763 Homework 5

1 a 9/9
b 7/9
c 8/9

2 a 9/9
b 7/9
c 9/9

3 9/9

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

5 10/10

Total 95/100

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```r
ratings <- read.csv("ratings.csv",header=TRUE)
attach(ratings)
```

The three main experimental factors

(a).

```r
lm.main <- lm(Classical ~ Instrument + Harmony + Voice)
lm.noins <- lm(Classical ~ Harmony + Voice)
lm.nohar <- lm(Classical ~ Instrument + Voice)
lm.novo <- lm(Classical ~ Instrument + Harmony)
anova(lm.main,lm.noins)
```

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

```r
anova(lm.main,lm.nohar)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Instrument + Harmony + 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
```

```r
anova(lm.main,lm.novo)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Instrument + Harmony + Voice
## Model 2: Classical ~ Instrument + Harmony
##   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
```

	P-value
Full vs. No Instrument	0.00
Full vs.No Harmony	0.00
Full vs.No Voice	0.00

9 Table 1: P-values from ANOVA, Linear Model

I checked the diagnostic plots for these linear models. The residual plots do not look bad. So these models are valid for testing.

Most of the explanatory variables in the full linear model with three main factors are statistically significant at 0.05 level(summary table was not included). Also as can be seen from the anova table summaries, p-values from anova table comparing model with 3 main effect, and models without instrument, harmony and voice are 0, 0 and 0.0003 respectively. We need to reject the null hypothesis respectively and conclude coefficient of instrument, harmony and voice is statistically different from zero for each test. The model fits better with the main effect as a fixed effect. This result implies all three main experimental factors are very influential in the main model individually.

(b)

(i).

$$
\begin{gathered}
y_i = \alpha_{j[i]} + \epsilon_i \\
\alpha_j = \beta_0 + \beta_1 * instrument + \beta_2 * harmony + \beta_3 * voice + \eta_j \\
\epsilon_i \sim (iid)\ N(0, \sigma^2) \\
\eta_j \sim (iid)\ N(0, \tau^2) \\
for\ i = 1, 2, 3, \ldots, 2493, and\ j = 1, 2, 3, \ldots, 70
\end{gathered}
$$

this woiuld be ok if I, V, and H were continuous, but since they are factors, multiplying doesn't make sense. One way to fix this is to include them in the indexing of the beta's.

(ii).

I checked both REML and ML analysis. The results were similar and I chose to use maximum likelihood analysis.

```
library(lme4)
library(arm)
lmer.subject <- lmer(Classical ~ 1 + Instrument + Harmony + Voice + (1|Subject),REML=F)
```

First method - AIC and BIC:

Multilevel model with random intercept has lower AIC and BIC value comparing with linear model. Both AIC and BIC drop about 700. Therefore adding random intercept significantly improves the model fit.

Second Method - test

	Value
Model without Random Intercept AIC	11230.45
Model with Random Intercept AIC	10468.86
Model without Random Intercept BIC	11282.84
Model with Random Intercept BIC	10527.07

Table 2: Checking Random Intercept by AIC and BIC

```r
library(RLRsim)
exactRLRT(lmer.subject)
```

```
## Using restricted likelihood evaluated at ML estimators.
## Refit with method="REML" for exact results.
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 763.37, p-value < 2.2e-16
```

Based on the test result, p-value based on 1000 simulated values is very close to 0, indicating the variance is significantly different from zero. Therefore the test results is consistent with the first result and I concluded that the random intercept is needed and improves the model fit.

(iii).

```r
lmer.noins <- lmer(Classical ~ Harmony + Voice + (1|Subject),REML=F)
lmer.nohar <- lmer(Classical ~ Instrument + Voice + (1|Subject),REML=F)
lmer.novo <- lmer(Classical ~ Instrument + Harmony + (1|Subject),REML=F)
anova(lmer.subject,lmer.noins)
```

```
## Data: NULL
## Models:
## lmer.noins: Classical ~ Harmony + Voice + (1 | Subject)
## lmer.subject: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
##              Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.noins    8 11408 11455 -5696.2    11392
## lmer.subject 10 10469 10527 -5224.4    10449 943.59      2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmer.subject,lmer.nohar)
```

```
## Data: NULL
## Models:
## lmer.nohar: Classical ~ Instrument + Voice + (1 | Subject)
## lmer.subject: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
```

