 & c_1 & r_2 & c_2 & r_3 & c_3 \end{array}$$

$$\begin{aligned} \rightarrow (A_1 A_2) A_3 &= A_1 (A_2 A_3) \\ &= 5000 \\ &\quad \begin{array}{l} 10 \times 5 \quad 5 \times 50 \\ \hline = 2500 \end{array} \quad \begin{array}{l} 10 \times 100 \quad 100 \times 50 \\ \hline = 50000 \end{array} \\ &5000 + 2500 = 7500 \quad \quad \quad = 75000 \end{aligned}$$

→ Multiplication sequence is judged by parenthesis.

⇒ For three matrices:

$$(i) (A_1 (A_2 A_3)) \quad (ii) ((A_1 A_2) A_3)$$

→ For Four Matrices:

A_1, A_2, A_3, A_4

(i) $((A_1 A_2) A_3) A_4 \quad : \text{Total cost } 5$

(ii) $(A_1 (A_2 A_3)) A_4$

(iii) $(A_1 (A_2 (A_3 A_4)))$

(iv) $((A_1 A_3) (A_2 A_4)) \quad : \text{Minimum cost}$

(v) $((A_1 A_4) (A_3 A_2)).$

→ (It is optimization problem
best for dynamic programming)

→ Minimization.

* After all multiplication, last step also contains two matrix multiplication:

$P_1 \quad P_2$
 $\overline{\text{(Sub Matrix Result)}}$ (Last Matrix)
(This sequence can be changed)

→ Possibilities

$$P(n) = \begin{cases} 1 & n=1 \\ \sum_{K=1}^{n-1} P(K) P(n-K) & n \geq 2 \end{cases}$$

$$\sum_{K=1}^{2^n}$$

* Guess:

$O(2^n)$

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

$$T(n) \leq C \cdot 2^n$$

$D(K) (P(n-K))$

$$C \cdot 2^k (C \cdot 2^{n-k})$$

$$C \cdot \left(2^k \cdot \frac{2^n}{2^k} \right)$$

$$C \cdot 2^n$$

$$C \cdot 2^n \leq C \cdot 2^n$$

(Proved)

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① Chain-Matrix Multiplication:

→ Matrix property of associativity

$$A_1(A_2 A_3) = (A_1 A_2) A_3$$

$$\begin{bmatrix} \square \end{bmatrix} \times \begin{bmatrix} \square \\ \square \end{bmatrix}$$

$p \times q \times r$

$$= \begin{bmatrix} \square \\ \square \end{bmatrix} p \times r$$

$(p \times q)$

$(q \times r)$

→ Way to parenthesize n Matrix.

$$A_1, A_2, A_3, \dots, A_n$$
$$\therefore (A_1)(A_2 A_3 \dots A_n)$$

$$(A_1 A_2)(A_3 \dots A_n)$$

$$(A_1 A_2 A_3) (\dots A_n)$$

$$(A_1 A_2 A_3 \dots) (A_n)$$

Not Proper Approach

Sub-problems
are of
overlapping
nature

$$\textcircled{O} \quad P(n) = \begin{cases} 1 & n=1 \\ \sum_{k=1}^{n-1} P(k)P(n-k) & n \geq 2 \end{cases}$$

$$\rightarrow \text{Catalan Number} = C(n) = \Omega\left(\frac{4^n}{n^{\frac{3}{2}}}\right)$$

$$P(n) = C(n-1)$$

→ Optimal substructure / In dynamic programming, there will be overlapping while in divide and conquer there will be distinct problems).

$$\textcircled{O} \quad A_{i..j} \text{ (products of all Matrix from } i \text{ till } j)$$
$$A_1 A_2 \dots (A_i \dots A_j) \dots A_n$$

$$\rightarrow A_i \text{ Dimension} = P_0 P_1$$

$$A_2 \dots = P_1 P_2 \quad 1 \leq i \leq j \leq n$$

$$A_{i..j} = P_{i-1} \cdot P_j$$

\rightarrow Substructure \rightarrow Optimal Substructure
 Build Recursion Solution

$A_i \dots A_j$
 ↑
 Optimal split
 (K)

