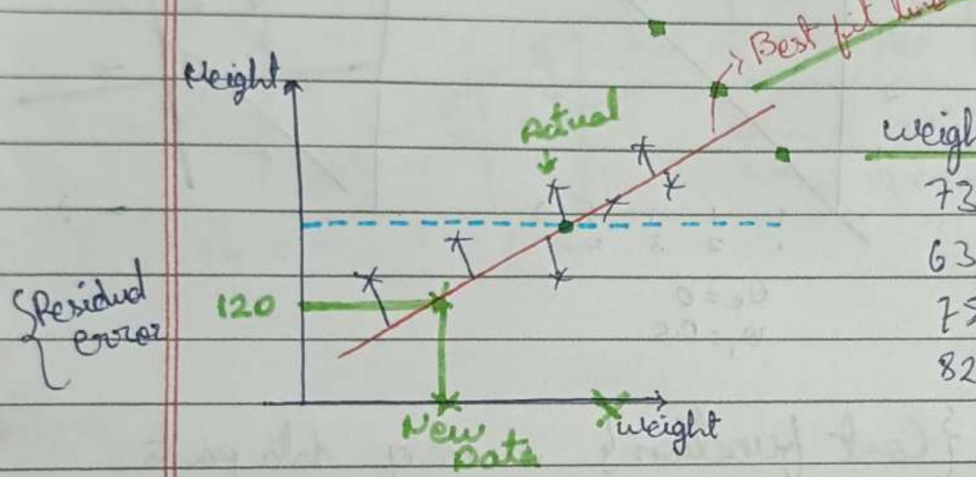
Linear Regression Algorithm

Linear Regression is a way to predict a number by drawing the best straight line through data points.

It learns the relationship between input(X) and output(Y) using a straight line.

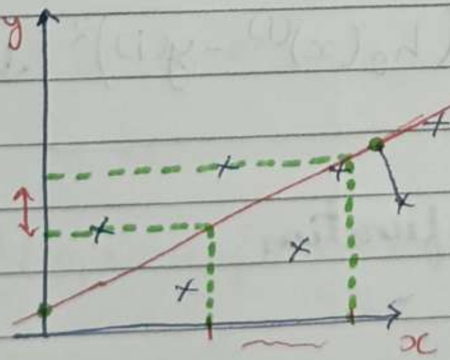


weight (kg)	Height (cm)
73	150
63	155
78	170
82	165

TRAIN → Model → Hypothesis

I/P weight → Hypothesis → O/P Height

Residual Error is difference between the actual value and predicted value



To find best fit line:

① $y = mx + c$

M = Slop or coffecient
C = Intercept

② $h_\theta(x) = \theta_0 + \theta_1 x_i$

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots \theta_n x_n$

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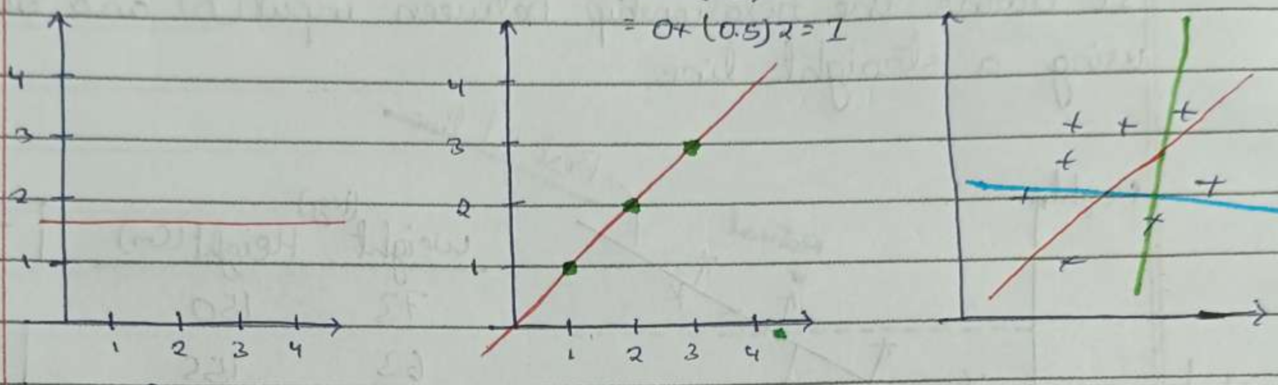
Hypothesis {y is a linear function of x}

