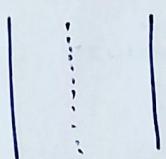


* Neuro-computing an introduction

Parking a vehicle.



Move left-right until parked
properly/perfectly.

The above learning is how
our neural network learns.

if labelled data \rightarrow supervised
if learns by getting feed back
 \rightarrow reinforcement learning.

* fundamental idea behind neural network?

The primary task of ANN or NN model try
to simulate the biological neural network
with electronic circuit.

Biological vs ANN.

- BNNs :
 - primary task is to control various function.
 - The brain consist of billions of neuron connected by synapses
 - It process the information in a massively parallel manner.
 - It can learn and adapt quickly with minimal effort.

→ ANN:-

- inspired by BNN.
- uses Mathematical Models (neurons) connected in layers.
- learns by adjusting weight using technique like back propagation.

* ANN can also called as connectionist model / PDP?
Connection list model because knowledge is stored in the connection (weight) between artificial neuron.

PDP (parallel distributed processing):-

Because computation occur in parallel across many neuron, similar to how brain process information.

Purpose of ANN:-

To achieve human like performance.

* Similarity b/w ANN & BNN:

- Gets g/p via synaptic connections.
- Accumulated input is transformed to a single output.
- output is transmitted through axon
- if $IP > 0$, the neuron fires. (if it crosses some threshold)
- Total opf \leftarrow Firing rate.

BNN

Synapse (receive signal)

Soma (process input)

Axon (transmit op)

threshold based firing

firing rate control op.

ANN

input connection (weights).

Weighted sum function

op neuron activation

Activation function
(RELU, sigmoid) etc.

Output magnitude
from activation
function.

* ANN: →

Massively parallel interconnect network,
of simple processing elements which are
intended to interact with the object of
real world in the same way as biological
system.

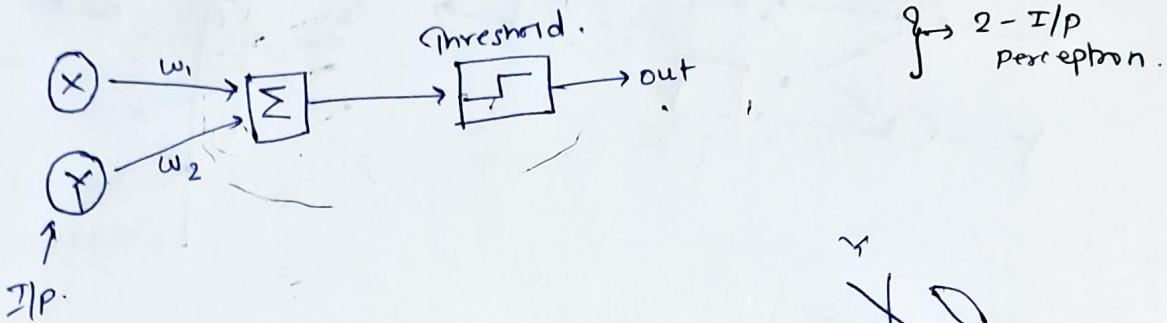
NN model an extreme simplification of human
neural system.

Computational elements (neuron/nodes/processes) are
analogous to neurons of biological system.

* Characteristics.

- learn from example
- generalize from previous example to new one
- abstract essential characteristics from inputs.

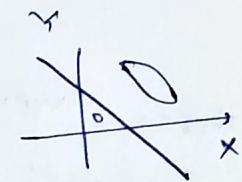
Perception :- A single neuron connected by weights to a set of inputs.



$$\text{if } w_1x + w_2y > \theta \rightarrow \text{OP} = 1$$

\uparrow
threshold.

$$w_1x + w_2y = \theta \rightarrow \text{separating line.}$$



* Learning rule :-

present a set of input pattern, adjust the weights until the desired output occur for each of them.

