# EchoSpot - Exploring Musical Features in Spotify Playlists

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May 29, 2024

**Abstract**

The EchoSpot project undertakes a detailed examination of musical features within Spotify's vast array of tracks. The goal of this exploration is to better discern patterns that dictate current music preferences and genre categorization. This analysis leverages two extensive datasets from Spotify's API, encompassing a comprehensive range of musical attributes across hundreds of thousands of tracks spanning various genres.

The core of the analysis employs statistical methods to quantify relationships between musical features such as tempo, energy, danceability and acousticness, and their impact on track popularity and genre classification. Preliminary findings suggest that attributes like danceability and energy may positively enhance a track's appeal, indicating a strategic production emphasis on these elements to align with listener preferences. Moreover, the investigation reveals a nuanced landscape in music where certain features and genres exhibit significant variance, reflecting the diverse musical tastes that streaming platforms accommodate.

This research not only maps out the interplay of various musical features but also introduces EchoSpot, a proposed platform that utilizes these analytical insights to generate personalized playlists. By integrating sophisticated data analysis with user interface design, EchoSpot aims to help users interact with music, making it a tailored experience. The outcomes of this study hold implications for music producers, strategists and technologists aiming to forecast trends and/or craft engaging musical experiences.

# 1 Introduction

In the transformative landscape of the music industry, streaming services like Spotify have become pivotal in reshaping how music is consumed and distributed globally. The project aims to dive deep into the intricate world of musical features within Spotify playlists, providing a comprehensive analysis of the trends and patterns that define current music consumption. This project leverages extensive datasets sourced from Spotify's API to explore the relationship between various musical attributes and their influence on both song popularity and genre categorization. By examining these datasets, the project aims to uncover the underlying factors that drive both listener preferences and track popularity on Spotify, offering insights that may not only be valuable for music producers and artists, but also for industry strategists looking to optimize their music distribution.

Music itself can be defined as "The science or art of ordering tones or sounds in succession, in combination, and in temporal relationships to produce a composition having unity and continuity." An important aspect of music is that the organization and variation of sounds are deliberate in order to invoke an emotional response. These are usually done through musical features such as tempo (overall pace of the song), rhythm, pitch, etc. In David Huron's *What is a Musical Feature? Forte's Analysis of Brahms's Opus 51 No. 1 Revisited*, he states that "A feature might pertain to a particular musical passage, a movement, work, composer, period, genre, style or culture. Features may be salient because of intratextual or intertextual treatments—including prevalence, primacy, recency, evocation, quotation, allusion, parody, and model." A musical feature may not only influence the interpretation of a piece, but also affect its reception and future scholarly analysis. It's important to highlight however, that musical features interconnected through the nature of musical compositions and their cultural contexts may supersede an analysis done through a statistical lens. Nonetheless, valuable insights can still be extracted through rigorous data analysis, which can allow for quantification and pattern recognition that might otherwise elude traditional methods of musical study.

Music universally impacts people across all demographics through this elicitation of emotional responses. In an article from Tallahassee Memorial Healthcare, the authors describe how music can influence brain and body functions through the release of neurotransmitters like dopamine, which enhances mood, focus, and motivation, and serotonin, which affects sleep and anxiety. Engaging actively in music, such as singing or playing instruments, not only fosters social connections through the release of oxytocin but also reduces stress.

The Iso-principle in music therapy suggests that music can match or alter one's emotional state by starting with music that reflects current feelings and gradually transitioning to tunes that evoke desired emotions. This approach can aid in managing moods and stress effectively. Behaviorally, music also serves various roles from enhancing shopping experiences, where it influences spending habits, to improving workplace morale and customer engagement in retail settings. The article touches upon Holiday music in particular and how it plays a significant role in community celebrations, evoking a wide range of emotions from joy to nostalgia, and even sadness. To be able to draw these meaningful conclusions regarding a song's genre and overall appeal, it's essential to thoroughly understand the features that they are comprised of.

# 2 Methods

## 2.1 Dataset Descriptions

There are two datasets that were used to conduct the analyses. The first dataset (Dataset A) contains a list of the 500 most streamed songs on Spotify by stream count as of 4/04/24. As described in Table **??** it's important to acknowledge that while a track may have been a hit in the past and acumulated a very high number of streams, its current popularity score will be low if it's not being streamed as frequently as others (as of 4/04/24). Essentially, songs that are heavily streamed now will achieve a higher popularity score compared to those that were popular historically, but are no longer streamed as much. The dataset consists of 13 features for each individual song. The following descriptions were sourced from Spotify's API documentation.

Table 1: Spotify Track Features Description

| **Feature** | **Description** |
|---|---|
| track_id | The Spotify ID for the track. |
| 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. |
| 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 typically range between -60 and 0 db. |
| 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. |
| 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). |
| 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. |
| 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. |
| 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. |

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**Table 1 continued from previous page**

| Feature | Description |
|---|---|
| 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. |
| duration_ms | The duration of the track in milliseconds. |
| 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. |
| popularity | The popularity of a track is a value between 0 and 100, with 100 being the most popular. |
| market | A markets object with an array of country codes. |

The second dataset (Dataset B) consists of 114,000 Spotify tracks compiled as of 2022. These tracks span evenly over 125 different genres and contain 20 features for each individual track. Provided below is a table of the unique features that didn't already appear in the previous dataset. The descriptions have also been sourced from Spotify's API documentation.

Table 2: Additional Spotify Track Features Description

| Feature | Description |
|---|---|
| artists | The artists' names who performed the track. |
| album_name | The album name in which the track appears. |
| track_name | Name of the track. |
| explicit | Whether or not the track has explicit lyrics (true = yes it does; false = no it does not OR unknown). |
| key | The key the track is in. Integers map to pitches using standard Pitch Class notation. E.g., 0 = C, 1 = C#/Db, 2 = D, etc. If no key was detected, the value is -1. |
| tempo | The overall estimated tempo of a track in beats per minute (BPM). |
| time_signature | An estimated time signature. The time signature ranges from 3 to 7 indicating time signatures of 3/4, to 7/4. |
| track_genre | The genre in which the track belongs. |

These datasets possess several strengths, including its sheer volume of tracks and variety in musical features. However, it's important to acknowledge a limitation of the data, which stems from its exclusive reliance on Spotify. Consequently, the dataset may not fully capture the entirety of the music consumption landscape, as it does not account for other streaming platforms, offline music consumption patterns and countries where Spotify is not currently available.

## 2.2 Data Collection

The analysis was conducted using two separate datasets sourced from Spotify. The data for Dataset A was sourced from Spotify's publicly available data, accessed through the Spotify Web API. The interface allows for the retrieval of detailed metadata about things such as music artists, albums and tracks directly from Spotify's music catalog. Access to the Spotify Web API was established using the Spotipy library, a Python library designed to simplify requests to the Spotify Web API. Authentication for these requests are managed through the Client Credentials Flow, appropriate for server-to-server requests where user data access is not required. The credentials required for this authentication flow, specifically the client ID and client secret, were obtained through the Spotify Developer Dashboard and stored as environment variables for accessibility within the Spotipy library.

The process of the data collection for Dataset A involved fetching tracks from a predetermined Spotify playlist, uniquely identified by its URI. This playlist contained the 500 songs with the most song streams on the platform. Spotify counts a song stream as "Someone listening for 30 seconds or more." This playlist was created by user 8823 on Spotify and was cross-referenced with Kworb.net to ensure its accuracy. During the retrieval, detailed information for each track, including unique track IDs, was collected. Additionally, the "audio_features" endpoint of the Spotify API was utilized to gather various musical attributes for each track, including but not limited to, energy, loudness, speechiness, valence and tempo. This also included the track's popularity score and its availability across different geographic markets.

Spotify's Web API employs pagination to manage the data returned in a single request. To navigate this, a recursive function was implemented to ensure the collection of all tracks from the playlist, thereby overcoming any limitations posed by pagination. To adhere to Spotify's rate limiting policies and to prevent being temporarily blocked for exceeding request limits, random sleep intervals were also introduced between consecutive API calls. Finally, the collected data was organized into a pandas DataFrame, with each row representing a track and columns for each of the musical attributes and metadata fetched. This structured data was then saved to a CSV file, top500songsnew.csv, serving as Dataset A for further analysis. The data for Dataset B was also sourced directly from the Spotify API, but was downloaded through Kaggle for the purpose of this analysis. The dataset was originally collected by Maharshi Pandya.

## 2.3 Methodology

For both the exploratory popular song analysis and genre analysis, the initial step involved data cleansing and data normalization to ensure a standardized scale for all numerical features aside from market count. This process was done to remove any potential biases from the various units of measurement. Specifically, we utilized StandardScaler from the scikit-learn library to normalize numeric features such as energy, loudness and tempo among others. It's important to note that due to this standardization, the observed values of features such as tempo and loudness no longer use their respective numeric systems (BPM and dB respectively).

Additionally, we converted the string representation of the market availability list into an actual list for each song and computed the market count (the number of markets each song is available in). An extensive analysis was conducted to uncover potential insights and patterns within these datasets. This process involved generating descriptive statistics, kernel density estimates (KDE), box plots, histograms and a correlation matrix for song features. These visualizations were instrumental in identifying distributions, trends and relationships among the various song attributes.

1. Descriptive Statistics: Served as a foundational analysis step by summarizing the central tendency, dispersion, and shape of the dataset's distribution, excluding NaN values.
2. Kernel Density Estimate (KDE) Plots: Helped in understanding the distribution of market counts and other numeric features within the dataset.
3. Box Plots: Provided insights into the distribution and potential outliers within each song attribute.
4. Histograms: Enabled us to visualize the frequency distributions of the song features.
5. Correlation Matrix: Offered a comprehensive overview of the relationships between different song features as well as the relationships between genres and song features, aiding in the identification of features that influence song popularity and define genres.

To further explore the datasets and reduce their dimensionality with maximum variance retention, Principal Component Analysis (PCA) was also applied. PCA allows for the datasets to be projected into a lower-dimensional space where the first few principal components capture the majority of the variation in the data. This step was pivotal in identifying underlying patterns and simplifying the dataset for subsequent analyses. In this instance, PCA can reveal the importance of various song features and their contributions to the principal components, which was visualized through a heatmap of PCA loadings. These loadings indicate the weight or contribution of each original feature to the principal components, offering insights into the underlying structure of the data.

Using Dataset B, Ordinary Least Squares (OLS) regression was also conducted to examine the relationship between a set of independent variables (song features) and two different dependent variables (song popularity, track genre). This analysis helped in further understanding the overall structure of the dataset as well as in identifying if musical features can influence the popularity of a song and/or the genre of a song. The regression model's summary provided coefficients, significance levels and other diagnostics to assess the model's fit as well as the influence of each predictor.

