Nested Designs in R

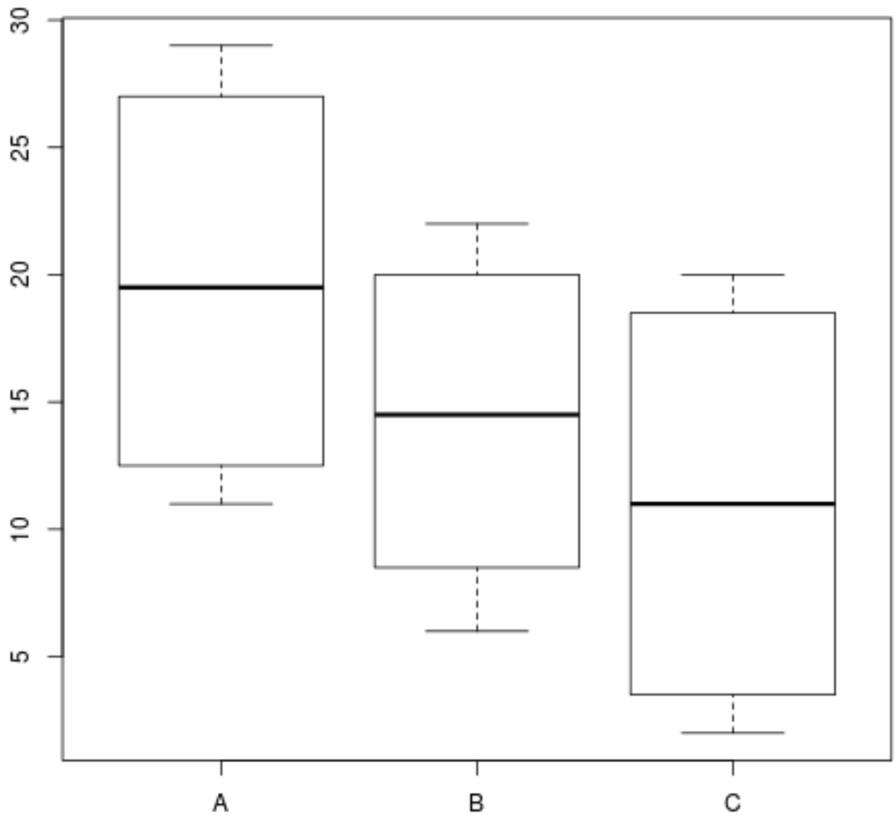
Example 1

To begin with, we will use the example I had in class. There are three schools, with two students nested in each school.

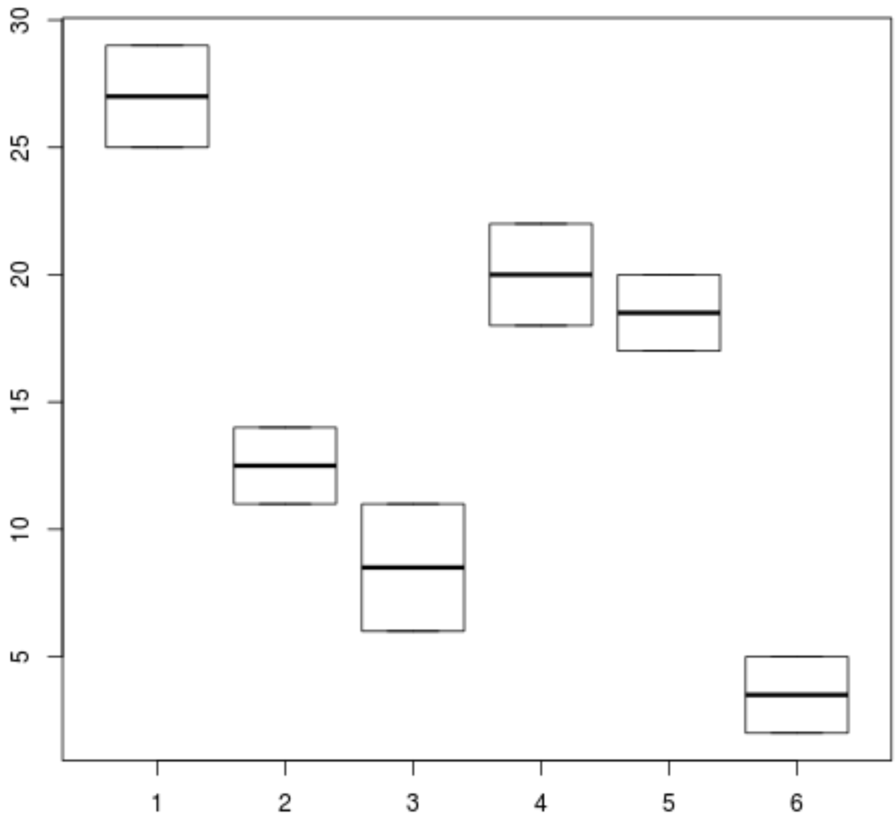
```
scores <- c(25, 29, 14, 11, 11, 6, 22, 18, 17, 20, 5, 2)
school <- factor(c("A", "A", "A", "A", "B", "B", "B", "B", "C",
"C", "C", "C"))
teacher <- factor(c(1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6))
teacher2 <- factor(c(1, 1, 2, 2, 1, 1, 2, 2, 1, 1, 2, 2))  #
This is the way the data is coded for problems in the book
```

Box plots for each teacher can be appropiate, as they are the experimental unit.

