

# Statistical Analysis of Designs with Repeated Measures by Linear Mixed Models

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## 1 Motivation

### 1.1 Import

```
load("./dataset/datiEEG_LMM_2x2.Rdata")
summary(dati)
```

```
##      Subj      Chan      Condition      Y
## s01      : 16    01:160    f:160    Min.    :-9.9964
## s02      : 16    02:160    n:160    1st Qu.:-2.5505
## s03      : 16                                Median :-0.8299
## s04      : 16                                Mean   :-0.6867
## s05      : 16                                3rd Qu.: 1.3913
## s06      : 16                                Max.    : 5.5468
## (Other):224
```

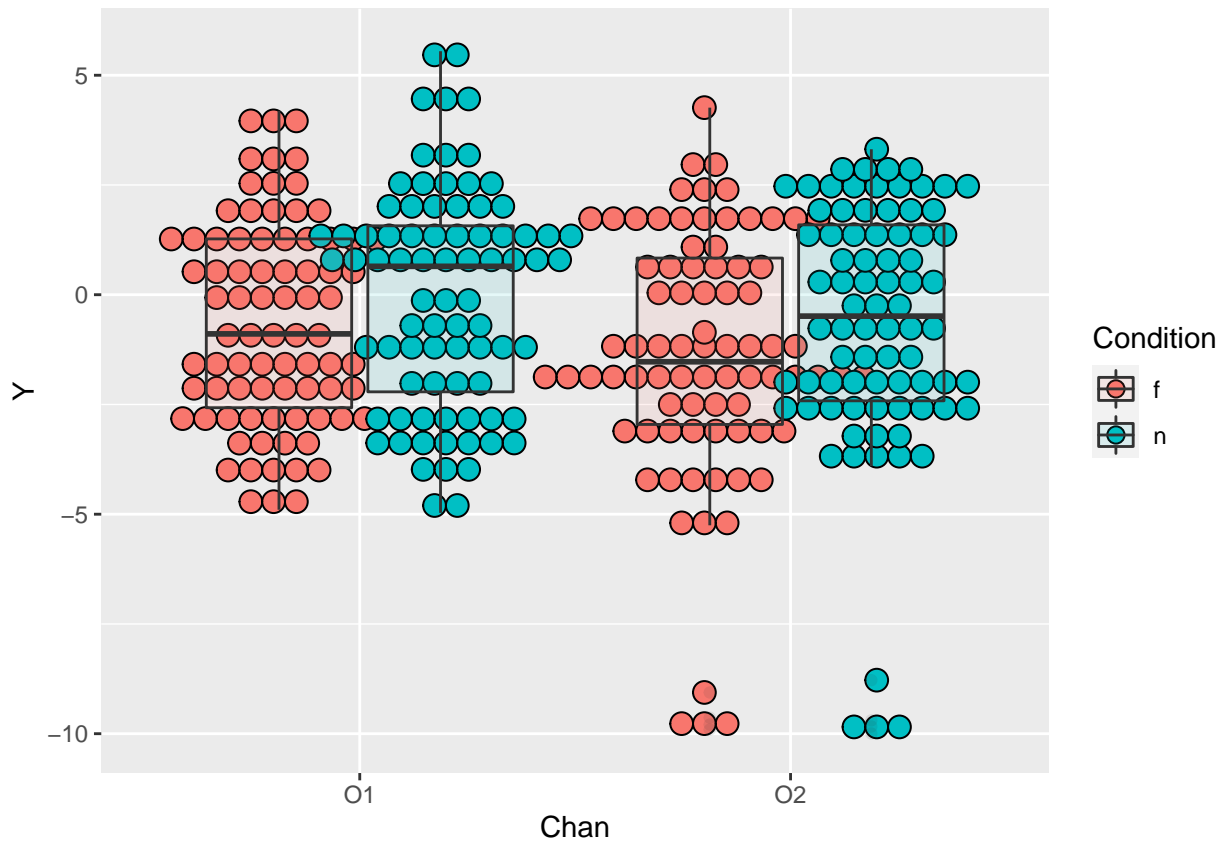
- 10 Subjects,
- 2-levels factor `Chan`
- 2-levels factor `Condition`

## 1.2 EDA

For Y: P300 Average Amplitude

```
library(ggplot2)
p <- ggplot(dati, aes(x=Chan, y=Y, fill=Condition))
p = p + geom_dotplot(binaxis = "y", position=position_dodge(0.8), stackdir = "center") + geom_boxplot(alpha=.1)
p
```

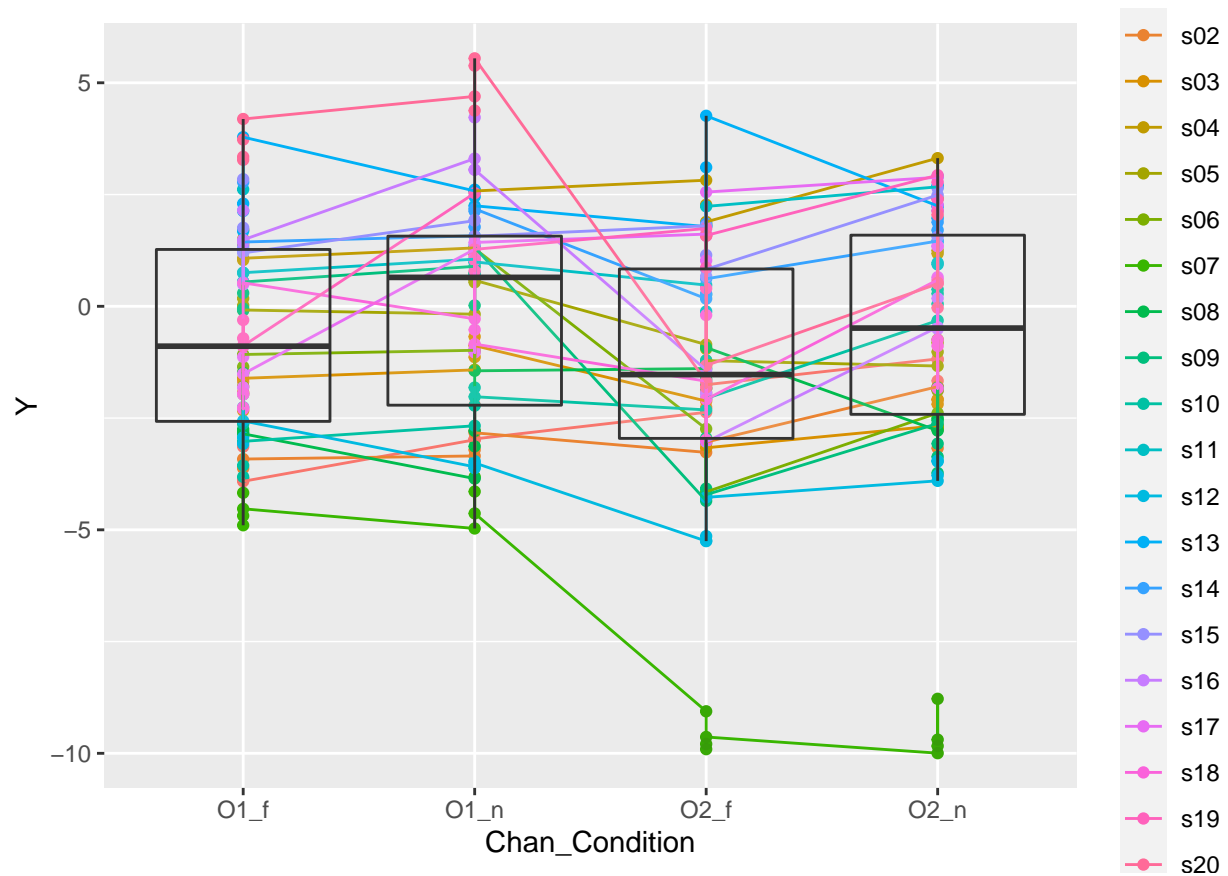
## Bin width defaults to 1/30 of the range of the data. Pick better value with 'binwidth'.



