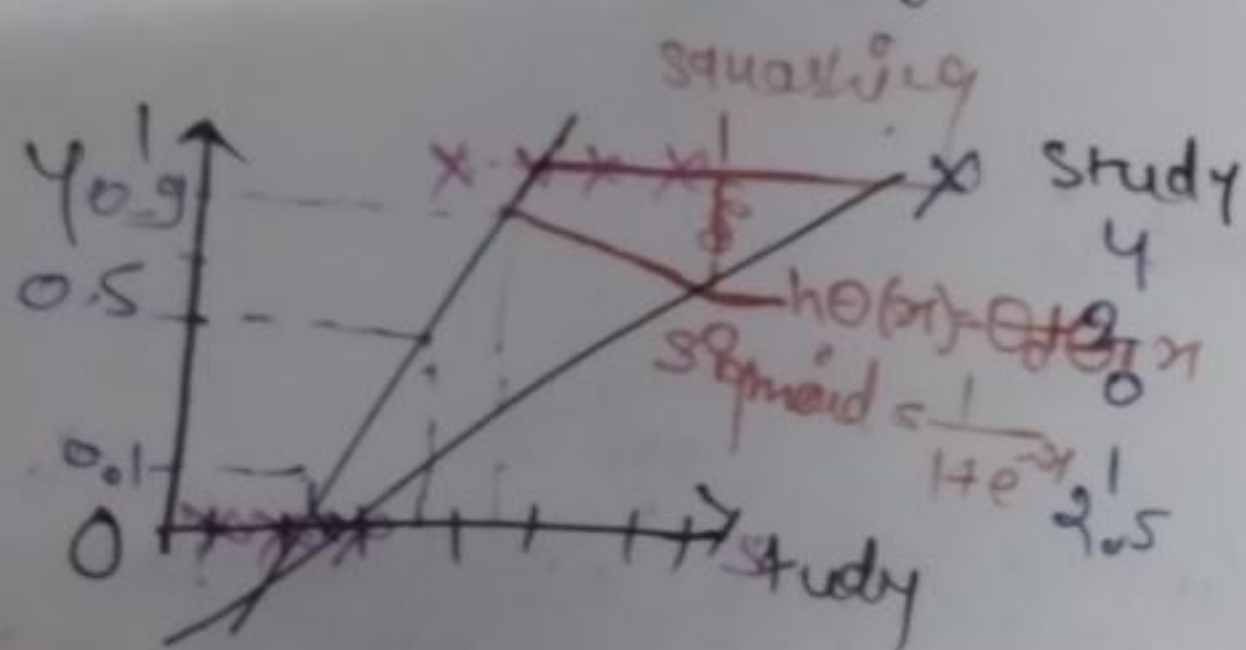


Logistic Regression - A statistical classification algorithm that predicts the probability of a binary outcome (0/1) (Yes/No) using a logistic sigmoid function.

→ output is always 0 and 1



Pass/Fail.
 Pass
 Fail
 Fail
 Fail
 Pass

when we try to solve this with linear Regression.

① Outlier - so Best fit line change.

② > 1 or < 0 .
 We cannot solve Classification through linear

Logistic - Mein esa line banana hai jo Bquesh ki kare or output bhi de.

squaring.

$$h_{\theta}(x) = g(\theta_0 + \theta_1 x) \text{ best fit line}$$

$$g = \frac{1}{1 + e^{-z}} \quad \text{where } z = \theta_0 + \theta_1 x$$

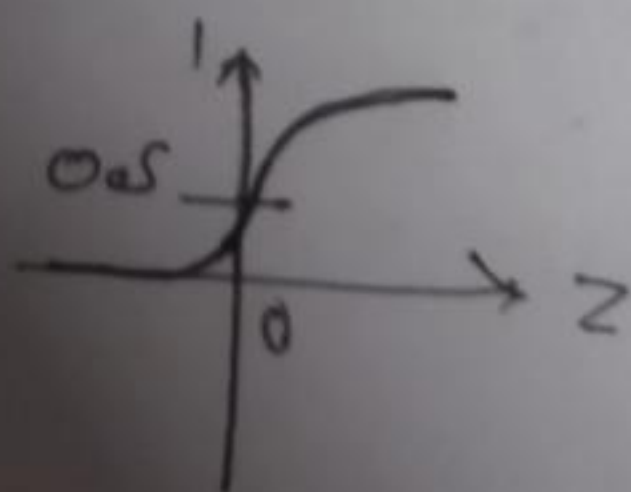
$$h_{\theta}(x) = \frac{1}{1 + e^{-z}} = \theta_0 + \theta_1 x$$

