Statistical Methods for Economists

Lecture (7 & 8)d

Four-Way Analysis of Variance (ANOVA) — Græco-Latin Squares

[Graeco / Greco]



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- Four-way ANOVA: Introduction
- Græco-Latin squares
- Four-way ANOVA simplified by using Græco-Latin squares

We have:

- a set of distinct cars
- a set of distinct drivers
- several types of car-fuel (e.g. fuel with various additives)
- several types of tyres

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, the type of the fuel, and on the type of the tyres.

In particular, we have:

- I distinct cars (i = 1, 2, ..., I)
- J distinct drivers (j = 1, 2, ..., J)
- K distinct types of fuel (k = 1, 2, ..., K)
- L distinct types of types (l = 1, 2, ..., L)



There are four factors in this example:

- factor A = the car (i = 1, 2, ..., I)
- factor B = the driver (j = 1, 2, ..., J)
- factor C = the type of the fuel (k = 1, 2, ..., K)
- factor D = the type of the tyres (l = 1, 2, ..., L)

There are $IJKL = I \times J \times K \times L$ distinct combinations of the factors.





Considering the $IJKL = I \times J \times K \times L$ distinct combinations of the factors

(the Cartesian product), we assume that each combination is tested n_{ijkl} -times. We thus have a sample

vie mus have a sample
$$y_{ijklm}$$
for $i = 1, 2, ..., I$ $j = 1, 2, ..., J$ $j = 1, 2, ..., J$ $k = 1, 2, ..., K$ $l = 1, 2, ..., L$ $Y_{ijklm}: \Omega \rightarrow \mathbb{R}$ $m = 1, 2, ..., n_{ijkl}$

These random variables are assumed to be normal $(Y_{ijkl} \sim \mathcal{N}(\mu_{ijk}, \sigma^2))$,

independent (uncorrelated) and homoscedastic (with the same variance σ^2).

秋

We assume that the effect of the factors A, B, C, D is additive.

Moreover, it is possible to distinguish many combinations of interactions, e.g.:

• No interactions between / among the factors:

 $Y_{ijklm} \approx \mu + \alpha_i + \beta_j + \gamma_k + \delta_l$

- Etc.
- All interactions between and among the factors:

$$\begin{split} Y_{ijklm} &\approx \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \\ &+ \lambda_{ij}^{AB} + \lambda_{ik}^{AC} + \lambda_{il}^{AD} + \lambda_{jk}^{BC} + \lambda_{jl}^{BD} + \lambda_{kl}^{CD} + \\ &+ \lambda_{ijk}^{ABC} + \lambda_{ijl}^{ABD} + \lambda_{ikl}^{ACD} + \lambda_{jkl}^{BCD} \end{split}$$

for
$$\begin{cases} i = 1, 2, ..., I \\ j = 1, 2, ..., J \\ k = 1, 2, ..., K \\ l = 1, 2, ..., L \\ m = 1, 2, ..., n_{ijkl} \end{cases}$$



We assume that the effect of the factors A, B, C, D is additive.

Moreover, it is possible to distinguish many combinations of interactions, e.g.:

$$Y_{ijklm} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijklm}$$

Etc.

$$Y_{ijklm} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l +$$
for
$$\begin{cases}
i = 1, 2, ..., I \\
j = 1, 2, ..., I \\
k = 1, 2, ..., K \\
l = 1, 2, ..., L \\
m = 1, 2, ..., n_{ijkl}
\end{cases}$$

$$+ \lambda_{ij}^{AB} + \lambda_{ik}^{AC} + \lambda_{il}^{AD} + \lambda_{jk}^{BC} + \lambda_{jl}^{BD} + \lambda_{kl}^{CD} + \lambda_{kl}^{ABC} + \lambda_{ijk}^{ABC} + \lambda_{ijl}^{ABD} + \lambda_{ikl}^{ACD} + \lambda_{jkl}^{BCD}$$

For simplicity, we shall consider the model with no interactions only:

$$Y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl}$$

where the parameters

 $\mu, \alpha_i, \beta_j, \gamma_k, \delta_l \in \mathbb{R}$

are <u>unknown</u> and normalized so that:

$$\sum_{i=1}^{I} \alpha_{i} = 0 \qquad \sum_{j=1}^{J} \beta_{j} = 0 \qquad \sum_{k=1}^{K} \gamma_{k} = 0 \qquad \sum_{l=1}^{L} \delta_{l} = 0$$





It is possible to consider the general situation with a general number $n_{ijkl} \ge 1$ of observations for each combination of the factors and it is also possible to formulate and test various null hypotheses $(\alpha_i = 0 / \lambda_{ij}^{AB} = 0 / \lambda_{ijk}^{ABC} = 0 / \lambda_{ijk}$

 $\lambda_{ijkl}^{ABCD} = 0$ / etc.), but there are plenty of calculations and the resulting formulas are complicated.

This is why we shall study the following special case only:

(see the next slide)



We assume for simplicity that the number of the levels of all four factors is the same:

$$I=J=K=L$$

In addition to that, we do not perform all the observations for each combination of the factors (because the number of the necessary experiments would soon become infeasible).

Instead, we perform either exactly one observation $(n_{ijkl} = 1)$ or no observation

at all $(n_{ijkl} = 0)$ according to the scheme called **Græco-Latin square**.





