Emotion Inertia Analysis

Rongrong (Emma) Mo

Contents


```r
feelings_initial <- load("feelings_initial.RData")
ls()
```

```
## [1] "dat"              "feelings_initial" "Iaro_wide"        "Ineg_wide"
## [5] "Ipos_wide"
```

```r
summary(feelings_initial)
```

```
##    Length     Class      Mode 
##         4 character character
```

```r
str(dat)
```

```
## 'data.frame':    16380 obs. of  9 variables:
##  $ subj     : Factor w/ 156 levels "f001","f002",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ trial.num: int  1 2 3 4 5 6 7 8 9 10 ...
##  $ trial.val: Factor w/ 3 levels "neg","neu","pos": 3 1 1 3 3 2 2 1 1 3 ...
##  $ sex      : Factor w/ 3 levels "male","female",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ age      : int  19 19 19 19 19 19 19 19 19 19 ...
##  $ ethn     : Factor w/ 7 levels "Asian or Pacific Islander",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ Ineg     : num  1 4 2 1 1 1 1 3 5 1 ...
##  $ Ipos     : num  3.69 1 1 1 4 ...
##  $ Iaro     : num  2.86 3 2 2 3 ...
```

0.1 Descriptive statistics

```r
summary(dat[, c("Ineg", "Ipos", "Iaro")])
```

```
##       Ineg            Ipos            Iaro      
##  Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000  
##  Median :2.000   Median :2.000   Median :3.000  
##  Mean   :3.075   Mean   :3.066   Mean   :3.265  
##  3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:5.000  
##  Max.   :9.000   Max.   :9.000   Max.   :9.000
```

- Mean score of Iaro is higher than the other two

```r
# identify NAs
colSums(is.na(dat))
```

```
##      subj trial.num trial.val       sex       age      ethn      Ineg      Ipos 
##         0         0         0         0         0         0         0         0 
##      Iaro 
##         0
```

There are no NAs in the dataset.

```
# identify outliers using z-score

# Calculate Z-scores for Ineg, Ipos, and Iaro
dat$z_Ineg <- scale(dat$Ineg)
dat$z_Ipos <- scale(dat$Ipos)
dat$z_Iaro <- scale(dat$Iaro)

# Identify outliers (Z-score > 3 or < -3)
outliers_Ineg <- dat[abs(dat$z_Ineg) > 3, ]
outliers_Ineg
```

```
##  [1] subj      trial.num trial.val sex       age       ethn      Ineg
##  [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

```
outliers_Ipos <- dat[abs(dat$z_Ipos) > 3, ]
outliers_Ipos
```

```
##  [1] subj      trial.num trial.val sex       age       ethn      Ineg
##  [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

```
outliers_Iaro <- dat[abs(dat$z_Iaro) > 3, ]
outliers_Iaro
```

```
##  [1] subj      trial.num trial.val sex       age       ethn      Ineg
##  [8] Ipos      Iaro      z_Ineg    z_Ipos    z_Iaro
## <0 rows> (or 0-length row.names)
```

There are no outliers.

0.2 Linear Mixed Effects Model: emotional responses by trial type & demographics

- Each participant has multiple trials, so the trials within a participant are likely correlated
- Data is nested
- Each participant may have their own baseline level of emotional responses
- fixed effects (trial.val, sex, age, ethn) explain the variation between individuals
- random effects (1|subj) explain the correlation of repeated measures within individuals

0.2.1 How different trial types & demographics affect negative emotional response (Ineg)?

```r
library(lme4)
```

```
## Loading required package: Matrix
```

```r
# Mixed-effects model for predicting Ineg
model_ineg <- lmer(Ineg ~ trial.val + sex + age + ethn + (1|subj), data = dat)
summary(model_ineg)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Ineg ~ trial.val + sex + age + ethn + (1 | subj)
##    Data: dat
##
## REML criterion at convergence: 58969.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9915 -0.5714 -0.0487  0.5031  5.6660
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subj     (Intercept) 0.5259   0.7252
##  Residual             2.0745   1.4403
## Number of obs: 16380, groups:  subj, 156
##
## Fixed effects:
##                                                    Estimate Std. Error
## (Intercept)                                        5.218934   0.443816
## trial.valneu                                      -4.076439   0.034381
## trial.valpos                                      -4.086175   0.024311
## sexfemale                                          0.317543   0.121858
## sexother                                          -0.031652   0.747300
## age                                                0.001809   0.021086
## ethnBlack/African American                        -0.060943   0.237892
## ethnLatino/Hispanic                               -0.317652   0.232008
## ethnOther                                          0.138570   0.290750
## ethnWhite/Caucasian                                0.070420   0.155354
## ethnAmerican Indian/Native American or Alaskan Native -0.692261   0.393608
## ethnDecline to state                              -0.275510   0.543413
##                                                    t value
## (Intercept)                                         11.759
## trial.valneu                                      -118.566
## trial.valpos                                      -168.079
## sexfemale                                            2.606
```

```
## sexother                                                -0.042
## age                                                      0.086
## ethnBlack/African American                              -0.256
## ethnLatino/Hispanic                                     -1.369
## ethnOther                                                0.477
## ethnWhite/Caucasian                                      0.453
## ethnAmerican Indian/Native American or Alaskan Native   -1.759
## ethnDecline to state                                    -0.507
##
## Correlation of Fixed Effects:
##             (Intr) trl.vln trl.vlp sexfml sexthr age    etB/AA ethL/H ethnOt
## trial.valne -0.019
## trial.valps -0.027  0.354
## sexfemale   -0.197  0.000   0.000
## sexother    -0.070  0.000   0.000   0.084
## age         -0.941  0.000   0.000   0.021  0.059
## ethnBlck/AA -0.026  0.000   0.000   0.072 -0.002 -0.149
## ethnLtn/Hsp  0.065  0.000   0.000   0.072 -0.008 -0.250  0.334
## ethnOther   -0.081  0.000   0.000  -0.044 -0.006 -0.038  0.234  0.244
## ethnWht/Ccs -0.091  0.000   0.000   0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000   0.000   0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000   0.000   0.144  0.010 -0.027  0.139  0.145  0.096
##             ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092
```

- Random effects: each participant has a different baseline emotional response
  - `(1|subj)`: represents the random effect
    - each participant (subj) has a different baseline deviation (intercept).
    - This accounts for the correlation between multiple trial results from the same participant
- `REML score` (residual maximum likelihood estimate): assess the model fit
- Fixed Effects:
  - Intercept: Negative trial
  - `trial.valneu` (Neutral trial): Estimate = -4.08, t = -118.57, a very significant negative value.

    - Compared to the baseline (negative trial), **the neutral trial significantly decreases negative emotions (Ineg)**
  - `trial.valpos` (Positive trial): Estimate = -4.09, t = -168.08, also significant.
    - **the positive trial also significantly decreases negative emotions** compared to the negative trial
  - sexfemale: Estimate = 0.317543, t = 2.606.
    - **Females have significantly higher negative emotional responses (Ineg)** compared to males
  - The effects of age and ethnicity are small and not significant

