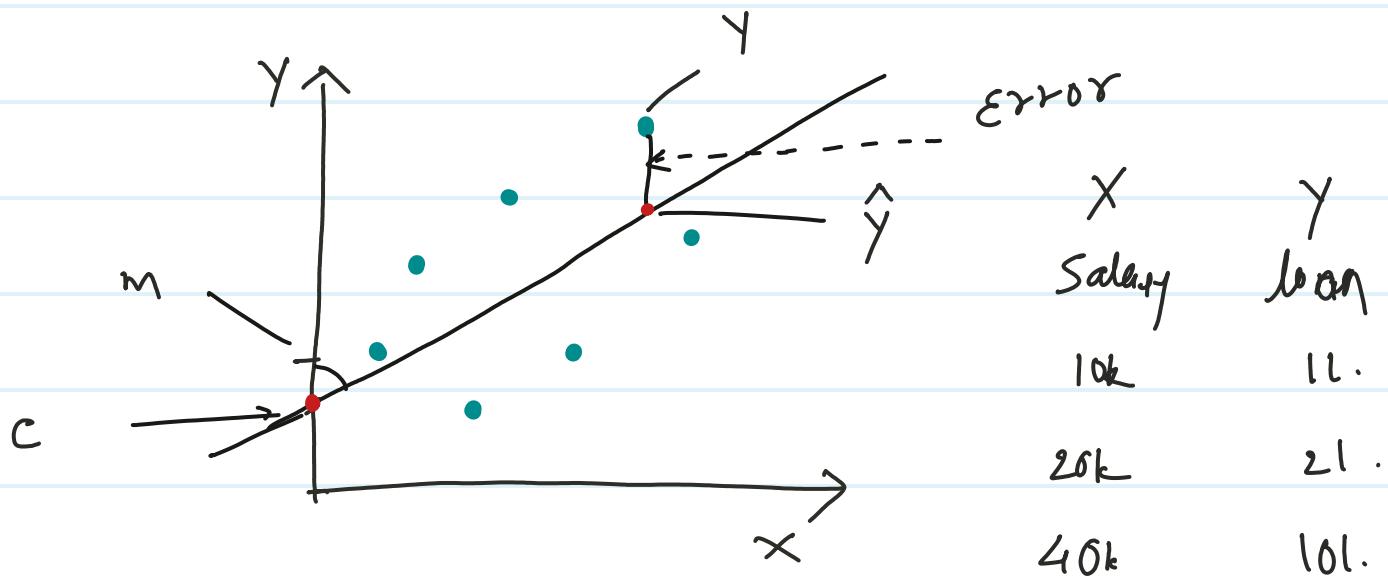


Linear Regression



Line eqn -

$$y = mx + c \quad \hat{y} = \text{predicted data}$$

y = Dependent variable

x = Independent variable

m = slope

c = Intercept

$y - \hat{y}$ = Residual error

Base equation

$$y = mx + c$$

OR

$$y = h_{\theta}(x)$$

OR

Simple linear eqn. $h_{\theta}(x) = \theta_0 + \theta_1 x_1$

multi
linear
eqn

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

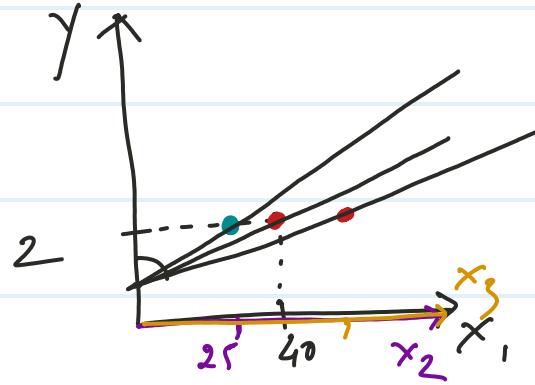
$$y = J = h_{\theta}(x)$$

$$J = J(\theta_0, \theta_1)$$

Loss function

$$J(\theta_0, \theta_1) = (y - \hat{y})^2$$