Is there a specificity of the Subject?

```
dati$Chan_Condition=paste(sep = "_",dati$Chan,dati$Condition)

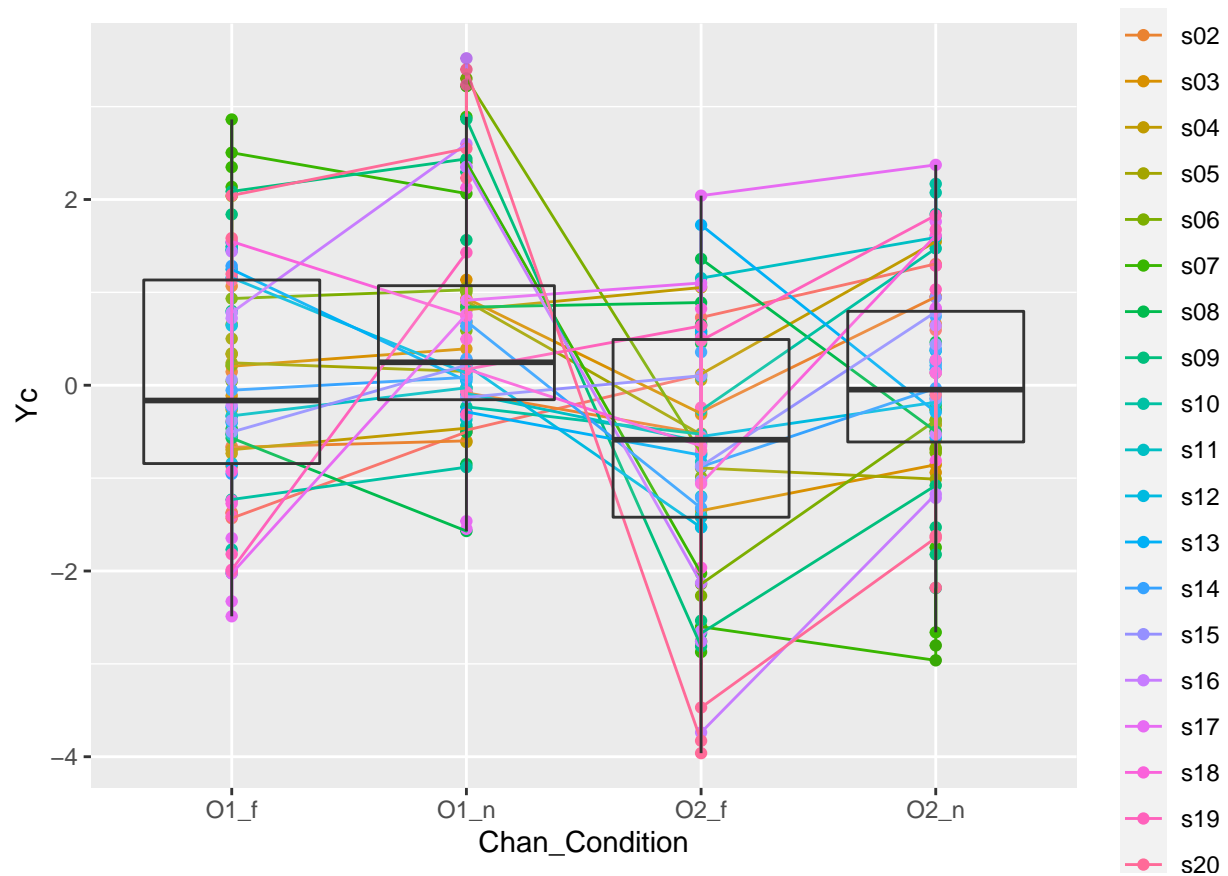
p <- ggplot(dati, aes(x=Chan_Condition, y=Y))
p+geom_point(aes(group = Subj, colour = Subj))+
  geom_line(aes(group = Subj, colour = Subj))+
  geom_boxplot(alpha=.1)
```



We subtract the Subject-specific effect (i.e. Subject's mean) to each observation.

```
mod=lm(Y~Subj,data=dati)
# summary(mod)
Y=residuals(mod)
dati$Yc=as.vector(Y)

library(ggplot2)
p <- ggplot(dati,aes(Chan_Condition,Yc))
p+geom_point(aes(group = Subj, colour = Subj))+
  geom_line(aes(group = Subj, colour = Subj))+
  geom_boxplot(alpha=.1)
```