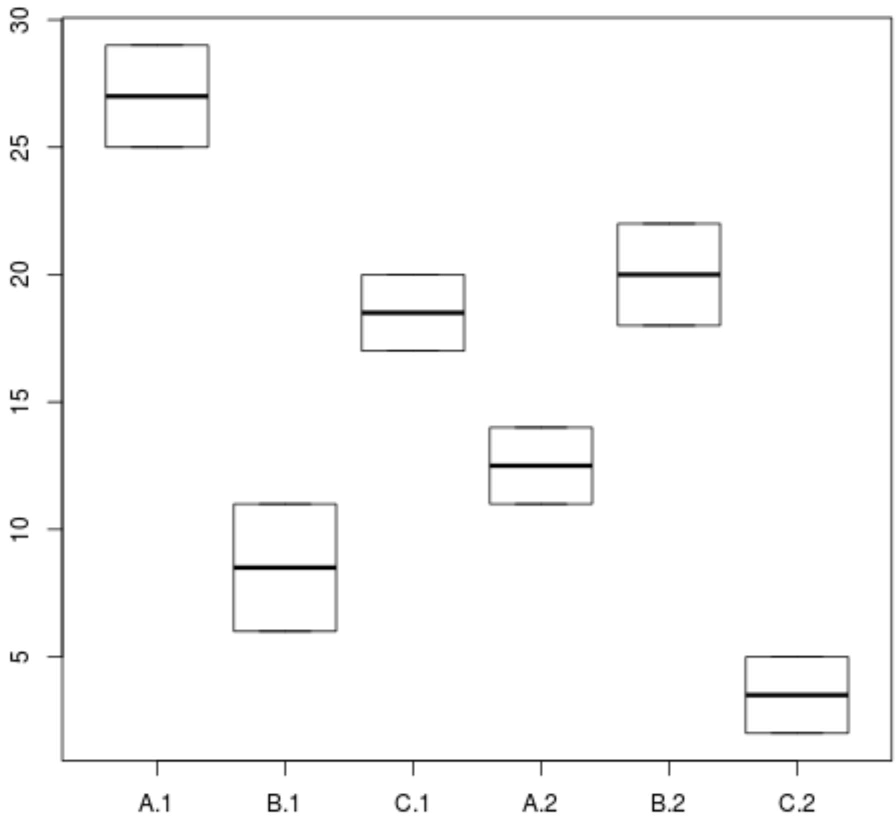
```
boxplot(scores ~ school)
```



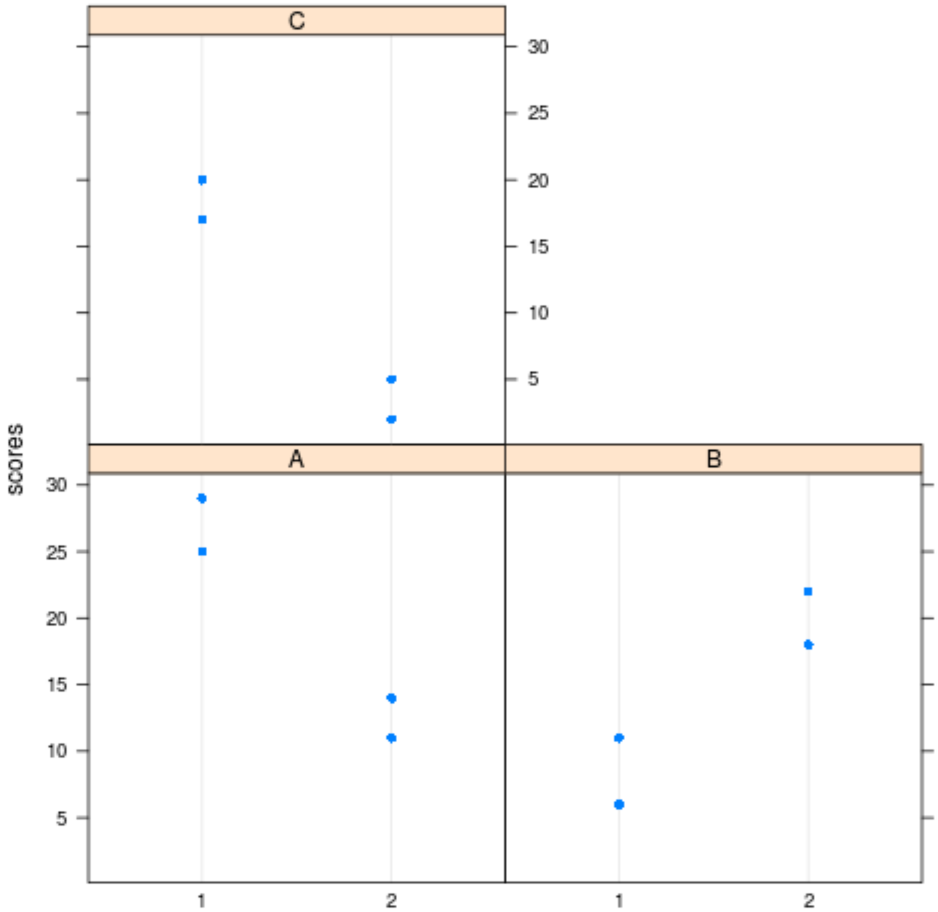

```
boxplot(scores ~ teacher)
```




```
boxplot(scores ~ school:teacher2)
```




```
library(lattice)
dotplot(scores ~ teacher2 | school)
```



