Hierarchical Linear Models HW 05_Sijia Wang

Import data as follows. Note that all the NA's were set as 0. Also, as the 'Subject` was not numbered correctly, we create a variable named 'subid' for the 70 listeners.

```
> library(lme4)
> music = read.table("ratings.csv", header = TRUE, sep = ",")
> music[is.na(music)] = 0
> attach(music)
> j = 1
> for (i in unique(Subject)){
+   music$subid[Subject == i] = j
+   j = j +1}
> attach(music)
```

1. The three main experimental factors

(a) Conventional linear models

```
> m1 = lm(Classical ~ Harmony + Instrument + Voice - 1)
> m2 = lm(Classical ~ Harmony + Instrument - 1)
> m3 = lm(Classical ~ Harmony + Voice - 1)
> m4 = lm(Classical ~ Instrument + Voice -1)
```

```
> anova(m1, m2)
Analysis of Variance Table

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

```
> anova(m1, m3)
Analysis of Variance Table

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

```
> anova(m1, m4)
Analysis of Variance Table

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

In comparing m1 and m2, the ANOVA test gives p-value < 0.05, which indicates that involving Voice significantly improves the goodness-of-fit. Similarly, the full model is significantly better than reduced models without Harmony or Instrument.

```
> summary(m1)

Call:
lm(formula = Classical ~ Harmony + Instrument + Voice - 1)
```

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

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
HarmonyI-IV-V      4.3402     0.1299   33.42  < 2e-16 ***
HarmonyI-V-IV      4.3091     0.1302   33.10  < 2e-16 ***
HarmonyI-V-VI      5.1092     0.1301   39.27  < 2e-16 ***
HarmonyIV-I-V      4.3902     0.1299   33.78  < 2e-16 ***
Instrumentpiano    1.3736     0.1130   12.16  < 2e-16 ***
Instrumentstring   3.1331     0.1123   27.90  < 2e-16 ***
Voicepar3rd       -0.4125     0.1127   -3.66 0.000258 ***
Voicepar5th       -0.3706     0.1126   -3.29 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:  0.8702,	Adjusted R-squared:  0.8698 
F-statistic:  2082 on 8 and 2485 DF,  p-value: < 2.2e-16
```

According to the full model, the fixed effects estimates of all levels of Harmony, Instrument or Voice have p-value < 0.05. The coefficients are interpreted as change in classical ratings when unit change happed to the corresponding category, holding other variables the same.

(b) Repeated measures model

(i) Mathematical expression

$$\begin{aligned} y_i &= \alpha_{0j[i]} + \alpha_{Instrument,3levels} + \alpha_{Harmony,4levels} + \alpha_{Voice,3leves} + \epsilon_i, \quad \epsilon_i \overset{i.i.d}{\sim} N(0,\sigma^2) \\ \alpha_{0j} &= \beta_0 + \eta_j, \quad \eta_j \overset{i.i.d}{\sim} N(0,\tau^2) \end{aligned}$$

Where the first term is the random effect, and the next three terms are the fixed effect of Instrument, Harmony, and Voice, respectively.

(ii) Test of random effect

```
> m5.2 = lmer(Classical ~ Instrument + Harmony + Voice + (1 | subid))
> AIC(m5.2)
[1] 10491.51
> BIC(m5.2)
[1] 10549.73
> AIC(m1)
[1] 11230.45
> BIC(m1)
[1] 11282.84
```

A repeated-measures model was built and compared with conventional linear model from 1 (a) in term of AIC and BIC. As the AICs and BICs of the repeated model are smaller than those of the conventional model, we conclude that a random intercept is necessary.

```
> exactRLRT(m5.2)

        simulated finite sample distribution of RLRT.
```

```
        (p-value based on 10000 simulated values)

data:
RLRT = 763.3759, p-value < 2.2e-16
```
The likelihood ratio also suggests that the random effect is necessary.

