1 a 9/9
b 9/9
c 8/9

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

3 8/9

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

5 10/10

Total 98/100

HW 05 – Anna Mayo

QUESTION 1

Building a model – Predicting Classical Ratings

1a)

Model choice – what to include?

Approach*: Building from the authors' hypotheses (i.e., determining the models based on the theory), I start with a model that includes only Instrument; this was predicted to have the strongest effect (Model 1 – see Table below). I then add voice, which is also expected to influence classical ratings (Model 2). Lastly, I add harmony, with referent group = I-V-VI, for which the authors were unsure of the effect (Model 3).

> **I chose this approach relative to an automated forward or backward selection approach to be in line with how research in Organizational Behavior is typically done.*

Model comparisons – using the function anova() – demonstrate that Model 3 is best fit to the data (and 2 fits better than 1). Thus, above and beyond accounting for the instrument, if we account for voice and also harmony, we significantly increase our ability to explain variance in the classical ratings.

Interpretation of results:

Instrument: Relative to Guitar, piano and string significantly increase classical ratings.

Voice: Relative to 'contrary', par3rd and par5th significantly decrease classical ratings.

Harmony: The category of interest (I-V-VI) leads to significantly higher ratings than three other harmonies.

Regression Table

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Predicting Classical Ratings			
	Dependent variable:		
	Classical Ratings		
	(1)	(2)	(3)
Inst-Piano	1.373*** (0.114)	1.373*** (0.114)	1.374*** (0.113)
Inst-String	3.133*** (0.114)	3.133*** (0.113)	3.133*** (0.112)
Voice-3		-0.413*** (0.114)	-0.412*** (0.113)
Voice-5		-0.369*** (0.114)	-0.371*** (0.113)
H:I-IV-V			-0.769*** (0.130)
H: I-V-IV			-0.800*** (0.130)
H: IV-I-V			-0.719*** (0.130)
Constant	4.276*** (0.081)	4.537*** (0.104)	5.109*** (0.130)
Observations	2,493	2,493	2,493
R2	0.235	0.239	0.255
Adjusted R2	0.234	0.238	0.253
Residual Std. Error	2.326 (df = 2490)	2.319 (df = 2488)	2.297 (df = 2485)
F Statistic	381.626*** (df = 2; 2490)	195.859*** (df = 4; 2488)	121.529*** (df = 7; 2485)
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: Estimates shown with standard errors in parentheses. For instrument (Inst), the reference is 'guitar'. For Voice, the reference is 'contrary'. For Harmony (H), the reference is 'I-V-VI'.

1b)

i) Mathematical hierarchical model with random intercept

$$y_i = \alpha_{0j[i]} + \alpha_1 \text{Inst}_i + \alpha_2 \text{Voice}_i + \alpha_3 \text{Harmony}_i + \varepsilon_i \,,\ \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$
$$\alpha_{0j} = \beta_0 + \eta_j \,,\ \eta_j \overset{iid}{\sim} N(0, \tau^2)$$

As fit in R:

```
lmer.Classical<-lmer(Classical ~  Instrument + Voice + Harmony + (1|Subject),data=Ratings, REML=F)
```

ii) Do we need the random intercept?

1) Yes – This model has a substantially lower AIC and BIC than the model without random intercepts (Model 3 from above)

	Linear model	Linear mixed-effects with random intercept
AIC	11,230.5	10,468.9
BIC	11,282.8	10,527.1

2) Yes – using exactLRT() to compare the model with random intercepts to the model without random intercepts: `LRT = 763.588, p-value < 2.2e-16`

iii) Interpretation of 3 factors: patterns remain the same, and all effects described above remain significant.

