Influencers of Classical and Popular Music Identification

Melody Han*
yazhuh@andrew.cmu.edu

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Abstract

In an experiment conducted by the University of Pittsburgh, listeners were asked to identify how classical or popular musical stimulus sound, and researchers were interested in identifying particular influencers that drive this identification process. To test the researchers' hypothesis, I modeled classical and popular ratings separately with fixed and random effect models through automated and qualitative variable selection processes exploring the effect of different covariates and their interactions. Overall, I found that instrument has the strongest effect, comparing to harmonic motion and voice leading, on classical and popular rating. The degree to which the listener is familiar to musical knowledge and classical or popular music influences the ratings as well. For further research, researchers should focus on including more interactions based on domain knowledge and conduct sensitivity analysis related to variables that are based on subjects' subjective views.

1 Introduction

In this experiment, listeners were asked to indicate the extent to which the stimuli sounds like popular or classical music. Musical excerpts were played using electric guitar, piano or a string quartet combining with contradictory harmonic motion and voice leading from common practices of popular music. The researcher′s main hypothesis is that instrument is more influential than harmonic motion and voice leading.

The three research questions we focus on for the experimental factors, Harmonic Motion, Voice Leading and Instrument, are listed below:

- Does Instrument have the strongest influence among the three experimental factors?
- Of Harmonic Motions, does I-V-VI have the strong effect on ratings and does this depend on whether the listener is familiar with Pachelbel rants or comedy bits?
- For Voice Leading, does the level contrary motion have the strong effect on classical ratings?

Two additional research questions we are interested in are:

*Department of Statistics & Data Science, Carnegie Mellon University

- What other factors drive classical and popular ratings and what are the differences in which they drive classical and popular ratings?
- What are the differences in the way that self-declared musicians and non-musicians identify classical and popular music?

To answer these research questions, we use data collected by Ivan Jimenez and Vincent Rossi from the University of Pittsburgh to explore the relationship between listener′s characteristic, stimuli′s characteristic and ratings (Jimenez, 2013).

2 Methods

In this section, we will go over the data collected from the experiment and the key methods deployed for this analysis. The original data collected from the experiment contains 70 listeners′ classical and popular ratings to 36 musical stimuli, a total of 2520 rows. Table 1 shows the detailed variable definitions.

Classical	How classical does the stimulus sound? (1 to 10, 1=not at all, 10=very classical sounding)
Popular	How popular does the stimulus sound? (1 to 10, 1=not at all, 10=very popular sounding)
Subject	Unique subject ID (1 to 70)
Harmony	Harmonic Motion (4 levels: I-V-VI, I-VI-V, I-V-IV, IV-I-V)
Instrument	Instrument (3 levels: String Quartet, Piano, Electric Guitar)
Voice	Voice Leading (3 levels: Contrary Motion, Parallel 3rds, Parallel 5ths)
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 previous 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

Table 1: Variable Definitions

With the original dataset, I first performed data preprocessing by fixing miscoding, extreme values, and missing data. Then, I created a new binary variable Musicians with 1 as self-declared musician and 0 as self-declared non-musician. Lastly, I transformed necessary continuous variables to normalize the distributions. Initial EDA is then performed, using scatter plots and boxplots, to explore the relationships of classical and popular ratings with other variables.

To answer the first set of research questions related to the three experimental factors only, I created regression models for classical and popular ratings separately using only the fixed and random effects of these three variables and its interactions. I used step-wise function with BIC criterion to determine the fixed effects and fitLMER function to determine the random effects. I also used diagnostic plots to check the validity of the model and ANOVA for model selection along each step.

To answer the research questions related to other factors and in particular Musicians, I created separate models for classical and popular ratings with a similar process as above but including other variables in the dataset and their interactions. While some variables are removed through the automated process by step-wise or fitLMER, some are removed for the interpretability of the model.

This analysis is conducted using the R language and environment for statistical computing (R Core Team, 2018), and details of the implementation can be found in the appendix.

3 Results

3.1 Data Preprocessing

Examining the raw data, we want to investigate and fix any problem of miscoding, missing data, and transformations. First, I found two major miscoding issues with the variable Subject and ConsInstr. Subject represents 70 listeners in the study. In the raw data, they are represented by nonconsecutive numbers. For the ease of later analysis, I relabeled the levels from 1 to 70. The variable ConsInstr represents the concentration scale on the instrument from 0 to 5. In the raw data, ConsInstr increments by a third giving us 14 levels total. To simplify the variable, I rounded the variable to increment by 1 with a total of 5 levels.

Second, I explored the problem of missingness. Some concerning variables with many missing values include ConsNotes, NoClass, X1stInstr and X2ndInstr. Since around half of the values in X1stInstr and X2ndInstr are missing values, I decided to remove these two columns since there

are not enough information to confidently estimate the missing values. For NoClass, I filled in the 288 missing values using median imputation of 1. For ConsNotes, I computed a conditional mode imputation. I looked at the missing ConsNotes at each level of ConsInstr and imputed the mode ConsNotes value conditional on the closest Selfdeclare value.

Finally, to ensure the validity of the dataset, I removed rows with Classical and Popular ratings above the maximum rating of 10. The cleaned dataset has a total of 1900 rows with the summary below in figure 1.

One of the secondary hypotheses of the researchers is that people who self-identify as musicians may be influenced by things differently than non-musicians. To better analyze this question, I dichotomized the variable Selfdeclare. Those with self-declare rating below 3 are labeled as non-musicians and others as musicians. With this dichotomization, 1079 rows are labeled at non-musicians and 821 rows are labeled as musicians.

Examining the distribution of the continuous variable in figure 2, I decided to log transform OMSI which has a right skewed distribution. Log transformation made the variable′s distribution closer to a normal distribution and maintains interpretability. Other continuous variables look reasonably normally distributed. NoClass appears to be right skewed but, since most of it's values are concentrated at 0 or 1, interpretable transformations were not able to improve the distributions significantly. Thus, I decided to only transform OMSI.

```
   Subject       Harmony     Instrument       Voice     Selfdeclare  X16.minus.17    ConsInstr ConsNotes Instr.minus.Notes PachListen
1      :  36   I-IV-V:476   guitar:635   contrary:633   1:252       Min.   :-4.000   0:108     0:457     Min.   :-4.0000   0:   0
2      :  36   I-V-IV:474   piano :629   par3rd  :633   2:827       1st Qu.: 0.000   1:208     1:336     1st Qu.: 0.0000   1:   0
3      :  36   I-V-VI:474   string:636   par5th  :634   3:360       Median : 1.000   2:288     3:565     Median : 0.6700   2: 108
5      :  36   IV-I-V:476                              4:353       Mean   : 1.626   3:468     4: 43     Mean   : 0.8105   3: 144
6      :  36                                           5: 72       3rd Qu.: 3.000   4:540     5:499     3rd Qu.: 2.0000   4:  36
8      :  36                                           6: 36       Max.   : 9.000   5:288               Max.   : 4.3300   5:1612
(Other):1684
ClsListen KnowRob  KnowAxis X1990s2000s X1990s2000s.minus.1960s1970s CollegeMusic    NoClass       APTheory Composing PianoPlay
0:288     0:1511   0:1469   0: 144      Min.   :-3.000               0: 396       Min.   :0.0000   0:1475   0:1116    0:1044
1:612     1: 144   1:  35   2: 108      1st Qu.: 0.000               1:1504       1st Qu.:0.0000   1: 425   1: 216    1: 496
3:713     5: 245   5: 396   3: 252      Median : 2.000                            Median :1.0000            2: 245    2:   0
4: 36                       4: 180      Mean   : 1.931                            Mean   :0.9237            3: 144    4: 144
5:251                       5:1216      3rd Qu.: 3.000                            3rd Qu.:1.0000            4: 143    5: 216
                                        Max.   : 5.000                            Max.   :8.0000            5:  36

GuitarPlay   Classical         Popular          OMSI.log     Musicians
0:1404     Min.   : 0.000   Min.   : 0.000   Min.   :2.398   0:1079
1: 215     1st Qu.: 3.000   1st Qu.: 3.000   1st Qu.:4.205   1: 821
2:  36     Median : 6.000   Median : 6.000   Median :4.990
4:  71     Mean   : 5.715   Mean   : 5.376   Mean   :4.969
5: 174     3rd Qu.: 8.000   3rd Qu.: 7.000   3rd Qu.:5.784
           Max.   :10.000   Max.   :10.000   Max.   :6.877
```

Figure 1: Summary of Cleaned Data

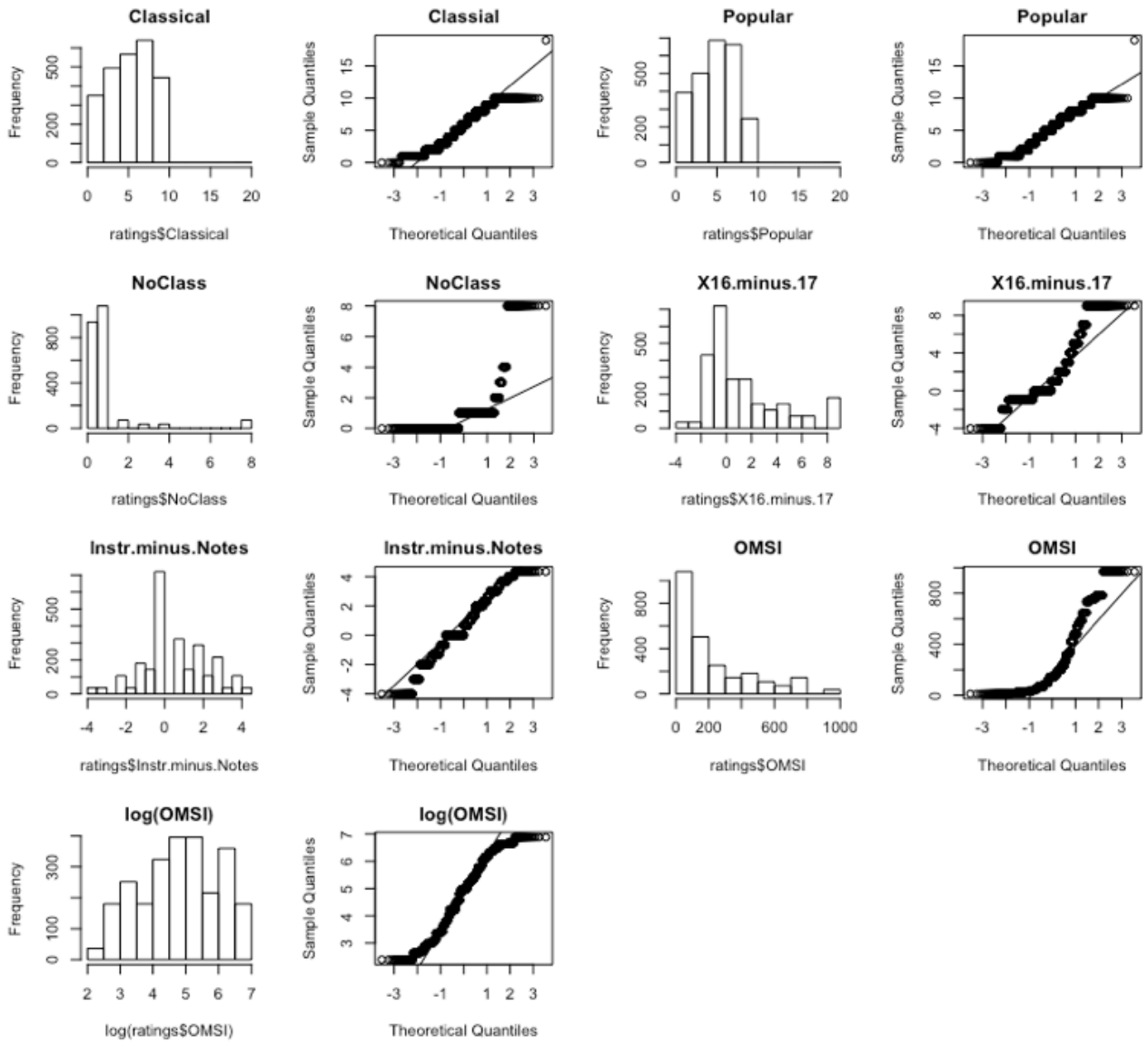


Figure 2: Normality Check of Continuous Variables

3.2 Exploratory Data Analysis

After data preprocessing, I performed EDA using boxplots in figure 3 to examine the relationship of ratings with other covariates. For classical ratings, we see that harmony level I-V-VI and music with string instruments seems to have higher median rating. ConsInstr, ClsListen, Selfdeclare, PianoPlay and GuitarPlay also seems to be significant variables to classical rating. For popular ratings, we see that harmony level I-V-IV, IV-I-V, string quartet music and contrary voice tend to have lower median ratings. Other potentially significant variables include PachListen, ConsNotes, KnowAxis and APTheory. For both ratings, many variables, such as KnowAxis, Composing and GuitarPlay, do not have a monotonic relationship with ratings. For example, the middle levels of the variable

might have the max or min median rating as oppose to the edge levels.

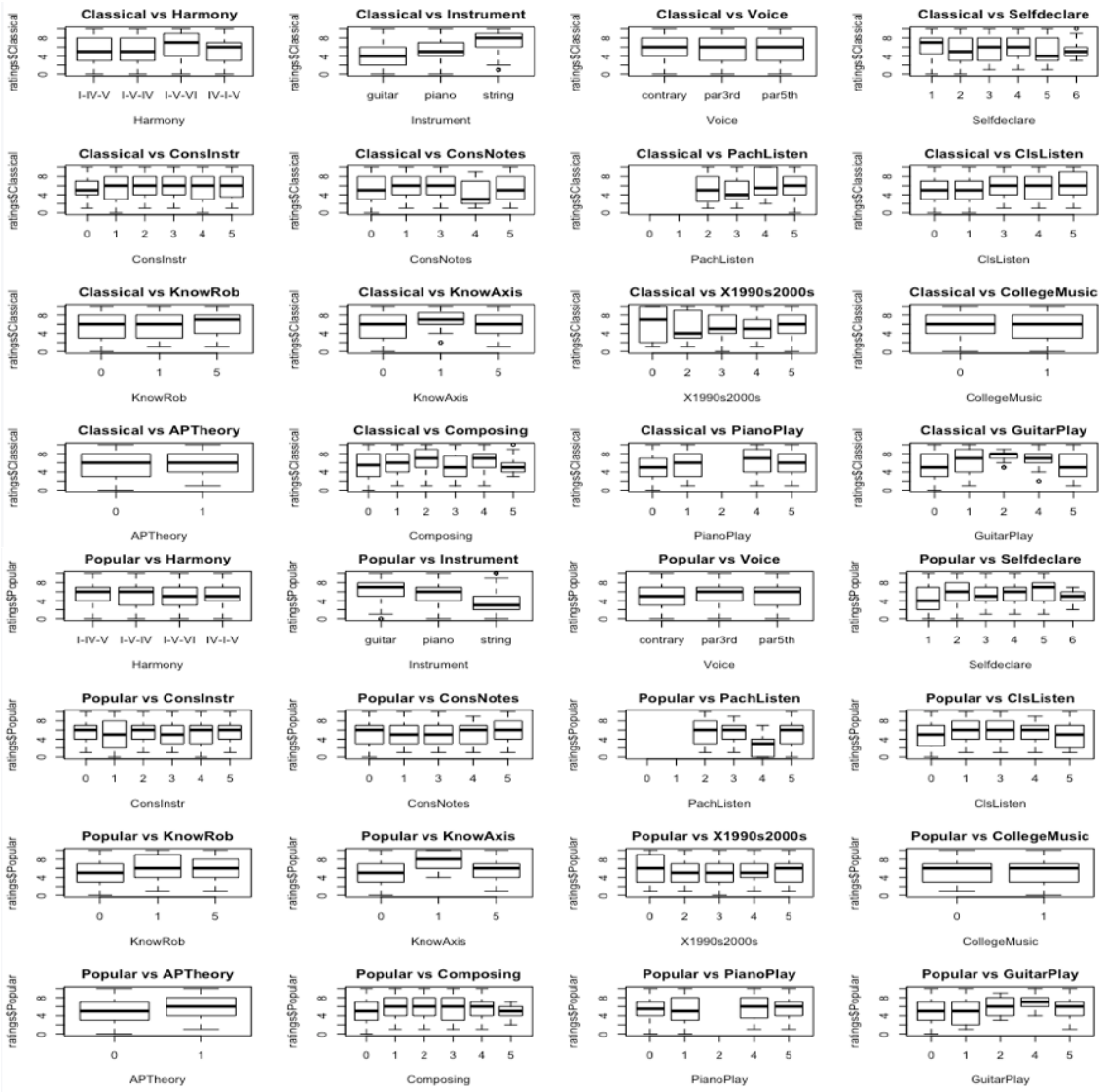


Figure 3: Boxplots of Classical(Popular) Rating vs Influencers

3.3 Effects of Experimental Factors on Classical and Popular Ratings

In this subsection, we will explore the effects of the three key experimental factors on classical and popular rating (appendix pp.9-18). In particular, we want to assess the influence of instrument, harmonic motion, harmonic motion conditional on knowledge of Pachelbel rants or comedy bits, and voice leading. I do so by creating a regression model only using Harmony, Instrument, and Voice looking at the interaction among them and Harmony′s interaction with KnowRob and KnowAxis. Below shows the equation and summary table of final fixed and random effects model of classical and popular ratings:

$$Classical \sim Harmony + Instrument + Voice +$$

$$(1|Subject) + (0 + Harmony|Subject) + (0 + Instrument|Subject)$$

$$Popular \sim Harmony + Instrument + Voice +$$

$$(1|Subject) + (0 + Harmony|Subject) + (0 + Instrument|Subject)$$

For classical rating, we included fixed effects for Harmony, Instrument, and Voice with random intercept and random effect on Harmony and Instrument. The interaction between Harmony and KnowRob or KnowAxis are not found to be significant. Model validation and selection process is shown in page 9 of the appendix. Based on figure 4, following are some key individual findings holding other variables constant:

- Instrument has the strongest influence on classical rating as shown by the largest coefficients. With electric guitar as baseline comparison, on average, stimuli played with piano has rating 1.47 higher, and stimuli played with string quartet has rating 3.40 higher. Intuitively, this makes sense as classical music are more often played with string quartet than with electric guitar. The random effects of Instrument have similar standard deviation around 1 to 1.3 for all levels. The level string quartet has random effect standard deviation, comparably, relatively small to the coefficient estimate. This suggests that after accounting for individual listener differences stimuli with string quartet still likely has the highest classical rating compare to other levels.

