Which Factors Influence How People Perceive Classical and Popular Music

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12/8/2019

Abstract:

This study analyzes various factors to understand what influences subjects to rate music as classical or popular. Forward and backward selection of random effects and fixed effects are used to select significant factors for the model. ANOVA and reduction in AIC or BIC are used for model comparison. It was found that instrument had the largest influence on rating. In addition, harmonic motion I-V-VI had a higher influence on classical ratings than other harmonies, and it had significant interactions with non-musicians and those that knew Paravonian's Pachelbel rant. Overall, it seems that the factors that caused high ratings for classical music were the factors that also caused low ratings for popular music, with slight variations of other factors for popular and classical music.

Introduction:

Music is very subjective, and what may be considered as classical or popular music for one person may vary from another. Understanding the leading factors of music classification may interest artists in understanding how their music will be adopted by the public. In 2012, Ivan Jimenez, a composer and musicologist, and Vincent Rossi, a student at the University of Pittsburgh collected data to measure the influence of instrument, harmonic motion, and voice on a listener's identification of music as classical and/or popular music. The levels for each factor are as follows:

- Instrument: String Quartet, Piano, and Electric Guitar
- Harmonic Motion: I-V-VI, I-VI-V, I-V-IV, and IV-I-V
- Voice Leading: Parallel 3rd, Parallel 5th, and Contrary Motion

The researchers hypothesized that instrument should have the largest influence on rating, voice leading contrary motion would be frequently rated as classical, and harmonic motion I-V-VI should have a high classical rating because it is the beginning of the famous Pachelbel's Canon in D and popular comedy bits have been made about (Axis of Awesome & Rob Paravonian's Pachelbel rant). In addition, music classification may vary by whether someone considers themselves as a musician or not.

In this analysis, Jimenez and Rossi's research is continued in attempt to understand the main influencers of classical and popular ratings. The following research questions are addressed:

- Which experimental factor, or combination of factors, has the strongest influence on ratings?
    - Does instrument have the strongest influence among the three main factors?

- Does harmonic motion I-V-VI have the strongest association with classical ratings compared to other harmonic motion levels, and does familiarity with one or both Pachelbel comedy bits (mentioned above) influence this in anyway?
  - Does contrary motion have the strongest association with classical ratings compared to other voice leading levels?
- What are the differences in the way musicians and non-musicians identify classical music?
- What are the differences in the main influencers of popular and classical ratings?

Methods:

Data:

In the study, 70 subjects from the population of undergraduates at the University of Pittsburgh were presented with 36 musical stimuli. The 36 stimuli were chosen from crossing the factors of instrument, harmonic motion, and voice. They rated the musical stimuli on a scale of 1 to 10 as Classical and/or Popular. They were told to treat the scales as independent, meaning high or low ratings for both classical and popular was allowed. In addition to classical ratings, popular ratings, and the three main factors, other variables were considered as well. A summary of the variables in the data set are provided below:

Variable	Variable Description	Levels	Data Type
Subject	Unique subject ID	Subject	Factor
Classical	How classical does the stimulus sound?	NA	Numeric
Popular	How popular does the stimulus sound?	NA	Numeric
OMSI	Score on a test of musical knowledge	NA	Numeric
X16.minus.17	Auxiliary measure of listener's ability to distinguish classical vs popular music	NA	Numeric
Harmony	Harmonic Motion	I-V-vi, I-VI-V, I-V-IV, IV-I-V	Factor
Instrument	Instrument	Electric Guitar, Piano, String Quartet	Factor
Voice	Voice Leading	Contrary Motion, Parallel 3rds, Parallel 5ths	Factor
Selfdeclare	Are you a musician?	1-6, 1 = not at all	Factor
ConsInstr	How much did you concentrate on the instrument while listening?	0-5, 0 = not at all	Factor
ConsNotes	How much did you concentrate on the notes while listening?	0-5, 0 = not at all	Factor
Instr.minus.Notes	Difference between the previous two variables	Various values	Factor
PachListen	How familiar are you with Pachelbel's Canon in D?	0-5, 0 = not at all	Factor
ClsListen	How much do you listen to classical music?	0-5, 0 = not at all	Factor
KnowRob	Have you heard Rob Pravonian's Pachelbel Rant?	0-5, 0 = not at all	Factor
KnowAxis	Have you hear Acis of Evil's Comedy bit on the 4 Pachelbel chords in popular music?	0-5, 0 = not at all	Factor
X1990s2000s	How much do you listen to pop and rock from the 90's andd 2000's?	0-5, 0 = not at all	Factor
X1990s2000s.minus.1960s1970s	Difference between the previous variable and a similar variable referring to 60's and 70's pop and rock	Various values	Factor
CollegeMusic	Have you taken a music class in college?	0 = no, 1 = yes	Factor
APTheory	Did you take AP Music Theory in high school?	0 = no, 1 = yes	Factor
NoClass	How many music classes have you taken?	Various values	Factor
Composing	Have you done any music composing?	0-5, 0 = not at all	Factor
PianoPlay	Do you play piano?	0-5, 0 = not at all	Factor
GuitarPlay	Do you play guitar?	0-5, 0 = not at all	Factor

In preparation for the analysis, there were several missing or invalid values in the data set that were either removed or imputed. Imputation was used as an alternative to data dropping because otherwise 39% of the data would be lost, and some of this data could provide useful insights. In addition, some variables were transformed and/or converted to different data types. Data cleaning steps, a summary of variable adjustment (Table 1), and a description of the final variables used for the analysis (Table 2) can be found in the Appendix.

