The extensive EDA at the beginning was nice. However, throughout the rest of the report you provided way too much raw output of R with way too little explanation. Very hard to follow.

1 a 7/9
b 6/9
c 8/9

2 a 5/9
b 3/9
c 9/9

3 7/9

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

5 8/10

Total 80/100

HW5

Shane Campbell

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1

First we'll do some EDA to see which variables look to have significant relationships with each kind of rating so that we can test whether the 3 experimental factors are significant when included with these variables in the model. (If you want to skip all of the EDA, the part where I start model fitting for 1a begins on page 11. Because all our professors have emphasized EDA, I didnt think I could justify moving straight to model fitting even though you mentioned not wanting to read long reports before Christmas.)

This is a nice bit of EDA and I thank you for it. However, it is a bit much for what I am looking for in this final problem set.

```
setwd("C:/Users/Valued Customer/Box Sync/MSP/Hierarchical Models/HW5")
base = read.csv(file = "ratings.csv", header = TRUE)
# dim(base)

# create factor variables
base$Subject = as.factor(base$Subject)
base$Harmony = as.factor(base$Harmony)
base$Instrument = as.factor(base$Instrument)
base$Voice = as.factor(base$Voice)
base$Selfdeclare = as.factor(base$Selfdeclare)

# we wont use the NAs for ConsNotes but we'll treat Instr.minus.Notes as a
# categorical variable because it is not a difference between continuous
# variables
base$Instr.minus.Notes = round(base$Instr.minus.Notes, digits = 0)
base$Instr.minus.Notes = as.factor(base$Instr.minus.Notes)
# round difference bc some people didnt rate with integers

base$PachListen = as.factor(base$PachListen)
base$ClsListen = as.factor(base$ClsListen)
base$KnowRob = as.factor(base$KnowRob)
base$KnowAxis = as.factor(base$KnowAxis)
base$X1990s2000s = as.factor(base$X1990s2000s)
base$X1990s2000s.minus.1960s1970s = factor(base$X1990s2000s.minus.1960s1970s)
base$CollegeMusic = as.factor(base$CollegeMusic)
base$APTheory = as.factor(base$APTheory)
base$Composing = as.factor(base$Composing)
base$PianoPlay = as.factor(base$PianoPlay)
base$GuitarPlay = as.factor(base$GuitarPlay)


# EDA
summary(base)  #some people made Classical or Popular ratings higher than 10
##        X               Subject       Harmony     Instrument       Voice
##  Min.   :   1.0   15      :  36   I-IV-V:630   guitar:840   contrary:840
##  1st Qu.: 630.8   16      :  36   I-V-IV:630   piano :840   par3rd  :840
##  Median :1260.5   17      :  36   I-V-VI:630   string:840   par5th  :840
##  Mean   :1260.5   18b     :  36   IV-I-V:630
```

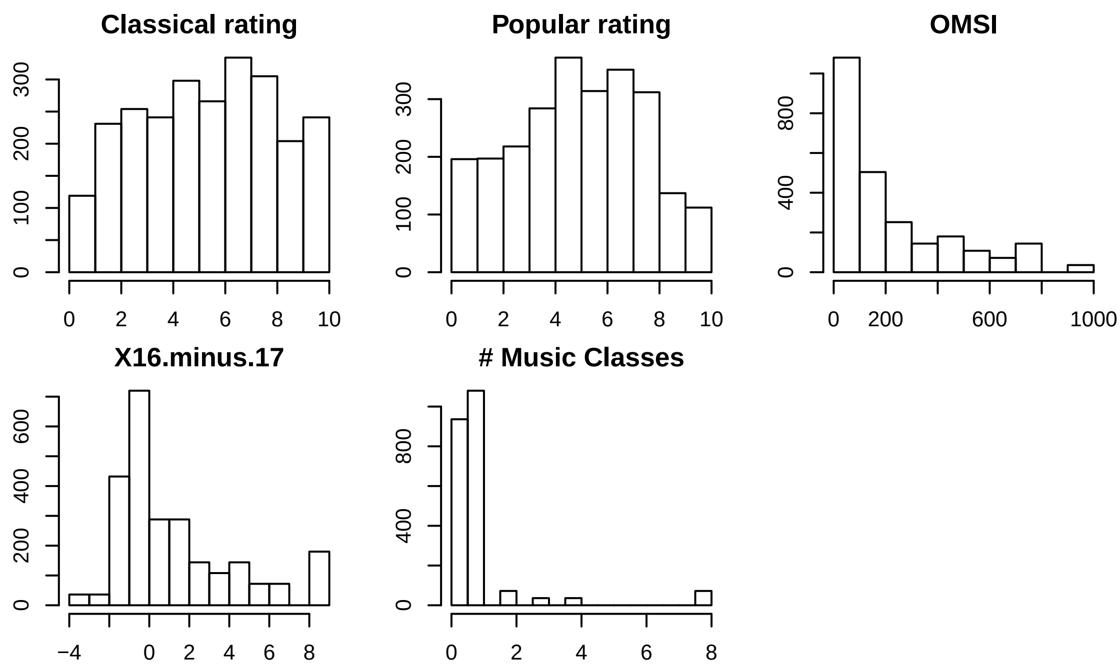
```
##  3rd Qu.:1890.2   19     :  36
##  Max.   :2520.0   20     :  36
##                   (Other):2304
##  Selfdeclare      OMSI        X16.minus.17      ConsInstr
##  1:576       Min.   : 11.0   Min.   :-4.000   Min.   :0.000
##  2:936       1st Qu.: 49.0   1st Qu.: 0.000   1st Qu.:1.670
##  3:468       Median :145.5   Median : 1.000   Median :3.000
##  4:432       Mean   :225.9   Mean   : 1.721   Mean   :2.857
##  5: 72       3rd Qu.:323.0   3rd Qu.: 3.000   3rd Qu.:4.330
##  6: 36       Max.   :970.0   Max.   : 9.000   Max.   :5.000
##
##    ConsNotes     Instr.minus.Notes PachListen  ClsListen  KnowRob
##  Min.   :0.000   0      :720       0   :  36   0   :396   0   :1836
##  1st Qu.:0.750   1      :468       1   :  36   1   :792   1   : 180
##  Median :3.000   2      :396       2   : 144   3   :936   5   : 324
##  Mean   :2.533   -1     :324       3   : 180   4   : 36   NA's: 180
##  3rd Qu.:5.000   3      :252       4   :  72   5   :324
##  Max.   :5.000   -2     :144       5   :1980   NA's: 36
##  NA's   :360     (Other):216       NA's:  72
##  KnowAxis    X1990s2000s X1990s2000s.minus.1960s1970s CollegeMusic
##  0   :1800   0   : 216   3      :756                  0   : 504
##  1   :  36   2   : 108   0      :504                  1   :1908
##  5   : 396   3   : 324   2      :432                  NA's: 108
##  NA's: 288   4   : 180   5      :288
##              5   :1548   1      :180
##              NA's: 144   (Other):180
##                          NA's   :180
##     NoClass       APTheory    Composing   PianoPlay GuitarPlay
##  Min.   :0.0000   0   :1764   0   :1476   0:1476    0:1872
##  1st Qu.:0.0000   1   : 540   1   : 252   1: 540    1: 324
##  Median :1.0000   NA's: 216   2   : 288   2:  36    2:  36
##  Mean   :0.9194               3   : 144   4: 216    4: 108
##  3rd Qu.:1.0000               4   : 252   5: 252    5: 180
##  Max.   :8.0000               5   :  36
##  NA's   :288                  NA's:  72
##    X1stInstr       X2ndInstr       first12       Classical
##  Min.   :1.000   Min.   :0.000   guitar: 720   Min.   : 0.000
##  1st Qu.:1.000   1st Qu.:1.000   piano : 720   1st Qu.: 4.000
##  Median :3.500   Median :1.000   string:1080   Median : 6.000
##  Mean   :2.786   Mean   :1.556                 Mean   : 5.783
##  3rd Qu.:4.000   3rd Qu.:2.000                 3rd Qu.: 8.000
##  Max.   :5.000   Max.   :4.000                 Max.   :19.000
##  NA's   :1512    NA's   :2196                  NA's   :27
##     Popular
##  Min.   : 0.000
##  1st Qu.: 4.000
##  Median : 5.000
##  Mean   : 5.381
##  3rd Qu.: 7.000
##  Max.   :19.000
##  NA's   :27
# base[base$Classical > 10 & !is.na(base$Classical),] #one person gave a 19
# for Classical, we'll convert to a 9 base[base$Popular > 10 &
```

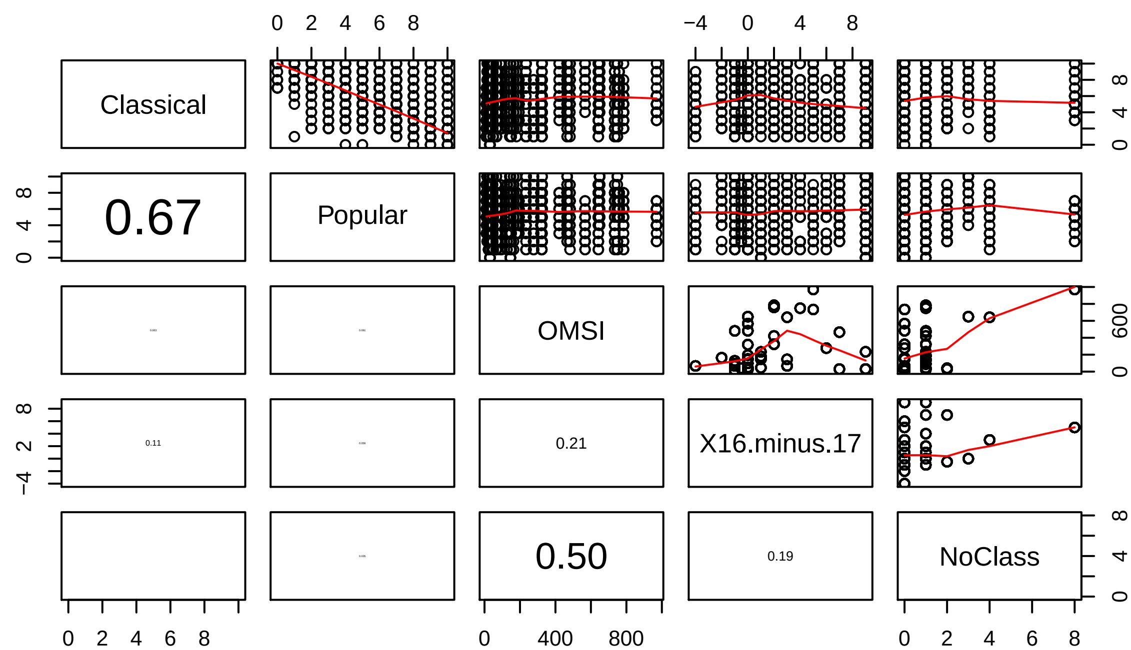
```r
# !is.na(base$Popular),] #another person gave a 19 for Popular, we'll
# convert to a 9

# any non-integer ratings? yes, 4, so we'll just round these to nearest
# integer base[!(base$Classical %% 1)==0,] base[!(base$Popular %% 1)==0,]

base$Classical = round(base$Classical, digits = 0)
base$Popular = round(base$Popular, digits = 0)

base$Classical = ifelse(base$Classical == 19, 9, base$Classical)
base$Popular = ifelse(base$Popular == 19, 9, base$Popular)

# base$complete=complete.cases(base) base.c=base[base$complete==TRUE,]
# dim(base.c) #180 rows = only 5 participants
```

Because there are a lot of NAs across plenty of different variables with the most coming in X1stInstr and X2ndInstr, using only complete cases leaves us with 180 rows and only 5 participants out of the initial 70, so we'll impute 0s for these NAs in these 2 variables, assuming that those who left it blank have no proficiency with either their first or second instrument, meaning they don't play an instrument at all or they don't play more than 1. Though this strongly biases these two variables, it is a reasonable assumption in lieu of not being able to do imputation and should maintain the majority of our participants.

```r
# impute 0s for NAs
base$X1stInstr = ifelse(is.na(base$X1stInstr), 0, base$X1stInstr)
base$X2ndInstr = ifelse(is.na(base$X2ndInstr), 0, base$X2ndInstr)

# create a variable that is combination of proficiency with 2 instruments
base$both.Inst = as.factor(base$X1stInstr + base$X2ndInstr)

base$complete = complete.cases(base)
base.c = base[base$complete == TRUE, ]
# dim(base.c) 1541/36 is just over 42 participants which is a large enough
# sample for our analysis

par(mfrow = c(2, 3), mar = c(2, 2, 2, 2), oma = c(2, 2, 2, 2))
hist(base$Classical, main = "Classical rating", breaks = seq(from = 0, to = 10,
    by = 1))
hist(base$Popular, main = "Popular rating", breaks = seq(from = 0, to = 10,
    by = 1))
hist(base$OMSI, main = "OMSI")
hist(base$X16.minus.17, main = "X16.minus.17")
hist(base$NoClass, main = "# Music Classes")

panel.cor <- function(x, y, digits = 2, prefix = "", cex.cor, ...) {
    usr <- par("usr")
    on.exit(par(usr))
    par(usr = c(0, 1, 0, 1))
    r <- abs(cor(x, y))
    txt <- format(c(r, 0.123456789), digits = digits)[1]
    txt <- paste0(prefix, txt)
    if (missing(cex.cor))
        cex.cor <- 0.8/strwidth(txt)
    text(0.5, 0.5, txt, cex = cex.cor * r)
```

```r
}
pairs(formula = ~Classical + Popular + OMSI + X16.minus.17 + NoClass, data = base.c,
    lower.panel = panel.cor, upper.panel = panel.smooth)
```

