Statistical Methods for Economists

Lecture (7 & 8)b

Two-Way Analysis of Variance (ANOVA)



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- Introduction
- Two-way ANOVA without interactions
- Two-way ANOVA with interactions





Assume that we test several distinct cars. We also have a set of distinct drivers.

We wish to test whether the mileage (the fuel consumption per 100 km) of the car

depends also upon the driver who drives the car. In particular,

let us have I distinct cars (i = 1, 2, ..., I) and J distinct drivers (j = 1, 2, ..., J).

There are two factors in this example:

- factor A = the car (i = 1, 2, ..., I)
- factor B = the driver (j = 1, 2, ..., J)

There are $IJ = I \times J$ distinct combinations of the factors (the Cartesian product).

Assume that each combination is tested n_{ij} -times.

We thus have a sample of observations

of the underlying random variables

These random variables are assumed to be normal
$$(Y_{ijk} \sim \mathcal{N}(\mu_{ij}, \sigma^2))$$
, independent (uncorrelated) and homoscedastic (with the same variance σ^2).

Two-factor ANOVA: Motivation & Introduction

Yijk

 $Y_{ijk}: \Omega \to \mathbb{R}$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$$

Two-factor ANOVA: Motivation & Introduction





We assume that the effect of the factors A and B is additive. Moreover, we distinguish two cases: the effecting is

either without the interaction of the factors, that is

$$Y_{ijk} \approx \mu + \alpha_i + \beta_j$$

$$Y_{ijk} \approx \mu + \alpha_i + \beta_j + \gamma_{ij}$$
 for

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$$

or
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$$

where $\mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$ are fixed constants (parameters).





either
$$Y_{ijk} \approx \mu + \alpha_i + \beta_j$$

or $Y_{ijk} \approx \mu + \alpha_i + \beta_j + \gamma_{ij}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

or more precisely:

either
$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

or $Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

where $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$ are random variables denoting the random deviations ("errors"); these random variables are mutually independent (uncorrelated),



either
$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

or $Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

NOTICE:

If the effect is not additive (e.g., it is multiplicative), then it <u>must</u> be converted to the additive form first (by taking, e.g., the logarithms) because we shall use the theory of (Multiple) Linear Regression.

iii We do not know the parameters $\mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$. We shall estimate them by



either
$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

or $Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

where the meaning of the (unknown) parameters $\mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$ is as follows:

- μ the common mean value
- α_i the effect of the level *i* of Factor A (for i = 1, 2, ..., I)
- β_j the effect of the level *j* of Factor B (for j = 1, 2, ..., J)
- γ_{ij} the interaction between the level i of Factor A and the level j of Factor B



either
$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

or $Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

Moreover, we assume that the (unknown) parameters $\alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$ are normalized so that:

$$\sum_{i=1}^{I} \alpha_i = 0 \qquad \sum_{i=1}^{I} \gamma_{ij} = 0 = \sum_{j=1}^{J} \gamma_{ij} \qquad \sum_{j=1}^{J} \beta_j = 0 \qquad \text{for} \quad \begin{cases} i = 1, 2, \dots, I \\ j = 1, 2, \dots, J \end{cases}$$

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Given any of the above models (either without interactions or with the interactions), we can test either of these two (null) hypotheses:

• The factor A has no effect, that is

$$H_0: \quad \alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$$

• The factor B has no effect, that is

$$H_0: \quad \beta_1 = \beta_2 = \cdots = \beta_J = 0$$

Considering the model with the interactions, we can also test the (null) hypothesis:

There are no interactions between the factors A and B, that is

H_a:
$$v_{ii} = 0$$
 for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \end{cases}$

Given either of the two above models $(Y_{ijk} \approx \mu + \alpha_i + \beta_j \text{ or } Y_{ijk} \approx \mu + \alpha_i + \beta_j + \gamma_{ij})$,

the null hypothesis that "the Factor A has no effect" means

$$H_0: \quad \alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$$

that is, the correct model is

either
$$Y_{ijk} = \mu + \beta_j$$
 $+ \varepsilon_{ijk}$
or $Y_{ijk} = \mu + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

respectively.

This null hypothesis is denoted by

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Given either of the two above models $(Y_{ijk} \approx \mu + \alpha_i + \beta_j \text{ or } Y_{ijk} \approx \mu + \alpha_i + \beta_j + \gamma_{ij})$, the null hypothesis that "the Factor B has no effect" means

null hypothoolo that <u>alo i aolor b hao ho ohoot</u> moand

$$H_0: \quad \beta_1 = \beta_2 = \cdots = \beta_J = 0$$

that is, the correct model is

either
$$Y_{ijk} = \mu + \alpha_i + \varepsilon_{ijk}$$

or $Y_{ijk} = \mu + \alpha_i + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$

respectively.

This null hypothesis is denoted by

Given the latter one of the two above models $(Y_{ijk} \approx \mu + \alpha_i + \beta_j + \gamma_{ij})$, the null hypothesis that "there is no interaction between the factors A and B" means $H_0: \gamma_{ij} = 0$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., I \end{cases}$

that is, the correct model is

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., n_{ij} \end{cases}$$

This null hypothesis is denoted by

H_{AB}

The alternative hypothesis is that $\gamma_{ij} \neq 0$





Although it is possible to consider the general situation with a general

number $n_{ij} \ge 1$ of observations for each combination of the factors,

the calculations and the resulting formulas are complicated then.

This is why we adopt the following simplification:

We assume that the number of the observations is the same in each case, that is

$$n_{ij} = K$$
 for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \end{cases}$

where $K \ge 1$ is some constant (fixed) natural number.

