Capstone Project 1: Track genre classification based on its audio features

Milestone Report

Problem Statement

There are many types of genres in music ranging from pop to rock to classical. The objective of this project is to see if there are any features that define these genres of music.This would be useful to companies putting out new music, but are trying to define what genre this music would fall under. This would also be useful to customers trying to find new music in a certain genre.

Dataset

The dataset/s to be used are tracks (or songs) from differing genres that are part of Spotify's catalog. The different genres of tracks in this project will be classical, country, hiphop, pop and rock. Each track can can be accessed by using Spotify's Developer API. There are two types of information for each track that is provided by Spotify, Audio Analysis and Audio Features. The Analysis gives data on 'low-level audio analysis for all of the tracks in the Spotify catalog. The Audio Analysis describes the track's structure and musical content, including rhythm, pitch, and timbre.' Whereas the Features gives track data on 'audio feature information' which include: acousticness, danceability, energy, instrumentalness, liveness, loudness, tempo, speechiness and valence. All of these features are measured from a scale of 0 to 1, except for tempo and loudness which are measured in BPM and dB, respectfully. A more detailed explanation of each feature can be found here.

For the analysis of the tracks, we are going to focus on the audio features. These features have been measured/evaluated by Spotify. In the future, there may be other things apart from the audio features like popularity or explicitness. But for now, we are going to focus on just the audio features.

Data Wrangling

The end goal of this data wrangling step would be to create a pandas dataframe that includes basic information and features of the tracks of a given playlist. The various steps included are below:

1. **Choose tracks for each genre:** Using Spotify, a genre oriented playlist was created that holds around 500 tracks each. Each track was either recommended by Spotify or chosen by the user and was screened for accuracy of classification.
2. **Familiarization with Spotify API:** The first step consisted of understanding how to utilize the Spotify API to get the track information and features among other commands. Luckily, the Spotify API and documentation is comprehensive. In order to get information from Spotify, be it playlist data or track data, one would have to submit a request from a url issues commands from Spotify. For example to get track info, you would use the url, https://api.spotify.com/v1/tracks/{track_id}. On top of the url, an authorization token is

also needed. This can be requested from Spotify. However, each token expires, so a new request would be needed every time the token expires. Commands that extract information are in json format.

3. **Extraction of track ids from playlist:** After familiarization with the API, a list of the track ids of a given playlist needs to be extracted. However, there was a max limit of 100 tracks issued for each command. Which means, if a playlist has more than 100 tracks, you would need to offset the command by a 100 or whatever set of hundred to get the rest of the tracks.
4. **Get track information:** Using the track ids, a command was issued to get the a specific set of (i.e. name, artists, album, etc.) information of each of the track ids. Once all the track info is combined into a list, that list is converted to a dataframe.
5. **Get track features:** Like the track info, a command was issued to get the features of each of the track ids. Also like the track info, this information was combined and then converted into a dataframe.
6. **Merge to form final dataframe:** Finally the end goal is reached by merging the two dataframes from above by their ‘id’.

Fortunately, it seems to be that the information from Spotify is pretty complete so there were no need to deal with missing values. As each track is screened for accuracy, the need to remove outliers should not be needed. Also, since there are multiple features for each track, it would be difficult to ascertain what an track outlier would be.

Using the steps above, I was able to successfully get information from the Spotify catalog using its API and converted it into a dataframe that would be the basis of further exploration and analysis.

Exploratory Data Analysis

It should be clear that different genres of music have different sounds to make them distinct from each other. In order to show if there any differences between the features with respect to the genres, I used a swarm plot in conjunction with a violin plot which show the different distributions.