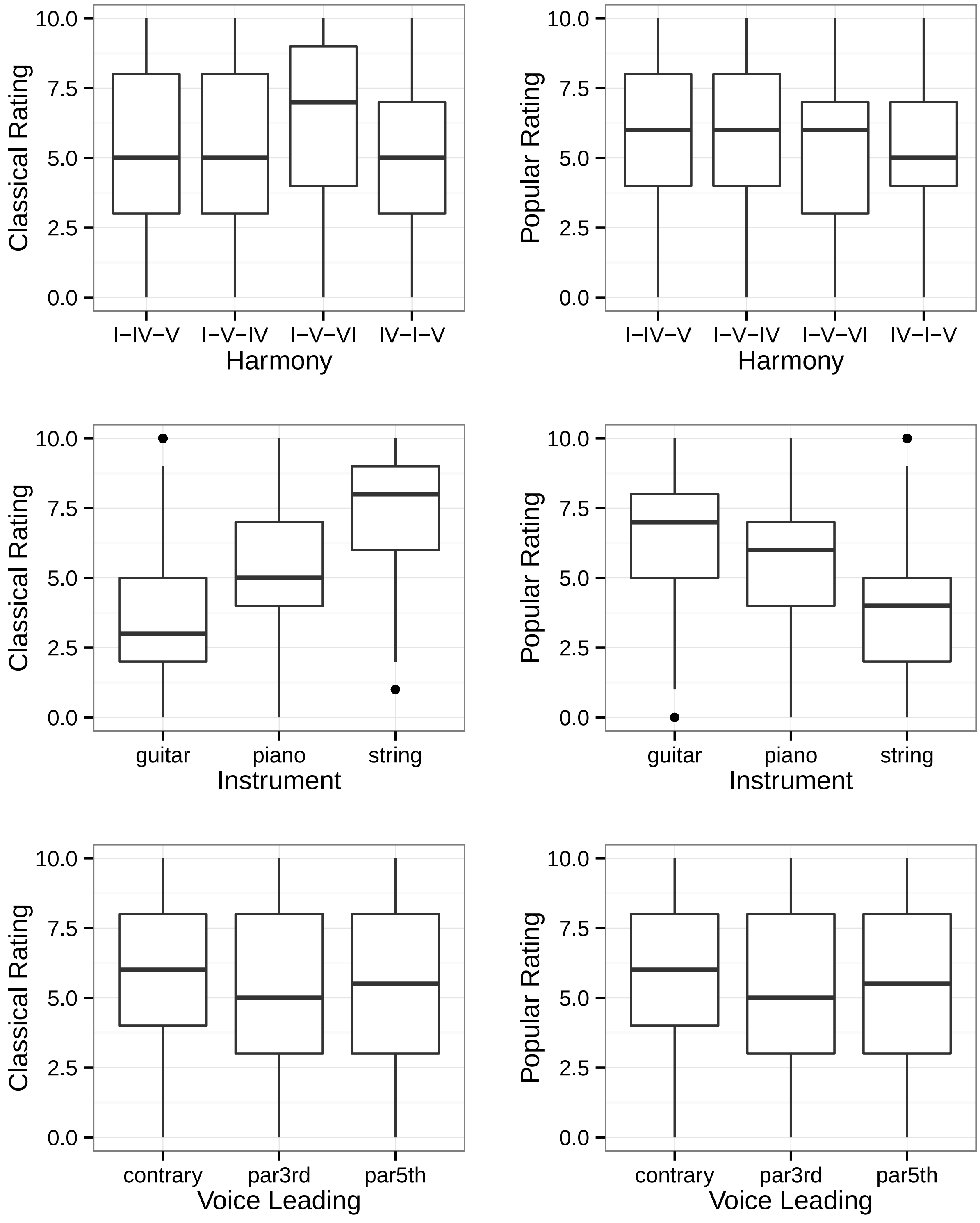




None of the quantitative variables seem to have relationships with Classical or Popular rating. As we would expect, there is a relatively strong negative relationship between Classical and Popular rating.

3 experimental factors

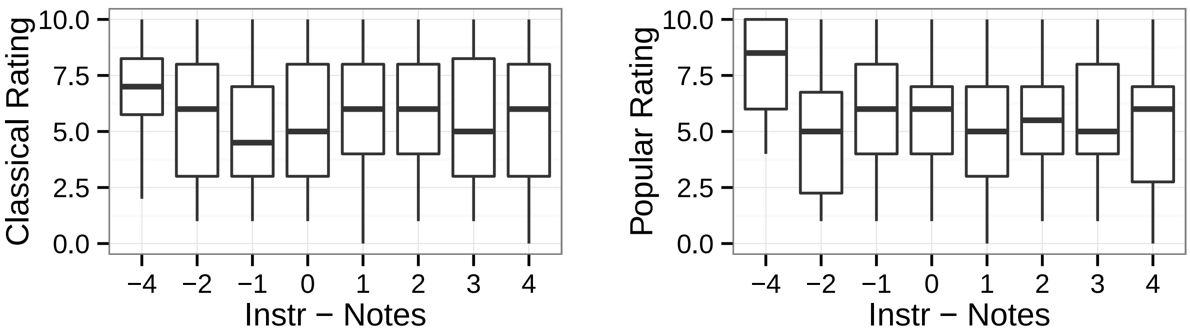
```r
library(ggplot2)
library(gridExtra)
harm.clas = ggplot(data = base.c, aes(x = Harmony, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Harmony", y = "Classical Rating")
harm.pop = ggplot(data = base.c, aes(x = Harmony, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Harmony", y = "Popular Rating")

inst.clas = ggplot(data = base.c, aes(x = Instrument, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Instrument", y = "Classical Rating")
inst.pop = ggplot(data = base.c, aes(x = Instrument, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Instrument", y = "Popular Rating")

voice.clas = ggplot(data = base.c, aes(x = Voice, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Voice Leading", y = "Classical Rating")
voice.pop = ggplot(data = base.c, aes(x = Voice, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Voice Leading", y = "Popular Rating")

grid.arrange(nrow = 3, ncol = 2, harm.clas, harm.pop, inst.clas, inst.pop, voice.clas,
    voice.pop)
```



Harmony and Voice Leading don't appear to have relationships with either type of rating but instrument does.

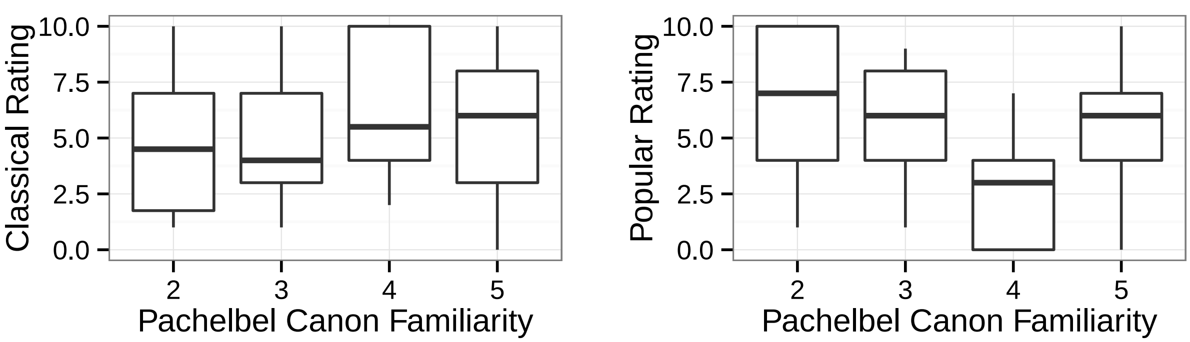
We'll look at some other variables

```
inst.min.notes.clas = ggplot(data = base.c, aes(x = Instr.minus.Notes, y = Classical)) +
    theme_bw() + geom_boxplot() + labs(x = "Instr - Notes", y = "Classical Rating")
inst.min.notes.pop = ggplot(data = base.c, aes(x = Instr.minus.Notes, y = Popular)) +
    theme_bw() + geom_boxplot() + labs(x = "Instr - Notes", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, inst.min.notes.clas, inst.min.notes.pop)
```



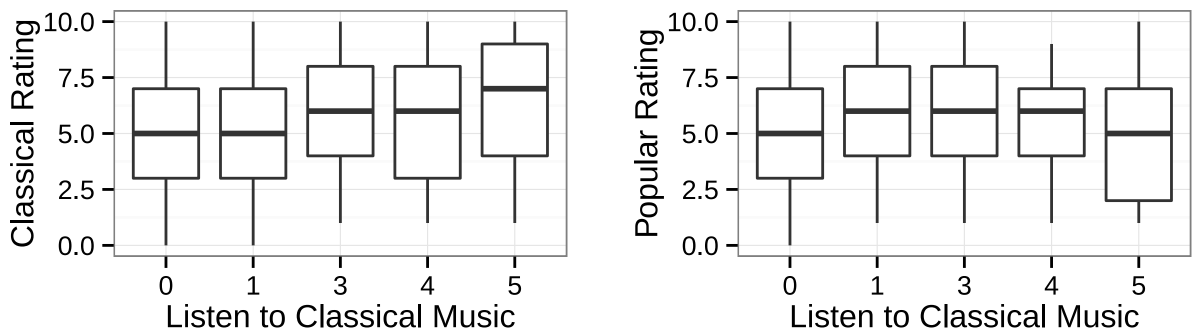
The only significant relationship here that is possible is that people who concentrate on the Notes 4 more than the Instrument look to give a significantly higher Popular rating. There do not appear to be any other levels within this variable that look to have a significant relationship with either rating.

```
pach.clas = ggplot(data = base.c, aes(x = PachListen, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Pachelbel Canon Familiarity", y = "Classical Rating")
pach.pop = ggplot(data = base.c, aes(x = PachListen, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Pachelbel Canon Familiarity", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, pach.clas, pach.pop)
```



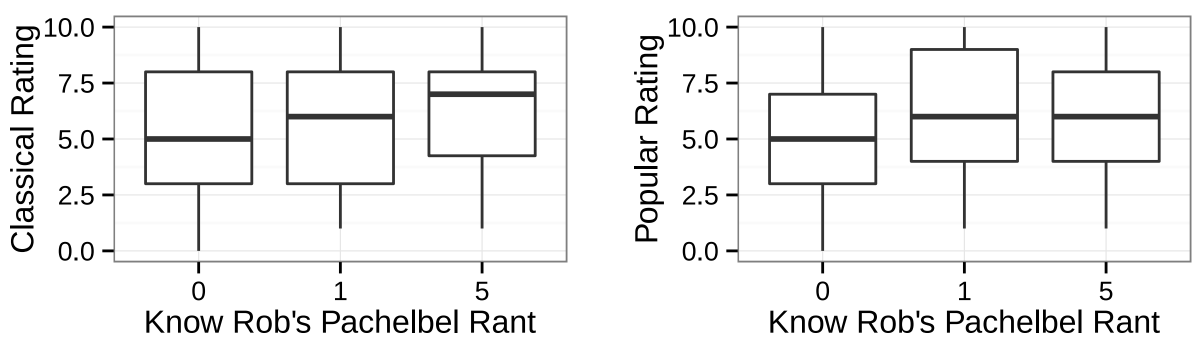
Familiarity with Pachelbel's Canon looks to have a relationship with a popular rating but not with classical.

```
claslisten.clas = ggplot(data = base.c, aes(x = ClsListen, y = Classical)) +
    theme_bw() + geom_boxplot() + labs(x = "Listen to Classical Music", y = "Classical Rating")
claslisten.pop = ggplot(data = base.c, aes(x = ClsListen, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Listen to Classical Music", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, claslisten.clas, claslisten.pop)
```



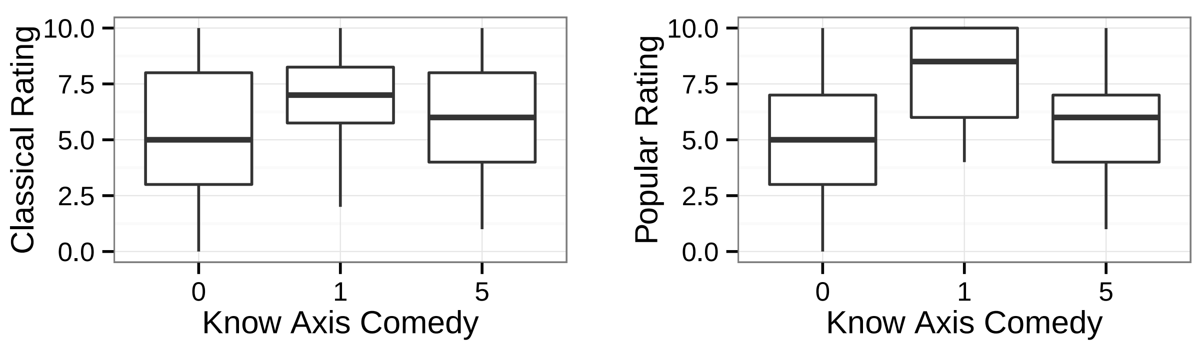
Oddly, listening to Classical music doesn't appear to have a relationship with either rating.

```
rob.clas = ggplot(data = base.c, aes(x = KnowRob, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Know Rob's Pachelbel Rant", y = "Classical Rating")
rob.pop = ggplot(data = base.c, aes(x = KnowRob, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Know Rob's Pachelbel Rant", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, rob.clas, rob.pop)
```



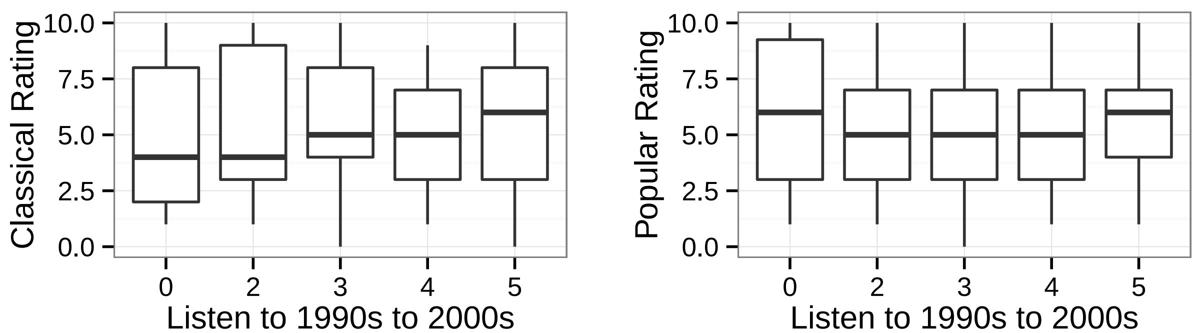
Knowing Rob's Pachelbel rant doesn't appear to have a relationship with either rating.

```
axis.clas = ggplot(data = base.c, aes(x = KnowAxis, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Know Axis Comedy", y = "Classical Rating")
axis.pop = ggplot(data = base.c, aes(x = KnowAxis, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Know Axis Comedy", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, axis.clas, axis.pop)
```



