Mixed models – Examples

The strengthTests data set

Question: Does higher training volume lead to increased strength?

Aim of the analysis: Determine the *difference* in strength gain between high and low-volume strength training.

Possible interpretations

Estimation (Cumming 2012)

- This analysis can be driven by the question and analyzed with the goal to *estimate the difference* between training conditions.
- The 95% CI interval can be used to specify the precision of our estimate.
- With our statistical model we are trying to estimate the true difference between training condition, the 95% CI can be interpreted as a interval of plausible values of the true mean difference.

Null hypothesis testing

- The question may be developed to an hypothesis and analyzed under the null hypothesis testing framework
- The null hypothesis will be that there are no differences between training conditions in strength development.
- An alternative hypothesis (should be used) defines the smallest difference of interest and determines the power of the test.
- The p-value will be used to test the hypothesis, this is a test against the null.

Other paradigms

- Bayesian/Likelihood analysis, instead of looking for a true unknown (fixed), we are interested in estimating the unknown random variable with (Bayesian) or without (Likelihood) prior knowledge. (Note to self: Check these definitions)

What to choose?

It is up to you to select the most appropriate way of analyzing your data! This may be difficult but a good starting point is to clearly define your question, look at the structure of the data (repeated or not repeated measures) and the define what model could capture your question.

A mixed model approach

Is a mixed model needed?

There are more than one observation per participant meaning the error will be correlated, a mixed model is needed. However, we could re-organize the data to compare for example change between groups instead. Then a simple t-test or ANCOVA model would suffice.

Fitting the model

```
# Load packages and data
library(tidyverse)
library(lme4)


strength <- read_csv("./data/strengthTests.csv")

# Filter the data
str <- strength %>%
  filter(exercise == "isom") %>% # Only use isometric data
  # Fixes the time point factor (order)
  # Adds a new factor with two pre-measures
  # Fix order or grouping variable
  mutate(timepoint = factor(timepoint, levels = c("pre", "session1", "post")),
         time = if_else(timepoint == "post", "post", "pre"),
         time = factor(time, levels = c("pre", "post")),
         group = factor(group, levels = c("single", "multiple")))


# A basic mixed model
m1 <- lmer(load ~ time * group + (1|subject), data = str)

# plot(m1)
# The residual plot indicates that there are no major problems with the model..
```

Appendix R-code

```
# Load packages and data
library(tidyverse)
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strength <- read_csv("./data/strengthTests.csv")

# Filter the data

str <- strength %>%
  filter(exercise == "isom") %>%
  mutate(timepoint = factor(timepoint, levels = c("pre", "session1", "post")),
```

```r
         time = if_else(timepoint == "post", "post", "pre"),
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         group = factor(group, levels = c("single", "multiple")))


# A basic mixed model
m1 <- lmer(load ~ time * group + (1|subject), data = str)

# plot(m1)
# The residual plot indicates that there are no major problems with the model..
```

The model (m1) contains information of the average load per group. These can be calculated from the regression table. This is very similar values to what can be calculated from group and time averages

```r
# Compare the fixed effects table...
summary(m1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: load ~ time * group + (1 | subject)
##    Data: str
##
## REML criterion at convergence: 982.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.78324 -0.51170 -0.06841  0.48257  2.60052
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subject  (Intercept) 3780.2   61.48
##  Residual              433.1   20.81
## Number of obs: 101, groups:  subject, 34
##
## Fixed effects:
##                       Estimate Std. Error t value
## (Intercept)            216.118     15.333  14.095
## timepost                33.353      6.182   5.396
## groupmultiple           -1.294     21.684  -0.060
## timepost:groupmultiple  17.994      8.875   2.027
##
## Correlation of Fixed Effects:
##             (Intr) timpst grpmlt
## timepost    -0.134
## groupmultpl -0.707  0.095
## tmpst:grpml  0.094 -0.697 -0.132
```

```r
# ... to averages per group and time
str %>%
  group_by(group, time) %>%
  summarise(mean = mean(load, na.rm = TRUE)) %>%
  print()
```

```
## `summarise()` regrouping output by 'group' (override with `.groups` argument)
```

```
## # A tibble: 4 x 3
## # Groups:   group [2]
##   group    time   mean
##   <fct>    <fct> <dbl>
## 1 single   pre    216.
## 2 single   post   249.
## 3 multiple pre    215.
## 4 multiple post   265.
```

Alternative approach

This data set can be reduced to remove multiple data points per participant by calculating each change score. Then we can use:

- Difference between groups in change scores in t-test
- Difference between groups in change scores using an ANCOVA with pre-values as a covariate.

