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

2 a 6/9
b 9/9
c 9/9

3 9/9

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

5 10/10

Total 91/100

Hierarchical Models HW05

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A writeup of the research below (Question 5)

The influence of Instrument, Harmony and Voice

Based on the analysis of conventional linear models and models with random effects, Instruments, Harmony and Voice are all predictive of both classical and popular ratings.

Harmony I-V-VI is expected to have a significantly higher classical rating and lower popular rating compared to the other three harmonic motions. Interestingly, when we account for the effect that listeners declare themselves to be musicians on the relationship between classical ratings and Harmony, we would find out that compared to non-musicians, musicians are slightly less likely to rate Harmony I-V-IV as classical and
10 more likely to rate Harmony I-V-VI as classical. Even though, non-musicians also tend to rate Harmony I-V-VI as classical compared to the other harmonies.

String Quartet is associated with the highest classical rating and the lowest popular rating compared to other instruments, while Electronic Guitar has the opposite features. Contrary motion is more frequently rated as classical compared to other kinds of voice leadings, and the Parallel 3rds and Parallel 5ths are comparable in both ratings.

Among the three predictors, Instrument has the largest influence on ratings because of two reasons. Firstly, the correlation coefficients for Instruments in each model are greater compared to the correlation coefficients of Harmony or Voice. This indicates that the change of instrument is expected to change the ratings on larger scales than the change of the other two main experimental factors. Secondly, the variance component of intercept that corresponds with Instrument is always the largest of the three. This means that the change of Instrument accounts for more variability in the ratings compared to the other two variables.

On the contrary, Voice is expected to be the least influential factor among the three. Because the random effects corresponding with Voice account for the least variability of the model. Another reason is that when other covariates are included, the variable Voice, along with its random effect term tend to lose their significance.

To conclude, all hypothesis listed are verified through the analysis.

Individual covariates

In order to improve the fit of the model, we also explore other potential predictors on the ratings. Some interesting results are shown through the analysis. A higher concentration level on notes, being more familiar with Pachelbel's Canon in D, a smaller number of music classes taken and having taken AP music theory class in high school are factors that will have positive influence on classical rating and negative influence on popular rating.

A better skill of playing piano is associated with higher classical rating but shows no significant effects on popular ratings.

Being more familiar with Rob Paravonian's Pachelbel Rant, and with Axis of Evil's Comedy bit on the 4 Pachelbel Chords in popular music, as well as listening to pop and rock from the 90's and 2000's more frequently are the factors that would increase both classical ratings and popular ratings.

Adding these predictors largely improve the fit of the model. Hence, more potential predictors could be examined in the future stage of the study to find the best prediction of the ratings.

Question 1

(a)

Have you converted Instr, harmony and voice to be factors? the levels do not make any sense as ordered or interval levels....

```
lm.1.a <- lm(Classical ~ Harmony + Instrument + Voice,data= ratings)
#display(lm.1.a)

# Test whether harmony is important
lm.1.a.h <- lm(Classical ~ Instrument + Voice,data= ratings)
#anova(lm.1.a.h,lm.1.a)

# Test whether instrument is important
lm.1.a.i <- lm(Classical ~ Harmony + Voice,data= ratings)
#anova(lm.1.a.i,lm.1.a)

# Test whether voice is important
lm.1.a.v <- lm(Classical ~ Harmony + Instrument,data= ratings)
#anova(lm.1.a.v,lm.1.a)
```

7

The ANOVA above report a p-value of 4.107e-11, smaller than 2.2e-16 and 0.00031 respectively. This means that all three variables are significant in our model and should not be excluded from the model.

