Understanding of Classical Music and Popular Music

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Abstract

We address the questions of what kinds of music features will influences listeners' ratings on music as popular, classical, or both. We especially focus on Instrument, Harmonic Motion, Voice leading and Musician's association with both classical and popular ratings. We conduct matrix plots, histograms, and boxplots to define variables that need to be revised and apply log transformation to them. We perform stepwise regression, automatic method of fitLMER, ANOVA test, and summary tables on all the linear regression models and multilevel regression models to select the best model to answer the question. We detect instrument has the strongest impacts on both classical and popular ratings but it has a large random effect in both models too. Level I-V-vi of Harmony has the strongest positive association with classical rating but it also has a large random effect. Comedy bit does matter to the classical ratings whereas Pachelbel rant does not matter according to the model. Voice Leading contrary motion has the strongest positive association with the classical rating. Moreover, musicians and non-musicians evaluate the music differently. Voice, Harmony, and Instrument drive popular and classical ratings oppositely. The modeling approach used is limited to the dataset and the model building method. It can be further improved by treating missing values cautiously and perform a more appropriately building model method.

1 Introduction

Throughout the years, there are many debates about classical music versus popular music. Some people believe that classical music is more superior to popular music. Others believe that both popular music and classical music are vital to understanding a society's culture. Many other people believe that popular music is better as they feel the connection between music and contemporary society. However, do those debates only exist between musicians? Otherwise, how do listeners identify the music in order to choose their preferred genre? Do they simply define them through melody, rhythm, instrument or combination of many influences? What kind of people can easily detect music? Do we need to learn some music theory and have exposures to both classical and popular music to some extent? With these questions in mind, this report will delve into the question that how do listeners define music. More specifically, what kind of music features would influence the ratings that each listener gave to the music that they were listening to in the designed experiment that is conducted by Ivan Jimenez and Vincent Rossi in the University of Pittsburgh in 2012. We will also address the following questions that researches are interested in.

- What experimental factor, or combination of factors, has the strongest influence on ratings?
  - Does Instrument exert the strongest influence among the three design factors (Instrument, Harmonic Motion, Voice Leading), as the researchers suspect?
  - Among the levels of Harmonic Motion does I-V-vi have a strong association (the strongest?) with classical ratings? Does it seem to matter whether the respondent is familiar with one or the other (or both) of the Pachelbel rants/comedy bits?
  - Among the levels of Voice Leading, does contrary motion have a strong (the strongest?) association with classical ratings?
- Are there differences in the way that musicians and non-musicians identify classical music?
- Are there differences in the things that drive classical, vs. popular, ratings?

2 Methods

We were provided a dataset from the study of Ivan Jimenez and Vincent Rossi (2013). The dataset was collected in a designed experiment in the University of Pittsburgh of the population of undergraduate students. The dataset contains both classical and popular ratings of 70 listeners after listening to 36 musical stimuli. Each row of the dataset provides 70 listeners' ratings on 36 musical stimuli and listeners' musical evaluations, such as how much did you listen to classical music from level 0 to 5.

For this report, we focused on the following 24 variables. The data are available in the file ratings.csv in the hw10 folder on Canvas (Jimenez, 2013). Readers should refer to Jimenez and Rossi (2013) for definitions, eligibility, inclusion/exclusion criteria, and so forth, for this dataset.

In all, 70 listeners are represented in the data available to us, and the following variables were measured on each.

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

After looking at the summary of the dataset and interpretation of each variable, we decided to delete two variables, X1ndInstr, X2ndInstr. These two variables have more than 1,500 NAs within a total of 2,520 observations' dataset so if we include these two variables in the dataset, they would skew the data (see appendix page 11 for details). We deleted and changed some observations for classical ratings and popular ratings. We also chose to delete certain rows based on the missing values of some variables in the model (see appendix page 11 for details). We looked at the scatter plots of all variables (see appendix page 12-13 for details) to identify the relationships between each variable. We made histograms and did log transformation to make the continuous variable to have a normal distribution (see appendix page 13-15 for details). We drew the box plots for the categorical variable to define the associations between variables and the ratings (see appendix page 16-18 for details). Based on the associations we found through boxplots, we built the initial model. Then, we built final models by applying stepwise regression, automatic method of fitLMER, added interactions, random effects to manually and automatically select variables for the model (see appendix page 24-27 for details). We conducted the ANOVA tests, summary tables and residuals plots to choose the best linear regression and multi-level models among various models in order to have better interpretations and predictions on both classical and popular ratings (see appendix page 26-28 for details). To investigate researchers' hypothesis on musicians' influences on ratings, we changed all the numeric and integer types of variables into factored variables except OMSI, X1990s2000s.minus.1960s1970s, X16.minus.17, Classical and Popular (see appendix page 27 for details). Then, we applied similar procedures as above to define final models for both classical ratings and popular ratings models that include the musician variable.

3 Results

3.1 Transformation and multicollinearity variable

Before heading to the results, we decided to delete and transform some variables in order to have a reasonable dataset to build models and answer the questions. First of all, we eliminated Instr.minus.Notes variables based on the matrix plot in Figure 1. According to this matrix plot, all the variables are correlated with each other so there is a suspicion that variable's influences on the ratings would be affected by other variables. Moreover, Instr.minus.Notes is the difference between ConsNotes and ConsInstr, which further proves that there is multicollinearity between Instr.minus.Notes and the other two variables. According to these inferences, we decided to delete Instr.minus.Notes variable.

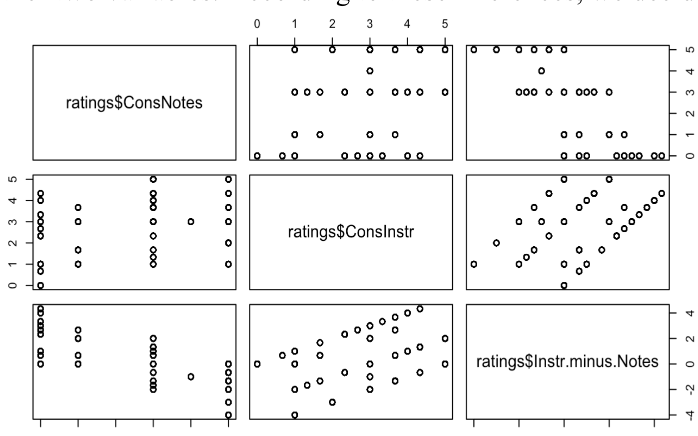


Figure 1: Matrix plot of ConsNotes, ConsInstr and Instr.minus.Notes

Second of all, we took the log transformation of the OMSI variable. According to the histogram of Figure 2, OMSI is totally right-skewed and it is hard to do further analyses based on the skewed distributions so we transformed this variable in order to do further analysis.

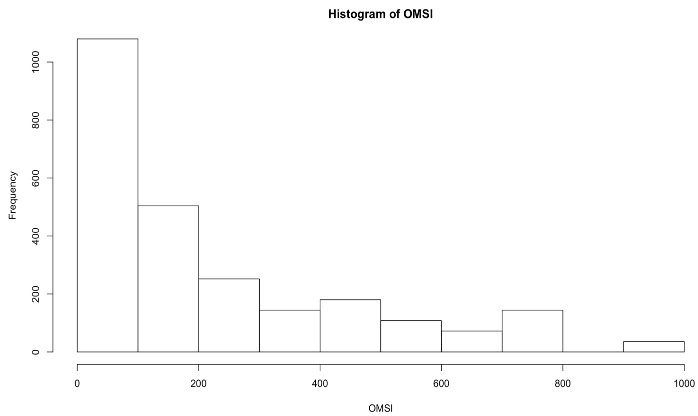


Figure 2: Histogram of OMSI

Then, based on the interpretations of classical ratings and popular ratings that they should only have 10 levels from integer 1 to 10, we changed 19 in both ratings to 10 as 9 and 0 are closed on the keyboard so 19 values are probably typo. We deleted all the 0 values and decimal numbers because there are many possibilities, missing values, typos, actual levels, to have those values so it is hard to decide how to change them to optimize the model.

The models in Figure 3 and Figure 4 are the final multilevel models that include all the influential fixed and random variables on classical ratings and popular ratings. These two models are based on the dataset that deleted all the missing values of variables in the model. We deleted missing values rather than applying imputation as for classical and popular ratings because doing imputation for too many missing values might skew the data. We also did residual plots on all the marginal, random effect, and conditional residuals and they all look good which proves that our selected model is a valid model (See appendix page 25-27 and page 37-39 for details)

3.21 Instrument's influences on both classical ratings and popular ratings

The summary tables in Figure 3 and Figure 4 are utilized to display whether the instrument variable exerts the strongest influence on both classical ratings and popular ratings. In Figure 3, there are 3.46 increases of the average classical ratings if the instrument level is changed from guitar to string and 1.52 increases of the average classical ratings if the instrument level is changed from guitar to piano, holding other variables constantly. Compare to the other three designed factors, the instrument has the largest absolute value of the coefficient. Moreover, coefficients' standard errors in Figure 3 prove that the instrument variable is statistically significant to the classical ratings because 95 percent confidence interval of the instrument, by adding and minoring two times standard errors from instrument's coefficients, doesn't contain 0. However, people's answers are varied on distinguishing music played by strings and piano are classical or not. For the random effects of instrument variable in Figure 3, there is a 1.85 spread of variance of the overall effect for instrument played by string and 1.31 spread of variance of the overall effect for instrument played by the piano. Comparing instrument variable's random effects' standard deviations with coefficient of instrument's fixed effects, both piano and string hold large variances. It indicates that there is a large proportion of responders who disagree with that the instrument would have positive effects on the classical ratings. Thus, the random effects of the instrument are significant to the classical rating model.

In Figure 4, there are 2.55 decreases of the average popular ratings if it is changed from guitar to string and 0.95 decreases of the average popular ratings if the instrument level is changed from guitar to the piano, holding other variables constantly. The instrument variable also exerts the strongest influences on popular ratings because it has the largest absolute value of the coefficient in contrast with the other three designed factors. Figure 4 further confirms that the instrument variable is statistically significant to the popular ratings because 95 percent confidence interval of the instrument doesn't contain 0. However, people's answers are also varied in distinguishing music played by strings and piano that are popular or not. In Figure 4, there is a 1.81 spread of variance of the overall effect for instrument played by string and 1.18 spread of variance of the overall effect for the instrument played by the piano. If we compare the instrument variable's random effect with the coefficient of the instrument's fixed effects, both piano and string hold large variances. Therefore, the random effects of the instrument are important to the popular rating model.

Based on the previous inferences, researchers offered the correct hypothesis that instrument has the strongest impacts on both classical and popular ratings among the three designed factors, instrument, harmonic motion, and voice leading. However, the random effects of the instrument variable are also significant for both classical ratings and popular ratings so they might cause the instrument's influences on both classical ratings and popular ratings to be varied. The contradiction between the significant instrument variable in the models and large random effects makes sense from the perspective that it is easier for people, no matter they knew many or a little about the music theory, to identify the instrument by listening to the music. Thus, they would probably use the instrument as a vital variable to evaluate the music. However, people's understanding of instruments is different which would cause a large random effect.

```
lmer(formula = Classical ~ GuitarPlay + PianoPlay + Composing +
    APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
    PachListen + Instrument + Harmony + Voice + (1 + Instrument +
    Harmony | Subject), data = ratings_try_factored, REML = FALSE,
    control = lmerControl(optimizer = "bobyqa"))
                  coef.est coef.se
(Intercept)        4.07     0.88
GuitarPlay1        1.21     0.78
GuitarPlay2        2.51     1.16
GuitarPlay4        3.19     1.22
GuitarPlay5       -0.97     1.00
PianoPlay1         0.19     0.50
PianoPlay4        -0.46     0.87
PianoPlay5        -0.83     0.52
Composing1         0.39     0.39
Composing2        -0.39     0.56
Composing3        -0.32     0.93
Composing4         2.59     0.82
Composing5         2.26     1.44
APTheory1          1.47     0.50
NoClass1           0.64     0.33
NoClass2           0.76     0.92
NoClass3          -5.72     1.89
NoClass4          -0.31     1.27
X1990s2000s2      -0.83     0.94
X1990s2000s3      -2.33     0.77
X1990s2000s4      -1.91     0.87
X1990s2000s5      -0.89     0.61
KnowAxis5         -0.08     0.32
ClsListen1        -0.24     0.42
ClsListen3         0.57     0.40
ClsListen4        -0.36     1.28
ClsListen5         0.00     0.61
PachListen3       -1.30     0.94
PachListen4        2.89     1.32
PachListen5       -0.02     0.64
Instrumentpiano    1.52     0.20
Instrumentstring   3.46     0.27
HarmonyI-V-IV      0.00     0.11
HarmonyI-V-VI      0.86     0.22
HarmonyIV-I-V      0.07     0.11
Voicepar3rd       -0.38     0.09
Voicepar5th       -0.29     0.09

Error terms:
 Groups   Name             Std.Dev. Corr
 Subject  (Intercept)      1.14
          Instrumentpiano  1.31     -0.07
          Instrumentstring 1.85     -0.47  0.60
          HarmonyI-V-IV    0.36      0.71 -0.59 -0.59
          HarmonyI-V-VI    1.36     -0.31 -0.31 -0.54  0.13
          HarmonyIV-I-V    0.15      0.23 -0.43  0.08  0.61 -0.18
 Residual                  1.54
---
number of obs: 1788, groups: Subject, 51
AIC = 7125.9, DIC = 7007.9
deviance = 7007.9
```

Figure 3: Summary table of classical rating's final model

```
lmer(formula = Popular ~ Harmony + Voice + Instrument + (1 +
    Harmony + Instrument | Subject), data = ratings_try_factored,
    REML = FALSE, control = lmerControl(optimizer = "bobyqa"))
                 coef.est coef.se
(Intercept)       6.61     0.18
HarmonyI-V-IV    -0.05     0.10
HarmonyI-V-VI    -0.30     0.14
HarmonyIV-I-V    -0.23     0.10
Voicepar3rd       0.14     0.08
Voicepar5th       0.17     0.08
Instrumentpiano  -0.95     0.16
Instrumentstring -2.55     0.23

Error terms:
 Groups   Name             Std.Dev. Corr
 Subject  (Intercept)      1.27
          HarmonyI-V-IV    0.31      0.48
          HarmonyI-V-VI    0.93     -0.15 -0.35
          HarmonyIV-I-V    0.46     -0.24 -0.53 -0.37
          Instrumentpiano  1.18     -0.22 -0.30 -0.18 -0.14
          Instrumentstring 1.81     -0.38 -0.45 -0.19  0.00  0.73
 Residual                  1.55
---
number of obs: 2455, groups: Subject, 70
AIC = 9740.5, DIC = 9680.5
deviance = 9680.5
```

Figure 4: summary table of popular rating's final model.

3.22 Association between classical ratings, Harmony I-V-vi, Pachelbel rants, and Comedy bits

For answering the association between classical ratings and Harmony I-V-vi, we examined the summary tables in Figure 3. According to Figure 3, Harmony I-V-vi has the largest absolute value of the coefficient compare to other levels. If the Harmony is changed from I-VI-V to I-V-vi, the average ratings of classical would increase by 0.86, holding other variables constantly. Thus, Harmony I-V-vi has the strongest positive association with classical ratings. Moreover, Harmony I-V-vi is a statistically significant variable to the classical ratings because its 95 percent confidence interval doesn't contain 0. However, Harmony I-V-vi has a 1.36 spread of variance of the overall effect based on Figure 3. After comparing the Harmony I-V-vi's random effect' standard deviation with its fixed effect's coefficient, Harmony I-V-vi holds large variance which indicates that its random effect is significant to the model and many responders disagreed that Harmony I-V-vi would increase the classical ratings.

For the second part of the question, whether classical ratings would be different if listeners are familiar with Pachelbel rants or Comedy bits, we analyzed the boxplots in Figure 5 and Figure 6 and further investigated it using the summary table in Figure 3. If we looked at the boxplots in Figure 5 and Figure 6, Comedy bit causes the average classical ratings to change whereas the Pachelbel rants don't make the average classical ratings to be different based on the boxplot. Therefore, we hypothesized that if the responders are familiar with Comedy bits, the classical ratings would be different. From the summary table, the Pachelbel rant doesn't matter to the classical rating as it was not selected into the model while Comedy bit matters because we have KnowAxis variable in the model. Moreover, if respondents are really familiar with comedy bits, which changes from 0 to 5, the average classical ratings would decrease by 0.08. Therefore, this model proves our previous hypothesis that the Comedy bit matters for the classical ratings. However, the Comedy bit is not statistically significant to the classical rating model because its 95 percent confidence interval includes 0 according to Figure 3.

In general, based on the previous inferences, Harmony I-V-vi has the strongest positive association with classical rating among three levels of harmony. However, it has a large random effect so many responders disagreed with Harmony I-V-vi would have a positive association with the classical rating. Responders' familiarity with Pachelbel rants did not matter to the classical ratings but the Comedy bit does. If respondents understood Comedy bit really well, they would give the lowest classical ratings among all levels even though this variable might not be statistically significant to the classical ratings' model. This negative association between Comedy bit and classical ratings are reasonable because Comedy bit is about popular music. Therefore, people who know Comedy bit pretty well have a high probability to recognize the genre of the music.

