STA 325 Final Project

Genre Classification using Spotify Data

Connie Wu, Jason McEachin, Joe Choo, Scott Heng

11/23/2020

1 Introduction

Cataloging and organizing music is an essential aspect of collecting and storing music. It allows us not only to identify and differentiate music, but also allows us to better understand the evolution of different types of music over periods of time. Genre has been the main and most efficient mode to categorize different kinds of music, and genre classification has always been a consistent challenge due to the complex nature of songs and the difficulty in differentiating the unique features specific to each genre. In the past, genre classification was largely performed by using pattern recognition after breaking the songs down frame by frame, and understanding the elements of chord progressions and stylistic features of the song [1]. However, the rise of big data has allowed us to more efficiently and accurately extract audio features and consequently automate the arduous task of classifying songs in particular genres. Genre classification is not only important in increasing the efficiency of cataloging music which is relevant to music companies and artists in organizing elements of their craft, but also for academics who wish to better understand the evolution of music and particular genres in their research.

Our study aims to build on modern statistical techniques that perform genre classification, by predicting the genre of songs based on multiple audio features each song possesses. Using well-known classification techniques such as logistic regression and support vector machines (SVM), we leverage the substantial capacity of modern computing to perform such statistical modeling on a large dataset of songs and various audio features taken from Spotify, and compare the performance of both classification techniques so as to evaluate their predictive accuracies, strengths and weaknesses of using either approach for genre classification. Using both methods to perform multi-group classification, this study aims to comprehensively and comparatively evaluate the effectiveness of both statistical methods with respect to music analytics.

Our paper is organized holistically and with simplicity to provide a comprehensive report on genre classification, starting with introducing research goals and providing the background motivations for the study. In Section 2, we provide a a description of the data as well as extensive exploratory data analysis which will motivate some design decisions during our statistical modeling. Section 3 describes our methodology with respect to implementing logistic regression and support vector machines for predicting genres of songs, structured with multi-group classification. In Section 4, we discuss our models' results as well as model diagnostics to evaluate the accuracy of each of the models' fit, and relate our results to relevant parties that will use genre classification. Finally in section 5, we consolidate our findings and conclude our study with its strengths and its limitations.

2 Data

Our data was taken from Spotify's API, that draws from its large database of songs and their respective audio features. The data set was consolidated and released on kaggle, containing 232,725 tracks across 26 genres [2]. Each data point represents a song along with its tagged genre and various audio attributes such as tempo, key, danceability, valence, acousticness etc. For a detailed description of each feature, please refer to Table 2.1.

Table 1: Table 2.1 Descriptions of data set variables

Col	Column.Name	Description	Value
1	acousticness	A measure of degree of how acousitc a track is. 1.0 is most acoustic	float (0.0-1.0)
2	danceability	A measure based on a combination of music elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 1.0 is most danceable	float (0.0-1.0)
3	duration_ms	Duration of the track in milliseconds	integer
4	energy	A perceptual measure of intensity and activity attributing dynamic range, perceived loudness, timbre, onset rate, and general entropy.	float (0.0-1.0)
5	instrumentalness	A measure of the presence of vocals, rap or spoken word. The higher the value, the greater likelihood the track contains no vocal content.	float (0.0-1.0)
6	key	Integers that map to pitches using the standard pitch class (C=1, C#=2 . . .)	integer
7	liveness	A measure that detects the presence of an audience in the recording. A value above 0.8 provides strong likelihood that the track is live	float (0.0-1.0)
8	loudness	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track. Values typical range between -60 and 0 db	float (0.0-1.0)
9	speechiness	A measure that detects the presence of spoken words in a track	float (0.0-1.0)
10	popularity	A measure of the song's popularity, calculated by considering the track's total number of plays and how recent those plays are.	integer (0-100)
11	tempo	The overall estimated tempo of a track in beats per minute (BPM)- the speed or pace of a given piece and derives directly from the average beat duration.	float (0.0-1.0)
12	valence	A measure describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric)	float (0.0-1.0)
13	year	Year that the track was released	integer
14	mode	Modality of the track (1=Major, 0=Minor)	integer
15	name	Name of track	string
16	genres	Genres associated with the track's artist(s)	array
17	artist	Name of the track's main artist	string

Before proceeding further, we performed some data cleaning. Firstly, we eliminated any observations that had the genre ‘acapella’, because it was a duplicate of a full song already included in the dataset and it had only 119 observations. We also removed any observations with ‘Comedy’ as they are lengthy tracks of spoken word by comedians, and we considered them not to be actual music. We also got rid of Children's Music due to faulty labeling, and Reggae because it is extremely similar to Ska.

