

→ Linear Regression (LR)

→ Statistical learning Algo, not a ML algo

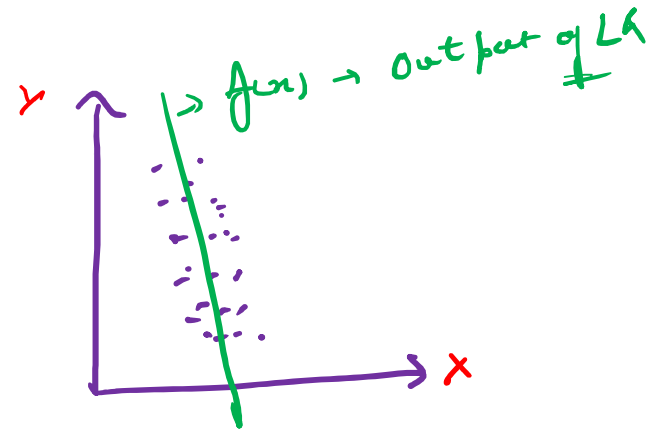
→ The output of a LR model is always a continuous variable

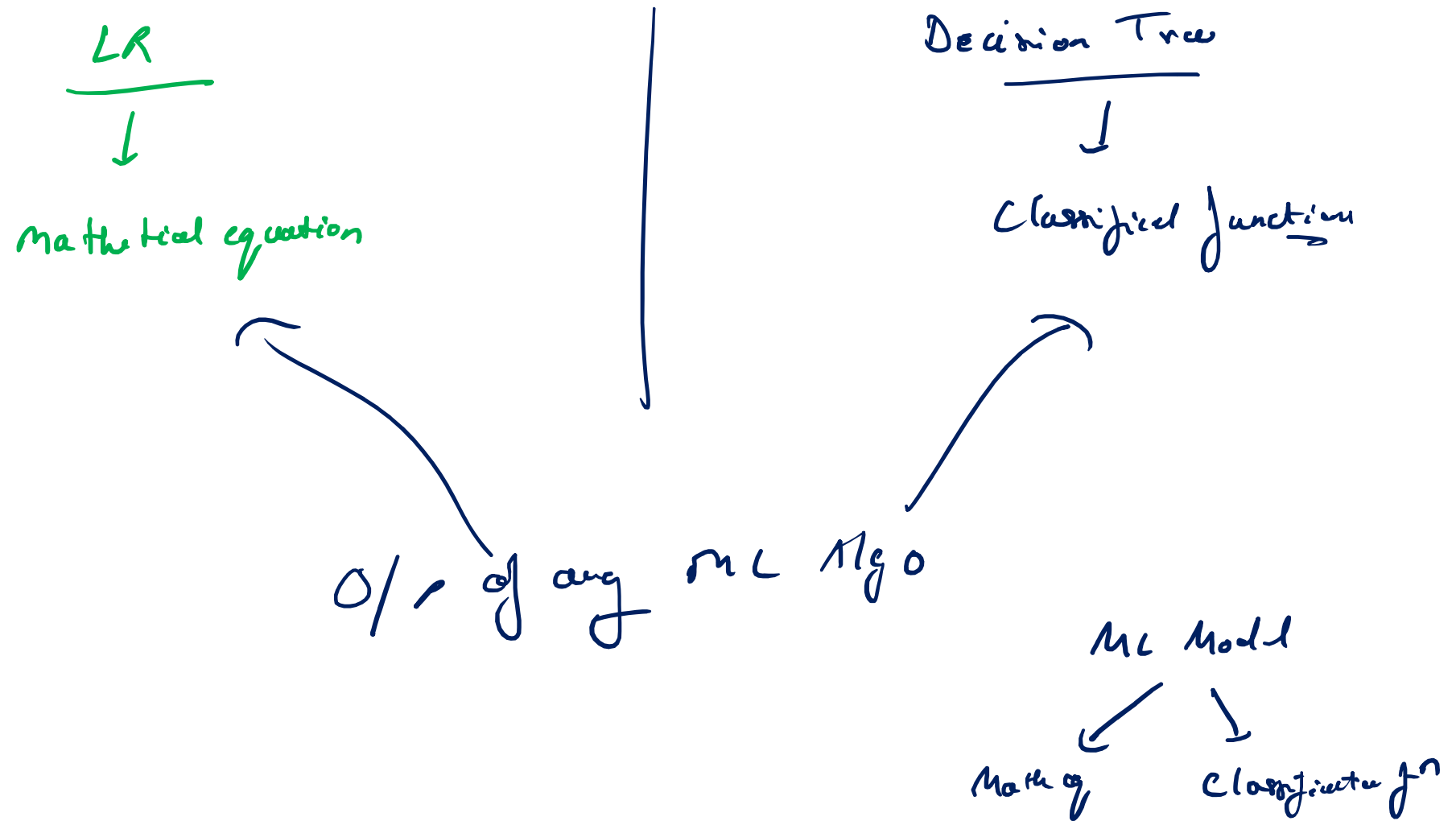
→ The target will be numerical → continuous | e.g. salary, stock price etc.

