

29 Lecture 29: April 21

Last time

- two-way anova

Today

- Analysis of Variance (JF chapter 8)
 - Testing hypotheses in two-way ANOVA

Testing hypotheses in two-way ANOVA

We follow the notations of JF for incremental sums of squares in ANOVA:

$$\mathbf{SS}(\gamma|\alpha, \beta) = \mathbf{SS}(\alpha, \beta, \gamma) - \mathbf{SS}(\alpha, \beta)$$

$$\mathbf{SS}(\alpha|\beta, \gamma) = \mathbf{SS}(\alpha, \beta, \gamma) - \mathbf{SS}(\beta, \gamma)$$

$$\mathbf{SS}(\beta|\alpha, \gamma) = \mathbf{SS}(\alpha, \beta, \gamma) - \mathbf{SS}(\alpha, \gamma)$$

$$\mathbf{SS}(\alpha|\beta) = \mathbf{SS}(\alpha, \beta) - \mathbf{SS}(\beta)$$

$$\mathbf{SS}(\beta|\alpha) = \mathbf{SS}(\alpha, \beta) - \mathbf{SS}(\alpha)$$

where $\mathbf{SS}(\alpha, \beta, \gamma)$ denotes the regression sum of squares for the full model which includes both sets of main effects and the interaction. $\mathbf{SS}(\alpha, \beta)$ denotes the regression sum of squares for the no-interaction model and $\mathbf{SS}(\alpha, \gamma)$ denotes the regression for the model that omits the column main-effect regressors. Note that the last model violates the principle of marginality because it includes the interaction regressors but omits the column main effects. However, it is useful for constructing the incremental sum of squares for testing the column main effects.

Additional readings: [Notes on 3 types of Sum of Squares](#) by Dr. Nancy Reid (attached on canvas site).

We now have the two-way ANOVA table

Table 1: Two-way ANOVA table

| Source | Sum of Squares | df | H_0 |
|-----------|---|------------------|---|
| R | $\mathbf{SS}(\alpha \beta, \gamma)$ | $r - 1$ | all $\alpha_j = 0$ |
| | $\mathbf{SS}(\alpha \beta)$ | $r - 1$ | all $\alpha_j = 0 \mid$ all $\gamma_{jk} = 0$ |
| C | $\mathbf{SS}(\beta \alpha, \gamma)$ | $c - 1$ | all $\beta_k = 0$ |
| | $\mathbf{SS}(\beta \alpha)$ | $c - 1$ | all $\beta_k = 0 \mid$ all $\gamma_{jk} = 0$ |
| RC | $\mathbf{SS}(\gamma \alpha, \beta)$ | $(r - 1)(c - 1)$ | all $\gamma_{jk} = 0$ |
| Residuals | $\mathbf{TSS} - \mathbf{SS}(\alpha, \beta, \gamma)$ | $n - rc$ | |
| Total | \mathbf{TSS} | $n - 1$ | |

where the residual sum of squares

$$RSS = \sum_i \sum_j \sum_k (Y_{ijk} - \bar{Y}_{jk})^2$$

When testing for the hypothesis, use the corresponding SS and df together with the residual SS and df to construct the F -statistic.

$$F = \frac{SS/df}{RSS/df_{residual}}$$

There are two reasonable procedures for testing main-effect hypotheses in two-way ANOVA:

1. Tests based on $\mathbf{SS}(\alpha|\beta, \gamma)$ and $\mathbf{SS}(\beta|\alpha, \gamma)$ (“type III” tests) employ models that violate the principle of marginality, but the tests are valid whether or not interactions are present.
2. Tests based on $\mathbf{SS}(\alpha|\beta)$ and $\mathbf{SS}(\beta|\alpha)$ (“type II” tests) conform to the principle of marginality but are valid only if interactions are absent, in which case they are maximally powerful.

