Hierarchical Final Project

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1

a

```
> ratings=read.csv("ratings.csv",header=TRUE)
> attach(ratings)
> lm1=lm(Classical~Instrument+Harmony+Voice)
> lm2=lm(Classical~Instrument+Voice)
> lm3=lm(Classical~Instrument+Harmony)
> lm4=lm(Classical~Harmony+Voice)
> anova(lm1,lm2)


Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Instrument + Voice
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2488 13381 -3   -273.65 17.293 4.107e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


> anova(lm1,lm3)


Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Instrument + Harmony
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 13193 -2    -85.64 8.1181 0.0003061 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


> anova(lm1,lm4)
```

```
Analysis of Variance Table

Model 1: Classical ~ Instrument + Harmony + Voice
Model 2: Classical ~ Harmony + Voice
  Res.Df   RSS Df Sum of Sq      F    Pr(>F)
1   2485 13108
2   2487 17235 -2   -4127.6 391.26 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From analysis of variance, we find that all three main factors are highly significant.

b

i

$$Classical_i = \alpha_{0j[i]} + \alpha_1 Instrument_i + \alpha_2 Harmony_i + \alpha_3 Voice_i + \epsilon_i, \epsilon_i \overset{i.i.d}{\sim} N(0, \sigma^2)$$

$$\alpha_{0j} = \beta_0 + \eta_j, \eta_j \overset{i.i.d}{\sim} N(0, \tau^2)$$

ii

Method 1: LRT

```
> lmer1=lmer(Classical~Instrument+Harmony+Voice+(1|Subject))
> exactRLRT(lmer1)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 763.3759, p-value < 2.2e-16
```

$P - value << 0.05$, so we strong reject $H_0 : \tau^2 = 0$ and keep the random effect.

Method 2: Comparing AIC and BIC

```
> bic=rbind(BIC(lm1),BIC(lmer1))
> aic=rbind(AIC(lm1),AIC(lmer1))
> comparison=(cbind(aic,bic))
> colnames(comparison)=c("BIC","AIC")
> rownames(comparison)=c("lm1","lmer.1")
> comparison

            BIC      AIC
lm1    11230.45 11282.84
lmer.1 10491.51 10549.73
```

Both AIC and BIC for the model with random intercept are smaller than the AIC and BIC of lm1. So the random effect is needed.

iii

```
> lmer2=lmer(Classical~Instrument+Voice+(1|Subject))
> lmer3=lmer(Classical~Instrument+Harmony+(1|Subject))
> lmer4=lmer(Classical~Harmony+Voice+(1|Subject))
> anova(lmer1,lmer2,lmer3,lmer4)


Data:
Models:
lmer2: Classical ~ Instrument + Voice + (1 | Subject)
lmer3: Classical ~ Instrument + Harmony + (1 | Subject)
lmer4: Classical ~ Harmony + Voice + (1 | Subject)
lmer1: Classical ~ Instrument + Harmony + Voice + (1 | Subject)
      Df   AIC   BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
lmer2  7 10539 10580 -5262.4    10525
lmer3  8 10489 10536 -5236.6    10473  51.691      1  6.494e-13 ***
lmer4  8 11408 11455 -5696.2    11392   0.000      0          1
lmer1 10 10469 10527 -5224.4    10449 943.588      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The AIC and BIC show that lmer2, lmer3, lmer4, each of which delete one of the three main effects, are all worse than lmer1. Therefore, Instrument, Harmony and Voice are all significant.

c

i

```
> lmer5=lmer(Classical~Instrument+Harmony+Voice+(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Vo
> bic1=rbind(BIC(lm1),BIC(lmer1),BIC(lmer5))
> aic1=rbind(AIC(lm1),AIC(lmer1),AIC(lmer5))
> comparison1=(cbind(aic1,bic1))
> colnames(comparison1)=c("BIC","AIC")
> rownames(comparison1)=c("lm1","lmer1","lmer5")
> comparison1


           BIC      AIC
lm1   11230.45 11282.84
lmer1 10491.51 10549.73
lmer5 10075.51 10145.37
```

Since in 1a and 1b, the best models are lm1 and lmer1 respectively, I only compare them to lmer5. The AIC and BIC from lmer5 are the smallest, meaning that having the three random effects are better than having a single random intercept.

