Steven Ways

Hierarchical Linear Models

12/10/13

Final

Problem #1

a.) First, let us examine the influence of the three main experimental factors (Instrument, Harmony, and Voice) on Classic ratings. For this section, we will use conventional linear models to examine the influences. Consider the table below that contains the summary of the full model. First notice that the coefficients for the levels of the Instrument variable are positive and the p-values corresponding to each level are very small. This indicates that piano and string instruments sound significantly more like Classical music compared to the guitar. Moreover, the levels of the Voice variable are significant at the five percent level and have negative corresponding coefficients. So, it appears that voices characterized as parallel thirds and parallel fifths sound significantly less like Classical music than do voices characterized as contrary motion. Now consider the levels of the variable Harmony. Only the I-V-VI harmony level is significantly different from I-VI-V harmony level.

	Coefficients	**Std. Error**	**p-value**
Intercept	**4.34**	**0.13**	**<0.001**
Harmony I-V-IV	**-0.03**	**0.13**	**0.813**
Harmony I-V-VI	**0.77**	**0.13**	**<0.001**
Harmony IV-I-V	**0.03**	**0.13**	**0.807**
Voice Parallel 3rd	**-0.40**	**0.11**	**<0.001**
Voice Parallel 5th	**-0.36**	**0.11**	**0.001**
Instrument Piano	**1.37**	**0.11**	**<0.001**
Instrument String	**3.12**	**0.11**	**<0.001**

In order to determine whether or not the variable Harmony is actually needed in the model, we can fit a similar model as above that does not include Harmony. The table given below displays the summary of the fitted reduced model. Each variable is significant, but in order to determine whether the Harmony variable is important to keep in the model, we can conduct a chi-square test. The p-value of this test is less than 0.001, which indicates that Harmony is useful in explaining how classical the music sounds and should be kept in the model. This conclusion is also evident when we consider the BIC for each model. The BIC value for the full model is 11250.58 and the BIC value for the reduced model is 11279.74 (Since the BIC value for the full model is much less than the BIC value for the reduced model, we should choose the full model with Harmony).

	Coefficients	Std. Error	p-value
Intercept	**4.53**	**0.10**	**<0.001**
Voice Parallel 3rd	**-0.40**	**0.11**	**<0.001**
Voice Parallel 5th	**-0.36**	**0.11**	**0.002**
Instrument Piano	**1.37**	**0.11**	**<0.001**
Instrument String	**3.12**	**0.11**	**<0.001**

Finally, from these models we can only make inferences and comparisons to the base group for each variable. It is more informative to compare all levels in each variable to one another to determine if there exist significant differences in how classical the music sounds between those levels. A post-hoc test for these variables would be useful to determine which levels are significantly different from one another.

b.)

i.) The mathematical form of the model that allows for a random intercept for each subject is given by:

$$Classical_i = \alpha_{0j[i]} + \alpha_1 Harmony + \alpha_2 Voice + \alpha_3 Instrument + \varepsilon_i,\ \varepsilon_i \sim N(0,\sigma^2)$$

$$\alpha_{0j[i]} = \beta_0 + \eta_j,\ \eta_j \sim N(0,\tau^2)$$

ii.) It may be the case that the random intercept is not needed in the model, and we can test for its importance using two different methods. First, we can use AIC and BIC to determine whether the model without the random effect is a better fit than the model with the random effect. The table given below summarizes the AIC and BIC values for each model. Notice that both the AIC and BIC values are much lower for the model which includes the random intercept. Hence the random intercept is needed in the model under this method.

	AIC	BIC
No Random Intercept	**11198.20**	**11250.58**
Random Intercept	**10453.25**	**10511.45**

Moreover, we can test whether or not the random intercept is needed using a restricted likelihood ratio test. Testing the model with the random effect against the model without the random effect, the test provides a p-value less than 0.001. This indicates that the random effect is useful in the model, and so we see that the random effect is needed in the model using both methods (the code is given at the end of the document).

iii.) Although we have accounted for the random effect in the model, the influence of the fixed effects have not changed much. The coefficients corresponding to the levels for each variable are similar in value and the same levels that were significant in the model without the random effect are the same levels that are significant in this model. As we did above when testing for whether Harmony was needed in the model, we can fit models (each with a different combination of fixed effects) to determine whether or not some of the fixed effects are needed. From the provided output, we see that the full model (the model with each fixed effect) is still the best choice when we include the random term in the model (in terms of AIC). Hence all of the three main experimental factors influence Classical ratings and should be kept in the model.

c.)

i.) Previously we fit a repeated measures model that allowed for the intercept to vary for each participant. Now, we can fit a model that accounts for personal bias in the ratings by allowing for random intercepts for the interactions between Subject and the three main experimental factors. Before we examine the results of this model, we can compare it to the two previous models we obtained in the previous parts. Unfortunately, since we are removing the random intercept for subjects and adding these three new random effects, we cannot use the restricted likelihood ratio test. Therefore, as we did in the previous part, we can check whether this new model is better or worse than the previous two models. Given below is a table of the AIC and BIC values for the each of the three models. Notice that the both the AIC and BIC values for the model with the interaction random intercepts are much lower than the AIC and BIC values for the other two models. Hence, it appears that the model that accounts for personal bias is better than either of the two previous models.

	AIC	**BIC**
No Random Intercept	**11198.20**	**11250.58**
Random Intercept (Subject)	**10453.25**	**10511.45**
Random Intercept (Interaction)	**10029.50**	**10099.35**

ii.) Just as we saw previously, the influence of the three main experimental factors on Classic ratings are roughly the same since they are treated as fixed effects in the model; we have only added/changed the random effects in our models. Just as we did above, we can re-examine the influence of the three main experimental factors. In the given output, notice that the AIC is lowest for the model that includes each main experimental factor. Hence each one influences Classical ratings in this personal bias model, so we keep each one in the model.

Moreover, we can examine the sizes of the three estimated variance components with respect to each other and with respect to the estimated residual variance. Given below is a table containing the variances for the random effects and the residuals. Notice that none of the variances are too close in value. The voice interaction has the smallest variance, and the harmony interaction has a moderately higher one. The variance for the instrument interaction, though, is much higher than the variances of the other two interaction random effects. What is interesting is that the variance for this interaction random effect is very similar in size to the variance of the residuals.