Some more jargon:

- Experimental unit (EU): entity to which experimental treatment is assigned.
For example, Assign fertilizer treatment to fields. Fields = EU.
- Measurement unit (MU): entity that is measured.
For example, Measure yields at several subplots within each field. MU: subplot
- Treatment structure: describes how different experimental factors are combined to generate treatments.
For example, Fertilizers: A, B, C; Irrigation: High, Low.
- Randomization structure: how treatments are assigned to EUs.

- Simplest treatment structure: single experimental factor with multiple levels. Ex. Fertilizers A vs B vs C.
- Simplest randomization structure: Completely randomized design – Experimental treatments assigned to EUs entirely at random.

Example: Honeybee data

Entomologist records energy expended (y) by $N = 27$ honeybees at $a = 3$ temperature (A) levels (20, 30, 40°C) consuming liquids with $b = 3$ levels of sucrose concentration (B) (20%, 40%, 60%) in a balanced, completely randomized crossed 3×3 design.

| Temp | Suc | Sample | | |
|------|-----|--------|------|------|
| 20 | 20 | 3.1 | 3.7 | 4.7 |
| 20 | 40 | 5.5 | 6.7 | 7.3 |
| 20 | 60 | 7.9 | 9.2 | 9.3 |
| 30 | 20 | 6 | 6.9 | 7.5 |
| 30 | 40 | 11.5 | 12.9 | 13.4 |
| 30 | 60 | 17.5 | 15.8 | 14.7 |
| 40 | 20 | 7.7 | 8.3 | 9.5 |
| 40 | 40 | 15.7 | 14.3 | 15.9 |
| 40 | 60 | 19.1 | 18.0 | 19.9 |

1. What is the experimental unit?
2. What is the treatment structure?
3. Finish the table below

| Source | df |
|--------------|----|
| A | |
| B | |
| $A \times B$ | |
| Residual | |
| Total | |

Answer:

4. Consider the model

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where $i = 1, 2, \dots, a$, $j = 1, 2, \dots, b$ and $k = 1, 2, \dots, n$ for a balanced design.

Deviation:

- total: $y_{ijk} - \bar{y}_{+++}$
- due to level i of factor A: $\bar{y}_{i++} - \bar{y}_{+++}$
- due to level j of factor B: $\bar{y}_{+j+} - \bar{y}_{+++}$
- due to levels i of factor A and j of factor B after subtracting main effects:

$$\bar{y}_{ij+} - \bar{y}_{+++} - (\bar{y}_{i++} - \bar{y}_{+++}) - (\bar{y}_{+j+} - \bar{y}_{+++}) = \bar{y}_{ij+} - \bar{y}_{i++} - \bar{y}_{+j+} + \bar{y}_{+++}$$

Use the following equations to calculate the Sum of Squares and fill out the ANOVA table.

$$\begin{aligned} SS[Total] &= \sum_i \sum_j \sum_k (y_{ijk} - \bar{y}_{+++})^2 \\ SS[A] &= \sum_i \sum_j \sum_k (\bar{y}_{i++} - \bar{y}_{+++})^2 \\ SS[B] &= \sum_i \sum_j \sum_k (\bar{y}_{+j+} - \bar{y}_{+++})^2 \\ SS[AB] &= \sum_i \sum_j \sum_k (\bar{y}_{ij+} - \bar{y}_{i++} - \bar{y}_{+j+} + \bar{y}_{+++})^2 \\ SS[E] &= \sum_i \sum_j \sum_k (\bar{y}_{ijk} - \bar{y}_{ij+})^2 \end{aligned}$$