What if we ignore the fact that the design is nested?

```
anova(lm(scores ~ school))
```

```
## Analysis of Variance Table
##
## Response: scores
##           Df Sum Sq Mean Sq F value Pr(>F)
## school     2    157    78.3    1.16   0.36
## Residuals  9    610    67.7
```

```
anova(lm(scores ~ school + teacher))
```

```
## Analysis of Variance Table
##
## Response: scores
##           Df Sum Sq Mean Sq F value Pr(>F)
## school     2    157    78.3    11.2 0.0095 **
## teacher    3    568   189.2    27.0 0.0007 ***
## Residuals  6     42     7.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

```
anova(lm(scores ~ school * teacher))
```

```
## Analysis of Variance Table
##
## Response: scores
##           Df Sum Sq Mean Sq F value Pr(>F)
## school     2    157    78.3    11.2 0.0095 **
## teacher    3    568   189.2    27.0 0.0007 ***
## Residuals  6     42     7.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

```
anova(lm(scores ~ school + teacher2))
```

```
## Analysis of Variance Table
##
## Response: scores
##           Df Sum Sq Mean Sq F value Pr(>F)
## school     2    157    78.3    1.25   0.34
## teacher2   1    108   108.0    1.72   0.23
## Residuals  8    502    62.7
```

```
anova(lm(scores ~ school * teacher2))
```

```
## Analysis of Variance Table
##
## Response: scores
##                 Df Sum Sq Mean Sq F value  Pr(>F)
## school           2    157    78.3    11.2 0.00947 **
## teacher2         1    108   108.0    15.4 0.00773 **
## school:teacher2  2    460   229.8    32.8 0.00059 ***
## Residuals        6     42     7.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

What if we do it correctly?

```
res1 <- lm(scores ~ school + school/teacher)
anova(res1)
```

```
## Analysis of Variance Table
##
## Response: scores
##                Df Sum Sq Mean Sq F value Pr(>F)
## school          2    157    78.3    11.2 0.0095 **
## school:teacher  3    568   189.2    27.0 0.0007 ***
## Residuals       6     42     7.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

```
res2 <- lm(scores ~ school + school/teacher2)
anova(res2)
```

```
## Analysis of Variance Table
##
## Response: scores
##                 Df Sum Sq Mean Sq F value Pr(>F)
## school           2    157    78.3    11.2 0.0095 **
## school:teacher2  3    568   189.2    27.0 0.0007 ***
## Residuals        6     42     7.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

Which schools are different?

```
TukeyHSD(aov(res1), "school")
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = res1)
##
## $school
##      diff    lwr     upr  p adj
## B-A -5.50 -11.24  0.2402 0.0586
## C-A -8.75 -14.49 -3.0098 0.0081
## C-B -3.25  -8.99  2.4902 0.2677
```

```
TukeyHSD(aov(res2), "school")
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = res2)
##
## $school
##      diff    lwr     upr  p adj
## B-A -5.50 -11.24  0.2402 0.0586
## C-A -8.75 -14.49 -3.0098 0.0081
## C-B -3.25  -8.99  2.4902 0.2677
```

Do we want all the teacher comparisons? Probably not.

