36-763 HLM (F13) hw5

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Question 1

1. The three main experimental factors.

1-(a)

Examine the influence of the three main experimental factors (Instrument, Harmony & Voice) on Classical ratings, using conventional linear models and/or analysis of variance models. Comment briefly on your findings, providing suitable brief evidence for each result. Hint: To determine whether Harmony is important, for example, one might compare the fit of a model with Harmony in it, to one without Harmony. To determine how particular kinds of harmony affect ratings, one might begin by looking at fixed effects estimates in a suitable model. Etc.

```
ratings<-read.csv("ratings.csv")
str(ratings)
attach(ratings)
m1<-lm(Classical ~ Instrument + Voice)
Coefficients:
  Estimate Std. Error t value Pr(>|t|)
(Intercept)        4.5367     0.1038  43.724  < 2e-16 ***
  Instrumentpiano    1.3730     0.1141  12.035  < 2e-16 ***
  Instrumentstring   3.1334     0.1134  27.631  < 2e-16 ***
  Voicepar3rd       -0.4134     0.1138  -3.633 0.000286 ***
  Voicepar5th       -0.3690     0.1137  -3.244 0.001193 **

m2<-lm(Classical ~ Instrument + Harmony + Voice)
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 **
  ---

anova(m1, m2)
Model 1: Classical ~ Instrument + Voice
Model 2: Classical ~ Instrument + Harmony + 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 ***

is.factor(Subject)

m3<-lm(Classical ~ Instrument + Harmony + Voice + Subject)
```

```
Coefficients:
  Estimate Std. Error t value Pr(>|t|)
  (Intercept)       4.06324    0.33091  12.279  < 2e-16 ***
  Instrumentpiano   1.37737    0.09319  14.780  < 2e-16 ***
  Instrumentstring  3.13154    0.09257  33.828  < 2e-16 ***
  HarmonyI-V-IV    -0.03262    0.10718  -0.304 0.760924
  HarmonyI-V-VI     0.77106    0.10718   7.194 8.36e-13 ***
  HarmonyIV-I-V     0.04988    0.10709   0.466 0.641432
  Voicepar3rd      -0.41523    0.09287  -4.471 8.14e-06 ***
  Voicepar5th      -0.37464    0.09281  -4.037 5.59e-05 ***
  Subject16         0.36111    0.44603   0.810 0.418241
  Subject17        -1.13889    0.44603  -2.553 0.010728 *
  ....
  Subject94        -0.47222    0.44603  -1.059 0.289829
  Subject98        -0.47222    0.44603  -1.059 0.289829
  ---

anova(m2, m3)
Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Instrument + Harmony + Voice + Subject
Res.Df     RSS Df Sum of Sq      F    Pr(>F)
1   2485 13107.5
2   2416  8651.5 69    4455.9 18.034 < 2.2e-16 ***
  ---

anova(m1, m2, m3)
Analysis of Variance Table

Model 1: Classical ~ Instrument + Voice
Model 2: Classical ~ Instrument + Harmony + Voice
Model 3: Classical ~ Instrument + Harmony + Voice + Subject
  Res.Df     RSS Df Sum of Sq      F    Pr(>F)
1   2488 13381.1
2   2485 13107.5  3     273.6 25.473 3.202e-16 ***
3   2416  8651.5 69    4455.9 18.034 < 2.2e-16 ***
```

As shown above, model 2 including `Harmony` variable is significantly different from model 1. And one of the `Harmony` dummy is significant in model 2. Thus model 2 is better than model 1. And we can interpret model 2 as that using piano and strings as well as a particular harmony (I-V-VI) have positive association with classical ratings, while Voice has negative association. When we add `Subject` for controlling for individual fixed effect, all the statistically significant coefficients have similar effect size with same direction. In `anova()`, we also found that model 3 is better than model 2. Overall, we saw that `Harmony` variable needs to be included in the model.

1-(b)

Since we have approximately 36 ratings from each participant, we can fit a random intercept for each participant if we wish. Such a model is called a "repeated measures" model.

1-(b)-i

Carefully write this model in mathematical terms as a hierarchical linear model.

$$ratings_i = \alpha_{0j[i]} + \alpha_1 Harmony_i + \alpha_2 Instrument_i + \alpha_3 Voice_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2)$$
$$\alpha_{0j} = \beta_0 + \eta_j, \quad \eta_j \sim N(0, \tau^2)$$

