UIU

UNITED INTERNATIONAL UNIVERSITY

QUEST FOR EXCELLENCE

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Department: A2 (1) ID No :

Course: 011221542 Section:

CW
2.6.24

AI

* Introduction to AI

CS188

→ Autonomous Car

→ Game playing

→ Natural Language Processing
  - → machine translation
  - → speech recognition
  - → spam filtering
    - ↳ algorithm (after mid)

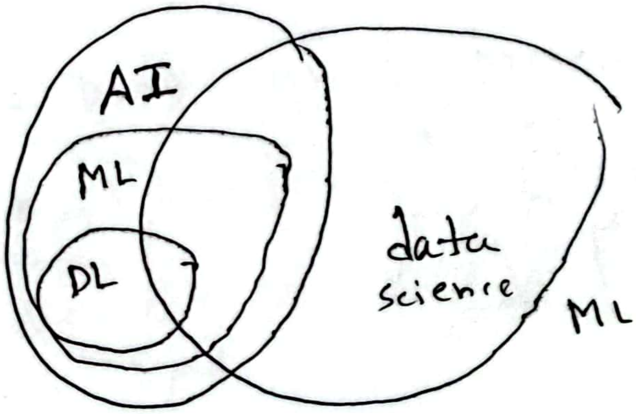
→ code automation

→ Image understanding.

→ Autonomous planning & scheduling.

→ Recommendation

→ Medicine



ML → Machine learning

DL → Deep learning

C.W
5.6.24

$\boxed{\text{UCB CS188}}$ → Course code

AI

* Agent type

- → Performance
- → Environment
- → Actuators
- → Sensors

} PEAS

C.W
9.6.24

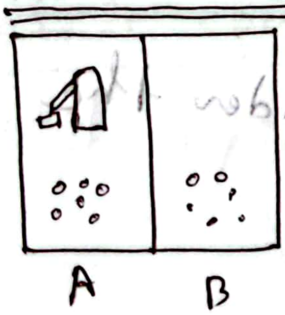
AI

* Problem formulation.

→ observable
→ discrete
→ known
→ deterministic

Steps
→ Initial state
→ Actions
→ Transition model
→ Goal test
→ Path cost * [no need to include]
→ state space
→ Solution (optimal)
→ Abstraction *

* Vaccum cleaner:



Vaccum → [T, F]

Dust → [T, F].

Initial state: Dust can be present or absent.

Action: (A, Dust) → [T, F], [T, F]

(A, clean, B) → [F, T], [F, T]
(move) Dust

Transition model:

$[T, F], [T, F] \xrightarrow{\text{clean}} [T, F], [F, F]$

$[T, F]$ → stay

$[F, F]$ → no dust

Goal Test: If the dust [F, F], The work is done.

state space: 2^2 for vaccum

2^2 for dust

2 for space.

* 8-puzzle

7	2	4
5		6
8	3	1

	1	2
3	4	5
6	7	8

Initial state: A matrix & consider the empty space as 0.

7	2	4
5	0	6
8	3	1

Action: move the zero to up, down, right, left to get the goal.

Transition model:

7	2	4
5	0	6
8	3	1

Down →

7	2	4
5	3	6
8	0	1

Goal test:

If the every row got the values in ascending order in left to right, the work is done.

state space: ~~board space~~ ~~all element movement~~

$\boxed{9!}$

8-queens problem

Initial state:

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
in which row	1	3	5	7	2	4	0	8

Actions: Every qween will move like $C_1R_1 \neq C_2R_1 \neq C_3R_1 \neq C_4R_1$ ...... and also no clash in 'X' shape movement with all queens. and also $C_1R_1 \neq C_1R_2 \neq C_1R_3$ -----.

Transition model:
any queen can move up, down, left, right ~~&~~ 'X' shape.

Goal test: if all the queens are arranged with no clash, the work is done.

state space:

board size (8×8) ~~&~~ 8^{64} → all queen movement.

* $\left\lfloor \sqrt{\sqrt{\sqrt{\sqrt{(4!)!}}}} \right\rfloor = 5$

Initial state: 4

Action: $\lfloor\ \rfloor$, $\sqrt{\ }$, !

Transition model: $\sqrt{\ } \longrightarrow \sqrt{(4)!} \longrightarrow \lfloor\ \rfloor$

Goal test: Desired positive integer

state space: n

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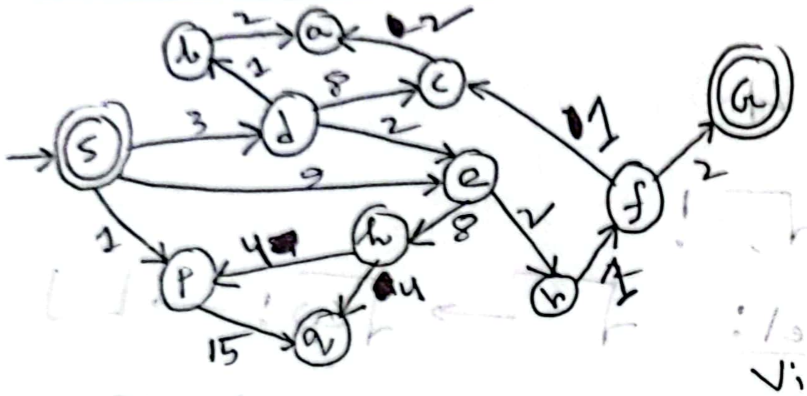
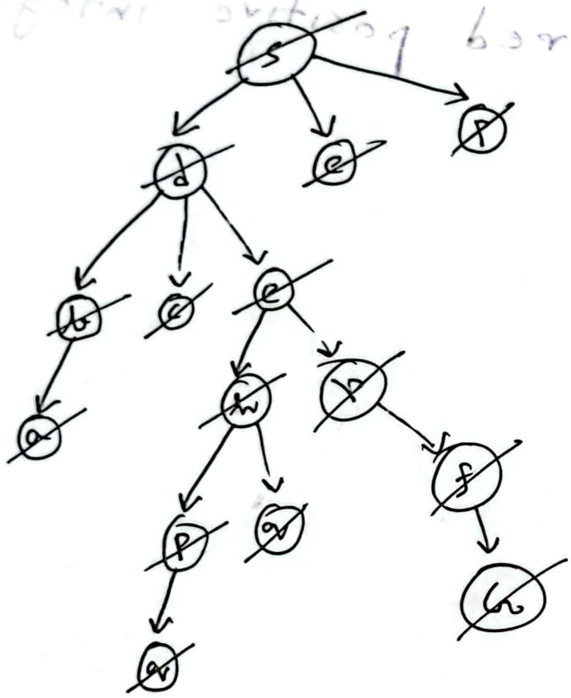
AI

DFS → With tree



Visited:
S d b a c e h p q
r f G
[Left most order]



DFS → S → d → e → r → f → G

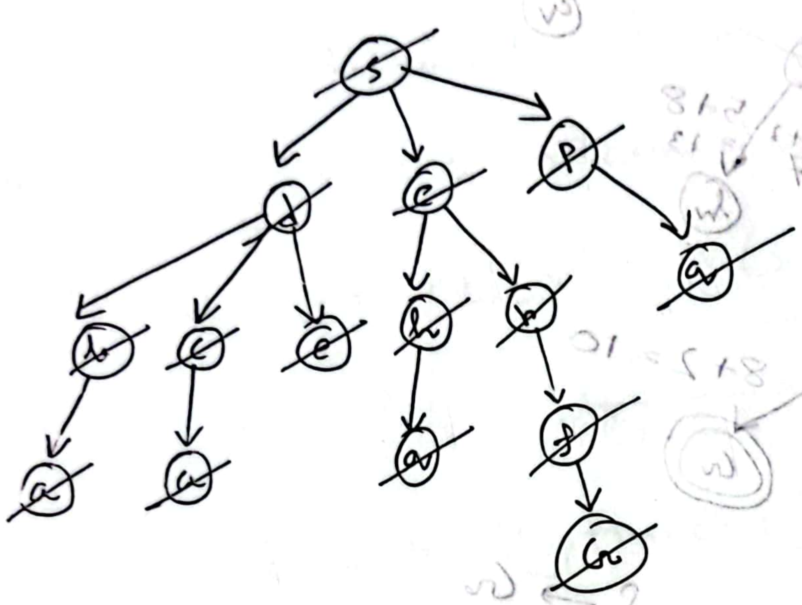
space → $O(b^m)$ b → branching factor
m → maximum depth

Time → $O(b^m)$

space for fringe → $O(b \cdot m)$

BFS → Tree

Same graph:



Visited: s d e p b c h r q a f G

[level order]

BFS → s → e → r → f → G

time → $O(b^s)$ [s tiers]

optimal → yes, if path cost = 1 or same. or unweighted graph.

space → $O(b^s)$

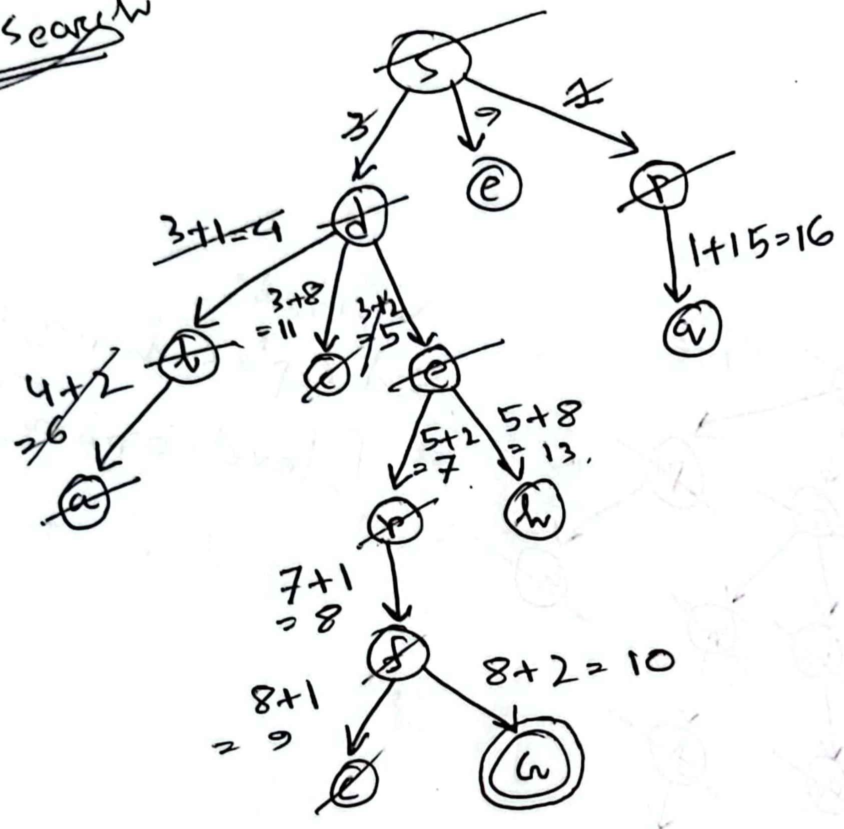
DLS → Depth Limited Search.

use DFS with a depth limit. $\boxed{L=5}$

Iterative Deepening → DSL with L = 1, 2, 3 . . . n, when need to be stop.

CamScanner

Uniform cost search



Visited:

S p d b e a r f c G

UCS → S → d → e → r → f → G

cost → 20 (min)

Time → $O(b^{c^*/\varepsilon})$

space → $O(b^{c^*/\varepsilon})$

optimal → yes.

C.W
23.6.24

AI

Search Heuristics → $f(x)$

* Heuristic function → $h(x)$
→ estimate distance of point to goal point.
→ greedy search → consider $h(x)$

A^* search → $h(x) + g(x)$
↳ $g(x)$ → ucs (backward cost)
↳ $h(x)$ → greedy (forward cost)

* h is admissible (optimistic):

$$0 \le h(n) \le h^*(n)$$
↳ $h^*(n)$ → original node heuristic

Admissible

Invalid | 0 | bad → good | $h^*(n)$ | Inadmissible

0 —— 15 (5, 8, 10, 15)
↳ 15 is better.

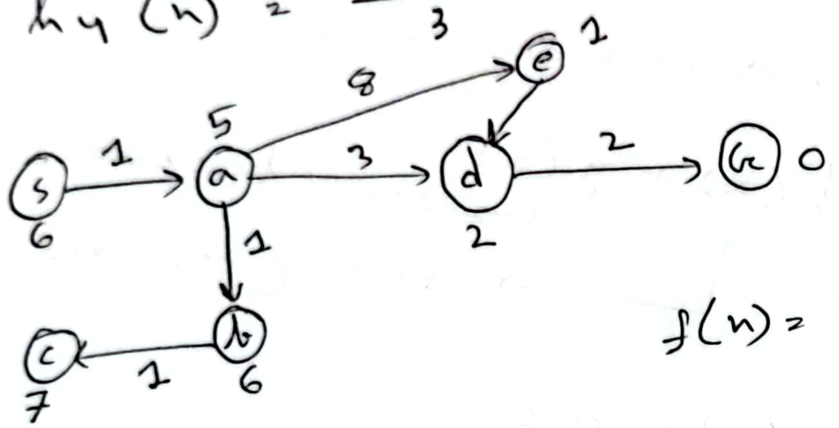
$h_1(n)$ → admissible	$h_1(n)$ → inadmissible
$h_2(n)$ → "	$h_2(n)$ → admissible
$h_3(n)$ → $\max(h_1, h_2)$ (better)	$h_3(n)$ → $\min(h_1, h_2)$ (better)

$h_1(n) = $ in adm

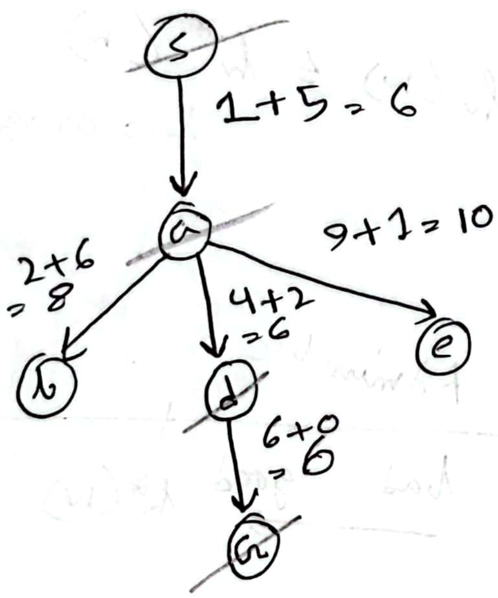
$h_2(n) = $ adm

$h_3(h) = $ adm $\longrightarrow$ better

$h_4(n) = \frac{h_2 + h_3}{3}$



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



Visited:
s, a, d, G

C.W 30.6.2...

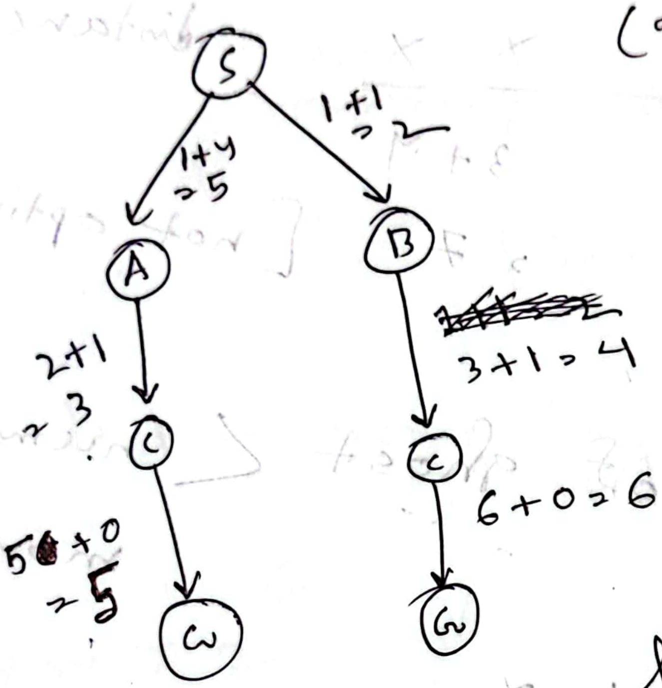
AI

$h_1(n)$ = admissible → better

$h_2(n)$ = admissible $h_2(n) \leq 1$

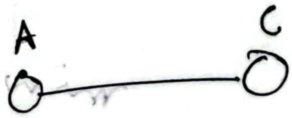
$h_3(n) = h_1, h_2$

(graph search)



heuristic → admissible → optimal (Graph Search) (no visit count)

$h(A) - h(C) \leq \text{cost}(A \text{ to } C)$



(i) ~~Yes, Admissible, Cause~~

(a) _ _ x x distance = 4

$3+4$

$= 7$ [not optimal]

(ii) number of ghost < number of move

(b) _ x x _ _

number of move = 3

number of ghost = 2

(iii) (c) _ x x _ _ [3

$2 \quad 3$

$\min(2, 3) = 2$

[admissible]

(iv)

distance = 4

ω — — $\frac{x}{3}$ $\frac{x}{4}$ —

remaining = 3×2 = 6

[inadmissible]

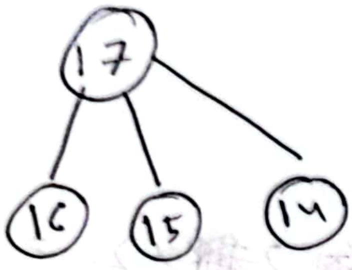
(a) goal test → remaining ghost zero.

