

Portfolio 4

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Link to code:

https://github.com/StudiegruppeEM3/Portfolio_4/blob/master/A4_P1_PhysiologicalCoordination_instructions.Rmd

Preprocessing (P)

It is important to clean heart rate (HR)-data, because there can be quite a lot of artifacts, that effect our data. Also, it is useful to downsample the dataset, to make it easier to work with.

Downsampling (A)

Our heart-rate measures are on a millisecond scale, but the human heart doesn't beat that fast, so many of the data points are redundant. Therefore, we down-sample, which makes the datasets more manageable. We do this by grouping the datapoints into groups of 100 and calculate the means of these. These means are our new data-points. This makes the dataset 100 times smaller.

Outliers (A)

Next, we consider outliers. Outliers are data-points are outside the normal range of our data. The most obvious case of outliers in HR-time-series, is if your HR changes more than is physically possible. However, some artifacts fall within the physically possible range.

To deal with these outliers, we replaceable datapoints that are more than 2.5 standard deviations (SD) from the mean with the mean-value. We also considered the approach where one makes the values over 2.5 SD from the mean to the exact value of 2.5 SD over or under the mean, one might argue that this approach could keep the integrity of the data, but we think that the outliers are due to artifacts and not reflect actual changes in heart rate.

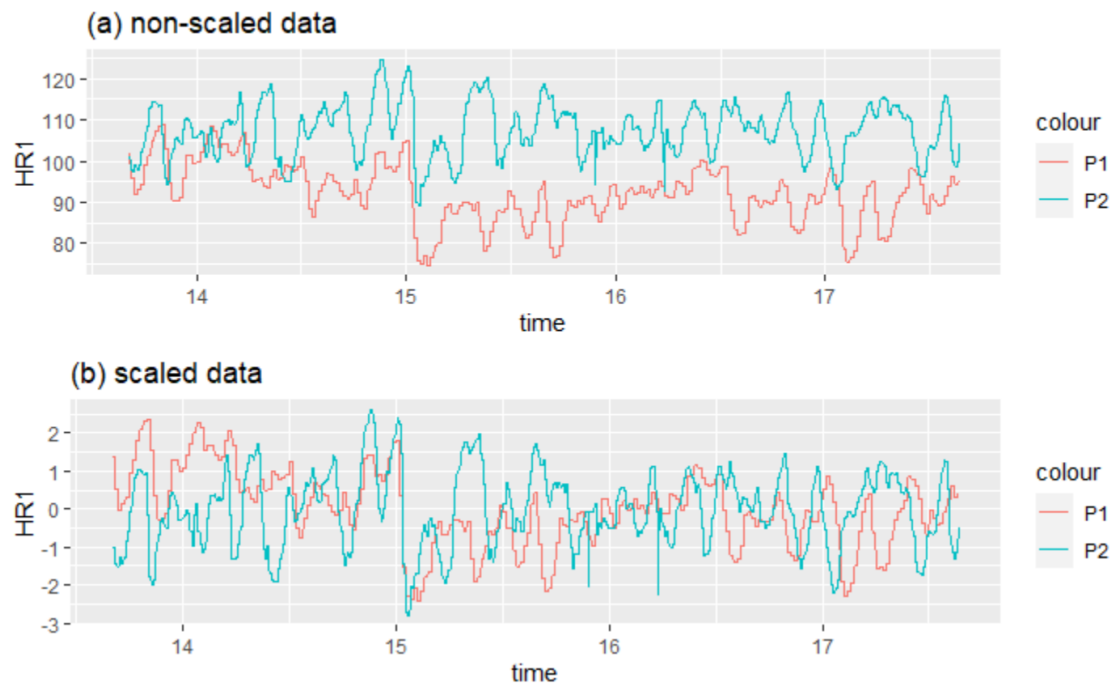


Plot 1; shows different ways of controlling for outliers, (a) shows no outlier correction. (b) shows how outliers, defined as 2.5 standard deviations from the mean, gets moved to be the mean value instead. (c) shows how the data would look if one would make outliers, again 2.5 standard deviations from the mean, to the exact value of 2.5 times the standard deviation over or below the mean.

Scaling (A)

Next, we scale the data. This is to ensure that the two participants are on the same scale, see plot2.

