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UNIT-3

Clustering and Regression

⟹ **Clustering:**

Clustering (or) cluster analysis is a machine learning techniques, which groups the unlabelled dataset. It can be defined as "A way of grouping the data points into different cluster, consisting of similar data points.

* The objects with the possible similarites remain in a group that has less (or) no similarites with another group.

* It does it by finding some similar patterns in the unlabelled dataset such as shape, size, color behaviour etc.... & divides them as per the presence & absence of the similar patterns.

* It is an unsupervised learning method, hence no supervision is provided to the algorithm & it deals with the unlabeled dataset.

* After applying this clustering technique, each cluster (or) group is provided with a cluster id. ml system can use this id to simplify the processing of large & complex datasets.

* The clustering technique is commonly used for statistical data analysis some most common users of this technique are,

1. Market segmentation.
2. statistical data Analytics,
3. Social network Analysis.

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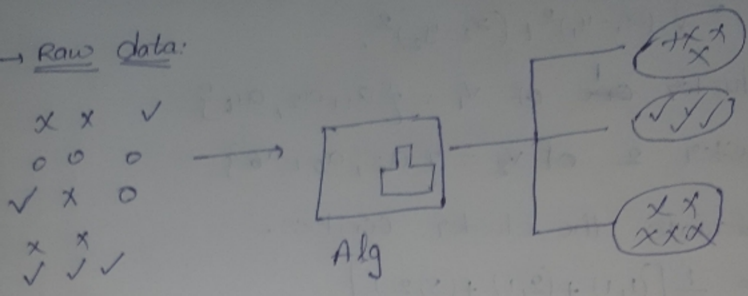
4. Image Segmentation
5. Anomaly detection etc...

→ Raw data:



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→ K means clustering Alg: to divide following data into 2 cluster ~~set~~

x_1	1	2	2	3	4	5
x_2	1	1	3	2	3	5

Ans:-

1. Chossing randomly 2 cluster sets

$v_1 = (2,1)$

$v_2 = (2,3)$

2. finding the distance b/w the cluster center & each data points

Distance Table:-

Data point	Distance from $v_1(2,1)$	Distance from $v_2(2,3)$	Assigned Centre
$a_1(1,1)$	1	$\sqrt{5} = 2.236$	v_1
$a_2(2,1)$	0	2	v_1
$a_3(2,3)$	2	0	v_2
$a_4(3,2)$	$\sqrt{2} = 1.414$	$\sqrt{2} = 1.414$	v_1
$a_5(4,3)$	$2\sqrt{2} = 2.828$	2	v_2
$a_6(5,5)$	5	$\sqrt{13} = 3.605$	v_2

→ Euclidian distance

(x_1, x_2) (y_1, y_2)

$$= \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2}.$$

→ 3. cluster ~~one~~ 1 of $v_1 = \{a_1, a_2, a_4\}$

cluster 2 of $v_2 = \{a_3, a_5, a_6\}$

4. Recalculate the cluster centres.

$$v_1 = \frac{1}{3}[(1,1) + (2,1) + (3,2)]$$

$$= \frac{1}{3}[(6,4)] = (2, 1.33).$$

$$v_2 = \frac{1}{3}[(2,3) + (4,3) + (5,5)].$$

$$= \frac{1}{3}[(11, 11)] = (3.67, 3.67).$$

5. Repeat from step 2, until we get same cluster centre (or) same cluster elements as in the previous iteration.

Data point	v_1 (2, 1.33)	v_2 (3.67, 3.67)	Assigned Centre
a_1 (1,1)	1.05	3.78	v_1
a_2 (2,1)	0.33	3.15	v_1
a_3 (2,3)	1.67	1.8	v_1
a_4 (3,2)	1.204	1.8	v_1
a_5 (4,3)	2.605	0.75	v_2
a_6 (5,5)	4.74	1.88	v_2

cluster 1 of $v_1 = \{a_1, a_2, a_3, a_4\}$
cluster 2 of $v_2 = \{a_5, a_6\}$

$$v_1 = \frac{1}{4}\left[(1,1) + (2,1) + (3,2) + (2,3)\right]$$
$$= \frac{1}{4}(8,7) = (2, 1.75).$$

$$v_2 = \frac{1}{2}\left[(4,3) + (5,5)\right]$$
$$= \frac{1}{2}(9,8) = (4.5, 4).$$

→ so, cluster Elements are not same as previous Elements.