2.1 Exploratory Data Analysis

We began our exploratory data analysis to better understand the composition of our dataset. Starting with understanding the breakdown of genres, we see from Fig 1 that there is a good amount of observations for each group (>6000), which tells us that there will be enough observations to classify each of our 22 genres, and techniques like bootstrapping or strategies to deal with limited data do not need to be considered.

We then looked to understand the compositions of audio features based on genres, by generating density plots for each audio feature. Fig 1.2 shows the density plots of 6 audio features, and we can observe that although for features such as danceability, energy and tempo, each genre has a relatively distinctive density

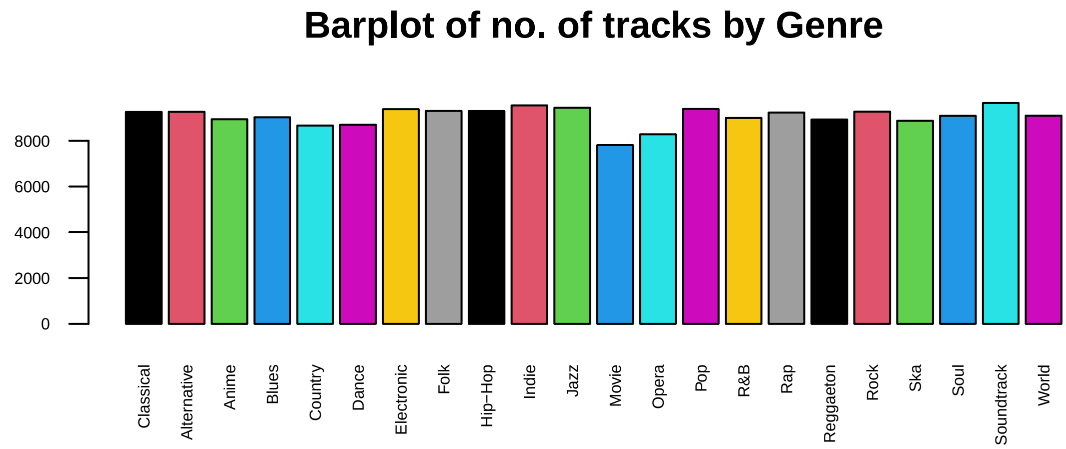

Barplot of no. of tracks by Genre

Figure 1: Count of tracks per Genre

plot while for features such as liveness, loudness and valence, the densities are much hard to differentiate. Please refer to the appendix for density plots for the remaining audio features.

