Hierarchical Linear Models - HW05

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Part 1

a.

```
> rating <- read.csv("ratings.csv", header=TRUE)
> attach(rating)
> fit1 <- lm(Classical~Instrument + Harmony + Voice)
> fit2 <- lm (Classical~Instrument + Harmony)
> fit3 <- lm(Classical~Instrument + Voice)
> fit4 <- lm(Classical~Harmony + Voice)
> anova(fit1,fit2)
```

```
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Instrument + Harmony
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 13193 -2    -85.64 8.1181 0.0003061 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> anova(fit1,fit3)
```

```
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(fit1,fit4)
```

```
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
```

```
> summary(fit1)

Call:
lm(formula = Classical ~ Instrument + Harmony + 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 ***
Instrumentpiano   1.37359    0.11298  12.158  < 2e-16 ***
Instrumentstring  3.13312    0.11230  27.899  < 2e-16 ***
HarmonyI-V-IV    -0.03108    0.13008  -0.239 0.811168    
HarmonyI-V-VI     0.76909    0.13008   5.913 3.83e-09 ***
HarmonyIV-I-V     0.05007    0.12997   0.385 0.700092    
Voicepar3rd      -0.41247    0.11271  -3.660 0.000258 ***
Voicepar5th      -0.37058    0.11264  -3.290 0.001016 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

Fit1 is the full model, and fit2-fit4, we dropped each main effect respectively. By comparing fit1 and fit2, as the p-value is 0.0003061<0.001, Voice is important.
By comparing fit1 and fit3, as the p-value <0.001, Harmony is important.
By comparing fit1 and fit4, as the p-value <0.001, Voice is important.
By summarizing the full model fit1, we obtain the estimator and its p-value for each particular harmony, instrument and voice. There is a significant difference among three kinds of instrument (p-value <2e-16), and estimators of instrument are large enough. For Harmony, the estimators are small, and compared to Harmony I-VI-V, only Harmony I-V-VI has significant difference(p-value<0.001). For Voice, the estimators are small but there is significant difference among three kinds of voice.
All of these prove that main hypotheses to some extent: instrument has the largest influence on classical rating; particular harmonic progression I-V-VI has a greater influence on classical rating compared to other harmony.

b.

i.

$$Classical_i = \beta_0 + \alpha_{j[i]} + \beta_1 * Instrument_i + \beta_2 * Harmony_i + \beta_3 * Voice_i + \epsilon_i,\ \epsilon_i \overset{i.i.d}{\sim} N(0, \tau^2)$$

$$\alpha_j = \gamma_0 + \eta_j,\ \eta_j \overset{i.i.d}{\sim} N(0, \sigma^2)$$

ii.

```
> lm1 <- lmer(Classical ~ 1 + Instrument + Harmony + Voice + (1|Subject))
> ###first method
> model1coma= list(lm1,fit1)
> sapply(model1coma,AIC)
```

```
[1] 10491.51 11230.45

> sapply(model1coma,BIC)

[1] 10549.73 11282.84

> ###second method
> exactRLRT(lm1)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 763.3759, p-value < 2.2e-16
```

First method: as the model with random effect has smaller BIC and AIC, we would say random effect is needed in the model;
Second method: as the p-value <0.001, we reject the hypothesis $\sigma^2 = 0$ and keep the random effect (1|Subject) in the model.

iii.

```
> lm2 <- lmer(Classical ~ 1 + Instrument + Harmony + (1|Subject))
> lm3 <- lmer(Classical ~ 1 + Instrument + Voice + (1|Subject))
> lm4 <- lmer(Classical ~ 1 + Harmony + Voice + (1|Subject))
> #fm2_ML <- update(lm2,REML=FALSE)
> #fm3_ML <- update(lm3,REML=FALSE)
> #fm4_ML <- update(lm4,REML=FALSE)
> ###There is no difference between a REML analysis and
> ###a maximum likelihood analysis, so keep using REML analysis.
>
> anova(lm1,lm2)

Data:
Models:
lm2: Classical ~ 1 + Instrument + Harmony + (1 | Subject)
lm1: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
    Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lm2  8 10489 10536 -5236.6    10473
lm1 10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(lm1,lm3)

Data:
Models:
lm3: Classical ~ 1 + Instrument + Voice + (1 | Subject)
lm1: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm3  7 10539 10580 -5262.4    10525
lm1 10 10469 10527 -5224.4    10449 75.931      3  2.288e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> anova(lm1,lm4)

Data:
Models:
lm4: Classical ~ 1 + Harmony + Voice + (1 | Subject)
lm1: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm4  8 11408 11455 -5696.2    11392
lm1 10 10469 10527 -5224.4    10449 943.59      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Lm1 is the full model, and lm2-lm4, we dropped each main effect respectively. By comparing lm1 and lm2, as the p-value <0.001, Voice is important.
By comparing lm1 and lm3, as the p-value <0.001, Harmony is important.
By comparing lm1 and lm4, as the p-value <0.001, Voice is important.

c.

i.

```
> lm5 <- lmer(Classical ~ 1 + Instrument + Harmony + Voice +
+               (1|Subject:Instrument)+ (1|Subject:Harmony) + (1|Subject:Voice))
> ###comparison with the best models in 1a and 1b
> ###linear model does not have DIC
> model2com <- list(lm5,lm1,fit1)
> sapply(model2com,AIC)

[1] 10075.51 10491.51 11230.45

> sapply(model2com,BIC)

[1] 10145.37 10549.73 11282.84

> cbind(extractDIC(lm5),extractDIC(lm1))

        [,1]     [,2]
DIC 10015.54 10426.21
```

From part1a and part1b, we each have a best model. We only compare them with lm5. From the results above, we could tell that this model is better than each models in 1a and 1b.