	Dependent variable:
	Classical Ratings
Inst-Piano	1.377*** (0.093)
Inst-String	3.132*** (0.092)
Voice-3	-0.415*** (0.093)
Voice-5	-0.374*** (0.093)
H:I-IV-V	-0.771*** (0.107)
H: I-V-IV	-0.803*** (0.107)
H: IV-I-V	-0.721*** (0.107)
Constant	5.115*** (0.188)
Observations	2,493
Log Likelihood	-5,224.431
Akaike Inf. Crit.	10,468.860
Bayesian Inf. Crit.	10,527.070
Note:	*p<0.1; **p<0.05; ***p<0.01

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1c)

i) Fit of Model with 3 Random Effects: The model with 3 random effects has a lower AIC and BIC than the previous models, suggesting it's a better fit:

	linear model	linear mixed-effects with random intercept	linear mixed-effects with 3 random effects
AIC	11,230.5	10,468.9	10,057.5
BIC	11,282.8	10,527.1	10,127.4

ii) Interpretation of effects

This model continues to demonstrate the same pattern and significance of fixed effects as before (table of fixed effects below).

Variance components (random effects listed below):

Instrument: quite meaningful to account for this personal bias. The size of the error variance component and that of the variance component accounting for personal biases specific to the instrument are quite similar (2.43 vs 2.16, respectively).

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?? how do you know?

Voice and Harmony: much less, if any bias, around these music features. The variance component is reasonably larger than the variance component for a voice personal bias (2.43 vs 0.43) and even more so for harmony (2.43 vs 0.02).

Random effects:

Groups	Name	Variance	Std.Dev
Subject:Harmony	(Intercept)	0.43285	0.6579
Subject:Voice	(Intercept)	0.02473	0.1573
Subject:Instrument	(Intercept)	2.16929	1.4729
Residual		2.43721	1.5612

Fixed effects:

	Dependent variable:
	Classical Ratings
Inst-Piano	1.364*** (0.261)
Inst-String	3.128*** (0.260)
Voice-3	-0.407*** (0.081)
Voice-5	-0.371*** (0.081)
H:I-IV-V	-0.771*** (0.142)
H: I-V-IV	-0.801*** (0.142)
H: IV-I-V	-0.714*** (0.142)
Constant	5.112*** (0.213)
Observations	2,493
Log Likelihood	-5,016.764
Akaike Inf. Crit.	10,057.530
Bayesian Inf. Crit.	10,127.380
Note:	*p<0.1; **p<0.05; ***p<0.01

iii) Model: Math and R code:

$$y_i = \alpha_{01j[i]}\text{Instrument}_i + \alpha_{02j[i]}\text{Voice}_i + \alpha_{03j[i]}\text{Harmony}_i + \varepsilon_i\,,\ \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2)$$

$$\alpha_{01j} = \beta_{01} + \eta_{01j}\,,\ \eta_j \overset{iid}{\sim} N(0, \tau^2_{01})$$

$$\alpha_{02j} = \beta_{02} + \eta_{02j}\,,\ \eta_j \overset{iid}{\sim} N(0, \tau^2_{02})$$

$$\alpha_{03j} = \beta_{03} + \eta_{03j}\,,\ \eta_j \overset{iid}{\sim} N(0, \tau^2_{03})$$

This model would be ok if you were treating the experimental factors as continuous, but they are actually factors, and so a slightly different model would be needed (index the alphas by levels of instr, voice & harmony, instead of multiplying).

```
lmer.Classical.3RandInt<-lmer(Classical ~ Instrument + Voice + Harmony + (1|Subject:Instrument) +
    (1|Subject:Voice) + (1|Subject:Harmony), data=Ratings, REML=F)
```

QUESTION 2

Covariates

2a)

Which covariates to include?

Approach: I started with what I view as factors that I anticipate will affect the extent to which a person rates a stimulus as Classical (Model 1 in table below). I then culled down, removing factors not significant at $p < .05$.