: $A_{i..j}$

(Thinking that
 it is optimal,
 its substructure
 will also be
 optimal)

$$A_{i..j} = (A_i, A_{i+1}, \dots, A_k) (A_{k+1}, A_{k+2}, \dots, A_j)$$

$$i \leq k \leq j$$

$$\rightarrow A_{i..j} = m[i, j]$$

(Scalar Multiplication) (Optimal number of computations to compute scalar multiplication)

$$= \underbrace{(A_i, A_{i+1}, \dots, A_k)}_{m[i, K]} \underbrace{(A_{k+1}, A_{k+2}, \dots, A_j)}_{m[K+1, j]}$$

$$\downarrow \\ m[i, K]$$

$$\downarrow \\ m[K+1, j]$$

$A_{i..K}$
 $(P_{i-1} \times P_K)$

$A_{K+1..j}$
 $(P_K \times P_j)$

Dimension $\hookrightarrow P_{i-1} \times P_K \times P_j$

$$m[i, j] = \begin{cases} 0 & i=j \\ \min_{i \leq k \leq j} \{ m[i, K] + m[K+1, j] + (P_{i-1} \times P_K \times P_j) \} & i \neq j \end{cases}$$

\rightarrow Bottom-up approach for optimization

A_1	A_2	A_3	A_4	A_5	A_6
P_0	P_1	$P_1 P_2$	$P_2 P_3$	$P_3 P_4$	$P_4 P_5 P_6$

$$\rightarrow m[1,2] = m[1,1] + m[2,2] + P$$

$$\rightarrow m[2,5] = 2m[2,2] + m[3,5]$$

$$A_{2..5} \quad \quad \quad 3m[2,3] + m[4,5]$$

$$4m[2,4] + m[5,5]$$

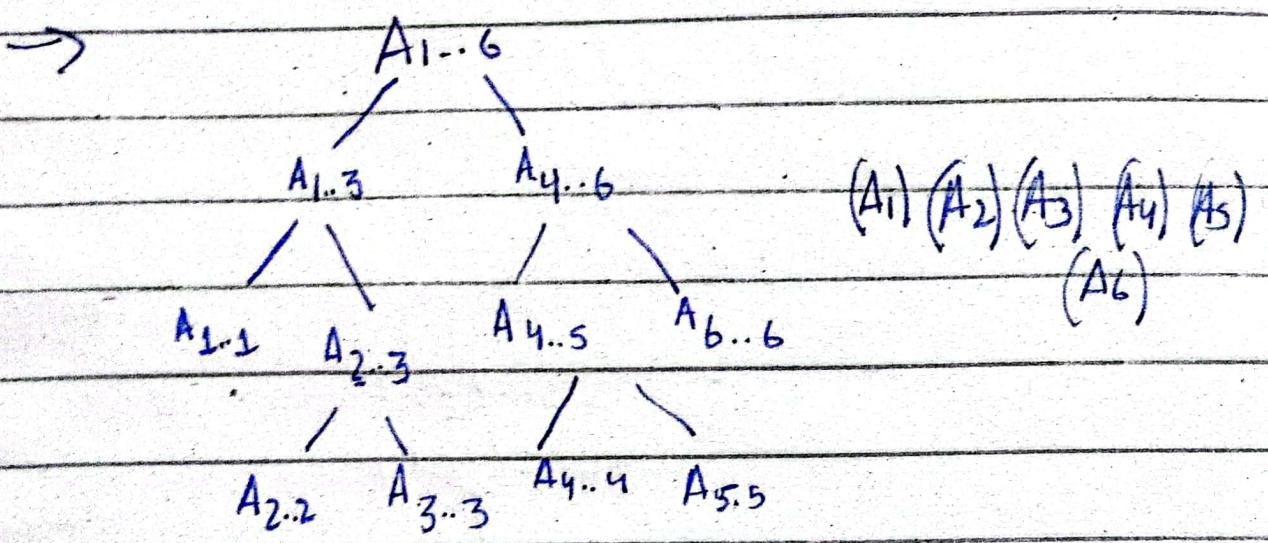
	1	2	3	4	5	6
1	0	15750	7875	9375	11,875	<u>15125</u>
2	0	2625	4735	7125	10500	
3		0	750	2500	5375	
4			0	1000	3500	
5				0	5000	
6					0	

2/1/25

$$\rightarrow A_1 \times A_2 \times A_3 \times A_4 \times A_5 \times A_6 \times \dots \times A_n$$

	1	2	3	4	5	6
1	1	1	3	3	3	3
2		2	3	3	3	3
3			3	3	3	
4				4	5	
5						5
6						

6x6



① Greedy Algorithms

→ Solves problem with more speed than dynamic programming

→ This approaches us to pick the choice of min and max by ourselves.

