

## Unit-7

Analysis of Variance :- The analysis of variance is a powerful statistical tool for tests of significance. The test of significance based on  $t$ -dist<sup>n</sup> is an adequate procedure only for testing the significance of the difference bet<sup>n</sup> two sample means. In a situation when we have three or more samples to consider at a time an alternative procedure is needed for testing the hypothesis that all the samples are drawn from the same pop<sup>n</sup>. i.e. they have the same mean.

eg :- Five fertilizers are applied to four plots each of wheat and yields of wheat on each of the plot is given. Now we are interested in finding out whether the effect of these fertilizers on the yield is significantly different or in other words, whether the samples have come from the same normal pop<sup>n</sup>.

The answer to this problem is provided by the technique of analysis of variance. Thus basic purpose of the analysis of variance is to test the homogeneity of several means.

The term "Analysis of Variance" was introduced by prof. R. A. Fisher in 1930's to deal with problem in the analysis of agronomical data.

Cochran Theorem - used to justify results relating to the prob. dist<sup>n</sup> of statistics that are used in ANOVA.

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Variation is inherent in nature. The total variation in any set of numerical data is due to a no. of causes which may be classified as

- Assignable causes, and
- Chance causes.

The variation due to assignable causes can be detected and measured whereas the variation due to chance causes is beyond the control of human hand and cannot be traced separately.

Definition :-

According to Prof. R.A. Fisher, Analysis of Variance (ANOVA) is the "separation of variance <sup>ascribable</sup> to one group of causes from the variance ascribable to other group.

to credit  
or assign  
to a cause

The ANOVA consists in the estimation of the amount of variation due to each of the indept. factors (causes) separately and then comparing this estimates due to assignable factors (causes) with the estimates due to chance factor (causes).

Assumption :- For the validity of the F-test in ANOVA, the following assumptions are made :-

- The obser<sup>n</sup>s are indept.
- Parent pop<sup>n</sup> from which observation are taken is normal and
- Various treatment and environmental effects are additive in nature.

Cochran's Theorem - Let  $X_1, X_2, \dots, X_n$  denote a s.s. from normal pop<sup>n</sup>  $N(0, \sigma^2)$ . Let the sum of the squares of these values are

$$\sum_{i=1}^n X_i^2 = Q_1 + Q_2 + \dots + Q_k$$

Where  $Q_j$  is a quadratic form of  $X_1, X_2, \dots, X_n$  with rank (d.f)  $r_j$ ;  $j=1, 2, \dots, k$ : Then the s.v.  $Q_1, Q_2, \dots, Q_k$  are mutually indept. and  $Q_j/\sigma^2$  is a  $\chi^2$  variate with  $r_j$  degrees of freedom.   
 if  $\sum_{j=1}^k r_j = n$ .

## ANOVA for One-way Classification — Let

(Add one obser<sup>n</sup> per cell) as

Suppose that  $N$  obser<sup>n</sup>  $x_{ij}$  ( $i=1, 2, \dots, k$ ;  $j=1, 2, \dots, n_i$ ) of a random variable  $X$  are grouped on some basis, into  $k$  classes of sizes  $n_1, n_2, \dots, n_k$  respectively. ( $N = \sum_{i=1}^k n_i$ ) as exhibited below

|          |          |     |            | Means       | Total    |
|----------|----------|-----|------------|-------------|----------|
| $x_{11}$ | $x_{12}$ | ... | $x_{1n_1}$ | $\bar{x}_1$ | $T_1$    |
| $x_{21}$ | $x_{22}$ | ... | $x_{2n_2}$ | $\bar{x}_2$ | $T_2$    |
| $\vdots$ | $\vdots$ |     |            | $\vdots$    | $\vdots$ |
| $x_{k1}$ | $x_{k2}$ | ... | $x_{kn_k}$ | $\bar{x}_k$ | $T_k$    |
|          |          |     |            |             | $G$      |

The total variation in the obser<sup>n</sup>  $x_{ij}$  can be split into the following two components:

- The variation bet<sup>n</sup> the classes or the variation due to different bases of classification, commonly known as treatments.
- The variations within the classes i.e. the inherent variation of the s.v. within the obser<sup>n</sup> of a class.