Thus

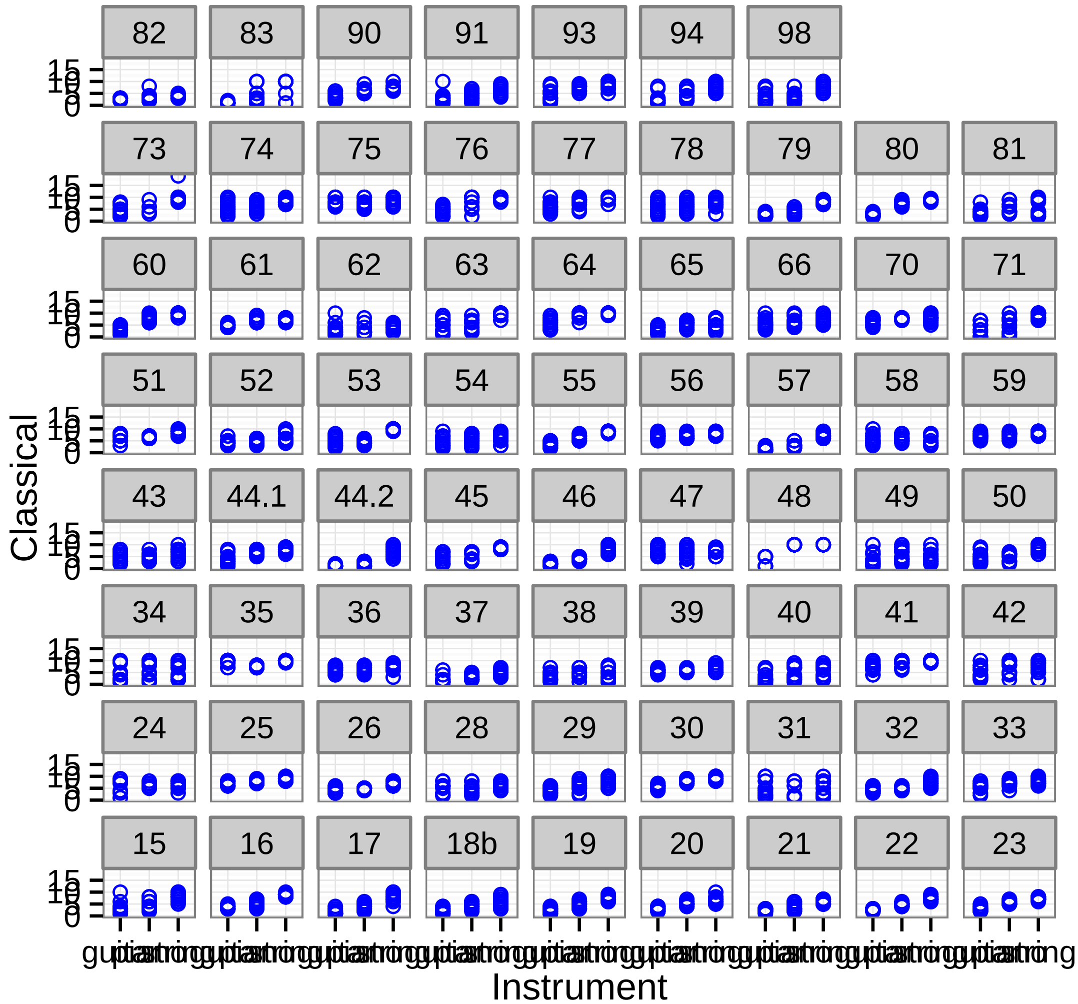
$$ratings_i = \beta_0 + \alpha_1 Harmony_i + \alpha_2 Instrument_i + \alpha_3 Voice_i + \eta_{j[i]} + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2)$$
$$\eta_j \sim N(0, \tau^2)$$

1-(b)-ii

Use at least two different methods to test whether the random intercept is needed in the model. Is the random effect needed? Justify your answer with evidence from your tests. [1]

```
library(ggplot2); theme_set(theme_bw())
library(arm)
library(lme4)
attach(ratings)

# comparing the models

# pooled regression graph
plot(Classical ~ 1,ylab="Classical ratings")
abline(lm(Classical ~ 1), col="red")

# unpooled, means only, with Instrument as X variable
ggplot(ratings,aes(x=Instrument,y=Classical)) +
  geom_point(pch=1,color="blue") +
  geom_smooth(method="lm", formula = Classical ~ 1, se=F, size=0.5,
             fullrange=T, color="black") +
  #scale_x_continuous(labels=NULL) +
  facet_wrap( ~ Subject,as.table=F)

# unpooled, means only, with Instrument as X variable
ggplot(ratings,aes(x=Instrument,y=Classical)) +
  geom_point(pch=1,color="blue") +
  geom_smooth(method="lm", formula = Classical ~ 1, se=F, size=0.5,
             fullrange=T, color="black") +
  #scale_x_continuous(labels=NULL) +
  facet_wrap( ~ Subject,as.table=F)

# comparing the models
summary(newm1<-lm(Classical ~ 1))
is.factor(Subject)
[1] TRUE
summary(newm2<-lm(Classical ~ Subject))

anova(newm1, newm2)
```

