# 763 Final Project

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

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

3 7/9

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

5 10/10

Total 95/100

## Read Data

```
ratings=read.csv("ratings.csv")
# summary(ratings), find NA's in Classical and Popular
# decide to remove NA's
ratings = ratings[!is.na(ratings$Popular),]
ratings = ratings[!is.na(ratings$Classical),]
# examine structure of ratings
# str(ratings)
# Harmony, Instrument, Voice have already been factorized
```

Sincere there are NA's in Classical and Popular, which are two important response variables we are looking into, I decide to remove the 27 observations with NA in Classical and Popular, and this number is quite small comparing to the whole dataset, so I believe the impact would be minimal.

ok, good.

## Exercise 1: Three main experimental factors

### (a)

```
attach(ratings)
fita=lm(Classical~Instrument+Harmony+Voice)
fita1=lm(Classical~Instrument+Harmony)
fita2=lm(Classical~Instrument+Voice)
fita3=lm(Classical~Harmony+Voice)
anova(fita,fita1)
```

```
## 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
```

```
anova(fita,fita2)
```

```
## 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(fita,fita3)
```

```
## 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
```

9 After we fit several models and use analysis of variance to compare models, we can see that the full model (fita) fits better than the reduced models (fita1), (fita2), and (fita3). Because the three p-values in three ANOVA table are significant, indicating that we should reject the null hypothesis that the left-out variable is not significant. So we believe the three main experimental factors should be kept in the model.

## (b).i

Multi-level model (a.k.a. Hierarchical linear model):

$Classical_i = \alpha_{0j[i]} + \alpha_1 Instrument_i + \alpha_2 Harmony_i + \alpha_3 Voice_i + \epsilon_i,\ \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$

$\alpha_{0j} = \beta_0 + \eta_j,\ \eta_j \overset{iid}{\sim} N(0, \tau^2)$

this woudl be ok if H, V, and I were continuous but since they are factors, multiplying is inadequate. Instead, include their levels as indices in the corresponding alphas.

## (b).ii

Method 1: AIC, BIC

```r
library(lme4)
```

```
## Loading required package: Matrix
```

```r
lmerb2=lmer(Classical~Instrument+Harmony+Voice+(1|Subject))
AIC(lmerb2,fita)
```

```
##        df      AIC
## lmerb2 10 10491.51
## fita    9 11230.45
```

```r
BIC(lmerb2,fita)
```

```
##        df      BIC
## lmerb2 10 10549.73
## fita    9 11282.84
```

Methods 2: LRT

```r
library(RLRsim)
```

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

```r
exactRLRT(lmerb2)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 763.38, p-value < 2.2e-16
```

For Method 1, the model with random intercept (model lmerb2) has both greatly smaller AIC and BIC, comparing to the model (model fita) in part (a), implying that we need the random effect.
For Method 2, since we are comparing the random effect, we cannot count on the p-value given by the ANOVA analysis. The exactRLRT result gives a significant p-value, indicating we need to keep the random intercept. Both methods are consistent and indicate that we need random effect.

## (b).iii

```r
lmerb3.h=lmer(Classical~Instrument+Voice+(1|Subject))
lmerb3.v=lmer(Classical~Instrument+Harmony+(1|Subject))
lmerb3.i=lmer(Classical~Harmony+Voice+(1|Subject))
anova(lmerb2,lmerb3.h)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmerb3.h: Classical ~ Instrument + Voice + (1 | Subject)
## lmerb2: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
##          Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmerb3.h  7 10539 10580 -5262.4    10525
## lmerb2   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(lmerb2,lmerb3.v)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmerb3.v: Classical ~ Instrument + Harmony + (1 | Subject)
## lmerb2: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
```

```
##          Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## lmerb3.v  8 10489 10536 -5236.6    10473
## lmerb2   10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(lmerb2,lmerb3.i)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmerb3.i: Classical ~ Harmony + Voice + (1 | Subject)
## lmerb2: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
##          Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmerb3.i  8 11408 11455 -5696.2    11392
## lmerb2   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
AIC(lmerb2,lmerb3.h,lmerb3.v,lmerb3.i)
```

```
##          df      AIC
## lmerb2   10 10491.51
## lmerb3.h  7 10552.74
## lmerb3.v  8 10505.58
## lmerb3.i  8 11423.04
```

```r
BIC(lmerb2,lmerb3.h,lmerb3.v,lmerb3.i)
```

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```
##          df      BIC
## lmerb2   10 10549.73
## lmerb3.h  7 10593.49
## lmerb3.v  8 10552.15
## lmerb3.i  8 11469.60
```

I fit several models where each leaves out one experimental factor. Since the full model (lmerb2) and the reduced model in each model are nested, and the only difference is the fixed effect, we could use analysis of variance to compare models. We can see that the full model (lmerb2) fits better than the reduced models (lmerb3.h), (lmerb3.v), and (lmerb3.i), because the three p-values in three ANOVA results are significant. So we should reject the null hypothesis that the left-out variable is not significant. Also, the full model (lmerb2) has the smallest AIC and BIC. So we believe the three main experimental factors should be kept in the model.

### (c).i

```r
lmerc1=lmer(Classical~Instrument+Harmony+Voice+
              (1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice))
AIC(lmerc1,lmerb2,fita)
```

```
##        df      AIC
## lmerc1 12 10075.51
## lmerb2 10 10491.51
## fita    9 11230.45
```

```r
BIC(lmerc1,lmerb2,fita)
```

```
##        df      BIC
## lmerc1 12 10145.37
## lmerb2 10 10549.73
## fita    9 11282.84
```

We can see that the model (lmerc1) in part (c).i with all three new random effect terms has the smallest AIC and BIC comparing to other two models, and the differences between AIC, BIC are great. So we believe this model fits better than the other two models.

## (c).ii

```r
lmerc2.i=update(lmerc1,.~. -Instrument)
lmerc2.h=update(lmerc1,.~. -Harmony)
lmerc2.v=update(lmerc1,.~. -Voice)
AIC(lmerc1,lmerc2.i,lmerc2.h,lmerc2.v)
```

```
##          df      AIC
## lmerc1   12 10075.51
## lmerc2.i 10 10176.17
## lmerc2.h  9 10101.74
## lmerc2.v 10 10092.66
```

