Mixed Models Exam

Question 1: contrasts for dataset "needle_litter_fall_rbd.txt"

This script is already included in the Answer for Homework Exercise 1

```
\#rm(list = ls()) \# Clean the workspace
#install.packages("lme4") # If necessary install the library
#install.packages("nlme") # If necessary install the library
library(lme4)
                           # Call the library to the workspace
library(car)
                           # Call the library to the workspace
library(lsmeans)
                         # Call the library to the workspace
                          # Call the library to the workspace
library(multcomp)
library(nlme)
                           # Call the library to the workspace
# Read the data
# "PUT HERE THE ADRESS OF THE FILE " #
myfile<-"C:/Users/toledo/Dropbox/UNIPD/Biostatistics Curse R Spring 2018/curso STAT phD 2018 Mixed Models/dat
rbd_litter<-read.table(file=myfile,stringsAsFactors = TRUE,header = TRUE,sep = "\t")</pre>
options(contrasts = c("contr.SAS", "contr.poly"))
                                                       # Change contrast options
rbd_litter$block<-as.factor(rbd_litter$block)</pre>
                                                         # Set block as factor
\#rbd\_litter\$treatment<-as.factor(rbd\_litter\$treatment) \# Set treatment as factor: not necessary because treatm
# Fit the mixed model
model.1<-lmer(needle_litter_fall ~ treatment + (1 | block), data = rbd_litter, REML = TRUE)
lsmeans(model.1, "treatment")
                                  # LSM
##
   treatment 1smean
                            SE
                                 df lower.CL upper.CL
                7.5 0.2198484 3.92 6.884785 8.115215
##
##
   Ι
                7.4 0.2198484 3.92 6.784785 8.015215
##
   TF
                 9.1 0.2198484 3.92 8.484785 9.715215
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
#Adding the contrasts to model.1
coef(model.1)
                               # See the coefficients of your model
## $block
##
     (Intercept) treatmentC treatmentI
                     -1.6
## 1
       8.853304
                                  -1.7
## 2
       9.130837
                       -1.6
                                  -1.7
                     -1.6
## 3
       9.624229
                                  -1.7
## 4
        8.791630
                     -1.6
                                  -1.7
##
## attr(,"class")
## [1] "coef.mer"
library(multcomp)
                              # Contrast treatment1 vs treatment2
K \leftarrow matrix(c(0, 1, -1), 1)
t <- glht(model.1, linfct = K)
                                           # fit a general linear hypothesis test
summary(t)
                                       # See the results: no differences among treatments
##
##
     Simultaneous Tests for General Linear Hypotheses
##
## Fit: lmer(formula = needle_litter_fall ~ treatment + (1 | block),
##
       data = rbd_litter, REML = TRUE)
##
## Linear Hypotheses:
##
          Estimate Std. Error z value Pr(>|z|)
## 1 == 0 0.1000
                     0.1374 0.728
                                         0.467
```

```
## (Adjusted p values reported -- single-step method)
K \leftarrow matrix(c(0, 1, 0), 1)
                            # Contrast treatment1 vs treatment3
t <- glht(model.1, linfct = K)
                                           # fit a general linear hypothesis test
summary(t)
                                       # See the results: signif. differences among treatments
##
##
     Simultaneous Tests for General Linear Hypotheses
##
## Fit: lmer(formula = needle_litter_fall ~ treatment + (1 | block),
##
       data = rbd_litter, REML = TRUE)
##
## Linear Hypotheses:
##
          Estimate Std. Error z value Pr(>|z|)
## 1 == 0 -1.6000
                     0.1374 -11.64 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
K \leftarrow matrix(c(0, 0, 1), 1)
                              # Contrast treatment2 vs treatment3
t <- glht(model.1, linfct = K)
                                           # fit a general linear hypothesis test
                                       # See the results: signif. differences among treatments
summary(t)
##
##
     Simultaneous Tests for General Linear Hypotheses
##
## Fit: lmer(formula = needle_litter_fall ~ treatment + (1 | block),
      data = rbd_litter, REML = TRUE)
##
##
## Linear Hypotheses:
          Estimate Std. Error z value Pr(>|z|)
##
## 1 == 0 -1.7000
                       0.1374 -12.37
                                      <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
K \leftarrow matrix(c(0, 1, 1), 1)
                           # Contrast treatment1+2 vs treatment3
t <- glht(model.1, linfct = K)
                                           # fit a general linear hypothesis test
summary(t)
                                       # See the results: signif. differences among t1 vs. t2+t3
##
##
     Simultaneous Tests for General Linear Hypotheses
##
## Fit: lmer(formula = needle_litter_fall ~ treatment + (1 | block),
##
       data = rbd_litter, REML = TRUE)
##
## Linear Hypotheses:
##
          Estimate Std. Error z value Pr(>|z|)
## 1 == 0 -3.300
                        0.238 - 13.86
                                      <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
#the first contrast tells you that there are no differences between t1 and t2,
#the further contrasts tell you that t3 is significantly different from 1 and 2
```