	Variances
Subject:Harmony	**0.456**
Subject:Instrument	**2.181**
Subject:Voice	**0.023**
Residual	**2.395**

iii.) The mathematical form of the model that allows for a random intercept for the three interactions between subject and harmony, instrument, and voice is given by:

$$Classical_i = \alpha_{0j[i]} + \alpha_{1j[i]} + \alpha_{2j[i]} + \alpha_1 Harmony + \alpha_2 Voice +$$
$$\alpha_3 Instrument + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma^2)$$
$$\alpha_{0j} = \beta_{\text{Subject:Harmony}} + \eta_{0j},\ \eta_{0j} \sim N(0, \tau_0^2)$$
$$\alpha_{1j} = \beta_{\text{Subject:Voice}} + \eta_{1j},\ \eta_{1j} \sim N(0, \tau_1^2)$$
$$\alpha_{2j} = \beta_{\text{Subject:Instrument}} + \eta_{2j},\ \eta_{2j} \sim N(0, \tau_2^2)$$

Problem #2

a.) Based on AIC and BIC, the best model obtained from the previous part is the model that accounts for personal bias (the model that contains the three interaction random intercept terms). This model only provides the effects of the three main experimental factors on Classical ratings, so we can add covariates to the model that also contribute to identifying a song as Classical or not (It is important to note, though, that there are numerous possible models we can fit since there are so many variables provided. To eliminate repetitiveness, we will only consider and compare certain models using the given variables). Before adding covariates, though, I have dichotomized the variables that I believe will be interesting/useful to include in the model. I did this because it is much more sensible to compare between two groups than between several groups (e.g. what does it mean to compare people who gave a 2 for listening to 90's music compared to those who gave a 5?). Using AIC, chi-square tests, and model summaries with vaiables that I thought were useful to add to the model to choose between full and reduced models, the list of variables included in the final model are: Harmony, Instrument, Voice, Composing (dichotomized version), and GuitarPlay (dichotomized version; the process of selection and summary of the work involved in decided on this final model are given at the end of the document). Note, though, that the data includes many null values for several of the variables. In order to properly compare models using AIC, each model needs to have the same number of observations. Hence, we have coded the null values as 0's. This is because if a participant does not provide information for one of the variables, then the participant most likely does not measure on the variables scale.

b.) Now that we have decided on what fixed effects should be kept/include in the model, we can check to see if all of the interaction random effects are necessary to keep in the model. Let us first decide whether or not the harmony interaction random effect is worth keeping in the model. Given in the attached output/code, we see that both BIC and the restricted likelihood ratio test indicate that this random effect should be kept in the model. On the other hand, it is clear that the voice interaction random effect should be dropped from the model. The restricted likelihood ratio test indicates that the effect should be dropped, and so do AIC and BIC. Hence, these results indicate that a personal bias in voice may not need accounted for in the model explaining Classical ratings, and so we will remove it from the model. Finally, we can test whether or not the instrument interaction random effect should be left in the model. Both BIC and the restricted likelihood ratio test suggest that the effect should be kept in the model. Hence the voice interaction random effect is the only change in our random effects in the model. (It is important to note that when we tested for the necessity of accounting for personal bias by instrument we had already removed the term accounting for voice personal bias. In other words, we did not test the term against the model that still included the voice interaction random effect in it.)

c.) Now that we have constructed this final model, we can interpret the effects of each variable on the Classical ratings. First, the interpretations of the three main experimental factors are similar to before. As mentioned, different harmonic motions have different effects on how classical a piece of music sounds. Also, voice leading characterized as parallel 3rds or parallel 5ths sounds much more classical than contrary motion voice leading, and piano and string instruments tend to sound more like classical music than electric guitars. Moving away from the three main experimental factors, let us examine the effects of the college music and AP Music Theory variables. Given below are the coefficients estimates of the Composing and GuitarPlay variables. First, consider the variable Composing. This variable is significant, and its corresponding coefficient is positive, which suggests that those who have more experience composing music tend to provide higher Classical ratings. Moreover, the GuitarPlay variable is significant, and its corresponding coefficient is negative. This indicates that those who play guitar more often typically give lower Classical ratings opposed to those that do not play guitar as often (this makes sense since guitars are linked to popular music).

	Coefficient	**Std. Error**
Composing	**1.180**	**0.447**
GuitarPlay	**-0.931**	**0.447**

Problem #3

One variable that we have failed to consider in the model is the "self-declared musician" variable. Participants were asked to rate themselves as a musician on a scale from 1 to 6 (1 represents not at all). In my opinion, if participants provide an answer that is anything but 1 then then somewhat consider themselves as a musician. Therefore, we can dichotomize the self-declared musician variable into those who do not declare themselves as musicians whatsoever (those who gave a score of 1) and those who at least somewhat consider themselves as musicians (those who gave a score between 2 and 6). This variable's name is Self2. From the attached output, we see that the new musician variable does not improve the model in terms of AIC. However, when we consider an interaction between this musician variable and the guitar play variable, we see that the model (in terms of AIC) is an improvement. Therefore, we will include the musician variable and this interaction in the model. In summary, the coefficients on these variables indicate that musicians provide lower classical ratings than non-musicians and that classical ratings increase for musicians who are also guitar players. One important thing to note, though, is that with the inclusion of these two new terms forces the Composing variable to become insignificant. In the attached output, we have tested whether or not this variable is needed in this model. As it turns out, the chi-square test indicates that the Composing variable is no longer needed in this model. Hence, the fixed effects included in the final model for classical ratings are as follows: Harmony, Voice, Instrument, GuitarPlay, Self2, and Self2:GuitarPlay.

Problem #4

So far we have only considered how the numerous variables affect the Classical ratings response variable. Now we can switch our focus and consider Popular ratings as the response variable. We will conduct identical analyses for Popular ratings as we did for Classical ratings, so much of the inferences are similar to above. Hence we will move more quickly through the Popular ratings and note any differences in the findings. Tests and model summaries are given in the output section when necessary.

a.) To begin, when using classical linear regression, we see that neither Voice nor Harmony improve the fit of the model that only includes Instrument. Hence the best model (using the lm function) is the simple model that only includes only the

Instrument variable. Specifically, since the coefficients for the levels of the instrument variable are negative, this model suggests that songs with guitars are linked to higher Popular ratings compared to songs with pianos and string instruments.

