Sapienza University of Rome

Engineering in Computer Science

SpotyVis

Visual Analytics Final Project

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Introduction

The music industry has undergone a radical transformation over the last few decades, shifting from physical media to digital streaming. Today, platforms like Spotify host libraries containing millions of tracks, each rich with metadata and complex ”audio features” that quantify abstract concepts like danceability, energy and acousticness.

Our project, **SpotyVis**, aims to solve this shortcoming by providing an interactive visual analytics tool designed to explore a curated dataset of over 2,500 tracks. Unlike standard music players, our tool exposes the hidden ”audio DNA” of the music library.

The final tool is a coordinated multiple-view system where a Bubble Plot, Box Plot, Parallel Coordinates Plot and t-SNE projection work together. This allows the user to drill down from high-level genre trends to individual track characteristics, highlighting patterns, outliers and sonic clusters that would be impossible to detect in a spreadsheet or playlist.

SpotyVis is directed at music enthusiasts, data analysts and industry researchers, and is designed to support three main activities:

- To discover new music based on specific sonic profiles.
- To find songs similar to the ones you like.
- To explore the current state and history of music production.

Related Works

Before the development of the project, to have an idea of what we could do, we analyzed the literature, studying papers with topics similar to ours. We were particularly interested in studies regarding music information retrieval (MIR) and visual analytics applied to audio datasets. We found several interesting studies published over the years, discussed in the following paragraphs.

In Decoding Spotify Hits: Statistical and Predictive Analysis of Track Features Driving Song Popularity (2025) [1], the authors base their work on a dataset of Spotify tracks, the same starting point as our project. The paper is a study about the correlation between specific audio features and a song’s popularity. The conclusion of this study is that popular songs often share specific characteristics, such as higher energy and loudness, while other features like speechiness might have a negative correlation with mass popularity.

Another interesting aspect we wanted to capture was the evolution of music over time. We eventually found Exploring Music Rankings with Interactive Visualization (2017) [2]. This paper focuses on the concept of ranking dynamics and uses it as a starting point to analyze what distinguishes top-performing tracks in charts. Our project integrates the notions presented by [2] and expands them, creating a bumb chart that allows the user to see the average trend of a certain genre over time.

To make the most of our interface, we researched technical papers on dashboard design. Eventually, we found Dashboard Design: Interactive and Visual Exploration of Spotify Songs (2024) [3]. This paper addresses the challenge of exploring correlations and dependencies in Spotify's audio attributes. Following the example of [3], we have implemented a dashboard that allows the user to perform accurate searches on the reference data.

Dataset

The main dataset used for the project is the Spotify Tracks Dataset, it contains contains $89,741$ songs, each associated with specific genres and various audio attributes. To ensure relevance, we do not utilize the entire corpus; rather, we filter these tracks against a secondary dataset.

The second datased used is the The Hot 100 Songs, it represents the music industry standard record chart in the United States, published weekly by Billboard magazine. This dataset allow us to filter to only the most famous song (no irrelevant data) and to graph the people's musical tastes.

To further enrich our data, we performed webscraping on the WhoSampled database. This process allowed us to integrate the year of publication and quantitative metadata regarding samples, covers and remixes. This added layer provides a deeper understanding of a song's cultural influence and historical context.

The resulting master dataset consists of $2,624$ unique observations across the following 19 attributes:
track_id, artists, track_name, popularity, duration_ms, danceability, energy, speechi-

ness, acousticness, instrumentalness, loudness, liveness, valence, track_genre, year, Sampled_by, Is_Sample, Covered_By, Is_Cover, Remixed_By, Is_Remix.

Notice that, the **Spotify Tracks Dataset** contains features with heterogeneous domains, while 'Valence' and 'Energy' naturally range from 0 to 1, other feature (e.g. 'Loudness') operate on vastly different scales. To visualize these dimensions effectively within the Parallel Coordinates Plot and other charts, it was necessary to normalize all numerical features to a common 0–100 scale.