```r
BIC(lmerc1,lmerc2.i,lmerc2.h,lmerc2.v)
```

```
##          df      BIC
## lmerc1   12 10145.37
## lmerc2.i 10 10234.38
## lmerc2.h  9 10154.13
## lmerc2.v 10 10150.87
```

```r
summary(lmerc1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice)
##
## REML criterion at convergence: 10051.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3942 -0.5683 -0.0013  0.5446  5.7495
```

```
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.44307  0.6656
##  Subject:Voice      (Intercept) 0.02809  0.1676
##  Subject:Instrument (Intercept) 2.19848  1.4827
##  Residual                       2.43753  1.5613
## Number of obs: 2493, groups:
## Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 210
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)        4.34106    0.21435  20.252
## Instrumentpiano    1.36384    0.26232   5.199
## Instrumentstring   3.12836    0.26203  11.939
## HarmonyI-V-IV     -0.03023    0.14317  -0.211
## HarmonyI-V-VI      0.77063    0.14316   5.383
## HarmonyIV-I-V      0.05618    0.14310   0.393
## Voicepar3rd       -0.40699    0.08174  -4.979
## Voicepar5th       -0.37084    0.08168  -4.540
##
## Correlation of Fixed Effects:
##              (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
## Instrumntpn -0.611
## Instrmntstr -0.611  0.500
## HrmnyI-V-IV -0.333  0.000     0.000
## HrmnyI-V-VI -0.333  0.000     0.000     0.499
## HrmnyIV-I-V -0.333  0.000     0.000     0.500  0.500
## Voicepar3rd -0.190 -0.001     0.000    -0.002  0.001  0.002
## Voicepar5th -0.190 -0.001     0.000    -0.001 -0.002 -0.001  0.500
```

After we fit several models where each leaves out one experimental factor, we can see that the full model (lmerc1) has the smallest AIC and BIC comparing to other models. So we believe the three main experimental factors should be kept in the model.

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The estimated variance for Subject:Harmony is 0.443 (sd=0.666), for Subject:Voice is 0.028 (sd=0.168), and for Subject:Instrument is 2.198 (sd=1.483). We see that the variance for Instrument is the largest, followed by Harmony, and Voice is the smallest. The estimated residual variance is 2.438 (sd=1.561), which is the largest comparing to the three estimated variance components.

## (c).iii

Multi-level model (a.k.a. Hierarchical linear model):

$Classical_i = \alpha_{0j[i]} + \alpha_{0k[i]} + \alpha_{0m[i]} + \alpha_1 Instrument_i + \alpha_2 Harmony_i + \alpha_3 Voice_i + \epsilon_i,\ \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$

$\alpha_{0j} = \beta_{01} + \eta_{0j},\ \eta_{0j} \overset{iid}{\sim} N(0, \tau_{01}^2)$

$\alpha_{0k} = \beta_{02} + \eta_{0k},\ \eta_{0k} \overset{iid}{\sim} N(0, \tau_{02}^2)$

similar comments to part b(i)

$\alpha_{0m} = \beta_{03} + \eta_{0m},\ \eta_{0m} \overset{iid}{\sim} N(0, \tau_{03}^2)$

## Exercise 2: Individual Covariates

### Prepare Data

```
data2=ratings
detach(ratings)
# summary(data2), find NA's in some variables
data2 = data2[!is.na(data2$ConsNotes),]
data2 = data2[!is.na(data2$PachListen),]
data2 = data2[!is.na(data2$ClsListen),]
data2 = data2[!is.na(data2$KnowRob),]
data2 = data2[!is.na(data2$KnowAxis),]
data2 = data2[!is.na(data2$X1990s2000s),]
data2 = data2[!is.na(data2$X1990s2000s.minus.1960s1970s),]
data2 = data2[!is.na(data2$CollegeMusic),]
data2 = data2[!is.na(data2$NoClass),]
data2 = data2[!is.na(data2$APTheory),]
# NA # of X1stInstr 1493 -> 821
# NA # of X2ndInstr 2177 -> 1361
# modify NA for the above two variables
data2.2=data2 # 1541 obs
data2.2$X1stInstr[is.na(data2.2$X1stInstr)]=0
data2.2$X2ndInstr[is.na(data2.2$X2ndInstr)]=0

# factorize proper variables
data2.2$CollegeMusic=factor(data2.2$CollegeMusic)
data2.2$APTheory=factor(data2.2$APTheory)
```

it is very good that you are thinking about the NAs. However, there are so many on the X1stInstr and X2ndInstr variables, that it might be better to either (a) find some sort of imputation, or (b) just not consider those variables in your analyses. I like that you have chosen to impute, and that you have given a reason for your imputation.

After reading the summary of the dataset, we see that there are NAs in several variables. To deal with NAs, for most variables, since the size of number of NAs is relatively small comparing to the whole sample size, I decided to remove the observations with NAs in those variables. However, for the variables "X1stInstr" and "X2ndInstr", the number of NAs is so big that even after removing observation with NAs in other columns, the numbers of NAs in "X1stInstr" and "X2ndInstr" are still large comparing to the whole sample size (NA # of X1stInstr: 1493 -> 821, NA # of X2ndInstr: 2177 -> 1361 ). Since excluding observations with NAs in these two variables may greatly impact the number of observations we can analyze, I decide to keep those observations and conservatively assume all NA responses to be 0 (assuming they don't play musical instruments at all), so that those observations could be included in the analysis.

For some variables with a scale as the response choice, I chose to treat them as continuous variable because there is an underlying measurement continuum, and I don't want to over-emphasize the different effects between scale scores. But for variables "CollegeMusic" and "APTheory", I decided to factorize them since they are strictly "Yes" or "No" question. Specifically, for variables "ConsInstr" and "Instr.minus.Notes", I noticed that they contain decimal values, thus I suppose the value is averaged for each subject, so I decided not to treat them as categorical variables.

ok

### (a)

```
attach(data2.2)
# refit best model from problem 1
lmer2=lmer(Classical~Instrument+Harmony+Voice+
              (1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice))
```

```r
#lmer2.Selfdeclare=update(lmer2,.~.+Selfdeclare)
#anova(lmer2.Selfdeclare,lmer2)
#   p-value=0.8019
#lmer2.OMSI=update(lmer2,.~.+OMSI)
#anova(lmer2.OMSI,lmer2)
#   p-value=0.2422
lmer2.X16.minus.17=update(lmer2,.~.+X16.minus.17)
anova(lmer2.X16.minus.17,lmer2)
```