Methods

To create a model explaining the main influencers of classical and popular ratings, random effects were considered because the ratings are subjective and might have correlation within subjects. First, an ANOVA test was used to see if a random effects model was necessary by comparing a pooled model with Classical or Popular regressed on Instrument, Harmony, and Voice to their respective random intercept model alternatives. Then, a random effects model was fit in three steps for both models: selection of random effects, selection of fixed effects, and selection of random effects again. When fixed effects are picked for the model, three models are considered: Forward Selection, Intuition, and EDA model. ANOVA tests, BIC and AIC reduction analysis, residual analysis, and model interpretability level was used to determine the best model for each rating.

Finally, to answer the remaining research questions (musician and non-musician rating differences in classical music and influence of the comedy bits on classical ratings in relation to Harmony), variables of interest were interacted with fixed effects in the final classical ratings model. These variables are KnowAxis, KnowRob, and a dichotomized version of Selfdeclare so that approximately half of the observations were classified as either "Musician" or "Non-musician". The analysis is broken in two parts: (1) model fitting for classical ratings, and (2) model fitting for popular ratings.

Results:

1 Model fitting for Classical Ratings:

1.1 EDA

Figure 1: Classical Ratings Vs. Three Main Factors

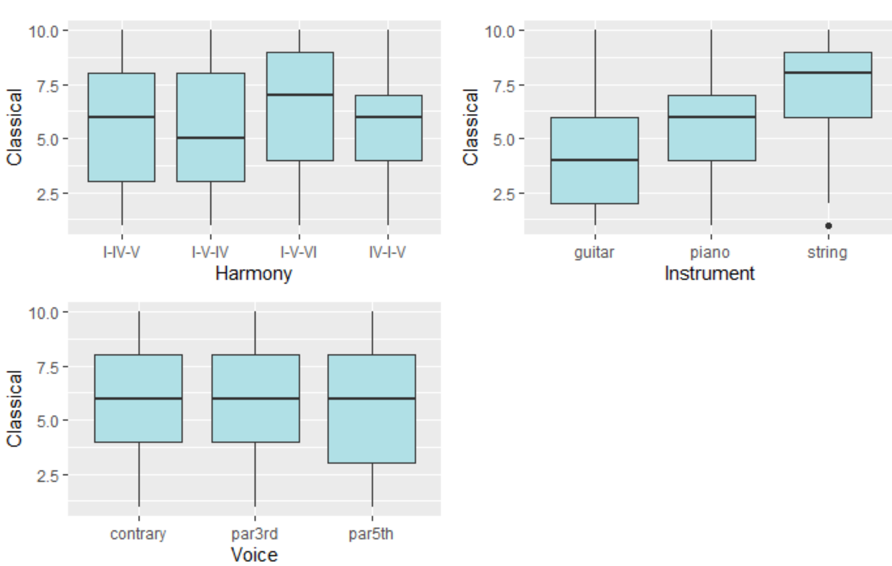

Figure 1 compares classical ratings to the three main experimental factors with no interactions, there does not seem to be a difference in classical rating for the Voice variable (Figure). There also seems to be minimal difference in classical ratings for the Harmony variable, except for I-V-VI having a higher average classical rating. Instrument, as expected, had the highest influence on classical rating. The average classical ratings were lowest for the electric guitar and highest for string quartet. Piano also had a high average, but string quartet still took the lead.