Final Model: Factors include Instrument, Voice and Harmony, as well as:

Selfdeclare	Are you a musician? (1-6, 1=not at all)
OMSI	Score on a test of musical knowledge
PachListen	How familiar are you with Pachelbel's Canon in D (0-5, 0=not at all)

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	Dependent variable:		
	Classical		
	(1)	(2)	(3)
Instrumentpiano	1.423*** (0.125)	1.415*** (0.124)	1.336*** (0.113)
Instrumentstring	3.178*** (0.124)	3.175*** (0.123)	3.120*** (0.113)
Voicepar3rd	-0.405*** (0.124)	-0.420*** (0.123)	-0.413*** (0.113)
Voicepar5th	-0.363*** (0.124)	-0.373*** (0.123)	-0.346*** (0.113)
HarmonyI-IV-V	-0.849*** (0.144)	-0.826*** (0.142)	-0.789*** (0.131)
HarmonyI-V-IV	-0.867*** (0.144)	-0.855*** (0.143)	-0.822*** (0.131)
HarmonyIV-I-V	-0.780*** (0.144)	-0.762*** (0.142)	-0.746*** (0.131)
Selfdeclare	-0.322*** (0.075)	-0.272*** (0.073)	-0.328*** (0.061)
OMSI	0.001*** (0.0004)	0.001*** (0.0003)	0.001*** (0.0003)
CollegeMusic	-0.126 (0.133)		
ConsInstr	0.058 (0.044)		
ConsNotes	-0.071** (0.034)	-0.050* (0.027)	
PachListen	0.190*** (0.050)	0.204*** (0.049)	0.125*** (0.043)
Constant	4.815*** (0.322)	4.659*** (0.272)	5.046*** (0.242)
Observations	2,037	2,073	2,433
R2	0.274	0.272	0.266
Adjusted R2	0.269	0.268	0.263
Residual Std. Error	2.291 (df = 2023)	2.293 (df = 2061)	2.276 (df = 2422)
F Statistic	58.678*** (df = 13; 2023)	69.898*** (df = 11; 2061)	87.664*** (df = 10; 2422)
Note:			*p<0.1; **p<0.05; ***p<0.01

2b)

Which random effects?

Code in R for mixed-effects models

```
lmer.Classical.Cov.RI <- lmer(Classical ~                    # mixed-effects model
    Instrument + Voice + Harmony + Selfdeclare +             # with random intercept
    OMSI + PachListen + (1|Subject),
    data=Ratings, REML=F)

lmer.Classical.Cov.3RE <- lmer(Classical ~                   # mixed-effects model
    Instrument + Voice + Harmony + Selfdeclare +             # with 3 random effects
    OMSI + PachListen + (1|Subject:Instrument) +
    (1|Subject:Voice)+ (1|Subject:Harmony),
    data=Ratings, REML=F)
```

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Model Comparisons: The final model with 3 random effects is best fit to the data as its AIC and BIC are lower. This is in line with what we found for models without covariates.

	linear model	linear mixed-effects with random intercept	linear mixed-effects with 3 random effects
AIC	10920.14	10201.6	9788.5
BIC	10989.71	10277.0	9875.4

2c)

Interpretation

- The main factors continue to influence classical ratings in the same way as above
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- The more a person self-declares him/herself a musician, the lower the ratings (B = -.325, p < .01)
- The higher the OMSI score of music knowledge, the higher the classical ratings (B = .001, p < .05)
- Familiarity with Pachelbel's Canon no longer influences classical ratings (B = .124, ns) in this model with random effects to account for personal biases in responses to the instrument, voice and harmony