(iii) Examine three main effects with repeated - measures model

```
> m6 = lmer(Classical ~ Harmony + Instrument + (1|subid))
> m7 = lmer(Classical ~ Voice + Harmony + (1|subid))
> m8 = lmer(Classical ~ Instrument + Voice + (1|subid))

> anova(m5.2, m6)
Data:
Models:
m6: Classical ~ Harmony + Instrument + (1 | subid)
m5.2: Classical ~ Instrument + Harmony + Voice + (1 | subid)
     Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
m6    8 10489 10536 -5236.6    10473
m5.2 10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***

> anova(m5.2, m7)
Data:
Models:
m7: Classical ~ Voice + Harmony + (1 | subid)
m5.2: Classical ~ Instrument + Harmony + Voice + (1 | subid)
     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m7    8 11408 11455 -5696.2    11392
m5.2 10 10469 10527 -5224.4    10449 943.59      2  < 2.2e-16 ***

> anova(m5.2, m8)
Data:
Models:
m8: Classical ~ Instrument + Voice + (1 | subid)
m5.2: Classical ~ Instrument + Harmony + Voice + (1 | subid)
     Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m8    7 10539 10580 -5262.4    10525
m5.2 10 10469 10527 -5224.4    10449 75.931      3  2.288e-16 ***
```

By comparing the AIC and BIC's, or investigating on the p-values from ANOVA tests, we conclude that involving Voice significantly improves the goodness-of-fit of the model. Similarly, the repeated-measures full model is significantly better than reduced models without Harmony or Instrument.

(c) varied personal bias vary with instrument, voice and harmony

(i) model with all the three new random effects

```
> m9 = lmer(Classical ~ Instrument + Harmony + Voice + (1|subid : Instrument)
+ (1|subid : Harmony) + (1| subid : Voice))
> AIC(m9)
[1] 10075.51
> BIC(m9)
[1] 10145.37
```
The smaller AIC and BIC indicates that the model with three new random effects are better than the conventional linear model and the repeated-measure model.

(ii) Test of the new random effect

```
> m10 = lmer(Classical ~ Harmony + Voice + (1|subid : Instrument) + (1|subid :
Harmony) + (1| subid : Voice))
> m11 = lmer(Classical ~ Instrument + Voice + (1|subid : Instrument) +
(1|subid : Harmony) + (1| subid : Voice))
> m12 = lmer(Classical ~ Instrument + Harmony + (1|subid : Instrument) +
(1|subid : Harmony) + (1| subid : Voice))

> anova(m9, m10)
Data:
Models:
m10: Classical ~ Harmony + Voice + (1 | subid:Instrument) + (1 |
subid:Harmony) +
m10:     (1 | subid:Voice)
m9: Classical ~ Instrument + Harmony + Voice + (1 | subid:Instrument) +
m9:     (1 | subid:Harmony) + (1 | subid:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m10 10 10160 10219 -5070.2    10140
m9  12 10058 10127 -5016.8    10034 106.89      2  < 2.2e-16 ***

> anova(m9, m11)
Data:
Models:
m11: Classical ~ Instrument + Voice + (1 | subid:Instrument) + (1 |
m11:     subid:Harmony) + (1 | subid:Voice)
m9: Classical ~ Instrument + Harmony + Voice + (1 | subid:Instrument) +
m9:     (1 | subid:Harmony) + (1 | subid:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m11  9 10090 10143 -5036.3    10072
m9  12 10058 10127 -5016.8    10034 39.013      3  1.724e-08 ***

> anova(m9, m12)
Data:
Models:
m12: Classical ~ Instrument + Harmony + (1 | subid:Instrument) + (1 |
m12:     subid:Harmony) + (1 | subid:Voice)
m9: Classical ~ Instrument + Harmony + Voice + (1 | subid:Instrument) +
m9:     (1 | subid:Harmony) + (1 | subid:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m12 10 10081 10140 -5030.6    10061
m9  12 10058 10127 -5016.8    10034 27.753      2  9.409e-07 ***
```

