Prediction of preference and choice of wines by EEG derived measures during taste and smell procedures.

Master thesis

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Abstract

Research within the field of consumer neuroscience shows that preference and choice of movies, food, and wine can be predicted by neural measures. Recent research showed that preference and choice of movie trailers can be predicted by EEG derived beta activity. The goal of this study was to examine whether neural measures make a valuable contribution to the prediction of preference and choice of wines. It was examined if EEG measures could be used as predictors of the evaluation of the wines. Participants indicated preference of four different wines after tasting and smelling the wines. EEG was recorded during the whole experiment to examine beta activity. Reported ratings of the wines by the participants and beta activity did not reveal preference for one of the wines. However, higher amplitudes of beta activity during the smell procedure were found compared to the activity during the taste procedure and the baseline measure. This could indicate that choice and preference of wine could be better indicated by beta activity during the smell procedure than during the taste procedure. Unfortunately, this study failed to confirm the question if neural measures could make a valuable contribution to the prediction and choice of wines. Several explanations could be noted, for example the attribute substitution heuristic which could explain that no preference was found for one of the wines. Also, the ambiguity of the predictive value of the different frequency bands and the researcher's degree of freedom could have been of influence on the fact that no preference for one of the wines was found.

Introduction

Consumer neuroscience combines psychology, neuroscience, and economics to examine neural explanations for consumer behaviour and predict consumer behaviour by these neural findings. This can be done by studying brain activity in response to advertisements and marketing strategies (Smidts et al., 2014; Khushaba et al., 2013; Yoon et al., 2012). This field of research links decision making to marketing research (Plassmann, Ramsoy & Milosavljevic, 2012). Neuroscience can provide marketers with information that is not obtainable by commonly used marketing methods (Ariely & Berns, 2010). This is mainly driven by the fact that conventional marketing methods are suffering from biases, making it questionable if these approaches provide accurate data (Boksem & Smidts, 2015). For example, asking participants to reflect on internal states and the process leading to a choice influences and could even alter outcomes of their judgements (Wilson & Schooler, 1991). It can cause people to discriminate less between the different alternatives (Wilson & Schooler, 1991; Dijksterhuis, 2004). When explicitly asked, people cannot fully explain their preferences. This is due to the fact that human behaviour is driven by processes operating below the level of conscious awareness (Calvert & Brammer, 2012; Dijksterhuis, 2004). These unconscious processes are reflected in brain activity and can be examined by using brain imaging techniques. Therefore, consumer neuroscience may be more reliable than conventional marketing methods (Boksem & Smidts, 2015; Khushaba et al., 2013).

Ariely and Berns (2010) noted several reasons for the growing interest in neuroscience by marketers. The first reason that is noted is that it is believed that consumers' brains contain information about their true preferences. Before a conscious decision is made, a pattern of brain activity is visible in the prefrontal, parietal, and temporal cortex. This activity presumably reflects the preparation of the upcoming decision (Siong Soon, Brass, Heinze & Haynes, 2008; Heekeren, Marrett, Bandettini & Ungerleider, 2004). It is important to keep in mind here that humans are still involved with the interpretation of the data. Interpretation by humans is inevitably subjective and can therefore result in bias (Kaptchuk, 2003). The second reason Ariely and Berns (201) noted is that brain data is considered less biased than data obtained by marketing methods; therefore, they argue that accurate predictions can be generated from smaller sample sizes. For that reason, neuroscience is considered cheaper and faster than traditional marketing methods.

Evidence from neuroscience suggests that multiple brain regions are involved in decision making and evaluation of products. Activity in the ventromedial part of the prefrontal cortex (VMPFC) seems predictive for the choices people make (Knutson et al. 2007). The VMPFC is associated with implicit valuation and processing preferences and goals (D'Argembeau et al., 2010; Damasio, Everitt & Bishop, 1996) and is active during choices between two comparable options (Deppe, Schwindt, Kugel, Plassmann & Kenning, 2005). Activity in the VMPFC in response to products or advertisements furthermore, seems predictive for population wide commercial success (Berns & Moore, 2012). Next to the VMPFC, the dorsolateral prefrontal cortex (DLPFC) and the orbitofrontal cortex (OFC) are also associated with decision making. Activity in the DLPFC is associated with decision making, since it known for being involved in cognitive control over emotions (Rilling, King-Casas & Sanfey, 2008). The OFC seems predictive for reported pleasantness and is involved with the weighting of benefits and costs (Baste, Biele, Heekeren & Fiebach, 2010).

Activity in the OFC also seems predictive for food choices. Kringelbach (2005) showed that activity in the OFC selectively decreased when the subjective pleasantness of the food eaten also decreased. Repetition of the experiment showed same effects for olfactory and gustatory judgements. Results of Kringelbach, O'Dohert, Rolls and Andrews (2003) showed that the sensory-specific nature of pleasure is represented in the OFC. In this study, the choice of liquids was examined. Castriota-Scanderberg et al. (2005) showed that also for the evaluation of wine the OFC and DLPFC are active. Neuroscience can thus not only provide predictive values for product choices but also for food choices and liquids such as wine. Kringelbach (2005) noted that this is not surprising since food intake is critical for survival and evolution. Research of Shipley and Ennis (1996) supports this statement by noting that smell and taste are used for reproductive/maternal functions and selection of food and that humans possess specialized systems for olfactory and gustatory inputs (Shipley & Ennis, 1996), for example the taste buds on the tongue (Spector, 2000) or the olfactory bulb which is part of the brain (Shipley & Ennis, 1996).

Despite the promising results of neuroscience for neuromarketing, there are some reasons to be careful about the usefulness of neuroscience in marketing practice. Although consumers are often not good at stating their preferences, individual stated preferences are not completely unrelated to the actual choice humans make. Measures of willingness to pay are for example reliable predictors of the actual choice (Boksem & Smidts, 2015; Ariely & Berns, 2010). Additionally, pleasantness of smell and taste of food can be indicated very clearly (Spector, 2000; Shipley & Ennis, 1996). Furthermore, evidence for the predictive value of neural measures originates mainly from functional magnetic resonance imaging (fMRI). fMRI has an advantage of being able to look into small structures and structures that are located deep in the brain, but the cost benefits trade off does not seem promising. An fMRI scanner is very costly (Ariely & Berns, 2010) and it is not the most natural environment; participants have to lie in a narrow tube and the machine exceeds typically noise levels of 90 dB (Boksem & Smidts, 2015). These adverse characteristics may have a substantial, even negative, impact on cognition and choice (Szalma & Hancock, 2011). This means that it could easily distort any relationship between brain activity and behaviour.

Research of Khushaba et al. (2013) and Vecchiato et al. (2011) showed that the electroencephalogram (EEG) can be used as an alternative for fMRI to discover predictive values of neuronal activity. Vecchiato et al. (2011) used EEG to examine brain responses to advertisements. This study showed that pleasantness of an advertisement can be predicted by increased brain activity in either the left or right hemisphere; pleasantness was reflected by increased activity in the right hemisphere while unpleasantness was associated with increased activity in the left hemisphere (Vecchiato et al., 2011). Khushaba et al. (2013) used EEG to investigate brain responses to crackers in a store. In this experiment, individual preferences were assessed for crackers by shape, flavour, and topping. At the end, an overall rating of the crackers was given. Highest activity was found in the alpha, beta, and delta bands in the frontal regions of the brain. It was found that activity in these bands was relevant for examining preference, since activity in the alpha, beta, and delta bands in the frontal regions of the brain gave an indication of individual preference. Especially, activity in the beta band showed that flavour and topping of the crackers had a significant impact on the preference of the cracker (Khushaba et al., 2013).

Boksem and Smidts (2015) used EEG to investigate brain responses to movie trailers. The goal of this research was to investigate whether choice could be predicted by neural measures and if these measures could make a valuable contribution to the prediction of population-wide commercial success. EEG of participants was recorded while watching cinematic trailers. Stated preference and willingness to pay for the viewed trailers were measured to determine preference. To measure relative preference, participants were asked to sort the movies they had seen in descending order of preference. Focus was on the beta frequency band, which ranges from 12 to 30 Hz (Cohen, 2014). Linear models showed that high beta activity while viewing the movie trailer was related to high preference for that movie. High beta activity was found in a cluster around the electrode FCz. It was also shown that higher amplitudes of beta EEG oscillations while viewing the movie-trailers were related to higher rankings of that movie. This indicates that beta activity is a predictor of individual preference (Boksem & Smidts, 2015). Adding the frontocentral beta activity to the statistical model, the fit of the model for individual preference increased, compared to the model which used stated preference of the movie as a predictor for individual preference. This indicates that the EEG captured information that was not captured by the stated preference. However, the added value of the EEG measures was quite low (Boksem & Smidts, 2015).

The aim of the current study is to examine whether neural measures make a valuable contribution to the prediction of preference and choice of wines. Furthermore, it will be investigated if EEG measures can be used as predictors for the evaluation of the wines. Individual preferences were indicated for four different wines in two sessions where in one of the sessions the labels of the wines were displayed. Here, only the label data is used. Participants judged various aspects of the wine, such as smell, taste, label, and gave a judgement about the price category to which the wines should belong. Also, an overall rating of the wines was given. EEG was recorded during the whole procedure to record the brain responses during the smell and taste procedure and various judgements. Research of Boksem and Smidts (2015) showed that higher amplitudes of the beta oscillations around the electrode FCz predict higher overall rankings (Boksem & Smidts, 2015). Therefore, it was expected to find higher amplitudes of beta EEG activity for FCz for the preferred wines. Since willingness to pay seems a predictor of choice (Boksem & Smidts, 2015; Ariely & Berns, 2010), it was expected that more beta activity for FCz is found for the wine which is assigned to the highest price category. Since subjective pleasantness can be predicted for food by neural measures (Kringelbach, 2005; Kringelbach, O'Doherty, Rolls & Andrews, 2003) and taste and smell are notable features for survival, e.g. to select food (Spector, 2000; Shipley & Ennis, 1996), it was expected that preferences for taste and smell of the wines were reflected by higher amplitudes for the beta frequency at the FCz position. Considering the olfactory system being directly related to the brain and the gustatory system not (Spector, 2000; Shipley & Ennis, 1996), it was therefore expected to find more beta activity at FCz during the smell procedure than during the taste procedure.

Method

Participants

Data was sampled of thirty participants, mainly employees of the University of Twente, with normal or corrected-to-normal vision and with no history of neurological disease. Handedness, with use of Annett's Handedness Inventory (Annett, 1970), and colour-blindness were tested. For the colour-blindness test participants reported the coloured numbers in the figures, if the participants reported the current numbers the test was passed (Ishihara, 1976). The handedness test revealed that 27 participants were right handed and three participants were left handed. In total 10 participants were female (M_{age} = 27.3, SD = 4.6, ranging from 23 to 39 years) and 20 participants were male (M_{age} = 26.2, SD = 3.4, ranging from 19 to 33 years). Participants originated from 17 different countries (Austria, Belarus, China, Cuba, France, Germany, Great Britain, Honduras, India, Italy, Lithuania, Mexico, the Netherlands, Pakistan, Poland, Spain, and Turkey). The local ethics committee at the Faculty of Behavioral Sciences of the University of Twente approved the employed procedures, which were all in line with the declaration of Helsinki.

Design, Task, and procedure

Participants were randomly assigned to either the label or the no label condition for the first appointment. For the second appointment, participants were assigned to the other condition dependent on the condition to which the participants were assigned to during the first appointment. During the label condition, participants judged wines when the bottle with label was present and visible. In the no label condition participants judged wines when the bottle and label of the wine were not visible or present. For analysis only the data of the label condition will be used.

Before participation, written instructions for the experiment and a questionnaire about wine drinking habits were sent by email to the participants. Upon arriving at the lab, participants received more detailed instructions on the experiment. At the start of the experiment, participants were requested to complete an informed consent and a questionnaire regarding their demographic details, neurological history, medication, eye correction, and handedness. Participants were reminded that they could abandon the experiment at any time. After these instructions, participants were seated in an office chair in front of a table on which the apparatus was placed. EEG acquisition was conducted in a quiet room with regular artificial lighting. General instructions for the task, displayed on the screen, were read aloud by the experimenter. Participants were asked to follow the instructions presented on the screen during the task. Furthermore, participants were requested to relax as much as possible and to be quiet in order to prevent distortion of the EEG signal.

During the preparation of the cap and electrodes, the participants were requested to read instructions about the judgment of the colour, smell, and taste of the wine. After the preparation, the task could be started. During the task, the experimenter presented the wines and made sure the participant performed the task as intended. Participant were requested to rinse their mouth with water. Next, a glass with wine was presented in front of a white paper to ensure the colours would be perceived in same conditions with the same background. Colour of the wine was judged by the participant. For the smell judgement, the glass of wine was rotated twice and the participant could smell the wine in-between the rotations. For the tasting judgment, the participants took a small sip of the wine. Colour, smell and taste judgement were indicated by the task.

The task was as follows: participants judged four wines in predetermined order on colour, smell and taste while their EEG was recorded. Before the wines were presented, instructions for the task were displayed. Start of the tasting procedure was marked by a line of text indicating that the experimenter chooses the wine to be judged next. Colour, smell, and taste judgement were indicated by instructions on the screen. Additionally, an overall rating of the wine was given using a Likert scale ranging from 1, very bad, to 6, excellent. Furthermore, participants were asked in which price category (1: 3-5, 2: 6-8, 3: 9-11, 4: 12-15, 5: 16-21, 6: 22-27 euros) the wine should be placed. Participants also rated the labels of the wines on a Likers scale from 1 to 6. The task was then repeated from the colour judgement until the label rating for the other wines. A schematic representation of the task can be found in Figure 1 on the next page. The detailed description of the task can be found in Appendix I.

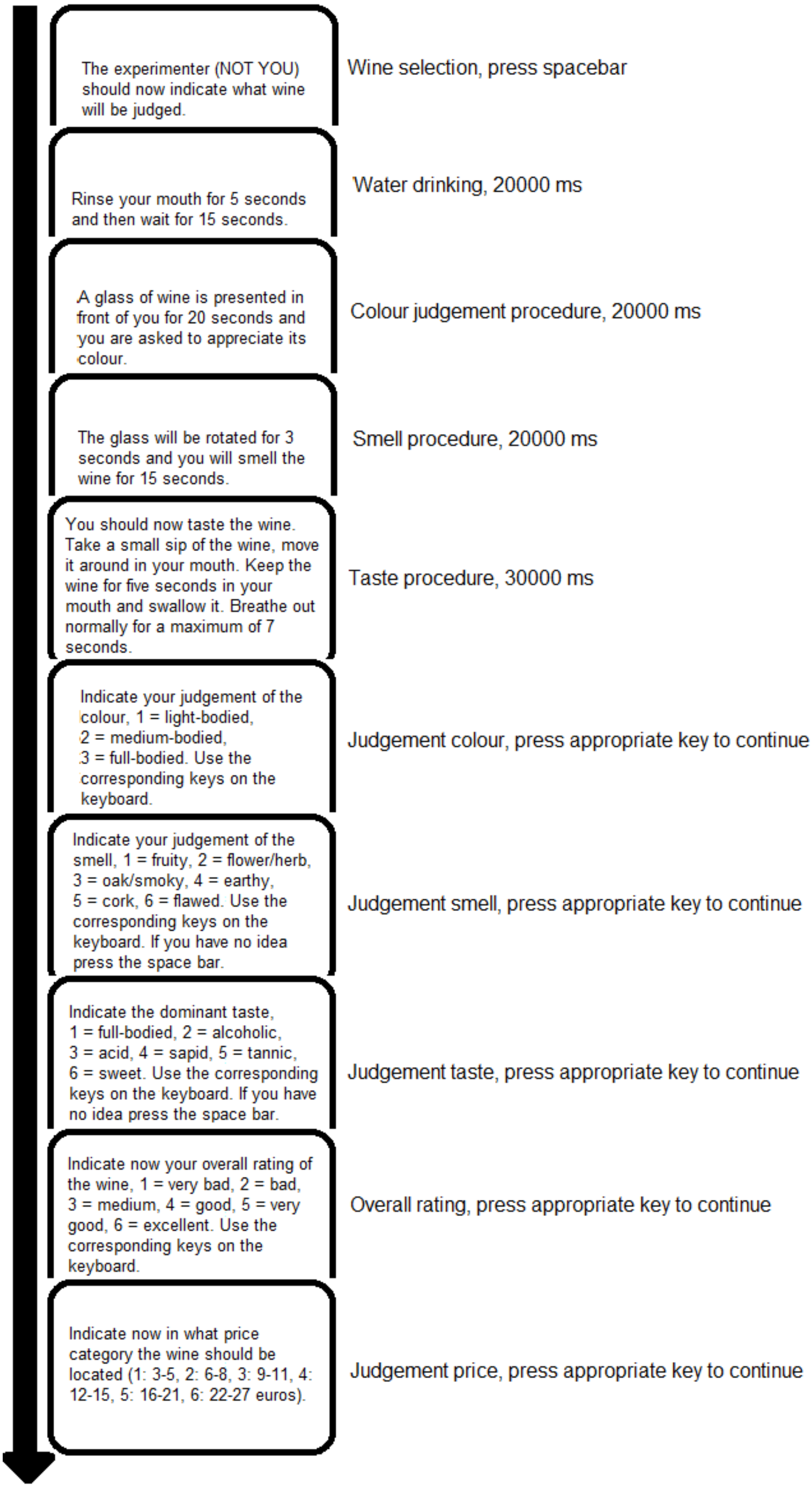


Figure 1. A schematic representation of the task used in the experiment of this study and the different components of the task. For each component, the displayed text in the task is shown, also the time window or the key that should be pressed to continue is shown.

Materials, Apparatus, and EEG recordings

Before participation, participants were requested to fill in a questionnaire about wine drinking habits, criteria for choosing wine, and their demographic details. The questionnaire consisted of 21 questions. Four questions were aimed on assessing wine drinking habits, three questions focused on criteria and habits for buying wine, nine questions assessed the importance of various criteria when choosing a wine, two questions focused on the country of origin of the wines, and the last question asked what kind of bottle design the participants preferred. For this research only the question assessing the frequency of wine drinking was used for further analysis to categorize participants in high or low frequency of wine drinking. Answer categories for this question were: once in two months, once a month, once a week, more than once a week, and daily. The complete questionnaire can be found in Appendix II.

Four different wines were used for the experiment. Two of the wines were of Italian origin, the other two wines of Chilean origin. Furthermore, the wines were categorized according to the price range; two belonged to the category 3 – 6 euro's (low), and two wines belonged to the category 23 – 27 euro's (high). The wines in the experiment were indicated according to the origin and price category: Italian high (IH), Italian low (IL), Chilean high (CH), Chilean low (CL). All four wines were red wines of the type Cabernet Sauvignon.

Participants sat on an office chair in front of a 24 inch AOC G2460P LED computer screen at a distance of approximately 85 cm. The task was displayed with Presentation software (Neurobehavioral Systems, Inc., 2012) installed on a separate computer. A QWERTY keyboard was used for the 1, 2, 3, 4, 5, 6, space, and CTRL buttons.

EEG recordings were performed using active Ag/AgCl electrodes at 32 locations in an elastic cap (Braincap, Brainproducts GmbH). The following positions were used: AFz, AF3, AF7, F5, F1, FCz, FC3, FT7, C5, C3, CP3, TP7, P5, P1, PO7, PO3, POz, PO4, PO8, P6, P2, CP4, TP8, C6, C4, FC4, FT8, F6, F2, AF4, and AF8. Figure 2 shows the used electrodes. The ground electrode was placed on the forehead of the participant and the reference electrode was placed in the Cz position in the cap. Horizontal and vertical electro-oculogram (hEOG and vEOG) were recorded by placing electrodes at the outer canthi of both eyes and above and below the left eye. The resistance of the electrodes could be kept below 10 Ω by using electrode gel and standard procedures to improve conductivity. The EOG, EEG, the ground and reference electrode were amplified using a Brainvision Quickamp-72 (Brain Products GmbH), and were recorded together with task related events, such as responses and stimulus onset, by using BrainVision Recorder software (Brain Products GmbH) installed on a separate computer.

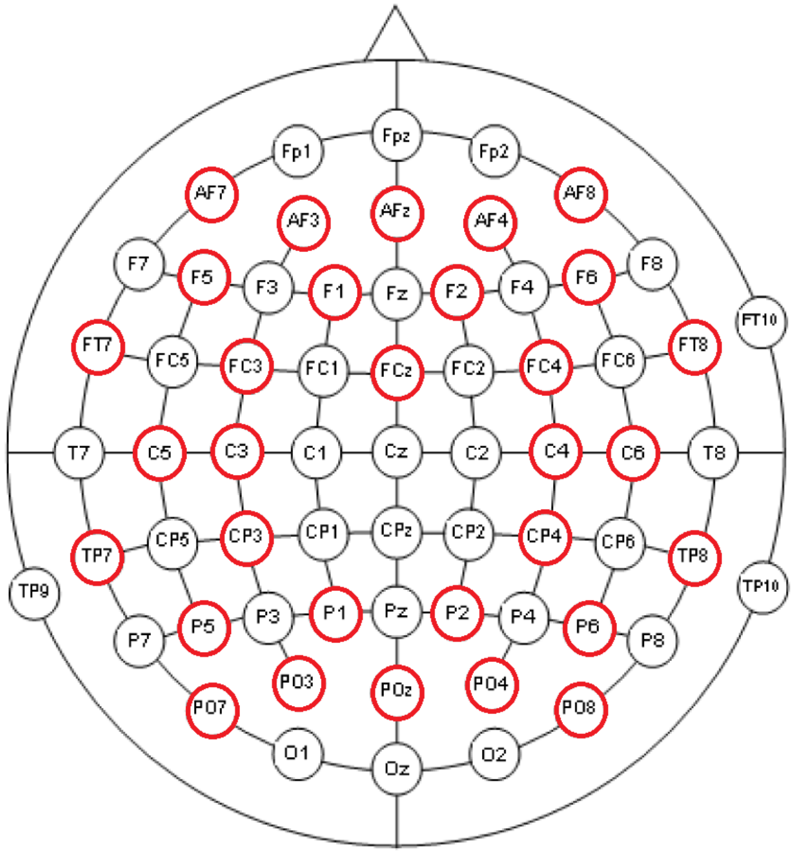


Figure 2. The red coloured electrode positions represent the used electrodes for the EEG acquisition.

Data processing and analysis

Data processing was carried out with BrainVision Analyzer 2.1 software (Brain Products GmbH. 2012). Data of the label condition was used for analysis. The data was partitioned in segments of 2500 to 19000 ms which were in turn partitioned in equal sized segments of 0.5 seconds for the colour, smell and taste part separately for the four different wines relative to the start of the tasting procedure. A baseline was created with segments of 0 to 5000 ms before the taste procedure started. This was done because in this time interval beta activity could not be elicited by the task. Next, an artefact rejection was performed on both the data and the baseline. The used criteria were: maximal allowed voltage step 30 µV/ms, min-max allowed amplitude +/- 150 µV, and low activity criterion of 0.5 µV. On the remaining data and baseline Fast Fourier Transformations (FFTs) were performed.

The used dataset consisted of the colour, smell, taste, overall, price, and label judgements, and the EEG beta measurements during tasting and smelling the wine for the four different wines. A distinction between participants was made based on the countries they were originating from. The distinction was made for countries in which wine consumption is high and in which wine consumption is low, according to the classification of Banks & Overton (2010). Furthermore, a distinction has been made between participants on the frequency of drinking wine based on the question on how often the participants drink wine in the questionnaire send before participation. Participants indicating drinking wine once a week, more than once a week, and daily were classified as high frequency of wine drinking. Participants indicating drinking wine once in two months or once a month were classified as low frequency of wine drinking.

Statistical analysis was performed with R software (1.0.44). Stan_glm and stam_glmer fucntions were used for the linear models (Gelman & Hill, 2007). At first, frequencies of the reported smell, taste, and price judgement were analysed by making cross tabled for these judgements for each wine. Linear models were composed to test if the overall ratings were influenced by the wine consumption based on the country of origin of the participants and the frequency of wine drinking. Logarithmic transformations were performed on the beta EEG data and baseline to correct for individual differences in beta power. Next, the EEG measures were investigated, starting with linear models examining the predictive value of the taste and smell EEG measures for the overall evaluation and the reported price category to which the wines were assigned by the participants. Additionally, linear models were composed to test the influence of the frequency of drinking, wine consumption in the country of origin according to the classification of Banks and Overton (2010), to test differences between the smell, taste and baseline EEG measurements, and the different wines on the beta activity recorded during the smell and taste procedures.