ii

```
> lmer6=update(lmer5,.~. -Instrument)
> lmer7=update(lmer5,.~. -Harmony)
> lmer8=update(lmer5,.~. -Voice)
> bic2=rbind(BIC(lmer6),BIC(lmer7),BIC(lmer8),BIC(lmer5))
> aic2=rbind(AIC(lmer6),AIC(lmer7),AIC(lmer8),AIC(lmer5))
> comparison2=(cbind(aic2,bic2))
> colnames(comparison2)=c("BIC","AIC")
> rownames(comparison2)=c("lmer6","lmer7","lmer8","lmer5")
> comparison2

           BIC      AIC
lmer6 10176.17 10234.38
lmer7 10101.74 10154.13
lmer8 10092.66 10150.87
lmer5 10075.51 10145.37

> summary(lmer5)

Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:Harmony

REML criterion at convergence: 10051.51

Random effects:
 Groups              Name        Variance Std.Dev.
 Subject:Harmony     (Intercept) 0.44307  0.6656
 Subject:Voice       (Intercept) 0.02809  0.1676
 Subject:Instrument (Intercept) 2.19850  1.4827
 Residual                        2.43753  1.5613
Number of obs: 2493, groups: Subject:Harmony, 280; Subject:Voice, 210; Subject:Instrument, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       4.34106    0.21435  20.252
Instrumentpiano   1.36384    0.26232   5.199
Instrumentstring  3.12836    0.26203  11.939
HarmonyI-V-IV    -0.03023    0.14317  -0.211
HarmonyI-V-VI     0.77063    0.14316   5.383
HarmonyIV-I-V     0.05618    0.14310   0.393
Voicepar3rd      -0.40699    0.08174  -4.979
Voicepar5th      -0.37084    0.08168  -4.540

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
Instrumntpn -0.611
Instrmntstr -0.611  0.500
HrmnyI-V-IV -0.333  0.000     0.000
HrmnyI-V-VI -0.333  0.000     0.000     0.499
HrmnyIV-I-V -0.333  0.000     0.000     0.500  0.500
Voicepar3rd -0.190 -0.001     0.000    -0.002  0.001  0.002
Voicepar5th -0.190 -0.001     0.000    -0.001 -0.002 -0.001  0.500
```

The AIC and BIC show that the best model is still the one with all three main factors. The model shows that stimulus played by piano or string are more likely to have higher classical rating than stimulus played by guitar. Harmony I-V-VI are more likely to be rated as classical music, compared to Harmony I-VI-V. The other two have no significant difference from harmony I-VI-V. Both voice leading of parallel 3rds and 5ths are less likely to rate higher in classical rating compared to contrary motion.

The variance of person/voice combination is the smallest (variance=0.03); the variance of the person/Harmony combination is the second smallest (0.44); the variance of person/instrument is the largest (2.20). They are all smaller than the variance of the residual(2.43). But their overall size is larger than the residual.

iii

$$Classical_i = \alpha_{0j[i]} + \alpha_{0k[i]} + \alpha_{0l[i]} + \alpha_1 Instrument_i + \alpha_2 Harmony_i + \alpha_3 Voice_i + \epsilon_i, \epsilon_i \overset{i.i.d}{\sim} N(0, \sigma^2)$$

$$\alpha_{0j} = \beta_{01} + \eta_j, \eta_j \overset{i.i.d}{\sim} N(0, \tau_1^2)$$

$$\alpha_{0k} = \beta_{02} + \eta_k, \eta_k \overset{i.i.d}{\sim} N(0, \tau_2^2)$$

$$\alpha_{0l} = \beta_{03} + \eta_l, \eta_l \overset{i.i.d}{\sim} N(0, \tau_3^2)$$

2

a

Since the study mainly estimate the three main effects about the stimulus, the individual factors I chose are the one's that may influence the perception of those three factors. There are several groups of factors that seems to be correlated and it may be better to add only one from a particular group.The possible variables I chose are Selfdeclare, (PachListen, ClsListen), (CollegeMusic, NoClass, APTheory as a group), (PianoPlay and GuitarPlay as a group).

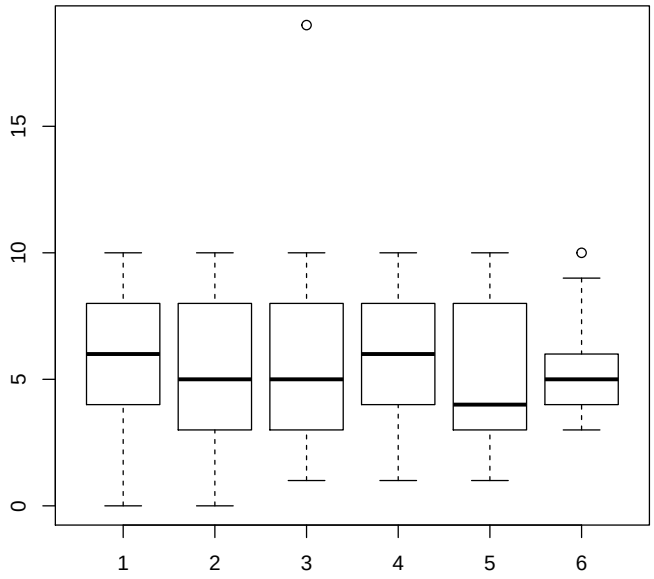
Data Cleaning

```
> newratings=subset(ratings, Selfdeclare!="NA" & PachListen!="NA" & ClsListen!="NA" & ClsListen!="NA" &
```

Since there are NA's in some columns, we cannot compare their AIC and BIC because of different sample size. After eliminating observations with NA's, there are 2088 observations left.

