

In earlier Example we had one Dependent variable i.e. y and one Independent variable i.e. x

So it was Case of Simple Linear Regression.

Ex sqftarea \rightarrow price $\Rightarrow \hat{y} = \beta_0 + \beta_1 x$

But if

x_1 Size (feet)²
 x_2 No of Bedrooms
 x_3 No of floor
 x_4 location

Price
 y

\leftarrow multiple
Linear
Regression.

The Linear Regression to express the above dependency is

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

General form of Multiple Linear Regression.

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$$

Here $\beta_0, \beta_1, \beta_2 \dots \beta_n$ $\begin{cases} +ve \\ OR \\ -ve \end{cases}$

$$h_0(x) = \beta_0 \underset{\substack{\uparrow \\ x_0=1}}{x_0} + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$$

Here $x_0, x_1, x_2 \dots x_n = \text{features}$

$\beta_0, \beta_1, \beta_2 \dots \beta_n \Rightarrow \text{Parameter/Coefficients.}$

let $X = \text{Feature Vector} = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$

$n+1 \times 1$
 $n = \text{no of features}$

$Q = \text{Parameter Vector} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}$ $n+1 \times 1$

$$\therefore \boxed{h_0(x) = Q^T \cdot X} = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 \dots & \beta_n \end{bmatrix} \begin{matrix} Q^T \end{matrix} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} X$$

$$\underline{\underline{h_0(x) = Q^T X = \beta_0 x_0 + \beta_1 x_1 + \dots + \beta_n x_n.}}$$

Let

x_0	x_1	x_2	y
1	7	2.6	78.5
1	1	2.9	74.3
1	11	5.6	104.3
1	11	3.1	87.6
1	7	5.2	95.9
1	11	5.5	109.2
1	3	7.1	102.7

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

To find β_0
 β_1
 β_2

Solve \rightarrow

Feature Vector = $X =$

$$\begin{bmatrix} 1 & 7 & 2.6 \\ 1 & 1 & 2.9 \\ 1 & 11 & 5.6 \\ 1 & 11 & 3.1 \\ 1 & 7 & 5.2 \\ 1 & 11 & 5.5 \\ 1 & 3 & 7.1 \end{bmatrix}_{4 \times 3}$$

$$Y = \begin{bmatrix} 78.5 \\ 74.3 \\ 104.3 \\ 87.6 \\ 95.9 \\ 109.2 \\ 102.7 \end{bmatrix}_{7 \times 1}$$

$$C = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} = \frac{(X^T \cdot X)^{-1} \cdot X^T \cdot Y}{\substack{\uparrow \\ \text{Coefficient} \\ \text{Vector} \quad \uparrow 3 \times 1}}$$

Solution

$$X = \begin{bmatrix} 1 & 7 & 2.6 \\ 1 & 1 & 2.9 \\ 1 & 11 & 5.6 \\ 1 & 11 & 3.1 \\ 1 & 7 & 5.2 \\ 1 & 11 & 5.5 \\ 1 & 3 & 7.1 \end{bmatrix}$$

$$(1) \text{ find } X^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 7 & 1 & 11 & 11 & 7 & 11 & 3 \\ 2.6 & 2.9 & 5.6 & 3.1 & 5.2 & 5.5 & 7.1 \end{bmatrix}$$

$$(2) \text{ find } X^T \cdot X \Rightarrow \begin{bmatrix} 7 & 57 & 32 \\ 51 & 471 & 235 \\ 32 & 235 & 163.84 \end{bmatrix}_{3 \times 3}$$

$$(3) \text{ find } (X^T \cdot X)^{-1} = \begin{bmatrix} 1.79 & -0.06 & -0.25 \\ -0.06 & 0.01 & -0.0011 \\ -0.25 & -0.0011 & 0.0001 \end{bmatrix}$$

$$= \begin{bmatrix} 1.79 & -0.06 & -0.25 \\ -0.06 & 0.01 & -0.0011 \\ -0.25 & -0.0011 & 0.0571 \end{bmatrix}$$

$$= \underline{(X^T \cdot X)^{-1}} \cdot X^T \cdot y$$

$$\underline{\underline{Q}} = \begin{bmatrix} 51.6 \\ 1.5 \\ 6.72 \end{bmatrix}_{3 \times 1}$$

$$\hat{y} = 51.6 + 1.5x_1 + 6.72x_2$$

What is y when $x_1 = 3$ $x_2 = 2$

$$y = 57.6 + (1.5 \times 3) + 6.72 \times 2 = \underline{69.54} //$$

Consider Formulae that will be used, when only 2 Independent Variables specified.

