Hierarchical Linear Models Homework 5

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1.

a.

```
> library(arm)
> library(lme4)
> library(RLRsim)
> setwd("C:/Users/CMU Stats Extra/Desktop/hierarchical/hw05")
> rating = read.csv("ratings.csv", head=T)
> attach(rating)
> fit0 = lm(Classical~Instrument+Harmony+Voice, data=rating)
> summary(fit0)

Call:
lm(formula = Classical ~ Instrument + Harmony + Voice, data = rating)

Residuals:
    Min      1Q  Median      3Q     Max
-6.8718 -1.7137 -0.0297  1.7576 11.4766

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       4.34016    0.12987  33.420  < 2e-16 ***
Instrumentpiano   1.37359    0.11298  12.158  < 2e-16 ***
Instrumentstring  3.13312    0.11230  27.899  < 2e-16 ***
HarmonyI-V-IV    -0.03108    0.13008  -0.239 0.811168
HarmonyI-V-VI     0.76909    0.13008   5.913 3.83e-09 ***
HarmonyIV-I-V     0.05007    0.12997   0.385 0.700092
Voicepar3rd      -0.41247    0.11271  -3.660 0.000258 ***
Voicepar5th      -0.37058    0.11264  -3.290 0.001016 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.297 on 2485 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.255,       Adjusted R-squared:  0.2529
F-statistic: 121.5 on 7 and 2485 DF,  p-value: < 2.2e-16

> fit1 = lm(Classical~Instrument+Harmony, data=rating)
> fit2 = lm(Classical~Instrument+Voice, data=rating)
> fit3 = lm(Classical~Harmony+Voice, data=rating)
> anova(fit0, fit1, fit2, fit3)
```

```
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Instrument + Harmony
Model 3: Classical ~ Instrument + Voice
Model 4: Classical ~ Harmony + Voice
  Res.Df   RSS Df Sum of Sq       F    Pr(>F)
1   2485 13108
2   2487 13193 -2     -85.6  8.1181 0.0003061 ***
3   2488 13381 -1    -188.0 35.6442 2.707e-09 ***
4   2487 17235  1   -3853.9
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> anova(fit0, fit3)
```

```
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Harmony + Voice
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 17235 -2   -4127.6 391.26 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the results, we can see that in the full model (with Instrument, Harmony, and Voice), all explanatory variables are statistically significant, except for HarmonyI-V-IV and HarmonyIV-I-V. Also, according to the ANOVA results, we can see that P-values are smaller than 0.01, which means that experimental factors Harmony, voice and Instrument are all statistically significant.

b.

i.

model:

$$Classical_i = \beta_0 + \beta_1 * Instrument + \beta_2 * Voice + \beta_3 * Harmony + \alpha_{j[i]} * Subject + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

,

$$\alpha_j = \gamma_0 + \phi_j,\ \phi_j \overset{iid}{\sim} N(0, \tau_0^2)$$

ii.

Method 1:

```
> rep0=lmer(Classical~Instrument+Voice+Harmony+(1|Subject),data=rating)
> list1 = list(rep0,fit0)
> sapply(list1, AIC)

[1] 10491.51 11230.45

> sapply(list1, BIC)

[1] 10549.73 11282.84
```

The AIC and BIC for the model without random effects are 11230.45 and 11282.84, respectively, which are higher than the AIC and BIC for the model with random effects, which are 10491.51, and 10549.73. Therefore, the random effect is needed.
Method 2:

```
> exactRLRT(rep0)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 763.3759, p-value < 2.2e-16
```

Since the p-value is less than 2.2e-16, we should reject the null hypothesis that the variation of the random effect is 0. Therefore, we should keep the random effect.

iii.

```
> rep1 = lmer(Classical~Harmony+Voice+(1|Subject), data=rating)
> rep2 = lmer(Classical~Harmony+Instrument+(1|Subject), data=rating)
> rep3 = lmer(Classical~Voice+Instrument+(1|Subject), data=rating)
> list2 = list(rep0,rep1,rep2,rep3)
> sapply(list2, AIC)

[1] 10491.51 11423.04 10505.58 10552.74

> sapply(list2, BIC)

[1] 10549.73 11469.60 10552.15 10593.49
```

According to the results, the AIC (10491.51) and BIC (10549.73) for the model that includes all three main experimental factors are the lowest, when compared to the AIC and BIC of other models. Therefore, we should keep the all three main factors.

c.

i.

```
> rep4 = lmer(Classical~Harmony+Voice+Instrument+(1|Harmony:Subject)+(1|Voice:Subject)+(1|Instrument:Sul
> list3 = list(fit0, rep0, rep4)
> sapply(list3, AIC)

[1] 11230.45 10491.51 10075.51

> sapply(list3, BIC)

[1] 11282.84 10549.73 10145.37
```

According to the results, the AIC (10075.51) and BIC (10145.37) of the model with three new random effect terms are smaller than the AIC and BIC of the models in problem 1a and 1b. Therefore, a model with three random effect terms is better.

ii.

```
> rep5 = lmer(Classical~Harmony+Voice+(1|Harmony:Subject)+(1|Voice:Subject), data=rating)
> rep6 = lmer(Classical~Harmony+Instrument+(1|Harmony:Subject)+(1|Instrument:Subject), data=rating)
> rep7 = lmer(Classical~Instrument+Voice+(1|Instrument:Subject)+(1|Voice:Subject), data=rating)
> list4 = list(rep4, rep5, rep6, rep7)
> sapply(list4, AIC)
```

