

## Randomized Complete Block Design (RCBD)

$y_{ij} = \mu + \tau_i + \beta_j + \epsilon_{ij}$ , Where  $i = \#$  of treatments,  $j = \#$  of blocks. ( $\mu$  Grand Mean), ( $\tau$  Treatment effect), ( $\beta$  Block effect).  
Constraint:  $\sum \tau_i = 0$ ,  $\sum \beta_j = 0$ .

Estimates: Grand Mean:  $\hat{\mu} = \bar{y}_{..}$ , Treatment Effect:  $\hat{\tau}_i = \bar{y}_{i.} - \bar{y}_{..}$ , Block Effect:  $\hat{\beta}_j = \bar{y}_{.j} - \bar{y}_{..}$ .

Grand Sample Average:  $\bar{y}_{..} = \frac{1}{ab} \sum_{i=1}^a \sum_{j=1}^b y_{ij}$

Sample Mean for  $i^{th}$  Treatment (averaged over all blocks):  $\bar{y}_{i.} = \frac{1}{b} \sum_{j=1}^b y_{ij}$

Sample Mean for  $j^{th}$  Block (averaged over all treatments):  $\bar{y}_{.j} = \frac{1}{a} \sum_{i=1}^a y_{ij}$

Fitted  $y_{ij}$  Values:  $\hat{y}_{ij} = \bar{y}_{i.} + \bar{y}_{.j} - \bar{y}_{..}$ .

### RCBD - ANOVA

Source	df	SS	MS	F
Treatments	$a - 1$	$SSTr$	$MSTr = \frac{SSTr}{a-1}$	$F = \frac{MSTr}{MSE}$
Blocks	$b - 1$	$SSB$	$MSB = \frac{SSB}{b-1}$	$F = \frac{MSB}{MSE}$
Error	$(a-1)(b-1)$	$SSE$	$MSE = \frac{SSE}{(a-1)(b-1)}$	
Total	$ab - 1$	$SST$		

Pooled sample variance(est.  $\sigma^2$ ):  $s^2 = MSE$ .

Test of Homogeneity of Treatment Effects:

$H_0: \tau_1 = \tau_2 = \dots = \tau_a = 0$ .

$H_a$ : not all  $\tau_i = 0$ .

Reject  $H_0$  if  $F > F_{\alpha, a-1, (a-1)(b-1)}$ , or p-value  $< \alpha$ .

**C.I for  $\mu_i$ :**  $\bar{y}_{i.} \pm t_{\alpha/2, df_{error}} \frac{s}{\sqrt{b}}$

**Fisher's LSD Multiple Comparison Test:** Treatment  $i$  and  $j$  are significantly different if  $|\bar{y}_{i.} - \bar{y}_{j.}| > t_{\alpha/2, df_{error}} s \sqrt{\frac{2}{b}}$ .

(Reject  $H_0: \tau_i = \tau_j$ ). **Fishers C.I.:** For all possible treatment differences,  $\bar{y}_{i.} - \bar{y}_{k.} \pm t_{\alpha/2, df_{error}} s \sqrt{\frac{2}{b}}$ .

**Tukey's Multiple Comparison Test:** Treatment  $i$  and  $j$  are significantly different if  $|\bar{y}_{i.} - \bar{y}_{j.}| > q_{\alpha, a, df_{error}} \frac{s}{\sqrt{b}}$ .

**Tukey's C.I.:** For all possible treatment differences,  $\bar{y}_{i.} - \bar{y}_{k.} \pm q_{\alpha, a, df_{error}} \frac{s}{\sqrt{b}}$ .

## Two Factor Design

$y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \epsilon_{ijk}$ . Constraint:  $\sum \tau_i = 0$ ,  $\sum \beta_j = 0$ , and  $\sum (\tau\beta)_{ij} = 0$  (for each fixed i,j).