~~Data po~~

Data point	v_1 (2, 1.75)	v_2 (4.5, 4)	Assigned Centre
a_1 (1,1)	1.25	4.61	v_1
a_2 (2,1)	0.75	3.9	v_1
a_3 (2,3)	1.25	2.69	v_1
a_4 (3,2)	1.03	2.5	v_1
a_5 (4,3)	2.36	1.12	v_2
a_6 (5,5)	4.42	1.12	v_2

→ cluster 1 of $v_1 = \{a_1, a_2, a_3, a_4\}$
cluster 2 of $v_2 = \{a_5, a_6\}$

cluster elements are same as in the previous iteration. so, our clusters

cluster 1 $= \{(1,1), (2,1), (2,3), (3,2)\}$
cluster 2 $= \{(4,3), (5,5)\}$

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→ HAC :- Hierachical Agglomerative clustering.

* HAC starts with one cluster, individual item in its own cluster & iteratively merge clusters until all the items belong to one cluster.

* Bottom up approach is followed to merge the clusters together.

* Dendrograms (or) pictorially used to represent the HAC

* HAC represents 3 techniques:

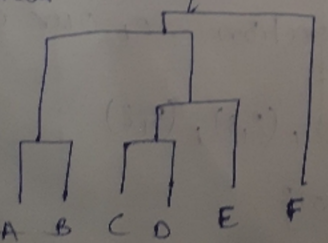
1. Single nearest (or) single linkage.
2. Complete -- farthest distance (or) complete linkage.
3. Average distance (or) Average linkage.

1. S.N :- This is the diff b/w the closest members of the two clusters.

2. C.L :- This is the diff b/w the members that or farthest apart

3. A.L :- This Method involves looking at a distance b/w all pairs & Averages all of these distance. this is also called unwaited pair group mean average

* Dendrogram :- A tree like structure which represent hierachical technique.



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Problem:-

* Find the clusters using single link technique & draw the denprogram diagram.

	x	Y
P_1	0.40	0.53
P_2	0.22	0.38
P_3	0.35	0.32
P_4	0.26	0.19
P_5	0.08	0.41
P_6	0.45	0.30

Sol:-

1. Euclidean distance

$$(x_1, y_1)\ (x_2, y_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

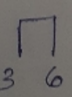
2.

	P_1	P_2	P_3	P_4	P_5	P_6
P_1	0					
P_2	0.23	0				
P_3	0.22	0.15	0			
P_4	0.37	0.20	0.15	0		
P_5	0.34	0.34	0.26	0.29	0	
P_6	0.23	0.25	0.11	0.22	0.39	0

Distance Table

→ Smallest element = 0.11

$P_3\ P_6$



Recalculate the distance Matrix

(2)

	P_1	P_2	P_3P_6	P_4	P_5
P_1	0				
P_2	0.23	0			
P_3P_6	0.22	0.15	0		
P_4	0.37	0.20	0.15	0	
P_5	0.34	0.34	0.26	0.29	0

0.14 → Small value.

$\min(\text{dist}(x, y))$

$\min(\text{dist}(P_3, P_6), P_1) = \min(\text{dist}((P_3, P_1), (P_6, P_1)))$

$= \min(\text{dist}(0.22, 0.23))$

$= 0.22$

(3) updated dist Matrix.

