Advanced Applied Statistics A computer session
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All data are recorded in the /.Data directory. Creating a directory .Data in a subdirectory will enable you to record data in this subdirectory. This is accomplished by issue the command splus CHAPTER in the subdirectory where you want to work. Change .Data/.Audit to be unwrittenable if you want to turn off Auditing.

Basics

```
 splus
> q()  #exit
> labor <- matrix(scan("labor.suppl.dat", skip=17),byrow=T,ncol=9)
#reading data from "labor.DATA"
> ?matrix
#this is the same as typing 'help(matrix)'.
> dimnames(labor) <- list(NULL, c("hours", "age", "earning", "job.pres",
    "edu", "rent", "hearning", "child", "unemploy"))
> labor[1:2,]
#take the first two rows
 hours age earning job.pres edu rent hearning child unemploy
     21  36  8.269       55  12 1010     2800     1     16.8
     40  35  6.059       29  10  268     2500     1     16.8
> edu
Problem: Object "edu" not found

> edu <- labor[,5]
#take a column out
> rm(edu)
#rm the vector edu from the data base

> labor.df <- data.frame(labor)
# create data frame
> attach(labor.df)
# each vector is now recognizable
> edu
 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
 36 35 33 30 43 45 39 33 48 55 30 47 54 45 51 52 37 36 33 36 52 33 36 48 32 30

> eduf <- rep("A",length(edu))
# create data vector of length 607
> eduf[edu < 16] <- "B"
> eduf[edu < 13] <- "C"
> eduf[edu < 12] <- "D"
> laborf <- data.frame(earning, eduf)
> laborf[1:3,]
# Show the first 3 cases
1   8.269    C
2   6.059    D
3  11.500    C

> sink("result")
> edu
> sink(on.exit=T)
```

One-Way ANOVA

We now use the female labor supply data in the East Germany. 607 women with job who live together with a partner have been asked for their weekly number of working hours. Furthermore, it has been recorded, if they have children less than 16 years old, the unemployment rate in the Land of the Federal Republic of Germany where she lives, the age of the woman, her wage per hour, the "Treiman prestige index" of her job (see Treiman, 1978), her years of education [introduction of this covariate makes sense because of the strongly regulated system of education in the former state of East Germany], her rent or redemption the monthly net income of her partner. For simplicity of illustration, we use only two variables. Hourly earning rate and education level (A = 16, B = 13-15, C = 12, D < 12. One naturally try to exam the data. Here are a few commands related to ANOVA.