(b) G

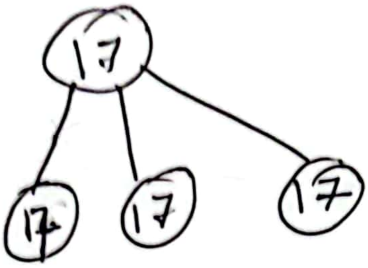
$m \times n \times 2$

CW
3.7.24

AI



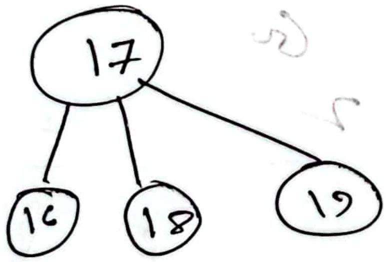
local maxima
(no better option)



plateau

* Simulated Annealing

$$e^{\frac{\Delta E}{T}}$$

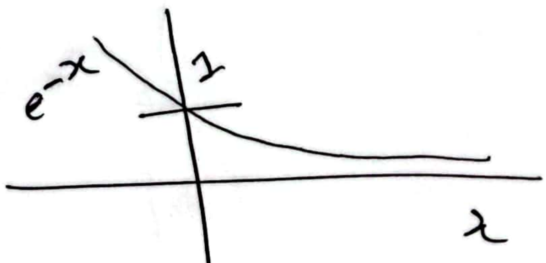


$\Delta E = 16-17 = -1 = e^{-1}$

$\Delta E = 18-17 = 1 = e^{1}$

$\Delta E = 19-17 = 2 = e^{2} \rightarrow$ Better.