0.2.2 How different trial types & demographics affect positive emotional response (Ipos)?

```r
# Mixed-effects model for predicting Ipos
model_ipos <- lmer(Ipos ~ trial.val + sex + age + ethn + (1|subj), data = dat)
summary(model_ipos)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Ipos ~ trial.val + sex + age + ethn + (1 | subj)
##    Data: dat
##
## REML criterion at convergence: 60034.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8302 -0.5834 -0.0294  0.5335  5.4659
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subj     (Intercept) 0.5687   0.7541
##  Residual             2.2138   1.4879
## Number of obs: 16380, groups:  subj, 156
##
## Fixed effects:
##                                                         Estimate Std. Error
## (Intercept)                                              0.71768    0.46141
## trial.valneu                                             0.33658    0.03552
## trial.valpos                                             4.03432    0.02511
## sexfemale                                                0.20020    0.12669
## sexother                                                -1.13135    0.77693
## age                                                      0.02213    0.02192
## ethnBlack/African American                               0.08731    0.24732
## ethnLatino/Hispanic                                     -0.33718    0.24121
## ethnOther                                               -0.01740    0.30228
## ethnWhite/Caucasian                                      0.13375    0.16151
```

```
## ethnAmerican Indian/Native American or Alaskan Native -0.93997    0.40921
## ethnDecline to state                                 -0.33289    0.56496
##                                                      t value
## (Intercept)                                            1.555
## trial.valneu                                           9.477
## trial.valpos                                         160.642
## sexfemale                                              1.580
## sexother                                              -1.456
## age                                                    1.010
## ethnBlack/African American                             0.353
## ethnLatino/Hispanic                                   -1.398
## ethnOther                                             -0.058
## ethnWhite/Caucasian                                    0.828
## ethnAmerican Indian/Native American or Alaskan Native  -2.297
## ethnDecline to state                                  -0.589
##
## Correlation of Fixed Effects:
##             (Intr) trl.vln trl.vlp sexfml sexthr age    etB/AA ethL/H ethnOt
## trial.valne -0.019
## trial.valps -0.027  0.354
## sexfemale   -0.197  0.000   0.000
## sexother    -0.070  0.000   0.000   0.084
## age         -0.941  0.000   0.000   0.021  0.059
## ethnBlck/AA -0.026  0.000   0.000   0.072 -0.002 -0.149
## ethnLtn/Hsp  0.065  0.000   0.000   0.072 -0.008 -0.250  0.334
## ethnOther   -0.081  0.000   0.000  -0.044 -0.006 -0.038  0.234  0.244
## ethnWht/Ccs -0.091  0.000   0.000   0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000   0.000   0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000   0.000   0.144  0.010 -0.027  0.139  0.145  0.096
##             ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092
```

- Intercept (negative trial): estimate = 0.72, t-value = 1.56. The effect of negative trial on positive emotions (Ipos) is small.
- `trial.valneu`: estimate = 0.34, t-value = 9.48. Compared to valneg, the neutral trial significantly increases positive emotions (Ipos).
- `trial.valpos`: estimate = 4.03, t-value = 160.64. Compared to valneg, the positive trial largely increases positive emotions (Ipos), and the effect is extremely significant.

- `sexfemale`: estimate = 0.20, t = 1.58. **Females tend to have slightly higher positive emotional responses** than males.
- `ethnAmerican Indian/Native American or Alaskan Native`: estimate = -0.94, t = -2.30. This ethnicity tends to have **significantly lower positive emotional responses** compared to the reference group.
- `trial.valneu` and `trial.valpos` have a correlation of 0.354, showing that the effects of neutral and positive trials are somewhat related.

0.2.3 How different trial types & demographics affect arousal emotional response (Iaro)?

```
# Mixed-effects model for predicting Iaro
model_aro <- lmer(Iaro ~ trial.val + sex + age + ethn + (1|subj), data = dat)
summary(model_aro)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Iaro ~ trial.val + sex + age + ethn + (1 | subj)
##    Data: dat
##
## REML criterion at convergence: 59841.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4843 -0.6288 -0.1072  0.5760  4.8022
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subj     (Intercept) 1.593    1.262
##  Residual             2.168    1.472
## Number of obs: 16380, groups:  subj, 156
##
## Fixed effects:
##                                                        Estimate Std. Error
## (Intercept)                                             2.92802    0.76311
## trial.valneu                                           -2.25913    0.03515
## trial.valpos                                           -0.30058    0.02485
## sexfemale                                               0.22642    0.20959
## sexother                                               -1.53358    1.28529
## age                                                     0.02904    0.03627
## ethnBlack/African American                              0.22313    0.40915
## ethnLatino/Hispanic                                     0.12385    0.39903
## ethnOther                                               0.52839    0.50007
## ethnWhite/Caucasian                                     0.06932    0.26720
## ethnAmerican Indian/Native American or Alaskan Native -0.85245    0.67697
## ethnDecline to state                                    0.07313    0.93462
##                                                        t value
```

```
## (Intercept)                                                   3.837
## trial.valneu                                                -64.279
## trial.valpos                                                -12.095
## sexfemale                                                     1.080
## sexother                                                     -1.193
## age                                                           0.801
## ethnBlack/African American                                    0.545
## ethnLatino/Hispanic                                           0.310
## ethnOther                                                     1.057
## ethnWhite/Caucasian                                           0.259
## ethnAmerican Indian/Native American or Alaskan Native        -1.259
## ethnDecline to state                                          0.078
##
## Correlation of Fixed Effects:
##             (Intr) trl.vln trl.vlp sexfml sexthr age    etB/AA ethL/H ethnOt
## trial.valne -0.012
## trial.valps -0.016  0.354
## sexfemale   -0.197  0.000   0.000
## sexother    -0.070  0.000   0.000   0.084
## age         -0.942  0.000   0.000   0.021  0.059
## ethnBlck/AA -0.026  0.000   0.000   0.072 -0.002 -0.149
## ethnLtn/Hsp  0.065  0.000   0.000   0.072 -0.008 -0.250  0.334
## ethnOther   -0.081  0.000   0.000  -0.044 -0.006 -0.038  0.234  0.244
## ethnWht/Ccs -0.091  0.000   0.000   0.107 -0.062 -0.171  0.468  0.496  0.357
## ethAI/NAoAN -0.141  0.000   0.000   0.123  0.012  0.029  0.176  0.178  0.134
## ethnDclntst -0.067  0.000   0.000   0.144  0.010 -0.027  0.139  0.145  0.096
##             ethW/C eIAoAN
## trial.valne
## trial.valps
## sexfemale
## sexother
## age
## ethnBlck/AA
## ethnLtn/Hsp
## ethnOther
## ethnWht/Ccs
## ethAI/NAoAN  0.271
## ethnDclntst  0.211  0.092
```

- Intercept (negative trial): estimate = 2.93, t-value = 3.84. The effect of negative trial on arousal (Iaro) is moderate.
- `trial.valneu`: estimate -2.26, t-value = -64.28. Compared to `valneg`, the **neutral trial significantly decreases arousal (Iaro)**, which can be expected.
- `trial.valpos`: estimate = -0.30, t-value = -12.10. Compared to `valneg`, the **positive trial also significantly decreases arousal (Iaro)**, but the effect is small.
- Other fixed effects are not significant.

0.3 Autoregressive Modeling

0.3.1 Assign 12 inertia scores for each participant

Assign 1 overall inertia score for pos, neg, and aro for each participant:

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(purrr)
library(broom)

# Create a function to return inertia (lag-1 beta value)
get_inertia <- function(x) {
  # Create lagged data
  lag_x <- dplyr::lag(x)
  df <- data.frame(current = x, lagged = lag_x)
  df <- na.omit(df)

  # Linear regression: current ~ lagged
  model <- lm(current ~ lagged, data = df)
  coef(model)["lagged"]
}

# find inertia scores for the 3 emotions for each participant
overall_inertia <- dat %>%
  group_by(subj) %>%
  summarise(
    pos_inertia = get_inertia(Ipos),
    neg_inertia = get_inertia(Ineg),
    aro_inertia = get_inertia(Iaro)
  )
overall_inertia
```

```
## # A tibble: 156 x 4
##    subj  pos_inertia neg_inertia aro_inertia
```

```
##    <fct>       <dbl>      <dbl>      <dbl>
##  1 f001      -0.0956    -0.149     -0.139
##  2 f002       0.0187     0.0682     0.0974
##  3 f003      -0.0855    -0.143      0.0149
##  4 f004       0.0648    -0.0705     0.0150
##  5 f005      -0.0433    -0.0918    -0.0962
##  6 f006      -0.0750     0.160      0.175
##  7 f007       0.0834     0.0245     0.190
##  8 f008      -0.0125    -0.0254     0.00949
##  9 f009       0.0162     0.0865    -0.136
## 10 f010       0.164      0.110      0.0143
## # i 146 more rows
```

For each of the 3 emotional reactions (pos, neg, aro), assign 1 inertia score for each of the 3 trial type (pos, neg, neu)

```r
library(tidyr)
```

```
##
## Attaching package: 'tidyr'
```

```
## The following objects are masked from 'package:Matrix':
##
##     expand, pack, unpack
```

