

Acetaminophen Attenuates Perception of Auditory Stimuli

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Previous research has shown that acetaminophen may make you less empathic to others and that acetaminophen can blunt your emotional responses to picture stimuli. Researchers have also found that participants who ingested acetaminophen made attenuated emotional judgments of pleasant and unpleasant pictures from the IAPS.

The goal of the current study was to test whether the emotional blunting effects of acetaminophen extend to the auditory and musical domains.

- **Subgoal 1:** Test whether there is a difference in attenuation among *natural sounds* (like waves or growls), *music*, and *speech*.
- **Subgoal 2:** Test whether acetaminophen blunts *perceived emotion* and *induced emotion* to different extents.

Background

Design

We (Lindsay Warrenburg and Baldwin Way) used a randomized, double-blind, parallel-group, placebo-controlled design to test these hypotheses. The study consisted of two blocks of trial: one for perceived emotion and one for induced emotion. These blocks were counterbalanced across participants. During the drug uptake period, participants completed a number of questionnaires relating to their musical experience, current mood, personality traits, socio-economic status, height and weight, other drugs they may have taken, and so on.

Perceived Emotion Block

The goal of the perceived emotion block was to judge the extent to which a sound conveys a certain affect. For the natural sounds stimuli, we used clips from the International Affective Digital Sounds (IADS). For speech stimuli, we used the Crowd-Sourced Emotional Multimodal Actors Dataset (CREMA-D). And for music stimuli, I used excerpts from film soundtracks, curated by Eerola & Vuoskoski (2011).

- In order to assess the valence of the perceived emotion in the stimuli, we asked “*To what extent does this audio file sound positive?*” and “*To what extent does this audio file sound negative?*”
- In order to assess the arousal of the perceived emotion in the stimuli, we asked “*To what extent does this audio file sound energetic/arousing?*”
- All three questions utilized an 11-point Likert scale.
- We also asked participants to identify which emotions the audio file represents by checking the appropriate emotions from a list.
 - Participants could select as many or as few emotions as they liked.
 - Once they chose the list of emotion terms, they were asked to choose which emotions (if any) strongly apply to the music.

- By asking participants to choose emotion terms that strongly apply, a three-level response gradient is available for analysis (i.e. does not apply, applies, strongly applies).

Induced Emotion Block

In the section on induced emotion, the stimuli were taken from the same databases as before. The stimuli were different from the ones in the Perceived Emotion section. No speech samples were used because the database instructions explicitly state that they should be used only in studies regarding perceived emotion. Participants were asked

- “To what extent does this audio file make you feel a positive emotional reaction?” (on an 11-point Likert scale)
- “To what extent does this audio file make you feel a negative emotional reaction?” (on an 11-point Likert scale)
- Once again, participants were asked to identify which emotions the audio file makes them feel by checking the appropriate emotions from a list. They were also asked to choose which emotions strongly apply.

Participants

- 244 participants took part in the experiment.
- A power analysis indicated that 200 participants are needed in order to show a reliable effect, if it is there.

Validation of Stimuli

- We tested the validity of the stimuli -- namely, whether a happy song tended to be perceived as happy, that angry speech was perceived as angry, etc.
- We found that the stimuli all behaved as predicted.

Executive Summary

Perceived Emotion

1. The results were consistent with the hypothesis that, **compared to a placebo, acetaminophen blunts people’s perception of positive and negative emotions in sound stimuli**. For example, on average, those who took a placebo rated emotional sounds as representing positive emotions at an intensity of 3.99 (out of 10), whereas those who took acetaminophen rated an intensity of positive emotions of 3.58.
2. There was **no difference in arousal ratings between drug and placebo conditions**.

Chart showing the mean ratings of **perceived emotion** in the drug and placebo conditions

	Positive Emotion Ratings	Negative Emotion Ratings	Arousal Ratings
Placebo	3.94*	3.86*	4.40
Acetaminophen	3.60*	3.65*	4.33

Induced Emotion

1. Unlike the findings in the study regarding picture stimuli, there was **no difference in the intensity of positive or negative emotions experienced by listeners in the drug and placebo conditions.**

Chart showing the mean ratings of **induced emotion** in the drug and placebo conditions

	Positive Emotion Ratings	Negative Emotion Ratings
Placebo	3.74	3.56
Acetaminophen	3.64	3.64

Initialize Workspace

```
/Users/home/Desktop/Research/Tylenol/Analysis
```

Click here to toggle on/off the raw code.

Goal 1: Long Form Analysis

The initial Qualtrics data was pre-processed in a separate R script. For this part of the analysis, we will build on those dataframes and perform the following tasks:

1. Examination of Missing Data
2. Checking for Duplicates
3. Adding High-Level Summary Features
4. Looking at Mean Differences between Drug and Placebo
 - Overall means
 - Stimulus type (music, natural sounds, and speech)
 - Emotion type (positive, negative, neutral)
 - Arousal and valence levels

We will do this separately for *induced* emotion data and *perceived* emotion data

1a. Induced Emotion Ratings

Read in the data.

```
original inducedLong shape: (4806, 33)
```

Missing Data

We will delete observations with no ID or without a drug/placebo indication. We cannot use these observations for analysis.

```
null shape: (4557, 33)
new inducedLong shape: (4554, 32)
```

Check for Duplicates

Duplicates would indicate an error with the participant ID number fed into the surveys on Qualtrics. These would lead to biased data, so we get rid of them.

```
Number of Induced Stimuli: 18

induced errors in stimuli: [55, 91, 92, 117, 133, 172]

fixed inducedLong shape: (4338, 32)

induced errors in stimuli: []
```

Add summary columns

We want to differentiate blunting effects between ***Positive*** and ***Negative*** stimuli, across ***Music, Speech, and Natural Sounds***, and by ***Arousal and Valence (Circumplex model from Russell et al., 1989)*** scores.

We will add a new column to summarize each of these features based on emotional theory and *a priori* stimulus analysis.

SoundType	Music	Natural Sounds
Stimulus		
Fear Music 1	241	0
Fear Music 2	241	0
Happy Music 1	241	0
Happy Music 2	241	0
Negative-Valence High-Arousal Human	0	241
Negative-Valence High-Arousal Non-human	0	241
Negative-Valence Low-Arousal Human	0	241
Negative-Valence Low-Arousal Non-human	0	241
Neutral Human	0	241
Neutral Non-human	0	241
Positive-Valence High-Arousal Human	0	241
Positive-Valence High-Arousal Non-human	0	241
Positive-Valence Low-Arousal Human	0	241
Positive-Valence Low-Arousal Non-human	0	241
Sad Music 1	241	0
Sad Music 2	241	0
Tender Music 1	241	0
Tender Music 2	241	0

Comparing Means Between Drug/Placebo

Now we can compare means in **induced** emotion ratings in drug and placebo conditions.

First, we prepare the data.

	FixedID	DrugCode	DrugPlacebo	Locus	Stimulus	Positive	Negative	A
2493	94.0	27E	Drug	Induced	Negative-Valence	0.0	6.0	N
					High-Arousal Non-human			N
2093	225.0	27D2	Drug	Induced	Tender Music 2	9.0	0.0	N
								N

2 rows × 35 columns

Overall Means

We examine the overall mean scores for *positive emotion ratings* and *negative emotion ratings* for participants who took the drug vs. participants who took the placebo.

We then compare the means using t-tests.

```
Induced Emotion Overall Means -- Positive
DrugPlacebo
Drug      3.64
Placebo   3.72
Name: Positive, dtype: float64
```

```
t = 0.74
p = 0.46
```

```
Induced Emotion Overall Means -- Negative
DrugPlacebo
Drug      3.64
Placebo   3.56
Name: Negative, dtype: float64
```

```
t = -0.78
p = 0.43
```

Conclusion: There is no difference in induced emotion ratings for positive emotions or negative emotions between drug and placebo conditions.

Stimulus Type (Music, Natural Sounds)

Although there were no differences in the overall means between drug and placebo conditions, we will look at the mean induced emotion ratings across different stimulus types.

We will *not* conduct t-tests to prevent any potential problems of multiple tests.

```
Induced Emotion Stimulus Type -- Positive
DrugPlacebo SoundType
Drug Music 4.72
Natural Sounds 2.78
Placebo Music 4.57
Natural Sounds 3.04
Name: Positive, dtype: float64
```

```
Induced Emotion Stimulus Type -- Negative
DrugPlacebo SoundType
Drug Music 3.14
Natural Sounds 4.04
Placebo Music 3.16
Natural Sounds 3.89
Name: Negative, dtype: float64
```

Emotion Type (Positive, Negative, Neutral)

Next, we will look at the induced emotion ratings for positive stimuli, negative stimuli, and neutral stimuli in both drug and placebo conditions.

```
Induced Emotion Emotion Type -- Positive
DrugPlacebo PosNeg
Drug Negative 1.65
Neutral 1.29
Positive 6.22
Placebo Negative 1.76
Neutral 1.52
Positive 6.23
Name: Positive, dtype: float64
```

```
Induced Emotion Emotion Type -- Negative
DrugPlacebo PosNeg
Drug Negative 5.88
Neutral 3.85
Positive 1.35
Placebo Negative 5.78
Neutral 3.60
Positive 1.33
Name: Negative, dtype: float64
```

Circumplex Type (Arousal and Valence Info)

Finally, we'll look at induced emotion ratings for different types of emotional stimuli:

- Negative Valence, High Arousal
- Negative Valence, Low Arousal
- Neutral
- Positive Valence, Low Arousal
- Positive Valence, High Arousal

```

Induced Emotion Circumplex -- Positive
DrugPlacebo  Russell
Drug          Neg-Valence High-Arousal    1.43
              Neg-Valence Low-Arousal     1.86
              Neutral                     1.29
              Pos-Valence High-Arousal     6.84
              Pos-Valence Low-Arousal      5.60
Placebo       Neg-Valence High-Arousal    1.56
              Neg-Valence Low-Arousal     1.97
              Neutral                     1.52
              Pos-Valence High-Arousal     6.90
              Pos-Valence Low-Arousal      5.56
Name: Positive, dtype: float64

```

```

Induced Emotion Circumplex -- Negative
DrugPlacebo  Russell
Drug          Neg-Valence High-Arousal    6.41
              Neg-Valence Low-Arousal     5.36
              Neutral                     3.85
              Pos-Valence High-Arousal     1.05
              Pos-Valence Low-Arousal      1.66
Placebo       Neg-Valence High-Arousal    6.27
              Neg-Valence Low-Arousal     5.30
              Neutral                     3.60
              Pos-Valence High-Arousal     0.99
              Pos-Valence Low-Arousal      1.67
Name: Negative, dtype: float64

```

Summary

There did not seem to be any significant differences in *induced* emotion ratings in drug vs. placebo conditions.

Before examining *perceived* emotions, we'll clean up the data and look at the pandas Profile Report.

	FixedID	DrugCode	DrugPlacebo	Locus	Stimulus	Positive	Negative	Arc
5	7.0	7J	0	Induced	Fear Music 1	8.0	0.0	No Me
6	9.0	9J	0	Induced	Fear Music 1	4.0	6.0	No Me

2 rows × 35 columns

1b. Perceived Emotion Ratings

Read in the data.


```
original perceivedLong shape: (9842, 33)
```

Missing Data

We will delete observations with no ID or without a drug/placebo indication. We cannot use these observations for analysis.

```
null shape: (9287, 33)
new perceivedLong shape: (9250, 32)
```

Check for Duplicates

Duplicates would indicate an error with the participant ID number fed into the surveys on Qualtrics. These would lead to biased data, so we get rid of them.

```
Number of Perceived Stimuli: 37

perceived errors in stimuli: [55, 91, 92, 117, 275]

fixed perceivedLong shape: (8880, 32)

perceived errors in stimuli: []
```

Add summary columns

We want to differentiate blunting effects between **Positive** and **Negative** stimuli, across **Music**, **Speech**, and **Natural Sounds**, and by **Arousal and Valence** scores.

We will add a new column to summarize each of these features based on emotional theory and *a priori* stimulus analysis.

SoundType	Music	Natural Sounds	Speech
Stimulus			
Fear Music 1	240	0	0
Fear Music 2	240	0	0
Fear Music 3	240	0	0
Fear Speech 1	0	0	240
Fear Speech 2	0	0	240
Fear Speech 3	0	0	240
Happy Music 1	240	0	0
Happy Music 2	240	0	0
Happy Music 3	240	0	0
Happy Speech 1	0	0	240
Happy Speech 2	0	0	240
Happy Speech 3	0	0	240
Negative-Valence High-Arousal Human	0	240	0
Negative-Valence High-Arousal Non-human	0	240	0
Negative-Valence Low-Arousal Human	0	240	0
Negative-Valence Low-Arousal Non-human	0	240	0
Neutral Human	0	240	0
Neutral Non-human	0	240	0
Neutral Speech 1	0	0	240
Neutral Speech 2	0	0	240
Neutral Speech 3	0	0	240
Positive-Valence High-Arousal Human	0	240	0
Positive-Valence High-Arousal Non-human	0	240	0
Positive-Valence Low-Arousal Human	0	240	0
Positive-Valence Low-Arousal Non-human	0	240	0
Sad Music 1	240	0	0
Sad Music 2	240	0	0
Sad Music 3	240	0	0
Sad Speech 1	0	0	240
Sad Speech 2	0	0	240
Sad Speech 3	0	0	240
Tender Music 1	240	0	0

	SoundType	Music	Natural Sounds	Speech
Stimulus				
Tender Music 2		240	0	0
Tender Music 3		240	0	0
Tender Music 4		240	0	0
Tender Music 5		240	0	0
Tender Music 6		240	0	0

Comparing Means Between Drug/Placebo

Now we can compare means in ***perceived*** emotion ratings in drug and placebo conditions.

We prep the data like we did above.

	FixedID	DrugCode	DrugPlacebo	Locus	Stimulus	Positive	Negative
4058	69.0	2E	Placebo	Perceived	Fear Speech 1	0.0	10.0
4979	192.0	25K2	Drug	Perceived	Happy Speech 1	10.0	0.0

2 rows × 35 columns

Overall Means

We examine the overall mean scores for *positive emotion ratings*, *negative emotion ratings*, and *arousal ratings* for participants who took the drug vs. participants who took the placebo.

We then compare the means using t-tests.

```
Perceived Emotion Overall Means -- Positive
DrugPlacebo
Drug          3.60
Placebo       3.94
Name: Positive, dtype: float64
```

```
t = 4.33
p = 0.0
```

```
Perceived Emotion Overall Means -- Negative
DrugPlacebo
Drug          3.65
Placebo       3.86
Name: Negative, dtype: float64
```

```
t = 2.85
p = 0.0
```

```
Perceived Emotion Overall Means -- Arousal
DrugPlacebo
Drug          4.33
Placebo       4.40
Name: Arousal, dtype: float64
```

```
t = 1.06
p = 0.29
```

Conclusion:

The results are consistent with the hypothesis that, compared to a placebo, acetaminophen blunts people's perception of positive and negative emotions in sound stimuli (both $ps < 0.05$)

- On average, those who took a placebo rated emotional sounds as representing *positive* emotions at an intensity of 3.94 (on a 0-10 scale), whereas those who took acetaminophen rated an intensity of positive emotions of 3.60.
- Those who took a placebo rated emotional sounds as representing *negative* emotions at an intensity of 3.86 (on a 0-10 scale), whereas those who took acetaminophen rated an intensity of positive emotions of 3.65.

The results are *not* consistent with the hypothesis that, compared to a placebo, acetaminophen blunts people's perception of arousal in sound stimuli.

Stimulus Type (Music, Speech, Natural Sounds)

We can examine to see whether the blunting effect of acetaminophen on perceived emotions is similar across different stimulus types.

We will *not* conduct t-tests on this data in order to prevent any potential problems of multiple tests.

Perceived Emotion Stimulus Type -- Positive

DrugPlacebo	SoundType	
Drug	Music	4.61
	Natural Sounds	3.44
	Speech	2.47
Placebo	Music	4.95
	Natural Sounds	3.65
	Speech	2.90

Name: Positive, dtype: float64

Perceived Emotion Stimulus Type -- Negative

DrugPlacebo	SoundType	
Drug	Music	3.18
	Natural Sounds	3.73
	Speech	4.17
Placebo	Music	3.39
	Natural Sounds	3.93
	Speech	4.41

Name: Negative, dtype: float64

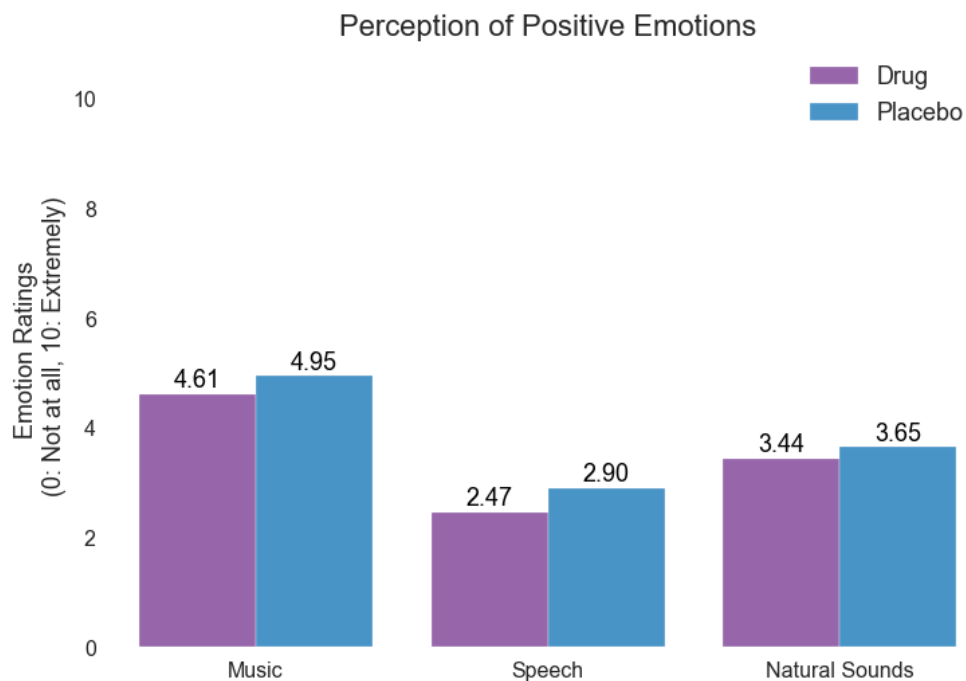
Perceived Emotion Stimulus Type -- Arousal

DrugPlacebo	SoundType	
Drug	Music	4.79
	Natural Sounds	4.65
	Speech	3.48
Placebo	Music	4.92
	Natural Sounds	4.69
	Speech	3.52

Name: Arousal, dtype: float64

Graph Stimulus Type: Positive

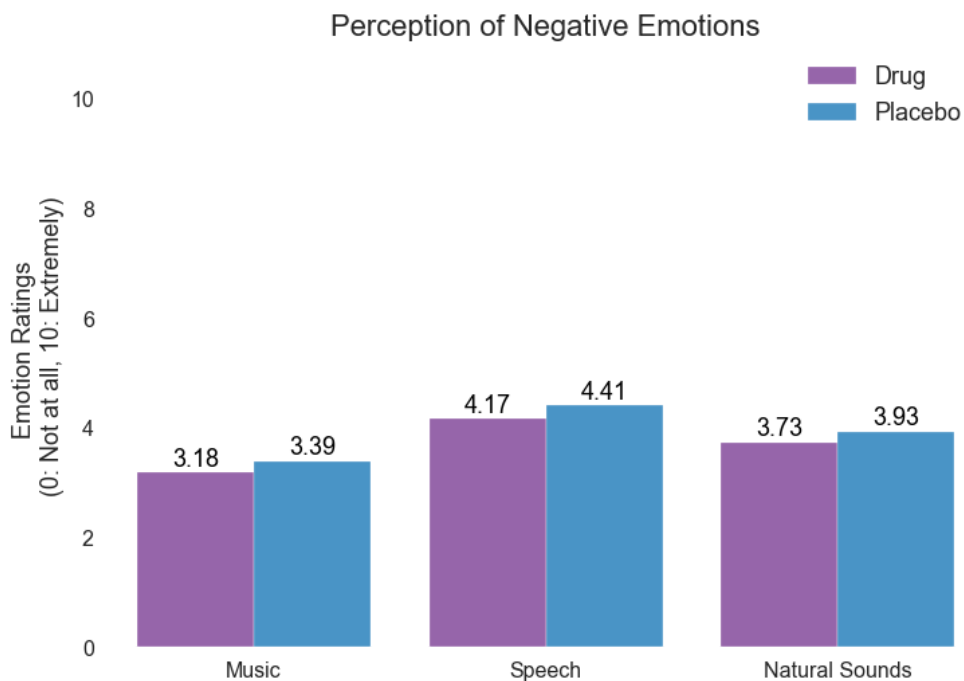
A graph will help showcase the attenuating effect of acetaminophen on perceived positive emotions.



