M21 202303 n250 lme

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This R script contains the code for analysing the morph 21 erp data for the 200-300 ms time window.

1. First we load the libraries we need

```
library(readr)
library(psych)
library(dplyr)
library(tidyr)
```

Compute PCA

Following Andrews and Lo (2013) this script computes a PCA for our spelling and vocabulary measures. Because the standardised spelling and vocabulary scores were correlated, to facilitate interpretation, two orthogonal measures of individual differences were derived from a principal components analysis. Analysis based on this tutorial

```
library(readr)
library(dplyr)
library(datawizard)
sv_202303 <- read_csv("m21_spell_vocab_raw.csv")
sv_202303.na <- na.omit(sv_202303)
sv_202303.na <- mutate(sv_202303.na, z_ART = standardise(ART_correct), z_vocab = standardise(vocab_corre

cor.test(sv_202303.na$z_vocab, sv_202303.na$z_spell)
```

```
    Pearson's product-moment correlation

data:  sv_202303.na$z_vocab and sv_202303.na$z_spell
t = 1.9352, df = 61, p-value = 0.05761
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.007724833  0.460807138
sample estimates:
      cor
0.2405005
```

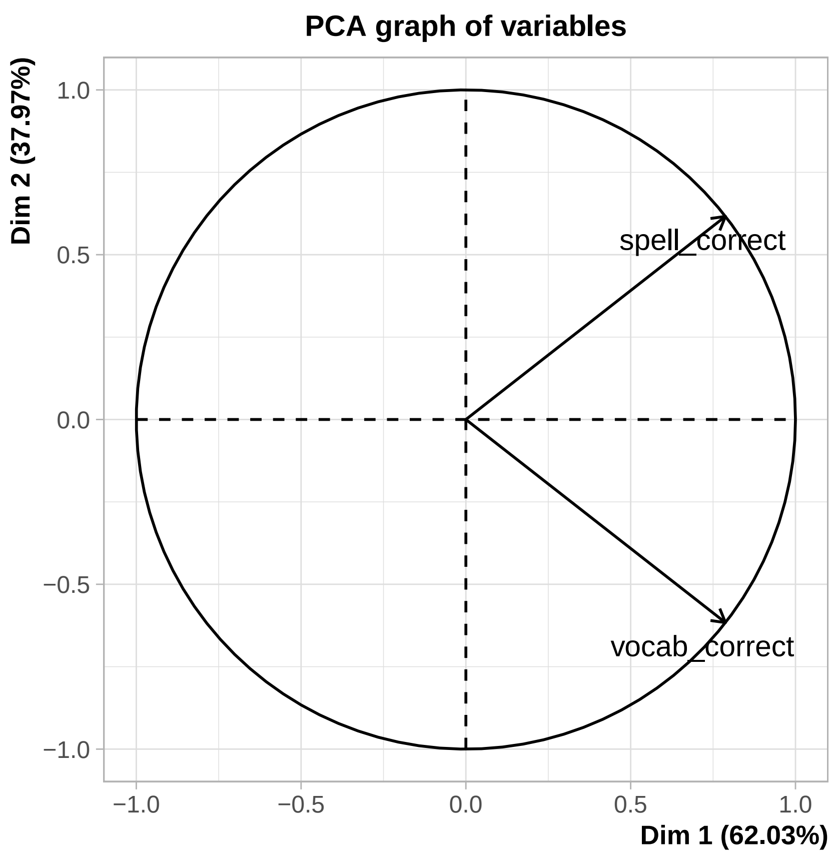
By default, the function `PCA()` in `FactoMineR`, standardizes the data automatically during the PCA; so you don't need do this transformation before the PCA.

- `X`: a data frame. Rows are individuals and columns are numeric variables
- `scale.unit`: a logical value. If TRUE, the data are scaled to unit variance before the analysis. This standardization to the same scale avoids some variables to become dominant just because of their large measurement units. It makes variable comparable.
- `ncp`: number of dimensions kept in the final results.
- `graph`: a logical value. If TRUE a graph is displayed.

