Determining the Effect of Instrument, Harmonic Motion, and Voice Leading on Listeners' Identification of Music as Classical or Popular

Irina Javed
irjaved@andrew.cmu.edu

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Abstract

We address the question of how instrument, harmonic motion, and voice leading affect how people rate music as classical and popular. To this end we build a linear mixed effects model to predict classical ratings from those variables. We find that all three are important in predicting classical ratings, specifically instruments, the harmonic motion I-V-vi, and contrary motion, and that many of these relationships vary by listener. We also find that identifying as a musician and other such musical backgrounds affect how listeners rate classical music. We finally repeat this process for popular ratings and find that many of the relationships we found for classical ratings are flipped for positive ratings.

1 Introduction

Classical and Popular music often sit at opposite ends of most musical discussions. But what makes them so different, and can we determine the aspects of music that contribute most to either type of music? And beyond their differences, many have highlighted their similarities, even for comedic effect. For example, the harmonic progression, I-V-vi, might be seen as classical because it is the beginning progression of the famous Pachelbel's Canon in D–however, it is also a very common chord progression in popular music of the past 20 years, something highlighted in comedy videos like Axis of Evil's "4 Chords" and Rob Paravonian's video "Pachelbel Rant". To answer these types of questions, Ivan Jimenez, a composer and musicologist, and student Vincent Rossi designed an experiment to measure the influence of different aspects of music–namely instrument, harmonic motion, and voice leading–on people's identification of music as "classical" or "popular". In this paper we hope to use the data from that experiment to answer that main question of how instrument, harmonic motion, and voice leading affect ratings. More specifically:

- Does instrument exert the strongest influence among the three design factors?
- Among the levels of Harmonic Motion, does I-V-vi have a strong association with classical ratings? And does it seem to matter whether the respondent is familiar with one or the other (or both) of the Pachelbel rants/comedy bits?
- Among levels of Voice Leading, does contrary motion have a strong association with classical ratings?

In addition to answering those main questions, we will address the following questions:

- Are there differences in the way that musicians and non-musicians identify classical music?
- Are there differences in the things that drive classical, vs. popular, ratings?

2 Methods

The data for this paper comes from Ivan Jimenez and Vincent Rossi's experiment, which took place in 2012 at the University of Pittsburgh. In this experiment, they presented 36 musical stimuli to 70 listeners, all undergraduates from the University of Pittsburgh, and asked the listeners to rate the music on two different scales: how classical does the stimuli sound (1 to 10, 1 being not all and 10 being very), and how popular does the stimuli sound (1 to 10). The listeners were told that the scales should be independent from each other (i.e. a listener could have given the stimuli a 10 on both scales). The 36 stimuli were chosen such that they represented all combinations of all levels of instrument, harmonic motion, and voice leading. These variables are our design variables, and are detailed below:

- Instrument: String Quartet, Piano, Electric Guitar
- Harmonic Motion: I-V-vi, I-VI-V, I-V-IV, IV-I-V
- Voice Leading: Contrary Motion, Parallel 3rds, Parallel 5ths

This data also contains additional information on each listeners' musical backgrounds and knowledge. The data set contains 2520 observations, and definitions of all variables in the data set are included in Table 1.

For our analysis we relied on the R language and environment for statistical computing (R Core Team, 2017). We used visual analysis using histograms and qqplots to aid in our understanding of the data. In order to explore the effects of the different design variables on classical and popular ratings we used linear modeling tools in R, namely linear regression and linear mixed effects models. We use step-wise variable selection to help us choose fixed effects, and partial F-tests, AIC, and BIC to compare the various models we made. We also used the R function fitLMER.fnc which allows us to back fit fixed effects and forward fit random effects of a linear mixed-effects model. We also relied on visual analysis using scatter plots to tell us if our models fit the data well, specifically plots of the conditional residuals. We use conditional residuals because they most closely mirror the residuals from regular linear models.

3 Results

3.1 Data transformation

After a preliminary exploration of the data we dropped X1stInstr and X2stInstr from the data set because they had a large amount of NA values, and we dropped Instr.minus.Notes because it was a linear combination of ConsInstr and ConsNotes. We treated all of the 0-5 ordinal variables as continuous, and looked at the distribution of all of the numeric variables. We found that OMSI is heavily right skewed and log transformed it. The histograms showing this transformation can be seen in Figure 1. We also found that for both KnowRob and KnowAxis, most values are either 0, 1,

Table 1: Variable Descriptions

Variable	Description
Classical	How classical does the stimulus sound?
Popular	How popular does the stimulus sound?
Subject	Unique subject ID
Harmony	Harmonic Motion (4 levels)
Instrument	Instrument (3 levels)
Voice	Voice Leading (3 levels)
Selfdeclare	Are you a musician? (1-6, 1=not at all)
OMSI	Score on a test of musical knowledge
X16.minus.17	Auxiliary measure of listener's ability to distinguish classical vs popular music
ConsInstr	How much did you concentrate on the instrument while listening (0-5, 0=not at all)
ConsNotes	How much did you concentrate on the notes while listening? (0-5, 0=not at all)
Instr.minus.Notes	Difference between prev. two variables
PachListen	How familiar are you with Pachelbel's Canon in D (0-5, 0=not at all)
ClsListen	How much do you listen to classical music? (0-5, 0=not at all)
KnowRob	Have you heard Rob Paravonian's Pachelbel Rant (0-5, 0=not at all)
KnowAxis	Have you heard Axis of Evil's Comedy bit on the 4 Pachelbel chords in popular music? (0-5, 0=not at all)
X1990s2000s	How much do you listen to pop and rock from the 90's and 2000's? (0-5, 0=not at all)
X1990s2000s.minus.1960s1970s	Difference between prev variable and a similar variable referring to 60's and 70's pop and rock.
CollegeMusic	Have you taken music classes in college (0=no, 1=yes)
NoClass	How many music classes have you taken?
APTheory	Did you take AP Music Theory class in High School (0=no, 1=yes)
Composing	Have you done any music composing (0-5, 0=not at all)
PianoPlay	Do you play piano (0-5, 0=not at all)
GuitarPlay	Do you play guitar (0-5, 0=not at all)
X1stInstr	How proficient are you at your first musical instrument (0-5, 0=not at all)
X2ndInstr	Same, for second musical instrument

or 5, so we transform those variables to be binary categorical variables with levels of 0 and greater than 0[1].

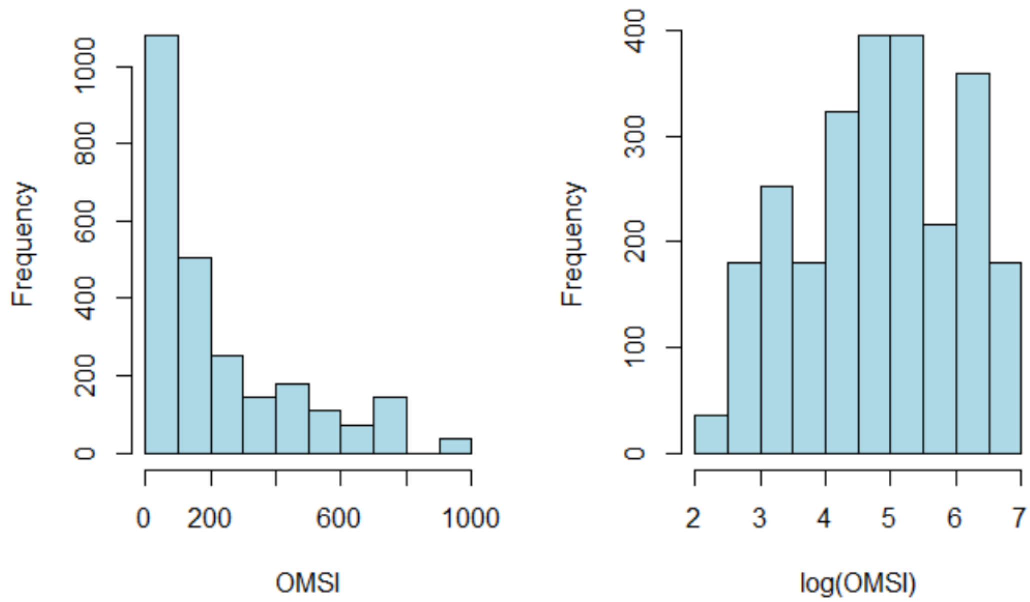

Figure 1: Histograms of OMSI, before and after log transformation.

We also found that several of the features, including the ratings, contained NA values. The ratings also contained invalid values that were beyond the 1 to 10 constraint. We removed them only when building a model that used that feature or outcome, which we will detail in later sections.

3.2 The Effects of Instrument, Harmonic Motion, and Voice Leading on Classical Ratings

3.2.1 Building the Model

The main question of this paper is to determine what the effects of the different levels of instrument, harmonic motion, and voice leading are on classical ratings. To do so we went through the process of creating a linear mixed effects model with fixed and random effects of the three design variables to predict classical ratings.

First we build a new data set. We removed all rows in which Classical, Instrument, Harmony, or Voice were missing. We also found nine Classical rating values outside of the 1-10 range (eight which were 0, one which was 19), and we removed those. Then we examined all possible fixed, or non-random, effects. We did so by first creating a full model of Instrument, Harmony, Voice, and all of their interactions, and then doing step-wise variable selection with AIC and BIC on this full model to see which variables were important to the model. Writing the models in R's notation, the model chosen by AIC was Classical Ĩnstrument + Harmony + Voice + Harmony:Voice (where Harmony:Voice represents the interaction of Harmony and Voice), and the model chosen by BIC was Classical Ĩnstrument + Harmony. When doing a partial F-test to compare the two models, we

[1]Code and plots for data cleaning can be found in the Technical Appendix, pgs. 1-9.

got an F-statistic of 4.1592 with a very small p-value. Because this p-value was small, we determined that these extra interaction terms were a significant improvement to the model [2].

We then reasoned that the way a listener identifies a stimuli as classical could vary person to person, due to personal bias. Because our intuition was that this personal bias would have an overall affect on ratings, we first checked to see if a random intercept for the subject variable (where each subject represented one listener) was needed. R denotes this random intercept as (1 | Subject). We did this by comparing our our previous model to a model with the random intercept for Subject added. We made this comparison by conducting an exact test for random effect, which gave a small p-value. This told us that the random intercept was needed.

Given that we added this random intercept, we went back and reassessed which of our fixed effects was needed. We started with the full model of Instrument, Harmony, Voice, their interactions, and the random intercept term (1 | Subject). We then used the fitLMER.fnc function to do step-wise variable selection of the fixed effects. We ended up with the model Classical Ĩnstrument + Harmony + Voice + (1 | Subject), with no interaction terms. We also looked at the conditional residuals for this model, since the marginal residuals are neither correlated or mean zero. The conditional residuals should be mean zero with no grouping structure, as well as homoskedastic, which for the most part is true for this model[3].

The random intercept accounts for general biases a person may have for rating stimuli, but we reasoned that this bias may differ along the design variables as well. Thus, we created seven linear mixed effects models, all with different combinations of random effects (e.g. Instrument given Subject or Instrument and Harmony given Subject). We then found the AIC and BIC for each of these models. The model with the lowest AIC and BIC was Classical Ĩnstrument + Harmony + Voice + (1 + Instrument + Harmony | Subject). That last term means that we have the random effect of the intercept, Instrument, and Harmony given Subject, all of which are correlated.

The next part of our process was to again reassess our fixed effects with the random effects we found to be best. In order to do so, we again decided to use the fitLMER.fnc function in R, start with a full model of Instrument, Harmony, Voice, all of their interactions, and the random effect of (1 + Instrument + Harmony | Subject). However, since the fitLMER.fnc does not work with random effects with two or more correlated random slope terms, we kept this random effect in mind and moved on to focus on the models which included only one random slope. We saw then the model with the lowest AIC and BIC among these models was Classical Ĩnstrument + Harmony + Voice + (1 + Instrument | Subject), and the conditional residuals for this model also looked good, all centering around zero and with mostly constant variance. We used this random effect in the reassessment of fixed effects, the idea being that once we found our fixed effects, we would then compare the model with those fixed effects and (1 + Instrument | Subject) and the model with those fixed effects and the random effect we had found before, (1 + Instrument + Harmony | Subject), to come up with a final model.

Once we did this process, we ended up with the same fixed effects as before–Instrument + Harmony + Voice, and so we simply added back in the random effect of Instrument and Harmony from before, as we had previously calculated that it had a lower AIC and BIC than the model with just the Instrument random effect. The conditional residuals for this model also look good[4].

And finally we added in other covariates apart from our design variables, most notably KnowRob

[2] Detailed process can be found in the Technical Appendix, pgs. 9-11.

[3] Code and output for model and plots can be found in the Technical Appendix, pgs. 11-14.

[4] Code and output for model and tests can be found in the Technical Appendix, pgs. 14-18.

and KnowAxis, as well as their interactions with Harmony. We added the covariates to see if a person's musical background aided in their ratings. We used fitLMER.fnc to again see whether these variables would be included in the model in the same way described as before. When adding all of the other covariates we found that none of them were added in. But, we did find that KnowRob and its interaction with Harmony was kept in the model. We then also tried to add a KnowRob random effect, but this was found to make the model worse. Thus, we arrived as a final model of Classical Ĩnstrument + Voice + Harmony + KnowRob + Harmony:KnowRob + (Instrument | Subject)[5].

When looking at this model, the intercept, Instrumentpiano, Instrumentstring, and HarmonyI-V-VI all have variances ranging from 1.5 to 3.4, which is not much different from the residual variance of 2.4, which tells us it's good to use random effects in modeling this data. HarmonyI-V-IV and HarmonyIV-I-V have smaller variances, but this isn't worrying because at least one of the harmonic motion variables has a larger variance. The conditional residuals for this model look good, with mean zero and constant spread, indicating that the model is a good fit. Any groupings are due to the discreteness of the response. These conditional residuals can be found in Figure 2.