As noted above, linear models were composed to test the influences between variables. The first linear model used the interaction effect between consumption of wine based on country and wine as predictors for the overall judgements of the wines. The model accounted for individual differences of the participants. The second linear model tested if overall ratings were predicted by the interaction effects of frequency of drinking wine and the four different wines. This model also accounted for individual differences among the participants. The third linear model tested the influence of the four different wines on the overall ratings of the wines. The fourth model used beta taste, beta smell, and label judgement as predictors for the overall judgement of the wines. The fifth linear model used beta taste, beta smell, and overall judgement as predictors for the price judgement of the wines. The sixth, seventh and eighth model test differences in smell, taste and baseline measure. The ninth and tenth models check if differences in beta activity for the smell and taste EEG measures are caused by the four different wines, the consumption based on country, and the frequency of wine drinking. Fixed effects were computed for the models, and residual checks were done to check if the residuals are normally distributed. The reproduceable data analysis report can be found in Appendix III.

Results

The following section will give an overview of the results of the analysis, starting with the smell, taste and price judgements of the wines. Next the preference for the wines was examined by the overall ratings. It was investigated if the wine consumption based on the country of origin of the participants and the reported frequency of wine consumption had an influence on the overall rating. After that it was checked if the EEG measures were predictive for the overall rating. Furthermore, it was checked if the beta activity during the smell and taste procedure differed between participants for which the wine consumption based on the country of origin was high or low and for participants which reported a high and low frequency of wine consumption. Additionally, differences in beta activity between the smell, taste, and baseline EEG measures were examined.

Smell, taste, and price judgement

During the experiment, participants described the smell of the four wines using the predetermined terms fruity, flower/herb, oak/smoky, earthy, cork, and flawed. Table 1 below displays how often the terms were used to describe the smell of the four different wines. Figure 3 below shows the frequency of the given description of the smell by the participants for the four different wines for the 6 different answer categories: 1 = fruity, 2 = flower/herb, 3 = oak/smoky, 4 = earthy, 5 = cork, and 6 = flawed. The smell of the CH wine was described most often as oak/smoky, but also often as flower/herb. None of the participants described the smell as flawed. Flower/herb was also often used to describe the smell of the CL wine. The smell of this wine was described as fruity, oak/smoky, and earthy for five participants per category. The IH wine was described the most as a wine that smells oaky/smoky, but also often as earthy. Furthermore, the smell of the IL wine was described by most participants as fruity or flower/herb. The participants most agreed on the smell of the IH wine, less agreement was found for the CL and IL wines. This indicates that participants were not unanimous about the smell of the wines.

Table 1. *Frequency of reported smell for the four wines by the participants.*

	Wine			
Smell	CH	CL	IH	IL
Fruity	5	5	4	6
Flower/herb	7	8	2	7
Oak/smoky	9	5	10	4
Earthy	3	5	7	2
Cork	2	1	2	4
Flawed	0	2	1	3

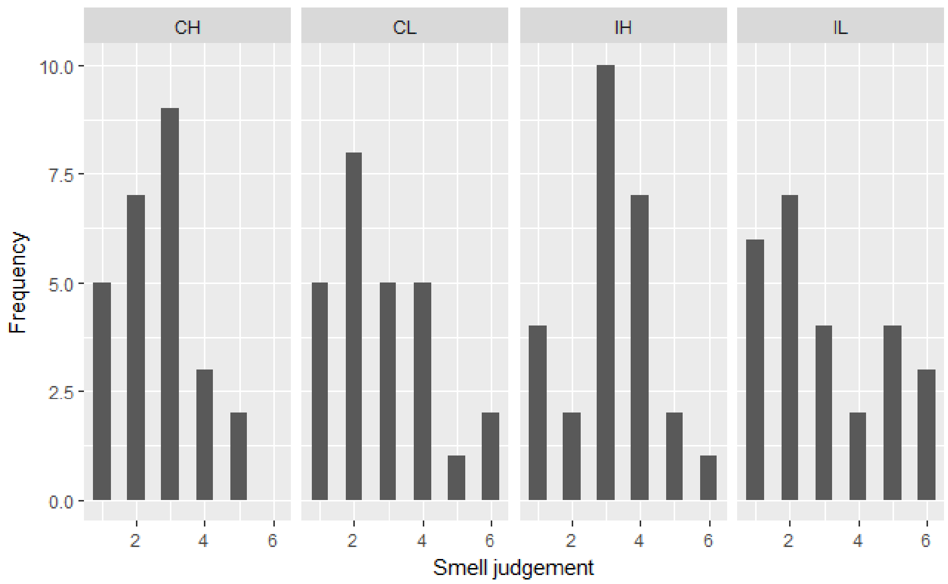


Figure 3. Frequency of the given description of the smell by the participants for the four different wines CH, CL, IH, and IL for the 6 different answer categories: 1 = fruity, 2 = flower/herb, 3 = oak/smoky, 4 = earthy, 5 = cork, and 6 = flawed.

The taste of the four wines was described using the terms full-bodied, alcoholic, acid, sapid, tannic, and sweet. The frequency of the terms ascribed to the wines can be found in Table 2 below. Figure 4 below gives an oversight of the given description of the taste by the participants for the four different wines for the 6 different answer categories: 1 = full-bodied, 2 = alcoholic, 3 = acid, 4 = sapid, 5 = tannic, and 6 = sweet. It can be found that the taste of the CH wine often described with the terms tannic, acid, and full-bodied. The terms alcoholic, sapid, and sweet were less often used to describe the taste of this wine. The CL wine was often described as sapid, full-bodied, acid, and as tannic. Less agreement of the participants is found for the description of the taste for the CL wine. More agreement among the participants is found for the IH wine, where most participants described the taste of the wine as tannic. The taste for this wine was also often reported as sapid. The taste of the IL wine was most often described as sweet. The terms full-bodied, acid, and tannic were even often used to describe the taste of the IL wine. This indicates little agreement among the participants about the taste of the wine.

Table 2. *Frequency of reported taste for the four wines by the participants.*

	Wine			
Taste	CH	CL	IH	IL
Full-bodied	5	6	4	5
Alcoholic	2	2	2	0
Acid	7	5	3	5
Sapid	2	7	6	3
Tannic	8	4	10	5
Sweet	2	2	1	8

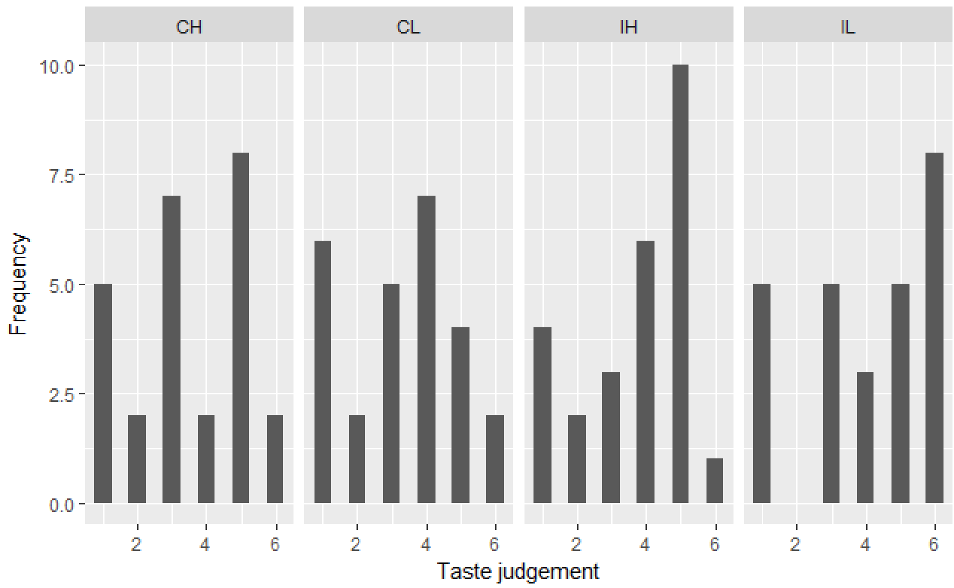


Figure 4. Frequency of the given description of the taste by the participants for the four different wines CH, CL, IH, and IL for the 6 different answer categories: 1 = full-bodied, 2 = alcoholic, 3 = acid, 4 = sapid, 5 = tannic, and 6 = sweet.

Next to smell and taste, participants reported to which price category the wines should belong. The following categories in euros were used: 3 – 5, 6 – 8, 9 – 11, 12 – 15, 16 – 21, and 22 – 27. Table 3 below displays the frequency of reported price categories to which the wines were assigned. Participants assigned the CH wine most often to the price category of 6 – 8 euros. Also, the categories 9 – 11 and 12 – 15 euros were reported often. The CL wine was most often assigned to the 6 – 8 euros' category, but also the 3 – 5 euros and 9 – 11 euros' categories were reported often. For both the Chilean wines, one participant assigned the wines to the highest price category (22 – 27 euros). For the IH wine, participants were most willing to pay 9 – 11 or 6 – 8 euros. Striking is that four participants assigned this wine to the price category of 16 – 21 euros. The IL wine was most often described to the price categories 6 – 8 and 3 – 5 euros. Highest frequency for the four wines was found for the price category 6 – 8 euros, but overall, little agreement among the participants was found to which price categories the wines should belong. Figure 5 below displays the distribution of the price categories to which the four wines were assigned by the participants. Here it can be seen that the median for the CH wine is found at answer option 3 and the upper quartile at option 4. Indicating that 50% to 75% of the participants indicated that the wine is probably priced above 9 euro's and less than 15 euro's. For the CL wine the median is reached at 2 and the upper quartile at 3.75. This means that 50 to 75% of the participants scaled the wine at 6 to 14 euro's. The median and the upper quartile of the IH wine are both set at 3, the lower quartile is found at 2. This means that 25 to 75% of the participants scaled the wine between 6 and 11 euro's. Furthermore, for the IL wine the median is found at 2 and the upper quartile at 3. This means that 50% to 75% of the participants indicated that this wine should cost between 6 and 11 euro's. The lower quartile is found at 1, indicating 25% of the people thought the wine should cost between 3 and 5 euro's.

Table 3. *Frequency of reported price category to which the wines should belong according to the participants.*

	Wine			
Price (in euros)	CH	CL	IH	IL
3 – 5	2	6	5	8
6 – 8	10	8	7	9
9 – 11	6	5	8	4
12 – 15	5	3	2	4
16 – 21	2	3	4	1
22 – 27	1	1	0	0

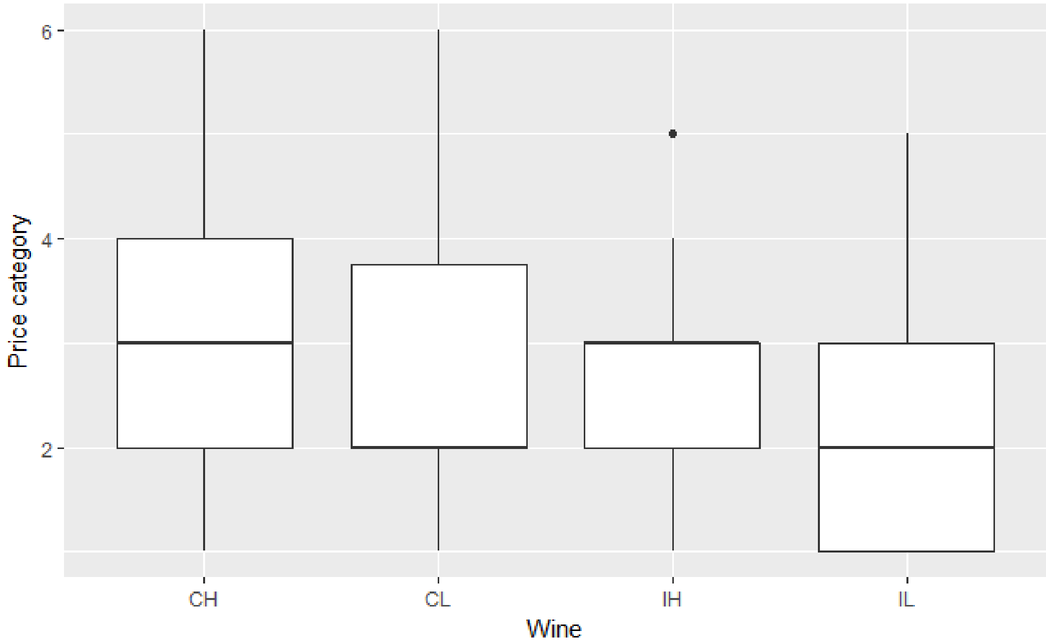


Figure 5. A boxplot displaying the distribution of the price categories to which the four wines were assigned by the participants. Used price categories in euros were: 1 = 3 – 5, 2 = 6 – 8, 3 = 9 – 11, 4 = 12 – 15, 5 = 16 – 21, 6 = 22 – 27.

Preference for the wines by the overall rating

At first, an overview will be given of the overall ratings for the four wines by the participants. Analysis of the four different wines and the overall rating of the wines showed that there was no clear preference for one of the wines. Mean overall ratings of the wines were similar: The CH wine (M = 3.85, SD = 0.92), the CL wine (M = 3.73, SD = 1.04), the IH wine (M = 3.61, SD = 1.09), and the IL wine (M = 3.46, SD = 1.02). Figure 6 below displays the frequency of the given overall ratings for the four wines. To test differences in the overall rating for the four wines, a linear model was computed. Table 4 below displays the fixed effects of the analysis. The expected overall rating for the CH wine is 3.84, with a 95% credibility interval of [3.44, 4.25]. This indicated that with 95% certainty it can be said that the overall rating of the CH in a next experiment will lay between 3.44 and 4.25. It seems that expected overall ratings for the CL, IH, and IL wine will be lower than the expected overall rating of the CH wine. However, the 95% credibility intervals are wide and uncertain. This indicates that for the CL, IH, and IL wine the overall rating in a following study can be lower, but the ratings could also be higher. This means that no conclusions can be formulated about differences in overall ratings for the four different wines.

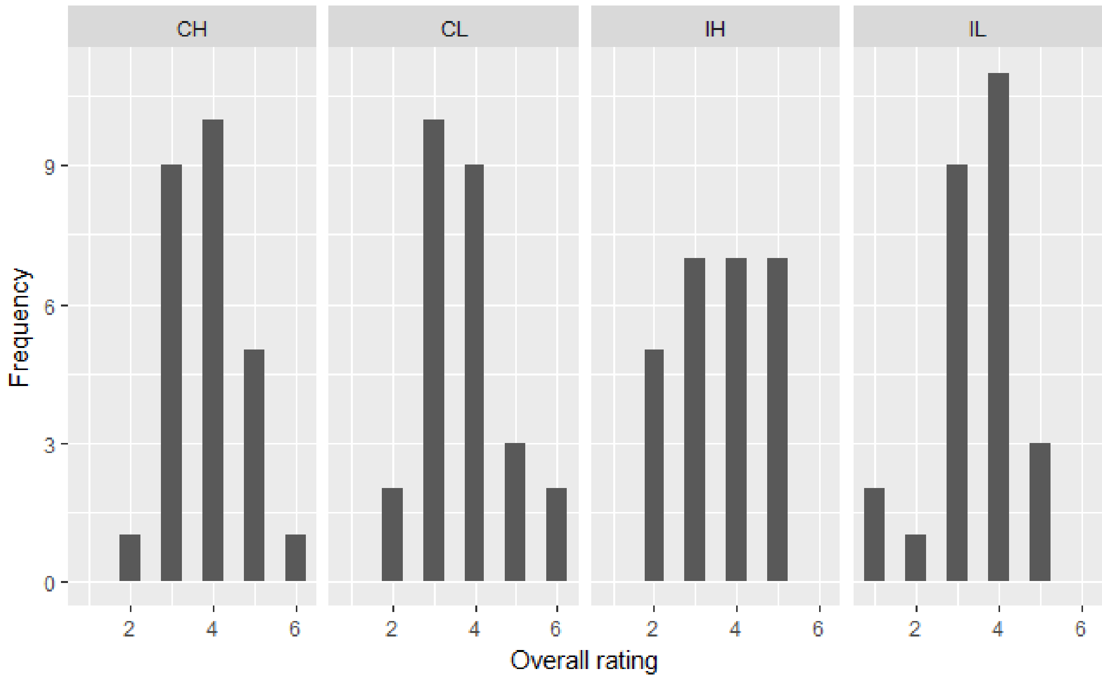


Figure 6. Frequency of the given overall ratings by the participants for the four different wines CH, CL, IH, and IL on the scale of 1, very bad, to 6, excellent.

Table 4. *Coefficient table with fixed effects of the linear model for the overall ratings with the wine as predictor of the overall rating. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected overall rating for the CH wine.*

Fixef	Center	Lower	Upper
Intercept	3.84	3.44	4.25
Wine CL	-0.11	-0.69	0.47
Wine IH	-0.23	-0.78	0.33
Wine IL	-0.38	-0.95	0.19

Overall ratings of the wines were also examined based on wine consumption based on the country of origin of the participants. Participants were divided into high and low wine consumption based on nationality. Mean overall rating for each wine given by participants originating from countries in which wine consumption is high were: CH wine (M = 4.00, SD = 1.18), CL wine (M = 4.09, SD = 1.14), IH wine (M = 3.30, SD = 1.06), and IL wine (M = 3.36, SD = 1.29). It seems that the Chilean wines were ranked higher than the Italian wines. Mean overall rating for the low wine consumption countries were: CH wine (M = 3.73, SD = 0.70), CL wine (M = 3.47, SD = 0.92), IH wine (M = 3.73, SD = 1.10), and IL wine (M = 3.53, SD = 0.83). Looking at the mean ratings and standard deviation, it seems that more variability in the overall ratings of the participants originating from countries in which wine consumption is high was found than for the overall ratings given by participants originating from countries in which wine consumption less frequent. Figure 7 displays the distribution of the overall ratings per wine for high and low wine consumption based on country. To test this, linear models were composed. The expected overall rating for high wine consumption for the CH wine is 3.99. This estimate is rather uncertain, with a wide 95% interval of 3.99[3.40, 4.56]. Expected overall rating for low wine consumption for the CH wine is 3.72, also with an uncertain and wide 95% interval of -0.27[-1.03, 0.50]. 95% intervals are also wide and uncertain for the values of the wines CL, IH, and IL, and for the interaction effects for wine consumption and the different wines. All results are displayed in table 5 below. Overall ratings for the different wines thus seem not reliably predicted by the wine consumption in the country of origin.

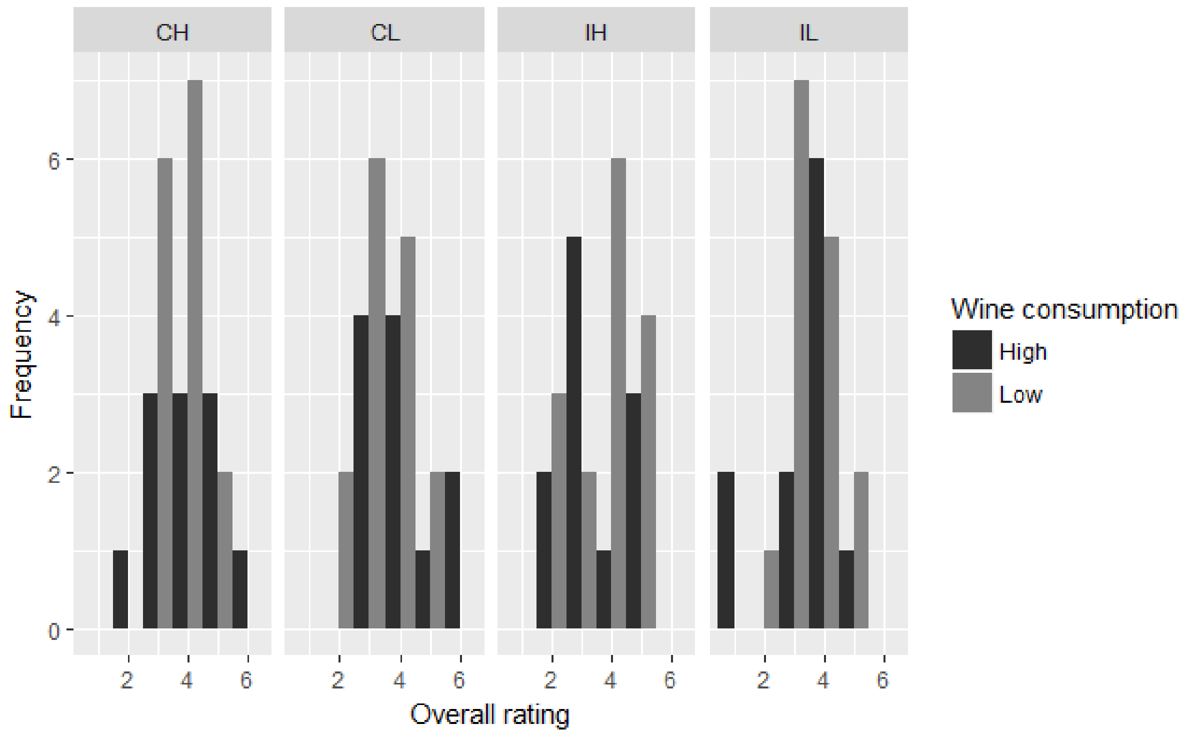


Figure 7. Frequency of the given overall ratings by the participants for the four different wines CH, CL, IH, and IL on the scale of 1, very bad, to 6, excellent divided by the wine consumption based on country of origin of the participants.

Table 5. *Coefficient table with fixed effects of the linear model for the overall ratings with the wine, wine consumption based on nationality, and interaction effects for the wine and wine consumption based on nationality. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected overall rating for the CH wine, for a high wine consumption based on nationality, and the high wine consumption based on nationality depending on the CH wine.*

Fixef	Center	Lower	Upper
Intercept	3.99	3.40	4.56
Consumption Low	-0.27	-1.03	0.50
Wine CL	0.08	-0.74	0.91
Wine IH	-0.68	-1.58	0.18
Wine IL	-0.64	-1.47	0.20
ConsumptionLow:WineCL	-0.35	-1.44	0.74
ConsumptionLow:WineIH	0.69	-0.45	1.82
ConsumptionLow:WineIL	0.42	-0.68	1.50

Furthermore, a distinction has been made between participants in how frequent they drink wine. Overall wine ratings were compared for frequent and non-frequent wine drinkers. Average overall ratings per wine for frequent wine drinkers are: CH wine (M = 3.91, SD = 1.14), CL wine (M = 3.55, SD = 1.04), IH wine (M = 3.18, SD = 1.25), and IL wine (M = 3.45, SD = 1.04). Non-frequent wine drinkers average overall ratings per wine are: CH wine (M = 3.80, SD = 0.77), CL wine (M = 3.87, SD = 1.06), IH wine (M = 3.93, SD = 0.88), and IL wine (M = 3.47, SD = 1.06). It seems that especially the CL and IH wines were rated higher by the non-frequent wine drinkers than the frequent wine drinkers. In addition, it seems that differences between ratings are smaller for the non-frequent wine drinkers than for the frequent wine drinkers. Figure 8 gives an overview of the given overall ratings per wine for high and low wine frequency of wine consumption. To test the influence of the frequency of wine drinking on the overall ratings of the wines, linear model analyses were performed. Results of the analysis are shown in table 6 below. Expected overall rating for frequent wine consumption for the CH wine is 3.89 with a 95% interval of [3.30, 4.51]. The expected overall rating for non-frequent wine drinkers for the CH wine is 3.81. The 95% interval -0.08[-0.87, 0.67] is wide and uncertain. Expected overall ratings for frequent and non-frequent wine drinkers are also lowered for each wine; respectively with 0.34 for the CL wine, with 0.70 for the IH wine, and with 0.42 for the IL wine. Also, these 95% intervals are rather wide and uncertain: for the CL wine -0.34[-1.20, 0.47], IH wine -0.70[-1.55, 0.15], and IL wine -0.43[-1.29, 0.40]. This means that overall ratings for the wines could also be increased for the wines relative to the CH wine. In addition, as displayed in table 2, 95% credibility intervals for the interaction effect for the frequency of wine consumption and the wines are also rather wide and uncertain. Frequency of wine drinking is thus not a reliable predictor for the overall ratings of the wines.

