36-763 HW 5

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

2 a 9/9
b 6/9
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3 8/9

4 a 6/9
b 7/9
c 9/9

5 10/10

Total 89/100

Problem 1

a)

First, we must deal with the large amount of NA's in the data. Simply removing them would leave us with approximately 1/10th of the original data, which is too much reduction. We made the following decisions:

-Remove observations with 5 or more NA's

Good to do all of this exploration and pre-processing!

-Remove observations with NA response variables

-Excluded instr.minus.notes since it is a linear combination of two other covariates

-Changed knowRob and knowAxis to 0 if 0 or NA,1 otherwise since all non-NA observations were either 0 or 5.

should this be "5, otherwise"?

-Changed NA's in ConsNotes, PachListen, 1990s2000s, 1990s2000sminus1960s1970s, X1stInstr, X2ndInstr to zeros

why?

-Created new variable - 1960s1970s to use instead of the 1990s2000sminus1960s1970s variable. This will not change the resulting model at all, but it is more interpretable to use this variable than a 'difference' variable

-Changed PianoPlay and GuitarPlay to 1 if >0 and 0 otherwise

We then built a simple linear model incorporating all available data and obtained the following model:

	Estimate	Std. Error	t value	Pr(>|t|)
HarmonyI-IV-V	4.1884	0.3383	12.3804	0.0000
HarmonyI-V-IV	4.1756	0.3383	12.3423	0.0000
HarmonyI-V-VI	5.0111	0.3383	14.8135	0.0000
HarmonyIV-I-V	4.2484	0.3383	12.5578	0.0000
Voicepar3rd	-0.3889	0.1112	-3.4971	0.0005
Voicepar5th	-0.3531	0.1112	-3.1759	0.0015
Instrumentpiano	1.4263	0.1114	12.8043	0.0000
Instrumentstring	3.2028	0.1108	28.8938	0.0000
Selfdeclare	-0.8584	0.0817	-10.5084	0.0000
OMSI	0.0016	0.0004	4.1766	0.0000
X16.minus.17	-0.0785	0.0184	-4.2685	0.0000
ConsInstr	0.1555	0.0408	3.8141	0.0001
ConsNotes	-0.0389	0.0340	-1.1438	0.2528
PachListen	0.1172	0.0469	2.5006	0.0125
ClsListen	0.2511	0.0439	5.7177	0.0000
KnowRob	-0.0579	0.1571	-0.3686	0.7125
KnowAxis	0.0738	0.1473	0.5010	0.6165
X1990s2000s	0.0444	0.0404	1.0983	0.2722
X1960s1970s	-0.1564	0.0392	-3.9880	0.0001
CollegeMusic	0.0012	0.1416	0.0087	0.9931
NoClass	-0.0213	0.0385	-0.5531	0.5802
APTheory	0.2936	0.1397	2.1016	0.0357
Composing	0.0784	0.0523	1.4974	0.1344

	Estimate	Std. Error	t value	Pr(>|t|)
PianoPlay	0.3974	0.1278	3.1092	0.0019
GuitarPlay	0.9656	0.1723	5.6044	0.0000
X1stInstr	0.1854	0.0351	5.2807	0.0000
X2ndInstr	-0.2877	0.0897	-3.2086	0.0014

We see that, all factors associated with 'Harmony' are considered significant, all of the 'Voice' and all 'Instrument' factors are determined to be significant.

8 relative to what baseline?

All of the Harmonies present in the dataset increase the 'Classical' rating by roughly 4-5 points, while Harmony I-V-VI increases it the most, by 5.01 points. The presence of voice par 3rd or voice par 5th decreases the classical rating by roughly -0.4. A piano presence increases the 'classical' rating by 1.4 and a string presence increases the 'classical' rating by 3.2.

b)

Let $X[j]$ represent the covariates describing the j^{th} subject in the study (Selfdeclare, OMSI, ..., X1stInstr, X2ndInstr). A repeated measures model can then be written as

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

since H, V, and I are factors, it doesn't work to simply multiply. They need to be indices for the alphas

9 what is X_j?

$$\alpha_j = \beta_0 + \beta X_j + \eta_j, \eta_j \sim N(0, \tau^2)$$

0

Using the AIC as a test, the random intercept should be included in the model. The AIC of the model in (a) is 1.026859×10^4 while the AIC of the repeated measures model is 9874.0694371 , which is a large enough decrease to warrant the inclusion of the random term. If we look at the BIC, we see the same trend. The BIC of the model in (a) is 1.0429631×10^4 while the BIC of the repeated measures model is 1.0040862×10^4 , which is also a significant decrease.