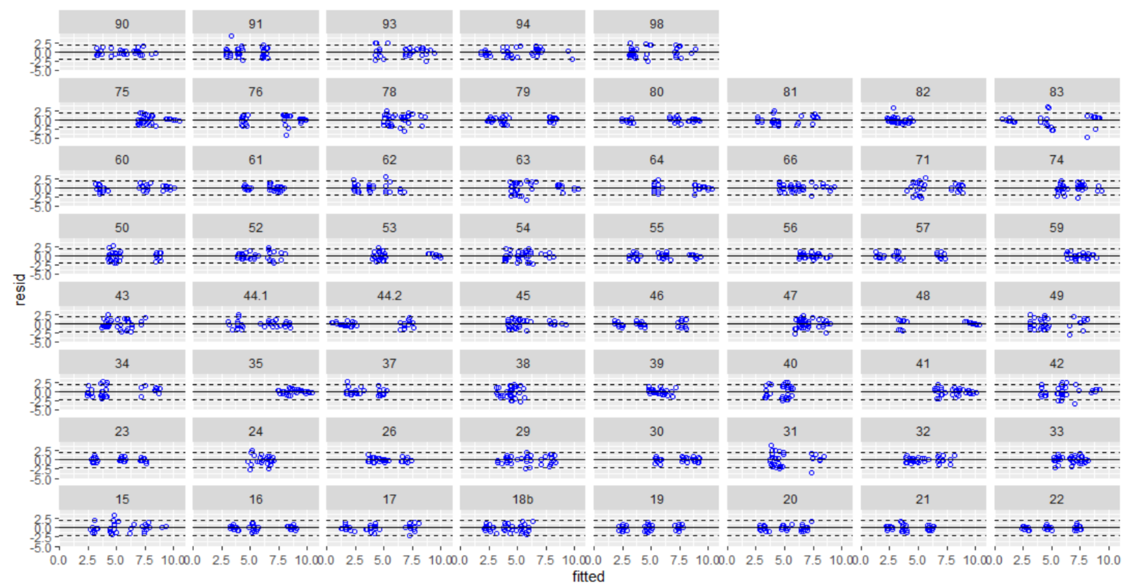

Figure 2: Conditional Residuals of the Linear Mixed Effects Model Predicting Classical Ratings.

3.2.2 Analysing the Model

The coefficients for the fixed effects in the final model can be found in Table 2.

Going back to the main questions set out by the paper, we first ask ourselves if instrument exerts the strongest influence among the three design variables. The fact that Instrumentpiano and Instrumentstring have the largest magnitude coefficients as well as the largest test statistics would indicate that this is the case. Instrumentstring has the largest positive coefficient, followed by Instrumentpiano, indicating that these two instruments have a strong positive association with classical ratings. Furthermore we find that the random effects of Instrumentpiano and Instrumentstring

[5]Code and output for model and tests can be found in the Technical Appendix, pgs. 18-23.

Table 2: Fixed Effects Coefficients for Linear Mixed Effects Model Predicting Classical Ratings

term	estimate	std.error	statistic
(Intercept)	3.778	0.238	15.853
Instrumentpiano	1.414	0.191	7.395
Instrumentstring	3.265	0.249	13.124
Voicepar5th	0.027	0.082	0.335
Voicecontrary	0.364	0.082	4.462
KnowRobTRUE	-0.111	0.429	-0.26
HarmonyI-V-IV	0.05	0.113	0.438
HarmonyI-V-VI	0.634	0.202	3.145
HarmonyIV-I-V	0.082	0.108	0.761
KnowRobTRUE:HarmonyI-V-IV	-0.119	0.229	-0.52
KnowRobTRUE:HarmonyI-V-VI	1.003	0.387	2.594
KnowRobTRUE:HarmonyIV-I-V	0.008	0.226	0.035

have a variance of 1.81 and 3.36, respectively, indicating a stronger variance of the relationships between instrument and rating by subject.

Next we ask, among the levels of harmonic motion, does I-V-vi have a strong association with classical ratings, and does it seem to matter whether the respondent is familiar with the Pachelbel rants/comedy bits? We see that HarmonyI-V-VI does have a positive coefficient and a high test statistic, indicating that it is strongly associated with classical ratings. We also find that that association becomes even stronger when someone is familiar with the Pachelbel Rant, seeing as how their interaction term is 1.003.

And finally, we ask ourselves if among the levels of voice leading, does contrary motion have a strong association with classical ratings? Looking at the coefficients table, we see that Voicecontrary has a positive coefficient and a high test statistic indicating that contrary motion is strongly associated with classical ratings; however, because the coefficient isn't big, we would not say that the relationship is very strong.

Ultimately, we found that all three design variables all had a significant effect on how someone associated a stimuli with classical music. We see that piano and string instruments have a positive relationship with classical ratings, as does the harmonic motion I-V-VI and contrary motion.

3.3 Do Musicians and Non-Musicians Identify Classical Music Differently?

One of our additional questions was to ask if there were any differences in the ways that musicians and non-musicians identified classical music. In order to answer this, we introduced a new "musician" variable where we set someone to be a musician if their self declare variable was above a 3. Afterwards, starting from our previous model, we created a linear mixed effects model with Instrument, Harmony, Voice, KnowRob, as well as all of their interactions with Musician, and the random effect for Instrument. We then used fitLMER.fnc to do step-wise variable selection of fixed effects, and it kept not only musician but the interaction between musician and Harmony. We added back in our original random effect of Instrument and Harmony, and that model had a lower BIC and AIC than just the model with the random effect of Instrument[6]. The coefficients for the fixed effects of this model can be found in Table 3.

Table 3:

term	estimate	std.error	statistic
(Intercept)	4.024	0.245	16.455
musicianTRUE	-0.565	0.434	-1.304
Instrumentpiano	1.331	0.184	7.233
Instrumentstring	3.113	0.246	12.642
KnowRobTRUE	-0.036	0.444	-0.081
HarmonyI-V-IV	-0.03	0.112	-0.266
HarmonyI-V-VI	0.374	0.191	1.963
HarmonyIV-I-V	0.002	0.11	0.022
Voicepar5th	0.037	0.079	0.469
Voicecontrary	0.373	0.079	4.717
KnowRobTRUE:HarmonyI-V-IV	-0.017	0.238	-0.071
KnowRobTRUE:HarmonyI-V-VI	0.86	0.395	2.179
KnowRobTRUE:HarmonyIV-I-V	-0.09	0.235	-0.383
musicianTRUE:HarmonyI-V-IV	0.037	0.232	0.16
musicianTRUE:HarmonyI-V-VI	1.01	0.385	2.621
musicianTRUE:HarmonyIV-I-V	0.379	0.23	1.648

Judging from this model, if someone is a musician AND the harmonic motion is I-V-vi (and to a lesser extent I-V-IV and IV-I-V), on average the classical rating will be higher. One should note that this does seem to be sensitive to the threshold, as if we put musician to be above 4 rather than 3, musician will no longer be included in the model when using fitLMER.

3.4 Differences in What Drives Popular Ratings

Our final question was to explore if there were any differences in what drove people to identify stimuli as classical vs. popular. In order to determine this we built a model to predict Popular ratings from the design variables of instrument, harmonic motion, and voice leading, as well as random effects and other covariates from the data set. The procedure we followed was identical to what we did for classical ratings[7].

We first cleaned the data to remove all NA values from the variables we planned on using. There were also twenty-four ratings of 0 and one rating of 19, so we removed those invalid data points. We started with the full model of Instrument, Harmony, Voice, and all of their interactions. We did step-wise selection with AIC and BIC, and none of the interaction terms were included. Thus, we made it so that we just had the main effects included in the model. We then tested various random effects given our fixed effects, and as with classical ratings, found that the random effect of intercept, Instrument, and Harmony was best to include. And when reassessing fixed effects given our random effects, again no interaction terms were added. We then tried to add in other covariates

[6]Code and output for model and tests can be found in the Technical Appendix, pgs. 24-25.
[7]Code and output for this process can be found in the Technical Appendix, pgs. 25-30.

such as KnowRob and KnowAxis and their interactions with Harmony, but unlike the model for Classical ratings, none of these terms were selected when doing step-wise variable selection with fitLMER.fnc. Thus the coefficients for the fixed effects of the final model are shown in Table 4.

Table 4:

term	estimate	std.error	statistic
(Intercept)	6.769	0.175	38.581
Instrumentpiano	-0.952	0.16	-5.951
Instrumentstring	-2.557	0.23	-11.095
HarmonyI-V-IV	-0.047	0.096	-0.489
HarmonyI-V-VI	-0.295	0.143	-2.07
HarmonyIV-I-V	-0.217	0.103	-2.096
Voicepar5th	0.01	0.077	0.131
Voicecontrary	-0.146	0.077	-1.905

When looking at this model, the intercept, Instrumentpiano, Instrumentstring, and Harmony-I-V-VI all have variances ranging from 0.8 to 3.3, which is not much different from the residual variance of 2.4. This tells us it's good to use random effects for this model. HarmonyI-V-IV and HarmonyIV-I-V have smaller variances, but this isn't worrying because at least one Harmony has a larger variance. The conditional residuals for this model also look good, being centered around zero and with constant variance, indicating that the model is a good fit. For this model, Instrumentpiano and Instrumentstring have negative coeffcients and high test statistics, as do Voicecontrary and HarmonyI-V-VI, indicating that they are all negatively associated with Popular ratings[8].

And as we did for classical ratings, we also checked to see if whether someone identifies as a musician changes how they perceive stimuli as popular music. To do this, we again set someone to be a musician if their self declare was above a 3. If we did that and fit our previous model (with just the instrument random effect) and possible interactions between Harmony and Voice, it kept not only musician but the interaction between musician and Harmony. This does seem sensitive to the threshold we used to assign someone to be a musician, as if we put musician to be a self declare above 4 rather than 3, musician will no longer be included in the model when using fitLMER. We also added back in our other random effect, and while the AIC was lower, the BIC was higher, so we kept just the instrument random effect. And for this model, if someone is a musician AND the harmonic motion is I-V-vi, on average the popular rating will be even lower. [9].

4 Discussion

Jimenez and Rossi designed an experiment intended to measure the influence of instrument, harmonic motion, and voice leading on listeners' identification of music as "classical" or "popular". In order to provide a statistical basis to this we first focused on classical ratings to define an iterative approach in constructing a model. Through various selection processes we created a mixed effects linear model to predict classical ratings using our design variables. Our final model for this part was

[8] Code and output for final model and residual plots can be found in the Technical Appendix, pgs. 27-28.

[9] Code and output for models and tests can be found in the Technical Appendix, pgs. 30-32.

predicting Classical ratings from Instrument, Harmony, and Voice, interactions between KnowRob and Harmony, as well as including random effects for the intercept, Harmony, and Instrument. This means that we include the variation that exists between subjects and how certain harmonic motions or instruments affect the way different people perceive music differently.

After checking to see if this model was a valid model, we turned to the coefficients for the fixed effects to tell us about the design variables and our main questions. We first asked if instrument exerted the strongest influence, and we can see that Instrumentpiano and Instrumentstring not only have a positive relationship with classical ratings, but also the largest coefficients for fixed effects, as well as the largest variances for random effects. We next asked if the harmonic motion I-V-vi had a strong association with classical ratings and if this changes depending on whether the listener is aware of the comedy bits described before. We then see that HarmonyI-V-VI has a positive relationship with classical ratings, and that this relationship is made stronger when someone has heard the Pachelbel rant. From this we can conclude that despite this chord progression being used often in popular music it is still strongly associated with classical music. But more interestingly, the Pachelbel rant by Rob Paravonian distinctly points out how this chord progression is found in all types of music, including popular music, but if a listener has heard this rant their association of I-V-vi with classical music becomes even stronger. Research into why this is could uncover a more nuanced explanation. We also asked if contrary voice leading was strongly associated with classical music and found that it was.

Our next big question was to determine if when a listener identifies as a musician their identification of classical music changes in any way, and we found that it did. We found that musicianship makes the positive association between the harmonic motion I-V-vi and classical ratings even stronger.

And our last question was whether any of the previous analysis was different for popular music, given that popular music is often contrasted with classical music. To explore this we again built a model, and our final model for this was predicting popular ratings from Instrument, Harmony, Voice, and the random effect of Instrument and Harmony given subject. We again found that the most important variable in predicting popular ratings seemed to be Instrument, but that string and piano instruments were negatively associated with popular music. We also found that the harmonic motions of I-V-vi and IV-I-V had slightly negative associations with popular ratings, but this association wasn't very strong. This might mean that listeners don't identify any single chord progression with popular music. And finally we found that contrary motion had a negative association with popular ratings.

We also did the musician analysis with popular ratings, and again found that if a person identified as a musician, the negative association of the harmonic motion of I-V-vi with popular ratings became even more negative. This means that musicianship overall causes people to more strongly relate this particular chord progression away from popular music and towards classical music. Adding in the interaction between musician and harmony also made the random effect for harmony less important to the model, indicating that the difference in subjects could have been captured well enough through this interaction term.

This is interesting because the experiment specifically told listeners to treat the rating systems as independent but in our analysis they were often opposed to each other. Instrumentpiano and Instrumentstring are positive associated with classical ratings but negatively associated with popular ratings. HarmonyI-V-vi is positively associated with classical ratings and negatively associated with popular ratings. Contrary motion is positively associated with classical ratings but negatively associated with popular ratings. Musicianship in both models makes the relationship between rating and HarmonyI-V-vi even stronger, and KnowRob is included in the model for classical ratings but not for popular ratings.

Now this could mean that listeners naturally treat classical and popular as opposing ends of a music spectrum, or in some way the experiment indirectly caused them to want to rate a stimuli differently on the two scales.

Overall, our findings support that each person has their own relationship with how they perceive music, and there are some interesting trends regarding the design variables to be found across everyone. Future research could be done as to why despite it's prevalence in popular music I-V-vi is still so strongly associated with classical music, but this paper provides a good foundation as the the differences in what makes up either type of music and how that affects how people perceive them.

