

Sample Mean (\bar{y})

A Sample mean (\bar{y}) of a random sample of n observations $y_1, y_2, y_3, \dots, y_n$ is given by

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

Note:

1) $\bar{y} \neq \mu$ (Population mean).

2) $E(\bar{y}) = \mu$.

Variance (s^2)

$$\text{Var}(y) = F^2 = E(y - \mu)^2$$
$$= E(y^2) - \mu^2$$

Sample Variance

$$s^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n-1} = \frac{\sum_{i=1}^n y_i^2 - n\bar{y}^2}{n-1}$$

NOTE: 1) $s^2 \neq \sigma^2$.

2) $E(s^2) = \sigma^2$.

Sample Co-variance:

$$s_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1} = \frac{\sum_{i=1}^n x_i y_i - n\bar{x}\bar{y}}{n-1}$$

$$\Gamma_{HdI} = \bar{y}$$

$$Hd \cdot Ir = \bar{R}$$

$$\text{Sum of squares} = \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n y_i^2 - n\bar{y}^2$$

• addition of square is always univocal : it is
the sum of each square terms and since, if x is
(x^2) univocal, square univocal will be just ok since
square also will be \geq

<u>person</u>	<u>Height(x)</u>	<u>weight (y in pounds)</u>	<u>$x_i y_i$</u>	<u>$(x_i - \bar{x})^2$</u>	<u>$(y_i - \bar{y})^2$</u>
1	69	153	10557	6.00	136.89
2	74	175	12950	6.50	106.09
3	68	155	10540	11.90	94.09
4	72	135	9450	2.10	882.09
5	72	172	12384	0.80	53.29
6	67	150	10050	19.80	216.09
7	66	115	7590	29.70	247.09
8	70	137	9570	2.90	767.29
9	76	200	15200	20.70	1246.09
10	68	130	8840	11.90	1204.09
11	72	140	10080	0.30	610.09
12	79	265	13690	57.00	1006.09
13	74	185	7504	6.50	412.09
14	67	112	9240	19.80	277.29
15	66	140	10650	29.70	610.09
16	71	150	12210	0.20	216.09
17	74	165	13875	6.50	0.09
18	75	185		12.60	412.09
19	75	210	15750	12.60	2058.09
20	76	220	16720	20.70	8058.09
	$\sum x = 1429$	$\sum y = 3294$	$\sum x_i y_i = 237805$	$\sum (x_i - \bar{x})^2 = 276.9$	$\sum (y_i - \bar{y})^2 = 27384$
	$\bar{x} = 71.64$	$\bar{y} = 164.7$			

Covariance:

$$\text{Cov} xy = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{n-1} = \underline{\underline{128.87894736842}}$$

NOTE: Covariance depends on units of variables.
i.e. if units are changes from inches to feet and
pounds to kgs in the previous example, covariance ($\text{Cov} xy$)
will also change

Correlation Co-efficient for Sample.

$$r_{xy} = \frac{S_{xy}}{S_x S_y}$$

$$= \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

$$S_{xy} = \sqrt{S_{xx}}, S_x^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1} = \frac{\sum_{i=1}^n x_i^2 - n \bar{x}^2}{n-1}$$

Correlation

Population Co-efficient of x & y :

$$C_{xy} = \frac{\text{Cov}(x, y)}{S_x S_y}$$

Note:

r_{xy} is independent of units and is a constant $-1 \leq r_{xy} \leq 1$.

If $r_{xy} = 1 \Rightarrow$ The variable x & y are perfectly co-related.

- If $r_{xy} = -1 \Rightarrow$ Then also x & y are perfectly correlated but in opposite direction.
i.e., one \uparrow other \downarrow .

- If $r_{xy} = 0 \Rightarrow$ There is no relation b/w x & y i.e., orthogonal.

For the adj example:

$$S_x^2 = \frac{276.9}{19} = 14.573$$

$$S_x = \underline{3.8175}$$

$$S_y^2 = \underline{1441.2631}$$

$$S_y = \underline{37.9639}$$

$$r_{xy} = \frac{128.88}{(3.8175)(37.9639)} = \frac{128.88}{(12.071) (144.1263)} = \frac{128.88}{12.071 \cdot 144.1263} = \frac{128.88}{1776.01} = 0.072 = .72$$

$$\left(\bar{x} \bar{y} - \bar{xy} \right) \frac{1}{n-1} = \frac{1}{18} = 0.0556$$

Covariance Matrix:

The Sample Covariance matrix $S = (S_{jk}) = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1p} \\ S_{21} & S_{22} & \cdots & S_{2p} \\ \vdots & \vdots & & \vdots \\ S_{p1} & S_{p2} & \cdots & S_{pp} \end{bmatrix}$
 is the matrix of sample variations and
 Covariances of P-variables.

NOTE: It's a Symmetric Matrix Since $S_{jk} = S_{kj}$

Ex: Location No.

	<u>y_1</u> (Available Soil Ca)	<u>y_2</u> (Exchanged soil Ca)	<u>y_3</u> (Turnip green Ca)
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1. 35 3.5 2.8

2. 35 4.9 2.7

3. 40 30 4.38

4. 10 2.8 3.21

5. 6 2.7 2.73

6. 20 2.8 2.81

7. 35 4.6 2.88

8. 35 10.9 2.9

9. 35 8 3.28

10. 30 1.6 3.2

$$\sum y_1 = 281 \quad \sum y_2 = 71.8 \quad \sum y_3 = 30.89$$

Find $S = \begin{bmatrix} S_{11} & S_{12} & S_{13} \\ S_{21} & S_{22} & S_{23} \\ S_{31} & S_{32} & S_{33} \end{bmatrix}$

$$\bar{y}_1 = 28.1$$

$$\bar{y}_2 = 7.18$$

$$\bar{y}_3 = 3.089$$

$$S_{11} = S_1^2 = \frac{1}{n-1} \left(\sum_{i=1}^n y_{1i}^2 - n \bar{y}_1^2 \right)$$

$$= \frac{1}{9} (9161 - 10(789.61)) = \frac{1}{9} (1264.9) = 140.545$$

$$S_{12} = \frac{1}{n-1} \left(\sum_{i=1}^n y_{1i} y_{2i} - n \bar{y}_1 \bar{y}_2 \right)$$

$$= 49.68$$

$$\underline{\underline{S_{12} = 49.68}}$$

$$\underline{\underline{S_{22} = 72.25}}$$

$$\underline{\underline{S_{23} = 3.68}}$$

$$\underline{\underline{S_{33} = 0.25}}$$

$$S = \begin{bmatrix} 140.54 & 49.68 & 1.94 \\ 49.68 & 72.25 & 3.68 \\ 1.94 & 3.68 & 0.25 \end{bmatrix}$$

#Correlation Matrix:

The random Correlation matrix b/w the j^{th} & k^{th} variables is defined as

$$r_{jk} = \frac{s_{jk}}{\sqrt{s_{jj} s_{kk}}} = \frac{s_{jk}}{s_j \cdot s_k}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix}$$

where $r_{jj} = 1$; $j=1, 2, 3, \dots, p$.

$$\equiv R = \begin{bmatrix} 1 & r_{12} & \cdots \\ r_{21} & 1 & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

→ Conversion of Correlation matrix to Covariance.

$$\begin{aligned} \text{define diagonal matrix, } D_s &= \text{diag}(\sqrt{s_{11}}, \sqrt{s_{22}}, \dots, \sqrt{s_{pp}}) \\ &= \text{diag}(s_1, s_2, \dots, s_p) \\ &= \begin{bmatrix} s_1 & 0 & \cdots & 0 \\ 0 & s_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & s_p \end{bmatrix} \end{aligned}$$

Note: $R = D_s^{-1} S D_s^{-1}$ (1)

$S = D_s R D_s$ where D_s^{-1} = inverse of D_s .