The plot shows the relationships between all variables. It can be interpreted as follow:

- Positively correlated variables are grouped together.
- Negatively correlated variables are positioned on opposite sides of the plot origin (opposed quadrants).
- The distance between variables and the origin measures the quality of the variables on the factor map. Variables that are away from the origin are well represented on the factor map.

```
library(FactoMineR)
library(factoextra)

res.pca <- PCA(sv_202303.na[,3:4], scale.unit = TRUE, ncp = 2, graph = FALSE)
plot(res.pca, choix = "varcor", graph.type = c("ggplot"))
```



The eigenvalues measure the amount of variation retained by each principal component. Eigenvalues are large for the first PCs and small for the subsequent PCs. That is, the first PCs corresponds to the directions with the maximum amount of variation in the data set.

We examine the eigenvalues to determine the number of principal components to be considered

```
(eig.val <- get_eigenvalue(res.pca))
```

```
      eigenvalue variance.percent cumulative.variance.percent
Dim.1  1.2405005         62.02503                    62.02503
Dim.2  0.7594995         37.97497                   100.00000
```

The quality of representation of the variables on factor map is called cos2 (square cosine, squared coordinates). A high cos2 indicates a good representation of the variable on the principal component. In this case the variable is positioned close to the circumference of the correlation circle. A low cos2 indicates that the variable is not perfectly represented by the PCs. In this case the variable is close to the center of the circle. For a given variable, the sum of the cos2 on all the principal components is equal to one. If a variable is perfectly represented by only two principal components (Dim.1 & Dim.2), the sum of the cos2 on these two PCs is equal to one. In this case the variables will be positioned on the circle of correlations.

```
res.pca$var$cos2
```

```
                  Dim.1     Dim.2
vocab_correct 0.6202503 0.3797497
spell_correct 0.6202503 0.3797497
```

The contributions of variables in accounting for the variability in a given principal component are expressed in percentage. Variables that are correlated with PC1 (i.e., Dim.1) and PC2 (i.e., Dim.2) are the most important in explaining the variability in the data set. Variables that do not correlated with any PC or correlated with the last dimensions are variables with low contribution and might be removed to simplify the overall analysis.

```
res.pca$var$contrib
```

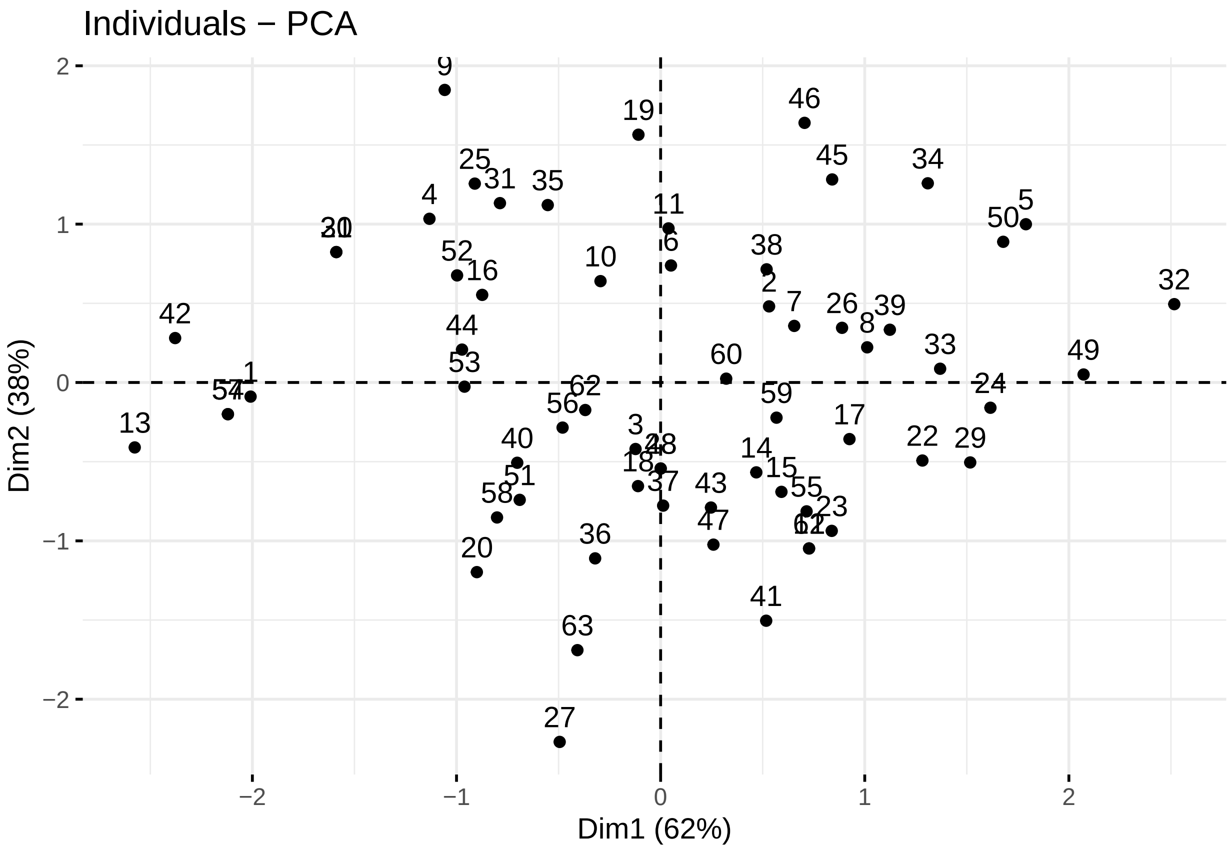
```
              Dim.1 Dim.2
vocab_correct    50    50
spell_correct    50    50
```

```
(res.desc <- dimdesc(res.pca, axes = c(1,2), proba = 0.05))
```

```
$Dim.1

Link between the variable and the continuous variables (R-square)
=================================================================================
              correlation      p.value
vocab_correct   0.7875597 1.913196e-14
spell_correct   0.7875597 1.913196e-14

$Dim.2

Link between the variable and the continuous variables (R-square)
=================================================================================
              correlation      p.value
spell_correct   0.6162384 7.592937e-08
vocab_correct  -0.6162384 7.592937e-08
```