References

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Technical Appendix

1 Data Cleaning

```
library(tidyverse)
library(broom)
library(stargazer)
ratings = read.csv('ratings.csv')[-1] %>% dplyr::select(-first12)

apply(ratings, FUN=function(x) sum(is.na(x)), MARGIN=2)
```

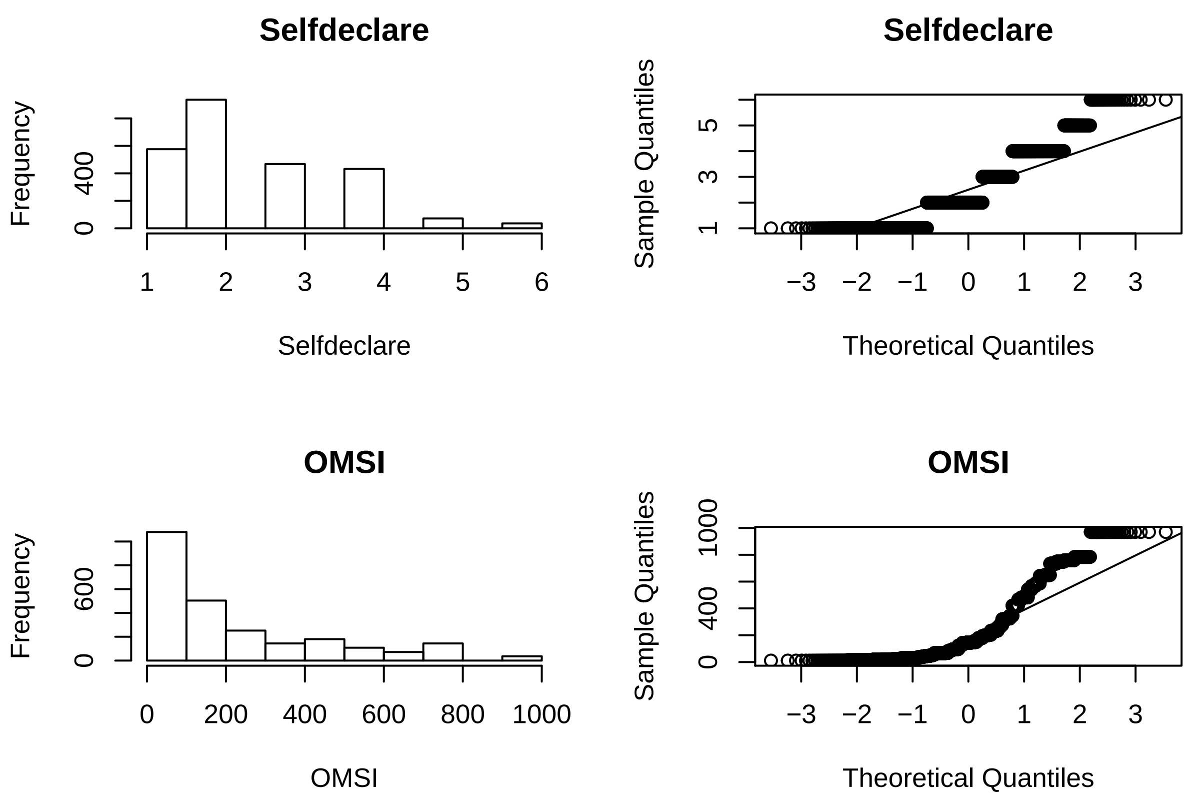
```
                Subject                 Harmony
                      0                       0
             Instrument                   Voice
                      0                       0
            Selfdeclare                    OMSI
                      0                       0
           X16.minus.17               ConsInstr
                      0                       0
              ConsNotes       Instr.minus.Notes
                    360                       0
             PachListen               ClsListen
                     72                      36
                KnowRob                KnowAxis
                    180                     288
            X1990s2000s X1990s2000s.minus.1960s1970s
                    144                     180
           CollegeMusic                 NoClass
                    108                     288
               APTheory               Composing
                    216                      72
              PianoPlay              GuitarPlay
                      0                       0
              X1stInstr               X2ndInstr
                   1512                    2196
              Classical                 Popular
                     27                      27
```

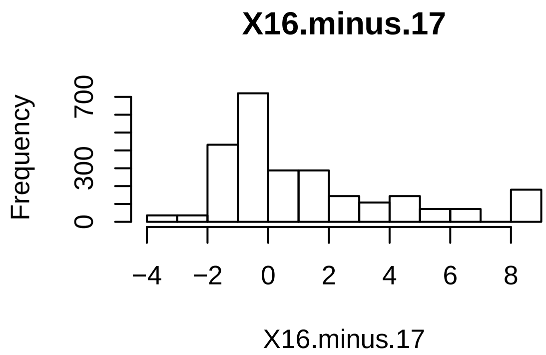
```
ratings$Voice = factor(ratings$Voice,
                       levels(ratings$Voice)[c(2,3,1)])
ratings = ratings %>% dplyr::select(-c(X1stInstr,X2ndInstr,
                                        Instr.minus.Notes))
ratings = ratings %>% mutate(
                        CollegeMusic = as.factor(CollegeMusic),
                        APTheory = as.factor(APTheory),
                        KnowRob = as.factor(KnowRob > 0),
                        KnowAxis = as.factor(KnowAxis > 0))
```

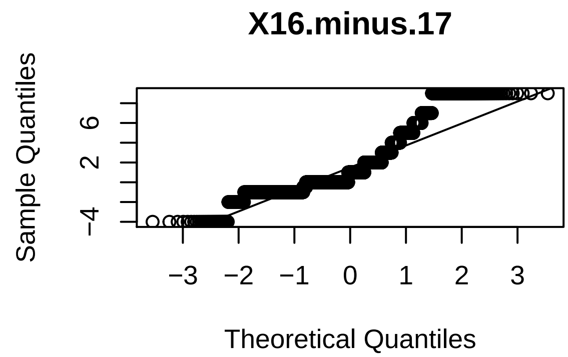
Here we look at the distributions of all of our numeric variables.

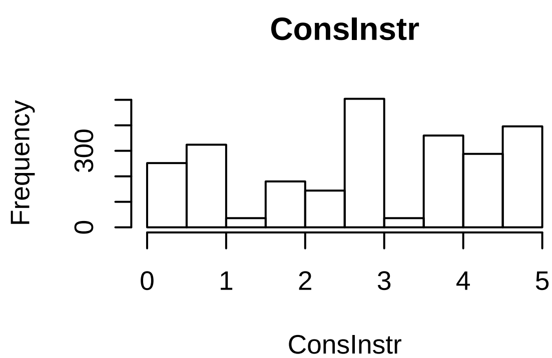
```
par(mfrow=c(2,2))
for (col in colnames(ratings)) {
    if (class(ratings[,col]) %in% c('integer','numeric')) {
```

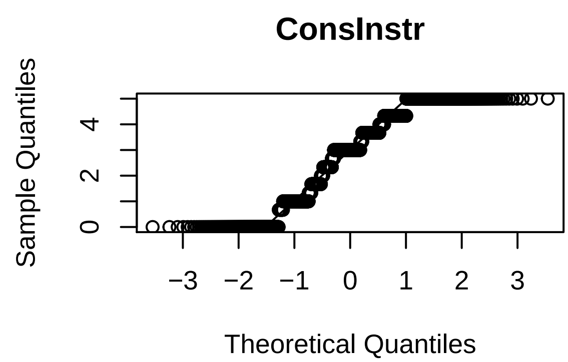
```
        hist(ratings[,col], main = col, xlab = col)
        qqnorm(ratings[,col], main = col)
        qqline(ratings[,col])
    }
}
```

