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

2 a 9/9
b 7/9
c 9/9

3 9/9

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

5 10/10

Total 96/100

HW5 - 36-763: Hierarchical Linear Models

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1. The three main experimental factors.

Part A.

I only included the variables I thought would be a good starting point for #2. I did this in the very beginning in order to run complete cases (running complete cases on the entire dataset caused at least half of the data to be removed). good

```
ratings = read.csv("ratings.csv")
ratings = ratings[,c("Harmony","Instrument","Voice","Composing", "Classical", "Subject",
                     "PachListen", "PianoPlay", "GuitarPlay", "APTheory",
                     "ClsListen", "Selfdeclare", "OMSI", "X16.minus.17",
                     "Instr.minus.Notes", "X1990s2000s.minus.1960s1970s", "NoClass")]
ratings = ratings[complete.cases(ratings),]
```

First I ran a simple linear regression model on the three main experimental factors. The residual plots were based on categorical variables, so I decided to plot a binned residuals plot, which looked good. Overall, diagnostics were good, and this model was decent for a preliminary approach.

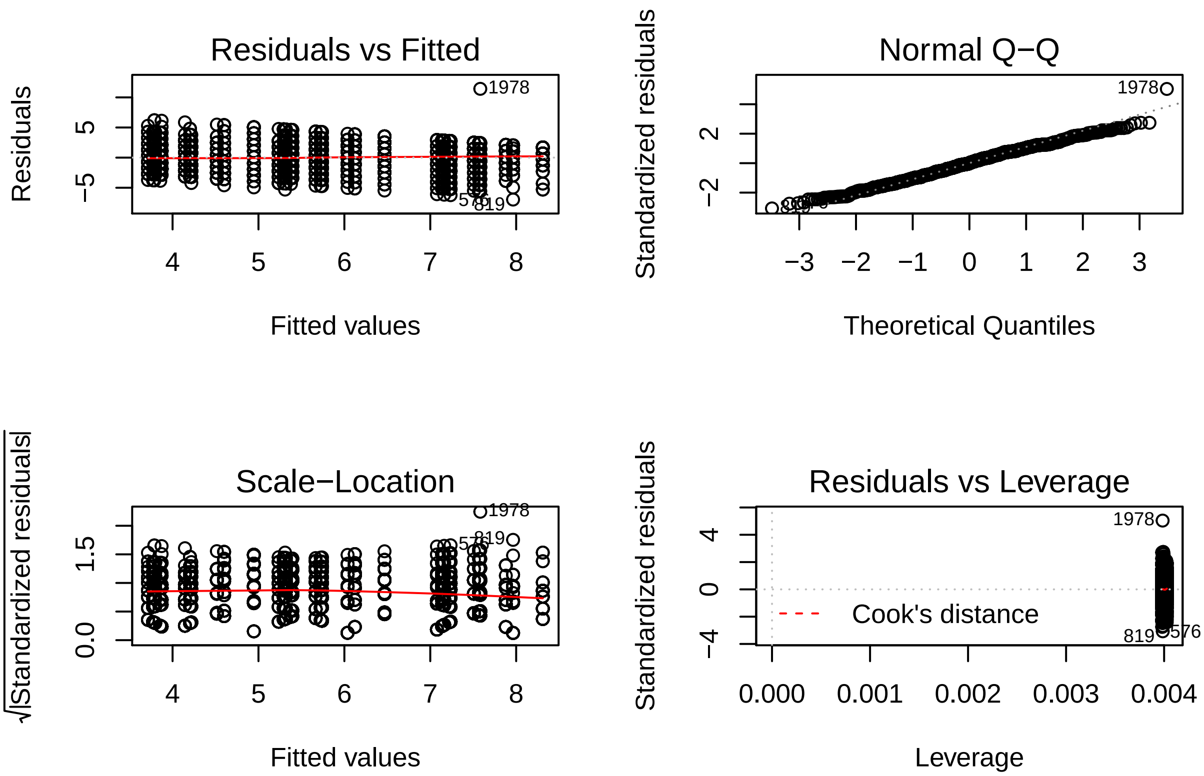
This shows how particular kinds of instrument, voice, and harmony affects ratings. All of the types of instrument (piano and string) were highly statistically significant and had relatively large positive coefficients, which suggest that they increase rating by a large amount. All of the types of voice (3rd and 5th) were highly statistically significant and had relatively small negative coefficients, which suggest that they decrease rating by a small amount. Only one of the types of harmony (I-V-VI) was statistically significant. This harmony had a positive somewhat large coefficient, which suggests that it increases rating but by a smaller amount than instruments.

```
model_lm = lm(Classical ~ Harmony + Instrument + Voice, data=ratings)
summary(model_lm)
```

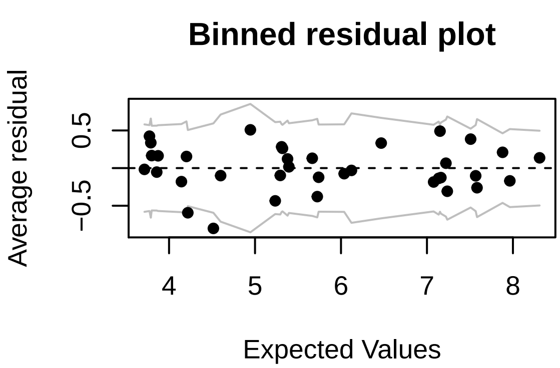
```
##
## Call:
## lm(formula = Classical ~ Harmony + Instrument + Voice, data = ratings)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.964 -1.665  0.036  1.691 11.418
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        4.20274    0.14338  29.312  < 2e-16 ***
## HarmonyI-V-IV     -0.05872    0.14352  -0.409 0.682475
## HarmonyI-V-VI      0.74331    0.14359   5.177 2.49e-07 ***
## HarmonyIV-I-V      0.01563    0.14345   0.109 0.913241
## Instrumentpiano    1.52149    0.12456  12.215  < 2e-16 ***
## Instrumentstring   3.36392    0.12390  27.149  < 2e-16 ***
## Voicepar3rd       -0.43048    0.12437  -3.461 0.000549 ***
```

```
## Voicepar5th      -0.34600    0.12432  -2.783 0.005435 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.27 on 1993 degrees of freedom
## Multiple R-squared:  0.2852, Adjusted R-squared:  0.2827
## F-statistic: 113.6 on 7 and 1993 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2))
plot(model_lm)
```




```r
binnedplot(predict(model_lm), residuals(model_lm, type="pearson"))
```



nice

In order to determine if any of the three experimental factors were important, I used anova to compare models including and removing the variable of interest. The significant p-values for each of the anova's suggest that including all three variables is important. Comparing AIC values further confirmed this.

```r
model_noharmony = lm(Classical ~ Instrument + Voice, data=ratings)

model_noinstrument = lm(Classical ~ Harmony + Voice, data=ratings)

model_novoice = lm(Classical ~ Harmony + Instrument, data=ratings)

anova(model_lm, model_noharmony)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Harmony + Instrument + Voice
## Model 2: Classical ~ Instrument + Voice
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1   1993 10273
## 2   1996 10490 -3   -216.54 14.004 4.915e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(model_lm, model_noinstrument)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Harmony + Instrument + Voice
## Model 2: Classical ~ Harmony + Voice
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1   1993 10273
## 2   1995 14084 -2   -3810.9 369.66 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(model_lm, model_novoice)
```

```
## Analysis of Variance Table
##
## Model 1: Classical ~ Harmony + Instrument + Voice
## Model 2: Classical ~ Harmony + Instrument
##   Res.Df   RSS Df Sum of Sq      F   Pr(>F)
## 1   1993 10273
## 2   1995 10342 -2   -69.345 6.7266 0.001226 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model Comparison:

```
##                          type df      AIC df.1      BIC
## model_lm         with Harmony  9 8969.967    9 9020.380
## model_noharmony    no Harmony  6 9005.708    6 9039.316
```

```
##                 type df      AIC df.1      BIC
## 1 with Instrument  9 8969.967    9 9020.380
## 2   no Instrument  7 9597.306    7 9636.516
```

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```
##         type df      AIC df.1      BIC
## 1 with Voice  9 8969.967    9 9020.380
## 2   no Voice  7 8979.429    7 9018.639
```

Part B.

