

$$\begin{aligned} SST, \sum (y_i - \bar{y})^2 &= SSE, \sum (y_i - \hat{y})^2 + SSR, \sum (\hat{y} - \bar{y})^2, \hat{\beta}_1^2 S_{xx}, \hat{\beta}_1 S_{xy} \\ E[]: \hat{\beta}_2^2 S_{xx} + (n-1)\sigma^2 &= (n-2)\sigma^2 + \sigma^2 + \hat{\beta}_1^2 S_{xx} \\ S_{xx} \sum_{i=1}^{10} (x_i - \bar{x})^2 &= 472, S_{yy} = \sum_{i=1}^{10} (y_i - \bar{y})^2 = 731, S_{xy} \sum_{i=1}^{10} (x_i - \bar{x})(y_i - \bar{y}) = 274 \\ \hat{\beta}_1 &= \frac{S_{xy}}{S_{xx}} = \frac{274}{472} = 0.5805 = \sum c_i y_i = r \frac{SD_y}{SD_x} = \frac{\sigma^2}{(n-1)S_x^2}; \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \\ \sigma^2 &= \frac{SSE}{n-2} = \frac{1}{8} (S_{yy} - \frac{S_{xy}^2}{S_{xx}}) = \frac{1}{8} (731 - \frac{274^2}{472}) = 71.4926 \\ \hat{\beta}_1 &\sim N(\beta_1, \frac{\sigma^2}{S_{xx}}); \hat{\beta}_0 \sim N(\beta_0, \sigma^2 [\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}]); \end{aligned}$$

$$\begin{aligned} Var(\hat{\beta}_0) &= \frac{71.4926}{472} = 0.1515; Var(\hat{\beta}_1) = 71.4926\left(\frac{1}{10} + \frac{x^2}{472}\right) \\ H_0 : \hat{\beta}_1 &= 0; t_0 = \frac{\hat{\beta}_1 - 0}{\sqrt{Var(\hat{\beta}_1)}} = \frac{0.5805}{\sqrt{0.1515}} = 1.4916 < t_{\frac{0.05}{2}, n-2} = 2.31 \text{ Fail to reject} \\ \hat{\beta}_1 \pm t_{\frac{0.05}{2}, n-2} se(\hat{\beta}_1) &= 0.5805 \pm 2.31\sqrt{0.1515}, (-0.3185, 1.4795) \end{aligned}$$

$$\begin{aligned}\hat{y} &= \hat{\beta}_0 + \hat{\beta}_1 x_0 = 168.3609; \bar{x} = 147.6923, S_{XX} = \sum_{i=1}^{13} (x_i - \bar{x})^2 = 6230.769 \\ \text{CI } se(y_0) &= \sqrt{MSE \left(\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{XX}} \right)} = \sqrt{275.06005 \left(\frac{1}{13} + \frac{(170 - 147.6923)^2}{6230.769} \right)} = 6.5671 \\ \hat{y} \pm t_{n-2, 0.025} se(y_0) &= 168.3609 \pm 2.200985 * 6.5671, (153.9068, 182.815)\end{aligned}$$

$$\text{PI } se(y_0) = \sqrt{MSE(1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{XX}})}; 168.3609 \pm 2.2 * 17.8378; (129.1002, 207.6216)$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 w_i + \beta_3 w_i x_i + \varepsilon_i, w_i = \begin{cases} 0 & 1 \leq i \leq \frac{n}{2} \\ 1 & \frac{n}{2} + 1 \leq i \leq n \end{cases}$$

$$\mathbf{Y}_{n \times 1} = \mathbf{X}_{n \times (k+1)} \boldsymbol{\beta}_{(k+1) \times 1} + \boldsymbol{\varepsilon}_{n \times 1}$$

equality of slopes $H_0: \beta_3 = 0, k = 3, r = 1$

$$dfE_{Ful} = n - (k + 1), dfE_{Red} = dfE_{Ful} = r$$

Partitioned regression...

(df)	SS_F	$-3, 4, 5$	$SS_{1,2}$	$-2, 4$	$SS_{1,3,5}$	df	SS_F	$-\alpha$	$SS_{\beta\gamma}$	$-\beta$	$SS_{\alpha\gamma}$	$-\alpha$	SS_γ
R	367(5)	-96(3)	271(2)	-153(2)	214(3)	α	2	110	-110	0	110	-110	0
E	336(69)	+96(3)	432(72)	+153(2)	489(71)	β	11	160	0	160	0	0	160
T	703(74)					γ	250	-10	240	-250	0	0	0
							22	300	+120	420	+250	550	+110
							135	820					660

$$H_0: \beta_3 = \beta_4 = \beta_5 = 0; r = 3; H'_0: \beta_2 = \beta_4 = 0; r = 2;$$

$$F_{p,3,69} = \frac{96/3}{336/69} = 6.5714; F' = \frac{153/2}{336/69} = 15.7098$$

$$p < 0.05 \text{ reject } H_0 \text{ at } 0.05 \text{ level of significance}$$

$$R^2 = \frac{SSR}{SST} = \frac{271}{703}; R^2_{adi} = 1 - \frac{SSE/dfe}{SST/dfT} = 1 - \frac{432/72}{703/74}; R^2_{vre} = 1 - \frac{PRESS}{SST}$$

coefficient of determination is the proportion of variation explained by regressor x

$$|r| = \sqrt{R^2} = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} = \frac{\text{Cov}(x,y)}{\sqrt{V_{XY}}} = \frac{\text{Cov}(\hat{\beta}_1, \hat{\beta}_0)}{se\hat{\beta}_1 se\hat{\beta}_0}$$

CI: $\hat{\beta}_1 \pm t_{\frac{\alpha}{2}, n-k-1} se(\hat{\beta}_1)$, $se(\hat{\beta}_1) = \sqrt{MSE \cdot C_{22}}$; Bonferroni: $t_{\frac{\alpha}{2(k+1)}}$, Scheffe $\sqrt{2F_{\alpha}}$

