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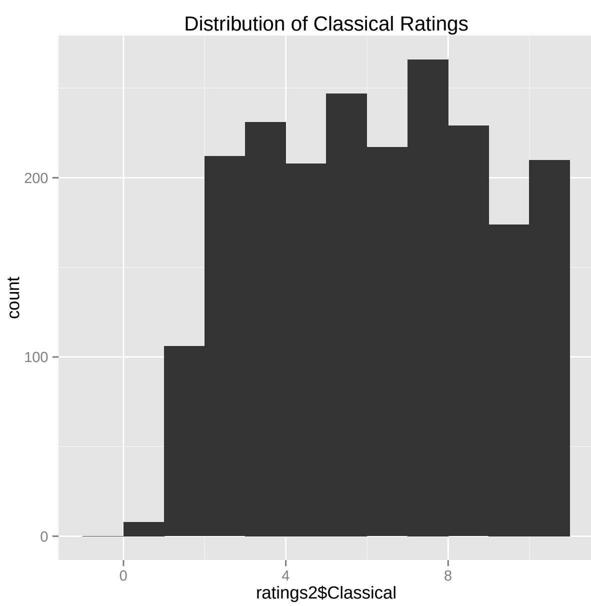
36-763
12/10/13

HW05

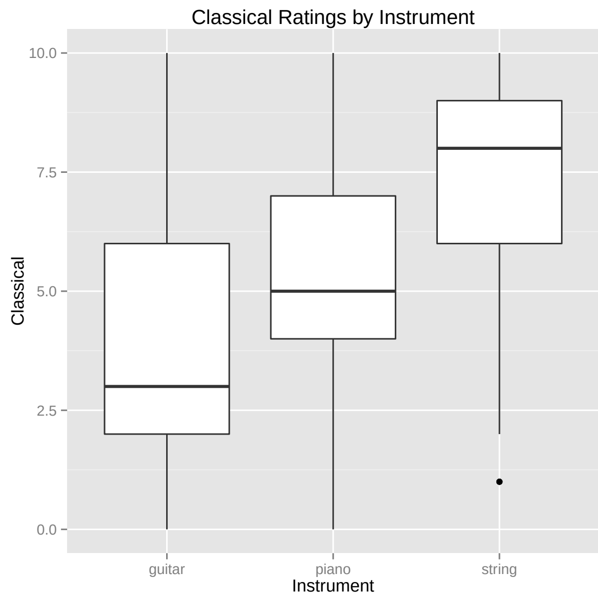
Problem 1

```
> library(ggplot2)
> library(arm)
> library(lme4)
> ratings=read.csv("ratings.csv")
> str(ratings)

> # Some EDA graphs
> summary(ratings$Classical) # one rating >10 ?? will probably want to eliminate
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   4.000   6.000   5.783   8.000  19.000      27
> ratings2 = ratings[ratings$Classical<=10,]
> ratings2 = ratings2[!is.na(ratings2$Classical),]
> ratings2 = ratings2[complete.cases(ratings2[,c(1:6,8:9,12,15,18,21,22,27:28)]),]
> qplot(ratings2$Classical, binwidth=1, main="Distribution of Classical Ratings")
> summary(ratings2$Classical)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   0.00    3.00    6.00    5.67    8.00   10.00
```

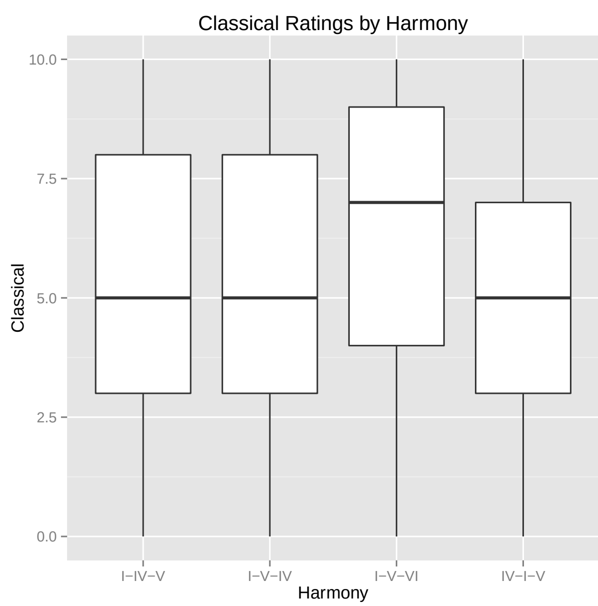


I began my analysis by performing some EDA first. When I looked at the five number summary for Classical ratings, I noticed there was one Classical rating of 19 in the dataset, which is beyond the upper limit for the ratings scale. Since I don't know why someone gave a rating of 19 or if this was a data entry error, I decided to exclude that one observation. Below are some boxplots comparing the distribution of Classical ratings for each factor level of the Instrument, Harmony, and Voicing variables.

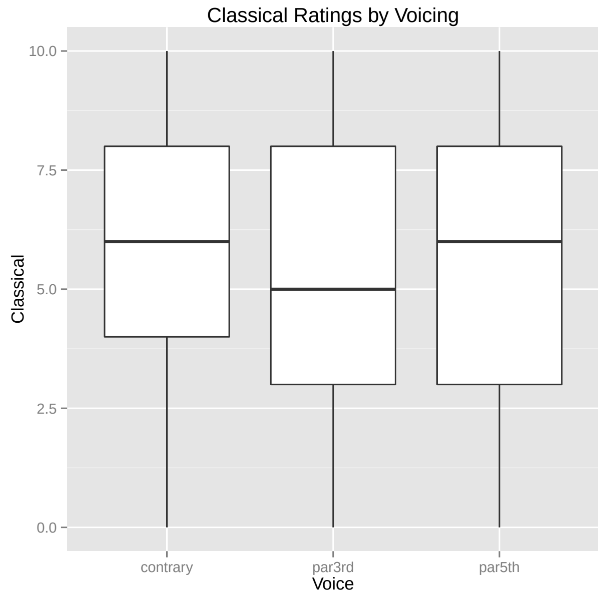
```
> ggplot(data=ratings2, aes(x=Instrument, y=Classical))+
+   geom_boxplot(aes(factor=Instrument)) +
+   ggtitle("Classical Ratings by Instrument")
```




```
> ggplot(data=ratings2, aes(x=Harmony, y=Classical))+
+   geom_boxplot(aes(factor=Harmony)) +
+   ggtitle("Classical Ratings by Harmony")
```




```
> ggplot(data=ratings2, aes(x=Voice, y=Classical))+
+   geom_boxplot(aes(factor=Voice)) +
+   ggtitle("Classical Ratings by Voicing")
```



Part a)

```
> AIC(lm.all, lm.no.instr, lm.no.harm, lm.no.voice)
            df       AIC
lm.all       9  9494.779
lm.no.instr  7 10132.949
lm.no.harm   6  9547.409
lm.no.voice  7  9500.990
> BIC(lm.all, lm.no.instr, lm.no.harm, lm.no.voice)
            df       BIC
lm.all       9  9545.660
lm.no.instr  7 10172.524
lm.no.harm   6  9581.330
lm.no.voice  7  9540.564
> anova(lm.all, lm.no.instr)
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice - 1
Model 2: Classical ~ Harmony + Voice - 1
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2100 11062
2   2102 15001 -2   -3939.4 373.94 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> anova(lm.all, lm.no.harm)
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice - 1
Model 2: Classical ~ Instrument + Voice - 1
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2100 11062
2   2103 11374 -3   -311.98 19.742 1.278e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> anova(lm.all, lm.no.voice)
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice - 1
Model 2: Classical ~ Instrument + Harmony - 1
  Res.Df   RSS Df Sum of Sq      F   Pr(>F)
1   2100 11062
2   2102 11115 -2   -53.713 5.0985 0.006182 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(lm.all)
Call:
lm(formula = Classical ~ Instrument + Harmony + Voice - 1, data = ratings2)

Residuals:
    Min      1Q  Median      3Q     Max
-6.9930 -1.7417 -0.0785  1.7842  6.3071

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
Instrumentguitar  4.05347    0.14120  28.708  < 2e-16 ***
Instrumentpiano   5.46963    0.14164  38.617  < 2e-16 ***
Instrumentstring  7.37969    0.14120  52.266  < 2e-16 ***
HarmonyI-V-IV     0.05393    0.14132   0.382  0.70279
HarmonyI-V-VI     0.92512    0.14139   6.543 7.55e-11 ***
HarmonyIV-I-V     0.05936    0.14132   0.420  0.67451
Voicepar3rd      -0.36058    0.12250  -2.943  0.00328 **
Voicepar5th      -0.31179    0.12246  -2.546  0.01097 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.295 on 2100 degrees of freedom
Multiple R-squared:  0.867,        Adjusted R-squared:  0.8664
F-statistic:  1710 on 8 and 2100 DF,  p-value: < 2.2e-16
```

I first began by testing for any interaction effects between Instrument, Harmony, and Voice. By looking at the p-values on the interaction terms and the AIC and BIC values for models with various combinations of interaction terms (results omitted for brevity), I came to the conclusion that the interaction terms were unnecessary as the p-values were generally statistically insignificant and AIC and BIC were higher than for the model without any interactions.