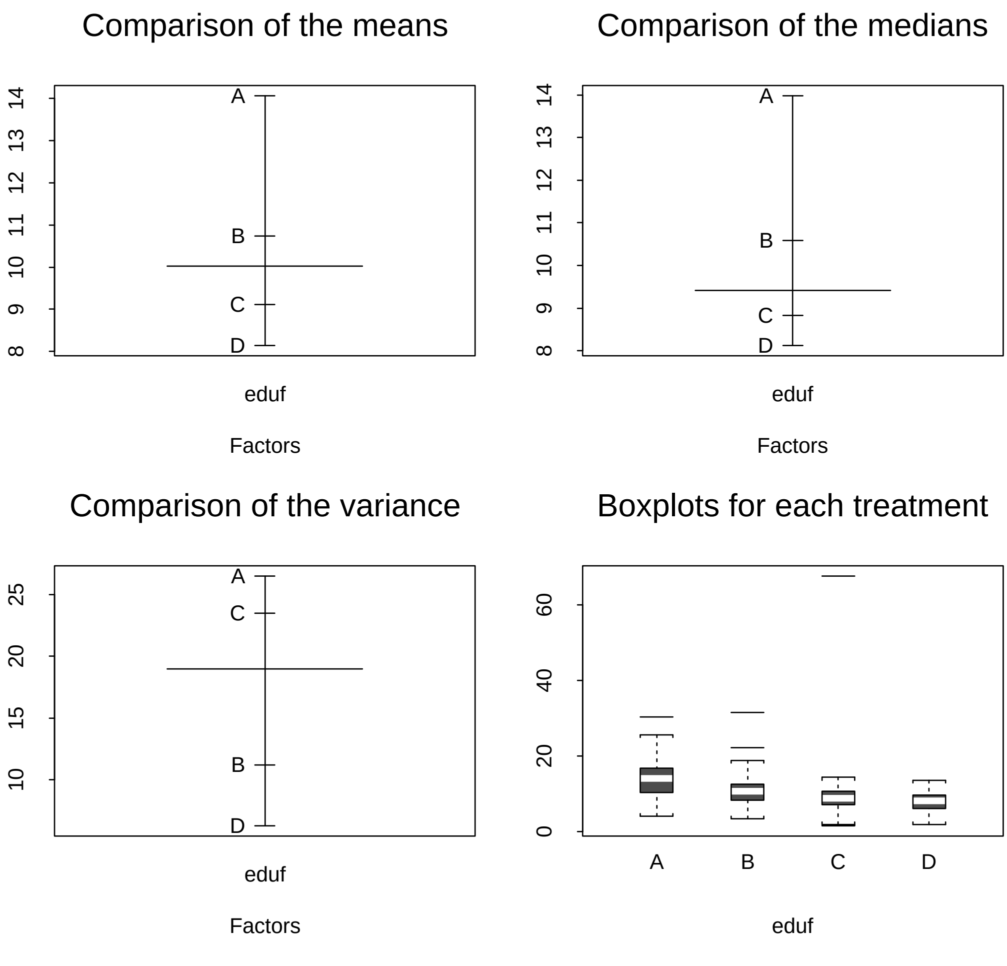

Figure 1: Visual inspection of the data

```
> postscript("labor.anova1.ps",width=5.5, height = 5,horizontal=F, pointsize=8);
#record the results in the file instead of on the screen
> par(mfrow=c(2,2),mar=c(5,3,3,1)+0.1)
#setting some paramgers
> plot.design(laborf)
#graphic plot using mean
> title("Comparison of the means")
> plot.design(laborf, fun=median)
> title("Comparison of the medians")
```

```
#graphic plot using median
> plot.design(laborf, fun=var)
#graphic plot for comparing variance
> title("Comparison of the variance")
> plot.factor(laborf)
> title("Boxplots for each treatment")
> dev.off()
#force to create the postscript now
> lm(earning ~ eduf)
#run a linear model fit
Call:
lm(formula = earning ~ eduf)

Coefficients:
 (Intercept)     eduf1     eduf2      eduf3
     10.51736 -1.664151 -1.098402 -0.7939263

     Degrees of freedom: 607 total; 603 residual
     Residual standard error: 3.991209
>options()$contrast
          factor      ordered
       "contr.helmert" "contr.poly"
>options(contrasts=c("contr.treatment"))
> options()$contrast
[1] "contr.treatment"
> lm(formula = earning ~ eduf)
Call:
lm(formula = earning ~ eduf)

Coefficients:
 (Intercept)     edufB     edufC     edufD
    14.07384 -3.328302 -4.959358 -5.938258

Degrees of freedom: 607 total; 603 residual
Residual standard error: 3.991209

> options(contrasts=c("contr.sum"))
> lm(earning~eduf)
Call:
lm(formula = earning ~ eduf)

Coefficients:
 (Intercept)    eduf1     eduf2     eduf3
    10.51736 3.556479 0.2281777 -1.402878

Degrees of freedom: 607 total; 603 residual
Residual standard error: 3.991209

>aov.labor <- aov(earning~eduf)
#run anova for the data
>summary(aov.labor)
           Df Sum of Sq  Mean Sq  F Value Pr(F)
     eduf   3  1884.844 628.2813 39.44076     0
Residuals 603  9605.637  15.9297
```

```
> multicomp(aov.labor,focus="eduf",method="bon")
        # Bonferroni method

> postscript("labor.anova2.ps",width=5.5, height = 5,horizontal=F, pointsize=8);
#record the results in the file instead of on the screen
> par(mfrow=c(2,2),mar=c(5,3,3,1)+0.1)
> residuals <- resid(aov.labor)
> hist(residuals)
#plot the histogram of the residuals
> plot(density(residuals),type="l")
#plot the density of the residuals
> qqnorm(residuals)
#Q-Q plot of the residuals
```

