

It was being used even

Neural Networks (before Machine Learning)

1940 - Walter Pittie

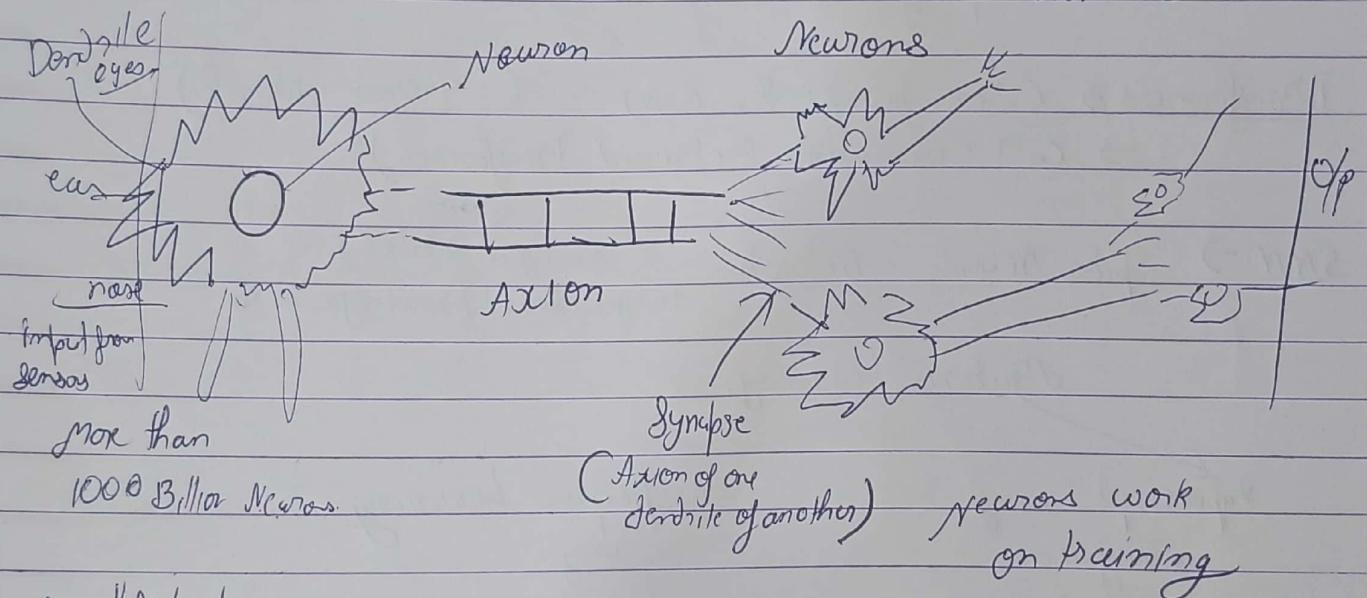
→ What is the reason for Human Intelligence

→ Structure of Body → Robotics M.E. CSE

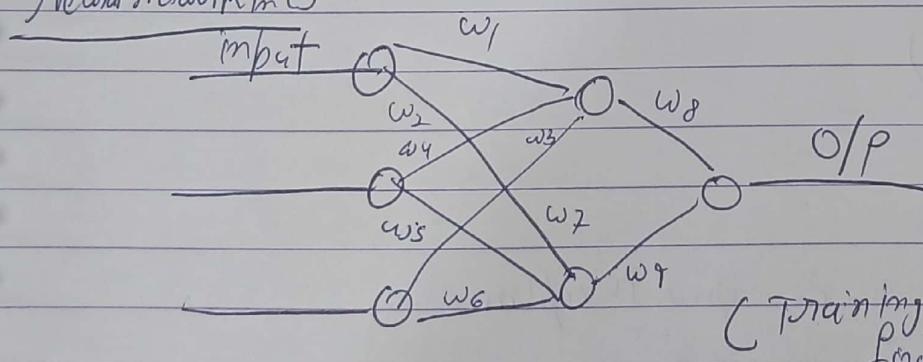
→ Good Brain → Machine Intelligence ECE

If we simulate the working of Human Brain → Neural Networks

CSE



Neural Networks in CS



(Training is nothing but finding weights)

$$O/P = f(I/P, W)$$

P.S.

Terms in NN

(Like Normal Neural Network)
(Work on numbers)

FNN → Feed Forward Neural Netw.

