

Lecture 7: Latin Square and Related Design

Montgomery: Section 4.2-4.3

Automobile Emission Experiment

Four cars and **four drivers** are employed in a study for possible differences between **four gasoline additives**(A, B, C, D). Even though cars can be identical models, slight systematic differences are likely to occur in their performance, and even though each driver may do his best to drive the car in the manner required by the test, slight systematic differences can occur from driver to driver. It would be desirable to eliminate both the car-to-car and driver-to-driver differences.

drivers	cars			
	1	2	3	4
1	A=24	B=26	D=20	C=25
2	D=23	C=26	A=20	B=27
3	B=15	D=13	C=16	A=16
4	C=17	A=15	B=20	D=20

Design Matrix and Orthogonality

drivers	cars	additives
1	1	A
1	2	B
1	3	D
1	4	C
2	1	D
2	2	C
2	3	A
2	4	B
3	1	B
3	2	D
3	3	C
3	4	A
4	1	C
4	2	A
4	3	B
4	4	D

Orthogonality: for any two columns, all possible combinations appear and appear only once.

Latin Square Design

- Design is represented in $p \times p$ grid, rows and columns are blocks and Latin letters are treatments.
 - Every row contains all the Latin letters and every column contains all the Latin letters.
- Standard Latin Square: letters in first row and first column are in alphabetic order.
- Examples

C	B	A
B	A	C
A	C	B

B	A	C
A	C	B
C	B	A

D	B	C	A
C	D	A	B
B	A	D	C
A	C	B	D

Latin Square Design

- Properties:
 - Block on two nuisance factors
 - Two restrictions on randomization
- Model and Assumptions

$$y_{ijk} = \mu + \alpha_i + \tau_j + \beta_k + \epsilon_{ijk}, \quad i, j, k = 1, 2, \dots, p$$

μ - grand mean

α_i - i th block 1 effect (i th row effect);

$$\sum_{i=1}^p \alpha_i = 0.$$

τ_j - j th treatment effect;

$$\sum_{i=1}^p \tau_j = 0$$

β_k - k th block 2 effect (k th column effect);

$$\sum_{k=1}^p \beta_k = 0$$

$\epsilon_{ijk} \sim N(0, \sigma^2)$; (Normality, Independence, Constant Variance).

Completely additive model (no interaction)

Estimation and Basic Hypotheses Testing

- Rewrite observation y_{ijk} as:

$$\begin{aligned} y_{ijk} &= \bar{y}_{...} + (\bar{y}_{i..} - \bar{y}_{...}) + (\bar{y}_{.j.} - \bar{y}_{...}) + (\bar{y}_{..k} - \bar{y}_{...}) + (y_{ijk} - \bar{y}_{i..} - \bar{y}_{.j.} - \bar{y}_{..k} + \dots) \\ &= \hat{\mu} + \hat{\alpha}_i + \hat{\tau}_j + \hat{\beta}_k + \hat{\epsilon}_{ijk} \end{aligned}$$

- Partition $\text{SS}_T = \sum \sum (y_{ijk} - \bar{y}_{...})^2$ into

$$\begin{aligned} p \sum (\bar{y}_{i..} - \bar{y}_{...})^2 &+ p \sum (\bar{y}_{.j.} - \bar{y}_{...})^2 &+ p \sum (\bar{y}_{..k} - \bar{y}_{...})^2 &+ \sum \sum \hat{\epsilon}_{ijk}^2 \\ = \text{SS}_{\text{Row}} &+ \text{SS}_{\text{Treatment}} &+ \text{SS}_{\text{Col}} &+ \text{SS}_{\text{E}} \\ df : (p-1) & p-1 & p-1 & (p-1)(p-2) \end{aligned}$$

Dividing SS by df gives MS: $\text{MS}_{\text{Treatment}}$, MS_{Row} , MS_{Col} and MS_{E}

- Basic hypotheses: $H_0 : \tau_1 = \tau_2 = \dots = \tau_p = 0$ vs H_1 .
- Test Statistic: $F_0 = \text{MS}_{\text{Treatment}} / \text{MS}_{\text{E}} \sim F_{p-1, (p-1)(p-2)}$ under H_0 .
- Caution testing row effects ($\alpha_i = 0$) and column effects ($\beta_k = 0$).

