model selection

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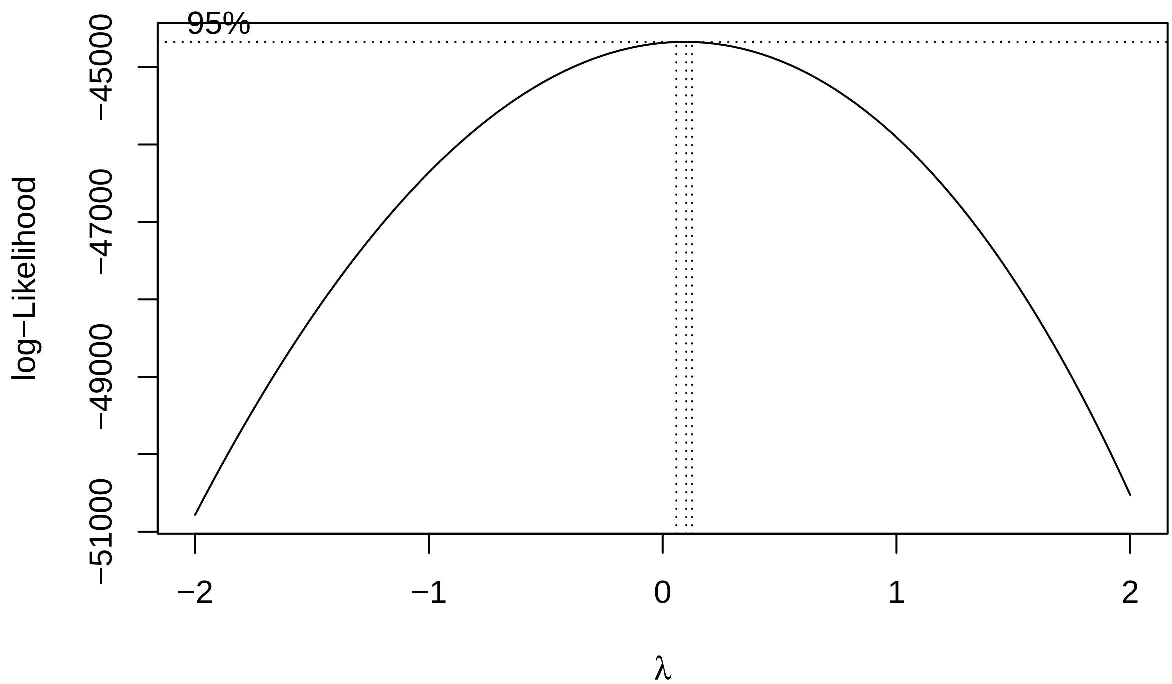
```
## Rows: 12000 Columns: 8
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): feedback
## dbl (7): code, block, trial, input_noise_magnitude, inpnoise_ascending, SoC,...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
## Rows: 48 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (4): ID, InternalLC, ExternalLC, CESDR
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Create one dataset containing both the experimental data and the questionnaire scores. Furthermore, exclude participant 12 and 14 from all statistical analyses.

Model selection for a linear model predicting performance (average distance to line throughout trial)

Distributional analysis:




```
## [1] 0.1010101
```

referring to: https://www.statisticshowto.com/probability-and-statistics/normal-distributions/box-cox-transformation/

lambda, the expected value is close to 0.0, implying a log transformation.

null model to explore random intercept effects

predict mean (independent of any predictors) performance rating

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: log(avg_dist_trialwise) ~ 1 + (1 | code)
##    Data: all_data
##
## REML criterion at convergence: 12763.5
##
## Scaled residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -3.3845 -0.7802 -0.0472  0.7711  4.1837
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02931  0.1712
##  Residual             0.17450  0.4177
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##             Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  3.48315    0.02502 46.99997   139.2   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

How much variance in performance is explained by the individual random intercept effect *code*?

```
## [1] 0.0008590761
```

Exploring fixed effects by likelihood ratio tests

We start with the most complex fixed effects structure (simply throwing fixed effects in the model that are specified by our hypotheses). Then we will test this model against less complex ones (where we eliminate individual fixed effects). For the model that predicts performance that is not overly complex…

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 |
##     code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   2371.6   2415.7  -1179.8   2359.6    11514
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8486 -0.6414 -0.0028  0.6533  6.6424
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02885  0.1699
##  Residual             0.07050  0.2655
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  3.261e+00  2.586e-02  5.825e+01 126.077  < 2e-16
## input_noise_magnitude2       5.849e-01  1.161e-02  1.150e+04  50.397  < 2e-16
## block                       -2.090e-02  1.601e-03  1.149e+04 -13.055  < 2e-16
## input_noise_magnitude2:block  1.100e-02  2.331e-03  1.150e+04   4.718  2.4e-06
##
## (Intercept)                 ***
```

```
## input_noise_magnitude2       ***
## block                        ***
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) inp__2 block
## inpt_ns_mg2 -0.239
## block       -0.289  0.686
## inpt_ns_m2:  0.213 -0.904 -0.737
```

And we only find significant effects. We can still try to eliminate the interaction effect and see what happens.

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(avg_dist_trialwise) ~ input_noise_magnitude + block + (1 |
##     code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   2391.8   2428.6  -1190.9   2381.8    11515
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9130 -0.6470 -0.0059  0.6558  6.6470
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02912  0.1706
##  Residual             0.07063  0.2658
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            3.235e+00  2.539e-02  5.308e+01  127.43   <2e-16 ***
## input_noise_magnitude2  6.345e-01  4.965e-03  1.147e+04  127.80   <2e-16 ***
## block                 -1.533e-02  1.083e-03  1.147e+04  -14.15   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) inp__2
## inpt_ns_mg2 -0.111
## block       -0.199  0.070
```

```
## Data: all_data
## Models:
## model1.1: log(avg_dist_trialwise) ~ input_noise_magnitude + block + (1 | code)
## model1.complex: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 | code)
##                npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model1.1          5 2391.8 2428.6 -1190.9   2381.8
## model1.complex    6 2371.6 2415.7 -1179.8   2359.6 22.241  1  2.404e-06 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We detect significance. That means that if we were to eliminate the interaction term, we would take out something crucial that reduces predictive power of our model. We will thus stick to model1.complex.

