36-763 Hierarchical Linear Models: Homework 5

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Problem 1

a.

```
> lm1a.1 = lm(Classical ~ 1 + Instrument + Harmony + Voice)
> lm1a.2 = lm(Classical ~ 1 + Harmony + Voice)
> lm1a.3 = lm(Classical ~ 1 + Instrument + Voice)
> lm1a.4 = lm(Classical ~ 1 + Instrument + Harmony)
> # Test fixed effect of Instrument
> anova(lm1a.1, lm1a.2)

Analysis of Variance Table

Model 1: Classical ~ 1 + Instrument + Harmony + Voice
Model 2: Classical ~ 1 + 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

> # Test fixed effect of Harmony
> anova(lm1a.1, lm1a.3)

Analysis of Variance Table

Model 1: Classical ~ 1 + Instrument + Harmony + Voice
Model 2: Classical ~ 1 + 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

> # Test fixed effect of voice
> anova(lm1a.1, lm1a.4)

Analysis of Variance Table

Model 1: Classical ~ 1 + Instrument + Harmony + Voice
Model 2: Classical ~ 1 + 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
```

The three F-tests for the significant of instrument, harmony and voice have p-values of 0, 0 and 0.0003 respectively. We therefore conclude that all three variables are highly significant predictors of Classical ratings.

b.

I

$$Classical_j = \beta_{0[j]} + \beta_1 Instrument + \beta_2 Harmony + \beta_3 Voice + \epsilon_j \overset{i.i.d}{\sim} N(0, \sigma^2)$$

$$\beta_{0[j]} = \alpha_0[j] + \epsilon_j \overset{i.i.d}{\sim} N(0, \tau^2)$$

II

```
> library(arm)
> library(RLRsim)
> # Define a L-Calc Functiont that calculates BIC, AIC, DIC, calculated using
> # BIC(), AIC() and display() for DIC
> LCalc <- function(arg1, arg2, n = nargs(), label = c("Model 1", "Model 2")){
+   if (n == 1){
+     mat = cbind(AIC(arg1)[1], BIC(arg1)[1], as.numeric(logLik(arg1)[1]))
+               }
+   if (n == 2){
+     mat = rbind(cbind(AIC(arg1)[1], BIC(arg1)[1], as.numeric(logLik(arg1)[1])),
+       cbind(AIC(arg2)[1], BIC(arg2)[1], as.numeric(logLik(arg2)[1])))
+       }
+     colnames(mat) = c("AIC", "BIC", "DIC")
+     if (n == 1)
+     rownames(mat) = c(paste(label[1]))
+     if (n == 2)
+     rownames(mat) = c(paste(label[1]), paste(label[2]))
+   return(mat)
+ }
> # Using BIC/AIC/DIC
> lmer1b.1 = lmer(Classical ~ (1|Subject) + Instrument + Harmony + Voice)
> lm1b.1 = lm(Classical ~ 1 + Instrument + Harmony + Voice)
> LCalc(lmer1b.1, lm1b.1, n = 2, label = c("Random Effect Intercept", "Fixed Effect Intercept"))

                              AIC      BIC       DIC
Random Effect Intercept 10491.51 10549.73 -5235.757
Fixed Effect Intercept  11230.45 11282.84 -5606.225
```

The differences in AIC and BIC are 500-600 lower in the random intercept model compared to the fixed effect intercept model. Based on the rule of thumb that a AIC/BIC difference of 3 is significant, the random effect model is a significantly better fit.

```
> # Using simulated restricted likelihood ratio test
> exactRLRT(lmer1b.1)
```

```
        simulated finite sample distribution of RLRT.

        (p-value based on 10000 simulated values)

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

III

The restricted likelihood ratio test for linear mixed models tests whether the variance of a random effect is 0 in a linear mixed model. Because p-value < 0.001, we reject the null and conclude that the random effect is significant.