Two-Way ANOVA without interactions

 $Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$



Assume that we have a sample

Yijk

of observations of the random variables

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

where $\mu, \alpha_i, \beta_j \in \mathbb{R}$ are fixed (but <u>unknown</u>) parameters normalized so that

$$\sum_{i=1}^{I} \alpha_i = 0 \qquad \text{and} \qquad \sum_{j=1}^{J} \beta_j = 0$$

and...



for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

Assume that we have a sample

of observations of the random variables

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

 $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$

...and

are mutually independent random variables
with the same variance
$$\sigma^2 \in \mathbb{R}^+$$

(the variance σ^2 is also unknown).

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$



for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

Stack the observations y_{ijk} into the (IJK)-dimensional vector

$$y = (y_{ijk})_{\substack{i=1,2,\dots,l\\j=1,2,\dots,J\\k=1,2,\dots,K}} \in \mathbb{R}^{I \times J \times K}$$

and introduce the sample mean:

$$\bar{y} = \frac{1}{IJK} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} y_{ijk}$$

This sample mean is an estimate of the parameter μ (the common mean value):

$$\overline{y} \approx \mu$$





Let $\mathbf{1} = (1)_{\substack{i=1,2,...,I\\j=1,2,...,J\\k=1,2,...,K}} \in \mathbb{R}^{I \times J \times K}$ be the vector of IJK ones and

introduce the line

$$L = \{ \mathbf{1}\lambda : \lambda \in \mathbb{R} \} =$$
$$= \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu, \ \mu \in \mathbb{R} \} =$$
$$= \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j, \ \mu \in \mathbb{R}, \ \alpha_i = 0, \ \beta_j = 0 \}$$

which corresponds to the null hypothesis that

$$H_0: \quad Y_{ijk} = \mu + \varepsilon_{ijk}$$

that is

(cf. one-way ANOVA)

for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

 H_{A} :

Moreover, introduce the subspace

$$H_{\mathbf{A}} = \left\{ \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \beta_j, \ \mu, \beta_j \in \mathbb{R}, \ \sum_{j=1}^J \beta_j = 0 \right\} =$$
$$= \left\{ \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j, \ \mu, \beta_j \in \mathbb{R}, \ \alpha_i = 0, \ \sum_{j=1}^J \beta_j = 0 \right\}$$

which corresponds to the null hypothesis

$$Y_{ijk} = \mu + \beta_j + \varepsilon_{ijk} \qquad \text{for} \quad \begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$

that is

$$\alpha_1 = \cdots = \alpha_I = 0$$

Observe that the line

 $L \subset H_A$



(i - 1) I

Introduce also the subspace

$$H_{\mathrm{B}} = \left\{ \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i, \ \mu, \alpha_i \in \mathbb{R}, \ \sum_{i=1}^{I} \alpha_i = 0 \right\} =$$
$$= \left\{ \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j, \ \mu, \alpha_i \in \mathbb{R}, \ \beta_j = 0, \ \sum_{i=1}^{I} \alpha_i = 0 \right\}$$

which corresponds to the null hypothesis

$$H_{B}: \quad Y_{ijk} = \mu + \alpha_{i} + \varepsilon_{ijk} \qquad \text{for} \quad \begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$

that is

$$\beta_1=\cdots=\beta_J=0$$

Observe that the line

 $L \subset H_{\rm B}$





Finally, introduce the subspace

$$M = \left\{ \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j, \ \mu, \alpha_i, \beta_j \in \mathbb{R}, \ \sum_{i=1}^{I} \alpha_i = \sum_{j=1}^{J} \beta_j = 0 \right\}$$

which corresponds to the model under consideration:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$



Two-way ANOVA with no interactions: Dimensions

Notice that the dimension of

— the line

$$L = \{ \mathbf{1}\lambda : \lambda \in \mathbb{R} \} = \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu, \ \mu \in \mathbb{R} \}$$
is

- the subspace

$$H_{\mathbf{A}} = \left\{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \beta_j, \ \mu, \beta_j \in \mathbb{R}, \ \sum_{j=1}^J \beta_j = 0 \right\}$$

s
$$(1+J) - 1 = J$$



Notice that the dimension of

— the subspace $H_{B} = \left\{ z \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_{i}, \ \mu, \alpha_{i} \in \mathbb{R}, \ \sum_{i=1}^{I} \alpha_{i} = 0 \right\}$ is (1+I) - 1 = I

— the subspace

$$M = \left\{ z \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j, \ \mu, \alpha_i, \beta_j \in \mathbb{R}, \ \sum_{i=1}^{I} \alpha_i = \sum_{j=1}^{J} \beta_j = 0 \right\}$$
is

$$(1 + I + J) - 2 = I + J - 1$$

Solve the Least Squares Problem:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu-\alpha_i-\beta_j)^2 \rightarrow \min$$

subject to

and



 $\mu,\,\alpha_1,\,\ldots,\,\alpha_I,\,\beta_1,\,\ldots,\,\beta_J\in\mathbb{R}$





Letting $\hat{y}_{ijk} = \mu - \alpha_i - \beta_j$, it is equivalent to solve the problem:

$$\min_{\widehat{\mathbf{y}}\in M}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{ijk}-\mu-\alpha_{i}-\beta_{j}\right)^{2} = \min_{\widehat{\mathbf{y}}\in M}\|\mathbf{y}-\widehat{\mathbf{y}}\|^{2} = RSS$$

Two-way ANOVA with no interactions







Two-way ANOVA with no interactions

Solve also:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \beta_j)^2 \to \min \quad \text{and} \quad \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \alpha_i)^2 \to \min$$

subject to

and



Letting $\hat{y}_{Aijk} = \mu - \beta_j$ and $\hat{y}_{Bijk} = \mu - \alpha_i$, respectively,

it is equivalent to solve the problems:

$$\min_{\widehat{\mathbf{y}}_{A}\in\mathcal{H}_{A}}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{ijk}-\mu-\beta_{j}\right)^{2} = \min_{\widehat{\mathbf{y}}_{A}\in\mathcal{H}_{A}}\|\mathbf{y}-\widehat{\mathbf{y}}_{A}\|^{2}$$

and

$$\min_{\widehat{\mathbf{y}}_{\mathsf{B}}\in H_{\mathsf{B}}} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \alpha_i)^2 = \min_{\widehat{\mathbf{y}}_{\mathsf{B}}\in H_{\mathsf{B}}} \|\mathbf{y} - \widehat{\mathbf{y}}_{\mathsf{B}}\|^2$$

respectively.