[1] 03-, 04-.r from lecture materials



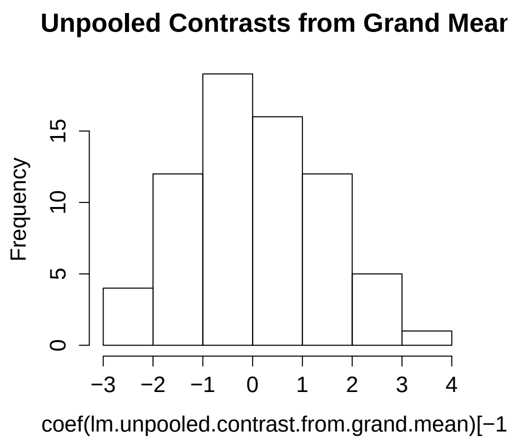

```
Model 1: Classical ~ 1
Model 2: Classical ~ Subject
Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1   2492 17595
2   2423 13132 69    4462.1 11.931 < 2.2e-16 ***

is.factor(Subject)
contrasts(Subject) <- contr.sum(70)
lm.unpooled.contrast.from.grand.mean <- lm(Classical ~  Subject)

summary(newm1)$coef

summary(lm.unpooled.contrast.from.grand.mean)$coef

anova(newm1,lm.unpooled.contrast.from.grand.mean)
Analysis of Variance Table
```

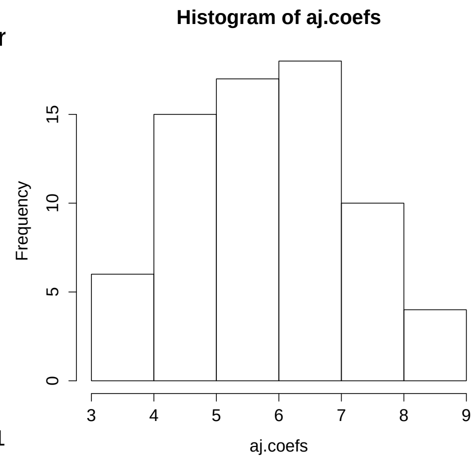
```
Model 1: Classical ~ 1
Model 2: Classical ~ Subject
Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2492 17595
2   2423 13132 69    4462.1 11.931 < 2.2e-16 ***

hist(coef(lm.unpooled.contrast.from.grand.mean)[-1],
     main="Unpooled Contrasts from Grand Mean")

############################################################

# How many Subjects have Classical means significantly different from
# the grand mean?

# forces Subject coefficients to sum to zero, so their
# values show how different each county mean is from the
# grand mean...

lm.unpooled.contrast.from.grand.mean <- lm(Classical ~ Subject)
summary(lm.unpooled.contrast.from.grand.mean)

length(unique(Subject))
[1] 70

sum(coef(summary(lm.unpooled.contrast.from.grand.mean))[,4]<0.05)
[1] 43

43/70
[1] 0.6142857

# hierarchical structure

aj.coefs <- NULL
for (Subj in sort(unique(Subject))) {
  aj.coefs <- c(aj.coefs,coef(lm(Classical ~ 1,subset=(Subject==Subj))))
}

hist(aj.coefs)
```

1-(b)-iii

Re-examine the influence of the three main experimental factors (Instrument, Harmony & Voice) on Classical ratings, using the repeated-measures model with the random intercept for participants.

```
lmer.intercept.only <- lmer( Classical ~ 1 + ( 1 | Subject ) )

summary(lmer.intercept.only)
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ 1 + (1 | Subject)

REML criterion at convergence: 11462.08
```






```
Random effects:
  Groups   Name        Variance Std.Dev.
Subject  (Intercept) 1.654    1.286
Residual             5.420    2.328
Number of obs: 2493, groups: Subject, 70

Fixed effects:
  Estimate Std. Error t value
(Intercept)   5.7872     0.1607   36.02

fixef(lmer.intercept.only)
(Intercept)
5.787247

ranef(lmer.intercept.only)


lmer1<-lmer(Classical ~ Instrument + Harmony + Voice + (1 | Subject))
display(lmer1)
lmer(formula = Classical ~ Instrument + Harmony + Voice + (1 |
    Subject))
                 coef.est coef.se
(Intercept)       4.34     0.19
Instrumentpiano   1.38     0.09
Instrumentstring  3.13     0.09
HarmonyI-V-IV    -0.03     0.11
HarmonyI-V-VI     0.77     0.11
HarmonyIV-I-V     0.05     0.11
Voicepar3rd      -0.42     0.09
Voicepar5th      -0.37     0.09

Error terms:
 Groups   Name        Std.Dev.
```

```
 Subject  (Intercept) 1.30
 Residual             1.89
---
number of obs: 2493, groups: Subject, 70
AIC = 10491.5, DIC = 10426.2
deviance = 10448.9
```

1-(c)

The random intercept in a repeated measures model can account for "personal biases" in ratings: perhaps person A is more inclined to rate everything as classical, and person B is more inclined to rate everything as popular. This can be accounted for by the random intercept. Alternatively, perhaps personal biases vary with the type of instrument, type of harmony, and/or type of voice leading. For example, perhaps people vary in the degree to which they are inclined to call music played by a string quartet "classical". This suggests, e.g., a random effect of the form `(1 | Subject:Instrument)`: a random draw is made from a single normal distribution, for each person/instrument combination. One could argue for a similar random effect for each person/harmony combination, and for each person/voice leading combination.