Part i. See below for the mathematical representation as a hierarchical linear model:

$$\text{Classical}_i = \alpha_{0j[i]} + \varepsilon_i \,, \quad \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

$$\alpha_{0j} = \beta_0 + \beta_1 \text{Instrument} + \beta_2 \text{Harmony} + \beta_3 \text{Voice} + \eta_j \,, \quad \eta_j \overset{iid}{\sim} N(0, \tau^2)$$

this works is I, V, H are continuous, but since they are factors, multiplying doesn't work. have to include their levels as indices for the betas.

Part ii.

I fit two repeated measures models: one with REML and one with MLE. They had similar estimates but were very slightly different. I decided to procede with using MLE to be safe for this portion.

```r
ranef_model_reml = lmer(Classical ~ Harmony + Instrument + Voice + (1|Subject), data=ratings)
summary(ranef_model_reml)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Classical ~ Harmony + Instrument + Voice + (1 | Subject)
##    Data: ratings
##
## REML criterion at convergence: 8472.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8997 -0.6343  0.0002  0.6420  5.3359
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept) 1.450    1.204
##  Residual             3.723    1.929
## Number of obs: 2001, groups:  Subject, 56
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       4.20780    0.20186   20.85
## HarmonyI-V-IV    -0.05998    0.12197   -0.49
## HarmonyI-V-VI     0.74595    0.12203    6.11
## HarmonyIV-I-V     0.01564    0.12191    0.13
## Instrumentpiano   1.52639    0.10598   14.40
## Instrumentstring  3.36102    0.10530   31.92
## Voicepar3rd      -0.43339    0.10569   -4.10
## Voicepar5th      -0.35061    0.10566   -3.32
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## HrmnyI-V-IV -0.302
```

```
## HrmnyI-V-VI -0.301  0.499
## HrmnyIV-I-V -0.302  0.500  0.499
## Instrumntpn -0.260  0.001  0.000  0.000
## Instrmntstr -0.261  0.000 -0.001  0.000  0.497
## Voicepar3rd -0.263  0.000  0.001  0.002  0.001     0.001
## Voicepar5th -0.261 -0.002 -0.002 -0.002  0.000     0.001     0.501
```

```
ranef_model_mle = lmer(Classical ~ Harmony + Instrument + Voice + (1|Subject), data=ratings,
                       REML=FALSE)
summary(ranef_model_mle)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: Classical ~ Harmony + Instrument + Voice + (1 | Subject)
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   8472.1   8528.2  -4226.1   8452.1     1991
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9053 -0.6360  0.0004  0.6433  5.3463
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept) 1.423    1.193
##  Residual             3.709    1.926
## Number of obs: 2001, groups:  Subject, 56
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)        4.20779    0.20051   20.99
## HarmonyI-V-IV     -0.05997    0.12175   -0.49
## HarmonyI-V-VI      0.74594    0.12181    6.12
## HarmonyIV-I-V      0.01564    0.12169    0.13
## Instrumentpiano    1.52638    0.10579   14.43
## Instrumentstring   3.36102    0.10511   31.98
## Voicepar3rd       -0.43339    0.10550   -4.11
## Voicepar5th       -0.35060    0.10547   -3.32
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## HrmnyI-V-IV -0.303
## HrmnyI-V-VI -0.303  0.499
## HrmnyIV-I-V -0.303  0.500  0.499
## Instrumntpn -0.261  0.001  0.000  0.000
## Instrmntstr -0.262  0.000 -0.001  0.000  0.497
## Voicepar3rd -0.264  0.000  0.001  0.002  0.001     0.001
## Voicepar5th -0.263 -0.002 -0.002 -0.002  0.000     0.001     0.501
```

Part iii.

One way to test whether the random intercept was needed was to use AIC/BIC values. Both the AIC and BIC values are much lower for the random measures model in comparison to the simple linear model fit earlier. Thus, we can conclude that adding a random intercept is needed.

Another way was to use intraclass correlation. It was calculated to be 0.277 using the variance components of the random effects. Since this is greater than 0, adding a random intercept is helpful. "0" means that you may as well run a simple regression and grouping by subjects is of no use.

A third way is to use an exact test of random effect. The very small p-value suggests that a random effect is needed.

```
c(AIC(ranef_model_mle), AIC(model_lm))
```

```
## [1] 8472.137 8969.967
```

```
c(BIC(ranef_model_mle), BIC(model_lm))
```

```
## [1] 8528.151 9020.380
```

```
intra_corr = 1.423/(1.423 + 3.709)
intra_corr
```

```
## [1] 0.2772798
```

```
exactRLRT(ranef_model_mle)
```

```
## Using restricted likelihood evaluated at ML estimators.
## Refit with method="REML" for exact results.
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 499.92, p-value < 2.2e-16
```

I re-examined the influence of the three main experimental factors in a similar way from Part A. I used AIC and BIC to compare models including and removing the variable of interest. Both the AIC and BIC were lower for the random measures model. The degree of difference was the greatest for Instrument. The degree of difference was the smallest for Voice.

```
ranef_model_noharmony = lmer(Classical ~ Instrument + Voice + (1|Subject), data=ratings,
                        REML=FALSE)

ranef_model_noinstrument = lmer(Classical ~ Harmony + Voice + (1|Subject), data=ratings,
                           REML=FALSE)

ranef_model_novoice = lmer(Classical ~ Instrument + Harmony + (1|Subject), data=ratings,
                           REML=FALSE)
```

```
##                       df      AIC df.1      BIC
## ranef_model_mle       10 8472.137   10 8528.151
## ranef_model_noharmony  7 8524.120    7 8563.330
```

```
##                          df      AIC df.1      BIC
## ranef_model_mle          10 8472.137   10 8528.151
## ranef_model_noinstrument  8 9291.728    8 9336.539
```

```
##                     df      AIC df.1      BIC
## ranef_model_mle     10 8472.137   10 8528.151
## ranef_model_novoice  8 8487.064    8 8531.875
```

Part C.

Part i.

Comparing the model with all three new random effect terms proved to perform much better than both models (random measures model and linear model) from the earlier parts in terms of both AIC and BIC.

```
model_1c = lmer(Classical ~ Harmony + Instrument + Voice + (1|Subject:Harmony) +
                  (1|Subject:Instrument) + (1|Subject:Voice), data=ratings, REML=FALSE)
```

```
##                 df      AIC df.1      BIC
## model_1c        12 8093.454   12 8160.671
## ranef_model_mle 10 8472.137   10 8528.151
## model_lm         9 8969.967    9 9020.380
```

Part ii.