**Interaction:** if  $(\tau\beta)_{ij} = 0$  for every i,j then there is no interaction between factors A and B.

**Estimates:**  $\bar{y}_{..} = \frac{1}{abn} \sum_{i=1}^a \sum_{j=1}^b \sum_{k=1}^n y_{ijk}$ .  $\bar{y}_{i..} = \frac{1}{bn} \sum_{j=1}^b \sum_{k=1}^n y_{ijk}$ .  $\bar{y}_{.j.} = \frac{1}{an} \sum_{i=1}^a \sum_{k=1}^n y_{ijk}$ .

**Fitted Values:**  $\hat{y}_{ijk} = \hat{\mu} + \hat{\tau}_i + \hat{\beta}_j + (\hat{\tau\beta})_{ij} = \bar{y}_{ijk}$ .

### 2 Factor - ANOVA

Source	df	SS	MS	F
Factor A	$a - 1$	$SSA$	$MSA = \frac{SSA}{a-1}$	$F = \frac{MSA}{MSE}$
Factor B	$b - 1$	$SSB$	$MSB = \frac{SSB}{b-1}$	$F = \frac{MSB}{MSE}$
AB Interaction	$(a-1)(b-1)$	$SSAB$	$MSAB = \frac{SSAB}{(a-1)(b-1)}$	$F = \frac{MSAB}{MSE}$
Error	$N - ab$	$SSE$	$MSE = \frac{SSE}{N-ab}$	
Total	$N - 1$	$SST$		

Note:  $N = abn$

If  $n = 1$  assume no interaction.

Test of significance of

AB Interaction should be done first.

If there is interaction it is not useful to test for significance of A and B.

**Test of Significance of AB Interaction:**  $H_0: (\tau\beta)_{11} = (\tau\beta)_{12} = \dots = (\tau\beta)_{ab} = 0$ .  $H_a$ : not all  $(\tau\beta)_{ij}$  are the same.

Reject  $H_0$  if  $F > F_{\alpha, (a-1)(b-1), N-ab}$ , or p-value  $< \alpha$ .

If  $H_0$  is rejected, conclude that there exists interaction between Factors A and B at significance level  $\alpha$ .

### Case 1: No Interaction between A and B

It is meaningful to test for the significance of the main effect of A and the main effect of B.

May combine the interaction sum of squares with the error sum of squares.

**Anova:** df:  $df_{error} = abn - a - b + 1$ , **SSE:**  $SSE' = SSAB + SSE$ , **MSE:**  $MSE' = \frac{SSE'}{abn-a-b+1}$ .

Note that F values must be updated with the new  $MSE'$  before testing.

**Tukeys C.I.:** For  $\tau_i - \tau_{i'}$  (or  $\beta$ ). Equivalent to FWE  $= \alpha$  for hypothesis test.

**Factor A:**  $\bar{y}_{i..} - \bar{y}_{i'..} \pm q_{\alpha, a, df_{error}} \sqrt{\frac{MSE}{bn}}$ . **Factor B:**  $\bar{y}_{.j.} - \bar{y}_{.j'.} \pm q_{\alpha, b, df_{error}} \sqrt{\frac{MSE}{an}}$

**Fisher's C.I.:** For  $\tau_i - \tau_{i'}$  (or  $\beta$ ). Equivalent to  $\alpha$  for hypothesis test.

**Factor A:**  $\bar{y}_{i..} - \bar{y}_{i'..} \pm t_{\alpha/2, df_{error}} \sqrt{\frac{2MSE}{bn}}$ . **Factor B:**  $\bar{y}_{.j.} - \bar{y}_{.j'.} \pm t_{\alpha/2, df_{error}} \sqrt{\frac{2MSE}{an}}$

## Case 2: Interaction between A and B

Not meaningful to test significance of main effect of A and B. Treat each individual factor-level combination of  $i^{th}$  level of A, and  $j^{th}$  level of B, as a treatment. So there are  $ab$  treatments. Test every pair of treatments using Tukey's or Fisher's.

