1 a 9/9
b 8/9
c 7/9

2 a 9/9
b 8/9
c 9/9

3 9/9

4 a 9/9
b 9/9
c 7/9

5 10/10

Total 94/100

36-763: Homework 5

Joe Pane

Due on Friday December 18 @ 11:59pm

1 Exercise 1

(a) Examine the influence of the three main experimental factors (Instrument, Harmony & Voice) on Classical ratings, using conventional linear models and/or analysis of variance models. Comment briefly on your findings, providing suitable brief evidence for each result.

Solution:

We fit every combination of the experimental factors (Harmony, Instrument, and Voice) and compared the AIC and BIC values to determine which model is best. Before we fit our models, we checked for NA values in ratings and eliminated them to start. After we fit the models, we compared AIC and BIC. The full model (Harmony, Instrument, and Voice) had the lowest BIC value and the lowest AIC value.The full model (BIC: 11282.84) barely had the minimum BIC, the model with Harmony and Instrument was very close (11283.43). We believe that the full model is the best model based off of these metrics. Summary output for the full model is in Table 2.

Table 1: AIC and BIC Values For All lm Models

	H, I, V	H, I	H, V	H	I, V	I	V
AIC	11230.45	11242.69	11908.94	11917.23	11275.96	11287.86	11942.32
BIC	11282.84	11283.43	11949.69	11946.34	11310.89	11311.14	11965.61

Table 2: Summary Results from the Full Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.3402	0.1299	33.42	0.0000
HarmonyI-V-IV	-0.0311	0.1301	-0.24	0.8112
HarmonyI-V-VI	0.7691	0.1301	5.91	0.0000
HarmonyIV-I-V	0.0501	0.1300	0.39	0.7001
Instrumentpiano	1.3736	0.1130	12.16	0.0000
Instrumentstring	3.1331	0.1123	27.90	0.0000
Voicepar3rd	-0.4125	0.1127	-3.66	0.0003
Voicepar5th	-0.3706	0.1126	-3.29	0.0010

9

The majority of all of the levels in the three variables are significant and the adjusted r-squared is highest in the first model compared to all of the other models, meaning the the proportion of the variance explained in classical ratings is attributed most in the full model. We look at boxplots of Classical ratings versus the the three categorical variables and their categories. One major point we notice is the outlier showing up at 19. This is interesting and considering that the values are only supposed to be from 1 through 10 we have reason to think that this data point is an error. There are several things we could do with this data point. We do not want to delete it because 1 and 9 are not next to each other on the keyboard of any computer and thus it probably is not a data entry error. We think that the user was trying to be smart and actually meant to put 19. Therefore, leaving it as a 19 will account for an even higher rating. We never believe it is a good thing to delete a data point so that is why we are not deleting it. There are enough observations in the dataset where leaving it in as a 19 should not hurt We notice there is not much difference in harmony and voice across the categories but instrument has noticeable differences in classical ratings across instrument. Figure 1 shows these boxplots.

good discussion

there are arguments for recoding this as a 10 (9 and 0 are adjacent on kbd) or just deleting it...

leaving it in is an option, but i could end up being a high leverage point in regressions...

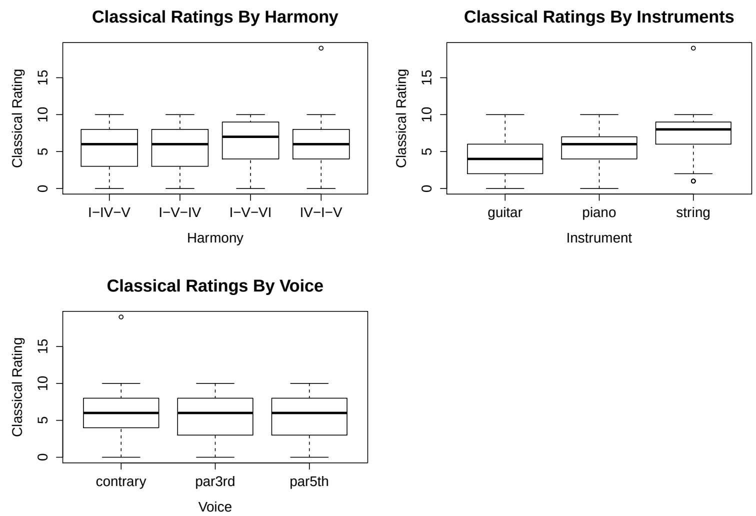

Figure 1: Boxplots of Classical Ratings by Harmony, Instrument, and Voice

The diagnostic plots for the full model are shown. We have reason to believe that the constant variance assumption may be violated. The errors look normal based off the QQ plot. Finally, there are a few high Cook's Distance points that may be potential outliers. We have no reason to believe that these points should not be in the dataset so we cannot remove them from our analysis.

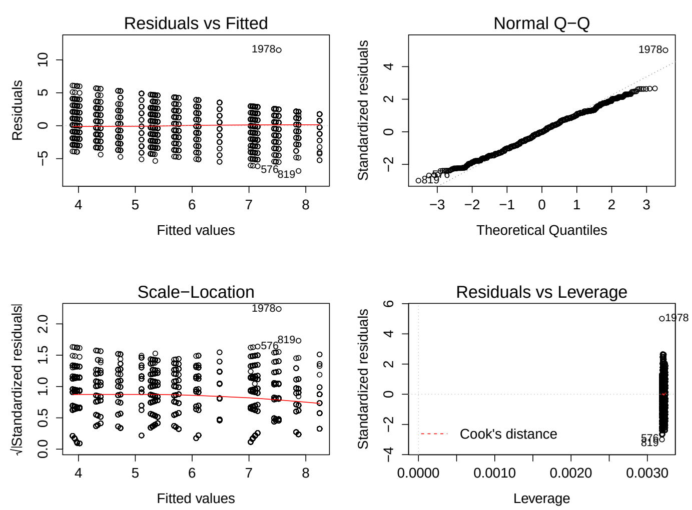

Figure 2: Diagnostic Plots for the Full Model

(b) Since we have approximately 36 ratings from each participant, we can fit a random intercept for each participant if we wish. Such a model is called a "repeated measures" model.

(i) Carefully write this model in mathematical terms as a hierarchical linear model.

Solution:

$$Classical_i = \alpha_{j[i]} + \beta_1(Harmony) + \beta_2(Instrument) + \beta_3(Voice) + \epsilon_i$$
$$\epsilon_i \sim Normal(0, \sigma^2)$$
$$\alpha_j \sim \beta_0 + \eta_j$$
$$\eta_j \sim Normal(0, \tau^2)$$

ok, if H, I and V are also indexed by i (since they change across observations...)

(ii) Use at least two different methods to test whether the random intercept is needed in the model. Is the random effect needed? Justify your answer with evidence from your tests.

Solution:

We fit the random intercept model using the following code in R and it provided the following summary output:

```
lmer_1 <- lmer(Classical ~ Harmony + Instrument +
                 Voice + (1 | Subject), data=ratings_classical)
lmer(formula = Classical ~ Harmony + Instrument +
    Voice + (1 | Subject), data = ratings_classical)
                            coef.est coef.se
(Intercept)                  4.34     0.19
Harmony)I-V-IV    -0.03     0.11
Harmony)I-V-VI     0.77     0.11
Harmony)IV-I-V     0.05     0.11
Instrumentpiano   1.38     0.09
Instrumentstring  3.13     0.09
Voicepar3rd      -0.42     0.09
Voicepar5th      -0.37     0.09

Error terms:
 Groups   Name        Std.Dev.
 Subject  (Intercept) 1.30
 Residual             1.89
---
number of obs: 2493, groups: Subject, 70
AIC = 10491.5, DIC = 10426.2
deviance = 10448.9
```

Notice that the AIC and BIC values for the lmer model are both lower than the AIC and BIC values for the fixed effect model fit with lm in R. The AIC and BIC values for the random effect model fit in lmer are 10491.51 and 10549.73, respectively. These are lower than the AIC and BIC values from the fixed effect model of 11230.45 and 11282.84, respectively. Based off of this method, we believe that the random effect model fit in lmer is a better model.

In addition, the second way we analyzed the random intercept model was by plotting the conditional, marginal, and random effect residuals. We compared these residuals to the residuals from Figure 2 in the linear model. For the most part it seems that the residuals are centered

ok. would like to see a second formal testing method....

at zero and do not show any apparent patterns in any of the plots. These look as good if not better than the linear model fit in number 1 and diagnostics shown in Figure 1.

Therefore, we will choose the random intercept model on subject as the best model. Plots of the conditional, marginal, and random effect residuals are below, in their respective orders (Figure 3, Figure 4, and Figure 5).