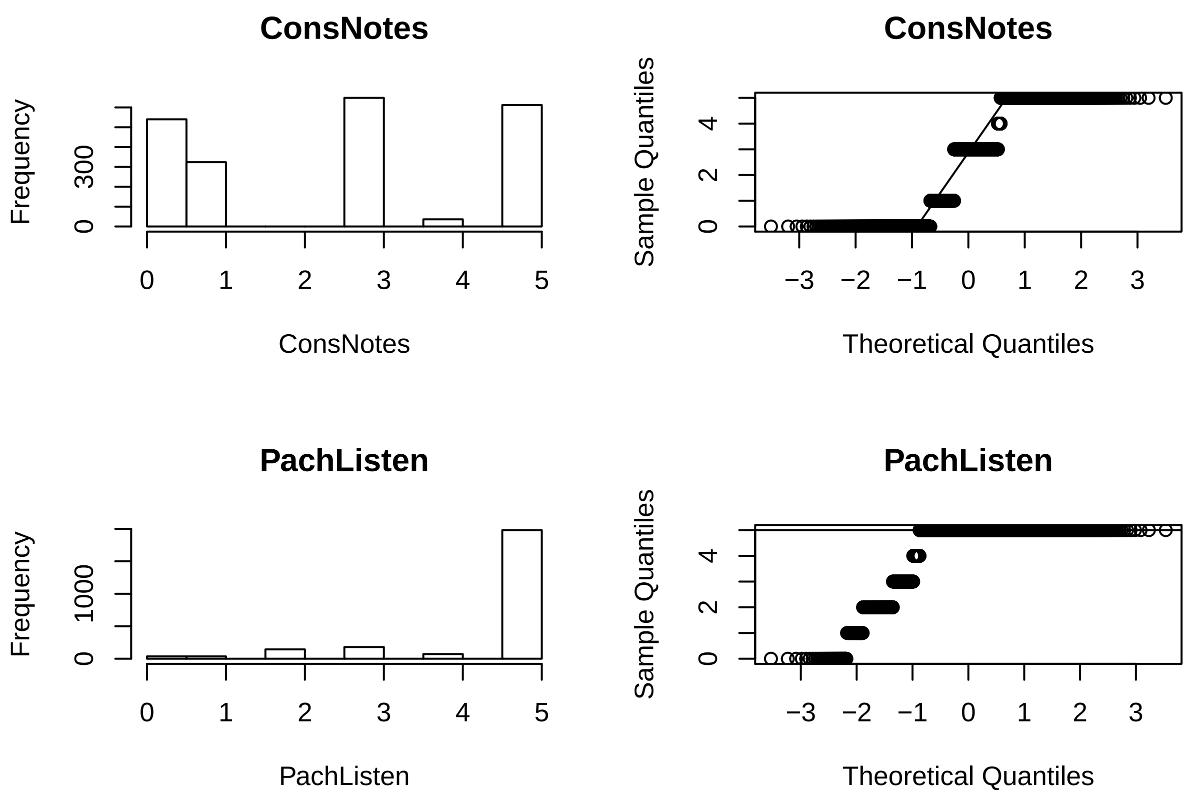


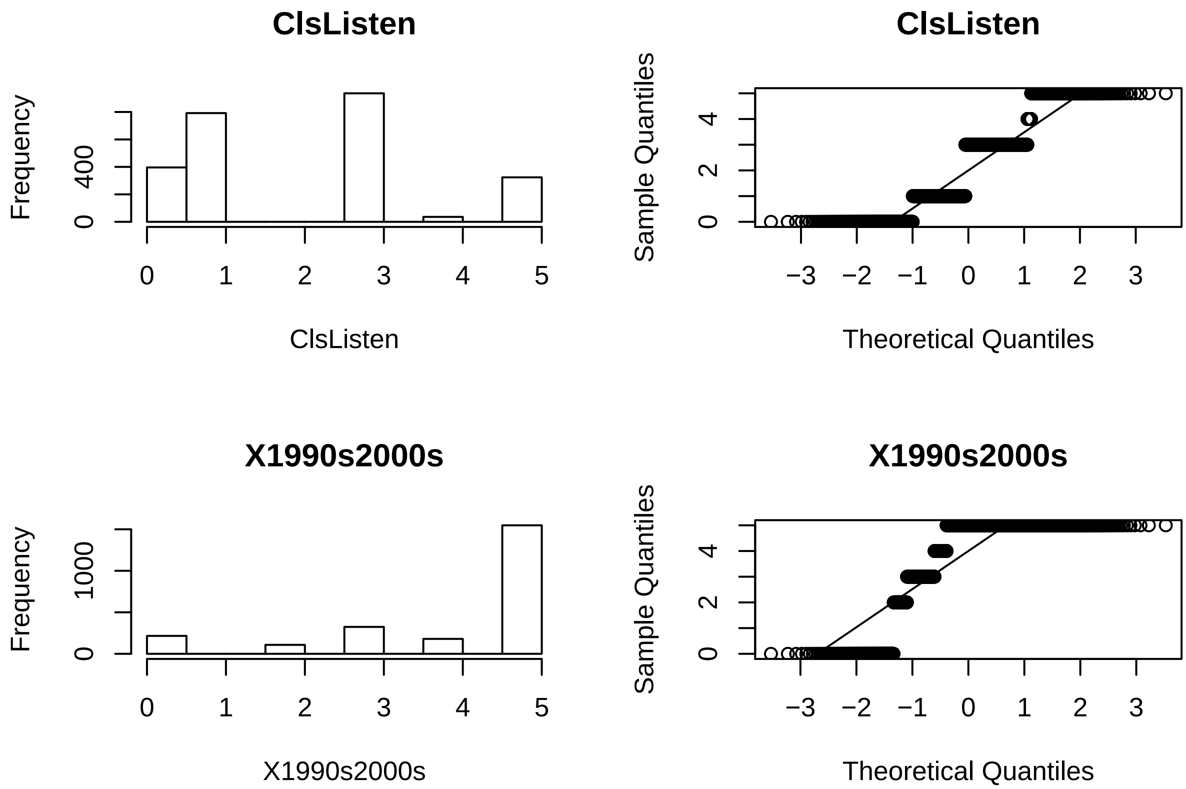

X16.minus.17
Frequency
0
300
700
−4
−2
0
2
4
6
8
X16.minus.17

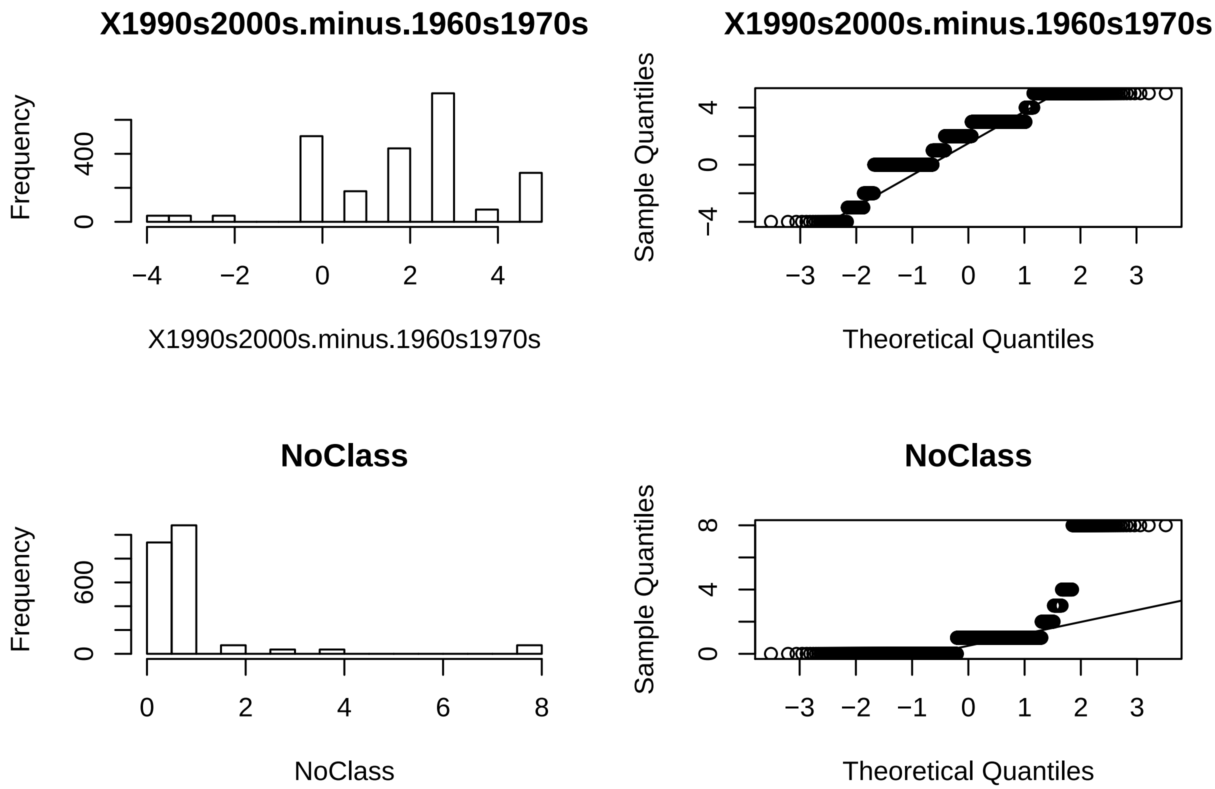

X16.minus.17
Sample Quantiles
−4
2
6
−3
−2
−1
0
1
2
3
Theoretical Quantiles

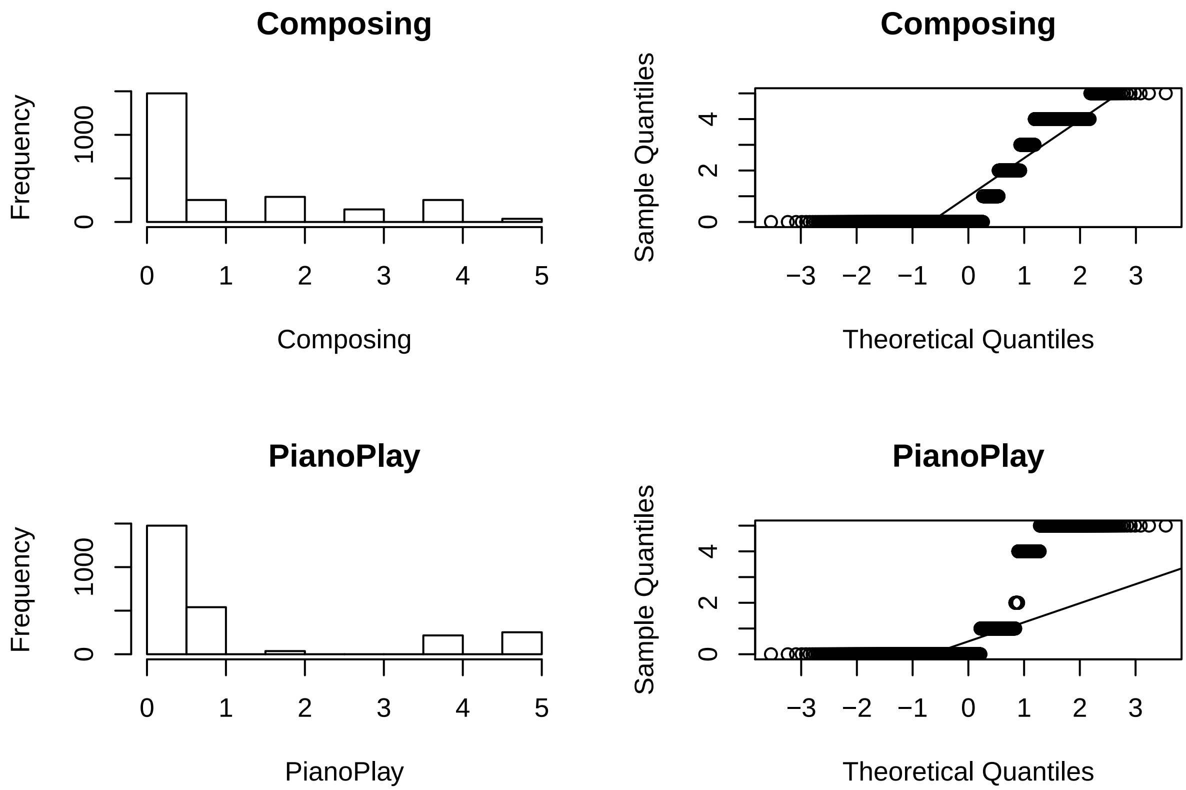

ConsInstr
Frequency
0
300
0
1
2
3
4
5
ConsInstr

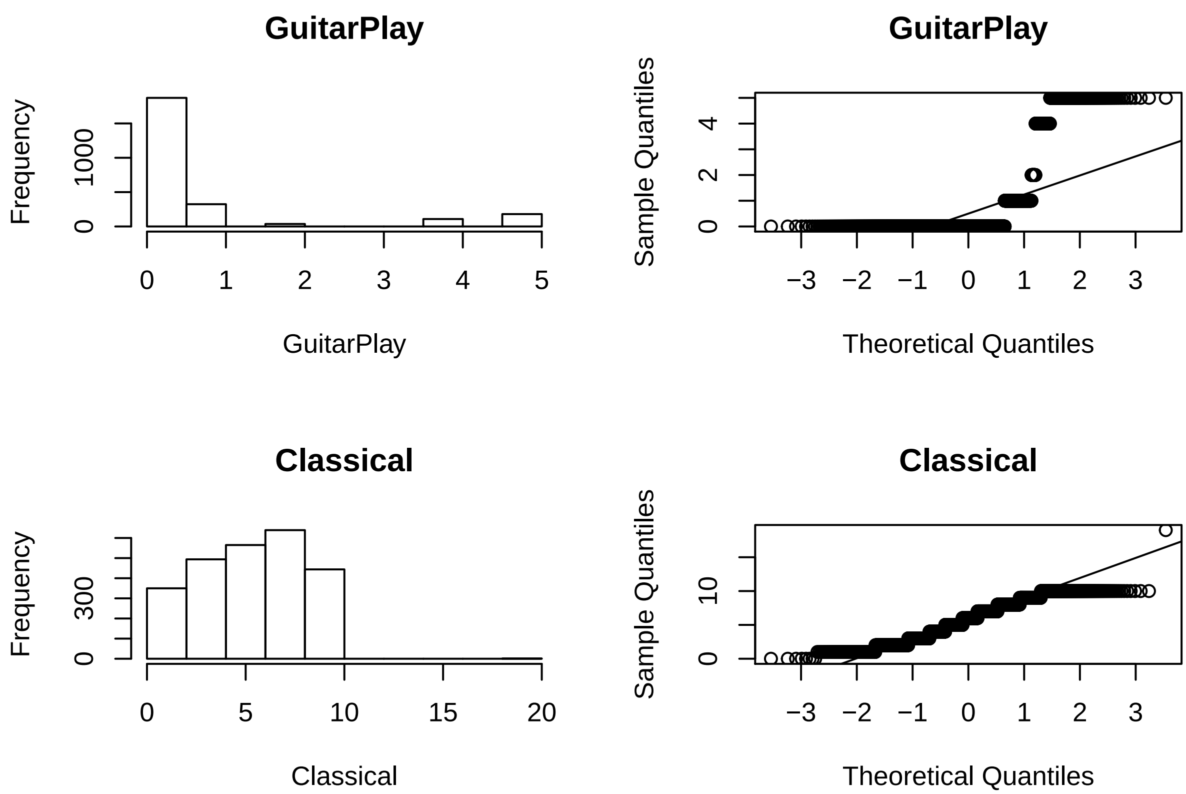

ConsInstr
Sample Quantiles
0
2
4
−3
−2
−1
0
1
2
3
Theoretical Quantiles

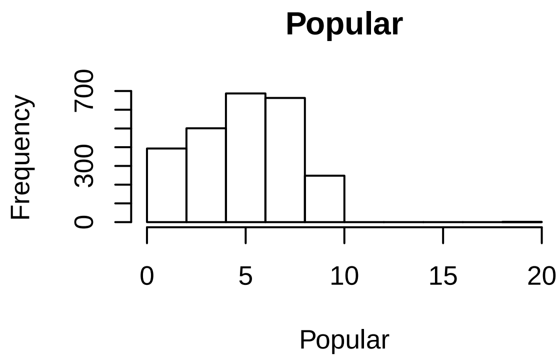

ConsNotes
Frequency
0
300
0 1 2 3 4 5
ConsNotes
ConsNotes
Sample Quantiles
0 2 4
−3 −2 −1 0 1 2 3
Theoretical Quantiles
PachListen
Frequency
0
1000
0 1 2 3 4 5
PachListen
PachListen
Sample Quantiles
0 2 4
−3 −2 −1 0 1 2 3
Theoretical Quantiles

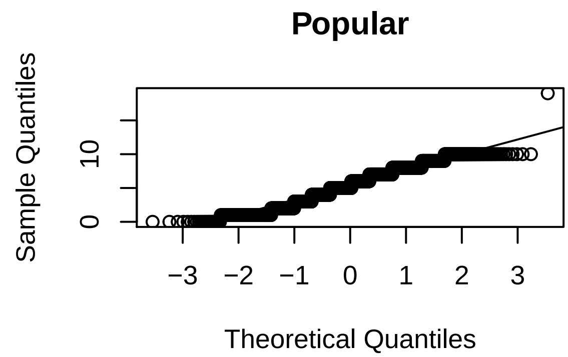

ClsListen
Frequency
0
400
0
1
2
3
4
5
ClsListen
ClsListen
Sample Quantiles
0
2
4
−3
−2
−1
0
1
2
3
Theoretical Quantiles
X1990s2000s
Frequency
0
1000
0
1
2
3
4
5
X1990s2000s
X1990s2000s
Sample Quantiles
0
2
4
−3
−2
−1
0
1
2
3
Theoretical Quantiles


X1990s2000s.minus.1960s1970s
Frequency
0
400
−4
−2
0
2
4
X1990s2000s.minus.1960s1970s
X1990s2000s.minus.1960s1970s
Sample Quantiles
4
0
−4
−3
−2
−1
0
1
2
3
Theoretical Quantiles
NoClass
Frequency
0
600
0
2
4
6
8
NoClass
NoClass
Sample Quantiles
8
4
0
−3
−2
−1
0
1
2
3
Theoretical Quantiles


Composing
Frequency
0
1000
0 1 2 3 4 5
Composing
Composing
Sample Quantiles
0 2 4
−3 −2 −1 0 1 2 3
Theoretical Quantiles
PianoPlay
Frequency
0
1000
0 1 2 3 4 5
PianoPlay
PianoPlay
Sample Quantiles
0 2 4
−3 −2 −1 0 1 2 3
Theoretical Quantiles


GuitarPlay
Frequency
0
1000
0 1 2 3 4 5
GuitarPlay
GuitarPlay
Sample Quantiles
0
2
4
−3 −2 −1 0 1 2 3
Theoretical Quantiles
Classical
Frequency
0
300
0 5 10 15 20
Classical
Classical
Sample Quantiles
0
10
−3 −2 −1 0 1 2 3
Theoretical Quantiles





From the histogram and qqplots, we can see that OMSI is heavily right skewed with values going to 1000, so we log-transform it

```
ratings$OMSI = log(ratings$OMSI)
```

2 Effects of Instrument, Harmony, and Voice on Classical Ratings

2.1 Data cleaning

```
na_locs = apply(is.na(ratings[,c("Classical", "Popular", "Instrument",
                 "Harmony", "Voice", "Subject")]),
                FUN=function(x) any(x), MARGIN=1)
new_ratings = ratings[!na_locs,]

classical_ratings = new_ratings %>%
      dplyr::select(c(Classical, Instrument, Harmony, Voice, Subject)) %>%
      filter(Classical > 0 & Classical <= 10)
```

2.2 Find fixed effects

Here we do stepwise variables selection.

```
library(MASS)
lm.c.aic = stepAIC(lm(Classical~(Instrument+Harmony+Voice)^3,
            data = classical_ratings), direction="both",k=2)
lm.c.bic = stepAIC(lm(Classical~(Instrument+Harmony+Voice)^3,
```

```r
           data = classical_ratings),
           direction="both",k=log(nrow(classical_ratings)))
```

Below we calculate the AIC and BIC for both models.

```r
AIC(lm.c.aic); AIC(lm.c.bic)
```

```
[1] 11136.43
```

```
[1] 11153.96
```

```r
BIC(lm.c.aic); BIC(lm.c.bic)
```

```
[1] 11223.7
```

```
[1] 11194.68
```

```r
anova(lm.c.aic, lm.c.bic)
```

```
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice + Harmony:Voice
Model 2: Classical ~ Instrument + Harmony
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2470 12720
2   2478 12893 -8   -172.84 4.1952 5.268e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model chosen by AIC is best.