for previous example,

$$R = \begin{bmatrix} 1 & 0.596 & 0.8 \\ 0.596 & 1 & 0.86 \\ 0.8 & 0.86 & 1 \end{bmatrix}$$

to find D_s given $S = \begin{bmatrix} 1.4054 & 49.68 & 1.941 \\ 49.68 & 72.25 & 3.68 \\ 1.941 & 3.68 & 0.25 \end{bmatrix}$

$$\begin{aligned} |D_s| &= 11.8551(8.4999 \times 0.5001) \\ &= 50.393658961449 \end{aligned}$$

$$D_s = \begin{bmatrix} 11.8551 & 0 & 0 \\ 0 & 8.4999 & 0 \\ 0 & 0 & 0.5001 \end{bmatrix}$$

$$\text{adj}(D_s)_C = \begin{bmatrix} 4.25 & 0 & 0 \\ 0 & 5.92873 & 0 \\ 0 & 0 & 10.07671 \end{bmatrix}$$

$$D_s^{-1} = \frac{\text{adj}(D_s)}{|D_s|} = \begin{bmatrix} 0.084 & 0 & 0 \\ 0 & 0.1176 & 0 \\ 0 & 0 & 1.9996 \end{bmatrix}$$

$$\text{adj}(D_s) = \begin{bmatrix} 4.25 & 0 & 0 \\ 0 & 5.92873 & 0 \\ 0 & 0 & 10.07671 \end{bmatrix}$$

$$\begin{aligned}
 R &= D_S^{-1} S D_S^{-1} = \begin{bmatrix} 0.084 & 0 & 0 \\ 0 & 0.1176 & 0 \\ 0 & 0 & 1.9996 \end{bmatrix} \begin{bmatrix} 140.54 & 49.68 & 19.61 \\ 49.68 & 72.25 & 3.68 \\ 19.61 & 3.68 & 0.25 \end{bmatrix} \begin{bmatrix} 0.084 & 0 & 0 \\ 0 & 0.1176 & 0 \\ 0 & 0 & 1.9996 \end{bmatrix} \\
 &= \begin{bmatrix} 11.80536 & 4.17312 & 0.163044 \\ 5.842368 & 8.4966 & 0.432768 \\ 3.8812236 & 7.358528 & 0.4999 \end{bmatrix} \begin{bmatrix} 0.084 & 0 & 0 \\ 0 & 0.1176 & 0 \\ 0 & 0 & 1.9996 \end{bmatrix} \\
 &\approx \begin{bmatrix} 0.9916 & 0.490758912 & 0.3260227824 \\ 0.490758912 & 0.9992006 & 0.8653628928 \\ 0.3260227824 & 0.8653628928 & 0.99960006 \end{bmatrix} \\
 &\approx \begin{bmatrix} 1 & 0.2 & 0.3 \\ 0.2 & 1 & 0.2 \\ 0.3 & 0.2 & 1 \end{bmatrix}
 \end{aligned}$$

Note:

$$\begin{bmatrix} 8.0 & 8.72 & 8.0 \\ 8.72 & 1 & 8.72 \\ 8.0 & 8.72 & 8.0 \end{bmatrix} \sim I_3$$

Mean Vectors and Co-Variance matrices for subsets of Variables:

Sometimes a researcher is interested in two diff kinds of variables of variables, both measured on same sampling unit.

Let us denote two subvectors by y & x , with p variables in y & q variables in x .

Thus each observation vector in a sample is partitioned as

$$(y_i) = \begin{pmatrix} y_i \\ x_i \end{pmatrix}, i=1, 2, \dots, n$$

Hence, there are $p+q$ variables in each of n observations vectors.
 for the sample of n observation vectors, the mean vector and the covariance matrix have the form.

$$\begin{pmatrix} \bar{y} \\ \bar{x} \end{pmatrix} = \begin{pmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \vdots \\ \bar{y}_p \\ \bar{x}_1 \\ \vdots \\ \bar{x}_q \end{pmatrix}; S = \begin{pmatrix} S_{yy} & S_{yx} \\ S_{xy} & S_{xx} \end{pmatrix}$$

where $[S_{yy}]_{p \times p}$, $[S_{yx}]_{p \times q}$, $[S_{xy}]_{q \times p}$, $[S_{xx}]_{q \times q}$

$\rightarrow S'_{yx} = S_{xy}$, where S'_{yx} is the transpose of S_{yx} .

Let, $p=2$ & $q=3$. Then,

$$S_{yy} = \begin{pmatrix} s_1^2 & s_{12} & s_{13} \\ s_{21} & s_2^2 & s_{23} \\ s_{31} & s_{32} & s_3^2 \end{pmatrix},$$

$$y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}; x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

$$S_{yy} = \begin{pmatrix} s_{y_1}^2 & s_{y_1 y_2} \\ s_{y_2 y_1} & s_{y_2}^2 \end{pmatrix}_{2 \times 2}; S_{yx} = \begin{pmatrix} s_{y_1 x_1} & s_{y_1 x_2} & s_{y_1 x_3} \\ s_{y_2 x_1} & s_{y_2 x_2} & s_{y_2 x_3} \end{pmatrix}_{2 \times 3}$$

$$= S'_{xy}$$

$$S_{xx} = \begin{pmatrix} s_{x_1}^2 & s_{x_1 x_2} & s_{x_1 x_3} \\ s_{x_2 x_1} & s_{x_2}^2 & s_{x_2 x_3} \\ s_{x_3 x_1} & s_{x_3 x_2} & s_{x_3}^2 \end{pmatrix}_{3 \times 3}$$

Ex: Research of Miller measured five variables in a comparison of normal Patients and diabetics.

x_1 = glucose tolerance, x_2 = insulin response to oral glucose,

x_3 = insulin resistance, y_1 = relative weight, y_2 = fasting plasma glucose.

$$S = \begin{bmatrix} 0.0162 & 0.216 & 0.7872 & -0.2138 & 2.189 \\ 0.216 & 70.56 & 26.23 & -23.96 & -20.84 \\ 0.7872 & 26.23 & 1106 & 396.7 & 108.4 \\ -0.2138 & -23.96 & 396.7 & 2382 & 1143 \\ 2.189 & -20.84 & 108.4 & 2136 & 2136 \end{bmatrix}_{5 \times 5}$$

$$S_{xx} = \begin{bmatrix} 1106 & 396.7 & 108.4 \\ 396.7 & 2382 & 1143 \\ 108.4 & 1143 & 2136 \end{bmatrix}_{3 \times 3}$$

$$S_{gy} = \begin{bmatrix} 0.0162 & 0.216 \\ 0.216 & 70.56 \end{bmatrix}_{2 \times 2}$$

$$S_{yx} = \begin{bmatrix} 0.7872 & -0.2138 & 2.189 \\ 26.23 & -23.96 & -20.84 \end{bmatrix}_{3 \times 2}$$

$$S_{xy} = \begin{bmatrix} 0.7872 & 26.23 \\ -0.2138 & -23.96 \\ 2.189 & -20.84 \end{bmatrix}_{3 \times 2}$$

Dependent Variable (D.V) & Independent Variable (I.V):

Covariates:

1	<u>Patient no.</u>	<u>y_1</u>	<u>y_2</u>	<u>x_1</u>	<u>x_2</u>	<u>x_3</u>	<u>y_1^2</u>	<u>y_2^2</u>	<u>$y_1 y_2$</u>	<u>$y_1 x_1$</u>	<u>$y_1 x_2$</u>	<u>x_1^2</u>	<u>x_2^2</u>	<u>x_3^2</u>	<u>$x_1 x_2$</u>
1		0.81	80	356	124	55									
2		0.95	97	289	117	76									
3		0.94	105	319	143	105									
4		1.04	90	356	199	108									
5	1	1	90	323	240	143									

$$S_{y_1}^2 = \frac{1}{n-1} (S_{y_1^2} - n\bar{y}_1^2)$$

$$\begin{bmatrix} S_{y_1^2} & S_{y_1 y_2} & S_{y_1 x_1} & S_{y_1 x_2} & S_{y_1 x_3} \\ S_{y_2 y_1} & S_{y_2^2} & S_{y_2 x_1} & S_{y_2 x_2} & S_{y_2 x_3} \\ S_{x_1 y_1} & S_{x_1 y_2} & S_{x_1^2} & S_{x_1 x_2} & S_{x_1 x_3} \\ S_{x_2 y_1} & S_{x_2 y_2} & S_{x_2 x_1} & S_{x_2^2} & S_{x_2 x_3} \\ S_{x_3 y_1} & S_{x_3 y_2} & S_{x_3 x_1} & S_{x_3 x_2} & S_{x_3^2} \end{bmatrix}$$

