HW2 - Nachi Lieder 314399114

File reading

First off we will observe the given dataset and undertstand the different values we have within each column. We can see that there is a difference in the scaling of the different parameters. Lets first address the personality features. We have seen from the previous project the difference in the distributions of the columns of the A,E,C,N,O (big 5) though we knew that the range was similar [ints from 1-7]. In this project we will address additional personality traits and metrics and evaluate them. Need for closure (NFC), Trait self-control (tsc) , and Life satisfaction (ls) are also ranged from 1-7 though in a float variable. Self-esteem (se) , Rumination and Depression are have a different range , and therefor we will consider scaling all features in the same range.

Next we will address the variables which indicate current feelings. Here too , we can see different scales per feature , where some have ranges of [-3,3] and others [0,4]. It is worth noting that the features that have a range of [0,4] have many missing values (~3300 which is ~50% of the dataset) and therefor we will consider fitting the dataset by removing all null values.

Last, we will explore the target variable - Meaning (meaningfulness) . This too ranges from [-3,3] and below we can observe the following distribution. Below is the histogram of the values of our target , where we can see that the two most answered scores were values 1 and 2.

Missing values

I will present two approaches to removing the issing values for this analysis.We will review the pros and cons , and evaluate both. One issue we have here is that many of the featured predictors that we are going to explore and exploit have ~50% missing values , while others have ~1-3% missing data. In our analysis, we will be taking pairs of predictors and running and evaluating a linear model using these two predictors and their interactions. This means that some pairs will include predictors with 50% missing data and some wont.

Consideration

One of the different aspects we will be evaluating are the T stats. We know that the T stat is subjective to the sample size N , and standalone wouldnt be an issue. This issue comes in to play once we compare and pool T stats into one analysis , while each test that we ran had a different sample size N. We will have a problem comparing the different T stats. On the other hand , another approach would be to be opertunistic and remove null per test, meaning different sample size , though each test will recieve its optimal maximal sample size , which may increase the significance of the model.

So in other words:

- Option A:

We will consider removing the null values at first , reducing the dataframe from 6686 rows to 3211 for the entire dataframe. Having the same sample size per each model would make the models more unified and more of one family.

- Option B:

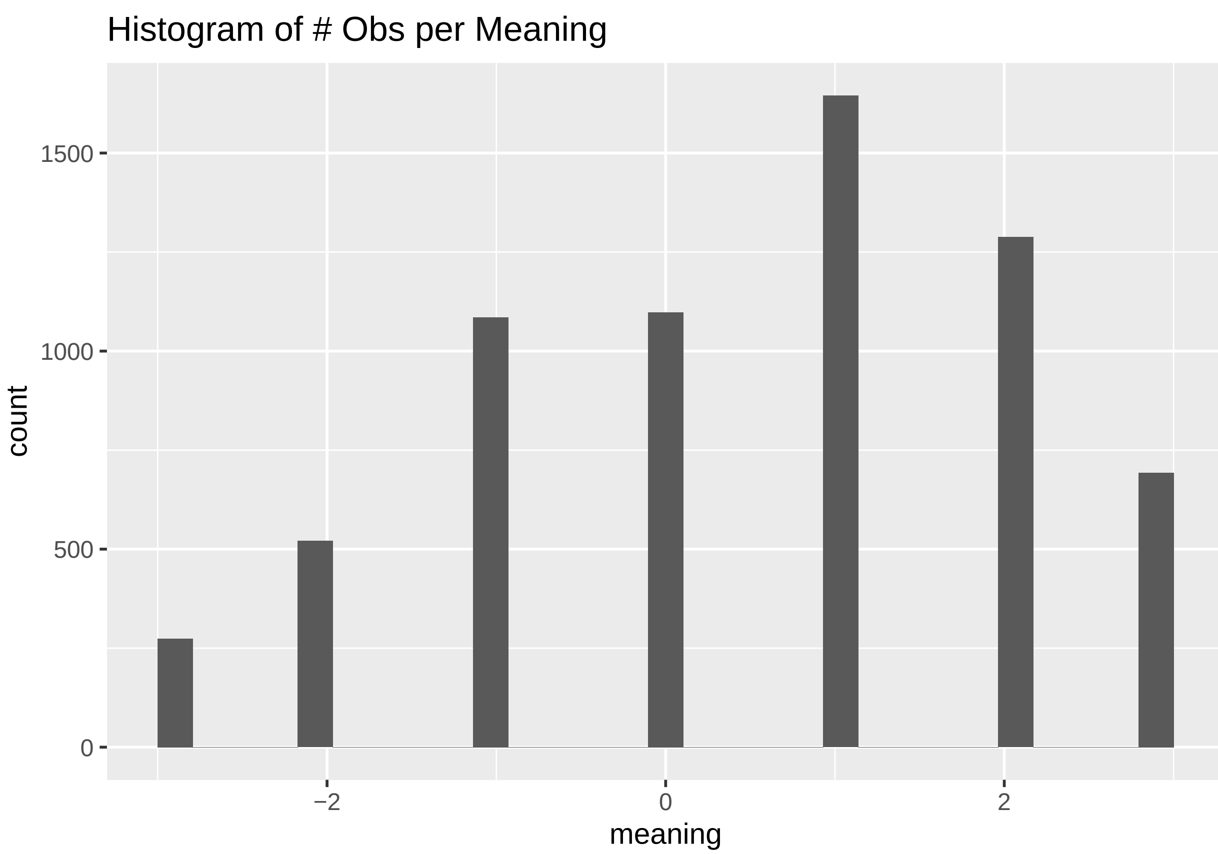
Per paired set which we will run our linear model , remove the null valued observations per that subset, bringing only some of the pairs to 50% , and others to 97%+.

I will evaulate both - and present both approaches. I will present the differences between the two and decide which one to continue with. The evaluation will include the plots of the T stats in both methods , and a Shapiro test to prove normality. We will see that both are distributed normal.

For the sake of the analysis , we will remain with the method of Option B, which will contain the different sample sizes , though has the advantage of using all the data we have rather than ommiting half of it. We will see very similar results in general , since most models are the same in terms of the input data for thier models. (Though both methods will be evaluated in the following analysis)

Meaningfulness

Let observe the meaningfulness feature. This will be defined as our target variable. Below is a distribution of the different values ranging from [-3,3] descretely. As shown , most observant have a score of 1 and 2.



Model Fitting

Next we will fit 108 models in the form of Meaninig ~ Personality + Feeling + Personality x Feeling. This represents both the individual affect each trait (personality and feeling) perform , as well as their interaction.

Lets look a the results. I will address the most interesting findings from the 108 models, and append to the end of the document the entire representation of all results. We can see that there are only a very small set of models which contain an interaction effect that can be considered significant with a confidence level of 0.05. In addition to the P val , I decicded to look at the absolute T value of larger than 3. We find that there are 3 models which answer the constraint of the T value , and only 1 of them also answers the threshold of the P value - including the P value constraint for adjusted P values , meaning that also the holm , hochberg and bonferroni are below 0.05. The model which answers this constraint is the interaction between religious and self-vs-other traits. Below we can see the tables of the following models which answer the given constraints of T values and adjust P values. we can see that there are 2 more models which have quite significantly absolute high T vals , being the interactions between extrovision and being under control , and between life satisfaction and self vs other.

In addition we can look at the histogram of the T values of the interactions between the feelings predictors and the personality predictors.

First off lets address the histogram. We can see a normal behavior to the values. Our median is 0.05 which is close enough to 0 , and ranges go from -3 to 3.5.

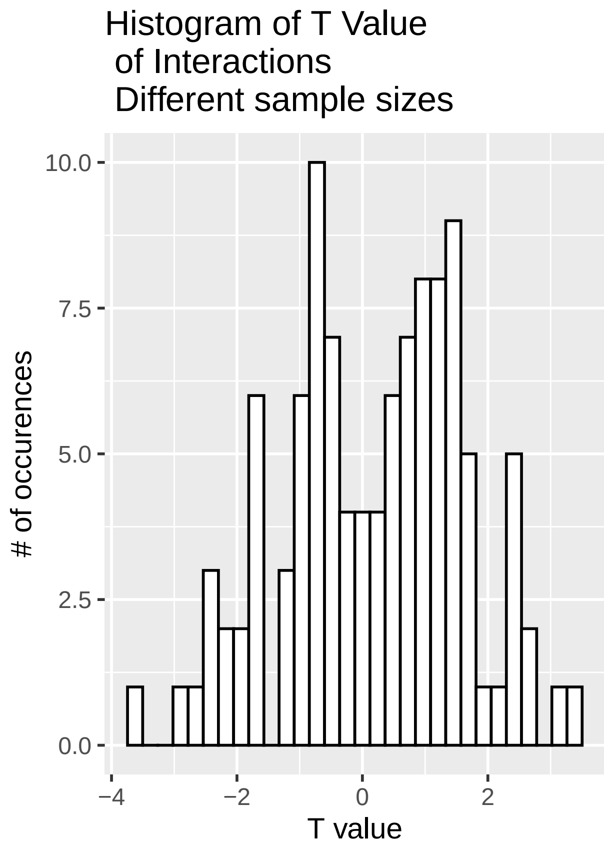
We can see that in terms of positive relationships the strongest relationships are the interactions between religious and focusing on other people (self vs others) , and life satifaction along with focusing on other people people. One could intuitively explain people that thinking of other people gives meaning to others, which is complimented by religious and life satisfaction.

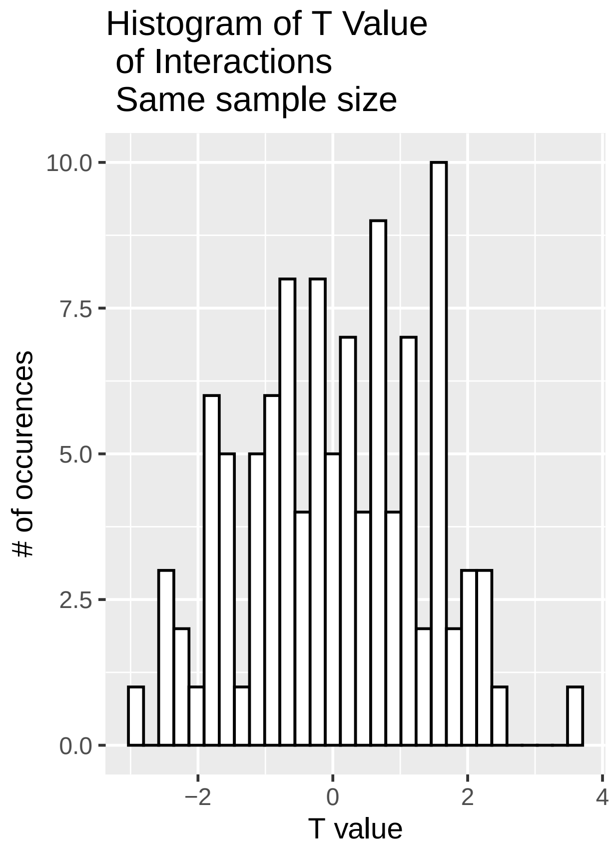
When viewing the two lowest T vals which indicate on negative relationships we see Extraversion along with control and depression along with focusing on others. this would suggest that people with great depression which dont think of others might not score the meaninigfullness as high (which may be due to self centered traits)

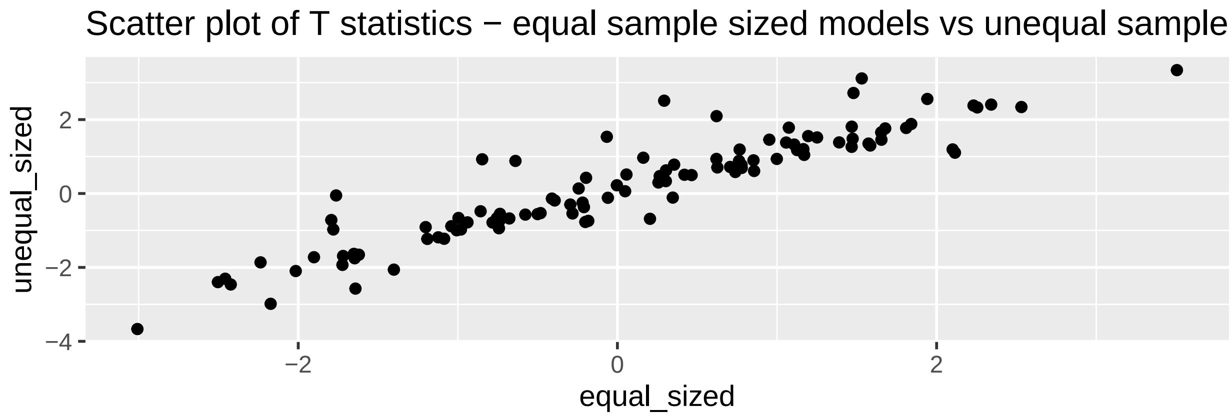
Its worth noting that the histogram of the non equal sample sizes seems to have a less normal distribution , though when checking the Shapiro test , we see that both sets have P values larger than 0.4 implying that both sets have a normal distribution.