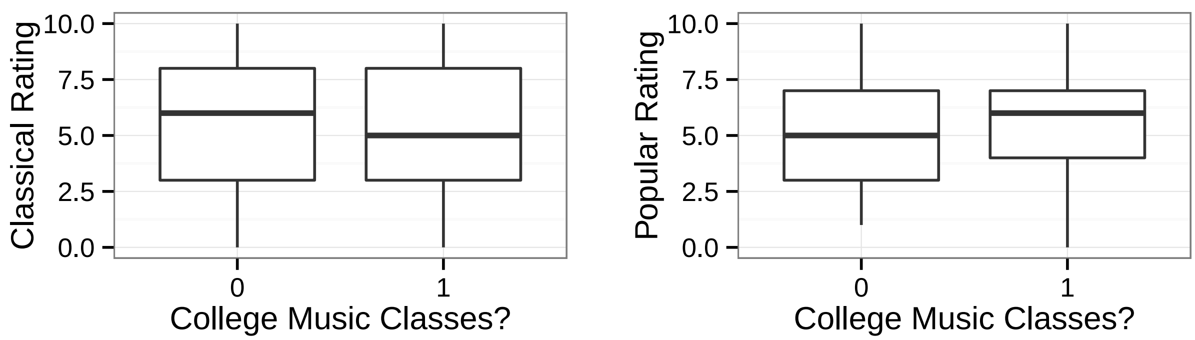
Knowing about Axis of Evil's comediy on Pachelbel chords doesn't look to have a relationship with either rating.

```
nineties.2ks.clas = ggplot(data = base.c, aes(x = X1990s2000s, y = Classical)) +
    theme_bw() + geom_boxplot() + labs(x = "Listen to 1990s to 2000s", y = "Classical Rating")
nineties.2ks.pop = ggplot(data = base.c, aes(x = X1990s2000s, y = Popular)) +
    theme_bw() + geom_boxplot() + labs(x = "Listen to 1990s to 2000s", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, nineties.2ks.clas, nineties.2ks.pop)
```



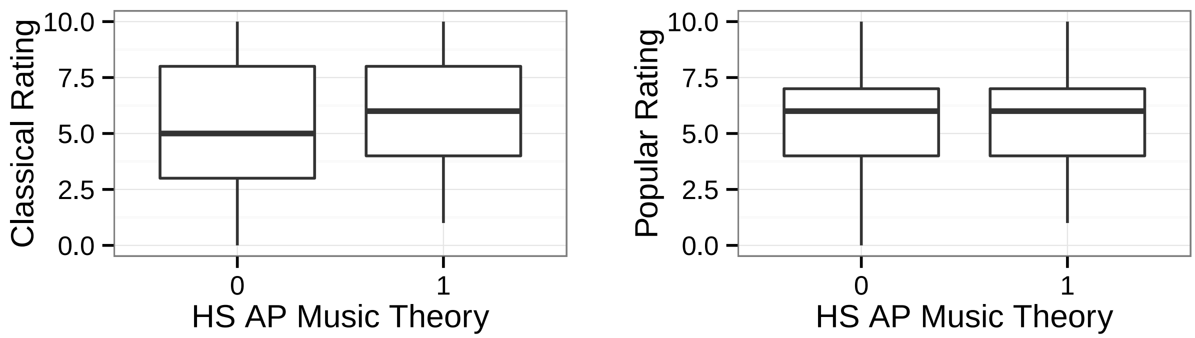
Listening to popular music from the 1990s to 2000s doesn't appear to have a relationship with either rating.

```
college.clas = ggplot(data = base.c, aes(x = CollegeMusic, y = Classical)) +
    theme_bw() + geom_boxplot() + labs(x = "College Music Classes?", y = "Classical Rating")
college.pop = ggplot(data = base.c, aes(x = CollegeMusic, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "College Music Classes?", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, college.clas, college.pop)
```



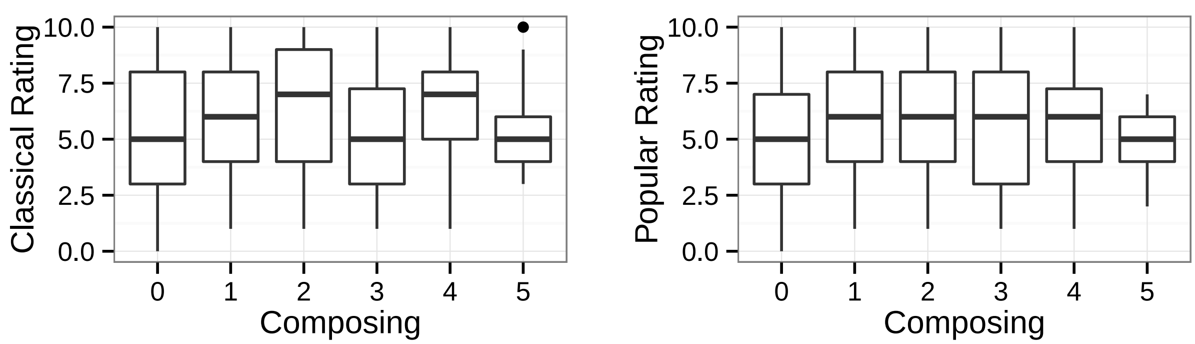
Interestingly, taking college music classes doesn't appear to influence either rating.

```
apthry.clas = ggplot(data = base.c, aes(x = APTheory, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "HS AP Music Theory", y = "Classical Rating")
apthry.pop = ggplot(data = base.c, aes(x = APTheory, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "HS AP Music Theory", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, apthry.clas, apthry.pop)
```



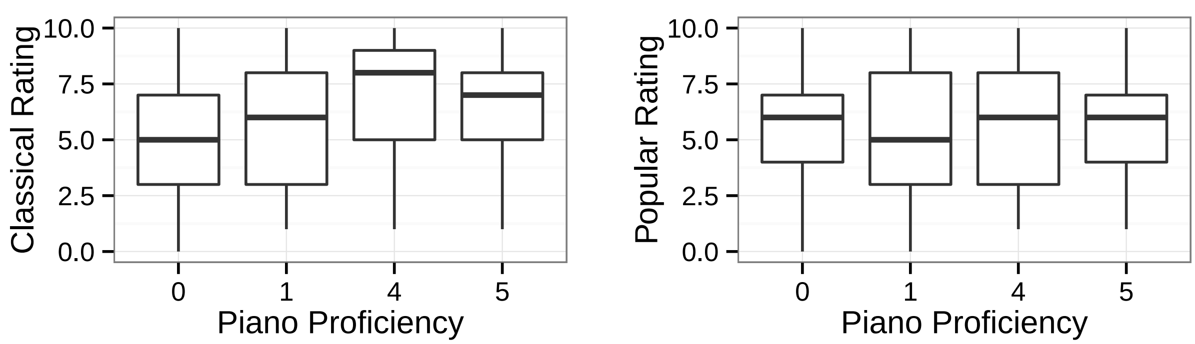
Whether someone took AP Music Theory in High School doesn't seem to influence their ratings, either.

```
compos.clas = ggplot(data = base.c, aes(x = Composing, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Composing", y = "Classical Rating")
compos.pop = ggplot(data = base.c, aes(x = Composing, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Composing", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, compos.clas, compos.pop)
```



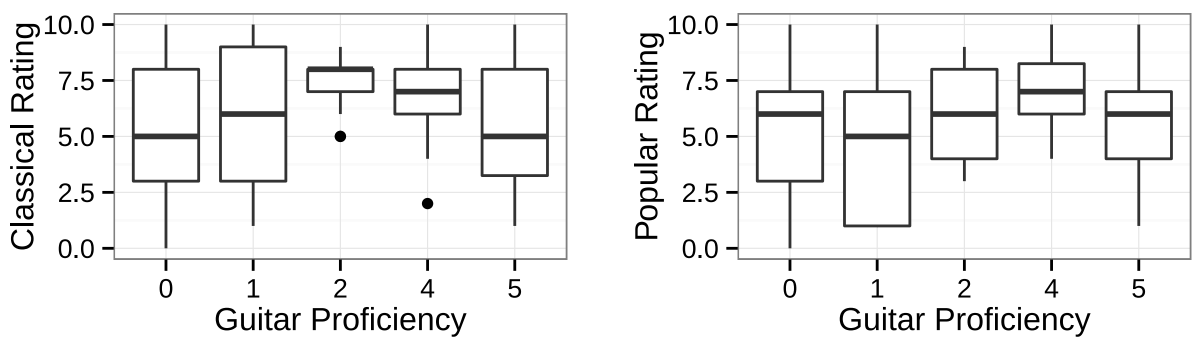
Whether someone composes their own music and how much doesn't look to have a relationship with ratings.

```
piano.clas = ggplot(data = base.c, aes(x = PianoPlay, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Piano Proficiency", y = "Classical Rating")
piano.pop = ggplot(data = base.c, aes(x = PianoPlay, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Piano Proficiency", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, piano.clas, piano.pop)
```



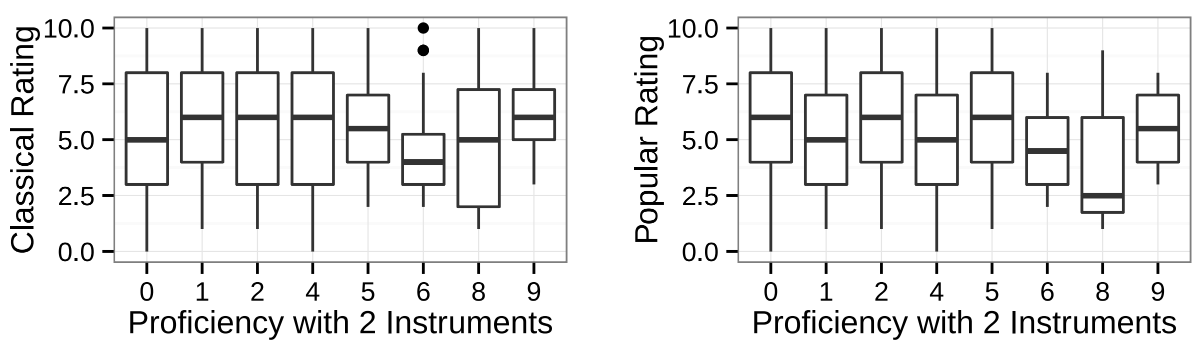
Increased piano proficiency looks to lead to lead to higher classical ratings.

```
guitar.clas = ggplot(data = base.c, aes(x = GuitarPlay, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Guitar Proficiency", y = "Classical Rating")
guitar.pop = ggplot(data = base.c, aes(x = GuitarPlay, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Guitar Proficiency", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, guitar.clas, guitar.pop)
```



Increasing guitar proficiency looks to generally lead to higher ratings for popular and classical music within levels 2 and 4, but not 5.

```
inst.clas = ggplot(data = base.c, aes(x = both.Inst, y = Classical)) + theme_bw() +
    geom_boxplot() + labs(x = "Proficiency with 2 Instruments", y = "Classical Rating")
inst.pop = ggplot(data = base.c, aes(x = both.Inst, y = Popular)) + theme_bw() +
    geom_boxplot() + labs(x = "Proficiency with 2 Instruments", y = "Popular Rating")
grid.arrange(nrow = 1, ncol = 2, inst.clas, inst.pop)
```



Proficiency with 2 instruments doesn't look to have a relationship with either classical or popular rating.

Start model fitting for 1a

Because the boxplots didn't reveal many relationships among the covariates with either response, we'll fit a model with a few covariates that are likely to have a relationship with rating classical music and the 3 experimental factors and see how valid the model is, making transformations if marginal model and residual plots suggest to do so and making sure there is no multicollinearity in our model so that we can do inference.

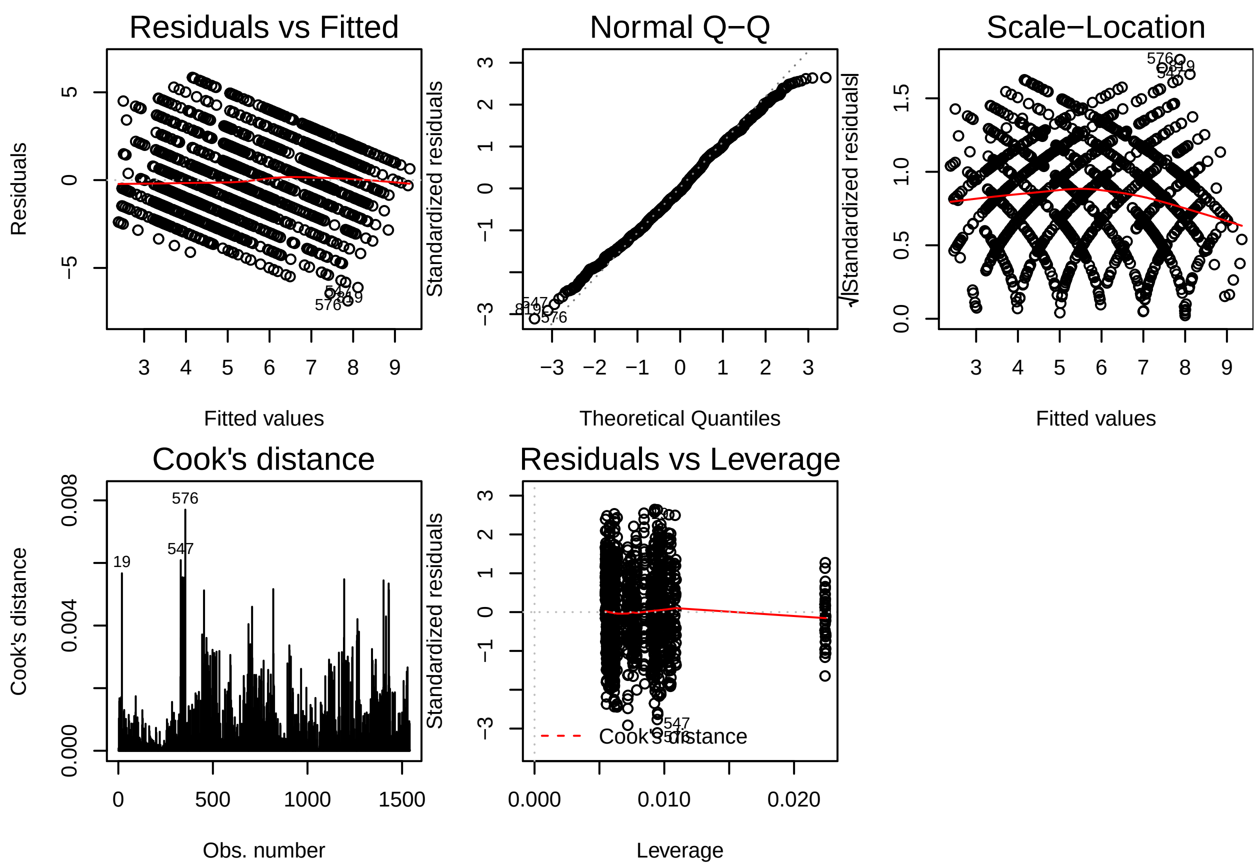
save these for #2. This part of the assignment only wants you to look at the design factors and the random effects.

```r
library(car)
library(arm)
full.lm = lm(data = base.c, formula = Classical ~ OMSI + X16.minus.17 + NoClass +
    APTheory + Harmony + Instrument + Voice)
summary(full.lm)
##
## Call:
## lm(formula = Classical ~ OMSI + X16.minus.17 + NoClass + APTheory +
##     Harmony + Instrument + Voice, data = base.c)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8747 -1.5576 -0.1307  1.6740  5.8450
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       3.7736506  0.1718926  21.954  < 2e-16 ***
## OMSI              0.0005180  0.0002719   1.905  0.05700 .
## X16.minus.17     -0.1014187  0.0190307  -5.329 1.13e-07 ***
## NoClass          -0.0817663  0.0485465  -1.684  0.09233 .
## APTheory1         0.8526385  0.1531961   5.566 3.08e-08 ***
## HarmonyI-V-IV     0.0030891  0.1599444   0.019  0.98459
## HarmonyI-V-VI     0.8486387  0.1600493   5.302 1.31e-07 ***
## HarmonyIV-I-V     0.0567070  0.1598404   0.355  0.72281
## Instrumentpiano   1.6624794  0.1387311  11.983  < 2e-16 ***
## Instrumentstring  3.5878921  0.1383139  25.940  < 2e-16 ***
## Voicepar3rd      -0.4077705  0.1385833  -2.942  0.00331 **
## Voicepar5th      -0.2966854  0.1385836  -2.141  0.03244 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.221 on 1529 degrees of freedom
## Multiple R-squared:  0.3442, Adjusted R-squared:  0.3395
## F-statistic: 72.96 on 11 and 1529 DF,  p-value: < 2.2e-16
vif(full.lm)
##                  GVIF Df GVIF^(1/(2*Df))
## OMSI         1.532987  1        1.238138
## X16.minus.17 1.069971  1        1.034394
## NoClass      1.389692  1        1.178852
## APTheory     1.297833  1        1.139225
## Harmony      1.000033  3        1.000006
## Instrument   1.000218  2        1.000055
## Voice        1.000022  2        1.000005
```