# 3 Results (Dataset A)

## 3.1 Summary Statistics and Market Count

Table 3: Descriptive Statistics of Song Features

| Feature | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| Energy | 500.00 | 0.00 | 1.00 | -3.21 | -0.65 | 0.11 | 0.76 | 1.99 |
| Loudness | 500.00 | 0.00 | 1.00 | -5.03 | -0.52 | 0.18 | 0.69 | 1.82 |
| Speechiness | 500.00 | 0.00 | 1.00 | -0.78 | -0.60 | -0.41 | 0.13 | 4.58 |
| Valence | 500.00 | 0.00 | 1.00 | -1.96 | -0.76 | -0.10 | 0.74 | 2.10 |
| Liveness | 500.00 | 0.00 | 1.00 | -1.04 | -0.58 | -0.39 | 0.18 | 4.70 |
| Tempo | 500.00 | 0.00 | 1.00 | -1.99 | -0.79 | -0.06 | 0.61 | 3.14 |
| Danceability | 500.00 | 0.00 | 1.00 | -3.41 | -0.60 | 0.09 | 0.68 | 2.09 |
| Acousticness | 500.00 | 0.00 | 1.00 | -0.90 | -0.76 | -0.41 | 0.38 | 3.12 |
| Duration_ms | 500.00 | 0.00 | 1.00 | -2.82 | -0.59 | -0.10 | 0.51 | 4.53 |
| Instrumentalness | 500.00 | 0.00 | 1.00 | -0.18 | -0.18 | -0.18 | -0.17 | 12.97 |
| Popularity | 500.00 | 0.00 | 1.00 | -2.85 | 0.13 | 0.41 | 0.58 | 1.07 |
| Market Count | 500.00 | 168.08 | 46.56 | 1.00 | 180.00 | 184.00 | 184.00 | 185.00 |

The minimum and maximum values of the standardized features in Table 3 indicate the range of variability, with features like loudness ranging from -5.03 (indicating quieter tracks) to 1.82 (indicating louder tracks). Similarly, tempos range from significantly slower than the average (-1.99) to much faster (3.14). The 25th percentile (Q1) and the 75th percentile (Q3) provide further insights into the distribution of these features. For example, danceability scores below -0.599 indicate the least danceable 25% of tracks, while scores above 0.684 represent the most danceable 25%.

Instrumentalness shows a notable aspect where the maximum value is significantly higher (12.97) compared to other features, suggesting a few songs with very high instrumental content compared to the rest. Popularity shows a median of approximately 0.41 after standardization, indicating a relatively balanced distribution around the mean, with half the songs having a below-average standardized popularity score and the other half above.

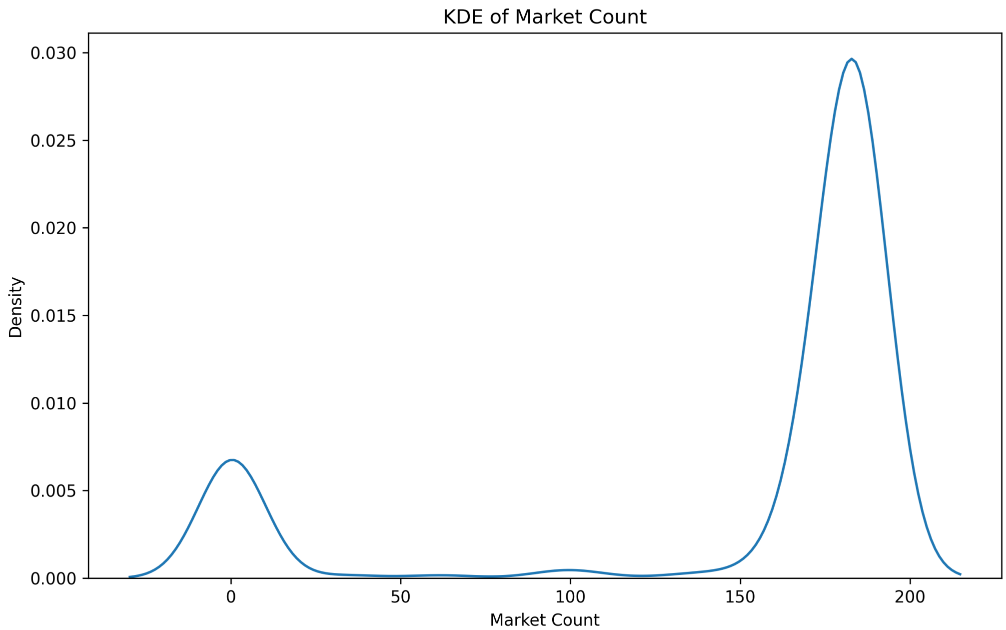


Figure 1: This plot contains the kernel density estimate of market counts in Dataset A.

Figure 1 reveals that the average market count across songs is 168.08 with a standard deviation of 46.56, indicating a relatively wide dispersion around the mean. This suggests significant variability in the availability of these songs across different markets. The minimum market count is 1 while the maximum market count is 185, indicating that some songs are almost universal availability. However, there are 32 tracks that only appear in one "market" and 1 track that appears in 3 "markets". This is likely due to an error regarding the listing of the track itself on Spotify, as the same result is shown when interacting directly within the Spotify API.

### 3.2 KDE & Histogram of Song Features

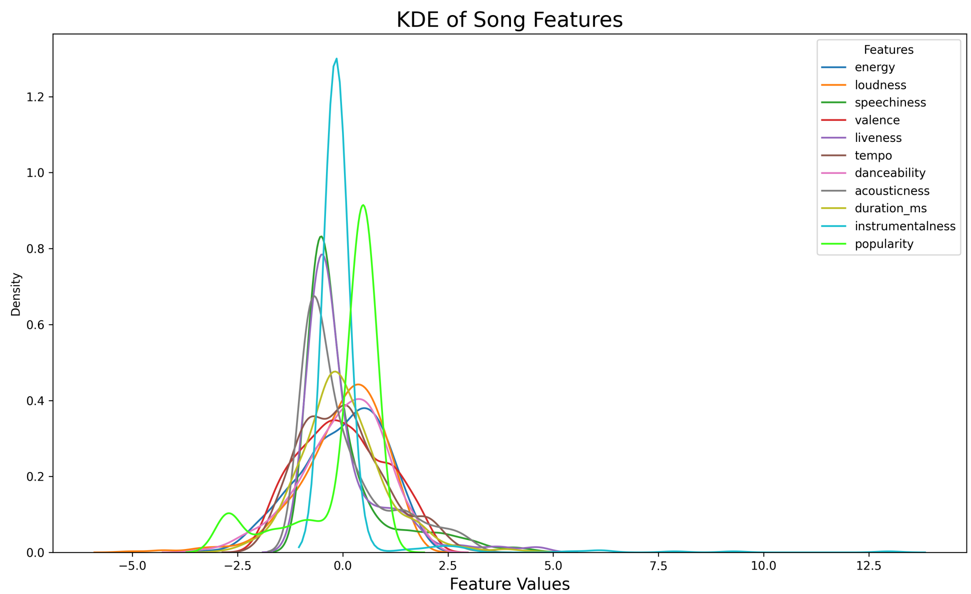


Figure 2: This plot contains the kernel density estimate of market counts in Dataset A.

The energy attribute exhibits a pronounced peak at 0.38, narrowly centered around the mean, which is characteristic of a dataset with a moderate level of song energy. Loudness, closely related to energy, mirrors this trend with a sharp central peak at 0.44, indicating a moderate sound level in the majority of the songs. Danceability also shows a distinct peak at 0.4 near the mean. On the other hand, speechiness appears to have a slender peak at 0.83 with higher overall density, indicating a higher prevalence of spoken words within the tracks. Acousticness peaks at about 0.67, but has a smaller spread in its distribution, showcasing the dataset's moderate use of acoustic composition with minimal variance. Instrumentalness shows a right-skewed distribution peaking at 1.3 with a long tail extending up to 12.97. This suggests a subset of the dataset contains tracks with a very strong instrumental focus, although such tracks are less frequent.

Table 4: Specific distribution values for each feature on the KDE plot

| Feature | Min x | Max x | Peak y at x |
|---|---|---|---|
| Energy | -3.21 | 1.99 | 0.38 at x = 0.51 |
| Loudness | -5.03 | 1.82 | 0.44 at x = 0.37 |
| Speechiness | -0.78 | 4.58 | 0.83 at x = -0.51 |
| Valence | -1.96 | 2.10 | 0.35 at x = -0.20 |
| Liveness | -1.04 | 4.70 | 0.79 at x = -0.49 |
| Tempo | -1.99 | 3.14 | 0.39 at x = 0.05 |
| Danceability | -3.41 | 2.09 | 0.40 at x = 0.38 |
| Acousticness | -0.90 | 3.12 | 0.67 at x = -0.68 |
| Duration_ms | -2.82 | 4.53 | 0.48 at x = -0.18 |
| Instrumentalness | -0.18 | 12.97 | 1.30 at x = -0.16 |
| Popularity | -2.85 | 1.07 | 0.91 at x = 0.48 |

Popularity demonstrates a slightly bimodal distribution, hinting at a bifurcation within the dataset. One peak is located near the central range of the popularity index, while another resides towards the higher end. Valence and liveness present distributions with less defined peaks at 0.21 and 0.47 respectively, suggesting variable degrees of positivity in a tracks mood as well as varying degrees of live recording ambiance. The tempo attribute peaks at 0.39 with a similar spread to that of energy and loudness. This suggests a moderate variation in the pace of the music, despite a convergence around typical beat patterns that are prevalent in popular genres.

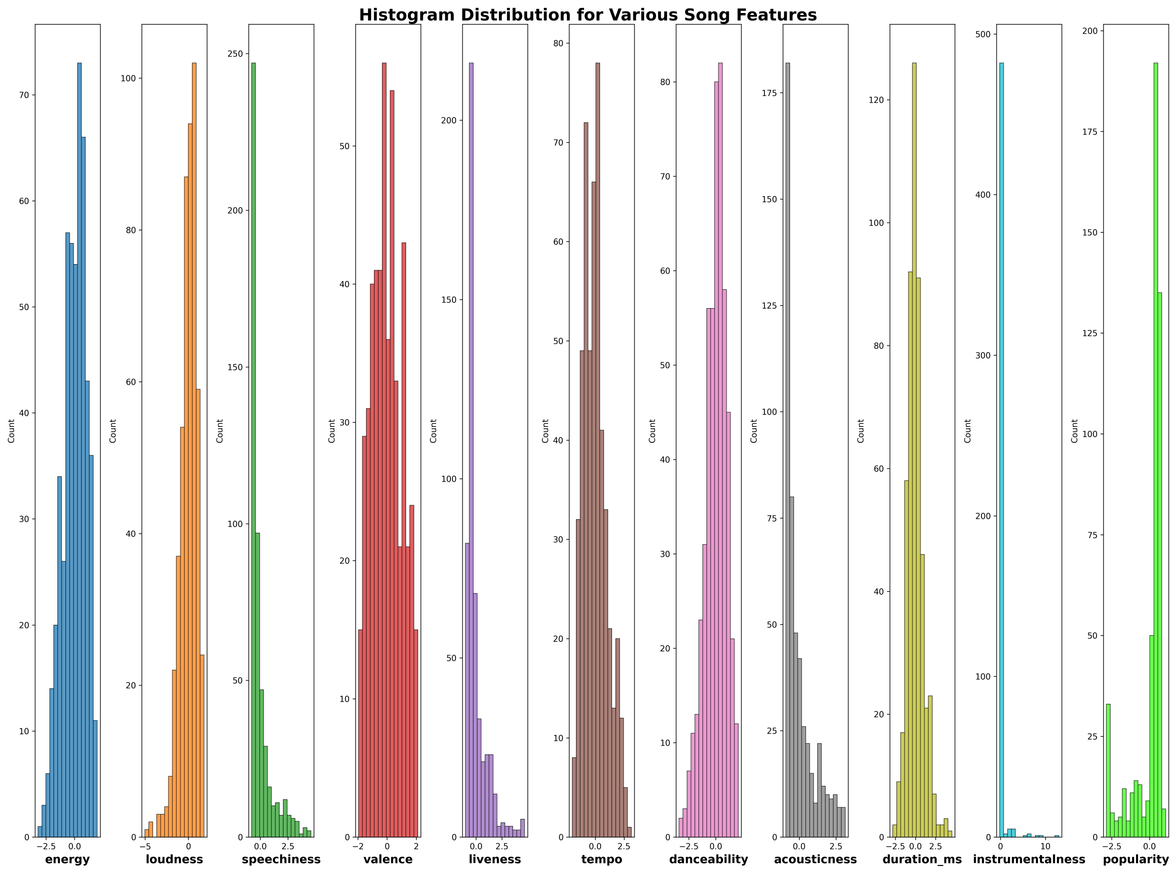


Figure 3: This plot contains the histograms of the musical features in Dataset A.