```r
summary(lm.c.aic)
```

```

Call:
lm(formula = Classical ~ Instrument + Harmony + Voice + Harmony:Voice,
    data = classical_ratings)

Residuals:
    Min      1Q  Median      3Q     Max
-6.8559 -1.7490 -0.0201  1.6515  6.1874

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                   4.0201     0.1703  23.611   <2e-16 ***
Instrumentpiano               1.3443     0.1119  12.012   <2e-16 ***
Instrumentstring              3.0817     0.1112  27.705   <2e-16 ***
HarmonyI-V-IV                -0.2075     0.2225  -0.932   0.3512
HarmonyI-V-VI                 0.4373     0.2231   1.960   0.0501 .
HarmonyIV-I-V                 0.3846     0.2236   1.720   0.0856 .
Voicepar5th                   0.0421     0.2231   0.189   0.8503
Voicecontrary                 0.2551     0.2223   1.148   0.2511
HarmonyI-V-IV:Voicepar5th     0.1495     0.3153   0.474   0.6355
HarmonyI-V-VI:Voicepar5th     0.2747     0.3155   0.871   0.3839
HarmonyIV-I-V:Voicepar5th    -0.4699     0.3157  -1.488   0.1368
HarmonyI-V-IV:Voicecontrary   0.3605     0.3149   1.145   0.2524
HarmonyI-V-VI:Voicecontrary   0.7296     0.3153   2.314   0.0207 *
HarmonyIV-I-V:Voicecontrary  -0.5554     0.3155  -1.761   0.0784 .
```

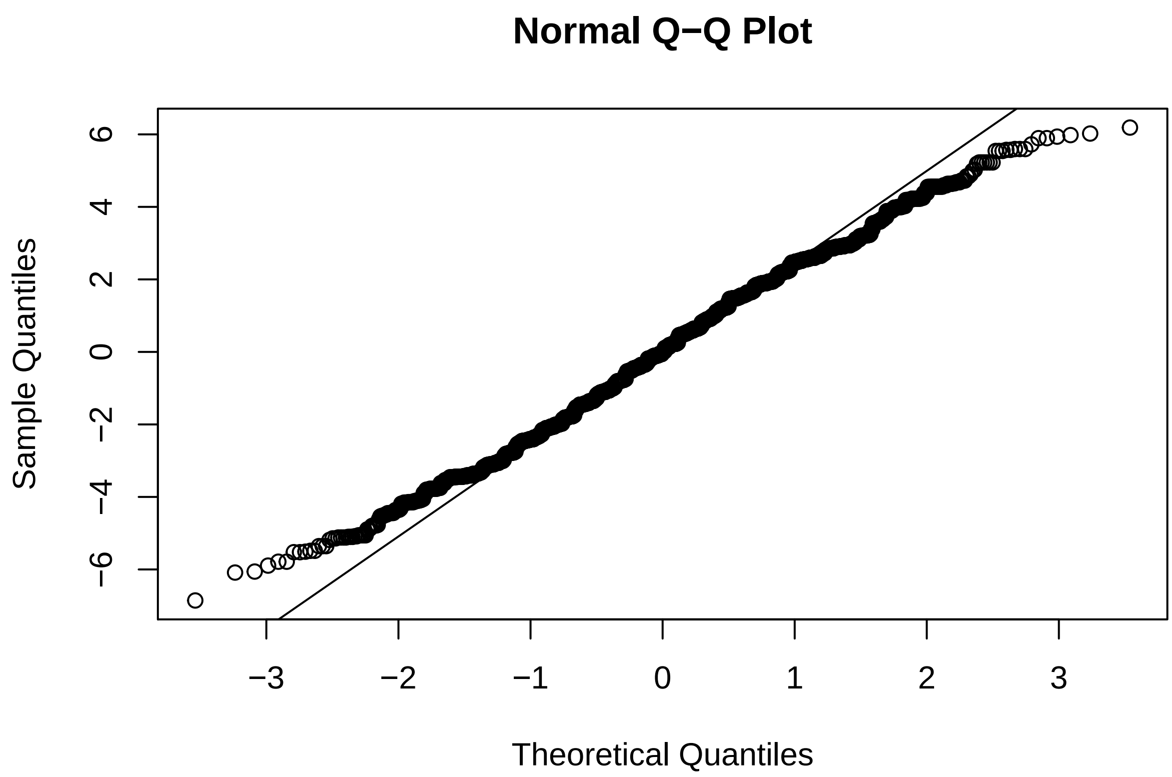
```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.269 on 2470 degrees of freedom
Multiple R-squared:  0.2584,	Adjusted R-squared:  0.2545
F-statistic:  66.2 on 13 and 2470 DF,  p-value: < 2.2e-16
```

```
#lmt = tidy(lm.c.aic)
#lmt[2:4] = round(lmt[2:4], digits=3)
#stargazer(lmt, summary = F, rownames = FALSE)
```

Below we look at our model's residuals, and see that for the most part they are normal, with some slight trailing off at the ends.

```
qqnorm(residuals(lm.c.aic))
qqline(residuals(lm.c.aic))
```



2.3 Random intercept model

Here we check to see if a random intercept is needed.

```
library(lme4)
library(LMERConvenienceFunctions)
library(RLRsim)

lm.intercept.only = lm(Classical ~ Instrument + Harmony*Voice,
                        data=classical_ratings)
lmer.subject.intercept <- lmer(Classical ~ Instrument + Harmony*Voice +
```

```r
                                  (1|Subject),
                           data=classical_ratings, REML=F)

# I then so the exact test of the random effect
exactRLRT(lmer.subject.intercept)
```

```
    simulated finite sample distribution of RLRT.

    (p-value based on 10000 simulated values)

data:
RLRT = 781.61, p-value < 2.2e-16
```

2.4 Check fixed effects again

```r
lmer.1 <- lmer(Classical ~ (Instrument + Harmony +
                            Voice)^3  + (1|Subject),
                           data=classical_ratings, REML=F)
lmer.1b <- fitLMER.fnc(lmer.1,method="BIC")
```

The interaction terms is removed.

```r
summary(lmer.1b)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
   Data: classical_ratings

REML criterion at convergence: 10372.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0439 -0.6436 -0.0150  0.6481  3.9231

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.687    1.299
 Residual             3.491    1.868
Number of obs: 2484, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       3.98090    0.18803  21.171
Instrumentpiano   1.34325    0.09225  14.561
Instrumentstring  3.08176    0.09165  33.625
HarmonyI-V-IV    -0.03949    0.10596  -0.373
HarmonyI-V-VI     0.77174    0.10600   7.281
HarmonyIV-I-V     0.04254    0.10600   0.401
Voicepar5th       0.03011    0.09183   0.328
Voicecontrary     0.39022    0.09190   4.246

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr5t
```

```
Instrumntpn -0.245
Instrmntstr -0.246  0.501
HrmnyI-V-IV -0.282  0.002     0.000
HrmnyI-V-VI -0.281  0.001    -0.001     0.499
HrmnyIV-I-V -0.280  0.000     0.000     0.499  0.499
Voicepar5th -0.244  0.000     0.002    -0.001 -0.003 -0.005
Voicecntrry -0.246  0.001     0.002     0.002  0.001 -0.002  0.501
```

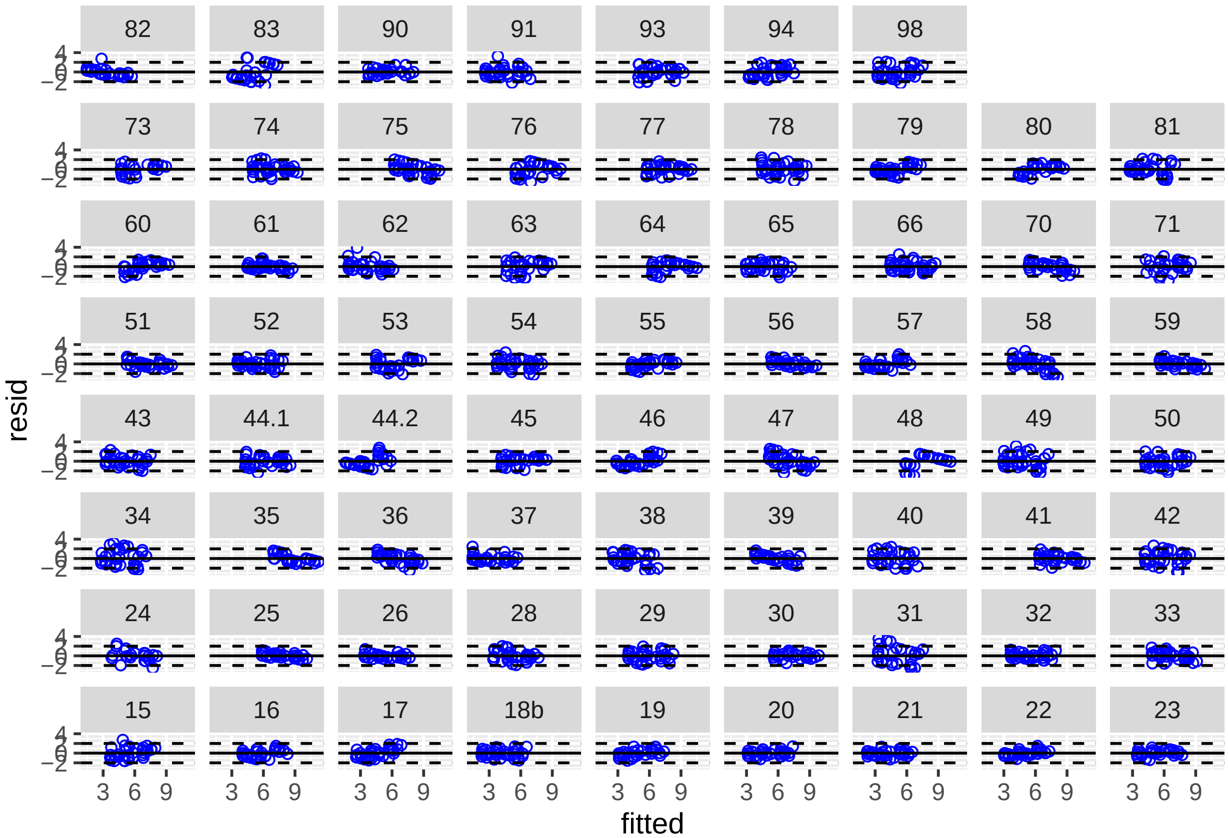
Checking the conditional Residuals.

```
library(arm)
source('mlm-facet-plots.r')
source('residual-functions.r')
res <- r.cond(lmer.1b)     ## standardized conditional residuals
robust.sd <- diff(quantile(res,c(.025,.975)))/(2*1.96)
res <- res/robust.sd
fit <- yhat.cond(lmer.1b)

newdata <- data.frame(Subject=classical_ratings$Subject,
                      resid=res,fitted=fit)

resparams <- data.frame(Subject=unique(classical_ratings$Subject),
                        int1=0,slo1=0,
                        int2=2,slo2=0,
                        int3=-2,slo3=0)

mlm_facets(newdata,"Subject",x="fitted",y="resid",params=resparams,
           lty=c(1,2,2),size=c(0.5,0.5,0.5))
```



2.5 More random effects

Here we try a variety of random effect combinations.

```
# three new random effects
lmer.2 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1  + Instrument + Harmony + Voice| Subject),
               data=classical_ratings, REML=F)

# two new random effects
lmer.3 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Instrument + Harmony| Subject),
               data=classical_ratings, REML=F)
lmer.4 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Harmony + Voice| Subject),
               data=classical_ratings, REML=F)
lmer.5 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Instrument + Voice| Subject),
               data=classical_ratings,REML=F)

# one new random effect
lmer.6 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Instrument| Subject),
               data=classical_ratings, REML=F)
lmer.7 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Harmony| Subject),
```

```
                data=classical_ratings, REML=F)
lmer.8 <- lmer(Classical ~ Instrument + Harmony +
                 Voice + (1 + Voice| Subject),
                data=classical_ratings, REML=F)

# compare all of the models
anova(lmer.2, lmer.3, lmer.4, lmer.5, lmer.6, lmer.7, lmer.8)
```

```
Data: classical_ratings
Models:
lmer.6: Classical ~ Instrument + Harmony + Voice + (1 + Instrument |
lmer.6:     Subject)
lmer.8: Classical ~ Instrument + Harmony + Voice + (1 + Voice | Subject)
lmer.7: Classical ~ Instrument + Harmony + Voice + (1 + Harmony | Subject)
lmer.5: Classical ~ Instrument + Harmony + Voice + (1 + Instrument +
lmer.5:     Voice | Subject)
lmer.3: Classical ~ Instrument + Harmony + Voice + (1 + Instrument +
lmer.3:     Harmony | Subject)
lmer.4: Classical ~ Instrument + Harmony + Voice + (1 + Harmony + Voice |
lmer.4:     Subject)
lmer.2: Classical ~ Instrument + Harmony + Voice + (1 + Instrument +
lmer.2:     Harmony + Voice | Subject)
       Df     AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.6 15 10004.4 10092 -4987.2   9974.4
lmer.8 15 10379.4 10467 -5174.7  10349.4   0.00      0          1
lmer.7 19 10281.8 10392 -5121.9  10243.8 105.54      4     <2e-16 ***
lmer.5 24 10013.1 10153 -4982.6   9965.1 278.72      5     <2e-16 ***
lmer.3 30  9848.6 10023 -4894.3   9788.6 176.54      6     <2e-16 ***
lmer.4 30 10296.7 10471 -5118.4  10236.7   0.00      0          1
lmer.2 45  9859.7 10122 -4884.9   9769.7 466.97     15     <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We see that lmer.3 is best, but move forward with lmer.6 for sake of the LMERfit.fnc function.