Analysis of Variance Table

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F_0
Rows	SS_{Row}	$p - 1$	MS_{Row}	
Treatment	$SS_{\text{Treatment}}$	$p - 1$	$MS_{\text{Treatment}}$	F_0
Column	SS_{Column}	$p - 1$	MS_{Column}	
Error	SS_E	$(p - 2)(p - 1)$	MS_E	
Total	SS_T	$p^2 - 1$		

$$SS_T = \sum \sum \sum y_{ijk}^2 - y_{...}^2/p^2; \quad SS_{\text{Row}} = \frac{1}{p} \sum y_{i..}^2 - y_{...}^2/p^2$$

$$SS_{\text{Treatment}} = \frac{1}{p} \sum y_{.j.}^2 - y_{...}^2/p^2 \quad SS_{\text{Column}} = \frac{1}{p} \sum y_{..k}^2 - y_{...}^2/p^2$$

$$SS_{\text{Error}} = SS_T - SS_{\text{Row}} - SS_{\text{Treatment}} - SS_{\text{Column}}$$

- Decision Rule:

If $F_0 > F_{\alpha, p-1, (p-2)(p-1)}$ then reject H_0 .

SAS Code

Consider an experiment to investigate the effect of 4 diets on milk production. There are 4 cows. Each lactation period the cows receive a different diet. Assume there is a washout period so previous diet does not affect future results. Will block on lactation period and cow. A 4 by 4 Latin square is used.

```
options nocenter ls=75; goptions colors=(none);

data new;
  input cow period trt resp @@;
cards;
  1 1 1 38 1 2 2 32 1 3 3 35 1 4 4 33
  2 1 2 39 2 2 3 37 2 3 4 36 2 4 1 30
  3 1 3 45 3 2 4 38 3 3 1 37 3 4 2 35
  4 1 4 41 4 2 1 30 4 3 2 32 4 4 3 33
;

proc glm;
  class cow trt period;
  model resp=trt period cow;
  means trt/ lines tukey;
```

```
means period cow;
output out=new1 r=res p=pred;

symbol1 v=circle;
proc gplot; plot res*pred;

proc univariate noprint normal;
histogram res / normal (L=1 mu=0 sigma=est) kernel (L=2);
qqplot res/normal (L=1 mu=0 sigma=est);
run;
```

Output

Dependent Variable: resp

Source	DF	Sum of			F Value	Pr > F
		Squares	Mean Square			
Model	9	242.5625000	26.9513889		33.17	0.0002
Error	6	4.8750000	0.8125000			
Corrected Total	15	247.4375000				

Source	DF	Type I SS		Mean Square	F Value	Pr > F
trt	3	40.6875000		13.5625000	16.69	0.0026
period	3	147.1875000		49.0625000	60.38	<.0001
cow	3	54.6875000		18.2291667	22.44	0.0012

Source	DF	Type III SS		Mean Square	F Value	Pr > F
trt	3	40.6875000		13.5625000	16.69	0.0026
period	3	147.1875000		49.0625000	60.38	<.0001
cow	3	54.6875000		18.2291667	22.44	0.0012