[> 2 features, use matrix Algebra].

Consider

X_1	X_2	Y
3	8	-3.7
4	5	3.5
5	7	2.5
6	3	11.5
2	1	5.7
3	2	2

$$y = Q_0 + Q_1 x_1 + Q_2 x_2$$

$$Q_0 = ?$$

$$Q_1 = ?$$

$$Q_2 = ?$$

$$Q_0 = \bar{y} - Q_1 \bar{x}_1 - Q_2 \bar{x}_2$$

$$Q_1 = \frac{(\sum x_2^2)(\sum x_1 y) - (\sum x_1 x_2)(\sum x_2 y)}{(\sum x_1^2)(\sum x_2^2) - (\sum x_1 x_2)^2}$$

$$\left. \begin{array}{l} \bar{y} = \\ \bar{x}_1 = \\ \bar{y}_1 = \end{array} \right\} \text{mean}$$

$$Q_2 = \frac{(\sum x_1^2)(\sum x_2 y) - (\sum x_1 x_2)(\sum x_1 y)}{(\sum x_1^2)(\sum x_2^2) - (\sum x_1 x_2)^2}$$

where

$$\sum x_1^2 = \sum x_1 x_2 - \frac{(\sum x_1)(\sum x_1)}{N}$$

$$\sum x_2^2 = \sum x_2 x_2 - \frac{(\sum x_2)(\sum x_2)}{N}$$

$$\sum X_2 = \sum X_2^2 - \frac{(\sum X_2)^2}{N}$$

$$\sum X_1 X_2 = \sum X_1 X_2 - \frac{(\sum X_1)(\sum X_2)}{N}$$

$$\sum X_1 Y = \sum X_1 Y - \frac{(\sum X_1)(\sum Y)}{N}$$

$$\sum X_2 Y = \sum X_2 Y - \frac{(\sum X_2)(\sum Y)}{N}$$

Sol = $y = 2.796 + 2.28x_1 - 1.67x_2$

HW

- * To Evaluate Performance of m.l models
- * To find how good the model fits on given data

① Karl Pearsons Coefficient of correlation (r)

→ To calculate relationship bet two variable

$$r = \frac{N \sum xy - \sum x \sum y}{\sqrt{(N \sum x^2 - (\sum x)^2) (N \sum y^2 - (\sum y)^2)}}$$

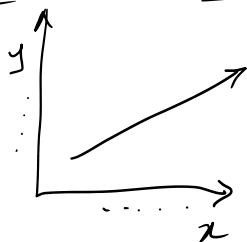
r = quantifies the strength of relationship betⁿ two variables.

The value of r be between +1 and -1

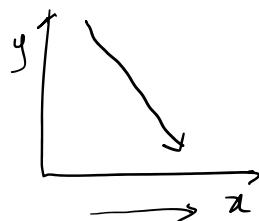
If $r = 1 \Rightarrow$ Total +ve correlation \Rightarrow If $x \uparrow$ then $y \uparrow$

If $r = -1 \Rightarrow$ Total -ve correlation \Rightarrow If $x \downarrow$ then $y \uparrow$

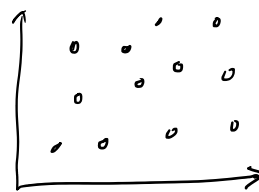
→ It gives strength (degree) & direction of correlation. or $x \uparrow$ then $y \downarrow$



+ve
Correlation



-ve
Correlation



Zero
Correlation.