Exploring random slope effects by referring to BIC

Now that we identified the fixed effects in our model we can work on the random effects structure. When it comes to selecting random slope effects though, the likelihood ratio test won't be sufficient anymore (not for comparing models with different random effects structures). Random slopes "open up" the fixed effects for the different groups of our random intercept effects: they split the model apart by introducing a lot more parameters. We can select random slope effects by referring to an **information criterion**. I usually use the **Bayes information criterion (BIC)**. It penalizes the number of data points used to fit the model (on top of the number of parameters). I like the idea of accounting for overfitting when selecting models. (An alternative to the BIC is the **Akaike information criterion (AIC)**, which only penalizes the number of parameters.)

Here we will start with the most complex random effects structure and reduce the complexity further and further until we don't detect singularity anymore or the BIC won't go smaller anymore (smaller BICs are preferred).

Just entering all the fixed effects as random slopes.

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.0196131 (tol = 0.002, component 1)
```

Failed to converge. Eliminating the interaction term in the random slope structure.

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.0392893 (tol = 0.002, component 1)
```

Also failed to converge. Only entering single random slope effects.

Let's compare these with the random intercept only model:

```
## Data: all_data
## Models:
## model1.complex: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 | code)
## model1.in: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 + input_noise_magnitude | co
## model1.bl: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 + block | code)
##                npar    AIC    BIC   logLik deviance  Chisq Df Pr(>Chisq)
## model1.complex    6 2371.6 2415.7 -1179.80   2359.6
## model1.in         8 1373.1 1431.9  -678.53   1357.1 1002.5  2  < 2.2e-16 ***
## model1.bl         8 2171.2 2230.0 -1077.59   2155.2    0.0  0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

model1.in, the model with input noise as random slope effect wins (it haas the smallest BIC). Now we can take a look at the main effects.

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(avg_dist_trialwise) ~ input_noise_magnitude * block + (1 +
##     input_noise_magnitude | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   1373.1   1431.9   -678.5   1357.1    11512
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.0672 -0.6422  0.0043  0.6344  6.8987
##
## Random effects:
##  Groups   Name                   Variance Std.Dev. Corr
##  code     (Intercept)            0.05848  0.2418
##           input_noise_magnitude2 0.02570  0.1603   -0.93
##  Residual                        0.06404  0.2531
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  3.259e+00  3.583e-02  5.232e+01  90.972  < 2e-16
## input_noise_magnitude2       5.844e-01  2.565e-02  6.673e+01  22.786  < 2e-16
## block                       -2.058e-02  1.580e-03  1.147e+04 -13.028  < 2e-16
## input_noise_magnitude2:block  1.116e-02  2.219e-03  1.147e+04   5.029 5.01e-07
##
## (Intercept)                 ***
## input_noise_magnitude2      ***
## block                       ***
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) inp__2 block
## inpt_ns_mg2 -0.889
## block       -0.206  0.289
## inpt_ns_m2:  0.147 -0.390 -0.717
```

Transform estimates back

means:

```
## (Intercept)
##    26.03315
```

```
## input_noise_magnitude2
##               1.793836
```

```
##    block
## 1.020792
```

```
## input_noise_magnitude2:block
##                     1.011219
```

standard errors:

```
## [1] "intercept:"

## [1] 1.036478

## [1] "input_noise_magnitude2:"

## [1] 1.025978

## [1] "block:"

## [1] 1.001581

## [1] "input_noise_magnitude2*block:"

## [1] 1.002221
```

...and run simulations based on the final selected model...

Generaring simulations based on the final selected model

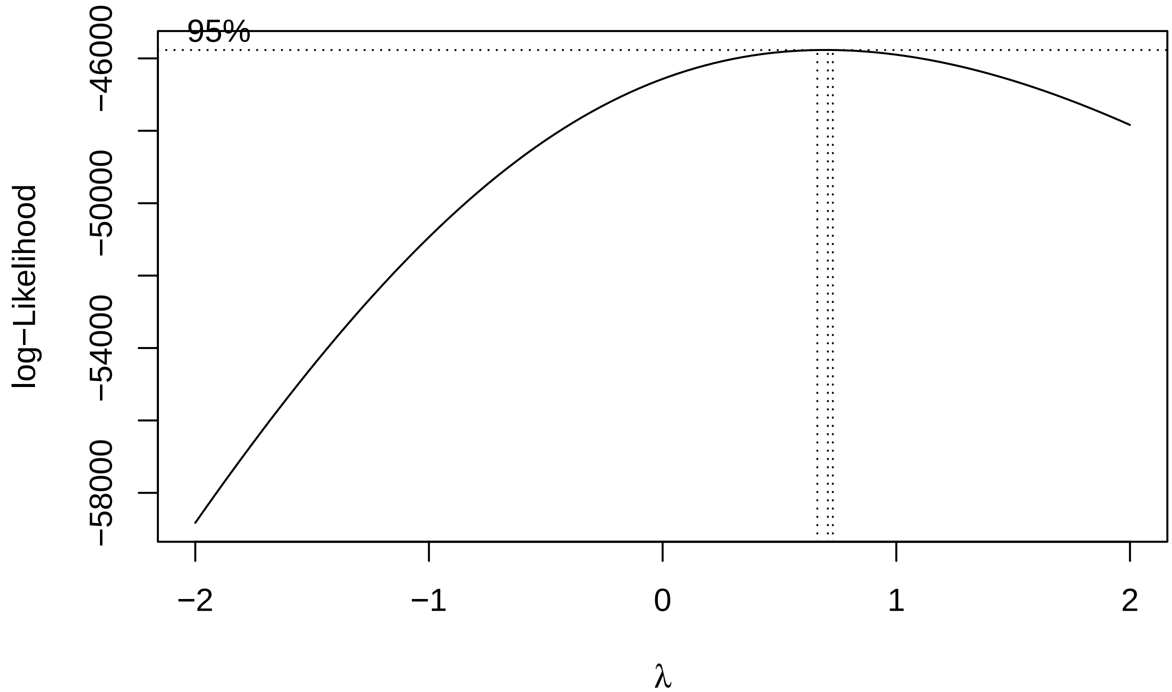
parametric bootstrap:

```
## Computing bootstrap confidence intervals ...

##
## 503 warning(s): Model failed to converge with max|grad| = 0.00200334 (tol = 0.002, component 1) (and

##                                     2.5 %      97.5 %
## input_noise_magnitude2        0.533586052  0.63558477
## block                        -0.023676032 -0.01747090
## input_noise_magnitude2:block  0.006779193  0.01549945

## [1] "input_noise_magnitude2:"

## [1] 1.705036

## [1] 1.888126

## [1] "block:"

## [1] -1.023959

## [1] -1.017624

## [1] "input_noise_magnitude2*block:"

## [1] 1.006802

## [1] 1.01562
```