→ Dynamic programming gives us global optimal value while in Greedy Algorithm we get local optimal which belongs to global.

→ It's not necessary that it can be applied on all problems but can be checked.

→ Activity Selection Problem:

: List of activities

$(a_1, a_2, a_3, \dots, a_n)$ a_i : activity

s_1, s_2, s_3

s_n

s_i

s : Start

f_1, f_2, f_3

f_n

f_i

$f \equiv \text{Finish}$

① Maximum set of compatible activities

(Independent
Not overlapping
Distinct)

② $[s_i, f_i]$

$a_j [s_j, f_j]$

$s_i > f_j$

$s_j > f_i$

i	1	2	3	4	5	6	7	8	9	10	11
s_i	1	3	0	5	3	5	6	8	8	2	12
f_i	4	5	6	7	9	9	10	11	12	14	16

$\{a_1, a_4\}, \{a_1, a_4, a_8, a_{11}\}, \{a_2, a_4, a_8, a_{11}\}$

Compatibility activities

s_{1n} $a_1, a_2, a_3, \dots, a_n$

s_{ij}

a_{ij}

(solution of s_{ij}) (Maximum set
of compatibility)

(a_k) (optimal activity)

s_{ik}

s_{kj}

a_{ik}

a_{kj}

→ Chapter #16 (16.1 (Activity Selection Problem),
Elements of Greedy) * Quiz (16.1)

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→ In Dynamic Programming, there is
option of backtracking while in
Greedy no backtracking.

→ Sometimes Greedy don't work
to give optimal value (Heuristic)

→ If we wanted to say Greedy
Algorithm is Greedy and working
properly) (we get that local
optimal value belongs to global or
not (it is Greedy or not)).

① Local optimal obtaining from
Greedy strategy at that stage what
is obtained

① For obtaining local optimal, we use Greedy strategy, less (earliest finish time) activity time will give us more time to do other activities.

→ It will become Greedy algorithm when optimal value from Greedy strategy or approach will be part of global part.

: Global also will contain local optimal value to be Greedy.

→ That decision will be part of Global solution, then it will be Greedy.

→ Graphs:

(Data structure contain vertices, edges, arcs)

(Directed or Undirected edge)

② Minimum Spanning Tree (MST):

→ Graph can be represented:

(i) Adjacency Matrix

(ii) Adjacency List

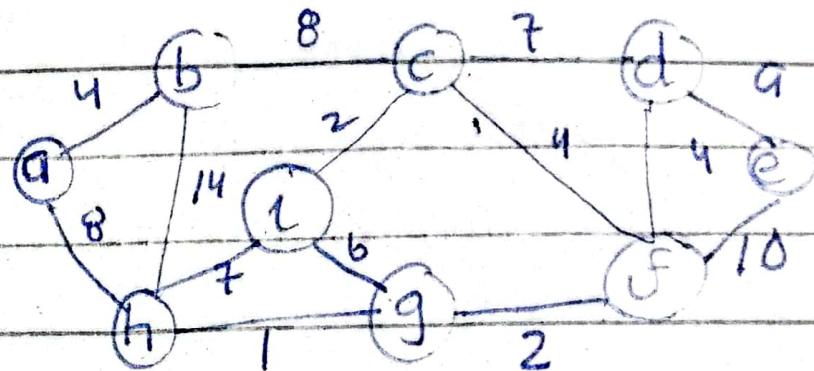
→ Graph is a set of Vertices and Edge : $[G : (V, E)]$

 : MST
(5 Real Life Application (Description))

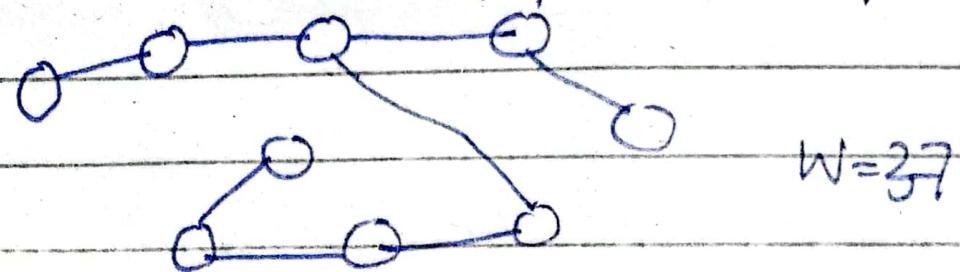
: Tree: Only one way to other node
(No cycle)

: Graph: Multiple paths.