Q.
81.60

x	y
151	63
174	81
138	56
186	91
128	47
136	57

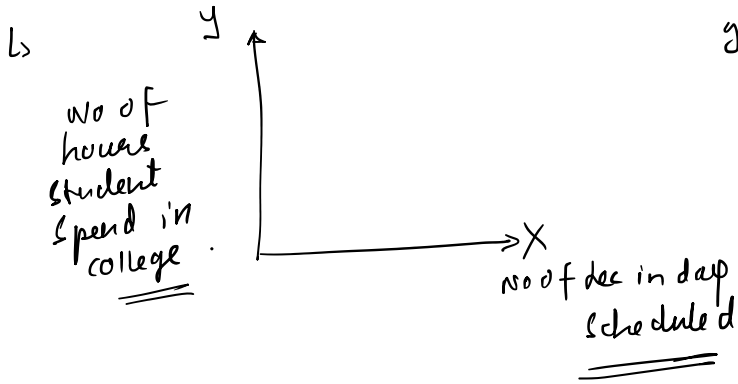
Find $r = ?$

0.9884

186	91
128	47
136	57
179	76
163	72
152	62
131	48

② R^2 method (R Square)

↳ It gives information about good of fit feature of the model.



if $r^2 = 0.85$
Variation in no of
hours that students spend
in college is 85%
dependent on no of hrs
scheduled.

↳ Indicates percentage of variance in dependent and independent variable pair

↳ Value varies from 0 to 1

if $r^2 = 1 \Rightarrow$ no diff betⁿ actual & predicted value.

$r^2 = 0$ means the model does not learn any relationship betⁿ variables.

$$\textcircled{1} SST (\text{Sum of squares of Total}) = \sum (y - \bar{y})^2$$

\uparrow actual $\quad \uparrow$ mean of y .
 y

$$\textcircled{2} SSR (\text{Sum of squares due to regression}) = \sum (\hat{y} - \bar{y})^2$$

\uparrow predicted $\quad \uparrow$ mean of y .
 \hat{y}

$$\textcircled{3} SSE (\text{Sum of squares of Error}) = \sum (y - \hat{y})^2$$

\uparrow actual $\quad \uparrow$ predicted
 y \hat{y}

$$R^2 = SSR / SST = \frac{\sum(\hat{y} - \bar{y})^2}{\sum(y - \bar{y})^2}$$

Q.
81.10

x	y	\hat{y}
151	63	
174	81	
138	56	
186	91	
128	47	
136	57	
179	76	
163	72	
152	62	
131	48	

to find R^2

to find predicted i.e. \hat{y}

$y = \beta_0 + \beta_1 x$

$\beta_0 = -38.455$

$\beta_1 = 0.6746$

find

$y = -38.455 + 0.6746x$

Now

$x = 151$ find $\hat{y} = 63.4$

$x = 174$ $\hat{y} = 78.92$

$x = 138$ $\hat{y} = 54.63$

Note

$$R^2 = \frac{\sum(\hat{y} - \bar{y})^2}{\sum(y - \bar{y})^2}$$

if line fits properly
then $\hat{y} \approx y$

$\therefore R^2 \approx 1$

③ Standard Error of Estimate →

* Measures the accuracy of Prediction.

$$* \underline{\underline{b_{est}}} = \sqrt{\frac{\sum (y - \hat{y})^2}{N}} = \sqrt{\underset{\substack{\uparrow \\ \text{(mean} \\ \text{square} \\ \text{error)}}}{MSE}} = \sqrt{\frac{SSE}{N}}$$

* It reflects how well the regression model fits the dataset.

* Smaller the value better it is

* Larger the value worst it is

y = actual value
 \hat{y} = predicted value.

Q.

81.10

x	y
151	63
174	81
138	56
186	91
128	47
136	57
179	76
163	72
152	62
131	48

$$b_{est} = 2.909$$

Classification →

Ex Mail → Spam^{+ve} / Not Spam^{-ve}

Online Transaction → Fraudulent^{+ve} / Non Fraudulent^{-ve}

Tumor → Malignant^{+ve} / Benign^{-ve}

where $y \in \{0, 1\}$ $\begin{cases} 0 \Rightarrow -ve \text{ class} \\ 1 \Rightarrow +ve \text{ class} \end{cases}$

Here y has Discrete Value.