- Harmonic motion I-V-VI′s association with rating is significantly different than other levels association. Stimuli with harmonic motion I-V-VI, on average, has classical rating 0.88 higher than other ratings. This is not affected by whether the respondent is familiar with Pachelbel rants or comedy bits given interactions of these variables are not included in the final model chosen with BIC. The random effects of harmonic motion have similar standard deviation around 0.8 to 1 for all levels. The standard deviation is relatively small comparing to the coefficient estimate of level I-V-VI. This shows that even after accounting for individual listener differences, harmonic motion I-V-VI on average is still expected to have the highest classical rating compare to other levels.

- Voice leading level contrary motion has the strongest association with classical rating. On average, voice leading level par3rd is associated with rating 0.39 lower than that of contrary motion. Voice leading level par5th is associated with rating 0.31 lower than that of contrary motion.

```
     AIC      BIC   logLik deviance df.resid
  7608.7   7753.0  -3778.4   7556.7     1874

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.7184 -0.5707  0.0238  0.5429  3.6410

Random effects:
 Groups    Name             Variance Std.Dev. Corr
 Subject   (Intercept)      0.5007   0.7076
 Subject.1 HarmonyI-IV-V    0.6799   0.8246
           HarmonyI-V-IV    0.9497   0.9745    0.98
           HarmonyI-V-VI    0.9668   0.9833   -0.12  0.02
           HarmonyIV-I-V    0.7399   0.8602    0.96  0.92 -0.05
 Subject.2 Instrumentguitar 1.7820   1.3349
           Instrumentpiano  1.6473   1.2835    0.47
           Instrumentstring 1.0800   1.0392   -0.28  0.17
 Residual                   2.4316   1.5594
Number of obs: 1900, groups:  Subject, 53

Fixed effects:
                   Estimate Std. Error         df t value Pr(>|t|)
(Intercept)         4.07184    0.25714   43.92953  15.835  < 2e-16 ***
HarmonyI-V-IV       0.03180    0.10604   52.42094   0.300 0.765467
HarmonyI-V-VI       0.87896    0.21209   52.67201   4.144 0.000124 ***
HarmonyIV-I-V       0.08678    0.10652   51.69890   0.815 0.418978
Instrumentpiano     1.46985    0.20483   52.68072   7.176 2.42e-09 ***
Instrumentstring    3.40336    0.27605   52.98244  12.329  < 2e-16 ***
Voicepar3rd        -0.38611    0.08766 1579.48249  -4.405 1.13e-05 ***
Voicepar5th        -0.31359    0.08763 1579.00160  -3.579 0.000356 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 4: Summary Table of Classical Rating

For popular rating, the optimal model includes fixed effects of Harmony, Instrument, and Voice with random intercept and random effect on Harmony and Instrument. As shown in the appendix page 13, in the linear model without random effects, the interaction between Harmony and KnowAxis is in the final model and is found to be significant. However, after adding in random effects, based on BIC and chi-squared test in ANOVA, I found an optimal model without the particular interaction as fixed effect. The variation from KnowAxis is likely explained in the model by the random effects of each subject. Based on figure 5, following are the key interpretations of each variable holding other variables constant in the final model:

- Instrument, of all variables, have the strongest influence on popular rating. Stimuli with electric guitar is associated with the highest popular rating, on average, compared to other instruments. Stimuli with piano, on average, is associated with popular rating 1.13 lower. Stimuli with string quartet, on average is associated with popular rating 3.03 lower. Looking at the standard deviation of the random effects, the standard deviation of guitar is almost half of that of piano or string quartet. We can conclude that, across individual listeners, we still expect stimuli with electric guitar to have higher popular rating. This is the opposite finding compared to classical rating and is as expected.

- Harmonic motion does not have a significant influence on popular rating. While harmonic motion I-V-VI significantly differ from other levels in a model with fixed effect only, in the final model including random effects, we do not have evidence to show that different harmonic motion levels have different associations with popular rating. The standard deviation of the random effect is around 1 to 1.4 for all levels.
- Voice leading level contrary motion is associated with the lowest popular rating compared to par3rd or par5th. Level par3rd, on average, is associated with rating 0.21 lower, and par5th is associated with rating 0.24 lower than contrary motion. This is an opposite finding comparing to classical rating.

```
     AIC      BIC   logLik deviance df.resid
  7630.8   7775.1  -3789.4   7578.8     1874

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9795 -0.5770  0.0305  0.5670  3.2716

Random effects:
 Groups    Name             Variance Std.Dev. Corr
 Subject   (Intercept)      0.0000   0.0000
 Subject.1 HarmonyI-IV-V    1.4730   1.2137
           HarmonyI-V-IV    1.9400   1.3928   0.98
           HarmonyI-V-VI    1.7997   1.3415   0.67  0.62
           HarmonyIV-I-V    1.0885   1.0433   0.88  0.79  0.46
 Subject.2 Instrumentguitar 0.3066   0.5537
           Instrumentpiano  0.9009   0.9491   -0.18
           Instrumentstring 1.2222   1.1055   -1.00  0.25
 Residual                   2.4978   1.5804
Number of obs: 1900, groups:  Subject, 53

Fixed effects:
                    Estimate Std. Error         df t value Pr(>|t|)
(Intercept)       6.750e+00  2.099e-01  5.203e+01  32.153  < 2e-16 ***
HarmonyI-V-IV     2.958e-03  1.118e-01  1.161e+02   0.026  0.97893
HarmonyI-V-VI    -3.166e-01  1.759e-01  5.427e+01  -1.800  0.07740 .
HarmonyIV-I-V    -2.345e-01  1.288e-01  6.652e+01  -1.821  0.07307 .
Instrumentpiano  -1.127e+00  1.852e-01  5.271e+01  -6.087 1.34e-07 ***
Instrumentstring -3.028e+00  2.444e-01  5.297e+01 -12.389  < 2e-16 ***
Voicepar3rd       2.132e-01  8.885e-02  1.634e+03   2.399  0.01654 *
Voicepar5th       2.415e-01  8.881e-02  1.633e+03   2.719  0.00661 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 5: Summary Table of Popular Rating

3.4 Regression Models for Classical and Popular Ratings

After investigating the effects of the experimental factor above, I will discuss results from the model with other covariates (appendix pp.19-31). I will discuss the effect of the variable Musicians and its interactions in the next section specifically.

For classical ratings, we see that Harmony, Instrument and Voice have similar interpretations of fixed and random effects as above. Other significant factors include X16.minus.17, ConsNotes,

PachListen, X1990s2000s.minus.1960s1970s, CollegeMusic, NoClass, GuitarPlay. Based on figure 6, below are detailed interpretations of the significant variables holding other variables constant:

- X16.minus.17: 1 unit increase in the auxiliary measure of listener′s ability to distinguish classical vs popular music is expected to decrease classical rating by 0.09.
- ConsNotes: those who concentrate on notes at level 4 is expected to have classical rating 1.1 lower than other levels.
- PachListen: those who are familiar with Pachelbel′s Canon in D at level 4 is expected to have classical rating 2.86 higher than other familiarity levels.
- X1990s2000s.minus.1960s1970s: 1 unit increase in the difference of how much one listens to pop and rock from 90s-20s and 60s-70s is expected to increase classical rating by 0.16.
- CollegeMusic: Those who have taken music classes in college is expected to give classical rating 1.32 lower than those who didn′t take music classes. This means that those who received any proper music education are more critical when judging how classical the stimuli is.
- NoClass: 1 additional music class the listener took is expected to increase classical rating by 1.72. The more music classes the listener took, the more likely they will be able to identify characteristics of classical music and give higher ratings.
- GuitarPlay: Those who don′t play guitar at all tend to have lower classical rating than level 1, 2 and 4. In particular, those with entry level (level 1) guitar playing skills tend to have classical rating 3.32 higher than level 0. This be inferred that those who play guitar likely have a better understanding a classical music.

```
     AIC      BIC   logLik deviance df.resid
  7597.9   7853.2  -3752.9   7505.9     1854

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.6724 -0.5687  0.0093  0.5580  3.6815

Random effects:
 Groups    Name             Variance  Std.Dev. Corr
 Subject   (Intercept)      0.0003108 0.01763
 Subject.1 (Intercept)      0.3983946 0.63119
           HarmonyI-V-IV    0.0415525 0.20384   0.47
           HarmonyI-V-VI    1.8369831 1.35535  -0.69  0.05
           HarmonyIV-I-V    0.0566252 0.23796   0.02 -0.43  0.16
 Subject.2 (Intercept)      1.1768442 1.08482
           Instrumentpiano  1.7197324 1.31139  -0.70
           Instrumentstring 3.3981235 1.84340  -0.86  0.59
 Residual                   2.4402889 1.56214
Number of obs: 1900, groups:  Subject, 53

Fixed effects:
                              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)                    3.07582    0.72371   64.91113   4.250 6.98e-05 ***
HarmonyI-V-IV                  0.02802    0.10519   52.37433   0.266 0.791012
HarmonyI-V-VI                  0.87882    0.21200   52.67512   4.145 0.000124 ***
HarmonyIV-I-V                  0.08532    0.10641   51.69758   0.802 0.426329
Instrumentpiano                1.73848    0.26628   52.60842   6.529 2.66e-08 ***
Instrumentstring               3.82450    0.35616   52.99519  10.738 6.58e-15 ***
Voicepar3rd                   -0.39136    0.08833 1586.34672  -4.431 1.00e-05 ***
Voicepar5th                   -0.29468    0.08829 1590.56892  -3.338 0.000864 ***
X16.minus.17                  -0.09326    0.04155   53.74052  -2.245 0.028940 *
ConsNotes1                     0.40296    0.32531  164.75570   1.239 0.217220
ConsNotes3                     0.34536    0.28503  169.69393   1.212 0.227329
ConsNotes4                    -1.09645    0.52722  206.83302  -2.080 0.038787 *
ConsNotes5                    -0.21885    0.30953  115.81524  -0.707 0.480964
PachListen3                   -1.14061    0.69245   52.55605  -1.647 0.105481
PachListen4                    2.85994    0.95539   49.69517   2.993 0.004289 **
PachListen5                    0.20512    0.55165   49.42759   0.372 0.711615
X1990s2000s.minus.1960s1970s   0.15963    0.06620   48.69930   2.411 0.019717 *
CollegeMusic1                 -1.31820    0.32590   47.82660  -4.045 0.000190 ***
NoClass                        1.72037    0.32567   47.77872   5.283 3.09e-06 ***
GuitarPlay1                    3.32347    0.85516   51.07493   3.886 0.000294 ***
GuitarPlay2                    1.61937    0.79152   48.79653   2.046 0.046176 *
GuitarPlay4                    1.78215    0.60922   49.08812   2.925 0.005198 **
GuitarPlay5                   -0.24838    0.46439   48.46522  -0.535 0.595204
Musicians1                     1.97337    0.46184   56.29394   4.273 7.52e-05 ***
NoClass:Musicians1            -1.69490    0.32677   47.64628  -5.187 4.33e-06 ***
Instrumentpiano:Musicians1    -0.61759    0.40464   52.81197  -1.526 0.132915
Instrumentstring:Musicians1   -0.96943    0.54063   52.98443  -1.793 0.078656 .
GuitarPlay1:Musicians1        -3.08198    0.97444   48.52846  -3.163 0.002695 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 6: Summary Table of Classical Rating

```
     AIC      BIC   logLik deviance df.resid
  7631.3   7903.2  -3766.6   7533.3     1851

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9420 -0.5841  0.0109  0.5730  3.3498

Random effects:
 Groups    Name             Variance Std.Dev. Corr
 Subject   (Intercept)      0.0000   0.0000
 Subject.1 (Intercept)      1.0163   1.0081
           HarmonyI-V-IV    0.1014   0.3184    0.63
           HarmonyI-V-VI    1.0934   1.0457   -0.32 -0.36
           HarmonyIV-I-V    0.3592   0.5993   -0.85 -0.71 -0.11
 Subject.2 (Intercept)      0.5894   0.7678
           Instrumentpiano  1.3947   1.1810   -0.67
           Instrumentstring 2.7492   1.6581   -1.00  0.65
 Residual                   2.4943   1.5793
Number of obs: 1900, groups:  Subject, 53

Fixed effects:
                      Estimate Std. Error         df t value Pr(>|t|)
(Intercept)           7.664e+00  4.932e-01  6.856e+01  15.540  < 2e-16 ***
HarmonyI-V-IV         2.794e-03  1.114e-01  1.014e+02   0.025 0.980047
HarmonyI-V-VI        -3.172e-01  1.765e-01  5.433e+01  -1.798 0.077784 .
HarmonyIV-I-V        -2.349e-01  1.314e-01  7.034e+01  -1.788 0.078118 .
Instrumentpiano      -1.127e+00  1.850e-01  5.271e+01  -6.092 1.32e-07 ***
Instrumentstring     -3.028e+00  2.444e-01  5.297e+01 -12.391  < 2e-16 ***
Voicepar3rd           2.130e-01  8.879e-02  1.631e+03   2.400 0.016529 *
Voicepar5th           2.419e-01  8.875e-02  1.630e+03   2.726 0.006482 **
X16.minus.17          2.021e-01  4.207e-02  5.494e+01   4.804 1.24e-05 ***
ConsInstr1           -2.141e+00  6.235e-01  5.511e+01  -3.434 0.001135 **
ConsInstr2           -4.680e-01  5.032e-01  5.489e+01  -0.930 0.356410
ConsInstr3           -3.001e-01  4.873e-01  5.491e+01  -0.616 0.540481
ConsInstr4           -2.613e-01  4.731e-01  5.490e+01  -0.552 0.583014
ConsInstr5            1.113e+00  5.586e-01  5.490e+01   1.993 0.051279 .
KnowAxis1             5.216e+00  1.796e+00  5.506e+01   2.904 0.005292 **
KnowAxis5             7.650e-01  2.922e-01  5.497e+01   2.618 0.011410 *
NoClass              -1.507e+00  3.273e-01  5.497e+01  -4.604 2.49e-05 ***
Composing1           -1.185e+00  4.558e-01  5.492e+01  -2.600 0.011949 *
Composing2           -8.028e-01  9.225e-01  5.556e+01  -0.870 0.387885
Composing3            1.553e+00  8.826e-01  5.493e+01   1.759 0.084141 .
Composing4            4.748e-01  6.517e-01  5.524e+01   0.729 0.469283
Composing5            1.860e+00  1.862e+00  5.489e+01   0.999 0.322147
GuitarPlay1           5.395e-01  4.275e-01  5.496e+01   1.262 0.212297
GuitarPlay2           1.482e+00  7.538e-01  5.489e+01   1.966 0.054393 .
GuitarPlay4          -6.217e-01  8.986e-01  5.495e+01  -0.692 0.491973
GuitarPlay5           3.229e-01  6.051e-01  5.560e+01   0.534 0.595684
Musicians1           -2.170e+00  4.415e-01  5.506e+01  -4.915 8.37e-06 ***
NoClass:Musicians1    1.309e+00  3.838e-01  5.507e+01   3.410 0.001223 **
Composing1:Musicians1 2.725e+00  7.597e-01  5.491e+01   3.587 0.000712 ***
Composing2:Musicians1 2.026e+00  9.688e-01  5.561e+01   2.091 0.041128 *
Composing3:Musicians1 1.736e-01  1.090e+00  5.489e+01   0.159 0.874070
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 7: Summary Table of Popular Rating

For popular ratings, Instrument and Voice have the same interpretation for fixed and random effects as the previous section. Harmony now is only significant at alpha = 0.1 in the model with other covariates. Other significant covariates include X16.minus.17, ConsInstr, KnowAxis, NoClass, and Composing. Based on figure 7, following is the detailed interpretation of each significant variable holding other variables constant:

- X16.minus.17: 1 unit increase in the auxiliary measure of listener′s ability to distinguish classical vs popular music is expected to increase popular rating by 2.02.

