I really like your thinking in many places. You think like a statistician. Nevertheless your score is a little low since you didn't follow through with many of the methods mentoioned in class (especially with respect to variable selection and model checking).

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

2 a 9/9
b 0/9
c 6/9

3 7/9

4 a 9/9
b 8/9
c 8/9

5 8/10

Total 81/100

Multilevel models hw05

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1.(a)

First step is to read in the data and check that everything is OK.

Very nice EDA!

```
library(lme4)

## Loading required package: Matrix

library(arm)

## Loading required package: MASS
##
## arm (Version 1.8-6, built: 2015-7-7)
##
## Working directory is C:/Users/Yifei Zheng/Desktop/Courses/Multilevel Model
s/final project

ratings=read.csv("ratings.csv")
str(ratings)

## 'data.frame':    2520 obs. of  28 variables:
##  $ X                         : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Subject                   : Factor w/ 70 levels "15","16","17",..: 1
1 1 1 1 1 1 1 1 1 ...
##  $ Harmony                   : Factor w/ 4 levels "I-IV-V","I-V-IV",..:
1 1 1 1 1 1 1 1 1 2 ...
##  $ Instrument                : Factor w/ 3 levels "guitar","piano",..: 1
1 1 2 2 2 3 3 3 1 ...
##  $ Voice                     : Factor w/ 3 levels "contrary","par3rd",..
: 1 2 3 1 2 3 1 2 3 1 ...
##  $ Selfdeclare               : int  5 5 5 5 5 5 5 5 5 5 ...
##  $ OMSI                      : int  734 734 734 734 734 734 734 734 734
734 ...
##  $ X16.minus.17              : num  5 5 5 5 5 5 5 5 5 5 ...
##  $ ConsInstr                 : num  4.33 4.33 4.33 4.33 4.33 4.33 4.33 4
.33 4.33 4.33 ...
##  $ ConsNotes                 : int  5 5 5 5 5 5 5 5 5 5 ...
##  $ Instr.minus.Notes         : num  -0.67 -0.67 -0.67 -0.67 -0.67 -0.67
-0.67 -0.67 -0.67 -0.67 ...
##  $ PachListen                : int  5 5 5 5 5 5 5 5 5 5 ...
##  $ ClsListen                 : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ KnowRob                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ KnowAxis                  : int  0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ X1990s2000s               : int  5 5 5 5 5 5 5 5 5 5 ...
##  $ X1990s2000s.minus.1960s1970s: int  2 2 2 2 2 2 2 2 2 2 ...
##  $ CollegeMusic              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ NoClass                   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ APTheory                  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Composing                 : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ PianoPlay                 : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ GuitarPlay                : int  5 5 5 5 5 5 5 5 5 5 ...
##  $ X1stInstr                 : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ X2ndInstr                 : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ first12                   : Factor w/ 3 levels "guitar","piano",..: 3
3 3 3 3 3 3 3 3 3 ...
##  $ Classical                 : num  3 3 1 3 2 8 10 6 5 1 ...
##  $ Popular                   : num  9 7 8 7 8 3 1 4 5 8 ...
```

```
table(ratings$Harmony)
```

```
##
## I-IV-V I-V-IV I-V-VI IV-I-V
##    630    630    630    630
```

```
table(ratings$Instrument)
```

```
##
## guitar  piano string
##    840    840    840
```

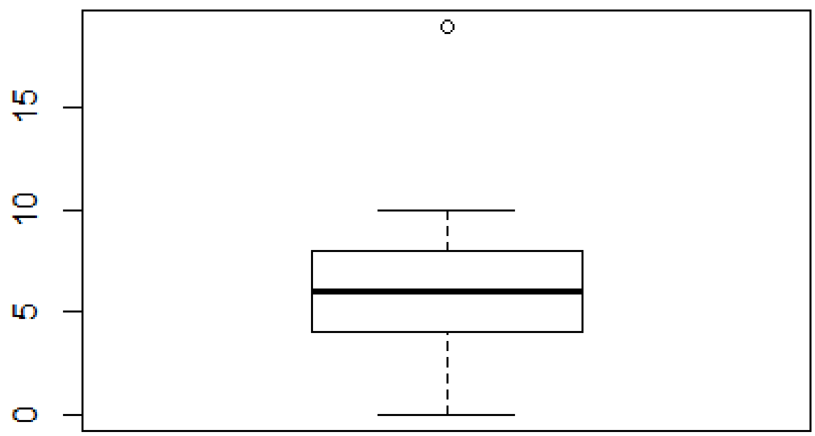
```
table(ratings$Voice)
```

```
##
## contrary   par3rd   par5th
##      840      840      840
```

```
summary(ratings$Classical)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   4.000   6.000   5.783   8.000  19.000      27
```

The maximum value of Classical is 19, which is obivously wrong, since the values of Classical are coded as 1-10. Let's check the boxplot for any more weird points:



It appears that only one observation had its Classical value mismeasured. Let's look at this observation in detail:

```
ratings[which.max(ratings$Classical),]
```

```
##         X Subject Harmony Instrument    Voice Selfdeclare OMSI
## 1978 1978      73  IV-I-V     string contrary           3  233
##      X16.minus.17 ConsInstr ConsNotes Instr.minus.Notes PachListen
## 1978           -1         5         5                 0          5
##      ClsListen KnowRob KnowAxis X1990s2000s X1990s2000s.minus.1960s1970s
## 1978         3      NA        0           5                            3
##      CollegeMusic NoClass APTheory Composing PianoPlay GuitarPlay
## 1978            1       0        1         1         0          0
##      X1stInstr X2ndInstr first12 Classical Popular
## 1978         4         1   piano        19       6
```

The mismeasurement occurred in observation 1978. Since I have no idea what the original value of Classical was, I will remove this observation before conducting further analyses: ok

```
ratings=ratings[-1978,]
```

To examine the influence of the three main experimental factors (instrument, harmony and voice), I will first fit a linear model with Classical as the response and all three factors as predictors, and look at the coefficient estimates for the fixed effects to determine how particular levels of these factors affect ratings:

```
fit.1.full=lm(Classical~Harmony+Instrument+Voice,data=ratings)
summary(fit.1.full)
```

```
##
## Call:
## lm(formula = Classical ~ Harmony + Instrument + Voice, data = ratings)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8673 -1.7092 -0.0252  1.7759  6.0942
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       4.33556    0.12924  33.547  < 2e-16 ***
## HarmonyI-V-IV    -0.03110    0.12944  -0.240 0.810132
## HarmonyI-V-VI     0.76909    0.12944   5.941 3.22e-09 ***
## HarmonyIV-I-V     0.03163    0.12939   0.244 0.806879
## Instrumentpiano   1.37360    0.11243  12.217  < 2e-16 ***
## Instrumentstring  3.11941    0.11179  27.904  < 2e-16 ***
## Voicepar3rd      -0.39867    0.11219  -3.553 0.000387 ***
## Voicepar5th      -0.35673    0.11212  -3.182 0.001483 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.286 on 2484 degrees of freedom
##   (27 observations deleted due to missingness)
## Multiple R-squared:  0.2551, Adjusted R-squared:  0.253
## F-statistic: 121.6 on 7 and 2484 DF,  p-value: < 2.2e-16
```

In terms of harmonic motion, using I-V-vi as the benchmark, the motions I-V-IV and IV-I-V do not have significant effects on classical rating since the coefficients are not significant. The motion I-V-VI increases the rating (sounds more like classical music to subjects). In terms of instrument, using electric guitar as the benchmark, it can be seen that both the piano and the string quartet are associated with a higher rating, with the string quartet having more impact than the piano since its coefficient is larger. In terms of voice leading, using contrary motion as the benchmark, the presence of parallel 3rds and 5ths are associated with lower ratings, since their coefficients are negative and significantly different from 0.

To determine which of the three main factors are most important to predicting rating, I fit three separate linear models, each with a factor missing. Then I used ANOVA to compare them with the full model. The magnitude of the F-test statistic is indicative of the importance of the missing factor in predicting rating.

```
fit.1.nHar=lm(Classical~Instrument+Voice,data=ratings)
fit.1.nVoi=lm(Classical~Harmony+Instrument,data=ratings)
fit.1.nIns=lm(Classical~Harmony+Voice,data=ratings)

anova(fit.1.full,fit.1.nHar)
```

```
## 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   2484 12975
## 2   2487 13252 -3   -277.16 17.687 2.33e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(fit.1.full,fit.1.nHar)
```

```
## 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   2484 12975
## 2   2487 13252 -3   -277.16 17.687 2.33e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


```r
anova(fit.1.full,fit.1.nHar)
```

```
## 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   2484 12975
## 2   2487 13252 -3   -277.16 17.687 2.33e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


It was found that the model missing Instrument had the largest F-test statistic, meaning that the variable instrument is the most important among the three factors.

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To sum up, the instrument variable has the largest influence on rating. As for particular levels within the three factors, the harmonic motion I-V-VI, string quartet and contrary motion contribute the most to a higher rating.

(b)

i.

$$y_i = \alpha_{j[i]} + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \varepsilon_i, \varepsilon_i \sim N(0,\sigma^2)$$
$$\alpha_j = \beta_0 + \eta_j, \eta_j \sim N(0,\tau^2)$$

this works if H, I, V are continous but in this case they are factors. Better to include them as additional indices on the betas.

ii. The first way to test if the random effects are needed is to compare the AIC/BIC of the linear model and the random intercept model to see if there is a significantly large difference:

```
fit.ranint=lmer(Classical~Harmony+Instrument+Voice+(1|Subject),data=ratings,R
EML=F)
AIC(fit.1.full)

## [1] 11201.7

AIC(fit.ranint)

## [1] 10434.28

BIC(fit.1.full)

## [1] 11254.09

BIC(fit.ranint)

## [1] 10492.49
```

The AIC and BIC for the hierarchical model are much lower, indicating that the random effects are indeed needed.

Another way to test the random effects:

```
library(RLRsim)

## Warning: package 'RLRsim' was built under R version 3.2.3

exactLRT(fit.ranint,fit.1.full)
```

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```
## No restrictions on fixed effects. REML-based inference preferable.