```
[1] 10075.51 11617.96 10097.52 10255.80
```

```
> sapply(list4, BIC)
```

```
[1] 10145.37 11670.35 10149.91 10302.37
```

From the results, we can see that the AIC (10075.51) and BIC (10145.37) for the model that includes all three main experimental factors are the lowest, when compared to the AIC and BIC of other models. Therefore, the the three main experimental factors are statistically significant, and we should keep the all three main factors.

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

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

There are three groups in the model with all three experimental factors and three random effect terms. The first group is Subject:Harmony, the size of this group is 280, which is larger than the size of Voice:Subject group (210) and Instrument:Subject group (210).The variance of the Harmony:Subject group is $0.67^2 = 0.4489$. For the Voice:Subject group,the variance is $0.17^2 = 0.0289$. For the Instrument:Subject group, the variance is $1.48^2 = 2.1904$. The residual variance for this model is $1.56^2 = 2.4336$.we can see that the variance of Instrument:Subject group is similar to the residual variance, and the Voice:Subject group has the smallest variance.

iii.

$Classical_i = \beta_0 + \beta_{1j[i]} * Subject : Instrument + \beta_{2j[i]} * Subject : Voice + \beta_{3j[i]} * Subject : Harmony + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$

,

$$\beta_{1j} = \zeta_0 + \psi_j, \ \psi_j \overset{iid}{\sim} N(0, \tau_1^2)$$

$$\beta_{2j} = \gamma_0 + \phi_j,\ \phi_j \overset{iid}{\sim} N(0, \tau_2^2)$$
$$\beta_{3j} = \delta_0 + \omega_j,\ \omega_j \overset{iid}{\sim} N(0, \tau_3^2)$$

2.

a.

Firstly, since there are many NA's in the data set, we need to determine whether to omit those NA's or impute values for those NA's.From all the variables, I picked 9 variables that I think are of interest in this study: Selfdeclare, OMSI, X16.minus.17, ConsInstr, ConsNotes, ClsListen, CollegeMusic, PianoPlay, GuitarPlay. Because I think those variables are enough to reflect one person's music knowledge, listening ability to distinguish a music type, how concentrated he is on the music, and how familiar he is with different music types. I think those are the key facts that influence how one person rates a classical/popular piece of music.

```
> rating1 = rating[!is.na(rating$Selfdeclare)&!is.na(rating$OMSI)&!is.na(rating$X16.minus.17)&!is.na(ra
> attach(rating1)

The following objects are masked from rating:

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, Harmony, Instr.minus.Notes,
    Instrument, KnowAxis, KnowRob, NoClass, OMSI, PachListen,
    PianoPlay, Popular, Selfdeclare, Subject, Voice, X, X16.minus.17,
    X1990s2000s, X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr
```

After I omitted all the rows that contain NA's in any of the nine columns picked, there are still 2088 observations, which is reasonable compared to the original 2520 observations. Therefore, I determined to omit those NA's
Secondly, we explored the explanatory variables to determine which ones need to be considered as factors.

```
> boxplot(Classical~Selfdeclare, data=rating1)
> boxplot(Classical~OMSI, data=rating1)
> boxplot(Classical~X16.minus.17, data=rating1)
> boxplot(Classical~ConsInstr, data=rating1)
> boxplot(Classical~ConsNotes, data=rating1)
> boxplot(Classical~ClsListen, data=rating1)
> boxplot(Classical~PianoPlay, data=rating1)
> boxplot(Classical~GuitarPlay, data=rating1)
> hist(rating1$PianoPlay)
> hist(GuitarPlay, data=rating1)
> hist(Selfdeclare)
> summary(rating1$PianoPlay)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  0.000   0.000   0.000   1.069   1.000   5.000

> summary(Selfdeclare)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   2.000   2.000   2.603   3.000   6.000

> rating1$musc[Selfdeclare<3]=0
> rating1$musc[Selfdeclare>=3]=1
> rating1$PianoPlay1[rating1$PianoPlay==0]=0
```

```
> rating1$PianoPlay1[rating1$PianoPlay>0]=1
> rating1$GuitarPlay1[rating1$GuitarPlay==0]=0
> rating1$GuitarPlay1[rating1$GuitarPlay>0]=1
> attach(rating1)

The following objects are masked from rating1 (position 3):

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, Harmony, Instr.minus.Notes,
    Instrument, KnowAxis, KnowRob, NoClass, OMSI, PachListen,
    PianoPlay, Popular, Selfdeclare, Subject, Voice, X, X16.minus.17,
    X1990s2000s, X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr
The following objects are masked from rating:

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, Harmony, Instr.minus.Notes,
    Instrument, KnowAxis, KnowRob, NoClass, OMSI, PachListen,
    PianoPlay, Popular, Selfdeclare, Subject, Voice, X, X16.minus.17,
    X1990s2000s, X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr
```

According to the boxplots, we decided that the following variables, out of the eleven variables picked, need to be considered factors: Selfdeclare, ConsNotes, ClsListen, PianoPlay, GuitarPlay, because those variables are divided into <= 6 groups. According to the histograms of different variables, I created three new variables: musc, PianoPlay1, GuitarPlay1. Musc denotes whether one person claims to be musician (musc=1 if Selfdeclare>=3, musc=0 if Selfdeclare<3). GuitarPlay1 and PianoPlay1 denote whether a person'playing Guitar and Piano frequency is high or low.

```
> model2.0 = lmer(Classical~Harmony+Voice+Instrument+(1|Harmony:Subject)+(1|Voice:Subject)+(1|Instrument
> add2.0 = update(model2.0,.~.+musc, data=rating1)
> anova(model2.0,add2.0)

Data: rating1
Models:
model2.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model2.0:     (1 | Voice:Subject) + (1 | Instrument:Subject)
add2.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.0:     (1 | Voice:Subject) + (1 | Instrument:Subject) + musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model2.0 12 8396.3 8463.9 -4186.1   8372.3
add2.0   13 8398.2 8471.5 -4186.1   8372.2 0.0597      1     0.8069

> add2.1 = update(model2.0, .~.+OMSI, data=rating1)
> anova(model2.0, add2.1)

Data: rating1
Models:
model2.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model2.0:     (1 | Voice:Subject) + (1 | Instrument:Subject)
add2.1: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.1:     (1 | Voice:Subject) + (1 | Instrument:Subject) + OMSI
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model2.0 12 8396.3 8463.9 -4186.1   8372.3
add2.1   13 8398.2 8471.5 -4186.1   8372.2 0.0176      1     0.8945

> add2.2 = update(model2.0,.~.+X16.minus.17, data=rating1)
> anova(model2.0, add2.2)
```