1-(c)-i

Determine whether a model with all three new random effect terms (but not the original single random intercept) is better or worse than each of the models in problems 1a and 1b. Provide suitable evidence to justify your answer.

```
lmer1<-lmer(Classical ~ Instrument + Harmony + Voice + (1 | Subject))
lmer2<-lmer(Classical ~ Instrument + Harmony + Voice + (Instrument + Harmony + Voice |
    Subject))
lmer3<-lmer(Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument))
lmer4<-lmer(Classical ~ Instrument + Harmony + Voice + (1 | Subject:Harmony))
lmer5<-lmer(Classical ~ Instrument + Harmony + Voice + (1 | Subject:Voice))

anova(lmer1, lmer2, lmer3, lmer4, lmer5)
Data:
Models:
lmer1: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
lmer3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument)
lmer4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Harmony)
lmer5: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Voice)
lmer2: Classical ~ Instrument + Harmony + Voice + (Instrument + Harmony + Voice | Subject
    )
      Df     AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1 10 10468.9 10527 -5224.4  10448.9
lmer3 10 10153.3 10212 -5066.6  10133.3 315.61      0     <2e-16 ***
lmer4 10 10613.4 10672 -5296.7  10593.4   0.00      0          1
lmer5 10 10691.7 10750 -5335.8  10671.7   0.00      0          1
lmer2 45  9971.1 10233 -4940.6   9881.1 790.57     35     <2e-16 ***
---

cbind(
  AIC=sapply(list(lmer1=lmer1, lmer2=lmer2, lmer3=lmer3, lmer4=lmer4, lmer5=lmer5, lmer2b
    =lmer2b, m3),AIC)
  ,
```

```
  DIC=sapply(list(lmer1=lmer1, lmer2=lmer2, lmer3=lmer3, lmer4=lmer4, lmer5=lmer5, lmer2b
    =lmer2b, m3), invisible(function(x) display(x)$DIC))
  ,
  BIC=sapply(list(lmer1=lmer1, lmer2=lmer2, lmer3=lmer3, lmer4=lmer4, lmer5=lmer5, lmer2b
    =lmer2b, m3),BIC)
)
       AIC      DIC      BIC
lmer1  10491.51 10426.21 10549.73
lmer2  10062.51 9789.693 10324.46
lmer3  10173.45 10113.06 10231.66
lmer4  10632.19 10574.56 10690.4
lmer5  10711.53 10651.81 10769.74
lmer2b 10034.59 9817.616 10296.54
       10332.74 NULL     10786.8
```

As shown AIC and BIC in the ANOVA test above, `lmer2` using random effects is better than `lmer1` from Question 1 (b) and other three models (lmer 3, 4, 5). (Although BIC for lmer3 is lowest, considering deviance and DIC, I would choose lmer2 as the best model among those.)