(b)

i. Level 1: $Classical_i \overset{indep}{\sim} N(\beta_1 * Harmony_i + \beta_2 * Instrument_i + \beta_3 * Voice_i + \alpha_{j[i]}, \sigma^2)$
   Level 2: $\alpha_j \overset{iid}{\sim} N(\beta_0, \tau^2)$

This would be ok if we were considering instr, harm & voice to be continuous covariates, but they are factors....

ii.

```
lmer.1.b <- lmer(Classical ~ Harmony + Instrument + Voice + (1|Subject),data= ratings)
# Method 1: comparing AIC
data.frame(AIC(lmer.1.b),AIC(lm.1.a))
```

7

```
##   AIC.lmer.1.b. AIC.lm.1.a.
## 1      10491.51    11230.45
```

```
# Method 2: use function "exactRLRT"
#exactRLRT(lmer.1.b)
```

The AIC of the model with random effect is approximately 739 smaller than the conventional linear model. The RLRT test shows a p-value smaller than 2.2e-16. Both provide evidence that the random effect is needed in our model.

iii.

```
# Test whether harmony is important
lmer.1.b.h <- lmer(Classical ~ Instrument + Voice + (1|Subject),data= ratings)
#anova(lmer.1.b.h,lmer.1.b)

# Test whether instrument is important
```

9

```
lmer.1.b.i <- lmer(Classical ~ Harmony  + Voice + (1|Subject),data= ratings)
#anova(lmer.1.b,lmer.1.b.i)

# Test whether voice is important
lmer.1.b.v <- lmer(Classical ~ Harmony + Instrument + (1|Subject),data= ratings)
#anova(lmer.1.b,lmer.1.b.v)

# Compare the three variables
#display(lmer.1.b)
```

The ANOVA above report a p-value of 2.288e-16, smaller than 2.2e-16 and 5.45e-06 respectively. This means that all three variables are significant in our model. Therefore they should all be included.
The correlation coefficients show that the change in instrument tend to have greater effect on the classical ratings.
Compared to Harmony I-VI-V, Harmony I-V-IV is slightly less likely to be rated as classical, while Harmony IV-I-V is slightly more likely to be rated as classical. However, Harmony I-V-VI is expected to have a 0.77 higher score in classical rating than Harmony I-VI-V on average. This is in accordance with the hypothesis.
Compared with stimuli played with electronic guitar, stimuli that are played by piano are expected to be 1.38 higher in classical ratings, and stimuli played by string quartet are expected to be 3.13 higher in ratings.
Compared with contrary motion, parallel 3rd would receive 0.42 lower score in classical ratings, and parallel 5ths would receive 0.37 lower score. This is in line with the hypothesis that contrary motion would be frequently rated as classical.

(c)

i.

	AIC	BIC
Model with three random effect terms	10075.51	10145.37
Full linear model	11230.45	11282.84
Linear model without Harmony	11275.96	11310.89
Linear model without Instrument	11908.94	11949.69
Linear model without Voice	11242.69	11283.43

Table 1: Comparison with models in part (a)

Table 1 shows that the model with all three random effect terms has the lowest AIC as well as BIC compared to all four models in part (a). Therefore we conclude that this model is better than the models in part (a).

	AIC	BIC
Model with three random effect terms	10075.51	10145.37
Repeated measures model	10491.51	10549.73
Repeated measures model without Harmony	10552.74	10593.49
Repeated measures model without Instrument	11423.04	11469.60
Repeated measures model without Voice	10505.58	10552.15

Table 2: Comparison with models in part (b)

Table 2 shows that the model with all three random effect terms has the lowest AIC as well as BIC compared to all four models in part (b). Therefore we conclude that this model is better than the models in part (b).

ii.

```r
# Test the influence of harmony
lmer.1.c.h <- lmer(Classical ~ Instrument + Voice + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)
#display(lmer.1.c.h)
#anova(lmer.1.c.h,lmer.1.c)

# Test the influence of instrument
lmer.1.c.i <- lmer(Classical ~ Harmony + Voice + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)
#display(lmer.1.c.i)
#anova(lmer.1.c.i,lmer.1.c)

# Test the influence of voice
lmer.1.c.v <- lmer(Classical ~ Harmony + Instrument + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)
#display(lmer.1.c.v)
#anova(lmer.1.c.v,lmer.1.c)
```