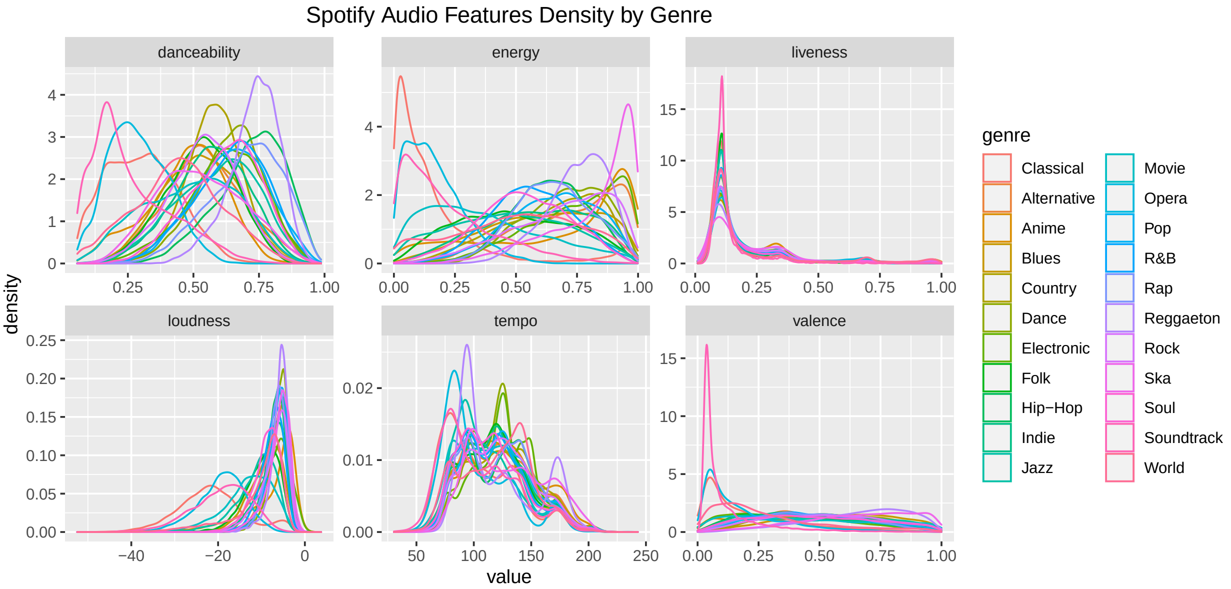

Spotify Audio Features Density by Genre

Fig 1.2 Density plots by Genre for 6 audio features

3 Methodology

3.1 Binary and Multinomial Logistic Regression

The first of our two classification techniques we chose to model to predict genres is logistic regression. Logistic regression is appropriately used in cases when the dependent variable is categorical, which in our study's dependent variable being genre. It is not only computationally efficient but is produces results that are easy to interpret. As our EDA has shown a substantial amount of observations (>6000 for each genre) that are much more than the number of features (~13), there is a high level of confidence that overfitting will not occur, however more comprehensive model diagnostics will be performed and described in the later sections. Logistic Regression is usually performed when the dependent variable is dichotomous, meaning that the model can perform predictive classification over 2 genres. Also known as the log-odds model, logistic regression can be written mathematically as:

$$l = \log(\frac{p}{1-p}) = \beta_0 + \sum_{i=1}^{13} \beta_i x_i$$

where l is the log-odds and $p = P(Y = 1)$ is the probability of the observation being classified as one group labelled $Y = 1$, β_0 is the intercept and β_i are the coefficients of the 13 predictors, in our study being audio features, represented as x_i.

While logistic regression can be used for binary classification between two genres, this approach can be easily expanded to perform multi-group classification. The extension appropriate for our study is called multinomial logistic regression, which is similar to binary logistic regression, with the exception of having J-1 equations instead of one, J being the number of categories encompassed in the model. This can be written in mathematical notation as:

$$l = log(\frac{\pi_{ij}}{\pi_{iJ}}) = \beta_0 + \mathbf{x_i}\boldsymbol{\beta_j}$$

where $\boldsymbol{\beta_j}$ is a vector of regression coefficients, similar to $\mathbf{x_i}$ being a vector of predictors. This produces $J-1$ multinomial logit equations that contrast each of the categories, compared to binary logistic regression that contrasts between successes $Y = 1$ and failures $Y = 0$.

3.2 Support Vector Machine (SVM)

The second classification technique is a supervised machine learning model, chosen appropriately as our data is completely labeled. SVM performs classification by generating one or multiple hyperplanes with p dimensions, p being the number of predictors included in the model. A function is intuitively set to divide the points between two classes, forming what is known as a separating hyperplane. Among the separating hyperplanes created, the one making the largest margin between the two classes is chosen as the optimal model and is used for predictions.

For both the multinomial logistic and SVM models, we will only be using the top 5 genres, as more genres significantly decreases the predictive accuracy of the multinomial model. These top 5 genres are Electronic, Indie, Jazz, Pop, and Soundtrack.

4 Results

4.1 Multinomial Logistic Regression

To obtain this model, we put in all variables other than "genre" into a multinomial logistic regression model and performed backwards step-wise selection. All variables were chosen except for `liveness`. We decided not to explore any interaction terms, as we believe that this would negatively affect the interpretability of our model.

The coefficients of our final model can be found in the Appendix. It is important to note that the "Electronic" genre is the baseline genre in this model. We can see that the log-odds of a song being Pop versus Electronic when all variables have a value of 0 is -13.1, whereas the log-odds of a song being Soundtrack versus Electronic when all variables have a value of 0 is 7.83. This means that when all variables are 0, the odds are high of the song being in the Soundtrack genre vs. Electronic, whereas the odds are very low of the song being in the Pop genre vs. Electronic.

One variable that had a broad range of coefficient values amongst all the genres was danceability. We can see that all coefficient values are negative, meaning that with each 1 unit increase in danceability, holding all else constant, the log-odds of a song being any of the four genres other than Electronic vs. Electronic decreases by some amount. For example, with a 1 unit increase in danceability, holding all else constant, the log-odds of a song being Soundtrack vs. Electronic decreases by -11.9, whereas it decreases by -3.04 for Pop. This means that Electronic typically has the highest danceability rating out of the other 4 genres, with Soundtrack typically having the lowest danceability rating.

Another interesting variable that we can interpret is popularity. We can see that all coefficient values are positive except for Sountrack's, meaning that with each 1 unit increase in popularity, holding all else constant, the log-odds of a song being Indie, Jazz, or Pop vs. Electronic increases by some amount, where the log-odds of a song being Soundtrack vs. Electronic decreases by some amount. More specifically, with a 1 unit increase in popularity, holding all else constant, the log-odds of a song being Soundtrack vs. Electronic decreases by -0.05, whereas it increases by 0.39 for Pop. In fact, because Pop's coefficient for popularity is the highest out the 4, we can see that Pop typically has the highest popularity, which makes sense because Pop music is typically what is played on mainstream radio stations. On the other hand, we can see that Soundtrack typically has the lowest popularity out of the 5 genres.