However `lmer2` contains random effect of intercept. So we need to remove it.

```
lmer2a <- lmer(Classical ~ Instrument + Harmony + Voice + (Instrument + Harmony + Voice -
     1 | Subject))
lmer2b <- lmer(Classical ~ Instrument + Harmony + Voice + (0 + Instrument + Harmony +
    Voice | Subject))
display(lmer2a)
display(lmer2b)

lmer(formula = Classical ~ Instrument + Harmony + Voice + (0 +
    Instrument + Harmony + Voice | Subject))
                 coef.est coef.se
(Intercept)       4.34     0.28
Instrumentpiano   1.37     0.19
Instrumentstring  3.13     0.28
HarmonyI-V-IV    -0.03     0.10
HarmonyI-V-VI     0.77     0.18
HarmonyIV-I-V     0.05     0.11
Voicepar3rd      -0.41     0.11
Voicepar5th      -0.37     0.10

Error terms:
 Groups   Name             Std.Dev. Corr
 Subject  Instrumentguitar 2.23
          Instrumentpiano  1.91      0.77
          Instrumentstring 1.77      0.40  0.55
          HarmonyI-V-IV    0.47      0.51  0.28  0.47
          HarmonyI-V-VI    1.29      0.32  0.10 -0.21  0.18
          HarmonyIV-I-V    0.55     -0.02  0.00  0.48  0.28 -0.08
          Voicepar3rd      0.69     -0.20  0.02  0.22 -0.17 -0.37  0.76
          Voicepar5th      0.55     -0.16  0.03  0.08 -0.40 -0.19  0.61  0.92
 Residual                  1.52
---
number of obs: 2493, groups: Subject, 70
AIC = 10034.6, DIC = 9817.6
```

```
deviance = 9881.1

anova(lmer1,lmer2,lmer3,lmer4,lmer5,lmer2a)
Data:
Models:
lmer1: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
lmer3: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument)
lmer4: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Harmony)
lmer5: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Voice)
lmer2: Classical ~ Instrument + Harmony + Voice + (Instrument + Harmony +
lmer2:     Voice | Subject)
lmer2a: Classical ~ Instrument + Harmony + Voice + (Instrument + Harmony +
lmer2a:     Voice - 1 | Subject)
       Df     AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1  10 10468.9 10527 -5224.4  10448.9
lmer3  10 10153.3 10212 -5066.6  10133.3 315.61      0     <2e-16 ***
lmer4  10 10613.4 10672 -5296.7  10593.4   0.00      0          1
lmer5  10 10691.7 10750 -5335.8  10671.7   0.00      0          1
lmer2  45  9971.1 10233 -4940.6   9881.1 790.57     35     <2e-16 ***
lmer2a 45  9971.1 10233 -4940.6   9881.1   0.00      0          1
---
Signif. codes:  0  ***   0.001   **   0.01   *   0.05   .   0.1        1
```

`lmer2a` and `lmer2b` provides the same results in ANOVA. However, variance components are different between `lmer2` and `lmer2a / lmer2b` because `lmer2a / lmer2b` removed random intercept effect. Thus we will use `lmer2b` (which is the same as `lmer2a`) hereafter.

In addition, we compare `lme2b` with my final linear model from the question 1-(a), `m3`.

```
# Comparing lme() model with lm() model
# my lm() model is m3; my lmer() model based on the results above is lmer2
# Compare lmer2b with m3

LRT.observed <- as.numeric(2*(logLik(lmer2b) - logLik(m3)))
nsim <- 9
LRT.sim <- numeric(nsim)
for (i in 1:nsim) {
  y <- unlist(simulate(m3))
  nullmod <- lm(Classical ~ Instrument + Harmony + Voice + Subject)
  altmod <- lmer(Classical ~ Instrument + Harmony + Voice + (0 + Instrument + Harmony +
    Voice | Subject))
  LRT.sim[i] <- as.numeric(2*(logLik(altmod) - logLik(nullmod)))
}
mean(LRT.sim > LRT.observed) #pvalue
```

1-(c)-ii

Re-examine the influence of the three main experimental factors (Instrument, Harmony & Voice) on Classical ratings, using the model with all three new random effect terms in it. Comment briefly on your findings, providing suitable brief evidence for each result. In addition, comment on the sizes of the three estimated variance components, with respect to each other and with respect to the estimated residual variance.

```
display(lmer2b)
lmer(formula = Classical ~ Instrument + Harmony + Voice + (0 +
```

```
    Instrument + Harmony + Voice | Subject))
                 coef.est coef.se
(Intercept)       4.34     0.28
Instrumentpiano   1.37     0.19
Instrumentstring  3.13     0.28
HarmonyI-V-IV    -0.03     0.10
HarmonyI-V-VI     0.77     0.18
HarmonyIV-I-V     0.05     0.11
Voicepar3rd      -0.41     0.11
Voicepar5th      -0.37     0.10

Error terms:
 Groups   Name             Std.Dev. Corr
 Subject  Instrumentguitar 2.23
          Instrumentpiano  1.91      0.77
          Instrumentstring 1.77      0.40  0.55
          HarmonyI-V-IV    0.47      0.51  0.28  0.47
          HarmonyI-V-VI    1.29      0.32  0.10 -0.21  0.18
          HarmonyIV-I-V    0.55     -0.02  0.00  0.48  0.28 -0.08
          Voicepar3rd      0.69     -0.20  0.02  0.22 -0.17 -0.37  0.76
          Voicepar5th      0.55     -0.16  0.03  0.08 -0.40 -0.19  0.61  0.92
 Residual                  1.52
---
number of obs: 2493, groups: Subject, 70
AIC = 10034.6, DIC = 9817.6
deviance = 9881.1
```

As shown above, in this `lmer2b` model, the coefficients are similar to previous `lm()` model. All the `Instrument` and `Voice` variables are significant, and one of the `Harmony` variable is significant. Two insignificant Harmony variables are shown to be highly correlated in terms of their error terms. Also we can see that all three Instrument variables (piano and string) have larger standard deviation than residual standard deviation, and Harmony (I-V-VI) has also large standard deviation.