##
##  simulated finite sample distribution of LRT. (p-value based on
##  10000 simulated values)
##
## data:
## LRT = 769.42, p-value < 2.2e-16
```

The resulting p-value is essentially 0, indicating that the random intercept improves the fit of the original linear model.

iii. Since the random intercept model does not alter the slopes of the predictors, the three factors influences the classical rating in the same way as the linear model.

(c)

i.

We already established that the random intercept model in part(b) is superior to the linear model in part(a) in terms of AIC/BIC. Now we compare the AIC/DIC between the model with the three new random effects and the random intercept model:

```
fit.newran=lmer(Classical~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1|Sub
ject:Instrument)+(1|Subject:Voice),data=ratings,REML=F)
display(fit.newran)
```

```
## lmer(formula = Classical ~ Harmony + Instrument + Voice + (1 |
##     Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice),
##     data = ratings, REML = F)
##                   coef.est coef.se
## (Intercept)        4.34     0.21
## HarmonyI-V-IV     -0.03     0.14
## HarmonyI-V-VI      0.77     0.14
## HarmonyIV-I-V      0.04     0.14
## Instrumentpiano    1.36     0.26
## Instrumentstring   3.12     0.26
## Voicepar3rd       -0.39     0.08
## Voicepar5th       -0.36     0.08
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.67
##  Subject:Instrument (Intercept) 1.47
##  Subject:Voice      (Intercept) 0.14
##  Residual                       1.55
## ---
## number of obs: 2492, groups: Subject:Harmony, 280; Subject:Instrument, 210
; Subject:Voice, 210
## AIC = 10015.5, DIC = 9991.5
## deviance = 9991.5
```

```r
display(fit.ranint)
```

```
## lmer(formula = Classical ~ Harmony + Instrument + Voice + (1 |
##     Subject), data = ratings, REML = F)
##                   coef.est coef.se
## (Intercept)        4.34     0.19
## HarmonyI-V-IV     -0.03     0.11
## HarmonyI-V-VI      0.77     0.11
## HarmonyIV-I-V      0.03     0.11
## Instrumentpiano    1.37     0.09
## Instrumentstring   3.12     0.09
## Voicepar3rd       -0.40     0.09
## Voicepar5th       -0.36     0.09
##
## Error terms:
##  Groups   Name        Std.Dev.
##  Subject  (Intercept) 1.29
##  Residual             1.88
## ---
## number of obs: 2492, groups: Subject, 70
## AIC = 10434.3, DIC = 10414.3
## deviance = 10414.3
```

The AIC/DIC for the new model is much lower, so it is a better model than either the linear model in part(a) and the random intercept model in part(b).

ii.

Instead of an intercept that varies by subject, we now have a model with an intercept that varies by each combination of subject and particular levels of the three factors. The slope coefficients estimates remain unchanged, and even though the standard errors of the estimates have increased, the significance of the coefficient estimates are the same as before.

We can look at ANOVA's of the three reduced models:

```
fit.newran.nh=lmer(Classical~Instrument+Voice+(1|Subject:Instrument)+(1|Subje
ct:Voice),data=ratings,REML=F)
fit.newran.ni=lmer(Classical~Harmony+Voice+(1|Subject:Harmony)+(1|Subject:Voi
ce),data=ratings,REML=F)
fit.newran.nv=lmer(Classical~Harmony+Instrument+(1|Subject:Harmony)+(1|Subjec
t:Instrument),data=ratings,REML=F)
anova(fit.newran,fit.newran.nh)

## Data: ratings
## Models:
## fit.newran.nh: Classical ~ Instrument + Voice + (1 | Subject:Instrument) +
(1 |
## fit.newran.nh:     Subject:Voice)
## fit.newran: Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
## fit.newran:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.nh  8 10211 10258 -5097.6  10195.2
## fit.newran    12 10016 10085 -4995.8   9991.5 203.72      4  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(fit.newran,fit.newran.ni)

## Data: ratings
## Models:
## fit.newran.ni: Classical ~ Harmony + Voice + (1 | Subject:Harmony) + (1 |
Subject:Voice)
## fit.newran: Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
## fit.newran:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.ni  9 11575 11627 -5778.3  11556.7
## fit.newran    12 10016 10085 -4995.8   9991.5 1565.1      3  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(fit.newran,fit.newran.nv)

## Data: ratings
## Models:
## fit.newran.nv: Classical ~ Harmony + Instrument + (1 | Subject:Harmony) +
```

```
(1 |
## fit.newran.nv:     Subject:Instrument)
## fit.newran: Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
## fit.newran:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                 Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.nv  9 10042 10095 -5012.2  10024.3
## fit.newran    12 10016 10085 -4995.8   9991.5 32.811      3   3.53e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It appears that instrument is still the most important factor in predicting classical ratings.

Among the three estimates variance components, the variance between subject and instrument is the largest, which again confirms that instrument has the larget influence on ratings. The estimated residual variance is larger than any of the three variance components.

