L- 9: Predictive Analytics & Revision

Agenda

- Review of last session
- Introduction to regression
- Method of least squares
- Simple linear regression

Covariance of X and Y

$$E(X) = \sum x\,P(x) = \int x\,f(x)\,dx$$

$$\mathrm{Cov}(X,Y) = \left[E\left(X-\mu_X\right)\left(Y-\mu_Y\right)\right]$$

$$= \sum_x \sum_y \left(x-\mu_x\right)\left(y-\mu_y\right) P(x,y)$$

joint p.d.f

if discrete

$$= \iint \left(x-\mu_x\right)\left(y-\mu_y\right) f(x,y)\,dx\,dy$$

joint prob. density fn

if continuous

innovate achieve lead

$$\operatorname{cov}(x, y)$$

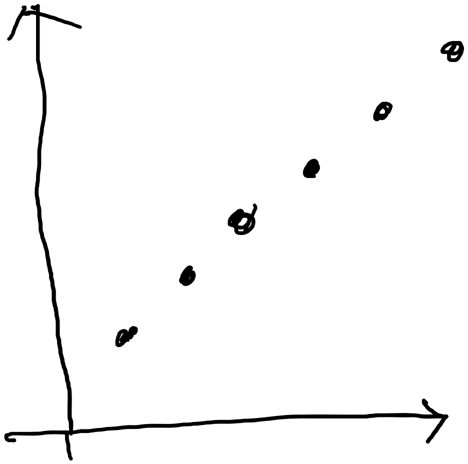
$$= \frac{\sum_{i=1}^{n} (x - \mu_x)(y - \mu_y)}{n-1}$$

And also

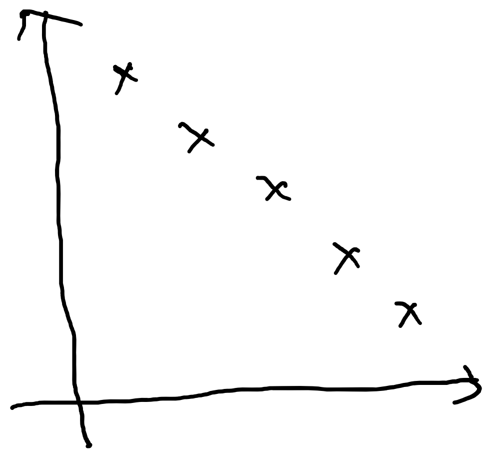
⇒ Farmer has an impression that if he uses more fertilizers, then the crop yield increases.

We need to validate this?

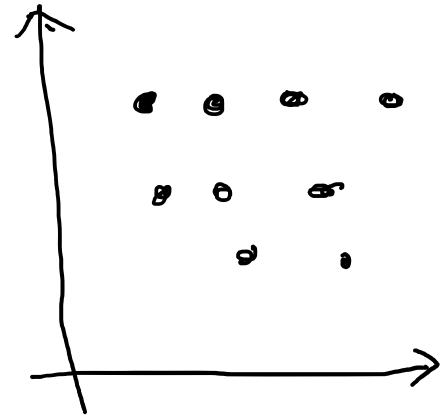
How → ?



