

Linear Regression Model

Lecture 5

(1)

→ Important Algo to understand concepts such as cost function, gradient decent, vectorization

→ Data set

(Independent/Input) feature

(Dependent/output) feature

Weight (x)

Height (y)

74

170 cm

80

180 cm

75

175.5 cm

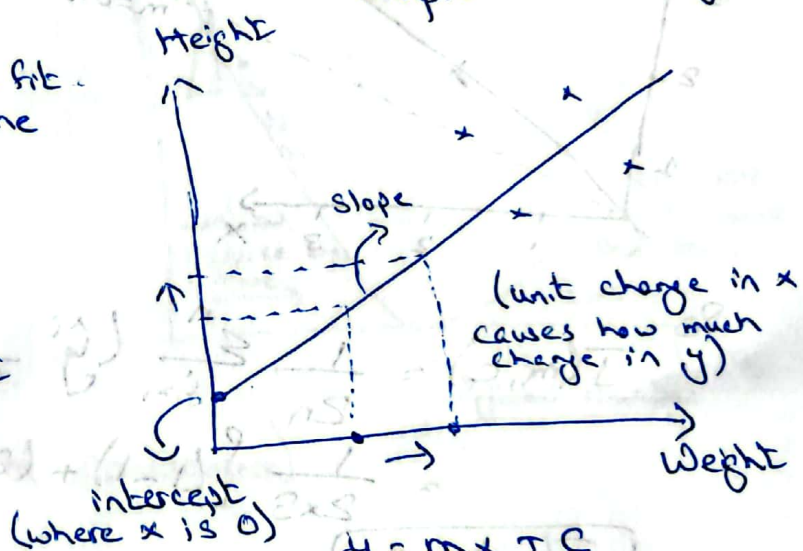
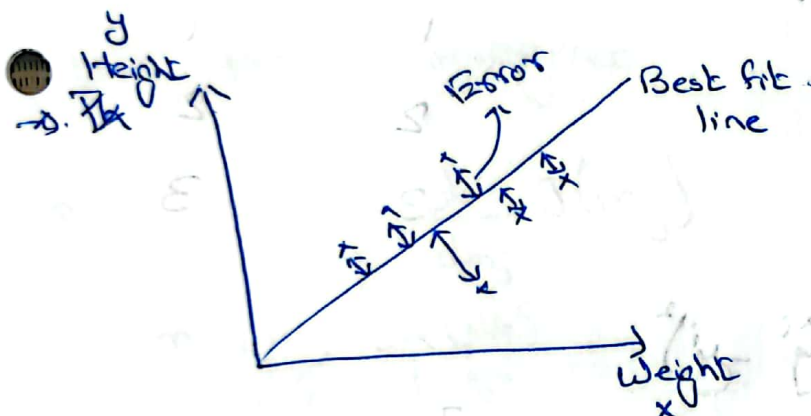
Train

New Weight

Model

Height

Simple Linear Regression



Error

Where \hat{y} is predicted value

● $\text{Error} = y - \hat{y}$

for one feature

$y = mx + c$

for many features

$y = c + m_1x_1 + m_2x_2 + \dots + m_nx_n$

→ The objective is to minimize the error by plotting best fit line by changing m & c in an optimization technique to get best fit line.

Cost Function

$$J(m, c) = \frac{1}{2m} \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

↳ (Mean Squared Error)

Final object of what we need to do is

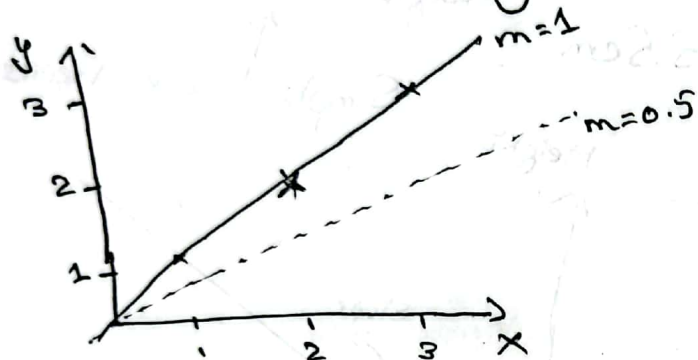
Minimize

$$J(m, c) = \frac{1}{2n} \sum_{i=1}^n (\hat{y}^i - y^i)^2$$

by changing m & c values.

Numerical Example

Let's assume $c=0$
(meaning x is passing through origin).