```r
# For each subj × trial.val × emotion
inertia_long <- dat %>%
  group_by(subj, trial.val) %>%
  summarise(
    pos_inertia = get_inertia(Ipos),
    neg_inertia = get_inertia(Ineg),
    aro_inertia = get_inertia(Iaro),
    .groups = "drop"
  )

# Reshape into wide format: 1 row per participant, 9 inertia scores
inertia_wide <- inertia_long %>%
  pivot_wider(
    names_from = trial.val,
    values_from = c(pos_inertia, neg_inertia, aro_inertia),
    names_glue = "{.value}_{trial.val}"
  )

inertia_wide
```

```
## # A tibble: 156 x 10
```

```
##    subj  pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##    <fct>           <dbl>           <dbl>           <dbl>           <dbl>
##  1 f001          -0.0233         NA              0.0214          -0.203
##  2 f002          -0.0233         -0.115         -0.00418          0.376
##  3 f003           0.131          -0.0939        -0.127           -0.106
##  4 f004          -0.0732         -0.0111         0.196            0.0689
##  5 f005           0.223          -0.0769         0.0571           0.107
##  6 f006          -0.0883         -0.161          0.239            0.416
##  7 f007          -0.0233         -0.0888         0.0636           0.191
##  8 f008           0.0422         -0.247          0.0363          -0.174
##  9 f009          -0.0560          0.0590         0.0652           0.0603
## 10 f010          -0.0233          0.0577         0.199            0.220
## # i 146 more rows
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

```r
# Find the reason of NAs

# Whether there's not enough data for each subj × trial.val group?

dat %>%
  group_by(subj, trial.val) %>%
  summarise(n = n()) %>%
  filter(n < 5)
```

```
## `summarise()` has grouped output by 'subj'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 0 x 3
## # Groups:   subj [0]
## # i 3 variables: subj <fct>, trial.val <fct>, n <int>
```

```r
# Whether some emotion ratings for certain trial type are always the same?

dat %>%
  group_by(subj, trial.val) %>%
  summarise(
    Ineg_var = var(Ineg),
    Ipos_var = var(Ipos),
    Iaro_var = var(Iaro)
  ) %>%
  filter(Ineg_var == 0 | Ipos_var == 0 | Iaro_var == 0)
```

```
## `summarise()` has grouped output by 'subj'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 106 x 5
## # Groups:   subj [80]
##    subj  trial.val Ineg_var Ipos_var Iaro_var
##    <fct> <fct>        <dbl>    <dbl>    <dbl>
##  1 f001  neu          0        0.267    0.352
##  2 f001  pos          0        1.61     1.08
##  3 f002  neu          0        1.26     1.35
##  4 f002  pos          0        1.51     1.14
##  5 f005  neu          0        0.267    0.0667
##  6 f007  neu          0        0.0663   0
##  7 f007  pos          0        0.786    0.382
##  8 f013  neu          0        0.0659   0
##  9 f019  neu          0.124    4.92     0
## 10 f020  neu          0        2.52     1.55
## # i 96 more rows
```

- The reason of NAs is not due to insufficient data for each subj $\times$ trial.val group
- NAs are also not likely to be caused by zero-variance of some emotion inertia ratings, since NAs from inertia_wide are more than the number of Var $= 0$.

```r
# Merge all inertia scores (by subj)
inertia_all <- overall_inertia %>%
  left_join(inertia_wide, by = "subj")
inertia_all
```

```
## # A tibble: 156 x 13
##    subj  pos_inertia neg_inertia aro_inertia pos_inertia_neg pos_inertia_neu
##    <fct>       <dbl>       <dbl>       <dbl>           <dbl>           <dbl>
##  1 f001      -0.0956     -0.149      -0.139          -0.0233         NA
##  2 f002       0.0187      0.0682      0.0974         -0.0233         -0.115
##  3 f003      -0.0855     -0.143       0.0149          0.131          -0.0939
##  4 f004       0.0648     -0.0705      0.0150         -0.0732         -0.0111
##  5 f005      -0.0433     -0.0918     -0.0962          0.223          -0.0769
##  6 f006      -0.0750      0.160       0.175          -0.0883         -0.161
##  7 f007       0.0834      0.0245      0.190          -0.0233         -0.0888
##  8 f008      -0.0125     -0.0254      0.00949         0.0422         -0.247
##  9 f009       0.0162      0.0865     -0.136          -0.0560          0.0590
## 10 f010       0.164       0.110       0.0143         -0.0233          0.0577
## # i 146 more rows
## # i 7 more variables: pos_inertia_pos <dbl>, neg_inertia_neg <dbl>,
## #   neg_inertia_neu <dbl>, neg_inertia_pos <dbl>, aro_inertia_neg <dbl>,
## #   aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

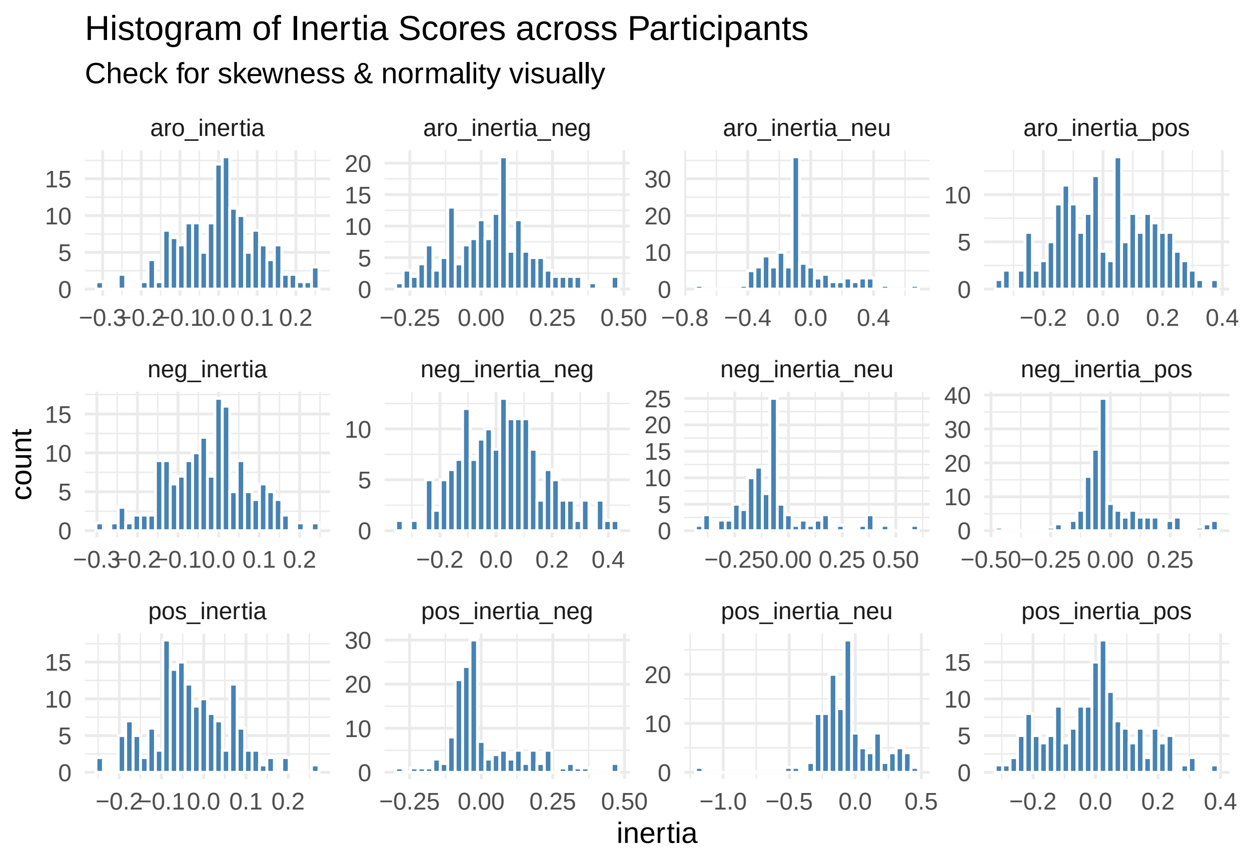
```r
library(ggplot2)
library(dplyr)
library(tidyr)
```