By comparing the AIC and BIC, or investigating on the p-values from ANOVA tests, we conclude that involving Voice significantly improves the goodness-of-fit of the model. Similarly, the full model with new random effects is significantly better than reduced models without Harmony or Instrument.

```
> summary(m9)
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (1 | subid:Instrument) +
(1 | subid:Harmony) + (1 | subid:Voice)

REML criterion at convergence: 10051.51

Random effects:
 Groups           Name        Variance Std.Dev.
 subid:Harmony    (Intercept) 0.44307  0.6656
 subid:Voice      (Intercept) 0.02809  0.1676
 subid:Instrument (Intercept) 2.19850  1.4827
 Residual                     2.43753  1.5613
Number of obs: 2493, groups: subid:Harmony, 280; subid:Voice, 210;
subid:Instrument, 210
```

The variance of subid: Instrument is the largest, and that of subid : Voice is the smallest. This indicates that people highly vary in the degrees to which they would identify music played by specific instruments as “classical”. There are small variations in the degrees to which people are inclined to identify music with specific leading voice as “classical.” Note that the variance of residual is also large, indicating the “personal bias” in general is large.

(iii) Mathematical expression

$$
\begin{aligned}
y_i &= \alpha_{1j[i]} + \alpha_{1k[i]} + \alpha_{1l[i]} + \epsilon_i, \quad \epsilon_i \overset{i.i.d}{\sim} N(0, \sigma^2) \\
\alpha_{1j} &= \beta_{1p} + \eta_{1j[i]}, \quad \eta_{1j[i]} \overset{i.i.d}{\sim} N(0, \tau_1^2) \\
\alpha_{2j} &= \beta_{2q} + \eta_{2k[i]}, \quad \eta_{2k[i]} \overset{i.i.d}{\sim} N(0, \tau_2^2) \\
\alpha_{3j} &= \beta_{3r} + \eta_{3l[i]}, \quad \eta_{3l[i]} \overset{i.i.d}{\sim} N(0, \tau_3^2)
\end{aligned}
$$

2. Individual covariates

(a) check fixed effect

```
> m13 = lmer(Classical ~ Harmony + Voice + Instrument + factor(Selfdeclare) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m13) # Selfdeclare is not significant

> m14 = lmer(Classical ~ Harmony + Voice + Instrument + OMSI + (1|subid :
Instrument) + (1|subid : Harmony) + (1| subid : Voice), data = music)
> anova(m9, m14) # OMSI is not significant

> m15 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m15) # x16.minus.17 is not significant

> m16 = lmer(Classical ~ Harmony + Voice + Instrument + factor(PachListen) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m16) # Selfdeclare is not significant

> m16 = lmer(Classical ~ Harmony + Voice + Instrument + factor(ConsInstr) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m16) # ConsInstr is not significant

> m17 = lmer(Classical ~ Harmony + Voice + Instrument + factor(ConsNotes) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m17) # ConsNotes is not significant

> m18 = lmer(Classical ~ Harmony + Voice + Instrument +
factor(Instr.minus.Notes) + (1|subid : Instrument) + (1|subid : Harmony) +
(1| subid : Voice))
> anova(m9, m18) # Selfdeclare is not significant

> m19 = lmer(Classical ~ Harmony + Voice + Instrument + factor(PachListen) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m19) # Selfdeclare is not significant

> m15 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m15) # X16.minus.17 is significant

> m20 = lmer(Classical ~ Harmony + Voice + Instrument + factor(ClsListen) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
```

```
> anova(m9, m20) # Selfdeclare is not significant
> m21 = lmer(Classical ~ Harmony + Voice + Instrument + factor(KnowRob) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m21) # Selfdeclare is not significant

> m22 = lmer(Classical ~ Harmony + Voice + Instrument + factor(KnowAxis) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m22) # Selfdeclare is not significant

> m23 = lmer(Classical ~ Harmony + Voice + Instrument + factor(X1990s2000s) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m23) # Selfdeclare is not significant

> m24 = lmer(Classical ~ Harmony + Voice + Instrument +
factor(X1990s2000s.minus.1960s1970s) + (1|subid : Instrument) + (1|subid :
Harmony) + (1| subid : Voice))
> anova(m9, m24) # Selfdeclare is not significant

> m25 = lmer(Classical ~ Harmony + Voice + Instrument + factor(GuitarPlay) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m25) # Selfdeclare is not significant

> m25 = lmer(Classical ~ Harmony + Voice + Instrument + factor(CollegeMusic)
+ (1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m25) # Selfdeclare is not significant

> m26 = lmer(Classical ~ Harmony + Voice + Instrument + NoClass + (1|subid :
Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m26) # Selfdeclare is not significant

> m27 = lmer(Classical ~ Harmony + Voice + Instrument + factor(APTheory) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m27) # Selfdeclare is not significant

> m28 = lmer(Classical ~ Harmony + Voice + Instrument + factor(Composing) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m28) # Selfdeclare is not significant

> m29 = lmer(Classical ~ Harmony + Voice + Instrument + factor(PianoPlay) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m29) # Selfdeclare is not significant

> m31 = lmer(Classical ~ Harmony + Voice + Instrument + factor(X1stInstr) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m31) # Selfdeclare is not significant

> m32 = lmer(Classical ~ Harmony + Voice + Instrument + factor(X2ndInstr) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m32) # X is not significant

> m33 = lmer(Classical ~ Harmony + Voice + Instrument + factor(first12) +
(1|subid : Instrument) + (1|subid : Harmony) + (1| subid : Voice))
> anova(m9, m33) # Selfdeclare is not significant
```