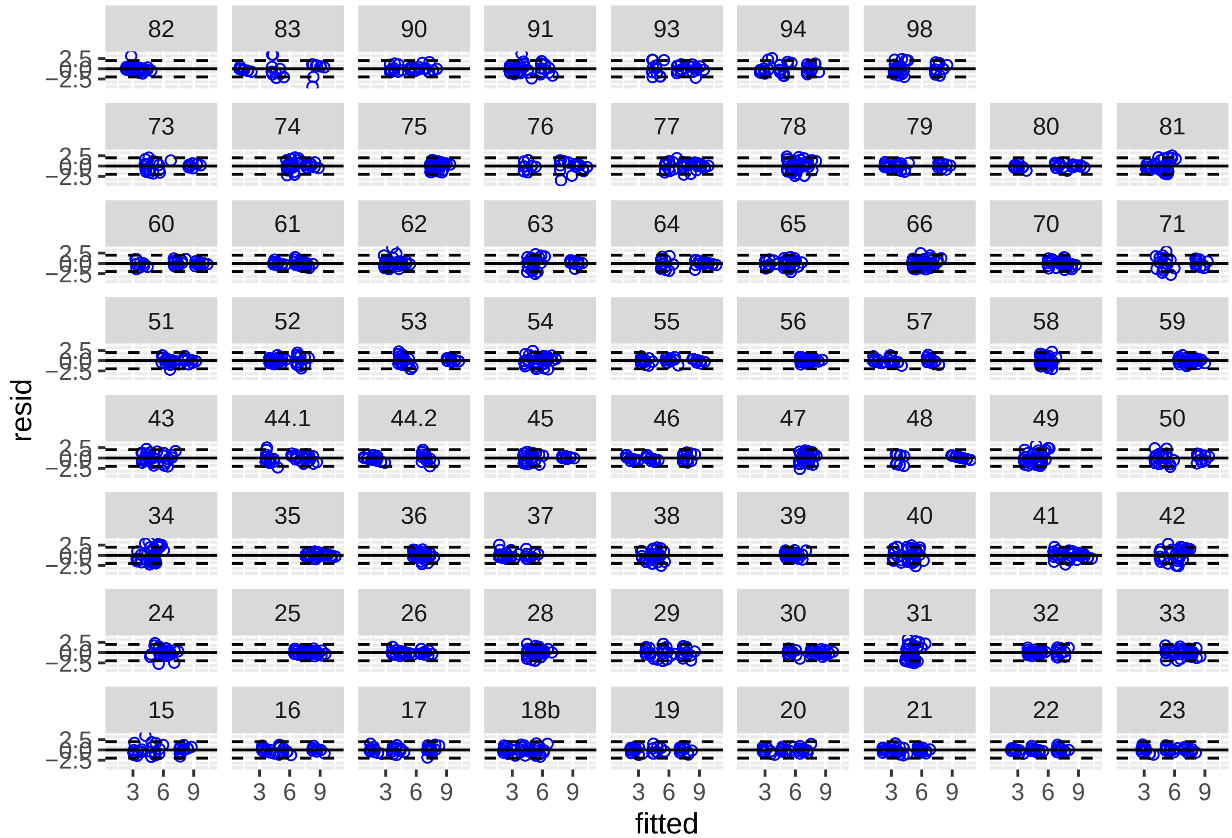
Check conditional residuals. These residuals again look good for the most part, the grouping structure that you do see probably arising due to the discreteness of the ratings. Subject 83 seems to have a couple of outliers however.

```
res <- r.cond(lmer.6)     ## standardized conditional residuals
robust.sd <- diff(quantile(res,c(.025,.975)))/(2*1.96)
res <- res/robust.sd
fit <- yhat.cond(lmer.6)

newdata <- data.frame(Subject=classical_ratings$Subject,
                      resid=res,fitted=fit)

resparams <- data.frame(Subject=unique(classical_ratings$Subject),
                        int1=0,slo1=0,
                        int2=2,slo2=0,
                        int3=-2,slo3=0)

mlm_facets(newdata,"Subject",x="fitted",y="resid",params=resparams,
           lty=c(1,2,2),size=c(0.5,0.5,0.5))
```



2.6 Check fixed effects again

```
lmer.7 <- lmer(Classical ~ (Instrument + Harmony + Voice)^3  +
                 (Instrument|Subject),
                          data=classical_ratings, REML=F)
lmer.7 <- fitLMER.fnc(lmer.7,  method="BIC")
```

We get the same fixed effects as before. Althought we have already compared the models, we compare them again.

```
summary(lmer.7)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (Instrument | Subject)
   Data: classical_ratings

REML criterion at convergence: 9995.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.4075 -0.5960 -0.0030  0.5771  3.8541

Random effects:
 Groups   Name           Variance Std.Dev. Corr
 Subject  (Intercept)    2.694    1.641
          Instrumentpiano 1.628    1.276    -0.44
```

```
          Instrumentstring 3.355    1.832    -0.64  0.66
 Residual                  2.711    1.646
Number of obs: 2484, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       3.98430    0.21742  18.325
Instrumentpiano   1.33608    0.17306   7.720
Instrumentstring  3.07973    0.23342  13.194
HarmonyI-V-IV    -0.03760    0.09338  -0.403
HarmonyI-V-VI     0.76894    0.09342   8.231
HarmonyIV-I-V     0.04385    0.09341   0.469
Voicepar5th       0.03074    0.08093   0.380
Voicecontrary     0.38779    0.08100   4.787

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr5t
Instrumntpn -0.438
Instrmntstr -0.603  0.628
HrmnyI-V-IV -0.215  0.001     0.000
HrmnyI-V-VI -0.214  0.001     0.000     0.499
HrmnyIV-I-V -0.213  0.000     0.000     0.499  0.499
Voicepar5th -0.186  0.000     0.001    -0.001 -0.003 -0.005
Voicecntrry -0.188  0.001     0.001     0.002  0.001 -0.002  0.501
convergence code: 0
Model failed to converge with max|grad| = 0.00205768 (tol = 0.002, component 1)
```

```
# compare the two random effects with the same fixed effects
anova(lmer.3, lmer.7)
```

```
Data: classical_ratings
Models:
lmer.7: Classical ~ Instrument + Harmony + Voice + (Instrument | Subject)
lmer.3: Classical ~ Instrument + Harmony + Voice + (1 + Instrument +
lmer.3:     Harmony | Subject)
       Df     AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.7 15 10004.4 10092 -4987.2   9974.4
lmer.3 30  9848.6 10023 -4894.3   9788.6 185.77     15  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

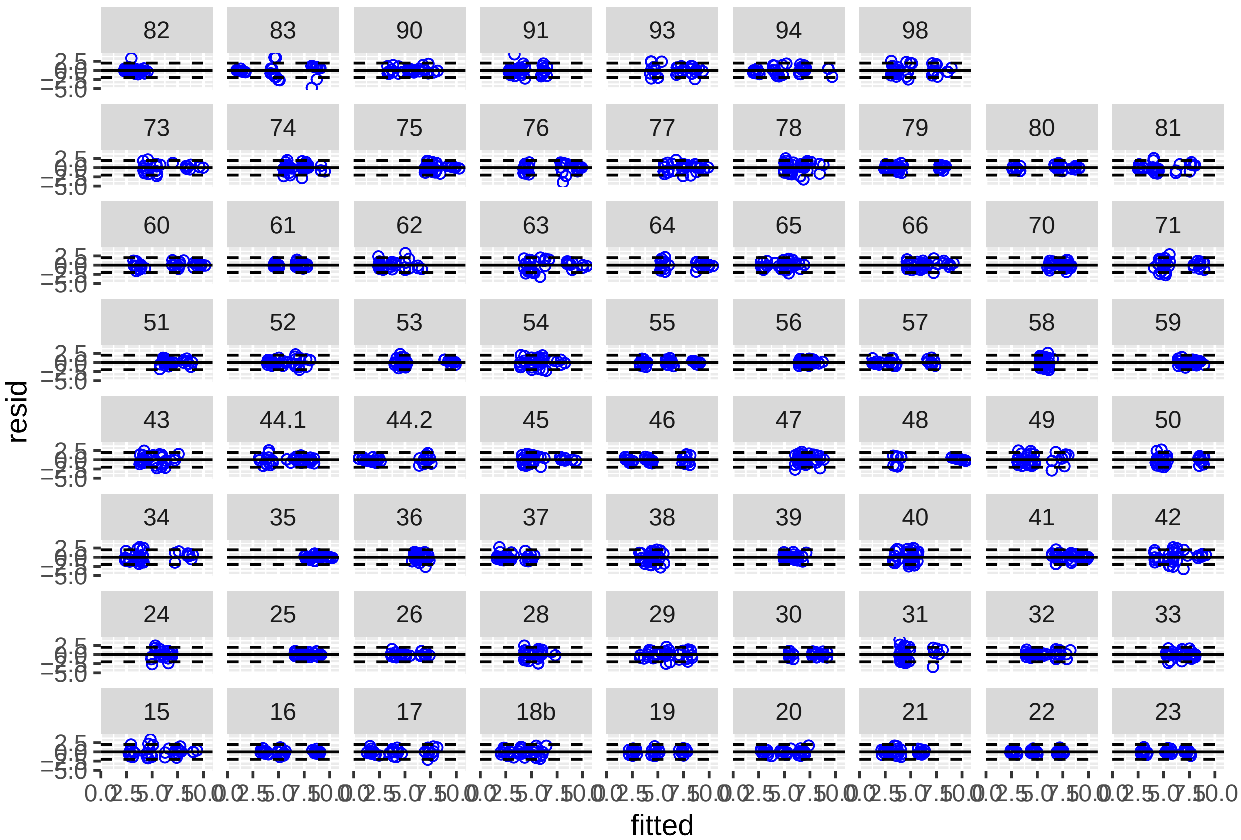
We check the conditional residuals.

```
res <- r.cond(lmer.3)     ## standardized conditional residuals
robust.sd <- diff(quantile(res,c(.025,.975)))/(2*1.96)
res <- res/robust.sd
fit <- yhat.cond(lmer.3)

newdata <- data.frame(Subject=classical_ratings$Subject,
                      resid=res,fitted=fit)

resparams <- data.frame(Subject=unique(classical_ratings$Subject),
                        int1=0,slo1=0,
                        int2=2,slo2=0,
                        int3=-2,slo3=0)
```

```
mlm_facets(newdata,"Subject",x="fitted",y="resid",params=resparams,
           lty=c(1,2,2),size=c(0.5,0.5,0.5))
```



2.7 Add in other covariates

Data Cleaning.

```
complete_ratings = ratings %>% dplyr::select(c(Classical, Popular, Instrument,
                                        Voice, KnowRob, KnowAxis, Harmony,
                                        Subject))
complete_ratings = complete_ratings[complete.cases(complete_ratings),]
comp_class_ratings = complete_ratings %>% dplyr::select(-c(Popular)) %>%
                  filter(Classical > 0 & Classical <= 10)
```

We try adding in other covariates. None are added in.

```
complete_ratings_old = ratings[complete.cases(ratings),]
comp_class_ratings_old = complete_ratings_old %>% dplyr::select(-c(Popular))

lmer.9_old <- lmer(Classical ~ Harmony + Instrument + Voice + Selfdeclare +
                  OMSI + X16.minus.17 + ConsInstr + ConsNotes +
                  PachListen + ClsListen + KnowRob + KnowAxis +
                  X1990s2000s + X1990s2000s.minus.1960s1970s +
                  CollegeMusic + NoClass + APTheory + Composing +
                  PianoPlay + GuitarPlay +
                  (Instrument|Subject),
                  data=comp_class_ratings_old, REML=F)
```

```r
lmer.9_old <- fitLMER.fnc(lmer.9_old,method="BIC")
```

```r
summary(lmer.9_old)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Harmony + Instrument + (Instrument | Subject)
   Data: comp_class_ratings_old

REML criterion at convergence: 6285.7

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3737 -0.5484 -0.0111  0.5439  3.5502

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      2.251    1.500
          Instrumentpiano  1.929    1.389    -0.36
          Instrumentstring 3.709    1.926    -0.66  0.63
 Residual                  2.880    1.697
Number of obs: 1541, groups:  Subject, 43

Fixed effects:
                  Estimate Std. Error t value
(Intercept)       3.636513   0.252075  14.426
HarmonyI-V-IV    -0.001263   0.122237  -0.010
HarmonyI-V-VI     0.842359   0.122323   6.886
HarmonyIV-I-V     0.056995   0.122148   0.467
Instrumentpiano   1.646371   0.236933   6.949
Instrumentstring  3.587608   0.312123  11.494

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp
HrmnyI-V-IV -0.242
HrmnyI-V-VI -0.242  0.499
HrmnyIV-I-V -0.242  0.500  0.499
Instrumntpn -0.387  0.001  0.000  0.000
Instrmntstr -0.638  0.000  0.000  0.000  0.603
```

2.8 Add in KnowRob and KnowAxis, and their interactions

```r
lmer.9 <- lmer(Classical ~ Instrument + Voice +
                 KnowRob*Harmony + KnowAxis*Harmony +
                  (Instrument|Subject),
                         data=comp_class_ratings, REML=F)
lmer.9 <- fitLMER.fnc(lmer.9,method="BIC")
```

KnowRob and interaction with Harmony is added in.

```r
summary(lmer.9)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula:
Classical ~ Instrument + Voice + KnowRob + Harmony + (Instrument |
    Subject) + KnowRob:Harmony
```

```
   Data: comp_class_ratings

REML criterion at convergence: 8740.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2584 -0.6022  0.0138  0.5538  3.8011

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      2.669    1.634
          Instrumentpiano  1.796    1.340    -0.42
          Instrumentstring 3.377    1.838    -0.62  0.65
 Residual                  2.719    1.649
Number of obs: 2169, groups:  Subject, 61

Fixed effects:
                            Estimate Std. Error t value
(Intercept)                 3.796337   0.252032  15.063
Instrumentpiano             1.412257   0.192592   7.333
Instrumentstring            3.265357   0.250808  13.019
Voicepar5th                 0.030508   0.086762   0.352
Voicecontrary               0.365812   0.086791   4.215
KnowRobTRUE                -0.199274   0.427018  -0.467
HarmonyI-V-IV               0.028308   0.114012   0.248
HarmonyI-V-VI               0.572468   0.114080   5.018
HarmonyIV-I-V               0.084739   0.114065   0.743
KnowRobTRUE:HarmonyI-V-IV -0.032060   0.238101  -0.135
KnowRobTRUE:HarmonyI-V-VI  1.274341   0.238134   5.351
KnowRobTRUE:HarmonyIV-I-V -0.004983   0.237715  -0.021

Correlation of Fixed Effects:
             (Intr) Instrmntp Instrmnts Vcpr5t Vccntr KnRTRUE HI-V-I
Instrumntpn  -0.392
Instrmntstr  -0.544  0.625
Voicepar5th  -0.173  0.001     0.001
Voicecntrry  -0.174  0.001     0.001     0.501
KnowRobTRUE  -0.390  0.001     0.001     0.001  0.001
HrmnyI-V-IV  -0.226  0.001     0.000     0.001  0.003  0.133
HrmnyI-V-VI  -0.226  0.000     0.000    -0.001  0.003  0.133   0.499
HrmnyIV-I-V  -0.225  0.000    -0.001    -0.003 -0.001  0.133   0.499
KRTRUE:HI-V-I  0.108  0.001     0.000     0.000  0.000 -0.278  -0.479
KRTRUE:HI-V-V  0.109  0.001     0.000    -0.003 -0.001 -0.278  -0.239
KRTRUE:HIV-    0.108  0.000     0.000    -0.002 -0.001 -0.278  -0.239
             HI-V-V HIV-I- KRTRUE:HI-V-I KRTRUE:HI-V-V
Instrumntpn
Instrmntstr
Voicepar5th
Voicecntrry
KnowRobTRUE
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V   0.499
KRTRUE:HI-V-I -0.239 -0.239
```

```
KRTRUE:HI-V-V -0.479 -0.239  0.498
KRTRUE:HIV-   -0.239 -0.480  0.499         0.499
```

We then compare the two random effect, find that Instrument and Harmony was best.

