Homework 5

36-736: Hierarchical Linear Models

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1 a 9/9
b 9/9
c 9/9

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

3 9/9

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

5 10/10

Total 100/100

1.

Before any models were fit the data was loaded and examine. When looking at the summary of the data and the variable definitions we can see that there are some variables which have no NA's and other variables that have a large marjority of NA's. For instance the variable X2ndInstr, which asks how proficient the subject is at a second instrument has over 2000 NA's suggesting not a lot of the participants play a second instrument. Infact there are also 1512 NA's for the 1st instrument as well. Another issue with the data is that each subject is entered in the data 36 times. Therefore, any variable that is specific to the subject and not to the piece of music the subject listened to is given 36 times.

Good EDA. Good to find the severe missingness, and to find thhe oddball value of classical!

When performing some EDA for the three main experimental factors and the response variable, Classical rating, an outlier becomes apparent. After viewing the powerpoint and reading more about the data, the Classical variable seems to take on values between 1 and 10. One observation has a value of 19 for Classical, this seems to be a data entry error, so the observation is removed.

a.

After the EDA, some conventional linear models can be fit to the data. All three of the main experimental factors that are being considered are categorical variables. Instrument consists of three different intsturments, piano, guitar, and string. There are three level of the voice variable and four levels of the harmony variable. A full model which includes all three of the variables was fit to the data. The results of the full model show that at least one category from each of the explanatory variables is significnat. To determine whether each of the variables improves the overal fit of the model, sepearate models were fit excluding the variable of interest. ANOVA was then used to compare each model to the full model to determine whether the fit was better when the variable of interest was not in the model. The ANOVA results determined that all three of the varaibles are important to the model (for each comparasion p-value $<.0005$ suggests rejecting the null hypothesis that the reduced model is a better fit). Therefore, each of the experiment factors, are important to the model. Another model was fit so that there was no baseline instrument and the intercepts for each type of instrument are shown in the model. This model was then used to analyze the fixed effects of the model. From these fixed effects, it appears that the type of instrument largely impacts the Classical rating scale. When a string instrument is present the classing rating is the highest. The presence of voice seems to decreases the rating, and significantly so. As far as harmonies go, the only harmony that seems to significantly change the rating is the I-V-VI harmony which increases the classical music rating (this is the chord in Cannon in D, so it seems plausible that it would increase peoples association of it with classical music.)

9

Table 1: Table continues below

	Estimate	Std. Error	t value
Instrumentpiano	5.709	0.1296	44.04
Instrumentstring	7.455	0.1292	57.72
HarmonyI-V-IV	-0.0311	0.1294	-0.2403
HarmonyI-V-VI	0.7691	0.1294	5.941
HarmonyIV-I-V	0.03163	0.1294	0.2445
Voicepar3rd	-0.3987	0.1122	-3.553
Voicepar5th	-0.3567	0.1121	-3.182
Instrumentguitar	4.336	0.1292	33.55

	Pr(>|t|)
Instrumentpiano	1.388e-313
Instrumentstring	0
HarmonyI-V-IV	0.8101
HarmonyI-V-VI	3.222e-09
HarmonyIV-I-V	0.8069
Voicepar3rd	0.0003873
Voicepar5th	0.001483
Instrumentguitar	8.032e-204

Table 3: Fitting linear model: Classical ~ Instrument - 1 + Harmony + Voice

Observations	Residual Std. Error	R^2	Adjusted R^2
2492	2.286	0.871	0.8706

b.

i. The model written as a hierarchical linear model, where the beta's represent the three main experimental factors, and the intercept varies by subject is shown below.

$$y_i = \alpha_{j[i]} + \beta_{IXi} + \beta_{VXi} + \beta_{HXi} + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

yes, except the X_i's are different for subscripting each beta...