Recategorize factor variables

```
> boxplot(Classical~Selfdeclare,newratings)
> newratings$musician=ifelse(newratings$Selfdeclare>1,1,0)
> # boxplot(Classical~PachListen,newratings)
> # boxplot(Classical~ClsListen,newratings)
> # boxplot(Classical~PianoPlay,newratings)
> # boxplot(Classical~GuitarPlay,newratings)
>
> newratings$PachListen1=ifelse(newratings$PachListen>2,"High","Low")
> newratings$ClsListen1=ifelse(newratings$ClsListen>2,"High","Low")
> newratings$PianoPlay1=ifelse(newratings$PianoPlay>2,"High","Low")
> newratings$GuitarPlay1=ifelse(newratings$GuitarPlay>2,"High","Low")
```



Since the categorical variables all have 6 levels and we can see little difference from the boxplots (I did not show all of them here), I recategorize them in a common standard in order to make them more likely to be significant. The only exception is Selfdeclare, I recategorize them to musician and non-musician.

Model Selection

I use forward method to add variables that are significant (tested by LRT), the results are shown in the table below:

Covariates	Add	Significance	p-value
musician	Yes	Not Significant	0.038
PachListen	No	Not Significant	0.433
ClsListen	Yes	Significant	0.005
CollegeMusic	No	Not Significant	0.327
NoClass	No	Not Significant	0.635
APTheory	No	Marginally Significant	0.067
PianoPlay1	No	Not Significant	0.904
GuitarPlay1	No	Not Significant	0.526

One thing that needs mentioning is that APTheory is marginally significant, but I still deleted it. This is because the BIC and AIc is worse than the model without APTheory.

So the final covariates I added are musician and ClsListen11.

b

```
> lmer5.inter=update(lmer5.final,.~.-(1 | Subject:Instrument) - (1 | Subject:Harmony) -(1 | Subject:Voic
> lmer5.final.1=update(lmer5.final,.~.-(1 | Subject:Instrument))
> lmer5.final.2=update(lmer5.final,.~.-(1 | Subject:Harmony))
> lmer5.final.3=update(lmer5.final,.~.-(1 | Subject:Voice))
```

```
> lm5.inter=lm(Classical~Instrument + Harmony + Voice + musician+factor(ClsListen)+ APTheory, newratings
> bic3=rbind(BIC(lmer5.final),BIC(lmer5.inter),BIC(lm5.inter),BIC(lmer5.final.1),BIC(lmer5.final.2),BIC
> aic3=rbind(AIC(lmer5.final),AIC(lmer5.inter),AIC(lm5.inter),AIC(lmer5.final.1),AIC(lmer5.final.2),AIC
> comparison3=(cbind(aic3,bic3))
> colnames(comparison3)=c("BIC","AIC")
> rownames(comparison3)=c("lmer5.final","lmer5.inter","lm5.inter","lmer5.final.1","lmer5.final.2","lmer5
> comparison3

                  BIC      AIC
lmer5.final   8384.550 8463.465
lmer5.inter   8778.362 8846.003
lm5.inter     9212.198 9296.749
lmer5.final.1 8854.008 8927.286
lmer5.final.2 8486.493 8559.771
lmer5.final.3 8384.187 8457.465
```

From AICs and BICs, the best model is lmer5.final.3, which keeps person/Instrument and person/Harmony combination as random effects.

