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

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

3 9/9

4 a 9/9
b 7/9
c 9/9

5 10/10

Total 98/100

Homework Five

Zongge Liu

1 Problem One

(a)

For this part, I compare 4 models: one with all these 3 factors, and the other 3 models with one specific factor missing. The fitting code is as following:

```
##
## arm (Version 1.8-6, built:  2015-7-7)
##
## Working directory is /Users/liuzongge1992/Desktop/course/33763-Hierachical Model/hw05
```

```
fit.lm.all <- lm(Classical ~ Instrument + Harmony + Voice)
fit.lm.nI <- lm(Classical ~ Harmony + Voice)
fit.lm.nH <- lm(Classical ~ Instrument  + Voice)
fit.lm.nV <- lm(Classical ~ Instrument + Harmony )
AIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.all)

##            df      AIC
## fit.lm.nV   7 11242.69
## fit.lm.nH   6 11275.96
## fit.lm.nI   7 11908.94
## fit.lm.all  9 11230.45

BIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.all)

##            df      BIC
## fit.lm.nV   7 11283.43
## fit.lm.nH   6 11310.89
## fit.lm.nI   7 11949.69
## fit.lm.all  9 11282.84

anova(fit.lm.all,fit.lm.nI)

## 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

anova(fit.lm.all,fit.lm.nH)
```

```
## 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
```

```
anova(fit.lm.all,fit.lm.nV)
```

```
## 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
```

9 From the analysis of variance table, the Instrument, Harmony and Voice are all necessary factors. The p-value for the three F-test are all less than 0.05, which is statistically significant.From the fitting results for different models under AIC and BIC, the models that onclude all 3 factors is clearly the best.

Therefore I would conclude these 3 factors can all improve the predictions, with Instrument>Harmony>Voice considering the reduction of AIC and BIC caused by the factors.

(b-i)

Following the lecture notes, the hierachical linear model can be written as

$$y_i = \beta_0 + \beta_{I[i]} + \beta_{H[i]} + \beta_{V[i]} + \theta_{j[i]} + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

$$\theta_j = \theta_0 + \eta_j, \eta_j \overset{iid}{\sim} N(0, \tau^2)$$

$$for\ i = 1, 2, , 2493, and\ j = 1, 2, , 70$$

where $\beta_{I[i]}, \beta_{H[i]}, \beta_{V[i]}$ are the fixed coefficients for the instrument, harmony and voice, β_0 is the fixed intercept and θ_j is the random intercept for different subjects.

(b-ii)

I would argue the random intercept is necessary, from the perspective of AIC/BIC and RLRsim. Firstly, check the AIC/BIC,

```
fit.lmer.all <- lmer(Classical ~ Instrument + Harmony + Voice + (1|Subject), REML=F)
AIC(fit.lm.all,fit.lmer.all)
```

```
##              df      AIC
## fit.lm.all    9 11230.45
## fit.lmer.all 10 10468.86
```

```
BIC(fit.lm.all,fit.lmer.all)
```

```
##              df      BIC
## fit.lm.all    9 11282.84
## fit.lmer.all 10 10527.07
```

From the results, you can see the AIC and BIC are getting significantly better after adding the random intercept.

Secondly, check the RLRsim,

```
exactRLRT(fit.lmer.all)

## 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
```

From the p-value which is smaller than 2.2e-16, we know we should reject the null-hypothesis: the linear model, and prefer to use the random intercept model.

(b-iii)

Again, I compare 4 models with random intercept: one with all these 3 factors, and the other 3 models with one specific factor missing.

```
fit.lmer.nI <- lmer(Classical ~ Harmony + Voice + (1|Subject), REML=F)
fit.lmer.nH <- lmer(Classical ~ Instrument + Voice + (1|Subject), REML=F)
fit.lmer.nV <- lmer(Classical ~ Instrument + Harmony + (1|Subject), REML=F)
AIC(fit.lmer.nV,fit.lmer.nH,fit.lmer.nI,fit.lmer.all)

##             df      AIC
## fit.lmer.nV  8 10489.10
## fit.lmer.nH  7 10538.79
## fit.lmer.nI  8 11408.45
## fit.lmer.all 10 10468.86

BIC(fit.lmer.nV,fit.lmer.nH,fit.lmer.nI,fit.lmer.all)

##             df      BIC
## fit.lmer.nV  8 10535.67
## fit.lmer.nH  7 10579.54
## fit.lmer.nI  8 11455.02
## fit.lmer.all 10 10527.07

anova(fit.lmer.all,fit.lmer.nI)

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

anova(fit.lmer.all,fit.lmer.nH)
```

```
## Data: NULL
## Models:
## fit.lmer.nH: Classical ~ Instrument + Voice + (1 | Subject)
## fit.lmer.all: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
##              Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.lmer.nH   7 10539 10580 -5262.4    10525
## fit.lmer.all 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(fit.lmer.all,fit.lmer.nV)
```

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

From the analysis of variance table, the Instrument, Harmony and Voice are all necessary factors. The
p-value for the three F-test are all less than 0.05, which is statistically significant. From the fitting results for
9 different models under AIC and BIC, quite the same with the previous discussion, the models that onclude
all 3 factors is clearly the best.

Therefore I would conclude these 3 factors can all improve the predictions, with Instrument>Harmony>Voice considering the reduction of AIC and BIC caused by the factors.

(c-i)

Construct a new model with all the random-intercepts required by the problem,

```r
fit.lmer.2.all <- lmer(Classical ~ Instrument + Harmony + Voice + (1|Subject:Instrument)+
                         (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
AIC(fit.lm.all,fit.lmer.all,fit.lmer.2.all)
```

```
##                df      AIC
## fit.lm.all      9 11230.45
## fit.lmer.all   10 10468.86
## fit.lmer.2.all 12 10057.53
```

```r
BIC(fit.lm.all,fit.lmer.all,fit.lmer.2.all)
```

```
##                df      BIC
## fit.lm.all      9 11282.84
## fit.lmer.all   10 10527.07
## fit.lmer.2.all 12 10127.38
```

Again, from the result, the new model indeed reduce AIC and BIC significantly. It's indeed better than the model in problem in (1a) and (1b).

(c-ii)

```r
display(fit.lmer.2.all)
```

```
## lmer(formula = Classical ~ Instrument + Harmony + Voice + (1 |
##     Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice),
```

```
##     REML = F)
##                   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
```

As you can see, the 3 main factors indeed have a strong influence: the estimates vary significantly with different intrument, harmony and voice (with strong to weak: Instrument>Harmony>Voice), with a relatively small error term. This agrees with the influence Instrument>Harmony>Voice.