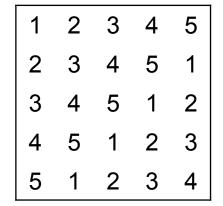


A Latin square of order *N* is an arrangement of *N* symbols, such as $\{1, 2, ..., N\}$, where each symbol is repeated *N*-times, into an $N \times N$ square table in such a way that

- · in each column, each symbol occurs exactly once and
- in each row, each symbol occurs exactly once.

For example:

1 2 3 2 3 1 3 1 2 1 2 3 3 1 2 2 3 1





Let *A* and *B* be two Latin squares (i.e. matrices) of order *N*. We say that the two Latin squares are **orthogonal** if and only if,

for each pair (r, s) of symbols $(r, s \in \{1, 2, ..., N\})$,

there exists (exactly one) pair (i, j) of indices $(i, j \in \{1, 2, ..., N\})$ so that

$$a_{ij} = r$$
 and $b_{ij} = s$

	3 1 2		2 1 3	=	1,□ 1 2,□ 3	2	3	
					3,□ 2	1,⊡ ੨	2,□ 1	



Let *A* and *B* be two Latin squares (i.e. matrices) of order *N*. We say that the two Latin squares are **orthogonal** if and only if,

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$$a_{ij} = r$$
 and $b_{ij} = s$

1	2	3	4		1	2	3	4	1,□ 2,□ 3,□ 4,□	
2	1	4	3	o	3	4	1	2	_ 1 2 3 4	
3	4	1	2	&	4	3	2	1	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	
4	3	2	1		2	1	4	3	$\begin{vmatrix} 3 & 4 & 1 & 2 \\ 3, \Box & 4, \Box & 1, \Box & 2, \Box \end{vmatrix}$	



The following statements are equivalent:

- The Latin squares A and B of order N are orthogonal.
- For each pair (r,s) of symbols (r,s ∈ {1, 2, ..., N}),
 there exists (exactly one) pair (i, j) of indices (i, j ∈ {1, 2, ..., N}) so that

$$a_{ij} = r$$
 and $b_{ij} = s$

For each pair (*i*, *j*) of indices (*i*, *j* ∈ {1, 2, ..., N}),
 there exists (exactly one) pair (*r*, *s*) of symbols (*r*, *s* ∈ {1, 2, ..., N}) so that

$$a_{ij} = r$$
 and $b_{ij} = s$

• For every $i, j, k, l \in \{1, 2, ..., N\}$



Let $A_1, A_2, ..., A_k$ be a collection of Latin squares (i.e. matrices) of order N. We say that the Latin squares $A_1, A_2, ..., A_k$ are **pairwise orthogonal** if and only if the squares A_i and A_j are orthogonal whenever $i, j \in \{1, 2, ..., k\}$ and $i \neq j$.

Let $\mathcal{N}(N)$ denote the maximal number k of (elements in a collection of) pairwise orthogonal Latin squares of order N.

It is easy to see:

$$1 \leq \mathcal{N}(N) \leq N-1$$



A collection $A_1, A_2, ..., A_k$ of pairwise orthogonal Latin squares of order N is called **complete** if and only if

$$k=N-1$$

The following is known:

- If N is a power of a prime number (that is $N = p^k$ for some prime number p and a natural number k), then $\mathcal{N}(N) = N - 1$.
- We have $\mathcal{N}(6) = 1$.
- If $N \ge 3$ and $N \ne 6$, then $\mathcal{N}(N) \ge 2$.
- If $N \ge 4$ and $\mathcal{N}(N) \ge N-3$, then $\mathcal{N}(N) = N-1$.

Orthogonal Latin squares: The following is known:

N	1	2	3	4	5	6	7	8	9	10
$\mathcal{N}(N)$		1	2	3	4	1	6	7	8	≥□ 2

Ν	11	12	13	14	15	16	17	18	19	20
$\mathcal{N}(N)$	10	≥□ 5	12	≥□ 3	≥□ 4	15	16	≥□ 3	18	≥□ 4

N	21	22	23	24	25	•••
$\mathcal{N}(N)$	≥□ 4	≥□ 3	22	≥□ 4	24	





A pair of orthogonal Latin squares is also called a Græco-Latin square or

Graeco-Latin square or Greco-Latin square.

The name "Græco-Latin square" is inspired by the work of Leonhard Euler

(1707–1783), a Swiss mathematician, physicist, astronomer, geographer,

logician, and engineer who used the upper-case letters of the Latin alphabet

and the lower-case letters of the Greek alphabet as the symbols in the respective

=

square:

А	В	С	D	
В	А	D	С	
С	D	А	В	
D	С	В	Α	

	α	β	γ	δ	
8	Y	δ γ	α	β	
Q	δ	Y	β	α	
	β	α	δ	Y	

Αα	Ββ	Сү	Dδ
Вγ	Aδ	Dα	Сβ
Сδ	Dγ	Αβ	Βα
Dβ	Сα	Βδ	Aγ

· Assume that each of the four factors A, B, C, D has the same number of levels

$$I = J = K = L = N$$

for some natural number $N \ge 2$. — iii Assume also that $N \ne 6$!!!

- Arrange (or denote) the factors A, B, C, D so that
 - we assume that factors A, B, C ("<u>blocking factors</u>") do have some effect on the observed values
 - we ask (test the hypothesis) whether factor D ("treatment") has any effect on the observed values





- Arrange the N×N = N² pairs (k, l) into a Græco-Latin square of order N.
 (We consider k, l ∈ {1, 2, ..., N}.)
- There are plenty of distinct Græco-Latin squares of order N.
- It is recommended: The Latin square should be chosen randomly.