**Test:**  $H_0: \mu_{11} = \mu_{12} = \dots = \mu_{ab}$  using the F test for CRD.

**Tukey's C.I.:**  $\bar{y}_{ij} - \bar{y}_{i'j'} \pm q_{\alpha, ab, abn-ab} \sqrt{\frac{MSE}{n}}$

**Fisher's C.I.:**  $\bar{y}_{ij} - \bar{y}_{i'j'} \pm t_{\alpha/2, abn-ab} \sqrt{\frac{2MSE}{n}}$

## $2^k$ Factorial Design Using the $[-1, +1]$ Notation

### 2 Factor - ANOVA

Std Order	A	B	AB	C	AC	BC	ABC
(1)	-	-	+	-	+	+	-
a	+	-	-	-	-	+	+
b	-	+	-	-	+	-	+
ab	+	+	+	-	-	-	-
c	-	-	+	+	-	-	+
ac	+	-	-	+	+	-	-
bc	-	+	-	+	-	+	-
abc	+	+	+	+	+	+	+

Note:  $A \times B = AB$  and so on.  
Factor interactions: There will be  $k$  main effects and  $\binom{k}{2}$  two-factor interactions,  $\binom{k}{3}$  three-factor interactions.

**Contrasts:**

Estimated main effect:  $\frac{1}{2^{k-1}} \cdot \sum_{i=1}^{2^k} c_i \bar{y}_i$

Standard Error:  $se(\hat{\text{Effect}}) = \sqrt{\frac{MSE}{n2^{k-2}}} = \frac{s}{\sqrt{n2^{k-2}}}$

C.I.:  $\hat{\text{Effect}} \pm t_{\alpha/2, df_{error}} \cdot se(\hat{\text{Effect}})$

**Model:** Standard error:  $se(\hat{\beta}) = \sqrt{\frac{\sigma^2}{n2^k}} = \sqrt{\frac{MSE}{n2^k}}$ . Confidence interval:  $\hat{\beta} \pm t_{\alpha/2, df_{error}} \cdot se(\hat{\beta})$

**Hypothesis Test:**  $H_0$ : True effect = x (usually 0).  $H_a$ : True effect  $\neq (< \text{or } >)$  x.

t test:  $t = \frac{\text{Effect} - x}{se(\text{Effect})} = \frac{\sqrt{n2^{k-2}} \cdot (\hat{\text{Effect}})}{\sqrt{MSE}}$ . Reject  $H_0$  if  $|t| > t_{\alpha/2, df_{error}}$  or p-value  $< \alpha$ .

F test:  $F = t^2$ . Reject if  $F > F_{\alpha/2, df_{error}}$  or p-value  $< \alpha$ .

Reject  $H_0$ , conclude that the main effect of Effect is significant.

**Sum of Squares:**  $SS_{effect} = (n2^{k-2})(\hat{\text{Effect}})^2$ .

**Notes on Anova:**

Main Effects:  $\hat{A} = 2\hat{\tau}_2 = -2\hat{\tau}_1$ .

From the Coefficients from Minitab:  $\hat{\tau}_1$  is Coef,  $se(\hat{\tau}_1)$  is SE Coef.

From the Coefficients from Minitab:  $(\tau\hat{\beta}\gamma)_{111}$  is Coef,  $se((\tau\hat{\beta}\gamma)_{111})$  is SE Coef.

From the Coded Coefficients from Minitab:  $\hat{\tau}_2$  is Coef,  $se(\hat{\tau}_2)$  is SE Coef.

From the Coded Coefficients from Minitab:  $(\tau\hat{\beta}\gamma)_{222}$  is Coef,  $se((\tau\hat{\beta}\gamma)_{222})$  is SE Coef.

**For  $2^2$  Design:** Sum of Squares of Effects:  $SS_{contrast} = \frac{(\sum_{i=1}^4 c_i \bar{y}_i)^2}{\frac{1}{n} \sum_{i=1}^4 c_i^2}$ .  $SS_{effect} = n(\frac{1}{2} \sum_{i=1}^4 c_i \bar{y}_i)^2 = n(\text{Main Effect})^2$ .