After that, I tested to see which of the three predictors should be kept in the model. To do so, I compared the fit of the model with all three predictors against a model without Instrument, one without Harmony, and one without Voice. Based on the results of AIC, the best fitting model was the one that included all three predictors, but BIC felt that the best model was the one without voicing. To try to decide between the two, I did an ANOVA comparison to try to determine which model offered the best fit. The results indicated that there was a statistically significant difference between the two. Furthermore, since the BIC between the model with all three predictors and the one without voicing only differed by 5 points and the r^2 for the model with all three predictors was slightly higher (0.8664 versus 0.8659), I decided to move forward and analyze the model with all three predictors.

As can be seen from the final model, the type of instrument seems to have the largest effect on how Classical-sounding the music was judged in terms of both practical and statistical significance (a trend which is also reflected in the EDA boxplots). Pieces played by a string quartet were judged to be most Classical-sounding while pieces played by an electric guitar were least Classical-sounding, with a difference of 3.3 points on average, when holding Harmony and Voicing constant. For types of harmony, only the harmonic progression of I-V-VI was judged to be significantly different from the I-IV-V progression; pieces that had a I-V-VI harmony were rated as being more classical by nearly 1 point. Finally, pieces that had a parallel 3rds or parallel 5ths voicing were seen as being less classical-sounding by around 0.30-0.35 points than pieces that had contrary motion. This difference was also statistically significant.

Part b)
part i)
$y_{i,j} = \alpha_{j[i]} + \alpha_1 Instrument + \alpha_2 Harmony + \alpha_3 Voicing + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$

$\alpha_j = \beta_0 + \eta_j, \qquad \eta_j \sim N(0, \tau^2)$

where $y_{i,j}$ is the classical rating for the ith sample by the jth subject and α_j is the random intercept for each subject

part ii)

```
> # random intercept model for each participant
> lmer.rand.int=lmer(Classical ~ 1+Instrument+Harmony+Voice+(1 | Subject), data=ratings2)
> # compare using AIC, BIC
> AIC(lmer.rand.int, lm.all)
              df      AIC
lmer.rand.int 10 8876.660
lm.all         9 9494.779
> BIC(lmer.rand.int, lm.all)
              df      BIC
lmer.rand.int 10 8933.195
lm.all         9 9545.660


> # directly testing the random effect
> library(RLRsim)
> exactRLRT(lmer.rand.int)
        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 641.2294, p-value < 2.2e-16
```

Based on AIC and BIC, the model with the random intercept does provide a better fit for the data. In addition, the restricted likelihood ratio test of the random effect gives us a p-value of less than 0.001 so we reject the null hypothesis and conclude that we should include the random intercept in the model.

part iii)

```
> # influence of Instrument, Harmony and Voice with random intercept
> summary(lmer.rand.int)
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
   Data: ratings2
```

```
REML criterion at convergence: 8856.66

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.700    1.304
 Residual             3.584    1.893
Number of obs: 2108, groups: Subject, 59

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.05868    0.20586   19.72
Instrumentpiano   1.41789    0.10128   14.00
Instrumentstring  3.32451    0.10069   33.02
HarmonyI-V-IV     0.05284    0.11657    0.45
HarmonyI-V-VI     0.92791    0.11663    7.96
HarmonyIV-I-V     0.06096    0.11657    0.52
Voicepar3rd      -0.36469    0.10105   -3.61
Voicepar5th      -0.31710    0.10102   -3.14

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
Instrumntpn -0.243
Instrmntstr -0.245  0.497
HrmnyI-V-IV -0.283  0.001     0.000
HrmnyI-V-VI -0.282  0.000    -0.001     0.499
HrmnyIV-I-V -0.283  0.000     0.001     0.500  0.499
Voicepar3rd -0.246  0.001     0.000     0.000  0.001  0.001
Voicepar5th -0.245  0.000     0.000    -0.002 -0.002 -0.003  0.501
```

Including a random intercept has not changed the influence of the three main predictors by much. Instrument continues to have the largest and most significant effect on how classical-sounding a piece was judged to be with pieces that had the same voicing and harmony but were played by string quartets being rated more than 3 points higher than pieces played by an electric guitar. Pieces played by a piano were 1.4 points more Classical-sounding than those by an electric guitar. In terms of harmony, pieces with a I-V-VI harmony were rated nearly one point more classical-sounding than those with a I-IV-V harmony while pieces with parallel 3rds or 5ths voicing were rated around 0.30-0.36 points less classical-sounding than pieces with contrary motion. As can be seen from the correlation between the fixed effects, different types of harmony and voicing had very little effect on how classical-sounding a string quartet or piano was compared to an electric guitar. Different types of harmony also did not affect how classical-sounding different types of voicing were judged to be, further supporting the idea of little interaction effects between these three predictors.

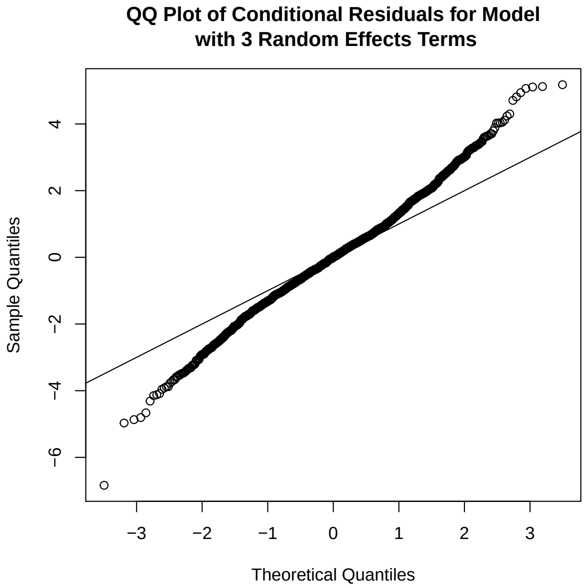
Part c)

part i)

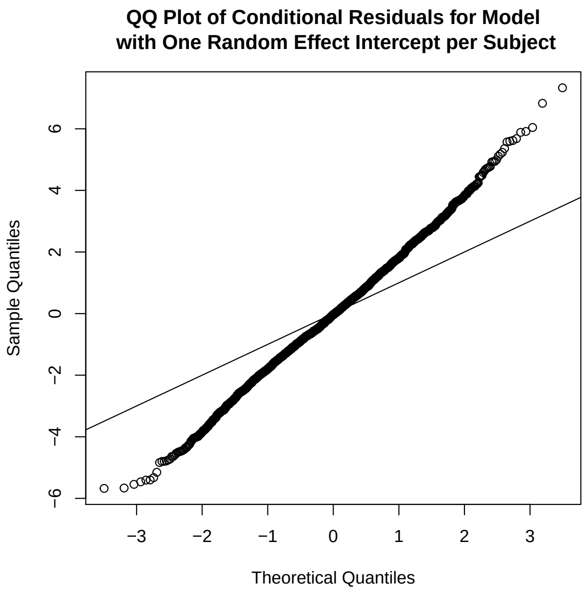
```
> # Model with random effects interactions
> lmer.3 = lmer(Classical ~ 1 + Instrument+Harmony+Voice+(1|Subject:Instrument)+
+                  (1|Subject:Harmony) +(1|Subject:Voice), data=ratings2)
> AIC(lm.all, lmer.rand.int, lmer.3)
              df      AIC
lm.all         9 9494.779
lmer.rand.int 10 8876.660
lmer.3        12 8483.550
> BIC(lm.all, lmer.rand.int, lmer.3)
```

```
               df      BIC
lm.all          9 9545.660
lmer.rand.int  10 8933.195
lmer.3         12 8551.391
```

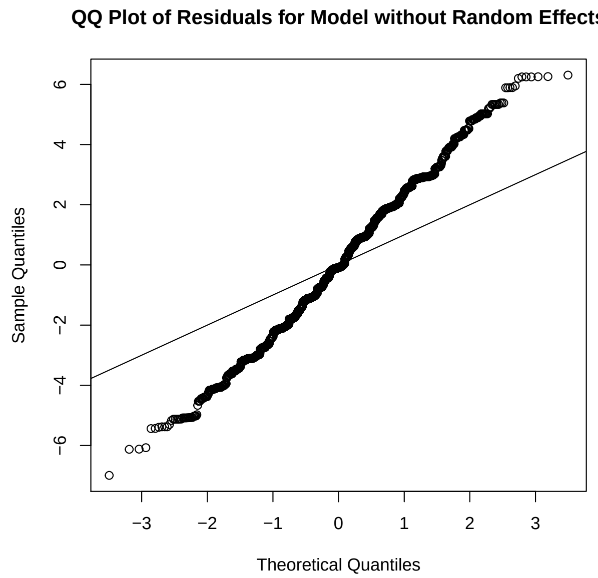
```
> # residual plots
> qqnorm(r.cond(lmer.3), main="QQ Plot of Conditional Residuals for Model\n with 3 Random Effects Te
> abline(a=0,b=1)
```




```
> qqnorm(r.cond(lmer.rand.int), main="QQ Plot of Conditional Residuals for Model\n with One Random E
> abline(a=0, b=1)
```



```
> qqnorm(lm.all$resid, main="QQ Plot of Residuals for Model without Random Effects")
> abline(a=0, b=1)
```