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$$S_{xx} = \begin{bmatrix} 1106 & 396.7 & 108.4 \\ 396.7 & 2382 & 1143 \\ 108.4 & 1143 & 2136 \end{bmatrix}_{3 \times 3}$$

$$S_{yx} = \begin{bmatrix} 0.7872 & -0.2138 & 2.189 \\ 26.23 & -23.96 & -20.84 \end{bmatrix}_{3 \times 2}$$

$$S_{gy} = \begin{bmatrix} 0.0162 & 0.216 \\ 0.216 & 70.56 \end{bmatrix}_{2 \times 2}$$

$$S_{xy} = \begin{bmatrix} 0.7872 & 26.23 \\ -0.2138 & -23.96 \\ 2.189 & -20.84 \end{bmatrix}_{3 \times 2}$$

Dependent Variable (D.V) & Independent Variable (I.V):

Covariates:

Patient no.	y_1	y_2	x_1	x_2	x_3	\bar{y}_1	\bar{y}_2	$\bar{y}_1 y_2$	$\bar{y}_1 x_1$	$\bar{y}_1 x_2$	$\bar{y}_1 x_3$	\bar{x}_1^2	\bar{x}_2^2	\bar{x}_3^2	$\bar{x}_1 x_2$
1	0.81	80	356	124	55										
2	0.95	97	289	117	76										
3	0.94	105	319	143	105										
4	1.04	90	356	199	108										
5	1	90	323	260	143										

$$S_{y_1^2} = \frac{1}{n-1} (S_{y_1^2} - n\bar{y}_1^2)$$

$$\begin{bmatrix} S_{y_1^2} & S_{y_1 y_2} & S_{y_1 x_1} & S_{y_1 x_2} & S_{y_1 x_3} \\ S_{y_2 y_1} & S_{y_2^2} & S_{y_2 x_1} & S_{y_2 x_2} & S_{y_2 x_3} \\ S_{x_1 y_1} & S_{x_1 y_2} & S_{x_1^2} & S_{x_1 x_2} & S_{x_1 x_3} \\ S_{x_2 y_1} & S_{x_2 y_2} & S_{x_2 x_1} & S_{x_2^2} & S_{x_2 x_3} \\ S_{x_3 y_1} & S_{x_3 y_2} & S_{x_3 x_1} & S_{x_3 x_2} & S_{x_3^2} \end{bmatrix}$$

Linear Combination of Variables:

Let, Z be the linear combination of the variables $y_1, y_2, y_3, \dots, y_p$.

$$Z = \sum_{i=1}^p a_i y_i = a_1 y_1 + a_2 y_2 + \dots + a_p y_p.$$

$$\text{Let, } a = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{pmatrix} \Rightarrow a' = (a_1, a_2, \dots, a_p).$$

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{pmatrix}$$

$$\Rightarrow Z = a'y.$$

If the Sample Co-efficient vector a is applied to each y_i in a sample, we have-

$$z_i = a_1 y_{i1} + a_2 y_{i2} + a_3 y_{i3} + \dots + a_p y_{ip},$$

$$= a'y_i, i=1, 2, \dots, n.$$

$$z_1 = a_1 y_{11} + a_2 y_{12} + \dots + a_p y_{1p} = a' \begin{pmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1p} \end{pmatrix} = a'y_1,$$

$$z_2 = a_1 y_{21} + a_2 y_{22} + \dots + a_p y_{2p} = a'y_2,$$

$$z_3 = a_1 y_{31} + a_2 y_{32} + \dots + a_p y_{3p} = a'y_3,$$

$$z_n = a_1 y_{n1} + \dots + a_p y_{np} = a'y_n.$$

Sample mean of Z will be:

$$\bar{z} = \frac{1}{n} \sum_{i=1}^n z_i = \frac{1}{n} \sum_{i=1}^n a'y_i = a' \frac{1}{n} \sum_{i=1}^n y_i = a'\bar{y}.$$

$$\bar{z} = a'\bar{y}.$$

$$\bar{y} = \frac{y_1 + y_2 + \dots + y_n}{n}.$$

Similarly, the Sample Variance of $z_i = a'y_i, i=1, 2, \dots, n$, can be found as the Sample variance of z_1, z_2, \dots, z_p or directly from a and S , where S is the Sample Covariance matrix of $y_1, y_2, y_3, \dots, y_n$.

$$S_z^2 = \frac{\sum_{i=1}^n (z_i - \bar{z})^2}{n-1} = a'Sa$$

$$S_z^2 = a'Sa.$$

Note: Since a Variable is always non-negative, $S_z^2 \geq 0$ and therefore $a' S a \geq 0$, for every a . Hence S is at least positive Semidefinite.

Let, $w \neq z$, is a new linear combination of y_i

$$w = b_1 y_1 + b_2 y_2 + \dots + b_p y_p.$$

$$\boxed{w = b'y}, \text{ where } b = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{pmatrix}, b' = (b_1, b_2, \dots, b_p).$$

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{pmatrix}$$

Then Sample Co-Variance of z and w is given by

$$S_{zw} = \frac{\sum_{i=1}^n (z_i - \bar{z})(w_i - \bar{w})}{n-1} = \boxed{a' S b = S_{zw}}.$$

The Sample Correlation between z and w is

$$r_{zw} = \frac{S_{zw}}{\sqrt{S_z^2 S_w^2}} = \boxed{\frac{a' S b}{\sqrt{(a' S a)(b' S b)}}} = r_{zw}.$$

Ex: Timm reported the results of an experiment where subjects responded to "probe words" at five positions in a sentence. The variables are response times for the j^{th} probe word, y_{ij} , $i=1, 2, \dots, 11$, $j=1, 2, \dots, 5$.

<u>Subject No.</u>	y_1	y_2	y_3	y_4	y_5	
1	51	36	50	35	42	
2	27	20	26	17	27	
3	37	22	41	37	30	
4	42	36	32	34	27	
5	27	18	33	14	29	
6	43	32	43	35	40	
7	41	22	36	25	38	
8	38	21	31	20	16	
9	36	23	27	25	28	
10	26	31	31	32	36	
11	29	20	25	26	25	
<u>Total:</u>	<u>397</u>	<u>281</u>	<u>325</u>	<u>300</u>	<u>338</u>	

$$z = 3y_1 - 2y_2 + 4y_3 - y_4 + y_5$$

Sol: Method-1:

$$z = \alpha'y$$

$$\boxed{\bar{z} = \alpha' \bar{y}}$$

$$\alpha' = (3, -2, 4, -1, 1)$$

$$\bar{y} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{pmatrix} = \begin{pmatrix} 36.09 \\ 25.54 \\ 34.09 \\ 27.27 \\ 30.73 \end{pmatrix}$$

$$\bar{z} = (3, -2, 4, -1, 1)_{\text{avg}} \begin{pmatrix} 36.09 \\ 25.54 \\ 34.09 \\ 27.27 \\ 30.73 \end{pmatrix}_{5 \times 1}$$

$$\bar{z} = (108.27 - 51.08 + 136.36 - 27.27 + 30.73)$$

$$\boxed{\bar{z} = 197.01}$$

$$(\bar{w}-ws)(\bar{s}-is) \sum_{i=1}^n \frac{1}{(i-N)}$$

Method-2:

$$z_1 = 3(51) + (-2)(36) + 4(50) - 35 + 42 = 288$$

$$z_2 = 3(27) + (-2)(20) + 4(26) - 17 + 27 = 155$$

$$z_3 = 224, z_4 = 175, z_5 = 192, z_6 = 242, z_7 = 236, z_8 = 192, z_9 = 173,$$

$$z_{10} = 144, z_{11} = 146.$$

$$\bar{z} = \frac{z_1 + z_2 + \dots + z_{11}}{11} = \frac{2167}{11}$$

$$\boxed{\bar{z} \approx 197.01}$$

$$S_z^2 = \frac{1}{(n-1)} \sum_{i=1}^n (z_i - \bar{z})^2$$

$$S_z^2 = \alpha' S_a$$

$$S = \begin{pmatrix} 65.09 & 33.65 & 47.59 & 36.77 & 25.43 \\ 33.65 & 46.07 & 28.95 & 40.34 & 28.36 \\ 47.59 & 28.95 & 60.69 & 37.37 & 41.13 \\ 36.77 & 40.34 & 37.37 & 62.82 & 31.68 \\ 25.43 & 28.36 & 41.13 & 31.68 & 58.22 \end{pmatrix}$$

$$W = y_1 + 3y_2 - y_3 + y_4 - 2y_5$$

$$\bar{W} = b' \bar{y} = 44.45$$

$$S_w^2 = b' S b = 605.67$$

$$\text{Covariance: } S_{zw} = a' S b$$

$$\frac{1}{(n-1)} \sum_{i=1}^n (z_i - \bar{z})(w_i - \bar{w})$$

$$\text{Correlation: } \frac{S_{zw}}{\sqrt{S_w^2 S_z^2}} = 0.0358$$

$$\frac{(\bar{z} - \bar{z})}{\sqrt{\frac{1}{n-1} \sum_{i=1}^n (z_i - \bar{z})^2}} = \frac{0}{\sqrt{\frac{1}{n-1} \sum_{i=1}^n (z_i - \bar{z})^2}} = 0$$

$$x^2 \approx \frac{1}{52}$$

let, $a = a_1, b = a_2$

$$\text{Define: } A = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1p} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2p} \end{pmatrix}_{2 \times p}$$

$$\text{and } z = \begin{pmatrix} a_1 y \\ a_2 y \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} y = Ay.$$

$$z = Ay.$$

$$z_i = A y_i, i = 1, 2, \dots, n$$

$$\bar{z} = \begin{pmatrix} \bar{z}_1 \\ \bar{z}_2 \end{pmatrix} = \begin{pmatrix} a_1 \bar{y} \\ a_2 \bar{y} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \bar{y}$$

$$\bar{z} = A \bar{y}$$

Sample Covariance matrix for \bar{z}

$$S_{\bar{z}} = \begin{pmatrix} S_{\bar{z}_1}^2 & S_{\bar{z}_1} S_{\bar{z}_2} \\ S_{\bar{z}_2} S_{\bar{z}_1} & S_{\bar{z}_2}^2 \end{pmatrix}$$

$$S_{\bar{z}} = \begin{pmatrix} a_1' S_{yy} & a_1' S_{yz} \\ a_2' S_{yy} & a_2' S_{yz} \end{pmatrix}$$

$$S_{\bar{z}} = \begin{pmatrix} a_1' \\ a_2' \end{pmatrix} S (a_1 a_2)$$

$$\boxed{S_{\bar{z}} = ASA'}$$

let, K linear transformations/combinations are expressed as -

$$z_1 = a_{11} y_1 + a_{12} y_2 + a_{13} y_3 + \dots + a_{1p} y_p = a_1' y$$

$$z_2 = a_{21} y_1 + a_{22} y_2 + \dots + a_{2p} y_p = a_2' y$$

$$\vdots$$

$$z_K = a_{K1} y_1 + a_{K2} y_2 + \dots + a_{Kp} y_p = a_K' y$$

$$\boxed{A Z A' = S^2}$$

OR in Matrix:

$$\begin{aligned}
 z &= A y \\
 \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_K \end{pmatrix}_{K \times 1} &= \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1P} \\ a_{21} & a_{22} & \cdots & a_{2P} \\ \vdots & & & \\ a_{K1} & a_{K2} & \cdots & a_{KP} \end{pmatrix}_{K \times P} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_P \end{pmatrix}_{P \times 1} \\
 &= \begin{pmatrix} a'_1 \\ a'_2 \\ \vdots \\ a'_K \end{pmatrix} y = a' y
 \end{aligned}$$

$\boxed{z = Ay}$

If $z_i = A y_i$, $i = 1, 2, \dots, n$.

The sample mean vector \bar{z} is

$$\bar{z} = \begin{pmatrix} a'_1 \bar{y} \\ a'_2 \bar{y} \\ \vdots \\ a'_K \bar{y} \end{pmatrix} = \begin{pmatrix} a'_1 \\ a'_2 \\ \vdots \\ a'_K \end{pmatrix} \bar{y}$$

$\boxed{\bar{z} = A \bar{y}}$

Sample Covariance matrix

$$S_Z = \begin{pmatrix} a'_1 S_{yy} & a'_1 S_{y2} & \cdots & a'_1 S_{yK} \\ a'_2 S_{yy} & a'_2 S_{y2} & \cdots & a'_2 S_{yK} \\ \vdots & \vdots & \ddots & \vdots \\ a'_K S_{yy} & a'_K S_{y2} & \cdots & a'_K S_{yK} \end{pmatrix}_{K \times K}$$

$$S_Z = \begin{pmatrix} a'_1 \\ a'_2 \\ \vdots \\ a'_K \end{pmatrix} S (a'_1 \ a'_2 \ \cdots \ a'_K)$$

$\boxed{S_Z = ASA'}$

NOTE:

$$\text{① } \text{tr}(ASA') = \sum_{i=1}^k a_i' S a_i$$

② A more general linear transformation

$$z_i = A y_i + b \text{ and } S_z = ASA'$$

$$\boxed{\bar{z} = A\bar{y} + b}$$

$$\text{③ } z_1 = y_1 + y_2 + y_3 + y_4 + y_5$$

$$z_2 = 2y_1 - 3y_2 + y_3 - 2y_4 - y_5$$

$$z_3 = -y_1 - 2y_2 + y_3 - 2y_4 + 3y_5$$

These linear combinations in matrix form can be written as.

$$\bar{z} = \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 2 & -3 & 1 & -2 & -1 \\ -1 & -2 & 1 & -2 & 3 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{pmatrix}$$

$$\bar{y} = \begin{pmatrix} 36.09 \\ 25.55 \\ 34.09 \\ 27.27 \\ 30.73 \end{pmatrix} \quad (\text{Previous ex})$$

$$\bar{z} = A\bar{y}$$

$$\bar{z} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 2 & -3 & 1 & -2 & -1 \\ -1 & -2 & 1 & -2 & 3 \end{pmatrix} \begin{pmatrix} 36.09 \\ 25.55 \\ 34.09 \\ 27.27 \\ 30.73 \end{pmatrix} = \begin{pmatrix} 153.43 \\ -55.65 \\ -15.45 \end{pmatrix}$$

NOTE:

④ Generated Sample Variance = $|S|$.

⑤ Total Sample Variance = $\text{tr}(S) = S_{11} + S_{22} + \dots + S_{pp}$

$$S_z = A S A'$$

$$R_z = D_z^{-1} S_z D_z^{-1}$$

$$\text{where } D_z = \begin{pmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{pmatrix}$$

1Q) y₁: available soil Calcium.

Y_2 : exchangeable soil Calcium.

Y₃: turnip green Calcium.

<u>Loc. no</u>	<u>y_1</u>	<u>y_2</u>	<u>y_3</u>
1	35	3.5	2.8
2	35	4.9	2.7
3	40	3.0	4.38
.	.	.	.
.	.	.	.
10	30	1.6	3.2

Define: $z = 3y_1 - y_2 + 2y_3$

Find \bar{z} and S_z^2 in two ways.

(a) Direct.

