Homework 5

Steph Eaneff
Hierachical Linear Models

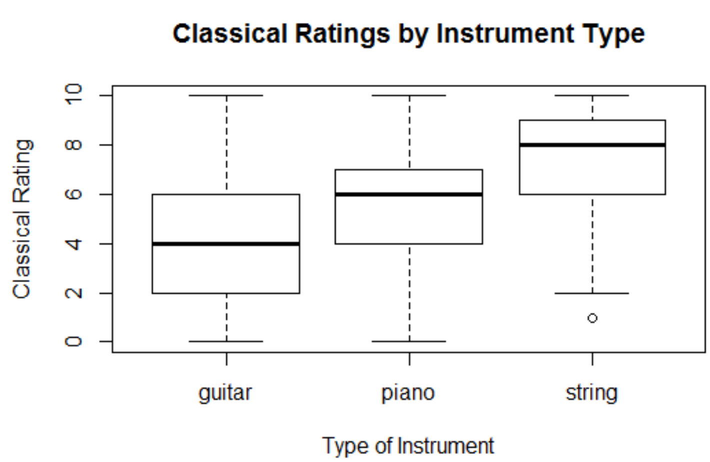
December 10, 2013

Problem 1

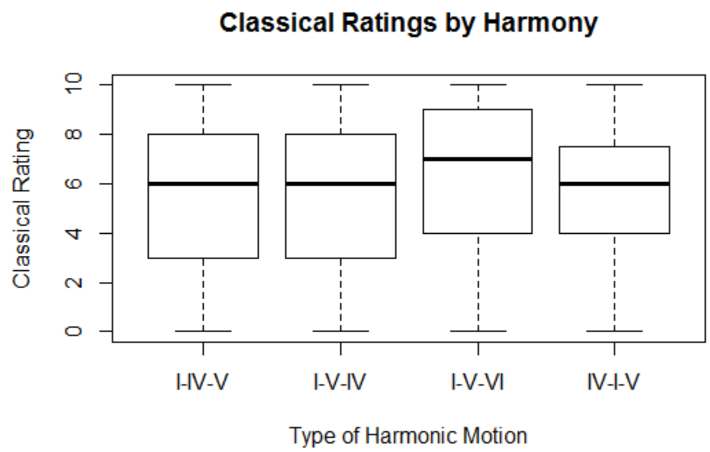
1a. Before analysis was conducted, data were cleaned and processed. Two outliers were removed which were associated with a classical rating score of 27 and a popular rating score of 19, respectively. Since the intended scale of music perception ranged from 1-10, these observations were clearly data entry errors.

Based on the boxplots generated during exploratory data analysis, shown below, it appears that ratings of how classical a given piece of music is percieved are influenced more by instrument type than by voice leading or type of harmony.

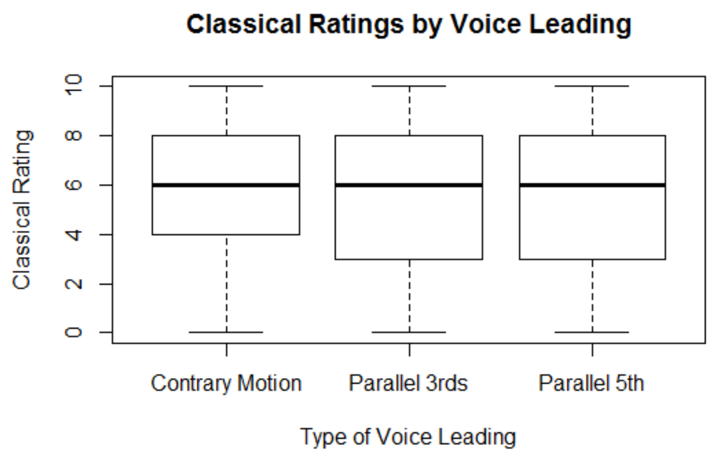
```
> # ratings<-ratings.i[,-26]
> # # ## remove variable first12, not used for analysis
> # # ## summary(ratings$Classical)
> #  ratings<-ratings[-which(ratings$Classical==max(ratings$Classical, na.rm=TRUE)),]
> # # ## summary(ratings$Popular)
> #  ratings<-ratings[-which(ratings$Popular==max(ratings$Popular, na.rm=TRUE)),]
```




```
> # boxplot(Classical ~ Instrument, data=ratings,
> #         xlab="Type of Instrument", ylab="Classical Rating",
> #         main="Classical Ratings by Instrument Type")
```




```
> # boxplot(Classical ~ Harmony, data=ratings,
> #         xlab="Type of Harmonic Motion", ylab="Classical Rating",
> #         main="Classical Ratings by Harmony")
```




```
> # library(plyr)
> # ratings$Voice<-revalue(ratings$Voice, c(contrary="Contrary Motion",
> #                                           par3rd="Parallel 3rds",
> #                                           par5th="Parallel 5th"))
> # boxplot(Classical ~ Voice, data=ratings,
> #          xlab="Type of Voice Leading", ylab="Classical Rating",
> #          main="Classical Ratings by Voice Leading")
```

In order to futher consider these preliminary findings, a series of generalized linear models were fit to the data. Single predictor fixed-effects linear models fit to the data indicated that, for each of the three considered explanatory variables (harmony, instrument, and voice) classical ratings scores varied in a statistically significant way at the $\alpha = 0.05$ level. As shown in the boxplots above, string instruments were identified to have the highest classical rating, followed by piano, and guitar. Similarly, Harmony I-V-VI had the highest classical rating, followed by Harmony IV-I-V, then Harmony I-IV-V, and lastly, Harmony I-V-IV. In the instance of harmony, only the difference between Harmony I-V-VI (associated with the highest classical rating) and Harmony I-V-IV (associated with the lowest classical rating) was found to be statistically significant. The highest classical ratings observed in the study were associated with the voice type Contrary motion, followed by Parallel 5th and then Parallel 3rd.

Based on consideration of the AIC, BIC, and residual deviance of each single-predictor regression, instrument was identified to be the most significant predictor of classical perception score. When a second predictor was added to this model, voice was the additional predictor that contributed most to the statistical significance of the model. However, the inclusion of the harmony variable in the model, in addition to instrument and voice, was still seen to improve the fit of the model based on consideration of AIC, BIC, and residual deviance, thus the three predictor model was identified as best fitting the data. In the context of the experiment, these findings suggest that people's perception of how "classical" music is is influenced strongly by the type of instrument, and less strongly by factors related to type of harmony or type of vocal leading. Specifically, string music is generally percieved as the most classical sounding type of music.

Model Predictors	AIC	BIC	Residual Deviance	Number of Predictors
Harmony, Instrument, Voice	11200	11250.58	11200	3
Harmony, Instrument	11240	11283.43	13190	2
Harmony, Voice	11880	11917.11	17060	2
Instrument, Voice	11240	11279.74	11240	2
Instrument	11260	11279.01	13330	1
Voice	11910	11933.94	17340	1
Harmony	11880	11912.88	17140	1

The final model discussed above, containing each of the predictors discussed above, is identified below.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.3353	0.1293	33.53	0.0000
Harmony (I-V-IV)	-0.0307	0.1295	-0.24	0.8129
Harmony (I-V-VI)	0.7691	0.1295	5.94	0.0000
Harmony (IV-I-V)	0.0316	0.1294	0.24	0.8069
Instrument (piano)	1.3739	0.1125	12.21	0.0000
Instrument (string)	3.1194	0.1118	27.90	0.0000
Voice (Par 3rd)	-0.3983	0.1122	-3.55	0.0004
Voice (Par5th)	-0.3567	0.1121	-3.18	0.0015

```
> # fullmodel<-glm(Classical~Harmony+Instrument+Voice, data=ratings)
> # ## print(fullmodel)
> # ## BIC(fullmodel)
> # novoicemodel<-glm(Classical~Harmony+Instrument, data=ratings)
> # ## print(novoicemodel)
> # ## BIC(novoicemodel)
> # noinstrumentmodel<-glm(Classical~Harmony+Voice, data=ratings)
> # ## print(noinstrumentmodel)
```

```
> # ## BIC(noinstrumentmodel)
> # noharmonymodel<-glm(Classical~Voice + Instrument, data=ratings)
> # ## print(noharmonymodel)
> # ## BIC(noharmonymodel)
> # instrumentonlymodel<-glm(Classical~Instrument, data=ratings)
> # ## print(instrumentonlymodel)
> # ## BIC(instrumentonlymodel)
> # voiceonlymodel<-glm(Classical~Voice, data=ratings)
> # ## print(voiceonlymodel)
> # ## BIC(voiceonlymodel)
> # harmonyonlymodel<-glm(Classical~Harmony, data=ratings)
> # ## print(harmonyonlymodel)
> # ## BIC(harmonyonlymodel)
> # # summary(lm(Classical~Instrument, data=ratings))
> # # summary(lm(Classical~Voice, data=ratings))
> # # summary(lm(Classical~Harmony, data=ratings))
```

1b.i. As a hierarchical linear model, a repeated-measures (or random intercept) model can be represented using the following form:

$$Classical_i = \alpha_{j[i]} + \beta_1 voice + \beta_2 harmony + \beta_3 instrument$$
$$\alpha_j = \beta_0 + \eta_j,\, \eta_j \sim N(0,\, \tau^2)$$

1b.ii. In order to consider the model identified above, both simulation and two model-fitting critieria (AIC and BIC) were considered. Based on examination of the AIC and BIC of the newly generated random intercept model (AIC=10453.3 and BIC=10511.45), it is apparent that the inclusion of the random intercept significantly improves the model fit from those identified above fit using only fixed effects.