The three anova tests report a p-value of 1.724e-08, 2.2e-16 and 9.409e-07 respectively, indicating that the three main experimental factors are all statistically significant, and should all be included in the model.
Compared to Harmony I-VI-V, Harmony I-V-IV is slightly less likely to be rated as classical, while Harmony IV-I-V is slightly more likely to be rated as classical. However, Harmony I-V-VI is expected to have a 0.77 higher score in classical rating than Harmony I-VI-V on average. This is in accordance with the hypothesis.
Compared with stimuli played with electronic guitar, stimuli that are played by piano are expected to be 1.36 higher in classical ratings, and stimuli played by string quartet are expected to be 3.13 higher in ratings.
Compared with contrary motion, parallel 3rd would receive 0.41 lower score in classical ratings, and parallel 5ths would receive 0.37 lower score. This is in line with the hypothesis that contrary motion would be frequently rated as classical.
The estimated variances of intercept due to Harmony, Instrument and Voice are 0.443, 2.198, 0.028 respectively.
7 Among the three estimated variances, the variance for Voice is the smallest, and the variance for Instrument is the largest. The estimated residual variance is 2.438, which is greater than all three estimated variance components. Therefore, Instrument accounts for more random effects of intercept compared to the other two factors.

iii. Level 1: $Classical_i \overset{indep}{\sim} N(\beta_1 * Harmony_i + \beta_2 * Instrument_i + \beta_3 * Voice_i + \alpha1_{j[i]} + \alpha2_{j[i]} + \alpha3_{j[i]}, \sigma^2)$
Level 2: $\alpha1_j \overset{iid}{\sim} N(\beta1_0, {\tau_1}^2)$
$\alpha2_j \overset{iid}{\sim} N(\beta2_0, {\tau_2}^2)$
$\alpha3_j \overset{iid}{\sim} N(\beta3_0, {\tau_3}^2)$

your notation doesn't yet reflect the structure of the model

Question 2

(a)

Our basic idea is to use stepwise selection for lmer model to pick up some interesting covariates based on AIC, then decide whether we should include the covariates in the model. Finally we will look at other covariates that are not picked by the stepwise selection but are likely to be predictive of the response variable. Firstly we fit the full model. We do not include Instr.minus.Notes here because it is calculated from two variables and does not provide new information. We also exclude X1stInstr and X2ndInstr because there are two many NAs for these two varialbes and these NAs will cause the number of observations to cut of by more than a half.
It is not necessary to factorize the model because all the categorical variables that are in the format of integer are ordered, which is meaningful in interpretation.

```r
lmer.2.all <- lmer(Classical ~ Harmony + Instrument + Voice + Selfdeclare + OMSI +
                   X16.minus.17 + ConsInstr + ConsNotes + PachListen + ClsListen +
                   KnowRob + KnowAxis + X1990s2000s +
                   X1990s2000s.minus.1960s1970s + CollegeMusic + NoClass +
                   APTheory + Composing + PianoPlay + GuitarPlay +
                   (1|Subject:Harmony) + (1|Subject:Instrument) +
                   (1|Subject:Voice),data= ratings)
#display(lmer.2.all)
data.frame(AIC(lmer.2.all),AIC(lmer.1.c))
```

```
##   AIC.lmer.2.all. AIC.lmer.1.c.
## 1        6299.809      10075.51
```

We can see that the full model has a much smaller AIC compared to the model in 1 (c).

```r
### Stepwise selection
library(LMERConvenienceFunctions)
```

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

```r
#bfFixefLMER_F.fnc(lmer.2.all,method = c("AIC"))
```

The stepwise selection highlights the following variables: ConsNotes, PachListen, KnowRob, KnowAxis, x1990S2000S, NoClass, APTheory and Pianoplay. Then we try fitting the selected model, examine the correlation coefficients, and decide whether to include these covariates.

```r
# Fit the selected model
lmer.2.select <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
    (1 | Subject:Voice), data = ratings)

# Check multicollinearity
variable.select <- ratings[,c("ConsNotes","PachListen","KnowRob","KnowAxis","X1990s2000s","NoClass","AP
variable.select <- na.omit(variable.select)
#cor(variable.select)

# Check the coefficients of covariates
#fixef(lmer.2.select)
```

Through AIC-based stepwise selection, this selected model gives the smallest AIC among all possible models. The correlation matrix shows that all correlations between pairs of covariates are smaller than 0.5. So we do not worry about multicollinearity.