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iii.

$$y_i = \alpha_{j_1[i]} + \alpha_{j_2[i]} + \alpha_{j_3[i]} + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \varepsilon_i, \varepsilon_i \sim N(0,\sigma^2)$$

$$\alpha_{j_1} = \beta_{01} + \eta_{j_1}, \eta_{j_1} \sim N(0,\tau_1^2)$$

$$\alpha_{j_2} = \beta_{02} + \eta_{j_2}, \eta_{j_2} \sim N(0,\tau_2^2)$$

$$\alpha_{j_3} = \beta_{03} + \eta_{j_3}, \eta_{j_3} \sim N(0,\tau_3^2)$$

same comments as for the prev model.

also will need to index the etas by levels of the exper factors (in addition to the j's)

2.

(a) For this part I started out with the model in 1(c), and added in all the variables except Popular (will be used as the response later), subject ID (no use), Instr.minus.Notes (difference between two existing variables), X1stInstr and X2ndInstr (because both have a bunch of NA's), and first12 (told to ignore for this project):

great

```
fit.indcov=lmer(Classical~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1|Sub
ject:Instrument)+(1|Subject:Voice)+Selfdeclare+OMSI+X16.minus.17+ConsInstr+Co
nsNotes+PachListen+ClsListen+KnowRob+KnowAxis+X1990s2000s+X1990s2000s.minus.1
960s1970s+CollegeMusic+NoClass+APTheory+Composing+PianoPlay+GuitarPlay,data=r
atings,REML=F)
summary(fit.indcov)

## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare +
##     OMSI + X16.minus.17 + ConsInstr + ConsNotes + PachListen +
##     ClsListen + KnowRob + KnowAxis + X1990s2000s + X1990s2000s.minus.1960s
1970s +
##     CollegeMusic + NoClass + APTheory + Composing + PianoPlay +
##     GuitarPlay
##    Data: ratings
```

```
##
##      AIC      BIC   logLik deviance df.resid
##   6232.9   6387.8  -3087.5   6174.9     1512
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2461 -0.5671 -0.0030  0.5414  3.3577
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.40860  0.6392
##  Subject:Instrument (Intercept) 1.34682  1.1605
##  Subject:Voice      (Intercept) 0.03679  0.1918
##  Residual                       2.48564  1.5766
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129
##
## Fixed effects:
##                                 Estimate Std. Error t value
## (Intercept)                    2.6090160  1.2071285   2.161
## HarmonyI-V-IV                 -0.0045957  0.1786308  -0.026
## HarmonyI-V-VI                  0.8499313  0.1786865   4.757
## HarmonyIV-I-V                  0.0597787  0.1785675   0.335
## Instrumentpiano                1.6475165  0.2690563   6.123
## Instrumentstring               3.5881585  0.2688637  13.346
## Voicepar3rd                   -0.4035219  0.1067532  -3.780
## Voicepar5th                   -0.3000683  0.1067533  -2.811
## Selfdeclare                   -0.3621569  0.2520351  -1.437
## OMSI                           0.0004303  0.0011657   0.369
## X16.minus.17                  -0.0882065  0.0576946  -1.529
## ConsInstr                      0.0434989  0.1183524   0.368
## ConsNotes                     -0.2114623  0.1060683  -1.994
## PachListen                     0.1997872  0.1756654   1.137
## ClsListen                      0.2410052  0.1212157   1.988
## KnowRob                        0.0981312  0.0912782   1.075
## KnowAxis                       0.0254281  0.0721753   0.352
## X1990s2000s                    0.1375925  0.1402054   0.981
## X1990s2000s.minus.1960s1970s  0.0777157  0.1155459   0.673
## CollegeMusic                  -0.1953863  0.4047870  -0.483
## NoClass                       -0.0681067  0.1380982  -0.493
## APTheory                       0.5214648  0.4184693   1.246
## Composing                      0.2256237  0.1368813   1.648
## PianoPlay                      0.3225209  0.0942471   3.422
## GuitarPlay                    -0.1174963  0.1498692  -0.784

##
## Correlation matrix not shown by default, as p = 25 > 20.
## Use print(x, correlation=TRUE)  or
##   vcov(x)     if you need it
```