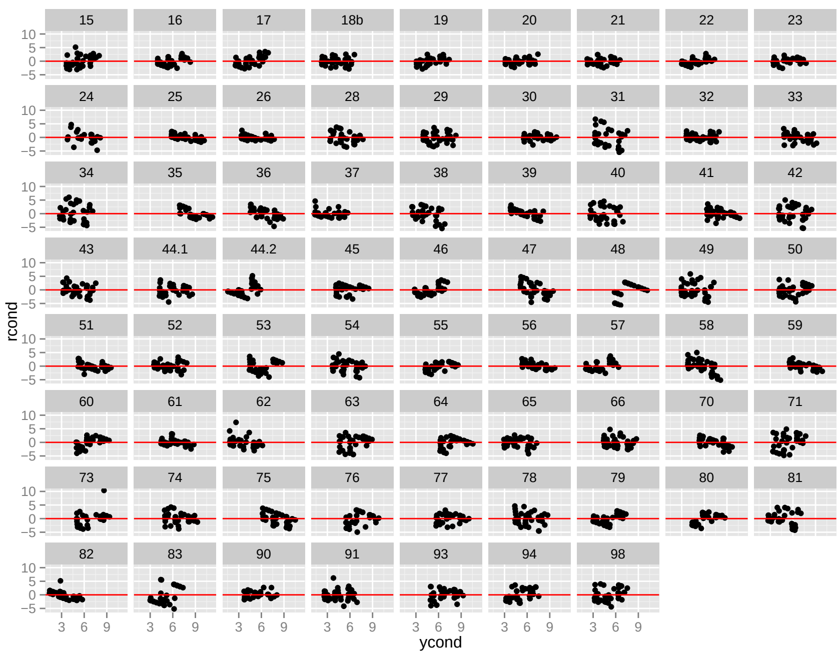

Figure 3: Conditional Residuals

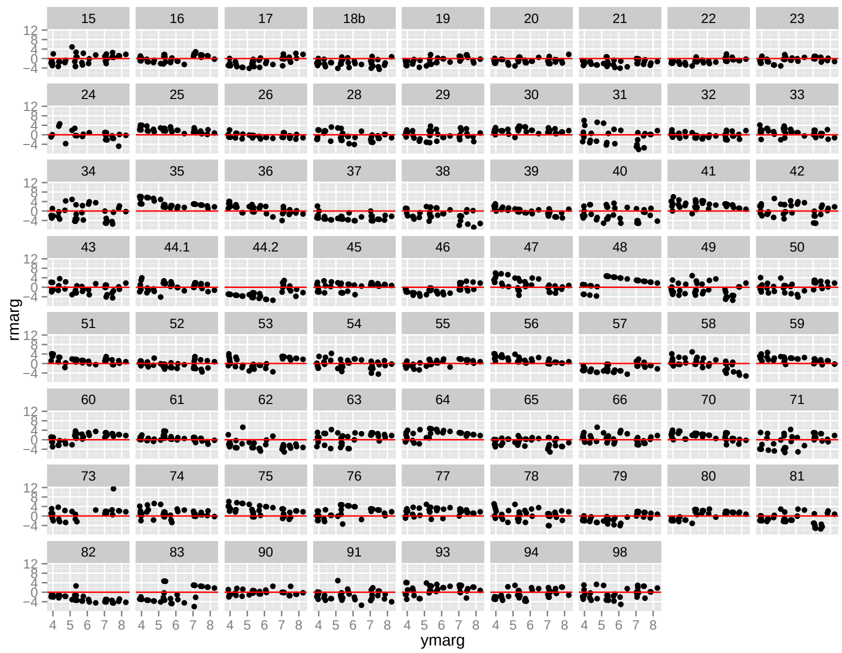

Figure 4: Marginal Residuals

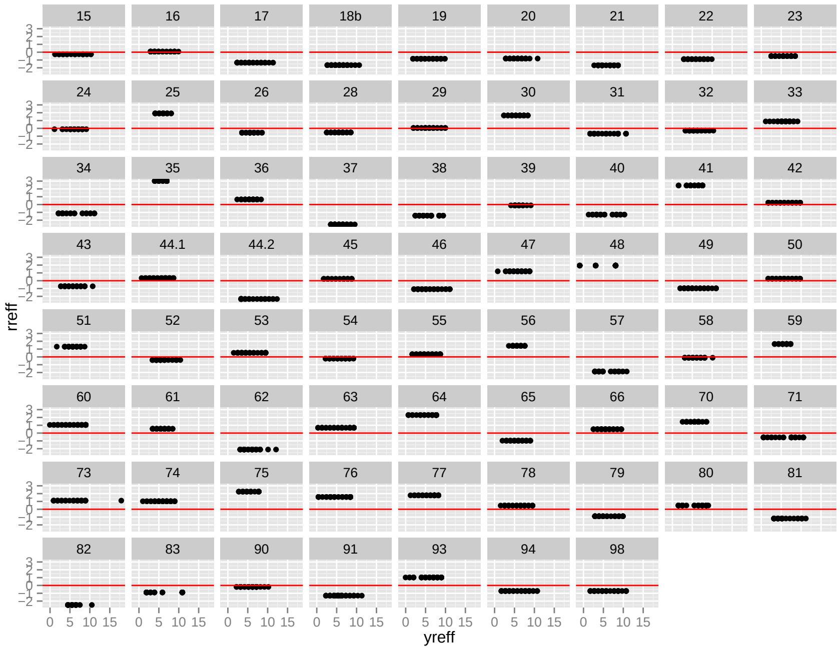

Figure 5: Random Effect Residuals

(iii) Re-examine the influence of the three main experimental factors (Instrument, Harmony & Voice) on Classical ratings, using the repeated-measures model with the random intercept for participants.

Solution:

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We look at all different combinations of Harmony, Instrument, and Voice with the random effect being Subject. For all of these models we calculate the AIC and BIC. We see that the full model (with Harmony, Instrument, and Voice) has the lowest AIC and BIC values, as we can see in Table 3. Output for the full lmer model is above in part ii of this problem. At this point, the repeated measures model containing harmony, instrument, and voice with subject as the random intercept is our best model thus far.

Table 3: AIC and BIC Values For All lmer Models

	H, I, V	H, I	H, V	H	I, V	I	V
AIC	10491.51	10505.58	11423.04	11429.98	10552.74	10566.14	11461.42
BIC	10549.73	10552.15	11469.6	11464.91	10593.49	10595.25	11490.53

(c) (i)

Solution:

We fit the lmer model with multiple random slopes below. The summary output for the model is below as well. We calculated the AIC and BIC values for this model and see that the AIC (10075.51) and the BIC (10145.37) are both lower than any of the models that we have fit thus far. Therefore, we can conclude that the lmer model with multiple random slopes for each category does better than any of the other models we have fit thus far in 1a and 1b according to the AIC and BIC.

```
lmer(formula = Classical ~ Harmony + Instrument +
    Voice + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
    (1 | Subject:Voice), data = ratings_classical)
                            coef.est coef.se
(Intercept)                  4.34     0.21
HarmonyI-V-IV    -0.03     0.14
HarmonyI-V-VI     0.77     0.14
HarmonyIV-I-V     0.06     0.14
Instrumentpiano   1.36     0.26
Instrumentstring  3.13     0.26
Voicepar3rd      -0.41     0.08
Voicepar5th      -0.37     0.08

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.67
 Subject:Instrument (Intercept) 1.48
 Subject:Voice      (Intercept) 0.17
 Residual                       1.56
---
number of obs: 2493, groups: Subject:Harmony, 280; Subject:Instrument, 210; Subject:Voice, 210
AIC = 10075.5, DIC = 10015.5
deviance = 10033.5
```

(ii)

Solution:

We first fit all of the possible models of Classical Ratings versus Harmony, Instrument, and Voice where we have a random intercept that is equal to the subject to account for the personal biases in the problem. At this point we fit all possible lmer multiple intercept models and again, the full model, that is the model of Classical ratings against all of the experimental fixed effects (Harmony, Instrument, and Voice) with random intercept accounting for all of the subjects personal biases of the different experimental factors, had the lowest AIC and BIC models. We will continue using this as our most updated model. The results for this model are shown in part (i).

In order to comment on the sizes of the three estimated variance components we first need to discuss what the three estimated variance components are. These components are each how much the experimental factor (harmony, instrument, and voice) varies by subject. Looking at the summary results from the lmer model we fit in part (i), we notice that the variance for the average intercept for a subject is .44307, which means how much the intercept is shifted to determine if harmony effects a subjects classical rating. Similarly, 2.20 is the variance for the average intercept for a subject; this shows how much the intercept is shifted to determine if instrument effects a subjects classical rating. We also notice that the variance for the average intercept for a subject is .02 which shows how much the intercept is shifted to determine if voice effects a subjects classical rating. The instrument random effect accounts for 2.2 out of the 2.44 total variance in the models random effects. Therefore, it seems that whatever instrument a user is playing will determine if someone thinks it is classical or not. We can see that the variance is highest between groups in the boxplots we plotted (Figure 1) in part 1a.

Table 4: AIC and BIC Values For All lmer Multiple Intercept Models

	H, I, V	H, I	H, V	H	I, V	I	V
AIC	10075.51	10092.66	10176.17	10194.3	10101.74	10118.89	10204.66
BIC	10145.37	10150.87	10234.38	10240.87	10154.13	10159.64	10245.41

(iii)

Solution:

We will use the full model (the model with the lowest AIC and BIC):

$$Classical_i = \alpha_{j[i]} + \beta_1(Harmony_i) + \beta_2(Instrument_i) + \beta_3(Voice_i) + \epsilon_i$$

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$$\epsilon_i \sim Normal(0, \sigma^2)$$

$$\alpha_j \sim \beta_0 + \eta_{0j} + \eta_{1j} + \eta_{2j}$$

$$\eta_{0j} \sim Normal(0, \tau_0^2)$$

fine, but the etas need to be indexed by the levels of trhe experimental factors (as well as by j

$$\eta_{1j} \sim Normal(0, \tau_1^2)$$

$$\eta_{2j} \sim Normal(0, \tau_2^2)$$

2 Exercise 2

(a) **Solution:**

We are going to take a brief look at all of the variables so we can appropriately consider all covariates given to us in the dataset. Some of these variables will need to be treated as factors, and some may have missing data that we should appropriately deal with. For lack of time, we will not use a method like multiple imputation or something similar but in the future we may want to consider this. We will explore several different variables that we think will be significant in our model:

- Selfdeclare

  There are no NA values in selfdeclare. The only change we made was making selfdeclare a factor.

- OMSI

  There are no NA values in OMSI.

- X16.minus.17

  There are no NA values in X16.minus.17

- ConsInstr

  There are no NA values in ConsInstr, but people did not answer with whole numbers so I am going to recode this variable. Any value inbetween two numbers will be rounded.

That is, .67 will be labeled as a 1 and 1.33 will be a 0. We used the round function in R to perform this analysis and recode ConsInstr. We then made ConsInstr a factor variable.

- ConsNotes

  There are 360 NA values in the ConsNotes variable. In order to handle the NA values, we will make them a zero because if they did not answer we can most likely assume that they did not use the notes at all. This is not an ideal answer to handling missing values, but it is a reasonable one. We then made this variable a factor.

- ClsListen

  There are 24 NA values in ClsListen. Again, I will code these 24 values as zeroes because they if they did not answer the question then we believe that it is reasonable to assume that they don't listen to classical music. We made this variable a factor.