Although we see a slight change in many of the coefficients for Harmony, Voice, and Instrument; there is not enough of a change to change the interpretation, and all terms remain significant.

c)

Using the same notation as in part (b), this model can be written as:

$$y_i = \alpha_{1j[i]} \cdot Harmony_i + \alpha_{2j[i]} \cdot Voice_i + \alpha_{3j[i]} \cdot Instrument_i + \epsilon_i, \epsilon_i \sim N(0, \sigma^2)$$

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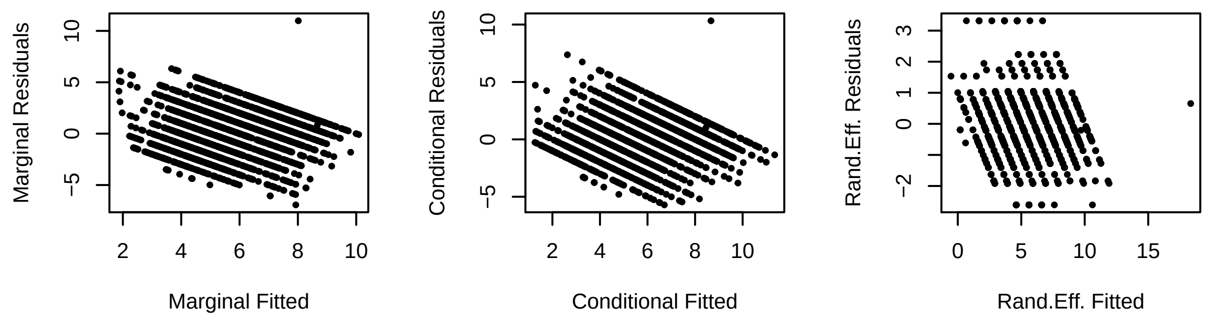
H, V, and I are factor variables, so multiplying doesn't work. Need to use them as additional indices for the alphas.

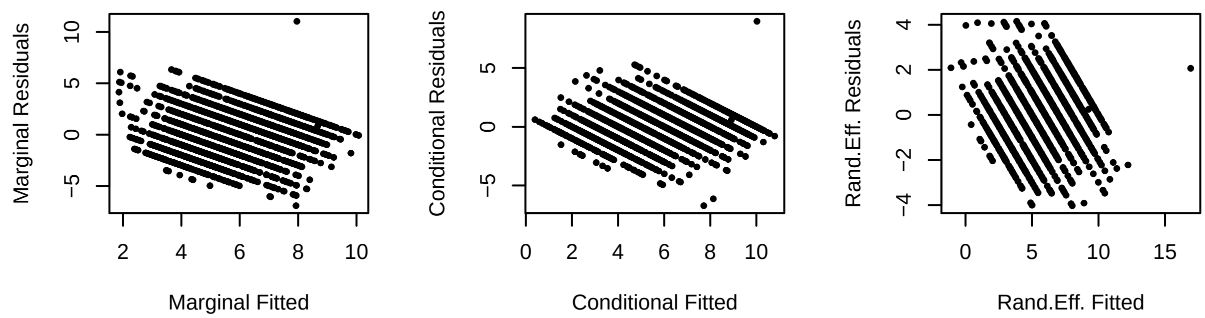
what are the x's?

$$\alpha_{1j} = \beta_{1j} + \beta X_j + \eta_{1j}, \eta_{1j} \sim N(0, \tau_1^2)$$

$$\alpha_{2j} = \beta_{2j} + \beta X_j + \eta_{2j}, \eta_{2j} \sim N(0, \tau_2^2)$$

$$\alpha_{3j} = \beta_{3j} + \beta X_j + \eta_{3j}, \eta_{3j} \sim N(0, \tau_3^2)$$





