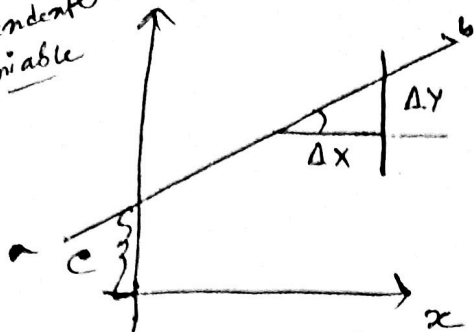


Linear Regression

dependently variable



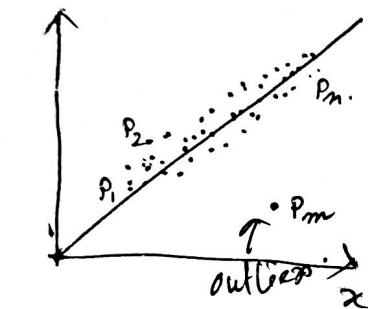
Equation of SL - as is

$$y = mx + c$$

\uparrow Slope \uparrow intercept on y-axis

So $m = \frac{\Delta y}{\Delta x}$ means for unit change in x what is the change in y .

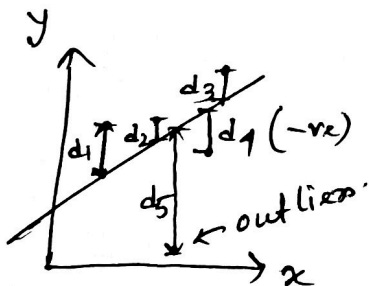
$c =$ When $x = 0$ what is the value of y .



line fitting to approximate the points.

→ linear regression.

So we have to find out the equation of SL that is best fit for the given points $P_1, P_2, P_3, \dots, P_n$.



Intuition of best fit is to minimize the total error distance of all the points from the fitted line.

$$\text{minimize } (d_1 + d_2 + d_3 + \dots + d_n)$$

Remember if we consider d_3, d_1, d_2 be positive (+ve) d_4 should be -ve. So Just adding the distance ~~not~~ would not work. So we need to -

- ① Take square of all distance,
- ② To minimize outliers effect take averagedis.

$$\text{MSE} = \text{mean square error} = \text{minimize } \sum_{i=1}^n \frac{(y - y_i)^2}{2n} \Rightarrow \text{Cost function}$$

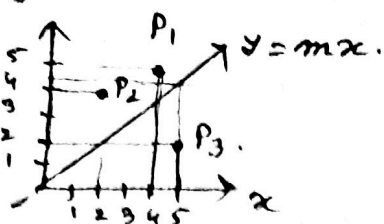
\Downarrow
 need to minimize

Let us consider for our case in

$$y = mx + c$$

$$c = 0 \text{ so.}$$

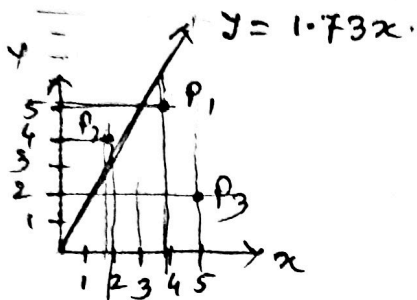
(1)



When $m = 1 (45^\circ) y = x$.

$$\begin{aligned} d_1 &= 1 \\ d_2 &= 2 \\ d_3 &= -2.5 \end{aligned} \quad \text{MSE} = \frac{1}{2 \times 3} (1^2 + 2^2 + (-2.5)^2) = \frac{1+4+6.25}{6} = \boxed{1.875}$$

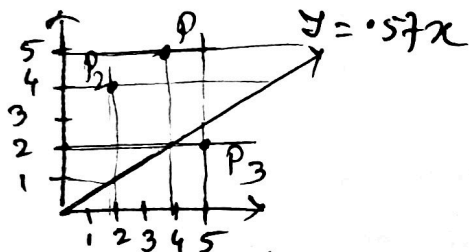
(2)



When $m = 1.73 (60^\circ)$

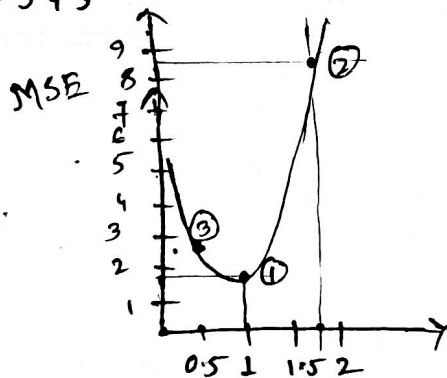
$$\begin{aligned} d_1 &= -1 \\ d_2 &= 1 \\ d_3 &= -7 \end{aligned} \quad \text{MSE} = \frac{(-1)^2 + 1^2 + (-7)^2}{6} = \frac{49+2}{6} = \boxed{8.5}$$