Doing the same thing as the previous question, comparing models by ANOVA,

```
fit.lmer.2.nI <- lmer(Classical ~  Harmony + Voice + (1|Subject:Instrument)+
                         (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
fit.lmer.2.nH <- lmer(Classical ~ Instrument + Voice + (1|Subject:Instrument)+
                         (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
fit.lmer.2.nV <- lmer(Classical ~ Instrument + Harmony + (1|Subject:Instrument)+
                         (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
anova(fit.lmer.2.all,fit.lmer.2.nI)
```

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

```
anova(fit.lmer.2.all,fit.lmer.2.nH)
```

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

```
## fit.lmer.2.nH: Classical ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
## fit.lmer.2.nH:     Subject:Harmony) + (1 | Subject:Voice)
## fit.lmer.2.all: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
## fit.lmer.2.all:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.lmer.2.nH   9 10090 10143 -5036.3    10072
## fit.lmer.2.all 12 10058 10127 -5016.8    10034 39.013      3  1.724e-08
##
## fit.lmer.2.nH
## fit.lmer.2.all ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(fit.lmer.2.all,fit.lmer.2.nV)
```

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

From the analysis of variance table, the Instrument, Harmony and Voice are all necessary factors. The p-value for the three F-test are all less than 0.05, which is statistically significant.

Checking the sizes of the three estimated variance components,

```
summary(fit.lmer.2.all)$varcor
```

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

The Subject:Instrument has the biggest variance and Subject: Voice has the smallest variance, which again indicates that the instrument has the most significant influence in the classical rating.

The variace of the residual is larger than all three terms, Subject:Harmony, Subject:Voice and Subject:Instrument, yet they are basically at the same scale. Both fixed effects and random effects perform well.Also notice that variation are small between individuals

(c-iii)

$$y_i = \alpha^I_{j[i]I[i]} + \alpha^H_{j[i]H[i]} + \alpha^V_{j[i]V[i]} + \beta_{I[i]} + \beta_{H[i]} + \beta_{V[i]} + \epsilon_i$$

$$\alpha^I_{j[i]I[i]} = \alpha^I_0 + \eta^I_{jk}$$

$$\alpha^H_{j[i]H[i]} = \alpha^H_0 + \eta^H_{jk}$$

great! nice expression of the model

$$\alpha^V_{j[i]V[i]} = \alpha^V_0 + \eta^V_{jk}$$

$$\epsilon_i \sim N(0, \sigma^2)$$
$$\eta^I_{jk} \sim N(0, \tau^2_{\eta_I})$$
$$\eta^H_{jk} \sim N(0, \tau^2_{\eta_H})$$
$$\eta^V_{jk} \sim N(0, \tau^2_{\eta_V})$$
$$for\ i = 1, 2, , 2493, and\ j = 1, 2, , 70$$

$\beta_{I[i]}, \beta_{H[i]}, \beta_{V[i]}$ are the fixed coefficients for the instrument, harmony and voice. $\alpha^I_{j[i]I[i]}, \alpha^H_{j[i]H[i]}, \alpha^V_{j[i]V[i]}$ stands for the random intercept of certain individual and certain Instrument, Harmony and Voice.

2 Problem Two

(a)

First, I convert the type of the variable CollegeMusic and APTheory (from integer to factor). Next, I find out there's a lot NAs in X1stInstr and X2ndInstr. In addtion, I move the X1990s2000s.minus.1960s1970s because the colinearity. From the values and meanings, I guess this is caused by the fact that people who doesn't know the intrument at all will tend to neglect this question, thus generaing lots of NAs. I reset these NAs as 0. ok. another option might be to just ignore these variables.

I use the lmer convenience package to perform the backward selection using AIC, and the key code is as following:

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

fitbs <- bfFixefLMER_F.fnc(lmertest, method='AIC')
```

You can check the following results

```
summary(fitbs)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
##     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
##     (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice)
##    Data: music.data
##
## REML criterion at convergence: 6228.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3151 -0.5585 -0.0017  0.5363  3.3133
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.44865  0.6698
##  Subject:Voice      (Intercept) 0.04856  0.2204
##  Subject:Instrument (Intercept) 1.70546  1.3059
##  Residual                       2.47957  1.5747
## Number of obs: 1541, groups:
```

```
## Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)       2.115307   0.986465   2.144
## HarmonyI-V-IV    -0.004452   0.183686  -0.024
## HarmonyI-V-VI     0.850076   0.183741   4.626
## HarmonyIV-I-V     0.059833   0.183624   0.326
## Instrumentpiano   1.649108   0.298412   5.526
## Instrumentstring  3.588496   0.298237  12.032
## Voicepar3rd      -0.403165   0.109181  -3.693
## Voicepar5th      -0.299892   0.109181  -2.747
## ConsNotes        -0.184582   0.080407  -2.296
## PachListen        0.199299   0.176825   1.127
## KnowRob           0.085961   0.087464   0.983
## KnowAxis          0.080629   0.070560   1.143
## X1990s2000s       0.188702   0.091422   2.064
## NoClass          -0.153935   0.106913  -1.440
## APTheory1         0.631875   0.364943   1.731
## PianoPlay         0.308238   0.088183   3.495
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r Vcpr5t
## HrmnyI-V-IV -0.093
## HrmnyI-V-VI -0.093  0.500
## HrmnyIV-I-V -0.093  0.500  0.500
## Instrumntpn -0.151  0.000  0.000  0.000
## Instrmntstr -0.151  0.000  0.000  0.000  0.500
## Voicepar3rd -0.055 -0.001 -0.001  0.001  0.000     0.000
## Voicepar5th -0.055 -0.001 -0.002 -0.001  0.000     0.000     0.500
## ConsNotes   -0.278  0.000 -0.001  0.000 -0.001     0.000     0.000  0.000
## PachListen  -0.862  0.000  0.000  0.000  0.000     0.000     0.000  0.000
## KnowRob      0.161  0.001  0.001  0.000  0.002     0.000     0.000  0.000
## KnowAxis    -0.169 -0.001 -0.001  0.000 -0.001     0.000     0.000  0.000
## X1990s2000s -0.408  0.000  0.000  0.000  0.001     0.000     0.000  0.000
## NoClass     -0.077  0.000  0.000  0.000  0.000     0.000     0.000  0.000
## APTheory1    0.135  0.001  0.000  0.000  0.001     0.000     0.000  0.000
## PianoPlay    0.045  0.000  0.000  0.000  0.000     0.000     0.000  0.000
##             CnsNts PchLst KnowRb KnwAxs X19902 NoClss APThr1
## HrmnyI-V-IV
## HrmnyI-V-VI
## HrmnyIV-I-V
## Instrumntpn
## Instrmntstr
## Voicepar3rd
## Voicepar5th
## ConsNotes
## PachListen   0.159
## KnowRob     -0.364 -0.165
## KnowAxis     0.313  0.057 -0.460
## X1990s2000s -0.120  0.051  0.061 -0.024
## NoClass      0.090 -0.032 -0.012  0.068  0.058
## APTheory1   -0.093 -0.145 -0.119  0.053 -0.060 -0.268
```

```
## PianoPlay   -0.271 -0.100  0.071 -0.052  0.095 -0.200 -0.239
```

You can compare the AIC and BIC's for the full model and the varaible-selected model. The decrease is significant in AIC/BIC criterion.