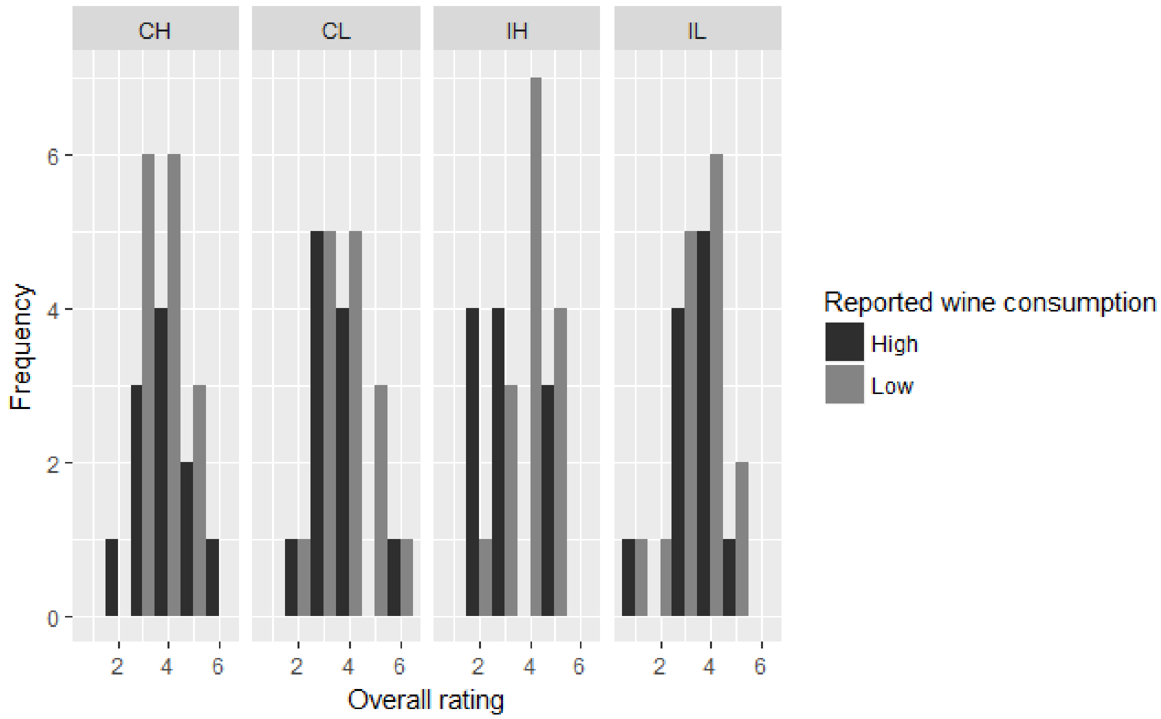


Figure 8. Frequency of the given overall ratings by the participants for the four different wines CH, CL, IH, and IL on the scale of 1, very bad, to 6, excellent divided by the reported frequency of wine consumption.

Table 6. *Coefficient table with fixed effects of the linear model for the overall ratings with the wine, frequency of wine drinking, and interaction effects for the wine and frequency of wine consumption of the participants. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected overall rating for the CH wine, for a high wine consumption based on drinking habits, and the high wine consumption based on drinking habits depending on the CH wine.*

Fixef	Center	Lower	Upper
Intercept	3.89	3.30	4.51
Freq_consumption Low	-0.08	-0.87	0.67
Wine CL	-0.34	-1.20	0.47
Wine IH	-0.70	-1.55	0.15
Wine IL	-0.43	-1.29	0.40
Freq_consumptionLow:WineCL	0.41	-0.73	1.50
Freq_consumptionLow:WineIH	0.83	-0.36	1.96
Freq_consumptionLow:WineIL	0.07	-0.99	1.20

EEG measures as predictors of the overall and price rating

Additionally, linear mixed model analyses were performed to check the influence of the beta EEG measures on the overall ratings and the price ratings. First the results of the linear model to check influences on the overall ratings are examined. Table 7 below displays the results of the analyses. Expected overall ratings without the influence of the taste and smell procedure, and without the label being displayed is 2.38 with a wide 95% interval [1.77, 2.97]. Overall ratings are expected to be lowered during the tasting procedure with -1.77 with a very wide and uncertain 95% interval [-6.10, 2.44]. Also the expected overall ratings are expected to be lowered during the smell procedure by -0.37 with also a wide 95% credibility interval [-3.68, 2.95]. Furthermore, the overall ratings are expected to be higher when the label is present. Overall ratings are expected to be higher by 0.38, with a 95% interval of [0.23, 0.53]. This means that with 95% certainty it can be said that overall ratings are positively influenced by the label. Beta taste and smell EEG measures seem to be no reliable predictors of the overall ratings of the wines, since the credibility intervals are wide and uncertain.

Table 7. *Coefficient table with fixed effects of the linear model for the overall ratings with the taste and smell beta EEG measurements and the label. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected overall rating.*

Fixef	Center	Lower	Upper
Intercept	2.38	1.77	2.97
Taste_corrected	-1.77	-6.10	2.44
Smell_corrected	-0.37	-3.68	2.95
Label	0.38	0.23	0.53

Additionally, the influence of the beta smell and taste EEG measures and the label on the price rating are tested. The results are shown in table 8 below. Like with the analysis of the overall ratings, 95% credibility intervals are wide and uncertain for the beta taste and smell EEG measurements. The expected overall rating without presence of the label and influence of the taste and smell of the wines is 2.08 with a 95% interval of [1.24, 2.96]. Taste procedure is expected to lower the overall ratings with a 95% credibility interval of -2.30[-8.27, 3.93]. Furthermore, smell is also expected to lower the overall ratings of the wines with an interval of -1.56 [-6.08, 3.03]. Beta EEG measurements during the taste and smell procedure do not seem reliable predictors for the overall ratings of the wines. In contrast to the results of the linear model for the overall ratings, label does not seem a reliable predictor of the price ratings. The expected price rating when the label is visible seems influenced minimal with a value of 0.20. Furthermore, the 95% credibility interval is wide and uncertain since it indicates that price ratings could also be negatively influenced by the presence of the label.

Table 8. *Coefficient table with fixed effects of the linear model for the price ratings with the taste and smell beta EEG measurements and the label. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected price rating.*

Fixef	Center	Lower	Upper
Intercept	2.08	1.24	2.96
Taste_corrected	-2.30	-8.27	3.93
Smell_corrected	-1.56	-6.08	3.03
Label	0.20	-0.02	0.41

Influence of wine consumption on EEG measures

Furthermore, it was tested which variables had effects on the taste and smell EEG measures. Linear models were computed for both the taste and smell measures independently. First the results for the taste EEG measures will be examined. Beta taste EEG measures for the CH wine and high wine consumption based on country and frequent wine drinking was 0.04, with a 95% interval of [0.01, 0.06]. For the CL wine beta activity was found to be somewhat lower, namely 0.00 with a 95% interval of [-0.03, 0.03]. Beta activity during the taste procedure was found to be similar for the IH and IL wines to the CL, with values of 0.01 and 0.00 with respectively 95% credibility intervals of 0.01 [-0.02, 0.04] and 0.00 [-0.02, 0.03]. This indicates that the different wines did not have a notable influence on the beta activity during the tasting procedure. Furthermore, similar values were found for the low wine consumption based on country and non-frequent wine drinkers. Both values were 0.00 with both a 95% interval of [-0.02, 0.02]. The results can be found in table 9 below. This indicates that also frequency of wine drinking and wine consumption based on country of origin did not have an influence on the beta activity measured during the tasting procedure.

Table 9. *Coefficient table with fixed effects of the linear model for the taste EEG measures with wines, consumption based on nationality, and frequency of wine drinking as predictors. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected beta activity during the tasting procedure for the CH wine, with a high wine consumption based on country and a high frequency of wine drinking.*

Fixef	Center	Lower	Upper
Intercept	0.04	0.01	0.06
Wine CL	0.00	-0.03	0.03
Wine IH	0.01	-0.02	0.04
Wine IL	0.00	-0.02	0.03
Consumption Low	0.00	-0.02	0.02
Freq_consumption Low	0.00	-0.02	0.02

Next, the results for the smell EEG measures will be examined. Beta smell EEG measures for the CH wine and high wine consumption based on country and frequent wine drinking was 0.05, with a 95% interval of [0.02, 0.07]. For the CL wine beta activity was found to be somewhat lower, namely 0.01 with a 95% interval of [-0.02, 0.04]. Beta activity during the taste procedure was found to be similar for the IH and IL wines to the CL wine, with values of both 0.01 with respectively 95% credibility intervals of 0.01 [-0.02, 0.05] and 0.01 [-0.02, 0.04]. This indicates that beta activity did not differ for the different wines during the smell procedure. Furthermore, similar values were found for the low wine consumption based on country, with expected beta EEG measures of 0.00 with a 95% interval of [-0.01, 0.04]. This indicates that also consumption based on country did not have an influence on the beta activity measured during the smell procedure. Frequent wine drinking did seem to have a small influence on the beta activity registered during the smell procedure with an expected value of -0.03 with a 95% credibility interval [-0.06, 0.00]. This credibility interval however indicates that beta activity can be unaffected during the smell procedure. This means that the measures are too uncertain to draw reliable conclusions about the influence of frequency of wine drinking on beta activity during the smell procedure. The results can be found in table 10 below.

Table 10. *Coefficient table with fixed effects of the linear model for the smell EEG measures with wines, consumption based on nationality, and reported frequency of wine drinking as predictors. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected beta activity during the smell procedure for the CH wine, with a high wine consumption based on country and a high frequency of wine drinking.*

Fixef	Center	Lower	Upper
Intercept	0.05	0.02	0.07
Wine CL	0.01	-0.02	0.04
Wine IH	0.01	-0.02	0.05
Wine IL	0.01	-0.02	0.04
Consumption Low	0.01	-0.01	0.04
Freq_consumption Low	-0.03	-0.06	0.00

Differences between taste, smell, and baseline EEG measures

The following paragraph gives an overview of the differences between the smell, taste and baseline EEG measures. The results of the comparison between the smell EEG measurements and the taste EEG measurements are shown in table 11 below. The expected beta activity during the taste procedure is 0.02, with a 95% credibility interval of [0.01, 0.04]. Beta activity for the smell EEG measures is expected to be higher with a value of 0.33, with a 95% credibility interval of [0.18, 0.50]. Although this is a wide credibility interval, the beta activity during the smell procedure is higher than the beta activity during the taste procedure.

Furthermore, it was found that beta activity during the smell procedure is higher than for the baseline measures. The expected beta activity during the smell procedure was 0.10 with a credibility interval of [0.06, 0.14]. Beta activity for the baseline measures was lowered with 0.18. Although the 95% is wide [-0.31, -0.04], it still indicated that the beta activity is lower for the baseline measures than for the smell measures. The results can also be found in table 12 below.

Table 13 below shows the differences in EEG activity during the taste procedure and the baseline measurement. The expected beta activity during the taste procedure is 0.04, with a 95% credibility interval of [0.00, 0.07]. Beta activity during the tasting procedure seems not to differ of the beta activity found for the baseline measure, since a value of 0.00 does not affect the expected value of the taste EEG measures. Nevertheless, the 95% credibility interval indicated that differences are possible since it ranges from -0.10 till 0.11. However, this interval is very wide and uncertain which indicates that no reliable conclusions can be made about the differences in beta activity for the taste and baseline measurements.

Table 11. *Coefficient table with fixed effects of the linear model with dependent variable the taste EEG measurements and predictor the smell EEG measurements. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected beta activity during the tasting procedure.*

Fixef	Center	Lower	Upper
Intercept	0.02	0.01	0.04
Smell_corrected	0.33	0.18	0.50

Table 12. *Coefficient table with fixed effects of the linear model with the dependent variable the smell EEG measurements and predictor the baseline EEG measurements. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected beta activity during the smell procedure.*

Fixef	Center	Lower	Upper
Intercept	0.10	0.06	0.14
logBaseline_FCz	-0.18	-0.31	-0.04

Table 13. *Coefficient table with fixed effects of the linear model with the dependent variable the taste EEG measurements and predictor the baseline EEG measurements. The center represents the expected values for the overall rating, the lower and upper are the values of the 95% credibility interval. The intercept represents the expected beta activity during the tasting procedure.*

Fixef	Center	Lower	Upper
Intercept	0.04	0.00	0.07
logBaseline_FCz	0.00	-0.10	0.11

Discussion

In this study, the question to be answered was if neural measures could make a valuable and significant contribution to the prediction of preference and choice of wines. Furthermore, it was investigated if EEG data could be used as a predictive value for the evaluation of the wines. Research by Boksem and Smidts (2015) and Khushaba et al. (2013) showed that individual preference is reflected by beta activity. Individual preference resulted in higher amplitudes of beta activity in the frontal-medial areas of the brain, especially around the electrode position FCz (Boksem & Smidts, 2015). Therefore, it was expected to find higher amplitudes of beta activity for FCz for the preferred wines. It was also expected that more beta activity would be found for the wine which was scaled in the highest price category. Since subjective pleasantness of food can be predicted by neural measures and taste is an important feature for survival (Kringelbach, 2005; Kringelbach, O'Doherty, Rolls & Andrews, 2003; Spector, 2000; Shipley & Ennis, 1996), it was expected that more beta activity would be present during the taste and smell procedure than for the baseline measure. Considering the fact that the olfactory system is directly linked to the brain (Shipley & Ennis, 1996), it was expected to find more beta activity at FCz during the smell procedure than for the taste procedure.

The smell, taste and price judgements of the wines were examined to see if participants chose the same categories to describe the smell and taste of the wines and if there were differences in the price categories to which the participants had assigned the wines. It became clear that participants were not unanimous about the description of the smell and taste of the wines, since different terms were chosen to describe the smell and taste of the wines. Participants were also not unanimous about the price categories to which the wines should be assigned, also some differences appeared when looking at the boxplot. The CH wine was most often scaled as 9 – 11 euro's, however, 75% of the ratings were given between 6 – 15 euro's. The CL wine was scaled most often as 6 – 8 euro's, with 75% of the scores ranging from 6 – 14 euro's. 75% of the scores of the IH wine ranged from 6 to 11 euro's, with the median at 9 – 11 euro's. The median of the IL wine was found at 6 – 8 euro's, but 75% of the scores ranged from 3 – 11 euro's. This indicates that the CH and IH were priced highest, looking at the median, but looking at the lower and upper quartiles, the CH and CL wines seem to be rated as the most expensive wines. This indicates that there was no preference for one of the wines.

Preference for the wines was also examined by the overall ratings of the wines. It seemed that the overall ratings were similar for the four different wines. On average the wines were rated with a 3/4, suggesting participants rated the wines as medium/good. Furthermore, it seemed that overall ratings of participants originating from countries in which wine consumption is high differed more than the ratings of participants originating from countries in which wine consumption was lower. Unfortunately, the linear model showed that the 95% credibility interval was rather wide and uncertain indicating that wine consumption based on the countries of which the participants are originating is not a reliable predictor for the overall rankings of the wines. Comparable results were found for the analysis of overall ratings by frequency of wine drinking. The CH and IH wines seemed to be rated higher by non-frequent drinkers and the ratings seem to differ more for frequent wine drinkers than for non-frequent drinkers. Nevertheless, frequency of wine drinking does not seem to be a reliable predictor of overall ratings by the participants since the 95% intervals were wide and uncertain. This again showed that there was no clear preference for one of the wines.

It was furthermore checked if the taste and smell EEG measures were predictors of the overall rating. Results however showed that beta activity during the smell and taste procedures were no reliable predictors for the overall and price ratings of the wines. 95% intervals were wide and uncertain. This means that the hypothesis of higher amplitudes for the preferred wines and for the wine scaled the highest price category were disconfirmed. After that, differences in beta activity during the smell, taste and baseline measures were examined. It was found that more beta activity during the smell procedure was found than during the taste procedure. This means that the hypothesis of more beta activity during the smell procedure than during the taste procedure was confirmed. It was also found that beta activity during the smell procedure was higher compared to the baseline measure. However, no higher amplitudes of beta activity were found during the taste procedure in comparison to the baseline measures. This means that our hypothesis, that more beta activity during the smell and taste procedure was expected to be found, was partially confirmed. This could indicate that choice and preference of wine could be better indicated by beta activity during the smell procedure than during the taste procedure, since higher amplitudes of beta activity were found for the smell procedure than for the taste procedure in comparison to the baseline.

Additionally, it was examined if the wines, frequency of wine drinking, and wine consumption based on the country of origin had an influence on the smell and taste EEG measures. Again 95% intervals were wide and uncertain, indicating that the different wines, frequency of wine drinking, and wine consumption based on country of origin were no reliable predictors of the beta activity during the smell and taste procedure. Preference of wine could not be indicated by examining the beta activity for the smell and taste EEG measures independently. Results of these linear models also indicate that disconfirmation of the hypotheses could not be ascribed to individual differences of the participants.

The results of the study failed to confirm the question if neural measures could make a valuable and significant contribution to the prediction of preference and choices of wine, since credibility intervals of the linear models were wide and uncertain. The EEG data acquired during this experiment could not be used as a predictor for the evaluation of the wines. Further research is needed to examine if beta activity could be used as a predictor of preference and choice. This indicates that, for now, studies within the field of neuromarketing should be handled with caution since there is some ambiguity about the usefulness of beta activity in the prediction of preferences and choices.

One possible explanation for the disconfirmations of the hypotheses is that there was no clear preference for one of the wines. Overall ratings were quite similar and among the participants little agreement was found for the judgement of the smell and taste of the wines. Participants had to judge colour, smell and taste of the wines on the basis of descriptions of the colour, smell and taste and could only choose from a few options. Although these descriptions were clearly different, people could not unanimously decide which colours, smells and tastes the wines had. A possible explanation for these results is the attribute substitution heuristic (Kahneman & Frederick, 2002). This heuristic states that the human intention to judge a target attribute initiates a search for a reasonable value. For some judgements, the target attribute does not come to mind immediately, and the search for it evokes other attributes that are conceptually or associatively related. Many judgements are made by this process of attribute substitution. Attribute substitution occurs when: 1. The target attribute is relatively inaccessible, 2. A semantically and associatively related candidate attribute is highly accessible, or 3. The substitution of the heuristic attribute in the judgement is not rejected by the critical operations of the reflective cognitive system (Kahneman & Frederick, 2002). According to the first comment, it could be possible that participants could not access the descriptions of the colour, smell, and taste when they needed it to judge the wines. Therefore, the participants choose a description that was easily accessible. According to the attribute substitution heuristic it seems realistic that the judgements were based on prejudices about wine or the participants just chose one of the terms that was displayed at the screen, because the terms were not accessible or the description of the terms was too hard to recall during the experiment (Kahneman & Frederick, 2002). This could indicate that the reliability and validity of these terms were not high. However, this is not proven yet. Therefore, future research is recommended which recognizes the attribute substitution heuristic. A suggestion for future research would be to provide the participants with the descriptions of the terms during the judgements procedures of the experiment. If participants then can describe the smell and taste of the wines unanimously, the terms are reliable and valid and the problem was to recall the descriptions during the experiment. Another suggestion, in the light of examining individual preferences, is to ask the participants to state preference for colour, smell, and taste of the wines. This could give more input about preferences displayed by brain activity.

Next to the attribution substitution theory, the choice of the frequency band could have been of importance to the results of this experiment. As noted before, research of Khushaba et al. (2013) showed that not only beta bands seem predictive for individual preference, also the α, and θ frequency bands in the frontal regions of the brain seem predictive for individual preference. Vecchiato et al. (2010) also examined the predictive values of neural measures. They investigated experienced pleasantness and unpleasantness of TV advertisements. It was found that the alpha and theta frequency bands were predictive for pleasantness and unpleasantness. Furthermore, research of Werkle-Bergner, Müller, Li, and Lindenberger (2006) and research of Summerfield and Mangels (2005) also found that theta band activity is a predictive value for preference. In addition, alpha and theta oscillations are found to reflect analytical processes (Klimesch, 1999). These processes are necessary for humans to be able to formulate a preference (Vecchiato et al., 2010). This would mean that beta activity was not the right choice to examine the predictive value of neural measures. This leaves the question how it is possible that Boksem & Smidts (2015) and Khushaba et al. (2013) found beta activity to be predictive. A possible answer could be found in the quantity of activity. At first, Vecchiato et al. (2010) also found beta activity to be significant for preference. Nevertheless, the quantity of this activity was quite low. It became clear that alpha and theta band activity were more notable and measurable via more electrodes than beta activity. This could mean that during the experiment of Boksem & Smidts (2015) and Khushaba et al. (2013) more beta activity was generated by the participants than during the experiment that was carried out for this study, since we used different stimuli for our experiment. For future research, it is recommended to include alpha and theta frequency bands to the analysis to test the predictive value of neural measurements for the preference and choice of wines.

As noted earlier in the introduction, humans are still involved with the interpretation of the data. This leads to the problem that interpretation is inevitably subjective and can result in bias (Kaptchuk, 2003). Gelman and Loken (2014) therefore correctly note that the researcher’s degree of freedom can lead to some problems. Multiple comparisons are possible, which could easily lead to “fishing” for results. The problem is that researchers are often not aware of this problem, and that “fishing” is happening without being aware of it. The problem of these multiple analyses is also called the garden of forking paths or p-hacking, although the “fishing” expedition is not only possible with analyses that deliver p-values. Linear models do not necessarily give p-values, but could also be used for “fishing”. Choices of main effects or interactions could already influence results and multiple combinations are possible. It is noted that especially in the field of psychology, including neuropsychology which is used for neuromarketing, the garden of forking paths is entered (Gelman & Loken, 2014). For example, a researcher using EEG first has to choose the number of electrodes that are going to be used. Furthermore, during the analysis, multiple analyses are possible and one could choose to use the data of just one of the electrodes but also of all the electrodes. This could possibly lead to problems in reproducibility. Since, there are more articles that imply that alpha and theta activity are predictors for preference than there are articles that stress for beta activity being a predictor, it could be that the researcher’s degree of freedom influenced some of the outcomes of the articles without the researcher being aware of the problem. Nevertheless, it appears that articles in top psychology journals which are suffering from the problem are published (Gelman & Loken, 2014). This could have major implications for the field, since articles could be mistrusted and caution is needed when reading articles. For researchers, it is important to be aware of the problem, to avoid “fishing” for results and to improve the quality of published articles (Gelman & Loken, 2014).

Combining all the above findings, future research is recommended which recognizes the following: 1. the attribution substitution hypothesis, 2. focuses next to beta on alpha and theta activity, and 3. limits the researcher’s degree of freedom. As mentioned above, the attribution substitution heuristic could be prevented by providing participants with descriptions of the used terms during the experiment. Furthermore, for each wine questions would be added which assess if participants liked the wine based on its smell and taste. Participants give a rating from 1, very bad, to 6, excellent, about smell and taste independently after the smell and taste procedure. Furthermore, it is recommended to add questions assessing the preference of the wines based on taste and smell. During the smell and taste procedure, EEG will be recorded. Analysis of the EEG signal will focus on alpha, beta, and theta activity. Furthermore, it is important to state clear hypotheses to make analysis of the data as clear and straightforward as possible to avoid confusion by the multiple analyses available and avoid eventually the problem of "fishing" for results. This is a recommendation that holds for the whole field, since being aware of the researcher's degree of freedom is already a step forward in avoiding problems coming with it.

References

Annett, M. (1970). A classification of hand preference by association analysis. *British journal of psychology*, *61*, 303-321.

Ariely, D., Berns, G. S. (2010). Neuromarketing: the hope and hype of neuroimaging in business. *Nature Reviews Neuroscience, 11*, 284-292. doi: 10.1038/nrn2795

Banks, G., Overton, J. (2010). Old world, new world, third world? Reconceptualising the worlds of wine. *Journal of Wine Research, 21*, 57-75. doi: 10.1080/09571264.2010.495854

Baste, U., Biele, G., Heekeren, H. R., Fiebach, C. J. (2010). How the brain integrates costs and benefits during decision making. *Proceedings of the National Academy of Sciences, 107*, 21767-21772. doi: 10.1073/pnas.0908104107

Boksem, M. A. S., Smidts, A. (2015). Brain responses to movie-trailers predict individual preferences for movies and their population-wide commercial success. *Journal of Marketing Research, 52,* 482-492. doi: 10.1509/jmr.13.0572

Calvert, G. A., Brammer, M. J. (2012). Predicting consumer behavior: using novel mind-reading approaches. *IEEE Pulse, 3,* 38-41. doi: 10.1109/MPUL.2012.2189167

Castriota-Scanderberg, A., Hagberg, G. E., Cerasa, A., Committeri, G., Galati, G., Patria, F., Pitzalis, S., Caltagirone, C., Frackowiak, R. (2005). The appreciation of wine by sommeliers: a functional magnetic resonance study of sensory integration. *Neuroimage, 25,* 570-578. doi: 10.1016/j.neuroimage.2004.11.045

Cohen, M. X. (2014). Analyzing neural time series data: theory and practice. Cambridge: MIT Press.

Damasio, A. R., Everitt, B. J., & Bishop, D. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex [and discussion]. *Philosophical Transactions of the Royal Society B: Biological Sciences, 351*, 1413-1420. doi: 10.1098/rstb.1996.0125

D'Argembeau, A., Stawarczyk, D., Majerus, S., Collette, F., Van der Linden, M., Feyers, D., Maquet, P., Salmon, E. (2010). The neural basis of personal goal processing when envisioning future events. *Journal of Cognitive Neuroscience, 22,* 1701–1713.

Deppe, M., Schwindt, W., Kugel, H., Plassmann, H., & Kenning, P. (2005). Nonlinear responses within the medial prefrontal cortex reveal when specific implicit information influences economic decision making. *Journal of Neuroimaging, 15,* 171-182.