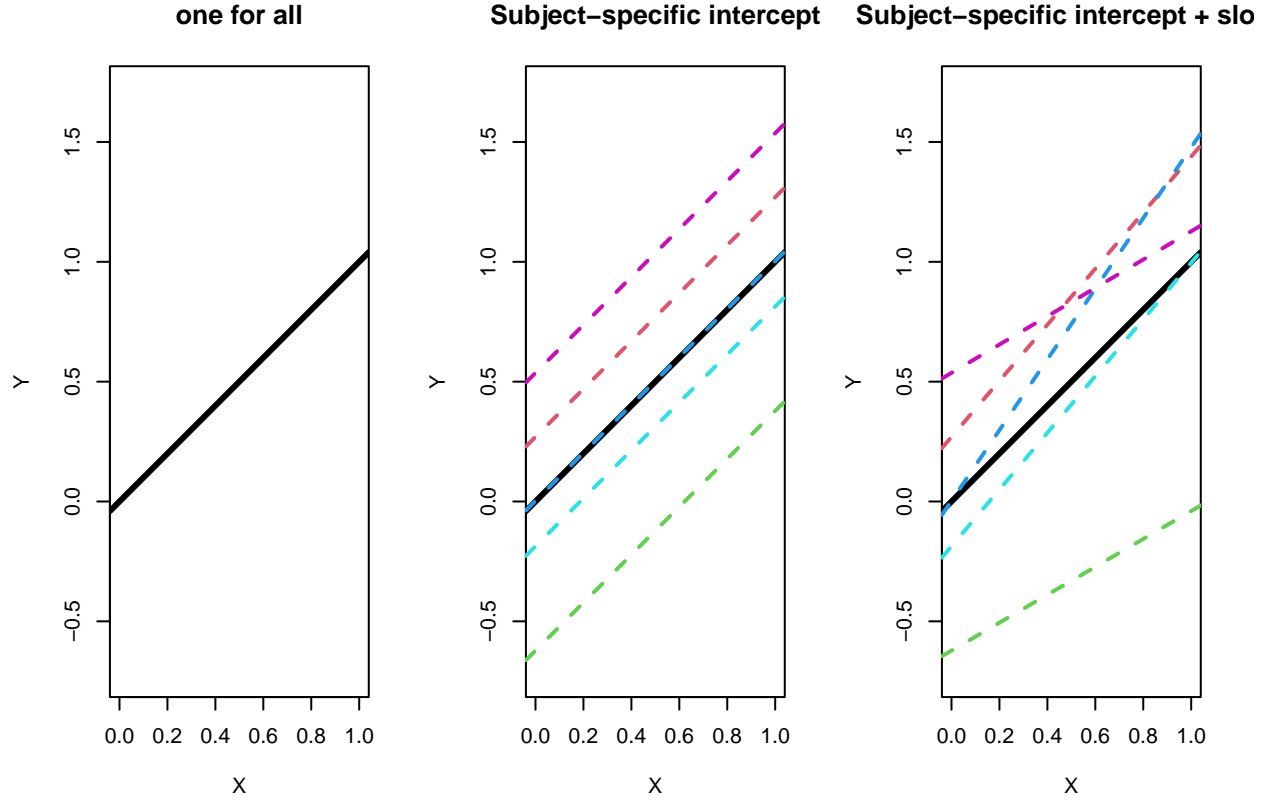
The dispersion of the data has been largely reduced. This effect is the one taken in account by the models for repeated measures.

## 2 Mixed models

### 2.1 IMPORTANT REMARK about contrasts in (mixed) linear models

```
# VERY IMPORTANT:
contrasts(dati$Condition) <- contr.sum(2) #2 is the number of levels
contrasts(dati$Chan) <- contr.sum(2) #2 is the number of levels
```

## 2.2 Intuition



Mixed models allow to model Subject-specific (average) effect by assuming that it is randomly drawn from the distribution of the population (which is normal).

I assume you are expert on mixed models, if not [https://en.wikipedia.org/wiki/Mixed\\_model](https://en.wikipedia.org/wiki/Mixed_model)  
 and much more on: [http://webcom.upmf-grenoble.fr/LIP/Perso/DMuller/M2R/R\\_et\\_Mixed/documents/Bates-book.pdf](http://webcom.upmf-grenoble.fr/LIP/Perso/DMuller/M2R/R_et_Mixed/documents/Bates-book.pdf)  
 and  
<https://cran.r-project.org/web/packages/lme4/vignettes/lmer.pdf>

Due to the small size of the dataset, in our example we only explore the scenario with random intercept and fixed slope (i.e. a simpler model, less parameters).

## 2.3 The model

Models with random effects can be defined as:

$$Y_{n \times 1} = X_{n \times p} B_{p \times 1} + Z_{n \times q} b_{q \times 1} + \varepsilon_{n \times 1}$$

where

$$\varepsilon \sim \mathcal{N}(0, \sigma^2 I_n)$$

In the models we will consider, the random effects are modeled as a multivariate normal random variable:

$$b \sim \mathcal{N}(0, \Sigma_{q \times q}),$$

In a *linear mixed model* the Conditional distribution ( $Y|\mathcal{B} = b$ ) is a *spherical* multivariate Gaussian.

In our case  $n = \#Subj \times \#Chan \times \#Condition = 10 \times 2 \times 2 = 40$ .  $X$  is the matrix of (dummified) predictors.  $Z$  can take many dimensions and values. Examples follow.

## 2.4 Different Models

### 2.4.1 ONLY Condition, restricted to Chan=O2 (i.e. 1 Factor)

```
library(lmerTest)

mod=lmer(Y~ Condition +(1+Condition|Subj),data=subset(dati,Chan=="O2"))

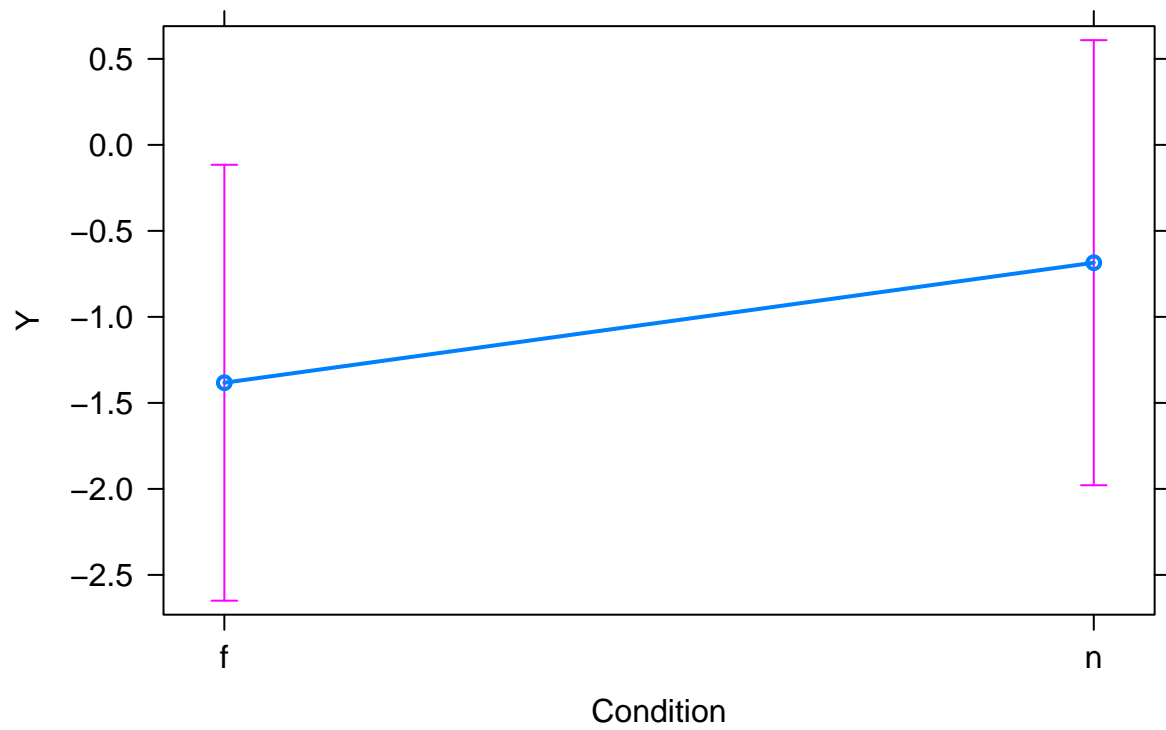
summary(mod)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: Y ~ Condition + (1 + Condition | Subj)
## Data: subset(dati, Chan == "O2")
##
## REML criterion at convergence: 456.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.8843 -0.6100 -0.0839  0.5110  3.2277
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## Subj (Intercept) 8.1738 2.8590
## Condition1 0.1115 0.3339 -0.09
## Residual 0.4838 0.6955
## Number of obs: 160, groups: Subj, 20
##
## Fixed effects:
## Estimate Std. Error df t value Pr(>|t|)
## (Intercept) -1.03388 0.64165 19.00049 -1.611 0.12361
## Condition1 -0.34883 0.09273 18.99999 -3.762 0.00132 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr)
## Condition1 -0.073
```