T = temperature
কমাতে হবে



x বাড়লে probability কমে
x কমলে " বাড়ে

Genetic Algo

→ Fitness Algo → which is the best from given 4 state

$x_1 = 9$

$x_2 = 23$

$x_3 = -16$

$x_4 = -19$

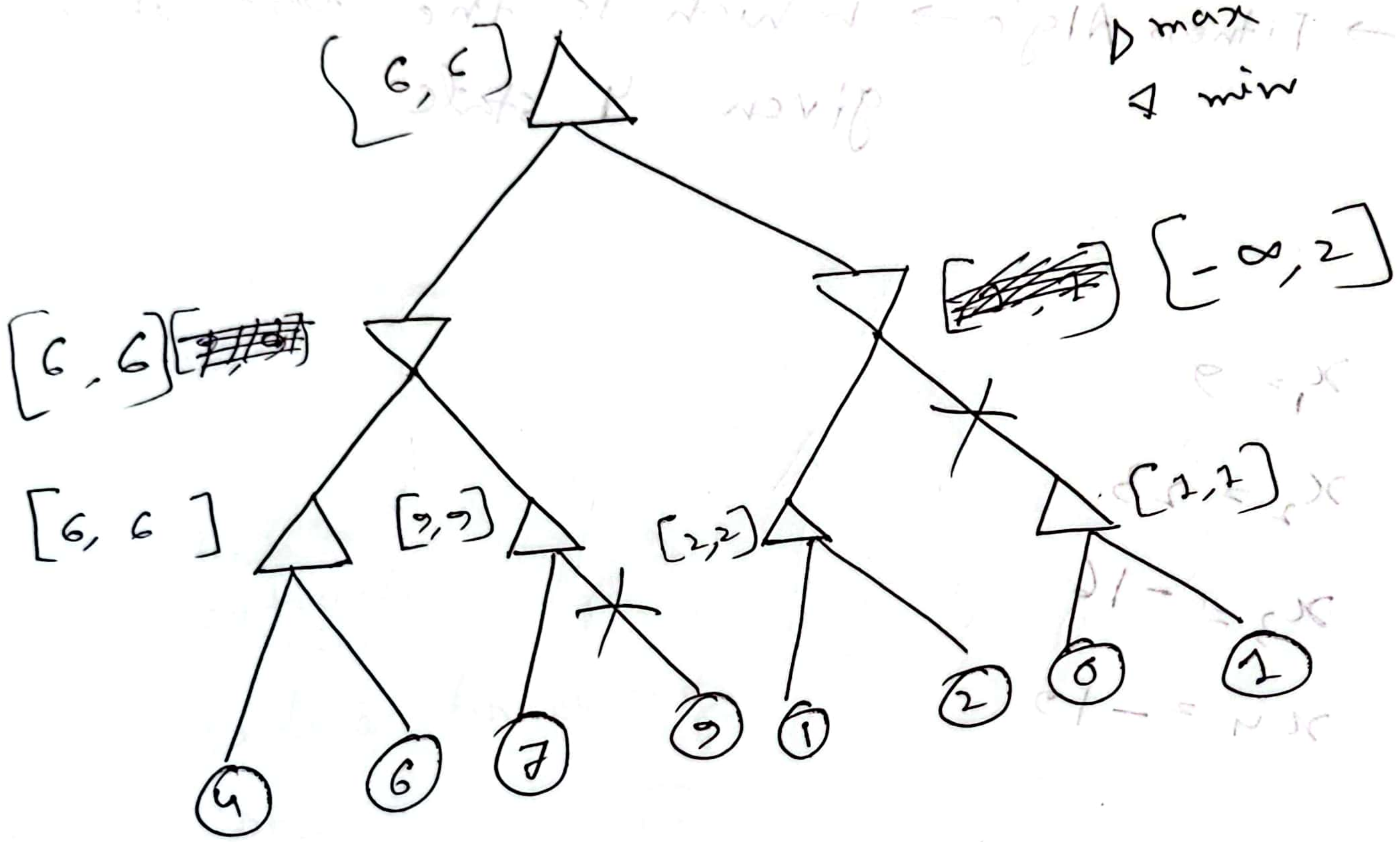
x_1 , x_2

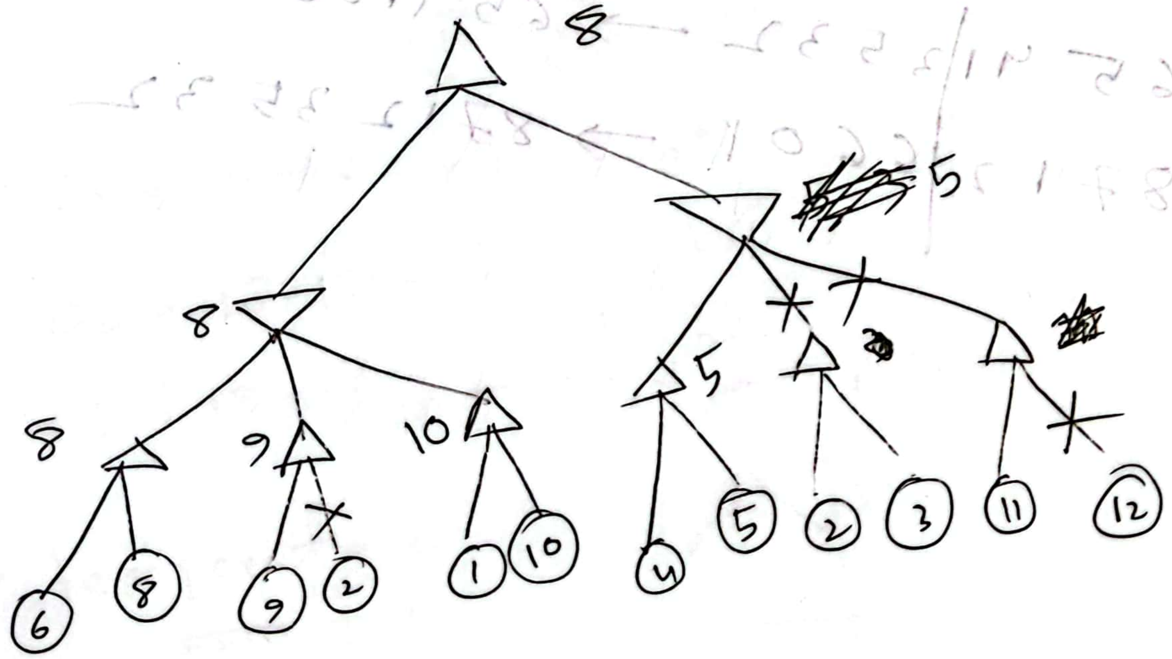
6541 | 3532 → 65416601

8712 | 6601 → 87123532

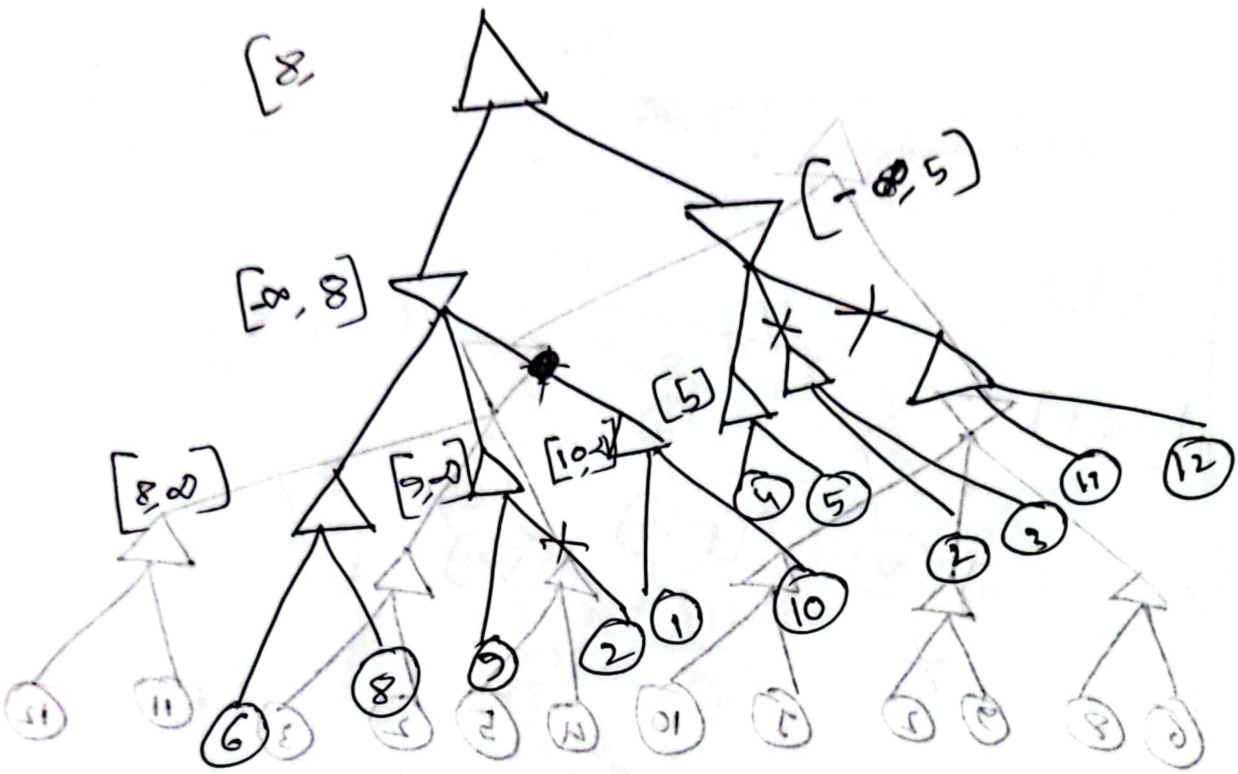
C.W
7.7.24

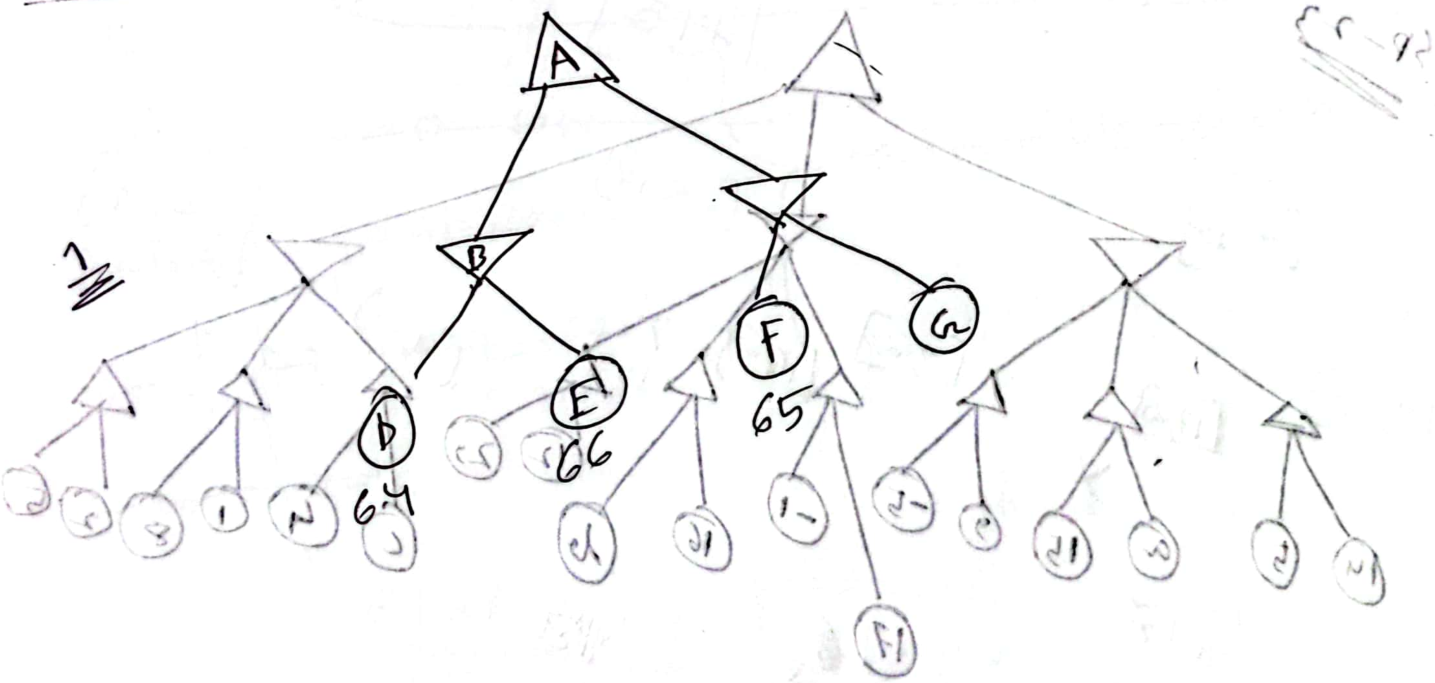
AI

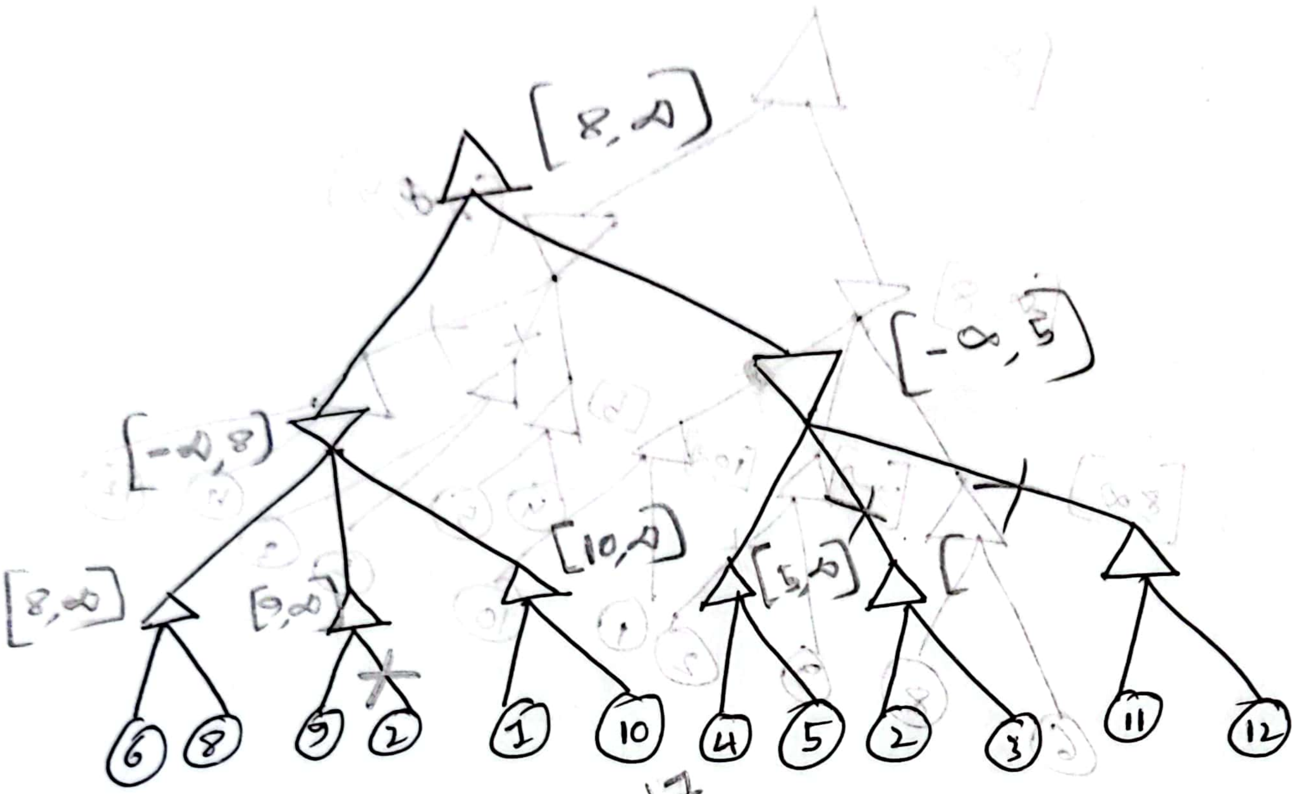




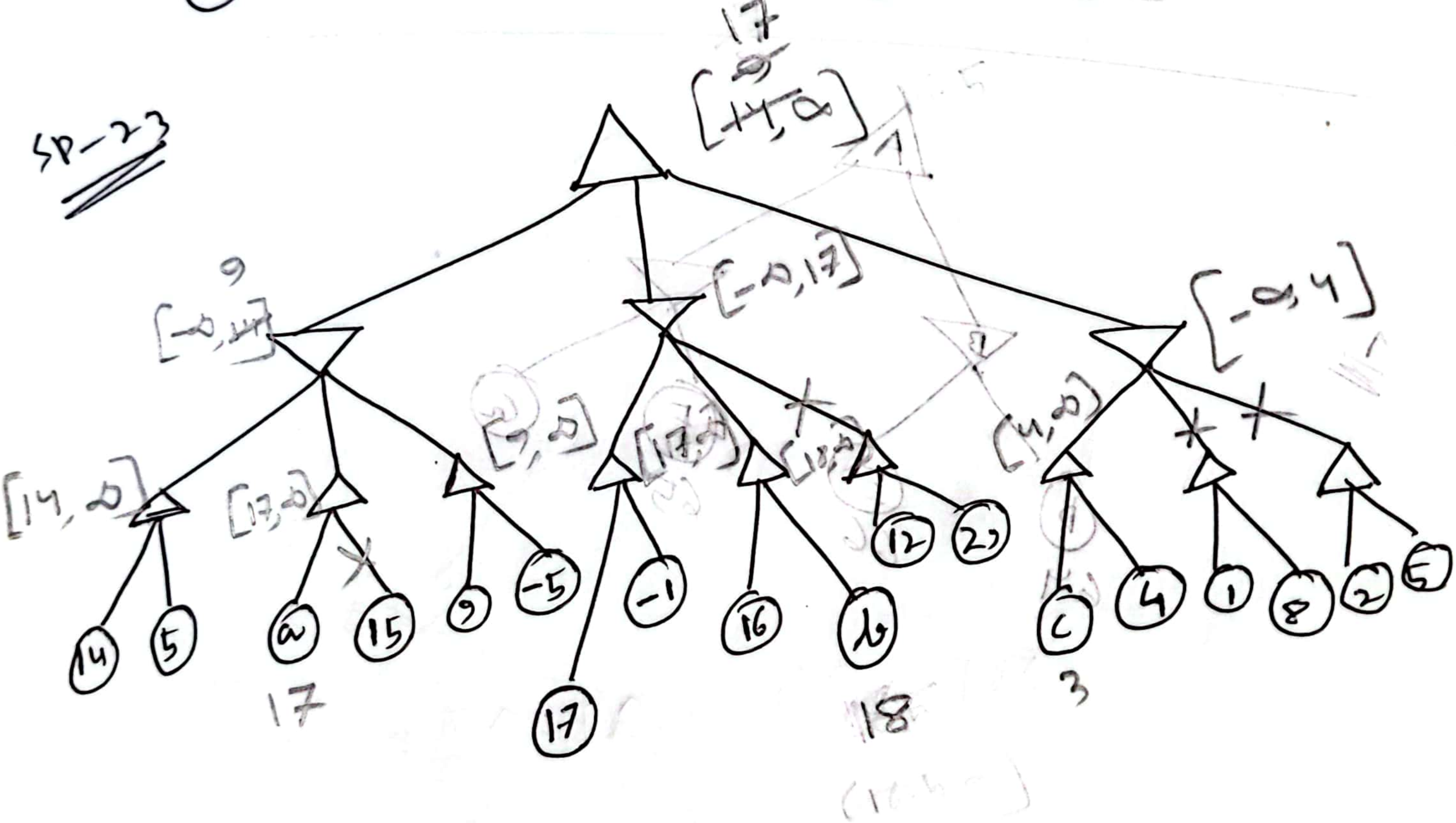
CamScanner


[8,
[-∞, 5]
[-∞, 8]
[5]
[8,∞]
[9,∞]
[10,∞]
6
8
9
2
1
10
4
5
2
3
11
12


A
B
D
E
F
G
64
66
65


[8, ∞]
8
[-∞, 8]
[-∞, 5]
[8, ∞]
[9, ∞]
[10, ∞]
[5, ∞]
6
8
9
2
1
10
4
5
2
3
11
12

SP-23


17
[14, ∞]
[-∞, 14]
9
[-∞, 17]
[-∞, 4]
[14, ∞]
[17, ∞]
[9, ∞]
[17, ∞]
[18, ∞]
[4, ∞]
14
5
2
15
9
-5
17
-1
16
2
12
22
6
4
1
8
2
5
17
18
3

Hill climbing Search

steepest - ascent version

→ always deep down to maximum element

stochastic hill climbing

→ choose random & maximum.

First choice hill climbing

→

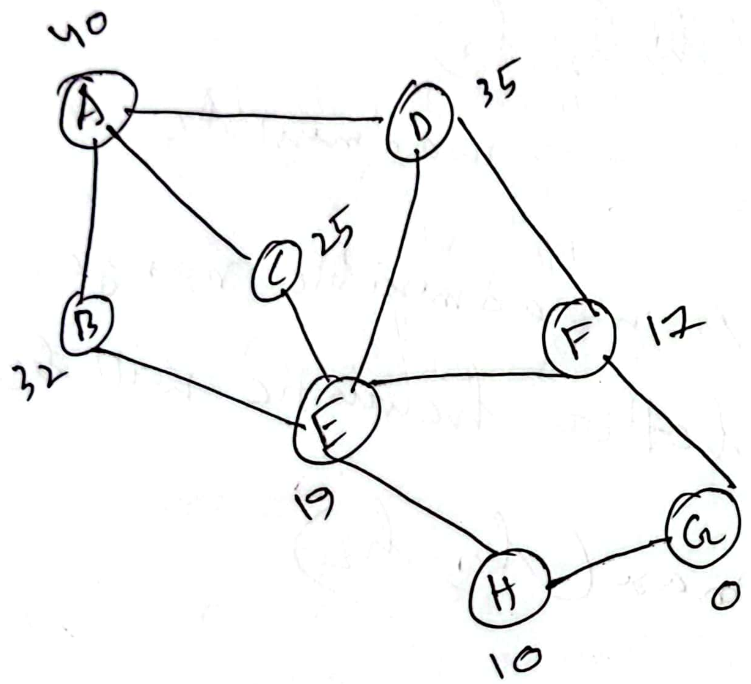
Random restart

→ no path found, again move to the next node.

* $e^{\frac{\Delta E}{T}}$ | $\boxed{T\uparrow \quad P\downarrow}$ $\boxed{T\downarrow \quad P\uparrow}$

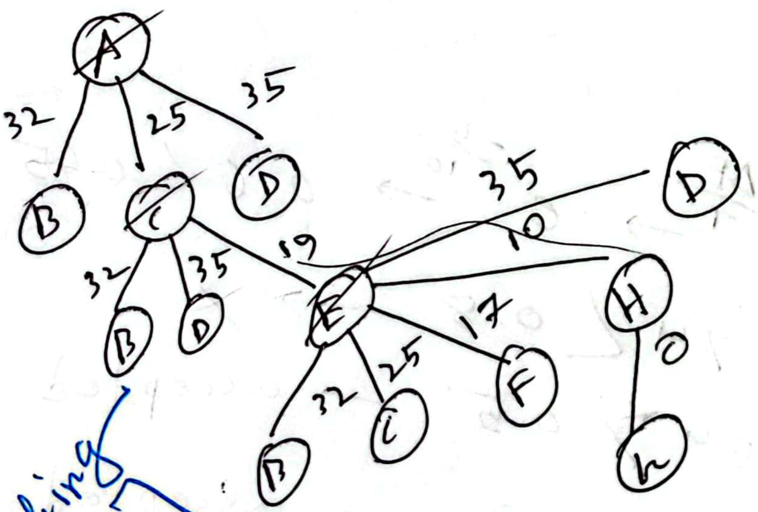
Beam Search

→ Greedy search with $\boxed{\text{limited space box}}$



Beam space = 2

B	~~C~~
B	~~E~~
B	H

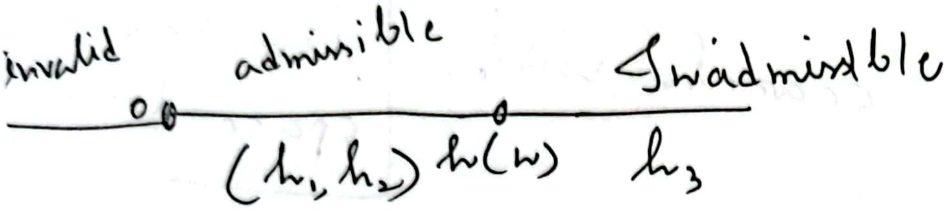


Beem k = ∞ (BFS)

Beem k = 1 [Hill climbing racing]

[A → C → F → H → G]

Fall 23 AJ



(i) $h_4(n) = \max(h_1, h_2, h_3)$

$\longrightarrow$ inadmissible

(ii) h_1 & h_2 is in admissible range.

So, the better heuristic will be

$h_7(n) = \max(h_1, h_2)$

spring-23

4) $T = 10$

1 $\rightarrow$ $e^{\frac{\Delta E}{T}} \rightarrow e^{\frac{-5}{10}} \rightarrow 0.6 < 0.65 \longrightarrow \times$

2 $\rightarrow$ $0.74 < 0.8 \longrightarrow \times$

3 $\rightarrow$ $0.54 > 0.5$ $\rightarrow$ accepted

4 $\rightarrow$ $1.22 > 0.2$ $\rightarrow$ accepted

5 $\rightarrow$ $0.67 > 0.4$ $\rightarrow$ accepted

3

(a)

Fall-22

$7 - 4 \le 5$ $\to h(E)$

$4 - 2 \le 2$

$\downarrow$

$h(C)$

$S \xrightarrow{5} E \xrightarrow{2} C \xrightarrow{3} G$

7 4 2 0

d

(i) $h_4(n) = 2 \times h_1(n)$ [possibly inadmissible]

suppose $\to$ 10 (admissible), 15 (inadmissible)

$\downarrow$

h_1

$2 \times 10 \to 20$ [inadmissible]

0 10 15 20 inadmissible.

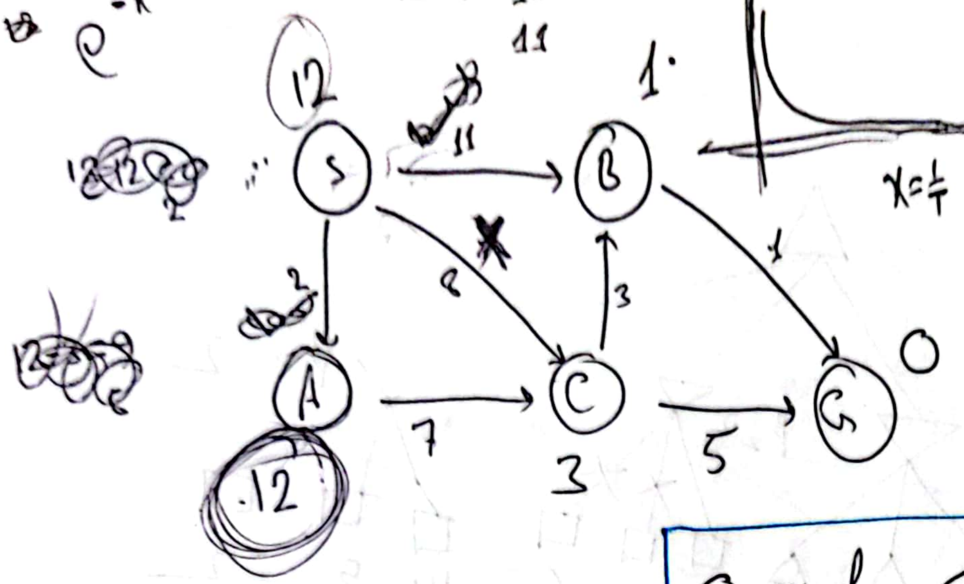
admissible

(ii) h_6

(iii)

(iv) h_7 is the best.

$12 - 1 = 11$



① A & C is ✓

② A & C ✗

③ Inad ✓

C – 11

$S = h^*\ 12 \le 12$ ✓

$A = h^*\ 11 \quad 12$ ✗

$$\boxed{\begin{array}{ccc} 0 \le & h & \le h^* \\ & 12 & 11 \end{array}}$$

S-C violates consistency.

A violates admissibility.

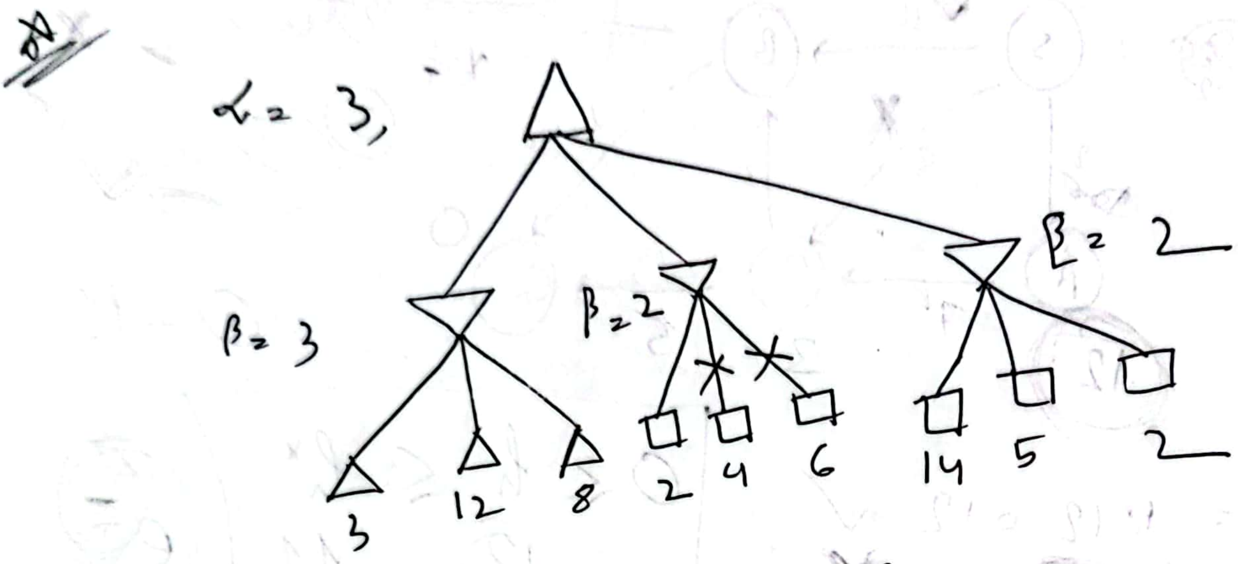
h_1 Inadmissible.