Dijksterhuis, A. (2004). Think different: the merits of unconscious thought in preference development and decision making. *Journal of Personality and Social Psychology, 87,* 586-598. doi: 10.1037/0022-3514.87.5.586

Gelman, A., Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models.* Cambridge, UK: Cambridge University Press.

Gelman, A., Loken, E. (2014). The garden of forking paths: Why multiple comparisons can be a problem, even when there is no "fishing expedition" or "p-hacking" and the research hypothesis was posited ahead of time. *American scientist, 102,* 460-469. doi: 10.1511/2014.111.460

Heekeren, H. R., Marrett, S., Bandettini, P. A., Ungerleider, L. G. (2004). A general mechanism for perceptual decision-making in the human brain. *Nature, 431,* 859 – 862. doi: 10.1038/nature02966

Ishihara, S. (1976). *Test for colour blindness, 38 plates edition*. Tokyo: Kanehara Shuppen Co.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, and D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment, 49*. New York: Cambridge University Press.

Kaptchuk, T. J. (2003). Effect of interpretative bias on research evidence. *BMJ, 326,* 1453-1455. doi: 10.1136/bmj.326.7404.1453

Khushaba, R. N., Wise, C., Kodagoda, S., Louviere, J., Kahn, B. E., Townsend, C. (2013). Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking. *Expert Systems with Applications, 40,* 3803-3812. doi 10.1016/j.eswa.2012.12.095

Kringelbach, M. I. (2005). The human orbitofrontal cortex: linking reward to hedonic experience. *Nature reviews neuroscience, 6*, 691-702. doi: 10.1038/nrn1747

Kringelbach, M. I., O'Doherty, J., Rolls, E. T., Andrews, C. (2003). Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness. *Cerebral cortex*, *13*, 1064-1071. doi: 10.1093/cercor/13.10.1064

Plassmann, H., Ramsoy, T. Z., Milosavljevic, M. (2012). Branding the brain: A critical review and outlook. *Journal of Consumer Psychology, 22*, 18 – 36. doi: 10.1016/j.jcps.2011.11.010

Rilling, J. K., King-Cases, B., Sanfey, A. G. (2008). The neurobiology of social decision-making. *Current Opinion in Neurobiology, 18,* 159-165.

Shipley, M. T., Ennis, M. (1996). Functional organization of olfactory system. *Developmental Neurobiology*, *30*, 123-176. doi: 10.1002/(SICI)1097-4695(199605)30:1<123::AID-NEU11>3.0.CO;2-N

Siong Soon, C., Brass, N., Heinze, H. J., Haynes, J. D. (2008). Unconscious determinants of free decision in the human brain. *Nature neuroscience, 11,* 543 – 545. doi: 10.1038/nn.2112

Smidts, A., Hsu, M., Sanfey, A. G., Boksem, M. A. S., Ebstein, R. B., Huettel, S. A., Kable. J. W., Karmarkar, U. R., Kitayama, S., Knutson, B., Liberzon, I., Lohrenz, T., Stallen, M., Yoon, C. (2014). Advancing consumer neuroscience. *Marketing letters, 25,* 257-267. doi: 10.1007/s11002-014-9306-1

Spector, A. C. (2000). Linking gustatory neurobiology to behavior in vertebrates. *Neuroscience & Biobehavioral Reviews, 24,* 391 – 416. doi: 10.1016/S0149-7634(00)00013-0

Summerfield, C., Mangels, J. A. (2005). Coherent theta-band EEG activity predicts iten-context binding during encoding. *Neuroimage, 24,* 692-703. doi: 10.1016/j.neuroimage.2004.09.012

Szalma, J. L., Hancock, P. A. (2011). Noise effects on human performance: A meta-analytic synthesis. *Psychological Bulletin, 137,* 682-707. doi: 10.1037/a0023987

Vecchiato, G., Toppi, J., Astolfi, L., De Vico Fallani, F., Cincotti, F., Mattia, D., Bez, F., Babiloni, F. (2011). Spectral EEG frontal asymmetries correlate with the experienced pleasantness of TV commercial advertisements. *Medical & Biological Engineering & Computing, 49,* 579-583. doi: 10.1007/s11517-011-0747-x

Werkle-Berger, M., Muller, V., Li, s., Lindenberger, U. (2006). Cortical EEG correlates of successful memory encoding: implications for lifespan comparisons. *Neuroscience & Biobehavioral Reviews, 30,* 839-854. doi: 10.1016/j.neubiorev.2006.06.009

Wilson, T. D., Schooler, J. W. (1991). Thinking too much: introspection can reduce the quality of preferences and decisions. *Journal of Personality and Social Psychology, 60,* 181-192. doi: 10.1037/0022-3514.60.2.181

Yoon, C., Gonzalez, R., Bechara, A., Berns, G. S., Dagher, A. A., Dubé, L., Huettel, S. A., Kable, J. W., Liberzon, I., Plassmann, H., Smidts, A., Spence, C. (2012). Decision neuroscience and consumer decision making. *Marketing Letters, 23,* 473-485. doi: 10.1007/s11002-012-9188-z

Appendix I

A detailed description of the used task

During the whole task, the letter type of all the text was Arial, the colour of the letters was black, and the background of the screen was white. At first, the title of the experiment was shown in font size 32, and for 5000 ms. The title was: “VIEWING, SMELLING, AND TASTING FOUR WINES (TASK1)”. Next, the general instructions about the task were given in font size 24. The explanation was: “In the current task, you will be asked to examine different features of four different wines. 1. You will be asked to rinse your mouth for 5 seconds and then wait/rest for 15 seconds. 2. A glass of wine is presented in front of you for 20 seconds and you are asked to appreciate its colour. 3. The glass will be rotated for 3 seconds and you will smell the wine for 15 seconds. 4. You will be asked to taste the wine. Take a small sip of the wine, move it around in your mouth. Keep the wine for 5 seconds in your mouth and swallow it. Breathe out normally for a maximum of 7 seconds. 5. Rate the wine on its colour, smell, and taste, and give an overall rating of the wine, all on a scale from 1 to 10. 6. Indicate in what price category the wine should be located (3-5, 6-8, 9-11, 16-21, 22-27 euros). This procedure will be carried out for four wines. PRESS THE SPACE BAR TO CONTINUE”.

The description of the task will now follow the different components of the task in chronological order. These components are: 1. Wine selection, 2. Water drinking, 3. Colour judgement procedure, 4. Smell procedure, 5. Taste procedure, 6. Judgement colour, 7. Judgement smell, 8. Judgement taste, 9. Overall rating, 10. Judgement price, and 11. Judgement label.

1. Wine selection. To mark the beginning of the tasting procedure of a wine, the following lines were shown: “The experimenter (NOT YOU) should now indicate what wine will be judged. All materials have to be ready for starting the procedure”. To continue to the wine tasting procedure, the space bar was pressed by the experimenter to make sure the next wine was selected correctly.
2. Water drinking. The tasting procedure started with drinking water. This was indicated by the following line: “Rinse you mouth for 5 seconds and then wait/rest for 15 seconds”. This was shown for 20000 ms.
3. Colour judgement procedure. Participants were instructed to judge the colour of the wine. The next line of text shows the instructions shown on the screen: “A

glass of wine is presented in front of you for 20 seconds and you are asked to appreciate its colour”. This text was also shown for 20000 ms.

4. Smell procedure. For another 20000 ms, the instructions to smell the wine were given. The explanation was given by the following text: “The glass will be rotated for 3 seconds and you will smell the wine for 15 seconds”.
5. Taste procedure. Participants were instructed to taste wine using the following lines of text: “You should now taste the wine. Take a small sip of the wine, move it around in your mouth. Keep the wine for five seconds in your mouth and swallow it. Breathe out normally for a maximum of 7 seconds”. This screen was shown for 30000 ms.
6. Judgement colour. The colour of the wine was now requested to be indicated by making a distinction between the body of the wine. A definition of these terms was found in the instructional paper that was read by the participant during the preparation of the EEG cap. The colour judgement was indicated by the text: “Indicate your judgement of the colour, 1 = light-bodied, 2 = medium-bodied, 3 = full-bodied. Use the corresponding keys on the keyboard. PRESS THE APPROPRIATE KEY TO CONTINUE”.
7. Judgement smell. Participants had to indicate the judgement of the smell of the wines next. Judgements were made on basis of the written description of different scents in the instructional paper. The following text displays the text used in the task: “Indicate your judgement of the smell, 1 = fruity, 2 = flower/herb, 3 = oak/smoky, 4 = earthy, 5 = cork, 6 = flawed. Use the corresponding keys on the keyboard. If you have no idea press the space bar. PRESS THE APPROPRIATE KEY TO CONTINUE”.
8. Judgement taste. The participants now had to judge the taste of the wine. This was indicated by the following text: “Indicate the dominant taste, 1 = full-bodied, 2 = alcoholic, 3 = acid, 4 = sapid, 5 = tannic, 6 = sweet. Use the corresponding keys on the keyboard. If you have no idea press the space bar. PRESS THE APPROPRIATE KEY TO CONTINUE”. The used definitions of the different tastes were described in the instructional paper that was read during the preparation of the EEG cap.
9. Overall rating. The overall rating of the wine could be indicated by using a Likert scale, ranging from 1, very bad, to 6, excellent. The following text was used in the task: “Indicate now your overall rating of the wine, 1 = very bad, 2 = bad, 3 =

medium, 4 = good, 5 = very good, 6 = excellent. Use the corresponding keys on the keyboard. PRESS THE APPROPRIATE KEY TO CONTINUE”.

10. Judgement price. This question was to indicate in which price category the wine should be located. This was shown by the following text: “Indicate now in what price category the wine should be located (1: 3-5, 2: 6-8, 3: 9-11, 4: 12-15, 5: 16-21, 6: 22-27 euros). PRESS THE APPROPRIATE KEY TO CONTINUE”.
11. Judgement label. The last question of the loop was to rate the label of the wine. The following text was shown: “Indicate your rating of the label of the wine, 1 = very bad, 2 = bad, 3 = medium, 4 = good, 5 = very good, 6 = excellent. Use the corresponding keys on the keyboard. PRESS THE APPROPRIATE KEY TO CONTINUE”.

After the first, second and third wine, the procedure was started again from the point at which the tasting procedure was indicated.

Appendix II

Wine Questionnaire

Date: 26-10-2016

Name Participant: Progressive Number Assigned ☐

Name	Surname	
Age	Nationality	Gender Male ☐ Female ☐
Education level ☐ Bachelor; ☐ Master; ☐ Graduated; ☐ PhD student; ☐ Post Doc; ☐ University employee; ☐ professor ☐ Other_______________________________		

N.	Question
1	Did you ever drink wine before? YES ☐ NO ☐ (If No you cannot participate)
2	When was the last time you drank wine? ☐ Yesterday; ☐ Last week; ☐ Last month; ☐ Last 6 months; ☐ 1 year ago; ☐ 2-5 years ago
3	How frequently do you normally drink wine? ☐ Once in two months; ☐ Once a month; ☐ Once a week; ☐ More than once a week; ☐ Daily
4	Under what circumstances do you drink wine (You may choose more than one option). ☐ With meals at home ☐ With meals at restaurant ☐ With meals at wine bar/ winery ☐ Gathering with friends ☐ Gathering with families ☐ In the evening when watching TV alone (Without meals) ☐ Celebration of special occasion ☐ Others, Please explain______________________________
5	How would you classify your wine knowledge? ☐ Amateur; ☐ Basic knowledge; ☐ Expert; ☐ Professional

6	What are your criteria for choosing wine? (You may choose more than one answer) □ Price; □ Quality ; □ Grape variety; □ Wine type; □ Bottle Design; □ Label □ Familiarity with the brand; □ Recommendation of friend(s)/relative(s)
7	Places where you mostly purchased wine during the last year? (You may choose more than one option) □ Supermarket (Albert Heijn, Jumbo, Coop, etc.); □ Discount Store (Lidl, Aldi, etc.); □ Winery; □ Online wine shop ; □ Others (explain)_________________________________
8	How much do you spend on average when you buy a bottle of wine? (You may choose more than one answers) □ 3-5 euros; □ 6-9 euros; □ 10-15 euros ; □ 15-20; □ 21-27; □ 28-34; □ 35-45; □ more than 50
9	When you buy wine how important is the "Country of origin"? □ Not important □ Not very important; □ Important; □ Very important; □ Extremely important
10	Indicate if you have ever tasted wine from any of the countries below: □Africa; □ Albania; □ Argentina; □ Armenia; □ Australia; □ USA (California); □ China; □ Chili; □ France; □ Georgia; Germany; □ Greece; □ Italy; □ New Zeeland; □ Portugal; □ Spain; □ South Africa; □ Other____________________________________
12	Could please rank the countries that you chose before from the best to the worst, according to your opinion (if you do not have one leave it blank):
13	When you buy wine, how important is the *type of grape* (e.g., Cabernet Sauvignon, Merlot, Syrah, Montepulciano, etc.) to you? □ Not important; □ Not very important; □ Important; Very important; □ Extremely important
14	When you buy wine, how important is the *wine type* (e.g., Chianti, Bordeaux, Amarone, Gewürztraminer, etc.)? □ Not important; □ Not very important; □ Important; □ Very important; □ Extremely important
15	When you buy wine, how important is the *brand* or the *producer* (e.g., Masi, Joseph Drouhin, Mommessin, Moët & Chandon, etc.)? □ Not important; □ Not very important; □ Important; □ Very important; □ Extremely important
16	When you buy wine, how important is the label (color, size, drawing, etc.)? (See Pag. 3) □ Not important; □ Not very important; □ Important; □ Very important; □ Extremely important
17	When you buy wine, how important is the design of the bottle? (See Pag. 3) □ Not important; □ Not very important; □ Important; □ Very important; □ Extremely important
18	Do you prefer a traditional bottle or a particular one (e.g., all colored, funny drawing, Swarovski, metallic, particular shape, etc.): □ YES (Traditional) □ NO (Particular)

19	How important are *advertisements* to you for buying wine (incl. printed, online and broadcasting media)? ☐ Not important; ☐ Not very important; ☐ Important; ☐ Very important; ☐ Extremely important
20	How important are the *opinions/suggestions from your family/friends/ wine shop's staff*? ☐ Not important; ☐ Not very important; ☐ Important; ☐ Very important; ☐ Extremely important
21	When you buy wine, how important is your own knowledge about the wine? ☐ Not important; ☐ Not very important; ☐ Important; ☐ Very important; ☐ Extremely important

http://www.montemaggiore.com/?method=blog.blogDrilldown&blogEntryID=2C240DC5-EDDA-2161-BC85-E879C25A2B78&originalMarketingURL=blog/All-you-need-to-know-about-Wine-Bottles

http://natashamonnereau.com/what-a-wine-bottle-can-tell-you-about-a-wine/

https://www.foodwise.marketing/trenduri-in-packaging-in-2016/

http://bestcreativity.com/blog/it/le-migliori-etichette-bottiglie-del-2013/b/

http://bestcreativity.com/blog/it/le-migliori-etichette-bottiglie-del-2013/p/

Appendix III

Reproduceable data analysis report

Syntax master thesis Janouk Kosters

Data analysis

Janouk Kosters

```
library(tidyverse)

## Warning: package 'tidyverse' was built under R version 3.3.3

## Loading tidyverse: ggplot2
## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr
## Loading tidyverse: dplyr

## Warning: package 'ggplot2' was built under R version 3.3.3

## Warning: package 'tibble' was built under R version 3.3.3

## Warning: package 'purrr' was built under R version 3.3.3

## Conflicts with tidy packages ------------------------------------------
---

## filter(): dplyr, stats
## lag():    dplyr, stats

library(rstanarm)

## Warning: package 'rstanarm' was built under R version 3.3.3

## Loading required package: Rcpp

## rstanarm (Version 2.14.1, packaged: 2017-01-16 18:47:11 UTC)

## - Do not expect the default priors to remain the same in future rstanarm
versions.

## Thus, R scripts should specify priors explicitly, even if they are just
the defaults.

## - For execution on a local, multicore CPU with excess RAM we recommend c
alling

## options(mc.cores = parallel::detectCores())

library(GGally)

## Warning: package 'GGally' was built under R version 3.3.3
```

```
##
## Attaching package: 'GGally'

## The following object is masked from 'package:dplyr':
##
##     nasa

library(nlme)

##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##     collapse

library(dplyr)
library(gmodels)

## Warning: package 'gmodels' was built under R version 3.3.3

library(devtools)
install_github("schmettow/mascutils")

## Skipping install of 'mascutils' from a github remote, the SHA1 (c4edf1b6
) has not changed since last install.
##   Use `force = TRUE` to force installation

install_github("schmettow/bayr")

## Skipping install of 'bayr' from a github remote, the SHA1 (e4e03959) has
not changed since last install.
##   Use `force = TRUE` to force installation

library(mascutils)
library(bayr)

##
## Attaching package: 'bayr'

## The following objects are masked from 'package:nlme':
##
##     fixef, ranef

## The following objects are masked from 'package:rstanarm':
##
##     fixef, ranef

## The following objects are masked from 'package:stats':
##
##     coef, predict
```

Set working directory, load data and log transformations of the EEG measurements

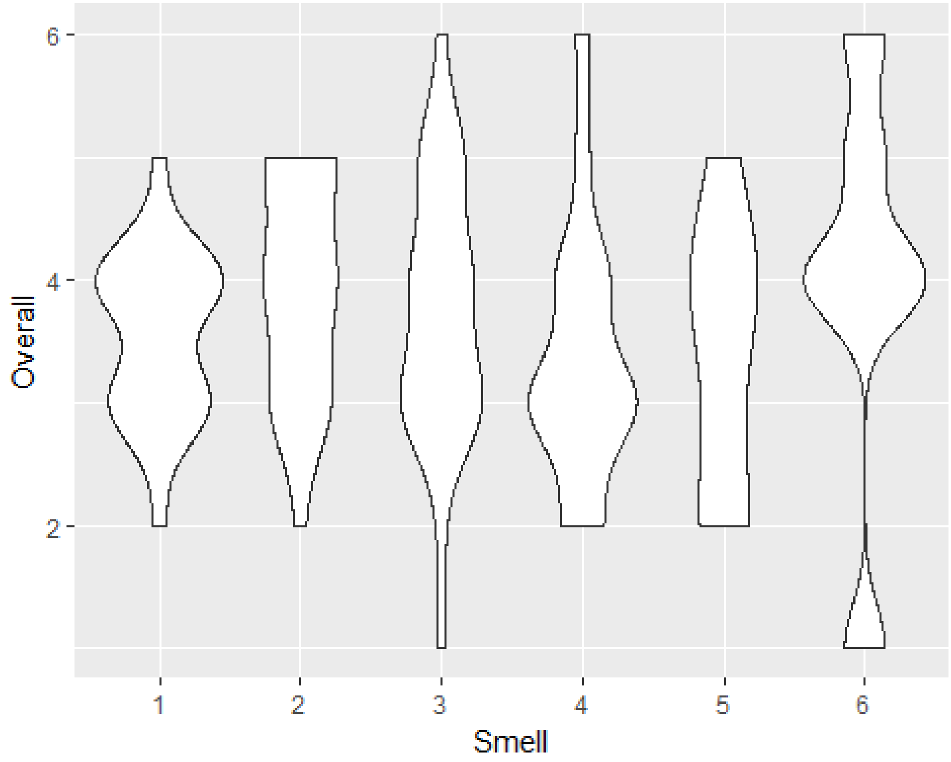
At first we check in which working directory we are currently working. Then we change the working directory to the preferred directory by using the setwd() command. Additionally, three dataframes are made. The first dataframe, EEG_num, recognizes the data of the colour, smell, and taste judgement as numeric data which can be used for plots. In the second dataframe, EEGdata, the variables colour, smell, and taste are transformed to factors with different levels since the data represents different answer categories. Furthermore, log transformations are performed on the EEG values. In the third dataframe, EEGdata_NA, missing values are deleted and this dataframe is used for analysis in which the variables should have the same length.

```
getwd()

## [1] "C:/Users/Janouk/Documents/Uni/Jaar 4/Master thesis"

setwd('C:/Users/Janouk/Documents/Uni/Jaar 4/Master thesis')

EEGdata_num <-
  readxl::read_excel("Data master thesis.xlsx", 1)

EEGdata <-
  EEGdata_num %>%
  mutate(Colour = as.factor(Colour),
         Smell = as.factor(Smell),
         Taste = as.factor(Taste),
         logSmell_FCz = log(Smell_FCz + 1),
         logTaste_FCz = log(Taste_FCz + 1),
         logBaseline_FCz = log(Baseline_FCz + 1),
         Smell_corrected = logSmell_FCz - logBaseline_FCz,
         Taste_corrected = logTaste_FCz - logBaseline_FCz)

EEGdata_NA <- na.omit(EEGdata)
```

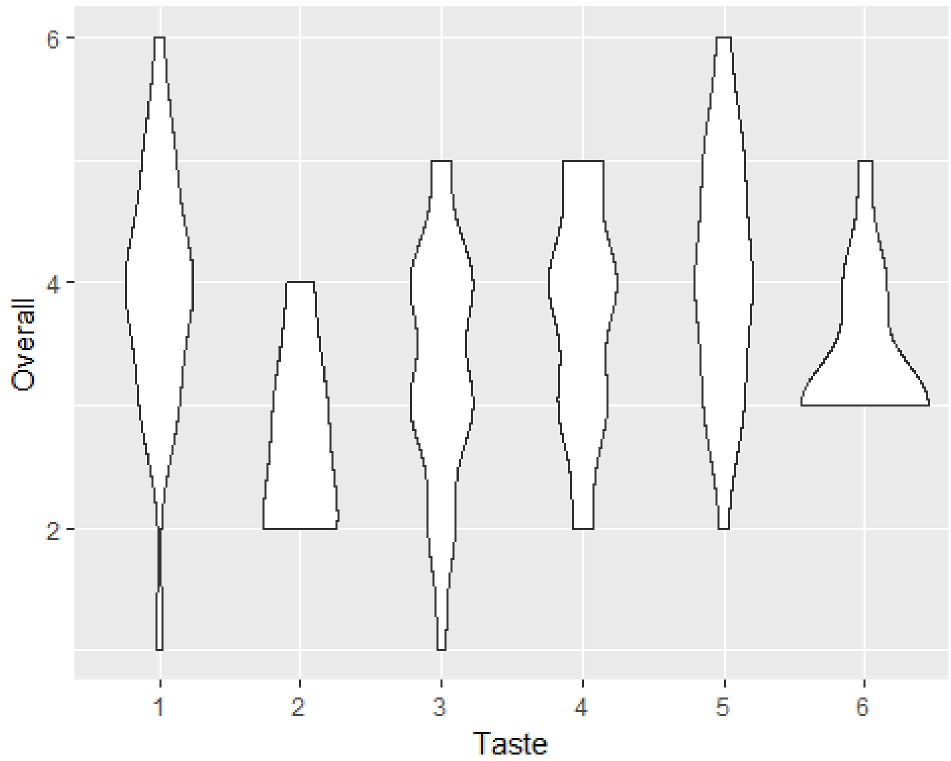
Plotting the data

Taking a first look at the data by computing violion plots and boxplots. This gives an idea of how the data is distributed.

```
EEGdata %>%
  ggplot(aes(x = Smell, y = Overall)) +
  geom_violin()
```

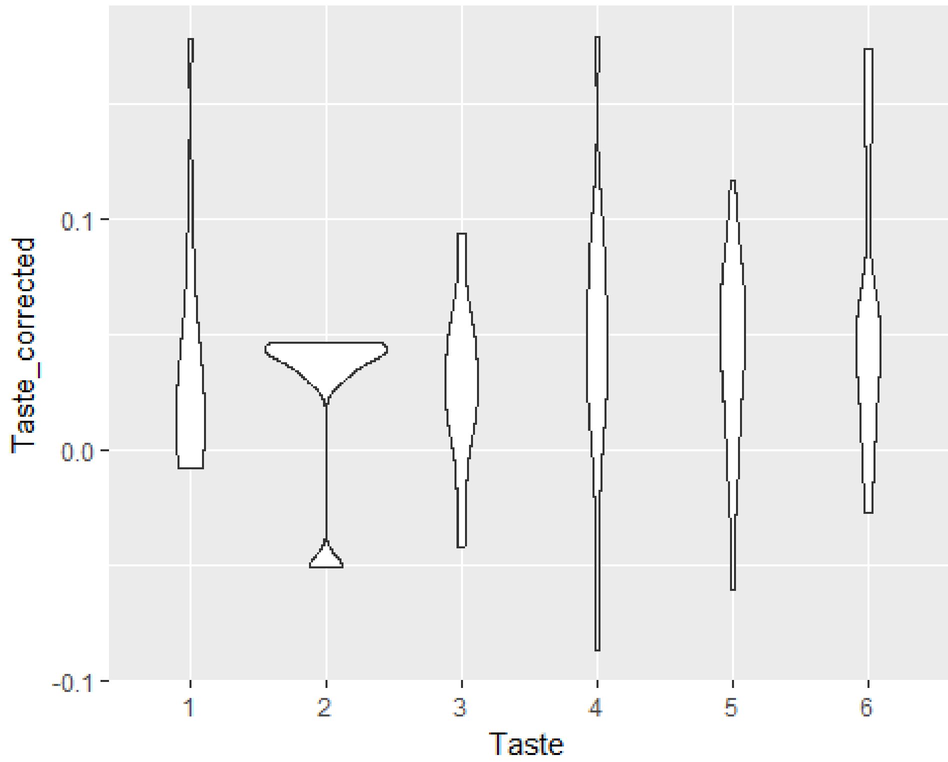



```
EEGdata %>%
  ggplot(aes(x = Taste, y = Overall)) +
  geom_violin()
```

