Spotify Music Analytics: What Makes a Hit Song?

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GitHub Repo: https://github.com/saanavig/Spotify-Visualization

Abstract

This project presents Spotify Music Explorer, an interactive visual analytics dashboard designed to examine how musical audio features relate to emotional tone and genre characteristics in streaming music. Using a cleaned dataset of over 232,000 Spotify tracks, the system visualizes relationships among attributes such as valence, danceability, energy, loudness, tempo, and popularity through coordinated interactive views built with Python, Pandas, Plotly, and Dash.

The dashboard enables users to explore global trends, compare genres, and inspect individual tracks using filtering and details-on-demand interactions. Our analysis reveals strong global relationships between valence and features such as danceability and energy, along with distinctive genre-specific audio profiles. In contrast, popularity exhibits only weak relationships with audio features, suggesting that factors beyond acoustic properties play a significant role in determining a song's success. Overall, this project demonstrates the effectiveness of interactive visualization for understanding large-scale music datasets and provides a foundation for future exploratory and predictive extensions.

Introduction

Music streaming platforms produce large volumes of data that describe both listening behavior and the acoustic properties of songs. Spotify provides a detailed set of audio features, including valence, danceability, energy, loudness, and tempo, which quantify emotional tone and musical structure. These features enable large scale analysis of how music varies across genres and how different characteristics relate to one another within modern streaming catalogs.

Additionally, popular features such as Spotify Wrapped have demonstrated the value of summarizing music data through visual representations. While these summaries focus primarily on individual listening patterns, they also highlight the potential for deeper exploration of the music itself. Interactive visualization offers an effective approach for examining relationships among multiple audio attributes across large datasets, allowing users to move beyond static summaries and engage directly with the underlying data.

The dashboard system is built on a cleaned dataset of over 232,000 Spotify tracks spanning 26 genres. Valence is used as a central measure of emotional tone, and its relationship with other audio features is examined through multiple visual encodings. The dashboard reveals clear relationships between valence, danceability, and energy, as well as distinctive patterns across genres. In contrast, popularity exhibits weaker relationships with most audio features, indicating that musical success on streaming platforms is influenced by factors beyond acoustic characteristics alone.

All in all, this project demonstrates how interactive visualization can support meaningful analysis of large and complex music datasets. By combining multiple coordinated views with user-controlled interaction, Spotify Music Explorer enables a deeper understanding of musical structure and genre variation and provides a foundation for future extensions in music analytics.

Dataset and Feature Description

Data Source:

The dataset used in this project is derived from the Ultimate Spotify Tracks Database, which aggregates Spotify audio features and metadata across a large collection of tracks. After data cleaning and preprocessing, the final dataset contains 176,514 tracks spanning 26 genres,

with each row representing an individual song. The dataset includes both acoustic attributes computed by Spotify and contextual information such as genre and popularity.

This dataset was selected due to its scale, diversity, and suitability for exploratory visual analysis. The availability of standardized audio features allows for consistent comparison across genres and supports multivariate analysis of musical characteristics. Figure 1 presents the distribution of tracks across genres in the cleaned dataset, illustrating the breadth of musical styles represented and motivating the need for interactive, genre-aware exploration.
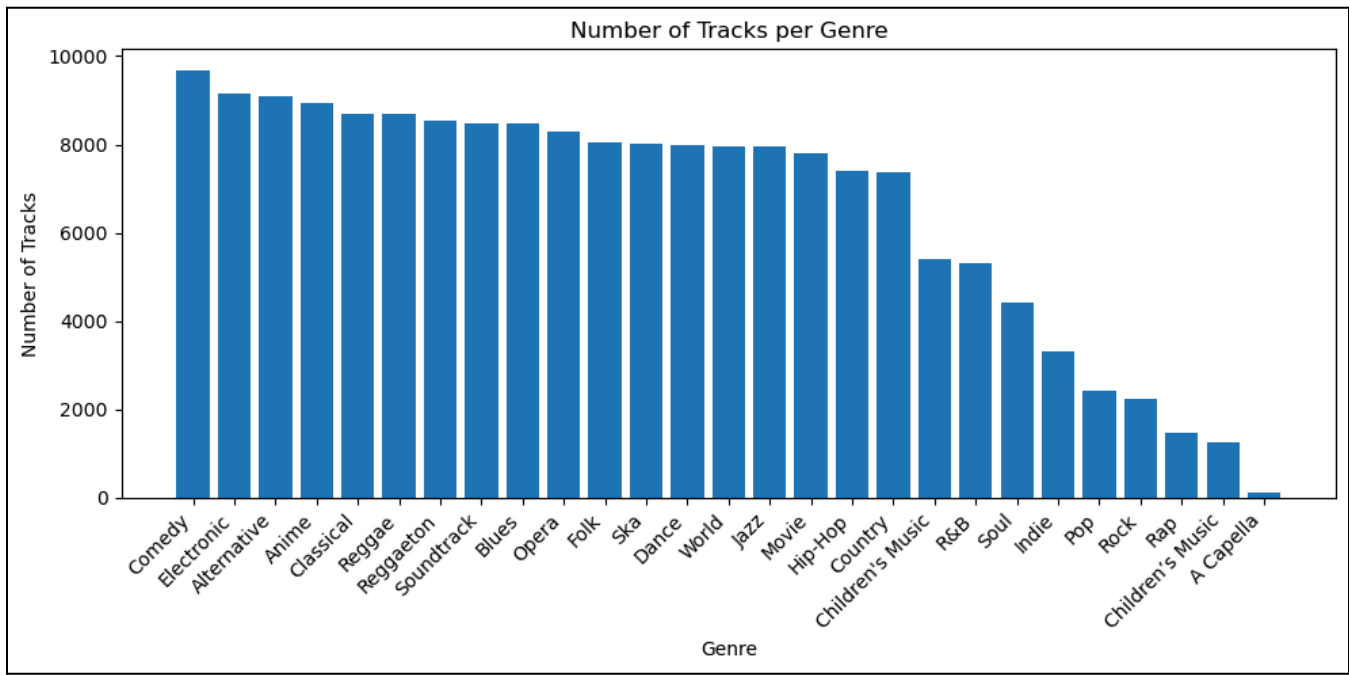
Data Cleaning and Preprocessing:

Several preprocessing steps were applied to ensure the dataset was suitable for visualization and analysis. Tracks containing missing or invalid values in key audio features such as valence, energy, danceability, tempo, or popularity were removed. Feature values were also validated to ensure they fell within expected ranges, particularly for normalized attributes such as valence and danceability, which are defined on a scale from 0 to 1.

Duplicate tracks were removed to prevent repeated entries from skewing aggregate trends. Genre labels were standardized to ensure consistency across records and to enable reliable grouping during analysis. These preprocessing steps reduced the dataset size while improving data quality, resulting in a cleaned dataset of 176,514 tracks that provides a stable foundation for interactive exploration. Figure 2 illustrates the impact of data cleaning by comparing the number of tracks before and after preprocessing, demonstrating that only a small fraction of records were removed to preserve dataset integrity.
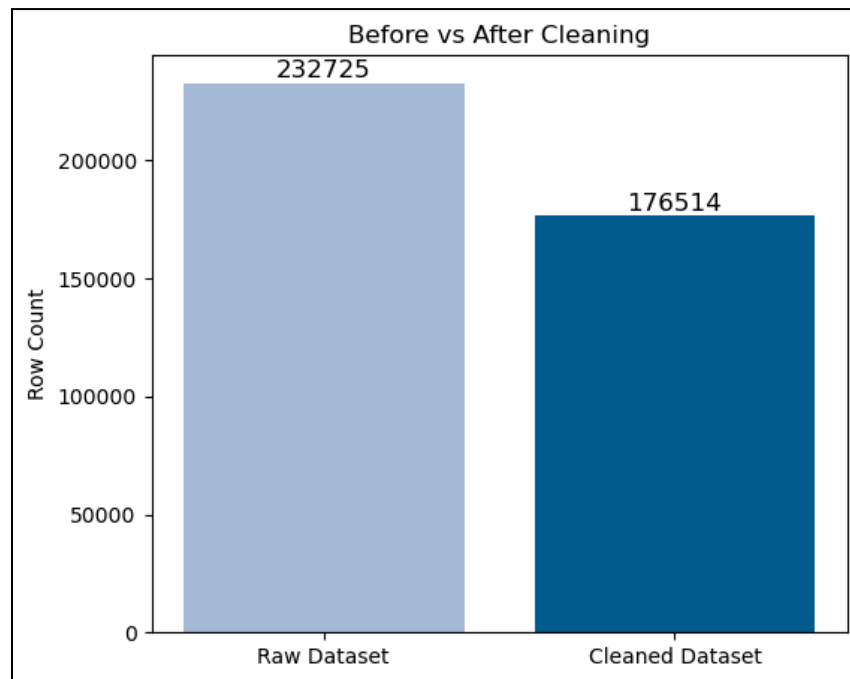