Since almost none of the covariates added have coefficients significantly different from 0, I tried removing some covariates with very small T-statistics. The result is a reduced model:

```
fit.indcov.reduce=lmer(Classical~Harmony+Instrument+Voice+(1|Subject:Harmony)
+(1|Subject:Instrument)+(1|Subject:Voice)+Selfdeclare+X16.minus.17+ConsNotes+
ClsListen+APTheory+PianoPlay,data=ratings,REML=F)
summary(fit.indcov.reduce)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare +
##     X16.minus.17 + ConsNotes + ClsListen + APTheory + PianoPlay
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   7807.9   7908.0  -3885.9   7771.9     1910
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2888 -0.5740  0.0068  0.5498  3.3493
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.39490  0.6284
##  Subject:Instrument (Intercept) 1.93168  1.3898
##  Subject:Voice      (Intercept) 0.02335  0.1528
##  Residual                       2.49527  1.5796
## Number of obs: 1928, groups:
## Subject:Harmony, 216; Subject:Instrument, 162; Subject:Voice, 162
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       4.58559    0.39770  11.530
## HarmonyI-V-IV    -0.02775    0.15805  -0.176
## HarmonyI-V-VI     0.83591    0.15809   5.287
## HarmonyIV-I-V     0.05236    0.15806   0.331
## Instrumentpiano   1.50415    0.28185   5.337
## Instrumentstring  3.27177    0.28153  11.621
## Voicepar3rd      -0.39412    0.09297  -4.239
## Voicepar5th      -0.38110    0.09295  -4.100
## Selfdeclare      -0.32031    0.13745  -2.330
## X16.minus.17     -0.07167    0.04433  -1.617
## ConsNotes        -0.06661    0.07201  -0.925
## ClsListen         0.20030    0.09028   2.219
## APTheory          0.63505    0.31996   1.985
## PianoPlay         0.15992    0.08720   1.834
##
## Correlation of Fixed Effects:
##              (Intr) HI-V-I HI-V-V HIV-I- Instrmntp Instrmnts Vcpr3r Vcpr5t
```

```
## HrmnyI-V-IV -0.199
## HrmnyI-V-VI -0.199  0.500
## HrmnyIV-I-V -0.199  0.500  0.500
## Instrumntpn -0.355  0.000  0.000  0.000
## Instrmntstr -0.354  0.000  0.000  0.000  0.499
## Voicepar3rd -0.117  0.000  0.001  0.000  0.000     0.000
## Voicepar5th -0.116 -0.001 -0.001 -0.002  0.000     0.000     0.501
## Selfdeclare -0.478  0.000  0.000  0.000  0.001     0.000     0.000  0.000
## X16.mins.17 -0.156  0.000  0.000  0.000  0.000     0.000     0.000  0.000
## ConsNotes   -0.289  0.000  0.000  0.000  0.001     0.000     0.000  0.000
## ClsListen   -0.216  0.000  0.000  0.000  0.001     0.000    -0.001 -0.001
## APTheory     0.044  0.001  0.000  0.000  0.003     0.000     0.000 -0.001
## PianoPlay    0.188  0.000  0.000  0.000 -0.003     0.000     0.000  0.001
##             Slfdcl X16..1 CnsNts ClsLst APThry
## HrmnyI-V-IV
## HrmnyI-V-VI
## HrmnyIV-I-V
## Instrumntpn
## Instrmntstr
## Voicepar3rd
## Voicepar5th
## Selfdeclare
## X16.mins.17 -0.295
## ConsNotes   -0.272  0.285
## ClsListen   -0.322  0.193  0.077
## APTheory    -0.129  0.083 -0.113 -0.038
## PianoPlay   -0.304 -0.051 -0.052 -0.151 -0.248
```

ok

9 It was found that the AIC/BIC increased by a large amount, so I chose to use the "full" model as the final model.

0 (b) Not sure what to do here. redo tests for random effects in the model you obtained after 2(a)

6 (c) For variables coded from 0-5, such as PachListen, ClsListen, etc. the coefficient estimate is the expected change in ratings when the variable moves up to the next level. For binary variables, such as College Music, the coefficient is the difference in rating for a subject with and without the variable. For numeric variables, such as OMSI, the coefficient is the change in ratings for each one unit increase in the variable.

interpret in terms of this data and these fitted values

3. First we look at the distribution of Selfdeclare:

```
table(ratings$Selfdeclare)
```

```
##
##   1   2   3   4   5   6
## 576 936 467 432  72  36
```

Since there are 2519 observations in the data, the first two values of Selfdeclare give us a little more than half of the observations (1512), so we can recode the variable to take on the value of 0 when Selfdeclare=1 or 2, and 1 otherwise:

yep

```
ratings$Selfdeclare[ratings$Selfdeclare<3]=0
ratings$Selfdeclare[ratings$Selfdeclare>=3]=1
```

I suspected that people who claimed themselves to be musicians might concentrate more on the notes when listening to the music provided in the experiment, so I included an interaction term between Selfdeclare and ConsNotes, and refit the model:

```
fit.indcov.new=lmer(Classical~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1
|Subject:Instrument)+(1|Subject:Voice)+Selfdeclare+ConsInstr+OMSI+X16.minus.1
7+Selfdeclare:ConsNotes+ConsNotes+PachListen+ClsListen+KnowRob+KnowAxis+X1990
s2000s+X1990s2000s.minus.1960s1970s+CollegeMusic+NoClass+APTheory+Composing+P
ianoPlay+GuitarPlay,data=ratings,REML=F)
summary(fit.indcov.new)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula:
## Classical ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare +
##     ConsInstr + OMSI + X16.minus.17 + Selfdeclare:ConsNotes +
##     ConsNotes + PachListen + ClsListen + KnowRob + KnowAxis +
##     X1990s2000s + X1990s2000s.minus.1960s1970s + CollegeMusic +
##     NoClass + APTheory + Composing + PianoPlay + GuitarPlay
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   6231.8   6392.0  -3085.9   6171.8     1511
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2392 -0.5770 -0.0052  0.5351  3.3606
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.40517  0.6365
##  Subject:Instrument (Intercept) 1.31354  1.1461
##  Subject:Voice      (Intercept) 0.03589  0.1894
##  Residual                       2.48667  1.5769
## Number of obs: 1541, groups:
## Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                   3.199984   1.244417   2.571
## HarmonyI-V-IV                -0.004623   0.178199  -0.026
## HarmonyI-V-VI                 0.849887   0.178255   4.768
## HarmonyIV-I-V                 0.059773   0.178136   0.336
## Instrumentpiano               1.647323   0.266171   6.189
## Instrumentstring              3.588139   0.265977  13.490
## Voicepar3rd                  -0.403544   0.106575  -3.786
## Voicepar5th                  -0.300072   0.106575  -2.816
```

```
## Selfdeclare                    -1.004643   0.814661  -1.233
## ConsInstr                       0.057880   0.117467   0.493
## OMSI                           -0.000808   0.001135  -0.712
## X16.minus.17                   -0.133027   0.058474  -2.275
## ConsNotes                      -0.423078   0.118786  -3.562
## PachListen                      0.115741   0.179543   0.645
## ClsListen                       0.032353   0.118988   0.272
## KnowRob                         0.080944   0.092026   0.880
## KnowAxis                        0.084423   0.077734   1.086
## X1990s2000s                     0.152403   0.143413   1.063
## X1990s2000s.minus.1960s1970s -0.052858   0.108629  -0.487
## CollegeMusic                   -0.080067   0.423118  -0.189
## NoClass                        -0.176511   0.147226  -1.199
## APTheory                        0.857422   0.433877   1.976
## Composing                       0.360919   0.157337   2.294
## PianoPlay                       0.307439   0.095002   3.236
## GuitarPlay                     -0.146634   0.153983  -0.952
## Selfdeclare:ConsNotes           0.401852   0.190814   2.106

##
## Correlation matrix not shown by default, as p = 26 > 20.
## Use print(x, correlation=TRUE)  or
##   vcov(x)     if you need it
```