→ It tries to find a straight line, that fit best to your data
↓
linear parameter

$$y = mx + c$$

Mathematical Ref of
a straight line.





$\rightarrow \frac{\text{Std. dev } (\sigma)}{\text{Avg dist from } \mu \text{ (1-var)}}$
 $\rightarrow \frac{\text{Variance } (\sigma^2)}{\text{Avg sq. dist from } \mu \text{ (1-var)}}$
 $\rightarrow \frac{\text{Co-variance } (\text{cov}(x,y))}{\text{dxn of rel}^2 \text{ +ve, -ve, 0 (2-var)}}$

↳ Co-Relation (r, p)

den + strength of
the relⁿ
(2-var)

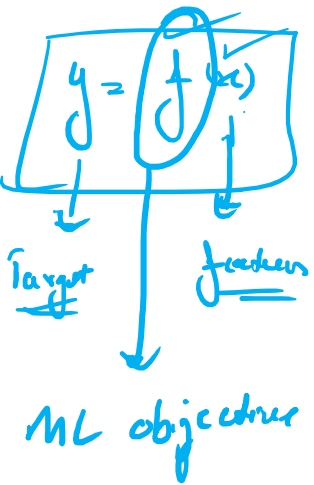
→ Linear Regression

$$\underline{d_{\text{in}}} + \underline{A_{\text{right}}} + \underline{\underline{RLT}}$$

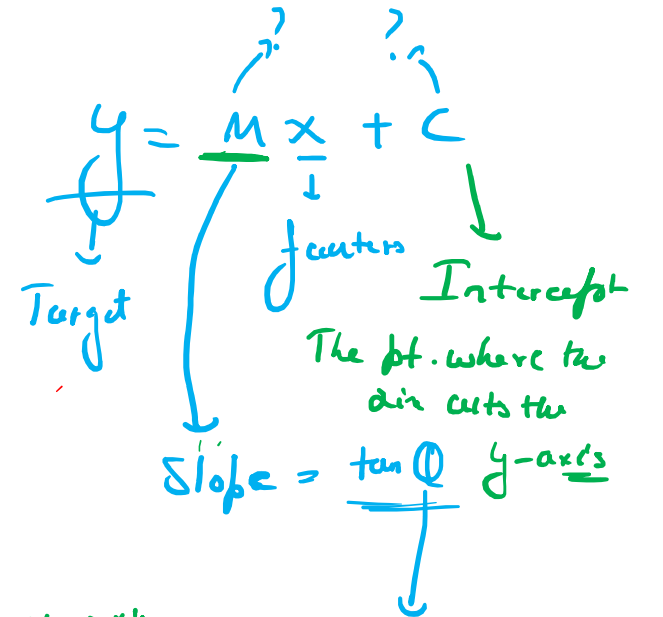
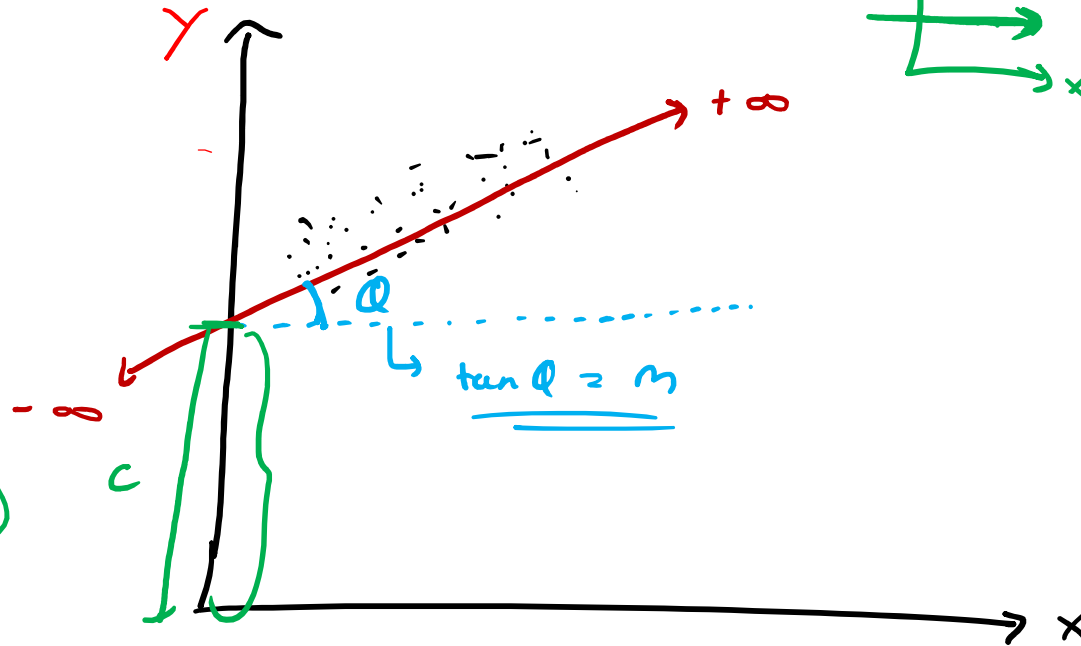
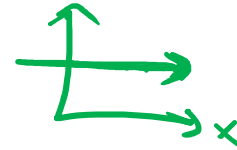
$$(2\text{-uav})$$

