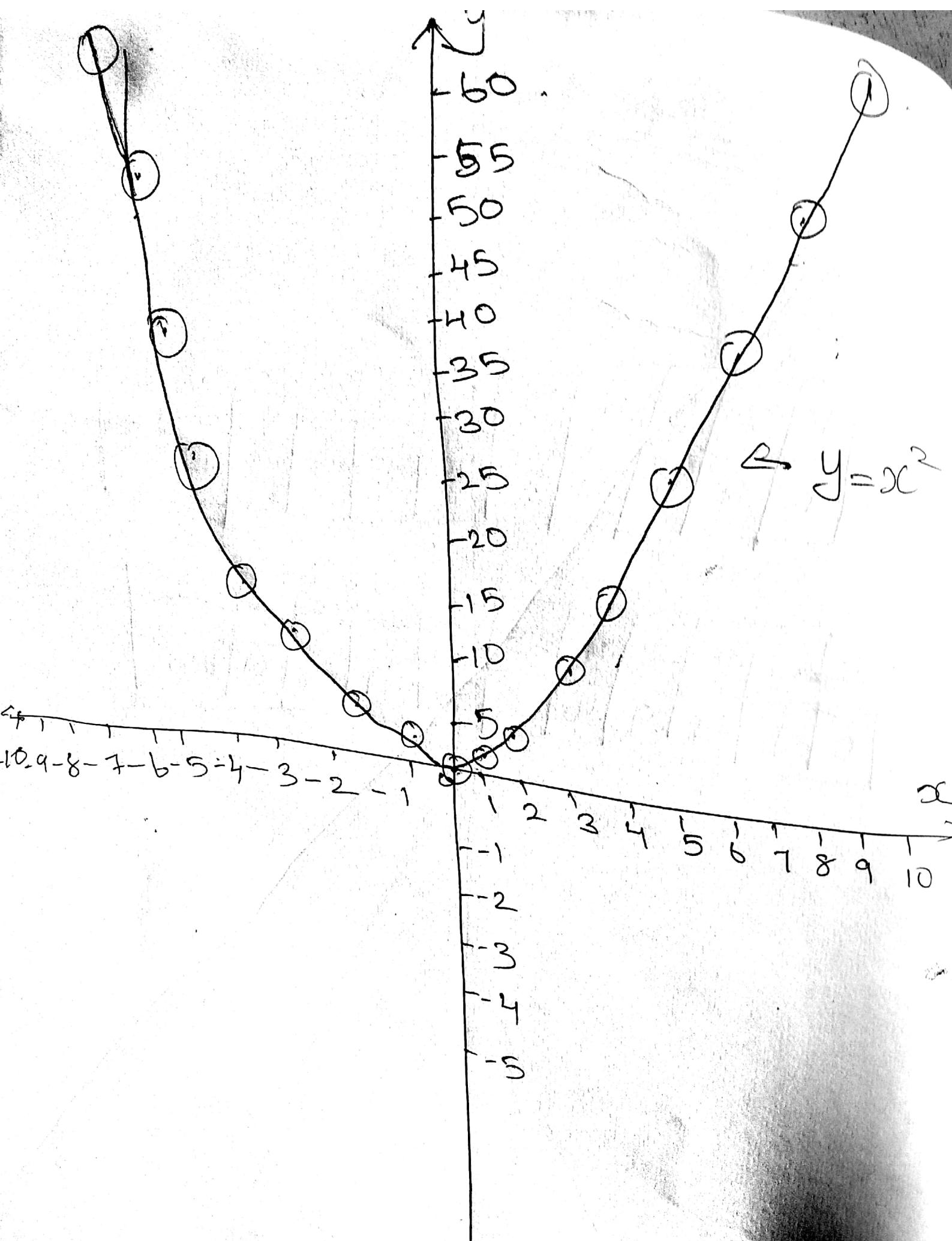


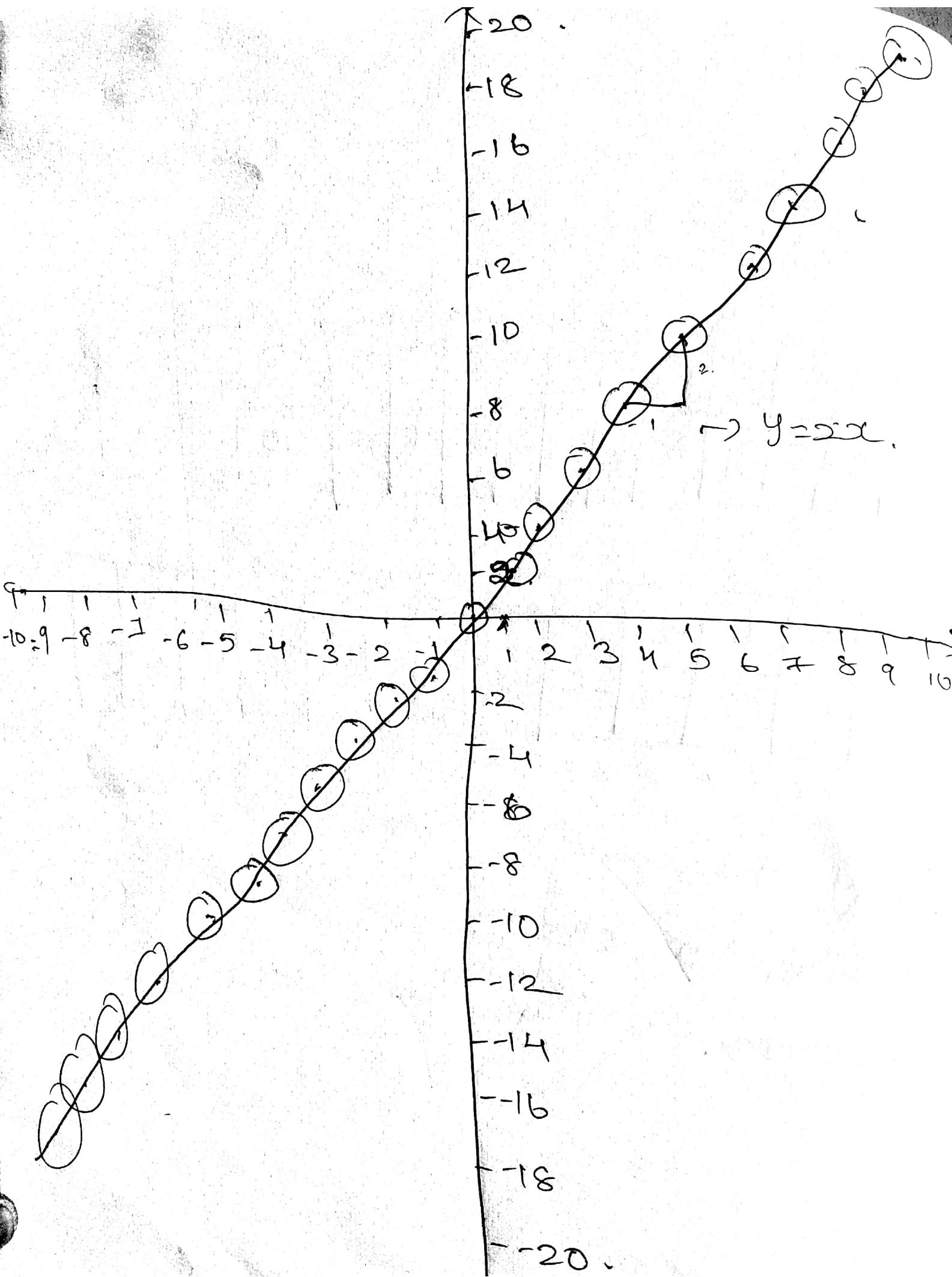
$$y = x^2$$

$$\frac{dy}{dx} = 2x.$$

x	0	1	2	3	4	5	6	7	8	9	10
y	0	2	4	6	8	10	12	14	16	18	20.

