Completely Random Designs

BIOE 498/598

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Three Types of Variables

- **Numerical** (or **continuous**) variables are modeled by real numbers using a single coefficient.
- **Ordinal** variables have discrete but *ordered* levels. If the levels are evenly spaced, we model them using integers.
- **Nominal** (or **categorical**) variables are unordered with no numeric relationship between levels.

One-hot encoding

- In one-hot encoding, a nominal variable with k levels is modeled with k binary dummy variables.
- Only one dummy variable is nonzero ("hot") at a time.
- Example: DNA $\in \{\text{A, C, G, T}\}$.

$$\beta_{\text{A}} x_{\text{A}} + \beta_{\text{C}} x_{\text{C}} + \beta_{\text{G}} x_{\text{G}} + \beta_{\text{T}} x_{\text{T}}$$

Fitting models with one-hot encoded variables

Consider a model with $x \in \{\text{low, medium, high}\}$:

$$y = \beta_0 + \beta_{\text{low}} x_{\text{low}} + \beta_{\text{med}} x_{\text{med}} + \beta_{\text{high}} x_{\text{high}}$$

which, after fitting is

$$y = 60 + 12 x_{\text{low}} - 20 x_{\text{med}} + 30 x_{\text{high}}$$

where

$$y(x_{\text{low}} = 1) = 72, \quad y(x_{\text{med}} = 1) = 40, \quad y(x_{\text{high}} = 1) = 90$$

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We could define another model with equivalent predictions:

$$y = 50 + 22 x_{\text{low}} - 10 x_{\text{med}} + 40 x_{\text{high}}$$

Degeneracy

There are infinitely many models with coefficients

$$\beta_0 - \Delta, \quad \beta_{\text{low}} + \Delta, \quad \beta_{\text{med}} + \Delta, \quad \beta_{\text{high}} + \Delta$$

all with the same predictions, residuals, etc.

To avoid the degeneracy, R will not estimate the first (or *base*) level of a factor variable is the model has an intercept. This ensures a unique solution.

Degeneracy in Matrix Form

Consider a design matrix with an intercept, a three-level categorical variable, and two replicates:

$$\mathbf{X} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \end{pmatrix}$$

This matrix is not full rank since the columns are not linearly independent. ($\mathbf{X}(:,1) = \mathbf{X}(:,2) + \mathbf{X}(:,3) + \mathbf{X}(:,4)$). If we drop any column the matrix will be full rank; R's choice to drop the second column is arbitrary.

Contrasts in the Rothamsted Experiment

The sugar beet experiment is modeled as a single variable with four treatments:

- (A) no fertilizer
- (B) plowed fertilizer in January
- (C) broadcast fertilizer in January
- (D) broadcast fertilizer in April

By default the first treatment (A) will be absorbed into the intercept. The remaining effect sizes are relative to the no fertilizer treatment:

$$\text{yield} = \beta_{\text{A}} + \beta_{\text{B}} x_{\text{B}} + \beta_{\text{C}} x_{\text{C}} + \beta_{\text{D}} x_{\text{D}}$$

Contrasts in the Rothamsted Experiment

- (A) no fertilizer
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- (C) broadcast fertilizer in January
- (D) broadcast fertilizer in April

What if we wanted to make other comparisons?

- Effect of broadcast vs. plowed: (C & D) = (B)
- Effect of early vs. late application: (B & C) = (D)
- Effect of any fertilizer: (A) = (B, C, & D)

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There are all *contrasts*, or comparisons between effect sizes. The null hypotheses for each contrast can be written as a linear combination of the model's coefficients:

$$\frac{1}{2}\beta_{\mathrm{C}} + \frac{1}{2}\beta_{\mathrm{D}} - \beta_{\mathrm{B}} = 0$$

When specifying contrasts, we require that the coefficient sum to zero (hence the 1/2 factors above).

How do we test contrasts?

- Fit a linear model with a categorical variable:

```
model <- lm(y ~ var1 + var2)
```

- Let's say var1 had three levels and we wanted to test if $\beta_1 = (\beta_2 + \beta_3)/2$. First we define the *contrast coefficients* for the null hypothesis.

```
contrast <- c(1, -0.5, -0.5, 0)
```

- Then we use the fit.contrast function from the gmodels package to test the contrast.

```
gmodels::fit.contrast(model, var1, contrast)
```

We can also test multiple contrasts at the same time using a contrast matrix as shown in the textbook.

Can we test any contrasts?

No. A contrast must be *estimable* for it to be tested. A contrast is estimable if

- its coefficients sum to zero
- it can be expressed as a linear combination of the rows of the design matrix.

Estimable Example: Measuring only main effects

$$\mathbf{X} = \begin{array}{c} \begin{matrix} \beta_0 & \beta_2 & \beta_3 & \beta_{12} & \beta_{13} & \beta_{23} \end{matrix} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

Any contrast about the interaction terms is not estimable. To test for an β_{12} effect ($H_0 : \beta_{12} - \beta_0 = 0$)

$$c = \begin{pmatrix} 1 & 0 & 0 & -1 & 0 & 0 \end{pmatrix}$$

which is not a combination of the rows in $\mathbf{X}$. In fact, we cannot fit this model since the interaction terms are confounded!

Testing all possible contrasts

As our models grow, the number of possible contrasts increases rapidly. It is likely that at least one random contrast passes our p-value threshold **even if there is not a true difference**.

When testing all contrasts in a model it is wise to adjust your p-value threshold accordingly. A good method is Tukey's HSD. See Section 2.8.2 for an example.