```r
library(e1071)   # for skewness
library(psych)   # for describe()
```

```
##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```r
# Convert to inertia_long format
inertia_long <- inertia_all %>%
  pivot_longer(-subj, names_to = "inertia_type", values_to = "inertia")

# Distribution & Skewness
inertia_long %>%
  group_by(inertia_type) %>%
  mutate(
    skew = skewness(inertia, na.rm = TRUE),
    normality_p = shapiro.test(inertia)$p.value
  ) %>%
  ggplot(aes(x = inertia)) +
  geom_histogram(bins = 30, fill = "steelblue", color = "white") +
  facet_wrap(~ inertia_type, scales = "free") +
  theme_minimal() +
  labs(title = "Histogram of Inertia Scores across Participants",
       subtitle = "Check for skewness & normality visually")
```

```
## Warning: Removed 159 rows containing non-finite outside the scale range
## (`stat_bin()`).
```




```r
# describe_stats for all 3 + 9 = 12 types of inertia
describe_stats <- inertia_long %>%
  group_by(inertia_type) %>%
  summarise(
    n = sum(!is.na(inertia)),
    sd = sd(inertia, na.rm = TRUE),
    Q1 = quantile(inertia, 0.25, na.rm = TRUE),
    Q3 = quantile(inertia, 0.75, na.rm = TRUE),
    skewness = skewness(inertia, na.rm = TRUE),
    normality_p = shapiro.test(inertia)$p.value
  )
describe_stats
```

```
## # A tibble: 12 x 7
##    inertia_type        n     sd       Q1        Q3 skewness normality_p
##    <chr>           <int>  <dbl>    <dbl>     <dbl>    <dbl>       <dbl>
##  1 aro_inertia       156 0.103  -0.0630  0.0666   -0.0809     6.10e- 1
##  2 aro_inertia_neg   156 0.150  -0.0772  0.124     0.230      1.39e- 1
##  3 aro_inertia_neu   117 0.208  -0.182  -0.00947   0.715      3.86e- 5
##  4 aro_inertia_pos   154 0.157  -0.117   0.134     0.0368     1.11e- 1
##  5 neg_inertia       156 0.0998 -0.0890  0.0316   -0.120      8.17e- 1
##  6 neg_inertia_neg   156 0.151  -0.0928  0.117     0.253      4.16e- 1
```

```
## 7 neg_inertia_neu    95 0.177  -0.166  -0.0635    1.30      1.30e- 7
## 8 neg_inertia_pos   141 0.139  -0.0694  0.0458    1.08      6.69e-10
## 9 pos_inertia       156 0.0927 -0.0889  0.0276    0.290     2.67e- 1
## 10 pos_inertia_neg   140 0.129  -0.0691  0.0479    1.27      2.32e- 9
## 11 pos_inertia_neu   130 0.216  -0.167   0.0242   -0.399     8.44e- 8
## 12 pos_inertia_pos   156 0.141  -0.119   0.0684    0.0816    1.17e- 1
```

Inertia scores that are not normal:

- neg_inertia_pos: normality_p = 6.689087e-10; skewness = 1.07982750
  - Under positive stimuli, negative emotion inertia is right-skewed: a few individuals have unusually persistent negative emotions
- pos_inertia_neg: normality_p = 2.318693e-09; skewness = 1.27067898
  - Under negative stimuli, positive emotion inertia is strongly right-skewed: most people have low inertia in positive feelings, with a few showing strong inertia
- pos_inertia_neu: normality_p = 8.436415e-08; skewness = -0.39896752
  - For neutral stimuli, positive emotion inertia is slightly left-skewed
- neg_inertia_neu: normality_p = 1.296106e-07; skewness = 1.29575508
  - For neutral stimuli, negative emotion inertia is strongly right-skewed
- aro_inertia_neu: normality_p = 3.859573e-05; skewness = 0.71497318
  - For neutral stimuli, arousal inertia is right-skewed

0.3.2 Normalize the skewed inertia types

```r
# Transform the skewed inertia types to normal
library(bestNormalize)

skewed_vars <- c(
  "neg_inertia_pos", "pos_inertia_neg", "pos_inertia_neu",
  "neg_inertia_neu", "aro_inertia_neu"
)

inertia_long_normalized <- inertia_long %>%
  group_by(inertia_type) %>%
  mutate(
    inertia_trans = if_else(
      inertia_type %in% skewed_vars,
      orderNorm(inertia)$x.t,  # transform only these
      inertia  # leave others unchanged
    )
  )
```

```
## Warning: There were 6 warnings in `mutate()`.
## The first warning was:
## i In argument: `inertia_trans = if_else(...)`.
## i In group 3: `inertia_type = "aro_inertia_neu"`.
## Caused by warning in `orderNorm()`:
## ! Ties in data, Normal distribution not guaranteed
## i Run `dplyr::last_dplyr_warnings()` to see the 5 remaining warnings.
```

```
inertia_long_normalized
```

```
## # A tibble: 1,872 x 4
## # Groups:   inertia_type [12]
##    subj  inertia_type    inertia inertia_trans
##    <fct> <chr>             <dbl>         <dbl>
##  1 f001  pos_inertia     -0.0956       -0.0956
##  2 f001  neg_inertia     -0.149        -0.149
##  3 f001  aro_inertia     -0.139        -0.139
##  4 f001  pos_inertia_neg -0.0233        0.244
##  5 f001  pos_inertia_neu NA            NA
##  6 f001  pos_inertia_pos  0.0214        0.0214
##  7 f001  neg_inertia_neg -0.203        -0.203
##  8 f001  neg_inertia_neu NA            NA
##  9 f001  neg_inertia_pos NA            NA
## 10 f001  aro_inertia_neg -0.187        -0.187
## # i 1,862 more rows
```

0.3.3 Compare means and sd of the 12 inertia types

```
# Find mean value of each of the 12 inertia types

inertia_means <- inertia_long_normalized %>%
  group_by(inertia_type) %>%
  summarise(
    mean_inertia = mean(inertia_trans, na.rm = TRUE),
    sd_inertia = sd(inertia_trans, na.rm = TRUE),
    n = sum(!is.na(inertia_trans))
  ) %>%
  arrange(desc(abs(mean_inertia)))

inertia_means
```

```
## # A tibble: 12 x 4
##    inertia_type     mean_inertia sd_inertia     n
##    <chr>                   <dbl>      <dbl> <int>
##  1 pos_inertia     -0.0324           0.0927   156
```

```
##  2 aro_inertia_neg  0.0308           0.150    156
##  3 neg_inertia     -0.0244           0.0998   156
##  4 neg_inertia_neg  0.0242           0.151    156
##  5 aro_inertia_pos  0.00693          0.157    154
##  6 pos_inertia_pos -0.00589          0.141    156
##  7 aro_inertia      0.00482          0.103    156
##  8 neg_inertia_neu -0.0000523        0.998     95
##  9 aro_inertia_neu -0.0000440        0.998    117
## 10 pos_inertia_neg -0.0000328        0.999    140
## 11 neg_inertia_pos -0.00000932       0.999    141
## 12 pos_inertia_neu  0.0000000373     0.999    130
```

- aro_inertia_neu: Extremely high SD (0.998) — suggests arousal inertia under neutral stimuli varies greatly across individuals
- neg_inertia_pos: Negative near-zero mean (-9.32e-06) but very high variance (sd = 0.999);
  - Negative emotion is likely to bounce back after positive stimuli, but the effect is extremely small
  - There's huge individual differences
- pos_inertia_neg: Negative near-zero mean (-3.28e-05) but very high variance (sd = 0.999);
  - Positive emotion is likely to bounce back after negative stimuli, but the effect is also small
  - There's huge individual differences
- aro_inertia_neg (mean = 0.031): clear positive inertia — arousal tends to linger more after negative stimuli
- neg_inertia_neg (mean = 0.024): negative emotions tend to persist more after negative stimuli
- **neg_inertia (mean = -0.024) vs. pos_inertia (mean = -0.032)**:
  - They both have negative mean — both neg and pos emotions drop off quickly
  - **neg_inertia is bigger than pos_inertia: negative emotions tend to last slightly longer than positive emotions** (Positive emotions bounce back faster than negative emotions)
- **neg_inertia_pos (mean = -9.32e-06) vs. pos_inertia_neg (-3.28e-05)**:
  - **Emotions tend to reset quickly when the stimulus is the opposite, meaning that people are likely to be affected by opposite stimuli**
  - **Positive emotions may dissipate faster in response to negative stimuli than negative emotions do in response to positive ones (positive emotion is more likely to be affected by negative stimuli)**

0.3.4 Compare emotional inertia types (pos_inertia, neg_inertia, aro_inertia) by demographics

