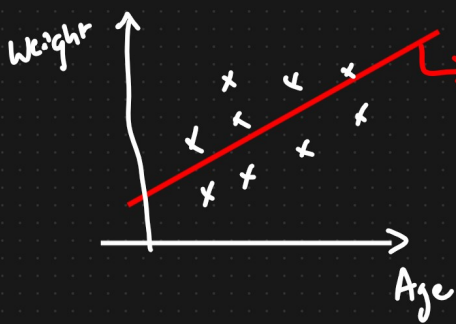


Tutorial 2 - Logistic Regression Maths Intuition

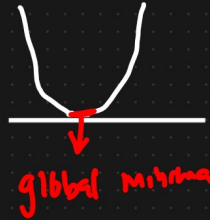
Linear Regression \rightarrow Regression problem statement

Cost function

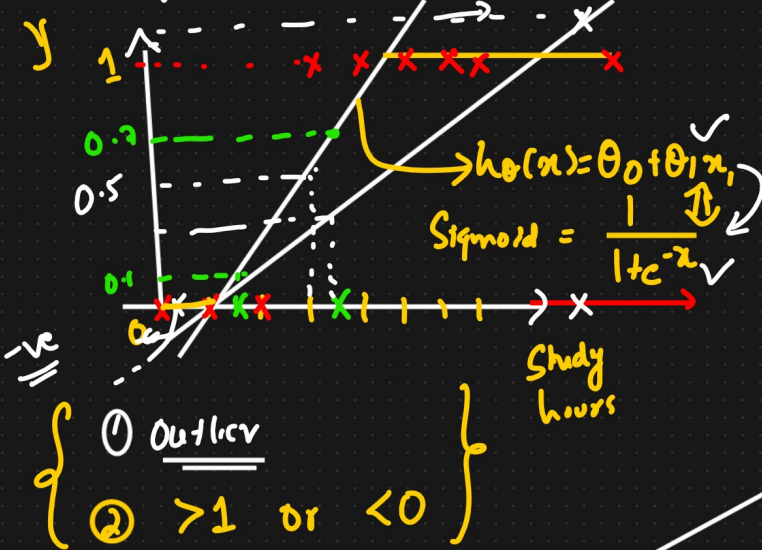


$$\underline{h_0(x) = \theta_0 + \theta_1 x_1}$$

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



Logistic Regression ^{You cannot solve} → Classification



Study hours	Pass/Fail	o/p
4	Pass	1
2	Fail	0
0	Fail	0
1	Fail	0
2.5	Pass	1

Binary Classification

0 to 1

$$h_{\theta}(x) = g(\theta_0 + \theta_1 x) \quad \text{where } z = \theta_0 + \theta_1 x$$

$g = \frac{1}{1 + e^{-z}}$ — Sigmoid

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

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

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

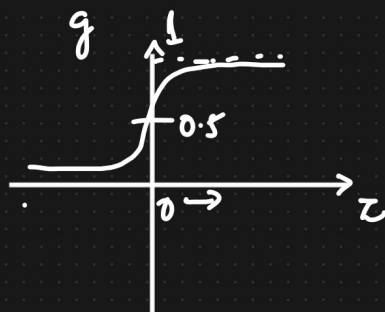
Logistic Hypothesis function

$\tau \angle 0$

$$g(z) \leq 0.5$$

Sigmoid

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



$$z > 0 \\ g(z) > 0.5$$

$$\text{Trainset} = \{ (x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \dots, (x^{(m)}, y^{(m)}) \}$$