CNN → Convolution Neural Network → Image process

RNN → Recurrent Neural Network

↳ Based on previous data, predict next
Autocorrect, grammarly, mlm

GAN → Generative Adversarial Networks → pur generate (content create)
(not deep fake (use input data))

Transformers → (More powerful than GAN) (queries chthoni h)
↳ GPT (Generative Pre-trained Transformers)

SNN → Spike Neural Network (mostly in robotics)
target class ki knowledge nahi

Machine Learning

Supervised Learning

Classification

(Neural Network is

part of Supervised Learning)

(Training data dya

target class jyahi)

most milestones

Unsupervised Learning

Clustering

1960 → Minsky → developed Perception

Perception

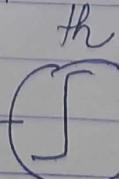
bias (apni knowledge add kiji)

x_1 w_1

x_2 w_2

(Magnifying
Input)

$$(\sum w_i x_i) + B$$



function

If input is greater than threshold
else



Suppose AND Gate

x_1	x_2	O/P
0	0	0
0	1	0
1	0	0
1	1	1

$$w_1 = 1 \quad B = 0 \quad th = 2$$

$$w_2 = 1$$

If $x_1 + x_2 \geq 2$ then 1
else 0

Standard threshold 0 while A

so $B = -1$ kinda

$$x_1 + x_2 - 1 \geq 0 \text{ then } 1$$

else 0

OR Gate $B = 0$

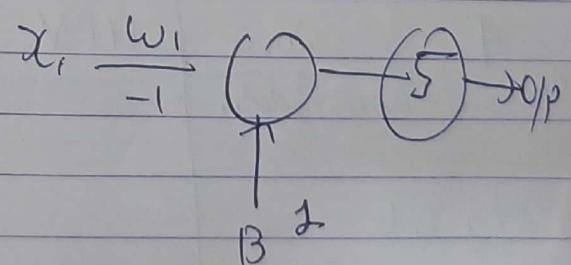
XOR Gate (2 perception here prega)

NOT

We work with SOP

x_1	x_2	OR POS
0	0	0

Inverted with 1 & 0	\rightarrow	0	1	1
	\rightarrow	1	0	1
		1	1	0



$$T_1 + T_2$$

$$\bar{x}_1 x_2 + x_1 \bar{x}_2$$

2005 → Geoffrey → Deep Learning

H/w Implement XOR using perceptron

Basic formula

$$f_A \cdot (w_i x_i + b)$$

no. of wheel	wheel	weight	Target class	H. L
2	2	200kg	Bike / motorcycle $\rightarrow 1$	1
2	150kg		Motorcycle	1
4	800kg		L PV (Light Passenger Vehicle)	1
4	50		Trolley	1
2	10		Bicycle	0
4	2000		MPV	1

(Training data)