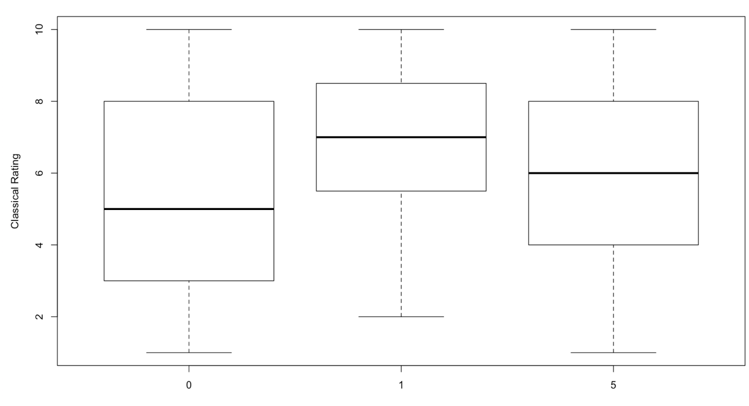


Figure 5: boxplot of classical ratings versus comedy bits

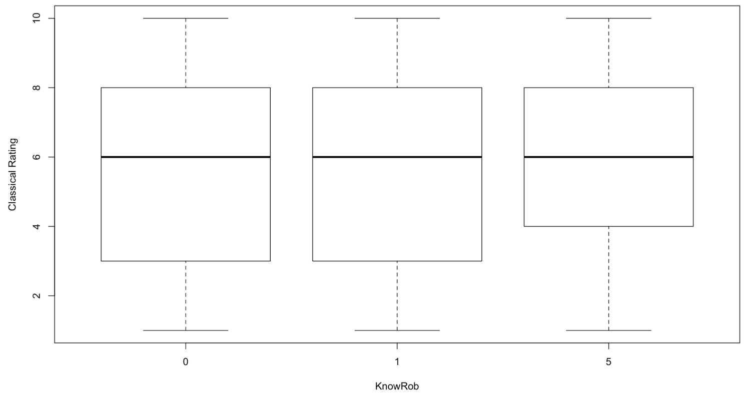


Figure 6: boxplot of classical ratings versus Pachelbel rants

3.23 Association between Voice leading, contrary motion and classical ratings

For analyzing whether contrary motion has the strongest association with classical ratings among the levels of voice leading, we utilized the summary table in Figure 7. Based on Figure 7, Voice leading contrary motion has the largest value of the coefficient compare to other levels. Thus, Voice leading contrary motion has the strongest positive association with the classical ratings. If the Voice leading is contrary motion, the average ratings of classical would increase by 4.07, holding other variables constantly. Also, Voice leading contrary motion is a statistically significant variable to the classical ratings because its 95 percent confidence interval doesn't contain 0.

According to the previous inferences, Voice Leading contrary motion has the strongest positive association with classical ratings and it is statistically significant for the classical rating but it doesn't have a random effect that can be applied to the classical rating model. The positive association between Voice Leading contrary motion and classical ratings are expected by the researchers as they assume that contrary motion would be frequently rated as classical.

```
lmer(formula = Classical ~ Voice - 1 + GuitarPlay + PianoPlay +
    Composing + APTheory + NoClass + X1990s2000s + KnowAxis +
    ClsListen + PachListen + Instrument + Harmony + (1 + Instrument +
    Harmony | Subject), data = ratings_try_factored, REML = FALSE,
    control = lmerControl(optimizer = "bobyqa"))
                 coef.est coef.se
Voicecontrary     4.07     0.88
Voicepar3rd       3.69     0.88
Voicepar5th       3.78     0.88
GuitarPlay1       1.21     0.78
GuitarPlay2       2.51     1.16
GuitarPlay4       3.19     1.22
GuitarPlay5      -0.97     1.00
PianoPlay1        0.19     0.50
PianoPlay4       -0.46     0.87
PianoPlay5       -0.83     0.52
Composing1        0.39     0.39
Composing2       -0.39     0.56
Composing3       -0.32     0.93
Composing4        2.59     0.82
Composing5        2.26     1.44
APTheory1         1.47     0.50
NoClass1          0.64     0.33
NoClass2          0.76     0.92
NoClass3         -5.72     1.89
NoClass4         -0.31     1.27
X1990s2000s2     -0.83     0.94
X1990s2000s3     -2.33     0.77
X1990s2000s4     -1.91     0.87
X1990s2000s5     -0.89     0.61
KnowAxis5        -0.08     0.32
ClsListen1       -0.24     0.42
ClsListen3        0.57     0.40
ClsListen4       -0.36     1.28
ClsListen5        0.00     0.61
PachListen3      -1.30     0.94
PachListen4       2.89     1.32
PachListen5      -0.02     0.64
Instrumentpiano   1.52     0.20
Instrumentstring  3.46     0.27
HarmonyI-V-IV     0.00     0.11
HarmonyI-V-VI     0.86     0.22
HarmonyIV-I-V     0.07     0.11

Error terms:
 Groups   Name             Std.Dev. Corr
 Subject  (Intercept)      1.14
          Instrumentpiano  1.31     -0.07
          Instrumentstring 1.85     -0.47  0.60
          HarmonyI-V-IV    0.36      0.71 -0.59 -0.59
          HarmonyI-V-VI    1.36     -0.31 -0.31 -0.54  0.13
          HarmonyIV-I-V    0.15      0.23 -0.43  0.08  0.61 -0.18
 Residual                  1.54
---
number of obs: 1788, groups: Subject, 51
AIC = 7125.9, DIC = 7007.9
deviance = 7007.9
```

Figure 7: summary table for classical ratings' final model with contrary motion of voice

3.3 Musicians versus non-musicians on identifying classical music

In order to examine the differences between musicians and non-musicians identify classical music, we used two different datasets to select the model. For the first dataset, it contains self-declare levels 1 and 2 as non-musicians and the rest as musicians. The second dataset includes self-declares levels 1, 2, and 3 as non-musicians and the rest as musicians. However, the final model that is selected by two datasets is the same, which means the model is not sensitive to where we dichotomize the dataset.

Therefore, we chose to display a model based on the first dataset as it separates the dataset evenly and the residual plots that we made for this model also indicate that this is a valid model (see appendix page 43-45 for detailed information). The model is presented in Figure 8.

Based on Figure 8, the musician evaluated lower classical ratings than non-musician in general. There are 1.91 decreases in the average classical ratings if it is changed from the non-musician to musician, holding other variables constantly. Although musician variable also has a 0.91 random effect, it is not significant to the model if we compare the musician variable's random effect with the coefficient of musician's fixed effects. Therefore, most responders agreed that the musicians would evaluate music less classical compare to the non-musician. This is plausible as musicians would have more rigorous standards on evaluating the music in contrast with the non-musician so they would give lower classical ratings to the music compare to the non-musicians.

For the musician variable's interaction with other variables, level 1 of composing was more influential for classical ratings of musicians than for non-musicians. There is a 4.98 increase of classical ratings if the responders are changed from non-musician to musician, holding other variables constantly. This level is also statistically significant to the model as its 95 percent confidence interval doesn't contain 0. Second of all, all the levels of the instrument have positive impacts on classical ratings of musicians than for non-musicians' based on Figure 8. However, the instrument variable is not statistically significant to the model as its 95% confidence interval contains 0. For the last interaction term, harmony has fewer influences for classical ratings for musicians than for non-musicians' ratings for classical. Especially for Harmony I-V-vi, there is a 1.42 decrease of classical ratings if the responders are changed from non-musician to musician, holding other variables constantly. However, all the levels of harmony are still not statistically significant to the classical ratings' model except for Harmony I-V-vi as their 95 percent confidence intervals contain 0.

It is logical for both Harmony and Instrument to have interaction with the musician. When we looked at the summary table in Figure 8, both Harmony and Instrument variables have large random effects, which indicate that many people disagreed with the associations that harmony and instrument have with classical ratings, which presented as their fixed effects coefficients. These large random effects could be one of the reasons that cause Instrument and Harmony to have interaction with musician variables so musicians and non-musicians would have significant differences in evaluating the classical ratings.

Based on the previous inferences, there are differences in the way that musicians and non-musicians identify classical music. More specifically, levels of music composing experiences and types of instruments would be more influential for classical ratings of musicians while levels of harmonic motion would be less influential for classical ratings of musicians in compare with non-musicians. However, these differences might not be significant to the classical rating except for the composing variable and the Harmony I-V-vi.

```
lmer(formula = Classical ~ GuitarPlay + PianoPlay + Composing +
    NoClass + X1990s2000s + PachListen + Instrument + Harmony +
    Voice + Musician + Composing:Musician + Instrument:Musician +
    Harmony:Musician + (1 + Instrument + Harmony + Musician |
    Subject), data = ratings_try_musician, REML = FALSE, control = lmerControl(optimizer =
"bobyqa"))
                                    coef.est coef.se
(Intercept)                          4.83     0.62
GuitarPlay1                          1.53     0.76
GuitarPlay2                          1.33     1.01
GuitarPlay4                         -1.36     1.04
GuitarPlay5                         -2.38     1.05
PianoPlay1                          -0.66     0.48
PianoPlay2                           3.97     1.02
PianoPlay4                           0.19     0.60
PianoPlay5                           0.08     0.59
Composing1                          -3.24     0.48
Composing2                           0.17     0.99
Composing3                          -0.33     0.85
Composing4                           2.22     0.93
Composing5                           1.12     1.48
NoClass1                             1.14     0.33
NoClass2                             1.72     0.98
NoClass3                            -0.44     0.82
NoClass4                             1.39     1.29
NoClass8                             0.67     0.89
X1990s2000s2                        -0.36     0.95
X1990s2000s3                        -0.60     0.67
X1990s2000s4                        -0.82     0.85
X1990s2000s5                         0.40     0.53
PachListen1                          1.76     0.89
PachListen2                         -0.01     0.69
PachListen3                         -0.05     0.62
PachListen4                          3.29     1.18
Instrumentpiano                      1.20     0.40
Instrumentstring                     2.67     0.56
HarmonyI-V-IV                        0.07     0.23
HarmonyI-V-VI                        1.87     0.40
HarmonyIV-I-V                        0.35     0.21
Voicepar3rd                         -0.40     0.08
Voicepar5th                         -0.32     0.08
Musiciannon-musician                -1.91     0.72
Composing1:Musiciannon-musician      4.98     0.78
Composing2:Musiciannon-musician     -0.16     1.13
Instrumentpiano:Musiciannon-musician  0.34    0.45
Instrumentstring:Musiciannon-musician 0.74    0.63
HarmonyI-V-IV:Musiciannon-musician  -0.18     0.26
HarmonyI-V-VI:Musiciannon-musician  -1.42     0.45
HarmonyIV-I-V:Musiciannon-musician  -0.38     0.24

Error terms:
 Groups   Name                 Std.Dev. Corr
 Subject  (Intercept)          1.14
          Instrumentpiano      1.25     -0.66
          Instrumentstring     1.84     -0.87  0.61
          HarmonyI-V-IV        0.31      0.30 -0.55 -0.34
          HarmonyI-V-VI        1.20     -0.16 -0.19 -0.34  0.15
          HarmonyIV-I-V        0.17     -0.18 -0.21  0.41  0.60 -0.38
          Musiciannon-musician 0.91     -0.35  0.46  0.29  0.42 -0.09  0.50
 Residual                      1.52
---
number of obs: 2039, groups: Subject, 58
AIC = 8063.3, DIC = 7921.3
deviance = 7921.3
```

Figure 8: summary table of classical ratings' model with musician variable

3.4 Different variables that drive classical ratings versus popular ratings

We conducted summary tables of classical and popular ratings' model in Figure 3, Figure 4 to distinguish different variables that would influence classical ratings and popular ratings. In general, popular ratings are influenced by fewer variables compare to classical ratings'. Specifically, comparing the summary table in Figure 3 and Figure 4, levels of guitar play, levels of piano play, levels of composing music experiences, whether took AP theory or not, numbers of music class had taken, levels of listening to pop from 1990s2000s, levels of listening to Comedy bits, levels of listening to classical ratings, and levels of familiarity with Pachelbel's Canon are influential to Classical ratings. Among these variables, levels of composing music experiences have the most positive impacts on classical ratings. Especially for the listeners who are really familiar with music composing, if the level of composing music experiences is changed from level 0 to level 4, the average classical rating would be increased by 2.59, holding other variables constantly. Oppositely, the number of music classes had taken has that most negative effects on classical ratings. Based on the summary table in Figure 3, the average classical ratings would be decreased by 5.72 if the number of music classes that responders had taken increase from 0 to 3 classes, holding other variables constantly. However, most of these variables that drive classical ratings to be different from popular ratings are not statistically significant except for level 4 of composing music experiences, music classes that respondents had taken, whether took AP theory, and levels of listening to pop from 1990s200s because only these 4 variables have 95 percent confidence interval that doesn't have 0.

For the three designed factors, although both classical ratings and popular ratings have these three factors, they have opposite signs based on Figure 3. Both harmony and instrument have positive effects on classical rating while negative impacts on popular ratings. Voice has negative influences on classical ratings whereas positive influences on popular ratings. However, both harmony and instrument's random effects are significant in both classical and popular rating model. Thus, people vary in the degree to which they are inclined to call music played by instruments and presented in different harmonies as classical or popular.

Based on the previous inferences, any variables in the classical rating model that are not three designed factors would drive classical ratings to be different from the popular ratings. This is reasonable as classical music is harder to define than popular music. Classical music contains a more complex structure of the melody and longer repeated phrases in contrast with the popular music. Therefore, the variables in the classical rating model are more varied (Hoffman, 2014). Moreover, although both models contain the same three designed ratings, they have opposite signs which indicate that they have opposite impacts on the ratings.

Discussion

Overall, for answering whether instrument exerts the strongest influences on both classical and popular ratings, we look at the summary tables in both Figure 3 and Figure 4 to recognize that instrument does have the strongest impacts on both classical and popular ratings among three designed factors, instrument, harmonic motion, and voice leading. However, since the random effects of the instrument variables are also significant in both classical and popular ratings, they would cause the instrument's influences to be varied as most responders hold different ideas than the instrument's coefficients indicated. In order to examine the hypothesis that Harmony I-V-vi has the strongest association with classical ratings, we made boxplots in Figure 5 and Figure 6. We also took a look at Figure 3. We identified that Harmony I-V-vi has the strongest positive association with classical ratings among three levels of harmony even though it has a large random effect. Moreover, to identify what matters, either Pachelbel rants or Comedy bit or both for responders to evaluate the classical ratings, we still delved into Figure 3. We found out that Pachelbel rant does not matter to responders on evaluating the classical rating but the Comedy bit does matter. For answering whether the contrary motion of the voice leading has the strongest association with classical ratings, we created the summary table in Figure 7 to claim that Voice Leading contrary motion has the strongest positive association with classical ratings. To figure out the differences between the way musicians and non-musicians to identify classical music. We built a new model with the musician variable and displayed it in Figure 8. Figure 8 indicates that there are differences in the way that musicians and non-musicians identify classical Music. Especially for levels of music composing experiences and types of instruments, they have more impacts on classical ratings of the musician. In contrast, levels of harmonic motion would be less influential for classical ratings of musicians than for non-musicians'. Finally, in order to distinguish the differences in the things that drive classical ratings and popular ratings, we examined Figure 3 and Figure 4 again. We figured out that all the variables in classical ratings except three designed factors would drive classical ratings to be different from the popular ratings. Additionally, three designed ratings have opposite influences on the ratings.

Our analyses are limited that we deleted all the missing values of all the variables except value 19 in popular ratings and classical rating. Therefore, our models might be problematic as the limited observations would reduce statistical power, which indicates that the probability of making true positive and false negative would decrease. Moreover, a smaller sample would reduce the representativeness of the samples and increase the bias of the parameters' estimations. Based on these limitations, our future analysis should have a better method to deal with the missing values. For example, we suggest using multiple regression imputation to solve the missing values problem, which would cause less bias.

Aside from missing values, the data also have problems that many variables' levels are not an integer. For example, classical rating supposes only has levels 1 to 10 but it contains many decimal numbers which leads us to delete those rows and it might cause the missing information and biased models. In the future, it would be better to understand the meaning of those decimal numbers and figure out the best method to deal with those numbers before simply deleting them.

When building the model, we always hold three design variables fixed in the model, which indicates that although some of these variables are not statistically significant to the ratings, we still included them in the model. This might cause the current model to be less accurate and have more errors or it would cause the coefficient of each variable to be different at least. So, our future analysis should exclude those variables if it is appropriate.

In summary, the models that we built indicate that instruments have the strongest associations with both classical ratings and popular ratings and it is always statistically significant in both models. More specifically, the instrument string has the strongest influences on both classical and popular ratings. However, the random effects of the instrument are big in both models which indicate that responders' answers and their personal biases are varied with the type of instrument. For the other two designed factors, Harmony and Voice, they are not statistically significant to the ratings. Aside from this model, we need to keep all the limitations in mind. In the future, if we can manipulate the missing data more cautiously and exclude variables appropriately, the result might be more valid and changed from the current analysis.

Reference

Ivan Jimenez and Vincent Rossi (2013), The Influence of Timbre, Harmony, and Voice Leading on Listeners' Distinction between Popular and Classical Music, University of Pittsburgh.

R Core Team (2017), R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www/R-project.org/.

Hoffman Academy (2013), Classical vs.Pop. Retrieved from https://www.hoffmanacademy.com/blog/classics-vs-pop/.