(b) Use $\bar{z} = a' \bar{y}$.

and $S_2^2 = a' Sa$.

2) Define $\omega = -2y_1 + 3y_2 + 4y_3$

Find g_{zw} in two ways.

} Data given in one of the recent examples.

$$\begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 2 & 1 \\ 1 & 3 & 1 & 2 & 3 \\ 1 & 2 & 1 & 3 & 2 \end{pmatrix} : \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = 5$$

(a) Direct.

(b) Matrix.

$$39) z_1 = y_1 + y_2 + y_3$$

$$z_2 = 2y_1 - 3y_2 + 2y_3$$

$$z_3 = -y_1 - 2y_2 - 3y_3$$

(a) Find \bar{z} and S_z .

(b) Find

$$(b) \text{ Find } R_Z \cdot \begin{pmatrix} 10.38 \\ 22.35 \\ 10.28 \\ 55.45 \\ 88.08 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 5 & 1 & 8 & 1 \\ 1 & 8 & 5 & 1 & 8 & 1 \end{pmatrix} = 5$$

Regression Analysis

$$\text{Marks}(Y) = \alpha \text{Hours}(x_1) + \beta \text{Lectures}(x_2)$$

D.V, Response Var

Independent Var

Input/Predictor Var.

$$\frac{\partial L}{\partial \beta} = 0$$

Linear regression:

$$(x_i, y_i), i=1, \dots, n$$

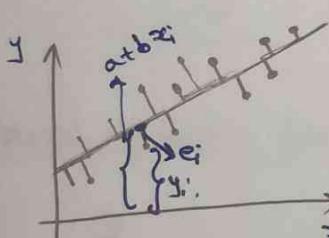
x = I.V, Predictor Var, Input Var.

y = D.V, Response Var.

x_i	0	1	2	3	4	5	6
y_i	25	20	30	40	45	50	50

$$x\hat{y} + \hat{y} = x\hat{y} + \hat{y} = \hat{y}$$

$$OFB = 322$$



Residuals: $e_i = |y_i - (a + bx_i)|$

$$y = a + bx \quad \text{where } b = \frac{\sum e_i^2}{\sum (x_i - \bar{x})^2} = \frac{\sum [y_i - a - bx_i]^2}{\sum (x_i - \bar{x})^2}$$

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2 = \sum_{i=1}^n x_i^2 - \frac{(\sum x_i)^2}{n}$$

$$S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) = \sum_{i=1}^n x_i y_i - \frac{\sum x_i \sum y_i}{n}$$

$$S_{yy} = \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n y_i^2 - \frac{(\sum y_i)^2}{n}$$

Note: In above notations, there's no ' $n-1$ '.

10 The least square line (regression line).

$$\hat{y} = \hat{\alpha} + \hat{\beta} x \quad (\text{Eqn of regression line } y \text{ vs } x)$$

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}}$$

$$\hat{x} = \bar{y} - \hat{\beta} \bar{x}$$

Residual Sum of squares / Error Sum of Squares:

$$SSE = \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta} x_i)^2$$

$$SSE = S_{yy} - \frac{S_{xy}^2}{S_{xx}}$$

$$\text{Ex1: } \hat{y} = \hat{\alpha} + \hat{\beta} x = 22 + 6x$$

$$SSE = 270.$$

Ex2: $x = \text{width}, y = \text{height}$

$$x = 50, \bar{x} = 88.36, \bar{y} = 305.58$$

$$S_{xx} = 7239.22, S_{xy} = 17840.1, S_{yy} = 66976.2$$

(a) Find the least square line for predicting height from width.

(b) " " " " width from height.

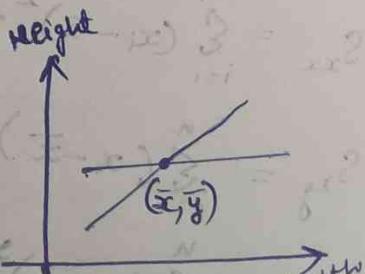
(c) Make a scatter plot & show both lines.

$$(2) \hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{17840.1}{7239.22} = 2.464$$

$$\hat{x} = \bar{y} - \hat{\beta} \bar{x} = 305.58 - 2.464 \times 88.36$$

$$\hat{\alpha} = 88.26$$

$$\hat{y} = \hat{\alpha} + \hat{\beta} x = 88.26 + 2.464 x$$

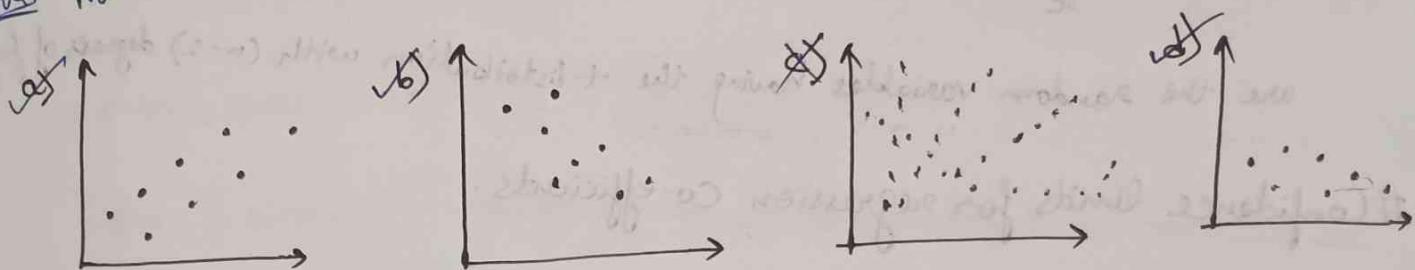


Method of Least Square

The procedure of finding the equation of regression line that best fits the set of paired data is called "method of least square".

Q Can we always get best fitting line for a set of paired data?

Ans No.



Standard error of the estimate (S_e)

$$S_e^2 = \frac{S_{yy} - \frac{S_{xy}^2}{S_{xx}}}{(n-2)} = \frac{SSE}{n-2}$$

Estimate of σ^2

$$E(\sigma^2) = S_e^2$$

Normal equation for Least Squares estimates

$$\sum_{i=1}^n (y_i - a - b x_i)^2$$

Differentiating partially w.r.t 'a' & 'b' and equating to zero, we get

w.r.t a

$$2 \sum_{i=1}^n (y_i - a - b x_i)(-1) = 0$$

$$\sum_{i=1}^n y_i = a n + b \sum_{i=1}^n x_i$$

w.r.t b

$$2 \sum_{i=1}^n (y_i - a - b x_i)(-x_i) = 0$$

$$\sum_{i=1}^n x_i y_i = a \sum_{i=1}^n x_i + b \sum_{i=1}^n x_i^2$$

$$y_i = a + b x_i$$

$$\begin{matrix} a \\ b \end{matrix} \Rightarrow \begin{matrix} \hat{a} \\ \hat{b} \end{matrix}$$

$$\Rightarrow \hat{y} = \hat{a} + \hat{b} x$$

t-statistics

$$t = \frac{(\hat{\alpha} - \alpha)}{S_e}$$

$$\sqrt{\frac{n S_{xx}}{S_{xx} + n(\bar{x})^2}}$$

and

$$t = \frac{(\hat{\beta} - \beta)}{S_e} \sqrt{S_{xx}}$$

are the random variables having the t-distribution with $(n-2)$ degrees of freedom.