Most of the covariates and their individual levels are significant at 95% confidence and all except 2 levels of Harmony significant at 90% confidence. OMSI and NoClass still have practical significance to classical rating and it makes sense for us to keep them in the model even though their coefficients are not significant at 95% confidence.

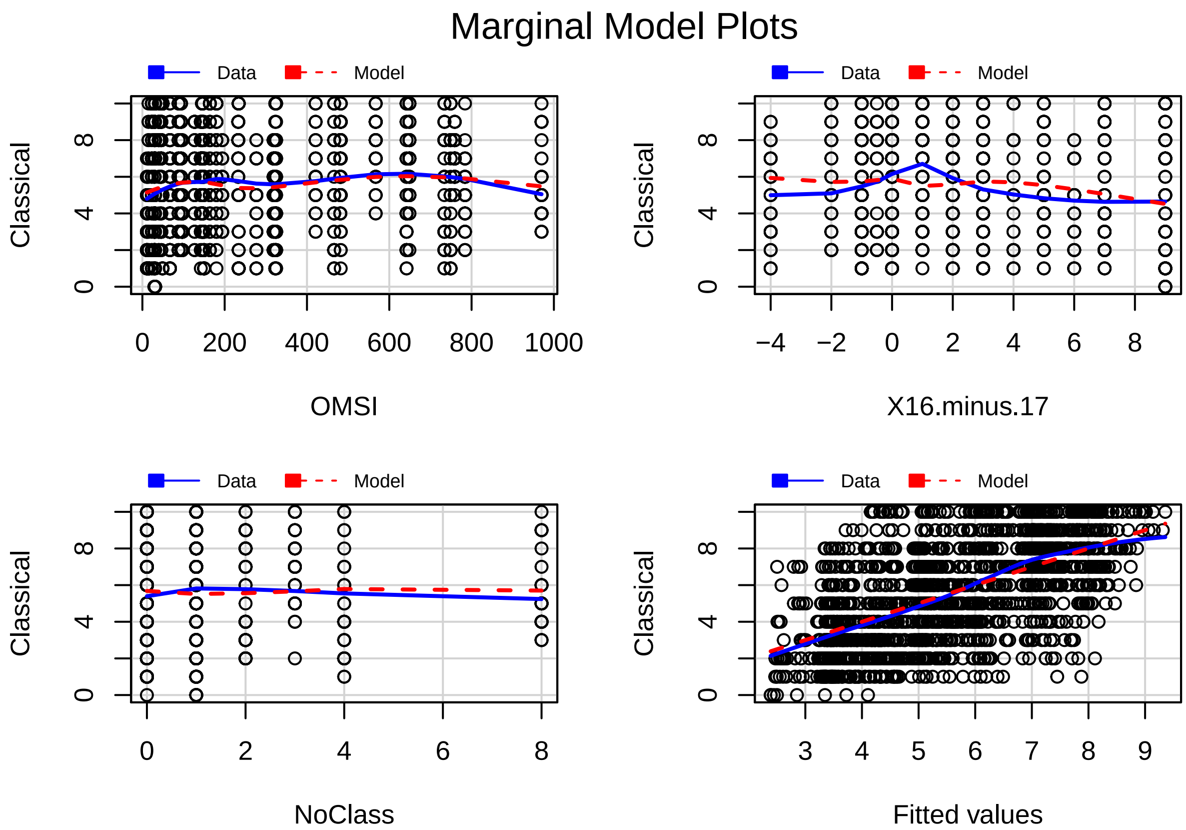
Additionally, we do not see any variance inflation factors above 1.5, indicating that we don't have significant multicollinearity that would prevent us from being confident in the coefficient estimates we see.

```r
par(mfrow = c(2, 3), mar = c(4, 4, 2, 0), oma = c(0, 0, 0, 0))
plot(full.lm, which = 1:5)
```

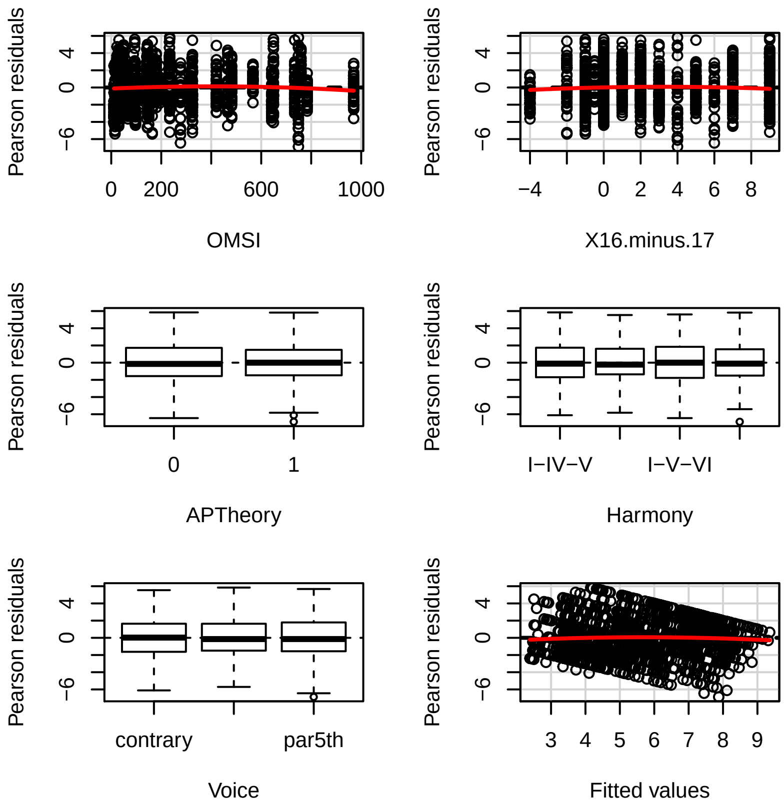


Though the residuals versus fitted and scale-location plots within our diagnostic plots don't show normal residuals, which is impossible with a discrete response, the mean of the residuals is approximately 0 with relatively constant variance. We also do not have any significant leverage points with values of Cook's Distance coming even close to 0.5.

```r
mmps(full.lm)
```




```r
residualPlots(full.lm, tests = FALSE)
```



Seeing that the parametric smoother for the data's relationship between each x and y and our model's representation of each covariate overlap in the marginal model plots tell us that we dont need to apply any transformations to these variables.

The residual plots are void of any significant patterns, confirming that we don't need to apply any transformations to the covariates because the conditional mean, though it may not be accurate in our model, is not mispecified per these plots.

Therefore, given that the response is discrete and we're using a linear model, this model meets our assumptions of constant variance in residuals with mean 0 and approximately normal residuals sufficiently enough to use to test the significance of the experimental factors.

Partial F test to test significance of Harmony

```
noharm.lm = lm(data = base.c, formula = Classical ~ OMSI + X16.minus.17 + NoClass +
    APTheory + Instrument + Voice)
anova(full.lm, noharm.lm)
## Analysis of Variance Table
##
## Model 1: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
##     Instrument + Voice
## Model 2: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Instrument +
##     Voice
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1   1529 7539.4
```

```
## 2   1532 7738.2 -3   -198.77 13.437 1.173e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The partial F-test to see whether the coefficient for Harmony is equal to zero while controlling for the other variables in the model yields a p-value that is numerically 0 at 1.173e-8, leading us to reject the null hypothesis that this coefficient is equal to 0 and conclude that Harmony has a significant relationship on whether someone rates music as classical while controlling for the other variables in the model.

Partial F test to test significance of Instrument

```
noinst.lm = lm(data = base.c, formula = Classical ~ OMSI + X16.minus.17 + NoClass +
    APTheory + Harmony + Voice)
anova(full.lm, noinst.lm)
## Analysis of Variance Table
##
## Model 1: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
##     Instrument + Voice
## Model 2: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
##     Voice
##   Res.Df     RSS Df Sum of Sq      F    Pr(>F)
## 1   1529  7539.4
## 2   1531 10863.4 -2     -3324 337.06 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The partial F test for whether the coefficient for Instrument is significantly different from zero while controlling for the other variables in the model yields a p-value that is numerically 0 at 2.2e-16, leading us to reject the null hypothesis that Instrument's coefficient is equal to zero. We are then able to conclude that the type of Instrument used has a significant relationship with how classical someone rates certain music.

Partial F test to test significance of Voice-Leading

```
novoice.lm = lm(data = base.c, formula = Classical ~ OMSI + X16.minus.17 + NoClass +
    APTheory + Harmony + Instrument)
anova(full.lm, novoice.lm)
## Analysis of Variance Table
##
## Model 1: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
##     Instrument + Voice
## Model 2: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
##     Instrument
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1   1529 7539.4
## 2   1531 7585.0 -2   -45.628 4.6268 0.009924 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The partial F-test for whether the coefficient for Voice-leading is equal to 0 also yields a p-value less than 0.05 at 0.0099, leading us to reject the null hypothesis that this variables coefficient is equal to 0 while controlling

7

for other variables in the model. Therefore, voice-leading does have a significant effect on how classical someone rates certain music.

b

i

$$
\begin{aligned}
Classical_i = \alpha_{j[i]} + \beta_1 OMSI + \beta_2 NoClass + \beta_3 X16.minus.17 + \beta_4 APTheory + \beta_5 Harmony(I-V-IV) \\
+ \beta_6 Harmony(I-V-VI) + \beta_7 Harmony(IV-I-V) + \beta_8 Instrument(Piano) \\
+ \beta_9 Instrument(String) + \beta_1 0 Voice(par3rd) + \beta_1 1 Voice(par5th) + \epsilon_i, \qquad \epsilon_i \sim N(0,\sigma^2) \\
\alpha_j = \beta_0 + \eta_j, \qquad \eta_j \sim N(0,\tau^2)
\end{aligned}
$$

ok

ii

```
library(lme4)
full.ranint = lmer(data = base.c, formula = Classical ~ OMSI + NoClass + X16.minus.17 +
    APTheory + Harmony + Instrument + Voice + (1 | Subject), REML = F)

compare.results.df = data.frame(Model = c("Linear Model 1 Intercept", "Varying-Intercept Model by Subje
    AIC = c(AIC(full.lm), AIC(full.ranint)), BIC = c(BIC(full.lm), BIC(full.ranint)))
compare.results.df
##                                 Model      AIC      BIC
## 1            Linear Model 1 Intercept 6845.827 6915.249
## 2 Varying-Intercept Model by Subject 6534.617 6609.380

anova(full.ranint, full.lm)
## Data: base.c
## Models:
## full.lm: Classical ~ OMSI + X16.minus.17 + NoClass + APTheory + Harmony +
## full.lm:     Instrument + Voice
## full.ranint: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## full.ranint:     Instrument + Voice + (1 | Subject)
##             Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## full.lm     13 6845.8 6915.2 -3409.9   6819.8
## full.ranint 14 6534.6 6609.4 -3253.3   6506.6 313.21      1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

6

We see that both the AIC and BIC are both significantly lower, 300 points lower, for the Varying-Intercept model, which is a significant decrease by all standards, and the p-value for the partial F test for whether the random intercept is necessary is also numerically 0, indicating that the random intercept is needed in the model.

need a 2nd test of the random intercept

iii

Test if Harmony is significant in varying-intercept model

```r
noharm.ranit = lmer(data = base.c, formula = Classical ~ OMSI + NoClass + X16.minus.17 +
    APTheory + Instrument + Voice + (1 | Subject), REML = F)
anova(full.ranint, noharm.ranit)
## Data: base.c
## Models:
## noharm.ranit: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Instrument +
## noharm.ranit:     Voice + (1 | Subject)
## full.ranint: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## full.ranint:     Instrument + Voice + (1 | Subject)
##              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## noharm.ranit 11 6581.5 6640.3 -3279.8   6559.5
## full.ranint  14 6534.6 6609.4 -3253.3   6506.6 52.914      3  1.913e-11
##
## noharm.ranit
## full.ranint  ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We see that the model without harmony included as a covariate has significantly higher AIC, BIC and deviance and lower log likelihood, leading to a p-value for the partial F test of the nested random intercep models of 1.913e-11, significantly less than 0.05. Therefore, we can reject the null hypothesis that the coefficient for Harmony is equal to 0 when controlling for other covariates in the random-intercept model and that the type of Harmony has a significant relationship with classical rating at 95% confidence.

Test if Instrument is significant in varying-intercept model

```r
noinst.ranit = lmer(data = base.c, formula = Classical ~ OMSI + NoClass + X16.minus.17 +
    APTheory + Harmony + Voice + (1 | Subject), REML = F)
anova(full.ranint, noinst.ranit)
## Data: base.c
## Models:
## noinst.ranit: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## noinst.ranit:     Voice + (1 | Subject)
## full.ranint: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## full.ranint:     Instrument + Voice + (1 | Subject)
##              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## noinst.ranit 12 7230.0 7294.1 -3603.0   7206.0
## full.ranint  14 6534.6 6609.4 -3253.3   6506.6 699.37      2  < 2.2e-16
##
## noinst.ranit
## full.ranint  ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The AIC, BIC and deviance for the random-intercept model without instrument are significantly higher and the log Likelihood is significantly lower than that of the full model based on the partial F test. This indicates that we can reject the null hypothesis that the coefficient for Instrument is not equal to 0 given the other inputs are in the model and conclude that Instrument has a signficant relationship with Classical rating at 95% confidence within the varying-intercept model.