where

$$\begin{aligned} \bar{y}_{ij+} &= \frac{1}{n} \sum_k y_{ijk} \\ \bar{y}_{i++} &= \frac{1}{b} \sum_j \bar{y}_{ij+} = \frac{1}{bn} \sum_j \sum_k y_{ijk} \\ \bar{y}_{+j+} &= \frac{1}{a} \sum_i \bar{y}_{ij+} = \frac{1}{an} \sum_i \sum_k y_{ijk} \\ \bar{y}_{+++} &= \frac{1}{a} \sum_i \bar{y}_{i++} = \frac{1}{b} \sum_j \bar{y}_{+j+} \\ &= \frac{1}{abn} \sum_i \sum_j \sum_k y_{ijk} \end{aligned}$$

| Source | df | Sum of Squares | Mean Square | F |
|--------------|----|----------------|-------------|---|
| A | | | | |
| B | | | | |
| $A \times B$ | | | | |
| Residual | | | | |
| Total | | | | |

Answer:

A three-factor example

In a balanced, complete, crossed design, $N = 36$ shrimp were randomized to $abc = 12$ treatment combinations from the factors below:

- A1: Temperature at $25^{\circ}C$
- A2: Temperature at $35^{\circ}C$
- B1: Density of shrimp population at 80 shrimp/40l
- B2: Density of shrimp population at 160 shrimp/40l
- C1: Salinity at 10 units
- C2: Salinity at 25 units
- C3: Salinity at 40 units

The response variable of interest is weight gain Y_{ijkl} after four weeks.

Three-way ANOVA model

$$\begin{aligned}
 Y_{ijkl} = & \mu + \alpha_i + \beta_j + \gamma_k \\
 & + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} \\
 & + (\alpha\beta\gamma)_{ijk} + \epsilon_{ijkl} \\
 & i = 1, 2 \\
 & j = 1, 2 \\
 & k = 1, 2, 3 \\
 & l = 1, 2, 3 \\
 & \epsilon_{ijkl} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)
 \end{aligned}$$

Many constraints such as (over one dimension):

$$\begin{aligned}\sum_i \alpha_i &= 0 \\ \sum_i (\alpha\beta)_{ij} &= \sum_j (\alpha\beta)_{ij} = 0 \quad \text{for all } i, j \\ \sum_i (\alpha\beta\gamma)_{ijk} &= \sum_j (\alpha\beta\gamma)_{ijk} = \sum_k (\alpha\beta\gamma)_{ijk} = 0 \quad \text{for all } i, j, k\end{aligned}$$

Now, please finish the table below

| Source | df |
|-----------------------|----|
| A | |
| B | |
| C | |
| $A \times B$ | |
| $A \times C$ | |
| $B \times C$ | |
| $A \times B \times C$ | |
| Residual | |
| Total | |

Answer:

The three-way ANOVA model includes parameters for

- Main effects: α_i , β_j and γ_k .
- Two-way interactions between each pair of factors: $(\alpha\beta)_{ij}$, $(\alpha\gamma)_{ik}$ and $(\beta\gamma)_{jk}$.
- Three-way interaction among all three factors: $(\alpha\beta\gamma)_{ijk}$.

Readings:

1. JF 8.3.1 on parameter estimates and hypothesis testing for three-way ANOVA model.
2. JF 8.3.2 on Higher-order classifications.

Analysis of Covariance

Analysis of covariance (ANCOVA) is a term used to describe linear models that contain both qualitative and quantitative explanatory variables. The method is, therefore, equivalent to

dummy-variable regression, discussed in the previous lectures, although the ANCOVA model is parametrized differently from the dummy-regression model.

Covariate is a variable known to affect the response that

1. differs among EUs
2. reflects differences that exist independently of experimental treatment.