The first type of variation is due to assignable causes which can be detected and controlled by human endeavour and the second type of variation is due to chance causes which are beyond the control of human hand.

$$N = \sum_{i=1}^K n_i$$

- (i) Effect of the rations (treatment)  $t_i$   $i=1, 2, 3, \dots, k$
- (ii) error  $\epsilon$  produced by numerous causes.

Mathematical Model :- Let the line. us consider the linear model will be

$$x_{ij} = \mu_i + \varepsilon_{ij}$$

$$= u + (\mu_i - u) + \varepsilon_{ij}$$

$$= u + \alpha_i + \varepsilon_{ij}, \text{ where } (i = 1, 2, \dots, k, j = 1, 2, \dots, n_i)$$

(i)  $x_{ij}$  is the yield from the  $j$ th cow, ( $j=1, 2, \dots, n_i$ ) fed on the  $i$ th rations ( $i=1, 2, \dots, k$ )

(ii)  $\mu$  is the general mean effect given by

$$\mu = \frac{\sum_{i=1}^k (n_i \mu_i)}{N} \quad \text{--- (2)}$$

where  $\mu_i$  is the fixed effect due to the  $i^{\text{th}}$  ration, i.e. if there were no treatment differences and no chance causes then the yield of each cow will be  $\mu_i$ .

(iii)  $\alpha_i$  is the effect of the  $i^{\text{th}}$  ration (Treatment) is given by

$$\alpha_i = \mu - \mu_i \quad (i=1, 2, \dots, k) \quad \text{--- (3)}$$

i.e. the  $i^{\text{th}}$  treatment (ration) increase or decrease the yield by an amount  $\alpha_i$ . On using (2), we get

$$\begin{aligned} \sum_{i=1}^k n_i \alpha_i &= \sum_{i=1}^k n_i (\mu_i - \mu) = \sum_{i=1}^k n_i \mu_i - \mu \sum_{i=1}^k n_i \\ &= N \cdot \mu - \mu \cdot N = 0 \end{aligned}$$

(iv)  $\epsilon_{ij}$  is the error effect due to chance.

### Assumption in the model

- (i) All the obser<sup>n</sup>  $x_{ij}$  are indept.
- (ii) Different effects are additive in nature
- (iii)  $\epsilon_{ij}$  are i.i.d.  $N(0, \sigma_e^2)$

under the (iii) assumption, the model (1) becomes

$$E(x_{ij}) = \mu_i = \mu + \alpha_i \quad ; \quad \begin{cases} i=1, 2, \dots, k \\ j=1, 2, \dots, n_i \end{cases}$$

Null hypothesis of one for ANOVA for one-way classification.

Here we want to test the equality of pop<sup>n</sup>. means i.e. the homogeneity of different ratios. Hence null hypothesis is given by

$$H_0: \mu_1 = \mu_2 = \dots = \mu_k = \mu$$

which from (3) reduces to

$$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_k = 0$$

Statistical Analysis of the Model :- let us write

$\bar{x}_i$  = mean of the  $i^{\text{th}}$  class.

$$= \frac{\sum_{j=1}^{n_i} x_{ij}}{n_i} \quad ; \quad (i=1, 2, \dots, k)$$

$$\bar{x}_{..} = \text{overall mean} = \frac{1}{N} \sum_{i=1}^k \sum_{j=1}^{n_i} x_{ij}$$

$$= \frac{1}{N} \sum_{i=1}^k n_i \bar{x}_i$$

The parameters  $\mu$  and  $\alpha_i$  in (1) are estimated by the principle of least squares on minimising the error (residual) sum of squares given by

$$E = \sum_i \sum_j \varepsilon_{ij}^2 = \sum_i \sum_j (x_{ij} - \mu - \alpha_i)^2 \quad \text{--- (1)}$$