Test if Voice-Leading is significant in varying-intercept model

```r
novoice.ranit = lmer(data = base.c, formula = Classical ~ OMSI + NoClass + X16.minus.17 +
    APTheory + Harmony + Instrument + (1 | Subject), REML = F)
anova(full.ranint, novoice.ranit)
## Data: base.c
## Models:
## novoice.ranit: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## novoice.ranit:     Instrument + (1 | Subject)
## full.ranint: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## full.ranint:     Instrument + Voice + (1 | Subject)
##               Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## novoice.ranit 12 6543.1 6607.2 -3259.5   6519.1
## full.ranint   14 6534.6 6609.4 -3253.3   6506.6 12.472      2   0.001958
##
## novoice.ranit
## full.ranint   **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The AIC for the full model is only barely lower than the AIC for the model without Voice-leading and BIC is actually slightly lower for the model without voice leading; deviance is lower for the full model. The p-value for the partial F-test is less than 0.05 at 0.00196, indicating that the coefficient for voice leading is significantly different from 0 at 95% confidence, but the significance does not appear to be very large as the BIC is lower for the reduced model without voice leading. Ultimately, voice-leading does not appear to have a substantial relationship with classical rating relative to the other experimental factors but still has a significant relationship within a random intercept model.

c

i

```r
all3.ranef = lmer(data = base.c, formula = Classical ~ OMSI + NoClass + X16.minus.17 +
    APTheory + Harmony + Instrument + Voice + (1 | Subject:Instrument) + (1 |
    Subject:Harmony) + (1 | Subject:Voice), REML = F)

ranef3.results = data.frame(Model = "Varying Intercept with 3 Random Effects",
    AIC = AIC(all3.ranef), BIC = BIC(all3.ranef))

compare.results.df2 = rbind.data.frame(compare.results.df, ranef3.results)
compare.results.df2
##                                     Model      AIC      BIC
## 1                Linear Model 1 Intercept 6845.827 6915.249
## 2      Varying-Intercept Model by Subject 6534.617 6609.380
## 3 Varying Intercept with 3 Random Effects 6243.977 6329.420
```

Comparing the model with 3 random effects to the linear model with 1 intercept and the varying intercept model by subject only, we see that the AIC and BIC for the model with 3 random effects for the intercept is significantly lower by 300 points for both measures, indicating a significantly better model.

ii

Test effect of Harmony in model with 3 random effects

```
all3.ranef.noharm = lmer(data = base.c, formula = Classical ~ OMSI + NoClass +
    X16.minus.17 + APTheory + Instrument + Voice + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice), REML = F)
anova(all3.ranef, all3.ranef.noharm)
## Data: base.c
## Models:
## all3.ranef.noharm: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Instrument +
## all3.ranef.noharm:     Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef.noharm:     (1 | Subject:Voice)
## all3.ranef: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## all3.ranef:     Instrument + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef:     (1 | Subject:Voice)
##                   Df    AIC    BIC  logLik deviance  Chisq Chi Df
## all3.ranef.noharm 13 6265.9 6335.3 -3119.9   6239.9
## all3.ranef        16 6244.0 6329.4 -3106.0   6212.0 27.915      3
##                   Pr(>Chisq)
## all3.ranef.noharm
## all3.ranef         3.784e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The reduced model without Harmony as a fixed effect has significantly higher deviance and AIC, a difference of 20 points on these measures, but only 6 points in BIC, because the BIC penalizes more for more terms. The p-value for the partial F test is 3.784e-06, which is less than our threshold of 0.05, indicating that we can reject the null hypothesis that the coefficient for the fixed effect of harmony is not equal to zero when accounting for all of the other coefficients in the model. Therefore, Harmony still has a significant relationship with a piece of music's Classical rating even after it is used within a random intercept.

Test effect of Instrument in model with 3 random effects

```
all3.ranef.noinst = lmer(data = base.c, formula = Classical ~ OMSI + NoClass +
    X16.minus.17 + APTheory + Harmony + Voice + (1 | Subject:Instrument) + (1 |
    Subject:Harmony) + (1 | Subject:Voice), REML = F)
anova(all3.ranef, all3.ranef.noinst)
## Data: base.c
## Models:
## all3.ranef.noinst: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## all3.ranef.noinst:     Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef.noinst:     (1 | Subject:Voice)
## all3.ranef: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## all3.ranef:     Instrument + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef:     (1 | Subject:Voice)
##                   Df    AIC    BIC  logLik deviance  Chisq Chi Df
## all3.ranef.noinst 14 6330.2 6404.9 -3151.1   6302.2
## all3.ranef        16 6244.0 6329.4 -3106.0   6212.0 90.206      2
##                   Pr(>Chisq)
## all3.ranef.noinst
## all3.ranef         < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The partial F test for whether the coefficient for the fixed effect of Instrument equals 0 yields a p-value that is numerically 0, indicating that we can confidently reject the null hypothesis that the coefficient for this fixed effect is significantly different from 0 and that the fixed effect of Instrument has a significant relationship with a music piece's Classical rating. Additionally, the AIC and BIC for the full model with the fixed effect for Instrument are lower by 86 and 75 points, respectively, which are significant drops that confirm the conclusion that this coefficient is still significantly different from 0.

Test effect of Voice Leading in model with 3 random effects

```
all3.ranef.novoice = lmer(data = base.c, formula = Classical ~ OMSI + NoClass +
    X16.minus.17 + APTheory + Harmony + Instrument + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice), REML = F)
anova(all3.ranef, all3.ranef.novoice)
## Data: base.c
## Models:
## all3.ranef.novoice: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## all3.ranef.novoice:     Instrument + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef.novoice:     (1 | Subject:Voice)
## all3.ranef: Classical ~ OMSI + NoClass + X16.minus.17 + APTheory + Harmony +
## all3.ranef:     Instrument + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony) +
## all3.ranef:     (1 | Subject:Voice)
##                    Df    AIC    BIC  logLik deviance  Chisq Chi Df
## all3.ranef.novoice 14 6253.7 6328.5 -3112.8   6225.7
## all3.ranef         16 6244.0 6329.4 -3106.0   6212.0 13.722      2
##                    Pr(>Chisq)
## all3.ranef.novoice
## all3.ranef           0.001048 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We saw that the fixed effect for voice-leading was barely significantly different from 0 at 95% confidence in the model with a single random intercept because the AIC and BIC of the full model did not differ significantly from that of the reduced model, even though the p-value was lower than 0.05. We see the same thing here where the AIC of the full model is only slightly better while the BIC is slightly poorer even though the p-value for the partial F test is less than 0.05. The fact that the deviance has a difference of 13 between the full and reduced models leads us to conclude that the coefficient for the fixed effect of voice leading still is significantly different from 0 and that voice leading does have a significant relationship with Classical rating at 95% confidence when the other terms are in the model.

Sizes of variance components with respect to each other and estimated residual variance

```
display(all3.ranef)
## lmer(formula = Classical ~ OMSI + NoClass + X16.minus.17 + APTheory +
##     Harmony + Instrument + Voice + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice), data = base.c,
##     REML = F)
##                  coef.est coef.se
## (Intercept)       3.78     0.30
## OMSI              0.00     0.00
## NoClass          -0.08     0.12
## X16.minus.17     -0.10     0.05
## APTheory1         0.83     0.37
## HarmonyI-V-IV     0.00     0.18
## HarmonyI-V-VI     0.85     0.18
## HarmonyIV-I-V     0.06     0.18
## Instrumentpiano   1.65     0.31
## Instrumentstring  3.59     0.31
```

```
## Voicepar3rd      -0.40     0.11
## Voicepar5th      -0.30     0.11
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.66
##  Subject:Voice      (Intercept) 0.21
##  Subject:Instrument (Intercept) 1.35
##  Residual                       1.57
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
## AIC = 6244, DIC = 6212
## deviance = 6212.0
```

We see that Instrument has the largest random effect among the 3 random effect terms at 1.57, which is interesting because the partial F test for the reduced model without the Instrument fixed effect yielded the largest difference in AIC and BIC and the lowest p-value. The random effect for Voice is the smallest at 0.21 and Harmony in the middle at 0.66. *The fixed effect for Instrument makes up $\frac{1.35}{1.57} = 90\%$ of the residual variance. Therefore, the random intercept resulting from the interaction between subject and instrument is the most significant random effect, explaining more variation in classical rating at the individual level than the other 2 fixed effects.

8

iii

$$
\begin{aligned}
Classical_i = \alpha_{j[i]} &+ \beta_1 OMSI + \beta_2 NoClass + \beta_3 X16.minus.17 + \beta_4 APTheory + \beta_5 Harmony(I-V-IV) \\
&+ \beta_6 Harmony(I-V-VI) + \beta_7 Harmony(IV-I-V) + \beta_8 Instrument(Piano) \\
&+ \beta_9 Instrument(String) + \beta_{10} Voice(par3rd) + \beta_{11} Voice(par5th) + \epsilon_i, \qquad \epsilon_i \sim N(0,\sigma^2) \\
\alpha_j = \beta_0 + \eta_{j1} + \eta_{j2} + \eta_{j3}, &\qquad \eta_{j1} \sim N(0,{\tau_1}^2), \qquad \eta_{j2} \sim N(0,{\tau_2}^2), \qquad \eta_{j3} \sim N(0,{\tau_3}^2)
\end{aligned}
$$

this is fine, but the eta's need to be indexed by the level of the corresponding design factor, as well as by j.

2

a

Because I already determined that the 4 covariates OMSI, NoClass, X16.minus.17 and APTheory should be included as covariates in an initial model to test the significance of the 3 experimental factors, I'll test whether these 4 variables and listening to classical music should be included in the model given that the fixed and random effects for Harmony, Instrument and Voice-leading are included in the model. The other variables in the dataset do not appear to have a practical influence on how Classical the music would sound to them so they will not be evaluated.

you haven't tested them in the current model.

```
all = lmer(data = base.c, formula = Classical ~ ClsListen + OMSI + NoClass +
    X16.minus.17 + APTheory + Harmony + Instrument + Voice + (1 | Subject:Instrument) +
    (1 | Subject:Harmony) + (1 | Subject:Voice), REML = F)

exp3 = lmer(data = base.c, formula = Classical ~ Harmony + Instrument + Voice +
    (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 | Subject:Voice),
    REML = F)

exp3.claslistn = lmer(data = base.c, formula = Classical ~ Harmony + Instrument +
    Voice + ClsListen + (1 | Subject:Instrument) + (1 | Subject:Harmony) + (1 |
```

```
    Subject:Voice), REML = F)

summary(all)
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula:
## Classical ~ ClsListen + OMSI + NoClass + X16.minus.17 + APTheory +
##     Harmony + Instrument + Voice + (1 | Subject:Instrument) +
##     (1 | Subject:Harmony) + (1 | Subject:Voice)
##    Data: base.c
##
##      AIC      BIC   logLik deviance df.resid
##   6242.9   6349.7  -3101.4   6202.9     1521
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2755 -0.5572 -0.0063  0.5434  3.3597
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.43232  0.6575
##  Subject:Voice      (Intercept) 0.04304  0.2075
##  Subject:Instrument (Intercept) 1.68805  1.2993
##  Residual                       2.47961  1.5747
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Voice, 129; Subject:Instrument, 129
##
## Fixed effects:
##                    Estimate Std. Error t value
## (Intercept)        3.546960   0.438667   8.086
## ClsListen1        -0.134751   0.423356  -0.318
## ClsListen3         0.714804   0.447813   1.596
## ClsListen4         0.369979   1.023789   0.361
## ClsListen5         0.829843   0.514276   1.614
## OMSI               0.000381   0.000702   0.543
## NoClass           -0.110413   0.122070  -0.905
## X16.minus.17      -0.087091   0.045372  -1.919
## APTheory1          0.671884   0.376335   1.785
## HarmonyI-V-IV     -0.004361   0.181608  -0.024
## HarmonyI-V-VI      0.851372   0.181663   4.687
## HarmonyIV-I-V      0.059816   0.181545   0.329
## Instrumentpiano    1.649175   0.297053   5.552
## Instrumentstring   3.589404   0.296877  12.091
## Voicepar3rd       -0.403232   0.107998  -3.734
## Voicepar5th       -0.298928   0.107998  -2.768
##
## Correlation of Fixed Effects:
##             (Intr) ClsLs1 ClsLs3 ClsLs4 ClsLs5 OMSI   NoClss X16..1 APThr1
## ClsListen1  -0.704
## ClsListen3  -0.655  0.713
## ClsListen4  -0.164  0.252  0.222
## ClsListen5  -0.575  0.610  0.601  0.222
## OMSI        -0.281  0.116  0.099 -0.361  0.030
## NoClass      0.045 -0.060 -0.188  0.240  0.007 -0.445
```

```
## X16.mins.17 -0.098 -0.042  0.040 -0.130  0.041 -0.099 -0.157
## APTheory1    0.141 -0.170 -0.223  0.123 -0.206 -0.396 -0.076  0.070
## HrmnyI-V-IV -0.207  0.000  0.000  0.000  0.000  0.001 -0.001  0.000  0.000
## HrmnyI-V-VI -0.207  0.000  0.000  0.000  0.000  0.000 -0.001  0.000  0.000
## HrmnyIV-I-V -0.207  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## Instrumntpn -0.339  0.000  0.001 -0.001  0.000  0.002 -0.002  0.001  0.001
## Instrmntstr -0.338  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## Voicepar3rd -0.123  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
## Voicepar5th -0.123  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
##             HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## ClsListen1
## ClsListen3
## ClsListen4
## ClsListen5
## OMSI
## NoClass
## X16.mins.17
## APTheory1
## HrmnyI-V-IV
## HrmnyI-V-VI  0.500
## HrmnyIV-I-V  0.500  0.500
## Instrumntpn  0.000  0.000  0.000
## Instrmntstr  0.000  0.000  0.000  0.500
## Voicepar3rd -0.001 -0.001  0.001  0.000     0.000
## Voicepar5th -0.001 -0.002 -0.001  0.000     0.000     0.500

anova(all, exp3)
## Data: base.c
## Models:
## exp3: Classical ~ Harmony + Instrument + Voice + (1 | Subject:Instrument) +
## exp3:     (1 | Subject:Harmony) + (1 | Subject:Voice)
## all: Classical ~ ClsListen + OMSI + NoClass + X16.minus.17 + APTheory +
## all:     Harmony + Instrument + Voice + (1 | Subject:Instrument) +
## all:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##      Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## exp3 12 6248.6 6312.6 -3112.3   6224.6
## all  20 6242.9 6349.7 -3101.4   6202.9 21.68      8   0.005545 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(all, exp3.claslistn)
## Data: base.c
## Models:
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
## all: Classical ~ ClsListen + OMSI + NoClass + X16.minus.17 + APTheory +
## all:     Harmony + Instrument + Voice + (1 | Subject:Instrument) +
## all:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## exp3.claslistn 16 6243.7 6329.2 -3105.9   6211.7
## all            20 6242.9 6349.7 -3101.4   6202.9 8.8549      4    0.06483
##
## exp3.claslistn
```

```
## all              .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

5

The partial F test for comparing the reduced model with the 3 experimental factors and their random effects plus the variable for listening to classical music, to the full model that also includes the 4 covariates of APTheory, OMSI, NoClass and X16.minus.17 yields a p-value of 0.06483, greater than 0.05, indicating that these 4 additional covariates' coefficients are not significantly different from 0 at 95% confidence when the 3 experimental factors, their random effects and the variable for listening to Classical music are included in the model.

b