"Compared to input noise magnitude 0.5, input noise magnitude 2.0 significantly increased the average distance to the line followed throughout a trial (beta=1.794, sigma=1.026, CI=[1.705, 1.888], p<.001)."

Model selection for a linear model predicting SoC

Distributional analysis:




```
## [1] 0.7070707
```

referring to: https://www.statisticshowto.com/probability-and-statistics/normal-distributions/box-cox-transformation/

lambda, the expected value is closer to 0.5 than 1 (1 would be ideal, suggesting no transformation). 0.5 implies a square root transformation, which we will apply. "a boxcox distributional analysis implied a square root transformation of the predicted variable"

null model to explore random intercept effects

predict mean (independent of any predictors) SoC rating

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: sqrt(SoC) ~ 1 + (1 | code)
##    Data: all_data
##
## REML criterion at convergence: 13270.3
##
```

```
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.90771 -0.65311  0.09259  0.79177  2.56225
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.03609  0.1900
##  Residual             0.18223  0.4269
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##             Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  1.93698    0.02771 47.00000   69.91   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

How much variance in SoC Ratings is explained by the individual random intercept effects?

```
## [1] 0.001302488
```

Exploring fixed effects by likelihood ratio tests

We start with the most complex fixed effects structure (simply throwing fixed effects in the model that are specified by our hypotheses). Then we will test this model against less complex ones (where we eliminate individual fixed effects).

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC +
##     CESDR + block + avg_dist_trialwise + feedback * ExternalLC +
##     feedback * InternalLC + feedback * input_noise_magnitude +
##     feedback * CESDR + input_noise_magnitude * block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5066.2   5213.3  -2513.1   5026.2    11500
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4736 -0.6216  0.0663  0.6891  3.8226
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02435  0.1560
##  Residual             0.08900  0.2983
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                                          Estimate Std. Error         df
## (Intercept)                             2.180e+00  1.377e-01  5.157e+01
## feedbackpositive                        3.184e-02  4.116e-02  1.147e+04
```

```
## feedbacknegative                          -1.018e-01  4.116e-02  1.147e+04
## input_noise_magnitude2                    -2.621e-01  1.621e-02  1.151e+04
## ExternalLC                                 1.104e-01  3.199e-02  5.093e+01
## InternalLC                                 9.921e-04  3.134e-02  5.094e+01
## CESDR                                     -1.053e-03  2.721e-03  5.091e+01
## block                                      1.543e-02  1.804e-03  1.149e+04
## avg_dist_trialwise                        -9.922e-03  2.594e-04  1.152e+04
## feedbackpositive:ExternalLC                3.721e-03  9.455e-03  1.147e+04
## feedbacknegative:ExternalLC               -1.610e-02  9.455e-03  1.147e+04
## feedbackpositive:InternalLC               -6.292e-04  9.264e-03  1.147e+04
## feedbacknegative:InternalLC                1.270e-02  9.264e-03  1.147e+04
## feedbackpositive:input_noise_magnitude2  7.876e-03  1.362e-02  1.147e+04
## feedbacknegative:input_noise_magnitude2  4.281e-03  1.362e-02  1.147e+04
## feedbackpositive:CESDR                    -3.580e-04  8.044e-04  1.147e+04
## feedbacknegative:CESDR                     2.581e-03  8.044e-04  1.147e+04
## input_noise_magnitude2:block              -1.947e-02  2.618e-03  1.151e+04
##                                           t value Pr(>|t|)
## (Intercept)                                15.823  < 2e-16 ***
## feedbackpositive                            0.774  0.43912
## feedbacknegative                           -2.473  0.01343 *
## input_noise_magnitude2                    -16.172  < 2e-16 ***
## ExternalLC                                  3.451  0.00113 **
## InternalLC                                  0.032  0.97487
## CESDR                                      -0.387  0.70037
## block                                       8.554  < 2e-16 ***
## avg_dist_trialwise                        -38.253  < 2e-16 ***
## feedbackpositive:ExternalLC                 0.394  0.69390
## feedbacknegative:ExternalLC                -1.702  0.08871 .
## feedbackpositive:InternalLC                -0.068  0.94585
## feedbacknegative:InternalLC                 1.371  0.17046
## feedbackpositive:input_noise_magnitude2   0.578  0.56304
## feedbacknegative:input_noise_magnitude2   0.314  0.75328
## feedbackpositive:CESDR                     -0.445  0.65623
## feedbacknegative:CESDR                      3.209  0.00134 **
## input_noise_magnitude2:block               -7.435 1.12e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 18 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

We see no significance for several of the effects. This is where we can start. I will target the interactions first and try keeping the main effects.

