# HW05-Lee-Jennifer

*Jennifer Lee (hlee1)*

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

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

3 8/9

4 a 9/9
b 8/9
c 9/9

5 10/10

Total 96/100

## 1a.

```
rating = read.csv("ratings.csv")
table(rating$Instrument)
```

```
##
## guitar  piano string
##    840    840    840
```

```
table(rating$Harmony)
```

```
##
## I-IV-V I-V-IV I-V-VI IV-I-V
##    630    630    630    630
```

```
table(rating$Voice)
```

```
##
## contrary   par3rd   par5th
##      840      840      840
```

```
lm1 = lm(Classical~Instrument+Harmony+Voice, data=rating)
summary(lm1)
```

```
##
## 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
```

```r
anova(lm1)
```

```
## Analysis of Variance Table
##
## Response: Classical
##              Df  Sum Sq Mean Sq  F value    Pr(>F)
## Instrument    2  4127.9 2063.96 391.2983 < 2.2e-16 ***
## Harmony       3   273.6   91.20  17.2911 4.121e-11 ***
## Voice         2    85.6   42.82   8.1181 0.0003061 ***
## Residuals  2485 13107.5    5.27
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lm(Classical~Instrument+Voice+Harmony, data=rating))
```

```
## Analysis of Variance Table
##
## Response: Classical
##              Df  Sum Sq Mean Sq  F value    Pr(>F)
## Instrument    2  4127.9 2063.96 391.2983 < 2.2e-16 ***
## Voice         2    85.6   42.80   8.1146 0.0003071 ***
## Harmony       3   273.6   91.22  17.2934 4.107e-11 ***
## Residuals  2485 13107.5    5.27
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lm(Classical~Voice+Harmony+Instrument, data=rating))
```

```
## Analysis of Variance Table
##
## Response: Classical
##              Df  Sum Sq Mean Sq  F value    Pr(>F)
## Voice         2    85.2   42.59   8.0739 0.0003198 ***
## Harmony       3   274.4   91.48  17.3431 3.823e-11 ***
## Instrument    2  4127.6 2063.78 391.2645 < 2.2e-16 ***
## Residuals  2485 13107.5    5.27
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The first three tables ensures that we have fairly equal (exactly equal in this case) sample sizes across the levels so that a certain level with a small sample size does not give misleading results.

The model fit, lm1 of instrument, harmony, and voice types against classical score show that all variables have significant coefficients, meaning that they have significant effects on classical scores.

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All levels of instrument have positive coefficients meaning that piano and string lead to higher classical scores relative to electric guitar, holding all other variables constant.

Only harmony I-V-IV has a negative coefficient, but it is not very significant and close to zero so we can say that harmony I-V-IV has almost no effect on classical score relative to the baseline, harmony I-VI-V, keeping all other variables constant. The other levels of harmony have positive coefficeints.

Both levels of voice are negative, meaning that they negatively affect classical score relative to the baseline, voice contrary motion, keeping all other variables constant. This somewhat supports the hypothesis that contrary motion is frequently rated as classical, but we would have to check again with the final model.

The three anova tables below the summary of the model show the decrease in sum of squared residuals and the significance for each variable, in order of them listed. Through the tables we can see that each variable instrument, harmony, and voice being added to a model with the other two in it yield significant decrease in sum of squared residuals, leading to a better fitting model.

### 1b.

The model would be $y_i = \alpha_{j[i]} + \epsilon_i$ where $\alpha_j = \beta_0 + \eta_j$ and j, i refers to each subject, observation respectively.

```
library(lme4)
library(arm)
library(RLRsim)
```

```
## Warning: package 'RLRsim' was built under R version 3.2.3
```

```
mm1 = lmer(Classical~Instrument+Harmony+Voice+(1|Subject), data=rating, REML=FALSE)

exactLRT(mm1, lm1)
```

```
##
##  simulated finite sample distribution of LRT. (p-value based on
##  10000 simulated values)
##
## data:
## LRT = 763.59, p-value < 2.2e-16
```

```
AIC(lm1); AIC(mm1)
```

```
## [1] 11230.45
```

```
## [1] 10468.86
```

```
BIC(lm1); BIC(mm1)
```

```
## [1] 11282.84
```

```
## [1] 10527.07
```

Our first method is the exactLRT test. Since the p-value from the exactLRT test is very small we reject h0 have evidence to keep the random effects. Our second method is to compare AIC and BIC, and we see that both the AIC and BIC prefer the multilevel model.