Plotting tools:

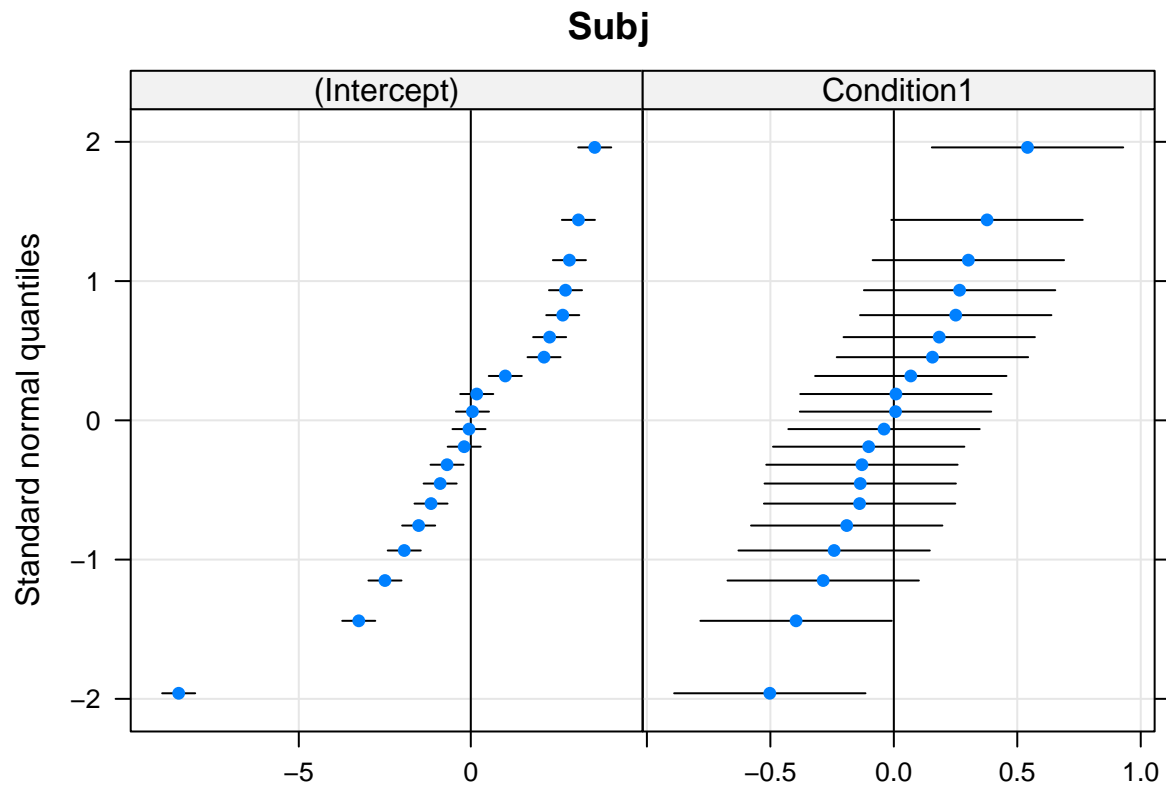
```
library(effects)
plot(allEffects(mod))
```

## Condition effect plot



```
#plot random effects:  
require(lattice)  
qqmath(ranef(mod, condVar=TRUE))
```

```
## $Subj
```



#### 2.4.2 Condition and Chan (i.e. 2 Factors)

##### Random effect for Subject (Random Intercept)

$Z$  is the matrix of dummy variables of the column `dati$Subj`.

```
library(lmerTest)

mod2=lmer(Y~ Condition*Chan +(1|Subj),data=dati)

summary(mod2)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: Y ~ Condition * Chan + (1 | Subj)
## Data: dati
##
## REML criterion at convergence: 1165
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.45740 -0.57314 -0.04347  0.69734  2.21259
##
## Random effects:
## Groups   Name                Variance Std.Dev.
```



```
## Subj      (Intercept) 5.647    2.376
## Residual          1.709    1.307
## Number of obs: 320, groups:  Subj, 20
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)   -0.68675    0.53639  19.00000  -1.280    0.216
## Condition1    -0.32723    0.07309 297.00000  -4.477 1.08e-05 ***
## Chan1         0.34713    0.07309 297.00000   4.749 3.18e-06 ***
## Condition1:Chan1  0.02160    0.07309 297.00000   0.295    0.768
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) Cndtn1 Chan1
## Condition1  0.000
## Chan1       0.000  0.000
## Cndtn1:Chn1 0.000  0.000  0.000
```

```
car::Anova(mod2,type=3,test="F")
```

```
## Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
##
## Response: Y
##              F Df Df.res   Pr(>F)
## (Intercept)   1.6392  1    19   0.2158
## Condition     20.0447  1   297 1.08e-05 ***
## Chan          22.5567  1   297 3.18e-06 ***
## Condition:Chan  0.0873  1   297   0.7678
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Random effect for Subject: Random Intercept + radom factors

```
library(lmerTest)
```

*# A trick to make the model fit working. But take care of the (slight) different interpretation: coeffi*

```
contrasts(dati$Condition)=contrasts(dati$Condition)/sqrt(nrow(dati))
contrasts(dati$Chan)=contrasts(dati$Chan)/sqrt(nrow(dati))
```

