1 a 9/9
b 9/9
c 6/9

2 a 8/9
b 9/9
c 9/9

3 8/9

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

5 10/10

Total 95/100

36-763 Homework 5

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Problem 1

(a)

The first model fitted is a simple linear regression model where **Classical** is the response, and **Instrument**, **Harmony** and **Voice** are the explanatory variables. The following is the R output.

```
model_1a = lm(Classical~Harmony+Instrument+Voice, data=ratings)
summary(model_1a)
```

```
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 ***
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
Instrumentpiano   1.37359    0.11298  12.158  < 2e-16 ***
Instrumentstring  3.13312    0.11230  27.899  < 2e-16 ***
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
```

According to the model output, the Harmonic motion "I-V-VI" sounds the most classical, "IV-I-V" the second, "I-IV-V" the third and "I-V-IV" the least classical. However, the two levels of **Harmony** "I-V-IV" and "IV-I-V" are not statistically significant.

Among the three instrument types in the problem, guitar sounds the least classical, piano sounds more classical than guitar, and string instrument sounds the most classical. All of the levels of **Instrument** are statistically significant.

Among the three voice leading types, "contrary" sounds the most classical, "par5th" sounds the second classical while "par3rd" sounds the least classical. All of the levels of **Voice** are statistically significant.

In order to consider the effect of each variable in the model, we fit partial models with one variable eliminated at each time, and compare them with the full model using variance analysis.

The following are the R outputs.

```
model_1a_HarmonyE = lm(Classical~Instrument+Voice, data=ratings)
anova(model_1a, model_1a_HarmonyE)
```

```
Model 1: Classical ~ Harmony + Instrument + Voice
Model 2: Classical ~ Instrument + Voice
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2488 13381 -3   -273.65 17.293 4.107e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model_1a_InstrumentE = lm(Classical~Harmony+Voice, data=ratings)
anova(model_1a, model_1a_InstrumentE)
```

```
Model 1: Classical ~ Harmony + Instrument + 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
```

```
model_1a_VoiceE = lm(Classical~Harmony+Instrument, data=ratings)
anova(model_1a, model_1a_VoiceE)
```

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```
Model 1: Classical ~ Harmony + Instrument + Voice
Model 2: Classical ~ Harmony + Instrument
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 13193 -2    -85.64 8.1181 0.0003061 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

According to partial F-tests, all of the explanatory variables **Instrument**, **Harmony** and **Voice** are statistically significant, which shows that **Instrument**, **Harmony** and **Voice** all have significant impact on the rating results of Classical music.

(b)

i.

The mathematical formula for this hierarchical model is the following:

$$
\begin{aligned}
Classical = \alpha_{0j} \\
&+ \alpha_{11} \cdot Harmony\_I - IV - V + \alpha_{12} \cdot Harmony\_I - V - IV \\
&+ \alpha_{13} \cdot Harmony\_I - V - VI + \alpha_{14} \cdot Harmony\_IV - I - V \\
&+ \alpha_{21} \cdot Voice\_contrary + \alpha_{22} \cdot Voice\_par3rd + \alpha_{23} \cdot Voice\_par5th \\
&+ \alpha_{31} \cdot Instrument\_guitar + \alpha_{32} \cdot Instrument\_piano \\
&+ \alpha_{33} \cdot Instrument\_string + \epsilon_i
\end{aligned}
$$

9

$\epsilon_i \sim N(0, \sigma^2)$

$$\alpha_{0j} = \eta_j$$

$\eta_j \sim N(0, \tau^2)$

ii.

The first method I use is to compare the AIC and BIC values of the model without random intercept of subjects and the model with it.

```
BIC(model_1a)
BIC(model_1b)
```

According to the R outputs, the model without the random intercept has AIC value 11230.45 and BIC value 11282.84, while the model with the random intercept has AIC value 10491.51 and BIC value 10549.73. Therefore, based on the BIC, the random effect is needed.