Appendix

Preprocessing

```
library(MASS)
library(lme4)

library(LMERConvenienceFunctions)
library(arm)

library(RLRsim)
library(dplyr)

library(car)

library(ggplot2)

###residual plots preparation

r.marg <- function(m) {
  y <- m@frame[,1]
  yhat <- model.matrix(m) %*% fixef(m)
  return(y-yhat)
}
r.cond <- function(m) {residuals(m)}
r.reff <- function(m) {r.marg(m) - r.cond(m)}
```

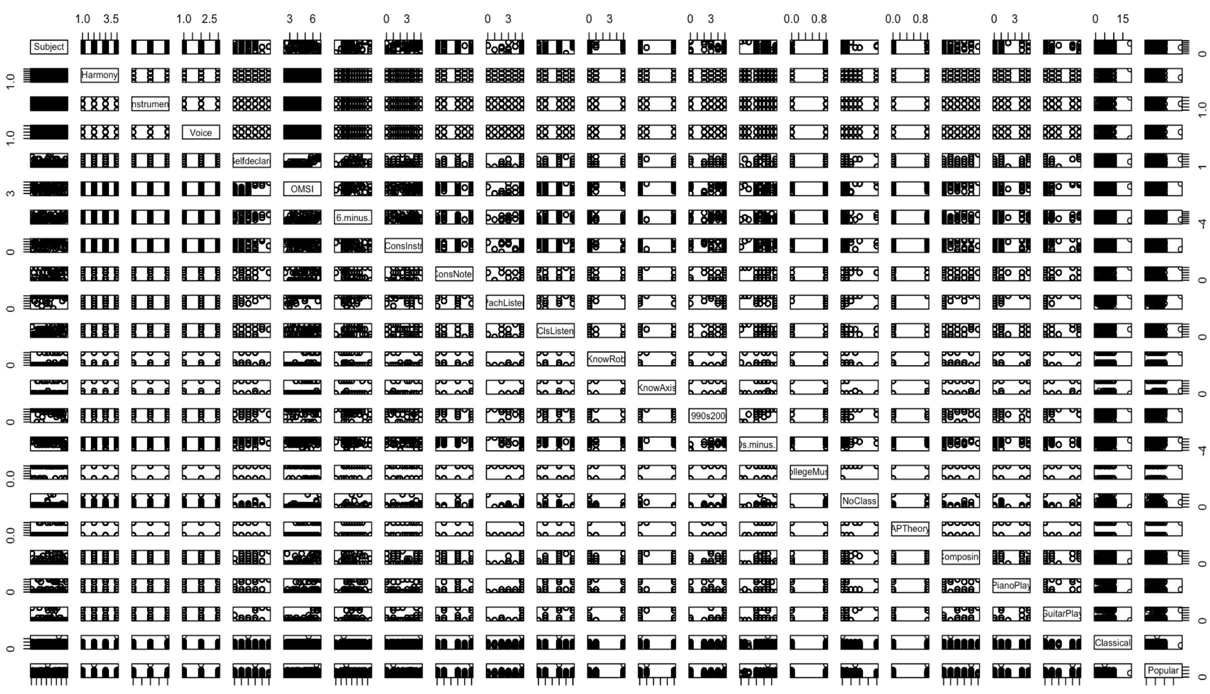
```
ratings <- read.csv('ratings.csv', header = TRUE)
summary(ratings)
```

```
       X            Subject     Harmony     Instrument      Voice      Selfdeclare       OMSI
 Min.   :   1.0   15     :  36   I-IV-V:630   guitar:840   contrary:840   Min.   :1.000   Min.   :2.398
 1st Qu.: 630.8   16     :  36   I-V-IV:630   piano :840   par3rd  :840   1st Qu.:2.000   1st Qu.:3.892
 Median :1260.5   17     :  36   I-V-VI:630   string:840   par5th  :840   Median :2.000   Median :4.980
 Mean   :1260.5   18b    :  36   IV-I-V:630                               Mean   :2.443   Mean   :4.832
 3rd Qu.:1890.2   19     :  36                                            3rd Qu.:3.000   3rd Qu.:5.778
 Max.   :2520.0   20     :  36                                            Max.   :6.000   Max.   :6.877
                  (Other):2304
 X16.minus.17      ConsInstr      ConsNotes     Instr.minus.Notes  PachListen      ClsListen
 Min.   :-4.000   Min.   :0.000   Min.   :0.000   Min.   :-4.0000   Min.   :0.000   Min.   :0.000
 1st Qu.: 0.000   1st Qu.:1.670   1st Qu.:0.750   1st Qu.: 0.0000   1st Qu.:5.000   1st Qu.:1.000
 Median : 1.000   Median :3.000   Median :3.000   Median : 0.3350   Median :5.000   Median :3.000
 Mean   : 1.721   Mean   :2.857   Mean   :2.533   Mean   : 0.6857   Mean   :4.515   Mean   :2.159
 3rd Qu.: 3.000   3rd Qu.:4.330   3rd Qu.:5.000   3rd Qu.: 2.0000   3rd Qu.:5.000   3rd Qu.:3.000
 Max.   : 9.000   Max.   :5.000   Max.   :5.000   Max.   : 4.3300   Max.   :5.000   Max.   :5.000
                  NA's   :360     NA's   :72      NA's   :36
   KnowRob          KnowAxis        X1990s2000s    X1990s2000s.minus.1960s1970s  CollegeMusic
NoClass
 Min.   :0.0000   Min.   :0.0000   Min.   :0.000   Min.   :-4.000               Min.   :0.000   Min.   :0.0000
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:3.000   1st Qu.: 0.000               1st Qu.:1.000   1st Qu.:0.0000
 Median :0.0000   Median :0.0000   Median :5.000   Median : 2.000               Median :1.000
Median :1.0000
```

```
 Mean   :0.7692   Mean   :0.9032   Mean   :4.061   Mean   : 2.015             Mean   :0.791   Mean   :0.9194
 3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:5.000   3rd Qu.: 3.000             3rd Qu.:1.000   3rd Qu.:1.0000
 Max.   :5.0000   Max.   :5.0000   Max.   :5.000   Max.   : 5.000             Max.   :1.000   Max.   :8.0000
 NA's   :180      NA's   :288      NA's   :144     NA's   :180                NA's   :108     NA's   :288
   APTheory       Composing    PianoPlay      GuitarPlay      X1stInstr      X2ndInstr       first12
 Min.   :0.0000   Min.   :0    Min.   :0.000   Min.   :0.0000   Min.   :1.000   Min.   :0.000   guitar: 720
 1st Qu.:0.0000   1st Qu.:0    1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:1.000   piano : 720
 Median :0.0000   Median :0    Median :0.000   Median :0.0000   Median :3.500   Median :1.000
string:1080
 Mean   :0.2344   Mean   :1    Mean   :1.086   Mean   :0.6857   Mean   :2.786   Mean   :1.556
 3rd Qu.:0.0000   3rd Qu.:2    3rd Qu.:1.000   3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:2.000
 Max.   :1.0000   Max.   :5    Max.   :5.000   Max.   :5.0000   Max.   :5.000   Max.   :4.000
 NA's   :216      NA's   :72                                    NA's   :1512    NA's   :2196
   Classical        Popular
 Min.   : 0.000   Min.   : 0.000
 1st Qu.: 4.000   1st Qu.: 4.000
 Median : 6.000   Median : 5.000
 Mean   : 5.783   Mean   : 5.381
 3rd Qu.: 8.000   3rd Qu.: 7.000
 Max.   :19.000   Max.   :19.000
 NA's   :27       NA's   :27
```

###scatter plot of variables

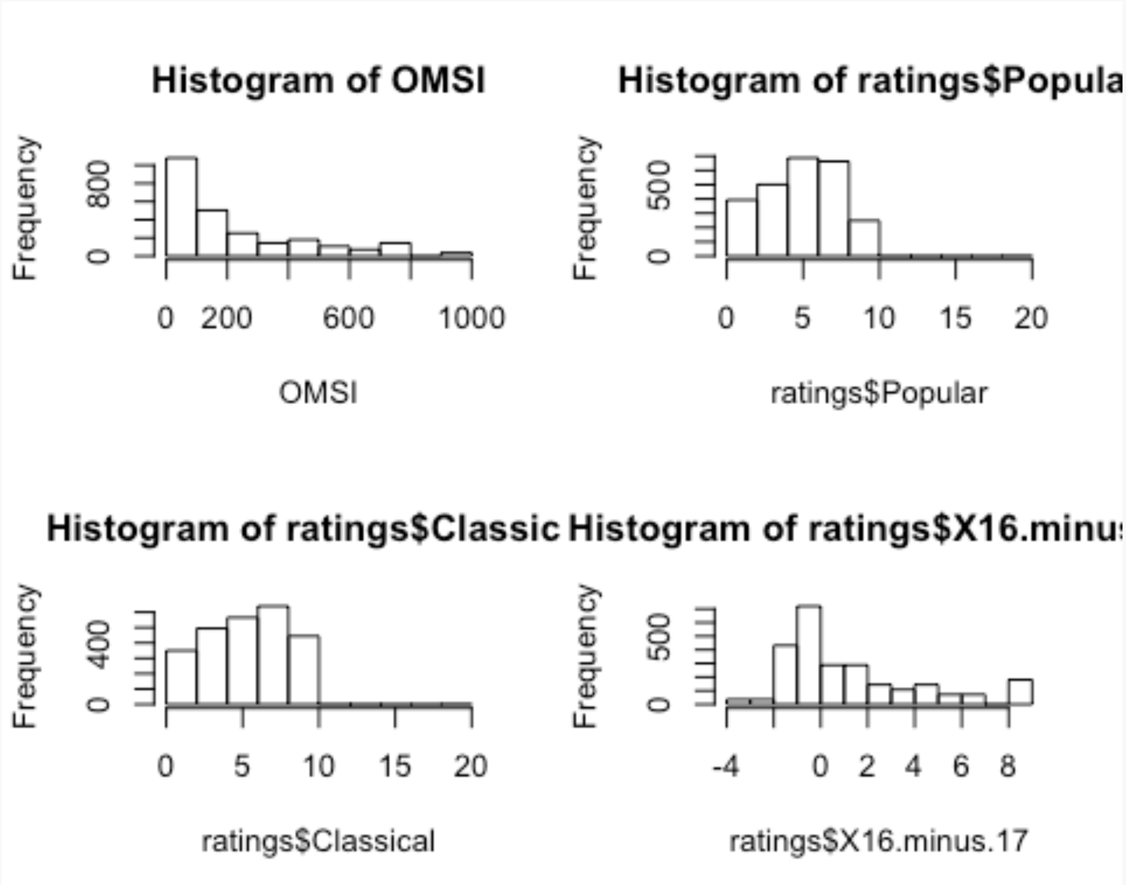
```
ratings_try <- ratings %>% dplyr::select(- Instr.minus.Notes ,- X, - first12, - X2ndInstr, - X1stInstr)
plot(ratings_try)
```

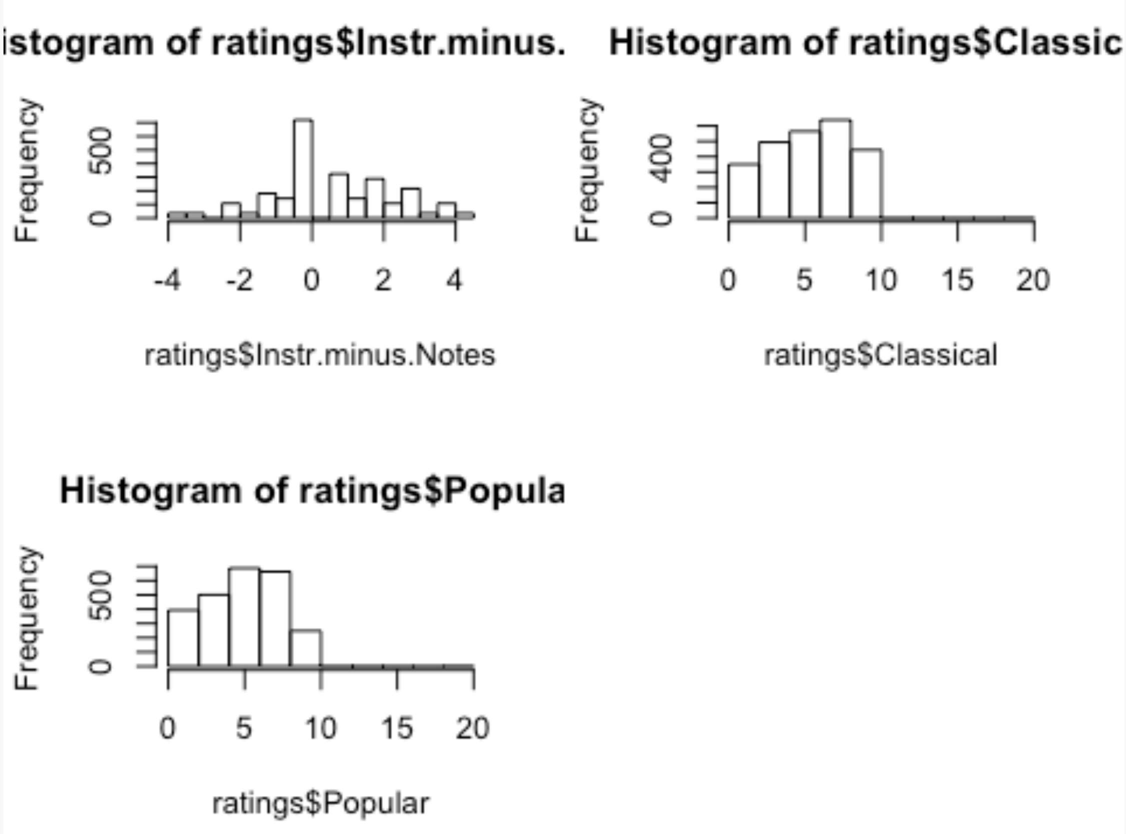


###Histograms of continuous variables

```
par(mfrow=c(2, 2))
hist(ratings$OMSI, main = 'Histogram of OMSI', xlab = 'OMSI')
hist(ratings$Popular)
```

```r
hist(ratings$Classical)
hist(ratings$X16.minus.17)

hist(ratings$Instr.minus.Notes)
hist(ratings$Classical)
hist(ratings$Popular)
```