Improved fit was also confirmed by directly testing the significance of the random intercept term using simulation-based methods. Based on these results, shown below, we reject the null hypothesis that the random intercept term should be removed from the model, and determine that the random intercept significantly improves the overall fit of the model.

```
 simulated finite sample distribution of RLRT.

 (p-value based on 10000 simulated values)

data:
RLRT = 769.4575, p-value < 2.2e-16
```

```
> # library(arm)
> # lmer.repeated<-lmer(Classical~ 1 + Voice + Harmony + Instrument + (1|Subject),
> #                      data=ratings)
> ## display(lmer.repeated)
> # summary(lmer.repeated)
> # BIC(lmer.repeated)
```

```
>
> # library(RLRsim)
> # exactRLRT(lmer.repeated)
```

1.b.iii. When the random intercept is introduced using the lmer model framework, the overall significance of the model predictors does not change dramatically, nor do the cofficients themselves. However, the model fit is improved when incorporating a random intercept, since additional variability in the outcome variable is accounted for. In general, the parameter estimates become less extreme when allowing for the inclusion of a random intercept in the model framework.

The model which was fit to address these questions is identified below. Based on the significant t-values associated with elements of each included factor, it is apparent that the full model fits the data well. This was confirmed by consideration of AIC and BIC of the full and reduced versions of the model.

```
Fixed effects:
                  Estimate Std. Error t value
(Intercept)        4.33812    0.18848   23.02
Voicepar3rd       -0.40033    0.09236   -4.33
Voicepar5th       -0.36103    0.09227   -3.91
HarmonyI-V-IV     -0.03005    0.10657   -0.28
HarmonyI-V-VI      0.77098    0.10652    7.24
HarmonyIV-I-V      0.03268    0.10648    0.31
Instrumentpiano    1.37553    0.09264   14.85
Instrumentstring   3.11874    0.09203   33.89
```

Consideration of AIC and BIC of the model which includes the random intercept but not selections of the fixed effects variables identified above suggests that, with the inclusion of the random intercept, the full model with each of the three predictors still best fits the data.

Model Predictors (in addition to random intercept)	AIC	BIC
Harmony, Instrument, Voice	10453	10511
Harmony, Voice	11387	11434
Harmony, Instrument	10466	10512
Voice, Instrument	10516	10557

```
> # display(lmer.repeated)
> # BIC(lmer.repeated)
> #
> # display(update(lmer.repeated, .~. -Instrument))
> # BIC(update(lmer.repeated, .~. -Instrument))
> #
> # display(update(lmer.repeated, .~. -Voice))
> # BIC(update(lmer.repeated, .~. -Voice))
> #
> # display(update(lmer.repeated, .~. -Harmony))
> # BIC(update(lmer.repeated, .~. -Harmony))
```

1.c.i When a model is fit which allows for "personal biases" in ratings (for instance, if a person has different opinions regarding different types instruments, harmonies, or voices in the model), the overall model fit is improved. The model fit which allows for a unique slope for each individual person-instrument combination, person-voice lead combination, and person-harmony combination is referred to as the "Personal Bias" model for the purpose of these analyses.

The full personal bias model, including all three new random intercept terms (but not the original single random intercept) better fits the data than the previously fit models, as shown by consideration of the AIC, BIC, DIC, and Residual Deviance, as shown below. Additionally, as also shown below, simulation-based methods using RLRT suggest that the inclusion of each random effect improves the model in a statistically significant way ($p < 0.0001$). Intuitively, this model can also be understood as a means of accounting for variation in individual preferences that change across music types.

Model Predictors	AIC	BIC	DIC	Residual Deviance
Full Fixed Effects Model	11200	11250.58	NA	11200
Random Intercept Model (lmer)	10410.5	10511.45	10387.8	10410
"Personal Bias" Random Effect	10029.5	10099.35	9969.4	9987.5

```
> exactRLRT(m=mA, m0=m0, mA=mA)

 simulated finite sample distribution of RLRT.

 (p-value based on 10000 simulated values)

data:
RLRT = 364.3006, p-value < 2.2e-16
```

```
> # lmer.personalbias<-lmer(Classical~ 1 + Voice + Harmony + Instrument +
> #                         (1|Subject:Instrument) +
> #                         (1|Subject:Harmony) +
> #                         (1|Subject:Voice),
> #                       data=ratings)
> ## display(lmer.personalbias)
> ## summary(lmer.personalbias)
> ## BIC(lmer.personalbias)
> # library(RLRsim)
> # m0<-lmer.repeated
> # attach(ratings)
> # mA<-update(lmer.repeated, .~. + (1|Subject: Instrument))
> # exactRLRT(m=mA, m0=m0, mA=mA)
> #
> # mA2<-update(lmer.repeated, .~. + (1|Subject: Voice))
> # exactRLRT(m=mA2, mA=mA2, m0=m0)
> #
> # mA3<-update(lmer.repeated, .~. + (1|Subject: Harmony))
> # exactRLRT(m=mA3, mA=mA3, m0=m0)
> #
> # detach(ratings)
```

1.c.ii. In the new personal bias model which includes the three new random effects, is is clear that string instruments, contrary motion vocal leading, and Harmony I-V-VI are associated with the perception of the most strongly "Classical" music. Conversely, music played on the guitar, in parallel third or fifth voice, and in Harmony I-V-IV or Harmony I-VI-V were perceived as the least Classical, based on the magnitude and signs of the coefficients estimated below. As before, instrument is identified as being the most statistically significant predictor of how classical a given piece of music is perceived as being (based on consideration of the level of significance of the instrument variable, not shown below).

Coefficient	Estimate
(Intercept)	4.34
Voice(parallel 3rd)	-0.39
Voice (parallel 5th)	-0.36
Harmony (I-V-IV)	-0.03
Harmony (I-V-VI)	0.77
Harmony (IV-I-V)	0.04
Instrument (piano)	1.37
Instrument (string)	3.12

Based on consideration of AIC and BIC considering sub-models of the full model, it is apparent that each of the random bias terms, as well as each of the fixed effect terms, is still seen to improve the overall fit of the model. Thus, the full model including all of these terms best fits the observed data.

Model Predictors	AIC	BIC
"Personal Bias" Random Effect	10023	10099
Remove Voice	10046	10104
Remove Harmony	10056	10108
Remove Instrument	10130	10188
Remove Instrument Bias	10590	10654
Remove Harmony Bias	10136	10200
Remove Voice Bias	10028	10093

```
> ## fixef(lmer.personalbias)
> ## summary(lmer.personalbias)
>
> # lmer.personalbias.1<-lmer(Classical~ 1 + Harmony + Instrument +
> #                           (1|Subject:Instrument) +
> #                           (1|Subject:Harmony) +
> #                           (1|Subject:Voice),
> #                       data=ratings)
> # display(lmer.personalbias.1)
> # BIC(lmer.personalbias.1)
> #
> # lmer.personalbias.2<-lmer(Classical~ 1 + Voice + Instrument +
> #                           (1|Subject:Instrument) +
> #                           (1|Subject:Harmony) +
> #                           (1|Subject:Voice),
```

```
> #                      data=ratings)
> # display(lmer.personalbias.2)
> # BIC(lmer.personalbias.2)
> #
> # lmer.personalbias.3<-lmer(Classical~ 1 + Voice + Harmony +
> #                          (1|Subject:Instrument) +
> #                          (1|Subject:Harmony) +
> #                          (1|Subject:Voice),
> #                      data=ratings)
> # display(lmer.personalbias.3)
> # BIC(lmer.personalbias.3)
> #
> # lmer.personalbias.4<-lmer(Classical~ 1 + Voice + Harmony + Instrument +
> #                          (1|Subject:Harmony) +
> #                          (1|Subject:Voice),
> #                      data=ratings)
> # display(lmer.personalbias.4)
> # BIC(lmer.personalbias.4)
> #
> # lmer.personalbias.5<-lmer(Classical~ 1 + Voice + Harmony + Instrument +
> #                          (1|Subject:Instrument) +
> #                          (1|Subject:Voice),
> #                      data=ratings)
> # display(lmer.personalbias.5)
> # BIC(lmer.personalbias.5)
> #
> # lmer.personalbias.6<-lmer(Classical~ 1 + Voice + Harmony + Instrument +
> #                          (1|Subject:Instrument) +
> #                          (1|Subject:Harmony),
> #                      data=ratings)
> # display(lmer.personalbias.6)
> # BIC(lmer.personalbias.6)
>
```