```
Data: rating1
Models:
model2.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model2.0:     (1 | Voice:Subject) + (1 | Instrument:Subject)
add2.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.2:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model2.0 12 8396.3 8463.9 -4186.1   8372.3
add2.2   13 8393.9 8467.2 -4184.0   8367.9 4.3258      1    0.03754 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> add2.3 = update(add2.2,.~.+ConsInstr, data=rating1)
> anova(add2.2,add2.3)

Data: rating1
Models:
add2.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.2:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17
add2.3: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.3:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.3:     ConsInstr
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add2.2 13 8393.9 8467.2 -4184.0   8367.9
add2.3 14 8395.8 8474.7 -4183.9   8367.8 0.1462      1     0.7022

> add2.4 = update(add2.2,.~.+factor(ConsNotes), data=rating1)
> anova(add2.2, add2.4)

Data: rating1
Models:
add2.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.2:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17
add2.4: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.4:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.4:     factor(ConsNotes)
       Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
add2.2 13 8393.9 8467.2 -4184.0   8367.9
add2.4 17 8395.8 8491.6 -4180.9   8361.8 6.128      4     0.1898

> add2.6 = update(add2.2,.~.+factor(ClsListen), data=rating1)
> anova(add2.2, add2.6)

Data: rating1
Models:
add2.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.2:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17
add2.6: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.6:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.6:     factor(ClsListen)
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add2.2 13 8393.9 8467.2 -4184.0   8367.9
add2.6 17 8391.8 8487.6 -4178.9   8357.8 10.123      4     0.0384 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> add2.7 = update(add2.6,.~.+factor(CollegeMusic), data=rating1)
> anova(add2.6, add2.7)

Data: rating1
Models:
add2.6: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.6:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.6:     factor(ClsListen)
add2.7: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.7:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.7:     factor(ClsListen) + factor(CollegeMusic)
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add2.6 17 8391.8 8487.6 -4178.9   8357.8
add2.7 18 8393.7 8495.2 -4178.9   8357.7 0.0744      1      0.785

> add2.8 = update(add2.6,.~.+PianoPlay1, data=rating1)
> anova(add2.6,add2.8)

Data: rating1
Models:
add2.6: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.6:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.6:     factor(ClsListen)
add2.8: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.8:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.8:     factor(ClsListen) + PianoPlay1
       Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
add2.6 17 8391.8 8487.6 -4178.9   8357.8
add2.8 18 8390.4 8491.9 -4177.2   8354.4 3.402      1    0.06512 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> add2.9 = update(add2.6,.~.+GuitarPlay1, data=rating1)
> anova(add2.6, add2.9)

Data: rating1
Models:
add2.6: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.6:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.6:     factor(ClsListen)
add2.9: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.9:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.9:     factor(ClsListen) + GuitarPlay1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add2.6 17 8391.8 8487.6 -4178.9   8357.8
add2.9 18 8389.9 8491.4 -4177.0   8353.9 3.8893      1     0.0486 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Out of the nine variables I chose, I tried to add one variable each time, and used ANOVA to test whether it is better to add this variables. If p-value of the ANOVA test is less than .05, then I keep the variable, if not, I don't keep it. Then I added another variable to the new model I got from the previous tests. According to the results, we need to add the following variables as fixed effects to the best model in problem1: X16.minus.17 (p-value=.02), ClsListen (p-value=.03), and GuitarPlay1 (p-value=.04).

b.

```
> rating1$ClsListen1 = factor(rating1$ClsListen)
> attach(rating1)

The following objects are masked from rating1 (position 3):

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, GuitarPlay1, Harmony,
    Instr.minus.Notes, Instrument, KnowAxis, KnowRob, musc, NoClass,
    OMSI, PachListen, PianoPlay, PianoPlay1, Popular, Selfdeclare,
    Subject, Voice, X, X16.minus.17, X1990s2000s,
    X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr
The following objects are masked from rating1 (position 4):

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, Harmony, Instr.minus.Notes,
    Instrument, KnowAxis, KnowRob, NoClass, OMSI, PachListen,
    PianoPlay, Popular, Selfdeclare, Subject, Voice, X, X16.minus.17,
    X1990s2000s, X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr
The following objects are masked from rating:

    APTheory, Classical, ClsListen, CollegeMusic, Composing, ConsInstr,
    ConsNotes, first12, GuitarPlay, Harmony, Instr.minus.Notes,
    Instrument, KnowAxis, KnowRob, NoClass, OMSI, PachListen,
    PianoPlay, Popular, Selfdeclare, Subject, Voice, X, X16.minus.17,
    X1990s2000s, X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr

> ch2.1 = update(add2.9,.~.-(1|Harmony:Subject), data=rating1)
> anova(add2.8, ch2.1)

Data: rating1
Models:
ch2.1: Classical ~ Harmony + Voice + Instrument + (1 | Voice:Subject) +
ch2.1:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
ch2.1:     GuitarPlay1
add2.8: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.8:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.8:     factor(ClsListen) + PianoPlay1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
ch2.1  17 8454.0 8549.8 -4210.0   8420.0
add2.8 18 8390.4 8491.9 -4177.2   8354.4 65.594      1   5.54e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> ch2.2 = update(add2.9,.~.-(1|Instrument:Subject), data=rating1)
> anova(add2.8, ch2.2)

Data: rating1
Models:
ch2.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
ch2.2:     (1 | Voice:Subject) + X16.minus.17 + factor(ClsListen) +
ch2.2:     GuitarPlay1
add2.8: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.8:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.8:     factor(ClsListen) + PianoPlay1
```

```
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
ch2.2  17 8871.0 8966.9 -4418.5   8837.0
add2.8 18 8390.4 8491.9 -4177.2   8354.4 482.63      1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> ch2.3 = update(add2.9,.~.-(1|Voice:Subject), data=rating1)
> anova(add2.8, ch2.3)
```

```
Data: rating1
Models:
ch2.3: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
ch2.3:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
ch2.3:     GuitarPlay1
add2.8: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.8:     (1 | Voice:Subject) + (1 | Instrument:Subject) + X16.minus.17 +
add2.8:     factor(ClsListen) + PianoPlay1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
ch2.3  17 8388.4 8484.3 -4177.2   8354.4
add2.8 18 8390.4 8491.9 -4177.2   8354.4 0.0462      1     0.8297
```