- CollegeMusic

  There were 96 NA values in CollegeMusic. We have reason to believe that they did not take a college music class if they did not answer the question. Obviously these ways of handling missing data are not ideal but we have reason to believe that these reasons for the missing data are valid. CollegeMusic was made as a factor.

- APTheory

  There were 204 NA values. Again, we will set the NAs equal to zero. They probably either did not know what the AP test was or they did not take the exam. We made APTheory a factor variable.

- Composing

  There were 72 NA values in Composing. If they did not answer the question we have reason to believe that they did not do any music composing so I just set them to zero.

- New Variable: *playinstr*

  We analyzed the ratings given for playing one instrument and playing a second instrument. There were a lot of missing values in both of these variables. As a result, we decided to drop the rating variables and simply take the information of them playing one music instrument, two instruments, or no instruments and making it a categorical variable. But first, let's double check to see if all of the people who rated a second instrument actually played a first instrument. Like we said, these ratings are not necessarily useful because of the many NA values and we do not want to omit all of the observations that do not play an instrument. We will instead make a variable that says if a user played one instrument, two instruments, or did not play any instrument. This variable is known as *playinstr*.

  ok

We are now ready to fit models by adding all of these variables as fixed effects and do model selection by exploring different combinations of the fixed effects. We will use our best model from part number 1 (part 1(c)) as our starting point and add different combinations of fixed effects. We then will compare our AIC and BIC values to determine our best model. As usual, all of our models are attached in the appendix. We have included the results for the best model fit based off of AIC and BIC.

We fit many different models; the first model we fit contained all of the covariates we were interested in. The added fixed effects we were interested in are the following (1) Are you a musician? (1-6, 1=not at all), (2) Score on a test of musical knowledge, (3) Auxiliary measure of listener?s ability to distinguish classical vs popular music, (4) How much did you concentrate on the instrument while listening (0-5, 0=not at all), (5) How much did you concentrate on the notes while listening? (0-5, 0=not at all), (6) How much do you listen to classical music? (0-5, 0=not at all), (7) Have you taken music classes in college (0=no, 1=yes), (8) Did you take AP Music Theory class in High School (0=no, 1=yes), (9) Have you done any music composing (0-5, 0=not at all), and (10) how many instruments do you play (1, at least 2, or none). We explored the distribution of the continuous variables. The only continuous variables were 2 and 3. The scores on a test of musical knowledge were skewed right and thus we used a log transformation. This improved the AIC and BIC considerably but we later found that it was not worth it to include the scores on a test of musical knowledge in this model. There were other variables like if someone took an AP Music Theory test that explained more variation in the model.

After exploring many different combinations of models (see the Appendix), we wanted to compare the BIC values of the model from number 1 to the best model we selected for this question. The AIC and BIC values can be found in Table 5. We notice that the AIC for the best model in problem 2 (accounting for many fixed effects) is better than the AIC in the model from problem 1. However, the BIC is lower for the model from problem 1. We know that BIC tends to favor smaller models; considering this and the fact that we want to be able to account for other variables or potential confounders, we will choose the best model we found in this exercise that accounts for several other covariates. Therefore, we will proceed with our analysis using the combined model from problem 1(c) and the added selected covariates. Added model output for the best model is below:

Table 5: AIC and BIC Values For Best lmer Model From 1 vs. Best lmer Fixed effect Model from 2

	Best lmer Model from 1	Best fixedeffect Model from 2
AIC	10075.51	10064.54
BIC	10145.37	10198.43

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ SelfDeclare_factor + X16.minus.17 + APTheory2 +
 Composing2 +
    Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 |      Subject:Instrument) + (1 | Subject:Voice)
   Data: ratings_classical

REML criterion at convergence: 10018.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3906 -0.5786 -0.0005  0.5460  5.7059

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.43873  0.6624
 Subject:Instrument (Intercept) 1.90887  1.3816
```

```
 Subject:Voice      (Intercept) 0.02742  0.1656
 Residual                       2.43854  1.5616
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument,
210; Subject:Voice, 210

Fixed effects:
                    Estimate Std. Error t value
(Intercept)          4.84390    0.29496  16.422
SelfDeclare_factor2 -0.97971    0.29934  -3.273
SelfDeclare_factor3 -0.63521    0.37353  -1.701
SelfDeclare_factor4 -1.26846    0.40685  -3.118
SelfDeclare_factor5 -1.69200    0.76304  -2.217
SelfDeclare_factor6 -0.92021    0.98786  -0.932
X16.minus.17        -0.11327    0.03911  -2.896
APTheory21           0.56545    0.31425   1.799
Composing21          0.59256    0.42252   1.402
Composing22          1.30148    0.38626   3.369
Composing23         -0.04598    0.50720  -0.091
Composing24          1.26989    0.41865   3.033
HarmonyI-V-IV       -0.02960    0.14275  -0.207
HarmonyI-V-VI        0.77120    0.14274   5.403
HarmonyIV-I-V        0.05635    0.14268   0.395
Instrumentpiano      1.36700    0.24604   5.556
Instrumentstring     3.12750    0.24574  12.727
Voicepar3rd         -0.40690    0.08164  -4.984
Voicepar5th         -0.37113    0.08158  -4.550

Correlation of Fixed Effects:
            (Intr) SlfD_2 SlfD_3 SlfD_4 SlfD_5 SlfD_6 X16..1 APTh21 Cmps21 Cmps22 Cmps23
            Cmps24 HI-V-I HI-V-V
SlfDclr_fc2 -0.601
SlfDclr_fc3 -0.438  0.525
SlfDclr_fc4 -0.386  0.505  0.522
SlfDclr_fc5 -0.204  0.291  0.292  0.259
SlfDclr_fc6 -0.128  0.177  0.152  0.214  0.043
X16.mins.17 -0.225  0.107 -0.022  0.005 -0.128 -0.126
APTheory21  -0.073 -0.059 -0.053 -0.313  0.135 -0.294 -0.013
Composing21 -0.011 -0.178 -0.154 -0.073 -0.358  0.089  0.101 -0.333
Composing22 -0.051 -0.058 -0.278 -0.312 -0.056  0.009 -0.143  0.108  0.113
Composing23  0.025 -0.115 -0.281 -0.196 -0.067  0.033 -0.174 -0.018  0.125  0.229
Composing24 -0.023 -0.103 -0.279 -0.330 -0.338  0.017  0.027 -0.047  0.244  0.257  0.197
HrmnyI-V-IV -0.241 -0.001 -0.001 -0.001  0.000  0.000  0.001  0.000  0.000  0.002  0.000
0.000
HrmnyI-V-VI -0.242  0.000 -0.001  0.000  0.000  0.000  0.000  0.000  0.000  0.001  0.000
0.000  0.499
HrmnyIV-I-V -0.242  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.001  0.000
0.000  0.500  0.500
Instrumntpn -0.417 -0.001  0.001  0.000  0.000 -0.001  0.000  0.002  0.002  0.001  0.000
0.000  0.000  0.000
Instrmntstr -0.417  0.001  0.001  0.001  0.001  0.000 -0.001  0.000  0.000 -0.002  0.000
0.000  0.000  0.000
Voicepar3rd -0.138 -0.001 -0.001 -0.001 -0.001  0.000  0.001  0.000  0.000  0.001  0.000
0.000 -0.002  0.001
Voicepar5th -0.137  0.000 -0.001  0.000  0.000  0.000  0.001  0.000 -0.001  0.000  0.000
```

