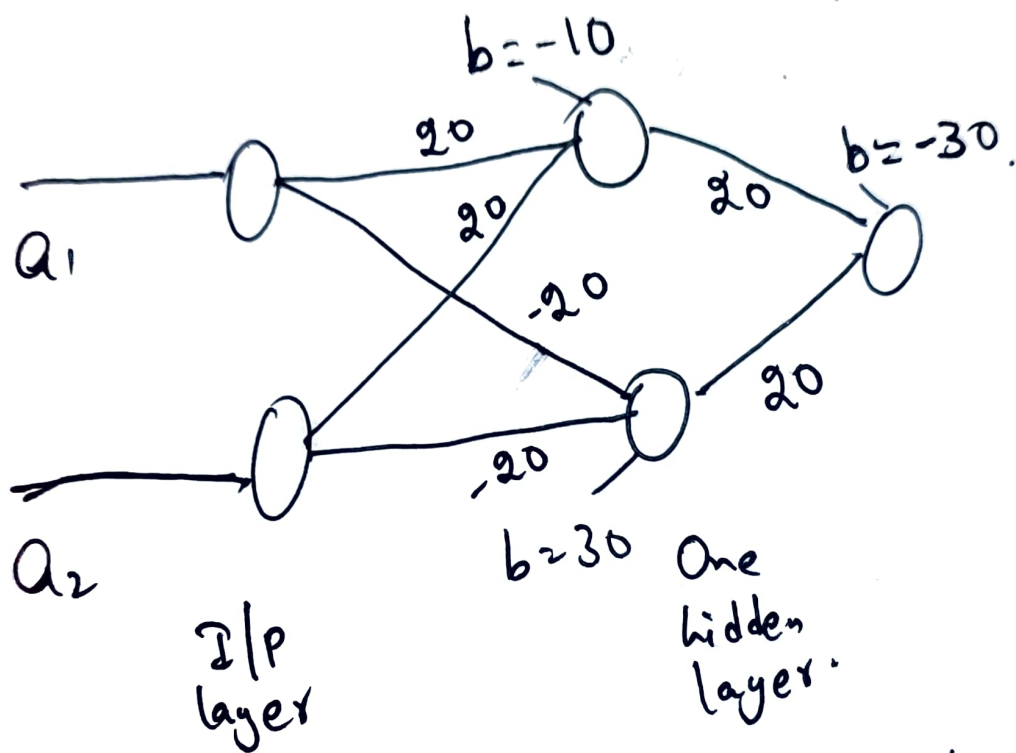
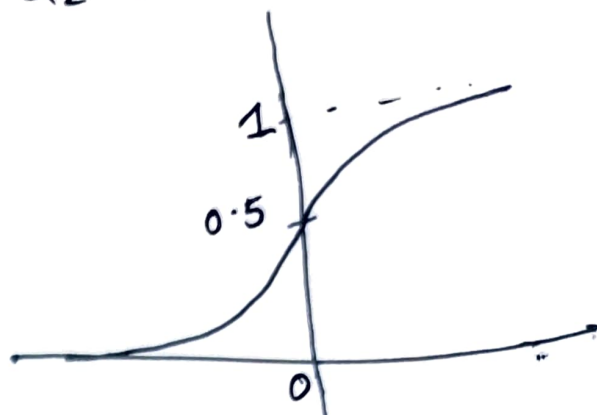


①  $a_1, a_2, y.$   
 a)  $T_1, T_1, F_0$   
 $T_1, F_0, T_1$   
 $F_0, T_1, T_1$   
 $F_0, F_0, F_0$

$$a_1 \bar{a}_2 + a_2 \bar{a}_1$$



add Sigmoid Functions in neurons of hidden layer and o/p layer.