Now, given the Græco-Latin square of type $N \times N$,

define the numbers n_{ijkl} as follows:

$$n_{ijkl} = \begin{cases} 1, & \text{if the pair } (k,l) \text{ is at the position } (i,j), \\ 0, & \text{otherwise.} \end{cases}$$

for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \end{cases}$$



Then,

- for each i = 1, 2, ..., N and for each j = 1, 2, ..., N,
- find the unique pair $k, l \in \{1, 2, ..., N\}$ such that $n_{ijkl} = 1$,
- set up Factor A to the level *i* and set up Factor B to the level *j*,
- set up Factor C to the level k and set up Factor D to the level l,
- · carry out the experiment,
- observe the numerical outcome y_{ijkl1} of the random variable Y_{ijkl1}

Recall that Factors A, B, C are assumed to have some effect ("blocks").



We assume that the effect of Factors A, B, C, D is additive and that there are no interactions between / among the factors:

$$Y_{ijkl1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

for $\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ & n_{ijkl} = 1 \end{cases}$

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

- μ the common mean value
- α_i the effect of the level *i* of Factor A (for i = 1, 2, ..., N)
- β_j the effect of the level *j* of Factor B (for j = 1, 2, ..., N)
- γ_k the effect of the level k of Factor C (for k = 1, 2, ..., N)
- δ_l the effect of the level l of Factor D (for l = 1, 2, ..., N)



We assume that the effect of Factors A, B, C, D is additive and that there are no interactions between / among the factors:

$$Y_{ijkl1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$$

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

$$\sum_{i=1}^{N} \alpha_i = 0 \qquad \qquad \sum_{j=1}^{N} \beta_j = 0 \qquad \qquad \sum_{k=1}^{N} \gamma_k = 0 \qquad \qquad \sum_{l=1}^{N} \delta_l = 0$$



We assume that the effect of Factors A, B, C, D is additive and that there are no interactions between / among the factors:

$$Y_{ijkl1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

for
$$\begin{cases} i = 1, 2, \dots, N \\ j = 1, 2, \dots, N \\ k = 1, 2, \dots, N \\ l = 1, 2, \dots, N \\ \& n_{ijkl} = 1 \end{cases}$$

We assume

- Factor A has some effect (that is $\alpha_i \neq 0$ for some $i \in \{1, 2, ..., N\}$)
- Factor B has some effect (that is $\beta_j \neq 0$ for some $j \in \{1, 2, ..., N\}$)
- Factor C has some effect (that is $\gamma_k \neq 0$ for some $k \in \{1, 2 \dots, N\}$)

We ask - test the null hypothesis - whether Factor D has any effect:

$$H_{\rm D}: \quad \delta_1 = \delta_2 = \cdots = \delta_N = 0$$

Four-Way ANOVA without interactions and simplified by using **Græco-Latin** squares

 $Y_{ijkl1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijk1}$



Assume that we have a sample

of observations of the random variables

$$Y_{ijk1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

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

so that

$$\sum_{i=1}^{N} \alpha_i = 0 \qquad \qquad \sum_{j=1}^{N} \beta_j = 0 \qquad \qquad \sum_{k=1}^{N} \gamma_k = 0 \qquad \qquad \sum_{l=1}^{N} \delta_l = 0$$



for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$$



Assume that we have a sample

of observations of the random variables

$$Y_{ijk1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

Yijkl1

...and

$$\varepsilon_{ijkl1} \sim \mathcal{N}(0,\sigma^2)$$

are mutually independent random variables with the same variance $\sigma^2 \in \mathbb{R}^+$ (the variance σ^2 is also unknown).



for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$$

秋

Denote the index set:

$$\mathcal{S} = \left\{ (i, j, k, l, 1) : i, j, k, l \in \{1, 2, \dots, N\}, n_{ijkl} = 1 \right\}$$

Notice that there are exactly N^2 elements in the index set S.

Indeed, for each pair (i, j) of the indices for i = 1, 2, ..., N and for j = 1, 2, ..., N, there exists exactly one pair (k, l) of symbols $k, l \in \{1, 2, ..., N\}$

such that $n_{ijkl} = 1$.

Stack the observations y_{ijk1} into the N²-dimensional vector

$$\mathbf{y} = \left(y_{ijkl1}\right)_{(i,j,k,l,1) \in \mathcal{S}} \in \mathbb{R}^{\mathcal{S}}$$

and introduce the sample mean:

$$\bar{y} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} y_{ijkl1}$$

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

 $\bar{y} \approx \mu$





$$L = \{ \mathbf{1}\lambda : \lambda \in \mathbb{R} \} =$$
$$= \{ \mathbf{z} \in \mathbb{R}^{S} : z_{ijkl1} = \mu, \ \mu \in \mathbb{R} \}$$

which corresponds to the null hypothesis that

*H*₀:
$$Y_{ijkl1} = \mu + \varepsilon_{ijkl1}$$
 for $\begin{cases} k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$

that is

$$\alpha_1 = \cdots = \alpha_N = 0$$
 $\beta_1 = \cdots = \beta_N = 0$ $\gamma_1 = \cdots = \gamma_N = 0$ $\delta_1 = \cdots = \delta_N = 0$