If only calculate single datapoint



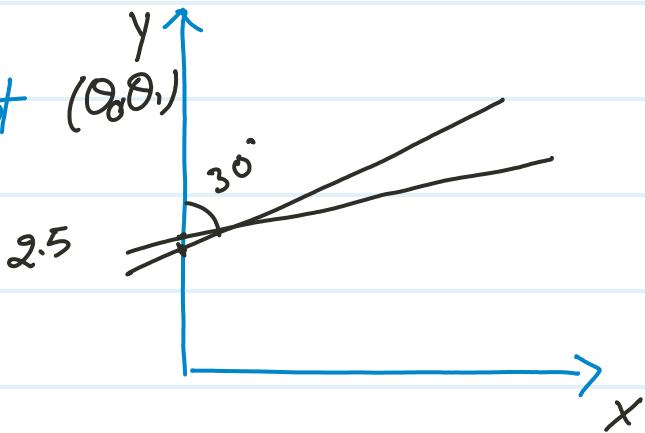
Cost function

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m [h_{\theta}(x^{(i)}) - y^{(i)}]^2$$

This is cost function to min. error by changing value of θ_0, θ_1

$$\theta_0 = \text{slop}$$

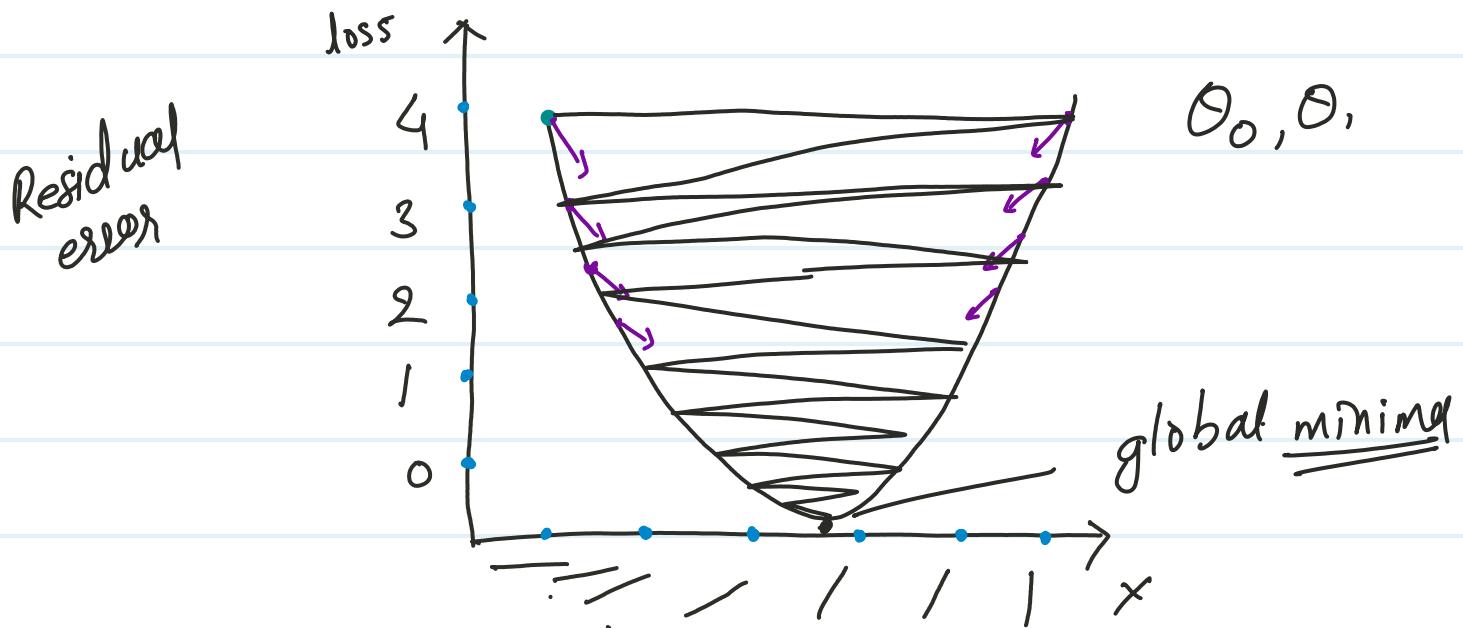
$$\theta_1 = \text{intercept } (\theta_0, \theta_1)$$



$$J(\theta) =$$

Repeat conversion theorem

$$\theta_j = \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta_j}$$



$$\underset{J(\theta_0, \theta_1)}{\text{J}} = \frac{1}{m} \sum_{i=1}^m [h_\theta(x^i) - y^i]^2$$