The above graph shows that acetaminophen attenuated the perception of positive emotion similarly in music, natural sounds, and speech stimuli.

Graph Stimulus Type: Negative

Now we can look at the attenuating effect of acetaminophen on perceived negative emotions.



The graph shows that acetaminophen also attenuated the perception of negative emotion similarly in music, natural sounds, and speech stimuli.

Comparing this graph to the graph above on positive emotions, we can see that the blunting effect of acetaminophen was similar across ratings of positive and negative emotions.

Emotion Type (Positive, Negative, Neutral)

Now we check whether acetaminophen blunts perceived emotion ratings for positive stimuli, negative stimuli, and natural stimuli.

```

Perceived Emotion Emotion Type -- Positive
DrugPlacebo  PosNeg
Drug          Negative    1.35
              Neutral     1.87
              Positive    6.36
Placebo       Negative    1.65
              Neutral     2.33
              Positive    6.72
Name: Positive, dtype: float64

```

```

Perceived Emotion Emotion Type -- Negative
DrugPlacebo  PosNeg
Drug          Negative    6.23
              Neutral     2.68
              Positive    1.40
Placebo       Negative    6.44
              Neutral     3.03
              Positive    1.55
Name: Negative, dtype: float64

```

```

Perceived Emotion Emotion Type -- Arousal
DrugPlacebo  PosNeg
Drug          Negative    4.40
              Neutral     1.72
              Positive    5.07
Placebo       Negative    4.39
              Neutral     1.76
              Positive    5.23
Name: Arousal, dtype: float64

```

Circumplex Type (Arousal and Valence Info)

And finally, we can look to see whether the drug attenuation affects perceived emotion ratings for different types of emotional stimuli:

- Negative Valence, High Arousal
- Negative Valence, Low Arousal
- Neutral
- Positive Valence, Low Arousal
- Positive Valence, High Arousal


```

Perceived Emotion Circumplex -- Positive
DrugPlacebo Russell
Drug      Neg-Valence High-Arousal    1.08
          Neg-Valence Low-Arousal     1.61
          Neutral                     1.87
          Pos-Valence High-Arousal     7.19
          Pos-Valence Low-Arousal      5.55
Placebo   Neg-Valence High-Arousal    1.34
          Neg-Valence Low-Arousal      1.97
          Neutral                     2.33
          Pos-Valence High-Arousal     7.55
          Pos-Valence Low-Arousal      5.90
Name: Positive, dtype: float64

```

```

Perceived Emotion Circumplex -- Negative
DrugPlacebo Russell
Drug      Neg-Valence High-Arousal    6.78
          Neg-Valence Low-Arousal     5.69
          Neutral                     2.68
          Pos-Valence High-Arousal     1.07
          Pos-Valence Low-Arousal      1.73
Placebo   Neg-Valence High-Arousal    6.93
          Neg-Valence Low-Arousal      5.94
          Neutral                     3.03
          Pos-Valence High-Arousal     1.20
          Pos-Valence Low-Arousal      1.89
Name: Negative, dtype: float64

```

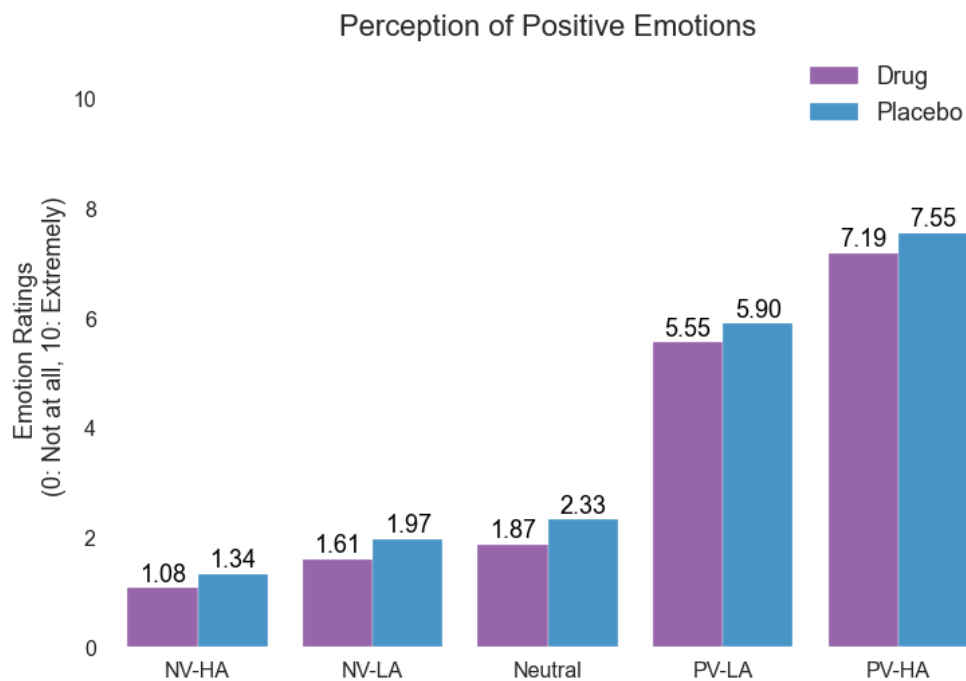
```

Perceived Emotion Circumplex -- Arousal
DrugPlacebo Russell
Drug      Neg-Valence High-Arousal    5.54
          Neg-Valence Low-Arousal     3.25
          Neutral                     1.72
          Pos-Valence High-Arousal     6.68
          Pos-Valence Low-Arousal      3.47
Placebo   Neg-Valence High-Arousal    5.46
          Neg-Valence Low-Arousal      3.32
          Neutral                     1.76
          Pos-Valence High-Arousal     6.75
          Pos-Valence Low-Arousal      3.74
Name: Arousal, dtype: float64

```

Graph Circumplex: Positive

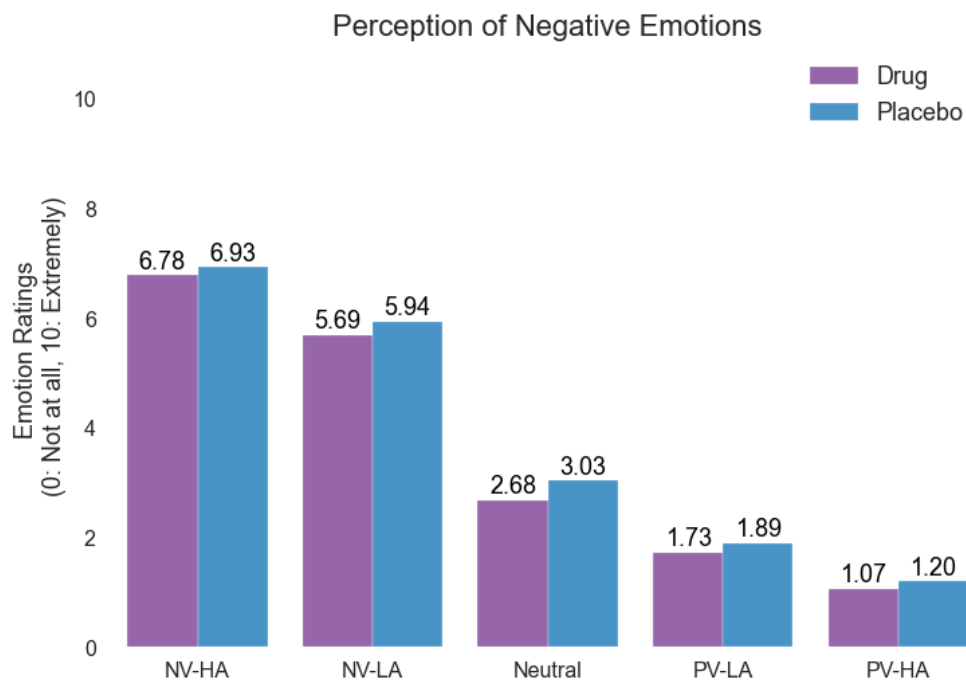
Once again, a graph will help visualize this effect.



Acetaminophen attenuated the perception of positive emotion similarly in stimuli classified as *negative valence-high arousal*, *negative valence-low arousal*, *neutral*, *positive valence-low arousal*, and *positive valence-high arousal*.

Graph Circumplex: Negative

And our last graph.



The above graph shows, once again, that acetaminophen blunts the perception of negative emotion similarly in stimuli classified as *negative valence-high arousal*, *negative valence-low arousal*, *neutral*, *positive valence-low arousal*, and *positive valence-high arousal*.

Furthermore, the attenuating effect of acetaminophen was similar across ratings of positive and negative perceived emotions.

Summary

We will make some small changes with the dataframe for future use and summarize the findings with a pandas profile.

FixedID	DrugCode	DrugPlacebo	Locus	Stimulus	Positive	Negative	A
8.0	8J	1	Perceived	Fear Music 1	NaN	NaN	N
4.0	4J	1	Perceived	Fear Music 1	3.0	6.0	9

2 rows × 35 columns

1c. Questionnaires

We follow the same data prep steps for the questionnaires, but we won't test any differences in emotion ratings across demographic and psychographic conditions. We'll leave that to the regression analysis.

original questionnaires shape: (262, 64)

Missing Data

new questionnaires shape: (250, 64)

59 columns contain null values

these columns have more than 10% of their values as null/missing:

```
['WhenLastExerciseHrs', 'MedsInfo', 'MarijuanaInSystem', 'CigarettesInSystem', 'OMSI']
```

final questionnaires shape: (250, 59)

Check for duplicates

```
questionnaire errors in participants: [91, 92, 117, 144, 193]
```

```
fixed questionnaires shape: (240, 59)
```

```
questionnaires errors in stimuli: []
```

2. Imputation of Missing Values

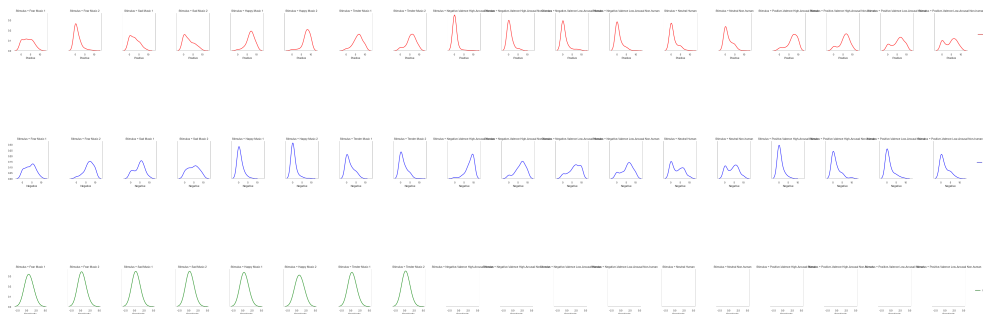
Before we can run a regression analysis, we need to perform some standard feature engineering, such as imputation of missing values, the creation of a single dataframe, and eliminating erroneous data.

In order to tell how we should impute the missing values with the least amount of bias, we need to plot the features that include missing data. The steps are as follows:

1. Find the columns that contain missing data
2. Look at the distributions of these columns
3. Impute using the appropriate method based on the distribution type of the data.

2a. Induced Emotion Ratings

Graph Features



(Note that it was an intentional choice of the researchers to avoid taking familiarity ratings for the natural sounds stimuli)

Because the data are skewed, it's best to use the median for imputation purposes.

We'll impute the values based on their closest neighbors--namely, we'll use the median rating of the feature for *each individual stimulus* to avoid bias.

Impute.

2b. Perceived Emotion Ratings

We repeat the same process for the perceived emotion ratings.

Graph Features



Once again, we'll impute the values based on their closest neighbors--namely, we'll use the median rating of the feature for *each individual stimulus* to avoid bias.

Impute

2c. Combine dataframes

Now we need to create a single dataframe for the regression analysis.

```
perceivedLong shape: (8880, 35)
```

```
inducedLong shape: (4338, 35)
```

```
questionnaires shape: (240, 59)
```

```
[ True  True  True  True  True  True  True  True  True  True  True  True
   True  True  True  True  True  True  True  True  True  True  True  True
   True  True  True  True  True  True  True  True  True  True  True  True]
```

```
perceived/induced shape: (13218, 35)
```

```
long shape: (13218, 91)
```

Double check about duplicates or participant ID numbers

All of the data seem to be okay! The only data that are still missing are due to:

- ID numbers in my hypothetical list that didn't correspond to any real participant ID
- Participants who only completed one block of the study (perceived emotion or induced emotion) but not the other one (technical errors, left early, etc.)
- People who completed the pre-test questionnaires but did not complete either stimulus block (perceived or induced emotion). These cases were dropped, as their data won't help the analysis.

3. Feature Engineering

Many of the features--especially in the questionnaire data--need to be transformed before they can be used in any statistical analysis. Some of the categorical columns should be coded on an ordinal, instead of nominal, scale. Others contain messy data that need to be cleaned up using regular expressions.

*In this section, we will use **feature engineering** to perform the necessary tasks to produce a suitable dataframe for analysis.*

```
shape of model dataframe: (13218, 91)
number of numeric columns: 65
number of categorical columns: 26
number of numeric + categorical columns: 91
```

We can see here that the dataframe currently has 65 numeric columns and 26 categorical columns. We will deal with the numeric columns first, followed by the categorical columns.

3a. Numeric Column Wrangling

The FixedID column (the participant IDs) are currently numeric. Since the "difference" between persons 1 and 2 should be the same as between persons 1 and 244, the feature should be categorical rather than numeric.

Turn IDs into a Categorical Variable

3b. Categorical Column Wrangling

There are several different ways we need to transform the categorical features. Below, we will perform the following operations:

- Drop theoretically redundant features
- Re-label binary variables as 0 and 1
- Convert ordinal variables from nominal Likert scales to numeric values (e.g., 1-7)
- Transforming uncategorized variables (that require unique transformations)
- One-hot encode certain nominal variables

First, we will examine the unique values in each categorical column.

DrugCode unique values:

```
[ '8J' '4J' '6J' '7J' '9J' '3J' '12J' '13J' '2J' '10J' '5J' '11J' '14J'
  '1J' '16J' '18J' '19J' '17J' '15J' '20J' '22J' '21J' '23J' '30J' '29J'
  '28J' '27J' '25J' '24J' '26J' '2K' '1K' '5K' '3K' '4K' '9K' '11K' '6K'
  '8K' '7K' '14K' '12K' '18K' '16K' '32J' '13K' '17K' '15K' '24K' '25K'
  '26K' '19K' '22K' '21K' '31K' '32K' '29K' '28K' '2E' '27K' '4E' '1E'
  '23K' '3E' '12E' '10E' '8E' '9E' '11E' '7E' '6E' '14E' '16E' '15E' '17E'
  '13E' '21E' '22E' '19E' '18E' '20E' '26E' '27E' '30K' '30E' '32E' '31E'
  '1D' '28E' '2D' '6D' '4D' '7D' '3D' '5D' '10D' '8D' '11D' '13D' '16D'
  '14D' '20D' '15D' '19D' '17D' '22D' '21D' '26D' '24D' '25D' '23D' '27D'
  '30D' '32D' '28D' '29D' '1J2' '31D' '8J2' '4J2' '5J2' '6J2' '7J2' '3J2'
  '9J2' '14J2' '10J2' '12J2' '11J2' '18J2' '16J2' '17J2' '15J2' '20J2'
  '22J2' '19J2' '13J2' '21J2' '2J2' '24J2' '23J2' '28J2' '26J2' '25J2'
  '29J2' '27J2' '3K2' '4K2' '31J2' '30J2' '2K2' '1K2' '10K2' '6K2' '7K2'
  '9K2' '12K2' '8K2' '11K2' '13K2' '14K2' '16K2' '15K2' '17K2' '18K2'
  '20K2' '19K2' '22K2' '21K2' '24K2' '23K2' '25K2' '26K2' '27K2' '29K2'
  '1D2' '4D2' '3D2' '5D2' '6D2' '7D2' '10D2' '11D2' '9D2' '13D2' '8D2'
  '12D2' '14D2' '21D2' '19D2' '17D2' '15D2' '18D2' '16D2' '23D2' '20D2'
  '22D2' '24D2' '29D2' '31D2' '27D2' '26D2' '1E2' '28D2' '30D2' '25D2'
  '30K2' '31K2' '32K2' '3E2' '5E2' '7E2' '9E2' '4E2' '2E2' '8E2' '6E2'
  '13E2' '16E2' '11E2' '15E2' '14E2' '17E2' '12E2' '19E2' '10E2' '18E2'
```

Drop Redundant Features

Features that are theoretically identical to another feature should be dropped from the analysis, in order to prevent multicollinearity.

DrugCode

```
(13218, 90)
```

Binary Variables

Variables with only two values (for example, **Yes** vs. **No** responses) should be recoded as 0 and 1.

Locus (Perceived Emotion vs. Induced Emotion)

```
Perceived    67.0
Induced      33.0
Name: Locus, dtype: float64
```

TakeMedsRecentlyYN

```
no    59.0
yes   41.0
Name: TakeMedsRecentlyYN, dtype: float64
```

BirthControlYN


```
no      79.0
yes     21.0
Name: BirthControlYN, dtype: float64
```

ArthritisYN

```
no      94.0
yes      6.0
Name: ArthritisYN, dtype: float64
```

ImmuneDisordersYN

```
no      100.0
yes       0.0
Name: ImmuneDisordersYN, dtype: float64
```

EndocrineDisordersYN

```
no      99.0
yes      1.0
Name: EndocrineDisordersYN, dtype: float64
```

DiabeticYN

```
no      100.0
yes, type 1      0.0
Name: DiabeticYN, dtype: float64
```

Ordinal Variables

Variables on Likert scales should be recoded as ordinal values, as there is an inherent order to these responses.