ii.

```
> lm6 <- update(lm5, .~. -Voice)
> lm7 <- update(lm5, .~. -Harmony)
> lm8 <- update(lm5, .~. -Instrument)
> anova(lm5,lm6)

Data:
Models:
lm6: Classical ~ Instrument + Harmony + (1 | Subject:Instrument) +
lm6:     (1 | Subject:Harmony) + (1 | Subject:Voice)
lm5: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5:     (1 | Subject:Harmony) + (1 | Subject:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
```

```
lm6 10 10081 10140 -5030.6    10061
lm5 12 10058 10127 -5016.8    10034 27.753      2  9.409e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(lm5,lm7)

Data:
Models:
lm7: Classical ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
lm7:     Subject:Harmony) + (1 | Subject:Voice)
lm5: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5:     (1 | Subject:Harmony) + (1 | Subject:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm7  9 10090 10143 -5036.3    10072
lm5 12 10058 10127 -5016.8    10034 39.013      3  1.724e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(lm5,lm8)

Data:
Models:
lm8: Classical ~ Harmony + Voice + (1 | Subject:Instrument) + (1 |
lm8:     Subject:Harmony) + (1 | Subject:Voice)
lm5: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5:     (1 | Subject:Harmony) + (1 | Subject:Voice)
    Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm8 10 10160 10219 -5070.2    10140
lm5 12 10058 10127 -5016.8    10034 106.89      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

lm5 is the full model, and lm2-lm4, we dropped each main effect respectively. By comparing lm5 and lm6, as the p-value <0.001, Voice is important.
By comparing lm5 and lm7, as the p-value <0.001, Harmony is important.
By comparing lm5 and lm8, as the p-value <0.001, Voice is important.
With all the results from part1, we know that the best model is lm5, i.e. lmer(Classical 1 + Instrument + Harmony + Voice + (1|Subject:Instrument)+ (1|Subject:Harmony) + (1|Subject:Voice))

Subject:Harmony	0.44307
Subject:Voice	0.02809
Subject:Instrument	2.19850
Residual:	2.43753

Specifically 0.44 shows the variability of the intercept across (Subject:Harmony),0.028 is the amount of variability in the intercept across (Subject:Voice), 2.20 is the amount of variability in the intercept across (Subject:Instrument). The variance of Subject:Voice is the smallest.
The variances of three components are smaller than the estimated residual variance. Considering the variance ratio, σ_1^2/τ^2, which is 0.18; σ_2^2/τ^2, which is 0.012; σ_3^2/τ^2, which is 0.90.

iii.

$$Classical_i = \beta_0 + \beta_1 * Instrument_i + \beta_2 * Harmony_i + \beta_3 * Voice_i + \alpha_{1j[i]} + \alpha_{2j[i]} + \alpha_{3j[i]} + \epsilon_i, \epsilon_i \overset{i.i.d}{\sim} N(0, \tau^2)$$

$$\alpha_{1j} = \gamma_{10} + \eta_{1j}, \eta_{1j} \overset{i.i.d}{\sim} N(0, \sigma_1^2)$$

$$\alpha_{2j} = \gamma_{20} + \eta_{2j}, \eta_{2j} \overset{i.i.d}{\sim} N(0, \sigma_2^2)$$

$$\alpha_{3j} = \gamma_{30} + \eta_{3j}, \eta_{3j} \overset{i.i.d}{\sim} N(0, \sigma_3^2)$$

α_{1j} is for (1|subject:harmony); α_{2j} is for (1|subject:voice); α_{3j} is for (1|subject:Instrument).

Part 2

a.

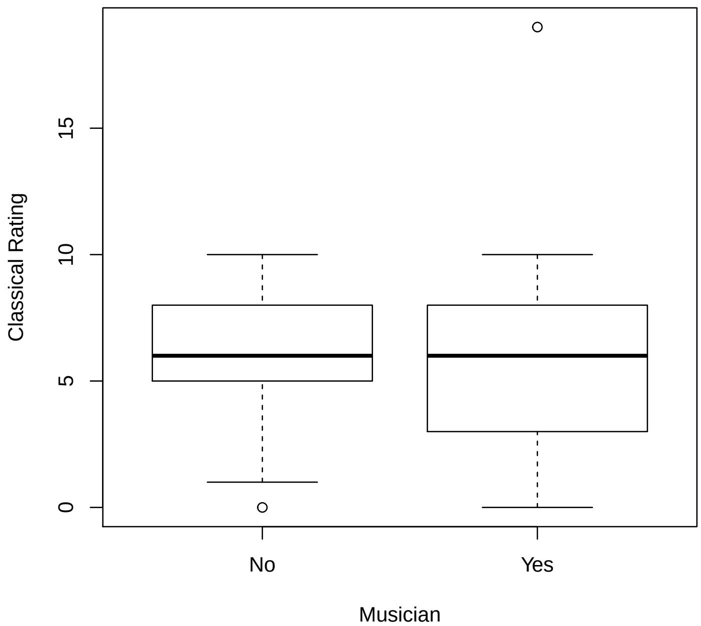
As the study mainly focuses on the influence of these three main effects on music rating, we will choose variables which may be related to these three variables. Also, considering that some variables may be correlated to each other, we will choose variables from different identical groups. In that case, Selfdeclare, X16.minus.17, PachListen, ClsListen, CollegeMusic and PianoPlay are chosen for classical rating.

Data Cleaning

Based on the variables we are interested in, we will delete the observations with these variables with value NA in order to compare different models in the same sample size.

```
> newrating <- subset(rating,Selfdeclare!='NA'&
+ X16.minus.17!='NA'&PachListen!='NA'&CollegeMusic!='NA'&
+ ClsListen!='NA'&PianoPlay!='NA' )
```

Also, to make things clear to interpret, we will reclassify categorical variables based on the results of EDA.