```
AIC(lmertest, fitbs)
```

```
##          df      AIC
## lmertest 30 6300.592
## fitbs    20 6268.579
```

```
BIC(lmertest,fitbs)
```

9

```
##          df      BIC
## lmertest 30 6460.798
## fitbs    20 6375.383
```

(b) Now create three models with one random intercept missing.

First, compare the AIC and BIC

```
AIC(lmertest, lmertest.nSI, lmertest.nSH, lmertest.nSV)
```

```
##              df      AIC
## lmertest     30 6300.592
## lmertest.nSI 19 6610.479
## lmertest.nSH 19 6330.534
## lmertest.nSV 19 6268.359
```

```
BIC(lmertest, lmertest.nSI, lmertest.nSH, lmertest.nSV)
```

```
##              df      BIC
## lmertest     30 6460.798
## lmertest.nSI 19 6711.943
## lmertest.nSH 19 6431.998
## lmertest.nSV 19 6369.823
```

From the above results, both AIC and BIC perfers a model without Voice term, which is surprising. Although the difference is small, it's stil highly preferable to use a simple model according to Occam's razor.

Then running the Restricted Likelihood Ratio Tests,

```
exactRLRT(lmertest.nSI0, mA = fitbs , m0 = lmertest.nSI)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 343.9, p-value < 2.2e-16
```

```
exactRLRT(lmertest.nSH0, mA = fitbs , m0 = lmertest.nSH)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
```

```
##
## data:
## RLRT = 63.955, p-value < 2.2e-16
```

```
exactRLRT(lmertest.nSV0, mA = fitbs , m0 = lmertest.nSV)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 1.7802, p-value = 0.0864
```

9 From the results, the p-value is really small for both suject:instrument and subject:harmony, yet subject:voice is larger p-value=0.0876 in this case, which means it's not statistically significant (p-value should be less than 0.05). Again it's an evidence that we should use the model without Subject:Voice term.

(c)

Please check the table for the best model

```
summary(lmertest.nSV)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
##     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
##     (1 | Subject:Instrument) + (1 | Subject:Harmony)
##    Data: music.data
##
## REML criterion at convergence: 6230.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3484 -0.5565  0.0137  0.5403  3.3947
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4466   0.6683
##  Subject:Instrument (Intercept) 1.7270   1.3142
##  Residual                       2.5154   1.5860
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)       2.115044   0.981092   2.156
## HarmonyI-V-IV    -0.004526   0.183939  -0.025
## HarmonyI-V-VI     0.850392   0.183992   4.622
## HarmonyIV-I-V     0.060229   0.183875   0.328
## Instrumentpiano   1.649137   0.300324   5.491
## Instrumentstring  3.588466   0.300147  11.956
## Voicepar3rd      -0.402680   0.098995  -4.068
## Voicepar5th      -0.299982   0.098995  -3.030
## ConsNotes        -0.184602   0.079961  -2.309
```

```
## PachListen        0.199297   0.175842   1.133
## KnowRob           0.085996   0.086982   0.989
## KnowAxis          0.080607   0.070169   1.149
## X1990s2000s       0.188716   0.090914   2.076
## NoClass          -0.153948   0.106319  -1.448
## APTheory1         0.631952   0.362921   1.741
## PianoPlay         0.308236   0.087693   3.515
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r Vcpr5t
## HrmnyI-V-IV -0.094
## HrmnyI-V-VI -0.094  0.500
## HrmnyIV-I-V -0.094  0.500  0.500
## Instrumntpn -0.153  0.000  0.000  0.000
## Instrmntstr -0.153  0.000  0.000  0.000  0.500
## Voicepar3rd -0.050 -0.001 -0.001  0.001  0.000     0.000
## Voicepar5th -0.050 -0.001 -0.002 -0.001  0.000     0.000     0.500
## ConsNotes   -0.278  0.000 -0.001  0.000 -0.001     0.000     0.000  0.000
## PachListen  -0.862  0.000  0.000  0.000  0.000     0.000     0.000  0.000
## KnowRob      0.161  0.001  0.001  0.000  0.002     0.000     0.000  0.000
## KnowAxis    -0.169 -0.001 -0.001  0.000 -0.001     0.000     0.000  0.000
## X1990s2000s -0.408  0.000  0.000  0.000  0.001     0.000     0.000  0.000
## NoClass     -0.077  0.000  0.000  0.000  0.000     0.000     0.000  0.000
## APTheory1    0.135  0.001  0.001  0.000  0.001     0.000     0.000  0.000
## PianoPlay    0.045  0.000  0.000  0.000  0.000     0.000     0.000  0.000
##             CnsNts PchLst KnowRb KnwAxs X19902 NoClss APThr1
## HrmnyI-V-IV
## HrmnyI-V-VI
## HrmnyIV-I-V
## Instrumntpn
## Instrmntstr
## Voicepar3rd
## Voicepar5th
## ConsNotes
## PachListen   0.159
## KnowRob     -0.364 -0.165
## KnowAxis     0.313  0.057 -0.460
## X1990s2000s -0.120  0.051  0.061 -0.024
## NoClass      0.090 -0.032 -0.012  0.068  0.058
## APTheory1   -0.093 -0.145 -0.119  0.053 -0.060 -0.268
## PianoPlay   -0.271 -0.100  0.071 -0.052  0.095 -0.200 -0.239
```

Let's discuss the cases when we changes one variable while holding others the same. For the main effects, comparing to guitar, holding all other variables constant, piano will increases the classical rating by 1.6491; string will increase the classical rating by 3.5885.compared to Harmony I-VI-V, Harmony I-V-IV will decrease the classical rating by 0.00452, Harmony I-V-VI will increase the classical rating by 0.850076; Harnomy IV-I-V will increases the classical rating by 0.0598. Comparing to contrary, paralell 3rd will decrease classical the rating by 0.403165; paralell 5th will decrease the classical rating by 0.2999. For the variables I introduced, from the summary, it's obvious that PachListen, KnowRob, KnowAxis, APTheory1, PianoPlay and X1990s2000s will have a positive effect on the classical ratings, while the ConsNotes and NoClass will have a negative effect on the classical ratings.

If PachListen increase by one, classical rating will increase by 0.1993; If KnowRob increase by one, classical rating will increase by 0.0860; If KnowAxis increase by one, classical rating will increase by 0.0806; If APTheory1 increase by one, classical rating will increase by 0.6320; If PianoPlay increase by one, classical

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rating will increase by 0.3082; If X1990s2000s increase by one, classical rating will increase by 0.1887

If ConsNotes increase by one, classical rating will decrease by 0.1846; If NoClass increase by one, classical rating will decrease by 0.1539.

3 Problem 3

First I need to find one way to devide the data so that half of them will be musician and half will not.