The second method is to use RLRsim package to test the random effect directly.

```
> exactRLRT(model_1b)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 763.38, p-value < 2.2e-16
```

9

The p-value of test is $< 2.2 * 10^{16}$, so we may conclude that the random effect is necessary.

iii.

The following is the summary of the model with the repeated-measures.

```
display(model_1b)
model_1b_HarmonyE = lmer(Classical ~ 1 + Instrument + Voice + (1|Subject), data=ratings)
model_1b_VoiceE = lmer(Classical ~ 1 + Instrument + Harmony + (1|Subject), data=ratings)
model_1b_InstrumentE = lmer(Classical ~ 1 + Voice + Harmony + (1|Subject), data=ratings)

anova(model_1b_HarmonyE, model_1b)
anova(model_1b_VoiceE, model_1b)
anova(model_1b_InstrumentE, model_1b)
```

```
lmer(formula = Classical ~ 1 + Instrument + Voice + Harmony +
    (1 | Subject), data = ratings)
                  coef.est coef.se
(Intercept)        4.34     0.19
Instrumentpiano    1.38     0.09
Instrumentstring   3.13     0.09
Voicepar3rd       -0.42     0.09
Voicepar5th       -0.37     0.09
HarmonyI-V-IV     -0.03     0.11
HarmonyI-V-VI      0.77     0.11
HarmonyIV-I-V      0.05     0.11

Error terms:
 Groups   Name        Std.Dev.
 Subject  (Intercept) 1.30
 Residual             1.89
---
number of obs: 2493, groups: Subject, 70
AIC = 10491.5, DIC = 10426.2
deviance = 10448.9
```

According to the display of the model, the coefficients of the fixed effects show the same relationships between the explanatory variables and the response rating. The random effect does not switch the fixed effects.

According to partial F-tests (anova tables), all of the explanatory variables **Instrument**, **Harmony** and **Voice** are statistically significant, which shows that **Instrument**, **Harmony** and **Voice** all have significant impact on the rating results of Classical music.

```
> anova(model_1b_HarmonyE, model_1b)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1b_HarmonyE: Classical ~ 1 + Instrument + Voice + (1 | Subject)
model_1b: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject)
                  Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model_1b_HarmonyE  7 10539 10580 -5262.4    10525
model_1b          10 10469 10527 -5224.4    10449 75.931      3  2.288e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(model_1b_VoiceE, model_1b)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1b_VoiceE: Classical ~ 1 + Instrument + Harmony + (1 | Subject)
model_1b: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject)
                Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
model_1b_VoiceE  8 10489 10536 -5236.6    10473
model_1b        10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(model_1b_InstrumentE, model_1b)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1b_InstrumentE: Classical ~ 1 + Voice + Harmony + (1 | Subject)
model_1b: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject)
                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model_1b_InstrumentE  8 11408 11455 -5696.2    11392
model_1b             10 10469 10527 -5224.4    10449 943.59      2  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

(c)

i.

We fit the model with all three random effect terms with the following R command and get the following outputs.

```
model_1c = lmer(Classical ~ 1 + Instrument + Voice + Harmony + (1|
    Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),
    data=ratings)
display(model_1c)
```

The AIC and BIC values of this model are 10075.5 and 10145.37 respectively. Therefore, based on AIC and BIC values, this model is better than models in both 1a and 1b.

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

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

ii.

According to the model display shown in part c-i, the interpretations of the fixed effects are still the same as the in the previous two models. The random effects do not switch the interpretations.

```
> anova(model_1c, model_1c_InstrumentE)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1c_InstrumentE: Classical ~ 1 + Voice + Harmony + (1 | Subject:Instrument) +
model_1c_InstrumentE:     (1 | Subject:Harmony) + (1 | Subject:Voice)
model_1c: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject:Instrument) +
model_1c:     (1 | Subject:Harmony) + (1 | Subject:Voice)
                     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model_1c_InstrumentE 10 10160 10219 -5070.2    10140
model_1c             12 10058 10127 -5016.8    10034 106.89      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

According to partial F-tests (anova tables), all of the explanatory variables **Instrument**, **Harmony** and **Voice** are also statistically significant, which shows that **Instrument**, **Harmony** and **Voice** all have significant impact on the rating results of Classical music.

iii.