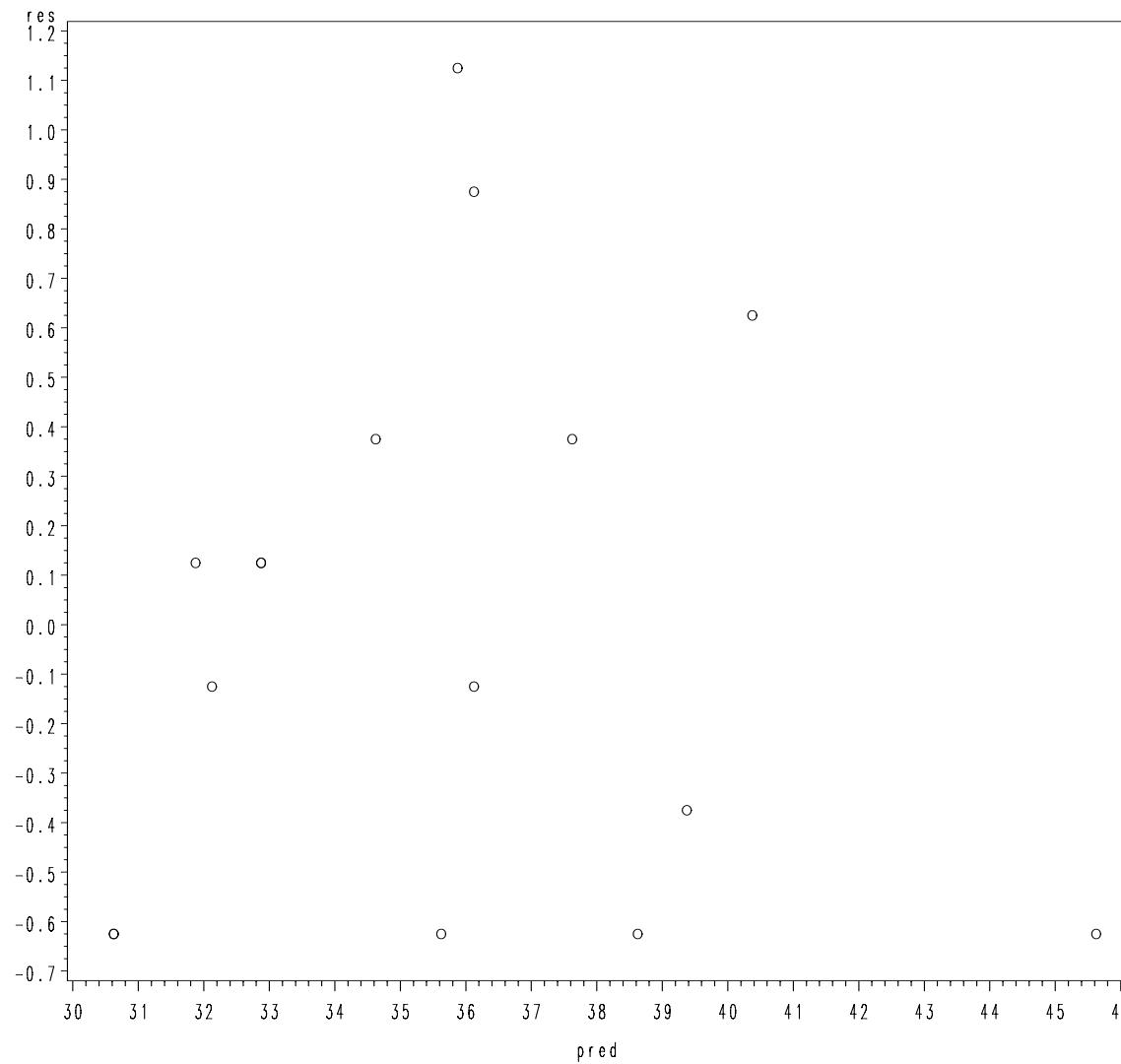
Output (continued)

Tukey's Studentized Range (HSD) Test for resp

Alpha	0.05
Error Degrees of Freedom	6
Error Mean Square	0.8125
Critical Value of Studentized Range	4.89559
Minimum Significant Difference	2.2064

	Mean	N	trt
A	37.5000	4	3
A	37.0000	4	4
B	34.5000	4	2
B	33.7500	4	1

Latin Square Design



Replicating Latin Squares

- Latin Squares result in small degree of freedom for SS_E :

$$df = (p - 1)(p - 2).$$

- If 3 treatments: $df_E = 2$
- If 4 treatments $df_E = 6$
- If 5 treatments $df_E = 12$

Use replication to increase df_E

- Different ways for replicating Latin squares:

1. Same rows and same columns
2. New rows and same columns
3. Same rows and new columns
4. New rows and new columns

Degree of freedom for SS_E depends on which method is used;

Often need to include an additional blocking factor for "replicate" effects.