Figure 2: Classical Ratings Vs. Categorical Variables

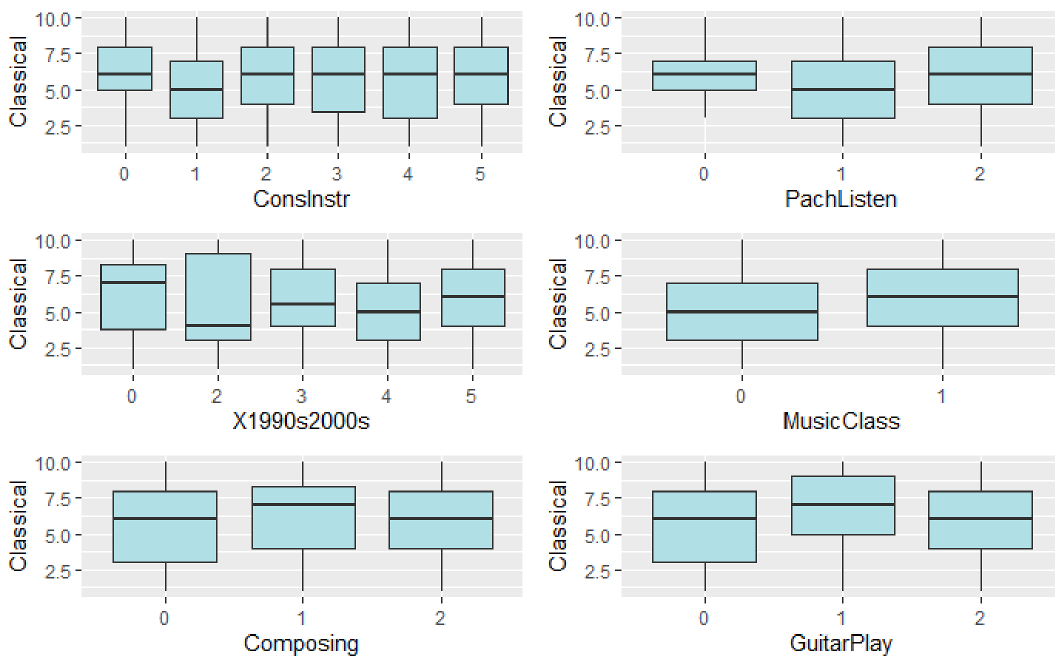

Figure 2 shows classical ratings plotted against categorical variables from the data set. The variables that had a visible difference in average compared to their other levels were ConsInstr, PachListen, X1990s2000s, MusicClass, Composing, and GuitarPlay (Figure). The most notable differences are for those who were familiar with Pachelbel's Canon in D and had taken a music class before; the average rating for classical music was higher for these variables. This makes sense as Pachelbel's Canon in D is very famous in classical music and taking a music class would most likely improve one's ability to identify elements of classical music (depending on the type of class). The other variables had less distinct patterns, but their middle level was often higher than if subjects rated "not at all". These variables are considered as fixed effect candidates for the EDA in the next section.

Finally, the correlation between the numeric variables and classical ratings were computed. X16.minus.17 had a correlation of -0.11 and sqrt_OMSI had a correlation of 0.02. Both correlations are not that strong and will not be considered in the EDA model in the next section.

2.2 Model Fitting & Proposal

An ANOVA test was used to compare a "completely pooled" model where classical ratings are regressed on the three main factors (regardless of subject) to a random intercept version of the same model (allowing for slightly different models for each subject).

Table 1: ANOVA to Test if Random Effects are Necessary for the Classical Ratings Model

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.1	9	10996.59	11048.83	-5489.294	10978.59	NA	NA	NA	NA
lm.2	10	10220.34	10278.39	-5100.170	10200.34	778.2481	1	0	Yes

The ANOVA results in Table 1 indicate that the random effects model is necessary. The coefficient of the random effects model is significantly different from the simpler model without the random effect. In addition, the AIC and BIC of the random effects model is lower than the simpler model. Therefore, the random intercept model is needed.

A summary of the process to obtain the final model can be found in the "Model Building – Classical" section of the Appendix. The final model proposed is as follows:

$$\text{Classical} = \alpha_{0j[i]} + \alpha_{j[i]}^{\text{Instrument}} + \alpha_{j[i]}^{\text{Harmony}} + \text{Voice} + \text{X16.minus.17} + \text{ClsListen} + \text{MusicClass} + \text{Harmony*KnowRob} + \text{Harmony*Musician}$$

Harmony I-V-VI had the highest coefficient for classical ratings compared to the other levels of harmonic motion. Instrument had the highest coefficients compared to all other elements of the model. Contrary motion did not have the highest correlation with classical rating compared to the other levels of Voice. Those who play a little bit of piano, listen to classical music a lot, or have taken a music class before rated higher for classical than for those who did not do either at all. Those that scored higher on the auxiliary measure test (X16.minus.17) rated lower for classical music. Musicians and those that know of Rob Paravonian's Pachelbel rant had higher classical ratings. The output of the summary of the model can be found in Figure 1 in the Appendix.

2 Model fitting for Popular Ratings:

2.1 EDA

Figure 3: Popular Ratings Vs. Three Main Factors

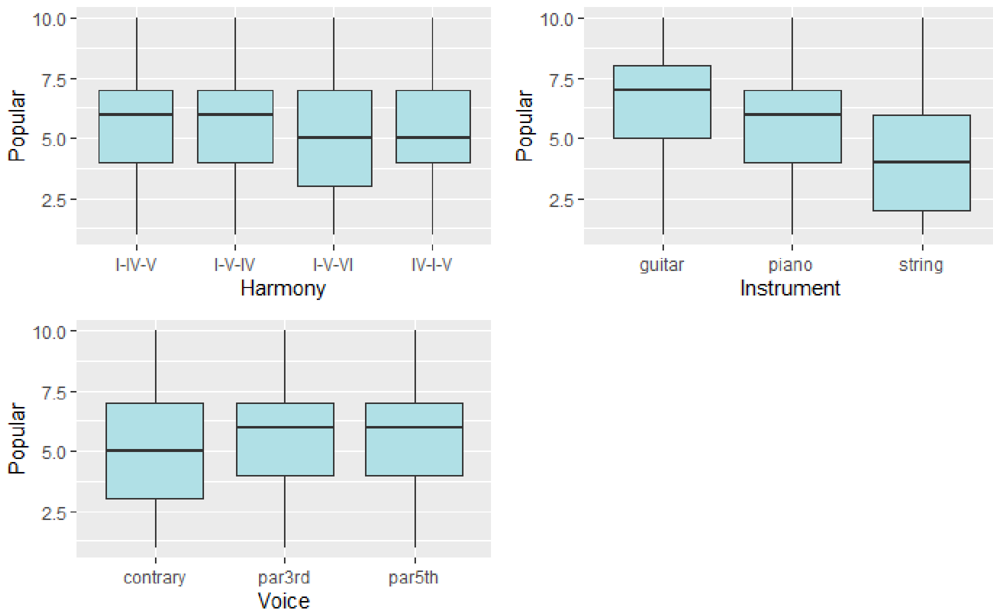

Figure 3 compares popular rating to the three main experimental factors with no interactions, the results were the opposite of classical. There seems to be a slight difference in the Voice variable, with contrary motion having the lowest average than the over levels. Harmony I-V-VI had the lowest average of the three levels as well. Finally, the guitar had the highest average popular rating and string quartet had the lowest rating. Piano had a high average but was still lower than electric guitar. This matches the researches assumptions that instrument has a strong influence on ratings.