```
## refitting model(s) with ML (instead of REML)

## Data: NULL
## Models:
## lmer2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2:     (1 | Subject:Harmony) + (1 | Subject:Voice)
## lmer2.X16.minus.17: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.X16.minus.17:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17
##                    Df    AIC    BIC  logLik deviance  Chisq Chi Df
## lmer2              12 6248.2 6312.3 -3112.1   6224.2
## lmer2.X16.minus.17 13 6245.6 6315.0 -3109.8   6219.6 4.6588      1
##                    Pr(>Chisq)
## lmer2
## lmer2.X16.minus.17    0.03089 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
###   p-value=0.031

#lmer2.ConsInstr=update(lmer2.X16.minus.17,.~.+ConsInstr)
#anova(lmer2.X16.minus.17,lmer2.ConsInstr)
#   p-value=0.3244
#lmer2.ConsNotes=update(lmer2.X16.minus.17,.~.+ConsNotes)
#anova(lmer2.X16.minus.17,lmer2.ConsNotes)
#   p-value=0.1148
#lmer2.Instr.minus.Notes=update(lmer2.X16.minus.17,.~.+Instr.minus.Notes)
#anova(lmer2.X16.minus.17,lmer2.Instr.minus.Notes)
#   p-value=0.3552
lmer2.PachListen=update(lmer2.X16.minus.17,.~.+PachListen)
anova(lmer2.X16.minus.17,lmer2.PachListen)
```

```
## refitting model(s) with ML (instead of REML)

## Data: NULL
## Models:
## lmer2.X16.minus.17: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.X16.minus.17:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17
## lmer2.PachListen: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.PachListen:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.PachListen:     PachListen
##                    Df    AIC    BIC  logLik deviance  Chisq Chi Df
## lmer2.X16.minus.17 13 6245.6 6315.0 -3109.8   6219.6
## lmer2.PachListen   14 6241.1 6315.8 -3106.5   6213.1 6.5245      1
```

```
##                     Pr(>Chisq)
## lmer2.X16.minus.17
## lmer2.PachListen      0.01064 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
###   p-value=0.011

lmer2.ClsListen=update(lmer2.PachListen,.~.+ClsListen)
anova(lmer2.ClsListen,lmer2.PachListen)
```

```
## refitting model(s) with ML (instead of REML)

## Data: NULL
## Models:
## lmer2.PachListen: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.PachListen:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.PachListen:     PachListen
## lmer2.ClsListen: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.ClsListen:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.ClsListen:     PachListen + ClsListen
##                  Df    AIC    BIC  logLik deviance  Chisq Chi Df
## lmer2.PachListen 14 6241.1 6315.8 -3106.5   6213.1
## lmer2.ClsListen  15 6234.7 6314.8 -3102.3   6204.7 8.3842      1
##                  Pr(>Chisq)
## lmer2.PachListen
## lmer2.ClsListen    0.003785 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
###   p-value=0.0038

#lmer2.KnowRob=update(lmer2.ClsListen,.~.+KnowRob)
#anova(lmer2.ClsListen,lmer2.KnowRob)
#   p-value=0.7208
#lmer2.KnowAxis=update(lmer2.ClsListen,.~.+KnowAxis)
#anova(lmer2.ClsListen,lmer2.KnowAxis)
#   p-value=0.1086
#lmer2.X1990s2000s=update(lmer2.ClsListen,.~.+ X1990s2000s)
#anova(lmer2.ClsListen,lmer2.X1990s2000s)
#   p-value=0.1577
lmer2.X1990s2000s.minus.1960s1970s=update(lmer2.ClsListen,.~.+
                                             X1990s2000s.minus.1960s1970s)
anova(lmer2.ClsListen,lmer2.X1990s2000s.minus.1960s1970s)
```

```
## refitting model(s) with ML (instead of REML)

## Data: NULL
## Models:
## lmer2.ClsListen: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.ClsListen:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.ClsListen:     PachListen + ClsListen
```

```
## lmer2.X1990s2000s.minus.1960s1970s: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrumen
## lmer2.X1990s2000s.minus.1960s1970s:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.X1990s2000s.minus.1960s1970s:     PachListen + ClsListen + X1990s2000s.minus.1960s1970s
##                                     Df    AIC    BIC  logLik deviance
## lmer2.ClsListen                     15 6234.7 6314.8 -3102.3   6204.7
## lmer2.X1990s2000s.minus.1960s1970s 16 6232.4 6317.8 -3100.2   6200.4
##                                      Chisq Chi Df Pr(>Chisq)
## lmer2.ClsListen
## lmer2.X1990s2000s.minus.1960s1970s 4.2925      1    0.03828 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
###   p-value=0.038

#lmer2.CollegeMusic =update(lmer2.X1990s2000s.minus.1960s1970s,.~.+CollegeMusic)
#anova(lmer2.CollegeMusic,lmer2.X1990s2000s.minus.1960s1970s)
#   p-value=0.9101
#lmer2.NoClass =update(lmer2.X1990s2000s.minus.1960s1970s,.~.+NoClass)
#anova(lmer2.NoClass,lmer2.X1990s2000s.minus.1960s1970s)
#   p-value=0.976
#lmer2.APTheory =update(lmer2.X1990s2000s.minus.1960s1970s,.~.+ APTheory)
#anova(lmer2.APTheory,lmer2.X1990s2000s.minus.1960s1970s)
#   p-value= 0.1587
#lmer2.Composing =update(lmer2.X1990s2000s.minus.1960s1970s,.~.+ Composing)
#anova(lmer2.Composing,lmer2.X1990s2000s.minus.1960s1970s)
#   p-value= 0.5887
lmer2.PianoPlay =update(lmer2.X1990s2000s.minus.1960s1970s,.~.+ PianoPlay)
anova(lmer2.PianoPlay,lmer2.X1990s2000s.minus.1960s1970s)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmer2.X1990s2000s.minus.1960s1970s: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrumen
## lmer2.X1990s2000s.minus.1960s1970s:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.X1990s2000s.minus.1960s1970s:     PachListen + ClsListen + X1990s2000s.minus.1960s1970s
## lmer2.PianoPlay: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer2.PianoPlay:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
## lmer2.PianoPlay:     PachListen + ClsListen + X1990s2000s.minus.1960s1970s + PianoPlay
##                                     Df    AIC    BIC  logLik deviance Chisq
## lmer2.X1990s2000s.minus.1960s1970s 16 6232.4 6317.8 -3100.2   6200.4
## lmer2.PianoPlay                     17 6227.7 6318.5 -3096.8   6193.7 6.697
##                                     Chi Df Pr(>Chisq)
## lmer2.X1990s2000s.minus.1960s1970s
## lmer2.PianoPlay                          1   0.009658 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
###   p-value= 0.0097