Question 2: linear model vs mixed model for dataset "needle_litter_fall_rbd.txt"

```
# Fit the linear model
model.2<-lm(needle_litter_fall ~ treatment + block ,data = rbd_litter)</pre>
Anova(model.2, type=3,test.statistic = "F") # ANOVA table SS type III
## Anova Table (Type III tests)
##
## Response: needle_litter_fall
##
               Sum Sq Df F value
                                     Pr(>F)
## (Intercept) 153.709 1 4068.765 9.982e-10 ***
               7.280 2
## treatment
                           96.353 2.753e-05 ***
                1.513 3
                           13.353 0.004593 **
## block
                0.227 6
## Residuals
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
lsmeans(model.2, "treatment")
                                 # LSM
##
   treatment 1smean
                            SE df lower.CL upper.CL
##
                7.5 0.09718253 6 7.262203 7.737797
   C
## I
                7.4 0.09718253 6 7.162203 7.637797
## IF
                9.1 0.09718253 6 8.862203 9.337797
##
## Results are averaged over the levels of: block
## Confidence level used: 0.95
#comparison with model 1:
Anova(model.1, type=3,test.statistic = "F") # ANOVA table SS type III
## Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
##
## Response: needle litter fall
##
                     F Df Df.res
                                    Pr(>F)
## (Intercept) 1713.310 1 3.922 2.503e-06 ***
              96.353 2 6.000 2.753e-05 ***
## treatment
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
lsmeans(model.1,"treatment")
                                  # LSM
   treatment lsmean
                           SE
                                df lower.CL upper.CL
##
## C
                7.5 0.2198484 3.92 6.884785 8.115215
## I
                7.4 0.2198484 3.92 6.784785 8.015215
##
   IF
                9.1 0.2198484 3.92 8.484785 9.715215
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
#no differences for the treatment effect and no differences in lsmeans
```

```
rbd<-read.table(file="C:/Users/toledo/Dropbox/UNIPD/Biostatistics Curse R Spring 2018/curso STAT phD 2018 Mix
                stringsAsFactors = TRUE,header = TRUE,sep = "\t")
rbd$block<-as.factor(rbd$block)</pre>
                                          # Set block as factor
rbd$fertilizer<-as.factor(rbd$fertilizer) # Set fertilizer as factor
contrasts(rbd$block)<-contr.SAS</pre>
                                          # Change the reference grid to SAS
contrasts(rbd$fertilizer)<-contr.SAS</pre>
                                          # Change the reference grid to SAS
# Fit the mixed model (here called model.3, in the lesson's exercises it is model.2)
model.3<-lmer(yield ~ fertilizer + (1 | block) ,data = rbd, REML = TRUE)
lsmeans(model.3, "fertilizer")
                               # LSM
##
   fertilizer lsmean
                               SE
                                    df lower.CL upper.CL
##
                9.50000 0.6680541 6.24 7.880260 11.11974
   1
               10.66667 0.6680541 6.24 9.046926 12.28641
## 2
##
               12.33333 0.6680541 6.24 10.713593 13.95307
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
#Adding the contrasts to model.3
coef(model.3)
                               # See the coefficients of your model
## $block
##
     (Intercept) fertilizer1 fertilizer2
## 1
        10.92403
                  -2.833333 -1.666667
## 2
       14.36899
                  -2.833333 -1.666667
## 3
      13.11628 -2.833333 -1.666667
      10.61085 -2.833333 -1.666667
## 4
## 5
       11.86357
                   -2.833333
                              -1.666667
## 6
       13.11628
                  -2.833333 -1.666667
##
## attr(,"class")
## [1] "coef.mer"
library(multcomp)
                              # Contrast Fertilizer1 vs Fertilizer2
K \leftarrow matrix(c(0, 1, -1), 1)
t <- glht(model.3, linfct = K)
                                           # fit a general linear hypothesis test
summary(t)
                                       # See the results: signif. differences among levels
##
     Simultaneous Tests for General Linear Hypotheses
##
##
## Fit: lmer(formula = yield ~ fertilizer + (1 | block), data = rbd,
       REML = TRUE)
##
##
## Linear Hypotheses:
          Estimate Std. Error z value Pr(>|z|)
##
## 1 == 0 -1.1667
                       0.3801
                               -3.07 0.00214 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
K \leftarrow matrix(c(0, 1, 0), 1)
                              # Contrast Fertilizer1 vs Fertilizer3
t <- glht(model.3, linfct = K)
                                           # fit a general linear hypothesis test
summary(t)
                                       # See the results: signif. differences among levels
##
##
     Simultaneous Tests for General Linear Hypotheses
##
```

```
## Fit: lmer(formula = yield ~ fertilizer + (1 | block), data = rbd,
     REML = TRUE)
##
##
## Linear Hypotheses:
         Estimate Std. Error z value Pr(>|z|)
##
## 1 == 0 -2.8333
                   0.3801 -7.455 8.99e-14 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
K <- matrix(c(0, 0, 1), 1) # Contrast Fertilizer2 vs Fertilizer3</pre>
t <- glht(model.3, linfct = K)
                                         # fit a general linear hypothesis test
summary(t)
                                      # See the results: signif. differences among levels
##
##
    Simultaneous Tests for General Linear Hypotheses
##
## Fit: lmer(formula = yield ~ fertilizer + (1 | block), data = rbd,
      REML = TRUE)
##
##
## Linear Hypotheses:
         Estimate Std. Error z value Pr(>|z|)
##
## 1 == 0 -1.6667
                    0.3801 -4.385 1.16e-05 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

Question 4-7