The normal eq<sup>n</sup> for estimating  $\mu$  and  $\alpha_i$  are

$$\frac{\partial E}{\partial \mu} = -2 \sum_i \sum_j (x_{ij} - \mu - \alpha_i) = 0 \quad \text{--- (2)}$$

$$\text{and } \frac{\partial E}{\partial \alpha_i} = -2 \sum_{j=1}^{n_i} (x_{ij} - \mu - \alpha_i) = 0 \quad \text{--- (3)}$$

from (\*), we get

$$\sum_i \sum_j x_{ij} - N\mu - \sum_i n_i \alpha_i = 0$$

$$\hat{\mu} = \frac{1}{N} \sum_i \sum_j x_{ij} = \bar{x}_{..}$$

$$[\because \sum_i n_i \alpha_i = 0]$$

from (\*\*), we get

$$\sum_j x_{ij} - n_i \hat{\mu} - n_i \hat{\alpha}_i = 0$$

$$\Rightarrow \hat{\alpha}_i = \frac{1}{n_i} \sum_j x_{ij} - \hat{\mu} = \bar{x}_{i.} - \bar{x}_{..}$$

$$\alpha_i = \bar{x}_{i.} - \bar{x}_{..}$$

Hence substituting the value of  $\mu$  &  $\alpha$  in (1) the model becomes

$$x_{ij} = \bar{x}_{..} + (\bar{x}_{i.} - \bar{x}_{..}) + (x_{ij} - \bar{x}_{i.})$$

We introduce the error component  $\epsilon_{ij}$  so that both the sides are equal. This is the deviation within the class which is due to randomisation. Transposing  $\bar{x}_{..}$  to the left squaring both sides and summing over  $i, j$  we get

$$\begin{aligned} \sum_i \sum_j (x_{ij} - \bar{x}_{..})^2 &= \sum_i \sum_j [\bar{x}_{i.} - \bar{x}_{..} + (x_{ij} - \bar{x}_{i.})]^2 \\ &= \sum_i \sum_j (\bar{x}_{i.} - \bar{x}_{..})^2 + \sum_i \sum_j (x_{ij} - \bar{x}_{i.})^2 \\ &\quad + 2 \sum_i (\bar{x}_{i.} - \bar{x}_{..}) \sum_j (x_{ij} - \bar{x}_{i.}) \end{aligned}$$

$$\sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{..})^2 = \sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{i.})^2 + \sum_i n_{i.} (\bar{x}_{i.} - \bar{x}_{..})^2 + 2 \sum_i \left[ (\bar{x}_{i.} - \bar{x}_{..}) \sum_j (x_{ij} - \bar{x}_{i.}) \right]$$

But  $\sum_{j=1}^{n_{i.}} (x_{ij} - \bar{x}_{i.}) = 0$  [algebraic sum of the deviation of the ratios from their mean is zero]

$$\therefore \sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{..})^2 = \sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{i.})^2 + \sum_i n_{i.} (\bar{x}_{i.} - \bar{x}_{..})^2 \quad \text{--- (1)}$$

$S_T^2 = \sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{..})^2$  is known as total sum of squares (T.S.S.)

$S_E^2 = \sum_i \sum_j n_{ij} (x_{ij} - \bar{x}_{i.})^2$  is called within sum of squares or error sum of squares (S.S.E.) and

$S_t^2 = \sum_i n_{i.} (\bar{x}_{i.} - \bar{x}_{..})^2$  is called S.S. due to treatments (S.S.T.)

Then  $T.S.S. = S.S.E. + S.S.T.$

Degrees of freedom for various S.S. :-

$S_T^2$ , the total S.S. will carry  $(N-1)$  d.f. (one d.f. lost because of the linear constraint)

$$\sum_{i=1}^k \sum_{j=1}^{n_{i.}} (x_{ij} - \bar{x}_{..}) = 0$$

similarly the treatment sum of squares  $S_t^2$  will have  $(k-1)$  d.f.

&  $S_E^2$  the error s.s. will have  $(N-k)$  d.f. . .