: Trees: No cycle
Graph: May or may not cycle.



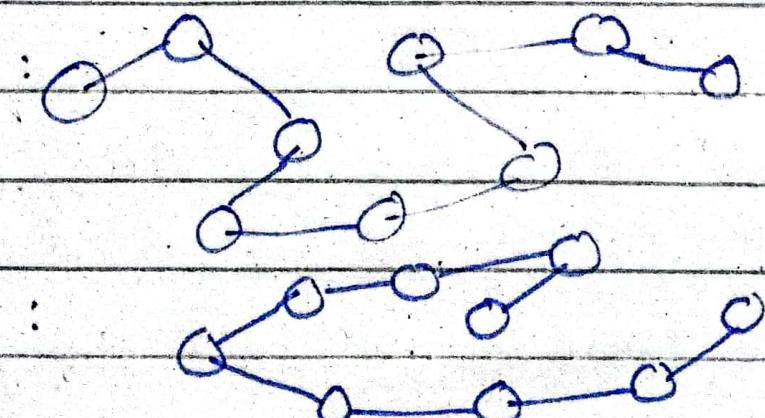
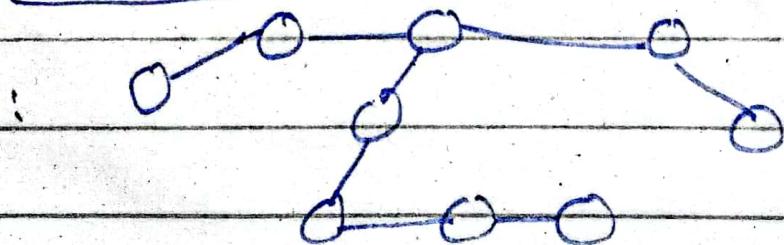
→ Find tree from graph which includes all nodes (Spanning Tree)



→ Minimum ST (whose edges are minimum and gives optimal value)

: Weight is overall minimized

→ Other ST:

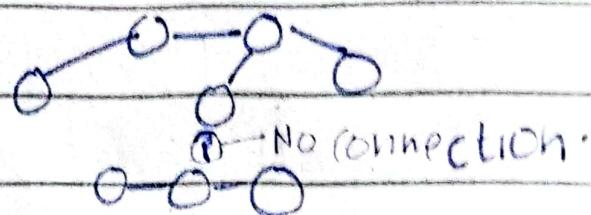


→ Free-Tree (where root node is not designated)

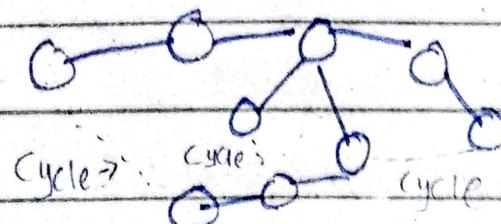
: N: Node

Edges = $N - 1$

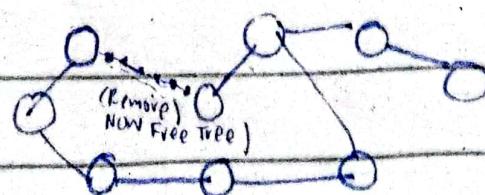
→ Forest (If Multiple trees are there:



→ If we add one edge more in generalization, then it will be cycle.



→ If we remove one edge from cycle, it will be tree.



→ E(Set of Edges), A(Subset (All possible edges of a Tree) of Edges) (Part of MST)

: There can be variable many MST.

Ch#23 (MST)
(Complete Read it)

→ subset of edges, which are part of MST (Viable set)

: Viable set of edges are edges that cannot make cycle.

→ More than one possible MST can occur because of similar weights.

→ Edge $(U,V) \rightarrow$ Safe Edge if after putting this edge in A , it will remain viable set.

→ Steps:

(i) Take Empty set.

(ii) Condition while MST terminates.

(iii) Selection of (U,V) edge and check its viability.

(iv) Repeat.

④ Example:

Graph of start:

$$E = \{(a,b), (b,c)\}$$

$$A = \{(a,b), (b,c), (c,d), (d,e), \\ (\text{Fig})\}$$

① Application of MST:

- (i) Network Design
- (ii) Road and Railway Construction
- (iii) Electrical Grid Design
- (iv) Cluster Analysis in Data Mining.
- (v) Water Supply Systems.