Hypothesis for Logistic

$$h_{\theta}(x) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 x)}}$$

Sigmoid - $g = \frac{1}{1 + e^{-z}}$

$$\begin{aligned} z < 0 & \quad z \geq 0 \\ g(z) < 0.5 & \quad g(z) \geq 0.5 \end{aligned}$$



train set $= \{ (x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}) \dots (x^{(m)}, y^{(m)}) \}$

$$x \in \begin{bmatrix} x_0 \\ x_1 \\ x_2 \end{bmatrix} \quad y \in \{0, 1\}$$

$$h_{\theta}(x) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 x)}}$$

$$z = \theta_0 + \theta_1 x \\ = \theta^T x$$

$$h_{\theta}(x) = \frac{1}{1 + e^{-(\theta^T x)}} \rightarrow \text{Hypothesis}$$

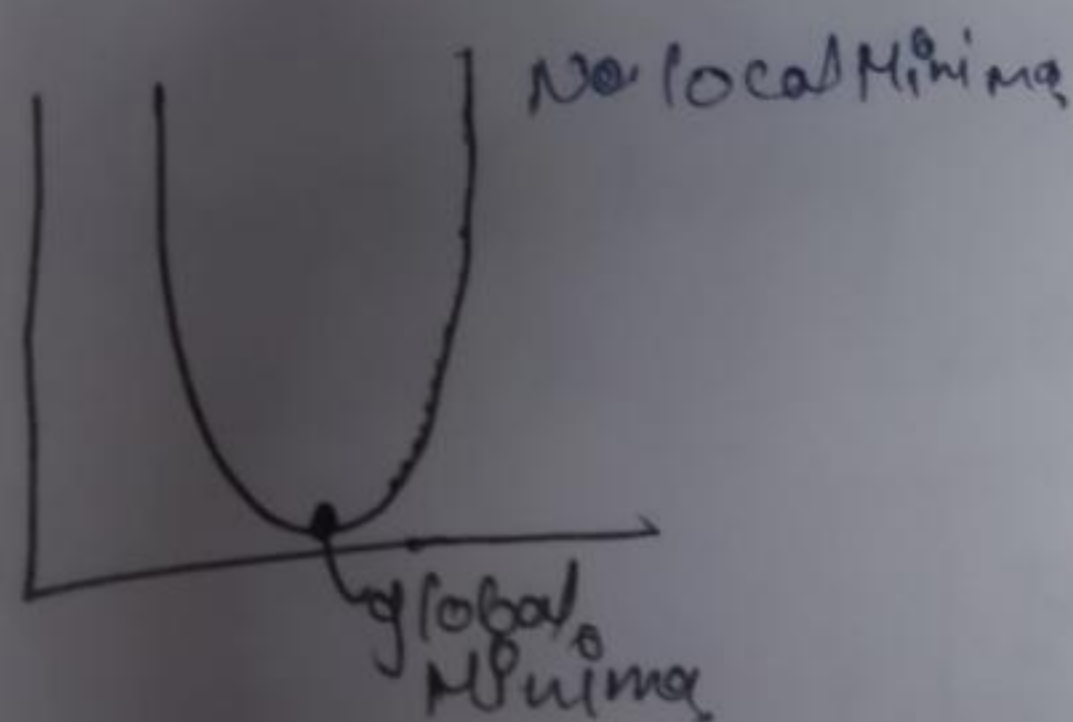
Linear Regression

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

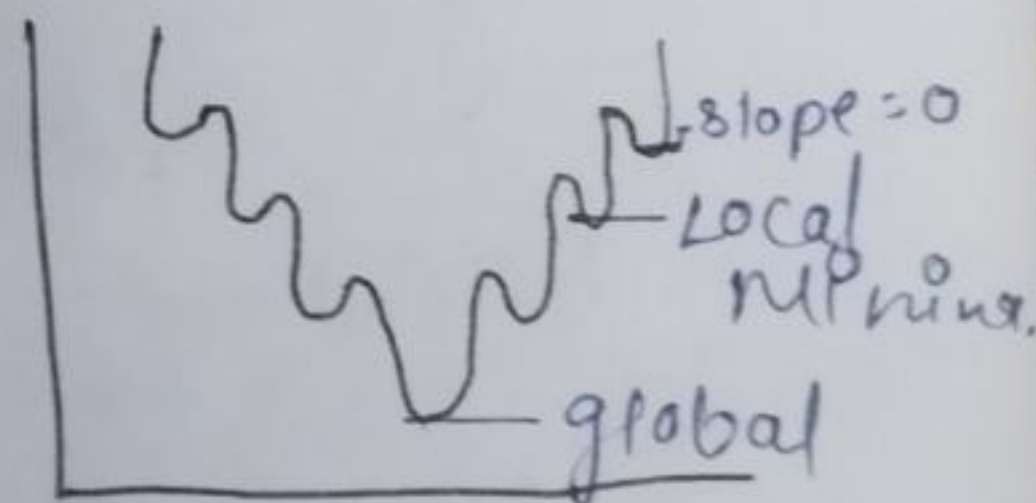
$$h_{\theta}(x) = \theta^T x \\ = \theta_0 + \theta_1 x$$