```
0.000 -0.001 -0.002
           HIV-I- Instrmntp Instrmnts Vcpr3r
SlfDclr_fc2
SlfDclr_fc3
SlfDclr_fc4
SlfDclr_fc5
SlfDclr_fc6
X16.mins.17
APTheory21
Composing21
Composing22
Composing23
Composing24
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Instrumntpn  0.000
Instrmntstr  0.000  0.500
Voicepar3rd  0.002 -0.001     0.000
Voicepar5th -0.001 -0.001     0.000     0.500
```

9

(b) **Solution:**

We look at our model from 2(a), the model with the subject random intercept and all three (harmony, instrument, and voice) random intercepts and compare it to the same model in terms of fixed effects but where there are no random intercepts other than the subject. We compare the AIC and BIC values for these models and conclude that we should keep the three (harmony, instrument, and voice) random intercepts in the model. As we can see in Table 6, the AIC value is lower by a magnitude of over 400 for the multiple random intercept (including harmony, instrument, and voice) in addition to the subject. In addition, the BIC is lower by a magnitude of over 450. Therefore, we will proceed in our analysis with the model from 2(a).

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Table 6: AIC and BIC Values For All random intercepts vs. only subject random intercept model

	Subj + (Har, Ins, Voi) Rand Int.	Only Subj Rand Int.
AIC	10064.54	10490.79
BIC	10198.43	10613.03

might also check the three individual groups of random effects....

(c) **Solution:**

very thorough

Interpretation of Fixed Effects:

9

- On average, the classical rating for a person who self-declared as a 2 from a scale from 1 to 6 on whether they are a musician or not is .98 less than a person who did not self-declare as a musician (put a 1), holding all other variables in the model constant. In addition, the classical rating for a person who self-declared as a 3 on whether they are a musician or not is .63 less on average compared to a person who did not self-declare as a musician, holding all other variables constant. The classical rating for a person who self-declared as a 4 on whether they are a musician or not is 1.26 less than someone who did not self declare as musician, holding all other variables in the model constant. The classical rating for a person who self-declared as a 5 on whether they are a musician or not is 1.69 less than someone who did not self declare as musician, holding all other variables in the model constant. The classical rating for a person who self-declared as a 6 on whether they are a musician or not is .92 less than someone who did not self declare as musician, holding all other variables in the model constant.

- For each additional unit increase in the "Auxiliary measure of listener?s ability to distinguish classical vs popular music", the classical rating decreases by .11 on average, holding all other variables in the model constant.

- A person who took the AP music theory test has a .57 higher rating on average than a person who did not take the AP music theory test, holding all other variables in the model constant.

- A person who said their composing was a 1 on the scale (on a scale from 0 to 5 where 0 means the person did no composing at all) has a classical rating .59 higher, on average compared to a person who reported not being a composer at all, holding all other variables in the model constant. A person who said their composing was a 2 on the scale has a classical rating 1.3 higher, on average compared to a person who reported not being a composer at all, holding all other variables in the model constant. A person who said their composing was a 3 on the scale has a classical rating .05 lower, on average compared to a person who reported not being a composer at all, holding all other variables in the model constant. A person who said their composing was a 4 on the scale has a classical rating 1.26 higher, on average compared to a person who reported not being a composer at all, holding all other variables in the model constant.

- A harmonic motion of I-V-IV has a classical rating .03 lower than a harmonic motion of I-IV-V, on average holding all other variables constant. A harmonic motion of I-V-VI has a classical rating .77 higher than a harmonic motion of I-IV-V, on average holding all other variables constant. A harmonic motion of IV-I-V has a classical rating .06 higher than a harmonic motion of I-IV-V, on average holding all other variables constant.

- A piano has a classical rating 1.37 higher on average than a guitar, holding all other variables constant. A string instrument has a classical rating 3.13 higher on average than a guitar, holding all other variables constant.

- A voice of par3rd has a classical rating .41 lower on average than a contrary voice, holding all other variables in the model constant.

Interpretation of Random Effects:

- The random effect we get from harmony takes into account .44 of the 2.44 random effect variance for a subject who is trying to determine how classical a piece of music is.

- The random effect we get from instrument takes into account 1.91 of the 2.44 random effect variance for a subject who is trying to determine how classical a piece of music is.

- The random effect we get from voice takes into account .03 of the 2.44 random effect variance for a subject variance for a subject who is trying to determine how classical a piece of music is.

- These random effect variances are determining how much a subject's intercept shifts when using harmony, instrument, or voice to determine whether a piece of music is classical.

3 Exercise 3: Musicians vs. Non-Musicians

After Dichotomizing self-declare, anyone who reported a 2 or lower is declared as not considered a self-declared musician. Anyone who reported greater than a 2 is considered a self-declared musician. This was as close to a 50-50 breakdown we could get. There are 1499 subjects considered as non-proclaimed musicians and 994 subjects considered as self-proclaimed musicians. We will use R to see if we should add any interactions in the model.

there are not that many subjects in the data set so you must mean something else

We take our best model after adding the fixed effects and use the dichotomized version of the self-declare variable. We tested several different interaction models (see code in Appendix) and compared the AIC and BIC values to the best model from number 2. Table 7 reports the AIC and BIC values for the model from number 2 but now using the dichotomized version of the self-declare variable and the best interaction model.

Table 7: AIC and BIC Values For 2(c) model Using Dichotomized Self-declared vs. Best Interaction Model

	2(c) model Using Dichotomized Self-declared	Best Interaction Model
AIC	10073.04	10069.66
BIC	10189.47	10191.91

We see that the AIC is better by a magnitude of 7 when including two interactions in the model. The only interaction that we ended up including was Auxiliary measure of listener?s ability to distinguish classical vs popular music with self-declared musician. The AIC of the interaction model is smaller by a factor of 4. The BIC is higher for the interaction model by a factor of 2. We suspect this because BIC prefers a less complex model. We were going to also include the interaction of self-declared musician and composing but lmer gave us a warning that said that the model was rank deficient. The interaction model output is below:

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ SelfDeclare2 * X16.minus.17 + APTheory2 + Composing2 +
    Harmony + Instrument + Voice + (1 | Subject:Harmony) + (1 |      Subject:Instrument)
    + (1 | Subject:Voice)
   Data: ratings_classical

REML criterion at convergence: 10027.7

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3201 -0.5723 -0.0044  0.5467  5.7173

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4395   0.6629
 Subject:Instrument (Intercept) 1.9472   1.3954
 Subject:Voice      (Intercept) 0.0275   0.1658
 Residual                       2.4384   1.5615
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210;
 Subject:Voice, 210

Fixed effects:
                           Estimate Std. Error t value
(Intercept)                 4.20889    0.23855  17.644
```

```
SelfDeclare21               0.20667    0.32156   0.643
X16.minus.17               -0.02740    0.04673  -0.586
APTheory21                  0.21073    0.30489   0.691
Composing21                 0.32720    0.39761   0.823
Composing22                 1.23202    0.38607   3.191
Composing23                 0.33254    0.53174   0.625
Composing24                 1.01339    0.41063   2.468
Composing25                 0.71121    1.00941   0.705
HarmonyI-V-IV              -0.02963    0.14283  -0.207
HarmonyI-V-VI               0.77117    0.14281   5.400
HarmonyIV-I-V               0.05638    0.14275   0.395
Instrumentpiano             1.36613    0.24826   5.503
Instrumentstring            3.12739    0.24796  12.613
Voicepar3rd                -0.40690    0.08165  -4.983
Voicepar5th                -0.37108    0.08159  -4.548
SelfDeclare21:X16.minus.17 -0.25547    0.08744  -2.922

Correlation of Fixed Effects:
            (Intr) SlfD21 X16..1 APTh21 Cmps21 Cmps22 Cmps23 Cmps24 Cmps25
             HI-V-I HI-V-V HIV-I- Instrmntp
SelfDeclr21 -0.213
X16.mins.17 -0.228  0.216
APTheory21  -0.107 -0.275 -0.117
Composing21 -0.155 -0.059  0.099 -0.294
Composing22 -0.109 -0.305 -0.104  0.068  0.148
Composing23 -0.092 -0.037  0.047 -0.100  0.138  0.214
Composing24 -0.101 -0.334  0.020 -0.037  0.191  0.275  0.204
Composing25 -0.005 -0.002  0.030 -0.273  0.144  0.127  0.187  0.143
HrmnyI-V-IV -0.299  0.000  0.001  0.000  0.000  0.002  0.000  0.000  0.000
HrmnyI-V-VI -0.299  0.000  0.000  0.000  0.000  0.001  0.000  0.000  0.000  0.499
HrmnyIV-I-V -0.299  0.000  0.001  0.000  0.000  0.001  0.000  0.000  0.000  0.500
0.500
Instrumntpn -0.521  0.001  0.000  0.002  0.002  0.001  0.000 -0.001 -0.001  0.000
  0.000  0.000
Instrmntstr -0.520  0.000 -0.001  0.000  0.000 -0.002  0.000  0.000  0.000  0.000
0.000  0.000  0.500
Voicepar3rd -0.171  0.000  0.001  0.000  0.000  0.001  0.000  0.000  0.000 -0.002
0.001  0.002 -0.001
Voicepar5th -0.170 -0.001  0.001  0.000 -0.001  0.000  0.000  0.000  0.000 -0.001
-0.002 -0.001 -0.001
SD21:X16..1  0.111 -0.539 -0.556  0.256 -0.051 -0.002 -0.310 -0.013 -0.236 -0.001
0.000  0.000  0.000
            Instrmnts Vcpr3r Vcpr5t
SelfDeclr21
X16.mins.17
APTheory21
Composing21
Composing22
Composing23
Composing24
Composing25
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
```

```
Instrumntpn
Instrmntstr
Voicepar3rd  0.000
Voicepar5th  0.000     0.500
SD21:X16..1  0.001    -0.001  0.000
```

From the output, we see that the interaction effect has a t-value of -2.922, which is significant controlling for all other variables in the model. Since it is significant and the AIC went down (BIC stayed about the same), we will keep the interaction in our model. We have sufficient evidence to
9 assert that a subject who declare themselves as musicians and have a high auxiliary music score, believe that a particular music piece sounds more classical, on average holding all variables in the model constant, than a subject who does not declare themselves as a musician.

4 Exercise 4: Classical vs. Popular

(a) **Solution:**

Similar to what we did in part 1(c), we looked at all of the possible lmer Multiple Intercept Models. Our results were very different for popular than they were for classical. The best AIC and BIC was not the full model. In fact, the best AIC model was the instrument random intercept only model (10083.91). The best BIC model was also the instrument random intercept model as well with a BIC value of 10124.66. Even though the instrument only model was the best model according to AIC and BIC, we still will use the full model because the researchers' intended for harmony, instrument, and voice to be in the model. One of the hypotheses the researchers made was instrument would have the largest influence on rating. It sure has the largest influence on determining if a musical piece is popular. For this reason, we will continue to keep the instrument only model so we can compare it to our future models.

Table 8: AIC and BIC Values For All POPULAR lmer Multiple Intercept Models

	H, I, V	H, I	H, V	H	I, V	I	V
AIC	10097.24	10091.75	10177.79	10172.41	10089.39	10083.91	10170.06
BIC	10167.09	10149.96	10236	10218.98	10141.78	10124.66	10210.81

We have provided output for the model we chose (that is including harmony, instrument, and voice as random intercept effects:

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

REML criterion at convergence: 10073.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6948 -0.5556 -0.0070  0.5822  5.2513

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.41144  0.6414
 Subject:Instrument (Intercept) 1.99986  1.4142
 Subject:Voice      (Intercept) 0.03226  0.1796
```

```
 Residual                        2.49033  1.5781
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210;
 Subject:Voice, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.57991    0.20709   31.77
HarmonyI-V-IV    -0.02557    0.14059   -0.18
HarmonyI-V-VI    -0.27156    0.14057   -1.93
HarmonyIV-I-V    -0.18545    0.14051   -1.32
Instrumentpiano  -0.94900    0.25152   -3.77
Instrumentstring -2.60587    0.25122  -10.37
Voicepar3rd       0.16380    0.08324    1.97
Voicepar5th       0.16206    0.08317    1.95