1.c.iii The model generated above can be designated mathematically using the following form:

$$Classical_i = \alpha_{1j[i]} + \alpha_{2j[i]} + \alpha_{3j[i]} + \beta_1 voice + \beta_2 harmony + \beta_3 instrument$$

$$\alpha_{1j}\alpha_1 + \eta_{ij},\, \eta \sim N(0\ ,\ \tau_1^2)$$

$$\alpha_{2j}\alpha_2 + \eta_{ij},\, \eta \sim N(0\ ,\ \tau_2^2)$$

$$\alpha_{3j}\alpha_3 + \eta_{ij},\, \eta \sim N(0\ ,\ \tau_3^2)$$

Problem 2

2.a In order to address missing values, individuals who did not respond to the questions related to their proficiency in their first and second instruments were recoded as having a score of '0' on these items, indicating that they were "not at all proficient" in their first and second instrument. Moreover, these variables were combined into a single "instrument" variable which was used as an indicator variable for whether or not an individual was proficient at either a first or both a first and a second instrument. Other variables, such as number of classes or AP Theory, were similarly coded when it was possible to reasonably infer that missing values were equivalent to a given value of the data.

```
> # par(mfrow=c(1,1))
> # boxplot(Classical~Selfdeclare, data=ratings)
> # plot(ratings$OMSI, ratings$Classical); abline(lm(Classical~OMSI, data=ratings))
> # plot(ratings$X16.minus.17, ratings$Classical); abline(lm(Classical~X16.minus.17,
> #                                                           data=ratings))
> # ## 16 minus 17 could be a good predictor
> # plot(ratings$ConsInstr, ratings$Classical); abline(lm(Classical~ConsInstr,
> #                                                       data=ratings))
> # plot(ratings$ConsNotes, ratings$Classical); abline(lm(Classical~ConsNotes,
> #                                                       data=ratings))
> # plot(ratings$Instr.minus.Notes, ratings$Classical)
> # abline(lm(Classical~Instr.minus.Notes, data=ratings))
> # plot(ratings$PachListen, ratings$Classical); abline(lm(Classical~PachListen,
> #                                                       data=ratings))
> # plot(ratings$ClsListen, ratings$Classical); abline(lm(Classical~ClsListen,
> #                                                       data=ratings))
> # ## Pach and Cls listen might be good too
> # plot(ratings$KnowAxis, ratings$Classical); abline(lm(Classical~KnowAxis,
> #                                                       data=ratings))
> # plot(ratings$X1990s2000s, ratings$Classical); abline(lm(Classical~X1990s2000s,
> #                                                       data=ratings))
> # plot(ratings$X1990s2000s.minus.1960s1970s, ratings$Classical);
> # abline(lm(Classical~X1990s2000s.minus.1960s1970s, data=ratings))
> # boxplot(Classical~CollegeMusic, data=ratings)
> # plot(ratings$NoClass, ratings$Classical); abline(lm(Classical~NoClass,
> #                                                       data=ratings))
> # boxplot(Classical~APTheory, data=ratings)
> # plot(ratings$Composing, ratings$Classical); abline(lm(Classical~Composing,
> #                                                       data=ratings))
> # ## Composing might be pretty good
> # plot(ratings$PianoPlay, ratings$Classical); abline(lm(Classical~PianoPlay,
> #                                                       data=ratings))
> # plot(ratings$GuitarPlay, ratings$Classical); abline(lm(Classical~GuitarPlay,
> #                                                       data=ratings))
> # plot(ratings$X1stInstr, ratings$Classical); abline(lm(Classical~X1stInstr,
> #                                                       data=ratings))
> # plot(ratings$X2ndInstr, ratings$Classical); abline(lm(Classical~X2ndInstr,
```

```
> #                                                          data=ratings))
> # ## 2nd Instr might be good, check correlation
> # plot(ratings$Popular, ratings$Classical); abline(lm(Classical~Popular,
> #                                                          data=ratings))
> # ## Really strongly correlated with popular, but won't use that because it's the other
>

> # ratings$newinstrument<-ifelse(complete.cases(ratings$X1stInstr), 1,
> #                                ifelse(complete.cases(ratings$X2ndInstr), 1, 0))
> #
> # table(ratings$X1stInstr, ratings$newinstrument)
> # table(ratings$X2ndInstr, ratings$newinstrument)
> # table(is.na(ratings$newinstrument))
> # ratings$CollegeMusic<-ifelse(!complete.cases(ratings$CollegeMusic),
> #                               0, ratings$CollegeMusic)
> # table(ratings$CollegeMusic)
> # table(is.na(ratings$CollegeMusic))
> # table(is.na(ratings$Voice))
> # table(is.na(ratings$Instrument))
> # table(is.na(ratings$Harmony))
> # table(is.na(ratings$Selfdeclare))
> # table(is.na(ratings$OMSI))
> # table(is.na(ratings$ConsInstr))
> # table(is.na(ratings$ConsNotes))
> # ratings$NoClass<-ifelse(!complete.cases(ratings$Composing),
> #                               0, ratings$Composing)
> # ratings<-ratings[complete.cases(ratings$ConsNotes),]
> # ratings<-ratings[complete.cases(ratings$PachListen),]
> # ratings$NoClass<-ifelse(!complete.cases(ratings$NoClass),
> #                               0, ratings$NoClass)
> # table(is.na(ratings$GuitarPlay))
> # table(is.na(ratings$PianoPlay))
>
```

The first model fit (lmer) included fixed effects regarding whether or not an individual listened to Pachelbel (PachListen), whether or not an individual listened to classical music (ClsListen), and an individual's level of experience with composing (Composing). These values were chosen to be considered as fixed effects since it was anticipated that their impact on classical music ratings would not change dramatically across different individuals. A second model, including fixed effects for playing guitar, playing piano, and composing, was found to be a less good fit to the data based on consideration of AIC, BIC, DIC, and residual deviance, as shown in the table below. This process was repeated considering multiple combinations of fixed effect predictors, informed by the exploratory data analyis carried out using the code above (although for the sake of space, these plots were not shown in the analysis).

As different sets of random effects were explored, it became apparent that it was important not only to achieve optimal values of AIC, BIC, and DIC, but also to keep in mind the relevant research question and interpretability of the model. In this case, fixed effects should be associated with person-level information which can be considered constant across the population. Predictors related to, for instance, how closely someone listened to a given piece of music likely do not meet this criteria, as we can expect a significant deal of variation the influence of these factors on different individuals. However, predictors such as number of years required to play an instrument or overall OMSI score, which reflects level of musical knowledge, can be expected to impact the perception of music as classical similarly for all individuals in the considered population.

Thus, the fixed effects included in the model were those which not only optimized measures of goodness of fit, but also could be logically included in the model based on their interpretation. In order to standardize consideration of AIC and BIC model fit criterion, observations with missing data which could not be inferred based on the survey design (such as variables which would reasonably be skipped if the answer were zero such as number of college music classes or proficiency in a musical isntrument) were removed from the analyses or not considered for inclusion in the model.

In this case, the best fit model which was identified based on eighteen rounds of model selection (informed by consideration of model fit criterion, significance of coefficients, and subject matter expertise) contained the fixed effects which addressed the extent to which each individual identified as a musician, the individual's experience with muisc composition, the extent to which the individual reported listening to classical music, and the extent to which the individual played the piano. The desired research question addressed by this model considers the impact of musical knowledge and familiarity (both through composing, listening, and piano-playing experience) on perception of classical music. I chose these variables as fixed effects not only because they logically fit the model as fixed effects and generate a model with desirable AIC and BIC ratings, but, more importantly, because they help to address the research question I am interested in.