$$w_p(t+1) = w_p(t) + \Delta_i;$$

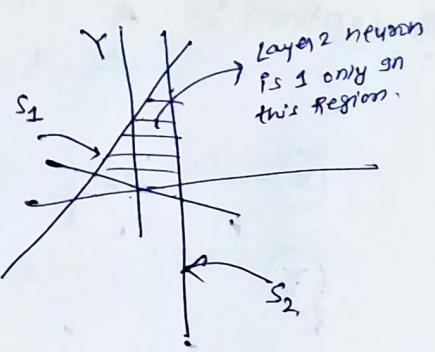
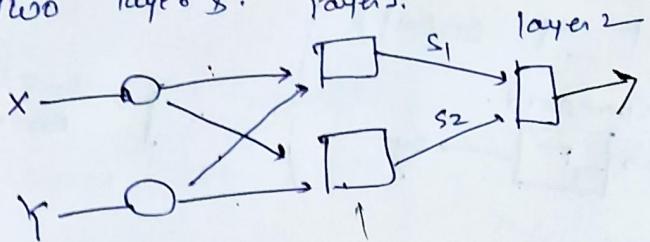
$$\Delta_i = \eta \delta x_i;$$

$$\delta = T - A \quad \{ \text{Target} - \text{Actual} \}.$$

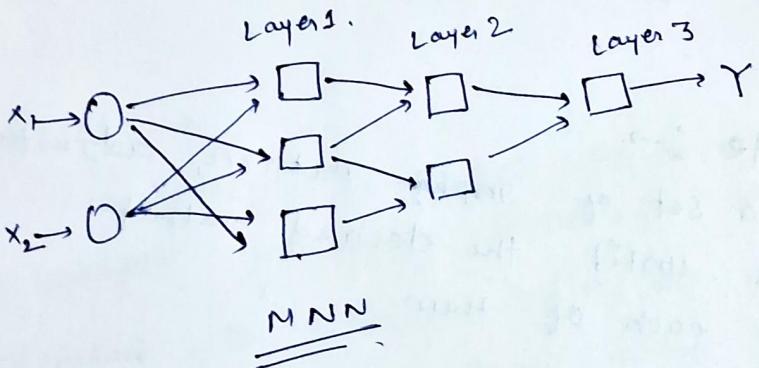
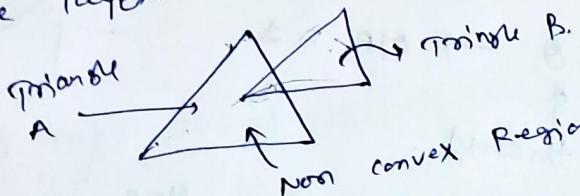
$\eta \rightarrow$ learning rate.

* if the set of pattern are linearly separable then single layer perceptron is enough.

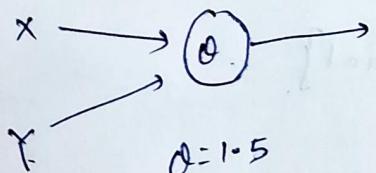
* Two layers :-



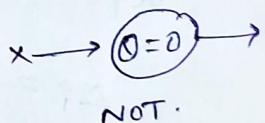
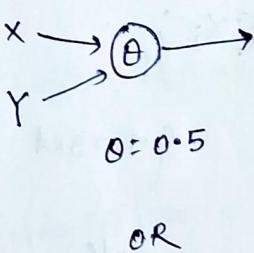
* Three layers :-



* Boolean function !-

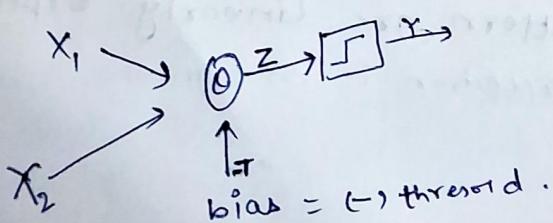


And



$$Z = \sum_i w_i x_i - T$$

$$Y = \begin{cases} 1 & \text{if } Z \geq 0 \\ 0 & \text{else.} \end{cases}$$



* SOFT Perception (logistic).

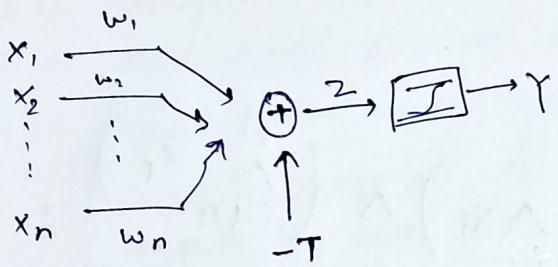
$$Z = \sum w_i x_i - T$$

$$Y = \frac{1}{1 + \exp(-Z)} = \frac{1}{1 + e^{-Z}}$$

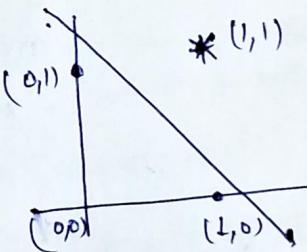
→ Sigmoid Activation.