The fviz_pca_ind() is used to produce the graph of individuals.

```
fviz_pca_ind(res.pca)
```




```
sv_202303.na<-bind_cols(sv_202303.na,res.pca$ind$coord)
```

We load the N250 erp data file and the word and non-word base frequency data

```
n250 <- read_csv("S101-177_n250.csv")
```

Then we join the demographic and erp data files. We will use the `inner_join` rather than the `full_join` function in order to eliminate rows with missing data.

```
n250 <- inner_join(sv_202303.na,n250, by = "SubjID")  #join subject PCA data
```

Divide participants based on median split of Dim2. Higher values on this factor indicate that spelling scores were relatively higher than vocabulary,

```
n250.median <- median(n250$Dim.2)
n250 <- n250 |>
    mutate(lang_type = case_when(
      Dim.2 < n250.median ~ "Semantic",
      Dim.2 > n250.median ~ "Orthographic"
    ))
```

5. Let's save a `.csv` file with the data from the combined dataset

```
write_csv(n250, "202303_sv_n250_rmna.csv")
```

6. For each dataset, we will create a subset with only the electrode sites we will be analysing—F3, Fz, F4, C3, Cz, C4, P3, Pz, P4

```
sites = c(3,2, 25, 7, 20, 21, 12, 11, 16)
n250_9 <- dplyr::filter(n250, chindex %in% sites)
```

7. We then create separate columns, one for each independent variable (anteriority, laterality, morphological family size). To do this we have to use the`mutate` function from the dplyr package along with the `case_when` function. The `case_when` function is a sequence of two-sided formulas. The left hand side determines which values match this case. The right hand side provides the replacement value.

```
n250_9 <- dplyr::mutate(n250_9,
                        anteriority = case_when(grepl("F", chlabel) ~ "Frontal",
                                                grepl("C", chlabel) ~ "Central",
                                                grepl("P", chlabel) ~ "Parietal"))

n250_9 <- dplyr::mutate(n250_9,
                        laterality = case_when(grepl("3", chlabel) ~ "Left",
                                               grepl("z", chlabel) ~ "Midline",
                                               grepl("Z", chlabel) ~ "Midline",
                                               grepl("4", chlabel) ~ "Right"))



n250_9 <- dplyr::mutate(n250_9,
                        fam_size = case_when(grepl("small", binlabel) ~ "Small",
                                             grepl("large", binlabel) ~ "Large"))
```

8. We then create a smaller dataset with only the columns we need

```
n250_9b <- dplyr::select(n250_9,
                             SubjID,
                             lang_type,
                             anteriority,
                             laterality,
                             fam_size,
                             value,
                             chlabel,
                             binlabel)
```

9. We then divide dataset into 3 separate ones—for "words", "simple nonwords" and "complex nonwords"

```
n250_words <- dplyr::filter(n250_9b, grepl("Critical_word",binlabel))
n250_nwsmpl <- dplyr::filter(n250_9b, grepl("simple",binlabel))
n250_nwcplx <- dplyr::filter(n250_9b, grepl("complex",binlabel))
```