In addition to this master file, we maintain a longitudinal dataset of 46000 rows from the Billboard Hot 100 (filtered for Spotify compatibility). This secondary structure enables the creation of temporal evolution charts, specifically focusing on genre-ranking shifts over time. This dual-dataset approach provides a robust framework for evaluating the evolution of musical tastes and industry trends across several decades.

Dimensionality reduction

The **dimensionality reduction** approach used in our project involves a preprocessing phase where we reduce the high-dimensional space of audio attributes into a 2-dimensional plane, followed by a clustering algorithm to identify distinct musical groups.

The results of this process, X and Y coordinates and a cluster label, are integrated into the main dataset and used to plot each song as a point in the scatterplot.The reason why this procedure is not performed at runtime is that t-SNE (t-Distributed Stochastic Neighbor Embedding) is a computationally intensive algorithm. Running it on a dataset of over 2,500 tracks takes significant time and resources, making it unsuitable for real-time interaction in a web browser.

The attributes used for the reduction are the following numerical audio features provided by the Spotify API: danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence.

Clustering Approach

To further aid the user in identifying patterns, we applied a clustering algorithm on the resulting projection. We used K-Means clustering (sklearn.cluster.KMeans) with $k = 8$ clusters. This algorithm groups tracks that are spatially close in the t-SNE projection, effectively assigning a "musical identity" to each region of the plot.

The final output consists of three new columns added to the main dataset:

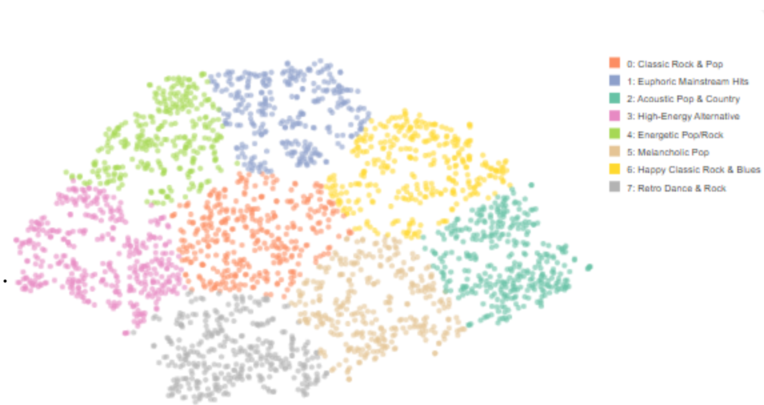
- tsne_x: the X coordinate for the visualization.
- tsne_y: the Y coordinate for the visualization.
- cluster_label: an integer from 0 to 7 representing the song's cluster.

In the final visualization, these coordinates determine the position of the points, while the cluster_label is used to assign a distinct color from the d3.schemeSet2 palette, allowing users to visually distinguish between different musical sub-genres instantly.

Visualizations & Interactions

The Scatterplot (t-SNE)

In the **scatterplot**, we visualize the results of the **t-SNE dimensionality reduction** algorithm. Using D3.js functions such as `d3.circle`, we plotted every track from the dataset as a circle, with its cx and cy attributes derived from the precomputed `tsne_x` and `tsne_y` columns.

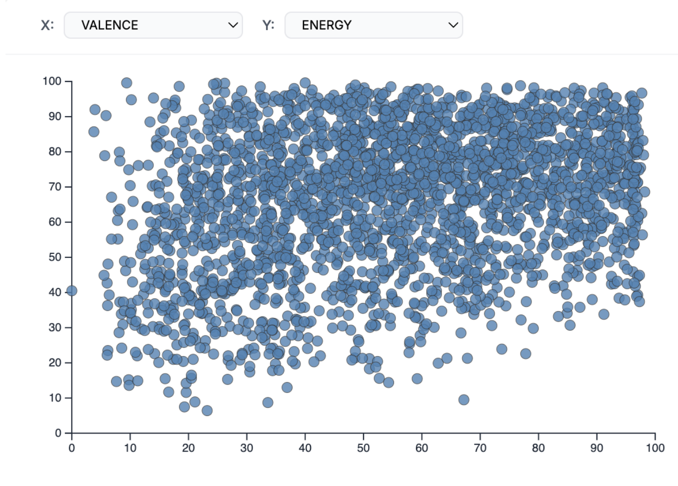


In this visualization, proximity implies similarity: the closer two songs are, the more they share similar sonic characteristics. To make the structure of the data immediately legible, we encoded the circles' colors based on the K-Means cluster labels (0–7) generated during the preprocessing phase.