```
TukeyHSD(aov(res1), "school:teacher")  #Yikes
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = res1)
##
## $`school:teacher`
##          diff     lwr    upr  p adj
## B:1-A:1    NA      NA     NA     NA
## C:1-A:1    NA      NA     NA     NA
## A:2-A:1 -14.5 -28.392 -0.608 0.0411
## B:2-A:1    NA      NA     NA     NA
## C:2-A:1    NA      NA     NA     NA
## A:3-A:1    NA      NA     NA     NA
## B:3-A:1 -18.5 -32.392 -4.608 0.0125
## C:3-A:1    NA      NA     NA     NA
## A:4-A:1    NA      NA     NA     NA
## B:4-A:1  -7.0 -20.892  6.892 0.5228
## C:4-A:1    NA      NA     NA     NA
## A:5-A:1    NA      NA     NA     NA
## B:5-A:1    NA      NA     NA     NA
## C:5-A:1  -8.5 -22.392  5.392 0.3212
## A:6-A:1    NA      NA     NA     NA
## B:6-A:1    NA      NA     NA     NA
## C:6-A:1 -23.5 -37.392 -9.608 0.0035
## C:1-B:1    NA      NA     NA     NA
## A:2-B:1    NA      NA     NA     NA
## B:2-B:1    NA      NA     NA     NA
## C:2-B:1    NA      NA     NA     NA
## A:3-B:1    NA      NA     NA     NA
## B:3-B:1    NA      NA     NA     NA
## C:3-B:1    NA      NA     NA     NA
## A:4-B:1    NA      NA     NA     NA
## B:4-B:1    NA      NA     NA     NA
## C:4-B:1    NA      NA     NA     NA
## A:5-B:1    NA      NA     NA     NA
## B:5-B:1    NA      NA     NA     NA
## C:5-B:1    NA      NA     NA     NA
## A:6-B:1    NA      NA     NA     NA
## B:6-B:1    NA      NA     NA     NA
## C:6-B:1    NA      NA     NA     NA
## A:2-C:1    NA      NA     NA     NA
## B:2-C:1    NA      NA     NA     NA
## C:2-C:1    NA      NA     NA     NA
## A:3-C:1    NA      NA     NA     NA
## B:3-C:1    NA      NA     NA     NA
## C:3-C:1    NA      NA     NA     NA
```

```
## A:4-C:1    NA      NA     NA     NA
## B:4-C:1    NA      NA     NA     NA
## C:4-C:1    NA      NA     NA     NA
## A:5-C:1    NA      NA     NA     NA
## B:5-C:1    NA      NA     NA     NA
## C:5-C:1    NA      NA     NA     NA
## A:6-C:1    NA      NA     NA     NA
## B:6-C:1    NA      NA     NA     NA
## C:6-C:1    NA      NA     NA     NA
## B:2-A:2    NA      NA     NA     NA
## C:2-A:2    NA      NA     NA     NA
## A:3-A:2    NA      NA     NA     NA
## B:3-A:2  -4.0 -17.892  9.892 0.9553
## C:3-A:2    NA      NA     NA     NA
## A:4-A:2    NA      NA     NA     NA
## B:4-A:2   7.5  -6.392 21.392 0.4477
## C:4-A:2    NA      NA     NA     NA
## A:5-A:2    NA      NA     NA     NA
## B:5-A:2    NA      NA     NA     NA
## C:5-A:2   6.0  -7.892 19.892 0.6884
## A:6-A:2    NA      NA     NA     NA
## B:6-A:2    NA      NA     NA     NA
## C:6-A:2  -9.0 -22.892  4.892 0.2702
## C:2-B:2    NA      NA     NA     NA
## A:3-B:2    NA      NA     NA     NA
## B:3-B:2    NA      NA     NA     NA
## C:3-B:2    NA      NA     NA     NA
## A:4-B:2    NA      NA     NA     NA
## B:4-B:2    NA      NA     NA     NA
## C:4-B:2    NA      NA     NA     NA
## A:5-B:2    NA      NA     NA     NA
## B:5-B:2    NA      NA     NA     NA
## C:5-B:2    NA      NA     NA     NA
## A:6-B:2    NA      NA     NA     NA
## B:6-B:2    NA      NA     NA     NA
## C:6-B:2    NA      NA     NA     NA
## A:3-C:2    NA      NA     NA     NA
## B:3-C:2    NA      NA     NA     NA
## C:3-C:2    NA      NA     NA     NA
## A:4-C:2    NA      NA     NA     NA
## B:4-C:2    NA      NA     NA     NA
## C:4-C:2    NA      NA     NA     NA
## A:5-C:2    NA      NA     NA     NA
## B:5-C:2    NA      NA     NA     NA
## C:5-C:2    NA      NA     NA     NA
## A:6-C:2    NA      NA     NA     NA
```