```
exp3.claslistn.1ranef = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject), REML = F)

anova(exp3.claslistn, exp3.claslistn.1ranef)
## Data: base.c
## Models:
## exp3.claslistn.1ranef: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                       Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.1ranef 14 6534.4 6609.1 -3253.2   6506.4
## exp3.claslistn        16 6243.7 6329.2 -3105.9   6211.7 294.65      2
##                       Pr(>Chisq)
## exp3.claslistn.1ranef
## exp3.claslistn         < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

exp3.claslistn.ranint11 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Instrument), REML = F)

exp3.claslistn.ranint12 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Harmony), REML = F)

exp3.claslistn.ranint13 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Voice), REML = F)

exp3.claslistn.ranint21 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Instrument) + (1 | Subject:Harmony),
    REML = F)

exp3.claslistn.ranint22 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Harmony) + (1 | Subject:Voice),
    REML = F)

exp3.claslistn.ranint23 = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Voice) + (1 | Subject:Instrument),
    REML = F)
```

```
anova(exp3.claslistn, exp3.claslistn.ranint11)
## Data: base.c
## Models:
## exp3.claslistn.ranint11: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrume
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.ranint11 14 6302.1 6376.9 -3137.1   6274.1
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 62.419      2
##                         Pr(>Chisq)
## exp3.claslistn.ranint11
## exp3.claslistn           2.792e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(exp3.claslistn, exp3.claslistn.ranint12)
## Data: base.c
## Models:
## exp3.claslistn.ranint12: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Harmony)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.ranint12 14 6593.2 6667.9 -3282.6   6565.2
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 353.44      2
##                         Pr(>Chisq)
## exp3.claslistn.ranint12
## exp3.claslistn           < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(exp3.claslistn, exp3.claslistn.ranint13)
## Data: base.c
## Models:
## exp3.claslistn.ranint13: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Voice)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.ranint13 14 6641.2 6715.9 -3306.6   6613.2
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 401.45      2
##                         Pr(>Chisq)
## exp3.claslistn.ranint13
## exp3.claslistn           < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(exp3.claslistn, exp3.claslistn.ranint21)
## Data: base.c
## Models:
## exp3.claslistn.ranint21: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrume
## exp3.claslistn.ranint21:     (1 | Subject:Harmony)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
```

```
## exp3.claslistn.ranint21 15 6243.3 6323.4 -3106.6   6213.3
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 1.5235      1
##                         Pr(>Chisq)
## exp3.claslistn.ranint21
## exp3.claslistn              0.2171

anova(exp3.claslistn, exp3.claslistn.ranint22)
## Data: base.c
## Models:
## exp3.claslistn.ranint22: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Harmony)
## exp3.claslistn.ranint22:     (1 | Subject:Voice)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.ranint22 15 6595.1 6675.2 -3282.5   6565.1
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 353.36      1
##                         Pr(>Chisq)
## exp3.claslistn.ranint22
## exp3.claslistn           < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(exp3.claslistn, exp3.claslistn.ranint23)
## Data: base.c
## Models:
## exp3.claslistn.ranint23: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Voice) +
## exp3.claslistn.ranint23:     (1 | Subject:Instrument)
## exp3.claslistn: Classical ~ Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) +
## exp3.claslistn:     (1 | Subject:Harmony) + (1 | Subject:Voice)
##                         Df    AIC    BIC  logLik deviance  Chisq Chi Df
## exp3.claslistn.ranint23 15 6303.9 6384.0 -3136.9   6273.9
## exp3.claslistn          16 6243.7 6329.2 -3105.9   6211.7 62.154      1
##                         Pr(>Chisq)
## exp3.claslistn.ranint23
## exp3.claslistn           3.176e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3

In doing partial F tests for varying combinations of included random effects from only (1|Subject) to all combinations of 2 interaction type random effects, e.g. (1|Subject:Instrument) and (1|Subject:Harmony), we see that the random effect of (1|Subject:Voice) is not significant at 95% confidence when the 4 covariates and the random effects (1|Subject:Instrument) and (1|Subject:Harmony) are already included in the model. Therefore, we'll only keep the random effects of (1|Subject:Instrument) and (1|Subject:Harmony) in addition to the 4 fixed effects.

partial F tests are not valid for testing random effects. Use one of the methods discussed in class.

c

```
exp3.claslistn.ranintf = lmer(data = base.c, formula = Classical ~ Harmony +
    Instrument + Voice + ClsListen + (1 | Subject:Instrument) + (1 | Subject:Harmony),
    REML = F)
display(exp3.claslistn.ranintf)
```

```
## lmer(formula = Classical ~ Harmony + Instrument + Voice + ClsListen +
##     (1 | Subject:Instrument) + (1 | Subject:Harmony), data = base.c,
##     REML = F)
##                  coef.est coef.se
## (Intercept)       3.45     0.42
## HarmonyI-V-IV     0.00     0.18
## HarmonyI-V-VI     0.85     0.18
## HarmonyIV-I-V     0.06     0.18
## Instrumentpiano   1.65     0.31
## Instrumentstring  3.59     0.31
## Voicepar3rd      -0.40     0.10
## Voicepar5th      -0.30     0.10
## ClsListen1       -0.07     0.43
## ClsListen3        0.88     0.43
## ClsListen4        0.31     0.96
## ClsListen5        1.10     0.51
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.66
##  Subject:Instrument (Intercept) 1.36
##  Residual                       1.58
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
## AIC = 6243.3, DIC = 6213.3
## deviance = 6213.3
```

Because we do not receive p-values for individual factor levels, we have to determine which levels are statistically significant by being 2 standard errors away from 0.

The intercept corresponds to a participant who is exposed to Harmony I-V-vi, Electric Guitar, Contrary Motion and Listens to Classical Music at the level of 2 on the scale of 1-5. We will interpret each variable relative to the intercept.

The average Classical rating for a person with the above characteristics described in the intercept is 3.45 on a scale from 1 to 10.

Harmony I-V-IV - Holding all else constant and changing the Harmony to I-V-IV leads to no change in average classical rating, the average classical rating is still 3.45.

Harmony I-V-VI - Holding all else constant and changing the Harmony to I-V-VI leads to an increase in the average classical rating by 0.85, up to 4.3. This change is statistically significant because the estimate. 0.85, is more than 2 standard errors from 0 with standard error 0.18.

Harmony IV-I-V - Holding all else constant and changing the Harmony to IV-I-V does not lead to a statistically significant change in average classical rating because the standard error for this level's coefficient is already larger than its coefficient estimate, so 2 standard errors from the coefficient estimate certainly contains 0.

Instrumet piano - Holding all else constant and changing the Instrument being played to piano leads to an increase in average classical rating by 1.65, up to 5.1, which is a statistically significant increase because this estimate is more than 2 standard errors from 0.

Instrument string - Holding all else constant and changing the Instrument being played to a string quartet leads to an average increase in classical rating by 3.59 points, up to 7.04. This is a statistcally significant increase because the coefficient's standard error is 0.31, twice of which is significantly lower than the estimate, making it significantly different from 0.

Voice par3rd - Holding all else constant and changing the voice leading to parallel thirds leads to an average decrease in classical rating of -0.40, down to 3.05. This is a statistically significant decrease with standard error 0.1, with 2 standard errors fro the estimate not including 0.

Voice par5th - Holding all else constant and changing the voice leading to parallel 5ths leads to an average decrease in classical rating by -0.30, down to 3.15. This is a statistically significant decrease that is more than 2 standard errors from 0.

ClsListen1 - Holding all else constant and changing the person being played to one who listens to classical music at the level of 1 on a scale of 1 to 5 leads to an average decrease of -0.07 in classical rating, but this coefficient's standard error is very large, making it not a statistically significant decrease.

ClsListen3 - Holding all else constant and changing the person being played to one who listens to classical music at the level of 3 on a scale of 1 to 5 leads to an average increase in classical rating of 0.88, up to 4.33. This is a statistically significant increase with the estimate being more than 2 standard errors from 0.

ClsListen4 - Holding all else constant and changing the person being played to one who listens to classical music at the level of 4 on a scale of 1 to 5 leads to an average increase in classical rating of 0.31, up to 4.33, but this coefficient's standard error is very large, making it not a statistically significant decrease.

ClsListen5 - Holding all else constant and changing the person being played to one who listens to classical music at the level of 5 on a scale of 1 to 5 leads to an average increase in classical rating of 1.10, up to 5.55. This is a statistically significant increase at 95% confidence.

The standard deviation for the random effect of (1|Subject:Harmony) indicates that 95% of the random effects added will be normally distributed between (-1.32, 1.32). Therefore, there will be as low as 1.32 points subtracted from a person's classical average classical rating based on which Harmony is played for them to as much as 1.32 added to their classical rating.

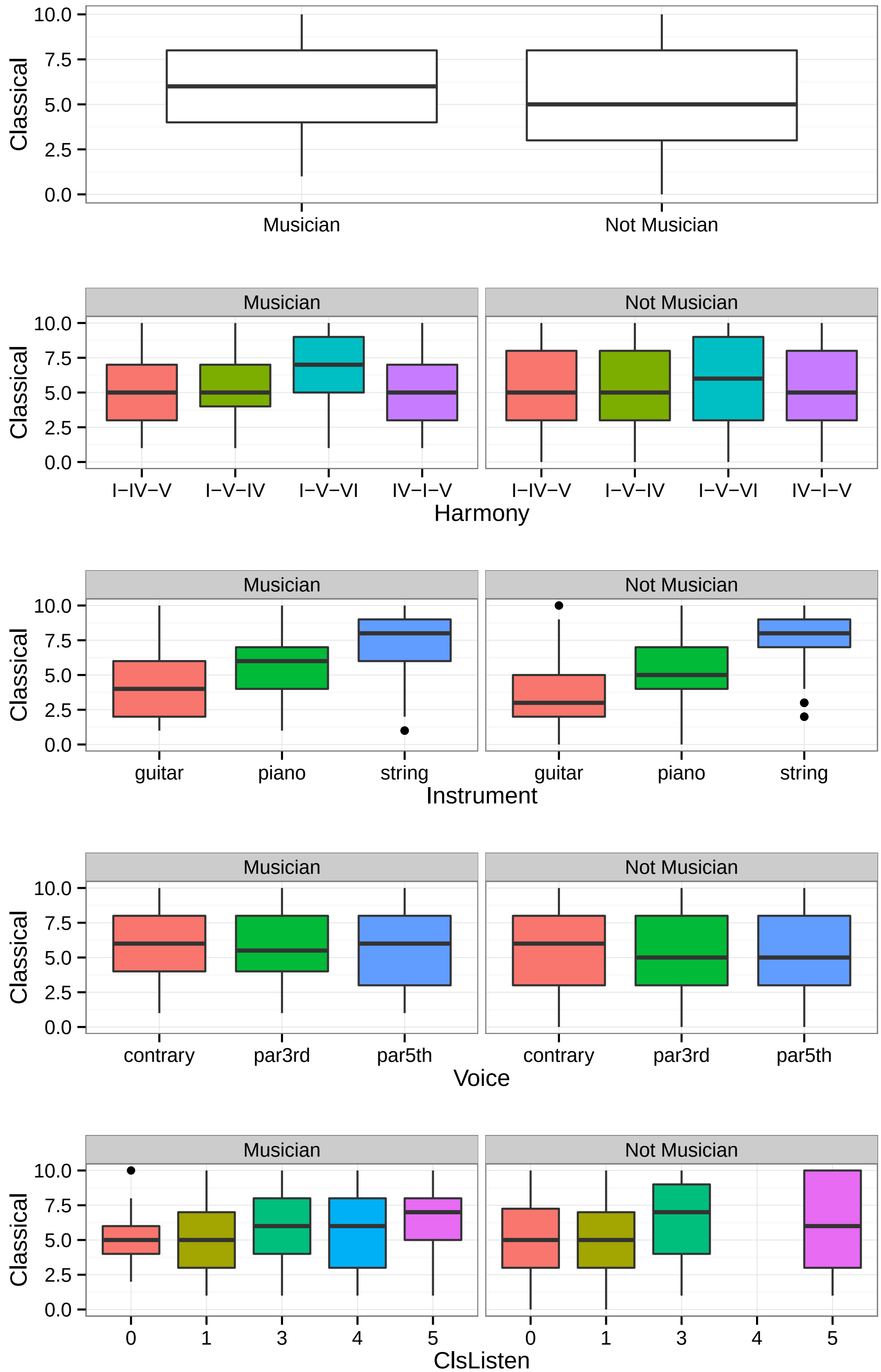
The standard deviation for the random effect of (1|Subject:Instrument) indicates that 95% of the random
effects added will be normally distributed between (-2.72, 2.72). This means that there will be as much as
9 2.72 points subtracted from their expected classical rating to as much as 2.72 points added based on which
instrument in played for them.