In order to test whether the previous random effects (the interaction of Subject and Harmony, Instrument, and Voice, respectively) are still valid. I tried to delete one interaction at a time, and used ANOVA test to see whether that term is statistically significant (if p-value is less than.05, I would keep the term, if the p-value is bigger than.05, I would not keep the term). If it is, I'll keep that term, if it is not, I'll delete that term from the model. According to the results, we need to keep the random effect of Subject:Harmony, and Subject:Instrument.

```
> add2.10 = update(ch2.3,.~.+(1|ClsListen1:Subject), data=rating1)
> anova(add2.10, ch2.3)
```

```
Data: rating1
Models:
ch2.3: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
ch2.3:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
ch2.3:     GuitarPlay1
add2.10: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.10:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
add2.10:     GuitarPlay1 + (1 | ClsListen1:Subject)
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
ch2.3   17 8388.4 8484.3 -4177.2   8354.4
add2.10 18 8369.4 8470.8 -4166.7   8333.4 21.072      1  4.424e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> add2.11 = update(add2.10,.~.+(1|GuitarPlay1:Subject), data=rating1)
> anova(add2.10, add2.11)
```

```
Data: rating1
Models:
add2.10: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.10:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
add2.10:     GuitarPlay1 + (1 | ClsListen1:Subject)
add2.11: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
add2.11:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
add2.11:     GuitarPlay1 + (1 | ClsListen1:Subject) + (1 | GuitarPlay1:Subject)
```

```
        Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
add2.10 18 8369.4 8470.8 -4166.7   8333.4
add2.11 19 8371.4 8478.5 -4166.7   8333.4     0      1          1

>
```

In order to test whether it is better to add other random effect of interaction terms into the model, I tried to add the interaction of Subject and other predictor variables as random effect one at a time. If the added term is statistically significant, which means the p-value of the ANOVA test is less than.05, I will keep the term and make a new model. If not, I will keep the previous model. According to the results, we need to add the random effect of Subject:ClsListen into the final model.

c.

```
> summary(add2.10)

Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +      (1 | Instrument:Subject
   Data: rating1

REML criterion at convergence: 8351.354

Random effects:
 Groups             Name        Variance Std.Dev.
 Harmony:Subject    (Intercept) 0.3518   0.5931
 Instrument:Subject (Intercept) 1.2994   1.1399
 ClsListen1:Subject (Intercept) 1.1281   1.0621
 Residual                       2.5134   1.5854
Number of obs: 2073, groups: Harmony:Subject, 232; Instrument:Subject, 174; ClsListen1:Subject, 58

Fixed effects:
                   Estimate Std. Error t value
(Intercept)         4.28736    0.51118   8.387
HarmonyI-V-IV      -0.01652    0.14776  -0.112
HarmonyI-V-VI       0.84156    0.14780   5.694
HarmonyIV-I-V       0.07918    0.14772   0.536
Voicepar3rd        -0.38952    0.08534  -4.565
Voicepar5th        -0.37510    0.08531  -4.397
Instrumentpiano     1.46617    0.22847   6.417
Instrumentstring    3.21740    0.22812  14.104
X16.minus.17       -0.09272    0.06037  -1.536
factor(ClsListen)1 -0.43641    0.55403  -0.788
factor(ClsListen)3  0.11244    0.56904   0.198
factor(ClsListen)4 -0.46261    1.45804  -0.317
factor(ClsListen)5  0.48273    0.73121   0.660
GuitarPlay1         0.60648    0.43553   1.393

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t Instrmntp Instrmnts
HrmnyI-V-IV -0.145
HrmnyI-V-VI -0.144  0.500
HrmnyIV-I-V -0.144  0.500  0.500
Voicepar3rd -0.084  0.000  0.001  0.001
Voicepar5th -0.083 -0.001 -0.001 -0.001  0.500
Instrumntpn -0.223  0.000  0.000  0.000  0.000  0.000
```

```
Instrmntstr -0.223  0.000  0.000  0.000  0.000  0.000  0.499
X16.mins.17 -0.266  0.000  0.000  0.000  0.000  0.000  0.000     0.000
fctr(ClsL)1 -0.780  0.000  0.000  0.000  0.000  0.000  0.000     0.000
fctr(ClsL)3 -0.776  0.000  0.000  0.000  0.000  0.000  0.001     0.000
fctr(ClsL)4 -0.272  0.000  0.000  0.000  0.000  0.000  0.000     0.000
fctr(ClsL)5 -0.618  0.000  0.000  0.000  0.000  0.000  0.000     0.000
GuitarPlay1  0.046  0.000  0.000  0.000  0.000  0.000  0.000     0.000
            X16..1 f(CL)1 f(CL)3 f(CL)4 f(CL)5
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Voicepar3rd
Voicepar5th
Instrumntpn
Instrmntstr
X16.mins.17
fctr(ClsL)1  0.081
fctr(ClsL)3  0.140  0.725
fctr(ClsL)4 -0.062  0.295  0.331
fctr(ClsL)5  0.163  0.582  0.631  0.290
GuitarPlay1 -0.175 -0.128 -0.294 -0.279 -0.358
```