The variance component for Subject:Instrument was the largest. The variance component for Subject:Voice was the smallest. The variance component for Subject:Harmony was in between the other two, relatively. The residual variance component was larger than all three. An intraclass correlation can be computed for each of the 3 intercepts. The intraclass correlation for Subject:Instrument is 0.448, for Subject:Harmony is 0.168, and for Subject:Voice is 0.016. So, grouping by "Subject:Instrument" is very helpful, grouping by "Subject:Harmony" is somewhat helpful, and grouping by "Subject:Voice" is slightly helpful.

The fixed effect coefficients are the same from the lm model and suggest the same influence as stated earlier.

I re-examined the influence of the three main experimental factors in a similar way from Part A. I used AIC and BIC to compare models including and removing the variable of interest. Both the AIC and BIC were lower for the new model. The degree of difference between the AIC and BIC values was the greatest for Instrument. The degree of difference between the AIC and BIC values was smaller for both Harmony and Voice equally. However, including all three variables in the model was significant.

So, model_1c was my best model, and I will continue to do the rest of the analysis using this model as the starting point.

```
summary(model_1c)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice)
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   8093.5   8160.7  -4034.7   8069.5     1989
##
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -4.3656 -0.5634 -0.0017  0.5409  5.7230
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.49401  0.7029
##  Subject:Instrument (Intercept) 1.98605  1.4093
##  Subject:Voice      (Intercept) 0.03917  0.1979
##  Residual                       2.44813  1.5647
## Number of obs: 2001, groups:
## Subject:Harmony, 224; Subject:Instrument, 168; Subject:Voice, 168
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       4.19826    0.23400  17.941
## HarmonyI-V-IV    -0.06059    0.16564  -0.366
## HarmonyI-V-VI     0.74827    0.16568   4.516
## HarmonyIV-I-V     0.02101    0.16560   0.127
## Instrumentpiano   1.51528    0.27999   5.412
## Instrumentstring  3.36563    0.27968  12.034
## Voicepar3rd      -0.42573    0.09354  -4.551
## Voicepar5th      -0.34881    0.09352  -3.730
##
## Correlation of Fixed Effects:
##             (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r
## HrmnyI-V-IV -0.354
## HrmnyI-V-VI -0.354  0.500
## HrmnyIV-I-V -0.354  0.500  0.500
## Instrumntpn -0.597  0.000  0.000  0.000
## Instrmntstr -0.598  0.000  0.000  0.000  0.499
## Voicepar3rd -0.201  0.000  0.001  0.001  0.000     0.000
## Voicepar5th -0.200 -0.001 -0.001 -0.001  0.000     0.000     0.500
```

```r
model_1c_noharmony = lmer(Classical ~ Instrument + Voice + (1|Subject:Harmony) +
                            (1|Subject:Instrument) + (1|Subject:Voice), data=ratings,
                          REML=FALSE)

model_1c_noinstrument = lmer(Classical ~ Harmony + Voice + (1|Subject:Harmony) +
                               (1|Subject:Instrument) + (1|Subject:Voice), data=ratings,
                             REML=FALSE)

model_1c_novoice = lmer(Classical ~ Instrument + Harmony + (1|Subject:Harmony) +
                          (1|Subject:Instrument) +
                          (1|Subject:Voice), data=ratings, REML=FALSE)
```

```
##                    df      AIC df.1      BIC
## model_1c           12 8093.454   12 8160.671
## model_1c_noharmony  9 8116.459    9 8166.872
```

```
##                       df      AIC df.1      BIC
## model_1c              12 8093.454   12 8160.671
## model_1c_noinstrument 10 8190.432   10 8246.446
```

```
##                  df      AIC df.1      BIC
```

```
## model_1c         12 8093.454   12 8160.671
## model_1c_novoice 10 8110.716   10 8166.730
```

Part iii. See below for the mathematical representation as a hierarchical linear model:

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$$\text{Classical}_i = \alpha_{0j[i]} + \alpha_{1j[i]} + \alpha_{2j[i]} + \varepsilon_i, \quad \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

comments similar to b(i)

$$\alpha_{0j[i]} = \beta_0 + \beta_1 \text{Instrument} + \eta_{0j}, \quad \eta_{0j} \overset{iid}{\sim} N(0, \tau_0^2)$$

$$\alpha_{1j[i]} = \beta_2 \text{Harmony} + \eta_{1j}, \quad \eta_{1j} \overset{iid}{\sim} N(0, \tau_1^2)$$

$$\alpha_{2j[i]} = \beta_3 \text{Voice} + \eta_{2j}, \quad \eta_{2j} \overset{iid}{\sim} N(0, \tau_2^2)$$

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

I decided to start off with the following added covariates as my initial guess/set of variables: PianoPlay, GuitarPlay, OMSI, Composing, PachListen, APTheory, ClsListen, X16.minus.17, X1990s2000s.minus.1960s1970s, and NoClass. I converted the ones that were actually factors into factors before inputting my full model into an automatic variable selection function for lmer.

The procedure decided to only add GuitarPlay, ClsListen, and X1990s2000s.minus.1960s1970s as additional covariates to my model based on AIC.

ok

Part A.

```r
ratings$Composing = factor(ratings$Composing)
ratings$PachListen = factor(ratings$PachListen)
ratings$APTheory = factor(ratings$APTheory)
ratings$ClsListen = factor(ratings$ClsListen)
ratings$X1990s2000s.minus.1960s1970s = factor(ratings$X1990s2000s.minus.1960s1970s)
ratings$GuitarPlay = factor(ratings$GuitarPlay)
ratings$PianoPlay = factor(ratings$PianoPlay)
ratings$X16.minus.17 = factor(ratings$X16.minus.17)
ratings$Instr.minus.Notes = factor(ratings$Instr.minus.Notes)
ratings$NoClass = factor(ratings$NoClass)

added_cov = lmer(Classical ~ Harmony + Instrument + Voice + PianoPlay + GuitarPlay + OMSI +
                   Composing + PachListen + APTheory + ClsListen + X16.minus.17 +
                   X1990s2000s.minus.1960s1970s + NoClass +
                   (1|Subject:Harmony) + (1|Subject:Instrument) +
                   (1|Subject:Voice), data=ratings, REML=F)

add_cov_final = fitLMER.fnc(added_cov, method="AIC", log.file = FALSE, threshold=3)
```

```r
summary(add_cov_final)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + GuitarPlay + ClsListen +
##     X1990s2000s.minus.1960s1970s + (1 | Subject:Harmony) + (1 |
##     Subject:Instrument) + (1 | Subject:Voice)
##    Data: ratings
##
## REML criterion at convergence: 8037.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3094 -0.5627 -0.0077  0.5453  5.7058
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.49638  0.7045
##  Subject:Instrument (Intercept) 1.72281  1.3126
##  Subject:Voice      (Intercept) 0.04142  0.2035
##  Residual                       2.45077  1.5655
## Number of obs: 2001, groups:
## Subject:Harmony, 224; Subject:Instrument, 168; Subject:Voice, 168
##
## Fixed effects:
##                                  Estimate Std. Error t value
## (Intercept)                       1.97965    1.10447   1.792
## HarmonyI-V-IV                    -0.06081    0.16593  -0.366
## HarmonyI-V-VI                     0.74828    0.16597   4.509
## HarmonyIV-I-V                     0.02104    0.16589   0.127
## Instrumentpiano                   1.51546    0.26268   5.769
## Instrumentstring                  3.36543    0.26235  12.828
## Voicepar3rd                      -0.42595    0.09401  -4.531
## Voicepar5th                      -0.34923    0.09399  -3.716
## GuitarPlay1                      -0.24670    0.63468  -0.389
## GuitarPlay2                       2.45667    0.94301   2.605
## GuitarPlay4                       0.50388    0.69885   0.721
## GuitarPlay5                      -0.79720    0.50830  -1.568
## ClsListen1                       -0.53836    0.38255  -1.407
## ClsListen3                        0.13080    0.38929   0.336
## ClsListen4                        0.27113    1.12995   0.240
9 ## ClsListen5                       1.50243    0.63518   2.365
## X1990s2000s.minus.1960s1970s-2 -1.88889    1.24920  -1.512
## X1990s2000s.minus.1960s1970s0   2.08412    1.04073   2.003
## X1990s2000s.minus.1960s1970s1   2.03053    1.19407   1.701
## X1990s2000s.minus.1960s1970s2   2.50073    1.04637   2.390
## X1990s2000s.minus.1960s1970s3   2.55754    1.04049   2.458
## X1990s2000s.minus.1960s1970s4   1.11759    1.21161   0.922
## X1990s2000s.minus.1960s1970s5   2.25213    1.13253   1.989
```

Part B.