A covariate does not need to be significant to include in a model as long as it has a reasonable correlation coefficient. The fixed effects above show that all the selected covariates have reasonable and interpretable coefficients, so we include all of them in our model.

you didn't show a table o estimated coefficients and standard errors, so it's difficult to verify your statements.

We also try adding two variables into our model which seem interesting. Self declare and OMSI are chosen because they provide very different information from the covariates we already have.

6

```
# Self declare
lmer.2.sd <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + Selfdeclare + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice), data = ratings)
#anova(lmer.2.sd,lmer.2.select)
#fixef(lmer.2.sd)

# OMSI
lmer.2.omsi <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + OMSI + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice), data = ratings)
#anova(lmer.2.omsi,lmer.2.select)
#fixef(lmer.2.omsi)
```

With p-values of 0.1764 and 0.1504, the ANOVA results suggest that both variables are not significant. The changes in coefficients and AIC value are very little. Therefore the two variables are unlikely to be predictive of the response variable. Therefore we keep our previous model.
The final set of variables: Harmony, Instrument, Voice, ConsNotes, PachListen, KnowRob, KnowAxis, X1990s2000s, NoClass, APTheory and PianoPlay

(b)

```
# Test the random effect of (1|Subject:Harmony)
lmer.2.b.h <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay +  (1 | Subject:Instrument) + (1 | Subject:Voice),
    data = ratings)
# display(lmer.2.b.h)
#AIC(lmer.2.b.h)

# Test the random effect of (1 | Subject:Instrument)
lmer.2.b.i <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay +  (1 | Subject:Harmony) + (1 | Subject:Voice),
    data = ratings)
# display(lmer.2.b.i)
#AIC(lmer.2.b.i)

# Test the random effect of (1|Subject:Voice)
lmer.2.b.v <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay +  (1 | Subject:Instrument) + (1 | Subject:Harmony),
    data = ratings)
#display(lmer.2.b.v)
#AIC(lmer.2.b.v)
```

9

Then we test the random effects in the model using AIC.

Based on the analysis above, the random effect of subject versus Harmony and Instrument should be kept because excluding these terms will largely increase AIC. However, the random effect of subject versus Voice should be removed from the model because the AIC becomes smaller when we remove it.

	AIC
Model with three random effect terms	6268.579
Model without random effect term of Harmony	6330.534
Model without random effect term of Instrument	6610.479
Model without random effect term of Voice	6268.359

Table 3: Test the influence of random effects

(c)

9

```
lmer.2.final <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + (1 | Subject:Harmony) + (1 | Subject:Instrument) ,
    data = ratings)
display(lmer.2.final)
```

```
## lmer(formula = Classical ~ Harmony + Instrument + Voice + ConsNotes +
##     PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
##     APTheory + PianoPlay + (1 | Subject:Harmony) + (1 | Subject:Instrument),
##     data = ratings)
##                  coef.est coef.se
## (Intercept)       2.12     0.98
## HarmonyI-V-IV     0.00     0.18
## HarmonyI-V-VI     0.85     0.18
## HarmonyIV-I-V     0.06     0.18
## Instrumentpiano   1.65     0.30
## Instrumentstring  3.59     0.30
## Voicepar3rd      -0.40     0.10
## Voicepar5th      -0.30     0.10
## ConsNotes        -0.18     0.08
## PachListen        0.20     0.18
## KnowRob           0.09     0.09
## KnowAxis          0.08     0.07
## X1990s2000s       0.19     0.09
## NoClass          -0.15     0.11
## APTheory          0.63     0.36
## PianoPlay         0.31     0.09
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.67
##  Subject:Instrument (Intercept) 1.31
##  Residual                       1.59
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
## AIC = 6268.4, DIC = 6157.5
## deviance = 6193.9
```

For random effect, the estimated variance of the intercept due to Harmony is 0.447, and the estimated variance due to Instrument is 1.727. The variance of residuals is 2.515. The Instrument accounts for more variance in intercept compared to Harmony.