The final model includes the following fixed effects: Harmony, Voice, Instrument, X16.minus.17, ClsListen, and GuitarPlay1; random effects: Harmony:Subject, Instrument:Subject, ClsListen:Subject. When other variables are zero, the classical rating of a music piece is 4.287. Holding other variables are constant, for a piece of Harmony motion I-V-IV, the classical rating will decrease .01652 unit, compared to the comparison group(HarmonyI-IV-V). Holding other variables are constant, for a piece of Harmony motion I-V-VI, the classical rating will increase .84156 unit, compared to the comparison group(HarmonyI-IV-V).Holding other variables are constant, for a piece of Harmony motion IV-I-V, the classical rating will increase .0792 unit, compared to the comparison group(HarmonyI-IV-V). Holding other variables constant, for a voice leading level of par3rd, the classical rating will decrease by .3895 unit, compared to the comparison group (VoiceContrary). Holding other variables constant, for a voice leading level of par5th, the classical rating will decrease by .3751 unit, compared to the comparison group (VoiceContrary). Holding other variables constant, for Instrument Piano, the classical rating will increase 1.466 units, compared to the comparison group (InstrumentGuitar) .Holding other variables constant, for Instrument string, the classical rating will increase 3.2174 units, compared to the comparison group (InstrumentGuitar). Holding other variables constant, for one unit increase in listener's ability to distinguish classical vs. popular music, the classical rating will decrease .09272 units. Holding other variables constant, from people in classical listening frequency level 1, the classical rating will decrease .4364 units , compared to the comparison group (ClsListen2). Holding other variables constant, from people in classical listening frequency level 3, the classical rating will increase .11244 units , compared to the comparison group (ClsListen2). Holding other variables constant, from people in classical listening frequency level 4, the classical rating will decrease .4626 units , compared to the comparison group (ClsListen2). Holding other variables constant, from people in classical listening frequency level 5, the classical rating will increase .4827 units , compared to the comparison group (ClsListen2). Holding other variables constant, people who play guitar (GuitarPlay=1) has a classical rating .6064 units higher than people who do not play guitar (GuitarPlay=0).

3.

```
> model3.0 = update(add2.10,.~.+musc, data=rating1)
> anova(add2.10, model3.0)

Data: rating1
Models:
add2.10: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
```

```
add2.10:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
add2.10:     GuitarPlay1 + (1 | ClsListen1:Subject)
model3.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.0:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.0:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add2.10  18 8369.4 8470.8 -4166.7   8333.4
model3.0 19 8371.1 8478.2 -4166.5   8333.1 0.3039      1     0.5815

> model3.1 = update(model3.0,.~.+musc:Harmony, data=rating1)
> anova(model3.0,model3.1)

Data: rating1
Models:
model3.0: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.0:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.0:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc
model3.1: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.1:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.1:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model3.0 19 8371.1 8478.2 -4166.5   8333.1
model3.1 22 8346.1 8470.1 -4151.1   8302.1 30.933      3  8.779e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> model3.2 = update(model3.1,.~.+musc:Instrument, data=rating1)
> anova(model3.1,model3.2)

Data: rating1
Models:
model3.1: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.1:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.1:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc
model3.2: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.2:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.2:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc +
model3.2:     Instrument:musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model3.1 22 8346.1 8470.1 -4151.1   8302.1
model3.2 24 8345.5 8480.8 -4148.7   8297.5 4.6394      2     0.0983 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> model3.3 = update(model3.1,.~.+musc:Voice, data=rating1)
> anova(model3.1,model3.3)

Data: rating1
Models:
model3.1: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.1:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.1:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc
model3.3: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.3:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.3:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc +
```

```
model3.3:     Voice:musc
         Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
model3.1 22 8346.1 8470.1 -4151.1   8302.1
model3.3 24 8349.2 8484.5 -4150.6   8301.2 0.905      2     0.6361

> model3.4 = update(model3.1,.~.+musc:X16.minus.17, data=rating1)
> anova(model3.4, model3.1)

Data: rating1
Models:
model3.1: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.1:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.1:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc
model3.4: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.4:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.4:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc +
model3.4:     X16.minus.17:musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model3.1 22 8346.1 8470.1 -4151.1   8302.1
model3.4 23 8339.3 8469.0 -4146.7   8293.3 8.8038      1   0.003006 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> model3.5 = update(model3.4,.~.+musc:GuitarPlay1, data=rating1)
> anova(model3.5, model3.4)

Data: rating1
Models:
model3.4: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.4:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.4:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc +
model3.4:     X16.minus.17:musc
model3.5: Classical ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model3.5:     (1 | Instrument:Subject) + X16.minus.17 + factor(ClsListen) +
model3.5:     GuitarPlay1 + (1 | ClsListen1:Subject) + musc + Harmony:musc +
model3.5:     X16.minus.17:musc + GuitarPlay1:musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model3.4 23 8339.3 8469.0 -4146.7   8293.3
model3.5 24 8337.9 8473.2 -4145.0   8289.9 3.4254      1     0.0642 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In order to test whether there are interactions between the musician variable(musc) and other predictors in this model, I added the interaction of musc and other predictors one at a time, and used ANOVA to test whether it is statistically significant to add the interaction.A term is significant if the p-value is less than .05. If it is significant, I would add the interaction and make a new model; if not, I would continue with the previous model. According to the results, we should only add the interaction of musc and Harmony. We can see from the results that people who self-identified as musician are influenced by Harmony that do not influence non-musicians. Therefore, the final model we have for classical rating includes the following fixed effects: Harmony, Voice, Instrument, X16.minus.17, ClsListen, musc, GuitarPlay1, musc:Harmony; random effects: Harmony:Subject, Instrument:Subject, ClsListen:Subject.

4.

a.

```
> model4.3 = lm(Popular~Harmony+Voice+Instrument, data=rating)
> lm4.0 = lmer(Popular~Harmony+Voice+Instrument+(1|Subject), data=rating)
> list4.0 = list(model4.3, lm4.0)
> sapply(list4.0, AIC)
```

```
[1] 11143.15 10453.12
```

```
> sapply(list4.0, BIC)
```

```
[1] 11195.54 10511.34
```

According to the results, the AIC(10453.12) and BIC(10511.34) of the model including random effect of Subject are lower than the AIC (11143.15) and BIC (11195.54) of the model without. Therefore, we need to include Subject as a random effect in the model.