$$h_{\theta}(x) = \frac{1}{1 + e^{-(\theta^T x)}} \\ \text{Non Convex function}$$

Convex



Non Convex



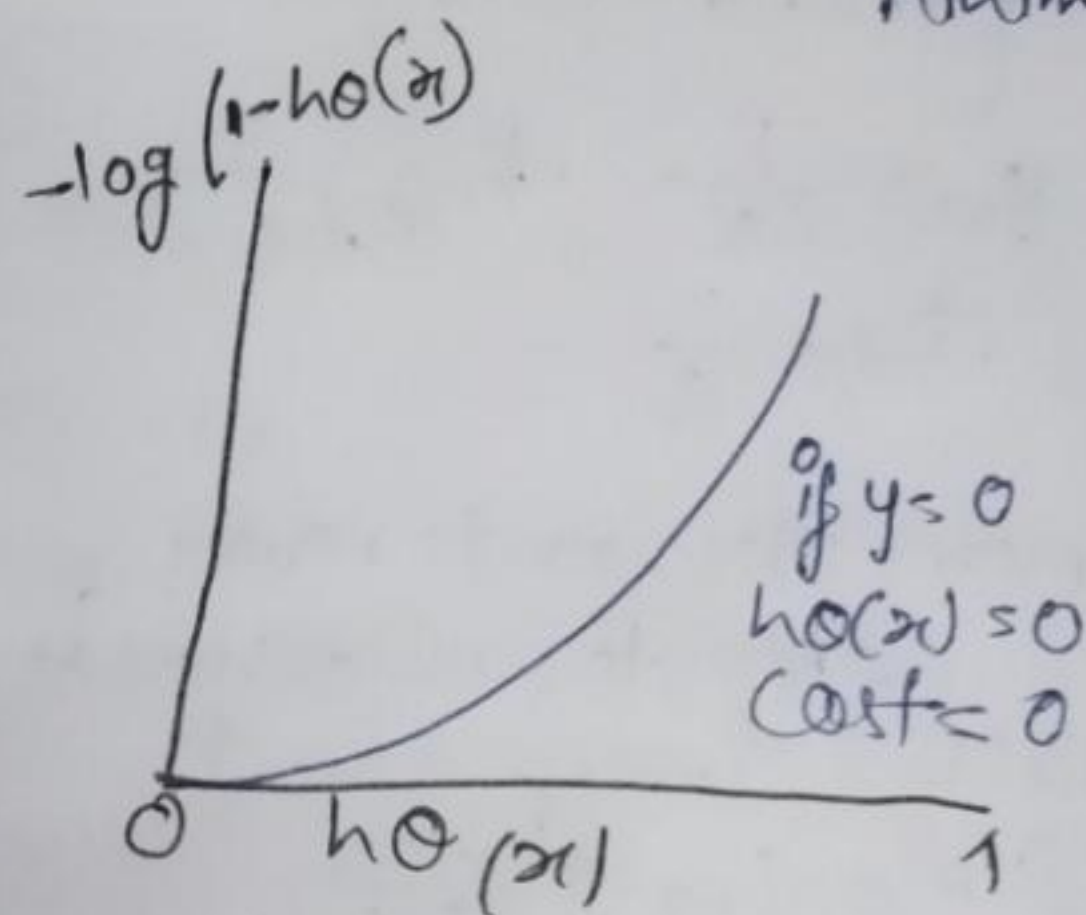
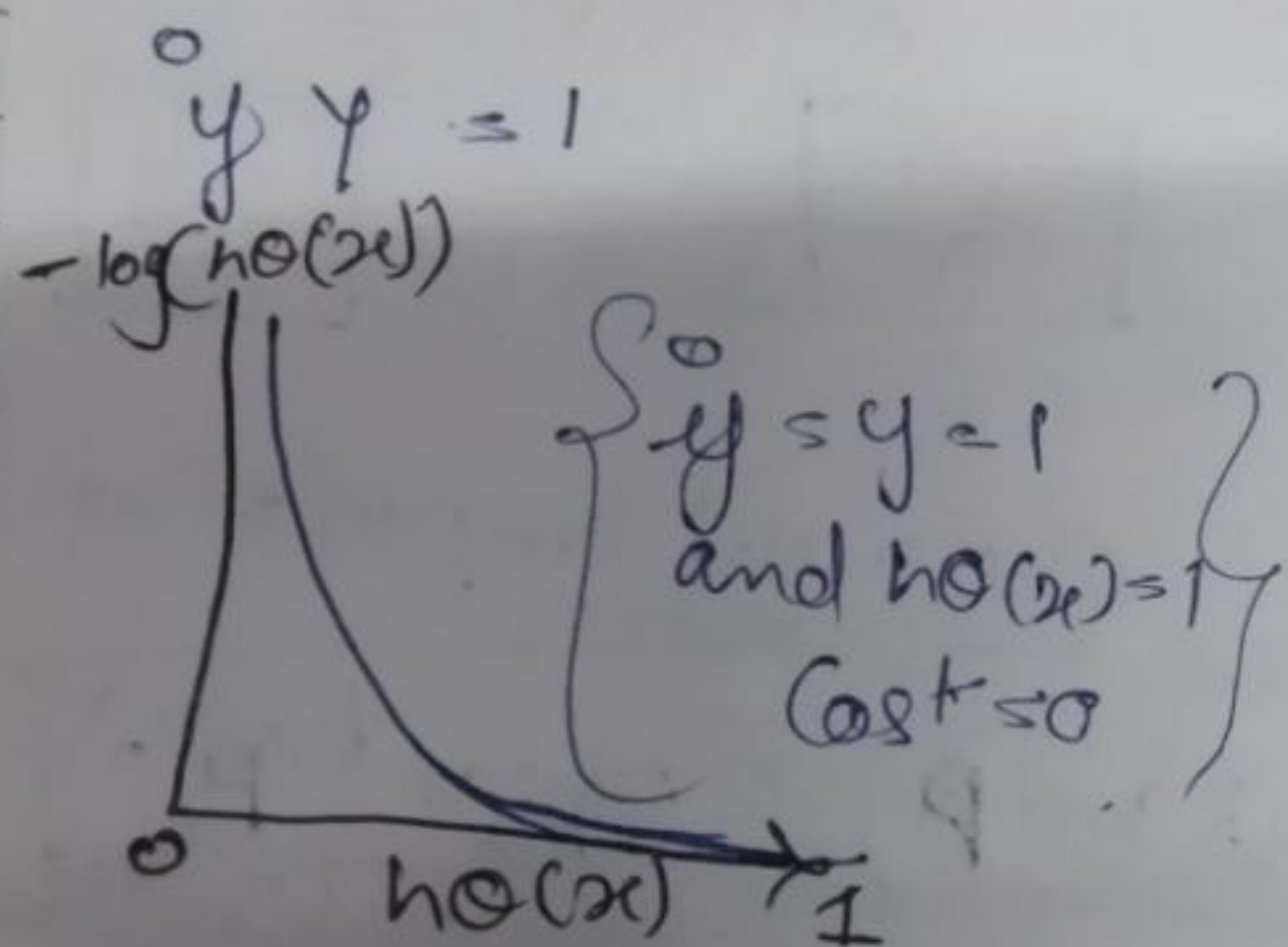
Logistic Regression $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$

$$h_{\theta}(x) = \frac{1}{1 + e^z} \quad (z = \theta_0 + \theta_1 x) \quad \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

$$\text{Cost}(h_0(x), y) = \begin{cases} -\log(h_0(x)) & \text{if } y=1 \\ -\log(1-h_0(x)) & \text{if } y=0 \end{cases}$$

when we use this Representation So, we will get Conver Curve or Single global minima.

Cost function



$$\text{Cost}(h_0(x), y) = -y \log(h_0(x)) - (1-y) \log(1-h_0(x))$$

$\text{if } y=1$

$$= -\log(h_0(x))$$

$\text{if } y=0$

$$= -\log(1-h_0(x))$$

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m y^{(i)} \log h_0(x^{(i)}) + (1-y^{(i)}) \log(1-h_0(x^{(i)}))$$

Cost function

Repeat

Convergence Repeat

$$\theta_j^0 \approx \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

This Convergence theorem yeh bataega curve me global minima kb pahanchege.