For example, for the question ***When you take Tylenol, how effective is it at reducing your pain?***, the possible responses were:

- I have never taken Tylenol
- Not effective at all
- Slightly effective
- Moderately effective
- Very effective
- Extremely effective

In this case, we can see that ***Not effective at all*** is less than ***Slightly effective***, and, in turn, ***Slightly effective*** is less than ***Moderately effective*** and so on. By transforming these variables to ordinal, we can capture this difference in any statistical analysis.

Without recoding, it would be difficult to compare ***Extremely effective*** vs. ***Not effective at all***, for instance.

MedsEffectiveness

```
['slightly' 'never taken' 'moderately' 'very' nan 'not at all' 'extremely']
```

Politics

```
['conservative' 'somewhat liberal' 'somewhat conservative' 'liberal'
 'moderate' 'very liberal' 'very conservative' nan]
```

HowMuchLastEat

```
['snack' 'full meal' 'light meal' nan]
```

CigarettesPerDay

```
['0' nan '1-10' '11-20']
```

FrequencyTakeMeds

```
['several times a month' 'never taken' 'at least once a month'
 'less than once a year' 'at least once a year' 'several times a year'
 'at least once a week' 'almost everyday' 'several times a week' nan]
```

WhenLastSick

```
['a few months ago' 'a year or more ago' 'a month ago'
 'a couple of weeks ago' 'a week ago' 'a couple of days ago' nan 'today']
```

MarijuanaFrequency

```
['never' 'several times a week' 'almost every day' 'at least once a month'
 nan 'at least once a year' 'several times a year' 'several times a month'
 'at least once a week']
```

YearUniversity

```
['1' '2' '3' 'None' '5' '4' nan]
```

Transforming Uncategorized Variables

There are additional variables that do not fit any of these categories that we need to transform.

Russell --> HighLow

```

Russell unique values:
  Pos-Valence High-Arousal    22.0
Neg-Valence Low-Arousal      22.0
Neg-Valence High-Arousal     22.0
Pos-Valence Low-Arousal      22.0
Neutral                      13.0
Name: Russell, dtype: float64

```

```

HighLow unique values:
  High    44.0
  Low     44.0
Neutral   13.0
Name: HighLow, dtype: float64

```

PreferredMeds

```

Ibuprofen                60.0
Acetaminophen            15.0
Unknown                   9.0
More Than One Type       6.0
Naproxen Sodium          4.0
Do Not Take Meds         3.0
Acetylsalicylic Acid     1.0
Pseudoephedrine Hydrochloride 0.0
Marijuana                0.0
Calcium Carbonate        0.0
Baclofen                 0.0
Name: PreferredMeds, dtype: float64

```

LastAlcoholDays

```

['5' '4' '7' '182.5' 'Never' '6' nan '2' '14' '3' '0.4166666666666667' '1'
 '30' '34' '10' '9' '365' '28' '24' '21' '270' '11' '60' '1.5'
 '0.5833333333333333' '0.5' '90' '23' '15' '0.625' '0.8333333333333333'
 '2.5' '300' '8' '0.6666666666666667' '240' '0.75' '20' '17'
 '0.7083333333333333' '0.3333333333333333']

```

One-Hot Encoding of Nominal Variables

```

Stimulus: ['Fear Music 1' 'Fear Music 2' 'Fear Music 3' 'Happy Music 1'
'Happy Music 2' 'Happy Music 3' 'Sad Music 1' 'Sad Music 2' 'Sad Music 3'
'Tender Music 1' 'Tender Music 2' 'Tender Music 3' 'Tender Music 4'
'Tender Music 5' 'Tender Music 6' 'Fear Speech 1' 'Fear Speech 2'
'Fear Speech 3' 'Happy Speech 1' 'Happy Speech 2' 'Happy Speech 3'
'Sad Speech 1' 'Sad Speech 2' 'Sad Speech 3' 'Neutral Speech 1'
'Neutral Speech 2' 'Neutral Speech 3'
'Negative-Valence High-Arousal Human'
'Negative-Valence High-Arousal Non-human'
'Negative-Valence Low-Arousal Human'
'Negative-Valence Low-Arousal Non-human' 'Neutral Human'
'Neutral Non-human' 'Positive-Valence High-Arousal Human'
'Positive-Valence High-Arousal Non-human'
'Positive-Valence Low-Arousal Human'
'Positive-Valence Low-Arousal Non-human']

PosNeg: ['Negative' 'Positive' 'Neutral']

HighLow: ['High' 'Low' 'Neutral']

SoundType: ['Music' 'Speech' 'Natural Sounds']

Gender: ['female' 'male' 'prefer not to answer' nan]

PoliticalParty: ['republican' 'democrat' 'libertarian' 'other' nan]

PreferredMeds: ['Ibuprofen' 'Do Not Take Meds' 'Acetaminophen' 'Other' nan]

Race: ['White' 'Asian' 'Black' 'Hispanic' 'White and Hispanic' nan
'White and Asian' 'Other' 'White and Black' 'Black and Hispanic'
'Hispanic and Asian' 'Black and Other']

```

Race

Instead of having separate categories for one-hot encoded multiple racial identities, like **White and Hispanic**, we will transform these columns so that if a person identifies with a single race, the value will be **1** and if they do not, the value will be **0**.

So, each person will have the following one-hot encoded variables:

- Race_Asian
- Race_Black
- Race_Hispanic
- Race_Other
- Race_White

If a person identifies as **Asian**, they will have the following values:

- **Race_Asian = 1**
- Race_Black = 0
- Race_Hispanic = 0
- Race_Other = 0
- Race_White = 0

If a person identifies as **White and Asian**, they will have the following values:

- ***Race_Asian = 1***
- Race_Black = 0
- Race_Hispanic = 0
- Race_Other = 0
- ***Race_White = 1***

```
---- Race_Asian ---  
0    79.0  
1    21.0  
Name: Race_Asian, dtype: float64
```

```
---- Race_Black ---  
0    92.0  
1     8.0  
Name: Race_Black, dtype: float64
```

```
---- Race_Hispanic ---  
0    95.0  
1     5.0  
Name: Race_Hispanic, dtype: float64
```

```
---- Race_Other ---  
0    99.0  
1     1.0  
Name: Race_Other, dtype: float64
```

```
---- Race_White ---  
1    67.0  
0    33.0  
Name: Race_White, dtype: float64
```

LastTimeTookMeds

This column is very messy.

- There are nonsensical values, like *15 NA* and *_years*.
- There are also values on all different scales, like *>1 years*, *215 days*, and *5 minutes*.

Here, we will transform the values so that the LastTimeTookMeds values are all measured in *days*.

```

before transformation: ['4 years' '10 years' '1 years' ' weeks' ' never' '1 mon
ths' '3 weeks'
'6 months' '3 days' '3 years' '2 days' '>1 weeks' ' months' '>1 years'
'3 months' '>1 months' '48 hours' '2 months' nan '1 weeks' '5 months'
'2 weeks' '24 hours' '2.5 weeks' '36 hours' ' unknown' '5 minutes'
'215 days' '2 years' '4 months' '40. hours' '15 NA' '0 NA' ' years'
'3.5 months' '6 years' '1 hours' '5 days' '20 hours' '4 days' '8 months'
'8 NA' '4 weeks' '1 days' '5 years']

```

```

after transformation: [1.46000000e+03 3.65000000e+03 3.65000000e+02 7.00000000e
+00
1.00000000e+00 3.00000000e+01 2.10000000e+01 1.80000000e+02
3.00000000e+00 1.09500000e+03 2.00000000e+00 9.00000000e+01
6.00000000e+01 nan 1.50000000e+02 1.40000000e+01
1.75000000e+01 1.50000000e+00 3.47222222e-03 2.15000000e+02
7.30000000e+02 1.20000000e+02 1.66666667e+00 1.50000000e+01
0.00000000e+00 1.05000000e+02 2.19000000e+03 4.16666667e-02
5.00000000e+00 8.33333333e-01 4.00000000e+00 2.40000000e+02
8.00000000e+00 2.80000000e+01 1.82500000e+03]

```

	FixedID	DrugPlacebo	Locus	Positive	Negative	Arousal	Familiarity	
0	8.0	1	0	3.0	5.0	7.0	0.0	(
1	4.0	1	0	3.0	6.0	9.0	0.0	(
2	6.0	1	0	2.0	8.0	10.0	0.0	(
3	7.0	0	0	3.0	3.0	8.0	1.0	(
4	9.0	0	0	4.0	6.0	6.0	0.0	(

5 rows × 144 columns

Check Transformations

```

shape of model dataframe: (13218, 144)
number of numeric columns: 143
number of categorical columns: 1
list of cat columns = ['FixedID']

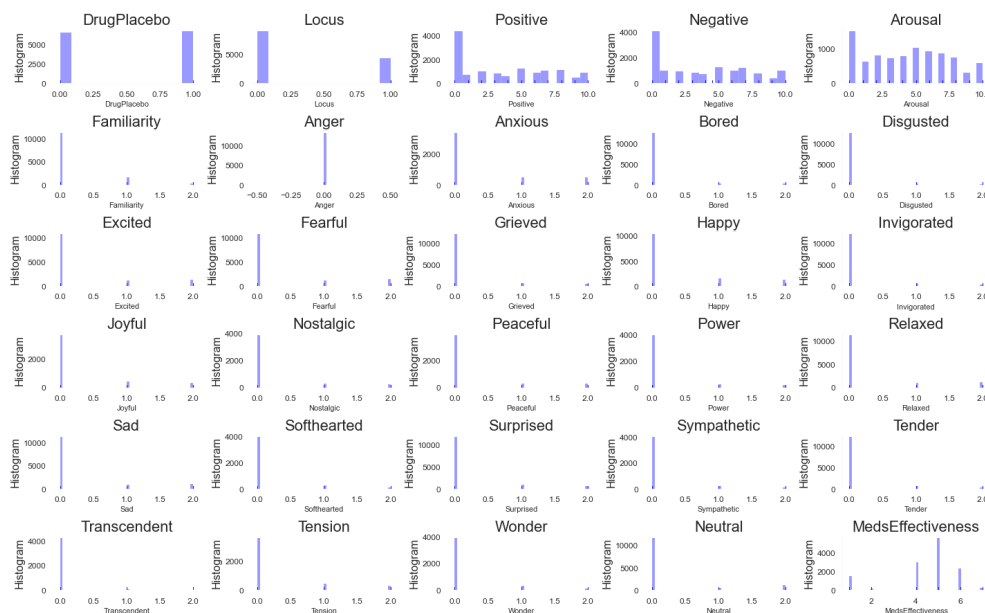
```

Now, 143 of the 144 features are numeric! The only one that is still categorical is FixedID. We can now proceed with the statistical analysis and exploratory data analysis.

3c. Plot

The next step is to make graphs of the distributions of the variables to see if we need to transform them in any other way.

There are 143 features to plot.

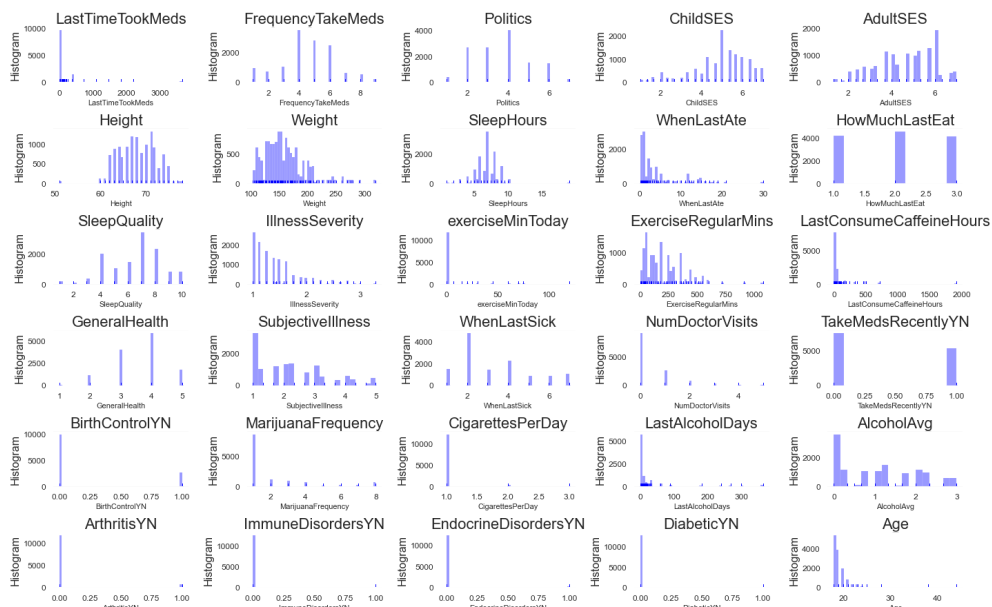


The three emotion ratings (positive, negative, arousal) are right skewed.

- We'll try transforming these later on.

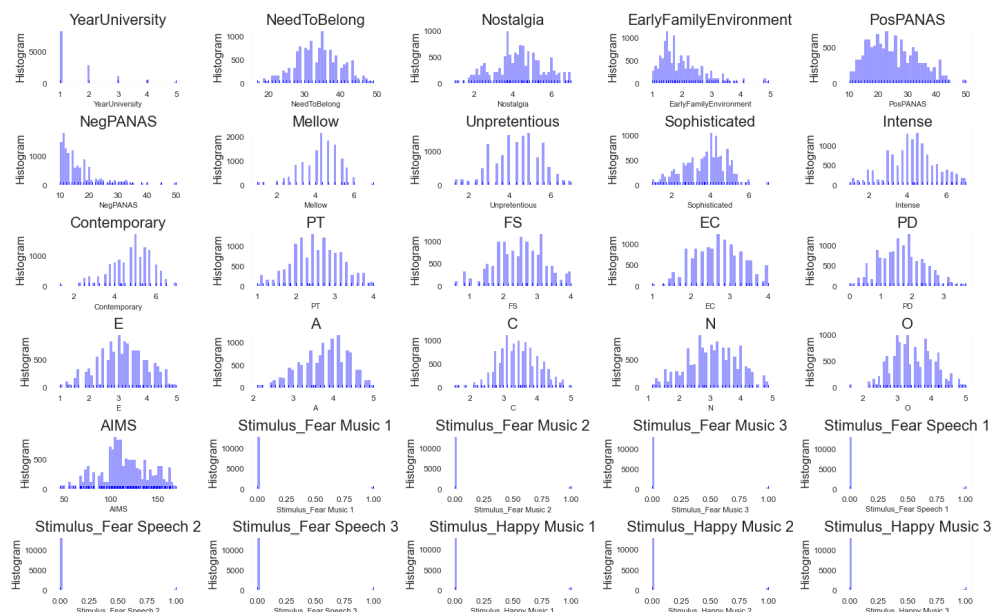
People don't seem to rate any of the specific emotions highly.

- We'll come back to this in the last part of the analysis.



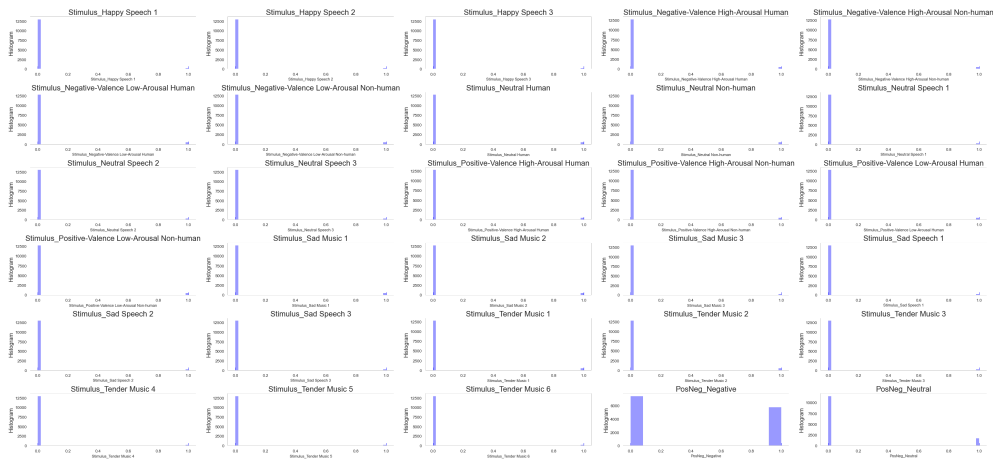
Some variables seem to have little variance, like *DiabeticYN* and *CigarettesPerDay*.

- We'll look for outliers and variability in the next step.

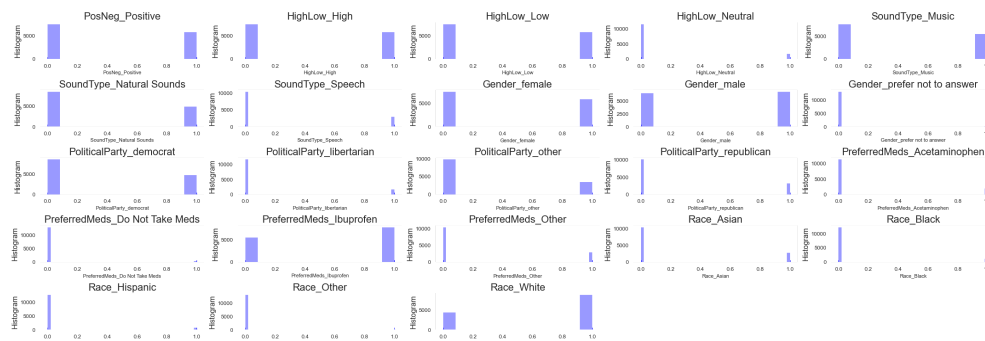


The psychographic variables, like *nostalgia*, *empathy* (PT, FS, EC, and PD), *personality* (E, A, C, N, and O), and *absorption in music* (AIMS) look reasonably normally distributed!

The Stimulus distributions are not useful, as the number of each stimulus was predetermined.



As stated above, the Stimulus distributions are not useful, as the number of each stimulus was predetermined.



Some of the one-hot encoded distributions look skewed

- We will investigate this more in the next section

3d. Feature Selection

We do not want to include features with a high level of missingness in the model, as imputing these values can lead to bias.

Similarly, features where almost every observation is the same will not inform us about how emotion ratings differ between those who took the drug and those who took the placebo.

Therefore, we will delete features with high level of missingness and very low variance

Look for variables that are missing > 10% of the data

Other than the specific emotions (which were not included in both perceived and induced), only 2 features are missing more than 10% of the data:

- *Arousal* -- 32.8% missing.
- *LastAlcoholDays* -- 30.9% missing.

The arousal values are missing because participants were not asked to rate arousal for the induced emotion stimuli -- we will therefore keep it in the model as is.

We will delete ***LastAlcoholDays***, though, because of its missingness.