```
> lmer1b.2 = lmer(Classical ~ (1|Subject) + Instrument + Harmony + Voice)
> lmer1b.3 = lmer(Classical ~ (1|Subject) + Harmony + Voice)
> lmer1b.4 = lmer(Classical ~ (1|Subject) + Instrument + Voice)
> lmer1b.5 = lmer(Classical ~ (1|Subject) + Instrument + Harmony)
> anova(lmer1b.2, lmer1b.3)

Data:
Models:
lmer1b.3: Classical ~ (1 | Subject) + Harmony + Voice
lmer1b.2: Classical ~ (1 | Subject) + Instrument + Harmony + Voice
         Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1b.3  8 11408 11455 -5696.2    11392
lmer1b.2 10 10469 10527 -5224.4    10449 943.59      2  < 2.2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

> anova(lmer1b.2, lmer1b.4)

Data:
Models:
lmer1b.4: Classical ~ (1 | Subject) + Instrument + Voice
lmer1b.2: Classical ~ (1 | Subject) + Instrument + Harmony + Voice
         Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
lmer1b.4  7 10539 10580 -5262.4    10525
lmer1b.2 10 10469 10527 -5224.4    10449 75.931      3  2.288e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

> anova(lmer1b.2, lmer1b.5)

Data:
Models:
lmer1b.5: Classical ~ (1 | Subject) + Instrument + Harmony
lmer1b.2: Classical ~ (1 | Subject) + Instrument + Harmony + Voice
         Df   AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
lmer1b.5  8 10489 10536 -5236.6    10473
lmer1b.2 10 10469 10527 -5224.4    10449 24.24      2   5.45e-06 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
```

The effect of the three predictor variables are once again highly significant (p-values = 0) even after the inclusion of the random effect intercepts.

Part C

I

```
> lmer9 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) + (1|Subject:Voice))
> LCalc(lmer9, lm1a.1, n = 2, label = c("Model 1c", "Model 1a"))

              AIC      BIC       DIC
Model 1c 10222.76 10251.87 -5106.382
Model 1a 11230.45 11282.84 -5606.225

> LCalc(lmer9, lmer1b.1, n = 2, label = c("Model 1c", "Model 1b"))

              AIC      BIC       DIC
Model 1c 10222.76 10251.87 -5106.382
Model 1b 10491.51 10549.73 -5235.757
```

Based on the AIC, BIC and DIC values. The model in 1C with the new random effect terms are significantly better than the all fixed effect model in 1a and the random intercept model in 1b.

II

```
> summary(lmer9)$varcor

 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.73500
 Subject:Voice      (Intercept) 0.25639
 Subject:Instrument (Intercept) 1.98726
 Residual                       1.56497
```

The estimated variance components are equal to 0.54022500, 0.06573583, 3.94920231, 2.44913110 for Harmony, Voice, Instrument and Residuals respectively. The variance component of the residual is similar in magnitude to the variance component for instrument. It is also marginally larger than the variance component for the harmony. This indicates that the model is appropriate with respect to instrument and harmony. However, the it is significantly larger than the variance component for voice, which indicates that adding a random effect term of the form person:voice might not be appropriate.

III

$$Classical_j = X_j\beta + \alpha_{ij} + \gamma_{ik} + \delta_{in} + \epsilon_j \overset{i.i.d}{\sim} N(0, \sigma^2)$$

$$\alpha_{ij} = \psi_{ij} + \eta \overset{i.i.d}{\sim} N(0, \kappa^2)$$

Where α_{ij} represents the estimate for ith individual, jth Instrument

$$\gamma_{ik} = \theta_{ik} + \nu \overset{i.i.d}{\sim} N(0, \lambda^2)$$

Where θ_{ik} represents the estimate for ith individual, kth Harmony

$$\delta_{il} = \tau_{in} + \pi \overset{i.i.d}{\sim} N(0, \mu^2)$$

Where τ_{ij} represents the estimate for ith individual, nth Voice

Problem 2

Part a

```
> # Fit new models with restricted dataset with all missing values ommited.
>
> lmer10 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                 (1|Subject:Voice),data = na.omit(ratings))
> sort(apply(apply(ratings, 2, (is.na)),2,mean))
```