Method 1: same rows and same columns in additional squares

Example:

	1	2	3	data	replication
1	A	B	C	7.0 8.0 9.0	
2	B	C	A	4.0 5.0 6.0	1
3	C	A	B	6.0 3.0 4.0	

	1	2	3	data	
1	C	B	A	8.0 4.0 7.0	
2	B	A	C	6.0 3.0 6.0	2
3	A	C	B	5.0 8.0 7.0	

	1	2	3	data	
1	B	A	C	9.0 6.0 8.0	
2	A	C	B	5.0 7.0 6.0	3
3	C	B	A	9.0 3.0 7.0	

Model and ANOVA Table for Method 1

Usually includes replicate (e.g., time) effects $(\delta_1, \dots, \delta_n)$

$$y_{ijkl} = \mu + \alpha_i + \tau_j + \beta_k + \delta_l + \epsilon_{ijkl} \quad \left\{ \begin{array}{l} i = 1, 2, \dots, p \\ j = 1, 2, \dots, p \\ k = 1, 2, \dots, p \\ l = 1, 2, \dots, n \end{array} \right.$$

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F
Rows	SS_{Row}	$p - 1$		
Columns	SS_{Column}	$p - 1$		
Replicate	$SS_{Replicate}$	$n - 1$		
Treatment	$SS_{Treatment}$	$p - 1$	$MS_{Treatment}$	F_0
Error	SS_E	$(p - 1)(n(p + 1) - 3)$	MS_E	
Total	SS_T	$np^2 - 1$		

data input and SAS code for Method 1

```
data new;  
input rep row col trt resp;  
datalines;  
1 1 1 1 7.0  
1 1 2 2 8.0  
1 1 3 3 9.0  
1 2 1 2 4.0  
1 2 2 3 5.0  
1 2 3 1 4.0  
1 3 1 3 6.0  
1 3 2 1 3.0  
1 3 3 2 4.0  
  
2 1 1 3 8.0  
2 1 2 2 4.0  
2 1 3 1 7.0  
2 2 1 2 6.0  
2 2 2 1 3.0  
2 2 3 3 6.0
```

2 3 1 1 5.0

2 3 2 3 8.0

2 3 3 2 7.0

3 1 1 2 9.0

3 1 2 1 6.0

3 1 3 3 8.0

3 2 1 1 5.0

3 2 2 3 7.0

3 2 3 2 6.0

3 3 1 3 9.0

3 3 2 2 3.0

3 3 3 1 7.0

;

```
proc glm data=new;
class rep row col trt;
model resp=rep row col trt;
run;
quit;
```

SAS Output for Method 1

Dependent Variable: resp

Sum of

Source	DF	Squares	Mean Square	F Value	Pr > F
Model	8	61.18518519	7.64814815	4.21	0.005
Error	18	32.66666667	1.81481481		
Corrected Total	26	93.85185185			
	R-Square	Coeff Var	Root MSE	resp Mean	
	0.651934	22.17870	1.347151	6.074074	

Source	DF	Type I SS	Mean Square	F Value	Pr > F
rep	2	5.62962963	2.81481481	1.55	0.2391
row	2	23.40740741	11.70370370	6.45	0.0077
col	2	9.85185185	4.92592593	2.71	0.0933
trt	2	22.29629630	11.14814815	6.14	0.0093

Method 2: New (different) rows and same columns

Example:

	1	2	3	data	replication
1	A	B	C	7.0 8.0 9.0	
2	B	C	A	4.0 5.0 6.0	1
3	C	A	B	6.0 3.0 4.0	

	1	2	3	data	
4	C	B	A	8.0 4.0 7.0	
5	B	A	C	6.0 3.0 6.0	2
6	A	C	B	5.0 8.0 7.0	

	1	2	3	data	
7	B	A	C	9.0 6.0 8.0	
8	A	C	B	5.0 7.0 6.0	3
9	C	B	A	9.0 3.0 7.0	

Model and ANOVA Table for Method 2

- Row effects are **nested** within square
- α_i can be different for different squares, so they are denoted $\alpha_{i(l)}$ for $i = 1, \dots, p$ and $l = 1, \dots, n$, and satisfy by $\sum_{i=1}^p \alpha_{i(l)} = 0$ for any fixed l .

$$y_{ijkl} = \mu + \alpha_{i(l)} + \tau_j + \beta_k + \delta_l + \epsilon_{ijkl} \quad \left\{ \begin{array}{l} i = 1, 2, \dots, p \\ j = 1, 2, \dots, p \\ k = 1, 2, \dots, p \\ l = 1, 2, \dots, n \end{array} \right.$$

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F
Rows	SS_{Row}	$n(p - 1)$		
Columns	SS_{Column}	$p - 1$		
Replicate	$SS_{\text{Replicate}}$	$n - 1$		
Treatment	$SS_{\text{Treatment}}$	$p - 1$	$MS_{\text{Treatment}}$	F_0
Error	SS_E	$(p - 1)(np - 2)$	MS_E	
Total	SS_T	$np^2 - 1$		

data input and SAS code for Method 2

```
data new;  
input rep row col trt resp;  
datalines;  
1 1 1 1 7.0  
1 1 2 2 8.0  
1 1 3 3 9.0  
1 2 1 2 4.0  
1 2 2 3 5.0  
1 2 3 1 4.0  
1 3 1 3 6.0  
1 3 2 1 3.0  
1 3 3 2 4.0  
  
2 4 1 3 8.0  
2 4 2 2 4.0  
2 4 3 1 7.0  
2 5 1 2 6.0  
2 5 2 1 3.0  
2 5 3 3 6.0
```

2 6 1 1 5.0

2 6 2 3 8.0

2 6 3 2 7.0

3 7 1 2 9.0

3 7 2 1 6.0

3 7 3 3 8.0

3 8 1 1 5.0

3 8 2 3 7.0

```
proc glm data=new;  
class rep row col trt;
```

3 8 3 2 6.0

```
model resp=rep row(rep) col trt;
```

3 9 1 3 9.0

```
run;
```

3 9 2 2 3.0

```
quit;
```

3 9 3 1 7.0

;

SAS ouput

Source	DF	Sum of		F Value	Pr > F
		Squares	Mean Square		
Model	12	74.00000000	6.16666667	4.35	0.0054
Error	14	19.85185185	1.41798942		
C.Total	26	93.85185185			
R-Square		Coeff Var	Root MSE	resp Mean	
0.788477		19.60453	1.190794	6.074074	
Source	DF	Type I SS	Mean Square	F Value	Pr > F
rep	2	5.62962963	2.81481481	1.99	0.1742
row(rep)	6	36.22222222	6.03703704	4.26	0.0120
col	2	9.85185185	4.92592593	3.47	0.0596
trt	2	22.29629630	11.14814815	7.86	0.0051

Latin Rectangle

- If there do not exist "replicate effects", the distinction between the squares can be neglected, so the replicated Latin squares form a Latin Rectangle with np separate rows.
- Row effects are $\alpha_1, \alpha_2, \dots, \alpha_{np}$ satisfying $\sum_{i=1}^{np} \alpha_i = 0$.
- Model:

$$y_{ijk} = \mu + \alpha_i + \tau_j + \beta_k + \epsilon_{ijk} \quad \left\{ \begin{array}{l} i = 1, 2, \dots, np \\ j = 1, 2, \dots, p \\ k = 1, 2, \dots, p \end{array} \right.$$