Look for variables where one response accounts for 95-100% of the variance

```
Anger
Bored
Disgusted
Transcendent
CigarettesPerDay
ImmuneDisordersYN
EndocrineDisordersYN
DiabeticYN
Stimulus_Fear Music 1
Stimulus_Fear Music 2
Stimulus_Fear Music 3
Stimulus_Fear Speech 1
Stimulus_Fear Speech 2
Stimulus_Fear Speech 3
Stimulus_Happy Music 1
Stimulus_Happy Music 2
Stimulus_Happy Music 3
Stimulus_Happy Speech 1
Stimulus_Happy Speech 2
Stimulus_Happy Speech 3
Stimulus_Negative-Valence High-Arousal Human
Stimulus_Negative-Valence High-Arousal Non-human
Stimulus_Negative-Valence Low-Arousal Human
Stimulus_Negative-Valence Low-Arousal Non-human
Stimulus_Neutral Human
Stimulus_Neutral Non-human
Stimulus_Neutral Speech 1
Stimulus_Neutral Speech 2
Stimulus_Neutral Speech 3
Stimulus_Positive-Valence High-Arousal Human
Stimulus_Positive-Valence High-Arousal Non-human
Stimulus_Positive-Valence Low-Arousal Human
Stimulus_Positive-Valence Low-Arousal Non-human
Stimulus_Sad Music 1
Stimulus_Sad Music 2
Stimulus_Sad Music 3
Stimulus_Sad Speech 1
Stimulus_Sad Speech 2
Stimulus_Sad Speech 3
Stimulus_Tender Music 1
Stimulus_Tender Music 2
Stimulus_Tender Music 3
Stimulus_Tender Music 4
Stimulus_Tender Music 5
Stimulus_Tender Music 6
Gender_prefer not to answer
PreferredMeds_Do Not Take Meds
Race_Hispanic
Race_Other
```

We want to keep all the one-hot encoded variables and specific emotions for later analysis.

However, we will delete the following columns that had only one value for 95-100% of the observations:

- CigarettesPerDay
- ImmuneDisordersYN
- EndocrineDisordersYN
- DiabeticYN

Delete

```
model.shape: (13218, 139)
```

3e. Outlier Detection

For each feature, we should investigate the percent of outliers present.

We will define **outlier** as **an observation that is more than 3 standard deviations outside of the mean (in either direction)**.

```
Sad
7 % outliers
```

```
Neutral
8 % outliers
```

```
ArthritisYN
5 % outliers
```

```
Race_Black
7 % outliers
```

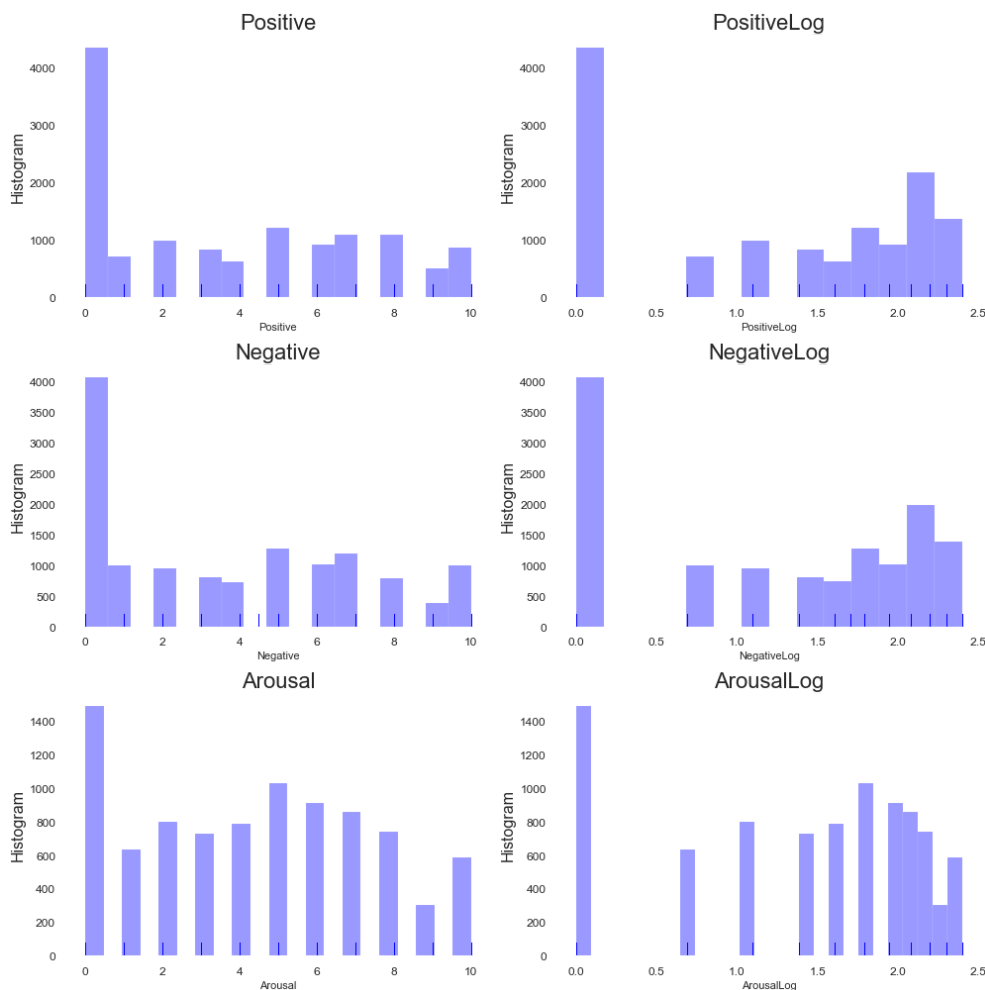
```
Race_Hispanic
5 % outliers
```

The only non 'one-hot encoded' value or 'specific emotion value' is **ArthritisYN** (with 5% of the cases being outliers). We will still keep it in the analysis for now.

3f. Transform Skewed Variables

Recall that the three emotion ratings (the dependent variables) were right skewed. We will try transforming them to see if that helps the distribution become more normal.

We will use a **$\log(1+x)$ transformation**.



The transformation didn't help the skew so we return to the original values to aid in interpretability.

3g. Impute missing values

There are some new missing values (for example, when people completed the stimuli blocks but not the questionnaires, etc.) We will, once again, impute these missing values with the column median.

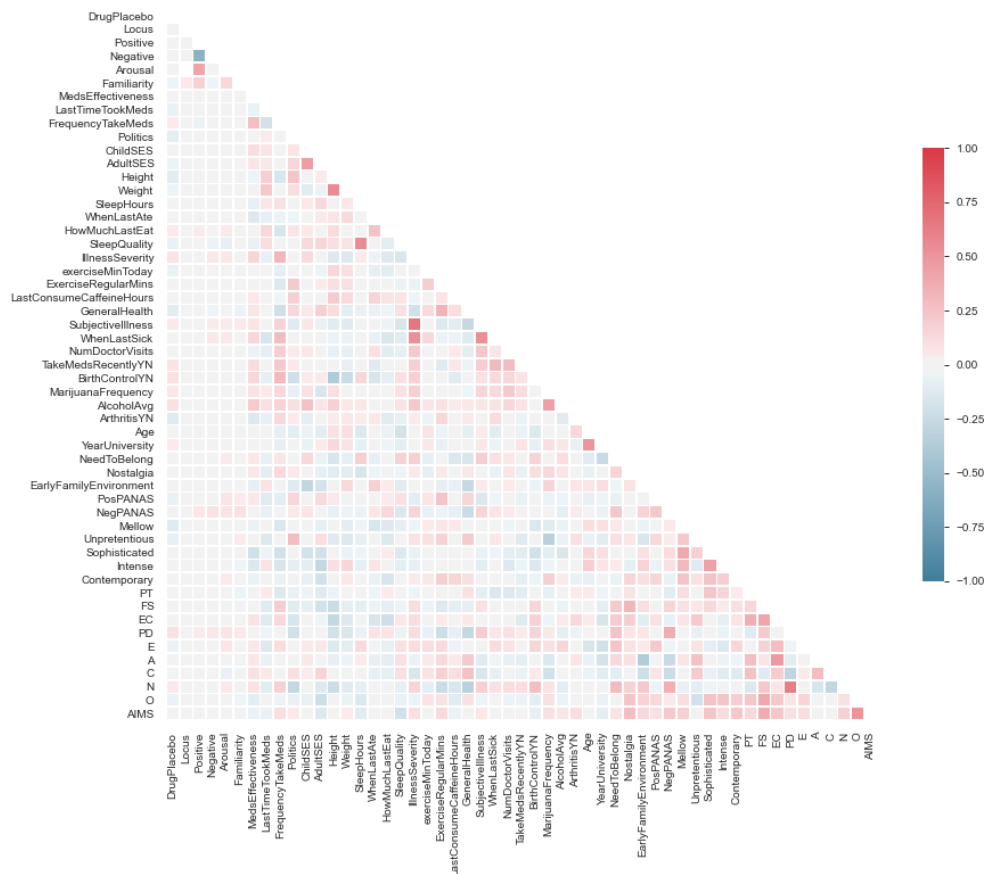
As discussed above, we will not impute the **arousal** values or the **specific emotion values**(like **Wonder** and **Sympathetic**), as these values are missing because of the *a priori* study design.

3h. Correlations

We will look for high correlations that may lead to multicollinearity problems.

Plot

```
<matplotlib.axes._subplots.AxesSubplot at 0x155066910>
```



There are a few high correlations, but the variables seem to be mostly reasonably uncorrelated.

We will look for more details, next.

List high correlations

```
maximum absolute value correlation: 0.68
```

The highest correlation (absolute value) is 0.68, so we don't have to worry too much about multicollinearity.

Regularization (L1) will take care of that if needed.

3i. View final dataframe and reset index

Summarize

```
final model shape: (13218, 139)
number of participants: 244
```

The final dataframe consists of 139 features for 244 participants.

Profile

4. Regression

Now that we have completed feature engineering, we can use linear regression to investigate which features contribute to emotion ratings!

Of course, we are the most interested in seeing whether those who took the drug give reduced (blunted) ratings, compared to those who took the placebo.

We will run a few models:

1. Predicting *positive* emotion ratings
2. Predicting *negative* emotion ratings
3. Predicting *arousal* ratings
4. Predicting *all* emotion ratings

For each of these models, we will run a few multiple linear regressions:

1. Simple OLS model
2. OLS model with lasso regularization to penalize complexity
3. Hierarchical/mixed model (with participant ID as the random effect).

Using ID as a random effect allows us to account for differences among participants and hence perform a within-subjects analysis.

4a. Predicting Positive Emotion Ratings

Data prep

We do not want every single column in these regression models.

The variables we do not need are the following:

- Negative emotion ratings and arousal ratings -- we are only focused on positive emotion ratings here.
- Specific stimulus names -- the features of each stimulus are encoded as Locus (perceived/induced), SoundType (music, speech, natural sounds), HighLow (arousal) and PosNeg (valence).
- Specific emotions -- these will be used in a separate analysis later on.

We also want to rename the Positive column to Ratings. This will allow us to combine the positive, negative, and arousal dataframes later on.

```
entire dataframe shape: (13218, 139)
positive dataframe shape: (13218, 77)
```

X and Y

- Y variable -- *Ratings*
- X variables -- *All other columns except FixedID (the random effect measured later)*

OLS regression

Note that interactions are already taken care of through the one-hot encoding

OLS Regression Results

```

=====
Dep. Variable:          Ratings    R-squared:                0.547
Model:                  OLS        Adj. R-squared:            0.544
Method:                 Least Squares    F-statistic:            226.5
Date:                  Thu, 26 Mar 2020    Prob (F-statistic):      0.00
Time:                  07:56:08    Log-Likelihood:          -29848.
No. Observations:      13218    AIC:                    5.984e+04
Df Residuals:          13147    BIC:                    6.037e+04
Df Model:              70
Covariance Type:       nonrobust
=====

```

```

=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.6756    0.383      1.763    0.078
-0.075    1.427
DrugPlacebo          -0.2338    0.045     -5.230    0.000
-0.321    -0.146
Locus                -0.1575    0.047     -3.352    0.001
-0.250    -0.065
Familiarity          0.4672    0.053      8.797    0.000
0.363    0.571
MedsEffectiveness   -0.0260    0.018     -1.420    0.156
-0.062    0.010
LastTimeTookMeds    -2.761e-05  4.86e-05     -0.569    0.570
-0.000    6.76e-05
FrequencyTakeMeds   -0.0753    0.017     -4.381    0.000
-0.109    -0.042
Politics            0.0839    0.025      3.406    0.001
0.036    0.132
ChildSES            0.0483    0.022      2.180    0.029
0.005    0.092
AdultSES            -0.0722    0.022     -3.265    0.001
-0.116    -0.029
Height              0.0106    0.009      1.240    0.215
-0.006    0.027
Weight              0.0036    0.001      4.226    0.000
0.002    0.005
SleepHours          -0.0782    0.017     -4.467    0.000
-0.112    -0.044
WhenLastAte         0.0009    0.005      0.172    0.864
-0.010    0.012
HowMuchLastEat      0.1088    0.031      3.466    0.001
0.047    0.170
SleepQuality        -0.0203    0.016     -1.294    0.196
-0.051    0.010
IllnessSeverity     0.1446    0.077      1.869    0.062
-0.007    0.296
exerciseMinToday    -0.0089    0.002     -5.376    0.000
-0.012    -0.006
ExerciseRegularMins -0.0003    0.000     -1.847    0.065
-0.001    1.82e-05
LastConsumeCaffeineHours -0.0003    0.000     -2.566    0.010

```


-0.001	-7e-05				
GeneralHealth		0.0377	0.036	1.051	0.293
-0.033	0.108				
SubjectiveIllness		-0.0545	0.030	-1.797	0.072
-0.114	0.005				
WhenLastSick		0.0635	0.018	3.596	0.000
0.029	0.098				
NumDoctorVisits		0.0922	0.032	2.854	0.004
0.029	0.156				
TakeMedsRecentlyYN		-0.1649	0.051	-3.207	0.001
-0.266	-0.064				
BirthControlYN		0.0696	0.071	0.984	0.325
-0.069	0.208				
MarijuanaFrequency		-0.0012	0.015	-0.076	0.940
-0.031	0.029				
AlcoholAvg		0.0404	0.031	1.320	0.187
-0.020	0.100				
ArthritisYN		0.1525	0.112	1.361	0.174
-0.067	0.372				
Age		0.0304	0.011	2.744	0.006
0.009	0.052				
YearUniversity		-0.0099	0.031	-0.314	0.754
-0.071	0.052				
NeedToBelong		0.0062	0.005	1.328	0.184
-0.003	0.015				
Nostalgia		-0.0659	0.020	-3.299	0.001
-0.105	-0.027				
EarlyFamilyEnvironment		0.0150	0.038	0.393	0.695
-0.060	0.090				
PosPANAS		0.0083	0.003	2.515	0.012
0.002	0.015				
NegPANAS		0.0219	0.004	5.086	0.000
0.013	0.030				
Mellow		-0.0393	0.027	-1.434	0.152
-0.093	0.014				
Unpretentious		-0.0378	0.028	-1.373	0.170
-0.092	0.016				
Sophisticated		0.1144	0.027	4.189	0.000
0.061	0.168				
Intense		-0.1285	0.024	-5.416	0.000
-0.175	-0.082				
Contemporary		0.0308	0.028	1.113	0.266
-0.023	0.085				
PT		0.0161	0.043	0.375	0.708
-0.068	0.101				
FS		-0.1584	0.039	-4.078	0.000
-0.235	-0.082				
EC		-0.0841	0.052	-1.619	0.105
-0.186	0.018				
PD		0.2485	0.042	5.904	0.000
0.166	0.331				
E		0.1282	0.033	3.877	0.000
0.063	0.193				
A		0.2752	0.051	5.378	0.000
0.175	0.376				
C		-0.0386	0.045	-0.853	0.394
-0.127	0.050				

N		-0.1498	0.040	-3.740	0.000
-0.228	-0.071				
O		0.0853	0.054	1.589	0.112
-0.020	0.191				
AIMS		-0.0008	0.001	-0.697	0.486
-0.003	0.001				
PosNeg_Negative		-1.8991	0.130	-14.631	0.000
-2.154	-1.645				
PosNeg_Neutral		-0.3592	0.130	-2.766	0.006
-0.614	-0.105				
PosNeg_Positive		2.9338	0.130	22.580	0.000
2.679	3.189				
HighLow_High		0.8216	0.130	6.331	0.000
0.567	1.076				
HighLow_Low		0.2131	0.130	1.640	0.101
-0.042	0.468				
HighLow_Neutral		-0.3592	0.130	-2.766	0.006
-0.614	-0.105				
SoundType_Music		0.7015	0.132	5.325	0.000
0.443	0.960				
SoundType_Natural Sounds		0.0147	0.132	0.112	0.911
-0.244	0.273				
SoundType_Speech		-0.0406	0.133	-0.305	0.760
-0.301	0.220				
Gender_female		1.0504	0.354	2.970	0.003
0.357	1.744				
Gender_male		0.8519	0.351	2.427	0.015
0.164	1.540				
Gender_prefer not to answer		0.5181	0.376	1.376	0.169
-0.220	1.256				
PoliticalParty_democrat		-0.7095	0.175	-4.063	0.000
-1.052	-0.367				
PoliticalParty_libertarian		-0.3243	0.184	-1.763	0.078
-0.685	0.036				
PoliticalParty_other		-1.0292	0.179	-5.745	0.000
-1.380	-0.678				
PoliticalParty_republican		-0.8987	0.186	-4.835	0.000
-1.263	-0.534				
PreferredMeds_Acetaminophen		-0.5405	0.175	-3.090	0.002
-0.883	-0.198				
PreferredMeds_Do Not Take Meds		-0.7738	0.222	-3.492	0.000
-1.208	-0.339				
PreferredMeds_Ibuprofen		-0.6816	0.179	-3.800	0.000
-1.033	-0.330				
PreferredMeds_Other		-0.9656	0.182	-5.316	0.000
-1.322	-0.610				
Race_Asian		0.3401	0.124	2.733	0.006
0.096	0.584				
Race_Black		0.0082	0.125	0.066	0.948
-0.237	0.253				
Race_Hispanic		-0.2477	0.121	-2.053	0.040
-0.484	-0.011				
Race_Other		-0.7092	0.276	-2.565	0.010
-1.251	-0.167				
Race_White		-0.1107	0.123	-0.902	0.367
-0.351	0.130				

=====

```

Omnibus:                126.402    Durbin-Watson:                1.815
Prob(Omnibus):           0.000    Jarque-Bera (JB):            186.558
Skew:                   0.102    Prob(JB):                     3.09e-41
Kurtosis:               3.545    Cond. No.                     1.68e+16
=====