Using the AIC as a test, the random intercept should be used instead of the model with the three random terms. The AIC of the model in (b) is 9874.0694371 while the AIC of the larger model is 9445.6545557 , which actually increased. This suggests that the number of terms that was added using the three random terms for Harmony, Instrument, and Voice, did not improve the fit enough to warrant their inclusion. We also do not see a significant change in the shape of the residual plots when including the additional random effects (see above).

looks to me like AIC decreased for the larger model, suggesting we keep the 3 random effects....

In this new model with more terms, however, we see that more of the effects of Harmony, Instrument, and Voice are included in the random effects instead of the fixed effects, and we thus see a change in the coefficients for each.

The estimated residual variance of the model is 2.42, while the estimated variance of the subject:harmony component is 0.473, the subject:voice component is 0.028, and the subject:instrument component is 1.95. Since the subject:harmony and the subject:voice variances are so small relative to the residual variance, this is further evidence that the interaction term is not needed.

Problem 2

a)

I decided to use the model from part (b), moving forward. The model in part (c) adds too much complexity in the random effects to be very interpretable, while the model in (a) is too simplistic and doesn't capture enough of the individual variation. I used a stepwise AIC analysis in both directions to determine the following model is the best fit for the data:

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	Estimate	Std. Error	t value
HarmonyI-IV-V	6.0877	1.8069	3.3692
HarmonyI-V-IV	6.0740	1.8069	3.3615
HarmonyI-V-VI	6.9108	1.8069	3.8246
HarmonyIV-I-V	6.1477	1.8069	3.4024
Voicepar3rd	-0.3900	0.0969	-4.0242
Voicepar5th	-0.3551	0.0969	-3.6653
Instrumentpiano	1.4284	0.0971	14.7058
Instrumentstring	3.2018	0.0966	33.1480
Selfdeclare2	-1.3533	0.7144	-1.8943
Selfdeclare3	-0.7060	0.9251	-0.7632
Selfdeclare4	-1.3863	1.6055	-0.8635
Selfdeclare5	-4.7804	2.4840	-1.9245
Selfdeclare6	-1.7561	2.9889	-0.5876
OMSI	-0.0012	0.0026	-0.4670
X16.minus.17	-0.0936	0.0725	-1.2910
ConsInstr	0.0339	0.1734	0.1953
PachListen1	-1.1377	2.1522	-0.5286
PachListen2	-2.3872	1.5520	-1.5381
PachListen3	-2.3900	1.5906	-1.5026
PachListen4	-1.4451	2.3122	-0.6250
PachListen5	-0.9116	1.2206	-0.7468
ClsListen1	-0.6607	0.7978	-0.8281
ClsListen3	0.0568	0.8503	0.0668
ClsListen4	3.0567	3.3338	0.9169
ClsListen5	0.1958	1.0504	0.1864
X1960s1970s1	-1.5551	1.2061	-1.2893
X1960s1970s2	-0.0881	0.5481	-0.1607
X1960s1970s3	-1.0717	0.7996	-1.3403
X1960s1970s4	-0.3994	1.2768	-0.3128
X1960s1970s5	0.0398	0.8131	0.0489
APTheory	0.4069	0.6048	0.6727
PianoPlay	0.5129	0.6120	0.8380
GuitarPlay	1.0955	0.7624	1.4369
X1stInstr1	1.5024	0.6855	2.1915
X1stInstr2	2.7688	2.0745	1.3347
X1stInstr3	0.1762	1.8716	0.0941
X1stInstr4	1.2022	0.6735	1.7851
X1stInstr5	2.0351	1.4558	1.3979
X2ndInstr1	-0.7766	0.9190	-0.8451
X2ndInstr2	-1.8541	1.9521	-0.9498
X2ndInstr3	-1.5176	2.3989	-0.6326
X2ndInstr4	-2.6060	2.1289	-1.2241

b)

To try to find a good balance between model complexity and the fit of the model, we built a model with interactions of subject with Instrument, Voice, and Harmony, and a model with an interaction with subject on each of them and obtained the results below:

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
final.mod	44	9818.296	10071.361	-4865.148	9730.296	NA	NA	NA

not totally clear to me what models these are...

