Examining Effect of Instruments, Vocal Leading and Harmonic Motion on Students' Identification of Music

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Abstract

We examine the effect of three experimental factors on subjects' ability to rate music as classical or popular. We employ multi-level models to examine data of 64 subjects measured 36 times. We found that there is a difference between how ratings are constructed and how the experimental factors influence the ratings. More specifically, more complex models were needed to predict popular music. Future research may examine a reduction of the subject-level effect and the addition of more subject-level measurements.

1 Introduction

Music is an integral part of modern culture. Musical genres serve to differentiate different types of music from one another. The defining characteristics of musical genres are often fluid and subjective. What influences individuals' classifications of music?

This question is critical in the context of ever-increasing global social media consumption. Genres of music allow for intentional and unintentional messaging. We will examine data from Professor Ivan Jiminez and Vincent Rossi (Jiminez and Rossi henceforth) to determine what factors influence subjects' classification of various sounds as either classical or popular in the presence of three experimental factors; instrument used, harmonic motion and vocal leading. The identification of classical and popular is critical because classical music carries a connotation of high-brow and boring while popular music is seen directly opposing classical music. We will additionally answer the following questions:

- Does instrument have the strongest influence of the three experimental factors on rating?
- Does harmonic motion $I - V - vi$ have a stronger association with classical classification rating than other motions?
- Does contrary vocal leading have the strongest (of the vocal leadings) influence on classical rating?
- Are there differences in how musicians and non-musicians identify classical music?

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- Are there differences in the factors that drive classical and popular music?

The data and the primary question are presented in homework 10 for 36-617, Applied Linear Models with Dr. Brian Junker, taught at Carnegie Mellon University in Fall 2019. Data provded by Dr. Ivan Jiminez and Vincent Rossi of the University of Pittsburgh.

2 Methods

price_grid_diagonal.png

Figure 1: Scatterplot matrix of Price, Parker's Rating (ParkerPoints), & Coates' Rating (CoatesPoints). From Sheather (2009, p. 10) and modifications by Kovacs.

The music rating data comes from research conducted by Dr. Ivan Jimenez and Vincent Rossi from the University of Pittsburgh. (2013). Data was collected as part of a designed experiment at the University of Pittsburgh in which 36 musical stimuli were presented to 70 students. The students were asked to rate the music on two ten point scales (1 indicating that the music was not at all fitting of a category, 10 the opposite) indicating how classical and popular the music sounded, respectively. The stimuli were comprised of each combination of the three design variables. No factor combination was repeated. The following variables were examined by the author:

$$\begin{aligned} Y_1 &= \text{Classical} = \text{How classical does the stimuli sound? (1-10, 1= not at all} \\ Y_2 &= \text{Popular} = \text{How popular does the stimuli sound? (1-10, 1= not at all} \end{aligned}$$

f_1 = Subject = Unique subject ID of the respondent.
z_1 = Harmony = The harmonic motion of the stimulus. 4 Levels.
z_2 = Harmony = The instrument used to create the stimulus. 3 Levels.
z_3 = Voice = The leading voice of the stimulus. 3 Levels.
x_1 = Selfdeclare = Student's response to the question "Are you a musician?".
x_2 = OMSI = Student's score on a test of musical knowledge. Data ranges from 11 to 970.
x_3 = X16.minus.17 = Auxiliary measure of listener's ability to distinguish classical vs. popular music.
x_4 = ConsInstr = How much did you concentrate on the instrument while listening? 0 (none) to 5.
x_5 = ConsNotes = How much did you concentrate on the notes while listening? 0 (none) to 5.
x_6 = Instr.minus.Notes = Difference between the two prior concentration variables.
x_7 = PachListen = How familiar are you with Pachelbel's Canon in D? 0 (none) to 5.
x_8 = ClsListen = How often do you listen to classical music? 0 (none) to 5.
x_9 = KnowRob = Have you heard Rob Paravonian's Pachelbel Rant? 0 (none) to 5.
x_{10} = KnowAxis = Have you heard Axis of Evil's Comedit bit on the 4 Pachelbel chords in popular music? 0
x_{11} = X1990s2000s = How much do you listen to pop and rock from the 90's and 2000's? 0 (none) to 5.
x_{12} = X1990s2000s.minus.1960s1970s = Difference between the prior variable and 60's and 70's rock music var
x_{13} = CollegeMusic = Binary variable indicating if the student had taken a music class in college. 0 = No
x_{14} = NoClass = How many music classes the subject had taken.
x_{15} = APTheory = Binary var. indicating if the subject took AP Music Theory class. 0 = No
x_{16} = Composing = Subject rating of their composing experience.
x_{17} = PianoPlay = Subject's self-rating of piano playing ability. 0 (not at all) to 5 scale.
x_{18} = isMusician = Author created variable classifying a subject as a musician
x_{19} = is154 = Author created variable classifying whether a sound uses a harmonic motion of I-V-iv
x_{18} = isContrary = Author created variable classifying whether a sound uses a contrary vocal motion

In creating models for the considerations we first sought to remove variables from consideration. An examination of the scatterplot matrix of all variables reveals surprising relationships. We initially see that OMSI is highly correlated with Selfdeclare and remove the former variable due to a preference for a self-reported variable. We also decided to remove both measures of individual concentration due to high correlation with one another and mathematical relationship to Instr.minus.notes.