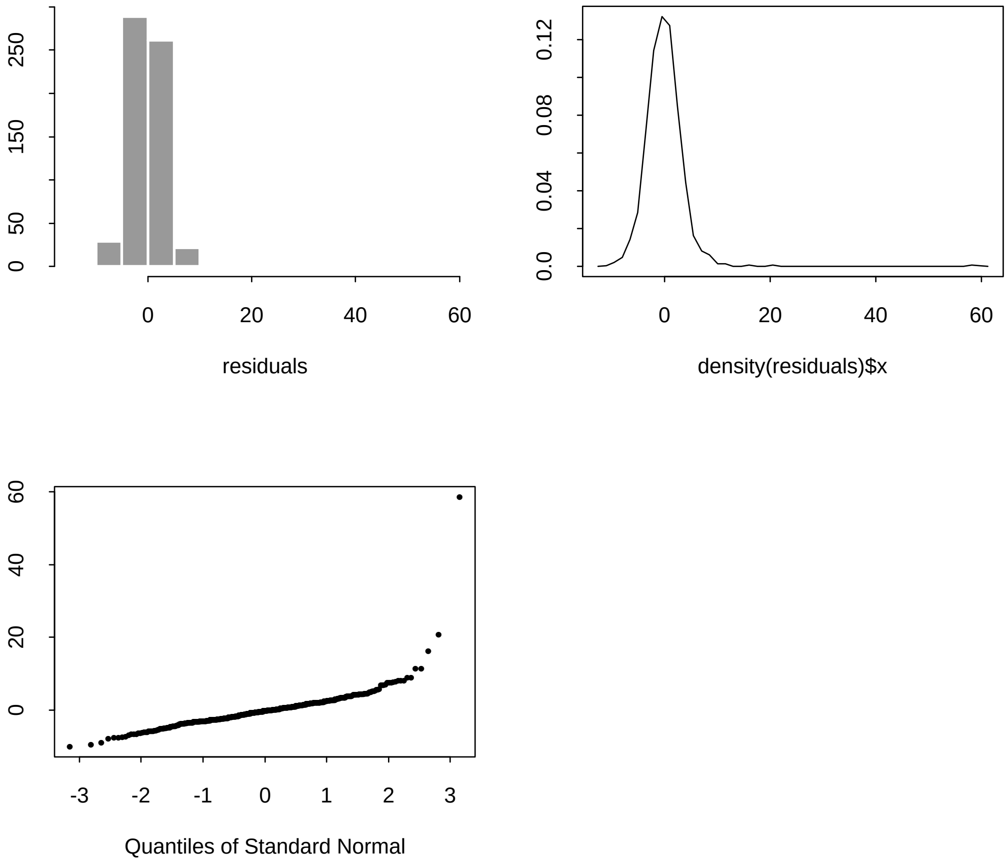

Figure 2: Visual inspection of the data

Two-way ANOVA models

```
> childf <- rep("Y",length(child))
> childf[child==0] <- 'N'
> chidlf[1:10]
> childf[1:10]
 [1] "Y" "Y" "Y" "Y" "Y" "N" "Y" "Y" "N" "Y"

> laborf <- data.frame(earning, eduf, childf)
#create the data flabor
> attach(laborf)
 attach(labor.df)
 plot.design(laborf)
#plot the mean of each group
 postscript("labor.anova3.ps",width=5.5, height = 5,horizontal=F,pointsize=8);
#record the results in the file instead of on the screen
 par(mfrow=c(2,2),mar=c(5,3,3,1)+0.1)
#setting some paramgers
 plot.factor(laborf)
#box plot for earnings of each level in each factor
 interaction.plot(childf, eduf,earning)
 title("Interactions between child and edu")
# intereaction plot for factors childf and eduf
 interaction.plot(unemploy, eduf, earning)
 title("Interactions between edu and employ")
# As a more complicated example, this plot the interaction between edu and
# employment rate
```

We now try to fit a two-way layout ANOVA model with interactions

```
> attach(laborf)
> options(contrasts=c("contr.treatment","contr.treatment"))
> lm(earning~childf*eduf)
### fitting a two-term interaction model
Call:
lm(formula = earning ~ childf * eduf)

Coefficients:
 (Intercept)     childf     edufB     edufC     edufD childfedufB
childfedufC
    14.40383 -0.4442179 -3.871236 -4.072304 -5.965286   0.7590709
-1.189399

 childfedufD
  -0.6810723
> options(contrasts=c("contr.sum","contr.sum"))
> lm(earning~childf*eduf)
Call:
lm(formula = earning ~ childf * eduf)

Coefficients:
 (Intercept)   childf    eduf1     eduf2     eduf3 childfeduf1 childfeduf2
   10.56559 0.361034 3.616132 0.1244307 -1.050872   -0.138925  -0.5184605

 childfeduf3
   0.4557743
```

