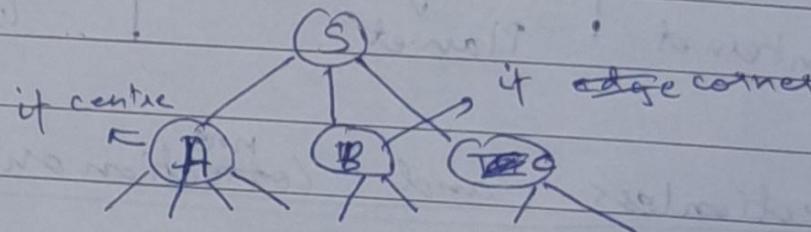


8 - Puzzle :	3	1	2
	5	4	
	6	7	8

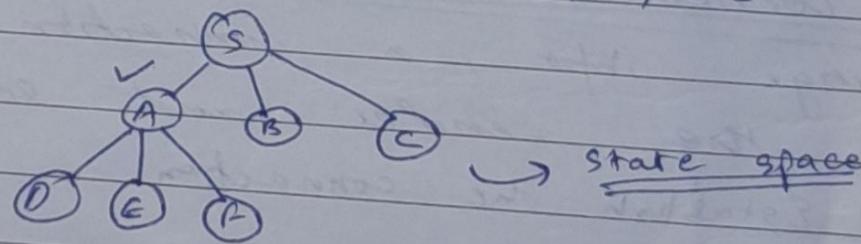
1	2	3
8		
7	6	5

(S)

Goal



$$\text{OPEN SET} = \{S\} \rightarrow \{A, B, C\} \rightarrow \{B, C, D, E, F\}$$

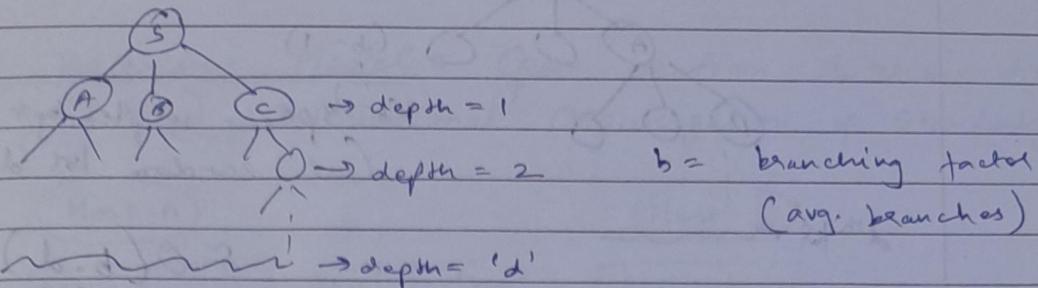


- 1) $\text{OPEN} \leftarrow \{S\}$
- 2) WHILE OPEN NOT EMPTY:
- 3) { Pick any node n from OPEN :
 if ($n == \text{GOAL}$) return TRUE
 else
 $\text{OPEN} \leftarrow \text{OPEN} \cup \{n\text{'s neighbours}\} - \text{closed}$

3)
 a) RETURN FAILURE

DFS

BFS

time complexity $\sim O(|\text{closed set}|)$ 

$$\begin{aligned}
 \underline{\text{DFS time}} &= \frac{1}{2} \left[\underbrace{\text{Goal at first node at depth } d_1}_{+} \underbrace{\text{Goal at last node at depth } d_l} \right] \\
 &= \frac{1}{2} \left[d + 1 + b + b^2 + \dots + b^{d-1} \right] \\
 &= \frac{1}{2} \left[d + \frac{b^{d+1}-1}{b-1} \right] \approx \frac{b^d}{2} \quad (\text{exponential})
 \end{aligned}$$

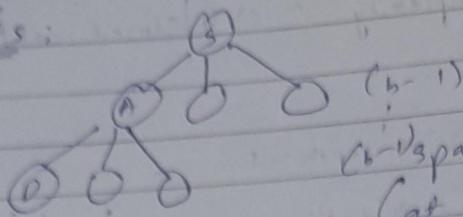
$$\begin{aligned}
 \underline{\text{BFS time}} &= \frac{1}{2} \left[\underbrace{\text{all nodes till depth } (d-1)}_{+} \underbrace{\text{Goal at 1st node} + \text{Goal at last node}} \right] \\
 &= \frac{1}{2} \left[\frac{b^d - 1}{b-1} + \frac{b^{d+1}-1}{b-1} \right] \\
 &= \frac{b^d}{2} \left(\frac{1+b}{b} \right) \\
 &= \frac{b^d}{2} \left(\frac{1+b}{b} \right) \quad (\text{Exponential})
 \end{aligned}$$

\Rightarrow DFS is better than BFS

BFS	$=$	$\frac{1+b}{b}$
DFS	$=$	$\frac{b^d}{2}$

Space Complexity \rightarrow examine by open set.

DFS:



$$(b-1) \text{ space complexity} = (d-1)b^{(b-1)}$$

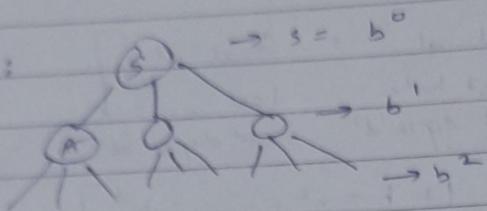
(at random for d)

difference

$$\approx O(b \cdot d)$$

(Linear)

BFS:



$$\text{at depth } d \rightarrow b^d$$

(Exponential)

∴ DFS is better than BFS in space complexity.

* Quality of soln : BFS \geq DFS
BFS gives optimal soln.

* Completeness :

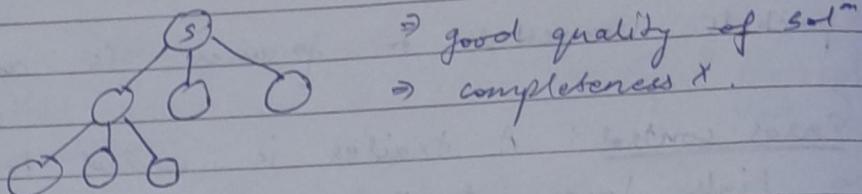
\Rightarrow both will be able to reach goal state. \therefore both are complete.

X-X

AI

* DB-DFS: Depth bound DFS

⇒ Set up a bound on depth (like $d = 3, 4, \dots$)
 DFS will only go till depth.



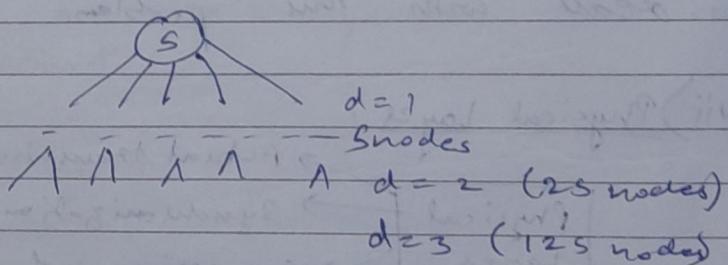
* DFID: Depth First iterative Deepening.