- ConsInstr: Those who concentrate on listening for instrument at level 1 tend to give popular rating lower by 2.14 comparing to all other levels.
- KnowAxis: Those who know Axis of Evil′s Comedy bit tend to give higher popular rating than those who have not heard of it at all. In particular, those with level 1 familiarity tend to have popular rating 5.22 higher than those with level 0.
- NoClass: 1 additional music class the listener took is expected to decrease popular rating by 1.51. The more music classes the listener took, the more technical they see the stimuli and the less likely they consider it popular music.
- Composing: Those at composing level 1 tend to have popular rating lower by 1.19 than those with no composing experience.

Comparing the additional covariates in the final models of both ratings, I will first compare variables that are present in both models. I found that X16.minus.17 and NoClass have opposite relationships with classical and popular rating. For instance, having taken more music classes is positively correlated with classical rating but it is negatively correlated with popular rating. In addition, we see that while GuitarPlay is included in both models, it is only significant to classical rating.

Next, I will address the importance of some variables that only appear in one model. For classical rating, the more the listener is familiar with Canon in D, the higher classical rating they are likely to give. It makes sense because Canon in D is a classical piece so those familiar with it likely has had more classical music exposure in the past. On the contrary, Canon in D has little to do with pop music, so it makes sense it is not important to popular rating. For popular rating, those who are more familiar with Comedy bit tend to give higher popular rating since Comedy bits is a pop music piece. Again, because Comedy bit has no association with classical music, it makes sense that it is not important to classical rating.

In conclusion, the models for classical and popular ratings contain common variables that can have opposite effects on the particular rating and also unique variables that only affect one type of rating.

3.5 Effects of Musicians and Non-musicians on Ratings

In this section, we will focus on the effect of Musicians on classical and popular ratings from the final models in figure 6 and 7.

For classical ratings, we see that those who are self-declared musicians tend to give classical ratings 1.97 higher than self-declared non-musicians. For popular ratings, we see that those who are self-declared musicians tend to give popular rating 2.17 lower than non-musicians. From this result, we can interpret that people who are more familiar with classical music tend to see themselves more as musicians. People who self-declare as non-musicians likely have limited technical music knowledge and also be more familiar with pop music.

As for interactions, in the classical ratings model, I included Musicians with NoClass, Instrument and GuitarPlay. We see that, though for non-musicians the number of classes the listener has taken is positively associated with classical rating, for musicians the number of classes taken has close to zero effects on classical rating. Self-declared non-musicians likely have limited music knowledge. Any additional courses they take will give a greater marginal increase to their music knowledge,

thus having a bigger effect on judging classical music. For self-declared musicians, they already have enough knowledge that they are comfortable with. One additional course will not greatly impact their view when judging a piece. Another significant interaction is GuitarPlay level 1 and Musicians. For non-musicians, guitar play level 1 tend to have 3.33 higher classical rating than that associated with guitar play level 0. For musicians, guitar play level 1 tend to have 0.3 higher classical rating than level 0. We see guitar play level $1'$s effect is smaller on rating when the listener is a self-declared musician.

In the popular ratings model, I included interactions between Musicians with NoClass and Composing. The interpretation of the interaction between Musicians and NoClass is similar to that of classical ratings but with different coefficients. The interaction between Musicians and Composing is also significant. For non-musicians, listeners with composing level 1 tend to have a 1.19 lower popular rating than those with no composing experience. For musicians, listeners with composing level 1 tend to have a 1.6 higher popular rating than those with no experience. We see the direction of the relationship between Composing level 1 and popular rating changes depending on whether the listener is a Musician.

Overall for both classical and popular rating, we see whether the listener is a musician and non-musician affect the association between the rating given and other listener characteristics. We also find that self-declared musicians tend to give higher classical rating and lower popular rating than non-musicians.

4 Discussion

In this section, I will first recap the major findings in this study, and discuss some limitation and suggestions for future research. In conclusion, the goal of this analysis is to assess the effects of the three experimental factors and the other variables on classical and popular rating. Researchers are interested in comparing the difference effects and difference factors used to estimate the ratings and in particular how being a musicians affects the associations.

From section 3.3, we learned that as the researchers hypothesized, instrument does have the strongest influence among the three experimental factors for both classical and popular ratings. Stimuli played with string quartet tend to have higher classical rating by around 3.4 (standard error = 0.28) comparing to electrical guitar. Stimuli played with electrical guitar tend to have higher popular rating by around 3.0 (standard error = 0.24) comparing to string quartet. Harmonic motion I-V-VI has the strongest effect on classical rating but has no significant difference from other levels for popular ratings. This relationship does not depend on whether the listener is familiar with either Pachelbel rants or comedy bits for both ratings. Lastly for both ratings, voice leading contrary motion has the strongest effect on both ratings comparing to other voice leading levels. Even after accounting for individual subject differences through random effects, we are confident about our findings given the random effect standard deviation is relatively small comparing to fixed effect coefficient estimates. Overall, this tells us listeners tend to judge how classical or popular a musical piece sounds primarily through the instrument it is played with. In reality, a genre of music is often played with specific types of instruments. Thus, we are not surprised that people draws a connection being genre and instrument when critiquing music.

From section 3.4 and 3.5, we learned that the number of music related classes the listener has taken in the past and whether the listen is a self-declared musician is significant to estimating both classical and popular rating. However, the effect of those variables are the opposite on the two type

of ratings. Holding other variables constant and as the number of classes increases, classical rating is expected to increase by 1.7 (standard error = 0.33), and popular rating is expected to decrease by around 1.5 (standard error = 0.33). Those identified as musicians is expected to have classical rating 1.97 (standard error = 0.46) higher and popular rating 2.17 (standard error = 0.44) lower. Together, this suggests that those with more music knowledge tend to give higher classical rating, and those with less music knowledge tend to give higher popular rating. We also find some factors that only are significant to one of the ratings. For example, the degree to which the listener is familiar with Canon in D is only significant to classical rating, and the degree to which the listener is familiar with comedy bits is only significant to popular rating. These variables are only related to either classical or popular music.

One major limitation in this analysis is that some variables are created through the subjects' subjective view such as whether they self-declare as musicians or how familiar they rate themselves with a given musical piece. More analysis can be conducted to analysis how sensitive the model is to the dichotomization and grouping of other variables. In addition, with more musical knowledge, more interactions among the variables and causal inferences can be explored.

References

Jimenez, I. & Rossi, V. (2013) *The Influence of Timbre, Harmony, and Voice Leading on Listeners' Distinction between Popular and Classical Music*, University of Pittsburgh, Pittsburgh, PA.

R Core Team (2018), *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Appendix

3.1 Data Preprocessing

This section shows code that relevels Subject, fill in and remove missing data, create new variable Musicians and transform OMSI for normality.

```
ratings <- read.csv("ratings.csv")
ratings <- ratings[, which(!(names(ratings) %in% c("X","first12")))]

summary(ratings)
```

```
##     Subject       Harmony     Instrument       Voice      Selfdeclare
##  15     :  36   I-IV-V:630   guitar:840   contrary:840   Min.   :1.000
##  16     :  36   I-V-IV:630   piano :840   par3rd  :840   1st Qu.:2.000
##  17     :  36   I-V-VI:630   string:840   par5th  :840   Median :2.000
##  18b    :  36   IV-I-V:630                               Mean   :2.443
##  19     :  36                                           3rd Qu.:3.000
##  20     :  36                                           Max.   :6.000
##  (Other):2304
##       OMSI        X16.minus.17      ConsInstr       ConsNotes
##  Min.   : 11.0   Min.   :-4.000   Min.   :0.000   Min.   :0.000
##  1st Qu.: 49.0   1st Qu.: 0.000   1st Qu.:1.670   1st Qu.:0.750
##  Median :145.5   Median : 1.000   Median :3.000   Median :3.000
##  Mean   :225.9   Mean   : 1.721   Mean   :2.857   Mean   :2.533
##  3rd Qu.:323.0   3rd Qu.: 3.000   3rd Qu.:4.330   3rd Qu.:5.000
##  Max.   :970.0   Max.   : 9.000   Max.   :5.000   Max.   :5.000
##                                                   NA's   :360
##  Instr.minus.Notes   PachListen      ClsListen        KnowRob
##  Min.   :-4.0000   Min.   :0.000   Min.   :0.000   Min.   :0.0000
##  1st Qu.: 0.0000   1st Qu.:5.000   1st Qu.:1.000   1st Qu.:0.0000
##  Median : 0.3350   Median :5.000   Median :3.000   Median :0.0000
##  Mean   : 0.6857   Mean   :4.515   Mean   :2.159   Mean   :0.7692
##  3rd Qu.: 2.0000   3rd Qu.:5.000   3rd Qu.:3.000   3rd Qu.:0.0000
##  Max.   : 4.3300   Max.   :5.000   Max.   :5.000   Max.   :5.0000
##                    NA's   :72      NA's   :36      NA's   :180
##     KnowAxis       X1990s2000s    X1990s2000s.minus.1960s1970s  CollegeMusic
##  Min.   :0.0000   Min.   :0.000   Min.   :-4.000                Min.   :0.000
##  1st Qu.:0.0000   1st Qu.:3.000   1st Qu.: 0.000                1st Qu.:1.000
##  Median :0.0000   Median :5.000   Median : 2.000                Median :1.000
##  Mean   :0.9032   Mean   :4.061   Mean   : 2.015                Mean   :0.791
##  3rd Qu.:0.0000   3rd Qu.:5.000   3rd Qu.: 3.000                3rd Qu.:1.000
##  Max.   :5.0000   Max.   :5.000   Max.   : 5.000                Max.   :1.000
##  NA's   :288      NA's   :144     NA's   :180                   NA's   :108
##     NoClass          APTheory        Composing    PianoPlay
##  Min.   :0.0000   Min.   :0.0000   Min.   :0    Min.   :0.000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0    1st Qu.:0.000
##  Median :1.0000   Median :0.0000   Median :0    Median :0.000
##  Mean   :0.9194   Mean   :0.2344   Mean   :1    Mean   :1.086
##  3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:2    3rd Qu.:1.000
##  Max.   :8.0000   Max.   :1.0000   Max.   :5    Max.   :5.000
##  NA's   :288      NA's   :216      NA's   :72
```

```
##    GuitarPlay       X1stInstr       X2ndInstr       Classical
##  Min.   :0.0000   Min.   :1.000   Min.   :0.000   Min.   : 0.000
##  1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.: 4.000
##  Median :0.0000   Median :3.500   Median :1.000   Median : 6.000
##  Mean   :0.6857   Mean   :2.786   Mean   :1.556   Mean   : 5.783
##  3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:2.000   3rd Qu.: 8.000
##  Max.   :5.0000   Max.   :5.000   Max.   :4.000   Max.   :19.000
##                   NA's   :1512    NA's   :2196    NA's   :27
##     Popular
##  Min.   : 0.000
##  1st Qu.: 4.000
##  Median : 5.000
##  Mean   : 5.381
##  3rd Qu.: 7.000
##  Max.   :19.000
##  NA's   :27
```

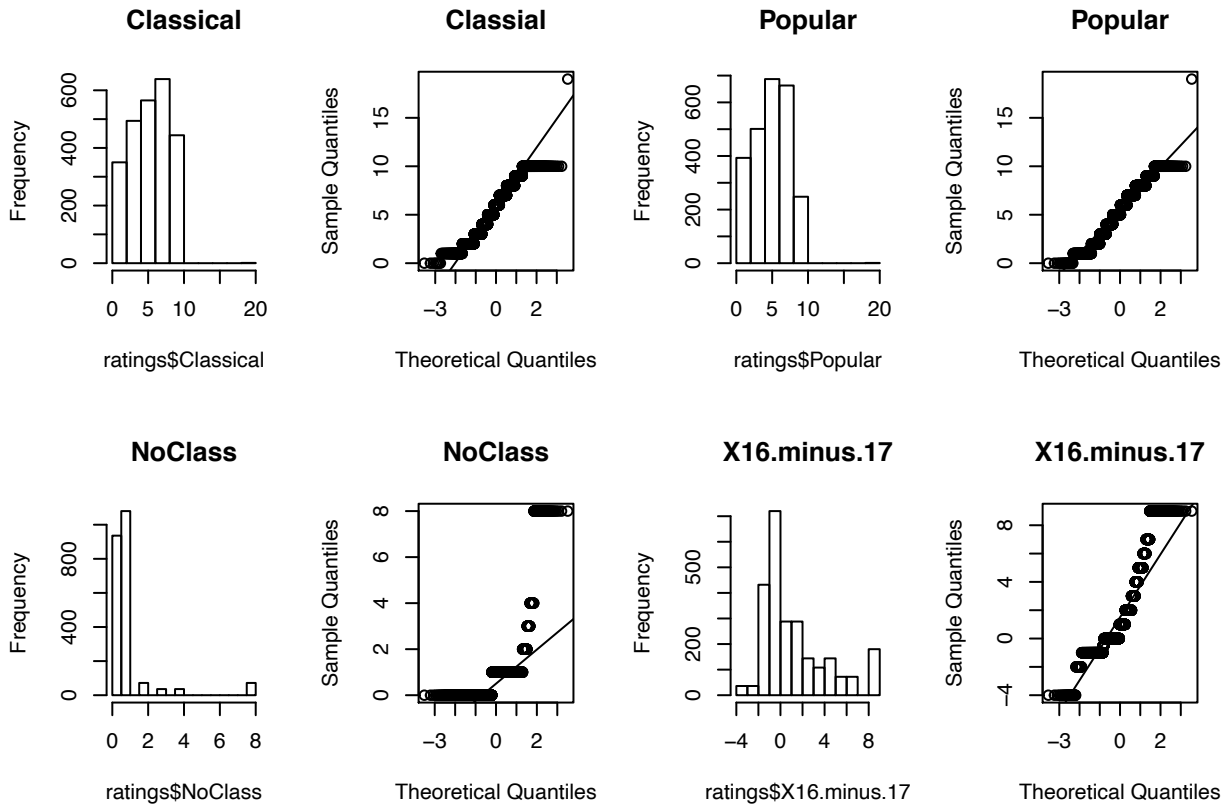
```
levels(ratings$Subject)
```

```
##  [1] "15"   "16"   "17"   "18b"  "19"   "20"   "21"   "22"   "23"   "24"
## [11] "25"   "26"   "28"   "29"   "30"   "31"   "32"   "33"   "34"   "35"
## [21] "36"   "37"   "38"   "39"   "40"   "41"   "42"   "43"   "44.1" "44.2"
## [31] "45"   "46"   "47"   "48"   "49"   "50"   "51"   "52"   "53"   "54"
## [41] "55"   "56"   "57"   "58"   "59"   "60"   "61"   "62"   "63"   "64"
## [51] "65"   "66"   "70"   "71"   "73"   "74"   "75"   "76"   "77"   "78"
## [61] "79"   "80"   "81"   "82"   "83"   "90"   "91"   "93"   "94"   "98"
```