A squashing function instead of a threshold at output.

Activation function! - The function that act on weighted combination of input (and threshold).

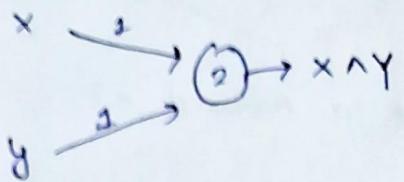


* In general one neuron is enough for linear function. (i.e. data will be linearly separable).

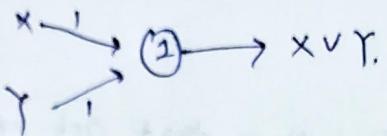


And is linearly separable.

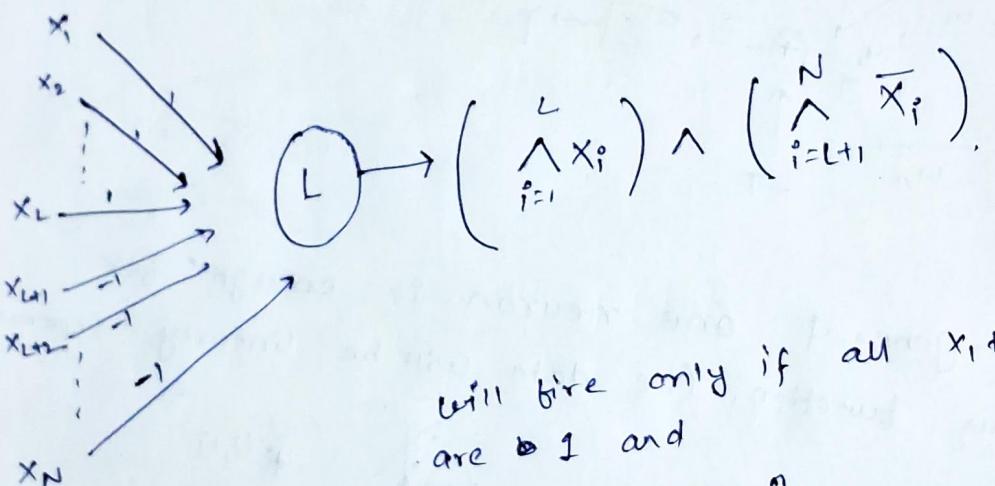
* Perception as a Boolean gate :-



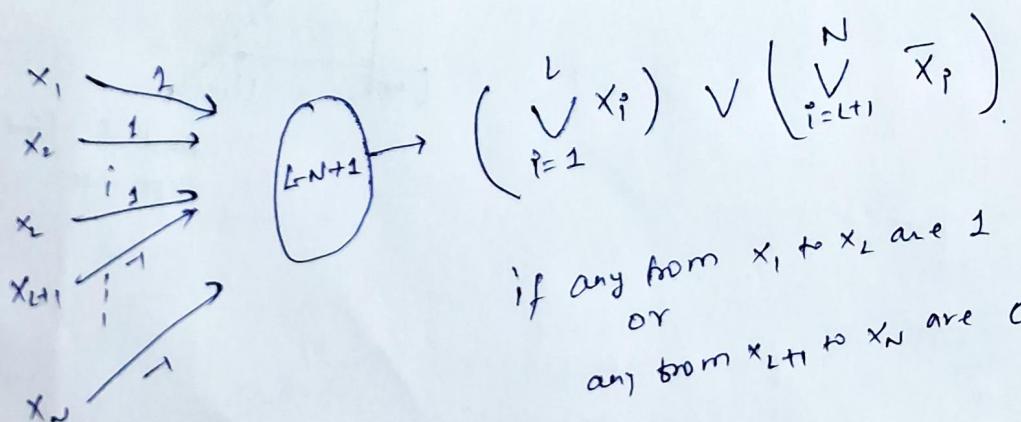
$$x \leftarrow 1 \rightarrow 0 \rightarrow x$$



A perceptron can model any simple binary Boolean gate.



will fire only if all x_1 to x_L are 1 and x_{L+1} to x_N are 0.



if any from x_1 to x_L are 1 or any from x_{L+1} to x_N are 0.

for atleast 1^c at place of 1 on thread put 1^c.