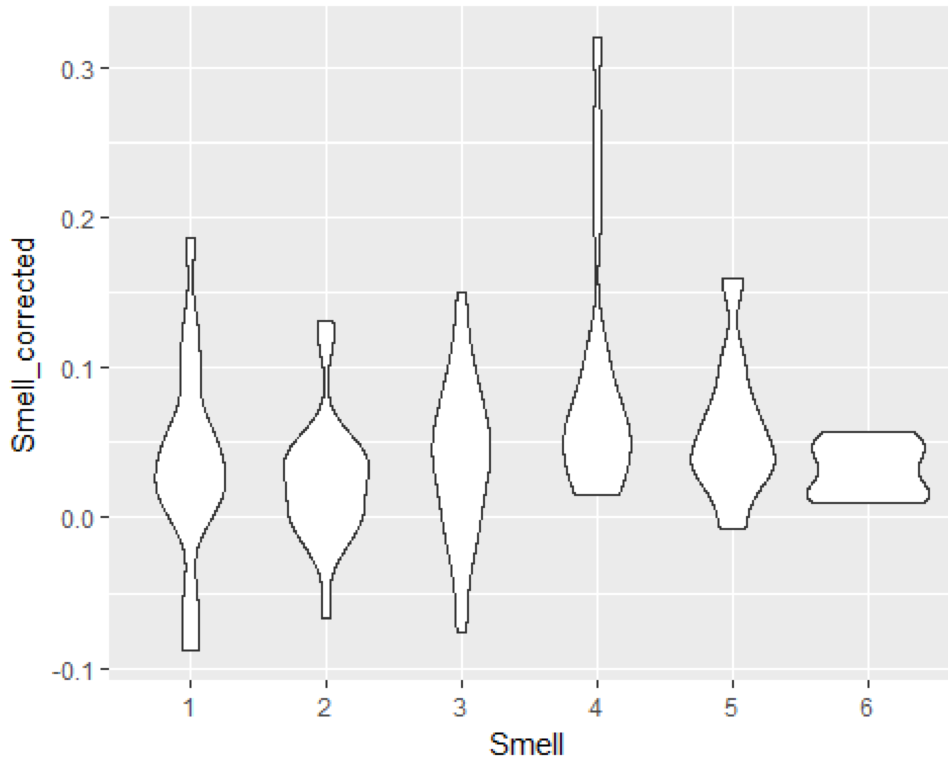



```
EEGdata %>%
  ggplot(aes(x = Taste, y = Taste_corrected)) +
  geom_violin()
```

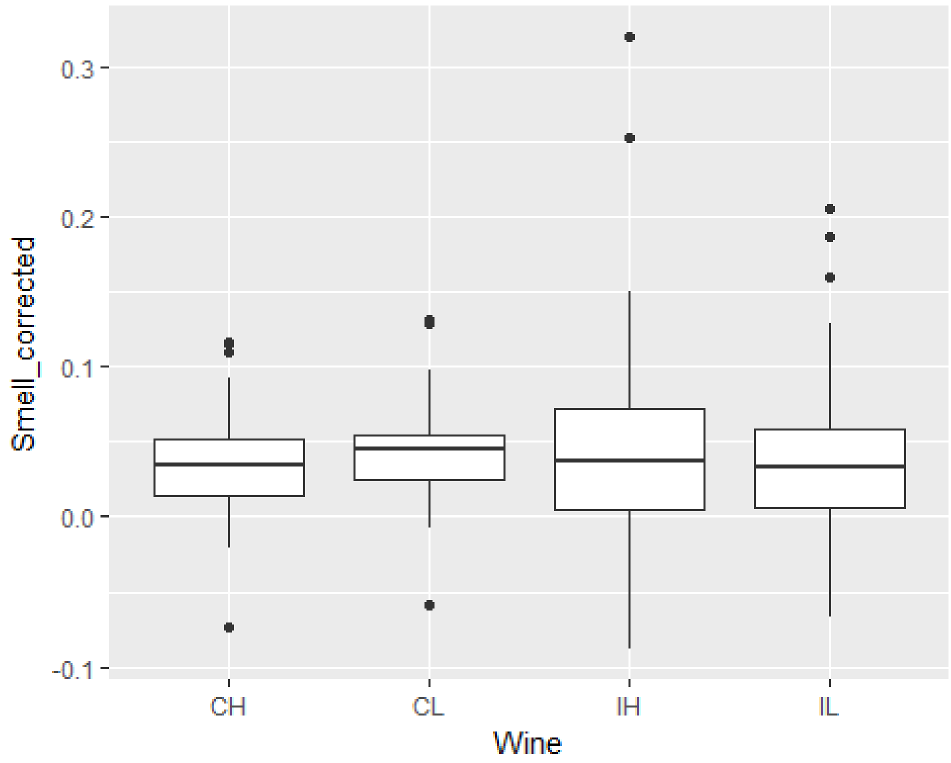
```
## Warning: Removed 1 rows containing non-finite values (stat_ydensity).
```



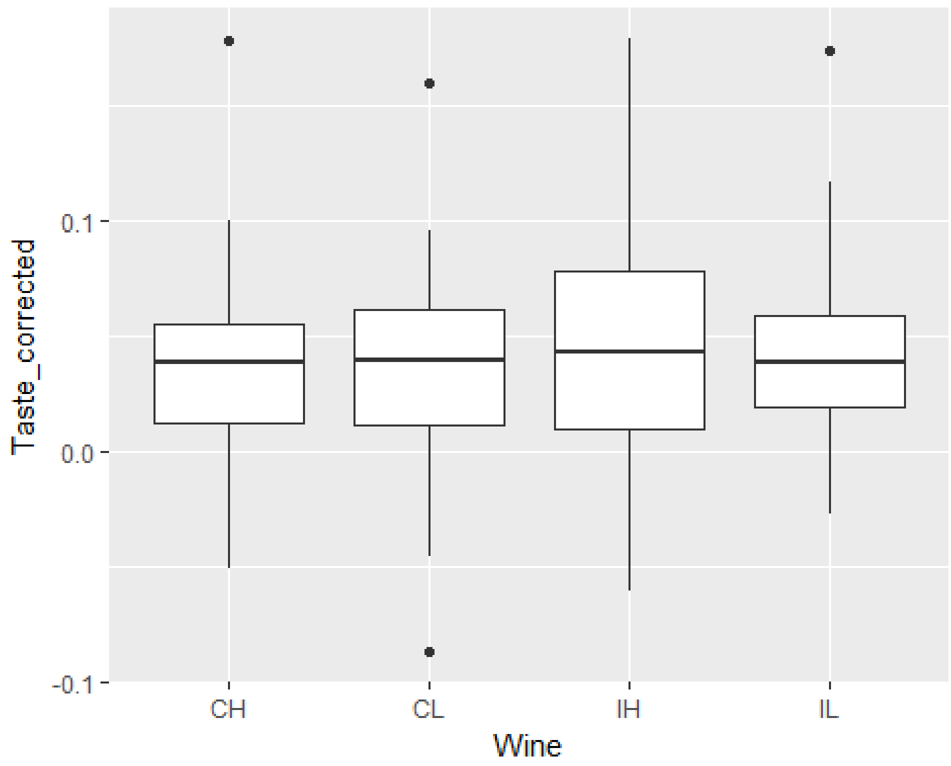

```
EEGdata %>%
  ggplot(aes(x = Smell, y = Smell_corrected)) +
  geom_violin()
## Warning: Removed 1 rows containing non-finite values (stat_ydensity).
```



```
EEGdata %>%
  ggplot(aes(x = Wine, y = Smell_corrected)) +
  geom_boxplot()

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
```




```
EEGdata %>%
  ggplot(aes(x = Wine, y = Taste_corrected)) +
  geom_boxplot()

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
```



Mean age and standard deviation methods

The mean age and standard deviation are computed separately for male and female participants. The results of this analysis can be found in the participants section of the method on page 6 of this master thesis.

```
EEGdata %>%
  group_by(Gender) %>%
  summarize(mean_Age = mean(Age), sd_Age = sd(Age)) %>%
  arrange(Gender)

## # A tibble: 2 × 3
##   Gender mean_Age   sd_Age
##    <chr>    <dbl>    <dbl>
## 1 Female    27.30 4.642060
## 2   Male    26.25 3.371213
```

Smell, taste, and price judgement.

The distribution of the categories used to describe the smell and taste of the wines and the price categories to which the wines were assigned are displayed with the following tables and graphs. The analyses are displayed on page 12 - 16 in the results section of this masterthesis. First, tables are computed in which the frequency of the given answers for the smell, taste and price of the wines are displayed. The table for the smell can be found as table 1 on page 13. Table 2 on page 14 displays the outcomes for the taste and table 3 on page 15 for the price judgement. Second, histograms are created in which the answers of the smell, taste, and price judgements are displayed for the four different wines. The histograms can be found as figure 3, 4, and 5 on pages 13, 14, and 16 of the master thesis.

```
CrossTable(EEGdata$Smell, EEGdata$Wine)

## 
## 
##    Cell Contents
## |-------------------------|
## |                       N |
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |         N / Table Total |
## |-------------------------|
## 
## 
## Total Observations in Table:  104 
## 
## 
##              | EEGdata$Wine 
## EEGdata$Smell |        CH |        CL |        IH |        IL | Row Tota
l |
## -------------|-----------|-----------|-----------|-----------|---------
--|
##            1 |         5 |         5 |         4 |         6 |        2
0 |
##              |     0.000 |     0.000 |     0.200 |     0.200 |          
|
##              |     0.250 |     0.250 |     0.200 |     0.300 |     0.19
2 |
##              |     0.192 |     0.192 |     0.154 |     0.231 |          
|
##              |     0.048 |     0.048 |     0.038 |     0.058 |          
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##            2 |         7 |         8 |         2 |         7 |        2
4 |
##              |     0.167 |     0.667 |     2.667 |     0.167 |          
|
##              |     0.292 |     0.333 |     0.083 |     0.292 |     0.23
1 |
##              |     0.269 |     0.308 |     0.077 |     0.269 |          
|
##              |     0.067 |     0.077 |     0.019 |     0.067 |          
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##            3 |         9 |         5 |        10 |         4 |        2
8 |
##              |     0.571 |     0.571 |     1.286 |     1.286 |          
|
##              |     0.321 |     0.179 |     0.357 |     0.143 |     0.26
```

```
9 |
##                |     0.346 |     0.192 |     0.385 |     0.154 |
|
##                |     0.087 |     0.048 |     0.096 |     0.038 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##              4 |         3 |         5 |         7 |         2 |        1
7 |
##                |     0.368 |     0.132 |     1.779 |     1.191 |
|
##                |     0.176 |     0.294 |     0.412 |     0.118 |     0.16
3 |
##                |     0.115 |     0.192 |     0.269 |     0.077 |
|
##                |     0.029 |     0.048 |     0.067 |     0.019 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##              5 |         2 |         1 |         2 |         4 |
9 |
##                |     0.028 |     0.694 |     0.028 |     1.361 |
|
##                |     0.222 |     0.111 |     0.222 |     0.444 |     0.08
7 |
##                |     0.077 |     0.038 |     0.077 |     0.154 |
|
##                |     0.019 |     0.010 |     0.019 |     0.038 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##              6 |         0 |         2 |         1 |         3 |
6 |
##                |     1.500 |     0.167 |     0.167 |     1.500 |
|
##                |     0.000 |     0.333 |     0.167 |     0.500 |     0.05
8 |
##                |     0.000 |     0.077 |     0.038 |     0.115 |
|
##                |     0.000 |     0.019 |     0.010 |     0.029 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##   Column Total |        26 |        26 |        26 |        26 |       10
4 |
##                |     0.250 |     0.250 |     0.250 |     0.250 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##
##
```

```r
CrossTable(EEGdata$Taste, EEGdata$Wine)
```

```
##
##
##    Cell Contents
## |-------------------------|
## |                       N |
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |         N / Table Total |
## |-------------------------|
##
##
## Total Observations in Table:  104
##
##
##               | EEGdata$Wine
## EEGdata$Taste |        CH |        CL |        IH |        IL | Row Tota
l |
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             1 |         5 |         6 |         4 |         5 |        2
0 |
##               |     0.000 |     0.200 |     0.200 |     0.000 |
|
##               |     0.250 |     0.300 |     0.200 |     0.250 |     0.19
2 |
##               |     0.192 |     0.231 |     0.154 |     0.192 |
|
##               |     0.048 |     0.058 |     0.038 |     0.048 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             2 |         2 |         2 |         2 |         0 |
6 |
##               |     0.167 |     0.167 |     0.167 |     1.500 |
|
##               |     0.333 |     0.333 |     0.333 |     0.000 |     0.05
8 |
##               |     0.077 |     0.077 |     0.077 |     0.000 |
|
##               |     0.019 |     0.019 |     0.019 |     0.000 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             3 |         7 |         5 |         3 |         5 |        2
0 |
##               |     0.800 |     0.000 |     0.800 |     0.000 |
|
##               |     0.350 |     0.250 |     0.150 |     0.250 |     0.19
2 |
##               |     0.269 |     0.192 |     0.115 |     0.192 |
|
##               |     0.067 |     0.048 |     0.029 |     0.048 |
|
```

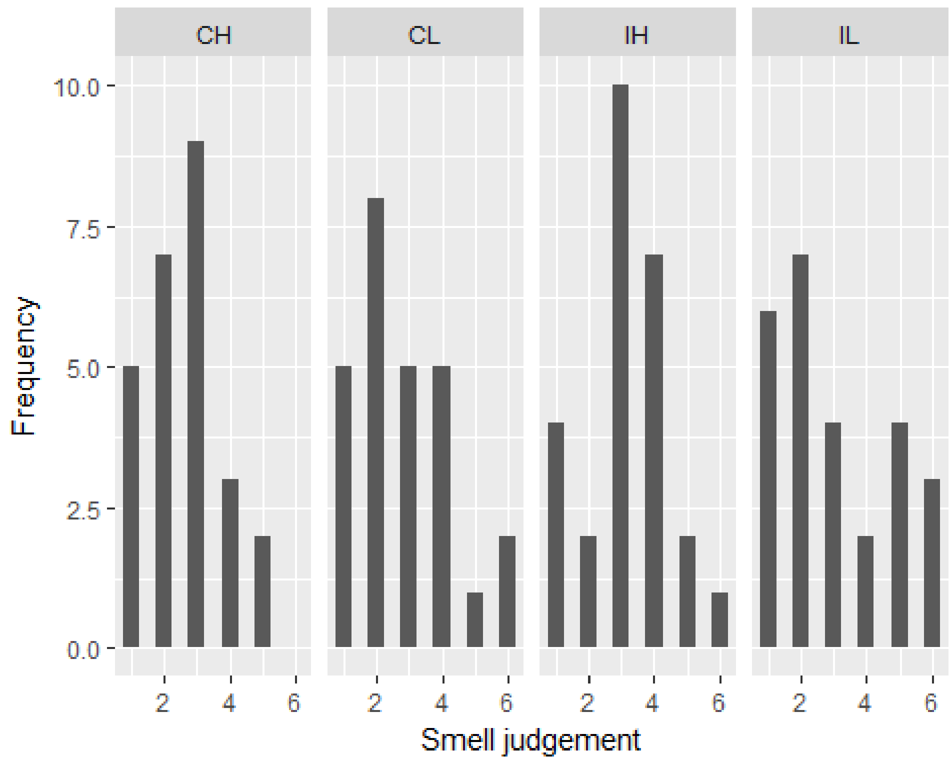
```
## --------------|-----------|-----------|-----------|-----------|---------
--|
##            4 |         2 |         7 |         6 |         3 |        1
8 |
##              |     1.389 |     1.389 |     0.500 |     0.500 |
|
##              |     0.111 |     0.389 |     0.333 |     0.167 |     0.17
3 |
##              |     0.077 |     0.269 |     0.231 |     0.115 |
|
##              |     0.019 |     0.067 |     0.058 |     0.029 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##            5 |         8 |         4 |        10 |         5 |        2
7 |
##              |     0.231 |     1.120 |     1.565 |     0.454 |
|
##              |     0.296 |     0.148 |     0.370 |     0.185 |     0.26
0 |
##              |     0.308 |     0.154 |     0.385 |     0.192 |
|
##              |     0.077 |     0.038 |     0.096 |     0.048 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##            6 |         2 |         2 |         1 |         8 |        1
3 |
##              |     0.481 |     0.481 |     1.558 |     6.942 |
|
##              |     0.154 |     0.154 |     0.077 |     0.615 |     0.12
5 |
##              |     0.077 |     0.077 |     0.038 |     0.308 |
|
##              |     0.019 |     0.019 |     0.010 |     0.077 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##  Column Total |        26 |        26 |        26 |        26 |       10
4 |
##              |     0.250 |     0.250 |     0.250 |     0.250 |
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##
##
```

```
CrossTable(EEGdata$Price, EEGdata$Wine)
```

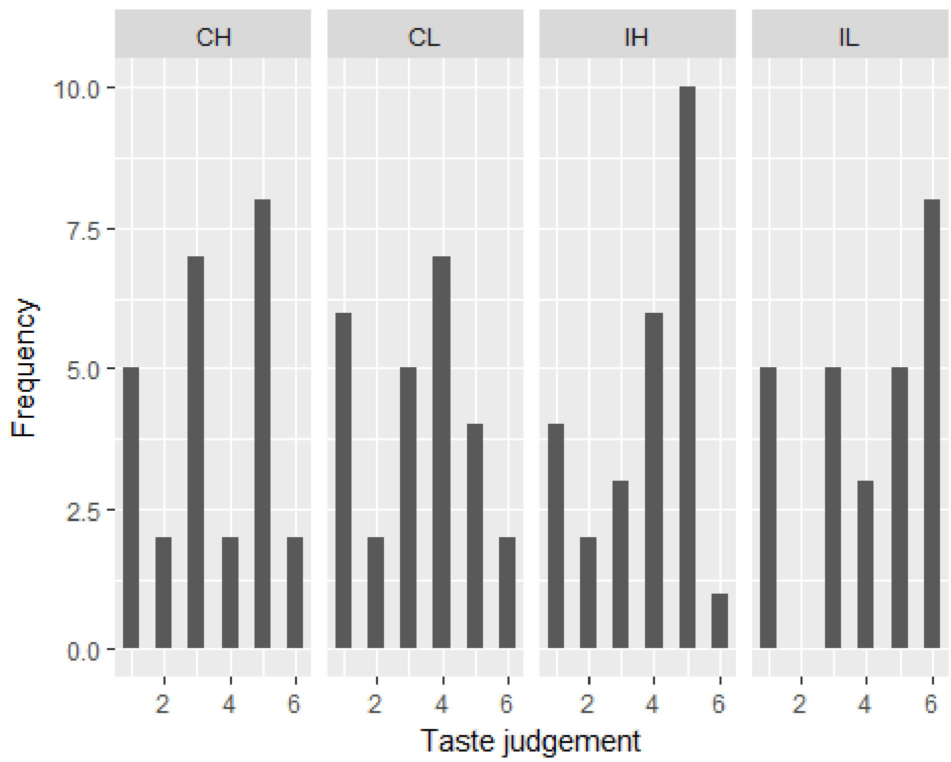
```
##
##
##    Cell Contents
## |-------------------------|
## |                       N |
```

```
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |         N / Table Total |
## |-------------------------|
##
##
## Total Observations in Table:  104
##
##
##               | EEGdata$Wine
## EEGdata$Price |        CH |        CL |        IH |        IL | Row Tota
l |
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             1 |         2 |         6 |         5 |         8 |        2
1 |
##               |     2.012 |     0.107 |     0.012 |     1.440 |          
|
##               |     0.095 |     0.286 |     0.238 |     0.381 |     0.20
2 |
##               |     0.077 |     0.231 |     0.192 |     0.308 |          
|
##               |     0.019 |     0.058 |     0.048 |     0.077 |          
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             2 |        10 |         8 |         7 |         9 |        3
4 |
##               |     0.265 |     0.029 |     0.265 |     0.029 |          
|
##               |     0.294 |     0.235 |     0.206 |     0.265 |     0.32
7 |
##               |     0.385 |     0.308 |     0.269 |     0.346 |          
|
##               |     0.096 |     0.077 |     0.067 |     0.087 |          
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             3 |         6 |         5 |         8 |         4 |        2
3 |
##               |     0.011 |     0.098 |     0.880 |     0.533 |          
|
##               |     0.261 |     0.217 |     0.348 |     0.174 |     0.22
1 |
##               |     0.231 |     0.192 |     0.308 |     0.154 |          
|
##               |     0.058 |     0.048 |     0.077 |     0.038 |          
|
## --------------|-----------|-----------|-----------|-----------|---------
--|
##             4 |         5 |         3 |         2 |         4 |        1
4 |
##               |     0.643 |     0.071 |     0.643 |     0.071 |          
```

```
|
##               |     0.357 |     0.214 |     0.143 |     0.286 |     0.13
5 |
##               |     0.192 |     0.115 |     0.077 |     0.154 |
|
##               |     0.048 |     0.029 |     0.019 |     0.038 |
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##             5 |         2 |         3 |         4 |         1 |         1
0 |
##               |     0.100 |     0.100 |     0.900 |     0.900 |
|
##               |     0.200 |     0.300 |     0.400 |     0.100 |     0.09
6 |
##               |     0.077 |     0.115 |     0.154 |     0.038 |
|
##               |     0.019 |     0.029 |     0.038 |     0.010 |
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##             6 |         1 |         1 |         0 |         0 |
2 |
##               |     0.500 |     0.500 |     0.500 |     0.500 |
|
##               |     0.500 |     0.500 |     0.000 |     0.000 |     0.01
9 |
##               |     0.038 |     0.038 |     0.000 |     0.000 |
|
##               |     0.010 |     0.010 |     0.000 |     0.000 |
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##  Column Total |        26 |        26 |        26 |        26 |        10
4 |
##               |     0.250 |     0.250 |     0.250 |     0.250 |
|
## -------------|-----------|-----------|-----------|-----------|---------
--|
##
##

EEGdata_num %>%
  ggplot(aes(x = Smell)) +
  geom_histogram(binwidth=.5, position="dodge") +
  facet_grid(. ~ Wine) +
  labs(x = "Smell judgement", y = "Frequency")
```

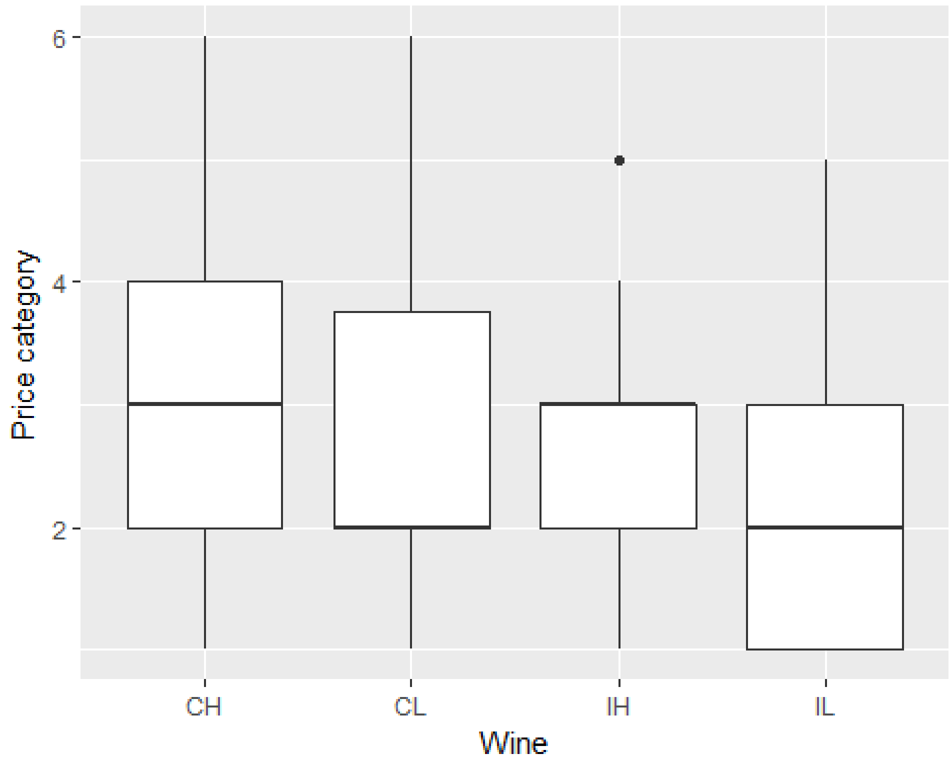



```
EEGdata_num %>%
  ggplot(aes(x = Taste)) +
  geom_histogram(binwidth=.5, position="dodge") +
  facet_grid(. ~ Wine) +
  labs(x = "Taste judgement", y = "Frequency")
```




```
EEGdata_num %>%
  ggplot(aes(x = Wine, y = Price)) +
```

```
  geom_boxplot() +
  labs(y = "Price category")
```