- ANOVA Table

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F
Rows	SS_{Row}	$np - 1$		
Columns	SS_{Column}	$p - 1$		
Treatment	$SS_{Treatment}$	$p - 1$	$MS_{Treatment}$	F_0
Error	SS_E	$(p - 1)(np - 2)$	MS_E	
Total	SS_T	$np^2 - 1$		

Method 3: Same rows and new (different) columns, is similar to Method 2. Details are omitted

Method 4: New (different) rows and now columns in additional squares

Example:

	1	2	3	data	replication
1	A	B	C	7.0 8.0 9.0	
2	B	C	A	4.0 5.0 6.0	1
3	C	A	B	6.0 3.0 4.0	

	4	5	6	data	
4	C	B	A	8.0 4.0 7.0	
5	B	A	C	6.0 3.0 6.0	2
6	A	C	B	5.0 8.0 7.0	

	7	8	9	data	
7	B	A	C	9.0 6.0 8.0	
8	A	C	B	5.0 7.0 6.0	3
9	C	B	A	9.0 3.0 7.0	

Model and ANOVA Table for Method 4

- Usually both row effects ($\alpha_{i(l)}$) and column effects ($\beta_{k(l)}$) are **nested** with squares.

$$y_{ijkl} = \mu + \alpha_{i(l)} + \tau_j + \beta_{k(l)} + \delta_l + \epsilon_{ijkl} \quad \left\{ \begin{array}{l} i = 1, 2, \dots, p \\ j = 1, 2, \dots, p \\ k = 1, 2, \dots, p \\ l = 1, 2, \dots, n \end{array} \right.$$

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F
Rows	SS _{Row}	$n(p - 1)$		
Columns	SS _{Column}	$n(p - 1)$		
Replicate	SS _{Replicate}	$n - 1$		
Treatment	SS _{Treatment}	$p - 1$	MS _{Treatment}	F ₀
Error	SS _E	$(p - 1)(n(p - 1) - 1)$	MS _E	
Total	SS _T	$np^2 - 1$		

Data input and SAS code

```
data new;  
input rep row col trt resp;  
datalines;  
1 1 1 1 7.0  
1 1 2 2 8.0  
1 1 3 3 9.0  
1 2 1 2 4.0  
1 2 2 3 5.0  
1 2 3 1 4.0  
1 3 1 3 6.0  
1 3 2 1 3.0  
1 3 3 2 4.0  
  
2 4 4 3 8.0  
2 4 5 2 4.0  
2 4 6 1 7.0  
2 5 4 2 6.0  
2 5 5 1 3.0  
2 5 6 3 6.0
```

2 6 4 1 5.0

2 6 5 3 8.0

2 6 6 2 7.0

3 7 7 2 9.0

3 7 8 1 6.0

3 7 9 3 8.0

3 8 7 1 5.0

3 8 8 3 7.0

```
proc glm data=new;
class rep row col trt;
```

3 8 9 2 6.0

```
model resp=rep row(rep) col(rep) trt;
```

3 9 8 2 3.0

```
run;
```

3 9 9 1 7.0

```
quit;
```

;

SAS output

Source	DF	Sum of				F Value	Pr > F
		Squares	Mean Square	Root MSE	resp Mean		
Model	16	77.70370370	4.85648148	2.20401481	3.01	0.0411	
Error	10	16.14814815	1.61481481	1.270754	6.074074		
C.Total	26	93.85185185					
R-Square		Coeff Var					
0.827940		20.92094					
Source	DF	Type I SS		Mean Square	F Value	Pr > F	
		5.62962963	36.22222222				
rep	2	5.62962963	36.22222222	2.81481481	1.74	0.2242	
row(rep)	6	13.55555556	22.29629630	6.03703704	3.74	0.0324	
col(rep)	6	13.55555556	22.29629630	2.25925926	1.40	0.3042	
trt	2	13.55555556	22.29629630	11.14814815	6.90	0.0131	

Crossover (Changeover) Design Consider an experiment for investigating the effects of 3 diets (A, B, C) on milk production. Suppose the experiment involves 3 lactation periods. Cows take different diets in different periods, that is, a cow will not take the same diet more than once (crossover).