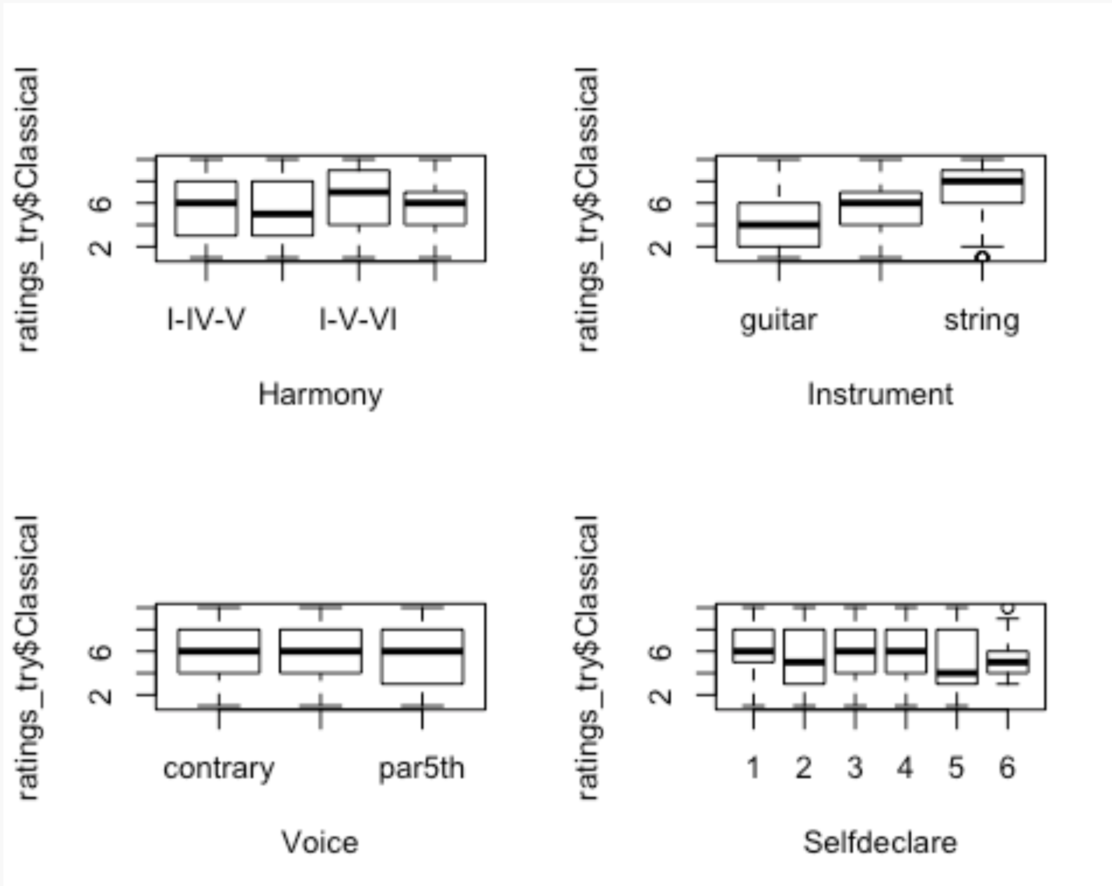


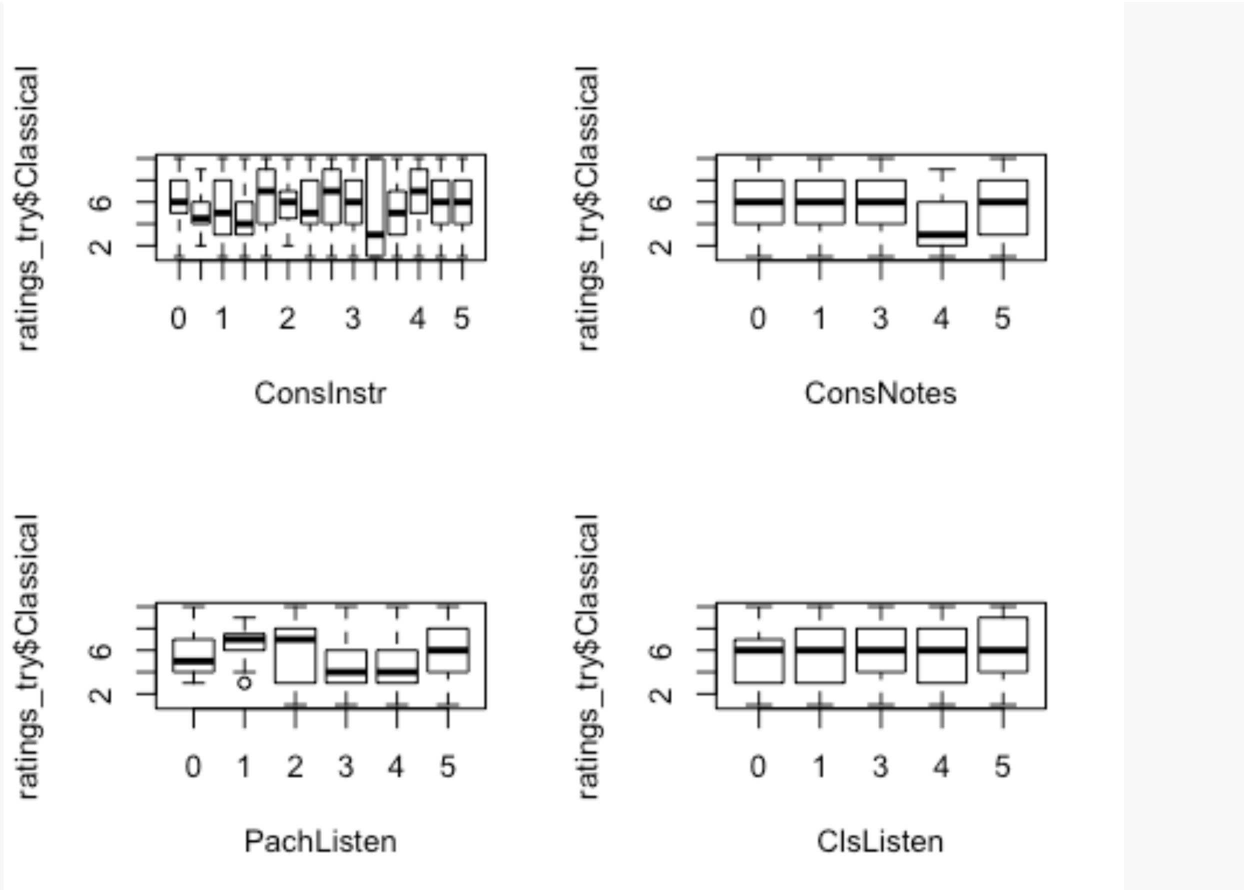


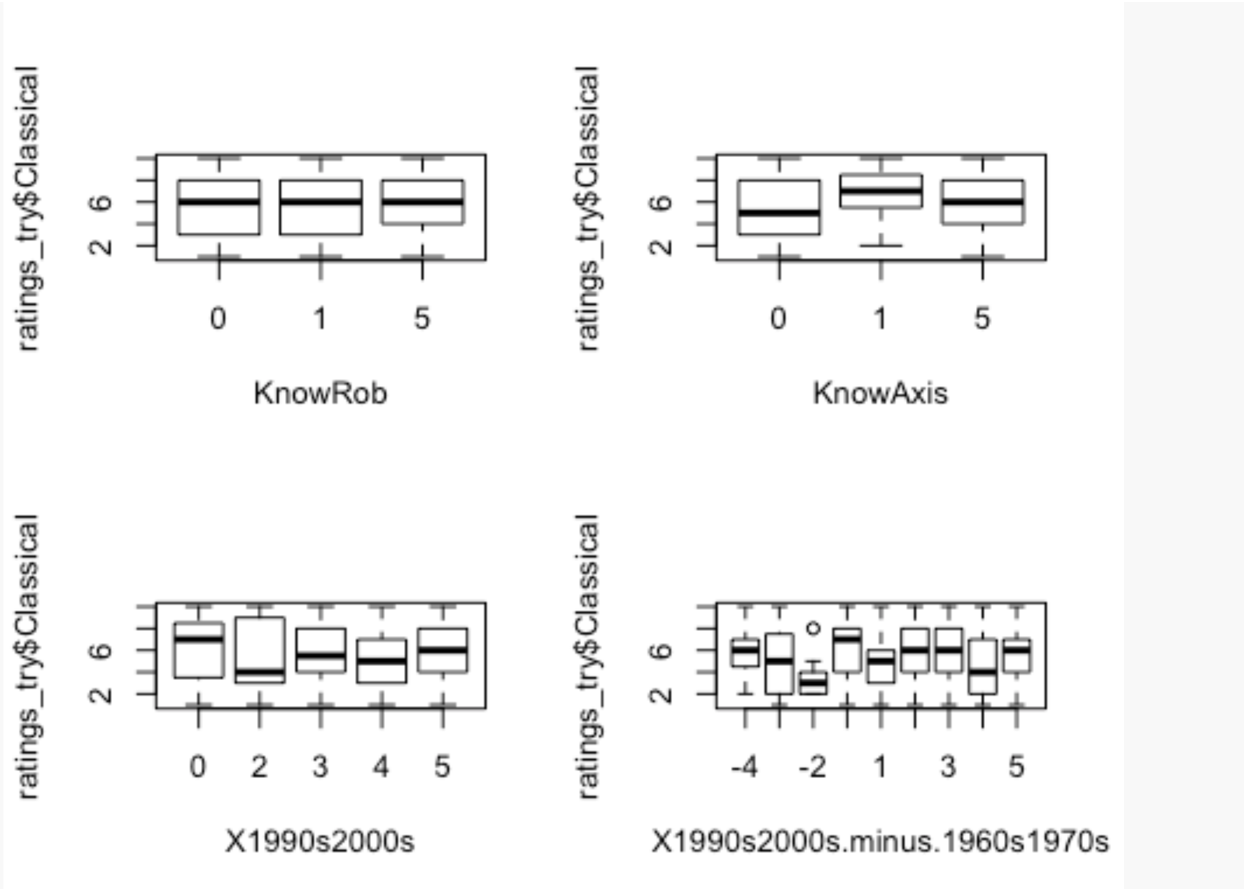

```
#log transformation of the OMSI
ratings$OMSI <- log(ratings$OMSI)


###deleting 5 variables

ratings_try <- ratings %>% dplyr::select(- Instr.minus.Notes ,- X, - first12, - X2ndInstr, - X1stInstr)



###Classical ratings and Popular ratings changes:

ratings_try$Classical[ratings_try$Classical == 19] <- 10
ratings_try$Popular[ratings_try$Popular == 19] <- 10
ratings_try <- ratings_try[!ratings_try$Classical == 0,]
ratings_try <- ratings_try[!ratings_try$Popular == 0, ]
ratings_try <- ratings_try[!ratings_try$Classical == 9.5,]
ratings_try <- ratings_try[!ratings_try$Classical == 4.6, ]
ratings_try <- ratings_try[!ratings_try$Classical == 3.5, ]
ratings_try <- ratings_try[!ratings_try$Classical == 4.2,]
ratings_try <- ratings_try[!ratings_try$Popular == 3.5,]
ratings_try <- ratings_try[!ratings_try$Popular == 4.6,]
ratings_try <- ratings_try[!ratings_try$Popular == 6.8,]
ratings_try <- ratings_try[!ratings_try$Popular == 4.2,]
```

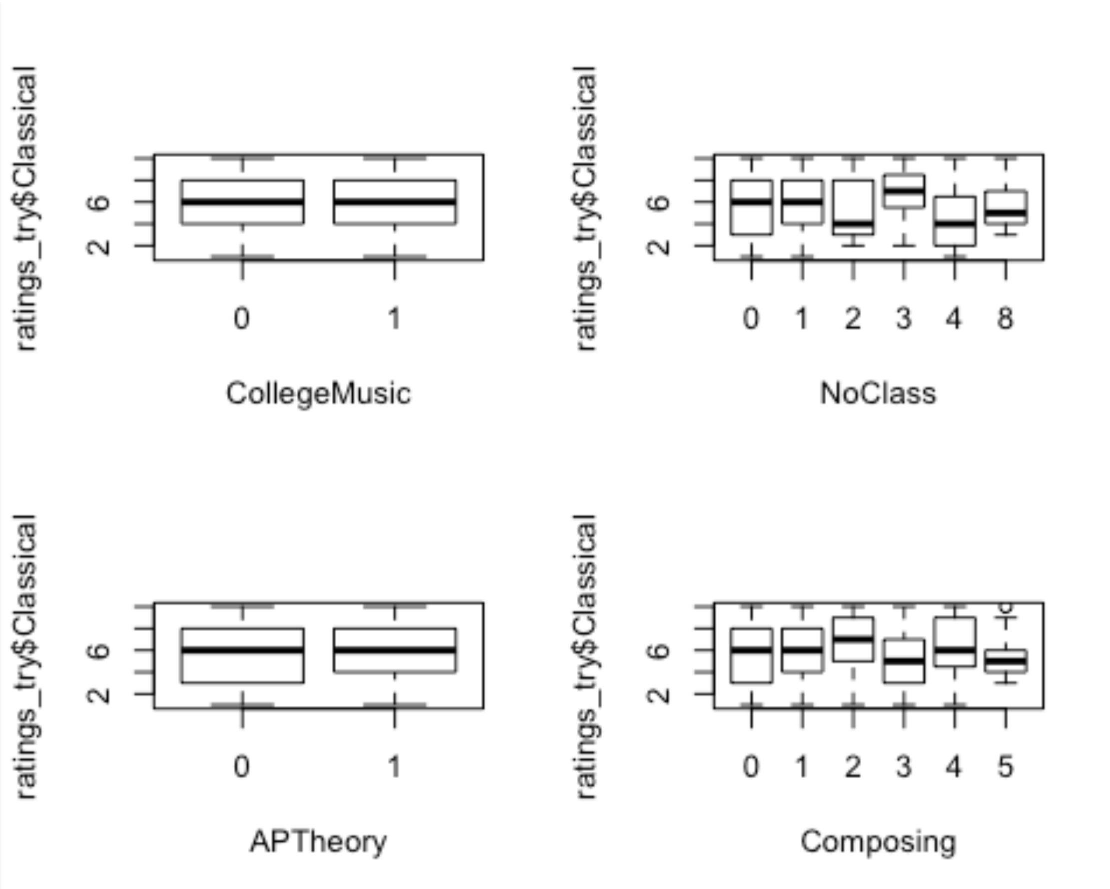
BOXPLOTS

```
###Classical
par(mfrow = c(2, 2))
for (i in names(ratings_try%>%dplyr::select(-OMSI, -Popular, - Subject, -X16.minus.17,-Classical))) {b
oxplot(ratings_try$Classical ~ ratings_try[,i], xlab = i)}
```

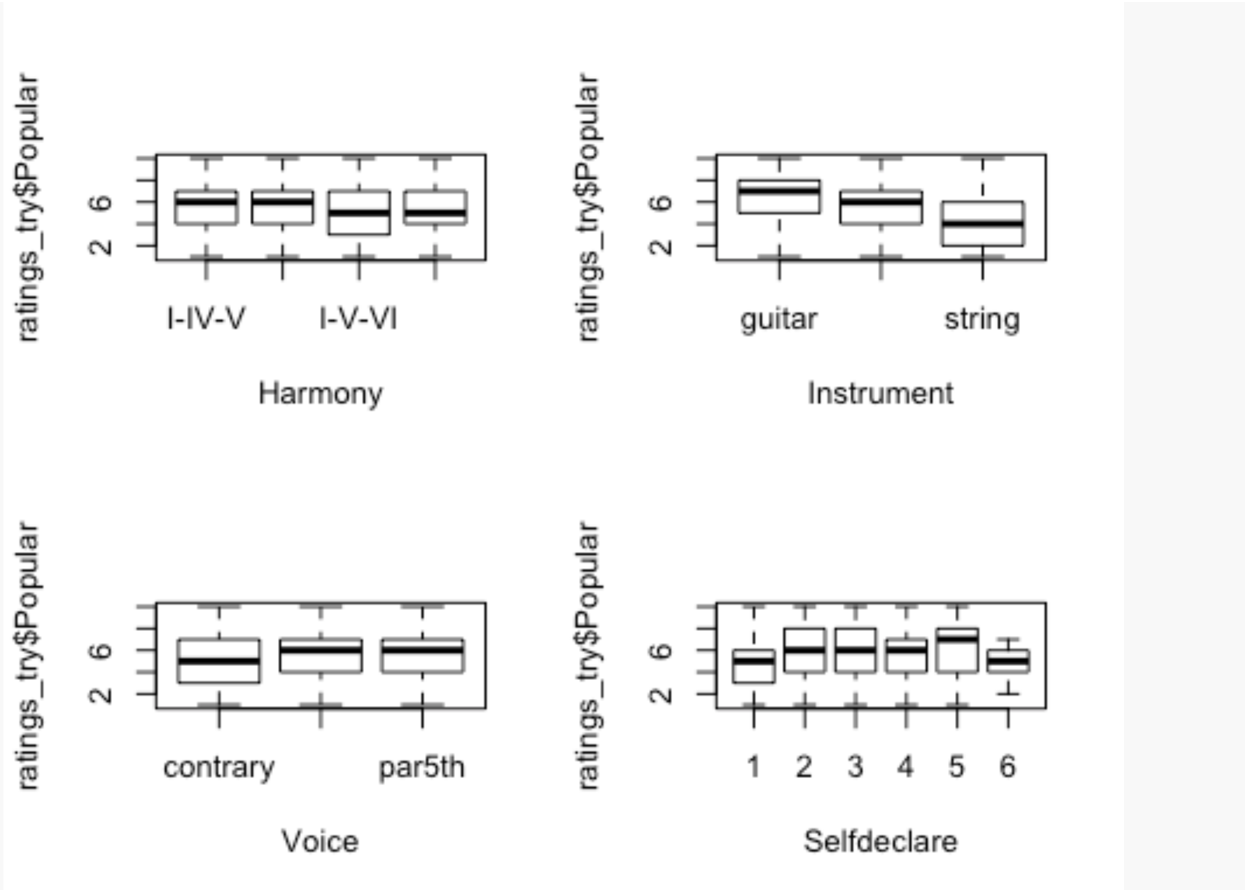


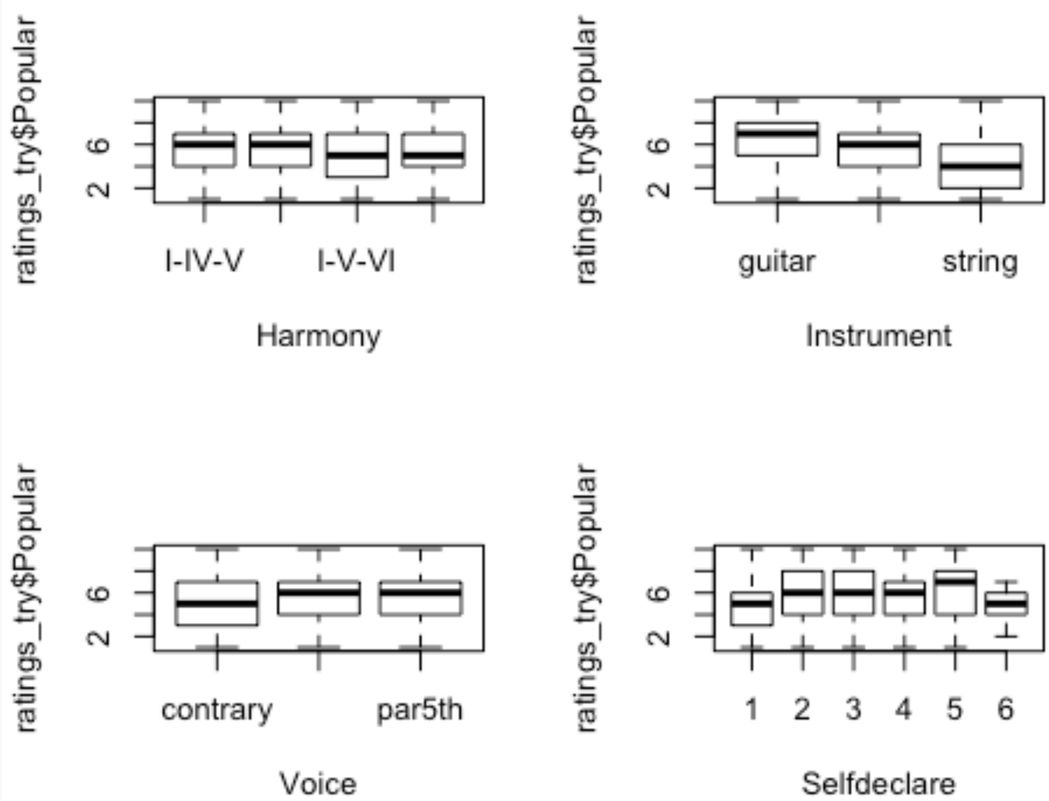

ratings_try$Classical
2 6
0 1 2 3 4 5
ConsInstr
ratings_try$Classical
2 6
0 1 3 4 5
ConsNotes
ratings_try$Classical
2 6
0 1 2 3 4 5
PachListen
ratings_try$Classical
2 6
0 1 3 4 5
ClsListen

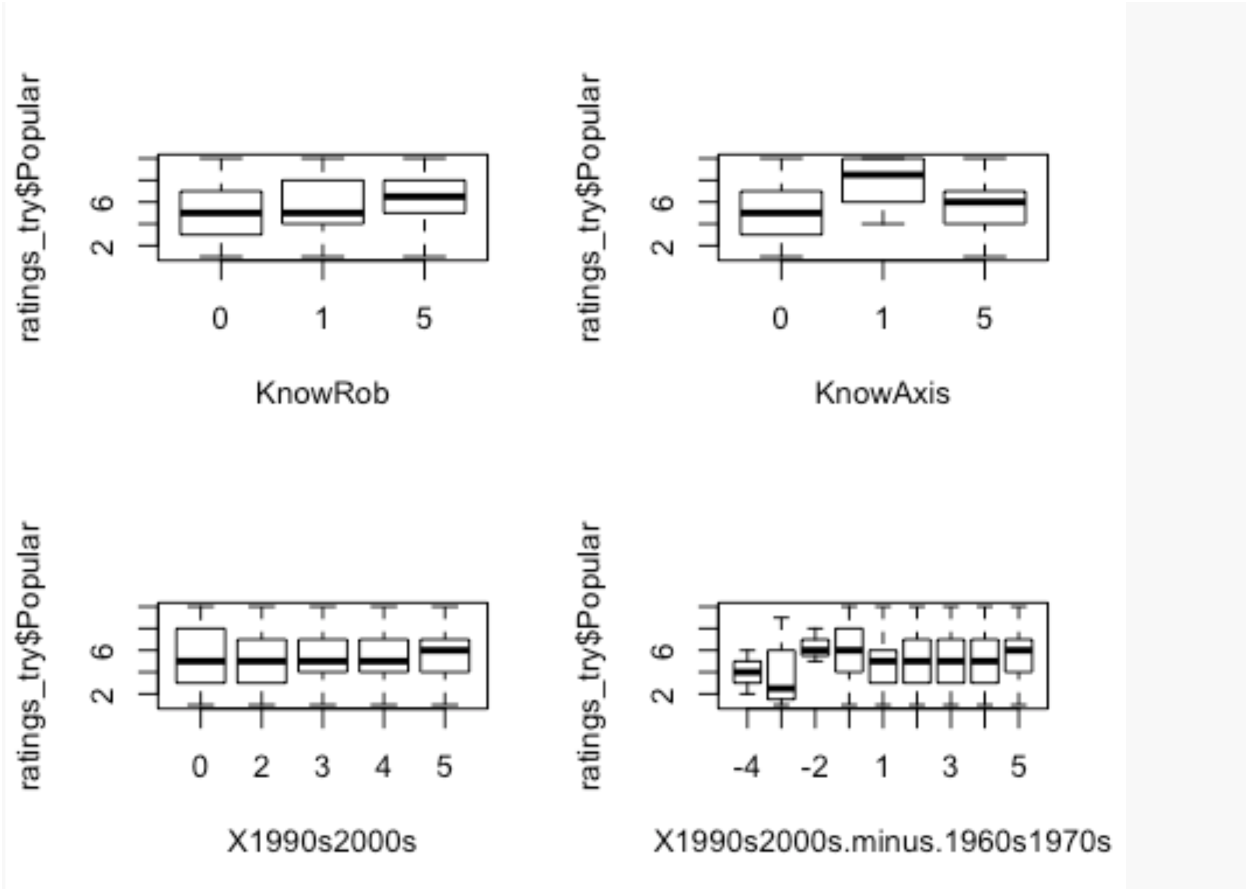

ratings_try$Classical
2
6
0
1
5
KnowRob
ratings_try$Classical
2
6
0
1
5
KnowAxis
ratings_try$Classical
2
6
0
2
3
4
5
X1990s2000s
ratings_try$Classical
2
6
-4
-2
1
3
5
X1990s2000s.minus.1960s1970s