```
##              Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.nohar    7 10539 10580 -5262.4    10525
## lmer.subject 10 10469 10527 -5224.4    10449 75.931      3  2.288e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmer.subject,lmer.novo)
```

```
## Data: NULL
## Models:
## lmer.novo: Classical ~ Instrument + Harmony + (1 | Subject)
## lmer.subject: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
##              Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## lmer.novo     8 10489 10536 -5236.6    10473
## lmer.subject 10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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	P-value
Full vs. No Instrument	0.00
Full vs.No Harmony	0.00
Full vs.No Voice	0.00

Table 3: P-values from ANOVA,lmer Model with 1 Random Intercept

Summary table (was not included in the homework) of lmer model with random intercept shows that most of the fixed effects are significant at 0.05 level. As can be seen from the above anova table summaries, p-values from anova table comparing repeated-measures model with 3 main effect and repeated-measures model without instrument, harmony and voice as fixed effect respectively are all close to 0. This implies that including instrument, harmony or voice to the reduced model significantly improves the model fit. All three main experimental factors are very influential in the multilevel model.

(c).

```r
lmer.sub3 <- lmer(Classical ~ Instrument + Harmony + Voice +
                    (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
```

(i).

I used BIC to compare the models. We already knew that models with all the three main effects are better and have lower BIC. So I did not include reduced model for comparison.

	BIC
lmer with 3 Random Intercepts	10127.38
lmer with 1 Random Intercept	10527.07
lm with 3 main effects	11282.84

Table 4: Model Comparison by BIC

New model with 3 random intercepts has the lowest BIC. Therefore it is better to include all new random intercepts.

(ii).

```r
lmer.noins3 <- lmer(Classical ~ Harmony + Voice
                    + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
lmer.nohar3 <- lmer(Classical ~ Instrument + Voice
                    + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
lmer.novo3 <- lmer(Classical ~ Instrument + Harmony
                   + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
anova(lmer.sub3,lmer.noins3)
```

```
## Data: NULL
## Models:
## lmer.noins3: Classical ~ Harmony + Voice + (1 | Subject:Instrument) + (1 |
## lmer.noins3:     Subject:Harmony) + (1 | Subject:Voice)
## lmer.sub3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.sub3:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##             Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.noins3 10 10160 10219 -5070.2    10140
## lmer.sub3   12 10058 10127 -5016.8    10034 106.89      2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmer.sub3,lmer.nohar3)
```

```
## Data: NULL
## Models:
## lmer.nohar3: Classical ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
## lmer.nohar3:     Subject:Harmony) + (1 | Subject:Voice)
## lmer.sub3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.sub3:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##             Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.nohar3  9 10090 10143 -5036.3    10072
## lmer.sub3   12 10058 10127 -5016.8    10034 39.013      3  1.724e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmer.sub3,lmer.novo3)
```

```
## Data: NULL
## Models:
## lmer.novo3: Classical ~ Instrument + Harmony + (1 | Subject:Instrument) +
## lmer.novo3:     (1 | Subject:Harmony) + (1 | Subject:Voice)
## lmer.sub3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.sub3:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##            Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.novo3 10 10081 10140 -5030.6    10061
## lmer.sub3  12 10058 10127 -5016.8    10034 27.753      2  9.409e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Similar to the previous questions, p-values from anova table comparing model with 3 main effect, 3 random intercepts and model without instrument, harmony and voice as fixed effect are all very close to 0. And I concluded that all three main experimental factors are very influential in the new multilevel model.

	P-value
Full vs. No Instrument	0.00
Full vs.No Harmony	0.00
Full vs.No Voice	0.00

Table 5: P-values from ANOVA,lmer Model with 3 Random Intercepts

