HW5

```
> library(lme4)
> library(arm)
> library(RLRsim)
> dtmusic=read.csv('ratings.csv')
>
```

1 a 7/9
b 5/9
c 5/9

2 a 4/9
b 5/9
c 7/9

3 5/9

4 a 7/9
b 5/9
c 5/9

5 6/10

Total 61/100

P1

```
> # (a)
> # This is the full model that includes all three variables
> m.1a.full=lm(dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument + dtmusic$Voice)
> summary(m.1a.full)

Call:
lm(formula = dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument +
    dtmusic$Voice)

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

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               4.34016    0.12987  33.420  < 2e-16 ***
dtmusic$HarmonyI-V-IV    -0.03108    0.13008  -0.239 0.811168
dtmusic$HarmonyI-V-VI     0.76909    0.13008   5.913 3.83e-09 ***
dtmusic$HarmonyIV-I-V     0.05007    0.12997   0.385 0.700092
dtmusic$Instrumentpiano   1.37359    0.11298  12.158  < 2e-16 ***
dtmusic$Instrumentstring  3.13312    0.11230  27.899  < 2e-16 ***
```

```
dtmusic$Voicepar3rd      -0.41247    0.11271  -3.660 0.000258 ***
dtmusic$Voicepar5th      -0.37058    0.11264  -3.290 0.001016 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.297 on 2485 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.255,        Adjusted R-squared:  0.2529
F-statistic: 121.5 on 7 and 2485 DF,  p-value: < 2.2e-16

> # holding other variables fixed:
> # HarmonyI-V-VI has on average 0.76909 higher score for Classic than HarmonyI-IV-V
> # Instrumentpiano has on average 1.37359 higher score for Classic than Instrumentguitar
> # Instrumentstring has on average 3.13312 higher score for Classic than Instrumentguitar
> # Voicepar3rd has on average 0.41247 lower score for Classic than contrary
> # Voicepar5th has on average 0.37058 lower score for Classic than contrary
>
> # This is the reduced model without Harmony
> m.1a.reduced1=lm(dtmusic$Classical ~ dtmusic$Instrument + dtmusic$Voice)
> summary(m.1a.reduced1)

Call:
lm(formula = dtmusic$Classical ~ dtmusic$Instrument + dtmusic$Voice)

Residuals:
    Min      1Q  Median      3Q     Max
-6.3011 -1.5407 -0.1233  1.7433 11.3299

Coefficients:
```

```
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)             4.5367     0.1038  43.724  < 2e-16 ***
dtmusic$Instrumentpiano    1.3730     0.1141  12.035  < 2e-16 ***
dtmusic$Instrumentstring   3.1334     0.1134  27.631  < 2e-16 ***
dtmusic$Voicepar3rd       -0.4134     0.1138  -3.633 0.000286 ***
dtmusic$Voicepar5th       -0.3690     0.1137  -3.244 0.001193 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.319 on 2488 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.2395,      Adjusted R-squared:  0.2383
F-statistic: 195.9 on 4 and 2488 DF,  p-value: < 2.2e-16

>
> # This is the reduced model without Instrument
> m.1a.reduced2=lm(dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Voice)
> summary(m.1a.reduced2)

Call:
lm(formula = dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Voice)

Residuals:
    Min      1Q  Median      3Q     Max
-6.6170 -2.2463  0.1549  2.1549 13.1024

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          5.84507    0.12896  45.326  < 2e-16 ***
```

```
dtmusic$HarmonyI-V-IV -0.02824    0.14910  -0.189  0.84979
dtmusic$HarmonyI-V-VI  0.77194    0.14910   5.177 2.43e-07 ***
dtmusic$HarmonyIV-I-V  0.05249    0.14898   0.352  0.72461
dtmusic$Voicepar3rd   -0.41065    0.12919  -3.179  0.00150 **
dtmusic$Voicepar5th   -0.37075    0.12911  -2.872  0.00412 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.632 on 2487 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.02044,    Adjusted R-squared:  0.01847
F-statistic: 10.38 on 5 and 2487 DF,  p-value: 7.201e-10

>
> # This is the reduced model without Voice
> m.1a.reduced3=lm(dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument)
> summary(m.1a.reduced3)

Call:
lm(formula = dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument)

Residuals:
    Min      1Q  Median      3Q     Max
-6.9812 -1.8483 -0.0797  1.7874 11.7370

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          4.07966    0.11280  36.166  < 2e-16 ***
dtmusic$HarmonyI-V-IV   -0.03234    0.13045  -0.248    0.804
```

```
dtmusic$HarmonyI-V-VI     0.76863    0.13045   5.892 4.33e-09 ***
dtmusic$HarmonyIV-I-V     0.05045    0.13034   0.387    0.699
dtmusic$Instrumentpiano   1.37327    0.11330  12.120  < 2e-16 ***
dtmusic$Instrumentstring  3.13294    0.11262  27.818  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.303 on 2487 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.2502,      Adjusted R-squared:  0.2487
F-statistic: 165.9 on 5 and 2487 DF,  p-value: < 2.2e-16

>
> # Then we use partial f-test to compare full model with each of the reduced models
> # to decide whether each variable is important, by anova
>
> anova(m.1a.reduced1,m.1a.full)
Analysis of Variance Table

Model 1: dtmusic$Classical ~ dtmusic$Instrument + dtmusic$Voice
Model 2: dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument + dtmusic$Voice
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2488 13381
2   2485 13108  3    273.65 17.293 4.107e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(m.1a.reduced2,m.1a.full)
Analysis of Variance Table
```