```

Warnings:

```

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.39e-23. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```

Conclusions:

- The measured variables explain 54% of the variance in positive emotion ratings (adjusted $R^2 = 0.54$)
- The ingestion of acetaminophen blunted ratings of positive emotions compared to the ingestion of a placebo.

Name	Coefficient	p	Interpretation
DrugPlacebo	-0.2338	0	Those who took acetaminophen rated positive emotions as less intense than those who took the placebo. Namely, acetaminophen blunted the emotional responses.
PosNeg_Positive	2.9338	0	Positively-valenced stimuli resulted in comparatively high positive emotion ratings.
PosNeg_Negative	-1.8991	0	Negatively-valenced stimuli resulted in comparatively low positive emotion ratings.
HighLow_High	0.8216	0	Stimuli that exhibit high arousal resulted in comparatively more intense positive emotion ratings.
SoundType_Music	0.7015	0	Musical stimuli resulted in comparatively higher ratings of positive emotion.
Familiarity	0.4672	0	Those who are more familiar with the (musical) stimuli rated positive emotions as more intense .
A	0.2752	0	Those who are more agreeable rated emotions as relatively more positive than those who score less high on this personality dimension.
PD	0.2485	0	Those who score higher on the Personal Distress component of empathy rated emotions as relatively more positive than those who score less high on this trait.
FS	-0.1584	0	Those who score higher on the Fantasy component of empathy rated emotions as relatively less positive than those who score less high on this trait.
Locus	-0.1575	0.001	Compared to perceived emotion ratings, induced emotion ratings were more positive .
N	-0.1498	0	Those who are more neurotic rated emotions as relatively less positive than those who score less high on this personality dimension.

Name	Coefficient	p	Interpretation
Intense	-0.1285	0	Those who prefer "Intense" music (Rock, Punk, Alternative, Heavy Metal) rated emotions as relatively less positive (broadly, in response to all stimuli) than those who do not like this genre of music.
E	0.1282	0	Those who are more extraverted rated emotions as relatively more positive than those who score less high on this personality dimension.
Sophisticated	0.1144	0	Those who prefer "Sophisticated" music (Blues, Jazz, Bluegrass, Folk, Classical, Gospel, Opera) rated emotions as relatively more positive (broadly, in response to all stimuli) than those who do not like this genre of music.
Nostalgia	-0.0659	0.001	Those who scored high on nostalgia rated relatively less intense positive ratings (although this effect is small).

OLS regression with lasso regularization

There's no way to look at standard errors, p-values, R^2 , etc. because the theory for these values is still being developed among statisticians.

Conclusions:

- This didn't change very much from the original mode.
- This chart shows the "non-zero" variables from the original OLS --> these are the only (significant) features kept in the regularized model
- Note that I used an arbitrary cutoff of 0.1 coefficient value to count as significant.

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
DrugPlacebo	-0.2338	-0.213441
PosNeg_Positive	2.9338	2.679953
PosNeg_Negative	-1.8991	-2.152853
PosNeg_Neutral	-0.3592	-1.489466
Race_Other	-0.7092	-0.566435
Familiarity	0.4672	0.4724
PoliticalParty_other	-1.0292	-0.439776
SoundType_Music	0.7015	0.410356
Race_Asian	0.3401	0.401408
PoliticalParty_republican	-0.8987	-0.343314
HighLow_High	0.8216	0.304188

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
PreferredMeds_Other	-0.9656	-0.270893
Gender_male	0.8519	-0.262979
PD	0.2485	0.238791
TakeMedsRecentlyYN	-0.1649	-0.189407
Gender_female	1.0504	-0.179473
PreferredMeds_Acetaminophen	-0.5405	0.159463
Locus	-0.1575	-0.154902
PreferredMeds_Do Not Take Meds	-0.7738	-0.139533
N	-0.1498	-0.137826
FS	-0.1584	-0.134634
PoliticalParty_democrat	-0.7095	-0.124515
Intense	-0.1285	-0.11814

Mixed Model

FixedID (the participant ID numbers) will be used as the grouping variable (the random effect)

Mixed Linear Model Regression Results

```

=====
Model:                               MixedLM           Dependent Variable:      Ra
tings
No. Observations:                    13218             Method:                RE
ML
No. Groups:                          244              Scale:                 4.
9020
Min. group size:                     18                Likelihood:            -2
9542.5375
Max. group size:                     55                Converged:             No
Mean group size:                     54.2

-----

```

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
const	24.794	743061.093	0.000	1.000	-1456348.186	1456397.774
DrugPlacebo	-0.233	0.123	-1.895	0.058	-0.475	0.008
Locus	-0.150	0.045	-3.340	0.001	-0.239	-0.062
Familiarity	0.390	0.054	7.284	0.000	0.285	0.495
MedsEffectiveness	-0.026	0.050	-0.507	0.612	-0.125	0.073
LastTimeTookMeds	-0.000	0.000	-0.212	0.832	-0.000	0.000
FrequencyTakeMeds	-0.075	0.048	-1.571	0.116	-0.168	0.018
Politics	0.084	0.068	1.234	0.217	-0.049	0.217
ChildSES	0.047	0.061	0.770	0.441	-0.073	0.167
AdultSES	-0.070	0.061	-1.155	0.248	-0.190	0.049
Height	0.011	0.024	0.471	0.637	-0.035	0.058
Weight	0.004	0.002	1.558	0.119	-0.001	0.008
SleepHours	-0.075	0.048	-1.552	0.121	-0.169	0.020
WhenLastAte	0.001	0.015	0.045	0.964	-0.029	0.030
HowMuchLastEat	0.110	0.087	1.266	0.205	-0.060	0.280
SleepQuality	-0.024	0.043	-0.557	0.577	-0.108	0.060
IllnessSeverity	0.147	0.214	0.689	0.491	-0.271	0.566
exerciseMinToday	-0.009	0.005	-1.946	0.052	-0.018	0.000
ExerciseRegularMins	-0.000	0.000	-0.659	0.510	-0.001	0.000

0.001					
LastConsumeCaffeineHours	-0.000	0.000	-0.934	0.351	-0.001
0.000					
GeneralHealth	0.035	0.099	0.354	0.724	-0.159
0.229					
SubjectiveIllness	-0.052	0.084	-0.626	0.531	-0.217
0.112					
WhenLastSick	0.062	0.048	1.274	0.203	-0.033
0.157					
NumDoctorVisits	0.091	0.089	1.018	0.308	-0.084
0.266					
TakeMedsRecentlyYN	-0.166	0.142	-1.166	0.243	-0.444
0.113					
BirthControlYN	0.065	0.195	0.332	0.740	-0.318
0.448					
MarijuanaFrequency	-0.000	0.042	-0.003	0.997	-0.083
0.082					
AlcoholAvg	0.041	0.084	0.485	0.628	-0.124
0.206					
ArthritisYN	0.170	0.302	0.562	0.574	-0.423
0.763					
Age	0.029	0.031	0.956	0.339	-0.031
0.089					
YearUniversity	-0.008	0.087	-0.088	0.930	-0.177
0.162					
NeedToBelong	0.006	0.013	0.477	0.633	-0.019
0.031					
Nostalgia	-0.067	0.055	-1.210	0.226	-0.175
0.041					
EarlyFamilyEnvironment	0.013	0.105	0.124	0.902	-0.193
0.219					
PosPANAS	0.009	0.009	0.946	0.344	-0.009
0.026					
NegPANAS	0.022	0.012	1.853	0.064	-0.001
0.045					
Mellow	-0.038	0.076	-0.497	0.619	-0.186
0.110					
Unpretentious	-0.033	0.076	-0.432	0.666	-0.181
0.116					
Sophisticated	0.115	0.075	1.522	0.128	-0.033
0.262					
Intense	-0.127	0.066	-1.945	0.052	-0.256
0.001					
Contemporary	0.028	0.076	0.366	0.714	-0.122
0.177					
PT	0.016	0.118	0.135	0.893	-0.215
0.247					
FS	-0.155	0.107	-1.450	0.147	-0.365
0.055					
EC	-0.086	0.143	-0.596	0.551	-0.367
0.196					
PD	0.248	0.115	2.154	0.031	0.022
0.474					
E	0.128	0.091	1.407	0.160	-0.050
0.305					
A	0.272	0.141	1.924	0.054	-0.005
0.549					

C	-0.043	0.124	-0.342	0.733	-0.287	
0.201						
N	-0.150	0.111	-1.353	0.176	-0.368	
0.067						
O	0.088	0.148	0.591	0.554	-0.203	
0.378						
AIMS	-0.001	0.003	-0.271	0.786	-0.007	
0.006						
PosNeg_Negative	-13.396	451632.948	-0.000	1.000	-885197.708	8
85170.916						
PosNeg_Neutral	3176.709					
PosNeg_Positive	-8.562	451684.161	-0.000	1.000	-885293.249	8
85276.126						
HighLow_High	-11.506					
HighLow_Low	-12.116					
HighLow_Neutral	-3201.251					
SoundType_Music	0.407	120061.108	0.000	1.000	-235315.040	2
35315.855						
SoundType_Natural Sounds	-0.312	113747.479	-0.000	1.000	-222941.273	2
22940.650						
SoundType_Speech	-0.365	119121.505	-0.000	1.000	-233474.225	2
33473.495						
Gender_female	1.059	0.980	1.080	0.280	-0.862	
2.979						
Gender_male	0.852	0.972	0.877	0.381	-1.053	
2.757						
Gender_prefer not to answer	0.530	1.042	0.509	0.611	-1.513	
2.573						
PoliticalParty_democrat	-10.223					
PoliticalParty_libertarian	-9.839					
PoliticalParty_other	-10.549					
PoliticalParty_republican	-10.412					
PreferredMeds_Acetaminophen	8.967					
PreferredMeds_Do Not Take Meds	8.736					
PreferredMeds_Ibuprofen	8.829					
PreferredMeds_Other	8.546					
Race_Asian	0.342	0.345	0.992	0.321	-0.334	
1.019						
Race_Black	-0.004	0.346	-0.011	0.991	-0.681	
0.674						
Race_Hispanic	-0.240	0.334	-0.719	0.472	-0.894	
0.414						
Race_Other	-0.700	0.766	-0.914	0.361	-2.201	
0.801						
Race_White	-0.112	0.340	-0.329	0.742	-0.777	
0.554						
Group Var	0.664					

=====

=====

Conclusions:

- The model did not converge

- **Basically no features are significant in the mixed model (because they are so redundant with the questionnaire data)**

4b. Predicting Negative Emotion Ratings

Data prep

```
entire dataframe shape: (13218, 139)  
negative dataframe shape: (13218, 77)
```

X and Y

OLS regression

OLS Regression Results

```

=====
Dep. Variable:          Ratings    R-squared:                0.488
Model:                  OLS        Adj. R-squared:            0.485
Method:                 Least Squares    F-statistic:            179.0
Date:                  Thu, 26 Mar 2020    Prob (F-statistic):      0.00
Time:                  07:56:34    Log-Likelihood:          -30464.
No. Observations:      13218    AIC:                     6.107e+04
Df Residuals:          13147    BIC:                     6.160e+04
Df Model:              70
Covariance Type:       nonrobust
=====

```

```

=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                1.9981    0.401      4.978    0.000
1.211    2.785
DrugPlacebo          -0.1973    0.047     -4.212    0.000
-0.289    -0.105
Locus                -0.2381    0.049     -4.837    0.000
-0.335    -0.142
Familiarity           0.0048    0.056      0.086    0.932
-0.104     0.114
MedsEffectiveness    -0.0431    0.019     -2.244    0.025
-0.081    -0.005
LastTimeTookMeds      1.593e-05  5.09e-05    0.313    0.754    -
8.38e-05    0.000
FrequencyTakeMeds      0.0042    0.018      0.232    0.817
-0.031     0.039
Politics              0.0773    0.026      2.997    0.003
0.027     0.128
ChildSES             -0.0681    0.023     -2.938    0.003
-0.114    -0.023
AdultSES              0.0104    0.023      0.451    0.652
-0.035     0.056
Height                0.0043    0.009      0.476    0.634
-0.013     0.022
Weight                0.0014    0.001      1.583    0.113
-0.000     0.003
SleepHours            0.0341    0.018      1.862    0.063
-0.002     0.070
WhenLastAte           0.0040    0.006      0.700    0.484
-0.007     0.015
HowMuchLastEat         0.1865    0.033      5.669    0.000
0.122     0.251
SleepQuality          -0.1064    0.016     -6.466    0.000
-0.139    -0.074
IllnessSeverity        0.1792    0.081      2.211    0.027
0.020     0.338
exerciseMinToday       0.0023    0.002      1.316    0.188
-0.001     0.006
ExerciseRegularMins    -0.0004    0.000     -2.395    0.017
-0.001   -7.36e-05
LastConsumeCaffeineHours -0.0005    0.000     -3.963    0.000

```

-0.001	-0.000				
GeneralHealth		-0.0959	0.038	-2.549	0.011
-0.170	-0.022				
SubjectiveIllness		-0.0597	0.032	-1.881	0.060
-0.122	0.003				
WhenLastSick		0.0704	0.018	3.808	0.000
0.034	0.107				
NumDoctorVisits		0.0450	0.034	1.331	0.183
-0.021	0.111				
TakeMedsRecentlyYN		-0.1845	0.054	-3.425	0.001
-0.290	-0.079				
BirthControlYN		-0.0029	0.074	-0.039	0.969
-0.148	0.142				
MarijuanaFrequency		0.0279	0.016	1.750	0.080
-0.003	0.059				
AlcoholAvg		0.1604	0.032	5.004	0.000
0.098	0.223				
ArthritisYN		0.3687	0.117	3.141	0.002
0.139	0.599				
Age		-0.0354	0.012	-3.054	0.002
-0.058	-0.013				
YearUniversity		-0.0283	0.033	-0.860	0.390
-0.093	0.036				
NeedToBelong		-0.0006	0.005	-0.132	0.895
-0.010	0.009				
Nostalgia		-0.0428	0.021	-2.044	0.041
-0.084	-0.002				
EarlyFamilyEnvironment		-0.0409	0.040	-1.024	0.306
-0.119	0.037				
PosPANAS		0.0084	0.003	2.434	0.015
0.002	0.015				
NegPANAS		0.0342	0.005	7.582	0.000
0.025	0.043				
Mellow		0.0769	0.029	2.680	0.007
0.021	0.133				
Unpretentious		-0.0967	0.029	-3.353	0.001
-0.153	-0.040				
Sophisticated		0.0369	0.029	1.290	0.197
-0.019	0.093				
Intense		-0.1078	0.025	-4.336	0.000
-0.156	-0.059				
Contemporary		0.0440	0.029	1.520	0.129
-0.013	0.101				
PT		-0.0047	0.045	-0.104	0.917
-0.093	0.084				
FS		-0.0467	0.041	-1.148	0.251
-0.127	0.033				
EC		0.2329	0.054	4.279	0.000
0.126	0.340				
PD		0.2260	0.044	5.125	0.000
0.140	0.312				
E		0.0246	0.035	0.709	0.478
-0.043	0.092				
A		0.0073	0.054	0.136	0.892
-0.098	0.112				
C		0.0350	0.047	0.738	0.460
-0.058	0.128				

N		-0.0835	0.042	-1.990	0.047
-0.166	-0.001				
O		-0.0439	0.056	-0.781	0.435
-0.154	0.066				
AIMS		-0.0026	0.001	-2.088	0.037
-0.005	-0.000				
PosNeg_Negative		3.2290	0.136	23.745	0.000
2.962	3.496				
PosNeg_Neutral		0.3566	0.136	2.622	0.009
0.090	0.623				
PosNeg_Positive		-1.5875	0.136	-11.662	0.000
-1.854	-1.321				
HighLow_High		0.8920	0.136	6.561	0.000
0.626	1.159				
HighLow_Low		0.7495	0.136	5.505	0.000
0.483	1.016				
HighLow_Neutral		0.3566	0.136	2.622	0.009
0.090	0.623				
SoundType_Music		0.3946	0.138	2.859	0.004
0.124	0.665				
SoundType_Natural Sounds		0.9590	0.138	6.948	0.000
0.688	1.230				
SoundType_Speech		0.6445	0.139	4.622	0.000
0.371	0.918				
Gender_female		2.0843	0.371	5.625	0.000
1.358	2.811				
Gender_male		1.7295	0.368	4.704	0.000
1.009	2.450				
Gender_prefer not to answer		1.3418	0.394	3.403	0.001
0.569	2.115				
PoliticalParty_democrat		-1.2575	0.183	-6.874	0.000
-1.616	-0.899				
PoliticalParty_libertarian		-0.8885	0.193	-4.612	0.000
-1.266	-0.511				
PoliticalParty_other		-1.4953	0.188	-7.967	0.000
-1.863	-1.127				
PoliticalParty_republican		-1.2431	0.195	-6.384	0.000
-1.625	-0.861				
PreferredMeds_Acetaminophen		-0.8895	0.183	-4.853	0.000
-1.249	-0.530				
PreferredMeds_Do Not Take Meds		-1.7970	0.232	-7.740	0.000
-2.252	-1.342				
PreferredMeds_Ibuprofen		-0.9961	0.188	-5.301	0.000
-1.364	-0.628				
PreferredMeds_Other		-1.2019	0.190	-6.316	0.000
-1.575	-0.829				
Race_Asian		0.1082	0.130	0.830	0.407
-0.147	0.364				
Race_Black		-0.1553	0.131	-1.186	0.236
-0.412	0.101				
Race_Hispanic		0.0401	0.126	0.317	0.751
-0.208	0.288				
Race_Other		-0.8999	0.290	-3.107	0.002
-1.468	-0.332				
Race_White		-0.2653	0.129	-2.062	0.039
-0.517	-0.013				

=====

```

Omnibus:                29.193    Durbin-Watson:                1.818
Prob(Omnibus):           0.000    Jarque-Bera (JB):           34.597
Skew:                   0.047    Prob(JB):                   3.07e-08
Kurtosis:               3.232    Cond. No.                   1.68e+16
=====

```

Warnings:

```

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.39e-23. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```

Conclusions:

- The measured variables explain 49% of the variance in negative emotion ratings (adjusted $R^2 = 0.49$)
- The ingestion of acetaminophen blunted ratings of negative emotions compared to the ingestion of a placebo.

Name	Coefficient	p	Interpretation
DrugPlacebo	-0.1973	0	Those who took acetaminophen rated negative emotions as less intense than those who took the placebo. Namely, acetaminophen blunted the emotional responses.
PosNeg_Negative	3.229	0	Negatively-valenced stimuli resulted in comparatively high negative emotion ratings.
PosNeg_Positive	-1.5875	0	Positively-valenced stimuli resulted in comparatively low negative emotion ratings.
SoundType_Natural Sounds	0.959	0	Natural Sounds resulted in comparatively higher ratings of negative emotion (and its effect is comparatively large next to speech and especially compared to music)
HighLow_High	0.892	0	Stimuli that exhibit high arousal resulted in comparatively more intense negative emotion ratings.
HighLow_Low	0.7495	0	Stimuli that exhibit low arousal resulted in comparatively higher negative emotion ratings (but the effect is smaller than the high arousal music).
SoundType_Speech	0.6445	0	Speech resulted in comparatively higher ratings of negative emotion (and its effect is comparatively large with musical stimuli)
SoundType_Music	0.3946	0.004	Musical stimuli resulted in comparatively higher ratings of negative emotion (but the effect is small compared to speech and natural sounds)
Locus	-0.2381	0	Compared to perceived emotion ratings, induced emotion ratings were less negative .
EC	0.2329	0	Those who score higher on the Empathic Concern component of empathy rated emotions as relatively more negative than those who score less high on this trait.