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
comb.mod.instr	44	9470.830	9723.895	-4691.415	9382.830	347.4660	0	0
comb.mod.voice	44	9945.354	10198.419	-4928.677	9857.354	0.0000	0	1
comb.mod.harmony	44	9854.911	10107.976	-4883.456	9766.911	90.4427	0	0
comb.mod.2	46	9373.879	9638.447	-4640.940	9281.879	485.0320	2	0

We conclude that the model which includes a random effect for each instrument:subject combinations improves the fit significantly over the model with no random term, and comes close to performing as well as the model with three random terms. We therefore proceed with the model described below:

which (if any) random effects are included in this model?

	Estimate	Std. Error	t value
HarmonyI-IV-V	6.1006	1.1635	5.2432
HarmonyI-V-IV	6.0866	1.1636	5.2310
HarmonyI-V-VI	6.9187	1.1636	5.9460
HarmonyIV-I-V	6.1607	1.1635	5.2948
Voicepar3rd	-0.3864	0.0850	-4.5470
Voicepar5th	-0.3502	0.0850	-4.1215
Instrumentpiano	1.4198	0.2628	5.4017
Instrumentstring	3.2053	0.2626	12.2079
Selfdeclare2	-1.3613	0.4557	-2.9874
Selfdeclare3	-0.7255	0.5901	-1.2294
Selfdeclare4	-1.3984	1.0241	-1.3656
Selfdeclare5	-4.7697	1.5844	-3.0104
Selfdeclare6	-1.7619	1.9067	-0.9241
OMSI	-0.0012	0.0016	-0.7149
X16.minus.17	-0.0929	0.0462	-2.0099
ConsInstr	0.0321	0.1107	0.2894
PachListen1	-1.1492	1.3730	-0.8370
PachListen2	-2.3744	0.9900	-2.3985
PachListen3	-2.3828	1.0145	-2.3487
PachListen4	-1.4636	1.4751	-0.9922
PachListen5	-0.9048	0.7785	-1.1621
ClsListen1	-0.6673	0.5090	-1.3110
ClsListen3	0.0553	0.5424	0.1020
ClsListen4	3.0077	2.1266	1.4143
ClsListen5	0.1949	0.6702	0.2908
X1960s1970s1	-1.5662	0.7696	-2.0351
X1960s1970s2	-0.1027	0.3498	-0.2937
X1960s1970s3	-1.0585	0.5101	-2.0750
X1960s1970s4	-0.3903	0.8145	-0.4791
X1960s1970s5	0.0183	0.5190	0.0352
APTheory	0.3804	0.3865	0.9842
PianoPlay	0.5298	0.3908	1.3558
GuitarPlay	1.0812	0.4864	2.2230
X1stInstr1	1.5088	0.4374	3.4498
X1stInstr2	2.7365	1.3234	2.0678
X1stInstr3	0.2275	1.1943	0.1905
X1stInstr4	1.1892	0.4299	2.7664
X1stInstr5	2.0223	0.9289	2.1772
X2ndInstr1	-0.8352	0.5878	-1.4210
X2ndInstr2	-1.8355	1.2455	-1.4736
X2ndInstr3	-1.5441	1.5310	-1.0085

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	Estimate	Std. Error	t value
X2ndInstr4	-2.5860	1.3579	-1.9043

c)

again, relative to what baseline?

Holding all other variables held constant, we see an increase in music ratings by 6-7 for all 'harmony' variables; and a small decrease (roughly -.38) for each 'voice' variable. The base 'Instrument' variable has the most variation on classical music ratings, with 'guitar' being the base; 'piano' increasing ratings by about 1.5, and 'string' increasing classical ratings by 3.2.

8

If the subjects described themselves as musicians, we see a decrease in classical ratings as compared to self-described non-musicians. OMSI, X16.minus.17, PachListen, and 1960s1970s variables all result in a slight decrease in classical ratings, while ClsListen, APTheory, PianoPlay, GuitarPlay, and first instrument variables will increase the classical music ratings.