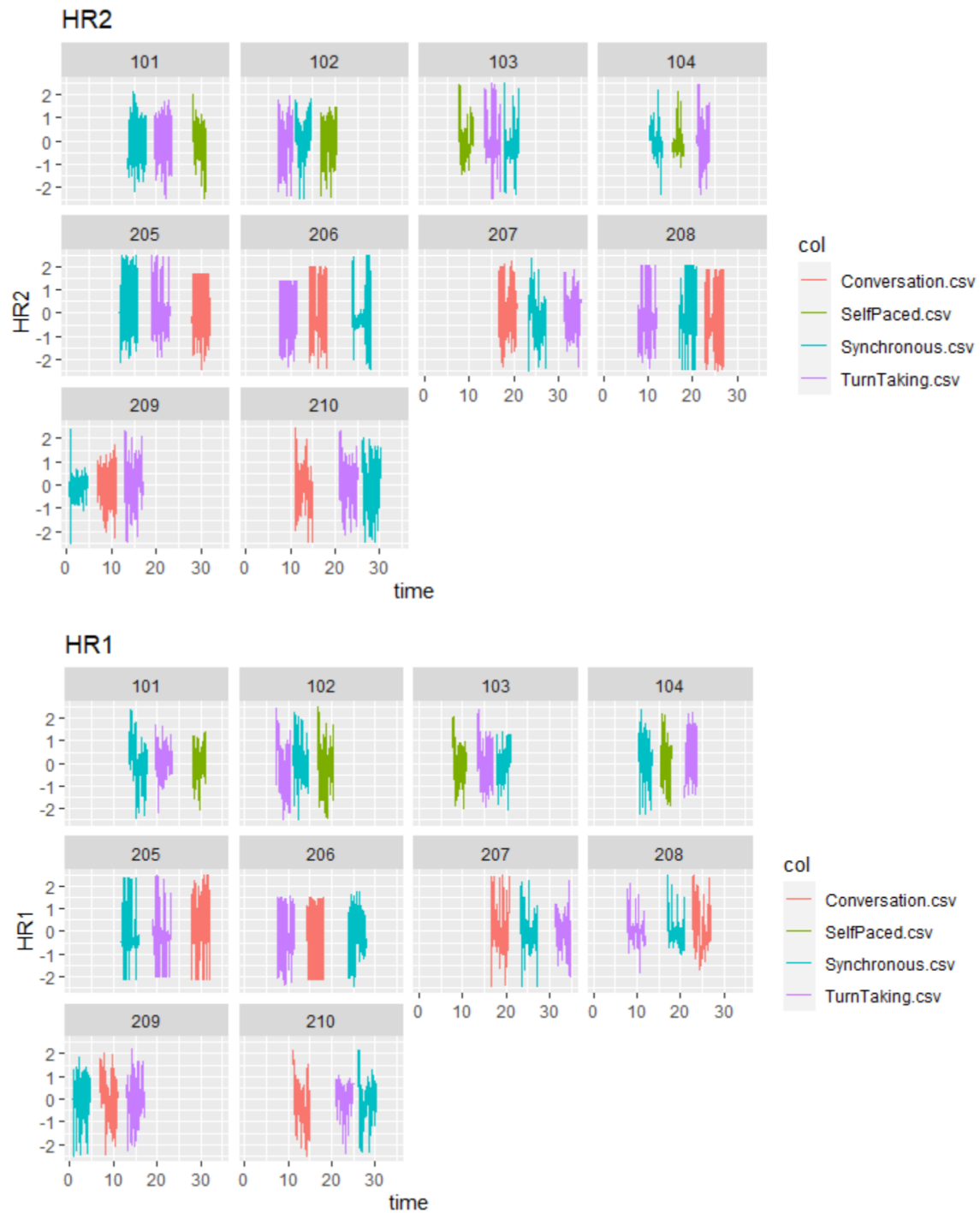
For example, it could be that P1 is in better shape, and therefore generally has a lower heart rate.