So

$$J(m, c) = \frac{1}{2n} \sum_{i=1}^n (\hat{y}^i - y^i)^2$$
$$= \frac{1}{2 \times 3} [(1-1)^2 + (2-2)^2 + (3-3)^2]$$

$$\boxed{J(m) = 0}$$

Now suppose $m=0.5$

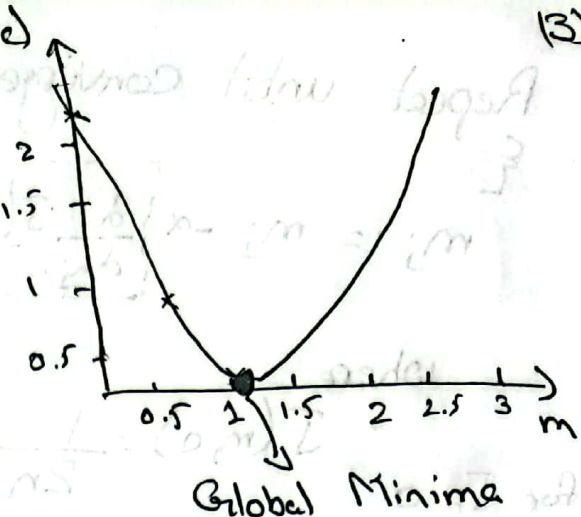
$$J(m) = \frac{1}{2 \times 3} [(0.5-1)^2 + (1-2)^2 + (1.5-3)^2] \text{ if } \begin{matrix} x=1 \\ x=2 \\ x=3 \end{matrix}$$
$$\approx 0.58$$

$$\hat{y} = m \times x$$
$$\begin{matrix} \hat{y}^1 = 0.5 \\ \hat{y}^2 = 1 \\ \hat{y}^3 = 1.5 \end{matrix}$$

Suppose $m=0$

$$J(m) = \frac{1}{2 \times 3} [(0-1)^2 + (0-2)^2 + (0-3)^2]$$
$$\approx 2.3$$

This curve is known as $J(m, c)$
 gradient decent and is
 derived by changing m & c .
 Best fit line is on global minima



→ Convergence Algorithm

The objective is to optimize the changes in m values.

Repeat until Convergence

$$m_j := m_j - \alpha \frac{d}{dm_j} J(m_j)$$

$$m_j = m_j - \alpha (\text{+ve})$$

$$= m_j - (\text{+ve})$$

$\alpha \equiv$ Learning rate (the rate of convergence)

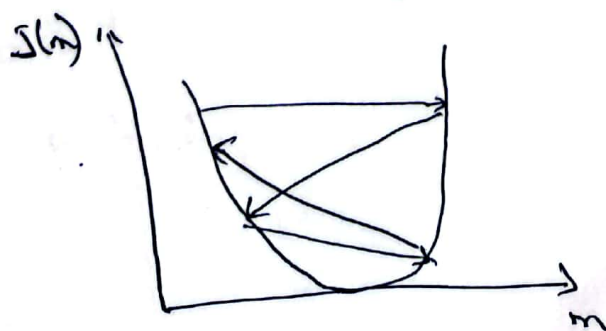
e.g. $\alpha = 0.001$

$$m_j := m_j - \alpha \frac{d}{dm_j} J(m_j)$$

$$m_j = m_j - \alpha (-\text{ve})$$

$$= m_j + \alpha$$

So till now we were considering that the best fit line is originating from origin, hence $c=0$. This was for better understanding on a 2D plot.



Repeat until convergence

ξ

$$m_j := m_j - \alpha \left[\frac{d}{dm_j} J(m, c) \right]$$

where

$$J(m, c) = \frac{1}{2n} \sum_{i=1}^n (\hat{y}^i - y^i)^2$$

for $J=0$

$$\begin{aligned} \frac{d}{dm_j} J(m, c) &= \frac{d}{dm_j} \cdot \frac{1}{2n} \left[\sum_{i=1}^n (\hat{y}^i - y^i)^2 \right] \\ &= \frac{1}{n} \sum_{i=1}^n (\hat{y}^i - y^i) \end{aligned}$$

for $J=1$

$$\begin{aligned} \frac{d}{dm} J(m, c) &= \frac{d}{dm} \cdot \frac{1}{2n} \left[\sum_{i=1}^n (c + mx) - y^i \right]^2 \\ &= \frac{1}{n} \sum_{i=1}^n (c + mx - y^i) x \end{aligned}$$