$8.1556 \pm t(0.005, 9) \sqrt{8.8436 * 0.2483}$, $8.1556 \pm 3.25 * 4.4071$; $(-6.1653, 22.4765)$
 $V(\hat{\beta}_1 - \hat{\beta}_2) = V(\hat{\beta}_1) + V(\hat{\beta}_2) - 2Cov(\hat{\beta}_1, \hat{\beta}_2) = MSE(C_{22} + C_{33} - 2C_{23})$
 $= 78.20842[0.2483 + 10.7694 - 2(-0.49669)] = 939.3676$ unbias est of var
 Lack of fit H_0 : There is no lack of fit, the model is appropriate

$$\begin{aligned} \sum_{j=1}^{\sum_{i=1}^m n_i} (y_{ij} - \hat{y}_i)^2 (SSE) &= \sum_{j=1}^{\sum_{i=1}^m n_i} (y_{ij} - \bar{y}_i)^2 (SS_{PE}) + \sum_{i=1}^m n_i (y_{ij} - \hat{y}_i)^2 (SS_{LOF}) \\ SS_{PE} &= \sum_{i=1}^m \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i)^2 = 28; SS_{LOF} = 703.87576 - 28 = 675.8758; \\ df_{PE} &= n - m = 12 - 9 = 3; MS_{PE} = 28/3; df_{LOF} = dfE - df_{PE} = m - (k + 1) = 6 \end{aligned}$$

$F = \frac{SS_{LOF}/df_{LOF}}{MS_{PE}} = \frac{675.87576/7}{28/3} = 10.34504 > F(0.05, 6, 3) = 8.94$. Reject H_0 .

CRD

$\mathbf{A}, \mathbf{f}_i, y_{ij} = \mu + \tau_i + \varepsilon_{ij}; \varepsilon_{ij} \sim iidN(0, \sigma^2); \mathbf{f} \sum_{i=1}^q \tau_i = 0; \mathbf{r}; \tau_i \sim iidN(0, \sigma_\tau^2)$

SS	df	MS	F	EMS	EMS _r
$SS_{\tau} = \sum_{i=1}^q n_i \bar{y}_{i.}^2 - n\bar{y}^2$	$q-1$	$MS_{\tau} = \frac{SS_{\tau}}{q-1}$	$\frac{MS_{\tau}}{MS_{\varepsilon}}$	$\sigma^2 + \frac{1}{n} \sum_{i=1}^q n_i \tau_i^2$	σ^2

$E \sum^n (y_{ij} - \bar{y}_{..})^2$	$a-1$	$\frac{\frac{a-1}{N-a}}{MS_E}$	$\sigma^2 + \frac{a-1}{a-1} \sigma^2 + n\sigma_\tau^2$
$E \sum^n (y_{ij} - \bar{y}_{i.})^2$	$a(n-1)$	$\frac{SS_E}{N-a}$	σ^2
$E \sum^n (y_{ij} - \bar{y}_{.j})^2$	$an-1$	$\frac{SS_T - MSE}{n}$	
$\hat{\sigma}^2 = MSE = \frac{SSE}{N-a}; \hat{\sigma}_\tau^2 = \frac{MS_{Int} - MSE}{n}$			

$$y_{ij} \sim n(\mu + \tau_i, \sigma^2); \bar{y}_i. \sim n(\mu + \tau_i, \frac{\sigma^2}{n}); \bar{y}_i. - \bar{y}_j. \sim n(\mu_i - \mu_j, \frac{2\sigma^2}{n})$$

$$E[y_{ij} - \bar{y}_i.] = V[] = \frac{n-1}{n} \sigma^2$$

$$\text{CI of } \mu_i: \bar{y}_i. \pm t_{\frac{\alpha}{2}} \sqrt{\frac{MS_E}{n}}; \text{ unbalanced } \bar{y}_i. \pm t_{\frac{\alpha}{2}} \sqrt{\frac{MS_E}{n_i}}$$

$$\mu_i - \mu_j: \bar{y}_i - \bar{y}_j \pm t_{\frac{\alpha}{2}} \sqrt{\frac{2MS_E}{n}}; \text{unbalanced } \bar{y}_i - \bar{y}_j \pm t_{\frac{\alpha}{2}} \sqrt{MS_E \left(\frac{1}{n_i} + \frac{1}{n_j} \right)}$$

$$\begin{aligned} \text{CI of prop of var } \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2} &= \frac{\bar{L}}{1 + \bar{L}}, \frac{\bar{U}}{1 + \bar{U}}; L = \frac{1}{n} \left(\frac{MS_{FH}}{MS_{F_{1-\alpha/2}}} - 1 \right); U = \frac{1}{n} \left(\frac{MS_{FH}}{MS_{F_{1-\alpha/2}}} - 1 \right) \\ H_0: \beta_1 &= 2\beta_3, \beta_2 = \beta_3, \beta_5 = 0 \\ \mathbf{T} &= \begin{bmatrix} 0 & 1 & 0 & -2 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 \end{bmatrix} \quad \mathbf{f} = \begin{bmatrix} \beta_0 \\ \vdots \end{bmatrix} \quad \mathbf{C} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad rank(T) = 3 \end{aligned}$$

$$\begin{array}{l} \text{contrast } \Gamma = \sum_{i=1}^a c_i \mu_i, C = \sum_{i=1}^a c_i \bar{y}_i; \sum_{i=1}^a c_i = 0; \text{Orthogonal } \sum_{i=1}^a c_i d_i = 0 \\ SS_C = \frac{(\sum_{i=1}^a c_i \bar{y}_i)^2}{\frac{1}{n} \sum_{i=1}^a c_i^2}, \sum_{i=1}^{a-1} SS_C = SS_{Trt}; V[\sum_{i=1}^a c_i y_i] = \sigma^2 \sum_{i=1}^a n_i c_i^2 \end{array}$$