Figure 4: Popular Ratings Vs. Categorical Variables

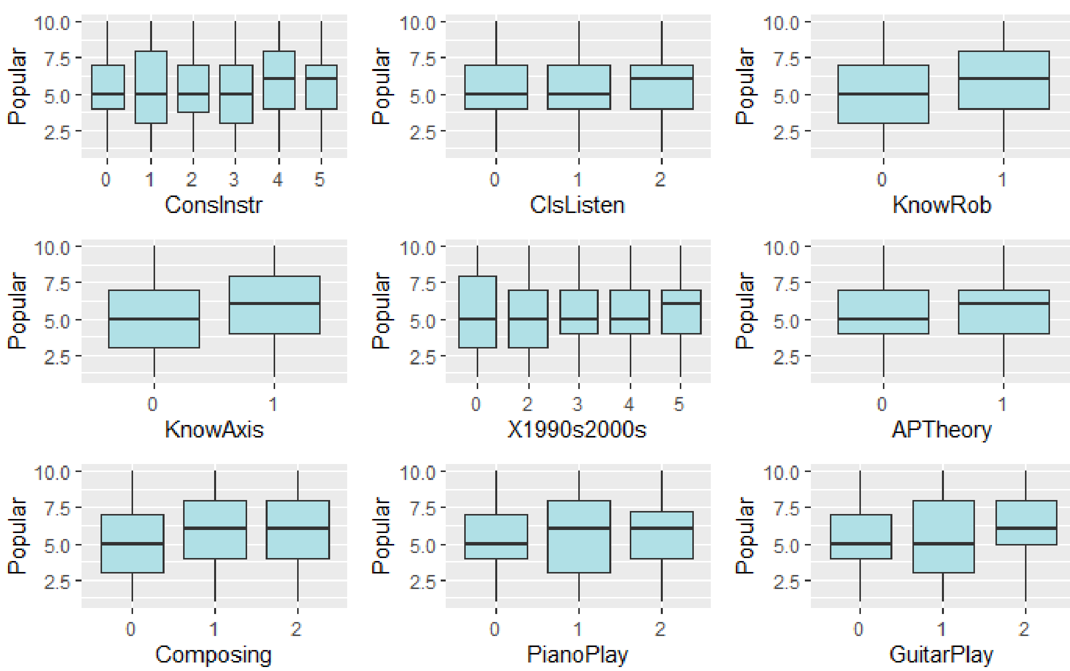

Figure 4 shows popular ratings plotted against categorical variables from the data set. The variables that had a visible difference in average compared to their other levels were ConsInstr, ClsListen, KnowRob, KnowAxis, X1990s2000s, APTheory, Composing, PianoPlay, and GuitarPlay. For each categorical variable, as the level increases from 0, the ratings for popular increase. This makes sense for ClsListen and X1990s2000s because those who listen to a lot of classical music or modern day songs can quickly identify if a song does not match their description of their preferred genre; the same can be inferred about those who took AP music theory in high school, compose, or play piano. Since electric guitar had very high popular ratings, it makes sense that those who concentrated on the instrument of the stimuli or play guitar rated higher for popular music.

Finally, the correlation between the numeric variables and popular ratings were computed. X16.minus.17 had a correlation of 0.12 (opposite of its correlation with classical ratings) and sqrt_OMSI had a correlation of 0.10. Both correlations are not that strong and will not be considered in the EDA model in the next section.

2.2 Model Fitting & Proposal

Table 2: ANOVA to Test if Random Effects are Necessary for the Popular Ratings Model

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.1	9	10850.17	10902.41	-5416.084	10832.17	NA	NA	NA	NA
lm.2	10	10159.57	10217.62	-5069.783	10139.57	692.6011	1	0	Yes

An ANOVA test was used to determine if a random intercept model was needed for popular ratings, and like the classical ratings model, the ANOVA indicates that the random effects model is necessary. The coefficient of the random effects model is significantly different from the simpler model without the random effect. In addition, the AIC and BIC of the random effects model is lower than the simpler model. Therefore, the random intercept model is needed.

A summary of the process to obtain the final model can be found in the “Model Building – Popular” section of the Appendix. The final model proposed is as follows:

$$\text{Popular} = \alpha_{0j[i]} + \alpha_{j[i]}^{\text{Instrument}} + \alpha_{j[i]}^{\text{Harmony}} + \text{Voice} + \text{X16.minus.17} + \text{KnowRob} + \text{Composing} + \text{Selfdeclare}$$

Harmony I-V-VI had the lowest coefficient for popular ratings compared to the other levels of harmonic motion. Instrument had the lowest coefficients compared to all other elements of the model. Contrary motion did not have the highest. Those who ranked themselves lower as musicians, composed a lot, knew of Rob Paravonian’s Pachelbel Rant, and scored higher on the auxiliary test rated higher for popular music. The output of the summary of the model can be found in Figure 2 in the Appendix.

Discussion:

Overall, factors contributing to higher classical and popular ratings were opposite of each other for the three main factors. Instrument was the highest for classical and lowest for popular. Similar pattern followed for Harmony, Voice, and X16.minus.17. In each model, it was the variable with the highest coefficient, so this confirms the researcher's hypothesis that it has the strongest influence on ratings. Harmony I-V-VI had the highest coefficient for classical ratings compared to its other levels, and it was also significant when interacted with Musician and KnowRob. This only occurs with harmony I-V-VI. This makes sense because those are the same notes that Rob rants about in his video. If subjects heard the chords, they may assume the song is more classical in nature. In addition, it was found that contrary motion did not have the strongest influence on classical ratings compared to the other levels of Voice. This makes sense because the researchers mention in their powerpoint (Jimenez, I. & Rossi, V., 2013) about the research that voice did not play a significant role on ratings.