```
> lmer.cla <- lmer(data=newrating,Classical ~ 1 + Instrument + Harmony + Voice +
+                (1|Subject:Instrument)+ (1|Subject:Harmony) + (1|Subject:Voice))
> lmer1 <- update(lmer.cla,.~.+newrating$musician)
> anova(lmer1,lmer.cla)

Data: newrating
Models:
lmer.cla: Classical ~ 1 + Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.cla:     (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer1: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer1:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician
         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.cla 12 9501.3 9570.5 -4738.7   9477.3
lmer1    13 9499.0 9574.0 -4736.5   9473.0 4.2737      1    0.03871 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

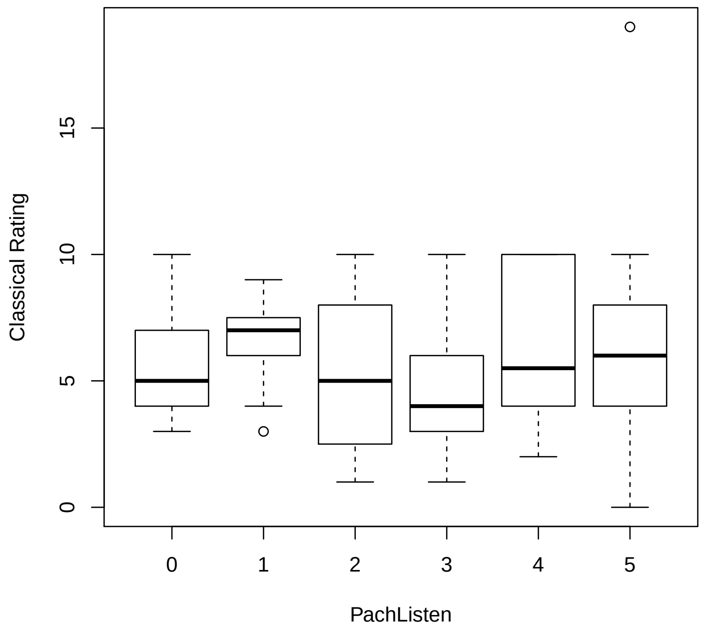
For Selfdeclare variable, we will group it into two levels as a new variable Musician. Since p-value of anova is 0.03871, we decide to keep this variable.

```
> #plot(newrating$X16.minus.17,newrating$Classical)
> lmer2 <- update(lmer1,.~.+newrating$X16.minus.17)
> anova(lmer2,lmer1)

Data: newrating
Models:
lmer1: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer1:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician
lmer2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer2:     newrating$X16.minus.17
```

```
      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1 13 9499.0 9574.0 -4736.5   9473.0
lmer2 14 9496.7 9577.4 -4734.4   9468.7 4.3349      1    0.03734 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

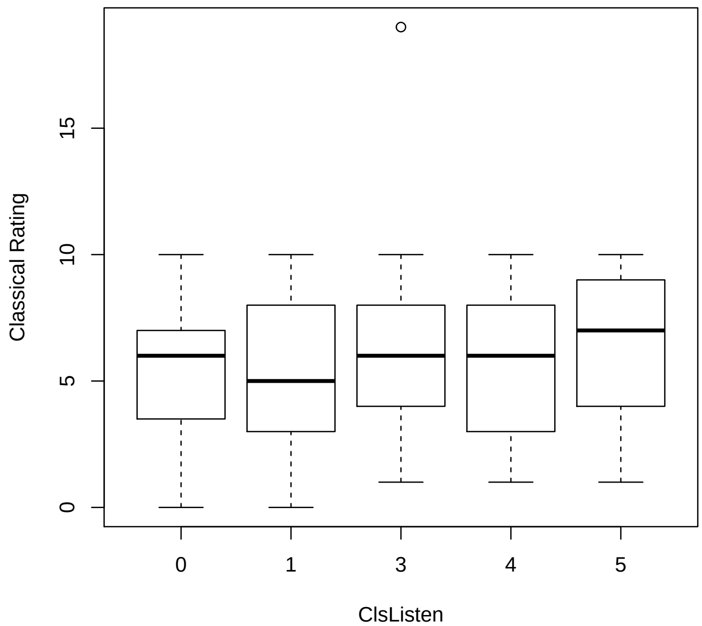
P-value=0.03734, we keep this variable in the model.




```
> lmer3 <- update(lmer2,.~.+newrating$Pachlevel)
> anova(lmer2,lmer3)

Data: newrating
Models:
lmer2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer2:     newrating$X16.minus.17
lmer3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer3:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer3:     newrating$X16.minus.17 + newrating$Pachlevel
      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2 14 9496.7 9577.4 -4734.4   9468.7
lmer3 15 9497.8 9584.3 -4733.9   9467.8 0.9494      1     0.3299
```

As these variables have 6 level, and there is no obvious difference among all the levels, we will relevel these variables. We set 0-2 as low level and 3-5 as high level. And we will do the same thing for other categorical variables. P-value= 0.3299, we do not keep this variable.




```
> lmer4 <- update(lmer2,.~.+newrating$Clslevel)
> anova(lmer4,lmer2)

Data: newrating
Models:
lmer2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer2:     newrating$X16.minus.17
lmer4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer4:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer4:     newrating$X16.minus.17 + newrating$Clslevel
      Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer2 14 9496.7 9577.4 -4734.4   9468.7
lmer4 15 9488.5 9575.0 -4729.2   9458.5 10.22      1    0.00139 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

P-value= 0.00139, we will keep this variable.

```
> lmer5 <- update(lmer4,.~.+newrating$CollegeMusic)
> anova(lmer4,lmer5)

Data: newrating
Models:
lmer4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer4:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer4:     newrating$X16.minus.17 + newrating$Clslevel
lmer5: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer5:     newrating$X16.minus.17 + newrating$Clslevel + newrating$CollegeMusic
      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
```

```
lmer4 15 9488.5 9575.0 -4729.2   9458.5
lmer5 16 9490.1 9582.3 -4729.0   9458.1 0.4197      1     0.5171
```

P-value= 0.5171, we will not keep this variable.

```
> boxplot(Classical~PianoPlay,data=newrating)
> newrating$Pialevel=ifelse(newrating$PianoPlay>2,"High","Low")
> lmer6 <- update(lmer4,.~.+newrating$Pialevel)
> anova(lmer4,lmer6)
```

```
Data: newrating
Models:
lmer4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer4:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer4:     newrating$X16.minus.17 + newrating$Clslevel
lmer6: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer6:     (1 | Subject:Harmony) + (1 | Subject:Voice) + newrating$musician +
lmer6:     newrating$X16.minus.17 + newrating$Clslevel + newrating$Pialevel
      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer4 15 9488.5 9575.0 -4729.2   9458.5
lmer6 16 9490.5 9582.8 -4729.2   9458.5 0.0047      1     0.9455
```

P-value=0.9455, we will not keep this variable.