⇒ here ^{depth} bound ~~is exact~~ as we do not get the solⁿ

⇒ good quality of solⁿ
 ⇒ completeness ✓

⇒ Time and space complexity of DFS.

⇒ The tree gets deleted as we increase d.



⇒ To ~~recheck~~ check at $d = 3$ we need to check all nodes at $d = 2$

∴ ratio = $\frac{1+5+25}{125} = \frac{31}{125}$ (not that significant)
 work

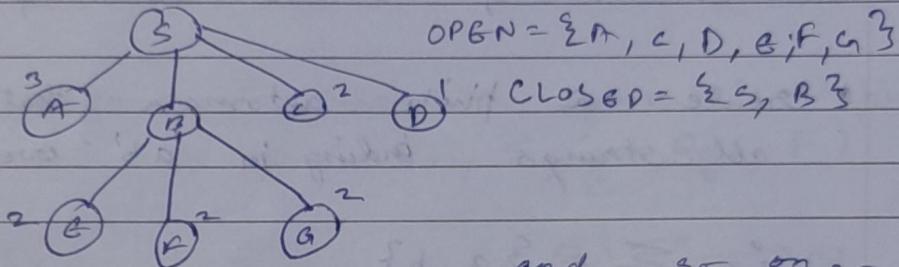
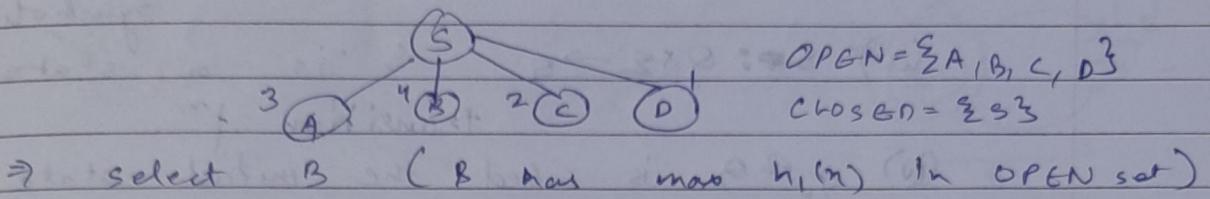
∴ we can delete and regenerate the whole tree again.

BFS, DPS, DB-DFS, DFID are blind algs as we don't know how close we are to the goal.

* Heuristic Algorithms : (we use heuristic f^m's to determine the node)

* Best First Search:

$$h_1(n) = \text{no. of visited nodes}$$



\Rightarrow Best way to maintain open set is in max heap. (node with highest $h_1(n)$ will be at root)

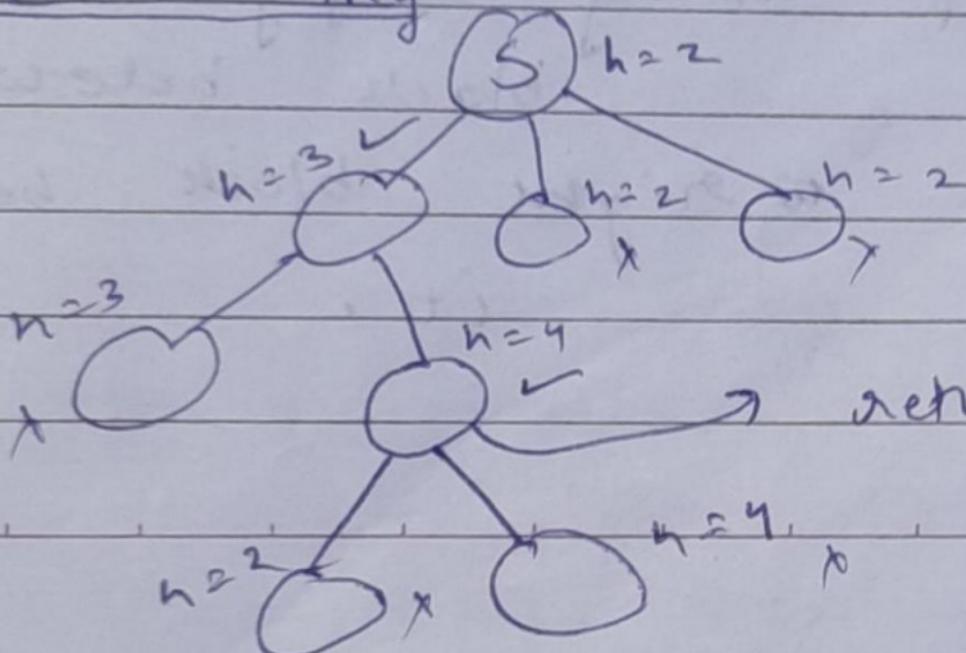
\Rightarrow time and space complexity depends on heuristic f^m.

\Rightarrow the heuristic algo we used is complete.

X X

AI

* Hill Climbing: → for all puzzles.

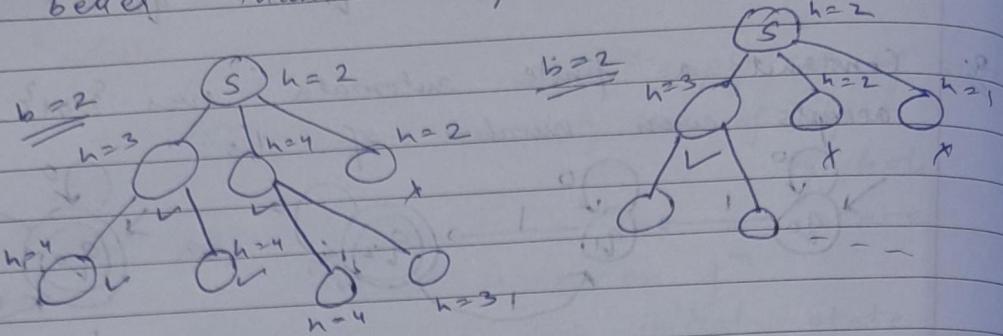


⇒ move strictly in the direction of inc/dec. $h(n)$.

→ return this ⇒ Not complete
⇒ Space complexity = const.
time comp = $O(n)$ ↗ best feature.

* BEAM SEARCH :

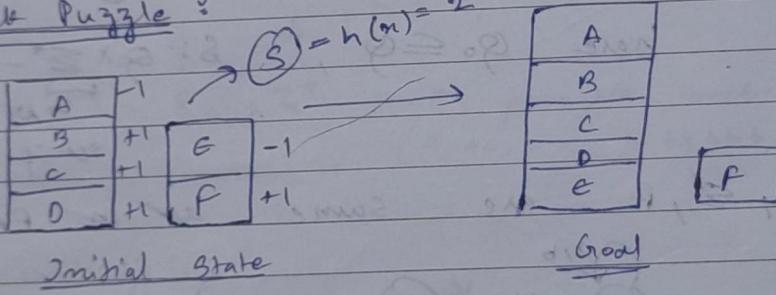
→ select ' b ' best nodes in each level (depth). If $b=1$ then it becomes Hill climbing.
 ⇒ All the nodes in ' b ' should be better than the parent.



time compex = linear, space com = const.