```
> fit4.0 = lmer(Popular~Harmony+Voice+Instrument+(1|Instrument:Subject)+(1|Voice:Subject)+(1|Harmony:Sub
> fit4.1 = lmer(Popular~Harmony+Voice+Instrument+(1|Instrument:Subject)+(1|Voice:Subject), data=rating)
> anova(fit4.0, fit4.1)
```

```
Data: rating
Models:
fit4.1: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
fit4.1:     (1 | Voice:Subject)
fit4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
fit4.0:     (1 | Voice:Subject) + (1 | Harmony:Subject)
       Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
fit4.1 11 10163 10227 -5070.5    10141
fit4.0 12 10079 10149 -5027.5    10055 86.066      1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> fit4.2 = lmer(Popular~Harmony+Voice+Instrument+(1|Instrument:Subject)+(1|Harmony:Subject), data=ratin
> anova(fit4.0, fit4.2)
```

```
Data: rating
Models:
fit4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
fit4.2:     (1 | Harmony:Subject)
fit4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
fit4.0:     (1 | Voice:Subject) + (1 | Harmony:Subject)
       Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
fit4.2 11 10078 10142 -5028.0    10056
fit4.0 12 10079 10149 -5027.5    10055 1.0217      1     0.3121
```

```
> fit4.3 = lmer(Popular~Harmony+Voice+Instrument+(1|Harmony:Subject), data=rating)
> anova(fit4.2, fit4.3)
```

```
Data: rating
Models:
fit4.3: Popular ~ Harmony + Voice + Instrument + (1 | Harmony:Subject)
fit4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
fit4.2:     (1 | Harmony:Subject)
       Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
```

```
fit4.3 10 10572 10630 -5276.1    10552
fit4.2 11 10078 10142 -5028.0    10056 496.23      1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In order to test whether there are personal biases in popular rating on Harmony, Voice, and Instrument, I started with a full model including the random effects of interactions between Subject and Harmony, Voice and Instrument, respectively. Then I deleted one interaction and used ANOVA test to see whether I need to keep the interaction according the p-value and AIC, BIC values. If the p-value is larger than .05, I would delete the interaction term, and move on with the reduced model to check on another interaction term. If p-value is smaller than.05, I would continue to check on another interaction with the same full model. According to the results, we need to include Subject:Harmony and Subject:Instrument as random effects of in the model.

```
> summary(fit4.2)

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

REML criterion at convergence: 10074.49

Random effects:
 Groups             Name        Variance Std.Dev.
 Harmony:Subject    (Intercept) 0.4099   0.6403
 Instrument:Subject (Intercept) 2.0268   1.4237
 Residual                       2.5133   1.5853
Number of obs: 2493, groups: Harmony:Subject, 280; Instrument:Subject, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.57983    0.20703   31.78
HarmonyI-V-IV    -0.02570    0.14069   -0.18
HarmonyI-V-VI    -0.27135    0.14068   -1.93
HarmonyIV-I-V    -0.18522    0.14062   -1.32
Voicepar3rd       0.16473    0.07784    2.12
Voicepar5th       0.16210    0.07778    2.08
Instrumentpiano  -0.94918    0.25316   -3.75
Instrumentstring -2.60618    0.25286  -10.31

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t Instrmntp
HrmnyI-V-IV -0.339
HrmnyI-V-VI -0.339  0.499
HrmnyIV-I-V -0.339  0.500  0.500
Voicepar3rd -0.187 -0.002  0.001  0.002
Voicepar5th -0.187 -0.001 -0.002 -0.001  0.500
Instrumntpn -0.610  0.000  0.000  0.000 -0.001 -0.001
Instrmntstr -0.611  0.000  0.000  0.000  0.000  0.000  0.500
```

Therefore, the final model for Popular ratings includes the following variables: fixed effects: Harmony, Voice, and Instrument; random effects: Subject: Harmony, Subject:Instrument. Holding other variables constant, the popular rating of HarmonyI-V-IV is .0257 units lower than the rating of HarmonyI-IV-V. Holding other variables constant, the popular rating of HarmonyI-V-VI is .2714 units lower than the rating of HarmonyI-IV-V. Holding other variables constant, the popular rating of HarmonyIV-I-V is .0257 units lower than the rating of HarmonyI-IV-V. Holding other variables constant, the popular rating of Voicepar3rd is .1647 units higher than the rating of VoiceGuitar group. Holding other variables constant, the popular rating of Voicepar5th is .1621 units higher than the rating of Voicecontrary group.Holding other variables constant, the popular rating of Instrument of piano group is .9592 units lower than the rating of instrument of guitar group.Holding other variables constant, the popular rating of Instrument of string group is 2.6062 units lower than the rating of instrument of guitar group. From the results, we can see that Instrument has larger effect on the classical rating than Harmony and Voice.

b.

```
> model4.0 = lmer(Popular~Harmony+Voice+Instrument+(1|Instrument:Subject)+(1|Harmony:Subject), data=rati
> add4.0 = update(model4.0,.~.+musc, data=rating1)
> anova(model4.0,add4.0)
```

what is "musc"?

```
Data: rating1
Models:
model4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
model4.0:     (1 | Harmony:Subject)
add4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.0:     (1 | Harmony:Subject) + musc
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model4.0 11 8458.9 8520.9 -4218.5   8436.9
add4.0   12 8456.3 8523.9 -4216.1   8432.3 4.6054      1    0.03187 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> add4.1 = update(add4.0, .~.+OMSI, data=rating1)
> anova(model4.0, add4.1)

Data: rating1
Models:
model4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
model4.0:     (1 | Harmony:Subject)
add4.1: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.1:     (1 | Harmony:Subject) + musc + OMSI
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model4.0 11 8458.9 8520.9 -4218.5   8436.9
add4.1   13 8457.9 8531.2 -4216.0   8431.9 4.9678      2    0.08342 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> add4.2 = update(add4.0,.~.+X16.minus.17, data=rating1)
> anova(model4.0, add4.2)

Data: rating1
Models:
model4.0: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
model4.0:     (1 | Harmony:Subject)
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model4.0 11 8458.9 8520.9 -4218.5   8436.9
add4.2   13 8455.8 8529.1 -4214.9   8429.8 7.0969      2    0.02877 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> add4.3 = update(add4.2,.~.+ConsInstr, data=rating1)
> anova(add4.2,add4.3)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.3: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.3:     (1 | Harmony:Subject) + musc + X16.minus.17 + ConsInstr
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.3 14 8457.4 8536.3 -4214.7   8429.4 0.3708      1     0.5426

> add4.4 = update(add4.2,.~.+factor(ConsNotes), data=rating1)
> anova(add4.2, add4.4)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.4: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.4:     (1 | Harmony:Subject) + musc + X16.minus.17 + factor(ConsNotes)
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.4 17 8462.0 8557.8 -4214.0   8428.0 1.8379      4     0.7656

> add4.6 = update(add4.2,.~.+ClsListen1, data=rating1)
> anova(add4.2, add4.6)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.6: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.6:     (1 | Harmony:Subject) + musc + X16.minus.17 + ClsListen1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.6 17 8461.4 8557.2 -4213.7   8427.4 2.4014      4     0.6624

> add4.7 = update(add4.2,.~.+factor(CollegeMusic), data=rating1)
> anova(add4.2, add4.7)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.7: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.7:     (1 | Harmony:Subject) + musc + X16.minus.17 + factor(CollegeMusic)
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.7 14 8457.2 8536.1 -4214.6   8429.2 0.5918      1     0.4417

> add4.8 = update(add4.2,.~.+PianoPlay1, data=rating1)
> anova(add4.2,add4.8)
```

```
Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.8: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.8:     (1 | Harmony:Subject) + musc + X16.minus.17 + PianoPlay1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.8 14 8457.6 8536.5 -4214.8   8429.6 0.1908      1     0.6622
```

```
> add4.9 = update(add4.2,.~.+GuitarPlay1, data=rating1)
> anova(add4.2, add4.9)
```

```
Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.9: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.9:     (1 | Harmony:Subject) + musc + X16.minus.17 + GuitarPlay1
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2 13 8455.8 8529.1 -4214.9   8429.8
add4.9 14 8457.5 8536.5 -4214.8   8429.5 0.2645      1     0.6071
```