0,0 input  
at  $h_1$

$$(20 \times 0 + 20 \times 0 - 10) = 0$$

at  $h_2$

$$(-20 \times 0 - 20 \times 0 + 30) = 1$$

at  $y$

$$(20 \times 0 + 20 \times 1 - 30) = \underline{0}$$

(1,0) input

$$(20 \times 1 + 20 \times 0 - 10) = 1$$

$$(-20 \times 1 - 20 \times 0 + 30) = 1$$

$$(20 \times 1 + 20 \times 1 - 30) = 1$$

(0,1) input

$$(20 \times 0 + 20 \times 1 - 10) = 1$$

$$(-20 \times 0 - 20 \times 1 + 30) = 1$$

$$(20 \times 1 + 20 \times 1 - 30) = 1$$

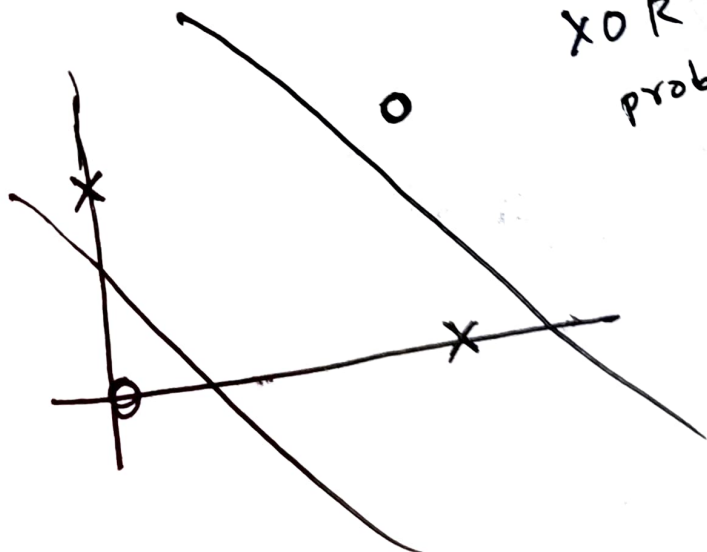
(1,1) input

$$(20 \times 1 + 20 \times 1 - 10) = 1$$

$$(-20 \times 1 - 20 \times 1 + 30) = 0$$

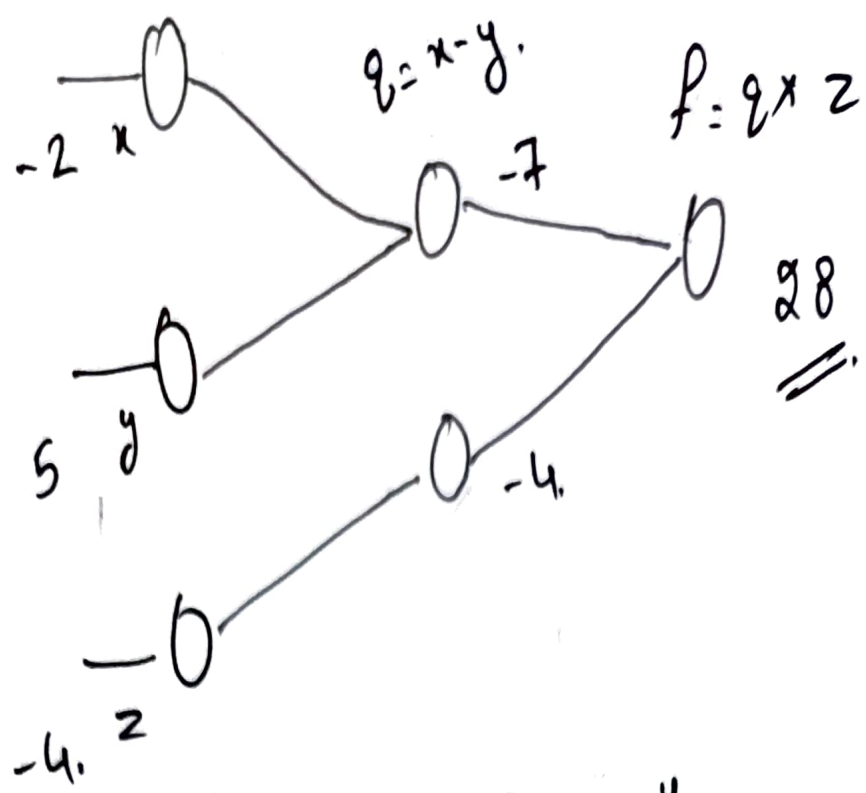
$$(20 \times 1 + 20 \times 0 - 30) = \underline{0}$$

XOR  
problem



①

b)



$$f = qz \quad q = x - y$$

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \times \frac{\partial q}{\partial x} = 2 \times (1) = 2$$

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \times \frac{\partial q}{\partial y} = 2 \times (-1) = -2$$

$$\frac{\partial f}{\partial z} = \frac{\partial f}{\partial z} = 28$$

(itself in between linear transformation)

Q2.

$$E(w) = - \sum_{n=1}^N \sum_{k=1}^K t_{kn} \ln y_k(x_n, w)$$

$K \rightarrow$  No. of classes  
 $N \rightarrow$  no. of data samples.