x	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
y	0	-2	-4	-6	-8	-10	-12	-14	-16	-18	-20

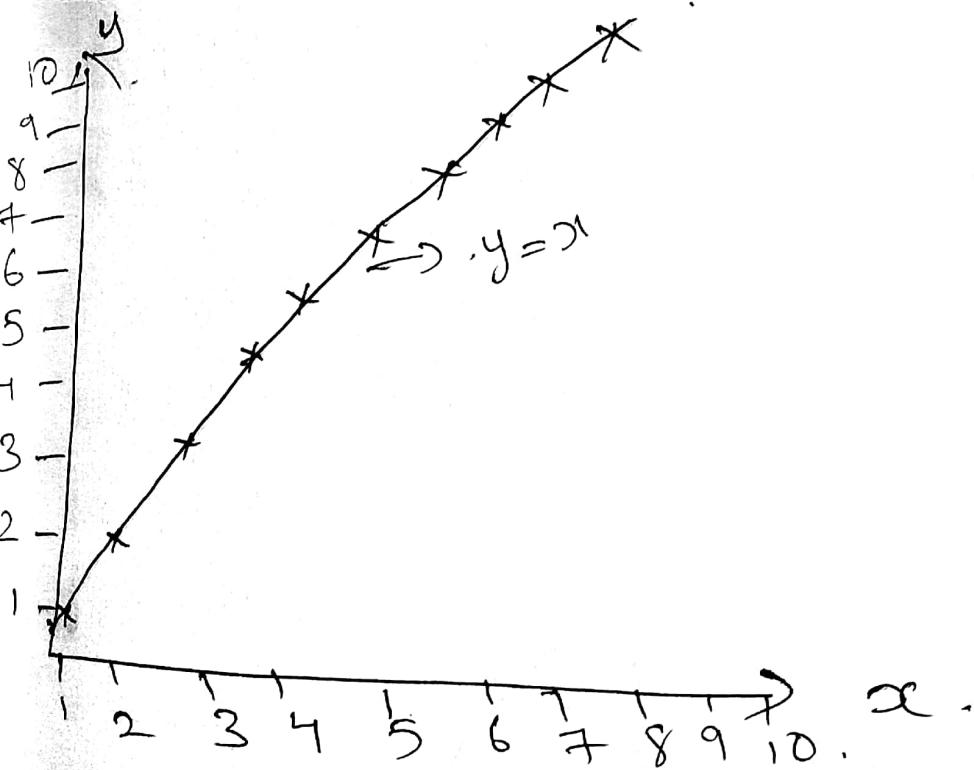




Gradient Descent

$$y = \alpha x$$

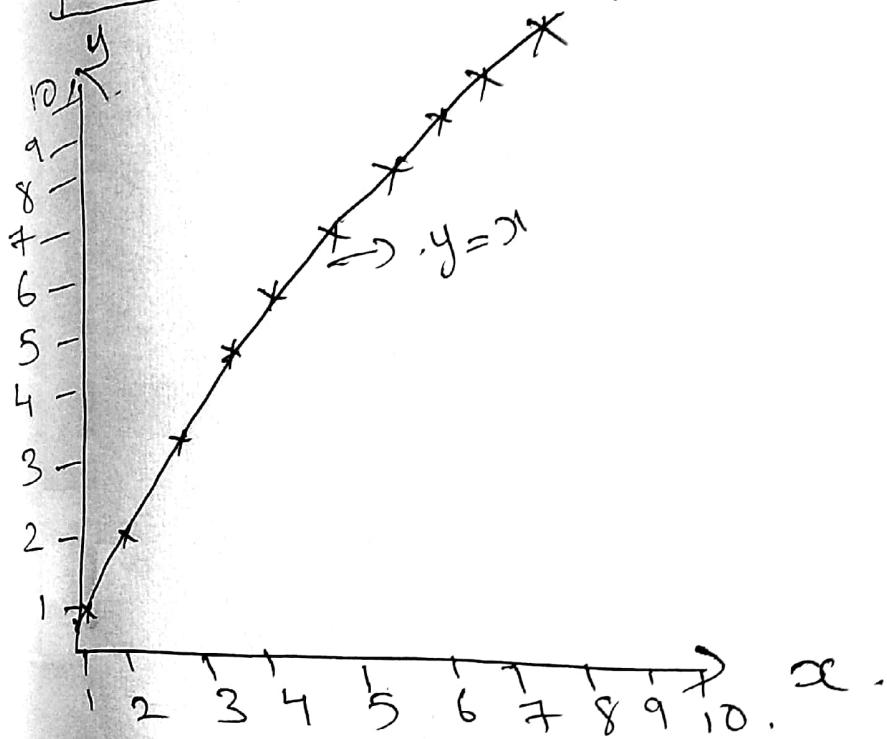
x	0	1	2	3	4	5	6	7	8	9	10
y	0	1	2	3	4	5	6	7	8	9	10