As can be seen from AIC and BIC, the model with the new random effects provides a better fit for the data than the models from 1a and 1b. The plot of the conditional residuals for this model also shows that they are more normally distributed than the models from 1a and 1b.

part ii)

```
> # Model with random effects interactions and fixed effects for Instrument, Harmony and Voice
> summary(lmer.3)
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject
   Data: ratings2

REML criterion at convergence: 8459.549

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.52536  0.7248
 Subject:Voice      (Intercept) 0.03656  0.1912
 Subject:Instrument (Intercept) 2.17024  1.4732
 Residual                       2.35588  1.5349
Number of obs: 2108, groups: Subject:Harmony, 236; Subject:Voice, 177; Subject:Instrument, 177

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.04979    0.23501  17.232
Instrumentpiano   1.41199    0.28351   4.980
Instrumentstring  3.32929    0.28326  11.754
HarmonyI-V-IV     0.05186    0.16356   0.317
HarmonyI-V-VI     0.92986    0.16359   5.684
HarmonyIV-I-V     0.06283    0.16357   0.384
Voicepar3rd      -0.35671    0.08920  -3.999
Voicepar5th      -0.31435    0.08918  -3.525
```

```
Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
Instrumntpn -0.602
Instrmntstr -0.603  0.500
HrmnyI-V-IV -0.348  0.000     0.000
HrmnyI-V-VI -0.348  0.000     0.000     0.500
HrmnyIV-I-V -0.348  0.000     0.000     0.500  0.500
Voicepar3rd -0.190  0.000     0.000     0.000  0.001  0.000
Voicepar5th -0.189  0.000     0.000    -0.001 -0.001 -0.002  0.501
```

The influence of Instrument, Harmony and Voice on Classical ratings has not changed much when we include the three new random effects terms. Instrument type continues to have the largest effect on how Classical-sounding a piece was rated with string quartets being the most Classical-sounding and electric guitar being the least. Only Harmonic progressions of I-V-VI had a significant impact on Classical ratings with pieces that had a I-V-VI progression being 0.93 points more Classical-sounding than pieces with a I-IV-V progression. Both parallel 3rds and parallel 5ths voicings were judged to be 0.30-0.35 points less Classical-sounding than pieces with contrary motion. We also continue to see little evidence of any interaction effects between Instrument, Harmony and Voice.

The variance for the subject-instrument distribution was the largest at 2.17 which suggests that most subjects had the largest variation in their ratings based on instrument-type. The variance for the subject-harmony and subject-voice distributions were 0.52 and 0.04, respectively, suggesting that for most subjects, their ratings did not change much based on harmonic progressions or voicing types. However, these three estimated variance components were all smaller than the estimated residual variance, indicating that there is more variation between different subjects than within each subject. Our intraclass correlation is $\frac{2.17+0.04+0.52}{2.36+2.17+0.04+0.52} = 0.53$ suggesting that grouping by subject does provide us with a decent amount of information about the variation in ratings.

part iii)
$y_{i,j} = \alpha_{0j[i]} + \alpha_1 Instrument + \alpha_2 Harmony + \alpha_3 Voicing + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$

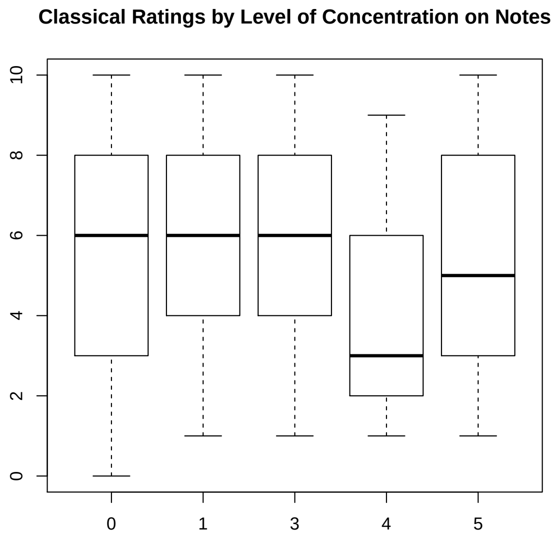
Where $\alpha_{0j[i]}$ is the sum of the following:
$\alpha_{0,1j} = \beta_0 + \beta_1 Instrument + \eta_{1j}, \qquad \eta_{1j} \sim N(0, \tau^2)$
$\alpha_{0,2j} = \beta_0 + \beta_1 Harmony + \eta_2 j, \qquad \eta_{2j} \sim N(0, \tau^2)$
$\alpha_{0,3j} = \beta_0 + \beta_1 Voicing + \eta_{3j}, \qquad \eta_{3j} \sim N(0, \tau^2)$

<u>Problem 2</u>

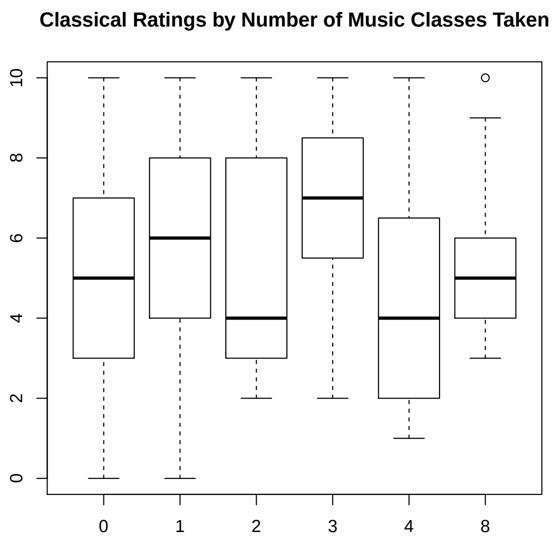
Part a) The covariates I decided to first try to add as fixed effects are: OMSI, ConsInstr, ConsNotes, NoClass, PianoPlay, GuitarPlay, ClsListen, X1990s2000s. I began with fitting a model with all of these predictors and then performed model reduction to keep only the predictors that had the most significant effect on Classical ratings or provided the best model fit. Since there were some missing values, I decided to exclude observations that had any missing values for any of these covariates. I chose to do this because I didn't feel I had any good way to impute the missing values and when I excluded the missings, I still had 2,108 observations in my dataset.

```
> # Some EDA For the predictors
> summary(ratings2$OMSI)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   11.0    67.0   150.0   246.5   345.0   970.0
> #qplot(ratings2$OMSI)
>
> summary(ratings2$ConsInstr)
```

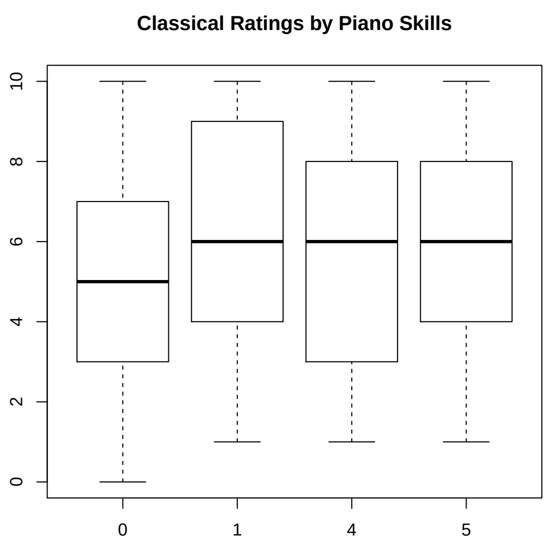
```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   1.670   3.000   2.935   4.330   5.000 
> #qplot(ratings2$ConsInstr)
> 
> summary(ratings2$ConsNotes)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  0.000   1.000   3.000   2.536   5.000   5.000     288 
> #boxplot(ratings2$ConsNotes)
> plot(as.factor(ratings2$ConsNotes),ratings2$Classical, main="Classical Ratings by Level of Concent
```



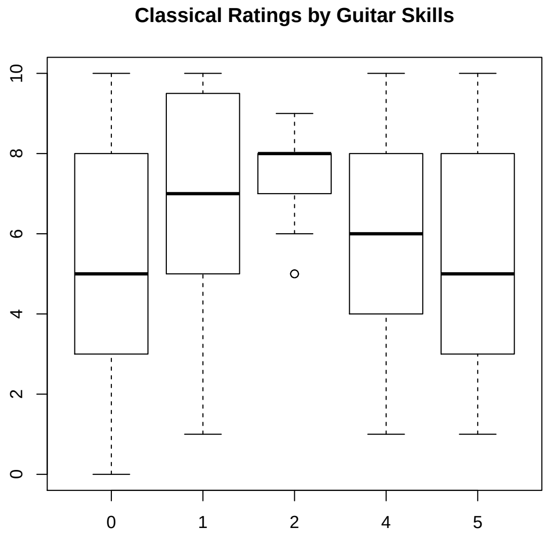

```
> table(ratings2$NoClass)

   0    1    2    3    4    8 
 782 1002   72   36   36   36 
> plot(as.factor(ratings2$NoClass), ratings2$Classical, main="Classical Ratings by Number of Music C
```