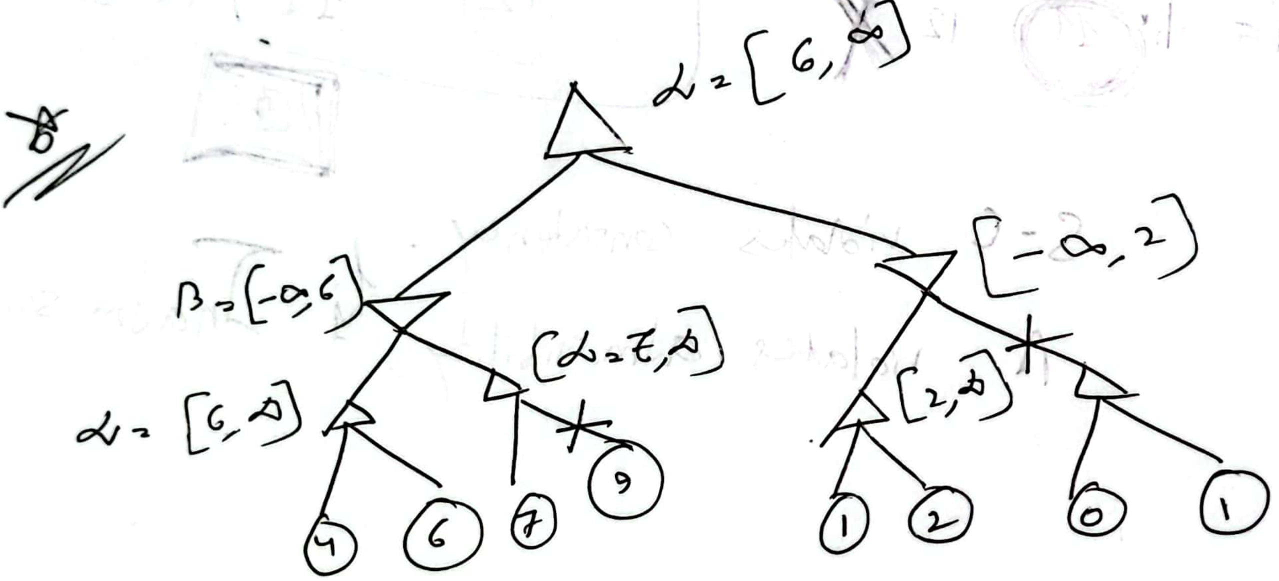
$G \le 1$

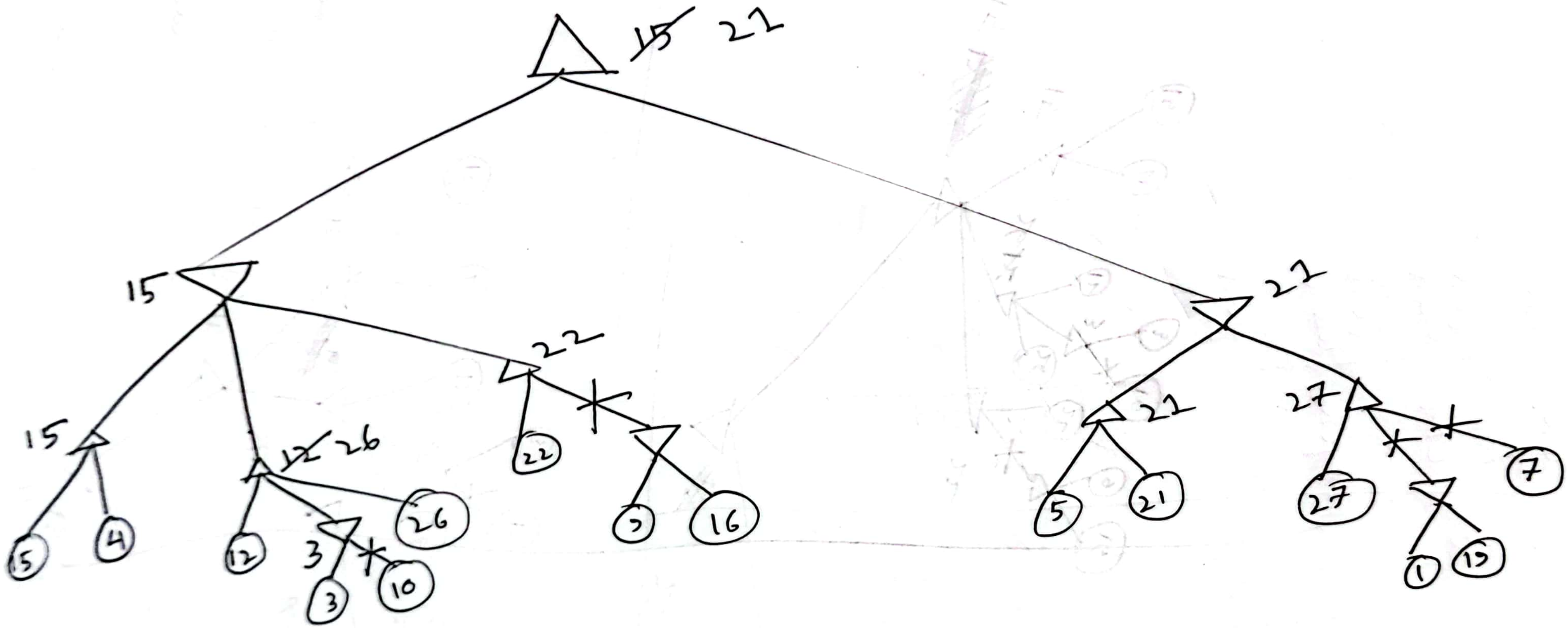
$12 - 3$

$a \not\le A$

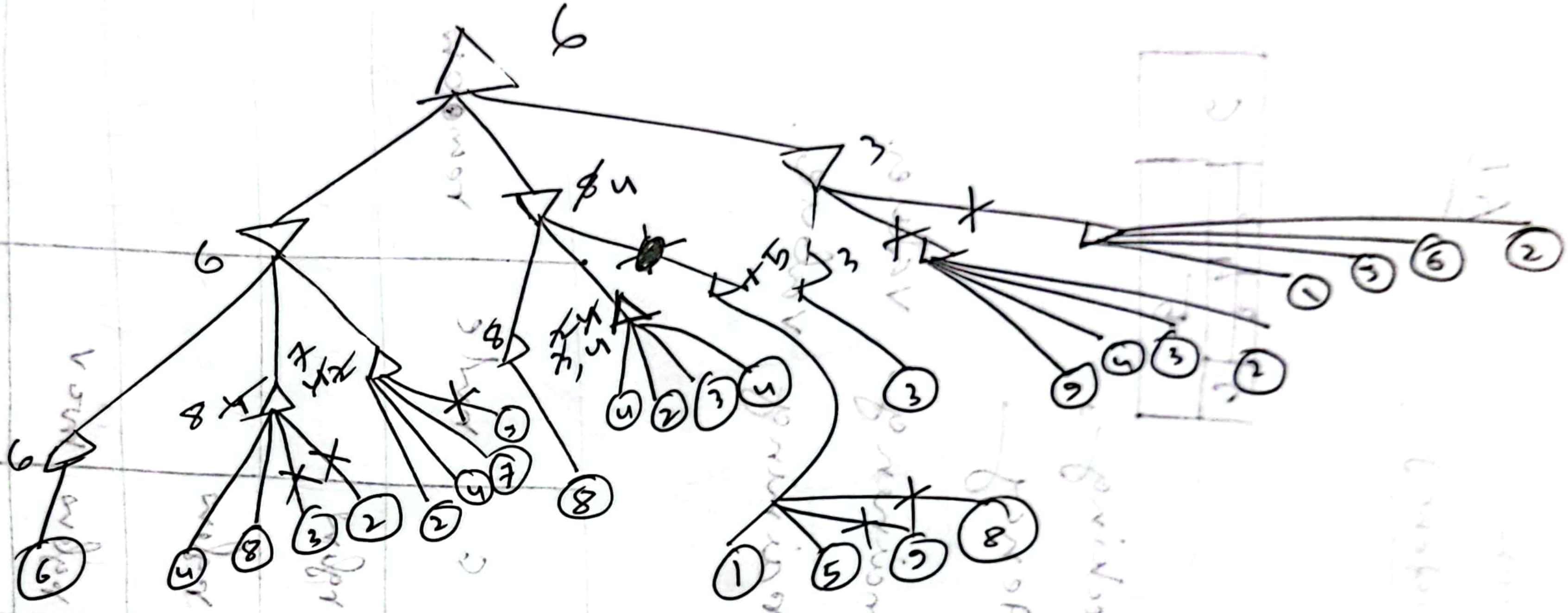
$\alpha - \beta$







~~15~~ 22
15
22
15
~~12~~ 26
22
27
3
15
4
12
3
10
26
22
16
5
21
27
7
1
13



admissible → $0 \le h(n) \le h^*(n)$

consistent → $h_1(n) - h_2(n) \le g(n)$

G.W
14.7.24

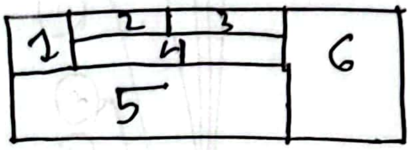
CSP solution

Arc Consistency

AI

* Remove from tail

head ← tail



Filtering : Forward checking,
Arc consistency

* MRV → Minimum remaining values.
LCV → Least Constraining value.

	1	2	3	4	5	6	rule	remove
	rgbw	rgbw	rgbw	rgbw	rgbw	rgbw		
constrains	$\boxed{r}$	rgbw	rgbw	rgbw	rgb	rgbw		
	$\boxed{r}$	gbw	rgbw	gbw	gb	rgbw	mrv	
	r	gbw	rgbw	bw	$\boxed{g}$	rbw	mrv, lcv	
	r	gw	rgw	b	g	rw	mrv, lcv	
	r	w	rg	b	g	rw	mrv, lcv	

$1 \rightarrow 2, 4, 5$

$5 \rightarrow 4, 6$

$4 \rightarrow \cancel{1}, 2, 3, \cancel{5}, 6$

$2 \rightarrow 3$

	1	2	3	4	5	6	rule	reason
3 = g	r	w	g	b	g	r	mrv, lcv	3 = r impact 1 var (6) 3 = g 0
= r	r	w	g	b	g	r	mrv	

$(1, 2, 4, 5, 6, \cancel{3}) = (\cancel{g}, r, w, g, b, g, r)$

5

AI

* $0 \le h(n) \le h^*(n) \rightarrow$ admissible

* $h_1(n) - h_2(n) \le g(n) \rightarrow$ consistent

h_1

$S \rightarrow a = 2$

$S = 12$, $A = 12$

$12 - 12 = 0 \le 2 \rightarrow$ consistent

$S \rightarrow b = 11$

$12 - 1 = 11 \le 11 \rightarrow$ consistent

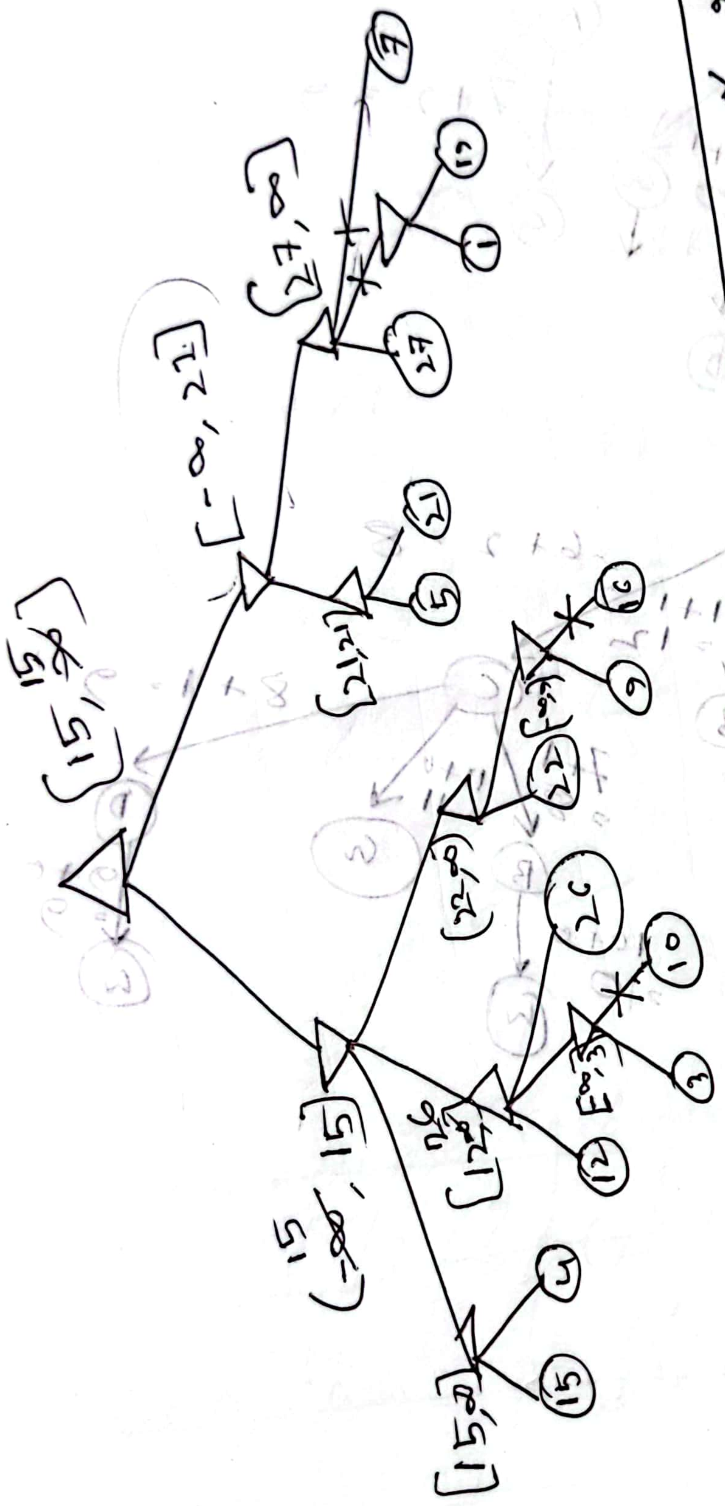
$S \rightarrow C = 8$

$12 - 3 = 9 > 8 \rightarrow$ inconsistent

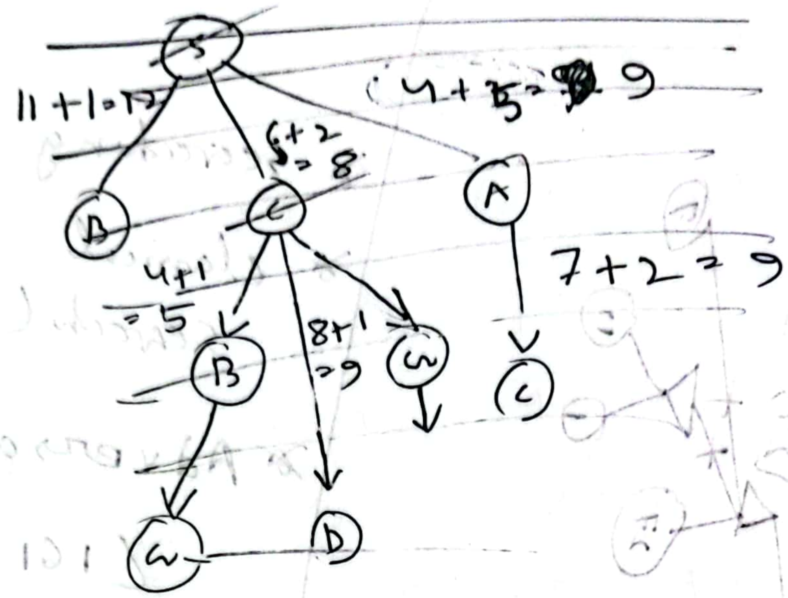
S $h^*(n) = 12$, $h(n) = 12 \rightarrow S \rightarrow$ admis