```r
summary(lmer.sub3)$varcor
```

```
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.65792
##  Subject:Voice      (Intercept) 0.15726
##  Subject:Instrument (Intercept) 1.47285
##  Residual                       1.56116
```

Subject:Instrument has the largest variance (1.47^2=2.19) comparing to other two variance components. This means that among these three variables for each individual, instrument variable varies the most on individual level.Subject:Voice is the opposite since it has the smallest variance(0.16^2=0.03). Residual variance (1.56^2=2.43) is larger than all three random intercept's variance. Even though the test results show that these random intercepts are significant statistically. But in practice, the magnitude of the variance is so small.

(iii).

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$$y_i = \alpha^I_{j[i]k[i]} + \alpha^H_{j[i]k[i]} + \alpha^V_{j[i]k[i]} + \alpha_1 * instrument_{[i]} + \alpha_2 * harmony_{[i]} + \alpha_3 * voice_{[i]} + \epsilon_i$$
$$\alpha^I_{j[i]k[i]} = \alpha^I_0 + \eta^I_j$$
$$\alpha^H_{j[i]k[i]} = \alpha^H_0 + \eta^H_j$$
$$\alpha^V_{j[i]k[i]} = \alpha^V_0 + \eta^V_j$$
$$\epsilon_i \sim (iid)N(0, \sigma^2)$$
$$\eta^I_j \sim (iid)N(0, \tau^2_{\eta I})$$
$$\eta^H_j \sim (iid)N(0, \tau^2_{\eta H})$$
$$\eta^V_j \sim (iid)N(0, \tau^2_{\eta V})$$
$$for\ i = 1, 2, 3, \ldots, 2493, and\ j = 1, 2, 3, \ldots, 70$$

much better

note that the eta's also have to be indexed by levels of the exper factors.

Individual covariates

My best model from problem 1 is the lmer model with 3 random intercepts from part c: lmer.sub3

(a).

Data cleaning:

In order to use model selection, I did some data manipulation. I was concerned about variable X1stInstr and X2ndInstr because most of the values are NAs. Since 0 indicates not proficient at all and there is no 0 in the X1stInstr column but some 0 in the X2ndInstr column, I am not sure NA means they didn't provide the answer or they were not proficient at all. Also I believe other variables in this data set have covered similar information these two variables can provide, I decided to drop these variables as well. I deleted 4 more variables and created a subset of the original data: first column of "row number" with no meaningful values, first12, Instr.minus.Notes,X1990s2000s.minus.1960s1970s because of co-linearity.

In summary, variables I deleted: "row number", Instr.minus.Notes, X1990s2000s.minus.1960s1970s,X1stInstr,X2ndInstr, first12 and Popular.

CollegeMusic and APTheory are categorical variables so I coded them as factors.

```
ratings0 <- ratings[,-c(1,11,17,24,25,26,28)]
ratings0$CollegeMusic <- as.factor(ratings0$CollegeMusic)
ratings0$APTheory <- as.factor(ratings0$APTheory)
```

I used backward selection method starting with a full lmer model with 20 fixed effects and 3 random intercepts from LMERConvenienceFuctions package.

```
lmer.forselection <- lmer(Classical ~ Harmony + Instrument + Voice +
                    Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
                    PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
                    CollegeMusic + NoClass + APTheory + Composing + PianoPlay +
                    GuitarPlay + (1|Subject:Instrument) + (1|Subject:Harmony) +
                    (1|Subject:Voice),data=ratings0,REML=F)
```

```
library(LMERConvenienceFunctions)
bfFixefLMER_F.fnc(lmer.forselection,method = "AIC",log.file = FALSE)
```

Backward model section chose 8 more fixed effects in addition to the original three main effects.

```
lmer.selected <- lmer(Classical ~ Harmony + Instrument + Voice + ConsNotes +
                      PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
                      APTheory + PianoPlay +(1|Subject:Instrument) +
                      (1|Subject:Harmony) +(1|Subject:Voice),
                      data=ratings0,REML=F)
```

My selected model is :

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Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen + KnowRob + KnowAxix + X1990s2000s + NoClass + APTheory + PianoPlay + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice)

From the above table we can see that backward selected model has the lowest AIC and BIC. Therefore variable ConsNotes, PachListen, KnowRob, KnowAxix, X1990s2000s, NoClass, APTheory and PianoPlay should be added to the original lmer model from problem 1.

(b).

	Value
Full AIC	6231.39
3 Main Effects AIC	10057.53
Backward Selected AIC	6232.59
Full BIC	6380.92
3 Main Effects BIC	10127.38
Backward Selected BIC	6339.39

Table 6: Model Comparison by AIC and BIC, lmer models

```
lm.selected <- lm(Classical ~ Harmony + Instrument + Voice + ConsNotes +
                      PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
                      APTheory + PianoPlay,data=ratings0)
```

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	Value
Model without Random Intercepts AIC	6743.03
Model with Random Intercepts AIC	6232.59
Model without Random Intercepts BIC	6833.82
Model with Random Intercepts BIC	6339.39

Table 7: Checking Random Intercepts with AIC and BIC

Table 7 shows us lmer model with random intercepts has the lower AIC and BIC. Therefore including the random intercepts improves my model. There is no need to change the random effects.

did you also check the random effects for each exper factor separately?

(c).