Audio Feature Definitions:

The analysis focuses on a subset of Spotify audio features that capture emotional tone, rhythmic structure, and perceived intensity in music. These features are selected due to their interpretability and relevance for exploratory visual analysis across a large and diverse collection of tracks.

Valence represents the emotional positivity of a track, with higher values corresponding to music that is perceived as happier or more uplifting. Danceability measures how suitable a track is for dancing and is computed based on a combination of tempo, rhythm stability, and beat strength. Energy reflects the perceived intensity and activity of a song and is commonly associated with dynamic range and overall loudness.

Loudness represents the overall perceived volume of a track and is measured in decibels, providing insight into production style and intensity. Tempo estimates the speed of a track in beats per minute and captures rhythmic pacing across musical styles. Popularity is a Spotify-defined metric that reflects relative listener engagement and is influenced by a range of external factors such as exposure, marketing, and cultural trends, in addition to acoustic properties.

Figure 3 presents the distributions of these key numeric features across the cleaned dataset. The figure shows that while many audio features are normalized and constrained within fixed ranges, their distributions vary widely, indicating substantial diversity in musical characteristics. These baseline distributions provide important context for subsequent visual analyses and motivate the use of continuous visual encodings and interactive filtering in the dashboard.
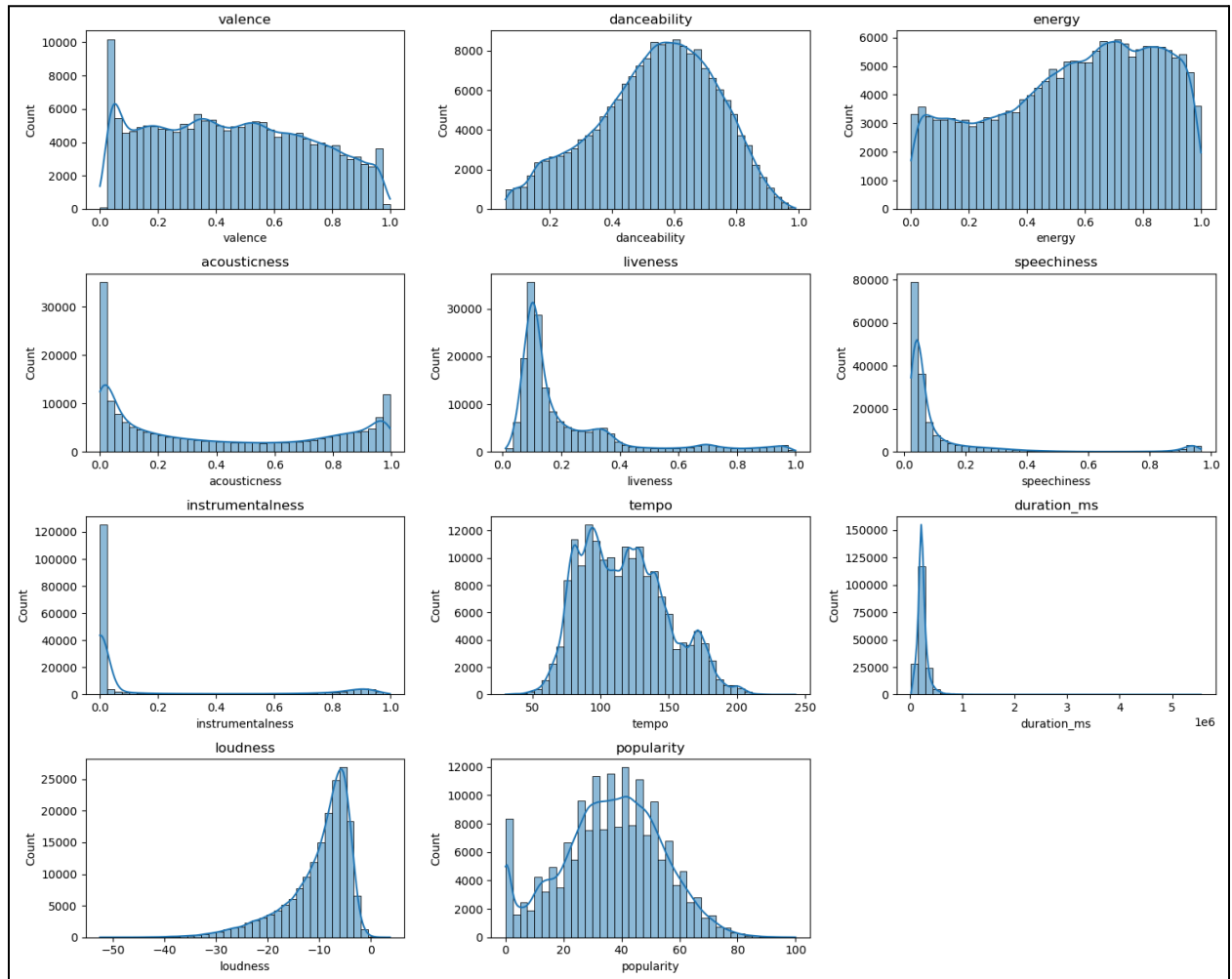
Genre and Popularity Attributes:

In addition to numeric audio features, the dataset includes categorical genre labels and a popularity metric that provide important contextual information for analysis. Genres serve as high-level groupings that allow tracks to be compared based on shared stylistic characteristics. Although genre labels are inherently broad and may overlap in practice, they provide a useful framework for identifying aggregate trends and differences in audio feature distributions across musical styles.

From Figure 1, it is known that popularity is included as a contextual attribute rather than a direct measure of musical quality. The popularity score is computed by Spotify and reflects relative listener engagement, but it is influenced by many non-acoustic factors such as marketing, playlist placement, and cultural trends. As a result, popularity is analyzed alongside audio features to assess whether consistent acoustic patterns are associated with higher levels of engagement.