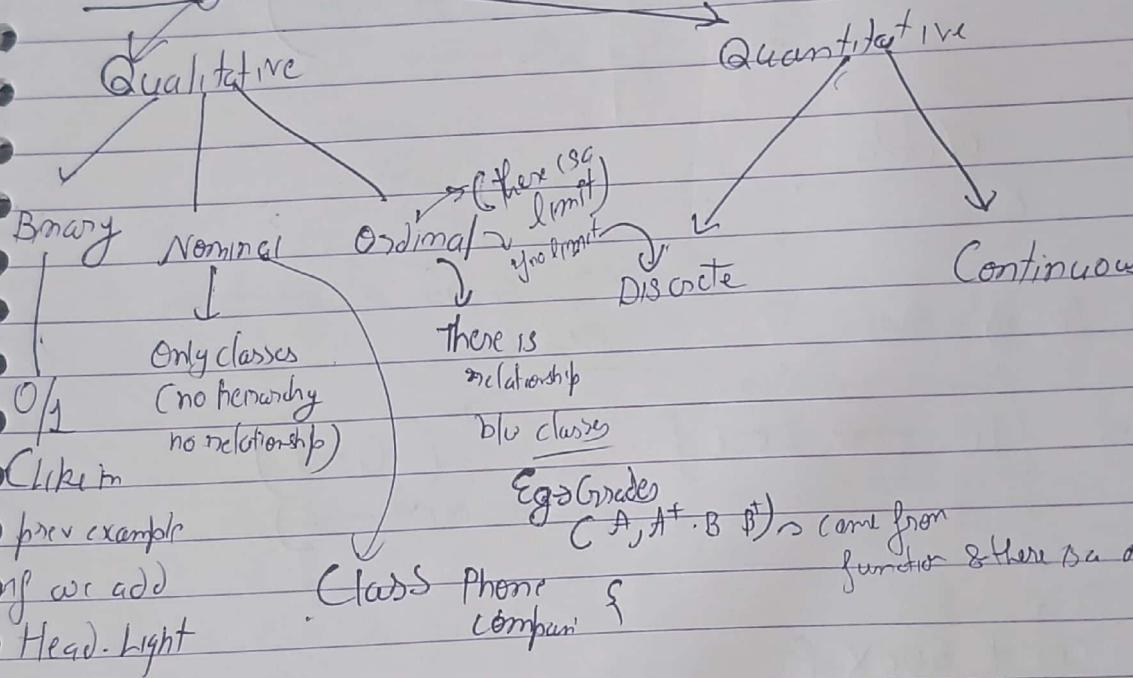
Testing Data

2 100 ??

(We cannot give this
data directly into model)

→ We need to prepare our data

Data types in Neural Network

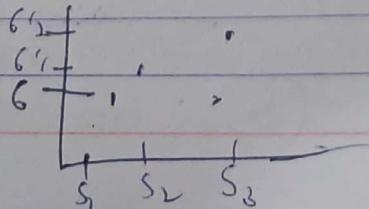


1, Abb', Mord, Gemsey, Notis

(no relationship b/w classes)
so no ordering of nos as well

Only classes b/w discrete b/w yes/no → Fuzzy Logic
(Quantitative)

Point Chart
→ Discrete Data



Line Chart → Continuous Data



- we need to represent classes with no's only
- we cannot deal equally with 10 & 10,000 (need to normalize)

(2) Normalisation of data

i) Min Max Normalization

$$\text{Let for } [10 - 2000] \xrightarrow{\text{map it to}} (0 - 1) \\ \text{or } (A - B)$$

Formula

$$10 + 500x$$

$$\left\{ \frac{x - \text{Min}}{\text{Max} - \text{Min}} \right\} (B-A) + A$$

$$\left(\frac{500 - 10}{2000 - 10} \right) \times 1 + 0$$

$$\frac{490}{1990} = 0.246$$

$$50 \rightarrow 50 \rightarrow 0 - 10$$

$$8878 \quad x = 55$$

$$\left(\frac{55 - 50}{60 - 50} \right) \times (10) + 0$$

- 5

ii) Decimal Scale Normalization

Suppose range is

$$\text{Min}_{\text{old}} \longrightarrow \text{Max}_{\text{old}}$$

(ensure no

negative no)

So most negative $\rightarrow 0$ (a) absolute value of
Add most negative in everyone

b) or change range acc to formula

Suppose highest no comes to be 999

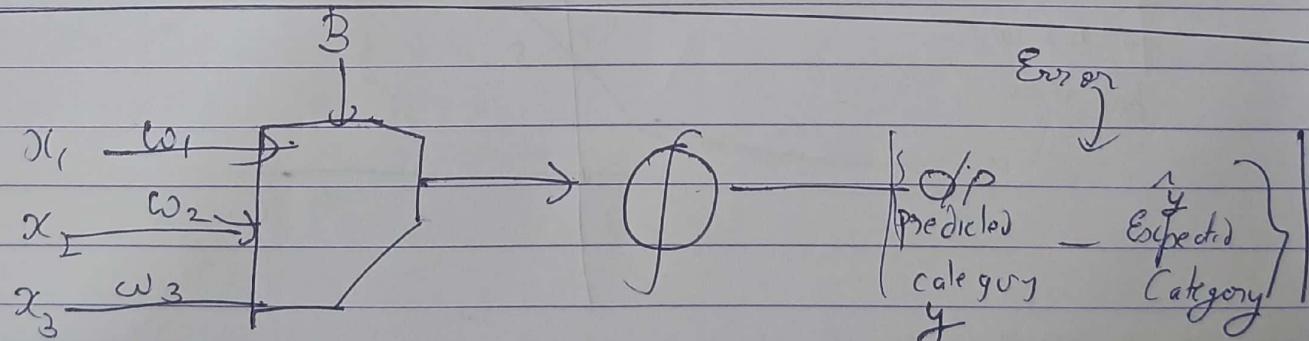
j_{\min} such that

Divide every no by j so that all no's align within 0-1

$$\frac{x}{10^j}$$



iii) Normalisation for genetic algorithms (work on binary nos.)