```
nested_trees<-read.table(file="C:/Users/toledo/Dropbox/UNIPD/Biostatistics Curse R Spring 2018/curso STAT phD
                         stringsAsFactors = TRUE,header = TRUE,sep = "\t")
options(contrasts = c("contr.SAS","contr.poly"))
                                                 # Change contrast options
nested_trees$Plot<-as.factor(nested_trees$Plot) # Set the variable as factor
nested_trees$Soil<-as.factor(nested_trees$Soil) # Set the variable as factor
#### Random Model
model.4<-lmer(Height_growth ~ Soil + (1|Soil:Plot), data = nested_trees ) # Fit a model with Random effect
summary(model.4)
                                 # See the results
## Linear mixed model fit by REML ['lmerMod']
## Formula: Height_growth ~ Soil + (1 | Soil:Plot)
      Data: nested_trees
##
##
## REML criterion at convergence: 8.1
##
## Scaled residuals:
##
       Min
                 1Q
                      Median
                                    3Q
                                            Max
## -1.88231 -0.58865 -0.08226 0.80333 2.32247
##
## Random effects:
## Groups
             Name
                          Variance Std.Dev.
## Soil:Plot (Intercept) 0.04221 0.2055
                          0.04783 0.2187
## Number of obs: 48, groups: Soil:Plot, 8
##
## Fixed effects:
##
              Estimate Std. Error t value
## (Intercept) 2.4500
                            0.1120 21.873
## SoilA
               -0.7500
                            0.1584 -4.735
##
## Correlation of Fixed Effects:
         (Intr)
##
## SoilA -0.707
                                                              # ANOVA
Anova(model.4, type=3,test.statistic = "F")
## Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
##
## Response: Height_growth
                    F Df Df.res
                                    Pr(>F)
##
## (Intercept) 478.428 1
                          6 5.965e-07 ***
               22.417 1
## Soil
                               6 0.003209 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
lsmeans(model.4, "Soil")
                                 # lsmeans
##
   Soil 1smean
                       SE df lower.CL upper.CL
          1.70 0.1120103 6 1.425921 1.974079
##
   Α
##
   В
           2.45 0.1120103 6 2.175921 2.724079
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

Question 8-9

```
# Read the data
myfile<-"C:/Users/toledo/Dropbox/UNIPD/Biostatistics Curse R Spring 2018/curso STAT phD 2018 Mixed Models/dat
mydata<-read.table(file=myfile,stringsAsFactors = TRUE,header = TRUE,sep = "\t")</pre>
options(contrasts = c("contr.SAS","contr.poly")) # Change contrast options
mydata$alluminium<-as.factor(mydata$alluminium)</pre>
                                                    # Set as factor
mydata$seedling<-as.factor(mydata$seedling)</pre>
                                                    # Set as factor
# Fit the same model with different types of variance and covariance
#model.a and model.b already included in homework exercises
model.a<-lme(height ~ alluminium + time + alluminium*time, data = mydata, # Model
            random = ~ 1|seedling,
                                                      # Random Effect
            weights = varIdent(form = ~ 1 | time),
                                                          # Constant variance(s)
            correlation = NULL)
                                                          # No correlation
model.b<-lme(height ~ alluminium + time + alluminium*time, data = mydata, # Model
                                                      # Random Effect
            random = ~ 1 seedling,
            weights = varIdent(form = ~ 1|time),
                                                          # Constant variance(s)
             correlation = corAR1())
                                                          # autocorrelation structure of order 1
#model.c included following question 8
model.c<-lme(height ~ alluminium + time + alluminium*time, data = mydata, # Model
            random = ~ 1|seedling,
                                                      # Random Effect
            weights = varIdent(form = ~ 1 | time),
                                                          # Constant variance(s)
             correlation = corCompSymm())
                                                               # compound symmetry
anova(model.a, model.b, model.c)
          Model df
                        AIC
                                        logLik
                                 BIC
                                                 Test L.Ratio p-value
## model.a 1 21 2479.600 2553.718 -1218.800
## model.b
             2 22 2392.086 2469.733 -1174.043 1 vs 2 89.51447 <.0001
## model.c
            3 22 2481.117 2558.764 -1218.558
#the best fitted model is model.b (question 9)
anova(model.b)
                  numDF denDF F-value p-value
## (Intercept)
                   1 189 270.38679 <.0001
                     3 63 1.02365 0.3882
## alluminium
## time
                      3 189 13.85646 <.0001
## alluminium:time 9 189 2.14919 0.0274
```