Two variables, X16.minus.17 and GuitarPlay, were added to the model with new random effects, which is the best one selected from problem 1. The final model is therefore:

```
> m34 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Instrument) + (1|subid : Harmony) + (1|
subid : Voice))
```

(b) check random effect

```
> m35 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Instrument) + (1|subid : Harmony))
> m36 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Instrument) + (1| subid : Voice))
> m37 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Voice))

> anova(m34, m35)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m34 17 10277 10376 -5121.5    10243 0.0999      1     0.7519

> anova(m34, m36)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m36 16 10359 10452 -5163.6    10327
m34 17 10277 10376 -5121.5    10243 84.149      1  < 2.2e-16 ***

> anova(m34, m37)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m37 16 10866 10959 -5416.7    10834
m34 17 10277 10376 -5121.5    10243 590.47      1  < 2.2e-16 ***
```

Therefore, the random effects of subid:Instrument (p-value < 0.05) and subid: Harmony (p-value < 0.05) are highly significant and were kept in the model. The random effect subid:Voice has p-value = 0.75 and was therefore dropped from the model.

(c)

```
> m35 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Instrument) + (1|subid : Harmony))
```

In the final model, we have fixed effects Harmony, Voice, Instrument, X16.minus.17, and GuitarPlay; as well as random effects subid:Instrument and subid:Harmony. The coefficients of fixed effects are displayed with command `fixef(m35)` and were interpreted as the increase in classical rating with unit increase of the quantitative variable, or the difference in classical rating in different categories.

3. Musician vs. Non-Musician

```
> summary((Selfdeclare == 1) | (Selfdeclare == 2))
   Mode   FALSE    TRUE    NA's
logical    1008    1512       0
```

We therefore categorize the 1008 listeners with Selfdeclare of 1 or 2 as “Nonmusician”, or “Musician = 0”; and the rest of people with higher scores as “Musician = 1”.

```
> m38 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician)
> m39 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician
+ Musician:Harmony)
> m40 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician
+ Musician:Voice)
> m41 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician
+ Musician:Instrument)
```

```
> m42 = lmer(Popular ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician:
X16.minus.17)

> anova(m35, m38)
    Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m38 17 10277 10376 -5121.5    10243 0.091      1     0.7629
> anova(m35, m39)
    Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m39 20 10257 10374 -5108.4    10217 26.23      4  2.844e-05 ***
> anova(m35, m40)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m40 19 10281 10391 -5121.3    10243 0.5164      3     0.9153
> anova(m35, m41)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m41 19 10278 10389 -5119.9    10240 3.2982      3     0.3479
> anova(m35, m42)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m35 16 10275 10368 -5121.6    10243
m42 17 10270 10369 -5118.0    10236 7.0289      1    0.00802 **
```