$$\alpha_j = \beta_0 + \eta_j, \eta_j \overset{iid}{\sim} N(0, \tau^2), j[i] = \text{subject for rating } i$$

ii. The multilevel model was fit keeping all three fixed effects as in part (a) and adding a random intercept for each participant. This repeated measures model was compared to the linear model using two different tests to determine whether the random intercept helped the fit. First the AIC and BIC of each model was calculated. For both AIC and BIC, the model including a random intercept was found to be lower (AIC: 10434.28, BIC: 10492.49) than the linear model (AIC: 11201.7, BIC: 11254.09) indicating the random intercept is needed in the model. The second method used to test whether the repeated measures model is a better fit was a simulation test. The test resulted in a p-value $< .0005$, which also indicated that the model which included the random intercept fit the data better. Thus, we keep the random intercept in the model. Diagnostic plots were also inspected for each of the model although due to the nature of the models, had a floor/ceiling affect.

```
## lmer(formula = Classical ~ Instrument - 1 + Harmony + Voice +
##     (1 | Subject), data = music2, REML = "FALSE")
##                   coef.est coef.se
## Instrumentguitar  4.34     0.19
## Instrumentpiano   5.71     0.19
## Instrumentstring  7.46     0.19
## HarmonyI-V-IV    -0.03     0.11
## HarmonyI-V-VI     0.77     0.11
## HarmonyIV-I-V     0.03     0.11
## Voicepar3rd      -0.40     0.09
## Voicepar5th      -0.36     0.09
##
## Error terms:
##  Groups   Name        Std.Dev.
##  Subject  (Intercept) 1.29
##  Residual             1.88
## ---
## number of obs: 2492, groups: Subject, 70
## AIC = 10434.3, DIC = 10414.3
## deviance = 10414.3
```

```
## [1] 10434.28
```

```
## [1] 11201.7
```

```
##
##  simulated finite sample distribution of LRT. (p-value based on
##  10000 simulated values)
```

9

```
##
## data:
## LRT = 769.42, p-value < 2.2e-16
```

iii. From the fit of the random intercept model we can see that the value of the variance on the random effect part is not small which further suggests the need for it in the model, the random intercept is accounting for variation between subjects. We can also see that as with the linear model, the type of instrument in the piece of music has the strongest impact on whether the music is rated classical. Within the instrument category, string instruments increase the rating the most, followed by piano. The only type of harmony that appears to be significant in affecting the rating is the I-V-VI harmony, which increases the rating and is the chord progression in Cannon in D. The presence of parallel 3rd of 5th leading voice also seems to be signifcant in lowering the rating for classical music. The results of the random intercept model also shows that some correlation does exist between the fixed effects, obviously a larger correlation exists for factors of the same categorical variable, but there are also some correlations between variables.

c.

i. A model was fit to the data using a random effect term for each subject and category combination. This model will account for personal biases that vary by each category, for example, if a person is bias based on the type of harmony they hear. Using AIC and BIC, (AIC: 10015.52, BIC: 10085.37), the model which includes a random effect for each person/harmony, person/instrument, and peron/voice combination fits the data better than the models in part 1a and 1b.

```
## lmer(formula = Classical ~ Instrument - 1 + Harmony + Voice +
##     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice),
##     data = music2, REML = FALSE)
##                  coef.est coef.se
## Instrumentguitar  4.34     0.21
## Instrumentpiano   5.70     0.21
## Instrumentstring  7.45     0.21
## HarmonyI-V-IV    -0.03     0.14
## HarmonyI-V-VI     0.77     0.14
## HarmonyIV-I-V     0.04     0.14
## Voicepar3rd      -0.39     0.08
## Voicepar5th      -0.36     0.08
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.67
##  Subject:Voice      (Intercept) 0.14
##  Subject:Instrument (Intercept) 1.47
##  Residual                       1.55
## ---
## number of obs: 2492, groups: Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 2
## AIC = 10015.5, DIC = 9991.5
## deviance = 9991.5
```

ii. Looking at the results of this new model, the influence of the three main effects is basically the same as the model fit in part (b) with only the random intercept. Insturment is the most influential, in the postitive direction with string instruments increasing the rating the most. Voice decreases the rating, and the harmony I-V-IV seems to be the only harmony that strongly influences the rating.

Considering the varaince components we can see they differ quite greatly between the main effects. The random effect for the person/instrument has the largest variance component values, 2.15, of the three effects. This suggests that there is a lot of varaition in which people are inclined to call music classical based on the type of instruments in the piece. The random effect for person/voice is very small, 0.02, which suggests that there is not a ton of variation between subjects in what they think is classical based on the voice. There is also a small variance componet for subject/harmony, 0.44, which suggests people vary some in what they are inlcined as to what the harmony of classical music is most like. The presence of the instruments varies the most between subjects. This random effect is also almost as large as the residual variance, which represents the unexplained variation in

9 the overall model. The other two are much smaller than the residual variance. So, we can conclude that personal biases with instruments has a large affect on the ratings. (Note, an additional model was fit that only included this person/instrument combination random effect and not the other two, the model was found to fit worse than the one that included all three.)