Model 1: dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Voice

Model 2: dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument + dtmusic$Voice

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	2487	17235			
2	2485	13108	2	4127.6	391.26 < 2.2e-16 ***

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

> anova(m.1a.reduced3,m.1a.full)

Analysis of Variance Table

Model 1: dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument

Model 2: dtmusic$Classical ~ dtmusic$Harmony + dtmusic$Instrument + dtmusic$Voice

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	2487	13193			
2	2485	13108	2	85.64	8.1181 0.0003061 ***

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

7 > # The result shows that the full model significantly fits the data better than any

answer is ok
too much raw R output

> # of the reduced models, so all three main experimental factors are important

>

> # (b)

> # i

> # Classic =αj[i] + α1*Harmony + + α2*Instrument+ α3* Voice + εi

> # αj[i] = β0 + ηj

your level 1 model works if H, I and V are continuous, but they are factors. Need to include them as (additional) indices for the alphas.

> # εi ~ N(0,σ^2)

> # ηj ~ N(0,τ^2)

>

> # ii

> # we first fit the model

```
> m.1b.full=lmer(Classical ~ 1 + Harmony + Instrument + Voice + (1|Subject),
+                data = dtmusic, REML = F)
> summary(m.1b.full)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 10468.9  10527.1  -5224.4  10448.9     2483

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.9844 -0.6404 -0.0182  0.6414  5.4886

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.677    1.295
 Residual             3.571    1.890
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
                    Estimate Std. Error t value
(Intercept)         4.34374    0.18809   23.09
HarmonyI-V-IV      -0.03251    0.10703   -0.30
HarmonyI-V-VI       0.77096    0.10702    7.20
HarmonyIV-I-V       0.04989    0.10694    0.47
Instrumentpiano     1.37705    0.09305   14.80
Instrumentstring    3.13161    0.09243   33.88
Voicepar3rd        -0.41506    0.09273   -4.48
```

```
Voicepar5th      -0.37438    0.09268   -4.04


Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
HrmnyI-V-IV -0.283
HrmnyI-V-VI -0.283  0.499
HrmnyIV-I-V -0.284  0.499  0.499
Instrumntpn -0.245  0.001  0.001 -0.001
Instrmntstr -0.246 -0.001 -0.001 -0.001  0.498
Voicepar3rd -0.246 -0.002  0.001  0.002 -0.001    -0.001
Voicepar5th -0.245 -0.002 -0.003 -0.001 -0.001     0.000     0.500
> AIC(m.1a.full, m.1b.full)
           df      AIC
m.1a.full  9 11230.45
m.1b.full 10 10468.86
> BIC(m.1a.full, m.1b.full)
           df      BIC
m.1a.full  9 11282.84
m.1b.full 10 10527.07
> # both AIC and BIC suggest that model with random intercept is better
>
> exactLRT(m0 = m.1a.full,m=m.1b.full)
No restrictions on fixed effects. REML-based inference preferable.


        simulated finite sample distribution of LRT. (p-value based on 10000 simulated values)


data:
LRT = 763.59, p-value < 2.2e-16
```

```
> # Since the p-value is extremely small,
> # the simulation method suggests that model with random intercept is better
>
> # iii
> summary(m.1b.full)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 10468.9  10527.1  -5224.4  10448.9     2483

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.9844 -0.6404 -0.0182  0.6414  5.4886

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.677    1.295
 Residual             3.571    1.890
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.34374    0.18809   23.09
HarmonyI-V-IV    -0.03251    0.10703   -0.30
HarmonyI-V-VI     0.77096    0.10702    7.20
HarmonyIV-I-V     0.04989    0.10694    0.47
Instrumentpiano   1.37705    0.09305   14.80
```

```
Instrumentstring  3.13161    0.09243   33.88
Voicepar3rd      -0.41506    0.09273   -4.48
Voicepar5th      -0.37438    0.09268   -4.04

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
HrmnyI-V-IV -0.283
HrmnyI-V-VI -0.283  0.499
HrmnyIV-I-V -0.284  0.499  0.499
Instrumntpn -0.245  0.001  0.001 -0.001
Instrmntstr -0.246 -0.001 -0.001 -0.001  0.498
Voicepar3rd -0.246 -0.002  0.001  0.002 -0.001    -0.001
Voicepar5th -0.245 -0.002 -0.003 -0.001 -0.001     0.000     0.500
> # holding other variables fixed:
> # HarmonyI-V-VI has on average 0.77096  higher score for Classic than HarmonyI-IV-V
> # Instrumentpiano has on average 1.37705 higher score for Classic than Instrumentguitar
> # Instrumentstring has on average 3.13161 higher score for Classic than Instrumentguitar
> # Voicepar3rd has on average 0.41506 lower score for Classic than contrary