#Plot Means

Get condition means

```r
#Define standard error of the mean function

sem <- function(x) sd(x)/sqrt(length(x))

(cw.cond.means <- n250_words |>
   group_by(fam_size, lang_type) |>
   summarise(mean = mean(value),
             se = sem(value),
             num_stim = n()))
```

```
# A tibble: 4 x 5
# Groups:   fam_size [2]
  fam_size lang_type      mean    se num_stim
  <chr>    <chr>         <dbl> <dbl>    <int>
1 Large    Orthographic  0.208 0.224      252
2 Large    Semantic     -0.666 0.167      252
3 Small    Orthographic  0.509 0.216      252
4 Small    Semantic     -0.504 0.201      252
```

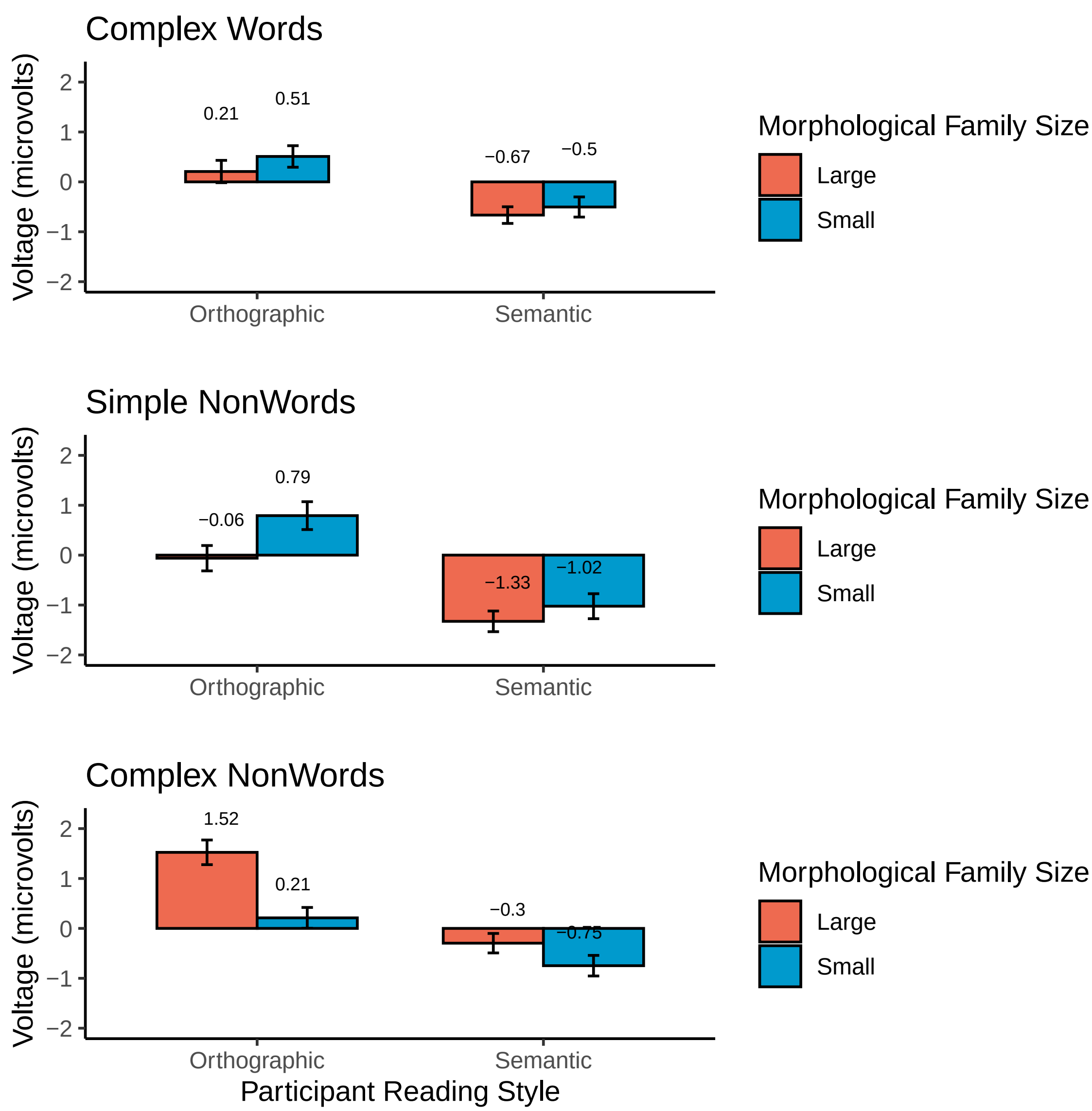
```r
(nw_smp.cond.means <- n250_nwsmpl |>
    group_by(fam_size, lang_type) |>
    summarise(mean = mean(value),
              se = sem(value),
              num_stim = n()))
```

```
# A tibble: 4 x 5
# Groups:   fam_size [2]
  fam_size lang_type       mean    se num_stim
  <chr>    <chr>          <dbl> <dbl>    <int>
1 Large    Orthographic -0.0614 0.254      252
2 Large    Semantic     -1.33   0.207      252
3 Small    Orthographic  0.792  0.279      252
4 Small    Semantic     -1.02   0.250      252
```

```r
(nw_cpx.cond.means <- n250_nwcplx |>
    group_by(fam_size, lang_type) |>
    summarise(mean = mean(value),
              se = sem(value),
              num_stim = n()))
```

```
# A tibble: 4 x 5
# Groups:   fam_size [2]
  fam_size lang_type      mean    se num_stim
  <chr>    <chr>         <dbl> <dbl>    <int>
1 Large    Orthographic  1.52  0.247      252
2 Large    Semantic     -0.296 0.196      252
3 Small    Orthographic  0.211 0.208      252
4 Small    Semantic     -0.748 0.206      252
```

