Lab 9 – Split-plot Designs

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THE ADDITIVE MODEL

$$y_{ijk} = \mu + \alpha_i + \beta_j + \alpha \beta_{ij} + \gamma_k + \delta_{ik} + \varepsilon_{ijk}$$

The α 's and β 's are fixed treatment effects. Note the interaction.

Because we want our inferences to apply to all roasts, δ_{ik} is random. Specifically:

$$\delta_{ik} \sim \mathsf{Normal}(0, \sigma_D^2)$$

We might treat block effects as random too:

$$\gamma_k \sim \mathsf{Normal}(0, \sigma_C^2)$$

And as always,

$$\varepsilon_{ijk} \sim \mathsf{Normal}(0, \sigma^2)$$

Scenario

We apply treatments to two experimental units: whole-units and sub-units

Examples:

- Ag fields are sprayed with herbicides, and fertilizers are applied to plots within fields.
- Tenderizer is applied to roasts, and cooking times are applied to cores

We're interested in treatment effects at both levels

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THE MEAT DATA

It's important that you have variables for the whole unit (roast) and the block (carcass).

```
meatData <- read.csv("meatData.csv")
str(meatData)

## 'data.frame': 72 obs. of 5 variables:
## $ Wbscore : num 8.25 7.5 4.25 3.5 7.25 6.25 3.5 3.5 6.5 4.5 ...
## $ tenderizer: Factor w/ 3 levels "C","P","V": 1 1 1 1 3 3 3 3 2 2 ...
## $ time : int 30 36 42 48 30 36 42 48 30 36 ...
## $ carcass : int 1 1 1 1 1 1 1 1 ...
## $ roast : int 1 1 1 1 2 2 2 2 3 3 ...</pre>
```

Don't forget to convert to factors

```
meatData$time <- factor(meatData$time)
meatData$carcass <- factor(meatData$carcass)
meatData$roast <- factor(meatData$roast)</pre>
```

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CARCASS (BLOCK) EFFECTS AS FIXED

```
summary(aov.meat1)
## Error: roast
            Df Sum Sq Mean Sq F value Pr(>F)
## tenderizer 2 20.715 10.358 190.00 1.11e-08 ***
## carcass
             5 3.903 0.781 14.32 0.000276 ***
## Residuals 10 0.545 0.055
##
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Error: Within
##
                 Df Sum Sq Mean Sq F value Pr(>F)
                 3 170.08 56.69 656.62 < 2e-16 ***
## tenderizer:time 6 9.56
                           1.59 18.46 1.11e-10 ***
## Residuals 45 3.89
                           0.09
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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EXPLORING THE INTERACTION

Is the time effect significant for each level of tenderizer?

Yes, it is

```
anova(lme.meatP, Terms="time")

## F-test for: time
## numDF denDF F-value p-value
## 1 3 15 126.6786 <.0001

anova(lme.meatV, Terms="time")

## F-test for: time
## numDF denDF F-value p-value
## 1 3 15 274.716 <.0001

anova(lme.meatC, Terms="time")

## F-test for: time
## numDF denDF F-value p-value
## 1 3 15 305.6551 <.0001
```

USING 1me INSTEAD OF aov

```
## numDF denDF F-value p-value
## (Intercept) 1 45 2105.6140 <.0001
## tenderizer 2 10 190.0001 <.0001
## time 3 45 656.6222 <.0001
## tenderizer:time 6 45 18.4585 <.0001
```

The interaction is significant. (You can Ignore the (Intercept) term)

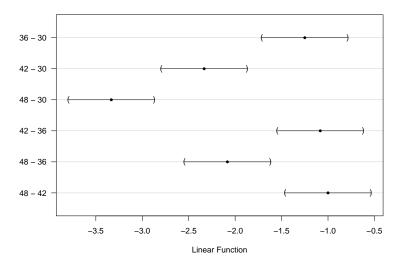
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Multiple comparisons using glht

```
# install.packages("multcomp")
library(multcomp)
mcP <- glht(lme.meatP, linfct=mcp(time="Tukey"))</pre>
summary(mcP)
   Simultaneous Tests for General Linear Hypotheses
## Multiple Comparisons of Means: Tukey Contrasts
## Fit: lme.formula(fixed = Wbscore ~ time, data = meatData, random = ~1 |
## carcass/roast, correlation = corCompSymm(), subset = tenderizer ==
## Linear Hypotheses:
##
             Estimate Std. Error z value Pr(>|z|)
## 36 - 30 == 0 -1.250 0.180 -6.944 <1e-05 ***
## 42 - 30 == 0 -2.333 0.180 -12.961 <1e-05 ***
## 48 - 30 == 0 -3.333 0.180 -18.516 <1e-05 ***
## 42 - 36 == 0 -1.083 0.180 -6.018 <1e-05 ***
## 48 - 36 == 0 -2.083
                           0.180 -11.573 <1e-05 ***
## 48 - 42 == 0 -1.000 0.180 -5.555 <1e-05 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
# confint(mcP)
# plot(mcP)
```

Differences between cooking times for "P" tenderizer

95% family-wise confidence level



NESTED AND CROSSED EXAMPLE

Nested and crossed is same as split-plot, but without the block

Design

- Sweet potato yield is studied in response to (a=3) types of herbicide.
- Each herbicide is applied to 5 fields
- Each field is divided into 4 plots. Each plot is treated with one of (b=4) fertilizers.

Exercise

- (1) Import yieldData.csv and conduct the appropriate ANOVA using aov and lme.
- (2) Does the effect of herbicide depend on fertilizer?
- (3) Use Tukey's test to determine which fertilizers differ

Upload your self-contained script to ELC the day before your next lab.

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