Also checking the corerlation between the two sets of T stats we see a 92.3% correlation.

In addition we can look at the scatter plot between the equal sized sample sets per model vs the unequal sample sized models. There are very few models which their T statistic per one set of models is considered significant while for the other it is not. Giving ourselves a threshold of an absolute T statistic of 3 , we can see that by adding more observations for some of the tests , we still maintain the same direction of relationship , and the same level of significance more or less. There are still some tests that the difference in the T stat is quite large , getting to a differnece of 2 , though this is a very small set, where the unequal sample size tests manages to pertain a stronger value rather than the equal sample sized which had a T val closer to 0. This stregthens our descision to continue with the unequal sample size set.


Histogram of T Value
of Interactions
Different sample sizes
# of occurences
T value
10.0
7.5
5.0
2.5
0.0
−4
−2
0
2


Histogram of T Value
of Interactions
Same sample size
# of occurences
T value
10.0
7.5
5.0
2.5
0.0
−2
0
2
4



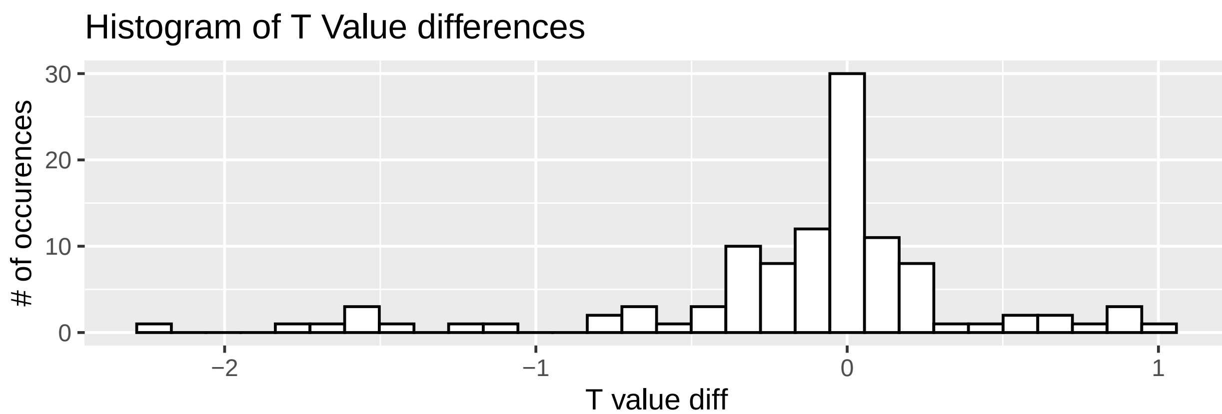


Table 1: Table continues below

	Interaction_estimate	Interaction_st_error
religious + selfother + religious * selfother + (1 | Subject)	0.06164	0.01846
E + control + E * control + (1 | Subject)	-0.07148	0.01949
ls + selfother + ls * selfother + (1 | Subject)	0.0581	0.01866

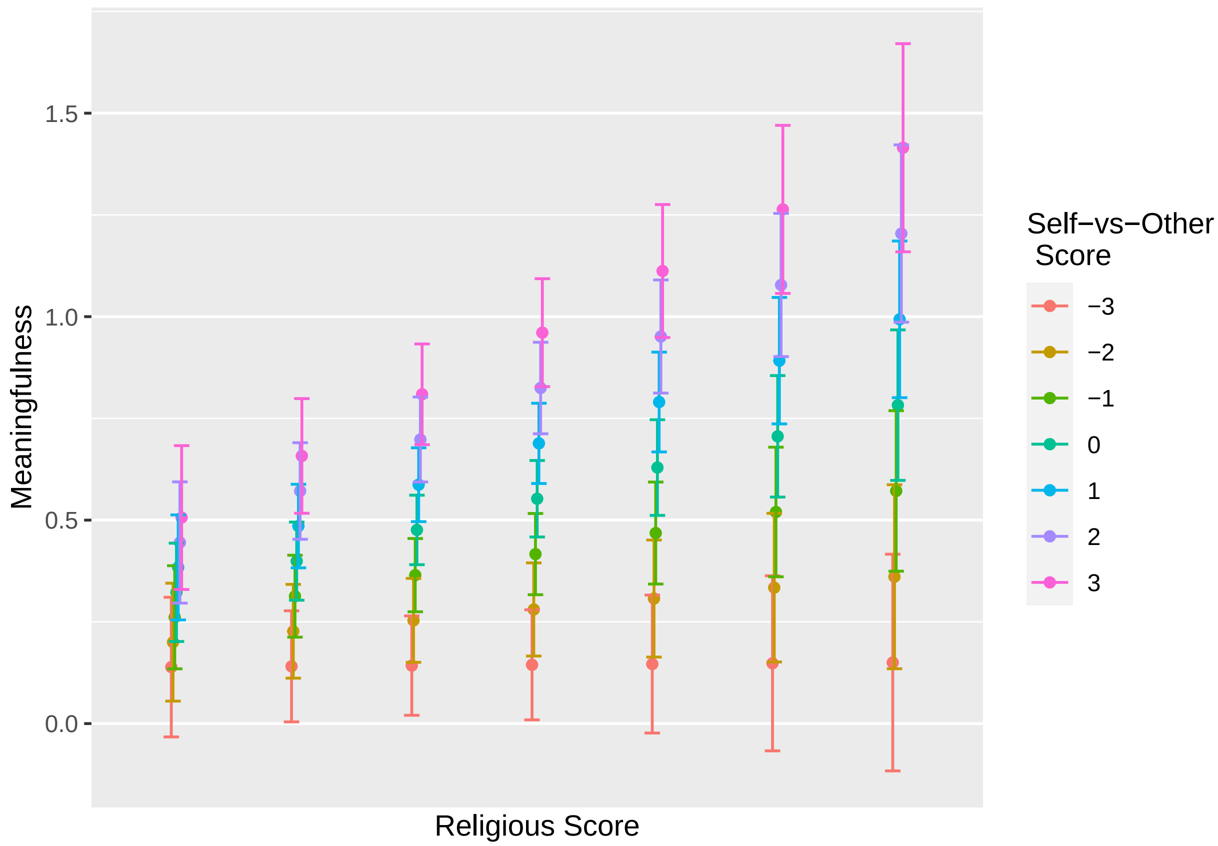
	Interaction_Tvalue
religious + selfother + religious * selfother + (1 | Subject)	3.339
E + control + E * control + (1 | Subject)	-3.668
ls + selfother + ls * selfother + (1 | Subject)	3.114

Table 3: Table continues below

	Personality	Feeling	p_val	hochberg_p_val	holm_p_val
18	E	control	0.0002468	0.02665	0.02665

	bonferroni_p_val
18	0.02665

Lets review the single significant model that answers all criterias we set for ourselves: The model which tests the interaction between religious and self-vs-other traits. The plot below describes the interactions of the two spoken traits , along with the ranges of the given CIs of 95% , where we can see the different plots of self-vs-other groups , vs the progress of the religious score. We can see per group of self-vs-other (a group here being a certain score given by the observants) , that as the score of the religoius increases , we see an increase in the predicted target (meaningfulness). We can see here that for an instance, per the lowest score of the religous , the differentiation between the predictions is a bit lower between the different scores of the self-vs-other score. Though per the highest score of religious we can see larger differentiations . Also worth noting that the prediction target for the lower groups is much lower than the higher.

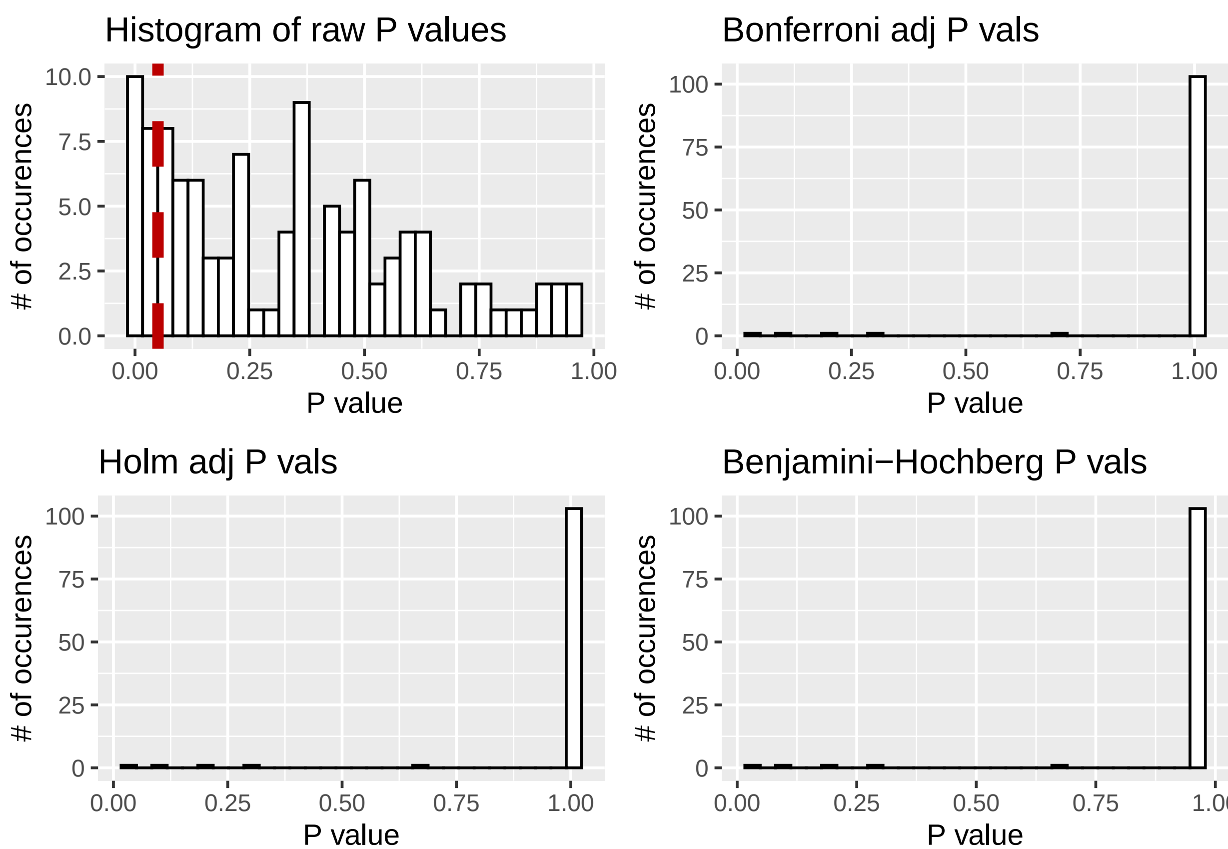


As stated, the t-statistics for fixed effects in the above models have approximately a standard normal distribution. We will now look at the aprox P values , as well as the Bonferroni-adjusted p-values, Holm-adjusted p-values and Benjamini-Hochberg adjusted p-values for the interaction terms.