$h_\theta(x) = \theta_0 + \theta_1 x_1$ → Cofficient

↳ Intercept

$= 0 + (0.5)1 = 0.5$

$= 0 + (0.5)2 = 1$



$\theta_0 = 1.5$ $\theta_1 = 0$ $\theta_0 = 0$ $\theta_1 = 0.5$

Solve {Cost function} m = No. of data points

Minimize $\sum_{i=1}^{m} \frac{1}{2m} \left(h_\theta(x)^{(i)} - y^{(i)}\right)^2$ ↓↓
θ_0, θ_1

x^2

$\frac{\partial(x^2)}{\partial x} = 2x^{2-1} = 2x$

$$\boxed{J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x)^{(i)} - y^{(i)}\right)^2}$$ ↓↓↓

↳ Squared Error function

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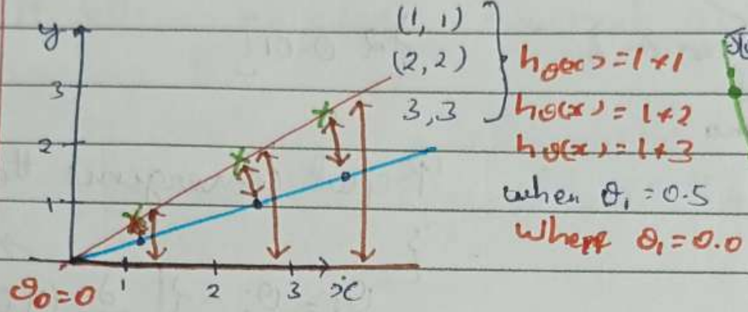
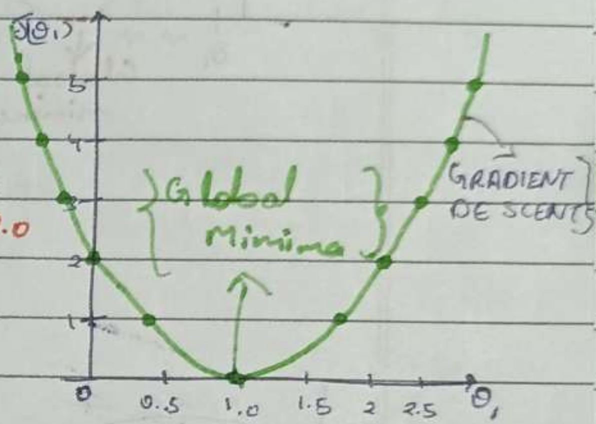
Hypothesis → Cost function

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

$h_\theta(x) = \theta_1 x_1$ let $\theta_0 = 0$

where $\theta_1 = 1$





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

$$= \frac{1}{6}\left[(0)^2 + (0)^2 + (0)^2\right]$$

$$= 0$$

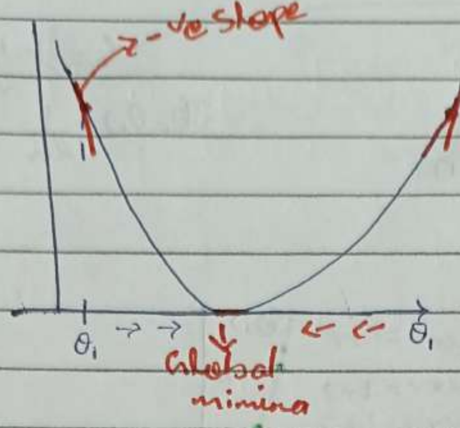
$$J(\theta_1) = \frac{1}{6}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right]$$

when $\theta = 0.5$

$$= \frac{1}{6}(3.5) = \simeq 0.58$$

$$J(\theta_1) = \frac{1}{6}\left[(0-1)^2 + (0-2)^2 + (0-3)^2\right]$$

$$= \frac{14}{6} = \simeq 2.3$$



$\alpha = 1000$

{Learning Rate}

$\{\alpha = 0.01\}$

Repeat convergence theorem

{

$$\theta_j := \theta_j - \alpha \overset{\text{slope}}{\boxed{\frac{\partial}{\partial \theta_j}(J(\theta_1))}}$$

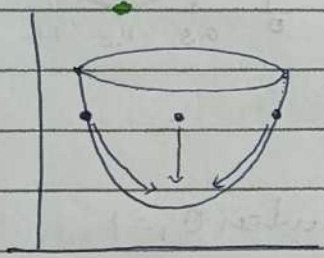
}

$\theta_1 := \theta_1 - \alpha(+ve)$ } Decrement

$\theta_1 := \theta_1 - \alpha(-ve)$ } increment

slope

$\theta_1 = \theta_1 +$



Outline

1. Start with θ_0 & θ_1

2. Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$ until we reach near global minima.

3. Convergen Theorem

{ $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j}(J(\theta_0, \theta_1)$

$j = 0$ and 1

}