Eliminating the interaction term between feedback and input_noise_magnitude:

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC +
##     CESDR + block + avg_dist_trialwise + feedback * ExternalLC +
##     feedback * InternalLC + feedback * CESDR + input_noise_magnitude *
```

```
##     block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5062.6   5194.9  -2513.3   5026.6    11502
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4739 -0.6231  0.0677  0.6889  3.8229
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02435  0.1560
##  Residual             0.08901  0.2983
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  2.177e+00  1.377e-01  5.148e+01  15.815  < 2e-16
## feedbackpositive             3.578e-02  4.059e-02  1.147e+04   0.882  0.37806
## feedbacknegative            -9.963e-02  4.059e-02  1.147e+04  -2.454  0.01413
## input_noise_magnitude2      -2.581e-01  1.416e-02  1.151e+04 -18.230  < 2e-16
## ExternalLC                   1.104e-01  3.199e-02  5.093e+01   3.451  0.00113
## InternalLC                   9.905e-04  3.134e-02  5.094e+01   0.032  0.97491
## CESDR                       -1.053e-03  2.721e-03  5.091e+01  -0.387  0.70039
## block                        1.543e-02  1.804e-03  1.149e+04   8.554  < 2e-16
## avg_dist_trialwise          -9.922e-03  2.593e-04  1.152e+04 -38.258  < 2e-16
## feedbackpositive:ExternalLC  3.721e-03  9.455e-03  1.147e+04   0.394  0.69390
## feedbacknegative:ExternalLC -1.610e-02  9.456e-03  1.147e+04  -1.702  0.08872
## feedbackpositive:InternalLC -6.292e-04  9.264e-03  1.147e+04  -0.068  0.94585
## feedbacknegative:InternalLC  1.270e-02  9.264e-03  1.147e+04   1.371  0.17046
## feedbackpositive:CESDR      -3.580e-04  8.044e-04  1.147e+04  -0.445  0.65623
## feedbacknegative:CESDR       2.581e-03  8.044e-04  1.147e+04   3.209  0.00134
## input_noise_magnitude2:block -1.947e-02  2.618e-03  1.151e+04  -7.435 1.12e-13
##
## (Intercept)                 ***
## feedbackpositive
## feedbacknegative            *
## input_noise_magnitude2      ***
## ExternalLC                  **
## InternalLC
## CESDR
## block                       ***
## avg_dist_trialwise          ***
## feedbackpositive:ExternalLC
## feedbacknegative:ExternalLC .
## feedbackpositive:InternalLC
## feedbacknegative:InternalLC
## feedbackpositive:CESDR
## feedbacknegative:CESDR      **
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 16 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

The p value is way above 0.05. This tells us that we fail to reject the null hypothesis. The models are "similar" meaning that we can use the less complex model and reduce the degrees of freedom (number of parameters).

Now with the package…

```
## Data: all_data
## Models:
## model2.1: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + av
## model2.complex: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + bloc
##                npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.1         18 5062.6 5194.9 -2513.3   5026.6
## model2.complex   20 5066.2 5213.3 -2513.1   5026.2 0.3353  2     0.8456
```

Checks out, same results! The Pr(>Chisq) is not significant, telling us that the models are not significantly different from another. This means we can use the less complex model (if we reduce the number of parameters by throwing out the interaction term, we're not loosing critical predictive power).

Proceeding with model2.1 and trying to eliminate further interaction terms. Here we try to eliminate the interaction between feedback and InternalLC. It also had no significance whatsoever above.

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC +
##     CESDR + block + avg_dist_trialwise + feedback * ExternalLC +
##     feedback * CESDR + input_noise_magnitude * block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5061.2   5178.8  -2514.6   5029.2    11504
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4765 -0.6257  0.0668  0.6915  3.8275
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02435  0.1560
##  Residual             0.08903  0.2984
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  2.163e+00  1.363e-01  4.937e+01  15.872  < 2e-16
## feedbackpositive             3.345e-02  2.165e-02  1.147e+04   1.545  0.12236
## feedbacknegative            -5.256e-02  2.165e-02  1.147e+04  -2.428  0.01522
## input_noise_magnitude2      -2.580e-01  1.416e-02  1.151e+04 -18.222  < 2e-16
## ExternalLC                   1.096e-01  3.197e-02  5.083e+01   3.429  0.00121
```