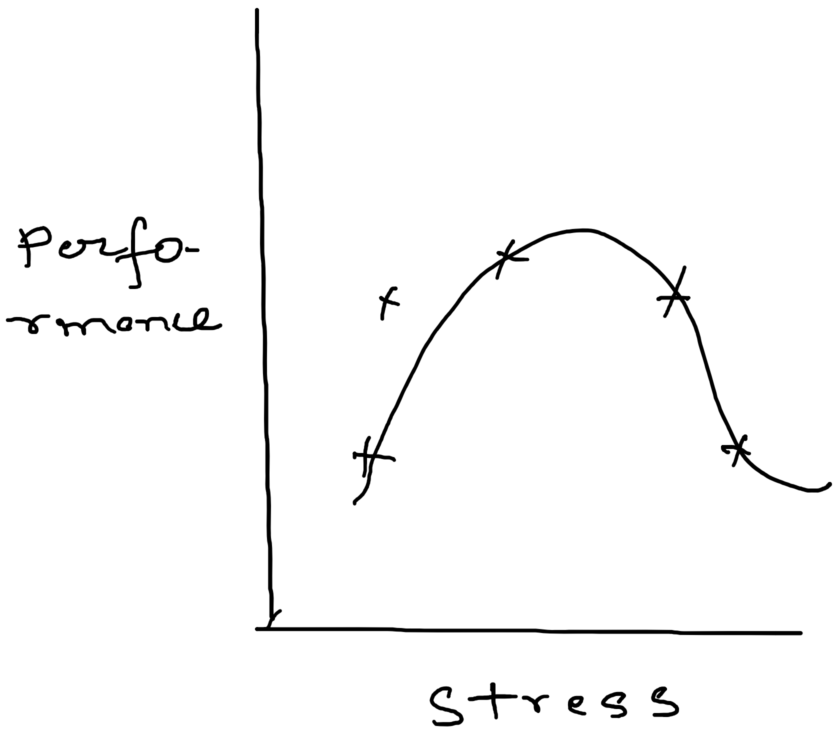
positive correlation



Negative correlation



No correlation


Performance
Stress


results
efforts

Coefficient of correlation:

$$r = \frac{\mathrm{cov}(x,y)}{\sigma_x \sigma_y} = \frac{\Sigma XY}{\sqrt{\Sigma X^2 \cdot \Sigma Y^2}}$$

where $X = x - \bar{x}$

$Y = y - \bar{y}$

$X^2 = (x - \bar{x})^2$

$Y^2 = (y - \bar{y})^2$

Coefficient of Correlation

$r = 1 \Rightarrow$ Perfect and positive relation

$r = -1 \Rightarrow$ " " negative relation

$r = 0 \Rightarrow$ no relation

$0 < r < 1 \Rightarrow$ Partial positive relation

$-1 < r < 0 \Rightarrow$ " negative "

Example - 1

x	1	2	3	4	5	6	7	8	9
y	10	11	12	14	13	15	16	17	18

$$\bar{x} = \frac{\Sigma x}{n} = \frac{45}{9} = 5$$

$$\bar{y} = \frac{\Sigma y}{n} = \frac{126}{9} = 14$$

r

x	$X = x-5$	X^2	y	$Y = y-14$	Y^2	XY
1	-4	16	10	-4	16	16
2	-3	9	11	-3	9	9
3	-2	4	12	-2	4	4
4	-1	1	14	0	0	0
5	0	0	13	-1	1	0
6	1	1	15	1	1	1
7	2	4	16	2	4	4
8	3	9	17	3	9	9
9	4	16	18	4	16	16
		60			60	Σ 59

$$r = \frac{\Sigma XY}{\sqrt{\Sigma X^2 \Sigma Y^2}}$$

$$= \frac{59}{\sqrt{60 \times 60}}$$

$$= 0.9833$$

x	$X = x-5$	X^2	y	$Y = y-14$	Y^2	XY
1	-4	16	10	-4	16	16
2	-3	9	11	-3	9	9
3	-2	4	12	-2	4	4
4	-1	1	14	0	0	0
5	0	0	13	-1	1	0
6	1	1	15	1	1	1
7	2	4	16	2	4	4
8	3	9	17	3	9	9
9	4	16	18	4	16	16
		60			60	Σ 59

$$\text{cov}(x, y) = \frac{\Sigma XY}{n-1} = \frac{59}{8} = 7.375$$

Coefficient of Determination

r is coeff. of correlation

r^2 is coeff of determination

Indicates the extent to which variation in one variable is explained by the variation in the other.

$r = 0.9 \Rightarrow r^2 = 0.81$

i.e. 81% of the variation in y due to variation in 'x'

remaining 19% is due to some other factors.

$$r = 0.9833$$

$$\mathrm{cov}(x, y) = 7.375$$

$$r^2 = 0.81$$

Interpretation

Regression

Regression :-

x	1	2	3	4	5
y	1	4	9	16	25

when x = 7 : y = ?

x	1	2	3	4	5
y	1	6	2	5	4

when x = 7, y = ?