Now lets address the Bonferroni-adjusted p-values as well as the Holm-adjusted p-values and Benjamini-Hochberg p vals. We perform adjustments to the Interaction predictor and view the histograms of the adjusted observations. We can see that most adjustments adjust the pvals to 1 in all 3 different types of adjustments. This is possibly mostly due to the high pvalues and the sample of 108 which we sampled from as well as the size of our sample set.

Lets address the single lowest P val from the Benjamini-Hochberg adjustment. This individual can easily be observed.The raw P val here is 0.004 and represents the predictor of the interaction between religious and selfother. Lets assume independence between tests for the sake of the analysis. According to this adjustment we can assume an alpha of 0.05 , giving us only 1 model without rejection vs several models using the original P vals (such as Extraversion:control and religous:arousal) . We can see the same phenomenon with the bonferroni and holm adjustments.

Note: As we know from the definition , each Pval_i_ (BH adjustment) <= Pval_i_(bonferroni) for each i-th test perfromed .



The plots below describes the distribution of P values per personality trait and per Feeling trait.

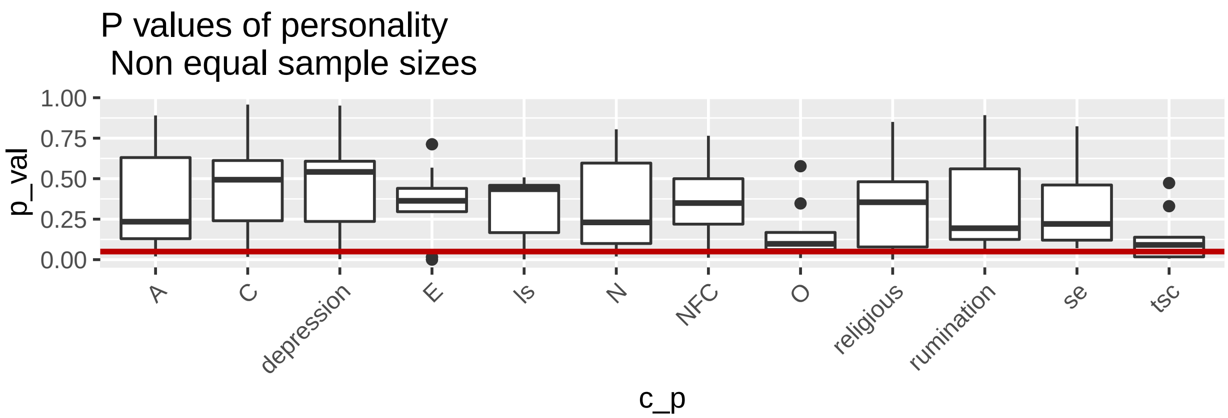
- First off we can see that the "self-control" trait (tsc) has a very low median and low variance, other than a couple outliers. This may indicate on a significant conscensus in the P values and interaction between this trait and all predictor feeilings.
- Second , lets look at the depression predictor. We can see here a very high median, suggesting that there is no significant phenomenon of an interaction effect between depression vs any predictor feelings. Its worth noting that there are some P values under depression that might be low enough to suit our confidense level , but the general phenomenon of the interaction between depression and feelings is suggesting no significance.

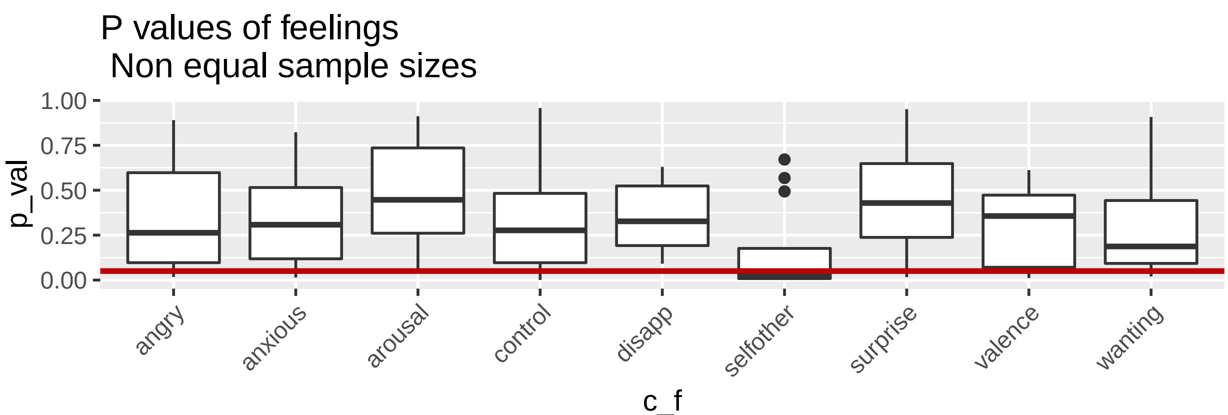
For now we will focus on those two personality traits since they seem to have the overall lowest P vlaues. These would be the self control predictor (tsc) and the Openness ("O").

Now lets look at the second box plot , of the p values grouped by feelings predictors.

- Here we can see that the feeling of “focus on yourself/others” (selfother) seems to have the most significance across all personalities towards predicting the meaningfullness of current thoughts. The median is the lowest and closest to 0.05 which was set as our benchmark threshold.
- Arousal seems to have the largest variance, which indicates some sort of disagreement between the different interactions of personalities as a predictor towards the meaningfullness of current thoughts.

Most of these predictors have medians close to 0.25 which isnt so confident in its significance.

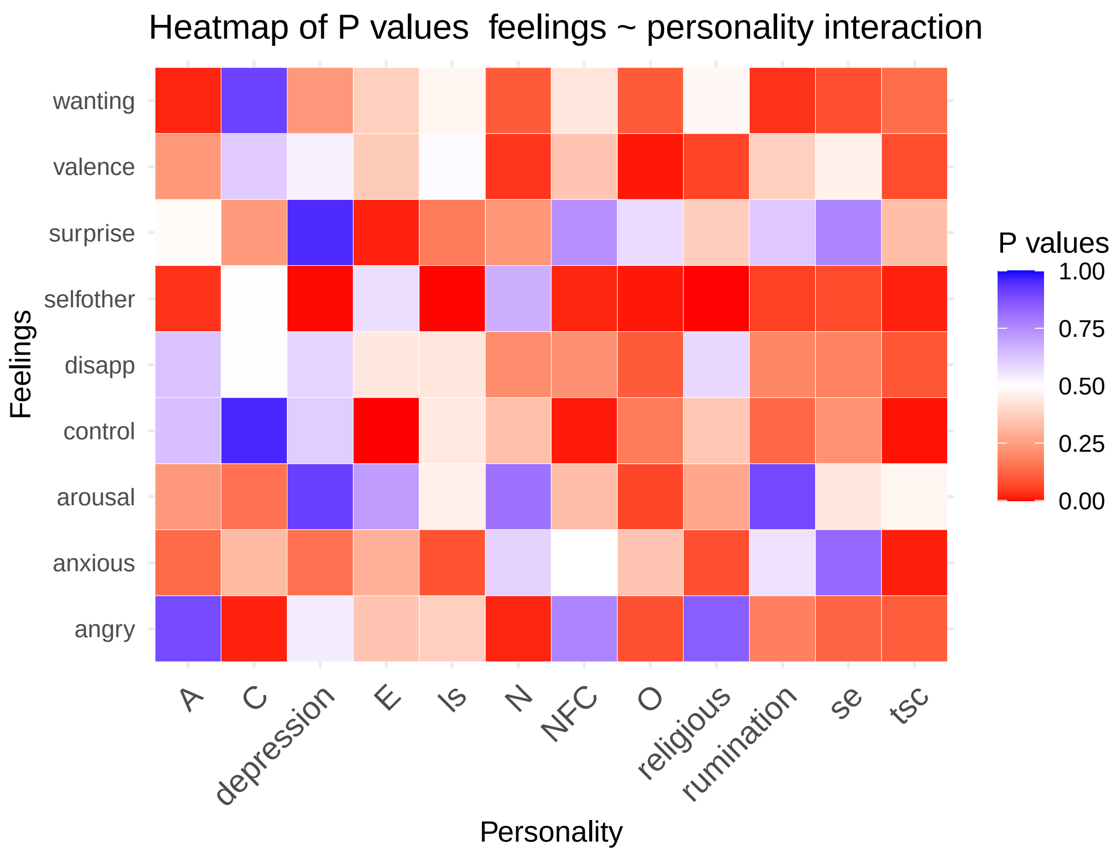




To look at these p values more in depth and in individual terms , lets look at the heatmap matrix below which can describe the pvalues more individually and the sole interaction effect between each 2 pairs of personality and feeling predictors. Lets address some of the elements here.

- As we stated before , TSC has pretty significant pvalues accross all Feeling predictors. It is has a weaker confidense interacting with the surprise feeling and valence. so generally speaking we can understand that the interaction of self control and surpise doesnt predict significantly the meaniningfullness.
- Lets look at the control feeling. Here we can see a wide range of values , though control interacted with Extraversion has a strong confidence. this makes sense since some traits under extraversion are assertaveness and talkative which compliments the feeling of control. This interaction has the most negative T value indicating a negative relationship between the given interaction and the targeted feature of meaningfullness. In ther words this would suggest that people that have strong extraversion and control traits and personalities have low meaningfullness scores. this is quite interesting since personality as itself and the feeling standalone have positive estimates and positive T values, though the interaction between them is low!

- Anger and Neuroticism interacted have a significantly low P value , which may indicate that may suggest angry neurotic people may be predictive towards meaningfullness . The combination of the P value and the positive significant T value indicates a positive relationship (angry + neuroticism -> meaningfullness)
- Self other and depression have a very low T value and P value, also indicating a singificant negative relation. We would assume that people that are focused on themselves and feel depressed tend to score meaningfullness with low scores. This is quite interesting. Diving into this interaction , we see that standalone the personality trait is with a negative T val (depression) though the Feeling trait is positive. This may indicate the strong negative relationship between depression and meaniningfullness.



Part 2

Lets assess the specific model of Meaning ~ Depression + Self-vs-Other + Depression:Self-vs-Other. Lets look at first at the raw P val of the interaction , and notice that it has a value of 0.002 , which relative to our benchmark of alpha 0.05 is low. This indicates on significance of our model.

Next lets observe the T values:

- We can see that the Personality predictor - Depression. This value is equal to -2.2 which is acceptably high in its absolute value , with a negative relation to our target variable. This indicates that significantly as the observants rated low scores in their depression question , they rated high in the meaningfulness question , and vice versa.