	P_1	P_2P_5	P_3P_6	P_4
P_1	0			
P_2P_5	0.23	0		
P_3P_6	0.22	0.15	0	
P_4	0.37	0.20	0.15	0

small element = 0.15

$\Rightarrow$ New cluster $[(P_2P_5)(P_3P_6)]$

	P_1	P_2P_5 P_3P_6	P_4
P_1	0		
P_2P_5 P_3P_6	0.22	0	
P_4	0.37	0.15	0

Small.

$\to \min(\text{dist}[(P_2P_5\ P_3P_6), P_1]$

$= \min(\text{dist}[(P_2P_5), P_1][(P_3\ P_6), P_1])$

$= \min(\text{dist}(0.23)(0.22))$

$= 0.22.$

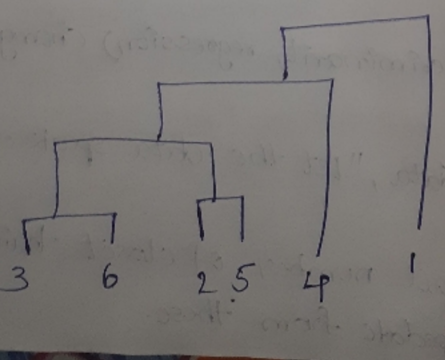
$\to \min(\text{dist}[(P_2P_5\ P_3P_6), P_4]$

$= 0.15.$

$\Rightarrow$ updated

	P_1	P_2P_5 P_3P_6 P_4
P_1	0	0.22
P_2P_5 P_3 P_6 P_4	0.22	0

Diagram :-



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→ Agglomerative clustering:

Distance b/w two groups G_i & G_j

1) single link

$$d(G_i, G_j) = \min d(x^r, x^s)$$

2) Complete-link

$$d(G_i, G_j) = \max d(x^r, x^s)$$

Dendrogram:- Decompose data objects into a several levels of nested partitioning (tree of clusters) - called a dendrogram.

⟹ Density Estimation:-

* Given the training set $x = \{x^t\}_t$ drawn iid from $p(x)$
* Divide data into bins of size h
* Histogram:-

$$\hat{p}(x) = \frac{\#\{x-h < x^t \leq x+h\}}{2NH}$$

⟹ Non parametric methods:

* parametric (single global model), Semiparametric (small number of Local models).
* Non-parametric : similar inputs have similar outputs.
* functions (pdf, discriminant, regression) change smoothly.
* Keep the training data, "Let the data speak for itself".
* Given x, find a small number of closet training instances & interpedate from these.

* Aka Lazy / memory-based / case-based / instance-based learning.

=) **Kernal Estimator:**

Kernal function, eg:- Gaussian

Kernal:-

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left[\frac{-u^2}{2}\right]$$

Kernal Estimator:- (parzen window)

$$\hat{p}(x) = \frac{1}{Nh} \sum_{t=1}^{n} K\left[\frac{x - x^t}{h}\right].$$

→ K= Nearest Neighbour Estimator.

$$\hat{p}(x) = \frac{k}{2N d_k(x)}.$$

Generalisation of multivariate data:

1. Kernal density Estimator.
2. multivariate Gussian kernal.
   ↓
   1. Spheric
   2. Ellipsoid

→ Hamming distance:

$$HD(x, x^t) = \sum_{j=1}^{d} 1(x_j \neq x_j^t).$$

→ Non-parametric Classification:

1. kernal estimator
2. KNW Estimator

→ Non-parametric Regression:

1. Running mean Smoother
2. Kernal smoother.

1. $$\hat{g}(x) = \frac{\sum_{i=1}^{N} w\left(\frac{x-x^t}{h}\right) r^t}{\sum_{t=1}^{N} w\left(\frac{x-x^t}{h}\right)}$$

2. $$\hat{g}(x) = \frac{\sum_{t=1}^{N} K\left(\frac{x-x^t}{h}\right) r^t}{\sum_{i=1}^{N} K\left(\frac{x-x^t}{h}\right)}$$

⇒ Linear Discrimination:

$$g_i(x_i / w_{i0}) = w^T x + w = \sum w x + w.$$

* likelihood Vs Discriminant Based Classification.