I ran the same automatic variable selection function again with added random effects based on the covariates that were added in the last step. The procedure decided not to add any of the new specified random effects.

7

wothwhile to individually recheck the three sets of random effects already in the model, also.

```
added_cov_ranef = lmer(Classical ~ Harmony + Instrument + Voice + GuitarPlay + ClsListen +
    X1990s2000s.minus.1960s1970s + (1 | Subject:Harmony) + (1 |
    Subject:Instrument) + (1 | Subject:Voice), data=ratings, REML=F)

added_cov_ranef_test = fitLMER.fnc(added_cov_ranef, method="AIC",
                   ran.effects=c("(GuitarPlay|Subject)","(ClsListen|Subject)",
                                 "(X1990s2000s.minus.1960s1970s|Subject)"),
                   log.file = FALSE, threshold=3)
```

```
formula(added_cov_ranef_test)
```

```
## Classical ~ Harmony + Instrument + Voice + GuitarPlay + ClsListen +
##     X1990s2000s.minus.1960s1970s + (1 | Subject:Harmony) + (1 |
##     Subject:Instrument) + (1 | Subject:Voice)
```

Part C.

The new variables that were added were GuitarPlay, ClsListen, and X1990s2000s.minus.1960s1970s. For example, switching from those who play no guitar to those who play guitar at a level of 1 reduces the rating by a small amount. Switching from those who play no guitar to guitar at a level of 2 increasing the rating by a relatively larger amount. Switching from those who don't listen to classical music to those who do listen to classical music at a level 2 or higher increases the rating. The increase in rating is the largest when switching from those who don't listen to classical music and to those who listen to classical music at a level of 5. Finally, switching from a non-positive difference between listening to pop and rock from the 90's and 2000's and listening to pop and rock from the 60's and 70's to a positive difference increases the rating.

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saying what the amounts are would also be useful.

3. Musicians vs. Non-musicians

I dichotomized the variable "Selfdeclare" based on the median value. This approximately split the participants in half. This new variable was defined as "mus".

I continued with the model found by the automatic variable selection method above and added interactions between the dichotomized musician variable and other predictors in the model.

The procedure decided to add the interaction between the dichotomized musician variable and Harmony, along with the dichotomized musician variable itself. Thus, there is some interaction between the harmonic chords and if a listener considers himself/herself a musician, which effects the rating depending on the type of harmonic chord.

```
median(ratings$Selfdeclare)

mus = factor(ifelse(ratings$Selfdeclare < 3, "0", "1"))

mus_model = lmer(Classical ~ Harmony + Instrument + Voice + GuitarPlay + ClsListen +
                   X1990s2000s.minus.1960s1970s + mus + mus:Harmony + mus:Instrument +
                   mus:Voice + mus:GuitarPlay + mus:ClsListen +
                   mus:X1990s2000s.minus.1960s1970s + (1 | Subject:Harmony) +
                   (1 | Subject:Instrument) + (1 | Subject:Voice), data=ratings, REML=F)

mus_model_test = fitLMER.fnc(mus_model, method="AIC", log.file = FALSE, threshold=3)
```

```r
summary(mus_model_test)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + ClsListen + X1990s2000s.minus.1960s1970s +
##     mus + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
##     (1 | Subject:Voice) + Harmony:mus
##    Data: ratings
##
## REML criterion at convergence: 8036.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2907 -0.5571 -0.0028  0.5255  5.7488
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.43572  0.6601
##  Subject:Instrument (Intercept) 1.81594  1.3476
##  Subject:Voice      (Intercept) 0.04171  0.2042
##  Residual                       2.44997  1.5652
## Number of obs: 2001, groups:
## Subject:Harmony, 224; Subject:Instrument, 168; Subject:Voice, 168
##
## Fixed effects:
##                                 Estimate Std. Error t value
## (Intercept)                      2.48393    1.06176   2.339
## HarmonyI-V-IV                   -0.10101    0.20714  -0.488
## HarmonyI-V-VI                    0.26713    0.20721   1.289
## HarmonyIV-I-V                   -0.06061    0.20714  -0.293
## Instrumentpiano                  1.51619    0.26893   5.638
## Instrumentstring                 3.36557    0.26861  12.529
## Voicepar3rd                     -0.42551    0.09405  -4.524
## Voicepar5th                     -0.34878    0.09403  -3.709
## ClsListen1                      -0.34886    0.38694  -0.902
## ClsListen3                       0.21547    0.40438   0.533
## ClsListen4                       0.05341    1.07875   0.050
## ClsListen5                       1.54592    0.55017   2.810
## X1990s2000s.minus.1960s1970s-2 -2.28649    1.29563  -1.765
## X1990s2000s.minus.1960s1970s0   1.92796    1.00564   1.917
## X1990s2000s.minus.1960s1970s1   1.57255    1.05014   1.497
## X1990s2000s.minus.1960s1970s2   1.96473    1.04319   1.883
## X1990s2000s.minus.1960s1970s3   2.27927    1.00581   2.266
## X1990s2000s.minus.1960s1970s4   0.72114    1.20030   0.601
## X1990s2000s.minus.1960s1970s5   1.91215    1.06711   1.792
## mus1                            -0.76597    0.35434  -2.162
## HarmonyI-V-IV:mus1               0.09862    0.32394   0.304
## HarmonyI-V-VI:mus1               1.17599    0.32400   3.630
## HarmonyIV-I-V:mus1               0.19886    0.32382   0.614
```