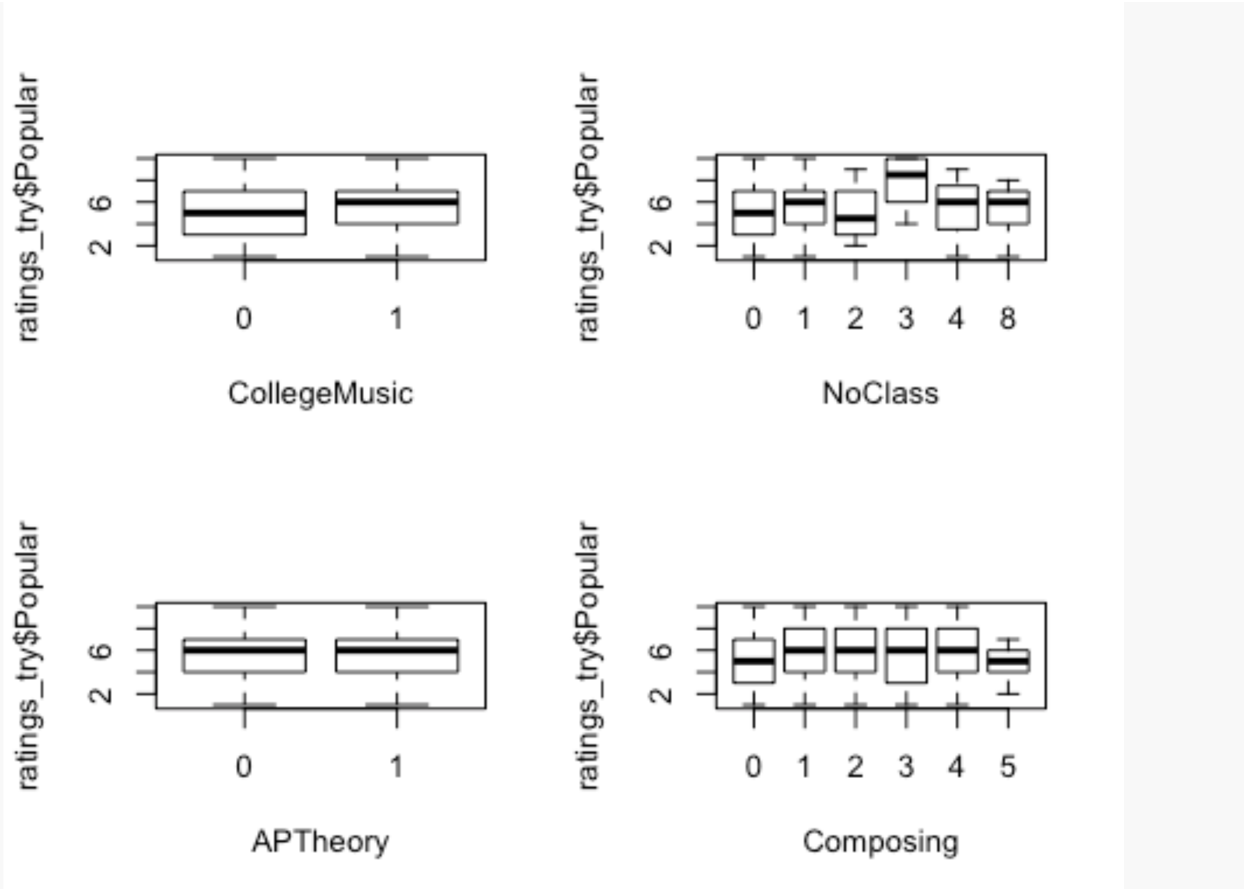



```
###Popular
par(mfrow=c(2, 2))
for (i in names(ratings_try%>%dplyr::select(-OMSI, -Popular, -Classical, - Subject, -X16.minus.17,-Clas
sical))) {boxplot(ratings_try$Popular ~ ratings_try[,i], xlab = i)}
```

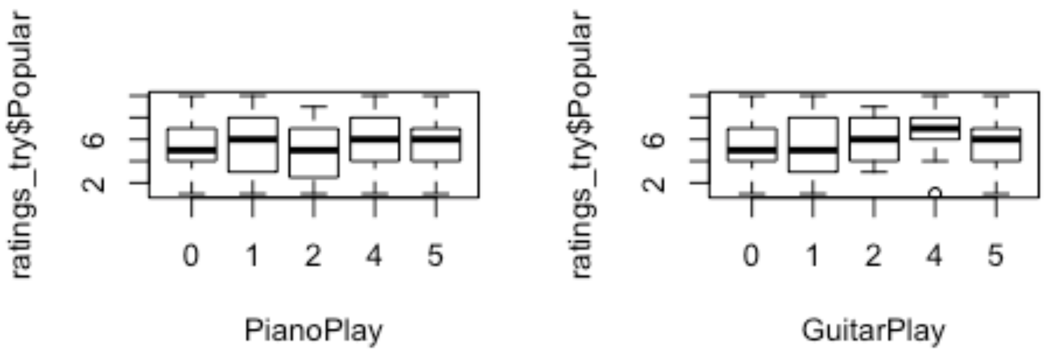

ratings_try$Popular
2 6
I-IV-V
I-V-VI
Harmony
ratings_try$Popular
2 6
guitar
string
Instrument
ratings_try$Popular
2 6
contrary
par5th
Voice
ratings_try$Popular
2 6
1 2 3 4 5 6
Selfdeclare


ratings_try$Popular
2 6
I-IV-V
I-V-VI
Harmony
ratings_try$Popular
2 6
guitar
string
Instrument
ratings_try$Popular
2 6
contrary
par5th
Voice
ratings_try$Popular
2 6
1 2 3 4 5 6
Selfdeclare


ratings_try$Popular
2 6
0 1 5
KnowRob
ratings_try$Popular
2 6
0 1 5
KnowAxis
ratings_try$Popular
2 6
0 2 3 4 5
X1990s2000s
ratings_try$Popular
2 6
-4 -2 1 3 5
X1990s2000s.minus.1960s1970s



ratings_try$Popular
2 6
0 1
CollegeMusic
ratings_try$Popular
2 6
0 1 2 3 4 8
NoClass
ratings_try$Popular
2 6
0 1
APTheory
ratings_try$Popular
2 6
0 1 2 3 4 5
Composing



3.1 Transformation and multicollinearity variable

```
pairs(ratings$ConsNotes ~ ratings$ConsInstr + ratings$Instr.minus.Notes)

boxplot(ratings_try$Classical ~ ratings_try$KnowAxis, xlab = 'KnowAxis', ylab = 'Classical Rating')
boxplot(ratings_try$Classical ~ ratings_try$KnowRob, xlab = 'KnowRob', ylab = 'Classical Rating')
```

Figure 3 Model

```
lm <- lm(Classical ~ Harmony*Instrument*Voice, data = ratings_try)
summary(lm)

stepAIC(lm, direction = 'backward',k = log(2520))

stepAIC(lm, direction = 'backward', k = 2)

lm.1 <- lm(Classical ~ Harmony + Instrument + Voice + Harmony:Voice, data = ratings_try)

lm.2 <- lm(Classical ~ Harmony + Instrument, data = ratings_try)

#reject null hypothesis, lm.1 is better

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

```
Analysis of Variance Table

Model 1: Classical ~ Harmony + Instrument + Voice
Model 2: Classical ~ Harmony + Instrument
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 13193 -2    -85.64 8.1181 0.0003061 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```r
anova(lm, lm.1)
```

```
Analysis of Variance Table

Model 1: Classical ~ Harmony * Instrument * Voice
Model 2: Classical ~ Harmony + Instrument + Voice + Harmony:Voice
  Res.Df   RSS  Df Sum of Sq      F Pr(>F)
1   2419 12450
2   2441 12531 -22   -81.791 0.7224 0.8205
```

```r
lmer.1 <- lmer(Classical ~ 1 + Harmony + Instrument + Voice + Harmony:Voice + (1|Subject), data = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))

anova(lmer.1, lm.1)
```

```
Data: ratings_try
Models:
lm.1: Classical ~ Harmony + Instrument + Voice
lmer.1: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject)
       Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm.1    9 11230 11283 -5606.2    11212
lmer.1 10 10469 10527 -5224.4    10449 763.59      1  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```r
AIC(lmer.1)

## [1] 10214.06

AIC(lm.1)

## [1] 10998.91

BIC(lmer.1)

## [1] 10306.95

BIC(lm.1)

## [1] 11086

#According to both AIC and BIC, the lmer.1 is better

lmer.2 <- fitLMER.fnc(lmer.1, ran.effects = c("(Instrument|Subject)", "(Harmony|Subject)", "(Voice|Subject)"), method = "BIC", keep.single.factors = TRUE)
```

```
display(lmer.2)

## lmer(formula = Classical ~ Harmony + Instrument + Voice + (1 |
##     Subject) + (Instrument | Subject) + (Harmony | Subject),
##     data = ratings_try, REML = TRUE, control = lmerControl(optimizer = "bobyqa"))
##                  coef.est coef.se
## (Intercept)       4.35     0.22
## HarmonyI-V-IV    -0.04     0.09
## HarmonyI-V-VI     0.78     0.18
## HarmonyIV-I-V     0.06     0.09
## Instrumentpiano   1.34     0.17
## Instrumentstring  3.05     0.23
## Voicepar3rd      -0.39     0.08
## Voicepar5th      -0.36     0.08
##
## Error terms:
##  Groups    Name             Std.Dev. Corr
##  Subject   (Intercept)      0.01
##  Subject.1 (Intercept)      1.12
##            Instrumentpiano  1.30     -0.64
##            Instrumentstring 1.84     -1.00  0.68
##  Subject.2 (Intercept)      1.31
##            HarmonyI-V-IV    0.18      0.52
##            HarmonyI-V-VI    1.28     -0.41  0.36
##            HarmonyIV-I-V    0.06      0.53  0.78 -0.20
##  Residual                   1.54

## Warning in optwrap(optimizer, devfun, x@theta, lower = x@lower, calc.derivs
## = TRUE, : convergence code 1 from bobyqa: bobyqa -- maximum number of
## function evaluations exceeded

## ---
## number of obs: 2455, groups: Subject, 70
## AIC = 9742.2, DIC = 9649.8
## deviance = 9670.0

lmer.2 <- lmer(Classical ~ 1 + Harmony + Instrument + Voice + (1 + Instrument + Harmony|Subject), dat
a = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))

lmer.try <- lmer(Classical ~  1 + Harmony + Instrument + Voice + (1+ Instrument + Harmony + Voice|S
ubject), data = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))

anova(lmer.2, lmer.try)
```

```
Data: ratings_try
Models:
lmer.2: Classical ~ 1 + Harmony + Instrument + Voice + (1 + Instrument +
lmer.2:     Harmony | Subject)
lmer.try: Classical ~ 1 + Harmony + Instrument + Voice + (1 + Instrument +
lmer.try:     Harmony + Voice | Subject)
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.2   30 9718.3 9892.4 -4829.1   9658.3
```

lmer.try 45 9730.6 9991.8 -4820.3   9640.6 17.708   15   0.2784

```
#null hypothesis: full model is not significant better. Alternative hypothesis: full model is significant bette
r.

#lmer.2 is better
```

FIXED EFFECTS AUTOMATIC + MANUALLY CHECKING

```
ratings_try_factored <- ratings_try %>% 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),
                              NoClass = as.factor(NoClass),
                              APTheory = as.factor(APTheory),
                              Composing = as.factor(Composing),
                              PianoPlay = as.factor(PianoPlay),
                              GuitarPlay = as.factor(GuitarPlay))

###REvised model (manually)
lm.bic_manual <- lm(Classical ~ GuitarPlay + PianoPlay + Composing + APTheory + NoClass + X1990s
2000s.minus.1960s1970s + X1990s2000s + KnowAxis + KnowRob + ClsListen + PachListen + ConsNot
es + ConsInstr + Selfdeclare + Instrument + Harmony, data = na.omit(ratings_try_factored))

row = nrow(ratings_try_factored%>%filter(is.na(GuitarPlay)==FALSE | is.na(PianoPlay)==FALSE | is.
na(Composing)==FALSE | is.na(APTheory)==FALSE | is.na(NoClass)==FALSE | is.na(X1990s2000s.
minus.1960s1970s)==FALSE | is.na(X1990s2000s)==FALSE | is.na(KnowAxis)==FALSE | is.na(Know
Rob)==FALSE | is.na(ClsListen)==FALSE | is.na(PachListen)==FALSE | is.na(ConsNotes)==FALSE | i
s.na(ConsInstr)==FALSE | is.na(Selfdeclare)==FALSE))

#revised model(manually + auto)
stepAIC(lm.bic_manual, k = log(2493))

lm.bic_manual_auto <- lm(Classical ~ GuitarPlay + PianoPlay + Composing +
                   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
                     PachListen + Instrument + Harmony, data =na.omit(ratings_try_factored))

lm.fixed.final <- lm(Classical ~ GuitarPlay + PianoPlay + Composing +
                   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
                     PachListen + Instrument + Harmony + Voice, data =  na.omit(ratings_try_factored))
```

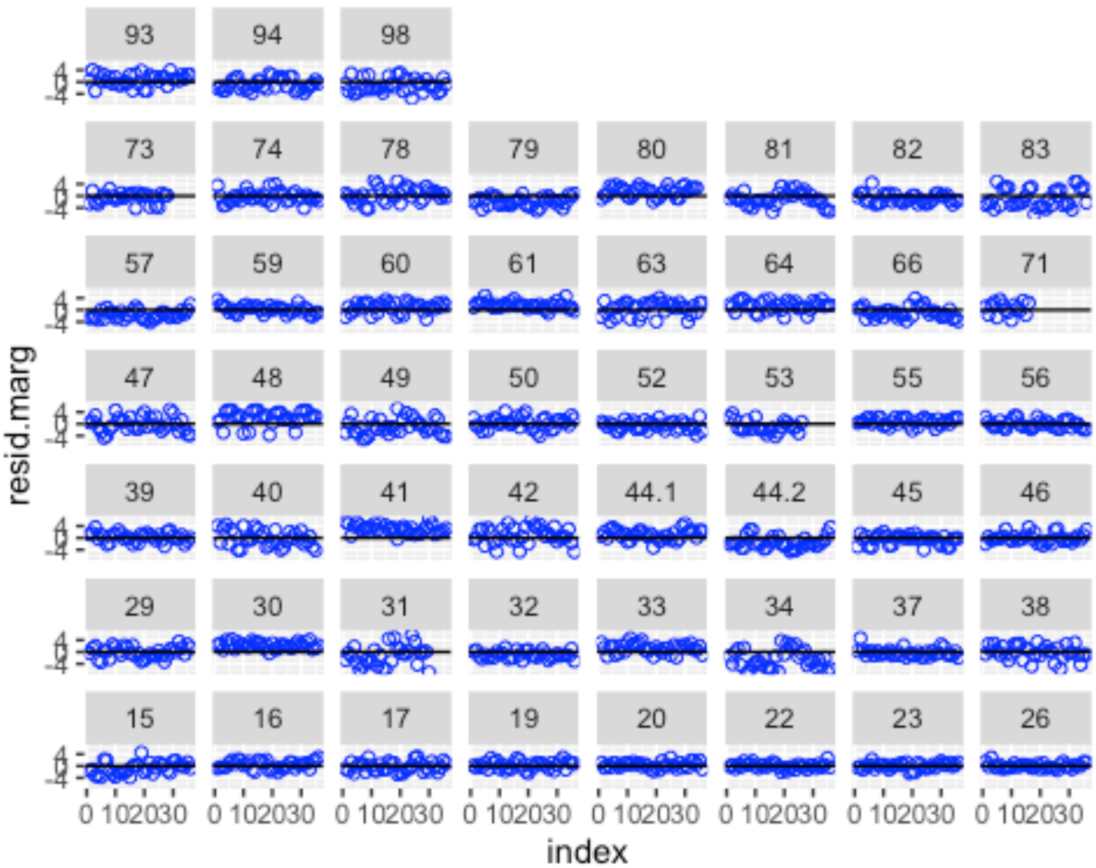
random effects