Gradient Descent

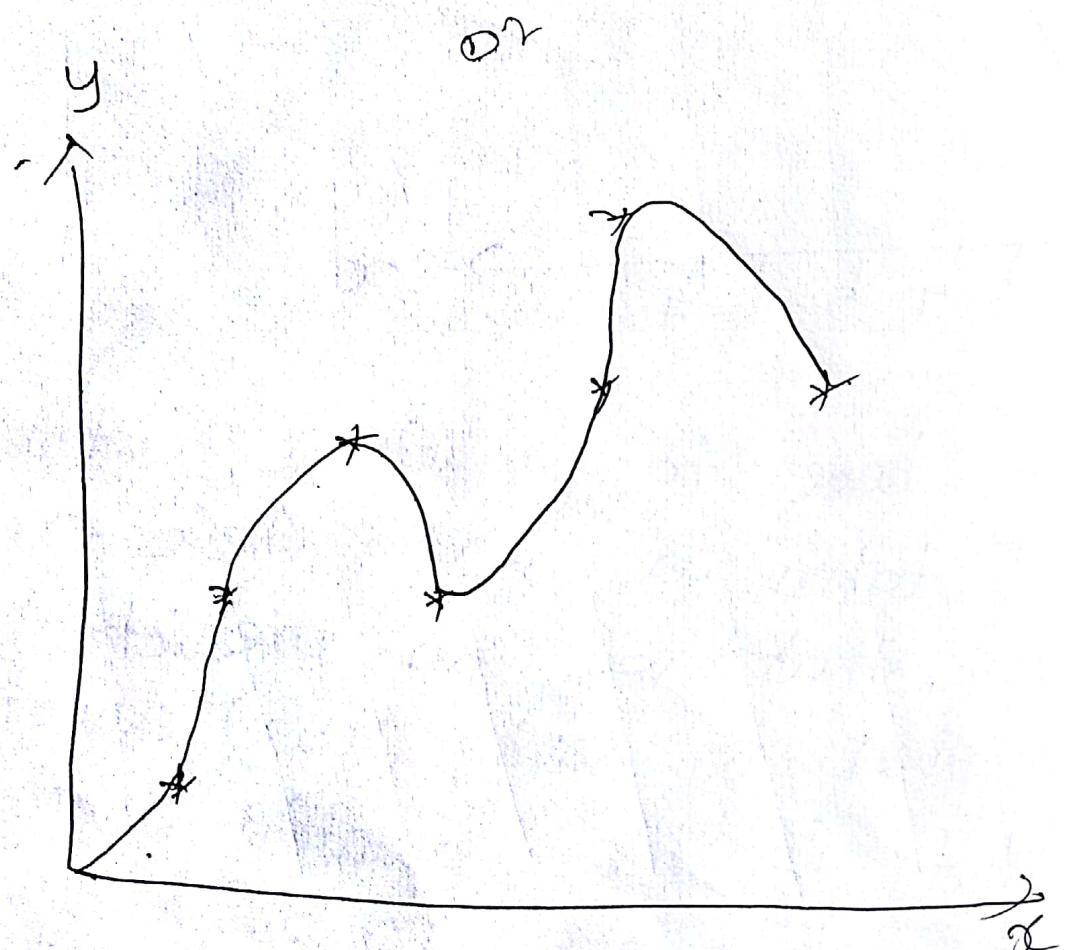
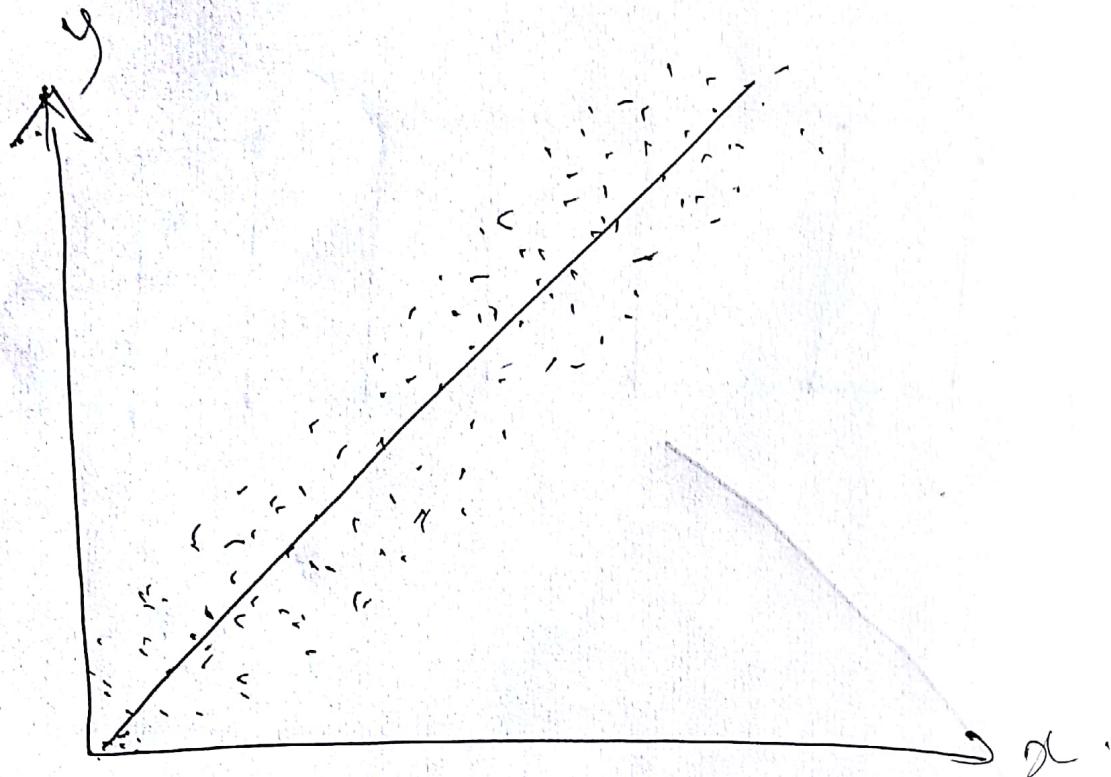
$$y = x$$

x	0	1	2	3	4	5	6	7	8	9	10
y	0	1	2	3	4	5	6	7	8	9	10



So we have to predict x & y when x is given. I taken a very simple example. Of course that we can predict y when x is given by seeing ($y = x$) equation. But what if the equation plotting point different that gives polynomial equation like $y = x^3 + x^2 + x^8 + x^3 + 1$.

or figure shown below.



for Simplification I go with $y=x$.
So that we write an orthonormal equation.

$$y = \theta x + b \rightarrow \text{General equation of}$$

$$\text{or} \\ y = m x + b.$$

Linear equation.

So we have to find the θ and b or slope and y-intercept where when x value is given, we have to predict the y value for equation $y = x$.

And by seeing that we can say that θ_0 value should be 1, θ_1 and b value should be 0. But we are going to randomly choose a θ and b value and we have to find the θ and b optimum value using Gradient descent. Let's start. I'm going to randomly initialize the value of $\theta = 0.5$ & $b = 0.1$ and I'm going to get the $\theta = 0$ and $b = 0$ using Gradient descent. I am using Mean Square Error Cost function but there are many Cost function to choose but again for simplicity I'm going

to use: Mean Square Error ^{Cost}
function.

$$\text{Mean Square Error} = \frac{1}{2} (\text{Target} - \text{Output})^2$$

First I'm going to plot for $\theta = 0.5$ and
 $b = 0.1$.