$$\text{Error} = |y - \hat{y}|$$

Neural Networking Algo & Back propagation will change w to reduce errors.

$$w = w + \Delta w$$

$$\beta = \beta + \Delta \beta$$

$$\Delta w \propto |y - \hat{y}|$$

shorter curves be focus

i) Mean Absolute Error

$$(MAE) = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

ii) Mean Squared Error

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

By errors
prefocus (outliers)

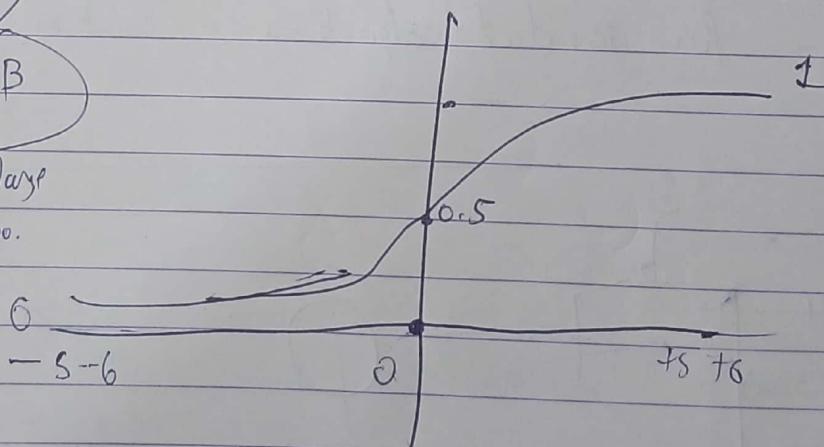
$$RMSE (\text{Root Mean Sq E}) = \sqrt{MSE}$$

Most common Activation function is Sigmoid / Logistic function

$$f(x) = \frac{1}{1+e^{-x}}$$

$$\omega_i x_i + b$$

will be a large
positive no.



Gradients of Activation function

Rate of change of ω_i will be according to rate of change of errors

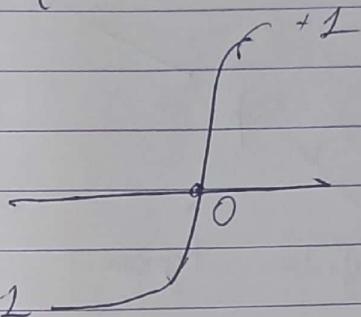
$$MSE = \frac{1}{N} \sum_{i=1}^N \left(\frac{1}{1+e^{-(\omega_i x_i + b)}} - y_i \right)^2$$

$$\tanh(\text{tanh hyperbolic}) = \frac{e^x + e^{-x}}{e^x - e^{-x}}$$

J

for better

(since aligned on 0)



rate of change of wt is prop to derivative of tanh

* Coefficient of Determinant (R)