```
summary(music.data$Selfdeclare)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   1.000   2.000   2.000   2.443   3.000   6.000
```

```
hist(music.data$Selfdeclare)
```

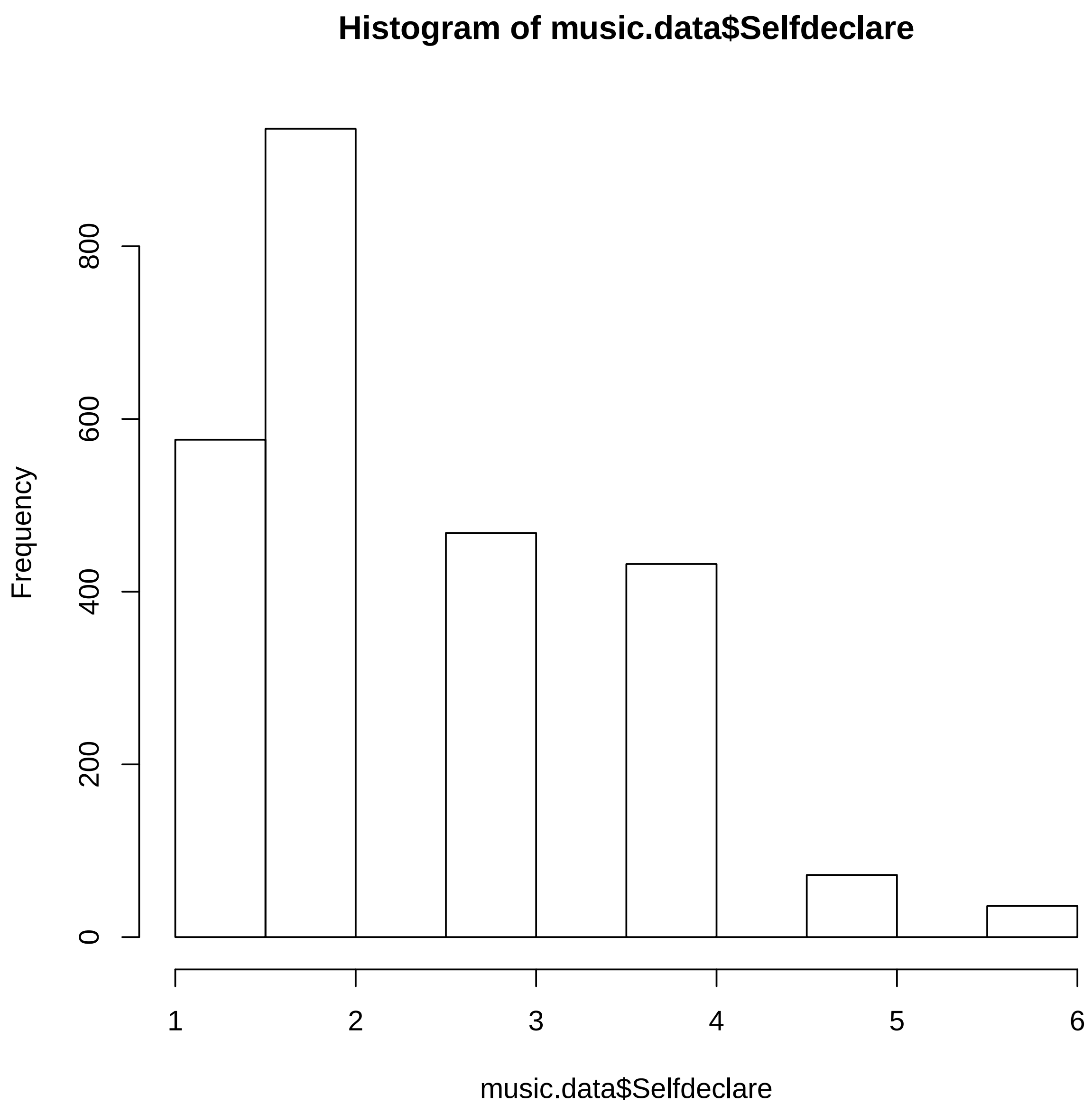

Figure 1: Histogram for self-declare

According to the statistic and the histogram Fig. 1, I would define 1/2 as nonmusician, and 3/4/5/6 as musician. Using the best model identified in the previous part, with the interaction term adding into it, we have

```
inds.myes <- music.data$Selfdeclare>2
music.data$dm <- inds.myes
lmerdm_full<-lmer(Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
                    KnowRob + KnowAxis+ X1990s2000s + NoClass + APTheory + PianoPlay
          + (1 | Subject:Instrument) + (1 | Subject:Harmony) +dm:Harmony + dm:Instrument + dm:Voice +
  dm:OMSI + dm:X16.minus.17 + dm:ConsInstr +dm:ConsNotes + dm:PachListen + dm:ClsListen + dm:KnowRob +
```

need a main effect for dm also

```
  dm:KnowAxis + dm:X1990s2000s + dm:CollegeMusic + dm:NoClass + dm:APTheory + dm:Composing +
  dm:PianoPlay +  dm:GuitarPlay + dm:X1stInstr +dm:X2ndInstr, data = music.data)
```

Perform a backward selection using AIC,

```
fitdm <- bfFixefLMER_F.fnc(lmerdm_full, method='AIC')
```

You can check the following results