The variable selection procedure is: one variable is added to Model "lmer.cla" at a time. The model with one additional variable is compared with model "lmer.cla" using ANOVA. If anova suggests that this variable should be included in the model, the new model becomes the comparison model. Otherwise, the old model would be used for comparison.
When we obtain the first significant variable, we will add a second variable to the model and use ANOVA to compare to the model with only one additional variable. After we are sure which variable should be the second variable added into the model. We will repeat the procedure until all variables have been explored. In sum, X16.minus.17, musician and Clslevel are added into the model in order.

b

```
> lmer.final <- update(lmer.cla, .~.+X16.minus.17+musician+Clslevel)
> lmer.com <- update(lmer.final, .~. -(1|Subject:Voice)
+         -(1|Subject:Harmony)-(1|Subject:Instrument)+(1|Subject))
> lmer.com1 <- update(lmer.final, .~. -(1|Subject:Instrument))
> lmer.com2 <- update(lmer.final, .~. -(1|Subject:Harmony))
> lmer.com3 <- update(lmer.final, .~. -(1|Subject:Voice))
> finalcoma <- list(lmer.final,lmer.com,lmer.com1,lmer.com2,lmer.com3)
> sapply(finalcoma,AIC)
```

```
[1]  9512.447  9939.599 10044.282  9618.933  9511.480
```

```
> sapply(finalcoma,BIC)
```

```
[1]  9598.949 10014.568 10125.018  9699.669  9592.216
```

```
> sapply(finalcoma,extractDIC)
```

```
     DIC      DIC      DIC      DIC      DIC
9434.538 9860.047 9963.088 9538.221 9435.124
```

```
> lmer.LRT1 <- update(lmer.final, .~.-(1|Subject:Harmony)
+                      -(1|Subject:Instrument))
> lmer.LRT2 <- update(lmer.final, .~. -(1|Subject:Voice)
+                      -(1|Subject:Instrument))
> lmer.LRT3 <- update(lmer.final, .~. -(1|Subject:Voice)
+                      -(1|Subject:Harmony))
> ###(subject:voice)
> exactRLRT(lmer.LRT1,lmer.final,lmer.com3)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 1.0339, p-value = 0.1482

> ###(subject:Harmony)
> exactRLRT(lmer.LRT2,lmer.final,lmer.com2)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 108.4862, p-value < 2.2e-16

> ###(subject:Instrument)
> exactRLRT(lmer.LRT3,lmer.final,lmer.com1)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 533.8359, p-value < 2.2e-16
```

When comparing the model with three random effects to the one with only random effect (1:subject), the criteria of AIC/BIC/DIC prefer the 3-random-effect model.
Then we study the model With the 3-random-effect model, the results of exactRLRT show that the random effect (1:subject|voice) can be dropped in the final model.

c.

```
                        Mean        SEM
Instrumentpiano   1.34759043 0.25955882
Instrumentstring  3.14348117 0.25932138
HarmonyI-V-IV    -0.03496627 0.14980247
HarmonyI-V-VI     0.81899766 0.14982901
HarmonyIV-I-V     0.04972924 0.14977029
Voicepar3rd      -0.40090566 0.07848716
Voicepar5th      -0.34816230 0.07846866
X16.minus.17     -0.07965427 0.03963477
musicianYes      -1.00777338 0.31899853
ClslevelLow      -0.80812703 0.25335351
```

Comment on the influences of three main effects (Fixed effects):
Holding other variables constant, compared to the instrument guitar, when the instrument is piano, the classical rating increases by 1.35 on average; when the instrument is string, the classical rating increases 3.14 by on average.
Holding other variables constant, compared to Harmony I-IV-V, when the Harmony is I-V-IV, the classical rating decreases by 0.03 on average; when the Harmony is I-V-VI, the classical rating increases by 0.82 on average; when the Harmony is IV-I-V, the classical rating increases by 0.05 on average.
Holding other variables constant, compared to the voice contrary, when the Voice is par 3rd, the classical rating decreases by 0.40 on average; when the Voice is par 5rd, the classical rating decreases by 0.35 on average.
Holding other variables constant, one unit increase in X16.minus.X17 (auxiliary measure of listener's ability to distinguish classical vs popular music), we will expect the classical rating decreases by 0.08 on average.
Holding other variables constant, a self-declared musician will rate a stimulus 1.14 units lower for classical compared to non self-declared musician on average.
Holding other variables constant, people who listen to classical music a lot will rate 0.81 units higher for classical compared to those who do not listen to classical music a lot.

```
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.68527
 Subject:Instrument (Intercept) 1.42028
 Residual                       1.55621
```

```
         (Intercept)
15:guitar  -0.7394337
15:piano   -0.3736223
15:string   0.7209759
16:guitar  -1.0887139
16:piano   -0.8744112
16:string   0.8262219
```

```
         (Intercept)
15:I-IV-V -0.49071014
15:I-V-IV -0.60975226
15:I-V-VI  0.54261693
15:IV-I-V  0.46657195
16:I-IV-V  0.08400238
16:I-V-IV  0.10623110
```

Random effects:
Specifically 0.68 shows the variability of the intercept across (Subject:Harmony),1.42 is the amount of variability in the intercept across (Subject:Instrument).
And the intercepts also are effected by main effects, as intercepts vary with different combinations of subject and harmony, subject and instrument.