```
                  X                         Subject
         0.00000000                      0.00000000
            Harmony                      Instrument
         0.00000000                      0.00000000
              Voice                      Selfdeclare
         0.00000000                      0.00000000
               OMSI                    X16.minus.17
         0.00000000                      0.00000000
          ConsInstr               Instr.minus.Notes
         0.00000000                      0.00000000
          PianoPlay                      GuitarPlay
         0.00000000                      0.00000000
            first12                       Classical
         0.00000000                      0.01071429
            Popular                       ClsListen
         0.01071429                      0.01428571
         PachListen                       Composing
         0.02857143                      0.02857143
       CollegeMusic                      X1990s2000s
         0.04285714                      0.05714286
            KnowRob X1990s2000s.minus.1960s1970s
         0.07142857                      0.07142857
           APTheory                        KnowAxis
         0.08571429                      0.11428571
            NoClass                       ConsNotes
         0.11428571                      0.14285714
          X1stInstr                       X2ndInstr
         0.60000000                      0.87142857
```

```
> names(sort(apply(apply(ratings, 2, (is.na)),2,mean)))
```

```
 [1] "X"                              "Subject"
 [3] "Harmony"                        "Instrument"
 [5] "Voice"                          "Selfdeclare"
 [7] "OMSI"                           "X16.minus.17"
 [9] "ConsInstr"                      "Instr.minus.Notes"
[11] "PianoPlay"                      "GuitarPlay"
[13] "first12"                        "Classical"
[15] "Popular"                        "ClsListen"
[17] "PachListen"                     "Composing"
[19] "CollegeMusic"                   "X1990s2000s"
[21] "KnowRob"                        "X1990s2000s.minus.1960s1970s"
[23] "APTheory"                       "KnowAxis"
```

```
[25] "NoClass"                      "ConsNotes"
[27] "X1stInstr"                    "X2ndInstr"

> # Calculating the BIC by adding one variable at a time
> BICCalc = NULL
> for (i in c(1:6,8:23))
+ {
+ BICCalc[i] = BIC(update(lmer10, paste(".~.+",names(ratings)[i+5])))
+ }
> # Finding the names with the 5 lowest BIC values
> A=cbind(c(6:11,"NA", 13:28),BICCalc)
> print(A)

           BICCalc
 [1,] "6"  "801.876178965197"
 [2,] "7"  "811.749212337818"
 [3,] "8"  "803.466227711475"
 [4,] "9"  "801.949630925903"
 [5,] "10" "803.132546582875"
 [6,] "11" "803.216903508562"
 [7,] "NA" NA
 [8,] "13" "803.535693054676"
 [9,] "14" "803.60843741513"
[10,] "15" "802.418393816524"
[11,] "16" "802.713999598956"
[12,] "17" "803.194466749332"
[13,] "18" "800.724085412866"
[14,] "19" "801.31020517473"
[15,] "20" "799.766877366058"
[16,] "21" "802.232136926553"
[17,] "22" "800.347033888035"
[18,] "23" "802.985753190926"
[19,] "24" "802.894956626512"
[20,] "25" "802.840333117005"
[21,] "26" "802.365327817851"
[22,] "27" "797.448891980899"
[23,] "28" "789.201356299935"

> names(ratings)[as.numeric(A[order(A[,2]),][3:7,1])]

[1] "APTheory"     "PianoPlay"    "CollegeMusic" "NoClass"      "Selfdeclare"

> # Construct new dataset with these 5 variables and omit any rows with missing values.
> ratings_new = data.frame(APTheory = ratings$APTheory, PianoPlay = ratings$PianoPlay,
+                          CollegeMusic = ratings$CollegeMusic, NoClass = ratings$NoClass,
+                          Selfdeclare = ratings$Selfdeclare, Instrument = ratings$Instrument,
+                          Voice = ratings$Voice, Harmony = ratings$Harmony,
+                          Classical = ratings$Classical, Popular = ratings$Popular,
+                          Subject = ratings$Subject)
> ratings_new = na.omit(ratings_new)
> lmer11a = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                 (1|Subject:Voice),data = ratings_new)
> lmer11b = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
```