```
summary(fitdm)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + ConsNotes + PachListen +
##     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + PianoPlay +
##     (1 | Subject:Instrument) + (1 | Subject:Harmony) + Harmony:dm +
##     dm:X16.minus.17 + PianoPlay:dm
##    Data: music.data
##
## REML criterion at convergence: 6202.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2538 -0.5651  0.0159  0.5259  3.5135
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.3499   0.5915
##  Subject:Instrument (Intercept) 1.5181   1.2321
##  Residual                       2.5167   1.5864
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
## Fixed effects:
##                         Estimate Std. Error t value
## (Intercept)             2.129696   0.974826   2.185
## HarmonyI-V-IV           0.009662   0.233966   0.041
## HarmonyI-V-VI           0.266841   0.234109   1.140
## HarmonyIV-I-V           0.004831   0.233966   0.021
## Instrumentpiano         1.649308   0.283694   5.814
## Instrumentstring        3.588690   0.283509  12.658
## Voicepar3rd            -0.402744   0.099020  -4.067
## Voicepar5th            -0.299988   0.099020  -3.030
## ConsNotes              -0.239786   0.082801  -2.896
## PachListen              0.350269   0.168699   2.076
## KnowRob                 0.088156   0.083151   1.060
## KnowAxis                0.029564   0.071196   0.415
## X1990s2000s             0.066637   0.101191   0.659
## NoClass                -0.077304   0.104248  -0.742
## APTheory1               0.415345   0.347568   1.195
## PianoPlay               0.736197   0.158665   4.640
## HarmonyI-IV-V:dmTRUE  0.621586   0.439453   1.414
## HarmonyI-V-IV:dmTRUE  0.591305   0.439526   1.345
## HarmonyI-V-VI:dmTRUE  1.876682   0.439568   4.269
```

```
## HarmonyIV-I-V:dmTRUE  0.740086   0.439453   1.684
## dmFALSE:X16.minus.17 -0.076594   0.066034  -1.160
## dmTRUE:X16.minus.17  -0.239328   0.078561  -3.046
## PianoPlay:dmTRUE     -0.573821   0.184004  -3.119

##
## Correlation matrix not shown by default, as p = 23 > 20.
## Use print(x, correlation=TRUE)  or
## vcov(x) if you need it
```

`9 You can see Harmony:dmTRUE and PianoPlay:dmTURE survive in the final model, which clearly indicates that this self-identification as musician will introduce more weights on harmony and PianoPlay. The assumption is confirmed.

Finally, compare the AIC and BIC

```
AIC(lmerdm_full,fitdm)

##             df      AIC
## lmerdm_full 53 6300.505
## fitdm       26 6254.631

BIC(lmerdm_full,fitdm)

##             df      BIC
## lmerdm_full 53 6583.535
## fitdm       26 6393.476
```

4 Problem 4

(a)

Now fit the following 4 linear model again, compare the AIC and BIC,

```
fit.lm.all <- lm(Popular ~ Instrument + Harmony + Voice)
fit.lm.nI <- lm(Popular ~ Harmony + Voice)
fit.lm.nH <- lm(Popular ~ Instrument  + Voice)
fit.lm.nV <- lm(Popular ~ Instrument + Harmony )

AIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.all)

##            df      AIC
## fit.lm.nV   7 11142.15
## fit.lm.nH   6 11143.26
## fit.lm.nI   7 11657.31
## fit.lm.all  9 11143.15

BIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.all)

##            df      BIC
## fit.lm.nV   7 11182.90
## fit.lm.nH   6 11178.19
## fit.lm.nI   7 11698.06
## fit.lm.all  9 11195.54

summary(fit.lm.all)
```

```
##
## 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
##   (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
```

From the above results, it seems that the model without Voice and the model without Harmony will have a sightly better performance in AIC/BIC to predict popular rating, this indicate these 2 factors may not have too much power in makeing prediction. Meanwhile, The influence of the Instrument is quite obvious: the AIC/BIC decreases by 500 when we include it in the model. To make our answer complete, compare a new model with just the instrument to other models again,

```
fit.lm.nHV <- lm(Popular ~ Instrument)
AIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.nHV,fit.lm.all)

##            df      AIC
## fit.lm.nV   7 11142.15
## fit.lm.nH   6 11143.26
## fit.lm.nI   7 11657.31
## fit.lm.nHV  4 11142.27
## fit.lm.all  9 11143.15

BIC(fit.lm.nV,fit.lm.nH,fit.lm.nI,fit.lm.nHV,fit.lm.all)

##            df      BIC
## fit.lm.nV   7 11182.90
## fit.lm.nH   6 11178.19
## fit.lm.nI   7 11698.06
## fit.lm.nHV  4 11165.55
## fit.lm.all  9 11195.54
```

Finally let's do the anova again,

```
anova(fit.lm.all, fit.lm.nV)

## Analysis of Variance Table
##
## Model 1: Popular ~ Instrument + Harmony + Voice
## Model 2: Popular ~ Instrument + Harmony
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1   2485 12656
## 2   2487 12672 -2   -15.263 1.4984 0.2237

anova(fit.lm.all, fit.lm.nH)

## Analysis of Variance Table
##
## Model 1: Popular ~ Instrument + Harmony + Voice
## Model 2: Popular ~ Instrument + Voice
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1   2485 12656
## 2   2488 12688 -3   -31.092 2.0349 0.1069

anova(fit.lm.all, fit.lm.nI)

## 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
```

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Only the intrument has a p-value that is less than 0.05, which is the only important factor to need to be considered amog 3 key factors.

In conclusion, you can see a model with the instrument will be just enough.

(b)

Starting from the model in (a), first consider the random effect from the subject,

but we should still include H, V, I, because they are exper design factors

```
fit.lmer.nI <- lmer(Popular ~ Harmony + Voice + (1|Subject), REML=F)
fit.lmer.nH <- lmer(Popular ~ Instrument + Voice + (1|Subject), REML=F)
fit.lmer.nHV <- lmer(Popular ~ Instrument  + (1|Subject), REML=F)
fit.lmer.nV <- lmer(Popular ~ Instrument + Harmony + (1|Subject), REML=F)
AIC(fit.lmer.nV,fit.lmer.nH,fit.lmer.nI,fit.lmer.nHV,fit.lmer.all)
BIC(fit.lmer.nV,fit.lmer.nH,fit.lmer.nI,fit.lmer.nHV,fit.lmer.all)
```

next consider the random effect from the subject combine with the 3 key factors,

```
fit.lmer.2.nHV <- lmer(Popular ~ Instrument + (1|Subject:Instrument)+
                         (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)

fit.lmer.2.nI <- lmer(Popular ~ Harmony + Voice + (1|Subject:Instrument)+
                        (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
fit.lmer.2.nH <- lmer(Popular ~ Instrument + Voice + (1|Subject:Instrument)+
                        (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
fit.lmer.2.nV <- lmer(Popular ~ Instrument + Harmony + (1|Subject:Instrument)+
```

```
                        (1|Subject:Harmony)+(1|Subject:Voice) , REML=F)
```

I find out fit.lmer.2.nHV is the best model. After this, I perform a backward selection

I use the lmer convenience package to perform the backward selection using AIC, and the key code is as following:

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

fitbs <- bfFixefLMER_F.fnc(lmertest, method='AIC')
```