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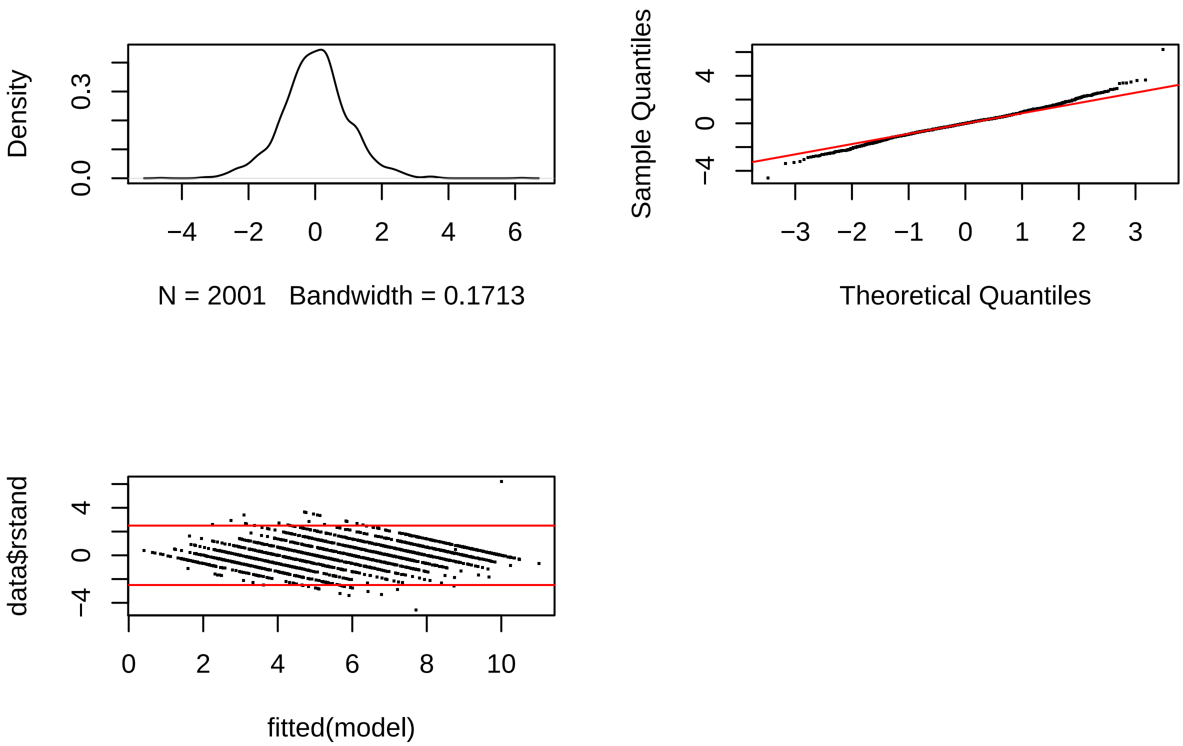
The final model for predicting the rating for Classical was the following:

```r
formula(mus_model_test)
```

```
## Classical ~ Harmony + Instrument + Voice + ClsListen + X1990s2000s.minus.1960s1970s +
##     mus + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
##     (1 | Subject:Voice) + Harmony:mus
```

```r
mcp.fnc(mus_model_test)
```



4. Classical vs. Popular

I set up the same variables as before but replaced Classical with Popular.

```r
ratings2 = read.csv("ratings.csv")
ratings2 = ratings2[,c("Harmony","Instrument","Voice","Composing", "Popular", "Subject",
                       "PachListen", "PianoPlay", "GuitarPlay", "APTheory",
                       "ClsListen", "Selfdeclare", "OMSI", "X16.minus.17",
                       "Instr.minus.Notes", "X1990s2000s.minus.1960s1970s", "NoClass")]
ratings2 = ratings2[complete.cases(ratings),]
```

Part A.

I ran a simple linear regression model on the three main experimental factors with Popular as the response this time. The binned residual plots look alright (there were “3 segments” that could be seen but the points were still scatterered.), so overall the diagnostics are alright.

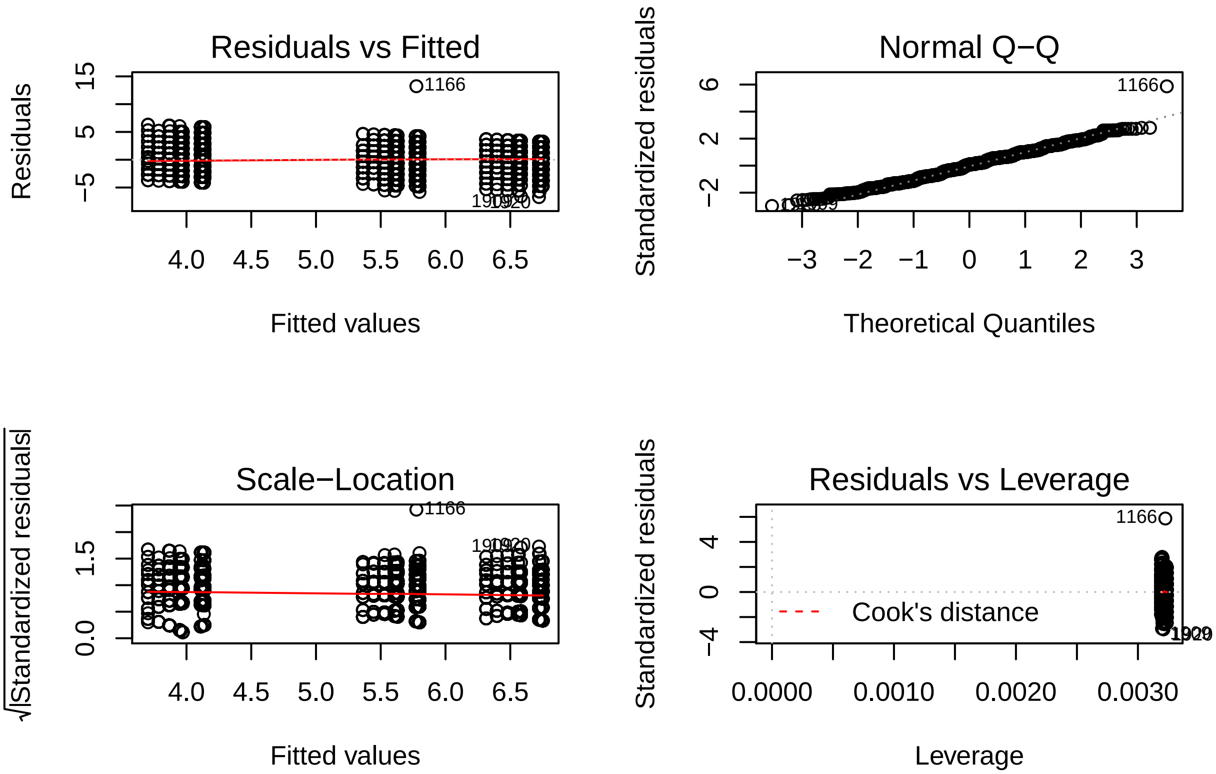
For the results, it is clear that all of the types of instrument (piano and string) were highly statistically significant and had relatively large negative coefficients, which suggest that they decrease rating by a large amount. All of the types of voice (3rd and 5th) were highly statistically significant and had relatively small positive coefficients, which suggest that they increase rating by a small amount. Only one of the types of harmony (I-V-VI) was statistically significant. This harmony had a somewhat negative large coefficient, which suggests that it decreases rating but by a smaller amount than instruments.

It is interesting to note that the experimental factors had an opposite effect on Popular ratings than they did on Classical ratings but each of the factors had the same magnitude of influence relative to each other.