The mathematical formula for this hierarchical model with three random effects is the following:

```
> anova(model_1c, model_1c_HarmonyE)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1c_HarmonyE: Classical ~ 1 + Voice + Instrument + (1 | Subject:Instrument) +
model_1c_HarmonyE:     (1 | Subject:Harmony) + (1 | Subject:Voice)
model_1c: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject:Instrument) +
model_1c:     (1 | Subject:Harmony) + (1 | Subject:Voice)
                  Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model_1c_HarmonyE  9 10090 10143 -5036.3    10072
model_1c          12 10058 10127 -5016.8    10034 39.013      3  1.724e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
> anova(model_1c, model_1c_VoiceE)
refitting model(s) with ML (instead of REML)
Data: ratings
Models:
model_1c_VoiceE: Classical ~ 1 + Harmony + Instrument + (1 | Subject:Instrument) +
model_1c_VoiceE:     (1 | Subject:Harmony) + (1 | Subject:Voice)
model_1c: Classical ~ 1 + Instrument + Voice + Harmony + (1 | Subject:Instrument) +
model_1c:     (1 | Subject:Harmony) + (1 | Subject:Voice)
                Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
model_1c_VoiceE 10 10081 10140 -5030.6    10061
model_1c        12 10058 10127 -5016.8    10034 27.753      2  9.409e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

$$
\begin{aligned}
Classical = \alpha_{1j} + \alpha_{2j} + \alpha_{3j} \\
&+ \alpha_{11} \cdot Harmony\_I-IV-V + \alpha_{12} \cdot Harmony\_I-V-IV \\
&+ \alpha_{13} \cdot Harmony\_I-V-VI + \alpha_{14} \cdot Harmony\_IV-I-V \\
&+ \alpha_{21} \cdot Voice\_contrary + \alpha_{22} \cdot Voice\_par3rd + \alpha_{23} \cdot Voice\_par5th \\
&+ \alpha_{31} \cdot Instrument\_guitar + \alpha_{32} \cdot Instrument\_piano \\
&+ \alpha_{33} \cdot Instrument\_string + \epsilon_i
\end{aligned}
$$

6

$\epsilon_i \sim N(0, \sigma^2)$

$$
\begin{aligned}
\alpha_{1j} &= \eta_{1j} \\
\alpha_{2j} &= \eta_{2j} \\
\alpha_{3j} &= \eta_{3j}
\end{aligned}
$$

you have the fixed effects correct, but there are actually random effects for each subject-by-level combination, for each of the three experimental factors. A simple way to represent this is to include both the subject index (j) and a level index for each experimental factor ir the corresponding random effect.

$\eta_{1j} \sim N(0, \tau_1^2)$, $\eta_{2j} \sim N(0, \tau_2^2)$, $\eta_{3j} \sim N(0, \tau_3^2)$.

Problem 2

Since the best model I derived in problem 1 is the model in part 1-c, I will begin with it.

(a)

After examining the dataset, I found that the indicator variables **CollegeMusic** and **APTheory** are treated as numeric, so I change them into factors.

good checking

All other variables with levels treated as numeric have ordered levels, so it is reasonable to keep them as numeric in the model. Since the variables **X1stInstr** and **X2ndInstr** contain NA's, we are going to change the NA's into 0's, but this change might not be reasonable.

what is the rationale for this recoding?

The model fitted with all the individual covariates is the following.