```r
# Pivot transformed inertia data to wide format

inertia_wide_trans <- inertia_long_normalized %>%
  select(subj, inertia_type, inertia_trans) %>%
  tidyr::pivot_wider(
    names_from = inertia_type,
    values_from = inertia_trans
  )

# Extract demographic info from your original dat

demo_info <- dat %>%
  select(subj, sex, age, ethn) %>%
  distinct()

# Merge the transformed inertia data with demographics
inertia_full <- inertia_wide_trans %>%
  left_join(demo_info, by = "subj")
inertia_full
```

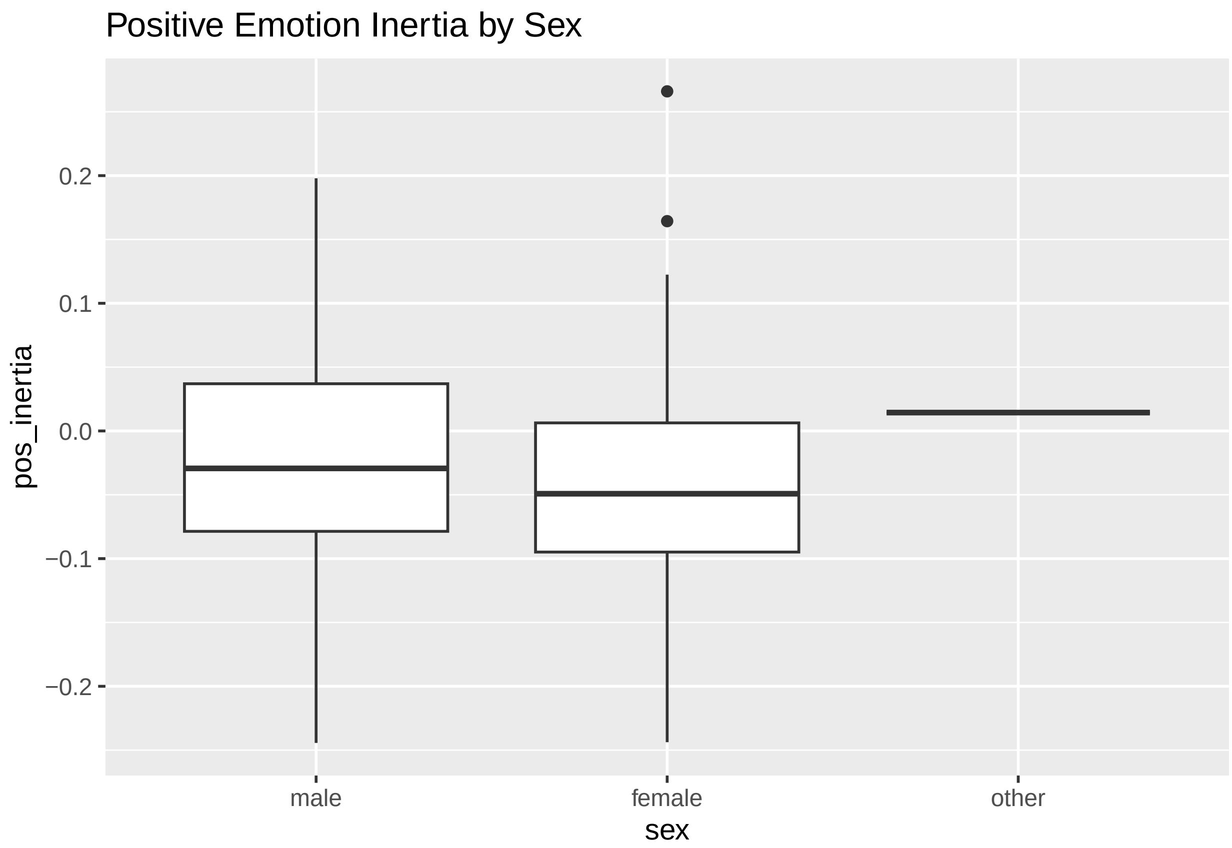
```
## # A tibble: 156 x 16
##    subj  pos_inertia neg_inertia aro_inertia pos_inertia_neg pos_inertia_neu
##    <fct>       <dbl>       <dbl>       <dbl>           <dbl>           <dbl>
##  1 f001      -0.0956     -0.149      -0.139            0.244         NA
##  2 f002       0.0187      0.0682      0.0974           0.244         -0.184
##  3 f003      -0.0855     -0.143       0.0149           0.935         -0.145
##  4 f004       0.0648     -0.0705      0.0150          -0.779          0.535
##  5 f005      -0.0433     -0.0918     -0.0962           1.49           0.0579
##  6 f006      -0.0750      0.160       0.175           -1.08          -0.581
##  7 f007       0.0834      0.0245      0.190            0.244         -0.0869
##  8 f008      -0.0125     -0.0254      0.00949          0.641         -1.10
##  9 f009       0.0162      0.0865     -0.136           -0.434          0.724
## 10 f010       0.164       0.110       0.0143           0.244          0.699
## # i 146 more rows
## # i 10 more variables: pos_inertia_pos <dbl>, neg_inertia_neg <dbl>,
## #   neg_inertia_neu <dbl>, neg_inertia_pos <dbl>, aro_inertia_neg <dbl>,
## #   aro_inertia_neu <dbl>, aro_inertia_pos <dbl>, sex <fct>, age <int>,
## #   ethn <fct>
```

```r
# Inertia types by Sex / Ethnicity (categorical)

# By sex
inertia_full %>%
```

```r
  group_by(sex) %>%
  summarise(across(starts_with("pos_inertia"):starts_with("aro_inertia"), ~mean(., na.rm = TRUI
```

```
## Warning: There was 1 warning in `summarise()`.
## i In argument: `across(...)`.
## Caused by warning in `x:y`:
## ! numerical expression has 4 elements: only the first used

## # A tibble: 3 x 4
##   sex    pos_inertia neg_inertia aro_inertia
##   <fct>        <dbl>       <dbl>       <dbl>
## 1 male       -0.0206     -0.0241     -0.0107
## 2 female     -0.0432     -0.0245      0.0188
## 3 other       0.0144     -0.0339     -0.0359
```

```r
# Visualize
ggplot(inertia_full, aes(x = sex, y = pos_inertia)) +
  geom_boxplot() +
  labs(title = "Positive Emotion Inertia by Sex")
```



- **Females have much lower positive inertia (-0.043) than males (-0.021) -> quicker drop in positive feelings**

- **Females have higher arousal inertia (0.019) than males (-0.011) -> more sustained arousal**
- It's surprising that neg_inertia is about the same for male and female, considering that females are twice as likely as males to get depression based on reports

```
# By ethnicity
inertia_full %>%
  group_by(ethn) %>%
  summarise(across(starts_with("pos_inertia"):starts_with("aro_inertia"), ~mean(., na.rm = TRUE
```

```
## Warning: There was 1 warning in 'summarise()'.
## i In argument: 'across(...)'.
## Caused by warning in 'x:y':
## ! numerical expression has 4 elements: only the first used
```

```
## # A tibble: 7 x 4
##   ethn                                       pos_inertia neg_inertia aro_inertia
##   <fct>                                            <dbl>       <dbl>       <dbl>
## 1 Asian or Pacific Islander                      -0.0460     -0.0169     0.00867
## 2 Black/African American                          0.00711    -0.0267    -0.00710
## 3 Latino/Hispanic                                -0.0172     -0.0306     0.00750
## 4 Other                                          -0.0102     -0.0207     0.0640
## 5 White/Caucasian                                -0.0373     -0.0327    -0.00488
## 6 American Indian/Native American or Alaska~     -0.0393      0.0856     0.0272
## 7 Decline to state                               -0.0831      0.00606    0.0983
```

- **American Indian/Native American or Alaskan Native: the only group with positive neg_inertia -> tend to stay in negative states longer**
- **Black/African American: the only group with pos_inertia -> tend to stay in positive states longer (which is unexpected)**
- **White/Caucasian: the only group with negative inertia across all three emotions -> tend to bounce back quickly overall (emotionally adaptive).**
  - This may reflect greater access to resources, social safety nets, and less exposure to systemic stressors for White people.
- Both "Other" and "Decline to state" have much higher aro_inertia than others.
  - This may suggest that the people who are less confident or more confused about their identities are likely to face heightened stress, social vigilance, or lack of belonging–all known to elevate arousal.