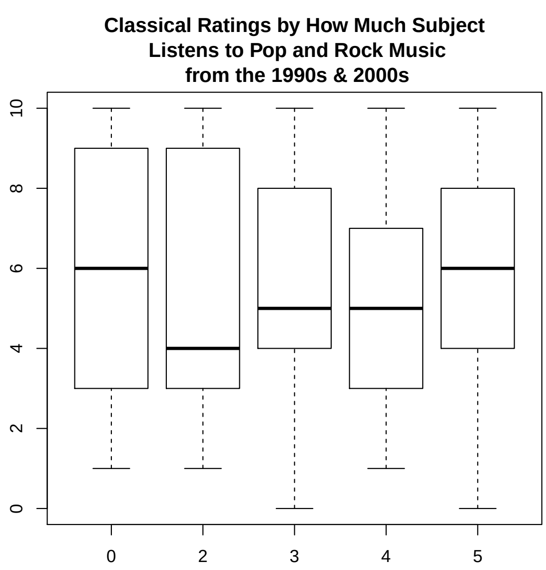

```
> table(ratings2$PianoPlay)
   0    1    4    5
1179  533  180  216
> plot(as.factor(ratings2$PianoPlay), ratings2$Classical, main="Classical Ratings by Piano Skills")
```



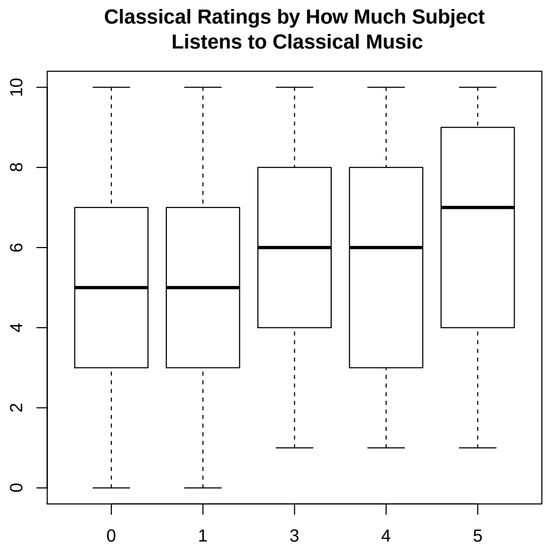

```
> table(ratings2$GuitarPlay)
   0    1    2    4    5
1539  251   36  108  174
> plot(as.factor(ratings2$GuitarPlay), ratings2$Classical, main="Classical Ratings by Guitar Skills'
```




```
> table(ratings2$ClsListen, ratings2$X1990s2000s)
     0   2   3   4   5
0    0   0  72   0 216
1   36  72   0  36 504
3  108   0 108 108 453
4    0   0   0   0  36
5   36  36  72  36  71
> plot(as.factor(ratings2$X1990s2000s), ratings2$Classical, main="Classical Ratings by How Much Subj
```




```
> plot(as.factor(ratings2$ClsListen), ratings2$Classical, main="Classical Ratings by How Much Subjec
```




```
> anova(lmer.2a.1, lmer.2a.2, lmer.2a.3, lmer.2a.4, lmer.2a.5, lmer.2a.6, lmer.2a.7)
Data: ratings2
Models:
lmer.2a.7: Classical ~ Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.2a.7:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer.2a.6: Classical ~ Instrument + Harmony + Voice + as.factor(PianoPlay) +
lmer.2a.6:     as.factor(ClsListen) + as.factor(X1990s2000s) + (1 | Subject:Instrument) +
lmer.2a.6:     (1 | Subject:Harmony) + (1 | Subject:Voice) + NoClass + ConsNotes
lmer.2a.4: Classical ~ Instrument + Harmony + Voice + ConsNotes + as.factor(PianoPlay) +
lmer.2a.4:     as.factor(GuitarPlay) + as.factor(ClsListen) + as.factor(X1990s2000s) +
lmer.2a.4:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer.2a.5: Classical ~ Instrument + Harmony + Voice + as.factor(PianoPlay) +
lmer.2a.5:     as.factor(GuitarPlay) + as.factor(ClsListen) + as.factor(X1990s2000s) +
lmer.2a.5:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice) +
lmer.2a.5:     NoClass
lmer.2a.3: Classical ~ Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.2a.3:     as.factor(PianoPlay) + as.factor(GuitarPlay) + as.factor(ClsListen) +
lmer.2a.3:     as.factor(X1990s2000s) + (1 | Subject:Instrument) + (1 |
lmer.2a.3:     Subject:Harmony) + (1 | Subject:Voice)
lmer.2a.2: Classical ~ Instrument + Harmony + Voice + ConsInstr + ConsNotes +
lmer.2a.2:     NoClass + as.factor(PianoPlay) + as.factor(GuitarPlay) +
lmer.2a.2:     as.factor(ClsListen) + as.factor(X1990s2000s) + (1 | Subject:Instrument) +
lmer.2a.2:     (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer.2a.1: Classical ~ 1 + Instrument + Harmony + Voice + OMSI + ConsInstr +
lmer.2a.1:     ConsNotes + NoClass + as.factor(PianoPlay) + as.factor(GuitarPlay) +
lmer.2a.1:     as.factor(ClsListen) + as.factor(X1990s2000s) + (1 | Subject:Instrument) +
lmer.2a.1:     (1 | Subject:Harmony) + (1 | Subject:Voice)
          Df    AIC    BIC  logLik deviance     Chisq Chi Df Pr(>Chisq)
lmer.2a.7 14 6782.7 6858.6 -3377.3   6754.7
lmer.2a.6 25 6471.3 6605.8 -3210.6   6421.3  333.3869     11     <2e-16 ***
lmer.2a.4 28 7039.7 7192.8 -3491.9   6983.7    0.0000      3     1.0000
lmer.2a.5 28 7473.3 7628.0 -3708.6   7417.3    0.0000      0     1.0000
lmer.2a.3 29 6473.1 6629.1 -3207.5   6415.1 1002.1790      1     <2e-16 ***
```

```
lmer.2a.2 30 6474.9 6636.3 -3207.5   6414.9    0.1815      1     0.6701
lmer.2a.1 31 6475.6 6642.4 -3206.8   6413.6    1.2753      1     0.2588
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> # FINAL MODEL:
> lmer.2a.final=lmer(Classical ~ 1+Instrument+Harmony+Voice+ConsNotes+
+                  NoClass+as.factor(PianoPlay)+as.factor(GuitarPlay)+
+                      as.factor(ClsListen)+as.factor(X1990s2000s)+
+                  (1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice),
+                data=ratings2)
```

To perform model selection, I looked at which predictors had the smallest coefficients and first tried dropping those one at a time. Each time after I dropped a predictor, I used ANOVA, AIC, and BIC to compare the new model with the dropped predictor against the original one to check if that improved the model fit. In the end, I dropped both the music test score and how much the subject said they were concentrating on the instrument being played. When I tried dropping the other predictors, the model fit tended to worsen.

The set of covariates I chose to include in my final model are:

- how much the subject concentrated on notes when listening
- number of music classes taken
- whether the subject plays the piano
- whether the subject plays the guitar
- how much the subject listens to classical music
- how much the subject listens to pop and rock from the 1990s and 2000s

Part b)

```
> lmer.2b=lmer(Classical ~ 1+Instrument+Harmony+Voice+ConsNotes+
+                  NoClass+as.factor(PianoPlay)+as.factor(GuitarPlay)+
+                      as.factor(ClsListen)+as.factor(X1990s2000s)+
+                  (1|Subject), data=ratings2)
> anova(lmer.2a.final, lmer.2b)
Data: ratings2
Models:
lmer.2b: Classical ~ 1 + Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.2b:     as.factor(PianoPlay) + as.factor(GuitarPlay) + as.factor(ClsListen) +
lmer.2b:     as.factor(X1990s2000s) + (1 | Subject)
lmer.2a.final: Classical ~ 1 + Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.2a.final:     as.factor(PianoPlay) + as.factor(GuitarPlay) + as.factor(ClsListen) +
lmer.2a.final:     as.factor(X1990s2000s) + (1 | Subject:Instrument) + (1 |
lmer.2a.final:     Subject:Harmony) + (1 | Subject:Voice)
              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.2b       27 6775.8 6921.0 -3360.9   6721.8
lmer.2a.final 29 6473.1 6629.1 -3207.5   6415.1 306.69      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The ANOVA test says there is a statistically significant difference between the model where we have the three random effects interaction intercepts and the model where we only have one random intercept for each subject. Based on AIC and BIC, it seems that keeping the three random effects interaction intercepts fits the data better.

Part c)

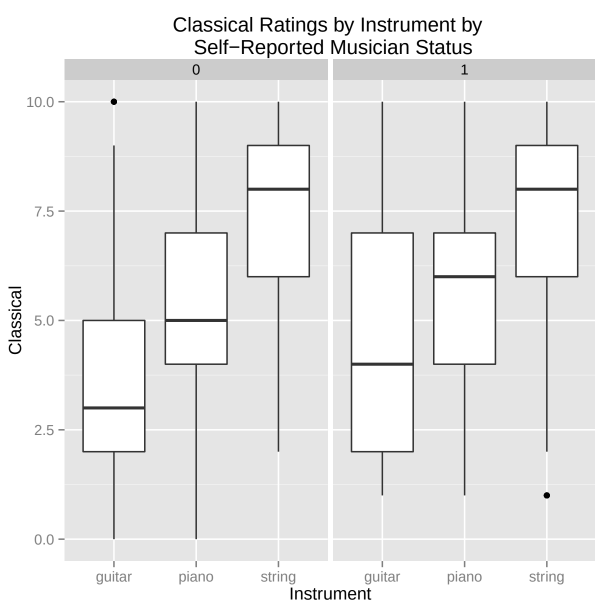
```
> #Final Model:
> display(lmer.2a.final)
lmer(formula = Classical ~ 1 + Instrument + Harmony + Voice +
    ConsNotes + NoClass + as.factor(PianoPlay) + as.factor(GuitarPlay) +
    as.factor(ClsListen) + as.factor(X1990s2000s) + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice), data = ratings2)
                        coef.est coef.se
(Intercept)              2.80     0.71
Instrumentpiano          1.65     0.29
Instrumentstring         3.61     0.29
HarmonyI-V-IV            0.03     0.18
HarmonyI-V-VI            0.88     0.18
HarmonyIV-I-V            0.07     0.18
Voicepar3rd             -0.40     0.11
Voicepar5th             -0.33     0.11
ConsNotes               -0.17     0.08
NoClass                 -0.09     0.14
as.factor(PianoPlay)1    0.52     0.38
as.factor(PianoPlay)4    1.28     0.80
as.factor(PianoPlay)5    0.92     0.50
as.factor(GuitarPlay)1   0.22     0.60
as.factor(GuitarPlay)2   1.40     1.23
as.factor(GuitarPlay)4   0.94     0.76
as.factor(GuitarPlay)5  -0.72     0.67
as.factor(ClsListen)1   -0.18     0.46
as.factor(ClsListen)3    0.89     0.45
as.factor(ClsListen)4    0.91     1.17
as.factor(ClsListen)5    0.89     0.60
as.factor(X1990s2000s)2  0.65     0.70
as.factor(X1990s2000s)3  0.88     0.63
as.factor(X1990s2000s)4  0.32     0.86
as.factor(X1990s2000s)5  1.07     0.52