- Next lets observe the Feeling T val - Self vs Other. This is equal to 12.6 which is more significant (given the equal scale between the 2) with a positive relationship. So the higher the Self vs Other score - the higher the meaningfullness score.

This is interesting that the two individual predictors have opposite relations with the target.

- Last lets review the interaction T val , where we see a negative value of -2.9 , which too is slightly significant. This would indicate that the interaction of the two traits would have a negative relation.

Its worth noting the standard error of the personality trait being the highest of the three predictors. Also there is a high negative correlation between the interaction predictor and the feeling predictor (self vs other)

	test results
Intercept__estimate	0.5248121
Personality__estimate	-0.08846888
Feeling__estimate	0.2399544
Interaction__estimate	-0.05448329
Intercept__st__error	0.03858519
Personality__st__error	0.03862418
Feeling__st__error	0.01898159
Interaction__st__error	0.01825422
Intercept__Tvalue	13.60139
Personality__Tvalue	-2.290505
Feeling__Tvalue	12.64143
Interaction__Tvalue	-2.984696
formula	depression + selfother + depression * selfother + (1 | Subject)

Table 6: Summary of meaning ~ depression * self-vs-other

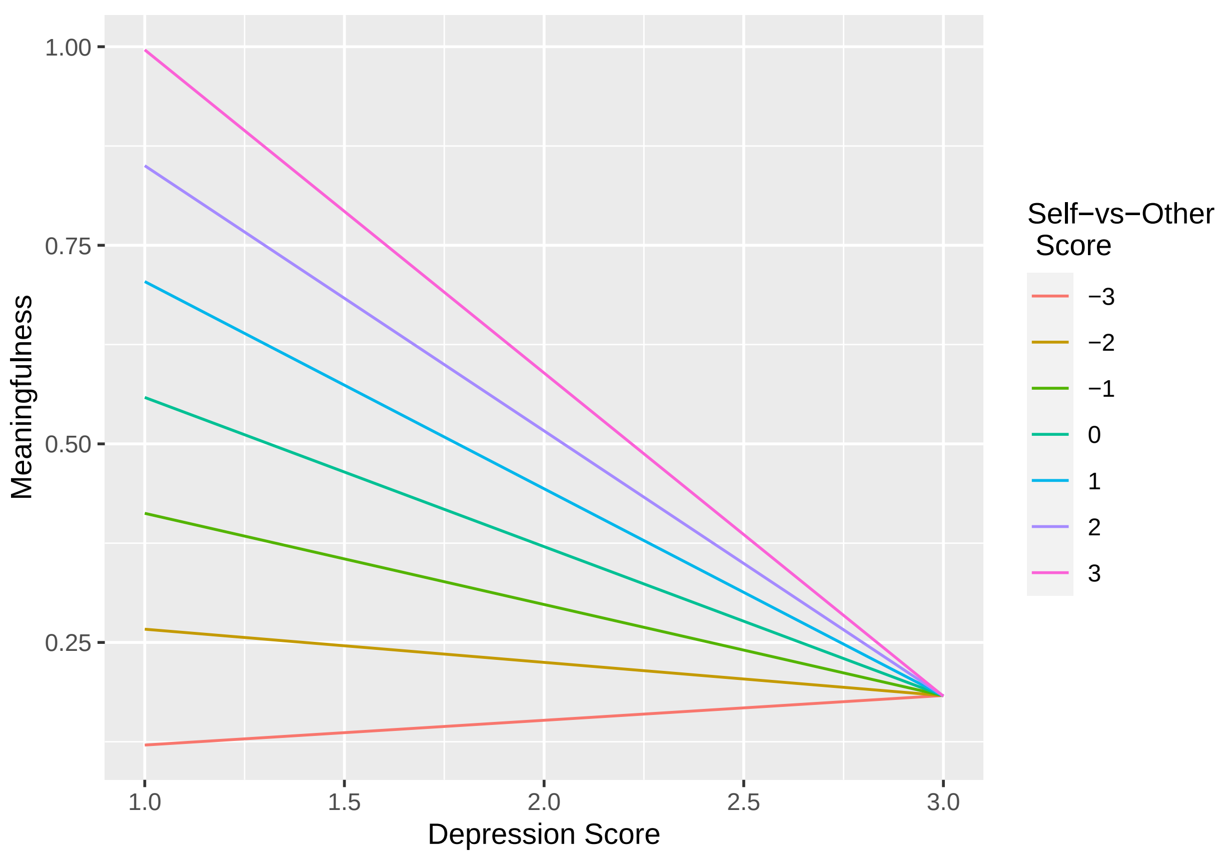
	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.5248	0.03859	6008	13.6	1.61e-41
depression	-0.08847	0.03862	469	-2.291	0.02243
selfother	0.24	0.01898	6008	12.64	3.592e-36
depression:selfother	-0.05448	0.01825	6008	-2.985	0.00285

Now lets look a little deeper into the effect of self-vs-other on meaningfulnessat different depression levels. Below we can read the table of the different confidence intervals relative to the X (depression Score) and our group (Self vs other). We can also look at the std error per set as well as the confidence intervals. Below the table we can see a graphical representation of the trends above, demonstrating the larger negative slopes as the self-vs-other score increases.

Generally speaking we can first address the slopes. On our X axis we can see the different scores of the depression , and the graphs represent the different scores of "self-vs-other" which would be 7 groups representing the disscrete values of [-3,3]. We can see from the slopes that as the values are larger for the self-vs-other trait score , we can get a larger negative slope.

We can also see the large variance in the predicted target varaible under depression scores of 1, vs score 3 which is much lower. This

x	predicted	std.error	conf.low	conf.high	group
1	0.1209	0.08583	-0.04738	0.2891	-3
1	0.2667	0.07257	0.1245	0.409	-2
1	0.4126	0.06326	0.2886	0.5366	-1
1	0.5585	0.05979	0.4413	0.6756	0
1	0.7043	0.06312	0.5806	0.828	1
1	0.8502	0.07232	0.7084	0.9919	2
1	0.9961	0.08552	0.8285	1.164	3
2	0.152	0.1051	-0.05393	0.358	-3
2	0.2249	0.0898	0.0489	0.4009	-2
2	0.2978	0.07947	0.142	0.4535	-1
2	0.3706	0.07614	0.2214	0.5199	0
2	0.4435	0.08069	0.2854	0.6017	1
2	0.5164	0.09195	0.3361	0.6966	2
2	0.5892	0.1078	0.3779	0.8006	3
3	0.1832	0.2358	-0.2789	0.6454	-3
3	0.1831	0.2016	-0.212	0.5782	-2
3	0.183	0.1783	-0.1666	0.5325	-1
3	0.1828	0.1706	-0.1516	0.5172	0
3	0.1827	0.1805	-0.171	0.5364	1
3	0.1825	0.2053	-0.2199	0.585	2
3	0.1824	0.2406	-0.2892	0.654	3



Lets look at the effect that we receive by fixing the depression levels to the values of 1,2,3. Generally speaking we are using a model in the following form:

$$y(x_{depression}, x_{self-vs-other}) = \beta_0 + \beta_1 x_{depression} + \beta_2 x_{self-vs-other} + \beta_3 x_{depression} * x_{self-vs-other} + \epsilon$$

We will fix the results of depression's predictor with the values 1,2,3 to form the following models:

- model 1:

$$y(1, x_{self-vs-other}) = \beta_0 + \beta_1 + \beta_2 x_{self-vs-other} + \beta_3 * x_{self-vs-other} + \epsilon$$

- model 2:

$$y(2, x_{self-vs-other}) = \beta_0 + \beta_1 * 2 + \beta_2 x_{self-vs-other} + \beta_3 * 2 * x_{self-vs-other} + \epsilon$$

- model 3:

$$y(3, x_{self-vs-other}) = \beta_0 + \beta_1 * 3 + \beta_2 x_{self-vs-other} + \beta_3 * 3 * x_{self-vs-other} + \epsilon$$

Using these models we will assess the different effects and understand the differences between the different models and values. From the table below we can see the three tests we performed, matching the three levels of depression that we stated. We can see that for depression score of 1 , the P val is very low close to 0 , and increases as the depression level increases. The statistic decreases which too indicates insignificance , specifically for depression= 3. We can see that the standard error increasaes as well , as the depression score increases.

Conclussion:

We can assume from here that as the depression level is lower, the influence of the predictor of the "self-vs-other" score is less significant. (worth noting that a very high score of depression will give a high absolute valued slope for the self other predictor - though a negative slope , hence the negative estimate for the depression = 3)

Table 8: Effect of Self-vs-Other as a function of Depression (continued below)

	estimate	std.error	statistic	p.value	beta0	df
Depression_1	0.1459	0.02045	50.86	9.922e-13	0	1
Depression_2	0.07287	0.02481	8.626	0.003314	0	1
Depression_3	-0.0001364	0.05541	6.055e-06	0.998	0	1

	lwr	upr
Depression_1	0.1058	0.186
Depression_2	0.02424	0.1215
Depression_3	-0.1087	0.1085

Appendix

Here we have the former representation of all the 108 models.

Table 10: Table continues below

	formula	Intercept_estimate
Estimate	religious + valence + religious * valence + (1 | Subject)	0.5265
Estimate1	religious + arousal + religious * arousal + (1 | Subject)	0.5264
Estimate2	religious + angry + religious * angry + (1 | Subject)	0.4857
Estimate3	religious + anxious + religious * anxious + (1 | Subject)	0.4848
Estimate4	religious + disapp + religious * disapp + (1 | Subject)	0.4874
Estimate5	religious + surprise + religious * surprise + (1 | Subject)	0.483
Estimate6	religious + wanting + religious * wanting + (1 | Subject)	0.4833
Estimate7	religious + selfother + religious * selfother + (1 | Subject)	0.5221
Estimate8	religious + control + religious * control + (1 | Subject)	0.5284
Estimate9	E + valence + E * valence + (1 | Subject)	0.5265
Estimate10	E + arousal + E * arousal + (1 | Subject)	0.5235
Estimate11	E + angry + E * angry + (1 | Subject)	0.4803
Estimate12	E + anxious + E * anxious + (1 | Subject)	0.4786
Estimate13	E + disapp + E * disapp + (1 | Subject)	0.4821
Estimate14	E + surprise + E * surprise + (1 | Subject)	0.4762
Estimate15	E + wanting + E * wanting + (1 | Subject)	0.4769
Estimate16	E + selfother + E * selfother + (1 | Subject)	0.5229
Estimate17	E + control + E * control + (1 | Subject)	0.5283
Estimate18	A + valence + A * valence + (1 | Subject)	0.5255
Estimate19	A + arousal + A * arousal + (1 | Subject)	0.5276
Estimate20	A + angry + A * angry + (1 | Subject)	0.4822
Estimate21	A + anxious + A * anxious + (1 | Subject)	0.4855
Estimate22	A + disapp + A * disapp + (1 | Subject)	0.4828
Estimate23	A + surprise + A * surprise + (1 | Subject)	0.4826
Estimate24	A + wanting + A * wanting + (1 | Subject)	0.4815
Estimate25	A + selfother + A * selfother + (1 | Subject)	0.5246
Estimate26	A + control + A * control + (1 | Subject)	0.5276
Estimate27	C + valence + C * valence + (1 | Subject)	0.5292
Estimate28	C + arousal + C * arousal + (1 | Subject)	0.5306
Estimate29	C + angry + C * angry + (1 | Subject)	0.4804
Estimate30	C + anxious + C * anxious + (1 | Subject)	0.482
Estimate31	C + disapp + C * disapp + (1 | Subject)	0.4848
Estimate32	C + surprise + C * surprise + (1 | Subject)	0.4882
Estimate33	C + wanting + C * wanting + (1 | Subject)	0.4839
Estimate34	C + selfother + C * selfother + (1 | Subject)	0.5291
Estimate35	C + control + C * control + (1 | Subject)	0.5311
Estimate36	N + valence + N * valence + (1 | Subject)	0.5215
Estimate37	N + arousal + N * arousal + (1 | Subject)	0.5276

