What Distinguishes Classical and Popular Music to a Listener?

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2019 December 06

Abstract

We analyze the effect of various covariates listeners interpretation of a piece of music as popular or classical. We utilize multilevel modeling, using the most explanatory models selected by BIC to make our conclusions. We find that classical ratings are driven most by what instrument is used in a piece, but also what harmonic progression is used and what voice leading is used. We find that popular ratings are driven almost entirely by instrument used. We also analyze some listener characteristics, and find that classical music listeners differ significantly from others in their ratings of classical music, reliant less on instrument. We also find that self declared artists differ significantly in their ratings of popular music, also more penalizing to instruments than non musicians. Finally, we found that canonical aspects of classical music, the I-V-VI harmonic progression and the contrary motion voice leading, were major drivers of subject interpretations of pieces.

1 Introduction

What distinguishes so called popular music from classical music? Certainly, formal definitions exist, but many of these definitions rely on vague descriptions of the genre, or are altogether too stringent, deferring to a temporal definition of the genres. All existing definitions are thus unsatisfying. The heart of the matter is then this: What is pop and what is classical is largely a matter of subjective opinion.

But what determines these subjective opinions? Certainly what is considered pop or classical will differ significantly across individuals, but there must be broader characteristics that drive these differences of opinion. These characteristics may either be inherent to the piece of music (ex. Primary instruments in the piece), or the individual (ex. What instruments they play). We seek to uncover these drivers of genre and opinion.

Formally, we examine the following questions:

- What experimental factors, inherent to music or individual, have the strongest influence on ratings?
  - What aspect of the music itself has the strongest effect on its perception as pop/classical?
  - Do those music-inherent factors that are typically associated with classical music actually drive listener interpretations of pieces?

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    - Are there any individual-inherent factors that are particularly explanatory?
- Are there differences in the way that musicians and non-musicians identify classical music?
- Are there differences in the things that drive classical, vs. popular, ratings?

2 Methods

2.1 Data Collection and Cleaning

The data used come from an experiment by Jimenex & Rossi. (2013). Listeners were asked to indicate the extent to which a series of three chord successions were popular or classical sounding. These came from musical excerpts played either by piano, electrical guitar, or string quartet. Additionally, these series had varying harmonic features and leading voice features that potentially confounded conventions of classical music (defined as Western art music of the 18th and 19th centuries) with those of popular music. We consider these to be the music-inherent features.

Listeners also recorded several features relevant to their understanding of music. Whether they had taken a musical theory class, were themselves musicians, or whether they had seen certain skits relevant to theory were among those recorded features. We consider these to be individual-inherent features.

The resulting data then consisted of 70 subjects, who each listened to 36 different series of the aforementioned chord progressions. These 36 different series were derived from every combination of 3 different instruments, 4 different harmonic progressions, and 3 different types of vocal leading. There are 2520 total observations.

Specifically, our data had the form:

Classical	How classical does the stimulus sound?
Popular	How popular does the stimulus sound?
Subject	Unique subject ID
Harmony	Harmonic Motion (4 levels)
Instrument	Instrument (3 levels)
Voice	Voice Leading (3 levels)
Selfdeclare	Are you a musician? (1-6, 1=not at all)
OMSI	Score on a test of musical knowledge
X16.minus.17	Auxiliary measure of listener's ability to distinguish classical vs popular music
ConsInstr	How much did you concentrate on the instrument while listening (0-5, 0=not at all)
ConsNotes	How much did you concentrate on the notes while listening? (0-5, 0=not at all)
Instr.minus.Notes	Difference between prev. two variables
PachListen	How familiar are you with Pachelbel's Canon in D (0-5, 0=not at all)
ClsListen	How much do you listen to classical music? (0-5, 0=not at all)
KnowRob	Have you heard Rob Paravonian's Pachelbel Rant (0-5, 0=not at all)
KnowAxis	Have you heard Axis of Evil's Comedy bit on the 4 Pachelbel chords in popular music? (0-5, 0=not at all)
X1990s2000s	How much do you listen to pop and rock from the 90's and 2000's? (0-5, 0=not at all)
X1990s2000s.minus.1960s1970s	Difference between prev variable and a similar variable referring to 60's and 70's pop and rock.
CollegeMusic	Have you taken music classes in college (0=no, 1=yes)
NoClass	How many music classes have you taken?
APTheory	Did you take AP Music Theory class in High School (0=no, 1=yes)
Composing	Have you done any music composing (0-5, 0=not at all)
PianoPlay	Do you play piano (0-5, 0=not at all)
GuitarPlay	Do you play guitar (0-5, 0=not at all)
X1stInstr	How proficient are you at your first musical instrument (0-5, 0=not at all)
X2ndInstr	Same, for second musical instrument