Confidence limits for regression co-efficients:

$$\alpha = \hat{\alpha} \pm t_{\alpha/2} \cdot S_e \sqrt{\frac{1}{n} + \frac{(\bar{x})^2}{S_{xx}}}$$

$$-t_{\alpha/2} < t < t_{\alpha/2}$$

and

$$\beta = \hat{\beta} \pm t_{\alpha/2} \cdot S_e \frac{1}{\sqrt{S_{xx}}}$$

$$\text{Ex: } n=10, S_{xx}=132000, S_{xy}=505.4, \bar{x}=200, S_{yy}=2.13745, \bar{y}=0.835$$

Construct a 95% confidence interval for the regression coefficient ' α '.

$$\text{Sol: } SSE = S_{yy} - \frac{S_{xy}^2}{S_{xx}}$$

$$= 2.13745 - \frac{(505.4)^2}{132000}$$

$$= 2.13745 - 1.93506 = \underline{\underline{0.20239}}$$

for 95% Confidence Interval the level of significance is $\alpha=0.05$

$$t_{\alpha/2, 8} = t_{0.025, 8} = 2.306$$

$$S_e^2 = \frac{SSE}{n-2} = \frac{0.20239}{8} = 0.0252$$

$$S_e = \underline{\underline{0.1587}}$$

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{505.4}{132000} = 0.0038$$

$$\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x} = 0.835 - 0.0038 \times 200 \\ = 0.835 - 0.765 \\ = \underline{0.07}$$

$$k = \hat{\alpha} \pm t_{\alpha/2} S_{\alpha} \sqrt{\frac{1}{n} + \frac{(\bar{x})^2}{S_{xx}}}$$

$$= 0.07 \pm 0.05 \times 0.1587 \sqrt{\frac{1}{10} + \frac{(200)^2}{132000}}$$

$$= 0.07 \pm 0.0079 \sqrt{0.1 + 0.30}$$

$$= 0.07 \pm 0.0079 \times 0.634$$

$$= 0.07 \pm 0.05$$

$$\hat{\beta} =$$

Q) Test the null hypothesis $\beta = 0$ against the alternate hypothesis $\beta \neq 0$ at the 0.05 level of significance.

Given, $\hat{\beta} = 0.003829$
 $s_e = 0.1531$

Sol

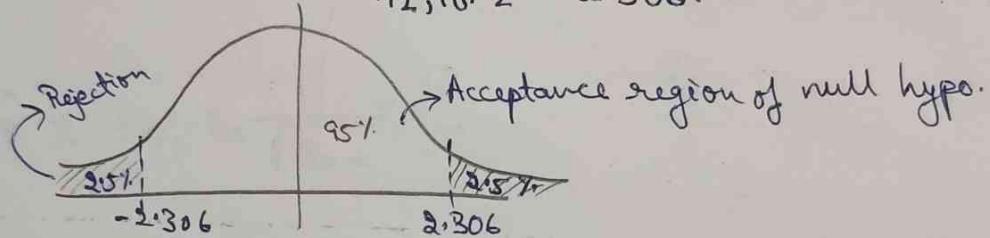
① Null hypothesis: $\beta = 0$.

Alternate hypothesis: $\beta \neq 0$.

② Level of Significance: $\alpha = 0.05$.

③ Criterion: Reject the null hypothesis if

$$|t| > t_{\alpha/2, 10, 2} = 2.306.$$



④ Calculation:

$$\begin{aligned} t &= \frac{(\hat{\beta} - \beta)}{s_e} \sqrt{s_{xx}} \\ &= \frac{(0.03829 - 0)}{0.1531} \sqrt{132000} = 8.744 \end{aligned}$$

$$\therefore 8.744 > t_{\alpha/2, 8} = 2.306$$

⑤ Decision: Null hypothesis must be rejected.

Given (x_i, y_i) to follow exp. growth or decay \Rightarrow $y_i = \alpha x_i^{\beta}$

Transformation,

$$y_i \rightarrow \log y_i, \sqrt{y_i}, \frac{1}{y_i}$$

$$x_i \rightarrow \log x_i$$

$$\text{SSE.P} = \frac{\sum e^2}{n} = \bar{e}^2$$

$$\text{SSE.P} = \frac{\sum (y_i - \hat{y}_i)^2}{n} = \bar{e}^2 = \bar{v}^2$$

1) Exponential type

$$y = \alpha \beta^x$$

$$\log y = \log \alpha + x \log \beta \quad \text{linear in } x \text{ & } \log y$$

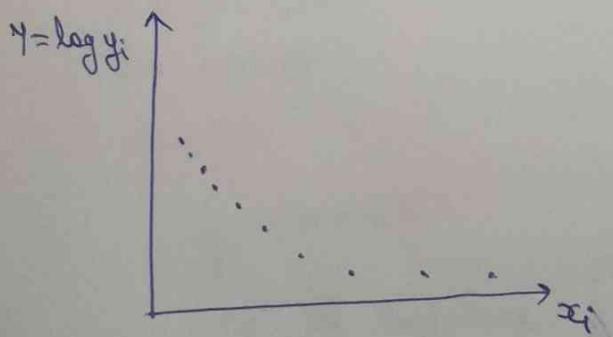
Ex: y = battery capacity (amp-hr)
 x = rate of discharge (amp)

Rate of discharge (A) x	Capacity (Ah) y	$y = \log y$
2	164.7	2.21
3	156.1	2.19
6	142.5	2.15
10	133.8	2.12
15	116.6	2.05
20	107.1	2.02

$$\sum y = 12.76$$

OR

$$\sum y = \log y = 29.42$$



b) Fit an exponential curve by applying the method of Least Square to the data points $(x_i, \log y_i)$.

$$\bar{x} = \frac{56}{6} = 9.3333$$

$$\bar{y} = \bar{\log y} = \frac{29.42552}{6} = 4.9043$$

$$S_{xy} = S_x \log y = 268.6762 - 29.42552 \left(\frac{56}{6} \right)$$

$$= -5.961987.$$

$$S_{xx} = 774 - \frac{(56)^2}{6} = 251.3333$$

Then the estimated slope

$$\frac{S_{xy}}{S_{xx}} = -0.02372$$

and the estimated intercept is

$$4.9043 + 9.3333(-0.02372) = 5.1257$$

$$Y = \text{Intercept} + \text{Slope} \cdot x$$

$$\ln y = 5.1257 - 0.02372 x$$

$$\Rightarrow \text{predicted } y = e^{5.1257 - 0.02372 x}$$

$$\hat{y} = e^{5.1257} \cdot e^{-0.02372 x}$$

$$\hat{y} = 16.9 \cdot e^{-0.02372 x}$$

Q) Solve normal eqⁿ and find the values for the least square to estimate.

$$\begin{aligned} 8135 &= 10a + 2000b \\ 217504 &= 2000a + 53200b \end{aligned} \quad \left. \begin{array}{l} \hat{\alpha} = ? \\ \hat{\beta} = ? \end{array} \right\}$$

$$y_i = a + bx_i$$

$$\sum_{i=1}^n y_i = a n + b \sum_{i=1}^n x_i \quad \text{--- } ①$$

$$\sum_{i=1}^n x_i y_i = a \sum_{i=1}^n x_i + b \sum_{i=1}^n x_i^2.$$

$$\hat{\alpha} = 0.069$$

$$\hat{\beta} = 0.08383$$

x	0	1	2	3	4	5	6
y _i	1/25	1/20	1/30	1/40	1/60	1/80	1/50
1/y _i	25	20	30	40	45	50	60
x _i y _i	0	20	60	80	180	200	300
x _i ²	0	1	4	9	16	25	36

$$24/8 = 3.$$

$$320/8 = 40.$$

$$1140.$$

$$102.$$

$$\hat{x} = \bar{y} - \hat{\beta} \bar{x}$$

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}}$$

Eqⁿ of regression line y on x.

$$\boxed{\hat{y} = \hat{\alpha} + \hat{\beta}x}$$

$$S_{xx} = \sum_{i=1}^n x_i^2 - n(\bar{x})^2 = 102 - 8(9) \Rightarrow 102 - 72 = 30.$$

$$S_{xy} = \sum_{i=1}^n x_i y_i - n(\bar{x})(\bar{y}) = 1140 - 960 \Rightarrow 180.$$