> # Voicepar5th has on average 0.37438 lower score for Classic than contrary
>
> # This is the reduced model without Harmony
> m.1b.reduced1=lmer(Classical ~ 1 + Instrument + Voice + (1|Subject),
+                    data = dtmusic, REML = F)
> summary(m.1b.reduced1)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Instrument + Voice + (1 | Subject)
   Data: dtmusic

    AIC      BIC   logLik deviance df.resid
```

```
 10538.8  10579.5  -5262.4  10524.8     2486

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.9233 -0.6292 -0.0267  0.6356  5.3280

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.673    1.293
 Residual             3.684    1.919
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)      4.54037    0.17687   25.67
Instrumentpiano  1.37638    0.09452   14.56
Instrumentstring 3.13185    0.09389   33.36
Voicepar3rd     -0.41603    0.09420   -4.42
Voicepar5th     -0.37278    0.09414   -3.96

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts Vcpr3r
Instrumntpn -0.264
Instrmntstr -0.267  0.498
Voicepar3rd -0.266 -0.001    -0.001
Voicepar5th -0.266 -0.001     0.000     0.500
>
> # This is the reduced model without Instrument
> m.1b.reduced2=lmer(Classical ~ 1 + Harmony + Voice + (1|Subject),
```

```
+                 data = dtmusic, REML = F)
> summary(m.1b.reduced2)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Voice + (1 | Subject)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 11408.4  11455.0  -5696.2  11392.4     2485

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.1053 -0.7210  0.0012  0.7220  5.2299

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.634    1.278
 Residual             5.270    2.296
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
             Estimate Std. Error t value
(Intercept)    5.85000    0.18972  30.835
HarmonyI-V-IV -0.02846    0.13003  -0.219
HarmonyI-V-VI  0.77441    0.13003   5.956
HarmonyIV-I-V  0.05289    0.12992   0.407
Voicepar3rd   -0.41236    0.11266  -3.660
Voicepar5th   -0.37408    0.11259  -3.322

Correlation of Fixed Effects:
```

```
          (Intr) HI-V-I HI-V-V HIV-I- Vcpr3r
HrmnyI-V-IV -0.341
HrmnyI-V-VI -0.341  0.499
HrmnyIV-I-V -0.342  0.499  0.499
Voicepar3rd -0.297 -0.002  0.001  0.002
Voicepar5th -0.296 -0.002 -0.003 -0.001  0.500
>
> # This is the reduced model without Voice
> m.1b.reduced3=lmer(Classical ~ 1 + Harmony + Instrument + (1|Subject),
+                  data = dtmusic, REML = F)
> summary(m.1b.reduced3)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + (1 | Subject)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 10489.1  10535.7  -5236.6  10473.1     2485

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0451 -0.6265 -0.0354  0.6446  5.6018

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1.675    1.294
 Residual             3.606    1.899
Number of obs: 2493, groups:  Subject, 70

Fixed effects:
```

```
                    Estimate Std. Error t value
(Intercept)          4.08120    0.18052   22.61
HarmonyI-V-IV       -0.03372    0.10757   -0.31
HarmonyI-V-VI        0.77050    0.10756    7.16
HarmonyIV-I-V        0.05029    0.10747    0.47
Instrumentpiano      1.37669    0.09351   14.72
Instrumentstring     3.13132    0.09290   33.71

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp
HrmnyI-V-IV -0.297
HrmnyI-V-VI -0.297  0.499
HrmnyIV-I-V -0.297  0.499  0.499
Instrumntpn -0.257  0.001  0.001 -0.001
Instrmntstr -0.258 -0.001 -0.001 -0.001  0.498
>
> AIC(m.1b.reduced1,m.1b.full)
               df      AIC
m.1b.reduced1  7 10538.79
m.1b.full     10 10468.86
> BIC(m.1b.reduced1,m.1b.full)
               df      BIC
m.1b.reduced1  7 10579.54
m.1b.full     10 10527.07
> AIC(m.1b.reduced2,m.1b.full)
               df      AIC
m.1b.reduced2  8 11408.45
m.1b.full     10 10468.86
> BIC(m.1b.reduced2,m.1b.full)
```

```
            df      BIC
m.1b.reduced2  8 11455.02
m.1b.full     10 10527.07
> AIC(m.1b.reduced3,m.1b.full)
            df      AIC
m.1b.reduced3  8 10489.10
m.1b.full     10 10468.86
> BIC(m.1b.reduced3,m.1b.full)
            df      BIC
m.1b.reduced3  8 10535.67
m.1b.full     10 10527.07
> # AIC and BIC suggest that the full model significantly fits the data better than any of the
> # reduced models, so all three main experimental factors are still important with random intercept
>
> # (c)
> # i
> m.1c.full=lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice),
+              data = dtmusic, REML = F)
> summary(m.1c.full)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 10057.5  10127.4  -5016.8  10033.5     2481

Scaled residuals:
```