```
ratings$CollegeMusic = factor(ratings$CollegeMusic)
ratings$APTheory = factor(ratings$APTheory)
for (i in 1:length(ratings$X1stInstr)) {
  if (is.na(ratings$X1stInstr[i])) {
    ratings$X1stInstr[i] = 0
  }
}
for (i in 1:length(ratings$X2ndInstr)) {
  if (is.na(ratings$X2ndInstr[i])) {
    ratings$X2ndInstr[i] = 0
  }
}

model_2a = lmer(Classical ~ Harmony + Instrument + Voice +
    Popular + Selfdeclare + OMSI + X16.minus.17 + ConsInstr +
    ConsNotes + PachListen + ClsListen + KnowRob + KnowAxis +
    X1990s2000s + CollegeMusic + NoClass + APTheory + Composing +
    PianoPlay + GuitarPlay + X1stInstr + X2ndInstr + (1|Subject:
    Instrument) + (1|Subject:Harmony) + (1|Subject:Voice), data=
    ratings)
```

Then I use the "LMERConvenienceFunctions" package to choose the individual covariates that should be included in the model as fixed effects based on AIC criterion.

```
bfFixefLMER_F.fnc(model_2a, method=c("AIC"))
```

According to the output, the model fitted contains the fixed effects for **Harmony**, **Instrument**, **Voice**, **Popular**, **ConsNotes**, **PachListen**, **ClsListen**, **KnowRob**, **KnowAxis**, **X1990s2000s**, **NoClass**, **APTheory**, **PianoPlay** and **X2ndInstr**.

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Harmony + Instrument + Voice + Popular + ConsNotes +
    PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
    NoClass + APTheory + PianoPlay + X2ndInstr + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice)
   Data: ratings
REML criterion at convergence: 5570.267
Random effects:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 5.233e-01
 Subject:Voice      (Intercept) 1.298e-07
 Subject:Instrument (Intercept) 1.015e+00
 Residual                       1.280e+00
Number of obs: 1541, groups:  Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
Fixed Effects:
     (Intercept)      HarmonyI-V-IV      HarmonyI-V-VI      HarmonyIV-I-V    Instrumentpiano  Instrumentstring
         6.27076            0.01116            0.70268           -0.08397            0.99357           1.85868
     Voicepar3rd        Voicepar5th            Popular          ConsNotes         PachListen         ClsListen
        -0.29312           -0.16584           -0.57194           -0.12293            0.05123           0.23124
         KnowRob           KnowAxis        X1990s2000s            NoClass          APTheory1         PianoPlay
         0.15572            0.11937            0.15290           -0.09295            0.65561           0.19044
       X2ndInstr
        -0.42710
```

8 We use the following code to fit the current model.

```
model_final = lmer(Classical ~ Harmony + Instrument + Voice +
    Popular + ConsNotes +  PachListen + ClsListen + KnowRob +
    KnowAxis + X1990s2000s +
NoClass + APTheory + PianoPlay + X2ndInstr + (1 | Subject:
    Instrument) +
(1 | Subject:Harmony) + (1 | Subject:Voice), data=ratings)
```

Since the AIC value of the current model is 5616.3, and that of the full model is 5650.58, we have evidence that the current model is better.

(b)

In order to check the validity of the random effects, we compare the AIC and BIC values between the current model and the model with one random effect eliminated from the current model at each time.

The current model with all the random effects has AIC and BIC values 5616.3 and 5739.091. The model without random effect $(1|Subject : Instrument)$ compared to the final model has AIC and BIC values 5850.707 and 5968.191.
9 The model without random effect $(1|Subject : Harmony)$ has AIC and BIC values 5669.546 and 5787.03. The model without random effect $(1|Subject : Voice)$ has AIC and BIC values 5614.267 and 5731.751.

Since the AIC and BIC values for the model without random effect $(1|Subject : Voice)$ compared to the final model has lower AIC and BIC values than the previous final model, we suspect that the random term is not statistically significant and will drop it from now on.