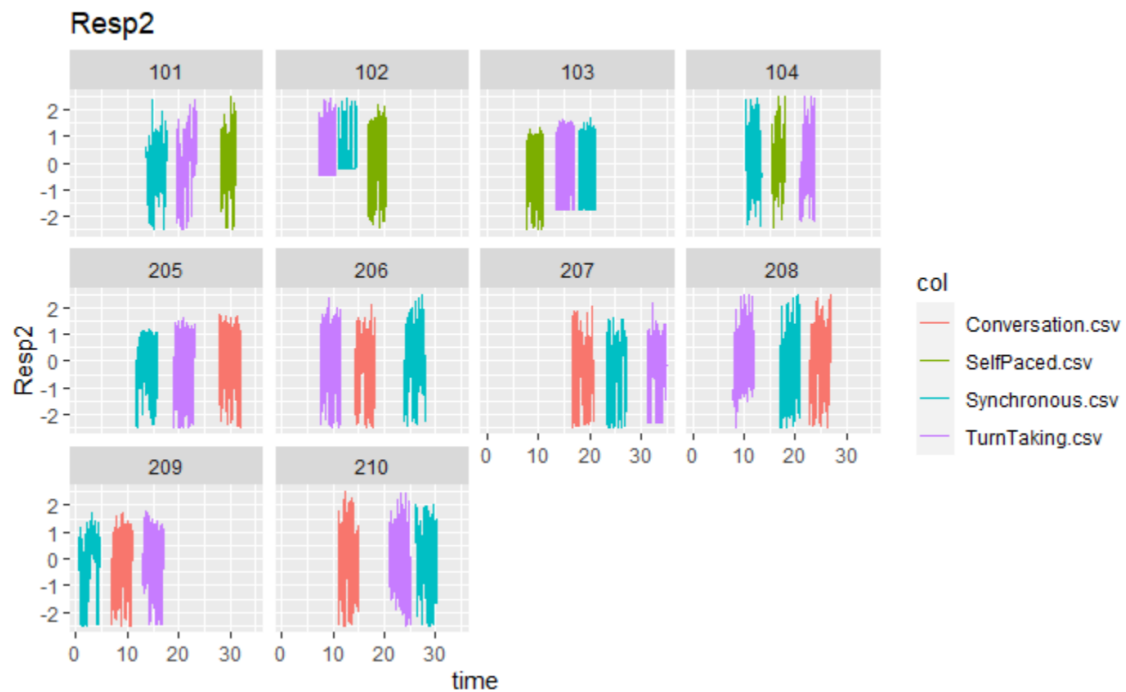
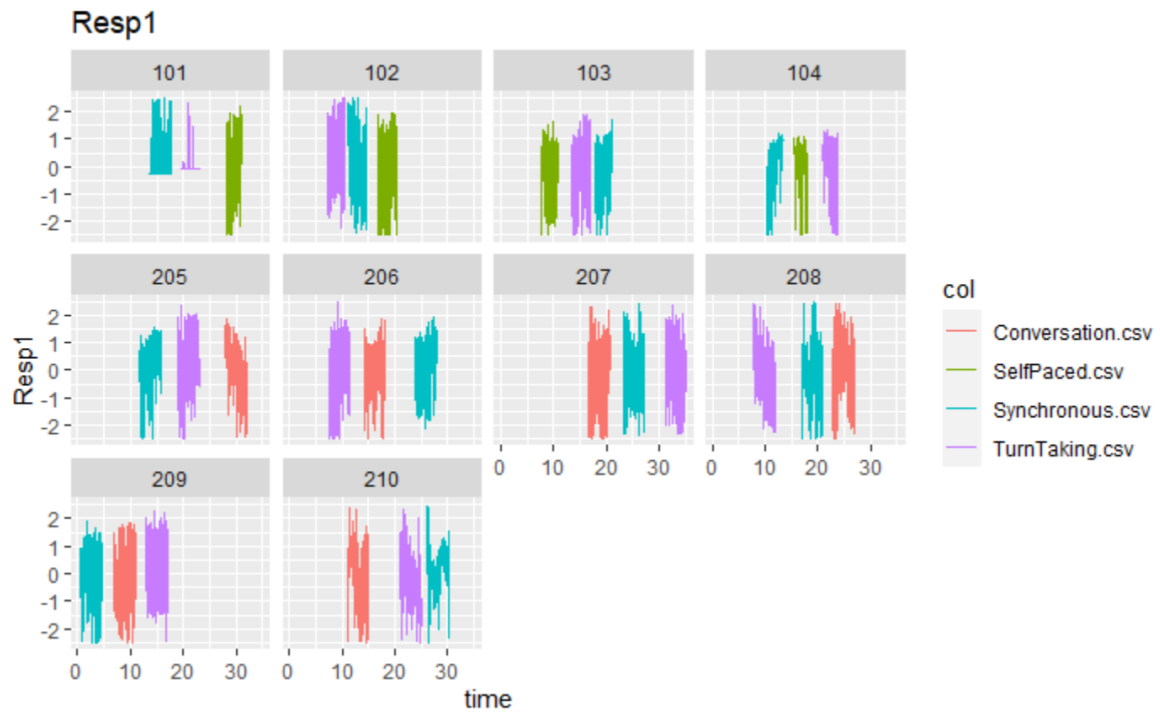
Plot2; shows how scaling the data, puts the two participants heart rate data on the same scale. (a) shows non-scaled data, whereas (b) shows scaled data.