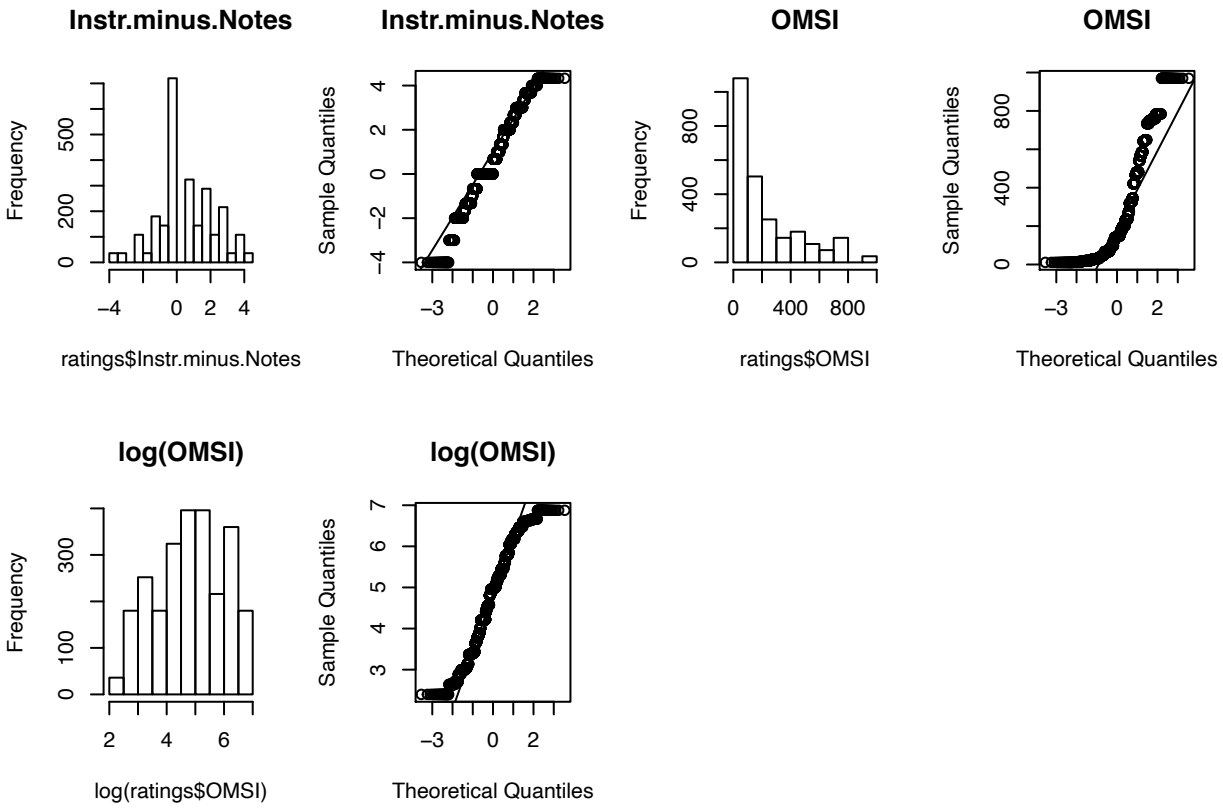
```
levels(ratings$Subject) = 1:70
ratings <- ratings %>% mutate(Selfdeclare = as.factor(Selfdeclare),
                              ConsInstr = as.factor(ConsInstr),
                              ConsNotes = as.factor(ConsNotes),
                              PachListen = as.factor(PachListen),
                              ClsListen = as.factor(ClsListen),
                              KnowRob = as.factor(KnowRob),
                              KnowAxis = as.factor(KnowAxis),
                              X1990s2000s = as.factor(X1990s2000s),
                              CollegeMusic = as.factor(CollegeMusic),
                              APTheory = as.factor(APTheory),
                              Composing = as.factor(Composing),
                              PianoPlay = as.factor(PianoPlay),
                              GuitarPlay = as.factor(GuitarPlay),
                              X1stInstr = as.factor(X1stInstr),
                              X2ndInstr = as.factor(X2ndInstr),
                              )
```

```
par(mfrow=c(2,4))

hist(ratings$Classical, main = "Classical")
qqnorm(ratings$Classical, main = "Classial")
qqline(ratings$Classical)

hist(ratings$Popular, main = "Popular")
qqnorm(ratings$Popular, main = "Popular")
qqline(ratings$Popular)
```

```r
hist(ratings$NoClass, main = "NoClass")
qqnorm(ratings$NoClass, main = "NoClass")
qqline(ratings$NoClass)

hist(ratings$X16.minus.17, main = "X16.minus.17")
qqnorm(ratings$X16.minus.17, main = "X16.minus.17")
qqline(ratings$X16.minus.17)
```




```r
hist(ratings$Instr.minus.Notes, main = "Instr.minus.Notes")
qqnorm(ratings$Instr.minus.Notes, main = "Instr.minus.Notes")
qqline(ratings$Instr.minus.Notes)

hist(ratings$OMSI, main="OMSI")
qqnorm(ratings$OMSI, main="OMSI")
qqline(ratings$OMSI)

hist(log(ratings$OMSI), main="log(OMSI)")
qqnorm(log(ratings$OMSI), main="log(OMSI)")
qqline(log(ratings$OMSI))
```




```
lvl.na = c()
for(l in levels(ratings$ConsInstr)){
  has.na = sum(is.na(ratings$ConsNotes[which(ratings$ConsInstr==as.numeric(l))]))
  if (has.na > 0){
    lvl.na = c(lvl.na, l)
  }
}

for(l in lvl.na){
  udf = unique(ratings[which(ratings$ConsInstr==l),c("Selfdeclare", "ConsNotes")])
  udf.full = udf[which(!is.na(udf$ConsNotes)),]
  udf.na = udf[which(is.na(udf$ConsNotes)),]
  if(length(unique(udf.full$ConsNotes)==1)){
    ratings$ConsNotes[which(ratings$ConsInstr==l
                            & is.na(ratings$ConsNotes))] = unique(na.omit(udf$ConsNotes))
  }
  else{
    sd.na = as.numeric(udf.na$Selfdeclare)
    if(sd.na %in% udf.full$Selfdeclare){
      ratings$ConsNotes[
        which(ratings$ConsInstr==l & is.na(ratings$ConsNotes))] =
        udf.full$ConsNotes[which(udf.full$Selfdeclare==sd.na)]
    }
    else if(sd.na+1 %in% udf.full$Selfdeclare){
      ratings$ConsNotes[which(ratings$ConsInstr==l & is.na(ratings$ConsNotes))] =
        udf.full$ConsNotes[which(udf.full$Selfdeclare==sd.na+1)]
    }
  }
```

```
}
```

```
## Warning in x[...] <- m: number of items to replace is not a multiple of
## replacement length
```

```
# median imputation
summary(ratings$NoClass)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  0.0000  0.0000  1.0000  0.9194  1.0000  8.0000     288
```

```
ratings$NoClass[which(is.na(ratings$NoClass))] = 1
summary(ratings$X1990s2000s.minus.1960s1970s)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -4.000   0.000   2.000   2.015   3.000   5.000     180
```

```
ratings$X1990s2000s.minus.1960s1970s[
  which(is.na(ratings$X1990s2000s.minus.1960s1970s))] = 2

ratings <- ratings %>%
   mutate(OMSI.log = log(OMSI),
          ConsNotes = as.factor(ConsNotes),
          ConsInstr = as.factor(round(as.numeric(as.character(ConsInstr))))) %>%
  filter(Classical<=10 & Popular<=10) %>%
  select(-X1stInstr, -X2ndInstr, -OMSI)

ratings <- na.omit(ratings)

Musicians = as.numeric(ratings$Selfdeclare)
Musicians[which(ratings$Selfdeclare==1 | ratings$Selfdeclare==2)] = 0
Musicians[which(Musicians!=0)] = 1
Musicians = as.factor(Musicians)
table(Musicians)
```

```
## Musicians
##    0    1
## 1079  821
```

```
ratings <- ratings %>% mutate(Musicians = Musicians)
summary(ratings)
```

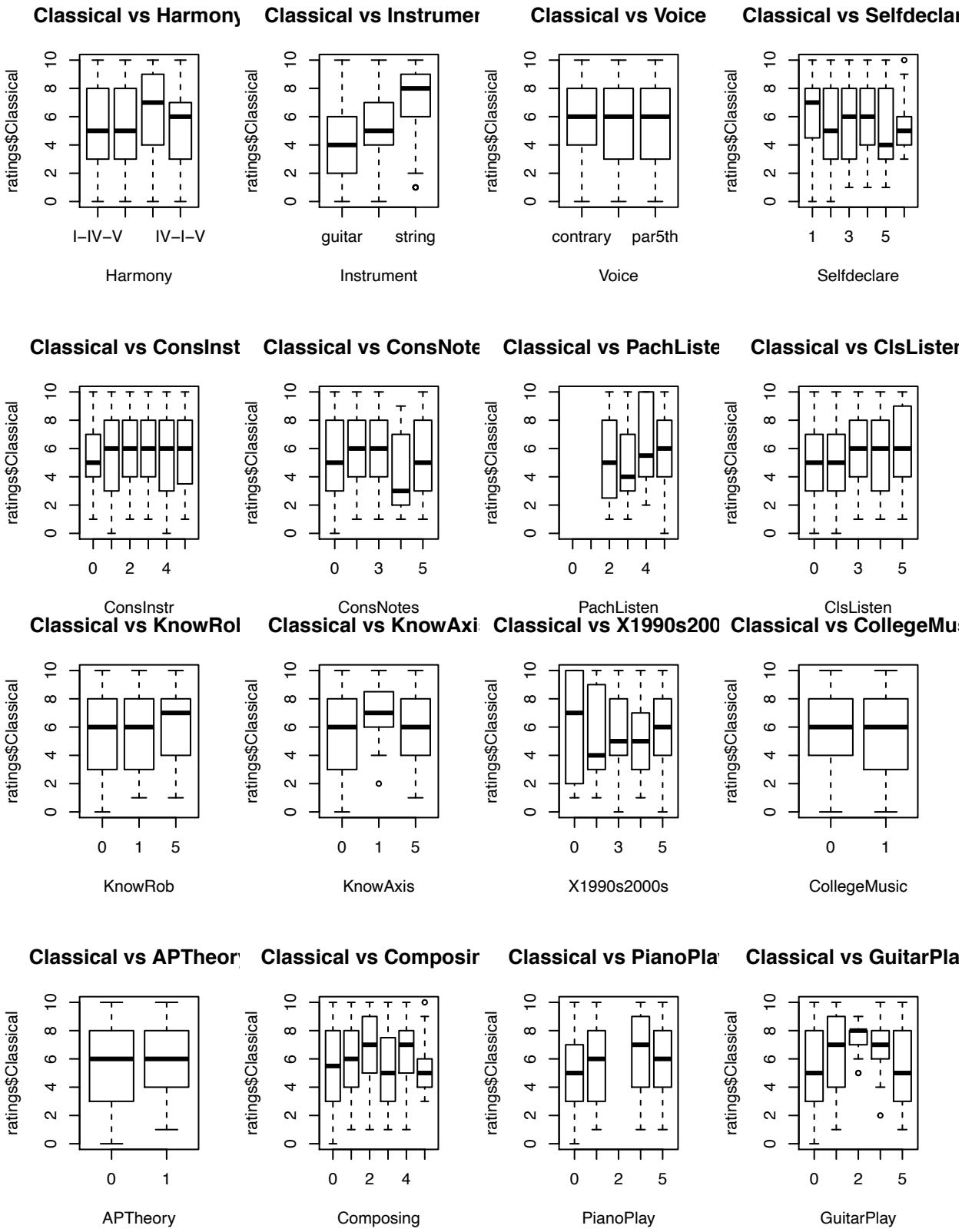
```
##     Subject       Harmony     Instrument       Voice     Selfdeclare
##  1      :  36   I-IV-V:476   guitar:635   contrary:633   1:252
##  2      :  36   I-V-IV:474   piano :629   par3rd  :633   2:827
##  3      :  36   I-V-VI:474   string:636   par5th  :634   3:360
##  5      :  36   IV-I-V:476                               4:353
##  6      :  36                                           5: 72
##  8      :  36                                           6: 36
##  (Other):1684
##   X16.minus.17    ConsInstr ConsNotes Instr.minus.Notes PachListen ClsListen
##  Min.   :-4.000   0:108     0:457     Min.   :-4.0000   0:   0     0:288
##  1st Qu.: 0.000   1:208     1:336     1st Qu.: 0.0000   1:   0     1:612
##  Median : 1.000   2:288     3:565     Median : 0.6700   2: 108     3:713
##  Mean   : 1.626   3:468     4: 43     Mean   : 0.8105   3: 144     4: 36
##  3rd Qu.: 3.000   4:540     5:499     3rd Qu.: 2.0000   4:  36     5:251
##  Max.   : 9.000   5:288               Max.   : 4.3300   5:1612
```

```
##
##  KnowRob  KnowAxis X1990s2000s X1990s2000s.minus.1960s1970s CollegeMusic
##  0:1511   0:1469   0: 144      Min.   :-3.000               0: 396
##  1: 144   1:  35   2: 108      1st Qu.: 0.000               1:1504
##  5: 245   5: 396   3: 252      Median : 2.000
##                    4: 180      Mean   : 1.931
##                    5:1216      3rd Qu.: 3.000
##                                Max.   : 5.000
##
##     NoClass       APTheory Composing PianoPlay GuitarPlay   Classical
##  Min.   :0.0000   0:1475   0:1116    0:1044    0:1404     Min.   : 0.000
##  1st Qu.:0.0000   1: 425   1: 216    1: 496    1: 215     1st Qu.: 3.000
##  Median :1.0000            2: 245    2:   0    2:  36     Median : 6.000
##  Mean   :0.9237            3: 144    4: 144    4:  71     Mean   : 5.715
##  3rd Qu.:1.0000            4: 143    5: 216    5: 174     3rd Qu.: 8.000
##  Max.   :8.0000            5:  36                         Max.   :10.000
##
##     Popular          OMSI.log     Musicians
##  Min.   : 0.000   Min.   :2.398   0:1079
##  1st Qu.: 3.000   1st Qu.:4.205   1: 821
##  Median : 6.000   Median :4.990
##  Mean   : 5.376   Mean   :4.969
##  3rd Qu.: 7.000   3rd Qu.:5.784
##  Max.   :10.000   Max.   :6.877
##
```

3.2 Exploratory Data Analysis

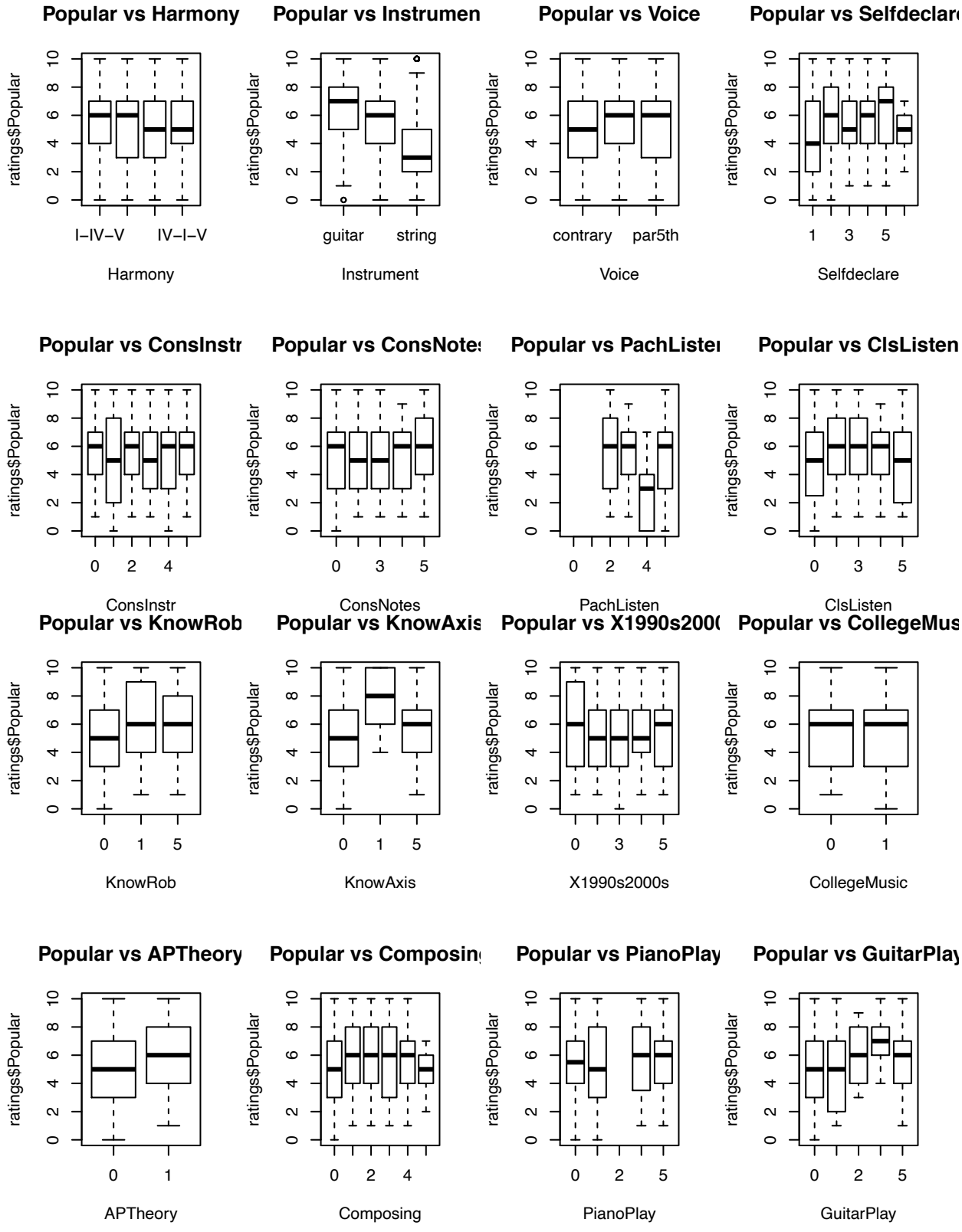
The code below creates boxplots that explores the relationship between classical (popular) ratings and other variables, and boxplots that explore the interaction between harmonic motion and KnowRob (KnowAxis).

```
par(mfrow=c(2,4))
for (i in c("Harmony","Instrument","Voice","Selfdeclare","ConsInstr","ConsNotes",
            "PachListen","ClsListen","KnowRob","KnowAxis","X1990s2000s",
            "CollegeMusic","APTheory","Composing","PianoPlay","GuitarPlay")) {
  boxplot(ratings$Classical ~ ratings[,i], xlab = i, main=paste0("Classical vs ",i))
}
```