```
+                 (1|Subject:Voice) + APTheory + PianoPlay + CollegeMusic +
+                 NoClass + Selfdeclare,data = ratings_new)
> LCalc(lmer11a, lmer11b, n = 2, label = c("Model 2a", "Model 1C "))

               AIC      BIC       DIC
Model 2a  8682.915 8711.185 -4336.458
Model 1C  8694.794 8751.334 -4337.397
```

We elected to select the 5 most impactful variables, as selected by BIC. After subsetting the original data and after excluding all the missing values, our subset still contained 2109 out of the original 2520 observations. The new model with 5 added predictor variables is a significantly better fit according to BIC, AIC, DIC.

Part B

```
> lmer11 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                 (1|Subject:Voice) + APTheory + PianoPlay + CollegeMusic +
+                 NoClass + Selfdeclare,data = ratings_new)
> lmer12 = lmer(Classical ~ (1|Subject:Harmony) + (1|Subject:Voice)
+               + APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> lmer13 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Voice)
+               + APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> lmer14 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony)
+               + APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> LCalc(lmer11, lmer12, n = 2, label = c("Full Model", "Without 1:Subject:Instrument"))

                                  AIC      BIC       DIC
Full Model                   8694.794 8751.334 -4337.397
Without 1:Subject:Instrument 9946.577 9997.462 -4964.288

> LCalc(lmer11, lmer13, n = 2, label = c("Full Model", "Without 1:Subject:Harmony"))

                               AIC      BIC       DIC
Full Model                8694.794 8751.334 -4337.397
Without 1:Subject:Harmony 8830.276 8881.161 -4406.138

> LCalc(lmer11, lmer14, n = 2, label = c("Full Model", "Without 1:Subject:Voice"))

                             AIC      BIC       DIC
Full Model              8694.794 8751.334 -4337.397
Without 1:Subject:Voice 8698.355 8749.241 -4340.178
```

Based on BIC, AIC and DIC values, which are tens to hundreds lower in the full model compared to the partial models without 1:Subject:Harmony or 1:Subject:Instrument, we can say that the full model is significantly better fitting than the model without 1:Subject:Instrument or 1:Subject:Harmony. However, the reduced model without 1:Subject:Voice has lower BIC and DIC values than the full model. So therefore, there is evidence to suggest that the random effect of 1:Subject:Voice is not needed when 5 of the most impactful predictors have been added.

Part C

```
> display(lmer14)
```

```
lmer(formula = Classical ~ (1 | Subject:Instrument) + (1 | Subject:Harmony) +
    APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare,
    data = ratings_new)
             coef.est coef.se
(Intercept)   5.72     0.55
APTheory      0.62     0.43
PianoPlay     0.08     0.11
CollegeMusic  0.41     0.44
NoClass      -0.05     0.12
Selfdeclare  -0.22     0.16

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.76
 Subject:Instrument (Intercept) 2.04
 Residual                       1.59
---
number of obs: 2109, groups: Subject:Harmony, 236; Subject:Instrument, 177
AIC = 8698.4, DIC = 8662.7
deviance = 8671.5
```

On average classical music are rated 5.72 points. Individuals who have taken AP Music Theory class gives 0.62 point in score. For every unit increase in piano playing skill, the score increases by 0.08 point. Those who have taken music class in college give 0.40 point in additional score. Those who have not taken music classes in their life tend to 0.05 point lower in score. Those who strongly identify as being a musician give 0.22 point lower in score for every point increase in their self-identification as a musician.

Problem 3