$A \rightarrow 11 \rightarrow h(n) = 12$

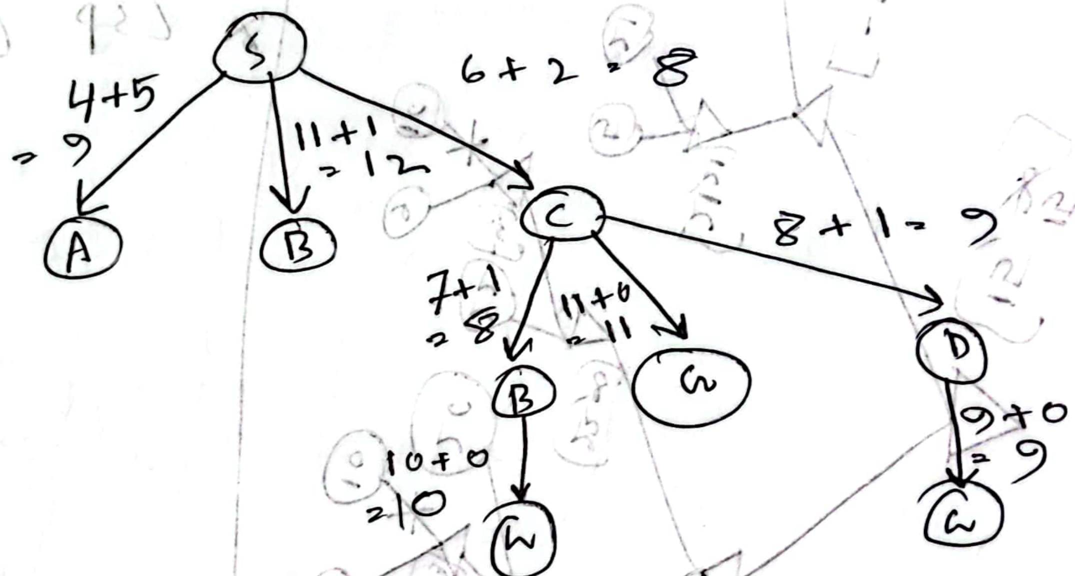
$h^*(n) = 11$, $h(n) = 12 > 11 \rightarrow$ inadmissible



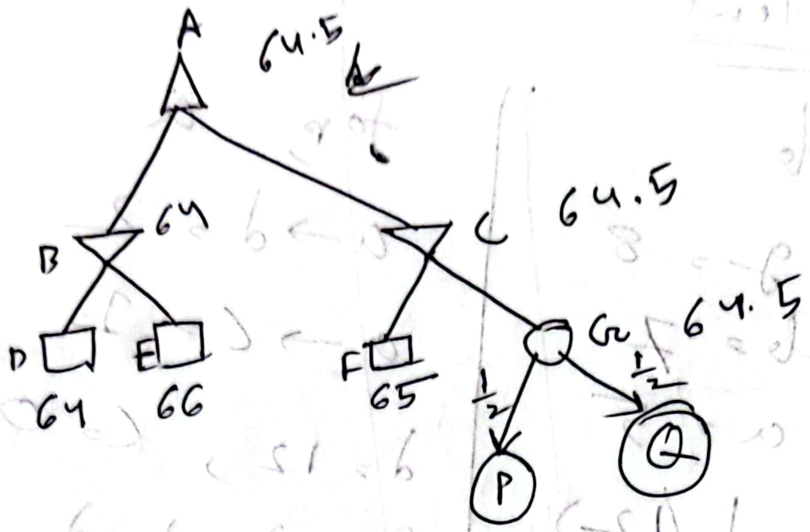
* searching (64-108)
* classical search (120-153)
* Adversarial Search (161-189)
* CSP (202-227)



graph search



$S \to C \to D \to G$



2

(a) $64 < C$

(b) $64 < \frac{1}{2}P + \frac{1}{2}Q < 65$

$64 < 64.5 < 65$

$G = 64.5$ Ans

spring-24

~~Admissible & consistent~~

$h_1, h_2 \le g(n)$ a, b

$c \to 0 \quad a \to c = 7 \quad a = 7, \quad b \to c = 5$

$a \to 7 - 0 = 7 \quad b = 5 - 7 = 4$

$a = 7$

~~inconsistent~~

$h \to a = 5$

$h = 10 \quad a = 3$

$10 - 3 = 7 > 5$ [~~inconsistent~~]

Fall-23

$3+8+4 = 15$

$11+6 = 17$

$$\overset{14}{S} \xrightarrow{3} \overset{11}{A} \xrightarrow{8} \overset{3}{B} \xrightarrow{4} \overset{0}{G}$$

$h(A) - h(B) = 8 \leq 8$ [consistent]

$h(B) - h(G) = 3 \leq 4$ [consistent]