The fixed effects of this model and their associated coefficients are included in the table below.

```
> #
> # lmer1<-lmer(Classical~ 1 + Voice + Harmony + Instrument +
> #                        (1|Subject:Instrument) +
> #                        (1|Subject:Harmony) +
> #                        (1|Subject:Voice) +
> #              Selfdeclare + OMSI + ConsInstr + ConsNotes +
> #              PachListen + ClsListen,
> #            data=ratings)
> #  display(lmer1)
> #  BIC(lmer1)
> #
> # lmer2<-update(lmer1, .~. -ConsNotes - ConsInstr)
> # display(lmer2)
> # BIC(lmer2)
> #
> # lmer3<-update(lmer2, .~. -PachListen)
> # display(lmer3)
> # BIC(lmer3)
```

Model	AIC	BIC
"Personal Bias" Random Effect	10029.5	10099.35
Lmer 1	8386	8476
Lmer 2	8384	8468
Lmer 3	8386	8465
Lmer 4	8386	8478
Lmer 5	8381	8278
Lmer 6	8379	8309
Lmer 7	8383	8478
Lmer 8	8221	8316
Lmer 9	8221	8316
Lmer 10	8220	8332
Lmer 11	8218	8325
Lmer 12	8228	8329
Lmer 13	8225	8321
Lmer 14	8386	8476
Lmer 15	8206	8307
Lmer 16	8203	8298
Lmer 17	8370	8311
Lmer 18	8204	8294

```
> #
> # lmer4<-update(lmer3, .~. +NoClass)
> # display(lmer4)
> # BIC(lmer4)
>
> # lmer5<-update(lmer4, .~. - NoClass + aptheorynew )
> # display(lmer5)
> #
> # lmer6<-update(lmer5, .~. - NoClass + noclasscat )
> # display(lmer6)
> #
> # lmer7<-update(lmer6, .~. - noclasscat + newinstrument)
> # display(lmer7)
> # BIC(lmer7)
> #
> # lmer8<-update(lmer7, .~. + Composing)
> # display(lmer8)
> # BIC(lmer8)
> #
> # lmer9<-update(lmer8, .~. - ClsListen)
> # display(lmer9)
> # BIC(lmer9)
> #
> # lmer10<-update(lmer9, .~. + ClsListen + GuitarPlay + PianoPlay)
> # display(lmer10)
> # BIC(lmer10)
```

Coefficient	Estimate
(Intercept)	4.66
Voice (par 3rd)	-0.38
Voice (par 5th)	-0.35
Harmony (I-V-IV)	-0.02
Harmony (I-V-VI)	0.85
Harmony (IV-I-V)	0.05
Instrument (piano)	1.42
Instrument (string)	3.16
Self-declare	-0.53
Composing	0.22
Classical Listen	0.22
Piano Play	0.23

```
> #
> # lmer11<-update(lmer10, .~. -newinstrument)
> # display(lmer11)
> # BIC(lmer11)
> #
> # lmer12<-update(lmer11,.~. -Selfdeclare)
> # display(lmer12)
> # BIC(lmer12)
> #
> # lmer13<-update(lmer12, .~. - GuitarPlay)
> # display(lmer13)
> # BIC(lmer13)
> #
> # lmer14<-update(lmer13, .~. - Composing)
> # display(lmer14)
> # BIC(lmer14)
> #
> # lmer15<-update(lmer11, .~. - OMSI)
> # display(lmer15)
> # BIC(lmer15)
> #
> # lmer16<-update(lmer15, .~. - GuitarPlay)
> # summary(lmer16)
> # BIC(lmer16)
> #
> # lmer17<-update(lmer16, .~. - Composing)
> # display(lmer17)
> #
> # lmer18<-update(lmer16, .~. - aptheorynew)
> # display(lmer18)
> # BIC(lmer18)
```

2b. Once the fixed effects were included in the model, it also makes sense to consider the potential inclusion of other random effects in the model. Of note, these random effects should be added intentionally in order to address the desired research question. In this case, the research question seeks to address the factors which most significantly influence the perception of whether or not music is percieved as classical. Additional random factors which help to account for the "noise" of the data may be able to help answer this question by accounting for additional variability in the observed results. For instance, it makes sense to consider the inclusion of random effects related to the level of concentration of each individual, which, while not a research question itself, does help to account for observed variation in perception of classical music across individuals.

Consideration of models which accounted for these random effects indicate that including the a random slope associated with how closely each subject concentrates on the instrument significantly improves the fit of the model. These findings are illustrated in the table below. This fits into the model logically, since during exploratory data analysis it was identified that instrument was hugely influential in whether or not listeners percieved music as being classical.

Model	AIC	BIC	DIC
"Personal Bias" Random Effect	10030	10099	9969
Personal Bias Fixed Effects	8204	8294	8116
Lmer 19	8195	8313	8097
Lmer 20	8190	8297	8099
Lmer 21	8189	8296	8098

```
> #
> # lmer19<-update(lmer18, .~. + (ConsInstr | Subject) + (ConsNotes | Subject),
> #                 data=ratings)
> # display(lmer19)
> # BIC(lmer19)
> #
> # lmer20<-update(lmer19, .~. - (ConsInstr | Subject) ,
> #                 data=ratings)
> # display(lmer20)
> # BIC(lmer20)
> #
> # lmer21<-update(lmer20, .~. + (ConsInstr | Subject) - (ConsNotes | Subject) ,
> #                 data=ratings)
> # display(lmer21)
> # BIC(lmer21)
>
```

2c. The model identified in the above analyses takes the form shown in the output below. In the context of this problem, the percpetion of how classical a given piece of music is is most strongly influenced by the type of instrument playing the song. Guitars are percieved as the least classical, while string instruements are percieved as being the most classical and pianos the second most classical, when controlling for the other variables included in the model. Songs with the Harmony I-V-IV were also percieved as being significantly more classical than other types of harmonies. Voice leading was also found to be a significant predictor of how classical a given piece of music was percieved, when controlling for all other variables. Music with contrary motion voice leading was percieved as the most classical, followed by parallel 5ths and parallel 3rds, which did not differ strongly from one another.

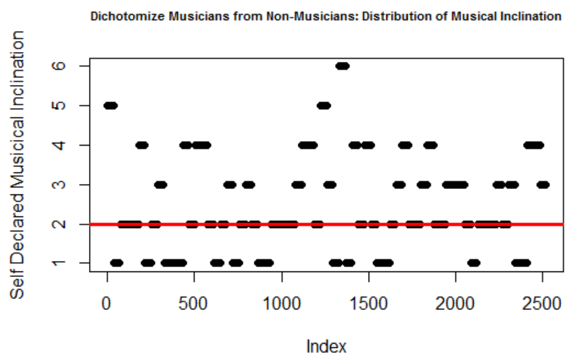
Those who identified themselves more strongly as "musicians" were less likely to identify a piece of music as classical, and those with increasinsg experience in composing music were more likely to report music as classical, as were those who played the piano more and those who listened more often to classical music.

In order to account for personal biases related to harmony, instrument, and voice leading preferences, a random effect was added which generated random draws from a single normal distribution for each combination of person and instrument, as well as each combination of person and voice leading and person and harmony. These random effects helped to ensure that the model was able to account for personal bias when attempting to identify overall population trends. A random effect was also added to account for changes in preference influenced by how closely people listened to instruments (under the assumption that how closely people listen to music may have different impacts on how classical they percieve the music to be across multiple people). This effect was incorporated into the model as a random slope, since it made intuitive sense that this variable would change how closely different people distinguished between different types of intruments. Fixed and random effects in this model were chosen for incorporation based on how strongly they contributed to the relevant research question.

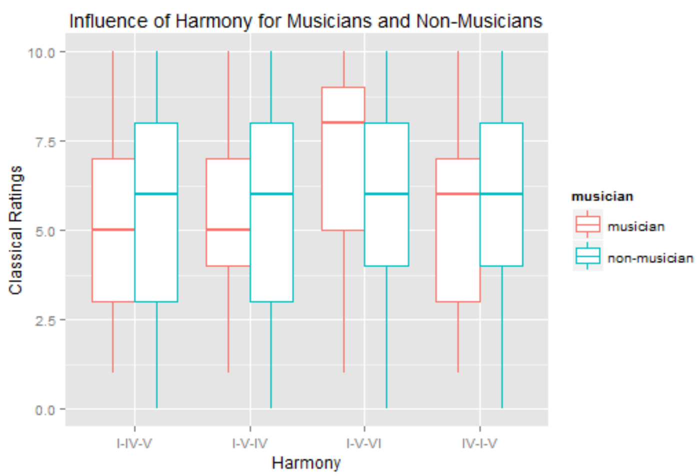
Coefficient	Estimate
(Intercept)	4.16
Voice (par 3rd)	-0.48
Voice (par 5th)	-0.34
Harmony (I-V-IV)	0.11
Harmony (I-V-VI)	2.16
Harmony (IV-I-V)	-0.23
Instrument (piano)	1.46
Instrument (string)	2.66
OMSI	0.01
First Instr	-0.14
Second Instr	-0.69