c

```
> summary(lmer5.final.3)

Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:Harmony
   Data: newratings

REML criterion at convergence: 8358.187

Random effects:
 Groups              Name        Variance Std.Dev.
 Subject:Harmony     (Intercept) 0.5049   0.7106
 Subject:Instrument (Intercept) 1.9636   1.4013
 Residual                        2.4626   1.5693
Number of obs: 2073, groups: Subject:Harmony, 232; Subject:Instrument, 174

Fixed effects:
                  Estimate Std. Error t value
(Intercept)       5.447116   0.435490  12.508
Instrumentpiano   1.481474   0.273780   5.411
Instrumentstring  3.328560   0.273484  12.171
HarmonyI-V-IV    -0.066681   0.164075  -0.406
HarmonyI-V-VI     0.761437   0.164107   4.640
HarmonyIV-I-V     0.004794   0.164037   0.029
Voicepar3rd      -0.408754   0.084471  -4.839
Voicepar5th      -0.338584   0.084449  -4.009
musician         -1.109915   0.349129  -3.179
ClsListen1Low    -0.774215   0.274046  -2.825

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t
Instrumntpn -0.313
```

```
Instrmntstr -0.314  0.499
HrmnyI-V-IV -0.188  0.000     0.000
HrmnyI-V-VI -0.188  0.000     0.000     0.500
HrmnyIV-I-V -0.188  0.000     0.000     0.500  0.500
Voicepar3rd -0.097  0.000     0.000     0.000  0.001  0.001
Voicepar5th -0.097  0.000     0.000    -0.001 -0.001 -0.001  0.500
musician    -0.802  0.000     0.000     0.000  0.000  0.000  0.000  0.000
ClsListn1Lw -0.629 -0.001     0.000     0.000  0.000  0.000  0.000  0.001
            musicn
Instrumntpn
Instrmntstr
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Voicepar3rd
Voicepar5th
musician
ClsListn1Lw  0.467
```

On average, a stimulus played by piano will be rated 1.48 higher than than one played by guitar, others factors held constant. On average, a stimulus played by string will be rated 3.33 higher than than one played by guitar, others factors held constant. On average, harmony I-V-VI is rated 0.76 higher than harmony I-IV-V, others factors held constant. The other two are not significantly different from Harmony I-IV-V. On average, a stimulus with Parallel 3rd is rated 0.41 below contrary motion, others held constant; a stimulus with Parallel 5rd is rated 0.34 below contrary motion, others held constant. A self-declared musician will rated a stimulus 1.11 lower as classical music. A person who listen to classical music a lot will rate 0.77 units higher score for the classical rating than a person who does not listen to classical music a lot.

3

```
> lmer5.IM=update(lmer5.final,.~.+musician*Instrument)
> lmer5.HM=update(lmer5.final,.~.+musician*Harmony)
> lmer5.VM=update(lmer5.final,.~.+musician*Voice)
> lmer5.cl=update(lmer5.final,.~.+musician*ClsListen)
> lmer5.ap=update(lmer5.final,.~.+musician*APTheory)
> anova(lmer5.IM,lmer5.final)


Data: newratings
Models:
lmer5.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.final:     ClsListen1
lmer5.IM: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.IM:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.IM:     ClsListen1 + Instrument:musician
            Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer5.final 14 8366.8 8445.7 -4169.4   8338.8
lmer5.IM    16 8368.7 8458.9 -4168.3   8336.7 2.116      2     0.3471


> anova(lmer5.HM,lmer5.final)
```

```
Data: newratings
Models:
lmer5.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.final:     ClsListen1
lmer5.HM: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.HM:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.HM:     ClsListen1 + Harmony:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer5.final 14 8366.8 8445.7 -4169.4   8338.8
lmer5.HM    17 8358.7 8454.5 -4162.3   8324.7 14.091      3   0.002784 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> anova(lmer5.VM,lmer5.final)

```
Data: newratings
Models:
lmer5.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.final:     ClsListen1
lmer5.VM: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.VM:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.VM:     ClsListen1 + Voice:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer5.final 14 8366.8 8445.7 -4169.4   8338.8
lmer5.VM    16 8370.4 8460.6 -4169.2   8338.4 0.3877      2     0.8238
```

> anova(lmer5.cl,lmer5.final)

```
Data: newratings
Models:
lmer5.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.final:     ClsListen1
lmer5.cl: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.cl:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.cl:     ClsListen1 + ClsListen + musician:ClsListen
            Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer5.final 14 8366.8 8445.7 -4169.4   8338.8
lmer5.cl    16 8369.0 8459.2 -4168.5   8337.0 1.763      2     0.4142
```

> anova(lmer5.ap,lmer5.final)

```
Data: newratings
Models:
lmer5.final: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.final:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
lmer5.final:     ClsListen1
lmer5.ap: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.ap:     (1 | Subject:Harmony) + (1 | Subject:Voice) + musician +
```