iii. Let k represent the type of instrument, let m represent the type of harmony, and let n represent the type of voice.

$$
\begin{aligned}
y_i &= \alpha_{j[i]k[i]} + \alpha_{j[i]m[i]} + \alpha_{j[i]n[i]} + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \\
\alpha_{jk} &= \beta_{0k} + \eta_{j1}, \eta_{j1} \overset{iid}{\sim} N(0, \tau_1^2), j[i]k[i] = \text{rating i for j subject and k instrument} \\
\alpha_{jm} &= \beta_{0m} + \eta_{j2}, \eta_{j2} \overset{iid}{\sim} N(0, \tau_2^2), j[i]m[i] = \text{rating i for j subject and m harmony} \\
\alpha_{jm} &= \beta_{0n} + \eta_{j3}, \eta_{j3} \overset{iid}{\sim} N(0, \tau_3^2), j[i]n[i] = \text{rating i for j subject and n voice}
\end{aligned}
$$

jn

2.

a. When deciding which covariates should be added to the model as fixed effects the variables were first analyzed to determine which one make sense to fit in the model instead of including all additional 20 possible covariates. This was done so as to not have a result which included an overly complicated model. For instance, some of the variables indicating prior music knowedlge (classes taken) can probably be represented using the OMSI score which tests the musical knowledge of the subject. Also, some of the variables involving whether a subject plays an instrument and how proficient they are will be combined into a variable which just indicates whether a subject plays an instrument or not, this will also help to eliminate the problem of the NA values in most of these variables. If this variable is determined to be siginifcant, then an additional part could be to further look into what aspects of playing an instrument influence the Classical rating. Other variables that are considered in the initial model include whether the subject thinks they are a musician, whether they have done any composing, what the subject concentrated on when listening, how familiar the subject is with Pachelbel's Canon in D, and the auxillary measure of the ability to distinguish between classical and popular. Several models were then created using these variables as a basis and comparing the AIC, BIC, and diagnostic plots of the models. The final model which balanced simplicity with improvement of the fit (AIC: 8193, BIC: 8322) includes: the three main experimental factors; the variable Selfdeclare which is the subjects opinion on whether they are a musician; the varible X16.minus.17 which is the auxilary measure of the listener's ability to distinguish classical and popular; the variables ConsInstr and ConsNotes which denote whether the subject was concentrating on the instruments or notes while listening and to what effect; the variable PachListen which is the subjects familiarity with Canon in D; the variable Composing which denotes whether the subject had composed any music; and finally the variable which denotes whether the subject plays an instrument (output results shown below).

```
## lmer(formula = Classical ~ Instrument - 1 + Harmony + Voice +
##     factor(Selfdeclare) + X16.minus.17 + ConsInstr + ConsNotes +
##     PachListen + Composing + play + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice), data = music2,
##     REML = FALSE)
##                        coef.est coef.se
```

```
## Instrumentguitar      3.95     0.63
## Instrumentpiano       5.37     0.63
## Instrumentstring      7.12     0.63
## HarmonyI-V-IV        -0.02     0.15
## HarmonyI-V-VI         0.85     0.15
## HarmonyIV-I-V         0.05     0.15
## Voicepar3rd          -0.38     0.09
## Voicepar5th          -0.35     0.09
## factor(Selfdeclare)2 -1.26     0.39
## factor(Selfdeclare)3 -0.92     0.47
## factor(Selfdeclare)4 -1.09     0.50
## factor(Selfdeclare)5 -1.97     0.87
## factor(Selfdeclare)6 -1.79     1.14
## X16.minus.17         -0.11     0.04
## ConsInstr             0.06     0.10
## ConsNotes            -0.07     0.08
## PachListen            0.23     0.12
## Composing             0.24     0.11
## play                  0.35     0.27
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.63
##  Subject:Voice      (Intercept) 0.13
##  Subject:Instrument (Intercept) 1.39
##  Residual                       1.55
## ---
## number of obs: 2036, groups: Subject:Harmony, 228; Subject:Voice, 171; Subject:Instrument, 
## AIC = 8193.1, DIC = 8147.1
## deviance = 8147.1
```

b. Once the fixed effects were settled, a model with all the fixed effects and only one random
intercept per subject was fit to the data. This model was then compared to the model with the
9 fixed effects and a random effect for the main factors and subject combinations. Both AIC and BIC
(AIC: 8561, BIC: 8679) suggest that keeping a random effect for the subject and factor combinations
is a better fit for the data than just one random intercept per subject. The diagnostic plots were
also considered. The variance components are discussed in part (c) and also help to justify using
this model.