```r
display(mm1)
```

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```
## lmer(formula = Classical ~ Instrument + Harmony + Voice + (1 |
##     Subject), data = rating, REML = FALSE)
##                   coef.est coef.se
## (Intercept)        4.34     0.19
## Instrumentpiano    1.38     0.09
## Instrumentstring   3.13     0.09
## HarmonyI-V-IV     -0.03     0.11
## HarmonyI-V-VI      0.77     0.11
## HarmonyIV-I-V      0.05     0.11
## Voicepar3rd       -0.42     0.09
## Voicepar5th       -0.37     0.09
##
## Error terms:
##  Groups   Name        Std.Dev.
##  Subject  (Intercept) 1.29
##  Residual             1.89
## ---
## number of obs: 2493, groups: Subject, 70
## AIC = 10468.9, DIC = 10448.9
## deviance = 10448.9
```

```r
summary(ranef(mm1)$Subject)
```

```
##   (Intercept)
##  Min.   :-2.5466
##  1st Qu.:-0.8943
##  Median :-0.1103
##  Mean   : 0.0000
##  3rd Qu.: 0.9874
##  Max.   : 3.0134
```

The fixed effects hardly changed and the summary of the random intercepts for each subject is below the summary of mm1. We can see that they center around zero, ranging from -2.5 to about 3.0.

## 1c.

great, except for some TeX subscripting typos.

The model would be $y_i = \alpha_{j[i]x[i]} + \alpha_{j[i]y[i]} + \alpha_{j[i]z[i]} + \epsilon_i$ where $\alpha_j x = \beta_x + \eta_j x$, $\alpha_j y = \beta_y + \eta_j y$, and $\alpha_j z = \beta_z + \eta_j z$. The j,i refer to each subject, observation respectively and x, y, z refer to instrument, harmony, and voice levels.

```r
mm2 = lmer(Classical~Instrument+Harmony+Voice+(1|Subject:Instrument)+(1|Subject:Harmony)
           +(1|Subject:Voice), data=rating, REML=FALSE)
display(mm2)
```

```
## lmer(formula = Classical ~ Instrument + Harmony + Voice + (1 |
##     Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice),
##     data = rating, REML = FALSE)
##                   coef.est coef.se
```

```
## (Intercept)       4.34     0.21
## Instrumentpiano   1.36     0.26
## Instrumentstring  3.13     0.26
## 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
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.66
##  Subject:Voice      (Intercept) 0.16
##  Subject:Instrument (Intercept) 1.47
##  Residual                       1.56
## ---
## number of obs: 2493, groups: Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 210
## AIC = 10057.5, DIC = 10033.5
## deviance = 10033.5
```

```r
AIC(lm1); AIC(mm1); AIC(mm2)
```

```
## [1] 11230.45
```

```
## [1] 10468.86
```

```
## [1] 10057.53
```

```r
BIC(lm1); BIC(mm1); BIC(mm2)
```

```
## [1] 11282.84
```

9

```
## [1] 10527.07
```

```
## [1] 10127.38
```

By comparing the AIC and BIC of the three models, we can see that both AIC and BIC prefer mm2, the mixed model with random intercepts for each combination of subjects with instruments, harmony, and voice.

We can see that the fixed effects again has almost no difference, except that Instrument coefficients now have larger standard errors, almost 3 times larger.

The three estimated variance components shown by the summary above (in standard deviations, but it could be squared to show the variances) is 0.66 for subject:harmony, 0.16 for subject:voice, 1.47 for subject:instrument. We can see that subject:voice has the smallest estimated variance meaning that subjects have little variability in how they respond to voice whie subject:instrument has the largest estimated variance showing that subjects have large variability in how the respond to instruments.