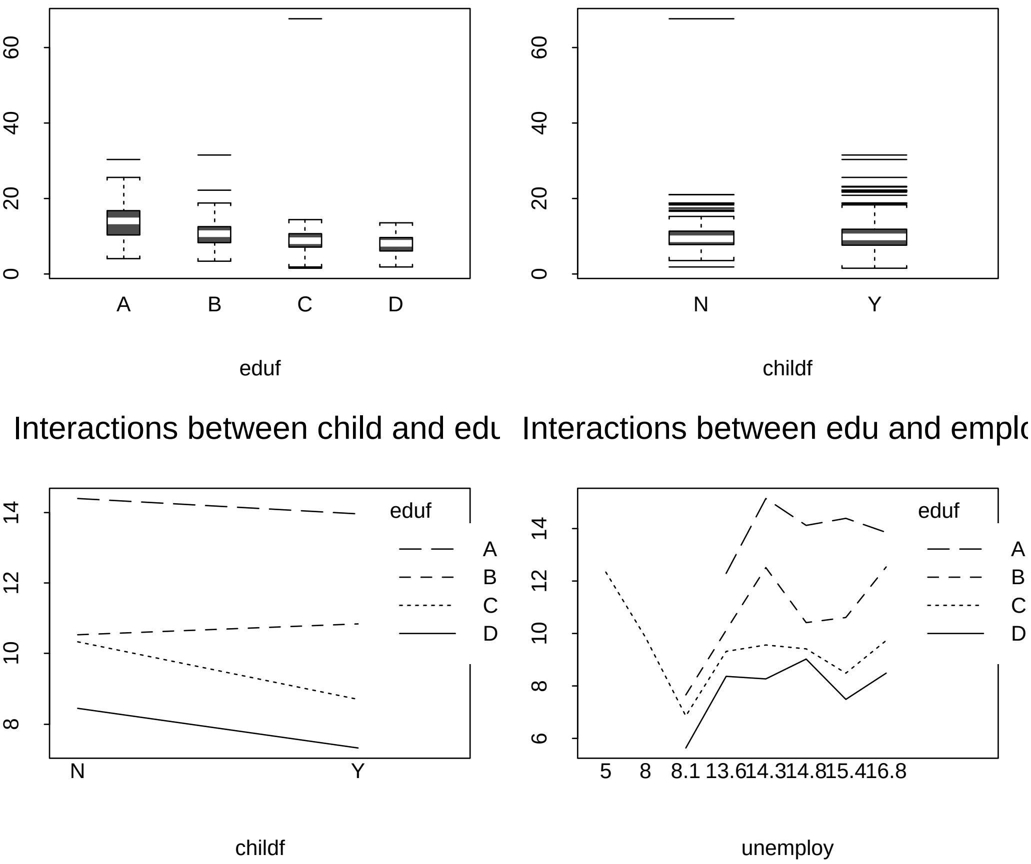

Figure 3: Visual inspection of the data with two factors

```
Degrees of freedom: 607 total; 599 residual
Residual standard error: 3.975031
> labor.aov <- aov(earning~childf*eduf)
> summary(labor.aov)
 summary(labor.aov)
             Df Sum of Sq  Mean Sq  F Value     Pr(F)
     childf   1     4.057   4.0575  0.25679 0.6125209
       eduf   3  1936.489 645.4964 40.85195 0.0000000
childf:eduf   3    85.213  28.4042  1.79764 0.1464194
  Residuals 599  9464.721  15.8009
```

We now try to fit a two-way layout ANOVA model with only the main effect

```
> options(contrasts=c("contr.treatment","contr.treatment"))
> lm(earning~childf+eduf)
Call:
lm(formula = earning ~ childf + eduf)

Coefficients:
 (Intercept)     childf     edufB     edufC     edufD
    14.57527 -0.6749966 -3.373208 -4.957911 -6.257954

Degrees of freedom: 607 total; 602 residual
Residual standard error: 3.982923

> summary(aov(earning~childf+eduf))
           Df Sum of Sq  Mean Sq  F Value     Pr(F)
   childf   1     4.057   4.0575  0.25577 0.6132244
     eduf   3  1936.489 645.4964 40.69021 0.0000000
Residuals 602  9549.934  15.8637
```