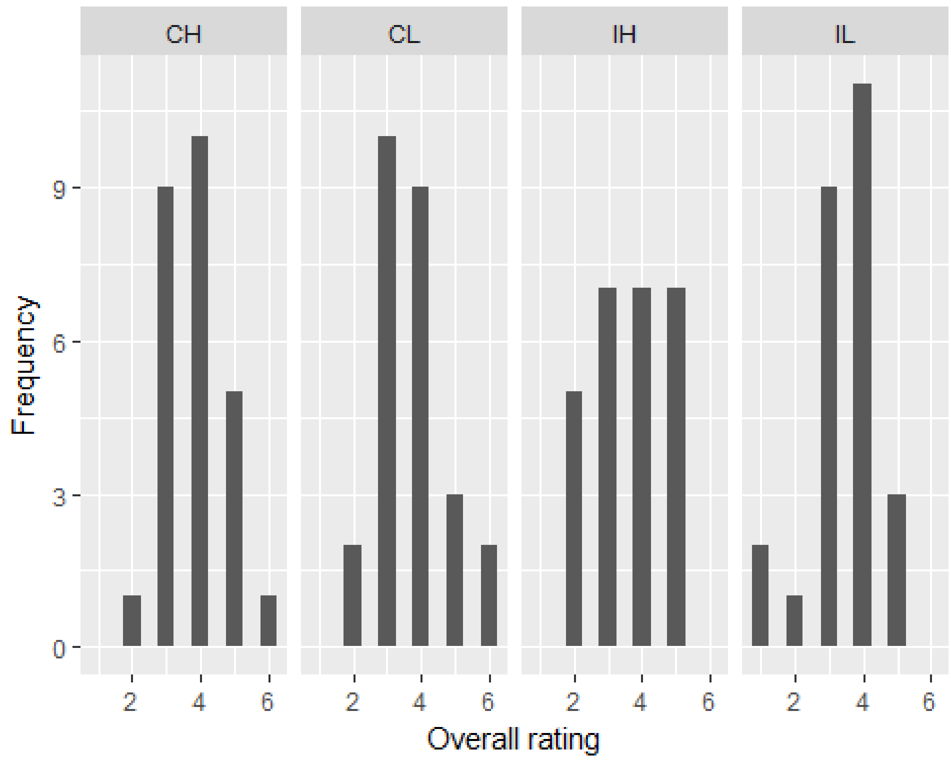


Preference of the wines by the overall rating

Preference of the wines was examined by the overall rating. At first a linear model which examines the influence of the different wines on the overall rating is used. The second model includes the frequency of wine consumption based on the country of origin of the participants. The third linear model checks for the influence of the reported frequency of the wine consumption of the participants on the overall rating. The results of these analyses can be found on page 16 - 21 in the results section. First, mean and standard deviation for the overall ratings of the four different wines are computed. Second, the frequency of the given overall ratings are visualized for each answer option for each of the four wines. The histogram can be found as figure 6 on page 17 of the master thesis.

```
EEGdata %>%
  group_by(Wine) %>%
  summarize(mean_Overall = mean(Overall), sd_Overall = sd(Overall)) %>%
  arrange(Wine)

## # A tibble: 4 × 3
##    Wine mean_Overall sd_Overall
##   <chr>        <dbl>      <dbl>
## 1    CH     3.846154  0.9248701
## 2    CL     3.730769  1.0414487
## 3    IH     3.615385  1.0982504
## 4    IL     3.461538  1.0288156
```

```r
EEGdata %>%
  ggplot(aes(x = Overall)) +
  geom_histogram(binwidth=.5, position="dodge") +
  scale_fill_grey() +
  facet_grid(. ~ Wine) +
  labs(x = "Overall rating", y = "Frequency")
```



By computing a linear model, it is checked if the four wines caused differences in the overall ratings of the wines. Residuals are checked for normality. Fixed effects are displayed in table 4 on page 17 of the thesis.

```r
require(bayr, quietly = T)
Overall_model <- stan_glm(Overall ~ Wine, data =  EEGdata)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.961 seconds (Warm-up)
##                1.552 seconds (Sampling)
```

```
##                 2.513 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.83 seconds (Warm-up)
##                0.961 seconds (Sampling)
##                1.791 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.398 seconds (Warm-up)
##                0.713 seconds (Sampling)
##                2.111 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
```

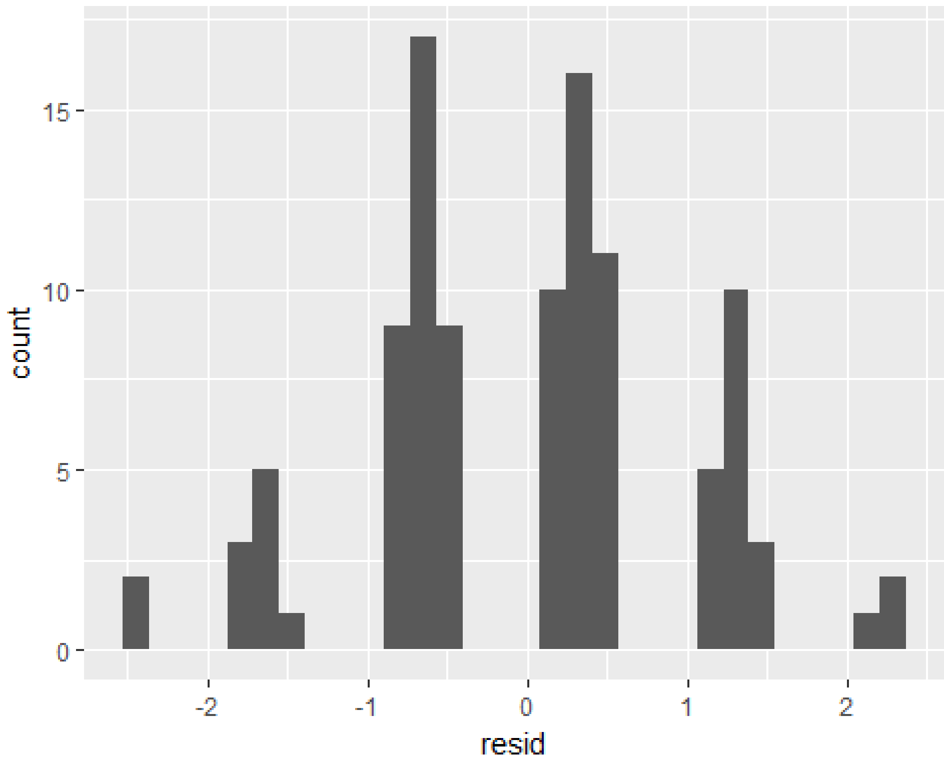
```
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.022 seconds (Warm-up)
##                1.25 seconds (Sampling)
##                2.272 seconds (Total)
```

```
fixef(Overall_model)
```

```
##
##
## Table:
##
## fixef             center        lower       upper
## ----------   -----------   -----------   ----------
## Intercept      3.8471490     3.4481433    4.2651477
## WineCL        -0.1205969    -0.6777144    0.4513450
## WineIH        -0.2323599    -0.7982650    0.3243428
## WineIL        -0.3877435    -0.9339238    0.1695030
```

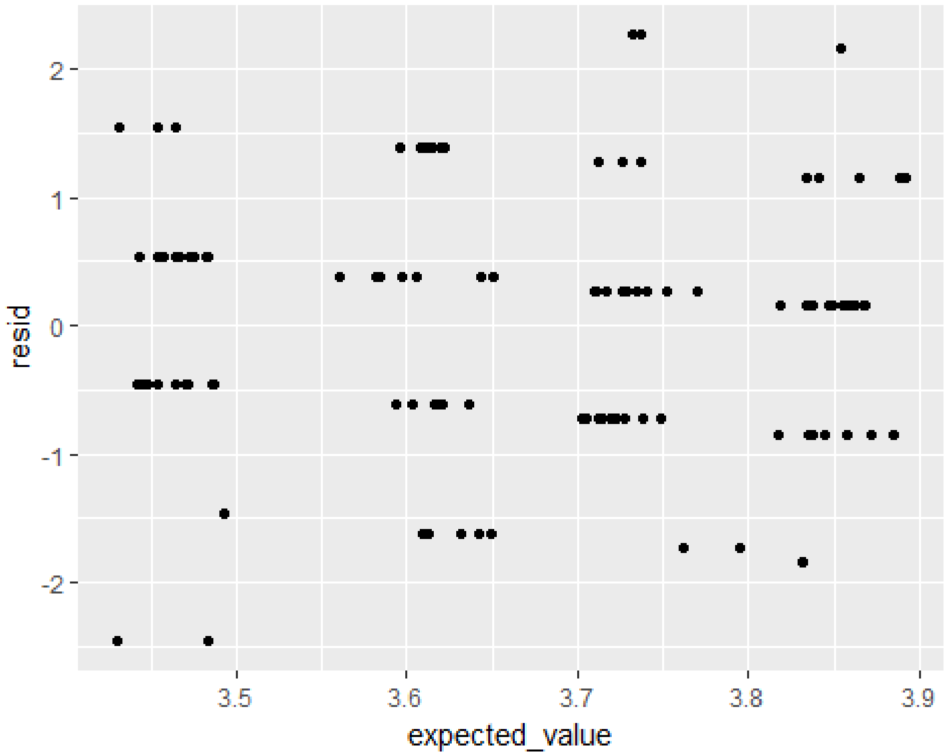
```
data_frame(resid = resid(Overall_model)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(Overall_model)$center,
                     resid = resid(Overall_model)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()
```

```
## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



First, compute mean and standard deviation for the high and low wine consumption based on coutnry of origin independently. Second, the frequency of the given answers on the overall ratings of the wines for both the high and low wine consumption are displayed independently in a bar chart. This graph can be found as figure 7 on page 18 of the master thesis. Third, a regression model is set up to check for the influence of the wine consumption based on the country of origin on the overall ratings of the wine. Fixed effects are displayed in table 5 on page 19. Residuals were checked for the model.

```
EEGdata %>%
  filter(Consumption == "High") %>%
  group_by(Wine) %>%
  summarize(mean_Overall = mean(Overall), sd_Overall = sd(Overall)) %>%
  arrange(Wine)
```

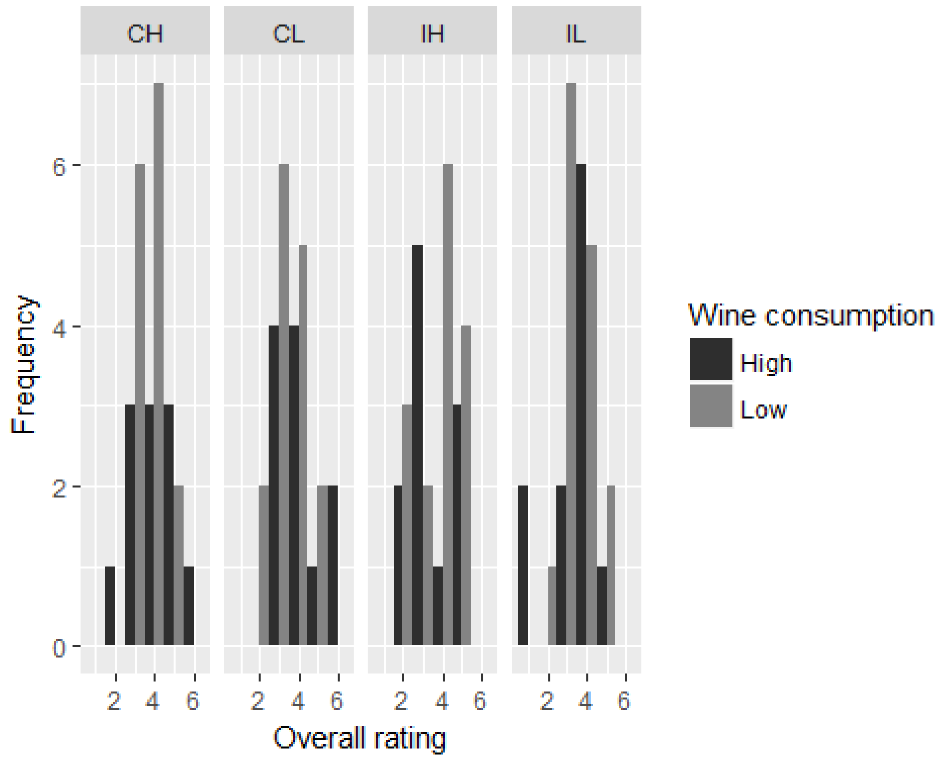
```
## # A tibble: 4 × 3
##    Wine mean_Overall sd_Overall
##   <chr>        <dbl>      <dbl>
## 1    CH     4.000000   1.183216
## 2    CL     4.090909   1.136182
## 3    IH     3.454545   1.128152
## 4    IL     3.363636   1.286291
```

```
EEGdata %>%
  filter(Consumption == "Low") %>%
  group_by(Wine) %>%
  summarize(mean_Overall = mean(Overall), sd_Overall = sd(Overall)) %>%
  arrange(Wine)
```

```
## # A tibble: 4 × 3
##    Wine mean_Overall sd_Overall
##   <chr>        <dbl>      <dbl>
## 1    CH     3.733333  0.7037316
## 2    CL     3.466667  0.9154754
## 3    IH     3.733333  1.0997835
## 4    IL     3.533333  0.8338094
```

```
EEGdata %>%
  ggplot(aes(x = Overall, fill = Consumption)) +
  geom_bar(binwidth = 1, position = "dodge") +
  scale_fill_manual(values=c("#2E2E2E", "#848484")) +
  facet_grid(. ~ Wine) +
  labs(x = "Overall rating", y = "Frequency", fill = "Wine consumption")
```

```
## Warning: `geom_bar()` no longer has a `binwidth` parameter. Please use
## `geom_histogram()` instead.
```




```
consumption_model1 <- stan_glmer(Overall ~ Consumption*Wine + (1|Participan
t), data =  EEGdata)
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
```

```
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 13.286 seconds (Warm-up)
##                6.467 seconds (Sampling)
##                19.753 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 9.915 seconds (Warm-up)
##                7.35 seconds (Sampling)
##                17.265 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 6.969 seconds (Warm-up)
##                6.096 seconds (Sampling)
##                13.065 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
```

```
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 8.68 seconds (Warm-up)
##                4.363 seconds (Sampling)
##                13.043 seconds (Total)
```

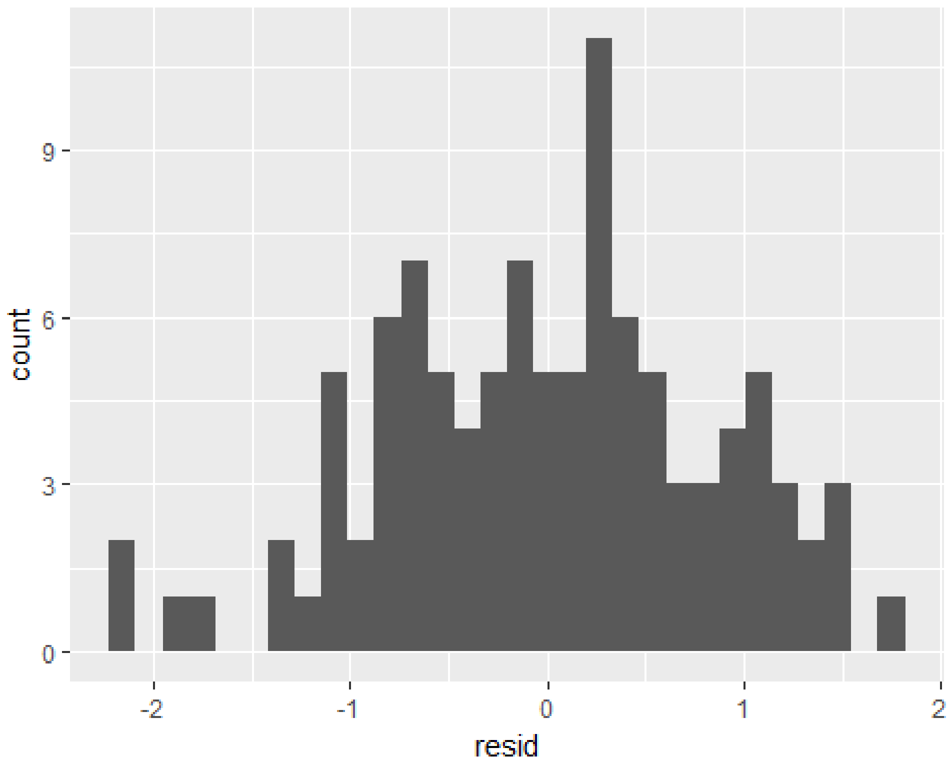
```
fixef(consumption_model1)
```

```
## Warning in sqrt(c(4.24748904842305, 3.97598982238485, 4.28039360617683,
:
## NaNs produced
```

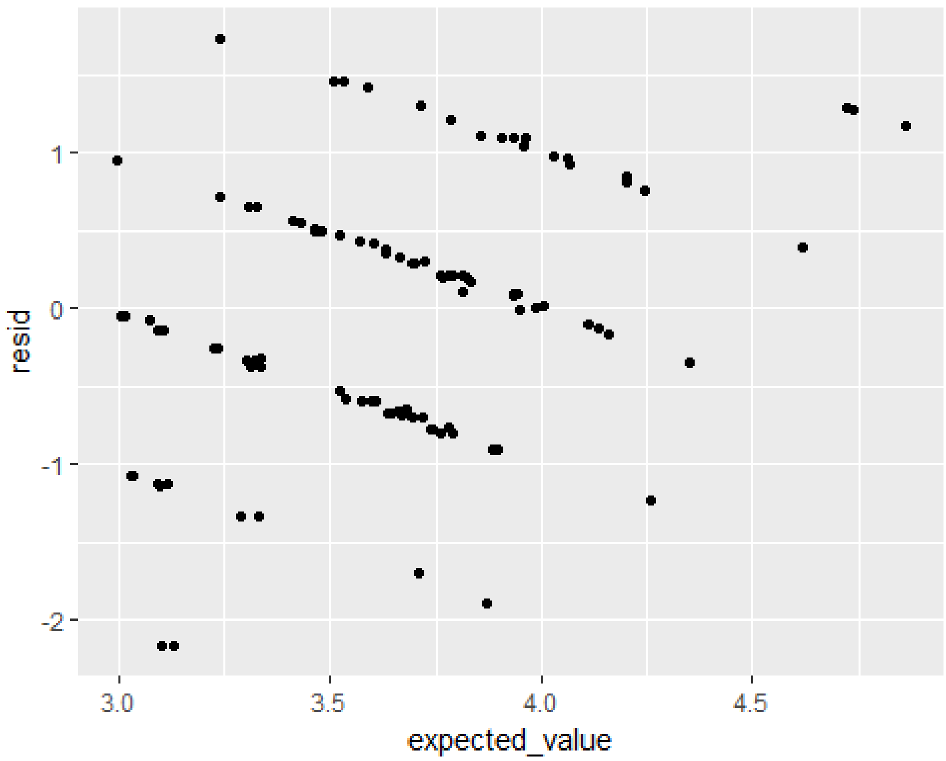
```
##
##
## Table:
##
## fixef                          center        lower       upper
## ----------------------  -----------  -----------  ----------
## Intercept                 4.0026439    3.3662399   4.5894258
## ConsumptionLow           -0.2609729   -1.0600418   0.5620163
## WineCL                    0.1048954   -0.6553422   0.8506794
## WineIH                   -0.5356542   -1.2941986   0.2244431
## WineIL                   -0.6233707   -1.3934849   0.1211743
## ConsumptionLow:WineCL    -0.3661119   -1.3387240   0.6504787
## ConsumptionLow:WineIH     0.5288318   -0.4486843   1.5578552
## ConsumptionLow:WineIL     0.4169723   -0.6021380   1.4366390
```

```
data_frame(resid = resid(consumption_model1)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



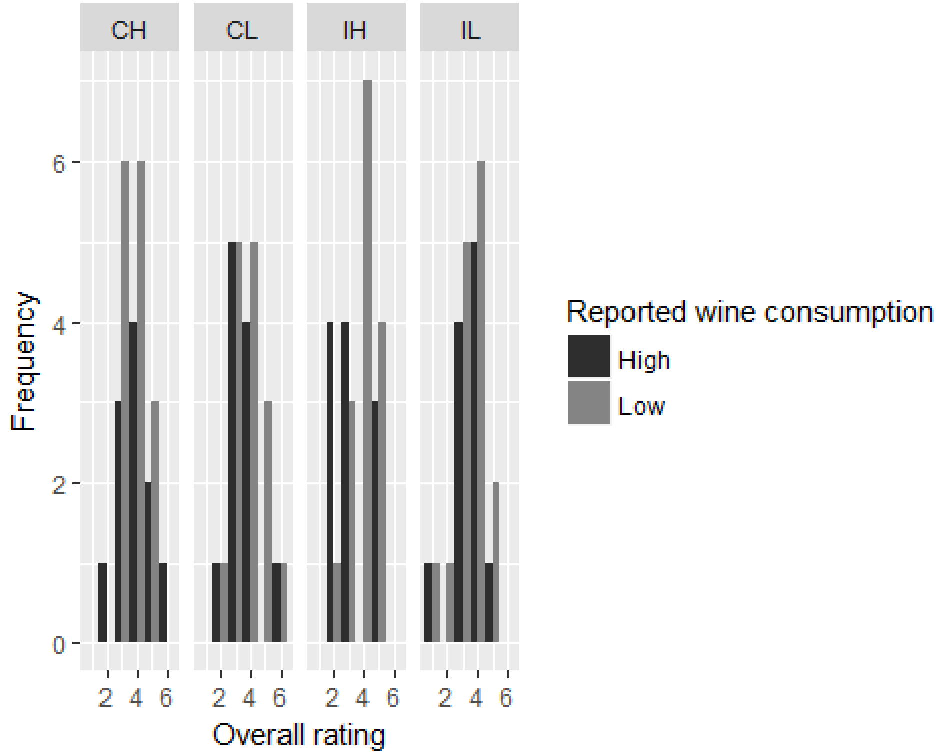

```
data_frame(expected_value = bayr::predict(consumption_model1)$center,
                     resid = resid(consumption_model1)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



First, mean and standard deviation for the high and low frequency of wine consumption are computed independently. Second, the frequency of the given answer on the overall ratings of the wines for both the high and low wine consumption are displayed independently in a bar chart. This chart can be found as figure 8 on page 20. Third, set up a regression model to check for the influence of the frequency of wine consumption on the overall ratings of the wine. Fixed effects are displayed in table 6 on page 21. Residuals were checked for the model.