7

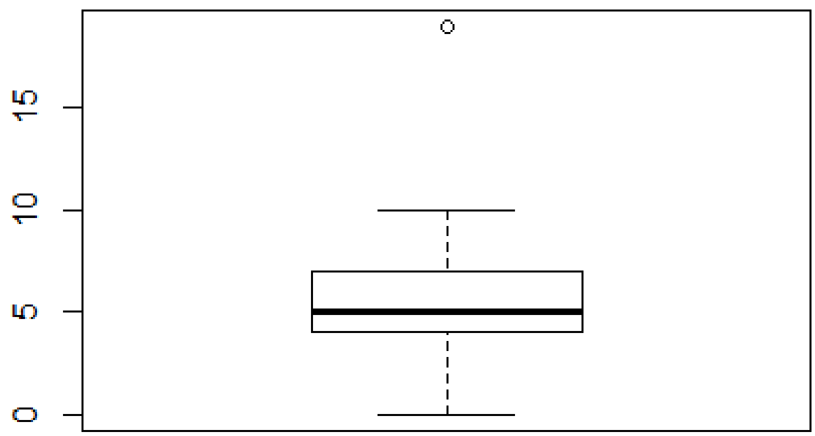
The coefficient for interaction term is significant, so the secondary hypothesis of the researchers that people who self-identify as musicians are indeed influenced by different things than non-musicians.

check for interactions with other covariates

4.(a)

Now using Popular as the response. Again there is a mismeasurement in the data:

```
boxplot(ratings$Popular)
```




```
ratings[which.max(ratings$Popular),]
```

```
##         X Subject Harmony Instrument  Voice Selfdeclare OMSI X16.minus.17
## 1166 1166      47  I-V-IV      piano par3rd           1  649            0
##      ConsInstr ConsNotes Instr.minus.Notes PachListen ClsListen KnowRob
## 1166         1         5                -4          5         3       5
##      KnowAxis X1990s2000s X1990s2000s.minus.1960s1970s CollegeMusic
## 1166        1           5                            3            1
##      NoClass APTheory Composing PianoPlay GuitarPlay X1stInstr X2ndInstr
## 1166       3        1         4         1          4        NA        NA
##      first12 Classical Popular
## 1166   piano         5      19
```

Removing this observation, and then fitting a hierarchical model similar to the one in 1(c):

```
ratings=ratings[-1166,]
fit.newran.2=lmer(Popular~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1|Sub
ject:Instrument)+(1|Subject:Voice),data=ratings,REML=F)
display(fit.newran.2)
```

```
## lmer(formula = Popular ~ Harmony + Instrument + Voice + (1 |
##     Subject:Harmony) + (1 | Subject:Instrument) + (1 | Subject:Voice),
##     data = ratings, REML = F)
##                   coef.est coef.se
## (Intercept)        6.59     0.20
## HarmonyI-V-IV     -0.04     0.14
## HarmonyI-V-VI     -0.27     0.14
## HarmonyIV-I-V     -0.19     0.14
```

```
## Instrumentpiano  -0.96     0.25
## Instrumentstring -2.61     0.25
## Voicepar3rd       0.15     0.08
## Voicepar5th       0.16     0.08
##
## Error terms:
##  Groups             Name        Std.Dev.
##  Subject:Harmony    (Intercept) 0.63
##  Subject:Instrument (Intercept) 1.40
##  Subject:Voice      (Intercept) 0.17
##  Residual                       1.57
## ---
## number of obs: 2491, groups: Subject:Harmony, 280; Subject:Instrument, 210
; Subject:Voice, 210
## AIC = 10041, DIC = 10017
## deviance = 10017.0
```

We can see that compared to when Classical is the response, the signs of the coefficients are now reversed. Parallel 5ths, electric guitar and I-V-vi are more predictive of popular ratings.