```
summary(lmer.selected)$varcor
```

```
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.65225
##  Subject:Voice      (Intercept) 0.20279
##  Subject:Instrument (Intercept) 1.24655
##  Residual                       1.57510
```

Subject: Voice has the smallest variance and therefore voice has the smallest variation by subject. Similarly, instrument has the largest variation among the three for each subject. However, these variances are all smaller than residual variance.

```
summary(lmer.selected)$coefficients
```

```
##                     Estimate Std. Error     t value
## (Intercept)       2.11540447 0.94821957  2.23092261
## HarmonyI-V-IV    -0.00429808 0.18074259 -0.02378012
## HarmonyI-V-VI     0.85004848 0.18079781  4.70165257
## HarmonyIV-I-V     0.05980821 0.18067988  0.33101752
## Instrumentpiano   1.64932424 0.28636547  5.75950799
## Instrumentstring  3.58844699 0.28618373 12.53896212
## Voicepar3rd      -0.40322941 0.10760882 -3.74717826
```

```
## Voicepar5th      -0.29986339 0.10760894 -2.78660300
## ConsNotes        -0.18465298 0.07726314 -2.38992323
## PachListen        0.19927280 0.16990540  1.17284560
## KnowRob           0.08611425 0.08405499  1.02449892
## KnowAxis          0.08054168 0.06780374  1.18786475
## X1990s2000s       0.18875122 0.08784502  2.14868443
## NoClass          -0.15398034 0.10272981 -1.49888666
## APTheory1         0.63225037 0.35068255  1.80291369
## PianoPlay         0.30821944 0.08473238  3.63756403
```

Harmony: Comparing to the base group I-VI-V, Harmony I-V-IV decreases the classical rating by 0.004 on average. However, Harmony I-V-VI and Harmony IV-I-V increases the classical rating by 0.85 and 0.6 respectively. The finding is consistent with Dr. Jimenez hypothesis since Harmony I-V-VI increases the classical rating the most. In summary, participants are willing to rate the music as classical when they hear Harmony I-V-VI.

Instrument: Comparing to base group electric guitar, if instrument is piano, the classical rating will increase by 1.65 on average, while the classical rating will increase by 3.59 on average if the instrument is string quartet. Hence, the order participants would like to rate music as classical music if the instrument is string quartet, piano and electric guitar.

Voice: Comparing to base group Contrary Motion, par3rd and par5th decreases the classical rating by 0.4 and 0.3 on average, respectively. This also support Dr.Jimenez's hypothesis: contrary motion would be frequently
9 rated as classical.

ConsNotes, NoClass: ConsNotes and NoClass are negatively associated with Classical ratings. If the student concentrated more on notes while listening, the less the student thought the stimulus is classical. Similarly, the more music classes a student took, the less the student considered the stimulus he or she heard is classical.

APTheory: Students who took AP Music Theory in high school are expected to rate the music they heard higher on classical.

PianoPlay: The more students play piano, the more they think the music they heard are classical.

PachListen, Know Rob, Know Axis, X1990s2000S: If a student is very familiar with Pachelbel's Canon, Rob's Pachelbel Rant, Axis of Evils's comedy in popular music(cannot find it on the internet :(), or pop and rock music in 90's and 2000's, the more they are willing to rate the music as classical.

Musicians vs. Non-musicians

Model Selection

Based on the answers from "Are you a musician", I created a new variable called musician and coded musician = 1 if Selfdeclare rate was more than 2, 0 otherwise. Therefore half is musician and half is non-musician.