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
HrmnyI-V-IV -0.338
HrmnyI-V-VI -0.339  0.499
HrmnyIV-I-V -0.339  0.500  0.500
```
9
```
Instrumntpn -0.606  0.000  0.000  0.000
Instrmntstr -0.607  0.000  0.000  0.000  0.500
Voicepar3rd -0.200 -0.002  0.001  0.002 -0.001     0.000
Voicepar5th -0.200 -0.001 -0.002 -0.001 -0.001     0.000     0.500
```

(b) **Solution:**

We took our model from 2(c) and fit the models using popular ratings and did model selection this way. We also decided to add the variable "How much do you listen to pop and rock from the 90s and 2000s? (0-5, 0=not at all)" because we believe that it would be very influential for popular ratings. Essentially, we did variable selection the same way we did in 2(c) and found that "How much do you listen to pop and rock from the 90?s and 2000?s? (0-5, 0=not at all)" is very significant in predicting the popular ratings along with "Auxiliary measure of listener?s ability to distinguish classical vs popular music", and the self-declared musician factor as well. We compare the AIC and BIC values for the full model from part 4(a) and the instrument only random intercept. Again, based off of Table 9, we find that the best model according to AIC is the only random intercept being instrument along with added covariates (fixed effects). The best BIC is the model from (a), we believe this is the case because it is the least complex model. The AIC value with all three random effects with added covariates is better than the model without the covariates from part (a). Thus, considering we want instrument, harmony, and voice in our model and we prefer AIC over BIC we will proceed with all three random effects with added covariates as our model. We have included the output for this model below:

Table 9: AIC and BIC Values for Popular

	Best part (a)	All 3 Ran Eff with covariates	Ran Eff Instr with covariates
AIC	10097.24	10093.41	10080.11
BIC	10167.09	10221.48	10179.07

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ SelfDeclare_factor + X16.minus.17 + Harmony + Instrument +
    Voice + x1990s2000s2 + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
       (1 | Subject:Voice)
```

```
   Data: ratings_popular

REML criterion at convergence: 10049.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7148 -0.5527 -0.0084  0.5765  5.2669

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4087   0.6393
 Subject:Instrument (Intercept) 1.8135   1.3467
 Subject:Voice      (Intercept) 0.0315   0.1775
 Residual                       2.4911   1.5783
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210;
Subject:Voice, 210

Fixed effects:
                    Estimate Std. Error t value
(Intercept)          6.00656    0.39230  15.311
SelfDeclare_factor2  1.09593    0.29801   3.677
SelfDeclare_factor3  1.22753    0.34295   3.579
SelfDeclare_factor4  1.02360    0.34200   2.993
SelfDeclare_factor5  1.37266    0.67890   2.022
SelfDeclare_factor6  0.75443    0.96580   0.781
X16.minus.17         0.08594    0.03859   2.227
HarmonyI-V-IV       -0.02528    0.14032  -0.180
HarmonyI-V-VI       -0.27135    0.14030  -1.934
HarmonyIV-I-V       -0.18536    0.14025  -1.322
Instrumentpiano     -0.94806    0.24071  -3.939
Instrumentstring    -2.60622    0.24040 -10.841
Voicepar3rd          0.16391    0.08312   1.972
Voicepar5th          0.16204    0.08305   1.951
x1990s2000s22       -0.93645    0.60748  -1.542
x1990s2000s23       -0.91078    0.43512  -2.093
x1990s2000s24       -0.92463    0.50046  -1.848
x1990s2000s25       -0.34453    0.34381  -1.002

Correlation of Fixed Effects:
            (Intr) SlfD_2 SlfD_3 SlfD_4 SlfD_5 SlfD_6 X16..1 HI-V-I HI-V-V HIV-I-
             Instrmntp Instrmnts Vcpr3r
SlfDclr_fc2 -0.292
SlfDclr_fc3 -0.421  0.497
SlfDclr_fc4 -0.322  0.508  0.436
SlfDclr_fc5 -0.068  0.264  0.203  0.219
SlfDclr_fc6 -0.050  0.173  0.143  0.169  0.073
X16.mins.17 -0.300  0.091 -0.022 -0.023 -0.134 -0.097
HrmnyI-V-IV -0.178  0.000 -0.001  0.000  0.000  0.000  0.001
HrmnyI-V-VI -0.178  0.000  0.000  0.000  0.000  0.000  0.001  0.499
HrmnyIV-I-V -0.178  0.000  0.000  0.000  0.000  0.000  0.000  0.500  0.500
Instrumntpn -0.307  0.000  0.002  0.001  0.000  0.000  0.000  0.000  0.000  0.000
Instrmntstr -0.307  0.000  0.001  0.001  0.000  0.000 -0.001  0.000  0.000  0.000
 0.500
Voicepar3rd -0.105 -0.001 -0.001 -0.001  0.000  0.000  0.001 -0.002  0.001  0.002
```

```
 -0.001     0.000
Voicepar5th -0.105  0.000 -0.001  0.000  0.000  0.000  0.001 -0.001 -0.002 -0.001
 -0.001     0.000     0.500
x1990200022 -0.311 -0.243 -0.076 -0.038 -0.064 -0.039  0.041  0.000  0.000  0.000
  0.000     0.001     0.000
x1990200023 -0.489 -0.161  0.072 -0.075 -0.041 -0.261  0.043 -0.001  0.000  0.000
  0.000     0.001    -0.001
x1990200024 -0.333 -0.237 -0.117 -0.120 -0.062 -0.041 -0.024 -0.001  0.000  0.000
  0.000     0.001    -0.001
x1990200025 -0.674 -0.224  0.088 -0.058 -0.160 -0.050  0.215 -0.001  0.000  0.000
 0.001     0.001    -0.001
            Vcpr5t x1990200022 x1990200023 x1990200024
SlfDclr_fc2
SlfDclr_fc3
SlfDclr_fc4
SlfDclr_fc5
SlfDclr_fc6
X16.mins.17
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Instrumntpn
Instrmntstr
Voicepar3rd
Voicepar5th
x1990200022  0.000
x1990200023 -0.001  0.349
x1990200024  0.000  0.318       0.401
x1990200025 -0.001  0.465       0.623       0.512
```

Interpretation of Fixed Effects:

- On average, the popular rating for a person who self-declared as a 2 from a scale from 1 to 6 on whether they are a musician or not is 1.09 more than a person who did not self-declare as a musician (put a 1), holding all other variables in the model constant. In addition, the popoular rating for a person who self-declared as a 3 on whether they are a musician or not is 1.23 more on average compared to a person who did not self-declare as a musician, holding all other variables constant. The popular rating for a person who self-declared as a 4 on whether they are a musician or not is 1.02 more than someone who did not self declare as musician, holding all other variables in the model constant. The popular rating for a person who self-declared as a 5 on whether they are a musician or not is 1.37 more than someone who did not self declare as musician, holding all other variables in the model constant. The popular rating for a person who self-declared as a 6 on whether they are a musician or not is .75 less than someone who did not self declare as musician, holding all other variables in the model constant.

- For each additional unit increase in the "Auxiliary measure of listener?s ability to distinguish classical vs popular music", the popular rating decreases by .09 on average, holding all other variables in the model constant.

- A harmonic motion of I-V-IV has a popular rating .03 lower than a harmonic motion of I-IV-V, on average holding all other variables constant. A harmonic motion of I-V-VI has a popular rating .27 higher than a harmonic motion of I-IV-V, on average holding all other variables constant. A harmonic motion of IV-I-V has a popular rating .19 higher than a harmonic motion of I-IV-V, on average holding all other variables constant.

- A piano has a popular rating .95 higher on average than a guitar, holding all other variables constant. A string instrument has a popular rating 2.6 higher on average than a guitar, holding all other variables constant.

- A voice of par3rd and voicepar5th have a popular rating .16 lower on average than a contrary voice, holding all other variables in the model constant.

- People who listen to listen to pop and rock from the 90?s and 2000?s more are have a smaller decreases how much the music piece sounds popular, holding all other variables in the model constant.

Interpretation of Random Effects:

- The random effect we get from harmony takes into account .41 of the 2.49 random effect variance for a subject who is trying to determine how popular a piece of music is.

- The random effect we get from instrument takes into account 1.81 of the 2.49 random effect variance for a subject who is trying to determine how popular a piece of music is.

- The random effect we get from voice takes into account .03 of the 2.49 random effect variance for a subject variance for a subject who is trying to determine how popular a piece of music is.

9

- These random effect variances are determining how much a subject's intercept shifts when using harmony, instrument, or voice to determine whether a piece of music is classical.

(c) **Solution:**

Again, after Dichotomizing self-declare, anyone who reported a 2 or lower is declared as not considered a self-declared musician. Anyone who reported greater than a 2 is considered a self-declared musician. This was as close to a 50-50 breakdown we could get. There are 1499 subjects considered as non-proclaimed musicians and 994 subjects considered as self-proclaimed musicians. We will use R to see if we should add any interactions in the model.

We take our model from the previous part of this problem (the one with harmony, instrument, and voice) since we need these effects in the model because they were the main stimuli in the study. We then compared AIC and BIC for all possible interaction models. We found that the interaction including the interaction of How much do you listen to pop and rock from the 90?s and 2000?s? and the dichotomized version of self-declared musician was the best model. We compare the AIC and BIC of this interaction model to the model in the previous part of this problem in Table 10. We see that the interaction is not hurting or helping the model.