For the following interpretation, we assume that when one variable changes, all the other variables are held

the same. For fixed effect, compared to Harmony I-VI-V, Harmony I-V-IV is slightly less likely to be rated as classical, while Harmony IV-I-V is slightly more likely to be rated as classical. However, Harmony I-V-VI is expected to have a 0.850 higher score in classical rating than Harmony I-VI-V on average. This is in accordance with the hypothesis.
Compared with stimuli played with electronic guitar, stimuli that are played by piano are expected to be 1.649 higher in classical ratings, and stimuli played by string quartet are expected to be 3.588 higher in ratings.
Compared with contrary motion, parallel 3rd would receive 0.403 lower score in classical ratings, and parallel 5ths would receive 0.300 lower score. This is in line with the hypothesis that contrary motion would be frequently rated as classical.
When the listener's concentration level on notes goes up by 1, the classical rating is expected to decrease by 0.185.
When the listener is one level more familiar with Pachelbel's Canon in D, the rating is expected to increase by 0.199.
When the listener is one level up in "having heard Rob Paravonian's Pachelbel Rant", the rating is expected to increase by 0.086.
When the listener is one level up in "having heard Axis of Evil's Comedy bit on the 4 Pachelbel Chords in popular music", the rating is expected to increase by 0.081.
When the listener is one level more frequent to listen to pop and rock from the 90's and 2000's, the rating is expected to increase by 0.189.
When the number of music class taken by the listener increases by one, the classical rating is expected to decrease by 0.154.
If a listener took AP music theory class in high school, his rating for the stimuli is expected to go up by 0.632 compared to a listener who did not.
When the listener's level of playing piano increases by 1, the rating is expected to increase by 0.308.

Question 3

9 First of all we dichotomize the variable "Self declare" with a threshold of 2. Listeners who report 1 or 2 are recognized as non-musicians. The rest are recognized as musicians. Non-musicians take up 60% of all the listeners.

```
#summary(ratings$Selfdeclare)
# Dichotomize "Self declare"
ratings$musician <- 1
ratings[ratings$Selfdeclare < 3,]$musician <-0
```

Again we apply stepwise selection based on AIC.

```
# Full model with the indicator of musician and all possible interactions
lmer.3.full <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + musician + musician:Harmony +
    musician:Instrument + musician:Voice +
    musician:ConsNotes + musician:PachListen +
    musician:KnowRob + musician:KnowAxis +
    musician:X1990s2000s + musician:NoClass +
    musician:APTheory + musician:PianoPlay +
    (1 | Subject:Harmony) + (1 | Subject:Instrument) , data = ratings)
#display(lmer.3.full)

# Stepwise selection
#bfFixefLMER_F.fnc(lmer.3.full,method = c("AIC"))
```

```r
lmer.3.select <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + musician + musician:Harmony +
    musician:PianoPlay + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) , data = ratings)
#anova(lmer.3.select,lmer.2.final)
```

The stepwise selection suggest that the interaction between the indicator of musician and Harmony and the interaction between the indicator and Pianoplay will improve the model in terms of AIC. The ANOVA reports a p-value of 1.548e-05. This means that including the indicator of musician as well as the interaction terms significantly improve the fit of the model. Therefore it is a good idea to keep both interaction terms. Then we examine the fixed and random effects of the new model.