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.66
 Subject:Voice      (Intercept) 0.23
 Subject:Instrument (Intercept) 1.28
 Residual                       1.56
---
number of obs: 1604, groups: Subject:Harmony, 180; Subject:Voice, 135; Subject:Instrument, 135
AIC = 6487, DIC = 6401.1
deviance = 6415.1
```

As can be seen in our final model, Instrument continus to have the largest impact on how Classical-sounding a piece was judged to be. String quartets were percieved to be the most Classical-sounding while electric guitars were least. Only the harmonic progression I-V-VI had a statistically significant effect with pieces following that progression being more Classical-sounding than pieces following a I-IV-V progression. Both parallel 3rds and parallel 5ths voicings were less Classical-sounding than contrary motion.

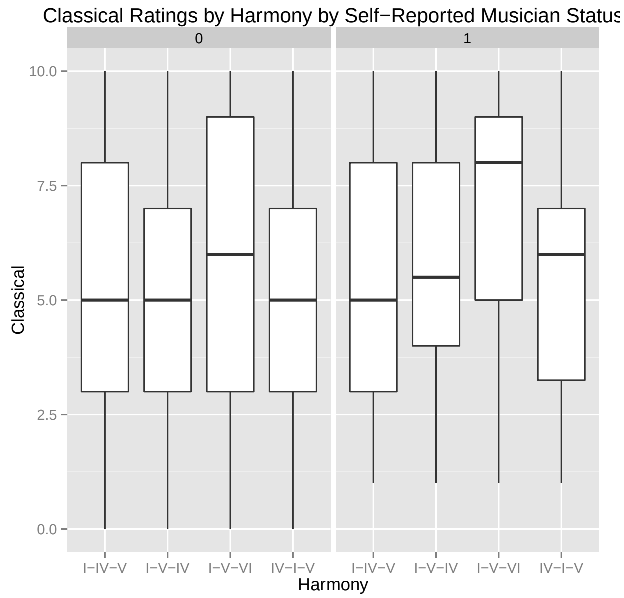
In addition to the effects of these three predictors, subjects who concentrated more on the notes played were slightly less likely to judge a piece as being classical-sounding. Those who had taken more music classes were also slightly less likely to judge a piece as being classical-sounding although this effect was not significant. Subjects who had any piano-playing abilities were more likely to judge pieces as being Classical-sounding and subjects who had any guitar-playing abilities (except for those with the highest proficiency in guitar) were also more likely to judge pieces as being more Classical-sounding. Those who listened to an average amount of classical music or a great deal of modern pop and rock music were more likely to judge pieces as being classical-sounding.

Problem 3

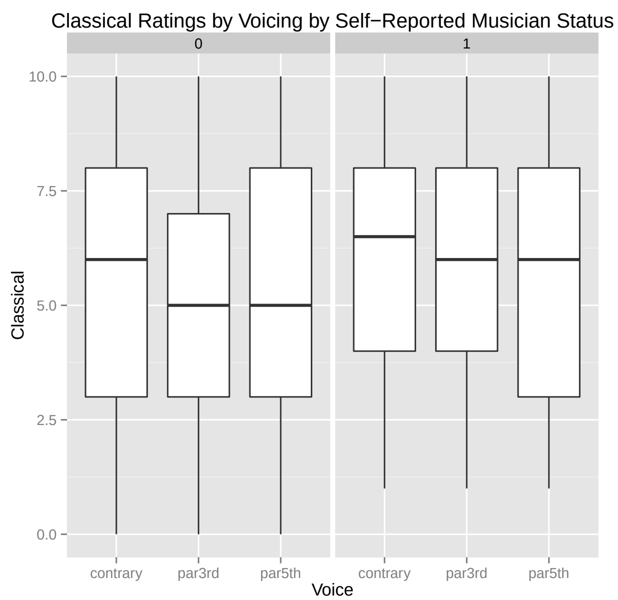
```
> # dichotomize Selfdeclare variable -> new musician variable
> table(ratings2$Selfdeclare)
  1   2   3   4   5   6
324 863 423 390  72  36
> musician=(ratings2$Selfdeclare>2)*1
> ratings3 = cbind(ratings2,musician)
> table(ratings3$musician)
   0    1
1187  921


> # some EDA plots
> ggplot(data=ratings3, aes(x=Instrument, y=Classical))+
+   geom_boxplot(aes(factor=Instrument)) + facet_wrap(~musician) +
+   ggtitle("Classical Ratings by Instrument by \n Self-Reported Musician Status")
```




```
> ggplot(data=ratings3, aes(x=Harmony, y=Classical))+
+   geom_boxplot(aes(factor=Harmony)) + facet_wrap(~musician)+
+   ggtitle("Classical Ratings by Harmony by Self-Reported Musician Status")
```




```
> ggplot(data=ratings3, aes(x=Voice, y=Classical))+
+   geom_boxplot(aes(factor=Voice)) + facet_wrap(~musician)+
+   ggtitle("Classical Ratings by Voicing by Self-Reported Musician Status")
```




```
> anova(lmer.2a.final2, lmer.3.1, lmer.3.3)
Data: ratings3
Models:
lmer.2a.final2: Classical ~ 1 + Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.2a.final2:     as.factor(PianoPlay) + as.factor(GuitarPlay) + as.factor(ClsListen) +
lmer.2a.final2:     as.factor(X1990s2000s) + (1 | Subject:Instrument) + (1 |
lmer.2a.final2:     Subject:Harmony) + (1 | Subject:Voice)
lmer.3.1: Classical ~ 1 + Instrument + Harmony + Voice + ConsNotes + NoClass +
lmer.3.1:     as.factor(PianoPlay) + as.factor(GuitarPlay) + as.factor(ClsListen) +
```