There were many limitations to this analysis. There was a lot of missing data that needed to be imputed. This may skew the results of the analysis, as the imputed values may not reflect the truth of the population. In addition, there was minimal interacted variables due to computation limitations and time restraint. In the future, further analysis should be done to see the effects of interactions. Finally, this analysis was only done on college students from the university of Pittsburgh. They results may only be true for that subset of the population, and it is hard to extend the findings of the studies on a larger scale.

Resources:

[Axis of Awesome]. (2011, July 20 it was posted). *4 Chords | Music Videos | The Axis Of Awesome* [Video file]. Retrieved from https://www.youtube.com/watch?v=oOlDewpCfZQ.

Jimenez, I. & Rossi, V. (2012). Ratings [Data file]. University of Pittsburgh. Retrieved from https://canvas.cmu.edu/courses/11853/files/folder/hw10

Jimenez, I. & Rossi, V. (2013). The Influence of Timbre, Harmony, and Voice Leading on Listener's Distinction between Popular and Classical Music [PowerPoint slides]. University of Pittsburgh. Retrieved from https://canvas.cmu.edu/courses/11853/files/folder/hw10/presentation

Paravonian, R. [RobRocks]. (2006, November 21). *Pachelbel Rant* [Video file]. Retrieved from https://www.youtube.com/watch?v=JdxkVQy7QLM.

R Core Team (2017), R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/.

Appendix:

Table 1: Final data set used for analysis after data transformation

Variable	Problem	Percent of Missing Data	Adjustment
Classical	Invalid & Missing Values	1.35%	Removed Missing Values
Popular			
OMSI	Skewed Right	None	Applied Square-root Transformation (New Variable = sqrt_OMSI)
ConsInstr	Invalid Values	40%	Rounded to Nearest Whole Number
ConsNotes	Missing Values	14.29%	Median Imputation
Instr.minus.Notes	Recomputation Neeed	None	Adjusted ConsInstr - Adjusted ConsNotes
PachListen	Missing Values & Levels	2.86%	Median Imputation & Reduced Levels
ClsListen	Missing Values & Levels	1.43%	Median Imputation & Reduced Levels
KnowAxis	Missing Values & Levels	11.43%	Median Imputation & Converted to Binary
KnowRob	Missing Values & Levels	7.14%	Median Imputation & Converted to Binary
X1990s2000s	Missing Values	5.71%	Median Imputation
X1990s2000s.minus.1960s1970s	Missing Values	7.14%	Median Imputation
NoClass	Missing Values & Levels	11.43%	Median Imputation & Converted to Binary (New Variable = MusicClass)
APTheory	Missing Values	8.57%	Median Imputation
CollegeMustic	Missing Values	4.29%	Median Imputation
Composing	Missing Values & Levels	2.86%	Median Imputation & Reduced Levels
GuitarPlay	Levels	None	Reduced Levels
PianoPlay	Levels	None	Reduced Levels
X1stInstr	Missing Values	60%	Removed Variable
X2ndInstr	Missing Values	87.14%	Removed Variable
First12	Out of Scope of Analysis	None	Removed Variable

Table 2: Final data set used for analysis after data transformations

Variable	Variable Description	Levels	Data Type
Subject	Unique subject ID	Subject	Factor
Classical	How classical does the stimulus sound?	NA	Numeric
Popular	How popular does the stimulus sound?	NA	Numeric
sqrt_OMSI	Square-root of score on a test of musical knowledge	NA	Numeric
X16.minus.17	Auxiliary measure of listener's ability to distinguish classical vs popular music	NA	Numeric
Harmony	Harmonic Motion	I-V-vi, I-VI-V, I-V-IV, IV-I-V	Factor
Instrument	Instrument	Electric Guitar, Piano, String Quartet	Factor
Voice	Voice Leading	Contrary Motion, Parallel 3rds, Parallel 5ths	Factor
Selfdeclare	Are you a musician?	1-6, 1 = not at all	Factor
Musician	Are you a musician?	0 = no, 1 = yes	Factor
ConsInstr	How much did you concentrate on the instrument while listening?	0-5, 0 = not at all	Factor
ConsNotes	How much did you concentrate on the notes while listening?	0-5, 0 = not at all	Factor
Instr.minus.Notes	Difference between the previous two variables	-3 to 4	Factor
PachListen	How familiar are you with Pachelbel's Canon in D?	0 = no, 1 = a little, 2 = a lot	Factor
ClsListen	How much do you listen to classical music?	0 = no, 1 = a little, 2 = a lot	Factor
KnowRob	Have you heard Rob Pravonian's Pachelbel Rant?	0 = no, 1 = yes	Factor
KnowAxis	Have you hear Acis of Evil's Comedy bit on the 4 Pachelbel chords in popular music?	0 = no, 1 = yes	Factor
X1990s2000s	How much do you listen to pop and rock from the 90's andd 2000's?	0-5, 0 = not at all	Factor
X1990s2000s.minus.1960s1970s	Difference between the previous variable and a similar variable referring to 60's and 70's pop and rock	-4 to 5	Factor
MusicClass	Have you taken a music class before?	0 = no, 1 = yes	Factor
APTheory	Did you take AP Music Theory in high school?	0 = no, 1 = yes	Factor
CollegeMusic	Have you taken music classes in college?	0 = no, 1 = yes	Factor
Composing	Have you done any music composing?	0 = no, 1 = a little, 2 = a lot	Factor
PianoPlay	Do you play piano?	0 = no, 1 = a little, 2 = a lot	Factor
GuitarPlay	Do you play guitar?	0 = no, 1 = a little, 2 = a lot	Factor

Model Building – Classical

To test which factor(s) would be best suited in the model's random effect, an ANOVA test is used to compare all possible combinations of random effects for the three main factors. The results of the ANOVA are summarized in Table 4. Key values for the Random Effects for each model is summarized in Table 3. The random effects for instrument and harmony were significantly different from the random intercept model for both classical and popular ratings and had the lowest AIC and BIC compared to the other models.