$\tau_1 + \tau_2 + \tau_3 = 0$	$\mu = 13.8$	(a) Contrast	(b) $\mu = 8.4$	$\tau_3 = 0$
$\hat{\mu} + \hat{\tau}_1 = \hat{y}_1 = 10.8$	$\hat{\tau}_1 = -3.0$	$10.8 \hat{\tau}_1 = 2.4$	$\hat{\mu} + \hat{\tau}_1 = \hat{y}_1 = 10.8$	
$\hat{\mu} + \hat{\tau}_2 = \hat{y}_2 = 22.2$	$\hat{\tau}_2 = 8.4$	$-9.0 \hat{\tau}_2 = -13.8$	$\hat{\mu} + \hat{\tau}_2 = \hat{y}_2 = 22.2$	
$\hat{\mu} + \hat{\tau}_3 = \hat{y}_3 = 8.4$	$\hat{\tau}_3 = -5.4$	$19.2 \hat{\tau}_3 = 0$	$\hat{\mu} + \hat{\tau}_3 = \hat{y}_3 = 8.4$	
$H_{C0,D0}; \sum_{i=1}^3 c_i d_i = 0$	$C, D \sum_{i=1}^a c_i, d_i; F_{1,12} $		$SS_{C,D} / MS_E$	

$$\begin{array}{l} \mu_1 - 2\mu_2 + \mu_3 = 0 \\ \mu_1 - \mu_3 = 0 \\ \text{RCBD} \\ \text{Trt}_f + \text{Blk}_f \end{array} \left| \begin{array}{l} \bar{y}_1, -2\bar{y}_2, +\bar{y}_3, \\ \bar{y}_1, -\bar{y}_3, \end{array} \right| \left| \begin{array}{l} C^2 / \frac{MS_E}{n} \sum_{i=1}^a c_i^2 \left((-25.2)^2 / \frac{16.9}{5} 6 \right) \\ D^2 / \frac{MS_E}{n} \sum_{i=1}^a d_i^2 \left(2.4^2 / \frac{16.9}{5} 2 \right) \end{array} \right|$$

$y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij}, \text{ for } \varepsilon_{ij} \sim iidN(0, \sigma^2), i = 1, \dots, a, j = 1, \dots, b$ $f: \sum_{i=1}^a \tau_i = 0, \sum_{j=1}^b \beta_j = 0; r: \beta_j \sim iidN(0, \sigma_\beta^2)$			
Trt	$b \sum^a (\bar{y}_{i.} - \bar{y}_{..})^2$	a-1	$\left \begin{array}{cc} \frac{SS_{Trt}}{a-1} & \frac{MS_{Trt}}{MS_E} \end{array} \right \sigma^2 + \frac{b \sum^a \tau_i^2}{a-1} \sigma^2 + b \sigma_\tau^2$
Blk	$a \sum^b (\bar{y}_{.j} - \bar{y}_{..})^2$	b-1	$\left \begin{array}{cc} \frac{SS_{Blk}}{b-1} & \frac{MS_{Blk}}{MS_E} \end{array} \right \sigma^2 + \frac{a \sum^b \tau_j^2}{b-1} \sigma^2 + a \sigma_\tau^2$
E	T-Trt-Blk	(a-1)(b-1)	$\left \begin{array}{cc} \frac{SS_E}{df_E} & \end{array} \right \sigma^2$
T	$\sum^a \sum^b (y_{ij} - \bar{y}_{..})^2$	ab-1	

Missing Values: Exact(partial) method $F_0 = \frac{(SS_{red} - SS_{ful})/r}{MSE_{ful}} = \frac{1403.7 - 921.5}{184.30(a-1)}$,
 Apporximation method $\hat{x} = \frac{ay'_1 + by'_1 - y''}{(a-1)(b-1)}$, $F_{adj} = \frac{MS_{Trt}}{SSE/df_{adj}} = \frac{162.08}{921.5/(6-1)}$
Latin Square

τ_i is effect of i^{th} treatment; α_j is effect of j^{th} block of factor R; β_k effect of k^{th} block of factor C; ε_{ijkl} is random error when i^{th} treatment is applied at j^{th} block of factor R and k^{th} block of factor C; y_{ijkl} is response ;
Assumptions: $\varepsilon_{ijk} \sim iidN(0, \sigma^2)$; $\sum \alpha = 0$; $\sum \beta = 0$; Indep

The Latin-Square design can only use 2 blocking factors, as we distribute the levels of the treatment factor on a table with rows of one blocking factor (each row is fore one block) and columns of the other blocking factor (each column is one block). To test three blocking factors by turning the Latin-square design into a Graeco-Latin square design, which allows to add a Greek letter to each entry in the table, where

each Greek letter stands for a block of the factor G. Graeco-Latin square: $y_{ijkl} = \mu + \theta_i + \tau_j + \omega_k + \psi_l + \varepsilon_{ijkl}$; $j, k, l = 1, 2, \dots, p$ where y_{ijk} is the observation in row i and column l for Latin letter j and Greek letter k , θ_i is the effect of the i th row, τ_j is the effect of Latin letter treatment j , ω_k is the effect of Greek letter treatment k , ψ_l is the effect of column l , and $\varepsilon_{ijkl} \sim iidN(0, \sigma^2)$ is a random error

LSDSS	df	GraeSS	df
Trt $p \sum_{i=1}^p (\bar{y}_{i..} - \bar{y}_{..})^2$	p-1	Trt1 $b \sum_{i=1}^a (\bar{y}_{i.} - \bar{y}_{..})^2$	p-1
		Trt2 $b \sum_{i=1}^a (\bar{u}_{i.} - \bar{u}_{..})^2$	p-1