A nutrition example

A nutrition scientist conducted an experiment to evaluate the effects of four vitamin supplements on the weight gain of laboratory animals. The experiment was conducted in a completely randomized design with $N = 20$ animals randomized to $a = 4$ supplement groups, each with sample size $n \equiv 5$. The response variable of interest is weight gain, but calorie intake z was measured simultaneously.

| Diet | $y(g)$ | Diet | y | Diet | y | Diet | y |
|------|---------------------|------|-----------------------|------|-----------------------|------|-----------------------|
| 1 | 48 | 2 | 65 | 3 | 79 | 4 | 59 |
| 1 | 67 | 2 | 49 | 3 | 52 | 4 | 50 |
| 1 | 78 | 2 | 37 | 3 | 63 | 4 | 59 |
| 1 | 69 | 2 | 75 | 3 | 65 | 4 | 42 |
| 1 | 53 | 2 | 63 | 3 | 67 | 4 | 34 |
| 1 | $\bar{y}_{1+} = 63$ | 2 | $\bar{y}_{2+} = 57.8$ | 3 | $\bar{y}_{3+} = 65.2$ | 4 | $\bar{y}_{4+} = 48.8$ |
| 1 | $s_1 = 12.3$ | 2 | $s_2 = 14.9$ | 3 | $s_3 = 9.7$ | 4 | $s_4 = 10.9$ |

Question: Is there evidence of a vitamin supplement effect?

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|-----------|----|--------|---------|---------|--------|
| Diet | 3 | 797.8 | 265.9 | 1.823 | 0.184 |
| Residuals | 16 | 2334.4 | 145.9 | | |

But calorie intake z was measured simultaneously:

| Diet | $y(g)$ | z | Diet | y | z | Diet | y | z | Diet | y | z |
|------|--------|-----|------|-----|-----|------|-----|-----|------|-----|-----|
| 1 | 48 | 350 | 2 | 65 | 400 | 3 | 79 | 510 | 4 | 59 | 530 |
| 1 | 67 | 440 | 2 | 49 | 450 | 3 | 52 | 410 | 4 | 50 | 520 |
| 1 | 78 | 440 | 2 | 37 | 370 | 3 | 63 | 470 | 4 | 59 | 520 |
| 1 | 69 | 510 | 2 | 75 | 530 | 3 | 65 | 470 | 4 | 42 | 510 |
| 1 | 53 | 470 | 2 | 63 | 420 | 3 | 67 | 480 | 4 | 34 | 430 |

Question: How and why could these new data be incorporated into analysis?

Answer: ANCOVA can be used to reduce unexplained variation.

ANCOVA model,

$$y_{ij} = \mu + \alpha_i + \beta z_{ij} + \epsilon_{ij}$$

where μ is the reference level, α_i is the main effect of treatment, β is the partial regression coefficient, and $\epsilon_{ij} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$. The model is equivalent as the dummy-variable regression model,

$$Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_z z_i + \epsilon_i \quad \text{for } i = 1, \dots, 20$$

Finish the table below

| Source | df |
|-----------|----|
| Diet | |
| Covariate | 1 |
| Residual | |
| Total | |

Answer:

To test for difference among treatments. The null hypothesis in terms of α_i is

$H_0 : \alpha_1 = \alpha_2 = \dots = \alpha_4 = 0$ v.s. $H_a : \text{at least one } \alpha_i \neq 0$

And the null hypothesis in terms of β_i is

$H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ v.s. $H_a : \text{at least one } \beta_i \neq 0$

Question: which two models do we compare when testing the above null hypothesis?

Answer:

Linear contrasts of means

With ANOVA (or ANCOVA) models, we do not generally test hypotheses about individual coefficients (but we can do so if we wish). For dummy-coded regressors in one-way ANOVA, a t -test or F -test of $H_0 : \alpha_1 = 0$, for example, is equivalent to testing for the difference in means between the first group and the baseline group, $H_0 : \mu_1 = \mu_m$.

Consider the one-way ANOVA model:

$$Y_{ij} = \mu_i + \epsilon_{ij}, i = 1, 2, \dots, t, \text{ and } j = 1, 2, \dots, n_i$$

with $\epsilon_{ij} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$.