5

answer's ok
too much raw R

```
   Min     1Q  Median     3Q    Max
-4.4000 -0.5698 -0.0016  0.5435  5.7596

Random effects:
 Groups           Name        Variance Std.Dev.
 Subject:Harmony  (Intercept) 0.43285  0.6579
 Subject:Instrument (Intercept) 2.16929  1.4729
 Subject:Voice    (Intercept) 0.02473  0.1573
 Residual                     2.43721  1.5612
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210; Subject:Voice, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)      4.34104    0.21292  20.388
HarmonyI-V-IV   -0.03028    0.14215  -0.213
HarmonyI-V-VI    0.77061    0.14213   5.422
HarmonyIV-I-V    0.05612    0.14208   0.395
Instrumentpiano  1.36381    0.26072   5.231
Instrumentstring 3.12835    0.26043  12.012
Voicepar3rd     -0.40695    0.08115  -5.015
Voicepar5th     -0.37070    0.08108  -4.572

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
HrmnyI-V-IV -0.333
HrmnyI-V-VI -0.333  0.499
HrmnyIV-I-V -0.333  0.500  0.500
Instrumntpn -0.611  0.000  0.000  0.000
Instrmntstr -0.612  0.000  0.000  0.000  0.500
```

```
Voicepar3rd -0.190 -0.002  0.001  0.002 -0.001     0.000
Voicepar5th -0.190 -0.001 -0.002 -0.001 -0.001     0.000     0.500
> AIC(m.1b.full, m.1c.full)
            df      AIC
m.1b.full 10 10468.86
m.1c.full 12 10057.53
> BIC(m.1b.full, m.1c.full)
            df      BIC
m.1b.full 10 10527.07
m.1c.full 12 10127.38
> # AIC and BIC both suggest that the model with three new random effect terms is better
>
> # ii
> summary(m.1c.full)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice)
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
 10057.5  10127.4  -5016.8  10033.5     2481

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.4000 -0.5698 -0.0016  0.5435  5.7596

Random effects:
 Groups           Name        Variance Std.Dev.
 Subject:Harmony  (Intercept) 0.43285  0.6579
```

```
 Subject:Instrument (Intercept) 2.16929  1.4729
 Subject:Voice      (Intercept) 0.02473  0.1573
 Residual                       2.43721  1.5612
Number of obs: 2493, groups:  Subject:Harmony, 280; Subject:Instrument, 210; Subject:Voice, 210

Fixed effects:
                Estimate Std. Error t value
(Intercept)      4.34104    0.21292  20.388
HarmonyI-V-IV   -0.03028    0.14215  -0.213
HarmonyI-V-VI    0.77061    0.14213   5.422
HarmonyIV-I-V    0.05612    0.14208   0.395
Instrumentpiano  1.36381    0.26072   5.231
Instrumentstring 3.12835    0.26043  12.012
Voicepar3rd     -0.40695    0.08115  -5.015
Voicepar5th     -0.37070    0.08108  -4.572

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
HrmnyI-V-IV -0.333
HrmnyI-V-VI -0.333  0.499
HrmnyIV-I-V -0.333  0.500  0.500
Instrumntpn -0.611  0.000  0.000  0.000
Instrmntstr -0.612  0.000  0.000  0.000  0.500
Voicepar3rd -0.190 -0.002  0.001  0.002 -0.001     0.000
Voicepar5th -0.190 -0.001 -0.002 -0.001 -0.001     0.000     0.500
> # holding other variables fixed:
> # HarmonyI-V-VI has on average 0.77061  higher score for Classic than HarmonyI-IV-V
> # Instrumentpiano has on average 1.36381 higher score for Classic than Instrumentguitar
> # Instrumentstring has on average 3.12835 higher score for Classic than Instrumentguitar
```

> # Voicepar3rd has on average 0.40695 lower score for Classic than contrary

> # Voicepar5th has on average 0.37070 lower score for Classic than contrary

>

> # It seems that the size of variance component for person/Instrument is big and even comparable to the

> # estimated residual variance, which means the kind of person/Instrument has a large influence

> # on the intercept. Different kinds of this combination may have intercept that varies greatly.

> # And the variance component for person/Voice is very small, which means the kind of

> # person/Instrument has a small influence on the intercept.

> # Different kinds of this combination may have intercept that does not vary too much.

>

> # iii

> # Classic =αk[i] + αl[i] + αm[i] + α1*Harmony + α2*Instrument+ α3*Voice + εi

> # αk[i] = βk + ηk comment similar to (b)(i)

> # αl[i] = βl + ηl

> # αm[i] = βi + ηm

> # εi ~ N(0,σ^2)

> # ηk ~ N(0,τk^2)

> # ηl ~ N(0,τl^2)

5 > # ηm ~ N(0,τm^2) ok answers, too much raw R

> # α1, α2 and α3 each has different values for each level of the categorical variables.

P2

> # (a)

> # To look for variables worth including as fixed effects, I start from including all

> # relevant variables.

> # The variables X1990s2000s.minus.1960s1970s and Instr.minus.Notes represent difference are not

> # so meaningful if we are just modeling Classical or Popular seperately.

> # The variable X1stInstr and X2stInstr have too many NA values, and is not so distinctively useful

> # when I already have many variables to measure the listeners' mastery of music

```
>
> # CollegeMusic and APTheory should be treated as factors since they are yes and no questions
> dtmusic$CollegeMusicf = as.factor(dtmusic$CollegeMusic)
> dtmusic$APTheoryf = as.factor(dtmusic$APTheory)
>
> m.2a.full = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                  (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+                  Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
+                  PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
+                  CollegeMusicf + NoClass + APTheoryf + Composing + PianoPlay +
+                  GuitarPlay ,
+                data = dtmusic, REML = F)
> summary(m.2a.full)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare +
    OMSI + X16.minus.17 + ConsInstr + ConsNotes + PachListen +
    ClsListen + KnowRob + KnowAxis + X1990s2000s + CollegeMusicf +
    NoClass + APTheoryf + Composing + PianoPlay + GuitarPlay
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
  6231.4   6380.9  -3087.7   6175.4     1513

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2521 -0.5703 -0.0045  0.5404  3.3522

Random effects:
```

Groups	Name	Variance	Std.Dev.
Subject:Harmony	(Intercept)	0.40907	0.6396
Subject:Instrument	(Intercept)	1.35159	1.1626
Subject:Voice	(Intercept)	0.03691	0.1921
Residual		2.48552	1.5766