(cf. one-way ANOVA)

i = 1, 2, ..., Nj = 1, 2, ..., N



Moreover, introduce the subspace

$$H_{\mathbf{A}} = \begin{cases} \mathbf{z} \in \mathbb{R}^{\mathcal{S}} : z_{ijkl1} = \mu + \beta_j + \gamma_k + \delta_l, & \mu, \beta_j, \gamma_k, \delta_l \in \mathbb{R}, \\ \sum_{j=1}^N \beta_j = \sum_{k=1}^N \gamma_k = \sum_{l=1}^N \delta_l = 0 \end{cases}$$

which corresponds to the null hypothesis

$$H_{\mathbf{A}}: \quad Y_{ijkl1} = \mu + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

that is

$$\alpha_1=\cdots=\alpha_N=0$$

Observe that the line

 $L \subset H_A$



for
$$\begin{cases} i = 1, 2, \dots, N \\ j = 1, 2, \dots, N \\ k = 1, 2, \dots, N \\ l = 1, 2, \dots, N \\ \& n_{ijkl} = 1 \end{cases}$$

Introduce also the subspace

$$H_{\mathbf{B}} = \begin{cases} z \in \mathbb{R}^{\delta} : z_{ijkl1} = \mu + \alpha_i + \gamma_k + \delta_l, & \mu, \alpha_i, \gamma_k, \delta_l \in \mathbb{R}, \\ \sum_{i=1}^{N} \alpha_i = \sum_{k=1}^{N} \gamma_k = \sum_{l=1}^{N} \delta_l = 0 \end{cases}$$

which corresponds to the null hypothesis

$$H_{\rm B}: \quad Y_{ijkl1} = \mu + \alpha_i + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

that is

$$\beta_1=\cdots=\beta_N=0$$

for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ & n_{ijkl} = 1 \end{cases}$$

Observe that the line

 $L \subset H_{\rm B}$



Introduce also the subspace

$$H_{C} = \begin{cases} \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : z_{ijkl1} = \mu + \alpha_{i} + \beta_{j} + \delta_{l}, & \mu, \alpha_{i}, \beta_{j}, \delta_{l} \in \mathbb{R}, \\ \sum_{i=1}^{N} \alpha_{i} = \sum_{j=1}^{N} \beta_{j} = \sum_{l=1}^{N} \delta_{l} = 0 \end{cases}$$

which corresponds to the null hypothesis

$$H_{\rm C}: \quad Y_{ijkl1} = \mu + \alpha_i + \beta_j + \delta_l + \varepsilon_{ijkl1}$$

that is

$$\gamma_1 = \cdots = \gamma_N = 0$$

for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$$

Observe that the line

 $L \subset H_{C}$

And introduce also the subspace

$$H_{\rm D} = \begin{cases} \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : \boldsymbol{z}_{ijkl1} = \boldsymbol{\mu} + \boldsymbol{\alpha}_i + \boldsymbol{\beta}_j + \boldsymbol{\gamma}_k, \quad \boldsymbol{\mu}, \boldsymbol{\alpha}_i, \boldsymbol{\beta}_j, \boldsymbol{\gamma}_k \in \mathbb{R}, \\ \sum_{i=1}^N \boldsymbol{\alpha}_i = \sum_{j=1}^N \boldsymbol{\beta}_j = \sum_{k=1}^N \boldsymbol{\gamma}_k = \boldsymbol{0} \end{cases}$$

which corresponds to the null hypothesis

$$H_{\rm D}: \quad Y_{ijkl1} = \mu + \alpha_i + \beta_j + \delta_l + \varepsilon_{ijkl1}$$

that is

$$\delta_1=\cdots=\delta_N=0$$

Observe that the line

 $L \subset H_{D}$



for $\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ \& n_{ijkl} = 1 \end{cases}$



Finally, introduce the subspace

$$M = \left\{ \begin{aligned} \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : \boldsymbol{z}_{ijk1} = \boldsymbol{\mu} + \boldsymbol{\alpha}_i + \boldsymbol{\beta}_j + \boldsymbol{\gamma}_k + \boldsymbol{\delta}_l, \ \boldsymbol{\mu}, \boldsymbol{\alpha}_i, \boldsymbol{\beta}_j, \boldsymbol{\gamma}_k, \boldsymbol{\delta}_l \in \mathbb{R}, \\ \sum_{i=1}^N \boldsymbol{\alpha}_i = \sum_{j=1}^N \boldsymbol{\beta}_j = \sum_{k=1}^N \boldsymbol{\gamma}_k = \sum_{l=1}^N \boldsymbol{\delta}_l = 0 \end{aligned} \right\}$$

which corresponds to the model under consideration:

$$Y_{ijkl1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1}$$

for
$$\begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., N \\ k = 1, 2, ..., N \\ l = 1, 2, ..., N \\ k = n_{ijkl} = 1 \end{cases}$$

Notice that the dimension of the line

is

$$L = \left\{ \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : z_{ijk1} = \mu, \ \mu \in \mathbb{R} \right\}$$