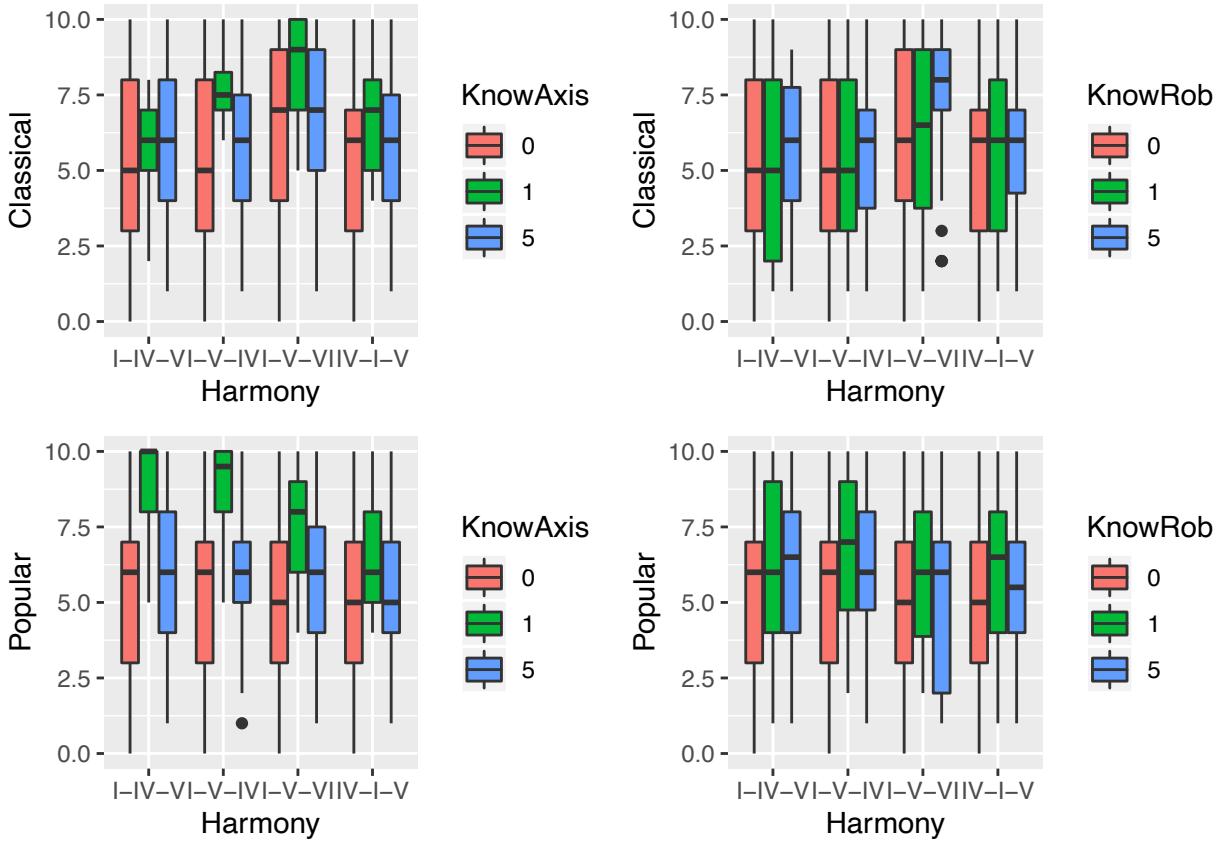



```
par(mfrow=c(2,4))
for (i in c("Harmony","Instrument","Voice","Selfdeclare","ConsInstr","ConsNotes",
            "PachListen","ClsListen","KnowRob","KnowAxis","X1990s2000s",
```

```
            "CollegeMusic","APTheory","Composing","PianoPlay","GuitarPlay")) {
  boxplot(ratings$Popular ~ ratings[,i], xlab = i, main=paste0("Popular vs ",i))
}
```



```
g1 <- ggplot(ratings, aes(x = Harmony, y = Classical,fill = KnowAxis))+geom_boxplot()
g2 <- ggplot(ratings, aes(x = Harmony, y = Classical,fill = KnowRob))+geom_boxplot()
g3 <- ggplot(ratings, aes(x = Harmony, y = Popular,fill = KnowAxis))+geom_boxplot()
g4 <- ggplot(ratings, aes(x = Harmony, y = Popular,fill = KnowRob))+geom_boxplot()
grid.arrange(g1, g2, g3, g4, ncol=2)
```



3.3 Effects of Experimental Factors on Classical and Popular Ratings

The code below creates model for classical and popular ratings using only experimental factors and its interactions. stepAIC with BIC criterion is used to pick fixed effects. fitLMER.fnc is used to choose random effects. I also looked at ANOVA results and diagnostic plots which shows my final model is valid and optimal.

```
# classical rating
m1 <- lm(Classical~Harmony*Instrument*Voice+Harmony:KnowRob+Harmony:KnowAxis, ratings)
m1.bic <- stepAIC(m1, scope = list(lower = ~Harmony+Instrument+Voice),  trace=F, k = log(1900))
lmer1.interp.only <- lmer(update.formula(m1.bic, .~. + (1 | Subject)),
                          ratings, REML=F, control = lmerControl(optimizer = "bobyqa"))
anova(lmer1.interp.only, m1.bic)
```

```
## Data: ratings
## Models:
## m1.bic: Classical ~ Harmony + Instrument + Voice
## lmer1.interp.only: Classical ~ Harmony + Instrument + Voice + (1 | Subject)
##                    Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
```

```
## m1.bic             9 8552.4 8602.3 -4267.2   8534.4
## lmer1.interp.only 10 8034.3 8089.8 -4007.2   8014.3 520.08      1  < 2.2e-16
##
## m1.bic
## lmer1.interp.only ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lmer2 <- fitLMER.fnc(lmer1.interp.only,
                     ran.effects=
                       c("(0+Voice|Subject)","(0+Harmony|Subject)","(0+Instrument|Subject)"),
            method = "BIC" , keep.single.factors = T)
```

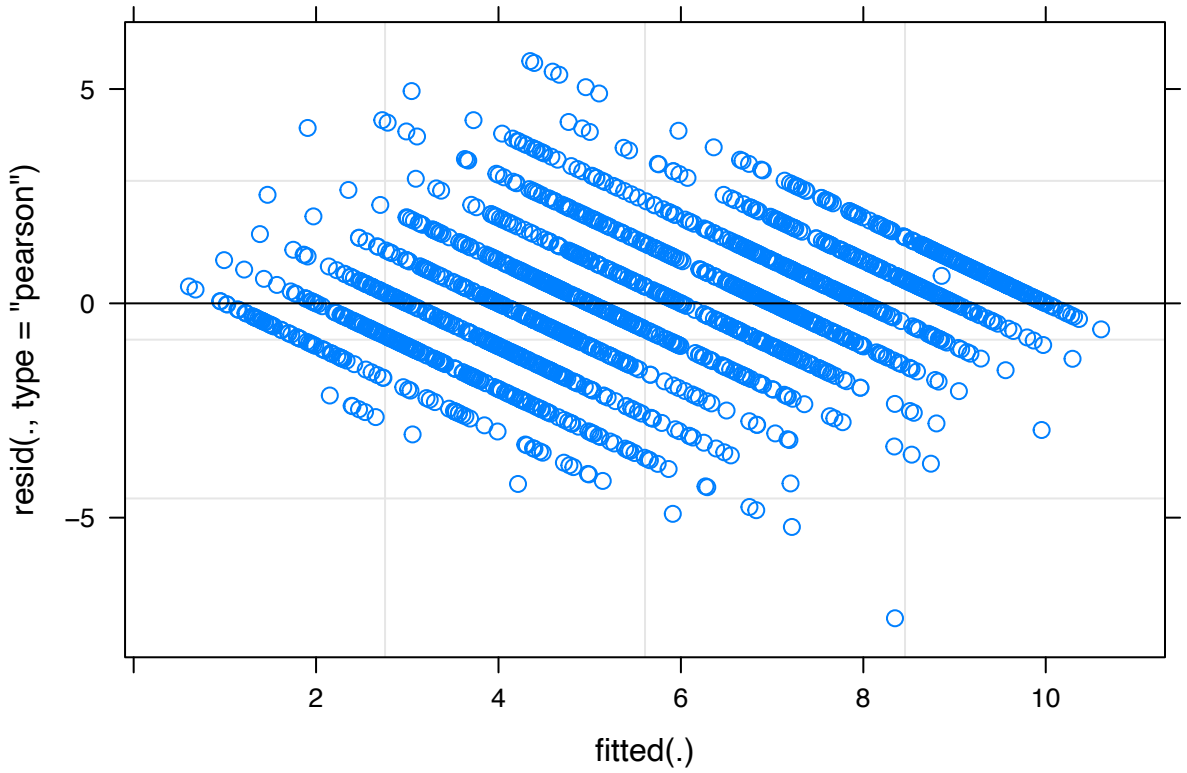
```
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## setting REML to FALSE
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
## evaluating addition of (0+Voice|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 0.9999997
##  not adding (0+Voice|Subject) to model
## evaluating addition of (0+Harmony|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 4.602083e-15
##  adding (0+Harmony|Subject) to model
## evaluating addition of (0+Instrument|Subject) to model
##  log-likelihood ratio test p-value = 3.011872e-76
##  adding (0+Instrument|Subject) to model
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## setting REML to FALSE
## resetting REML to TRUE

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unide
##  - Rescale variables?

## pruning random effects structure ...
##   nothing to prune
## log file is /var/folders/_6/x1ql75n53033623j51rd1r540000gp/T//Rtmp3K6dyx/fitLMER_log_Sun_Dec__8_11-4
```

```
anova(lmer1.interp.only,lmer2)
```

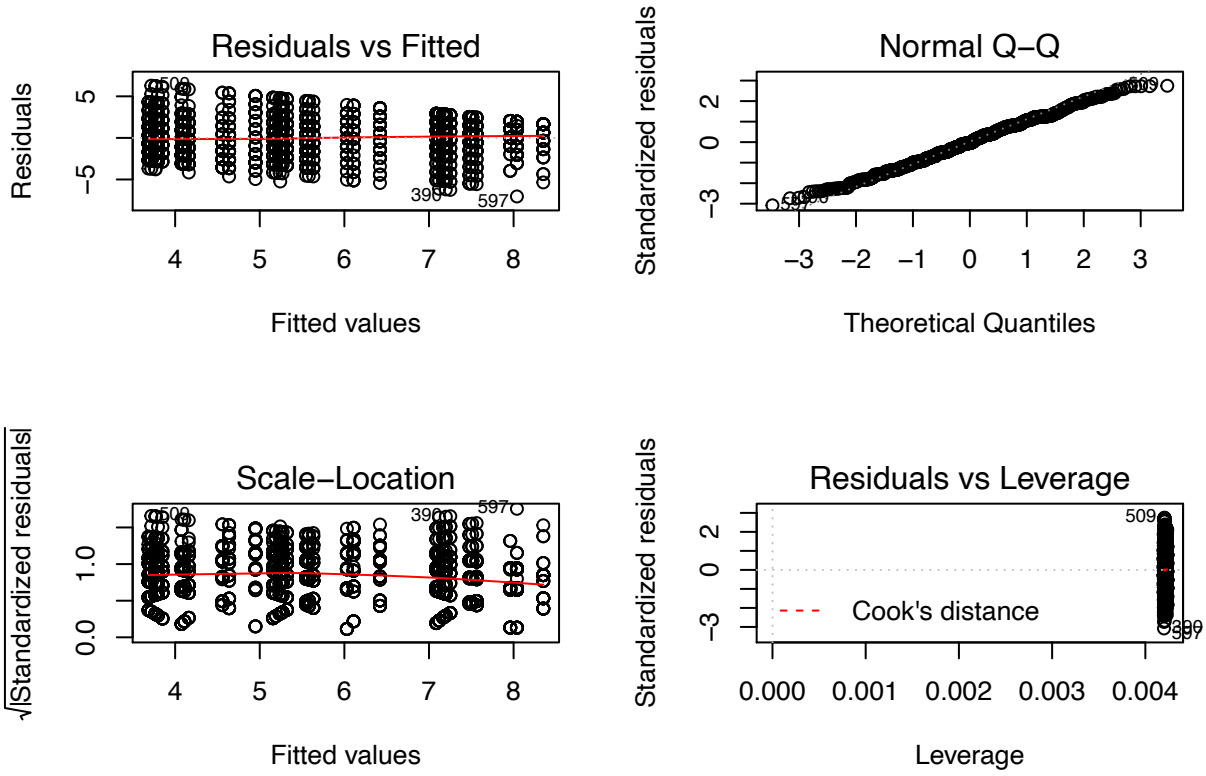
```
## refitting model(s) with ML (instead of REML)

## Data: ratings
## Models:
## lmer1.interp.only: Classical ~ Harmony + Instrument + Voice + (1 | Subject)
## lmer2: Classical ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
## lmer2:     Harmony | Subject) + (0 + Instrument | Subject)
```

```
##                   Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer1.interp.only 10 8034.3 8089.8 -4007.2   8014.3
## lmer2             26 7608.7 7753.0 -3778.4   7556.7 457.61     16  < 2.2e-16
##
## lmer1.interp.only
## lmer2             ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(lmer2)
```




```
par(mfrow=c(2,2))
plot(m1.bic)
```




```
summary(m1.bic)
```

```
##
## Call:
## lm(formula = Classical ~ Harmony + Instrument + Voice, data = ratings)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.0395 -1.6376 -0.0865  1.7481  6.2822
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        4.07537    0.14854  27.435  < 2e-16 ***
## HarmonyI-V-IV      0.03313    0.14867   0.223  0.82369
## HarmonyI-V-VI      0.87351    0.14867   5.875 4.97e-09 ***
## HarmonyIV-I-V      0.08597    0.14852   0.579  0.56276
## Instrumentpiano    1.47173    0.12889  11.418  < 2e-16 ***
## Instrumentstring   3.40181    0.12853  26.466  < 2e-16 ***
## Voicepar3rd       -0.39070    0.12879  -3.034  0.00245 **
## Voicepar5th       -0.31123    0.12874  -2.418  0.01572 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.291 on 1892 degrees of freedom
## Multiple R-squared:  0.2874, Adjusted R-squared:  0.2847
## F-statistic:   109 on 7 and 1892 DF,  p-value: < 2.2e-16
```

```
# final model
summary(lmer2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Classical ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
##     Harmony | Subject) + (0 + Instrument | Subject)
##    Data: ratings
## Control: lmerControl(optimizer = "bobyqa")
##
## REML criterion at convergence: 7574.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.7089 -0.5688  0.0241  0.5394  3.6224
##
## Random effects:
##  Groups    Name             Variance Std.Dev. Corr
##  Subject   (Intercept)      0.6007   0.7751
##  Subject.1 HarmonyI-IV-V    0.6267   0.7917
##            HarmonyI-V-IV    0.9022   0.9499    0.97
##            HarmonyI-V-VI    0.9191   0.9587   -0.22 -0.05
##            HarmonyIV-I-V    0.6878   0.8293    0.95  0.91 -0.15
##  Subject.2 Instrumentguitar 1.7996   1.3415
##            Instrumentpiano  1.6622   1.2893    0.46
##            Instrumentstring 1.0840   1.0412   -0.30  0.16
##  Residual                   2.4346   1.5603
## Number of obs: 1900, groups:  Subject, 53
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)       4.07178    0.25952  15.690
## HarmonyI-V-IV     0.03175    0.10706   0.297
## HarmonyI-V-VI     0.87898    0.21413   4.105
## HarmonyIV-I-V     0.08685    0.10756   0.807
## Instrumentpiano   1.46984    0.20680   7.108
## Instrumentstring  3.40338    0.27870  12.212
## Voicepar3rd      -0.38601    0.08772  -4.401
## Voicepar5th      -0.31360    0.08768  -3.577
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## HrmnyI-V-IV -0.112
## HrmnyI-V-VI -0.362  0.237
## HrmnyIV-I-V -0.187  0.424  0.270
## Instrumntpn -0.422  0.001  0.000  0.000
## Instrmntstr -0.630  0.000  0.000  0.000  0.597
## Voicepar3rd -0.169  0.000 -0.001  0.001  0.001     0.000
## Voicepar5th -0.169 -0.001 -0.001 -0.001  0.000     0.000     0.500
## convergence code: 0
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
# popular rating
m5.1 <- lm(Popular~Harmony*Instrument*Voice+Harmony:KnowRob+Harmony:KnowAxis, ratings)
m5.1.bic <- stepAIC(m5.1, scope = list(lower = ~Harmony+Instrument+Voice),  trace=F, k = log(1900))
lmer5.1.interp.only <- lmer(update.formula(m5.1.bic, .~. + (1 | Subject)),
                            ratings, REML=F, control = lmerControl(optimizer = "bobyqa"))
```

```r
anova(lmer5.1.interp.only, m5.1.bic)
```

```
## Data: ratings
## Models:
## m5.1.bic: Popular ~ Harmony + Instrument + Voice + Harmony:KnowAxis
## lmer5.1.interp.only: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + Harmony:KnowAxis
##                      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## m5.1.bic             17 8385.1 8479.4 -4175.5   8351.1
## lmer5.1.interp.only 18 7931.1 8031.0 -3947.5   7895.1 456.01      1  < 2.2e-16
##
## m5.1.bic
## lmer5.1.interp.only ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
lmer5.2 <- fitLMER.fnc(lmer5.1.interp.only, ran.effects=c("(0+Voice|Subject)","(0+Harmony|Subject)","(0+
           method = "BIC" , keep.single.factors = T)
```

```
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## setting REML to FALSE
## processing model terms of interaction level 2
##   iteration 1
##     p-value for term "Harmony:KnowAxis" = 0.0268 >= 0
##     not part of higher-order interaction
##     BIC simple = 7988; BIC complex = 8031; decrease = -43 < 5
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
## evaluating addition of (0+Voice|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 0.9404948
##  not adding (0+Voice|Subject) to model
## evaluating addition of (0+Harmony|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 5.349948e-12
##  adding (0+Harmony|Subject) to model
## evaluating addition of (0+Instrument|Subject) to model

## Warning in optwrap(optimizer, devfun, getStart(start, rho$lower, rho$pp), :
## convergence code 1 from bobyqa: bobyqa -- maximum number of function evaluations
## exceeded

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 6.011931e-53
##  adding (0+Instrument|Subject) to model
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
```

```
## setting REML to FALSE

## Warning in optwrap(optimizer, devfun, getStart(start, rho$lower, rho$pp), :
## convergence code 1 from bobyqa: bobyqa -- maximum number of function evaluations
## exceeded

## boundary (singular) fit: see ?isSingular

## resetting REML to TRUE

## Warning in optwrap(optimizer, devfun, getStart(start, rho$lower, rho$pp), :
## convergence code 1 from bobyqa: bobyqa -- maximum number of function evaluations
## exceeded

## boundary (singular) fit: see ?isSingular

## pruning random effects structure ...
##   nothing to prune
## log file is /var/folders/_6/x1ql75n53033623j51rd1r540000gp/T//Rtmp3K6dyx/fitLMER_log_Sun_Dec__8_11-43
```

```
lmer5.2.1 <- lmer(update.formula(lmer5.2,.~.+Harmony:KnowAxis),
                  ratings, REML=F, control = lmerControl(optimizer = "bobyqa"))
```

```
## boundary (singular) fit: see ?isSingular
```

```
anova(lmer5.1.interp.only,lmer5.2)
```

```
## refitting model(s) with ML (instead of REML)

## Data: ratings
## Models:
## lmer5.1.interp.only: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + Harmony:KnowAxis
## lmer5.2: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
## lmer5.2:     Harmony | Subject) + (0 + Instrument | Subject)
##                     Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer5.1.interp.only 18 7931.1 8031.0 -3947.5   7895.1
## lmer5.2             26 7630.8 7775.1 -3789.4   7578.8 316.29      8  < 2.2e-16
##
## lmer5.1.interp.only
## lmer5.2             ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(lmer5.1.interp.only,lmer5.2.1)
```