Problem 3

We decided to split the Self Declare variable into the set of subjects who reported a 1 or 2, and subjects who reported a 3 or above. This means that we have 1367 self-declared non-musicians, and 958 self-declared musicians. We created an interaction term between this new 'musician' variable and all of the other variables that were originally included in the model. We then used the automated fitLMER.fnc function with the BIC evluation metric to backward-select fixed effects and re-evaluate the random effects terms. This produces the following model fixed effects, as well as the same random effects as before:

There aren't that many musicians in the data set. What do you really mean here?

which random effects?

8

	Estimate	Std. Error	t value
HarmonyI-IV-V	4.3303	0.2289	18.9156
HarmonyI-V-IV	4.2842	0.2289	18.7145
HarmonyI-V-VI	4.8319	0.2290	21.1031
HarmonyIV-I-V	4.3127	0.2289	18.8388
Voicepar3rd	-0.3863	0.0841	-4.5934
Voicepar5th	-0.3514	0.0841	-4.1803
Instrumentpiano	1.4174	0.2723	5.2049
Instrumentstring	3.2056	0.2721	11.7824
X16.minus.17	-0.0713	0.0403	-1.7687
GuitarPlay	1.2951	0.2979	4.3480
musicianTRUE	0.1828	0.4613	0.3964
HarmonyI-V-IV:musicianTRUE	0.1456	0.2366	0.6152
HarmonyI-V-VI:musicianTRUE	1.4767	0.2367	6.2396
HarmonyIV-I-V:musicianTRUE	0.3613	0.2362	1.5295
X16.minus.17:musicianTRUE	-0.5782	0.1512	-3.8242

so including the dichotomized 'musician' variable and interactions with the other variables has led to a smaller model. The interactions terms included are all Harmony variables as well as the X16minus17 variable, which is a measure of a listener's ability to distinguish classical from pop music. This suggests that the way different Harmonies are the X16minus17 variables impact the classical music ratings changes based on whether or not the person is a musician; while the other variables have the same effect regardless of whether or not the person is a self-described musician.

Problem 4

a)

We first used a stepwise AIC procedure to determine the fixed effects in the model. We then proceeded with building five models with random effects - one with a random effect for each subject, one with a random effect for each subject:instrument combination, one with a random effect for each subject:voice combination, one for each subject:harmony combination, and one containing all three random effect combinations. We obtain the following anova results:

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
pop.repeated	56	9694.733	10016.816	-4791.367	9582.733	NA	NA	NA
pop.instr	56	9413.616	9735.698	-4650.808	9301.616	281.11777	0	0
pop.voice	56	9709.474	10031.556	-4798.737	9597.474	0.00000	0	1
pop.harmony	56	9663.040	9985.123	-4775.520	9551.040	46.43336	0	0
pop.all	58	9347.249	9680.835	-4615.625	9231.249	319.79103	2	0

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pop.all has lowest aic/bic; why not choose it??

to provide both good fit and interpretability, we decide to proceed with the model containing only a random effect for each subject:instrument combination (model pop.instr in the anova table).

We see that each of the 'harmony' variables increases the pop music ratings by roughly 1 point, each 'voice' variable increases the pop music ratings by less than a half a point, and 'piano' and 'string' decreases the pop music ratings by 1-2, while a 'guitar' is the base factor.

The variance of the subject:instrument random effect is 1.16, as compared to the overal residual variance of 2.832.

b)

The covariates included in the model are summarized in the table below. Each of the interpretations are similar to the interpretations for the classical model (with the different numbers), and we exclude a similar interpretation for reasons of space and readability.