Table 3: Key for Random Effects Models

Model	Random Effect(s)
lm.2	Random Intercept Only
lmer.1	Instrument
lmer.2	Harmony
lmer.3	Voice
lmer.4	Instrument & Harmony
lmer.5	Instrument & Voice
lmer.6	Harmony & Voice
lmer.7	Instrument, Harmony, and Voice

Table 4: Random Effects 1st Round of Forward Selection

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.2	10	10159.566	10217.617	-5069.783	10139.566	NA	NA	NA	NA
lmer.1	15	9864.677	9951.753	-4917.338	9834.677	304.8895	5	0	Yes
lmer.3	15	10230.318	10317.394	-5100.159	10200.318	0.0000	0	1	No
lmer.2	19	10132.225	10242.521	-5047.113	10094.225	106.0934	4	0	Yes
lmer.5	24	9874.181	10013.503	-4913.091	9826.181	268.0441	5	0	Yes
lmer.4	30	9711.315	9885.467	-4825.657	9651.315	174.8662	6	0	Yes
lmer.6	30	10147.118	10321.270	-5043.559	10087.118	0.0000	0	1	No
lmer.7	45	9723.856	9985.084	-4816.928	9633.856	453.2619	15	0	Yes

Next, fixed effects were added to the model above. At first, the fitLMER function from the "LMERConvenienceFunctions" package in R was used, but it did not yield useful results for analysis. Therefore, a manual forward selection process was used to determine which variables should be considered as fixed effects for the model. A summary of significance and AIC/BIC information for each model that was compared can be found in Table 6. Key values for the variables added for each model is summarized in Table 5.

Table 5: Key for Variables Added to Model

Model	Variable	Model	Variable
lm.1	Selfdeclare	lm.10	KnowAxis
lm.2	sqrt_OMSI	lm.11	X1990s2000s
lm.3	X16.minus.17	lm.12	X1990s2000s.minus.1960s1970s
lm.4	ConsInstr	lm.13	CollegeMusic
lm.5	ConsNotes	lm.14	MusicClass
lm.6	Instr.minus.Notes	lm.15	APTheory
lm.7	PachListen	lm.16	Composing
lm.8	ClsListen	lm.17	GuitarPlay
lm.9	KnowRob	lm.18	PianoPlay

Table 6: Adding Fixed Variables

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.base	30	9711.315	9885.467	-4825.657	9651.315	NA	NA	NA	NA
lm.2	31	9712.811	9892.769	-4825.406	9650.811	0.5033551	1	0.4780296	No
lm.3	31	9710.807	9890.764	-4824.403	9648.807	2.0047895	0	0.0000000	Yes
lm.9	31	9713.018	9892.975	-4825.509	9651.018	0.0000000	0	1.0000000	No
lm.10	31	9712.737	9892.694	-4825.368	9650.737	0.2815682	0	0.0000000	Yes
lm.13	31	9713.283	9893.240	-4825.642	9651.283	0.0000000	0	1.0000000	No
lm.14	31	9709.389	9889.346	-4823.694	9647.389	3.8943596	0	0.0000000	Yes
lm.15	31	9710.537	9890.494	-4824.269	9648.537	0.0000000	0	1.0000000	No
lm.7	32	9713.220	9898.982	-4824.610	9649.220	0.0000000	1	1.0000000	No
lm.8	32	9710.473	9896.236	-4823.237	9646.473	2.7462094	0	0.0000000	Yes
lm.16	32	9712.143	9897.905	-4824.072	9648.143	0.0000000	0	1.0000000	No
lm.17	32	9708.203	9893.965	-4822.102	9644.203	3.9399795	0	0.0000000	Yes
lm.18	32	9709.718	9895.480	-4822.859	9645.718	0.0000000	0	1.0000000	No
lm.5	34	9716.750	9914.122	-4824.375	9648.750	0.0000000	2	1.0000000	No
lm.11	34	9715.051	9912.423	-4823.525	9647.051	1.6991446	0	0.0000000	Yes
lm.1	35	9717.554	9920.731	-4823.777	9647.554	0.0000000	1	1.0000000	No
lm.4	35	9716.706	9919.884	-4823.353	9646.706	0.8472181	0	0.0000000	Yes
lm.6	38	9724.692	9945.285	-4824.346	9648.692	0.0000000	3	1.0000000	No
lm.12	38	9717.243	9937.835	-4820.621	9641.243	7.4498231	0	0.0000000	Yes

When selecting the final fixed effects, three models were compared based on forward selection, intuition, and EDA. An ANOVA test was used to compare which reduced AIC the most. A summary of the model keys and ANOVA output are in Tables 7 and 8, respectively.