Checking this final model,

```
summary(fitbs)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
##     X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice)
##    Data: music.data
##
## REML criterion at convergence: 6342.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.5796 -0.5615  0.0033  0.5611  5.0590
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.45261  0.6728
##  Subject:Voice      (Intercept) 0.06257  0.2501
##  Subject:Instrument (Intercept) 1.78618  1.3365
##  Residual                       2.69692  1.6422
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)        7.49926    1.00136   7.489
## Instrumentpiano   -1.14827    0.30603  -3.752
## Instrumentstring  -3.02445    0.30585  -9.889
## ConsNotes          0.09936    0.07934   1.252
## PachListen        -0.25424    0.18032  -1.410
## KnowRob            0.07241    0.08942   0.810
## KnowAxis           0.07219    0.07222   1.000
## X1990s2000s        0.01391    0.09327   0.149
## NoClass            0.09633    0.10736   0.897
## APTheory1         -0.03344    0.36320  -0.092
##
## Correlation of Fixed Effects:
```

```
##              (Intr) Instrmntp Instrmnts CnsNts PchLst KnowRb KnwAxs X19902
## Instrumntpn -0.152
## Instrmntstr -0.153  0.500
## ConsNotes   -0.279 -0.001     0.000
## PachListen  -0.870  0.000     0.000     0.138
## KnowRob      0.159  0.002     0.000    -0.359 -0.159
## KnowAxis    -0.169 -0.002     0.000     0.311  0.052 -0.458
## X1990s2000s -0.418  0.001     0.000    -0.098  0.061  0.055 -0.019
## NoClass     -0.070 -0.001     0.000     0.038 -0.053  0.002  0.059  0.079
## APTheory1    0.151  0.001     0.000    -0.169 -0.175 -0.105  0.042 -0.038
##             NoClss
## Instrumntpn
## Instrmntstr
## ConsNotes
## PachListen
## KnowRob
## KnowAxis
## X1990s2000s
## NoClass
## APTheory1   -0.331
```

Check the random intercept again,

```
lmertest.nSI <- update(fitbs, .~.-(1|Subject:Instrument))
lmertest.nSH <- update(fitbs, .~.-(1|Subject:Harmony))
lmertest.nSV <- update(fitbs, .~.-(1|Subject:Voice))
```

Compare the AIC and BIC

```
AIC(lmertest, lmertest.nSI, lmertest.nSH, lmertest.nSV)

##              df      AIC
## lmertest     25 6412.461
## lmertest.nSI 13 6616.554
## lmertest.nSH 13 6423.600
## lmertest.nSV 13 6370.727

BIC(lmertest, lmertest.nSI, lmertest.nSH, lmertest.nSV)

##              df      BIC
## lmertest     25 6545.966
## lmertest.nSI 13 6685.976
## lmertest.nSH 13 6493.023
## lmertest.nSV 13 6440.150
```

Therefore my final model will be lmertest.nSV,

```
summary(lmertest.nSV)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
##     X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony)
```

```
##    Data: music.data
##
## REML criterion at convergence: 6344.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4460 -0.5744  0.0081  0.5699  5.1053
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4497   0.6706
##  Subject:Instrument (Intercept) 1.8372   1.3555
##  Residual                       2.7412   1.6557
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       7.49928    0.99977   7.501
## Instrumentpiano  -1.14833    0.31017  -3.702
## Instrumentstring -3.02454    0.30998  -9.757
## ConsNotes         0.09934    0.07917   1.255
## PachListen       -0.25422    0.17994  -1.413
## KnowRob           0.07243    0.08924   0.812
## KnowAxis          0.07217    0.07207   1.001
## X1990s2000s       0.01393    0.09308   0.150
## NoClass           0.09631    0.10714   0.899
## APTheory1        -0.03341    0.36246  -0.092
##
## Correlation of Fixed Effects:
##             (Intr) Instrmntp Instrmnts CnsNts PchLst KnowRb KnwAxs X19902
## Instrumntpn -0.155
## Instrmntstr -0.155  0.500
## ConsNotes   -0.279 -0.001     0.000
## PachListen  -0.870  0.000     0.000     0.138
## KnowRob      0.159  0.002     0.000    -0.359 -0.159
## KnowAxis    -0.168 -0.002     0.000     0.311  0.052 -0.458
## X1990s2000s -0.418  0.001     0.000    -0.098  0.061  0.055 -0.019
## NoClass     -0.070 -0.001     0.000     0.038 -0.053  0.002  0.059  0.079
## APTheory1    0.151  0.001     0.000    -0.169 -0.175 -0.105  0.042 -0.038
##             NoClss
## Instrumntpn
## Instrmntstr
## ConsNotes
## PachListen
## KnowRob
## KnowAxis
## X1990s2000s
## NoClass
## APTheory1   -0.331
```

Let's discuss the cases when we changes one variable while holding others the same. For the 3 main factors, compared to guitar, piano will cause 1.14833 decrease in popular rating, string will cause 3.02454 decrease in popular rating. For the new viables introduced, from the summary, it's obvious that ConsNotes, KnowRob, KnowAxis, X1990s2000s and NoClass will have a positive effect on the popular ratings, while the PachListen and APTheory1 will have a negative effect on the popular ratings.

If ConsNotes increase by one, popular rating will increase by 0.0993; If KnowRob increase by one, popular rating will increase by 0.0724; If KnowAxis increase by one, popular rating will increase by 0.07217; If NoClass increase by one, popular rating will increase by 0.0963; If X1990s2000s increase by one, popular rating will increase by 0.0139.

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If PachListen increase by one, popular rating will decrease by 0.2542; If APTheory1 increase by one, popular rating will decrease by 0.0334.

(c)

```
lmerdm_full<-lmer(Popular ~ Instrument + ConsNotes + PachListen +
                    KnowRob + KnowAxis+ X1990s2000s + NoClass + APTheory
          + (1 | Subject:Instrument) + (1 | Subject:Harmony)   + dm:OMSI + dm:X16.minus.17 + dm:ConsIns
  dm:KnowAxis + dm:X1990s2000s + dm:CollegeMusic + dm:NoClass + dm:APTheory + dm:Composing +
  dm:PianoPlay +  dm:GuitarPlay + dm:X1stInstr +dm:X2ndInstr
 , data = music.data)
```

Perform a backward selection using AIC,

same comment as for #3

```
fitdm <- bfFixefLMER_F.fnc(lmerdm_full, method='AIC')
```