```
lmer.3.1:     as.factor(X1990s2000s) + as.factor(musician) + (1 | Subject:Instrument) +
lmer.3.1:     (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer.3.3: Classical ~ 1 + Instrument + Instrument:musician + Harmony +
lmer.3.3:     Harmony:musician + Voice + Voice:musician + ConsNotes + +NoClass +
lmer.3.3:     NoClass:musician + ConsNotes:musician + as.factor(PianoPlay) +
lmer.3.3:     as.factor(GuitarPlay) + as.factor(ClsListen) + as.factor(X1990s2000s) *
lmer.3.3:     musician + musician + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
lmer.3.3:     (1 | Subject:Voice)
               Df    AIC    BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
lmer.2a.final2 29 6473.1 6629.1 -3207.5   6415.1
lmer.3.1       30 6474.2 6635.6 -3207.1   6414.2  0.8575      1   0.354428
lmer.3.3       43 6465.7 6697.1 -3189.9   6379.7 34.5168     13   0.001004 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> display(lmer.3.3)
lmer(formula = Classical ~ 1 + Instrument + Instrument:musician +
    Harmony + Harmony:musician + Voice + Voice:musician + ConsNotes +
    +NoClass + NoClass:musician + ConsNotes:musician + as.factor(PianoPlay) +
    as.factor(GuitarPlay) + as.factor(ClsListen) + as.factor(X1990s2000s) *
    musician + musician + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
    (1 | Subject:Voice), data = ratings3)
                                 coef.est coef.se
(Intercept)                       4.39     1.16
Instrumentpiano                   1.97     0.39
Instrumentstring                  4.12     0.39
HarmonyI-V-IV                     0.02     0.23
HarmonyI-V-VI                     0.32     0.23
HarmonyIV-I-V                     0.05     0.23
Voicepar3rd                      -0.45     0.15
Voicepar5th                      -0.27     0.15
ConsNotes                        -0.22     0.10
NoClass                           0.02     0.38
as.factor(PianoPlay)1             0.75     0.42
as.factor(PianoPlay)4             1.87     0.88
as.factor(PianoPlay)5             0.72     0.55
as.factor(GuitarPlay)1            0.42     0.82
as.factor(GuitarPlay)2            0.86     1.33
as.factor(GuitarPlay)4            0.72     0.89
as.factor(GuitarPlay)5           -1.51     0.91
as.factor(ClsListen)1            -0.24     0.46
as.factor(ClsListen)3             0.40     0.52
as.factor(ClsListen)4             0.86     1.31
as.factor(ClsListen)5             0.62     0.73
as.factor(X1990s2000s)2          -1.10     1.25
as.factor(X1990s2000s)3          -1.05     1.07
as.factor(X1990s2000s)4          -0.56     1.32
as.factor(X1990s2000s)5          -0.61     1.01
musician                         -1.78     1.33
Instrumentpiano:musician         -0.70     0.57
Instrumentstring:musician        -1.10     0.57
musician:HarmonyI-V-IV            0.01     0.34
musician:HarmonyI-V-VI            1.22     0.34
musician:HarmonyIV-I-V            0.05     0.34
```

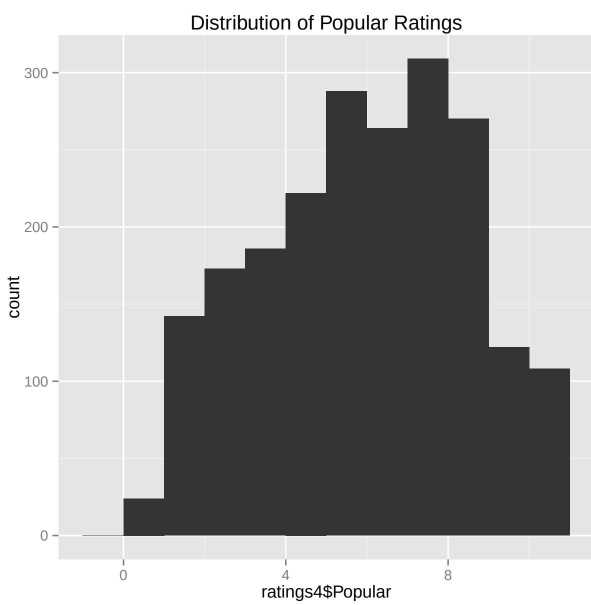
```
musician:Voicepar3rd              0.11     0.22
musician:Voicepar5th             -0.13     0.22
musician:NoClass                 -0.12     0.45
musician:ConsNotes                0.06     0.20
musician:as.factor(X1990s2000s)2  1.90     1.68
musician:as.factor(X1990s2000s)3  3.77     1.44
musician:as.factor(X1990s2000s)4  0.60     1.92
musician:as.factor(X1990s2000s)5  2.59     1.23

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.60
 Subject:Voice      (Intercept) 0.23
 Subject:Instrument (Intercept) 1.27
 Residual                       1.56
---
number of obs: 1604, groups: Subject:Harmony, 180; Subject:Voice, 135; Subject:Instrument, 135
AIC = 6479, DIC = 6366.4
deviance = 6379.7
```

Self-described musicians in general were less likely to judge pieces as being Classical sounding. In terms of the three main predictors, musicians were less likely to judge string quartet pieces as being Classical-sounding than non-musicians did. Musicians were also more likely to rate the I-V-VI harmonic progression as being Classical-sounding. However, the effect of being a musician on judging voicing was pretty small and statistically insignificant.

Other interaction effects from being a musician that were notable included how musicians who listened to any amount of pop and rock music from the 1990s to 2000s were much more likely to judge pieces as being classical-sounding by several points. However, the interactions effects of being a musician with other predictors such as concentrating on notes or the number of music classes taken were negligible.

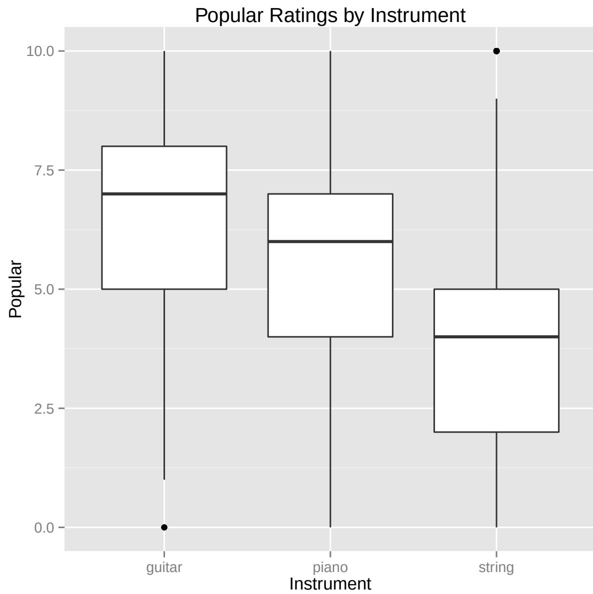
Problem 4

```
> library(ggplot2)
> library(arm)
> library(lme4)
> library(gridExtra)
> ratings=read.csv("ratings.csv")
> str(ratings)


> # Some EDA graphs
> summary(ratings$Popular) # one rating >10 ?? will probably want to eliminate
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   4.000   5.000   5.381   7.000  19.000      27
> ratings4 = ratings[ratings$Popular<=10,]
> ratings4 = ratings4[!is.na(ratings4$Popular),] # eliminate NAs
> ratings4 = ratings4[complete.cases(ratings4[,c(1:6,8:9,12,15,18,21,22,27:28)]),]
> qplot(ratings4$Popular, binwidth=1, main="Distribution of Popular Ratings")
```

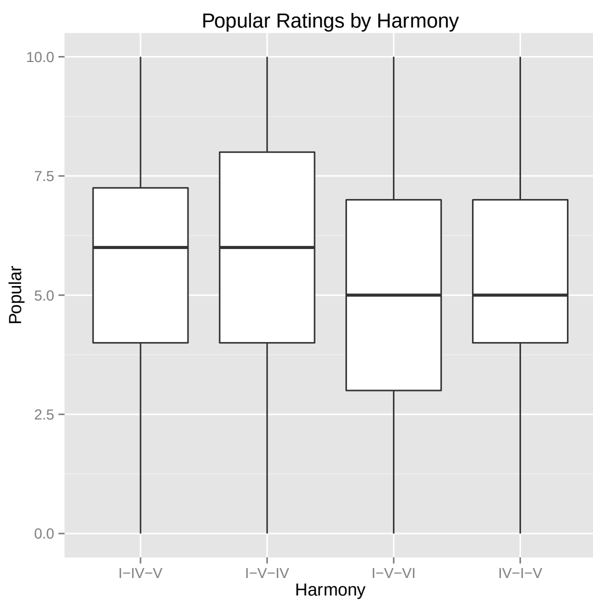


There appears to be one Popular rating of 19 in the dataset, which is beyond the upper limit for the ratings scale. Since I don't know why someone gave a rating of 19 or if this was a data entry error, I decided to exclude that one observation.

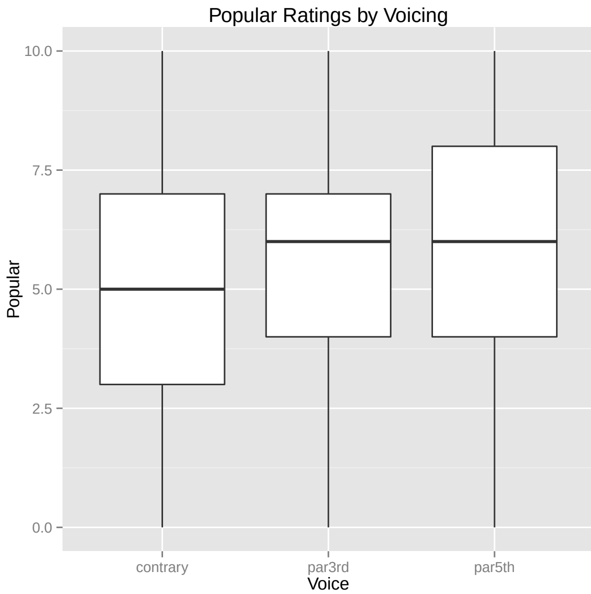
```
> ggplot(data=ratings4, aes(x=Instrument, y=Popular))+
+   geom_boxplot(aes(factor=Instrument)) +
+   ggtitle("Popular Ratings by Instrument")
```




```
> ggplot(data=ratings4, aes(x=Harmony, y=Popular))+
+   geom_boxplot(aes(factor=Harmony)) +
+   ggtitle("Popular Ratings by Harmony")
```




```
> ggplot(data=ratings4, aes(x=Voice, y=Popular))+
+   geom_boxplot(aes(factor=Voice)) +
+   ggtitle("Popular Ratings by Voicing")
```



Part a)