```
## B:6-C:2    NA      NA     NA     NA
## C:6-C:2    NA      NA     NA     NA
## B:3-A:3    NA      NA     NA     NA
## C:3-A:3    NA      NA     NA     NA
## A:4-A:3    NA      NA     NA     NA
## B:4-A:3    NA      NA     NA     NA
## C:4-A:3    NA      NA     NA     NA
## A:5-A:3    NA      NA     NA     NA
## B:5-A:3    NA      NA     NA     NA
## C:5-A:3    NA      NA     NA     NA
## A:6-A:3    NA      NA     NA     NA
## B:6-A:3    NA      NA     NA     NA
## C:6-A:3    NA      NA     NA     NA
## C:3-B:3    NA      NA     NA     NA
## A:4-B:3    NA      NA     NA     NA
## B:4-B:3  11.5  -2.392 25.392 0.1122
## C:4-B:3    NA      NA     NA     NA
## A:5-B:3    NA      NA     NA     NA
## B:5-B:3    NA      NA     NA     NA
## C:5-B:3  10.0  -3.892 23.892 0.1901
## A:6-B:3    NA      NA     NA     NA
## B:6-B:3    NA      NA     NA     NA
## C:6-B:3  -5.0 -18.892  8.892 0.8471
## A:4-C:3    NA      NA     NA     NA
## B:4-C:3    NA      NA     NA     NA
## C:4-C:3    NA      NA     NA     NA
## A:5-C:3    NA      NA     NA     NA
## B:5-C:3    NA      NA     NA     NA
## C:5-C:3    NA      NA     NA     NA
## A:6-C:3    NA      NA     NA     NA
## B:6-C:3    NA      NA     NA     NA
## C:6-C:3    NA      NA     NA     NA
## B:4-A:4    NA      NA     NA     NA
## C:4-A:4    NA      NA     NA     NA
## A:5-A:4    NA      NA     NA     NA
## B:5-A:4    NA      NA     NA     NA
## C:5-A:4    NA      NA     NA     NA
## A:6-A:4    NA      NA     NA     NA
## B:6-A:4    NA      NA     NA     NA
## C:6-A:4    NA      NA     NA     NA
## C:4-B:4    NA      NA     NA     NA
## A:5-B:4    NA      NA     NA     NA
## B:5-B:4    NA      NA     NA     NA
## C:5-B:4  -1.5 -15.392 12.392 1.0000
## A:6-B:4    NA      NA     NA     NA
## B:6-B:4    NA      NA     NA     NA
```

```
## C:6-B:4 -16.5 -30.392 -2.608 0.0222
## A:5-C:4    NA      NA     NA     NA
## B:5-C:4    NA      NA     NA     NA
## C:5-C:4    NA      NA     NA     NA
## A:6-C:4    NA      NA     NA     NA
## B:6-C:4    NA      NA     NA     NA
## C:6-C:4    NA      NA     NA     NA
## B:5-A:5    NA      NA     NA     NA
## C:5-A:5    NA      NA     NA     NA
## A:6-A:5    NA      NA     NA     NA
## B:6-A:5    NA      NA     NA     NA
## C:6-A:5    NA      NA     NA     NA
## C:5-B:5    NA      NA     NA     NA
## A:6-B:5    NA      NA     NA     NA
## B:6-B:5    NA      NA     NA     NA
## C:6-B:5    NA      NA     NA     NA
## A:6-C:5    NA      NA     NA     NA
## B:6-C:5    NA      NA     NA     NA
## C:6-C:5 -15.0 -28.892 -1.108 0.0351
## B:6-A:6    NA      NA     NA     NA
## C:6-A:6    NA      NA     NA     NA
## C:6-B:6    NA      NA     NA     NA
```

```
TukeyHSD(aov(res2), "school:teacher2")
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = res2)
##
## $`school:teacher2`
##          diff      lwr    upr  p adj
## B:1-A:1 -18.5 -29.0297  -7.97 0.0033
## C:1-A:1  -8.5 -19.0297   2.03 0.1155
## A:2-A:1 -14.5 -25.0297  -3.97 0.0115
## B:2-A:1  -7.0 -17.5297   3.53 0.2179
## C:2-A:1 -23.5 -34.0297 -12.97 0.0009
## C:1-B:1  10.0  -0.5297  20.53 0.0619
## A:2-B:1   4.0  -6.5297  14.53 0.6712
## B:2-B:1  11.5   0.9703  22.03 0.0341
## C:2-B:1  -5.0 -15.5297   5.53 0.4836
## A:2-C:1  -6.0 -16.5297   4.53 0.3294
## B:2-C:1   1.5  -9.0297  12.03 0.9899
## C:2-C:1 -15.0 -25.5297  -4.47 0.0097
## B:2-A:2   7.5  -3.0297  18.03 0.1764
## C:2-A:2  -9.0 -19.5297   1.53 0.0936
## C:2-B:2 -16.5 -27.0297  -5.97 0.0060
```