Number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	2.5836873	1.2081958	2.138
HarmonyI-V-IV	-0.0045435	0.1786908	-0.025
HarmonyI-V-VI	0.8500134	0.1787465	4.755
HarmonyIV-I-V	0.0597795	0.1786275	0.335
Instrumentpiano	1.6477207	0.2694679	6.115
Instrumentstring	3.5881405	0.2692757	13.325
Voicepar3rd	-0.4035422	0.1067781	-3.779
Voicepar5th	-0.3000910	0.1067782	-2.810
Selfdeclare	-0.2897619	0.2282112	-1.270
OMSI	0.0001769	0.0011047	0.160
X16.minus.17	-0.0885014	0.0577726	-1.532
ConsInstr	0.0506034	0.1180431	0.429
ConsNotes	-0.2274329	0.1035191	-2.197
PachListen	0.1727230	0.1712312	1.009
ClsListen	0.1986123	0.1036847	1.916
KnowRob	0.1003800	0.0913426	1.099
KnowAxis	0.0365872	0.0703401	0.520
X1990s2000s	0.1948853	0.1115145	1.748
CollegeMusicf1	-0.1890744	0.4052357	-0.467
NoClass	-0.0822241	0.1366812	-0.602

```
APTheoryf1       0.5946418  0.4046317   1.470
Composing        0.2528513  0.1309394   1.931
PianoPlay        0.3265436  0.0941872   3.467
GuitarPlay      -0.1360389  0.1475155  -0.922

Correlation matrix not shown by default, as p = 24 > 20.
Use print(x, correlation=TRUE)  or
            vcov(x)  if you need it

> display(m.2a.full)
lmer(formula = Classical ~ 1 + Harmony + Instrument + Voice +
   (1 | Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice) +
   Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
   PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
   CollegeMusicf + NoClass + APTheoryf + Composing + PianoPlay +
   GuitarPlay, data = dtmusic, REML = F)
              coef.est coef.se
(Intercept)      2.58     1.21
HarmonyI-V-IV    0.00     0.18
HarmonyI-V-VI    0.85     0.18
HarmonyIV-I-V    0.06     0.18
Instrumentpiano  1.65     0.27
Instrumentstring 3.59     0.27
Voicepar3rd     -0.40     0.11
Voicepar5th     -0.30     0.11
Selfdeclare     -0.29     0.23
OMSI             0.00     0.00
X16.minus.17    -0.09     0.06
ConsInstr        0.05     0.12
```

```
ConsNotes       -0.23     0.10
PachListen       0.17     0.17
ClsListen        0.20     0.10
KnowRob          0.10     0.09
KnowAxis         0.04     0.07
X1990s2000s      0.19     0.11
CollegeMusicf1  -0.19     0.41
NoClass         -0.08     0.14
APTheoryf1       0.59     0.40
Composing        0.25     0.13
PianoPlay        0.33     0.09
GuitarPlay      -0.14     0.15

Error terms:
 Groups           Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.64
 Subject:Instrument (Intercept) 1.16
 Subject:Voice      (Intercept) 0.19
 Residual                       1.58
---
number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129
AIC = 6231.4, DIC = 6175.4
deviance = 6175.4
> # We can see that ConsNotes, ClsListen and PianoPlay are significant,
> # so I keep these 3 variables as fixed effect
>
> m.2a.reduced = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                 (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+                 ConsNotes + ClsListen + PianoPlay,
```

```
+                data = dtmusic, REML = F)
> summary(m.2a.reduced)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice) + ConsNotes +      ClsListen + PianoPlay
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
  8555.6   8640.4  -4262.8   8525.6     2094

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3379 -0.5738  0.0013  0.5415  5.6962

Random effects:
 Groups           Name        Variance Std.Dev.
 Subject:Harmony  (Intercept) 0.36961  0.6080
 Subject:Instrument (Intercept) 2.15133  1.4667
 Subject:Voice    (Intercept) 0.01947  0.1395
 Residual                     2.51860  1.5870
Number of obs: 2109, groups:  Subject:Harmony, 236; Subject:Instrument, 177; Subject:Voice, 177

Fixed effects:
                 Estimate Std. Error t value
(Intercept)      3.93787    0.32079  12.275
HarmonyI-V-IV    -0.02750    0.14862  -0.185
HarmonyI-V-VI     0.81835    0.14866   5.505
HarmonyIV-I-V     0.07495    0.14858   0.504
Instrumentpiano   1.45442    0.28321   5.135
```

```
Instrumentstring  3.21452    0.28293  11.362
Voicepar3rd      -0.40374    0.08851  -4.562
Voicepar5th      -0.38358    0.08848  -4.335
ConsNotes        -0.07932    0.06492  -1.222
ClsListen         0.17145    0.08095   2.118
PianoPlay         0.12592    0.07923   1.589

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r Vcpr5t CnsNts ClsLst
HrmnyI-V-IV -0.232
HrmnyI-V-VI -0.232  0.500
HrmnyIV-I-V -0.232  0.500  0.500
Instrumntpn -0.442  0.000  0.000  0.000
Instrmntstr -0.441  0.000  0.000  0.000  0.500
Voicepar3rd -0.138  0.000  0.001  0.001  0.000     0.000
Voicepar5th -0.137 -0.001 -0.001 -0.001  0.000     0.000     0.500
ConsNotes   -0.443  0.000  0.000  0.000  0.002     0.000     0.000  0.000
ClsListen   -0.457  0.000  0.000  0.000  0.001     0.000     0.000 -0.001 -0.056
PianoPlay   -0.015  0.000  0.000  0.000 -0.001     0.000     0.000  0.001 -0.182 -0.268
>
>
> # (b)
> # Let me try all combinations of the random effect terms and use AIC to compare
> m.2b.1 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                 (1|Subject:Instrument)+ (1|Subject:Voice) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> m.2b.2 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
```