 $\dim L = 1$





is

$$H_{\mathbf{A}} = \begin{cases} \mathbf{z} \in \mathbb{R}^{\mathcal{S}} : z_{ijkl1} = \mu + \beta_j + \gamma_k + \delta_l, & \mu, \beta_j, \gamma_k, \delta_l \in \mathbb{R}, \\ \sum_{j=1}^N \beta_j = \sum_{k=1}^N \gamma_k = \sum_{l=1}^N \delta_l = 0 \end{cases}$$

$$\dim H_{A} = (1 + N + N + N) - 1 - 1 - 1 = 3N - 2$$



$$H_{\rm B} = \begin{cases} z \in \mathbb{R}^{\mathcal{S}} : z_{ijkl1} = \mu + \alpha_i + \gamma_k + \delta_l, \quad \mu, \alpha_i, \gamma_k, \delta_l \in \mathbb{R}, \\ \sum_{i=1}^N \alpha_i = \sum_{k=1}^N \gamma_k = \sum_{l=1}^N \delta_l = 0 \end{cases}$$

 $\dim H_{\rm B} = (1 + N + N + N) - 1 - 1 - 1 = 3N - 2$



is

$$H_{C} = \begin{cases} \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : \boldsymbol{z}_{ijkl1} = \boldsymbol{\mu} + \boldsymbol{\alpha}_{i} + \boldsymbol{\beta}_{j} + \boldsymbol{\delta}_{l}, & \boldsymbol{\mu}, \boldsymbol{\alpha}_{i}, \boldsymbol{\beta}_{j}, \boldsymbol{\delta}_{l} \in \mathbb{R}, \\ \sum_{i=1}^{N} \boldsymbol{\alpha}_{i} = \sum_{j=1}^{N} \boldsymbol{\beta}_{j} = \sum_{l=1}^{N} \boldsymbol{\delta}_{l} = 0 \end{cases}$$

$$\dim H_{\rm C} = (1 + N + N + N) - 1 - 1 - 1 = 3N - 2$$



$$H_{\rm D} = \begin{cases} \boldsymbol{z} \in \mathbb{R}^{\mathcal{S}} : \boldsymbol{z}_{ijkl1} = \boldsymbol{\mu} + \boldsymbol{\alpha}_i + \boldsymbol{\beta}_j + \boldsymbol{\gamma}_k, \quad \boldsymbol{\mu}, \boldsymbol{\alpha}_i, \boldsymbol{\beta}_j, \boldsymbol{\gamma}_k \in \mathbb{R}, \\ \sum_{i=1}^{N} \boldsymbol{\alpha}_i = \sum_{j=1}^{N} \boldsymbol{\beta}_j = \sum_{k=1}^{N} \boldsymbol{\gamma}_k = \boldsymbol{0} \end{cases}$$

$$\dim H_{\rm D} = (1 + N + N + N) - 1 - 1 - 1 = 3N - 2$$



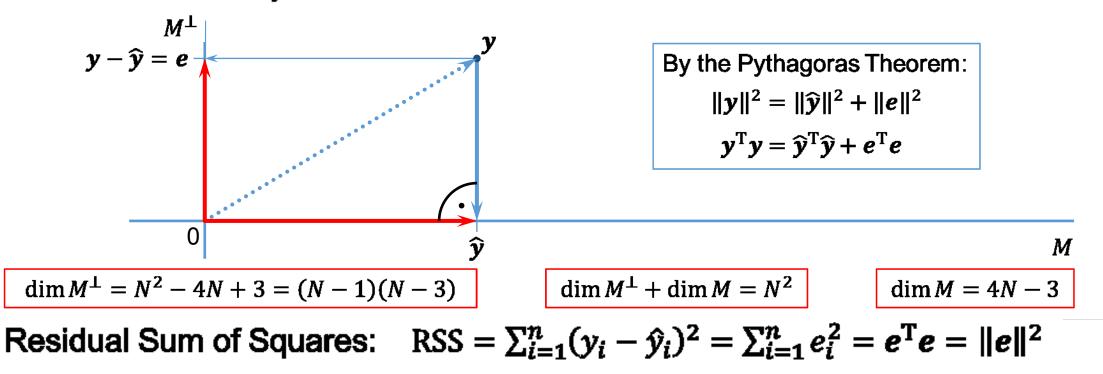
$$M = \left\{ \begin{aligned} \mathbf{z} \in \mathbb{R}^{\mathcal{S}} : z_{ijk1} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l, \ \mu, \alpha_i, \beta_j, \gamma_k, \delta_l \in \mathbb{R}, \\ \sum_{i=1}^N \alpha_i = \sum_{j=1}^N \beta_j = \sum_{k=1}^N \gamma_k = \sum_{l=1}^N \delta_l = 0 \end{aligned} \right\}$$

 $\dim M = (1 + N + N + N + N) - 1 - 1 - 1 - 1 = 4N - 3$



Letting $\hat{y}_{ijkl1} = \mu - \alpha_i - \beta_j - \gamma_k - \delta_l$, solve the Least Squares Problem:

$$\min_{\widehat{\mathbf{y}}\in M}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{\substack{l=1\\n_{ijkl}=1}}^{N}(y_{ijkl1}-\mu-\alpha_{i}-\beta_{j}-\gamma_{k}-\delta_{l})^{2} = \min_{\widehat{\mathbf{y}}\in M}||\mathbf{y}-\widehat{\mathbf{y}}||^{2} = RSS$$





Letting

$$\hat{y}_{Aijkl1} = \mu - \beta_j - \gamma_k - \delta_l$$
 and $\hat{y}_{Bijkl1} = \mu - \alpha_i - \gamma_k - \delta_l$

solve also the problems:

$$\min_{\hat{y}_{A} \in H_{A}} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl}=1}}^{N} (y_{ijkl1} - \mu - \beta_{j} - \gamma_{k} - \delta_{l})^{2} = \min_{\hat{y}_{A} \in H_{A}} ||y - \hat{y}_{A}||^{2}$$

and

$$\min_{\widehat{\mathbf{y}}_{B}\in H_{B}} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} \sum_{l=1}^{N} \left(y_{ijkl1} - \mu - \alpha_{i} - \gamma_{k} - \delta_{l} \right)^{2} = \min_{\widehat{\mathbf{y}}_{B}\in H_{B}} \|\mathbf{y} - \widehat{\mathbf{y}}_{B}\|^{2}$$