Whole dataset (P)

After we have pre-processed the whole dataset, we plot the data to visually inspect it for errors. In plot 3 we display only the data from study 1 and 2, to save space.



Plot 3a; displays scaled heart rate for the individual participants (HR1 / HR2) in studies 1 and 2 in the different conditions.



Plot 3b; displays scaled respiration data for the individual participants (Resp1 / Resp2) in studies 1 and 2 in the different conditions.

The Resp1 data looks a bit odd for participant 101 (study 1, group 1) during the synchronous and turn taking conditions (see Plot 3b). We remove the respiration data for this participant in these two trials.

Analysis (D)

When analyzing the data, we use two differential equations from Ferrer & Helm, 2013.

$$\frac{dHR_{self}}{dt} = a_1 * (HR_{ideal} - HR_{self_{lag}}) + a_2(HR_{other_{lag}} - HR_{self_{lag}})$$

$$\frac{dHR_{other}}{dt} = b_1 * (HR_{ideal} - HR_{other_{lag}}) + b_2(HR_{self_{lag}} - HR_{other_{lag}})$$

If a_1 and b_1 are positive the change in heartrate (either in oneself or the other person) will move towards the ideal HR for that participant (HR_{ideal}). Therefore, the values a_1 will tell us whether our participants self-regulate and b_1 will tell us whether our participants co-regulate.

For the purpose of our analysis, we will combine these two equations into one. This means we only get two estimates instead of four. We assume that our first estimate is an average of a_1 and b_1 and our second estimate will be an average of a_2 and b_2 . Furthermore, in our models we assume that the HR_{ideal} term is the mean of the heart rate, and since we have scaled our heart rate data this term is 0.

First we made a model that predicted change in heart rate from $-HR_{self_{lag}}$ and from the difference between the others heart rate and HR_{self} (dif). We also included participant as a random intercept.

| | Estimate | Std. error | Df | t-value | p-value |
|-----------------|----------|------------|--------|---------|---------|
| Intercept | 0.00014 | 0.00046 | 356100 | 0.3 | 0.76 |
| self-regulation | 0.0414 | 0.00067 | 356100 | 62.12 | 0 |
| Co-regulation | 0.0013 | 0.00046 | 356100 | 2.866 | 0.004 |