Barplots



LME

```
library(lme4)
```

COMPLEX WORDS

```
cw_null.model = lmer(value ~ 1 + (1|SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_null.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
```

```
Formula: value ~ 1 + (1 | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4555.6   4570.4  -2274.8   4549.6     1005

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2085 -0.6434 -0.0517  0.5876  3.5597

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.713    2.390
 Residual             4.490    2.119
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
            Estimate Std. Error t value
(Intercept)  -0.2065     0.3292  -0.627
```

```
# Main effects models with random intercepts
cw_main.model = lmer(value ~ lang_type + fam_size + (1 + fam_size|SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_main.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4355.9   4390.3  -2171.0   4341.9     1001

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2595 -0.5434 -0.0448  0.5302  3.1335

Random effects:
 Groups   Name          Variance Std.Dev. Corr
 SubjID   (Intercept)   6.219    2.494
          fam_sizeSmall 4.843    2.201    -0.33
 Residual               3.212    1.792
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                  Estimate Std. Error t value
(Intercept)        0.07077    0.47708   0.148
lang_typeSemantic -0.75676    0.64605  -1.171
fam_sizeSmall      0.21463    0.31765   0.676

Correlation of Fixed Effects:
            (Intr) lng_tS
lng_typSmnt -0.689
fam_sizSmll -0.258  0.000
```

```r
# Interaction effects models with random intercepts
cw_inter.model = lmer(value ~ lang_type * fam_size + (1 + fam_size|SubjID) ,
                      data= n250_words, REML=FALSE)
summary(cw_inter.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4357.9   4397.2  -2170.9   4341.9     1000

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2605 -0.5431 -0.0447  0.5318  3.1324

Random effects:
 Groups   Name         Variance Std.Dev. Corr
 SubjID   (Intercept)  6.219    2.494
          fam_sizeSmall 4.840    2.200    -0.33
 Residual              3.212    1.792
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                     0.04968    0.49326   0.101
lang_typeSemantic              -0.71528    0.69150  -1.034
fam_sizeSmall                   0.26897    0.45295   0.594
lang_typeSemantic:fam_sizeSmall -0.10688    0.63522  -0.168

Correlation of Fixed Effects:
            (Intr) lng_tS fm_szS
lng_typSmnt -0.713
fam_sizSmll -0.356  0.254
lng_typS:_S  0.254 -0.357 -0.713
```

```r
anova(cw_null.model,cw_main.model)
```

```
Data: n250_words
Models:
cw_null.model: value ~ 1 + (1 | SubjID)
cw_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
cw_null.model    3 4555.6 4570.4 -2274.8   4549.6
cw_main.model    7 4355.9 4390.3 -2171.0   4341.9 207.73  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(cw_main.model,cw_inter.model)
```

```
Data: n250_words
Models:
```

```
cw_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
cw_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
               npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
cw_main.model     7 4355.9 4390.3 -2171.0   4341.9
cw_inter.model    8 4357.9 4397.2 -2170.9   4341.9 0.0283  1     0.8664
```