	Estimate	Std. Error	t value
HarmonyI-IV-V	1.0204	2.1226	0.4808
HarmonyI-V-IV	0.9860	2.1227	0.4645
HarmonyI-V-VI	0.7146	2.1227	0.3366
HarmonyIV-I-V	0.8126	2.1226	0.3828
Voicepar3rd	0.1825	0.0855	2.1341
Voicepar5th	0.1615	0.0855	1.8891
Instrumentpiano	-1.0057	0.2076	-4.8441
Instrumentstring	-2.7258	0.2073	-13.1499
Selfdeclare2	1.5397	0.4365	3.5276
Selfdeclare3	-0.2136	0.5802	-0.3681
Selfdeclare4	-4.4472	1.2124	-3.6681
Selfdeclare5	-7.3163	2.4577	-2.9768
Selfdeclare6	-11.5748	2.9082	-3.9800
NoClass1	-0.7182	0.4039	-1.7783
NoClass2	-6.9353	2.6970	-2.5715
NoClass3	1.6470	1.1035	1.4925
NoClass4	0.9349	1.1971	0.7809
NoClass8	4.2310	1.4857	2.8478

was this the result of some variable selection procedure?

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	Estimate	Std. Error	t value
PachListen1	7.6093	1.8356	4.1454
PachListen2	6.4128	1.5504	4.1362
PachListen3	3.9507	1.6318	2.4210
PachListen4	3.8447	2.0586	1.8676
PachListen5	4.7090	1.4720	3.1991
X1stInstr1	-2.7882	0.3952	-7.0553
X1stInstr2	6.7898	2.4671	2.7521
X1stInstr3	-1.4400	1.1046	-1.3036
X1stInstr4	-1.0220	0.4512	-2.2651
X1stInstr5	0.2573	1.1721	0.2195
KnowRob	0.7828	0.4453	1.7581
X2ndInstr1	1.3064	0.7602	1.7185
X2ndInstr2	5.5160	2.8637	1.9262
X2ndInstr3	-3.5496	1.6077	-2.2078
X2ndInstr4	2.3862	1.4146	1.6868
X1960s1970s1	0.7026	0.6468	1.0862
X1960s1970s2	0.0583	0.3818	0.1526
X1960s1970s3	1.1467	0.6440	1.7806
X1960s1970s4	-2.3100	1.0428	-2.2152
X1960s1970s5	0.3493	0.5600	0.6238
OMSI	0.0098	0.0022	4.4861
X1990s2000s2	0.6481	1.0944	0.5922
X1990s2000s3	-2.2479	0.7439	-3.0219
X1990s2000s4	0.3154	0.9835	0.3207
X1990s2000s5	-1.4659	0.7004	-2.0930
Composing1	-0.7186	0.6682	-1.0755
Composing2	-0.7854	0.5791	-1.3562
Composing3	-2.4443	1.0066	-2.4283
Composing4	1.1452	0.7869	1.4554
GuitarPlay	-0.5681	0.5364	-1.0590
ConsInstr	0.3149	0.1371	2.2969
X16.minus.17	0.1127	0.0505	2.2329
ClsListen1	0.5444	0.4038	1.3482
ClsListen3	0.4780	0.4531	1.0548
ClsListen5	0.1616	0.6606	0.2446
CollegeMusic	-0.5188	0.6075	-0.8539

c)

Here, we repeated the same process as in problem 3, using the ‘popular music’ ratings instead of the ‘classical music’ ratings and so the final model that we obtain is:

	Estimate	Std. Error	t value
HarmonyI-IV-V	6.6882	0.2205	30.3275
HarmonyI-V-IV	6.6116	0.2205	29.9802
HarmonyI-V-VI	6.6154	0.2206	29.9893
HarmonyIV-I-V	6.5110	0.2205	29.5238
Instrumentpiano	-1.0100	0.2843	-3.5521
Instrumentstring	-2.7266	0.2841	-9.5979
musicianTRUE	0.5674	0.3178	1.7851
HarmonyI-V-IV:musicianTRUE	0.1998	0.2391	0.8356

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	Estimate	Std. Error	t value
HarmonyI-V-VI:musicianTRUE	-1.0863	0.2391	-4.5430
HarmonyIV-I-V:musicianTRUE	-0.1428	0.2386	-0.5982

which suggests that Harmony and Instrument are the variables that have the biggest impact on popular music ratings, with all of the Harmonies increasing the rating by roughly 6.5, and the piano and string instrument decreasing the ratings. We also see that self-described musicians rate pop songs with Harmonies I-V-IV, I-V-VI, and IV-I-V lower than self-described non-musicians.