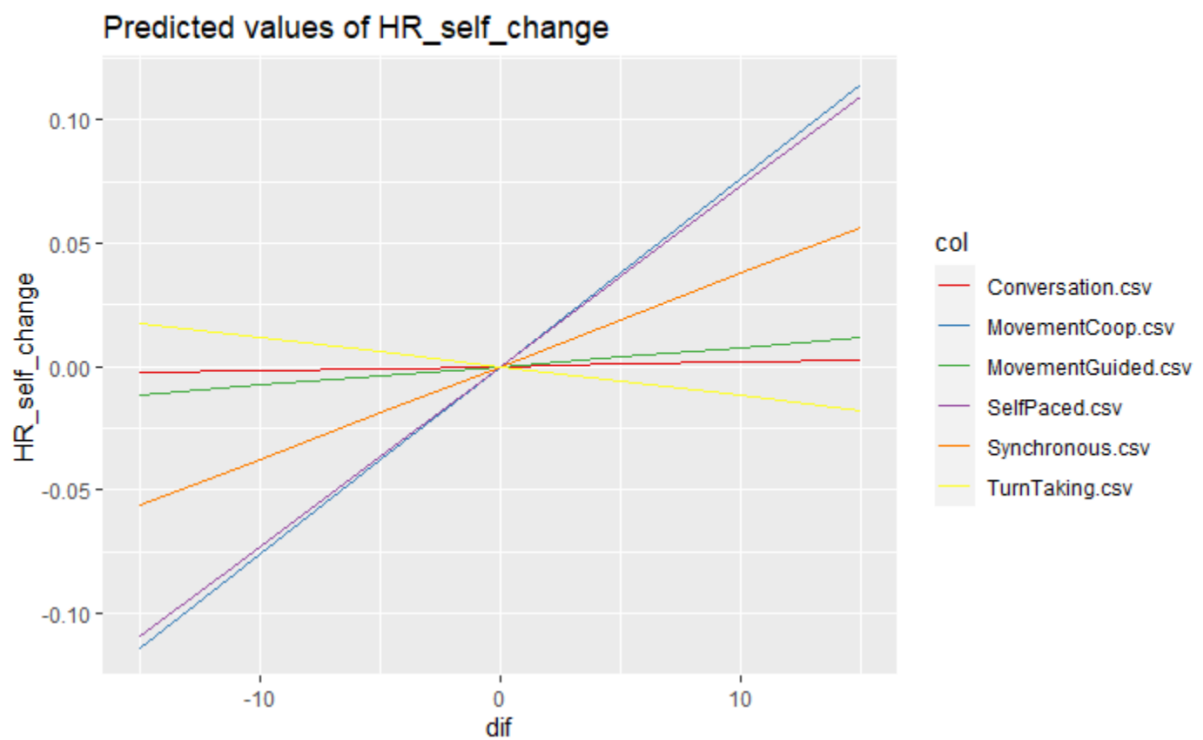
Table 1

Table one shows the output from this model. Since both estimates are positive, it seems like the participants self-regulate and co-regulate.

Next, we included condition as an interaction effect as well as random slope per participant. In this model it is important to note that all the interaction estimates are compared to 0 (and not a baseline condition).



Plot 4a; visually displays the slope coefficients of self-regulation from table2, where positive slopes indicate self-regulation



Plot 4b; visually displays the slope coefficients of co-regulation from table2, where positive slopes indicate co-regulation

| | Estimate | Std. Error | Df | t-value | p-value |
|----------------------------------|----------|------------|--------|---------|---------|
| Intercept | 0.00014 | 0.00046 | 356100 | 0.3 | 0.76 |
| Self-regulation, conversation | 0.0399 | 0.0013 | 356100 | 30.8 | >0.001 |
| Self-regulation, movement coop | 0.0556 | 0.0033 | 356100 | 16.8 | >0.001 |
| Self-regulation, movement guided | 0.0523 | 0.0029 | 356100 | 18.0 | >0.001 |
| Self-regulation, self-paced | 0.0413 | 0.0036 | 356100 | 11.4 | >0.001 |
| Self-regulation, synchronous | 0.0479 | 0.0012 | 356100 | 38.6 | >0.001 |
| Self-regulation, turn taking | 0.0332 | 0.0011 | 356100 | 28.3 | >0.001 |
| Co-regulation, conversation | 0.00018 | 0.0009 | 356100 | 0.2 | 0.84 |
| Co-regulation, movement coop | 0.0076 | 0.0021 | 356100 | 3.562 | >0.001 |
| Co-regulation, movement guided | 0.00077 | 0.0020 | 356100 | 0.38 | 0.7 |
| Co-regulation, self paced | 0.0073 | 0.0023 | 356100 | 3.14 | >0.01 |
| Co-regulation, synchronous | 0.0038 | 0.0008 | 356100 | 4.44 | >0.001 |
| Co-regulation, turn taking | -0.0012 | 0.0008 | 356100 | -1.4 | >0.16 |