### 3.3 Boxplot Distribution

The median energy levels of songs lie above the zero line, suggesting a collection inclined towards high-energy tracks, with the IQR indicating moderate variability. Outliers are evident, denoting a few songs that are significantly lower in energy levels from the main corpus. Loudness showcases a slightly smaller distribution with its median tilted towards louder tracks. The presence of outliers reflects songs with lower loudness levels. Speechiness is predominantly low across the songs, yet there are many outliers that highlight certain tracks with pronounced vocal content. Valence and Tempo exhibit a symmetrical distribution around their median, revealing a balanced mix of emotions and tempos in the song selection. Liveness presents a median below 0 with outliers towards the upper end, signaling the inclusion of live-sounding tracks as more of an outlier to the dataset. Danceability's skewed median towards higher values and fewer outliers suggest a dataset favoring rhythm and beat conducive to dancing.

Acousticness has an assortment of outliers towards higher acoustic values despite its median lying below zero, pointing towards an overall representation of less acoustic songs. Duration showcases a standard spread around a central median with outliers indicating tracks with atypical lengths. Instrumentalness is heavily skewed towards the lower end, with outliers underscoring the few highly instrumental tracks. Popularity spans a wide range with the median closer to the upper quartile, indicating a dataset leaning towards tracks that are currently relevant. However, the outliers present a minority of tracks with divergent popularity scores.

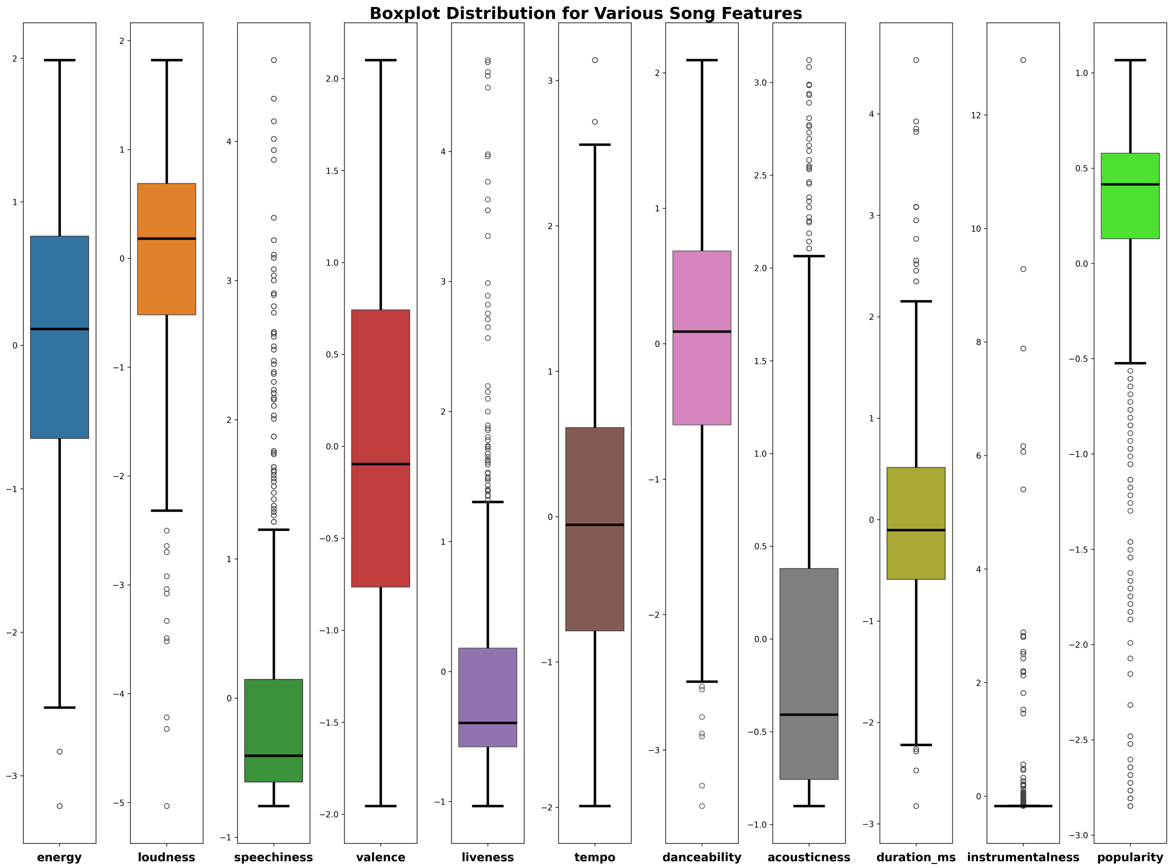


Figure 4: This plot contains the boxplots of the musical features in Dataset A.

## 3.4 Feature Correlation Heatmap

Energy and loudness share a high positive correlation (0.69), signifying that tracks with higher energy tend to be louder. Valence and danceability also showcase a moderate positive correlation (0.38), implying that songs perceived as more cheerful (high valence) may often tend to be more danceable. There is also a noticeable negative correlation between acousticness and energy (-0.59) as well as acousticness and loudness (-0.40), indicating that songs with higher acousticness are typically less energetic and quieter. Popularity has a modest positive correlation with market count (0.32), suggesting that songs available in more markets have a tendency to be more popular. All of these features appear to be relatively expected given our understanding of sound and popularity.

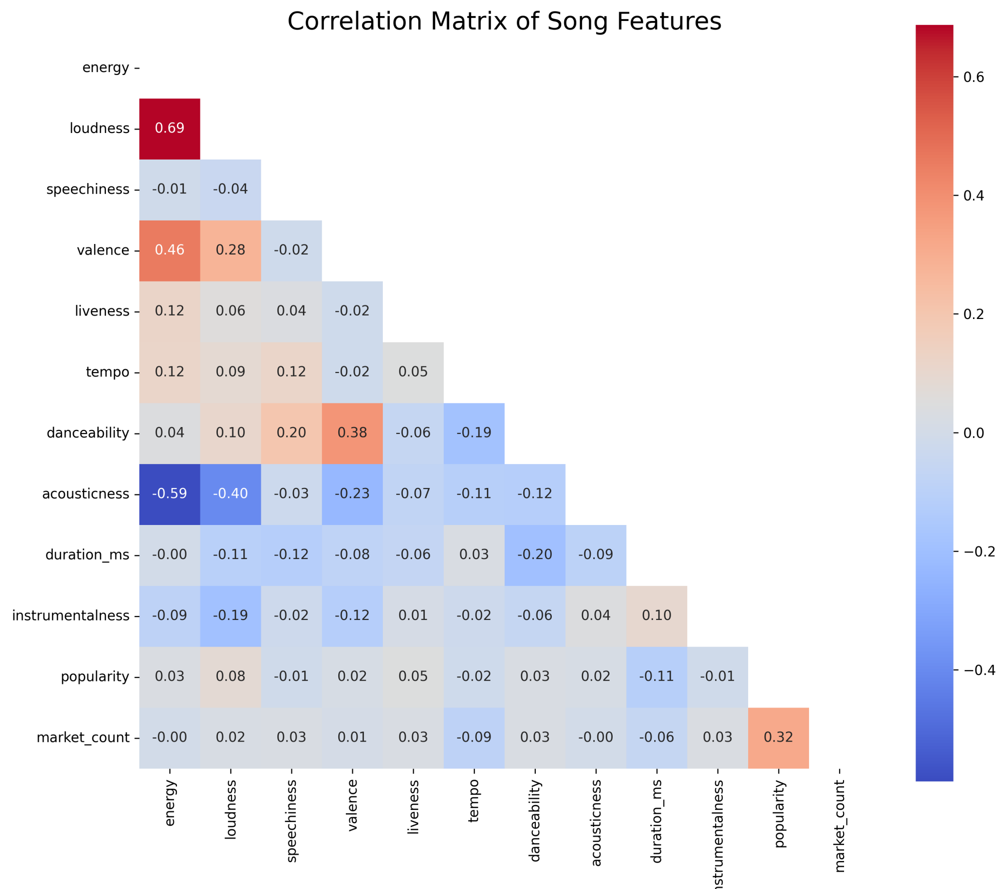


Figure 5: This plot contains the correlation matrix heatmap of the musical features in Dataset A.

### 3.5 PCA Loadings

The principal component analysis performed on the dataset resulted in six principal components that capture distinct variances within the song features. The explained variance by each principal component is a measure of how much information (variability) each component captures from the data.

The first principal component (PC1) accounts for approximately 22.6% of the variance in the data, indicating that just under a quarter of the total variability in the dataset is captured by the features strongly associated with this component. PC1 appears to be strongly influenced by features related to the power and volume of the music. PC1 contains high negative loadings from 'energy' (-0.56) and 'loudness' (-0.5) while containing a high positive value for 'acousticness' (0.44). This suggests that as values for energy and loudness decrease, acousticness increases.

The second principal component (PC2) explains about 13.36% of the variance. While it captures less variability than PC1, it still represents a significant proportion of the data's structure PC2 has a strong negative loading from 'danceability' (-0.61), indicating an inverse relationship between danceable properties of a track and the second principal component. It also has a positive loading from 'tempo' (0.35) and 'duration_ms' (0.46), suggesting that faster and longer tracks score higher on this component.

The third principal component (PC3) explains 10.75% of the variance, adding to the cumulative insight in a similar level to that of PC2. PC3 shows a significant positive loading from 'speechiness' (0.5), 'liveness' (0.45), and 'tempo' (0.49) as well as a strong negative loading from 'duration_ms'.

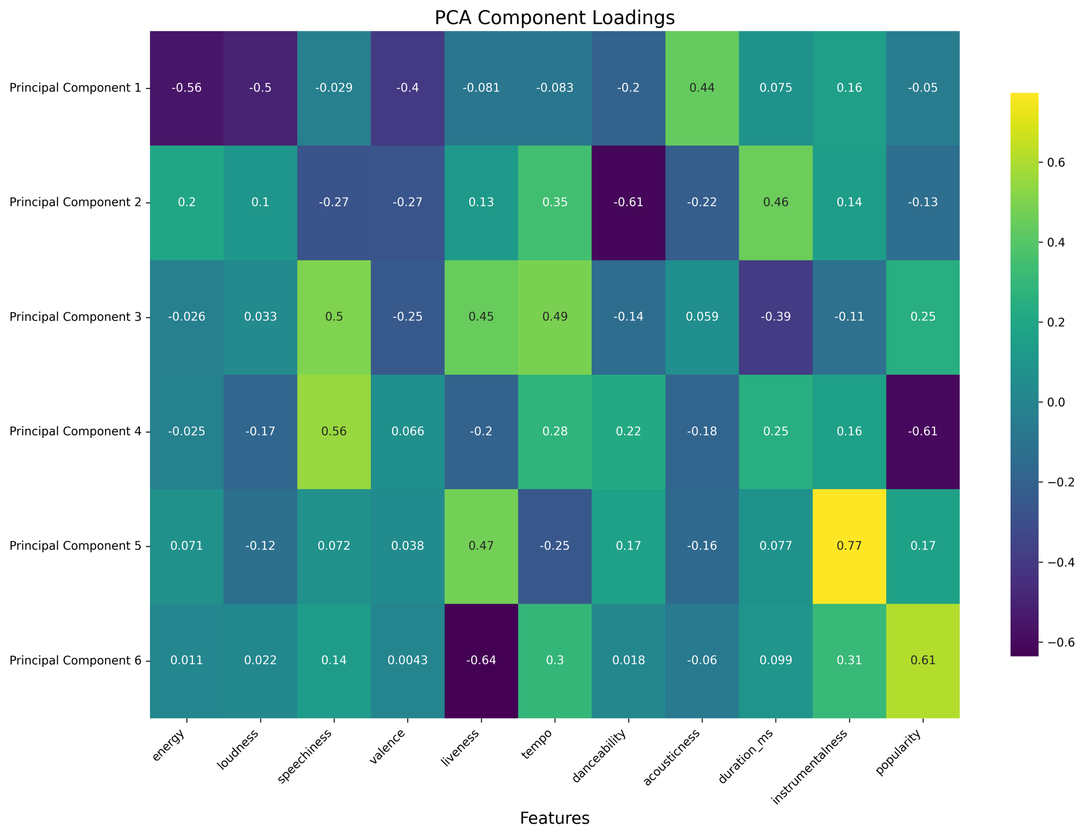


Figure 6: This plot contains the principle component analysis heatmap of the musical features in Dataset A.