Bubbleplot

The **Bubbleplot** serves as the central analytical tool within the **SpotyVis** dashboard, offering a versatile environment for exploring relationships between musical features.

This visualization plots songs as individual circles on a 2D plane, where the X and Y axes are fully customizable by the user. Through interactive dropdown menus, users can map any two audio features to these axes, allowing for the immediate identification of correlations or clusters within the dataset.

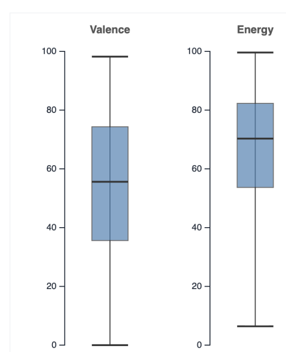


A key capability of this chart is its **Group By** functionality, which aggregates individual song data into broader categories. When a grouping is active, the bubbles resize dynamically to represent the count of songs within each group, and their positions shift to reflect the average feature values of that cluster.

Boxplot

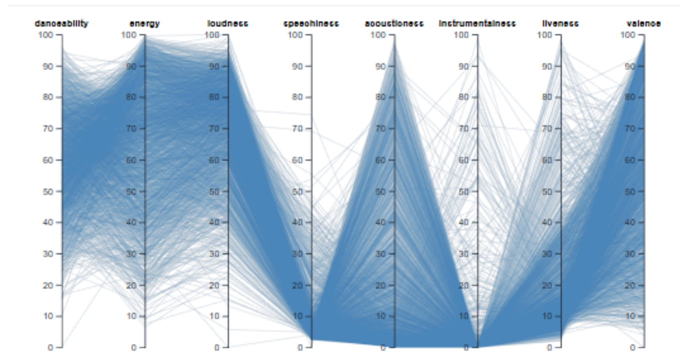
The **Box Plot** component complements the Bubble Plot by providing a statistical summary of the selected X and Y audio features across the entire current dataset.

Positioned alongside the main scatter view, this visualization displays two distinct box-and-whisker diagrams—one for the X-axis attribute and one for the Y-axis attribute.



This immediate statistical breakdown allows users to quickly assess the spread, central tendency, and skewness of the chosen features without needing to interpret the density of hundreds of individual data points.

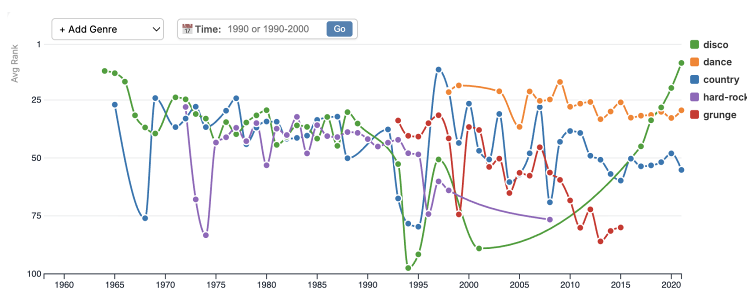
The Parallel Coordinates



To represent the high-dimensional nature of our audio data, we implemented a **Parallel Coordinates** visualization. This chart displays 8 continuous audio features from the Spotify API: danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, and valence.

Each song is represented as a polyline that traverses these 8 vertical axes at heights corresponding to its specific values. To ensure readability and fair comparison between attributes with different scales, all axes were normalized to a fixed 0–100 scale. This allows the user to easily spot patterns, such as the inverse relationship often found between energy and acousticness.

