Lsn 13_AY_23

Clark

Admin

Our text discusses a study in Vitamin C levels using 3 brands and 2 temperatures. There are six glasses of orange juice in their study. Here the data is:

```
OJ1 <- read.table("http://www.isi-stats.com/isi2/data/OJ-n6.txt",header=T)
OJ1</pre>
```

```
## VitC Brand Temp
## 1 2.38 GreatValue Refrigerator
## 2 2.32 GreatValue Room
## 3 2.34 Meijer Refrigerator
## 4 1.86 Meijer Room
## 5 2.01 MinuteMaid Refrigerator
## 6 2.01 MinuteMaid Room
```

They look at the data:

```
OJ1 %>% ggplot(aes(x=Brand,y=VitC,color=Temp))+
  geom_line(aes(group=Temp))+geom_point()
```

Since they just had MA376 they decide to fit this model:

```
OJ1 <- OJ1 %>% mutate(Brand=as.factor(Brand))%>%
  mutate(Temp = as.factor(Temp))
contrasts(OJ1$Brand)=contr.sum
contrasts(OJ1$Temp)=contr.sum
OJ.lm<-lm(VitC~Brand*Temp, data=OJ1)
coef(OJ.lm)
                      Brand1
                                                  Temp1 Brand1:Temp1 Brand2:Temp1
##
    (Intercept)
                                    Brand2
     2.15333333
                                             0.09000000 -0.06000000
                  0.19666667 -0.05333333
                                                                       0.15000000
levels(OJ1$Brand)
## [1] "GreatValue" "Meijer"
                                  "MinuteMaid"
```

levels(OJ1\$Temp)

```
## [1] "Refrigerator" "Room"
```

So their fitted model is:

```
anova(OJ.lm)
```

```
## Warning in anova.lm(OJ.lm): ANOVA F-tests on an essentially perfect fit are
## unreliable
## Analysis of Variance Table
##
## Response: VitC
##
              Df Sum Sq Mean Sq F value Pr(>F)
               2 0.12413 0.062067
## Brand
                                      NaN
                                             NaN
## Temp
               1 0.04860 0.048600
                                      NaN
                                             NaN
## Brand:Temp 2 0.06840 0.034200
                                      NaN
                                             NaN
## Residuals
               0.00000
                              NaN
```

What's going on?

Remember that any statistical test or confidence interval relies on being able to compute a variance.

```
OJ1 %>% group_by(Brand,Temp)%>%summarize(Mean=mean(VitC),Sd=sd(VitC))
```

```
## `summarise()` has grouped output by 'Brand'. You can override using the
## `.groups` argument.
## # A tibble: 6 x 4
## # Groups:
               Brand [3]
##
    Brand
                Temp
                              Mean
                                      Sd
##
     <fct>
                <fct>
                             <dbl> <dbl>
## 1 GreatValue Refrigerator 2.38
## 2 GreatValue Room
                              2.32
                                      NA
## 3 Meijer
                Refrigerator 2.34
                                      NA
## 4 Meijer
                Room
                              1.86
                                      NA
## 5 MinuteMaid Refrigerator 2.01
                                      NA
## 6 MinuteMaid Room
                              2.01
                                      NA
```

Without replication we CANNOT compute a variance so we cannot do any statistical tests. Our book calls a blocked design with replication a generalized block design . A picture:
A quick way to see if we can fit a model is to do a degrees of freedom calculation.
If we didn't have replication, what models could we fit:
Note how we can continue to expand this as we get more replication. Let's say we are also interested in Water PH. How many treatments do we have if we consider brand as a blocking variable (not a treatment). So, within each block we could run a 2×2 factorial design. Again a picture:
How many glasses of orange juice would we need in our study?
If we have 12 glasses of orange juice what would could our model be?
Our ANOVA table would be:

What would happen if we include an interaction between water, brand, and temperature?