Model output for the best model (including the interaction of How much do you listen to pop and rock from the 90?s and 2000?s? and the dichotomized version of self-declared musician):

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ SelfDeclare2 + X16.minus.17 + Harmony + Instrument +
    Voice + SelfDeclare2:x1990s2000s2 + (1 | Subject:Harmony) +
```


check for other interactions?

Table 10: AIC and BIC Values For 2(c) model Using Dichotomized Self-declared vs. Best Interaction Model

	2(c) model Using Dichotomized Self-declared	Best Interaction Model
AIC	10093.41	10094.83
BIC	10221.48	10222.9

```
    (1 | Subject:Instrument) + (1 | Subject:Voice)
   Data: ratings_popular

REML criterion at convergence: 10050.8

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6949 -0.5544 -0.0078  0.5753  5.2529

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.40966  0.6400
 Subject:Instrument (Intercept) 1.86541  1.3658
 Subject:Voice      (Intercept) 0.03185  0.1785
 Residual                       2.49076  1.5782
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210;
Subject:Voice, 210

Fixed effects:
                            Estimate Std. Error t value
(Intercept)                  5.61019    0.48886  11.476
SelfDeclare21                1.85667    0.58720   3.162
X16.minus.17                 0.07827    0.04001   1.956
HarmonyI-V-IV               -0.02555    0.14041  -0.182
HarmonyI-V-VI               -0.27152    0.14039  -1.934
HarmonyIV-I-V               -0.18551    0.14034  -1.322
Instrumentpiano             -0.94801    0.24377  -3.889
Instrumentstring            -2.60560    0.24346 -10.702
Voicepar3rd                  0.16377    0.08317   1.969
Voicepar5th                  0.16200    0.08311   1.949
SelfDeclare20:x1990s2000s22  1.01443    0.78424   1.294
SelfDeclare21:x1990s2000s22 -2.04036    0.97593  -2.091
SelfDeclare20:x1990s2000s23  0.27938    0.60539   0.461
SelfDeclare21:x1990s2000s23 -1.48803    0.58302  -2.552
SelfDeclare20:x1990s2000s24  0.70765    0.77833   0.909
SelfDeclare21:x1990s2000s24 -1.27778    0.63404  -2.015
SelfDeclare20:x1990s2000s25  0.77244    0.48288   1.600
SelfDeclare21:x1990s2000s25 -0.64067    0.45182  -1.418

Correlation of Fixed Effects:
                (Intr) SlfD21 X16..1 HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
                Vcpr5t SD20:1990200022
SelfDeclr21     -0.688
X16.mins.17     -0.156 -0.143
HrmnyI-V-IV     -0.142 -0.002  0.001
```

```
HrmnyI-V-VI     -0.143 -0.001  0.001  0.499
HrmnyIV-I-V     -0.143 -0.001  0.001  0.500  0.500
Instrumntpn     -0.249  0.000  0.000  0.000  0.000  0.000
Instrmntstr     -0.251  0.002 -0.001  0.000  0.000  0.000  0.500
Voicepar3rd     -0.083 -0.002  0.001 -0.002  0.001  0.002 -0.001     0.000
Voicepar5th     -0.084 -0.001  0.001 -0.001 -0.002 -0.001 -0.001     0.000
0.500
SD20:1990200022 -0.551  0.425  0.123 -0.001  0.000  0.000  0.000     0.001
   -0.001  0.000
SD21:1990200022  0.019 -0.216 -0.123  0.000  0.000  0.000  0.000     0.000
    0.000  0.000 -0.015
SD20:1990200023 -0.677  0.584 -0.072 -0.002 -0.001 -0.001  0.000     0.002
    -0.002 -0.001  0.420
SD21:1990200023 -0.019 -0.409  0.120  0.000  0.000  0.000  0.000     0.000
    0.000  0.000  0.015
SD20:1990200024 -0.535  0.447 -0.005 -0.001 -0.001 -0.001  0.000     0.001
  -0.001 -0.001  0.333
SD21:1990200024  0.000 -0.360  0.000  0.000  0.000  0.000  0.000     0.000
    0.000  0.000  0.000
SD20:1990200025 -0.876  0.707  0.085 -0.002 -0.001 -0.001  0.000     0.002
  -0.002 -0.001  0.548
SD21:1990200025 -0.039 -0.540  0.246  0.001  0.000  0.000  0.002     0.000
   0.000  0.000  0.030
                SD21:1990200022 SD20:1990200023 SD21:1990200023 SD20:1990200024
                 SD21:1990200024 SD20:1990200025
SelfDeclr21
X16.mins.17
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Instrumntpn
Instrmntstr
Voicepar3rd
Voicepar5th
SD20:1990200022
SD21:1990200022
SD20:1990200023  0.009
SD21:1990200023  0.221          -0.009
SD20:1990200024  0.001           0.433          -0.001
SD21:1990200024  0.217           0.000           0.363           0.000
SD20:1990200025 -0.010           0.691           0.010           0.542           0.000
SD21:1990200025  0.274          -0.018           0.538          -0.001           0.468
```

From the output, we see that the interaction effect has t-values varying from -2.55 to -.046 depending on the level. But 4 out of 6 of the levels, there is a significant interaction controlling for all other variables in the model. The AIC and BIC stayed the same, therefore we will not keep the interaction in our model. However, we have sufficient evidence to assert that a subject who declare themselves as musicians and have a listened to pop and rock in the 1990s and 7 2000, believe that a particular music piece sounds less popular, on average holding all variables in the model constant, than a subject who does not declare themselves as a musician.

5 Exercise 5: Brief Writeup

We analyzed how stimuli such as harmonic motion, influence of instrument, and voice, and other variables effect listener's identification of classical and popular music. We fit two different kinds of models, one for predicting the classical music rating and another for predicting the popular music rating. We analyzed a designed experiment done at the University of Pittsburgh by Dr. Jimenez and student Vincent Rossi. The data was a random sample of University of Pittsburgh undergraduates. Dr. Jimenez and Vincent Rossi believed that instruments should have the greatest influence on rating, one particular harmonic progression, I-V-VI, might be frequently rated as classical, because it is the beginning progression for Pachelbel?s Canon in D, which many people have heard, and based on previous research, it was expected that contrary motion would also be frequently rated as classical. We attempt to see whether these hypotheses are true as well as other questions surrounding the data.

We started our analysis by performing simple linear models but soon found out that in both sets of models (predicting for classical and predicting for popular ratings) variance components for the three stimuli and for each subject was necessary and made the models better in terms of AIC and BIC. The variance components are used to account for personal differences that may not be explained in the data. The variance components performed well using the three stimuli but we also wanted to explore other variables that would determine if a music piece is classical or popular. We noticed that whether or not they took an AP test, if they declared as a musician, auxiliary measure of listener?s ability to distinguish classical vs popular music, if they did any music composing influences their classical ratings, and the type of instrument playing. We treated these added covariates as fixed effects in the model. We made several conclusions such as a piano has a classical rating 1.37 higher on average than a guitar, holding other variables constant. Similarly, a string instrument has a classical rating 3.13 higher on average than a guitar, holding other variables constant. We saw that there was an interaction between if subjects self-proclaimed themselves as musicians and their auxiliary music score.

We noticed that whether or not they declared as a musician, auxiliary measure of listener?s ability to distinguish classical vs popular music, the type of instrument playing, and how much do you listen to pop and rock from the 90's and 2000's have an effect on predicting popular ratings. Again, we were able to make many conclusions but comparing to the example we made for the classical model, a piano has a popular rating .95 higher on average compared to a guitar, holding all variables constant. And a string instrument has a popular rating 2.6 higher on average than a guitar, holding all other variables constant.

We notice that the instrument stimuli is indeed has the most influence on rating for both classical
and popular music. As said above, a string instrument has a classical rating 3.13 and 2.6 rating
points higher on average than a guitar when predicting a classical rating and popular rating, re-
10 spectively. The other stimuli, harmonic motion and voice have a lower classical and popular rating
relative to contrary motion, further making Dr. Jimenez look like a genius.

Our random effects were essential in our models and even though an instrument has the most influence on rating of classical and popular music, it also attributed the most variance of our three stimuli. A few suggestions we have for Dr. Jimenez is to consider the interaction we metnioned (self-proclaimed musicians and auxiliary music score) when predicting both classical and popular music. Similarly, when predicting classical ratings, we should look at AP test scores or some education factor and when predicting popular ratings, we should look at how much subjects listen to 1990s and/or 2000s music.

In summary, we were able to verify Dr. Jimenez's hypotheses and make suggestions for him to continue to analyze. We fit two separate models to understand the stimuli and new covariates' influence on classical and popular ratings of a random sample of undergraduates attending the University of Pittsburgh.

6 Appendix

```
###################### Data ####################
ratings <- read.csv("ratings.csv")
library(xtable)
ratings_classical <- ratings[which(ratings$Classical!='NA'),]

###################### 1. The Three Experimental Factors ####################
#############
#### (a) ####
#############

names(ratings_classical)
lm_1 <- lm(Classical ~ Harmony + Instrument +
             Voice, data=ratings_classical)
lm_2 <- lm(Classical ~ Harmony + Instrument,
           data=ratings_classical)
lm_3 <- lm(Classical ~ Harmony + Voice,
           data=ratings_classical)
lm_4 <- lm(Classical ~ Harmony, data=ratings_classical)
lm_5 <- lm(Classical ~ Instrument + Voice,
           data=ratings_classical)
lm_6 <- lm(Classical ~ Instrument, data=ratings_classical)
lm_7 <- lm(Classical ~ Voice, data=ratings_classical)

anova(lm_1, lm_2, lm_3, lm_4, lm_5, lm_6, lm_7)
lm_models <- list(lm_1, lm_2, lm_3, lm_4, lm_5, lm_6, lm_7)
lm_AIC_list <- lapply(lm_models, AIC)
library(xtable)
lm_BIC_list <- lapply(lm_models, BIC)
lapply(lm_AIC_list, min)

#Summary stats of lm_1
xtable(lm_1)

#Boxplots
par(mfrow=c(2,2))
boxplot(ratings_classical$Classical ~ ratings_classical$Harmony,
        main="Classical Ratings By Harmony", xlab="Harmony",
        ylab="Classical Rating")
boxplot(ratings_classical$Classical ~ ratings_classical$Instrument,
        main="Classical Ratings By Instruments", xlab="Instrument",
        ylab="Classical Rating")
boxplot(ratings_classical$Classical ~ ratings_classical$Voice,
        main="Classical Ratings By Voice", xlab="Voice", ylab="Classical Rating")

#Diagnostics
par(mfrow=c(2,2))
plot(lm_1)

#############
#### (b) ####
#############
```

```
##(i)##
# no code

##(ii)##
library(arm)
source("residual-functions.r")

lmer_1 <- lmer(Classical ~ Harmony + Instrument +
                 Voice + (1 | Subject), data=ratings_classical)
display(lmer_1)
AIC(lmer_1)
BIC(lmer_1)
# Both the AIC, 10491.51 and the BIC, 10549.73 are lower than in the full model
# from lm.