Letting

$$\hat{y}_{Cijkl1} = \mu - \alpha_i - \beta_j - \delta_l$$
 and $\hat{y}_{Dijkl1} = \mu - \alpha_i - \beta_j - \gamma_k$

solve also the problems:

$$\min_{\widehat{y}_{C}\in H_{C}} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} \sum_{l=1}^{N} (y_{ijkl1} - \mu - \alpha_{l} - \beta_{j} - \delta_{l})^{2} = \min_{\widehat{y}_{C}\in H_{C}} ||y - \widehat{y}_{C}||^{2}$$

and

$$\min_{\hat{y}_{D}\in H_{D}} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} (y_{ijkl1} - \mu - \alpha_{i} - \beta_{j} - \gamma_{k})^{2} = \min_{\hat{y}_{D}\in H_{D}} ||y - \hat{y}_{D}||^{2}$$

Finally, letting

$$\bar{y} = \mu$$

solve the Least Squares Problem:

$$\min_{\mathbf{1}\bar{y}\in L}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{\substack{l=1\\n_{ijkl}=1}}^{N}\left(y_{ijkl1}-\mu\right)^{2} = \min_{\mathbf{1}\bar{y}\in L}||\mathbf{y}-\mathbf{1}\bar{y}||^{2}$$



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We have and denote:

$$\underbrace{\|\underline{y} - \mathbf{1}\overline{y}\|^2}_{SS_{TOTAL}} = \underbrace{\|\widehat{y} - \widehat{y}_A\|^2}_{SS_A} + \underbrace{\|\widehat{y} - \widehat{y}_B\|^2}_{SS_B} + \underbrace{\|\widehat{y} - \widehat{y}_C\|^2}_{SS_C} + \underbrace{\|\widehat{y} - \widehat{y}_D\|^2}_{SS_D} + \underbrace{\|e\|^2}_{RSS}$$

where, recall, we have:

$$\begin{split} \hat{y}_{ijkl1} &= \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\gamma}_k \\ \hat{y}_{Aijkl1} &= \hat{\mu} + \hat{\beta}_j + \hat{\gamma}_k + \hat{\delta}_l \\ \hat{y}_{Cijkl1} &= \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\delta}_l \\ \hat{y}_{Cijkl1} &= \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\delta}_l \\ \bar{y} &= \mu \end{split}$$



Four-way ANOVA with no interactions

$$SS_{TOTAL} = \|\mathbf{y} - \mathbf{1}\bar{\mathbf{y}}\|^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (y_{ijkl1} - \bar{\mathbf{y}})^2 =$$

$$=\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{\substack{l=1\\n_{ijkl}=1}}^{N}\left(y_{ijkl1}-\hat{\mu}\right)^{2}$$



Four-way ANOVA with no interactions

$$RSS = \|\boldsymbol{e}\|^2 = \|\boldsymbol{y} - \hat{\boldsymbol{y}}\|^2 = \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^N \sum_{\substack{l=1\\n_{ijkl}=1}}^N \left(y_{ijkl1} - \hat{y}_{ijkl1} \right)^2 =$$

$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} (y_{ijkl1} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_l)^2$$

$$SS_{A} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{A}\|^{2} = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl}=1}}^{N} (\widehat{y}_{ijkl1} - \widehat{y}_{Aijkl1})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl}=1}}^{N} (\widehat{\mu} + \widehat{\alpha}_{i} + \widehat{\beta}_{j} + \widehat{\gamma}_{k} + \widehat{\delta}_{l} - \widehat{\mu} - \widehat{\beta}_{j} - \widehat{\gamma}_{k} - \widehat{\delta}_{l})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl}=1}}^{N} \widehat{\alpha}_{i}^{2} = N \sum_{i=1}^{N} \widehat{\alpha}_{i}^{2}$$



$$SS_{B} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{B}\|^{2} = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl} = 1}}^{N} (\widehat{y}_{ijkl1} - \widehat{y}_{Bijkl1})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl} = 1}}^{N} (\widehat{\mu} + \widehat{\alpha}_{i} + \widehat{\beta}_{j} + \widehat{\gamma}_{k} + \widehat{\delta}_{i} - \widehat{\mu} - \widehat{\alpha}_{i} - \widehat{\gamma}_{k} - \widehat{\delta}_{i})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \\ n_{ijkl} = 1}}^{N} \widehat{\beta}_{j}^{2} = N \sum_{j=1}^{N} \widehat{\beta}_{j}^{2}$$



$$SS_{C} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{C}\|^{2} = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (\widehat{y}_{ijkl1} - \widehat{y}_{Cijkl1})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (\widehat{\mu} + \widehat{\alpha}_{i} + \widehat{\beta}_{j} + \widehat{\gamma}_{k} + \widehat{\delta}_{i} - \widehat{\mu} - \widehat{\alpha}_{i} - \widehat{\beta}_{j} - \widehat{\delta}_{i})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{n_{ijkl}=1 \ n_{ijkl}=1}}^{N} \widehat{\gamma}_{k}^{2} = N \sum_{k=1}^{N} \widehat{\gamma}_{k}^{2}$$