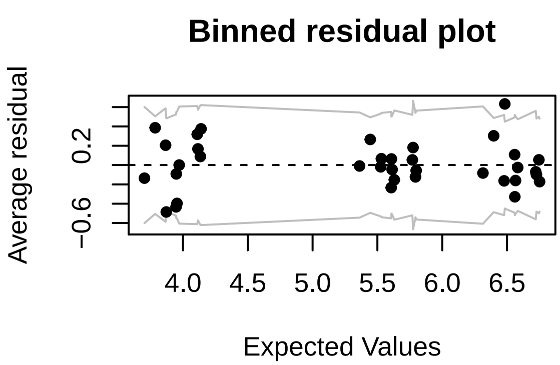
```r
model_lm2 = lm(Popular ~ Harmony + Instrument + Voice, data=ratings2)
summary(model_lm2)
```

```
##
## Call:
## lm(formula = Popular ~ Harmony + Instrument + Voice, data = ratings2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7218 -1.7026  0.2008  1.4691 13.2248
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        6.58263    0.12761  51.583   <2e-16 ***
## HarmonyI-V-IV     -0.02405    0.12782  -0.188   0.8508
## HarmonyI-V-VI     -0.26829    0.12782  -2.099   0.0359 *
## HarmonyIV-I-V     -0.18564    0.12772  -1.454   0.1462
## Instrumentpiano   -0.95200    0.11102  -8.575   <2e-16 ***
## Instrumentstring -2.61173    0.11035 -23.667   <2e-16 ***
## Voicepar3rd        0.16859    0.11075   1.522   0.1281
## Voicepar5th        0.16326    0.11068   1.475   0.1403
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.257 on 2485 degrees of freedom
##   (27 observations deleted due to missingness)
## Multiple R-squared:  0.1901, Adjusted R-squared:  0.1878
## F-statistic: 83.32 on 7 and 2485 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2))
plot(model_lm2)
```




```r
binnedplot(predict(model_lm2), residuals(model_lm2, type="pearson"))
```



the "three segments" have to do with the discreteness of the response variables. The only surprise is that there weren't more than three groups, based on fitted/expected values.

From running anova's and comparing AIC/BIC values for models including and excluding the experimental factors, it was interesting to see that including Voice and Harmony to the model was not really necessary. However, including Instrument was still important.

The difference between the BIC values for the model including and excluding the experimental factor was greater than the difference between the AIC values (these did not show significant enough difference), suggesting that removing Voice and Harmony led to a better model.

However, since all 3 of these are important, I will leave them in the model for the rest of the analysis.

```r
model_noharmony2 = lm(Popular ~ Instrument + Voice, data=ratings2)

model_noinstrument2 = lm(Popular ~ Harmony + Voice, data=ratings2)

model_novoice2 = lm(Popular ~ Harmony + Instrument, data=ratings2)
```

```r
anova(model_lm2, model_noharmony2)
```

```
## Analysis of Variance Table
##
## Model 1: Popular ~ Harmony + Instrument + Voice
## Model 2: Popular ~ Instrument + Voice
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1   2485 12656
## 2   2488 12688 -3   -31.092 2.0349 0.1069
```

```r
anova(model_lm2, model_noinstrument2)
```

```
## Analysis of Variance Table
##
## Model 1: Popular ~ Harmony + Instrument + Voice
## Model 2: Popular ~ Harmony + Voice
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1   2485 12656
## 2   2487 15580 -2   -2923.9 287.05 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(model_lm2, model_novoice2)
```

```
## Analysis of Variance Table
##
## Model 1: Popular ~ Harmony + Instrument + Voice
## Model 2: Popular ~ Harmony + Instrument
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1   2485 12656
## 2   2487 12672 -2   -15.263 1.4984 0.2237
```

Model Comparison:

```
##                          type df      AIC df.1      BIC
## model_lm2        with Harmony  9 11143.15    9 11195.54
## model_noharmony2   no Harmony  6 11143.26    6 11178.19
```

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```
##               type df      AIC df.1      BIC
## 1 with Instrument  9 11143.15    9 11195.54
## 2   no Instrument  7 11657.31    7 11698.06
```

```
##          type df      AIC df.1      BIC
## 1 with Voice  9 11143.15    9 11195.54
## 2   no Voice  7 11142.15    7 11182.90
```

Part B.

Once again, the model with interactions in the random effects performs the best with the lowest AIC and BIC values compared to a simple random measures model and a simple linear model.

```r
ranef_model_mle2 = lmer(Popular ~ Harmony + Instrument + Voice + (1|Subject),
                        data=ratings2, REML=FALSE)

model_1c_2 = lmer(Popular ~ Harmony + Instrument + Voice + (1|Subject:Harmony) +
                  (1|Subject:Instrument) + (1|Subject:Voice), data=ratings2, REML=FALSE)
```

```
##   df      AIC df.1      BIC
## 1  9 11143.15    9 11195.54
## 2 10 10430.30   10 10488.51
## 3 12 10078.97   12 10148.82
```

I re-ran the automatic variable selection function with the same covariates I tested from the Classical analysis. The procedure decided to add PachListen, APTheory, X16.minus.17, X1990s2000s.minus.1960s1970s, and NoClass. It also decided to remove Harmony. (I still chose to let it remain in the model since it was identified as one of the main experimental factors.) good

There were a lot of levels for each variable that was added so I will just give a brief interpretation. Switching from not playing guitar to playing guitar at a level or 2 or 5 increases the rating, and switching from not playing guitar to playing guitar at a level of 1 or 4 decreases the rating. Switching from being completely unfamiliar to Pachelbel's Canon to being familiar at a level of 1, 2, 3, or 5 increases the rating. Switching from no class on AP Theory or having a class in AP Theory decreases the rating. Basically, switching from listening to a lot of 60's and 70's pop and rock to listening to a smaller amount of 60's and 70's pop and rock or more 90's and 2000's pop and rock increases the rating. Switching from having no music classes to 3 or 8 music classes increases the rating, and switching from having no music classes to 1, 2, or 4 music classes decreases the rating. Finally, switching from having a very low auxiliary measure of a listener's ability to distinguish classical vs popular music to having a high measure increases the rating. great

```r
ratings2$Composing = factor(ratings2$Composing)
ratings2$PachListen = factor(ratings2$PachListen)
ratings2$APTheory = factor(ratings2$APTheory)
ratings2$ClsListen = factor(ratings2$ClsListen)
ratings2$X1990s2000s.minus.1960s1970s = factor(ratings2$X1990s2000s.minus.1960s1970s)
ratings2$GuitarPlay = factor(ratings2$GuitarPlay)
ratings2$PianoPlay = factor(ratings2$PianoPlay)
ratings2$X16.minus.17 = factor(ratings2$X16.minus.17)
ratings2$Instr.minus.Notes = factor(ratings2$Instr.minus.Notes)
ratings2$NoClass = factor(ratings2$NoClass)

added_cov2 = lmer(Popular ~ Harmony + Instrument + Voice + PianoPlay + GuitarPlay +
                    OMSI +
                    Composing + PachListen + APTheory + ClsListen + X16.minus.17 +
                    X1990s2000s.minus.1960s1970s + NoClass +
                   (1|Subject:Harmony) + (1|Subject:Instrument) +
                   (1|Subject:Voice), data=ratings2, REML=F)

added_cov_test2 = fitLMER.fnc(added_cov2, method="AIC", log.file = FALSE, threshold=2)
```

```r
summary(added_cov_test2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Instrument + Voice + GuitarPlay + PachListen + APTheory +
```