Out of the nine variables I chose, I tried to add one variable each time, and used ANOVA to test whether it is better to add this variables. If p-value of the ANOVA test is less than .05, then I keep the variable, if not, I don't keep it. Then I added another variable to the new model I got from the previous tests. According to the results, we need to add the following variables as fixed effects to the best model in problem1: X16.minus.17 (p-value=.02), musc(p-value=.03).

```
> model4.10 = update(add4.2,.~.-(1|Instrument:Subject), data=rating1)
> anova(model4.10, add4.2)
```

```
Data: rating1
Models:
model4.10: Popular ~ Harmony + Voice + Instrument + (1 | Harmony:Subject) +
model4.10:     musc + X16.minus.17
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
          Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model4.10 12 8846.5 8914.2 -4411.3   8822.5
add4.2    13 8455.8 8529.1 -4214.9   8429.8 392.71      1  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> model4.11 = update(add4.2,.~.-(1|Harmony:Subject), data=rating1)
> anova(model4.11, add4.2)
```

```
Data: rating1
Models:
model4.11: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
model4.11:     musc + X16.minus.17
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
          Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model4.11 12 8512.0 8579.7 -4244.0   8488.0
add4.2    13 8455.8 8529.1 -4214.9   8429.8 58.223      1  2.341e-14 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In order to test whether the previous random effects (the interaction of Subject and Harmony, and Instrument, respectively) are still valid. I tried to delete one interaction at a time, and used ANOVA test to see whether that term is statistically significant. If it is, I'll keep that term, if it is not, I'll delete that term from the model. According to the results, we need to keep the random effect of Subject:Harmony, and Subject:Instrument, since the p-values are much less than .05 in the ANOVA tests where I compared the full model (with the two random effect interactions) and reduced model (reduced by one random effect interaction).

```
> summary(add4.2)

Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +      (1 | Harmony:Subject)
   Data: rating1

REML criterion at convergence: 8452.395

Random effects:
 Groups             Name        Variance Std.Dev.
 Harmony:Subject    (Intercept) 0.3796   0.6161
 Instrument:Subject (Intercept) 2.0031   1.4153
 Residual                       2.6298   1.6217
Number of obs: 2073, groups: Harmony:Subject, 232; Instrument:Subject, 174

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.49167    0.25445  25.513
HarmonyI-V-IV    -0.04444    0.15246  -0.291
HarmonyI-V-VI    -0.30915    0.15250  -2.027
HarmonyIV-I-V    -0.22611    0.15242  -1.483
Voicepar3rd       0.15045    0.08729   1.724
Voicepar5th       0.15172    0.08727   1.739
Instrumentpiano  -1.00815    0.27714  -3.638
Instrumentstring -2.66737    0.27683  -9.635
musc              0.42788    0.24830   1.723
X16.minus.17      0.06530    0.04182   1.561

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t Instrmntp Instrmnts
HrmnyI-V-IV -0.300
HrmnyI-V-VI -0.299  0.500
HrmnyIV-I-V -0.300  0.500  0.500
Voicepar3rd -0.172  0.000  0.001  0.001
Voicepar5th -0.171 -0.001 -0.001 -0.001  0.500
Instrumntpn -0.544  0.000  0.000  0.000  0.000  0.000
Instrmntstr -0.544  0.000  0.000  0.000  0.000  0.000  0.499
musc        -0.376  0.000  0.000  0.000  0.000  0.000  0.002     0.000
X16.mins.17 -0.167  0.000  0.000  0.000  0.000  0.001 -0.001     0.000
            musc
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Voicepar3rd
```

```
Voicepar5th
Instrumntpn
Instrmntstr
musc
X16.mins.17 -0.231
```

The final model includes the following fixed effects: Harmony, Voice, Instrument, X16.minus.17, and musc; random effects: Harmony:Subject, Instrument:Subject. When other variables are zero (that is to say, for the comparison group), the popular rating of a music piece is 6.492. Holding other variables are constant, for a piece of Harmony motion I-V-IV, the popular rating will decrease .0444 unit, compared to the comparison group(HarmonyI-IV-V). Holding other variables are constant, for a piece of Harmony motion I-V-VI, the popular rating will increase .3091 unit, compared to the comparison group(HarmonyI-IV-V).Holding other variables are constant, for a piece of Harmony motion IV-I-V, the popular rating will increase .22611 unit, compared to the comparison group(HarmonyI-IV-V). Holding other variables constant, for a voice leading level of par3rd, the popular rating will increase .1504 unit, compared to the comparison group (VoiceContrary). Holding other variables constant, for a voice leading level of par5th, the popular rating will increase by .1517 unit, compared to the comparison group (VoiceContrary). Holding other variables constant, for Instrument Piano, the popular rating will decrease 1.008 units, compared to the comparison group (InstrumentGuitar) .Holding other variables constant, for Instrument string, the popular rating will decrease 2.667 units, compared to the comparison group (InstrumentGuitar). Holding other variables constant, for one unit increase in listener's ability to distinguish classical vs. popular music, the popular rating will increase .0653 units. Holding other variables constant, people who self-identifies himself as musician has a popular rating .4279 units higher than people who self-identifies as non-musician.

c.