Although we have found that Voice and Harmony variables are not needed in the classical linear model, we will include them in the random effects model since they are the three main experimental factors of interest. With that being said, let us add a random effect to the model that allows for the intercept to vary by subject. Just like we did previously with the Classical model, we can test whether or not this random effect is needed in the model. Using AIC, BIC, and the restricted likelihood ratio test, we have that the random effect is needed in the model. As we saw previously with the Classical ratings, the fixed effect coefficients do not change greatly, but we now have a better understanding of the random variation among subjects in the model.

Moreover, we can fit a model that allows for personal bias in Popular ratings. This is done by adding the three random interaction effects to the model (we first remove the subject random effect that we considered previously). Using both AIC and BIC, we see that the random interaction model that accounts for personal bias among subjects is preferred over both the full, classical model and the full, random effect model examined above. Therefore, we will use this random interaction model as our base model moving forward.

b.) Now that we have a base model to work with, we can see which covariates to add to the model in the same manner as we did for the Classical ratings. The attached output shows the process for selecting which variables to include in the model (using AIC). The variables that we will include in the model that describes Popular ratings are: Harmony, Voice, Instrument, and Composing (recall that there are numerous possible models that we can consider and compare, but it would be very repetitive to consider each one). In this model, the fixed effects have not changed much since the first model with fit with Popular ratings as the response: certain harmonies and voices sound more popular than others for subjects, and guitars sound more like popular music than do pianos and string instruments. Moreover, notice that the composing variable has a positive coefficient. This indicates that those with composing experience tend to give higher popular ratings.

Now that we have settled on the covariates in this model, we can also check to see if there is anything we need to change about the random effects. Observe from the output that we arrive at the same results as we did for the Classical ratings: the personal bias for harmony and instrument are important, but the personal bias for voice is not necessary in the model. Hence, we remove this personal bias from the model.

c.) Lastly, we can also check to see whether or not the self-declared musician variable affects Popular ratings. Using the same dichotomized musician variable created previously, we use a chi-square test to determine whether the model with this variable is a better fit than the model without it. Notice from the output that the AIC is 2 units lower for the model with the musician variable, and the inclusion of this term in the model is marginally significant ($p = 0.58$). There appears to be a relationship between Popular ratings and being a self-declared musician, so we will include this term in the model. Moreover, notice that when we add this term to the model, the composing variable is no longer significant, but the coefficient is still positive (we saw this happen when examining Classical ratings). Using a chi-square test, we see that the composing variable is no longer useful to keep in the model when we have the self-declared musician variable in the model. Hence, we will once again remove this variable. Also, notice that the variable on the musician variable is negative, which means that musicians provide lower Popular ratings than non-musicians (this variable, though, is only marginally significant). Maybe the most interesting aspect about this new model, though, is that when we include this musician variable in the model, the coefficients on the instrument levels are positive and significantly different from zero. This indicates that when we hold all else constant, piano and string instruments indicate higher Popular ratings. This is a very interesting occurrence, and we may need further insight from the investigator as to why this might be.

Interactions with other fixed effects?

4: 18
5: 18

36

nice job. would have liked to see a little bit of statistical detail in main body of report

Problem 5

In attempting to explain classical and popular ratings, all three main experimental factors (Harmony, Voice, and Instrument) proved to impact the results. Using the results from our fitted models and the given boxplots below, we were able to determine which harmony, voice, and instrument sounded most like classical or popular music. In terms of harmony motion, the I-V-VI motion sounds the most classical to listeners, and the I-IV-V motion sounds the most like popular music. Moreover, different voices fall on different ends of the classical/popular music spectrum. Voice leading labeled as contrary motion sounds much more classical to listeners than other voice leading types, and the parallel 5ths voice leading sounds the most like popular music. Finally, it should come to no surprise that the guitars sound much more like popular music whereas piano and string instruments tend to sound more classical.

These results were also evident when we allowed for personal bias in the model. It may be the case that one person tends to rate everything as classical and another subject tends to report everything as popular. After allowing for this bias in our random effects model, we see similar results across each of the three main experimental factors.

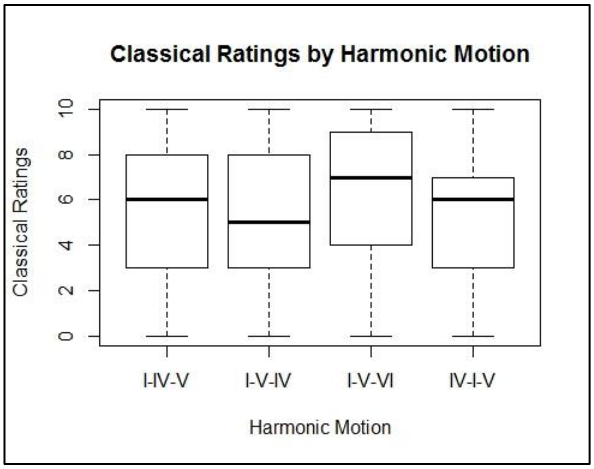
Although we have examined the influence of the three main experimental factors in the model, there still may be other significant factors that cause subjects to rate pieces of music one way or the other. For classical music, we arrived at a model that also included composing and guitar playing experience. Those who had more composing experience tended to provide higher classical ratings, but on the other hand, people who had more experience playing the guitar tended to provide lower classical ratings. Moreover, with the inclusion of these new terms, there was no longer an important effect of personal bias in terms of voice. This was an interesting result and may warrant a further investigation.

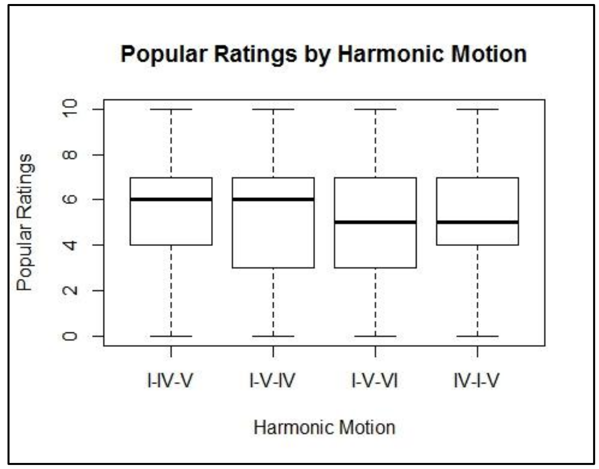
Along with the three main experimental factors, we have also added the composing variable to the model describing popular ratings. Similar to what we saw with classical ratings, the coefficient on composing was positive, which indicates that those with composing experience gave higher popular ratings. Hence, it must be the case that more composing experience leads those to either rate music as highly classical or highly popular. Furthermore, formal tests also proved that the personal bias for voice was not necessary to include in the model.