#lmer2.GuitarPlay =update(lmer2.PianoPlay,.~.+ GuitarPlay)
#anova(lmer2.PianoPlay,lmer2.GuitarPlay)
#   p-value= 0.7594
```

```
#lmer2.X1stInstr =update(lmer2.PianoPlay,.~.+ X1stInstr)
#anova(lmer2.PianoPlay,lmer2.X1stInstr)
#   p-value= 0.269
#lmer2.X2ndInstr =update(lmer2.PianoPlay,.~.+ X2ndInstr)
#anova(lmer2.PianoPlay,lmer2.X2ndInstr)
#   p-value= 0.4558
```

Final set of variables I would add to the problem 1 model as fixed effects:
"X16.minus.17", "PachListen", "ClsListen", "X1990s2000s.minus.1960s1970s" and "PianoPlay". ok
Best model from problem 1 has variables: Harmony, Instrument, Voice, and three random effects.

9 I chose these variables based on p-value from anova output, since the added covariates are all fixed effects. I started from my best model in problem 1, and added one variable at a time to my best model, and used anova() to compare the best model to the model with the added variable. I kept the added variable in my best model if the p-value in anova result turned out to be significant ($< 0.05$). Then I added one new variable to the new model, and used the same criteria from anova output to decide whether to keep the new variable or not. Finally, I obtained a model with the added variables as above. (The anova output for insignificant result is not shown considering space)

## (b)

```
# 3 options with 2 random effects
lmer2b1.1=update(lmer2.PianoPlay,.~.-(1 | Subject:Instrument))
lmer2b1.2=update(lmer2.PianoPlay,.~.-(1 | Subject:Harmony))
lmer2b1.3=update(lmer2.PianoPlay,.~.-(1 | Subject:Voice))

# 3 options with 1 random effect
lmer2b1.4=update(lmer2.PianoPlay,.~.-(1 | Subject:Instrument)
                 -(1 | Subject:Harmony))
lmer2b1.5=update(lmer2.PianoPlay,.~.-(1 | Subject:Instrument)
                 -(1 | Subject:Voice))
lmer2b1.6=update(lmer2.PianoPlay,.~.-(1 | Subject:Harmony)
                 -(1 | Subject:Voice))

AIC(lmer2.PianoPlay,lmer2b1.1,lmer2b1.2,
    lmer2b1.3,lmer2b1.4,lmer2b1.5,lmer2b1.6)
```

```
##                 df      AIC
## lmer2.PianoPlay 17 6258.027
## lmer2b1.1       16 6599.164
## lmer2b1.2       16 6319.837
## lmer2b1.3       16 6257.786
## lmer2b1.4       15 6647.763
## lmer2b1.5       15 6597.387
## lmer2b1.6       15 6318.205
```

```
BIC(lmer2.PianoPlay,lmer2b1.1,lmer2b1.2,
    lmer2b1.3,lmer2b1.4,lmer2b1.5,lmer2b1.6)
```

```
##                 df      BIC
## lmer2.PianoPlay 17 6348.810
```

```
## lmer2b1.1       16 6684.607
## lmer2b1.2       16 6405.280
## lmer2b1.3       16 6343.229
## lmer2b1.4       15 6727.865
## lmer2b1.5       15 6677.490
## lmer2b1.6       15 6398.307
```

Several models with different random effects are fit. Models lmer2b1.1, lmer2b1.2, and lmer2b1.3 each has 2 random effects of experimental variable. Models lmer2b1.3, lmer2b1.4, and lmer2b1.5 each has only 1 random
9 effect of experimental variable.

We see that AIC chose lmer2b1.3 and lmer2.PianoPlay (due to their small difference in AIC), and BIC chose lmer2b1.3. So I decided to keep model lmer2b1.3, which dropped the random effect (1 | Subject:Voice), because this model is preferred by both AIC and BIC.

### (c)

```r
lmer2c=lmer2b1.3
summary(lmer2c)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + X16.minus.17 + PachListen + ClsListen +
##     X1990s2000s.minus.1960s1970s + PianoPlay
##
## REML criterion at convergence: 6225.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2852 -0.5646 -0.0024  0.5332  3.4563
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4451   0.6672
##  Subject:Instrument (Intercept) 1.6984   1.3032
##  Residual                       2.5154   1.5860
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                   1.109789   0.916728   1.211
## Instrumentpiano               1.646906   0.298095   5.525
## Instrumentstring              3.588382   0.297919  12.045
## HarmonyI-V-IV                -0.005045   0.183745  -0.027
## HarmonyI-V-VI                 0.849966   0.183798   4.624
## HarmonyIV-I-V                 0.060224   0.183681   0.328
## Voicepar3rd                  -0.402742   0.098996  -4.068
## Voicepar5th                  -0.300033   0.098996  -3.031
## X16.minus.17                 -0.100866   0.045090  -2.237
## PachListen                    0.388206   0.174133   2.229
```

```
## ClsListen                      0.259444   0.097521   2.660
## X1990s2000s.minus.1960s1970s   0.166097   0.085313   1.947
## PianoPlay                      0.207142   0.081103   2.554
##
## Correlation of Fixed Effects:
##             (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t
## Instrumntpn -0.162
## Instrmntstr -0.162  0.500
## HrmnyI-V-IV -0.100  0.000     0.000
## HrmnyI-V-VI -0.100  0.000     0.000     0.500
## HrmnyIV-I-V -0.100  0.000     0.000     0.500  0.500
## Voicepar3rd -0.054  0.000     0.000    -0.001 -0.001  0.001
## Voicepar5th -0.054  0.000     0.000    -0.001 -0.002 -0.001  0.500
## X16.mins.17 -0.027  0.001     0.000     0.000  0.000  0.000  0.000  0.000
## PachListen  -0.892  0.000     0.000     0.000  0.000  0.000  0.000  0.000
## ClsListen   -0.262  0.000     0.000     0.000  0.000  0.000  0.000  0.000
## X19902000.. -0.432 -0.001     0.000     0.000  0.000  0.000  0.000  0.000
## PianoPlay    0.073  0.000     0.000     0.000  0.000  0.000  0.000  0.000
##             X16..1 PchLst ClsLst X19902
## Instrumntpn
## Instrmntstr
## HrmnyI-V-IV
## HrmnyI-V-VI
## HrmnyIV-I-V
## Voicepar3rd
## Voicepar5th
## X16.mins.17
## PachListen  -0.140
## ClsListen    0.182 -0.030
## X19902000..  0.225  0.162  0.445
## PianoPlay   -0.089 -0.101 -0.299 -0.051
```