```
## InternalLC                   5.022e-03  3.088e-02  4.801e+01   0.163  0.87150
## CESDR                       -9.089e-04  2.714e-03  5.041e+01  -0.335  0.73912
## block                        1.543e-02  1.804e-03  1.149e+04   8.552  < 2e-16
## avg_dist_trialwise          -9.926e-03  2.594e-04  1.152e+04 -38.270  < 2e-16
## feedbackpositive:ExternalLC  3.602e-03  9.294e-03  1.147e+04   0.388  0.69833
## feedbacknegative:ExternalLC -1.371e-02  9.295e-03  1.147e+04  -1.475  0.14022
## feedbackpositive:CESDR      -3.355e-04  7.326e-04  1.147e+04  -0.458  0.64701
## feedbacknegative:CESDR       2.125e-03  7.326e-04  1.147e+04   2.901  0.00372
## input_noise_magnitude2:block -1.947e-02  2.619e-03  1.151e+04  -7.434 1.12e-13
##
## (Intercept)                 ***
## feedbackpositive
## feedbacknegative            *
## input_noise_magnitude2      ***
## ExternalLC                  **
## InternalLC
## CESDR
## block                       ***
## avg_dist_trialwise          ***
## feedbackpositive:ExternalLC
## feedbacknegative:ExternalLC
## feedbackpositive:CESDR
## feedbacknegative:CESDR      **
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 14 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
## Data: all_data
## Models:
## model2.2: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + av
## model2.1: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + av
##          npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.2   16 5061.2 5178.8 -2514.6   5029.2
## model2.1   18 5062.6 5194.9 -2513.3   5026.6 2.6355  2     0.2677
```

Again the test statistic tells us that there is no significant difference. Proceeding with model2.2

Now we target the interaction between feedback and ExternalLC and try to eliminate this one.

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC +
##     CESDR + block + avg_dist_trialwise + feedback * CESDR + input_noise_magnitude *
##     block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5061.1   5164.0  -2516.5   5033.1    11506
```

```
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4876 -0.6263  0.0668  0.6891  3.8625
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02435  0.1560
##  Residual             0.08906  0.2984
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                              Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                 2.169e+00  1.358e-01  4.877e+01  15.970  < 2e-16
## feedbackpositive            4.067e-02  1.101e-02  1.147e+04   3.693 0.000223
## feedbacknegative           -8.005e-02  1.102e-02  1.147e+04  -7.267 3.90e-13
## input_noise_magnitude2     -2.581e-01  1.416e-02  1.151e+04 -18.228  < 2e-16
## ExternalLC                  1.063e-01  3.152e-02  4.801e+01   3.372 0.001484
## InternalLC                  5.010e-03  3.088e-02  4.801e+01   0.162 0.871803
## CESDR                      -8.775e-04  2.714e-03  5.037e+01  -0.323 0.747763
## block                       1.543e-02  1.804e-03  1.149e+04   8.552  < 2e-16
## avg_dist_trialwise         -9.920e-03  2.594e-04  1.152e+04 -38.245  < 2e-16
## feedbackpositive:CESDR     -3.024e-04  7.277e-04  1.147e+04  -0.416 0.677726
## feedbacknegative:CESDR      1.999e-03  7.277e-04  1.147e+04   2.748 0.006010
## input_noise_magnitude2:block -1.947e-02  2.619e-03  1.151e+04  -7.433 1.13e-13
##
## (Intercept)                ***
## feedbackpositive           ***
## feedbacknegative           ***
## input_noise_magnitude2     ***
## ExternalLC                 **
## InternalLC
## CESDR
## block                      ***
## avg_dist_trialwise         ***
## feedbackpositive:CESDR
## feedbacknegative:CESDR     **
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) fdbckp fdbckn inp__2 ExtrLC IntrLC CESDR  block  avg_d_
## feedbckpstv  -0.040
## feedbckngtv  -0.041  0.500
## inpt_ns_mg2  -0.036  0.003 -0.004
## ExternalLC   -0.295  0.000  0.000  0.014
## InternalLC   -0.842  0.000  0.000  0.004 -0.184
## CESDR        -0.492  0.105  0.105 -0.004 -0.178  0.408
## block        -0.067 -0.001  0.001  0.601  0.009 -0.004 -0.001
## avg_dst_trl  -0.036 -0.007  0.009 -0.389 -0.008 -0.017  0.007  0.076
## fdbckp:CESDR  0.032 -0.786 -0.393  0.000  0.000  0.000 -0.134  0.000  0.000
## fdbckn:CESDR  0.032 -0.393 -0.786  0.000  0.000  0.000 -0.134  0.000  0.000
## inpt_ns_m2:   0.049  0.000  0.000 -0.830 -0.014  0.003  0.002 -0.735 -0.006
```

```
##              fdbckp:CESDR fdbckn:CESDR
## feedbckpstv
## feedbckngtv
## inpt_ns_mg2
## ExternalLC
## InternalLC
## CESDR
## block
## avg_dst_trl
## fdbckp:CESDR
## fdbckn:CESDR  0.500
## inpt_ns_m2:   0.000        0.000
```

```
## Data: all_data
## Models:
## model2.3: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + a
## model2.2: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + a
##          npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.3   14 5061.1 5164.0 -2516.5   5033.1
## model2.2   16 5061.2 5178.8 -2514.6   5029.2 3.8632  2     0.1449
```

Again no difference between the models, so we can kick the interaction term and don't loose critical predictive power. Proceeding with model2.3.

We will target our first main effect: InternalLC:

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR +
##     block + avg_dist_trialwise + feedback * CESDR + input_noise_magnitude *
##     block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5059.1   5154.7  -2516.6   5033.1    11507
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4876 -0.6262  0.0668  0.6893  3.8626
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02436  0.1561
##  Residual             0.08906  0.2984
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                          Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)             2.188e+00  7.339e-02  5.130e+01  29.813  < 2e-16
## feedbackpositive        4.067e-02  1.101e-02  1.147e+04   3.693 0.000223
## feedbacknegative       -8.005e-02  1.102e-02  1.147e+04  -7.267 3.90e-13
## input_noise_magnitude2 -2.581e-01  1.416e-02  1.151e+04 -18.229  < 2e-16
## ExternalLC              1.072e-01  3.099e-02  4.801e+01   3.460 0.001144
## CESDR                  -1.057e-03  2.478e-03  5.089e+01  -0.427 0.671474
```