```r
ratings0$musician <- ifelse(ratings$Selfdeclare >2,1,0)
table(ratings0$musician)
```

```
##
##    0    1
## 1512 1008
```

```r
lmer.formusician  <-lmer(Classical ~ Harmony + Harmony:musician + Instrument +
                          Instrument:musician + Voice + Voice:musician + ConsNotes +
                          ConsNotes:musician + PachListen + PachListen:musician +
                          KnowRob + KnowRob:musician + KnowAxis + KnowAxis:musician +
                          X1990s2000s + X1990s2000s:musician +NoClass + NoClass:musician +
                          APTheory + APTheory:musician + PianoPlay + PianoPlay:musician +
                          (1|Subject:Instrument) + (1|Subject:Harmony) +(1|Subject:Voice),
                        data=ratings0, REML=F)
bfFixefLMER_F.fnc(lmer.formusician,method = "AIC",log.file = FALSE)
```

Testing Interaction Term

```r
lmer.interaction <- lmer(Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
                          KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
                          (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice) +
                          Harmony:musician + PianoPlay:musician, data=ratings0,REML=F)
anova(lmer.selected,lmer.interaction)
```

```
## Data: ratings0
## Models:
## lmer.selected: Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
## lmer.selected:     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
## lmer.selected:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)
## lmer.interaction: Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
## lmer.interaction:     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
## lmer.interaction:     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice) +
## lmer.interaction:     Harmony:musician + PianoPlay:musician
##                  Df    AIC    BIC  logLik deviance  Chisq Chi Df
## lmer.selected    20 6232.6 6339.4 -3096.3   6192.6
## lmer.interaction 25 6212.8 6346.3 -3081.4   6162.8 29.795      5
##                  Pr(>Chisq)
## lmer.selected
## lmer.interaction  1.619e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Partial F-test indicates that adding interaction term Harmony:musician and PianoPlay:musician significantly improves the model.

	Value
Model without Interaction AIC	6232.59
Model with Interaction AIC	6212.79
Model without Interaction BIC	6339.39
Model with Interaction BIC	6346.30

Table 8: Checking Interaction Term with AIC and BIC

AIC prefers the model with interaction but BIC prefers simpler model. I would like to keep the interaction terms in my model.

Interpretation

```r
summary(lmer.interaction)$coefficient
```

```
##                            Estimate Std. Error     t value
## (Intercept)             1.626706187 0.94744999  1.71693093
## HarmonyI-V-IV           0.009661836 0.22777778  0.04241782
## HarmonyI-V-VI           0.266819159 0.22792399  1.17064973
## HarmonyIV-I-V           0.004830918 0.22777778  0.02120891
## Instrumentpiano         1.650997205 0.27745607  5.95048149
## Instrumentstring        3.588698516 0.27726977 12.94298520
## Voicepar3rd            -0.403329279 0.10723482 -3.76117837
## Voicepar5th            -0.299825828 0.10723482 -2.79597460
## ConsNotes              -0.193756108 0.07480995 -2.58997764
## PachListen              0.277226509 0.16420135  1.68833271
## KnowRob                 0.117678016 0.08122771  1.44874226
## KnowAxis                0.028811509 0.06725292  0.42840534
## X1990s2000s             0.221429995 0.08665687  2.55525023
## NoClass                -0.135960202 0.09995496 -1.36021466
## APTheory1               0.578146564 0.33637842  1.71873857
## PianoPlay               0.761479659 0.15611526  4.87767614
## HarmonyI-IV-V:musician  0.082466801 0.39349025  0.20957775
## HarmonyI-V-IV:musician  0.053574755 0.39370488  0.13607847
## HarmonyI-V-VI:musician  1.337390344 0.39374322  3.39660537
## HarmonyIV-I-V:musician  0.199972531 0.39349025  0.50820200
## PianoPlay:musician     -0.605654440 0.18102623 -3.34567227
```

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If the participants are self-declared musicians, identifying Harmony I-V-VI increases the classical rating more by 1.34. However, the more often piano the self-declared musicians play, the lower they will rate the music as classical.

4. Classical vs. Popular

(a).