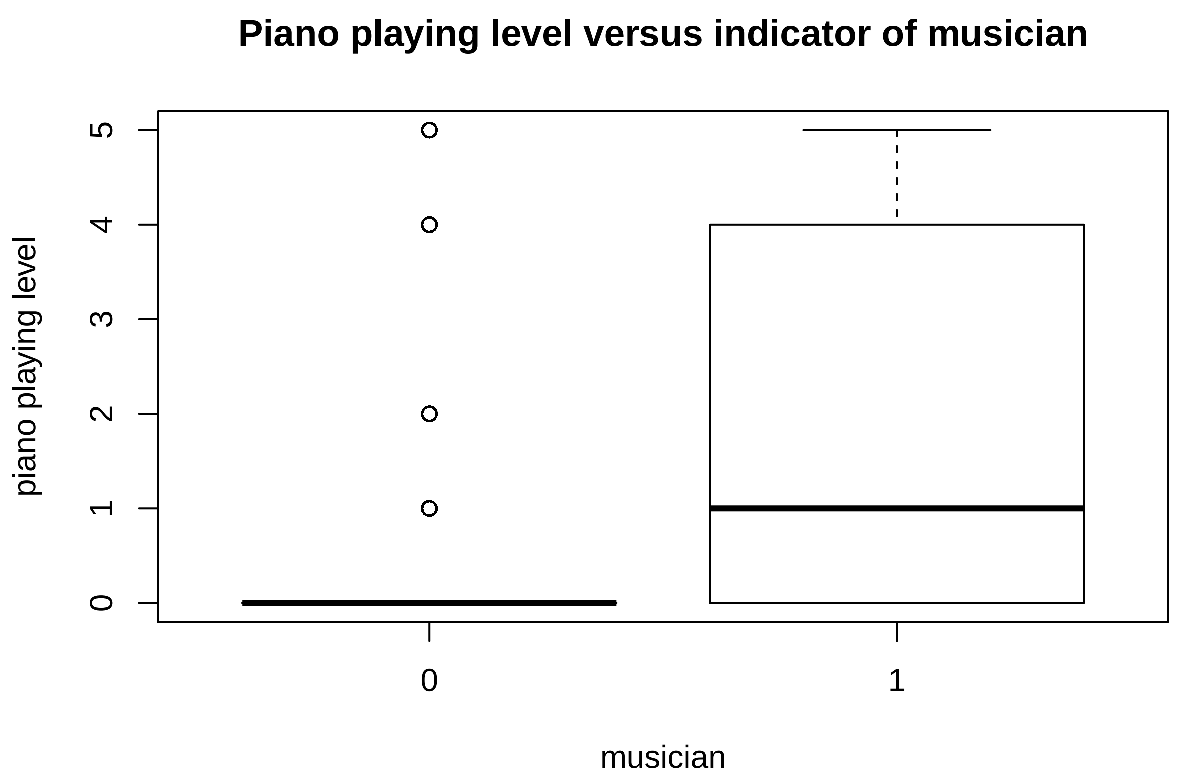
```r
display(lmer.3.select)
```

```
## lmer(formula = Classical ~ Harmony + Instrument + Voice + ConsNotes +
##     PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
##     APTheory + PianoPlay + musician + musician:Harmony + musician:PianoPlay +
##     (1 | Subject:Harmony) + (1 | Subject:Instrument), data = ratings)
##                        coef.est coef.se
## (Intercept)             1.63     0.99
## HarmonyI-V-IV           0.01     0.24
## HarmonyI-V-VI           0.27     0.24
## HarmonyIV-I-V           0.00     0.24
## Instrumentpiano         1.65     0.29
## Instrumentstring        3.59     0.29
## Voicepar3rd            -0.40     0.10
## Voicepar5th            -0.30     0.10
## ConsNotes              -0.19     0.08
## PachListen              0.28     0.17
## KnowRob                 0.12     0.08
## KnowAxis                0.03     0.07
## X1990s2000s             0.22     0.09
## NoClass                -0.14     0.10
## APTheory                0.58     0.35
## PianoPlay               0.76     0.16
## musician                0.08     0.41
## HarmonyI-V-IV:musician -0.03     0.35
## HarmonyI-V-VI:musician  1.26     0.35
## HarmonyIV-I-V:musician  0.12     0.34
## PianoPlay:musician     -0.61     0.19
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.60
##  Subject:Instrument (Intercept) 1.28
##  Residual                       1.59
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
## AIC = 6253.6, DIC = 6122.5
## deviance = 6164.0
```

The random effects of intercept due to both Harmony and Instrument decrease in this model, and the total

random effects of this model also decrease. The random effect might shrink but the model fits better overall based on ANOVA and AIC calculation.
Most fixed effects do not change much, but there are some noticeable changes among the correlation coefficients. The correlation coefficient of "KnowAxis" has the largest proportional change. The new model suggests that the listeners will rate the stimuli higher as their level of "KnowAxis" goes up by 1, but the increase is smaller than the estimated increase in the last model.
The interaction terms alter the relationship between classical ratings and Harmony as well as PianoPlay. Compared to non-musicians, musicians are slightly less likely to rate HarmonyI-V-IV as classical and more likely to rate HarmonyI-V-VI and Harmony IV-I-V as classical, especially Harmony I-V-VI. Even though, non-musicians also tend to rate Harmony I-V-VI as classical compared to the other harmonies.
Among people who declare to be non-musician, one level's increase in playing piano corresponds to 0.761 higher score in classical ratings. However, among musicians, this figure is only 0.156.

```
boxplot(ratings$PianoPlay~ratings$musician, main="Piano playing level versus indicator of musician",xla
```



Nice idea.