Name	Coefficient	p	Interpretation
PD	0.226	0	Those who score higher on the Personal Distress component of empathy rated emotions as relatively more negative than those who score less high on this trait.
Intense	-0.1078	0	Those who prefer "Intense" music (Rock, Punk, Alternative, Heavy Metal) rated emotions as relatively less negative (broadly, in response to all stimuli) than those who do not like this genre of music.
Unpretentious	-0.0967	0.001	Those who prefer "Unpretentious" music (Pop, Country, Religious) rated emotions as relatively less negative (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
N	-0.0835	0.047	Those who are more neurotic rated emotions as relatively more negative than those who score less high on this personality dimension (although this effect is small).
Mellow	0.0769	0.007	Those who prefer "Mellow" music (Dance/Electronica, New Age, World) rated emotions as relatively more negative (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
Nostalgia	-0.0428	0.041	Those who scored high on nostalgia rated relatively less intense negative ratings (although this effect is small).

OLS regression with lasso regularization

Conclusions:

- This didn't change very much from the original mode.
- This chart shows the "non-zero" variables from the original OLS --> these are the only (significant) features kept in the regularized model
- Note that I used an arbitrary cutoff of 0.1 coefficient value to count as significant.

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
DrugPlacebo	-0.2338	-0.170217
PosNeg_Negative	-1.8991	2.784016
PosNeg_Positive	2.9338	-2.03266
PreferredMeds_Do Not Take Meds	-0.7738	-0.752959
PoliticalParty_other	-1.0292	-0.588811
Race_Other	-0.7092	-0.56928

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
PosNeg_Neutral	-0.3592	-0.552684
PoliticalParty_democrat	-0.7095	-0.357943
PoliticalParty_republican	-0.8987	-0.340561
SoundType_Music	0.7015	-0.262282
Race_Asian	0.3401	0.257602
Locus	-0.1575	-0.236797
TakeMedsRecentlyYN	-0.1649	-0.192641
Gender_female	1.0504	0.183484
Gender_male	0.8519	-0.183096
Race_Hispanic	-0.2477	0.172875
PreferredMeds_Other	-0.9656	-0.16225
HowMuchLastEat	0.1088	0.150585
PD	0.2485	0.146022
Intense	-0.1285	-0.119339
PreferredMeds_Acetaminophen	-0.5405	0.117664
WhenLastSick	0.0635	0.094308
N	-0.1498	-0.092503
Politics	0.0839	0.080004
A	0.2752	-0.074981
HighLow_High	0.8216	0.07116
PreferredMeds_Ibuprofen	-0.6816	0.063047
E	0.1282	-0.055616
ChildSES	0.0483	-0.049005
FS	-0.1584	-0.047957
NumDoctorVisits	0.0922	0.047311
Nostalgia	-0.0659	-0.046546
NegPANAS	0.0219	0.033516
AdultSES	-0.0722	0.030117
SleepHours	-0.0782	0.022598
Familiarity	0.4672	0.01509
PosPANAS	0.0083	0.011698

Mixed Model

Mixed Linear Model Regression Results

```

=====
Model: MixedLM Dependent Variable: R
atings
No. Observations: 13218 Method: R
EML
No. Groups: 244 Scale:
5.3771
Min. group size: 18 Likelihood: -
30153.4846
Max. group size: 55 Converged: N
o
Mean group size: 54.2
-----
-----
Coef. Std.Err. z P>|z| [0.025
0.975]
-----
-----
const 6.683 2059769.340 0.000 1.000 -4037067.041 4
037080.406
DrugPlacebo -0.207 0.130 -1.586 0.113 -0.463
0.049
Locus -0.231 0.047 -4.900 0.000 -0.324
-0.139
Familiarity -0.071 0.056 -1.261 0.207 -0.181
0.039
MedsEffectiveness -0.043 0.053 -0.807 0.420 -0.148
0.062
LastTimeTookMeds 0.000 0.000 0.158 0.875 -0.000
0.000
FrequencyTakeMeds 0.004 0.050 0.087 0.931 -0.094
0.103
Politics 0.082 0.072 1.134 0.257 -0.060
0.223
ChildSES -0.068 0.065 -1.054 0.292 -0.195
0.059
AdultSES 0.009 0.065 0.132 0.895 -0.118
0.135
Height 0.005 0.025 0.215 0.830 -0.044
0.054
Weight 0.001 0.003 0.523 0.601 -0.004
0.006
SleepHours 0.038 0.051 0.745 0.456 -0.062
0.138
WhenLastAte 0.005 0.016 0.315 0.753 -0.026
0.036
HowMuchLastEat 0.185 0.092 2.020 0.043 0.006
0.365
SleepQuality -0.111 0.045 -2.439 0.015 -0.200
-0.022
IllnessSeverity 0.187 0.226 0.828 0.408 -0.256
0.631
exerciseMinToday 0.002 0.005 0.364 0.716 -0.008
0.011

```


ExerciseRegularMins	-0.000	0.000	-0.771	0.441	-0.001
0.001					
LastConsumeCaffeineHours	-0.000	0.000	-1.390	0.164	-0.001
0.000					
GeneralHealth	-0.092	0.105	-0.880	0.379	-0.298
0.113					
SubjectiveIllness	-0.061	0.089	-0.687	0.492	-0.235
0.113					
WhenLastSick	0.073	0.051	1.429	0.153	-0.027
0.174					
NumDoctorVisits	0.043	0.095	0.451	0.652	-0.143
0.228					
TakeMedsRecentlyYN	-0.189	0.150	-1.254	0.210	-0.483
0.106					
BirthControlYN	0.012	0.207	0.059	0.953	-0.393
0.418					
MarijuanaFrequency	0.029	0.045	0.641	0.521	-0.059
0.116					
AlcoholAvg	0.155	0.089	1.738	0.082	-0.020
0.330					
ArthritisYN	0.304	0.320	0.950	0.342	-0.323
0.932					
Age	-0.033	0.032	-1.033	0.302	-0.097
0.030					
YearUniversity	-0.023	0.092	-0.255	0.799	-0.203
0.156					
NeedToBelong	0.001	0.014	0.049	0.961	-0.026
0.027					
Nostalgia	-0.047	0.058	-0.807	0.419	-0.162
0.067					
EarlyFamilyEnvironment	-0.042	0.111	-0.381	0.703	-0.260
0.176					
PosPANAS	0.008	0.010	0.805	0.421	-0.011
0.026					
NegPANAS	0.035	0.013	2.762	0.006	0.010
0.060					
Mellow	0.073	0.080	0.909	0.363	-0.084
0.230					
Unpretentious	-0.091	0.080	-1.130	0.258	-0.248
0.067					
Sophisticated	0.028	0.080	0.354	0.724	-0.128
0.184					
Intense	-0.111	0.069	-1.606	0.108	-0.247
0.025					
Contemporary	0.048	0.081	0.595	0.552	-0.110
0.206					
PT	0.003	0.125	0.023	0.982	-0.242
0.248					
FS	-0.048	0.113	-0.425	0.671	-0.270
0.174					
EC	0.236	0.152	1.555	0.120	-0.061
0.534					
PD	0.208	0.122	1.707	0.088	-0.031
0.447					
E	0.026	0.096	0.273	0.785	-0.162
0.214					
A	0.016	0.150	0.107	0.915	-0.277

0.309							
C	0.028	0.132	0.212	0.832	-0.230		
0.286							
N	-0.081	0.117	-0.692	0.489	-0.312		
0.149							
O	-0.035	0.157	-0.224	0.823	-0.342		
0.272							
AIMS	-0.002	0.003	-0.700	0.484	-0.009		
0.004							
PosNeg_Negative	0.905	1130753.423	0.000	1.000	-2216235.080	2	
216236.890							
PosNeg_Neutral	38.721	6263343.490	0.000	1.000	-12275888.942	12	
275966.385							
PosNeg_Positive	-3.910	1130434.240	-0.000	1.000	-2215614.307	2	
215606.487							
HighLow_High	-0.818	1227962.135	-0.000	1.000	-2406762.378	2	
406760.741							
HighLow_Low	-0.963	1227713.185	-0.000	1.000	-2406274.589	2	
406272.664							
HighLow_Neutral	-42.043	6720455.194	-0.000	1.000	-13171892.184	13	
171808.098							
SoundType_Music	-0.424						
SoundType_Natural Sounds	0.109						
SoundType_Speech	-0.204						
Gender_female	2.110	1.038	2.033	0.042	0.076		
4.143							
Gender_male	1.767	1.029	1.717	0.086	-0.250		
3.784							
Gender_prefer not to answer	1.384	1.104	1.253	0.210	-0.780		
3.547							
PoliticalParty_democrat	1.936	2229494.508	0.000	1.000	-4369727.003	4	
369730.874							
PoliticalParty_libertarian	2.281	2229494.508	0.000	1.000	-4369726.657	4	
369731.220							
PoliticalParty_other	1.679	2229494.508	0.000	1.000	-4369727.260	4	
369730.617							
PoliticalParty_republican	1.920	2229494.508	0.000	1.000	-4369727.018	4	
369730.859							
PreferredMeds_Acetaminophen	-4.094	2229494.508	-0.000	1.000	-4369733.033	4	
369724.844							
PreferredMeds_Do Not Take Meds	-4.984	2229494.508	-0.000	1.000	-4369733.922	4	
369723.955							
PreferredMeds_Ibuprofen	-4.192	2229494.508	-0.000	1.000	-4369733.131	4	
369724.746							
PreferredMeds_Other	-4.394	2229494.508	-0.000	1.000	-4369733.332	4	
369724.545							
Race_Asian	0.109	0.365	0.297	0.766	-0.608		
0.825							
Race_Black	-0.141	0.366	-0.385	0.700	-0.859		
0.576							
Race_Hispanic	0.021	0.353	0.060	0.952	-0.671		
0.714							
Race_Other	-0.892	0.811	-1.100	0.271	-2.482		
0.698							
Race_White	-0.288	0.360	-0.802	0.423	-0.993		
0.417							
Group Var	0.747	0.041					

Conclusions:

- The model did not converge
- Basically no features are significant in the mixed model (because they are so redundant with the questionnaire data)

4c. Predicting Arousal Ratings

Data prep

```
arousal dataframe shape: (13218, 77)
entire dataframe shape: (13218, 139)
arousal dataframe shape: (8880, 77)
```

X and Y

Note that we also delete the **Locus** (Perceived or Induced) column because all arousal ratings are related to perceived emotion.

OLS regression

OLS Regression Results

```

=====
Dep. Variable:          Ratings    R-squared:                0.390
Model:                  OLS       Adj. R-squared:            0.386
Method:                 Least Squares    F-statistic:          81.78
Date:                  Thu, 26 Mar 2020    Prob (F-statistic):    0.00
Time:                  07:57:01    Log-Likelihood:       -20454.
No. Observations:      8880    AIC:                  4.105e+04
Df Residuals:          8810    BIC:                  4.154e+04
Df Model:              69
Covariance Type:       nonrobust
=====

```

```

=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                        1.6504      0.489      3.378      0.001
0.693    2.608
DrugPlacebo                 -0.1015      0.057     -1.774      0.076
-0.214    0.011
Familiarity                  0.6654      0.071      9.352      0.000
0.526    0.805
MedsEffectiveness           -0.0378      0.024     -1.606      0.108
-0.084    0.008
LastTimeTookMeds            0.0001    6.21e-05      2.020      0.043    3.
71e-06    0.000
FrequencyTakeMeds           -0.0260      0.022     -1.183      0.237
-0.069    0.017
Politics                     0.0530      0.032      1.684      0.092
-0.009    0.115
ChildSES                    0.0436      0.028      1.539      0.124
-0.012    0.099
AdultSES                    0.0017      0.028      0.059      0.953
-0.054    0.057
Height                      0.0037      0.011      0.342      0.732
-0.018    0.025
Weight                      0.0004      0.001      0.331      0.741
-0.002    0.003
SleepHours                  -0.0896      0.022     -4.017      0.000
-0.133   -0.046
WhenLastAte                 -0.0173      0.007     -2.482      0.013
-0.031   -0.004
HowMuchLastEat              0.1787      0.040      4.457      0.000
0.100    0.257
SleepQuality                -0.1054      0.020     -5.291      0.000
-0.144   -0.066
IllnessSeverity              0.0199      0.099      0.202      0.840
-0.173    0.213
exerciseMinToday            -0.0069      0.002     -3.245      0.001
-0.011   -0.003
ExerciseRegularMins         2.524e-05      0.000      0.122      0.903
-0.000    0.000
LastConsumeCaffeineHours    0.0003      0.000      2.331      0.020    5.
48e-05    0.001
GeneralHealth               -0.0618      0.046     -1.352      0.176

```

-0.151	0.028				
SubjectiveIllness		0.0284	0.039	0.733	0.463
-0.047	0.104				
WhenLastSick		0.0573	0.023	2.527	0.012
0.013	0.102				
NumDoctorVisits		0.0735	0.041	1.780	0.075
-0.007	0.155				
TakeMedsRecentlyYN		-0.0647	0.066	-0.984	0.325
-0.194	0.064				
BirthControlYN		0.1500	0.091	1.657	0.098
-0.027	0.327				
MarijuanaFrequency		-0.0257	0.019	-1.319	0.187
-0.064	0.012				
AlcoholAvg		0.1291	0.039	3.303	0.001
0.052	0.206				
ArthritisYN		0.3384	0.145	2.326	0.020
0.053	0.624				
Age		-0.0083	0.014	-0.588	0.556
-0.036	0.019				
YearUniversity		0.0706	0.040	1.768	0.077
-0.008	0.149				
NeedToBelong		0.0110	0.006	1.832	0.067
-0.001	0.023				
Nostalgia		-0.0533	0.026	-2.087	0.037
-0.103	-0.003				
EarlyFamilyEnvironment		-0.0971	0.049	-1.995	0.046
-0.193	-0.002				
PosPANAS		0.0240	0.004	5.688	0.000
0.016	0.032				
NegPANAS		0.0164	0.005	2.976	0.003
0.006	0.027				
Mellow		-0.0324	0.035	-0.928	0.353
-0.101	0.036				
Unpretentious		-0.1594	0.035	-4.544	0.000
-0.228	-0.091				
Sophisticated		0.1047	0.035	2.996	0.003
0.036	0.173				
Intense		0.0205	0.030	0.675	0.500
-0.039	0.080				
Contemporary		0.1279	0.035	3.607	0.000
0.058	0.197				
PT		0.0613	0.055	1.122	0.262
-0.046	0.168				
FS		-0.1671	0.050	-3.357	0.001
-0.265	-0.070				
EC		0.1969	0.066	2.965	0.003
0.067	0.327				
PD		0.2692	0.054	4.997	0.000
0.164	0.375				
E		0.2895	0.043	6.797	0.000
0.206	0.373				
A		0.1713	0.065	2.628	0.009
0.044	0.299				
C		-0.2885	0.058	-4.998	0.000
-0.402	-0.175				
N		-0.0338	0.051	-0.661	0.508
-0.134	0.066				

O		0.0136	0.069	0.198	0.843
-0.121	0.148				
AIMS		-0.0049	0.002	-3.274	0.001
-0.008	-0.002				
PosNeg_Negative		0.7421	0.166	4.483	0.000
0.418	1.067				
PosNeg_Neutral		-0.3712	0.165	-2.244	0.025
-0.696	-0.047				
PosNeg_Positive		1.2796	0.166	7.718	0.000
0.955	1.605				
HighLow_High		2.4821	0.166	14.994	0.000
2.158	2.807				
HighLow_Low		-0.4604	0.166	-2.777	0.006
-0.785	-0.135				
HighLow_Neutral		-0.3712	0.165	-2.244	0.025
-0.696	-0.047				
SoundType_Music		0.7480	0.168	4.455	0.000
0.419	1.077				
SoundType_Natural Sounds		1.1220	0.168	6.679	0.000
0.793	1.451				
SoundType_Speech		-0.2196	0.168	-1.308	0.191
-0.549	0.109				
Gender_female		1.1362	0.452	2.514	0.012
0.250	2.022				
Gender_male		1.0100	0.449	2.251	0.024
0.131	1.889				
Gender_prefer not to answer		0.7875	0.481	1.638	0.102
-0.155	1.730				
PoliticalParty_democrat		-1.2030	0.223	-5.394	0.000
-1.640	-0.766				
PoliticalParty_libertarian		-0.4850	0.235	-2.065	0.039
-0.945	-0.025				
PoliticalParty_other		-1.5415	0.229	-6.738	0.000
-1.990	-1.093				
PoliticalParty_republican		-1.2120	0.238	-5.102	0.000
-1.678	-0.746				
PreferredMeds_Acetaminophen		-0.7674	0.224	-3.433	0.001
-1.206	-0.329				
PreferredMeds_Do Not Take Meds		-1.4631	0.283	-5.168	0.000
-2.018	-0.908				
PreferredMeds_Ibuprofen		-1.0057	0.229	-4.389	0.000
-1.455	-0.557				
PreferredMeds_Other		-1.2053	0.232	-5.194	0.000
-1.660	-0.750				
Race_Asian		0.3715	0.159	2.336	0.020
0.060	0.683				
Race_Black		0.5499	0.160	3.439	0.001
0.236	0.863				
Race_Hispanic		0.1529	0.154	0.991	0.322
-0.149	0.455				
Race_Other		0.4364	0.353	1.235	0.217
-0.256	1.129				
Race_White		0.2457	0.157	1.566	0.117
-0.062	0.553				
=====					
Omnibus:		22.511	Durbin-Watson:		1.768
Prob(Omnibus):		0.000	Jarque-Bera (JB):		18.176

```

Skew:                0.020    Prob(JB) :                0.000113
Kurtosis:            2.782    Cond. No.                1.49e+16
=====

```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 1.19e-23. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Conclusions:

- The measured variables explain 39% of the variance in the arousal ratings (adjusted $R^2 = 0.39$)
- There was *no difference* in arousal ratings between those who took acetaminophen and those who took a placebo.

Name	Coefficient	p	Interpretation
HighLow_High	2.4821	0	Stimuli that exhibit high arousal resulted in comparatively more energetic ratings.
PosNeg_Positive	1.2796	0	Positively-valenced stimuli resulted in comparatively high energy ratings.
SoundType_Natural Sounds	1.122	0	Natural Sounds resulted in comparatively higher energy ratings (<i>and its effect is comparatively large next to music and especially compared to speech, which is not significant</i>)
SoundType_Music	0.748	0	Musical stimuli resulted in comparatively higher energy ratings (<i>compared to speech, which was non-significant</i>)
PosNeg_Negative	0.7421	0	Negatively-valenced stimuli resulted in comparatively higher energy ratings.
Familiarity	0.6654	0	Those who are more familiar with the (musical) stimuli rated the stimuli as being higher in energy .
HighLow_Low	-0.4604	0.006	Stimuli that exhibit low arousal resulted in comparatively lower energy ratings.
E	0.2895	0	Those who are more extraverted rated emotions as relatively more energetic than those who score less high on this personality dimension.
C	-0.2885	0	Those who are more conscientious rated emotions as relatively less energetic than those who score less high on this personality dimension.
PD	0.2692	0	Those who score higher on the Personal Distress component of empathy rated emotions as relatively more energetic than those who score less high on this trait.
EC	0.1969	0.003	Those who score higher on the Empathic Concern component of empathy rated emotions as relatively more energetic than those who score less high on this trait.