```
mod3=lmer(Y~ Condition*Chan +(1+Condition+Chan|Subj),data=dati)
```

*# It could also work with +(1+Condition+Chan|Subj)  
# but we simplify here the problem.*

```
summary(mod3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: Y ~ Condition * Chan + (1 + Condition + Chan | Subj)
## Data: dati
```

```
##
## REML criterion at convergence: 857.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.1500 -0.6171 -0.1416  0.4583  3.2781
##
## Random effects:
##   Groups   Name                Variance Std.Dev. Corr
##   Subj      (Intercept)         5.7243  2.3926
##           Condition1          29.7257  5.4521  -0.30
##           Chan1              354.3697 18.8247  -0.27 -0.11
##   Residual                0.4808  0.6934
## Number of obs: 320, groups:  Subj, 20
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)    -0.6867     0.5364   18.9992  -1.280 0.215849
## Condition1     -5.8536     1.4025   18.9995  -4.174 0.000515 ***
## Chan1           6.2096     4.2661   19.0013    1.456 0.161832
## Condition1:Chan1 6.9110    12.4038 259.0001    0.557 0.577893
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) Cndtn1 Chan1
## Condition1   -0.258
## Chan1        -0.262 -0.091
## Cndtn1:Chn1   0.000  0.000  0.000

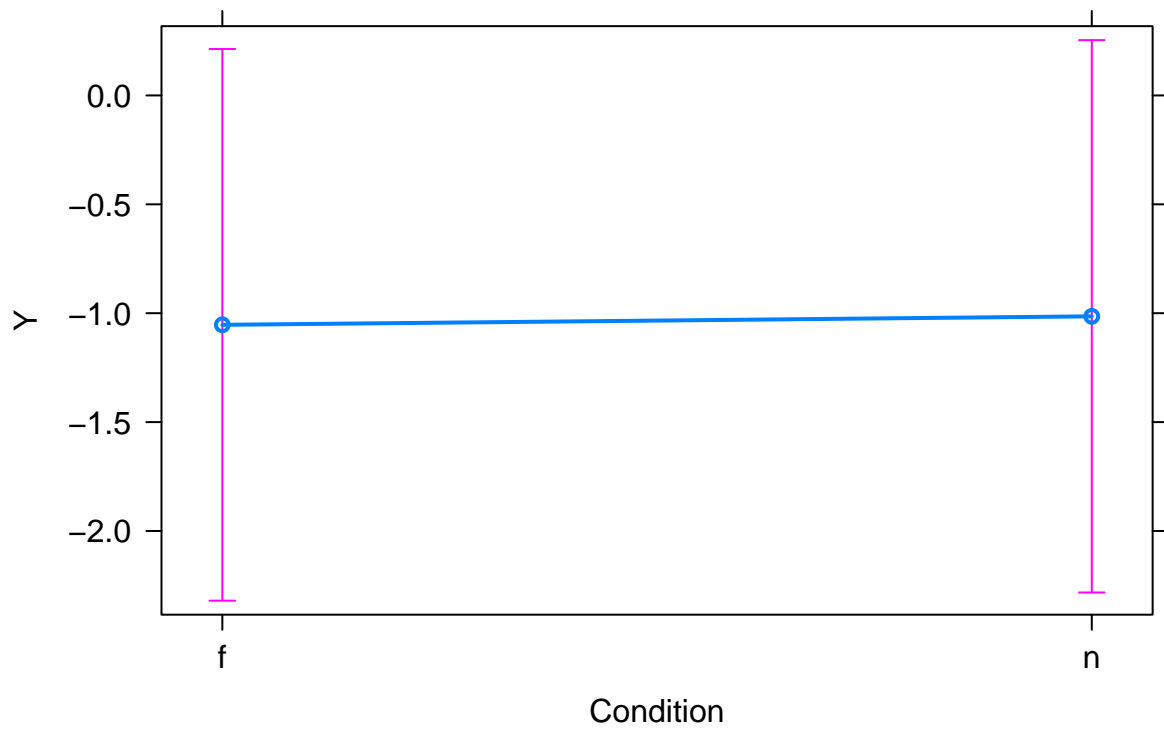
car::Anova(mod3,type=3,test="F")

## Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
##
## Response: Y
##              F Df Df.res    Pr(>F)
## (Intercept)   1.6392  1     19 0.2158482
## Condition    17.4193  1     19 0.0005154 ***
## Chan         2.1187  1     19 0.1618332
## Condition:Chan 0.3104  1    259 0.5778929
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 2.5 Plotting tools

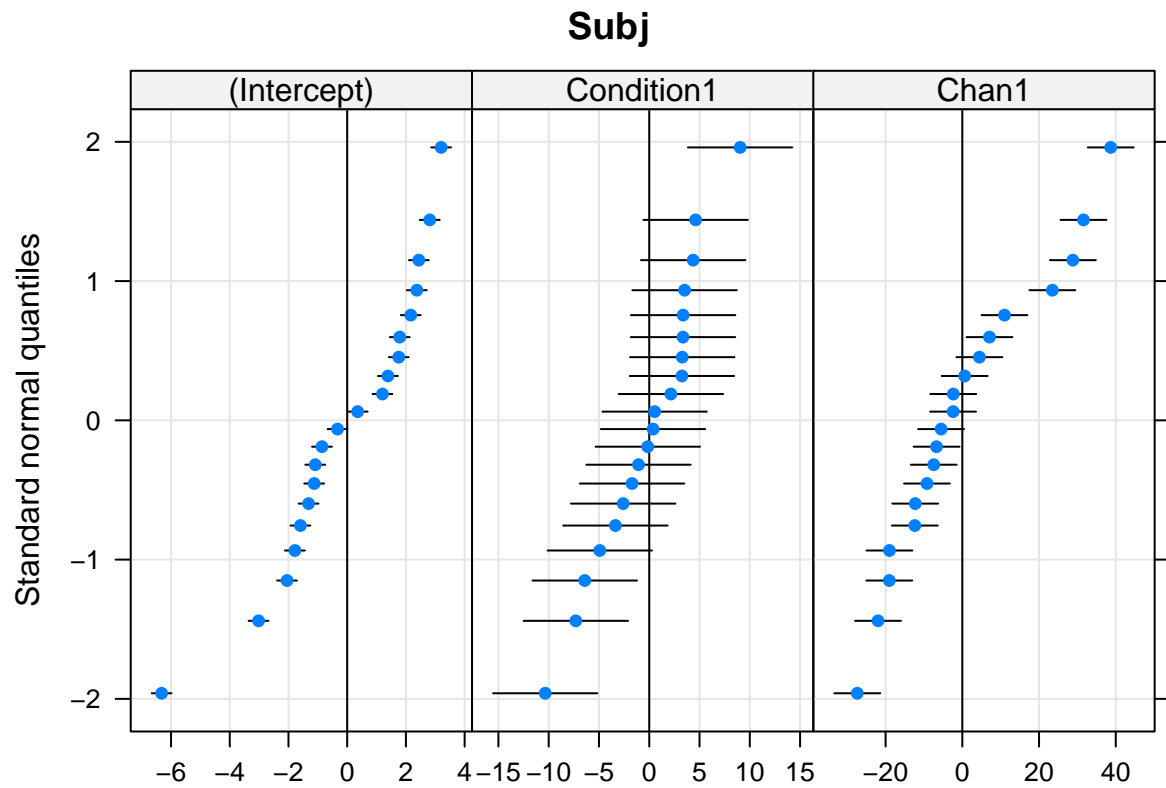
```
library(effects)
plot(allEffects(mod))
```