```
lmer5.ap:     ClsListen1 + APTheory + musician:APTheory
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer5.final 14 8366.8 8445.7 -4169.4   8338.8
lmer5.ap    16 8366.0 8456.2 -4167.0   8334.0 4.8078      2    0.09036 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> summary(lmer5.HM)

```
Linear mixed model fit by REML ['lmerMod']
Formula: Classical ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:Harmony
   Data: newratings

REML criterion at convergence: 8343.371

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.45442  0.6741
 Subject:Voice      (Intercept) 0.03978  0.1995
 Subject:Instrument (Intercept) 1.96434  1.4015
 Residual                       2.43361  1.5600
Number of obs: 2073, groups: Subject:Harmony, 232; Subject:Voice, 174; Subject:Instrument, 174

Fixed effects:
                     Estimate Std. Error t value
(Intercept)           5.83515    0.47897  12.183
Instrumentpiano       1.48210    0.27367   5.416
Instrumentstring      3.32846    0.27338  12.175
HarmonyI-V-IV        -0.18182    0.36302  -0.501
HarmonyI-V-VI        -0.35354    0.36302  -0.974
HarmonyIV-I-V        -0.31313    0.36302  -0.863
Voicepar3rd          -0.40958    0.09179  -4.462
Voicepar5th          -0.33967    0.09177  -3.701
musician             -1.58778    0.42770  -3.712
ClsListen1Low        -0.77478    0.27406  -2.827
HarmonyI-V-IV:musician  0.14281    0.40341   0.354
HarmonyI-V-VI:musician  1.37610    0.40343   3.411
HarmonyIV-I-V:musician  0.39256    0.40339   0.973

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HrI-V-IV HrI-V-VI HrIV-I-V Vcpr3r Vcpr5t
Instrumntpn -0.285
Instrmntstr -0.285  0.500
HrmnyI-V-IV -0.379  0.000     0.000
HrmnyI-V-VI -0.379  0.000     0.000     0.500
HrmnyIV-I-V -0.379  0.000     0.000     0.500    0.500
Voicepar3rd -0.096  0.000     0.000     0.000    0.000    0.000
Voicepar5th -0.096  0.000     0.000     0.000    0.000    0.000    0.500
musician    -0.836  0.000     0.000     0.424    0.424    0.424    0.000  0.000
ClsListn1Lw -0.572 -0.001     0.000     0.000    0.000    0.000    0.000  0.001
HrmnI-V-IV:  0.341  0.000     0.000    -0.900   -0.450   -0.450    0.000 -0.001
HrmnI-V-VI:  0.341  0.000     0.000    -0.450   -0.900   -0.450    0.000 -0.001
HrmnIV-I-V:  0.341  0.000     0.000    -0.450   -0.450   -0.900    0.001 -0.001
```

```
            musicn ClsL1L HI-V-IV: HI-V-VI:
Instrumntpn
Instrmntstr
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Voicepar3rd
Voicepar5th
musician
ClsListn1Lw  0.381
HrmnI-V-IV: -0.472  0.000
HrmnI-V-VI: -0.472  0.000  0.500
HrmnIV-I-V: -0.472  0.000  0.500    0.500
```

By LRT, the interaction between dichotomized musician and Harmony are significant at level 0.01. This means that compared to non-musicians who hear harmony I-V-VI, musicians who hear harmony I-V-VI will rate the stimulus 1.38 units higher to be classical music. This is reasonable and agrees with the researchers second hypothesis.

4

a

Linear Model

```
> lm1.1=lm(Popular~Instrument+Harmony+Voice)
> lm2.1=lm(Popular~Instrument+Voice)
> lm3.1=lm(Popular~Instrument+Harmony)
> lm4.1=lm(Popular~Harmony+Voice)
> anova(lm1.1,lm2.1)


Analysis of Variance Table

Model 1: Popular ~ Instrument + Harmony + 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


> anova(lm1.1,lm3.1)


Analysis of Variance Table

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


> anova(lm1.1,lm4.1)
```

```
Analysis of Variance Table

Model 1: Popular ~ Instrument + Harmony + 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
```

In simple linear regression, except for Instrument, Voice and Harmony are not significant in popular ratings.

Examine Random Intercept

```
> lmer1.1=lmer(Popular~Instrument+Harmony+Voice+(1|Subject))
> exactRLRT(lmer1.1)

        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

data:
RLRT = 714.7425, p-value < 2.2e-16
```

$P - value << 0.05$, so we strong reject $H_0 : \tau^2 = 0$ and keep the random effect.