Correlation	Regression
→ Measuring strength or degree of the relationship between two variables	→ Having an algebraic equation between two variables
→ no estimation	→ estimation
→ both variables are independent	→ one is dept variable and other indepn Variables

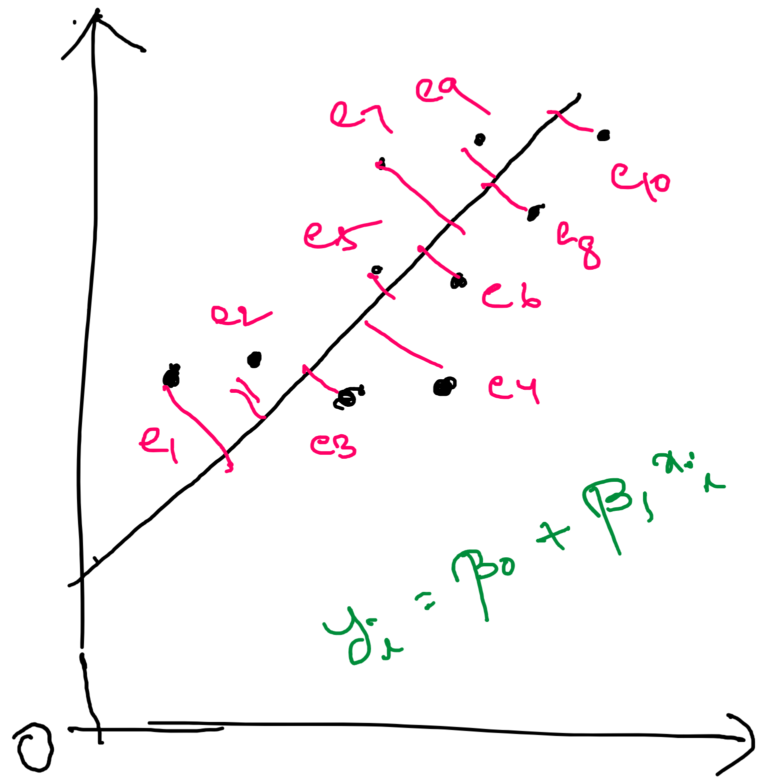
Method of Least squares

y : Dependent Variable

x : Independent Variable

predictor variable

response Variable



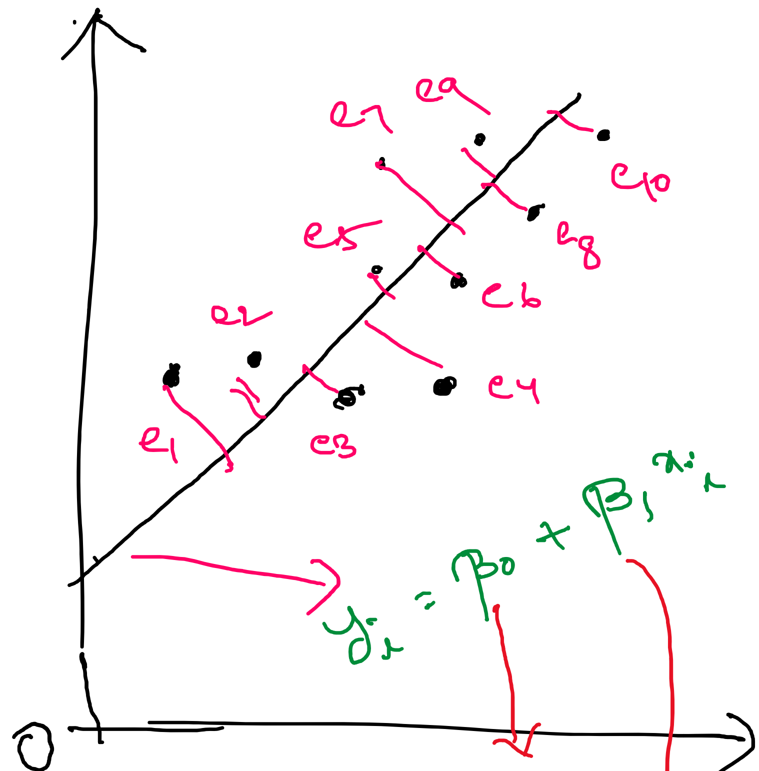
$$y_i = \beta_0 + \beta_1 x_i$$

Method of Least squares

" minimizing the error "