I started by fitting a model with instrument, harmony, voice and their random effects for each subject. And I used anova to test the influence of instrument, harmony and voice on popular ratings.

```r
lmer.pop3 <- lmer(Popular ~ 1 + Instrument + Harmony + Voice +
                    (1|Subject:Instrument)+((1|Subject:Harmony))+(1|(Subject:Voice)),REML=F)
lmer.noinsp3 <- lmer(Popular ~ Harmony + Voice
                    + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
lmer.noharp3 <- lmer(Popular ~ Instrument + Voice
                    + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
lmer.novop3 <- lmer(Popular ~ Instrument + Harmony
                  + (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice),REML=F)
anova(lmer.pop3,lmer.noinsp3)
```

```
## Data: NULL
## Models:
```

```
## lmer.noinsp3: Popular ~ Harmony + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## lmer.noinsp3:     (1 | Subject:Voice)
## lmer.pop3: Popular ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.pop3:     ((1 | Subject:Harmony)) + (1 | (Subject:Voice))
##              Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## lmer.noinsp3 10 10162 10220 -5070.9    10142
## lmer.pop3    12 10079 10149 -5027.5    10055 86.87      2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmer.pop3,lmer.noharp3)
```

```
## Data: NULL
## Models:
## lmer.noharp3: Popular ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
## lmer.noharp3:     Subject:Harmony) + (1 | Subject:Voice)
## lmer.pop3: Popular ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.pop3:     ((1 | Subject:Harmony)) + (1 | (Subject:Voice))
##              Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.noharp3  9 10078 10130 -5030.0    10060
## lmer.pop3    12 10079 10149 -5027.5    10055 5.1175      3     0.1634
```

```r
anova(lmer.pop3,lmer.novop3)
```

```
## Data: NULL
## Models:
## lmer.novop3: Popular ~ Instrument + Harmony + (1 | Subject:Instrument) + (1 |
## lmer.novop3:     Subject:Harmony) + (1 | Subject:Voice)
## lmer.pop3: Popular ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer.pop3:     ((1 | Subject:Harmony)) + (1 | (Subject:Voice))
##             Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer.novop3 10 10080 10138 -5030.0    10060
## lmer.pop3   12 10079 10149 -5027.5    10055 5.0782      2    0.07894 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

	P-value
Full vs. No Instrument	0.00
Full vs.No Harmony	0.16
Full vs.No Voice	0.08

9 Table 9: P-values from ANOVA,lmer Model with 3 Random Intercepts on popular ratings

Based on the anova output, p-value of 0.16 indicates we should reject the null hypothesis and conclude that coefficient for harmony term is 0. Similarly, p-value of 0.08 also indicates the coefficient for voice is 0. Therefore, compare to instrument, harmony and voice have minimal influences on popular ratings.

(b).

Model Selection

I want to use model selection too if other variables are influential on popular ratings. I create another subset with the same variables and exchange Classical with popular.

```r
pop <- ratings[-c(1,11,17,24,25,26,27)]
pop$CollegeMusic <- as.factor(pop$CollegeMusic)
pop$APTheory <- as.factor(pop$APTheory)
lmer.forselectionp <- lmer(Popular ~ Harmony + Instrument + Voice +
                    Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
                    PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
                    CollegeMusic + NoClass + APTheory + Composing + PianoPlay +
                    GuitarPlay + (1|Subject:Instrument) + (1|Subject:Harmony) +
                    (1|Subject:Voice),data=pop,REML=F)
```

```r
library(LMERConvenienceFunctions)
bfFixefLMER_F.fnc(lmer.forselectionp,method = "AIC",log.file = FALSE)
```

My selected model based on AIC is: Popular ~ Instrument + ConsNotes + PachListen + KnowRob +
9 KnowAxis + X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)

```r
lmer.selectedpop <- lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob +
                        KnowAxis + X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) +
                         (1 | Subject:Harmony) + (1 | Subject:Voice), data=pop)
```

As expected, harmony and voice have been dropped since they do not have much influence on popular ratings.

Testing Random Effects

Now I want to see whether random effects should be added to the model.

```r
#Testing Subject:Instrument
library(RLRsim)
lmer.ins.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                      X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument),data = pop)

lmer.nosins.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                         X1990s2000s + NoClass + APTheory+ (1| Subject:Harmony) +
                         (1| Subject:Voice), data = pop)

exactRLRT(lmer.ins.pop, mA=lmer.selectedpop,m0 = lmer.nosins.pop)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 248.16, p-value < 2.2e-16
```

P-values is less than 0.05, therefore we should keep (1|Subject:Instrument)

```r
#Testing Subject:Harmony
lmer.har.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                      X1990s2000s + NoClass + APTheory + (1 | Subject:Harmony) , data = pop)
```

```r
lmer.noshar.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                         X1990s2000s + NoClass + APTheory+ (1| Subject:Instrument) +
                         (1| Subject:Voice), data = pop)

exactRLRT(lmer.har.pop, mA=lmer.selectedpop,m0 = lmer.noshar.pop)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 55.208, p-value < 2.2e-16
```

P-value is still less than 0.05. Therefore we should keep (1|Subject:Harmony) in the model.