ANN (MLP)

- A NN consist of layers of ~~neurod~~ artificial neuron and connection b/w them.
- each connection is associate with weight.
- Training done to get right weight and bias so that error get minimized.

* NN Learning:-

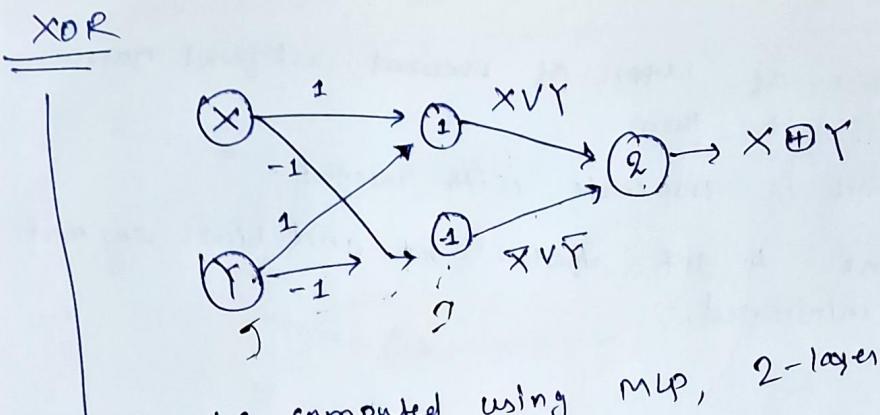
1. → input fed into I/P layer.
- 2 → Weighted o/p fed into hidden layer.
- 3 → Activation function applied.
- 4 → repeat to next layer.
- 5 → Weighted o/p of last hidden layer are inputs to units making up the o/p layer.

* A Network containing 2 hidden layers is called 3-layer neural network.

→ (depend on activation function.)
↳ on 3-hidden layer.

* Decision boundary:-

- | | | |
|-----------------|---------------------------------|-----------------|
| 0- hidden layer | → linear classifier. | open or closed. |
| 1- hidden layer | → boundary of convex region. | |
| 2- hidden " | → combination of convex region. | |
- $z = \sum(w_i \cdot x_i) + b \rightarrow$ decision boundary $z=0$.



can be computed using MLP, 2-layer NN.

* MLPs can compute any boolean function.

* Input to node:

$$I_i = \sum_{\substack{\text{All} \\ \text{connected} \\ \text{node}}} \text{Weight} * \text{o/p of previous node.}$$

$$\text{Output of } I^m \text{ node} = f(I_i)$$

↑
Activation function.

* Weight updation:

$$E = \frac{1}{2} \sum (t_i - o_i)^2 \rightarrow \text{for learning correct weight reduce } E \text{ as much as possible.}$$

① Gradient descent technique:-

$$\Delta w_{ji} \propto -\frac{\partial E}{\partial w_{ji}} = -\eta \frac{\partial E}{\partial w_{ji}} = -\eta \frac{\partial E}{\partial I_j} \cdot \frac{\partial I_j}{\partial w_{ji}}$$

$$= \eta \delta_j o_i + ^n$$

$$\delta_j = -\frac{\partial E}{\partial I_j} = -\frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial I_j} = -\frac{\partial E}{\partial o_j} f'(I_j).$$

for nodes on op layer.

$$\Delta w_{ji} = \eta \left(-\frac{\partial E}{\partial o_j} \right) f'(I_j) O_i .$$

for hidden layer.

$$\begin{aligned} \frac{\partial E}{\partial o_j} &= \sum_k \frac{\partial E}{\partial I_k} \frac{\partial I_k}{\partial o_j} = \sum_k \frac{\partial E}{\partial I_k} \frac{\partial \sum_l w_{kl} o_l}{\partial o_j} \\ &= \sum_k \frac{\partial E}{\partial I_k} w_{kj} \\ &= \sum_k (-\delta) w_{kj} . \end{aligned}$$

$$\Delta w_{ji} = \eta \left(\sum_k \delta_k w_{kj} \right) f'(I_j) O_i$$

if $O_j \rightarrow$ sigmoid.