Figure 5 compares popularity distributions across genres using boxplots. The substantial overlap observed across genres suggests that popularity cannot be fully explained by genre membership or audio characteristics alone, motivating deeper multivariate exploration through interactive visual analysis.
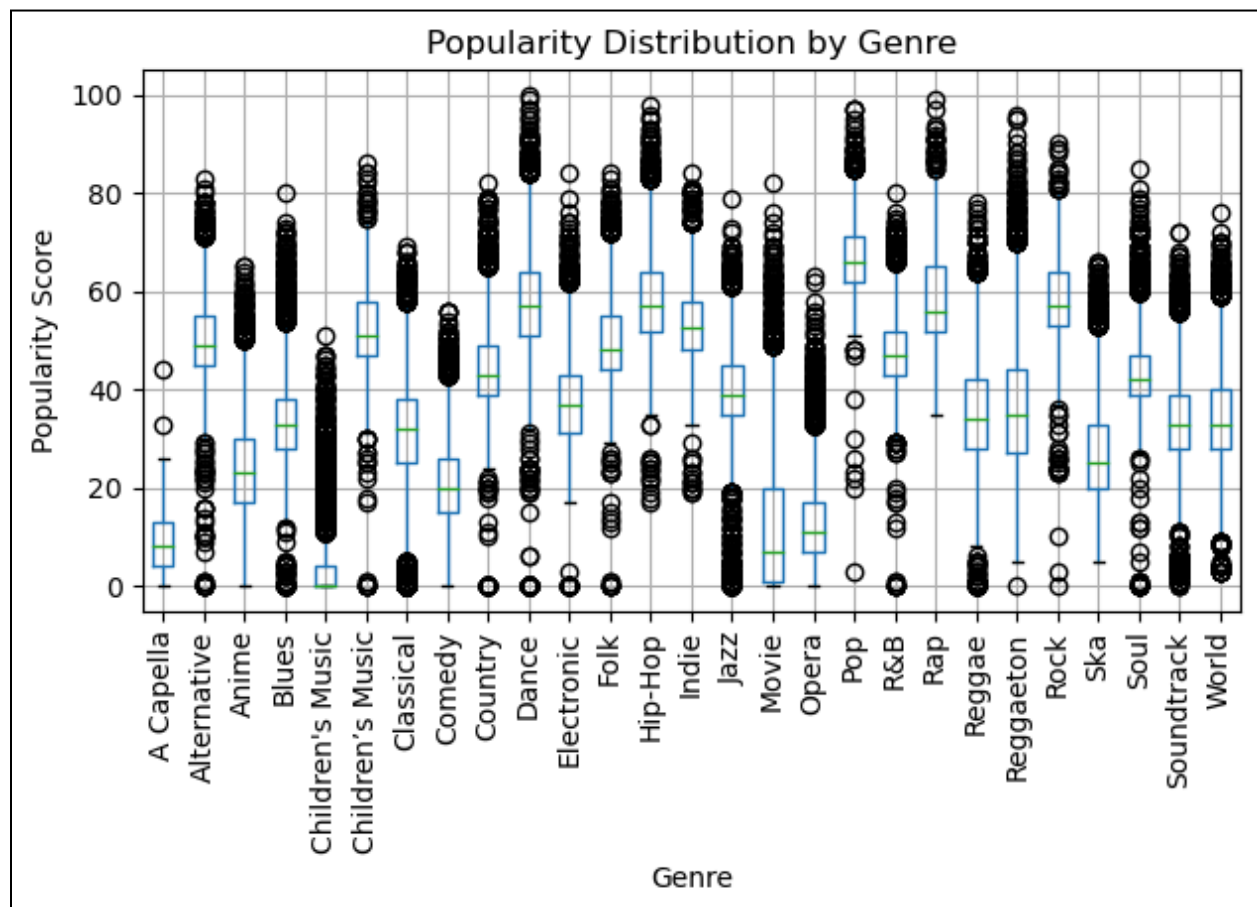
Summary of Dataset Characteristics:

The cleaned dataset combines large-scale coverage with a rich set of standardized audio features, making it well suited for exploratory visualization. The inclusion of both numeric and categorical attributes enables analysis across emotional tone, musical structure, genre, and listener engagement. Baseline distributions of audio features reveal substantial variability across tracks, while genre and popularity attributes provide contextual dimensions that support comparison and interpretation.

Together, these characteristics form a strong foundation for the interactive visual analytics dashboard described in subsequent sections. The dataset structure and feature composition directly inform the visualization design choices, which are discussed in the following section.

Visualization Design and Rationale

The design of the Spotify Music Explorer dashboard emphasizes interactive exploration, coordinated views, and clear visual encodings to support analysis of large-scale music data. Rather than presenting static summaries, the dashboard enables users to dynamically investigate relationships among audio features, genres, and individual tracks. Each visualization was selected to support a specific analytical task, such as identifying global trends, comparing genres, or inspecting individual songs in detail.

The dashboard is implemented using Dash and Plotly, allowing visual components to update interactively in response to user input. Dropdown controls are used extensively to enable feature selection, genre filtering, and track-level inspection, ensuring that users can flexibly explore the dataset without overwhelming the interface.

Feature–Valence Relationship Exploration:

A central goal of the dashboard is to examine how emotional tone, represented by valence, relates to other musical attributes. To support this, the primary visualization in the dashboard is an interactive scatter plot that displays valence on the horizontal axis and a user-selected audio feature on the vertical axis.

Figure 6 shows this scatter plot, which updates dynamically based on the selected feature and optional genre filter. This design allows users to observe overall trends across the full dataset or focus on specific genres. Scatter plots are well suited for this task because they reveal both correlation structure and data density, making it possible to identify patterns, clusters, and outliers.

Dropdown controls allow users to switch between features such as danceability, energy, tempo, and loudness, enabling rapid comparison without changing the visual layout. This consistency reduces cognitive load and encourages exploratory analysis by allowing users to focus on changes in the data rather than changes in the interface.
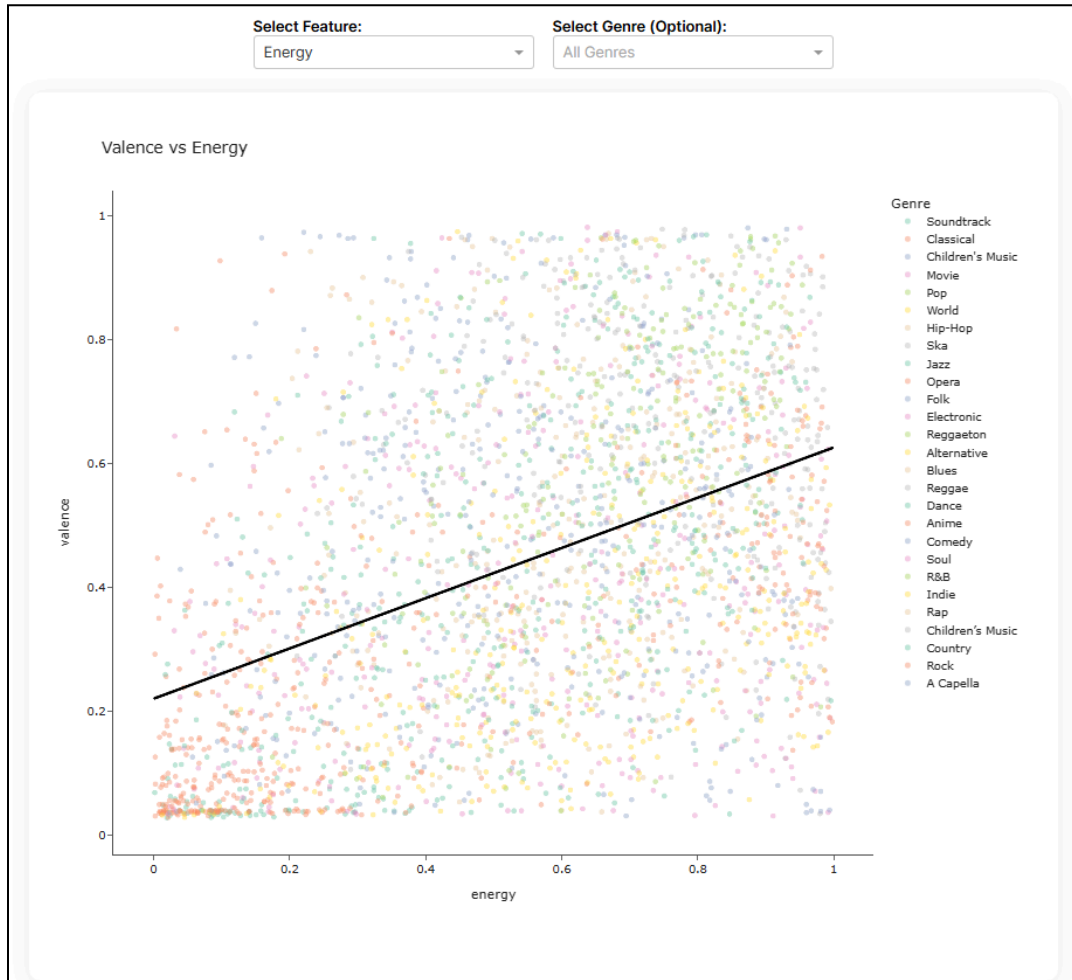
Feature Distribution Analysis:

To complement the relational scatter plot, the dashboard includes a histogram that displays the distribution of the currently selected audio feature. Figure 7 presents this histogram, which updates in coordination with the feature and genre selections applied to the scatter plot.