4.1.1 Model Validation and Diagnostics

We performed 5-fold cross-validation on our model, the results of which can be found in our Appendix. We partitioned the data into 90% for the training set and 10% for the test set. We then partitioned the training set 5 more times to obtain several estimates for 5-fold cross-validation. We averaged these estimates and obtained 0.747, or 74.7% accuracy. Then, we trained the model on the whole training set (90% of the data) and predicted on the testing set (10% of the data) and obtained a prediction accuracy of 74.2%. This is relatively accurate and all of the estimates are around the same, indicating that our model is not overfitting the test set.

From this residual plot, it appears that less than 5% of the observations lie outside of the gray lines, which represent the ±2 standard error bands. Additionally, the residuals appear to be mostly randomly scattered, although a large amount of the residuals are crowded at the left end of the plot. Overall, we can see that our model suits the data relatively well.

4.2 SVM

The SVM model was fit using the variables chosen from backward selection as in

the case for Multinomial Logistic Regression to keep consistent. As a result, the only variable not chosen in the final model was that of liveliness

The output from the SVM model indicates that from our training dataset tells us

there are 1982 support vectors. We fit the model with a relatively low cost gives that was rather robust. The number of support vectors given the training data follows from our choice of C as we increase C there are fewer support fewer vectors. Further,As shown in the resulting table, 99% of our training observations were correctly classified.

5 Conclusions

Perhaps the largest takeaway of this project is seeing how Multinomial Logistic Regression (MLR) and Support Vector Machines (SVM) are related to each other, as well as limitation of use for each model.

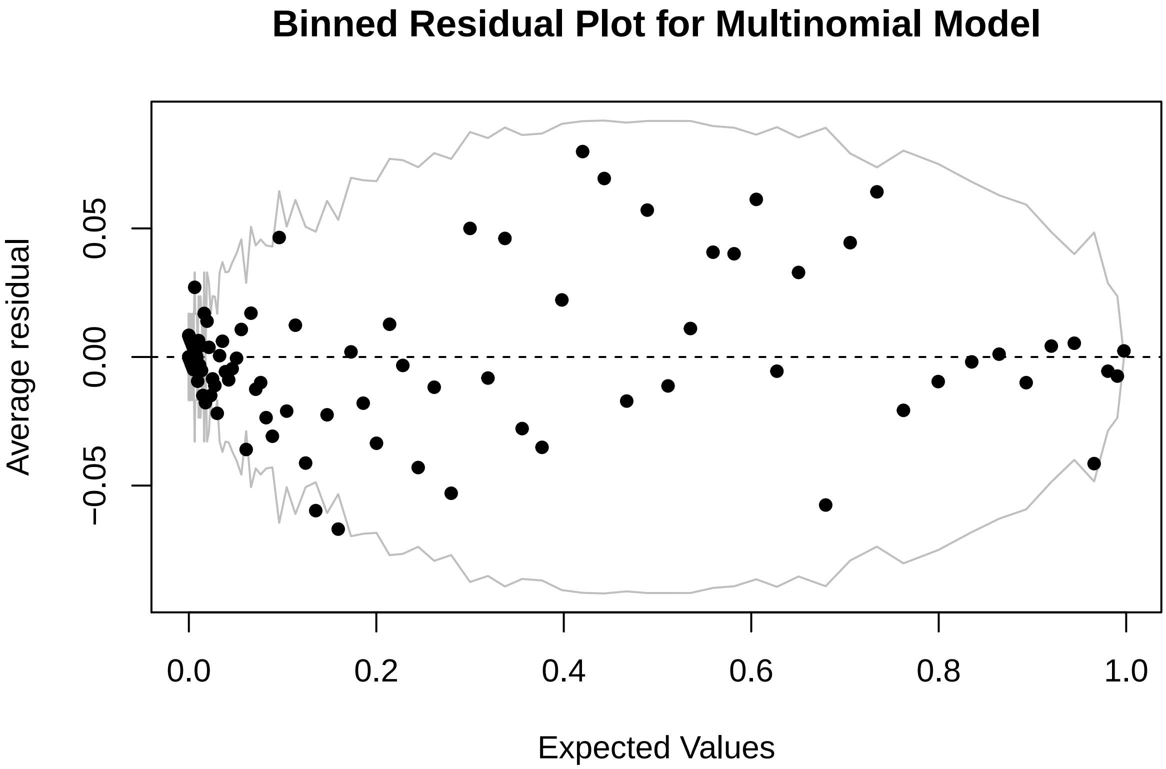


Figure 2: Binned Residual Plot for Multinomial Model

The test accuracy for MLR and SVM were 74.2% and 75.74% respectively, and although SVM is more efficient and accurate, we sacrifice interpretability as to how each predictor may affect the likelihood of a particular genre being correctly classfied. With more knowledge about the distribution of our data through empirical and EDA observations, we determined that SVM with a radial kernal was most appropriate for predicting our data. This was because natural clusters (not linear separations) formed depending on the genres' predictors. These separations were better identified through SVM which may account for the slightly higher test accuracy.