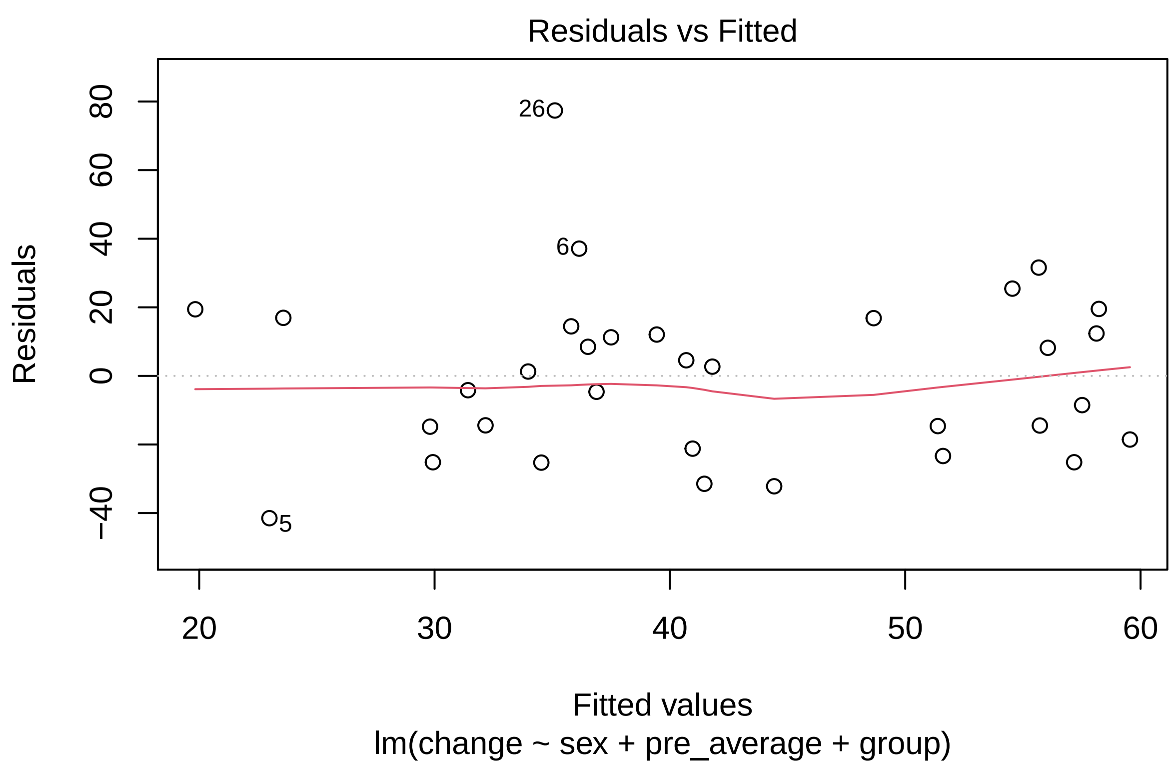
```
# Re-format the data set
str2 <- str %>%
  select(-time) %>% #removes the new time variable
  # Create a wide data set
  pivot_wider(names_from = timepoint,
              values_from = load) %>%
  rowwise() %>%
  # Rowwise calculation of means over two variables
  # to calculate the average at baseline
  mutate(pre_average = mean(c(pre, session1), na.rm = TRUE)) %>%
  ungroup() %>%
  # Calculate the change score
  mutate(change = post - pre_average) %>%
   print()
```