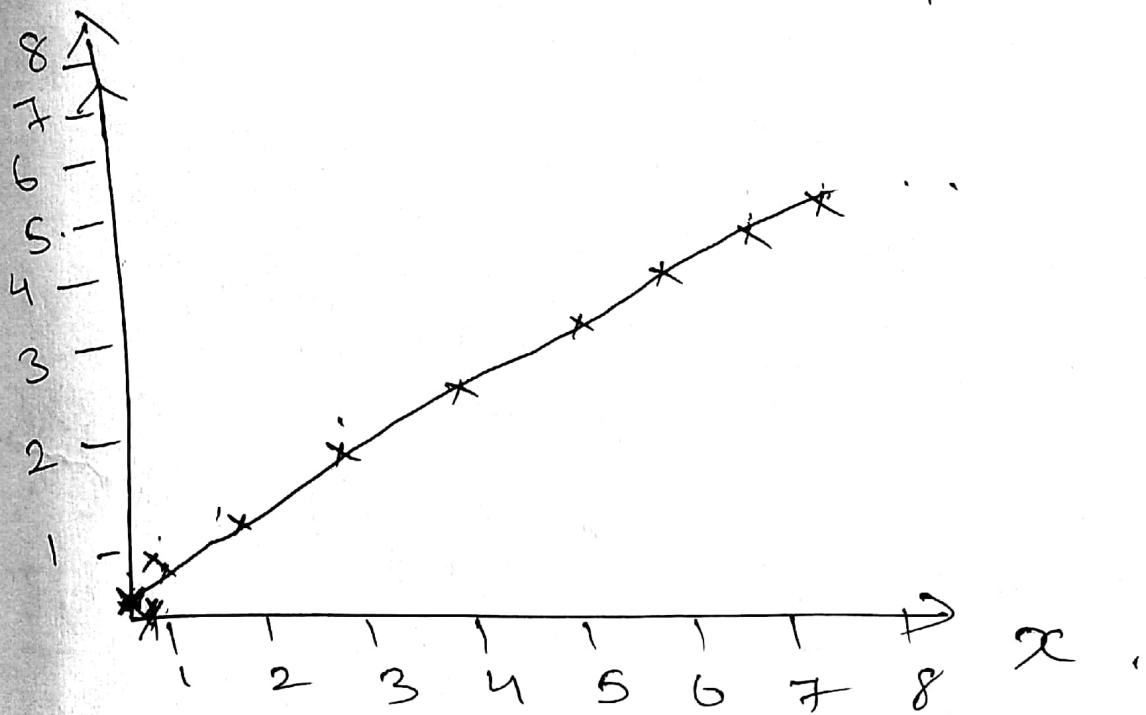
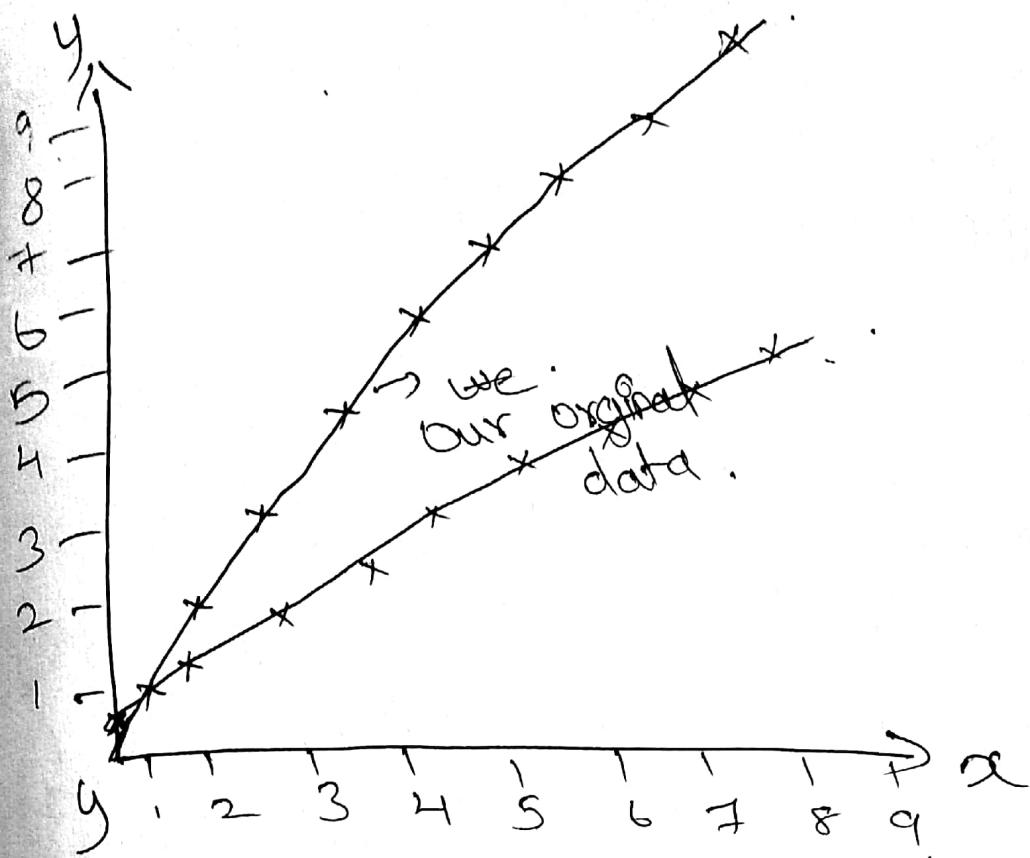
$$y = \theta x + b. \quad y = (0.5)x + 0.1$$

x	0	1	2	3	4	5	6	7	8
y	0.1	0.6	1.1	1.6	2.1	2.6	3.1	3.6	4.1

But we want .

x	0	1	2	3	4	5	6	7	8
y	0	1	2	3	4	5	6	7	8

So let plot.



By using Gradient descent we have to optimize the problem equation.

$$J(\theta_0, b) = \text{Cost function} = \frac{1}{2m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)})^2$$

$$\begin{aligned} \frac{\partial J(\theta_0, b)}{\partial \theta_0} &= \frac{1}{2m} \sum_{i=1}^m ((\theta_0 x^{(i)} + b) - y^{(i)}) \\ &= \frac{1}{2m} \sum_{i=1}^m ((\theta_0 x^{(i)} + b) - y^{(i)}) x^{(i)}. \end{aligned}$$

$$\begin{aligned} \frac{\partial J(\theta_0, b)}{\partial b} &= \frac{1}{2m} \sum_{i=1}^m ((\theta_0 x^{(i)} + b) - y^{(i)})^2 \\ &= \frac{1}{2m} \sum_{i=1}^m ((\theta_0 x^{(i)} + b) - y^{(i)}) (1) \\ &= \frac{1}{m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)}) \end{aligned}$$