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E - Set of edges : Edges talk

A - Subset Minimum Entry of Edges
(Part of MST)

→ Verify Safe Edge and add it to the 'A'.

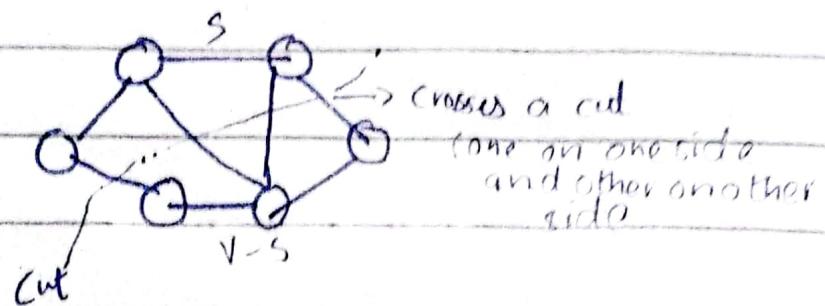
→ Minimum edge would be picked and repeat process and the global solution will be optimized.

→ **Theorems:**

: Now vertices talk

② cut: Distributing the vertices into two disjoint sets is called cut.

- If one vertex is S , then other will be $V-S$
 $(S, V-S)$



- It respects the A , if because of cut, all edges of A are on one side.

If one edge is one side and on other side also,
so it do not respect A .

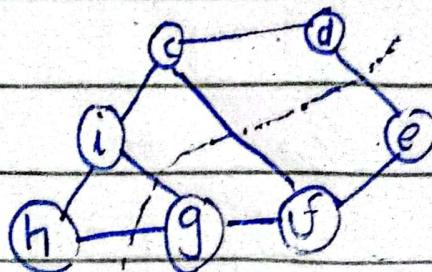
- Safe edges will be those edges which are crossing the cut.

- We pick cut respects A , then find safe edge and that will be which are on cut.

- Light edge: The cut which respects A , weight is less than this safe edge will be light edge.

① Proof by Contradiction:

→ suppose T is tree
and w is minimum weight
and this is not on cut side,
so we will prove it by
contradiction (Prove it wrong)



(i,j,g), (h,i,g)

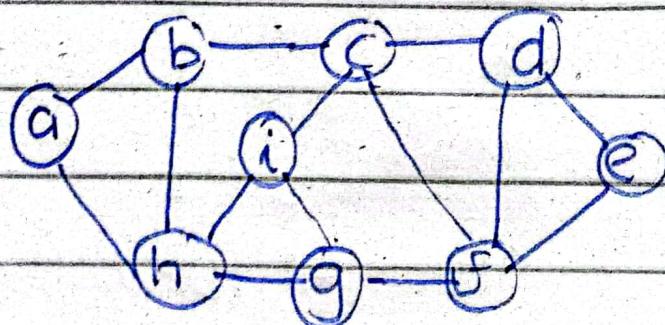
→ If there is cycle and we cut then there would be even edges on cut side below

→ If edge is added, the weight of added ^{edge} is less than removed edge. Then, it will not be MST before.

$$w(e_1) < w(e_2)$$

① Kruskal's Algorithm: defines disjoint set data structure, in which we:

- (i) Create set (`Create_Set()`) : less than $O(n)$
 - (ii) Find set (`Find_Set()`)
 - (iii) Union set (`Union_Set()`)
- {a,b,c} {d,e} {f,g,h,i}



→ Steps:

- 1) Create Disjoint Against Vertices
- 2) Sort each Edges on basis of weight
(In Ascending Order)

→ We should have viable set which is empty in start:

$$A = \emptyset$$

→ If we apply on edge vertices `find_Set()`, it would be selected

: Kruskal (make forest merge in last)
: Prim (In start make tree)

if it would be part of distinct trees (so no cycle).

→ After selecting edge, we would join 'h' or 'g', so we call Union_Set() function.

→ Then we add it to viable set:

$$A = \{ (h,g) \dots \}$$

(Now we repeat this step)
for (c,i)

$$\rightarrow A = \{ (h,g), (c,i) \}$$

: Now we add {f,g,h}

$$\rightarrow A = \{ (h,g)(i,k), (g,f), (a,b)(c,f), (c,d) \}$$

: Overall Running Time will be $O(E \log E)$.

→ Prims Algorithm Read by yourself and included in exam.

→ MinHeap and Priority Queue will be part of it.