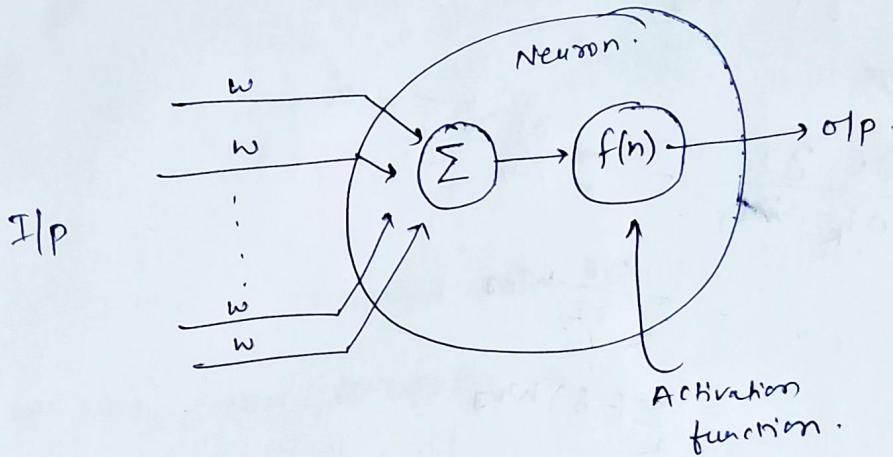
$$\text{then } f'(O_j) = O_j(1-O_j)$$

NOTE :-

$$\Delta w_{ji} = \begin{cases} \eta \left(-\frac{\partial E}{\partial o_j} \right) O_j(1-O_j) O_i & \rightarrow \text{op layer.} \\ \eta \left(\sum_k \delta_k w_{kj} \right) O_j(1-O_j) O_i & \rightarrow \text{hidden layer.} \end{cases}$$

large value of η will lead to oscillation.
so to just increase the momentum without oscillation
add bias $\Delta w_{ji}(t)$.

Artificial Neuron



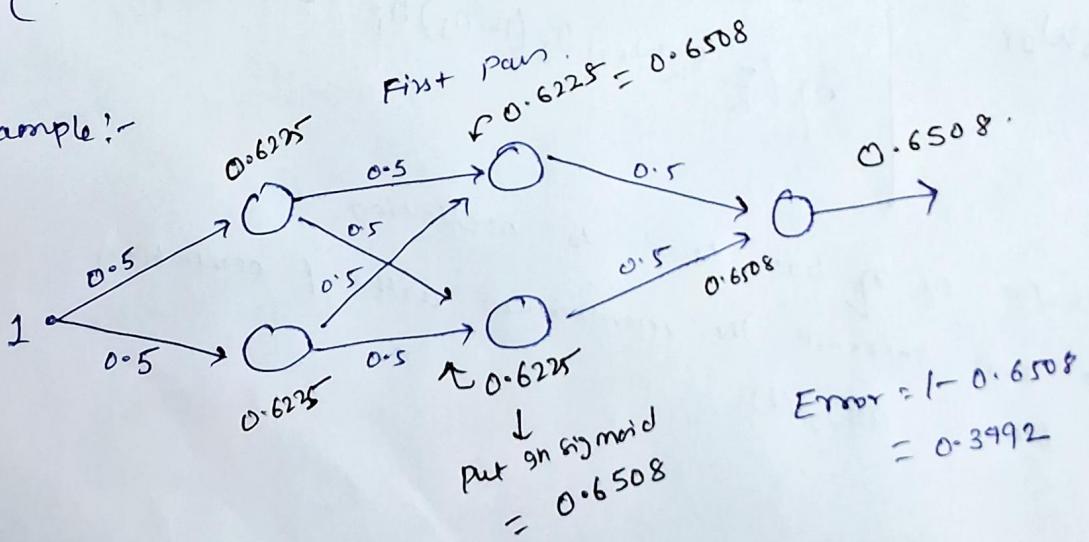
* Back-propagation:-

[Gradient of neuron (G) = slope of activation / transfer function.]