```
# Inertia types by Age (continuous)

inertia_full %>%
  summarise(across(
    starts_with("pos_inertia"):starts_with("aro_inertia"),
    ~ cor(., age, use = "complete.obs")
  ))
```

```
## Warning: There was 1 warning in `summarise()`.
## i In argument: `across(...)`.
## Caused by warning in `x:y`:
## ! numerical expression has 4 elements: only the first used
```

```
## # A tibble: 1 x 3
##   pos_inertia neg_inertia aro_inertia
##         <dbl>       <dbl>       <dbl>
## 1     -0.0107      -0.128      0.0286
```

- As age increases, neg_inertia (-0.128) decreases more than pos_inertia (-0.011).
  - Negative emotions drop significantly faster with increasing age -> **older participants are more resilient to negative emotions**
- Arousal shows a slight increase with age (0.029)

0.3.5 Compare the effect of trial types (pos, neg, neu) by demographics

```
# By sex
inertia_full %>%
  group_by(sex) %>%
  summarise(across(("pos_inertia_neg"):("aro_inertia_pos"), ~ mean(., na.rm = TRUE)))
```

```
## # A tibble: 3 x 10
##   sex    pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##   <fct>            <dbl>           <dbl>           <dbl>           <dbl>
## 1 male             0.126         -0.0479       -0.000842          0.0250
## 2 female          -0.0984         0.0620       -0.0106            0.0239
## 3 other           -0.881         -1.51          0.0190            0.00201
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

- pos_inertia_neg: male(0.1255) vs. female(-0.0984)
  - **Females tend to lose positive emotions quickly in response to negative stimuli**
- neg_inertia_pos: male (-0.0489) vs. female(0.0297)
  - **Females are more likely to retain negative emotions even with positive stimuli -> showing difficulty to let go of negativity**
- This may partly explain why females are more likely to get depression
- Female: pos_inertia = -0.0432 vs. pos_inertia_neu = 0.0620

  - **It's weird that pos_inertia shows that females generally lose positive emotions quickly, but pos_inertia_neu shows that females tend to retain positive emotions under neutral stimuli**

```
# by age
inertia_full %>%
  summarise(across(("pos_inertia_neg"):("aro_inertia_pos"), ~ cor(., age, use = "complete.obs"
```

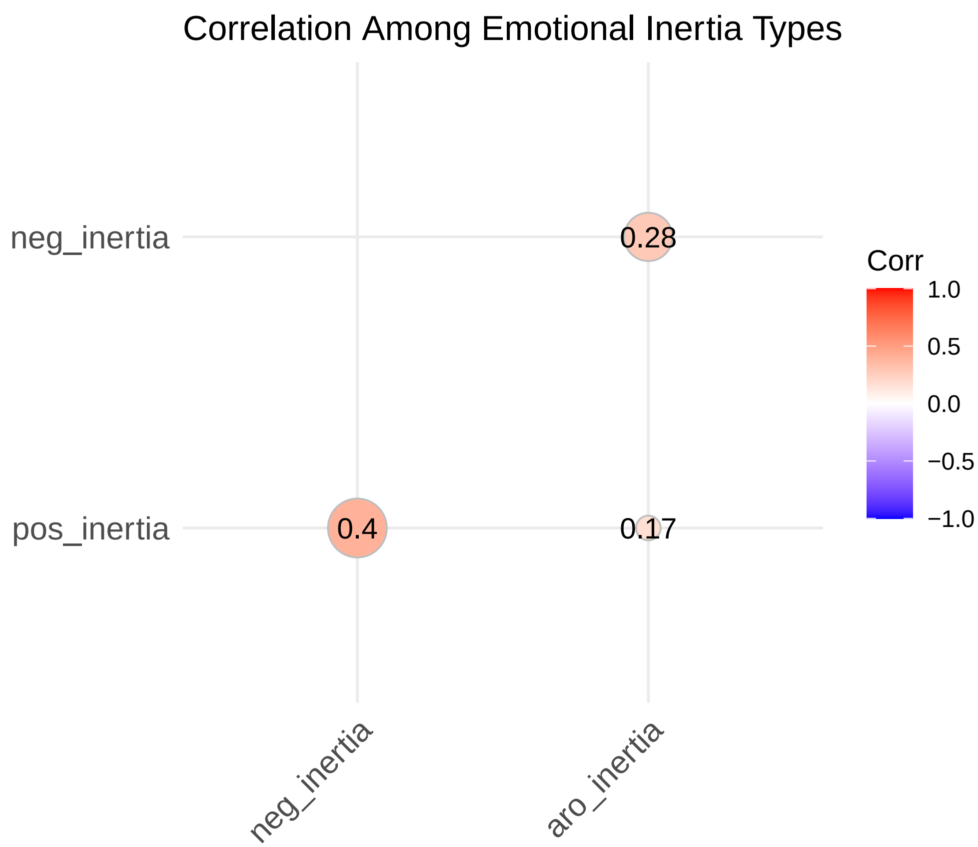
```
## # A tibble: 1 x 9
##   pos_inertia_neg pos_inertia_neu pos_inertia_pos neg_inertia_neg
##             <dbl>           <dbl>           <dbl>           <dbl>
## 1         -0.0459          -0.196          0.0220          0.0270
## # i 5 more variables: neg_inertia_neu <dbl>, neg_inertia_pos <dbl>,
## #   aro_inertia_neg <dbl>, aro_inertia_neu <dbl>, aro_inertia_pos <dbl>
```

0.3.6 Correlation between inertia types

```
inertia_core <- inertia_full %>%
  select(subj, pos_inertia, neg_inertia, aro_inertia)
cor_matrix <- cor(inertia_core[,-1], use = "complete.obs")
cor_matrix
```

```
##             pos_inertia neg_inertia aro_inertia
## pos_inertia   1.0000000   0.4013880   0.1681746
## neg_inertia   0.4013880   1.0000000   0.2784501
## aro_inertia   0.1681746   0.2784501   1.0000000
```

```
library(ggcorrplot)

ggcorrplot(cor_matrix,
           method = "circle",
           type = "lower",
           lab = TRUE,
           title = "Correlation Among Emotional Inertia Types")
```



- `pos_inertia` and `neg_inertia` have moderate positive correlation: people who tend to hold onto positive emotions also tend to hold onto negative emotions, suggesting emotional stickiness
- `aro_inertia` and `neg_inertia` have small-to-moderate positive correlation: those who hold onto negative emotions also tend to stay aroused longer

0.4 Manova: inertia types by sex

How different inertia types (pos_inertia, neg_inertia, aro_inertia) vary by sex?

```
manova_model <- manova(cbind(pos_inertia, neg_inertia, aro_inertia) ~ sex, data = inertia_full)
summary(manova_model, test = "Wilks")
```

```
##             Df   Wilks approx F num Df den Df Pr(>F)
## sex          2 0.95394   1.2009      6    302 0.3056
## Residuals 153
```