1. Assume model for $P(x|c_i)$, use Baye's rule to calculate $P(c_i|x)$ $g_i(x) = \log P(c_i|x)$.

2. D.B.C = Assume model for $g(x|\phi_i)$ NO density Estimation. Estimating the boundary is enough. No need to accurately Estimate the densities inside the boundaries.

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→ KNN Algorithm:-

* KNN is a Non-parametric classification Method.
* It is used for classification & regression.
* It is very simple Easy to implement supervised Machine learning algorithm.

Advantages:-

* more Effective of training data is large.

→ problem :-

S.NO	maths	CS	Result
1	4	3	Fail
2	6	7	pass
3	7	8	pass
4	5	5	fail
5	8	8	pass
6	6	8	?

select K neighbours
$K = 3$.

$X = (\text{math} - 6, \ CS - 8)$.

→ Euclidean Distance:-

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

x_2, y_2 - Observe values

x_1, y_1 - Actual values.

1. $= \sqrt{(6-4)^2 + (8-3)^2}$
   $= \sqrt{4 + 25} = \sqrt{29} = 5.38$

2. $\sqrt{(6-6)^2 + (8-7)^2} = 1$

3. $\sqrt{(6-7)^2 + (8-8)^2} = 1$

4. $\sqrt{(6-5)^2 + (8-5)^2} = \sqrt{10} = 3.16$.

5. $\sqrt{(6-8)^2 + (8-8)^2} = \sqrt{4} = \cancel{3.6}\ 2$

→ As per result $K = 3$

2 - pass

3 - pass

5 - pass

so, 3 greater than 0, probability of pass is high.

Hence, x (math = 6, CS = 8 is pass).

9/12/23

→ Decision tree:

* Decision tree is a tree like a predictive model used for Classification & Regression.

* It is a supervised learning method.

⇒ Learning Algorithm used:

① Cart – Regression ⟶ Gini index.

② ID3 Algorithm – Classification

↓ Entropy, information Gain.

→ $\underset{(D)}{\text{Entropy}} = \sum_{i=1}^{c} -P_i \log_2(P_i)$

→ $\text{Gain}(D,A) = \text{Entropy}(D) - \sum_{v \in \text{value}(A)} \frac{|D_v|}{|D|} \times \text{Entropy}(D_v)$

Problem:

It is used to generate Decision Tree from a Dataset.

→ Classify the given training set using ID_3 Algorithm Construct the decision Tree.

Size	Color	Shape	Class
Small	yellow	Round	A
Big	yellow	Round	A
Big	Red	Round	A
Small	Red	Round	A
Small	Black	(~~Cube~~) Round	B
Big	Black	Cube	B
Big	yellow	Cube	B
Big	Black	Round	B
Small	yellow	Cube	B

Sol:-
A=4
B=5
m=2

. Calculate the Entropy (D):-

$$Entropy(D) = -\sum_{i=1}^{m} P_i \log_2(P_i)$$

$$= -\sum_{i=1}^{2} 4/9 \log_2(4/9)$$

$$= -4/9 \log_2(4/9) - 5/9 \log_2(5/9).$$

$$= (-0.444 * -1.171) - (0.555 * -0.850)$$

$$= 0.520 + 0.472$$

$$= 0.992.$$

Gain = Entn - I

$A \log_2(A)$

$4/9 \quad 5/9$

0.44
-1.18

→ Identify the splitting attribute, Calculate the gain.

* Attribute - size

	A	B	
Small	2	2	-4
Big	2	3	-5

$$Gain(D, size) = 0.992 - \left[\frac{4}{9}\left(-\frac{2}{4}\log_2(2/4) - \frac{2}{4}\log_2(2/4)\right) + \frac{5}{9}\left(-\frac{3}{5}\log_2(3/5) - \frac{2}{5}\log_2(2/5)\right)\right].$$

$$= 0.992 - [0.444 + 0.539]$$

$$= 0.992 - 0.983$$

$$= 0.009$$

* Attribute - Color.