A limitation/obstacle in the course of this case study was choosing how many different genres to consider in our models. Unfortunately, we had to immediately rule out using all/most of the cleaned 22 genres to choose from, due to computational limits in our local machines when running a MLR. Additionally, in the scope of Spotify's mission to provide popular songs to stream, analyze, and curate playlists from, it made sense to look at a "Top 10" genres, which ruled out more niche genres such as Anime, Ska, and Blue. However, due to overlap in many of the different indicators (many of which were scaled in a range of 0-1 as determined by Spotify), predictive power was lacking so we decided to narrow the field further and use the "Top 5" genres. Therefore to create meaningful models in context of usefulness for Spotify and to explore and analyze the nuances of MLR and SVM largely drove this project.

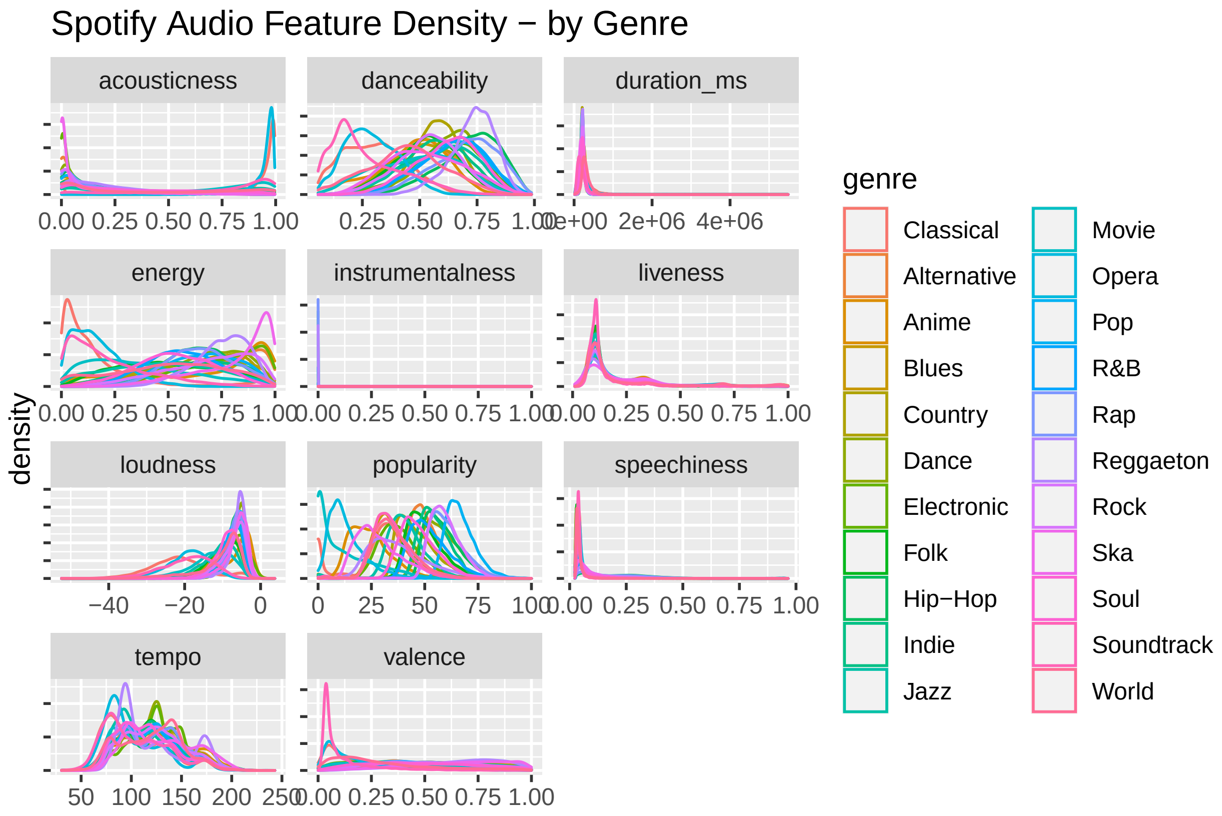
In terms of impacts, having a high level of accuracy is important so Spotify can classify, organize, and ultimately recommend specific genres and songs to its users. While we only looked at the Top 5 genres, grouping models into bins of 5 might be an effective way to maintain fairly high predictability as well as manage computational limits. For example, in future analysis, we can take the Top 6-10 genres, the Top 11-15 genres, and the Top 16-22 genres and apply it to unknown genre-classified songs. This would allow for several possible predictions to which ultimately the highest likelihood for example could be chosen to finally label and predict the song's genre. This segmentation eases computational load and maintains higher accuracy as the possible outcomes are more clear to predict instead of a particular genre being among a crowd of other 21 genres with similar key predictors. In order to improve the results in future findings, perhaps more predictor variables would be useful. The indicators as given by Spotify reflect the aggregate of a particular song and does not account for, say: chord progression; change of keys, tempo, or loudness throughout the course of a song; and thematic or descriptive traits that might be indicative of a genre.