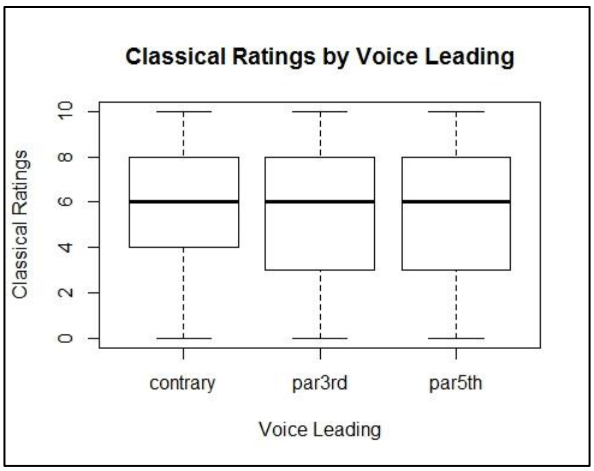
Finally, there was believed to be a connection between self-declared musicians and classical and popular ratings. In both models, it appears that self-declared musicians seem to provide lower ratings. Maybe more noticeable, though, is that when we add this self-declared musician variable to the model, it changes the effects of the composing variable (in both models) and the instrument variable (in the popular model). Clearly there is some relationship between being a self-declared musician and other factors in our model.

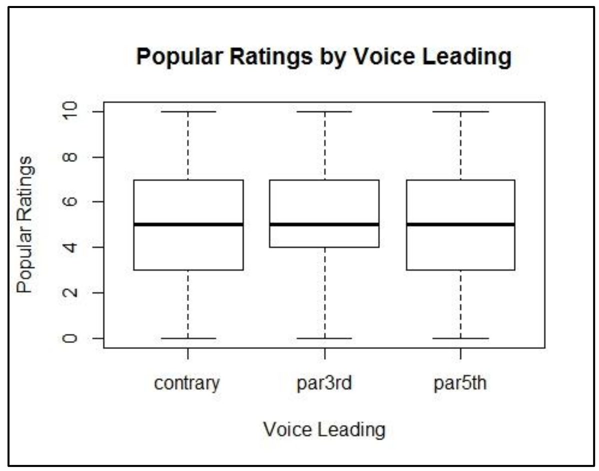
Overall, it is clear that the three main experimental factors influence the ratings for classical and popular music. Moreover, other factors such as composing and guitar experience and being a self-declared musician seem to have effects on ratings. Numerous other potential factors exist and could be considered for inclusion in our models, but not every possible model was fit. Further examination of the variables and new models may lead to different understandings of classical and popular ratings.

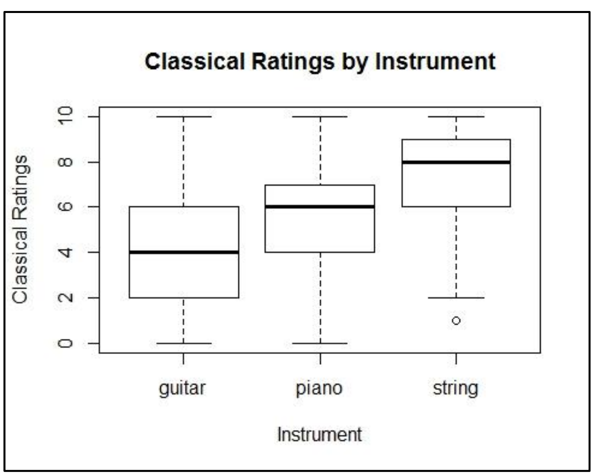
I think you could write a bit more specifically about your results in the writeup for sect 5.

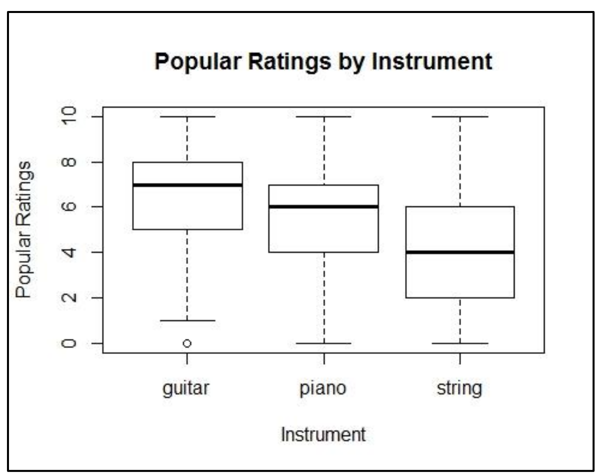

Classical Ratings by Harmonic Motion
Classical Ratings
0
2
4
6
8
10
I-IV-V
I-V-IV
I-V-VI
IV-I-V
Harmonic Motion


Popular Ratings by Harmonic Motion
Popular Ratings
0
2
4
6
8
10
I-IV-V
I-V-IV
I-V-VI
IV-I-V
Harmonic Motion


Classical Ratings by Voice Leading
Classical Ratings
0
2
4
6
8
10
contrary
par3rd
par5th
Voice Leading


Popular Ratings by Voice Leading
Popular Ratings
0
2
4
6
8
10
contrary
par3rd
par5th
Voice Leading


Classical Ratings by Instrument
Classical Ratings
0
2
4
6
8
10
guitar
piano
string
Instrument


Popular Ratings by Instrument
Popular Ratings
0
2
4
6
8
10
guitar
piano
string
Instrument

Code/Output

```
#### Steven Ways ####
####    Final    ####
####   12/10/13  ####


library("foreign")
library("arm")
library("lme4")
library("ggplot2")
library("R2jags")
library("rube")
library("RLRsim")

music <- read.csv("ratings.csv")
music$X[music$Classical >10]
music1 <- music[-1978,]
music1$X[music$Popular >10]
music2 <- music1[-1166,]
music2[is.na(music2)] <- 0


attach(music2)
```