$$x \in \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$y \in \{0, 1\}$$

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

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

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

Linear Regression

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

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

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

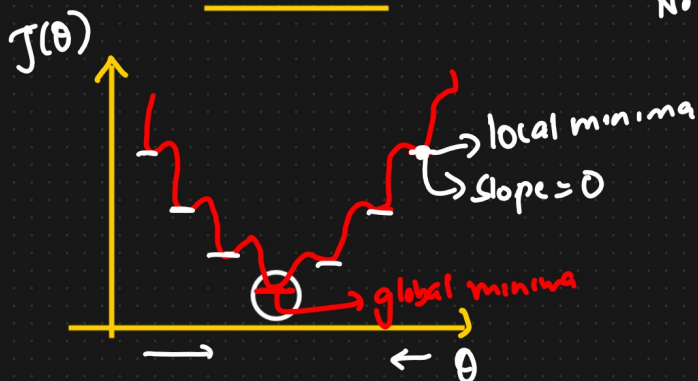
Logistic Regression

Cost $(h_\theta(x), y)$

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

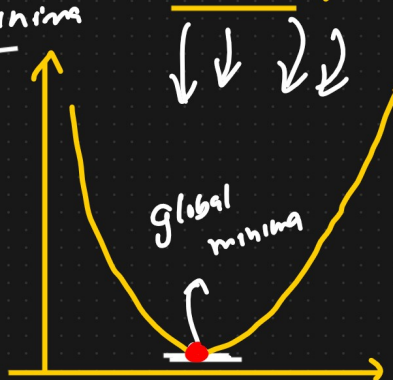
Non convex function

Non Convex



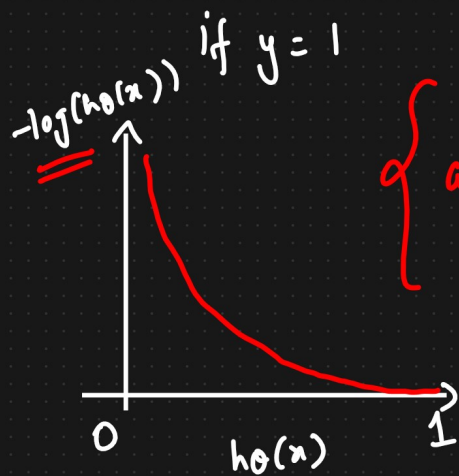
No local minima

Convex function

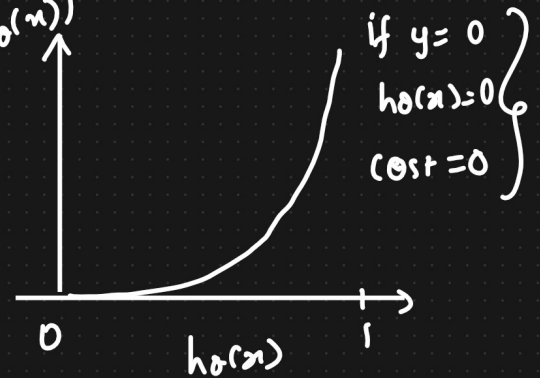


$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (\underbrace{h_{\theta}(x^{(i)}) - y^{(i)}}_{\downarrow})^2 \quad h_{\theta}(x^{(i)}) = \frac{1}{1+e^{-z}} \quad z = \theta_0 + \theta_1 x$$

$$\text{cost}(h_{\theta}(x^{(i)}), y) = \begin{cases} -\log(h_{\theta}(x)) & \text{if } y=1 \\ -\log(1-h_{\theta}(x)) & \text{if } y=0 \end{cases} \Rightarrow \text{cost function}$$



$\left. \begin{aligned} &\text{if } y=1 \\ &\text{and } h_{\theta}(x)=1 \\ &\text{cost}=0 \end{aligned} \right\}$



$$\text{cost}(h_{\theta}(x), y) = -y \log(h_{\theta}(x)) - (1-y) \log(1-h_{\theta}(x))$$

$\left. \begin{aligned} &\text{if } y=1 \\ &= -\log(h_{\theta}(x)) \\ &\text{if } y=0 \\ &= -\log(1-h_{\theta}(x)) \end{aligned} \right\}$

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

\downarrow
cost function

\downarrow

Convergence Report

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

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