

Task 1 - SMLP 2022: Analysis MS 2

By Monica Vanoncini

Cardiac synchrony and its role in language development

This is part of my PhD project which examines the role of mother-infant interpersonal synchrony on language development. Specifically, in this script, I test the following RQ. Does mother-infant cardiac synchrony predict infants' word segmentation ability? We include data of 29 dyads who performed two different tasks:

- **word-segmentation task:** infants underwent an eye-tracking task. During the familiarization phase they were listening to a story containing target words (i.e., familiar words). Then, they were tested with familiar (6 trials) and novel (6 trials) words. We measured their looking time (LT) in msec while listening to novel vs. familiar words. LT was our dependent variable.
- **5-minutes free play interaction:** mothers were asked to play with the baby as they would do at home. During this time we recorded dual ECG. We then followed the following processing steps:
 1. we extracted offline Interbeat-intervals (IBIs)
 2. we calculated Respiratory Sinus Arrhythmia (RSA)
 3. to collect a more continuous measure of RSA, a sliding window of 15 s was used to extract a continuous estimate of cardiac vagal tone for both participants
 4. to identify coupling/synchrony between mothers' and infants' RSA time-series we used cross-recurrence quantification analysis (CRQA)
 5. CRQA gave us a bunch of metrics: RR, det, NRLINE, maxline, entropy, lam, TT
 6. we ran principal component analysis and we decide to include the first two components (pc1 and pc2), which had eigenvalues higher than 1 (Kaiser Rule).

Part 1: data preparation

```
library(readxl)
```

```
## Warning: package 'readxl' was built under R version 4.0.5
```

```
lang_ECG <- read.csv("D:/PhD project/Conferences-SummerSchools/SMLP 2022/lang_ECG.csv", header=TRUE, sep=";", as.is=TRUE)
str(lang_ECG)
```

```
## 'data.frame':  426 obs. of  7 variables:
## $ Participant: int  10 10 10 10 10 10 10 10 10 10 ...
## $ Phase      : chr  "familiarization" "familiarization" "familiarization" "familiarization" ...
## $ Familiarity: chr  "famphase" "famphase" "famphase" "famphase" ...
## $ LT         : num  1.17 2.65 15.26 11.68 5.49 ...
## $ PC1        : num  -0.572 -0.572 -0.572 -0.572 -0.572 ...
## $ PC2        : num  -0.092 -0.092 -0.092 -0.092 -0.092 ...
## $ PC3        : num  -2.25 -2.25 -2.25 -2.25 -2.25 ...
```

```
lang_ECG$Participant <- as.factor(lang_ECG$Participant)
lang_ECG$Phase <- as.factor(lang_ECG$Phase)
lang_ECG$Familiarity <- as.factor(lang_ECG$Familiarity)
str(lang_ECG)
```

```
## 'data.frame': 426 obs. of 7 variables:
## $ Participant: Factor w/ 29 levels "10","14","17",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Phase : Factor w/ 2 levels "familiarization",...: 1 1 1 1 2 2 2 2 2 2 ...
## $ Familiarity: Factor w/ 3 levels "familiar","famphase",...: 2 2 2 2 3 1 1 3 1 1 ...
## $ LT : num 1.17 2.65 15.26 11.68 5.49 ...
## $ PC1 : num -0.572 -0.572 -0.572 -0.572 -0.572 ...
## $ PC2 : num -0.092 -0.092 -0.092 -0.092 -0.092 ...
## $ PC3 : num -2.25 -2.25 -2.25 -2.25 -2.25 ...
```

```
#select only the data of the test phase
lang_ECG <- subset(lang_ECG, lang_ECG$Phase != "familiarization")

summary(lang_ECG)
```

```
## Participant Phase Familiarity LT
## 14 : 12 familiarization: 0 familiar:160 Min. : 1.059
## 19 : 12 testing :310 famphase: 0 1st Qu.: 3.378
## 30 : 12 novel :150 Median : 5.938
## 32 : 12 Mean : 7.893
## 33 : 12 3rd Qu.:10.002
## 37 : 12 Max. :31.696
## (Other):238
## PC1 PC2 PC3
## Min. : -4.8247 Min. : -2.19475 Min. : -2.25027
## 1st Qu.: -1.0780 1st Qu.: -0.76545 1st Qu.: -0.42031
## Median : -0.2899 Median : 0.05161 Median : 0.20945
## Mean : -0.0308 Mean : 0.01955 Mean : 0.03938
## 3rd Qu.: 1.0833 3rd Qu.: 0.78577 3rd Qu.: 0.57058
## Max. : 5.3849 Max. : 2.03139 Max. : 1.40010
##
```

```
#set contrasts
library(stats)
levels(droplevels(lang_ECG$Familiarity))
```

```
## [1] "familiar" "novel"
```

```
contrasts(lang_ECG$Familiarity)
```

```
## famphase novel
## familiar 0 0
## famphase 1 0
## novel 0 1
```

```
#center predictors
lang_ECG$pc1C <- lang_ECG$PC1 - mean(lang_ECG$PC1)
lang_ECG$pc2C <- lang_ECG$PC2 - mean(lang_ECG$PC2)
```