Problem 1

Part A

```
full.classic <- lm(Classical ~ Harmony + Voice + Instrument)
summary(full.classic)
plot(full.classic)
histogram(full.classic$residuals)

reduced.classic <- lm(Classical ~ Voice + Instrument)
summary(reduced.classic)
plot(reduced.classic)
histogram(reduced.classic$residuals)

anova(reduced.classic, full.classic)

BIC(full.classic)
BIC(reduced.classic)
```

Part B

```
random.int.fit <- lmer(Classical ~ Harmony + Voice + Instrument +
(1|Subject))
summary(random.int.fit)
ranef(random.int.fit)
```

ii

```
AIC(random.int.fit)
AIC(full.classic)
BIC(random.int.fit)
BIC(full.classic)

exactRLRT(random.int.fit)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 749.3479, p-value < 2.2e-16
```

iii

```
random.int.fit2 <- lmer(Classical ~ Harmony + Voice + (1|Subject))
random.int.fit3 <- lmer(Classical ~ Harmony + Instrument + (1|Subject))
random.int.fit4 <- lmer(Classical ~ Voice + Instrument + (1|Subject))

temp <- list(random.int.fit, random.int.fit2, random.int.fit3,
random.int.fit4)

sapply(temp, AIC)
```

```
10711.04 11628.03 10721.76 10766.02
```

Part C

```
random.interaction <- lmer(Classical ~ Harmony + Voice + Instrument +
(1|Subject:Harmony) +
                              (1|Subject:Voice) + (1|Subject:Instrument))
summary(random.interaction)

fixef(random.interaction)
```

i

```
anova(random.int.fit, random.interaction)

AIC(random.interaction)
AIC(full.classic)

BIC(random.interaction)
BIC(full.classic)
```

```
AIC(random.interaction)
AIC(random.int.fit)

BIC(random.interaction)
BIC(random.int.fit)
```

ii

```
random.interaction2 <- lmer(Classical ~ Harmony + Voice + (1|Subject:Harmony)
+ (1|Subject:Voice) + (1|Subject:Instrument))

random.interaction3 <- lmer(Classical ~ Harmony + Instrument +
(1|Subject:Harmony) + (1|Subject:Voice) + (1|Subject:Instrument))

random.interaction4 <- lmer(Classical ~ Voice + Instrument +
(1|Subject:Harmony) + (1|Subject:Voice) + (1|Subject:Instrument))

temp2 <- list(random.interaction, random.interaction2, random.interaction3,
random.interaction4)

sapply(temp2, AIC)

10264.11 10361.69 10280.26 10289.34
```

Problem 2

Part A

```
music2$ConsInstr2 =0
music2$ConsInstr2[music2$ConsInstr >2] =1

music2$ConsNotes2 =0
music2$ConsNotes2[music2$ConsNotes >2] =1

music2$ClsListen2 =0
music2$ClsListen2[music2$ClsListen >2] =1

music2$x90s =0
music2$x90s[music2$X1990s2000s >2] =1

music2$Composing2 =0
music2$Composing2[music2$Composing >2] =1

music2$PianoPlay2 =0
music2$PianoPlay2[music2$PianoPlay >2] =1

music2$GuitarPlay2 =0
```

```
music2$GuitarPlay2[music2$GuitarPlay >2] =1

music2$Self2 =0
music2$Self2[music2$Selfdeclare >2] =1

music2$Pach2 =0
music2$Pach2[music2$PachListen >2] =1

music2$X1stInstr2 =0
music2$X1stInstr2[music2$X1stInstr >2] =1

music2$X2ndInstr2 =0
music2$X2ndInstr2[music2$X2ndInstr >2] =1



#Adding OMSI
random.interaction2 <- update(random.interaction, .~. + OMSI)
anova(random.interaction, random.interaction2)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
random.interaction	12	10246	10316	-5111.1	10222			
random.interaction2	13	10248	10324	-5111.1	10222	0.0108	1	0.9173

```
#Adding ConsInstr
random.interaction3 <- update(random.interaction, .~. + ConsInstr2)
anova(random.interaction,random.interaction3)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
random.interaction	12	10246	10316	-5111.1	10222			
random.interaction3	13	10248	10324	-5111.1	10222	0.0016	1	0.9678

```
#Adding ConsNotes
random.interaction4 <- update(random.interaction, .~. + ConsNotes2)
anova(random.interaction,random.interaction4)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
random.interaction	12	10246	10316	-5111.1	10222			
random.interaction4	13	10248	10324	-5110.9	10222	0.3363	1	0.562

```
#Adding ClsListen
random.interaction5 <- update(random.interaction, .~. + ClsListen2)
anova(random.interaction,random.interaction5)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
random.interaction	12	10246	10316	-5111.1	10222			
random.interaction5	13	10246	10322	-5109.9	10220	2.4529	1	0.1173

```
#Adding X1990s2000s
random.interaction6 <- update(random.interaction, .~. + x90s)
anova(random.interaction,random.interaction6)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
random.interaction	12	10246	10316	-5111.1	10222			

```
random.interaction6 13 10248 10324 -5111.0    10222 0.2145      1     0.6433


#Adding CollegeMusic
random.interaction7 <- update(random.interaction, .~. + CollegeMusic)
anova(random.interaction,random.interaction7)

                    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction  12 10246 10316 -5111.1    10222
random.interaction7 13 10248 10324 -5111.0    10222 0.1112      1     0.7388


#Adding APTheory
random.interaction8 <- update(random.interaction, .~. + APTheory)
anova(random.interaction,random.interaction8)

                    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction  12 10246 10316 -5111.1    10222
random.interaction8 13 10247 10323 -5110.6    10221 0.9199      1     0.3375


#Adding Composing
random.interaction9 <- update(random.interaction, .~. + Composing2)
anova(random.interaction,random.interaction9)

                    Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
random.interaction  12 10246 10316 -5111.1    10222
random.interaction9 13 10248 10324 -5110.9    10222 0.389      1     0.5328

#AIC does not prefer this new model, but I strongly believe composing will
#effect the Classical ratings variable, so we will add it to the model

#Adding PianoPlay
random.interaction10 <- update(random.interaction9, .~. + PianoPlay2)
anova(random.interaction9,random.interaction10)

                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction9  13 10248 10324 -5110.9    10222
random.interaction10 14 10250 10331 -5110.8    10222 0.1033      1     0.7479

#Adding GuitarPlay
random.interaction11 <- update(random.interaction9, .~. + GuitarPlay2)
anova(random.interaction9,random.interaction11)