The data as provided initially contained 2520 rows and 21 variables. 70 Subjects were measured 36 times each with one observation corresponding to a subject receiving a combination of treatment variables. The data was initially 8% null. Imputation techniques such as cold-deck encoding, regression imputation and classification tree imputation were utilized to fill in missing values. Subjects that were missing values in the response variables or for whom imputation would not be practical, such as the case in which the variables used to create the regression model are blank, were ultimately removed from the data. The isMusician variable was created by the author to classify subjects as musicians or not. Musician designations were assigned to those subjects that have a SelfDeclare value of 2 or greater or have a selfDeclare value of 1 in addition to playing an insturment. The is154 and isContrary variables were created as binary variables indicating if their experimental factors were of those values. The filtered data contains 2304 observations that correspond to 64 subjects. The data is available in the file `ratings.csv` and cleaning code is present in the code appendix.

To analyze the data we used multi-level modeling involving the three experimental variables with random effects by Subject. We also used ANOVA models to evaluate if the binary variables are significant in with respect to other ratings. Evaluating the model was conducted by removing correlated covariates and those not statistically significant. The models and code were produced in the R language.

3 Results

This harmonic motion is recognized by some as the opening to Pachelbel's Canon in D, a well-known piece of classical music. An examination of the model created to predict classical rating allows us to examine the relationship between harmonic motion I-V-vi and classical rating. The coefficient of the fixed effect for motion I-V-vi is larger than those for the other levels. and does not overlap with a 95% confidence interval for the other factors. Furthermore that I-V-vi motion is the only statisticall significant level of harmonic motion. This observation means that having a harmonic motion I-V-vi has a larger effect on Classical rating holding all other factors constant irrespective of subject. This effect does not change when those subjects are familiar with Pachelbel or any comedy routine about the musical piece.

An examination of the model initially does not allow us to discern the influence of contrary vocal leading on classical rating. The fixed effects of all levels of voice are statistically significant. An examination of the fixed effect coefficients for the levels of voice show that the other levels of vocal leading have larger coefficients than contrary motion. We can determine that a contrary vocal motion is associated with smaller classical ratings yet we cannot claim that contrary motion is more important than the other factors.

Music has been called a science and art. Trained musicians have a unique understanding of its structure and meaning. A model of classical rating against harmony, instrument, OMSI, KnowAxis and AP Theory with a random intercept of isMusician. We found that no random intercepts were appropriate due to correlation with isMusician.

Following a similar procedure we created a model for Popular classification that included the variables harmony, instrument, voice, OMSI and knowAxis with a random intercept of subject and random slope of APTheory. We found that APTheory was associated with lower classical ratings for non-musicians. We also found that the fixed effects of the three experimental factors were extremely similar to the relationships found in our initial classical rating model. A similar model for Popular music showed included far more variables and additional random slopes for X1990s2000s and X16.minus.17 in addition to the random intercept of isMusician. The fixed effects were reduced in magnitude yet increased in frequency meaning that the model for popular music may be seen as "finer". Furthermore the presence of additional random effects indicates that ones designation as a musician indeed changes how they perceive certain stimuli and how it influences their ratings. We therefore determine that musician status does change how individuals analyze music yet note these differences are more apparent in a popular setting.

The prior results lead to our final inquiry; are there differences in the things that drive classical and popular ratings? The totality of our allows us to claim there is a difference; albeit quite minor. Models created to examine classical ratings were often less complex and relied heavily on the experimental factors. Models for popular rating were extremely complex and relied on one experimental factor. More specifically models with random effects of musician designation rather than subject were incredibly complex yet produced similar predictions to the classical model. We conclude that while each rating are equally easy to predict popular ratings are more complex.

4 Discussion

The data provided displayed many interesting patterns throughout. Our initial exploration of the data found relatively little correlation amongst the other variables yet many models displayed high variances in their coefficients. This variance was concerning due to the relative lack of data. While the data presented nearly 2000 data points adding the random effect of subject resulted in merely 36 data points used per subject. While not damming this observation could be negated by the presence of multiple data for each subject. Through repeatedly measuring the subjects on the same conditions the amount of data per subject would reduce the variability seen.

The requirement to always include a random effect of subject or musician designation made the model-fitting process difficult. The relative lack of subjects (64 considered in our analysis) may have over-stated individual subject effects. Future analyses could explore the data without strong considerations to subjects initially.

To summarize we see that many factors beyond the experimental factors relate to classical and popular ratings. Of the experimental factors instrument proved to be the strongest influence while among levels of harmony the famed I-V-vi harmonic motion was more meaningful. Contrary vocal motion was shown to have a negative relationship with rating predictions. Non-musicians were shown to influence the initial rating (i.e. the intercept) for classical rating yet resulted in extremely complex models that depended on musician status for popular predictions.

References

R Core Team (2019), *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

R Core Team (2019). *lme4::lmer().* R Foundation for Statistical Computing, Vienna, Austria.