SIMPLE NONWORDS

```
nw.smpl_null.model = lmer(value ~ 1 + (1|SubjID) ,
                          data= n250_nwsmpl, REML=FALSE)
summary(nw.smpl_null.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ 1 + (1 | SubjID)
   Data: n250_nwsmpl

     AIC      BIC   logLik deviance df.resid
  5144.8   5159.6  -2569.4   5138.8     1005

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.6813 -0.5297  0.0084  0.5082  5.1466

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 8.104    2.847
 Residual             8.159    2.856
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
            Estimate Std. Error t value
(Intercept)  -0.4552     0.3944  -1.154
```

```
# Main effects models with random intercepts
nw.smpl_main.model = lmer(value ~ lang_type + fam_size + (1 + fam_size|SubjID) ,
                          data= n250_nwsmpl, REML=FALSE)
summary(nw.smpl_main.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
   Data: n250_nwsmpl

     AIC      BIC   logLik deviance df.resid
  4705.1   4739.5  -2345.5   4691.1     1001

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.0247 -0.5423 -0.0160  0.4965  4.5999

Random effects:
 Groups   Name          Variance Std.Dev. Corr
```

```
 SubjID   (Intercept)    9.513   3.084
          fam_sizeSmall 12.482   3.533    -0.45
 Residual                4.403   2.098
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                  Estimate Std. Error t value
(Intercept)        0.07474    0.57456   0.130
lang_typeSemantic -1.44317    0.75682  -1.907
fam_sizeSmall      0.40733    0.49454   0.824

Correlation of Fixed Effects:
            (Intr) lng_tS
lng_typSmnt -0.670
fam_sizSmll -0.342  0.000
```

```
# Interaction effects models with random intercepts
nw.smpl_inter.model = lmer(value ~ lang_type * fam_size + (1 + fam_size|SubjID) ,
                           data= n250_nwsmpl, REML=FALSE)
summary(nw.smpl_inter.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
   Data: n250_nwsmpl

     AIC      BIC   logLik deviance df.resid
  4707.0   4746.4  -2345.5   4691.0     1000

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.0238 -0.5405 -0.0141  0.4983  4.5990

Random effects:
 Groups   Name          Variance Std.Dev. Corr
 SubjID   (Intercept)    9.511   3.084
          fam_sizeSmall 12.469   3.531    -0.45
 Residual                4.403   2.098
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                                Estimate Std. Error t value
(Intercept)                      0.03195    0.60831   0.053
lang_typeSemantic               -1.35905    0.85276  -1.594
fam_sizeSmall                    0.51502    0.70525   0.730
lang_typeSemantic:fam_sizeSmall -0.21166    0.98876  -0.214

Correlation of Fixed Effects:
            (Intr) lng_tS fm_szS
lng_typSmnt -0.713
fam_sizSmll -0.461  0.329
lng_typS:_S  0.329 -0.461 -0.713
```

```r
anova(nw.smpl_null.model,nw.smpl_main.model)
```

```
Data: n250_nwsmpl
Models:
nw.smpl_null.model: value ~ 1 + (1 | SubjID)
nw.smpl_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.smpl_null.model    3 5144.8 5159.6 -2569.4   5138.8
nw.smpl_main.model    7 4705.1 4739.5 -2345.6   4691.1 447.71  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(nw.smpl_main.model,nw.smpl_inter.model)
```

```
Data: n250_nwsmpl
Models:
nw.smpl_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
nw.smpl_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
                    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.smpl_main.model     7 4705.1 4739.5 -2345.6   4691.1
nw.smpl_inter.model    8 4707.0 4746.4 -2345.5   4691.0 0.0458  1     0.8305
```