Name	Coefficient	p	Interpretation
A	0.1713	0.009	Those who are more agreeable rated emotions as relatively more energetic than those who score less high on this personality dimension.
FS	-0.1671	0.001	Those who score higher on the Fantasy component of empathy rated emotions as relatively less energetic than those who score less high on this trait.
Unpretentious	-0.1594	0	Those who prefer "Unpretentious" music (Pop, Country, Religious) rated emotions as relatively less energetic (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
Contemporary	0.1279	0	Those who prefer "Contemporary" music (Rap/Hip Hop, Soul/R&B, Funk, Reggae) rated emotions as relatively more energetic (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
Sophisticated	0.1047	0.003	Those who prefer "Sophisticated" music (Blues, Jazz, Bluegrass, Folk, Classical, Gospel, Opera) rated emotions as relatively more energetic (broadly, in response to all stimuli) than those who do not like this genre of music.
Nostalgia	-0.0533	0.037	Those who scored high on nostalgia rated the stimuli as being relatively less energetic than those who score low on this trait (although this effect is small).

OLS regression with lasso regularization

Conclusions:

- This didn't change very much from the original mode.
- This chart shows the "non-zero" variables from the original OLS --> these are the only (significant) features kept in the regularized model
- Note that I used an arbitrary cutoff of 0.1 coefficient value to count as significant.

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
PosNeg_Neutral	-0.3712	-2.166824
HighLow_High	2.4821	1.47148
HighLow_Low	-0.4604	-1.47148
PosNeg_Positive	1.2796	0.865751
Familiarity	0.6654	0.686584
Race_Black	0.5499	0.609665
SoundType_Natural Sounds	1.122	0.589999

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
PoliticalParty_other	-1.5415	-0.542389
Gender_male	1.01	-0.517634
PreferredMeds_Do Not Take Meds	-1.4631	-0.470649
ArthritisYN	0.3384	0.393543
Gender_female	1.1362	-0.362125
PoliticalParty_libertarian	-0.485	0.351171
Race_Asian	0.3715	0.343275
PosNeg_Negative	0.7421	0.328635
PoliticalParty_republican	-1.212	-0.32835
PoliticalParty_democrat	-1.203	-0.315477
C	-0.2885	-0.312441
EC	0.1969	0.251219
PreferredMeds_Acetaminophen	-0.7674	0.217798
PreferredMeds_Other	-1.2053	-0.213326
SoundType_Music	0.748	0.208025
HowMuchLastEat	0.1787	0.201207
A	0.1713	-0.193694
FS	-0.1671	-0.180844
EarlyFamilyEnvironment	-0.0971	-0.172594
PD	0.2692	0.154598
AlcoholAvg	0.1291	0.144398
Unpretentious	-0.1594	-0.127286
E	0.2895	0.124883
Sophisticated	0.1047	0.105058

Mixed Model

Mixed Linear Model Regression Results

```

=====
Model:                               MixedLM           Dependent Variable:      Rat
ings
No. Observations:                     8880           Method:                REM
L
No. Groups:                           240           Scale:                  5.1
277
Min. group size:                      37           Likelihood:            -20
122.0205
Max. group size:                      37           Converged:              No
Mean group size:                      37.0

-----
Coef.      Std.Err.      z      P>|z|      [0.025
0.975]
-----
const      -1.845
DrugPlacebo -0.105      0.157 -0.668 0.504      -0.412
0.202
Familiarity 0.573      0.070  8.192 0.000      0.436
0.710
MedsEffectiveness -0.037      0.065 -0.577 0.564      -0.164
0.089
LastTimeTookMeds 0.000      0.000  0.735 0.462      -0.000
0.000
FrequencyTakeMeds -0.026      0.060 -0.435 0.663      -0.144
0.092
Politics    0.054      0.086  0.629 0.529      -0.115
0.224
ChildSES    0.043      0.078  0.554 0.580      -0.109
0.196
AdultSES    0.003      0.078  0.038 0.970      -0.149
0.155
Height      0.004      0.030  0.135 0.893      -0.055
0.063
Weight      0.000      0.003  0.127 0.899      -0.006
0.006
SleepHours  -0.089      0.061 -1.458 0.145      -0.209
0.031
WhenLastAte -0.017      0.019 -0.903 0.366      -0.055
0.020
HowMuchLastEat 0.180      0.110  1.635 0.102      -0.036
0.395
SleepQuality -0.106      0.055 -1.940 0.052      -0.213
0.001
IllnessSeverity 0.018      0.271  0.066 0.948      -0.513
0.548
exerciseMinToday -0.007      0.006 -1.184 0.237      -0.018
0.005
ExerciseRegularMins 0.000      0.001  0.043 0.966      -0.001
0.001
LastConsumeCaffeineHours 0.000      0.000  0.846 0.397      -0.000
0.001

```

GeneralHealth 0.182	-0.063	0.125	-0.505	0.613	-0.309
SubjectiveIllness 0.238	0.030	0.106	0.287	0.774	-0.178
WhenLastSick 0.179	0.057	0.062	0.915	0.360	-0.065
NumDoctorVisits 0.295	0.073	0.113	0.642	0.521	-0.149
TakeMedsRecentlyYN 0.291	-0.063	0.180	-0.349	0.727	-0.416
BirthControlYN 0.638	0.151	0.248	0.608	0.543	-0.336
MarijuanaFrequency 0.079	-0.025	0.053	-0.474	0.635	-0.130
AlcoholAvg 0.340	0.130	0.107	1.208	0.227	-0.081
ArthritisYN 1.124	0.342	0.399	0.856	0.392	-0.440
Age 0.068	-0.008	0.039	-0.214	0.831	-0.084
YearUniversity 0.284	0.069	0.110	0.632	0.527	-0.146
NeedToBelong 0.043	0.011	0.016	0.685	0.494	-0.021
Nostalgia 0.083	-0.054	0.070	-0.773	0.440	-0.191
EarlyFamilyEnvironment 0.166	-0.095	0.134	-0.715	0.475	-0.357
PosPANAS 0.047	0.024	0.012	2.084	0.037	0.001
NegPANAS 0.046	0.017	0.015	1.107	0.268	-0.013
Mellow 0.156	-0.031	0.096	-0.324	0.746	-0.219
Unpretentious 0.030	-0.158	0.096	-1.646	0.100	-0.347
Sophisticated 0.292	0.104	0.096	1.084	0.278	-0.084
Intense 0.183	0.020	0.083	0.245	0.807	-0.143
Contemporary 0.318	0.127	0.097	1.308	0.191	-0.063
PT 0.354	0.060	0.150	0.402	0.688	-0.233
FS 0.100	-0.168	0.137	-1.227	0.220	-0.435
EC 0.555	0.198	0.182	1.085	0.278	-0.159
PD 0.559	0.269	0.148	1.823	0.068	-0.020
E 0.519	0.290	0.117	2.478	0.013	0.061
A 0.523	0.172	0.179	0.962	0.336	-0.179
C 0.022	-0.289	0.158	-1.822	0.068	-0.599
N	-0.035	0.140	-0.248	0.804	-0.310

```

0.240
O                                0.012      0.188  0.064  0.949      -0.357
0.381
AIMS                             -0.005      0.004 -1.192  0.233      -0.013
0.003
PosNeg_Negative                  2.346
PosNeg_Neutral                 -19.298
PosNeg_Positive                 2.885
HighLow_High                    4.758
HighLow_Low                     1.817
HighLow_Neutral                22.437
SoundType_Music                 0.355    56791.604  0.000  1.000   -111309.144  11
1309.854
SoundType_Natural Sounds       0.694    26497.446  0.000  1.000   -51933.346   5
1934.734
SoundType_Speech               -0.647    55920.062 -0.000  1.000  -109601.955  10
9600.661
Gender_female                   1.154      1.239  0.931  0.352      -1.275
3.583
Gender_male                     1.023      1.231  0.831  0.406      -1.389
3.435
Gender_prefer not to answer     0.807      1.319  0.612  0.541      -1.778
3.392
PoliticalParty_democrat        -19.722  3779355.264 -0.000  1.000  -7407419.924  740
7380.479
PoliticalParty_libertarian     -19.008  3779355.264 -0.000  1.000  -7407419.209  740
7381.194
PoliticalParty_other           -20.067  3779355.264 -0.000  1.000  -7407420.269  740
7380.135
PoliticalParty_republican      -19.734  3779355.264 -0.000  1.000  -7407419.936  740
7380.467
PreferredMeds_Acetaminophen    17.747  3779355.264  0.000  1.000  -7407382.454  740
7417.949
PreferredMeds_Do Not Take Meds 17.056  3779355.264  0.000  1.000  -7407383.146  740
7417.258
PreferredMeds_Ibuprofen        17.509  3779355.264  0.000  1.000  -7407382.692  740
7417.711
PreferredMeds_Other            17.310  3779355.264  0.000  1.000  -7407382.892  740
7417.512
Race_Asian                     0.368      0.436  0.844  0.398      -0.487
1.224
Race_Black                     0.547      0.439  1.247  0.212      -0.313
1.407
Race_Hispanic                  0.156      0.423  0.370  0.712      -0.673
0.986
Race_Other                     0.440      0.969  0.454  0.650      -1.459
2.340
Race_White                     0.236      0.430  0.549  0.583      -0.607
1.079
Group Var                       1.064
=====
=====

```

Conclusions:

- **The model did not converge**
- **Basically no features are significant in the mixed model (because they are so redundant with the questionnaire data)**

4d. Predicting All Ratings

Data prep

Here, we combine the *positive*, *negative*, and *arousal* dataframes into a single dataframe.

```
positive shape: (13218, 78)
```

```
negative shape: (13218, 78)
```

```
arousal shape: (8880, 78)
```

```
pos/neg colnames: [ True  True  True  True  True  True  True  True  True  True  True  True
 True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True]
```

```
pos/ar colnames: [ True  True  True  True  True  True  True  True  True  True  True  True
 True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True]
```

```
ar/neg colnames: [ True  True  True  True  True  True  True  True  True  True  True  True
 True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True  True  True  True  True  True  True
 True  True  True  True  True  True]
```

```
alldata shape: (35316, 78)
```

X and Y

OLS regression

OLS Regression Results

```

=====
Dep. Variable:          Ratings    R-squared:                0.093
Model:                  OLS        Adj. R-squared:            0.092
Method:                 Least Squares    F-statistic:           50.46
Date:                  Thu, 26 Mar 2020    Prob (F-statistic):      0.00
Time:                  07:57:19    Log-Likelihood:         -91076.
No. Observations:      35316    AIC:                    1.823e+05
Df Residuals:          35243    BIC:                    1.829e+05
Df Model:              72
Covariance Type:       nonrobust
=====
=====

```

		coef	std err	t	P> t	
[0.025	0.975]					

const		1.2371	0.276	4.478	0.000	
0.696	1.779					
DrugPlacebo		-0.1878	0.038	-4.991	0.000	
-0.262	-0.114					
Locus		-0.3237	0.045	-7.269	0.000	
-0.411	-0.236					
Familiarity		0.3066	0.045	6.784	0.000	
0.218	0.395					
MedsEffectiveness		-0.0343	0.015	-2.222	0.026	
-0.065	-0.004					
LastTimeTookMeds		2.722e-05	4.09e-05	0.666	0.506	-5.
29e-05	0.000					
FrequencyTakeMeds		-0.0339	0.014	-2.342	0.019	
-0.062	-0.006					
Politics		0.0747	0.021	3.605	0.000	
0.034	0.115					
ChildSES		0.0029	0.019	0.153	0.878	
-0.034	0.039					
AdultSES		-0.0219	0.019	-1.175	0.240	
-0.058	0.015					
Height		0.0064	0.007	0.886	0.376	
-0.008	0.020					
Weight		0.0020	0.001	2.751	0.006	
0.001	0.003					
SleepHours		-0.0382	0.015	-2.597	0.009	
-0.067	-0.009					
WhenLastAte		-0.0025	0.005	-0.538	0.591	
-0.011	0.007					
HowMuchLastEat		0.1570	0.026	5.942	0.000	
0.105	0.209					
SleepQuality		-0.0745	0.013	-5.646	0.000	
-0.100	-0.049					
IllnessSeverity		0.1269	0.065	1.951	0.051	
-0.001	0.254					
exerciseMinToday		-0.0041	0.001	-2.979	0.003	
-0.007	-0.001					
ExerciseRegularMins		-0.0003	0.000	-1.908	0.056	
-0.001	7.01e-06					
LastConsumeCaffeineHours		-0.0002	9.73e-05	-2.098	0.036	

-0.000	-1.34e-05				
GeneralHealth		-0.0390	0.030	-1.290	0.197
-0.098	0.020				
SubjectiveIllness		-0.0349	0.026	-1.368	0.171
-0.085	0.015				
WhenLastSick		0.0642	0.015	4.314	0.000
0.035	0.093				
NumDoctorVisits		0.0697	0.027	2.562	0.010
0.016	0.123				
TakeMedsRecentlyYN		-0.1478	0.043	-3.416	0.001
-0.233	-0.063				
BirthControlYN		0.0640	0.060	1.074	0.283
-0.053	0.181				
MarijuanaFrequency		0.0036	0.013	0.282	0.778
-0.021	0.029				
AlcoholAvg		0.1075	0.026	4.173	0.000
0.057	0.158				
ArthritisYN		0.2880	0.095	3.043	0.002
0.102	0.474				
Age		-0.0041	0.009	-0.442	0.659
-0.022	0.014				
YearUniversity		0.0031	0.026	0.118	0.906
-0.049	0.055				
NeedToBelong		0.0050	0.004	1.266	0.205
-0.003	0.013				
Nostalgia		-0.0545	0.017	-3.238	0.001
-0.087	-0.021				
EarlyFamilyEnvironment		-0.0342	0.032	-1.067	0.286
-0.097	0.029				
PosPANAS		0.0123	0.003	4.455	0.000
0.007	0.018				
NegPANAS		0.0252	0.004	6.949	0.000
0.018	0.032				
Mellow		0.0065	0.023	0.281	0.779
-0.039	0.052				
Unpretentious		-0.0901	0.023	-3.892	0.000
-0.135	-0.045				
Sophisticated		0.0832	0.023	3.618	0.000
0.038	0.128				
Intense		-0.0838	0.020	-4.197	0.000
-0.123	-0.045				
Contemporary		0.0599	0.023	2.573	0.010
0.014	0.106				
PT		0.0180	0.036	0.498	0.619
-0.053	0.089				
FS		-0.1174	0.033	-3.589	0.000
-0.182	-0.053				
EC		0.1045	0.044	2.390	0.017
0.019	0.190				
PD		0.2441	0.035	6.888	0.000
0.175	0.314				
E		0.1284	0.028	4.604	0.000
0.074	0.183				
A		0.1491	0.043	3.465	0.001
0.065	0.233				
C		-0.0731	0.038	-1.920	0.055
-0.148	0.002				

N		-0.0967	0.034	-2.869	0.004
-0.163	-0.031				
O		0.0198	0.045	0.438	0.661
-0.069	0.108				
AIMS		-0.0025	0.001	-2.527	0.012
-0.004	-0.001				
PosNeg_Negative		0.6284	0.094	6.675	0.000
0.444	0.813				
PosNeg_Neutral		-0.1628	0.094	-1.730	0.084
-0.347	0.022				
PosNeg_Positive		0.7715	0.094	8.182	0.000
0.587	0.956				
HighLow_High		1.2057	0.094	12.809	0.000
1.021	1.390				
HighLow_Low		0.1942	0.094	2.059	0.039
0.009	0.379				
HighLow_Neutral		-0.1628	0.094	-1.730	0.084
-0.347	0.022				
SoundType_Music		0.5603	0.096	5.838	0.000
0.372	0.748				
SoundType_Natural Sounds		0.6139	0.096	6.399	0.000
0.426	0.802				
SoundType_Speech		0.0628	0.097	0.649	0.517
-0.127	0.253				
Gender_female		1.4605	0.298	4.906	0.000
0.877	2.044				
Gender_male		1.2206	0.295	4.132	0.000
0.642	1.800				
Gender_prefer not to answer		0.8962	0.317	2.829	0.005
0.275	1.517				
PoliticalParty_democrat		-1.0349	0.147	-7.043	0.000
-1.323	-0.747				
PoliticalParty_libertarian		-0.5747	0.155	-3.714	0.000
-0.878	-0.271				
PoliticalParty_other		-1.3326	0.151	-8.839	0.000
-1.628	-1.037				
PoliticalParty_republican		-1.1059	0.156	-7.069	0.000
-1.413	-0.799				
PreferredMeds_Acetaminophen		-0.7306	0.147	-4.962	0.000
-1.019	-0.442				
PreferredMeds_Do Not Take Meds		-1.3271	0.186	-7.116	0.000
-1.693	-0.962				
PreferredMeds_Ibuprofen		-0.8806	0.151	-5.834	0.000
-1.176	-0.585				
PreferredMeds_Other		-1.1098	0.153	-7.260	0.000
-1.409	-0.810				
Race_Asian		0.2579	0.105	2.462	0.014
0.053	0.463				
Race_Black		0.0814	0.105	0.774	0.439
-0.125	0.288				
Race_Hispanic		-0.0396	0.102	-0.390	0.697
-0.239	0.159				
Race_Other		-0.4925	0.233	-2.116	0.034
-0.949	-0.036				
Race_White		-0.0824	0.103	-0.797	0.425
-0.285	0.120				
RatingType_Arousal		0.8362	0.096	8.697	0.000


```

0.648      1.025
RatingType_Negative      0.1939      0.095      2.038      0.042
0.007      0.380
RatingType_Positive      0.2070      0.095      2.175      0.030
0.020      0.394
=====
Omnibus:      13596.035      Durbin-Watson:      1.916
Prob(Omnibus):      0.000      Jarque-Bera (JB):      1985.370
Skew:      0.206      Prob(JB):      0.00
Kurtosis:      1.914      Cond. No.      2.33e+16
=====

```

Warnings:

```

[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.93e-23. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

```

Conclusions:

- The measured variables explain 9% of the variance in overall emotion ratings (adjusted $R^2 = 0.09$)
- The ingestion of acetaminophen--overall--blunted ratings of positive emotions compared to the ingestion of a placebo.
- The low variance explained means that people used there is little similarities in how people used the three types of scales (positive emotions, negative emotions, and arousal).
- It's likely that there's effects going in opposite directions--for example, people use the opposite criteria to judge positive and negative emotion ratings--so it makes sense the R^2 is much closer to 0.
- The order of the features (in terms of absolute values of the coefficients) is very similar to the order that they are entered into the equation during the regression. This hints that the feature importances can't be determined reliably.

Name	Coefficient	p	Interpretation
DrugPlacebo -0.1878 0	<i>Those who took acetaminophen rated emotions as lower overall compared to those who took the placebo. Namely, acetaminophen blunted the emotional responses.</i>		
HighLow_High	1.2057	0	Stimuli that exhibit high arousal resulted in comparatively higher overall ratings .
RatingType_Arousal	0.8362	0	Arousal ratings were overall comparatively high in number (compared to positive and negative emotion ratings).
PosNeg_Positive	0.7715	0	Positively-valenced stimuli resulted in comparatively higher overall ratings .