* $\left[\sum \text{[weight of neuron to the next neuron} \cdot \text{gradient of next neuron } g \right]$

[Gradient of o/p :- slope of transfer function * error.]

example:-



CNN (convolution Neural network)

Neural n/w with ~~at least~~ convolution operation instead of matrix multiplication in at least one of the layers.

Architecture :-

CNN is a deep learning model designed for image processing and pattern recognition. It extracts spatial hierarchies of feature from an image using convolutional layers.

A CNN consist of four types of layer:-

1 → input layer

takes an image (e.g RGB of size $224 \times 224 \times 3$)
No of channel depend on the image type.
(1 for grayscale, 3 for RGB).

2 → convolutional layer (feature extraction) :-

- Applies filter/kernel (small matrices like 3×3 or 5×5) to detect feature.
- Captures edge, texture, shapes and patterns.
- Output:- A feature mapped (transformed representation of the image).
- Op-size = $\frac{(I - F + 2P)}{S} + 1$

$I \rightarrow$ Input size. $P \rightarrow$ padding
 $F \rightarrow$ filter size $S \rightarrow$ stride.

ex:- $I = 32 \times 32$
 $f = 3 \times 3$
Strid = 1
padding = 0

Op featuremaps = 30×30

3 → Activation function:- (non-linearity).
Typically ReLU (Rectified Linear unit) is used

$$f(x) = \max(0, x)$$

- introduces non-linearity in model, allowing it to learn complex features.

4 → Pooling layer (Down-sampling)

→ Reduces feature map size while preserving important information.

Types:-

- Max pooling → Takes the maximum value in small window (e.g. 2×2).
- Average pooling → Takes the average value.

ex:- 82×32 feature map

↓ after 2×2 pooling.
 16×16

5 → fully connected layer (classification):
• flattens the feature map onto a 1D vector.
• uses dense fully connected layer to make prediction.

ex:- if predicting cat or dog → final layer has 2 neurons.

6 → Output layer (softmax / sigmoid) →

- Softmax → used for multi-class classification.
- Sigmoid → used for binary class classification.

* Convolution :-

It is a fundamental mathematical operation used in image processing, signal processing, and deep learning. It helps to extract features, enhance image and perform transformation like smoothing, sharpening and edge detection.

$$y(m,n) = \sum_i \sum_j x(i,j) \cdot h(m-i, n-j)$$

$x(m,n)$ → I/P image

$h(m,n)$ → kernel/mask (filter)

$y(m,n)$ → feature map.

each value in the output is a weighted sum of nearby input values, with weights given by kernel.

example :-

$$x(m,n) = \begin{pmatrix} 9 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

$$h(m,n) = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$y(n_1, n_2) = \sum_{k_1=0}^{\infty} \sum_{k_2=0}^{\infty} x(k_1, k_2) h(n_1 - k_1, n_2 - k_2)$$

perform convolution b/w x and h .

$$x(m,n) = \begin{matrix} 0 & 1 & 2 \\ 1 & \left[\begin{matrix} 4 & 5 & 6 \\ 7 & 8 & 9 \\ 0 & & \end{matrix} \right]_{2 \times 3} \\ 2 & \end{matrix}$$

$$\begin{aligned} x(0,0) &= 4 \\ x(0,1) &= 5 \\ x(0,2) &= 6 \\ x(1,0) &= 7 \\ x(1,1) &= 8 \\ x(1,2) &= 9 \end{aligned}$$

$$h(m,n) = \begin{matrix} 0 & \left[\begin{matrix} 1 \\ 1 \\ 1 \end{matrix} \right] \\ 1 & \\ 2 & \end{matrix}_{3 \times 1}$$

$$\begin{aligned} h(0,0) &= 1 \\ h(1,1) &= 1 \\ h(2,1) &= 1 \end{aligned}$$

dim of op:- $\dim(x) + \dim(h) - 1$

$$= 4 \times 3$$

$$y(m,n) = \begin{pmatrix} y(0,0) & y(0,1) & y(0,2) \\ y(1,0) & y(1,1) & y(1,2) \\ y(2,0) & y(2,1) & y(2,2) \\ y(3,0) & y(3,1) & y(3,2) \end{pmatrix}$$

$$y(m,n) = \begin{bmatrix} 4 & 5 & 6 \\ 11 & 13 & 15 \\ 11 & 13 & 15 \\ 7 & 8 & 9 \end{bmatrix}$$

done zero padding
when needed.

