

ANALYSIS OF BALANCED FACTORIAL DESIGNS

Estimates of model parameters and contrasts can be obtained by the method of Least Squares. Additional constraints must be added to estimate non-estimable parameters.

Example: The cell means are estimable. For three factors, the Least Squares estimates of the cell means are $\bar{y}_{ijk\cdot}$.

From the cell-means model and one-way analysis of variance, we have the following:

- The *error sum of squares* ssE is the sum of squared deviations from the fits $\bar{y}_{ijk\cdot}$.

Example: For 3 factors, $ssE = \sum_i \sum_j \sum_k \sum_t (y_{ijkt} - \bar{y}_{ijk\cdot})^2$

- ssE has associated degrees of freedom $n - v$
Example: For 3 factors, ssE has $abc(r-1)$ degrees of freedom.
- The *mean square error* msE is ssE divided by its degrees of freedom.
Example: For 3 factors, $msE = ssE / abc(r-1)$ degrees of freedom.
- msE is an estimate for the variance σ^2 .
- The standard error of the residuals $y_{ijkt} - \bar{y}_{ijk\cdot}$ is $ssE/(n-1)$

Before doing inference, we should use the fits and residuals to check the model assumptions of independent, normal errors with constant variance.

Example: Pollution filter data

Note: To get a column for Treatment easily, use $100*SIZE + 10*TYPE + SIDE$

Hypothesis Tests and Analysis of Variance Table:

Submodels can be tested against larger models by F-tests, with F-statistic obtained as a ratio of mean squares.

The *error sum of squares* of a model is the sum of the squared deviations from the fits from that model.

Example: For three factors, the error sum of squares for a model is

$$\sum_i \sum_j \sum_k \sum_t (y_{ijkt} - \hat{y})^2, \text{ where } \hat{y} \text{ is the fit for the model.}$$

Special case I: Since the fit for the complete model is $\bar{y}_{ijk\cdot}$, the error sum of squares for the complete model is ssE mentioned above.

Special case II: The *total sum of squares* is the error sum of squares for the model

$$y_{ijkt} = \mu + \epsilon_{ijkt}$$

Since the fit for this model is the overall sample mean, the total sum of squares can be described as the sum of the squared deviations from the overall sample mean.

Example: For 3 factors,
$$s_{stot} = \sum_i \sum_j \sum_k \sum_t (y_{ijkt} - \bar{y}_{\dots})^2$$

The total sum of squares has $n-1$ associated degrees of freedom, where n = total number of observations (e.g., abc for 3 factors).

Recall that for three factors, the null hypothesis for “no three-way interaction” is

$$H_0^{ABC}: [(\alpha\beta\gamma)_{i+1,jk} - (\alpha\beta\gamma)_{ijk}] - [(\alpha\beta\gamma)_{i+1,qk} - (\alpha\beta\gamma)_{iqk}] \\ - [(\alpha\beta\gamma)_{i+1,jr} - (\alpha\beta\gamma)_{ijr}] - [(\alpha\beta\gamma)_{i+1,qr} - (\alpha\beta\gamma)_{iqr}] = 0 \text{ for all } i, j, k, q, r$$

If we let ssE_0^{ABC} denote the error sum of squares for the submodel where H_0^{ABC} is true, then we define *the sum of squares for three-way interaction* to be

$$ssABC = ssE_0^{ABC} - ssE$$

It has associated degrees of freedom $(a-1)(b-1)(c-1)$. We define

$$msABC = ssABC / (a-1)(b-1)(c-1).$$

Then $MSABC/MSE$ has an F distribution with $(a-1)(b-1)(c-1)$ and $n-v$ degrees of freedom. This gives us an F-test for H_0^{ABC} .

Example: Pollution filter data.