COMPLEX NONWORDS

```r
nw.cplx_null.model = lmer(value ~ 1 + (1|SubjID) ,
                          data= n250_nwcplx, REML=FALSE)
summary(nw.cplx_null.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ 1 + (1 | SubjID)
   Data: n250_nwcplx

     AIC      BIC   logLik deviance df.resid
  4850.0   4864.8  -2422.0   4844.0     1005

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7570 -0.6195 -0.0018  0.5511  4.5243

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.766    2.401
 Residual             6.106    2.471
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
            Estimate Std. Error t value
(Intercept)  0.07054    0.33308   0.212
```

```r
# Main effects models with random intercepts
nw.cplx_main.model = lmer(value ~ lang_type + fam_size + (1 + fam_size|SubjID) ,
                          data= n250_nwcplx, REML=FALSE)
summary(nw.cplx_main.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
   Data: n250_nwcplx

     AIC      BIC   logLik deviance df.resid
  4581.1   4615.5  -2283.5   4567.1     1001

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6153 -0.5471 -0.0371  0.4674  4.5554

Random effects:
 Groups   Name          Variance Std.Dev. Corr
 SubjID   (Intercept)   7.127    2.670
          fam_sizeSmall 6.883    2.624    -0.48
 Residual               4.044    2.011
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                  Estimate Std. Error t value
(Intercept)         1.0944     0.4955   2.208
lang_typeSemantic  -1.2141     0.6455  -1.881
fam_sizeSmall      -0.8137     0.3759  -2.164

Correlation of Fixed Effects:
            (Intr) lng_tS
lng_typSmnt -0.663
fam_sizSmll -0.370  0.000
```

```r
# Interaction effects models with random intercepts
nw.cplx_inter.model = lmer(value ~ lang_type * fam_size  + (1 + fam_size|SubjID),
                           data= n250_nwcplx, REML=FALSE)
summary(nw.cplx_inter.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
   Data: n250_nwcplx

     AIC      BIC   logLik deviance df.resid
  4582.1   4621.4  -2283.0   4566.1     1000

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6061 -0.5459 -0.0389  0.4639  4.5463

Random effects:
 Groups   Name          Variance Std.Dev. Corr
 SubjID   (Intercept)   7.092    2.663
```

```
         fam_sizeSmall 6.745    2.597    -0.47
 Residual              4.044    2.011
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
                                Estimate Std. Error t value
(Intercept)                       1.2771     0.5282   2.418
lang_typeSemantic                -1.5735     0.7405  -2.125
fam_sizeSmall                    -1.1889     0.5314  -2.237
lang_typeSemantic:fam_sizeSmall   0.7376     0.7453   0.990

Correlation of Fixed Effects:
            (Intr) lng_tS fm_szS
lng_typSmnt -0.713
fam_sizSmll -0.490  0.349
lng_typS:_S  0.349 -0.490 -0.713
```

```
anova(nw.cplx_null.model,nw.cplx_main.model)
```

```
Data: n250_nwcplx
Models:
nw.cplx_null.model: value ~ 1 + (1 | SubjID)
nw.cplx_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.cplx_null.model    3 4850.0 4864.8 -2422.0   4844.0
nw.cplx_main.model    7 4581.1 4615.5 -2283.5   4567.1 276.94  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(nw.cplx_main.model,nw.cplx_inter.model)
```

```
Data: n250_nwcplx
Models:
nw.cplx_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
nw.cplx_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
                    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.cplx_main.model     7 4581.1 4615.5 -2283.5   4567.1
nw.cplx_inter.model    8 4582.1 4621.4 -2283.1   4566.1 0.9705  1     0.3246
```