A look at the ANOVA results:

```
fit.newran.nh2=lmer(Popular~Instrument+Voice+(1|Subject:Instrument)+(1|Subjec
t:Voice),data=ratings,REML=F)
fit.newran.ni2=lmer(Popular~Harmony+Voice+(1|Subject:Harmony)+(1|Subject:Voic
e),data=ratings,REML=F)
fit.newran.nv2=lmer(Popular~Harmony+Instrument+(1|Subject:Harmony)+(1|Subject
:Instrument),data=ratings,REML=F)
anova(fit.newran.2,fit.newran.nh2)

## Data: ratings
## Models:
## fit.newran.nh2: Popular ~ Instrument + Voice + (1 | Subject:Instrument) +
(1 |
## fit.newran.nh2:     Subject:Voice)
## fit.newran.2: Popular ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
## fit.newran.2:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.nh2  8 10128 10174 -5055.9    10112
## fit.newran.2   12 10041 10111 -5008.5    10017 94.702      4  < 2.2e-16
##
## fit.newran.nh2
## fit.newran.2   ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(fit.newran.2,fit.newran.ni2)
```

```
## Data: ratings
## Models:
## fit.newran.ni2: Popular ~ Harmony + Voice + (1 | Subject:Harmony) + (1 | S
ubject:Voice)
## fit.newran.2: Popular ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
## fit.newran.2:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                 Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.ni2  9 11294 11346 -5637.8    11276
## fit.newran.2   12 10041 10111 -5008.5    10017 1258.6      3  < 2.2e-16
##
## fit.newran.ni2
## fit.newran.2   ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(fit.newran.2,fit.newran.nv2)
```

```
## Data: ratings
## Models:
## fit.newran.nv2: Popular ~ Harmony + Instrument + (1 | Subject:Harmony) + (
1 |
## fit.newran.nv2:     Subject:Instrument)
## fit.newran.2: Popular ~ Harmony + Instrument + Voice + (1 | Subject:Harmon
y) +
9 ## fit.newran.2:     (1 | Subject:Instrument) + (1 | Subject:Voice)
##                 Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## fit.newran.nv2  9 10042 10094 -5011.8    10024
## fit.newran.2   12 10041 10111 -5008.5    10017 6.5161      3    0.08903 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It appears that instrument is still the most influential factor.

(b) We try the model used in 2(c)

```
fit.indcov.2=lmer(Popular~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1|Sub
ject:Instrument)+(1|Subject:Voice)+Selfdeclare+OMSI+X16.minus.17+ConsInstr+Co
nsNotes+PachListen+ClsListen+KnowRob+KnowAxis+X1990s2000s+X1990s2000s.minus.1
960s1970s+CollegeMusic+NoClass+APTheory+Composing+PianoPlay+GuitarPlay,data=r
atings,REML=F)
summary(fit.indcov.2)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: Popular ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare +
##     OMSI + X16.minus.17 + ConsInstr + ConsNotes + PachListen +
##     ClsListen + KnowRob + KnowAxis + X1990s2000s + X1990s2000s.minus.1960s
1970s +
##     CollegeMusic + NoClass + APTheory + Composing + PianoPlay +
##     GuitarPlay
```

```
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   6325.1   6479.9  -3133.5   6267.1     1511
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.5945 -0.5634  0.0119  0.5690  3.0927
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.40689  0.6379
##  Subject:Instrument (Intercept) 1.45942  1.2081
##  Subject:Voice      (Intercept) 0.04211  0.2052
##  Residual                       2.65060  1.6281
## Number of obs: 1540, groups:
## Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129
##
## Fixed effects:
##                              Estimate Std. Error t value
## (Intercept)                  6.301663   1.211637   5.201
## HarmonyI-V-IV                0.001962   0.180849   0.011
## HarmonyI-V-VI               -0.257930   0.180850  -1.426
## HarmonyIV-I-V               -0.251454   0.180725  -1.391
## Instrumentpiano             -1.165023   0.279799  -4.164
## Instrumentstring            -3.024028   0.279581 -10.816
## Voicepar3rd                  0.174188   0.110896   1.571
## Voicepar5th                  0.234545   0.110844   2.116
## Selfdeclare                 -0.794441   0.479000  -1.659
## OMSI                         0.001691   0.001145   1.477
## X16.minus.17                 0.168295   0.060898   2.764
## ConsInstr                    0.010284   0.122419   0.084
## ConsNotes                    0.251345   0.109450   2.296
## PachListen                  -0.331835   0.181452  -1.829
## ClsListen                   -0.029820   0.112621  -0.265
## KnowRob                      0.057159   0.094877   0.602
## KnowAxis                     0.126920   0.075392   1.683
## X1990s2000s                  0.178791   0.145487   1.229
## X1990s2000s.minus.1960s1970s -0.108412   0.112177  -0.966
## CollegeMusic                 0.592016   0.430475   1.375
## NoClass                     -0.071867   0.144612  -0.497
## APTheory                     0.351733   0.431511   0.815
## Composing                    0.182475   0.142989   1.276
## PianoPlay                   -0.109646   0.097899  -1.120
## GuitarPlay                  -0.218568   0.156776  -1.394