Part 3. interactions with musician

```
> ###we consider the interactions of musician and all other fixed effects
> ###0.5345
> lmer.music1 <- update(lmer.final, .~. + musician:Instrument, data=newrating)
> anova(lmer.final,lmer.music1)

Data: newrating
Models:
```

```
lmer.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.final:     musician + Clslevel
lmer.music1: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music1:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music1:     musician + Clslevel + Instrument:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.final  15 9488.5 9575.0 -4729.2   9458.5
lmer.music1 17 9491.2 9589.3 -4728.6   9457.2 1.2527      2     0.5345

> ###0.00096
> lmer.music2 <- update(lmer.final, .~. + musician:Harmony, data=newrating)
> anova(lmer.final,lmer.music2)

Data: newrating
Models:
lmer.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.final:     musician + Clslevel
lmer.music2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music2:     musician + Clslevel + Harmony:musician
            Df    AIC  BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.final  15 9488.5 9575 -4729.2   9458.5
lmer.music2 18 9478.2 9582 -4721.1   9442.2 16.341      3  0.0009653 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> ###0.9397
> lmer.music3 <- update(lmer.music2, .~. + musician:Voice, data=newrating)
> anova(lmer.music3,lmer.music2)

Data: newrating
Models:
lmer.music2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music2:     musician + Clslevel + Harmony:musician
lmer.music3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music3:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music3:     musician + Clslevel + Harmony:musician + Voice:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.music2 18 9478.2 9582.0 -4721.1   9442.2
lmer.music3 20 9482.0 9597.4 -4721.0   9442.0 0.1243      2     0.9397

> ###0.5432
> lmer.music4 <- update(lmer.music2, .~. + musician:X16.minus.17, data=newrating)
> anova(lmer.music4,lmer.music2)

Data: newrating
Models:
lmer.music2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music2:     musician + Clslevel + Harmony:musician
lmer.music4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music4:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
```

```
lmer.music4:     musician + Clslevel + Harmony:musician + X16.minus.17:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.music2 18 9478.2 9582.0 -4721.1   9442.2
lmer.music4 19 9479.8 9589.4 -4720.9   9441.8 0.3697      1     0.5432

> ###0.07646
> lmer.music6 <- update(lmer.music2, .~. + musician:Clslevel, data=newrating)
> anova(lmer.music6,lmer.music2)

Data: newrating
Models:
lmer.music2: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music2:     musician + Clslevel + Harmony:musician
lmer.music6: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.music6:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmer.music6:     musician + Clslevel + Harmony:musician + musician:Clslevel
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.music2 18 9478.2 9582.0 -4721.1   9442.2
lmer.music6 19 9477.0 9586.6 -4719.5   9439.0 3.1387      1    0.07646 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

                                Mean        SEM
Instrumentpiano           1.34816402 0.25859980
Instrumentstring          3.14337082 0.25836325
HarmonyI-V-IV            -0.16239316 0.32445997
HarmonyI-V-VI            -0.24786325 0.32445997
HarmonyIV-I-V            -0.17948718 0.32445997
Voicepar3rd              -0.40151792 0.08353066
Voicepar5th              -0.34888305 0.08351232
X16.minus.17             -0.08302566 0.03947416
musicianYes               0.08945867 0.96307415
ClslevelLow               0.80977495 0.96000219
HarmonyI-V-IV:musicianYes  0.15922466 0.36219219
HarmonyI-V-VI:musicianYes  1.32885183 0.36220958
HarmonyIV-I-V:musicianYes  0.28550895 0.36217209
musicianYes:ClslevelLow   -1.73762824 0.99463981
```

The two statistically significant (p value less than 0.1) interactions are those between musician and harmony, between musician and Clslevel.
By looking at the interactions of musician variable in the model we selected, we know that some of them have a relatively large estimated value.
In sum, interactions between musician variable and other predictors in the model could improve the model. Thus, the hypothesis that people who self-identify as musicians may be influenced by things that do not influence non-musicians is proved in some degree.

Part4 Popular Rating

a.

Linear Models

```
> fit1.p <- lm(Popular~Instrument + Harmony + Voice)
> fit2.p <- lm (Popular~Instrument + Harmony)
> fit3.p <- lm(Popular~Instrument + Voice)
> fit4.p <- lm(Popular~Harmony + Voice)
> anova(fit1.p,fit2.p)

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(fit1.p,fit3.p)

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(fit1.p,fit4.p)

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

> summary(fit1.p)

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
```

Fit1.p is the full model, and fit2.p-fit4.p, we dropped each main effect respectively. By comparing fit1.p and fit2.p, as the p-value is 0.2237, Voice is not significant.
By comparing fit1.p and fit3.p, as the p-value =0.1069, Harmony is not significant.
By comparing fit1.p and fit4.p, as the p-value <0.001, Instrument is important, which satisfies the hyphothesis that instrument has the largest influence on rating.
Anyway, these three variables will be kept in this model as we are interested in their influences on music rating.

Examine random effects

```
> lm1.p<-lmer(Popular~Instrument+Harmony+Voice+(1|Subject))
> exactRLRT(lm1.p)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 714.7425, p-value < 2.2e-16
```

As the p-value is smaller than 0.05, we would say random effect is needed in the model.

Comparisons of models

```
> lm5.p <- lmer(Popular~Instrument + Harmony + Voice +
+                (1|Subject:Instrument)+ (1|Subject:Harmony) + (1|Subject:Voice))
> model2com.p <- list(lm5.p,lm1.p,fit1.p)
> sapply(model2com.p,AIC)

[1] 10097.24 10453.12 11143.15

> sapply(model2com.p,BIC)

[1] 10167.09 10511.34 11195.54

> cbind(extractDIC(lm5.p),extractDIC(lm1.p))

       [,1]     [,2]
DIC 10036.7 10387.47
```

From the results above, we could tell that the model with three random effects is the best among these three.