Row	$\sum_{j=1}^p (\bar{y}_{.j} - \bar{y}_{...})^2$	p-1	Row	$\sum_{j=1}^p (\bar{y}_{.j} - \bar{y}_{...})^2$	p-1
Col	$\sum_{k=1}^p (\bar{y}_{.k} - \bar{y}_{...})^2$	p-1	Col	$\sum_{j=1}^p (\bar{y}_{.j} - \bar{y}_{...})^2$	p-1
E	$SS_T - SS_{\cdot}$	(p-1)(p-2)	E	$SS_T - SS_{\cdot}$	(p-1)(p-3)
T	$\sum^p \sum^p \sum^p (y_{ijk} - \bar{y}_{...})^2$	$p^2 - 1$	T	$\sum^p \sum^p \sum^p (y_{ijk} - \bar{y}_{...})^2$	$p^2 - 1$

	Case1	Case2	Case3		1	2	(g _{ijkl})	(g...)	p	1
Irt	p-1	p-1	p-1		Aα	Bβ	Cγ	Dδ		
Row	p-1	n(p-1)	n(p-1)		Bδ	Aγ	Dβ	Cα		
Col	p-1	p-1	n(p-1)		Cβ	Dα	Aδ	Bγ		
Rep	n-1	n-1	n-1							

$$\text{Relative Efficiency} = \frac{(df_{E(LS)}+1)(df_{E(CRD)}+3)MS_{CRD}}{(df_{E(LS)}+3)(df_{E(CRD)}+1)MS_{LS}} = 2.3$$

$$df_{E(LS)} = (p-1)(p-2)=20, df_{E(GS)} = (p-1)(p-3)=15, df_{E(CRD)}=a(n-1)=7, 2, 32$$

BIBD

$$y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij}; i = 1, \dots, a, j = 1, \dots, b; y_{i.} = \sum_j y_{ij}, \bar{y}_{.j} = \frac{1}{k} \sum_i y_{ij} = \frac{y_{j.}}{k};$$

$$Q_i = (y_{i.} - \sum_{j=1}^b n_{ij} \bar{y}_{.j}) \text{ where } n_{ij} = \begin{cases} 1 & i^{th} \text{ trt appears in } j^{th} \text{ blk} \\ 0 & \text{o.w.} \end{cases}$$

SS	df	Repr = 15
Trt $\frac{k}{\lambda a} \sum^a Q_i^2 = \frac{k}{\lambda a} \sum^a (y_{i.} - \sum^b n_{ij} \bar{y}_{.j})^2$	a-1	Trta = 7
Blk $k \sum_{j=1}^b (\bar{y}_{.j} - \bar{y}_{..})^2$	b-1	Blkb = $\binom{7}{5} = 21$
E T-Trt _{adj} -Blk	N-a-b+1	Sizek = 5

$T = \sum_{i=1}^a \sum_{j=1}^b (y_{ij} - \bar{y}_{..})^2$ $\left| \begin{smallmatrix} N-1 \\ N = ar = bk = 105 \end{smallmatrix} \right|$
 replications of each pair $\lambda = \frac{(k-1)}{a-1}r = \frac{k(k-1)}{a(a-1)}b = 10 = \frac{2}{3}r \in \mathbf{N}^+$
 the smallest number of observations per treatment is a multiple of 3 and 5
Fixed v.s. random; crossed v.s. nested

(a) Fixed effects are constant across individuals, random effects vary. Effects are fixed if they are interesting in themselves or random if there is interest in the underlying population. When a sample exhausts the population, the corresponding variable is fixed; when the sample is a small part of the population the corresponding variable is random. If an effect is assumed to be a realized value of a random variable, it is

Example: A lab want to test the quality of products. There are only two specific test machines. Each machine assigned two operators who randomly selected from a large amount of operators. Each operator test the products in three specific temperature. In this test, the factor machine and temperature have fixed effects. The factor operator

(b) Two factors are crossed when every category of one factor co-occurs in the design with every category of the other factor. There is at least one observation in every combination of categories for the two factors.

occurs with only one category of the other. An observation has to be within one category of Factor 2 in order to have a specific category of Factor 1. All combinations of categories are not represented. You can calculate an interaction between two crossed factors. If they are nested, you cannot because you do not have every combination of one factor along with every sample item of the other.

In **Example (a)**, Three temperature are applied on each machine. Thus, temperature and machine have crossed effect. The operators were assigned to each machine are different. The operators are nested in the levels of factor machine. Thus, the effects of the factor operator are nested effect.

k factors, p generators; 2^p blocks/fraction; 2^{k-p} Run, Blk size;
 $2^p - 1$ alias; $2^p - p - 1$ auto confounded;
 $I = ABC = BCD = AD$
 $AD+, ABC-, BCD-; (1), bc, abd, acd; ABC + BCD +, b, c, ad, abcd$
 $AD-, ABC-, BCD+; ab, ac, bcd, d; ABC + BCD-, a, abc, bd, cd$

