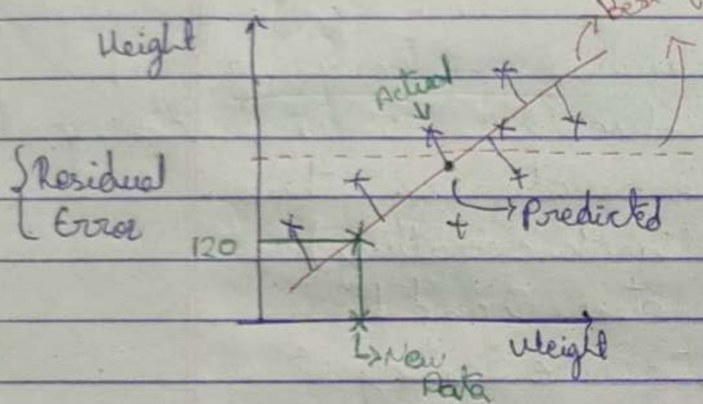
Linear Regression Algorithm

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.



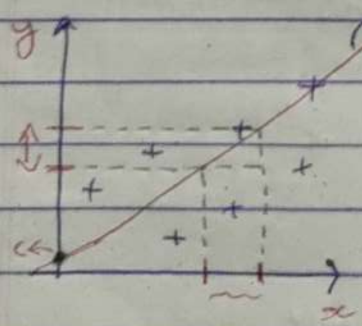
Weight (kg)	Height(cm)
73	150
63	155
78	170
82	165

TRAIN → Model → hypothesis → O/P Height

I/P weight → hypothesis

Residual Error is difference between the acual value and the predicted value.

Aim: To find best fit line with minimal error.



To find best fit line

① $y = Mx + C$

M = Slop or coffecient
C = Intercept

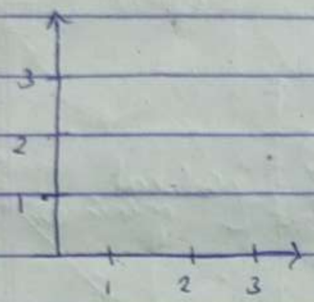
② $h_\theta(x) = \theta_0 + \theta_1 x_1$

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

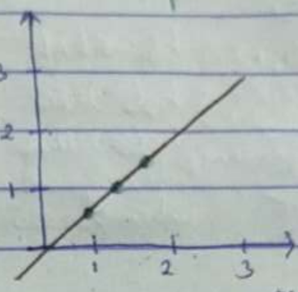
Hypothesis {y is a linear function of x}

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

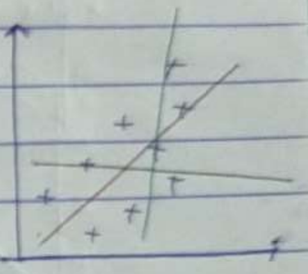
θ_0 ↳ intercept, θ_1 > coefficient



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



$\theta_0 = 0 \Rightarrow 0(0.5)1 = 0.5$
$\theta_1 = 0.5 \Rightarrow 0 + (0.5)2 = 1$
$\Rightarrow 2$



Solve {Cost function}

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

x^2

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

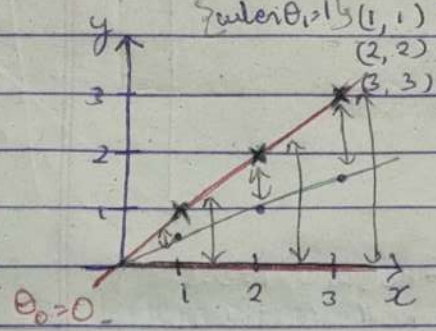
$$\boxed{J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2}$$

(also called)
↳ Squared Error Function

Hypothesis

lets $\theta_0 = 0$

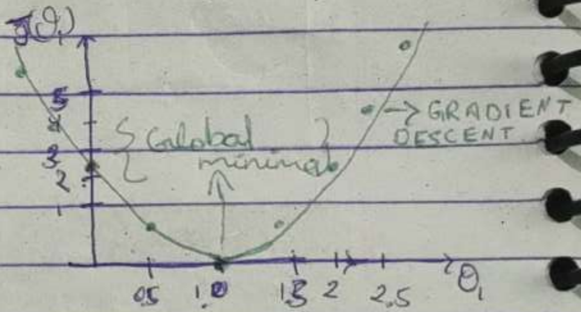
$h_\theta(x) = \theta_0 + \theta_1 x_1$



$h_\theta(x) = 1 \times 1$
$h_\theta(x) = 1 \times 2$
$h_\theta(x) = 1 \times 3$
when $\theta_1 = 0.5$
when $\theta_1 = 0.0$

Cost function

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



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

when $\theta_1 = 1$

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

$= 0$

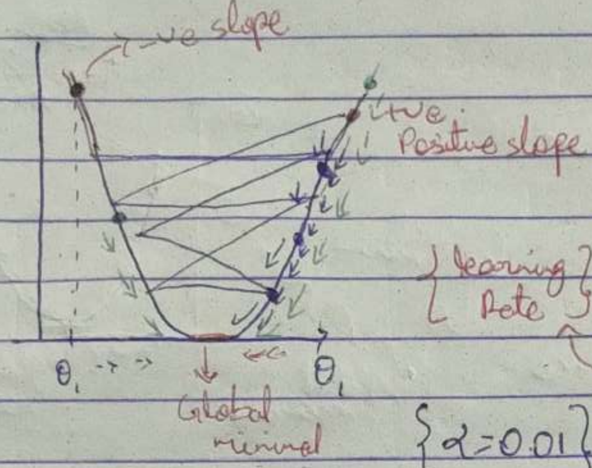
$J(\theta_1) = \frac{1}{6} \left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^3 \right]$

when $\theta_1 = 0.5$

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

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

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



Repeat convergens theorem

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

{learning Rate}

slope

$\{\alpha = 0.01\}$

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

slope

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

$\theta_1 = \theta_1 +$

Outline

1 Start with θ_0 & θ_1

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

3 Convergens iteration

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

$j = 0$ and 1

}