Problem 3

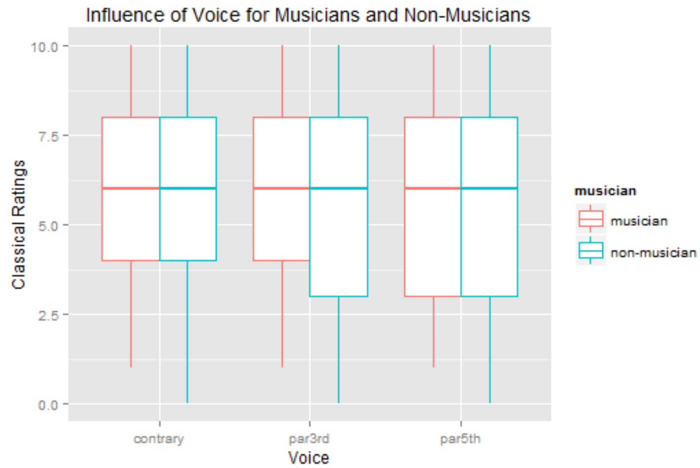
3a. The model identified above was further examined to consider whether individuals who self identify as musicians are influenced by things that do not influence non-musicians. As shown in the plot below, the variable in which individuals self-delcared their level of musical inclination on a scale of 1-6 was split at the median value (2) in order to distinguish those who identified themselves as "musicians" from those who identified themselves as "non-musicians." Since only dicrete values were allowed for this scale, those who gave themselves a rating of 2 were classified as non-musicians (so the non-musician group is slightly larger).



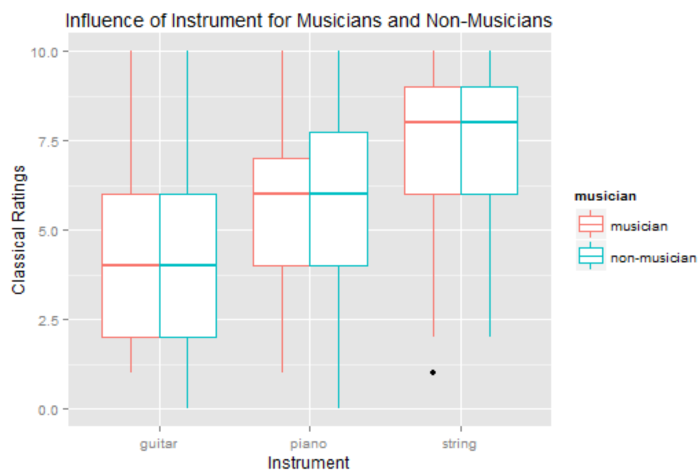
As can be seen in the series of side-by-side boxplots shown below, those who self-identified as musicians were influenced differently by harmony than those who identified as non-musicians, though these differences were not always found to be statistically significant. In general, musicians were more likely than non-musicians to identify Harmony I-V-VI as being associated with classical music. The dichotomy between musician and non-musician perception of the influence of vocal leading and instrument is less pronounced than the influence of harmony, as shown in the following plots.



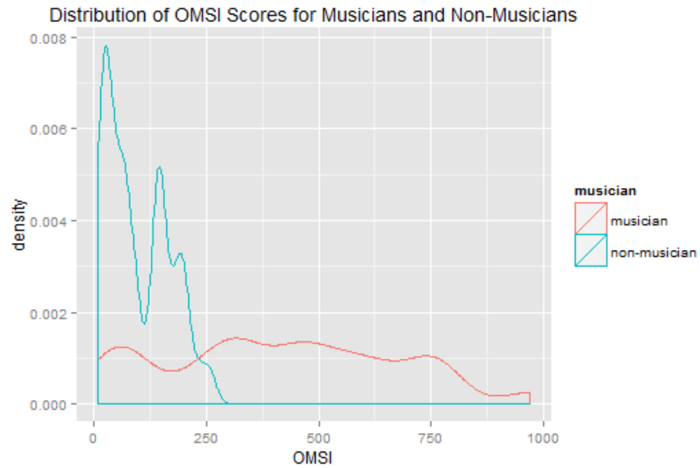
Based on the plot below (and the remarkably similar boxplots), it does not appear that those who self-identify as musicians are more or less influenced by different types of vocal leading than those who identify as non-musicians.



Based on the final boxplot, it does not appear that those who self-identify as musicians are influenced differently than those who do not self-identify as musicians by choice of instrument.



As expected, those who identified as non-musicians in the study had lower OMSI scores than those who identified as musicians, though those who identified as musicians had a broad range of OMSI scores that was much less distinct than the more narrow distribution of OMSI scores for non-musicians. This analysis was performed out of curiosity related to the relationship between OMSI and self-identified musicianship. Overall, there was no significiant interaction identified between OMSI score and perception of classical music (though this figure is not shown).



As shown in the table below, the impact of including the dichotomized musician variable was also considered through iterative model selection. Allowing the effect of harmony, voice, and instrument to vary between musicians and non-musicians did not improve the fit of the model, as demonstrated through AIC and BIC Scores. However, when only an interaction term between harmony and musician was included in the model, the fit of the model was found to improve based on consideration of AIC and BIC. This finding suggests that musicians and non-musicians may percieve harmony differently with respect to its influence on whether or not music is classical.

Model	AIC	BIC
"Personal Bias" Random Effect	10029.5	10099.35
Best Fit Model (2C)	8189	8296
Musician*Harmony	8168	8298
Musician*Instrument	8188	9312
Musician*Voice	9195	8318
All interactions	8174	8325

The fixed effects of the model discussed above are shown in the table below. Of note, musicians are more likely than non-musicians to percieve both piano and string music as classical.

```
> # # plot(ratings$Selfdeclare, ylab="Self Declared Musicical Inclination",
> # #         main="Dichotomize Musicians from Non-Musicians: Distribution of Musical Incl
> #
> # # abline(h=median(ratings$Selfdeclare), lwd=3, col="red")
> # # median(ratings$Selfdeclare)
> # ratings$musician<-ifelse(ratings$Selfdeclare>2,
> #                          "musician", "non-musician")
> # ## table(ratings$musician, ratings$Selfdeclare)
> # # library(ggplot2)
> # #
> # box<-ggplot(ratings, aes(Harmony, Classical, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Harmony for Musicians and Non-Musicians") +
```

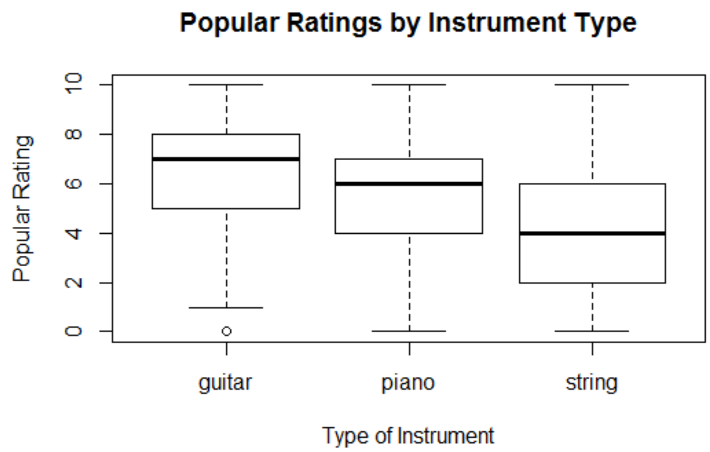
Coefficient	Estimate
(Intercept)	6.38
Voice (par 3rd)	-0.38
Voice (par 5th)	-0.35
Harmony (I-V-IV)	-0.02
Harmony (I-V-VI)	0.85
Harmony (IV-I-V)	0.05
Instrument (piano)	1.07
Instrument (string)	2.67
Self-declare	-0.87
Composing	0.25
Cassical Listen	0.17
Piano Play	0.26
musician	-1.42
Piano*musician	0.64
String*musician	0.90

```
> #   ylab("Classical Ratings")
> #
> # box<-ggplot(ratings, aes(Voice, Classical, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Voice for Musicians and Non-Musicians") +
> #   ylab("Classical Ratings")
> #
> # box<-ggplot(ratings, aes(Instrument, Classical, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Instrument for Musicians and Non-Musicians") +
> #   ylab("Classical Ratings")
> #
> # ggplot(ratings, aes(OMSI, col=musician)) + geom_density() +
> #   ggtitle("Distribution of OMSI Scores for Musicians and Non-Musicians")
> #
> # ggplot(ratings, aes(OMSI, Classical, col=musician)) + geom_boxplot() +
> #   ggtitle("Influence of OMSI on Classical Music Perceptions")
> #
> # ggplot(ratings, aes(X1stInstr, col=musician)) + geom_bar(position="dodge") +
> #   ggtitle("First Instrument Skill Scores for Musicians and Non-Musicians")
> #
> # ggplot(ratings, aes(X1stInstr, Classical, col=musician)) + geom_boxplot() +
> #   ggtitle("Influence of OMSI on Classical Music Perceptions")
> #
> # # # box<-ggplot(ratings, aes(Harmony, Popular, col=musician)) + geom_boxplot()
> # # # box + ggtitle("Influence of Harmony for Musicians and Non-Musicians") +
> # # #   ylab("Popular Ratings")
> # #
> # # box<-ggplot(ratings, aes(Voice, Popular, col=musician)) + geom_boxplot()
> # # box + ggtitle("Influence of Voice for Musicians and Non-Musicians") +
> # #   ylab("Popular Ratings")
> # #
```