This design supports comparison between global distributions and genre-specific subsets, allowing users to assess whether observed trends are driven by shifts in feature distributions or by localized patterns. Histograms are appropriate for this task because they clearly convey skewness, spread, and concentration within continuous variables.
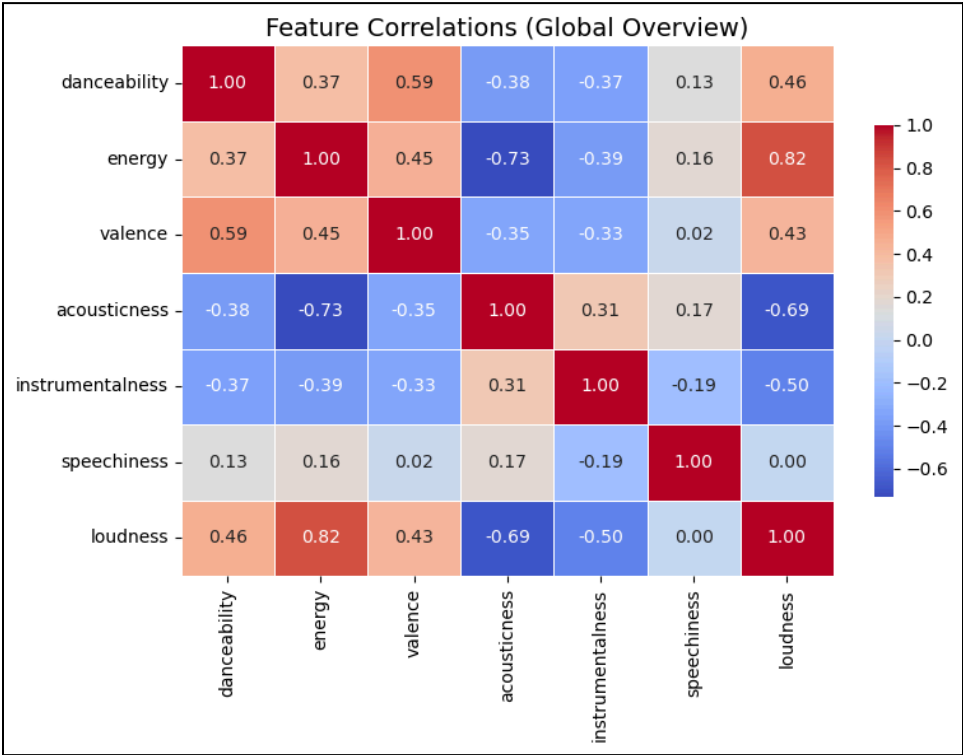
By placing the histogram directly below the scatter plot, the dashboard encourages users to interpret relational patterns in the context of underlying distributions, reinforcing a multiview analytical workflow.
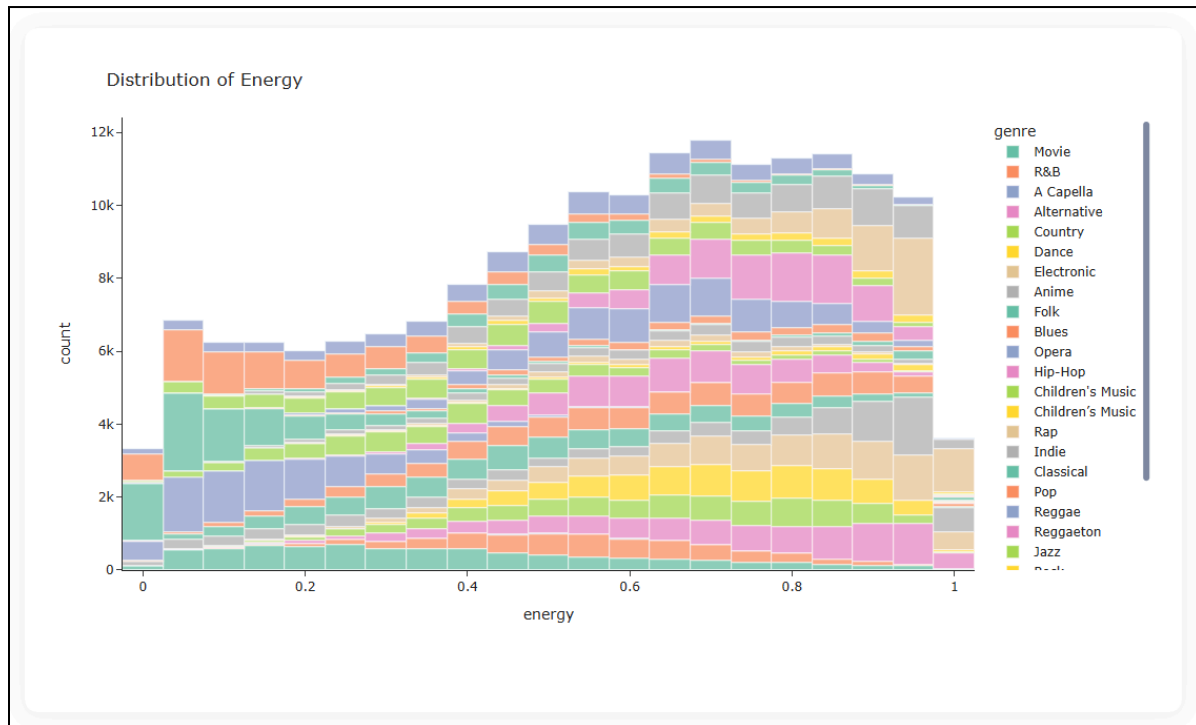
Genre Comparison Through Aggregated Views:

To support direct comparison between musical styles, the dashboard provides tools for selecting and comparing two genres simultaneously. Users can choose two genres of interest, and the system computes aggregated feature values for each genre. Figure 8 displays a genre comparison heatmap that encodes average audio feature values using color intensity. This visualization allows users to quickly identify similarities and differences across multiple features at once. Heatmaps are particularly effective for comparing multivariate summaries, as they support rapid visual scanning and pattern recognition. This design choice enables high-level

comparison while avoiding the clutter that would result from overlaying multiple distributions or scatter plots.

Figure: Feature Correlations (Global Overview)

|	danceability	energy	valence	acousticness	instrumentalness	speechiness	loudness
danceability	1.00	0.37	0.59	-0.38	-0.37	0.13	0.46
energy	0.37	1.00	0.45	-0.73	-0.39	0.16	0.82
valence	0.59	0.45	1.00	-0.35	-0.33	0.02	0.43
acousticness	-0.38	-0.73	-0.35	1.00	0.31	0.17	-0.69
instrumentalness	-0.37	-0.39	-0.33	0.31	1.00	-0.19	-0.50
speechiness	0.13	0.16	0.02	0.17	-0.19	1.00	0.00
loudness	0.46	0.82	0.43	-0.69	-0.50	0.00	1.00

Genre Feature Profiling with Radar Charts:

While the heatmap supports pairwise genre comparison, the dashboard also provides a radar chart to visualize the overall feature profile of a single genre. Figure 9 presents this radar chart, which displays normalized average values for selected audio features.