$R \to 3$

$A \to 2$

$M \to 2$

$S \to 1$

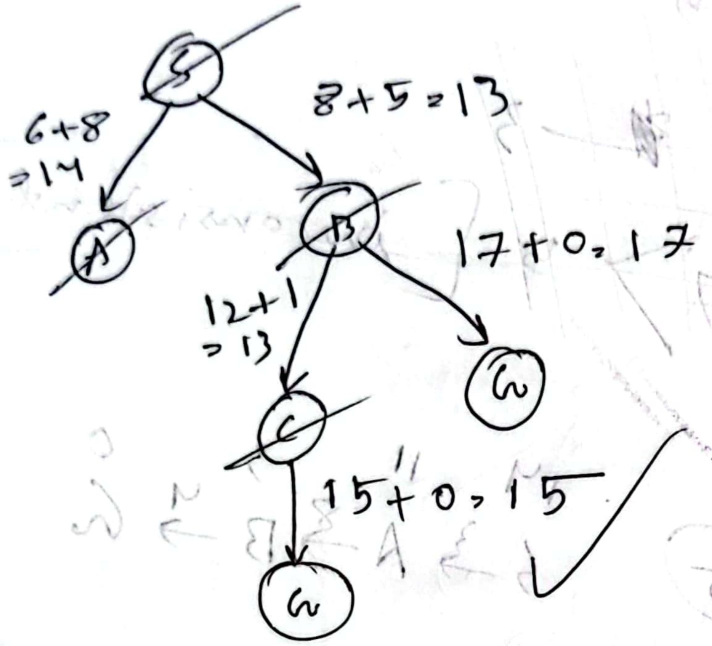
} One of the solution

$A = \{$

A

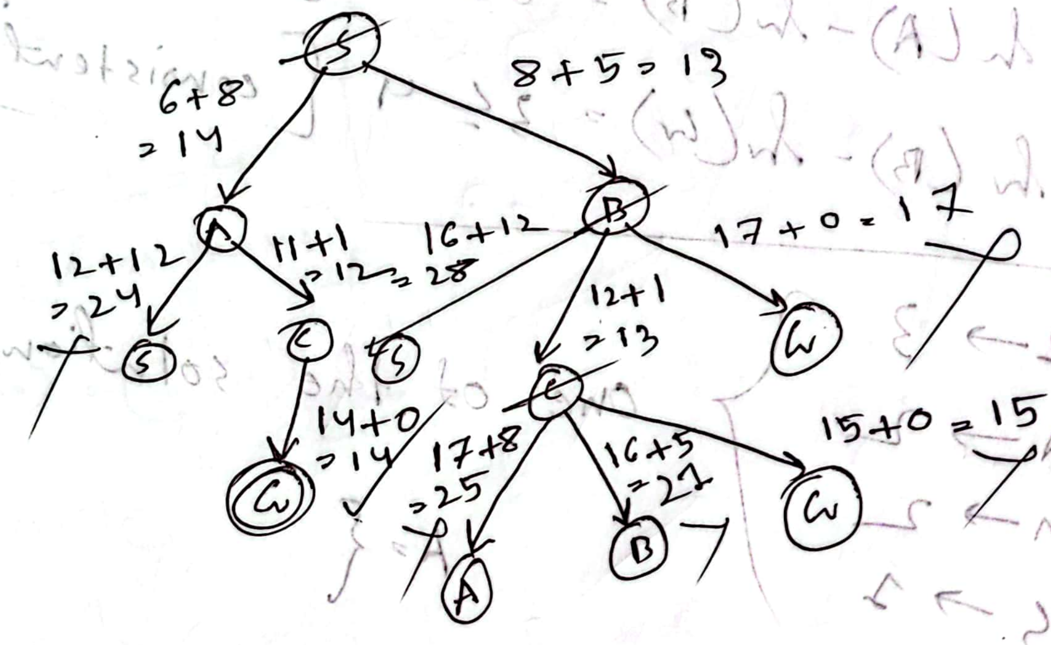
tree

S, B, C, A, G,

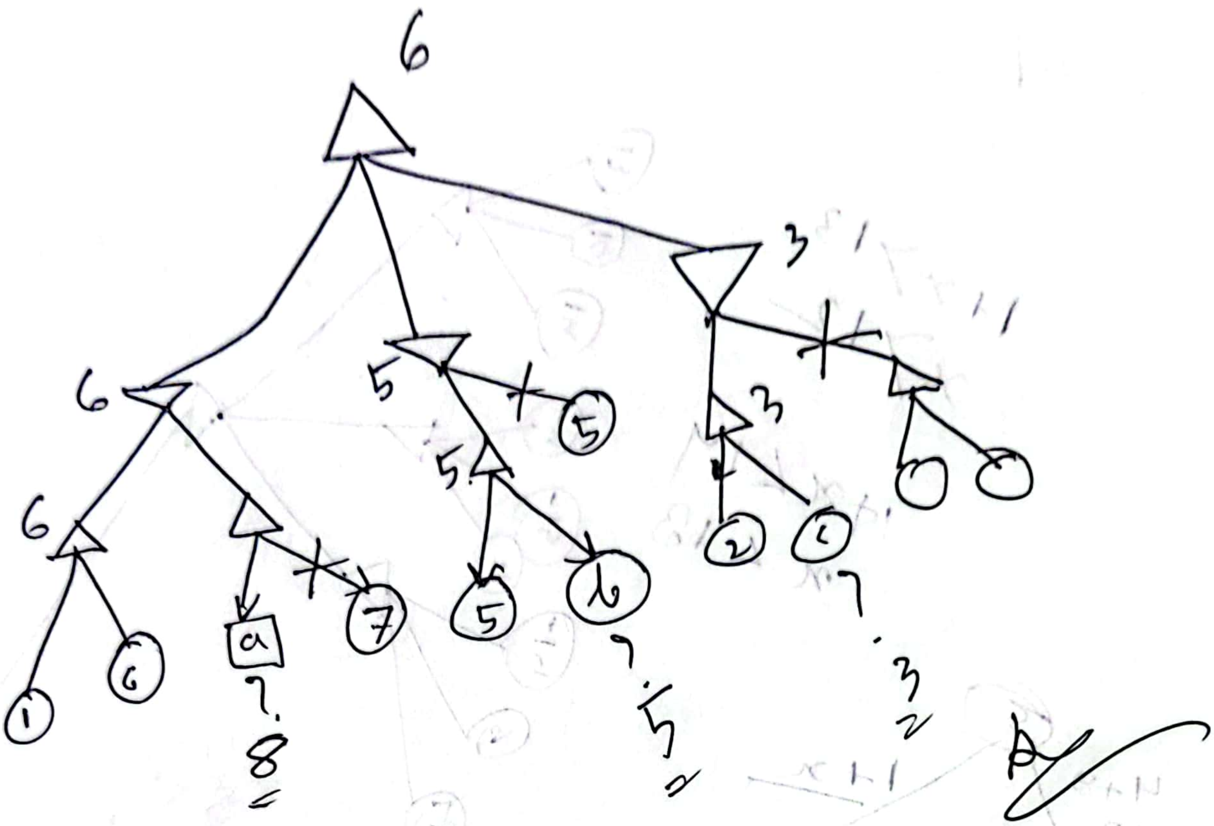


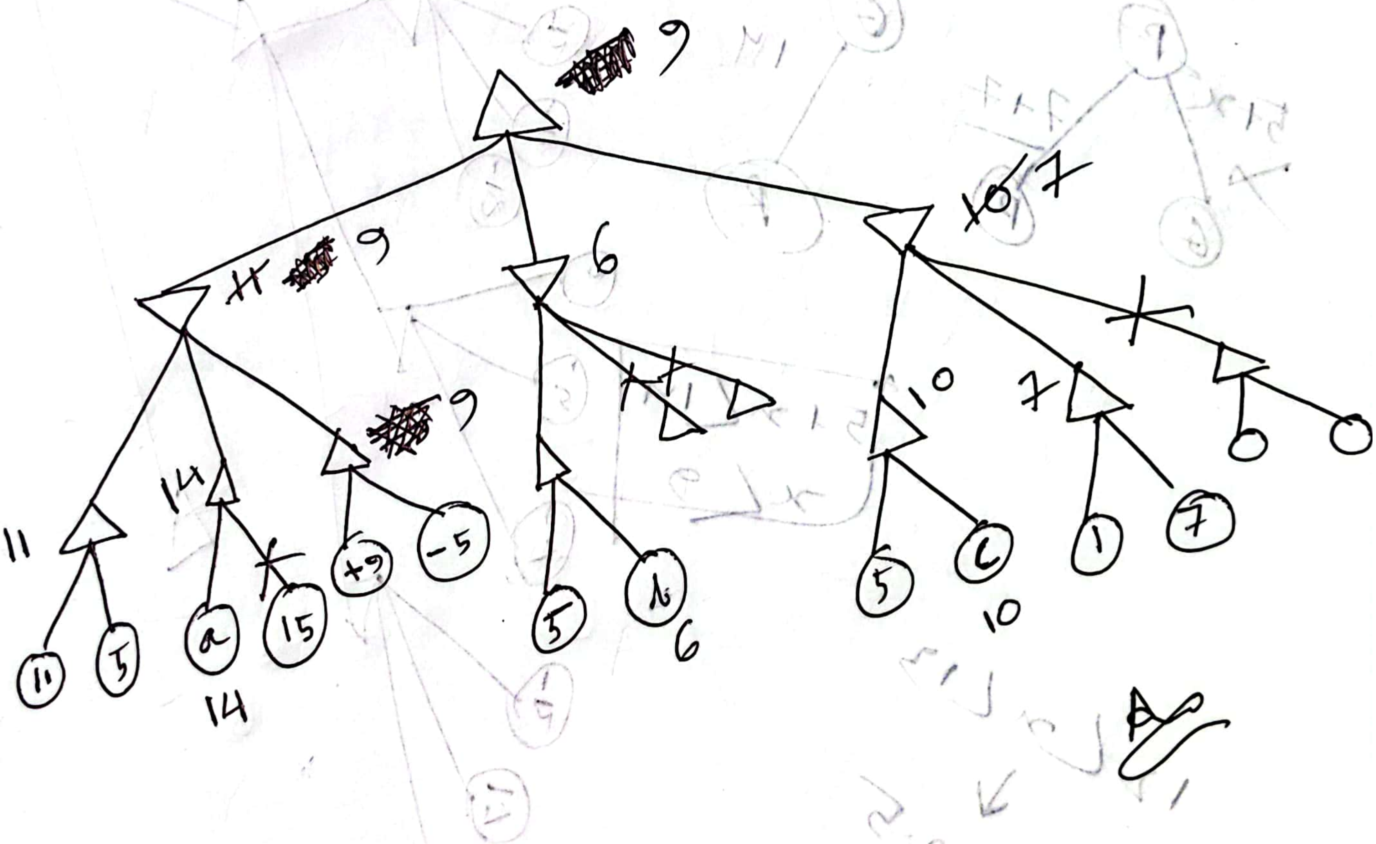
S → B → C → G

graph



S → A → C → G



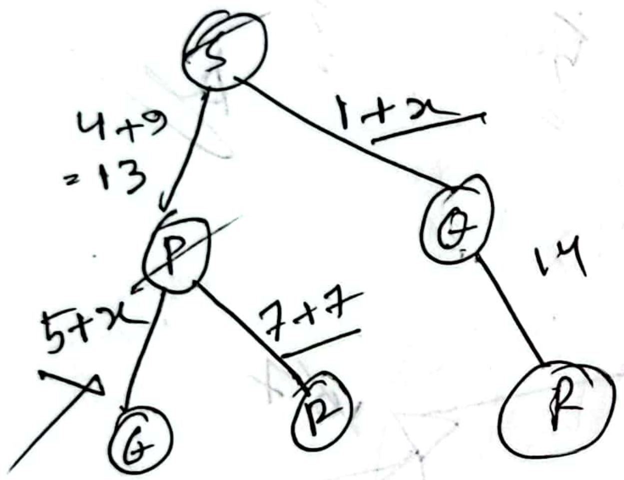


Q, R

S → P

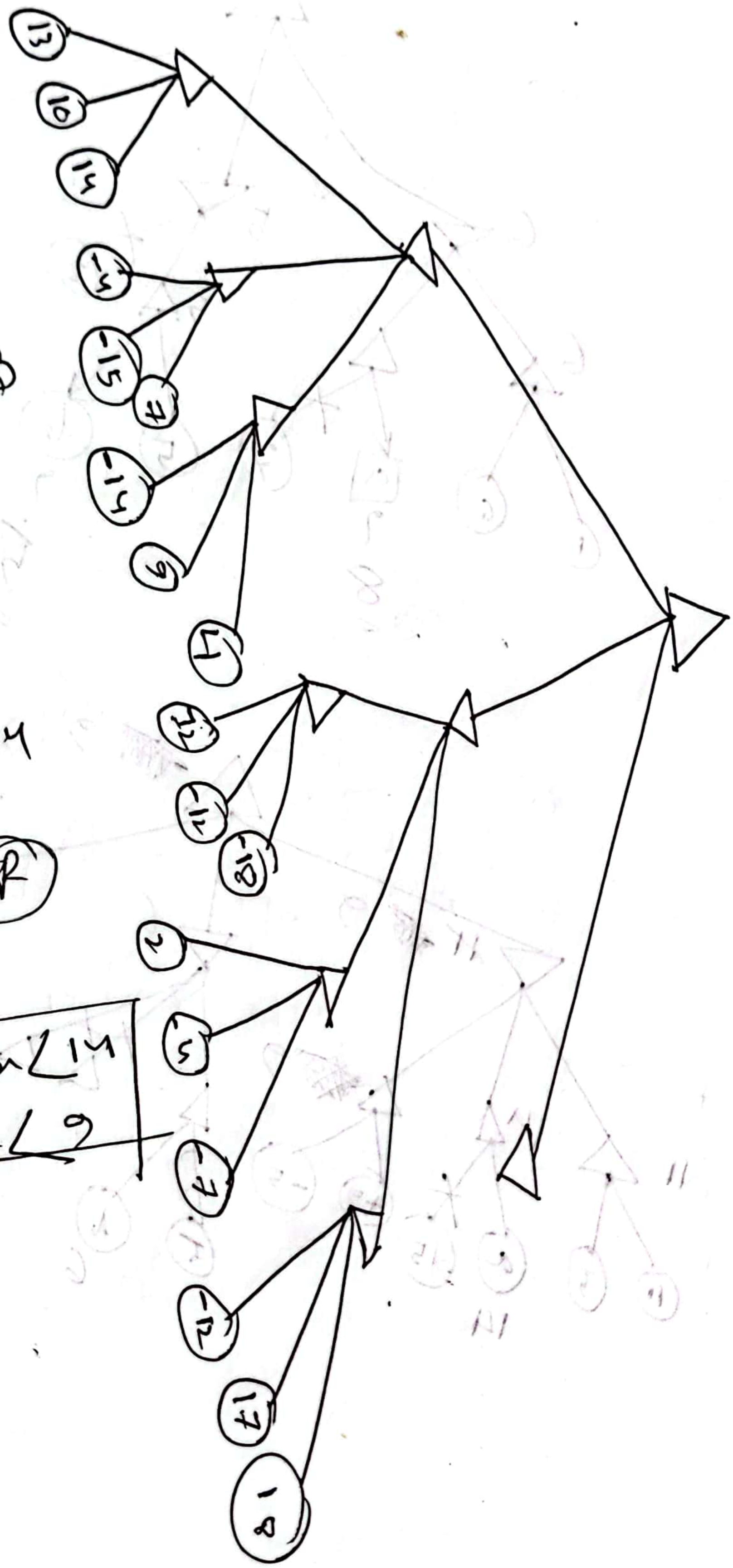
$1 + x > 13$
$x > 12$

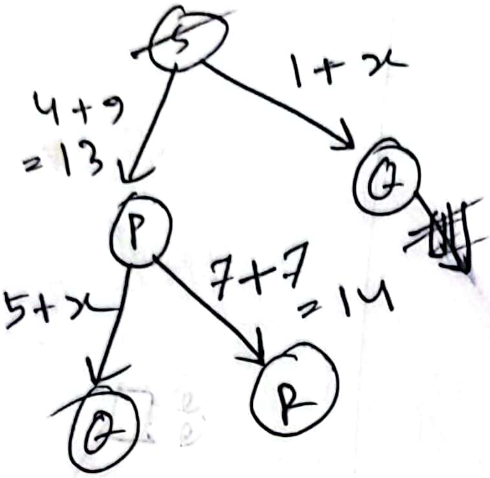
$1 + x < 14$
$x < 13$



$\boxed{\begin{array}{c} 5 + x < 14 \\ x < 9 \end{array}}$

$12 < x < 13$
↓
12.5



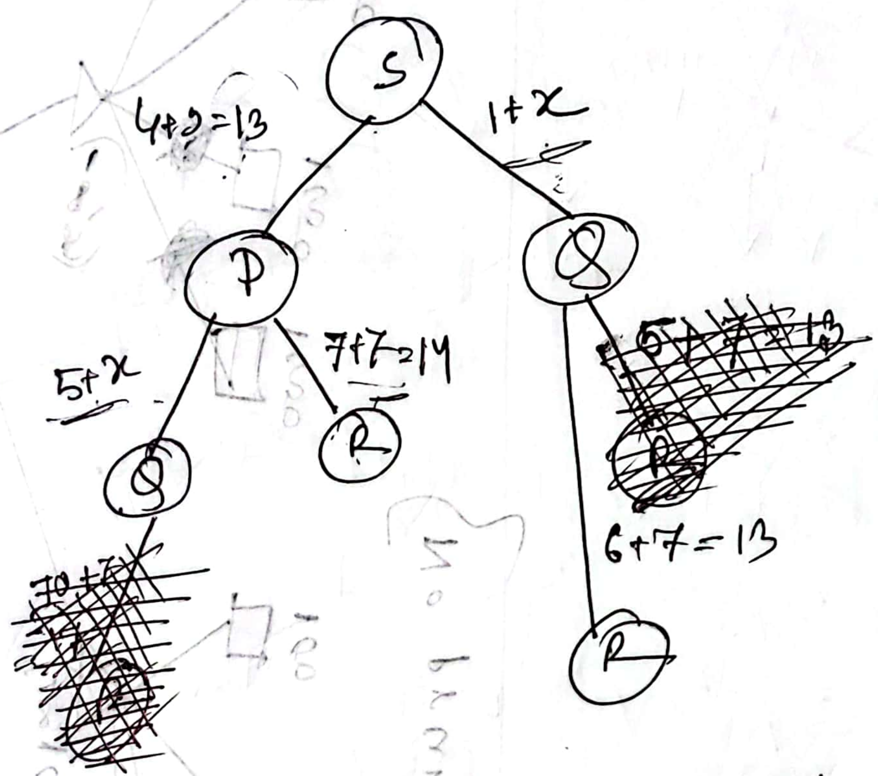


$1+x > 13$

$x > 12$

$5+x < 14$

$x < 9$



$x < 12$

$1+x > 13$

$x > 12$

$5+x < 14$

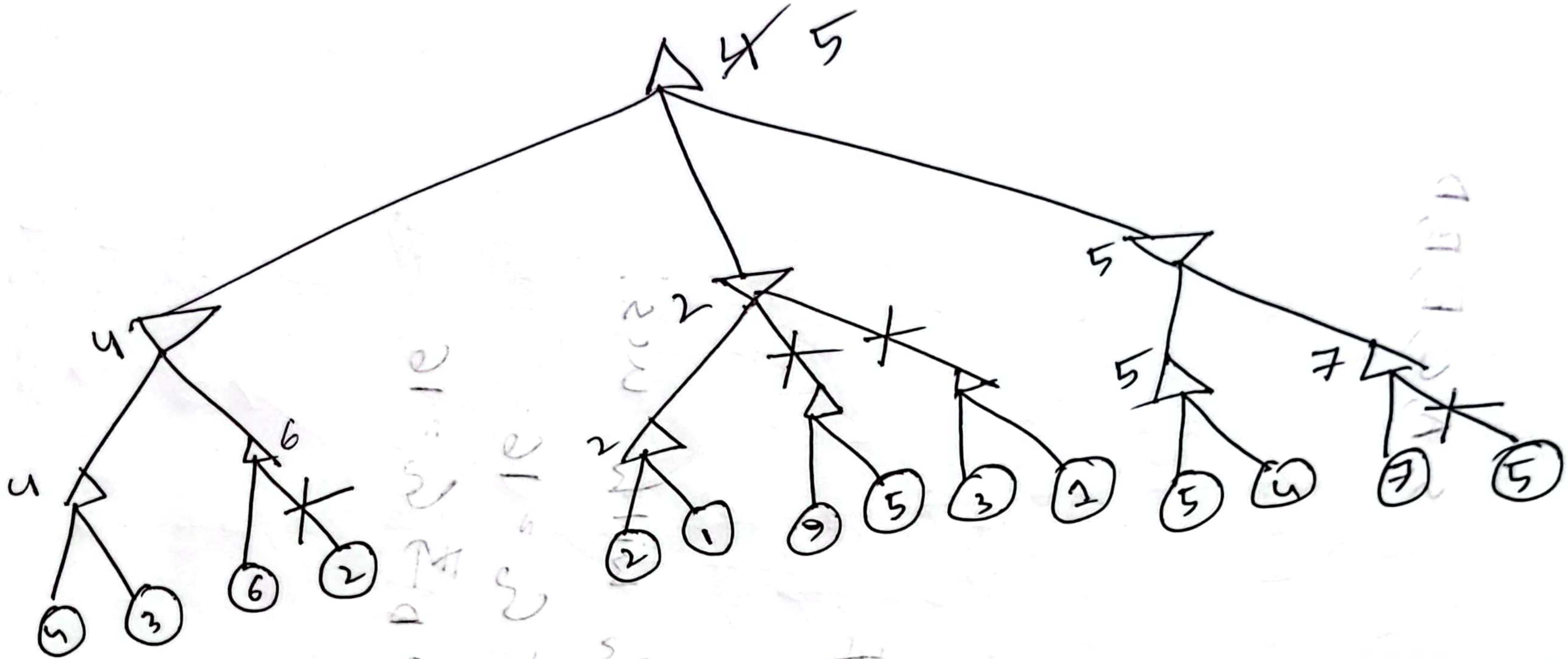
$= x < 9$

$S \to P \to Q \to R$

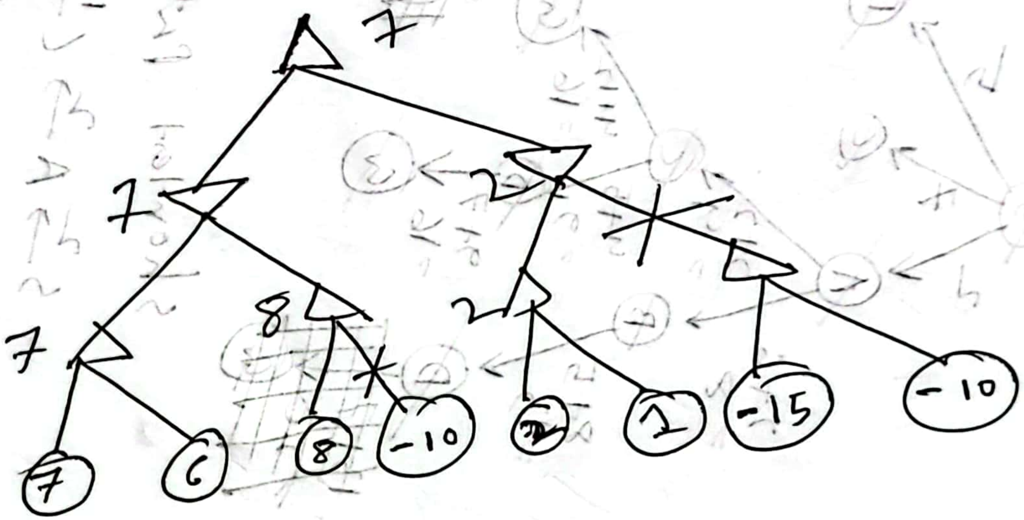
$1+x > 14$

$x > 13$

$12 < x < 13$



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

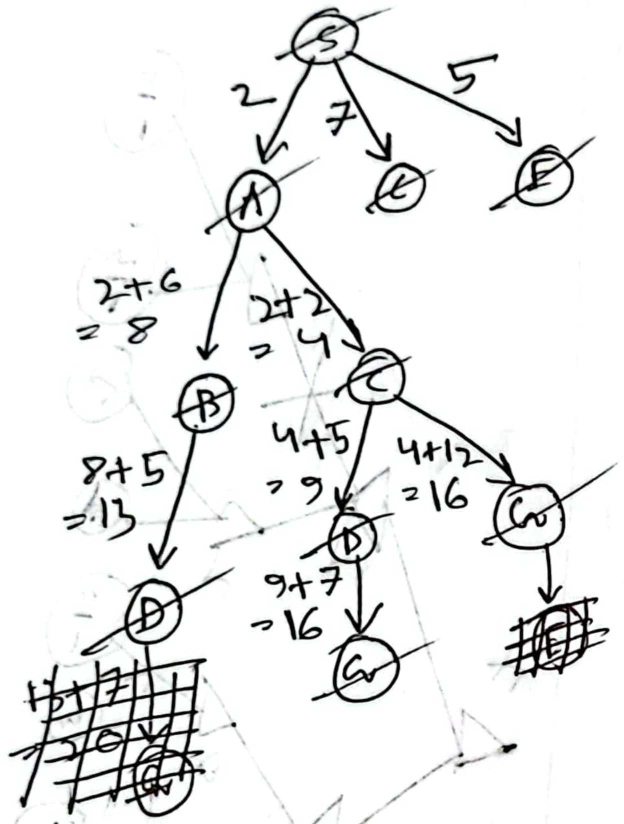


7
7
2
7
8
2
7 6 8 -10 1 -15 -10

Spring-2024

2

(a)



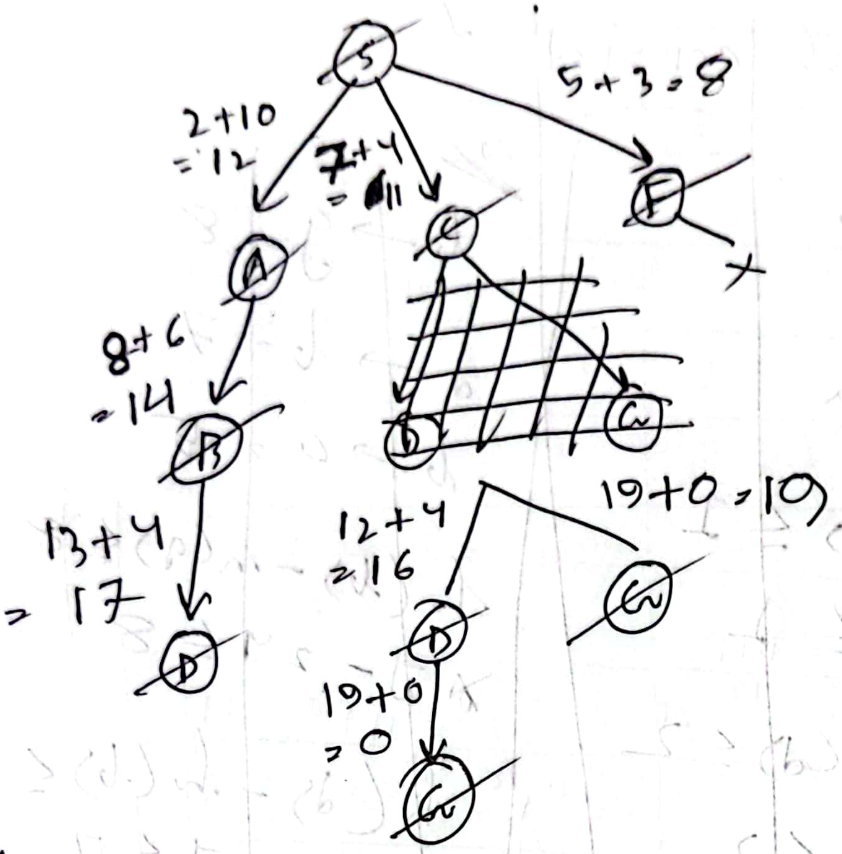
S, A, C, E, B, D

Shortest Path with UCS:

$S \xrightarrow{2} A \xrightarrow{2} C \xrightarrow{12} G = 16$

$S \xrightarrow{2} A \xrightarrow{2} C \xrightarrow{5} D \xrightarrow{7} G = 16$

S, E, C, A, B,



A*

$S \rightarrow C \rightarrow G$

$S \rightarrow C \rightarrow D \rightarrow G$

4(a)

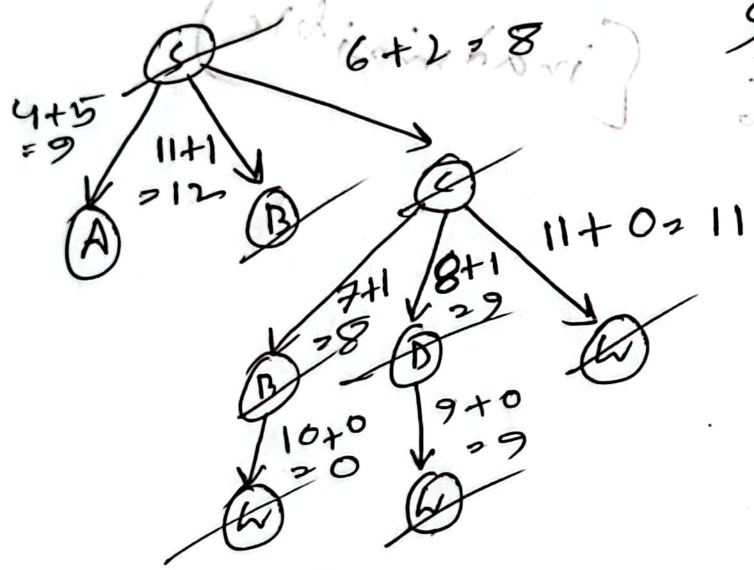
$S \xrightarrow{3} A \xrightarrow{8} B \xrightarrow{4} G$

14   11   3   0

2 (c)

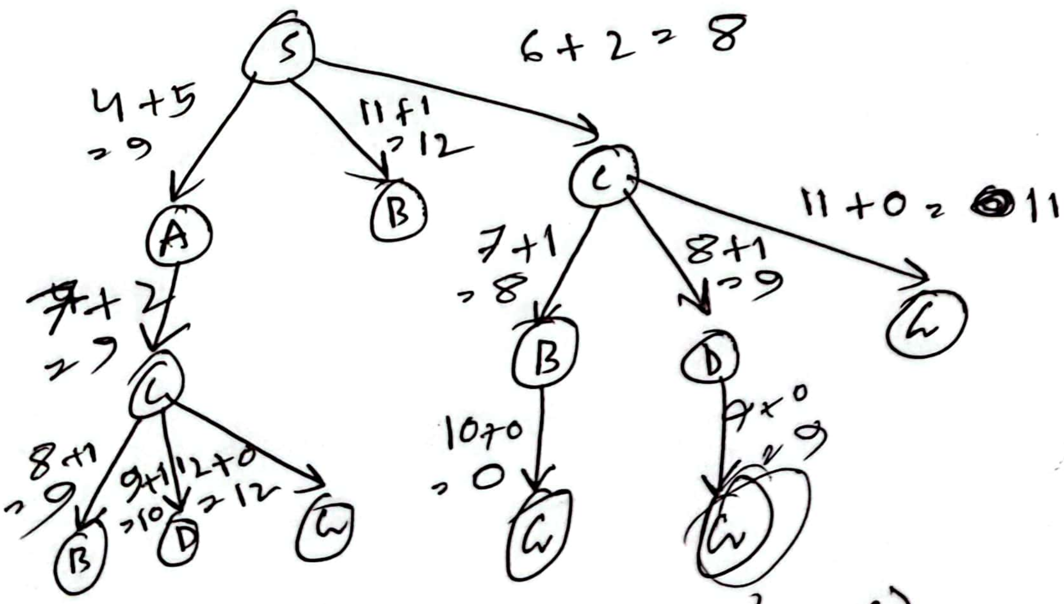
tree

S, C, D, G



$S \to C \to D \to G = (9)$

graph



(same)

Sp-23

h_1 consistency check:

$S \to a = 2$

$12 - 12 \leq 2$

$0 \leq 2$

$S \to C = 8$

$12 - 3 \leq 8$

$9 \nleq 0$ [not consistent]

admisibility check

$h^*(n) \; S \xrightarrow{8} C \xrightarrow{3} B \xrightarrow{1} G = 12$ $\quad S = 12$ admissible

$h^*(n) \; A \xrightarrow{7} C \xrightarrow{3} B \xrightarrow{1} G = 11$ $\quad h(n) = 12 \; (A)$ [inadmissible]

$h(n) \leq h^*(n)$ break

h_2

$S \to A = 2$

$11 - 4 = 7 > 2$ [not consistent]

$h^*(n) \quad S \xrightarrow{8} C \xrightarrow{3} B \xrightarrow{1} G = 12 \geq h(n) = 11$ [adm]

$h^*(n) \quad A \to C \to B \to G = 11 \geq h(n) = 4$ [adm]

$h^*(n) \quad B \to G = 1 \geq h(n) = 1$ [adm]

$h^*(n) \quad C \to G = 5 \geq h(n) = 2$ [adm]

[inconsistent]

h3

$S \to A = 2 \leq 10 - 8 = 2$ [consistent]

$S \to B = 11 \leq 10 - 1 = 9$ [consistent]

$S \to C = 8 \leq 10 - 3 = 7$ [consistent]

$A \to C = 7 \leq 8 - 3 = 5$ ["]

$C \to B = 3 \leq 3 - 1 = 2$ ["]

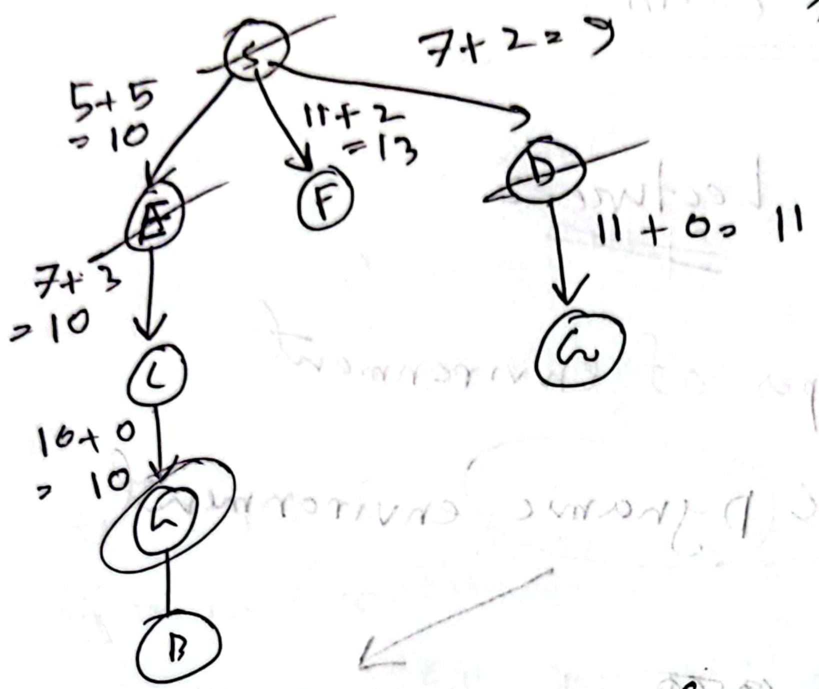
$C \to G = 5 \leq 3 - 0 = 3$ ["]

$B \to G = 1 \leq 1 - 0 = 1$ ["]

[admissible & consistent]

Sum 22

S, D, E, G



S → E → C → G = (10)

Book lecture (mid)

1.1, 1.4, 2.1, 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, 4.1,
5.1, 5.2, 5.3, 6.1, 6.2, 6.3, 6.4

Online class

AI

Lecture-1, Lecture-2

* PEAS, Types of environment

* static & Dynamic environment

এক Action থেকে অনেক n বার মধ্যে কোনো change হবে না।

। change হয়।

* Dicrete & continuous environment।

state space fixed

state space infinite

Lecture-3

search

Lecture-4

* DFS is better for space complexity only. O(bm)

* not complete.

* n optimal

* In DFS

→ Expanded path can be deleted if the path contains no solution.
So it takes low memory!

* BFS

→ complete
→ not optimal (optimal if cost equal or no cost.)
→ $o(b^s)$ → { s is the solution path (nearest to parent) }.

* DLS

→ Not complete (complete if limit ≥ goal)
→ not optimal
→ time → $o(b^l)$
→ space → $o(bl)$

* Iterative ~~Deeping~~ Deepening (BFS + DFS)

→ l = 0, 1, 2, 3 .... (every visit, if goal obtained break)
→ dfs with iteration
→ complete, → not optimal. (optimal if ---)
→ time = $o(b^l)$, → space = $o(bl)$

Lecture-5

* Uniform cost Search (U.C.S)

→ complete, optimal

→ Time & space com → $O(b^{c^*/\varepsilon})$ [bad]

Heuristic

* Greedy Search

→ Expand node with minimum heuristic.

→ complete not.

→ not optimal.

→ Better in time & space.

Lecture-6

* A* search

→ Complete, → (time & space better)

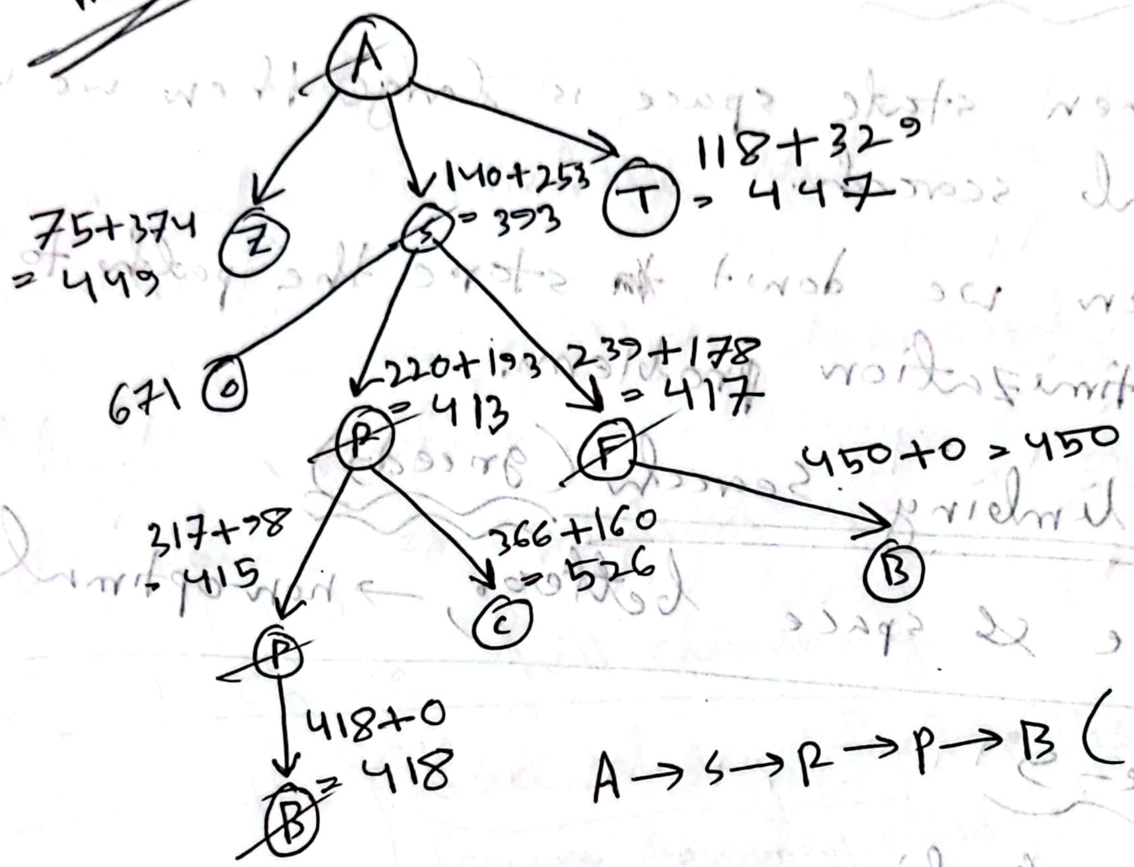
→ not optimal (optimal if heuristic is better)

* Admissible

$0 \le h(n) \le h^*(n)$

↳ (parent to goal minimum cost)

slide map



A → S → R → P → B (418)

Lecture-7

* Dominent ↦ Between two admissible heuristics the maximum one.

Lecture-8

→ maximum node expands if (heuristic = 0).

A* graph search

→ not optimal (optimal if heuristic is consistent)

Local search

→ When state space is large then we use local search.

→ when we don't ~~to~~ store the path to goal.

→ optimization problems.

Hill climbing search (greedy)

→ time & space better. → non-optimal.

Lecture-9

* Hill-climbing

→ stuck on local maxima.

→ 8 queen → (14% case passed
86% " failed)

→ (side ways move with limit will pass
94%)

Lecture-10

* stochastic hill climbing

→ not only best child but also better child.
→ choose better children randomly.
→ bigger variation.
→ depending on goodness of solution.

* First choice hill climbing

→ when the (branching factor [on avg how many child.]) is very high.
→ choose child one by one and compare with parent if good or bad. If good than expand.

* Random Restart hill climbing

→ if fail that starts with another random state.
→ always optimal.

Simulated annealing

→ worst node কে সুযোগ দেয়।

→ [for maximization problem]

20 E_1 → 2 E_2

child is very bad than parent.

So choosing the child node (probability) is also low.

$(\Delta E = E_1 - E_2)$

But

20 E_1 → 19 E_2

child is not very bad than parent.

So choosing the child node (probability) is high.

$\Delta E \uparrow$	$P \downarrow$

$\Delta E \downarrow$	$P \uparrow$

$\boxed{e^{\frac{\Delta E}{T}}}$

→ $\boxed{T}$ → can be controlled by user.

$T \uparrow$	$P \uparrow$

→

$T \downarrow$	$P \downarrow$

T select in high &

T decrease slowly.