Re-examine three main effects

```
> lm6.p <- update(lm5.p, .~. -Voice)
> lm7.p <- update(lm5.p, .~. -Harmony)
> lm8.p <- update(lm5.p, .~. -Instrument)
> anova(lm5.p,lm6.p)

Data:
Models:
lm6.p: Popular ~ Instrument + Harmony + (1 | Subject:Instrument) + (1 |
lm6.p:     Subject:Harmony) + (1 | Subject:Voice)
lm5.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5.p:     (1 | Subject:Harmony) + (1 | Subject:Voice)
      Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm6.p 10 10080 10138 -5030.0    10060
lm5.p 12 10079 10149 -5027.5    10055 5.0782      2    0.07894 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(lm5.p,lm7.p)

Data:
Models:
lm7.p: Popular ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
lm7.p:     Subject:Harmony) + (1 | Subject:Voice)
lm5.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5.p:     (1 | Subject:Harmony) + (1 | Subject:Voice)
      Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lm7.p  9 10078 10130 -5030.0    10060
lm5.p 12 10079 10149 -5027.5    10055 5.1175      3     0.1634

> anova(lm5.p,lm8.p)

Data:
Models:
lm8.p: Popular ~ Harmony + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
lm8.p:     (1 | Subject:Voice)
lm5.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lm5.p:     (1 | Subject:Harmony) + (1 | Subject:Voice)
      Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lm8.p 10 10162 10220 -5070.9    10142
lm5.p 12 10079 10149 -5027.5    10055 86.87      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The results show that Voice is marginally significant, Harmony is not important and Instrument is significant. It satisfies the hyphothesis that instrument has the largest influence on rating. Because these three main effects are design variables in the experiment, the three experimental factors will still be included.

```
                        Mean        SEM
Instrumentpiano  -0.94900457 0.25152571
Instrumentstring -2.60586528 0.25122319
HarmonyI-V-IV    -0.02556901 0.14058560
HarmonyI-V-VI    -0.27156455 0.14057016
HarmonyIV-I-V    -0.18544920 0.14051190
Voicepar3rd       0.16380012 0.08323662
Voicepar5th       0.16206270 0.08317281
```

Comment on the influences of three main effects:
Holding other variables constant, compared to the instrument guitar, when the instrument is piano, the popular rating decreases by 0.95 on average; when the instrument is string, the popular rating decreases by 2.61 on average.
Holding other variables constant, compared to Harmony I-IV-V, when the Harmony is I-V-IV, the Popular rating decreases by 0.03 on average; when the Harmony is I-V-VI, the Popular rating decreases by 0.27 on average; when the Harmony is IV-I-V, the Popular rating decreases by 0.19 on average.
Holding other variables constant, compared to the voice contrary, when the Voice is par 3rd, the Popular rating increases by 0.16 on average; when the Voice is par 5rd, the Popular rating increases by 0.16 on average.
In addition, we could tell that there is a significant difference among three kinds of instrument (p-value <2e-16 and p-value=0.000224), and estimators of instrument are relatively larger than those of other two main effects. For Harmony, the estimators are small, and compared to Harmony I-VI-V, only Harmony I-V-VI has a significant difference(p-value=0.054950). For Voice, the estimators are relatively small but there is a significant difference among three kinds of voice (p-value: 0.051,0.54).
All of these prove that main hypotheses to some extent: instrument has the largest influence on popular rating; particular harmonic progression I-V-VI has a greater influence on popular rating compared to other harmony.

b.

As what we have done in part(2), in this part, Selfdeclare, X16.minus.17, KnowAxis, X1990s2000s, CollegeMusic and GuitarPlay are chosen for Popular rating.
We will conduct the same procedures (data cleaning, reorganize factor variables, model selection) as what we have done in classical rating section.

```
> ###data cleaning
> pnewrating <- subset(rating,Selfdeclare!='NA'&
+ X16.minus.17!='NA'&KnowAxis!='NA'&CollegeMusic!='NA'&
+  X1990s2000s!='NA'&GuitarPlay!='NA')

Data: pnewrating
Models:
lmer.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer.p:     (1 | Subject:Harmony) + (1 | Subject:Voice)
lmer1.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer1.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.p  12 8264.6 8332.1 -4120.3   8240.6
lmer1.p 13 8255.9 8328.9 -4114.9   8229.9 10.742      1   0.001047 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For Selfdeclare variable, we will group it into two levels, p-value=0.001047, we decide to keep this variable.

```
> #plot(pnewrating$X16.minus.17,pnewrating$Popular)
> lmer2.p <- update(lmer1.p,.~.+pnewrating$X16.minus.17)
> anova(lmer2.p,lmer1.p)

Data: pnewrating
Models:
lmer1.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer1.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician
lmer2.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
```

```
lmer2.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer2.p:     pnewrating$X16.minus.17
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1.p 13 8255.9 8328.9 -4114.9   8229.9
lmer2.p 14 8255.1 8333.7 -4113.5   8227.1 2.8059      1    0.09392 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

p-value=0.09392(<0.1), keep the varialbe in the model.

Reorganize variables
As these categorical variables have 6 levels, we will relevel these variables. We set 0-2 as low level and 3-5 as high level.

```
> pnewrating$knowlevel=ifelse(pnewrating$KnowAxis>2,"High","Low")
> lmer3.p <- update(lmer2.p,.~.+pnewrating$knowlevel)
> anova(lmer2.p,lmer3.p)

Data: pnewrating
Models:
lmer2.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer2.p:     pnewrating$X16.minus.17
lmer3.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer3.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer3.p:     pnewrating$X16.minus.17 + pnewrating$knowlevel
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2.p 14 8255.1 8333.7 -4113.5   8227.1
lmer3.p 15 8255.2 8339.5 -4112.6   8225.2 1.8636      1     0.1722
```

p-value = 0.1722, we do not keep the variable.