ANOVA Decompositions: Balanced vs Unbalanced

Comparison two ANOVA decompositions. For balanced design, the decomposition is unconditional. For inbalanced design, the decomposition is conditional.

```
> battery                          #balanced design data set

   Brand      Duty resp
 1 named  Alkaline  611
 2 named  Alkaline  537
 3 named  Alkaline  542
 4 named  Alkaline  593
 5 named Heavyduty  445
 6 named Heavyduty  490
 7 named Heavyduty  384
 8 named Heavyduty  413
 9 store  Alkaline  923
10 store  Alkaline  794
```

```
11 store  Alkaline  827
12 store  Alkaline  898
13 store Heavyduty  476
14 store Heavyduty  569
15 store Heavyduty  480
16 store Heavyduty  460

> attach(battery)
> summary(aov(resp~Brand))
#ANOVA decomposition with one factor

          Df Sum of Sq  Mean Sq  F Value      Pr(F)
    Brand  1  124609.0 124609.0 5.259052 0.03783034
Residuals 14  331718.7  23694.2

> summary(aov(resp~Brand+Duty))
          Df Sum of Sq  Mean Sq  F Value        Pr(F)
    Brand  1  124609.0 124609.0 20.32142 0.0005886884
     Duty  1  252004.0 252004.0 41.09719 0.0000230424
Residuals 13   79714.7   6131.9
#ANOVA decomposition with two factors.  Note that the contribution due
# to BRAND does not change so does it in the following two models.

> summary(aov(resp~Duty+Brand))
          Df Sum of Sq  Mean Sq  F Value        Pr(F)
     Duty  1  252004.0 252004.0 41.09719 0.0000230424
    Brand  1  124609.0 124609.0 20.32142 0.0005886884
Residuals 13   79714.8   6131.9

> summary(aov(resp~Duty*Brand))
           Df Sum of Sq  Mean Sq  F Value        Pr(F)
      Duty  1  252004.0 252004.0 106.4337 0.0000002555
     Brand  1  124609.0 124609.0  52.6285 0.0000100835
Duty:Brand  1   51302.2  51302.2  21.6675 0.0005558051
 Residuals 12   28412.5   2367.7

#The situations changes dramatically for unbalanced design in
#the earning data.  Note that the different sum of squares reductions
#due to eduf.  They are conditional reductions.

> summary(aov(earning~eduf))
           Df Sum of Sq  Mean Sq  F Value Pr(F)
     eduf   3  1884.844 628.2813 39.44076     0
Residuals 603  9605.637  15.9297

> summary(aov(earning~eduf+childf))
           Df Sum of Sq  Mean Sq  F Value      Pr(F)
     eduf   3  1884.844 628.2813 39.60502 0.00000000
   childf   1    55.703  55.7030  3.51135 0.06143388
Residuals 602  9549.934  15.8637

> summary(aov(earning~childf+eduf))
           Df Sum of Sq  Mean Sq  F Value     Pr(F)
   childf   1     4.057   4.0575  0.25577 0.6132244
```

```
     eduf   3  1936.489 645.4964 40.69021 0.0000000
Residuals 602  9549.934  15.8637

> summary(aov(earning~childf*eduf))
             Df Sum of Sq  Mean Sq  F Value     Pr(F)
     childf   1     4.057   4.0575  0.25679 0.6125209
       eduf   3  1936.489 645.4964 40.85195 0.0000000
childf:eduf   3    85.213  28.4042  1.79764 0.1464194
  Residuals 599  9464.721  15.8009

> summary(aov(earning~eduf*childf))
             Df Sum of Sq  Mean Sq  F Value     Pr(F)
       eduf   3  1884.844 628.2813 39.76245 0.0000000
     childf   1    55.703  55.7030  3.52531 0.0609242
eduf:childf   3    85.213  28.4042  1.79764 0.1464194
  Residuals 599  9464.721  15.8009
```