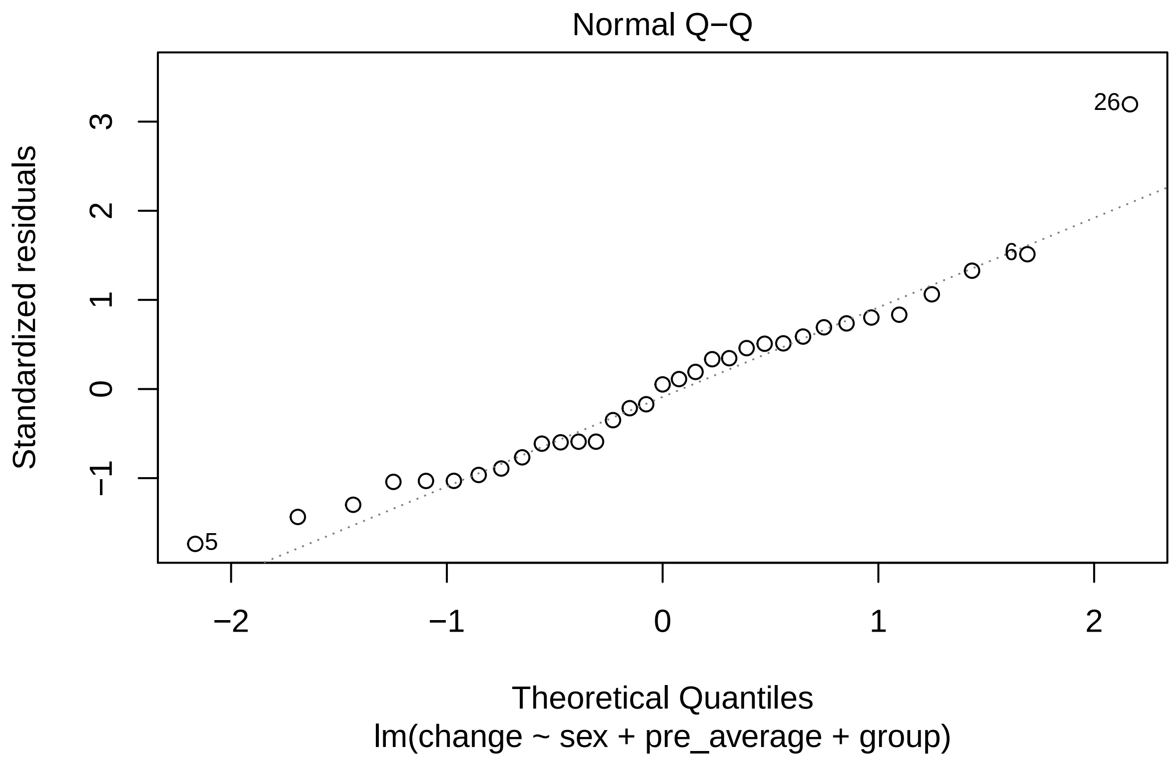
```
## # A tibble: 34 x 9
##    subject exercise sex    group      pre session1  post pre_average change
##    <chr>   <chr>    <chr>  <fct>    <dbl>    <dbl> <dbl>       <dbl>  <dbl>
##  1 FP11    isom     male   single    256.      252   281         254.   27.2
##  2 FP12    isom     female single    246.      290.  308         268.   40.5
##  3 FP13    isom     male   multiple  204       210.  294.        207.   87.2
##  4 FP14    isom     female single    197       184.  226         191.   35.2
##  5 FP15    isom     male   single    321       311   298.        316   -18.5
##  6 FP16    isom     female single    154.      195   248         175.   73.2
##  7 FP17    isom     male   multiple  314.      318   336.        316.   19.8
##  8 FP19    isom     male   single    238.      259   266         248.   17.8
##  9 FP2     isom     female multiple  138       152   216.        145    70.5
## 10 FP20    isom     female single    130.      142.  146.        136.   10
## # ... with 24 more rows
```

```
# Alternativ 1: t-test
# A t-test can be performed on the change scores
t <- t.test(change ~ group, data = str2)
t
```