Gradient descent

$$b = b - \alpha \cancel{\frac{1}{m} \sum_{i=1}^m (\frac{\partial J(\theta_0, b)}{\partial b})}$$

$$\theta = \theta - \alpha \frac{\partial J(\theta_0, b)}{\partial \theta}$$

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

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

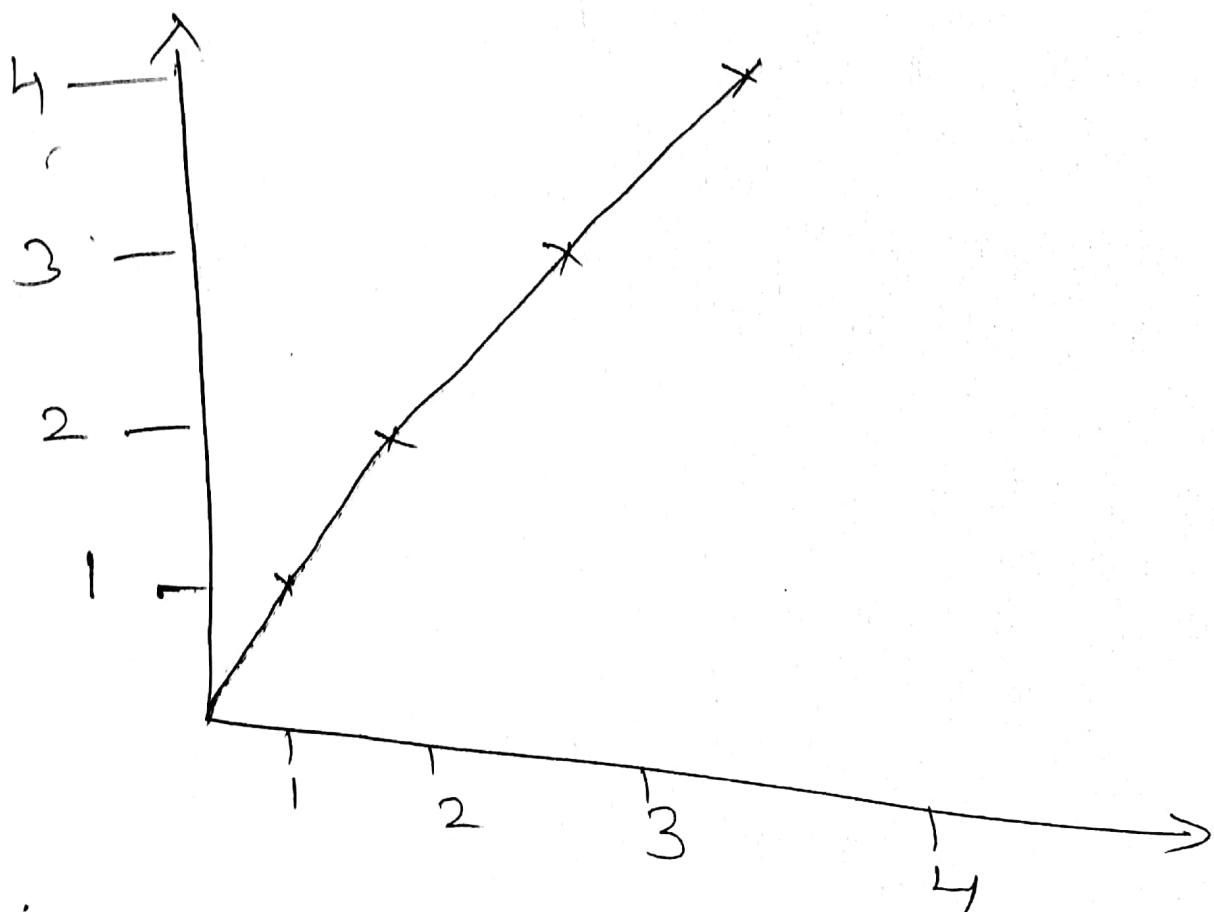
$$b = b - \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)}_{\text{output}} - y^{(i)}_{\text{desired}}) x^{(i)}$$

$$\theta = \theta - \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)}_{\text{output}} - y^{(i)}_{\text{desired}}) x^{(i)}$$

Desired Output ($y_{desired}$)

$$y = x$$

x	0	1	2	3	4
y	0	1	2	3	4



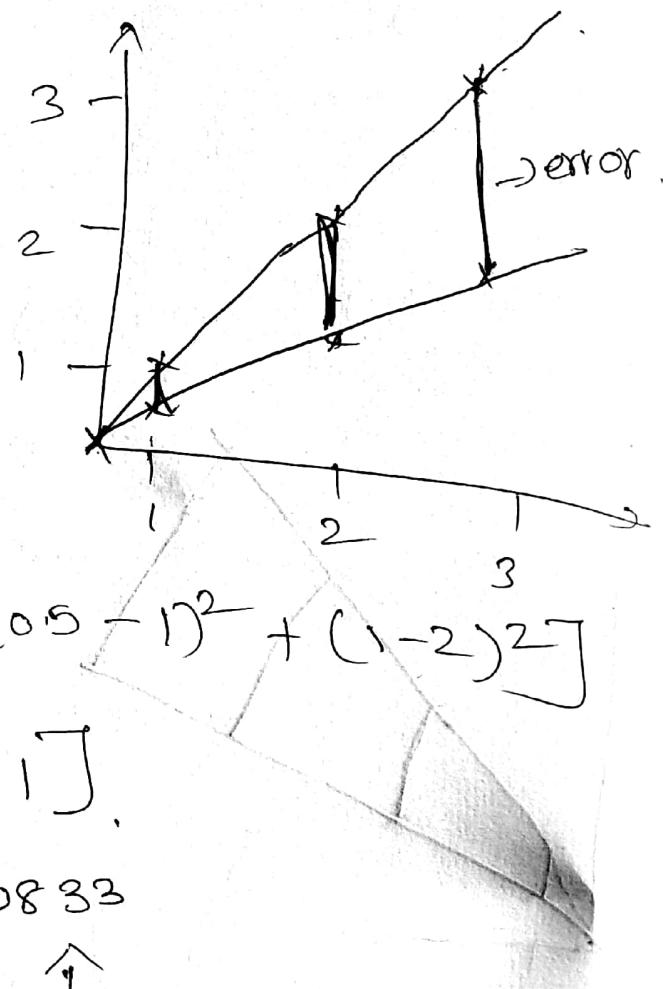
First Random Initialization of θ & b .

$$\theta = 0.5$$

$$y = \theta x + b$$

$$y = 0.5x + 0.$$

x	0	1	2
y	0	0.5	1



$$J(\theta, b) = \frac{1}{2m} [(0-0)^2 + (0.5-1)^2 + (1-2)^2]$$

$$m = 3$$

$$= \frac{1}{6} [0 + 0.25 + 1]$$

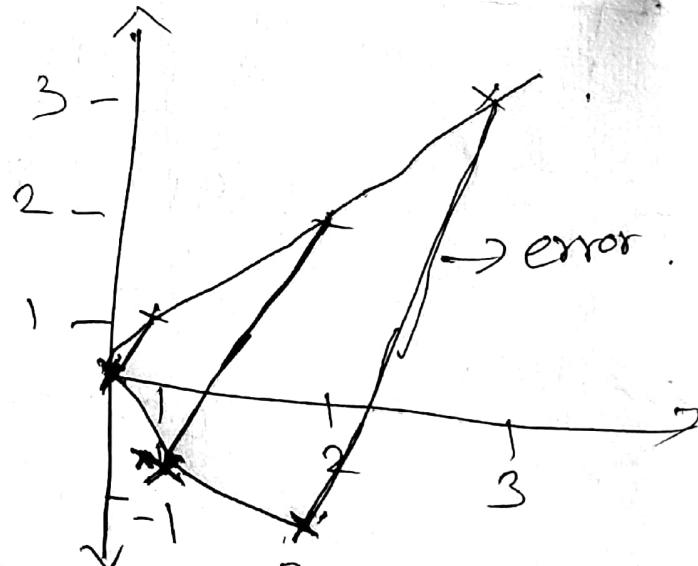
$$= \frac{1.25}{6} \Rightarrow 0.20833$$