Two-way ANOVA with no interactions

Lastly, solve:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu)^2 \to \min$$

subject to

 $\mu \in \mathbb{R}$

By letting $\bar{y} = \mu$, equivalently:

$$\min_{\mathbf{1}\overline{\mathbf{y}}\in L}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{ijk}-\mu\right)^{2} = \min_{\mathbf{1}\overline{\mathbf{y}}\in L}\|\mathbf{y}-\mathbf{1}\overline{\mathbf{y}}\|^{2}$$



Two-way ANOVA with no interactions



Put together, we have:

$$\|y\|^{2} = \|\hat{y}\|^{2} + \|e\|^{2}$$
$$\|y\|^{2} = \|\hat{y}\|^{2} + \|y - \hat{y}\|^{2}$$
$$\|y - 1\bar{y}\|^{2} = \|\hat{y} - 1\bar{y}\|^{2} + \|(y - 1\bar{y}) - (\hat{y} - 1\bar{y})\|^{2}$$
$$\|y - 1\bar{y}\|^{2} = \|\hat{y} - 1\bar{y}\|^{2} + \|y - \hat{y}\|^{2}$$
$$\|y - 1\bar{y}\|^{2} = \|\hat{y} - 1\bar{y}\|^{2} + \|e\|^{2}$$
$$\|y - 1\bar{y}\|^{2} = \|\hat{y} - \hat{y}_{A}\|^{2} + \|\hat{y} - \hat{y}_{B}\|^{2} + \|e\|^{2}$$



We have and denote:

$$\underbrace{\|\boldsymbol{y} - \mathbf{1}\bar{\boldsymbol{y}}\|^2}_{SS_{TOTAL}} = \underbrace{\|\widehat{\boldsymbol{y}} - \widehat{\boldsymbol{y}}_A\|^2}_{SS_A} + \underbrace{\|\widehat{\boldsymbol{y}} - \widehat{\boldsymbol{y}}_B\|^2}_{SS_B} + \underbrace{\|\boldsymbol{e}\|^2}_{RSS}$$

where, recall, we have:

$$\hat{y}_{ijk} = \mu + \alpha_i + \beta_j$$

$$\hat{y}_{Aijk} = \mu + \beta_j \qquad \qquad \hat{y}_{Bijk} = \mu + \alpha_i$$

$$\overline{y} = \mu$$



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Two-way ANOVA with no interactions

We thus have:

$$SS_{TOTAL} = \|\boldsymbol{y} - \boldsymbol{1}\bar{\boldsymbol{y}}\|^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{\boldsymbol{y}})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu)^2$$

$$RSS = \|\boldsymbol{e}\|^2 = \|\boldsymbol{y} - \hat{\boldsymbol{y}}\|^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{y}_{ijk})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \alpha_i - \beta_j)^2$$



Two-way ANOVA with no interactions

We thus have:

$$SS_{A} = \|\widehat{\boldsymbol{y}} - \widehat{\boldsymbol{y}}_{A}\|^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\widehat{y}_{ijk} - \widehat{y}_{Aijk})^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\mu + \alpha_{i} + \beta_{j} - \mu - \beta_{j})^{2} =$$

$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_i^2 = JK \sum_{i=1}^{I} \alpha_i^2$$


We thus have:

$$SS_{B} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{B}\|^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\widehat{y}_{ijk} - \widehat{y}_{Bijk})^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\mu + \alpha_{i} + \beta_{j} - \mu - \alpha_{i})^{2} =$$

$$=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\beta_{j}^{2} = IK\sum_{j=1}^{J}\beta_{j}^{2}$$



By solving the above Least Squares Problems $(\partial^F/\partial\mu = \partial^F/\partial\alpha_i = \partial^F/\partial\beta_j = 0$ etc.; <u>do it as an exercise</u>), we obtain:

$$\hat{\mu} = \frac{1}{IJK} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} y_{ijk} = \bar{y}$$

$$\hat{\alpha}_i = \frac{1}{JK} \sum_{j=1}^J \sum_{k=1}^K y_{ijk} - \hat{\mu} = \bar{y}_{i..} - \bar{y}$$
 for $i = 1, 2, ..., I$

$$\hat{\beta}_j = \frac{1}{IK} \sum_{i=1}^{I} \sum_{k=1}^{K} y_{ijk} - \hat{\mu} = \bar{y}_{.j.} - \bar{y}$$
 for $j = 1, 2, ..., J$

Put together, we have:

SS_{TOTAL} =
$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{\mu})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y})^2$$

$$SS_A = JK \sum_{i=1}^{I} \hat{\alpha}_i^2 = JK \sum_{i=1}^{I} (\bar{y}_{i..} - \bar{y})^2$$

$$SS_{B} = IK \sum_{j=1}^{J} \hat{\beta}_{j}^{2} = IK \sum_{j=1}^{J} (\bar{y}_{.j} - \bar{y})^{2}$$