```
#Using fitLMER to do the selection
lmer.random <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
                   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
                     PachListen + Instrument + Harmony + Voice + (1|Subject) + (Instrument|Subject) + (Ha
```

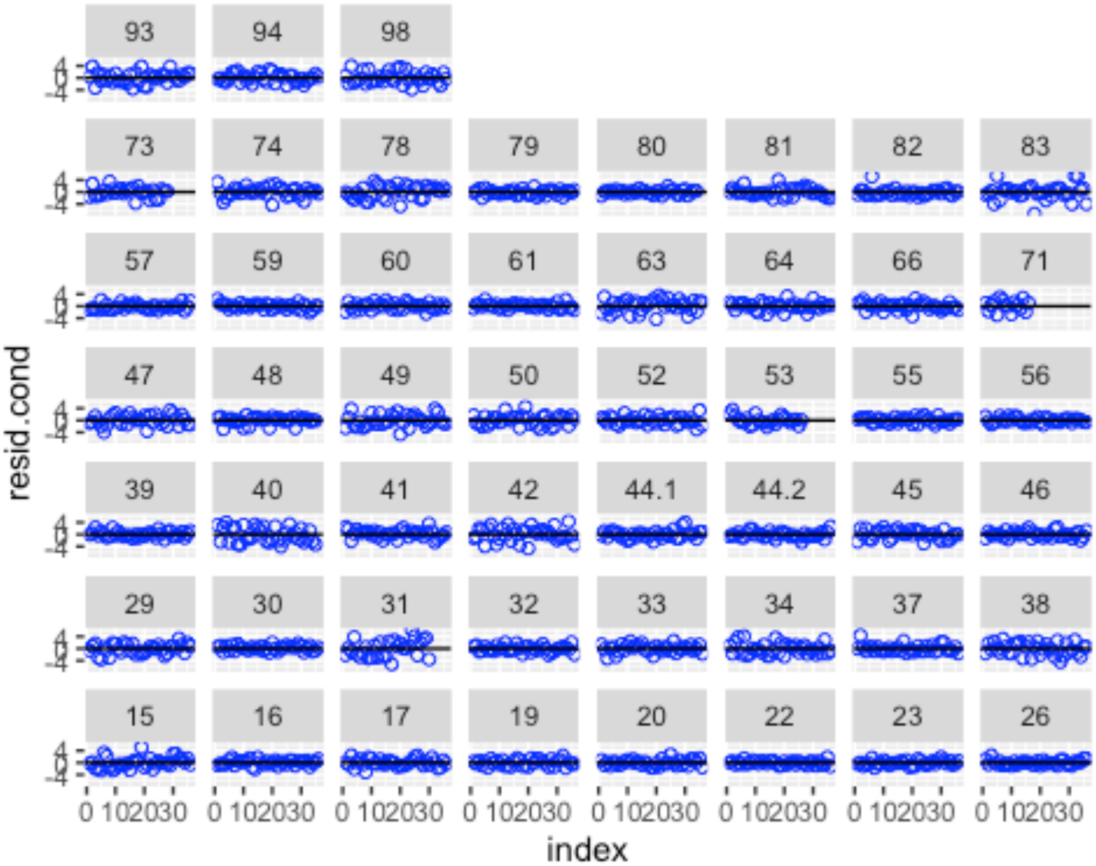
```
rmony |Subject) , data = na.omit(ratings_try_factored), REML = FALSE, control = lmerControl(optimiz
er = 'bobyqa'))

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

## boundary (singular) fit: see ?isSingular

lmer_random_new <- fitLMER.fnc(lmer.random, ran.effects = c("(Selfdeclare|Subject)", "(OMSI|Subjec
t)", "(ConsInstr|Subject)", "(ConsNotes|Subject)", "(PachListen|Subject)", "(ClsListen|Subject)", "(Know
Rob|Subject)", "(KnowAxis|Subject)", "(X1990s2000s| Subject)", "(X1990s2000s.minus.1960s1970s|Sub
ject)", "(CollegeMusic|Subject)", "(NoClass|Subject)", "(APTheory|Subject)"),  method = 'llrt')

lmer_final <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
   PachListen + Instrument + Harmony + Voice + (1 + Instrument + Harmony | Subject), data = ratings_tr
y_factored, REML = FALSE,
   control = lmerControl(optimizer = "bobyqa"))

lmer_final_fake <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
   PachListen + Instrument + Harmony  + (1 + Instrument + Harmony | Subject), data = ratings_try_factor
ed, REML = FALSE, control = lmerControl(optimizer = "bobyqa"))

anova(lmer_final_same, lmer_final_fake)

#null hypothesis: full model is not significant better. Alternative hypothesis: full model is significant bette
r.
#lmer_final_same is better

display(lmer_final)
```

Residual plots for Figure 3’s model:

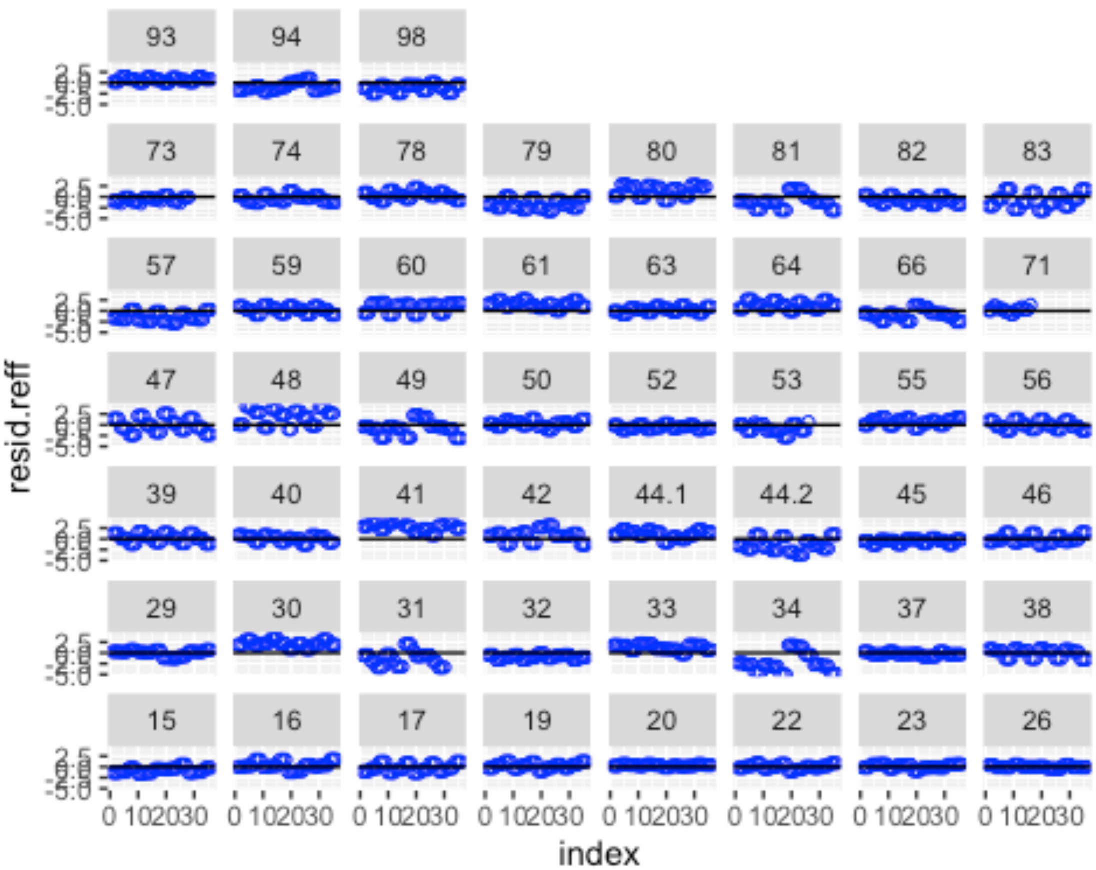
```
ratings_try_residual <- ratings_try_factored%>%filter(is.na(Classical)==FALSE & is.na(Composing) ==
 FALSE & is.na(APTheory) == FALSE & is.na(NoClass)== FALSE & is.na(X1990s2000s)== FALSE
& is.na(KnowAxis)==FALSE & is.na(ClsListen)==FALSE & is.na(PachListen)==FALSE)
sub <- as.numeric(ratings_try_residual$Subject)
index <- sub
for (j in unique(sub)) {
  len <- sum(sub==j)
  index[sub==j] <- 1:len
}


#Marginal residual plot
resid.marg <- r.marg(lmer_final)
new.data <- data.frame(index,resid.marg,ratings_try_residual)
names(new.data) <- c("index","resid.marg","subject")
ggplot(ratings_try_residual,aes(x=index,y=resid.marg)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)
```




```r
#Conditional residual plot
resid.cond <- r.cond(lmer_final)
new.data <- data.frame(index,resid.cond,ratings_try_residual$Subject)
names(new.data) <- c("index","resid.cond","subject")
ggplot(ratings_try_residual,aes(x=index,y=resid.cond)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)
```




```
#random effect residual plot
resid.reff <- r.reff(lmer_final)
new.data <- data.frame(index,resid.reff,ratings_try_residual$Subject)
names(new.data) <- c("index","resid.reff","subject")
ggplot(ratings_try_residual,aes(x=index,y=resid.reff)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)
```




```
par(mfrow=c(2,2))
plot(resid.marg,xlab="Index",ylab="Marginal Residuals")
abline(0,0)
plot(resid.cond,xlab="Index",ylab="Conditional Residuals")
abline(0,0)
plot(resid.reff,xlab="Index",ylab="Random Effects")
abline(0,0)
```

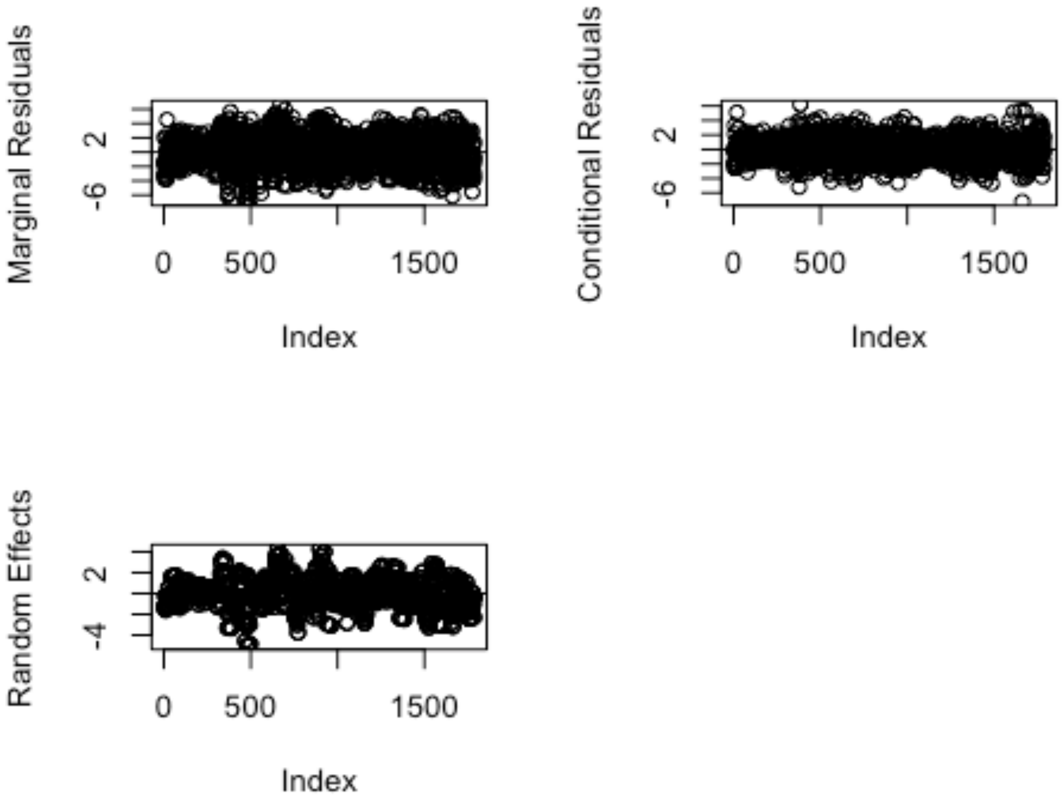
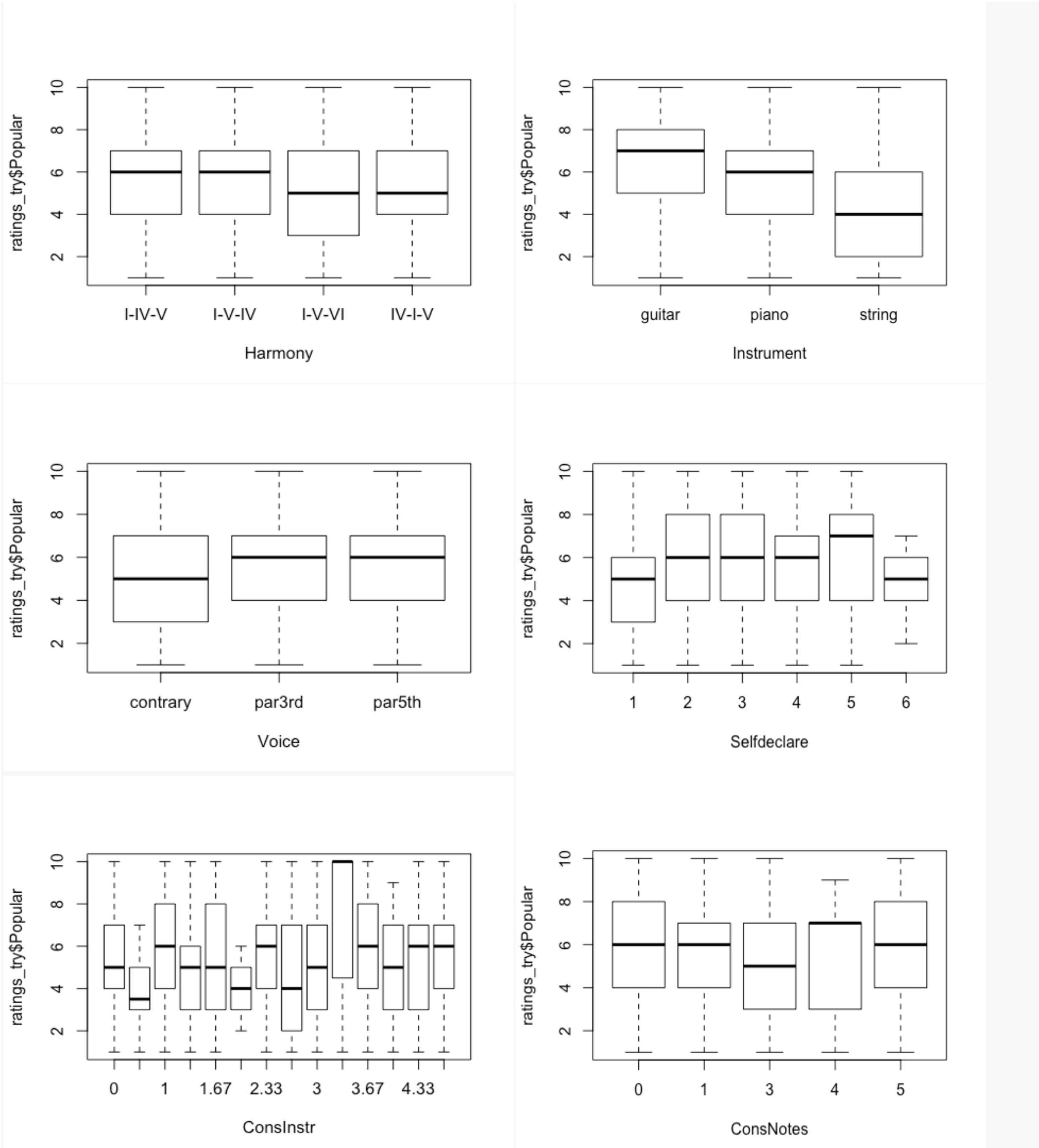
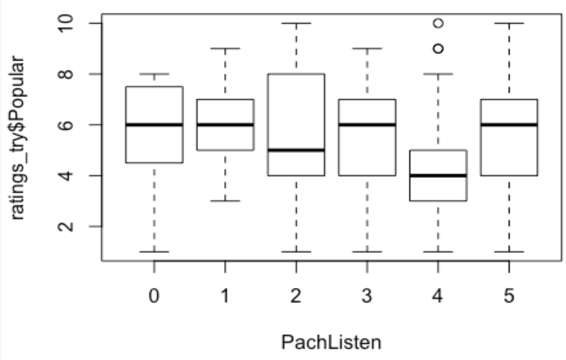


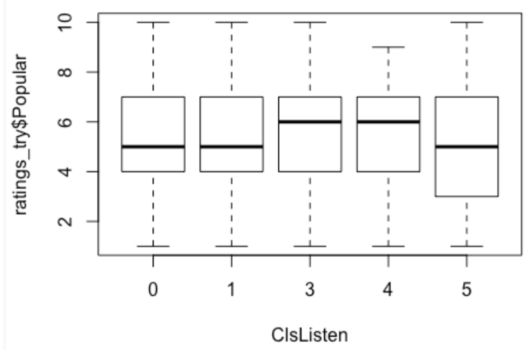
Figure 4’s model

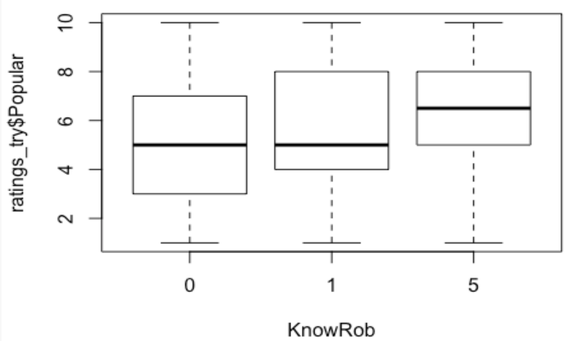
FIXED EFFECTS

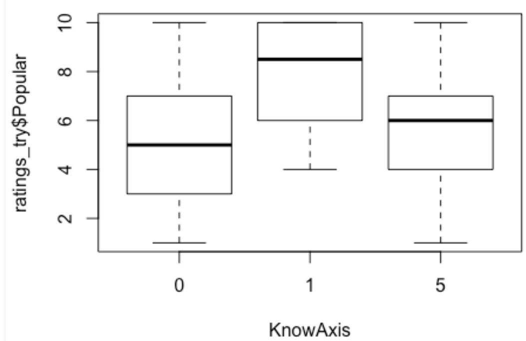
```
for (i in names(ratings_try%>%dplyr::select(-OMSI, -Popular, -Classical, - Subject, -X16.minus.17,-Clas
sical))) {boxplot(ratings_try$Popular ~ ratings_try[,i], xlab = i)}
```

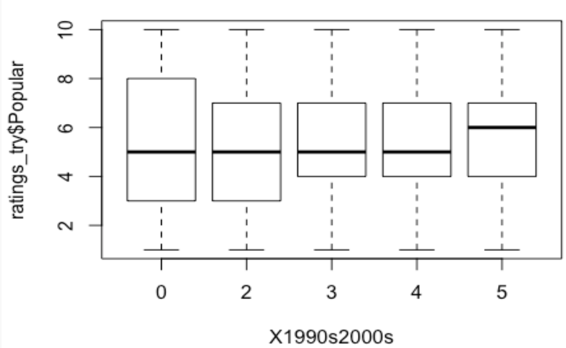

ratings_try$Popular
Harmony
I-IV-V
I-V-IV
I-V-VI
IV-I-V
Instrument
guitar
piano
string
Voice
contrary
par3rd
par5th
Selfdeclare
ConsInstr
0
1
1.67
2.33
3
3.67
4.33
ConsNotes

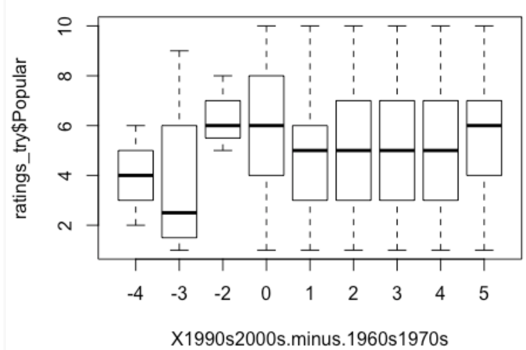

ratings_try$Popular
2 4 6 8 10
0 1 2 3 4 5
PachListen

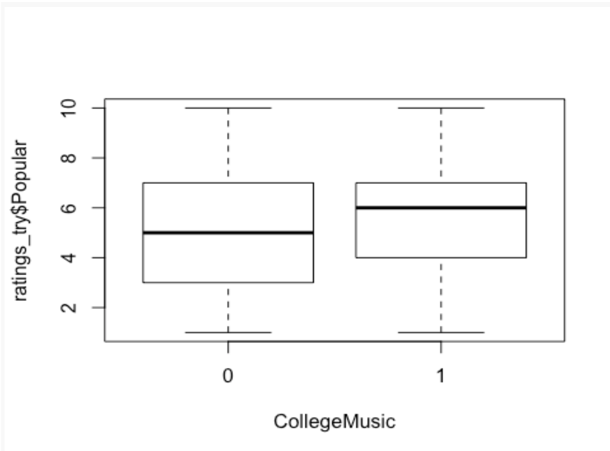

ratings_try$Popular
2 4 6 8 10
0 1 3 4 5
ClsListen

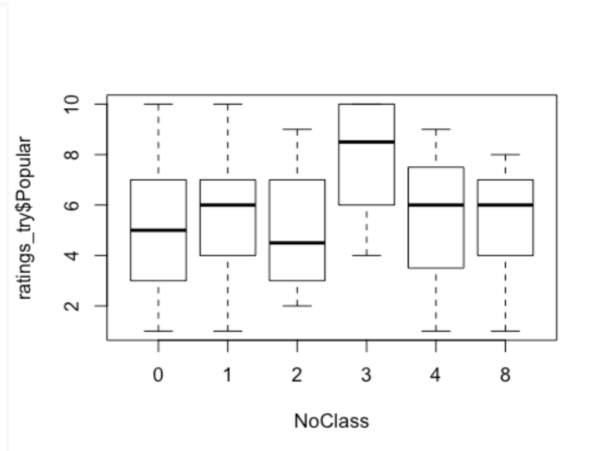

ratings_try$Popular
2 4 6 8 10
0 1 5
KnowRob

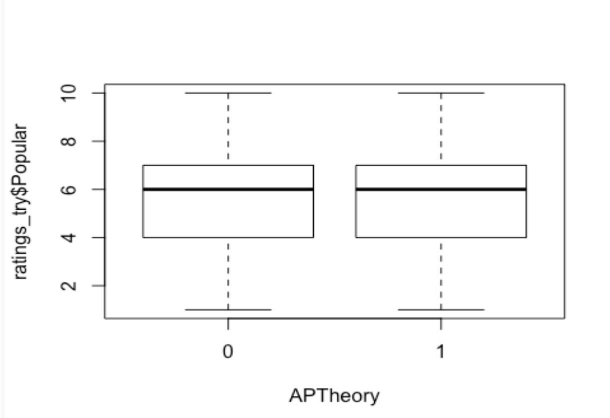

ratings_try$Popular
2 4 6 8 10
0 1 5
KnowAxis

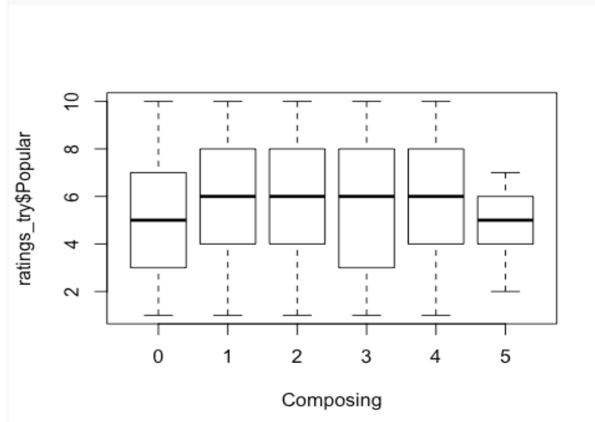

ratings_try$Popular
2 4 6 8 10
0 2 3 4 5
X1990s2000s

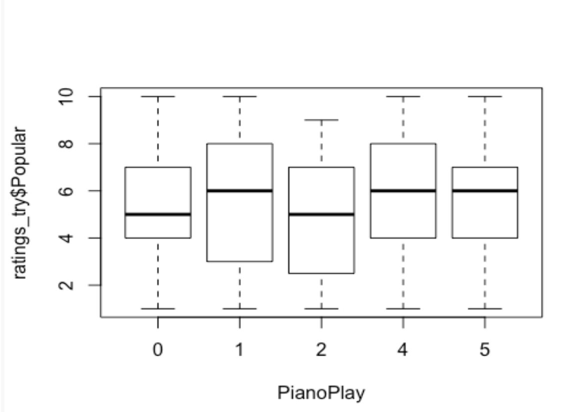

ratings_try$Popular
2 4 6 8 10
-4 -3 -2 0 1 2 3 4 5
X1990s2000s.minus.1960s1970s

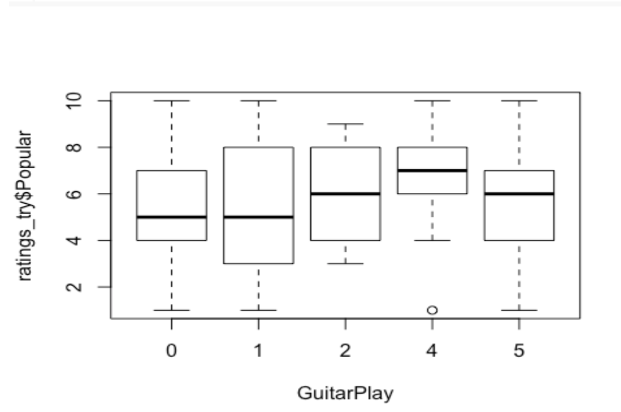