$$R = 1 - \frac{\sum(y - \bar{y})^2}{\sum(y - \bar{y})^2}$$

\bar{y} mean

target class
can be

determined
perfectly

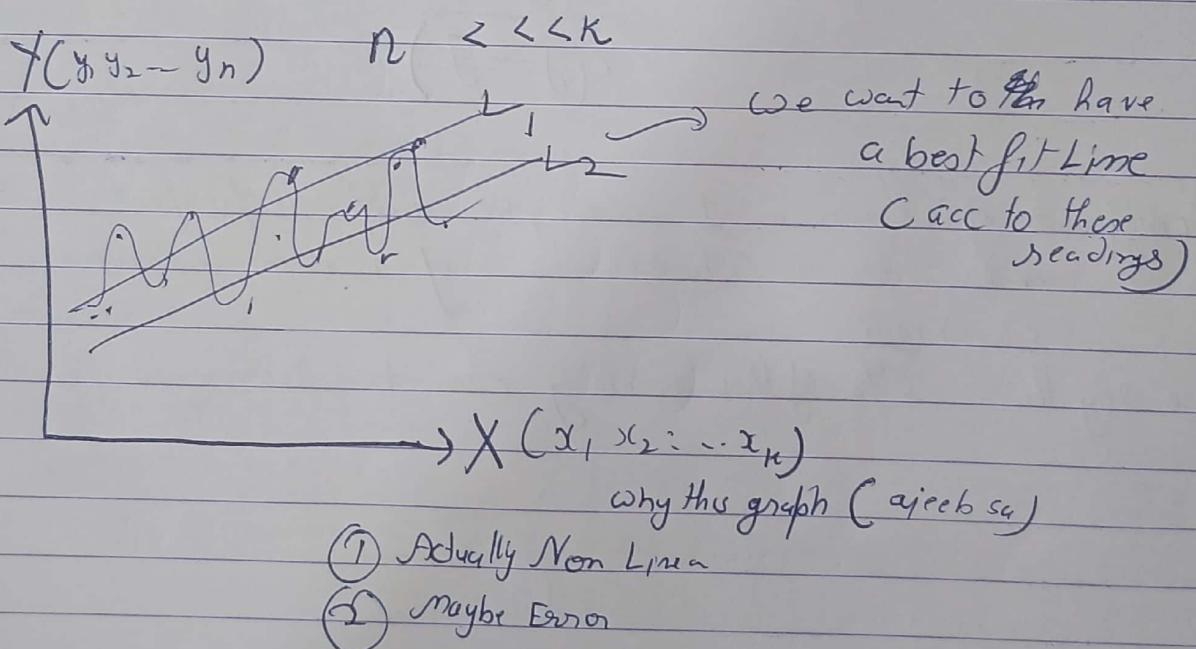
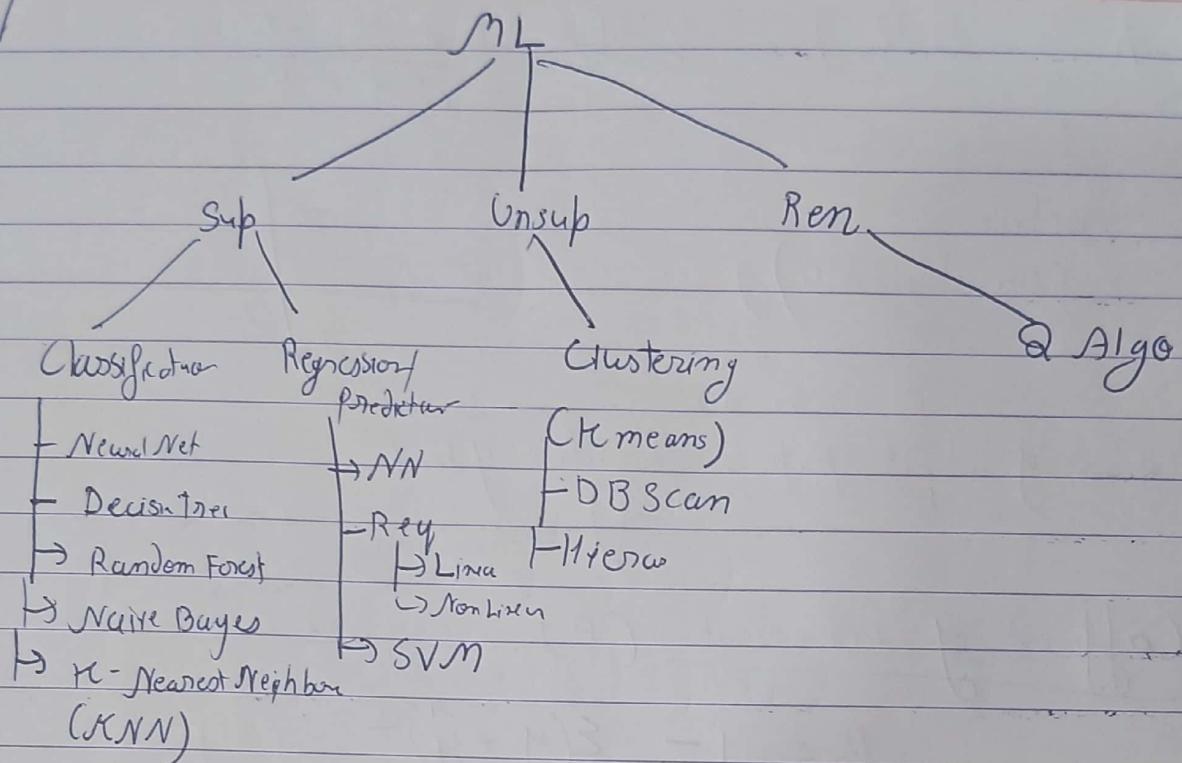
coefficient of determination 1 means, the output is perfect

it works in (when variation of x is in consideration)