Analysis of Covariance

The analysis of Covariance does not make any extra difficulty. Please note that the ANOVA decomposition is valid in conditional sense. The unconditional decomposition holds only when linear spaces are orthogonal (design matrix are blockwise orthogonal) Compare the ANOVA decomposition for different orders. Compare different meaning of contrasts in different models.

```
> attach(labor.df)
> lm(earning ~ eduf + age + job.pres)
Call:
lm(formula = earning ~ eduf + age + job.pres)

Coefficients:
 (Intercept)    eduf1      eduf2      eduf3        age  job.pres
    4.522455 -1.16764 -0.5829174 -0.4750492 0.02124989 0.1185623

Degrees of freedom: 607 total; 601 residual
Residual standard error: 3.787025

> lm(earning ~ age + job.pres)
Call:
lm(formula = earning ~ age + job.pres)

Coefficients:
 (Intercept)         age  job.pres
    3.224799 0.003113607 0.1590534

Degrees of freedom: 607 total; 604 residual
Residual standard error: 3.880508

>  summary(aov(earning ~ eduf + age + job.pres))
           Df Sum of Sq  Mean Sq  F Value     Pr(F)
     eduf   3  1884.844 628.2813 43.80844 0.0000000
      age   1    32.268  32.2683  2.24999 0.1341406
 job.pres   1   954.093 954.0929 66.52645 0.0000000
```

```
Residuals 601  8619.276  14.3416

>  summary(aov(earning ~age + eduf + job.pres))
           Df Sum of Sq  Mean Sq  F Value     Pr(F)
      age   1     2.484   2.4838  0.17319 0.6774415
     eduf   3  1914.628 638.2094 44.50071 0.0000000
 job.pres   1   954.093 954.0929 66.52645 0.0000000
Residuals 601  8619.276  14.3416

> summary(aov(earning ~job.pres + eduf + age))
           Df Sum of Sq  Mean Sq  F Value     Pr(F)
 job.pres   1  2394.842 2394.842 166.9862 0.0000000
     eduf   3   461.556  153.852  10.7277 0.0000007
      age   1    14.806   14.806   1.0324 0.3100069
Residuals 601  8619.276   14.342

> options(contrasts=c("contr.treatment"))
> summary(lm(earning ~job.pres + eduf + age))

Call: lm(formula = earning ~ job.pres + eduf + age)
Residuals:
    Min     1Q  Median    3Q   Max
 -9.492 -1.758 -0.1898 1.575 57.09

Coefficients:
              Value Std. Error t value Pr(>|t|)
(Intercept)  6.7481  1.1958     5.6430  0.0000
   job.pres  0.1186  0.0145     8.1564  0.0000
      edufB -2.3353  0.5373    -4.3465  0.0000
      edufC -2.9164  0.5809    -5.0205  0.0000
      edufD -3.6508  0.6582    -5.5470  0.0000
        age  0.0212  0.0209     1.0161  0.3100

Residual standard error: 3.787 on 601 degrees of freedom
Multiple R-Squared: 0.2499
F-statistic: 40.04 on 5 and 601 degrees of freedom, the p-value is 0

Correlation of Coefficients:
         (Intercept) job.pres   edufB   edufC   edufD
job.pres -0.6256
   edufB -0.4702      0.2235
   edufC -0.6205      0.4131   0.7504
   edufD -0.3965      0.4684   0.6802  0.7068
     age -0.6440     -0.0590   0.0036  0.0738 -0.2573


> lm(earning ~job.pres + eduf)
Call:
lm(formula = earning ~ job.pres + eduf)

Coefficients:
 (Intercept)  job.pres     edufB    edufC     edufD
    7.530575 0.1194338 -2.337265 -2.95995 -3.478709
```

```
Degrees of freedom: 607 total; 602 residual
Residual standard error: 3.787127

> lm(earning~eduf)
Call:
lm(formula = earning ~ eduf)

Coefficients:
 (Intercept)     edufB     edufC     edufD
    14.07384 -3.328302 -4.959358 -5.938258

Degrees of freedom: 607 total; 603 residual
Residual standard error: 3.991209
```

