

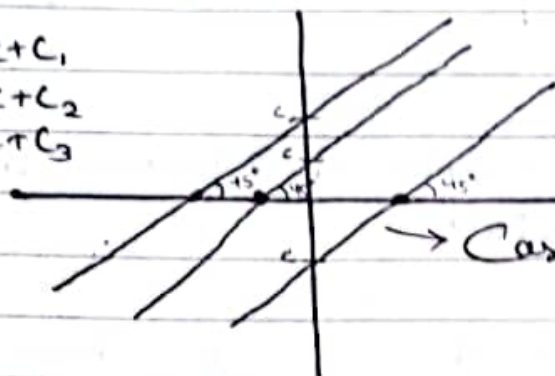
~~Hyperplane~~

$$\Pi_d : w^T x + w_0 = 0$$

d-dimension

→ Hyperplane

$$\begin{aligned} y &= mx + c_1 \\ y &= mx + c_2 \\ y &= mx + c_3 \end{aligned}$$

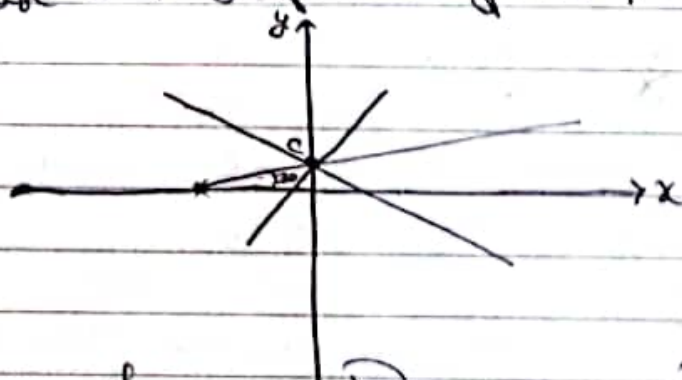


* Significance
of m & c *

→ Case 1 * ^{Same} Slope (m) is same

• Intercept (c) is different

Case 2 * Slope is different, intercept same



$$\Rightarrow y = mx + c_1$$

$$y = mx + c_2$$

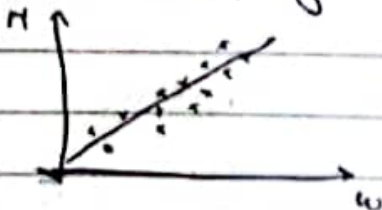
$$y = mx + c_3$$

* Linear Regression Algorithm *

Supervised, Regression technique

$$D_n = \{ (x_i, y_i)_{i=1}^n \mid x_i \in \mathbb{R}^d, y_i \in \mathbb{R} \}$$

Data (x_i, y_i) → Linear Reg → $f \rightarrow$ line (m, c)



$$y = mx + c$$

$$\text{height} = m * \text{weight} + c$$

weight → $f(m, c)$ → Height

$$\text{Height} = m * \text{weight} + c$$

Here 2 variable, height & weight

i.e. called Simple linear regression

* Simple linear Regression *

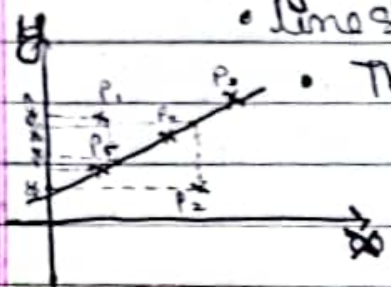
$$D_n = \{ (x_i, y_i)_{i=1}^n \mid x_i \in \mathbb{R}^1, y_i \in \mathbb{R} \}$$

Task \rightarrow to get m & c

- To find a line that passes through the given data.

- Line should be best fit all the dataset

- That line will be known as predictor



$$\begin{aligned} \text{for } P_1 &\rightarrow e_1 = y_1 - \hat{y}_1 \\ P_2 &\rightarrow e_2 = y_2 - \hat{y}_2 \\ P_3 &\rightarrow e_3 = 0, e_4 = 0, e_5 = 0 \end{aligned}$$

$$\text{total error} = e_1 + e_2 + e_3 + e_4 + e_5$$

$$= y_1 - \hat{y}_1 + y_2 - \hat{y}_2 + 0 + 0 + 0$$

\therefore +ve & -ve errors can cancel out each other and give wrong result so let's square them

$$\therefore \text{Total error} = (y_1 - \hat{y}_1)^2 + (y_2 - \hat{y}_2)^2 + 0^2 + 0^2 + 0^2$$

$$\boxed{\text{Total error} = \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Note:- line with least total error is the best predictor

* Optimization Theory

$$m^*, c^* = \arg \min_{(m, c)} \left\{ \sum_{i=1}^n (y_i - \hat{y}_i)^2 \right\} \because \hat{y}_i = mx_i + c$$

$$m^*, c^* = \arg \min_{(m, c)} \left\{ \sum_{i=1}^n (y_i - (mx_i + c))^2 \right\}$$

It's, Ordinary Least Square