```r
#Testing Subject:Voice
lmer.vo.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                     X1990s2000s + NoClass + APTheory + (1 | Subject:Voice) , data = pop)

lmer.nosvo.pop = lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
                        X1990s2000s + NoClass + APTheory+ (1| Subject:Instrument) +
                        (1| Subject:Harmony), data = pop)

exactRLRT(lmer.vo.pop, mA=lmer.selectedpop,m0 = lmer.nosvo.pop)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 2.3345, p-value = 0.0552
```

P-value is 0.06 after 10000 simulation. And we can conclude that (1|Subject:Voice) is not necessary in the model.

Interpretation

```r
lmer.pop.nointeraction <- lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob +
                                 KnowAxis + X1990s2000s + NoClass + APTheory +
                                 (1 | Subject:Instrument) + (1|Subject:Harmony), data = pop)
summary(lmer.selectedpop)$coefficients
```

```
##                     Estimate Std. Error     t value
## (Intercept)       7.49925915 1.00135997  7.48907422
## Instrumentpiano  -1.14827396 0.30603392 -3.75211332
## Instrumentstring -3.02444769 0.30584833 -9.88871722
## ConsNotes         0.09936063 0.07933651  1.25239476
```

```
## PachListen       -0.25423590 0.18031892 -1.40992361
## KnowRob           0.07240654 0.08941933  0.80974144
## KnowAxis          0.07219136 0.07222041  0.99959774
## X1990s2000s       0.01391152 0.09327395  0.14914690
## NoClass           0.09633169 0.10736045  0.89727353
## APTheory1        -0.03343748 0.36320427 -0.09206247
```

```r
summary(lmer.pop.nointeraction)$varcor
```

```
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.67058
##  Subject:Instrument (Intercept) 1.35545
##  Residual                       1.65567
```

Instrument: As expected, order for popular ratings from high to low is : Electric Guitar, Piano, String Quartet. Comparing with the base group guitar, if the instrument is string quartet, the popular ratings will drop 3.02 on average, while piano will drop 1.15 on average.

ConNotes and NoClass: The more participants was concentrated on notes, and the more music lessons they took, the higher the popular ratings are expected.

APTheory: Students who took AP Music Theory in high school are less likely to rate the music as popular.

PachListen: If a student is very familiar with Pachelbel's Canon, the less they are willing to rate the music as popular.

Above results are all consistent with the findings from classical ratings. Namely, the more they are willing to rate the music as classical based on the predictors, the less they rate music as popular based on the same predictor.

Know Rob, Know Axis, X1990s2000s: If the participant is very familiar with Rob's Pachelbel Rant, Axis of Evils's comedy in popular music, or pop and rock music in 90's and 2000's, the more they are willing to rate the music as popular. These variables are also positively associated with classical ratings.

Pianoplay is no longer influential in the popular ratings.

The variance of residuals is the largest, followed by subject:instrument and subject:harmony. Again, instrument varies the more by subject than harmony.

(c).

Model Selection

This time, musician is coded based on self declare rate more than 3.

```r
pop$musician <- ifelse(pop$Selfdeclare<3,0,1)
table(pop$musician)
```

```
##
##    0    1
## 1512 1008
```

I started my model selection based on the model from (b): Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) + (1|Subject:Harmony)

```r
lmer.formusician.pop  <-lmer(Popular ~ Instrument + Instrument:musician + ConsNotes +
                              ConsNotes:musician + PachListen + PachListen:musician +  KnowRob +
                              KnowRob:musician + KnowAxis + KnowAxis:musician + X1990s2000s +
                              X1990s2000s:musician + NoClass + NoClass:musician + APTheory +
                              APTheory:musician +(1|Subject:Instrument) + (1|Subject:Harmony),
                              data=pop, REML=F)
bfFixefLMER_F.fnc(lmer.formusician.pop, method = "AIC",log.file = FALSE)
```

The model selected based on AIC is: Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) + (1 | Subject:Harmony) + PachListen:musician + X1990s2000s:musician

Two interaction terms are added: PachListen:musician, X1990S2000s:musician.