```
> boxplot(Popular~X1990s2000s,data=pnewrating)
> pnewrating$X1920=ifelse(pnewrating$X1990s2000s>2,"High","Low")
> lmer4.p <- update(lmer2.p,.~.+pnewrating$X1920)
> anova(lmer4.p,lmer2.p)

Data: pnewrating
Models:
lmer2.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer2.p:     pnewrating$X16.minus.17
lmer4.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer4.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer4.p:     pnewrating$X16.minus.17 + pnewrating$X1920
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2.p 14 8255.1 8333.7 -4113.5   8227.1
lmer4.p 15 8257.1 8341.4 -4113.5   8227.1 0.0045      1     0.9465
```

p-value= 0.9465, we do not keep the variable.

```
> lmer5.p <- update(lmer2.p,.~.+pnewrating$CollegeMusic)
> anova(lmer2.p,lmer5.p)
```

```
Data: pnewrating
Models:
lmer2.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer2.p:     pnewrating$X16.minus.17
lmer5.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer5.p:     pnewrating$X16.minus.17 + pnewrating$CollegeMusic
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2.p 14 8255.1 8333.7 -4113.5   8227.1
lmer5.p 15 8257.1 8341.3 -4113.5   8227.1 0.0187      1     0.8911
```

p-value = 0.8911, we do not keep the variable.

```
> #boxplot(Popular~GuitarPlay,data=pnewrating)
> pnewrating$Guilevel=ifelse(pnewrating$GuitarPlay>2,"High","Low")
> lmer6.p <- update(lmer2.p,.~.+pnewrating$Guilevel)
> anova(lmer2.p,lmer6.p)
```

```
Data: pnewrating
Models:
lmer2.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer2.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer2.p:     pnewrating$X16.minus.17
lmer6.p: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer6.p:     (1 | Subject:Harmony) + (1 | Subject:Voice) + pnewrating$musician +
lmer6.p:     pnewrating$X16.minus.17 + pnewrating$Guilevel
        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2.p 14 8255.1 8333.7 -4113.5   8227.1
lmer6.p 15 8254.9 8339.2 -4112.4   8224.9 2.2106      1     0.1371
```

p-value=0.1371, we will not keep GuitarPlay variable in the model.
In sum, we add two more variables X16.minus.17 and musician as fixed effects in the model.

Go back and check intercepts

```
> lmerp.final <- update(lmer.p, .~.+X16.minus.17+musician)
> lmerp.com <- update(lmerp.final, .~. -(1|Subject:Voice)
+                        -(1|Subject:Harmony)-(1|Subject:Instrument)+(1|Subject))
> lmerp.com1 <- update(lmerp.final, .~. -(1|Subject:Instrument))
> lmerp.com2 <- update(lmerp.final, .~. -(1|Subject:Harmony))
> lmerp.com3 <- update(lmerp.final, .~. -(1|Subject:Voice))
> popcoma <- list(lmerp.final,lmerp.com,lmerp.com1,lmerp.com2,lmerp.com3)
> sapply(popcoma,AIC)

[1] 8276.781 8557.640 8639.462 8357.394 8276.299

> sapply(popcoma,BIC)

[1] 8355.450 8625.070 8712.512 8430.444 8349.349

> sapply(popcoma,extractDIC)

     DIC      DIC      DIC      DIC      DIC
8205.369 8483.588 8565.934 8283.530 8206.321
```

```
> lmerp.pLRT1 <- update(lmerp.final, .~.-(1|Subject:Harmony)
+                      -(1|Subject:Instrument))
> lmerp.pLRT2 <- update(lmerp.final, .~. -(1|Subject:Voice)
+                       -(1|Subject:Instrument))
> lmerp.pLRT3 <- update(lmerp.final, .~. -(1|Subject:Voice)
+                        -(1|Subject:Harmony))
> ###(subject:voice)
> exactRLRT(lmerp.pLRT1,lmerp.final,lmerp.com3)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 1.5179, p-value = 0.0995

> ###(subject:Harmony)
> exactRLRT(lmerp.pLRT2,lmerp.final,lmerp.com2)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 82.6128, p-value < 2.2e-16

> ###(subject:Instrument)
> exactRLRT(lmerp.pLRT3,lmerp.final,lmerp.com1)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 364.6815, p-value < 2.2e-16
```

When comparing the model with three random effects to the one with only random effect (1:subject), the criteria of AIC/BIC/DIC prefer the 3-random-effect model.
Then we study the model with the 3-random-effect model, the results of exactRLRT show that the random effect (1:subject|voice) can be dropped in the final model.

```
                         Mean        SEM
Instrumentpiano  -1.136562032 0.26249415
Instrumentstring -2.964125177 0.26217015
HarmonyI-V-IV    -0.002221693 0.16145471
HarmonyI-V-VI    -0.342993546 0.16148942
HarmonyIV-I-V    -0.234204624 0.16141300
Voicepar3rd       0.182236954 0.08671114
Voicepar5th       0.217927370 0.08668711
X16.minus.17      0.066830996 0.04025920
musicianYes       1.095608604 0.33408894
```

Comment on the influences of three main effects in the final model(Fixed effects):
Holding other variables constant, compared to the instrument guitar, when the instrument is piano, the popular rating decreases by 1.14 on average; when the instrument is string, the popular rating decreases by 3.00 on average.

Holding other variables constant, compared to Harmony I-IV-V, when the Harmony is I-V-IV, the popular rating increases by 0.01 on average; when the Harmony is I-V-VI, the popular rating decreases by 0.33 on average; when the Harmony is IV-I-V, the popular rating decreases by 0.23 on average.
Holding other variables constant, compared to the voice contrary, when the Voice is par 3rd, the popular rating increases by 0.20 on average; when the Voice is par 5rd, the popular rating increases by 0.25 on average.
Holding other variables constant, one unit increase in X16.minus.X17 (auxiliary measure of listener's ability to distinguish classical vs popular music), we will expect the popular rating increases by 0.07 on average.
Holding other variables constant, a self-declared musician will rate a stimulus 1.06 units higher for popular compared to non self-declared musician on average.