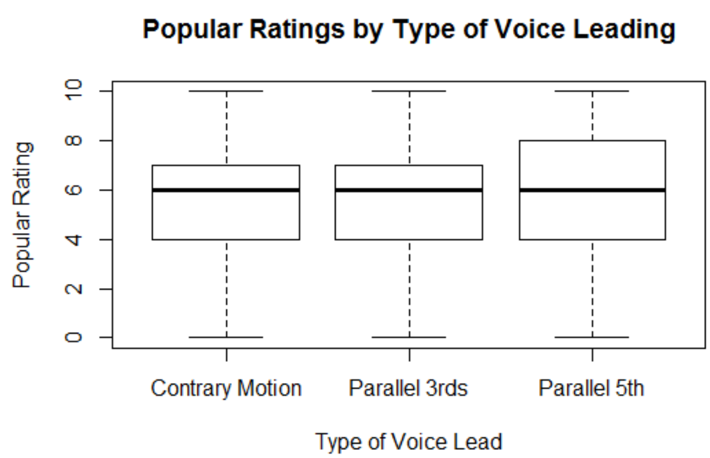
```
> # box<-ggplot(ratings, aes(Instrument, Popular, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Instrument for Musicians and Non-Musicians") +
> #   ylab("Popular Ratings")
> #
> # lmer22<-update(lmer21, .~. + musician*Harmony, data=ratings)
> # display(lmer22)
> #
> #
> # lmer23<-update(lmer21, .~. + musician*Instrument, data=ratings)
> # display(lmer23)
> # BIC(lmer23)
> #
> # lmer24<-update(lmer21, .~. + musician*Voice, data=ratings)
> # display(lmer24)
> # BIC(lmer24)
> #
> # lmer25<-update(lmer21, .~. + musician*Voice + musician*Instrument +
> #                  musician*Harmony, data=ratings)
> # display(lmer25)
> # BIC(lmer25)
> #
> # summary(lmer22)
> # library(xtable)
> # xtable(as.table(fixef(lmer22)))
```

Problem 4

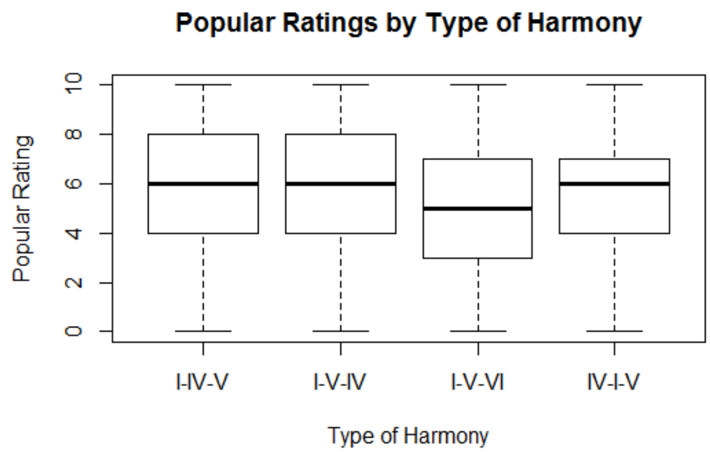
4a. Based on the figures shown below, it is clear that the perception of popularity is less influenced by type of vocal leading and type of harmony than by instrumenet type. In fact, perception of popularity appears to be at least somewhat inversely related to perception of classical music, since guitars are percieved as being the intsrument associated with the most popular music, followed by pianos, and then strings (which were, before, associated with the highest classical scores).




```
> #   boxplot(Popular ~ Instrument, data=ratings,
> #             xlab="Type of Instrument", ylab="Popular Rating",
> #             main="Popular Ratings by Instrument Type")
```




```
> #   boxplot(Popular ~ Voice, data=ratings,
> #             xlab="Type of Voice Lead", ylab="Popular Rating",
> #             main="Popular Ratings by Type of Voice Leading")
```




```
> # boxplot(Popular ~ Harmony, data=ratings,
> #          xlab="Type of Harmony", ylab="Popular Rating",
> #          main="Popular Ratings by Type of Harmony")
```

Consideration of a generalized linear model considering the impact of harmony, vocal lead, and instrument on perception of how popular a given piece of music in suggests, as shown in the plots below, that perception of popularity is most strongly influenced by instrument. Specifically, music from guitars was identified as being the most popular, followed by music from pianos and music from string instruments. The difference between perception of popularity between guitars and string music and pianos and string music was found to be statistically significant at $\alpha = 0.05$. The impact of vocal lead was identified as being only marginally significant ($p < 0.2$), where parallel 5th harmonies were most strongly associated with popularity, followed closely by parallel thirds, and lastly by contrary motion. Of note, the variation in popularity scores for music with contrary motion voice leading was larger than the variation in popularity scores for music with parallel thirds and fifths. The harmony I-V-VI was observed to be associated with lower popularity scores than other harmonies, and also had more variable popularity ratings than the other scores. The harmony with the highest popularity rating was harmony I-V-IV, which was followed closely by harmony I-IV-V. The results of the generalized linear regression model are presented below.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.7718	0.1398	48.43	0.0000
Voice (Parallel 3rds)	0.1289	0.1213	1.06	0.2882
Voice (Parallel 5th)	0.1328	0.1213	1.10	0.2736
Harmony (I-V-IV)	-0.0736	0.1400	-0.53	0.5993
Harmony (I-V-VI)	-0.2750	0.1400	-1.96	0.0496
Harmony (IV-I-V)	-0.2112	0.1399	-1.51	0.1313
Instrument (piano)	-0.9541	0.1215	-7.85	0.0000
Instrument (string)	-2.5811	0.1209	-21.35	0.0000

```
> #  fullglm<-glm(Popular~Voice + Harmony + Instrument, data=ratings)
> #  summary(fullglm)
```

```
> #  xtable(summary(fullglm))
```

4b. The final best-fit model, identified below in the table as "lmer 36" includes fixed effects for voice, harmony, instrument (the experimental variables). Fixed effects are also included to account for whether or not the individual took AP Theory and whether or not the individual has taken music classes in the past. Once these fixed effects were determined, random effects were also added into the model.

Model Description	AIC	BIC	DIC
Full GLM	9252	9302	NA
"Personal Bias"	8457	8525	8400
Lmer 26	8489	8613	8358
Lmer 27	8484	8602	8312
Lmer 28	8480	8592	8364
Lmer 29	8478	8585	8363
Lmer 30	8464	8566	8376
Lmer 31	8461	8558	8377
Lmer 32	8457	8547	8403
best fixed effects: lmer 33	8453	8538	8384
Lmer 34	8454	8533	8389
Lmer 35	8435	8547	8357
best full model: lmer 36	8431	8527	8360
Lmer 37	8455	8533	8389

The final best fit model was determined to contain the fixed effects identified above, as well as random intercepts of which accounted for varying personal biases related to instrument, harmony, or voice leading opinions. Random slope effects were also added which accounted for how closely each subject concentrated on the notes while they listened to the music. It is appropriate to include this variable as a random effect in the model since it can reasonably be assumed that the variable influences different individuals in the study differently, reflecting both personal bias and variation in the levels of importance each individual assigns to different parts of musical composition.

Specifically, the model identified as best fitting the data suggests that voice leading of contrary motion is percieved as the least popular type of voice leading, followed by parrallel fifths and parallel thirds, though these differences are not identified as being statistically significant. Similarly, harmony I-V-IV was percieved as being the least popular and harmony I-IV-V was percieved as being the most popular. These differences between these most and least popular harmonies were found to be statistically significant at the $\alpha = 0.05$ level. Instrument was identified as being a statistically significant predictor of perception of popularity, where guitars were percieved as being associated most strongly with popular music, followed by pianos and then by string instruments. Those who had taken AP Theory in high school were less likely than those who had not taken AP Theory in high school to identify music as popular, though this difference was not identified as being statistically significant. However, interestingly, those who had taken courses in music were found to be more likely than those who had not taken music courses to percieve music as popular. Although these differences were not found to be statistically significant, these findings imply that there may be a difference in the ways in which different levels of coureses (high school vs. college or AP vs. non-AP, for instance) may influence the ways in which people percieve popular music. Additional research would be required in order to further consider this hypothesis.