1-(c)-iii

Carefully write this model in mathematical terms as a hierarchical linear model. Because they are design variables in the experiment, the three experimental factors, Instrument, Harmony, and Voice, should be included in all models for the remainder of this homework, regardless of what you found about their influence or lack of influence on ratings.

$$ratings_i = \alpha_0 + \alpha_{1j[i]} Instrument_i + \alpha_{2j[i]} Harmony_i + \alpha_{3j[i]} Voice_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2)$$
$$\alpha_{1j[i]} = \beta_1 + \eta_{1j}, \quad \eta_{1j} \sim N(0, \tau_1^2)$$
$$\alpha_{2j[i]} = \beta_2 + \eta_{2j}, \quad \eta_{2j} \sim N(0, \tau_2^2)$$
$$\alpha_{3j[i]} = \beta_3 + \eta_{3j}, \quad \eta_{3j} \sim N(0, \tau_3^2)$$

Thus

$$ratings_i = \alpha_0 + \beta_1 Instrument_i + \beta_2 Harmony_i + \beta_3 Voice_i + \eta_1 Instrument_i + \eta_2 Harmony_i + \eta_3 Voice_i + \epsilon_i$$
$$, \epsilon_i \sim N(0, \sigma^2)$$
$$\eta_{1j} \sim N(0, \tau_1^2)$$
$$\eta_{2j} \sim N(0, \tau_2^2)$$
$$\eta_{3j} \sim N(0, \tau_3^2)$$

Since the three experiment variables (`Instrument, Harmony, Voice`) are factors, we can rewrite equation above as follow:

Let $Instrumentpiano = I_1$, $Instrumentstring = I_2$, $HarmonyI-V-IV = H_1$, $HarmonyI-V-VI = H_2$, $HarmonyIV-I-V = H_3$, $Voicepar3rd = V_1$, $Voicepar5th = V_2$, then

$$\begin{aligned} ratings_i &= \alpha_0 + \alpha_{1j[i]} Instrument_i + \alpha_{2j[i]} Harmony_i + \alpha_{3j[i]} Voice_i + \epsilon_i \\ &= \alpha_0 + \alpha_{1j[i]} I_{1i} + \alpha_{2j[i]} I_{2i} + \alpha_{3j[i]} H_{1i} + \alpha_{4j[i]} H_{2i} + \alpha_{5j[i]} H_{3i} + \alpha_{6j[i]} V_{1i} + \alpha_{7j[i]} V_{2i} + \epsilon_i \end{aligned}$$

$$\begin{aligned} \alpha_{1j[i]} &= \beta_1 + \eta_{1j}, \quad \eta_{1j} \sim N(0, \tau_1^2) \\ \alpha_{2j[i]} &= \beta_2 + \eta_{2j}, \quad \eta_{2j} \sim N(0, \tau_2^2) \\ \alpha_{3j[i]} &= \beta_3 + \eta_{3j}, \quad \eta_{3j} \sim N(0, \tau_3^2) \\ \alpha_{4j[i]} &= \beta_4 + \eta_{4j}, \quad \eta_{4j} \sim N(0, \tau_4^2) \\ \alpha_{5j[i]} &= \beta_5 + \eta_{5j}, \quad \eta_{5j} \sim N(0, \tau_5^2) \\ \alpha_{6j[i]} &= \beta_6 + \eta_{6j}, \quad \eta_{6j} \sim N(0, \tau_6^2) \\ \alpha_{7j[i]} &= \beta_7 + \eta_{7j}, \quad \eta_{7j} \sim N(0, \tau_7^2) \end{aligned}$$

so that we can match $\hat{\eta_1} - \hat{\eta_7}$ to the random effects shown in `lmer2b` results above. The R code will be as follows:

```
# R code:
lmer2b <- lmer(Classical ~ Instrument + Harmony + Voice + (0 + Instrument + Harmony +
    Voice | Subject))
```

Question 2

Individual covariates. For this problem, begin with your best model from problem 1.

2-(a)