Table 2

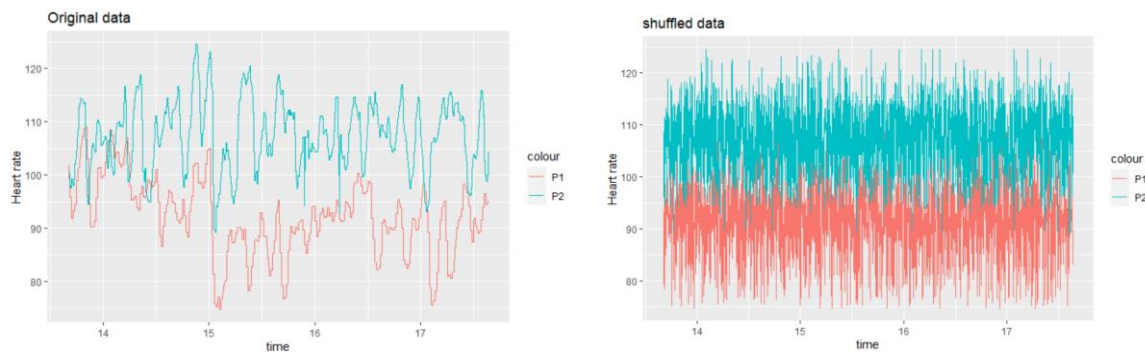
As can be seen from table 2 and the plots 4a and 4b, the participants self-regulate in all conditions (all estimates for self-regulation are positive)

Next, we see that in some of the conditions the two persons co-regulate (synchronous, self-paced and movement-Coop conditions). We also see that the two persons (anti) co-regulate in the condition Turn-Taking, this can be seen from the negative estimate, however this effect is non-significant.

Shuffled dataset (J)

It could be that these effects are due to the sequence of the data. To break this temporal dependency, we create a new random order of the heart rate datapoints (shuffle). We analysis this new dataset in the same way, that we did for the original dataset. Finally, we make a model that compares that uses shuffle/original as an interaction effect, with shuffle as the baseline.

We expect the self-regulation to be much higher in the shuffled dataset, since the effect on oneself is more drastic, when the order is random. See plot 5. Here its easily visible that in the shuffled dataset it looks like the participants self-regulate more dramatically which we would see with increased values of the slopes for self-regulation. Due to this fact we can't use the shuffled control data to compare self-regulation, but only co-regulation.



Plot 5; shows the difference in the same participants in the shuffled data-set compared to the original data-set



Plot 6b: visually displays the slope coefficients of co-regulation from table2, where positive slopes indicate co-regulation in both shuffled controls and the original data.

| | Estimate | Std. Error | Df | t-value | p-value |
|--------------------------------|----------|------------|--------|---------|---------|
| Intercept | 0.0258 | 0.0042 | 28.68 | 6.1 | >0.001 |
| Co-regulation, conversation | 0.0005 | 0.0033 | 712200 | 0.15 | 0.88 |
| Co-regulation, movement coop | 0.0016 | 0.0075 | 712200 | 0.21 | 0.83 |
| Co-regulation, movement guided | 0.0137 | 0.0078 | 712200 | 1.7 | 0.08 |
| Co-regulation, self-paced | 0.0219 | 0.0090 | 712200 | 2.4 | 0.02 |
| Co-regulation, synchronous | 0.0023 | 0.0032 | 712200 | 0.7 | 0.47 |
| Co-regulation, turn taking | -0.0060 | 0.0032 | 712200 | -1.9 | 0.06 |

Table 3: regression estimates for co-regulation with shuffled controls as baseline.