```
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.67627
 Subject:Instrument (Intercept) 1.32145
 Residual                       1.59684
```

```
          (Intercept)
15:guitar  0.03251671
15:piano  -0.06861495
15:string -0.51951672
16:guitar  1.40138928
16:piano   1.15167177
16:string -1.15655317
```

```
          (Intercept)
15:I-IV-V  0.06284943
15:I-V-IV  0.20143789
15:I-V-VI -0.13701056
15:IV-I-V -0.27279328
16:I-IV-V  0.03629683
16:I-V-IV -0.03093964
```

Random effects:
Specifically 0.69 shows the variability of the intercept across (Subject:Harmony),1.34 is the amount of variability in the intercept across (Subject:Instrument).
And the intercepts also are effected by main effects, as intercepts vary with different combinations of subject and harmony, subject and instrument.

c. interactions with musician

```
> lmerp.music1 <- update(lmerp.final, .~. + musician:Instrument, data=pnewrating)
> anova(lmerp.final,lmerp.music1)
```

```
Data: pnewrating
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.final:     musician
lmerp.music1: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.music1:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.music1:     musician + Instrument:musician
             Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final  14 8255.1 8333.7 -4113.5   8227.1
lmerp.music1 16 8258.9 8348.8 -4113.5   8226.9 0.1569      2     0.9245
```

```
> lmerp.music2 <- update(lmerp.final, .~. + musician:Harmony, data=pnewrating)
> anova(lmerp.final,lmerp.music2)

Data: pnewrating
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.final:     musician
lmerp.music2: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.music2:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.music2:     musician + Harmony:musician
             Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final  14 8255.1 8333.7 -4113.5   8227.1
lmerp.music2 17 8255.9 8351.5 -4111.0   8221.9 5.1458      3     0.1614

> lmerp.music3 <- update(lmerp.final, .~. + musician:Voice, data=pnewrating)
> anova(lmerp.music3,lmerp.final)

Data: pnewrating
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.final:     musician
lmerp.music3: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.music3:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.music3:     musician + Voice:musician
             Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final  14 8255.1 8333.7 -4113.5   8227.1
lmerp.music3 16 8258.9 8348.9 -4113.5   8226.9 0.1311      2     0.9365

> lmerp.music4 <- update(lmerp.final, .~. + musician:X16.minus.17, data=pnewrating)
> anova(lmerp.music4,lmerp.final)

Data: pnewrating
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.final:     musician
lmerp.music4: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.music4:     (1 | Subject:Harmony) + (1 | Subject:Voice) + X16.minus.17 +
lmerp.music4:     musician + X16.minus.17:musician
             Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final  14 8255.1 8333.7 -4113.5   8227.1
lmerp.music4 15 8256.1 8340.4 -4113.1   8226.1 0.9742      1     0.3236
```

There is no significant interaction variable between musician and other predictors in the model.

what do you get if you just
interact musician with all the
other fixed effects?

4: 18
5: 20

38 nice job

The Influence of Instrument, Harmony, and Voice Leading on Classical and Popular Ratings

In this experiment, the researchers were interested in the influence of three main experimental factors (Instrument, Harmony & Voice) on listeners' identification of music as "classical" or "popular". There are three kinds of instrument: String Quartet, Piano, Electric Guitar; four kinds of harmonic motion: I-V-vi, I-VI-V, I-V-IV, IV-I-V; voice leading: Contrary Motion, Parallel 3rds, Parallel 5ths. 36 (3*4*4) musical stimuli were assigned to 70 listeners. Listeners were asked to indicate the extent to which a series of three-chord successions were popular or classical music sounding.

The analysis results show that the influence of these three factors varies for classical rating and popular rating. For classical rating, all the three factors are significant while for popular rating, only instrument matters a lot. For both ratings, there is a significant difference among three kinds of instrument. And the estimators of instrument are relatively larger than those of the other two main effects, which reflect that instrument has the largest influence on rating. Additionally, other harmonic motions have a significant difference from Harmony I-V-VI and stimuli in Harmony I-V- VI are rated higher in classical among all four harmonic motion. These findings conform to one of the main hypothesis: I-V- VI might be frequently rated as classical because it is the beginning progression for Pachlbel's Canon in D, which many people have heard. Specially, stimulus played by instrument guitar is likely to have a higher popular rating while that played by string is with a higher classical rating. Besides, stimulus in contrary motion is likely to have a higher classical rating but a lower popular rating among three kinds of voice leading.

A standard repeated measures model has only the simple subject random intercept in it, just as we discussed in problem #1b. From the model selection results we showed to problem #1c and problem #2b, we know that the model with three random effects (the combinations of subject with instrument, harmony and voice) is better than the model with only the simple subject random intercept. Furthermore, the results of extractRLRT( ) of problem #2b and problem #4 indicate that the random effect subject:voice could be dropped from the models both for popular and classical ratings. In that case, we need to at least include variance components of subject:instrument and subject:harmony in the model. Therefore, this is not a standard repeated measures model.

There are different individual covariates included in the models for classical and popular ratings. The common variables are musician and X16.minus.17. Musician implies whether a person declares himself as a musician or not. X16.minus.17 is the auxiliary measure of listener's ability to distinguish classical versus popular music. It seems that a self-declared musician is more likely to rate a stimulus higher on popular rating but lower on classical rating. Similarly, one unit increases in X16.minus.17, we would expect a slight increase in popular rating and a slight decrease in classical rating on average. For classical rating, the model has one more unique individual covariate: ClsListen (how much do you listen to classical music). Compared to people who listen to classical music a lot, people who listen to it a little will rate a stimulus 0.81 units lower on average.

Our findings conform to the main hypotheses of the researchers. We study the influence of the three main experimental factors well. Moreover, some other covariates are included in the model to help explain the variability of ratings after reasonable analyses.