c. Looking at the fixed effects on the variables kept in the model, the effect on the main factors seem to be very similar to the models fit in #1. The presence of a string instrument has significant influence on tne classical rating increasing. The voice variable seems to have a more signifcant affect however the effect is still smaller. The classical music rating decreases significantly when subjects self-identify as a musician, the subjects who rated themselves as 5, have the lowest average classical rating of the levels. Whether a subject composed music or not significantly increases the classical rating. Higher auxillary scores also significantly decreases the rating. The variables that determine what the subject concentrated on when listening are not significant.

9

Looking at the variance components, once again it is apparent that the Subject:instrument random effect has the highest variation, although it is now a good bit smaller than the estimated residual variance, suggesting that some of the other covariates that were included as fixed effects, helped to predict this instrument bias per subject. This makes sense as some of the fixed effects that were included denote the subjects knowledge on music. (The actual estimate values can be seen in the table in part (a) above.

3.

When dichotomizing the self-declared variable, the values 1 and 2 on the rating scale will be considered "not a musician" and values 3-6 will be considered a musician. This makes it so 28 subjects are considered musicians and 42 subjects are considred not musicians.

Models were fit including interactions between the new dichotomized musician variable and the other pedictors in the final model in part 2c (the models all include the random effect terms for each of the main factors). The self-declare variable was removed from this model since the new musician variable was created using the information from the self-declare variable. The first model fit considered interactions with only the three main factors considered, Intrument, Harmony, and Voice. Another model included interactions with the musician variable and every predictor variable in the model in which an interaction would make sense. For example, an interaction between the created variable which designates whether a subject has played an instrument and whether they are a musician does not make much sense in the context. The AIC values suggest the model which includes an interaction term with every predictor is a better fit. This result suggests that at least
9 one other predictor variable, besides the main three factors, is influenced by whether the subject is a musician or not. The BIC value suggests that the model where the interaction with only the three main factors is the better fit, but not by much. This disagreement makes sense due to AIC favoring large values.

The results of the model with the interaction terms on all predictors are analyzed. The fixed effects show significance in the interactions with the harmony variable, with the strongest impact being the influence of musician and non musician on the chord in Canon in D beng present (t-stat = -4.47). The estimate is positive (1.29), which suggests that those who are considered musicians are more likely to rate a piece as classical when that chord is present than those who are not considered musicians. Other significant interactions include the variable representing the subjects auxiliary ability to distinguish between classical and popular music and prior experience composing. Both of these interactions make sense that being a musician or not would influence them when rating classical music. The fixed effects without interaction terms are very similar to the results seen in #2. The variance components have decreased (harmony = 0.28, voice = 0.014, instrument: 1.78) while the overall resdiual variance is very similar to the model without interactions. This result suggests that including the influence of being a musician accounts for some of the bias between subject and each of the main factors.

```
##
##   1   2   3   4   5   6
## 564 935 459 426  72  36
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
```

```
## Formula:
## Classical ~ musician * Instrument + musician * Harmony + musician *
##     Voice + musician * X16.minus.17 + musician * ConsInstr +
##     musician * ConsNotes + musician * PachListen + musician *
##     Composing + play + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
##     (1 | Subject:Voice)
##    Data: music2
##
##      AIC      BIC   logLik deviance df.resid
##   8162.6   8336.8  -4050.3   8100.6     2005
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2515 -0.5748  0.0036  0.5403  3.5706
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.28614  0.5349
##  Subject:Voice      (Intercept) 0.01407  0.1186
##  Subject:Instrument (Intercept) 1.79669  1.3404
##  Residual                       2.41435  1.5538
## Number of obs: 2036, groups:
## Subject:Harmony, 228; Subject:Voice, 171; Subject:Instrument, 171
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)                3.26837    0.69623   4.694
## musician                   1.43320    1.46951   0.975
## Instrumentpiano            1.71296    0.35905   4.771
## Instrumentstring           3.57452    0.35905   9.956
## HarmonyI-V-IV             -0.02509    0.18912  -0.133
## HarmonyI-V-VI              0.26624    0.18922   1.407
## HarmonyIV-I-V              0.05735    0.18912   0.303
## Voicepar3rd               -0.42683    0.11793  -3.619
## Voicepar5th               -0.30183    0.11793  -2.559
## X16.minus.17               0.04571    0.05302   0.862
## ConsInstr                  0.06215    0.13465   0.462
## ConsNotes                 -0.15868    0.09311  -1.704
## PachListen                 0.16558    0.12215   1.356
## Composing                  0.72590    0.23763   3.055
## play                       0.01422    0.25270   0.056
## musician:Instrumentpiano  -0.64477    0.53234  -1.211
## musician:Instrumentstring -0.89986    0.53163  -1.693
## musician:HarmonyI-V-IV     0.01010    0.28066   0.036
## musician:HarmonyI-V-VI     1.28872    0.28072   4.591
## musician:HarmonyIV-I-V    -0.01706    0.28067  -0.061
## musician:Voicepar3rd       0.09361    0.17538   0.534
## musician:Voicepar5th      -0.10268    0.17534  -0.586
```

```
## musician:X16.minus.17     -0.37664    0.08423  -4.471
## musician:ConsInstr        -0.21079    0.20099  -1.049
## musician:ConsNotes         0.10536    0.15243   0.691
## musician:PachListen        0.03196    0.29589   0.108
## musician:Composing        -0.64655    0.27426  -2.357
```

```
##
## Correlation matrix not shown by default, as p = 27 > 20.
## Use print(x, correlation=TRUE)  or
##   vcov(x)     if you need it
```

```
## [1] 8177.825
```

```
## [1] 8162.578
```

```
## [1] 8323.912
```

```
## [1] 8336.76
```