The residual standard deviation of 1.58 means that 95% of the errors between our estimate and the actual rating fall between 3.16 points below the actual rating and 3.16 points above the actual rating.

3

```
# 2 and below are not musicians, 3 and above are so that approximately half
# and half
base.c$Selfdeclare.split = ifelse(base.c$Selfdeclare %in% c("1", "2"), "Not Musician",
    "Musician")

library(ggplot2)
# interactions with other variables in model - harmony, instrument, voice
# leading, listen to classical music

musc.rating = ggplot(data = base.c, aes(x = Selfdeclare.split, y = Classical)) +
    geom_boxplot() + theme_bw() + theme(axis.title.x = element_blank())

harm.musc.rating = ggplot(data = base.c, aes(x = Harmony, y = Classical, fill = Harmony)) +
    facet_grid(~Selfdeclare.split) + geom_boxplot() + theme_bw() + theme(legend.position = "none")

inst.musc.rating = ggplot(data = base.c, aes(x = Instrument, y = Classical,
```

```
    fill = Instrument)) + facet_grid(~Selfdeclare.split) + geom_boxplot() +
    theme_bw() + theme(legend.position = "none")

voice.musc.rating = ggplot(data = base.c, aes(x = Voice, y = Classical, fill = Voice)) +
    facet_grid(~Selfdeclare.split) + geom_boxplot() + theme_bw() + theme(legend.position = "none")

clslstn.rating = ggplot(data = base.c, aes(x = ClsListen, y = Classical, fill = ClsListen)) +
    facet_grid(~Selfdeclare.split) + geom_boxplot() + theme_bw() + theme(legend.position = "none")

grid.arrange(ncol = 1, nrow = 5, musc.rating, harm.musc.rating, inst.musc.rating,
    voice.musc.rating, clslstn.rating)
```


Classical
10.0
7.5
5.0
2.5
0.0
Musician
Not Musician
Harmony
I−IV−V
I−V−IV
I−V−VI
IV−I−V
Instrument
guitar
piano
string
Voice
contrary
par3rd
par5th
ClsListen
0
1
3
4
5

```
table(base.c$Selfdeclare.split, base.c$ClsListen)
##
##                   0   1   3   4   5
##   Musician       36 252 282  36 108
##   Not Musician 180 324 216   0 107
round(prop.table(table(base.c$Selfdeclare.split, base.c$ClsListen), margin = 1),
    digits = 2)
##
##                    0    1    3    4    5
##   Musician      0.05 0.35 0.39 0.05 0.15
##   Not Musician 0.22 0.39 0.26 0.00 0.13
```

We dont see significant differences in Classical ratings for Musicians and Non-Musicians or for the interaction between Musicians and Non-Musicians with any of the terms already in the model based on the boxplots. We'll do some tests with reduced and full models to see if adding any of these terms to the model reveals that they're significant.

```
# anova partial F tests for each interaction in model
base.3 = lmer(data = base.c, formula = Classical ~ Harmony + Instrument + Voice +
    ClsListen + (1 | Subject:Instrument) + (1 | Subject:Harmony), REML = F)

three.slf2 = lmer(data = base.c, formula = Classical ~ Harmony + Instrument +
    Voice + Selfdeclare.split + ClsListen + (1 | Subject:Instrument) + (1 |
    Subject:Harmony), REML = F)

three.slf2.harm = lmer(data = base.c, formula = Classical ~ Selfdeclare.split *
    Harmony + Instrument + Voice + ClsListen + (1 | Subject:Instrument) + (1 |
    Subject:Harmony), REML = F)

three.slf2.inst = lmer(data = base.c, formula = Classical ~ Selfdeclare.split *
    Instrument + Harmony + Voice + ClsListen + (1 | Subject:Instrument) + (1 |
    Subject:Harmony), REML = F)

three.slf2.voic = lmer(data = base.c, formula = Classical ~ Selfdeclare.split *
    Voice + Harmony + Instrument + ClsListen + (1 | Subject:Instrument) + (1 |
    Subject:Harmony), REML = F)

three.slf2.cls = lmer(data = base.c, formula = Classical ~ Voice + Harmony +
    Instrument + Selfdeclare.split * ClsListen + (1 | Subject:Instrument) +
    (1 | Subject:Harmony), REML = F)

partialf.results.3.df = data.frame(full.model = c("base + self declare(Musician/Non)",
    "base + self declare(Musician/Non) * Harmony", "base + self declare(Musician/Non) * Instrument",
    "base + self declare(Musician/Non) * Voice", "base + self declare(Musician/Non) * ClsListen"),
    reduced.model = c("base", "base + self declare(Musician/Non)", "base + self declare(Musician/Non)",
        "base + self declare(Musician/Non)", "base + self declare(Musician/Non)"),
    coefficient.tested = c("self declare(Musician/Non)", "self declare*Harmony",
        "self declare * Instrument", "self declare*Voice", "self declare*ClsListen"),
    anova.p.value = c(round(anova(base.3, three.slf2)$"Pr(>Chisq)"[2], digits = 3),
        round(anova(three.slf2, three.slf2.harm)$"Pr(>Chisq)"[2], digits = 3),
        round(anova(three.slf2, three.slf2.inst)$"Pr(>Chisq)"[2], digits = 3),
        round(anova(three.slf2, three.slf2.voic)$"Pr(>Chisq)"[2], digits = 3),
        round(anova(three.slf2, three.slf2.cls)$"Pr(>Chisq)"[2], digits = 3)))
```

```
partialf.results.3.df
##                                      full.model
## 1               base + self declare(Musician/Non)
## 2    base + self declare(Musician/Non) * Harmony
## 3 base + self declare(Musician/Non) * Instrument
## 4      base + self declare(Musician/Non) * Voice
## 5  base + self declare(Musician/Non) * ClsListen
##                        reduced.model         coefficient.tested
## 1                               base self declare(Musician/Non)
## 2 base + self declare(Musician/Non)       self declare*Harmony
## 3 base + self declare(Musician/Non)  self declare * Instrument
## 4 base + self declare(Musician/Non)         self declare*Voice
## 5 base + self declare(Musician/Non)     self declare*ClsListen
##   anova.p.value
## 1         0.875
## 2         0.000
## 3         0.149
## 4         0.629
## 5         0.598
```

7

The results of the partial F tests tell us that adding this dichotomized variable of whether people self-declare themselves as musicians by itself is not significant in the model, but the interaction between this self-declare variable and Harmony is significant at 95% confidence. The interactions between the other experimental factors and listening to classical music are not significant at 95% confidence.

What you have done is OK but both somewhat laborious and somewhat incomplete. It would be simpler just to include interactions with most/all fixed effects and run a backwards variable selection algorithm.

4

a

To test the effects of Harmony, Voice and Instrument on Popular Ratings, we'll compare full models with covariates in addition to these 3 to reduced models without each of these variables to see if they're significant.

```
full.lmer.pop = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Instrument + Voice + (1 |
    Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice), REML = F)

single.ranint.subj = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Instrument + Voice + (1 |
    Subject), REML = F)

ranint2.noharm = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Instrument + Voice + (1 |
    Subject:Instrument) + (1 | Subject:Voice), REML = F)

ranint2.noinst = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Instrument + Voice + (1 |
    Subject:Harmony) + (1 | Subject:Voice), REML = F)

ranint2.novoice = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Instrument + Voice + (1 |
    Subject:Harmony) + (1 | Subject:Instrument), REML = F)
```

```
full.noharm = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    PianoPlay + GuitarPlay + Instrument + Voice + (1 | Subject:Harmony) + (1 |
    Subject:Instrument) + (1 | Subject:Voice), REML = F)

full.novoice = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    PianoPlay + GuitarPlay + Harmony + Instrument + (1 | Subject:Harmony) +
    (1 | Subject:Instrument) + (1 | Subject:Voice), REML = F)

full.noinst = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    PianoPlay + GuitarPlay + Harmony + Voice + (1 | Subject:Harmony) + (1 |
    Subject:Instrument) + (1 | Subject:Voice), REML = F)

compare.models.4a = data.frame(full.model = c("full"), reduced.model = c("Single Random Intercept By Sul
    "Full - Subject:Harmony random int", "Full - Subject:Instr random intercept",
    "Full - Subject:Voice random intercept", "Full - Harmony fixed effect",
    "Full - Voice fixed effect", "Full - Instrument fixed effect"), coefficients.tested = c("(1|Subject
    "(1|Subject:Harmony)", "(1|Subject:Instrument)", "(1|Subject:Voice)", "Harmony",
    "Voice", "Instrument"), AIC.full.model = AIC(full.lmer.pop), AIC.reduced.model = c(AIC(single.ranin
    AIC(ranint2.noharm), AIC(ranint2.noinst), AIC(ranint2.novoice), AIC(full.noharm),
    AIC(full.novoice), AIC(full.noinst)), BIC.full.model = BIC(full.lmer.pop),
    BIC.reduced.model = c(BIC(single.ranint.subj), BIC(ranint2.noharm), BIC(ranint2.noinst),
        BIC(ranint2.novoice), BIC(full.noharm), BIC(full.novoice), BIC(full.noinst)),
    anova.p.value = c(anova(full.lmer.pop, single.ranint.subj)$"Pr(>Chisq)"[2],
        anova(full.lmer.pop, ranint2.noharm)$"Pr(>Chisq)"[2], anova(full.lmer.pop,
            ranint2.noinst)$"Pr(>Chisq)"[2], anova(full.lmer.pop, ranint2.novoice)$"Pr(>Chisq)"[2],
        anova(full.lmer.pop, full.noharm)$"Pr(>Chisq)"[2], anova(full.lmer.pop,
            full.novoice)$"Pr(>Chisq)"[2], anova(full.lmer.pop, full.noinst)$"Pr(>Chisq)"[2]))

compare.models.4a
##   full.model                         reduced.model
## 1       full    Single Random Intercept By Subject
## 2       full     Full - Subject:Harmony random int
## 3       full Full - Subject:Instr random intercept
## 4       full Full - Subject:Voice random intercept
## 5       full           Full - Harmony fixed effect
## 6       full             Full - Voice fixed effect
## 7       full        Full - Instrument fixed effect
##                                                  coefficients.tested
## 1 (1|Subject:Harmony) + (1|Subject:Instrument) + (1|Subject:Voice)
## 2                                                (1|Subject:Harmony)
## 3                                             (1|Subject:Instrument)
## 4                                                  (1|Subject:Voice)
## 5                                                            Harmony
## 6                                                              Voice
## 7                                                         Instrument
##   AIC.full.model AIC.reduced.model BIC.full.model BIC.reduced.model
## 1       6314.831          6497.753       6475.037          6647.278
## 2       6314.831          6361.264       6475.037          6516.130
## 3       6314.831          6539.161       6475.037          6694.026
## 4       6314.831          6313.880       6475.037          6468.746
## 5       6314.831          6312.793       6475.037          6456.978
## 6       6314.831          6315.528       6475.037          6465.054
## 7       6314.831          6398.978       6475.037          6548.503
```

```
##   anova.p.value
## 1  2.572769e-41
## 2  3.417243e-12
## 3  3.765995e-51
## 4  3.057248e-01
## 5  2.656303e-01
## 6  9.550208e-02
## 7  7.231106e-20

confint(full.lmer.pop)
##                          2.5 %       97.5 %
## .sig01                0.49337206  0.781410945
## .sig02                0.95970566  1.325604985
## .sig03                0.00000000  0.376798854
## .sigma                1.56592063  1.695777577
## (Intercept)           6.96409805 12.518062987
## Instr.minus.Notes-2 -5.26703658  0.030394031
## Instr.minus.Notes-1 -3.92361595  1.029861533
## Instr.minus.Notes0  -3.83224090  1.013178042
## Instr.minus.Notes1  -4.77496584  0.173437810
## Instr.minus.Notes2  -4.24838119  0.645777587
## Instr.minus.Notes3  -4.71157014  0.550922703
## Instr.minus.Notes4  -4.92965919  0.370999271
## X1990s2000s2        -2.35717917  0.280354661
## X1990s2000s3        -2.80088539 -0.119546842
## X1990s2000s4        -2.76913845  0.702086334
## X1990s2000s5        -1.92063633  0.437931432
## PianoPlay1          -1.73450878 -0.269958614
## PianoPlay4          -1.91528276  1.461661202
## PianoPlay5          -1.79923981  0.113835425
## GuitarPlay1         -2.30775074  0.003967946
## GuitarPlay2         -1.05858616  3.169545454
## GuitarPlay4         -0.45200260  3.123390811
## GuitarPlay5          0.15947085  2.067190280
## HarmonyI-V-IV       -0.35452770  0.355071614
## HarmonyI-V-VI       -0.61279593  0.097035887
## HarmonyIV-I-V       -0.60620113  0.103143354
## Instrumentpiano     -1.69035957 -0.646389031
## Instrumentstring    -3.54437275 -2.501196956
## Voicepar3rd         -0.04587989  0.391746982
## Voicepar5th          0.01504198  0.452665595
```

The results of the various partial F tests shows that the fixed effects for Harmony and Voice along with the random intercept effect for Subject and Voice are not significant at 95% confidence when controlling for all of the other random intercepts and fixed effects in the model. We'll remove the variance component for Subject and Voice but keep the fixed effects of Harmony and Voice for final evaluation. Additionally, the AIC for the models without these effects is about the same, indicating the reduced models without these effects do not perform significantly worse, while the reduced models without the other random and fixed effects see significant increases in AIC and decreases in fit.

Different levels of Harmony (fixed effects) do not have a significant effect on Popular music rating at 95% confidence when controlling for other factors, which is supported in the confidence intervals for the coefficients of this variable because each 95% confidence interval for the estimate contains 0 in each interval and in the p-value for the partial F test that is not less than 0.05 leading us to retain the null hypothesis that this coefficient is not significantly different from 0.

Different Voice leading methods (fixed effects) also do not significantly influence Popular music rating per the partial F test for this variables coefficient. However, the 95% confidence interval for the level of this parallel 5ths does not contain 0, (0.015, 0.453). Even though the 95% confidence interval doesn't contain 0, 9 the p-value for this variable in the partial F-test is 0.0955, which is notably above our 0.05 threshold, so we'll retain the null hypthesis that this level's coefficient is not significantly different from 0.