(3)



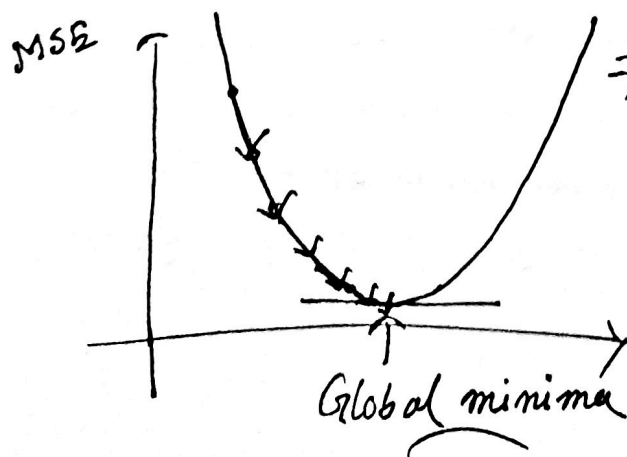
When $m = 0.577 (30^\circ)$

$$\begin{aligned} d_1 &= 2.5 \\ d_2 &= 3 \\ d_3 &= -1 \end{aligned} \quad \text{MSE} = \frac{(2.5)^2 + 3^2 + (-1)^2}{6} = \frac{15.25}{6} = 2.70$$



If we plot m and MSE we will get a curve like in the left hand.

Gradient Descent Algorithm:



$$\Rightarrow y = F(\theta_1)$$

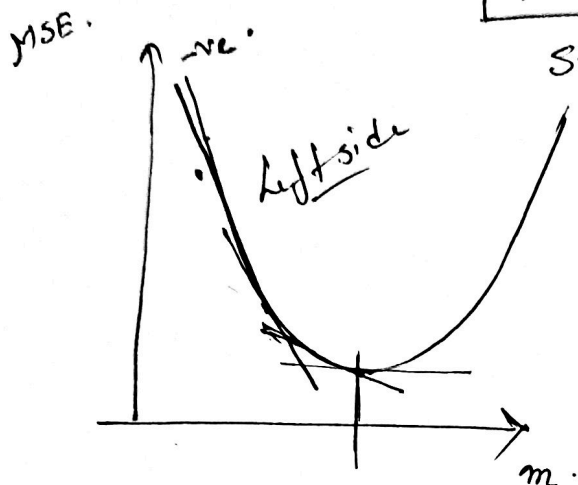
To minimize - y

$$\frac{\partial}{\partial \theta_1} y \Rightarrow \frac{\partial}{\partial \theta_1} F(\theta_1)$$

$$\text{Global minima} \Rightarrow \theta_1 \Rightarrow \frac{\partial}{\partial \theta_1} F(\theta_1) = 0$$

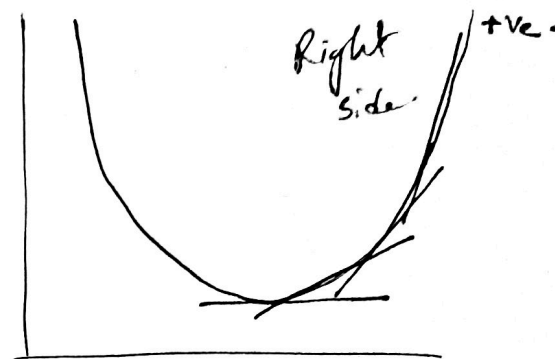
Theory of Convergence

$$\theta_{t+1} = \theta_t - \underbrace{\frac{\partial}{\partial \theta} F(\theta)}_{\text{Step size}} \alpha \quad \leftarrow \begin{array}{l} \text{learning rate.} \\ \text{(very small} \\ \text{value} \\ \text{like 0.001)} \end{array}$$



at the left side

$$\frac{\partial}{\partial \theta} F(\theta) = -ve$$



On Right

$$\frac{\partial}{\partial \theta} F(\theta) = +ve$$

$$\theta_{t+1} \Rightarrow \theta_t - (+ve)$$

$$\theta_{t+1} < \theta_t$$

$$\theta_{t+1} \Rightarrow \theta_t - (-ve) \Rightarrow \theta_t + (+ve)$$

$$\theta_{t+1} > \theta_t \Rightarrow \underline{\text{So the eqn. converge.}}$$

Learning Rate