4.

The data was reexamined using a response variable for Popular ratings instead of Classical ratings.

a. First an analysis was done only on the three main factors in the study, Instrument, Harmony, and Voice, and their influence on Popular ratings. Linear models were fit to the data to determine whether all three factors influenced ratings or whether there was a main factor that was "unimportant" to the model. The ANOVA analysis between linear models determined that a model including only Instrument was a better fit when predicting Popular ratings. This differed from Classical rating, which found all three main factors to be influential.

Next the random effects models were fit. The random effect model fiting only a random intercept per subject was determined to fit better, using both the AIC/BIC (Linear AIC: 11138, BIC: 11161.
9 Random: AIC: 10426, BIC: 10484) method as well as the simulation (LRT: 723.9, p-value $< .0005$). The model with a random effect for each subject/instrument combination, each subject/harmony combination, and each subject/voice combination was also fit to the data. This model was found to have the best fit of the models considered (AIC: 10076, BIC: 10146). So, as was with when predicting Classical ratings, there are personal biases present that vary with intsrument type, harmony, and voice presence. The results of this model are displayed below. Unlike with Classical ratings, the presence of a guitar seems to have bigger impact in increasing the ratings than the presence of a string (as was with Classical music). The other fixed effects do not have that strong of signicance in the ratings. Looking at the variance components the variance for the random instrument/subject effect is fairly large (1.97), especially compared to the other two random effects (0.4, 0.029). The resdiual variance is estimated to be 2.49. These values suggest that there is a strong bias between subjects based on instruments present in the piece of music. This varaition is not higher than the overall unexplained variation in the model.

```
## lmer(formula = Popular ~ Instrument - 1 + Harmony + Voice + (1 |
##     Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice),
##     data = music2, REML = FALSE)
##                  coef.est coef.se
## Instrumentguitar  6.58     0.21
## Instrumentpiano   5.63     0.21
## Instrumentstring  3.97     0.21
## HarmonyI-V-IV    -0.03     0.14
## HarmonyI-V-VI    -0.27     0.14
## HarmonyIV-I-V    -0.19     0.14
## Voicepar3rd       0.16     0.08
## Voicepar5th       0.16     0.08
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.63
##  Subject:Voice      (Intercept) 0.17
##  Subject:Instrument (Intercept) 1.40
##  Residual                       1.58
## ---
## number of obs: 2492, groups: Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 
## AIC = 10076.1, DIC = 10052.1
## deviance = 10052.1
```

b. Using the same type of logic in part 2a above, several different models were fit to include additional covariates in the model for Popular ratings. The summary of the final model (the model found to have the lowest AIC and BIC) is shown below. This final model includes some similiar covariates to the model for Classical but is not entirely the same. The covariates included for Popular are the auxillary measure of the ability to distinguish between classical and popular, how much the subject concentrated on notes when listening, how familiar the subject is with Pachebel's
9 Cannon in D, whether the subject had prior composing experience and whether the subject had previously played an instrument before. For the fixed effects as was in part (a) the presences of a guitar is highly significant and positive in the model. Having prior composing experince is significant and positive although does not have as great as an effect as intstrument. Having previously played before had a negative impact on the Popular rating. The variance components are smaller than the values in part (a). Therefore it seems that some of the other covariates that were included as fixed effects, helped to predict this instrument bias per subject.