```r
lmer.9 = lmer(Classical ~ Instrument + Voice + KnowRob*Harmony +
                (Instrument | Subject),
                          data=comp_class_ratings, REML=F)
lmer.9a = lmer(Classical ~ Instrument + Voice + KnowRob*Harmony +
                (Instrument + Harmony| Subject),
                          data=comp_class_ratings, REML=F)
anova(lmer.9, lmer.9a)
```

```
Data: comp_class_ratings
Models:
lmer.9: Classical ~ Instrument + Voice + KnowRob * Harmony + (Instrument |
lmer.9:     Subject)
lmer.9a: Classical ~ Instrument + Voice + KnowRob * Harmony + (Instrument +
lmer.9a:     Harmony | Subject)
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.9  19 8754.7 8862.6 -4358.3   8716.7
lmer.9a 34 8635.7 8828.9 -4283.9   8567.7 148.94     15  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(lmer.9a)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula:
Classical ~ Instrument + Voice + KnowRob * Harmony + (Instrument +
    Harmony | Subject)
   Data: comp_class_ratings

     AIC      BIC   logLik deviance df.resid
  8635.7   8828.9  -4283.9   8567.7     2135

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.5903 -0.5826  0.0085  0.5411  4.3127

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      2.326428 1.52526
          Instrumentpiano  1.817197 1.34803  -0.36
          Instrumentstring 3.367079 1.83496  -0.52  0.65
          HarmonyI-V-IV    0.071230 0.26689   0.84 -0.68 -0.85
          HarmonyI-V-VI    1.454382 1.20598   0.02 -0.33 -0.54  0.20
          HarmonyIV-I-V    0.009939 0.09969   0.05 -0.14  0.09  0.15 -0.04
 Residual                  2.404894 1.55077
Number of obs: 2169, groups:  Subject, 61

Fixed effects:
                           Estimate Std. Error t value
(Intercept)                3.778244   0.238329  15.853
Instrumentpiano            1.413950   0.191208   7.395
Instrumentstring           3.264590   0.248747  13.124
```

```
Voicepar5th                0.027326   0.081628   0.335
Voicecontrary              0.364242   0.081633   4.462
KnowRobTRUE               -0.111298   0.428629  -0.260
HarmonyI-V-IV              0.049581   0.113079   0.438
HarmonyI-V-VI              0.633808   0.201522   3.145
HarmonyIV-I-V              0.082344   0.108255   0.761
KnowRobTRUE:HarmonyI-V-IV -0.119130   0.228904  -0.520
KnowRobTRUE:HarmonyI-V-VI  1.003486   0.386888   2.594
KnowRobTRUE:HarmonyIV-I-V  0.007841   0.225516   0.035

Correlation of Fixed Effects:
              (Intr) Instrmntp Instrmnts Vcpr5t Vccntr KnRTRUE HI-V-I
Instrumntpn   -0.342
Instrmntstr   -0.461  0.624
Voicepar5th   -0.172  0.001     0.001
Voicecntrry   -0.173  0.001     0.001     0.501
KnowRobTRUE   -0.414  0.001     0.001     0.001  0.001
HrmnyI-V-IV    0.022 -0.184    -0.242     0.001  0.003   0.051
HrmnyI-V-VI   -0.156 -0.226    -0.391    -0.001  0.002   0.186   0.285
HrmnyIV-I-V   -0.214 -0.015     0.009    -0.003 -0.001   0.118   0.476
KRTRUE:HI-V-I  0.046  0.001     0.000    -0.001  0.000  -0.110  -0.464
KRTRUE:HI-V-V  0.175  0.000     0.000    -0.002 -0.001  -0.422  -0.099
KRTRUE:HIV-    0.102  0.000     0.000    -0.002 -0.001  -0.246  -0.229
              HI-V-V HIV-I- KRTRUE:HI-V-I KRTRUE:HI-V-V
Instrumntpn
Instrmntstr
Voicepar5th
Voicecntrry
KnowRobTRUE
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V    0.259
KRTRUE:HI-V-I -0.094 -0.236
KRTRUE:HI-V-V -0.441 -0.137  0.214
KRTRUE:HIV-   -0.127 -0.480  0.493         0.287
convergence code: 0
boundary (singular) fit: see ?isSingular
```

```r
#t = tidy(lmer.9a)[1:12,-c(5)]
#t[2:4] = round(t[2:4], digits=3)
#stargazer(t, summary = F, rownames = FALSE,
#          title = "")
```

We also try interactions with KnowRob, which makes the model worse.

```r
lmer.9b = lmer(Classical ~ Instrument + Voice + KnowRob*Harmony +
                (Instrument + Harmony + KnowRob| Subject),
                          data=comp_class_ratings, REML=F)
anova(lmer.9a, lmer.9b)
```

```
Data: comp_class_ratings
Models:
lmer.9a: Classical ~ Instrument + Voice + KnowRob * Harmony + (Instrument +
lmer.9a:     Harmony | Subject)
lmer.9b: Classical ~ Instrument + Voice + KnowRob * Harmony + (Instrument +
lmer.9b:     Harmony + KnowRob | Subject)
```

```
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.9a 34 8635.7 8828.9 -4283.9   8567.7
lmer.9b 41 8643.4 8876.3 -4280.7   8561.4 6.3679      7     0.4975
```

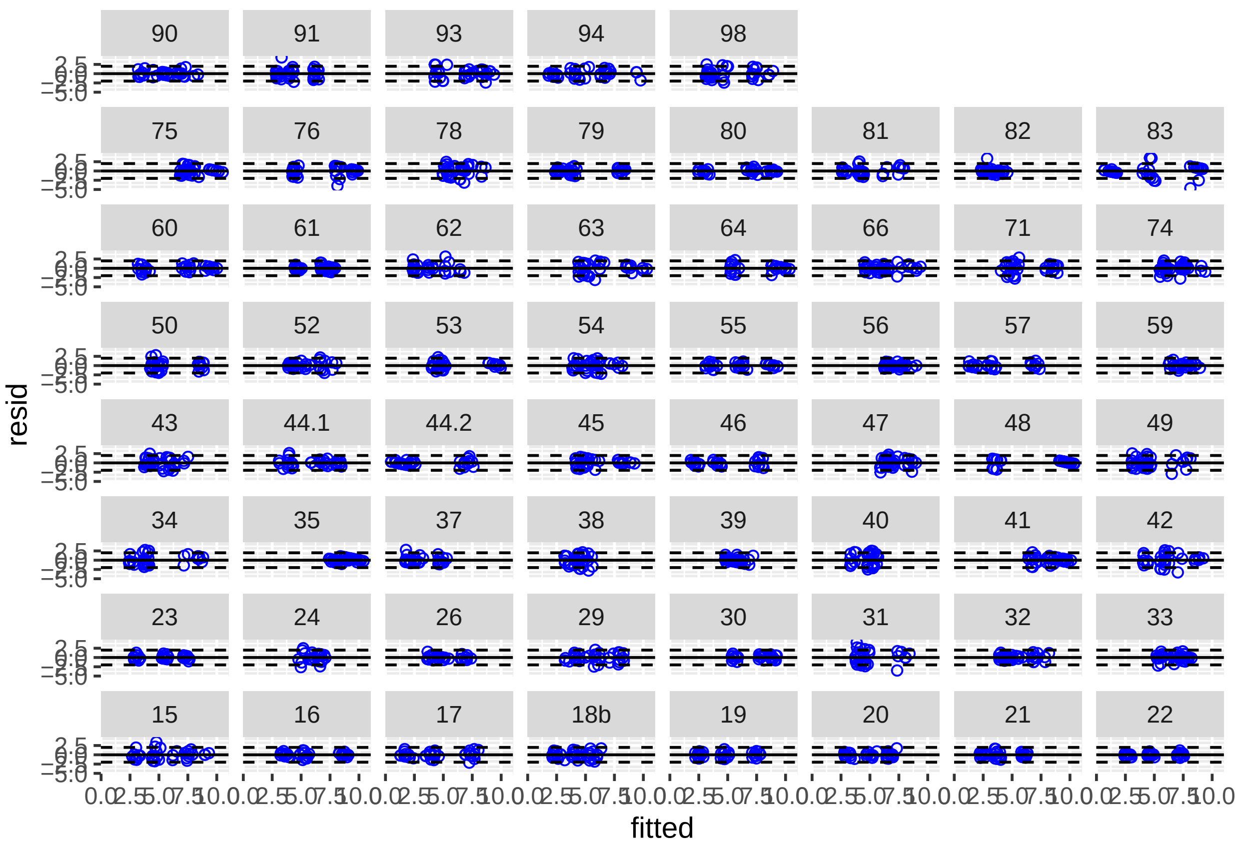
We check the conditional residuals of our final model.

```
res <- r.cond(lmer.9a)      ## standardized conditional residuals
robust.sd <- diff(quantile(res,c(.025,.975)))/(2*1.96)
res <- res/robust.sd
fit <- yhat.cond(lmer.9a)

newdata <- data.frame(Subject=comp_class_ratings$Subject,
                      resid=res,fitted=fit)

resparams <- data.frame(Subject=unique(comp_class_ratings$Subject),
                        int1=0,slo1=0,
                        int2=2,slo2=0,
                        int3=-2,slo3=0)

mlm_facets(newdata,"Subject",x="fitted",y="resid",params=resparams,
           lty=c(1,2,2),size=c(0.5,0.5,0.5))
```



3 How Does Self Identifying as a Musician Affect Classical Ratings?

```
temp = new_ratings %>% dplyr::select(Classical, Selfdeclare, Instrument,
                              Harmony, Voice, KnowRob, Subject) %>%
                        filter(Classical > 0 & Classical <= 10)
temp$musician = temp$Selfdeclare > 3
lmer.15 = lmer(Classical ~ musician*Instrument + musician*Harmony +
                 musician*Voice + musician*KnowRob + (1 + Instrument | Subject),
             data=temp, REML=F)
lmer.15 = fitLMER.fnc(lmer.15,method="BIC")
```

The relationship between musician and Harmony is kept in.

Below we check which random effect is better, and Instrument and Harmony is better.

```
summary(lmer.15)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ musician + Instrument + Harmony + Voice + KnowRob +
    (1 + Instrument | Subject) + musician:Harmony
   Data: temp

REML criterion at convergence: 9305.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.4827 -0.5897  0.0070  0.5592  3.8321

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      2.740    1.655
          Instrumentpiano  1.768    1.329    -0.46
          Instrumentstring 3.543    1.882    -0.64  0.67
 Residual                  2.703    1.644
Number of obs: 2313, groups:  Subject, 65

Fixed effects:
                            Estimate Std. Error t value
(Intercept)                 4.007242   0.252857  15.848
musicianTRUE               -0.680116   0.430803  -1.579
Instrumentpiano             1.329930   0.185253   7.179
Instrumentstring            3.114114   0.248090  12.552
HarmonyI-V-IV              -0.047371   0.110190  -0.430
HarmonyI-V-VI               0.455789   0.110251   4.134
HarmonyIV-I-V              -0.005627   0.110238  -0.051
Voicepar5th                 0.040013   0.083779   0.478
Voicecontrary               0.374964   0.083805   4.474
KnowRobTRUE                 0.150173   0.417461   0.360
musicianTRUE:HarmonyI-V-IV  0.095816   0.229474   0.418
musicianTRUE:HarmonyI-V-VI  1.464536   0.229504   6.381
musicianTRUE:HarmonyIV-I-V  0.326224   0.229129   1.424
```

```
lmer.15 = lmer(Classical ~ musician + Instrument + KnowRob*Harmony + Voice +
                 (1 + Instrument | Subject) + musician:Harmony,
```

```
                data = temp, REML=F)
lmer.15a = lmer(Classical ~ musician + Instrument + KnowRob*Harmony + Voice +
                  (1 + Instrument + Harmony| Subject) + musician:Harmony,
                data = temp, REML=F)
anova(lmer.15, lmer.15a)
```

```
Data: temp
Models:
lmer.15: Classical ~ musician + Instrument + KnowRob * Harmony + Voice +
lmer.15:     (1 + Instrument | Subject) + musician:Harmony
lmer.15a: Classical ~ musician + Instrument + KnowRob * Harmony + Voice +
lmer.15a:     (1 + Instrument + Harmony | Subject) + musician:Harmony
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.15  23 9303.0 9435.2 -4628.5   9257.0
lmer.15a 38 9208.7 9427.1 -4566.4   9132.7 124.28     15  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#t = tidy(lmer.15a)[1:16,-c(5)]
#t[2:4] = round(t[2:4], digits=3)
#stargazer(t, summary = F, rownames = FALSE,
#          title = "")
```

4 Previous Analysis, but with Popular Ratings

```
popular_ratings = new_ratings %>% dplyr::select(-Classical) %>%
                      filter(Popular > 0 & Popular <= 10)
lm.p.aic = stepAIC(lm(Popular~(Instrument+Harmony+Voice)^3,
           data = popular_ratings), direction="both",k=2)
lm.p.bic = stepAIC(lm(Popular~(Instrument+Harmony+Voice)^3,
           data = popular_ratings),
           direction="both",k=log(nrow(classical_ratings)))
```

No interaction term is added in either.

```
anova(lm.p.aic, lm.p.bic)
```

```
Analysis of Variance Table

Model 1: Popular ~ Instrument + Harmony
Model 2: Popular ~ Instrument
  Res.Df   RSS Df Sum of Sq     F  Pr(>F)
1   2461 11984
2   2464 12021 -3   -36.363 2.489 0.05867 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.1 Try Random Effects

```
# three new random effects
lmer.17 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1  + Instrument + Harmony + Voice| Subject),
               data=popular_ratings, REML=F)
```

```r
# two new random effects
lmer.18 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Instrument + Harmony| Subject),
               data=popular_ratings, REML=F)
lmer.19 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Harmony + Voice| Subject),
               data=popular_ratings, REML=F)
lmer.20 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Instrument + Voice| Subject),
               data=popular_ratings,REML=F)

# one new random effect
lmer.21 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Instrument| Subject),
               data=popular_ratings, REML=F)
lmer.22 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Harmony| Subject),
               data=popular_ratings, REML=F)
lmer.23 <- lmer(Popular ~ Instrument + Harmony +
                 Voice + (1 + Voice| Subject),
                data=popular_ratings, REML=F)

# compare all of the models
anova(lmer.17, lmer.18, lmer.19, lmer.20, lmer.21, lmer.22, lmer.23)
```

```
Data: popular_ratings
Models:
lmer.21: Popular ~ Instrument + Harmony + Voice + (1 + Instrument | Subject)
lmer.23: Popular ~ Instrument + Harmony + Voice + (1 + Voice | Subject)
lmer.22: Popular ~ Instrument + Harmony + Voice + (1 + Harmony | Subject)
lmer.20: Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Voice |
lmer.20:     Subject)
lmer.18: Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony |
lmer.18:     Subject)
lmer.19: Popular ~ Instrument + Harmony + Voice + (1 + Harmony + Voice |
lmer.19:     Subject)
lmer.17: Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony +
lmer.17:     Voice | Subject)
        Df     AIC     BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
lmer.21 15  9890.1  9977.3 -4930.1   9860.1
lmer.23 15 10236.7 10323.9 -5103.4  10206.7   0.000      0          1
lmer.22 19 10183.3 10293.7 -5072.6  10145.3  61.415      4  1.462e-12 ***
lmer.20 24  9903.4 10042.8 -4927.7   9855.4 289.927      5  < 2.2e-16 ***
lmer.18 30  9802.7  9977.0 -4871.4   9742.7 112.662      6  < 2.2e-16 ***
lmer.19 30 10201.2 10375.5 -5070.6  10141.2   0.000      0          1
lmer.17 45  9820.5 10082.0 -4865.3   9730.5 410.663     15  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Doesn't add any interaction terms.