- Case 1: 3 cows are used.

	cow 1	cow 2	cow 3
period 1	A	B	C
period 2	B	C	A
period 3	C	A	B

- Case 2: 6 cows are employed:

	cow 1	cow 2	cow 3	cow 4	cow 5	cow 6
pd 1	A	B	C	A	B	C
pd 2	B	C	A	C	A	B
pd 3	C	A	B	B	C	A

Crossover (Changeover) Design

- In general, there are p treatments, np experimental units, and p periods. n Latin squares ($p \times p$) are needed to form a rectangle ($p \times np$). So that
 - I. Each unit has each treatment for one period
 - II. In each period, each treatment is used on n units.

Source of Variation	DF
units	$np - 1$
periods	$p - 1$
treatment	$p - 1$
error	$np^2 - (n + 2)p + 2$
total	$np^2 - 1$

- Residual effects and washout periods
- Balanced for residual effects:
 - III. Each treatment follows every other treatment n times.

Graeco-Latin Square: An Example

An experiment is conducted to compare four gasoline additives by testing them on four cars with four drivers over four days. Only four runs can be conducted in each day. The response is the amount of automobile emission.

Treatment factor: gasoline additive, denoted by A, B, C and D .

Block factor 1: driver, denoted by 1, 2, 3, 4.

Block factor 2: day, denoted by 1, 2, 3, 4.

Block factor 3: car, denoted by $\alpha, \beta, \gamma, \delta$.

drivers	days			
	1	2	3	4
1	$A\alpha = 32$	$B\beta = 25$	$C\gamma = 31$	$D\delta = 27$
2	$B\delta = 24$	$A\gamma = 36$	$D\beta = 20$	$C\alpha = 25$
3	$C\beta = 28$	$D\alpha = 30$	$A\delta = 23$	$B\gamma = 31$
4	$D\gamma = 34$	$C\delta = 35$	$B\alpha = 29$	$A\beta = 33$

Graeco-Latin Square Design Matrix:

driver	day	additive	car
1	1	A	α
1	2	B	β
1	3	C	γ
1	4	D	δ
:	:	:	:
4	1	D	γ
4	2	C	δ
4	3	B	α
4	4	A	β

- Two $p \times p$ Latin squares are said to be **orthogonal** if the two squares when superimposed have the property that each pair of letters appears once.
- the superimposed square is called Graeco-Latin square.
- tables available for $p \leq 8$ in Wu&Hamada.
- 6×6 Graeco-Latin square does not exist

Model and Assumptions

$$y_{ijkl} = \mu + \alpha_i + \tau_j + \beta_k + \zeta_l + \epsilon_{ijkl} \quad \left\{ \begin{array}{l} i = 1, 2, \dots, p \\ j = 1, 2, \dots, p \\ k = 1, 2, \dots, p \end{array} \right.$$

μ - grand mean

α_i - i th block 1 effect (row effect) $\sum \alpha_i = 0$

τ_j - j th treatment effect $\sum \tau_j = 0$

β_k - k th block 2 effect (column effect) $\sum \beta_k = 0$

ζ_l - l th block 3 effect (Greek letter effect) $\sum \zeta_l = 0$

$\epsilon_{ijk} \sim N(0, \sigma^2)$ (independent)

- Completely additive model (no interaction)