eg-

 2×14
$$f(x) = 1$$
$$\underline{1.87 + 2.75}$$



the range of output will always be $[-\infty, +\infty]$



the angle the line is making w.r.t x -axis

$$\sin(\theta) \Rightarrow (-1, +1)$$

$$\cos(\theta) \Rightarrow (-1, +1)$$

$$\tan(\theta) \Rightarrow [-\infty, +\infty]$$

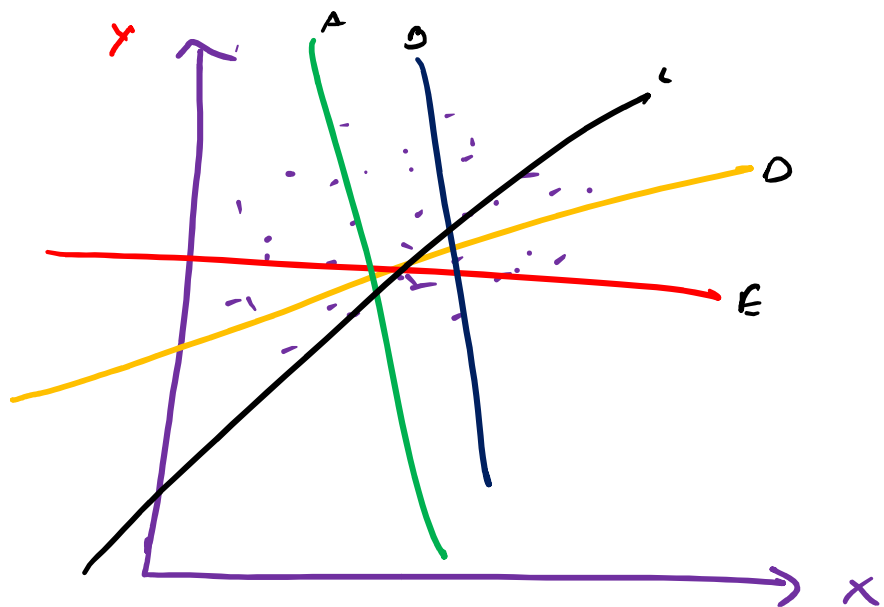
$\times \neq \} \underline{m=0} \Rightarrow$ the line is parallel to x -axis