The fourth principal component (PC4) explains 10.02% of the variance, nearly the same level of insight to that of PC3. PC4 is notably affected by the high positive value for 'speechiness' (0.56) and the negative value for popularity (-0.61).

The fifth principal component (PC5) accounts for 9.24% of the variance, indicating that it still holds relevant information despite starting to explain less variance than the previous components. PC5 presents a very high positive loading from 'instrumentalness' (0.77) and liveness (0.47), which can be interpreted as this component being a strong representative of the instrumental aspect of tracks.

Finally, the sixth principal component (PC6) explains 8.36% of the variance. Although it captures the least variance among the six components, it still contains great value in understanding the dataset. PC6 seems to be most influenced by 'popularity' (0.61) and liveness (-0.64) suggesting that currently relevant songs may not feel like a live production.

Based on the PCA heatmap and subsequent analysis, the interpretation of the PCA components for Dataset A can be represented as:

1. Acoustic Vs. Power: Dominated by the dynamics of music's power, it inversely correlates energy and loudness with acoustic features, characterizing a trade-off between electronically amplified and acoustic sounds.

2. Tempo + Duration Vs. Dance: Reflects the tempo and duration of tracks, inversely associating danceability with longer, faster tracks.

3. Verbal Liveness: Captures the verbal and live performance aspects of tracks, contrasting speechiness and liveness with shorter track duration.

4. Speechiness Vs. Popularity: Emphasizes the verbal content over popularity, suggesting a delineation between talkative tracks and those with broad appeal.

5. Instrumental Essence: Highlights the instrumental nature of music, strongly associating with tracks rich in instrumental elements.

6. Industry Standard Production: Suggests a dichotomy between the popularity of tracks and their live performance attributes, indicating popular tracks may have less of a 'live' feel.

# 4 Results (Dataset B)

## 4.1 Summary Statistics & Boxplot

Table 5: Descriptive Statistics of Song Features

| Feature | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| Popularity | 114000.00 | 0.00 | 1.00 | -1.49 | -0.73 | 0.08 | 0.75 | 2.99 |
| Duration_ms | 114000.00 | 0.00 | 1.00 | -2.13 | -0.50 | -0.14 | 0.31 | 46.69 |
| Danceability | 114000.00 | 0.00 | 1.00 | -3.27 | -0.64 | 0.08 | 0.74 | 2.41 |
| Energy | 114000.00 | 0.00 | 1.00 | -2.55 | -0.67 | 0.17 | 0.85 | 1.43 |
| Key | 114000.00 | 5.31 | 3.56 | 0.00 | 2.00 | 5.00 | 8.00 | 11.00 |
| Loudness | 114000.00 | 0.00 | 1.00 | -8.21 | -0.35 | 0.25 | 0.65 | 2.54 |
| Mode | 114000.00 | 0.64 | 0.48 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| Speechiness | 114000.00 | 0.00 | 1.00 | -0.80 | -0.46 | -0.34 | 0.00 | 8.33 |
| Acousticness | 114000.00 | 0.00 | 1.00 | -0.95 | -0.90 | -0.44 | 0.85 | 2.05 |
| Instrumentalness | 114000.00 | 0.00 | 1.00 | -0.50 | -0.50 | -0.50 | -0.35 | 2.73 |
| Liveness | 114000.00 | 0.00 | 1.00 | -1.12 | -0.61 | -0.43 | 0.31 | 4.13 |
| Valence | 114000.00 | 0.00 | 1.00 | -1.83 | -0.83 | -0.04 | 0.81 | 2.01 |
| Tempo | 114000.00 | 0.00 | 1.00 | -4.07 | -0.76 | 0.00 | 0.60 | 4.04 |
| Time_Signature | 114000.00 | 3.90 | 0.43 | 0.00 | 4.00 | 4.00 | 4.00 | 5.00 |

Popularity, a pivotal metric of the dataset, displays a wide range of values with a minimum at approximately -1.49 and a maximum at 2.99, indicating that it's made up of lesser relevant songs to current hits. The keys of songs span from 0 to 11, aligning with the 12 unique keys in Western music. The time signature, primarily clustered around a mean of 3.9, suggests a commonality of 4/4 time in modern music as reflected by the 25th, 50th, and 75th percentile all positioned at a value of 4. Energy and loudness, attributes often linked to the intensity and volume of a track, show similar spreads with the majority of the values around the mean. However, there are also potential outliers that stretch to both its higher and lower extremes. Speechiness, instrumentalness and liveness all present significant spreads throughout the data. Speechiness also peaks at around 8.33, suggesting the presence of tracks with substantial spoken words. Instrumentalness peaks at about 2.73, indicating a strong presence of tracks with very little to no vocal content. Liveness reaches up to 4.13, indicating a number of tracks that carry a live recorded feel.

Danceability and valence feature prominently as well with upper limits of 2.41 and 2.01 respectively, signifying that the dataset likely includes many tracks conducive to dancing and with a happy tone. Duration extends to nearly 47 standard deviations above the mean, suggesting the inclusion of exceedingly long tracks within the dataset. Acousticness peaks with a value of 2.05, pointing towards a significant acoustic presence in certain tracks. A small group of outliers fall into this higher acousticness category that is well beyond the general population of songs in the dataset. Tempo shows a relatively narrow interquartile range but with extremes that reach up to over 4 standard deviations from the mean, highlighting a diversity in the pace of the songs analyzed.

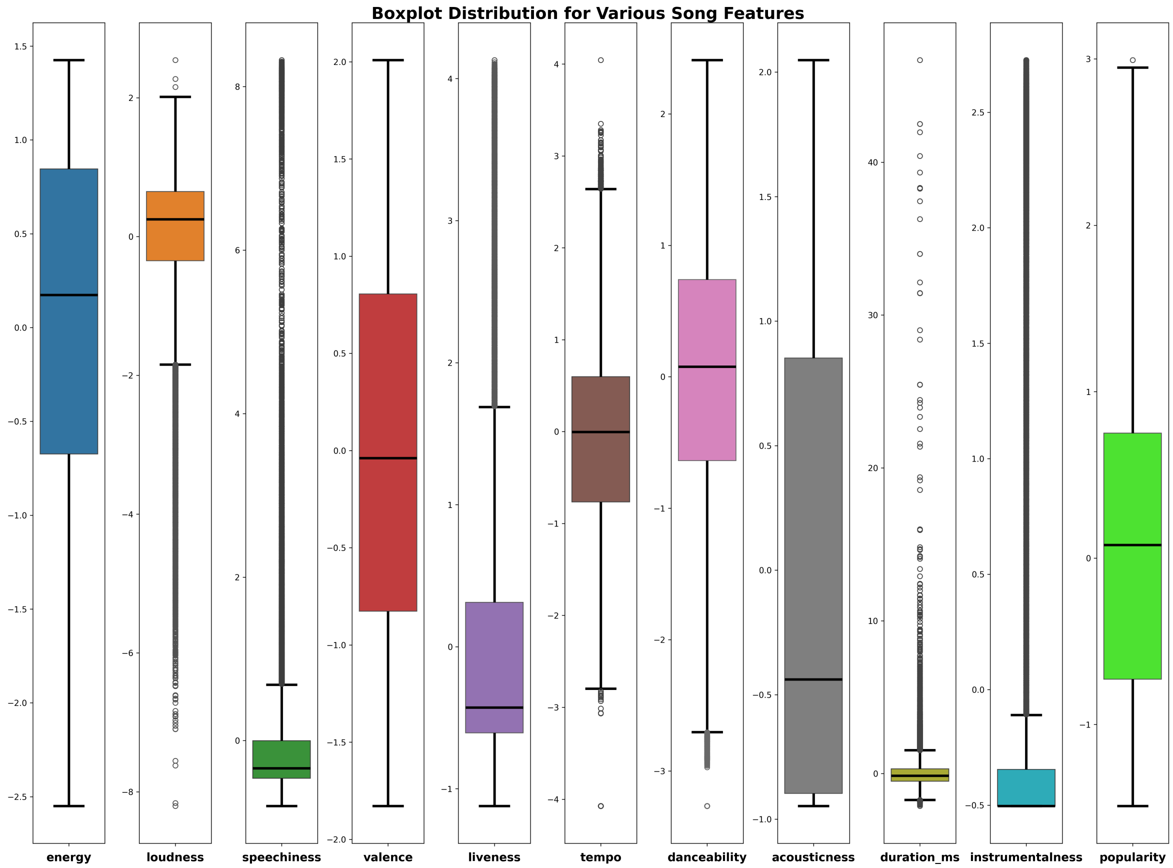


Figure 7: This plot contains the boxplots of the musical features in Dataset B.

## 4.2 KDE & Histogram of Song Features

The plot illustrates a stark concentration of density around the mean for most features, suggesting a close clustering of values with a relatively small spread. This indicates uniformity in song features such as energy, loudness, and tempo across the dataset. The sharp peaks observed throughout the plot signifies that a high number of songs share similar values for certain attributes, thus pointing to a standardization in these features within the music industry. For example, the peaks in instrumentalness (3.02), acousticness (1.37), and speechiness (1.97) suggest these attributes are relatively homogeneous among the analyzed songs.

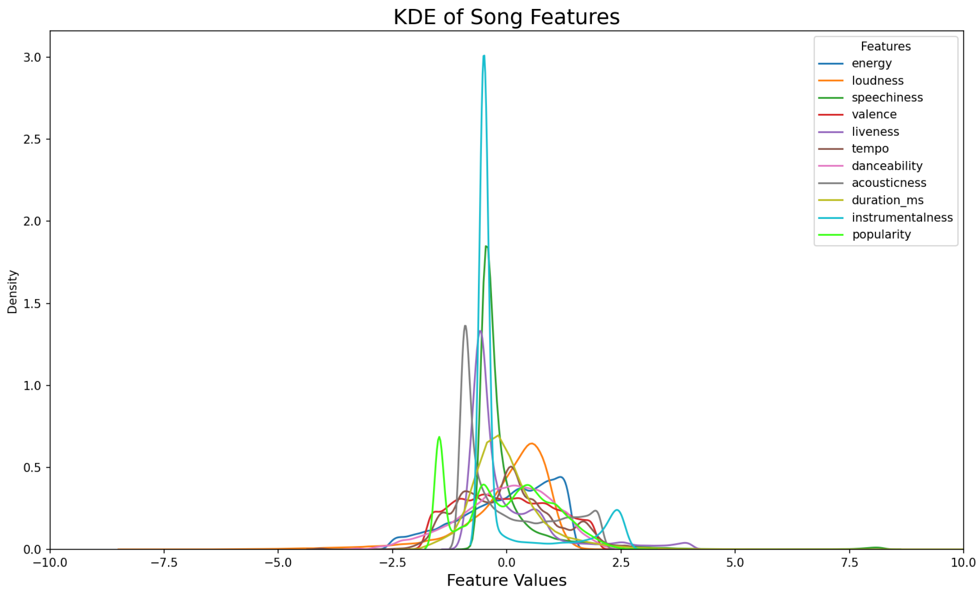


Figure 8: This plot contains the kernel density estimates of the musical features in Dataset B.