- Wilks' Lambda = 0.954 -> near 1, meaning the difference is small
- P-value = 0.3056, which is not significant
- Conclusion: **the difference of pos_inertia, neg_inertia, aro_inertia between sex is not significant**

Test each inertia type separately:

```r
summary.aov(manova_model)
```

```
##  Response pos_inertia :
##              Df  Sum Sq   Mean Sq F value Pr(>F)
## sex           2 0.02199 0.0109960  1.2839 0.2799
## Residuals   153 1.31040 0.0085647
##
##  Response neg_inertia :
##              Df Sum Sq   Mean Sq F value Pr(>F)
## sex           2 0.0001 0.0000492  0.0049 0.9951
## Residuals   153 1.5448 0.0100965
##
##  Response aro_inertia :
##              Df Sum Sq  Mean Sq F value Pr(>F)
## sex           2 0.0353 0.017652  1.6816 0.1895
## Residuals   153 1.6061 0.010497
```

- Also shows not significant for each of the 3 inertia types

0.5 CLPM

0.5.1 Estimate inertia score of positive, negative, and arousal emotions

```r
library(lavaan)
```

```
## This is lavaan 0.6-19
## lavaan is FREE software! Please report any bugs.
```

```
##
## Attaching package: 'lavaan'
```

```
## The following object is masked from 'package:psych':
##
##     cor2cov
```

```r
library(dplyr)

clpm_data <- dat %>%
  arrange(subj, trial.num) %>%
  group_by(subj) %>%
  mutate(
    Ipos_lag1 = lag(Ipos),
```

```r
    Ineg_lag1 = lag(Ineg),
    Iaro_lag1 = lag(Iaro)
  ) %>%
  filter(!is.na(Ipos_lag1))

model_inertia <- '
  # Autoregressive (inertia) paths
  Ipos ~ a1 * Ipos_lag1
  Ineg ~ a2 * Ineg_lag1
  Iaro ~ a3 * Iaro_lag1
'

fit <- sem(model_inertia, data = clpm_data)
summary(fit, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 28 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                         9
##
##   Number of observations                         16224
##
## Model Test User Model:
##
##   Test statistic                              1402.952
##   Degrees of freedom                                 6
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             17555.797
##   Degrees of freedom                                12
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.920
##   Tucker-Lewis Index (TLI)                       0.841
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -103647.128
##   Loglikelihood unrestricted model (H1)    -102945.652
##
##   Akaike (AIC)                              207312.257
##   Bayesian (BIC)                            207381.505
```

```
##   Sample-size adjusted Bayesian (SABIC)     207352.904
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.120
##   90 Percent confidence interval - lower         0.115
##   90 Percent confidence interval - upper         0.125
##   P-value H_0: RMSEA <= 0.050                    0.000
##   P-value H_0: RMSEA >= 0.080                    1.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.082
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.200    0.006   33.112    0.000    0.200    0.194
##   Ineg ~
##     Ineg_lag1 (a2)    0.202    0.006   34.422    0.000    0.202    0.196
##   Iaro ~
##     Iaro_lag1 (a3)    0.329    0.006   55.531    0.000    0.329    0.333
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.668    0.061  -60.479    0.000   -3.668   -0.540
##    .Iaro              1.199    0.040   29.621    0.000    1.199    0.239
##  .Ineg ~~
##    .Iaro              1.897    0.042   44.857    0.000    1.897    0.376
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              6.764    0.075   90.067    0.000    6.764    0.962
##    .Ineg              6.835    0.076   90.067    0.000    6.835    0.962
##    .Iaro              3.720    0.041   90.067    0.000    3.720    0.889
```

- Positive inertia (0.200) and negative inertia (0.202) are about the same. Negative is slightly higher than positive.
- Arousal inertia (0.329) is much higher than the other two, meaning that arousal emotion is likely to persist.

0.5.2 Cross-lag paths (how one emotion affect another at the next time point)

```r
model_clpm <- '
  # Autoregressive (inertia) paths
  Ipos ~ a1 * Ipos_lag1
  Ineg ~ a2 * Ineg_lag1
  Iaro ~ a3 * Iaro_lag1

  # Cross-lagged paths
  Ipos ~ b1 * Ineg_lag1 + b2 * Iaro_lag1
  Ineg ~ c1 * Ipos_lag1 + c2 * Iaro_lag1
  Iaro ~ d1 * Ipos_lag1 + d2 * Ineg_lag1
'

fit_clpm <- sem(model_clpm, data = clpm_data)
summary(fit_clpm, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 30 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        15
##
##   Number of observations                         16224
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Model Test Baseline Model:
##
##   Test statistic                             17555.797
##   Degrees of freedom                                12
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    1.000
##   Tucker-Lewis Index (TLI)                       1.000
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -102945.652
##   Loglikelihood unrestricted model (H1)    -102945.652
##
```

```
##   Akaike (AIC)                              205921.305
##   Bayesian (BIC)                            206036.718
##   Sample-size adjusted Bayesian (SABIC)     205989.049
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.000
##   90 Percent confidence interval - lower         0.000
##   90 Percent confidence interval - upper         0.000
##   P-value H_0: RMSEA <= 0.050                       NA
##   P-value H_0: RMSEA >= 0.080                       NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.000
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.137    0.011   12.869    0.000    0.137    0.137
##   Ineg ~
##     Ineg_lag1 (a2)    0.143    0.011   12.894    0.000    0.143    0.143
##   Iaro ~
##     Iaro_lag1 (a3)    0.414    0.009   43.903    0.000    0.414    0.414
##   Ipos ~
##     Ineg_lag1 (b1)    0.165    0.011   14.920    0.000    0.165    0.166
##     Iaro_lag1 (b2)    0.010    0.012    0.795    0.427    0.010    0.008
##   Ineg ~
##     Ipos_lag1 (c1)    0.173    0.011   16.158    0.000    0.173    0.172
##     Iaro_lag1 (c2)   -0.008    0.013   -0.650    0.516   -0.008   -0.007
##   Iaro ~
##     Ipos_lag1 (d1)   -0.043    0.008   -5.289    0.000   -0.043   -0.053
##     Ineg_lag1 (d2)   -0.063    0.008   -7.507    0.000   -0.063   -0.078
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.425    0.058  -59.271    0.000   -3.425   -0.526
##    .Iaro              1.218    0.040   30.743    0.000    1.218    0.249
##  .Ineg ~~
##    .Iaro              1.886    0.041   45.562    0.000    1.886    0.383
##
```

```
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              6.482    0.072   90.067    0.000    6.482    0.974
##    .Ineg              6.549    0.073   90.067    0.000    6.549    0.975
##    .Iaro              3.700    0.041   90.067    0.000    3.700    0.860
```

- Arousal inertia (0.414) is much higher than positive inertia (0.137) and negative inertia (0.143)
- Ipos ~ Ineg_lag1 (0.165): negative emotion predicts positive emotion in the next moment, which might reflect emotional rebound
- Ineg ~ Ipos_lag1 (0.173): positive emotion enhances negative emotion in the next moment, which might reflect emotional mix or trial order effect
- Iaro ~ Ipos_lag1 (-0.043): positive emotion decreases arousal at the later stage
- Iaro ~ Ineg_lag1 (-0.063): negative emotion decreases arousal at the later stage
- Ipos ~ Iaro_lag1 and Ineg ~ Iaro_lag1 are not significant
- Conclusion:
  - **Both positive and negative emotions predict more of the opposite in the next moment — possibly due to Emotion regulation attempts, Rebound effects, and Task structure**
  - **Arousal is reduced by both positive and negative emotions** — maybe a sign of emotional resolution or recovery