If $m > 0 \rightarrow +ve$ dxn

$m < 0 \rightarrow -ve$ dxn

$$\tan 0^\circ = 0, \quad \tan(90^\circ) = +\infty$$

$$\tan(270^\circ) = \tan(-90^\circ) = -\infty$$



Multiple lines can pass through the data

Inf lines \rightarrow fitting \rightarrow

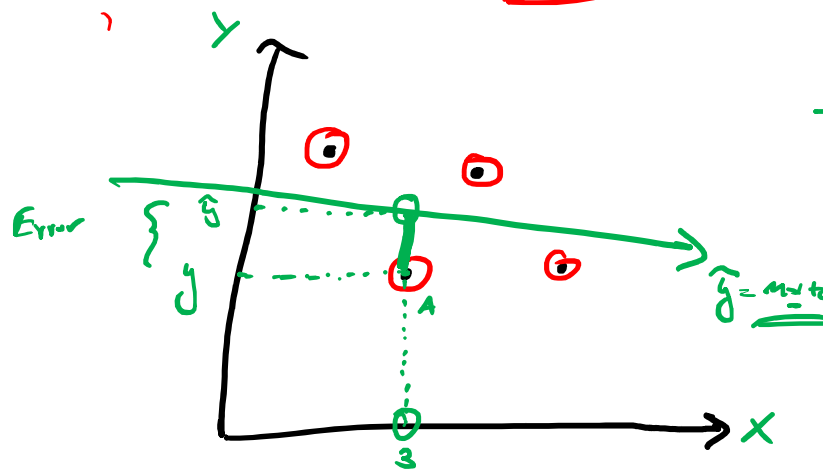
\hookrightarrow 1 Best line
 \perp

\rightarrow Best fit line

\rightarrow least Error

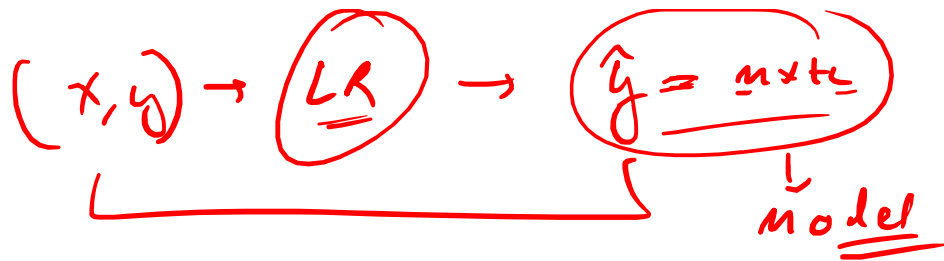
Minimum error

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



\rightarrow

x	y
-3	2
-1	1
1	1
3	4



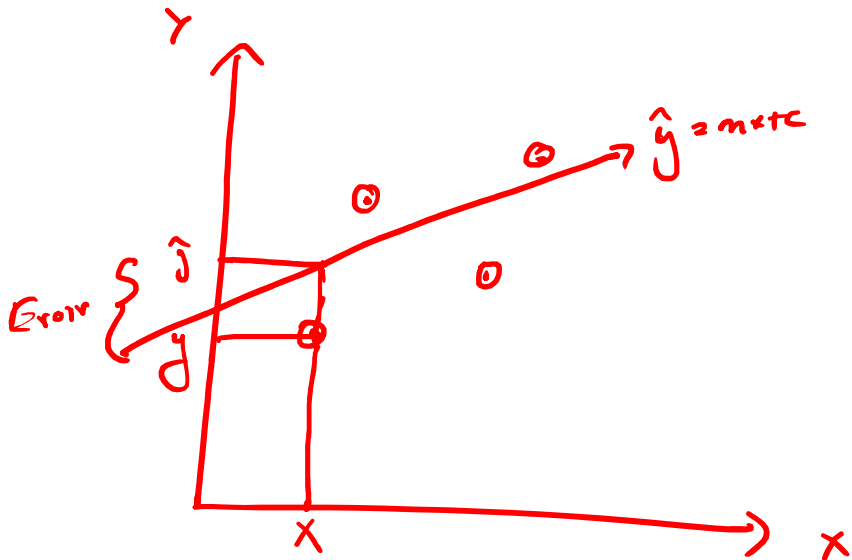
$\hat{y} = 3x + 1$
 $(\hat{y}) = -2x + 1$

feature	target	Pred
x	y	\hat{y}
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.

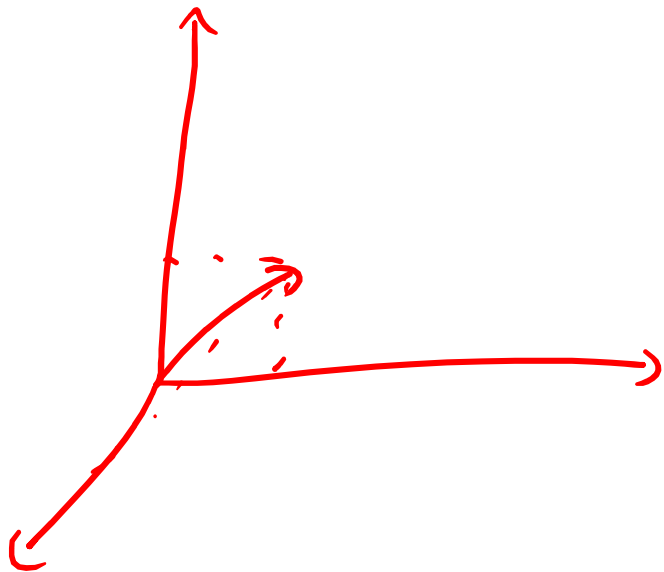
$\begin{matrix} x_{\text{train}} & y_{\text{train}} \\ x_{\text{test}} & y_{\text{test}} \end{matrix}$