c. Models were fit including interactions between the new dichotomized musician variable (created in #3) and the other pedictors in the final model in part 4b (the models all include the random effect terms for each of the main factors). The final model included interactions with the musician variable and every predictor variable in the model in which an interaction would make sense. This model has a much lower AIC and BIC value which suggests that there are indeed certain things that musicians may be influenced by that non-musicians are not. As with Classical, the fixed effects show significance in the interactions with the harmony variable, with the strongest impact being the influence of musician and non musician on the chord in Canon in D beng present (t-stat = -2.534).
9 The estimate is negative (-0.75), which suggests that those who are considered musicians are less likely to rate a piece as popular when that chord is present than those who are not considered

musicians. Other significant interactions include the variable representing the subjects concentration on the notes, which also has a negative estimate, indicating that the more musicians focus on the notes, the lower the popular rating they will give than non-musicians. The fixed effects without interaction terms are very similar to the results seen in #b. The variance components have decreased (harmony = 0.32, voice = 0.029, instrument: 1.57) while the overall resdiual variance is very similar to the model without interactions. This result suggests that including the influence of being a musician accounts for some of the bias between subject and each of the main factors.

It should also be noted that in general the variance components for the random effects for the models for popular ratings are lower than those for classical music. This suggests that there is less subject bias for popular music than for classical music and makes sense, it is probably more likely that most subjects are familiar with popular music whereas perhaps only a subset are familiar with classical music.

5. Professional Summary

The purpose of this analysis was to determine what influences how people rate a musical piece, focusing on Classical and Popular styles of music. The data used was collected from a study on 70 subjects, where each subject listened to 36 musical stimuli and then rated the music on how Classical and how Popular the music excerpt sounded. The three main experimental factors considered in the study are the type of insturment (piano, strings, guitar), the harmonies, and the voice leading.

First an analysis was done on Classical ratings. The analysis first consider only the three main experimental factors and found whether a linear model, a repeated measures model, or a model with additional random effects was the best fit for the data. As I showed in part 1b and c, the model with additional random effects fit the data the best. This model had variance components for not only each subject but for each subject and insturment combination, subject and harmony combination, and subject and voice combination. These added variance components helped to adjust for some of the bias that exists on each subjects own background experience. The fixed effects of this model showed that the piano was very influential in increasing classical ratings, as well as the presence of the harmony in Cannon in D. After the three main experimental factors where considered, additional covariates were added to the model. For the Classical ratings, the covariates that were the most influential were the previous measure of the subjects ability to distinguish between classical and popular which had a negative impact on the rating and whether the subject had past composing experince which had a positive impact on the rating. Finally, the consideration of whether musicians are influenced by certain factors that non-musicians are not influenced by was found to be singnificant, as shown in #3.

The language here is a little vague. It would be better to say how being a musician affected each factor for which there was an interaction.

10

A second analysis was done on Popular ratings. The analysis and final model had many similarities when compared to Classical ratings. The model used was still a model that went beyond a standard repeated measures model and had the same additional varaiance components as for the Classical rating analysis. The main experimental factor of type of instrument present has the most influence, but unlike for classical ratings, the presence of a guitar increases the Popular ratings. The additional covariates, as discussed in #4, that have the biggest influence on Popular ratings were found to be whether the subject had past composing experience (increased ratings) and the familiarity of the subject with Cannon in D. Finally, the consideration of whether musicians are influenced by certain factors that non-musicians are not influenced by was found to be singnificant, as shown in #4, although not as significantly as for Classical ratings.

again, vague. More specific language is going to help Jiminez more

In summary, the models found to fit the data the best were random effect models, that went beyond a standard repeated measures model which only includes a variance component for each subject. These models also included variance components for a combination of subject/intsrument, subject/harmony, and subject voice. Including these additional effects helped to account for additional personal biases. Of the three main experimental factors considered in the study (Instrument, Harmony, Voice) for both Classical and Popular ratings, the factor Insturment seems to have the most influence on the rating. The type of instrument which increases the ratings changes when comparing Classical and Popular ratings. For Classical ratings, the presence of string instruments is most influential in increasing the rating. However for popular music the presence of a guitar increases the ratings. Also similarily between the two ratings, the only harmony that seemed to create much impact was the I-IV-vi chord which is the popular one from Pachebel's Cannon in D. The three levels of voice in the pieces of music did not influence the ratings as much as the other two main experimental factors. This analyis also provided support for the secondary research hypothesis that people who self-identified as musicians may be influenced by things that do not influence non-musicians.