Say we want to include all interactions, our model would become:

```
OJ3=read.table("http://www.isi-stats.com/isi2/data/OJ-n24.txt", header=T)
OJ3<-OJ3 %>% mutate(Brand=as.factor(Brand))%>%
  mutate(Temp=as.factor(Temp))%>%
 mutate(Water=as.factor(Water))
full.lm<-lm(VitC1000~Brand*Temp*Water,data=0J3)
anova(full.lm)
## Analysis of Variance Table
##
## Response: VitC1000
##
                   Df Sum Sq Mean Sq F value
                                                   Pr(>F)
## Brand
                    2 0.70081 0.35040 934.4111 6.745e-14 ***
## Temp
                   1 0.17682 0.17682 471.5111 5.329e-11 ***
## Water
                    1 0.05415 0.05415 144.4000 4.762e-08 ***
                  2 0.23666 0.11833 315.5444 4.221e-11 ***
## Brand:Temp
## Brand:Water
                   2 0.00167 0.00084
                                       2.2333 0.149780
## Temp:Water
                    1 0.00482 0.00482 12.8444 0.003755 **
## Brand:Temp:Water 2 0.00016 0.00008
                                       0.2111 0.812628
## Residuals
                 12 0.00450 0.00037
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
3 Way interaction... The interaction between temperature and water depends on brand. (Figure 3.3.10)
OJ3 %>% ggplot(aes(x=Temp,y=predict(full.lm),color=Water))+
  geom_line(aes(group=Water))+geom_point() +
  facet_wrap(vars(Brand))
What happens if we don't add 3 way
mod.lm<-lm(VitC1000~Brand+Temp+Water+Brand:Temp+Water:Brand+Water:Temp,data=0J3)
anova(mod.lm)
## Analysis of Variance Table
## Response: VitC1000
```

```
##
              Df Sum Sq Mean Sq F value
                                             Pr(>F)
               2 0.70081 0.35040 1053.093 5.474e-16 ***
## Brand
## Temp
               1 0.17682 0.17682 531.399 1.556e-12 ***
               1 0.05415 0.05415
                                  162.741 4.249e-09 ***
## Water
## Brand:Temp
               2 0.23666 0.11833
                                  355.623 9.989e-13 ***
## Brand:Water 2 0.00167 0.00084
                                    2.517 0.116463
## Temp:Water
               1 0.00482 0.00482
                                   14.476 0.001933 **
## Residuals
              14 0.00466 0.00033
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Our test is more powerful if we don't consider everything. Couple of thoughts. Some folks believe that we shouldn't interact blocks with our treatments. Let's read through pg. 257

A study by Jung et al. looked at hurricane names and their perceived threat. They thought if hurricanes had male names they would be perceived as more dangerous than if they had female names. In one part of the study, the participants were given a weather map showing a hurricane moving toward the area where they lived. Participants were told the name of the hurricane and then rated the riskiness of the hurricane on a seven point scale (1 low, 7 high)

1. Based on your understanding of the study, fill in a possible Sources of Variation diagram

2. Suppose the researchers had two participants in the study and the carried out the matched pairs design for these two participants and obtained the results given on the top of page 258 of our text. From this data, fill out the sources and degrees of freedom for a model that includes main effects and interactions (problem 6 on page 258)

Here we see that we cannot fit an interaction as we have no degrees of freedom left over for error. Clearly we would need replication.

The researchers also considered whether the name sounded 'old' or 'young'. Looking at Table 3.3.3 in our text, how many treatments are in the study?

In the actual study, researchers used 346 students, each of whom rated each of the 10 hurricane names (5 of each gender).

```
hurricanes <- read.table("http://www.isi-stats.com/isi2/data/hurricanesB.txt",header=T)
hurricanes <- hurricanes %>% mutate(HurricaneGender=as.factor(HurricaneGender))%>%
mutate(HurricaneAge = as.factor(HurricaneAge))%>%
```

```
mutate(ParticipantID = as.factor(ParticipantID))

contrasts(hurricanes$HurricaneGender)=contr.sum
contrasts(hurricanes$HurricaneAge)=contr.sum
contrasts(hurricanes$ParticipantID)=contr.sum
```

Using R and the Code above, carry out a two-vairable model including the interaction between hurricane gender and hurricane age adjusting for the blocing variable. How much variation in ratings of hurricanes is explaned by this model?

From the ANOVA table, explain where each of the degrees of freedom come from

From your lm object, find the residuals. Would you consider the validiting conditions for the theory-based F test to be met? Why or why not?

In both symbols and words, state the null and laternative hypothesis for ther interaction, what is your conclusion?

State the null and alternative hypotheses for the gender effect. What is your conclusion?

Create a 95% CI for the differences in hurricane gender effect.

If you couldn't use TukeyHSD command how would you find this CI?
Using the model you produced what is the estimated response for an individual given a Male hurricane with an old name?
Based on your analysis, is there evidence that blocking on participant was worthwhile?