To explain the rest of the ANOVA output, consider, for example

$$H_0^{BC+ABC}: \text{There is no three-way interaction and no BC interaction.}$$

This can be expressed in terms of the parameters as

$$H_0^{BC+ABC}: [(\beta\gamma)_{ij} - (\beta\gamma)_{iq}] - [(\beta\gamma)_{sj} - (\beta\gamma)_{sq}] = 0 \text{ for all } i \neq s, j \neq q \\ \text{and } [(\alpha\beta\gamma)_{i+1,jk} - (\alpha\beta\gamma)_{ijk}] - [(\alpha\beta\gamma)_{i+1,qk} - (\alpha\beta\gamma)_{iqk}] \\ - [(\alpha\beta\gamma)_{i+1,jr} - (\alpha\beta\gamma)_{ijr}] - [(\alpha\beta\gamma)_{i+1,qr} - (\alpha\beta\gamma)_{iqr}] = 0 \text{ for all } i, j, k, q, r$$

However, it is traditional to use instead the following test:

$$H_0^{BC}: \text{All } (\beta\gamma)_{ij}^* \text{'s are equal}$$

$$H_a^{BC}: \text{At least two of the } (\beta\gamma)_{ij}^* \text{'s are different,}$$

where the $(\beta\gamma)_{ij}^*$'s are defined in a manner analogous to the α_i^* 's for two-way ANOVA as the $(\beta\gamma)_{ij}$'s plus averages over the higher interaction terms.

The idea is to test whether or not the “levels” of BC interaction, averaged over the levels of other factors, have the same average effect on the response. If there is no higher-order interaction, then the two null hypotheses, H_0^{BC+ABC} and H_0^{BC} (and hence the corresponding submodels) should be the same.

We define

$$ssE_0^{BC} = \text{the sum of squares for the model assuming } H_0^{BC} \text{ is true,}$$

and *the sum of squares for BC*

$$ssBC = ssE_0^{BC} - ssE.$$

Then $ssBC$ has $(b-1)(c-1)$ degrees of freedom. Defining $msBC = ssBC / (b-1)(c-1)$, we get F-statistic $msBC/mSE$, with degrees of freedom $(b-1)(c-1)$ and $n-v$. This gives us an F-test for H_0^{BC} .

In general, the degrees of freedom for a sum of squares for an item in the ANOVA table is the product of one less than the number of levels for each factor involved in the item.

<i>Examples:</i>	Sum of squares for	Degrees of freedom
	A	a-1
	AB	(a-1)(b-1)
	BC	(b-1)(c-1)
	ABC	(a-1)(b-1)(c-1)

The total sum of squares partitions into (is the sum of) the error sum of squares plus the sums of squares for all items in the model.

The degrees of freedom add correspondingly. For example, for the complete 3-way model, this is just the algebraic identity

$$(a-1)(b-1)(c-1) + (a-1)(b-1) + (a-1)(c-1) + (b-1)(c-1) + (a-1) + (b-1) + (c-1) + abc - abc = abc - 1$$

Note: If we are dealing with another model, the error sum of squares for that model will have a different number of degrees of freedom. The degrees of freedom for error are usually most easily found by subtracting the other degrees of freedom from the total degrees of freedom.

The *mean square* for an item is the sum of squares for that item divided by its degrees of freedom.

Example: $msBC = ssBC/(b-1)(c-1)$

The F-statistic for an item is the mean square for the item divided by the mean square error, with corresponding degrees of freedom in the numerator in denominator.

Example: Pollution Filter Data

Contrasts

Contrasts are defined and estimated as in the cell means model. There are various labels that are given to certain types of contrasts; see p. 199 for details. Contrasts can also be defined relative to submodels, in which case parameters not present in the submodel are omitted from the contrast. The various methods for simultaneous confidence intervals still apply. There is a modification that can be used for finding simultaneous confidence intervals for contrasts in the levels of a single factor: Replace v by the number of levels of the factor in question, and replace r by the number of observations on each level of the factor of interest. (See p. 205 for an example.)

Example: In the Pollution Filter Data, the main interest is in comparing levels of Type (the second factor).

- If this is interpreted as “on average”:
- If this is interpreted as “for each combination of size and side”:

Comments:

- We can also do *unbalanced* ANOVA via GLM, similarly to the 2-way case.
- Similar considerations/variations hold for “small experiments” (i.e., one observation per cell.)
- Sometimes transformations are helpful (e.g., to obtain constant variance or normality, or to remove interaction).
- There are also other approaches – e.g., non-parametric (in particular the Kruskal-Wallis method, which uses a χ^2 test based on rankings, doesn't require normality – but is less powerful than ANOVA) and Bayesian methods