Put together, we have:

$$RSS = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j)^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y} - \bar{y}_{i..} + \bar{y} - \bar{y}_{.j.} + \bar{y})^2 =$$

$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{i\cdots} - \bar{y}_{.j.} + \bar{y})^{2}$$

<u>Remark:</u> The quantity

$$s^{2} = \frac{\text{RSS}}{(I-1)(J-1) + IJ(K-1)}$$

Recall that it holds:

$$SS_{TOTAL} = SS_A + SS_B + RSS$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y})^2 = JK \sum_{i=1}^{I} (\bar{y}_{i\cdots} - \bar{y})^2 + IK \sum_{j=1}^{J} (\bar{y}_{\cdot j} - \bar{y})^2 + IK \sum_$$

$$+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\bar{y}_{i..}-\bar{y}_{.j.}+\bar{y})^{2}$$





We use the theory of Linear Regression (Theorem 8) to test Hypothesis H_A :

If the null hypothesis

$$H_{\mathbf{A}}: \quad \alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$$

holds true, then

$$\frac{SS_{A}}{RSS} / \frac{I-1}{(I-1)(J-1) + IJ(K-1)} \sim F_{I-1,(I-1)(J-1) + IJ(K-1)}$$

that is

$$\frac{JK \sum_{i=1}^{I} (\bar{y}_{i\cdots} - \bar{y})^{2}}{\sum_{i=1}^{I} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{i\cdots} - \bar{y}_{\cdot j\cdot} + \bar{y})^{2}} / \frac{I - 1}{(I - 1)(J - 1) + IJ(K - 1)} \sim$$





- Given the sample y_{ijk} of the random variables $Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$ where
 - $\mu, \alpha_i, \beta_j \in \mathbb{R}$ are (unknown) parameters such that $\sum_{i=1}^{I} \alpha_i = \sum_{j=1}^{J} \beta_j = 0$ and $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$ are mutually independent random variables for i = 1, 2, ..., I, j = 1, 2, ..., J, and k = 1, 2, ..., K, formulate the null hypothesis: H_{A} : $\alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$

• The alternative hypothesis is $H_{A1} \equiv \neg H_A$, i.e. $\alpha_i \neq 0$ for some $i \in \{1, 2, ..., I\}$



Calculate the statistic

$$F = \frac{SS_{A}}{RSS} / \frac{DF_{A}}{DF_{RSS}} = \frac{JK \sum_{i=1}^{I} (\bar{y}_{i..} - \bar{y})^{2}}{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y})^{2}} / \frac{I - 1}{(I - 1)(J - 1) + IJ(K - 1)}$$

• If the null hypothesis is true, then we have by the Theorem

$$F \sim F_{I-1,(I-1)(J-1)+IJ(K-1)}$$

• Choose the level of significance, a small number $\alpha > 0$, such as $\alpha = 5$ %, other popular values are $\alpha = 10$ % or $\alpha = 1$ % or $\alpha = 0.1$ % etc.



find the critical value

$$c = F_{I-1,(I-1)(J-1)+IJ(K-1)} (1-\alpha)$$

so that $\int_{c}^{+\infty} f(x) dx = \alpha$ where f is the density of the *F*-distribution with I - 1 and (I - 1)(J - 1) + IJ(K - 1) degrees of freedom

- if $F \in [c, +\infty)$, the critical region, then <u>reject</u> the null hypothesis
- if $F \in [0, c)$, then <u>do not reject</u> (or <u>fail to reject</u>) the null hypothesis

We can test Hypothesis $H_{\rm B}$ analogously:

If the null hypothesis

$$H_{\rm B}: \quad \beta_1 = \beta_2 = \cdots = \beta_J = 0$$

holds true, then

$$\frac{SS_{B}}{RSS} / \frac{J-1}{(I-1)(J-1) + IJ(K-1)} \sim F_{J-1,(I-1)(J-1)+IJ(K-1)}$$

that is

$$\frac{IK \sum_{j=1}^{J} (\bar{y}_{.j.} - \bar{y})^2}{\sum_{i=1}^{I} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y})^2} / \frac{J-1}{(I-1)(J-1) + IJ(K-1)} \sim$$



 $Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$



Assume that we have a sample

Yijk

of observations of the random variables

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$$

where $\mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$ are fixed (but <u>unknown</u>) parameters normalized so that

$$\sum_{i=1}^{I} \alpha_{i} = 0 \qquad \sum_{i=1}^{I} \gamma_{ij} = 0 = \sum_{j=1}^{J} \gamma_{ij} \qquad \sum_{j=1}^{J} \beta_{j} = 0 \qquad \text{for} \quad \begin{cases} i = 1, 2, \dots, I \\ j = 1, 2, \dots, J \end{cases}$$



for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$

Assume that we have a sample

Yijk

of observations of the random variables

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$$

 $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$

...and

are mutually independent random variables
with the same variance
$$\sigma^2 \in \mathbb{R}^+$$

(the variance σ^2 is also unknown).

for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$



Stack the observations y_{ijk} into the (IJK)-dimensional vector

$$y = (y_{ijk})_{\substack{i=1,2,\dots,l\\j=1,2,\dots,J\\k=1,2,\dots,K}} \in \mathbb{R}^{I \times J \times K}$$

and introduce the sample mean:

$$\bar{y} = \frac{1}{IJK} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} y_{ijk}$$