Instrumentalness contains the highest peak while displaying a slightly broader distribution. This could point to a diverse mix of genres represented in the dataset, encompassing both heavily instrumental tracks and those with more vocal content. Popularity is also represented as a slightly bimodal distribution with a discrete peak before and after zero. The histogram reveals similar trends that are represented in the KDE plot. Energy and loudness exhibit a high frequency around their mean values and the concentrated bars near the center of these histograms indicate that variations from the norm are less frequent. Speechiness shows a skewed distribution with a majority of songs featuring lower levels of spoken words, signifying that a vast majority of Dataset B is made up of tracks with a balance of spoken words and its instrumental. Meanwhile, valence has a relatively uniform distribution that spans across a range of values, indicating that the songs of this dataset encapsulate a broad spectrum of emotional tones from positive to negative. Liveness and tempo also display a central clustering, but with tempo showing a slight rightward skew. This might reflect a preference for mid to uptempo songs in the dataset, with fewer songs having a very slow or very fast tempo.

Table 6: Feature Analysis Results

| Feature | Min x | Max x | Peak y at x |
|---|---|---|---|
| Energy | -2.55 | 1.43 | 0.44 at x = 1.18 |
| Loudness | -8.21 | 2.54 | 0.65 at x = 0.54 |
| Speechiness | -0.8 | 8.33 | 1.87 at x = -0.44 |
| Valence | -1.83 | 2.01 | 0.34 at x = -0.49 |
| Liveness | -1.12 | 4.13 | 1.34 at x = -0.58 |
| Tempo | -4.07 | 4.04 | 0.51 at x = 0.09 |
| Danceability | -3.27 | 2.41 | 0.39 at x = 0.17 |
| Acousticness | -0.95 | 2.05 | 1.37 at x = -0.91 |
| Duration_ms | -2.13 | 46.69 | 0.7 at x = -0.27 |
| Instrumentalness | -0.5 | 2.73 | 3.02 at x = -0.5 |
| Popularity | -1.49 | 2.99 | 0.69 at x = -1.48 |

Danceability presents a normal-like distribution, hinting at a consistent emphasis on rhythm and beat across the board. Acousticness reveals an interesting bimodal distribution, suggesting that songs tend to cluster around either high or low acousticness but less so in the middle range. Instrumentalness also reveals a somewhat bimodal distribution, with peaks at the lower and higher ends. Duration_ms demonstrates a right-skewed distribution, suggesting that while most adhere to the conventional three-to-four-minute format, there is a subset of longer-duration tracks that could represent different or more progressive musical forms. Popularity reveals a multi-modal distribution with several peaks. Below is a table of the specific distribution values for each feature on the plot as well as the histogram.

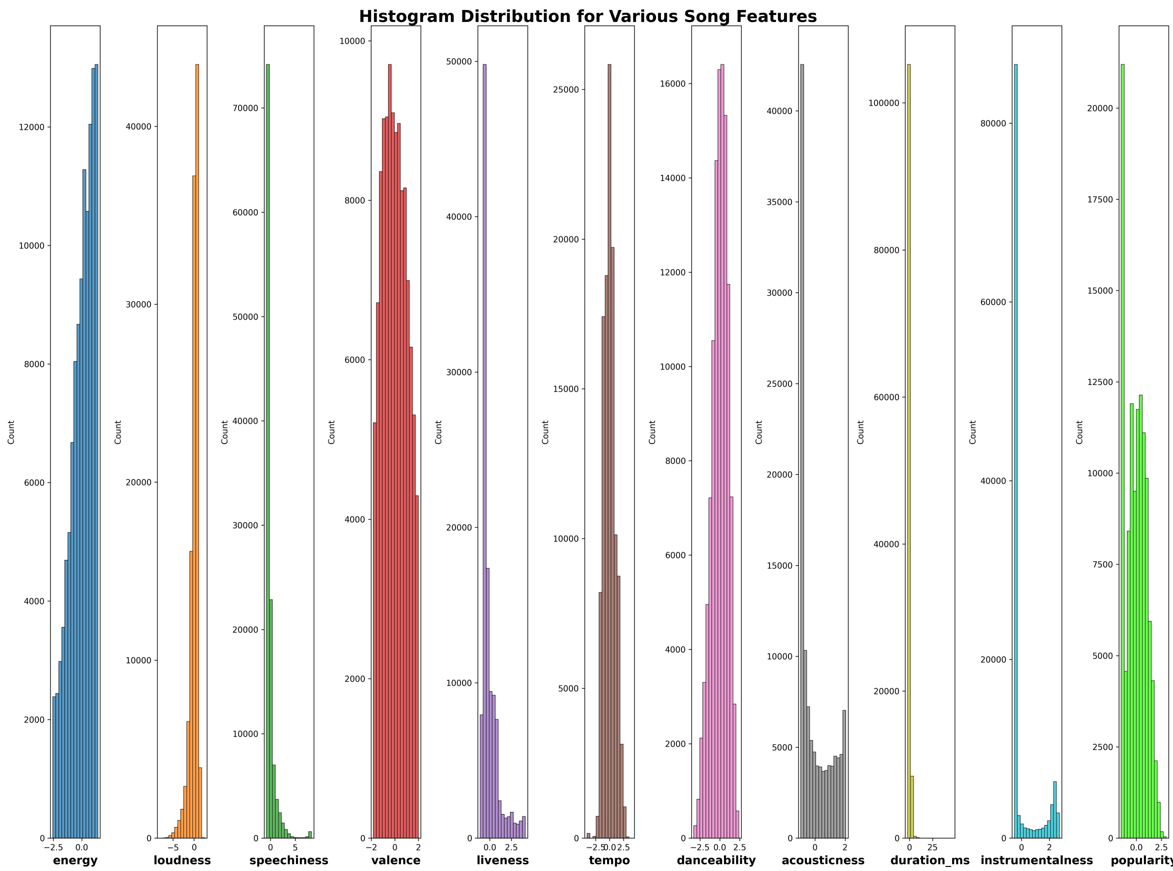


Figure 9: This plot contains the histograms of the musical features in Dataset B.

Popularity demonstrates a slightly bimodal distribution, hinting at a bifurcation within the dataset. One peak is located near the central range of the popularity index, while another resides towards the higher end. Valence and liveness present distributions with less defined peaks at 0.21 and 0.47 respectively, suggesting variable degrees of positivity in a tracks mood as well as varying degrees of live recording ambiance. The tempo attribute peaks at 0.39 with a similar spread to that of energy and loudness. This suggests a moderate variation in the pace of the music, despite a convergence around typical beat patterns that are prevalent in popular genres.

## 4.3 Feature Correlation Heatmap

The popularity and liveness of the tracks do not demonstrate a significant correlation with any other features. The lack of significant correlation between popularity and other musical features suggests that popularity may be influenced by a complex interplay of factors beyond just the measurable audio characteristics. Popular music can spans a wide range of styles, catering to diverse tastes. This diversity may signify that no single set of musical features consistently predicts popularity across all tracks. Other factors such as marketing, artist reputation, social media presence, cultural trends and popular media may also heavily influence a song's popularity. These factors are external to the audio features and can overshadow their impact. As for liveness, this independence may be due to the diverse production techniques that are used to simulate or enhance live performance elements, regardless of the track's other characteristics. Furthermore, liveness may be influenced more by the recording environment rather than the inherent musical features, reflecting a varied approach in capturing the 'live' feel across different tracks.

Duration mildly inversely correlates with valence (-0.15), suggesting that shorter tracks tend to be slightly more positive. Danceability displays a slight positive correlation with loudness (0.26) and moderate positive correlation with valence (0.48). A particularly strong bond exists between energy and loudness (0.76), reflecting that songs which are energetically charged often come with increased volume. Conversely, acousticness shows a substantial negative correlation with both energy (-0.73) and loudness (-0.59), aligning with the contemplative and softer nature of acoustic tracks. A notable inverse relationship is also observed between instrumentalness and loudness (-0.43) while valence and danceability (0.48) is observed to be positive. Both tempo and time signature also have slight correlations with energy (0.25) and danceability (0.21) respectively.

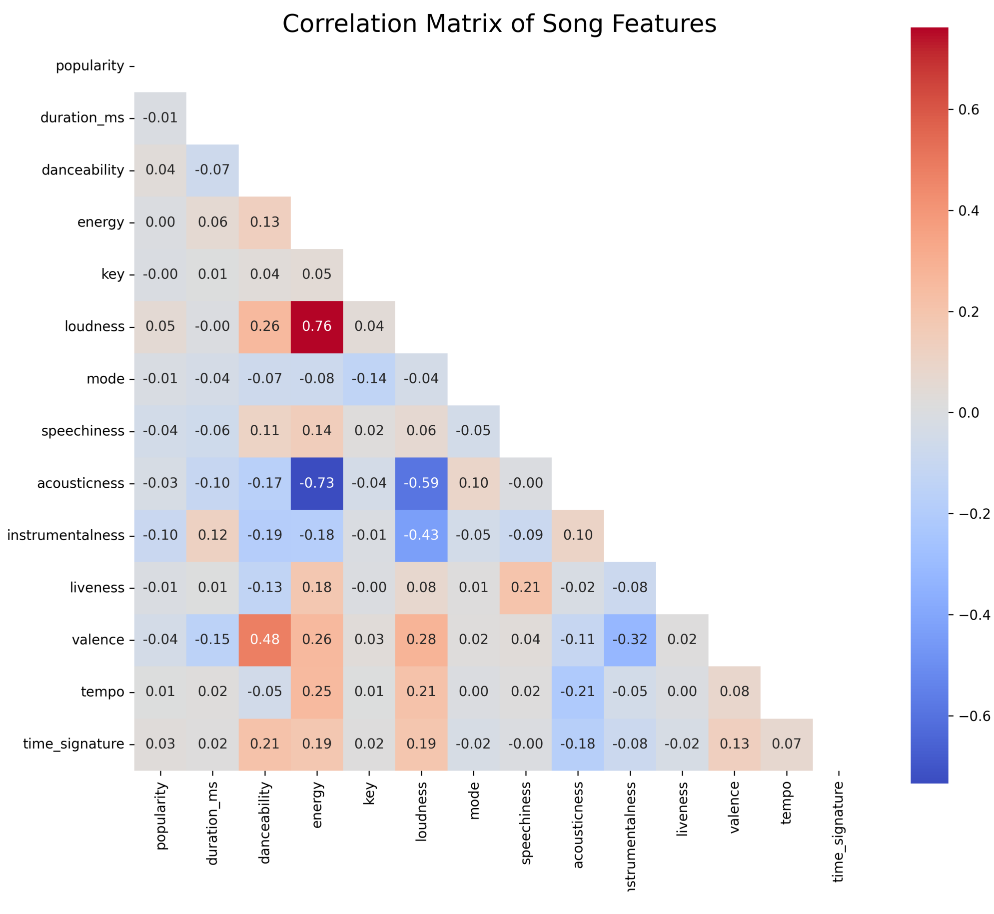


Figure 10: This plot contains the correlation matrix heatmap of the musical features in Dataset B.

## 4.4 Genre & Feature Correlation Heatmap

The feature correlation heatmaps have provided valuable insights into how various musical attributes interrelate. However, to further understand how these attributes manifest within different musical contexts, it is crucial to examine how they correlate with specific genres. By exploring the genre and feature correlation heatmap, we can uncover genre-specific production traits and preferences, offering a deeper understanding of the distinctive characteristics that define each genre. The heatmap was divided into 3 distinct groups for readability.

