



## Introduction to Linear Contrasts

Επιστημονική Επιμέλεια

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### Linear contrasts

- Pairwise comparisons of means are a special case of linear contrasts
- Comparison of one group with another group with general **weights**

$$\mu_1 = \mu_2$$

$$\mu_3 = \mu_4$$

$$\mu_1 = (\mu_3 + \mu_4)/2$$

- Linear contrasts take the form of a linear combination of the means

$$L = a_1\bar{Y}_1 + a_2\bar{Y}_2 + \dots + a_k\bar{Y}_k$$

$$= \sum a_j\bar{Y}_j$$

## Linear contrasts

- Restriction

$$\sum a_j = 0$$

- Suppose we had three means and wanted to compare the first and the second only. This could be done by having  $a_1 = 1$ ,  $a_2 = -1$ , and  $a_3 = 0$

$$L = (1)\bar{Y}_1 + (-1)\bar{Y}_2 + 0\bar{Y}_3 = \bar{Y}_1 - \bar{Y}_2$$

## Linear contrasts

- Linear contrasts allow us to express the sum of squared differences between the *means* of sets of treatments (formula assumes equal sample sizes)

$$SS_{\text{contrast}} = \frac{nL^2}{\sum a_j^2} = \frac{n(\sum a_j \bar{Y}_j)^2}{\sum a_j^2}$$

### Example

- Suppose we had  $\bar{Y}_1 = 1.5, \bar{Y}_2 = 2.0, \bar{Y}_3 = 3.0, n = 10$

- We can easily compute

$$\begin{aligned}SS_{\text{treat}} &= n \sum (\bar{Y}_j - \bar{Y})^2 \\ &= 10((1.5 - 2.17)^2 + (2 - 2.17)^2 + (3 - 2.17)^2) \\ &= 10(0.44 + 0.028 + 0.694) = 11.667\end{aligned}$$

- Let's say we wanted to compare the average of treatments 1 and 2 to treatment 3. Thus

$$L = \sum a_j \bar{Y}_j = (1)1.5 + (1)2.0 + (-2)3.0 = -2.5$$

$$SS_{\text{contrast}_1} = \frac{nL^2}{\sum a_j^2} = \frac{10(-2.5)^2}{6} = 10.417$$

### Example

- Now suppose we wanted to compare groups 1 and 2:

$$L = \sum a_j \bar{Y}_j = (1)1.5 + (-1)2.0 + (0)3.0 = -0.5$$

$$SS_{\text{contrast}_2} = \frac{nL^2}{\sum a_j^2} = \frac{10(-0.5)^2}{6} = 1.25$$

- Note that the sum of the two  $SS_{\text{contrast}}$  is

$$\begin{aligned}SS_{\text{treat}} &= SS_{\text{contrast}_1} + SS_{\text{contrast}_2} \\ 11.667 &= 10.417 + 1.25\end{aligned}$$

- In this case, we can say that the contrasts *completely partition*  $SS_{\text{treat}}$

## F test for contrast

- Note that the *absolute* value of the contrast weights does not matter

Means:  $Y_1$   $Y_2$   $Y_3$   $Y_4$   $Y_5$

$$a_j: \begin{cases} 2 & 2 & 2 & -3 & -3 \\ 1 & 1 & 1 & -1.5 & -1.5 \end{cases}$$

- The *significance* of a contrast can be tested with an *F* test

$$F = \frac{MS_{\text{contrast}}}{MS_{\text{error}}} = \frac{nL^2 / \sum a_j^2}{MS_{\text{error}}}$$

## Contrasts

- The square root of the *F* for a simple contrast ( $a_1 = 1, a_2 = -1$ ) is the same value obtained in a *t* test
  - *t* tests are special cases of linear contrasts
- Note however that if you run several contrasts, the familywise error will be much larger than  $\alpha$ 
  - Bonferroni correction can be used
  - Run fewer contrasts! Only as many as needed
  - If they were really a priori, probably ok without correction (some people would agree with that)

## Orthogonal contrasts

- Some contrasts are independent of one another, while others “share” information
- Independent contrasts are called *orthogonal*

$$\sum a_j = 0$$

$$\sum b_j = 0$$

$$\sum a_j b_j = 0$$

- Contrasts given by  $a_j$  and  $b_j$  are orthogonal

## Orthogonal contrasts

- It is useful to have orthogonal contrasts because they **exactly partition**  $SS_{\text{treat}}$
- However, it is not strictly necessary that all contrasts be orthogonal
  - But remember that in this case the contrasts do **not** convey independent information

## Degrees of freedom

- For a contrast, we have

$$F = \frac{MS_{\text{contrast}}}{MS_{\text{error}}}$$

- What are the *numerator* degrees of freedom?
- Consider  $df$  for  $SS_{\text{contrast}}$
- A contrast always compares two quantities

$$\mu_1 = \mu_2$$

$$\mu_3 = \mu_4$$

$$\mu_1 = (\mu_3 + \mu_4) / 2$$

## Degrees of freedom

- Thus  $SS_{\text{contrast}}$  has  $df = 1$
- Another way to think of the  $df$  is that the  $F$  for a contrast can in fact be written in the usual way

$$F = \frac{(SSE(R) - SSE(F)) / (df_R - df_F)}{SSE(F) / df_F}$$

- To determine  $df_R$ , we must determine the number of *independent* parameters in the **restricted model** which are associated with the contrast
- Consider the following null hypothesis:

$$H_0 : \frac{1}{3}\mu_1 + \frac{1}{3}\mu_2 + \frac{1}{3}\mu_3 - \mu_4 = 0$$

## Degrees of freedom

- The corresponding *restricted* model is

$$Y_{ij} = \mu_j + \varepsilon_{ij}$$

where  $1/3\mu_1 + 1/3\mu_2 + 1/3\mu_3 - \mu_4 = 0$

- Model has 4 parameters but only 3 are *independent*
- In the general case for  $a$  groups, we would have  $a - 1$  independent parameters

- Thus

$$\begin{aligned} df_R - df_F &= [N - (a - 1)] - (N - a) \\ &= 1 \end{aligned}$$

## Bibliography

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