$I=ABCD F=ABDE G=CEFG; CE=FG, CF=EG, CG=EF$ minimum aberration

2 ^k -p ² ^k	2 ^p 2 ^k -p ²	Generator	AB	CDEF	AB	ABCD	Run	
2 ³ -1 ¹	8	2	4	C=AB	+	+	(1)	I=ABCE=BCDF=ADEF
2 ¹ 1 ¹	16	2	8	D=ABC	+	+	ae	A = BCE = DEF = ABCDF
2 ⁵ -1 ¹	32	2	16	E=ABCD	+	+	bef	B = ACE = CDF = ABDEF
2 ⁵ -2 ¹	32	4	8	D=AB;E=AC	+	+	abf	C = ABE = BDF = ACDEF
2 ⁵ -2 ¹	32	4	8	D=AB;E=AC	+	+	cef	D = BCF = AEF = ABCDE
2 ¹ 1 ¹	64	2	32	F=ABCDE	+	+	acf	E = ABC = ADE = BCDEF
2 ⁶ -1 ¹	64	4	16	E=ABC;F=BCD	+	+	bc	F = BCD = ADE = ABCEF
2 ⁶ -3 ¹	64	8	8	D=AB;E=AC;F=BC	+	+	abce	BF = CD = ACEF = ABDE
2 ¹ 1 ¹	128	2	64	G=ABCDEF	+	+	df	AC = CE = ACFD = BDEF
2 ⁷ -1 ¹	128	4	32	F=ABCD;G=ABDE	+	+	adef	AC = BE = ABDF = CDEF
2 ⁷ -2 ¹	128	8	16	E=ABC;F=BCD;G=ACD	+	+	bde	AD = EF = BCDE = ABCE
2 ⁷ -2 ¹	128	8	16	E=ABC;F=BCD;G=ACD	+	+	abd	AE = BC = DF = ABCDEF
2 ⁷ -3 ¹	128	16	8	D=AB;E=AC;F=BC;G=AB	+	+	cde	AF = DE = BCEF = ABCD
2 ⁷ -3 ¹	128	16	8	D=AB;E=AC;F=BC;G=AB	+	+	bcd	BD = CF = ACDE = ABCE
2 ⁷ -3 ¹	128	16	8	D=AB;E=AC;F=BC;G=AB	+	+	abcdf	ABD = CDE = ACF = BEF
2 ⁷ -3 ¹	128	16	8	D=AB;E=AC;F=BC;G=AB	+	+	abcdf	ACD = BDE = ABF = CEF

ANOVA-df: T= 2^kn - 1;Blk= 2^p - 1;E= 2^k(n - 1);others=1

SS_{Block} = $\frac{1}{25}C_{ABC}^2 = SS_{ABC}$; $SS_{AB} = \frac{1}{4}C_{AB}^2 = \frac{n}{4}(\bar{y}_{(1)} - \bar{y}_a - \bar{y}_b + \bar{y}_{ab})^2$

A_f × **B**_f *y*_{ijkl} = μ + τ_i + β_j + (τβ)_{ij} + ε_{ijk},

i = 1, 2; *j* = 1, 2, 3; *k* = 1, 2, 3, 4; *l* = 1, 2, [*a* = 2, *b* = 3, *n* = 4] where μ overall mean

τ_i is fixed main effect of *i*th level of Factor A; β_j *j*th B;

(τβ)_{ij} is fixed interaction effect of *i*th level of Factor A and *j*th level of Factor B;

ε_{ijkl} is random error for the *k*th replicate EU when *i*th level of Factor A and *j*th level of Factor B are applied; *y*_{ijkl} is response for the;

Assumptions: ε_{ijk} ~ iidN(0,σ²) (constant variance, zero mean, independent);

Σ_{*i*}² τ_i = 0; Σ_{*j*}³ β_j = 0; Σ_{*i*}² (τβ)_{ij} = 0; Σ_{*j*}³ (τβ)_{ij} = 0;indep

term	i(f)	j(f)	k(r)	df	SS		MS	EMS
A _f τ _i	0	b	n	a-1	$bn \sum^a (\bar{y}_{i..} - \bar{y}_{...})^2$; $\frac{\sum^a y_{i..}^2}{bn} - \frac{y_{...}^2}{abn}$,96	96	$\sigma^2 + \frac{bn \sum^a \tau_i^2}{a-1}$	
B _f β _j	a	0	n	b-1	$an \sum^b (\bar{y}_{.j.} - \bar{y}_{...})^2$; $\frac{\sum^b y_{.j.}^2}{an} - \frac{y_{...}^2}{abn}$,208	104	$\sigma^2 + \frac{an \sum^b \beta_j^2}{b-1}$	
AB (τβ) _{ij}	0	0	n	(a-1)(b-1)	$n \sum^a \sum^b (y_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2$;112			
Eε _{ijk} r	1	1	1	ab(n-1),18	$SST - \sum SS_i ; (n-1) \sum^a \sum^b S_{ij}^2$;126	7	σ^2	
Total				abn-1,23	$\sum \sum \sum (y_{ijk} - \bar{y}_{...})^2$ $\sum \sum \sum y_{ijk}^2 - \frac{y_{...}^2}{abn}$;542			
if Blk			1	n-1	$df_E=(ab-1)(n-1)$; $\frac{\sum^a y_{k.}^2}{ab} - \frac{y_{...}^2}{abn}$		$\sigma^2 + ab\sigma_\delta^2$	

*H*₀ : (τβ)_{ij} = 0*∀i, j*; *F*_{p,2,18} $\frac{MS_{AB}}{MS_E} = \frac{56}{7} = 8$; *F*_{0.05,2,8} = 3.55. There is enough evidence to reject *H*₀. The model may not be reduced, as the interaction effects is significant at 5% significance level.

$\bar{y}_{12..} - \bar{y}_{22..} \pm t_{\frac{\alpha}{2},18} \sqrt{\frac{2MSE}{n}} = 14 - 8 \pm 2.1 \sqrt{\frac{2 \times 7}{4}} = 6 \pm 3.9287$;[2.0713,9.9287]

$E[SS_A] = bn \sum_{i=1}^a E[(\bar{y}_{i..} - \bar{y}_{...})^2] = bn \sum_{i=1}^a (E[\bar{y}_{i..}^2 + V[\bar{y}_{i..}]] = bn \sum_{i=1}^a (\tau_i^2 + (a-1)\sigma^2) \dots$