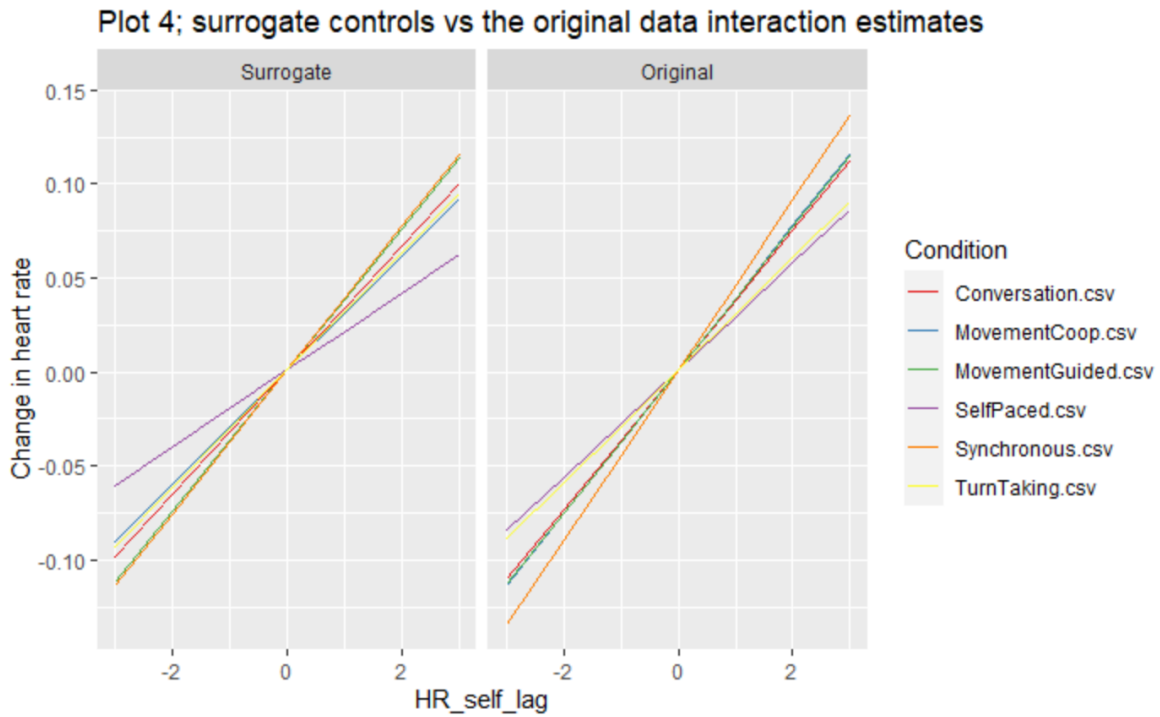
Co-regulation is now only significant in the self-paced condition (see table 3). This co-regulation is positive, meaning that the person does co-regulate more with their partner compared to a shuffled control. One can also see that movement-guided also is close to significant $p = 0.08$ also in a positive direction. One can also see that the turn-taking condition is close to being significant this however in a negative direction, again meaning that the two person anti-co-regulate.

Surrogate pairs (J,D,P,A)

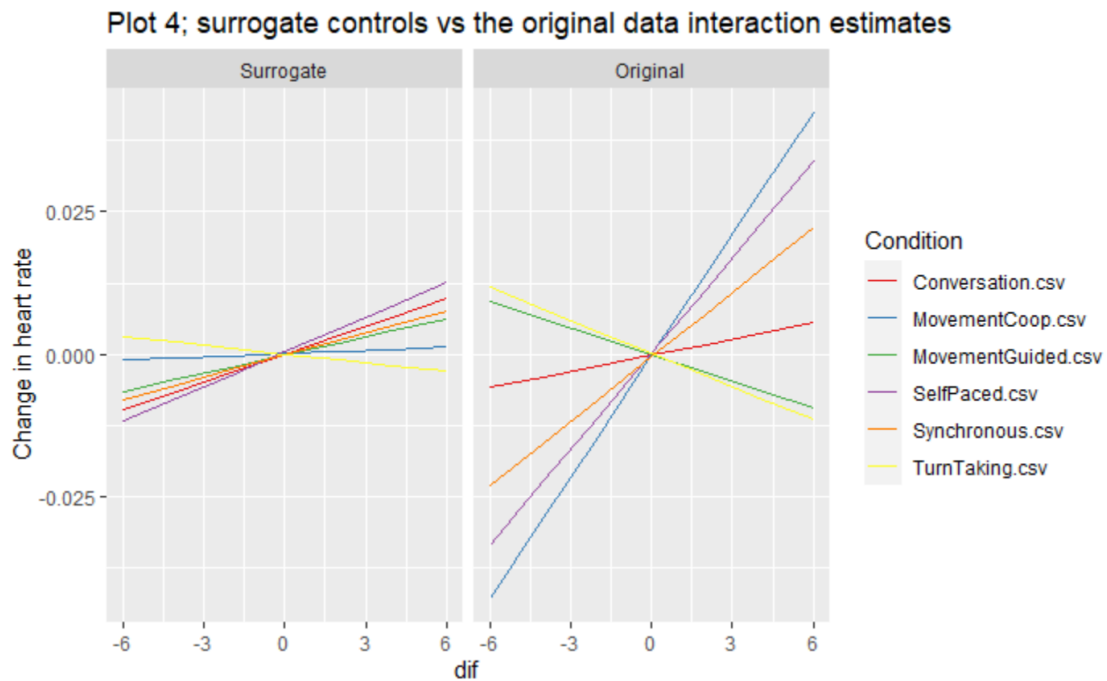
Finally, to check that the participants are effect by each other and not just the task that they are performing, we created surrogate pairs. Surrogate pairs are combinations of datasets from two participants who completed the same task but with different partners.