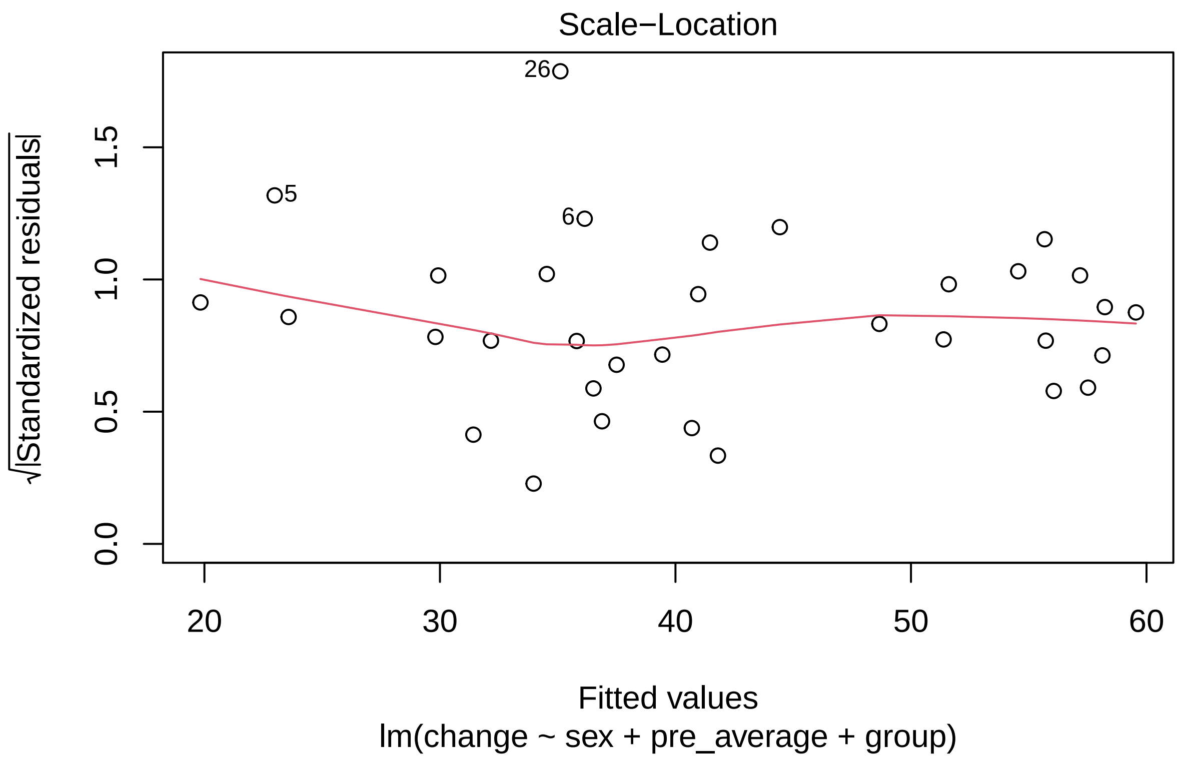
```
##
##  Welch Two Sample t-test
##
## data:  change by group
## t = -2.0271, df = 28.324, p-value = 0.05216
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -36.2557690   0.1804014
## sample estimates:
##   mean in group single mean in group multiple
##               33.35294               51.39062
```