```
contrast(res2, list(school = "A", teacher = "1"), list(school =
"A", teacher = "2"))  #Bummer
```

```
## Error: could not find function "contrast"
```

```
library(lsmeans)
lsmeans(res2, pairwise ~ school:teacher2)
```

```
## $`school:teacher2 lsmeans`
##  school teacher2 lsmean    SE df lower.CL upper.CL
##       A        1   27.0 1.871  6   22.422   31.578
##       B        1    8.5 1.871  6    3.922   13.078
##       C        1   18.5 1.871  6   13.922   23.078
##       A        2   12.5 1.871  6    7.922   17.078
##       B        2   20.0 1.871  6   15.422   24.578
##       C        2    3.5 1.871  6   -1.078    8.078
##
## $`school:teacher2 pairwise differences`
##              estimate    SE df t.ratio p.value
## A, 1 - B, 1     18.5 2.646  6  6.9923 0.00330
## A, 1 - C, 1      8.5 2.646  6  3.2127 0.11548
## A, 1 - A, 2     14.5 2.646  6  5.4805 0.01150
## A, 1 - B, 2      7.0 2.646  6  2.6458 0.21791
## A, 1 - C, 2     23.5 2.646  6  8.8822 0.00090
## B, 1 - C, 1    -10.0 2.646  6 -3.7796 0.06192
## B, 1 - A, 2     -4.0 2.646  6 -1.5119 0.67121
## B, 1 - B, 2    -11.5 2.646  6 -4.3466 0.03414
## B, 1 - C, 2      5.0 2.646  6  1.8898 0.48362
## C, 1 - A, 2      6.0 2.646  6  2.2678 0.32937
## C, 1 - B, 2     -1.5 2.646  6 -0.5669 0.98991
## C, 1 - C, 2     15.0 2.646  6  5.6695 0.00972
## A, 2 - B, 2     -7.5 2.646  6 -2.8347 0.17641
## A, 2 - C, 2      9.0 2.646  6  3.4017 0.09359
## B, 2 - C, 2     16.5 2.646  6  6.2364 0.00600
##     p values are adjusted using the tukey method for 6 means
```

Using lsmeans gives the same results as TukeyHSD. However, you can get p-values that are not adjusted.