This sample mean is an estimate of the parameter μ (the common mean value):

$$\overline{y} \approx \mu$$





Let $\mathbf{1} = (1)_{\substack{i=1,2,\dots,I\\j=1,2,\dots,J\\k=1,2,\dots,K}} \in \mathbb{R}^{I \times J \times K}$ be the vector of IJK ones and

introduce the line

$$L = \{ \mathbf{1}\lambda : \lambda \in \mathbb{R} \} =$$
$$= \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu, \ \mu \in \mathbb{R} \} =$$
$$= \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, \ \mu \in \mathbb{R}, \ \alpha_i = 0, \ \beta_j = 0, \ \gamma_{ij} = 0 \}$$

which corresponds to the null hypothesis that

$$H_0: \quad Y_{ijk} = \mu + \varepsilon_{ijk}$$

that is

(cf. one-way ANOVA)

for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$



Moreover, introduce the subspace

$$H_{\mathbf{A}} = \left\{ \begin{aligned} \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, & \mu, \beta_j, \gamma_{ij} \in \mathbb{R}, & \alpha_i = 0, \\ \sum_{j=1}^J \beta_j = 0, & \sum_{i=1}^I \gamma_{ij} = 0, & \sum_{j=1}^J \gamma_{ij} = 0 \end{aligned} \right\}$$

which corresponds to the null hypothesis

H_A:
$$Y_{ijk} = \mu + \beta_j + \gamma_{ij} + \varepsilon_{ijk}$$
 for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

that is

$$\alpha_1 = \cdots = \alpha_I = 0$$

Observe that the line

 $L \subset H_{\mathbf{A}}$



$$H_{\rm B} = \left\{ \begin{aligned} \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, & \mu, \alpha_i, \gamma_{ij} \in \mathbb{R}, & \beta_j = 0, \\ \sum_{i=1}^{I} \alpha_i = 0, & \sum_{i=1}^{I} \gamma_{ij} = 0, & \sum_{j=1}^{J} \gamma_{ij} = 0 \end{aligned} \right\}$$

which corresponds to the null hypothesis

Here the the manufactor
$$H_{\mathbf{B}}$$
: $Y_{ijk} = \mu + \alpha_i + \gamma_{ij} + \varepsilon_{ijk}$ for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$
 $\beta_1 = \cdots = \beta_J = 0$

that is

$$L \subset H_{\rm B}$$



$$H_{AB} = \begin{cases} z \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, & \mu, \alpha_i, \beta_j \in \mathbb{R}, & \gamma_{ij} = 0, \\ \sum_{i=1}^{I} \alpha_i = 0, & \sum_{j=1}^{J} \beta_j = 0 \end{cases}$$

which corresponds to the null hypothesis

$$H_{AB}: \quad Y_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

that is

$$y_{ij} = 0$$
 for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \end{cases}$

for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$

Observe that the line

$$L \subset H_{AB}$$



$$M = \left\{ \begin{array}{c} \boldsymbol{z} \in \mathbb{R}^{I \times J \times K} : \boldsymbol{z}_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, \quad \mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}, \\ \sum_{i=1}^{I} \alpha_i = 0, \quad \sum_{j=1}^{J} \beta_j = 0, \quad \sum_{i=1}^{I} \gamma_{ij} = 0, \quad \sum_{j=1}^{J} \gamma_{ij} = 0 \end{array} \right\}$$

which corresponds to the model under consideration:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ijk} + \varepsilon_{ijk} \quad \text{for} \quad \begin{cases} j = 1, 2, ..., J \\ k = 1, 2, ..., K \end{cases}$$



(i = 1, 2, ..., I)



Two-way ANOVA with interactions: Dimensions

Notice that the dimension of

- the line

$$L = \{ \mathbf{1}\lambda : \lambda \in \mathbb{R} \} = \{ \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu, \ \mu \in \mathbb{R} \}$$
is

- the subspace

$$M = \begin{cases} \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, \quad \mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}, \\ \sum_{i=1}^{I} \alpha_i = 0, \quad \sum_{j=1}^{J} \beta_j = 0, \quad \sum_{i=1}^{I} \gamma_{ij} = 0, \quad \sum_{j=1}^{J} \gamma_{ij} = 0 \end{cases}$$
is

$$(1 + I + I + II) - 1 - 1 - I - I + 1 = II$$



Two-way ANOVA with interactions: Dimensions

Notice that the dimension of

- the subspace

$$H_{A} = \begin{cases} z \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_{i} + \beta_{j} + \gamma_{ij}, \quad \mu, \beta_{j}, \gamma_{ij} \in \mathbb{R}, \quad \alpha_{i} = 0, \\ \sum_{j=1}^{J} \beta_{j} = 0, \quad \sum_{i=1}^{I} \gamma_{ij} = 0, \quad \sum_{j=1}^{J} \gamma_{ij} = 0 \end{cases}$$
is

$$(1 + J + IJ) - 1 - J - I + 1 = IJ - I + 1 = I(J - 1) + 1$$
- the subspace

$$H_{B} = \begin{cases} z \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_{i} + \beta_{j} + \gamma_{ij}, \quad \mu, \alpha_{i}, \gamma_{ij} \in \mathbb{R}, \quad \beta_{j} = 0, \\ \sum_{i=1}^{I} \alpha_{i} = 0, \quad \sum_{i=1}^{I} \gamma_{ij} = 0, \quad \sum_{j=1}^{J} \gamma_{ij} = 0 \end{cases}$$
is



Two-way ANOVA with interactions: Dimensions

Notice that the dimension of

- the subspace

$$H_{AB} = \begin{cases} \mathbf{z} \in \mathbb{R}^{I \times J \times K} : z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij}, \quad \mu, \alpha_i, \beta_j \in \mathbb{R}, \quad \gamma_{ij} = 0, \\ \sum_{i=1}^{I} \alpha_i = 0, \quad \sum_{j=1}^{J} \beta_j = 0 \end{cases}$$
is
$$(1 + I + J) - 1 - 1 = I + J - 1$$