y_{pred}

100, 1m, 2B



Error = $y - \hat{y}$



throw

$$\boxed{\hat{y} = m_1 x_1 + c} \rightarrow 2D$$

$$\boxed{\hat{y} = m_1 x_1 + m_2 x_2 + c} \rightarrow 3D$$

$$\hat{y} = m_1 x_1 + m_2 x_2 + m_3 x_3 + \dots$$

$\hat{y} \rightarrow y$

$m_n x_n$ $+c$

$$\underline{\text{Subs} = 2 \cdot \text{TU} + 3 \text{N} + 1.5 \text{Rad} + 100}$$

Ans, $um \rightarrow$ $690x + 1400$

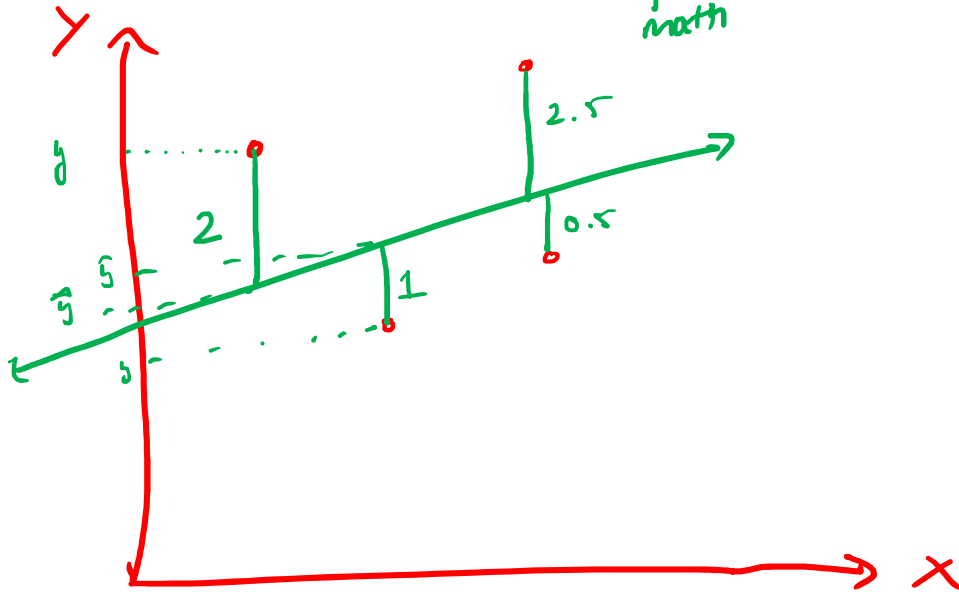
$$\underbrace{6900 + 1400 = 8300}_{10}$$

$$y > \hat{y} = +ve$$

$$y < \hat{y} = -ve$$

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

↑
math



$$Total Error = \sum (y - \hat{y})$$

$$\Rightarrow 2 + (-1) + 2.5 + (-0.5)$$

$$\Rightarrow 3$$

How to get rid of (-ve) sign?