Radar charts are useful for summarizing multidimensional profiles and highlighting the relative strengths and weaknesses of a genre across multiple attributes. In this context, the radar chart allows users to visually assess whether a genre tends to be more energetic, acoustic, danceable, or instrumental. The inclusion of a genre selection dropdown allows users to compare

mental models across genres by switching between profiles while maintaining a consistent visual structure.
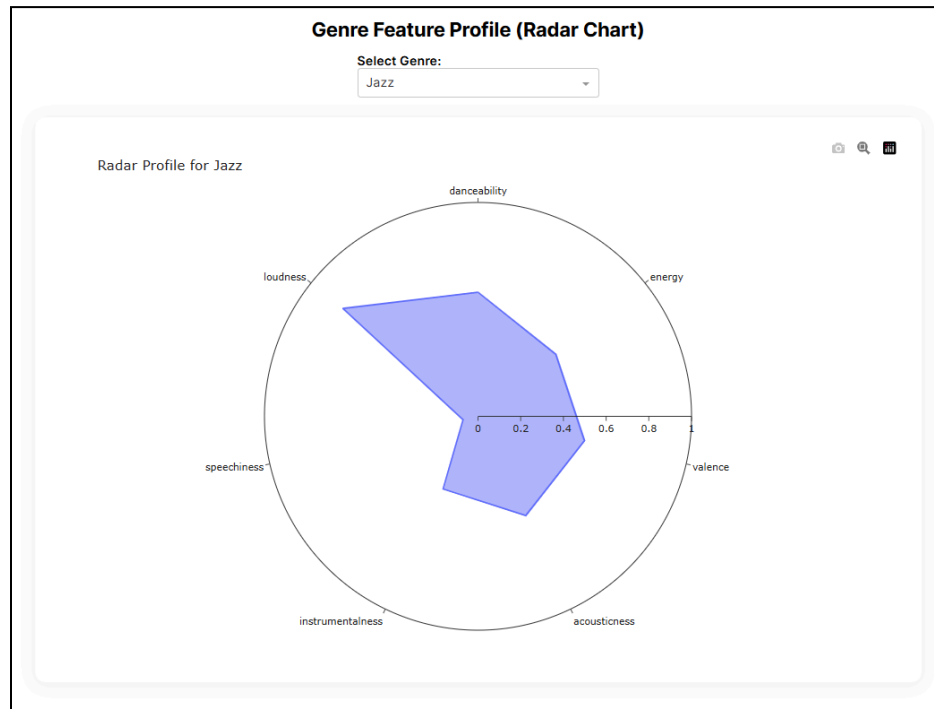
Correlation Analysis Across Audio Features:

To examine relationships among audio features more systematically, the dashboard includes an interactive correlation heatmap. Figure 10 displays pairwise correlations between numeric audio features, with optional genre-based filtering. Correlation heatmaps are effective for summarizing linear relationships across many variables simultaneously. This visualization allows users to identify strong positive or negative associations, such as the relationship between energy and loudness, while also observing how these relationships may vary across genres. Providing an optional genre filter enables users to compare global correlation patterns with genre-specific structures, supporting deeper exploratory analysis.

Correlation Heatmap

Select Genre (Optional):
Anime

Correlation Heatmap — Anime
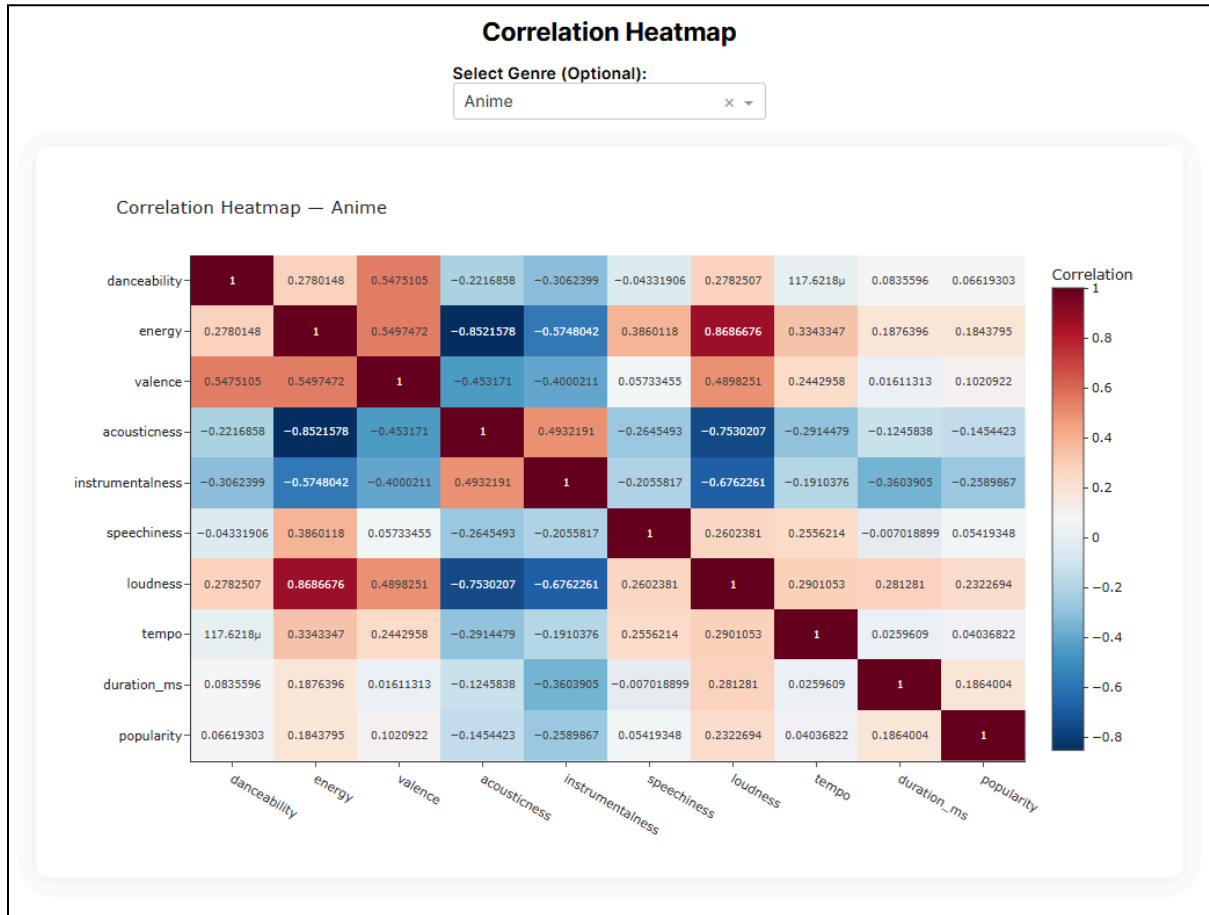
Track-Level Exploration and Details on Demand:

In addition to aggregate analysis, the dashboard supports inspection of individual tracks through a searchable dropdown. Once a track is selected, the dashboard displays a feature profile visualization summarizing its audio attributes. Figure 11 presents this track-level feature profile, which enables users to contextualize individual songs within the broader dataset. This view supports details-on-demand interaction, allowing users to move seamlessly from global patterns to specific examples. This design reinforces the exploratory nature of the dashboard and ensures that users can connect abstract trends with concrete musical instances.