```
## block                         1.543e-02  1.804e-03  1.150e+04   8.553  < 2e-16
## avg_dist_trialwise           -9.919e-03  2.593e-04  1.152e+04 -38.248  < 2e-16
## feedbackpositive:CESDR       -3.024e-04  7.277e-04  1.147e+04  -0.416 0.677726
## feedbacknegative:CESDR        1.999e-03  7.277e-04  1.147e+04   2.748 0.006010
## input_noise_magnitude2:block -1.947e-02  2.619e-03  1.151e+04  -7.434 1.13e-13
##
## (Intercept)                  ***
## feedbackpositive             ***
## feedbacknegative             ***
## input_noise_magnitude2       ***
## ExternalLC                   **
## CESDR
## block                        ***
## avg_dist_trialwise           ***
## feedbackpositive:CESDR
## feedbacknegative:CESDR       **
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) fdbckp fdbckn inp__2 ExtrLC CESDR  block  avg_d_
## feedbckpstv  -0.074
## feedbckngtv  -0.076  0.500
## inpt_ns_mg2  -0.060  0.003 -0.004
## ExternalLC   -0.847  0.000  0.000  0.015
## CESDR        -0.301  0.115  0.116 -0.006 -0.115
## block        -0.130 -0.001  0.001  0.601  0.009  0.001
## avg_dst_trl  -0.094 -0.007  0.009 -0.389 -0.011  0.015  0.076
## fdbckp:CESDR  0.059 -0.786 -0.393  0.000  0.000 -0.147  0.000  0.000
## fdbckn:CESDR  0.059 -0.393 -0.786  0.000  0.000 -0.147  0.000  0.000
## inpt_ns_m2:   0.096  0.000  0.000 -0.830 -0.013  0.000 -0.735 -0.006
##              fdbckp:CESDR fdbckn:CESDR
## feedbckpstv
## feedbckngtv
## inpt_ns_mg2
## ExternalLC
## CESDR
## block
## avg_dst_trl
## fdbckp:CESDR
## fdbckn:CESDR  0.500
## inpt_ns_m2:   0.000        0.000
```

```
## Data: all_data
## Models:
## model2.4: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR + block + avg_dist_trialw
## model2.3: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + InternalLC + CESDR + block + av
##          npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.4   13 5059.1 5154.7 -2516.6   5033.1
## model2.3   14 5061.1 5164.0 -2516.5   5033.1 0.0263  1     0.8711
```

Yep we can safely kick InternalLC. Proceeding with model2.4.

Now it get's a little more tricky. We find no significance for the main effects of CESDR and also no significance for one of its interaction effects. But the other interaction effect is significant… Is it safe to eliminate the whole interaction term or the main effect? We'll see.

Eliminating the complete interaction term:

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR +
##     block + avg_dist_trialwise + input_noise_magnitude * block +
##     (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5066.9   5147.8  -2522.5   5044.9    11509
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4656 -0.6272  0.0647  0.6887  3.8131
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02436  0.1561
##  Residual             0.08915  0.2986
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  2.181e+00  7.322e-02  5.083e+01  29.790  < 2e-16
## feedbackpositive             3.708e-02  6.815e-03  1.147e+04   5.441 5.42e-08
## feedbacknegative            -5.626e-02  6.815e-03  1.147e+04  -8.256  < 2e-16
## input_noise_magnitude2      -2.581e-01  1.417e-02  1.151e+04 -18.220  < 2e-16
## ExternalLC                   1.072e-01  3.099e-02  4.801e+01   3.460  0.00114
## CESDR                       -4.914e-04  2.442e-03  4.801e+01  -0.201  0.84138
## block                        1.543e-02  1.805e-03  1.150e+04   8.549  < 2e-16
## avg_dist_trialwise          -9.919e-03  2.595e-04  1.152e+04 -38.227  < 2e-16
## input_noise_magnitude2:block -1.947e-02  2.620e-03  1.151e+04  -7.430 1.16e-13
##
## (Intercept)                  ***
## feedbackpositive             ***
## feedbacknegative             ***
## input_noise_magnitude2       ***
## ExternalLC                   **
## CESDR
## block                        ***
## avg_dist_trialwise           ***
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) fdbckp fdbckn inp__2 ExtrLC CESDR  block  avg_d_
## feedbckpstv -0.045
## feedbckngtv -0.048  0.500
## inpt_ns_mg2 -0.060  0.004 -0.006
```

```
## ExternalLC  -0.849  0.000  0.000  0.015
## CESDR       -0.294  0.000  0.000 -0.006 -0.117
## block       -0.130 -0.001  0.001  0.601  0.009  0.001
## avg_dst_trl -0.094 -0.011  0.014 -0.389 -0.011  0.016  0.076
## inpt_ns_m2:  0.097  0.000  0.000 -0.830 -0.013  0.000 -0.735 -0.006
```

```
## Data: all_data
## Models:
## model2.5: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR + block + avg_dist_trialw
## model2.4: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR + block + avg_dist_trialw
##          npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.5   11 5066.9 5147.8 -2522.5   5044.9
## model2.4   13 5059.1 5154.7 -2516.6   5033.1 11.814  2   0.002721 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We see significance. This means that the models are significantly different from another in their predictive power and we shouldn't just throw out the interaction term. But because it's the feedback:positive * CESDR -interaction that is the weak point, we can create columns in our data set that are separate for *negative* and *positive* feedback.

Now we put the individual columns in the model but leave out the interaction between positive_feedback and CESDR:

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude +
##     ExternalLC + CESDR + block + avg_dist_trialwise + negative_feedback *
##     CESDR + input_noise_magnitude * block + (1 | code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   5057.3   5145.5  -2516.6   5033.3    11508
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4876 -0.6263  0.0672  0.6877  3.8626
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  code     (Intercept) 0.02436  0.1561
##  Residual             0.08906  0.2984
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                              Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                 2.190e+00  7.326e-02  5.094e+01  29.889  < 2e-16
## negative_feedback          -8.185e-02  1.013e-02  1.147e+04  -8.081 7.09e-16
## positive_feedback           3.708e-02  6.811e-03  1.147e+04   5.443 5.33e-08
## input_noise_magnitude2     -2.581e-01  1.416e-02  1.151e+04 -18.229  < 2e-16
## ExternalLC                  1.072e-01  3.099e-02  4.801e+01   3.460 0.001144
## CESDR                      -1.208e-03  2.451e-03  4.872e+01  -0.493 0.624262
## block                       1.543e-02  1.804e-03  1.150e+04   8.553  < 2e-16
```

```
## avg_dist_trialwise           -9.919e-03  2.593e-04  1.152e+04 -38.248  < 2e-16
## negative_feedback:CESDR       2.151e-03  6.302e-04  1.147e+04   3.413 0.000645
## input_noise_magnitude2:block -1.947e-02  2.619e-03  1.151e+04  -7.434 1.13e-13
##
## (Intercept)                  ***
## negative_feedback            ***
## positive_feedback            ***
## input_noise_magnitude2       ***
## ExternalLC                   **
## CESDR
## block                        ***
## avg_dist_trialwise           ***
## negative_feedback:CESDR      ***
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ngtv_f pstv_f inp__2 ExtrLC CESDR  block  avg_d_ n_:CES
## negtv_fdbck -0.057
## postv_fdbck -0.045  0.336
## inpt_ns_mg2 -0.060 -0.004  0.004
## ExternalLC  -0.848  0.000  0.000  0.015
## CESDR       -0.296  0.064  0.000 -0.006 -0.116
## block       -0.130  0.001 -0.001  0.601  0.009  0.001
## avg_dst_trl -0.094  0.010 -0.011 -0.389 -0.011  0.016  0.076
## ngtv_:CESDR  0.034 -0.740  0.000  0.000  0.000 -0.086  0.000  0.000
## inpt_ns_m2:  0.097  0.000  0.000 -0.830 -0.013  0.000 -0.735 -0.006  0.000

## Data: all_data
## Models:
## model2.6: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + ExternalLC + C
## model2.4: sqrt(SoC) ~ feedback + input_noise_magnitude + ExternalLC + CESDR + block + avg_dist_trial
##          npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2.6   12 5057.3 5145.5 -2516.6   5033.3
## model2.4   13 5059.1 5154.7 -2516.6   5033.1 0.1727  1     0.6777
```