```
> AIC(pop.lm.all, pop.lmer.rand.int, pop.lmer.3)
                  df      AIC
pop.lm.all         9 9395.799
pop.lmer.rand.int 10 8803.459
pop.lmer.3        12 8523.625
> BIC(pop.lm.all, pop.lmer.rand.int, pop.lmer.3)
                  df      BIC
pop.lm.all         9 9446.681
pop.lmer.rand.int 10 8859.994
pop.lmer.3        12 8591.467


> # Model with random effects interactions and fixed effects for Instrument, Harmony and Voice
> summary(pop.lmer.3)
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:H
   Data: ratings4

REML criterion at convergence: 8499.625

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.45360  0.6735
 Subject:Voice      (Intercept) 0.03509  0.1873
 Subject:Instrument (Intercept) 1.90993  1.3820
 Residual                       2.45903  1.5681
Number of obs: 2108, groups: Subject:Harmony, 236; Subject:Voice, 177; Subject:Instrument, 177

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.78449    0.22354  30.350
Instrumentpiano  -1.06076    0.26806  -3.957
```

```
Instrumentstring -2.86367    0.26776 -10.695
HarmonyI-V-IV    -0.02808    0.15723  -0.179
HarmonyI-V-VI    -0.35982    0.15723  -2.289
HarmonyIV-I-V    -0.21867    0.15716  -1.391
Voicepar3rd       0.16228    0.09055   1.792
Voicepar5th       0.18484    0.09050   2.042

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
Instrumntpn -0.598
Instrmntstr -0.599  0.499
HrmnyI-V-IV -0.351  0.001     0.000
HrmnyI-V-VI -0.351  0.000     0.000     0.500
HrmnyIV-I-V -0.352  0.000     0.000     0.500  0.500
Voicepar3rd -0.203  0.000     0.000     0.001  0.001  0.001
Voicepar5th -0.202  0.000     0.000    -0.001 -0.001 -0.001  0.500
```

After determining that the model with the three random effects interactions offered the best fit for the data, we see that instrument type has the largest effect on how Popular-sounding a piece was rated. Electric guitar pieces were judged to be the most Popular-sounding and string quartet the least with an average difference of 2.86 points, given the same harmony and voicing. The Harmonic progressions I-V-IV, I-V-VI, and IV-I-V were all less Popular-sounding by 0.03 to 0.35 points but only the progression I-V-VI had a statistically significant impact. Both parallel 3rds and parallel 5ths voicings were judged to be around 0.16 points more Popular-sounding than pieces with contrary motion. We also see little evidence of any interaction effects between Instrument, Harmony and Voice.

The variance for the subject-instrument distribution was the largest at 1.91 which suggests that most subjects had the largest variation in their ratings based on instrument-type. The variance for the subject-harmony and subject-voice distributions were 0.45 and 0.03 respectively, suggesting that for most subjects, their ratings did not change much based on harmonic progressions or voicing types. However, these three estimated variance components were all smaller than the estimated residual variance indicating that there is more variation between the different subjects than within each subject. Our intraclass correlation is $\frac{1.91+0.45+0.03}{2.46+1.91+0.45+0.03} = 0.49$ suggesting that grouping by subject does provide us with a decent amount of information about the variation in ratings.

Part b)

why this model?

```
> #Final Model:
> display(pop.lmer.2a.final)
lmer(formula = Popular ~ 1 + Instrument + Harmony + Voice + ConsNotes +
    NoClass + as.factor(PianoPlay) + as.factor(GuitarPlay) +
    as.factor(ClsListen) + as.factor(X1990s2000s) + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice), data = ratings4)
                       coef.est coef.se
(Intercept)             5.78     0.69
Instrumentpiano        -1.10     0.28
Instrumentstring       -2.89     0.28
HarmonyI-V-IV          -0.01     0.18
HarmonyI-V-VI          -0.29     0.18
HarmonyIV-I-V          -0.25     0.18
Voicepar3rd             0.15     0.11
Voicepar5th             0.23     0.11
ConsNotes               0.09     0.08
NoClass                -0.06     0.14
```

```
as.factor(PianoPlay)1   -0.69     0.36
as.factor(PianoPlay)4    0.38     0.78
as.factor(PianoPlay)5   -0.93     0.49
as.factor(GuitarPlay)1  -0.61     0.58
as.factor(GuitarPlay)2  -0.39     1.19
as.factor(GuitarPlay)4   2.74     0.74
as.factor(GuitarPlay)5   0.77     0.65
as.factor(ClsListen)1    1.48     0.44
as.factor(ClsListen)3    1.05     0.43
as.factor(ClsListen)4    0.48     1.14
as.factor(ClsListen)5    0.13     0.58
as.factor(X1990s2000s)2 -0.46     0.68
as.factor(X1990s2000s)3  0.03     0.61
as.factor(X1990s2000s)4 -0.08     0.84
as.factor(X1990s2000s)5  0.01     0.51

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.64
 Subject:Voice      (Intercept) 0.21
 Subject:Instrument (Intercept) 1.24
 Residual                       1.62
---
number of obs: 1604, groups: Subject:Harmony, 180; Subject:Voice, 135; Subject:Instrument, 135
AIC = 6569.8, DIC = 6481.5
deviance = 6496.6
```

The set of covariates I chose to include in my final model are:

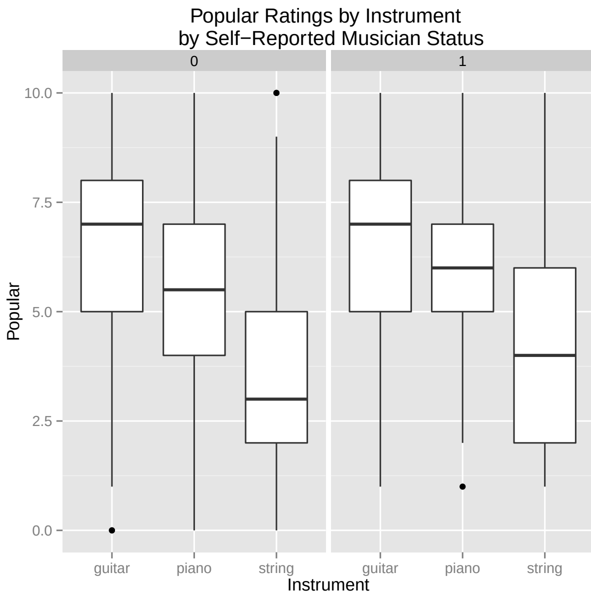
- how much the subject concentrated on notes when listening
- number of music classes taken
- whether the subject plays the piano
- whether the subject plays the guitar
- how much the subject listens to classical music
- how much the subject listens to pop and rock from the 1990s and 2000s

As can be seen in our final model, Instrument continus to have the largest impact on how Popular-sounding a piece was judged to be. Electric guitars were percieved to be the most Popular-sounding while string quartets were least. The harmonic progressions I-V-VI and IV-I-V were perceived as less Popular-sounding than the I-IV-V progression by 0.25-0.30 points. Both parallel 3rds and parallel 5ths voicings were more Popular-sounding than contrary motion by 0.15-0.23 points.

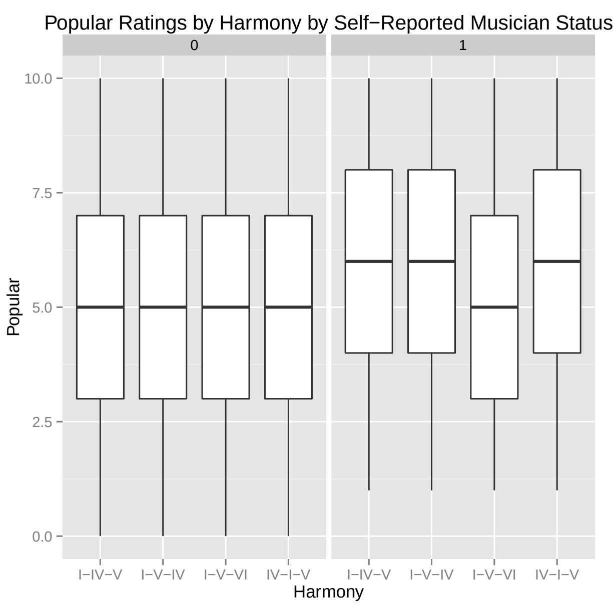
In addition to the effects of these three predictors, subjects who concentrated more on the notes played were slightly more likely to judge a piece as being Popular-sounding while those who had taken more music classes were slightly less likely to judge a piece as being Popular-sounding although neither of these effects were statistically significant. Those who were either beginner or expert piano players were less likely to judge pieces as being Popular-sounding while advanced guitar players were more likely to judge pieces as being Popular-sounding than beginner or non-guitar players. People who listened to any amount of classical music were more likely to judge pieces as being Popular-sounding. Those who did not listen to modern pop or rock music were less likely to judge the pieces as Popular-sounding but the effect of listening to such music very often on ratings was negligible.

Part c)

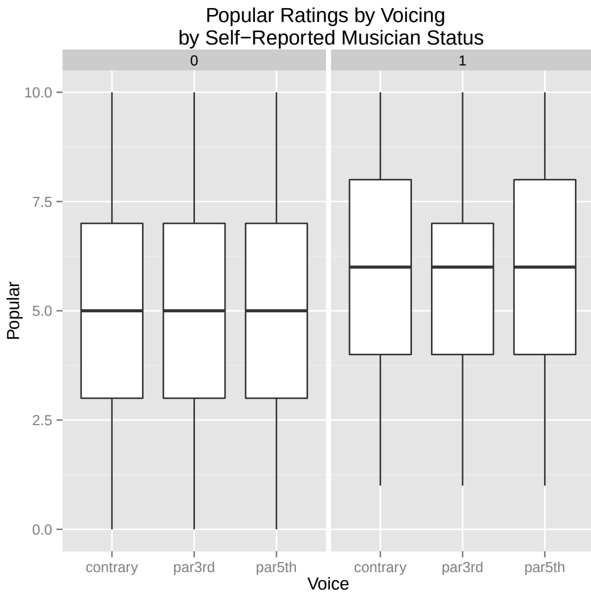
```
> # some EDA plots for Musician Effect
> ggplot(data=ratings5, aes(x=Instrument, y=Popular))+
+   geom_boxplot(aes(factor=Instrument)) + facet_wrap(~musician)+
+   ggtitle("Popular Ratings by Instrument \n by Self-Reported Musician Status")
```