## 2a.

Although the variables that are on scales (0-5) are categorical since they have levels, they are ordinal and monotone so they will be kept as quantitative. Otherwise, most of the covariates cannot be included due to lack of variability. In choosing the full model to start with, the following are the reasonings in why I excluded certain variables:

- I used the variables that indicated differences when possible because the scales (0-5, 0=not at all) are very subjective, making the relationship between those two variables more valuable than the actual value. For example, it would be more informative to know that a certain subject listens to much more 1990-2000's music than 1960-1970 music while another subject listens to both types of music in equal amounts rather than to compare the subjectively reported scaled values.
- The variables KnowRob and KnowAxis were not included because they seemed too specific and also slightly misleading as a subject could listen to popular music but not know Axis of Evil's Comedy. It is not clear if these two variables are representative samples of classical and popular music.
- Similar to KnowRob and KnowAxis, it is intuitively not clear whether PianoPlay and GuitarPlay would be representative of either classical music or popular music knowledge. They are instruments that many people learn regardless of actual music study (which is usually based on classical music). Both instruments are largely used in both classical and popular music. Thus, I removed PianoPlay and GuitarPlay as I'm not sure if they are representative variables as in if they would behave consistently on another group of subjects.

Nice description of your reasoning for each group of covariates you considered.

- It should be noted that Composing is an indicator of actual music study, which is why I included it even though composition is not limited to classical or popular music.
- The three variables CollegeMusic, NoClass, and APTheory are presumed to be correlated as there could be large overlap for these variables. I chose the variable that would cover most of these cases, which would be NoClass.
- Only X2ndInstr was included while X1stInstr wasn't because I believe it is safe to assume that the majority of people these days know or have at least attempted to learn 1 instrument. The skills of the second instrument would have more information and variability. Including both would probably lead to correlation issues.

```r
lmfull = lm(Classical~Instrument+Harmony+Voice+OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s
              +NoClass+Composing+X2ndInstr, data=rating)
summary(lmfull)
```

```
##
## Call:
## lm(formula = Classical ~ Instrument + Harmony + Voice + OMSI +
##     Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + Composing + X2ndInstr, data = rating)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2228 -1.2274 -0.0006  1.3605 10.4560
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.758100   1.458841   0.520  0.60374
## Instrumentpiano              1.777335   0.293652   6.053 4.85e-09 ***
```

```
## Instrumentstring              3.385417   0.285522  11.857  < 2e-16 ***
## HarmonyI-V-IV                 0.068152   0.334395   0.204  0.83866
## HarmonyI-V-VI                 1.834844   0.334395   5.487 9.55e-08 ***
## HarmonyIV-I-V                 0.053867   0.334395   0.161  0.87215
## Voicepar3rd                  -0.560916   0.290113  -1.933  0.05425 .
## Voicepar5th                  -0.331587   0.289383  -1.146  0.25289
## OMSI                          0.010949   0.004497   2.435  0.01556 *
## Instr.minus.Notes            -0.323608   0.199030  -1.626  0.10515
## ClsListen                     0.945268   0.386495   2.446  0.01511 *
## X1990s2000s.minus.1960s1970s  0.344012   0.178806   1.924  0.05543 .
## NoClass                       1.773361   0.893887   1.984  0.04830 *
## Composing                    -0.375538   0.394541  -0.952  0.34205
## X2ndInstr                    -1.696912   0.586174  -2.895  0.00411 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.978 on 265 degrees of freedom
##   (2240 observations deleted due to missingness)
## Multiple R-squared:  0.4555, Adjusted R-squared:  0.4267
## F-statistic: 15.83 on 14 and 265 DF,  p-value: < 2.2e-16
```