Output:

```
Random effects:

 Groups              Name        Variance Std.Dev.
 Subject:Harmony     (Intercept) 0.44936  0.6703
 Subject:Voice       (Intercept) 0.02297  0.1516
 Subject:Instrument (Intercept) 2.10150  1.4497
 Residual                        2.40223  1.5499

Fixed effects:


================================================
                        Dependent variable:
                    ---------------------------
                              classical
------------------------------------------------
Instrumentpiano           1.331*** (0.260)
Instrumentstring          3.121*** (0.260)
Voicepar3rd               -0.409*** (0.081)
Voicepar5th               -0.348*** (0.081)
HarmonyI-IV-V             -0.792*** (0.145)
HarmonyI-V-IV             -0.828*** (0.145)
HarmonyIV-I-V             -0.745*** (0.145)
Selfdeclare               -0.325** (0.152)
OMSI                       0.001* (0.001)
PachListen                  0.124 (0.107)
Constant                  5.049*** (0.548)
------------------------------------------------
Observations                   2,433
Log Likelihood               -4,879.240
Akaike Inf. Crit.             9,788.480
Bayesian Inf. Crit.           9,875.433
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

QUESTION 3

what was your choice of dichotomization, and why?

Interactions

I built on the model from Question 2, but I removed the variable Selfdeclare from the model, adding in its place the dichotomized version and its interaction with all other predictors. The output is below. My interpretation of the interaction terms are as follows:

- Harmony x Musician
  - The interaction terms are significant, suggesting that self-declaration as a musician impacts the random effect of harmony. Specifically:
    - On average, hearing I-V-VI leads to higher ratings than when the other harmonies are heard
    - However, when someone self-describes him/herself as a musician, the difference between the effect of I-V-VI on ratings and the effect of the other harmonies on ratings diminishes
- No difference depending on whether a person self-describes as a musician for the effects of:
  - Instrument, Voice, OMSI, PachListen

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```
Random effects:
      Groups              Name        Variance Std.Dev.
      Subject:Harmony     (Intercept) 0.36393  0.6033
      Subject:Voice       (Intercept) 0.02286  0.1512
      Subject:Instrument (Intercept) 2.14510  1.4646
      Residual                        2.40117  1.5496

Fixed effects:
    ================================================
                                 Dependent variable:
                             ---------------------
                                     Classical
    ------------------------------------------------
    Instrumentpiano                1.427*** (0.298)
    Instrumentstring               3.329*** (0.297)
    Voicepar3rd                   -0.383*** (0.092)
    Voicepar5th                   -0.349*** (0.092)
    HarmonyI-IV-V                 -0.469*** (0.154)
    HarmonyI-V-IV                 -0.525*** (0.154)
    HarmonyIV-I-V                 -0.501*** (0.154)
    OMSI                           0.001 (0.001)
    PachListen                     0.066 (0.112)
    Musician                      -1.438 (2.907)
    Instrumentpiano:Musician      -0.431 (0.634)
    Instrumentstring:Musician     -0.940 (0.633)
    Voicepar3rd:Musician          -0.118 (0.196)
    Voicepar5th:Musician           0.006 (0.196)
    HarmonyI-IV-V:Musician        -1.466*** (0.329)
    HarmonyI-V-IV:Musician        -1.371*** (0.330)
    HarmonyIV-I-V:Musician        -1.106*** (0.329)
    OMSI:Musician                 -0.0002 (0.002)
    PachListen:Musician            0.448 (0.518)
    Constant                      4.335*** (0.531)
    ------------------------------------------------
    Observations                      2,433
    Log Likelihood                -4,866.831
    Akaike Inf. Crit.              9,781.662
    Bayesian Inf. Crit.            9,920.787
    ================================================
    Note:                  *p<0.1; **p<0.05; ***p<0.01
```

Average effects of these harmony levels relative to the referent group: I-V-VI

Effect of Harmony on the random effects

QUESTION 4

Predicting Popular Ratings

4a)

Influence of main factors

i) Compare OLS to HLM with a random intercept (Model 2), and HLM with 3 random effects (Model 3). Note that the influence of the main factors changes across models – The role of Voice is picked up once random effects are included.