	A	B	
yellow	2	2	-4
Red	2	0	-2
Black	3	0	-3

$$Gain(D, color) = 0.992 - \left[\frac{4}{9}\left(-\frac{2}{4}\log_2\left(\frac{2}{4}\right) - \frac{2}{4}\log_2\left(\frac{2}{4}\right)\right) + \frac{2}{9}\left(-\frac{2}{2}\log_2\left(\frac{2}{2}\right)\right) + \frac{3}{9}\left(-\frac{0}{3}\log_2(0/3) - \frac{3}{3}\log_2(3/3)\right)\right]$$

$$= 0.992 - [0.444 + 0 + 0]$$

$$= 0.55.$$

* Attribute - Shape

	A	B	
Round	4	2	-6
Cube	3	0	-3

$$Gain(D, shape) = 0.992 - \left[\frac{6}{9}\left(-\frac{4}{6}\log_2(4/6) - \frac{2}{6}\log_2(2/6)\right) + \frac{3}{9}\left(-\frac{3}{3}\log_2(3/3)\right)\right]$$

$$= 0.992 - 0.612$$

$$= 0.38.$$

→ Information Gain

Attribute	Gain
Size	0.009
Color	0.55
Shape	0.379

* Color has the longest gain, so its becomes the root node.

→ Color

Yellow:

size	shape	Class
Small	R	A
Big	R	A
Big	C	B
Small	C	B

↓ ?

Red:

size	shape	Class
Big	R	A
Small	R	A

Class A

Black:

size	Shape	Class
S	Round	B
B	class	B
B	Round	B

↓ Class B

23/08/23 yellow:

$$Entropy(D) = -\frac{2}{4}\log_2 2/4 - \frac{2}{4}\log_2 2/4$$

$$= 1.$$

→ Attribute = size.

	A	B	
Small	1	1	2
Big	1	1	2

$$Gain(D, size) = 1 - \left[2/4\left(-1/2 \log_2 1/2 - 1/2 \log_2 1/2\right) + \frac{2}{4}\left(-1/2 \log_2 1/2 - 1/2 \log_2 1/2\right)\right]$$

$$= 1 - [0.5 + 0.5]$$

$$= 0.$$

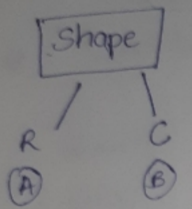
→ Attribute : shape.

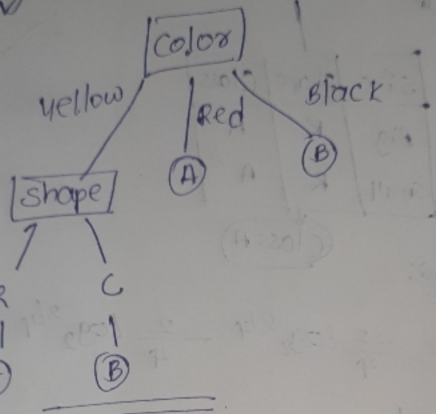
	A	B	
Round	2	0	2
Cube	0	2	2

$$\text{Gain}(D,\text{shape}) = 1 - \left[\frac{2}{4}\left(-\frac{2}{2}\log_2\frac{2}{2}\right) + \frac{2}{4}\left(-\frac{2}{2}\log_2\frac{2}{2}\right)\right]$$

$$= 1 - 0 = 1.$$

Attribute	Gain
Size	0
Shape	1 ✓





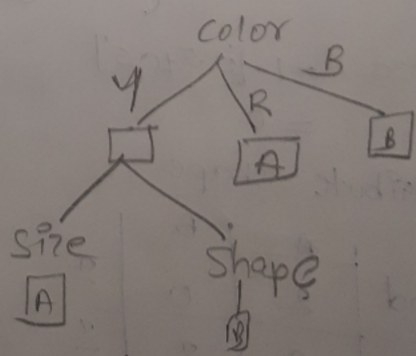
* IPS:-
* Entropy $= \frac{-P}{P+n}\log_2\left(\frac{P}{P+n}\right) - \frac{n}{P+n}\log_2\left(\frac{n}{P+n}\right)$.