```
##     X16.minus.17 + X1990s2000s.minus.1960s1970s + NoClass + (1 |
##     Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice)
##    Data: ratings2
##
## REML criterion at convergence: 8005.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7012 -0.5602  0.0025  0.5869  5.0891
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.44099  0.6641
##  Subject:Instrument (Intercept) 1.30666  1.1431
##  Subject:Voice      (Intercept) 0.03041  0.1744
##  Residual                       2.55248  1.5976
## Number of obs: 2001, groups:
## Subject:Harmony, 224; Subject:Instrument, 168; Subject:Voice, 168
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                    2.47986    2.90390   0.854
## Instrumentpiano               -1.02169    0.23333  -4.379
## Instrumentstring              -2.78898    0.23296 -11.972
## Voicepar3rd                    0.21471    0.09354   2.295
## Voicepar5th                    0.20873    0.09352   2.232
## GuitarPlay1                   -3.21836    0.87515  -3.677
## GuitarPlay2                    0.18139    0.93337   0.194
## GuitarPlay4                   -0.43686    1.07140  -0.408
## GuitarPlay5                    0.12088    0.87253   0.139
## PachListen1                    1.18553    2.42549   0.489
## PachListen2                    3.67671    2.25440   1.631
## PachListen3                    0.24136    2.22269   0.109
## PachListen4                   -1.74682    3.20600  -0.545
## PachListen5                    0.60703    2.17885   0.279
## APTheory1                     -0.24715    0.40355  -0.612
## X16.minus.17-2                 1.47461    1.54343   0.955
## X16.minus.17-1                 0.96354    0.91561   1.052
## X16.minus.17-0.5               2.80351    1.86667   1.502
## X16.minus.170                  0.53499    0.99166   0.539
## X16.minus.171                  0.42393    1.14674   0.370
## X16.minus.172                  1.59774    1.12877   1.415
## X16.minus.173                  1.45156    1.29572   1.120
## X16.minus.174                  0.16621    1.56568   0.106
## X16.minus.175                  0.49024    1.41950   0.345
## X16.minus.176                  4.29273    1.45473   2.951
## X16.minus.177                  1.18866    1.33723   0.889
## X16.minus.179                  1.25912    1.02645   1.227
## X1990s2000s.minus.1960s1970s-2  4.07004    1.31672   3.091
## X1990s2000s.minus.1960s1970s0   3.94415    1.12900   3.493
## X1990s2000s.minus.1960s1970s1   2.61099    1.59215   1.640
## X1990s2000s.minus.1960s1970s2   2.90330    1.12877   2.572
## X1990s2000s.minus.1960s1970s3   2.43483    1.03029   2.363
## X1990s2000s.minus.1960s1970s4   0.72182    1.22756   0.588
```

```
## X1990s2000s.minus.1960s1970s5   2.81758    1.29003   2.184
## NoClass1                       -0.36840    0.35019  -1.052
## NoClass2                       -2.31284    1.17317  -1.971
## NoClass3                        3.97859    1.42700   2.788
## NoClass4                       -0.57529    1.53551  -0.375
## NoClass8                        0.15056    1.95537   0.077
```

I re-ran the variable selection function again with added random effects based on the covariates that were added in the last step, but no random effects were chosen.

```
added_cov_ranef2 = lmer(Popular ~ Instrument + Voice + GuitarPlay + PachListen +
                          APTheory + X16.minus.17 + X1990s2000s.minus.1960s1970s +
                          NoClass + (1 |Subject:Harmony) + (1 | Subject:Instrument) +
9                         (1 | Subject:Voice), data=ratings2, REML=F)

added_cov_ranef_test2 = fitLMER.fnc(added_cov_ranef2, method="AIC",
                                    ran.effects=c("(PachListen|Subject)", "(APTheory|Subject)",
                                                  "(X1990s2000s.minus.1960s1970s|Subject)",
                                                  "(NoClass|Subject)"),
                                    log.file = FALSE, threshold=3)
```

```
formula(added_cov_ranef_test2)
```

```
## Popular ~ Instrument + GuitarPlay + PachListen + APTheory + X16.minus.17 +
##     X1990s2000s.minus.1960s1970s + NoClass + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice)
```

Part C.

Finally, I dichotomized the variable "Selfdeclare" based on the median value. This approximately split the participants in half. This new variable was defined as "mus".

I continued with the model found by the automatic variable selection method above and added interactions between the dichotomized musician variable and other predictors in the model.

The procedure decided to add the interaction between the dichotomized musician variable and PachListen, along with the dichotomized musician variable itself. Thus, there is some interaction between the familiarity of Pachelbel's Canon and if a listener considers himself/herself a musician, which effects the rating depending on different levels of familiarity.

```
median(ratings2$Selfdeclare)

mus2 = factor(ifelse(ratings2$Selfdeclare < 3, "0", "1"))

mus2_model = lmer(Popular ~ Harmony + Voice + Instrument + PachListen + APTheory +
                    X16.minus.17 + X1990s2000s.minus.1960s1970s + NoClass + mus2 +
                    mus2:Harmony + mus2:X16.minus.17 +
                    mus2:Instrument + mus2:Voice + mus2:PachListen +
                    mus2:APTheory + mus2:X1990s2000s.minus.1960s1970s + mus2:NoClass +
                    (1 | Subject:Harmony) + (1 |Subject:Instrument) +
                    (1|Subject:Voice),
                  data=ratings2, REML=F)

mus2_model_test = fitLMER.fnc(mus2_model, method="AIC", log.file = FALSE, threshold=2)
```

```r
summary(mus2_model_test)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Popular ~ Voice + Instrument + PachListen + APTheory + X1990s2000s.minus.1960s1970s +
##     NoClass + mus2 + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
##     (1 | Subject:Voice) + PachListen:mus2
##    Data: ratings2
##
## REML criterion at convergence: 8048.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.6652 -0.5533 -0.0034  0.5736  5.0736
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.45093  0.6715
##  Subject:Instrument (Intercept) 1.42995  1.1958
##  Subject:Voice      (Intercept) 0.03274  0.1809
##  Residual                       2.54980  1.5968
## Number of obs: 2001, groups:
## Subject:Harmony, 224; Subject:Instrument, 168; Subject:Voice, 168
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                    4.24079    1.65735   2.559
## Voicepar3rd                    0.21415    0.09394   2.280
## Voicepar5th                    0.20819    0.09392   2.217
## Instrumentpiano               -1.02006    0.24257  -4.205
## Instrumentstring              -2.78947    0.24221 -11.517
## PachListen1                   -0.70139    1.60526  -0.437
## PachListen2                    3.50726    1.65808   2.115
## PachListen3                    1.03775    1.57303   0.660
## PachListen4                   -2.61761    1.98921  -1.316
## PachListen5                   -0.28766    1.41736  -0.203
## APTheory1                      0.05661    0.30036   0.188
## X1990s2000s.minus.1960s1970s-2  3.18726    1.22947   2.592
## X1990s2000s.minus.1960s1970s0   2.81934    0.90222   3.125
## X1990s2000s.minus.1960s1970s1   2.14477    1.07904   1.988
## X1990s2000s.minus.1960s1970s2   2.27391    0.93203   2.440
## X1990s2000s.minus.1960s1970s3   1.60324    0.89333   1.795
## X1990s2000s.minus.1960s1970s4   2.05607    1.07775   1.908
## X1990s2000s.minus.1960s1970s5   3.47855    1.01118   3.440
## NoClass1                       0.18312    0.28667   0.639
## NoClass2                      -1.51720    0.71194  -2.131
## NoClass3                       3.00681    0.88619   3.393
## NoClass4                      -0.27497    0.92694  -0.297
## NoClass8                      -0.67361    1.11112  -0.606
## mus21                          0.73149    0.29131   2.511
## PachListen2:mus21             -5.51758    1.22451  -4.506
## PachListen3:mus21             -3.29264    1.33107  -2.474
## fit warnings:
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

The final model for predicting ratings for Popular was the following (I added the Harmony back in):