$$SS_{D} = \|\widehat{\mathbf{y}} - \widehat{\mathbf{y}}_{D}\|^{2} = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl} = 1}}^{N} (\widehat{y}_{ijkl1} - \widehat{y}_{Dijkl1})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl} = 1}}^{N} (\widehat{\mu} + \widehat{\alpha}_{i} + \widehat{\beta}_{j} + \widehat{\gamma}_{k} + \widehat{\delta}_{l} - \widehat{\mu} - \widehat{\alpha}_{i} - \widehat{\beta}_{j} - \widehat{\gamma}_{k})^{2} =$$
$$= \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl} = 1}}^{N} \widehat{\delta}_{l}^{2} = N \sum_{l=1}^{N} \widehat{\delta}_{l}^{2}$$





$$(\partial^{F}/\partial_{\mu} = \partial^{F}/\partial_{\alpha_{i}} = \partial^{F}/\partial_{\beta_{j}} = \partial^{F}/\partial_{\gamma_{k}} = \partial^{F}/\partial_{\delta_{l}} = 0$$
 etc.; do it as an exercise), we obtain:

$$\hat{\mu} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} y_{ijkl1} = \bar{y} = \bar{y}...$$



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

$$\hat{\alpha}_{i} = \frac{1}{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} y_{ijkl1} - \hat{\mu} = \bar{y}_{i...} - \bar{y}$$

for i = 1, 2, ..., N



$$\left(\frac{\partial F}{\partial \mu} = \frac{\partial F}{\partial \alpha_i} = \frac{\partial F}{\partial \beta_j} = \frac{\partial F}{\partial \gamma_k} = \frac{\partial F}{\partial \delta_l} = 0$$
 etc.; do it as an exercise), we obtain:

$$\hat{\beta}_{j} = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} y_{ijkl1} - \hat{\mu} = \bar{y}_{.j..} - \bar{y}$$

for j = 1, 2, ..., N



$$(\partial^{F}/\partial\mu = \partial^{F}/\partial\alpha_{i} = \partial^{F}/\partial\beta_{j} = \partial^{F}/\partial\gamma_{k} = \partial^{F}/\partial\delta_{i} = 0$$
 etc.; do it as an exercise), we obtain:

$$\hat{\gamma}_{k} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{\substack{l=1\\n_{ijkl}=1}}^{N} y_{ijkl1} - \hat{\mu} = \bar{y}_{..k} - \bar{y}$$

for k = 1, 2, ..., N



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

$$\hat{\delta}_{l} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{\substack{k=1 \ n_{ijkl}=1}}^{N} y_{ijkl1} - \hat{\mu} = \bar{y}_{\dots l} - \bar{y}$$

for l = 1, 2, ..., N

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It together, we have:

$$SS_{TOTAL} = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (y_{ijkl1} - \hat{\mu})^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (y_{ijkl1} - \bar{y})^2$$

RSS =
$$\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (y_{ijkl1} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\gamma}_k - \hat{\delta}_l)^2 =$$

$$=\sum_{l=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{\substack{l=1\\n_{ijkl}=1}}^{N}\left(y_{ijkl1}-\bar{y}_{i...}-\bar{y}_{..k}-\bar{y}_{..l}+3\bar{y}\right)^{2}$$

Remark: The quantity

$$s^2 = \frac{\text{RSS}}{\dim M^{\perp}} = \frac{\text{RSS}}{(N-1)(N-3)}$$

is an estimate of the unknown σ^2 , that is $s^2 \approx \sigma^2$. It holds

$$\mathbf{E}[s^2] = \sigma^2$$

Recall that dim $M^{\perp} = N^2 - \dim M = (N - 1)(N - 3)$ — see the figure above!



No.

Put together, we have:

$$SS_{A} = N \sum_{i=1}^{N} \hat{\alpha}_{i}^{2} = N \sum_{i=1}^{N} (\bar{y}_{i}... - \bar{y})^{2}$$
$$SS_{B} = N \sum_{j=1}^{N} \hat{\beta}_{j}^{2} = N \sum_{j=1}^{N} (\bar{y}_{.j}.. - \bar{y})^{2}$$

No.

Put together, we have:

$$SS_{C} = N \sum_{k=1}^{N} \hat{\gamma}_{k}^{2} = N \sum_{k=1}^{N} (\bar{y}_{..k} - \bar{y})^{2}$$
$$SS_{D} = N \sum_{l=1}^{N} \hat{\delta}_{l}^{2} = N \sum_{l=1}^{N} (\bar{y}_{..l} - \bar{y})^{2}$$

Recall that it holds:

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

$$\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{\substack{l=1 \ n_{ijkl}=1}}^{N} (y_{ijkl1} - \bar{y})^2 =$$

$$= N \sum_{i=1}^{N} (\bar{y}_{i...} - \bar{y})^2 + N \sum_{j=1}^{N} (\bar{y}_{.j..} - \bar{y})^2 + N \sum_{k=1}^{N} (\bar{y}_{..k.} - \bar{y})^2 + N \sum_{l=1}^{N} (\bar{y}_{..l} - \bar{y})^2 +$$

$$+ \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} (y_{ijkl1} - \bar{y}_{i...} - \bar{y}_{..k.} - \bar{y}_{..l} + 3\bar{y})^2$$