⇒ still not complete.

* Block Puzzle :



Can put blocks on table or on top of another blocks

heuristic: -1 if wrong config (correct block below it)

+1 if right block below it.

not applicable
all puz

* SAT :

$$(a \vee b) \wedge (c' \vee d) \wedge (d \vee e') : \text{CNF}$$

\Rightarrow 3-clauses \Rightarrow 2 literals inside each clause
 \therefore 2-SAT

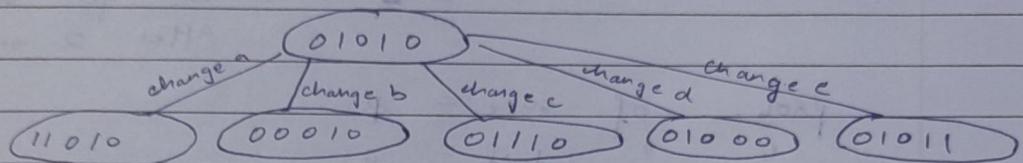
\Rightarrow total 5 literals.

\rightarrow K-SAT
 for $K \geq 3$: NP
 else : Polynomial time (2-SAT*)

3SAT: e.g. $(a \vee b \vee c') \wedge (d \vee a' \vee b') \wedge (e \vee d \vee c')$

take random:

$$a = 0, b = 1, c = 0, d = 1, e = 0$$



take heuristic value = no. of ~~costly~~ clauses having 1.

* VARIABLE NEIGHBOURHOOD APPROXIMATION (VNA)

In 3SAT:

not applicable for puzzles e.g. 8 puzzle if you change 1 bit: 5 nodes = ${}^n C_1$
 all puzzles: 2 bits: 10 nodes = ${}^n C_2$
 n = no. of literals.

\Rightarrow increasing the no. of nodes \rightarrow our prob. of getting the right answer.

\Rightarrow VNA says apply at start apply such that ~~min~~ neighbourhood is minimum. After a few bits increase, the density (no. of bits).
 (first sparse and go ~~dense~~ dense) (by changing n^{th} f^m).

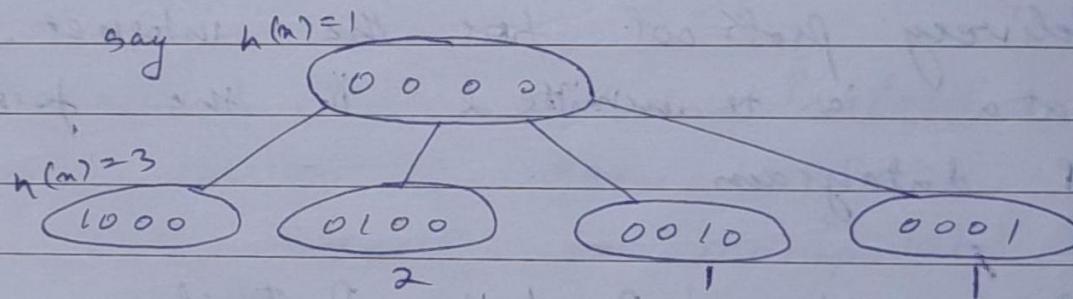
~~AI~~

* ITERATED NC : Using multiple start positions in NC
(Also not complete)

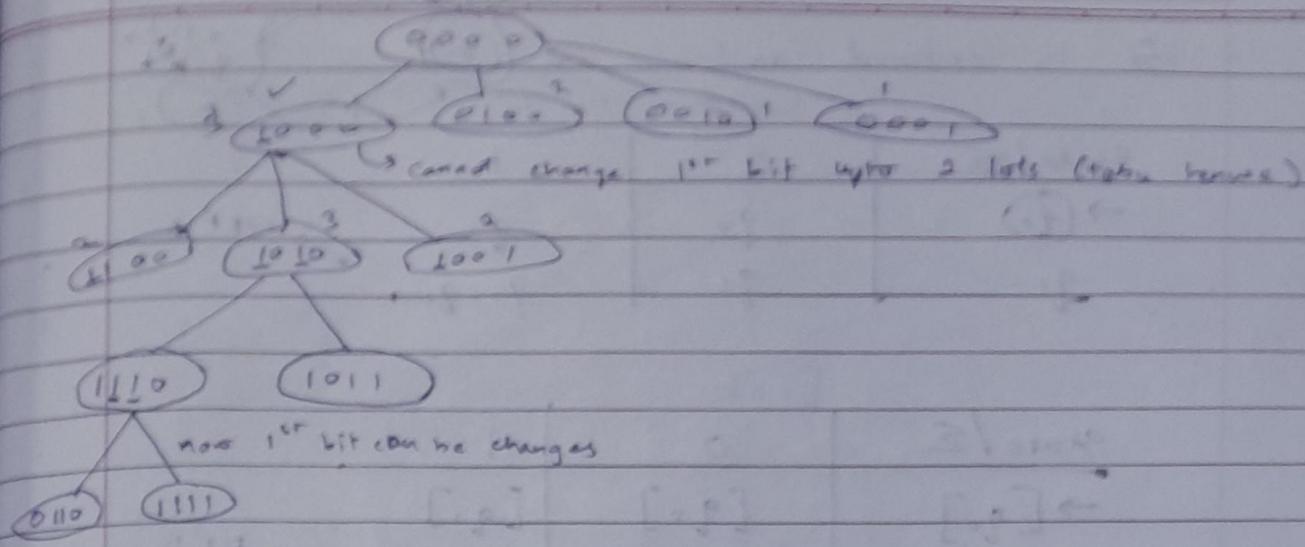
* TABU SEARCH : (concept of NC) (not best first)

4 literals : a, b, c, d

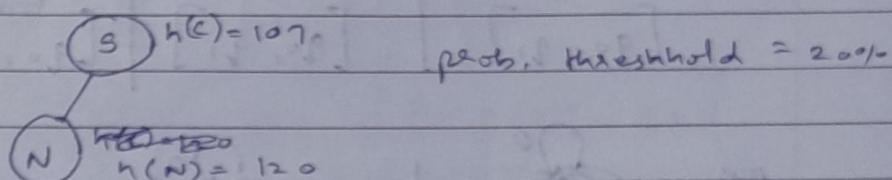
(a_vb) \wedge (c_vd') \wedge (a_vb') \wedge (a_vd')



tabu tenure = 2 (can change the 1st bits of change bit again for 2 bits)