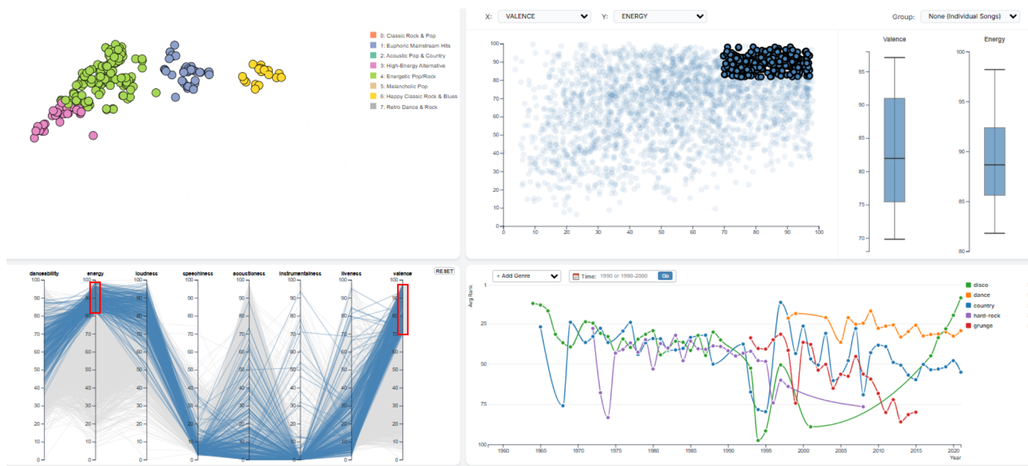
Bump Chart



The **Ranking Plot** offers a longitudinal perspective on the music industry, utilizing a Bump Chart technique to visualize the fluctuating popularity of different musical genres over decades.
Users can actively curate their analysis by dynamically selecting specific genres to add or remove from the comparison, allowing them to isolate specific narratives. The component is highly interactive, featuring temporal controls that allow users to define specific year ranges in which to view the trend.

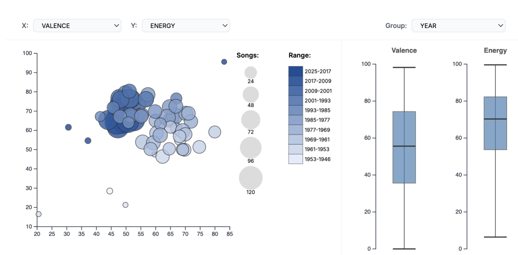
Interactions and Coordination

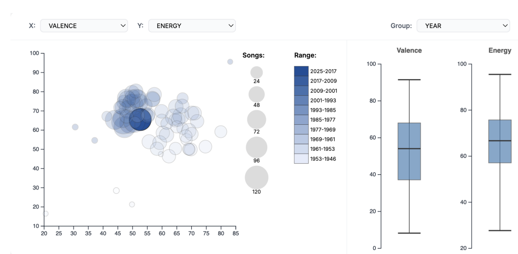
The **user interactions** within the **SpotyVis** dashboard are not limited to the individual components described previously. Instead, the system relies on a "Coordinated Multiple Views" (CMV) architecture, where an action in one chart propagates immediately to others, creating a unified and responsive exploration experience.
The following interactions trigger multi-view updates:



- **Brushing the Parallel Coordinates**: when a user applies a brush filter to one or more axes in the Parallel Coordinates plot (e.g. selecting tracks with high energy and high valence), the system identifies the subset of tracks matching these criteria. This selection triggers three simultaneous updates:
  - t-SNE Scatterplot: the matching songs are highlighted , while non-matching songs fade to the background, revealing the cluster distribution of the specific audio profile.
  - Bubble Plot: similar to the scatterplot, bubbles containing the selected tracks remain fully visible, while others are dimmed.
  - Box Plots: the statistical distributions for the currently selected X and Y axes are instantaneously recomputed to reflect only the brushed subset, allowing the user to compare the filtered statistics against the global dataset.