R-CODE

```
#1
setwd("C:/Users/Katelyn Monoskey/Desktop/36-763/Homework 05")
#Load in and examine the data
music <- read.csv("ratings.csv")
summary(music)
head(music)

unique(music$Subject)

hist(music$Classical)

music2 <- music[(music$Classical != 19),]
hist(music2$Classical)

table(music2$Instrument)

table(music2$Harmony)

table(music2$Voice)

#1a

full <- lm(data = music2, Classical ~ Instrument + Harmony + Voice)
noIns <- lm(data = music2, Classical ~ Harmony + Voice)
noHar <- lm(data = music2, Classical ~ Instrument + Voice)
noVoc <- lm(data = music2, Classical ~ Instrument + Harmony)

anova(noIns, full)
anova(noHar, full)
anova(noVoc, full)

full2 <- lm(data = music2, Classical ~ Instrument - 1 + Harmony + Voice)
summary(full2)

#1b
library(arm)
library(lme4)
rand1 <- lmer(data = music2, Classical ~ Instrument - 1 + Harmony +
                Voice + (1|Subject), REML = "FALSE")

display(rand1)

AIC(rand1)
AIC(full)
```

```r
BIC(rand1)
BIC(full)
plot(rand1)
plot(full)


#1bii
#Check the random intercept using simulations.
library(RLRsim)

exactRLRT(rand1)
exactLRT(m = rand1, m0 = full)

#1ci
rand4 <- lmer(data = music2,
              Classical ~ Instrument - 1 + Harmony + Voice +(1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)
display(rand4)

AIC(rand4)
BIC(rand4)

#2
music2$play <- ifelse(is.na(music2$X1stInstr), 0, 1)

rand6 <- lmer(data = music2,
              Classical ~ Instrument - 1 + Harmony + Voice + Selfdeclare + OMSI +
                X16.minus.17  + ConsInstr + ConsNotes + PachListen +
                Composing + factor(play)  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)



rand8 <- lmer(data = music2,
              Classical ~ Instrument - 1 + Harmony + Voice + factor(Selfdeclare)
              + OMSI +  X16.minus.17   + PachListen +
                Composing + play  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)


rand9 <- lmer(data = music2,
              Classical ~ Instrument - 1 + Harmony + Voice +
                factor(Selfdeclare) +  X16.minus.17 + ConsInstr +
                ConsNotes  + PachListen +
                Composing + play  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)
```

```
display(rand9)


#2b
rand9_int <- lmer(data = music2,
              Classical ~ Instrument - 1 + Harmony + Voice +
                factor(Selfdeclare) +  X16.minus.17 + ConsInstr +
                ConsNotes  + PachListen +
                Composing + play  + (1 | Subject), REML = FALSE)


AIC(rand9)
BIC(rand9)
AIC(rand9_int)
BIC(rand9_int)




#3
table(music2$Selfdeclare)
music2$musician <- ifelse(music2$Selfdeclare <= 2, 0, 1)


inter1 <- lmer(data = music2,
              Classical ~ musician*Instrument + musician*Harmony + musician*Voice
              + X16.minus.17 + ConsInstr + ConsNotes  + PachListen +
                Composing + play  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)

inter2 <- lmer(data = music2,
              Classical ~ musician*Instrument + musician*Harmony + musician*Voice
              + musician*X16.minus.17 + musician*ConsInstr + musician*ConsNotes
              + musician*PachListen + musician*Composing + play
              + (1 | Subject:Instrument) + (1|Subject:Harmony)
              + (1|Subject:Voice), REML = FALSE)

summary(inter1)
summary(inter2)

AIC(inter1)
AIC(inter2)

BIC(inter1)
BIC(inter2)
```

```r
#4
#a
fullP <- lm(data = music2, Popular ~ Instrument + Harmony + Voice)
noInsP <- lm(data = music2, Popular ~ Harmony + Voice)
noHarP <- lm(data = music2, Popular ~ Instrument + Voice)
noVocP <- lm(data = music2, Popular ~ Instrument + Harmony)
instP <- lm(data = music2, Popular ~ Instrument - 1)

anova(noInsP, fullP)
anova(noHarP, fullP)
anova(noVocP, fullP)
anova(instP, fullP)
anova(instP, noHarP)
anova(instP, noVocP)

full2 <- lm(data = music2, Classical ~ Instrument - 1 + Harmony + Voice)
summary(full2)


library(arm)
library(lme4)
rand1P <- lmer(data = music2, Popular ~ Instrument - 1 + Harmony +
                Voice + (1|Subject), REML = "FALSE")

display(rand1)

AIC(rand1P)
AIC(instP)

BIC(rand1P)
BIC(instP)
plot(rand1P)
plot(instP)


#Check the random intercept using simulations.
library(RLRsim)

exactRLRT(rand1)
exactLRT(m = rand1P, m0 = instP)


rand4P <- lmer(data = music2,
              Popular ~ Instrument - 1 + Harmony + Voice +(1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)
```

```r
display(rand4)
AIC(rand4)
BIC(rand4)


music2$play <- ifelse(is.na(music2$X1stInstr), 0, 1)

rand6p <- lmer(data = music2,
              Popular ~ Instrument - 1 + Harmony + Voice + Selfdeclare + OMSI +
                X16.minus.17  + ConsInstr + ConsNotes + PachListen +
                Composing + factor(play)  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)


rand7p <- lmer(data = music2,
              Popular ~ Instrument - 1 + Harmony + Voice  + OMSI +
                X16.minus.17 + ConsNotes + PachListen +
                Composing + factor(play)  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)

rand10p <- lmer(data = music2,
              Popular ~ Instrument - 1 + Harmony + Voice  +
                X16.minus.17 + ConsNotes + PachListen +
                Composing + factor(play)  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)

rand10p_int <- lmer(data = music2,
              Popular ~ musician*Instrument - 1 + musician*Harmony + musician*Voice  +
                musician*X16.minus.17 + musician*ConsNotes + musician*PachListen +
                musician*Composing + play  + (1 | Subject:Instrument)
              + (1|Subject:Harmony) + (1|Subject:Voice), REML = FALSE)

summary(rand10p_int)
```