We can see in the summary that only Composing has an insignificant slope while others are either significant or very close (only ClsListen is slight insignificant with a p-value of 0.105). The only variable to possibly exclude is Composing.

```
lmred = lm(Classical~Instrument+Harmony+Voice+OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s
              +NoClass+X2ndInstr, data=rating)
summary(lmred)
```

```
##
## Call:
## lm(formula = Classical ~ Instrument + Harmony + Voice + OMSI +
##     Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr, data = rating)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3500 -1.2948  0.0201  1.3643 10.7206
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   1.955930   0.737801   2.651  0.00851 **
## Instrumentpiano               1.753351   0.292518   5.994 6.64e-09 ***
## Instrumentstring              3.385417   0.285471  11.859  < 2e-16 ***
## HarmonyI-V-IV                 0.068109   0.334335   0.204  0.83873
## HarmonyI-V-VI                 1.834844   0.334336   5.488 9.47e-08 ***
## HarmonyIV-I-V                 0.053823   0.334335   0.161  0.87223
## Voicepar3rd                  -0.560916   0.290062  -1.934  0.05420 .
## Voicepar5th                  -0.328517   0.289314  -1.136  0.25719
## OMSI                          0.007681   0.002903   2.646  0.00864 **
## Instr.minus.Notes            -0.157025   0.094764  -1.657  0.09870 .
## ClsListen                     0.636746   0.210477   3.025  0.00273 **
```

```
## X1990s2000s.minus.1960s1970s  0.183700   0.060031   3.060  0.00244 **
## NoClass                       1.135998   0.592053   1.919  0.05609 .
## X2ndInstr                    -1.366782   0.472468  -2.893  0.00413 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.978 on 266 degrees of freedom
##   (2240 observations deleted due to missingness)
## Multiple R-squared:  0.4536, Adjusted R-squared:  0.4269
## F-statistic: 16.99 on 13 and 266 DF,  p-value: < 2.2e-16
```

```
anova(lmred, lmfull)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Instrument + Harmony + Voice + OMSI + Instr.minus.Notes +
##     ClsListen + X1990s2000s.minus.1960s1970s + NoClass + X2ndInstr
## Model 2: Classical ~ Instrument + Harmony + Voice + OMSI + Instr.minus.Notes +
##     ClsListen + X1990s2000s.minus.1960s1970s + NoClass + Composing +
##     X2ndInstr
##   Res.Df    RSS Df Sum of Sq     F Pr(>F)
## 1    266 1040.5
## 2    265 1037.0  1    3.5452 0.906  0.342
```

I would like to see a little more effort at variable selection.

We can see that the coefficients have not changed much by taking Composing out and the anova also suggests that the change in sum of squared residuals is insignificant, so I can safely take out Composing. Another reasoning to why it would be okay to take out composing is that NoClass probably overlaps with Composing because those who did take music classes likely learned how to compose.

Our final set of fixed effects is shown by the covariates in lmred, which is applied to a mixed model below.

```
mm3 = lmer(Classical~Instrument+Harmony+Voice+OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
              +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice),
              data=rating, REML=FALSE)
display(mm3)
```

```
## lmer(formula = Classical ~ Instrument + Harmony + Voice + OMSI +
##     Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
##     (1 | Subject:Voice), data = rating, REML = FALSE)
##                              coef.est coef.se
## (Intercept)                   2.00     1.32
## Instrumentpiano               1.71     0.42
## Instrumentstring              3.39     0.42
## HarmonyI-V-IV                 0.09     0.46
## HarmonyI-V-VI                 1.83     0.46
## HarmonyIV-I-V                 0.07     0.46
## Voicepar3rd                  -0.56     0.27
## Voicepar5th                  -0.34     0.27
## OMSI                          0.01     0.01
## Instr.minus.Notes            -0.15     0.18
## ClsListen                     0.61     0.39
```

```
## X1990s2000s.minus.1960s1970s  0.18     0.11
## NoClass                       1.10     1.11
## X2ndInstr                    -1.32     0.89
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.74
##  Subject:Voice      (Intercept) 0.25
##  Subject:Instrument (Intercept) 0.68
##  Residual                       1.67
## ---
## number of obs: 280, groups: Subject:Harmony, 32; Subject:Voice, 24; Subject:Instrument, 24
## AIC = 1174.5, DIC = 1138.5
## deviance = 1138.5
```

```r
AIC(mm2); AIC(mm3)
```

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```
## [1] 10057.53

## [1] 1174.514
```

```r
BIC(mm2); BIC(mm3)
```

```
## [1] 10127.38

## [1] 1239.94
```

The fixed effect coefficients are similar to those in the linear model. We can see that there is a large improvement in AIC BIC after adding the 6 covariates.

## 2b.