$$\textcircled{1} \text{ Modulus} = \sum |y - \hat{y}| =$$

CAE
Absolute Error

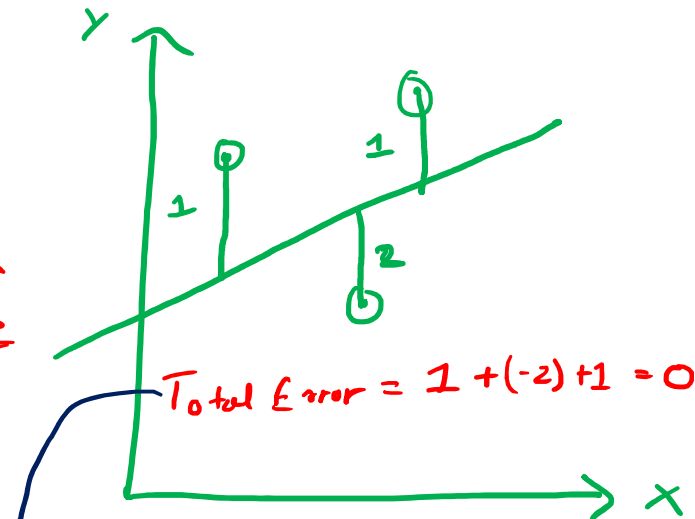
Error fn

$$\textcircled{2} \text{ Square} = \sum (y - \hat{y})^2 =$$

SSE, Sum of Sq. Errors

$$\textcircled{3} \text{ Root of Square} = \sqrt{\sum (y - \hat{y})^2} =$$

RSE, root of Sum of Sq. Error



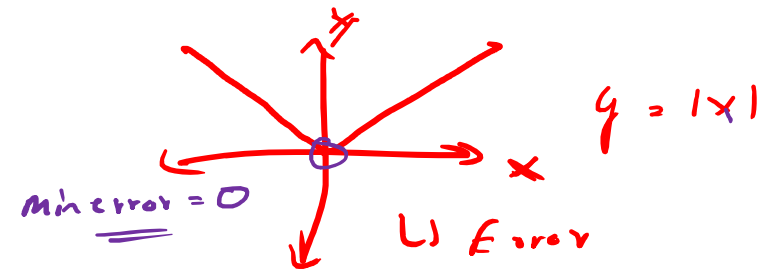
$$Total Error = 1 + (-2) + 1 = 0$$

Is this logically correct?
logically incorrect
because of (-ve) sign

$$\text{Error } f_n = \text{Cost } f_n = \boxed{h(\theta)} \quad r, p, \sigma, \alpha, \mu$$

$$h(\theta) = \text{SAE} = \sum |y - \hat{y}| \rightarrow \text{degree} = 1 \rightarrow \text{linear} \rightarrow \text{straight line}$$

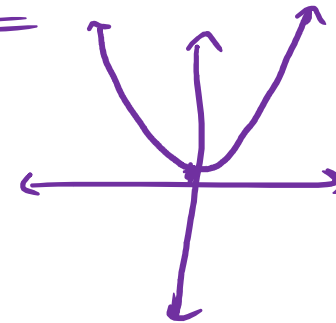
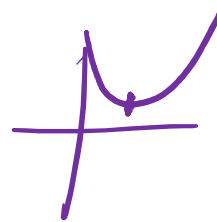
$$h(\theta) = \text{RSS} = \sqrt{\sum (y - \hat{y})^2} \xrightarrow{1/2 * 2} \text{degree} = 1$$



Best fit line is minimum error

$$\boxed{h(\theta) = \text{SSE} = \sum (y - \hat{y})^2} \Rightarrow \text{degree} = 2 \Rightarrow \text{parabola}$$

Took the best line



$$y = |2x|$$

4x

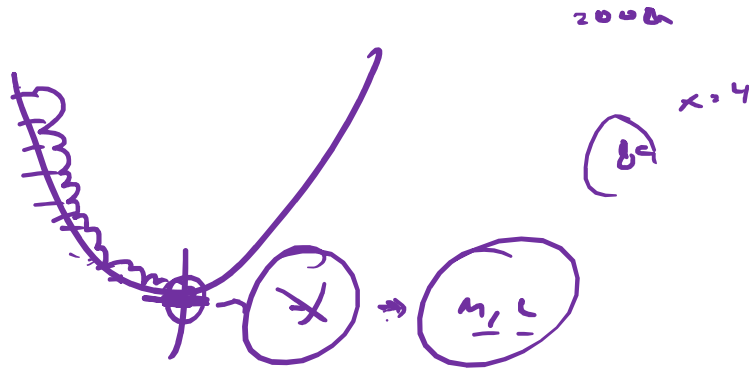
$$y = x^2$$

$$y = \frac{3x^2}{(3x+2)^2}$$

→ degree = 1 → Abne
runder

degree = 2 : $y = 2x^2 + 3$
 $4x^2 - 9$

$\frac{dy}{dx} = \frac{2ax + b}{2ax}$
 $x = 100$

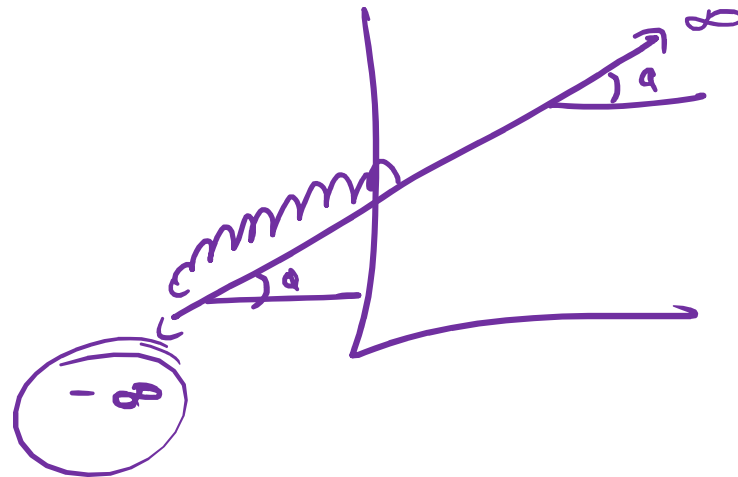


$y = 2x + 3$
 $4x - 9$

$y = ax + b$

$\frac{dy}{dx} = \underline{a}$
↳ slope

$x = \infty$
 $x = 100$
 $x = -1.39$



→ Gradient Descent (Linear Regression)