```
> ratings_new$Ind.Selfdeclare = 0
> ratings_new$Ind.Selfdeclare = (ratings_new$Selfdeclare > 2)*1
> lmer15 = lmer(Classical ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+               APTheory + PianoPlay + CollegeMusic + NoClass + Ind.Selfdeclare +
+                 Ind.Selfdeclare*APTheory + Ind.Selfdeclare*PianoPlay +
+                 Ind.Selfdeclare*CollegeMusic + Ind.Selfdeclare*NoClass, data = ratings_new)
> LCalc(lmer14, lmer15, n = 2, label = c("Model Prob 2C", "Model Prob 3"))

                   AIC      BIC       DIC
Model Prob 2C 8698.355 8749.241 -4340.178
Model Prob 3  8703.278 8776.779 -4338.639
```

As for the effect of the interaction terms, self declared musicians who have taken AP Music gives a higher score (0.47), plays piano gives a lower score (-0.04*PianoPlay), have taken college music classes gives a lower score (-0.50) and have not taken music class gives a lower score (-0.15).
The AIC and BIC values were higher for the new model. DIC values are lower. Because BIC and AIC has much harsher penalties for model complexity, the model for problem 3 was penalized for the introduction of many interaction terms. Even with the interaction terms, the new model is not any better at prediction classical scores than the model found in problem 2, part c.

Problem 4

Part A

```
> lmer16= lmer(Popular ~ (1|Subject) + Instrument + Harmony + Voice, data = ratings_new)
> lm4 = lm(Popular ~ 1 + Instrument + Harmony + Voice, data= ratings_new)
> LCalc(lmer14, lm4, n = 2, label = c("Random Effect Intercept", "Fixed Effect Intercept"))

                              AIC      BIC       DIC
Random Effect Intercept 8698.355 8749.241 -4340.178
Fixed Effect Intercept  9439.576 9490.461 -4710.788
```

The random intercept model is once again a better fit than the fixed intercept model.

```
> lmer16 = lmer(Popular ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                 (1|Subject:Voice) + APTheory + PianoPlay + CollegeMusic +
+                 NoClass + Selfdeclare,data = ratings_new)
> lmer17 = lmer(Popular ~ (1|Subject:Harmony) + (1|Subject:Voice)+
+                 APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> lmer18 = lmer(Popular ~ (1|Subject:Instrument) + (1|Subject:Voice) +
+                 APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> lmer19 = lmer(Popular ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                 APTheory + PianoPlay + CollegeMusic + NoClass + Selfdeclare, data = ratings_new)
> LCalc(lmer16, lmer17, n = 2, label = c("Full Model", "Without Instrument"))

                         AIC      BIC       DIC
Full Model         8657.694 8714.234 -4318.847
Without Instrument 9683.693 9734.579 -4832.847

> LCalc(lmer16, lmer18, n = 2, label = c("Full Model", "Without Harmony"))

                      AIC      BIC       DIC
Full Model      8657.694 8714.234 -4318.847
Without Harmony 8736.812 8787.698 -4359.406

> LCalc(lmer16, lmer19, n = 2, label = c("Full Model", "Without Voice"))

                    AIC      BIC       DIC
Full Model    8657.694 8714.234 -4318.847
Without Voice 8657.096 8707.982 -4319.548
```

The effect of instrument is once again highly significant. The model without instrument is a significantly worse fit than the full model. The AIC, BIC and DIC value differences on the order of magnitudes of hundreds. The models without Harmony and Voice are still worse fits than the full models, but only marginally. We therefore conclude that all three predictor variables are significant in the prediction of popular music scores.

Part B

must include all of the experimental factors, even if not significant

```
> display(lmer16)

lmer(formula = Popular ~ (1 | Subject:Instrument) + (1 | Subject:Harmony) +
    (1 | Subject:Voice) + APTheory + PianoPlay + CollegeMusic +
    NoClass + Selfdeclare, data = ratings_new)
             coef.est coef.se
```

```
(Intercept)  4.90     0.51
APTheory     0.07     0.40
PianoPlay    0.00     0.10
CollegeMusic 0.03     0.41
NoClass      0.02     0.11
Selfdeclare  0.18     0.15