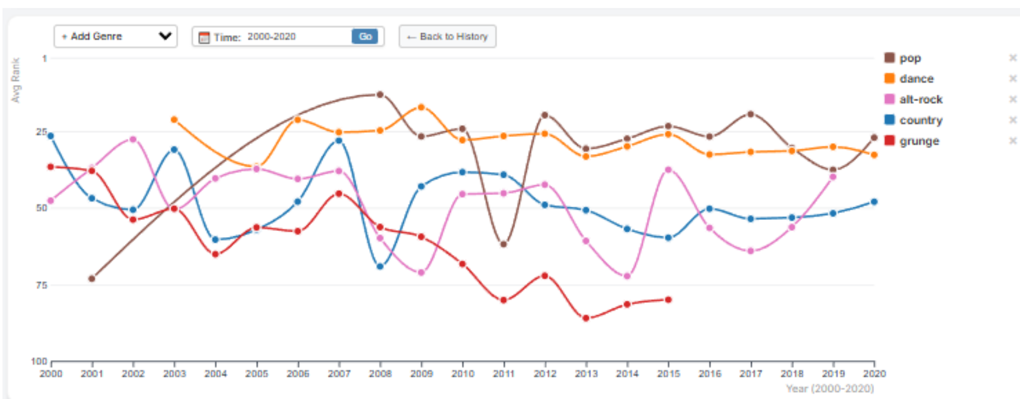
- **Brushing the t-SNE Scatterplot**: users can also select a cluster of songs directly from the 2D projection by brushing a rectangular area. This spatial selection propagates in reverse:
  - Parallel Coordinates & Centroid Calculation: the polylines corresponding to the selected cluster are isolated and highlighted in blue. Simultaneously, the system triggers a real-time computation to calculate the Centroid (average audio profile) of the selection. This calculated "average song" is overlaid as a bold, dashed red line on top of the individual tracks. This allows the user to instantly inspect the mathematical "fingerprint" of the selected cluster.
  - Bubble Plot & Box Plots: these views update identically as described above, ensuring consistent feedback across all analytical views.





- **Group by selection**: a powerful feature of the SpotyVis dashboard is the analysis capability that links the aggregated view to the statistical view. When the user utilizes the "Group By" function to cluster songs, for example, by year, and selects a specific bubble (representing a single year), the Box Plot automatically recalculates to reflect only that specific subset. This interaction allows users to isolate a single group from the global dataset, instantly revealing the specific statistical distribution (quartiles, median, and outliers) of that category's audio features without the noise of the surrounding data.

- **Changing Bubble Plot Axes**: the Bubble Plot acts as the controller for the Box Plots. When a user changes the attribute mapped to the X or Y axis, the corresponding Box Plot immediately updates to display the statistical distribution (median, quartiles and outliers) of the newly selected feature.

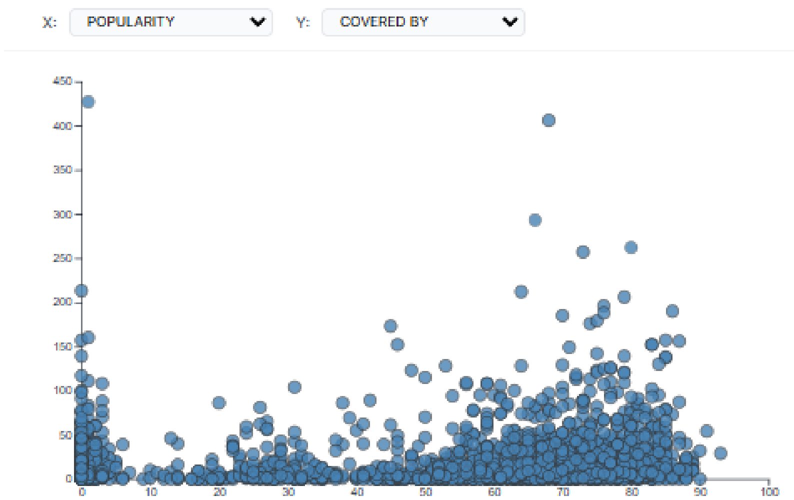


- **Independent View (Ranking Bump Chart)**: it is important to note that the Ranking Bump Chart operates independently from the filtering mechanism described above. This visualization is powered by a separate longitudinal dataset designed to show the historical popularity trends of genres over decades. While it provides essential context for the "Music Evolution" theme, it remains static during track-level filtering to preserve the historical overview while the user explores specific song characteristics in the other linked views.