$$\theta = -0.5$$

$$y = \theta x + b$$

$$y = -0.5x + 0.$$

x	0	1	2
y	0	-0.5	-1



$$J(\theta, b) = \frac{1}{2m} [(0-0)^2 + (-0.5-1)^2 + (-1-2)^2]$$

$$= \frac{1}{6} [0 + 2.25 + 9]$$

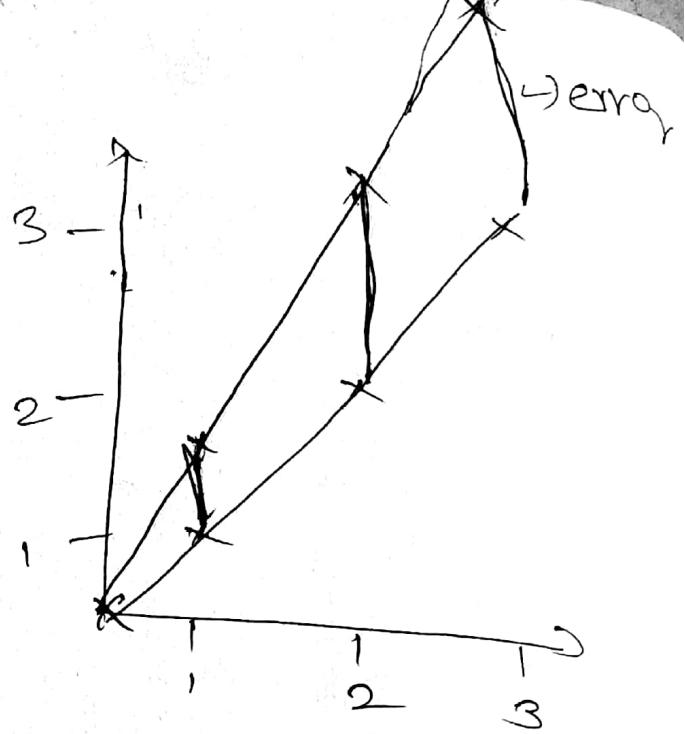
$$= 1.875$$

$$\theta = 1.5, b = 0.$$

$$y = \theta x + b.$$

$$y = 1.5x + 0.$$

x	0	1	2
y	0	1.5	3.