A_r × **B**_r + **A**_r × **C**_r *y*_{ijkl} = μ + τ_i + β_j + γ_k + (τβ)_{ij} + (τγ)_{ik} + ε_{ijk}

iid ε_{ijk} ~ iidN(0,σ²_i); τ_i ~ iidN(0,σ²_τ); β_j ~ iidN(0,σ²_β); γ_k ~ iidN(0,σ²_γ); (τβ)_{ij} ~ iidN(0,σ²_{τβ}); (τγ)_{ik} ~ iidN(0,σ²_{τγ}); indep

	i	j	k	df	SS	EMS	F
τ _i	1	b	c	a-1	$\sigma^2 + b\sigma_{\tau\gamma}^2 + c\sigma_{\tau\beta}^2 + bc\sigma_{\tau}^2 \mid \frac{1}{bc} \sum_{i=1}^a y_{i..}^2 - \frac{1}{abc} y_{...}^2$		A/(AB+AC-E)
β _j	a	1	c	b-1	$\sigma^2 + c\sigma_{\tau\beta}^2 + ac\sigma_{\beta}^2 \mid \frac{1}{ac} \sum_{j=1}^b y_{.j.}^2 - \frac{1}{abc} y_{...}^2$		MS _B / MS _{AB}
γ _k	a	b	1	c-1	$\sigma^2 + b\sigma_{\tau\gamma}^2 + ab\sigma_{\gamma}^2 \mid \frac{1}{ab} \sum_{k=1}^c y_{...k}^2 - \frac{1}{abc} y_{...}^2$		C / AC
(τβ) _{ij}	1	1	c	(a-1)(b-1)	$\sigma^2 + c\sigma_{\tau\beta}^2 \mid \frac{\sum^a y_{i..}^2}{c} - \frac{\sum^a y_{i..}^2}{bc} - \frac{\sum^b y_{.j.}^2}{ac} + \frac{y_{...}^2}{abc}$		AB/E
(τγ) _{ik}	1	b	1	(a-1)(c-1)	$\sigma^2 + b\sigma_{\tau\gamma}^2 \mid \frac{\sum^a y_{i..}^2}{b} - \frac{\sum^a y_{i..}^2}{bc} - \frac{\sum^c y_{...k}^2}{ab} + \frac{y_{...}^2}{abc}$		AC/E
ε _{ijk}	1	1	1	a(b-1)(c-1)	$\sigma^2 \mid \sum^a \sum^b \sum^c y_{ijk}^2 - \frac{\sum^a \sum^b y_{ij.}^2}{c} - \frac{\sum^a \sum^c y_{i.k}^2}{b} + \frac{\sum^a y_{i..}^2}{bc}$		
Total				abc - 1	$\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^c y_{ijk}^2 - \frac{1}{abc} y_{...}^2$		

$F_{dfn,dfd} = \frac{MS'_f}{MS'_n}$; $df_n = df_c$; $df_d = \frac{(AC+BC+ABC)^2}{df_{AC} + df_{BC} + \frac{ABC^2}{df_{ABC}}}$

Mixed model

A_f × **B**_r:*y*_{ijk} = μ + τ_i + β_j + (τβ)_{ij} + ε_{ijk}

iidε_{ijk} ~ iidN(0,σ²); Σ_{*i*=1}^a τ_i = 0; Σ_{*i*=1}^a (τβ)_{ij} = 0 (restricted model); β_j ~ iidN(0,σ²_β);

(τβ)_{ij} ~ iidN(0, $\frac{a-1}{a}\sigma_{\tau\beta}^2$)

$E(SS_{AB}) = E[\sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^n (\widehat{\tau\beta})_{ij}^2] = n \sum_{i=1}^a \sum_{j=1}^b E[(\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2] =$

$V[\sum^a \sum^b \sum^n (\widehat{\tau\beta})_{ij}^2] + 0 = (a-1)(b-1)(n\sigma_{\tau\beta}^2 + \sigma^2) = n \sum^a \sum^b (\bar{y}_{ij.} - \bar{y}_{...})^2 - SS_A - SS_B$

Nested model

	i	j	k	df	EMS	B _r in A _f	F	B _f in A _f	B _r in A _r
α _f :f	0	b	n	a-1	$\sigma_{\epsilon}^2 + n\sigma_{\beta}^2 + \frac{bn \sum^a \alpha_f^2}{a-1}$	A/AB	$\sigma_{\epsilon}^2 + \frac{bn \sum^a \alpha_f^2}{a-1}$	$\sigma_{\epsilon}^2 + n\sigma_{\beta}^2 + bn\sigma_{\alpha}^2$	
β _j :r	0	1	n	a(b-1)	$\sigma_{\epsilon}^2 + n\sigma_{\beta}^2$	AB/E	$\sigma_{\epsilon}^2 + \frac{n \sum^a \sum^b \beta_j^2}{a(b-1)}$	$\sigma_{\epsilon}^2 + n\sigma_{\beta}^2$	
ε _{ijk} :r	1	1	1	ab(n-1)	σ_{ϵ}^2		σ_{ϵ}^2	σ_{ϵ}^2	
T				abn-1					

ε_{(ijk)l} ~ iidN(0,σ²) Σ_{*i*=1}² τ_i = 0 Σ_{*k*=1}³ γ_k = 0 β_{j(i)} ~ iidN(0,σ²_β)

Σ_{*i*=1}² (τγ)_{ik} = 0 Σ_{*k*=1}² (τγ)_{ik} = 0 Σ_{*i*=1}² (βγ)_{j(i)k} = 0 (βγ)_{j(i)k} ~ iidN(0, $\frac{2-1}{2}\sigma_{\beta\gamma}^2$)

B_r-in-**A**_f *y*_{ijk} = μ + α_i + β_{ij} + ε_{ijk}; Σ_{*i*=1}^a α_i = 0, β_{ij} ~ N(0,σ²_β), ε_{ij} ~ N(0,σ²_ε)

Cov(*y*₁₁₁,*y*₁₁₂) = Cov(β₁₁ + ε₁₁₁,β₁₁ + ε₁₁₂) = Var(β₁₁) + Cov(ε₁₁₁,ε₁₁₂) = σ²_β

Cov(*y*₁₁₁,*y*₁₂₁) = Cov(β₁₁ + ε₁₁₁,β₁₂ + ε₁₂₁) = Cov(β₁₁,β₁₂) + Cov(ε₁₁₁,ε₁₂₁) = 0

Cov(*y*₁₁₁,*y*₂₁₁) = Cov(β₁₁ + ε₁₁₁,β₂₁ + ε₂₁₁) = Cov(β₁₁,β₂₁) + Cov(ε₁₁₁,ε₂₁₁) = 0

Var(*y*₁₁₁) = σ²_β + σ²_ε = Var(*y*₁₁₂);

Cor(*y*₁₁₁,*y*₁₁₂) = $\frac{\sigma_{\beta}^2}{\sigma_{\beta}^2 + \sigma_{\epsilon}^2}$ Cor(*y*₁₁₁,*y*₁₂₁) = Cor(*y*₁₁₁,*y*₂₁₁) = 0

A linear combination of normal distributed random variables and constants are normal distributed.