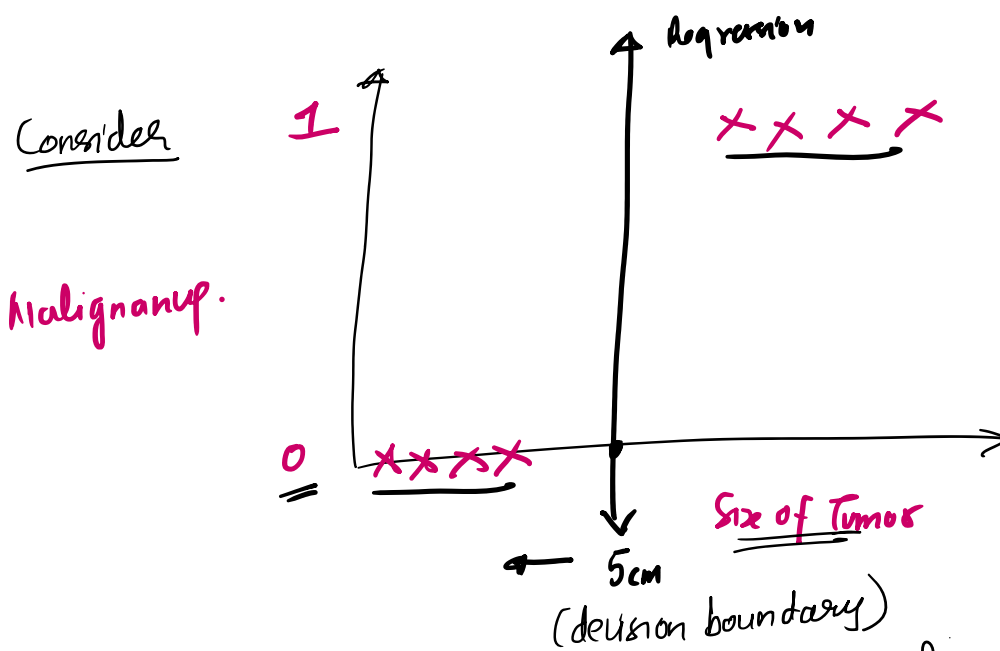
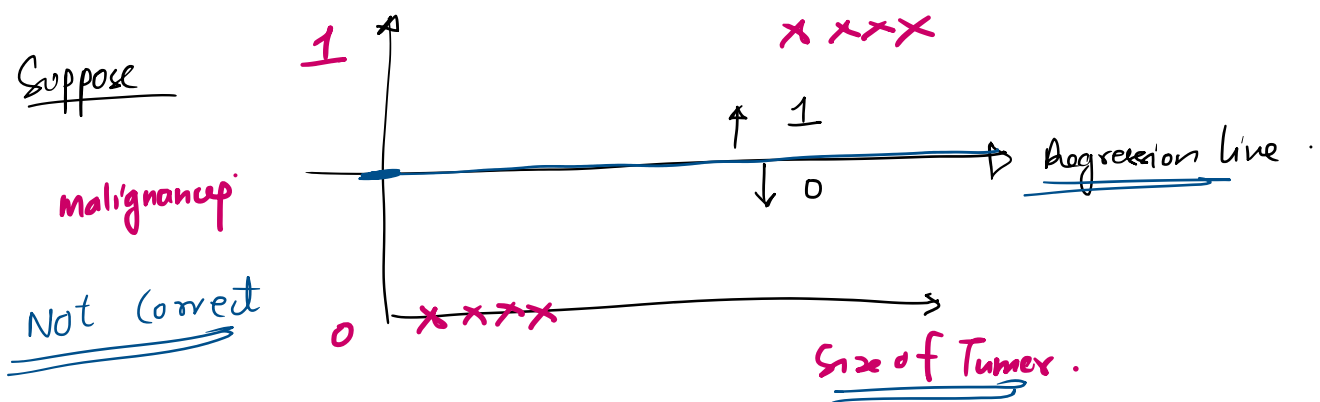
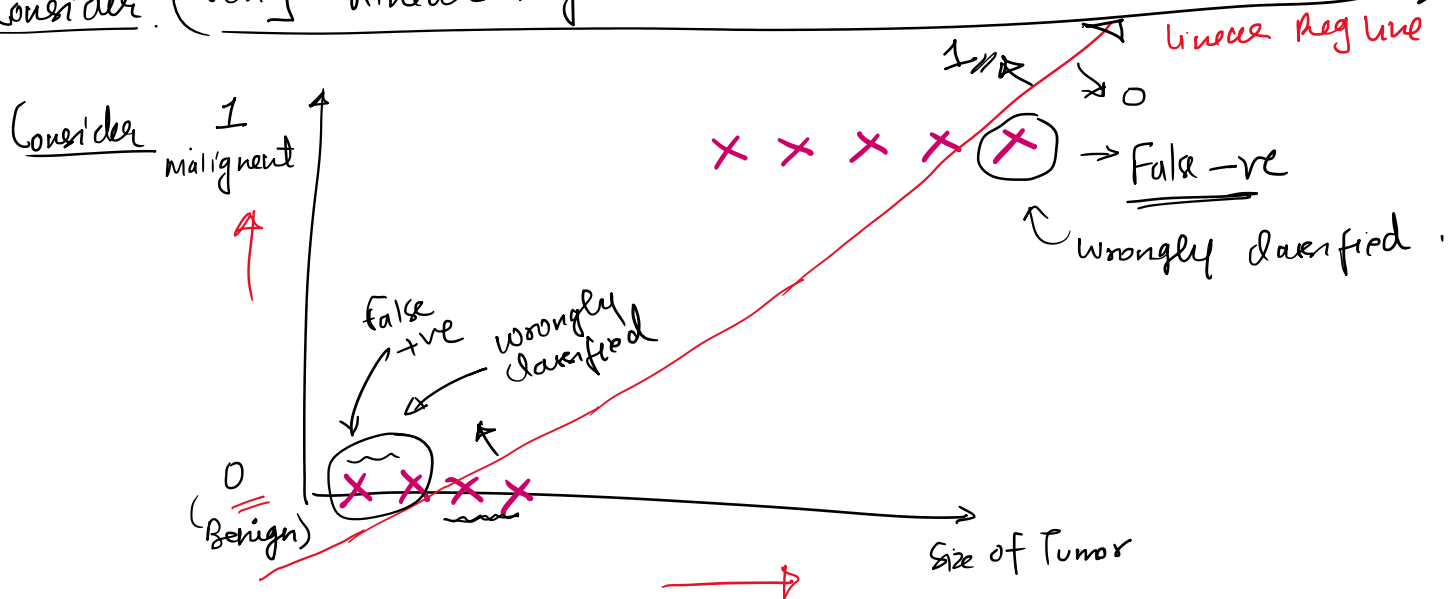
In above case o/p has only 2 class $\begin{cases} 0 \\ 1 \end{cases}$ } Binary classification.

