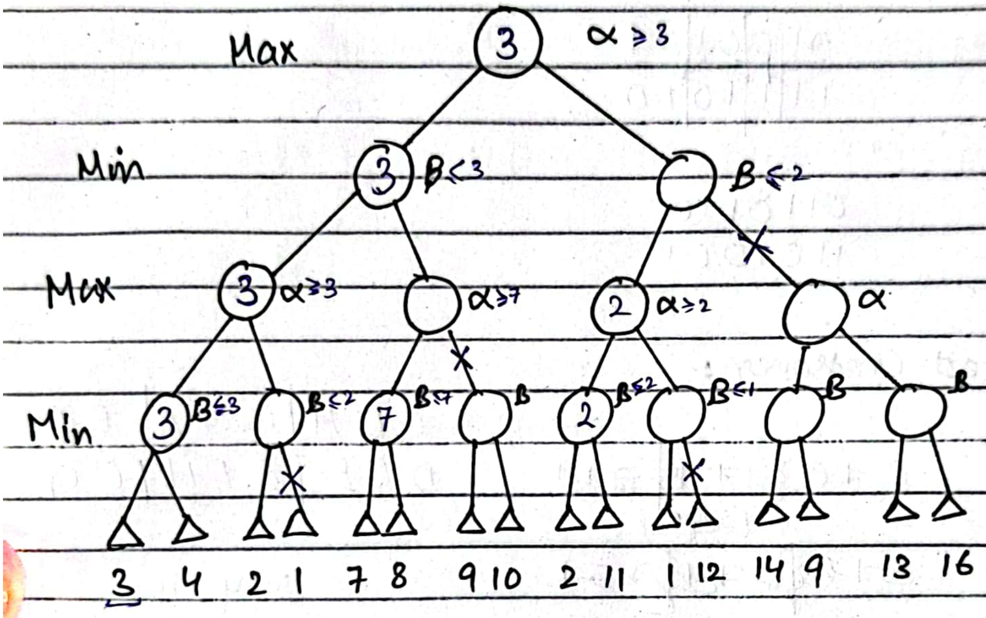
Mid Practice

AI

Alpha Beta Pruning :

worst case $O(b^d)$

Best case : $O(b^{d/2})$



Genetic Algorithm :

initial → Fitness → selection → crossover → Mutation

Types of crossover :

1) Single Point Crossover

eg

01000
11011

crossover after 2nd bit

01 | 000
11 | 011

now → 01011
11000

2) Two point crossover :

crossover after 2nd and 3rd

eg

01 | 0 | 00
11 | 0 | 11

→ 01000
11111

3) K - Point Crossover :-

eg. 01|0|01|01
11|1|10|10

0110110
1101001

4) Ordered Crossover :-

CDH|BGA|FE
DBE|AFH|CG

swap the middle one.

DBG|AFH|EC
EFH|BGA|CD

FECDHBGA
ECDBG

CGDBEAFH
CDEFH

5) Uniform Crossover :-

001011
100100

1 → swap
0 → unchanged.

Tosing : 1 0 0 1 1 0

101101
000010

Q. Max ⇒ $f(x) = x^2$ with x in [0-31]

① Generate 4 random chromosomes / genotypes

eg. 01101(13), 11000(24), 01000(8), 10011(19)

② Calculate fitness.

1) convert into an integer
2) Apply the fitness function.

$(13)^2 \Rightarrow 169$, $(24)^2 \Rightarrow 576$, $(8)^2 \Rightarrow 64$, $(19)^2 \Rightarrow 361$

③ select 2 parents based on their fitness in P_i.

$$P_i = f_i / \left(\sum_{j=1 \text{ to } n} f_j\right)$$

#	Initial Population	x	f(x)	Pi	Expected count N* Pi	Actual count
1	01101	13	169	0.14	0.56	1
2	11000	24	576	0.49	1.96	2 ←
3	01000	8	64	0.06	0.24	0
4	10011	19	361	0.31	1.24	1
Sum			Σ = 1170	Σ = 1	Σ = 4	
Avg			292.5	0.25	1	
Max			576	0.49	1.96	

Max chance of getting selected

* eliminate least value one and replace with max.

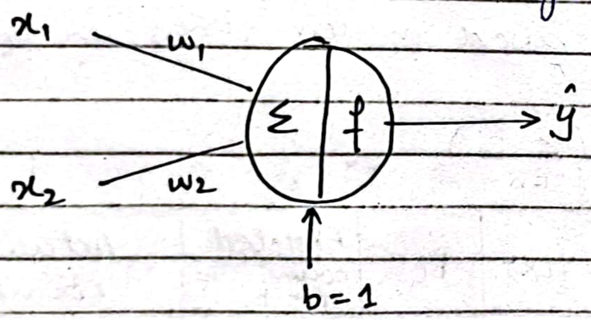
#	String	Crossover pts	Offspring after cross over	x	f(x)
1	0110|1	4	01100	12	144
2	1100|0	4	11001	25	625
2	11|000	2	11011	27	729
4	10|011	2	10000	16	256
					1754

#	offspring after crossover	offspring after mutation	x	f(x)
1	01100	11100	26	676
2	11001	11001	25	625
2	11011	11011	27	729
4	10000	10100	18	324
				2354

Neural Networks :-

1) Hebb's Rule :

Single layer perceptron



Weigth update : $w_i(new) = w_i(old) + x_i y$

- set all weigths to zero, $w_i = 0$ for $i = 1$ to n, and bias to zero.