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{180}{30} \Rightarrow 6.$$

$$\hat{x} = \bar{y} - \hat{\beta} \bar{x}$$

$$\hat{x} = 40 - 6(3)$$

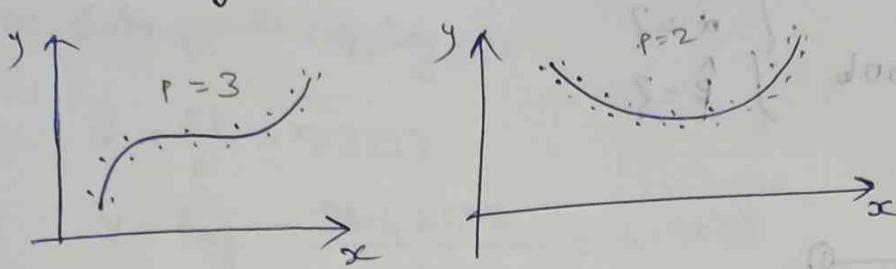
$$\hat{x} = 40 - 18$$

$$\hat{x} = 22$$

$$\frac{1}{y} = a + bx$$

$$\text{eqn of reg.line: } \boxed{\frac{1}{y} = 22 + 6x.}$$

Polynomial Regression:



The general equation of path degree polynomial.

$$y = b_0 + b_1 x + b_2 x^2 + \dots + b_p x^p \quad \rightarrow$$

Given a set of data consisting of n -points (x_i, y_i) , we estimate the co-efficients $b_0, b_1, b_2, \dots, b_p$ of the p^{th} degree polynomial by minimizing

$$\sum_{i=1}^n [y_i - (b_0 + b_1 x_i + b_2 x_i^2 + \dots + b_p x_i^p)]^2$$

Taking the partial derivatives w.r.t $b_0, b_1, b_2, \dots, b_p$ equating these partial derivatives to zero.

from 0,

$$\sum_{i=1}^n y = n b_0 + b_1 \sum x_i + b_2 \sum x_i^2 + \dots + b_p \sum x_i^p$$

$$\sum x y = b_0 \sum x_i + b_1 \sum x_i^2 + \dots + b_p \sum x_i^{p+1}$$

$$\sum x^p y = b_0 \sum x_i^p + b_1 \sum x_i^{p+1} + \dots + b_p \sum x_i^{2p}$$

NOTE:

$$\sum = \sum_{i=1}^n, \quad \sum x y = \sum_{i=1}^n x_i y_i, \quad \sum x^p = \sum_{i=1}^n x_i^p$$

$$\sum x^p y = \sum_{i=1}^n x_i^p y_i$$

The eqⁿ of best fitting curve will be given by

$$y = \hat{B}_0 + \hat{B}_1 x + \hat{B}_2 x^2 + \dots + \hat{B}_p x^p$$

where $\hat{B}_0 = b_0$ (Best estimated)
 $\hat{B}_1 = b_1$
 \vdots
 $\hat{B}_p = b_p$

Ex: The following are data on the drying time of a certain varnish and the amount of an additive that is intended to reduce the drying time.

Amount of varnish additive x (grams)	Drying time y (hours)
0	12
1	10.5
2	10
3	8
4	7
5	7.5
6	8.5
7	9
8	-

(a) Find a second degree polynomial.

(b) Predict the drying time of varnish when 6.5 g of the additive is added.

$y = b_0 + b_1 x + b_2 x^2$ [General 2nd-degree polynomial].
 The Normal eq's are:

$$\sum y = n b_0 + b_1 \sum x + b_2 \sum x^2$$

$$\sum xy = b_0 \sum x + b_1 \sum x^2 + b_2 \sum x^3$$

$$\sum x^2 y = b_0 \sum x^2 + b_1 \sum x^3 + b_2 \sum x^4$$

(concatenating columns to above table)

x^2	x^3	x^4	xy	x^2y
0	0	0	0	0
1	1	1	10.5	10.5
4	8	16	20	40
9	27	81	24	72
16	64	256	28	112
25	125	625	40	200
36	216	1296	45	270
49	343	2401	51.5	416.5
64	512	4096	72	576

Now, the normal eqn's will be

$$80.5 = 9b_0 + 36b_1 + 204b_2$$

$$299 = 36b_0 + 204b_1 + 1296b_2$$

$$1697 = 204b_0 + 1296b_1 + 8772b_2$$

$$D = \begin{bmatrix} 9 & 36 & 204 \\ 36 & 204 & 1296 \\ 204 & 1296 & 8772 \end{bmatrix}_{3 \times 3}$$

$$D_1 = \begin{bmatrix} 80.5 & 36 & 204 \\ 299 & 204 & 1296 \\ 1697 & 1296 & 8772 \end{bmatrix} \Rightarrow b_0 = \frac{|D_1|}{|D|}$$

$$D_2 = \begin{bmatrix} 9 & 80.5 & 204 \\ 36 & 299 & 1296 \\ 204 & 1697 & 8772 \end{bmatrix} \Rightarrow b_1 = \frac{|D_2|}{|D|}$$

$$D_3 = \begin{bmatrix} 9 & 36 & 80.5 \\ 36 & 204 & 299 \\ 204 & 1296 & 1697 \end{bmatrix} \Rightarrow b_2 = \frac{|D_3|}{|D|}$$

$$B = \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix}_{3 \times 1}$$

$$C = \begin{bmatrix} 80.5 \\ 299 \\ 1697 \end{bmatrix}_{3 \times 1}$$

$$DB = C$$

$$\Rightarrow B = D^{-1}C$$

Augmented Matrix:

$$\left[\begin{array}{ccc|c} 9 & 36 & 204 & 80.5 \\ 36 & 204 & 1296 & 299 \\ 204 & 1296 & 8772 & 1697 \end{array} \right]$$

out of memory to next
step of successive iteration
if continued

$[x_0^2 + x_1^2 + \dots + x_n^2] \rightarrow$

Alternate:

$$R_2 \rightarrow 4R_1 - R_2, R_3 \rightarrow R_3 - \frac{204}{9} R_1$$

$$\sim \left[\begin{array}{ccc|c} 9 & 36 & 204 & 80.5 \\ 0 & -60 & -480 & 23 \\ 0 & 480 & 4148 & -127.67 \end{array} \right]$$

$$R_3 \rightarrow R_3 + 8R_2, R_2 \rightarrow -\frac{1}{60}R_2$$

$$\sim \left[\begin{array}{ccc|c} 9 & 36 & 204 & 80.5 \\ 0 & 1 & 8 & -23/60 \\ 0 & 0 & 308 & 56.33 \end{array} \right]$$

$$[(x_0^2 + x_1^2 + \dots + x_n^2) - b] \rightarrow$$

$$308b_2 = 56.33$$

$$\Rightarrow b_2 = 0.1828$$

$$b_1 + 8b_2 = -23/60$$

$$\Rightarrow b_1 = -1.845$$

$$9b_0 + 36b_1 + 204b_2 = 80.5$$

$$\Rightarrow b_0 = 12.1848$$

\therefore The eqn of the least square polynomial is:

$$\hat{y} = 12.1848 - 1.845x + 0.183x^2$$

$$(b) \hat{y} (x=6.5) = \underline{7.9 \text{ hrs.}}$$

Multiple Regression (Linear):

	y	x_1	x_2	x_n
1	y_1	x_{11}	x_{12}	x_{1n}
2	y_2	x_{21}	x_{22}	x_{2n}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
n	y_n	x_{n1}	x_{n2}	x_{nn}

$n \times (n+1)$ tuples.
 $i = 1, 2, 3, \dots, n.$

$$y = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n$$

Sum of squares of the vertical distances from the observations y_i .

$$\sum_{i=1}^n [y_i - (b_0 + b_1 x_1 + \dots + b_n x_n)]^2$$

Let $n=2$,

$$\sum_{i=1}^n [y_i - (b_0 + b_1 x_1 + b_2 x_2)]^2$$

$$y = b_0 + b_1 x_1 + b_2 x_2.$$

$$\sum y = nb_0 + b_1 \sum x_1 + b_2 \sum x_2.$$

$$\sum x_1 y = b_0 \sum x_1 + b_1 \sum x_1^2 + b_2 \sum x_1 x_2.$$

$$\sum x_2 y = b_0 \sum x_2 + b_1 \sum x_1 x_2 + b_2 \sum x_2^2.$$

Normal equations

$$\sum x_1 = \sum_{i=1}^n x_i,$$

$$\sum x_1 x_2 = \sum_{i=1}^n x_{1i} x_{2i}$$

$$\sum x_1 y = \sum_{i=1}^n x_{1i} y_i$$

The eqⁿ of regression curve is

$$\hat{y} = \hat{b}_0 + \hat{b}_1 x_1 + \hat{b}_2 x_2$$

$$\hat{b}_0 = b_0, \quad \hat{b}_1 = b_1, \quad \hat{b}_2 = b_2$$

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2$$

Ex: The following are data on the number of twists required to break a certain kind of forged alloy bar and the % of two alloying elements present in the metal.