Re-examine the three main factors having random intercept

```
> lmer2.1=lmer(Popular~Instrument+Voice+(1|Subject))
> lmer3.1=lmer(Popular~Instrument+Harmony+(1|Subject))
> lmer4.1=lmer(Popular~Harmony+Voice+(1|Subject))
> anova(lmer1.1,lmer2.1)

Data:
Models:
lmer2.1: Popular ~ Instrument + Voice + (1 | Subject)
lmer1.1: Popular ~ Instrument + Harmony + Voice + (1 | Subject)
        Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer2.1  7 10433 10474 -5209.7    10419
lmer1.1 10 10430 10488 -5205.1    10410 9.0032      3    0.02925 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(lmer1.1,lmer3.1)

Data:
Models:
lmer3.1: Popular ~ Instrument + Harmony + (1 | Subject)
lmer1.1: Popular ~ Instrument + Harmony + Voice + (1 | Subject)
        Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer3.1  8 10431 10477 -5207.4    10415
lmer1.1 10 10430 10488 -5205.1    10410 4.429      2     0.1092
```

```
> anova(lmer1.1,lmer4.1)


Data:
Models:
lmer4.1: Popular ~ Harmony + Voice + (1 | Subject)
lmer1.1: Popular ~ Instrument + Harmony + Voice + (1 | Subject)
        Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer4.1  8 11138 11184 -5560.8    11122
lmer1.1 10 10430 10488 -5205.1    10410 711.31      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The LRTs show that voice is not significant in the model. Harmony and Instrument are significant.

Examining three random effects

```
> lmer5.1=lmer(Popular~Instrument+Harmony+Voice+(1|Subject:Instrument)+(1|Subject:Harmony)+(1|Subject:Vo
> lmer5.2=update(lmer5.1,.~.-(1|Subject:Voice))
> lmer5.3=update(lmer5.1,.~.-(1|Subject:Harmony))
> lmer5.4=update(lmer5.1,.~.-(1|Subject:Instrument))
> bic1.1=rbind(BIC(lm1.1),BIC(lmer1.1),BIC(lmer5.1),BIC(lmer5.2),BIC(lmer5.3),BIC(lmer5.4))
> aic1.1=rbind(AIC(lm1.1),AIC(lmer1.1),AIC(lmer5.1),AIC(lmer5.2),AIC(lmer5.3),AIC(lmer5.4))
> comparison1.1=(cbind(aic1.1,bic1.1))
> colnames(comparison1.1)=c("BIC","AIC")
> rownames(comparison1.1)=c("lm1.1","lmer1.1","lmer5.1","lmer5.2","lmer5.3","lmer5.4")
> comparison1.1


             BIC      AIC
lm1.1   11143.15 11195.54
lmer1.1 10453.12 10511.34
lmer5.1 10097.24 10167.09
lmer5.2 10096.49 10160.52
lmer5.3 10183.36 10247.40
lmer5.4 10593.35 10657.39
```

The AIC and BIC from lmer5.2 are the smallest, meaning that having 1|Subject:Harmony and 1|Subject:Instrument as random effects are better than having a single random intercept.

Re-examine the three main factors having two random factors

```
> lmer6.1=update(lmer5.2,.~. -Instrument)
> lmer7.1=update(lmer5.2,.~. -Harmony)
> lmer8.1=update(lmer5.2,.~. -Voice)
> anova(lmer6.1,lmer5.2)


Data:
Models:
lmer6.1: Popular ~ Harmony + Voice + (1 | Subject:Instrument) + (1 | Subject:Harmony)
lmer5.2: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
```

```
lmer5.2:     (1 | Subject:Harmony)
        Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer6.1  9 10160 10213 -5071.2    10142
lmer5.2 11 10078 10142 -5028.0    10056 86.356      2  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> anova(lmer7.1,lmer5.2)
```

```
Data:
Models:
lmer7.1: Popular ~ Instrument + Voice + (1 | Subject:Instrument) + (1 |
lmer7.1:     Subject:Harmony)
lmer5.2: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.2:     (1 | Subject:Harmony)
        Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer7.1  8 10077 10124 -5030.5    10061
lmer5.2 11 10078 10142 -5028.0    10056 5.1001      3     0.1646
```

```
> anova(lmer8.1,lmer5.2)
```

```
Data:
Models:
lmer8.1: Popular ~ Instrument + Harmony + (1 | Subject:Instrument) + (1 |
lmer8.1:     Subject:Harmony)
lmer5.2: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmer5.2:     (1 | Subject:Harmony)
        Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer8.1  9 10080 10132 -5030.9    10062
lmer5.2 11 10078 10142 -5028.0    10056 5.881      2    0.05284 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> summary(lmer5.2)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:Harmony)

REML criterion at convergence: 10074.49

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4099   0.6403
 Subject:Instrument (Intercept) 2.0268   1.4237
 Residual                       2.5133   1.5853
Number of obs: 2493, groups: Subject:Harmony, 280; Subject:Instrument, 210

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.57983    0.20703   31.78
Instrumentpiano  -0.94918    0.25316   -3.75
```