##
## Correlation matrix not shown by default, as p = 25 > 20.
## Use print(x, correlation=TRUE)  or
##   vcov(x)     if you need it
```

I would like to see greater
exploration of variable selection

8 Removing variables with the smallest t-statistics again resulted in an increase in AIC/BIC, so I chose the "full" model. For variables coded from 0-5, such as PachListen, ClsListen, etc. the coefficient estimate is the expected change in ratings when the variable moves up to the next level. For binary variables, such as College Music, the coefficient is the difference in rating for a subject with and without the variable. For numeric variables, such as OMSI, the coefficient is the change in ratings for each one unit increase in the variable.

(c)

The interaction between Selfdeclare and ConsNotes is no longer significant, however, I found that the interaction between Selfdeclare and PachListen is significantly different from 0:

```
fit.indcov.new2=lmer(Popular~Harmony+Instrument+Voice+(1|Subject:Harmony)+(1|
Subject:Instrument)+(1|Subject:Voice)+Selfdeclare*PachListen+X16.minus.17+OMS
I+ConsInstr+ConsNotes+ClsListen+KnowRob+KnowAxis+X1990s2000s+X1990s2000s.minu
s.1960s1970s+CollegeMusic+NoClass+APTheory+Composing+PianoPlay+GuitarPlay,dat
a=ratings,REML=F)
summary(fit.indcov.new2)

## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: Popular ~ Harmony + Instrument + Voice + (1 | Subject:Harmony) +
##     (1 | Subject:Instrument) + (1 | Subject:Voice) + Selfdeclare *
##     PachListen + X16.minus.17 + OMSI + ConsInstr + ConsNotes +
##     ClsListen + KnowRob + KnowAxis + X1990s2000s + X1990s2000s.minus.1960s
1970s +
##     CollegeMusic + NoClass + APTheory + Composing + PianoPlay +
##     GuitarPlay
##    Data: ratings
##
##      AIC      BIC   logLik deviance df.resid
##   6322.4   6482.6  -3131.2   6262.4     1510
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.5903 -0.5624  0.0074  0.5647  3.0925
##
## Random effects:
##  Groups             Name        Variance Std.Dev.
##  Subject:Harmony    (Intercept) 0.40436  0.6359
##  Subject:Instrument (Intercept) 1.40107  1.1837
##  Subject:Voice      (Intercept) 0.04141  0.2035
##  Residual                       2.65133  1.6283
## Number of obs: 1540, groups:
## Subject:Harmony, 172; Subject:Instrument, 129; Subject:Voice, 129
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                   7.727584   1.361274   5.677
## HarmonyI-V-IV                 0.001907   0.180533   0.011
```

```
## HarmonyI-V-VI                   -0.258034   0.180535  -1.429
## HarmonyIV-I-V                   -0.251452   0.180410  -1.394
## Instrumentpiano                 -1.164983   0.274911  -4.238
## Instrumentstring                -3.023940   0.274689 -11.009
## Voicepar3rd                      0.174245   0.110762   1.573
## Voicepar5th                      0.234624   0.110710   2.119
## Selfdeclare                     -5.008459   1.991816  -2.515
## PachListen                      -0.683384   0.240824  -2.838
## X16.minus.17                     0.184265   0.060423   3.050
## OMSI                             0.002197   0.001151   1.909
## ConsInstr                       -0.014194   0.121091  -0.117
## ConsNotes                        0.251916   0.107795   2.337
## ClsListen                        0.081098   0.122056   0.664
## KnowRob                          0.011608   0.095758   0.121
## KnowAxis                         0.170880   0.076948   2.221
## X1990s2000s                      0.171098   0.143331   1.194
## X1990s2000s.minus.1960s1970s -0.011856   0.119049  -0.100
## CollegeMusic                     0.508832   0.425694   1.195
## NoClass                         -0.021808   0.144272  -0.151
## APTheory                         0.281196   0.426234   0.660
## Composing                        0.023503   0.158619   0.148
## PianoPlay                       -0.185928   0.102584  -1.812
## GuitarPlay                      -0.215356   0.154412  -1.395
## Selfdeclare:PachListen           0.904218   0.415230   2.178

##
## Correlation matrix not shown by default, as p = 26 > 20.
## Use print(x, correlation=TRUE)  or
##   vcov(x)     if you need it
```

8

Therefore the secondary hypothesis of the researchers that people who self-identify as musicians are influenced by different things than non-musicians is true.

check interactions with other covariates

5.

Among the three main experiment factors, instrument has the most influence on both Classical and Popular ratings. In terms of particular levels of the three factors, the harmonic motion I-V-VI, the string quartet and the contrary motion contribute the most to a higher Classical rating, while parallel 5ths, electric guitar and I-V-vi are more predictive of popular ratings.

8

Having compared the AIC/DIC of the repeated measures model and the model with three random intercepts, it was found that the three random intercept model is superior to the repeated measures model, with the AID/DIC lower by around 400.

Few of the other individual covariates are significant in the hierarchical model, however removing caused the model AIC/BIC to increase dramatically, so almost all of the varibles in the original dataset were included in the final model.

discussion of results of #3 (and corresponding models for #4)?