Problem 5

Throughout this summary, we refer to the final models obtained in question 3 for classical music ratings, and question 4c for popular music ratings. For both classical and popular music ratings, we have found that the variable with the largest effect is Harmony. Each of the four harmonies (I-IV-V, I-V-IV, I-V-VI, IV-I-V)
10 increased the rating in popular music by at least six points, and increased the rating for classical music by at least four. This suggests that the presence of a specific harmony in a given genre is not a large factor in the rating, but the difference in effect between the classical and the popular ratings is significant. In classical music, the increase is likely smaller due to the effects of other variables having a larger contribution. There were less overall variables included in the popular music rating model, which would lead to a larger effect of harmonies on the rating.

Instrument was found to be the second most influential variable included in each of the models. For classical music, the presence of a piano instead of a guitar increases the rating by 1.42, while the presence of a string instrument instead of a guitar increases the rating by 3.2. This suggests that people are more likely to rate classical music highest if there is a string instrument, and lowest if there is only a guitar presence. In addition, both of the models included a variance component for each subject:instrument combination. That is, individuals rated different instruments differently enough that we could justify using a random effect in each case. Although this is harder to quantify the exact effect, we can comment on the variability of the effect in each model. For popular music, the variance among the different subject:instrument combinations was 2.39, and for classical music, this variance was 2.18. Not only is this value is relatively large for ratings that only take on values in the range 1-10, it is also on the same scale as the overall residual variance (2.73 for classical ratings, 2.79 for popular ratings). This suggests that there is a large amount of variability among individuals in the way they perceive the effect of instruments on their final ratings.

We found 'voice' to be the least influential of the three main variables in each of the models. In our final trimmed model found for popular music ratings, the voice variables were excluded entirely. Before pruning, however, the 3rd voice increased the rating by .18 compared to the 'contrary' voice, while the 5th voice increased the rating by .16 compared to the 'contrary' voice. In the classical music ratings model, the presence of 3rd or 5th voice decreased the ratings by roughly .35 as compared to the 'contrary' voice. We then conclude that 'voice' has a significantly different effect on the ratings between classical and popular music; and is therefore one of the main ways to distinguish a difference between the two.

To reiterate, this is not a standard repeated measures model, as we did not simply include a different intercept term for each individual. Since we included a separate intercept for each combination of subject and instrument, we could think of it as a repeated measures model for each of those combinations. This allows for each subject to have a different 'base rating' for each song based on which instrument is present.

In the final models for each genre of music, in which we have removed as many extraneous variables as possible, we see that for the 'classical' music ratings, the other variables of interest are 'X16minus17', 'GuitarPlay', and the dichotomous 'musician'. We found that those subjects who scored higher on the 'X16minus17' measure by one point would decrease their rating of classical music slightly, while those who played the guitar would increase the ratings by 1.3, and those who identified as musicians would increase the rating by .18. Another interesting point is that the dichotomous musician variables interacts with each of the harmony ratings - when a person self-identifies as a musician, they rate the 'classical' songs differently based on harmony than those who do not self-identify as musicians. These musicians will rate the harmony I-V-VI roughly 1.5 points higher than non-musicians, and will rate the other harmonies slightly ($<.5$) higher.

For popular music, the only other variable of interest was the dichotomous musician variable. These self-identified musicians would rate popular songs .5 points higher than non-musicians. We see a similar interaction between musicians and harmonies as for the classical music ratings model, but in an opposite way. Musicians would rate songs with a presence of Harmony I-V-VI one point lower than non-musicians, which is the opposite trend as the one found for classical music.

Overall, we have found that Harmony and Instrument are the most important variables when it comes to predicting song ratings for both classical and popular music. We have found that individuals react to the presence of different instruments differently, while the overall trends for both 'voice' and 'harmony' are more uniform across different people. Finally, we have found that the other variable that is influential for both classical and popular music is whether or not a person identifies as a musician; and that this self-identification has a significant change on how people rate songs with the presence of different harmonies.