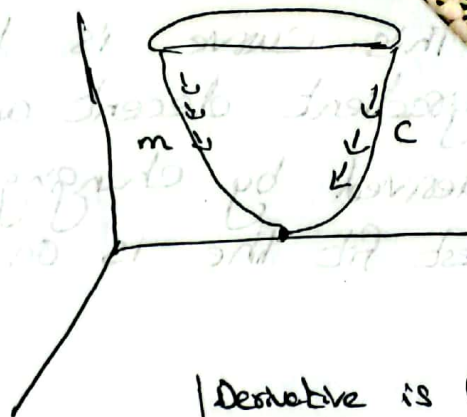
Repeat until convergence

ξ

$$c := c - \alpha \frac{1}{n} \sum_{i=1}^n (\hat{y}^i - y^i)$$

$$m := m - \alpha \frac{1}{n} \sum_{i=1}^n (\hat{y}^i - y^i) x^i$$

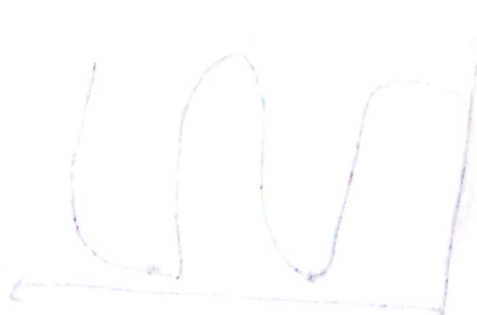
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Derivative is finding the slope

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

$$\frac{d}{dx} x^n = nx^{n-1}$$



Confusion Matrix:-

		Predicted		
		No	Yes	
Actual	No	165 [TN] 50	60 [FP] 10	60
	Yes	5 [FN]	105 [TP] 100	105
		55	110	