Determine which individual covariates should be added to the model as fixed effects. Show a suitable summary of your work, and list the final set of variables that you would include in the model. Hint: Some covariates that are actually factor variables are coded as numeric. Be careful to treat them as factors!

```
# Model selection!
names(ratings)
"OMSI"  Score on a test of musical knowledge
```

```
"X16.minus.17" Auxiliary measure of listeners ability to distinguish classical vs popular
     music
"X1stInstr" ow proficient are you at your first musical instrument (0-5, 0=not at all)
"Selfdeclare"    Are you a musician? (1-6, 1=not at all)

tmp<-lm(Classical~Instrument + Harmony + Voice + OMSI + X16.minus.17 + X1stInstr +
    Selfdeclare)
summary(tmp)

# OMSI, X16.minus.17, and Selfdeclare variables look like having association with
    experiment variables and response variable (Classical).

lmer.covariate.1a <- update(lmer2b, . ~ . + OMSI)
lmer.covariate.1b <- update(lmer2b, . ~ . + X16.minus.17)
lmer.covariate.1c <- update(lmer2b, . ~ . + Selfdeclare)
lmer.covariate.1d <- update(lmer2b, . ~ . + OMSI + X16.minus.17 + Selfdeclare)

anova(lmer2b,lmer.covariate.1a, lmer.covariate.1b, lmer.covariate.1c, lmer.covariate.1d)
Df    AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2b            45 9971.1 10233 -4940.6   9881.1
lmer.covariate.1a 46 9972.9 10241 -4940.4   9880.9 0.2336      1     0.6288
lmer.covariate.1b 46 9969.8 10238 -4938.9   9877.8 3.0585      0     <2e-16 ***
lmer.covariate.1c 46 9973.1 10241 -4940.5   9881.1 0.0000      0     1.0000
lmer.covariate.1d 48 9975.5 10255 -4939.8   9879.5 1.5587      2     0.4587

# AIC and BIC shows weak preference of new models (only for lmer.covariate.1b) with
    additional covariates.
# Try with other covariates

tmp2<-lm(Classical~Instrument + Harmony + Voice + factor(CollegeMusic) + factor(APTheory)
    )
summary(tmp2)
tmp3<-lm(Classical~Instrument + Harmony + Voice + factor(APTheory) + X1stInstr + NoClass)
summary(tmp3)

lmer.covariate.2a <- update(lmer2b, . ~ . + factor(APTheory))
lmer.covariate.2b <- update(lmer2b, . ~ . + X1stInstr)
lmer.covariate.2c <- update(lmer2b, . ~ . + NoClass)
lmer.covariate.2d <- update(lmer2b, . ~ . + factor(APTheory) + X1stInstr + NoClass)

anova(lmer2b,lmer.covariate.1b, lmer.covariate.2a, lmer.covariate.2b, lmer.covariate.2c,
    lmer.covariate.2d)
Df    AIC     BIC  logLik deviance     Chisq Chi Df Pr(>Chisq)
lmer2b            45 9971.1 10233.1 -4940.6   9881.1
lmer.covariate.1b 46 9969.8 10237.6 -4938.9   9877.8    3.2921      1    0.06961 .
lmer.covariate.2a 46 9172.7  9436.6 -4540.4   9080.7  797.0726      0    < 2e-16 ***
lmer.covariate.2b 46 3996.3  4222.1 -1952.1   3904.3 5176.4428      0    < 2e-16 ***
lmer.covariate.2c 46 8863.0  9125.4 -4385.5   8771.0    0.0000      0    1.00000
lmer.covariate.2d 48 3569.8  3799.9 -1736.9   3473.8 5297.2223      2    < 2e-16 ***
---
```

```
# AIC prefer lmer.covariate.2d a lot.

formula(lmer.covariate.2d)
Classical ~ Instrument + Harmony + Voice + (0 + Instrument + Harmony + Voice | Subject) +
     factor(APTheory) + X1stInstr + NoClass

lmer.ranef.0<-lmer(Classical ~ Instrument + Harmony + Voice + factor(APTheory) +
    X1stInstr + NoClass + (0 + Instrument + Harmony + Voice | Subject))
lmer.ranef.1 <- lmer(Classical ~ Instrument + Harmony + Voice + factor(APTheory) +
    X1stInstr + NoClass + (0 + Instrument + Harmony + Voice + factor(APTheory) | Subject)
    )
lmer.ranef.2 <- lmer(Classical ~ Instrument + Harmony + Voice + factor(APTheory) +
    X1stInstr + NoClass + (0 + Instrument + Harmony + Voice + X1stInstr | Subject))
lmer.ranef.3 <- lmer(Classical ~ Instrument + Harmony + Voice + factor(APTheory) +
    X1stInstr + NoClass + (0 + Instrument + Harmony + Voice + NoClass | Subject))

anova(lmer.ranef.0, lmer.ranef.1, lmer.ranef.2, lmer.ranef.3)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer.ranef.0 48 3569.8 3799.9 -1736.9   3473.8
lmer.ranef.1 57 3581.7 3854.9 -1733.9   3467.7 6.0502      9     0.7349
lmer.ranef.2 57 3577.7 3850.9 -1731.8   3463.7 4.0121      0     <2e-16 ***
lmer.ranef.3 57 3580.1 3853.3 -1733.0   3466.1 0.0000      0     1.0000
---

# AIC prefers lmer.ranef.0

formula(lmer.ranef.0)
Classical ~ Instrument + Harmony + Voice + factor(APTheory) +
    X1stInstr + NoClass + (0 + Instrument + Harmony + Voice |
    Subject)
```

2-(b)