The following code is used to test the random effects.

```
model_final_I = lmer(Classical ~ Harmony + Instrument + Voice +
    Popular + ConsNotes +  PachListen + ClsListen + KnowRob +
    KnowAxis + X1990s2000s +  NoClass + APTheory + PianoPlay +
    X2ndInstr +  (1 | Subject:Harmony) + (1 | Subject:Voice), data=
    ratings)
model_final_H = lmer(Classical ~ Harmony + Instrument + Voice +
    Popular + ConsNotes +  PachListen + ClsListen + KnowRob +
    KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
    X2ndInstr + (1 | Subject:Instrument) +  (1 | Subject:Voice),
    data=ratings)
model_final_V = lmer(Classical ~ Harmony + Instrument + Voice +
    Popular + ConsNotes + PachListen + ClsListen + KnowRob +
    KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
    X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony),
    data=ratings)

AIC(model_final_I)
BIC(model_final_I)
AIC(model_final_H)
BIC(model_final_H)
AIC(model_final_V)
BIC(model_final_V)
```

Therefore, the final model chosen is the current model without the random effect $(1|Subject : Voice)$.

(c)

The following is the display of the final model.

```
                coef.est coef.se
(Intercept)      6.27     0.80
HarmonyI-V-IV    0.01     0.15
HarmonyI-V-VI    0.70     0.15
HarmonyIV-I-V   -0.08     0.15
Instrumentpiano  0.99     0.23
Instrumentstring 1.86     0.24
Voicepar3rd     -0.29     0.08
Voicepar5th     -0.17     0.08
Popular         -0.57     0.02
ConsNotes       -0.12     0.06
PachListen       0.05     0.14
ClsListen        0.23     0.07
KnowRob          0.16     0.07
KnowAxis         0.12     0.05
X1990s2000s      0.15     0.08
NoClass         -0.09     0.08
APTheory1        0.66     0.28
PianoPlay        0.19     0.07
X2ndInstr       -0.43     0.16

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.52
 Subject:Instrument (Intercept) 1.01
 Residual                       1.28
---
number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
AIC = 5614.3, DIC = 5458.9
deviance = 5514.6
```

According to the output, the Harmonic type "I-V-VI" has highest ratings in **Classical**, "I-V-IV" the second, "I-IV-V" the third and "IV-I-V" the fourth.

The instrument guitar has the lowest rating as classical music, piano the second, and string the most classical.

The voice type "contrary" is considered the most classical, "par5th" the second, and "par3rd" the least classical.

9m

The more popular the stimulus sounds, the more the subject concentrates on the notes while listening to the piece, the fewer music classes the subject has taken, the better the subject plays a second instrument, the lower it will be rated as classical music.

The more familiar the subject is familiar with Pachelbel's Canon, the more the subject listens to classical music, the more the subject knows about Rob Pravonian's Pachelbel Rant, the more the subject knows about Axis of Evil's Comedy bit on the four Pachelbel chords in popular music, the more the subject listens to pop and rock from the 90's and 2000's, the better the subject plays piano, the higher the subject is going to rate the piece as classical music.

Also, subjects who have taken AP Music Theory class in High School would give higher rates than those who have not.

Problem 3

The variable **Selfdeclare** is currently a numeric variable with five discrete values that are ordered. Therefore, we should factorize it when including it in the model.

The following is the table of **Selfdeclare**.

```
> table(ratings$Selfdeclare)

  1   2   3   4   5   6
576 936 468 432  72  36
```

According to the table, the distribution of **Selfdeclare** is very right skewed. We could dichotomize **Selfdeclare** into musician if **Selfdeclare** > 2 and not-musician if **Selfdeclare** $<= 2$. Therefore, there are 1512 non-musicians, and 1008 musicians.

there are not that many participants in the data set so you must mean something else

The following code creates the variable **musician** with two levels 0 and 1 with the above criterion.

```
ratings$musician = rep(0, length(ratings$Selfdeclare))
ratings$musician[which(ratings$Selfdeclare >=2)] = 1
ratings$musician = factor(ratings$musician)
```