Mixed effect models:

```
############# Analyzing the battery data using the random effect model
> repl <- c(rep(1,4), rep(2,4), rep(3,4), rep(4,4))
###### create index for cluster
> battery <- cbind(repl, battery)
> attach(battery)
> options(contrasts=c("contr.treatment","contr.treatment"))
> Fit1 <- lme(fixed= resp ~ Brand * Duty, random = ~Brand*Duty,
              cluster = ~repl, data=battery)
> summary(Fit1)
Call:
  Fixed: resp ~ Brand * Duty
 Random:  ~ Brand * Duty
Cluster:  ~ repl
   Data: battery

Estimation Method: RML
Convergence at iteration: 1
Restricted Loglikelihood: -66.41792
Restricted AIC: 162.8358
Restricted BIC: 174.4247

Variance/Covariance Components Estimate(s):
  Structure: unstructured
  Parametrization: matrixlog
  Standard Deviation(s) of Random Effect(s)
 (Intercept)   Brand    Duty Brand:Duty
     48.6591 48.6591 48.6591    48.6591
 Correlation of Random Effects
          (Intercept) Brand Duty
     Brand 0
      Duty 0           0
Brand:Duty 0           0     0
```

```
 Cluster Residual Variance: 2367.708

Fixed Effects Estimate(s):
               Value Approx. Std.Error z ratio(C)
(Intercept)  570.75          54.40253  10.491240
      Brand  289.75          91.03285   3.182917
       Duty -137.75          91.03285  -1.513190
 Brand:Duty -226.50         153.87360  -1.471987

 Conditional Correlation(s) of Fixed Effects Estimates
           (Intercept)      Brand       Duty
     Brand -0.5976143
      Duty -0.5976143   0.3571429
Brand:Duty  0.3535534  -0.5916080 -0.5916080

Random Effects (Conditional Modes):
    (Intercept) Brand Duty Brand:Duty
1 -9.094947e-14     0    0          0
2  0.000000e+00     0    0          0
3  0.000000e+00     0    0          0
4  0.000000e+00     0    0          0


Standardized Population-Average Residuals:
       Min         Q1        Med        Q3      Max
 -1.366651 -0.6897476 -0.3724894 0.7847966 1.495095

Number of Observations: 16
Number of Clusters: 4

>  Fit2 <- lme(fixed= resp ~ Brand + Duty, random = ~Brand+Duty,
              cluster = ~repl, data=battery)
> anova(Fit1,Fit2)
Response: resp
Fit1
 fixed: (Intercept), Brand, Duty, Brand:Duty
 random: (Intercept), Brand, Duty, Brand:Duty
 block: list(1:4)
 covariance structure: unstructured
 serial correlation structure: identity
 variance function: identity
Fit2
 fixed: (Intercept), Brand, Duty
 random: (Intercept), Brand, Duty
 block: list(1:3)
 covariance structure: unstructured
 serial correlation structure: identity
 variance function: identity
     Model Df    AIC    BIC  Loglik    Test Lik.Ratio  P value
Fit1     1 15 162.84 174.42 -66.418
Fit2     2 10 166.52 174.25 -73.260 1 vs. 2    13.683 0.017751
########## the reduced model fits reasonably
> summary(Fit2)
Call:
```

```
  Fixed: resp ~ Brand + Duty
 Random:  ~ Brand + Duty
Cluster:  ~ repl
   Data: battery

Estimation Method: RML
Convergence at iteration: 4
Restricted Loglikelihood: -73.2596
Restricted AIC: 166.5192
Restricted BIC: 174.2451

Variance/Covariance Components Estimate(s):
  Structure: unstructured
  Parametrization: matrixlog
  Standard Deviation(s) of Random Effect(s)
 (Intercept)    Brand     Duty
    67.09202 58.69031 58.69031
 Correlation of Random Effects
      (Intercept)     Brand
Brand 0.4713093
 Duty 0.4713093   0.3343843
 Cluster Residual Variance: 2367.71

Fixed Effects Estimate(s):
                 Value Approx. Std.Error z ratio(C)
(Intercept)  593.2371          67.73186   8.758612
      Brand  213.1806         107.14465   1.989652
       Duty -214.3194         107.14465  -2.000281

 Conditional Correlation(s) of Fixed Effects Estimates
      (Intercept)       Brand
Brand -0.46457409
 Duty -0.46457409 -0.06703392

Random Effects (Conditional Modes):
  (Intercept)      Brand       Duty
1   -19.87368  -8.193694  -8.193694
2    28.06737  13.278977  23.401594
3    28.06737  23.401594  13.278977
4   -36.26106 -28.486877 -28.486877


Standardized Population-Average Residuals:
       Min         Q1        Med     Q3      Max
 -1.312942 -0.6702421 -0.3724892 0.7862 1.441386