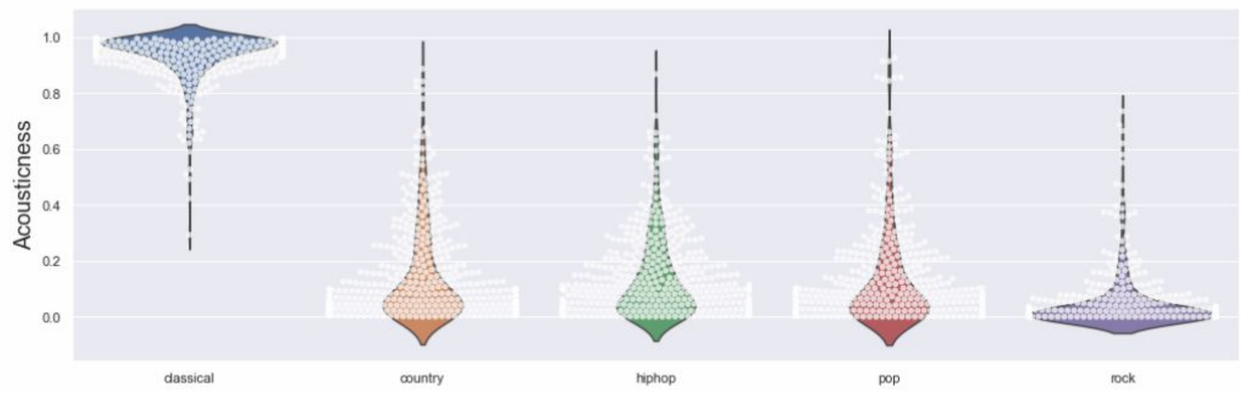


Figure 1. Feature plot showing the difference of acousticness of each track based on their genre. Each white dot correlates with a different track.

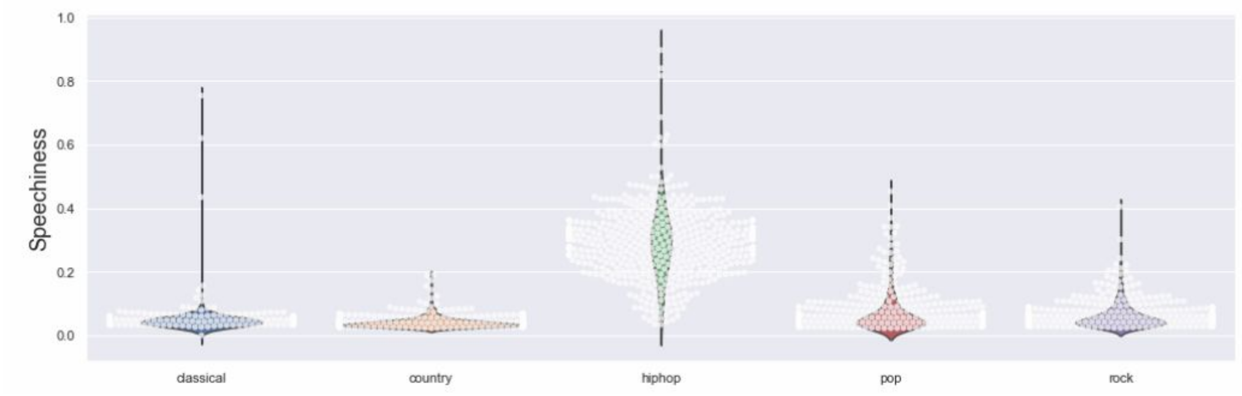


Figure 2. Feature plot showing the difference of speechiness of each track based on their genre. Each white dot correlates with a different track.