* Average info:

$$I(\text{Attribute}) = \sum \frac{P_i+n_i}{P+n}\,\text{Entropy}(s).$$

$$\text{Gain} = \text{Entropy}(s) - I(\text{Attribute}).$$

→ ~~Entropy~~



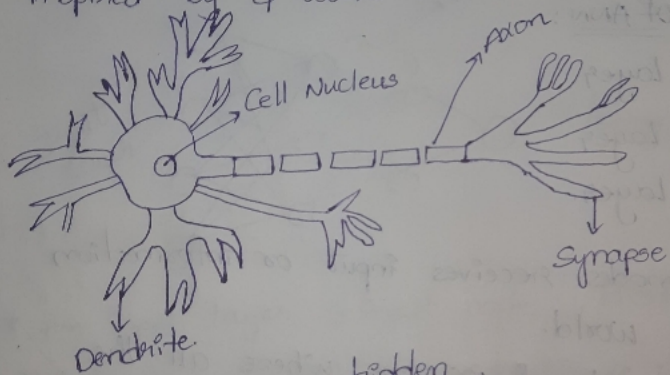
$\frac{2}{2}\log_2 \frac{2}{2}))$

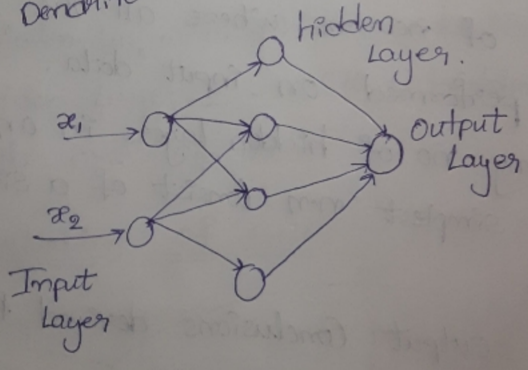
25/03/23.

Unit-4

Artificial Neural Network

* ANN is inspired by a working of human brain.
* The human brain has neurons interconnected to one another, ANN also have neurons that are interconnected to one another in various Layers of the N/w. This neurons are known as nodes.
* Neural Networks are set of Algorithm that tries to recognise the patterns, relationships & information from the data through the process which is inspired by & works likes the human brain.





Biological	Artifical
* Dentrits	* Inputs
* Cell Nucleus	* Nodes.
* Synapse	* weights
* Axon	* output.

* Components of ANN :
    1. Input layer
    2. Hidden Layer
    3. Output layer.

1. I.L: Input nodes receives input or information from outside world.

2. H.L: H.L is set of neurons where all the computations are performed on input data.

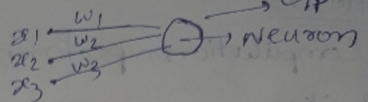
* There can be any no. of hidden layers in an neural n/w. The simplest n.n consist of a single hidden layer.

3. O.L :- O.L is the output conclusions derived from all the computations performed

* There can be single (or) multiple nodes in the output layer. if we have a binary classification problem the output known is 1. But in case of multi class classification, the output nodes can be more than 1.