```
# library(arm)
# or use display(lmer2c) for short output
detach(data2.2)
```

very nice, complete summary here.

**(Instrument)piano**: Holding other variables fixed, when the Instrument is piano, the classical rating on average increases by 1.65, comparing to the rating when the Instrument is guitar.

**(Instrument)string**: Holding other variables fixed, when the Instrument is string quartet, the classical rating on average increases by 3.59, comparing to the rating when the Instrument is guitar.

**(Harmony)I-V-IV**: Holding other variables fixed, when the Harmony is I-V-IV, the classical rating on average decreases by 0.005, comparing to the rating when Harmony is I-IV-V.

**(Harmony)I-V-VI**: Holding other variables fixed, when the Harmony is I-V-VI, the classical rating on average increases by 0.85, comparing to the rating when Harmony is I-IV-V.

**(Harmony)IV-I-V**: Holding other variables fixed, when the Harmony is IV-I-V, the classical rating on average increases by 0.06, comparing to the rating when Harmony is I-IV-V.

**(Voice)par3rd**: Holding other variables fixed, when the Voice is par 3rd, the classical rating on average decreases by 0.40, comparing to the rating when the Voice is contrary motion.

**(Voice)par5th**: Holding other variables fixed, when the Voice is par 5rd, the classical rating on average decreases by 0.3, comparing to the rating when the Voice is contrary motion.

9 **X16.minus.17**: Holding other variables fixed, when the auxiliary measure of listener's ability to distinguish classical vs popular music increases by 1 unit, the classical rating on average decreases by 0.1.

**PachListen**: Holding other variables fixed, when people's rating for familiarity with Pachelbel's Canon in D increases by 1 unit, the classical rating on average increases by 0.388.

**ClsListen**: Holding other variables fixed, when people's rating for frequency of listening to classical increases by 1 unit, the classical rating on average increases by 0.259.

**X1990s2000s.minus.1960s1970s**: Holding other variables fixed, when the difference between X1990s2000s and a similar variable referring to 60's and 70's pop and rock increases by 1 unit, the classical rating on average increases by 0.166.

**PianoPlay**: Holding other variables fixed, when people's rating for piano playing increases by 1 unit, the classical rating on average increases by 0.207.

**Subject:Harmony**: Standard deviation is 0.6672 (variance=0.4451). This represents the part that personal biases vary with the type of Harmony.

**Subject:Instrument**: Standard deviation is 1.3032 (variance=1.6984). This represents the part that personal biases vary with the type of Instrument.

**Residual**: The estimate of the residual variance 2.5154, with standard deviation equal to 1.5860, represents the variability of individual classical ratings around the individual regression lines.

## Exercise 3

```
# check "Selfdeclare's" median
median(data2.2$Selfdeclare)
```

```
## [1] 2
```

```
# and boxplot (not shown)
# boxplot(data2.2$Selfdeclare)

# dichotomize "Selfdeclare"
data2.2$self[data2.2$Selfdeclare>2]=1
data2.2$self[data2.2$Selfdeclare<=2]=0
# check table(data2.2$self), 827 self=0, 714 self=1. indeed around half

attach(data2.2)
lmer3=update(lmer2c,.~.+data2.2$self)
#lmer3i=update(lmer3,.~.+data2.2$self:data2.2$Instrument)
#anova(lmer3,lmer3i)
# p-value=0.1128 not significant

lmer3h=update(lmer3,.~.+data2.2$self:data2.2$Harmony)
anova(lmer3,lmer3h)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmer3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
```

```
## lmer3:     (1 | Subject:Harmony) + X16.minus.17 + PachListen + ClsListen +
## lmer3:     X1990s2000s.minus.1960s1970s + PianoPlay + data2.2$self
## lmer3h: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer3h:     (1 | Subject:Harmony) + X16.minus.17 + PachListen + ClsListen +
## lmer3h:     X1990s2000s.minus.1960s1970s + PianoPlay + data2.2$self +
## lmer3h:     data2.2$self:data2.2$Harmony
##        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer3  17 6228.7 6319.4 -3097.3   6194.7
## lmer3h 20 6216.1 6322.9 -3088.0   6176.1 18.586      3   0.000333 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
### significant p-value, and significant difference between AIC and BIC
### decide to keep this interaction

#lmer3v=update(lmer3h,.~.+data2.2$self:data2.2$Voice)
#anova(lmer3v,lmer3h)
# p-value=0.6361 not significant

#lmer3x16=update(lmer3h,.~.+data2.2$self:data2.2$X16.minus.17)
#anova(lmer3x16,lmer3h)
# p-value=0.08183 not significant

#lmer3pl=update(lmer3h,.~.+data2.2$self:data2.2$PachListen)
#anova(lmer3pl,lmer3h)
# p-value=0.0591 not significant

#lmer3cl=update(lmer3h,.~.+data2.2$self:data2.2$ClsListen)
#anova(lmer3cl,lmer3h)
# p-value=0.1801 not significant

#lmer3x1990=update(lmer3h,.~.+data2.2$self:data2.2$X1990s2000s.minus.1960s1970s)
#anova(lmer3x1990,lmer3h)
# p-value=0.08381 not significant

lmer3pp=update(lmer3h,.~.+data2.2$self:data2.2$PianoPlay)
anova(lmer3pp,lmer3h)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
## lmer3h: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer3h:     (1 | Subject:Harmony) + X16.minus.17 + PachListen + ClsListen +
## lmer3h:     X1990s2000s.minus.1960s1970s + PianoPlay + data2.2$self +
## lmer3h:     data2.2$self:data2.2$Harmony
## lmer3pp: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer3pp:     (1 | Subject:Harmony) + X16.minus.17 + PachListen + ClsListen +
## lmer3pp:     X1990s2000s.minus.1960s1970s + PianoPlay + data2.2$self +
## lmer3pp:     data2.2$self:data2.2$Harmony + data2.2$self:data2.2$PianoPlay
##         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer3h  20 6216.1 6322.9 -3088.0   6176.1
## lmer3pp 21 6206.5 6318.6 -3082.2   6164.5 11.607      1  0.0006571 ***
```

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

7