Solve the Least Squares Problem:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu-\alpha_i-\beta_j-\gamma_{ij})^2 \to \min$$

subject to

and

$$\sum_{i=1}^{I} \alpha_i = 0 \qquad \sum_{i=1}^{I} \gamma_{ij} = 0 = \sum_{j=1}^{J} \gamma_{ij} \qquad \sum_{j=1}^{J} \beta_j = 0$$

 $\mu, \alpha_i, \beta_j, \gamma_{ij} \in \mathbb{R}$





Letting $\hat{y}_{ijk} = \mu - \alpha_i - \beta_j - \gamma_{ij}$, it is equivalent to solve the problem:

$$\min_{\widehat{\mathbf{y}}\in M}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{ijk}-\mu-\alpha_{i}-\beta_{j}-\gamma_{ij}\right)^{2} = \min_{\widehat{\mathbf{y}}\in M}\|\mathbf{y}-\widehat{\mathbf{y}}\|^{2} = RSS$$



Solve also:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu-\beta_j-\gamma_{ij})^2 \rightarrow \min$$

subject to

and



 $\mu, \beta_j, \gamma_{ij} \in \mathbb{R}$



Solve also:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu-\alpha_i-\gamma_{ij})^2 \rightarrow \min$$

subject to



and

 $\mu, \alpha_i, \gamma_{ij} \in \mathbb{R}$





Letting $\hat{y}_{Aijk} = \mu - \beta_j$ and $\hat{y}_{Bijk} = \mu - \alpha_i$, respectively,

it is equivalent to solve the problems:

$$\min_{\widehat{\mathbf{y}}_{A}\in\mathcal{H}_{A}}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(y_{ijk}-\mu-\beta_{j}-\gamma_{ij}\right)^{2} = \min_{\widehat{\mathbf{y}}_{A}\in\mathcal{H}_{A}}\|\mathbf{y}-\widehat{\mathbf{y}}_{A}\|^{2}$$

and

$$\min_{\widehat{\mathbf{y}}_{\mathsf{B}}\in H_{\mathsf{B}}} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \alpha_i - \gamma_{ij})^2 = \min_{\widehat{\mathbf{y}}_{\mathsf{B}}\in H_{\mathsf{B}}} ||\mathbf{y} - \widehat{\mathbf{y}}_{\mathsf{B}}||^2$$

respectively.

No.

Solve also the Least Squares Problem:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu-\alpha_i-\beta_j)^2 \rightarrow \min$$

subject to



 $\mu,\,\alpha_1,\,\ldots,\,\alpha_I,\,\beta_1,\,\ldots,\,\beta_J\in\mathbb{R}$

and



Letting $\hat{y}_{ABijk} = \mu - \alpha_i - \beta_j$, it is equivalent to solve the problem:

$$\min_{\widehat{\mathbf{y}}_{AB}\in H_{AB}} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \left(y_{ijk} - \mu - \alpha_i - \beta_j \right)^2 = \min_{\widehat{\mathbf{y}}_{AB}\in H_{AB}} \|\mathbf{y} - \widehat{\mathbf{y}}_{AB}\|^2$$

Lastly, solve:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu)^2 \to \min$$

subject to

 $\mu \in \mathbb{R}$

By letting $\bar{y} = \mu$, equivalently:

$$\min_{\mathbf{1}\overline{\mathbf{y}}\in L}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\mu)^{2} = \min_{\mathbf{1}\overline{\mathbf{y}}\in L}||\mathbf{y}-\mathbf{1}\overline{\mathbf{y}}||^{2}$$





Put together, we have:

$$\begin{aligned} \|y\|^{2} &= \|\widehat{y}\|^{2} + \|e\|^{2} \\ \|y\|^{2} &= \|\widehat{y}\|^{2} + \|y - \widehat{y}\|^{2} \\ \|y - 1\overline{y}\|^{2} &= \|\widehat{y} - 1\overline{y}\|^{2} + \|(y - 1\overline{y}) - (\widehat{y} - 1\overline{y})\|^{2} \\ \|y - 1\overline{y}\|^{2} &= \|\widehat{y} - 1\overline{y}\|^{2} + \|y - \widehat{y}\|^{2} \\ \|y - 1\overline{y}\|^{2} &= \|\widehat{y} - 1\overline{y}\|^{2} + \|e\|^{2} \\ \|y - 1\overline{y}\|^{2} &= \|\widehat{y} - \widehat{y}_{A}\|^{2} + \|\widehat{y} - \widehat{y}_{B}\|^{2} + \|\widehat{y} - \widehat{y}_{AB}\|^{2} + \|e\|^{2} \end{aligned}$$





We have and denote:

$$\underbrace{\|\mathbf{y} - \mathbf{1}\bar{\mathbf{y}}\|^2}_{SS_{TOTAL}} = \underbrace{\|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_A\|^2}_{SS_A} + \underbrace{\|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_B\|^2}_{SS_B} + \underbrace{\|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{AB}\|^2}_{SS_{AB}} + \underbrace{\|\mathbf{e}\|^2}_{RSS}$$

where, recall, we have:

$$\begin{split} \hat{y}_{ijk} &= \mu + \alpha_i + \beta_j + \gamma_{ij} \\ \hat{y}_{Aijk} &= \mu + \beta_j \\ \bar{y}_{ABijk} &= \mu + \gamma_{ij} \\ \bar{y} &= \mu + \alpha_i \\ \bar{y} &= \mu \end{split}$$



We thus have:

$$SS_{TOTAL} = \|\boldsymbol{y} - \boldsymbol{1}\bar{\boldsymbol{y}}\|^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{\boldsymbol{y}})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu)^2$$