You can check the following results

```
summary(fitdm)

## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Instrument + ConsNotes + PachListen + KnowRob + KnowAxis +
##     X1990s2000s + NoClass + APTheory + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + dm:X16.minus.17 + dm:X1stInstr
##    Data: music.data
##
## REML criterion at convergence: 6340.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4638 -0.5639 -0.0012  0.5764  5.1302
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4453   0.6673
##  Subject:Instrument (Intercept) 1.6311   1.2771
##  Residual                       2.7419   1.6559
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129
##
## Fixed effects:
##                        Estimate Std. Error t value
## (Intercept)             7.25296    0.98296   7.379
## Instrumentpiano        -1.14538    0.29431  -3.892
## Instrumentstring       -3.02451    0.29412 -10.283
## ConsNotes               0.11793    0.08325   1.416
## PachListen             -0.34364    0.17433  -1.971
## KnowRob                 0.12421    0.08685   1.430
```

```
## KnowAxis               0.04385    0.07288   0.602
## X1990s2000s            0.15224    0.10461   1.455
## NoClass               -0.06382    0.11276  -0.566
## APTheory1              0.11045    0.35113   0.315
## dmFALSE:X16.minus.17   0.05268    0.07122   0.740
## dmTRUE:X16.minus.17    0.25692    0.07547   3.404
## dmFALSE:X1stInstr      0.07033    0.11349   0.620
## dmTRUE:X1stInstr      -0.28951    0.09133  -3.170
##
## Correlation of Fixed Effects:
##             (Intr) Instrmntp Instrmnts CnsNts PchLst KnowRb KnwAxs X19902
## Instrumntpn -0.150
## Instrmntstr -0.150  0.500
## ConsNotes   -0.262 -0.001     0.000
## PachListen  -0.810 -0.001     0.000     0.082
## KnowRob      0.165  0.003     0.000    -0.333 -0.160
## KnowAxis    -0.152 -0.002     0.000     0.391  0.036 -0.451
## X1990s2000s -0.454  0.002     0.000    -0.090 -0.004  0.066 -0.078
## NoClass     -0.040 -0.002     0.000     0.078 -0.022 -0.065  0.131 -0.086
## APTheory1    0.146  0.002     0.000    -0.182 -0.171 -0.075  0.004  0.006
## dFALSE:X16. -0.066  0.000     0.000     0.406 -0.105 -0.017  0.281  0.048
## dTRUE:X16.. -0.160  0.003     0.000    -0.041 -0.112  0.094 -0.154  0.496
## dmFALSE:X1I -0.066  0.000     0.000    -0.035 -0.056 -0.062 -0.065  0.089
## dmTRUE:X1sI -0.096 -0.002     0.000    -0.006  0.047 -0.179  0.082 -0.014
##             NoClss APThr1 dFALSE:X16 dTRUE:X16 dFALSE:X1I
## Instrumntpn
## Instrmntstr
## ConsNotes
## PachListen
## KnowRob
## KnowAxis
## X1990s2000s
## NoClass
## APTheory1   -0.361
## dFALSE:X16.  0.052 -0.048
## dTRUE:X16.. -0.354  0.103  0.035
## dmFALSE:X1I  0.092 -0.073 -0.229      0.160
## dmTRUE:X1sI  0.286 -0.109 -0.010     -0.354     0.169
```

dmFALSE:X16.minus.17, dmTRUE:X16.minus.17 and dmFALSE:X1stInstr survive in the popular rating, which shows non-musician will rely more on X1stInstr and X16.minus.17, musican will rely on X16.minus.17 for the popular rating. Again, this factor also have some impact on the popular rating.

Compare the AIC and BIC,

```
AIC(lmerdm_full,fitdm)
```

```
##             df      AIC
## lmerdm_full 40 6402.846
## fitdm       17 6374.828
```

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```
BIC(lmerdm_full,fitdm)
```

```
##             df      BIC
## lmerdm_full 40 6616.453
## fitdm       17 6465.612
```

5 Problem 5

5.1 Introduction

In this experiment, Dr. Jimenez and Vincent Rossi are trying to measure the influence of instrument, harmonic motion, and voice leading and other factors on listeners identification of music as classical or popular. Moreover, we wish to study the following assumptions.

- Instrument should have the largest influence on rating.
- One particular harmonic progression, I-V-VI, might be frequently rated as classical

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- Contrary motion would also be frequently rated as classical

5.2 Methods

My main model is the multilevel linear model. I use backward selection as the method and the AIC/BIC as the indicator for our model selection process.

I study the influence of 3 main factors on the classical rating and popular rating using a simple linear model first. Then I add the random intercept from each indiviual and their interaction with the 3 main factors into the model. Next, I perform a backward selection to include more covariates on the individual to make my model more predictive. After that, I go back and check whether the random intercepts should be kept or not. Lastly, I divide the group into ”musician” and ”non-musican” to check whether this factor will have interaction with other covariates and whether the ”musician” group are influenced by more factors.

5.3 Results

For the classical rating, I find out the instrument has the largest impact in p.1(a) when comparing models by AIC/BIC/ANOVA, following by harmony and voice, which agrees with the first hypothesis. For popular rating in the model in p.4(a), similar phenonmenon is observed. Morevoer, in the model I show in p.1(c ii), on the group level the standard deviation for Subject:Instrument is the largest, which again agrees with our first assumption. Similar phenonmenon happens in model in p.4 for popular ratings, the influence of Subject:Voice and Subject:Harmony is so trival that the AIC/BIC criterion throw them away.

The coefficient for the Harmony I-V-VI is 0.77 in the classical rating(the largest in Harmony) according p.1(c), yet it’s -0.26829(the smallest in Harmony) in popular rating according to p.4(a), which proves our second assumption that I-V-VI is frequently rated as classical.

The coefficients for the Voicepar3rd and Voicepar5th compared with Voicecontrary are negative in the classical rating (they are less classical compared with contrary motion) according p.1(c), yet they are both positive in popular rating (they are more popular compared with contrary motion) according to p.4(a), which proves our third assumption that contrary motion would also be frequently rated as classical.

Besides that, I constructed a model with random intercept by the interaction between Subject and 3 key factors. It performs better than the naive linear model or random intercept model with just Subject according to p.1(c-ii).

I also performs a backward selection on individual covariates, re-check the random intercepts and finally build a multilevel linear model which I believe to be the most predictive. The expression is in p.2(b) for classical rating and p.4(b) for popular rating.

The last thing I check whether people who selfidentify as musicians may be influenced by things that do not influence non-musicians. I set Selfdeclare>2 as the standard for musician, adding the interaction term into the model and perform a backward selection. It turns out that for classical and popular rating, the musician interaction survives with different factors involved. This indeed agrees with our assumption that this self-identification will make people consider special factors when doing the rating.

5.4 Discussion

In conclusion, the previous 3 assumptions are all proved by the data. A linear hierachical model to predict the classical and popular rating is proposed. Furthermore, we’ve proved the secondary hypothesis that the self-recognizion as musician will have an impact on the classical rating and the popular rating.

6 Some Other Thoughts

6.1 Writing a forward selection code using AIC

In Problem 2, I directly use the lmer convinience function to perform a backward selection, which is very simple to apply. Actually, it's not hard to write down a forward or backward code yourself. I've try this and the result is similar to the convinience package.