$$\theta_j = \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta_j}$$

update eqnⁿ

for θ_0

$$\frac{\partial J(\theta)}{\partial \theta_0} = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^i) - \hat{y}^i) \quad \text{--- (1)}$$

for θ_1

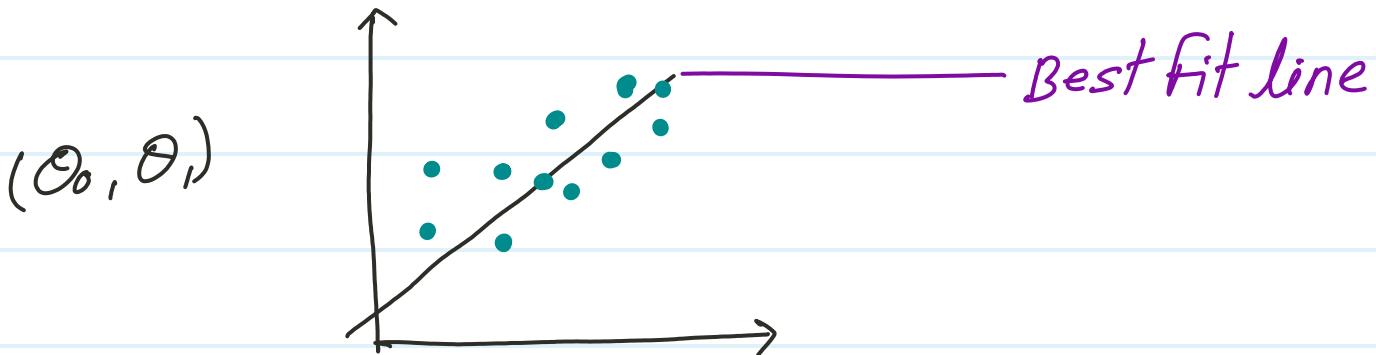
$$\frac{\partial J(\theta)}{\partial \theta_1} = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^i) - \hat{y}^i) * x^i \quad \text{--- (2)}$$

update $\theta_0 = \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^i) - \hat{y}^i)$

update $\theta_1 = \theta_1 - \alpha \frac{1}{m} \sum (h_\theta(x^i) - \hat{y}^i) * x^i$

α is learning rate

$$(0.01, 0.05, 0.1, 0.25, 0.3, 0.4, \dots)$$



* Model evaluation or performance metric

- ① MSE (mean squared error)
- ② RMSE (Root mean square error)
- ③ MAE (mean absolute error)
- ④ R²
- ⑤ Adj. R²

2 - 3	(1) - 1
3 - 4	(1) - 1
5 - 5	(2) - 0

① MSE

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

$$\frac{2}{3} \Rightarrow 0.5 \downarrow$$

② RMSE

$$\text{RMSE} = \frac{1}{n} \sqrt{\sum_{i=1}^n (\gamma - \hat{\gamma})^2}$$

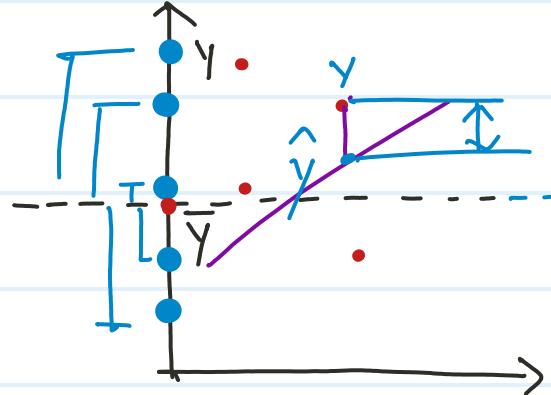
③ MAE

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\gamma - \hat{\gamma}|$$

lower value better.