RSS =
$$\|\boldsymbol{e}\|^2 = \|\boldsymbol{y} - \hat{\boldsymbol{y}}\|^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{y}_{ijk})^2 =$$

= $\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \mu - \alpha_i - \beta_j - \gamma_{ij})^2$
We thus have:

$$SS_{A} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{A}\|^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\widehat{\mathbf{y}}_{ijk} - \widehat{\mathbf{y}}_{Aijk})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\mu + \alpha_{i} + \beta_{j} + \gamma_{ij} - \mu - \beta_{j} - \gamma_{ij})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_{i}^{2} = JK \sum_{i=1}^{I} \alpha_{i}^{2}$$



We thus have:

$$SS_{B} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{B}\|^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\widehat{\mathbf{y}}_{ijk} - \widehat{\mathbf{y}}_{Bijk})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\mu + \alpha_{i} + \beta_{j} + \gamma_{ij} - \mu - \alpha_{i} - \gamma_{ij})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{j}^{2} = IK \sum_{i=1}^{I} \beta_{j}^{2}$$



We thus have:

$$SS_{AB} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{AB}\|^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\widehat{\mathbf{y}}_{ijk} - \widehat{\mathbf{y}}_{ABijk})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (\mu + \alpha_{i} + \beta_{j} + \gamma_{ij} - \mu - \alpha_{i} - \beta_{j})^{2} =$$
$$= \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{ij}^{2} = K \sum_{i=1}^{I} \sum_{j=1}^{J} \gamma_{ij}^{2}$$





By solving the above Least Squares Problems

 $(\partial F/\partial \mu = \partial F/\partial \alpha_i = \partial F/\partial \beta_j = \partial F/\partial \gamma_{ij} = 0$ etc.; <u>do it as an exercise</u>), we obtain:

$$\hat{\mu} = \frac{1}{IJK} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} y_{ijk} = \bar{y} = \bar{y}...$$



By solving the above Least Squares Problems

 $(\partial F/\partial \mu = \partial F/\partial \alpha_i = \partial F/\partial \beta_j = \partial F/\partial \gamma_{ij} = 0$ etc.; <u>do it as an exercise</u>), we obtain:

$$\hat{\alpha}_i = \frac{1}{JK} \sum_{j=1}^J \sum_{k=1}^K y_{ijk} - \hat{\mu} = \bar{y}_{i..} - \bar{y}$$
 for $i = 1, 2, ..., I$

$$\hat{\beta}_{j} = \frac{1}{IK} \sum_{i=1}^{I} \sum_{k=1}^{K} y_{ijk} - \hat{\mu} = \bar{y}_{.j.} - \bar{y}$$
 for $j = 1, 2, ..., J$



By solving the above Least Squares Problems

 $(\partial F/\partial \mu = \partial F/\partial \alpha_i = \partial F/\partial \beta_j = \partial F/\partial \gamma_{ij} = 0$ etc.; <u>do it as an exercise</u>), we obtain:

$$\hat{\gamma}_{ij} = \frac{1}{K} \sum_{k=1}^{K} y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j = \bar{y}_{ij} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y} = \bar{y}_{ij} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...}$$

for i = 1, 2, ..., I and for j = 1, 2, ..., J

Put together, we have:

$$SS_{TOTAL} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{\mu})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y})^2$$

$$SS_A = JK \sum_{i=1}^{I} \hat{\alpha}_i^2 = JK \sum_{i=1}^{I} (\bar{y}_{i\cdots} - \bar{y})^2$$

$$SS_B = IK \sum_{j=1}^{J} \hat{\beta}_j^2 = IK \sum_{j=1}^{J} (\bar{y}_{.j\cdots} - \bar{y})^2$$

$$SS_{AB} = K \sum_{i=1}^{I} \sum_{j=1}^{J} \hat{\gamma}_{ij}^2 = K \sum_{i=1}^{I} \sum_{j=1}^{J} (\bar{y}_{ij\cdots} - \bar{y}_{.i\cdots} - \bar{y}_{.j\cdots} + \bar{y}_{...})^2$$



Two-way ANOVA with interactions

Put together, we have:

$$RSS = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_{ij})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{ij})^2$$

Remark: The quantity

$$s^2 = \frac{\text{RSS}}{IJ(K-1)}$$

is an estimate of the unknown σ^2 , that is $s^2 \approx \sigma^2$. We have $E[s^2] = \sigma^2$.

秋

Recall that it holds:

$$SS_{TOTAL} = SS_A + SS_B + SS_{AB} + RSS$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y})^2 = JK \sum_{i=1}^{I} (\bar{y}_{i\cdots} - \bar{y})^2 + IK \sum_{j=1}^{J} (\bar{y}_{.j\cdots} - \bar{y})^2 + K \sum_{j=1}^$$

$$+K\sum_{i=1}^{I}\sum_{j=1}^{J}(\bar{y}_{ij.}-\bar{y}_{i..}-\bar{y}_{.j.}+\bar{y}_{...})^{2}+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\bar{y}_{ij.})^{2}$$



We use the theory of Linear Regression (Theorem 8) to test Hypothesis H_A :

If the null hypothesis

$$H_{\mathbf{A}}: \quad \alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$$

holds true, then

$$\frac{SS_A}{RSS} / \frac{\dim M - \dim H_A}{IJK - \dim M} = \frac{SS_A}{RSS} / \frac{I-1}{IJ(K-1)} \sim F_{I-1,IJ(K-1)}$$

that is

$$\frac{JK\sum_{i=1}^{I}(\bar{y}_{i\cdots}-\bar{y})^{2}}{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(y_{ijk}-\bar{y}_{ij\cdot})^{2}} / \frac{I-1}{IJ(K-1)} \sim F_{I-1,IJ(K-1)}$$