* STOCHASTIC HILL CLIMBING: (only goes one state)



use Sigmoid $\frac{1}{1+e^{-\Delta E/T}}$ to calc. prob. fix T at start (say $T=10$)

\Rightarrow change T iteration by iteration. (start with high T)
Simulated Annealing \leftarrow go to low T

at Study Branch n Bound
 $x \rightarrow$
 TOC

* Conversion of NDFA \rightarrow DFA

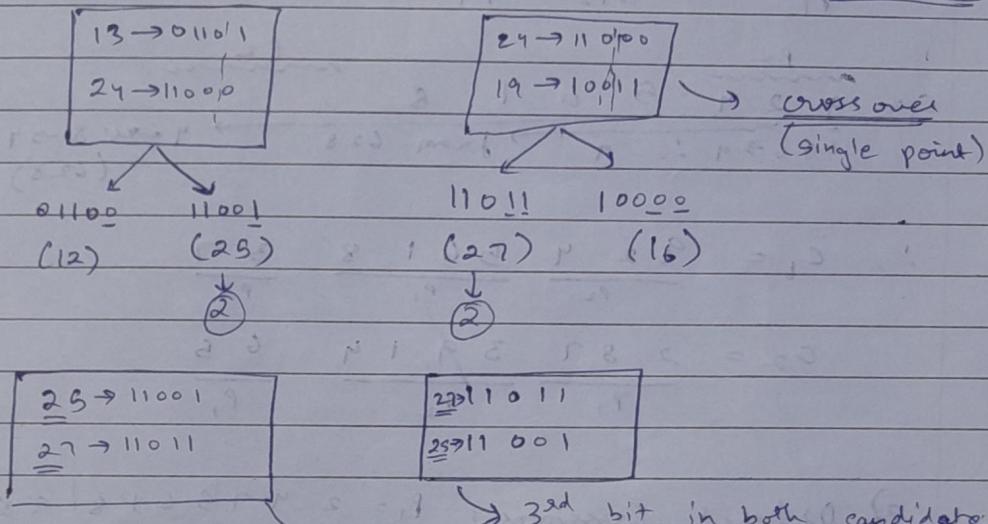
g. Construct a DFA equivalent to
 $M = (\{q_0, q_1\}, \{0, 1\}, \delta, q_0, \{q_0\})$ where

AI* Genetic Algorithm:

a Selection b cross-over c Mutation uses random sdⁿ.

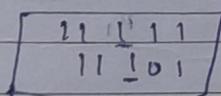
	<u>n</u>	<u>eval f^m(n²)</u>	<u>Prob (4 outcomes)</u>
eg.	13 01101	169	$4 \times \frac{169}{170} \approx 0.8 - ①$
	24 11000	576	$4 \times \frac{576}{170} \approx 1.67 - ②$
	8 01000	64	$4 \times \frac{64}{170} \approx 0 - x$
	19 10011	361	$4 \times \frac{361}{170} \approx 1.2 - ①$
		<u>170</u>	

↑ selection



→ 3rd bit in both candidate is zero. So we will never reach the answer. ∴ we use mutation

mutation: change one bit in order to get to the answer.

* TSP:

using Gen. Algo.

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Date _____

$$P_1 = 2 \ 4 \ 7 \ 5 \ 6 \ 1 \ 8 \ 9 \ 3 \quad ? \text{ path representation}$$

$$P_2 = 6 \ 2 \ 8 \ 3 \ 9 \ 1 \ 4 \ 5 \ 7$$

1) Partially Mapped Crossover:

$$P_1 = 2 \ 4 \ 7 \ | \ 5 \ 6 \ 1 \ 8 \ | \ 9 \ 3$$

$$P_2 = 6 \ 2 \ 8 \ | \ 3 \ 9 \ 1 \ 4 \ | \ 5 \ 7$$

$$P_1 \qquad \qquad P_1 \qquad P_2$$

$$C_1 = \begin{matrix} 5 & 6 & 1 & 8 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ 3 & 9 & 1 & 4 \end{matrix} \quad \text{mapping (if value already there then use the mapped value)}$$

$$C_2 = \begin{matrix} 9 & 2 & 4 & 5 & 6 & 1 & 8 \\ \overbrace{\quad \quad \quad \quad \quad \quad}^P_2 & \overbrace{\quad \quad \quad \quad \quad \quad}^P_1 & \overbrace{\quad \quad \quad \quad \quad \quad}^P_1 \end{matrix}$$

$$C_1 = \begin{matrix} 9 & 2 & 4 & 5 & 6 & 1 & 8 \\ \overbrace{\quad \quad \quad \quad \quad \quad}^P_2 & \overbrace{\quad \quad \quad \quad \quad \quad}^P_1 & \overbrace{\quad \quad \quad \quad \quad \quad}^P_1 \end{matrix}$$

$$\xrightarrow{6 \rightarrow 9 \dots} \text{from } 628 \rightarrow 9 \cancel{2} \cancel{8} \rightarrow 4$$

$$(628)$$

$$\therefore C_1 = \frac{9 \ 2 \ 4}{P_2} \ \frac{5 \ 6 \ 1 \ 8}{P_1} \ \frac{3 \ 7}{P_2}$$

$$C_2 = \frac{2 \ 8 \ 7}{P_1} \ \frac{3 \ 9 \ 1 \ 4}{P_2} \ \frac{6 \ 5}{P_1}$$

2) Ordered Crossover:

$$P_1 = 2 \ 4 \ 7 \ 5 \ 6 \ 1 \ 8 \ 9 \ 3$$

$$P_2 = 6 \ 2 \ 8 \ 3 \ 9 \ 1 \ 4 \ 5 \ 7$$

$$C_1 = \begin{matrix} 5 & 6 & 1 & 8 \\ \overbrace{\quad \quad \quad \quad}^{P_1} & \overbrace{\quad \quad \quad \quad}^{P_2} \end{matrix}$$

$$C_2 = \begin{matrix} 3 & 9 & 1 & 8 \\ \overbrace{\quad \quad \quad \quad}^{P_2} & \overbrace{\quad \quad \quad \quad}^{P_1} \end{matrix}$$

* Ordinal Representation

→ study on your own.

$$INDBX = 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9$$

$$P_1 = 2 \ 3 \ 5 \ 3 \ | \ 3 \ 1 \ 2 \ 2 \ 1$$

$$P_2 = 6 \ 2 \ 6 \ 2 \ | \ 5 \ 1 \ 1 \ 1 \ 1$$

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Date

$$\begin{array}{l}
 c_1 = \underbrace{2 \ 3 \ 5 \ 3}_{P_1} \ . \underbrace{5 \ 1 \ 1 \ 1 \ 1}_{P_2} \\
 c_2 = \underbrace{6 \ 2 \ 6 \ 2}_{P_2} \quad \underbrace{3 \ 1 \ 2 \ 2 \ 1}_{P_1}
 \end{array}
 \quad \left. \right\} \text{using single pt. crossover}$$