#### 4.4.1 Group 1 (Figure 11)

Starting with the acoustic genre, we observe a substantial amount of negative correlations across the board, but there's an especially strong negative association with energy (-0.82) and loudness (-0.24). Genres such as ambient ((-1.61, -2.06)) and classical ((-1.8, -2.36)) further underscore this trend with similarly low values for these features but show a substantial positive correlation with acousticness, reflecting the natural soundscapes or unamplified instruments typical of these styles.

On the other end of the spectrum, genres like afrobeat ((0.87, 0.59)) and dancehall (0.6, 0.96) demonstrate high mean scores for valence and danceability, highlighting the rhythmic nature inherent to these music styles that encourage movement. Moreover, there are genres like disco (0.63, 0.38) and funk (0.64) that display moderate to high mean scores for danceability, illustrating the upbeat and rhythmic quality of music in a similar manner to afrobeat and dancehall. The genre of comedy stands out with its significantly high mean score for speechiness (6.35), which aligns with the spoken word content often found in comedic tracks. This is contrasted by the low value for danceability (-0.5), suggesting that these tracks aren't as melodic as others in the dataset. Genres such as death-metal (1.15) and dubstep (0.47) show high mean scores for energy. Other genres like children's music (0.85) reveal a higher positive correlation for valence, reflecting the positive emotions typically associated with music in this category.

Interestingly, the Disney genre has a negative correlation with valence (-0.41), signifying that the Disney songs in this dataset may not possess positive emotions in the way that children's music does. The heatmap also reveals interesting patterns such as the pronounced positive score for instrumentalness in genres like classical (1.5), emphasizing the significant role of instruments rather than vocals in these genres. On the contrary, genres like emo (-0.41) and folk (-0.38) showcase much lower mean scores for instrumentalness.

#### 4.4.2 Group 2 (Figure 12)

Genres like garage, german and gospel show varying degrees of correlation with song features, suggesting diverse influences and attributes. For example, german music exhibits a strong negative correlation with loudness (-0.61) and valence (-0.37) while gospel exhibits a strong positive correlation with duration_ms (0.79). Grindcore stands out with strong positive correlations with energy (1.12) and instrumentalness (1.24) but a strong negative one with danceability (-1.7), which aligns with the genre's intense style. Danceability also exhibits various negative correlations in genres such as heavy metal (-0.8), iranian (-1.53), metalcore (-0.82) and new age (-1.26). Energy is also presented with strong positive correlations in genres such as happy (1.02), hardstyle (1.03) and metalcore (1.09) and very strong negative correlations in genres such as guitar (-1.26), honky tonk (-1.09), jazz (-1.15) and new age (-1.7). New age also contains a negative correlation of -2.03 with loudness, signifying that new age music has a strong ambient and calming feel compared to most other genres.

Groove ((0.49, 0.37)) and grunge ((0.64, 0.52)) show moderate correlations with features like energy and loudness. Instrumentalness also reveals strong positive correlations with various other genres such as guitar (1.16), idm (1.68), iranian (1.4), minimal techno (1.9) and new age (1.8). Popularity contains strong positive correlations with genres such as k-pop (1.06), grunge (0.73) and indian (0.73) while also containing strong negative correlations with genres such as iranian (-1.39) and latin (-1.12). These correlations may be a reflection of the general musical landscape on Spotify at the time that this data was collected.

#### 4.4.3 Group 3 (Figure 13)

Genres such as opera ((-1.29, -1.06)), piano ((-1.28, -1.74)), romance ((-1.38, -0.98)) and sleep ((-1.19, -3.17)) stand out with significant negative correlations with energy and loudness. Conversely, genres like pagode, party and reggaeaton show strong positive correlations with danceability, valence and energy, indicating a lively, rhythmic and energetic characteristics typical of music meant to uplift audiences.

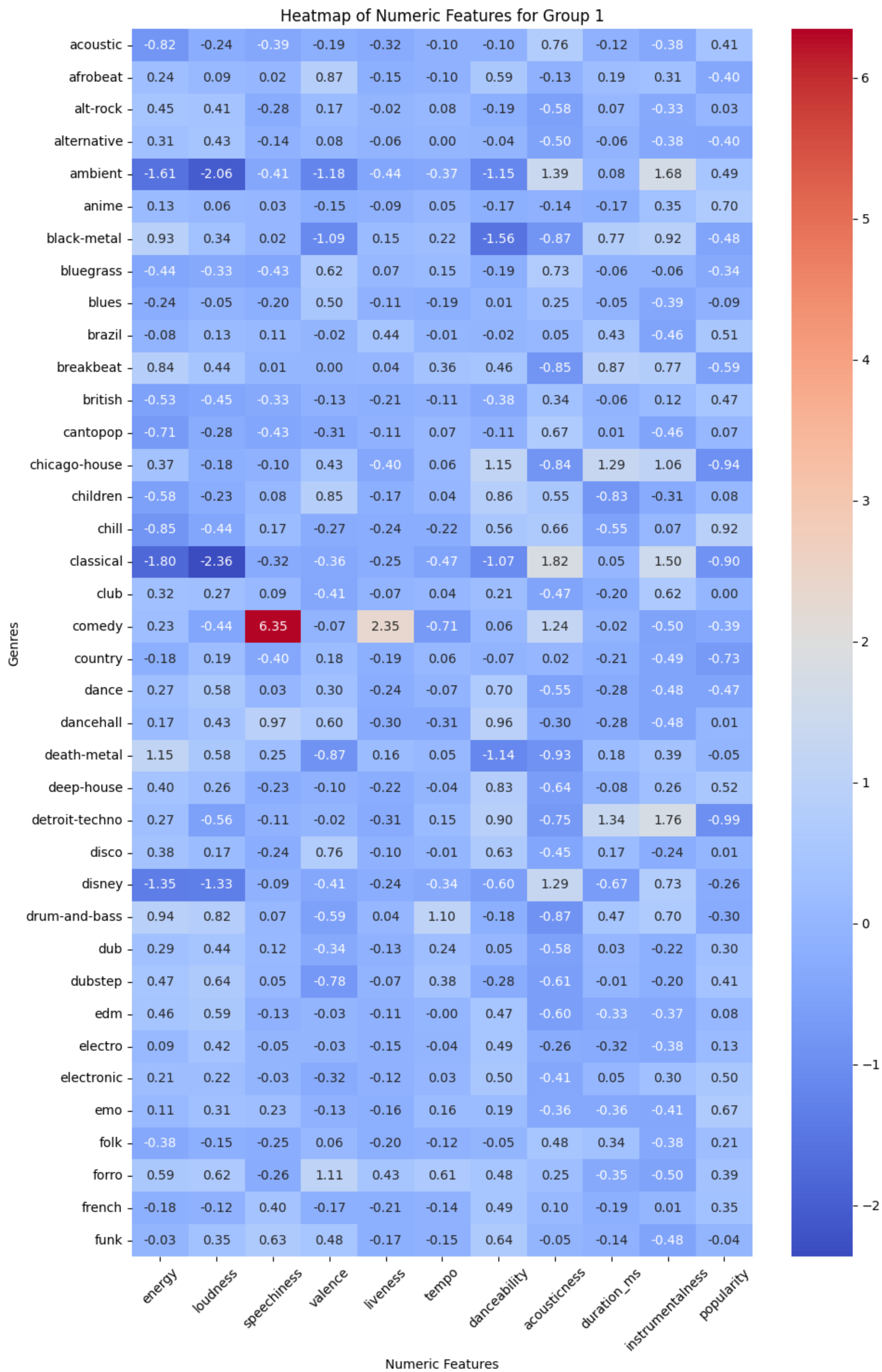


Figure 11: This plot contains the correlation matrix heatmap of genres and musical features in Group 1 of Dataset B.

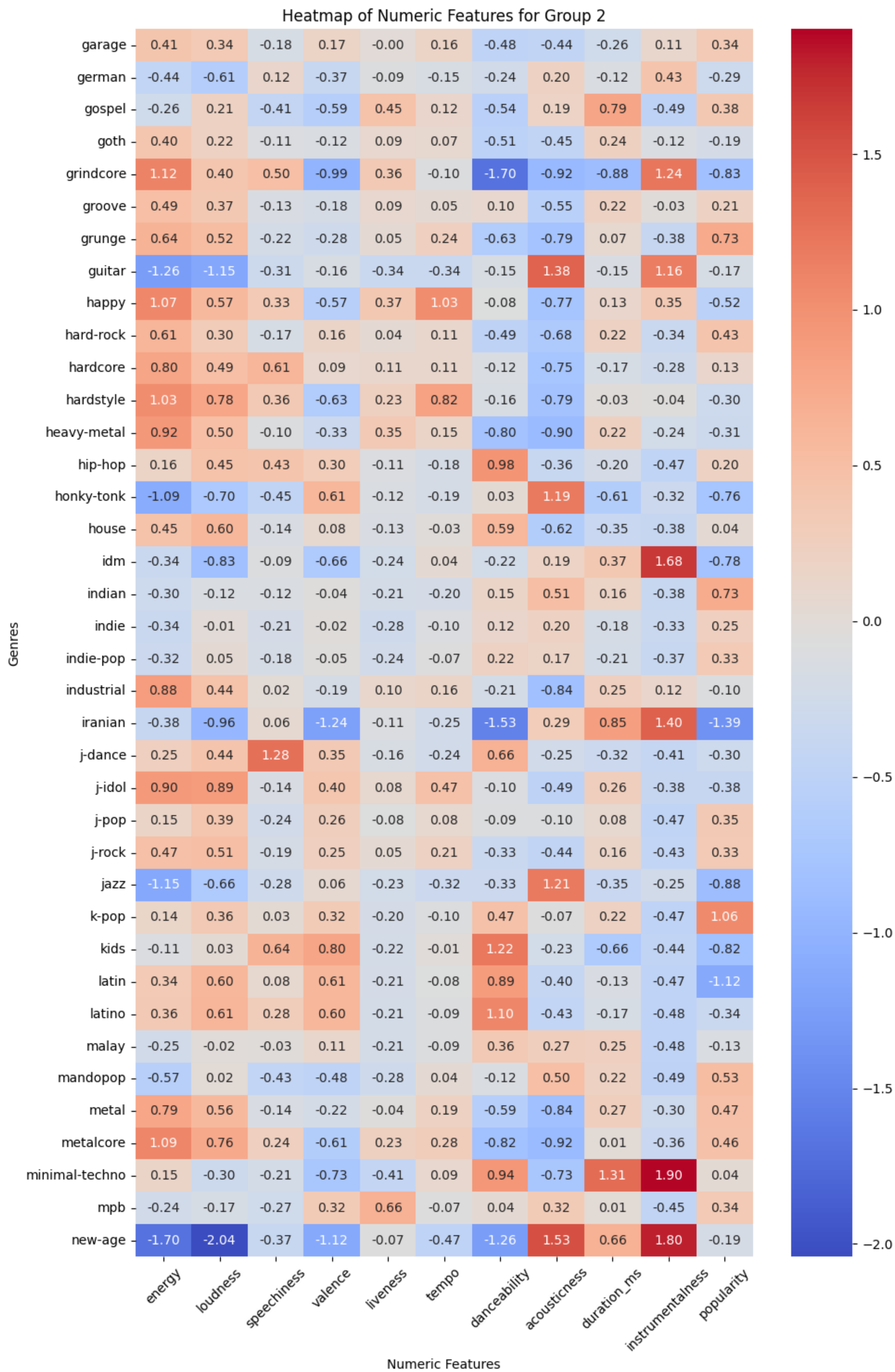

Figure 12: This plot contains the correlation matrix heatmap of genres and musical features in Group 2 of Dataset B.