We first consider all the interactions terms between **musician** and other predictors in the previous final model and then apply the "LMERConvenienceFunctions" package to choose the individual covariates that should be included in the model as fixed effects based on AIC criterion.

```r
model_final_V_inter = lmer(Classical ~ Harmony + Instrument + Voice
    + Popular + ConsNotes + PachListen + ClsListen + KnowRob +
    KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
    X2ndInstr + musician + (1 | Subject:Instrument) + (1 | Subject:
    Harmony) + Harmony:musician + Instrument:musician + Voice:
    musician + Popular:musician + ConsNotes:musician + PachListen:
    musician + ClsListen:musician + KnowRob:musician + KnowAxis:
    musician + X1990s2000s:musician +  NoClass:musician + APTheory:
    musician + PianoPlay:musician + X2ndInstr:musician, data=
    ratings)
bfFixefLMER_F.fnc(model_final_V_inter, method=c("AIC"))
```

The following is the output of the model selected.

```
Formula: Classical ~ Harmony + Instrument + Voice + Popular + ConsNotes +
    PachListen + ClsListen + KnowAxis + X1990s2000s + NoClass +
    musician + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
    Popular:musician + ConsNotes:musician + musician:KnowRob +      musician:APTheory + musician:X2ndInstr
   Data: ratings
REML criterion at convergence: 5548.525
Random effects:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.5155
 Subject:Instrument (Intercept) 0.9541
 Residual                       1.2766
Number of obs: 1541, groups:  Subject:Harmony, 172; Subject:Instrument, 129
Fixed Effects:
       (Intercept)         HarmonyI-V-IV          HarmonyI-V-VI          HarmonyIV-I-V      Instrumentpiano
          6.638337              0.008166               0.711679              -0.074824             0.993648
   Instrumentstring           Voicepar3rd            Voicepar5th                Popular            ConsNotes
          1.845951             -0.286847              -0.160753              -0.750177             1.179618
        PachListen             ClsListen               KnowAxis            X1990s2000s              NoClass
          0.041993              0.295839               0.140921               0.113178            -0.074443
         musician1      Popular:musician1    ConsNotes:musician1      musician1:KnowRob   musician1:APTheory1
         -0.267301              0.189333              -1.302094               0.158992             0.935713
musician1:X2ndInstr
         -0.530436
```

8

why?

Therefore, there are four four important interaction terms selected $ConsNotes : musician$, $musician : KnowRob$, $musician : APTheory$ and $musician : X2ndInstr$. The AIC and BIC values of the model selected are 5596.525 and 5724.69, while those for the previous final model are 5614.267 and 5731.751. Therefore, we have evidence that the interaction terms are effective in the model.

The interaction terms show that for musicians, the effect of how much they concentrate on music notes while listening is reversed from that for non-musicians, i.e., the more the focus, the less the classical rating is supposed to be; being familiar with Rob Paravonian's Pachelbel Rant would increase their popular rating; the positive effect on classical rating of taking AP Theory course is only valid for musicians; the negative effect on classical rating of being good at a second instrument is only valid for musicians.

Problem 4

(a)

We first fit the model with all the predictors in the dataset and random intercepts $(1|Subject : Instrument)$, $(1|Subject : Harmony)$ and $(1|Subject :$