                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction9  13 10248 10324 -5110.9    10222
random.interaction11 14 10248 10330 -5110.1    10220 1.5234      1     0.2171

#AIC indicates that either model can be chosen. I also believe that knowing
#how to play guitar will effect Classical ratings, so I would prefer to
#add this to the model as well

#Adding Pach2
random.interaction13 <- update(random.interaction11, .~. + Pach2)
anova(random.interaction11,random.interaction13)

                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction11 14 10248 10330 -5110.1    10220
random.interaction13 15 10250 10338 -5110.1    10220 0.0877      1     0.7671
```

```
#Adding X1stInstr2
random.interaction14 <- update(random.interaction11, .~. + X1stInstr2)
anova(random.interaction11,random.interaction14)
```

```
                     Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
random.interaction11 14 10248 10330 -5110.1    10220
random.interaction14 15 10250 10338 -5110.1    10220 0.105      1     0.7459
```

```
#Adding X2ndInstr2
random.interaction15 <- update(random.interaction11, .~. + X2ndInstr2)
anova(random.interaction11,random.interaction15)
```

```
                     Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
random.interaction11 14 10248 10330 -5110.1    10220
random.interaction15 15 10250 10338 -5110.1    10220 3e-04      1     0.9863
```

Part B

```
random.interaction11.harm.only <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Harmony) + Composing2 + GuitarPlay2)

random.interaction11.no.harm <- lmer(Classical ~ Harmony + Voice + Instrument
+ (1 | Subject:Voice) + (1 | Subject:Instrument) + Composing2 + GuitarPlay2)

exactRLRT(random.interaction11.harm.only, random.interaction11,
random.interaction11.no.harm)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 92.0473, p-value < 2.2e-16
```

```
BIC(random.interaction11.no.harm)
```

```
10432.36
```

```
BIC(random.interaction11)
```

```
10348.15
```

```
random.interaction11.voice.only <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Voice) + Composing2 + GuitarPlay2 )

random.interaction11.no.voice <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
```

```
Composing2 + GuitarPlay2)

exactRLRT(random.interaction11.voice.only, random.interaction11,
random.interaction11.no.voice)

simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 0.1716, p-value = 0.3233


BIC(random.interaction11.no.voice)

10340.49

BIC(random.interaction11)

10348.15

AIC(random.interaction8.no.voice)

9098.716

AIC(random.interaction8)

10265.86

random.instrument.only <- lmer(Classical ~ Harmony + Voice + Instrument +
                                          (1 | Subject:Instrument) +
Composing2 + GuitarPlay2)

random.no.instrument <- lmer(Classical ~ Harmony + Voice + Instrument +
                                        (1 | Subject:Harmony) +
                                        Composing2 + GuitarPlay2)

random.interaction15 <- lmer(Classical ~ Harmony + Voice + Instrument +
                               (1 | Subject:Harmony) + (1|Subject:Instrument)
+
                               Composing2 + GuitarPlay2)

exactRLRT(random.instrument.only, random.interaction15, random.no.instrument)

simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 601.6406, p-value < 2.2e-16


BIC(random.no.instrument)

10934.3

BIC(random.interaction14)

10356.51
```

```
AIC(random.no.instrument)
```

10864.32

```
AIC(random.interaction14)
```

10269.05

Part C

```
summary(random.interaction15)

music2$Self2 =0
music2$Self2[music2$Selfdeclare >1] =1
```

Problem 3

```
rand.int.self <- update(random.interaction15, .~. + Self2)
anova(random.interaction15, rand.int.self)
```

```
                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
random.interaction15 13 10246 10322 -5110.2    10220
rand.int.self        14 10245 10327 -5108.5    10217 3.2969      1    0.06941
```

```
rand.int.self2 <- update(rand.int.self, .~. + Self2:GuitarPlay)
anova(rand.int.self, rand.int.self2)
```

```
               Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
rand.int.self  14 10245 10327 -5108.5    10217
rand.int.self2 15 10242 10330 -5106.2    10212 4.6937      1    0.03027 *
```

```
summary(rand.int.self2)
```

```
Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.67070    0.30421  15.354
HarmonyI-V-IV    -0.05294    0.14166  -0.374
HarmonyI-V-VI     0.73508    0.14163   5.190
HarmonyIV-I-V     0.02690    0.14166   0.190
Voicepar3rd      -0.39941    0.07805  -5.118
Voicepar5th      -0.34601    0.07802  -4.435
Instrumentpiano   1.27589    0.26825   4.756
Instrumentstring  3.15637    0.26825  11.766
Composing2        0.34027    0.38883   0.875
GuitarPlay2      -3.51508    1.48125  -2.373
Self2            -0.62957    0.29087  -2.164
Self2:GuitarPlay  0.71528    0.33383   2.143
```

```
fit1 <- update(rand.int.self2, .~. - Composing2)
summary(fit1)

anova(fit1, rand.int.self2)
```

```
               Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
fit1           14 10241 10323 -5106.6    10213
rand.int.self2 15 10242 10330 -5106.2    10212 0.7895      1     0.3743
```

Problem 4

Part A

```
full.popular <- lm(Popular ~ Harmony + Voice + Instrument)
summary(full.popular)
```

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       6.55474    0.13014  50.368   <2e-16 ***
HarmonyI-V-IV    -0.07336    0.13017  -0.564   0.5731
HarmonyI-V-VI    -0.29349    0.13012  -2.256   0.0242 *
HarmonyIV-I-V    -0.19810    0.13017  -1.522   0.1282
Voicepar3rd       0.14629    0.11275   1.297   0.1946
Voicepar5th       0.17036    0.11272   1.511   0.1308
Instrumentpiano  -1.04693    0.11272  -9.288   <2e-16 ***
Instrumentstring -2.55965    0.11272 -22.708   <2e-16 ***
```

```
plot(full.popular)
histogram(full.popular$residuals)

reduced.popular <- lm(Popular ~ Voice + Instrument)
summary(reduced.popular)
```

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)        6.4136     0.1030  62.297   <2e-16 ***
Voicepar3rd        0.1461     0.1128   1.295    0.195
Voicepar5th        0.1703     0.1128   1.510    0.131
Instrumentpiano   -1.0470     0.1128  -9.283   <2e-16 ***
Instrumentstring  -2.5596     0.1128 -22.694   <2e-16 ***
```