To find potential explanation, we draw a boxplot and find an interesting pattern. People who can play piano are very unlikely to declare themselves to be non-musicians. Therefore the coefficient 0.761 is not very meaningful since it is calculated using very few data points.

Question 4

(a)

```
lmer.4.a <- lmer(Popular ~ Harmony + Instrument + Voice + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)
```

```
# Test the influence of harmony
lmer.4.a.h <- lmer(Popular ~ Instrument + Voice + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)

#display(lmer.4.a.h)
#anova(lmer.4.a.h,lmer.4.a)

# Test the influence of instrument
lmer.4.a.i <- lmer(Popular ~ Harmony + Voice + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)

#display(lmer.4.a.i)
#anova(lmer.4.a.i,lmer.4.a)

# Test the influence of voice
lmer.4.a.v <- lmer(Popular ~ Harmony + Instrument + (1|Subject:Harmony) +
                     (1|Subject:Instrument) + (1|Subject:Voice),data= ratings)

#display(lmer.4.a.v)
#anova(lmer.4.a.v,lmer.4.a)
```

9

The ANOVA test of Harmony reports a p-value of 0.1634, which is not statistically significant, meaning that different types of harmonies do not have significant influence on the popular ratings. The ANOVA test of Instrument reports a p-value smaller than 2.2e-16, meaning that the variable instrument is statistically significant, and should be included in the model. The ANOVA test of Voice reports a p-value of 0.07894, which is significant with 0.1 significance level. Since the AIC values of the models with or without voice are very similar, we can keep the variable in our model.

(b)

We do not keep Harmony in this model fitting process.

Harmony is a design variable and therefore it should be included no matter what (especially if (1|s:h) is in the model).

```
lmer.4.all <- lmer(Popular ~ Instrument + Voice + Selfdeclare + OMSI +
                   X16.minus.17 + ConsInstr + ConsNotes + PachListen + ClsListen +
                   KnowRob + KnowAxis + X1990s2000s +
                   X1990s2000s.minus.1960s1970s + CollegeMusic + NoClass +
                   APTheory + Composing + PianoPlay + GuitarPlay +
                   (1|Subject:Harmony) + (1|Subject:Instrument) +
                   (1|Subject:Voice),data= ratings)
#display(lmer.4.all)

### Stepwise selection
#bfFixefLMER_F.fnc(lmer.4.all,method = c("AIC"))
```

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The stepwise selection highlights the following variables: ConsNotes, PachListen, KnowRob, KnowAxis, x1990S2000S, NoClass and APTheory. Then we try fitting the selected model.

```
# Fit the selected model
#lmer.4.select <- lmer(Popular ~  Instrument + Voice +
#    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
#    APTheory + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
#    (1 | Subject:Voice), data = ratings)
```

```r
# Check multicollinearity (Already checked in question 2)

# Check the coefficients of covariates
#fixef(lmer.4.select)
```

The fixed effects above show that all the selected covariates have reasonable and interpretable coefficients, so we include all of them in our model.
We also try adding Self declare and OMSI into our model. The ANOVA tests report p-values of 0.8491 and 0.5231 respectively. Both variables are not significant, and we do not include them in our model.
The final set of variables: Instrument, Voice, ConsNotes, PachListen, KnowRob, KnowAxis, X1990s2000s, NoClass and APTheory
Then we test the random effects in the model using AIC.