```
### significant p-value, and significant difference between AIC and BIC
### decide to keep this interaction
detach(data2.2)
```

(The comparison results with insignificant p-value are not shown considering space)
Several models with different interactions are fit. Firstly we see that adding the interactions between the dichotomized variable "self" and "Harmony" makes the model (lmer3h) a better fit, supported by the significant p-value $< 0.001$ from the anova output. Then adding the interaction between the dichotomized variable "self" and "PianoPlay"" makes the new model (lmer3pp) even a better fit comparing to the previous model (lmer3h), supported by the significant p-value $< 0.05$.
So I decide to keep these two statistically significant interactions including "self" and "harmony", "self" and "PianoPlay" in the model.

can you interpret the interactions you found?

# Exercise 4

## (a).i influence in linear model

```
attach(ratings)
lm4a=lm(Popular~Instrument+Harmony+Voice)
summary(lm4a)
```

```
##
## Call:
## lm(formula = Popular ~ Instrument + Harmony + Voice)
##
## 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
## Multiple R-squared:  0.1901, Adjusted R-squared:  0.1878
## F-statistic: 83.32 on 7 and 2485 DF,  p-value: < 2.2e-16
```

```r
fit4a1=lm(Popular~Instrument+Harmony)
fit4a2=lm(Popular~Instrument+Voice)
fit4a3=lm(Popular~Harmony+Voice)
#anova(lm4a,fit4a1)
# insignificant p-value=0.2237
#anova(lm4a,fit4a2)
# insignificant p-value=0.1069
anova(lm4a,fit4a3)
```

```
## Analysis of Variance Table
##
## Model 1: Popular ~ Instrument + Harmony + Voice
## Model 2: Popular ~ Harmony + Voice
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1   2485 12656
## 2   2487 15580 -2   -2923.9 287.05 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the model summary, we see that except for one level of "Harmony":I-V-VI, only the coefficients for all "Instrument" are statistically significant, not "Harmony" and "Voice" for Popular rating. I also used anova analysis and found that p-value is only significant when comparing the full model with the "Harmony" and "Voice" only model, indicating categorical variable "Instrument" as a whole is influential. So it seems that "Instrument" has a statistically significant influence on Popular rating, but "Harmony" and "Voice" don't have. Since the three are design variables, they are kept in the model regardless of the influence.

### (a).ii repeated measures

```r
lmer4b2=lmer(Popular~Instrument+Harmony+Voice+(1|Subject))

lmer4b3.h=lmer(Popular~Instrument+Voice+(1|Subject))
lmer4b3.v=lmer(Popular~Instrument+Harmony+(1|Subject))
lmer4b3.i=lmer(Popular~Harmony+Voice+(1|Subject))
#AIC(lm4a,lmer4b2,lmer4b3.i,lmer4b3.v,lmer4b3.h)
#BIC(lm4a,lmer4b2,lmer4b3.i,lmer4b3.v,lmer4b3.h)
# lmer4b3.v  with smallest AIC 10447.40
# lmer4b3.h  with smallest BIC 10488.24
```

The model with personal biases seems fitting better than linear model in the previous (a).i, but again with personal biases included in the model, the two models (lmer4b3.v) and (lmer4b3.h) which exclude either "Voice" or "Harmony" seem to have favorable AIC and BIC. This result is not surprising since we found these two variables are not significant for Popular rating from previous part (a).i. But we keep them in the model.

### (a).iii varied personal biases

```r
lmer4c1=lmer(Popular~Instrument+Harmony+Voice+
               (1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice))
#AIC(lmer4c1,lmer4b2)
```

```r
#BIC(lmer4c1,lmer4b2)
# lmer4c1 with smaller AIC 10097.24 and smaller BIC 10167.09
# indicating three new random effects fit better
# than a single intercept random effect

lmer4c2.i=update(lmer4c1,.~. -Instrument)
lmer4c2.h=update(lmer4c1,.~. -Harmony)
lmer4c2.v=update(lmer4c1,.~. -Voice)

#AIC(lmer4c1,lmer4c2.i,lmer4c2.h,lmer4c2.v)
9 #BIC(lmer4c1,lmer4c2.i,lmer4c2.h,lmer4c2.v)
# lmer4c2.h  with smallest AIC 10089.39
# lmer4c2.h  with smallest BIC 10141.78
```

After we see that (from the above) three new random effects fit better than a single intercept random effect, again we want to know the influence of three experimental factors, and both AIC and BIC choses (lmer4c2.h). This model left out "Harmony", and this result is not surprising since we found "Harmony" is not significant for Popular rating from part (a).i.

## (a).iv. variance component summary

```r
library(arm)
```

```
## Loading required package: MASS
##
## arm (Version 1.8-6, built: 2015-7-7)
##
## Working directory is C:/Users/Chushan Chen/Desktop/763/final proj
```

```r
display(lmer4c1)
```

```
## lmer(formula = Popular ~ Instrument + Harmony + Voice + (1 |
##     Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice))
##                   coef.est coef.se
## (Intercept)        6.58     0.21
## Instrumentpiano   -0.95     0.25
## Instrumentstring  -2.61     0.25
## HarmonyI-V-IV     -0.03     0.14
## HarmonyI-V-VI     -0.27     0.14
## HarmonyIV-I-V     -0.19     0.14
## Voicepar3rd        0.16     0.08
## Voicepar5th        0.16     0.08
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.64
##  Subject:Voice      (Intercept) 0.18
##  Subject:Instrument (Intercept) 1.41
##  Residual                       1.58
## ---
```

```
## number of obs: 2493, groups: Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 210
## AIC = 10097.2, DIC = 10036.7
## deviance = 10055.0
```

```r
detach(ratings)
```

With the full model including random effects, the estimated variance for Subject:Harmony is 0.411 (sd=0.64), for Subject:Voice is 0.032 (sd=0.18), and for Subject:Instrument is 2.000 (sd=1.41). We see that the variance for Instrument is the largest, followed by Harmony, and Voice is the smallest, same as for Classical ratings. The estimated residual variance is 2.490 (sd=1.58), which is the largest comparing to the three estimated variance components, same as for Classical ratings.