```
lsmeans(res2, pairwise ~ school:teacher2, adjust = "none")
```

```
## $`school:teacher2 lsmeans`
##  school teacher2 lsmean    SE df lower.CL upper.CL
##       A        1   27.0 1.871  6   22.422   31.578
##       B        1    8.5 1.871  6    3.922   13.078
##       C        1   18.5 1.871  6   13.922   23.078
##       A        2   12.5 1.871  6    7.922   17.078
##       B        2   20.0 1.871  6   15.422   24.578
##       C        2    3.5 1.871  6   -1.078    8.078
##
## $`school:teacher2 pairwise differences`
##             estimate    SE df t.ratio p.value
## A, 1 - B, 1     18.5 2.646  6  6.9923 0.00043
## A, 1 - C, 1      8.5 2.646  6  3.2127 0.01830
## A, 1 - A, 2     14.5 2.646  6  5.4805 0.00154
## A, 1 - B, 2      7.0 2.646  6  2.6458 0.03825
## A, 1 - C, 2     23.5 2.646  6  8.8822 0.00011
## B, 1 - C, 1    -10.0 2.646  6 -3.7796 0.00918
## B, 1 - A, 2     -4.0 2.646  6 -1.5119 0.18132
## B, 1 - B, 2    -11.5 2.646  6 -4.3466 0.00484
## B, 1 - C, 2      5.0 2.646  6  1.8898 0.10768
## C, 1 - A, 2      6.0 2.646  6  2.2678 0.06386
## C, 1 - B, 2     -1.5 2.646  6 -0.5669 0.59131
## C, 1 - C, 2     15.0 2.646  6  5.6695 0.00130
## A, 2 - B, 2     -7.5 2.646  6 -2.8347 0.02977
## A, 2 - C, 2      9.0 2.646  6  3.4017 0.01447
## B, 2 - C, 2     16.5 2.646  6  6.2364 0.00079
##     p values are not adjusted
```

Since we are only intrested in the three of the pairwise comparisons, the Bonferonni adjusted p-value is \(\frac{\alpha}{g} \), where g is the number of comparisons. Since g=3, any adjusted p-value less than .017 is significant. Therefore they are all significant. In the end, you can use the TukeyHSD and just look at the interesting contrasts.

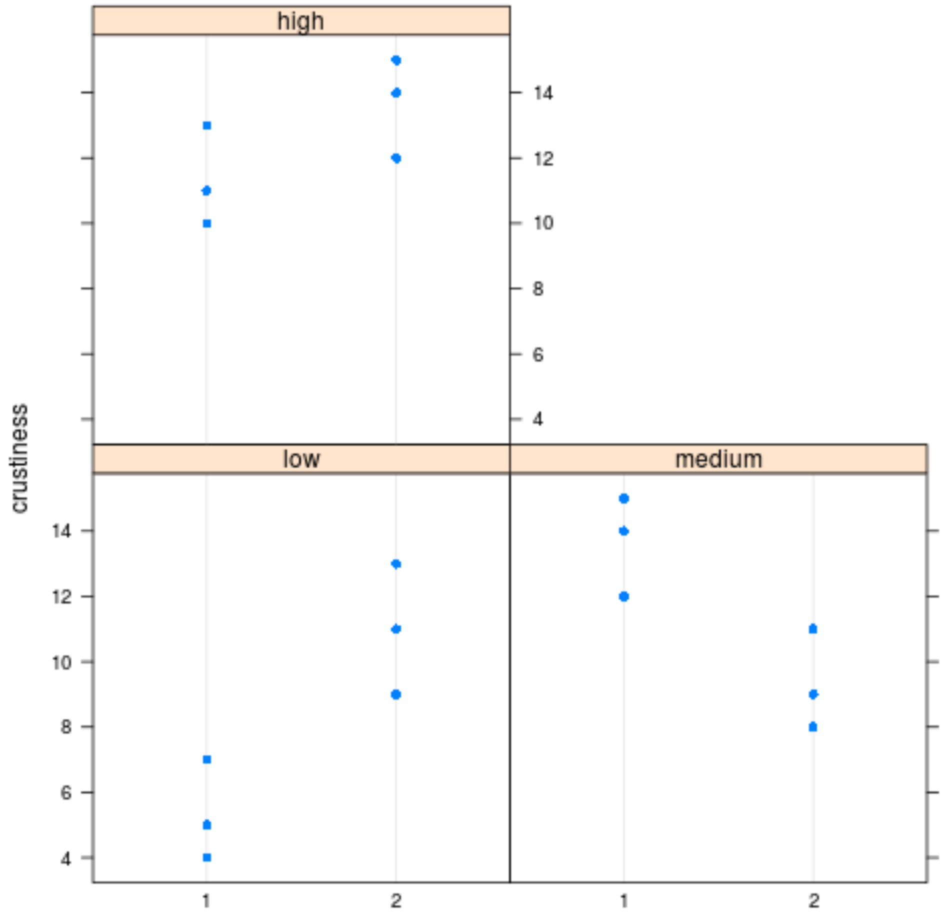
Example 2: Subsampling

Another form of a nested model is sub-sampling. For example, you with to determine if the crustiness of bread depends on the temperature at which the bread is baked. The experimental unit in this case is a batch of flour mix, for which we have six bathces. Each batch is randomly assigned a temperature. If we baked one loaf of bread, this would be a simple one factor ANOVA. However, we bake three loaves of bread from each batch of flour and cook at the same time. This is subsamping.

In this case, each batch of three loaves is nested within temperature. By using three loaves, more information can be obtained about the error in measuring the crustiness of bread. However, the way the experiment is designed, temperature can only be applied to a set of three loaves from the same batch (the EU).

Another example would be to treat a series of trees with three different anti-fungal formulas. The EU is the tree. However, on each tree, you sample 6 leaves and measure a variable. The leaves are nested within trees, as you can't move the leaf to another tree nor can you apply the anti-fungal treatment to just one leaf. When you measure the six leaves, you are getting information about the variability in measuring the variable of interest.

```
ex2.data <- read.table("CH26TA09.txt", col.names =
c("crustiness", "temp", "batch",
    "loaf"))
ex2.data <- within(ex2.data, tempF <- factor(temp, labels =
c("low", "medium",
    "high")))
ex2.data <- within(ex2.data, batchF <- factor(batch))
dotplot(crustiness ~ batchF | tempF, data = ex2.data)
```



Again, you can ignore the fact the design is nested. Let \(\alpha \)=.01 in this example.