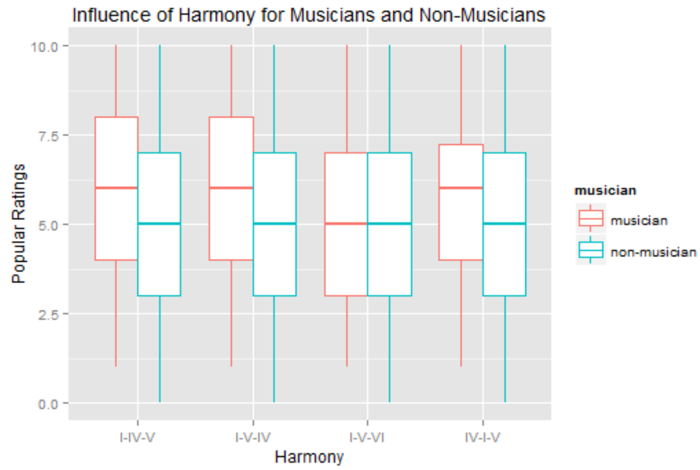
The fixed effects identified and described above can be seen in the table below.

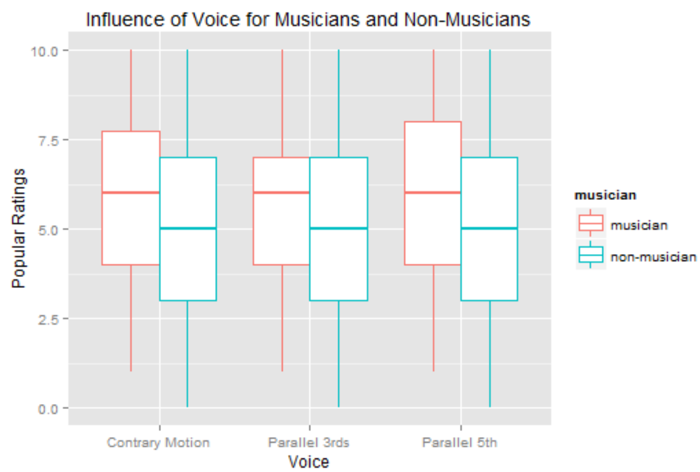
Coefficient	Estimate
(Intercept)	6.57
Voice (Parallel 3rds)	0.13
Voice (Parallel 5th)	0.13
Harmony (I-V-IV)	-0.06
Harmony (I-V-VI)	-0.28
Harmony (IV-I-V)	-0.21
Instrument (piano)	-0.95
Instrument (string)	-2.58
AP Theory	-0.30
Classes	0.49

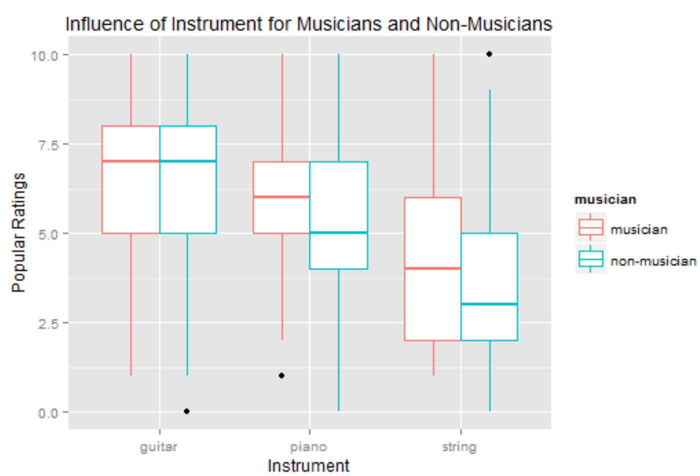
```
> #  summary(fullglm)
> #  BIC(fullglm)
> #
> # lmer.personalbias2<-lmer(Popular~ 1 + Voice + Harmony + Instrument +
> #                         (1|Subject:Instrument) +
> #                         (1|Subject:Harmony) +
> #                         (1|Subject:Voice),
> #                     data=ratings)
> # display(lmer.personalbias2)
> # BIC(lmer.personalbias2)
> #
> # lmer26<-update(lmer.personalbias2, .~. + OMSI + Selfdeclare + ClsListen +
> #                  GuitarPlay + PianoPlay + aptheorynew + musician + noclasscat +
> #                  CollegeMusic + newinstrument, data=ratings)
> # display(lmer26)
> # BIC(lmer26)
> # summary(lmer26)
> #
> # lmer27<-update(lmer26, .~. - PianoPlay)
> # display(lmer27)
> # BIC(lmer27)
> # summary(lmer27)
> #
> # lmer28<-update(lmer27, .~. - GuitarPlay)
> # display(lmer28)
> # BIC(lmer28)
> # summary(lmer28)
> #
> # lmer29<-update(lmer28, .~. -musician)
> # display(lmer29)
```

```
> # BIC(lmer29)
> #
> # lmer30<-update(lmer29, .~. -OMSI)
> # display(lmer30)
> # BIC(lmer30)
> #
> # lmer31<-update(lmer30, .~. -CollegeMusic)
> # display(lmer31)
> # BIC(lmer31)
> #
> # lmer32<-update(lmer31, .~. -ClsListen)
> # display(lmer32)
> # BIC(lmer32)
> #
> # lmer33<-update(lmer32, .~. -Selfdeclare)
> # display(lmer33)
> # BIC(lmer33)
> #
> # lmer34<-update(lmer33, .~. -newinstrument)
> # display(lmer34)
> # BIC(lmer34)
> #
> # lmer35<-update(lmer34, .~. + (ConsInstr | Subject) + (ConsNotes | Subject),
> #                data=ratings)
> # display(lmer35)
> # BIC(lmer35)
> #
> # lmer36<-update(lmer35, .~. - (ConsInstr | Subject))
> # display(lmer36)
> # BIC(lmer36)
> #
> # lmer37<-update(lmer36, .~. - (ConsNotes | Subject))
> # display(lmer37)
> # BIC(lmer37)
```

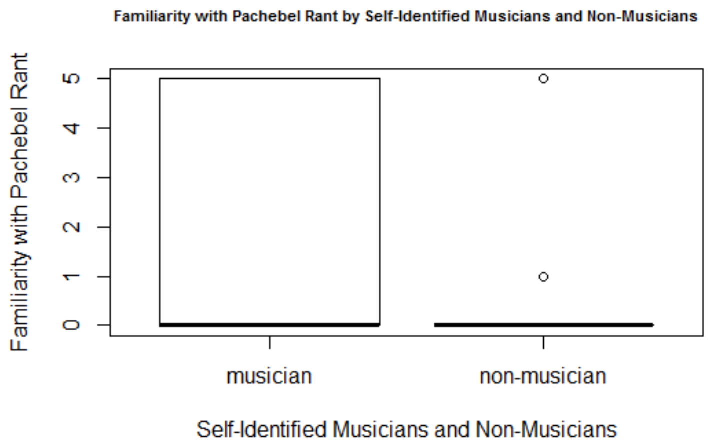
4c. Based on the plot identified below, it is apparent that those who identified as musicians were, in general, more likely than those who identified as non-musicians to percieve music as popular, across all values of harmony and voice. Musicians were also as likely or more likely to percieve music as being popular for each instrument type.