EX: -2:

$$x(m,n) = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

$$h(m,n) = \begin{pmatrix} :: \\ :: \\ :: \end{pmatrix}$$

$$y(m,n) = \begin{pmatrix} 1 \\ 5 \\ 12 \\ :: \\ 7 \end{pmatrix}$$

$$\rightarrow \begin{pmatrix} 1 & 2 & 3 \\ 5 & 4 & 6 \\ 12 & 15 & 9 \end{pmatrix}$$
$$\rightarrow \begin{pmatrix} 1 & 3 & 3 & 0 \\ 5 & 12 & 6 & 0 \\ 12 & 27 & 9 & 0 \end{pmatrix}$$
$$\vdots \quad \begin{pmatrix} 1 & 3 & 3 & 5 & 3 \\ 5 & 12 & 6 & 16 & 9 \\ 12 & 27 & 18 & 33 & 18 \\ :: & :: & :: & :: & :: \\ 11 & 24 & 16 & 33 & 18 \\ 7 & 15 & 12 & 27 & 18 \end{pmatrix}$$

I/P Matrix $x(m, n)$ and $h(m, n)$

$$x(m, n) = \begin{pmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}_{2 \times 3}$$

$$h(m, n) = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}_{3 \times 1} \quad h(-m, -n)$$

dimension of resultant matrix = $\begin{cases} \text{no of rows of } x(m, n) + \\ \text{no of rows of } h(m, n) \\ - 1, \\ \text{no of column of } x(m, n) \\ + \text{no of column of } h(m, n)^{-1} \end{cases}$

$$\text{op} = 4 \times 3.$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} =$$

$$\begin{bmatrix} 4 & 5 & 6 \\ 11 & 13 & 15 \\ 11 & 13 & 15 \\ 7 & 8 & 9 \end{bmatrix}$$

$$Q: 2 \Rightarrow x(m, n) = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \quad h(m, n) = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

\downarrow
 $h(-m, -n)$

$$\text{op dim} = (3+3-1) * (3+2-1)$$

$$= 5 \times 4.$$

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 3 & 0 \\ 0 & 4 & 5 & 6 & 0 \\ 0 & 7 & 8 & 9 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 3 & 5 & 3 & 0 \\ 5 & 12 & 14 & 9 \\ 12 & 27 & 33 & 18 \\ 11 & 24 & 28 & 15 \\ 7 & 15 & 17 & 9 \end{bmatrix}$$

Q:8: $x(m,n) = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$ $h(m,n) = (3,4,5)$

Linear convolution

$$\text{OP OUT: } (3+1-1) * (3+3-1) \\ = 3 \times 5.$$

$$h(m,-n) = (5,4,3)$$

$$\begin{matrix} 0 & 0 & 1 & 2 & 3 & 0 & 0 \\ 0 & 0 & 4 & 5 & 6 & 0 & 0 \\ 0 & 0 & 7 & 8 & 9 & 0 & 0 \end{matrix} \Rightarrow \begin{bmatrix} 5 & 14 \\ 14 & \end{bmatrix}$$

$$= \begin{bmatrix} 3 & 10 & 22 & 22 & 15 \\ 12 & 31 & 48 & 49 & 80 \\ 21 & 52 & 94 & 76 & 45 \end{bmatrix}.$$

* Co-relation:
by $h(m,n) \leftarrow$ as it is, perform same above operation.

* Determine Co-relation b/w two matrices:

$$x_1[m,n] = \begin{bmatrix} 3 & 1 \\ 2 & 4 \end{bmatrix} \quad x_2[m,n] = \begin{bmatrix} 1 & 5 \\ 2 & 3 \end{bmatrix} \Rightarrow x_2[-m,-n] = \begin{bmatrix} 3 & 2 \\ 5 & 1 \end{bmatrix}$$

Step 1: rotate one matrix by 180° i.e. $x_2[-m,-n]$

Step 2: Now perform linear convolution b/w $x_1[m,n]$ and $x_2[-m,-n]$.