	formula	Intercept_estimate
Estimate38	N + angry + N * angry + (1 | Subject)	0.4761
Estimate39	N + anxious + N * anxious + (1 | Subject)	0.485
Estimate40	N + disapp + N * disapp + (1 | Subject)	0.4804
Estimate41	N + surprise + N * surprise + (1 | Subject)	0.4824
Estimate42	N + wanting + N * wanting + (1 | Subject)	0.4865
Estimate43	N + selfother + N * selfother + (1 | Subject)	0.5267
Estimate44	N + control + N * control + (1 | Subject)	0.5315
Estimate45	O + valence + O * valence + (1 | Subject)	0.5181
Estimate46	O + arousal + O * arousal + (1 | Subject)	0.5218
Estimate47	O + angry + O * angry + (1 | Subject)	0.48
Estimate48	O + anxious + O * anxious + (1 | Subject)	0.4792
Estimate49	O + disapp + O * disapp + (1 | Subject)	0.4808
Estimate50	O + surprise + O * surprise + (1 | Subject)	0.4802
Estimate51	O + wanting + O * wanting + (1 | Subject)	0.4757
Estimate52	O + selfother + O * selfother + (1 | Subject)	0.5206
Estimate53	O + control + O * control + (1 | Subject)	0.5204
Estimate54	NFC + valence + NFC * valence + (1 | Subject)	0.5263
Estimate55	NFC + arousal + NFC * arousal + (1 | Subject)	0.5251
Estimate56	NFC + angry + NFC * angry + (1 | Subject)	0.4842
Estimate57	NFC + anxious + NFC * anxious + (1 | Subject)	0.4841
Estimate58	NFC + disapp + NFC * disapp + (1 | Subject)	0.4874
Estimate59	NFC + surprise + NFC * surprise + (1 | Subject)	0.4824
Estimate60	NFC + wanting + NFC * wanting + (1 | Subject)	0.4844
Estimate61	NFC + selfother + NFC * selfother + (1 | Subject)	0.5228
Estimate62	NFC + control + NFC * control + (1 | Subject)	0.5269
Estimate63	tsc + valence + tsc * valence + (1 | Subject)	0.5243
Estimate64	tsc + arousal + tsc * arousal + (1 | Subject)	0.5293
Estimate65	tsc + angry + tsc * angry + (1 | Subject)	0.4798
Estimate66	tsc + anxious + tsc * anxious + (1 | Subject)	0.476
Estimate67	tsc + disapp + tsc * disapp + (1 | Subject)	0.4789
Estimate68	tsc + surprise + tsc * surprise + (1 | Subject)	0.4838
Estimate69	tsc + wanting + tsc * wanting + (1 | Subject)	0.4879
Estimate70	tsc + selfother + tsc * selfother + (1 | Subject)	0.5272
Estimate71	tsc + control + tsc * control + (1 | Subject)	0.5236
Estimate72	se + valence + se * valence + (1 | Subject)	0.5321
Estimate73	se + arousal + se * arousal + (1 | Subject)	0.5292
Estimate74	se + angry + se * angry + (1 | Subject)	0.4927
Estimate75	se + anxious + se * anxious + (1 | Subject)	0.484
Estimate76	se + disapp + se * disapp + (1 | Subject)	0.4944
Estimate77	se + surprise + se * surprise + (1 | Subject)	0.4844

	formula	Intercept_estimate
Estimate78	se + wanting + se * wanting + (1 | Subject)	0.4874
Estimate79	se + selfother + se * selfother + (1 | Subject)	0.5276
Estimate80	se + control + se * control + (1 | Subject)	0.5332
Estimate81	rumination + valence + rumination * valence + (1 | Subject)	0.5325
Estimate82	rumination + arousal + rumination * arousal + (1 | Subject)	0.5291
Estimate83	rumination + angry + rumination * angry + (1 | Subject)	0.4809
Estimate84	rumination + anxious + rumination * anxious + (1 | Subject)	0.4821
Estimate85	rumination + disapp + rumination * disapp + (1 | Subject)	0.482
Estimate86	rumination + surprise + rumination * surprise + (1 | Subject)	0.4845
Estimate87	rumination + wanting + rumination * wanting + (1 | Subject)	0.494
Estimate88	rumination + selfother + rumination * selfother + (1 | Subject)	0.5269
Estimate89	rumination + control + rumination * control + (1 | Subject)	0.5348
Estimate90	depression + valence + depression * valence + (1 | Subject)	0.5304
Estimate91	depression + arousal + depression * arousal + (1 | Subject)	0.5274
Estimate92	depression + angry + depression * angry + (1 | Subject)	0.4815
Estimate93	depression + anxious + depression * anxious + (1 | Subject)	0.476
Estimate94	depression + disapp + depression * disapp + (1 | Subject)	0.4908
Estimate95	depression + surprise + depression * surprise + (1 | Subject)	0.4843
Estimate96	depression + wanting + depression * wanting + (1 | Subject)	0.4887
Estimate97	depression + selfother + depression * selfother + (1 | Subject)	0.5248
Estimate98	depression + control + depression * control + (1 | Subject)	0.5302
Estimate99	ls + valence + ls * valence + (1 | Subject)	0.5338
Estimate100	ls + arousal + ls * arousal + (1 | Subject)	0.5304
Estimate101	ls + angry + ls * angry + (1 | Subject)	0.4813
Estimate102	ls + anxious + ls * anxious + (1 | Subject)	0.4764
Estimate103	ls + disapp + ls * disapp + (1 | Subject)	0.4826
Estimate104	ls + surprise + ls * surprise + (1 | Subject)	0.4862
Estimate105	ls + wanting + ls * wanting + (1 | Subject)	0.4867
Estimate106	ls + selfother + ls * selfother + (1 | Subject)	0.5281
Estimate107	ls + control + ls * control + (1 | Subject)	0.5335

Table 11: Table continues below

	Personality_estimate	Feeling_estimate
Estimate	0.1914	0.09317
Estimate1	0.1883	0.1989
Estimate2	0.1712	0.01371
Estimate3	0.172	0.1289
Estimate4	0.1696	0.009819
Estimate5	0.1609	0.1409
Estimate6	0.1699	0.07416
Estimate7	0.1763	0.2333
Estimate8	0.1978	0.153
Estimate9	0.1638	0.0901
Estimate10	0.1632	0.2001
Estimate11	0.2215	0.01697
Estimate12	0.2255	0.1283
Estimate13	0.2222	0.0154
Estimate14	0.2163	0.1408
Estimate15	0.2185	0.07481
Estimate16	0.164	0.2386
Estimate17	0.1675	0.1556
Estimate18	0.1405	0.09323
Estimate19	0.155	0.2016
Estimate20	0.1594	0.02127
Estimate21	0.1661	0.137
Estimate22	0.1572	0.01644
Estimate23	0.1592	0.1513
Estimate24	0.1515	0.07898
Estimate25	0.1361	0.2365
Estimate26	0.138	0.151
Estimate27	0.1768	0.09159
Estimate28	0.1865	0.2014
Estimate29	0.1799	0.01906
Estimate30	0.1907	0.135
Estimate31	0.18	0.01936
Estimate32	0.189	0.1569
Estimate33	0.1802	0.08244
Estimate34	0.1809	0.2397
Estimate35	0.1643	0.1481
Estimate36	-0.1684	0.09181
Estimate37	-0.1861	0.2022
Estimate38	-0.2058	0.01875
Estimate39	-0.2189	0.1429
Estimate40	-0.204	0.0176
Estimate41	-0.2021	0.1511
Estimate42	-0.2002	0.08439
Estimate43	-0.1845	0.2401
Estimate44	-0.1617	0.1472
Estimate45	0.2009	0.09339
Estimate46	0.1966	0.2012
Estimate47	0.2248	0.01409
Estimate48	0.2234	0.1258
Estimate49	0.2254	0.009349
Estimate50	0.2187	0.1467

	Personality_estimate	Feeling_estimate
Estimate51	0.2198	0.07129
Estimate52	0.1986	0.239
Estimate53	0.1977	0.1508
Estimate54	0.006757	0.09153
Estimate55	0.002788	0.2025
Estimate56	-0.01797	0.01862
Estimate57	-0.02766	0.1328
Estimate58	-0.01363	0.0143
Estimate59	-0.02709	0.1497
Estimate60	-0.02434	0.07728
Estimate61	0.007699	0.2401
Estimate62	0.006662	0.1538
Estimate63	0.2272	0.08973
Estimate64	0.2409	0.2028
Estimate65	0.2502	0.02362
Estimate66	0.2659	0.1397
Estimate67	0.2521	0.02298
Estimate68	0.2555	0.1528
Estimate69	0.2581	0.08865
Estimate70	0.2353	0.2359
Estimate71	0.2227	0.1493
Estimate72	0.1432	0.08695
Estimate73	0.1621	0.2016
Estimate74	0.1725	0.03192
Estimate75	0.1889	0.1425
Estimate76	0.1716	0.0325
Estimate77	0.1797	0.1556
Estimate78	0.1744	0.08103
Estimate79	0.1566	0.2373
Estimate80	0.1402	0.1468
Estimate81	-0.1361	0.08605
Estimate82	-0.1448	0.2017
Estimate83	-0.1691	0.02203
Estimate84	-0.1865	0.1419
Estimate85	-0.1695	0.01912
Estimate86	-0.1724	0.1516
Estimate87	-0.1854	0.08625
Estimate88	-0.1425	0.2371
Estimate89	-0.1292	0.1461
Estimate90	-0.07728	0.0877
Estimate91	-0.09082	0.2013
Estimate92	-0.1052	0.02439
Estimate93	-0.1297	0.1368
Estimate94	-0.09332	0.02608
Estimate95	-0.09903	0.1507
Estimate96	-0.09877	0.08316
Estimate97	-0.08847	0.24
Estimate98	-0.07079	0.1492
Estimate99	0.001367	0.09312
Estimate100	0.02255	0.2033
Estimate101	0.04102	0.01588
Estimate102	0.05847	0.1309

	Personality_estimate	Feeling_estimate
Estimate103	0.04015	0.01234
Estimate104	0.03766	0.1491
Estimate105	0.03886	0.07813
Estimate106	0.01892	0.2358
Estimate107	0.001602	0.1514