```
> ggplot(data=ratings5, aes(x=Harmony, y=Popular))+geom_boxplot(aes(factor=Harmony)) +
+   facet_wrap(~musician)+
+   ggtitle("Popular Ratings by Harmony by Self-Reported Musician Status")
```




```
> ggplot(data=ratings5, aes(x=Voice, y=Popular))+geom_boxplot(aes(factor=Voice)) +
+   facet_wrap(~musician)+
+   ggtitle("Popular Ratings by Voicing \n by Self-Reported Musician Status")
```




```
> #final model
> display(pop.lmer.3.3)
lmer(formula = Popular ~ 1 + Instrument + Instrument:musician +
    Harmony + Harmony:musician + Voice + Voice:musician + ConsNotes +
    ConsNotes:musician + NoClass + NoClass:musician + as.factor(PianoPlay) +
    as.factor(GuitarPlay) + as.factor(ClsListen) + as.factor(X1990s2000s) *
    musician + musician + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
    (1 | Subject:Voice), data = ratings5)
                                  coef.est coef.se
(Intercept)                        2.05     1.08
Instrumentpiano                   -1.32     0.35
Instrumentstring                  -3.41     0.35
HarmonyI-V-IV                      0.00     0.23
HarmonyI-V-VI                      0.10     0.23
HarmonyIV-I-V                     -0.24     0.23
Voicepar3rd                        0.28     0.15
Voicepar5th                        0.18     0.15
ConsNotes                          0.29     0.09
NoClass                           -0.37     0.35
as.factor(PianoPlay)1             -0.64     0.39
as.factor(PianoPlay)4             -1.15     0.81
as.factor(PianoPlay)5             -0.53     0.51
as.factor(GuitarPlay)1            -1.14     0.76
as.factor(GuitarPlay)2             1.33     1.23
as.factor(GuitarPlay)4             2.93     0.82
as.factor(GuitarPlay)5             0.69     0.84
as.factor(ClsListen)1              1.51     0.43
as.factor(ClsListen)3              2.03     0.48
as.factor(ClsListen)4              1.88     1.21
as.factor(ClsListen)5              0.78     0.68
as.factor(X1990s2000s)2            3.55     1.15
as.factor(X1990s2000s)3            3.41     0.99
as.factor(X1990s2000s)4            2.83     1.22
```

```
as.factor(X1990s2000s)5            3.36     0.93
musician                           4.89     1.23
Instrumentpiano:musician           0.46     0.52
Instrumentstring:musician          1.11     0.52
musician:HarmonyI-V-IV            -0.01     0.34
musician:HarmonyI-V-VI            -0.84     0.34
musician:HarmonyIV-I-V            -0.02     0.34
musician:Voicepar3rd              -0.27     0.22
musician:Voicepar5th               0.11     0.22
musician:ConsNotes                -0.58     0.18
musician:NoClass                   0.38     0.42
musician:as.factor(X1990s2000s)2 -3.93     1.55
musician:as.factor(X1990s2000s)3 -5.23     1.33
musician:as.factor(X1990s2000s)4 -3.05     1.77
musician:as.factor(X1990s2000s)5 -4.08     1.14

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.61
 Subject:Voice      (Intercept) 0.20
 Subject:Instrument (Intercept) 1.14
 Residual                       1.62
---
number of obs: 1604, groups: Subject:Harmony, 180; Subject:Voice, 135; Subject:Instrument, 135
AIC = 6556.1, DIC = 6434.7
deviance = 6452.4
```

Self-described musicians were much more likely to judge pieces as being popular-sounding by nearly 5 points. In terms of the three main predictors, musicians were more likely to rate string quartets as being Popular-sounding than non-musicians were. Musicians were also more inclined to rate the I-V-VI progression as less Popular-sounding which was the opposite of non-musicians. Another difference was that musicians were less likely to rate parallel 3rds voicing as being Popular-sounding. However, the magnitude of the harmony and voicing effects were not very large, all less than an one point difference.

Other interaction effects from being a musician included musicians who concentrated more on the notes being played were less likely to judge a piece as being Popular-sounding while musicians who took more music classes were more likely to judge a piece as being Popular-sounding (although this effect was not statistically significant). Finally, musicians who listened to any amount of pop and rock music from the 1990s to 2000s were much less likely to judge pieces as being Popular-sounding.

Problem 5

To explore the effect of different musical properties on listeners' perceptions of music, I built a hierarchical linear model to explore the effect of the instrument played, harmonic motion and voice leading on listeners' ratings of a musical stimuli as being classical-sounding. As reflected in my final model for part 2b, the type of instrument that was played had the most important effect on listeners' ratings. Pieces played by string quartets were seen as the most classical-sounding while pieces played by electric guitars were the least. String quartet pieces were judged, on average, to be 3.61 points more classical-sounding than electric guitars. Pieces played by a piano were 1.65 points more classical-sounding. The influence of harmonic motion on classical ratings was smaller. Only the I-V-VI progression was judged as being more classical-sounding by 0.88 points. The other types of harmonic motion did not have much of an influence on listeners' ratings. Finally, both parallel 3rds and parallel 5ths voice leadings were rated as less classical-sounding by -0.40 and -0.33 points, respectively, compared to contrary motion.

In addition to the effect of instrument, harmonic motion and voice leading, several other factors played a role in determining how classical-sounding a piece seemed to be. For example, listeners who concentrated on the notes being played rated pieces as being less classical-sounding by -0.17 points. Listeners with some musical abilities such as being able to play the piano or guitar tended to rate pieces as being more classical-sounding. Finally, subjects who listened to an average amount of classical music or a great deal of modern pop or rock tended to rate pieces as being more classical-sounding.

Being a self-described musician also affected how subjects perceived the musical stimuli in different ways from non-musicians. Musicians tended to rate pieces played by string quartets as less classical-sounding than non-musicians, but were even more likely to rate the I-V-VI harmonic progression as being classical-sounding. In addition, musicians who listened to modern pop or rock music at least somewhat often were more likely to perceive pieces as being more classical-sounding.

In addition to exploring classical ratings, I also analyzed how various factors affected listeners' perceptions of how "popular" musical stimuli sounded. Similar to classical ratings, instrument played the largest role in determining how popular pieces sounded. However, for the popular ratings, pieces played by an electric guitar were judged to be most popular-sounding while pieces played by a string quartet were least popular-sounding. The difference on average was nearly 3 points. Pieces played by a piano were -1.1 point less popular sounding than those played by an electric guitar. The different harmonic progressions had less of an effect with listeners judging the I-V-VI sequence to be -0.30 points less popular-sounding. The different voice structures also had a smaller effect on perceptions. Listeners found parallel 3rds and parallel 5ths to be more popular-sounding than contrary motion by 0.15 and 0.23 points, respectively.

In addition to instrument, harmony and voicing, listeners who could play the piano or guitar also were likely to perceive the stimuli differently. Listeners who had some familiarity with how to play the piano tended to judge pieces as being less popular-sounding while those who were proficient in the guitar rated pieces to be much more popular-sounding, on average. Subjects who listened to classical music relatively infrequently were also more likely to judge pieces as being 1-1.5 points more popular sounding. However, the frequency with which subjects listened to modern pop and rock music did not have much of an effect on popular ratings.

Finally, self-described musicians did differ from non-musicians in their assessment of how popular-sounding a piece was in several ways. Being a musician was associated with nearly a 5 point increase in popular ratings. In addition, musicians tended to perceive pieces played by a piano or string quartet as much more popular-sounding than non-musicians did. On the other hand, musicians were less likely to feel the I-V-VI harmonic progression was popular sounding. The effect of being a musician on the different types of voicing was not significant. Musicians who concentrated on the notes played were less likely to judge the piece as being popular-sounding. Finally, musicians who listened to any amount of modern pop or rock music were much less likely to rate pieces as being popular-sounding than did non-musicians. This effect was quite large with a difference of between 3-5 points.

In building these models, I included other variance components. As can be seen from my results in part 2b, including random effects for each person/instrument, person/harmony, and person/voicing combination significantly improves the fit of these models. It seems that the degree to which listeners are inclined to rate pieces as being more classical or popular-sounding does tend to vary with the type of instrument, harmony and voice leading.

4: 18/20

5; 20/20

38/40