6 Works Cited

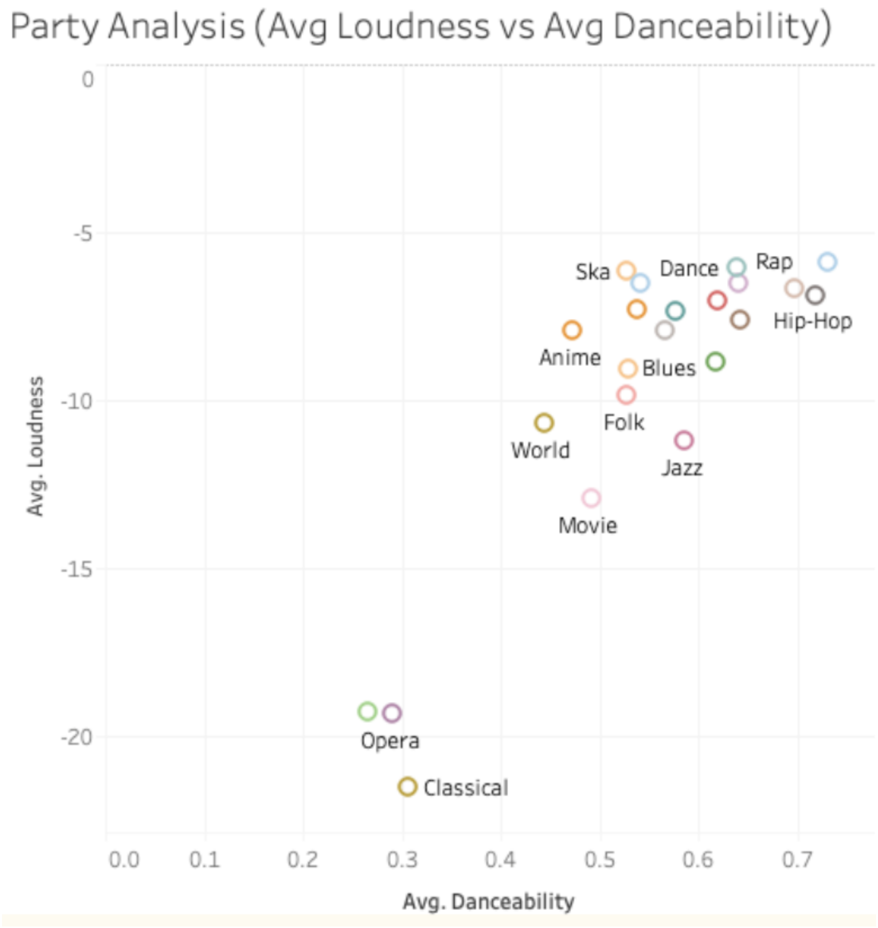
[1] C.N. Silla Jr., A.L. Koerich, C.A.A. Kaestner A machine learning approach to automatic music genre classification J Braz Comput Soc, 14 (3) (2008)