Figure 1: Explicit definitions of the variables.

We immediately find that our data contains many missing values. Some of these are likely appropriate and may have meaning, however, many others may not.

We first examine all subject-constant variables, to ensure they are constant across trials within a subject. We then ensure that variables in an implicit set, such as two variables and their difference, are consistent with one another. If they are not, the missing values are interpolated from the included pairs. We also ensure that variables that have a close relationship to one another do not contradict one another. In particular, we ascertain that whether a subject plays a guitar or piano to some level is not inconsistent with whether they play any instrument to some level. For example, a subject who plays their primary instrument to level 3 should not be able to play piano to level 5.

After these repairs, if we find any variables with extreme numbers of missing values, those variables will be dropped from analysis. We also choose only those variables with a concise meaning, dropping the highly composite variables or variables that would lead to tautological conclusions.

Finally, we consider whether or not to drop variables due to possible redundancy or incongruity due to other included variables. We are left with a handful of missing values and choose to develop two final datasets, given the research questions.

2.2 Modeling and Outcome Measure

We choose to analyze this data through the use of several multilevel hierarchical models, and model selection thereof. These models consist of both fixed effects, that are fit across all the data, and random effects that represent the random variation across subjects. By forward and backward selecting model fixed and random effects based on BIC, and rarely AIC, we find models that best answer each of our research questions.

2.2.1 Exploring the Music-inherent Features

We explore the music-inherent features using multilevel modeling on the subjects. The subjects form an implicit partition of the data upon which to build these models. Each subject likely has implicit biases that drive their ratings of each progression. This bias is addressable through the use of random effects. We thus first consider only the music-inherent features of instrument, harmonic progression, and voice leading. Initially, we examine the importance of these in a simple linear regression. We then introduce a random intercept model, and compare it with a nonrandom intercept only model. The fixed effects are then forward selected by BIC. After these fixed effects are established, we select our random effects using the same method of forward BIC. We then perform backward selection of the fixed effects, again by BIC, in order to determine if the random effects have reduced the need for any. Our final model via this selection process best explains the variation we see in the data.

2.2.2 Exploring the Individual-inherent Features

We also explore the individual-inherent features that may determine how a piece is rated as classical or popular. The model selection is largely the same as for music-inherent features, but we begin with the final model of the music-inherent feature selection process as our base model. We build from this, using forward BIC selection initially. We find that no model reduces BIC over the base model, and thus switch to AIC for selection. The fixed effects are selected, followed by random effects, and then fixed effects are again back selected.

2.2.3 Musicians vs. Non-Musicians

Finally, we explore in particular the individual-inherent feature of whether or not a subject is a musical artist. This is a self reported score, but we choose to bisect it in order to simply partition the subjects into artists and non-artists. Several different splits are attempted, and any differences in results explored.

2.3 Pachelbel and Contrary Motion

We also wish to emphasize briefly the importance of two music-inherent features, and the individual-inherent features that may emphasize or de-emphasize their effects.

Pachelbel's *Canon in D* is a widely recognized piece that contains the I-V-VI harmonic progression. Thus those pieces containing this progression may be more often rated as highly classical.

However, this progression has also been very popular in popular music for the past 20 years, and comedy has been written on this subject. Thus we expect that a subject who has listened to either Pachelbel's *Canon* or the comedy bits derived from it may differ systematically from those subjects that have not.