" minimize

$e_1^2 + e_2^2 + e_3^2 + \cdots e_{10}^2$



$y_i = \beta_0 + \beta_1 x_i$

y-intercept

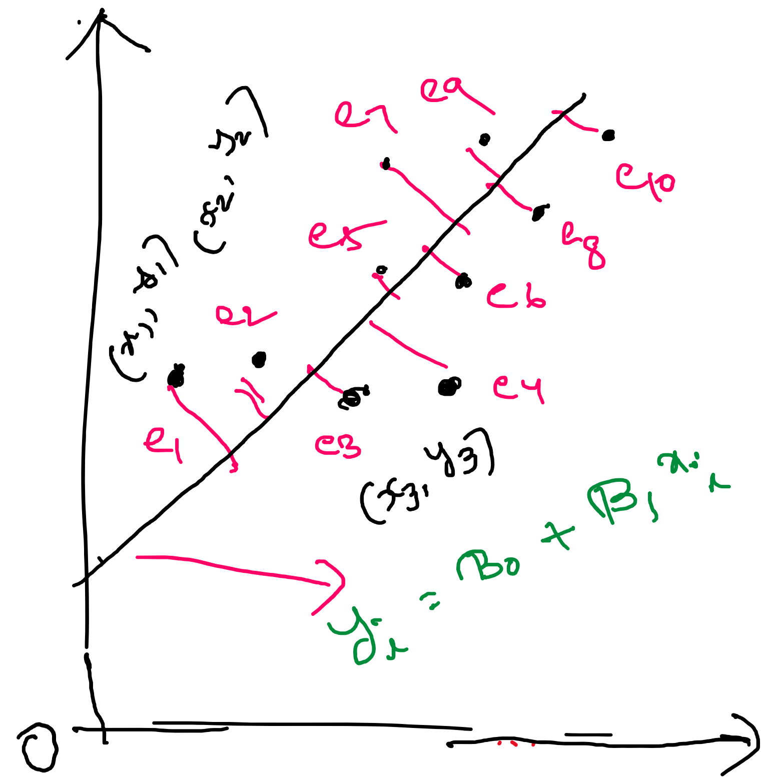
Slope of the line

Method of Least squares

$S(\beta_0, \beta_1)$

$$= \underbrace{\sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 x_i \right)^2}$$

we need to choose β_0 and β_1 which minimizes the error.



Method of Least squares

$$S(\beta_0, \beta_1) = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2$$

$$\frac{\partial S}{\partial \beta_0} = 0 \Rightarrow 2 \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)(-1)$$

$$\Rightarrow \boxed{\sum_{i=1}^{n} y_i = n\beta_0 + \beta_1 \sum_{i=1}^{n} x_i}$$

$$\frac{\partial S}{\partial \beta_1} = 0 \Rightarrow 2 \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)(2)(-x_i)$$

$$\Rightarrow \boxed{\sum_{i=1}^{n} x_i y_i = \beta_0 \sum x_i + \beta_1 \sum x_i^2}$$

on solving these, we get β_0 & β_1 which minimizes error.

Linear regression

$$y = \beta_0 + \beta_1 x$$

$$\left.\begin{aligned} \sum y &= \beta_0 n + \beta_1 \sum x \\ \sum xy &= \beta_0 \sum x + \beta_1 \sum x^2 \end{aligned}\right\}$$

Normal equations.