$(R=1)$ means

We say that $x\%$ of this variability can be determined

7th Feb / 2025



Principle of Least Squares (Using PDE)

If you have suitable no. of readings w.r.t. PDE you can find a line such that error is minimum (pass through most of points)

Expansion

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!}$$

$$f(a) = f(x) + \frac{f'(x)}{1!}(x-a) + \frac{f''(x)}{2!}(x-a)^2$$

Taylor Series

$$\sum_{n=0}^{\infty} f^{(n)}(x) \frac{(x-a)^n}{n!}$$

Newton changes this formula zone how
Newton Raphson (allowed to find roots of poly) \rightarrow E_b error ka function
o hoga

$$f(x+h) = f(x) + h f'(x) + \frac{h^2 f''(x)}{2!}$$

$\left[\begin{array}{l} \text{if we discard higher order terms} \\ \text{put } 0 \end{array} \right]$

$$0 \Rightarrow -\frac{f(x)}{f'(x)} = h$$

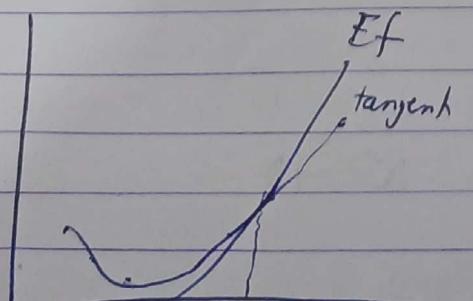
What is our line

$$y = ax + b \rightarrow a \& b \text{ are variable}$$

so error function will be

$$E_f = (y - (ax + b))^2$$

Actual Predicted



tangent at x_0 at which pt meets x-axis
 (Root is but close proximity m. h)

$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)} \leftrightarrow h$$

$$0 = f(r) \approx f(\text{root})$$



$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$$

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)}$$

Eqn of tangent

$$y - y_0 = \text{slope} \cdot (x - x_0)$$

$$y - y_0 = f'(x_0) \cdot (x - x_0)$$

where cutting
x axis $\rightarrow y - f(x_0) = f'(x_0) (x - x_0)$

this is close to 0
 $f(x_0)$ (since near root)

$$(x_1 - x_0) = -\frac{f(x_0)}{f'(x_0)}$$

$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$$

When $f(x)$ will be 0

my variable
function be equal
done by stages
won't deviate

Q) Evaluate $\sqrt{12}$ correct to 3 decimal places.

Soh

$$\text{Suppose } x = \sqrt{12}$$

$$x^2 = 12$$

$$x^2 - 12$$

If we find the root of $f(x) = x^2 - 12$

$$f(x) = 2x$$

when $x=3 \rightarrow f(x) = -ve$
 $\uparrow \quad x=4 \rightarrow f(x) = +ve$

We will with close closer approximat. - (3 & 4)

$$x_0 = 3.5$$

$$x_1 = 3.5 - \frac{f(x_0)}{f'(x_0)}$$

$$= 3.5 - \frac{(12.25 - 12)}{2 \times 3.5}$$

$$= 3.5 - \frac{0.25}{7}$$

$$= 3.5 - 0.0357$$

$$= 3.4643$$

x_1

$$x_2 = 3.4643 - \frac{(12.00137 - 12)}{2 \times 3.4643}$$

$$= 3.4643 - 0.00019$$

$$= 3.46411$$

$$x_3 = 3.46411 - \frac{(0.000058)}{2 \times }$$

$$= 3.4641$$

$$\sum_{i=1}^N |y_i - (a + bx_i)|$$

sum of errors
 mean error
 mean abs error

But there is problem of finding derivatives of absolute fn

so we use mean square err

$$\sum_{i=1}^N (|y_i - (a + bx_i)|)^2$$

we are talking about variance

$$\frac{1}{N} \sum_{i=1}^N |y_i - (a + bx_i)|^2$$

if error choti ($10 \rightarrow 100$)
 $2 \rightarrow 4$

$$\frac{1}{N} \sum_{i=1}^N (y_i - (a + bx_i))^2$$

Date of change of errors
 $\Delta = 8$ ($\Delta = 96$)