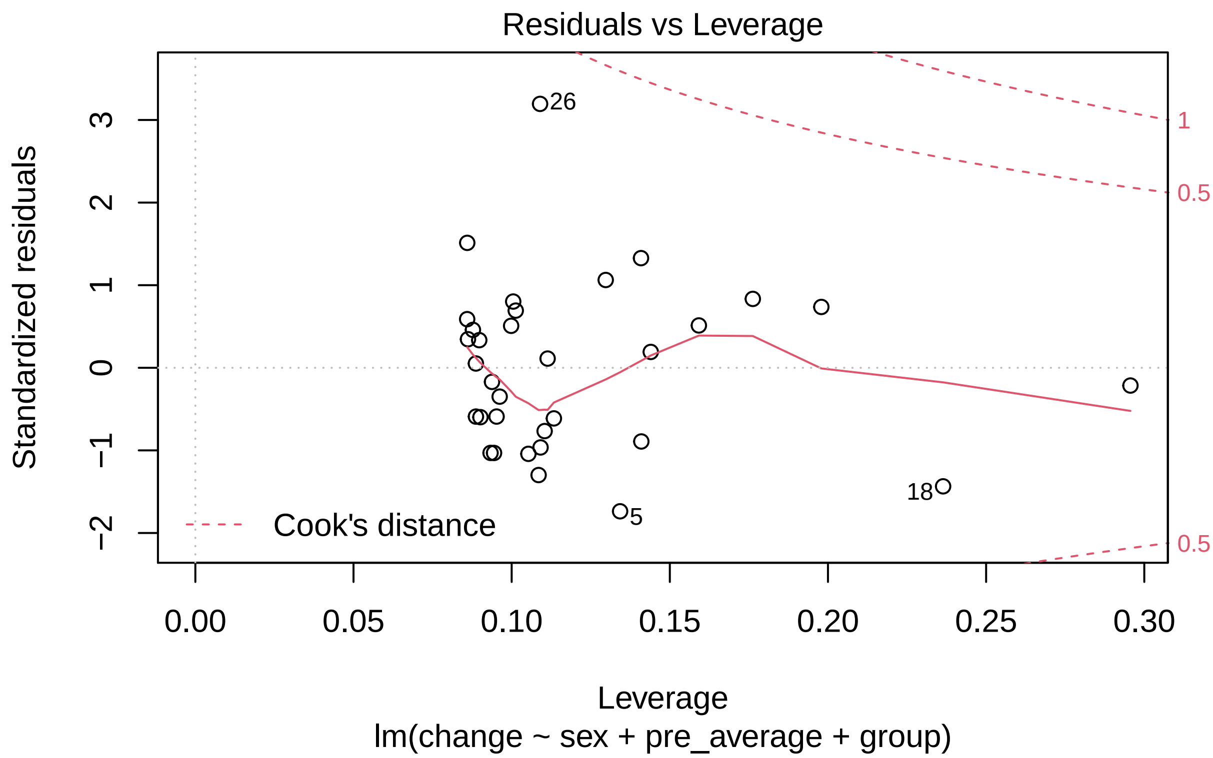
```
# ANCOVA
# the ANCOVA canm controll for the expected relationship between
# the baseline and change values... (regression to the mean)
# We might have to take care of sex diferences, adding sex to the
# model will accomplish this
m2 <- lm(change ~ sex + pre_average + group, data = str2)

# The ancova model can be checked with ordinary assumption checks
plot(m2)
```





Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(change ~ sex + pre_average + group)
26
6
5
3
2
1
0
−1
−2
−1
0
1
2


Scale−Location
√|Standardized residuals|
Fitted values
lm(change ~ sex + pre_average + group)
0.0
0.5
1.0
1.5
20
30
40
50
60
26
5
6




```r
# The results can be plotted
summary(m2)
```

```
##
## Call:
## lm(formula = change ~ sex + pre_average + group, data = str2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -41.482 -18.551   1.274  14.444  77.387
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   59.83059   18.25450   3.278  0.00272 **
## sexmale        5.98212   11.99282   0.499  0.62168
## pre_average   -0.13554    0.09428  -1.438  0.16124
## groupmultiple 17.95071    8.94336   2.007  0.05413 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 25.66 on 29 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1833, Adjusted R-squared:  0.0988
## F-statistic: 2.169 on 3 and 29 DF,  p-value: 0.1131
```

Appendix R-code

In your reports (for the mappeeksamen) you should keep the report clean from code and printouts (remove all print() from your code). Instead use `eval = FALSE, echo = TRUE` with a copy of the code in the end of the report as an appendix.

```r
# Load the data
library(tidyverse)

strength <- read_csv("./data/strengthTests.csv")

# Filter the data

strength %>%
  filter(exercise == "isom") %>%
  mutate(timepoint = factor(timepoint))
  print()
```

References

Cumming, Geoff. 2012. *Understanding the New Statistics : Effect Sizes, Confidence Intervals, and Meta-Analysis*. Book. Multivariate Applications Series. New York: Routledge.