```
EEGdata %>%
  filter(Freq_consumption == "High") %>%
  group_by(Wine) %>%
  summarize(mean_Overall = mean(Overall), sd_Overall = sd(Overall)) %>%
  arrange(Wine)

## # A tibble: 4 × 3
##    Wine mean_Overall sd_Overall
##   <chr>        <dbl>      <dbl>
## 1    CH     3.909091   1.136182
## 2    CL     3.545455   1.035725
## 3    IH     3.181818   1.250454
## 4    IL     3.454545   1.035725

EEGdata %>%
  filter(Freq_consumption == "Low") %>%
  group_by(Wine) %>%
  summarize(mean_Overall = mean(Overall), sd_Overall = sd(Overall)) %>%
  arrange(Wine)

## # A tibble: 4 × 3
##    Wine mean_Overall sd_Overall
##   <chr>        <dbl>      <dbl>
```

```
## 1     CH      3.800000  0.7745967
## 2     CL      3.866667  1.0600988
## 3     IH      3.933333  0.8837151
## 4     IL      3.466667  1.0600988

EEGdata %>%
  ggplot(aes(x = Overall, fill = Freq_consumption)) +
  geom_bar(binwidth = 1, position = "dodge") +
  scale_fill_manual(values=c("#2E2E2E", "#848484")) +
  facet_grid(. ~ Wine) +
  labs(x = "Overall rating", y = "Frequency", fill = "Reported wine consump
tion")

## Warning: `geom_bar()` no longer has a `binwidth` parameter. Please use
## `geom_histogram()` instead.
```




```
Freq_consumption1 <- stan_glmer(Overall ~ Freq_consumption*Wine + (1|Partic
ipant), data =  EEGdata)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
```

```
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 6.162 seconds (Warm-up)
##                5.001 seconds (Sampling)
##                11.163 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 5.368 seconds (Warm-up)
##                4.411 seconds (Sampling)
##                9.779 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 5.483 seconds (Warm-up)
##                4.532 seconds (Sampling)
##                10.015 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 3.356 seconds (Warm-up)
##                3.146 seconds (Sampling)
##                6.502 seconds (Total)
```

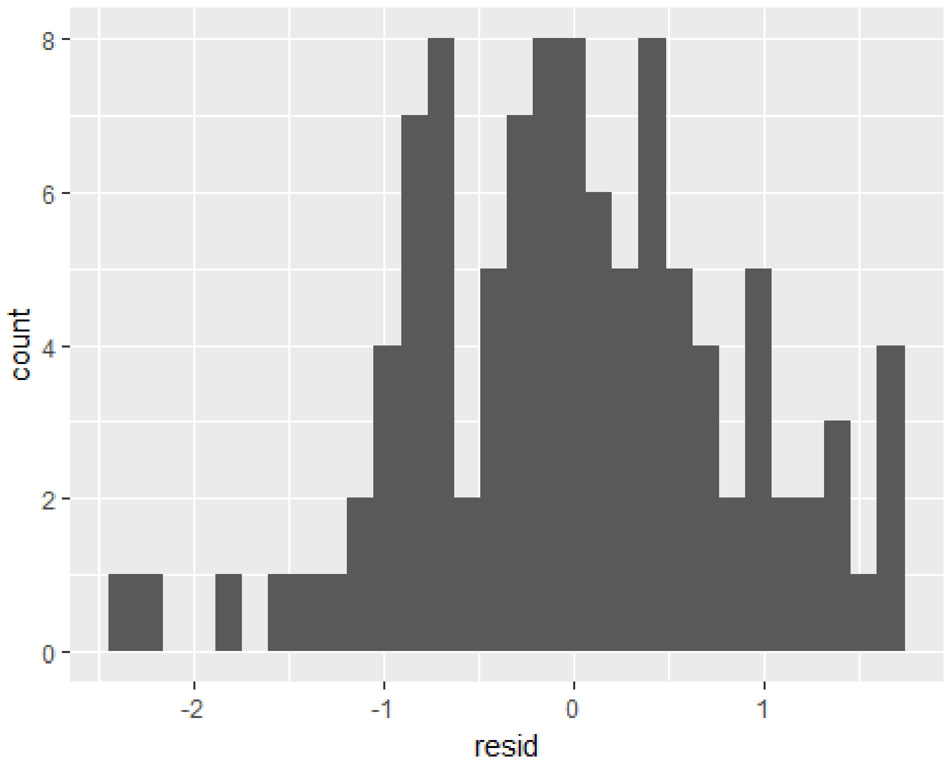
```
fixef(Freq_consumption1)
```

```
## Warning in sqrt(c(3.62057163306506, 3.68484488514924, 3.51545896197306,
:
## NaNs produced
```

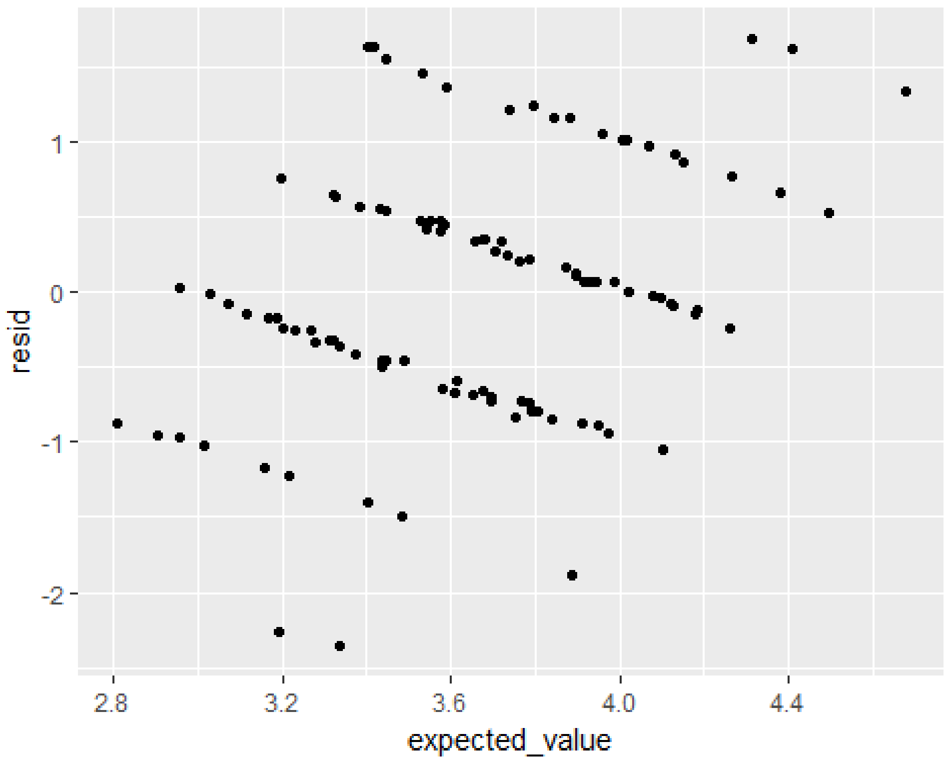
```
##
##
## Table:
##
## fixef                                center        lower        upper
## ---------------------------  -----------  -----------  ----------
## Intercept                      3.8870758    3.2823173   4.5340010
## Freq_consumptionLow           -0.0893473   -0.9329827   0.7212644
## WineCL                        -0.3499767   -1.1406031   0.4222195
## WineIH                        -0.7084832   -1.4859065   0.0719160
## WineIL                        -0.4287074   -1.2307227   0.3370993
## Freq_consumptionLow:WineCL     0.3994406   -0.5976132   1.4489783
## Freq_consumptionLow:WineIH     0.8437166   -0.1678869   1.8803327
## Freq_consumptionLow:WineIL     0.0894464   -0.9148369   1.1264396
```

```
data_frame(resid = resid(Freq_consumption1)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(Freq_consumption1)$center,
                    resid = resid(Freq_consumption1)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



EEG measures as predictors of the overall and price ratings.

Taste and smell EEG measures were used as predictors of the overall and price ratings to examine if neural measures could be used as reliable predictors of preference. Two linear models were computed for the overall and price ratings independently. The results of these analyses can be found on page 21 - 23 in the results section of the master thesis. The first linear model examines the influences of the taste and smell EEG measures, the label rating, wine consumption based on country of origin of the participants, and the reported frequency of wine consumption on the overall ratings. Fixed effects are displayed in table 7 on page 22 of the master thesis. Residuals were checked for the model. The second linear model was computed to check the influences of the taste and smell EEG measures, the label rating, wine consumption based on country, and frequency of wine consumption on the price ratings. Fixed effects are displayed in table 8 on page 23 of the master thesis. Residuals were also checked for this model.

```
wine.model1 = stan_glm(Overall ~ Taste_corrected + Smell_corrected + Label
+ Consumption + Freq_consumption, data=EEGdata_NA)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
```

```
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.585 seconds (Warm-up)
##                0.781 seconds (Sampling)
##                1.366 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.558 seconds (Warm-up)
##                0.617 seconds (Sampling)
##                1.175 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.567 seconds (Warm-up)
##                0.582 seconds (Sampling)
##                1.149 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
```

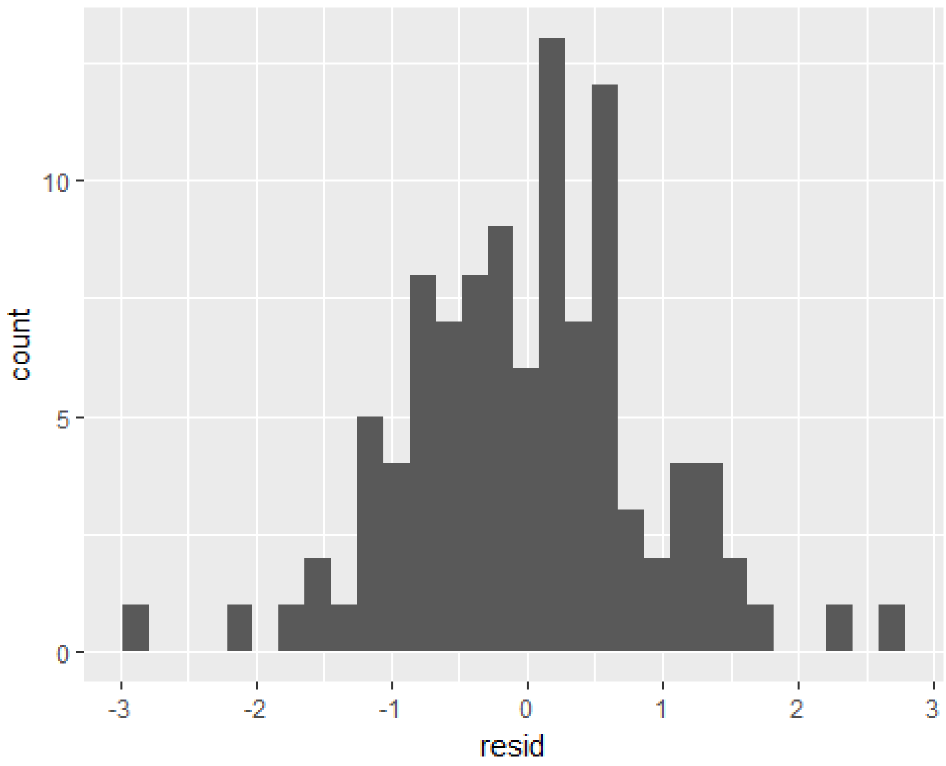
```
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.574 seconds (Warm-up)
##                0.605 seconds (Sampling)
##                1.179 seconds (Total)
```

```
fixef(wine.model1)
```

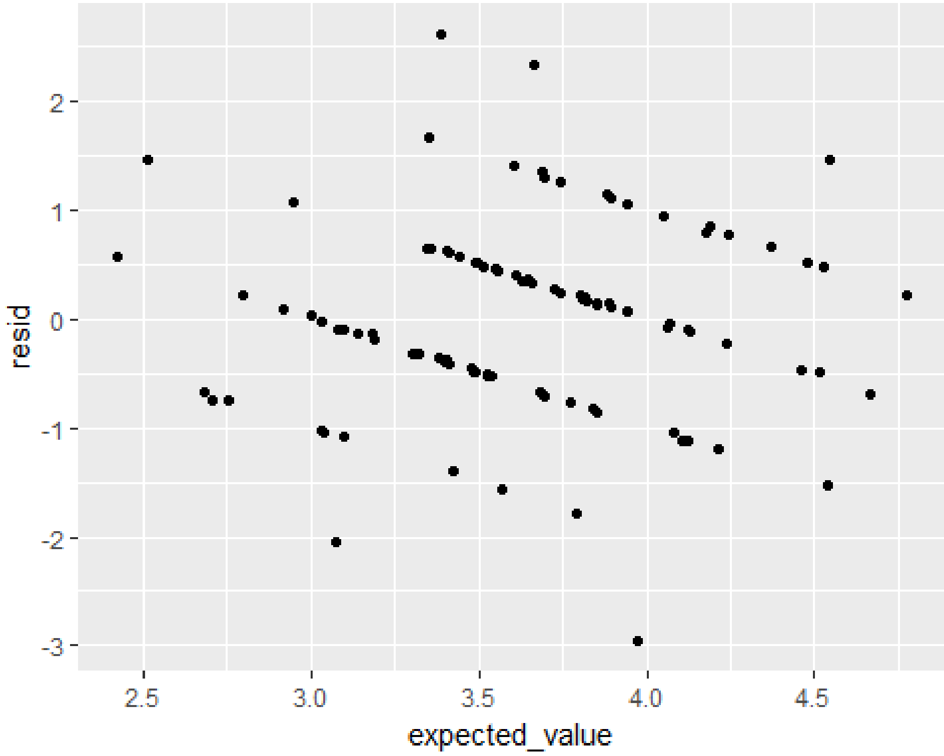
```
##
##
## Table:
##
## fixef                      center        lower       upper
## --------------------  -----------  -----------  ----------
## Intercept               2.3383726    1.6668874   2.9874897
## Taste_corrected        -1.8946113   -6.1407671   2.4593151
## Smell_corrected         0.0689884   -3.2699017   3.4439550
## Label                   0.3794062    0.2333113   0.5316699
## ConsumptionLow         -0.2727907   -0.6703165   0.1299746
## Freq_consumptionLow     0.2669329   -0.1140254   0.6875834
```

```
data_frame(resid = resid(wine.model1)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(wine.model1)$center,
                     resid = resid(wine.model1)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```




```
price.model1 = stan_glm(Price ~ Taste_corrected + Smell_corrected + Label +
Consumption + Freq_consumption, data=EEGdata_NA)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.816 seconds (Warm-up)
##                0.833 seconds (Sampling)
##                1.649 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.755 seconds (Warm-up)
##                0.906 seconds (Sampling)
##                1.661 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.221 seconds (Warm-up)
##                0.993 seconds (Sampling)
##                2.214 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.043 seconds (Warm-up)
##                0.97 seconds (Sampling)
##                2.013 seconds (Total)
```

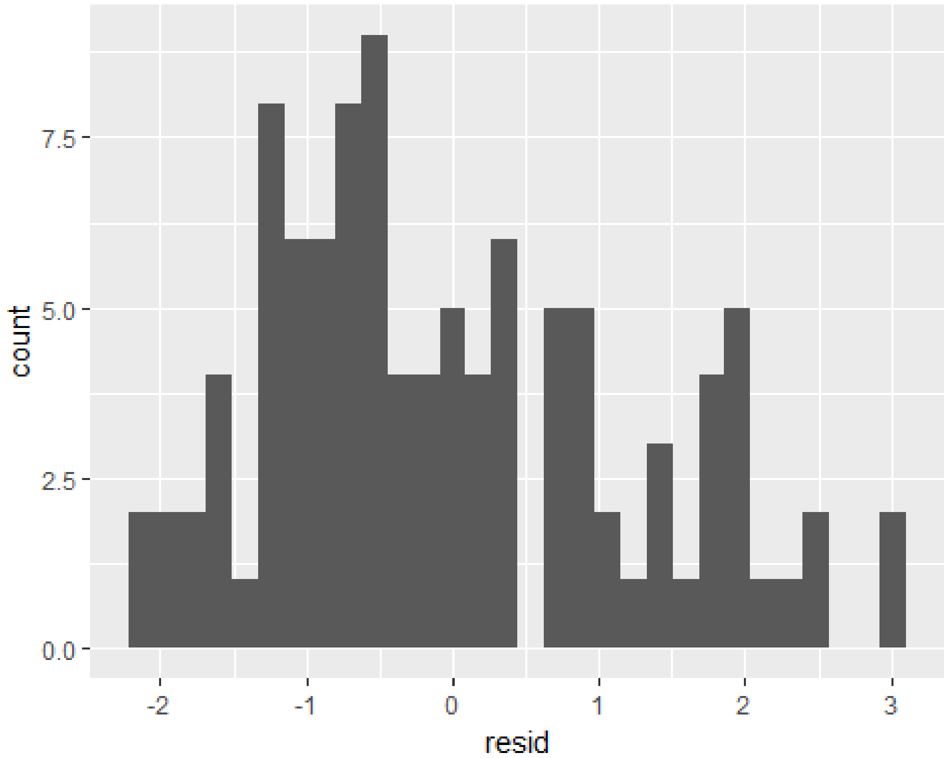
```
fixef(price.model1)
```

```
##
##
## Table:
##
```

```
## fixef                        center        lower       upper
## --------------------  -----------  -----------  ----------
## Intercept               1.8338815    0.9665829   2.7224822
## Taste_corrected        -2.7911900   -8.8285876   3.1937761
## Smell_corrected        -0.2226027   -4.8693571   4.5168479
## Label                   0.1978474   -0.0093162   0.3996019
## ConsumptionLow         -0.3035943   -0.8512987   0.2122556
## Freq_consumptionLow     0.6776273    0.1304619   1.2041317
```

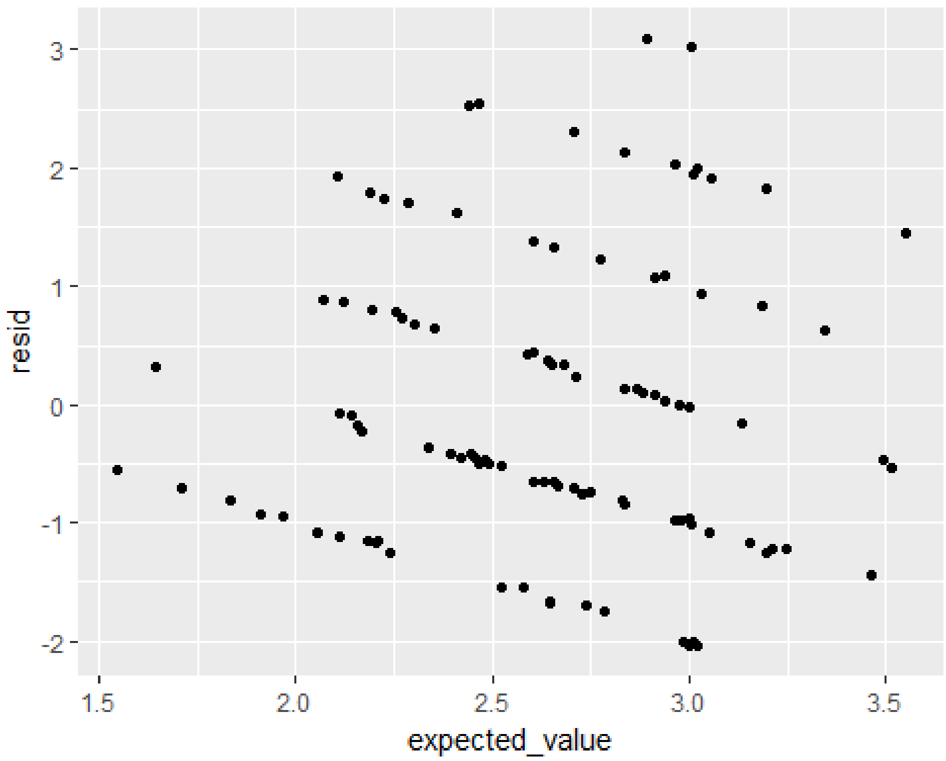
```
data_frame(resid = resid(price.model1)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(price.model1)$center,
                          resid = resid(price.model1)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()
```

```
## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



Influence of wine consumption on EEG measures.

The influence of the wine consumption based on the country of origin of the participants and the reported frequency of wine drinking on the taste and smell EEG measures was tested. This was done to ensure that individual differences had no influence on the predictive value of the EEG measures. At first a linear model was computed which used the beta activity during the taste procedure as dependent variable. Fixed effects of this linear model are displayed in table 9 on page 24 of the master thesis. The second linear model tests the influences on theb ta activity during the smell procedure. Fixed effects are displayed in table 10 on page 25 of the master thesis. Both the linear models use the wines, wine consumption based on country of origin, and reported frequency of wine consumption as predictors of the EEG measures. Residuals were checked for these models. The analyses are displayed on page 23 - 25 in the results section of the master thesis.

```
TasteEEG.model = stan_glm(Taste_corrected ~ Wine + Consumption + Freq_consu
mption, data=EEGdata)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.646 seconds (Warm-up)
##                2.907 seconds (Sampling)
##                4.553 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 3.039 seconds (Warm-up)
##                1.23 seconds (Sampling)
##                4.269 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.705 seconds (Warm-up)
##                1.244 seconds (Sampling)
##                2.949 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
```

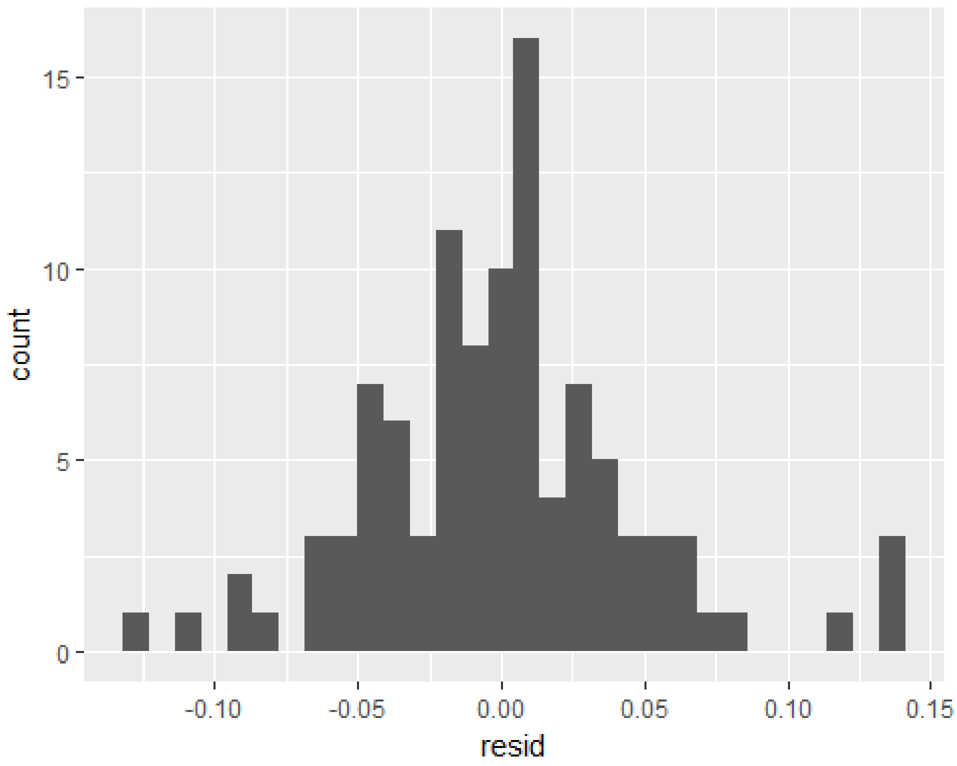
```
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.58 seconds (Warm-up)
##                0.929 seconds (Sampling)
##                2.509 seconds (Total)
```

```
fixef(TasteEEG.model)
```

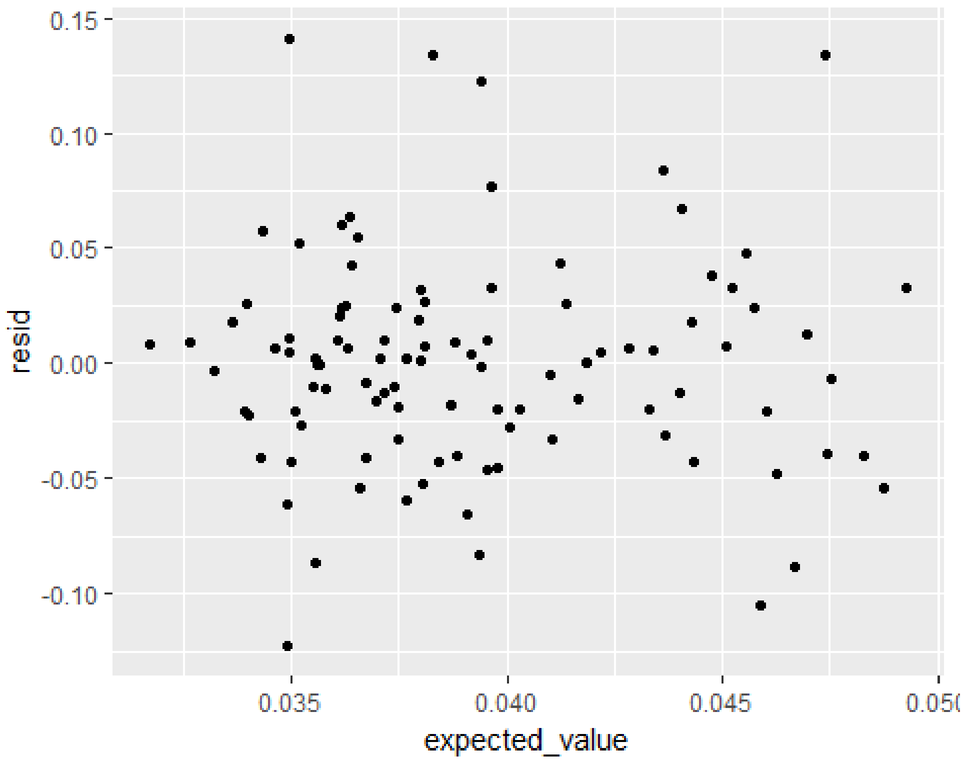
```
##
##
## Table:
##
## fixef                      center        lower       upper
## --------------------  -----------  -----------  ----------
## Intercept               0.0367392    0.0142901   0.0599808
## WineCL                  0.0003212   -0.0259493   0.0254130
## WineIH                  0.0092306   -0.0175123   0.0351652
## WineIL                  0.0028058   -0.0242732   0.0294333
## ConsumptionLow          0.0025402   -0.0186468   0.0239852
## Freq_consumptionLow    -0.0037250   -0.0246240   0.0164821
```

```
data_frame(resid = resid(TasteEEG.model)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(TasteEEG.model)$center,
                     resid = resid(TasteEEG.model)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```