Hence we see that the

$$N-1 = (N-k) + (k-1)$$

### Mean Sum of Squares (M.S.S.)

~~Defn~~ The

The sum of squares divided by its degrees of freedom gives the corresponding variance or the mean sum of squares (M.S.S.). Thus

$$\frac{S_t^2}{(k-1)} = \frac{S.S.T.}{(k-1)} = S_t^2 \text{ is M.S.S. due to treatment}$$

$$\& \frac{S_E^2}{N-k} = \frac{S.S.E.}{(N-k)} = S_E^2 \text{ is M.S.S. due to error.}$$

Hence the test statistic for  $H_0$  provided by the variance ratio

$$F = \frac{S_t^2}{S_E^2} \quad (\text{---XXX---})$$

If  $H_0$  is true the  $F$ - should take the value 1, otherwise it should be greater than unity. In order to find out if an observed value of  $F$  is significantly greater than unity. we have

to obtain the sampling dist<sup>n</sup> of the F-statistic defined as

$$F = \frac{S_t^2}{S_E^2}$$

Under  $H_0$  by Cochran's thm.,  $\frac{S_t^2}{\sigma_e^2}$  &  $\frac{S_E^2}{\sigma_e^2}$  are independently distributed as  $\chi^2$  variates with  $(K-1)$  and  $(N-K)$  d.f. respectively.

Hence the statistic

$$F = \left[ \frac{S_t^2}{\sigma_e^2} \cdot \frac{1}{K-1} \right] \div \left[ \frac{S_E^2}{\sigma_e^2} \cdot \frac{1}{(N-K)} \right] = \frac{S_t^2}{S_E^2}$$

follows Snedecor's  $F$  (central) dist<sup>n</sup> with  $[K-1, (N-K)]$  d.f.

Thus if an observed value of  $F$  obtained from (xxx) is greater than tabulated value of  $F$  for  $(K-1, N-K)$  d.f. at specified level of significance (usually 5% or 1%) then  $H_0$  is refuted at that level otherwise  $H_0$  may be retained.

The above statistical analysis is very elegantly presented in the following table

ANOVA Table for ONE-WAY CLASSIFIED DATA

| Sources of Variation  | Sum of Squares | d.f.  | Mean Sum of Squares         | Variance Ratio                       |
|-----------------------|----------------|-------|-----------------------------|--------------------------------------|
| Treatment (Locations) | $S_t^2$        | $K-1$ | $S_t^2 = \frac{S_t^2}{K-1}$ | $\frac{S_t^2}{S_E^2} = F_{K-1, N-K}$ |
| Error                 | $S_E^2$        | $N-K$ | $S_E^2 = \frac{S_E^2}{N-K}$ |                                      |
| Total                 | $S_T^2$        | $N-1$ |                             |                                      |

Remark: For practical point of view, various sum of squares reduced to a great extent by using following simplified formulae

$$\begin{aligned}\text{Total S.S.} &= \sum_i \sum_j (x_{ij} - \bar{x}_{i.})^2 \\ &= \sum_i \sum_j x_{ij}^2 - \frac{(\sum_i \sum_j x_{ij})^2}{N} \\ &= \sum_i \sum_j x_{ij}^2 - \frac{O^2}{N}\end{aligned}$$

where  $O$  is the grand total of all the obser<sup>n</sup> and  $N = n_1 + n_2 + \dots + n_k = \sum x_i$

The expression  $\sum_i \sum_j x_{ij}^2$  the sum of squares of all the obser<sup>n</sup> is known as Raw sum of squares (R.S.S.) and the expression  $\frac{O^2}{N}$  is called the correction factor (C.F.).