```r
mmtest = lmer(Classical~Instrument+Harmony+Voice+OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
              +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice)
              +(NoClass|Subject),
              data=rating, REML=FALSE)
mmtest2 = lmer(Classical~Instrument+Harmony+Voice+OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
              +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice)
              +(Instr.minus.Notes|Subject),
              data=rating, REML=FALSE)
AIC(mm3); AIC(mmtest); AIC(mmtest2)
```

```
## [1] 1174.514

## [1] 1180.514

## [1] 1180.514
```

8

```
BIC(mm3); BIC(mmtest); BIC(mmtest2)
```

```
## [1] 1239.94
## [1] 1256.844
## [1] 1256.844
```

did you also check that all three random effect from 1c were still needed?

ok

Above are two examples (out of many to try fitting random slopes for the covariates) to show that the AIC and BIC increase when adding another random effect based on the new covaraties. I have evidence that more random effects are not needed and I will move on with mm3.

### 2c.

The effects of instrument, harmony, and voice are similar to the models explained above. Harmony I-V-IV now has a positive slope, but it is not very significant to note the change.

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The variables with a positive coefficients are ClsListen, X1990s2000s.minus.1960s1970s, and NoClass, meaning that an increase in these variables leads to a higher classical score. OMSI is also positive, but close to zero. The slope relatively small likely because the range of OMSI is large (11-970).

The variables with negative coefficients are Instr.minus.Notes and X2ndInstr. It is interesting how X2ndInstr has a significantly negative coefficient as it indicates that an individual with high proficiency leads to lower classical score.

### 3.

OK, why this choice?

```
rating$Selfdeclare2 = as.numeric(rating$Selfdeclare>2)
lmint = lm(Classical~Instrument+Selfdeclare2*Harmony+Voice
              +OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr,
              data=rating)
mmint = lmer(Classical~Instrument+Selfdeclare2*Harmony+Voice
              +OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
              +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice),
              data=rating, REML=FALSE)
summary(lmint)
```

```
##
## Call:
## lm(formula = Classical ~ Instrument + Selfdeclare2 * Harmony +
##     Voice + OMSI + Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr, data = rating)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7861 -1.1069 -0.0985  1.2000 11.0524
##
## Coefficients:
```

```
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  1.765252   0.757514   2.330  0.02055 *
## Instrumentpiano              1.777193   0.282846   6.283 1.37e-09 ***
## Instrumentstring             3.385417   0.275015  12.310  < 2e-16 ***
## Selfdeclare2                 0.457324   0.602326   0.759  0.44838
## HarmonyI-V-IV                0.388889   0.449098   0.866  0.38732
## HarmonyI-V-VI                0.972222   0.449098   2.165  0.03130 *
## HarmonyIV-I-V                0.611111   0.449098   1.361  0.17476
## Voicepar3rd                 -0.551091   0.279460  -1.972  0.04966 *
## Voicepar5th                 -0.311906   0.278765  -1.119  0.26421
## OMSI                         0.009130   0.003159   2.890  0.00417 **
## Instr.minus.Notes           -0.127134   0.096171  -1.322  0.18733
## ClsListen                    0.646161   0.202995   3.183  0.00163 **
## X1990s2000s.minus.1960s1970s  0.150751   0.066756   2.258  0.02475 *
## NoClass                      1.290823   0.591555   2.182  0.02999 *
## X2ndInstr                   -1.641939   0.533764  -3.076  0.00232 **
## Selfdeclare2:HarmonyI-V-IV  -0.660630   0.644444  -1.025  0.30625
## Selfdeclare2:HarmonyI-V-VI   1.776275   0.644445   2.756  0.00626 **
## Selfdeclare2:HarmonyIV-I-V  -1.147558   0.644444  -1.781  0.07612 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.905 on 262 degrees of freedom
##   (2240 observations deleted due to missingness)
## Multiple R-squared:  0.5006, Adjusted R-squared:  0.4681
## F-statistic: 15.45 on 17 and 262 DF,  p-value: < 2.2e-16
```