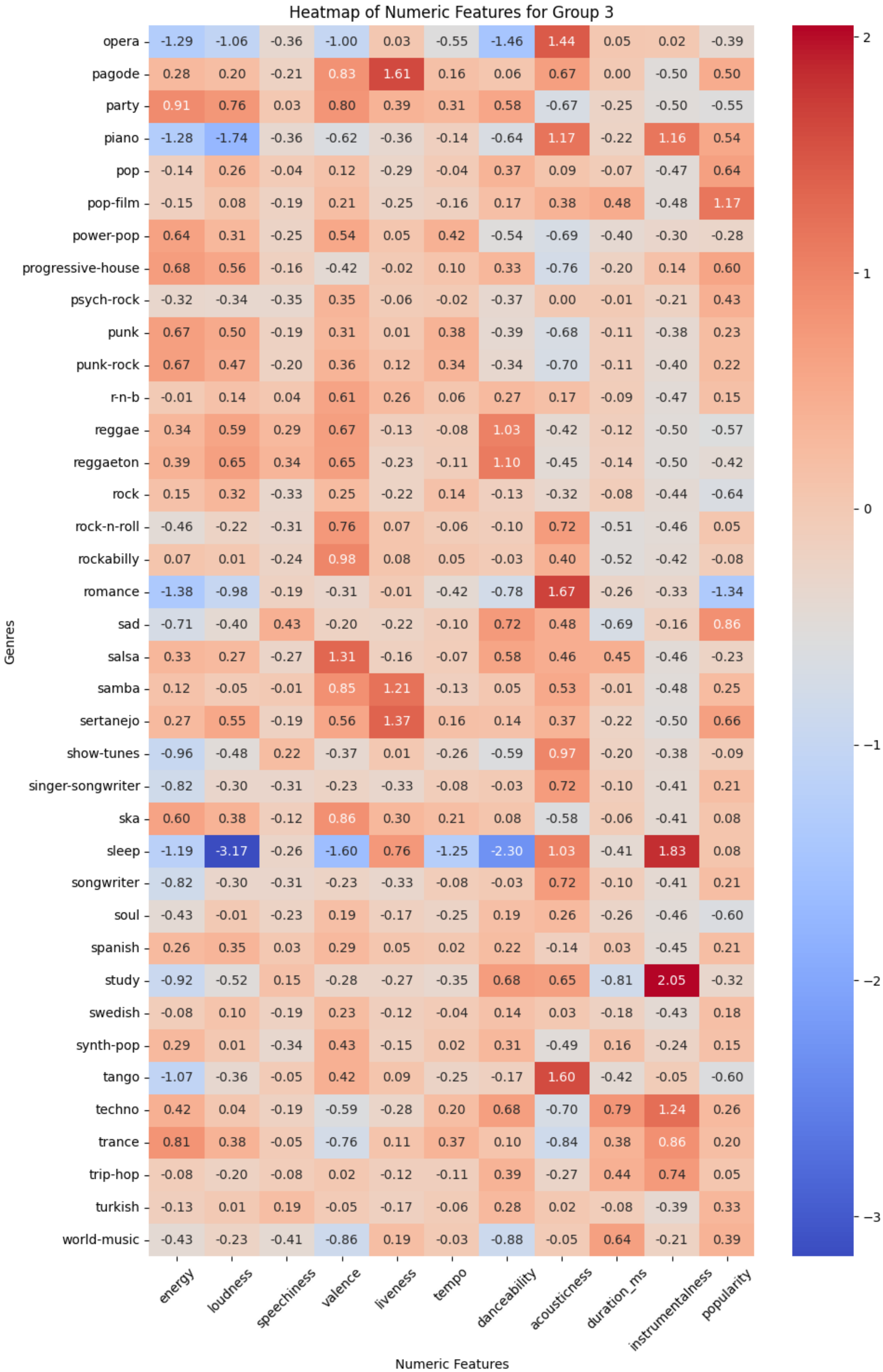


Figure 13: This plot contains the correlation matrix heatmap of genres and musical features in Group 2 of Dataset B.

Sleep music reveals a stark contrast with extremely high negative correlations with loudness (-3.17), danceability (-2.3) and valence (-1.6), but positive correlations with acousticness (1.03) and instrumentalness (1.83), embodying its purpose to soothe and calm listeners. Samba ((0.85, 1.21)), sertanejo ((0.56, 1.37)) and padoge ((0.83, 1.61)) genres demonstrate strong positive correlations with valence and liveness, which can be attributed to their traditional live recordings and positive feelings. Conversely, techno ((1.24, 0.42)) and trance ((0.86, 0.81)) exhibit strong positive correlations with instrumentalness and energy, which are characteristic of genres designed to excite without relying on vocal performance. Genres generally related to rock show a balanced mix of correlations, suggesting a diverse range of expressions within these genres, from aggressive and loud to soft and melodic. Study music interestingly shows a strong positive correlation with instrumentalness (2.05) and a negative correlation with loudness (-0.92) and energy (-0.52), implying a focus on non-vocal music conducive to concentration. Other strong positive correlations for acousticness include opera (1.44), piano (1.17), romance (1.67) and tango (1.6).

## 4.5 PCA Loadings

The first principal component (PC1) accounts for approximately 26.14% of the variance in the data, indicating that over a quarter of the total variability in the dataset is captured by the features strongly associated with this component. PC1 is characterized by strong negative loadings on energy (-0.51) and loudness, (-0.52) and a strong positive loading on acousticness (0.44), suggesting that this component captures the dichotomy between loud, energetic tracks and softer acoustic tracks.

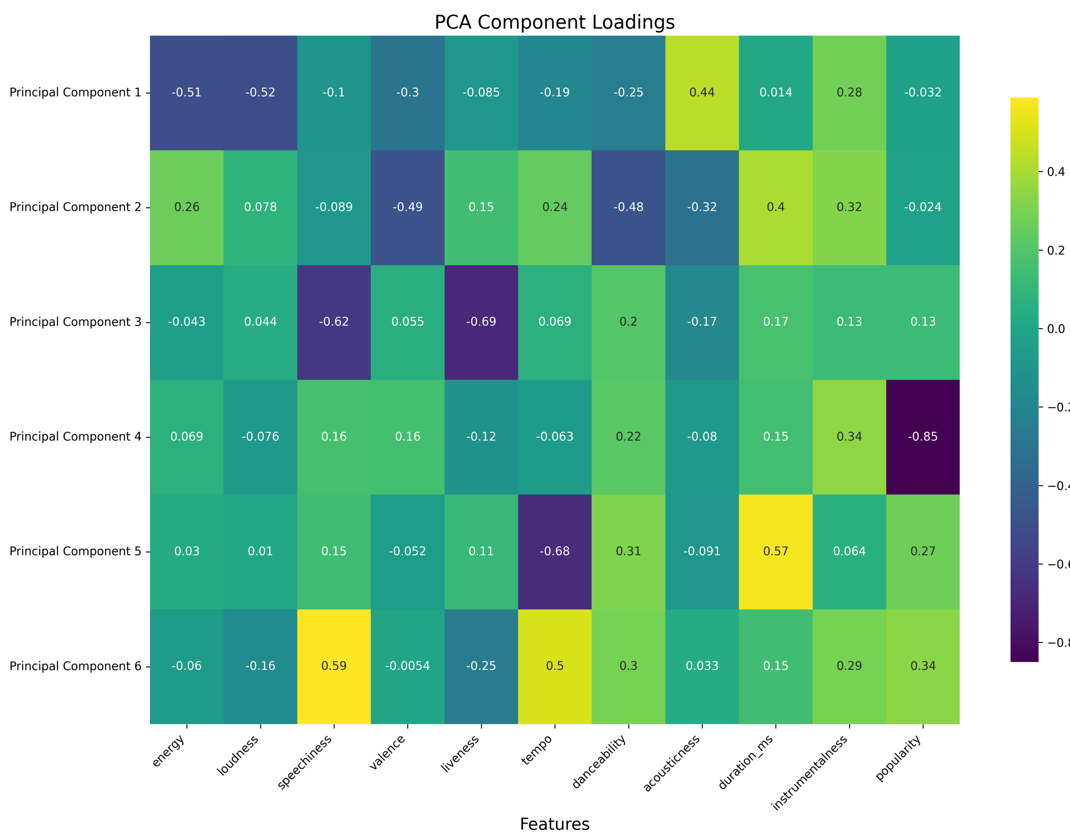


Figure 14: This plot contains the principle component analysis heatmap of the musical features in Dataset B.

The second principal component (PC2) explains about 13.86% of the variance. While it captures less variability than PC1, it still represents a significant proportion of the data's structure. PC2 displays a moderate negative loading on valence (-0.49) and danceability (-0.48), hinting at its alignment with less upbeat and danceable songs. It also shows a positive loading on duration_ms (0.4) and instrumentalness (0.32), possibly capturing tracks with a greater emphasis on instruments and length over vocals.

The third principal component (PC3) explains 11.25% of the variance, adding to the cumulative insight provided by the first two components. PC3 has significant negative loadings on speechiness (-0.62) and liveness (-0.69), which may reflect studio-produced tracks with less spoken words. It also shows a slight positive association with danceability, suggesting a component that slightly favors danceable music.

The fourth principal component (PC4) contributes 9.54% to the explained variance. PC4 reveals an interesting pattern with relatively balanced loadings, but notably, it exhibits a very strong negative loading on popularity (-0.85) and a slight positive loading on instrumentalness (0.34). This might imply that PC4 captures less relevant tracks that favor their instrumental over other areas such as vocals.

The fifth principal component (PC5) accounts for 8.74% of the variance, indicating that it still holds relevant information despite starting to explain less variance than the previous components. PC5 stands out with a strong positive loading on duration_ms (0.57) and a negative loading on tempo (-0.68), suggesting that this component may correspond to longer duration and slower tempo tracks.

Finally, the sixth principal component (PC6) explains 7.85% of the variance. Although it captures the least variance among the six components, it remains a valuable dimension for understanding the dataset's complexity. PC6 shows a strong positive loading on speechiness (0.59), tempo (0.5) and popularity (0.34) as well as a negative loading on liveness (-0.25), hinting at a component that focuses on relevant studio-produced tracks with a heavy focus on vocals.

The interpretation of the PCA components for Dataset B can be represented as:

1. Acoustic Vs Power: Captures the contrast between loud, high-energy tracks and softer, more acoustic ones, representing the balance between amplified and unamplified sound elements.

2. Mood + Duration Vs. Dance: Aligns with longer, less upbeat and danceable songs, indicating a component that encapsulates the presence of extended instrumentals over vocals.

3. Studio Production Focus: Reflects studio-produced tracks with a lower presence of live elements and spoken words, with a slight favor towards danceability.

4. Non-Popularity Instrumentality: Highlights less popular tracks with a focus on instrumentals, potentially indicating niche or non-mainstream preferences.

5. Leisurely Focus: Corresponds to tracks with longer durations and slower tempos as well as slight trends in popularity and danceability, suggesting a component that may relate to trendy music that is more laid-back in feel

6. Vocal Prominence in Studio Tracks: Focuses on relevant, vocal-heavy studio-produced tracks that combine speechiness and tempo, distinct from live performance attributes.

### 4.6 Genre Regression

The first OLS regression analysis was conducted to investigate the impact of various musical features on the popularity of songs. The model included the ten predictors: energy, loudness, speechiness, valence, liveness, tempo, danceability, acousticness, duration_ms, and instrumentalness. The dependent variable was the song's popularity. The sample used Dataset B which consisted of 114,000 observations.

The model's R-squared value was 0.023, indicating that approximately 2.3% of the variance in song popularity can be explained by the musical features included in the model. While this suggests a relatively small effect overall, the analysis still provides insights into the relationships between individual features and popularity.