Table 12: Table continues below

	Interaction_estimate	Intercept_st_error
Estimate	0.03828	0.03781
Estimate1	0.02112	0.03837
Estimate2	-0.005607	0.04409
Estimate3	0.05204	0.0442
Estimate4	-0.01638	0.04407
Estimate5	0.02518	0.04374
Estimate6	0.02051	0.04402
Estimate7	0.06164	0.03796
Estimate8	0.01775	0.03778
Estimate9	-0.01816	0.0384
Estimate10	-0.006951	0.0387
Estimate11	0.0274	0.04343
Estimate12	0.0307	0.04348
Estimate13	0.02316	0.04348
Estimate14	0.06893	0.04291
Estimate15	0.02599	0.04331
Estimate16	-0.01039	0.03816
Estimate17	-0.07148	0.03823
Estimate18	0.0247	0.03846
Estimate19	0.02292	0.03883
Estimate20	-0.004059	0.04428
Estimate21	0.04343	0.04427
Estimate22	-0.01372	0.04428
Estimate23	0.01955	0.04365
Estimate24	0.06891	0.04395
Estimate25	0.03927	0.03849
Estimate26	0.008864	0.03845
Estimate27	0.0101	0.03807
Estimate28	0.02811	0.03842
Estimate29	-0.07019	0.04375
Estimate30	-0.02914	0.04399
Estimate31	-0.0193	0.04406
Estimate32	0.03367	0.04342
Estimate33	-0.003398	0.04386
Estimate34	-0.01278	0.03795
Estimate35	-0.001033	0.0382
Estimate36	-0.04086	0.03808
Estimate37	-0.004715	0.03841
Estimate38	0.06703	0.04364
Estimate39	-0.01503	0.04395
Estimate40	0.03686	0.04381
Estimate41	0.03337	0.04328

	Interaction_estimate	Intercept_st_error
Estimate42	-0.04816	0.04374
Estimate43	0.00784	0.03789
Estimate44	0.01819	0.03827
Estimate45	0.05238	0.03774
Estimate46	-0.0356	0.03837
Estimate47	-0.05186	0.04338
Estimate48	-0.02786	0.04361
Estimate49	-0.04842	0.04345
Estimate50	-0.01675	0.04313
Estimate51	0.04839	0.04354
Estimate52	-0.04801	0.03781
Estimate53	0.02676	0.03785
Estimate54	0.01857	0.03918
Estimate55	-0.01834	0.03954
Estimate56	-0.008595	0.04494
Estimate57	-0.01948	0.0451
Estimate58	-0.03463	0.04501
Estimate59	0.009546	0.04443
Estimate60	-0.02322	0.04494
Estimate61	-0.04268	0.03891
Estimate62	0.04677	0.03905
Estimate63	0.03585	0.03717
Estimate64	-0.01275	0.03747
Estimate65	-0.04893	0.04289
Estimate66	-0.0703	0.0428
Estimate67	-0.05069	0.04298
Estimate68	-0.02625	0.04247
Estimate69	0.04217	0.04302
Estimate70	0.0419	0.03715
Estimate71	0.05095	0.03721
Estimate72	-0.01476	0.03865
Estimate73	0.0147	0.03875
Estimate74	0.04807	0.04455
Estimate75	0.006595	0.04438
Estimate76	0.03966	0.04471
Estimate77	0.009021	0.04364
Estimate78	0.05171	0.04416
Estimate79	0.03232	0.03827
Estimate80	-0.02322	0.03847
Estimate81	0.01826	0.03863
Estimate82	0.00254	0.03872
Estimate83	0.04017	0.04402
Estimate84	0.01717	0.04413
Estimate85	0.03797	0.04407
Estimate86	0.01448	0.04348
Estimate87	-0.05927	0.04412
Estimate88	-0.03516	0.03823
Estimate89	0.03092	0.03854
Estimate90	0.01214	0.03899
Estimate91	-0.002297	0.0391
Estimate92	0.0173	0.0448
Estimate93	0.04203	0.04465

	Interaction_estimate	Intercept_st_error
Estimate94	-0.01494	0.04511
Estimate95	0.001803	0.04399
Estimate96	-0.03416	0.04456
Estimate97	-0.05448	0.03859
Estimate98	0.009334	0.03879
Estimate99	-0.01327	0.0392
Estimate100	-0.01513	0.0394
Estimate101	-0.02611	0.045
Estimate102	-0.05239	0.04504
Estimate103	-0.02298	0.04514
Estimate104	0.04158	0.04424
Estimate105	0.02143	0.04473
Estimate106	0.0581	0.03886
Estimate107	-0.01452	0.03897

Table 13: Table continues below

	Personality_st_error	Feeling_st_error
Estimate	0.03764	0.02051
Estimate1	0.0382	0.01963
Estimate2	0.0441	0.02964
Estimate3	0.04421	0.0298
Estimate4	0.04408	0.02973
Estimate5	0.04377	0.02911
Estimate6	0.04403	0.03009
Estimate7	0.03779	0.01896
Estimate8	0.0376	0.01993
Estimate9	0.03849	0.02058
Estimate10	0.03876	0.01972
Estimate11	0.04336	0.02957
Estimate12	0.04341	0.02978
Estimate13	0.04341	0.02968
Estimate14	0.04285	0.02897
Estimate15	0.04324	0.03
Estimate16	0.03821	0.01904
Estimate17	0.03828	0.01991
Estimate18	0.03847	0.02055
Estimate19	0.03882	0.01966
Estimate20	0.04424	0.02977
Estimate21	0.04421	0.02992
Estimate22	0.04425	0.02992
Estimate23	0.04359	0.02899
Estimate24	0.04393	0.03004
Estimate25	0.03849	0.01897
Estimate26	0.03844	0.01991
Estimate27	0.03767	0.02054
Estimate28	0.03794	0.01964
Estimate29	0.04329	0.02963
Estimate30	0.04356	0.02985
Estimate31	0.04363	0.02989
Estimate32	0.04296	0.02899

	Personality_st_error	Feeling_st_error
Estimate33	0.04345	0.03007
Estimate34	0.03747	0.01898
Estimate35	0.03776	0.01993
Estimate36	0.03803	0.02062
Estimate37	0.03832	0.01971
Estimate38	0.04371	0.02975
Estimate39	0.04407	0.02994
Estimate40	0.04387	0.03008
Estimate41	0.0433	0.02894
Estimate42	0.04386	0.03008
Estimate43	0.0378	0.019
Estimate44	0.03819	0.01994
Estimate45	0.03777	0.0205
Estimate46	0.03842	0.01963
Estimate47	0.04341	0.02955
Estimate48	0.04365	0.02975
Estimate49	0.04349	0.02967
Estimate50	0.04322	0.02903
Estimate51	0.04357	0.03
Estimate52	0.03785	0.01894
Estimate53	0.0379	0.01988
Estimate54	0.03841	0.02066
Estimate55	0.03875	0.01974
Estimate56	0.04475	0.02988
Estimate57	0.04493	0.03005
Estimate58	0.04492	0.02994
Estimate59	0.04424	0.02927
Estimate60	0.04481	0.03036
Estimate61	0.03814	0.01906
Estimate62	0.03827	0.01996
Estimate63	0.03675	0.02056
Estimate64	0.03695	0.01966
Estimate65	0.04251	0.02972
Estimate66	0.04241	0.02972
Estimate67	0.04259	0.02997
Estimate68	0.0421	0.02885
Estimate69	0.04261	0.02997
Estimate70	0.03665	0.01894
Estimate71	0.03672	0.01993
Estimate72	0.03896	0.02064
Estimate73	0.039	0.01966
Estimate74	0.04466	0.02991
Estimate75	0.0445	0.02998
Estimate76	0.04483	0.03021
Estimate77	0.0438	0.02901
Estimate78	0.04429	0.03013
Estimate79	0.03851	0.01896
Estimate80	0.03874	0.01997
Estimate81	0.03857	0.02069
Estimate82	0.03862	0.01967
Estimate83	0.04346	0.02993
Estimate84	0.04357	0.02997

	Personality_st_error	Feeling_st_error
Estimate85	0.0435	0.03005
Estimate86	0.04293	0.02901
Estimate87	0.04364	0.03026
Estimate88	0.03813	0.01898
Estimate89	0.03844	0.01998
Estimate90	0.03924	0.02083
Estimate91	0.0392	0.01967
Estimate92	0.0459	0.03021
Estimate93	0.04537	0.03013
Estimate94	0.04648	0.03061
Estimate95	0.04409	0.02906
Estimate96	0.0449	0.03028
Estimate97	0.03862	0.01898
Estimate98	0.03905	0.02018
Estimate99	0.03917	0.02071
Estimate100	0.03929	0.01977
Estimate101	0.04506	0.03015
Estimate102	0.04502	0.03009
Estimate103	0.04526	0.0305
Estimate104	0.04423	0.02904
Estimate105	0.04487	0.03023
Estimate106	0.03875	0.01898
Estimate107	0.03888	0.02001

Table 14: Table continues below

	Interaction_st_error	Intercept_Tvalue	Personality_Tvalue
Estimate	0.02035	13.92	5.085
Estimate1	0.01912	13.72	4.929
Estimate2	0.02973	11.02	3.883
Estimate3	0.02955	10.97	3.89
Estimate4	0.02975	11.06	3.847
Estimate5	0.02806	11.04	3.675
Estimate6	0.0291	10.98	3.86
Estimate7	0.01846	13.75	4.666
Estimate8	0.01916	13.99	5.26
Estimate9	0.01998	13.71	4.255
Estimate10	0.01885	13.53	4.212
Estimate11	0.02928	11.06	5.108
Estimate12	0.02939	11.01	5.195
Estimate13	0.03002	11.09	5.119
Estimate14	0.02864	11.1	5.049
Estimate15	0.02947	11.01	5.053
Estimate16	0.0182	13.7	4.291
Estimate17	0.01949	13.82	4.376
Estimate18	0.02072	13.66	3.652
Estimate19	0.01927	13.59	3.994
Estimate20	0.0295	10.89	3.604
Estimate21	0.02863	10.97	3.756
Estimate22	0.02852	10.9	3.553
Estimate23	0.02821	11.05	3.653

	Interaction_st_error	Intercept_Tvalue	Personality_Tvalue
Estimate24	0.02959	10.96	3.448
Estimate25	0.01876	13.63	3.537
Estimate26	0.01883	13.72	3.59
Estimate27	0.01992	13.9	4.693
Estimate28	0.0193	13.81	4.915
Estimate29	0.02928	10.98	4.155
Estimate30	0.02928	10.96	4.378
Estimate31	0.02892	11	4.126
Estimate32	0.02866	11.24	4.398
Estimate33	0.02942	11.03	4.146
Estimate34	0.01866	13.94	4.828
Estimate35	0.01944	13.9	4.352
Estimate36	0.01983	13.7	-4.427
Estimate37	0.01909	13.74	-4.858
Estimate38	0.02865	10.91	-4.709
Estimate39	0.02836	11.04	-4.967
Estimate40	0.02918	10.97	-4.649
Estimate41	0.0278	11.15	-4.667
Estimate42	0.02925	11.12	-4.566
Estimate43	0.01846	13.9	-4.882
Estimate44	0.01878	13.89	-4.235
Estimate45	0.02048	13.73	5.318
Estimate46	0.0191	13.6	5.118
Estimate47	0.02959	11.07	5.18
Estimate48	0.02963	10.99	5.119
Estimate49	0.02923	11.07	5.183
Estimate50	0.03003	11.13	5.059
Estimate51	0.02925	10.93	5.046
Estimate52	0.01866	13.77	5.247
Estimate53	0.01941	13.75	5.216
Estimate54	0.01984	13.43	0.1759
Estimate55	0.01884	13.28	0.07194
Estimate56	0.02877	10.78	-0.4015
Estimate57	0.02887	10.73	-0.6156
Estimate58	0.02819	10.83	-0.3035
Estimate59	0.0286	10.86	-0.6123
Estimate60	0.0296	10.78	-0.5431
Estimate61	0.01851	13.44	0.2019
Estimate62	0.01863	13.49	0.1741
Estimate63	0.02011	14.11	6.182
Estimate64	0.01777	14.12	6.518
Estimate65	0.02996	11.19	5.886
Estimate66	0.02856	11.12	6.271
Estimate67	0.02998	11.14	5.92
Estimate68	0.02696	11.39	6.068
Estimate69	0.02845	11.34	6.057
Estimate70	0.0176	14.19	6.42
Estimate71	0.01873	14.07	6.064
Estimate72	0.02002	13.77	3.675
Estimate73	0.01883	13.66	4.157
Estimate74	0.03095	11.06	3.863
Estimate75	0.02954	10.91	4.244