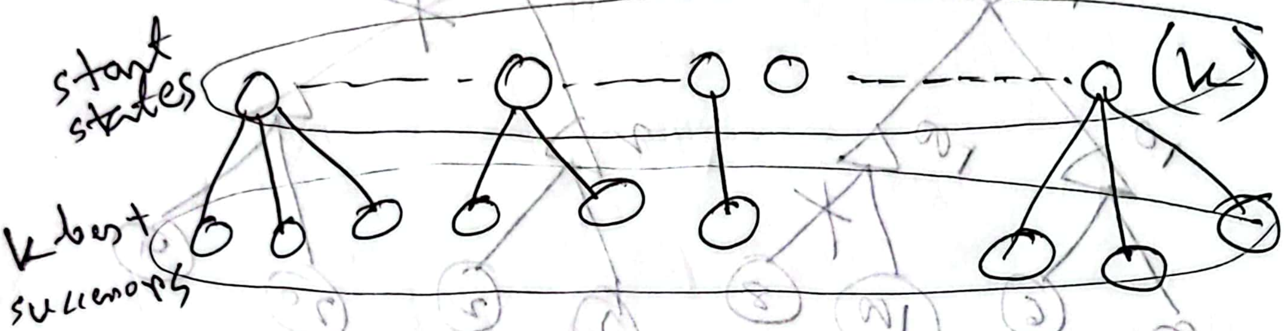
(If T = 0 return parent) (kind of first choice hill climbing)

Lecture-11 (Population based search)

* Local beam search

→ multiple start states (k numbers)

→ choose k best children. (successors)



→ diversification → broadly cover area

* Genetic Algorithm

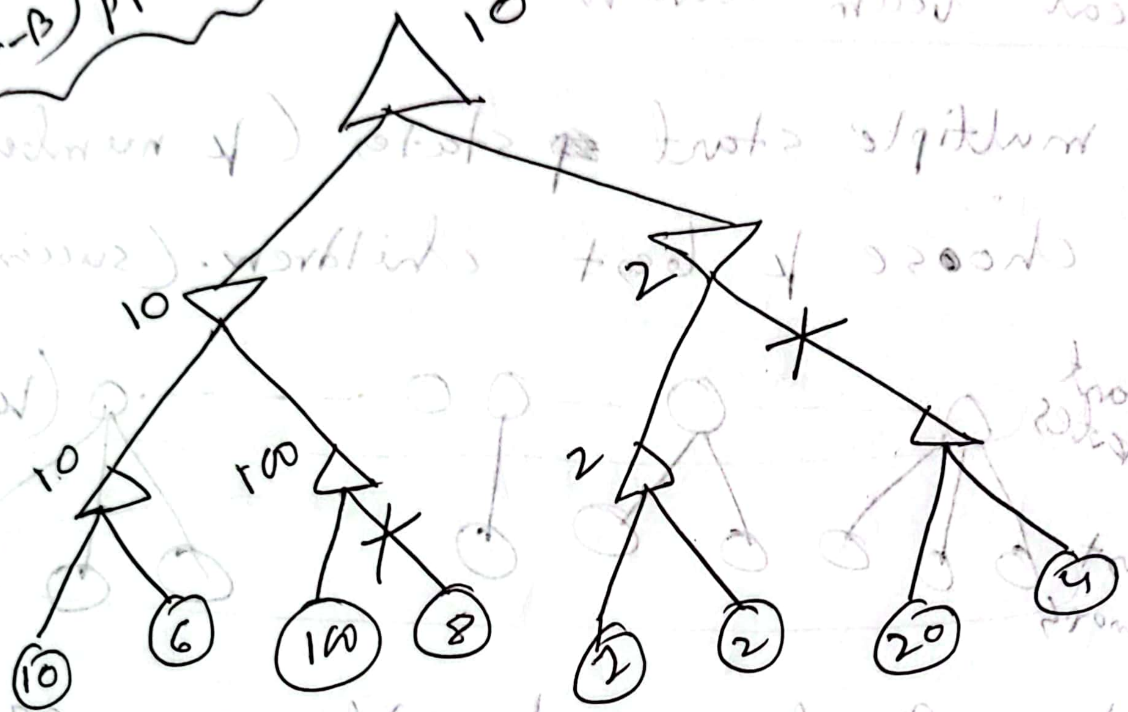
→ mutation → (randomly change any one element)

---

* minimum node expand → $h = g$
* maximum " " → $h = 0$

Lecture-13

(α-β) pruning



Lecture-14

[redacted]

Lecture-15

CSP

CW
4.10.24

AI

Lec-13

Probability

random variable

Probability distribution:

$$\boxed{\sum p = 1}$$

$P(T)$

hot	0.5
cold	0.5

$P(T = hot) = 0.5$

$P(cold) = 0.5$

Joint Distribution

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

$P(hot \;\&\; sun) = 0.4$

$P(hot) = 0.4 + 0.1 = 0.5$

$P(hot \text{ or } sun) = 0.4 + 0.1 + 0.$
$= 0.7$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

$P(+x, +y) = 0.2$

$P(+x) = 0.2 + 0.3 = 0.5$

$P(-y \text{ or } +x) = 0.3 + 0.2 + 0.1$
$= 0.6$

Marginal Distributions

P(X)

$P(x) = \sum_y P(x, y)$

X	P
+x	0.5
-x	0.5

P(Y)

$P(y) = \sum_x P(x, y)$

Y	P
+y	0.6
-y	0.4

C.W
8.9.24

AI

Conditional probabilities

$$\boxed{P(a|b) = \frac{P(a,b)}{P(b)}}$$

$$P(W=s \mid T=c) = \frac{P(s,c)}{P(c)} = \frac{0.2}{0.2+0.3}$$

$$P(+x \mid +y) = \frac{0.2}{0.2+0.4}$$

$$P(-x \mid +y) = \frac{0.4}{0.2+0.4}$$

$$P(-y \mid +x) = \frac{0.3}{0.2+0.3}$$

$$P(W \mid T=hot) = \frac{P(W,T)}{P(T=hot)}$$

Normalization

$P(X / Y = -y)$

$+x$	$-y$	0.3
$-x$	$-y$	0.1

$$p(+x/-y) = \frac{0.3}{0.3+0.1}$$

$$p(-x/-y) = \frac{0.1}{0.3+0.1}$$

Inference by Enumeration

$p(W)$

W	P
sun	0.65
rain	0.35

$p(W / \text{winter})$

S	T	W	P
winter	hot	sun	0.1
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

S	W	P
winter	sun	0.25
winter	rain	0.25

$\rightarrow \frac{0.25}{0.5}$

$\rightarrow \frac{0.25}{0.5}$

Product rule

$$p(a/b) = \frac{p(a,b)}{p(b)}$$

$$\boxed{p(b)\,p(a/b) = p(a,b)}$$

C.W
11.9.24

AI

Chain rule

$$P(x_1, x_2) = P(x_1) \cdot P(x_2 | x_1)$$

$$P(x_1, x_2, x_3, x_4) = P(x_1) \cdot P(x_2 | x_1) \cdot P(x_3 | x_1, x_2) \cdot P(x_4 | x_1, x_2, x_3)$$

$$= \cancel{P(x_1)} \; \frac{\cancel{P(x_1, x_2)}}{\cancel{P(x_1)}} \; \frac{\cancel{P(x_1, x_2, x_3)}}{\cancel{P(x_1, x_2)}} \; \frac{P(x_1, x_2, x_3, x_4)}{\cancel{P(x_1, x_2, x_3)}}$$

Bayes' Rule

$$P(x/y) = \frac{P(x, y)}{P(y)} \Rightarrow P(x, y) = P(y) \cdot P(x/y)$$

$$P(y/x) = \frac{P(x, y)}{P(x)} \Rightarrow P(x, y) = P(x) \cdot P(y/x)$$

$$P(y) \cdot P(x/y) = P(x)\, P(y/x)$$

$$P(x/y) = \frac{P(x) \cdot P(y/x)}{P(y)}$$

$P(W)$

R	P
sun	0.8
rain	0.2

$P(D/W)$

D	W	P
wet	sun	0.1
dry	sun	0.9
wet	rain	0.7
dry	rain	0.3

$P(W/dry)$

W	~~D~~	P
sun	dry	
rain	dry	

Independence

$$P(x, y) = P(x)\, P(y)$$

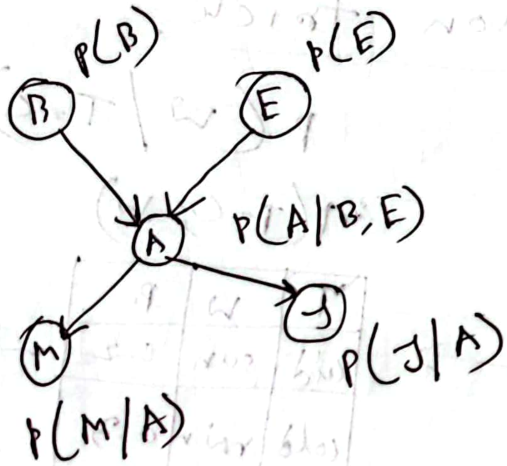
$$P(x \mid y) = P(x) \quad \boxed{x \,\&\, y \text{ independent}}$$

15.7.24

Bayes' nets (graphical model)

[[start to Bayes' Net] CT (next sunday)]

Cause → effect



C.W
18.9.24

AI

Variable Elimination

→ Hidden variable গুলোকে query side এ আনবো, then যোগ দিবো।

---

* Normalization trick

P(T, W)

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

→

P(W / T=c)

P(T=c, W)

T	W	P
cold	sun	0.2
cold	rain	0.3

→

P(W / T=c)

W	T	P
sun	cold	0.4
rain	cold	0.6

* Inference by Enumeration

P(S, T, W)

S	T	W	P
um	hot	sun	0.30
um	hot	rain	0.05
um	cold	sun	0.10
um	cold	rain	0.05
in	hot	sun	0.10
in	hot	rain	0.05
in	cold	sun	0.15
in	cold	rain	0.20

→

P(W)

W	P
sun	0.65
rain	0.35

$p(w / \text{winder})$

W	S	P
sun	win	0.25
rain	win	0.25

Bayes Rule

$$p(x/y) = \frac{p(x,y)}{p(y)} \quad \Bigg| \quad p(y/x) = \frac{p(x,y)}{p(x)}$$

$$p(x/y) = \frac{p(y/x) \cdot p(x)}{p(y)}$$

Inference by Enumeration in Baye's Net

$$p(+b / +j, +m) \propto p(+b, +j, +m)$$

$$p(+b, +j, +m) = p(+b, e, a, +j, +m)$$

Joint factor

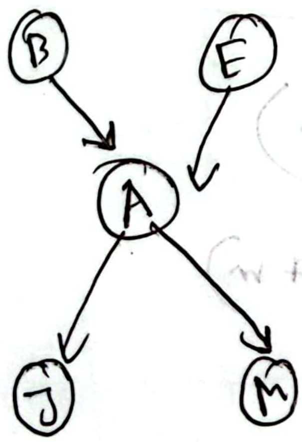
* $P(R) \times P(T/R) = P(R,T)$
* $P(R,T) \times P(L/T) = P(R,T,L)$

Eliminate

$P(R,T) \xrightarrow[\text{sum } R]{\text{marginal}} P(T)$

$\boxed{\text{multiple join, multiple eliminate = Inference by Enumeration}}$

Variable Elimination



$\boxed{P(B),\ P(E),\ P(A/B,E),\ P(J/A),\ P(M/A)}$

$\boxed{P(B/j,m) = ?}$

Choose E:

$P(E)$, $P(A/BE) \longrightarrow P(E, A/B)$

$\downarrow$

$P(A/B)$

$\boxed{P(A/B),\ P(B),\ P(J/A),\ P(M/A)}$

Choose A:

$P(A/B)$, $P(J/A)$, $P(M/A) \longrightarrow P(A, J, M/B)$

$\downarrow$

$P(J, M/B)$

$\boxed{P(J, M/B),\ P(B)}$

Choose B $\longrightarrow P(J, M, B)$

$\downarrow$

$P(B/J, M)$

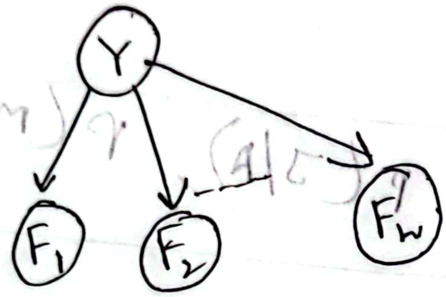
C.W

AI

Naive bayes

→ Classification

→ spam / classification.



$$P(y, F_1, \ldots F_n) = P(y) \cdot P(F_1/y) \cdot P(F_2/y) \ldots P(F_n/y)$$

Laplace smoothing

~~regular~~

$x \rightarrow$ r r b

$$P(x) = \left(\frac{2}{3}, \frac{1}{3}\right)$$

imaginary

r b

$x \rightarrow$ r r b

$$P_{LAP}(x) = \left(\frac{3}{5}, \frac{2}{5}\right)$$

[k = 1]

$$P_{LAP} = \frac{C+k}{N+k|x|}$$

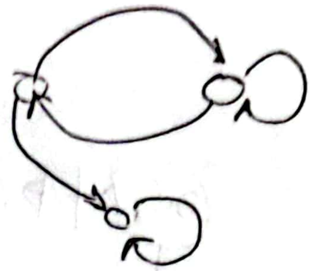
C.W
29.09.24

AI

Markov models

$x_1 \to x_2 \to x_3 \to x_n \to$

$p(x_1)$ $p(x_2/x_1)$



$$P_\infty(sun) = p(sun/sun) \cdot P_\infty(sun) + p(sun/rain)\, P_\infty(rain)$$

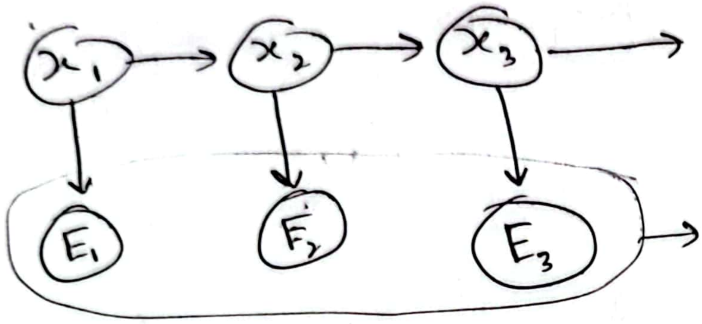
$$3P_\infty(rain) = P_\infty(sun) \quad \text{— (1)}$$

$$\boxed{P_\infty(sun) + P_\infty(rain) = 1}$$ (always given)

CW
30.9.24

AI

Hidden Markov models



observation

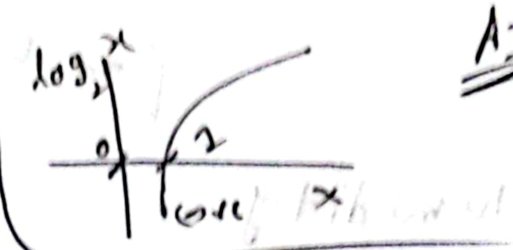
Last class (Naive ~~b~~ bayes, markov model,
hidden markov model,
DT)

[Shannon's Info Theory]

G.W

AI

Decision tree



entropy → $\boxed{-p_+ \log_2 p_+ - p_- \log_2 p_-}$

$P_+ = \frac{21}{26}$

$P_- = \frac{5}{26}$

$$= -\frac{21}{26}\log_2\frac{21}{26} - \frac{5}{26}\log_2\frac{5}{26}$$

$$\text{Gain}, S = 0.99 - \frac{26}{64} \times 0.71 - \frac{38}{64} \times 0.74$$

Scaling factor

$\boxed{\text{Gain} \uparrow,\ \text{entropy} \downarrow}$

[9+, 5-]

Humidity.

$$S = -\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14}$$
$$= 0.940$$

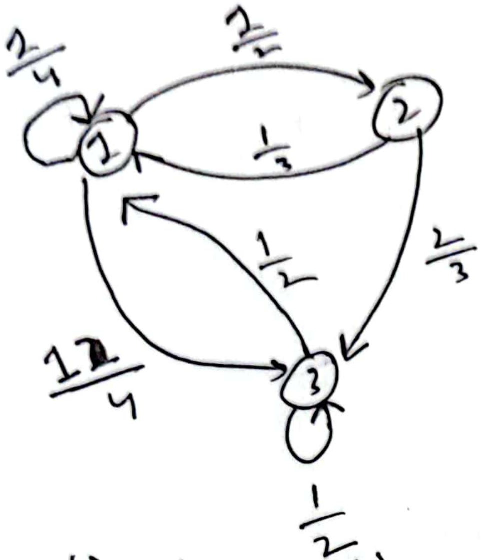
high → [3+, 4-] → 0.985

Normal → [6+, 1-] → 0.592

$$\text{Gain} = 0.940 - \frac{7}{14} \times 0.985 - \frac{7}{14} \times 0.592$$

$$= 0.151$$

1/



(a)/

		(c) 1	(s) 2	(w) 3	total
(c)	1	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{4}$	1
(s)	2	$\frac{1}{3}$	0	$\frac{2}{3}$	1
(w)	3	$\frac{1}{2}$	0	$\frac{1}{2}$	1

(d)/

$P(t_2 = \text{cheerful})$

$$\begin{pmatrix}1\\0\\0\end{pmatrix} \rightarrow \ldots = \begin{pmatrix}1-\frac{1}{4}\\0.125\\0.125\end{pmatrix} = \begin{pmatrix}0.75\\0.125\\0.125\end{pmatrix}$$

c/