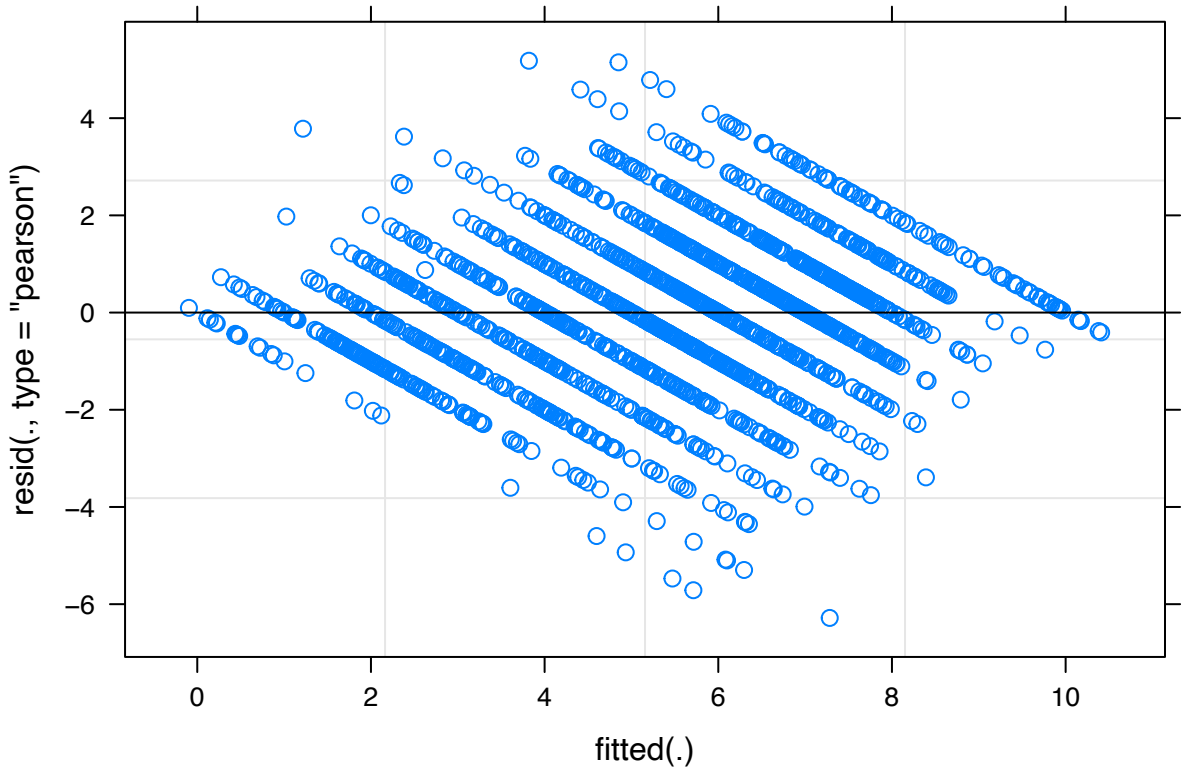
```
## Data: ratings
## Models:
## lmer5.1.interp.only: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + Harmony:KnowAxis
## lmer5.2.1: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
## lmer5.2.1:     Harmony | Subject) + (0 + Instrument | Subject) + Harmony:KnowAxis
##                     Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer5.1.interp.only 18 7931.1 8031.0 -3947.5   7895.1
## lmer5.2.1           34 7637.4 7826.1 -3784.7   7569.4 325.66     16  < 2.2e-16
##
## lmer5.1.interp.only
## lmer5.2.1           ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(lmer5.2,lmer5.2.1)
```

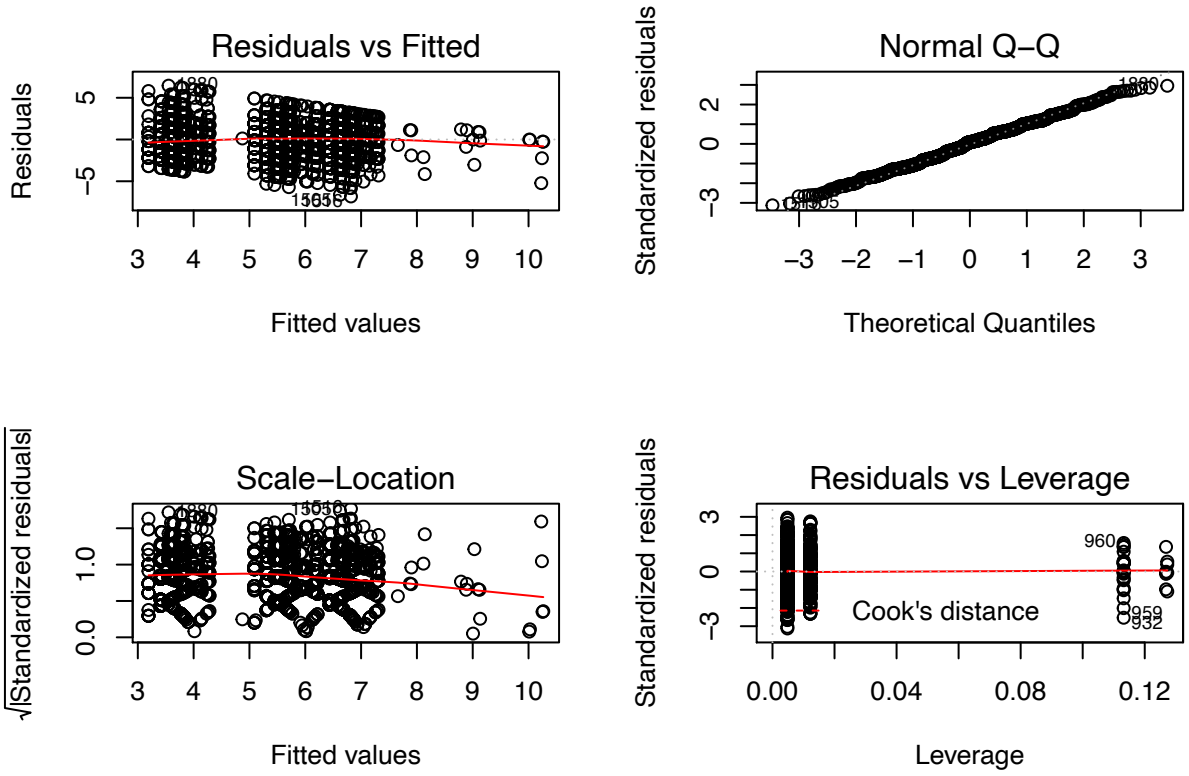
```
## refitting model(s) with ML (instead of REML)
```

```
## Data: ratings
## Models:
## lmer5.2: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
## lmer5.2:     Harmony | Subject) + (0 + Instrument | Subject)
## lmer5.2.1: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
## lmer5.2.1:     Harmony | Subject) + (0 + Instrument | Subject) + Harmony:KnowAxis
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer5.2   26 7630.8 7775.1 -3789.4   7578.8
## lmer5.2.1 34 7637.4 7826.1 -3784.7   7569.4 9.3738      8     0.3118
```

```
plot(lmer5.2)
```




```
par(mfrow=c(2,2))
plot(m5.1.bic)
```




```
summary(m5.1.bic)
```

```
##
## Call:
## lm(formula = Popular ~ Harmony + Instrument + Voice + Harmony:KnowAxis,
##     data = ratings)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8187 -1.6217  0.1669  1.4711  6.4484
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)               6.62171    0.15188  43.599  < 2e-16 ***
## HarmonyI-V-IV            -0.04226    0.16140  -0.262 0.793485
## HarmonyI-V-VI            -0.40276    0.16152  -2.494 0.012728 *
## HarmonyIV-I-V            -0.17670    0.16129  -1.095 0.273442
## Instrumentpiano          -1.13101    0.12309  -9.189  < 2e-16 ***
## Instrumentstring         -3.02786    0.12274 -24.669  < 2e-16 ***
## Voicepar3rd               0.21491    0.12299   1.747 0.080726 .
## Voicepar5th               0.23925    0.12293   1.946 0.051784 .
## HarmonyI-IV-V:KnowAxis1   3.39098    0.73817   4.594 4.64e-06 ***
## HarmonyI-V-IV:KnowAxis1   3.44531    0.78202   4.406 1.11e-05 ***
## HarmonyI-V-VI:KnowAxis1   2.57152    0.73821   3.483 0.000506 ***
## HarmonyIV-I-V:KnowAxis1   1.45656    0.73817   1.973 0.048617 *
## HarmonyI-IV-V:KnowAxis5   0.31017    0.24771   1.252 0.210676
## HarmonyI-V-IV:KnowAxis5   0.49384    0.24778   1.993 0.046401 *
## HarmonyI-V-VI:KnowAxis5   0.82404    0.24785   3.325 0.000902 ***
## HarmonyIV-I-V:KnowAxis5   0.21414    0.24771   0.864 0.387444
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.188 on 1884 degrees of freedom
## Multiple R-squared:  0.272,  Adjusted R-squared:  0.2662
## F-statistic: 46.92 on 15 and 1884 DF,  p-value: < 2.2e-16
```

```
# final model
summary(lmer5.2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Popular ~ Harmony + Instrument + Voice + (1 | Subject) + (0 +
##     Harmony | Subject) + (0 + Instrument | Subject)
##    Data: ratings
## Control: lmerControl(optimizer = "bobyqa")
##
## REML criterion at convergence: 7596.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9721 -0.5750  0.0302  0.5669  3.2752
##
## Random effects:
##  Groups    Name             Variance  Std.Dev.  Corr
##  Subject   (Intercept)      3.817e-08 0.0001954
##  Subject.1 HarmonyI-IV-V    1.504e+00 1.2264251
##            HarmonyI-V-IV    1.982e+00 1.4079810 0.98
##            HarmonyI-V-VI    1.840e+00 1.3565004 0.67  0.61
##            HarmonyIV-I-V    1.115e+00 1.0558904 0.88  0.79  0.46
##  Subject.2 Instrumentguitar 3.146e-01 0.5608561
##            Instrumentpiano  9.193e-01 0.9588129 -0.18
##            Instrumentstring 1.246e+00 1.1163034 -1.00  0.25
##  Residual                   2.502e+00 1.5818736
## Number of obs: 1900, groups:  Subject, 53
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)       6.750506   0.211743  31.881
## HarmonyI-V-IV     0.003048   0.112141   0.027
## HarmonyI-V-VI    -0.316609   0.177349  -1.785
## HarmonyIV-I-V    -0.234524   0.129561  -1.810
## Instrumentpiano  -1.127151   0.186954  -6.029
## Instrumentstring -3.028399   0.246779 -12.272
## Voicepar3rd       0.213136   0.088931   2.397
## Voicepar5th       0.241513   0.088892   2.717
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## HrmnyI-V-IV -0.074
## HrmnyI-V-VI -0.334  0.142
## HrmnyIV-I-V -0.440  0.157  0.151
## Instrumntpn -0.297  0.001  0.000  0.000
## Instrmntstr -0.415  0.000  0.000  0.000  0.618
## Voicepar3rd -0.210  0.000 -0.001  0.001  0.001     0.000
## Voicepar5th -0.210 -0.001 -0.002 -0.001  0.000     0.000     0.500
```

```
## convergence code: 1
## boundary (singular) fit: see ?isSingular
```