A linear function of the group means of the form

$$\theta = c_1\mu_1 + c_2\mu_2 + \dots + c_t\mu_t$$

is called a linear combination of the treatment means. And the c_i 's are the coefficients of the linear combination. If

$$c_1 + c_2 + \dots + c_t = \sum_{j=1}^t c_j = 0,$$

the linear combination is called a contrast. Contrasts with more than two non-zero coefficients are called complex contrasts.

Let two contrasts θ_1 and θ_2 be given by

$$\begin{aligned}\theta_1 &= c_1\mu_1 + \dots + c_t\mu_t = \sum_{j=1}^t c_j\mu_j \\ \theta_2 &= d_1\mu_1 + \dots + d_t\mu_t = \sum_{j=1}^t d_j\mu_j,\end{aligned}$$

then the two contrasts θ_1 and θ_2 are mutually orthogonal if the products of their coefficients sum to zero:

$$c_1d_1 + \dots + c_td_t = \sum_{j=1}^t c_jd_j = 0$$

θ_i and θ_j are orthogonal $\implies \hat{\theta}_i$ and $\hat{\theta}_j$ are statistically independent.

Types of effects

Consider the following two-way ANOVA model:

$$\begin{aligned}Y_{ijk} &= \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk} \\ i &= 1, 2 = a \text{ and } j = 1, 2 = b \text{ and } k = 1, 2, \dots, 7 = n.\end{aligned}$$

$\epsilon_{ijk} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$. Parameter constraints: $\sum_i \alpha_i = \sum_j \beta_j = 0$ and $\sum_i (\alpha\beta)_{ij} = 0$ for each j and $\sum_j (\alpha\beta)_{ij} = 0$ for each i .

- Factor A: AGE has $a = 2$ levels - A_1 : younger and A_2 : older
- Factor B: GENDER has $b = 2$ levels - B_1 : female and B_2 : male

Three kinds of effects in this 2×2 design:

1. Simple effects are simple contrasts.
 - $\mu(A_1B) = \mu_{12} - \mu_{11}$ - simple effect of gender for young folks.
 - $\mu(AB_1) = \mu_{21} - \mu_{11}$ - simple effect of age for women.
2. Interaction effects are differences of simple effects: $\mu(AB) = \mu(AB_2) - \mu(AB_1) = (\mu_{22} - \mu_{12}) - (\mu_{21} - \mu_{11})$
 - difference between simple age effects for men and women
 - difference between simple gender effects for old and young folks
 - interaction effect of AGE and GENDER.
3. Main effects are averages or sums of simple effects

$$\mu(A) = \frac{1}{2}(\mu(AB_1) + \mu(AB_2))$$

$$\mu(B) = \frac{1}{2}(\mu(A_1B) + \mu(A_2B))$$

Sampling distribution of linear contrast estimates

For a linear contrast

$$\theta = c_1\mu_1 + \cdots + c_t\mu_t$$

The *best* estimator for a contrast of interest can be obtained by substituting treatment group sample means \bar{y}_{i+} for treatment population means μ_i in the contrast θ :

$$\hat{\theta} = c_1\bar{Y}_{1+} + c_2\bar{Y}_{2+} + \cdots + c_t\bar{Y}_{t+}$$

Example

Recall the binding fraction data that investigate binding fraction for several antibiotics using $n = 20$ bovine serum samples:

| Antibiotic | Binding Percentage | Sample mean |
|-----------------|---------------------|-------------|
| Penicillin G | 29.6 24.3 28.5 32.0 | 28.6 |
| Tetracyclin | 27.3 32.6 30.8 34.8 | 31.4 |
| Streptomycin | 5.8 6.2 11.0 8.3 | 7.8 |
| Erythromycin | 21.6 17.4 18.3 19 | 19.1 |
| Chloramphenicol | 29.2 32.8 25.0 24.2 | 27.8 |

Consider the pairwise contrast comparing penicillin (population) mean to Tetracyclin mean:

$$\theta = \mu_1 - \mu_2 = (1)\mu_1 + (-1)\mu_2 + (0)\mu_3 + (0)\mu_4 + (0)\mu_5$$

Obtain a point estimator of θ .