No conclusion
Too much raw R

```
+                (1|Subject:Harmony) + (1|Subject:Voice) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> m.2b.3 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Harmony) + (1|Subject:Instrument) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
> m.2b.4 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Harmony) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> m.2b.5 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Instrument) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> m.2b.6 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Voice) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> m.2b.7 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject) +
+                 ConsNotes + ClsListen + PianoPlay,
+               data = dtmusic, REML = F)
>
> AIC(m.2a.reduced,m.2b.1,m.2b.2,m.2b.3,m.2b.4,m.2b.5,m.2b.6,m.2b.7)
```

```
              df     AIC
m.2a.reduced 15 8555.573
m.2b.1       14 8617.477
m.2b.2       14 9055.490
m.2b.3       14 8553.973
m.2b.4       13 9036.899
m.2b.5       13 8615.477
m.2b.6       13 9083.965
m.2b.7       13 8903.981
> # No other reduced models are significantly better than the model we have in 2(a),
> # So I decide not to change the random effects.
>
> # (c)
> summary(m.2a.reduced)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice) + ConsNotes +      ClsListen + PianoPlay
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
  8555.6   8640.4  -4262.8   8525.6     2094

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3379 -0.5738  0.0013  0.5415  5.6962

Random effects:
 Groups           Name        Variance Std.Dev.
 Subject:Harmony  (Intercept) 0.36961  0.6080
```

seems like you might have been able to remove one rand effect group.

too much raw R

5

Subject:Instrument (Intercept) 2.15133 1.4667

Subject:Voice (Intercept) 0.01947 0.1395

Residual 2.51860 1.5870

Number of obs: 2109, groups: Subject:Harmony, 236; Subject:Instrument, 177; Subject:Voice, 177

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	3.93787	0.32079	12.275
HarmonyI-V-IV	-0.02750	0.14862	-0.185
HarmonyI-V-VI	0.81835	0.14866	5.505
HarmonyIV-I-V	0.07495	0.14858	0.504
Instrumentpiano	1.45442	0.28321	5.135
Instrumentstring	3.21452	0.28293	11.362
Voicepar3rd	-0.40374	0.08851	-4.562
Voicepar5th	-0.38358	0.08848	-4.335
ConsNotes	-0.07932	0.06492	-1.222
ClsListen	0.17145	0.08095	2.118
PianoPlay	0.12592	0.07923	1.589

Correlation of Fixed Effects:

	(Intr)	HI-V-I	HI-V-V	HIV-I-	Instrmntp	Instrmnts	Vcpr3r	Vcpr5t	CnsNts	ClsLst
HrmnyI-V-IV	-0.232									
HrmnyI-V-VI	-0.232	0.500								
HrmnyIV-I-V	-0.232	0.500	0.500							
Instrumntpn	-0.442	0.000	0.000	0.000						
Instrmntstr	-0.441	0.000	0.000	0.000	0.500					
Voicepar3rd	-0.138	0.000	0.001	0.001	0.000	0.000				
Voicepar5th	-0.137	-0.001	-0.001	-0.001	0.000	0.000	0.500			
ConsNotes	-0.443	0.000	0.000	0.000	0.002	0.000	0.000	0.000		

```
ClsListen   -0.457  0.000  0.000  0.000  0.001     0.000     0.000 -0.001 -0.056
PianoPlay   -0.015  0.000  0.000  0.000 -0.001     0.000     0.000  0.001 -0.182 -0.268
> # holding other variables fixed:
> # HarmonyI-V-VI has on average 0.81835 higher score for Classic than HarmonyI-IV-V
> # Instrumentpiano has on average 1.45442 higher score for Classic than Instrumentguitar
> # Instrumentstring has on average 3.21452 higher score for Classic than Instrumentguitar
> # Voicepar3rd has on average 0.40374 lower score for Classic than contrary
> # Voicepar5th has on average 0.38358 lower score for Classic than contrary
> # Every unit score increase of ClsListen on average predict 0.17145 higher score for Classic
> # ConsNotes and PianoPlay are for controlling confounding effect
>
>
```

7

P3

```
> # Dichotomizing selfdeclare
> summary(dtmusic$Selfdeclare)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   2.000   2.000   2.443   3.000   6.000
> # Since the median is 2, we let those whose score is bigger than 2 to be self-decalred musicians
> dtmusic$musician = 0
> dtmusic$musician = as.numeric(dtmusic$Selfdeclare > 2)
> dtmusic$musicianf = as.factor(dtmusic$musician)
>
> # I will try out the models with interaction between self-declared musician with the three main
> # experimental factors
>
> m.3 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                 (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+                 ConsNotes + ClsListen + PianoPlay + musicianf,
```

what about interactions with other fixed effects that you found important in 2(a)?

```
+                 data = dtmusic, REML = F)
>
> m.3full = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + ClsListen + PianoPlay + musicianf +
+           musicianf:Harmony+musicianf:Instrument+musicianf:Voice,
+         data = dtmusic, REML = F)
>
> m.31 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + ClsListen + PianoPlay +
+           musicianf:Harmony,
+         data = dtmusic, REML = F)
> m.32 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + ClsListen + PianoPlay +
+           musicianf:Instrument,
+         data = dtmusic, REML = F)
> m.33 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + ClsListen + PianoPlay +
+           musicianf:Voice,
+         data = dtmusic, REML = F)
> m.34 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + ClsListen + PianoPlay +
+           musicianf:Harmony+musicianf:Instrument,
+         data = dtmusic, REML = F)
> m.35 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
```

```
+            (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+            ConsNotes + ClsListen + PianoPlay +
+            musicianf:Harmony+musicianf:Voice,
+          data = dtmusic, REML = F)
> m.36 = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+            (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+            ConsNotes + ClsListen + PianoPlay +
+            musicianf:Voice+musicianf:Instrument,
+          data = dtmusic, REML = F)
>
> AIC(m.3,m.3full,m.31,m.32,m.33,m.34,m.35,m.36)
       df      AIC
m.3     16 8556.992
m.3full 23 8536.571
m.31    19 8532.164
m.32    18 8558.180
m.33    18 8560.112
m.34    21 8533.436
m.35    21 8535.298
m.36    20 8561.303
> BIC(m.3,m.3full,m.31,m.32,m.33,m.34,m.35,m.36)
       df      BIC
m.3     16 8647.455
m.3full 23 8666.613
m.31    19 8639.590
m.32    18 8659.952
m.33    18 8661.884
m.34    21 8652.169
m.35    21 8654.031
```