$Voice$). Then we use the "LMERConvenienceFunctions" package to choose the individual covariates that should be included in the model as fixed effects based on AIC criterion.

```
model_41 = lmer(Popular ~ Harmony + Instrument + Voice +
    Selfdeclare +
                    OMSI + X16.minus.17 + ConsInstr + ConsNotes +
                        PachListen +
                    ClsListen + KnowRob + KnowAxis + X1990s2000s +
                        CollegeMusic + NoClass +
                    APTheory + Composing + PianoPlay + GuitarPlay +
                    X1stInstr + X2ndInstr + (1|Subject:Instrument) +
                    (1|Subject:Harmony) + (1|Subject:Voice), data=
                        ratings)
bfFixefLMER_F.fnc(model_41, method=c("AIC"))
```

```
Formula: Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
    X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice)
   Data: ratings
REML criterion at convergence: 6342.393
Random effects:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.6728
 Subject:Voice      (Intercept) 0.2501
 Subject:Instrument (Intercept) 1.3365
 Residual                       1.6422
Number of obs: 1541, groups:  Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
Fixed Effects:
     (Intercept)  Instrumentpiano  Instrumentstring          ConsNotes        PachListen           KnowRob
         7.49926         -1.14827          -3.02445            0.09936          -0.25424           0.07241
       KnowAxis       X1990s2000s           NoClass          APTheory1
         0.07219          0.01391           0.09633           -0.03344
```

We then evaluate the random effects in the model by fitting models without one random effect at each time and compare the AIC and BIC values.

The AIC and BIC values for model with all the random effects are 6370.393 and 6445.155. Those for the model without random effect $(1|Subject : Instrument)$ are 6616.554 and 6685.976. Those for the model without random effect $(1|Subject : Harmony)$ are 6423.6 and 6493.023. Those for the model without random effect
9 $(1|Subject : Voice)$ are 6370.727 and 6440.15.

Based on the AIC and BIC values, the random effects $(1|Subject : Harmony)$ and $(1|Subject : Voice)$ are not statistically significant, and will be eliminated from the model.

Therefore, the display of our final model is the following:

Based on this model, **Harmony** type "I-V-IV" is expected to have the highest popular ratings, "I-IV-V" the second, and types "I-V-VI" and "IV-I-V" are about the same low.

Instrument type guitar is expected to have the highest popular ratings, piano the second, and string the least popular.

Voice type "par5th" has the highest popular ratings, "par3rd" the second, and "contrary" the least popular.

```
lmer(formula = Popular ~ Instrument + Harmony + Voice + ConsNotes +
    PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + (1 | Subject:Instrument), data = ratings)
                 coef.est coef.se
(Intercept)       7.48     1.00
Instrumentpiano  -1.15     0.33
Instrumentstring -3.02     0.33
HarmonyI-V-IV     0.02     0.13
HarmonyI-V-VI    -0.25     0.13
HarmonyIV-I-V    -0.25     0.13
Voicepar3rd       0.20     0.11
Voicepar5th       0.23     0.11
ConsNotes         0.10     0.08
PachListen       -0.25     0.18
KnowRob           0.07     0.09
KnowAxis          0.07     0.07
X1990s2000s       0.01     0.09
NoClass           0.10     0.11
APTheory1        -0.03     0.36

Error terms:
 Groups             Name        Std.Dev.
 Subject:Instrument (Intercept) 1.46
 Residual                       1.75
---
number of obs: 1541, groups: Subject:Instrument, 129
AIC = 6431.6, DIC = 6328.7
deviance = 6363.2
```

(b)

Based on the model in part 4-a, the more the subject concentrates on the music notes while listening, the more the subject is familiar with Rob Paravonian's Pachelbel Rant, the more the subject is familiar with Axis of Evil's Comedy
9 bit on the four Pachelbel chords in popular music, the more the subject listens to pop an drock from 90's and 2000's and the more music classes taken by the subject, the higher the subject is going to rate the music piece as popular.

However, the more the subject is familiar with Pachelbel's Canon, the lower the subject is going to rate the music piece as popular.

Also, subjects who have taken AP Music Theory class in High School are expected to rate the music lower as popular than those who have not.

(c)

We first consider all the interactions terms between **musician** and other predictors in the previous final model and then apply the "LMERConvenienceFunctions" package to choose the individual covariates that should be included in the model as fixed effects based on AIC criterion.

The final model selected is the following.