```
# input the originial model fitbest
lmtest.a <- fitbest
for(jj in Js:Jf){
  #backup your model in each loop
   lmbackup <- lmtest.a
   newft <- as.name(colnames(music.data[jj]))
   #update the model with new feature
   lmtest.a <- update(lmtest.a, bquote(.~.+.(newft)))
   # if AIC is smaller, keep it; or set it back to the backup model
   if(AIC(lmbackup)<AIC(lmtest.a)) {
     lmtest.a <- lmbackup
   }
 }

 display(lmtest.a)
```

6.2 Musician VS Non-musician

Another way to test our secondary hypothesis about the musician and non-musician is that we can just split the data into the musician and non-musician set.

```
inds.myes <- music.data$Selfdeclare>2
music.data$dm <- inds.myes
attach(music.data)

## The following objects are masked from music.data (pos = 3):
##
##    APTheory, Classical, ClsListen, CollegeMusic, Composing,
##    ConsInstr, ConsNotes, first12, GuitarPlay, Harmony,
##    Instr.minus.Notes, Instrument, KnowAxis, KnowRob, NoClass,
##    OMSI, PachListen, PianoPlay, Popular, Selfdeclare, Subject,
##    Voice, X, X16.minus.17, X1990s2000s,
##    X1990s2000s.minus.1960s1970s, X1stInstr, X2ndInstr

music.data.myes <- music.data[inds.myes,]
music.data.mno <- music.data[!inds.myes,]
```

Then I use the lmer convenience package to perform the backward selection using AIC. You can check the following results

```
summary(fitbs.m)

## Linear mixed model fit by REML ['lmerMod']
## Formula: Classical ~ Harmony + Instrument + X16.minus.17 + ConsNotes +
##     KnowRob + X1990s2000s + NoClass + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice)
```

```
##    Data: music.data.myes
##
## REML criterion at convergence: 2950.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9321 -0.5401 -0.0579  0.5987  3.1981
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.4782   0.6915
##  Subject:Voice      (Intercept) 0.0000   0.0000
##  Subject:Instrument (Intercept) 1.2646   1.1245
##  Residual                       2.8463   1.6871
## Number of obs: 714, groups:
## Subject:Harmony, 80; Subject:Voice, 60; Subject:Instrument, 60
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)       4.515687   0.780643   5.785
## HarmonyI-V-IV    -0.023131   0.282405  -0.082
## HarmonyI-V-VI     1.522055   0.282405   5.390
## HarmonyIV-I-V     0.124527   0.282189   0.441
## Instrumentpiano   1.289473   0.388219   3.322
## Instrumentstring  2.950000   0.387525   7.612
## X16.minus.17     -0.236790   0.080624  -2.937
## ConsNotes        -0.013313   0.109682  -0.121
## KnowRob           0.075572   0.087581   0.863
## X1990s2000s      -0.018604   0.124254  -0.150
## NoClass          -0.004549   0.098574  -0.046
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts X16..1 CnsNts
## HrmnyI-V-IV -0.182
## HrmnyI-V-VI -0.182  0.499
## HrmnyIV-I-V -0.181  0.500  0.500
## Instrumntpn -0.252  0.001  0.001  0.000
## Instrmntstr -0.248  0.000  0.000  0.000  0.499
## X16.mins.17 -0.685  0.001  0.001  0.000  0.004     0.000
## ConsNotes   -0.344  0.000  0.000  0.000 -0.001     0.000     0.153
## KnowRob     -0.266  0.002  0.002  0.000  0.005     0.000     0.187 -0.173
## X1990s2000s -0.703  0.001  0.001  0.000  0.004     0.000     0.563 -0.172
## NoClass     -0.055  0.000  0.000  0.000 -0.001     0.000    -0.185 -0.068
##             KnowRb X19902
## HrmnyI-V-IV
## HrmnyI-V-VI
## HrmnyIV-I-V
## Instrumntpn
## Instrmntstr
## X16.mins.17
## ConsNotes
## KnowRob
## X1990s2000s  0.211
```

```
## NoClass      0.034 -0.064
```

```r
summary(fitbs.nm)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Classical ~ Instrument + ConsNotes + PachListen + KnowAxis +
##     NoClass + APTheory + Composing + PianoPlay + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice)
##    Data: music.data.mno
##
## REML criterion at convergence: 3220.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8780 -0.5396  0.0396  0.4684  3.1602
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.2362   0.4860
##  Subject:Voice      (Intercept) 0.1515   0.3892
##  Subject:Instrument (Intercept) 1.4339   1.1975
##  Residual                       2.1702   1.4732
## Number of obs: 827, groups:
## Subject:Harmony, 92; Subject:Voice, 69; Subject:Instrument, 69
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       0.47643    1.18844   0.401
## Instrumentpiano   1.96179    0.37476   5.235
## Instrumentstring  4.14476    0.37476  11.060
## ConsNotes        -0.27420    0.09357  -2.930
## PachListen        0.62495    0.23489   2.661
## KnowAxis          0.05793    0.08720   0.664
## NoClass          -0.10147    0.33243  -0.305
## APTheory1         0.25057    0.60438   0.415
## Composing         0.83809    0.25067   3.343
## PianoPlay         0.65604    0.16456   3.987
##
## Correlation of Fixed Effects:
##             (Intr) Instrmntp Instrmnts CnsNts PchLst KnwAxs NoClss APThr1
## Instrumntpn -0.158
## Instrmntstr -0.158  0.500
## ConsNotes   -0.412  0.000     0.000
## PachListen  -0.944  0.000     0.000     0.263
## KnowAxis     0.162  0.000     0.000    -0.055 -0.209
## NoClass     -0.063  0.000     0.000     0.171 -0.092 -0.182
## APTheory1    0.279  0.000     0.000    -0.227 -0.322 -0.053  0.280
## Composing   -0.228 -0.001    -0.001    -0.088  0.245  0.044 -0.280 -0.349
## PianoPlay   -0.123  0.000     0.000    -0.069  0.141 -0.150 -0.267 -0.267
##             Cmpsng
## Instrumntpn
## Instrmntstr
## ConsNotes
## PachListen
```

```
## KnowAxis
## NoClass
## APTheory1
## Composing
## PianoPlay   -0.011
```

Quite interestingly, there seems to be no clues that if you fit the model using the musician data, you will get more covariates in your final model. Yet the REML convergence of the musician data is indeed smaller than the non-musician data, which means the classical rating for the musicians are more standardized and more easier to trace than the non-musicians.