```
plot(reduced.popular)
histogram(reduced.popular$residuals)

anova(full.popular,reduced.popular)
```

```
  Res.Df   RSS Df Sum of Sq      F Pr(>F)
1   2510 13387
2   2513 13419 -3   -32.103 2.0065  0.111
```

```
BIC(full.popular)
```

11423.29

```
BIC(reduced.popular)
```

11405.83

```
reduced.popular2 <- lm(Popular ~  Instrument)
summary(reduced.popular2)
```

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)       6.51905    0.07974  81.754   <2e-16 ***
Instrumentpiano  -1.04706    0.11280  -9.282   <2e-16 ***
Instrumentstring -2.55945    0.11280 -22.690   <2e-16 ***
```

```
anova(full.popular,reduced.popular2)
```

```
  Res.Df   RSS Df Sum of Sq      F Pr(>F)
1   2510 13387                           
2   2515 13433 -5   -46.353 1.7383 0.1225
```

```
random.int.pop <- lmer(Popular ~ Harmony + Voice + Instrument + (1|Subject))
summary(random.int.pop)
```

```
Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.637    1.279   
 Residual             3.716    1.928   
Number of obs: 2518, groups: Subject, 70
```

```
Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.55242    0.18757   34.93
HarmonyI-V-IV    -0.06947    0.10866   -0.64
HarmonyI-V-VI    -0.29349    0.10862   -2.70
HarmonyIV-I-V    -0.19958    0.10866   -1.84
Voicepar3rd       0.15032    0.09412    1.60
Voicepar5th       0.17147    0.09409    1.82
Instrumentpiano  -1.04401    0.09409  -11.10
Instrumentstring -2.56076    0.09409  -27.21
```

```
ranef(random.int.pop)
```

```
AIC(random.int.pop)
```

10683.35

```
AIC(full.popular)
```

11370.81

```
BIC(random.int.pop)
```

10741.67

```
BIC(full.popular)
```

11423.29

```
exactRLRT(random.int.pop)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 711.8901, p-value < 2.2e-16
```

```
random.interaction.pop <- lmer(Popular ~ Harmony + Voice + Instrument +
(1|Subject:Harmony) + (1|Subject:Voice) + (1|Subject:Instrument))
```

```
Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.36749  0.6062
 Subject:Instrument (Intercept) 2.18972  1.4798
 Subject:Voice      (Intercept) 0.03515  0.1875
 Residual                       2.62155  1.6191
Number of obs: 2518, groups: Subject:Harmony, 280; Subject:Instrument, 210;
Subject:Voice, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.55260    0.21298  30.767
HarmonyI-V-IV    -0.06734    0.13722  -0.491
HarmonyI-V-VI    -0.29349    0.13719  -2.139
HarmonyIV-I-V    -0.19462    0.13722  -1.418
Voicepar3rd       0.14820    0.08517   1.740
Voicepar5th       0.16775    0.08515   1.970
Instrumentpiano  -1.04241    0.26232  -3.974
Instrumentstring -2.55704    0.26232  -9.748
```

```
summary(random.interaction.pop)

fixef(random.interaction.pop)
```

```
AIC(random.interaction.pop)
```

10311.06

```
AIC(full.popular)
```

11370.81

```
BIC(random.interaction.pop)

10381.03

BIC(full.popular)

11423.29


AIC(random.interaction.pop)

10311.06

AIC(random.int.pop)

10683.35


BIC(random.interaction.pop)

10381.03

BIC(random.int.pop)

10741.67
```

Part B

```
#Adding OMSI
random.interaction.pop2 <- update(random.interaction.pop, .~. + OMSI)
anova(random.interaction.pop, random.interaction.pop2)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop2 13 10291 10367 -5132.5    10265 4.0655      1
0.04377 *

#Notice that the test and AIC indicate that we should add this to our model.
#However, further analyses that are not included here show that adding this
#term may not be useful. Thus we will keep it out of the model.

#Adding ConsInstr
random.interaction.pop3 <- update(random.interaction.pop, .~. + ConsInstr2)
anova(random.interaction.pop,random.interaction.pop3)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
```

```
random.interaction.pop3 13 10295 10371 -5134.4    10269 0.1853      1
0.6669


#Adding ConsNotes
random.interaction.pop4 <- update(random.interaction.pop, .~. + ConsNotes2)
anova(random.interaction.pop,random.interaction.pop4)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop4 13 10294 10370 -5133.9    10268 1.2483      1
0.2639


#Adding ClsListen
random.interaction.pop5 <- update(random.interaction.pop, .~. + ClsListen2)
anova(random.interaction.pop,random.interaction.pop5)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop5 13 10294 10370 -5134.0    10268 0.8987      1
0.3431


#Adding X1990s2000s
random.interaction.pop6 <- update(random.interaction.pop, .~. + x90s)
anova(random.interaction.pop,random.interaction.pop6)

                        Df   AIC   BIC  logLik deviance Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop6 13 10294 10370 -5134.2    10268 0.613      1
0.4337


#Adding CollegeMusic
random.interaction.pop7 <- update(random.interaction.pop, .~. + CollegeMusic)
anova(random.interaction.pop,random.interaction.pop7)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop7 13 10294 10370 -5134.0    10268 1.0305      1
0.31



#Adding APTheory
random.interaction.pop8 <- update(random.interaction.pop, .~. + APTheory)
anova(random.interaction.pop,random.interaction.pop8)

                        Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop8 13 10295 10371 -5134.4    10269 0.1759      1
0.675
```

```
#Adding Composing
random.interaction.pop9 <- update(random.interaction.pop, .~. + Composing2)
anova(random.interaction.pop,random.interaction.pop9)

                         Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop  12 10293 10363 -5134.5    10269
random.interaction.pop9 13 10290 10366 -5132.2    10264 4.5205      1
0.03349 *


#Adding PianoPlay
random.interaction.pop10 <- update(random.interaction.pop9, .~. + PianoPlay2)
anova(random.interaction.pop9,random.interaction.pop10)

                         Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop9  13 10290 10366 -5132.2    10264
random.interaction.pop10 14 10291 10373 -5131.5    10263 1.5075      1
0.2195


#Adding GuitarPlay
random.interaction.pop11 <- update(random.interaction.pop9, .~. +
GuitarPlay2)
anova(random.interaction.pop9,random.interaction.pop11)

                         Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop9  13 10290 10366 -5132.2    10264
random.interaction.pop11 14 10291 10373 -5131.6    10263 1.2281      1
0.2678

#Adding X1stInstr2
random.interaction.pop14 <- update(random.interaction.pop9, .~. + X1stInstr2)
anova(random.interaction.pop9,random.interaction.pop14)
                         Df   AIC   BIC  logLik deviance Chisq Chi Df
Pr(>Chisq)
random.interaction.pop9  13 10290 10366 -5132.2    10264
random.interaction.pop14 14 10292 10374 -5132.2    10264 1e-04      1
0.9933


#Adding X2ndInstr2
random.interaction.pop15 <- update(random.interaction.pop9, .~. + X2ndInstr2)
anova(random.interaction.pop9,random.interaction.pop15)

                         Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop9  13 10290 10366 -5132.2    10264
random.interaction.pop15 14 10290 10372 -5131.1    10262 2.2831      1
0.1308


summary(random.interaction.pop9)

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.36717  0.6059
 Subject:Instrument (Intercept) 2.14944  1.4661
```

```
 Subject:Voice      (Intercept) 0.03505  0.1872
 Residual                       2.62164  1.6191
Number of obs: 2518, groups: Subject:Harmony, 280; Subject:Instrument, 210;
Subject:Voice, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.44384    0.21776  29.592
HarmonyI-V-IV    -0.06728    0.13719  -0.490
HarmonyI-V-VI    -0.29349    0.13716  -2.140
HarmonyIV-I-V    -0.19464    0.13719  -1.419
Voicepar3rd       0.14826    0.08516   1.741
Voicepar5th       0.16777    0.08513   1.971
Instrumentpiano  -1.04236    0.26011  -4.007
Instrumentstring -2.55705    0.26011  -9.831
Composing2        0.63419    0.29968   2.116
```

```
random.interaction.pop9.harm.only <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Harmony) + Composing2)

random.interaction.pop9.no.harm <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Voice) + (1 | Subject:Instrument) + Composing2)


exactRLRT(random.interaction.pop9.harm.only, random.interaction.pop9,
random.interaction.pop9.no.harm)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 49.0982, p-value < 2.2e-16
```

```
BIC(random.interaction.pop9.no.harm)

10426.25

BIC(random.interaction.pop9)

10384.98
```

```
random.interaction.pop9.voice.only <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Voice) + Composing2)

random.interaction.pop9.no.voice <- lmer(Classical ~ Harmony + Voice +
Instrument + (1 | Subject:Harmony) + (1 | Subject:Instrument) + Composing2)

exactRLRT(random.interaction.pop9.voice.only, random.interaction.pop9,
random.interaction.pop9.no.voice)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)
```

```
data:
RLRT = 0, p-value = 1
```

```
BIC(random.interaction.pop9.no.voice)
```