Rate of change of errors \Rightarrow derivatives

kaifiya gya

$$E(a, b) = \sum_{i=1}^n (y_i - (a + bx_i))^2 \quad (\text{Ignore } N \text{ for now})$$

E_{fn} if we want to minimize Error

$$\frac{\partial E}{\partial a} = 0 \quad \text{and} \quad \frac{\partial E}{\partial b} = 0$$

$$\left(2 \sum_{i=1}^n (y_i - (a + bx_i))(-1) \right) = 0$$

for a

$$\sum y_i = na + b \sum x_i$$

①

wrt b

$$\left(2 \sum y_i - (a + bx_i) \right) \cdot (-x_i) = 0$$

$$\sum x_i y_i = a \sum x_i + b \sum x_i^2 \quad \text{--- (2)}$$

Comb (1) & (2)

$$\begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix}$$

this should be invertible (determinant non zero)

Determinant $n \sum x_i^2 - \sum x_i \sum x_i$

$$n \sum x_i^2 - (n \bar{x})^2$$

$$\bar{x} = \frac{\sum x_i}{n}$$

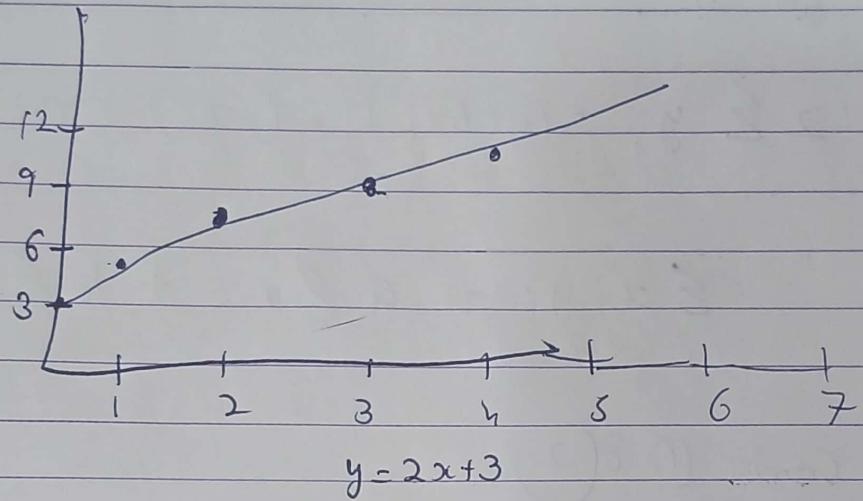
$$n^2 \left(\frac{\sum x_i^2}{n} - \bar{x}^2 \right)$$

$$\sum x_i = n \bar{x}$$

∴ Agar sare values same hogi

toh zero ho

puchega



~~(a) Jcf~~

$$78 = 7a + 28b$$

$$371 = 28a + 140b$$

$$371 = 140b$$

$$312 = 112b$$

$$= b = \frac{58}{28}$$

$$b = 2.107$$

$$a = 2.714$$

$$y = 2.107x + 2.714$$

$$\begin{array}{c} \sum x^2 = 140 \\ n = 7 \\ \sum x_i = 28 \end{array}$$

$$\sum y_i = 78$$

31

28

18

6

7

58

Sybbos - Shore change h

$$\begin{array}{ccccc} x^2 & & x & y & x_i y_i \\ 1 & 5 & & & 5 \end{array}$$

$$\begin{array}{ccccc} 2 & 7 & 3 & 9 & 27 \\ 4 & & 10.5 & & 42 \\ 5 & 14 & & & 70 \\ 6 & 14.5 & & & 82 \end{array}$$

Obs min

Shore
fault

We can similarly fit

$$y = ax + bx^2 + c$$

a & b & c be subject P.D.
& then solve

$$\begin{array}{r}
 2 \\
 29 \\
 \times 3 \\
 \hline
 87
 \end{array}$$

What is formula of slope (b)

$$\sum y_i = n a + b \sum x_i$$

$$a = \frac{\sum y_i - b \sum x_i}{n}$$

$$\begin{aligned}
 \sum x_i y_i &= a \sum x_i + b \sum x_i^2 \\
 &= \frac{\sum y_i - b \sum x_i}{n} \sum x_i + b \sum x_i^2 \\
 \sum x_i y_i &= \frac{\sum y_i \sum x_i + b (\sum x_i^2 - (\frac{\sum x_i}{n})^2)}{n}
 \end{aligned}$$