Track Search & Feature Profile

Search Track:

La foule

Feature Profile — La foule
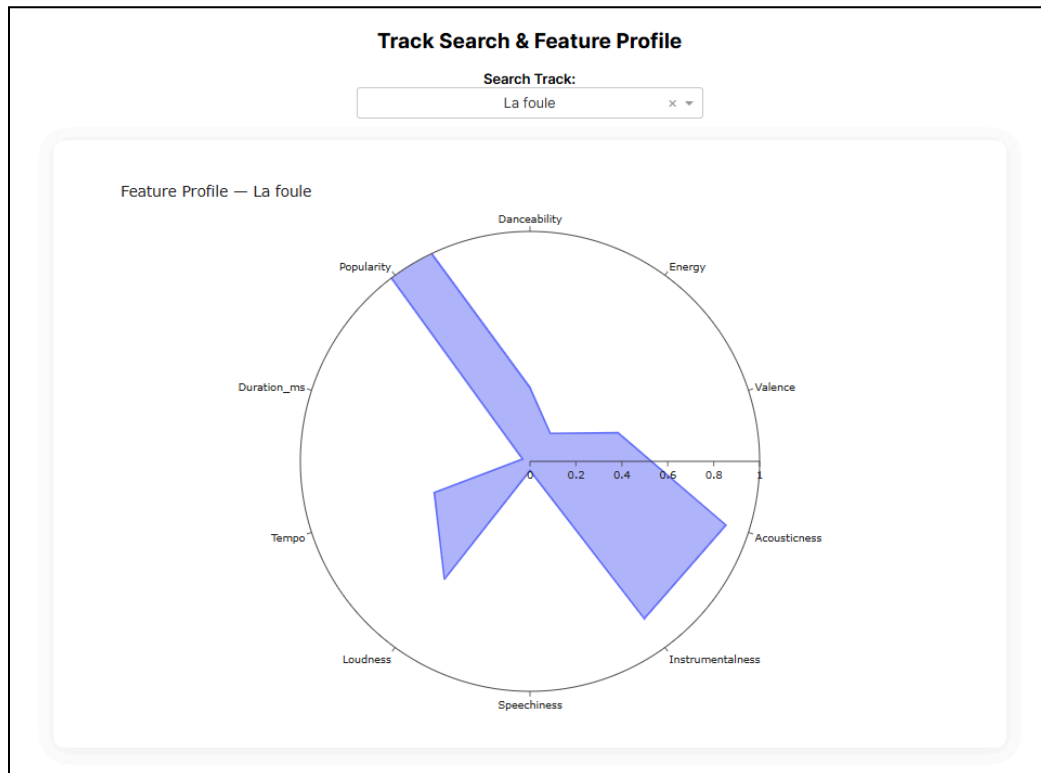
Design Summary:

The visualization design of Spotify Music Explorer is guided by principles of consistency, interactivity, and task-oriented analysis. Scatter plots and histograms support exploration of continuous feature relationships, while heatmaps and radar charts enable efficient comparison across genres. Dropdown-based interaction ensures flexibility while maintaining a clean and accessible interface.

Together, these visual components form a cohesive system that supports both high-level trend analysis and detailed inspection, preparing the foundation for the results and observations discussed in the following section.

Exploratory Analysis and Findings

Global Trends in Spotify Audio Features:

The exploratory analysis begins by examining global trends across all tracks in the cleaned dataset. Visualizing feature distributions and relationships at this level provides a foundation for understanding how musical attributes are structured across the broader Spotify catalog. As shown previously in Figure 4, most audio features exhibit non-uniform distributions, reflecting the diversity of musical styles and production choices represented in the data.

Valence and danceability are both concentrated around mid-range values, suggesting that extremely positive or negative emotional tones and highly dance-oriented tracks are less common. Energy and loudness display a wider spread, indicating substantial variation in intensity and production style across songs. In contrast, popularity remains heavily right-skewed, with a small subset of tracks achieving high engagement. This imbalance reinforces the idea that popularity is not evenly distributed and cannot be easily inferred from acoustic features alone.

To further contextualize these observations, the correlation heatmap shown in Figure 5 highlights several consistent relationships across the dataset. Valence is moderately correlated with danceability and energy, suggesting that emotionally positive music tends to be more rhythmic and energetic. Energy and loudness also exhibit a strong positive relationship, reflecting well-established production characteristics. However, popularity shows weak correlations with all other features, underscoring the limited explanatory power of audio attributes alone.

Valence and Its Relationship to Key Audio Features:

Given its role as a proxy for emotional tone, valence serves as a focal point for more detailed analysis. Scatterplots comparing valence with other key features allow for a more granular examination of how emotional positivity interacts with musical structure. Figure 6 presents scatterplots of valence versus danceability and valence versus energy across all tracks.

These visualizations reveal clear positive trends in both cases. Tracks with higher valence values are more likely to exhibit higher danceability, indicating that happier music often aligns with rhythmic stability and groove. A similar, though slightly more dispersed, relationship is observed between valence and energy, suggesting that emotional positivity is frequently associated with higher perceived intensity but allows for greater stylistic variation.

Despite these trends, the scatterplots also show substantial spread, particularly at mid-range valence levels. This dispersion highlights the expressive flexibility of music, where songs with similar emotional tone can differ significantly in rhythmic and energetic characteristics. These findings reinforce the value of interactive filtering, which allows users to isolate specific genres or valence ranges to examine more targeted patterns.

Danceability vs Valence by Genre
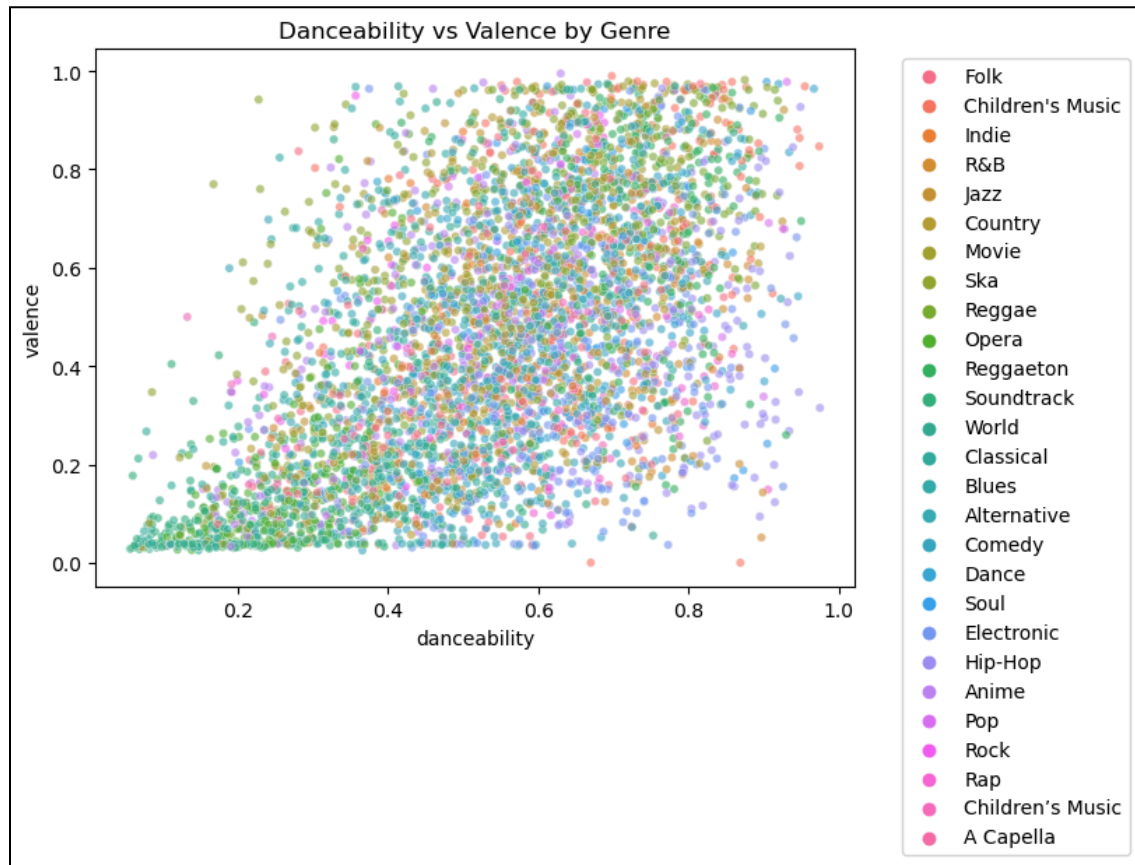
Genre-Level Differences in Emotional Tone:

While global trends provide useful context, many musical patterns become clearer when examined at the genre level. To explore how emotional tone varies across musical styles, the dashboard includes aggregated and distribution-based genre visualizations. Figure 7 shows the average valence by genre, offering a high-level comparison of emotional characteristics across the 26 genres in the dataset.