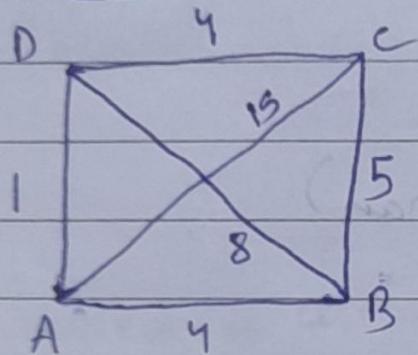
$$c_1 = 2 \ 4 \ 7 \ 5 \ 9 \ 1 \ 3 \ 6 \ 8 \quad \left. \right\} \text{path dep.}$$

$\times \rightarrow$
TOC

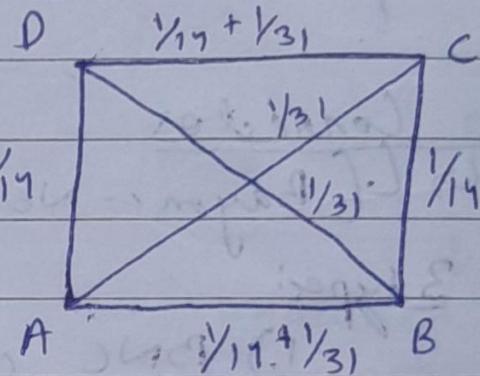
AI

* Ant Colony Optimization

cost matrix



Pheromone Matrix



Path 1 \rightarrow ABCDA = 14 \Rightarrow To update the list of

Path 2 \rightarrow ACDBA = 31 pheromone in pheromone

matrix, we use the path sum reciprocal

Now to find prob. of another ant going from A based on cost or pheromone lvl

$$A \rightarrow D = \frac{0.07 \times \text{cost}(A \rightarrow D)}{\text{sum of all cost from } A} = \frac{0.07 \times 1}{(0.07 \times 1 + 0.03 \times \gamma_S + 0.1 \times \gamma_D)}$$

$$A \rightarrow B = \frac{0.3 \times \gamma_S}{\Sigma}$$

$$A \rightarrow C = \frac{0.1 \times \gamma_D}{\Sigma}$$

Vaporization effect: let $\rho = 0.6$

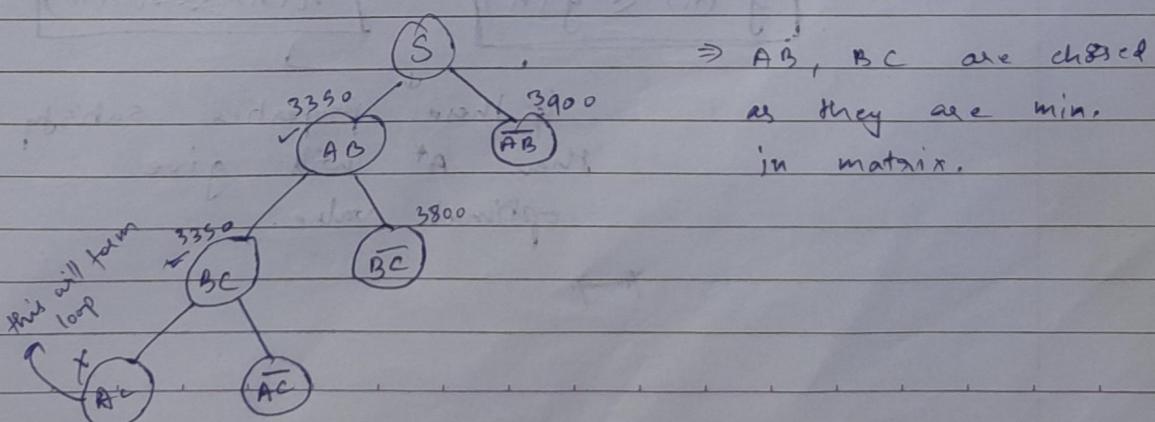
$$\therefore (1 - \rho) \times \text{initial lvl} = (1 - 0.6) \times 1 = 0.4$$

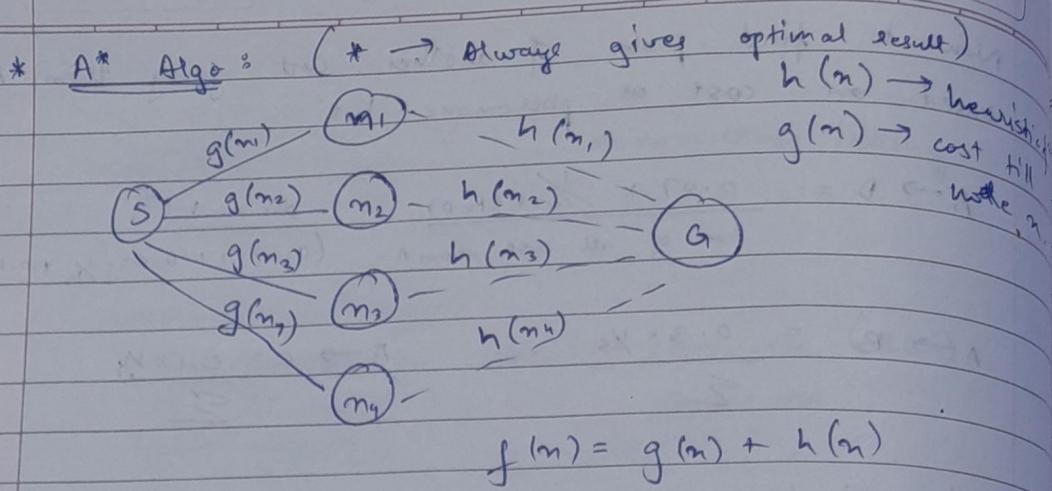
of pheromone

* Branch n Bound \Leftrightarrow (TSP) $\xrightarrow{\text{ant col}}$ $\xrightarrow{\text{genetic}}$

	A	B	C	D	E		\overline{AB} edge
A	0	(300)	(600)	900	1000	\rightarrow 900	$600 + 900$
B	(300)	0	(500)	800	1200	\rightarrow 800	$500 + 800$
C	(600)	(500)	0	1100	1400	\rightarrow 1100	$1100 + 1400$
D	(900)	(800)	1100	0	1500	\rightarrow 1700	$1100 + 1500$
E	(1000)	(1200)	1400	1500	0	\rightarrow 2200	$1400 + 1500$
						<u>6700</u>	<u>$7800 \rightarrow 7800/2$</u> <u>= 3900</u>

$$\therefore \text{Estimate cost / bound} = 6700 = 3350$$





8-puzzle:

1	7	4		1	2	3
2		5	→	8		4
3	8	6	(start)	7	6	5

$h(n) =$ no. of correct

$g(n) =$ no. of tiles travelled.