```
Instrumentstring -2.60618    0.25286  -10.31
HarmonyI-V-IV    -0.02570    0.14069   -0.18
HarmonyI-V-VI    -0.27135    0.14068   -1.93
HarmonyIV-I-V    -0.18522    0.14062   -1.32
Voicepar3rd       0.16473    0.07784    2.12
Voicepar5th       0.16210    0.07778    2.08

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r
Instrumntpn -0.610
Instrmntstr -0.611  0.500
HrmnyI-V-IV -0.339  0.000     0.000
HrmnyI-V-VI -0.339  0.000     0.000     0.499
HrmnyIV-I-V -0.339  0.000     0.000     0.500  0.500
Voicepar3rd -0.187 -0.001     0.000    -0.002  0.001  0.002
Voicepar5th -0.187 -0.001     0.000    -0.001 -0.002 -0.001  0.500
```

The LRTs show that Harmony is insignificant in the model and Voice is marginally significant at 0.1 level. Combining the results from above, we find either Harmony or Voice or both of them are not significant. Since the three main factors are design variables, we do not delete any of them. But we do find that there may be lack of influence in Harmony and Voice for popular music rating. The only factor that is obviously significant is Instrument, which shows that, compared to a stimulus that is played by guitar, one played by piano is rated 0.95 lower for popular music. Compared to a stimulus that is played by guitar, one played by string is rated 2.61 lower for popular music.

b

Firstly check if the possible fixed effects are significant. The method is the same as 2(a).

The final model is:

```
> summary(lmerp.final)


Linear mixed model fit by REML ['lmerMod']
Formula: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +      (1 | Subject:Harmony)
   Data: newratings

REML criterion at convergence: 8393.877

Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.4598   0.6781
 Subject:Instrument (Intercept) 1.7843   1.3358
 Residual                       2.5489   1.5965
Number of obs: 2073, groups: Subject:Harmony, 232; Subject:Instrument, 174

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       6.62394    0.47520  13.939
Instrumentpiano  -0.99938    0.26272  -3.804
Instrumentstring -2.78229    0.26241 -10.603
HarmonyI-V-IV    -0.01343    0.16031  -0.084
```

```
HarmonyI-V-VI    -0.29829    0.16034  -1.860
HarmonyIV-I-V    -0.20307    0.16027  -1.267
Voicepar3rd       0.19646    0.08594   2.286
Voicepar5th       0.18514    0.08591   2.155
musician          0.77037    0.30487   2.527
PachListen1Low    0.78198    0.42093   1.858
GuitarPlay1Low   -0.70609    0.34497  -2.047

Correlation of Fixed Effects:
            (Intr) Instrmntp Instrmnts HI-V-I HI-V-V HIV-I- Vcpr3r Vcpr5t
Instrumntpn -0.275
Instrmntstr -0.276  0.499
HrmnyI-V-IV -0.168  0.000     0.000
HrmnyI-V-VI -0.168  0.000     0.000     0.500
HrmnyIV-I-V -0.169  0.000     0.000     0.500  0.500
Voicepar3rd -0.091  0.000     0.000     0.000  0.001  0.001
Voicepar5th -0.090  0.000     0.000    -0.001 -0.001 -0.001  0.500
musician    -0.642  0.001     0.000     0.000  0.000  0.000  0.000  0.000
PachLstn1Lw -0.093  0.000     0.000     0.000  0.000  0.000  0.000  0.000
GuitrPly1Lw -0.710 -0.001     0.000    -0.001 -0.001  0.000  0.000  0.000
            musicn PchL1L
Instrumntpn
Instrmntstr
HrmnyI-V-IV
HrmnyI-V-VI
HrmnyIV-I-V
Voicepar3rd
Voicepar5th
musician
PachLstn1Lw  0.145
GuitrPly1Lw  0.177 -0.094
```

On average, a stimulus played by piano will be rated 1.00 lower than than one played by guitar to be popular music, others factors held constant. On average, a stimulus played by string will be rated 2.78 lower than than one played by guitar to be popular music, others factors held constant.On average, harmony I-V-VI is rated 0.30 lower than harmony I-IV-V, others factors held constant. The other two are not significantly different from Harmony I-IV-V. On average, a stimulus with Parallel 3rd is rated 0.20 higher than contrary motion, others held constant; a stimulus with Parallel 5rd is rated 0.19 higher than contrary motion, others held constant.A self-declared musician will rated a stimulus 0.77 higher as popular music than a non-musician. A person who listen to Pachbel's Canon a lot will rate 0.78 units lower as popular music than a person who does not listen to Pachbel's Canon a lot. A person who play guitar a lot will rate the stimulus 0.71 units higher to be popular music rating than a person who did not play guitar a lot.

c

```
> lmerp.IM=update(lmerp.final,.~.+musician*Instrument)
> lmerp.HM=update(lmerp.final,.~.+musician*Harmony)
> lmerp.VM=update(lmerp.final,.~.+musician*Voice)
> lmerp.pa=update(lmerp.final,.~.+musician*PachListen1)
> anova(lmerp.IM,lmerp.final)

Data: newratings
Models:
```

why not check musician interaction with multiple covariates, instead of one-at-a-time?