3.4 Regression Models for Classical and Popular Ratings

Code below creates the final regression model for classical and popular rating including other variables as well as Musician. Similar procedure as the code in 3.3.

```
# classical rating
m3 <- lm(Classical~. -Subject-Popular-X1990s2000s-Instr.minus.Notes-Musicians, ratings)
m3.bic <- stepAIC(m3, scope = list(lower = ~Harmony+Instrument+Voice),
                  trace=F, k = log(nrow(ratings)))
m4 <- update(m3.bic, .~.+Musicians*.-Musicians:Selfdeclare-Selfdeclare)
m4.bic <- stepAIC(m4, scope = list(lower = ~Harmony+Instrument+Voice),
                  trace=F, k=log(nrow(ratings)))
m4.best <- stepAIC(update(m4.bic, .~.-X1990s2000s:Musicians),
                   scope = list(lower = ~Harmony+Instrument+Voice), trace=F, k=log(nrow(ratings)))
summary(m4.best)
```

```
##
## Call:
## lm(formula = Classical ~ Harmony + Instrument + Voice + X16.minus.17 +
##     ConsNotes + PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
##     NoClass + GuitarPlay + Musicians + Instrument:Musicians +
##     NoClass:Musicians + GuitarPlay:Musicians, data = ratings)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.696 -1.311 -0.029  1.325  6.829
##
## Coefficients: (3 not defined because of singularities)
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     3.28378    0.36226   9.065  < 2e-16 ***
## HarmonyI-V-IV                   0.02877    0.13180   0.218 0.827213
## HarmonyI-V-VI                   0.87477    0.13180   6.637 4.18e-11 ***
## HarmonyIV-I-V                   0.08358    0.13166   0.635 0.525618
## Instrumentpiano                 1.73287    0.15150  11.438  < 2e-16 ***
## Instrumentstring                3.81808    0.15150  25.202  < 2e-16 ***
## Voicepar3rd                    -0.40728    0.11435  -3.562 0.000378 ***
## Voicepar5th                    -0.27909    0.11426  -2.442 0.014678 *
## X16.minus.17                   -0.09791    0.01985  -4.931 8.89e-07 ***
## ConsNotes1                      0.84567    0.19670   4.299 1.80e-05 ***
## ConsNotes3                      0.54354    0.17184   3.163 0.001586 **
## ConsNotes4                     -1.85191    0.33159  -5.585 2.68e-08 ***
## ConsNotes5                     -0.48411    0.17179  -2.818 0.004882 **
## PachListen3                    -1.52571    0.33055  -4.616 4.18e-06 ***
## PachListen4                     2.56002    0.44413   5.764 9.58e-09 ***
## PachListen5                     0.09975    0.25682   0.388 0.697764
## X1990s2000s.minus.1960s1970s    0.17395    0.03063   5.678 1.57e-08 ***
## CollegeMusic1                  -1.45482    0.14999  -9.699  < 2e-16 ***
## NoClass                         1.77387    0.14954  11.862  < 2e-16 ***
## GuitarPlay1                     3.18606    0.40580   7.851 6.87e-15 ***
## GuitarPlay2                     1.51125    0.36625   4.126 3.85e-05 ***
```

```
## GuitarPlay4                    2.26496    0.28363   7.985 2.42e-15 ***
## GuitarPlay5                   -0.52028    0.21658  -2.402 0.016389 *
## Musicians1                     1.88926    0.21413   8.823  < 2e-16 ***
## Instrumentpiano:Musicians1    -0.61627    0.23077  -2.670 0.007640 **
## Instrumentstring:Musicians1   -0.96301    0.22988  -4.189 2.93e-05 ***
## NoClass:Musicians1            -1.72855    0.14972 -11.545  < 2e-16 ***
## GuitarPlay1:Musicians1        -3.19056    0.45170  -7.064 2.28e-12 ***
## GuitarPlay2:Musicians1              NA         NA      NA       NA
## GuitarPlay4:Musicians1              NA         NA      NA       NA
## GuitarPlay5:Musicians1              NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.031 on 1872 degrees of freedom
## Multiple R-squared:  0.4459, Adjusted R-squared:  0.4379
## F-statistic: 55.79 on 27 and 1872 DF,  p-value: < 2.2e-16
```

```
lmer4.0 <- lmer(update.formula(m4.best, .~.+ (1 | Subject)), ratings,
                REML=F, control = lmerControl(optimizer = "bobyqa"))
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
anova(lmer4.0, m4.best)
```

```
## Data: ratings
## Models:
## m4.best: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## m4.best:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## m4.best:     NoClass + GuitarPlay + Musicians + Instrument:Musicians +
## m4.best:     NoClass:Musicians + GuitarPlay:Musicians
## lmer4.0: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## lmer4.0:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## lmer4.0:     NoClass + GuitarPlay + Musicians + (1 | Subject) + Instrument:Musicians +
## lmer4.0:     NoClass:Musicians + GuitarPlay:Musicians
##         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## m4.best 29 8114.4 8275.3 -4028.2   8056.4
## lmer4.0 30 7999.9 8166.4 -3970.0   7939.9 116.47      1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
lmer4.1 <- fitLMER.fnc(lmer4.0,
                       ran.effects=c("(Harmony|Subject)","(Instrument|Subject)","(Voice|Subject)"),
                       method = "BIC", keep.single.factors = T)
```

```
## ========================================================
## ===              backfitting fixed effects           ===
## ========================================================
## setting REML to FALSE
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
## processing model terms of interaction level 2
##   iteration 1
##     p-value for term "Instrument:Musicians" = 0 >= 0
##     not part of higher-order interaction
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
##     BIC simple = 8171; BIC complex = 8166; decrease = 5 >= 5
##     skipping term
## length = 3
##   iteration 2
##     p-value for term "GuitarPlay:Musicians" = 7e-04 >= 0
##     not part of higher-order interaction
##     BIC simple = 8169; BIC complex = 8166; decrease = 3 < 5
##     removing term
##   iteration 3
##     p-value for term "Instrument:Musicians" = 0 >= 0
##     not part of higher-order interaction
##     BIC simple = 8174; BIC complex = 8169; decrease = 5 >= 5
##     skipping term
## length = 2
##   iteration 4
##     p-value for term "NoClass:Musicians" = 1e-04 >= 0
##     not part of higher-order interaction
##     BIC simple = 8176; BIC complex = 8169; decrease = 6 >= 5
##     skipping term
## length = 1
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
## evaluating addition of (Harmony|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 4.261701e-15
##  adding (Harmony|Subject) to model
## evaluating addition of (Instrument|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 3.569822e-72
##  adding (Instrument|Subject) to model
## evaluating addition of (Voice|Subject) to model

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 0.7393474
##  not adding (Voice|Subject) to model
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## setting REML to FALSE

## boundary (singular) fit: see ?isSingular

## processing model terms of interaction level 2
##   iteration 1
##     p-value for term "Instrument:Musicians" = 0.1677 >= 0
##     not part of higher-order interaction

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unide
##  - Rescale variables?

##     BIC simple = 7840; BIC complex = 7851; decrease = -12 < 5
```

```
##     removing term
##   iteration 2
##     p-value for term "NoClass:Musicians" = 1e-04 >= 0
##     not part of higher-order interaction
##     BIC simple = 7846; BIC complex = 7840; decrease = 6 >= 5
##     skipping term
## length = 1
## resetting REML to TRUE
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unide
##  - Rescale variables?
```

```
## pruning random effects structure ...
##   nothing to prune
## log file is /var/folders/_6/x1ql75n53033623j51rd1r540000gp/T//Rtmp3K6dyx/fitLMER_log_Sun_Dec__8_11-4
```

```
lmer4.2 <- lmer(update.formula(lmer4.1, .~. + Instrument:Musicians +
    NoClass:Musicians + GuitarPlay:Musicians), ratings,
                  REML=F, control = lmerControl(optimizer = "bobyqa"))
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unide
##  - Rescale variables?
```

```
anova(lmer4.1, lmer4.0)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: ratings
## Models:
## lmer4.0: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## lmer4.0:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## lmer4.0:     NoClass + GuitarPlay + Musicians + (1 | Subject) + Instrument:Musicians +
## lmer4.0:     NoClass:Musicians + GuitarPlay:Musicians
## lmer4.1: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## lmer4.1:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## lmer4.1:     NoClass + GuitarPlay + Musicians + (1 | Subject) + (Harmony |
## lmer4.1:     Subject) + (Instrument | Subject) + NoClass:Musicians
##         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer4.0 30 7999.9 8166.4 -3970.0   7939.9
## lmer4.1 43 7600.9 7839.5 -3757.4   7514.9 425.04     13  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

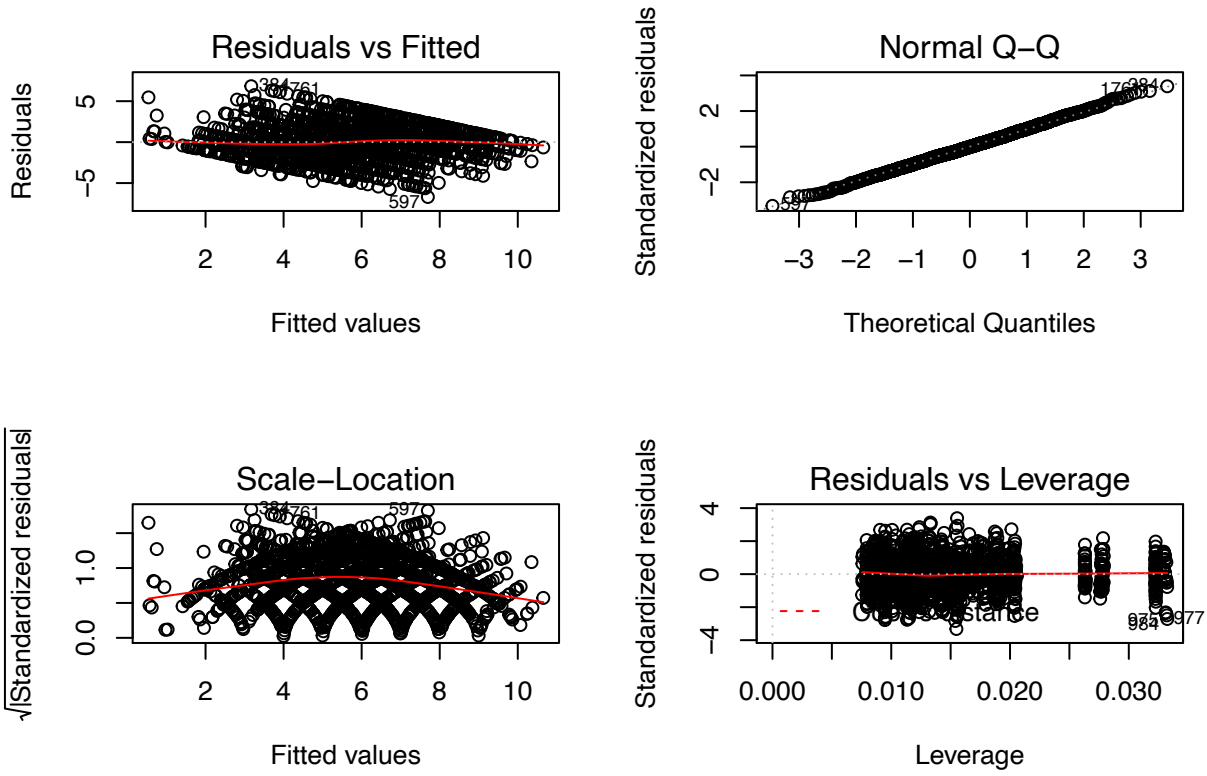
```
anova(lmer4.2, lmer4.1)
```

```
## refitting model(s) with ML (instead of REML)
```

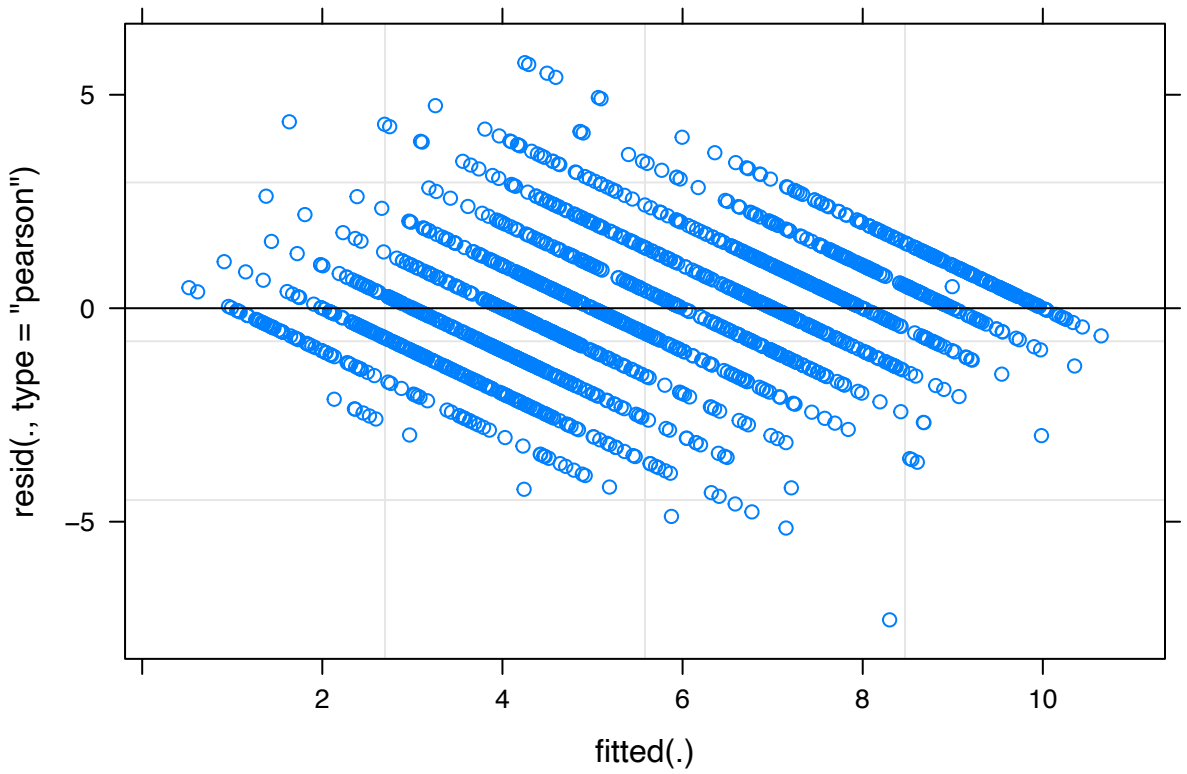
```
## Data: ratings
## Models:
## lmer4.1: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## lmer4.1:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## lmer4.1:     NoClass + GuitarPlay + Musicians + (1 | Subject) + (Harmony |
## lmer4.1:     Subject) + (Instrument | Subject) + NoClass:Musicians
## lmer4.2: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
## lmer4.2:     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
## lmer4.2:     NoClass + GuitarPlay + Musicians + (1 | Subject) + (Harmony |
## lmer4.2:     Subject) + (Instrument | Subject) + NoClass:Musicians + Instrument:Musicians +
```

```
## lmer4.2:     GuitarPlay:Musicians
##          Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer4.1 43 7600.9 7839.5 -3757.4   7514.9
## lmer4.2 46 7597.9 7853.2 -3752.9   7505.9 8.9756      3    0.02962 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow=c(2,2))
plot(m4.best)
```




```
plot(lmer4.2)
```




```
# final model
summary(lmer4.2)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: Classical ~ Harmony + Instrument + Voice + X16.minus.17 + ConsNotes +
##     PachListen + X1990s2000s.minus.1960s1970s + CollegeMusic +
##     NoClass + GuitarPlay + Musicians + (1 | Subject) + (Harmony |
##     Subject) + (Instrument | Subject) + NoClass:Musicians + Instrument:Musicians +
##     GuitarPlay:Musicians
##    Data: ratings
## Control: lmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##   7597.9   7853.2  -3752.9   7505.9     1854
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.6724 -0.5687  0.0093  0.5580  3.6815
##
## Random effects:
##  Groups    Name              Variance  Std.Dev. Corr
##  Subject   (Intercept)       0.0003108 0.01763
##  Subject.1 (Intercept)       0.3983946 0.63119
##            HarmonyI-V-IV     0.0415525 0.20384   0.47
##            HarmonyI-V-VI     1.8369831 1.35535  -0.69  0.05
##            HarmonyIV-I-V     0.0566252 0.23796   0.02 -0.43  0.16
##  Subject.2 (Intercept)       1.1768442 1.08482
##            Instrumentpiano   1.7197324 1.31139  -0.70
##            Instrumentstring  3.3981235 1.84340  -0.86  0.59
##  Residual                    2.4402889 1.56214
```

```
## Number of obs: 1900, groups:  Subject, 53
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                    3.07582    0.72371   4.250
## HarmonyI-V-IV                  0.02802    0.10519   0.266
## HarmonyI-V-VI                  0.87882    0.21200   4.145
## HarmonyIV-I-V                  0.08532    0.10641   0.802
## Instrumentpiano                1.73848    0.26628   6.529
## Instrumentstring               3.82450    0.35616  10.738
## Voicepar3rd                   -0.39136    0.08833  -4.431
## Voicepar5th                   -0.29468    0.08829  -3.338
## X16.minus.17                  -0.09326    0.04155  -2.245
## ConsNotes1                     0.40296    0.32531   1.239
## ConsNotes3                     0.34536    0.28503   1.212
## ConsNotes4                    -1.09645    0.52722  -2.080
## ConsNotes5                    -0.21885    0.30953  -0.707
## PachListen3                   -1.14061    0.69245  -1.647
## PachListen4                    2.85994    0.95539   2.993
## PachListen5                    0.20512    0.55165   0.372
## X1990s2000s.minus.1960s1970s   0.15963    0.06620   2.411
## CollegeMusic1                 -1.31820    0.32590  -4.045
## NoClass                        1.72037    0.32567   5.283
## GuitarPlay1                    3.32347    0.85516   3.886
## GuitarPlay2                    1.61937    0.79152   2.046
## GuitarPlay4                    1.78215    0.60922   2.925
## GuitarPlay5                   -0.24838    0.46439  -0.535
## Musicians1                     1.97337    0.46184   4.273
## NoClass:Musicians1            -1.69490    0.32677  -5.187
## Instrumentpiano:Musicians1    -0.61759    0.40464  -1.526
## Instrumentstring:Musicians1   -0.96943    0.54063  -1.793
## GuitarPlay1:Musicians1        -3.08198    0.97444  -3.163
##
## Correlation matrix not shown by default, as p = 28 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
##
## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
## convergence code: 0
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```r
# popular rating
m5.3 <- lm(Popular~.-Subject-Classical-Musicians-ClsListen-PachListen-Instr.minus.Notes+
            KnowAxis:Harmony, ratings)
m5.3.bic <- stepAIC(m5.3, scope=list(lower=~Harmony+Instrument+Voice),
                    trace=F, k = log(nrow(ratings)))
m5.4 <- update(m5.3.bic, .~.+Musicians*.-Musicians:Selfdeclare
               -Selfdeclare)
m5.4.bic <- stepAIC(m5.4,scope=list(lower=~Harmony+Instrument+Voice),  trace=F,
                    k=log(nrow(ratings)))
summary(m5.4.bic)
```