```
> add4.11 = update(add4.2,.~.+musc:Instrument, data=rating1)
> anova(add4.2, add4.11)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.11: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.11:     (1 | Harmony:Subject) + musc + X16.minus.17 + Instrument:musc
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2  13 8455.8 8529.1 -4214.9   8429.8
add4.11 15 8457.4 8541.9 -4213.7   8427.4 2.4324      2     0.2964
```

there is a more comprehensive way to test interactions with musc

```
> add4.12 = update(add4.2,.~.+musc:X16.minus.17, data=rating1)
> anova(add4.2, add4.12)

Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.12: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.12:     (1 | Harmony:Subject) + musc + X16.minus.17 + musc:X16.minus.17
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2  13 8455.8 8529.1 -4214.9   8429.8
add4.12 14 8457.7 8536.6 -4214.8   8429.7 0.1263      1     0.7223

> add4.13 = update(add4.2,.~.+musc:Harmony, data=rating1)
> anova(add4.2, add4.13)
```

```
Data: rating1
Models:
add4.2: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.2:     (1 | Harmony:Subject) + musc + X16.minus.17
add4.13: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.13:     (1 | Harmony:Subject) + musc + X16.minus.17 + Harmony:musc
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.2  13 8455.8 8529.1 -4214.9   8429.8
add4.13 16 8447.9 8538.1 -4208.0   8415.9 13.873      3   0.003083 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> add4.14 = update(add4.13,.~.+musc:Voice, data=rating1)
> anova(add4.13, add4.14)

Data: rating1
Models:
add4.13: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.13:     (1 | Harmony:Subject) + musc + X16.minus.17 + Harmony:musc
add4.14: Popular ~ Harmony + Voice + Instrument + (1 | Instrument:Subject) +
add4.14:     (1 | Harmony:Subject) + musc + X16.minus.17 + Harmony:musc +
add4.14:     Voice:musc
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
add4.13 16 8447.9 8538.1 -4208.0   8415.9
add4.14 18 8449.8 8551.3 -4206.9   8413.8 2.1046      2     0.3491
```

In order to test whether there are interactions between the musician variable(musc) and other predictors in this model, I added the interaction of musc and other predictors one at a time, and used ANOVA to test whether it is statistically significant to add the interaction. If it is significant, I would add the interaction and make a new model; if not, I would continue with the previous model. According to the results, we should only add the interaction of musc and Harmony. We can see from the results that people who self-identified as musician are influenced by Harmony that do not influence non-musicians. Therefore, the final model we have for popular rating includes the following fixed effects: Harmony, Voice, Instrument, X16.minus.17, musc, musc:Harmony; random effects: Harmony:Subject, Instrument:Subject.

5.

As I showed in my answer to 2.c., for classical music rating, Instrument has the largest effect, compared to Harmony and Voice. For Harmony, the HarmonyI-V-IV group has the lowest classical rating, which means the piece of music with HarmonyI-V-IV are least likely to be rated as classical music, holding other variables constant. For Voice, the contrary motion are highest rated, which means that the contrary motion are most likely to be rated as classical music, holding other variables constant. For Instrument, the guitar group have the lowest popular rating, which means that music played by guitar are least likely to be rated as classical, holding other variables constant. Also, there are personal biases in classical rating. Specifically, personal biases vary with the type of instrument, and type of harmony.

As I showed in my answer to part 4.b., for popular music rating, Instrument has the largest effect, compared to Harmony and Voice. For Harmony, the HarmonyI-IV-V group has the highest popular rating, which means the piece of music with HarmonyI-IV-V are most likely to be rated as popular music, holding other variables constant. For Voice, the contrary motion are lowest rated, which means that the contrary motion are least likely to be rated as popular music, holding other variables constant. For Instrument, the guitar group have the highest popular rating, which means that music played by guitar are most likely to be rated as popular, holding other variables constant. Also, there are personal biases in popular rating. Specifically, personal biases vary with the type of instrument, and type of harmony.

As I showed in my answers to part 1.c, and part 4.a, the standard repeated measures model, with a random effect of Subject, is not the best fit model here according to the ANOVA test. The best models (for Classical and Popular) we have is with random effects of interactions between Subject and Harmony, and Subject and Instrument. That is to say,there are personal biases in the models for Classical and Popular ratings, and the personal biases vary with the type of instrument, and type of harmony. Since we also included a random effect of interaction of Subject and ClsListen in the model for Classical rating, there is also personal bias with how much one person listens to classical music. Therefore, the variance components we have for classical rating are Subject:Harmony, Subject:Instrument, Subject:ClsListen; the variance components we have for classical rating are Subject:Harmony, Subject:Instrument.

As shown in problem 3.c, I included the following covariates, other than the three experimental factors, into the final model for Classical model: X16.minus.17, ClsListen, GuitarPlay, musc, musc:Harmony. In this model, holding other variables constant, the higher one person's score is as the listener's ability to distinguish classical vs. popular music, the higher one rates gives higher classical rating. Holding other variables constant, the more frequent one person listens to classical music, the higher he gives classical rating. Holding other variables constant, self-identified musicians gives higher classical rating than self-identified non-musicians. As shown in problem 4.c, I included the following covariates, other than the three experimental factors, into the final Popular model: musc, X16.minus.17. In this model, holding other variables constant, the higher one person's score is as the listener's ability to distinguish classical vs. popular music, the higher one rates gives higher popular rating. Holding other variables constant, self-identified musicians gives higher popular rating than self-identified non-musicians.

4: 18
5: 20

38