Two-way ANOVA with interactions: Test for H_{Δ} It holds: M^{\perp} $\cot^2 \varphi = \frac{(\widehat{\boldsymbol{y}} - \widehat{\boldsymbol{y}}_A)^{\mathrm{T}} (\widehat{\boldsymbol{y}} - \widehat{\boldsymbol{y}}_A)}{\mathrm{RSS}}$ (the orthogonal complement = = the space of $e = y - \hat{y}$ the residuals) $(\cot an \varphi)^2 / \frac{I-1}{IIK-II} \sim F_{I-1,IJK-IJ}$ subspace of dimension IJK - IJМ subspace of dimension]] $H_{\mathbf{A}}$ subspace of dimension the dimension of its complement within the subspace of dimension IJ is I(J - 1) + 1



$$H_{\mathbf{A}}: \quad \alpha_1 = \alpha_2 = \cdots = \alpha_I = 0$$

• The alternative hypothesis is $H_{A1} \equiv \neg H_A$, i.e. $\alpha_i \neq 0$ for some $i \in \{1, 2, ..., I\}$



Calculate the statistic

$$F = \frac{\mathrm{SS}_{\mathrm{A}}}{\mathrm{RSS}} \Big/ \frac{\mathrm{DF}_{\mathrm{A}}}{\mathrm{DF}_{\mathrm{RSS}}} = \frac{JK \sum_{i=1}^{I} (\bar{y}_{i\cdots} - \bar{y})^{2}}{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{ij})^{2}} \Big/ \frac{I - 1}{IJ(K - 1)}$$

• If the null hypothesis is true, then we have by the Theorem

 $F \sim F_{I-1,IJ(K-1)}$

• Choose the level of significance, a small number $\alpha > 0$, such as $\alpha = 5$ %, other popular values are $\alpha = 10$ % or $\alpha = 1$ % or $\alpha = 0.1$ % etc.



find the critical value

$$c = F_{I-1,IJ(K-1)} (1-\alpha)$$

so that $\int_{c}^{+\infty} f(x) dx = \alpha$ where f is the density of the *F*-distribution with I - 1 and IJ(K - 1) degrees of freedom

- if $F \in [c, +\infty)$, the critical region, then <u>reject</u> the null hypothesis
- if $F \in [0, c)$, then <u>do not reject</u> (or <u>fail to reject</u>) the null hypothesis

We can test Hypothesis H_B analogously:

If the null hypothesis

$$H_{\rm B}: \quad \beta_1 = \beta_2 = \cdots = \beta_J = 0$$

holds true, then

$$\frac{SS_{B}}{RSS} / \frac{\dim M - \dim H_{B}}{IJK - \dim M} = \frac{SS_{B}}{RSS} / \frac{J-1}{IJ(K-1)} \sim F_{J-1,IJ(K-1)}$$

that is

$$\frac{IK\sum_{j=1}^{J} (\bar{y}_{.j.} - \bar{y})^2}{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{ij.})^2} / \frac{J-1}{IJ(K-1)} \sim F_{J-1,IJ(K-1)}$$



We use the theory of Linear Regression (Theorem 8) to test Hypothesis H_{AB} :

If the null hypothesis

*H*_{AB}:
$$\gamma_{ij} = 0$$
 for $\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \end{cases}$

holds true, then

$$\frac{SS_{AB}}{RSS} / \frac{\dim M - \dim H_{AB}}{IJK - \dim M} = \frac{SS_{AB}}{RSS} / \frac{(I-1)(J-1)}{IJ(K-1)} \sim F_{(I-1)(J-1),IJ(K-1)}$$

that is

$$\frac{K \sum_{i=1}^{I} \sum_{j=1}^{J} \left(\bar{y}_{ij} - \bar{y}_{i} - \bar{y}_{i} + \bar{y}_{i} \right)^{2}}{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \left(y_{ijk} - \bar{y}_{ij} \right)^{2}} / \frac{(I-1)(J-1)}{IJ(K-1)} \sim F_{(I-1)(J-1),IJ(K-1)}$$





*H*_{AB}:
$$\gamma_{ij} = 0$$
 for $\begin{cases} l = 1, 2, ..., I \\ j = 1, 2, ..., J \end{cases}$

• The alternative hypothesis is $H_{AB1} \equiv \neg H_{AB}$,



Calculate the statistic

$$F = \frac{SS_{AB}}{RSS} / \frac{DF_{AB}}{DF_{RSS}} = \frac{K \sum_{i=1}^{I} \sum_{j=1}^{J} (\bar{y}_{ij} - \bar{y}_{ij} - \bar{y}_{ij} + \bar{y}_{ij})^2}{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (y_{ijk} - \bar{y}_{ij})^2} / \frac{(I-1)(J-1)}{IJ(K-1)}$$

· If the null hypothesis is true, then we have by the Theorem

$$F \sim F_{(l-1)(j-1), Ij(K-1)}$$

• Choose the level of significance, a small number $\alpha > 0$, such as $\alpha = 5$ %, other popular values are $\alpha = 10$ % or $\alpha = 1$ % or $\alpha = 0.1$ % etc.



find the critical value

$$c = F_{(I-1)(J-1),IJ(K-1)} (1-\alpha)$$

so that $\int_{c}^{+\infty} f(x) dx = \alpha$ where f is the density of the *F*-distribution with (I-1)(J-1) and IJ(K-1) degrees of freedom

- if $F \in [c, +\infty)$, the critical region, then <u>reject</u> the null hypothesis
- if $F \in [0, c)$, then <u>do not reject</u> (or <u>fail to reject</u>) the null hypothesis