	Interaction_st_error	Intercept_Tvalue	Personality_Tvalue
Estimate76	0.02994	11.06	3.828
Estimate77	0.03029	11.1	4.103
Estimate78	0.02916	11.04	3.938
Estimate79	0.01787	13.79	4.066
Estimate80	0.01896	13.86	3.618
Estimate81	0.02071	13.79	-3.529
Estimate82	0.01875	13.67	-3.75
Estimate83	0.02974	10.92	-3.892
Estimate84	0.02951	10.92	-4.28
Estimate85	0.02924	10.94	-3.896
Estimate86	0.02906	11.14	-4.015
Estimate87	0.02825	11.2	-4.247
Estimate88	0.0182	13.78	-3.736
Estimate89	0.02015	13.88	-3.362
Estimate90	0.01939	13.6	-1.97
Estimate91	0.02079	13.49	-2.317
Estimate92	0.02835	10.75	-2.291
Estimate93	0.02888	10.66	-2.859
Estimate94	0.02766	10.88	-2.008
Estimate95	0.02951	11.01	-2.246
Estimate96	0.02881	10.97	-2.2
Estimate97	0.01825	13.6	-2.291
Estimate98	0.01818	13.67	-1.813
Estimate99	0.02004	13.62	0.0349
Estimate100	0.02042	13.46	0.5738
Estimate101	0.02952	10.7	0.9104
Estimate102	0.03038	10.58	1.299
Estimate103	0.02942	10.69	0.8871
Estimate104	0.03008	10.99	0.8514
Estimate105	0.02984	10.88	0.866
Estimate106	0.01866	13.59	0.4881
Estimate107	0.01885	13.69	0.04121

	Feeling_Tvalue	Interaction_Tvalue
Estimate	4.543	1.881
Estimate1	10.13	1.104
Estimate2	0.4627	-0.1886
Estimate3	4.326	1.761
Estimate4	0.3303	-0.5505
Estimate5	4.84	0.8975
Estimate6	2.464	0.705
Estimate7	12.3	3.339
Estimate8	7.68	0.926
Estimate9	4.379	-0.909
Estimate10	10.15	-0.3687
Estimate11	0.574	0.9358
Estimate12	4.308	1.045
Estimate13	0.5187	0.7717
Estimate14	4.86	2.407
Estimate15	2.494	0.8819
Estimate16	12.54	-0.5708

	Feeling_Tvalue	Interaction_Tvalue
Estimate17	7.818	-3.668
Estimate18	4.537	1.192
Estimate19	10.26	1.189
Estimate20	0.7144	-0.1376
Estimate21	4.58	1.517
Estimate22	0.5494	-0.4812
Estimate23	5.221	0.693
Estimate24	2.629	2.329
Estimate25	12.47	2.093
Estimate26	7.583	0.4708
Estimate27	4.46	0.5071
Estimate28	10.26	1.456
Estimate29	0.6432	-2.398
Estimate30	4.523	-0.9951
Estimate31	0.6479	-0.6674
Estimate32	5.411	1.175
Estimate33	2.742	-0.1155
Estimate34	12.63	-0.6847
Estimate35	7.43	-0.05316
Estimate36	4.453	-2.06
Estimate37	10.26	-0.247
Estimate38	0.6302	2.34
Estimate39	4.773	-0.5299
Estimate40	0.5852	1.263
Estimate41	5.223	1.2
Estimate42	2.806	-1.647
Estimate43	12.64	0.4246
Estimate44	7.379	0.9686
Estimate45	4.557	2.558
Estimate46	10.25	-1.864
Estimate47	0.477	-1.753
Estimate48	4.228	-0.9404
Estimate49	0.3152	-1.656
Estimate50	5.053	-0.5578
Estimate51	2.376	1.654
Estimate52	12.62	-2.573
Estimate53	7.589	1.379
Estimate54	4.43	0.9357
Estimate55	10.26	-0.9736
Estimate56	0.6231	-0.2987
Estimate57	4.419	-0.6749
Estimate58	0.4777	-1.229
Estimate59	5.113	0.3338
Estimate60	2.546	-0.7845
Estimate61	12.6	-2.306
Estimate62	7.708	2.511
Estimate63	4.365	1.782
Estimate64	10.31	-0.7175
Estimate65	0.7948	-1.633
Estimate66	4.702	-2.462
Estimate67	0.767	-1.691
Estimate68	5.295	-0.9738