Likewise, a vocal leading of contrary motion is highly affiliated with classical music. We therefore expect pieces containing it to be rated as particularly classical by our subjects.

3 Results

3.1 EDA and Cleaning

We find that the individual-inherent covarites are not inconsistent within observations of the same subject. However, we do find many inconsistencies across related variables, which we repair. We also find some variables that cannot be adequately repaired and which we drop.

Specifically, we find that the values for ‘Instr.minus.Notes‘ do not appear to be the differences between ‘ConsInstr‘ and ‘ConsNotes‘ as they should be. Upon inspection, this was discovered to primarily be due to missing values in ‘ConsNotes‘. These missing values can then be defined as ‘ConsInstr‘ minus ‘Instr.minus.Notes‘, if both of these are defined. Both of these being defined implies that earlier researchers were comfortable interpreting missing values in ‘ConsNotes‘ to be zero, or failed to pass these zeroes along to us. Thus we defer to their decision here. We also filter those rows of the data missing either ‘Popular‘ or ‘Classical‘, as there are very few, and these are the primary variables of analysis. Interpolating them could very well effect our primary results.

Many other variables have missing values, and potentially incorrect values. The following can be checked using other variables or be used to check other varaibles:

- ‘CollegeMusic‘
- ‘NoClass‘

If ‘NoClass‘ is greater than zero, then ‘CollegeMusic‘ should be true. Likewise, if ‘CollegeMusic‘ is true, then ‘NoClass‘ should be 1 or greater.

- ‘PianoPlay‘
- ‘GuitarPlay‘
- ‘X2ndInstr‘
- ‘X1stInstr‘

If one plays guitar or piano to some competence level, then that individual’s ‘X1stInstr‘ measure should be, at least that competence level, if we consider these to be on the same scale. This is a reasonable assumption, as both are competency measure defined on the same range. If both guitar and piano are played to some level, then ‘X2ndInstr‘ should be at least as great as the lesser of these measures, following the same assumption of common scaling.

Despite these repairs, we still find many missing values in ‘X1stInstr‘, ‘X2ndInstr‘, and so choose to drop these covariates.

We then choose to develop a new variable from ‘APTheory‘ and ‘CollegeMusic‘, which we call ‘Theory‘, and which measures whether a subject took either of these groups. We then drop these two variables, in favor of the composite and largely equivalent in meaning ‘Theory‘, which also has fewer missing values.

We next choose only those variables with a concise meaning, dropping the highly composite variables of ‘OMSI‘, a score on a test of musical comprehension, ‘X16.minus.17‘, an auxiliary measure of a listeners ability to distinguish classical and popular music. Conclusions in our analysis which include these variables would be tautological or overly vague, and thus uninformative. For example