Answers:

Question: How good is this estimate? In other words, how much uncertainty associated with the estimate?

We want to characterize the sampling distribution of $\hat{\theta}$. According to our model setup, Y_{ij} follow normal distributions. $\hat{\theta}$ is a linear function of Y_{ij} , so that $\hat{\theta}$ follows a normal distribution. We want to derive the mean and variance (the two sufficient statistics) to characterize the normal distribution that $\hat{\theta}$ follows:

$$\hat{\theta} \sim \mathcal{N}(\theta, \text{Var}(\hat{\theta}))$$

Derive expressions for the mean and the variance:

Therefore, the standard error:

$$SE(\hat{\theta}) = \sqrt{\text{Var}(\hat{\theta})} = \sqrt{\sigma^2 \sum_{j=1}^t \frac{c_j^2}{n_j}}$$

which is estimated by

$$\widehat{SE}(\hat{\theta}) = \sqrt{MS[E] \sum_{j=1}^t \frac{c_j^2}{n_j}}$$

To test $H_0 : \theta = \theta_0$ (often 0) versus $H_1 : \theta \neq \theta_0$, use t -test:

$$t = \frac{\hat{\theta} - \theta_0}{\widehat{SE}(\hat{\theta})} \stackrel{H_0}{\sim} t_{N-t}$$

At level α , the critical value for this test is $t(N-t, \alpha/2)$ and $100(1-\alpha)\%$ confidence interval for a contrast $\theta = \sum c_j \mu_j$ is given by

$$\sum c_j \bar{Y}_{j+} \pm t(N-t, \alpha/2) \sqrt{MS[E] \sum \frac{c_j^2}{n_j}}$$

Multiple Comparisons

Let's first review type I and type II errors.

| | H_0 is True | H_0 is False |
|--------------------|--------------------------|-------------------------|
| Don't reject H_0 | Probability $1 - \alpha$ | Probability β |
| Reject H_0 | Probability α | Probability $1 - \beta$ |

- Type I error: rejection of a true null hypothesis (false positive).
- Type II error: failure to reject a false null hypothesis (false negative).
- Type I error rate or significance level (α): the probability of rejecting the null hypothesis given the null hypothesis is true.
- Type II error rate (β): the probability of failure to reject the null hypothesis given the null hypothesis is false. $1 - \beta$ gives the power of a test.

Now, let's consider all simple (pairwise) contrasts for the binding fraction data with $t = 5$ antibiotic treatments of the form $\theta = \mu_i - \mu_j$.

- We have $\binom{5}{2} = 10$ tests for significance each at level $\alpha = 0.05$
- what is the probability of committing at least one type I error?

We need to consider the familywise error rate (fwe) when testing k contrasts:

$$fwe = \Pr(\text{at least one type I error})$$

Methods for simultaneous inference for multiple contrasts include

- Bonferroni
- Scheffé
- Tukey

When the number of comparisons is in the hundreds or thousands (e.g. genome-wide association studies), and FWE control is hopeless, more manageable type I error rate is the False Discovery Rate (FDR):

$$FDR = E\left(\frac{\text{Falsely rejected null hypotheses}}{\text{Number of rejected null hypotheses}}\right)$$

Bonferroni correction

Suppose interest lies in exactly k contrasts. The Bonferroni adjustment to α controls fwe is

$$\alpha_{\text{bonferroni}} = \frac{\alpha}{k}$$

and simultaneous 95% confidence intervals for the k contrasts are given by

$$\begin{aligned} & a_1 \bar{Y}_{1+} + \cdots + a_t \bar{Y}_{t+} \pm t\left(\frac{\alpha_{bonferroni}}{2}, \nu\right) \sqrt{MS[E] \sum \frac{a_j^2}{n_j}} \\ & b_1 \bar{Y}_{1+} + \cdots + b_t \bar{Y}_{t+} \pm t\left(\frac{\alpha_{bonferroni}}{2}, \nu\right) \sqrt{MS[E] \sum \frac{b_j^2}{n_j}} \\ & \quad \dots \\ & k_1 \bar{Y}_{1+} + \cdots + k_t \bar{Y}_{t+} \pm t\left(\frac{\alpha_{bonferroni}}{2}, \nu\right) \sqrt{MS[E] \sum \frac{k_j^2}{n_j}} \end{aligned}$$

where ν denotes df for error.