ADDITIONAL R-CODE

The following was R-code used to check diagnostics on models throughout the anlaysis.

```r
# Define functions to get residuals (given on course )
r.marg <- function(m) {
  y <- m@frame[,1]
  yhat <- model.matrix(m) %*% fixef(m)
  return(y-yhat)
}

r.cond <- function(m) {residuals(m)}
```

```r
r.reff <- function(m) {r.marg(m) - r.cond(m)}

# suitable fitted values to plot them against...
# (you can plot them against other things as well...

yhat.marg <- function(m) { model.matrix(m) %*% fixef(m) }

yhat.cond <- function(m) {
  y <- m@frame[,1]
  y - r.cond(m)
}

yhat.reff <- function(m) { yhat.marg(m) + r.cond(m) }

#lmer model
marg_res_2 <- r.marg(rand7)
cond_res_2 <- r.cond(rand7)
randeff_res_2 <- r.reff(rand7)
marg_fit_2 <- yhat.marg(rand7)
cond_fit_2 <- yhat.cond(rand7)
randeff_fit_2 <- yhat.reff(rand7)


par(mfrow = c(3, 2))
plot(marg_fit_2, marg_res_2, main = "Model 2 Marginal",
     xlab = "Marginal Fitted Values", ylab = "Marginal Residuals")

plot(cond_fit_2, cond_res_2, main = "Model 2 Conditional",
     xlab = "Conditional Fitted Values", ylab = "Conditional Residuals")

plot(randeff_fit_2, randeff_res_2, main = "Model 2 Random Effect",
     xlab = "Random Effect Fitted Values", ylab = "Random Effect Residuals")

#QQplots
Q <- qqnorm(cond_res_2,
            main = "Normal Q-Q Plot for \nConditional Residuals (Model 2)");
abline(lm(y ~ x, data=Q))

Q <- qqnorm(randeff_res_2,
            main = "Normal Q-Q Plot for \nRandom Effect Residuals (Model 2)");
abline(lm(y ~ x, data=Q))
```