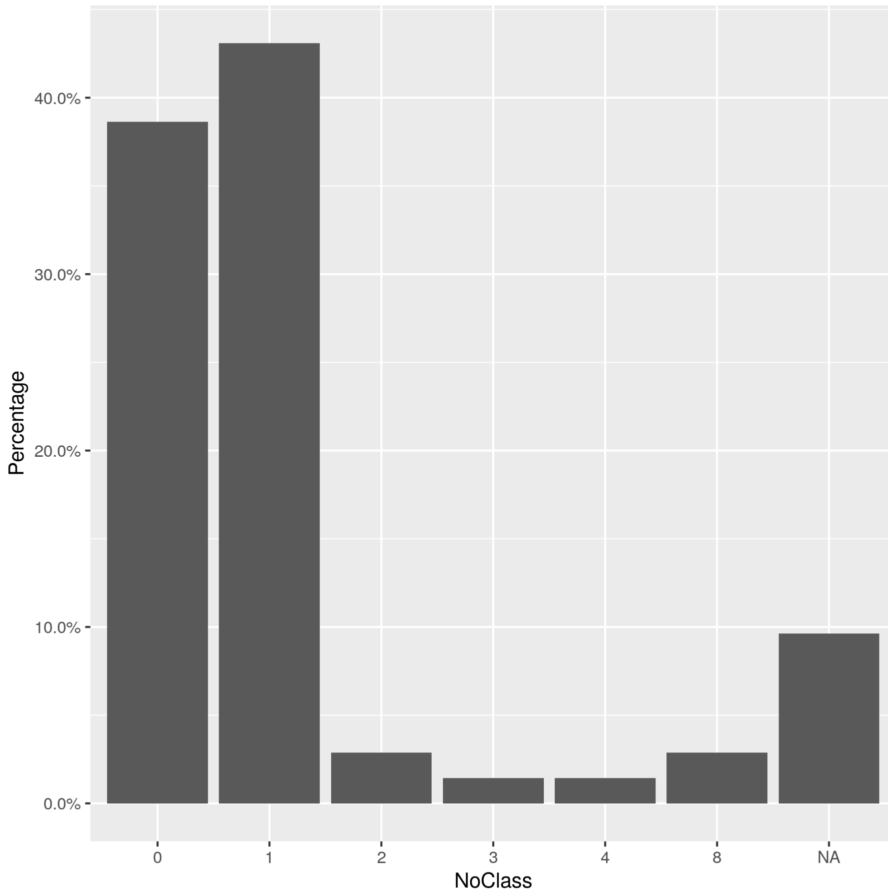

Figure 2: Distribution of NoClass. There are few values above 1.

to say "a listeners music comprehension effects their Classical Rating in this way" is extremely vague, while "A listeners ability to distinguish classical and popular music effects their ability to distinguish classical music in this way" is tautological.

We also drop ‘X1990s.minus.1960s1970s‘ as previous researchers have chosen not to include the feature ‘X1960s.1970s‘. The exact meaning of this composite is somehat difficult to determine, as the scale of the variables it is derived from is arbitarary. Also, having two variables measuring how often pop is listened two is somewhat incongruent, given that we only have one variable measuring how often classical music is listened to.

Finally, we choose to drop NoClass as it has a large number of missing values despite our efforts, and the vast majority of existing values are ‘0‘ or ‘1‘ and thus this variable likely does not add much more than our derived ‘Theory‘ feature.

Thus we are left with a handful of missing values in ‘PachListen‘, ‘ClsListen‘, ‘KnowRob‘, ‘KnowAxis‘, ‘X1990s2000s‘, ‘Composing‘, and ‘Theory‘. We then choose to develop two final datasets, given the primary research questions. In the first, primary dataset, we drop ‘PachListen‘, ‘KnowRob‘, and ‘KnowAxis‘, and filter to only complete cases on the remaining variables. This contains 2289 observations. In the secondary dataset, we filter to complete cases including these. This then contains 1973 observations.

3.2 Exploring the Music-inherent Features

3.2.1 Simple Linear Analysis

Reviewing and comparing the results of all selection methods for our initial linear model, we find a model containing all of the first order ‘Instrument‘, ‘Harmony‘, and ‘Voice‘ best explained the data when considering classical scores, and ‘Instrument‘ by itself best explained the popular scores.

We find that those pieces featuring an electric guitar are less likely to be interpreted as classical by subjects, scoring only 4.29 points in expectation on the classical scale when paired with a I-VI-V harmonic progression and contrary motion, all else equal. Pieces featuring the piano were in expectation scored 1.46 points higher than guitars on the classical scale by the subjects, all else equal. Pieces featuring string instruments scored 3.25 points higher than the guitar baseline, in expectation with all else equal.

Likewise, those pieces featuring an I-V-IV harmonic progression scored in expectation .005 points lower than those with a I-VI-V harmonic, all else equal, though this effect is not statistically significant. Those pieces featuring an IV-I-V harmonic progression were likewise in expectation scored .08 points higher compared to the same baseline, though this effect is not statistically significant wither. Finally, the harmonic progression I-V-VI score in expectation 0.76 more highly. This final effect was significant, and was the progression for Pachelbel’s Canon in D, a canonical classical piece which many people have heard.