Model Comparisons

```
anova(cw_null.model,cw_main.model)
```

```
Data: n250_words
Models:
cw_null.model: value ~ 1 + (1 | SubjID)
cw_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
cw_null.model    3 4555.6 4570.4 -2274.8   4549.6
cw_main.model    7 4355.9 4390.3 -2171.0   4341.9 207.73  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(cw_main.model,cw_inter.model)
```

```
Data: n250_words
Models:
cw_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
cw_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
               npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
cw_main.model     7 4355.9 4390.3 -2171.0   4341.9
cw_inter.model    8 4357.9 4397.2 -2170.9   4341.9 0.0283  1     0.8664
```

```r
anova(nw.smpl_null.model,nw.smpl_main.model)
```

```
Data: n250_nwsmpl
Models:
nw.smpl_null.model: value ~ 1 + (1 | SubjID)
nw.smpl_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.smpl_null.model    3 5144.8 5159.6 -2569.4   5138.8
nw.smpl_main.model    7 4705.1 4739.5 -2345.6   4691.1 447.71  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(nw.smpl_main.model,nw.smpl_inter.model)
```

```
Data: n250_nwsmpl
Models:
nw.smpl_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
nw.smpl_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
                    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.smpl_main.model     7 4705.1 4739.5 -2345.6   4691.1
nw.smpl_inter.model    8 4707.0 4746.4 -2345.5   4691.0 0.0458  1     0.8305
```

```r
anova(nw.cplx_null.model,nw.cplx_main.model)
```

```
Data: n250_nwcplx
Models:
nw.cplx_null.model: value ~ 1 + (1 | SubjID)
nw.cplx_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
                   npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.cplx_null.model    3 4850.0 4864.8 -2422.0   4844.0
nw.cplx_main.model    7 4581.1 4615.5 -2283.5   4567.1 276.94  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(nw.cplx_main.model,nw.cplx_inter.model)
```

```
Data: n250_nwcplx
Models:
nw.cplx_main.model: value ~ lang_type + fam_size + (1 + fam_size | SubjID)
nw.cplx_inter.model: value ~ lang_type * fam_size + (1 + fam_size | SubjID)
```

```
                    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
nw.cplx_main.model     7 4581.1 4615.5 -2283.5   4567.1
nw.cplx_inter.model    8 4582.1 4621.4 -2283.1   4566.1 0.9705  1     0.3246
```

```
# COMPLEX WORDS

cw_null.model = lmer(value ~ 1 + (1|SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_null.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ 1 + (1 | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4555.6   4570.4  -2274.8   4549.6     1005

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2085 -0.6434 -0.0517  0.5876  3.5597

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.713    2.390
 Residual             4.490    2.119
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
            Estimate Std. Error t value
(Intercept)  -0.2065     0.3292  -0.627
```

```
# Main effects models with random intercepts
cw_main.model = lmer(value ~ lang_type + (1 |SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_main.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ lang_type + (1 | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4556.3   4575.9  -2274.1   4548.3     1004

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2184 -0.6464 -0.0459  0.5910  3.5496

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.564    2.359
 Residual             4.490    2.119
Number of obs: 1008, groups:  SubjID, 55
```

```
Fixed effects:
                  Estimate Std. Error t value
(Intercept)         0.1854     0.4638   0.400
lang_typeSemantic  -0.7699     0.6502  -1.184

Correlation of Fixed Effects:
            (Intr)
lng_typSmnt -0.713
```

```
anova(cw_null.model,cw_main.model)
```

```
Data: n250_words
Models:
cw_null.model: value ~ 1 + (1 | SubjID)
cw_main.model: value ~ lang_type + (1 | SubjID)
              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
cw_null.model    3 4555.6 4570.4 -2274.8   4549.6
cw_main.model    4 4556.3 4575.9 -2274.1   4548.3 1.3842  1     0.2394
```

```
# COMPLEX WORDS

cw_null.model = lmer(value ~ 1 + (1|SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_null.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: value ~ 1 + (1 | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4555.6   4570.4  -2274.8   4549.6     1005

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2085 -0.6434 -0.0517  0.5876  3.5597

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.713    2.390
 Residual             4.490    2.119
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
            Estimate Std. Error t value
(Intercept)  -0.2065     0.3292  -0.627
```

```
# Main effects models with random intercepts
cw_main.model = lmer(value ~ fam_size + (1 |SubjID) ,
                     data= n250_words, REML=FALSE)
summary(cw_main.model)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
```

```
Formula: value ~ fam_size + (1 | SubjID)
   Data: n250_words

     AIC      BIC   logLik deviance df.resid
  4554.6   4574.3  -2273.3   4546.6     1004

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.1601 -0.6427 -0.0446  0.6039  3.5108

Random effects:
 Groups   Name        Variance Std.Dev.
 SubjID   (Intercept) 5.714    2.390
 Residual             4.476    2.116
Number of obs: 1008, groups:  SubjID, 55

Fixed effects:
              Estimate Std. Error t value
(Intercept)    -0.3225     0.3359   -0.96
fam_sizeSmall   0.2319     0.1333    1.74

Correlation of Fixed Effects:
            (Intr)
fam_sizSmll -0.198
```

```
anova(cw_null.model,cw_main.model)
```

```
Data: n250_words
Models:
cw_null.model: value ~ 1 + (1 | SubjID)
cw_main.model: value ~ fam_size + (1 | SubjID)
              npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
cw_null.model    3 4555.6 4570.4 -2274.8   4549.6
cw_main.model    4 4554.6 4574.3 -2273.3   4546.6 3.024  1    0.08204 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```