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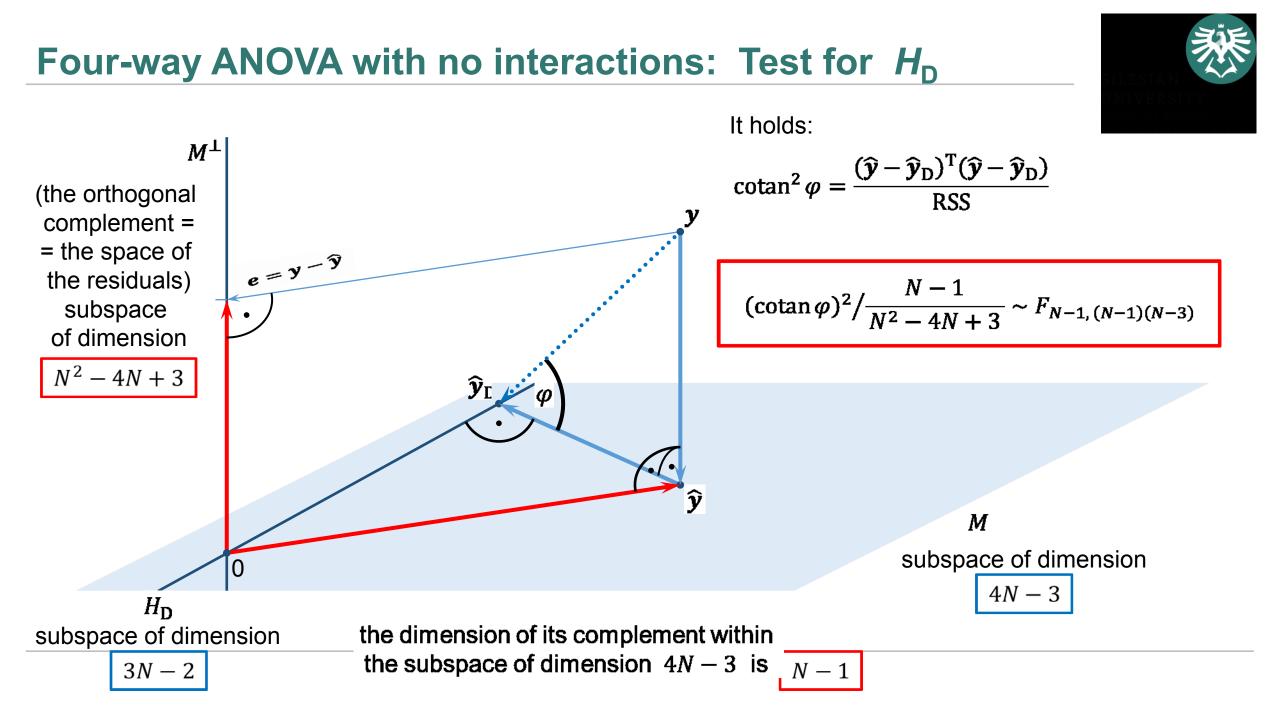
We use the theory of Linear Regression (Theorem 8) to test Hypothesis H_D :

If the null hypothesis

$$H_{\rm D}: \quad \gamma_1 = \gamma_2 = \cdots = \gamma_N = 0$$

holds true, then

$$\frac{SS_{D}}{RSS} / \frac{\dim M - \dim H_{D}}{N^{2} - \dim M} = \frac{SS_{D}}{RSS} / \frac{N-1}{(N-1)(N-2)} \sim F_{N-1,(N-1)(N-2)}$$





• Given the sample y_{ijkl1} of the random variables

$$\begin{split} Y_{ijkl1} &= \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl1} \\ \text{where } \mu, \alpha_i, \beta_j, \gamma_k, \delta_l \in \mathbb{R} \text{ are (unknown) parameters such that} \\ \sum_{i=1}^N \alpha_i &= \sum_{j=1}^N \beta_j = \sum_{k=1}^N \gamma_k = \sum_{l=1}^N \delta_l = 0 \text{ and } \varepsilon_{ijkl1} \sim \mathcal{N}(0, \sigma^2) \\ \text{are mutually independent random variables for } i = 1, 2, \dots, N, \ j = 1, 2, \dots, N, \\ k &= 1, 2, \dots, N, \ l = 1, 2, \dots, N \text{ such that } n_{ijkl} = 1, \text{ formulate the null hypothesis:} \\ H_D: \quad \delta_1 = \delta_2 = \dots = \delta_N = 0 \end{split}$$



Calculate the statistic

$$F = \frac{SS_{\rm D}}{RSS} / \frac{DF_{\rm D}}{DF_{RSS}} = \frac{N \sum_{l=1}^{N} (\bar{y}_{...l} - \bar{y})^2}{\sum_{l=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} (y_{ijkl1} - \bar{y}_{i...} - \bar{y}_{..k} - \bar{y}_{...l} + 3\bar{y})^2} / \frac{N - 1}{N^2 - 4N + 3}$$

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

$$F \sim F_{N-1,(N-1)(N-3)}$$



- Choose the level of significance, a small number $\alpha > 0$, such as $\alpha = 5 \%$
- Find the critical value

$$c = F_{N-1,(N-1)(N-3)} (1-\alpha)$$

so that $\int_{c}^{+\infty} f(x) dx = \alpha$ where f is the density of the *F*-distribution with N - 1 and (N - 1)(N - 3) 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