This visualization reveals clear genre-specific differences. Genres such as pop and dance tend to exhibit higher average valence, reflecting their emphasis on upbeat and accessible musical structures. In contrast, genres such as metal and blues show lower average valence,

aligning with darker or more introspective emotional themes. These aggregate trends provide an entry point for deeper genre-based exploration.

However, average values alone can obscure within-genre variability. To address this limitation, Figure 8 presents boxplots of valence distribution by genre. These plots show that even within genres with lower average valence, there is considerable emotional range. This observation highlights the importance of examining distributions rather than relying solely on summary statistics.
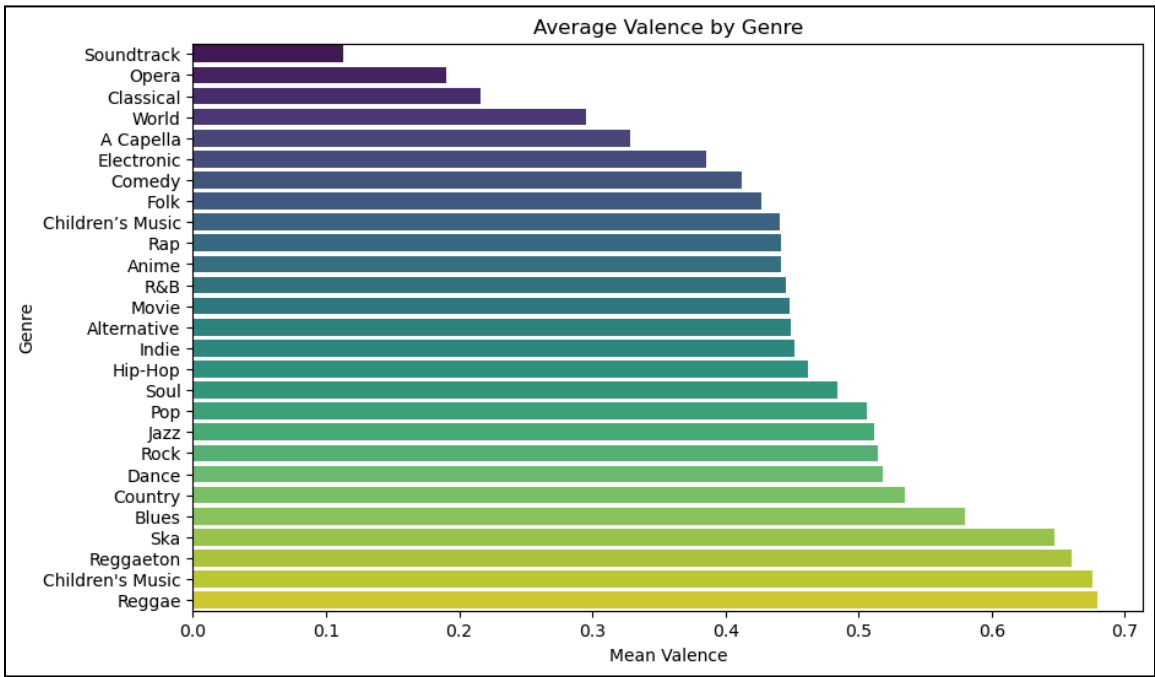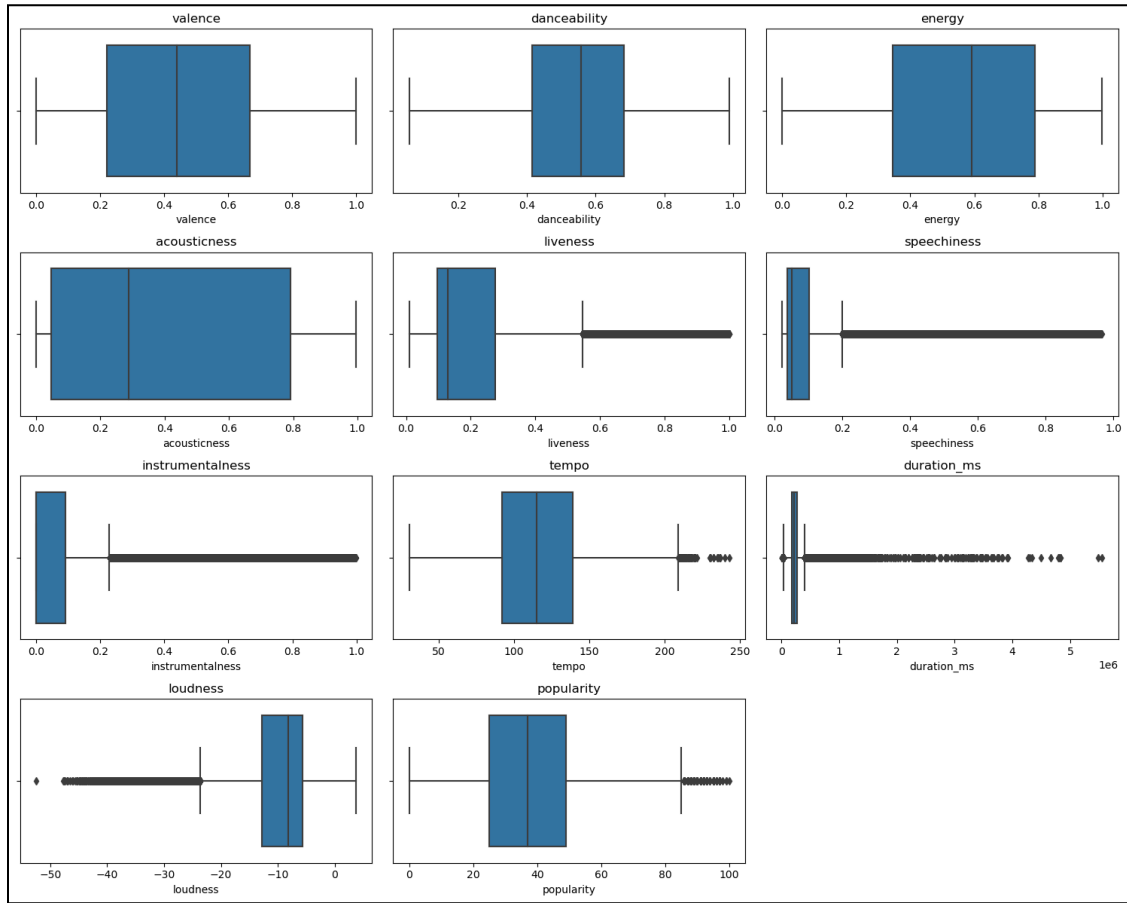
Multivariate Genre Comparisons:

To examine how emotional tone interacts with multiple audio features at the genre level, the dashboard supports a boxplot-based visualization that shows distributions of selected features across genres. Figure 9 presents faceted boxplots for valence, danceability, and energy grouped by genre. This design allows for simultaneous comparison of central tendencies and variability for multiple features while highlighting within-genre diversity.