Four interaction terms are selected into the model. Since the predictors **Voice** and **Harmony** should remain in the model, our final model will be the previous model plus the two predictors.

```
model_45 = lmer(Popular ~ Instrument + Harmony + Voice + ConsNotes
    + PachListen +
```

```
Formula: Popular ~ Instrument + ConsNotes + PachListen + KnowAxis + X1990s2000s +
    NoClass + (1 | Subject:Instrument) + PachListen:musician +
    musician:KnowRob + X1990s2000s:musician + musician:APTheory
   Data: ratings
REML criterion at convergence: 6389.106
Random effects:
 Groups             Name        Std.Dev.
 Subject:Instrument (Intercept) 1.402
 Residual                       1.751
Number of obs: 1541, groups:  Subject:Instrument, 129
Fixed Effects:
          (Intercept)       Instrumentpiano      Instrumentstring            ConsNotes
              8.39370              -1.14760              -3.02456              0.05326
           PachListen              KnowAxis           X1990s2000s              NoClass
             -3.46985               0.03505               3.17177              0.06359
 PachListen:musician1     musician1:KnowRob  X1990s2000s:musician1   musician1:APTheory1
              3.10801               0.09841              -3.20527              0.02296
```

9

```
                    KnowAxis + X1990s2000s +  NoClass + (1 | Subject:
                        Instrument) +
                    PachListen:musician +  musician:KnowRob +
                        X1990s2000s:musician +
                    musician:APTheory, data=ratings)
```

The AIC and BIC values for the model with the interaction terms are 6426.351 and 6527.815, while those for the previous final model are 6430.964 and 6580.489 respectively. Therefore, we have evidence that the interaction terms are interactive.

The interaction terms show that for musicians, the effect of familiarity with Pachelbel's Canon on the popular rating is much smaller than for non-musicians; being familiar with Rob Paravonian's Pachelbel Rant would increase their popular rating; the effect of listening to pop and rock from 90's and 2000's is reversed from that for non-musicians, namely, the more they listen to those music, the lower the popular rating they will give; the effect of having taken AP Theory course in High School is stronger on the popular rating.

Problem 5

Introduction

Music researches are interested in the factors that would influence how listeners would consider a music piece classical or popular. The main factors considered are the Harmonic Motion, the instrument and the voice leading type in the music piece. The result of the study shows that the type of music instrument has a very large impact of the rating of the music. String instruments are considered very classical, and guitar are considered very popular. Voice leading type also has small impact on the music ratings. However, Harmonic Motion does not seem to have a strong impact on the music ratings.

Methods

The methods used in examining the factors of music ratings are two hierarchical models where either the popular rating or classical rating is the response, and some other selected factors are predictors. The hierarchical models take into account the bias from the fact that some subject might rate all music pieces unusually high or low. They also consider the differences in rating behaviors between musicians and non-musicians.

For each potential factor, if its interpretations in the two models agree, it should be an influential factor to the music ratings. Otherwise, the potential factor might not be significant in explaining the music ratings.

Results

Based on the model fitted, we found that the type of music instrument has a
10 very large impact of the rating of the music. String instruments are considered very classical, and guitar are considered very popular.

However, the effects of Harmonic Motion do not agree in the two hierarchical models, which indicates that Harmonic Motion might not be an influential factor on the music ratings.

Even though the influence of voice leading type turns out small in the two hierarchical models, since the interpretations of voice leading type agree in the two models, we think that voice leading type does have significant impact on the music ratings. Specifically, the types par3rd and par5th are considered more classical than the contrary type.

Some other factors that might influence the music rating include the amount of pop and rock music from the 90's and 2000's the subjects listen, the number of music classes the subjects have taken and how much the subjects concentrate on music notes while listening to the piece.

It is also interesting that the fact of a subject being a musician would change and even switch the relationship between some factors and the subject's rating of the music. For instance, the effect of listening to pop and rock from 90's and

2000's on the music rating is the opposite for musicians and non-musicians. For musicians, the more they listen to those music, the lower the popular rating they will give, and vice versa.