	AIC
Model with three random effect terms	6374.919
Model without random effect term of Harmony	6428.234
Model without random effect term of Instrument	6621.348
Model without random effect term of Voice	6374.569

Table 4: Test the influence of random effects

Based on the analysis, the random effect of subject versus Harmony and Instrument should be kept because excluding these terms will largely increase AIC. However, the random effect of subject versus Voice should be removed from the model because the AIC becomes smaller when we remove it.

ok

```r
# Fit the final model
lmer.4.final <- lmer(Popular ~  Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + (1 | Subject:Harmony) + (1 | Subject:Instrument), data = ratings)
display(lmer.4.final)
```

```
## lmer(formula = Popular ~ Instrument + Voice + ConsNotes + PachListen +
##     KnowRob + KnowAxis + X1990s2000s + NoClass + APTheory + (1 |
##     Subject:Harmony) + (1 | Subject:Instrument), data = ratings)
##                  coef.est coef.se
## (Intercept)       7.36     1.00
## Instrumentpiano  -1.15     0.31
## Instrumentstring -3.02     0.31
## Voicepar3rd       0.19     0.10
## Voicepar5th       0.23     0.10
## ConsNotes         0.10     0.08
## PachListen       -0.25     0.18
## KnowRob           0.07     0.09
## KnowAxis          0.07     0.07
## X1990s2000s       0.01     0.09
## NoClass           0.10     0.11
## APTheory         -0.03     0.36
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.67
##  Subject:Instrument (Intercept) 1.36
##  Residual                       1.65
```

```
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
## AIC = 6374.6, DIC = 6290.2
## deviance = 6317.4
```

The interpretation is as follows:
For random effect, the estimated variance of the intercept due to Harmony is 0.451, and the estimated variance due to Instrument is 1.837. The variance of residuals is 2.733. The Instrument accounts for more variance in intercept compared to Harmony.
For the following interpretation, we assume that when one variable changes, all the other variables are held the same. Compared with stimuli played with electronic guitar, stimuli that are played by piano are expected to be 1.148 lower in popular ratings, and stimuli played by string quartet are expected to be 3.024 lower in ratings.
Compared with contrary motion, parallel 3rd would receive 0.192 higher score in popular ratings, and parallel 5ths would receive 0.234 higher score. When the listener's concentration level on notes goes up by 1, the popular rating is expected to increase by 0.099.
When the listener is one level more familiar with Pachelbel's Canon in D, the rating is expected to decrease by 0.254.
When the listener is one level up in "having heard Rob Paravonian's Pachelbel Rant", the rating is expected to increase by 0.072.
When the listener is one level up in "having heard Axis of Evil's Comedy bit on the 4 Pachelbel Chords in popular music", the rating is expected to increase by 0.072.
When the listener is one level more frequent to listen to pop and rock from the 90's and 2000's, the rating is expected to increase by 0.014.
When the number of music class taken by the listener increases by one, the popular rating is expected to increase by 0.096.
If a listener took AP music theory class in high school, his rating for the stimuli is expected to go down by 0.0334 compared to a listener who did not.
The covariates in the model of popular and classical ratings are very similar, the only difference is the "PianoPlayer". **It is very interesting that the correlation coefficients for most variables change sign in the model for popular rating except for "KnowRob", "KnowAxis" and "X1990s2000s". Overall, the variables tend to be predictive of the two ratings at the same time, but mostly have opposite effects.** yes, agreed that this is interesting!

(c)

Again we apply stepwise selection based on AIC.

```r
# Full model with the indicator of musician and all possible interactions
lmer.4.full <- lmer(Popular ~ Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + musician +
    musician:Instrument + musician:Voice +
    musician:ConsNotes + musician:PachListen +
    musician:KnowRob + musician:KnowAxis +
    musician:X1990s2000s + musician:NoClass +
    musician:APTheory +
    (1 | Subject:Harmony) + (1 | Subject:Instrument) , data = ratings)
#display(lmer.4.full)

# Stepwise selection
#bfFixefLMER_F.fnc(lmer.4.full,method = c("AIC"))
```

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```
lmer.4.select.1 <- lmer(Classical ~ Harmony + Instrument + Voice +
    ConsNotes + PachListen + KnowRob + KnowAxis + X1990s2000s + NoClass +
    APTheory + PianoPlay + musician + musician:Harmony +
    musician:PianoPlay + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) , data = ratings)
#anova(lmer.3.select,lmer.2.final)
```

The stepwise selection suggest that the indicator of musician and its interactions with all other predictors will increase the AIC value. Therefore none of them should be included in our model. We still keep our final model from question 4 (b).

Question 5

Please refer to the first page.