```
##
```

```
## Call:
## lm(formula = Popular ~ Harmony + Instrument + Voice + X16.minus.17 +
##     ConsInstr + KnowAxis + NoClass + Composing + GuitarPlay +
##     Musicians + NoClass:Musicians + Composing:Musicians, data = ratings)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.4902 -1.3947  0.0237  1.3768  6.4054
##
## Coefficients: (2 not defined because of singularities)
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              7.75994    0.25349  30.612  < 2e-16 ***
## HarmonyI-V-IV           -0.00478    0.13216  -0.036  0.97115
## HarmonyI-V-VI           -0.31604    0.13216  -2.391  0.01688 *
## HarmonyIV-I-V           -0.23325    0.13201  -1.767  0.07742 .
## Instrumentpiano         -1.12977    0.11461  -9.858  < 2e-16 ***
## Instrumentstring        -3.02446    0.11425 -26.471  < 2e-16 ***
## Voicepar3rd              0.21703    0.11448   1.896  0.05815 .
## Voicepar5th              0.24252    0.11443   2.119  0.03419 *
## X16.minus.17             0.15252    0.02023   7.538 7.41e-14 ***
## ConsInstr1              -2.71361    0.30076  -9.022  < 2e-16 ***
## ConsInstr2              -0.24623    0.24182  -1.018  0.30871
## ConsInstr3              -0.47159    0.23425  -2.013  0.04424 *
## ConsInstr4              -0.38634    0.22741  -1.699  0.08951 .
## ConsInstr5               0.80368    0.26846   2.994  0.00279 **
## KnowAxis1                8.94567    0.86546  10.336  < 2e-16 ***
## KnowAxis5                0.60549    0.14062   4.306 1.75e-05 ***
## NoClass                 -1.49388    0.15753  -9.483  < 2e-16 ***
## Composing1              -0.51180    0.21915  -2.335  0.01963 *
## Composing2              -0.87138    0.44582  -1.955  0.05079 .
## Composing3               0.85659    0.42446   2.018  0.04373 *
## Composing4              -0.66291    0.31505  -2.104  0.03550 *
## Composing5               2.14349    0.89485   2.395  0.01670 *
## GuitarPlay1              0.19667    0.20570   0.956  0.33916
## GuitarPlay2              1.47672    0.36228   4.076 4.77e-05 ***
## GuitarPlay4             -1.00162    0.43227  -2.317  0.02061 *
## GuitarPlay5              1.23088    0.29436   4.182 3.03e-05 ***
## Musicians1              -1.72991    0.21280  -8.129 7.76e-16 ***
## NoClass:Musicians1       1.06046    0.18503   5.731 1.16e-08 ***
## Composing1:Musicians1    1.84196    0.36526   5.043 5.03e-07 ***
## Composing2:Musicians1    2.62670    0.46883   5.603 2.42e-08 ***
## Composing3:Musicians1    0.80231    0.52407   1.531  0.12596
## Composing4:Musicians1         NA         NA      NA       NA
## Composing5:Musicians1         NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.037 on 1869 degrees of freedom
## Multiple R-squared:  0.3742, Adjusted R-squared:  0.3641
## F-statistic: 37.25 on 30 and 1869 DF,  p-value: < 2.2e-16
```

```
lmer5.4.0 <- lmer(update.formula(m5.4.bic, .~.+(1 | Subject)),
              ratings, REML=F, control = lmerControl(optimizer = "bobyqa"))
```

```
## fixed-effect model matrix is rank deficient so dropping 2 columns / coefficients
```

```r
anova(lmer5.4.0, m5.4.bic)
```

```
## Data: ratings
## Models:
## m5.4.bic: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## m5.4.bic:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## m5.4.bic:     NoClass:Musicians + Composing:Musicians
## lmer5.4.0: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## lmer5.4.0:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## lmer5.4.0:     (1 | Subject) + NoClass:Musicians + Composing:Musicians
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## m5.4.bic  32 8127.6 8305.2 -4031.8   8063.6
## lmer5.4.0 33 7935.6 8118.7 -3934.8   7869.6 194.03      1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

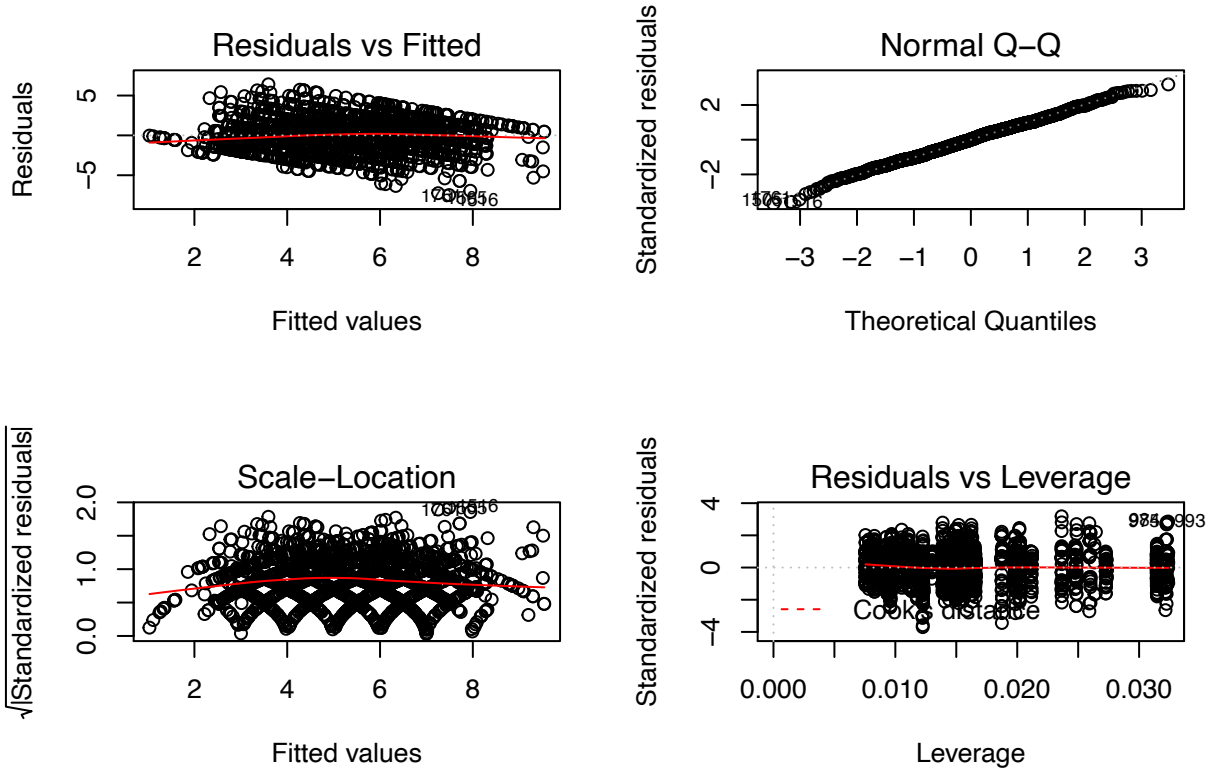
```r
lmer5.4.1 <- fitLMER.fnc(lmer5.4.0,
                         ran.effects=c(
                           "(Harmony|Subject)","(Instrument|Subject)","(Voice|Subject)"),
                        method = "BIC", keep.single.factors = T)
```

```
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## setting REML to FALSE
## fixed-effect model matrix is rank deficient so dropping 2 columns / coefficients
## processing model terms of interaction level 2
##   iteration 1
##     p-value for term "Composing:Musicians" = 0.0348 >= 0
##     not part of higher-order interaction
##     BIC simple = 8104; BIC complex = 8119; decrease = -15 < 5
##     removing term
##   iteration 2
##     p-value for term "NoClass:Musicians" = 0.0208 >= 0
##     not part of higher-order interaction
##     BIC simple = 8102; BIC complex = 8104; decrease = -2 < 5
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
## evaluating addition of (Harmony|Subject) to model
## boundary (singular) fit: see ?isSingular
##  log-likelihood ratio test p-value = 4.554306e-11
##  adding (Harmony|Subject) to model
## evaluating addition of (Instrument|Subject) to model
## boundary (singular) fit: see ?isSingular
##  log-likelihood ratio test p-value = 1.287143e-53
##  adding (Instrument|Subject) to model
## evaluating addition of (Voice|Subject) to model
```

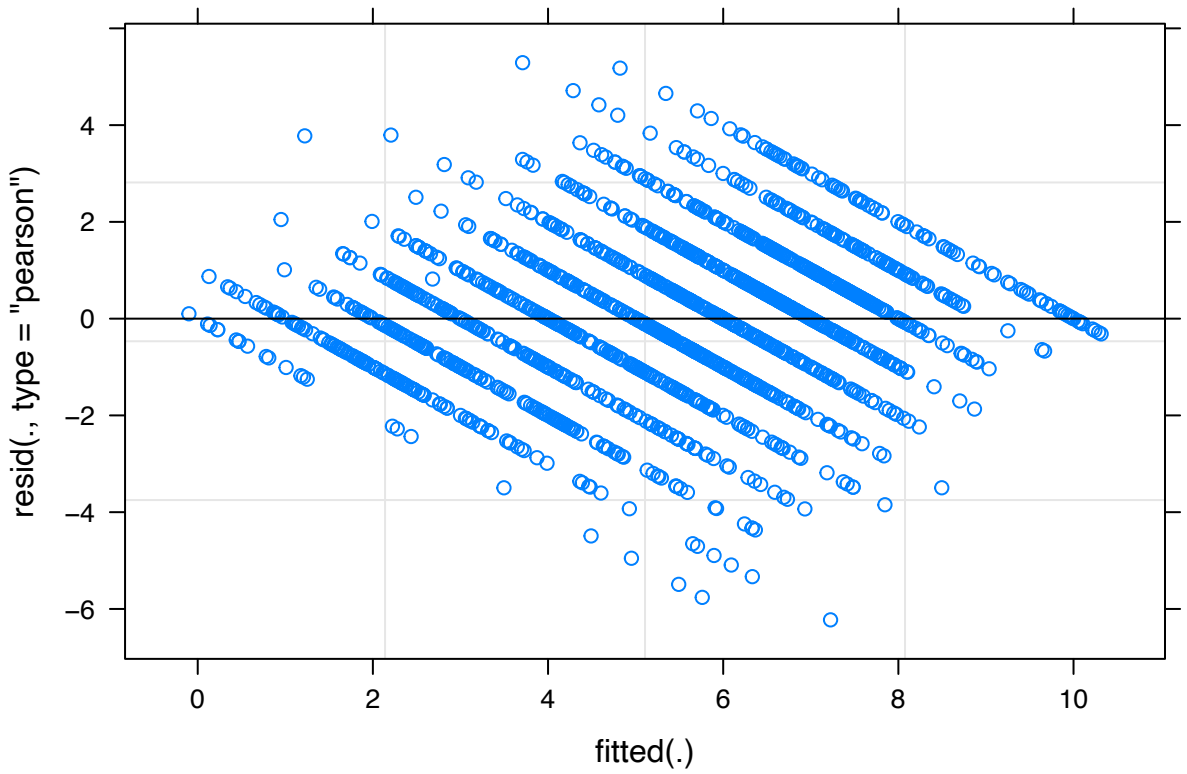
```
## Warning in optwrap(optimizer, devfun, getStart(start, rho$lower, rho$pp), :
## convergence code 1 from bobyqa: bobyqa -- maximum number of function evaluations
## exceeded

## boundary (singular) fit: see ?isSingular

##  log-likelihood ratio test p-value = 0.6296547
##  not adding (Voice|Subject) to model
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## setting REML to FALSE

## boundary (singular) fit: see ?isSingular

## resetting REML to TRUE

## boundary (singular) fit: see ?isSingular

## pruning random effects structure ...
##   nothing to prune
## log file is /var/folders/_6/x1ql75n53033623j51rd1r540000gp/T//Rtmp3K6dyx/fitLMER_log_Sun_Dec__8_11-4
lmer5.4.2 <- lmer(update.formula(lmer5.4.1, .~. + NoClass:Musicians + Composing:Musicians),
                  ratings, REML=F, control = lmerControl(optimizer = "bobyqa"))

## fixed-effect model matrix is rank deficient so dropping 2 columns / coefficients

## boundary (singular) fit: see ?isSingular
anova(lmer5.4.1,lmer5.4.0)

## refitting model(s) with ML (instead of REML)

## Data: ratings
## Models:
## lmer5.4.0: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## lmer5.4.0:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## lmer5.4.0:     (1 | Subject) + NoClass:Musicians + Composing:Musicians
## lmer5.4.1: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## lmer5.4.1:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## lmer5.4.1:     (1 | Subject) + (Harmony | Subject) + (Instrument | Subject)
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer5.4.0 33 7935.6 8118.7 -3934.8   7869.6
## lmer5.4.1 45 7641.0 7890.7 -3775.5   7551.0 318.55     12  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
anova(lmer5.4.1,lmer5.4.2)

## refitting model(s) with ML (instead of REML)

## Data: ratings
## Models:
## lmer5.4.1: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## lmer5.4.1:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## lmer5.4.1:     (1 | Subject) + (Harmony | Subject) + (Instrument | Subject)
## lmer5.4.2: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
## lmer5.4.2:     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
## lmer5.4.2:     (1 | Subject) + (Harmony | Subject) + (Instrument | Subject) +
## lmer5.4.2:     NoClass:Musicians + Composing:Musicians
```

```
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer5.4.1 45 7641.0 7890.7 -3775.5   7551.0
## lmer5.4.2 49 7631.3 7903.2 -3766.6   7533.3 17.726      4   0.001396 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow=c(2,2))
plot(m5.4.bic)
```




```
plot(lmer5.4.2)
```




```
# final model
summary(lmer5.4.2)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: Popular ~ Harmony + Instrument + Voice + X16.minus.17 + ConsInstr +
##     KnowAxis + NoClass + Composing + GuitarPlay + Musicians +
##     (1 | Subject) + (Harmony | Subject) + (Instrument | Subject) +
##     NoClass:Musicians + Composing:Musicians
##    Data: ratings
## Control: lmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##   7631.3   7903.2  -3766.6   7533.3     1851
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9420 -0.5841  0.0109  0.5730  3.3498
##
## Random effects:
##  Groups    Name             Variance Std.Dev. Corr
##  Subject   (Intercept)      0.0000   0.0000
##  Subject.1 (Intercept)      1.0163   1.0081
##            HarmonyI-V-IV    0.1014   0.3184    0.63
##            HarmonyI-V-VI    1.0934   1.0457   -0.32 -0.36
##            HarmonyIV-I-V    0.3592   0.5993   -0.85 -0.71 -0.11
##  Subject.2 (Intercept)      0.5894   0.7678
##            Instrumentpiano  1.3947   1.1810   -0.67
##            Instrumentstring 2.7492   1.6581   -1.00  0.65
##  Residual                   2.4943   1.5793
## Number of obs: 1900, groups:  Subject, 53
```

```
##
## Fixed effects:
##                         Estimate Std. Error t value
## (Intercept)             7.664424   0.493219  15.540
## HarmonyI-V-IV           0.002794   0.111442   0.025
## HarmonyI-V-VI          -0.317234   0.176468  -1.798
## HarmonyIV-I-V          -0.234859   0.131369  -1.788
## Instrumentpiano        -1.127193   0.185030  -6.092
## Instrumentstring       -3.028157   0.244380 -12.391
## Voicepar3rd             0.213047   0.088788   2.400
## Voicepar5th             0.241917   0.088749   2.726
## X16.minus.17            0.202106   0.042069   4.804
## ConsInstr1             -2.141120   0.623461  -3.434
## ConsInstr2             -0.467968   0.503156  -0.930
## ConsInstr3             -0.300142   0.487292  -0.616
## ConsInstr4             -0.261289   0.473131  -0.552
## ConsInstr5              1.113009   0.558554   1.993
## KnowAxis1               5.216493   1.796245   2.904
## KnowAxis5               0.764983   0.292222   2.618
## NoClass                -1.507220   0.327338  -4.604
## Composing1             -1.185088   0.455789  -2.600
## Composing2             -0.802829   0.922482  -0.870
## Composing3              1.552518   0.882597   1.759
## Composing4              0.474849   0.651669   0.729
## Composing5              1.860143   1.861885   0.999
## GuitarPlay1             0.539485   0.427502   1.262
## GuitarPlay2             1.481776   0.753793   1.966
## GuitarPlay4            -0.621658   0.898604  -0.692
## GuitarPlay5             0.322938   0.605105   0.534
## Musicians1             -2.170038   0.441525  -4.915
## NoClass:Musicians1      1.308811   0.383837   3.410
## Composing1:Musicians1   2.725196   0.759733   3.587
## Composing2:Musicians1   2.025633   0.968828   2.091
## Composing3:Musicians1   0.173630   1.090415   0.159

##
## Correlation matrix not shown by default, as p = 31 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 2 columns / coefficients
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```