```r
display(mmint)
```

```
## lmer(formula = Classical ~ Instrument + Selfdeclare2 * Harmony +
##     Voice + OMSI + Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
##     (1 | Subject:Voice), data = rating, REML = FALSE)
##                              coef.est coef.se
## (Intercept)                   1.88     1.17
## Instrumentpiano               1.72     0.41
## Instrumentstring              3.39     0.40
## Selfdeclare2                  0.31     0.85
## HarmonyI-V-IV                 0.39     0.51
## HarmonyI-V-VI                 0.97     0.51
## HarmonyIV-I-V                 0.61     0.51
## Voicepar3rd                  -0.56     0.26
## Voicepar5th                  -0.32     0.26
## OMSI                          0.01     0.01
## Instr.minus.Notes            -0.12     0.16
## ClsListen                     0.61     0.33
## X1990s2000s.minus.1960s1970s  0.15     0.11
## NoClass                       1.20     0.97
## X2ndInstr                    -1.50     0.86
## Selfdeclare2:HarmonyI-V-IV   -0.63     0.73
## Selfdeclare2:HarmonyI-V-VI    1.76     0.73
## Selfdeclare2:HarmonyIV-I-V   -1.11     0.73
##
## Error terms:
```

```
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.45
##  Subject:Voice      (Intercept) 0.17
##  Subject:Instrument (Intercept) 0.64
##  Residual                       1.68
## ---
## number of obs: 280, groups: Subject:Harmony, 32; Subject:Voice, 24; Subject:Instrument, 24
## AIC = 1168.8, DIC = 1124.8
## deviance = 1124.8
```

```r
AIC(mm3); AIC(mmint)
```

```
## [1] 1174.514
```

```
## [1] 1168.807
```

```r
BIC(mm3); BIC(mmint)
```

```
## [1] 1239.94
```

```
## [1] 1248.773
```

```r
anova(mm3, mmint)
```

```
## Data: rating
## Models:
## mm3: Classical ~ Instrument + Harmony + Voice + OMSI + Instr.minus.Notes +
## mm3:     ClsListen + X1990s2000s.minus.1960s1970s + NoClass + X2ndInstr +
## mm3:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)
## mmint: Classical ~ Instrument + Selfdeclare2 * Harmony + Voice + OMSI +
## mmint:     Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
## mmint:     NoClass + X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## mmint:     (1 | Subject:Voice)
##       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## mm3   18 1174.5 1239.9 -569.26   1138.5
8 ## mmint 22 1168.8 1248.8 -562.40   1124.8 13.706      4   0.008294 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The AIC and anova test shows that the added interaction term of Selfdeclare2 and Harmony lead to a significantly better fit. The BIC disagrees, but it is likely because BIC prefers smaller models, and I will move on with mmint, the mixed model with interaction.

Almost all levels of the interaction between selfdeclare2 and harmony are significant. We can see that the interaction is especially significant because the coefficients (which are significantly different from zero) are completely opposite. When subjects self declare themselves as musicians and listen to HarmonyI-V-VI, they give higher classical scores, but when self-declared musicians listen to HarmonyIV-I-V, they lower classical scores.

## 4a.

```r
poplm = lm(Popular~Instrument+Harmony+Voice, data=rating)
summary(poplm)
```

```
##
## Call:
## lm(formula = Popular ~ Instrument + Harmony + Voice, data = rating)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7218 -1.7026  0.2008  1.4691 13.2248
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        6.58263    0.12761  51.583   <2e-16 ***
## Instrumentpiano   -0.95200    0.11102  -8.575   <2e-16 ***
## Instrumentstring  -2.61173    0.11035 -23.667   <2e-16 ***
## HarmonyI-V-IV     -0.02405    0.12782  -0.188   0.8508
## HarmonyI-V-VI     -0.26829    0.12782  -2.099   0.0359 *
## HarmonyIV-I-V     -0.18564    0.12772  -1.454   0.1462
## Voicepar3rd        0.16859    0.11075   1.522   0.1281
## Voicepar5th        0.16326    0.11068   1.475   0.1403
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.257 on 2485 degrees of freedom
9 ##   (27 observations deleted due to missingness)
## Multiple R-squared:  0.1901, Adjusted R-squared:  0.1878
## F-statistic: 83.32 on 7 and 2485 DF,  p-value: < 2.2e-16
```