$$\begin{aligned}
 b &= \frac{\sum x_i y_i - \frac{\sum y_i \sum x_i}{n}}{\sum x_i^2 - (\frac{\sum x_i}{n})^2} \\
 &= \frac{\sum x_i y_i - \frac{\sum y_i \sum x_i}{n}}{\sum x_i^2 - \frac{(\sum x_i)^2}{n}}
 \end{aligned}$$

$$\begin{aligned}
 y &= \sin x \\
 &\hookrightarrow \text{Fourier Transformation}
 \end{aligned}$$

$$\underline{y = ax + bx^2}$$

$$\epsilon_i = \sum_{i=1}^n (y_i - (ax_i + bx_i^2))^2$$

$$\frac{\partial E}{\partial a} = 2 \left(\sum (y_i - ax_i - bx_i^2) \cdot (-x_i) \right) =$$

4-5 Numerical (Linear Regression) \rightarrow HW

Today's Topic Curve Fitting using Principles of Least square
& Newton Raphson Method of finding the roots

$$\frac{\partial E}{\partial a} = 0$$

$$\sum y_i x_i - a \sum x_i^2 - b \sum x_i^3 = 0 \quad (1)$$

$$\sum x_i y_i = a \sum x_i^2 + b \sum x_i^3$$

$$\frac{\partial E}{\partial b} = 0$$

$$2 \sum y_i - (a x_i + b x_i^2) (-x_i^2) = 0$$

$$2 \sum y_i x_i^2 = a \sum x_i^3 + b \sum x_i^4 = 0 \quad (2)$$

x	y	$\sum x_i y_i$	$\sum x_i^2$	$\sum x_i^3$	$\sum y_i x_i^2$	$\sum x_i^4$
1	5	5	1	1	5	1
2	15	30	4	8	60	16
3	25	75	9	27	225	81
4	47	188	16	64	3688	256
5	68	340	25	125	1900	625
6	88	528	36	216	3168	1296
7	115	805	49	343	5635	2401
		1971	140	784	8377	676
					11545	

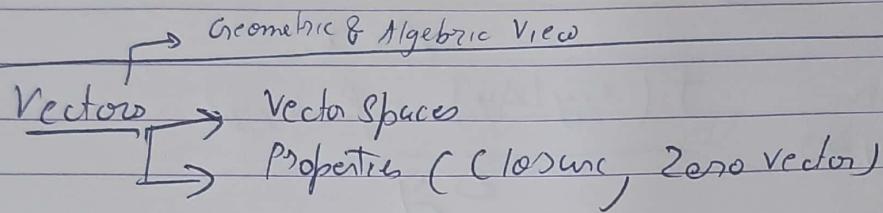
$$1971 = a 140 + b(784)$$

$$8377 = a(784) + b(4676)$$

Book ↴

Computer Based Numerical & Statistical Analysis

Linear Regression Analysis



Linear Independence

Norm of a Vector

Rank of a Matrix

Imp

Basis of a Matrix

Dot Product

(Adjust weights for similarity)

Higher the value of dot product, higher similarity

↳ Foundation for GPT

↳ Recommendation System

Search Engines

PCA

ML Prerequisites

Partial Derivative

$$f_x(x, y) = \lim_{\Delta x \rightarrow 0} \frac{f(x + \Delta x, y) - f(x, y)}{\Delta x}$$

$$f_y(x, y) = \lim_{\Delta y \rightarrow 0} \frac{f(x, y + \Delta y) - f(x, y)}{\Delta y}$$

Total derivative

$$\frac{dz}{dt} = \frac{\partial f}{\partial x} \cdot \frac{dx}{dt} + \frac{\partial f}{\partial y} \cdot \frac{dy}{dt}$$

Power rule

$$\frac{d}{dx} (f(x, y))^n = n f(x, y)^{n-1} \cdot \frac{\partial f}{\partial x}$$

Product Rule-

$$\frac{d}{dx} (f(x, y) \cdot g(x, y)) = f(x, y) \cdot \frac{d}{dx} g(x, y) + g(x, y) \cdot \frac{d}{dx} f(x, y)$$

Quotient Rule

Chain Rule

Gradient of a function

↳ If we want to minimize the function

error.

Gradient (reduce loss in MLL) w.r.t more in
the opp direct of the gradient

log loss