Once the fixed effects are settled, go back and check to see whether there should be any change in the random effects. Provide suitable evidence to justify your answer.

```
# As shown in Question 2-(a), lmer.ranef.1~3 were compared to lmer.ranef.0 model. And AIC
     prefer lmer.ranef.0, which has no random effects for additional covariates.
```

2-(c)

Briefly interpret the effect of each variable kept in the final model, on Classical ratings.

```
summary(lmer.ranef.0)
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + factor(APTheory) +      X1stInstr +
    NoClass + (0 + Instrument + Harmony + Voice |      Subject)

REML criterion at convergence: 3514.515

Random effects:
 Groups   Name             Variance Std.Dev. Corr
```

```
 Subject  Instrumentguitar 1.1821   1.0872
          Instrumentpiano  2.2885   1.5128    0.73
          Instrumentstring 4.8691   2.2066    0.33  0.67
          HarmonyI-V-IV    0.1921   0.4383    0.25 -0.30  0.11
          HarmonyI-V-VI    1.9360   1.3914   -0.18 -0.29 -0.35 -0.01
          HarmonyIV-I-V    0.5412   0.7357    0.18 -0.07  0.32  0.68 -0.01
          Voicepar3rd      0.3667   0.6055   -0.10  0.07  0.08 -0.18 -0.28  0.32
          Voicepar5th      0.8405   0.9168    0.23  0.48  0.28 -0.34  0.05  0.30  0.78
 Residual                  2.2482   1.4994
Number of obs: 892, groups: Subject, 25

Fixed effects:
                  Estimate Std. Error t value
(Intercept)        3.72638    0.56667   6.576
Instrumentpiano    1.89656    0.24168   7.847
Instrumentstring   3.59833    0.44004   8.177
HarmonyI-V-IV      0.12874    0.16691   0.771
HarmonyI-V-VI      1.01150    0.31246   3.237
HarmonyIV-I-V      0.03325    0.20452   0.163
Voicepar3rd       -0.50448    0.17270  -2.921
Voicepar5th       -0.40667    0.22081  -1.842
factor(APTheory)1  1.46045    0.51471   2.837
X1stInstr          0.02702    0.13612   0.199
NoClass           -0.09016    0.35412  -0.255

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t f(APT) X1stIn
Instrumntpn -0.051
Instrmntstr -0.093  0.612
HrmnyI-V-IV -0.057 -0.314    -0.005
HrmnyI-V-VI -0.118 -0.185    -0.238     0.186
HrmnyIV-I-V -0.036 -0.180     0.166     0.551  0.151
Voicepar3rd -0.104  0.121     0.088    -0.066 -0.175  0.165
Voicepar5th  0.013  0.328     0.137    -0.151  0.039  0.177  0.656
fctr(APTh)1 -0.242  0.003     0.000     0.000  0.000  0.000  0.000 -0.002
X1stInstr   -0.736  0.001     0.000     0.000  0.000  0.000  0.000  0.000 -0.110
NoClass     -0.572 -0.001     0.000     0.000  0.000  0.000  0.000  0.001  0.249  0.169
```

Although the effect size has slightly changed, the original experimental variables has simlar effects on Classical ratings with the same direction and significance. In addition to these variables, taking AP music class has positive effect on Classical ratings, and its effect size is relatively large. But as shown above, the random effect of AP music class was insignificant and excluded from the model.

Question 3

Musicians vs. Non-musicians. One of the secondary hypotheses of the researchers is that people who self- identify as musicians may be influenced by things that do not influence non-musicians. Dichotomize "Self- declare" ("are you a musician?") so that about half the participants are categorized as self-declared musicians, and half not. Examine and report on any interactions between the dichotomized musician variable and other predictors in the model. Provide suitable evidence for, and comment on, your results.

Question 4

Classical vs. Popular. Please re-examine the data in terms of the "Popular" ratings, instead of the "Classical" ratings, using similar hierarchical linear models. Provide brief answers to the following questions:

4-(a)

no answers provided....

Comment on the influence of Instrument, Harmony & Voice on Popular ratings, providing suitable brief evidence for each result.

4-(b)

Question 2c, for Popular ratings.

4-(c)

Question 3, for Popular ratings.

Question 5

Brief write up. Write a one page professional-quality summary of your findings for Classical and Popular ratings, suitable for Dr. Jimenez. Be sure to address:

- The influence of the three main experimental factors (Instrument, Harmony & Voice);
- A brief discussion of variance componentsis this a standard repeated measures model, or did we need to include other variance components?
- A discussion of other individual covariates in the model. You may refer to your earlier work (e.g. "As I showed in my answer to part 1b, blah-blah-blah.."). Don't be sloppy about the statistical findings, but try to highlight things that will be of substantive interest to Dr. Jimenez. Make your summary very readable and clear.