<u>no. of twists</u>	<u>% of element A</u>	<u>% of element B</u>
41	1	5
49	2	5
69	3	5
65	4	5
40	2	10
50	3	10
58	4	10
57	2	10
31	1	15
36	2	15
44	3	15
57	4	15
19	1	20
31	2	20
33	3	20
43	4	20

fit a least squares regression plane and use its equation to estimate the number of twists required to break one of bars when $x_1=25$ & $x_2=12$.

Solⁿ: Using Computer software:

THE REGRESSION EQUATION IS:

$$Y = 46.4 + 7.78X_1 - 1.65X_2 \quad (1)$$

PREDICTOR	COEFF	STD.DEV	T-RATIO	P
CONSTANT	46.438	3.517	13.20	0.000
X_1	7.775	0.9485	8.20	0.000
X_2	-1.655	0.1897	-8.72	0.000

$S = 4.242$	(6)
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$R-SQ = 91.7\%$	(5)
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ANALYSIS OF VARIANCE

SOURCE	DF	SS	MS
REGRESSION	2	25.785	12.893
ERROR	13	233.9	18.10
TOTAL	15	2812.4	

- ① The least squares regression plane $\hat{Y} = 46.4 + 7.78X_1 - 1.65X_2$
 This eqⁿ estimates that the average number of twists required to break a bar increases by 7.78 if the % of element A is increased by 1% and X_2 remains fixed.

- ② The least square estimates and their corresponding estimated error are:

$$\hat{\beta}_0 = 46.438 \text{ with estimated standard error } 3.517.$$

$$\hat{\beta}_1 = 7.775 \text{ - - - - - - - - - } 0.9485.$$

$$\hat{\beta}_2 = -1.655 \text{ - - - - - - - - - } 0.1897.$$

- ③ The t-ratio 13.2, 8.2, -8.72 are all highly significant so all the terms are needed in the model.

$$\textcircled{4} \quad \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \sum_{i=1}^n (\hat{y}_i - \bar{y})^2$$

total sum of squares error sum of squares regression sum of squares

$$2812.4 = 233.9 + 2578.5$$

$$\textcircled{5} \quad R^2 = \frac{\text{regression SS}}{\text{total SS}} = \frac{2578.5}{2812.4} = 0.917$$

The estimate of σ^2 is

$$s_e^2 = \frac{233.9}{13} = 18$$

$$\text{or } s_e = 4.242$$

The $\textcircled{7}$ p-values confirm the significance of the t-ratios and thus the fact that all the terms are required in the model.

Alternate method:

Normal equations,

$$723 = 16b_0 + 40b_1 + 200b_2$$

$$1963 = 40b_0 + 120b_1 + 500b_2$$

$$8210 = 200b_0 + 500b_1 + 3000b_2$$

$$\Rightarrow \hat{b}_0 = 46.4, \hat{b}_1 = 7.78, \hat{b}_2 = -1.65$$

$$\therefore \hat{y} = 46.4 + 7.78x_1 - 1.65x_2$$

Multiple Linear Regression (Matrix Notation):

$$X = \begin{bmatrix} 1 & x_{11} & x_{21} \\ 1 & x_{12} & x_{22} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \end{bmatrix}_{n \times 3}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1} \quad \text{and } b = \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix}_{3 \times 1}$$

$\hat{\beta}$, the least squares estimates of the multiple regression coefficient.

$$\hat{\beta} = (X'X)^{-1} X'y$$

where X' is the transpose of matrix X .

$(X'X)^{-1}$ is the inverse of matrix $X'X$.

$$X'X = \begin{bmatrix} n & \sum x_1 & \sum x_2 \\ \sum x_1 & \sum x_1^2 & \sum x_1 x_2 \\ \sum x_2 & \sum x_2 x_1 & \sum x_2^2 \end{bmatrix}_{3 \times 3}$$

$$X'X b = \begin{bmatrix} b_0 n + b_1 \sum x_1 + b_2 \sum x_2 \\ b_0 \sum x_1 + b_1 \sum x_1^2 + b_2 \sum x_1 x_2 \\ b_0 \sum x_2 + b_1 \sum x_2 x_1 + b_2 \sum x_2^2 \end{bmatrix}_{3 \times 1}$$

$$X'y = \begin{bmatrix} \sum y \\ \sum x_1 y \\ \sum x_2 y \end{bmatrix}_{3 \times 1}$$

$$\Rightarrow X'X b = X'y$$

$$\underbrace{(X'X)^{-1}}_I (X'X) b = (X'X)^{-1} X'y$$

$$\Rightarrow b = (X'X)^{-1} X'y$$

$$\text{Ex: } \sum x_1 = 40, \sum x_2 = 200, \sum x_1^2 = 120,$$

$$\sum x_1 x_2 = 500, \sum x_2^2 = 3000, n = 16$$

$$\sum y = 723, \sum x_1 y = 1963 \text{ & } \sum x_2 y = 8210$$

Sol:

Here,

$$X'X = \begin{bmatrix} 16 & 40 & 200 \\ 40 & 120 & 500 \\ 200 & 500 & 3000 \end{bmatrix}$$

$$X'X = \begin{bmatrix} n & \sum x_1 & \sum x_2 & \sum x_3 \\ \sum x_1 & \sum x_1^2 & \sum x_1 x_2 & \sum x_1 x_3 \\ \sum x_2 & \sum x_2 x_1 & \sum x_2^2 & \sum x_2 x_3 \\ \sum x_3 & \sum x_3 x_1 & \sum x_3 x_2 & \sum x_3^2 \end{bmatrix}$$

$$\begin{bmatrix} 110000 & -20000 & -4000 \\ -20000 & 8000 & 0 \\ -4000 & 0 & 320 \end{bmatrix}$$

where $|X'X| = 1,60,000$

$$\beta = (x' x)^{-1} x' y = \begin{bmatrix} 46.4375 \\ 7.7750 \\ -1.6550 \end{bmatrix}$$

$$\begin{array}{ccccc} E & L & 1 & 0 & x \\ \hline 1 & 8 & 4 & P & 8 \end{array}$$

Residual sum of squares:

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} \\ 1 & x_{21} & x_{22} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \end{bmatrix}_{3 \times 3} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix}_{3 \times 1}$$

$$\text{or } \boxed{\hat{y} = x \hat{\beta}}_{3 \times 1}$$

then residual sum of squares

$$\sum_{i=1}^n (y_i - \hat{y}_i)^2 = (y - \hat{y})' (y - \hat{y})$$

$$= (y - x \hat{\beta})'_{1 \times 3} (y - x \hat{\beta})_{3 \times 1}$$

the estimate s_e^2 of σ^2 can be expressed as -

$$\boxed{s_e^2 = \frac{1}{n-3} (y - x \hat{\beta})' (y - x \hat{\beta})}$$

$$\# \quad x = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & x_{23} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} & \dots & x_{nk} \end{bmatrix} \quad \beta = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_k \end{bmatrix}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \quad \boxed{\hat{\beta} = (x' x)^{-1} x' y}$$

$$\boxed{s_e^2 = \frac{1}{(n-k-1)} (y - x \hat{\beta})' (y - x \hat{\beta})}$$

df = n - no of β 's = n - (k+1)