Example: for the binding fraction example, consider only pairwise comparisons with Penicillin:

$$\theta_1 = \mu_1 - \mu_2, \theta_2 = \mu_1 - \mu_3, \theta_3 = \mu_1 - \mu_4, \theta_4 = \mu_1 - \mu_5$$

We have $k = 4$, $\alpha_{bonferroni} = 0.05/k = 0.0125$ and $t(\frac{\alpha_{bonferroni}}{2}, 15) = 2.84$. Substitution leads to

$$\begin{aligned} & t\left(\frac{\alpha_{bonferroni}}{2}, 15\right) \sqrt{MS[E] \left(\frac{1^2}{4} + \frac{(-1)^2}{4} + \frac{0^2}{4} + \cdots + \frac{0^2}{4} \right)} \\ & = 2.84 \sqrt{(9.05) \frac{2}{4}} = 6.0 \end{aligned}$$

so that **simultaneous** 95% confidence intervals for $\theta_1, \theta_2, \theta_3$ and θ_4 take the form

$$\bar{y}_{1+} - \bar{y}_{i+} \pm 6.0$$

Scheffé

Another method to construct **simultaneous** 95% confidence intervals for **ALL** contrasts, use

$$\sum_{j=1}^t c_j \bar{y}_{j+} \pm \sqrt{(t-1)(F^*)MS[E] \sum_{j=1}^t \frac{c_j^2}{n_j}}$$

where $F^* = F(\alpha, t-1, N-t)$. For a pairwise comparisons of means, μ_j and μ_k , this yields

$$\bar{y}_{j+} - \bar{y}_{k+} \pm \sqrt{(t-1)(F^*)MS[E](1/n_j + 1/n_k)}$$

Using $\alpha = 0.05$, need to specify

- t (from the design)
- F^* (same critical value as for $H_0 : \alpha_i \equiv 0$).
- $MS[E]$ (from the data)
- $\bar{y}_{j+}, \bar{y}_{k+}$

- n_j, n_k (from the data)

For binding fraction data,

$$\sqrt{(t-1)(F^*)MS[E]\left(\frac{1}{n_j} + \frac{1}{n_k}\right)} = \sqrt{(5-1)(3.06)9.05\left(\frac{1}{4} + \frac{1}{4}\right)} = 7.44$$

If any two sample means differ by more than 7.44, they differ significantly.

Tukey

Tukey's method is better than Scheffé's method when making **all pairwise** comparisons in balanced designs ($n = n_1 = n_2 = \dots = n_t$). It is conservative, controlling the experimentwise error rate, and has a lower type II error rate in these cases than Scheffé. (It is more powerful.)

For simple contrasts of the form

$$\theta = \mu_j - \mu_k$$

to test

$$H_0 : \theta = 0 \text{ vs } H_1 : \theta \neq 0$$

reject H_0 at level α if

$$|\hat{\theta}| > q(t, N-t, \alpha) \sqrt{\frac{MS[E]}{n}}$$

where $q(t, N-t, \alpha)$ denotes α level studentized range for t means and $N-t$ degrees of freedom, the quantity $q(t, N-t, \alpha) \sqrt{\frac{MS[E]}{n}}$ is referred to as Tukey's honestly significant difference (HSD).

The studentized ranges can be calculated using R function `qtukey(1 - α , t , $N - t$)`.