```
#first
lm_pop <- lm(Popular ~ Harmony*Instrument*Voice, data = ratings_try)
stepAIC(lm_pop, direction = 'backward',k = log(nrow(ratings_try)))

lm_pop <- lm(Popular ~ Instrument, data = ratings_try)

lm.pop.1 <- lm(Popular ~ Instrument + Harmony:Instrument:Voice, data = ratings_try)

anova(lm_pop, lm.pop.1)

#null hypothesis: full model is not significant better. Alternative hypothesis: full model is significant bette
r.
```

Analysis of Variance Table

```
Model 1: Popular ~ Instrument
Model 2: Popular ~ Instrument + Harmony:Instrument:Voice
  Res.Df   RSS Df Sum of Sq     F Pr(>F)
1   2517 12714
2   2484 12528 33    185.59 1.115 0.2991
```

```
#p = 0.2112, we cannot reject null hypothesis, the reduced model is better.lm_pop is better
```

RANDOM EFFECTS

```
lmer.pop1 <- lmer(Popular ~ Instrument + (1|Subject), data = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))
lmer.pop2 <- lmer(Popular ~ Instrument + (1+Instrument|Subject), data = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))

anova(lmer.pop1, lmer.pop2)
#null hypothesis: full model is not significant better(reduced model is better). Alternative hypothesis: full model is significant better.

## Data: ratings_try
## Models:
## lmer.pop1: Popular ~ Instrument + (1 | Subject)
## lmer.pop2: Popular ~ Instrument + (1 + Instrument | Subject)
##           Df     AIC     BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.pop1  5 10173.9 10203.0 -5082.0  10163.9
## lmer.pop2 10  9840.8  9898.8 -4910.4   9820.8 343.16      5  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

 #lmer.pop2 is better

lmer.pop3 <- lmer(Popular ~ Instrument + Harmony + Voice + (1|Subject), data = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))
lmer.pop4 <- fitLMER.fnc(lmer.pop3, ran.effects = c("(Instrument|Subject)", "(Harmony|Subject)", "(Voice|Subject)"), method = "BIC", keep.single.factors  = TRUE)

display(lmer.pop4)

## lmer(formula = Popular ~ Instrument + Harmony + Voice + (1 |
##     Subject) + (Instrument | Subject) + (Harmony | Subject),
##     data = ratings_try, REML = TRUE, control = lmerControl(optimizer = "bobyqa"))
##                 coef.est coef.se
## (Intercept)       6.61     0.18
## Instrumentpiano  -0.95     0.16
## Instrumentstring -2.55     0.23
## HarmonyI-V-IV    -0.05     0.10
## HarmonyI-V-VI    -0.30     0.14
## HarmonyIV-I-V    -0.23     0.10
## Voicepar3rd       0.14     0.08
## Voicepar5th       0.17     0.08
```

```
##
## Error terms:
##  Groups    Name            Std.Dev. Corr
##  Subject   (Intercept)      0.02
##  Subject.1 (Intercept)      0.58
##            Instrumentpiano  1.19     -0.64
##            Instrumentstring 1.83     -0.95  0.73
##  Subject.2 (Intercept)      1.18
##            HarmonyI-V-IV    0.29      0.34
##            HarmonyI-V-VI    0.94     -0.26 -0.42
##            HarmonyIV-I-V    0.45     -0.26 -0.66 -0.39
##  Residual                   1.55

## Warning in optwrap(optimizer, devfun, x@theta, lower = x@lower, calc.derivs
## = TRUE, : convergence code 1 from bobyqa: bobyqa -- maximum number of
## function evaluations exceeded

## ---
## number of obs: 2455, groups: Subject, 70
## AIC = 9756.7, DIC = 9664.1
## deviance = 9684.4

lmer.pop4 <- lmer(Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony|Subject), data
 = ratings_try, REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))
```

FIXED EFFECTS AUTOMATIC + MANUALLY CHECKING

```
ratings_try_factored <- ratings_try %>% 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),
                              NoClass = as.factor(NoClass),
                              APTheory = as.factor(APTheory),
                              Composing = as.factor(Composing),
                              PianoPlay = as.factor(PianoPlay),
                              GuitarPlay = as.factor(GuitarPlay))

#MANUALLY CHECKING THE VARIABLES

###########Look at the boxplots
for (i in names(ratings_try%>%dplyr::select(-OMSI, -Popular, - Subject, -X16.minus.17,-Classical))) {b
oxplot(ratings_try$Popular ~ ratings_try[,i], xlab = i)}

###REvised model (manually)
lm.bic_popmanual <- lm(Popular ~ .-Subject - Classical, data = na.omit(ratings_try_factored))
#revised model(manually + auto)
stepAIC(lm.bic_popmanual, k = log(nrow((na.omit(ratings_try_factored)))))
```

```
lm.fixedpop_final <- lm(Popular ~ Instrument + Selfdeclare + OMSI + X16.minus.17 +
    ConsNotes + PachListen + ClsListen + KnowRob + X1990s2000s +
    NoClass + APTheory, data =  na.omit(ratings_try_factored))
```

random effects

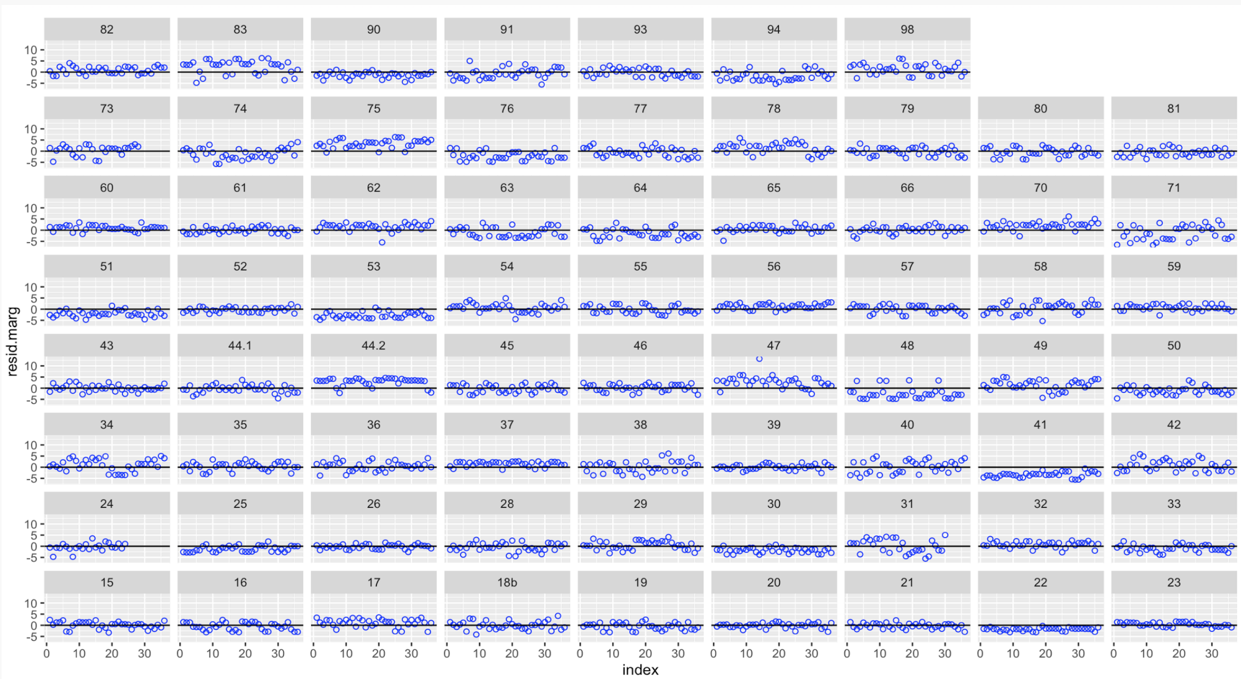
```
#Using fitLMER to do the selection
lmer.randompop <- lmer(Popular ~ Instrument + Harmony + Voice + Selfdeclare + OMSI + X16.minus.1
7 +
    ConsNotes + PachListen + ClsListen + KnowRob + X1990s2000s +
    NoClass + APTheory + (1|Subject) , data = na.omit(ratings_try_factored), REML = FALSE, control =
lmerControl(optimizer = 'bobyqa'))

## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient

lmer_random_newpop <- fitLMER.fnc(lmer.randompop, ran.effects = c("(Instrument|Subject)", "(Harmo
ny |Subject)","(Selfdeclare|Subject)", "(OMSI|Subject)", "(ConsInstr|Subject)", "(ConsNotes|Subject)", "(
PachListen|Subject)", "(ClsListen|Subject)", "(KnowRob|Subject)", "(KnowAxis|Subject)", "(X1990s200
0s| Subject)", "(X1990s2000s.minus.1960s1970s|Subject)", "(CollegeMusic|Subject)", "(NoClass|Subject)
", "(APTheory|Subject)"),  method = 'BIC')

display(lmer_random_newpop)