```r
lmer.24 <- lmer(Popular ~ (Instrument + Harmony + Voice)^3  +
                 (Instrument|Subject),
                          data=popular_ratings, REML=F)
lmer.24 <- fitLMER.fnc(lmer.24,  method="BIC")
```

```r
summary(lmer.18)
```

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula:
Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony |
    Subject)
   Data: popular_ratings

     AIC      BIC   logLik deviance df.resid
  9802.7   9977.0  -4871.4   9742.7     2437

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.0111 -0.5939  0.0152  0.5808  3.2993

Random effects:
 Groups   Name              Variance Std.Dev. Corr
 Subject  (Intercept)       1.61105  1.2693
          Instrumentpiano   1.37890  1.1743   -0.21
          Instrumentstring  3.29832  1.8161   -0.38  0.73
          HarmonyI-V-IV     0.09818  0.3133    0.43 -0.29 -0.41
          HarmonyI-V-VI     0.87851  0.9373   -0.14 -0.19 -0.20 -0.35
          HarmonyIV-I-V     0.20466  0.4524   -0.23 -0.14 -0.02 -0.57 -0.32
 Residual                   2.40544  1.5509
Number of obs: 2467, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.76861    0.17544  38.581
Instrumentpiano  -0.95234    0.16004  -5.951
Instrumentstring -2.55665    0.23043 -11.095
HarmonyI-V-IV    -0.04698    0.09613  -0.489
HarmonyI-V-VI    -0.29542    0.14274  -2.070
HarmonyIV-I-V    -0.21690    0.10350  -2.096
Voicepar5th       0.01000    0.07653   0.131
Voicecontrary    -0.14586    0.07656  -1.905

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr5t
Instrumntpn -0.266
Instrmntstr -0.381  0.684
HrmnyI-V-IV -0.085 -0.097    -0.151
HrmnyI-V-VI -0.251 -0.130    -0.147     0.176
HrmnyIV-I-V -0.319 -0.063    -0.009     0.275  0.132
Voicepar5th -0.216 -0.002     0.001    -0.001 -0.004 -0.006
Voicecntrry -0.218  0.000     0.001     0.001 -0.002 -0.004  0.500
convergence code: 0
Model failed to converge with max|grad| = 0.0500973 (tol = 0.002, component 1)
```

```r
#t = tidy(lmer.18)[1:8,-c(5)]
#t[2:4] = round(t[2:4], digits=3)
#stargazer(t, summary = F, rownames = FALSE,
#          title = "")
```

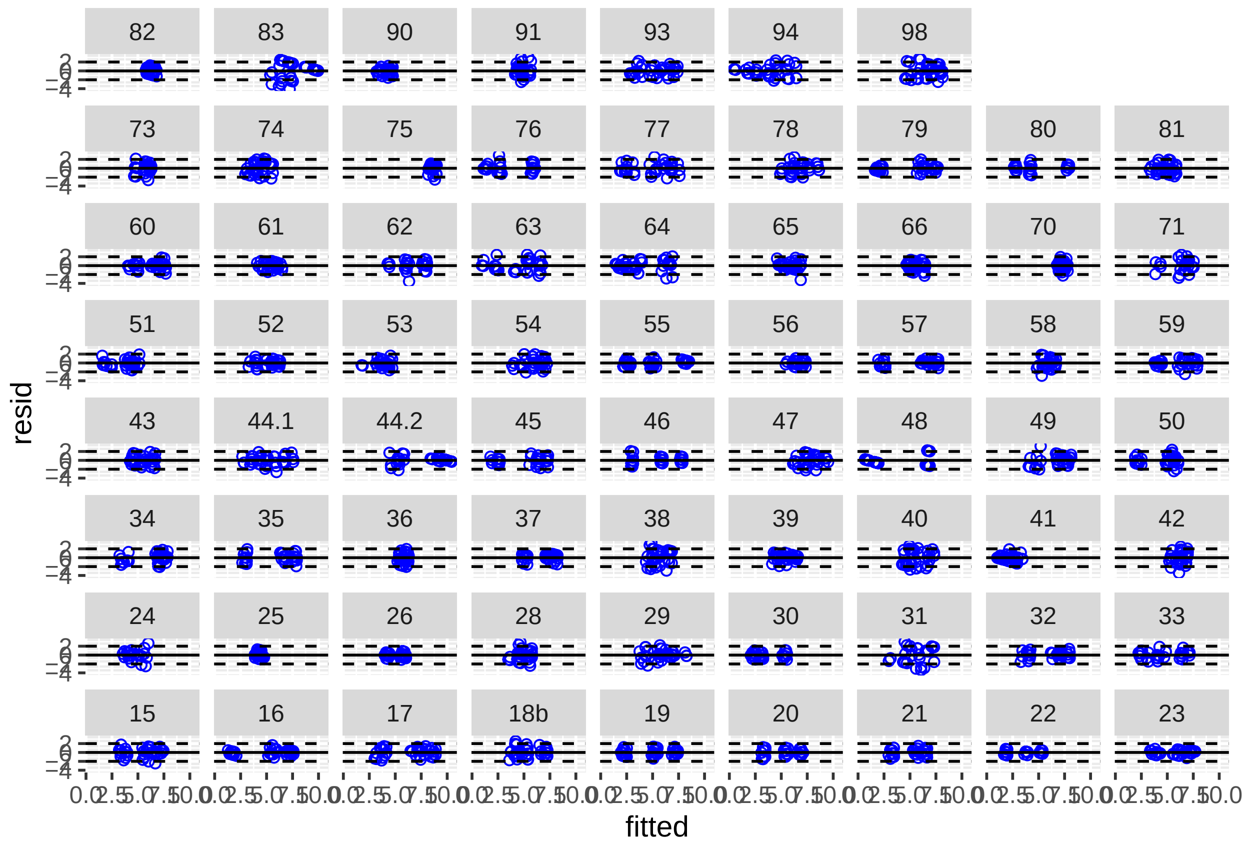
Below, I look at the conditional residuals for the model and they look fairly good, and they look fairly good for the most part.

```
res <- r.cond(lmer.18)      ## standardized conditional residuals
robust.sd <- diff(quantile(res,c(.025,.975)))/(2*1.96)
res <- res/robust.sd
fit <- yhat.cond(lmer.18)

newdata <- data.frame(Subject=popular_ratings$Subject,
                      resid=res,fitted=fit)

resparams <- data.frame(Subject=unique(popular_ratings$Subject),
                        int1=0,slo1=0,
                        int2=2,slo2=0,
                        int3=-2,slo3=0)

mlm_facets(newdata,"Subject",x="fitted",y="resid",params=resparams,
           lty=c(1,2,2),size=c(0.5,0.5,0.5))
```



4.1.1 Add in other covariates

```
comp_pop_ratings = complete_ratings %>% dplyr::select(-c(Classical)) %>%
                      filter(Popular > 0 & Popular <= 10)
```

We try adding in other covariates. None are added in.

```r
comp_pop_ratings_old = complete_ratings_old %>% dplyr::select(-c(Classical))

lmer.25_old <- lmer(Popular ~ Harmony + Instrument + Voice + Selfdeclare +
                  OMSI + X16.minus.17 + ConsInstr + ConsNotes +
                  PachListen + ClsListen + KnowRob + KnowAxis +
                  X1990s2000s + X1990s2000s.minus.1960s1970s +
                  CollegeMusic + NoClass + APTheory + Composing +
                  PianoPlay + GuitarPlay +
                  (Instrument|Subject),
                  data=comp_pop_ratings_old, REML=F)
lmer.25_old <- fitLMER.fnc(lmer.25_old,method="BIC")
```

```r
summary(lmer.25_old)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Instrument + (Instrument | Subject)
   Data: comp_pop_ratings_old

REML criterion at convergence: 6346.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.4717 -0.5895  0.0383  0.5923  5.4252

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      1.307    1.143
          Instrumentpiano  1.770    1.331    -0.19
          Instrumentstring 2.617    1.618    -0.36  0.72
 Residual                  3.067    1.751
Number of obs: 1541, groups:  Subject, 43

Fixed effects:
                 Estimate Std. Error t value
(Intercept)        6.8658     0.1907  36.009
Instrumentpiano   -1.1477     0.2306  -4.977
Instrumentstring  -3.0238     0.2698 -11.209

Correlation of Fixed Effects:
            (Intr) Instrmntp
Instrumntpn -0.288
Instrmntstr -0.414  0.672
```

4.2 Add in KnowRob and KnowAxis and interactions with Harmony

None are added in.

```r
lmer.25 <- lmer(Popular ~ Instrument + Voice +
                 KnowRob*Harmony + KnowAxis*Harmony +
                  (Instrument|Subject),
                         data=comp_pop_ratings, REML=F)
lmer.25 <- fitLMER.fnc(lmer.25,method="BIC")
```

```r
summary(lmer.25)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Instrument + (Instrument | Subject)
   Data: comp_pop_ratings

REML criterion at convergence: 8650.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9613 -0.5998  0.0165  0.5993  3.1340

Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      1.522    1.234
          Instrumentpiano  1.413    1.189    -0.20
          Instrumentstring 2.858    1.690    -0.40  0.70
 Residual                  2.752    1.659
Number of obs: 2152, groups:  Subject, 61

Fixed effects:
                 Estimate Std. Error t value
(Intercept)        6.7236     0.1696   39.64
Instrumentpiano   -1.0875     0.1757   -6.19
Instrumentstring  -2.8178     0.2339  -12.05

Correlation of Fixed Effects:
            (Intr) Instrmntp
Instrumntpn -0.292
Instrmntstr -0.440  0.655
```

4.3 Repeat Musician Analysis.

```
temp1 = new_ratings %>% dplyr::select(Popular, Selfdeclare, Instrument,
                              Harmony, Voice, Subject)
temp1$musician = temp1$Selfdeclare > 3
lmer.26 = lmer(Popular ~ musician*Instrument + musician*Harmony +
                 musician*Voice + (1 + Instrument | Subject),
             data=temp1, REML=F)
lmer.26 = fitLMER.fnc(lmer.26,method="BIC")
```

The interaction between Musician and Harmony is kept.

Below we compare the two random effects.

```
summary(lmer.26)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ musician + Instrument + Harmony + (1 + Instrument |
    Subject) + musician:Harmony
   Data: temp1

REML criterion at convergence: 10051.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6909 -0.5948  0.0042  0.5948  5.4871
```

```
Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      1.599    1.264
          Instrumentpiano  1.402    1.184    -0.26
          Instrumentstring 3.359    1.833    -0.40  0.72
 Residual                  2.771    1.665
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
                            Estimate Std. Error t value
(Intercept)                  6.58660    0.19008  34.651
musicianTRUE                 0.47303    0.37981   1.245
Instrumentpiano             -0.94753    0.16372  -5.788
Instrumentstring            -2.60564    0.23373 -11.148
HarmonyI-V-IV               -0.07339    0.10636  -0.690
HarmonyI-V-VI               -0.02670    0.10636  -0.251
HarmonyIV-I-V               -0.15475    0.10630  -1.456
musicianTRUE:HarmonyI-V-IV  0.22493    0.22987   0.978
musicianTRUE:HarmonyI-V-VI -1.13004    0.22987  -4.916
musicianTRUE:HarmonyIV-I-V -0.15122    0.22947  -0.659

Correlation of Fixed Effects:
             (Intr) msTRUE Instrmntp Instrmnts HI-V-I HI-V-V HIV-I-
musicinTRUE  -0.429
Instrumntpn  -0.288  0.000
Instrmntstr  -0.377  0.000  0.674
HrmnyI-V-IV  -0.279  0.140  0.000    -0.001
HrmnyI-V-VI  -0.279  0.140  0.000     0.000     0.499
HrmnyIV-I-V  -0.279  0.140 -0.001     0.000     0.499  0.499
mTRUE:HI-V-I  0.129 -0.302  0.001     0.000    -0.463 -0.231 -0.231
mTRUE:HI-V-V  0.129 -0.302  0.001     0.000    -0.231 -0.463 -0.231
mTRUE:HIV-I   0.129 -0.302  0.000     0.000    -0.231 -0.231 -0.463
             mTRUE:HI-V-I mTRUE:HI-V-V
musicinTRUE
Instrumntpn
Instrmntstr
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
mTRUE:HI-V-I
mTRUE:HI-V-V  0.498
mTRUE:HIV-I   0.499        0.499
```

```r
lmer.26 = lmer(Popular ~ musician + Instrument + Harmony +
                 (1 + Instrument |  Subject) + musician:Harmony,
               data=temp1, REML=F)
lmer.27 = lmer(Popular ~ musician + Instrument + Harmony +
                 (1 + Instrument + Harmony |  Subject) + musician:Harmony,
               data=temp1, REML=F)
anova(lmer.26, lmer.27)
```

```
Data: temp1
Models:
lmer.26: Popular ~ musician + Instrument + Harmony + (1 + Instrument |
```

```
lmer.26:     Subject) + musician:Harmony
lmer.27: Popular ~ musician + Instrument + Harmony + (1 + Instrument +
lmer.27:     Harmony | Subject) + musician:Harmony
        Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.26 17 10066 10166 -5016.3  10032.5
lmer.27 32 10000 10186 -4968.1   9936.2 96.321     15   6.47e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```