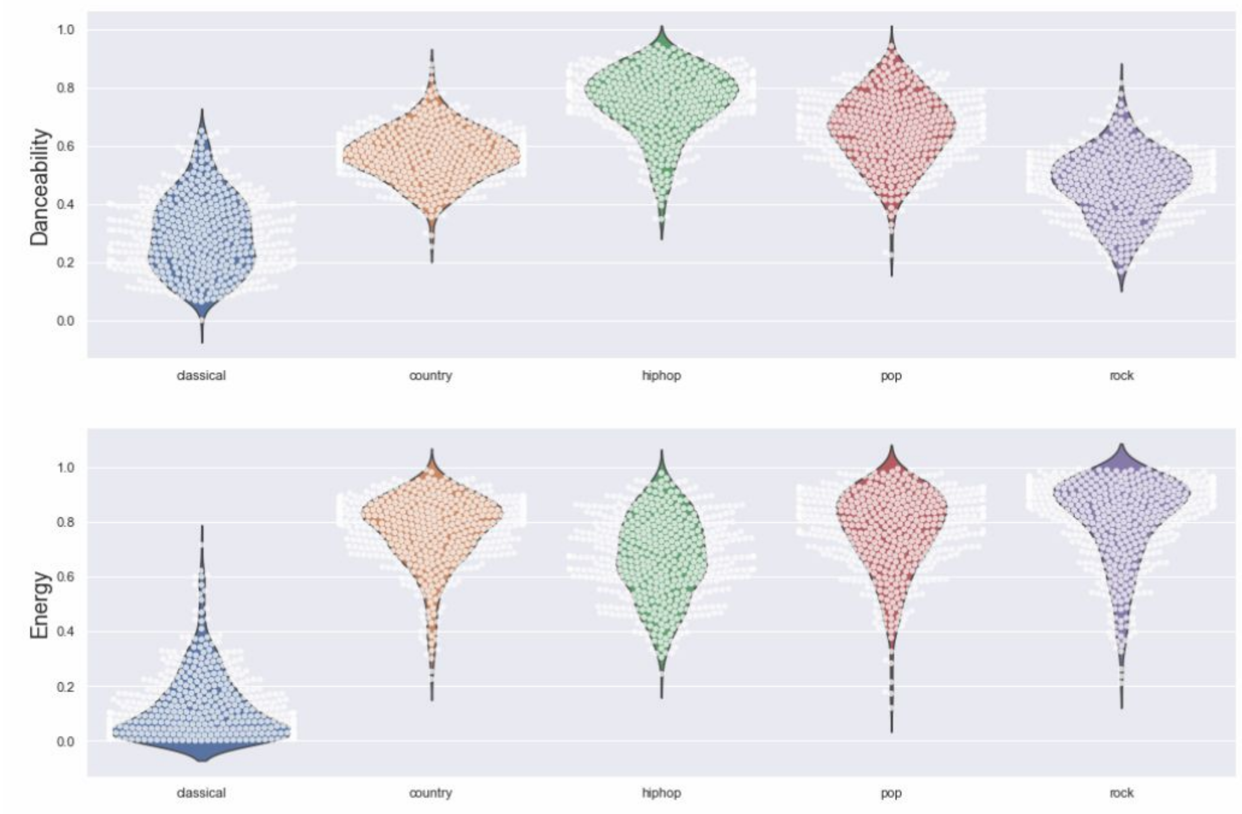
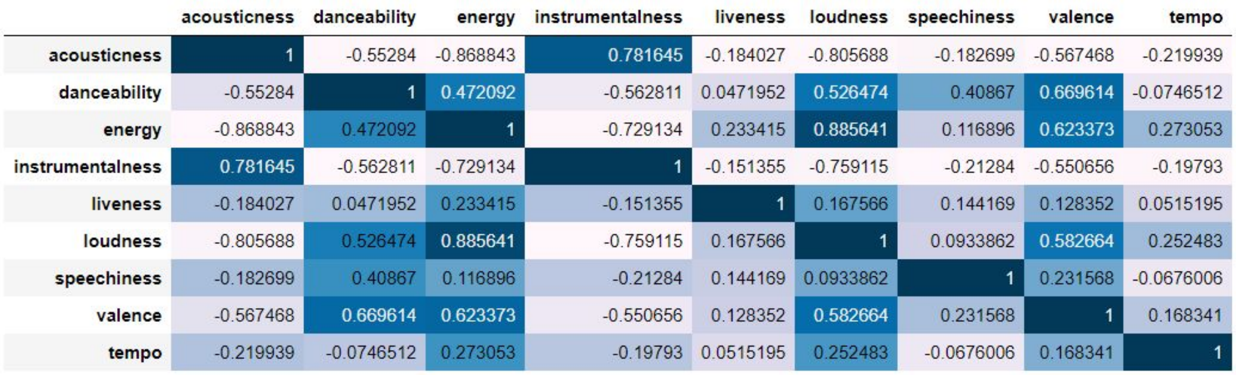


Figure 3. Feature plots showing the danceability and energy of each track based on their genre. Each white dot correlates with a different track.

As we can from above, some of the different features have the same distributions as other features while some features are very different from the others. In order to quantitatively measure this, we can use a correlation matrix between the different features to see their correlations with one another. The following would tell us how strong a relationship is between the different features depending on their correlation value:

- |1.00| A perfect linear relationship
- |0.70| A strong linear relationship
- |0.50| A moderate relationship
- |0.30| A weak linear relationship
- |0.00| No linear relationship

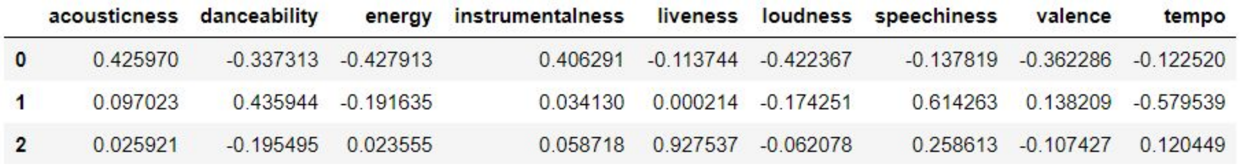
Basically, the closer the the correlation value is to one, the stronger the relationship between the two features are.



	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	valence	tempo
acousticness	1	-0.55284	-0.868843	0.781645	-0.184027	-0.805688	-0.182699	-0.567468	-0.219939
danceability	-0.55284	1	0.472092	-0.562811	0.0471952	0.526474	0.40867	0.669614	-0.0746512
energy	-0.868843	0.472092	1	-0.729134	0.233415	0.885641	0.116896	0.623373	0.273053
instrumentalness	0.781645	-0.562811	-0.729134	1	-0.151355	-0.759115	-0.21284	-0.550656	-0.19793
liveness	-0.184027	0.0471952	0.233415	-0.151355	1	0.167566	0.144169	0.128352	0.0515195
loudness	-0.805688	0.526474	0.885641	-0.759115	0.167566	1	0.0933862	0.582664	0.252483
speechiness	-0.182699	0.40867	0.116896	-0.21284	0.144169	0.0933862	1	0.231568	-0.0676006
valence	-0.567468	0.669614	0.623373	-0.550656	0.128352	0.582664	0.231568	1	0.168341
tempo	-0.219939	-0.0746512	0.273053	-0.19793	0.0515195	0.252483	-0.0676006	0.168341	1

Table 1. Correlation matrix of the different features.

According to the matrix above, acousticness, energy, instrumentalness, and loudness have strong linear relationships with each other as they all have correlations above .7 (positive or negative) from each other. Since we are finding strong relationships, we need to find a way to combine them. A good method to do this is to do a principal component analysis (PCA). A PCA basically takes the features and transforms them into an array with the same amount of features that loses all the correlations between the features. Table 2 (below) shows the transformation of the feature values to the first three principal components.



	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	valence	tempo
0	0.425970	-0.337313	-0.427913	0.406291	-0.113744	-0.422367	-0.137819	-0.362286	-0.122520
1	0.097023	0.435944	-0.191635	0.034130	0.000214	-0.174251	0.614263	0.138209	-0.579539
2	0.025921	-0.195495	0.023555	0.058718	0.927537	-0.062078	0.258613	-0.107427	0.120449

Table 2. The ‘weight’ matrix of the first 3 principal components with respect to the various features.

Another useful feature of PCA is that the principal components are ordered by the amount of variance of each component meaning that the first couple of principal components will contain a bulk of the variance. This can lead to dimension reduction in modeling as you want to explain as much variance as possible with as little features.

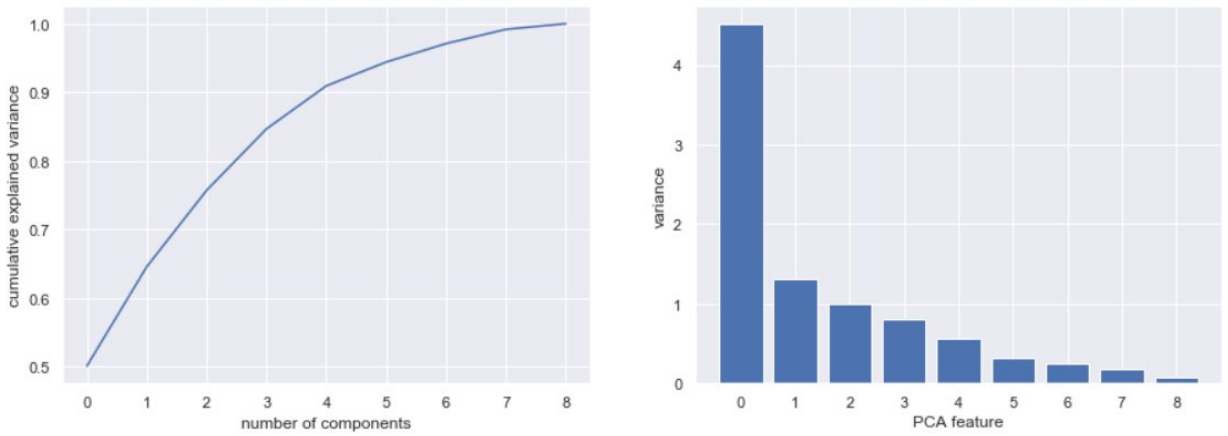


Figure 4. Explained variance of the PCA.

Another useful feature about PCA is that you can plot the first two principal components and see if you can find anything interesting. This is seen below:

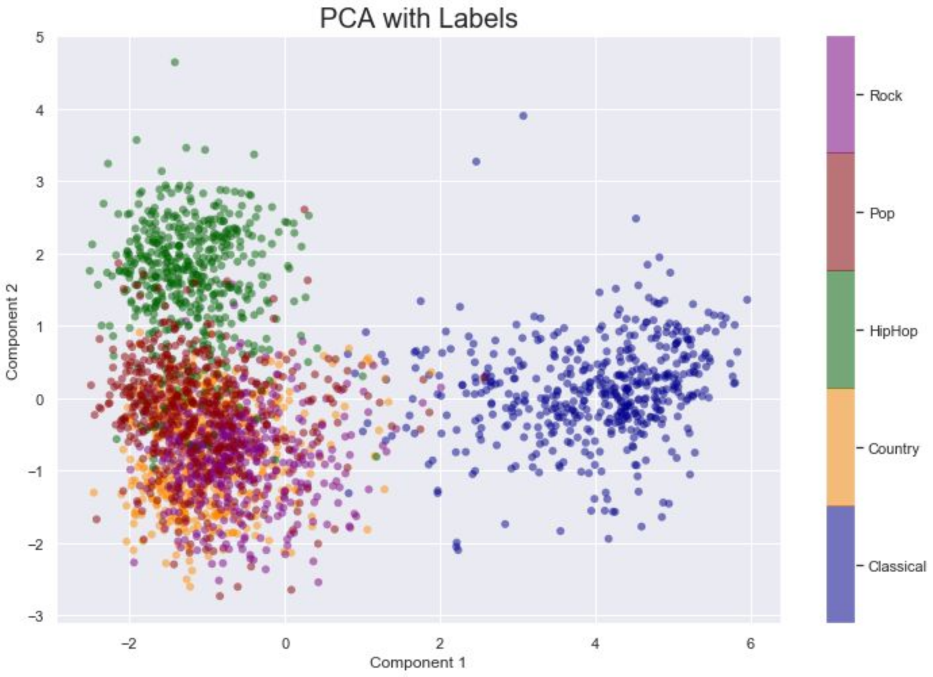


Figure 5. PCA graph of the first two principal components of the dataset labeled in their different respective genres (i.e. rock, pop, hiphop, country and classical).

As you can see above, classical and hiphop have populations that are separate from each other. Whereas the other three categories have populations that are on top of each other. This may mean that based on the feature values, it would be easy to differentiate a track that is classical or hiphop and would be difficult to differentiate the other three among each other. In other words, country, pop and rock may have feature values that similar to each other.