$$\text{Total S.S.} = \text{R.S.S.} - \text{C.F.}$$

$$\begin{aligned}\text{Error S.S.} &= \sum_i \sum_j (x_{ij} - \bar{x}_{i.})^2 = \sum_i \left\{ \sum_j (x_{ij} - \bar{x}_{i.})^2 \right\} \\ &= \sum_i \left[ \sum_j x_{ij}^2 - \frac{(\sum_j x_{ij})^2}{n_i} \right] = \sum_i \left[ \sum_j x_{ij}^2 - \frac{T_{i.}^2}{n_i} \right] \\ S_E^2 &= \sum_i \sum_j x_{ij}^2 - \sum_i \left( \frac{T_{i.}^2}{n_i} \right)\end{aligned}$$

where  $T_{i.}$  is the total yield from the units receiving the  $i$ th treatment

$$\begin{aligned}\text{f Treatment S.S.} &= S_t^2 = \text{T.S.S.} - \text{S.S.E.} \\ &= \sum \left( \frac{T_{i.}^2}{n_i} \right) - \frac{O^2}{N} \\ &= \sum \left( \frac{T_{i.}^2}{n_i} \right) - \text{C.F.}\end{aligned}$$

## ANOVA for Two-way Classification (with one obs<sup>n</sup> per cell)

Let us consider the case when there are two factors which may affect the variate values  $x_{ij}$ .  
eg. the yield of milk may be affected by difference of treatments i.e. rations as well as the difference in variety i.e. breed and stock of the cows. Let us now suppose that the  $N$  cows are divided into  $h$  different groups or classes according to their breed and stock, each group containing  $k$  cows and then let us consider the effect of  $k$  treatments (i.e. rations given at random to cow in each group) on the yield of milk.

Let us suffix  $i$  refer to the treatments (rations) and suffix  $j$  refer to the varieties (breed of the cow). Then the yield of milk  $x_{ij}$  ( $i=1, 2, \dots, k$ ,  $j=1, 2, \dots, h$ ) of  $N = h \times k$  cows furnish the data for the comparison of the treatments. The yield may be expressed as variate values in the following  $k \times h$  two-way table

|       |             |             |         |             | Mean    | total       |             |       |
|-------|-------------|-------------|---------|-------------|---------|-------------|-------------|-------|
|       | $x_{11}$    | $x_{12}$    | $\dots$ | $x_{1j}$    | $\dots$ | $x_{1h}$    | $\bar{x}_1$ | $T_1$ |
|       | $x_{21}$    | $x_{22}$    | $\dots$ | $x_{2j}$    | $\dots$ | $x_{2h}$    | $\bar{x}_2$ | $T_2$ |
|       | $\vdots$    |             |         |             |         |             |             |       |
|       | $x_{h1}$    | $x_{h2}$    | $\dots$ | $x_{hj}$    | $\dots$ | $x_{hk}$    | $\bar{x}_h$ | $T_h$ |
|       | $\vdots$    |             |         |             |         |             |             |       |
|       | $x_{k1}$    | $x_{k2}$    | $\dots$ | $x_{kj}$    | $\dots$ | $x_{kh}$    | $\bar{x}_k$ | $T_k$ |
| Mean  | $\bar{x}_1$ | $\bar{x}_2$ | $\dots$ | $\bar{x}_j$ | $\dots$ | $\bar{x}_h$ | $\bar{x}_k$ |       |
| total |             |             |         |             |         |             |             |       |

|       |     |     |     |     |
|-------|-----|-----|-----|-----|
| total | T.1 | T.2 | T.j | T.h |
|-------|-----|-----|-----|-----|

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Mathematical Model :- Let  $x_{ij}$  be the yield from the row of  $j^{\text{th}}$  variety fed on the  $i^{\text{th}}$  ration ( $i=1,2,\dots,k$ ,  $j=1,2,\dots,h$ ).