Regression Coefficients

→ $y = a + bx$ regression line of y on x

b_{yx} : Regression coeff of y on x

→ $x = c + dy$ regression line of x on y

b_{xy} : regression coeff of y on x

Correlation coefficient

$$r = \sqrt{b_{yx} \times b_{xy}}$$

innovate achieve lead

Example :-

Company	Advt Expt	Sales / Revenue
A	1	1
B	3	2
C	4	2
D	6	4
E	8	6
F	9	8
G	11	8
H	14	9

$$y = a + bx$$

$$\Sigma y = an + b\Sigma x$$

$$\Sigma xy = a\Sigma x + b\Sigma x^2$$

Example :-

Sales Revenue y	Advt expr. x	x^2	xy
1	1	1	1
2	3	9	6
2	4	16	8
4	6	36	24
6	8	64	48
8	9	81	72
8	11	121	88
9	14	196	126
Σ 40	Σ 56	Σ 524	Σ 373

$$\Sigma y = n\beta_0 + \beta_1 \Sigma x$$

$$\Sigma xy = \beta_0 \Sigma x + \beta_1 \Sigma x^2$$

$$\Rightarrow 40 = 8\beta_0 + 56\beta_1$$

$$373 = 56\beta_0 + 524\beta_1$$

on solving

$$\beta_0 = 0.072$$

$$\beta_1 = 0.704$$

$$\boxed{\text{i.e. } y = (0.072) + (0.704)x}$$

ie $y = (0.072) + (0.704)x$

when $x = 0.075$, then

$$y = (0.072) + (0.704)(0.075)$$

$$= 0.1248 \approx 12.48\%$$

Example:

Consider the following data

x	1	2	4	0
y	0.5	1	2	0

Fit a linear regression line

Estimate y when $x = 5$.

x	y	xy	x^2
1	0.5	0.5	1
2	1	2	4
4	2	8	16
0	0	0	0
$\Sigma = 7$	$\Sigma\, 3.5$	Σ 10.5	Σ 21

$$y = \beta_0 + \beta_1 x$$

$$\Sigma y = n\beta_0 + \beta_1 \Sigma x$$

$$\Sigma xy = \beta_0 \Sigma x_1 + \beta_1 \Sigma x^2$$

$$3.5 = 4\beta_0 + \beta_1 (7)$$

$$10.5 = 7\beta_0 + \beta_1 (21)$$

on solving these

$$\beta_0 = 0$$

$$\beta_1 = 0.5$$

ie $y = 0 + (0.5)x$

$$\boxed{\text{when } x = 5, \quad y = (0.5)5 = 0.25}$$

Linear regression
(Multiple regression)