library(ggplot2)
ggplot_data <- data.frame(lmer_1@frame, fixed.reff = fitted(lmer_1),
                          rmarg = r.marg(lmer_1), rcond = r.cond(lmer_1),
                          rreff = r.reff(lmer_1), ymarg = yhat.marg(lmer_1),
                          ycond = yhat.cond(lmer_1), yreff = yhat.reff(lmer_1))
qplot(data = ggplot_data, x=ymarg, y=rmarg, facets=~Subject) +
  geom_abline(slope=0, intercept=0, colour="red")

qplot(data=ggplot_data, x=ycond, y=rcond, facets=~Subject) +
  geom_abline(slope=0, intercept=0, colour="red")

qplot(data=ggplot_data, x=yreff, y=rreff, facets=~Subject) +
  geom_abline(slope=0, intercept=0, colour="red")

##(iii)##

lmer_2 <- lmer(Classical ~ Harmony + Instrument +
               (1 | Subject), data=ratings_classical)
lmer_3 <- lmer(Classical ~ Harmony + Voice + (1 | Subject),
           data=ratings_classical)
lmer_4 <- lmer(Classical ~ Harmony + (1 | Subject), data=ratings_classical)
lmer_5 <- lmer(Classical ~ Instrument + Voice +  (1 | Subject),
           data=ratings_classical)
lmer_6 <- lmer(Classical ~ Instrument + (1 | Subject), data=ratings_classical)
lmer_7 <- lmer(Classical ~ Voice + (1 | Subject), data=ratings_classical)

lmer_models <- list(lmer_1, lmer_2, lmer_3, lmer_4, lmer_5, lmer_6, lmer_7)
lmer_AIC <- lapply(lmer_models, AIC)
lmer_BIC <- lapply(lmer_models, BIC)

#############
#### (c) ####
#############

##(i)##
lmer_mult_1 <- lmer(Classical ~ Harmony + Instrument +
                      Voice + (1 | Subject:Harmony) +
                     (1 | Subject:Instrument) + (1 | Subject:Voice),
                   data=ratings_classical)
```

```
display(lmer_mult_1)
AIC(lmer_mult_1)
BIC(lmer_mult_1)

#This model (lmer with multiple random slopes for each category) does better
#in terms of AIC and BIC.

##(ii)##

lmer_mult_2 <- lmer(Classical ~ Harmony + Instrument +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_classical)
lmer_mult_3 <- lmer(Classical ~ Harmony + Voice +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_classical)
lmer_mult_4 <- lmer(Classical ~ Harmony + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_classical)
lmer_mult_5 <- lmer(Classical ~ Instrument + Voice +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_classical)
lmer_mult_6 <- lmer(Classical ~ Instrument + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_classical)
lmer_mult_7 <- lmer(Classical ~ Voice + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_classical)

lmer_mult_models <- list(lmer_mult_1, lmer_mult_2, lmer_mult_3, lmer_mult_4,
                         lmer_mult_5, lmer_mult_6, lmer_mult_7)
lmer_mult_AIC <- lapply(lmer_mult_models, AIC)
lmer_mult_BIC <- lapply(lmer_mult_models, BIC)

##(iii)##

# No code for 1(c) part iii

########################## 2. Individual Covariates #########################
#############
#### (a) ####
#############

# Our best model from number 1 was:
lmer_mult_1 <- lmer(Classical ~ Harmony + Instrument +
                      Voice + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_classical)

# Check variables
head(ratings_classical)
str(ratings_classical)

#I am first going to select some variables that I think will be useful in the model
# and then I will check to see if we need to factor those variables or deal with
```

```
# missing values in an appropraite way.

# List of possible variables:
# (1) Selfdeclare:::Are you a musician? (1-6, 1=not at all)
# (2) OMSI:::Score on a test of musical knowledge
# (3) X16.minus.17::: Auxiliary measure of listener?s ability to distinguish classical vs popular mu
# (4) ConsInstr::: How much did you concentrate on the instrument while listening (0-5, 0=not at all
# (5) ConsNotes::: How much did you concentrate on the notes while listening? (0-5, 0=not at all)
# (6) ClsListen::: How much do you listen to classical music? (0-5, 0=not at all)
# (7) CollegeMusic::: Have you taken music classes in college (0=no, 1=yes)
# (8) APTheory::: Did you take AP Music Theory class in High School (0=no, 1=yes)
# (9) Composing::: Have you done any music composing (0-5, 0=not at all)
# (10) X1stInstr:::How proficient are you at your first musical instrument (0-5, 0=not at all)
# (11) X2ndInstr:::How proficient are you at your 2nd musical instrument (0-5, 0=not at all)


# Now that we have our list of possible variables, let's check to make sure factors
# are factors and that there are no NA values.

# (1)
table(is.na(ratings_classical$Selfdeclare)) #There are no NAs
SelfDeclare_factor <- as.factor(ratings_classical$Selfdeclare)

# (2)
table(is.na(ratings_classical$OMSI)) #There are no NAs

# (3)
table(ratings_classical$X16.minus.17, useNA="always") #There are no NAs

# (4)
table(ratings_classical$ConsInstr, useNA="always") #No NAs. But peole did not answer
# with whole numbers so I am going to recode this variable. Any value inbetween two
# numbers will be rounded. That is, .67 will be labeled as a 1 and 1.33 will be a zero.

ConsInstr2 <- round(ratings_classical$ConsInstr)
ConsInstr2 <- factor(ConsInstr2)

# (5)
table(ratings_classical$ConsNotes, useNA="always") #There are 360 NA values here.
# In order to handle the NA values, we will make them a zero because if they did not
# answer we can most likely assume that they did not use the notes at all.
ConsNotes2 <- ratings_classical$ConsNotes

ConsNotes2[which(is.na(ratings_classical$ConsNotes))] <- 0
ConsNotes2 <- as.factor(ConsNotes2)

#(6)
table(ratings_classical$ClsListen, useNA="always") #There are 24 NA values.
# Again, I will code these 24 valus as zeroes because they probably just don't
# listen to classical music so they avoided the question.

ClsListen2 <- ratings_classical$ClsListen
ClsListen2[which(is.na(ratings_classical$ClsListen))] <- 0
ClsListen2 <- as.factor(ClsListen2)
```

```
#(7)
table(ratings_classical$CollegeMusic, useNA="always") # There were 96 NA values.
#We have reason to believe that they did not take a college music class if they
#did not answer the question. Obviously these ways of handling missing data is not
# ideal but we have reason to believe that it is true.

CollegeMusic2 <- ratings_classical$CollegeMusic
CollegeMusic2[which(is.na(ratings_classical$CollegeMusic))] <- 0
CollegeMusic2 <- as.factor(CollegeMusic2)

#(8)
table(ratings_classical$APTheory, useNA="always") # There were 204 NA values.
# Again, we will set the NAs equal to zero. They probably either did not what the
# AP test was or they did not take the exam.

APTheory2 <- ratings_classical$APTheory
APTheory2[which(is.na(ratings_classical$APTheory))] <- 0
APTheory2 <- as.factor(APTheory2)

#(9)
table(ratings_classical$Composing, useNA="always") # There were 72 NA values.
# if they did not answer the question we have reason to believe that they did
# not do any music composing so I just set them to zero.

Composing2 <- ratings_classical$Composing
Composing2[which(is.na(ratings_classical$Composing))] <- 0
Composing2 <- as.factor(Composing2)

#(10) and (11) Combined to one variable that is How many instruments someone plays:

table(ratings_classical$X2ndInstr, useNA="always")
# 2177 NA values. This is because we believe a lot of people did not play a
# second instrument. We are not going to use this variable for that reason.

table(ratings_classical$X1stInstr, useNA="always")

# let's double check to see if all of the people who rated a second instrument
# actually played a first instrument. These ratings are not necessarily useful because
# of the many NA values and we do not want to omit all of the observations that
# do not play an instrument. We will instead make a variable that says if a user
# played one instrument, two instruments, or did not play any instrument.

# (10) How many instruments someone plays

# Plays one instrument
one <- which(ratings_classical$X1stInstr!='NA')

# Plays two instruments
two <- which(ratings_classical$X2ndInstr!='NA')

play_instr <- rep("None", nrow(ratings_classical))
play_instr[one] <- "One"
play_instr[two] <- "Two"
```

```
play_instr <- as.factor(play_instr)

lmer_fixedef_1 <- lmer(Classical ~ SelfDeclare_factor + OMSI + X16.minus.17 +
                            ConsInstr2 + ConsNotes2 + ClsListen2 + CollegeMusic2 +
                            APTheory2 + Composing2 + play_instr + Harmony +
                            Instrument + Voice + (1 | Subject:Harmony) +
                            (1 | Subject:Instrument) + (1 | Subject:Voice),
                          data=ratings_classical)
summary(lmer_fixedef_1)
AIC(lmer_fixedef_1) # 10082.81
BIC(lmer_fixedef_1) # 10315.66

lmer_fixedef_2 <- lmer(Classical ~ SelfDeclare_factor + log(OMSI) + X16.minus.17 +
                         ConsInstr2 + ConsNotes2 + ClsListen2 + CollegeMusic2 +
                         APTheory2 + Composing2 + play_instr + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_2)
AIC(lmer_fixedef_2) # 10073.43
BIC(lmer_fixedef_2) # 10306.27

lmer_fixedef_3 <- lmer(Classical ~ SelfDeclare_factor + log(OMSI) + X16.minus.17 +
                         ConsInstr2  + ClsListen2 + CollegeMusic2 +
                         APTheory2 + Composing2 + play_instr + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_3)
AIC(lmer_fixedef_3) # 10070.73
BIC(lmer_fixedef_3) # 10280.3

lmer_fixedef_4 <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
                         ConsInstr2  + ClsListen2 + CollegeMusic2 +
                         APTheory2 + Composing2 + play_instr + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_4)
AIC(lmer_fixedef_4) # 10066.83
BIC(lmer_fixedef_4) # 10270.57

lmer_fixedef_5 <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
                          ClsListen2 + CollegeMusic2 +
                         APTheory2 + Composing2 + play_instr + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_5)
AIC(lmer_fixedef_5) # 10064.41
BIC(lmer_fixedef_5) # 10239.04


lmer_fixedef_6 <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
```

```
                         CollegeMusic2 + APTheory2 + Composing2 + play_instr +
                         Harmony + Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_6)
AIC(lmer_fixedef_6) # 10063.75
BIC(lmer_fixedef_6) # 10215.1

lmer_fixedef_7 <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
                         APTheory2 + Composing2 + play_instr + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_7)
AIC(lmer_fixedef_7) # 10062.45
BIC(lmer_fixedef_7) # 10207.98