Use Branch & Bound.

$$f(n) = g(n) + h(n) \Rightarrow \text{Value we evaluate}$$

$$f^*(n) = g^*(n) + h^*(n) \Rightarrow \text{actual value / optimal}$$

$$\boxed{g^*(n) \leq g(n)}$$

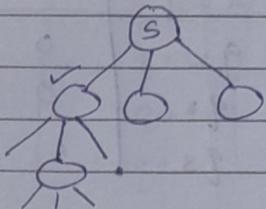
$$\boxed{h(n) \leq h^*(n)}$$

if these properties satisfy
then A* will give
optimal value.



AI

- * IDA* ; (Iterative Deepening A*) \rightarrow learn eg. from YI.

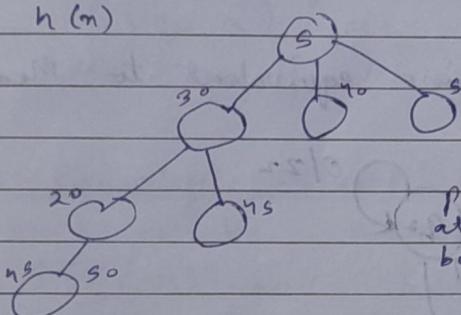


$$f(n) = g(n) + h(n)$$

\Rightarrow Instead of lvs, take generate till $f(n)$ increases more than a certain bound, or you get the answer.
(Almost same as D*ID)

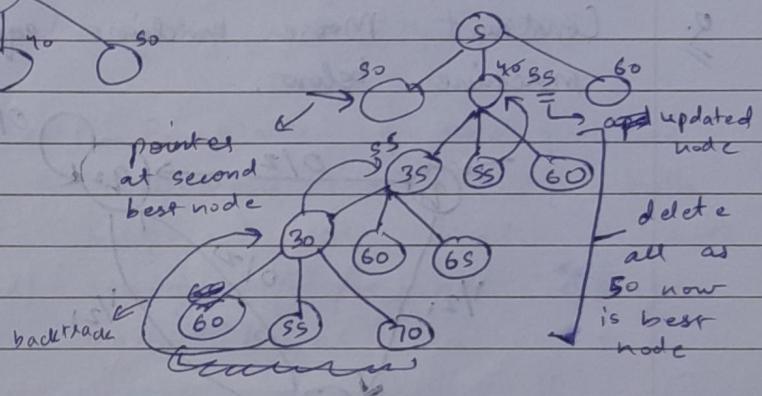
- * Best First Search:

$$h(n)$$



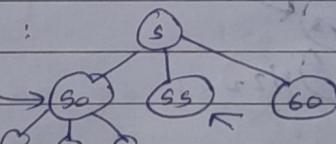
- * Recursive Best First Search

$$f(n) = g(n) + h(n)$$



\therefore new tree :

Expand this



\Rightarrow Recursive BFS saves space

\Rightarrow Thrashing

\Rightarrow Values can be updated in Rec. BFS but not in BFS.

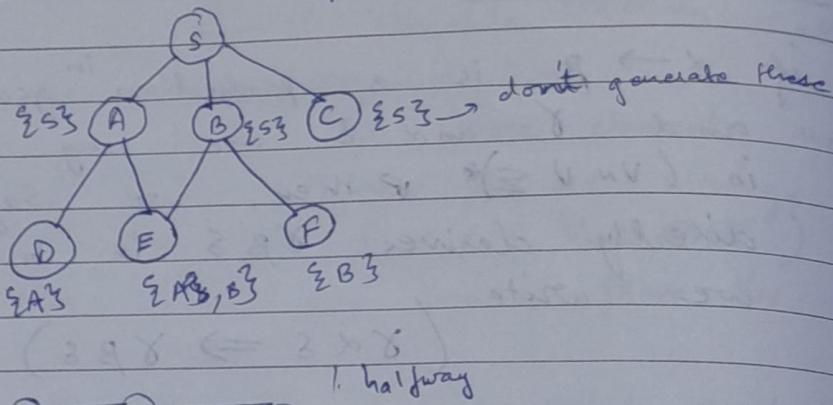
* *

X X
AI

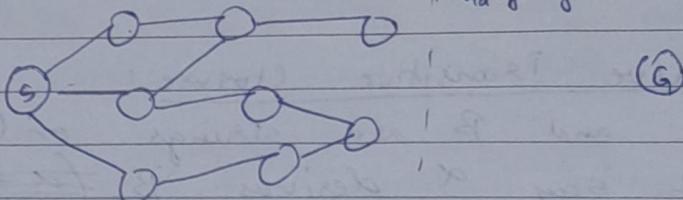
* PRUNING THE CLOSED LIST:

- ⇒ Stop looking back (not exploring the already explored nodes)
- ⇒ Path construction: path from starting to goal node.

1) DCFS : (Divide n Conquer Frontier Search)



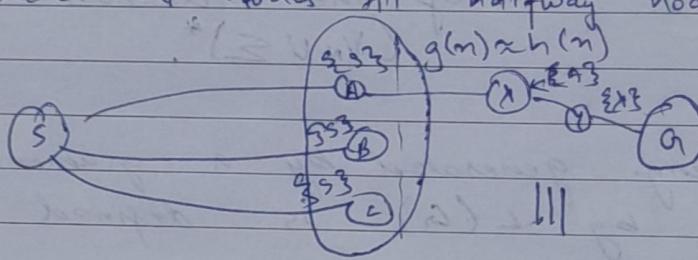
1. halfway



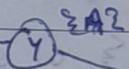
$$\text{At halfway } f(n) = g(n) + h(n)$$

$$g(n) \approx h(n)$$

Delete all nodes till halfway nod



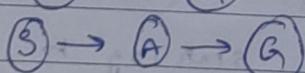
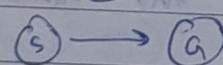
III