We can safely proceed with model2.6.

There is no significant main effect of CESDR, but it is involved in a significant interaction effect and it's a numeric variable. We will just leave the effect in the model. This is our final fixed effects structure. Now we can start to explore random effects structure.

Exploring random slope effects by referring to BIC

Now that we identified the fixed effects in our model we can work on the random effects structure. When it comes to selecting random slope effects though, the likelihood ratio test won't be sufficient anymore (not for comparing models with different random effects structures). Random slopes "open up" the fixed effects for the different groups of our random intercept effects: they split the model apart by introducing a lot more parameters. We can select random slope effects by referring to an **information criterion**. I usually use the **Bayes information criterion (BIC)**. It penalizes the number of data points used to fit the model (on top of the number of parameters). I like the idea of accounting for overfitting when selecting models. (An alternative to the BIC is the **Akaike information criterion (AIC)**, which only penalizes the number of parameters.)

Here we will start with the most complex random effects structure and reduce the complexity further and further until we don't detect singularity anymore or the BIC won't go smaller anymore (smaller BICs are preferred).

Just entering all the fixed effects as random slopes.

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## unable to evaluate scaled gradient
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge: degenerate Hessian with 2 negative eigenvalues
```

```
## Warning: Model failed to converge with 2 negative eigenvalues: -2.5e+01
## -5.1e+01
```

That took a while and the model is drastically overparameterized (failed to converge)… We will first eliminate interaction effects.

eliminating negative_feedback*CESDR

```
## boundary (singular) fit: see help('isSingular')
```

Detecting singularity…

Throwing out input_noise_magnitude*block.

```
## boundary (singular) fit: see help('isSingular')
```

Still singular. Hmmmm maybe we should start keeping only a single random slope effect. Starting with input_noise_magnitude.

That one worked. Ok than let's just build single random slope models and compare those.

```
## boundary (singular) fit: see help('isSingular')
```

That one is singular. We will omit it in the model comparison.

```
## boundary (singular) fit: see help('isSingular')
```

Also singular.

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.165883 (tol = 0.002, component 1)
```

That one actually failed to converge

Let's compare the non-singular models and the random intercept only one.

```
## Data: all_data
## Models:
## model2.6: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + ExternalLC + CE
## model2.in: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + ExternalLC + C
## model2.nfeedback: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + Externa
## model2.pfeedback: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + Externa
## model2.block: sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude + ExternalLC
##                  npar    AIC    BIC   logLik deviance  Chisq Df Pr(>Chisq)
## model2.6           12 5057.3 5145.5 -2516.64   5033.3
## model2.in          14 1913.2 2016.1  -942.59   1885.2 3148.1  2  < 2.2e-16 ***
## model2.nfeedback   14 5025.1 5128.1 -2498.56   4997.1    0.0  0
## model2.pfeedback   14 5031.0 5133.9 -2501.49   5003.0    0.0  0
## model2.block       14 3928.8 4031.7 -1950.40   3900.8 1102.2  0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The only statistic of interest for us in this output is the BIC and we're searching for the smallest BIC. model2.in (input_noise_magnitude as random slope effect) has the lowest BIC even outcompeting the random intercept only model.

We can try to add additional random slope effects now. Starting with the interaction: input_noise_magnitude*block

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00255302 (tol = 0.002, component 1)
```

Failed to converge again. Maybe without the interaction and just main effects?