Number of Observations: 16
Number of Clusters: 4




################### Now analyzing earning data using the fixed effect model
```

```
#############

> subj <- 1:607                   #index of subjects
> labor.df <- cbind(subj, labor.df)
#create the data structure.  Now, fitting the mixed effect model.

> options(contrasts=c("contr.treatment"))

> fit1 <- lme(fixed = earning ~ job.pres + eduf, random = ~job.pres,
         cluster = ~subj, data = labor.df)

> fit1
Call:
  Fixed: earning ~ job.pres + eduf
 Random:  ~ job.pres
Cluster:  ~ subj
   Data: labor.df

Variance/Covariance Components Estimate(s):

  Structure: unstructured
  Parametrization: matrixlog
  Standard Deviation(s) of Random Effect(s)
 (Intercept)  job.pres
    3.954585 0.1562136
 Correlation of Random Effects
         (Intercept)
job.pres -0.9995454

 Cluster Residual Variance: 4.688236
Fixed Effects Estimate(s):
  (Intercept)  job.pres     edufB     edufC     edufD
    6.981957 0.1196808 -1.923901 -2.420932 -2.891313

Number of Observations: 607
Number of Clusters: 607

> summary(fit1)
Call:
  Fixed: earning ~ job.pres + eduf
 Random:  ~ job.pres
Cluster:  ~ subj
   Data: labor.df

Estimation Method: RML
Convergence at iteration: 21
Restricted Loglikelihood: -1614.309
Restricted AIC: 3246.619
Restricted BIC: 3286.295

Variance/Covariance Components Estimate(s):
  Structure: unstructured
  Parametrization: matrixlog
  Standard Deviation(s) of Random Effect(s)
```

```
 (Intercept)  job.pres
    3.954585 0.1562136
 Correlation of Random Effects
         (Intercept)
job.pres -0.9995454

 Cluster Residual Variance: 4.688236

Fixed Effects Estimate(s):
                  Value Approx. Std.Error z ratio(C)
(Intercept)  6.9819575        0.81369392   8.580570
   job.pres  0.1196808        0.01404981   8.518320
      edufB -1.9239006        0.56941088  -3.378756
      edufC -2.4209323        0.56969742  -4.249506
      edufD -2.8913125        0.59338188  -4.872600

 Conditional Correlation(s) of Fixed Effects Estimates
         (Intercept)   job.pres      edufB      edufC
job.pres -0.7808967
   edufB -0.6517678   0.1205890
   edufC -0.7730549   0.2762658  0.8297304
   edufD -0.7988673   0.3378071  0.8053631  0.8575673

Random Effects (Conditional Modes):
numeric matrix: 607 rows, 2 columns.
   (Intercept)      job.pres
 1  2.00850276 -0.0794373091
 2  0.67667535 -0.0269097177
 3 -2.34723761  0.0930087067
............................

Standardized Population-Average Residuals:
       Min         Q1         Med        Q3      Max
 -2.862184 -0.3486928 -0.01130397 0.2635739 6.325188

Number of Observations: 607
Number of Clusters: 607

#  Now I am fitting the model with only random intercepts and
#  see if the model can be reduced to this simplified model.

> fit2 <- lme(fixed = earning ~ job.pres + eduf, random = ~1,
                 cluster = ~subj, data = labor.df)

> fit2
Call:
  Fixed: earning ~ job.pres + eduf
 Random:  ~ 1
Cluster:  ~ subj
   Data: labor.df

Variance/Covariance Components Estimate(s):

  Structure: unstructured
```

```
  Parametrization: matrixlog
  Standard Deviation(s) of Random Effect(s)
 (Intercept)
    3.651806

 Cluster Residual Variance: 1.006645
Fixed Effects Estimate(s):
  (Intercept)  job.pres     edufB    edufC     edufD
    7.530575 0.1194338 -2.337265 -2.95995 -3.478709

Number of Observations: 607
Number of Clusters: 607

> anova(fit1,fit2)
Response: earning
fit1
 fixed: (Intercept), job.pres, edufB, edufC, edufD
 random: (Intercept), job.pres
 block: list(1:2)
 covariance structure: unstructured
 serial correlation structure: identity
 variance function: identity
fit2
 fixed: (Intercept), job.pres, edufB, edufC, edufD
 random: (Intercept)
 block: list(1:1)
 covariance structure: unstructured
 serial correlation structure: identity
 variance function: identity
     Model Df    AIC    BIC  Loglik    Test Lik.Ratio P value
fit1     1  9 3246.6 3286.3 -1614.3
fit2     2  7 3356.5 3387.4 -1671.3 1 vs. 2    113.91       0

####### So the model can not be simplified further  #######
```