m.36 20 8674.382

> # AIC and BIC both suggest that m.31 is the best model, which has an interaction term between

5

> # musicianf and Harmony interpretation?

> too much raw R

P4

> # The variable and model selection for Popular start from the same model from P1 and find fixed

> # effect first like in P2(a)

```
> m.4a.fixfull = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+                (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+                Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
+                PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
+                CollegeMusicf + NoClass + APTheoryf + Composing + PianoPlay +
+                GuitarPlay ,
+               data = dtmusic, REML = F)
> display(m.4a.fixfull)
lmer(formula = Popular ~ 1 + Harmony + Instrument + Voice + (1 |
    Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice) +
    Selfdeclare + OMSI + X16.minus.17 + ConsInstr + ConsNotes +
    PachListen + ClsListen + KnowRob + KnowAxis + X1990s2000s +
    CollegeMusicf + NoClass + APTheoryf + Composing + PianoPlay +
    GuitarPlay, data = dtmusic, REML = F)
              coef.est coef.se
(Intercept)       6.78     1.27
HarmonyI-V-IV     0.03     0.18
HarmonyI-V-VI    -0.26     0.18
HarmonyIV-I-V    -0.25     0.18
Instrumentpiano  -1.15     0.28
Instrumentstring -3.02     0.28
```

Voicepar3rd 0.19 0.11

Voicepar5th 0.23 0.11

Selfdeclare -0.38 0.24

OMSI 0.00 0.00

X16.minus.17 0.15 0.06

ConsInstr 0.00 0.12

ConsNotes 0.26 0.11

PachListen -0.30 0.18

ClsListen 0.05 0.11

KnowRob 0.08 0.10

KnowAxis 0.08 0.07

X1990s2000s 0.13 0.12

CollegeMusicf1 0.43 0.43

NoClass 0.03 0.14

APTheoryf1 0.26 0.42

Composing 0.12 0.14

PianoPlay -0.11 0.10

GuitarPlay -0.17 0.15

Error terms:

Groups	Name	Std.Dev.
Subject:Harmony	(Intercept)	0.65
Subject:Instrument	(Intercept)	1.23
Subject:Voice	(Intercept)	0.21
Residual		1.64

---

number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129

AIC = 6358, DIC = 6302

deviance = 6302.0

```
> # We can see that ConsNotes and X16.minus.17 are significant,
> # so I keep these two variables as fixed effect for Popular
> m.4a.reduced = lmer(Classical ~ 1 + Harmony + Instrument + Voice +
+                     (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+                     ConsNotes + X16.minus.17,
+                   data = dtmusic, REML = F)
> summary(m.4a.reduced)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: Classical ~ 1 + Harmony + Instrument + Voice + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice) + ConsNotes +      X16.minus.17
   Data: dtmusic

     AIC      BIC   logLik deviance df.resid
  8664.8   8744.1  -4318.4   8636.8     2119

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3026 -0.5790 -0.0046  0.5509  5.6555

Random effects:
 Groups           Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.36377  0.6031
 Subject:Instrument (Intercept) 2.17428  1.4745
 Subject:Voice      (Intercept) 0.02053  0.1433
 Residual                       2.53525  1.5922
Number of obs: 2133, groups:  Subject:Harmony, 240; Subject:Instrument, 180; Subject:Voice, 180

Fixed effects:
                Estimate Std. Error t value
```

```
(Intercept)      4.63429    0.29879  15.510
HarmonyI-V-IV   -0.02656    0.14716  -0.181
HarmonyI-V-VI    0.80253    0.14714   5.454
HarmonyIV-I-V    0.07792    0.14707   0.530
Instrumentpiano  1.44405    0.28247   5.112
Instrumentstring 3.18383    0.28210  11.286
Voicepar3rd     -0.41273    0.08850  -4.664
Voicepar5th     -0.40075    0.08842  -4.532
ConsNotes       -0.07486    0.06433  -1.164
X16.minus.17    -0.09614    0.04068  -2.363

Correlation of Fixed Effects:
            (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r Vcpr5t CnsNts
HrmnyI-V-IV -0.245
HrmnyI-V-VI -0.246  0.499
HrmnyIV-I-V -0.246  0.499  0.499
Instrumntpn -0.472  0.000  0.001  0.000
Instrmntstr -0.472  0.000  0.000  0.000  0.500
Voicepar3rd -0.148 -0.002  0.001  0.002 -0.001    -0.001
Voicepar5th -0.147 -0.002 -0.002 -0.001 -0.001     0.000     0.500
ConsNotes   -0.599  0.000  0.000  0.000  0.001     0.000     0.000 -0.001
X16.mins.17 -0.363  0.001  0.001  0.001  0.000    -0.001     0.001  0.001  0.216
>
> # (a) & (b)
> # holding other variables fixed:
> # HarmonyI-V-VI has on average 0.80253 higher score for Classic than HarmonyI-IV-V
> # Instrumentpiano has on average 1.44405 higher score for Classic than Instrumentguitar  but nonsignificant?
> # Instrumentstring has on average 3.18383 higher score for Classic than Instrumentguitar
> # Voicepar3rd has on average 0.41273 lower score for Classic than contrary
```

```
> # Voicepar5th has on average 0.40075 lower score for Classic than contrary
> # Every unit score increase of X16.minus.17 on average predict 0.09614 lower score for Classic
> # ConsNotes is for controlling confounding effect
>
> # (c)
> # I will try out the models with interaction between self-declared musician with the three main
> # experimental factors for Popular
>                                                    what aobut ConsNotes and
                                                     X16.minus.17?
> m.4 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + X16.minus.17,
+         data = dtmusic, REML = F)
>
> m.4full = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+             (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+             ConsNotes + X16.minus.17+
+             musicianf:Harmony+musicianf:Instrument+musicianf:Voice,
+           data = dtmusic, REML = F)
>
> m.41 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + X16.minus.17+
+           musicianf:Harmony,
+         data = dtmusic, REML = F)
> m.42 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+           (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+           ConsNotes + X16.minus.17+
+           musicianf:Instrument,
+         data = dtmusic, REML = F)
```

```
> m.43 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+             (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+             ConsNotes + X16.minus.17+
+             musicianf:Voice,
+           data = dtmusic, REML = F)
> m.44 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+             (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+             ConsNotes + X16.minus.17+
+             musicianf:Harmony+musicianf:Instrument,
+           data = dtmusic, REML = F)
> m.45 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+             (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+             ConsNotes + X16.minus.17+
+             musicianf:Harmony+musicianf:Voice,
+           data = dtmusic, REML = F)
> m.46 = lmer(Popular ~ 1 + Harmony + Instrument + Voice +
+             (1|Subject:Harmony) + (1|Subject:Instrument)+ (1|Subject:Voice) +
+             ConsNotes + X16.minus.17+
+             musicianf:Voice+musicianf:Instrument,
+           data = dtmusic, REML = F)
>
> AIC(m.4,m.4full,m.41,m.42,m.43,m.44,m.45,m.46)
       df      AIC
m.4    14 8724.426
m.4full 22 8717.817
m.41   18 8712.909
m.42   17 8725.090
m.43   17 8725.515
m.44   20 8715.171
```