$t \rightarrow$  expected o/p.

$y_k \rightarrow$  n/w o/p.

$$y_k(x_n, w) = P(t_k=1|x)$$

$$y_k(x, w) = \frac{\exp(a_k(x, w))}{\sum_j \exp(a_k(x, w))}$$

$$\Rightarrow \frac{\partial E}{\partial a_k} = \frac{\partial E}{\partial y_k} \times \frac{\partial y_k}{\partial a_k}$$

$$\frac{\partial y_k}{\partial a_k} = \frac{\exp(a_k(x, w)) \sum_j \exp(a_j(x, w)) - \exp(a_k(x, w)) \exp(a_k(x, w))}{\left( \sum_j \exp(a_j(x, w)) \right)^2}$$

$k=j$

$$= y_k(1 - y_k)$$

$$\frac{\partial y_k}{\partial a_k} = \frac{0 - e^{a_k} \cdot e^{a_j}}{\left( \sum e^{a_k} \right)^2} = - y_k y_j$$

$k \neq j$

Now 
$$\frac{\partial E}{\partial y_k} = - \sum_{n=1}^N \sum_{k=1}^K t_{kn} \cdot \frac{1}{y_k(x_n, w)}$$

$$\frac{\partial E}{\partial a_k} = - \sum_{k \neq n} \sum_{k=1}^K t_{kn} \cdot \frac{1}{y_k(x_n, w)} \times \frac{\partial y_k}{\partial a_k} - \cancel{\sum_{k=1}^K t_{kn} y_k}$$

$$- t_{kn} \times \frac{1}{y_k} \times \frac{\partial y_k}{\partial a_k}$$

$$= - \sum_{k \neq n} \sum_{k=1}^K \frac{t_{kn}}{y_k(x_n, w)} (-y_k y_i) - \frac{t_{kn}}{y_k} y_k (1 - y_k)$$

$$\frac{\partial E}{\partial a_k} = \sum_{k \neq n} \sum_{k=1}^K t_{kn} y_k + t_{kn} y_k - t_{kn}$$

$$= \sum_{k \neq n} \sum_{k=1}^K t_{kn} y_k - t_{kn}$$

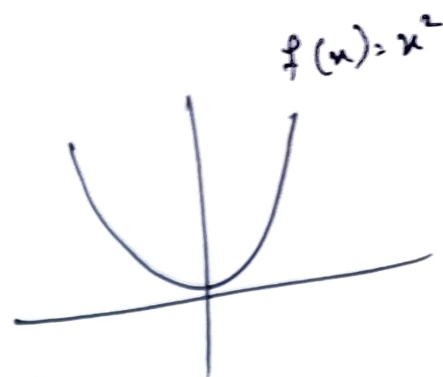
$$= y_k \underbrace{\sum_{k \neq n} \sum_{k=1}^K t_{kn}} - t_{kn}$$

↓  
This will be 1

$$\therefore \boxed{\frac{\partial E}{\partial a_k} = y_k - t_k}$$

$$(3) f(x) = x^2 \quad E_{AV} = \frac{1}{M} \sum_{m=1}^M E_x [(y_m(x) - f(x))^2]$$

$$E_{ENS} = E_x \left[ \frac{1}{M} \sum_{m=1}^M (y_m(x) - f(x))^2 \right]$$



$$E_{ENS} = E_x \left[ \frac{1}{M} \sum_{m=1}^M (y_m(x) - f(x))^2 \right]$$

$$E_{AV} = \frac{1}{M} \sum_{m=1}^M E_x [(y_m(x) - f(x))^2]$$

Rearranging

$$E_x \left[ \frac{1}{M} \sum_{m=1}^M y_m(x) - f(x)^2 \right] \leq \frac{1}{M} \sum_{m=1}^M E_x [(y_m(x) - f(x))^2]$$

all the terms of  $E_{ENS}$  are continuous in  $E_{AV}$  and hence proved.

$$E_{ENS} \leq E_{AV}$$

It is hold for any error function  $E(y)$  not just for sum of squares.