Ques:- formation of block matrix
 + equal to number of ~~rows~~ columns :-
 Here we have 2 columns in X_1 hence.
 A block matrix will be then.
 $H_0 \& H_1$.

Ques:- H_0 will be formed from first row of X_1 .
 i.e 3 1

$$\begin{bmatrix} 3 & 0 \\ 1 & 3 \\ 0 & 1 \end{bmatrix}$$

Ques:- H_1 will be formed from 2nd row of X_1 (M, n)

$$H_1 = \begin{bmatrix} 2 & 0 \\ 4 & 2 \\ 0 & 4 \end{bmatrix}$$

Step 3:- formation of block - top left matrix.

$$A = \begin{bmatrix} H_0 & 0 \\ H_1 & H_0 \\ 0 & H_1 \end{bmatrix}$$

No of zero to be appended in block matrix A
 depend on the number of rows of X_1 (M, n).

NOW Substitute the value of H_0 & H_1 .

$$\begin{bmatrix} 3 & 0 & 0 & 0 & 7 \\ 1 & 3 & 0 & 0 & \\ 0 & 1 & 0 & 0 & \\ 0 & 0 & 2 & 0 & \\ 0 & 0 & 4 & 2 & \\ 0 & 0 & 0 & 4 & \end{bmatrix} = \begin{bmatrix} 3 & 2 & 5 & 1 \\ 9 & 9 & 2 & \\ 10 & 2 & 4 & \end{bmatrix}$$

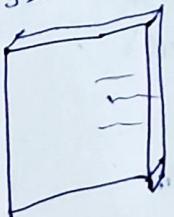
$$\begin{bmatrix} H_0 & 0 \\ H_1 & H_0 \\ 0 & H_1 \end{bmatrix}$$

$$\begin{bmatrix} 3 & 0 & 0 & 0 \\ 1 & 3 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 2 & 0 & 3 & 0 \\ 4 & 2 & 1 & 3 \\ 0 & 4 & 0 & 1 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 4 & 2 \\ 0 & 0 & 0 & 4 \end{bmatrix} * \begin{bmatrix} 3 \\ 2 \\ 5 \\ 1 \end{bmatrix} = \begin{bmatrix} 9 \\ 9 \\ 2 \\ 21 \\ 24 \\ 9 \\ 10 \\ 22 \\ 4 \end{bmatrix}$$

$$Y[m,n] = 3 \times 3 = \begin{bmatrix} 9 & 9 & 2 \\ 21 & 24 & 9 \\ 10 & 22 & 4 \end{bmatrix}$$

* Convolution Layer :-

$32 \times 32 \times 3$, 9 image.



filter.
 $5 \times 5 \times 3$

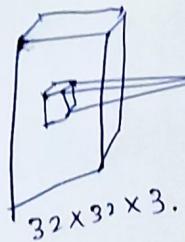
1 number.

filter always extend
the full depth of
volume.

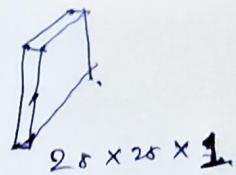
convolve the filter
with the image
i.e. slide over the
image spatially,
computing dot
product.

Result of taking dot product b/w
small chunck & filter.
i.e. $5 \times 5 \times 3 = 75$ -dimensional dot product + 1 bias.

$W^T x + b$

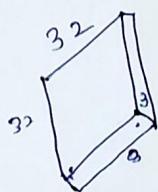


convolve (slide)
over all
Spatial location

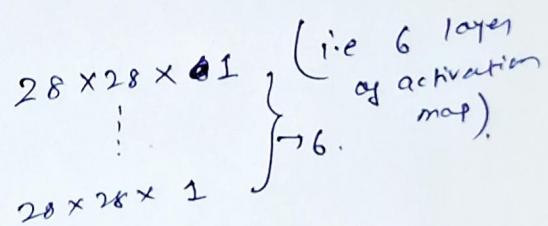


Activation map.

if we have 6, 5×5 filters then we'll get 6 separate activation maps.



Convolution
layer.



will stack up all those to get
a new image of size $28 \times 28 \times 6$