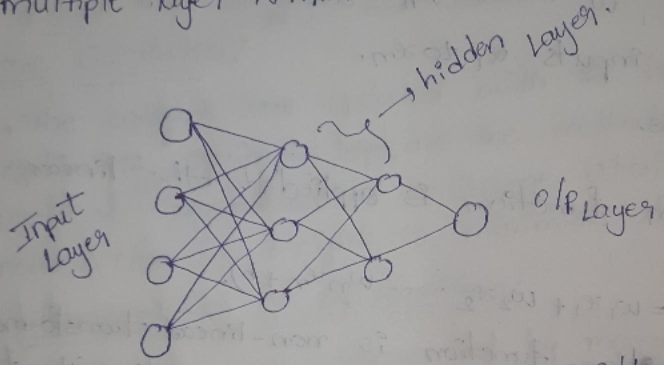
* ~~perception~~:- perception :

* perception is a simple form of N·N/w & Consists of single Layer where all the mathematical Computations are performed.



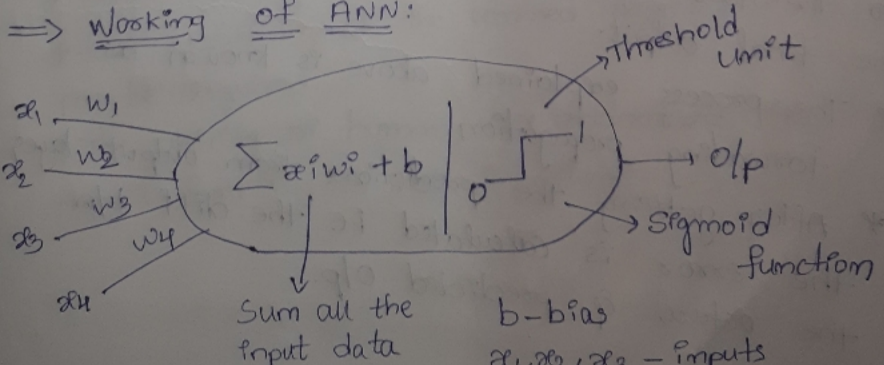
* Multilayer perception :

* M·P is also known as A·N·N Consists of more than 1 perceptron which is grouped together to form multiple layer N·N/w.



* An input layer, 6 input nodes, hidden Layer-1, ~~(hidden La)~~ with 4 hidden nodes (or) 4 perceptrons, hidden Layer-2 - with 4 hidden nodes, o/p Layer with one o/p node.

⟹ Working of ANN :



b - bias

x_1, x_2, x_3 - inputs

w_1, w_2, w_3 - weights of Connection.

* bias is the Constant that helps the model to fit in the best way possible.

27/03/23

* Computation perform in hidden Layers done in 2 steps:

1. All the inputs are multiplied by their weights

Step-1: $z_1 = w_1x_1 + w_2x_2 + \cdots + w_nx_n + b$

where,
$w_1, w_2, w_3 \cdots w_n$ are the weights assigned to inputs x_1 to x_n.

$b \rightarrow$ bias.

Step-2:

Activation function is applied to the linear equation.

$z_1 : (z_1 = w_1x_1 + w_2x_2 \cdots w_nx_n + b)$.

* the activation function is non-linear transformation that is applied to the input before sending it to the next Layer of neurons.

Step-3:

The Computation results from hidden layer passed to the last layer i.e output layer which gives as the final output.

* The process explained above is known as forwading propagation.
* After getting the predictions from output layer the error is calculated i.e the diff b/w the actual & predicted o/p.

* If the Error is large, then the steps are taken to minimize the error & for the same purpose, Back Propagation is performed.

⇒ * Back propagation:

* It is process of updating & finding the Optimal values of weights (or) Co-efficients which helps to minimise the error i.e diff b/w the actual & predicted value.

* How the weights are updated & new weights are Calculated?

→ The weights are updated with the help of optimises, optimises (opt) are the methods (or) mathematical formulation to change attributes of neural N/w i.e weight to minimises the error.

* Characteristics of B.P Algorithm:

* instances are represented by many attributes.
* The target function output (may be) discrete value, real value, (or) a vector of several real (or) discrete value attributes.
* The training examples may contain error.
* large training times are acceptable.
* fast evalution of the learned target function may be required.
* The ability of humans to understand the learned target function is not important.