Accuracy Matrix

$$R^2 = 1 - \frac{RSS}{TSS}$$

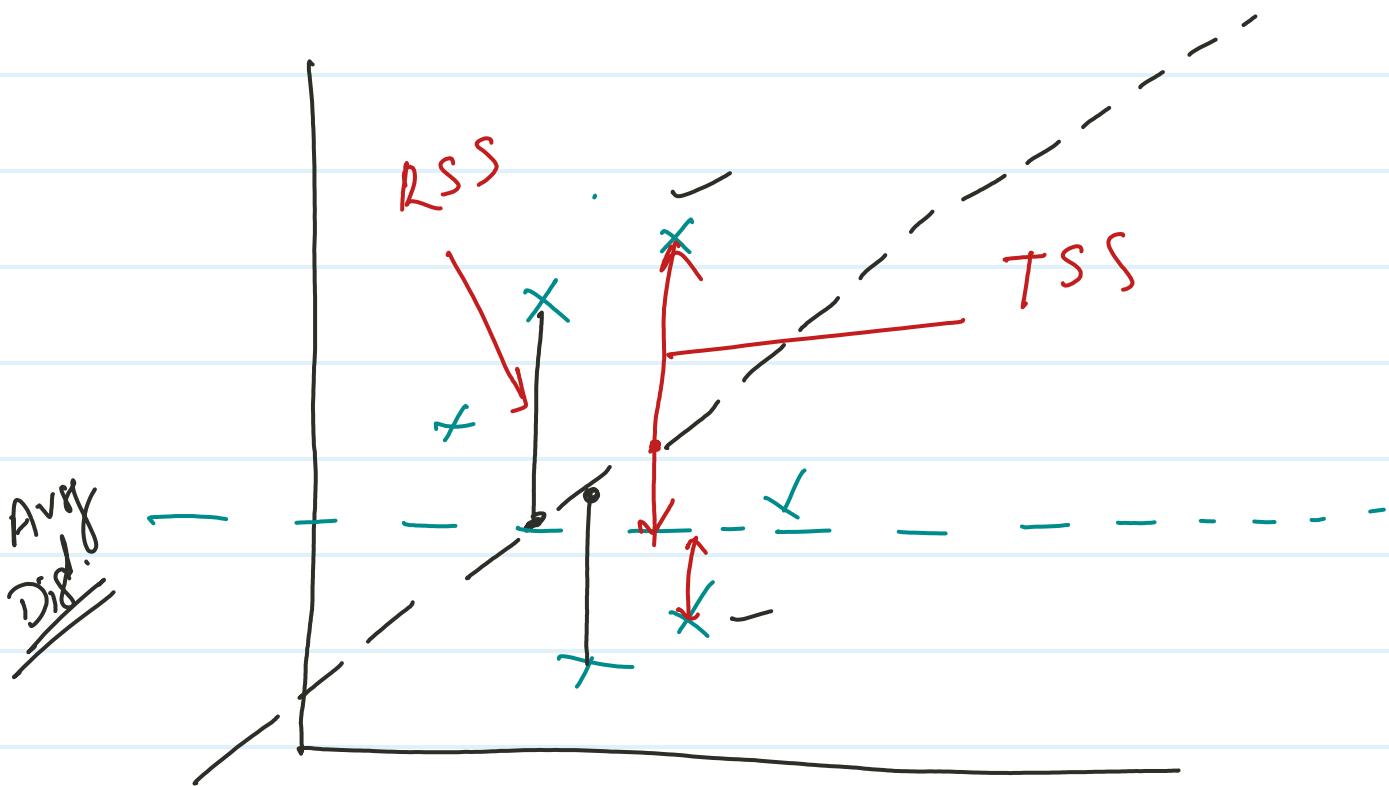


R^2 = coeff. of determination

RSS = sum of square of residual

RSS = Distance b/w γ and $\hat{\gamma}$

TSS = Distance b/w γ and $\bar{\gamma}$



$$RSS = \sum (y - \hat{y})^2$$

$$TSS = \sum (y - \bar{y})^2$$

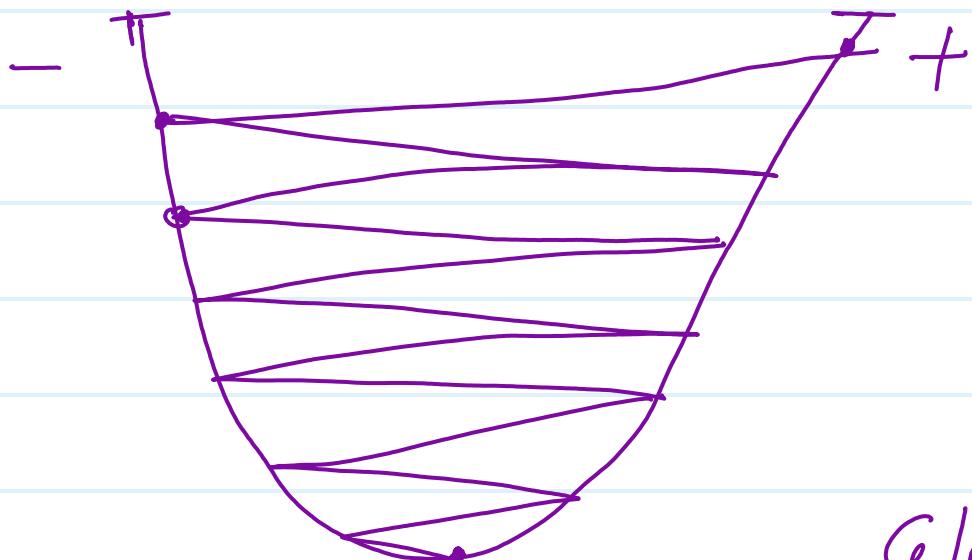
TSS Avg distance

② Adj. R^2

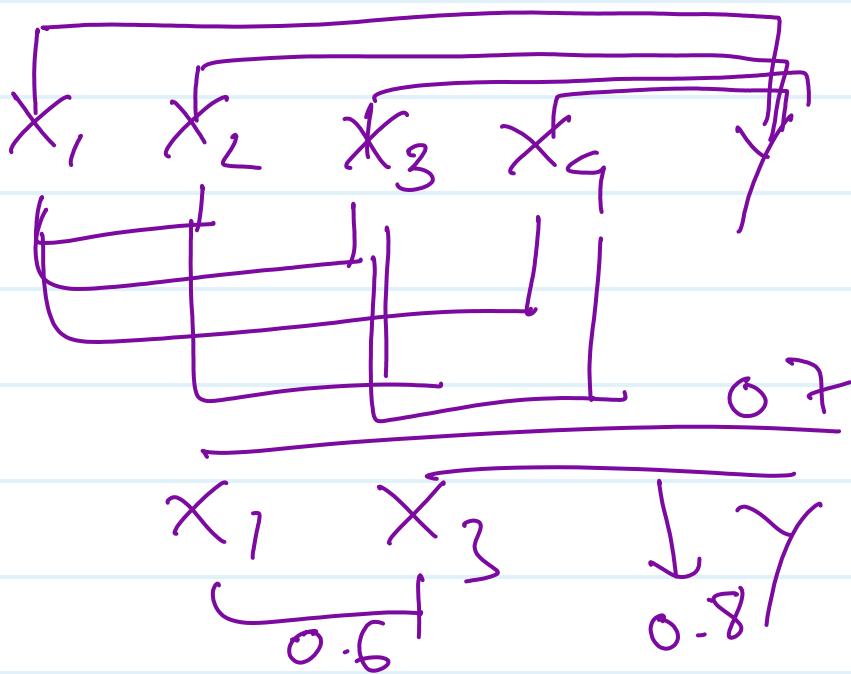
$$\text{Adj. } R^2 = 1 - \frac{(1-R^2)(N-1)}{N-P-1}$$

N = no. of datapoint in our dataset

P = no. of independent variable
(x_1, x_2, x_3, \dots)



Global
minimum



* To find multi co-linearity

X_1	X_2	X_3	X_4	Y
←			→	←

$X_1 X_2 \quad X_2 X_3$
 $X_1 X_3 \quad X_2 X_4$
 $X_1 X_4 \quad X_3 X_4$

$\boxed{X_1 X_3 X_4 \quad Y}$

*

VIF (variance inflation factors)

$$VIF = \frac{1}{1 - R^2}$$

$$\left. \begin{array}{l} X_1 = 3 \\ X_2 = 6 \\ X_3 = 4 \\ X_4 = 5 \end{array} \right]$$

VIF = start 1 and it has no limit

If 1 or less than 5 so
no. multicollinearity

If > 5 so there will be co-linearity
btw indep. feature.

over fitting :-

low biased
high variance]

under fitting

high biased
low variance]

Best fitting

low biased
low variance]