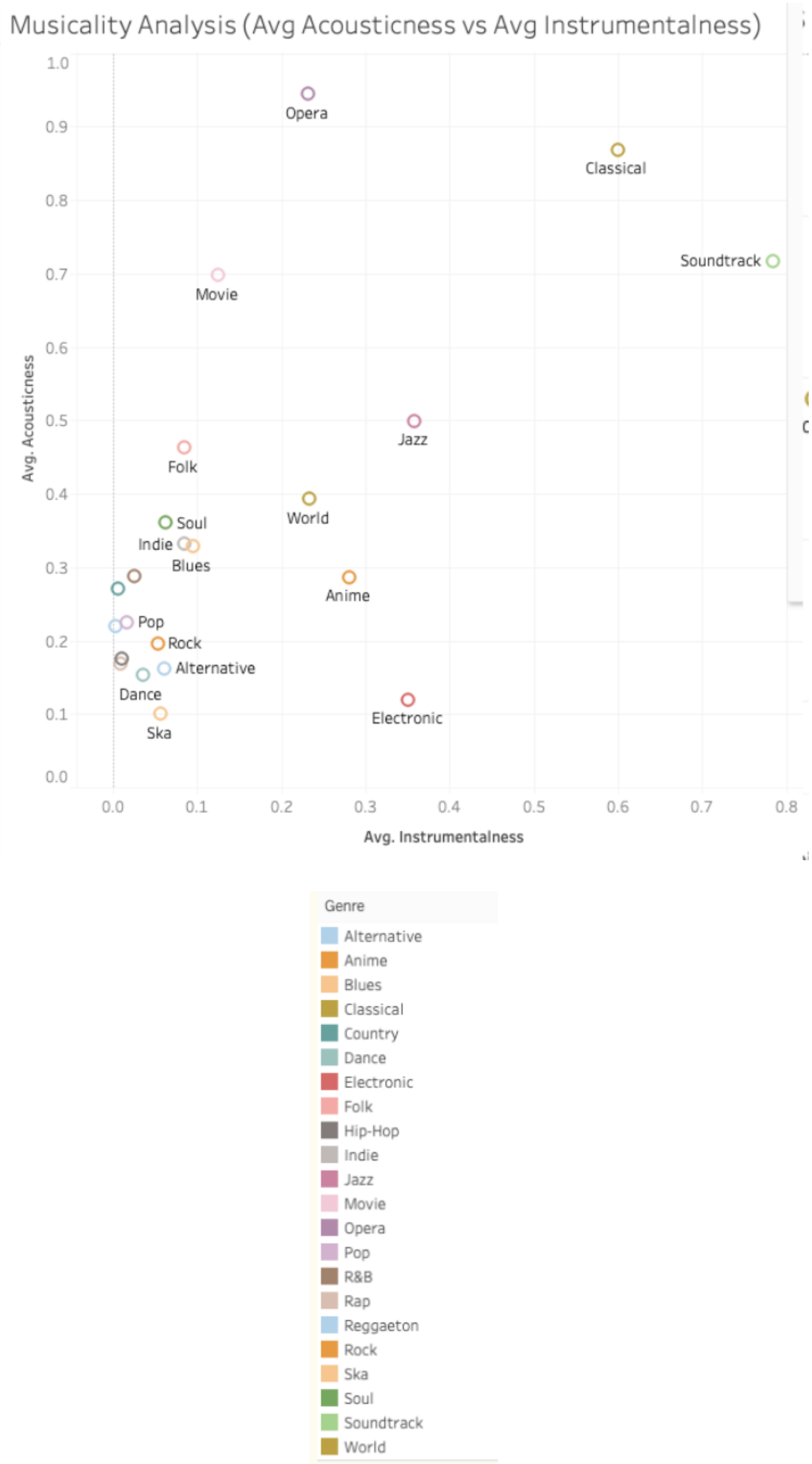
[2]https://www.kaggle.com/zaheenhamidani/ultimate-spotify-tracks-db

7 Appendix


Spotify Audio Feature Density − by Genre
acousticness
danceability
duration_ms
energy
instrumentalness
liveness
loudness
popularity
speechiness
tempo
valence
density
0.00 0.25 0.50 0.75 1.00
0.25 0.50 0.75 1.00
0e+00 2e+06 4e+06
−40 −20 0
0 25 50 75 100
50 100 150 200 250
genre
Classical
Alternative
Anime
Blues
Country
Dance
Electronic
Folk
Hip−Hop
Indie
Jazz
Movie
Opera
Pop
R&B
Rap
Reggaeton
Rock
Ska
Soul
Soundtrack
World

7.1 EDA


Party Analysis (Avg Loudness vs Avg Danceability)
0
-5
-10
-15
-20
Avg. Loudness
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Avg. Danceability
Ska
Dance
Rap
Hip-Hop
Anime
Blues
Folk
World
Jazz
Movie
Opera
Classical