Let us suppose that  $x_{ij}$  ( $i=1,2,\dots,k$ ;  $j=1,2,\dots,h$ ) are indept., normally distributed as  $N(\mu_{ij}, \sigma_e^2)$ . The linear mathematical model becomes

$$E(x_{ij}) = \mu_{ij}$$

$$\text{or } x_{ij} = \mu_{ij} + \epsilon_{ij} \quad \text{--- (1)}$$

where  $\epsilon_{ij}$  are i.i.d.  $N(0, \sigma_e^2)$

$\mu_{ij}$  is further split into the following parts:

- (i) The general mean effect  $\mu$  given by

$$\mu = \frac{\sum_i \sum_j \mu_{ij}}{N} \quad \text{--- (2)}$$

- (ii) The effect  $\alpha_i$  ( $i=1,2,\dots,k$ ) due to the  $i^{\text{th}}$  ration given by

$$\alpha_i = \mu_{i.} - \mu$$

$$\text{where } \mu_{i.} = \frac{1}{h} \sum_{j=1}^h \mu_{ij} \quad ; \quad (i=1,2,\dots,k) \quad \text{--- (3)}$$

$$\text{obviously } \sum_{i=1}^k \alpha_i = 0$$

- (iii) The effect  $\beta_j$ , ( $j=1,2,\dots,h$ ) due to  $j^{\text{th}}$  variety (breed of row) given by

$$\beta_j = \mu_{.j} - \mu$$

$$\mu_{.j} = \frac{1}{K} \sum_{i=1}^K \mu_{ij} \quad ; \quad (j=1, 2, \dots, h)$$

obviously  $\sum_{j=1}^h \beta_j = 0$

(iv) The interaction effect  $\gamma_{ij}$ , when the  $i$ th level of first factor (rations) and  $j$ th level of second factor (breed of cow) occur simultaneously and given by

$$\begin{aligned} \gamma_{ij} &= \mu_{ij} - \mu_{i.} - \mu_{.j} + \mu \\ \sum_i \gamma_{ij} &= 0, \quad \forall j = 1, 2, \dots, h \\ \sum_j \gamma_{ij} &= 0, \quad \forall i = 1, 2, \dots, K \end{aligned} \quad \left\{ \begin{aligned} \sum_{i=1}^K \mu_{ij} - \sum_{i=1}^K \mu_{i.} - K\mu_{.j} + K\mu \\ K\mu_{.j} - K\mu_{i.} - K\mu_{.j} + K\mu \end{aligned} \right.$$

and thus we have

$$\mu_{ij} = \mu + (\mu_{i.} - \mu) + (\mu_{.j} - \mu) + (\mu_{ij} - \mu_{i.} - \mu_{.j} + \mu)$$

and consequently (1) becomes

$$x_{ij} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ij} \quad \text{--- (6)}$$

Where  $\epsilon_{ij}$  is the error effect due to chance &

$$\sum_{i=1}^K \alpha_i = 0 = \sum_{j=1}^h \beta_j$$

$$\sum_i \sum_j \gamma_{ij} = \sum_j \sum_i \gamma_{ij} = 0$$

As there is only one obser<sup>n</sup> in each cell, the obser<sup>n</sup> corresponding to the  $i$ th level of ration &  $j$ th level of breed of cow is only one i.e.  $x_{ij}$ . But we cannot estimate by one value alone. Hence in this case of one obser<sup>n</sup>-per cell the interaction effect  $\gamma_{ij} = 0$  and the model (6) reduces to

$$x_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij} \quad \text{--- (7)}$$

### Statistical Analysis of the model

Let us write

$$\begin{aligned} \bar{x}_{i.} &= \text{Mean yield of } i^{\text{th}} \text{ ration} \\ &= \frac{1}{h} \sum_{j=1}^h x_{ij} \quad (i = 1, 2, \dots, k) \end{aligned}$$

$$\begin{aligned} \bar{x}_{.j} &= \text{mean yield of } j^{\text{th}} \text{ variety} \\ &= \frac{1}{k} \sum_{i=1}^k x_{ij} \quad (j = 1, 2, \dots, h) \end{aligned}$$

$$\begin{aligned} \bar{x}_{..} &= \text{Overall mean} = \frac{1}{hk} \sum_i \sum_j x_{ij} \\ &= \frac{1}{h} \sum_j \left( \frac{1}{k} \sum_i x_{ij} \right) = \frac{1}{h} \sum_j \bar{x}_{.j} \\ &= \frac{1}{k} \sum_i \left( \frac{1}{h} \sum_j x_{ij} \right) = \frac{1}{k} \sum_i \bar{x}_{i.} \end{aligned}$$