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.65
 Subject:Voice      (Intercept) 0.19
 Subject:Instrument (Intercept) 1.88
 Residual                       1.59
---
number of obs: 2109, groups: Subject:Harmony, 236; Subject:Voice, 177; Subject:Instrument, 177
AIC = 8657.7, DIC = 8618.1
deviance = 8627.9
```

On average popular music are rated 4.90 points. Individuals who have taken AP Music Theory class gives 0.07 point in score. The effect of piano playing is negligible. Those who have taken music class in college give 0.03 point in additional score. Those who have not taken music classes in their life tend to 0.02 point lower in score. Those who strongly identify as being a musician give 0.18 point higher in score for every point increase in their self-identification as a musician.

Part C

```
> lmer20 = lmer(Popular ~ (1|Subject:Instrument) + (1|Subject:Harmony) +
+                  APTheory + PianoPlay + CollegeMusic + NoClass + Ind.Selfdeclare +
+                  Ind.Selfdeclare*APTheory + Ind.Selfdeclare*PianoPlay +
+                  Ind.Selfdeclare*CollegeMusic + Ind.Selfdeclare*NoClass, data = ratings_new)
> LCalc(lmer20, lmer16, n = 2, label = c("Model Prob4c", "Model Prob4a"))

                  AIC      BIC       DIC
Model Prob4c 8658.083 8731.584 -4316.041
Model Prob4a 8657.694 8714.234 -4318.847
```

The AIC and BIC values were higher for the new model. DIC value was lower because the new model contained more predictor variables, which lead to a lower deviance. The complexity of the new model was heavily penalized by AIC and more so by BIC. Even with the interaction terms, the new model is not any better at prediction popular music scores than the model found in problem 4, part A.

4: 16
5: 18

34

Problem 5

Classical and Popular Music Differentiation by Instrument, Harmony and Voice

The classification of aural stimuli as either 'classical' or 'popular' is heavily influenced by the instruments used, the harmonic motion present and the type of voice leading. An anova analysis of a simple linear regression in problem 1, part A indicates that all three of instrument, harmonic motion, and voice leading are significant predictors of both classical and popular music.

Repeated Measure Model

By fitting a repeated measures model with a random intercept for each participant, we were able to better estimate the popular and classical scores when compared to a simple linear model. The effects of the instruments used, the harmonic motion present and the type of voice leading was once again significant even after taking into account the personal bias of each of the 36 participants.

Random Intercept Model

However, the bias for each of the 36 participants may not be personal, but is rather a function of instrument, harmonic motion or voice leading. After fitting a model with varying intercepts for each of the participant and instrument, harmonic motion and voice leading pairs, the estimated variance components for Subject:Voice and variance components for the residuals indicates that voice is not an appropriate predictor in this model. Therefore, we conclude that the 36 participants have significant biases toward specific types of harmonic motion and instrument, but were much more forgiving in terms of the voice leading.

Personal Bias Model

After adding in five of the most significant predictors of classical and popular - whether the participant has taken AP Music, plays piano, has taken college music classes, has ever taken a music class, or self-identifies as a musician. The new model with 5 added predictors is significantly better at predicting popular and classical scores compared to our random intercept model.

Musicians vs Non-Musicians Model

When the predictor variable 'SelfIdentify' was dichotamized into roughly two equal levels, the interactions between the indicator for self-identifying musicians and participants who plays the piano, have taken college music classes, or have not taken music classes were significant. Individuals who have more exposure to music are better able to distinguish classical music. Most significantly, participates who have taken AP Music gave classical stimuli a score that is 0.47 higher! However, being a musician only marginally increases one ability to identify popular music stimuli.

not sure what data this is based on. there are no gold standards in this study

Conclusion

Instrument and harmony are the two most significant predictors of popular and classical music identification. Participants have significant biases toward the identification of classical and popular music. Some participants are better than other participants with similar qualifications at identifying either popular or classical music. Participants also have significant biases toward different types of instrument and harmony. Being a musician increases one's ability to identify classical music, but only marginally increases one's ability to identify popular music.