Finally, those pieces featuring a parallel 3rds voice part scored 0.39 points lower than those featuring a contrary motion voice segment, all else equal. Those pieces featuring a parallel 5ths voice part likewise scored .35 points lower.

For popular scores, we find that those pieces featuring an electric guitar are more likely to be interpreted as popular by subjects, scoring 6.59 points in expectation on the popular scale, all else equal. Pieces featuring the piano were in expectation scored 1.02 points lower than guitars on the popular scale by the subjects, all else equal. Pieces featuring string instruments scored 2.74 points lower than the guitar baseline, in expectation with all else equal.

3.2.2 Multilevel Model

We first find that a random intercept is appropriate to the data. We find an estimated fixed intercept of 6.84 for classical scores, and an intercept of 5.33 for popular scores, with random effect variances of 1.24 and 1.19 respectively.

We then find that including all the fixed effects of Instrument, Harmony, and Voice leads to the greatest decrease in BIC for classical scores. With the fixed effects in place, we move onto establishing the random effects. We find a model including only the random effects of Instrument and Harmony best explains the data. Thus our final model for classical scores had the form:

$$
\begin{aligned}
\text{Classical}_i = {} & \alpha_{0j[i]} + \alpha_{1j[i]} I(\text{Instrument} = \text{piano})_i + \alpha_{2j[i]} I(\text{Instrument} = \text{string})_i \\
& + \alpha_{3j[i]} I(\text{Harmony} = \text{I-V-IV}) + \alpha_{4j[i]} I(\text{Harmony} = \text{I-V-VI})_i + \alpha_{5j[i]} I(\text{Harmony} = \text{IV-I-V})_i \\
& + \alpha_6 I(\text{Voice} = \text{Parallel 3rds})_i + \alpha_7 I(\text{Voice} = \text{Parallel 5ths})_i \\
& + \alpha_8 I(\text{ClsListen}) \\
& + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \\
\alpha_{0j} &= \beta_{00} + \eta_{0j}, \eta_{0j} \overset{iid}{\sim} N(0, \tau_0^2) \\
\alpha_{1j} &= \beta_{10} + \eta_{1j}, \eta_{1j} \overset{iid}{\sim} N(0, \tau_1^2) \\
\alpha_{2j} &= \beta_{20} + \eta_{2j}, \eta_{2j} \overset{iid}{\sim} N(0, \tau_2^2) \\
\alpha_{3j} &= \beta_{30} + \eta_{3j}, \eta_{3j} \overset{iid}{\sim} N(0, \tau_3^2) \\
\alpha_{4j} &= \beta_{40} + \eta_{4j}, \eta_{4j} \overset{iid}{\sim} N(0, \tau_3^2) \\
\alpha_{5j} &= \beta_{50} + \eta_{5j}, \eta_{5j} \overset{iid}{\sim} N(0, \tau_3^2)
\end{aligned}
$$

Our final model for popular scores was:

$$
\begin{aligned}
\text{Popular}_i = {} & \alpha_{0j[i]} + \alpha_{1j[i]} I(\text{Instrument} = \text{piano})_i + \alpha_{2j[i]} I(\text{Instrument} = \text{string})_i \\
& + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \\
\alpha_{0j} &= \beta_{00} + \eta_{0j}, \eta_{0j} \overset{iid}{\sim} N(0, \tau_0^2) \\
\alpha_{1j} &= \beta_{10} + \eta_{1j}, \eta_{1j} \overset{iid}{\sim} N(0, \tau_1^2) \\
\alpha_{2j} &= \beta_{20} + \eta_{2j}, \eta_{2j} \overset{iid}{\sim} N(0, \tau_2^2)
\end{aligned}
$$