	Dependent variable:		
	Popular Ratings		
	OLS	linear mixed-effects	
	(1)	(2)	(3)
Inst-Piano	-0.952*** (0.111)	-0.945*** (0.092)	-0.949*** (0.250)
Inst-String	-2.612*** (0.110)	-2.607*** (0.092)	-2.606*** (0.250)
Voice-3	0.169 (0.111)	0.170* (0.092)	0.164** (0.083)
Voice-5	0.163 (0.111)	0.165* (0.092)	0.162** (0.083)
H:I-IV-V	0.268** (0.128)	0.272** (0.106)	0.272* (0.140)
H: I-V-IV	0.244* (0.128)	0.247** (0.106)	0.246* (0.140)
H: IV-I-V	0.083 (0.128)	0.086 (0.106)	0.086 (0.140)
Constant	6.314*** (0.128)	6.305*** (0.183)	6.308*** (0.206)
Observations	2,493	2,493	2,493
R2	0.190		
Adjusted R2	0.188		
Log Likelihood		-5,205.149	-5,027.484
Akaike Inf. Crit.		10,430.300	10,078.970
Bayesian Inf. Crit.		10,488.510	10,148.820
Residual Std. Error	2.257 (df = 2485)		
F Statistic	83.321*** (df = 7; 2485)		
Note:			*p<0.1; **p<0.05; ***p<0.01

ii) Select a model: Based on the substantial drop in AIC and BIC seen in model 3, I choose that model.

iii) Interpret the influence of the main factors (based on Model 3 in the above table):

a. Instrument: Guitar is associated with significantly higher Popular ratings than piano and string
b. Voice: Contrary Motion is associated with significantly lower Popular ratings than Parallel 3rds, or Parallel 5ths
c. Harmony: The referent group is associated with significantly lower Popular ratings than I-IV-V and I-V-IV, but is not associated with ratings significantly different from ratings when the harmony is IV-I-V

4b)

Covariates and interpretation

I started with the following covariates I expected might be related to popular ratings: OMSI, PachListen, ConsInstr, ConsNotes, CollegeMusic.

I then manually removed the smallest, non-significant effect one at a time until the remaining covariates were significant (essentially a manual backwards stepwise approach). The only significant covariate was Selfdeclare: the more participants identify as a musician, the higher their Popular ratings.

```
> display(lmer.Popular.3RandInt.Cov)
lmer(formula = Popular ~ Instrument + Voice + Harmony + Selfdeclare +
    (1 | Subject:Instrument) + (1 | Subject:Voice) + (1 | Subject:Harmony),
    data = Ratings, REML = F)
                coef.est coef.se
(Intercept)      5.66     0.30
Instrumentpiano -0.95     0.25
Instrumentstring -2.61    0.24
Voicepar3rd      0.16     0.08
Voicepar5th      0.16     0.08
HarmonyI-IV-V    0.27     0.14
HarmonyI-V-IV    0.25     0.14
HarmonyIV-I-V    0.09     0.14
Selfdeclare      0.27     0.09

Error terms:
 Groups             Name        Std.Dev.
 Subject:Harmony    (Intercept) 0.63
 Subject:Voice      (Intercept) 0.17
 Subject:Instrument (Intercept) 1.37
 Residual                       1.58
```

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4c) (next page)

4c)

Interactions

For this, I remove Selfdeclare from the model and instead use the dichotomized version of the variable.

	Dependent variable:
	Popular
Instrumentpiano	-1.005*** (0.284)
Instrumentstring	-2.701*** (0.283)
Voicepar3rd	0.110 (0.093)
Voicepar5th	0.142 (0.093)
HarmonyI-IV-V	0.026 (0.149)
HarmonyI-V-IV	-0.049 (0.149)
HarmonyIV-I-V	-0.125 (0.149)
Musician	-0.923* (0.498)
Instrumentpiano:Musician	0.263 (0.613)
Instrumentstring:Musician	0.446 (0.612)
Voicepar3rd:Musician	0.252 (0.200)
Voicepar5th:Musician	0.096 (0.200)
HarmonyI-IV-V:Musician	1.144*** (0.323)
HarmonyI-V-IV:Musician	1.377*** (0.323)
HarmonyIV-I-V:Musician	0.982*** (0.323)
Constant	6.506*** (0.230)
Observations	2,493
Log Likelihood	-5,015.706
Akaike Inf. Crit.	10,071.410
Bayesian Inf. Crit.	10,187.840
Note:	*p<0.1; **p<0.05; ***p<0.01

Interpretations:

- Instrument: On average, guitar continues to appear to be associated with significantly higher Popular ratings than string instruments (B_{string} = -2.7, $p < .001$) or the piano (B_{piano} = -1.0, $p < .001$). Identifying as a musician does not significantly affect the differences in ratings of guitar versus string or guitar versus piano.