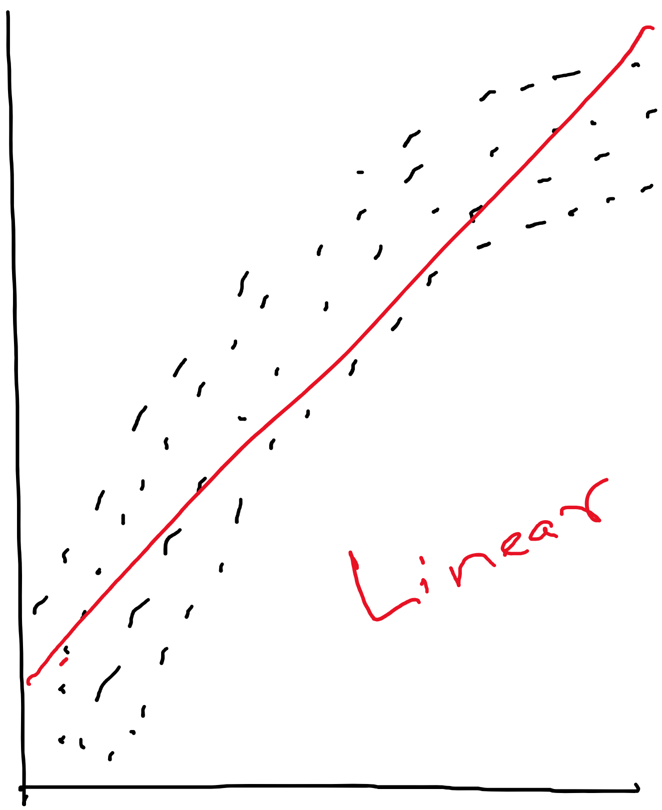
Example:-

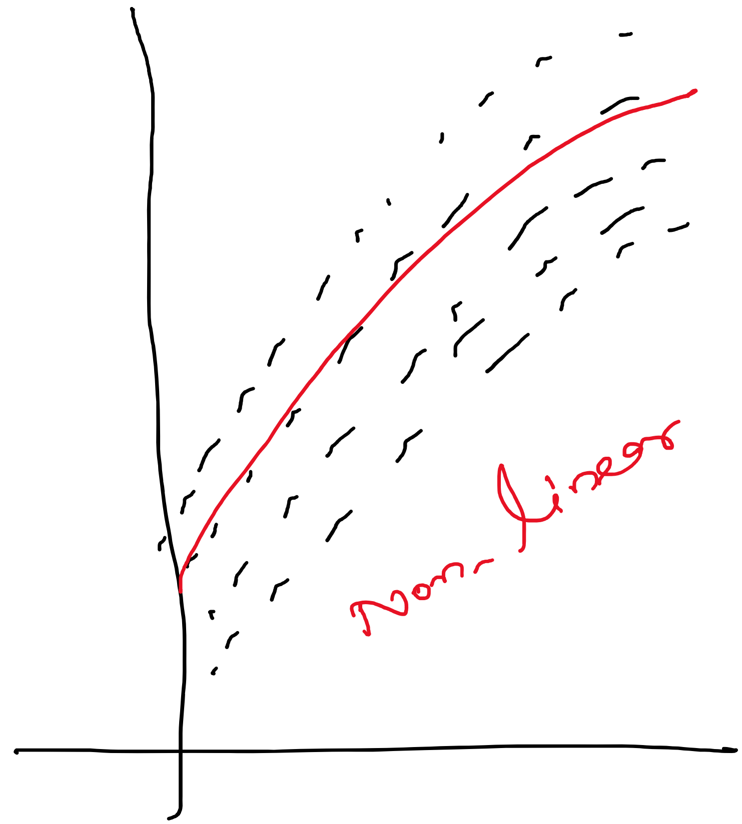
x_0	size	No of rooms	No of floors	Age of home	Price Lakhs
1	2000	5	2	45	4000
1	1400	3	1	40	2000
1	1600	3	2	30	3000
1	800	2	1	35	2000
	x_1	x_2	x_3	x_4	y

Multiple Linear regression

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

Other regressions
just a look





Suppose $y = ae^{bx}$ $\rightarrow$ exponential curve

$$\log y = \log a + b \log x$$

$$Y \quad\quad A \quad\quad\quad X$$

ie $Y = A + bX$

$$\sum Y = An + b\sum X \rightarrow (1)$$

$$\sum XY = A\sum X + b\sum X^2 \rightarrow (2)$$

$A = ?$ $\Rightarrow$ a ✓

b ✓

Hence, we get $y = ae^{bx}$

Suppose $y = ax^b$ → Power Curve

Matrix Approach:

Let $y = \beta_0 + \beta_1 x_1 + \cdots\cdots + \beta_{p-1} x_{p-1}$

observations $y_i = 1, 2, \ldots n \rightarrow$ by a vector Y

unknowns $\beta_0, \beta_1 \ldots \beta_{p-1} \rightarrow$ " " β

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p-1} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p-1} \\ \vdots & & & & \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np-1} \end{bmatrix}$$

$$\underset{n\times 1}{\hat{Y}} = \underset{n\times p}{X} \; \beta_{p\times 1}$$

Find β to minimize

$$S(\beta) = \sum_{i=1}^{m} \left(y_i - \beta_0 - \beta_1 x_1 - \beta_2 x_2 - \cdots \right)^2$$

$$= \| Y - X\beta \|^2 = \| Y - \hat{Y} \|^2$$

Diff S wrt to each β we get Linear eqn

$$X^T X \hat{\beta} = X^T Y \longrightarrow \text{normal eqns}$$

If $X^T X$ is non-singular, the soln is

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

Computationally, it is sometimes unwise even to form the normal equations because the multiplications involved in forming $X^T X$ can introduce undesirable round-off error.

→ If $X^T X$ is non-invertible ... ?

✓ Redundant features

✓ too many features

Revision

Revision

Revision

Thanks