The boxplots reveal that upbeat genres such as pop and dance tend to have higher median valence and danceability, while metal and blues show lower valence but a wider spread in energy. This visualization makes the internal structure of each genre clear and highlights

differences that are less obvious in single-feature analyses. Furthermore, it emphasizes that even

within genres, there is substantial variability, underscoring the importance of distributional

analysis rather than relying solely on averages. By organizing features into a faceted layout,

users can rapidly compare multiple attributes across all genres, supporting both exploratory

analysis and detailed pattern recognition.
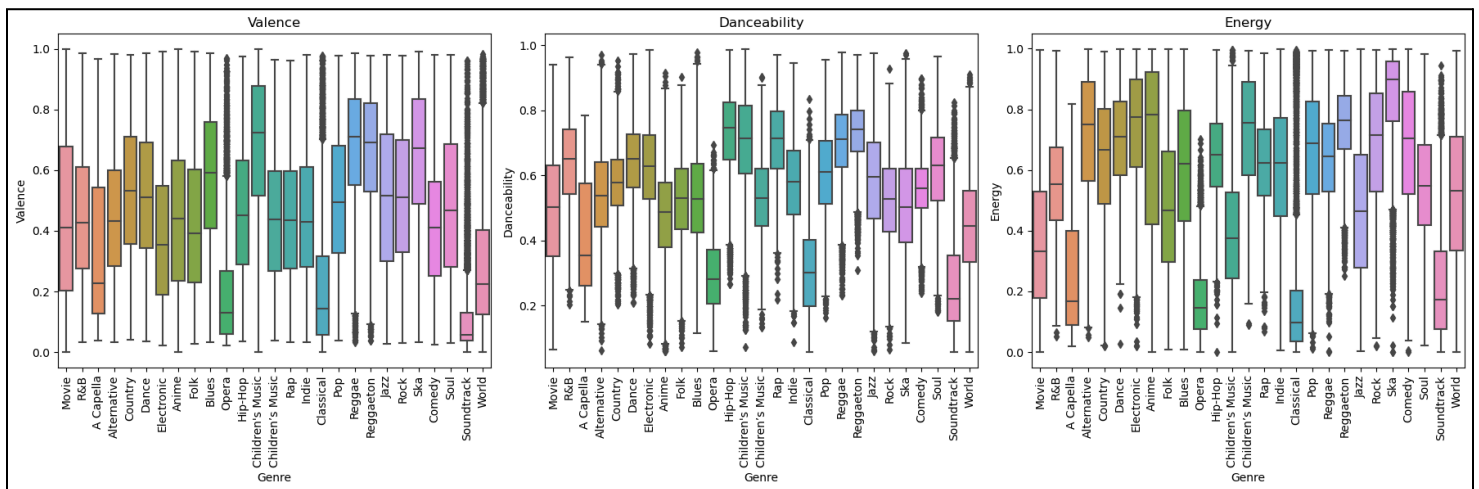
Popularity and Its Limited Relationship to Audio Features:

A recurring observation throughout the analysis is the weak relationship between

popularity and audio features. Scatterplots and correlations consistently show that popularity

does not strongly align with valence, danceability, or energy. This pattern suggests that factors

such as marketing, artist visibility, cultural trends, and platform-driven recommendations play a

significant role in shaping listener engagement.

This finding is particularly important in the context of music recommendation and

discovery systems. While audio features provide valuable signals for similarity and mood-based

exploration, they are insufficient on their own to explain why certain songs become popular. The

dashboard makes this limitation visually apparent, encouraging users to consider external factors beyond the dataset.

Interaction Techniques and User Scenarios

The Spotify Music Explorer dashboard is designed to support exploratory analysis through a range of interactive features. Interactivity allows users to navigate the high-dimensional dataset, focus on patterns of interest, and connect global trends with individual track characteristics. These capabilities reinforce the dashboard's role as an exploratory tool rather than a static reporting interface.

Feature and Genre Selection:

Dropdown menus enable users to select audio features and optionally filter by genre. This dynamic filtering supports side-by-side comparison of different musical attributes, allowing users to examine relationships such as valence versus danceability, or energy versus loudness. By selecting specific genres, users can isolate stylistic trends and explore within-genre variability, as illustrated in the faceted boxplots (Figure 9). The ability to switch features and genres interactively facilitates hypothesis-free exploration and encourages iterative investigation of patterns.

Comparative Genre Analysis:

The dashboard includes tools for comparing two genres across multiple audio features. Users can select genres using dedicated dropdowns, and the system generates visual summaries of feature differences. These comparisons are particularly useful for identifying contrasts in emotional tone, energy, and rhythmic structure. For example, users may compare pop and metal

to observe differences in valence and energy distributions, providing insight into genre-specific musical characteristics.

Track-Level Inspection:

To support detailed, instance-level exploration, the dashboard offers a searchable track selector. Once a track is chosen, the dashboard presents a feature profile plot that summarizes its audio attributes (Figure 11). This "details-on-demand" capability allows users to contextualize individual songs within broader patterns, connecting macro-level trends to specific musical examples. For instance, users can investigate whether a particularly popular track aligns with the genre's typical valence and energy profiles.

Coordinated Views and Multiview Interaction:

The dashboard employs coordinated views, in which interactions in one visualization update related visualizations across the interface. For example, selecting a specific genre or feature updates scatterplots, histograms, and track-level profiles simultaneously. This design supports consistent mental models and reinforces connections between global and local perspectives. Users can iteratively refine filters and feature selections to uncover nuanced patterns in both genre-level and track-level data.

User Scenarios:

The dashboard supports a variety of practical use cases that illustrate its value for exploratory analysis. For example, a user interested in comparing musical characteristics between pop and rock can quickly observe that pop tracks generally exhibit higher valence and danceability, whereas rock tracks display more moderate valence and energy. The faceted boxplots and

scatterplots provide both distributional insights and summary-level information, allowing users to identify contrasts across multiple audio features simultaneously.

In another scenario, a user may wish to investigate a specific track to determine whether it aligns with typical patterns within its genre or exhibits unique characteristics. By selecting the track from the search menu, the dashboard presents a detailed feature profile (Figure 11), making it possible to contextualize individual songs within broader genre-level patterns. This functionality is particularly useful for tasks such as playlist curation, music recommendation research, or understanding trends in listener engagement.

Finally, the dashboard supports exploration of global trends across the Spotify catalog. Users can examine the relationships between valence and other features, such as danceability or energy, using scatterplots and histograms. By applying genre filters, these trends can be compared with genre-specific deviations, providing insights into both general patterns and stylistic distinctions. This combination of macro- and micro-level analysis highlights the dashboard's ability to support flexible, hypothesis-free exploration of large music datasets.

Limitations and Future Work

While the Spotify Music Explorer provides valuable insights into music characteristics, several limitations should be acknowledged. First, the analysis relies exclusively on the audio features provided by Spotify, which, while standardized and widely used, do not capture all aspects of musical perception. Features such as lyrical content, cultural context, and temporal trends in listener behavior are absent, limiting the scope of conclusions regarding song popularity or emotional impact.

Second, the dashboard is based on a static dataset covering approximately 176,514 tracks. As Spotify's catalog evolves rapidly, newly released songs and emerging genres may exhibit different patterns, which are not reflected in the current analysis. Incorporating real-time data updates could improve the relevance of insights and support longitudinal studies of musical trends.

Finally, while the dashboard supports interactive exploration, certain visualizations may become cluttered when comparing a large number of genres or features simultaneously. Future work could include more advanced aggregation techniques, dimensionality reduction, or clustering to summarize patterns more effectively. Additionally, predictive modeling could be integrated to assess the contribution of audio features to song popularity, complementing the descriptive visual analytics presented here.

Conclusion

The Spotify Music Explorer demonstrates the potential of interactive visualization for understanding large-scale music datasets. By integrating multiple audio features, genre information, and track-level details into a cohesive dashboard, users are able to explore global trends, compare genres, and investigate individual songs in a flexible, intuitive manner. Analysis of valence, danceability, energy, and other features reveals both expected patterns and surprising variability, highlighting the complexity of musical expression across genres.

The project emphasizes the importance of combining multivariate visualizations with interactivity to support hypothesis-free exploration and targeted analysis. While limitations exist, such as the absence of lyrical and contextual data, the dashboard provides a solid foundation for future extensions, including predictive modeling, real-time data integration, and enhanced

multivariate comparisons. Ultimately, this work illustrates how data-driven visualization can enhance understanding of music characteristics and inform applications ranging from music recommendation to cultural analysis.

References

Kaggle: [Spotify Tracks DB](#)

Repository: https://github.com/saanavig/Spotify-Visualization