We therefore include the main effect of musician, as well as its interaction with X16.minus .17 and Harmony, into the model. This result shows that musicians are more proven to be influenced by the harmony motion of music, compared with those who do not consider themselves as musicians. The final model is therefore:

```
> m44 = lmer(Classical ~ Harmony + Voice + Instrument + X16.minus.17 +
factor(GuitarPlay) + (1|subid : Harmony) + (1| subid : Instrument) + Musician:
X16.minus.17 + Musician:Harmony)
```

4. Classical vs. Popular

(a) effects of Instrument, Harmony and Voice on popular ratings

```
> m45 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1|subid : Harmony) + (1| subid : Voice))
> m45.2 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid))
> m45.3 = lm(Popular ~ Instrument + Harmony + Voice)
> m46 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1|subid : Harmony))
> m47 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid : Instrument)
+ (1| subid : Voice))
> m48 = lmer(Popular ~ Instrument + Harmony + Voice +(1|subid : Harmony) +
(1| subid : Voice))
> AIC(m45, m45.2, m45.3, m46, m47, m48)
      df      AIC
m45   12 10347.47
m45.2 10 10723.52
m45.3  9 11412.30
m46   11 10346.92
m47   11 10419.14
m48   11 10898.07
> BIC(m45, m45.2, m45.3, m46, m47, m48)
      df      BIC
m45   12 10417.46
```

```
m45.2 10 10781.84
m45.3  9 11464.79
m46   11 10411.07
m47   11 10483.29
m48   11 10962.22
> anova(m45, m46)
m46 11 10329 10393 -5153.3    10307
m45 12 10330 10400 -5152.7    10306 1.1986      1     0.2736
> anova(m45, m47)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m47 11 10399 10463 -5188.6    10377
m45 12 10330 10400 -5152.7    10306 71.741      1  < 2.2e-16 ***
> anova(m45, m48)
    Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
m48 11 10894 10959 -5436.2    10872
m45 12 10330 10400 -5152.7    10306 566.9      1  < 2.2e-16 ***
```

The AIC's and BIC's of the model with new random effect is smaller than the conventional linear model and the repeated measures model. Taking the model with the new random effect, we found the subid:Harmony and subid:Instrument are significant, but subid:Voice was not.

```
> summary(m46)
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Instrument + Harmony + Voice + (1 | subid:Instrument) +
(1 | subid:Harmony)

REML criterion at convergence: 10324.92

Random effects:
 Groups           Name        Variance Std.Dev.
 subid:Harmony    (Intercept) 0.3749   0.6123
 subid:Instrument (Intercept) 2.2415   1.4972
 Residual                     2.6753   1.6356
```

The variance of subid: Instrument is the larger than that of subid : Harmony. This indicates that people highly vary in the degrees to which they would identify music played by specific instruments as "popular". There are small variations in the degrees to which people are inclined to identify music with specific harmony process as "popular". Note that the variance of residual is also large, indicating the "personal bias" in general is large.

(b) question 2 c, for popular ratings

Use similar process as in 2c, we investigated the influence of each of the variables and find out the Selfdeclare, OMSI, KnowRob, KnowAxis, and X1990s2000s.minus.19601970s are significant and therefore should be added to the model.

```
> m49 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1|subid : Harmony) + (1| subid : Voice) + Selfdeclare + OMSI +
KnowRob + KnowAxis + X1990s2000s.minus.1960s1970s)
> m50 = lmer(Popular ~ Instrument + Harmony + Voice +(1|subid : Harmony) +
(1| subid : Voice) + Selfdeclare + OMSI + KnowRob + KnowAxis +
X1990s2000s.minus.1960s1970s)
> m49 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1|subid : Harmony) + (1| subid : Voice) + Selfdeclare + OMSI +
KnowRob + KnowAxis + X1990s2000s.minus.1960s1970s)
> m50 = lmer(Popular ~ Instrument + Harmony + Voice +(1|subid : Harmony) +
(1| subid : Voice) + Selfdeclare + OMSI + KnowRob + KnowAxis +
X1990s2000s.minus.1960s1970s)
```

```
> m51 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1| subid : Voice) + Selfdeclare + OMSI + KnowRob + KnowAxis +
X1990s2000s.minus.1960s1970s)
> m52 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid :
Instrument)+(1|subid : Harmony) + Selfdeclare + OMSI + KnowRob + KnowAxis +
X1990s2000s.minus.1960s1970s)

> anova(m49, m50)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m50 16 10851 10945 -5409.6    10819
m49 17 10325 10424 -5145.5    10291 528.25      1  < 2.2e-16 ***

> anova(m49, m51)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m51 16 10395 10488 -5181.3    10363
m49 17 10325 10424 -5145.5    10291 71.544      1  < 2.2e-16 ***

> anova(m49, m52)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m52 16 10324 10418 -5146.1    10292
m49 17 10325 10424 -5145.5    10291 1.1672      1       0.28
```