## Condition effect plot



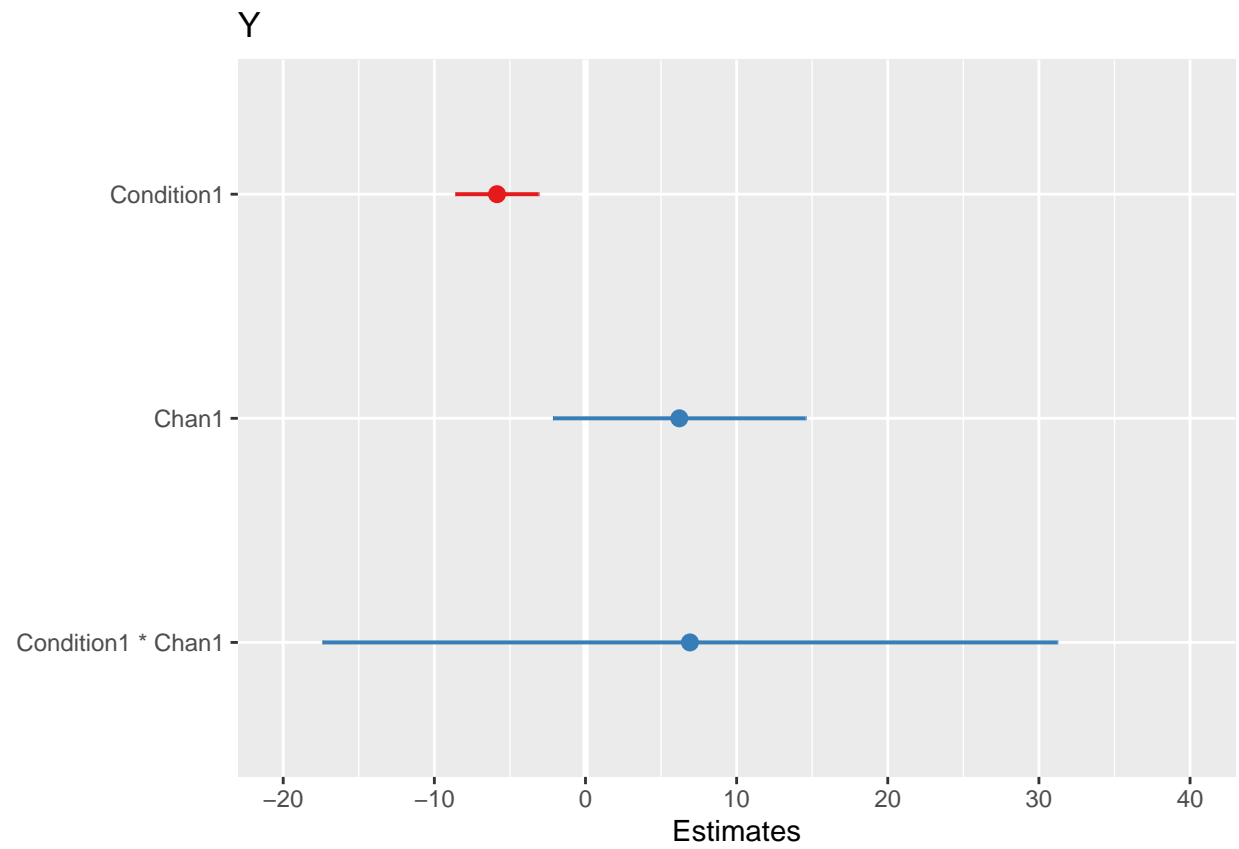
```
#plot random effects:  
require(lattice)  
qqmath(ranef(mod3, condVar=TRUE))
```

```
## $Subj
```