Valence and Instrumentalness exhibited the strongest negative relationships with popularity, with coefficients of -0.1138 and -0.1134, respectively (both p ¡ 0.001). This suggests that songs perceived as less happy or more instrumental are associated with lower popularity. Danceability showed the most robust positive relationship with popularity, with a coefficient of 0.0715 (p ¡ 0.001), indicating that songs with higher danceability tend to be more popular. Speechiness and Energy were slightly negatively associated with popularity, with coefficients of -0.0595 and -0.0304, respectively (both p ¡ 0.001). This finding suggests that songs with more spoken words or lower energy levels are likely to be slightly less popular. Other features such as Loudness, Liveness, Tempo, Acousticness, and Duration_ms also demonstrated significant relationships with popularity, albeit with very small effect sizes. The model diagnostics indicated that the residuals aren't perfectly normally distributed, as shown by the significant Omnibus and Jarque-Bera tests (both p ¡ 0.001), which suggests potential deviations from normality or presence of outliers. The Durbin-Watson statistic of 0.568 points to the potential for autocorrelation in the residuals, which should be considered when interpreting the results.

The second OLS regression analysis was conducted to assess how various musical features influence genre classification as determined by the labeled genre. The analysis also utilized Dataset B, but was conducted with eleven predictors: energy, loudness, speechiness, valence, liveness, tempo, danceability, acousticness, duration_ms, instrumentalness, and popularity. The model also yielded an R-squared value of 0.026, indicating that only 2.6% of the variability in the genre labels could be explained by these musical features. This highlights the complexity in genre classification based on audio features alone.

Speechiness showed a strong negative association with genre classification with a coefficient of -3.3747 (p ¡ 0.001), suggesting that tracks with more spoken words are significantly less likely to be associated with certain genres. Instrumentalness also exhibited a negative relationship with a coefficient of -2.5259 (p ¡ 0.001), indicating that more instrumental tracks tend to fall into specific genres less frequently. Acousticness was positively associated with genre classification having a coefficient of 2.3769 (p ¡ 0.001), implying that acoustic features strongly influence the genre categorization. Liveness and Valence were also significant positive predictors with coefficients of 1.7032 (p ¡ 0.001) and 1.4709 (p ¡ 0.001) respectively, suggesting that live recordings and tracks with higher valence are more likely to be classified into particular genres. Popularity had a positive coefficient of 0.8596 (p ¡ 0.001), indicating a slight relationship between the track's popularity and its genre classification.

The model's diagnostics also indicated poor fit with a Durbin-Watson statistic of 0.027, suggesting substantial autocorrelation in the residuals. The Omnibus and Jarque-Bera tests both were also significant (p ¡ 0.001), indicating non-normality in the residuals.

# 5 Discussion

The analysis of both KDE plots revealed that most tracks maintain a consistent intensity, suggesting a production standardization aimed at reaching a broader listener base. The peaks observed around a specific danceability score underscores the importance of rhythm, highlighting a preference for tracks that balance energy and accessibility. Additionally, the distribution of features suggests a favoring of instrumentation or singing over spoken word, which was expected from a dataset almost entirely composed of "music". The bimodal distribution seen in Dataset A's popularity indicates a clear divide between tracks that were formerly relevant and those that continue to attract significant attention, reflecting the dynamic nature of musical preferences. The bimodal distribution seen in Dataset B's instrumentalness could be indicative of a divide between acoustic and electronic music within the popular genres. which may correspond to the prevalence of either vocal-dominated tracks or those that are heavily instrumental

The correlation matrices between musical features provided further insights, aligning with the intuitive expectation that more energetic songs feature higher volumes and dynamic ranges, characteristic of dance music designed to evoke positive emotions. Furthermore, it resonates with the intuitive expectation that more rhythmic and danceable tracks often possess a more upbeat and positive character. Conversely, acoustic tracks tend to be softer and more mellow which may also reflect their emphasis on dramatism over energy as shown by their lower energy and loudness. Based on the results, it's important to note that the elements defining popularity are diverse and not easily attributable to specific song features.

After analyzing the component construction of both Datasets A and B as well as the plots created throughout the data analysis , it can be ultimately concluded that there aren't many statistically significant differences between a dataset composed of tracks with billions of streams and a dataset with an immensely wide variety of streams. When looking at the PCA heatmaps specifically, the first two components are nearly identical for both Dataset A and B. Furthermore, the rest of the components contain strong similarities to their counterparts in the other dataset, as seen especially in Principle Components 4 and 6. The differences that do present themselves between the datasets may simply be attributed to the difference in observations between both datasets, but further testing would be required to substantiate this claim.

The genre analysis of correlations reveals various interesting influences on song characteristics. For instance, the acousticness feature contained lower associations in genres like metal and higher in classical and Disney, suggesting genre-specific production traits. Liveness in metal could also be a significant component in regards to the sense of presence and energy that is felt within the music. Also, the acousticness feature only had a correlation of 0.76 with the acoustic genre while genres such as disney and classical were significantly higher, indicating that there may be certain aspects about songs defined as "acoustic" that don't align with Spotify's definition of "acousticness". Interestingly, children's music, designed to be engaging and accessible, aligns with higher levels of valence while Disney had negative levels, indicating that although Disney music is generally considered to be child-friendly, it may not commonly evoke positive emotions. This can also be observed when listening to a few of the highest streamed Disney and children's songs on Spotify. Tracks such as *All I Want*, *I'll Make a Man out of You* and *A Whole New World* don't evoke "positivity" in the same way that tracks such as *Johny Johny Yes Papa* and *Baby Shark* do. Genres like emo and electronic both contain low instrumentalness levels, as emo generally has a very strong reliance on vocals while electronic music may encapsulate tracks that also use vocals. On the other hand, minimal techno, techno, trance and new age likely have high instrumentalness levels due to the fact these genres are primarily focused on the instrumental content created through electronics as opposed to the vocals used in other electronic songs.

The significant predictors identified in the OLS regression models provide valuable insights, though they account for a relatively small proportion of the variance in song popularity and genre classification. The non-linearity of the dataset highlights the complex and multifaceted nature of musical appeal and genre identity, suggesting that linear models may only capture a small fraction of these dynamics. Future research could benefit from employing more sophisticated machine learning techniques to better understand the non-linear relationships as well as the intricate interactions among different audio features.

The creation of the EchoSpot website is intended to allow any individual to generate playlists based on the analysis conducted in this report. EchoSpot leverages the powerful features of Spotify's API to craft custom playlists that align with preferences set by the listener. Its functionality hinges on integrating the musical attributes analyzed throughout the report into a playlist generation process. Through an intuitive interface, users can specify their desired traits for a playlist, which EchoSpot uses to retrieve song recommendations from Spotify. Additionally, EchoSpot provides flexibility in curation by allowing users to choose specific genres as seeds for the recommendation algorithm as well as the option to omit entire features altogether. The website hopes to offer a user-friendly platform for both casual listeners and music enthusiasts to explore new music tailored to whatever they can imagine, reflecting the underlying patterns unearthed by the research encapsulated in this report.

# 6 Conclusion

The EchoSpot project has provided a comprehensive exploration of musical attributes across a broad spectrum of tracks on Spotify, yielding insights into how various features correlate with both song popularity and genre distinctions. This analytical journey reveals the intricate balance between musical components that collectively shape user preferences and market trends.

The findings indicate that certain attributes, such as danceability and energy, significantly contribute to a track's appeal, affirming the music industry's strategic focus on creating music that resonates with a dynamic listener base. However, the diverse nature of music consumption today necessitates a nuanced approach to understanding these patterns as demonstrated by the variance in attributes like instrumentalness and speechiness across different genres.

The genre analysis of correlations underscores the diverse production traits and emotional tones contained within different music genres. For example, acousticness varies significantly, being lower in metal and higher in classical and Disney, reflecting distinct genre-specific characteristics. Moreover, the emotional impact of music, as seen in higher valence in children's music versus lower valence in Disney tracks, reveal that genres designed for specific demographics do not always align with expected emotional responses. These findings highlight the intricate relationships between musical features and genre, emphasizing the varied nature of music production and listener experiences as a whole.

The analysis encapsulates the multi-dimensional essence of the music tracks in the dataset. It underscores the presence of typical values around which certain song features such as energy, loudness and danceability are concentrated, while also illustrating the diversity and complexity within the musical elements of tempo, valence and acousticness. The findings illustrate a rich tapestry of musical styles and elements, with a clear emphasis on how production choices and genre-specific characteristics influence listener preferences and song classification.

The analysis has not only mapped the existing landscape but also paved the way for future research. By leveraging data-driven insights, music producers and strategists can better navigate the complexities of the digital music era. Moreover, the potential of the EchoSpot platform to customize user experiences highlights the transformative impact of integrating analytical tools with consumer interfaces, enhancing engagement through user-generated content.

The project underscores the importance of harnessing analytical insights to inform production choices and marketing strategies within the music industry. As streaming services continue to dominate music consumption, such data-centric approaches will undoubtedly play a pivotal role in shaping the future of music, making it more accessible, enjoyable, and aligned with listener preferences across the globe. However, it's important to acknowledge that music will never be entirely understood through data science. As a final thought, I'd like to include another quote from David Huron which encapsulates this thought very well. "When making observations about music, the analyst is free to choose or construct any descriptive language. However, the value of the resulting description can be evaluated only by inviting the possibility of failure. At a minimum, one needs to discern whether the description offered succeeds in distinguishing the object of interest from other similar objects. It is surprisingly easy to inadvertently describe features that may be characteristic of music in general while wrongly supposing that one is describing features of a particular work."

## 7 Acknowledgements

Special thanks to Peter J. Mucha and Olivia Chu for their assistance and feedback throughout the creation of the EchoSpot project. I'd also like to thank Spotify for allowing their API to be used in limited capacities for free, allowing for this analysis to be possible.

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# 9 Appendices

When EchoSpot was in its earliest stages, I originally wanted to use musical features to make predictions regarding a song's mood. This model would have then been used to create a website where users could either input a song to find its mood or to input certain moods to create a playlist from. Ultimately, I decided to analyze the features from a perspective of their general popularity and genre, but I hope to expand upon EchoSpot in the near future to include these features as they were originally intended. This inspiration stemmed from articles written by Rachelle Palmer and Cristóbal V which are cited in the references above.

Another strong influence in what the future of EchoSpot could hold lies within everynoise.com. Created by Glenn Mcdonald, Every Noise at Once was an attempt at an algorithmically-generated scatter-plot of the musical genre-space, based on genre-shaped distinctions from Spotify as of 2023-11-19. The website is no longer being updated, but contains very interesting features such as the ability to observe this scatter-plot with over 6,000 genres, listen to a playlist with a song from every single one of these genres and the ability to sort genres by a wide variety of options such as popularity, country, tempo, etc. In the future, I'd hope to be able to expand upon the genre analysis conducted in this report and be able to create sortable genres in the similar way to that of Every Noise at Once.

Furthermore, there are a multitude of ways that I would've liked to have expanded upon this project. Firstly, I would like to integrate data from other music streaming platforms such as Apple Music and YouTube Music to provide a more comprehensive analysis of the attributes alongside the inclusion of new ones such as song release dates. The inclusion of more data would hopefully reduce the variability of my analysis and allow for EchoSpot to work on more platforms. I'd also like to consider studying the dynamics of musical features over a period of time to see how certain genres evolved with age. Finally, I would've liked to have implemented a more sophisticated machine learning model to try to predict the popularity and/or genre of a song based on its respective musical features.

Here is the link to EchoSpot: www.echospot.com (not currently deployed)

Here is the link to the GitHub repository: https://github.com/rafaelgdnh/EchoSpot