## (b).i. search for new individual covariates

```r
attach(data2.2)
# refit the full model
lmer42=lmer(Popular~Instrument+Harmony+Voice+
              (1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Voice))
#lmer42.Selfdeclare=update(lmer42,.~.+Selfdeclare)
#anova(lmer42.Selfdeclare,lmer42)
# p-value=0.3853
#lmer42.OMSI=update(lmer42,.~.+OMSI)
#anova(lmer42.OMSI,lmer42)
# p-value=0.2156
#lmer42.X16.minus.17=update(lmer42,.~.+X16.minus.17)
#anova(lmer42.X16.minus.17,lmer42)
# p-value=0.2928
#lmer42.ConsInstr=update(lmer42,.~.+ConsInstr)
#anova(lmer42,lmer42.ConsInstr)
# p-value=0.5395
#lmer42.ConsNotes=update(lmer42,.~.+ConsNotes)
#anova(lmer42,lmer42.ConsNotes)
# p-value=0.1133
#lmer42.Instr.minus.Notes=update(lmer42,.~.+Instr.minus.Notes)
#anova(lmer42,lmer42.Instr.minus.Notes)
# p-value=0.1993
#lmer42.PachListen=update(lmer42,.~.+PachListen)
#anova(lmer42,lmer42.PachListen)
# p-value=0.1956
#lmer42.ClsListen=update(lmer42,.~.+ClsListen)
#anova(lmer42.ClsListen,lmer42)
# p-value=0.8149
#lmer42.KnowRob=update(lmer42,.~.+KnowRob)
#anova(lmer42,lmer42.KnowRob)
# p-value=0.1148
#lmer42.KnowAxis=update(lmer42,.~.+KnowAxis)
#anova(lmer42,lmer42.KnowAxis)
# p-value=0.2454
#lmer42.X1990s2000s=update(lmer42,.~.+ X1990s2000s)
#anova(lmer42,lmer42.X1990s2000s)
# p-value=0.7807
```

```r
#lmer42.X1990s2000s.minus.1960s1970s=update(lmer42,.~.+
#                                             X1990s2000s.minus.1960s1970s)
#anova(lmer42,lmer42.X1990s2000s.minus.1960s1970s)
# p-value=0.9766
#lmer42.CollegeMusic =update(lmer42,.~.+CollegeMusic)
#anova(lmer42.CollegeMusic,lmer42)
# p-value=0.4591
#lmer42.NoClass =update(lmer42,.~.+NoClass)
#anova(lmer42.NoClass,lmer42)
# p-value=0.4623
#lmer42.APTheory =update(lmer42,.~.+ APTheory)
#anova(lmer42.APTheory,lmer42)
# p-value= 0.7317
#lmer42.Composing =update(lmer42,.~.+ Composing)
#anova(lmer42.Composing,lmer42)
# p-value= 0.1715
#lmer42.PianoPlay =update(lmer42,.~.+ PianoPlay)
#anova(lmer42.PianoPlay,lmer42)
# p-value= 0.8435
#lmer42.GuitarPlay =update(lmer42,.~.+ GuitarPlay)
#anova(lmer42,lmer42.GuitarPlay)
# p-value= 0.1677
#lmer42.X1stInstr =update(lmer42,.~.+ X1stInstr)
#anova(lmer42,lmer42.X1stInstr)
# p-value=  0.1802
#lmer42.X2ndInstr =update(lmer42,.~.+ X2ndInstr)
#anova(lmer42,lmer42.X2ndInstr)
# p-value=  0.1677
```

Unfortunately, following the same procedure as in problem 2, no individual covariates are added to the model for popular ratings because none of the adding effect is significant according to the p-value from anova output. So we continue with our model (lmer42) including three experimental factors and three random effects.

## (b).ii. check change in the random effects

```r
# 3 options with 2 random effects
lmer4b.1=update(lmer42,.~.-(1 | Subject:Instrument))
lmer4b.2=update(lmer42,.~.-(1 | Subject:Harmony))
lmer4b.3=update(lmer42,.~.-(1 | Subject:Voice))

# 3 options with 1 random effect
lmer4b.4=update(lmer42,.~.-(1 | Subject:Instrument)
                 -(1 | Subject:Harmony))
lmer4b.5=update(lmer42,.~.-(1 | Subject:Instrument)
                 -(1 | Subject:Voice))
lmer4b.6=update(lmer42,.~.-(1 | Subject:Harmony)
                 -(1 | Subject:Voice))

AIC(lmer42,lmer4b.1,lmer4b.2,
    lmer4b.3,lmer4b.4,lmer4b.5,lmer4b.6)
```

```
##          df      AIC
```

```
## lmer42   12 6357.983
## lmer4b.1 11 6605.232
## lmer4b.2 11 6409.142
## lmer4b.3 11 6357.623
## lmer4b.4 10 6648.220
## lmer4b.5 10 6603.755
## lmer4b.6 10 6407.572
```

```r
BIC(lmer42,lmer4b.1,lmer4b.2,
    lmer4b.3,lmer4b.4,lmer4b.5,lmer4b.6)
```

```
##          df      BIC
## lmer42   12 6422.065
## lmer4b.1 11 6663.974
## lmer4b.2 11 6467.884
## lmer4b.3 11 6416.365
## lmer4b.4 10 6701.622
## lmer4b.5 10 6657.157
## lmer4b.6 10 6460.974
```

Several models with different random effects are fit. Models lmer4b.1, lmer4b.2, and lmer4b.3 each has 2 random effects of experimental variable. Models lmer4b.4, lmer4b.5, and lmer4b.6 each has only 1 random effect of experimental variable.

We see that AIC chose lmer4b.3 and lmer42 (due to their small difference in AIC), and BIC chose lmer4b.3. So I decided to keep model lmer4b.3, which also dropped the random effect (1 | Subject:Voice), since this model is preferred by both AIC and BIC.