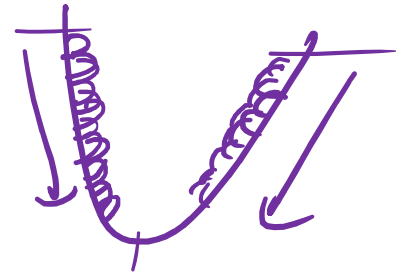
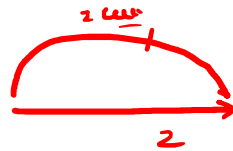
$$h(\theta) = \text{SSE} = \sum (y - \hat{y})^2$$

$$\text{MSE} = \frac{1}{n} \sum (y - \hat{y})^2$$

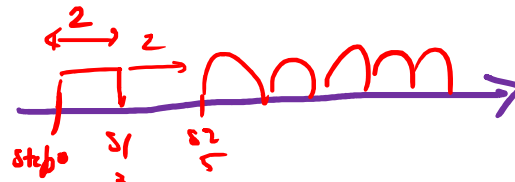
$$h(\theta) = \frac{1}{N} \sum (y - (mx + c))^2$$

$$h(\theta) = \frac{1}{N} \sum (y - mx - c)^2$$

$$\hat{y} = mx + c$$



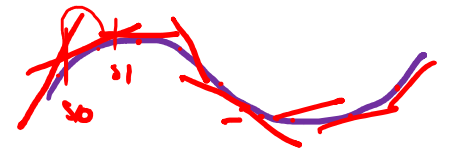
Gradient Descent
↓
Down



$$S_1 = S_0 + \text{step size}$$

$$S_2 = S_1 + \text{step size}$$

Moving on a straight path



$$S_1 = S_0 + (\text{step size} \times \text{step})$$

move on a curved path

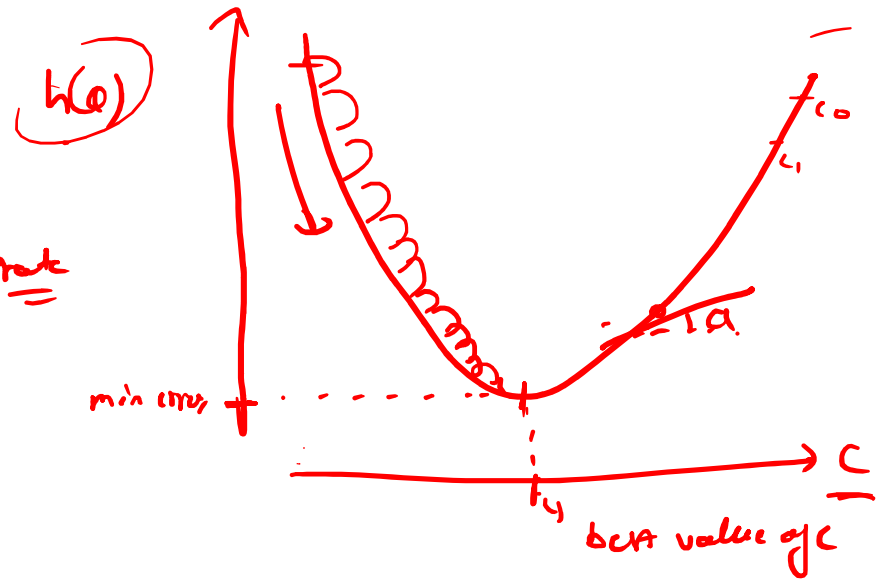
$C_0 =$ Arbitrary value

$$C_1 = C_0 - \text{Step size} \times \text{slope} \rightarrow \alpha$$

$$C_2 = C_1 - \alpha \times \frac{d h(c)}{d c}$$

$$\frac{d h(c)}{d c}$$

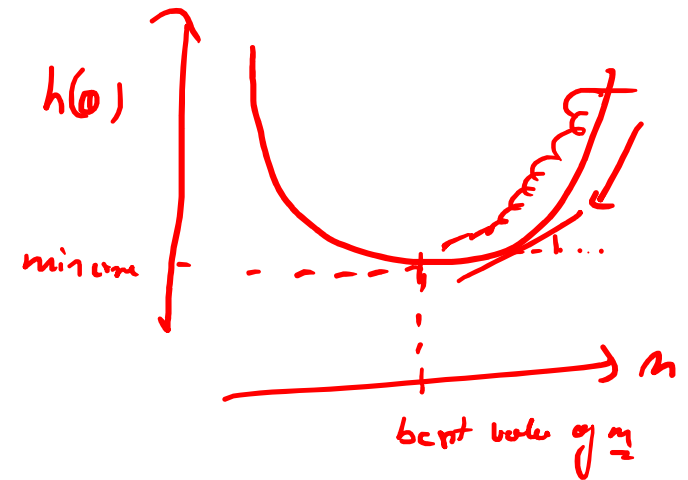
$\alpha = \text{step size} = \text{learning rate}$



Any
↑

$m_0 =$ Arbitrary value

$$m_1 = m_0 - \alpha \times \frac{d h(m)}{d m}$$