delete X

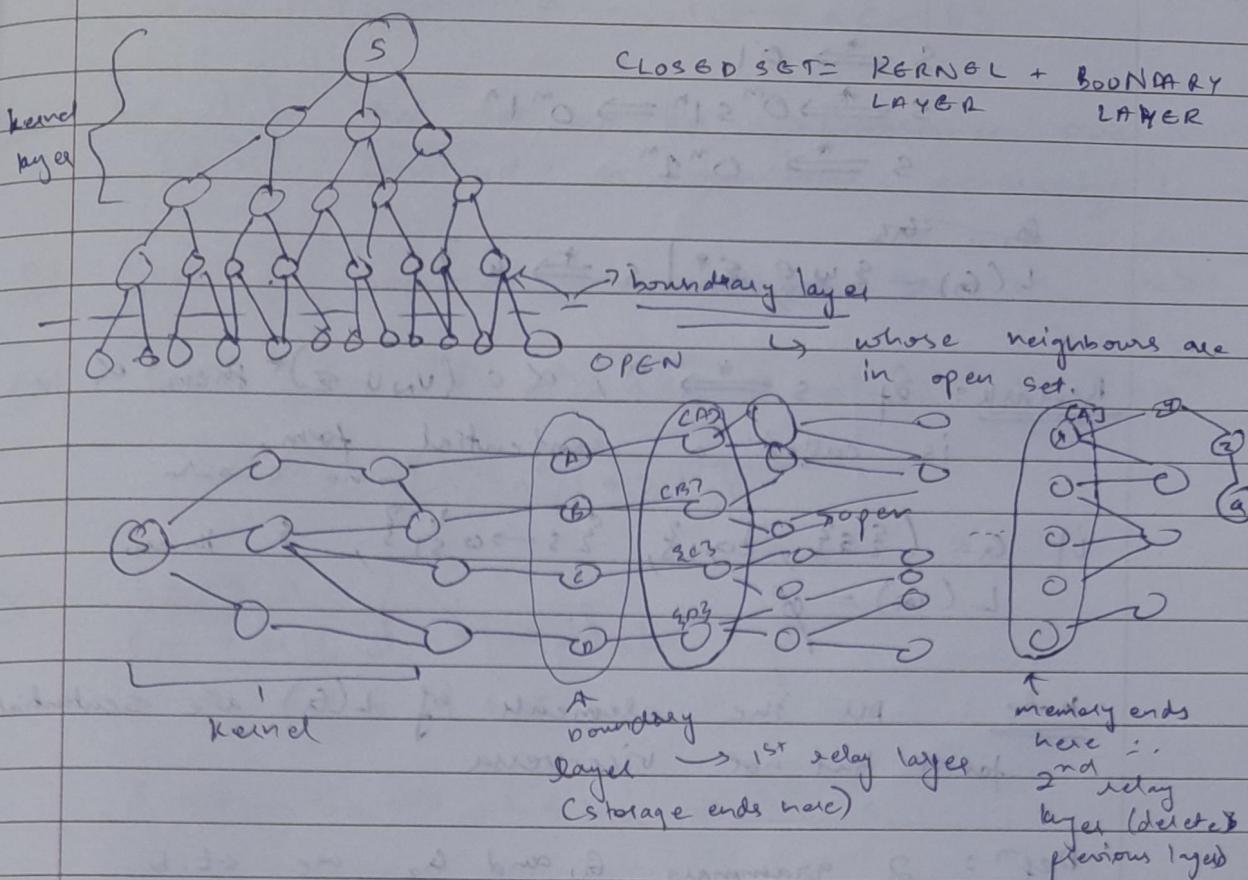
\Rightarrow At every node, after the relay layer we will delete the previous explored node and the list will contain the parent only from relay layer.

(S)



and so on..

2) Sparse Memory Graph Search:



⇒ Delete kernel layer - {S}

⇒ never delete boundary (eg keep 1st bound layer b even during nth kernel layer being deleted.)

Path reconstruction: $(S \rightarrow A) + (A \rightarrow \alpha) + \alpha \rightarrow Y \rightarrow Z \rightarrow G$

q. $G = (\{S\}, \{\alpha, \beta, \gamma\}, \{S \rightarrow OS_1, S \rightarrow \alpha, \beta, \gamma\}, S)$. Find $L(G)$

= Autonata $S \rightarrow OS_1 / \alpha$

$G = (V_N, \Sigma, P, S) \rightarrow \in V_N$ starting symbol

Set of terminals $\alpha \rightarrow \beta$

variables, (capital Alphabets) $\in (V_N \cup \Sigma)^*$

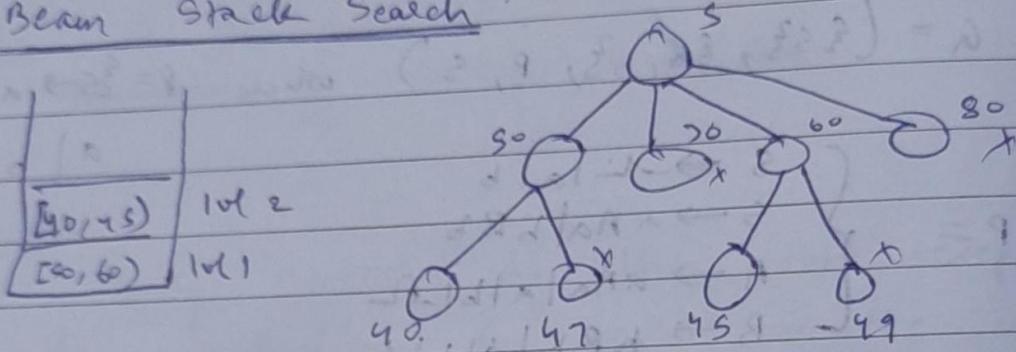
AI

* Pruning the OPEN list:

- Hill Climbing
- Beam Search
- BAMS - (Breadth First, heuristic search)
- Beam Stack Search

In this we set an upper bound depending on a heuristic f^m and if the heuristic val. is higher than bound then we discard that node.

* Beam Stack Search:



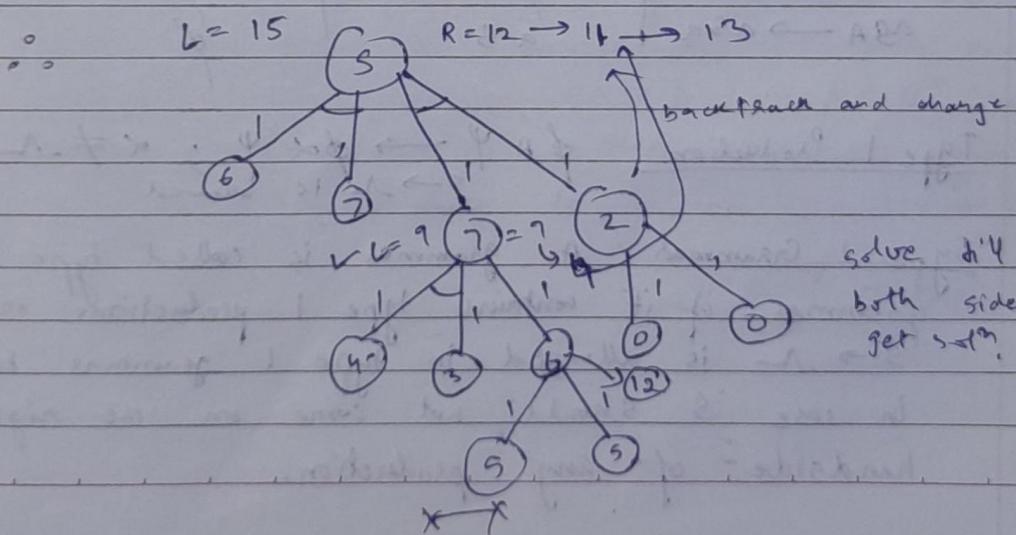
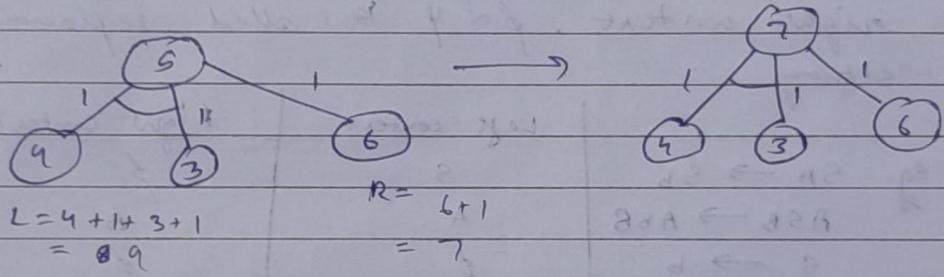
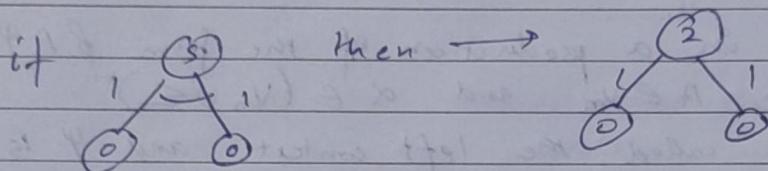
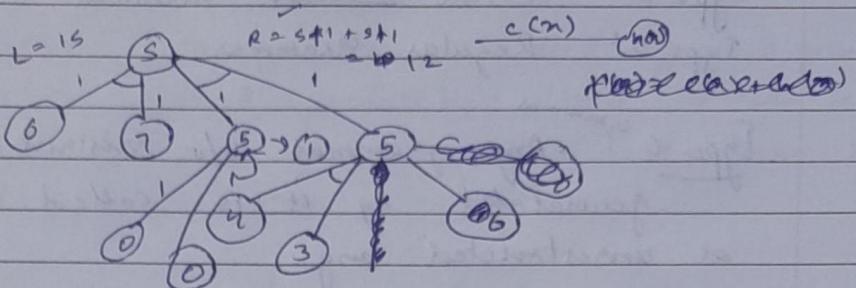
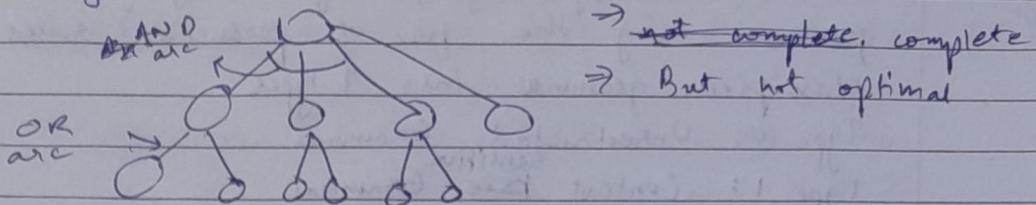
⇒ if we don't get ans from [40, 45]
then we change stack lvl 2 from
[40, 45] → [45, 47] and so on.

⇒ if we don't get a result in lvl n
the backtrack to lvl n-1

⇒ Complete Algo.

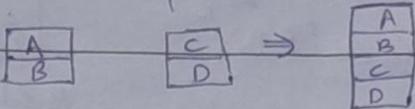
⇒ Study DCBSS and DCBFNS

* AO* Algo :



AI

Planning : Set of States



Initial State

on table (B)
 on table (D)
 on (A, B)
 on (C, D)
 Arm Empty (AB)
 Clean (A)
 Clean (C)

Represent States

Domain Predicate (S)

on (x, y) \rightarrow x is on y

on table \Rightarrow on Table (T(x))

Clean (x) \rightarrow no one is above x.

Holding (x) \rightarrow Robert holds x.

Arm Empty \rightarrow Robert not holding

Action (Y)

Pickup (x) \Rightarrow x on table

No one is above.

Put Down (x) \Rightarrow Putting block on table

Unstack (x, y) \Rightarrow Pick

x from y.

X from Y.

Stack (x, y) \Rightarrow Putting anything

x on y

Pre Cond:

- on T(x) and clean (x) and \neg AE \leftarrow For pickup
- Holding (x) \leftarrow For putdown (x)
- on (x, y) and clean (x) and \neg AE \leftarrow Unstack (x, y)
- Clean (y) and Holding (y) \leftarrow Stack (x, y)

After Action Effects:

Holding (x)

AE, on table, clean (x)

Holding (x), clean (x)

AE clean x, on (x, y)

Action unstack (A, B)

S domain predicate
unstack (C, D)

FSSP (Forward State Space Planning)

holding (A)

\Rightarrow All of Algos we have learned
that come under this

Clean (B)

$S \rightarrow S'$

on (C, D)

$S' = (S - \text{effect}^-(a)) \vee (\text{effect}^+(a))$

clean (C)

G

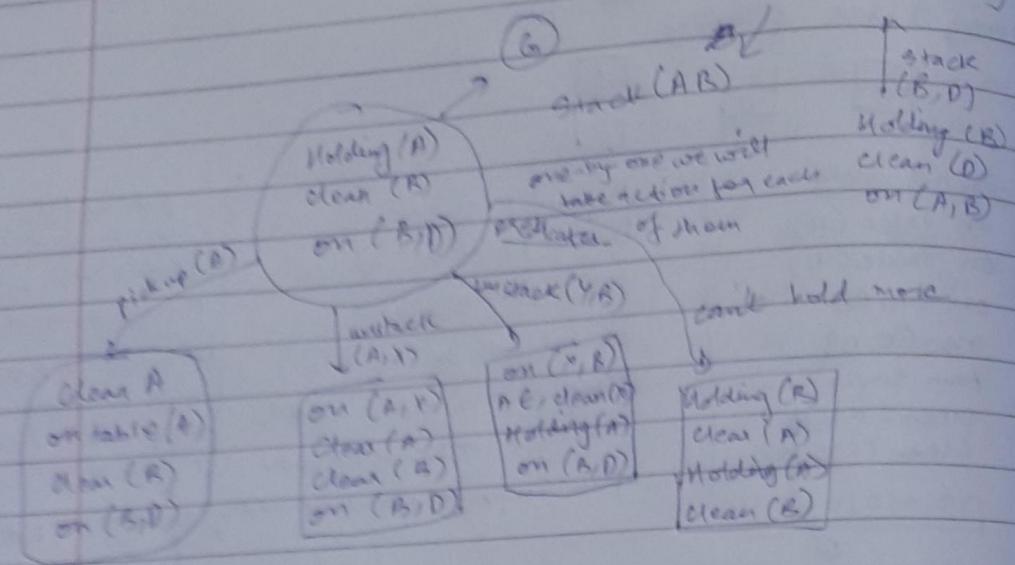
In BSSP (Backward State Space Planning)

$$G \rightarrow G'$$

$$G' = [G - \text{effect}^+(a)] \cup \text{precond}^-(a)$$

$\text{on}(A, B) \wedge \text{on}(B, D)$

Now



Goal State Planning:

