A Data Mining Investigation

WHAT ARE THE DIFFERENT MUSIC TASTES OF COUNTRIES AROUND THE WORLD?

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Introduction

Spotify has changed the world by making music more freely available and accessible to anyone with internet. As a result, music is evolving more rapidly than ever before. New sounds are being shared, more collaborations are possible, and lesser known artists are being discovered -- all through Spotify's unique and robust database.

Now that the ability for people to instantly listen and discover music from all corners of the globe exists, it would be interesting to see how music tastes differ from country to country. Is music truly universal or does culture play a part in the preference of rhythm and tune?

With this in mind, this investigation aims to discover whether songs can be classified by country based on its audio features. This analysis also hopes to answer these additional questions:

- What are the most common key modes?
- What songs are the most joyful (valence)?
- Who are the most popular artists by country and overall?
- Are there any song attributes that are positively/negatively correlated?
- What is the average value for each song characteristic for each country?
- Do song titles matter?
- What patterns exist among the world's top songs?
- Does language play a role in the tracks that are popular by country?

Data

The data set contains the Top 50 songs as of September 12, 2018 from ten select countries: The United States, Germany, Hong Kong, Norway, New Zealand, Singapore, Australia, the United Kingdom, Portugal, and Mexico. These countries were also selected based on their locations (diverse enough to represent taste in music around the globe) and the availability of their "Top 50 Songs" playlists through Spotify.

Aside from the track name and artist, each song is broken down by the following audio features: danceability, energy, loudness, mode, speechiness, acoustincness, instrumentalness, liveness, valence, tempo, duration (in milliseconds), time signature, and key mode. [*]

Data Gathering

The data set is created using the Spotify API. In order to access Spotify data, one must first create a developer account that is linked to a Spotify Profile. Once a developer profile is created, a "Client ID" and "Client Secret" is assigned, which will be used in the API call. The package "Spotifyr," developed by Charlie Thompson offers a quick and easy way to gather song and audio data through specific Spotify profiles and playlists.

For this experiment, the playlists from the general Spotify user is used. After receiving every single playlist created by this user, the data frame is filtered to only playlists containing the top 50 songs from

[*] A table detailing each attribute is available in the Appendix.

the selected countries. Next, the audio feature data for each of the 500 tracks in our data frame are called, thus creating the data set needed for the experiment. This data frame is called "GlobalAudioAttributes" and is saved since it contains all the original data.

General Preprocessing and Cleaning

To begin preprocessing and cleaning, the original data is duplicated into a new data frame called "SpotifyDF."

The first step in preparing the data for analysis is to create labels. Since the question at hand is "What are the different Music Tastes of Countries around the world?" the most appropriate labels would be the country. Conveniently, the "playlist_name" column already includes out this data, so the column is copied and transformed into the "country" column. A quick "gsub" is used to filter out the words "Top 50" from all the values. The "country" column is then transformed into a factor, since is it categorical data.

Next, the "track_uri" and "playlist_name" columns are deleted from the data frame as they do not provide any relevant information for to this analysis. The columns are then re-ordered so that "country" is the first listed column for ease of analysis.

Since many of the data mining methods used in this experiment can process numerical data only. "SpotifyDF" is copied and subset out into another data frame that contains only numeric attributes. The numerical dataset will only contain the attributes of country, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence, tempo, duration_ms, and time_signature. A separate data frame is created that contains only categorical data. The categorical data dataset will only contain country, key, mode, and key_mode.

Further preprocessing steps will have to be taken depending on which methods are used. But the general cleaning and preprocessing is now complete.

Preprocessing for Text Mining

Text mining analysis can only be used on the track names since that is the only variable with a large amount of text. Therefore, a new data frame must be created containing just the track_name column.

The function "wordcloud" will conveniently create the corpus and remove punctuation and stop words, which takes care of those preprocessing aspects.

Preprocessing for Clustering

For clustering, the numerical dataset created in preprocessing must be scaled so that the attributes are all weighted equally. This is done using the "preProcess" and "predict" functions included in the "caret" package. The "preProcess" function estimates the parameters of each operation and the "predict" function applies those parameters to the data set. When scaling, the country labels must be removed, since they are not a numeric value.

Next, the scaled data is combined once again with is original labels. The data set is now scaled and ready to be clustered.

Preprocessing for K-Nearest Neighbor and Support Vector Machines

Similar to clustering, the data for KNN and SVM must also be scaled. An additional step of randomizing the data is also necessary. Before beginning this process, “set.seed” is set to 1234 (an arbitrary number) in order to ensure that the randomized results are still reproducible in the future. Then, using the function “runif,” 500 random numbers between 0 and 1 are created. These numbers are used to shuffle the numeric Spotify data set into a random order.

Next, the same steps as those taken in preprocessing for clustering are used to scale the data. Lastly, the scaled and randomized data set are broken out into training and testing data sets for analysis. 80% of the original dataset is used for training and the remaining 20% is set aside for testing.

Preprocessing for Naive Bayes and Random Forest

Since Naive Bayes, Decision Tree, and Random forest do not require any further processing, the only action left is to create training and testing data sets from the numeric Spotify data. And index is created to split out 80% of the data set for training and the remaining 20% for testing. The labels are also removed from the data and saved separately.

Preprocessing for Decision Tree

Decision tree algorithm is unique in that it can also process categorical data. In order to clean up the data set, the columns of valence, danceability, energy, and loudness were converted into categorical data using the min, median, and max to create levels.

Preprocessing for Association Rule Mining

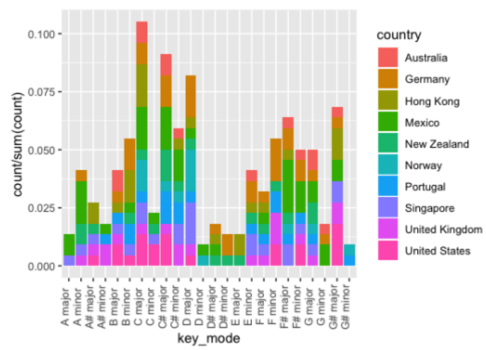
Association Rule Mining requires transactional data. Since a handful of variables are already converted from the decision tree preprocessing, a data frame is created with the categorized data. Keep in mind that this will limit the analysis to the attributes of key_mode, valence, danceability, energy, and loudness.

Analysis

Exploratory Data Analysis

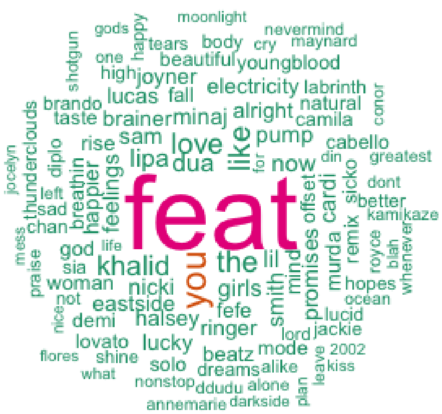
The most basic questions are answered in the exploratory data analysis to get a better understanding of the data that has been retrieved. Since most data mining methods are limited to only numerical data, this was an opportunity to investigate the small portion of categorical data that was broken out of the original data set.

The first question that can be answered through categorical data exploration is "What are the most common key modes among popular songs?" A simple color-coded bar graph rendered through "ggplot2" reveals that among the playlists in this dataset, C major, C# Major, and D major are by far the most popular. However, the distribution of countries within each key mode is still too close to call – so the overall pattern is established. But there seems to be no immediately obvious correlation between a certain key mode and country.



Text Mining

Next, text mining is implemented through the means of a world cloud. Since text mining is not a relevant method to our data mining exploration, it is included as part of our exploratory data analysis to answer "Do the titles of songs matter when it comes to popularity?"



Interestingly enough, this analysis reveals that the name of the song is completely overshadowed by the inclusion of featured artists titles. In other words, a large portion of the songs that ended up in the top 50's playlists were songs with featured collaborations. The word "feat" is by far the most used word in song titles and some of the artists names that appear in the word cloud were Nicki Minaj, Halsey, and Cardi B.

The discovery of featured artists as an overarching pattern in track names is satisfactory, as the question is not pivotal to answering the main data question and the removal of artists names would difficult since a word bank of their names is not available.

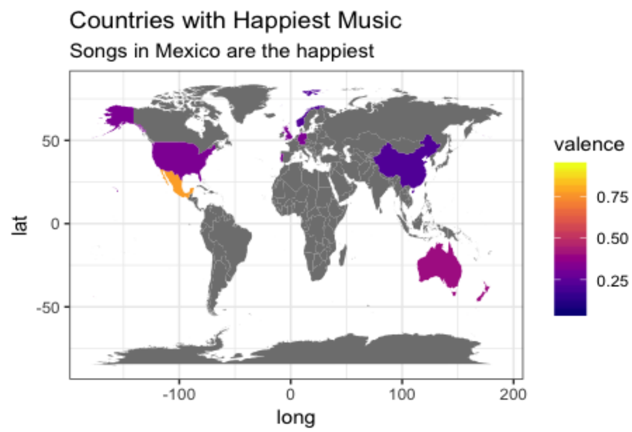
Song and Artist Exploration

This section of the exploratory analysis sets the foundation of the hypotheses that will be used to guide the investigation. It looks for patterns in audio features, artists preferences, and finds the average of each attribute by country.

First the attribute of valence is explored for a better understanding of the attribute's definition. This helps answer the question "What songs are the most joyful?"

track_name	valence
Shape of You	0.931
Habibo	0.926
Dona Maria	0.924
Ahora Te Puedes Marchar	0.909
Mala Mía	0.901

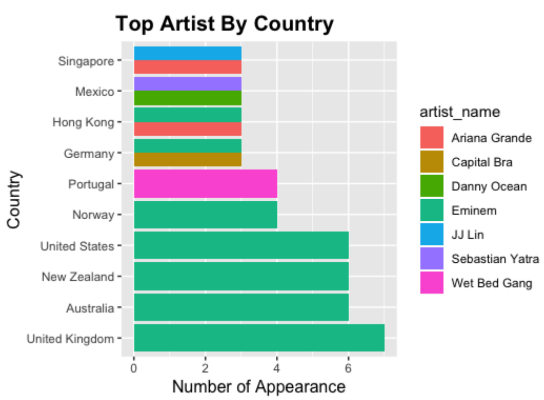
The results show that although “Shape of You” by Ed Sheeran is the most joyful song in the data set, the majority of songs that are joyful are in Spanish.

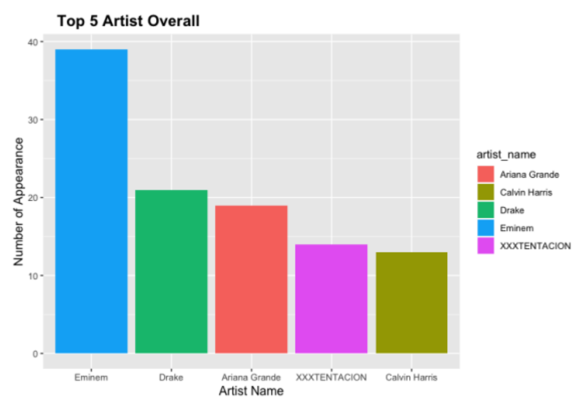


To follow up this discovery, a valence map confirms that Mexico, indeed, has the most joyful collection of top songs! Furthermore, it looks like songs in Hong Kong (represented by China on the map) and Norway are more depressing.

Already, some patterns are forming.

An investigation into the most popular artists is next. The two bar graphs below depict the top artists from each of the ten countries as well as the top artists overall.





The most notable finding here is that Eminem is the most popular artist overall – winning the top place in the countries of Norway, United States, New Zealand, Australia, and United Kingdom. Notice that four out of five of these are English-speaking countries. Eminem is also tied for first place in Hong Kong and Germany.

Aside from Eminem and Ariana Grande, the three remaining artists in the “Top 5 Artists Overall” chart do not appear in the “Top Artists By Country” chart. Drake, XXXTENTACION, and Calvin Harris must have a smaller but wider following among the countries in the dataset.

Furthermore, Hong Kong and Singapore intriguingly both list Ariana Grande as their top artist. These are two Chinese-speaking countries that are close in culture. This begs the question of whether culture has any influence on music taste.

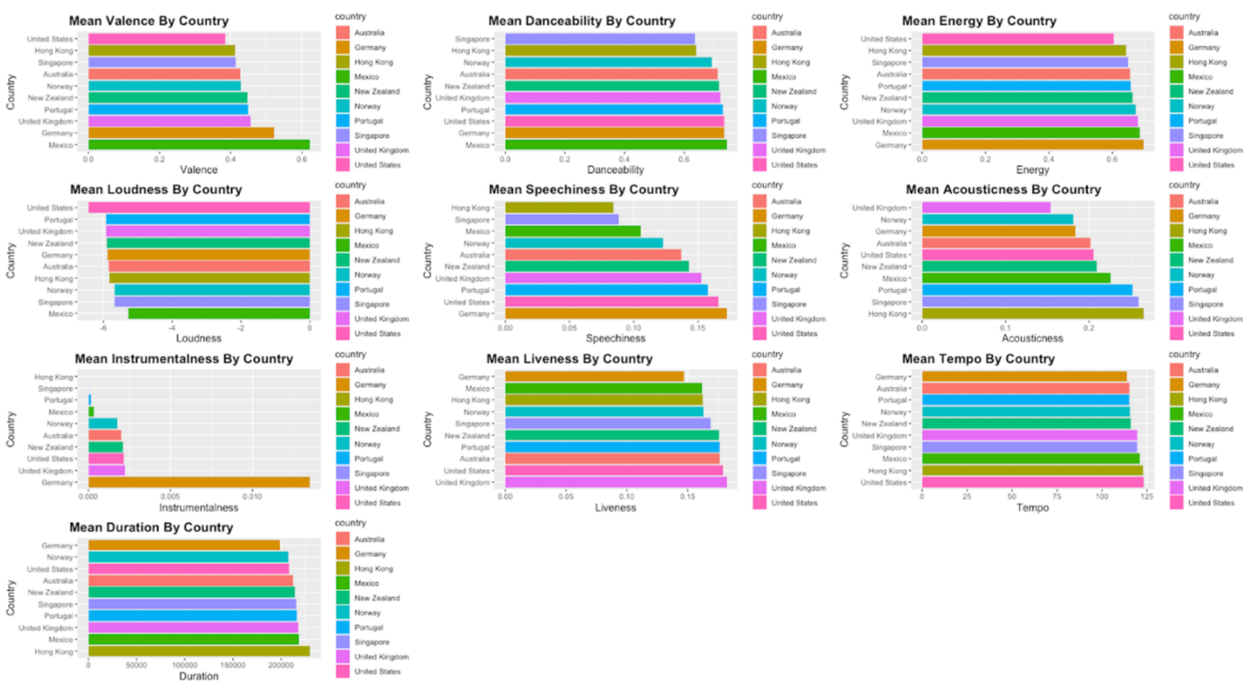
Lastly, Portugal and Mexico are the only countries that march to the beat of their own drums. Portugal’s sole top artist is Wet Bed Gang, whereas Mexico lists two unique artists – Sebastian Yatra and Danny

Ocean. Other exclusive artists that made the cut are JJ Lin and Capital Bra who are all tied with others as the top artist in Singapore and Germany, respectively.

Audio Features Exploration

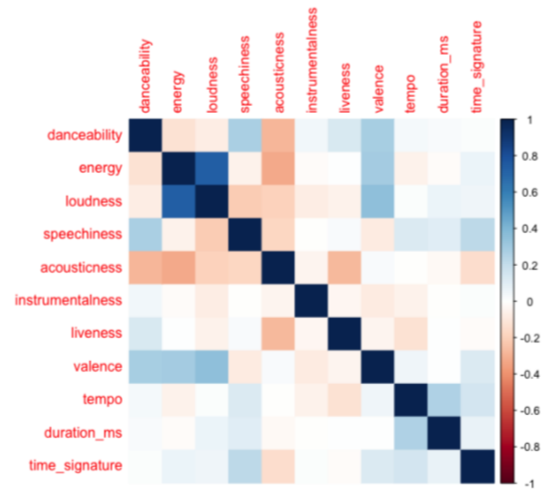
To explore audio features, the mean of each attribute is broken out by country and put into a grid of easy comparison. These charts reveal some clear differentiators among countries. For example, Mexico's song valence clearly dominates – which is previously established observation. Some new findings are that Germany has a strong preference for more instrumental music. Germany also prevails in the areas of danceability, energy, and speechiness. (Do Germans love high energy party tracks?) Hong Kong's tracks have a longer average duration than all of the other countries.

The main takeaway from these charts is that perhaps valence, speechiness, acousticness, and instrumentalness are good variables to use when targeting the country variable during data mining analysis.



Correlation and Scatterplots

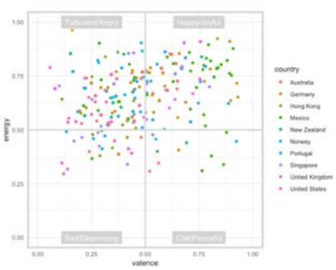
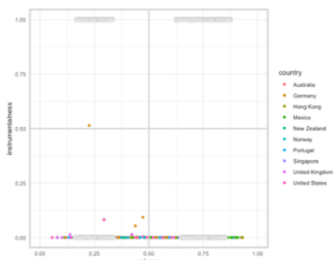
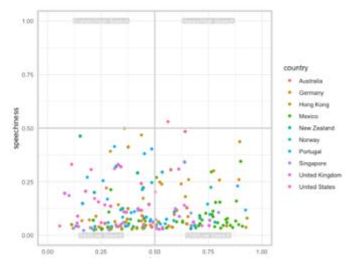
The last exercise in the exploratory data analysis is to investigate the correlation between variables. The following heat map illustrates the positive or negative correlations between each variable.



Energy and loudness have a clear and strong positive correlation. Loudness and valence also have a mildly positive correlation. Most of the other variables seem to have very light to no correlations with one another.

A grid of scatterplots is created between some select variables to get some better visualizations of these correlations. The scatterplots below offer a preview for some methods such as clustering, k-nearest neighbor, and support vector machines.

The conclusion from the scatterplots is a bit worrisome. Notice how all the different color points are distributed throughout every plane – this will make it difficult to the algorithms to group tracks successfully. There are only a few outlying examples in which a single country exists in its own quadrant. But those data points are most-likely not influential enough to be a determining factor when it comes to categorization.

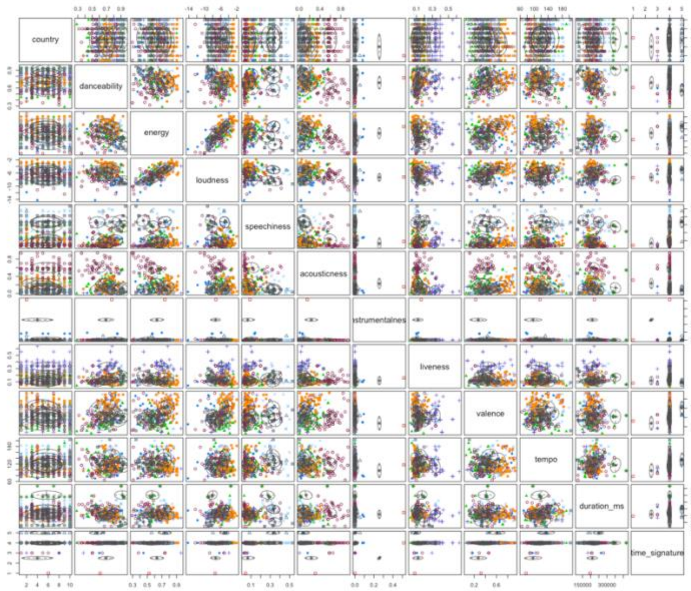





Clustering

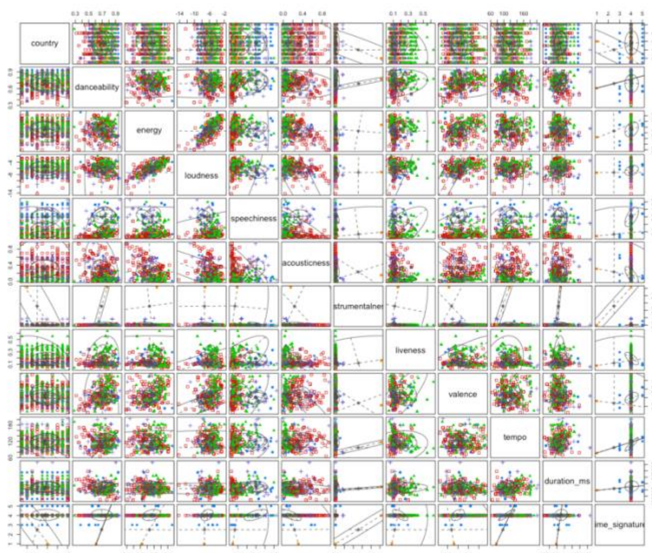
In this experiment, the normalized data is clustered in three ways: model-based clustering, k-means, and hierarchical clustering.

Model-Based Clustering

Model-based clustering is implemented through the function “mcluster.” The first model is built with ten clusters assigned -- the number ten is chosen because data set contains the top 50 songs from ten different countries. The scatterplots from this model offers a preview of how the attributes are related to each other.



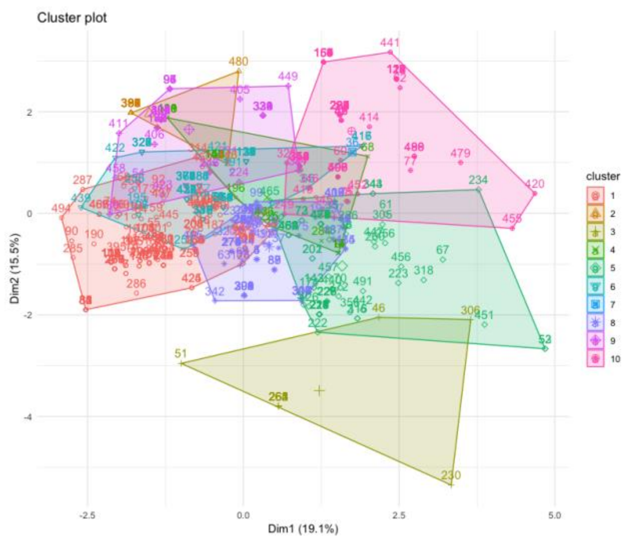
A second model is built without assigning any “k” value, allowing the algorithm to determine the number of clusters appropriate. Interestingly enough, the scatterplots that resulted are much busier but only contained only four clusters.



K-Means

Clustering with k-means offered a much more decipherable visual. Using the “kmeans” function, the parameters are set at k=10 once again, with the “max iterations” and “nstart” both set at 100. The number 100 is arbitrarily selected.

The results show that although the k-means algorithm is able to visually pick out ten clusters, it has a hard time correctly categorizing the songs. For example, although Cluster 1 is clearly dominated by Mexico, the majority of songs for other countries are also classified in this cluster. This is likely the cluster in which most of the songs that are popular world-wide and not country specific are categorized. Cluster 7 has a single track belonging to Germany. The algorithm also has some trouble deciphering between songs from Hong Kong and Singapore. It is possible that because these two countries are similar in language and culture, their music has more overlapping points than others.




```
515  ### Dominating countries by Cluster:
516  #1 = Mexico
517  #2= Germany or Portugal
518  #3 = Hong Kong, Norway, or Singapore
519  #4 = Portugal
520  #5 = Hong Kong or Singapore
521  #6 = Australia, Hong Kong, Mexico, Singapore, or UK
522  #7 = Germany
523  #8 = Hong Kong
524  #9 = United Kingdom
525  #10 = United States
526
```

525:20 Chunk 5: Analysis: Clustering

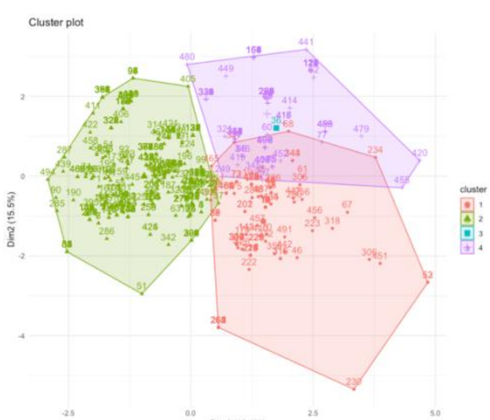
Console Terminal R Markdown

~/Desktop/Syracuse/IST 565/Project/

	1	2	3	4	5	6	7	8	9	10
Australia	12	1	1	3	7	8	0	6	4	8
Germany	20	2	1	3	3	3	1	6	4	7
Hong Kong	7	1	2	1	13	8	0	13	3	2
Mexico	23	0	0	1	4	8	0	4	5	5
New Zealand	12	1	1	3	6	6	0	8	5	8
Norway	14	1	2	2	4	7	0	9	5	6
Portugal	15	2	0	4	6	7	0	7	3	6
Singapore	11	1	2	2	14	8	0	9	1	2
United Kingdom	14	1	0	3	3	8	0	7	6	8
United States	4	1	0	3	9	7	0	10	5	11

Out of curiosity, a second k-means model is created based on the results of the model-based clustering. For this model, k is set to 4, which is the number of clusters predicted by the “mcluster” algorithm.

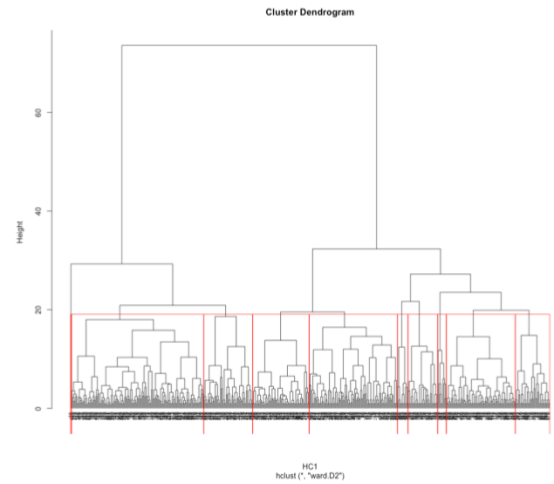
This time, Cluster 2 seem to be the cluster in which popular, overlapping songs are categorized. Cluster 3 show the same pattern of a single song that belong to Germany. Cluster 4 show some strong similarities in music taste between Australia, Germany, New Zealand, United Kingdom, and United States. This is interesting because aside from Germany, the countries in Cluster 4 are all English-speaking countries.

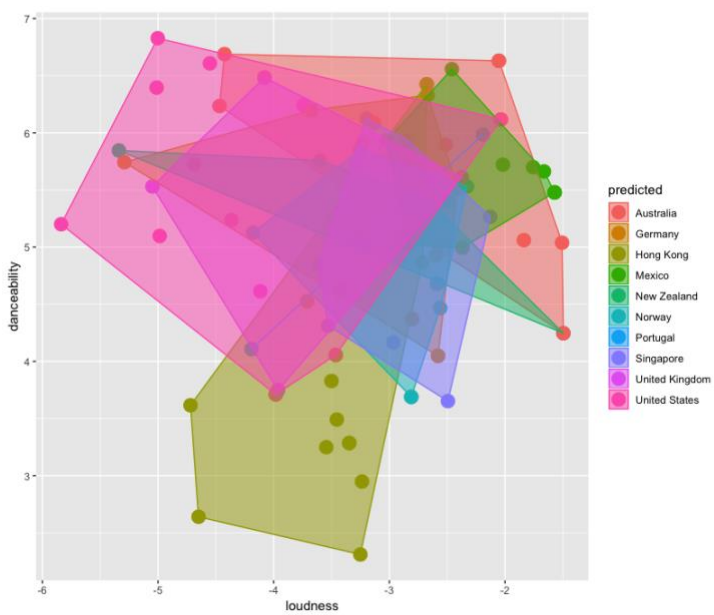


	1	2	3	4
Australia	11	29	0	10
Germany	4	34	1	11
Hong Kong	19	28	0	3
Mexico	5	40	0	5
New Zealand	9	31	0	10
Norway	11	31	0	8
Portugal	11	31	0	8
Singapore	20	27	0	3
United Kingdom	7	33	0	10
United States	14	23	0	13

Hierarchical Clustering

This last form of clustering is hierarchical clustering, which creates a dendrogram. First, a distance matrix is created using Euclidean distance. The matrix was then clustered using the “hclust” function. However, due to the fact that there are a large number of attributes and values, the dendrogram is quite undecipherable. However, the dendrogram is still able to be visually broken into clusters by using the “rect.hclust.” This visual offered similar insight to that of the model and k-means clustering in that it depicted one larger cluster of songs as well as one very thin cluster – most likely consisting of the single track from Germany that continues to be an outlier.





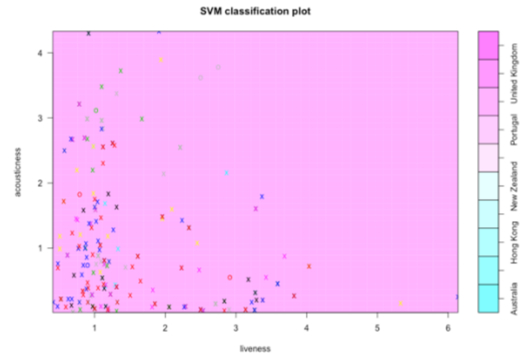
K-Nearest Neighbor

For K-Nearest Neighbor, the number for k is defined as the square root of the number of rows in the dataset (500 rows). Then, the KNN model was built using the randomized and scaled “SpotifyTrainSet” and tested using “SpotifyTestSet.” Of course, both training and testing data must not contain the labels, so the country column was removed.

Once the KNN model is complete, a dataframe must be built in preparation for the visualization. In addition, a function is created find the hull of which the boundary points of each cluster will be based.

Although the visualization seems able to break out some clusters, it seems that the overall accuracy of the KNN model is low – only 17% in fact. A confusion matrix cross-referencing the results with the labels is created to determine this statistic.

Support Vector Machines



Initially, the SVM algorithm is attempted on a randomized and scaled dataset, with the labels unchanged. This resulted in some issues. The first model, which has the parameters set at the polynomial kernel and c at 0.1, predicts with an accuracy of only 14%. After tuning and changing c to 1, the accuracy is even lower -- 13%. Since SVM can only classify objects into two classes, the algorithm is not equipped to handle the dataset in its current state.

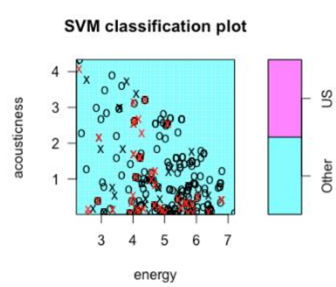
Thus, it becomes necessary to break out the dataset by country and create 10 different SVM models. This method, known as “one-against-all,” requires redefining the dataset by a single label versus everything else (i.e. Germany vs. Other). Because this process is so labor intensive, tuning parameters are used as part of the initial model-- the best cost is determined to be 0.001 for each individual country. And all models are built using the polynomial kernel.

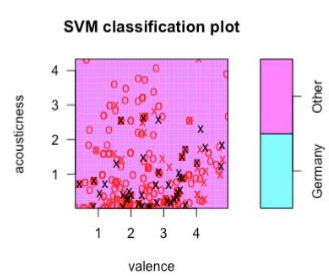
Once the dataset is broken out accordingly, the accuracy of each SVM model shoots up. The following table details the accuracy rate of each model by country.

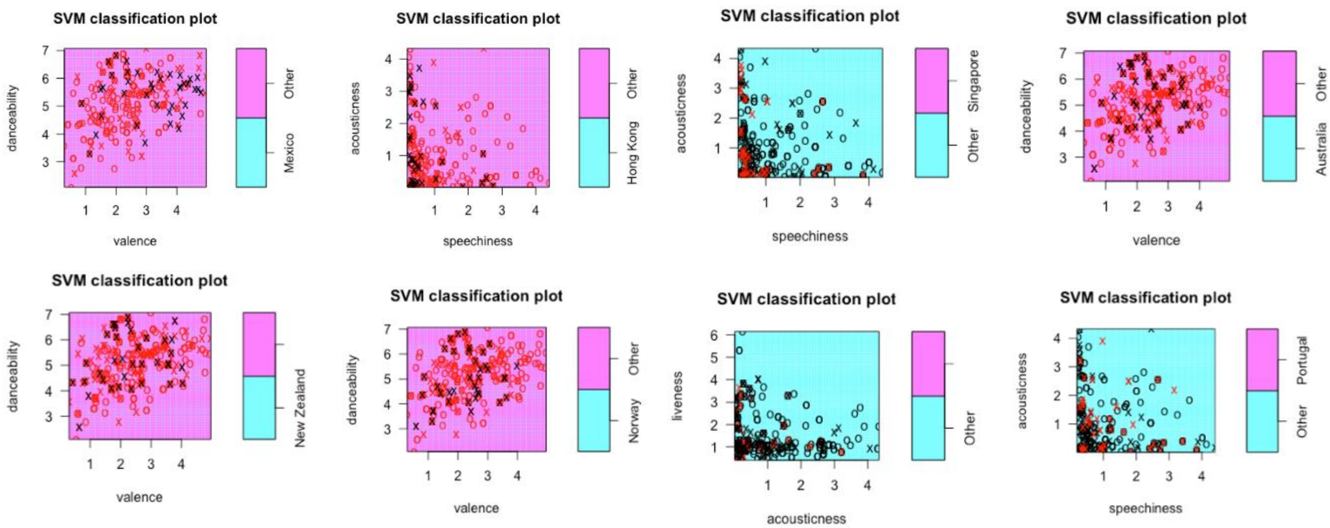
MODEL	PREDICTION ACCURACY
UNITED STATES	91%
GERMANY	92%
MEXICO	89%
HONG KONG	90%
SINGAPORE	91%
AUSTRALIA	91%
NEW ZEALAND	86%
NORWAY	88%
UNITED KINGDOM	92%
PORTUGAL	90%

Overall, Germany and the UK has the best accuracy at 92%, while New Zealand actually had the lowest accuracy of the models at 86%.

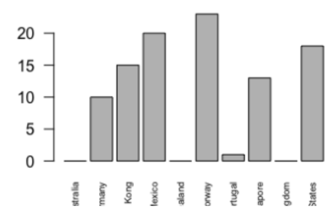
The most interesting part of this exercise is that even though the algorithm is able to categorize the songs to country with great accuracy, the visualizations show no margin since all the points are distributed throughout the plane. This is something that was anticipated from the scatterplots in the exploratory analysis. But all-in-all, it is great to see that SVM is still able to categorize the countries regardless of the margin.



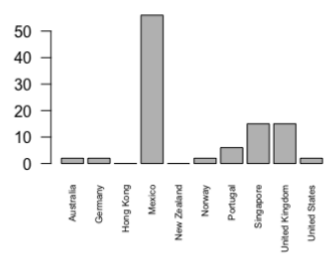




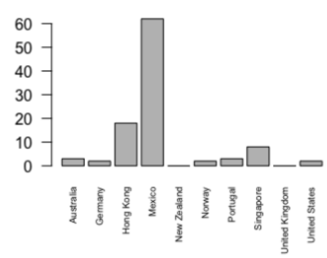
Naïve Bayes



As usual, the first model of Naive Bayes is created using all the attributes to target the country label. This resulted in a model with only 11% accuracy, with the majority of songs attributed to Mexico.



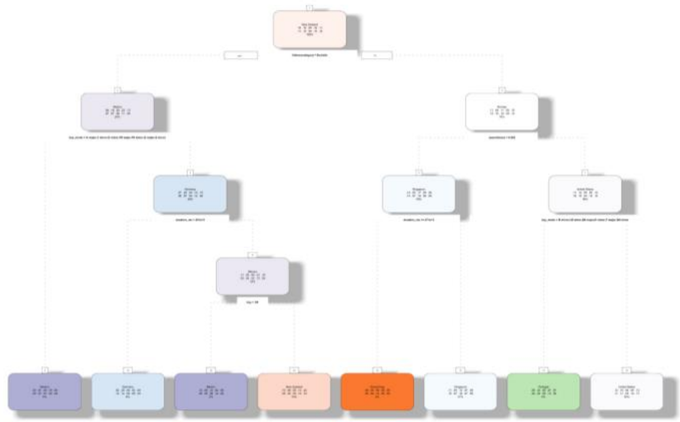
But in the second model, in which the parameters are revised to only using danceability and valence to target country, the distribution of songs among countries look much more even. New Zealand, Australia, and United Kingdom seem to be left out of the mix, with minimal number of songs being categorized to those countries. But Model 2 still results in a low accuracy rate of only 14%.



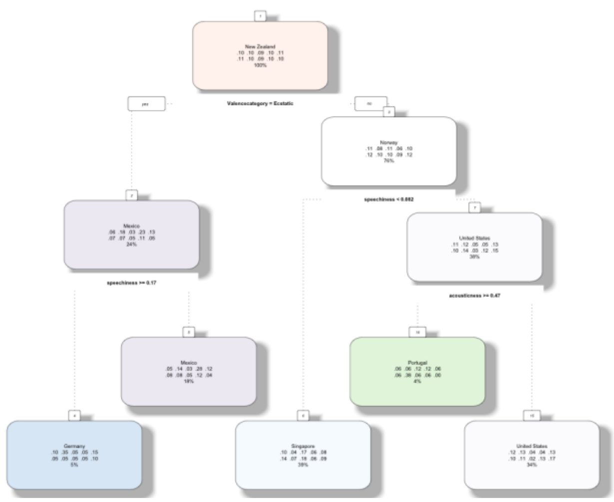
The final attempt with a third model uses the parameters of danceability, valence, speechiness, and instrumentalness – these are all variables of importance as dictated by Random Forest analysis. Unfortunately, the added variables do not help at all as the accuracy returns to 11%. Once again, the results favor Mexico, but the distribution is a little spread out than the first model.

Decision Tree

The first model of the decision tree algorithm, using all the attributes to target country, results in 24.5% accuracy. The decision tree accuracy is calculated using the "tree" function in the "tree" package. The accuracy of the first decision tree model is relatively low, but still much higher than that of KNN. Interestingly, New Zealand sits at the top of the decision tree. This is surprising since New Zealand did not stand out as a unique country during exploratory analysis. But with a 24.5% accuracy, such abnormalities can be disregarded.

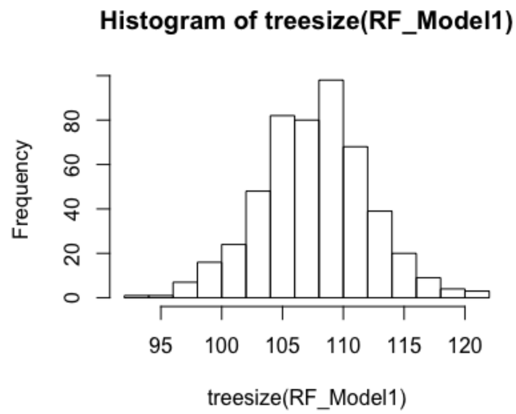


After pruning the tree and targeting country with variables of valence, acousticness, speechiness, and instrumentalness, which are the variables that are hypothesized to be most powerful during exploratory analysis, the accuracy actually drops to 17.5%. These results are surprising as they are possible indications that the chosen variables are not as important as originally thought.



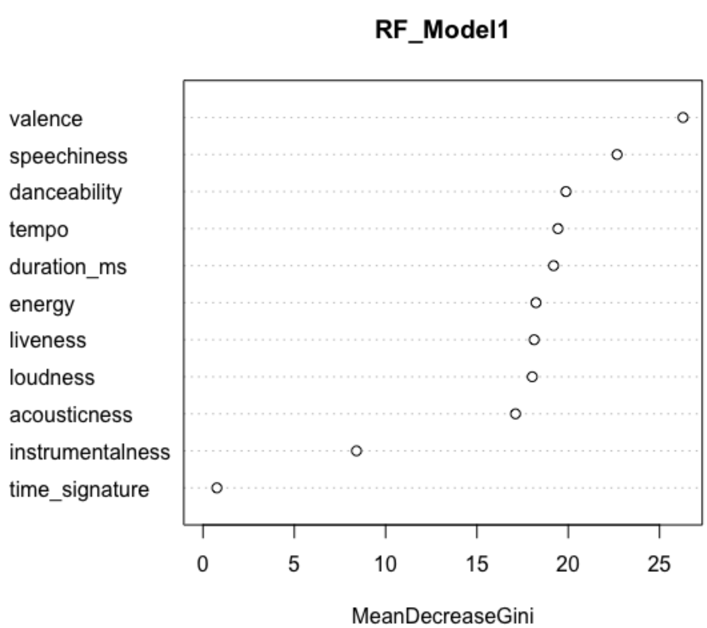
Random Forest

Using the “randomforest” function from the “randomforest” package, the initial model is created targeting country using all attributes. Despite having a normal distribution in tree size, a confusion matrix reveals that this model is only 11% accurate.



However, Random Forest is able to offer a chart of variable importance. Based on the chart: valence, speechiness, danceability, and tempo are the four most important variables when predicting country. These variables differ greatly from the initial assumption since instrumentalism and acousticness showed such high variability in the exploratory analysis. But random forest makes it clear that those two variables are likely skewed by outliers.

Furthermore, the four most important variables are actually used in the third Naive Bayes Model with little success. Thus, the accuracy of that table of variable importance is still to be debated.



Association Rule Mining

Before attempting Association Rule Mining, be sure to detach the “tm” package, if it is installed. The “inspect” function conflicts with the one included in the “arules” package.

The analysis using Association Rule Mining is rather brief because the initial results did not seem promising. The “apriori” function is used to create the rule. When attempting to limit the RHS to specific countries, support levels cannot exceed beyond 0.02 and confidence levels stay at 0.2 for the majority of attempts.

Over the three countries attempted (United States, Germany, and Mexico), Mexico emerges with the highest confidence and support, at 41% and 2.2% respectively. The determining factors were very loud and very happy music.

```
    lhs                                   rhs                       support confidence lift count
[1] {danceabilitycategory=Two-Step,
     Valencecategory=Sad}              => {country=United States}   0.012        0.40  4.0     6
[2] {danceabilitycategory=Two-Step,
     Energycategory=Relaxing}          => {country=United States}   0.012        0.26  2.6     6
[3] {Energycategory=Relaxing,
     Loudcategory=Medium}              => {country=United States}   0.012        0.23  2.3     6
[4] {danceabilitycategory=Two-Step,
     Loudcategory=Soft}                => {country=United States}   0.010        0.23  2.3     5
[5] {key_mode=G# major}                => {country=United States}   0.014        0.21  2.1     7

[1] {danceabilitycategory=Two-Step,
    Loudcategory=Medium}               => {country=Germany}   0.012        0.29  2.9     6
[2] {Energycategory=Ratchet,
    Loudcategory=Medium}               => {country=Germany}   0.010        0.26  2.6     5
[3] {danceabilitycategory=Two-Step,
     Energycategory=Ratchet,
     Valencecategory=Ecstatic}         => {country=Germany}   0.012        0.22  2.2     6

[1] {danceabilitycategory=Two-Step,
     Loudcategory=Banger,
     Valencecategory=Ecstatic}         => {country=Mexico}   0.022        0.41  4.1    11
```

Results

Overall, it seems that songs are classifiable based on audio features, as demonstrated through the SVM algorithm; the caveat is that the analysis must be focused on only one country at a time. When the tracks of all countries are analyzed together, the popular tracks that are common across the globe create too much noise.

All other methods used render very low accuracy rates, but still generate some interesting insight. For example, the outlying track from Germany in all of the clusters is called “Risiko” by Bonez MC. This song seems to greatly stand out among the 500 top tracks.

Another interesting example is Mexico’s dominance in the Naïve Bayes and association rule mining analysis. Although Mexico establishes its position as a country with its own unique music taste during the exploratory analysis, it is strange to see that so many songs are attributed to this country through Naïve Bayes. Perhaps the strength of the valence in its songs are skewing the algorithms in its favor since valence turns out to be the most important variable overall (according to random forest).

Random forest may have disproved the initial assumption that acousticness and instrumentalness are strong determining variables. However, since the accuracy of that model is rather low, it is hard to say how reliable that data truly is.

Conclusion

To answer the main data question of this experiment: music tastes do, in fact, vary by country. The influence of culture and language in music is also demonstrated by the correlation between the music tastes of Hong Kong and Singapore, as well as the English-speaking countries of the United States, the United Kingdom, Australia, and New Zealand. Countries such as Germany, Mexico, and Portugal seem to be less influenced by mainstream English-speaking songs and have their own unique taste. Mexico enjoys very happy music, whereas Germany tends to lean towards high energy dance tracks.

Overall, top tracks do elicit a pattern; they are higher energy, danceable, and have a quick tempo. But this begs the question: what is the average age of the Spotify user and does age have any influence on the popularity of songs around the world? The current collection of top 50's playlists seem to be dictated by a younger, more high energy audience.

Furthermore, tracks tend to be more popular when they have a featured artist. This makes sense because the popularity of the song is then doubled by the followers of both artists.

Ideally, an experiment like this should also have many more data points and include more than ten countries. Since the findings of this investigation are promising, a deeper diver can be done with expanded data and more targeted questions.

Appendix

The following table details the definition of each attribute, taken directly from Spotify's developer documentation.

Attribute	Definition
Danceability	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
Energy	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
Key	The key the track is in. Integers map to pitches using standard Pitch Class notation . E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on.
Loudness	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db.
Mode	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
Speechiness	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
Acousticness	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
Instrumentalness	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
Liveness	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
Valence	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).
Tempo	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.

Duration_ms	The duration of the track in milliseconds.
Time Signature	An estimated overall time signature of a track. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure).
Key_mode	Combination of Key and Mode

References

https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/

https://www.rcharlie.com/spotifyr/