- Voice: When including an effect of musician on the random intercept of voice (i.e., the interaction term of Voice*Musician), the effect of voice is washed out and not significant. There is no average effect of Parallel 3rds, or Parallel 5ths, compared with Contrary Motion, nor does whether or not a participant identifies as a musician influence the difference in ratings across those levels.

- Harmony: On average, there is not a significant difference in the ratings of the harmony referent category (I-V-VI) and the other three categories. However, when a participant identifies as a musician, there is a difference such that the referent category (I-V-VI) is rated as less popular than the other three categories ($B_{I\text{-}IV\text{-}V*Musician}$ = 1.14, $p < .001$; $B_{I\text{-}V\text{-}IV*Musician}$ = 1.38, $p < .001$; $B_{IV\text{-}I\text{-}V*Musician}$ = 0.98, $p < .001$).

Random effects from the above model:

```
Random effects:
 Groups             Name        Variance Std.Dev.
 Subject:Harmony    (Intercept) 0.33276  0.5769
 Subject:Voice      (Intercept) 0.02624  0.1620
 Subject:Instrument (Intercept) 2.00056  1.4144
 Residual                       2.48920  1.5777
```

QUESTION 5

10

RESULTS

Unsurprisingly (!), a very nice summary.

Classical Ratings

Results are based on the model in Question 3; regression results are shown in tables in Question 3. Starting with the average effects of the manipulated features of the musical stimuli, I find that, on average, stimuli with a piano sound and a string sound receive higher classical ratings than stimuli with a guitar sound (B = 1.427, $p < .001$; B = 3.329, $p < .001$; respectively). This is, as predicted, the strongest effect on classical ratings among the predictors included. Additionally, I find that, on average, stimuli with vocal leading that is Parallel 3rds and Parallel 5ths receive lower classical ratings than if the vocal leading is Contrary Motion (B = -0.383, $p < .001$; B = -0.349, $p < .001$; respectively). That is, as predicted, vocal leading affects classical ratings, such that Contrary Motion is perceived as more classical than the other forms. Lastly, I find that, on average, stimuli with harmonies of the form I-IV-V, I-V-IV, and IV-I-V receive lower classical ratings than that of the form I-V-VI (B = -0.469, $p < .001$; B = -0.525, $p < .001$; B = -0.501, $p < .001$; respectively). That is, the beginning progression for Pachelbel's Canon D is perceived as more classical than the three other progressions.

Second, I explore the random effects by examining the variance components in the estimated model. Of note is the random effect for instrument. This captures 43% (2.14/2.14 2.40+.36+.02) of the variance. It seems there is a substantial amount of variance in how individuals respond to the instrument. The random effects for harmony and voice are not as substantial, indicating there may be little to no individual difference in responses to harmony and voice.

Next, I explore the role of self-identification as a musician. This dichotomous variable does not have an average effect on classical ratings. However, it does significantly impact the random effect of harmony (see question 3).

Lastly, I find neither OMSI scores nor familiarity with Pachelbel's Canon in D affect classical ratings.

Popular Ratings

Results are based on the final model in Question 4; results are shown in Tables at the end of Question 4. As seen in the description of result for Question 4, instrument and harmony appear to impact popular ratings (in part contingent on whether or not a person identifies as a musician), whereas voice does not appear to impact popular ratings. (See Question 4 for detailed description of the results.)

In line with the findings for predicting classical ratings, I also find that the instrument variance component is comparable to the error variance component, suggesting substantial variance in the person-to-person responses to instrument. This is less the case for the harmony variance component, and even less so for the voice component, suggesting little to no differentiation across people in how they responded to harmony and voice.