As expected, the signs are opposite of the coefficients for the model predicting Classical score. The coefficients are slightly less significant than it was for Classical score, but they are not problematically insignificant.

### 4b.

```r
popmm = lmer(Popular~Instrument+Harmony+Voice
             +OMSI+Instr.minus.Notes
             +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
             +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice),
             data=rating, REML=FALSE)
display(popmm)
```

```
## lmer(formula = Popular ~ Instrument + Harmony + Voice + OMSI +
##     Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
##     (1 | Subject:Voice), data = rating, REML = FALSE)
##                              coef.est coef.se
## (Intercept)                   5.25     1.22
## Instrumentpiano              -0.57     0.46
## Instrumentstring             -1.88     0.45
## HarmonyI-V-IV                -0.08     0.37
```

```
## HarmonyI-V-VI                -0.21      0.37
## HarmonyIV-I-V                -0.24      0.37
## Voicepar3rd                   0.08      0.24
## Voicepar5th                   0.16      0.24
## OMSI                          0.00      0.01
## Instr.minus.Notes            -0.12      0.16
## ClsListen                     0.45      0.36
## X1990s2000s.minus.1960s1970s  0.35      0.10
## NoClass                       0.54      1.03
## X2ndInstr                    -0.60      0.82
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.48
##  Subject:Voice      (Intercept) 0.00
##  Subject:Instrument (Intercept) 0.77
##  Residual                       1.64
## ---
## number of obs: 280, groups: Subject:Harmony, 32; Subject:Voice, 24; Subject:Instrument, 24
## AIC = 1152.6, DIC = 1116.6
## deviance = 1116.6
```

8

it doesn't look like (1|S:V) should be in there... did you re-test these variance components after selecting fixed effects?

The coefficients of instrument, harmony, and voice are similar to the linear model above. However, unlike how instrument, harmony, and voice showed opposite signs relative to the model fit for classical score, none of the additional predictors show opposite signs. This indicates evidence that the predictors weren't actually affecting classical scores, but simply leading to higher/lower classical or popular score, as in more definite/confident responses. For variables such as X2ndInstr or OMSI, it is understandable but this result is unexpected for variables such as NoClass or ClsListen.

## 4c.

```
popmmint = lmer(Popular~Instrument+Selfdeclare2*Harmony+Voice
              +OMSI+Instr.minus.Notes
              +ClsListen+X1990s2000s.minus.1960s1970s+NoClass+X2ndInstr
              +(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice),
              data=rating, REML=FALSE)
display(popmmint)
```

```
## lmer(formula = Popular ~ Instrument + Selfdeclare2 * Harmony +
##     Voice + OMSI + Instr.minus.Notes + ClsListen + X1990s2000s.minus.1960s1970s +
##     NoClass + X2ndInstr + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
##     (1 | Subject:Voice), data = rating, REML = FALSE)
##                              coef.est coef.se
## (Intercept)                   5.56     1.11
## Instrumentpiano              -0.59     0.44
## Instrumentstring             -1.88     0.43
## Selfdeclare2                 -0.80     0.77
## HarmonyI-V-IV                -0.17     0.39
## HarmonyI-V-VI                 0.25     0.39
## HarmonyIV-I-V                -1.06     0.39
## Voicepar3rd                   0.08     0.24
```

```
## Voicepar5th                    0.16     0.24
## OMSI                           0.00     0.00
## Instr.minus.Notes             -0.16     0.15
## ClsListen                      0.45     0.32
## X1990s2000s.minus.1960s1970s  0.39     0.11
## NoClass                        0.36     0.93
## X2ndInstr                     -0.27     0.82
## Selfdeclare2:HarmonyI-V-IV     0.19     0.55
## Selfdeclare2:HarmonyI-V-VI    -0.92     0.55
## Selfdeclare2:HarmonyIV-I-V     1.67     0.55
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.00
##  Subject:Voice      (Intercept) 0.00
##  Subject:Instrument (Intercept) 0.73
##  Residual                       1.64
## ---
## number of obs: 280, groups: Subject:Harmony, 32; Subject:Voice, 24; Subject:Instrument, 24
## AIC = 1143, DIC = 1099
## deviance = 1099.0
```