Mixed models

```

library(lme4)

## Loading required package: Matrix

library(lmerTest)

## Warning: package 'lmerTest' was built under R version 4.0.5

##
## Attaching package: 'lmerTest'

## The following object is masked from 'package:lme4':
##
##      lmer

## The following object is masked from 'package:stats':
##
##      step

options(scipen = 999)
lang_ECG$Familiarity <- relevel(lang_ECG$Familiarity, ref = "familiar")

#run different models
pc0 =lmer(log(LT)~Familiarity+(1|Participant), data=lang_ECG, REML=FALSE)
pc1=lmer(log(LT)~Familiarity*pc1C+(1|Participant), data=lang_ECG, REML=FALSE)
pc2=lmer(log(LT)~Familiarity*pc1C+Familiarity*pc2C+(1|Participant), data=lang_ECG, REML=FALSE)
#compare models with Anova
anova(pc0,pc1,pc2)

## Data: lang_ECG
## Models:
## pc0: log(LT) ~ Familiarity + (1 | Participant)
## pc1: log(LT) ~ Familiarity * pc1C + (1 | Participant)
## pc2: log(LT) ~ Familiarity * pc1C + Familiarity * pc2C + (1 | Participant)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## pc0      4 689.45 704.39 -340.72   681.45
## pc1      6 693.34 715.76 -340.67   681.34 0.1029  2    0.94984
## pc2      8 691.46 721.35 -337.73   675.46 5.8801  2    0.05286 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(pc2)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(LT) ~ Familiarity * pc1C + Familiarity * pc2C + (1 | Participant)
## Data: lang_ECG
##
##      AIC      BIC   logLik deviance df.resid
##    691.5    721.4   -337.7    675.5     302

```

```
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.02876 -0.61309 -0.07738  0.63312  2.50248
##
## Random effects:
##   Groups      Name      Variance Std.Dev.
## Participant (Intercept) 0.1280   0.3578
## Residual              0.4546   0.6743
## Number of obs: 310, groups: Participant, 29
##
## Fixed effects:
##              Estimate Std. Error      df t value
## (Intercept)      1.739135   0.085355  42.369320  20.375
## Familiaritynovel    0.051108   0.076938 281.615839   0.664
## pc1C              0.011466   0.041902  42.172058   0.274
## pc2C              0.028178   0.082346  41.993264   0.342
## Familiaritynovel:pc1C 0.003251   0.036957 280.777680   0.088
## Familiaritynovel:pc2C -0.174237   0.074902 281.417164  -2.326
##
##              Pr(>|t|)
## (Intercept)    <0.0000000000000002 ***
## Familiaritynovel    0.5071
## pc1C              0.7857
## pc2C              0.7339
## Familiaritynovel:pc1C 0.9300
## Familiaritynovel:pc2C 0.0207 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) Fmlrty pc1C   pc2C   Fml:1C
## Familrtynovl -0.434
## pc1C          -0.013  0.006
## pc2C          0.002  0.011  0.000
## Fmlrtynv:1C  0.006  0.000 -0.443 -0.001
## Fmlrtynv:2C  0.011  0.001 -0.001 -0.429 -0.018
```

```
#plot results
```

```
library(performance)
```

```
## Warning: package 'performance' was built under R version 4.0.5
```