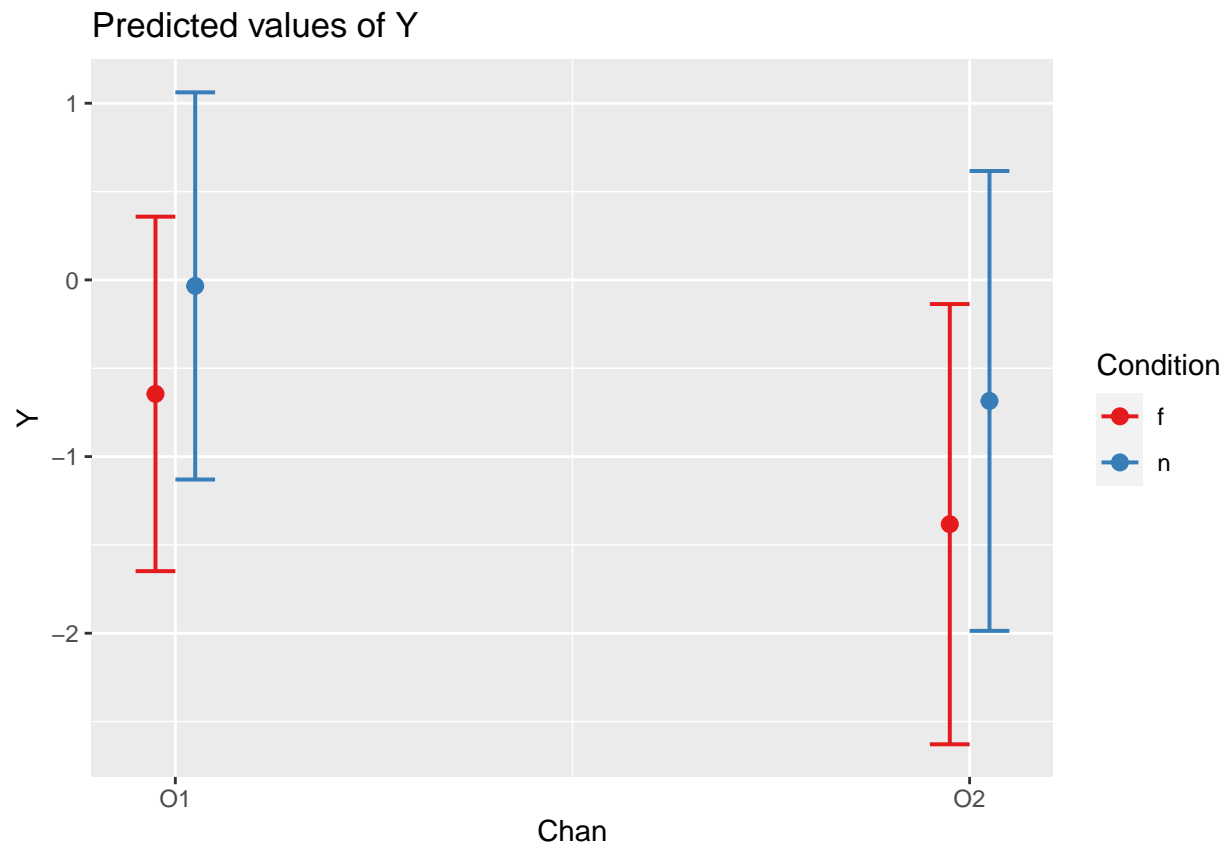


An alternative plotting tool:

```
library(sjPlot)
library(ggplot2)
plot_model(mod3, type = "est")
```

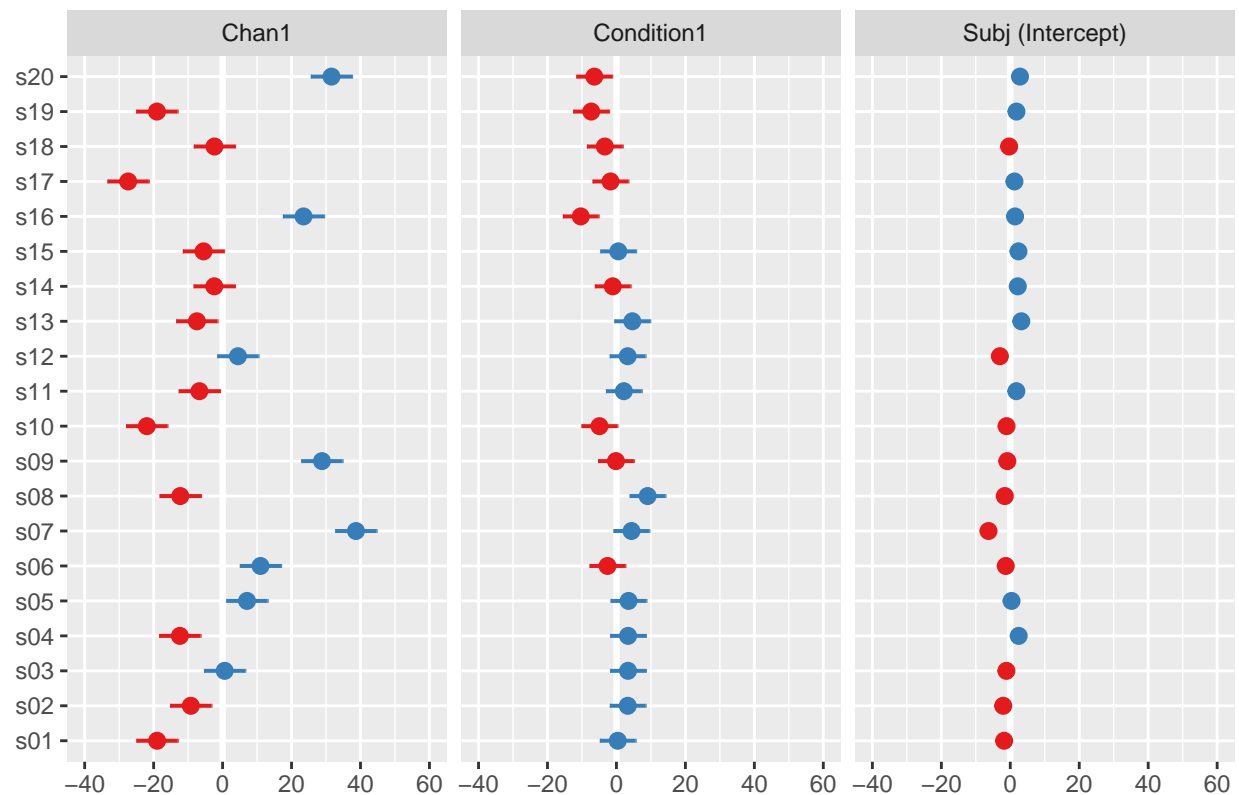


```
plot_model(mod3, type = "eff", terms = c("Chan", "Condition"))
```



```
plot_model(mod3, type = "re", terms = c("Chan", "Condition"))
```