3.3 Exploring the Individual-inherent Features

Moving onto a consideration of the individual characteristics, we find only ‘ClsListen‘ to be significant when considering classical music and ‘Selfdeclare‘ when considering popular music. The final classical model then has the form:

$$
\begin{aligned}
\text{Classical}_i = {} & \alpha_{0j[i]} + \alpha_{1j[i]} I(\text{Instrument} = \text{piano})_i + \alpha_{2j[i]} I(\text{Instrument} = \text{string})_i \\
& + \alpha_{3j[i]} I(\text{Harmony} = \text{I-V-IV}) + \alpha_{4j[i]} I(\text{Harmony} = \text{I-V-VI})_i + \alpha_{5j[i]} I(\text{Harmony} = \text{IV-I-V})_i \\
& + \alpha_6 I(\text{Voice} = \text{Parallel 3rds})_i + \alpha_7 I(\text{Voice} = \text{Parallel 5ths})_i \\
& + \alpha_8 I(\text{ClsListen}) \\
& + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \\
\alpha_{0j} = {} & \beta_{00} + \eta_{0j}, \eta_{0j} \overset{iid}{\sim} N(0, \tau_0^2) \\
\alpha_{1j} = {} & \beta_{10} + \eta_{1j}, \eta_{1j} \overset{iid}{\sim} N(0, \tau_1^2) \\
\alpha_{2j} = {} & \beta_{20} + \eta_{2j}, \eta_{2j} \overset{iid}{\sim} N(0, \tau_2^2) \\
\alpha_{3j} = {} & \beta_{30} + \eta_{3j}, \eta_{3j} \overset{iid}{\sim} N(0, \tau_3^2) \\
\alpha_{4j} = {} & \beta_{40} + \eta_{4j}, \eta_{4j} \overset{iid}{\sim} N(0, \tau_3^2) \\
\alpha_{5j} = {} & \beta_{50} + \eta_{5j}, \eta_{5j} \overset{iid}{\sim} N(0, \tau_3^2)
\end{aligned}
$$

We find that those pieces featuring an electric guitar are less likely to be interpreted as classical by subjects, scoring only 3.26 points in expectation on the classical scale when paired with a I-VI-V harmonic progression, not being a listener of classical music, and . Pieces featuring the piano were in expectation scored 1.54 points higher than guitars on the classical scale by the subjects. Pieces featuring string instruments scored 3.46 points higher than the guitar baseline, in expectation with all else equal.

Those pieces featuring an I-VI-V and guitar scored only 3.74 points in expectation on the classical scale, all else equal. This baseline is modified bases on instrument used. Those pieces featuring an I-V-IV harmonic progression were in expectation score .0007 points higher than those with a I-VI-V harmonic, all else equal, though this effect is not statistically significant. Those pieces featuring an IV-I-V harmonic progression were in expectation score .042 points higher than those with a I-VI-V harmonic, all else equal, though this effect is not statistically significant. Finally, and most significantly for harmonics, the harmonic progression I-V-VI score in expectation 0.87 more highly than those with a I-VI-V harmonic, all else equal. This effect was significant, and was progression for Pachelbel's Canon in D, which many people have heard.

Listeners who described themselves as classical music listeners scored pieces 0.31 higher on the classical music scale in expectation. Listeners with a 1 point difference in auxiliary discernment scores had a .11 difference in their classical scoring of a piece, in expectation, with the listener with a higher score scoring a piece lower on the scale in expectation.

The final popular model has the form:

$$
\begin{aligned}
\text{Popular}_i = {} & \alpha_{0j[i]} + \alpha_{1j[i]} I(\text{Instrument} = \text{piano})_i + \alpha_{2j[i]} I(\text{Instrument} = \text{string})_i \\
& + \alpha_3 \text{Selfdeclare} \\
& + \epsilon_i, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \\
\alpha_{0j} = {} & \beta_{00} + \eta_{0j}, \eta_{0j} \overset{iid}{\sim} N(0, \tau_0^2) \\
\alpha_{1j} = {} & \beta_{10} + \eta_{1j}, \eta_{1j} \overset{iid}{\sim} N(0, \tau_1^2) \\
\alpha_{2j} = {} & \beta_{20} + \eta_{2j}, \eta_{2j} \overset{iid}{\sim} N(0, \tau_2^2)
\end{aligned}
$$

3.4 Musicians vs. Non-Musicians

We find that splitting individuals into musicians and non-musicians along ‘Selfdeclare‘ equal to 3 creates the most explanatroy bisection when combined with our optimum classical model, and at 1 when combined with our optimum popular model.