```
res1 <- lm(crustiness ~ tempF, data = ex2.data)
anova(res1)
```

```
## Analysis of Variance Table
##
## Response: crustiness
##           Df Sum Sq Mean Sq F value Pr(>F)
## tempF      2   61.8   30.89       4  0.041 *
## Residuals 15  115.8    7.72
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

However, the correct analysis is to nest the batches within the temperature, since you have subsamples.

```
res2 <- lm(crustiness ~ tempF/batchF, data = ex2.data)
anova(res2)
```

```
## Analysis of Variance Table
##
## Response: crustiness
##              Df Sum Sq Mean Sq F value Pr(>F)
## tempF         2   61.8   30.89    11.8 0.0015 **
## tempF:batchF  3   84.5   28.17    10.8 0.0010 **
## Residuals    12   31.3    2.61
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1
```

Which temperatures different?

```
TukeyHSD(aov(res1), "tempF", conf = 0.99)
```

```
##   Tukey multiple comparisons of means
##     99% family-wise confidence level
##
## Fit: aov(formula = res1)
##
## $tempF
##              diff    lwr   upr  p adj
## medium-low  3.333 -2.153 8.820 0.1283
## high-low    4.333 -1.153 9.820 0.0411
## high-medium 1.000 -4.486 6.486 0.8098
```

```
TukeyHSD(aov(res2), "tempF", conf = 0.99)
```

```
##   Tukey multiple comparisons of means
##     99% family-wise confidence level
##
## Fit: aov(formula = res2)
##
## $tempF
##               diff       lwr   upr  p adj
## medium-low  3.333  0.004603 6.662 0.0099
## high-low    4.333  1.004603 7.662 0.0015
## high-medium 1.000 -2.328731 4.329 0.5484
```

Yes, the loaves are different within each batch, but do you care? (Bonf p-value = 0.0033)

```
TukeyHSD(aov(res2), "tempF:batchF", conf = 0.99)
```

```
##   Tukey multiple comparisons of means
##     99% family-wise confidence level
##
## Fit: aov(formula = res2)
##
## $`tempF:batchF`
##                          diff      lwr    upr  p adj
## medium:1-low:1     8.333e+00   2.6414 14.025 0.0004
## high:1-low:1       6.000e+00   0.3080 11.692 0.0068
## low:2-low:1        5.667e+00  -0.0253 11.359 0.0103
## medium:2-low:1     4.000e+00  -1.6920  9.692 0.0860
## high:2-low:1       8.333e+00   2.6414 14.025 0.0004
## high:1-medium:1   -2.333e+00  -8.0253  3.359 0.5176
## low:2-medium:1    -2.667e+00  -8.3586  3.025 0.3852
## medium:2-medium:1 -4.333e+00 -10.0253  1.359 0.0566
## high:2-medium:1    1.776e-15  -5.6920  5.692 1.0000
## low:2-high:1      -3.333e-01  -6.0253  5.359 0.9998
## medium:2-high:1   -2.000e+00  -7.6920  3.692 0.6617
## high:2-high:1      2.333e+00  -3.3586  8.025 0.5176
## medium:2-low:2    -1.667e+00  -7.3586  4.025 0.7985
## high:2-low:2       2.667e+00  -3.0253  8.359 0.3852
## high:2-medium:2    4.333e+00  -1.3586 10.025 0.0566
```

```
lsmeans(res2, pairwise ~ tempF:batchF, adjust = "none")
```

```
## $`tempF:batchF lsmeans`
##   tempF batchF lsmean     SE df lower.CL upper.CL
##     low      1  5.333 0.9329 12    3.301    7.366
##  medium      1 13.667 0.9329 12   11.634   15.699
##    high      1 11.333 0.9329 12    9.301   13.366
##     low      2 11.000 0.9329 12    8.967   13.033
##  medium      2  9.333 0.9329 12    7.301   11.366
##    high      2 13.667 0.9329 12   11.634   15.699
##
## $`tempF:batchF pairwise differences`
##                          estimate    SE df t.ratio p.value
## low, 1 - medium, 1    -8.333e+00 1.319 12 -6.3161 0.00004
## low, 1 - high, 1      -6.000e+00 1.319 12 -4.5476 0.00067
## low, 1 - low, 2       -5.667e+00 1.319 12 -4.2950 0.00104
## low, 1 - medium, 2    -4.000e+00 1.319 12 -3.0318 0.01043
## low, 1 - high, 2      -8.333e+00 1.319 12 -6.3161 0.00004
## medium, 1 - high, 1    2.333e+00 1.319 12  1.7685 0.10236
## medium, 1 - low, 2     2.667e+00 1.319 12  2.0212 0.06615
## medium, 1 - medium, 2  4.333e+00 1.319 12  3.2844 0.00653
## medium, 1 - high, 2   -4.441e-16 1.319 12  0.0000 1.00000
## high, 1 - low, 2       3.333e-01 1.319 12  0.2526 0.80481
## high, 1 - medium, 2    2.000e+00 1.319 12  1.5159 0.15544
## high, 1 - high, 2     -2.333e+00 1.319 12 -1.7685 0.10236
## low, 2 - medium, 2     1.667e+00 1.319 12  1.2632 0.23050
## low, 2 - high, 2      -2.667e+00 1.319 12 -2.0212 0.06615
## medium, 2 - high, 2   -4.333e+00 1.319 12 -3.2844 0.00653
##     p values are not adjusted
```