Table 7: Summary of Various Models

Classical		
Forward Selection	**Intuition**	**EDA**
Instrument	Instrument	Instrument
Harmony	Harmony	Harmony
Voice	Voice	Voice
X16.minus.17	ConsInstr	PachListen
ClsListen	ClsListen	ConsInstr
MusicClass	X1990s2000s	X1990s2000s
PianoPlay	MusicClass	MusicClass
Random Effect for Instrument & Harmony	Composing	Composing
	PianoPlay	GuitarPlay
	GuitarPlay	Random Effect for Instrument & Harmony
	Random Effect for Instrument & Harmony	

Table 8: ANOVA to Test Best Set of Fixed Effects

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.base	30	9711.315	9885.467	-4825.657	9651.315	NA	NA	NA	NA
cls1	36	9706.706	9915.689	-4817.353	9634.706	16.608731	6	0.0108341	Yes
cls3	46	9714.679	9981.712	-4811.340	9622.679	12.027050	10	0.2832502	No
cls2	48	9712.275	9990.918	-4808.137	9616.275	6.404291	2	0.0406748	Yes

Again, an ANOVA test was used to compare which model was significantly different from the model found from the first ANOVA test to determine Instrument and Harmony as random effects. The forward selection model reduced AIC and BIC and was significantly different from the base model. Finally, random effects were tested again for all combinations, but instrument and harmony still reduced AIC and BIC the most. A summary of the ANOVA can be found in Table 9

Table 9: Random Effects 2nd Round of Forward Selection

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lmer.1	21	9863.730	9985.636	-4910.865	9821.730	NA	NA	NA	NA
lmer.3	21	10229.497	10351.403	-5093.748	10187.497	0.00000	0	1e+00	No
lmer.2	25	10130.658	10275.785	-5040.329	10080.658	106.83845	4	0e+00	Yes
lmer.5	30	9872.449	10046.601	-4906.224	9812.449	268.20928	5	0e+00	Yes
lm.2	31	9736.191	9916.149	-4837.096	9674.191	138.25746	1	0e+00	Yes
lmer.4	36	9706.706	9915.689	-4817.353	9634.706	39.48533	5	2e-07	Yes
lmer.6	36	10144.282	10353.265	-5036.141	10072.282	0.00000	0	1e+00	No
lmer.7	51	9718.547	10014.606	-4808.274	9616.547	455.73490	15	0e+00	Yes

Model Building – Popular

The same process for the Classical model was followed for the Popular model

Table 10: Random Effects 1st Round of Forward Selection

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.2	10	10159.566	10217.617	-5069.783	10139.566	NA	NA	NA	NA
lmer.1	15	9824.296	9911.372	-4897.148	9794.296	345.27068	5	0	Yes
lmer.3	15	10169.443	10256.519	-5069.721	10139.443	0.00000	0	1	No
lmer.2	19	10114.719	10225.015	-5038.359	10076.719	62.72365	4	0	Yes
lmer.5	24	9837.350	9976.672	-4894.675	9789.350	287.36862	5	0	Yes
lmer.4	30	9734.721	9908.873	-4837.361	9674.721	114.62909	6	0	Yes
lmer.6	30	10131.628	10305.780	-5035.814	10071.628	0.00000	0	1	No
lmer.7	45	9749.976	10011.204	-4829.988	9659.976	411.65115	15	0	Yes

Table: 11 Adding Fixed Variables

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.base	30	9734.721	9908.873	-4837.361	9674.721	NA	NA	NA	NA
lm.2	31	9736.191	9916.149	-4837.096	9674.191	0.5297440	1	0.4667145	No
lm.3	31	9733.248	9913.206	-4835.624	9671.248	2.9429897	0	0.0000000	Yes
lm.9	31	9732.039	9911.996	-4835.019	9670.039	1.2098129	0	0.0000000	Yes
lm.10	31	9734.561	9914.518	-4836.281	9672.561	0.0000000	0	1.0000000	No
lm.13	31	9736.558	9916.515	-4837.279	9674.558	0.0000000	0	1.0000000	No
lm.14	31	9736.402	9916.359	-4837.201	9674.402	0.1564952	0	0.0000000	Yes
lm.15	31	9736.708	9916.665	-4837.354	9674.708	0.0000000	0	1.0000000	No
lm.7	32	9738.291	9924.053	-4837.145	9674.291	0.4172297	1	0.5183226	No
lm.8	32	9737.897	9923.659	-4836.948	9673.897	0.3940640	0	0.0000000	Yes
lm.16	32	9733.370	9919.133	-4834.685	9669.370	4.5260831	0	0.0000000	Yes
lm.17	32	9737.120	9922.882	-4836.560	9673.120	0.0000000	0	1.0000000	No
lm.18	32	9737.432	9923.194	-4836.716	9673.432	0.0000000	0	1.0000000	No
lm.5	34	9739.439	9936.811	-4835.720	9671.439	1.9932902	2	0.3691157	No
lm.11	34	9740.869	9938.241	-4836.434	9672.869	0.0000000	0	1.0000000	No
lm.1	35	9731.729	9934.907	-4830.865	9661.729	11.1396141	1	0.0008450	Yes
lm.4	35	9742.144	9945.321	-4836.072	9672.144	0.0000000	0	1.0000000	No
lm.6	38	9740.100	9960.693	-4832.050	9664.100	8.0441118	3	0.0451088	Yes

Table 12: Summary of Various Models

Popular		
Forward Selection	**Intuition**	**EDA**
Instrument	Instrument	Instrument
Harmony	Harmony	Harmony
Voice	Voice	Voice
X16.minus.17	GuitarPlay	APTheory
KnowRob	X1990s2000s	KnowRob
Composing	ClsListen	KnowAxis
Selfdeclare	ConsInstr	X1990s2000s
Random Effect for Instrument & Harmony	Random Effect for Instrument & Harmony	Composing
		PianoPlay
		GuitarPlay
		ClsListen
		ConsInstr
		Random Effect for Instrument & Harmony