Next, we created a model, that compares the surrogate pairs to the original dataset, just like we compared the original dataset to the shuffled dataset.

We expected our self-regulation estimates to be identical to the original data, since participants were still being compared to themselves. However due to some data loss in the preprocessing stages the estimates vary a little.



Plot 7a: visually displays the slope coefficients of self-regulation from table2, where positive slopes indicate self-regulation in both surrogate controls and the original data.



Plot 7b: visually displays the slope coefficients of co-regulation from table2, where positive slopes indicate co-regulation in both surrogate controls and the original data.

| | Estimate | Std. Error | Df | t-value | p-value |
|--------------------------------|----------|------------|---------|---------|---------|
| Intercept | 0.0012 | 0.0001 | 2490000 | 8 | >0.001 |
| Co-regulation, conversation | -0.0007 | 0.0009 | 2490000 | -0.7 | 0.46 |
| Co-regulation, movement coop | 0.0068 | 0.0021 | 2490000 | 3.3 | >0.001 |
| Co-regulation, movement guided | -0.0026 | 0.0021 | 2490000 | -1.2 | 0.22 |
| Co-regulation, self paced | 0.0035 | 0.0027 | 2490000 | 1.3 | 0.19 |
| Co-regulation, synchronous | 0.0025 | 0.0009 | 2490000 | 2.8 | 0.005 |
| Co-regulation, turn taking | -0.0014 | 0.0009 | 2490000 | -1.6 | 0.10 |

Table 4: regression estimates for co-regulation with surrogate pairs as baseline

From table 4, we can see that participants seem to co-regulate in the conditions: movement coop, synchronous.

All in all our analyses suggest that the effect of co-regulation is very small and not very consistent. In the shuffled control analysis we found significant effects for self-paced, which was non-significant in the surrogate pairs control condition. In the surrogate pair analysis we found significant co-regulation in the synchronous and movement coop condition, which was not found in the shuffled control analysis.

Another interesting finding was that in the turn-taking condition all the estimate were negative, both in the shuffled control analysis and the surrogate pairs' analysis. This means that the participants anti-coregulate.

We aren't quite sure why we don't find better results, it may be due to the fact that there is no effect present or maybe our use of inadequate analysis that could provide us with too low statistical power, one would preferably use the package "CRQA" in R.

Limitations of surrogate pairs as control baseline:

There may be some issues with time when we combine two participants who did not do the task at the same time. For example, for the turn-taking condition pairs might have switched at slightly different times.

Effects of respiration coordination on heart rate coordination (J,D,P,A)

To test the effects of respiration coordination on heart rate coordination we would need a longer data format. So, like we merge the equations (1) and (2), we would need to include the respiration data as well. The data-structure would look like;

| |
|------------|
| X |
| HR_self |
| HR_other |
| Resp_self |
| Resp_other |

Then we would make columns for change and lag and make a model that would look something like this:

Change of $X \sim (HR_other - HR_self) * (Resp_other - Resp_self) * condition$

We would use this model to test whether respiration coordination effects heartrate coordination.

If the interaction effect is significant, respiration coordination effects heartrate coordination. Adding the condition interaction allows us to check if this effect is different for different conditions.

We are unsure how we would do this in R and how the other columns (fixed effects) would look like.

Bibliography.

Ferrer, E., & Helm, J. L. (2013). Dynamical systems modeling of physiological coregulation in dyadic interactions. *International Journal of Psychophysiology*, 88(3), 296–308.

<https://doi.org/10.1016/j.ijpsycho.2012.10.013>