# lmer_fixedef_7 is our final model.

lmer_fixedef_8 <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
                         APTheory2 + Composing2 + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_fixedef_8)
AIC(lmer_fixedef_8) # 10064.54
BIC(lmer_fixedef_8) # 10198.43

# lmer_fixedef_8 is our final model.

#############
#### (b) ####
#############
lmer_fixedef_onlysubj <- lmer(Classical ~ SelfDeclare_factor  + X16.minus.17 +
                         APTheory2 + Composing2 + Harmony +
                         Instrument + Voice + (1 | Subject),
                       data=ratings_classical)
summary(lmer_fixedef_onlysubj)
AIC(lmer_fixedef_onlysubj) # 10064.54
BIC(lmer_fixedef_onlysubj) # 10198.43

#############
#### (C) ####
#############

# No Code

####################### 3. Musicians vs. Non-Musicians #######################
# Test interactions with self-declare
length(which(ratings_classical$Selfdeclare<=2)) # 1499
length(which(ratings_classical$Selfdeclare>2)) # 994

SelfDeclare2 <- rep(NA, nrow(ratings_classical))
SelfDeclare2[which(ratings_classical$Selfdeclare<=2)] <- 0
```

```
SelfDeclare2[which(ratings_classical$Selfdeclare>2)] <- 1
SelfDeclare2 <- as.factor(SelfDeclare2)

#This is the best breakdown so we have close to a 50-50 breakdown.
# Therefore, after Dichotomizing self-declare, anyone who reported a 2 or lower is
# declared as not considered a self-declared musician. Anyone who reported greater
# than a 2 is considered a self-declared musician.

# Refit model with dichotomized self-declare variable:

lmer_final_self_dec <- lmer(Classical ~ SelfDeclare2  + X16.minus.17 +
                         APTheory2 + Composing2 + Harmony +
                         Instrument + Voice + (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_classical)
summary(lmer_final_self_dec)
AIC(lmer_final_self_dec) # 10073.04
BIC(lmer_final_self_dec) # 10189.47

# The AIC went up by a magnitude of about 10 and the BIC went down by about a magnitude of 10.

# Test for interactions:

lmer_final_self_dec_inter1 <- lmer(Classical ~ SelfDeclare2*X16.minus.17 +
                                     SelfDeclare2*APTheory2 + SelfDeclare2*Composing2 + Harmony +
                              Instrument + Voice + (1 | Subject:Harmony) +
                              (1 | Subject:Instrument) + (1 | Subject:Voice),
                            data=ratings_classical)
summary(lmer_final_self_dec_inter1)
AIC(lmer_final_self_dec_inter1) # 10067.42
BIC(lmer_final_self_dec_inter1) # 10218.77

lmer_final_self_dec_inter2 <- lmer(Classical ~ SelfDeclare2*X16.minus.17 + APTheory2 +
                                     SelfDeclare2*Composing2 + Harmony +
                                     Instrument + Voice + (1 | Subject:Harmony) +
                                     (1 | Subject:Instrument) + (1 | Subject:Voice),
                                   data=ratings_classical)
summary(lmer_final_self_dec_inter2)
AIC(lmer_final_self_dec_inter2) # 10066.73
BIC(lmer_final_self_dec_inter2) # 10212.26

lmer_final_self_dec_inter3 <- lmer(Classical ~ SelfDeclare2*X16.minus.17 + APTheory2 +
                                     Composing2 + Harmony +
                                     Instrument + Voice + (1 | Subject:Harmony) +
                                     (1 | Subject:Instrument) + (1 | Subject:Voice),
                                   data=ratings_classical)
summary(lmer_final_self_dec_inter3)
AIC(lmer_final_self_dec_inter3) # 10069.66
BIC(lmer_final_self_dec_inter3) # 10191.91

# lmer_final_self_dec_inter2 is the best.

####################### 4. Classical vs. Popular #######################
```

```
#############
#### (a) ####
#############
ratings_popular <- ratings[which(ratings$Popular!='NA'),]

lmer_mult_1_pop <- lmer(Popular ~ Harmony + Instrument +
                      Voice + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_popular)
lmer_mult_2_pop <- lmer(Popular ~ Harmony + Instrument +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_popular)
lmer_mult_3_pop <- lmer(Popular ~ Harmony + Voice +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_popular)
lmer_mult_4_pop <- lmer(Popular ~ Harmony + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_popular)
lmer_mult_5_pop <- lmer(Popular ~ Instrument + Voice +
                      (1 | Subject:Harmony) + (1 | Subject:Instrument) +
                      (1 | Subject:Voice), data=ratings_popular)
lmer_mult_6_pop <- lmer(Popular ~ Instrument + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_popular)
lmer_mult_7_pop <- lmer(Popular ~ Voice + (1 | Subject:Harmony) +
                      (1 | Subject:Instrument) + (1 | Subject:Voice),
                    data=ratings_popular)

lmer_mult_models_pop <- list(lmer_mult_1_pop, lmer_mult_2_pop, lmer_mult_3_pop,
                             lmer_mult_4_pop, lmer_mult_5_pop, lmer_mult_6_pop,
                             lmer_mult_7_pop)
lmer_mult_AIC_pop <- lapply(lmer_mult_models_pop, AIC)
lmer_mult_BIC_pop <- lapply(lmer_mult_models_pop, BIC)


#############
#### (b) ####
#############
x1990s2000s2 <- ratings_popular$X1990s2000s
x1990s2000s2[which(is.na(ratings_popular$X1990s2000s))] <- 0
x1990s2000s2 <- as.factor(x1990s2000s2)

lmer_fixedef_popular <- lmer(Popular ~ SelfDeclare_factor  + X16.minus.17  +
                               Harmony + Instrument + Voice + x1990s2000s2 +
                               (1 | Subject:Harmony) +
                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                       data=ratings_popular)
summary(lmer_fixedef_popular)
AIC(lmer_fixedef_popular)
BIC(lmer_fixedef_popular)

lmer_fixedef_instrument <- lmer(Popular ~ SelfDeclare_factor  + X16.minus.17 +
                                  Instrument + x1990s2000s2 +
                                  (1 | Subject:Harmony) +
```

```
                                (1 | Subject:Instrument) + (1 | Subject:Voice),
                              data=ratings_popular)
summary(lmer_fixedef_instrument)
AIC(lmer_fixedef_instrument)
BIC(lmer_fixedef_instrument)

#############
#### (c) ####
#############
# Test interactions with self-declare
length(which(ratings_popular$Selfdeclare<=2)) # 1499
length(which(ratings_popular$Selfdeclare>2)) # 994

SelfDeclare2 <- rep(NA, nrow(ratings_popular))
SelfDeclare2[which(ratings_popular$Selfdeclare<=2)] <- 0
SelfDeclare2[which(ratings_popular$Selfdeclare>2)] <- 1
SelfDeclare2 <- as.factor(SelfDeclare2)

# Refit model with dichotomized self-declare variable:

lmer_final_self_dec_pop <- lmer(Popular ~ SelfDeclare2  + X16.minus.17  +
                                Harmony + Instrument + Voice + x1990s2000s2 +
                                (1 | Subject:Harmony) +
                                (1 | Subject:Instrument) + (1 | Subject:Voice),
                              data=ratings_popular)
summary(lmer_final_self_dec_pop)
AIC(lmer_final_self_dec_pop) # 10101.34
BIC(lmer_final_self_dec_pop) # 10206.12

lmer_final_self_dec_pop_inst <- lmer(Popular ~ SelfDeclare2  + X16.minus.17 +
                                Instrument + x1990s2000s2 +
                                (1 | Subject:Harmony) +
                                (1 | Subject:Instrument) + (1 | Subject:Voice),
                              data=ratings_popular)
summary(lmer_final_self_dec_pop_inst)
AIC(lmer_final_self_dec_pop_inst) # 10088.03
BIC(lmer_final_self_dec_pop_inst) # 10163.7

# Test for interactions:

lmer_final_self_dec_inter1_pop <- lmer(Popular ~ SelfDeclare2  + SelfDeclare2:X16.minus.17  +
                                   Harmony + Instrument + Voice + SelfDeclare2:x1990s2000s2 +
                                   (1 | Subject:Harmony) +
                                   (1 | Subject:Instrument) + (1 | Subject:Voice),
                                 data=ratings_popular)
summary(lmer_final_self_dec_inter1_pop)
AIC(lmer_final_self_dec_inter1_pop) # 10099.79
BIC(lmer_final_self_dec_inter1_pop) # 10233.68

lmer_final_self_dec_inter2_pop <- lmer(Popular ~ SelfDeclare2  + X16.minus.17  +
                                       Harmony + Instrument + Voice + SelfDeclare2:x1990s2000s2 +
                                       (1 | Subject:Harmony) +
                                       (1 | Subject:Instrument) + (1 | Subject:Voice),
                                     data=ratings_popular)
```

```
summary(lmer_final_self_dec_inter2_pop)
AIC(lmer_final_self_dec_inter2_pop) # 10094.83
BIC(lmer_final_self_dec_inter2_pop) # 10222.9

lmer_final_self_dec_inter3_pop <- lmer(Popular ~ SelfDeclare2  + SelfDeclare2:X16.minus.17  +
                                         Harmony + Instrument + Voice + x1990s2000s2 +
                                         (1 | Subject:Harmony) +
                                         (1 | Subject:Instrument) + (1 | Subject:Voice),
                                       data=ratings_popular)
summary(lmer_final_self_dec_inter3_pop)
AIC(lmer_final_self_dec_inter3_pop) # 10106.46
BIC(lmer_final_self_dec_inter3_pop) # 10217.07

# lmer_final_self_dec_inter2_pop is the best.
```