## lmer(formula = Popular ~ Instrument + (1 | Subject) + (Instrument |
##     Subject), data = data, REML = TRUE, control = lmerControl(optimizer = "bobyqa"))
##                  coef.est coef.se
## (Intercept)       6.88     0.19
## Instrumentpiano  -1.15     0.23
## Instrumentstring -2.93     0.27
##
## Error terms:
##  Groups    Name             Std.Dev. Corr
##  Subject   (Intercept)      0.76
##  Subject.1 (Intercept)      0.85
##            Instrumentpiano  1.31     -0.29
##            Instrumentstring 1.62     -0.61  0.74
##  Residual                   1.69
## ---
## number of obs: 1508, groups: Subject, 43
## AIC = 6135.4, DIC = 6104.7
## deviance = 6109.1

lmer_finalpop <- lmer(Popular ~ Instrument + (1+Instrument|Subject), data =na.omit(ratings_try_factore
d), REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))
lmer_finalpop2 <- lmer(Popular ~ Instrument + Harmony + Voice + (1+Instrument|Subject), data =na.o
mit(ratings_try_factored), REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))
lmer_finalpop3 <- lmer(Popular ~ Instrument + Harmony + Voice + (1+Instrument+Harmony|Subject), d
ata =na.omit(ratings_try_factored), REML = FALSE, control = lmerControl(optimizer = 'bobyqa'))

lmer_finalpop4 <- lmer(Popular ~ Instrument + Harmony + Voice + (1+Instrument+Harmony+Voice|Sub
ject), data =na.omit(ratings_try_factored), REML = FALSE, control = lmerControl(optimizer = 'bobyqa'
))
```

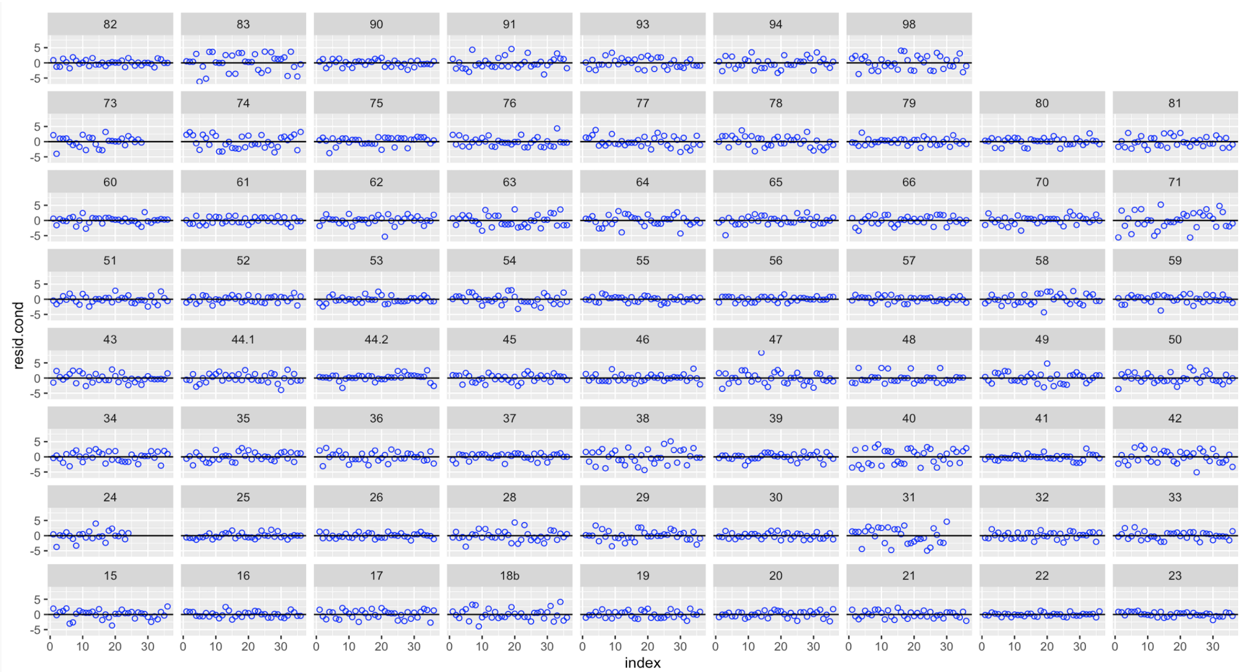
```
anova(lmer_finalpop, lmer_finalpop2, lmer_finalpop3, lmer_finalpop4)

#lmer_finalpop3 is better

## Data: na.omit(ratings_try_factored)
## Models:
## lmer_finalpop: Popular ~ Instrument + (1 + Instrument | Subject)
## lmer_finalpop2: Popular ~ Instrument + Harmony + Voice + (1 + Instrument | Subject)
## lmer_finalpop3: Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony |
## lmer_finalpop3:     Subject)
## lmer_finalpop4: Popular ~ Instrument + Harmony + Voice + (1 + Instrument + Harmony +
## lmer_finalpop4:     Voice | Subject)
##                Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer_finalpop  10 6129.1 6182.2 -3054.5   6109.1
## lmer_finalpop2 15 6121.0 6200.7 -3045.5   6091.0 18.103      5    0.00282
## lmer_finalpop3 30 6077.9 6237.5 -3009.0   6017.9 73.020     15  1.287e-09
## lmer_finalpop4 45 6095.7 6335.0 -3002.8   6005.7 12.238     15    0.66092
##
## lmer_finalpop
## lmer_finalpop2 **
## lmer_finalpop3 ***
## lmer_finalpop4


####Final Model

lmer_finalpop <- lmer(Popular ~ Harmony + Voice + Instrument + (1 + Harmony + Instrument|Subject),
data = ratings_try_factored%>%filter(!is.na(ratings_try_factored$Subject)), REML = FALSE, control = l
merControl(optimizer = 'bobyqa'))

display(lmer_finalpop)
```

Residual plots of Figure 4

```
ratings_try_factored_residual <- ratings_try_factored %>%fiilter(!is.na(ratings_try_factored$Popular))

sub <- as.numeric(ratings_try_factored_residual$Subject)
index <- sub
for (j in na.action(unique(sub))) {
  len <- sum(sub==j)
  index[sub==j] <- 1:len}

#Marginal residual plot
resid.marg <- r.marg(lmer_finalpop)
new.data <- data.frame(index,resid.marg,ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.marg","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.marg)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)

#Conditional residual plot
resid.cond <- r.cond(lmer_finalpop)
```

```
new.data <- data.frame(index,resid.cond,ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.cond","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.cond)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0

#random effect residual plot
resid.reff <- r.reff(lmer_finalpop)
new.data <- data.frame(index,resid.reff, ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.reff","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.reff)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)
```





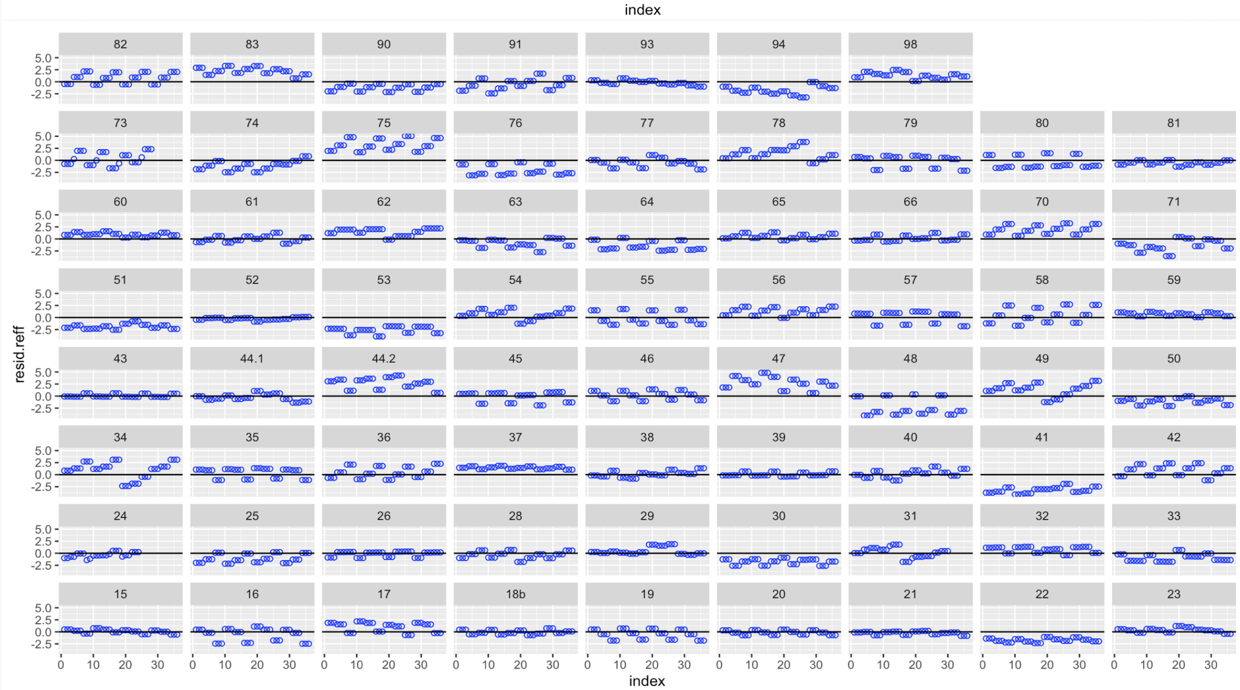


Figure 7's model

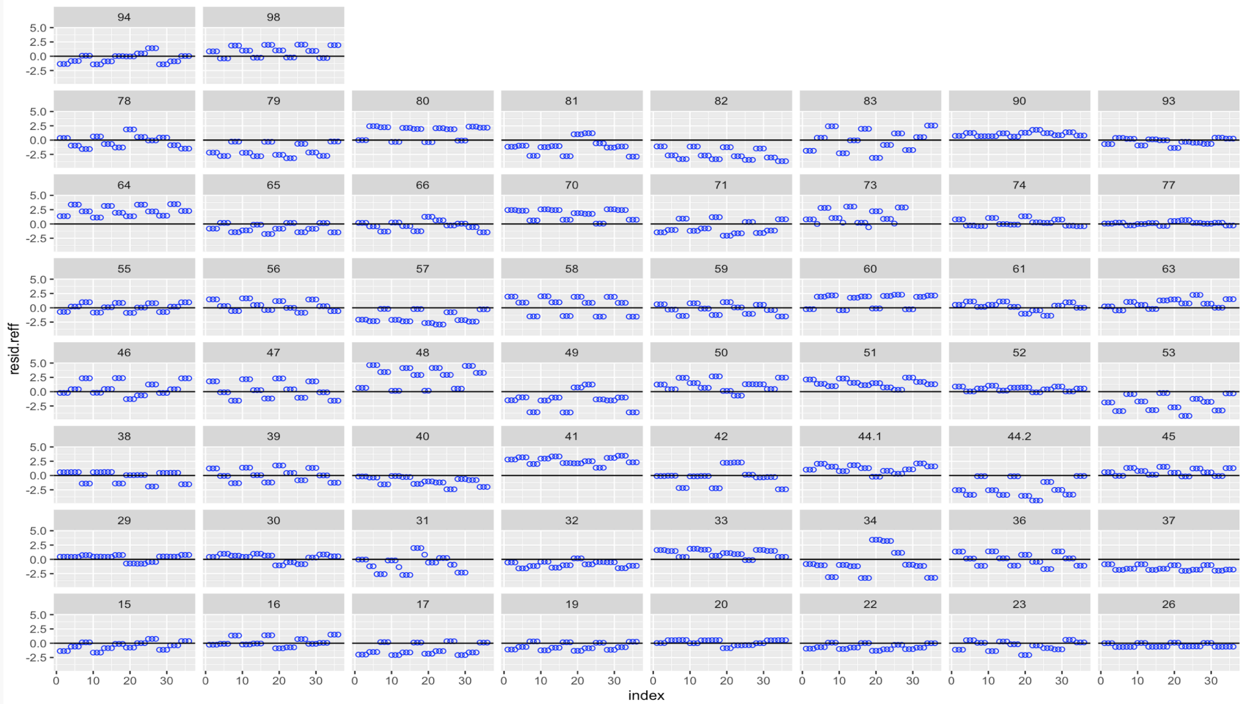
```
lmer_final_same <- lmer(Classical ~ Voice-1 + GuitarPlay + PianoPlay + Composing +
    APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
    PachListen + Instrument + Harmony + (1 + Instrument + Harmony | Subject), data = ratings_try_factor
ed, REML = FALSE, control = lmerControl(optimizer = "bobyqa"))

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

display(lmer_final_same)
```

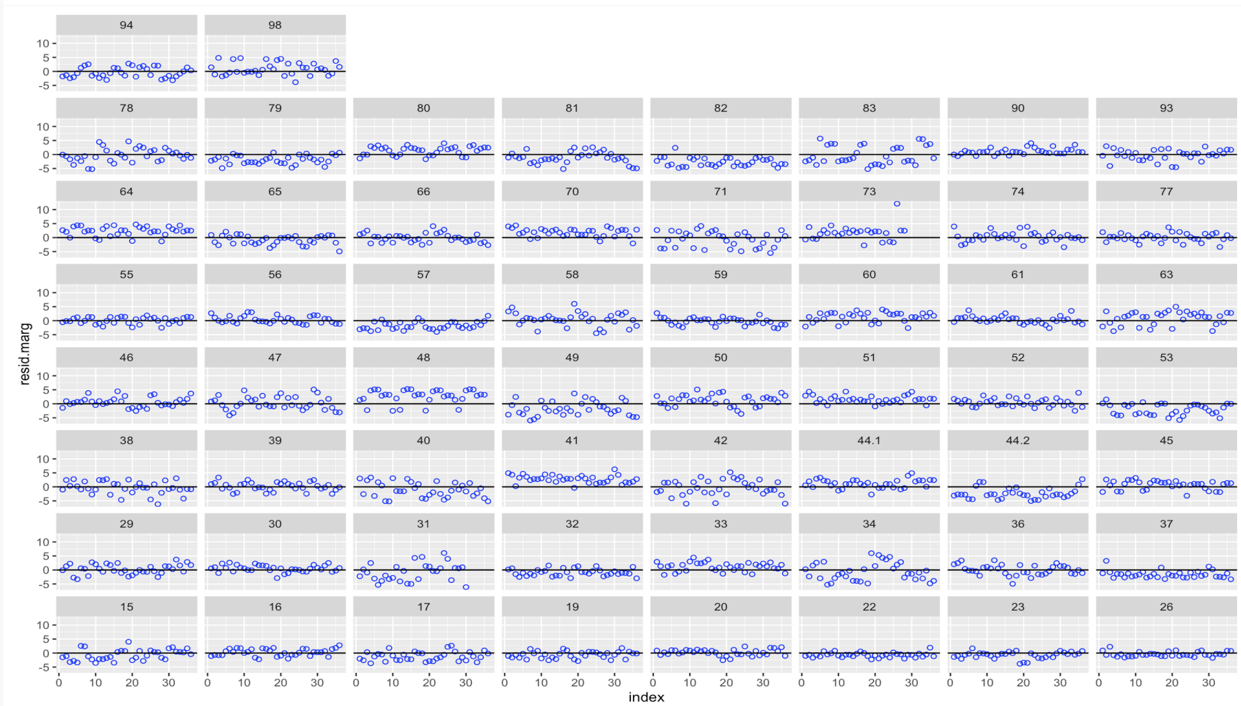
Figure 8's model

```r
#add a musician column
ratings_try_factored$Musician <- ifelse(as.numeric(ratings_try_factored$Selfdeclare) == 1 | as.numeric(
ratings_try_factored$Selfdeclare) == 2, 'non-musician', 'musician')
ratings_try_factored <- ratings_try_factored %>% select(-Selfdeclare)
#Add all the interaction terms with Musician.
lm_musician_fix <- lm(Classical ~ GuitarPlay + PianoPlay + Composing +
   APTheory + NoClass + X1990s2000s + KnowAxis + ClsListen +
   PachListen + Instrument + Harmony + Voice + Musician + GuitarPlay:Musician + PianoPlay:Musician
 + Composing:Musician + APTheory:Musician + NoClass:Musician + X1990s2000s:Musician +
   KnowAxis:Musician +ClsListen:Musician + PachListen:Musician + Instrument:Musician + Harmony:
Musician +
   Voice:Musician, data = na.omit(ratings_try_factored))
stepAIC(lm_musician_fix, direction = 'backward', k = log(nrow(na.omit(ratings_try_factored))))

#After BIC, all the fixed effects include the interaction that I choose is
lm_musician_fix_revised <- lm(Classical ~ GuitarPlay + PianoPlay + Composing +
   APTheory + NoClass + ClsListen + PachListen + Instrument +
   Harmony + Musician + Composing:Musician + ClsListen:Musician +
   Instrument:Musician + Harmony:Musician,
   data = na.omit(ratings_try_factored))


#####random effects. add an additional voice variable
lmer_random1 <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
   NoClass + X1990s2000s + PachListen + Instrument + Harmony +
   Voice + Musician + Composing:Musician + Instrument:Musician + Harmony:Musician + (1 + Instrum
ent + Harmony + Musician| Subject), data = ratings_try_factored, REML = FALSE, control = lmerContr
ol(optimizer = "bobyqa"))

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

## boundary (singular) fit: see ?isSingular

lmer_random2 <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
   NoClass + X1990s2000s + PachListen + Instrument + Harmony +
   Voice + Musician + Composing:Musician + Instrument:Musician + Harmony:Musician + (1 + Instrum
ent + Harmony + Musician| Subject) + (1|Musician), data = ratings_try_factored, REML = FALSE, contr
ol = lmerControl(optimizer = "bobyqa"))

## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
## boundary (singular) fit: see ?isSingular

lmer_random3 <- lmer(Classical ~ GuitarPlay + PianoPlay + Composing +
   NoClass + X1990s2000s + PachListen + Instrument + Harmony +
   Voice + Musician + Composing:Musician + Instrument:Musician + Harmony:Musician + (1 + Instrum
ent + Harmony| Subject), data = ratings_try_factored, REML = FALSE, control = lmerControl(optimizer
 = "bobyqa"))

## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
## boundary (singular) fit: see ?isSingular
```

```
#Accoording to this anova, lmer_random1 is better
anova(lmer_random1, lmer_random2, lmer_random3)

display(lmer_random1)
```

Figure 8’s residual plots






```
ratings_try_factored_residual <-ratings_try_factored%>%filter(!is.na(ratings_try_factored$Classical)&!is
.na(GuitarPlay)&!is.na(PianoPlay)&!is.na(Composing)&!is.na(NoClass)&!is.na(X1990s2000s)&!is.na(P
achListen)&!is.na(Musician))

sub <- as.numeric(ratings_try_factored_residual$Subject)
index <- sub
for (j in na.action(unique(sub))) {
  len <- sum(sub==j)
```

```
  index[sub==j] <- 1:len}

#Marginal residual plot
resid.marg <- r.marg(lmer_random1)
new.data <- data.frame(index,resid.marg,ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.marg","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.marg)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)

#Conditional residual plot
resid.cond <- r.cond(lmer_random1)
new.data <- data.frame(index,resid.cond,ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.cond","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.cond)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0

#random effect residual plot
resid.reff <- r.reff(lmer_random1)
new.data <- data.frame(index,resid.reff, ratings_try_factored_residual$Subject)
names(new.data) <- c("index","resid.reff","subject")
ggplot(ratings_try_factored_residual,aes(x=index,y=resid.reff)) +
  facet_wrap( ~ Subject, as.table=F) +
  geom_point(pch=1,color="Blue") +
  geom_hline(yintercept=0)
```