Table 13: ANOVA to Test Best Set of Fixed Effects

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lm.base	30	9734.721	9908.873	-4837.361	9674.721	NA	NA	NA	NA
pop1	39	9728.170	9954.568	-4825.085	9650.170	24.550924	9	0.0035102	Yes
pop2	43	9753.706	10003.324	-4833.853	9667.706	0.000000	4	1.0000000	No
pop3	50	9758.672	10048.925	-4829.336	9658.672	9.033813	7	0.2502375	No

Table 14: Random Effects 2^{nd} Round of Forward Selection

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)	Significant
lmer.1	24	9815.021	9954.343	-4883.511	9767.021	NA	NA	NA	NA
lmer.3	24	10168.873	10308.195	-5060.437	10120.873	0.0000	0	1	No
lmer.2	28	10113.672	10276.214	-5028.836	10057.672	63.2009	4	0	Yes
lm.2	31	9736.191	9916.149	-4837.096	9674.191	383.4808	3	0	Yes
lmer.5	33	9826.948	10018.516	-4880.474	9760.948	0.0000	2	1	No
lmer.4	39	9728.170	9954.568	-4825.085	9650.170	110.7781	6	0	Yes
lmer.6	39	10129.854	10356.251	-5025.927	10051.854	0.0000	0	1	No
lmer.7	54	9743.256	10056.729	-4817.628	9635.256	416.5980	15	0	Yes

Figure 1: Classical Model Summary

```
Random effects:
 Groups   Name             Variance Std.Dev. Corr
 Subject  (Intercept)      2.478418 1.57430
          Instrumentpiano  1.657730 1.28753  -0.41
          Instrumentstring 3.330346 1.82492  -0.63  0.68
          HarmonyI-V-IV    0.048940 0.22122   0.79 -0.68 -0.54
          HarmonyI-V-VI    1.117469 1.05710  -0.14 -0.22 -0.36  0.24
          HarmonyIV-I-V    0.008195 0.09053  -0.42 -0.33  0.46  0.00 -0.20
 Residual                  2.359265 1.53599
Number of obs: 2453, groups:  Subject, 70

Fixed effects:
                          Estimate Std. Error t value
(Intercept)               3.584773   0.516838   6.936
Voicepar5th              -0.385137   0.076056  -5.064
Voicecontrary            -0.354858   0.076024  -4.668
Instrumentpiano           1.338473   0.171917   7.786
Instrumentstring          3.058863   0.231336  13.223
HarmonyI-V-IV            -0.046001   0.120417  -0.382
HarmonyI-V-VI             0.256972   0.199460   1.288
HarmonyIV-I-V             0.057433   0.116340   0.494
MusicianNo               -0.461907   0.376149  -1.228
KnowRob1                 -0.456330   0.446600  -1.022
X16.minus.17             -0.079865   0.045810  -1.743
ClsListen1               -0.132958   0.420185  -0.316
ClsListen2                0.517640   0.418390   1.237
MusicClass1               0.799704   0.412445   1.939
PianoPlay1                0.806158   0.367852   2.192
PianoPlay2                0.340983   0.396141   0.861
HarmonyI-V-IV:MusicianNo -0.002093   0.193493  -0.011
HarmonyI-V-VI:MusicianNo  0.864187   0.317879   2.719
HarmonyIV-I-V:MusicianNo -0.036465   0.188589  -0.193
HarmonyI-V-IV:KnowRob1    0.049310   0.236445   0.209
HarmonyI-V-VI:KnowRob1    0.888672   0.389338   2.283
HarmonyIV-I-V:KnowRob1    0.080725   0.229930   0.351
```

Figure 2: Popular Model Summary

```
Random effects:
 Groups   Name              Variance Std.Dev. Corr
 Subject  (Intercept)       1.10739  1.0523
          Instrumentpiano   1.37474  1.1725   -0.14
          Instrumentstring  3.29269  1.8146   -0.44  0.74
          HarmonyI-V-IV     0.09767  0.3125    0.34 -0.30 -0.45
          HarmonyI-V-VI     0.86850  0.9319   -0.01 -0.18 -0.19 -0.35
          HarmonyIV-I-V     0.20834  0.4564   -0.24 -0.14  0.00 -0.52 -0.37
 Residual                   2.39261  1.5468
Number of obs: 2453, groups:  Subject, 70

Fixed effects:
                 Estimate Std. Error t value
(Intercept)       5.47426    0.27195  20.129
Instrumentpiano  -0.95172    0.15992  -5.951
Instrumentstring -2.54824    0.23036 -11.062
HarmonyI-V-IV    -0.04786    0.09605  -0.498
HarmonyI-V-VI    -0.30374    0.14232  -2.134
HarmonyIV-I-V    -0.23390    0.10381  -2.253
Voicepar5th       0.14225    0.07661   1.857
Voicecontrary     0.16721    0.07656   2.184
X16.minus.17      0.10088    0.04073   2.477
KnowRob1          0.72473    0.32992   2.197
Composing1        0.22542    0.32718   0.689
Composing2        0.40560    0.38399   1.056
Selfdeclare2      1.20628    0.31418   3.839
Selfdeclare3      0.86586    0.39288   2.204
Selfdeclare4      0.45208    0.41507   1.089
Selfdeclare5      0.89556    0.77050   1.162
Selfdeclare6     -0.20897    1.06048  -0.197
```