$$h(\theta) = \frac{1}{N} \sum (y - mx - c)^2$$

$$\frac{d(h(\theta))}{dm} = \frac{1}{N} (2) \cdot (-2x) \sum (y - mx - c) = \frac{-2x}{N} \sum (y - mx - c) = \frac{-2x}{N} \sum (y - \hat{y})$$

$$\frac{d(h(\theta))}{dc} = \frac{1}{N} (2) \cdot (-1) \sum (y - mx - c) = \frac{-2}{N} \sum (y - mx - c) = \frac{-2}{N} \sum (y - \hat{y})$$

α - step size \rightarrow learning rate

m_0

m_1

m_2

\vdots

$m_n = \infty$

m_0

m_1

m_2

\vdots

$m_{12} \rightarrow \min$

$$\alpha = 1$$

$$\alpha = 0.1$$

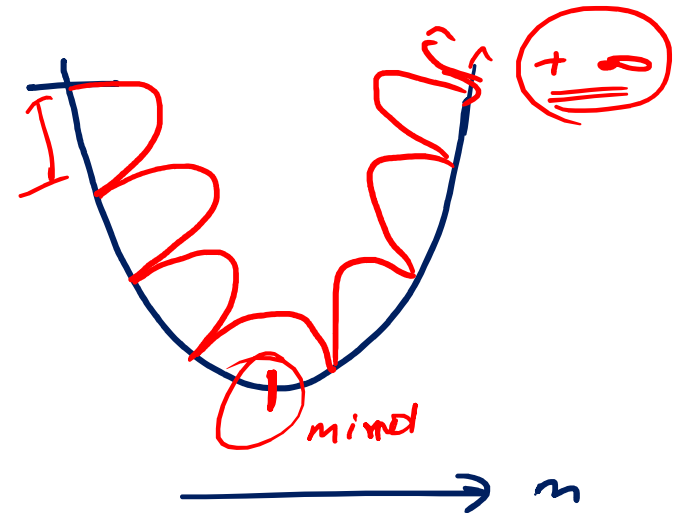
$$\hat{y} = m + c$$

$$m = 2.1$$

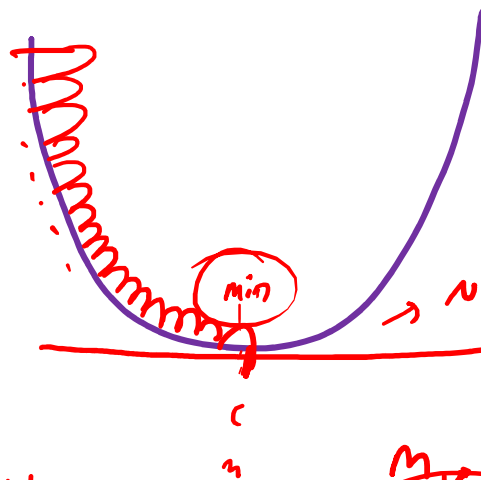
$$c = -4.9$$

$$\hat{y} = 2.1x - 4.9$$

$h(w)$ ↑



while moving if we reach ∞
it means the minimum is missed



Not able to move forward \rightarrow

Slope = 0

Convergence

$$m_1 = m_0 - \alpha \cdot \text{slope}$$

$$m_{12} = m_{11} - \alpha \cdot \text{slope}$$

$$m_{12} = m_{11}$$

$$m_{19} = m_{11}$$

$$m_{21} = m_{12}$$