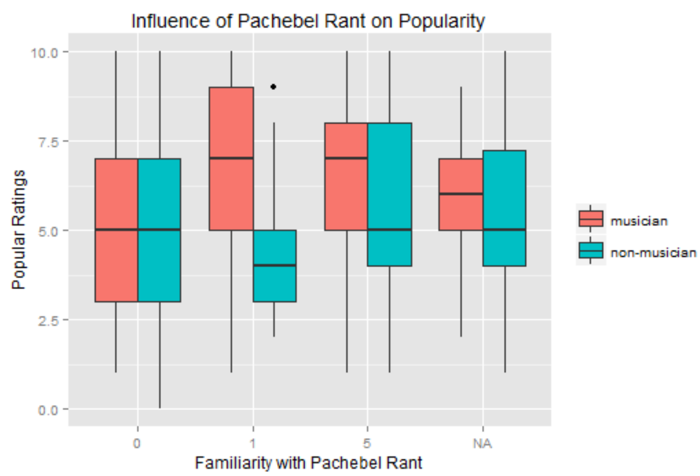




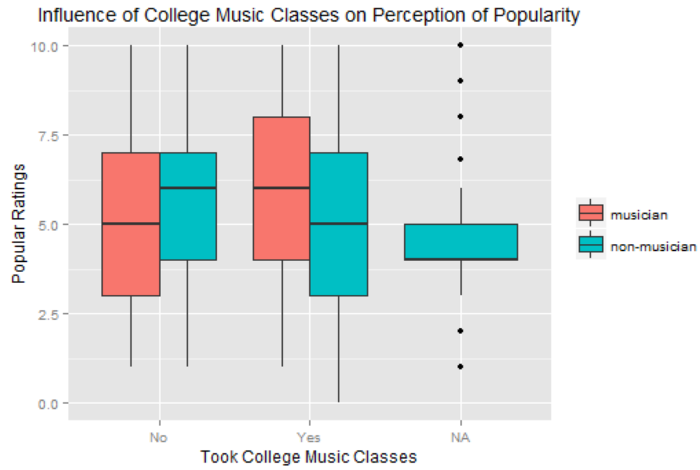


Musicians were also much more likely than non-musicians to be familiar with Pachebel's Rant by Rob Paravonian. Of those who were moderately familiar with or familiar with the rant, musicians were, in general, more likely to rate music as being popular. Although this variable was not included into the model fit above, it was considered for the sake of personal intereset because Rob Parvonian is awesome.

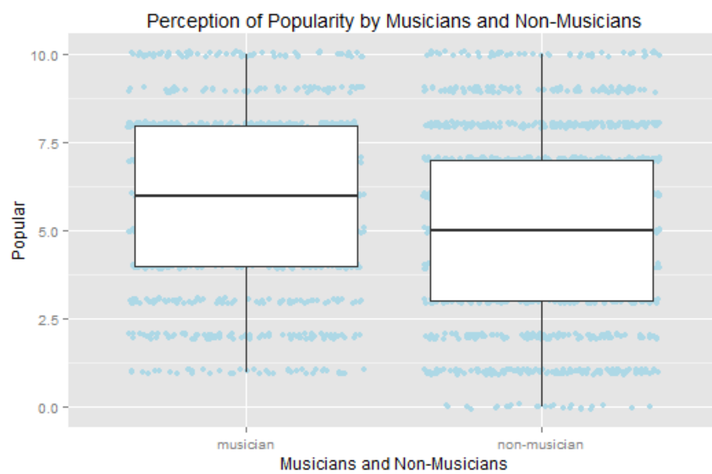




For those who did not take college music, musicians were slightly less likely to percieve music as popular. For those who did take college music, musicians were slightly more likely to percieve muisc as popular, though these differences were not identified as being statistically significant.



The overall answer to the research question is that those who identify as musicians were found to be more likely those who did not identify as musicians to percieve music as being popular, presemably due to the musicians' increased familarity with musical compositions.




```
> # library(ggplot2)
> #
> # ratings$musician<-ifelse(ratings$Selfdeclare>2,
> #                           "musician", "non-musician")
> # ## table(ratings$musician, ratings$Selfdeclare)
> #
> # # box<-ggplot(ratings, aes(Harmony, Popular, col=musician)) + geom_boxplot()
> # # box + ggtitle("Influence of Harmony for Musicians and Non-Musicians") +
> # #   ylab("Popular Ratings")
> #
> # box<-ggplot(ratings, aes(Voice, Popular, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Voice for Musicians and Non-Musicians") +
> #   ylab("Popular Ratings")
```

```
> #
> # box<-ggplot(ratings, aes(Instrument, Popular, col=musician)) + geom_boxplot()
> # box + ggtitle("Influence of Instrument for Musicians and Non-Musicians") +
> #   ylab("Popular Ratings")
> #
> # #  boxplot(KnowRob~musician, data=ratings,
> # #          xlab="Self-Identified Musicians and Non-Musicians",
> # #          ylab="Familiarity with Pachebel Rant",
> # #          main="Familiarity with Pachebel Rant by Self-Identified Musicians and Non-M
> #
> # # p <- ggplot(ratings, aes(factor(KnowRob), Popular))
> # # p + geom_boxplot(aes(fill = factor(ratings$musician))) +
> # #   guides(fill=guide_legend(title=NULL)) +
> # #   ggtitle("Influence of Pachebel Rant on Popularity") +
> # #   ylab("Popular Ratings") + xlab("Familiarity with Pachebel Rant")
> #
> # ratings$mc<-ifelse(ratings$CollegeMusic==1, "Yes",
> #                    ifelse(ratings$CollegeMusic=="NA", "NA", "No"))
> # # table(ratings$mc, ratings$CollegeMusic)
> # p <- ggplot(ratings, aes(factor(mc), Popular))
> # p + geom_boxplot(aes(fill = factor(ratings$musician))) +
> #   guides(fill=guide_legend(title=NULL)) +
> #   ggtitle("Influence of College Music Classes on Perception of Popularity") +
> #   ylab("Popular Ratings") + xlab("Took College Music Classes")
> #
> # p <- ggplot(ratings, aes(factor(musician), Popular))
> # p + geom_jitter(col="light blue") + geom_boxplot()+
> #   xlab("Musicians and Non-Musicians") +
> #   ggtitle("Perception of Popularity by Musicians and Non-Musicians")
> #
>
```

Final Summary

When considering the impact of voice, harmony, and instrument on perception of music as either classical of popular, it is clear that perception of both the classicality and popularity of a given piece of music is influenced most strongly by the type of instrument being played. String instruments are percieved more strongly as being associated with classical music than guitars or pianos, and this difference is identified as being statistically significant when controlling for the impact of harmony and voice leading ($p < 0.05$). Conversely, guitars are associated more strongly with perception of popularity, a difference which is also identified as being statistically significant when controlling for harmony and voice leading ($p < 0.05$). These findings are illustrated below in figures 1 and 2.

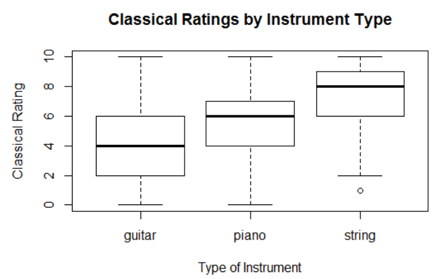


Figure 1

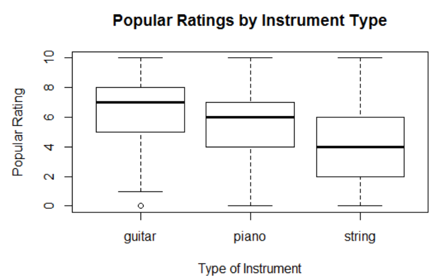


Figure 2

In addition to the impact of instrument choice, perception of both classicality and popularity were identified as being significantly impacted by both type of voice leading and type of harmony. While music with contrary motion vocal leads was percieved as being the most classical, music with parallel fifths was percieved as being the most popular. Although individuals were asked to evaluate classicality and popularity independently, these findings suggest that, in general, characteristics which are associated with music being percieved as classical were often also associated with music being percieved as *less* popular. This was also the case for type of harmonic motion, for which I-V-VI harmonies were percieved as being the most classical, while the harmony I-IV-V was percieved as being the most popular. The differences identified above were identified as being statistically significant predictors of music's classicality and popularity, respectively.

It also became apparent following the inclusion of a random personal bias coefficient for each individual, that perception of music's popularity and classicality was often influenced by the individual's personal bias. Similarly, perception of popularity and classicality of music was also influenced differently among multiple individiuals depending on how closely the individual concentrated on the type of instrument and notes of the music. Thus, the model for the data was improved by the consideration of these additional variance components which addressed individual bias and tendency to focus to focus on different elements of musical composition.

Perception of the classicality of a given piece of music was identified as being significantly impacted by how strongly individuals identify themselves as being musicians (musicians were found to be significantly less likely to identify music as being classical when controlling for other variables). Those with increasing composing experience, classical music-listening, and piano experience were observed to identify music as being more classical than those without these characterisitics. Conversely, those who had taken high school AP Theory courses were less likely to identify music as being popular, although, in general, individuals who had taken more musical classes were found to be more likely to identify music as being popular. This finding suggests that non-AP Theory classes increase perception of music's popularity, while, in general, AP Theory courses influence this perception less strongly than other types of courses, perhaps due to the strong classical focus of many of these types of classes.

Thus, perception of popularity and classicality of music is impacted strongly by individual personal bias, as well and an individual's level of focus on different elements of the musical composition (such as notes or intrument type). The most significant predictor of how classical or how popular a given musical piece was generally percieved was identified to be instrument type, where guitar music was identified as being the most popular when controlling for other variables, and string music was identified as being the most classical when controlling for other varirables.