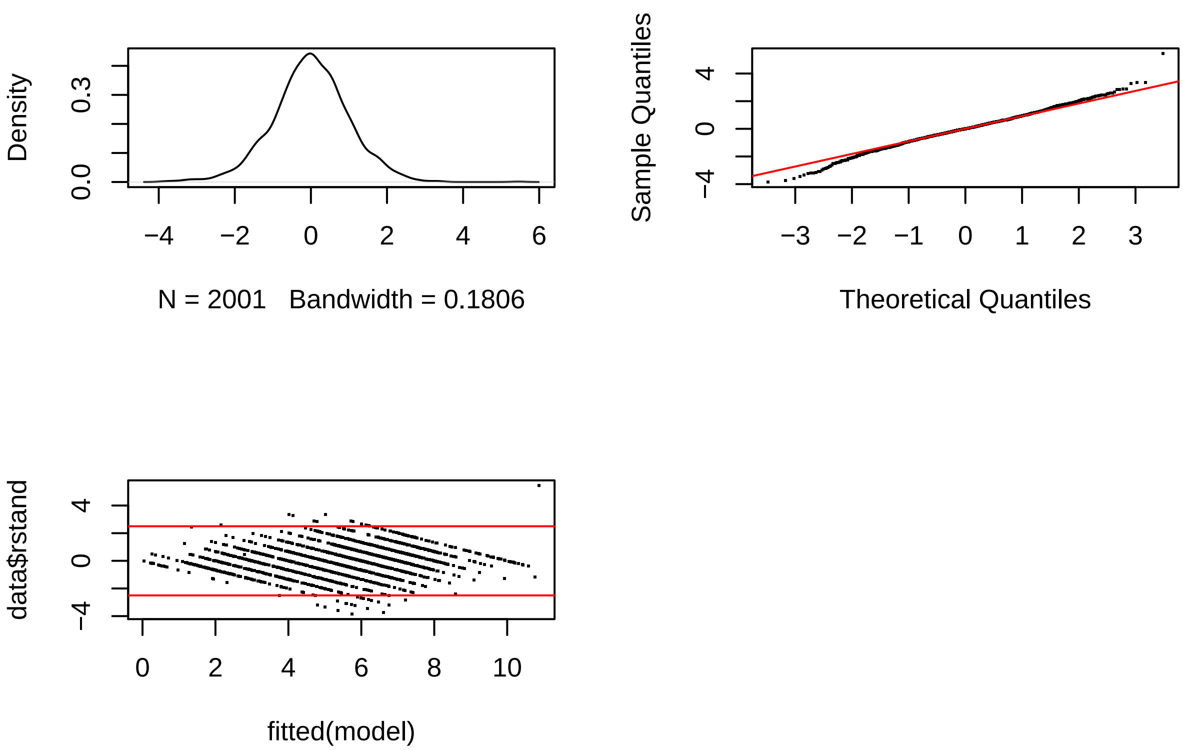
9

```r
final_model = lmer(Popular ~ Harmony + Voice + Instrument + PachListen + APTheory +
             X1990s2000s.minus.1960s1970s +
             NoClass + mus2 + (1 | Subject:Harmony) + (1 | Subject:Instrument) +
             (1 | Subject:Voice) + PachListen:mus2, data=ratings2, REML=F)

formula(final_model)
```

```
## Popular ~ Harmony + Voice + Instrument + PachListen + APTheory +
##     X1990s2000s.minus.1960s1970s + NoClass + mus2 + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + PachListen:mus2
```

```r
mcp.fnc(final_model)
```



HW5: IMRaD/Writeup

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Introduction

Dr. Jimenez and his research group is interested in measuring the influence of instrument, harmonic motion, and voice leading on listeners' identification of music as "classical" or "popular". They are also interested in testing hypotheses that instrument has the largest influence on rating, a particular harmonic progression (I-V-vi) is frequently rated as classical, and that contrary motion is also frequently rated as classical. Data was collected by presenting 36 musical stimuli to 70 listeners who were recruited from the population of undergraduates at the University of Pittsburgh. This data included variables assessing listeners' music abilities and music knowledge.

Methods

Several conventional linear and hierarchical linear models were fit to the data. First, analysis was done on classical ratings. A simple linear model was fit to the data with the three main experimental factors (instrument, harmonic motion, and voice leading). This model was then compared to three models where each of the three experimental factors were removed respectively to assess each experimental factor's influence on classical rating. Then, a repeated measures model was fit, and a similar analysis was done with this model as was done with the simple linear model. After this, random effects from the repeated measures model was tweaked to account for personal biases in ratings. The influence of the three main experimental factors were re-examined with this new model. Next, other variables were added to the previous model using an automatic variable selection procedure. Finally, interactions between a dichotomized musician variable that categorized listeners into musicians and non-musicians and other predictors in the model was examined. A similar analysis was done on popular ratings.

Results

First, the effect on classical ratings will be discussed. Based on the simple linear model, all three main experimental factors did indeed have a significant effect on classical ratings. Instrument had the largest influence on rating, followed by the harmonic progression I-V-vi, and then voice leading. Holding other variables constant, piano and string instruments increase rating when compared to the electric guitar. The harmonic progression I-V-vi also increases ratings when compared to the harmonic progression I-VI-V, holding other variables constant. On the other hand, parallel 3rds and parallel 5ths for voice leading decrease rating when compared to contrary motion, holding other variables constant. After fitting a random measures model and a model in which the random effects from the repeated measures model was tweaked to account for personal biases in ratings, it was determined that the latter
10 was a better model out of the three since it fit the data better. It also introduced variance components for each listener/experimental factor combination. As expected, the variance component for the person/instrument combination was the largest, and the variance component for the person/voice combination was the smallest. This suggests that grouping by a listener/instrument combination is very helpful, grouping by a listener/harmony combination is somewhat helpful, and grouping by a listener/voice combination is slightly helpful.

The final best model for classical ratings, after additional variables from the dataset were added included the three main experimental factors, whether the subject is a musician or non-musician, how much classical music the subject listens to, how much 90s/2000s pop/rock versus 60s/70s pop/rock the subject listens to, and an interaction between the harmonic progressions and if a subject considers himself/herself a musician. This interaction affects the rating depending on the type of harmonic progression. In addition, those who do listen to classical music at a level 2 or higher increases the rating with respect to those who do not listen to classical music. Those who listen to more

90s/2000s pop/rock than 60s/70s pop/rock increases the rating, as well.

Results for popular ratings were different, however. It is interesting to note that the experimental factors have an opposite effect in terms of direction on popular ratings than they do on classical ratings. The factors voice and harmonic progression do not have very influential effects on popular ratings, but instrument has a very influential effect. The final best model for popular ratings, after additional variables from the dataset were added to a model in which the random effects from the repeated measures model was tweaked to account for personal biases in ratings, included the three main experimental factors, a musician variable representing self-declared musicians and non-musicians, familiarity with Pachelbels Canon, how much 90s/2000s pop/rock versus 60s/70s pop/rock the subject listens to, the number of music classes taken, if AP Theory was taken or not, and an interaction between the familiarity with Pachelbels Canon and if a subject considers himself/herself a musician. This interaction affects the rating depending on different levels of familiarity. Being familiar with Pachelbels Canon increases the rating with respect to being completely unfamiliar to it. Having a class in AP Theory decreases the rating with respect to having no class on AP Theory. Having taken a lower number of music classes increases the rating, but having taken a higher number of music classes decreases the rating with respect to having taken no music classes at all.

Discussion

In conclusion, the three main experimental factors have an opposite effect in terms of direction on popular ratings than they do on classical ratings. The researchers' hypotheses were proved to be correct. Instrument did indeed have the largest effect on rating, whether it was for classical or popular. The (I-V-vi) harmonic progression and contrary motion for voice leading both increase the rating for classical, as well. Different additional variables have influential effects on classical and popular ratings. There are some limitations to the experiment since they may not capture some possible confounders such as gender.