7.2 Multinomial Logistic Regression Model Coefficients

```
## Call:
```

```
## multinom(formula = genre ~ popularity + acousticness + danceability +
##     duration_ms + energy + instrumentalness + loudness + speechiness +
##     tempo + valence, data = train5)
##
## Coefficients:
##            (Intercept)  popularity acousticness danceability   duration_ms
## Indie       -0.1621498  0.19073438     1.739542    -5.187256 -4.836917e-06
## Jazz         4.1162811  0.02743972     1.853528    -4.972872  2.714906e-07
## Pop        -13.0611427  0.39393495     1.480342    -3.045157 -5.347594e-06
## Soundtrack   7.8328288 -0.04928726     1.397582   -11.878656 -7.318617e-06
##               energy instrumentalness    loudness speechiness        tempo
## Indie      -5.378662      -2.02572993  0.18382104  -2.7388335 -0.003380295
## Jazz       -6.066768      -0.04108421  0.02128958  -1.1968175 -0.007950603
## Pop        -5.429040      -2.24413299  0.29988810   0.1732901 -0.002966148
## Soundtrack -3.117103       1.99873541 -0.17905762  -5.2492121 -0.007306684
##              valence
## Indie      2.1337518
## Jazz       4.7591732
## Pop        2.0413673
## Soundtrack 0.9078647
##
## Std. Errors:
##             (Intercept)   popularity acousticness danceability  duration_ms
## Indie      4.529557e-06 0.0002508127 1.093684e-06 2.713171e-06 6.368455e-07
## Jazz       5.816945e-06 0.0002475939 2.737776e-06 3.370431e-06 4.213654e-07
## Pop        2.345541e-06 0.0001441456 3.006941e-07 1.496770e-06 5.936776e-07
## Soundtrack 2.496237e-06 0.0000954572 1.698863e-06 1.201521e-06 4.791655e-07
##                  energy instrumentalness     loudness  speechiness        tempo
## Indie      3.212523e-06     4.007419e-07 2.950040e-05 5.152618e-07 0.0009973387
## Jazz       2.893413e-06     1.765160e-06 6.112257e-05 5.098701e-07 0.0008777136
## Pop        1.767150e-06     8.056668e-08 1.381450e-05 2.604704e-07 0.0005750063
## Soundtrack 8.518546e-07     1.370789e-06 3.730441e-05 1.580633e-07 0.0003820034
##                 valence
## Indie      2.777095e-06
## Jazz       2.935101e-06
## Pop        1.719798e-06
## Soundtrack 8.776291e-07
##
## Residual Deviance: 3703.08
## AIC: 3791.08
```

7.2.1 Multinomial Cross Validation Results

```
## # weights:  60 (44 variable)
## initial  value 9766.069253
## iter  10 value 7094.303915
## iter  20 value 5222.951456
## iter  30 value 4379.187798
## iter  40 value 3929.692676
## iter  50 value 3882.967002
## iter  60 value 3881.528720
## final  value 3881.526834
## converged
## # weights:  60 (44 variable)
## initial  value 9766.069253
## iter  10 value 7054.856554
## iter  20 value 5356.808212
## iter  30 value 4415.294131
## iter  40 value 3948.612821
## iter  50 value 3893.270773
## iter  60 value 3892.013171
## final  value 3892.009087
## converged
## # weights:  60 (44 variable)
## initial  value 9766.069253
## iter  10 value 6882.799927
## iter  20 value 5125.796361
## iter  30 value 4357.108660
## iter  40 value 3922.084565
## iter  50 value 3874.988549
## iter  60 value 3874.016720
## final  value 3874.014448
## converged
## # weights:  60 (44 variable)
## initial  value 9766.069253
## iter  10 value 7006.459608
## iter  20 value 5627.407997
## iter  30 value 4338.487811
## iter  40 value 3918.320191
## iter  50 value 3837.148379
## iter  60 value 3835.593484
## final  value 3835.591811
## converged
## # weights:  60 (44 variable)
## initial  value 9766.069253
## iter  10 value 6843.570171
## iter  20 value 5249.695759
## iter  30 value 4405.019868
## iter  40 value 3961.497982
## iter  50 value 3908.506751
## iter  60 value 3906.700836
## final  value 3906.699292
## converged
```

```
## [1] 0.7369809 0.7475280 0.7481872 0.7574160 0.7468688
```

```
## [1] 0.7473962
```

```
## # weights:  60 (44 variable)
## initial  value 12207.586566
## iter  10 value 8738.454259
## iter  20 value 6353.506944
## iter  30 value 5384.023406
## iter  40 value 4925.452171
## iter  50 value 4854.955465
## iter  60 value 4853.215507
## final  value 4853.212273
## converged
```

```
##
## preds        Electronic Indie Jazz Pop Soundtrack
##   Electronic        270    22   68   2         16
##   Indie              38   250   45  65          6
##   Jazz               46    28  238   1         21
##   Pop                 9    78    2 306          0
##   Soundtrack         12     4   24   1        343
```

```
## [1] 0.7424802
```