9

missing text?

The only interactions that did not lead to collinearity issues The interaction coefficients are opposite of those in the model fit for classical. This further supports that only instrument, harmony (part of the interaction term in this model), and voice are actual identifiers of classical or popular music.

Again, would want to see that you checked other possible interactions.

# IMRaD

IMRaD works!

## Introduction

Genres in music have been increasingly growing and becoming diverse as music technology improved over time. Researchers at University of Pittsburgh are interested in how listeners identify the genres of music pieces, specifically classical or popular. An experiment was conducted on 70 listeners consisting of undergraduate students at University of Pittsburgh to study the influence of instrument, harmonic motion, and voice on their decisions to whether the given piece was classical or popular. Using this data, we focused on the effects of instrument, harmonic motion, and voice on listeners' measured classical and popular scores. Other variables that characterize musical traits were also added to the model to examine the effects on music identification.

## Methods

To show the relationship between music identification and various traits of the sample piece and listener, a multilevel model was built. This allows subjects, who each had about 36 ratings, to have unique responses to different musical characteristics. This allows the model to be more detailed and accurate as we can see variables' effects for each subject.

The final model formula was the following:

$y_i = \beta_0 + \beta_{OMSI} + \beta_{Instr.minus.Notes} + \beta_{ClsListen} + \beta_{X1990s2000s.minus.1960s1970s} + \beta_{NoClass} + \beta_{X2ndInstr} + \alpha_{j[i]x[i]} + \alpha_{j[i]y[i]} + \alpha_{j[i]z[i]} + \epsilon_i$ where $\alpha_j x = \beta_x + \eta_j x$, $\alpha_j y = \beta_y + \eta_j y$, and $\alpha_j z = \beta_z + \eta_j z$. The j,i refer to each subject, observation respectively and x, y, z refer to instrument, harmony, and voice levels.

The final model was a mixed model that allowed each subject to have individual responses or reactions to instruments, harmonic motions, and voices that will effect the classical or popular scores. Since we are looking at each combination of subjects and instruments, harmonic motions, and voices, this is not a standard repeated measures model as these interactions between subjects and musical variables are not calculated as
10 group effects. The model also measured the fixed (not individual, but grouped) effects represented by the betas in the final model formula. From the definition of the variables, we can see that while instruments, harmonic motions, and voices are characteristics of the sample music, all other variables are musical traits of the listeners.

## Results

The researcher hypothesized that instrument has the largest influence on rating and that harmony I-V-vi that contrary motion voice are frequently rated as classical. Our modeling supported all these hypotheses. The final model was fit for both classical and popular scores, and we found out that instrument had the most significant coefficients. Harmony I-V-vi and contrary motion voice led to relatively higher classical scores and lower popular scores.

We also found out that the coefficients for variables that measured musical traits of the listeners did not greatly change whether it was fit for classical or popular scores. We believe that this may be an indication that those listener trait variables lead to stronger or more confident opinions rather than inclining to either classical or popular identification.

## Discussion

Overall the variables of interest (instrument, harmonic motion, and voice) lead to expected effects and additional experimentations with a random sample would further strengthen the results. Adding more variables that are related to the listeners' musical traits would also be useful, especially those linked to classical or popular music. A suggestion would be to improve the variables KnowRob and KnowAxis so that they are linked to classical and popular music, but not using a single title or piece.