$$J(\theta, b) = \frac{1}{2m} [(0-0)^2 + (1.5-1)^2 + (3-2)^2]$$

$$m=3 = \frac{1}{6} [0 + 0.25 + 1]$$

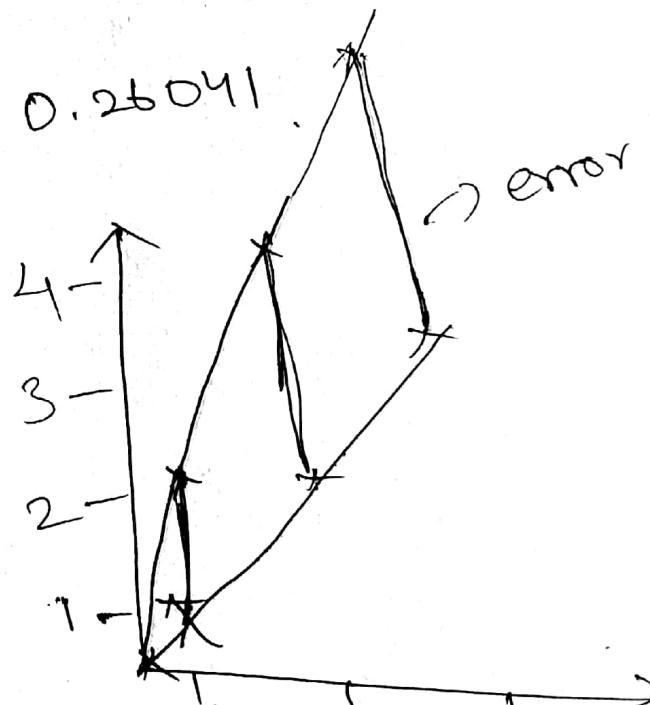
$$= \frac{1.25}{6} \Rightarrow 0.2083$$

$$\theta = 2, b = 0.$$

$$y = \theta x + b$$

$$y = 2x + 0.$$

x	0	1	2
y	0	2	4



$$J(\theta, b) = \frac{1}{2m} [(0-0)^2 + (2-1)^2 + (4-2)^2]$$

$$= \frac{1}{6} [0 + 1 + 4]$$

$$= \frac{5}{6} \Rightarrow 0.833$$

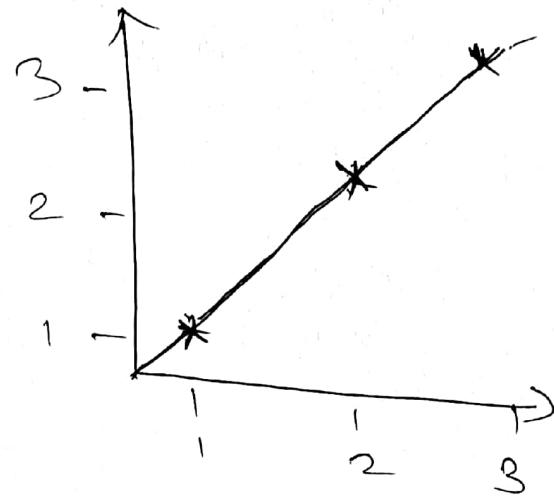
$$\theta = 1$$

$$b = 0$$

$$y = \theta x + b$$

$$y = (1)x + 0$$

x	0	1	2
y	0	1	2

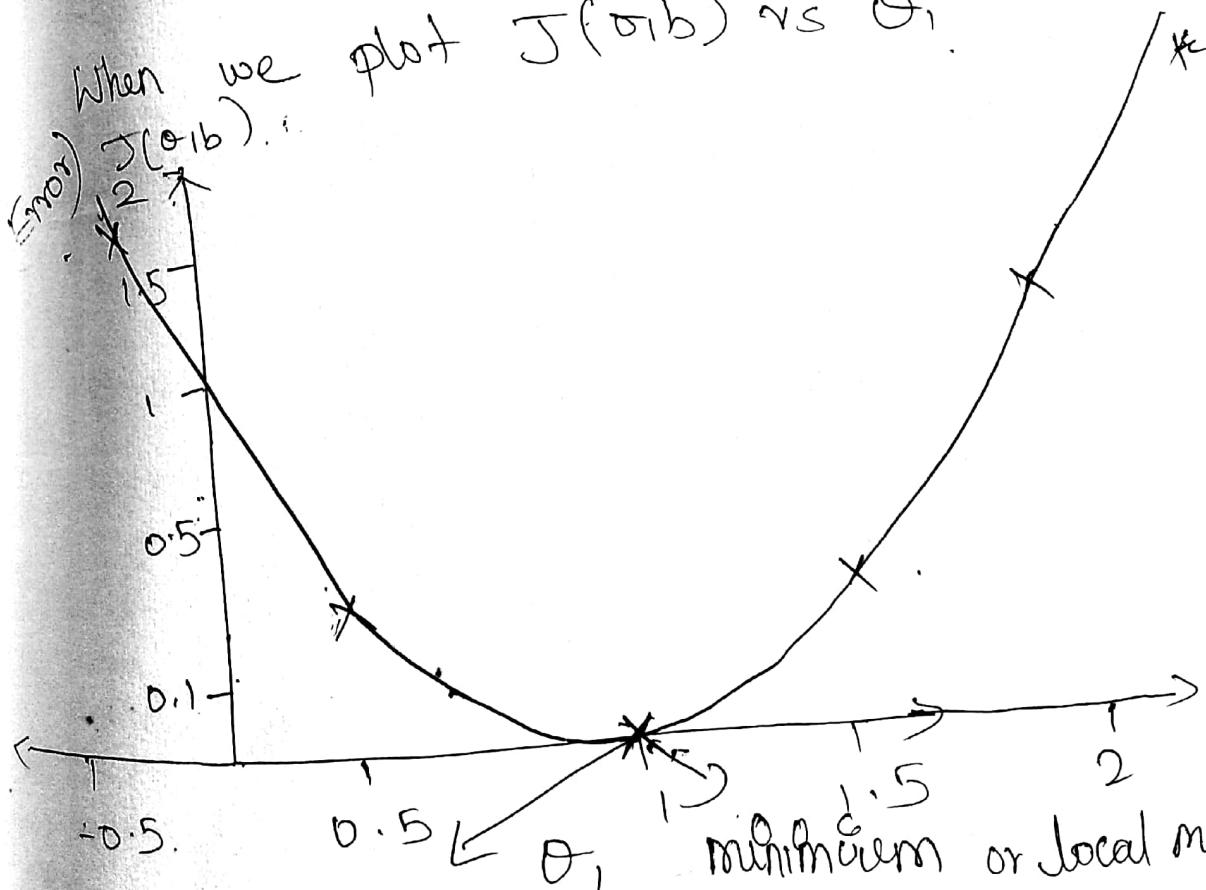


$$J(\theta_1, b) = \frac{1}{2m} [(0-0)^2 + (1-1)^2 + (2-2)^2]$$

$$= \frac{1}{6} [0 + 0 + 0]$$

$$= 0$$

When we plot $J(\theta_1, b)$ vs θ_1 ,



Error w.r.t θ_1
When $\theta_1 = 1$, $b = 0$.

minimum or local minimum.

Gradient descent

$$b = b - \alpha \frac{1}{m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)})$$

$$\theta = \theta - \alpha \frac{1}{m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)}) x^{(i)}$$

Here b is already in optimum value.
 So I'm not going to derive for b .

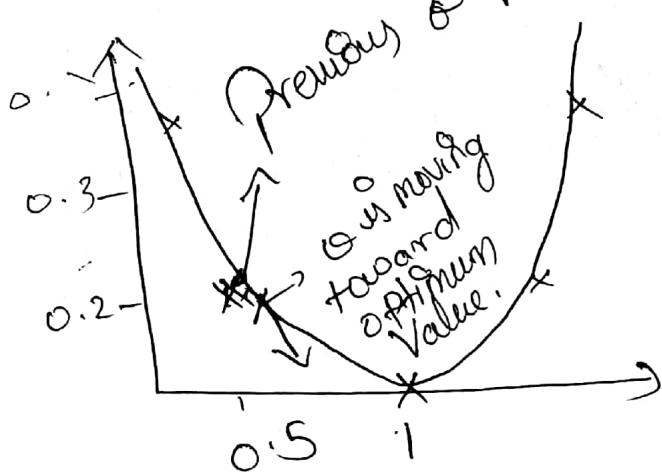
$$\theta = 0.5 \quad b = 0$$

$$y = \theta x + b$$

$$y = 0.5x + 0.$$

x	0	1	2
y	0	0.5	1

$$\alpha = 0.1$$



$$\theta = \theta - \alpha \frac{1}{m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)}) x^{(i)}$$

$$= \theta - (0.1) \frac{1}{3} [(0-0) + (0.5-1) + (1-2)]$$

$$= 0.5 - (-0.0833) = 0.5 + 0.05$$

$$= 0.5833$$

$\rightarrow \theta$ value is increasing.

If

$$\theta = 1.5, b = 0$$

$$y = \theta x + b$$

$$y = 1.5x + 0$$

x	0	1	2
y	0	1.5	3

$$\alpha = 0.1$$

$$\theta = \theta - \alpha \frac{1}{m} \sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)})$$

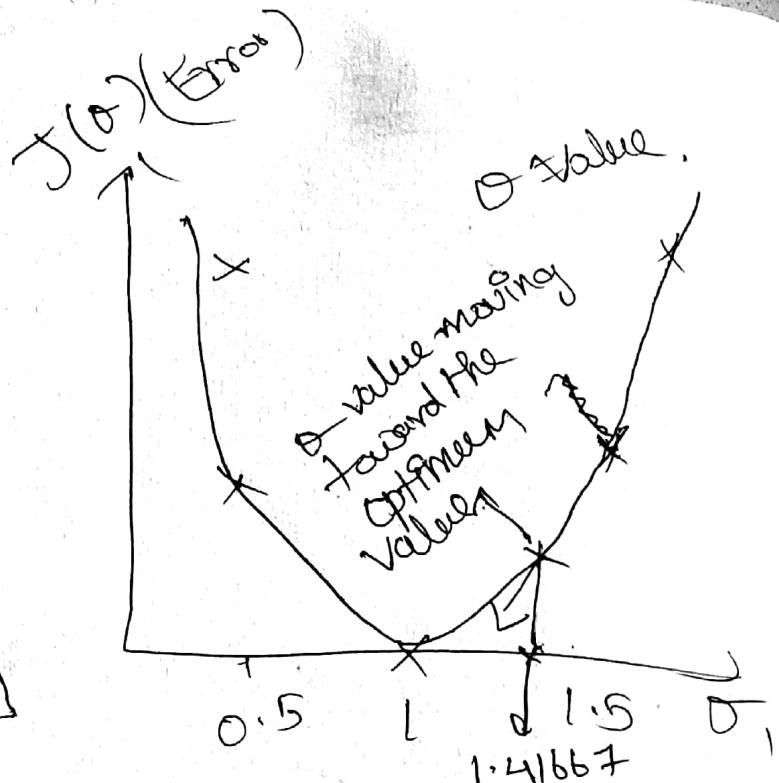
$$= \theta - (0.1) \frac{1}{3} [(0-0)^{(0)} + (1.5-1)^{(1)} + (3-2)^{(2)}]$$