m.45 20 8715.553

m.46 19 8727.744

> BIC(m.4,m.4full,m.41,m.42,m.43,m.44,m.45,m.46)

df BIC

m.4 14 8803.740

m.4full 22 8842.453

m.41 18 8814.884

m.42 17 8821.400

m.43 17 8821.825

m.44 20 8828.477

m.45 20 8828.859

m.46 19 8835.384

> # AIC and BIC both suggest that m.41 is the best model, which has an interaction term between

> # musicianf and Harmony

interpretation?

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Summary of the Analysis

Explanation:
Since we already have too many variables with random intercept, including interaction term will further complicate the interpretation of the model and how the variables influence the scores for Classic and Popular. After all, music should be nice and simple, but not complex and ugly. Therefore, although the model with interaction fits the data better, I decide to use the best model without interaction to report to Dr.Jimenez. which interactions are you leaving out?

Summary for the Ratings of Classic:
All three main experimental factors have significantly influence on the ratings of Classic.
Holding other variables fixed:

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1. HarmonyI-V-VI has on average 0.81835 higher score for Classic than HarmonyI-IV-V
2. Instrumentpiano has on average 1.45442 higher score for Classic than Instrumentguitar
3. Instrumentstring has on average 3.21452 higher score for Classic than Instrumentguitar
4. Voicepar3rd has on average 0.40374 lower score for Classic than contrary
5. Voicepar5th has on average 0.38358 lower score for Classic than contrary
6. Every unit score increase of ClsListen on average predict 0.17145 higher score for Classic
7. ConsNotes and PianoPlay are for controlling confounding effect ? not sure what you mean

Summary for the Ratings of Popular:
All three main experimental factors have significantly influence on the ratings of Popular
Holding other variables fixed: do you mean popular?

1. HarmonyI-V-VI has on average 0.80253 higher score for Classic than HarmonyI-IV-V
2. Instrumentpiano has on average 1.44405 higher score for Classic than Instrumentguitar
3. Instrumentstring has on average 3.18383 higher score for Classic than Instrumentguitar
4. Voicepar3rd has on average 0.41273 lower score for Classic than contrary
5. Voicepar5th has on average 0.40075 lower score for Classic than contrary
6. Every unit score increase of X16.minus.17 on average predict 0.09614 lower score for Classic
7. ConsNotes is for controlling confounding effect

Discussion on Random Effect:

It seems that the size of variance component for person/Instrument is big and even comparable to the estimated residual variance, which means the kind of person/Instrument has a large influence on the intercept. Different kinds of this combination may have intercept that varies greatly. And the variance component for person/Voice is very small, which means the kind of person/Instrument has a small influence on the intercept. Different kinds of this combination may have intercept that does not vary too much. good

Conclusion for researchers' main hypothesis:
They are all examined by data to be true!

1. Instrument does have the largest influence on the ratings both for Classic and Popular numerically.
2. Harmony I-V-VI is frequently rated as classical and popular, which is actually the only significant level of Harmony compared to Harmony I-IV-V.
3. Both Voicepar3rd and Voicepar5th on average receive significantly lower ratings for Classic than contrary, so vice versa, contrary motion is frequently rated as Classic