$E[\bar{y}_{ij.}] = E[\frac{1}{n} \sum_{k=1}^n y_{ijk}] = \frac{\sum_{k=1}^n}{n} E[\mu + \alpha_i + \beta_{ij} + \epsilon_{ijk}] = \mu + \alpha_i, \forall i = 1, ..., a; j = 1, ..., b$

$Var[\bar{y}_{ij.}] = Var[\frac{1}{n} \sum_{k=1}^n y_{ijk}] = \frac{\sum_{k=1}^n}{n^2} Var[\mu + \alpha_i + \beta_{ij} + \epsilon_{ijk}] = \frac{1}{n} (\sigma_{\beta}^2 + \sigma_{\epsilon}^2), \forall i$

$f(\bar{y}_{i1.},...,\bar{y}_{ib.}) = \prod_{j=1}^b f(\bar{y}_{ij.}) = (2\pi)^{\frac{\sigma_{\beta}^2 + \sigma_{\epsilon}^2}{n}})^{-\frac{b}{2}} \exp[\frac{-n}{2(\sigma_{\beta}^2 + \sigma_{\epsilon}^2)} \sum_{j=1}^b (\bar{y}_{ij.} - \mu - \alpha_i)^2]$

$\hat{\alpha}_1 - \hat{\alpha}_2 \sim N(\alpha_1 - \alpha_2, \frac{2}{b} \sigma_{\beta}^2 + \frac{2}{bn} \sigma_{\epsilon}^2)$

$SSE = \sum^a \sum_{j=1}^b \sum_{k=1}^n (y_{ijk} - \mu - \alpha_i - \beta_{ij})^2$; $\frac{\partial SSE}{\partial \alpha_i} = 2 \sum_{j=1}^b \sum_{k=1}^n (y_{ijk} - \mu - \alpha_i - \beta_{ij})(-1) \stackrel{set}{=} 0$;

$\hat{\alpha}_i = \frac{\sum_{j=1}^b \sum_{k=1}^n y_{ijk}}{bn} - \mu - \frac{\sum_{j=1}^b \beta_{ij}}{b} = \bar{y}_{i..} - \mu$

$\hat{\alpha}_1 - \hat{\alpha}_2 = \bar{y}_{1..} - \mu - (\bar{y}_{2..} - \mu) = \frac{1}{bn} \sum_{j=1}^b \sum_{k=1}^n (y_{1jk} - y_{2jk})$

$= \frac{1}{bn} \sum_{j=1}^b \sum_{k=1}^n (\alpha_1 - \alpha_2 + \beta_{1j} - \beta_{2j} + \epsilon_{1jk} - \epsilon_{2jk}) = \alpha_1 - \alpha_2 + \bar{\beta}_1. - \bar{\beta}_2. + \bar{\epsilon}_{1..} - \bar{\epsilon}_{2..}$

$E[\hat{\alpha}_1 - \hat{\alpha}_2] = \alpha_1 - \alpha_2$;
 $Var[\hat{\alpha}_1 - \hat{\alpha}_2] = Var[\bar{\beta}_1. - \bar{\beta}_2. + \bar{\epsilon}_{1..} - \bar{\epsilon}_{2..}]$

$= \frac{1}{b^2} \sum_{j=1}^b (Var[\beta_{1j.}] + Var[\beta_{2j.}]) + \frac{1}{b^2 n^2} \sum_{j=1}^b \sum_{k=1}^n (Var[\epsilon_{1..}] + Var[\epsilon_{2..}]) = \frac{2}{b} \sigma_{\beta}^2 + \frac{2}{bn} \sigma_{\epsilon}^2$

$\bar{y}_{ij.} - \bar{y}_{i..} = \mu + \alpha_i + \beta_{ij} + \bar{\epsilon}_{ij.} - (\mu + \alpha_i + \bar{\beta}_i. + \bar{\epsilon}_{i..}) = \beta_{ij} - \bar{\beta}_i. + \bar{\epsilon}_{ij.} - \bar{\epsilon}_{i..}$

$E[\bar{y}_{ij.} - \bar{y}_{i..}] = E[\beta_{ij} - \bar{\beta}_i. + \bar{\epsilon}_{ij.} - \bar{\epsilon}_{i..}] = 0$

$Cov(\beta_{ij}, \bar{\beta}_i.) = \frac{1}{b} Cov(\beta_{ij}, \sum_{j=1}^b \beta_{ij}) = \frac{1}{b} [1 \cdot \sigma_{\beta}^2 + (b-1) \cdot 0]$

$Cov(\bar{\epsilon}_{ij.}, \bar{\epsilon}_{i..}) = Cov(\frac{1}{n} \sum_{k=1}^n \epsilon_{ijk}, \frac{1}{bn} \sum_{j=1}^b \sum_{k=1}^n \epsilon_{ijk}) = \frac{\sum_{k=1}^n Cov(\epsilon_{ijk}, \sum_{j=1}^b \epsilon_{ijk})}{bn^2} = \frac{\sigma_{\epsilon}^2}{bn}$