Name	Coefficient	p	Interpretation
PosNeg_Negative	0.6284	0	Negatively-valenced stimuli resulted in comparatively higher overall ratings (but not as much as positively-valenced stimuli).
SoundType_Natural Sounds	0.6139	0	Natural Sounds resulted in comparatively higher overall ratings (compared to music and especially compared to speech, which wasn't significant)*
SoundType_Music	0.5603	0	Natural Sounds resulted in comparatively higher overall ratings (compared to speech, which wasn't significant)*
Locus	-0.3237	0	Compared to perceived emotion ratings, induced emotion ratings were lower in overall score .
Familiarity	0.3066	0	Those who are more familiar with the (musical) stimuli rated stimuli comparatively higher overall compared to people less familiar with the music.
PD	0.2441	0	Those who score higher on the Personal Distress component of empathy rated emotions as relatively higher overall than those who score less high on this trait.
RatingType_Positive	0.207	0.03	Positive emotion ratings were overall comparatively high in number (compared to negative ratings).
HighLow_Low	0.1942	0.039	Stimuli that exhibit low arousal resulted in comparatively high overall ratings (but the effect is smaller than the high arousal music).
RatingType_Negative	0.1939	0.042	Negative emotion ratings were overall comparatively high in number (but low compared to arousal ratings and positive emotion ratings).
A	0.1491	0.001	Those who are more agreeable rated emotions as relatively higher overall than those who score less high on this personality dimension.
E	0.1284	0	Those who are more extraverted rated emotions as relatively higher overall than those who score less high on this personality dimension.

Name	Coefficient	p	Interpretation
FS	-0.1174	0	Those who score higher on the Fantasy component of empathy rated emotions as relatively lower overall than those who score less high on this trait.
EC	0.1045	0.017	Those who score higher on the Empathic Concern component of empathy rated emotions as relatively higher overall than those who score less high on this trait.
N	-0.0967	0.004	Those who are more neurotic rated emotions as relatively lower overall than those who score less high on this personality dimension.
Unpretentious	-0.0901	0	Those who prefer "Unpretentious" music (Pop, Country, Religious) rated emotions as relatively lower overall (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
Intense	-0.0838	0	Those who prefer "Intense" music (Rock, Punk, Alternative, Heavy Metal) rated emotions as relatively lower overall (broadly, in response to all stimuli) than those who do not like this genre of music.
Sophisticated	0.0832	0	Those who prefer "Sophisticated" music (Blues, Jazz, Bluegrass, Folk, Classical, Gospel, Opera) rated emotions as relatively higher overall (broadly, in response to all stimuli) than those who do not like this genre of music.
Contemporary	0.0599	0.01	Those who prefer "Contemporary" music (Rap/Hip Hop, Soul/R&B, Funk, Reggae) rated emotions as relatively higher overall (broadly, in response to all stimuli) than those who do not like this genre of music (although this effect is small).
Nostalgia	-0.0545	0.001	Those who scored high on nostalgia rated relatively lower overall (although this effect is small).

OLS regression with lasso regularization

Conclusions:

- This didn't change very much from the original mode.
- This chart shows the "non-zero" variables from the original OLS --> these are the only (significant) features kept in the regularized model
- Note that I used an arbitrary cutoff of 0.1 coefficient value to count as significant.

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
DrugPlacebo	-0.1878	-0.162255
RatingType_Arousal	0.8362	0.871276
Gender_prefer not to answer	0.8962	-0.617293
PoliticalParty_other	-1.3326	-0.524402
HighLow_High	1.2057	0.505651
HighLow_Low	0.1942	-0.505651
PosNeg_Positive	0.7715	0.463598
PreferredMeds_Do Not Take Meds	-1.3271	-0.451093
PoliticalParty_republican	-1.1059	-0.343582
Race_Asian	0.2579	0.332973
Locus	-0.3237	-0.322413
PosNeg_Negative	0.6284	0.320646
Familiarity	0.3066	0.317096
ArthritisYN	0.288	0.314295
Gender_male	1.2206	-0.293518
PoliticalParty_democrat	-1.0349	-0.256109
RatingType_Positive	0.207	0.242152
Race_Other	-0.4925	-0.231538
RatingType_Negative	0.1939	0.229102
PreferredMeds_Other	-1.1098	-0.212399
PD	0.2441	0.182542
PoliticalParty_libertarian	-0.5747	0.178751
TakeMedsRecentlyYN	-0.1478	-0.167184
EC	0.1045	0.165425
SoundType_Natural Sounds	0.6139	0.158922
PreferredMeds_Acetaminophen	-0.7306	0.155727
HowMuchLastEat	0.157	0.145694
FS	-0.1174	-0.113215

Features Remaining In the Model	OLS Coefficient	OLS with lasso regularization Coefficient
AlcoholAvg	0.1075	0.106252
SoundType_Music	0.5603	0.10102

Mixed Model

Conclusions:

- **The model did not converge --> the matrix was singular**
- **Basically no features are significant in the mixed model (because they are so redundant with the questionnaire data)**

4e. Predicting Drug vs. Placebo from a Logistic Regression

In order to use people's ratings to predict whether they were given the drug or a placebo, we have to change the data back to a wide format.

Namely, there should be one row for each participant.

Turn one-hot encoded stimuli back into a single column

First, we have to turn all the one-hot encoded values back to a single categorical column.

```
(13218, 139)
(13218, 139)
```

Stimulus

PosNeg

HighLow

SoundType

PoliticalParty

PreferredMeds

Gender

Rearrange columns

```
(13218, 89)
```

Separate into perceived/induced/questionnaires

We need to separate the three study components (perceived emotion ratings, induced emotion ratings, and questionnaire responses) into separate dataframes.

Each of these dataframes should have 244 rows--one for each participant.

Questionnaires

First, we need to pull out all of the questions from the questionnaires.

```
wideQ shape: (244, 57)
```

	FixedID	DrugPlacebo	MedsEffectiveness	LastTimeTookMeds	FrequencyTakeMeds
0	1.0	0	4.0	1095.0	1.0
1	2.0	1	4.0	365.0	4.0
2	3.0	0	1.0	1.0	5.0
3	4.0	1	1.0	3650.0	1.0
4	5.0	0	5.0	180.0	4.0

```
5 rows × 57 columns
```

Perceived

Next, we need to extract all of the perceived emotion information.

We ideally want there to be several columns per stimulus. For Fear Music 1, for example:

- Perceived_Positive_Fear Music 1
- Perceived_Negative_Fear Music 1
- Perceived_Arousal_Fear Music 1
- Perceived_Familiarity_Fear Music 1

In order to create these columns, we need to first stack all of the ratings (positive, negative, arousal, familiarity) on top of each other under a single column: **Ratings**. That's what is done here.

```
wideP: (35520, 6)
```

	FixedID	DrugPlacebo	Stimulus	Rating	Locus	RatingType
0	1.0	0	Neutral Speech 2	1.0	Perceived	Positive
1	1.0	0	Tender Music 5	0.0	Perceived	Familiarity
2	1.0	0	Fear Speech 1	0.0	Perceived	Familiarity
3	1.0	0	Happy Speech 3	0.0	Perceived	Familiarity
4	1.0	0	Neutral Speech 1	0.0	Perceived	Familiarity

Induced

We repeat the above process for induced emotion.

Note that there are no arousal ratings for induced emotion.

```
wideI: (13014, 6)
```

	FixedID	DrugPlacebo	Stimulus	Rating	Locus	RatingType
0	1.0	0	Fear Music 2	2.0	Induced	Positive
1	1.0	0	Tender Music 1	6.0	Induced	Negative
2	1.0	0	Happy Music 2	3.0	Induced	Negative
3	1.0	0	Neutral Human	6.0	Induced	Negative
4	1.0	0	Positive-Valence High-Arousal Non-human	3.0	Induced	Negative

Make Wide P and I dataframe

Next, we stack the induced and perceived dataframes on top of each other. Then, we unstack them in order to make the wide dataframe.

The resulting dataframe will have 244 rows--one for each participant.

For each stimulus, there are 7 ratings. For example:

- Induced_Positive_Fear Music 1
- Induced_Negative_Fear Music 1
- Induced_Familiarity_Fear Music 1
- Perceived_Positive_Fear Music 1
- Perceived_Negative_Fear Music 1
- Perceived_Arousal_Fear Music 1
- Perceived_Familiarity_Fear Music 1

```

null shape: (7, 204)
null values: Empty DataFrame
Columns: [0]
Index: []
widePI shape: (244, 204)

```

	FixedID	DrugPlacebo	Induced_Familiarity_Fear Music 1	Induced_Familiarity_Fear Music 2	Induc
0	1.0	0	0.0	0.0	0.0
1	2.0	1	0.0	0.0	0.0
2	3.0	0	0.0	0.0	0.0
3	4.0	1	2.0	1.0	1.0
4	5.0	0	0.0	0.0	0.0

5 rows × 204 columns

Combine Wide Questionnaires, Perceived, and Induced into one dataframe

Finally, we create the wide dataframe with info about the questionnaires, perceived, and induced blocks.

```

shapes equal? True
wide shape: (244, 259)

```

	FixedID	DrugPlacebo	MedsEffectiveness	LastTimeTookMeds	FrequencyTakeMeds
0	1.0	0	4.0	1095.0	1.0
1	2.0	1	4.0	365.0	4.0
2	3.0	0	1.0	1.0	5.0
3	4.0	1	1.0	3650.0	1.0
4	5.0	0	5.0	180.0	4.0

5 rows × 259 columns

Logistic Regression predicting Drug vs. Placebo

Now we can perform logistic regression, with DrugPlacebo as the dependent variable.

Correlations

Examining correlations for multicollinearity purposes.

Regression with L1 regularization

Because there's so many columns (especially compared to rows), we need to use a regularization parameter. L1 regularization is the best fit, since it can fit feature values to 0.

Conclusions:

- The model did not converge, even with regularization
- The matrix was singular, indicating that some features perfectly predict others
- Therefore, the logistic regression cannot be carried out in this form

3. Are Emotion Terms Used Differently

The last goal of this analysis is to test whether those who ingested acetaminophen and those who took a placebo believe the same emotions apply to the stimuli.

Recall that participants were asked to answer the following questions about the specific emotions:

- Identify which emotion(s) the audio file [*represents or makes you feel*] by checking the appropriate emotion(s) from the following list. You may select as few or as many as you like
- Given this list of emotion terms you chose, which one(s), if any, strongly apply?

These responses were coded on a 3-point scale:

- Does not apply = 0
- Applies = 1
- Strongly applies = 2

We will investigate this question graphically.

3a. Make dataframe

First we need to make a dataframe with all the specific emotion ratings.

```
perceived shape: (8880, 52)
induced shape: (4338, 52)
emotions shape: (13218, 52)
```

3b. Plot distributions of Drug vs Placebo

In order to compare the specific emotions rated by those who took the drug vs. those who took the placebo, an exploratory graph can give us a lot of information. We will first do this with the perceived emotion ratings and then with the induced emotion ratings.

Perceived Emotion

Dataframe creation

There were fewer emotions examined in the perceived emotions section. We will delete the ones not studied first.

Means

Examine the means of emotions from drug conditions vs. placebo conditions.

Note: The possible range is from 0-2, NOT from 0-1!

	Anger	Bored	Disgusted	Excited	Fearful	Grieved	Happy	Invigora
Drug	0.0	0.07	0.06	0.32	0.32	0.13	0.34	0.13
Placebo	0.0	0.08	0.05	0.30	0.31	0.12	0.33	0.12

Percents

Examine the percent of time the emotion term applipercents of time the emotion term applies or strongly applies or strongly applies to the stimuli.

	Anger	Bored	Disgusted	Excited	Fearful	Grieved	Happy	Invi
Drug	0.0	4.623632	4.645968	20.348448	20.303775	9.157918	23.051150	9.69
Placebo	0.0	5.677947	3.497615	19.486714	19.327731	8.289802	22.711787	8.53

Summary Table

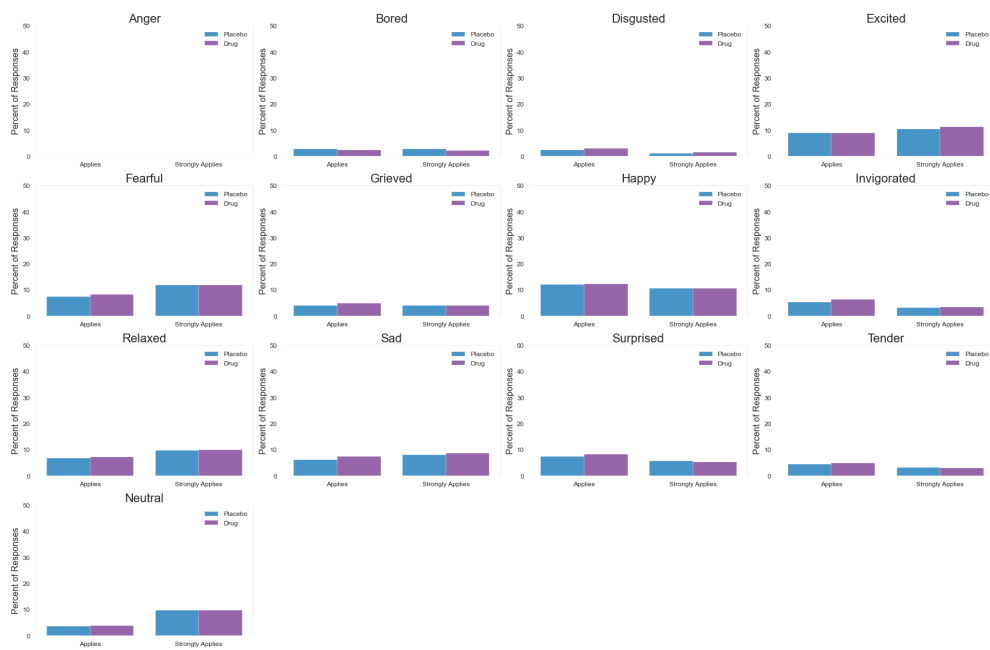
Next, we will make a summary table comparing the following features of the emotions:

- Sum of the emotion terms (for each emotion, summing the 0s, 1s, and 2s)
- Mean of the emotion terms (with a possible range of 0-2)
- The SD of the emotion terms
- The percent of people who said each term "Applies" to the stimuli
- The percent of people who said each term "Strongly applies" to the stimuli
- Whether the person doing the ratings ingested the drug or placebo
- The emotion in question

```
perceivedSummary shape: (26, 8)
26
```

	Emotion	DrugPlacebo	Mean	SD	variable	value
12	Neutral	Placebo	0.229843	0.608772	Applies	3.633886
27	Bored	Placebo	0.084261	0.363529	Strongly Applies	2.748126
23	Surprised	Drug	0.190083	0.511101	Applies	8.286799
50	Tender	Drug	0.111459	0.402012	Strongly Applies	3.127094
4	Fearful	Placebo	0.311379	0.671362	Applies	7.517602

Plot



Conclusions:

- There doesn't seem to be much of a difference between the placebo and drug conditions.
- I will not follow up with statistical tests.

Induced Emotion

Dataframe creation

Means

	Anger	Anxious	Bored	Disgusted	Excited	Fearful	Grieved	Happy
Drug	0.0	0.37	0.06	0.05	0.25	0.27	0.10	0.26
Placebo	0.0	0.30	0.06	0.06	0.24	0.27	0.08	0.25

2 rows × 23 columns

Percents

	Anger	Anxious	Bored	Disgusted	Excited	Fearful	Grieved	Ha
Drug	0.0	24.453552	3.825137	4.326047	17.167577	17.896175	7.331512	19.1
Placebo	0.0	20.168067	4.435107	4.154995	16.246499	18.300654	6.255836	18.3

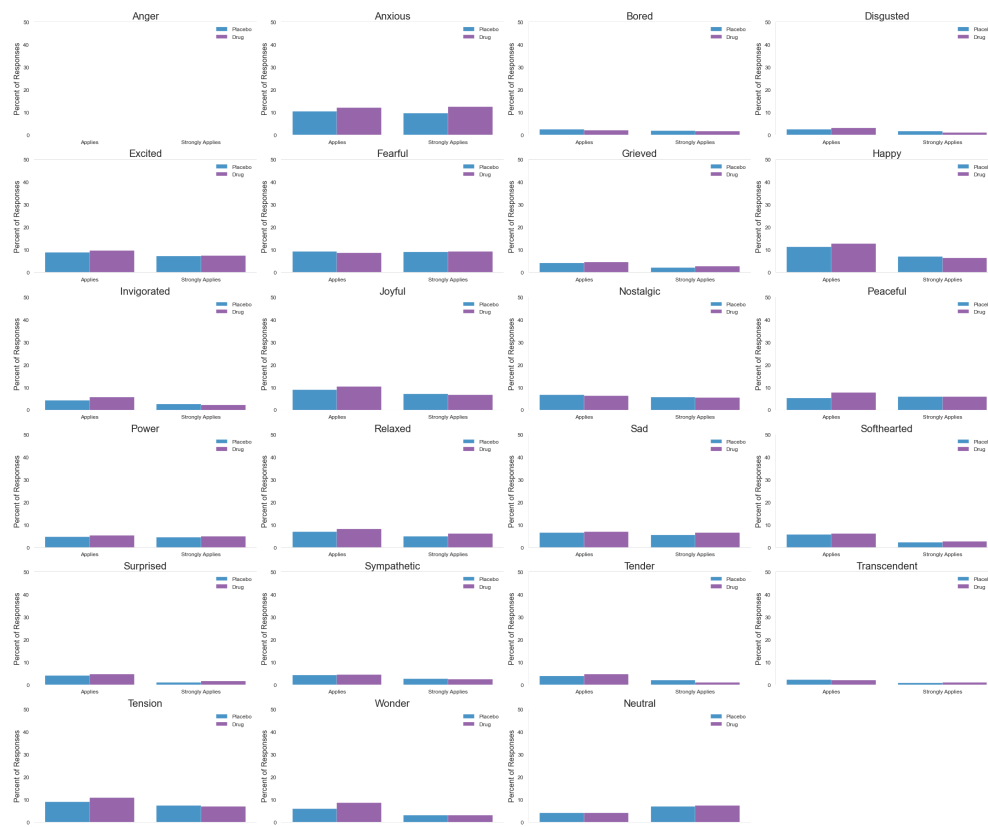
2 rows × 23 columns

Summary Table

inducedSummary shape: (46, 8)
46

	Emotion	DrugPlacebo	Mean	SD	variable	value
77	Invigorated	Drug	0.099271	0.363706	Strongly Applies	2.140255
40	Sympathetic	Drug	0.094718	0.367407	Applies	4.553734
38	Softhearted	Drug	0.114754	0.394196	Applies	6.102004
27	Excited	Drug	0.246357	0.578948	Applies	9.699454
20	Tension	Placebo	0.236228	0.571987	Applies	8.963585

Plot



Conclusions:

- There doesn't seem to be much of a difference between the placebo and drug conditions.
- I will not follow up with statistical tests.

4. Post-Hoc Tests