```r
lmer.pop.interaction <- lmer(Popular ~ Instrument + ConsNotes + PachListen + KnowRob +
                              KnowAxis +X1990s2000s + NoClass + APTheory +
                              (1 | Subject:Instrument) +  (1 | Subject:Harmony) +
                              PachListen:musician + X1990s2000s:musician, data=pop,REML=F)
```

Testing Interaction Terms

AIC and BIC suggest the model with interaction term is better.

	Value
Model with Interaction AIC	6349.72
Model without Interaction AIC	6370.73
Model with Interaction BIC	6429.82
Model without Interaction BIC	6440.15

Table 10: Checking Interaction Term with AIC and BIC

```r
summary(lmer.pop.interaction)$coefficients
```

```
##                         Estimate Std. Error     t value
## (Intercept)           7.19629926 0.96596511   7.4498542
## Instrumentpiano      -1.14854548 0.29316523  -3.9177411
## Instrumentstring     -3.02451778 0.29297013 -10.3236389
## ConsNotes             0.09917075 0.07770942   1.2761741
## PachListen           -0.45294636 0.20139498  -2.2490449
## KnowRob               0.02978199 0.08836226   0.3370443
## KnowAxis              0.09645141 0.07031519   1.3717010
## X1990s2000s           0.28922516 0.17091337   1.6922325
9 ## NoClass           0.06223142 0.10626553   0.5856219
## APTheory1             0.19252411 0.37123264   0.5186077
## PachListen:musician   0.33238209 0.17992035   1.8473847
## X1990s2000s:musician -0.36208731 0.19470325  -1.8596881
```

If the participant self declared themselves as musician and they are familiar with Canon, they will rate the music as popular even less, comparing to non-musicians.

On the other hand, a musician who listen to a lot of rock and pop from the 90s to 2000s are willing to rate the music as popular even more, comparing to non-musicians.

Multilevel Analysis on Listener's Identification on Music

By Caoshiyi Wang

Executive Summary

Classical music and popular music share many aspects of music. But there are significant differences between them. Dr. Jimenez and student Vincent Rossi are interested in the influence of instrument, harmony and voice leading on listener's distinction between popular and classical music. 36 musical stimuli were presented to 70 undergraduates at the University of Pittsburgh. The participants were asked to rate the music on classical and popular scales. Multilevel analysis was used to determine whether instrument, harmony and voice influence on the listener's ability to identify music type. As expected, instrument have the largest effect on rating, both classical and popular. Harmonic progression, I-V-vi is frequently rated as classical. Among voice leading, contrary motion is frequently rated as classical as well.

Introduction

Dr. Jimenez and his student Vincent Rossi intended to measure the influence of instrument, harmonic motion and voice leading on listener's identification of classical and popular music. Listeners were asked to indicate the extent to which series of three-chord successions were popular or classical music sounding. 70 undergraduates at University of Pittsburgh were recruited for this study.

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Methods

Classical ratings and popular ratings were examined separately. Multilevel models determined the effects of instrument, harmony, voice leading and other variables on classical or poplar ratings, taking individual subjects into account. AIC and BIC were used to compare multilevel models with and without certain variables or interaction terms. RLRsim package was used to test the random effects of multilevel models. Models were chose based on AIC backward selection on multilevel models.

Results

Models adjusted for personal bias for classical and popular ratings support Dr. Jimenez's hypothesis. Instrument have the largest influence on rating. Instrument type has a relatively larger positive effect on classical ratings and larger negative effects on popular ratings among instrument, harmony and voice leading. String quartet was considered the most "classical" instrument, followed by piano and electric guitar. Participants are willing to rate the music as classical when they hear Harmony I-V-VI. Harmonic progression I-V-vi is frequently rated as classical and least popular. Comparing to parallel 3^{rd} and parallels 5^{th}, contrary motion is rated as classical most frequently. The relationships are consistent for both classical and poplar ratings. The variances of random intercepts are very small compared to residual variance. Combination of subject and instrument has the largest variance among the three combinations, indicating instrument varies the most by individual. Other variables may affect classical or popular ratings include number of classes took, whether took AP Music Theory in high school, and familiar level with Pachelbel's cannon. Interestingly, if the participant is very familiar with Rob's Pachelbel Rant, Axis of Evils's comedy in popular music, or pop and rock music in 90's and 2000's, they are willing to rate the music as both classical and popular. Considering interaction term, if the participants are self-declared musicians, identifying Harmony I-V-VI increases the classical rating more than non-musicians. However, the more often piano the self-declared musicians play, the lower they will rate the music as classical music.