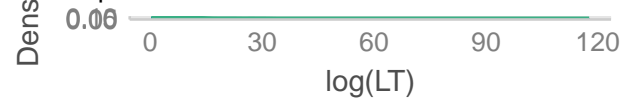
```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.0.5
```

```
check_model(pc2)
```

Posterior Predictive Check

Model-predicted lines should resemble observed data



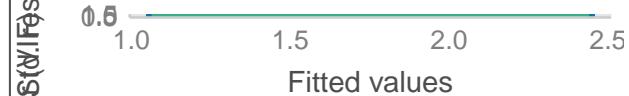
Linearity

Reference line should be flat and horizontal



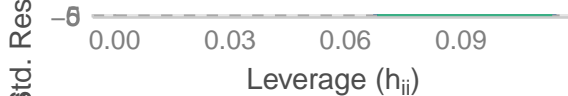
Homogeneity of Variance

Reference line should be flat and horizontal



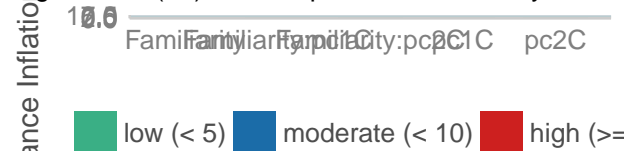
Influential Observations

Points should be inside the contour lines



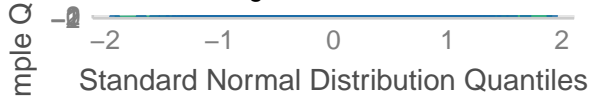
Collinearity

Higher bars (>5) indicate potential collinearity issues



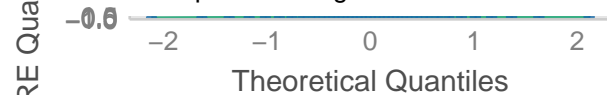
Normality of Residuals

Dots should fall along the line



Normality of Random Effects (Participant)

Dots should be plotted along the line



```
library(effects)
```

```
## Warning: package 'effects' was built under R version 4.0.5
```

```
## Loading required package: carData
```

```
## lattice theme set by effectsTheme()
```

```
## See ?effectsTheme for details.
```

```
myef <- effect("Familiarity*pc2C", pc2)
```

```
myef_df <- data.frame(myef)
```

```
head(myef_df)
```

```
##   Familiarity pc2C      fit      se   lower   upper
## 1    familiar -2.0 1.682780 0.18533732 1.318073 2.047486
## 2     novel -2.0 2.082363 0.18784213 1.712727 2.451998
## 3    familiar -1.0 1.710957 0.11847729 1.477818 1.944097
## 4     novel -1.0 1.936303 0.11953564 1.701081 2.171525
## 5    familiar -0.1 1.736317 0.08573388 1.567610 1.905024
## 6     novel -0.1 1.804849 0.08684260 1.633961 1.975738
```

```
ggplot(myef_df, aes(x=pc2C, y=fit, linetype=Familiarity, fill=Familiarity, size=Familiarity)) +
  geom_path(data=myef_df, aes(x=pc2C, y=fit), size=1.5) + # for plotting the lines
```

```
geom_ribbon(data=myef_df, aes(x=pc2C, ymin=lower, ymax=upper, group=Familiarity), alpha=.3) +
geom_point(data=lang_ECG, aes(x=pc2C, y=log(LT), shape=Familiarity, colour=Participant), size=1.5) +
#scale_y_continuous(trans='logit') + # y-scale is now reflecting the logit space
#theme_bw()
#xlab("pc2 centered") + ylab("LT (fit)") +
labs(x = "pc2 (centered)", y = "Log LT for test trials") +
scale_fill_manual(values=c("black","black"))+
guides(shape = guide_legend(title = "Trial type"), colour=FALSE, fill=FALSE, size=FALSE) +
labs(linetype="Group")+
theme(axis.title = element_text(size = 15), axis.text = element_text(size = 12),
      legend.text = element_text(size = 10), legend.title = element_text(size = 10))
```

```
## Warning: 'guides(<scale> = FALSE)' is deprecated. Please use 'guides(<scale> =
## "none")' instead.
```

```
## Warning: Using size for a discrete variable is not advised.
```