$$\rightarrow \text{Accuracy} = \frac{TP + TN}{\text{Total}}$$

$$= (100 + 50) / 165$$

$$= 0.91$$

$$\rightarrow \text{Error} = 1 - \text{accuracy}$$

or

$$\frac{FP + FN}{\text{Total}}$$

$$= 0.09$$

$$\bullet \text{ Precision} = \frac{TP}{\text{Predicted Yes}}$$

$$= \frac{100}{110} = 0.64$$

$$\text{Recall} = \frac{TP}{\text{Actual Yes}}$$

$$= \frac{100}{105} = 0.95$$

t-test

Left Tailed Test

$$H_0: \mu \geq 60$$

$$H_1: \mu < 60$$

$$\alpha: 5\% = 0.05$$

$$\text{Sample size } n = 16$$

$$\text{Standard deviation } S = 40$$

$$\text{Mean } \bar{x} = 70$$

$$t = \frac{\bar{x} - \mu}{S / \sqrt{n}} = \frac{70 - 60}{40 / \sqrt{16}}$$

$$t = 10/10 = 1$$

$$DF (\text{Degree of freedom}) = 16 - 1$$

$$= 15$$

Right Tailed Test

$$H_0: \mu \leq 400$$

$$H_1: \mu > 400$$

$$\alpha: 5\%$$

$$n = 12$$

$$S = 40$$

$$\bar{x} = 415$$

$$t = \frac{\bar{x} - \mu}{S / \sqrt{n}}$$

$$= \frac{415 - 400}{40 / \sqrt{12}}$$

$$t = 1.297$$

$$df = 12 - 1 = 11$$

Two tailed test

$$H_0: \mu = 10$$

$$H_1: \mu \neq 10$$

$$n = 16$$

$$S = 20$$

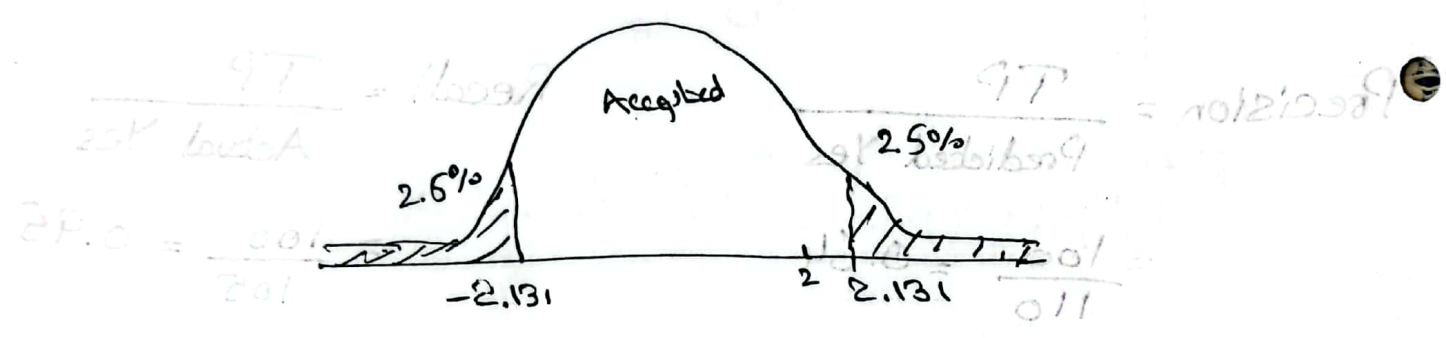
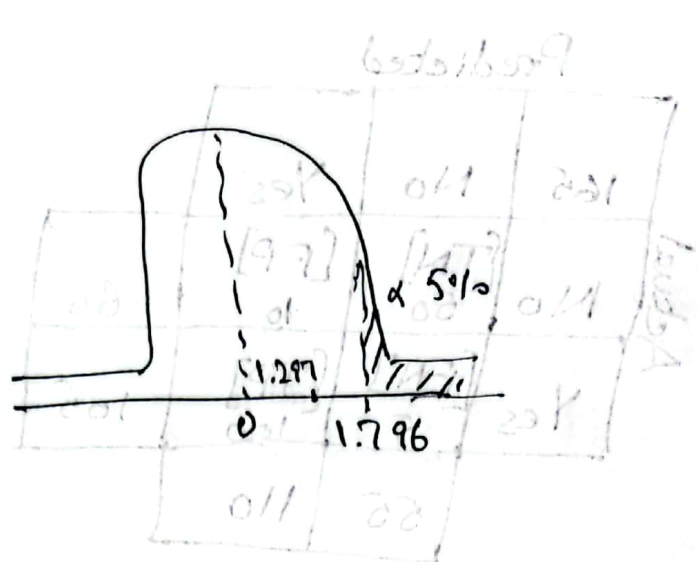
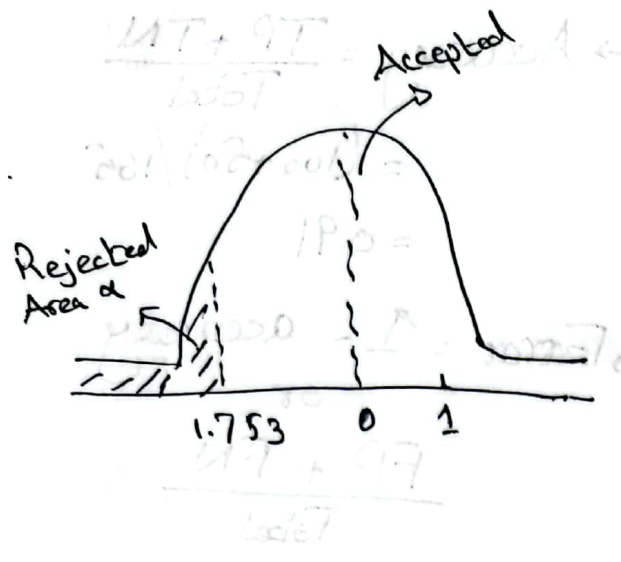
$$\bar{x} = 20$$

$$\alpha = 5\%$$

$$t = \frac{20 - 10}{20 / \sqrt{16}}$$

$$= 10/5$$

$$t = 2$$



Left Tailed Test
 $H_0: \mu \geq \mu_0$
 $H_1: \mu < \mu_0$
 $\alpha = 0.05$
 $n = 10$
 $\bar{x} = 50$
 $s = 10$
 $t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{50 - 60}{10/\sqrt{10}} = -3.16$
 $t_{\alpha, n-1} = t_{0.05, 9} = 1.833$
 $t < -t_{\alpha, n-1}$
 $\therefore \text{Reject } H_0$

Right Tailed Test
 $H_0: \mu \leq \mu_0$
 $H_1: \mu > \mu_0$
 $\alpha = 0.05$
 $n = 10$
 $\bar{x} = 50$
 $s = 10$
 $t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{50 - 60}{10/\sqrt{10}} = -3.16$
 $t_{\alpha, n-1} = t_{0.05, 9} = 1.833$
 $t > t_{\alpha, n-1}$
 $\therefore \text{Reject } H_0$

Two Tailed Test
 $H_0: \mu = \mu_0$
 $H_1: \mu \neq \mu_0$
 $\alpha = 0.05$
 $n = 10$
 $\bar{x} = 50$
 $s = 10$
 $t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} = \frac{50 - 60}{10/\sqrt{10}} = -3.16$
 $t_{\alpha/2, n-1} = t_{0.025, 9} = 2.262$
 $|t| > t_{\alpha/2, n-1}$
 $\therefore \text{Reject } H_0$