Using a different instrument does have a significant impact on Popular music rating, with the popular music rating for when the piano is played ranging from 0.64 to 1.69 points less than the average Popular music rating when the guitar is played. Additionally, playing a string quartet leads to a popular rating that is lower than a rating when the guitar is played by 2.5 to 3.5 points. Therefore, the Electric Guitar leads to the higher Popular music ratings while the string quartet leads to significantly lower Popular ratings and piano leading to slightly lower ratings.

b

```
final.lmer.pop = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Instrument + (1 | Subject:Harmony) +
    (1 | Subject:Instrument), REML = F)

display(final.lmer.pop)
## lmer(formula = Popular ~ Instr.minus.Notes + X1990s2000s + PianoPlay +
##     GuitarPlay + Instrument + (1 | Subject:Harmony) + (1 | Subject:Instrument),
##     data = base.c, REML = F)
##                     coef.est coef.se
## (Intercept)          9.75     1.40
## Instr.minus.Notes-2 -2.62     1.34
## Instr.minus.Notes-1 -1.45     1.25
## Instr.minus.Notes0  -1.41     1.23
## Instr.minus.Notes1  -2.30     1.25
## Instr.minus.Notes2  -1.80     1.24
## Instr.minus.Notes3  -2.08     1.33
## Instr.minus.Notes4  -2.28     1.34
## X1990s2000s2        -1.04     0.67
## X1990s2000s3        -1.46     0.68
## X1990s2000s4        -1.03     0.88
## X1990s2000s5        -0.74     0.60
## PianoPlay1          -1.00     0.37
## PianoPlay4          -0.23     0.85
## PianoPlay5          -0.84     0.48
## GuitarPlay1         -1.15     0.58
## GuitarPlay2          1.06     1.07
## GuitarPlay4          1.34     0.90
## GuitarPlay5          1.11     0.48
## Instrumentpiano     -1.17     0.27
## Instrumentstring    -3.02     0.26
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.65
##  Subject:Instrument (Intercept) 1.13
##  Residual                       1.64
```

```
## ---
## number of obs: 1541, groups: Subject:Harmony, 172; Subject:Instrument, 129
## AIC = 6313.4, DIC = 6265.4
## deviance = 6265.4
```

The coefficients for the different levels of Instr.minus.Notes, Piano and X1990s2000s are not significantly different from 0, because their confidence intervals contain 0. Therefore, the difference in how much more participants concentrate on the instruments instead of the notes does not have any effect on what how much they rate the music as Popular. How much a participant listens to pop and rock from the 1990s also doesn't have a significant relationship with what kind of popular rating is given. How much a participant plays the piano also has no effect on how Popular they rate the music. Both of these variables, despite not being significant 95% confidence, were kept in the model to be understand the relationship Harmony, Voice and Instrument on total damages awarded.

The only level for which playing the Guitar has a significant difference on how Popular a participant rates the music is for people who play the guitar at the level of 5: these people tend to give ratings that are significantly higher than people who play the guitar at a level of 3, which is in the base case. All other levels of guitar playing do not lead to significantly higher or lower Popular music ratings.

The type of instrument that is played does have a significant difference on how Popular the participant rates the music, with piano being played having a rating that is lower than the average Popular rating for the electric guitar by 1.17 points, and the string quartet has an average Popular rating lower than the guitar by 3 points.

The intercept random effect for subject:Harmony has a standard deviation of 0.65, meaning that the range that the mean popular rating is altered by a random draw from a distribution of all Subject:Harmony combinations spans from -1.3 to 1.3.

9

The intercept random effect for subject:Instrument has a standard deviation of 1.13, meaning that he range that the mean popular rating is altered by a random draw from a distribution of all Subject:Instrument combinations spans from -2.26 to 2.26.

c

We'll test whether the interaction term for self declared musicians is significant when combined with individual variables in the model.

```r
# base model to compare to that includes selfdeclare along with other
# covariates but not interaction
base.4c = lmer(data = base.c, formula = Popular ~ Selfdeclare.split + Instr.minus.Notes +
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Voice + Instrument + (1 |
    Subject:Harmony) + (1 | Subject:Instrument), REML = F)

slf2.instminusnotes = lmer(data = base.c, formula = Popular ~ Selfdeclare.split *
    Instr.minus.Notes + X1990s2000s + PianoPlay + GuitarPlay + Harmony + Voice +
    Instrument + (1 | Subject:Harmony) + (1 | Subject:Instrument), REML = F)

slf2.x9020s = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + Selfdeclare.split *
    X1990s2000s + PianoPlay + GuitarPlay + Harmony + Voice + Instrument + (1 |
    Subject:Harmony) + (1 | Subject:Instrument), REML = F)

slf2.piano = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    Selfdeclare.split * PianoPlay + GuitarPlay + Harmony + Voice + Instrument +
    (1 | Subject:Harmony) + (1 | Subject:Instrument), REML = F)
```

```r
slf2.guitar = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    PianoPlay + Selfdeclare.split * GuitarPlay + Harmony + Voice + Instrument +
    (1 | Subject:Harmony) + (1 | Subject:Instrument), REML = F)

slf2.inst = lmer(data = base.c, formula = Popular ~ Instr.minus.Notes + X1990s2000s +
    PianoPlay + GuitarPlay + Harmony + Voice + Selfdeclare.split * Instrument +
    (1 | Subject:Harmony) + (1 | Subject:Instrument), REML = F)

intxns.slf2.4c.df = data.frame(interaction.tested = c("SelfDeclare*Instr.minus.Notes",
    "SelfDeclare*X1990s2000s", "SelfDeclare*PianoPlay", "SelfDeclare*GuitarPlay",
    "SelfDeclare*Instrument"), partial.F.pvalue = c(anova(base.4c, slf2.instminusnotes)$"Pr(>Chisq)"[2]
    anova(base.4c, slf2.x9020s)$"Pr(>Chisq)"[2], anova(base.4c, slf2.piano)$"Pr(>Chisq)"[2],
    anova(base.4c, slf2.guitar)$"Pr(>Chisq)"[2], anova(base.4c, slf2.inst)$"Pr(>Chisq)"[2]))

intxns.slf2.4c.df
##              interaction.tested partial.F.pvalue
## 1 SelfDeclare*Instr.minus.Notes     6.455337e-07
## 2       SelfDeclare*X1990s2000s     2.527158e-01
## 3         SelfDeclare*PianoPlay     8.540745e-03
## 4        SelfDeclare*GuitarPlay     3.603692e-02
## 5        SelfDeclare*Instrument     1.144017e-01
```

The interaction for self-declaring as a musician or not has a significant relationship with 3 of the variables relative to popular music rating: Instr.minus.Notes, the difference in how much more someone focused on the instrument than the notes, is most significant, and how much a participant plays the piano and the guitar also showed interactions significant at 95% confidence per the partial F-test. We'll include the interaction between SelfDeclare and Instr.minus.Notes in the final model.

We'll test if the fixed effects of PianoPlay and X1990s2000s are significantly different from 0 to determine whether we should remove them from the model.

```r
# full model for comparison
slf2.instminusnotes = lmer(data = base.c, formula = Popular ~ Selfdeclare.split *
    Instr.minus.Notes + X1990s2000s + PianoPlay + GuitarPlay + Harmony + Voice +
    Instrument + (1 | Subject:Harmony) + (1 | Subject:Instrument), REML = F)
# reduced model
chk.piano.x9020s = lmer(data = base.c, formula = Popular ~ Selfdeclare.split *
    Instr.minus.Notes + GuitarPlay + Harmony + Voice + Instrument + (1 | Subject:Harmony) +
    (1 | Subject:Instrument), REML = F)

anova(slf2.instminusnotes, chk.piano.x9020s)
## Data: base.c
## Models:
## chk.piano.x9020s: Popular ~ Selfdeclare.split * Instr.minus.Notes + GuitarPlay +
## chk.piano.x9020s:     Harmony + Voice + Instrument + (1 | Subject:Harmony) + (1 |
## chk.piano.x9020s:     Subject:Instrument)
## slf2.instminusnotes: Popular ~ Selfdeclare.split * Instr.minus.Notes + X1990s2000s +
## slf2.instminusnotes:     PianoPlay + GuitarPlay + Harmony + Voice + Instrument + (1 |
## slf2.instminusnotes:     Subject:Harmony) + (1 | Subject:Instrument)
##                     Df    AIC    BIC  logLik deviance  Chisq Chi Df
## chk.piano.x9020s    28 6289.2 6438.7 -3116.6   6233.2
## slf2.instminusnotes 35 6288.8 6475.7 -3109.4   6218.8 14.371      7
##                     Pr(>Chisq)
## chk.piano.x9020s
```

```
## slf2.instminusnotes    0.04496 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# 2nd reduced model - no x1990s200s
chk.x9020s = lmer(data = base.c, formula = Popular ~ Selfdeclare.split * Instr.minus.Notes +
    GuitarPlay + PianoPlay + Harmony + Voice + Instrument + (1 | Subject:Harmony) +
    (1 | Subject:Instrument), REML = F)

anova(slf2.instminusnotes, chk.x9020s)
## Data: base.c
## Models:
## chk.x9020s: Popular ~ Selfdeclare.split * Instr.minus.Notes + GuitarPlay +
## chk.x9020s:     PianoPlay + Harmony + Voice + Instrument + (1 | Subject:Harmony) +
## chk.x9020s:     (1 | Subject:Instrument)
## slf2.instminusnotes: Popular ~ Selfdeclare.split * Instr.minus.Notes + X1990s2000s +
## slf2.instminusnotes:     PianoPlay + GuitarPlay + Harmony + Voice + Instrument + (1 |
## slf2.instminusnotes:     Subject:Harmony) + (1 | Subject:Instrument)
##                     Df    AIC    BIC  logLik deviance  Chisq Chi Df
## chk.x9020s          31 6284.7 6450.3 -3111.3   6222.7
## slf2.instminusnotes 35 6288.8 6475.7 -3109.4   6218.8 3.9082      4
##                     Pr(>Chisq)
## chk.x9020s
## slf2.instminusnotes     0.4186
```

9 As a result, how much someone listens to pop and rock from the 1990s and 2000s is actually not significantly associated with how Popular someone rates a piece of music, but playing the piano is. We'll still keep both variables in the model instead of removing them because Dr. Jimenez will want to know about the significance of the piano variable and also that we accounted for how much someone listened to pop and rock, "popular" music from the 1990s and 2000s when discerning the relationships of the other variables to Popular music rating.

Same comment as for #3.

5

The effects discussed below for both Classical and Popular ratings are observed when the variable discussed is the only one that is changed and all other factors are held constant.

Results for Classical Ratings

The final model for measuring the influence of the 3 main experimental factors' effects on Classical ratings included the following terms: the Harmony, Instrument and Voice-leading the participant was exposed to, ClsListen - how much the participant listens to Classical Music(0-5), Selfdeclare - whether the individual self-identifies as a musician, an interaction between Selfdeclare and Harmony and 2 variance components accounting for personal biases between Subject and Harmony and Subject and Instrument.

Effects of Experimental Factors

*The only type of Harmony that had a significant relationship with how Classical the participant rated the music was I-V-VI, which, when combined with the effect of participants who did not declare themselves musicians, yielded an average increase in Classical rating of 0.65 points more than those who did declare themselves musicians.

*The piano and string quartet are both associated with significantly higher average Classical ratings than the electric guitar: an average of 1.65 points higher when piano was played and an average 3.6 points higher when the string quartet was played.

*The parallel 3rds and parallel 5ths were both significantly related to an decrease in Classical music rating: parallel 3rds led to an average decrease in Classical rating .4 points below the average rating for contrary motion and parallel 5ths led to an average decrease of .3 points below the average Classical rating for contrary motion.

Variance Components

Variance components accounting for personal biases between Subject and Instrument and Subject and Harmony were incorporated within the model because subjects were shown to rate certain pieces as more or less Classical based on the Instrument and Harmony exposed to them.

interpret the size of each variance component...

8

Other variables

The only other variable in the model shown to have a significant effect on how Classical subjects rated the music played was, unsuprisingly, how much subjects listened to Classical. Those who reported listening to Classical music at the level of 5 on a scale of 1-5 were observed to rate music 1.1 points higher on average than those who listened to Classical music at the level of 2.

Results for Popular Ratings

The final model for determining the effect of the experimental factors on Popular ratings includes the 3 experimental factors, Harmony, Voice and Instrument, along with how much the participant plays the Guitar and Piano, how much they listen to pop and rock from the 1990s and 2000s an interaction between whether someone self-declares themself to be a musician and how much more he concentrated on the instrument versus notes and 2 variance effects accounting for personal biases with Harmony and Instrument.

Effects of Experimental Factors

*Harmony - the type of Harmony the subject was exposed to did not have a significant effect on how Popular they rated the music when accounting for the other variables in the model at 95% confidence.

*Voice-leading - The parallel 5ths are shown to lead to a significant average decrease in Popular rating by .23 points less than the average rating for contrary motion. The parallel 3rds were not shown to yield a significant effect on Popular rating relative to contrary motion.

*Instrument - Playing the piano yielded a significant average decrease in popular rating by 1.16 points as compared to the average rating for the Electric Guitar. Playing the string quartet yielded a significant average decrease in Popular rating of 3 points less than the Electric Guitar.

Variance Components

Variance components accounting for personal biases between Subject and Instrument and Subject and Harmony were incorporated within the model, which was also incorporated in the model for Classical ratings, because subjects were shown to rate certain pieces as more or less Classical based on the Instrument and Harmony exposed to them.

...

Other variables

*The interaction between someone not declaring themself a musician and someone who concentrated on the instrument 2 units more than the notes led to a significant decrease in average Popular rating by 1.3 points as compared to a similar person who did declare themself to be a musician.

*Participants who reported playing the piano at level 1 on a scale of 0-5 are shown to assign a lower Popular rating by 1.1 points on average as compared to someone who plays the piano at a level of 0. None of the other levels of piano playing are associated with significant differences in Popular rating.

*How much participants played the Guitar was not shown to have a significant relationship with popular rating but this variable was kept in the model because the Electric Guitar instrument was shown to have significantly higher average popular rating than the piano and string quartet.

*How much participants listened to pop and rock from the 1990s and 2000s was also not shown to have a significant relationship with popular rating, but this variable was also included in the model to control for a variable that most would think to have a significant relationship with Popular music rating.