27/09/23

* perceptron learning Algorithm:

1. Initialise weights & threshold.

* Define $w_i(t)$, $(0 \le i \le n)$, to be the weight from input i at the time t, & θ to be the threshold value in the output node.

* set w_0 to be $-\theta$, the bias, & x_0 to be always 1.

2. present input & desired output.

* present input $x_0, x_1, x_2 \dots x_n$ & desired o/p $d(t)$.

3. Calculate actual o/p.

$$y(t) = f_n\left[\sum_{i=0}^{n} w_i(t)\, x_i(t)\right]$$

4. Adapt weights.

if Correct $w_i(t+1) = w_i(t)$

* if o/p 0, should be 1 (class A) $w_i(t+1) = w_i(t) + x_i(t)$.

* if o/p 1, should be 0 (class B) $w_i(t+1) = w_i(t) - x_i(t)$.

→ Adapt weights - modified. Version.

* if Correct, $w_i(t+1) = w_i(t)$.

* if output 0, should be 1 (class A), $w_i(t+1) = w_i(t) + \eta x_i(t)$.

* if output 1, should be 0 (class B), $w_i(t+1) = w_i(t) - \eta x_i(t)$.

where $0 \le \eta \le 1$, a positive gain term that Console the adaption rate.

* The error term Δ can be written

$$\Delta = d(t) - y(t).$$

→ Adapt weights — widrow-Hoff delta rule.

$$\Delta = d(t) - y(t).$$

$$w_i(t+1) = w_i(t) + \eta \cdot \Delta x_i(t)$$

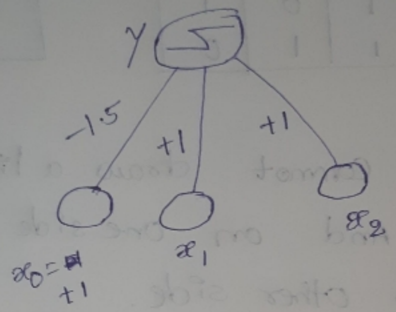
$$d(t) = \begin{cases} +1, & \text{if input from class } A \\ 0, & \text{if input from Class } B. \end{cases}$$

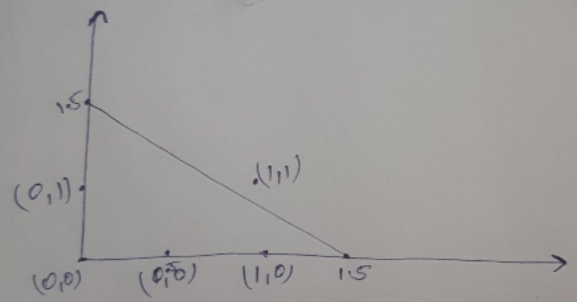
* Input of o/p for the and function:

Learning Boolean function:

AND

x_1	x_2	r
0	0	0
0	1	0
1	0	0
1	1	1





* In a Booleam function,

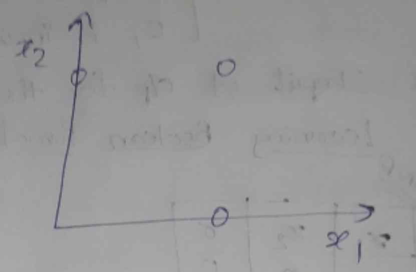
The perceptron that implements And and its geomatric interpretation.

* in a Booleam function, that inputs are binary & output is 1, if the Corresponding function value is true ~~& the inputs~~ (or) zero otherwise therefore, it can be seen as a 2 class classification problem.

* Input of o/p for XOR function

XOR.

x_1	x_2	r
0	0	0
0	1	1
1	0	1
1	1	0



* we cannot draw a line where empty circle and on one side & filled circles are on other side.

* XOR process is not linearly separable.