```
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1
lmerp.IM: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.IM:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1 +
lmerp.IM:     Instrument:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final 14 8403.9 8482.9 -4188.0   8375.9
lmerp.IM    16 8407.6 8497.8 -4187.8   8375.6 0.3271      2     0.8491
```

> anova(lmerp.HM,lmerp.final)

```
Data: newratings
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1
lmerp.HM: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.HM:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1 +
lmerp.HM:     Harmony:musician
            Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final 14 8403.9 8482.9  -4188   8375.9
lmerp.HM    17 8402.0 8497.8  -4184   8368.0 7.9464      3    0.04713 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

> anova(lmerp.VM,lmerp.final)

```
Data: newratings
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1
lmerp.VM: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.VM:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1 +
lmerp.VM:     Voice:musician
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final 14 8403.9 8482.9 -4188.0   8375.9
lmerp.VM    16 8407.8 8498.0 -4187.9   8375.8 0.1726      2     0.9173
```

> anova(lmerp.pa,lmerp.final)

```
Data: newratings
Models:
lmerp.final: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.final:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1
lmerp.pa: Popular ~ Instrument + Harmony + Voice + (1 | Subject:Instrument) +
lmerp.pa:     (1 | Subject:Harmony) + musician + PachListen1 + GuitarPlay1 +
lmerp.pa:     musician:PachListen1
            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmerp.final 14 8403.9 8482.9 -4188.0   8375.9
lmerp.pa    15 8404.8 8489.4 -4187.4   8374.8 1.1167      1     0.2906
```

Same as classical music rating, there is interaction between harmony and musician.

5

Summary

1. Three main experimental factors

The influence of the three main experimental factors (Instrument, Harmony and Voice) differs for classical rating and popular rating. For Classical rating, all three factors are significant. In particular, a stimulus played by piano or string will both be rated higher than than one played by guitar. However, for Harmony, only I-V-IV is significantly different from I-IV-V, the other two are not significantly different from I-IV-V. More specifically, I-V-IV is rated higher than I-IV-V on classical rating. For Voice, both parallel 3rds and parallel 5ths are significantly different from contrary motion:both parallel 3rd and 5ths are rated higher than contrary motion on classical motion. But there is little difference between parallel 3rds and parallel 5ths. These may suggest that harmony and voice could be treated as dummy variables if we want to further explore the three main effects.

However, only instrument influence the popular music rating. Both harmony and voice does not significantly influence the popular rating. The influence of instrument is that a stimulus played by piano or string will both be rated lower than one played by guitar.

The two kinds of ratings show that instrument have the largest influence on rating. Piano and string are considered to be the instrument played in classical music while guitar played in popular music. It seems popular music are more diverse since harmony and voice will not help one determine whether a stimulus is a popular music or not.

2. Variance components

The best models we find are not a standard repeated measure model. When not adding individual covariates, we add the variance of person/Instrument, person/Harmony and person/Voice combination in the classical ratings model. Meaning that the classical rating varies according to different raters along with the three mains characters of a stimulus. After adding individual covariates, both classical rating model and popular rating model add the variance of person/Instrument and per/Harmony combination and do not add the variance of person/Voice. This means that both of the ratings do not vary significantly across raters with different voice leading the stimulus. **nor are there differences in individual biases that are driven by voice.**

3. Individual covariates

There are different covariates included in the two models. The common covariate is musician, which indicates whether one declare oneself as a musician or not. It seems that a self-declared musician will more likely to rate a stimulus higher on popular rating and lower on classical rating.

For classical rating, the unique covariates is ClsListen, specifically, a person who listen to classical music a lot will rate 0.65 units higher score for the classical rating than a person who does not listen to classical music a lot. It seems that people with more experience in listening to classical music will more likely rate higher on classical rating.

For popular rating, the unique significant covariates are PachListen and GuitarPlay. GuitarPlay is a supplementary of the variable Instrument. Since we have known that a stimulus with guitar are more likely to rated as popular music. What is interesting is that PachListen is not significant in classical rating as we expected, but is significant in popular rating. But understandably, it negatively influence the popular music rating.

There are much more covariates that can be considered to add into the model. For further study, we could put more possible covariates into the model in order to add more meaningful aspects to the model.

nice summary

4: 18
5: 20

38