The least square estimates of the parameters  $\mu$ ,  $\alpha_i$  and  $\beta_j$  are obtained on minimizing

the error sum of squares

$$E = \sum_{i=1}^k \sum_{j=1}^h \varepsilon_{ij}^2 = \sum_{i,j} (x_{ij} - \mu - \alpha_i - \beta_j)^2$$

The normal eq<sup>n</sup> for eq estimating  $\mu$ ,  $\alpha_i$  &  $\beta_j$  are respectively

$$\frac{\partial E}{\partial \mu} = 0 = -2 \sum_{i,j} (x_{ij} - \mu - \alpha_i - \beta_j)$$

$$\frac{\partial E}{\partial \alpha_i} = 0 = -2 \sum_j (x_{ij} - \mu - \alpha_i - \beta_j)$$

$$\frac{\partial E}{\partial \beta_j} = 0 = -2 \sum_i (x_{ij} - \mu - \alpha_i - \beta_j)$$

since  $\sum_i \alpha_i = 0 = \sum_j \beta_j$ : we get from the above eq<sup>n</sup>.

$$\hat{\mu} = \frac{1}{hk} \sum_{i,j} x_{ij} = \bar{x}_{..}$$

$$\hat{\alpha}_i = \frac{1}{h} \sum_j x_{ij} - \hat{\mu} = \bar{x}_{i.} - \bar{x}_{..}$$

$$\hat{\beta}_j = \frac{1}{k} \sum_i x_{ij} - \hat{\mu} = \bar{x}_{.j} - \bar{x}_{..}$$

Thus linear model (7) becomes

$$x_{ij} = \bar{x}_{..} + (\bar{x}_{i.} - \bar{x}_{..}) + (\bar{x}_{.j} - \bar{x}_{..}) + (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})$$

The error term  $\varepsilon_{ij}$  being so chosen that both sides are equal

Transposing  $\bar{x}_{..}$  to the left side, squaring

and summing both sides over  $i$  &  $j$ , we get

$$\sum_i \sum_j (x_{ij} - \bar{x}_{..})^2 = \sum_i \sum_j [(x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..}) + (\bar{x}_{i.} - \bar{x}_{..}) + (\bar{x}_{.j} - \bar{x}_{..})]^2$$

$$= \sum_i \sum_j (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})^2 + \sum_i \sum_j (\bar{x}_{i.} - \bar{x}_{..})^2$$

$$+ \sum_i \sum_j (\bar{x}_{.j} - \bar{x}_{..})^2 + 2 \sum_i \sum_j (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})$$

$$(\bar{x}_{i.} - \bar{x}_{..}) + 2 \sum_i \sum_j (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})$$

$$(\bar{x}_{.j} - \bar{x}_{..}) + 2 \sum_i \sum_j (\bar{x}_{i.} - \bar{x}_{..})(\bar{x}_{.j} - \bar{x}_{..})$$

Since algebraic sum of deviation of a set of obser<sup>n</sup> about their mean is zero.

Similarly other product terms also vanishes.

Hence

$$\sum_i \sum_j (x_{ij} - \bar{x}_{..})^2 = \sum_i \sum_j (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})^2 + k \sum_i (\bar{x}_{i.} - \bar{x}_{..})^2 + k \sum_j (\bar{x}_{.j} - \bar{x}_{..})^2$$

$$S_T^2 = S_E^2 + S_t^2 + S_v^2$$

T.S.S. = S.S. due to error + S.S. due to treatments + S.S. due to varieties.