### (b).iii. Question 2c. interpret the effect

```r
summary(lmer4b.3)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony)
##
## REML criterion at convergence: 6335.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4749 -0.5712  0.0125  0.5766  5.0825
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4445   0.6667
##  Subject:Instrument (Intercept) 1.8519   1.3608
##  Residual                       2.7326   1.6531
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
```

```
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)         6.8451     0.2599  26.333
## Instrumentpiano    -1.1483     0.3112  -3.690
## Instrumentstring   -3.0242     0.3110  -9.723
## HarmonyI-V-IV       0.0266     0.1867   0.142
## HarmonyI-V-VI      -0.2586     0.1868  -1.385
## HarmonyIV-I-V      -0.2519     0.1866  -1.350
## Voicepar3rd         0.1920     0.1032   1.861
## Voicepar5th         0.2346     0.1032   2.273
##
## Correlation of Fixed Effects:
##              (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
## Instrumntpn -0.598
## Instrmntstr -0.598  0.500
## HrmnyI-V-IV -0.359  0.000     0.000
## HrmnyI-V-VI -0.358  0.000     0.000      0.500
## HrmnyIV-I-V -0.359  0.000     0.000      0.500  0.500
## Voicepar3rd -0.199  0.000     0.000     -0.001 -0.001  0.001
## Voicepar5th -0.198  0.000     0.000     -0.001 -0.002 -0.001  0.500
```

**(Instrument)piano**: Holding other variables fixed, when the Instrument is piano, the popular rating on average decreases by 1.15, comparing to the rating when the Instrument is guitar.

**(Instrument)string**: Holding other variables fixed, when the Instrument is string quartet, the popular rating on average decreases by 3.02, comparing to the rating when the Instrument is guitar.

**(Harmony)I-V-IV**: Holding other variables fixed, when the Harmony is I-V-IV, the popular rating on average increases by 0.0266, comparing to the rating when Harmony is I-IV-V.

**(Harmony)I-V-VI**: Holding other variables fixed, when the Harmony is I-V-VI, the popular rating on
9 average decreases by 0.26, comparing to the rating when Harmony is I-IV-V.

**(Harmony)IV-I-V**: Holding other variables fixed, when the Harmony is IV-I-V, the popular rating on average decreases by 0.25, comparing to the rating when Harmony is I-IV-V.

**(Voice)par3rd**: Holding other variables fixed, when the Voice is par 3rd, the popular rating on average increases by 0.19, comparing to the rating when the Voice is contrary motion.

**(Voice)par5th**: Holding other variables fixed, when the Voice is par 5rd, the popular rating on average increases by 0.23, comparing to the rating when the Voice is contrary motion.

**Subject:Harmony**: Standard deviation is 0.6667 (variance=0.4445). This represents the part that personal biases vary with the type of Harmony.

**Subject:Instrument**: Standard deviation is 1.3608 (variance=1.8519). This represents the part that personal biases vary with the type of Instrument.

**Residual**: The estimate of the residual variance 2.7326, with standard deviation equal to 1.6531, represents the variability of individual popular ratings around the individual regression lines.

### (c)

```r
lmer4c=update(lmer4b.3,.~.+data2.2$self)

#lmer4c.i=update(lmer4c,.~.+data2.2$self:Instrument)
```

```r
#anova(lmer4c,lmer4c.i)
# p-value= 0.199 not significant

lmer4c.h=update(lmer4c,.~.+data2.2$self:Harmony)
anova(lmer4c,lmer4c.h)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: NULL
## Models:
9 ## lmer4c: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer4c:     (1 | Subject:Harmony) + data2.2$self
## lmer4c.h: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## lmer4c.h:     (1 | Subject:Harmony) + data2.2$self + Harmony:data2.2$self
##          Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## lmer4c   12 6344.5 6408.6 -3160.3   6320.5
## lmer4c.h 15 6342.4 6422.6 -3156.2   6312.4 8.0992      3    0.04401 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#lmer4c.v=update(lmer4c.h,.~.+data2.2$self:Voice)
#anova(lmer4c.v,lmer4c.h)
# p-value=0.3244 not significant
```

Models with different interactions are fit. We see that adding the interactions between the dichotomized variable "self" and "Harmony" makes the model (lmer4c.h) a better fit, supported by the significant p-value $< 0.05$ from the anova output. So I decide to keep this statistically significant interaction between "self" and "harmony" in the model.

## Exercise 5

Please see the next page.

What Factors Affect Music's Ratings as Classical or Popular?

Chushan Chen

## Introduction

Dr. Jimenez was interested in the influence of instrument, harmonic motion, and voice leading on listeners' identification of music as "classical" or "Popular". 36 musical stimuli based on those three experimental factors were presented to 70 listeners. Music ratings and other 21 variables were collected.

## Methods

The large amount of NAs in first and second instruments of observations were imputed to be 0, assuming the subjects don't play musical instruments at all. Simple linear and hierarchical models were fitted to explore the factors' effects, with model fit and variable significance tests.

## Results

For Classical ratings, whether before or after considering personal biases toward music ratings, the influence of the three main experimental factors including Instrument, Harmony and Voice is all significant. After taking into account personal biases, I found that the model with varied personal biases is better than unvaried personal biases, which is a standard repeated measures model. In the final model, personal biases vary with the type of instrument and harmony, but not voice. So for example people vary in the degree to which they are inclined to call music played by a string quartet or with I-V-vi motion "Classical".

Other individual covariates which improve the model fit include auxiliary measure of
10 listener's ability to distingue classical vs. popular music (X16.minus.17), familiarity with Pachelbel's Canon (PachListen), frequency of listening to classical music (ClsListen), difference in frequency of listening to pop/rock from 90's/2000's and 60's/70's (X1990s2000s.minus.1960s1970s), proficiency in piano (PianoPlay), and self-identity as musicians or not (dichotomized Selfdeclare). The model also suggested that there are interactions between self-identify and harmony, as well as between self-identity and proficiency in piano.

For Popular ratings, whether before or after considering personal biases toward music ratings, the influence of Instrument is always significant, but not Harmony and Voice. I also found that the model with varied personal biases is better than unvaried personal biases. In the final model, personal biases vary with the type of instrument and harmony, but not voice, also same as Classical ratings. Other individual covariates which improve the model fit include only self-identity and interaction term between self-identity and harmony.

Overall, the researchers' main hypotheses on the effects of instruments, one particular harmonic progression I-V-vi, and contrary motion are all supported based on my analysis. Firstly, Instrument is a significant factor in both Classical and Popular ratings. Secondly, holding other variables fixed, comparing to the base level I-IV-V, when the harmony is I-V-vi, on average Popular rating decreases and Classical rating increases. This effect is the same for the contrary motion, comparing to other voice leadings.