## Random effects



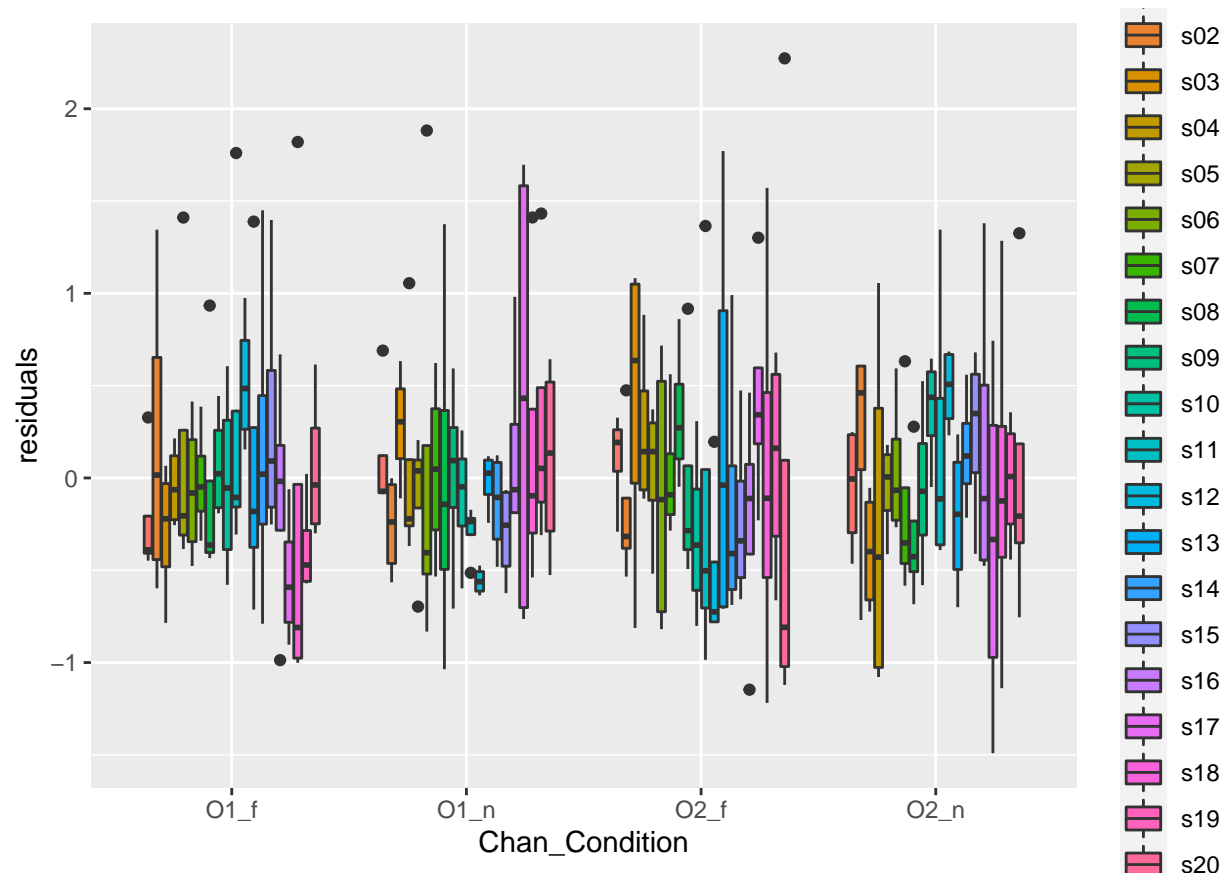
## 2.6 Validity of the assumptions

- Independence of the residuals?
- Normality of the residuals?
- Homoscedasticity of the residuals (i.e. same variance between Subject/Condition/Chan?)
- outliers?
- Leverage? (influential observations)

Please, do not test for normality, for homoscedasticity, sphericity etc.

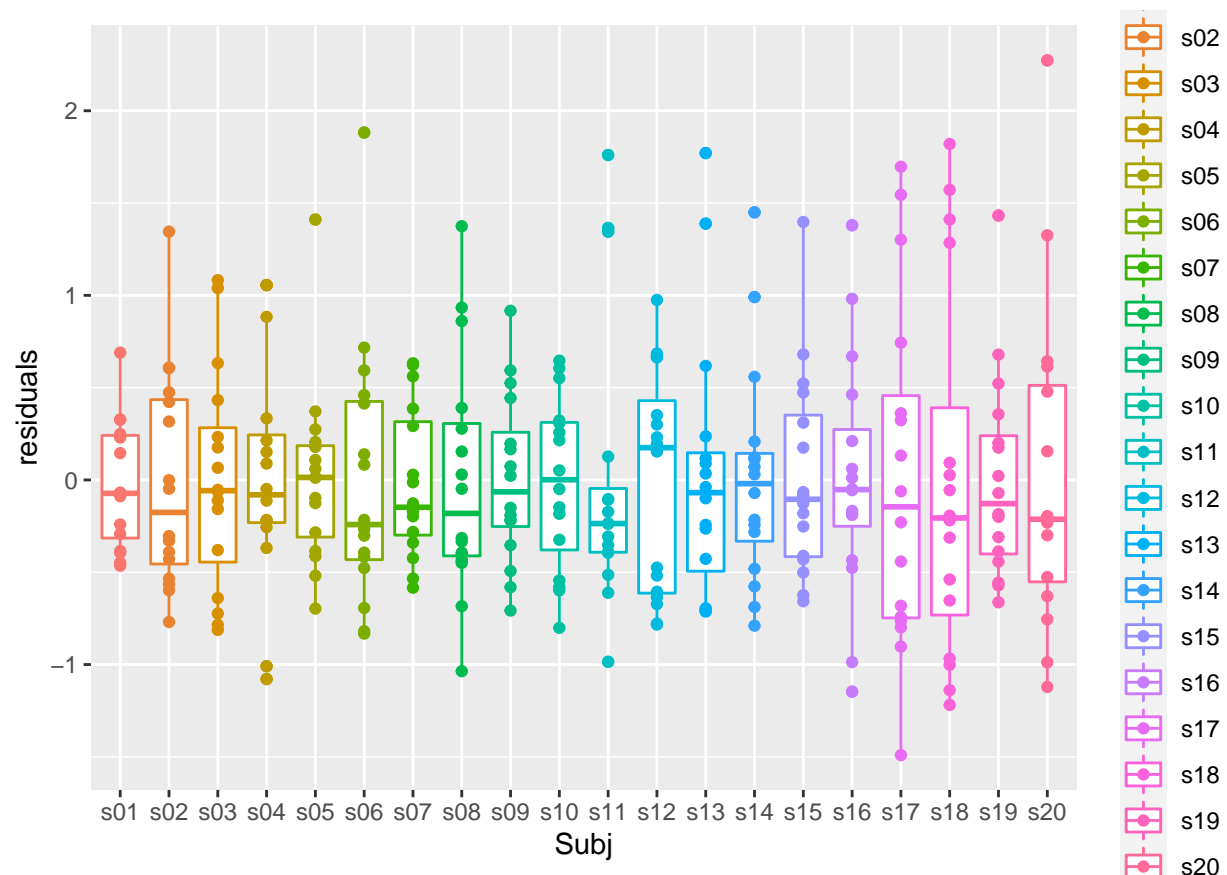
Use Exploratory data Analysis, instead!

```
dati$residuals=residuals(mod3)
p <- ggplot(dati, aes(x=Chan_Condition, y=residuals, fill=Subj)) + geom_boxplot()
p
```



```
p <- ggplot(dati, aes(x=Subj, y=residuals,col=Subj)) + geom_boxplot()+ geom_point(aes(group = interaction(Subj, Chan_Condition)))
p
```





### 3 (minimal) Bibliography

Jonathan Baron (2011) Notes on the use of R for psychology experiments and questionnaires [https://www.sas.upenn.edu/~baron/from\\_cattell/rpsych/rpsych.html](https://www.sas.upenn.edu/~baron/from_cattell/rpsych/rpsych.html)

and Course material of

ST 732, Applied Longitudinal Data Analysis, NC State University by Marie Davidian <https://www.stat.ncsu.edu/people/davidian/courses/st732/notes/chap5.pdf> from <https://www.stat.ncsu.edu/people/davidian/courses/st732/>

About Type I, II, III SS: <https://mcfromnz.wordpress.com/2011/03/02/anova-type-iiiiii-ss-explained/>

About Mixed models:

[http://webcom.upmf-grenoble.fr/LIP/Perso/DMuller/M2R/R\\_et\\_Mixed/documents/Bates-book.pdf](http://webcom.upmf-grenoble.fr/LIP/Perso/DMuller/M2R/R_et_Mixed/documents/Bates-book.pdf)

and

<https://cran.r-project.org/web/packages/lme4/vignettes/lmer.pdf>