Null hypothesis:- We set up the null hypothesis that treatment as well as varieties are homogeneous. In other words, the null hypothesis for treatment and varieties are respectively

$$H_t = \mu_1 = \mu_2 = \dots = \mu_k = \mu$$

$$H_v = \mu_{.1} = \mu_{.2} = \dots = \mu_{.h} = \mu$$

Q1

$$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_k = 0$$

$$H_1: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

**Degrees of freedom for various S.S.** :- The total S.S.,  $S_T^2$

being computed from  $N = hk$  quantities,  $(\bar{x}_{ij} - \bar{x}_{..})$ , which are subject to one linear constraint  $\sum (\bar{x}_{ij} - \bar{x}_{..}) = 0$ , will carry  $(N-1)$  d.f.

similarly for  $S_t^2$  will be based on  $(k-1)$  d.f. since  $\sum_i (\bar{x}_{i.} - \bar{x}_{..}) = 0$

$S_v^2$  will have  $(h-1)$  d.f. since  $\sum_j (\bar{x}_{.j} - \bar{x}_{..}) = 0$  will carry  $(h-1)$  d.f.

hence  $S_E^2$  will carry  $(N-1) - (k-1) - (h-1) = (h-1)(k-1)$  d.f.

Thus the partitioning of d.f. is as follows

$$(hk-1) = (k-1) + (h-1) + (h-1)(k-1)$$

which  $\Rightarrow$  that d.f. are additive.

**Test statistic** :- To obtain appropriate test statistic to test the hypothesis  $H_0$  &  $H_1$ , we need the expectation of the various mean sum of squares due to each indept factors.

$$\text{m.s.s. due to treatment} = \frac{S_t^2}{k-1} = S_t^2$$

$$\text{M.S.S. due to variety} = \frac{S_V^2}{h-1} = S_V^2$$

$$\text{error M.S.S.} = \frac{S_E^2}{(h-1)(k-1)} = S_E^2$$

Since various S.S. and d.f. are additive and since under  $H_T$  &  $H_V$ , each of  $S_T^2$ ,  $S_V^2$  &  $S_E^2$  provides an unbiased estimates of  $\sigma_e^2$ , under the assumption of normal parent pop<sup>n</sup>, we get by Cochran's thm

$$\frac{S_T^2}{\sigma_e^2}, \frac{S_V^2}{\sigma_e^2} \text{ \& } \frac{S_E^2}{\sigma_e^2} \text{ are mutually indept.}$$

$\chi^2$  with  $(K-1)$ ,  $(h-1)$  &  $(h-1)(k-1)$  d.f. respectively. Hence under  $H_T$  and  $H_V$  respectively, we get

$$F_T = \frac{S_T^2}{\sigma_e^2(k-1)} \div \frac{S_E^2}{\sigma_e^2(h-1)(k-1)} = \frac{S_T^2}{S_E^2} \sim F_{K-1, (h-1)(k-1)}$$

$$F_V = \frac{S_V^2}{\sigma_e^2(h-1)} \div \frac{S_E^2}{\sigma_e^2(h-1)(k-1)} = \frac{S_V^2}{S_E^2} \sim F_{h-1, (h-1)(k-1)}$$

### ANVA for two-way classified data

| Sources of variatio- | Sum of squares                                                               | d.f.         | M.S.S.                             | Variance Ratio                                            |
|----------------------|------------------------------------------------------------------------------|--------------|------------------------------------|-----------------------------------------------------------|
| Treatments           | $S_T^2 = \sum_i h(\bar{x}_{i.} - \bar{x}_{..})^2$                            | $K-1$        | $S_T^2 = \frac{S_T^2}{K-1}$        | $F_T = \frac{S_T^2}{S_E^2}$<br>$\sim F_{K-1, (h-1)(k-1)}$ |
| varieties            | $S_V^2 = \sum_j k(\bar{x}_{.j} - \bar{x}_{..})^2$                            | $h-1$        | $S_V^2 = \frac{S_V^2}{h-1}$        | $F_V = \frac{S_V^2}{S_E^2}$<br>$\sim F_{h-1, (h-1)(k-1)}$ |
| residuals            | $S_E^2 = \sum_{i,j} (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})^2$ | $(h-1)(k-1)$ | $S_E^2 = \frac{S_E^2}{(h-1)(k-1)}$ |                                                           |
| Total                |                                                                              | $N-1$        |                                    |                                                           |