$Var[\bar{y}_{ij.} - \bar{y}_{i..}] = Var[\beta_{ij} - \bar{\beta}_i. + \bar{\epsilon}_{ij.} - \bar{\epsilon}_{i..}] = Var[\beta_{ij} - \bar{\beta}_i.] + Var[\bar{\epsilon}_{ij.} - \bar{\epsilon}_{i..}]$

$= Var[\beta_{ij}] + Var[\bar{\beta}_i.] - 2Cov(\beta_{ij}, \bar{\beta}_i.) + Var[\bar{\epsilon}_{ij.}] + Var[\bar{\epsilon}_{i..}] - 2Cov(\bar{\epsilon}_{ij.}, \bar{\epsilon}_{i..})$

$= \sigma_{\beta}^2 + \frac{1}{b} \sigma_{\beta}^2 - \frac{2}{b} \sigma_{\beta}^2 + \frac{1}{n} \sigma_{\epsilon}^2 + \frac{1}{bn} \sigma_{\epsilon}^2 - \frac{2}{bn} \sigma_{\epsilon}^2 = \frac{b-1}{b} (\sigma_{\epsilon}^2 + \frac{1}{n} \sigma_{\epsilon}^2)$

$E[\sum_{i=1}^a \sum_{j=1}^b (\bar{y}_{ij.} - \bar{y}_{i..})^2] = \sum_{i=1}^a \sum_{j=1}^b (Var[\bar{y}_{ij.} - \bar{y}_{i..}] + E[\bar{y}_{ij.} - \bar{y}_{i..}]^2)$

$= \sum_{i=1}^a \sum_{j=1}^b [\frac{b-1}{b} (\sigma_{\epsilon}^2 + \frac{1}{n} \sigma_{\epsilon}^2) + 0] = a(b-1) (\sigma_{\beta}^2 + \frac{1}{n} \sigma_{\epsilon}^2)$

$\hat{\sigma}_{\beta}^2 = \frac{MS_{AB} - MS_E}{n}$; $E[\hat{\sigma}^2] = \frac{1}{n} (n\sigma_{\beta}^2 + \sigma_{\epsilon}^2 - \sigma_{\epsilon}^2) = \sigma_{\beta}^2$

$E(MS_{B_f(A_f)}) = \frac{a}{a(b-1)} \sum_{i=1}^a \sum_{j=1}^b E[(\bar{y}_{ij.} - \bar{y}_{i..})^2] = \sigma^2 + \frac{n}{a(b-1)} \sum_{i=1}^a \sum_{j=1}^b \beta_{j(i)}^2$

Nested-Three-stages C_r-in-B_r-in-A_f *y*_{ijkl} = μ + τ_i + β_{j(i)} + γ_{k(ij)} + ε_{(ijk)l}

ε_{ijkl} ~ iid N(0,σ²); Σ_{*i*=1}^a τ_i = 0; β_{j(i)} ~ iid N(0,σ²_β) ; γ_{k(ij)} ~ iid N(0,σ²_γ)

	i	j	kl	df	SS	EMS	F
A _f τ _i	0	b	c	n	a-1	$\sigma^2 + n\sigma_{\gamma}^2 + c n\sigma_{\beta}^2 + \frac{bcn \sum^a \tau_i^2}{a-1} \mid \frac{\sum^a y_{i..}^2}{bcn} - \frac{y_{...}^2}{abcn}$	A/B(A)
B(A) _r β _{j(i)}	1	1	c	n	a(b-1)	$\sigma^2 + n\sigma_{\gamma}^2 + c n\sigma_{\beta}^2 \mid \frac{\sum^a \sum^b y_{ij.}^2}{cn} - \frac{\sum^a y_{i..}^2}{bcn}$	B(A)/C(A(B))
C(B(A) _r)rγ _{k(ji)}	1	1	1	n	ab(c-1)	$\sigma^2 + n\sigma_{\gamma}^2 \mid \frac{1}{n} \sum^a \sum^b \sum^c y_{ijk}^2 - \frac{1}{cn} \sum^a \sum^b y_{ij.}^2$	C(A(B))/E
ε _{(ijk)l}	1	1	1	1	abc(n-1)	$\sigma^2 \mid \sum^a \sum^b \sum^c \sum^n y_{ijkl}^2 - \frac{1}{n} \sum^a \sum^b \sum^c y_{ijk.}^2$	
T					abcn-1	$\sum^a \sum^b \sum^c \sum^n y_{ijkl}^2 - \frac{1}{abcn} y_{...}^2$	

Nested-Factorial Factors B_r-in-A_f × C_f

	i	j	kl	df	EMS	F	
$A_f\tau_i$	0	b	c	n	$a-1$	$\sigma^2 + cn\sigma_{\beta}^2 + \frac{bcn\sum_{i=1}^a\tau_i^2}{a-1}$	$MS_A/B(A)$
$B(A)_r\beta_{j(i)}$	1	1	c	n	$a(b-1)$	$\sigma^2 + cn\sigma_{\beta}^2$	$B(A)/E$
$C_f(\gamma)_k$	a	b	0	n	$c-1$	$\sigma^2 + n\sigma_{\gamma}^2 + \frac{abn\sum^c\gamma_k^2}{c-1}$	$C/CB(A)$
$AC_f(\tau\gamma)_{ik}$	0	b	0	n	$a-1)(c-1)$	$\sigma^2 + n\sigma_{\gamma}^2 + \frac{bn\sum^a\sum^c(\tau\gamma)_{ik}^2}{(a-1)(c-1)}$	$AC/CB(A)$
$CB(A)_r(\gamma\beta)_{kj(i)}$	1	1	0	n	$a(b-1)(c-1)$	$\sigma^2 + n\sigma_{\gamma}^2$	$CB(A)/E$
$\varepsilon_{(ijk)l}$	1	1	1	1	$abc(n-1)$	σ^2	
T					$abcn-1$		