AND Gate . with Bipolar Data .

Input			Target
x_1	x_2	b	y
-1	-1	1	-1
-1	1	1	-1
1	-1	1	-1
1	1	1	1

Step 1 : all weight and bias to zero.

$$W = [0\ 0\ 0]^T \quad b = 0.$$

Step 2 : set input vector $X_i = S_i$ for $i = 1$ to 4

$X_1 = [-1\ -1\ 1]^T$
$X_2 = [-1\ 1\ 1]^T$
$X_3 = [1\ -1\ 1]^T$
$X_4 = [1\ 1\ 1]^T$

Step 3 : Output value set to $y = t$.

Step 4: Modify using Hebb's rule. $(w_{(new)} = w_{(old)} + x_i y_i)$

Iteration 1: $[0\ 0\ 0]^T + [-1\ -1\ 1]^T \cdot [-1]$

$= [1\ 1\ -1]^T$

Iteration 2: $[1\ 1\ -1]^T + [-1\ 1\ 1]^T \cdot [-1]$

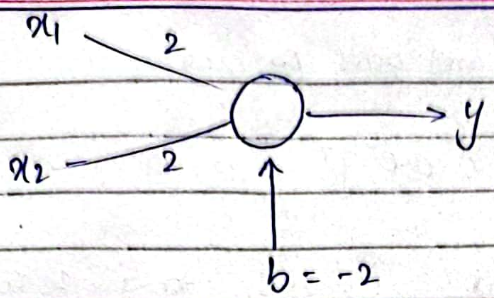
$= [2\ 0\ -2]^T$

Iteration 3: $[2\ 0\ -2]^T + [1\ -1\ 1]^T \cdot [-1]$

$= [1\ 1\ -3]^T$

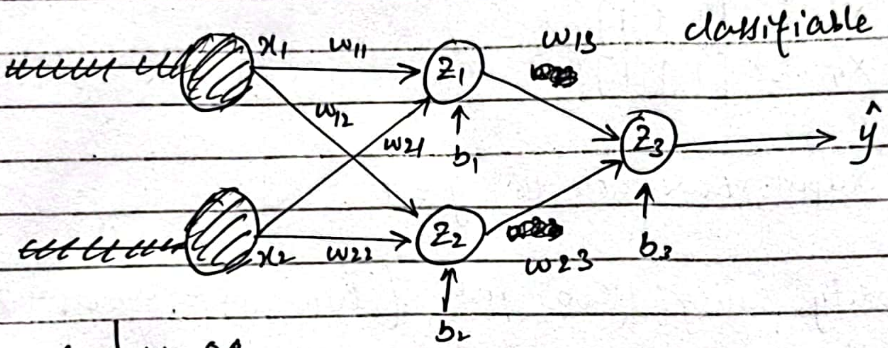
Iteration 4: $[1\ 1\ -3]^T + [1\ 1\ 1]^T \cdot [1] =$

$= [2\ 2\ -2]^T$



Delta Rule:

* Data is not linearly classifiable.



$x_1 = 1$	$w = 0.1$
$x_2 = 1$	$w_{23} = 1$
$y = 1$	$\delta = 0.2$

↳ learning rate.

Activation function to use:

$= \text{sigmoid} = g(x) = \dfrac{1}{1 + e^{-x}}$

Absolute Err (E) $= |y - \hat{y}|$ — ①

$g'(x) = x(1-x)$

Squared Err $= \frac{1}{2} \cdot (y - \hat{y})^2$ — ②

$\delta \uparrow$ local minima and maxima

$\uparrow$ time reach optimal

$$\Delta Z = E \times g'(Z) \text{ — ③}$$

$$w_{new} = w_{old} + \delta \times \Delta Z \times \text{input value}$$

$$b_{new} = b_{old} + \delta \Delta Z$$

same

linear Activation

$$g'(x) = x \times (1-x)$$

$$g(x) = \frac{1}{1+e^{-\gamma}} \rightarrow \text{gamma}$$

sympoid Activation

$$h_1 = (x_1 w_1 + x_2 w_3 + x_3 w_5) + b_1 = g(h_1) =$$
$$h_2 = (x_1 w_2 + x_2 w_4 + x_3 w_6) + b_2 = g(h_2) =$$
$$O_1 = (h_1 \times w_7 + h_2 w_9) + b_3 = g(O_1) =$$
$$O_2 = (h_1 \times w_8 + h_2 w_{10}) + b_4 = g(O_2) =$$

$$\Delta O_1 = E \times g'(O_1)$$

$\boxed{3\text{dp}}$.

$$\Delta O_2 = E \times g'(O_2)$$

$$\Delta h_1 = \{\Delta O_1 \times g'(h_1) w_7 + \Delta O_2 \times g'(h_2) w_8\}$$

$$\Delta h_2 = \{\Delta O_1 \times g'(h_2) w_9 + \Delta O_2 \times g'(h_2) w_{10}\}$$

$$w_4 = w_4^{old} + \gamma \Delta h_2 \times x_2$$

↳ learning rate

$$w_{10} = w_{10}^{old} + h_2 \times \Delta O_2 + \gamma$$

$$b = b^{old} + \gamma \Delta h$$

↳ eg $b_1 = b_1^{old} + \gamma \Delta h_1$