```
SmellEEG.model = stan_glm(Smell_corrected ~ Wine + Consumption + Freq_consu
mption, data=EEGdata)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.575 seconds (Warm-up)
##                1.06 seconds (Sampling)
##                2.635 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.29 seconds (Warm-up)
##                1.951 seconds (Sampling)
##                3.241 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.462 seconds (Warm-up)
##                1.078 seconds (Sampling)
##                2.54 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.156 seconds (Warm-up)
##                1.147 seconds (Sampling)
##                2.303 seconds (Total)
```

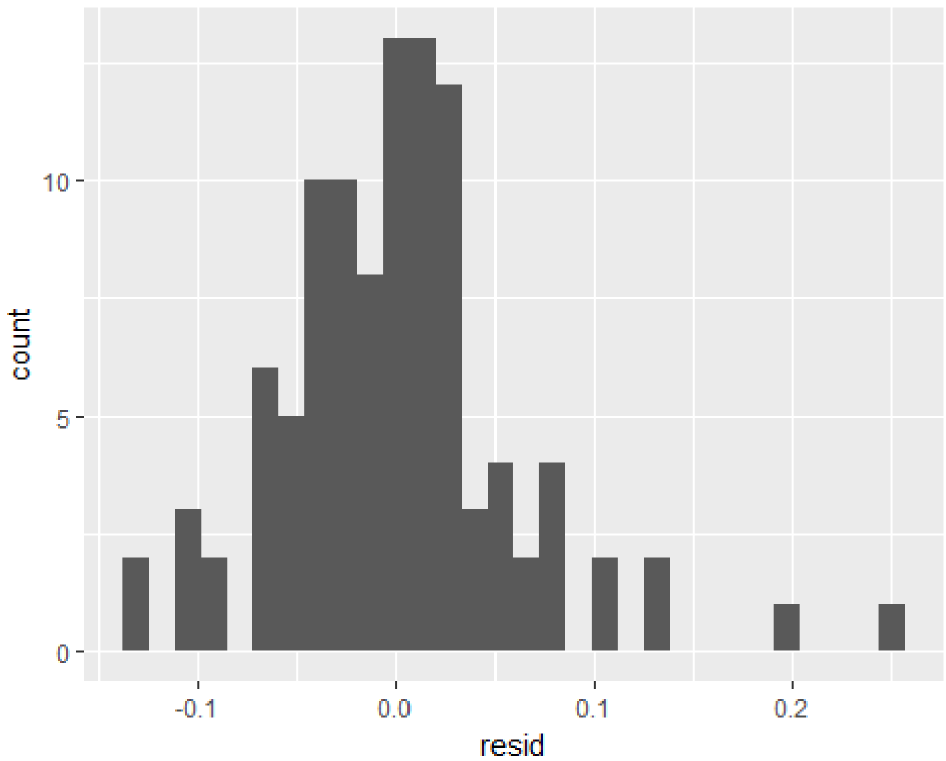
```
fixef(SmellEEG.model)
```

```
##
##
## Table:
##
```

```
## fixef                         center        lower        upper
## --------------------  -----------  -----------  -----------
## Intercept               0.0447968    0.0160185    0.0733903
## WineCL                  0.0085853   -0.0254068    0.0434738
## WineIH                  0.0135765   -0.0195059    0.0470931
## WineIL                  0.0091414   -0.0253087    0.0435615
## ConsumptionLow          0.0141158   -0.0121968    0.0410196
## Freq_consumptionLow    -0.0283878   -0.0555414   -0.0024781
```

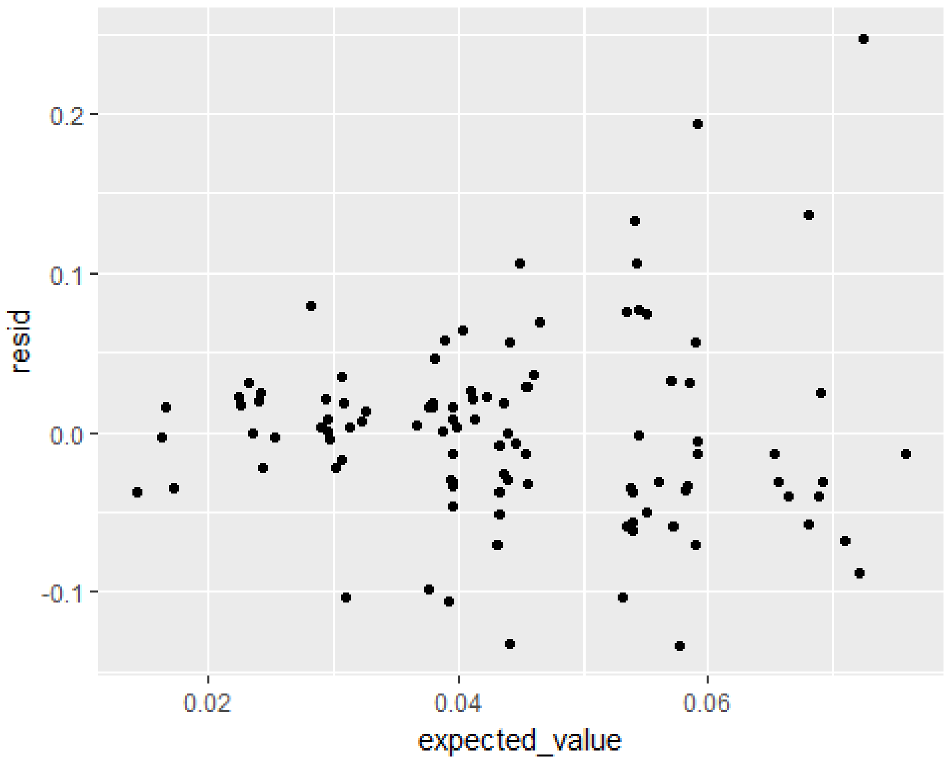
```
data_frame(resid = resid(SmellEEG.model)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(SmellEEG.model)$center,
                          resid = resid(SmellEEG.model)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()
```

```
## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



Differences between taste, smell, and baseline EEG measures.

Linear models are computed to examine differences in beta activity between the smell, taste, and baseline measures. This was done to test if beta activity during the smell and taste procedure is higher than for the baseline measure and if beta activity is higher during the smell than during the taste procedure. The first linear model tests differences between beta activity during the smell and taste procedure of the experiment. The second model test differences in beta activity between the smell and baseline measurements. The third model checks differences in beta activity between the taste and baseline measurements. The results can be found in table 11, 12, and 13 on page 26 of the master thesis. Residuals were checked for the models. The analyses kan be found on page 25 - 26 in the results section of the master thesis.

```
Taste_Smell <- stan_glm(Taste_corrected ~ Smell_corrected, data =  EEGdata_
NA)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
```

```
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.894 seconds (Warm-up)
##                0.869 seconds (Sampling)
##                1.763 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.937 seconds (Warm-up)
##                1.432 seconds (Sampling)
##                2.369 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.751 seconds (Warm-up)
##                1.451 seconds (Sampling)
##                3.202 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
```

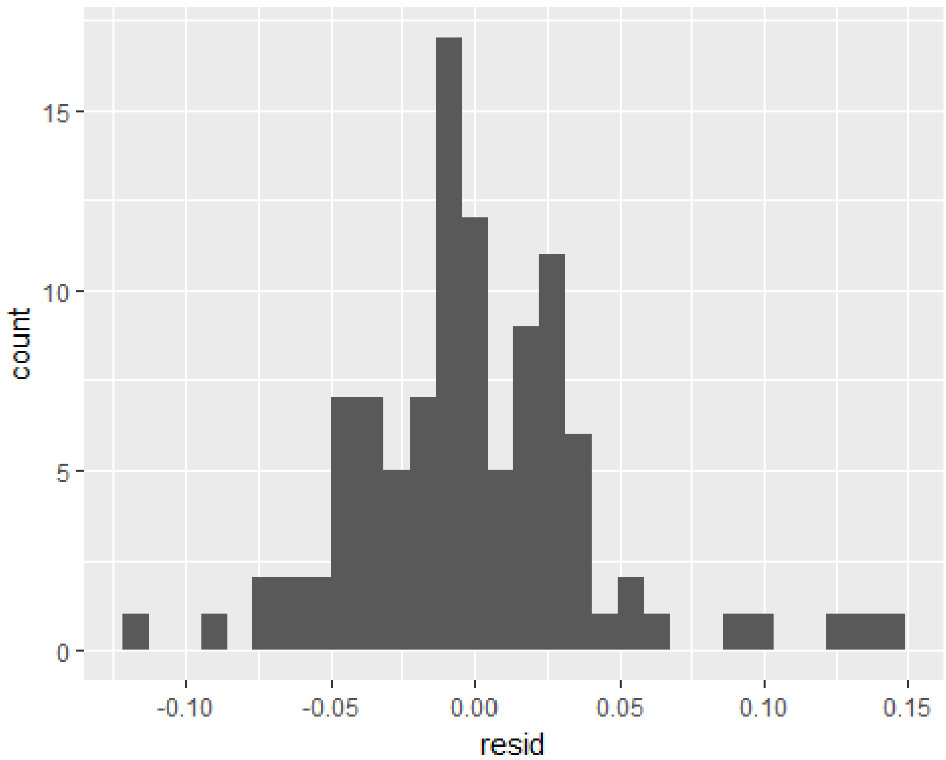
```
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 1.415 seconds (Warm-up)
##                0.479 seconds (Sampling)
##                1.894 seconds (Total)
```

```
fixef(Taste_Smell)
```

```
##
##
## Table:
##
## fixef                  center       lower       upper
## ----------------  ----------  ----------  ----------
## Intercept          0.0244211   0.0144515   0.0345633
## Smell_corrected    0.3302961   0.1991947   0.4615858
```

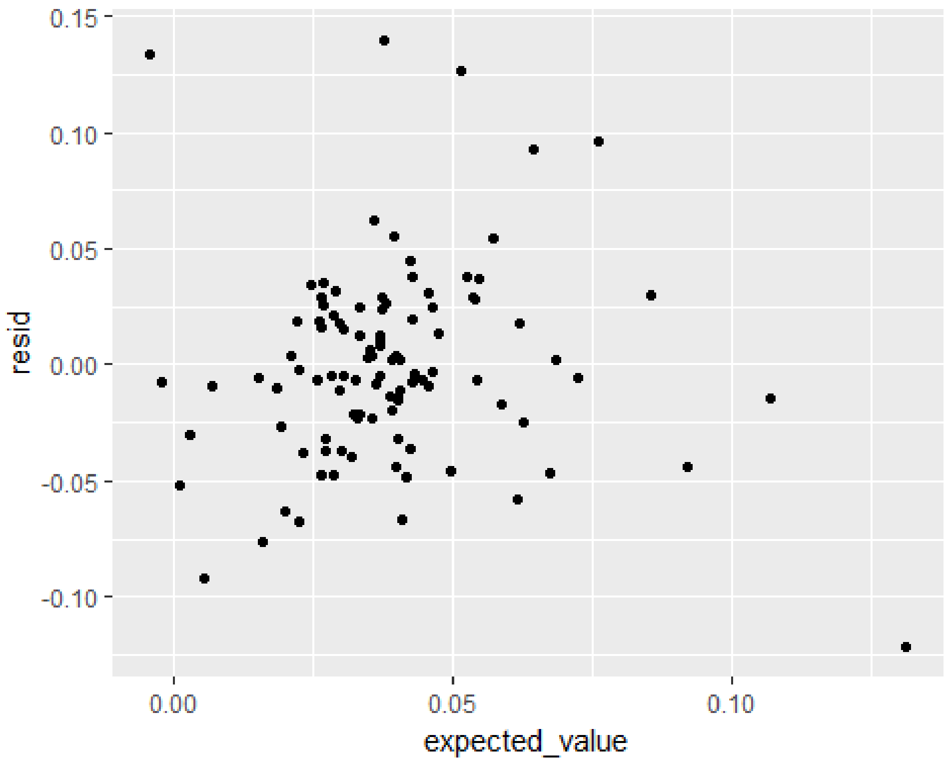
```
data_frame(resid = resid(Taste_Smell)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
data_frame(expected_value = bayr::predict(Taste_Smell)$center,
                     resid = resid(Taste_Smell)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
```

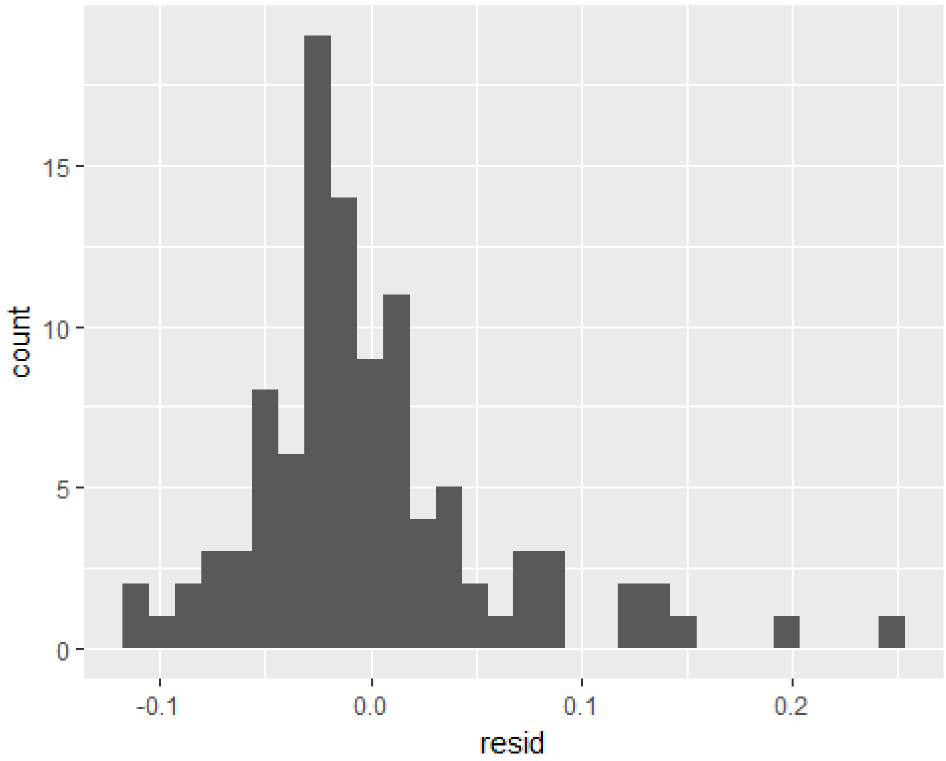
```
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```



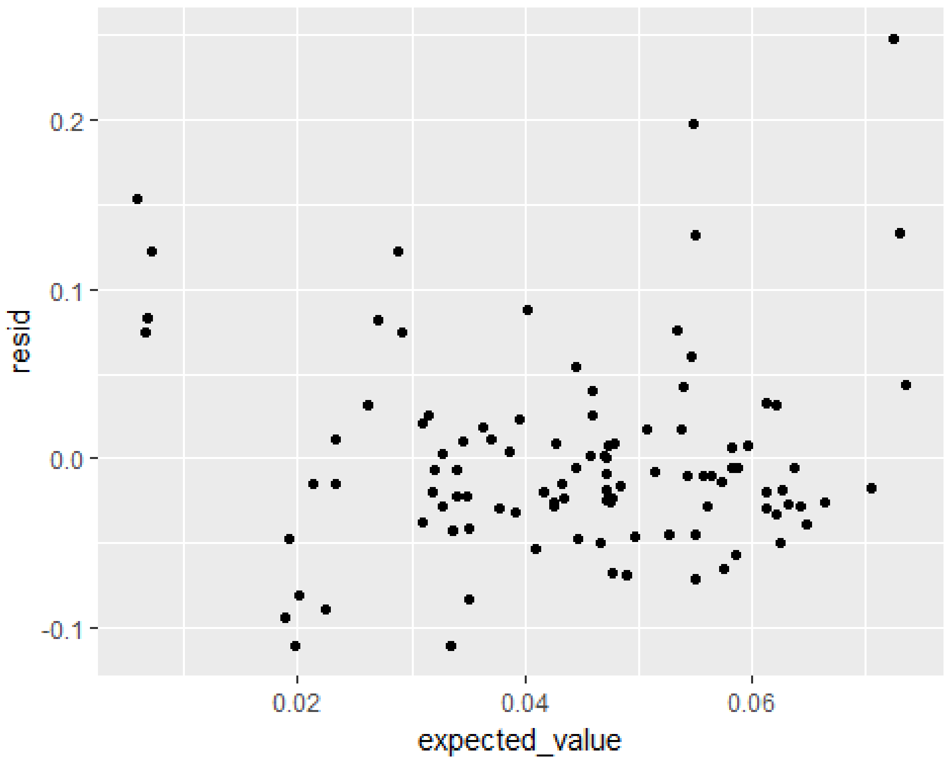

```
Baseline_Smell <- stan_glm(Smell_corrected ~ logBaseline_FCz, data =  EEGda
ta_NA)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.667 seconds (Warm-up)
##                0.635 seconds (Sampling)
##                1.302 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
```

```
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.709 seconds (Warm-up)
##                0.557 seconds (Sampling)
##                1.266 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.543 seconds (Warm-up)
##                0.49 seconds (Sampling)
##                1.033 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.533 seconds (Warm-up)
##                0.47 seconds (Sampling)
##                1.003 seconds (Total)
```

```r
fixef(Baseline_Smell)

##
##
## Table:
##
## fixef                  center       lower       upper
## ----------------  -----------  -----------  -----------
## Intercept           0.0975026    0.0542389    0.1416002
## logBaseline_FCz    -0.1751140   -0.3208013   -0.0344290

data_frame(resid = resid(Baseline_Smell)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
data_frame(expected_value = bayr::predict(Baseline_Smell)$center,
                     resid = resid(Baseline_Smell)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()

## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```




```
Baseline_Taste <- stan_glm(Taste_corrected ~ logBaseline_FCz, data =  EEGda
ta_NA)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
##
## Chain 1, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.592 seconds (Warm-up)
##                0.462 seconds (Sampling)
##                1.054 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
##
## Chain 2, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2, Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 2, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.541 seconds (Warm-up)
##                0.486 seconds (Sampling)
##                1.027 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
##
## Chain 3, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.543 seconds (Warm-up)
##                0.493 seconds (Sampling)
##                1.036 seconds (Total)
##
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
##
## Chain 4, Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4, Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4, Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4, Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4, Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4, Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4, Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4, Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4, Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4, Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4, Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4, Iteration: 2000 / 2000 [100%]  (Sampling)
##  Elapsed Time: 0.768 seconds (Warm-up)
##                0.682 seconds (Sampling)
##                1.45 seconds (Total)
```

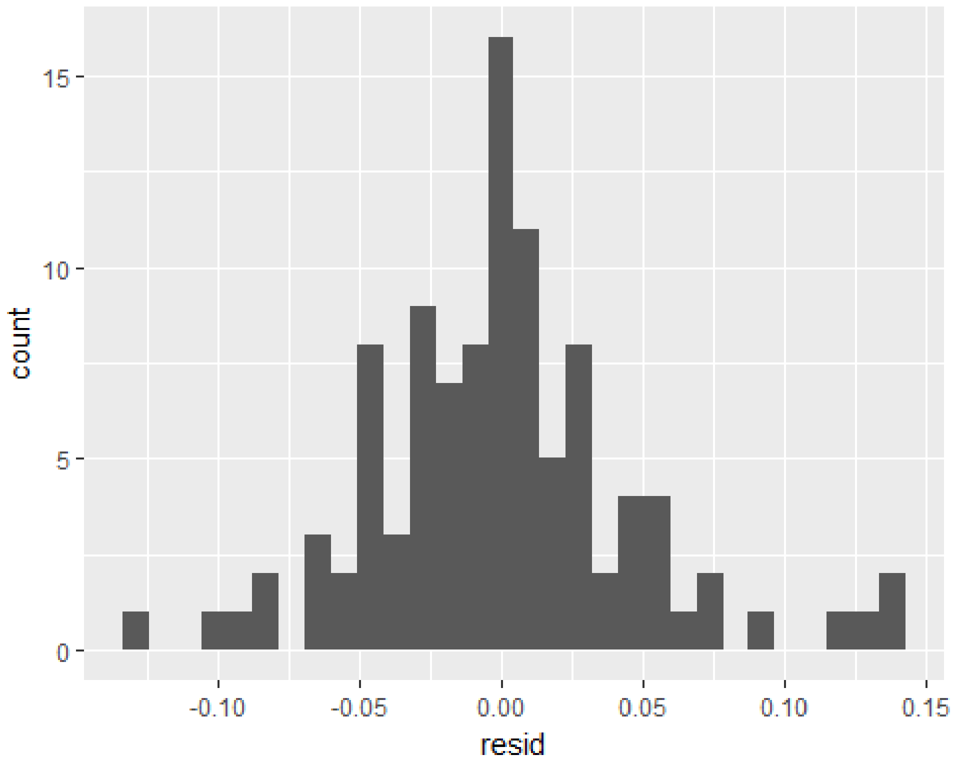
```
fixef(Baseline_Taste)
```

```
##
##
## Table:
##
```

```
## fixef                  center       lower       upper
## ----------------  ----------  -----------  ----------
## Intercept          0.0370454    0.0034783   0.0708513
## logBaseline_FCz    0.0061362   -0.1014980   0.1127831
```

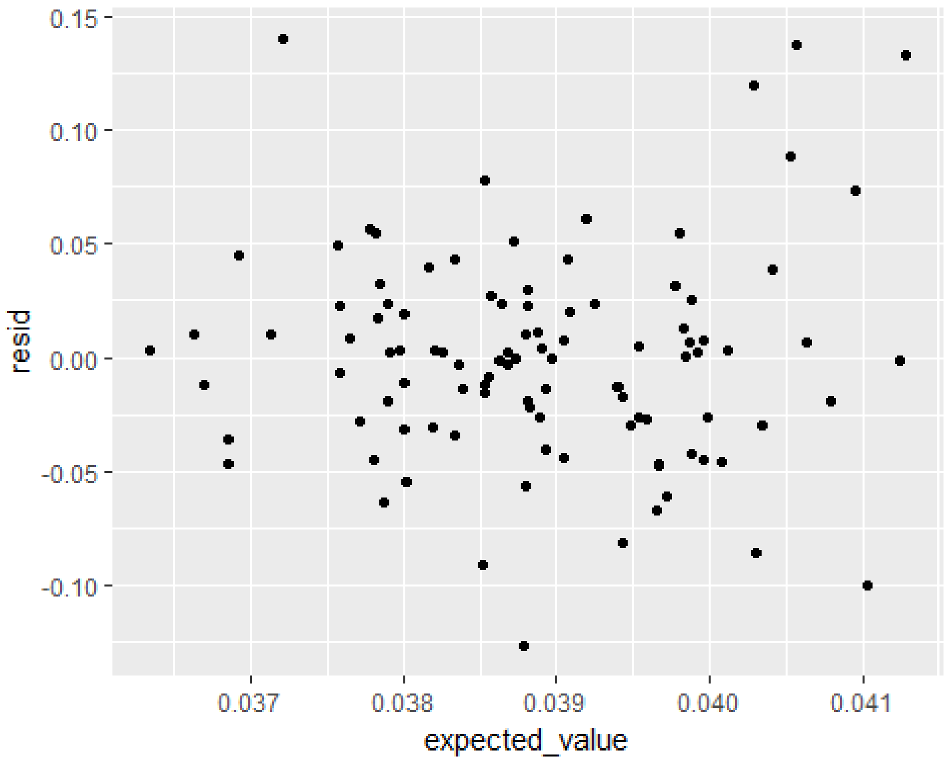
```r
data_frame(resid = resid(Baseline_Taste)) %>%
    ggplot(aes(x = resid)) +
    geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
data_frame(expected_value = bayr::predict(Baseline_Taste)$center,
                     resid = resid(Baseline_Taste)) %>%
    ggplot(aes(x = expected_value, y = resid)) +
    geom_point() +
    geom_quantile()
```

```
## Warning: Computation failed in `stat_quantile()`:
## Package `quantreg` required for `stat_quantile`.
## Please install and try again.
```


0.15
0.10
0.05
0.00
-0.05
-0.10
resid
0.037
0.038
0.039
0.040
0.041
expected_value