For classical music we find extreme variation in interaction based on where we place the split. Considering the ”best” split, on 3, we find that ”artists” score pieces .01 less classical on average in general, all else equal. They are also less reliant on the instrument than non-artists, scoring pieces with pianos .34 less, and strings 0.83 less in expectation compared to non-artists. They also are more likely to recognize the I-V-VI harmonic progression, and score pieces with it 1.49 points higher on the classical scale in expectation all else equal, than non-artists. They do not change their ratings based on voice all that much, once the other effects are accounted for. The ordinality of these effects is largely preserved for splits on other levels, excepting 1, which likely introduces too many non-artists to really call those in the group ”musicians”.

For popular music we find that ‘Selfdeclare‘ is best bisected by splitting on 1, likely extremely casual artists.

There is extreme variation in interaction based on where we place the split. Considering the ”best” split, on 1, we find that ”artists” score pieces 1.42 points more popular on average in general, all else equal. They are also more penalizing to instruments than non-artists, scoring pieces with pianos .57 less, and strings .78 less in expectation compared to non-artists.

3.5 Other Results

We finally find that, though specific knowledge of it is not implicitly necessary, pieces with Pachelbel’s harmonic progression are scored as more classical, though its effect is less important to popular scoring. We also find that a contrary motion of voice leading also drives higher classical ratings.

4 Discussion

Our findings above largely validate Jimenez’s findings on the drivers of Subjects interpretation of pieces as Classical or Popular. Our modeling regarding Classical scores suggest the same results as Jimenez’s hypothesis - that primary instrument is far and away the most primary driver of a subjects consideration of a piece as Classical, supported by the pieces harmonic progression. We also extend Jimenez’s work to consider those design variables with the most significant effect on a subjects consideration of a piece as Popular. We find again that primary instrument is the greatest driver of subjects conception of a piece as Popular, but fail to find a similarly strong relationship when considering harmonic progression. The consideration of additional covarites is found not to significantly increase our understanding of these effects, though considering the auxiliary discrimination score or a subject and whether they listen to classical music could arguably be included in the model considering Classical rating. We find that those self identifying as musicians do differ in statistically significant ways from those who do not, though those models including these terms are not necessarily more useful for explaining the data. Those identifying as ”Artists” are, as Jimenez suggested, less reliant on instrument and more reliant on harmonic progression than non-artists when discerning Classical music. They are, however, more reliant on instrument when discerning Popular music.

Our findings suggest that many of the covariates have effects that are either not related to discerning a piece as Classical or Popular, or are otherwise largely accounted for in the instrument of a piece, its harmonic progression, or voice leading. Those that have a useful place in an explanatory model have small effects relative to the design variables. The usefulness of whether a subject defines themselves as classical music listeners or not also has a difficult to usefully interpret effect on Classical score. If one considers oneself to be a listener of classical music, our analysis find that one scores pieces as more classical than otherwise. Is this due to some sort of Bayesian effect, with a more classical prior? And is the listener more or less accurate due to this covariates effect? Likewise, what does it mean to be a self declared artist of level 1? This seems to have the most effect on classical scores, but does this mean amateurs rate everything popular, or does it mean that not much training is needed to distinguish popular music?

Ultimately, we find the design variables of most use, and random effects considering them to significantly improve our model. That is, their effects seem to vary by subject, in a significant way. We find that only two of the design variables have useful relationships with classical score, and only one has a useful relationship with Popular score. In accordance with Jimenez's hypothesis, the instrument of a piece is the primary driver of a users interpretation of that piece, followed by harmony, and finally voice. Pachelbel's progression is also very significant in this determination, as is the contrary motion vocal progression for classical music.

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