Estimation and ANOVA

- Rewrite observation as:

$$\begin{aligned}y_{ijkl} &= \bar{y}_{....} + (\bar{y}_{i...} - \bar{y}_{....}) + (\bar{y}_{.j..} - \bar{y}_{....}) + (\bar{y}_{..k.} - \bar{y}_{....}) + \\&(\bar{y}_{...l} - \bar{y}_{....}) + (y_{ijkl} - \bar{y}_{i...} - \bar{y}_{.j..} - \bar{y}_{..k.} - \bar{y}_{...l} + 3\bar{y}_{....}) \\&= \hat{\mu} + \hat{\alpha}_i + \hat{\tau}_j + \hat{\beta}_k + \hat{\zeta}_l + \hat{\epsilon}_{ijkl}\end{aligned}$$

- Partition SS_T into:

$$\begin{aligned}p \sum (\bar{y}_{i...} - \bar{y}_{....})^2 + p \sum (\bar{y}_{.j..} - \bar{y}_{....})^2 + p \sum (\bar{y}_{..k.} - \bar{y}_{....})^2 + \\p \sum (\bar{y}_{...l} - \bar{y}_{....})^2 + \sum \sum \hat{\epsilon}_{ijkl}^2 \\= SS_{Row} + SS_{Treatment} + SS_{Col} + SS_{Greek} + SS_E\end{aligned}$$

with degree of freedom $p - 1, p - 1, p - 1, p - 1$ and $(p - 3)(p - 1)$, respectively.

Analysis of Variance Table

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F_0
Rows	SS_{Row}	$p - 1$	MS_{Row}	
Treatment	$SS_{Treatment}$	$p - 1$	$MS_{Treatment}$	F_0
Column	SS_{Column}	$p - 1$	MS_{Column}	
Greek	SS_{Greek}	$p - 1$	MS_{Greek}	
Error	SS_E	$(p - 3)(p - 1)$	MS_E	
Total	SS_T	$p^2 - 1$		

$$SS_T = \sum \sum \sum y_{ijkl}^2 - y_{...}^2 / p^2; \quad SS_{Row} = \frac{1}{p} \sum y_{i...}^2 - y_{...}^2 / p^2;$$

$$SS_{Treatment} = \frac{1}{p} \sum y_{.j..}^2 - y_{...}^2 / p^2 \quad SS_{Column} = \frac{1}{p} \sum y_{..k.}^2 - y_{...}^2 / p^2;$$

$$SS_{Greek} = \frac{1}{p} \sum y_{...l}^2 - y_{...}^2 / p^2; \quad SS_{Error} = \text{Use subtraction};$$

Decision Rule: If $F_0 > F_{\alpha, p-1, (p-3)(p-1)}$ then reject H_0

Sas Code and Output

```
data new; input row col trt greek resp @@; datalines;
1 1 1 1 32 1 2 2 2 25
1 3 3 3 31 1 4 4 4 27
2 1 2 4 24 2 2 1 3 36
2 3 4 2 20 2 4 3 1 25
3 1 3 2 28 3 2 4 1 30
3 3 1 4 23 3 4 2 3 31
4 1 4 3 34 4 2 3 4 35
4 3 2 1 29 4 4 1 2 33
;
proc glm data=new;
class rowcol trt greek;
model resp=row col trt greek;
run;
```

Output

Source	DF	Sum of		F Value	Pr > F
		Squares	Mean Square		
Model	12	296.7500000	24.7291667	2.83	0.2122
Error	3	26.1875000	8.7291667		
CoTotal	15	322.9375000			

R-Square	Coeff Var	Root MSE	resp Mean
0.918908	10.20999	2.954516	28.93750

Source	DF	Type I SS	Mean Square	F Value	Pr > F
row	3	90.6875000	30.2291667	3.46	0.1674
col	3	68.1875000	22.7291667	2.60	0.2263
trt	3	36.6875000	12.2291667	1.40	0.3942
greek	3	101.1875000	33.7291667	3.86	0.1481

Multiple comparison can be carried out using similar methods