0.5.3 Difference in paths by sex

```r
# Group by sex

fit_clpm_sex <- sem(model_clpm,
                    data = clpm_data,
                    group = "sex")
```

```
## Warning: lavaan->lavParTable():
##    using a single label per parameter in a multiple group setting implies
##    imposing equality constraints across all the groups; If this is not
##    intended, either remove the label(s), or use a vector of labels (one for
##    each group); See the Multiple groups section in the man page of
##    model.syntax.
```

```r
summary(fit_clpm_sex, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 161 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        54
##   Number of equality constraints                    18
##
##   Number of observations per group:
##     female                                        8632
##     other                                          104
##     male                                          7488
##
## Model Test User Model:
##
##   Test statistic                                70.669
##   Degrees of freedom                                18
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
##     female                                      19.632
##     other                                       30.323
##     male                                        20.714
##
## Model Test Baseline Model:
##
##   Test statistic                             17419.660
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.997
##   Tucker-Lewis Index (TLI)                       0.994
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -102756.204
##   Loglikelihood unrestricted model (H1)    -102720.870
##
##   Akaike (AIC)                              205584.409
##   Bayesian (BIC)                            205861.402
##   Sample-size adjusted Bayesian (SABIC)     205746.996
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.023
##   90 Percent confidence interval - lower         0.018
##   90 Percent confidence interval - upper         0.029
##   P-value H_0: RMSEA <= 0.050                    1.000
```

```
##   P-value H_0: RMSEA >= 0.080                    0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.011
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [female]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.136
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.137
##   Iaro ~
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.413
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.164
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.166
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.007
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.058
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.083
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -3.913    0.087  -44.726    0.000   -3.913   -0.549
##    .Iaro              1.264    0.058   21.802    0.000    1.264    0.241
##  .Ineg ~~
##    .Iaro              2.077    0.061   34.120    0.000    2.077    0.395
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.204    0.057   38.710    0.000    2.204    0.818
##    .Ineg              2.299    0.057   40.163    0.000    2.299    0.850
##    .Iaro              2.366    0.043   55.253    0.000    2.366    1.118
##
## Variances:
```

```
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              7.090    0.108   65.696    0.000    7.090    0.977
##    .Ineg              7.158    0.109   65.696    0.000    7.158    0.978
##    .Iaro              3.866    0.059   65.696    0.000    3.866    0.863
##
##
## Group 2 [other]:
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.132
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.134
##   Iaro ~
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.356
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.213
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.121
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.005
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.048
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.093
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -1.115    0.287   -3.881    0.000   -1.115   -0.412
##    .Iaro             -0.095    0.175   -0.541    0.589   -0.095   -0.053
##  .Ineg ~~
##    .Iaro              1.072    0.258    4.149    0.000    1.072    0.445
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              1.176    0.144    8.159    0.000    1.176    0.815
##    .Ineg              2.231    0.192   11.631    0.000    2.231    1.155
##    .Iaro              1.197    0.127    9.441    0.000    1.197    0.900
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.003    0.278    7.211    0.000    2.003    0.962
##    .Ineg              3.667    0.508    7.211    0.000    3.667    0.983
##    .Iaro              1.581    0.219    7.211    0.000    1.581    0.894
##
##
## Group 3 [male]:
```

```
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Ipos ~
##     Ipos_lag1 (a1)    0.136    0.011   12.796    0.000    0.136    0.136
##   Ineg ~
##     Ineg_lag1 (a2)    0.137    0.011   12.379    0.000    0.137    0.137
##   Iaro ~
##     Iaro_lag1 (a3)    0.408    0.009   43.375    0.000    0.408    0.402
##   Ipos ~
##     Ineg_lag1 (b1)    0.163    0.011   14.827    0.000    0.163    0.163
##     Iaro_lag1 (b2)    0.005    0.012    0.385    0.700    0.005    0.004
##   Ineg ~
##     Ipos_lag1 (c1)    0.167    0.011   15.630    0.000    0.167    0.166
##     Iaro_lag1 (c2)   -0.009    0.012   -0.705    0.481   -0.009   -0.007
##   Iaro ~
##     Ipos_lag1 (d1)   -0.045    0.008   -5.657    0.000   -0.045   -0.055
##     Ineg_lag1 (d2)   -0.065    0.008   -7.826    0.000   -0.065   -0.079
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .Ipos ~~
##    .Ineg             -2.915    0.075  -38.669    0.000   -2.915   -0.500
##    .Iaro              1.155    0.054   21.448    0.000    1.155    0.256
##  .Ineg ~~
##    .Iaro              1.651    0.056   29.644    0.000    1.651    0.365
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              2.062    0.053   39.082    0.000    2.062    0.844
##    .Ineg              2.033    0.053   38.352    0.000    2.033    0.830
##    .Iaro              2.178    0.040   54.163    0.000    2.178    1.083
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Ipos              5.821    0.095   61.188    0.000    5.821    0.975
##    .Ineg              5.849    0.096   61.188    0.000    5.849    0.976
##    .Iaro              3.504    0.057   61.188    0.000    3.504    0.867
```

- Most of the paths are similar between men and women
- Only arousal inertia for women is slightly higher than men

```
# Check for significant difference between men and women

model_clpm_free <- '
  # Inertia paths
  Ipos ~ c(a1f, a1m, a1o)*Ipos_lag1
```

```r
  Ineg ~ c(a2f, a2m, a2o)*Ineg_lag1
  Iaro ~ c(a3f, a3m, a3o)*Iaro_lag1

  # Cross-lag
  Ipos ~ c(b1f, b1m, b1o)*Ineg_lag1 + c(b2f, b2m, b2o)*Iaro_lag1
  Ineg ~ c(c1f, c1m, c1o)*Ipos_lag1 + c(c2f, c2m, c2o)*Iaro_lag1
  Iaro ~ c(d1f, d1m, d1o)*Ipos_lag1 + c(d2f, d2m, d2o)*Ineg_lag1
'


fit_free <- sem(model_clpm_free, data = clpm_data, group = "sex")

# Whether there's significant difference between sex in at least one path
anova(fit_clpm_sex, fit_free)
```

```
##
## Chi-Squared Difference Test
##
##              Df    AIC    BIC  Chisq Chisq diff    RMSEA Df diff Pr(>Chisq)
## fit_free      0 205550 205965  0.000
## fit_clpm_sex 18 205584 205861 70.669     70.669 0.023261      18  3.482e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- This shows that at least one or more paths (inertia or cross-lag) differ between males and females

```r
# Check which paths are significantly different

lavTestScore(fit_clpm_sex)
```

```
## $test
##
## total score test:
##
##    test     X2 df p.value
## 1 score 68.394 18       0
##
## $uni
##
## univariate score tests:
##
##     lhs op   rhs     X2 df p.value
## 1   .p1. == .p28.  0.493  1   0.483
## 2   .p1. == .p55.  3.462  1   0.063
## 3   .p2. == .p29.  3.167  1   0.075
```

```
## 4   .p2. == .p56.  1.512  1   0.219
## 5   .p3. == .p30. 10.313  1   0.001
## 6   .p3. == .p57. 17.559  1   0.000
## 7   .p4. == .p31.  3.800  1   0.051
## 8   .p4. == .p58.  1.048  1   0.306
## 9   .p5. == .p32.  0.254  1   0.614
## 10  .p5. == .p59.  0.120  1   0.729
## 11  .p6. == .p33.  1.387  1   0.239
## 12  .p6. == .p60.  1.372  1   0.241
## 13  .p7. == .p34.  0.082  1   0.775
## 14  .p7. == .p61.  0.722  1   0.396
## 15  .p8. == .p35.  0.353  1   0.552
## 16  .p8. == .p62.  3.460  1   0.063
## 17  .p9. == .p36.  0.131  1   0.717
## 18  .p9. == .p63.  2.193  1   0.139
```

- .p3. vs. .p30. and .p3. vs. .p57. are significant ($p < 0.05$)

```r
# Understand which paths are them

pe <- parameterEstimates(fit_clpm_sex, standardized = TRUE)
pe[c(3, 30, 57), c("lhs", "op", "rhs", "group", "est", "std.all")]
```

```
##     lhs op       rhs group   est std.all
## 3   Iaro  ~ Iaro_lag1     1 0.408   0.413
## 30  Iaro  ~ Iaro_lag1     2 0.408   0.356
## 57  Iaro  ~ Iaro_lag1     3 0.408   0.402
```

- females (0.413) and males (0.402) are significantly different in arousal inertia
- females (0.413) and other (0.356) are also significantly different in arousal inertia