To check Weather.

Possible o/p $\begin{cases} \text{Windy} \\ \text{Sunny} \\ \text{Cloudy} \\ \text{Rainy} \end{cases}$ } o/p has more than one class
[multi class classification]

* Classification bothers about label and not the Exact value.

Consider (Why Linear Regression is not used for Classification)



here we can observe for above Regression line

If Tumor Size $\leq 5\text{cm}$ \rightarrow Yes (1) Malignant

If tumor size $\leq 5\text{cm}$ \rightarrow Yes (1) Malignant
 tumor size $> 5\text{cm}$ \rightarrow No (0) Benign

we can say let 'P' denote Probability that $y=1$ when $X=x$.

$$y = \underline{\underline{P_x(y=1 | X=x)}} = \underline{\underline{\beta_0 + \beta_1 x}}_{\text{In linear Reg}}$$

P = probability lies betⁿ 0 to 1

But linear function are unbounded.

and Expected o/p here is 0 or 1

So we cannot use Regression to build Classifier

∴ Linear Regression is not suitable for Classification.

For Classification we will use Logistic Regression.

* In Logistic Regression we get Probability Score.

* It predicts the probability of occurrence of event

$$\text{Odd} = \frac{\text{No of time the Event happens}}{\text{No of time the Event will not happen.}}$$

Represents chances that the event will occur

Ex If odd of India winning against W.I is $\frac{4}{1} = \frac{\text{No of India win}}{\text{No of India not win}}$

$$= \frac{4}{1}$$

Best Case \Rightarrow The odd of India winning against W.I = ∞

If odd of W.I winning against India is $1:4$

$$= \frac{\text{No of W.I win}}{\text{No of W.I not win}} = \frac{1}{4}$$

Worst Case \Rightarrow W.I is winning 0 match = Odd = 0

Range of value that odd can take = 0 to ∞

Relationship between Odd & Probability = $\text{Odd} = \frac{P}{1-P}$