	Feeling_Tvalue	Interaction_Tvalue
Estimate69	2.958	1.482
Estimate70	12.45	2.381
Estimate71	7.491	2.72
Estimate72	4.212	-0.7374
Estimate73	10.26	0.781
Estimate74	1.067	1.553
Estimate75	4.755	0.2233
Estimate76	1.076	1.325
Estimate77	5.364	0.2979
Estimate78	2.689	1.774
Estimate79	12.51	1.809
Estimate80	7.351	-1.225
Estimate81	4.159	0.8818
Estimate82	10.26	0.1355
Estimate83	0.7363	1.351
Estimate84	4.734	0.5818
Estimate85	0.6364	1.299
Estimate86	5.225	0.4982
Estimate87	2.851	-2.098
Estimate88	12.49	-1.932
Estimate89	7.314	1.535
Estimate90	4.211	0.6259
Estimate91	10.24	-0.1105
Estimate92	0.8074	0.6101
Estimate93	4.54	1.455
Estimate94	0.8519	-0.5403
Estimate95	5.185	0.06108
Estimate96	2.746	-1.186
Estimate97	12.64	-2.985
Estimate98	7.394	0.5135
Estimate99	4.498	-0.6621
Estimate100	10.29	-0.7407
Estimate101	0.5266	-0.8845
Estimate102	4.351	-1.724
Estimate103	0.4047	-0.7811
Estimate104	5.133	1.382
Estimate105	2.584	0.718
Estimate106	12.42	3.114
Estimate107	7.565	-0.7705

```r
## ----setup, include=FALSE------------------------------------------------------------
knitr::opts_chunk$set(echo = FALSE)

## ----setup, include=FALSE-------------------------------------------------------------------------
knitr::opts_chunk$set(echo = FALSE)


## ---- echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE---------------------------------------
# import libraries
library(rmarkdown)
library(plyr)
library(dplyr)
```

```r
library(ggplot2)
library(tidyr)
library(pivottabler)
library(gtsummary)
library(ggpubr)
library(ggfortify)
library(cluster)
library(MASS)
library(lmtest)
library(fBasics)
library(rcompanion)
library(gridExtra)
library(cowplot)
library(kableExtra)
library(haven)
library(tidyverse)
library(rstatix)
library(ggpubr)
library(lme4)
library(reshape2)
library(kableExtra)
library(pander)
library(performance)
library(pROC)
library(sqldf)
library(nlme)
library(ggeffects)
library(doBy)




## ---- echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE---------------------------------------
# reading the data and storing in df
#setwd("School/courses/applied_stats/p2_2")

path = file.path( "ETT_ESM_Study1.sav")
df = read_sav(path)


## ----define_df , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-----------------------------
# define columns for analysis and filter only those.
cols_for_analysis<- c('Subject','religious','E','A','C','N','O','NFC','tsc','se','rumination','depressi
  'valence','arousal','angry','anxious','disapp','surprise','wanting','selfother','control',
  'meaning')

df <- df[cols_for_analysis]

#summary(df[c('religious','E','A','C','N','O','NFC','tsc','se','rumination','depression','ls')])
#summary(df[c('valence','arousal','angry','anxious','disapp','surprise','wanting','selfother','control'

# plot histogram of observation counts per value of Meaning
p<-ggplot(df, aes(x=meaning)) + geom_histogram() +ggtitle('Histogram of # Obs per Meaning')
```

```r
grid.arrange(p,ncol = 1, nrow = 1)

df$ls <- as.numeric(df$ls)
# remove null vals
df_na <- na.omit(df)



df_cpy <- df_na
df[c('religious','E','A','C','N','O','NFC','tsc','se','rumination','depression','ls',
  'valence','arousal','angry','anxious','disapp','surprise','wanting','selfother','control')] <- scale(d
  'valence','arousal','angry','anxious','disapp','surprise','wanting','selfother','control')] )





## ----df_run_models , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-------------------------

personality_c <- c('religious','E','A','C','N','O','NFC','tsc','se','rumination','depression','ls')
feelings_c <- c('valence','arousal','angry','anxious','disapp','surprise','wanting','selfother','control

# define columns for constructed dataframe
all_results_columns <- c("formula","Intercept_estimate"  , "Personality_estimate" ,"Feeling_estimate"
"Personality_st_error" ,"Feeling_st_error"   ,  "Interaction_st_error" ,"Intercept_Tvalue" ,    "Persona
"Feeling_Tvalue"   ,    "Interaction_Tvalue" )

# initiate df
all_results_df <- data.frame(matrix(ncol = 13, nrow = 0))
all_results_df_p_vals <- data.frame(matrix(ncol = 7, nrow = 0))
all_results_df_na <- data.frame(matrix(ncol = 13, nrow = 0))
all_results_df_p_vals_na <- data.frame(matrix(ncol = 7, nrow = 0))

colnames(all_results_df) <- all_results_columns

# loop through both sets of predictors and run model per pair.
# save information in constructed df
for (c_p in personality_c){
  for (c_f in feelings_c){
  single_mixed = lmer(as.formula(sprintf( "meaning ~ %s + %s  + %s*%s+ (1 | Subject)",c_p,c_f,c_p,c_f))

  # get the formula
  formula <-  single_mixed@call[["formula"]]

  # get the sumary stats
  summary_single <- summary(single_mixed)$coef
  ss<- as.data.frame(summary_single)
  estimates <- t(ss["Estimate"])
  colnames(estimates) <- c("Intercept_estimate","Personality_estimate","Feeling_estimate","Interaction_e

  st_error  <- t(ss["Std. Error"])
  colnames(st_error) <- c("Intercept_st_error","Personality_st_error","Feeling_st_error","Interaction_st

  t_vals    <- t(ss["t value"])
```

```
  colnames(t_vals) <- c("Intercept_Tvalue","Personality_Tvalue","Feeling_Tvalue","Interaction_Tvalue")

  combined_res <- data.frame(estimates,st_error,t_vals)
  combined_res$formula <- as.character(formula)[3]

  all_results_df <- rbind(all_results_df, combined_res)

  # run model and get p val
  m1 <- lme(as.formula(sprintf( "meaning ~ %s + %s  + %s*%s",c_p,c_f,c_p,c_f))
          ,random=~1|Subject, na.action=na.omit,data=df)
  anov <- anova(m1)
  p_val <- anov$`p-value`[4]
  l_pvals <- length(anov$`p-value`)

  # append data from single model to large df with all results
  combined_res_p_val <- data.frame(c_p,c_f,p_val)
  all_results_df_p_vals <- rbind(all_results_df_p_vals, combined_res_p_val)

}
}

############################
# Lets run this again for the equal sample sized DF (the one where we globally ommited the nulls prior
for (c_p in personality_c){
  for (c_f in feelings_c){
  single_mixed = lmer(as.formula(sprintf( "meaning ~ %s + %s  + %s*%s+ (1 | Subject)",c_p,c_f,c_p,c_f))

  # get the formula
  formula <-  single_mixed@call[["formula"]]

  # get the sumary stats
  summary_single <- summary(single_mixed)$coef
  ss<- as.data.frame(summary_single)
  estimates <- t(ss["Estimate"])
  colnames(estimates) <- c("Intercept_estimate","Personality_estimate","Feeling_estimate","Interaction_

  st_error  <- t(ss["Std. Error"])
  colnames(st_error) <- c("Intercept_st_error","Personality_st_error","Feeling_st_error","Interaction_s

  t_vals    <- t(ss["t value"])
  colnames(t_vals) <- c("Intercept_Tvalue","Personality_Tvalue","Feeling_Tvalue","Interaction_Tvalue")

  combined_res <- data.frame(estimates,st_error,t_vals)
  combined_res$formula <- as.character(formula)[3]

  all_results_df_na <- rbind(all_results_df_na, combined_res)

  # run model and get p val
  m1 <- lme(as.formula(sprintf( "meaning ~ %s + %s  + %s*%s",c_p,c_f,c_p,c_f))
          ,random=~1|Subject, na.action=na.omit,data=df)
  anov <- anova(m1)
  p_val <- anov$`p-value`[4]
  l_pvals <- length(anov$`p-value`)
```

```
  # append data from single model to large df with all results
  combined_res_p_val_na <- data.frame(c_p,c_f,p_val)
  all_results_df_p_vals_na <- rbind(all_results_df_p_vals_na, combined_res_p_val_na)

}
}



## ----display results , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE----------------------

# histogram of tvalues of interactions
p1<- ggplot() + aes(all_results_df$Interaction_Tvalue)+ geom_histogram( colour="black", fill="white")+ g
  xlab("T value") + ylab("# of occurences")


# histogram of tvalues of interactions
p2<- ggplot() + aes(all_results_df_na$Interaction_Tvalue)+ geom_histogram( colour="black", fill="white")
  xlab("T value") + ylab("# of occurences")

grid.arrange(p1,p2, ncol = 2, nrow = 1)



# shapiro.test for both sets of T stats
#print(shapiro.test(all_results_df_na$Interaction_Tvalue))
#print(shapiro.test(all_results_df$Interaction_Tvalue))

#cor(all_results_df_na$Interaction_Tvalue,all_results_df$Interaction_Tvalue)

tvals <- cbind(equal_sized = all_results_df_na$Interaction_Tvalue,unequal_sized=all_results_df$Interacti

p3 <- ggplot(tvals, aes(x=equal_sized, y=unequal_sized)) + geom_point()+ ggtitle("Scatter plot of T stat

# histogram of T differences
x <- all_results_df_na$Interaction_Tvalue - all_results_df$Interaction_Tvalue
p4<- ggplot() + aes(x)+ geom_histogram( colour="black", fill="white")+ ggtitle("Histogram of T Value dif
  xlab("T value diff") + ylab("# of occurences")

grid.arrange(p3,p4, ncol = 1, nrow = 2)



## ----tables , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE--------------------------------

# calculate the adj. p vals
all_results_df_p_vals$hochberg_p_val <-  p.adjust(all_results_df_p_vals$p_val, method = "hochberg")
all_results_df_p_vals$holm_p_val <-  p.adjust(all_results_df_p_vals$p_val, method = "holm")
all_results_df_p_vals$bonferroni_p_val <-  p.adjust(all_results_df_p_vals$p_val, method = "bonferroni")


# filter models which t val camoe out more than 3 absolute val
tmp <- all_results_df[abs(all_results_df$Interaction_Tvalue) > 3, c('formula','Interaction_estimate','In
```

```r
# set formula as index for visualization
rownames(tmp) <- tmp$formula

tmp<- tmp[c('Interaction_estimate','Interaction_st_error','Interaction_Tvalue')]
pander(tmp)

# filter set of all mdoels with hoch p val less than 0.05
tmp2 <- all_results_df_p_vals[all_results_df_p_vals$hochberg_p_val < 0.05,]

#c('c_p','c_f','p_val','holm_p_val', 'hochberg_p_val', 'bonferroni_p_val')]

# rename columns for visualization
tmp2 <- tmp2 %>%
  rename(
    Personality = c_p,
    Feeling = c_f
    )

pander(tmp2)



## ----display_results , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE----------------------
# dive into specific model
c_p <-  'religious'
c_f <- 'selfother'
m1 <- lme(as.formula(sprintf( "meaning ~ %s + %s  + %s*%s",c_p,c_f,c_p,c_f))
          ,random=~1|Subject,data=df_na)

mydf<- ggpredict(m1, terms=c('religious[1,2,3,4,5,6,7]','selfother'))

# plot interaction between two predictors
p <- ggplot(mydf, aes(x, predicted, colour = group)) +
  geom_point(position = position_dodge(.1)) +
  geom_errorbar(
    aes(ymin = conf.low, ymax = conf.high),
    position = position_dodge(.1)
  ) +
  scale_x_discrete(breaks = 1:3, labels = get_x_labels(mydf))+
xlab("Religious Score") +
ylab("Meaningfulness")+
 labs(color='Self-vs-Other\n Score')

grid.arrange(p, ncol = 1, nrow = 1)


# marginal effects of interaction terms
#ggplot(mydf, aes(x, predicted, colour = group)) + geom_line()




## ----Bonferroni , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE---------------------------
```

```r
# hist of p vals -raw
p1 <- ggplot() + aes(all_results_df_p_vals$p_val)+ geom_histogram( colour="black", fill="white")+  geom_
  xlab("P value") + ylab("# of occurences")

# hist of p vals bonferroni
p2 <- ggplot() + aes(all_results_df_p_vals$bonferroni_p_val, method = "bonferroni")+ geom_histogram( col
  xlab("P value") + ylab("# of occurences")

# hist of p vals - holm
p3 <- ggplot() + aes(p.adjust(all_results_df_p_vals$p_val, method = "holm"))+ geom_histogram( colour="bl
  xlab("P value") + ylab("# of occurences")

# hist of p vals - hoch
p4 <- ggplot() + aes(p.adjust(all_results_df_p_vals$p_val, method = "hochberg"))+ geom_histogram( colou
  xlab("P value") + ylab("# of occurences")

grid.arrange(p1,p2,p3,p4, ncol = 2, nrow = 2)




## ----pvals_per_group , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-----------------------
# box plot of p vals pooled per predictor in personality
p1 <- ggplot(all_results_df_p_vals, aes(x=c_p, y=p_val)) +
  geom_boxplot() + geom_hline(aes(yintercept = 0.05), colour="#BB0000",size=1)+ ggtitle("P values of pe

# box plot of p vals pooled per predictor in feelings
p2 <- ggplot(all_results_df_p_vals, aes(x=c_f, y=p_val)) +
  geom_boxplot()+ geom_hline(aes(yintercept = 0.05), colour="#BB0000",size=1)+ ggtitle("P values of fee



grid.arrange(p1,p2,ncol = 1, nrow = 2)


## ----heatmap , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-------------------------------
# heatmap of p vals between pairs of predictors
ggplot(data = all_results_df_p_vals, aes(x=c_p, y=c_f, fill=p_val)) +geom_tile(color = "white")+
 scale_fill_gradient2(low = "red", high = "blue", mid = "white",
   midpoint = 0.5, limit = c(0,1), space = "Lab",
   name="P values") +
  theme_minimal()+
 theme(axis.text.x = element_text(angle = 45, vjust = 1,
    size = 12, hjust = 1))+
 coord_fixed()+ ggtitle("Heatmap of P values  feelings ~ personality interaction")+xlab("Personality") +

#all_results_df[order(all_results_df$Interaction_Tvalue),]


## ----part2 , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE---------------------------------

# find specific test from large df
formula_<- 'depression + selfother + depression * selfother + (1 | Subject)'
```

```r
# filter that given test
single_test <- filter(all_results_df, formula == formula_)
single_test <- t(single_test)
colnames(single_test) <- c('test results')

pander(single_test)

# rerun the test for full display of stats
c_p <- "depression"
c_f <- "selfother"
m1 <- lme(as.formula(sprintf( "meaning ~ %s + %s  + %s:%s",c_p,c_f,c_p,c_f))
          ,random=~1|Subject,data=df, na.action=na.omit)

s<-summary(m1)
pander(s$tTable,caption = "Summary of meaning ~ depression * self-vs-other ")





## ----test_effect_grouped , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-------------------

# create variable which rounds the depression score to nearest 1
df_cpy$depression_groups <- round_any(df_cpy$depression, 1)



## ----test_effect_grouped_results , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE-----------

#lmer(meaning ~ depression+ selfother + depression*selfother+  (1 | Subject) ,data=df_cpy)

# fit models per depression group

x<- lapply(split(df_cpy,df_cpy$depression_groups),lmer, formula = meaning ~ depression+ selfother + depr


# look at each model independantly
x1 <- x[1]$`1`
s_x_1<- summary(x1)
coefs<- s_x_1$coefficients
#pander(coefs,caption = "Group 1")


x2 <- x[2]$`2`
s_x_2<- summary(x2)
coefs<- s_x_2$coefficients
#pander(coefs,caption = "Group 2")

#anov <- anova(x4)
#p_val <- anov$`p-value`[4]
#l_pvals <- length(anov$`p-value`)
```

```r
sub_group_df <-  df_cpy[df_cpy$depression_groups==2,]
m1 <- lme(as.formula(sprintf( "meaning ~ %s  ",c_f))
          ,random=~1|Subject,data=df_cpy)
anov <- anova(m1)
p_val <- anov$`p-value`[4]




# look at effects
m1<-lmer(meaning ~ depression+ selfother + depression:selfother+  (1 | Subject) ,data=df_na)

mydf<- ggpredict(m1, terms=c('depression[1,2,3]','selfother'))
pander(mydf)


# marginal effects of interaction terms
p<- ggplot(mydf, aes(x, predicted, colour = group)) +
  geom_line() +
xlab("Depression Score") +
ylab("Meaningfulness")+
 labs(color='Self-vs-Other\n Score')
grid.arrange(p, ncol = 1, nrow = 1)





## ----do_by_effect , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE--------------------------
# create the representation of the three models with fixed depression scores
Depression_1 <- c(0,0,1,1)
Depression_2 <- c(0,0,1,2)
Depression_3 <- c(0,0,1,3)
# assess the 3 models we created
z<- esticon(m1, rbind(Depression_1,Depression_2,Depression_3),conf.int = FALSE)

pander(z, caption ="Effect of Self-vs-Other as a function of Depression")




## ----appendix , echo=FALSE , echo=FALSE, warning=FALSE,message=FALSE------------------------------
# full results of all 108 models
colnames(all_results_df)

col_order<- c(,
"formula","Intercept_estimate"  , "Personality_estimate", "Feeling_estimate"    , "Interaction_estimate
 "Intercept_st_error"  , "Personality_st_error", "Feeling_st_error"   ,   "Interaction_st_error",
 "Intercept_Tvalue"    ,  "Personality_Tvalue" ,  "Feeling_Tvalue"   ,    "Interaction_Tvalue")
my_data2 <- all_results_df[, c(5, 4, 1, 2, 3)]
pander(all_results_df)
```