10334.36

```
BIC(random.interaction.pop9)
```

10384.98

```
AIC(random.interaction.pop9.no.voice)
```

10264.39

```
AIC(random.interaction.pop9)
```

10309.18

```
random.instrument.only.pop <- lmer(Classical ~ Harmony + Voice + Instrument +
                                (1 | Subject:Instrument) + Composing2)

random.no.instrument.pop <- lmer(Classical ~ Harmony + Voice + Instrument +
                               (1 | Subject:Harmony) + Composing2)

random.interaction.pop.final <- lmer(Classical ~ Harmony + Voice + Instrument
+ (1 | Subject:Harmony) + (1|Subject:Instrument) +Composing2)

exactRLRT(random.instrument.only.pop, random.interaction.pop.final,
random.no.instrument.pop)
```

```
simulated finite sample distribution of RLRT.

(p-value based on 10000 simulated values)

data:
RLRT = 602.1073, p-value < 2.2e-16
```

```
BIC(random.no.instrument.pop)
```

10928.64

```
BIC(random.interaction.pop.final)
```

10334.36

```
AIC(random.no.instrument.pop)
```

10864.49

```
AIC(random.interaction.pop.final)

10264.39
```

Part C

```
rand.pop.self <- update(random.interaction.pop.final, .~. + Self2)
anova(random.interaction.pop.final, rand.pop.self)

                             Df   AIC   BIC  logLik deviance  Chisq Chi Df
Pr(>Chisq)
random.interaction.pop.final 12 10246 10316 -5110.9    10222
rand.pop.self                13 10244 10320 -5109.1    10218 3.5942      1
0.05798 .


summary(rand.pop.self)

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4187   0.6471
 Subject:Instrument (Intercept) 2.3530   1.5340
 Residual                       2.5547   1.5983
Number of obs: 2518, groups: Subject:Harmony, 280; Subject:Instrument, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.67063    0.30659  15.234
HarmonyI-V-IV    -0.05284    0.14171  -0.373
HarmonyI-V-VI     0.73508    0.14168   5.188
HarmonyIV-I-V     0.02692    0.14171   0.190
Voicepar3rd      -0.39934    0.07804  -5.117
Voicepar5th      -0.34602    0.07802  -4.435
Instrumentpiano   1.27597    0.27077   4.712
Instrumentstring  3.15638    0.27077  11.657
Composing2        0.34261    0.32074   1.068
Self2            -0.54149    0.28785  -1.881


fit2 <- update(rand.pop.self, .~. - Composing2)
anova(fit2, rand.pop.self)

              Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
fit2          12 10243 10313 -5109.7    10219
rand.pop.self 13 10244 10320 -5109.1    10218 1.165      1     0.2804


summary(fit2)

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4187   0.6471
 Subject:Instrument (Intercept) 2.3548   1.5345
 Residual                       2.5547   1.5983
Number of obs: 2518, groups: Subject:Harmony, 280; Subject:Instrument, 210

Fixed effects:
```

	Estimate	Std. Error	t value
(Intercept)	4.67065	0.30668	15.230
HarmonyI-V-IV	-0.05287	0.14171	-0.373
HarmonyI-V-VI	0.73508	0.14168	5.188
HarmonyIV-I-V	0.02693	0.14171	0.190
Voicepar3rd	-0.39938	0.07804	-5.117
Voicepar5th	-0.34603	0.07802	-4.435
Instrumentpiano	1.27594	0.27086	4.711
Instrumentstring	3.15639	0.27086	11.653
Self2	-0.46536	0.27898	-1.668