The anova tests show that the random effects of subid:Voice was not significant, but subid:Instrument and subid : Harmony are significant.

cannot use conventional significance tests with rand effects

Note that the popular rating is generally influenced by the listener's musical knowledge and how familiar he is with the Pachelbel's Canon. This result helps to support one of our previous hypotheses the harmonic progression in the beginning progression for Pachelbel's Canon was frequently rated as classical, even though it appears in popular music a lot.

(c) question 3, for popular ratings

m53 = lmer(Popular ~ Instrument + Harmony + Voice + (1|subid : Instrument)+(1|subid : Harmony) + Selfdeclare + OMSI + KnowRob + KnowAxis + X1990s2000s.minus.1960s1970s + Musician)

Starting with model m53, we tested the terms regarding Musician and its interaction with each of the fixed effect, only to find that the interaction between Musician and Harmony is significant, while all the other interactions are not. This result shows that in identifying a piece of music as popular, musicians are more proven to be influenced by the harmony motion of music, compared with those who do not consider themselves as musicians. Note that this result is in accordance with our finding regarding the association between musician and classical rating in part 3.

4: 18
5: 20

38 nice job

Summary

A study was conducted to understand factors that would affect people's identification of music as "classical" or "popular". Three main effects: instrument, harmonic motion and voice leading were investigated with the conventional linear model, repeated measures model, and varied personal-bias model. Result shows that the model with varied personal-biased random effects is the best. It can be told from the results that instruments have the largest effects on rating. Other covariates, such as whether or not the subject was familiar with Pachelbel's Canon, would also influence the rating. Results also show that people who selfidentify as musicians are more prone to be influenced by harmony motion of the music.

Introduction

A total of 36 musical stimuli were presented to 70 listeners, who rate the music as "popular" or "classical". The 36 stimuli were chosen by completely crossing the factors of instrument, harmonic motion, and voice leading. Also note that some of the listeners selfidentify as musicians while others not. Other factors, such as the listeners' capability in composing, playing guitar and playing piano, were also collected in the study. The researchers are interested in understanding the factors that would influence the listeners' rating.

Methods

Three main effects: instrument, harmonic motion and voice leading were investigated with the conventional linear model, repeated measures model, and varied personal-bias model. A series of ANOVA test was applied to assess the significance of variables or interactions between two variables.

Results and Discussion

First, we found that the model with varied personal-biased random effects is better than conventional linear model and repeated measures model, in terms of smaller AIC and BIC's. That is, some of the listeners are more inclined to rate music played by a specific instrument, say string, as classical.

We also found that instruments have the largest effects on rating. That is, The variance of the term subid: Instrument is the largest, and that of subid : Voice is the smallest. Moreover, factors other than the three main effects influence the listener's rating. Specifically, the classical rating is influenced by whether or not the listener plays guitar. One the other hand, the popular rating is generally influenced by the listener's musical knowledge and how familiar he is with the Pachelbel's Canon. This result helps to support one of our previous hypotheses that the harmonic progression in the beginning progression for Pachelbel's Canon was frequently rated as classical, even though it appears in popular music a lot.

Finally, we found that people who selfidentify as musicians are more prone to be influenced by harmony motions of the music. This was shown as a significant interaction term in the model regarding both classical and popular ratings. Note that we classify the listeners with higher declaration scores as "musicians" and those with lower scores as "non-musicians" in the study.