$$= \theta - (0.1) \frac{1}{3} [0 + 0.5 + 2]$$

$$= \theta - (0.1) (0.8333)$$

$$= 1.5 - 0.08333$$

$$= 1.41667 \rightarrow \text{decreasing}$$



$$\theta = 1 \quad b = 0.$$

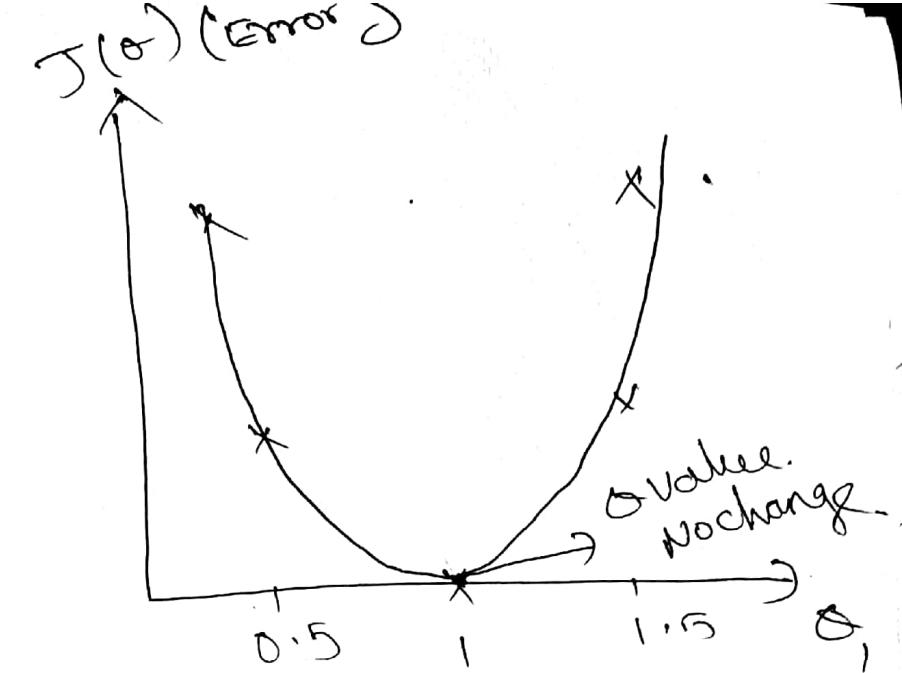
$$y = \theta x + b$$

$$y = 1x + 0.$$

x	0	1	2
y	0	1	2

$$\alpha = 0.1$$

$$\theta = \theta - \alpha \cdot \frac{1}{m}$$



$$\sum_{i=1}^m (y_{\text{output}}^{(i)} - y_{\text{desired}}^{(i)}) x_i^{(i)}$$

$$= \theta - (0.1) \frac{1}{3} [(0-0) + (1-1)(1) + (2-2)(2)]$$

$$= \theta - 0$$

$\Rightarrow 1 - 0 = 1 \rightarrow$ No change because
the θ reached.

The optimum Value.

So if you choose $\theta = 1.5$ it will keep on decreasing until it reaches the optimum value of θ in our case $\theta = 1$ for $y = x$. On the other hand if $\theta = 0.5$ it will keep on increasing until it reaches the optimum value of θ in our case $\theta = 1$ for $y = x$.

Slope



→ positive slope.

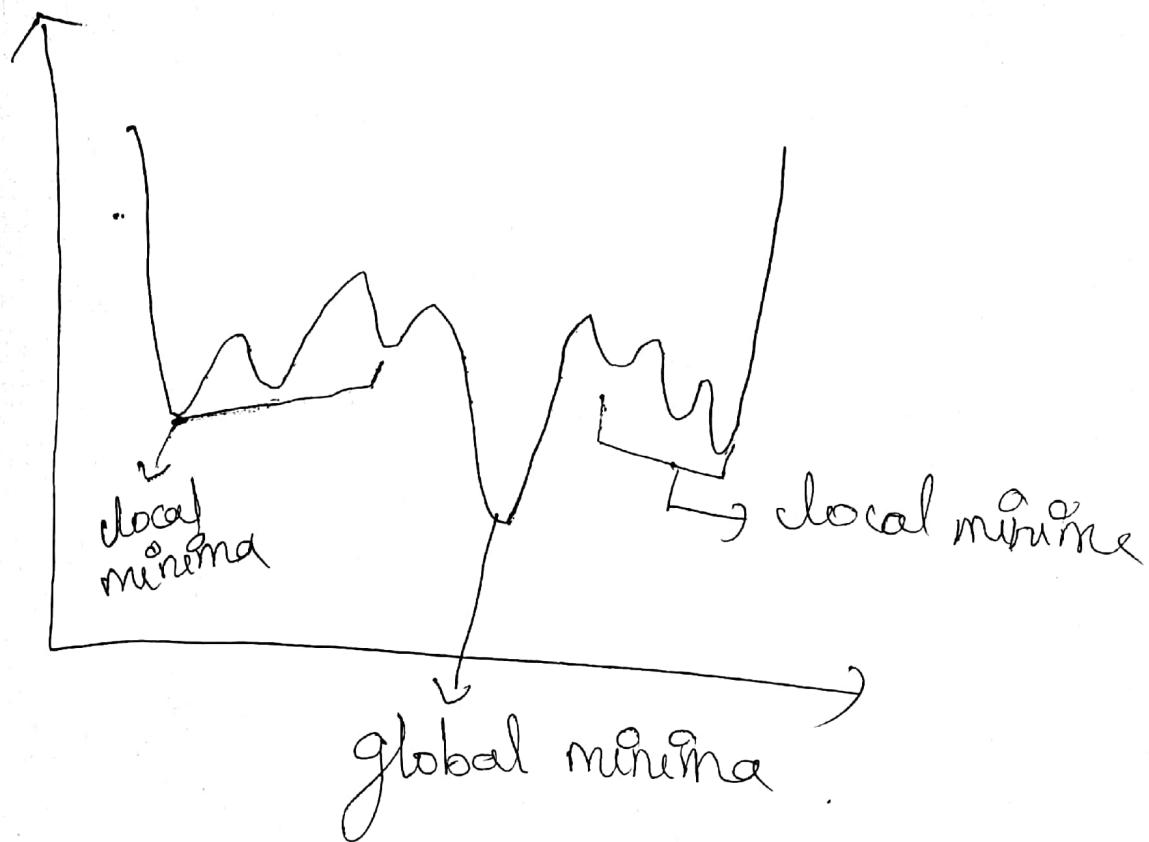
y



→ negative slope.

x

local minima ki Global minima



Local Maxima & Global maxima