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00279096 (tol = 0.002, component 1)
```

Nope. Let's take model2.in as our final model as adding further random slopes will only end up in a worse fit. Now we can take our first look at the effects.

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## sqrt(SoC) ~ negative_feedback + positive_feedback + input_noise_magnitude +
##     ExternalLC + CESDR + block + avg_dist_trialwise + negative_feedback *
##     CESDR + input_noise_magnitude * block + (1 + input_noise_magnitude |
##     code)
##    Data: all_data
##
##      AIC      BIC   logLik deviance df.resid
##   1913.2   2016.1   -942.6   1885.2    11506
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -5.5719 -0.5815  0.0522  0.6015  4.6763
##
## Random effects:
##  Groups   Name                   Variance Std.Dev. Corr
##  code     (Intercept)            0.04451  0.2110
##           input_noise_magnitude2 0.09213  0.3035   -0.67
```

```
##  Residual                        0.06644  0.2578
## Number of obs: 11520, groups:  code, 48
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  2.210e+00  7.613e-02  5.672e+01  29.026  < 2e-16
## negative_feedback           -8.148e-02  8.749e-03  1.142e+04  -9.314  < 2e-16
## positive_feedback            3.680e-02  5.883e-03  1.142e+04   6.256 4.09e-10
## input_noise_magnitude2      -2.820e-01  4.549e-02  5.446e+01  -6.199 7.92e-08
## ExternalLC                   1.017e-01  3.114e-02  4.800e+01   3.265  0.00202
## CESDR                       -5.459e-04  2.461e-03  4.852e+01  -0.222  0.82536
## block                        6.915e-03  1.616e-03  1.146e+04   4.279 1.89e-05
## avg_dist_trialwise          -8.984e-03  2.271e-04  1.147e+04 -39.565  < 2e-16
## negative_feedback:CESDR      2.150e-03  5.443e-04  1.142e+04   3.950 7.86e-05
## input_noise_magnitude2:block -1.927e-02  2.263e-03  1.145e+04  -8.515  < 2e-16
##
## (Intercept)                 ***
## negative_feedback           ***
## positive_feedback           ***
## input_noise_magnitude2      ***
## ExternalLC                  **
## CESDR
## block                       ***
## avg_dist_trialwise          ***
## negative_feedback:CESDR     ***
## input_noise_magnitude2:block ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ngtv_f pstv_f inp__2 ExtrLC CESDR  block  avg_d_ n_:CES
## negtv_fdbck -0.048
## postv_fdbck -0.038  0.336
## inpt_ns_mg2 -0.270 -0.001  0.001
## ExternalLC  -0.820  0.000  0.000  0.004
## CESDR       -0.285  0.055  0.000 -0.002 -0.116
## block       -0.112  0.001 -0.001  0.156  0.008  0.001
## avg_dst_trl -0.080  0.010 -0.011 -0.106 -0.010  0.014  0.078
## ngtv_:CESDR  0.028 -0.740  0.000  0.000  0.000 -0.074  0.000  0.000
## inpt_ns_m2:  0.080  0.000  0.000 -0.223 -0.011  0.000 -0.710 -0.006  0.000
```

Back-transformation

means:

```
## (Intercept)
##    4.882552
```

```
## negative_feedback
##       0.006639666
```

```
## positive_feedback
##       0.001354507
```

```
## input_noise_magnitude2
##             0.07954416
```

```
## ExternalLC
##   0.010335
```

```
##        CESDR
## 2.980259e-07
```

```
##        block
## 4.781432e-05
```

```
## avg_dist_trialwise
##       8.070707e-05
```

```
## negative_feedback:CESDR
##             4.62267e-06
```

```
## input_noise_magnitude2:block
##                 0.0003712566
```

standard errors:

```
## [1] "intercept:"
```

```
## [1] 0.005795448
```

```
## [1] "negative_feedback:"
```

```
## [1] 7.653976e-05
```

```
## [1] "positive_feedback:"
```

```
## [1] 3.460823e-05
```

```
## [1] "input_noise_magnitude2:"
```

```
## [1] 0.002069699
```

```
## [1] "ExternalLC:"
```

```
## [1] 0.0009694341
```

```
## [1] "CESDR:"
```

```
## [1] 6.055187e-06
```

```
## [1] "block:"
```

```
## [1] 2.611162e-06

## [1] "avg_dist_trialwise:"

## [1] 5.155591e-08

## [1] "negative_feedback*CESDR:"

## [1] 2.962887e-07

## [1] "input_noise_magnitude2*block:"

## [1] 5.12066e-06
```

Generaring simulations based on the final selected model

parametric bootstrap:

```
## Computing bootstrap confidence intervals ...

##
## 181 warning(s): Model failed to converge with max|grad| = 0.00200148 (tol = 0.002, component 1) (and

##                                     2.5 %       97.5 %
## negative_feedback            -0.099079119 -0.064289019
## positive_feedback             0.025204015  0.047975512
## input_noise_magnitude2       -0.371335049 -0.193213762
## ExternalLC                    0.041552809  0.164827711
## CESDR                        -0.005585758  0.004406567
## block                         0.003797198  0.010063422
## avg_dist_trialwise           -0.009427785 -0.008545179
## negative_feedback:CESDR       0.001079844  0.003229721
## input_noise_magnitude2:block -0.023712643 -0.014914305
```

"…bounds of the 95% confidence interval were obtained by a parametric bootstrap with {N_iterations} iterations."

```
## [1] "negative_feedback:"

## [1] -0.009816672

## [1] -0.004133078

## [1] "positive_feedback:"

## [1] 0.0006352424

## [1] 0.00230165
```

```
## [1] "input_noise_magnitude2:"

## [1] -0.1378897

## [1] -0.03733156

## [1] "ExternalLC:"

## [1] 0.001726636

## [1] 0.02716817

## [1] "CESDR:"

## [1] -3.120069e-05

## [1] 1.941783e-05

## [1] "block:"

## [1] 1.441871e-05

## [1] 0.0001012725

## [1] "avg_dist_trialwise:"

## [1] -8.888313e-05

## [1] -7.302008e-05

## [1] "negative_feedback*CESDR:"

## [1] 1.166063e-06

## [1] 1.04311e-05

## [1] "input_noise_magnitude2*block:"

## [1] -0.0005622894

## [1] -0.0002224365
```

reporting our effect: …compared to input noise magnitude=0.5, increasing the magnitude of input noise to 2.0 significantly decreases SoC (beta=0.080, sigma=0.002, CI=[-0.138, -0.037], p<.001).