Insights

During the exploration of the **SpotyVis** dashboard, several interesting patterns emerged that validate the utility of our multi-view approach.

First insight

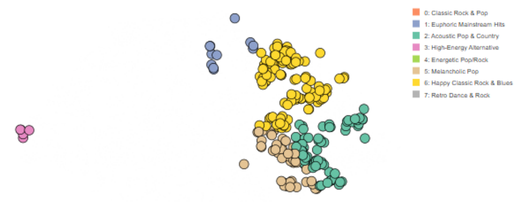


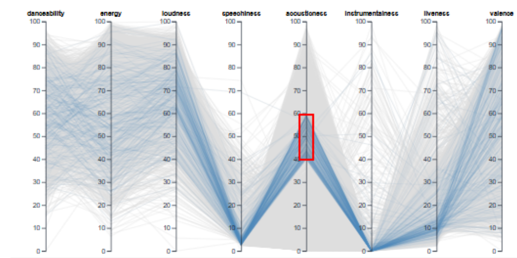
One of the most common assumptions in the music industry is that the most popular songs are also the most influential. To test this, we utilized the Bubble Plot to correlate a track's current Popularity (X-axis) against its Cover Count (Y-axis).
As shown in the resulting scatterplot, the data reveals a counter-intuitive trend: there is no direct linear correlation between a song's current popularity score and the number of times it has been covered.

On the far left of the chart (near 0 Popularity), we observe a massive outlier with the highest cover count in the entire dataset (> 400 covers). This song is essential for musicians to learn and re-record every year, resulting in a massive number of covers, even if its "current popularity" score drops significantly outside of the holiday season.

Conversely, the cluster of data points on the far right (High Popularity) that also maintains high cover counts corresponds largely to The Beatles. This contradicts the idea that popularity is fleeting; instead, it demonstrates that true "Legends" maintain a dual status.

Second insight

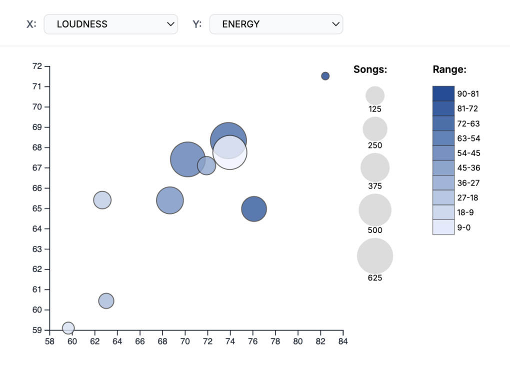


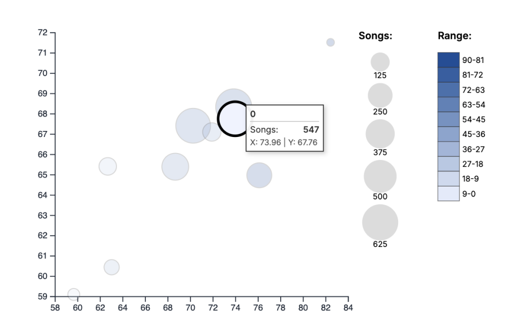


A key insight emerged when we focused on "Middle Acousticness" (songs that are roughly half acoustic and half electronic). Usually, genres are very divided on this measure: rock and electronic music are typically near 0%, while folk and classical are near 100%. However, by selecting this middle range, we found a unique mix of songs.

As expected, this filter highlighted most of the "Country" and "Classic Rock" tracks, which naturally blend acoustic guitars with electric instruments. But surprisingly, it also picked out a small, specific group of songs from the "High-Energy Alternative" cluster. This confirms that musical genres are not rigid boxes; even aggressive rock categories contain softer tracks that sound similar to Folk or Pop, a hidden connection that is only visible when filtering by audio data instead of category names.

Third insight



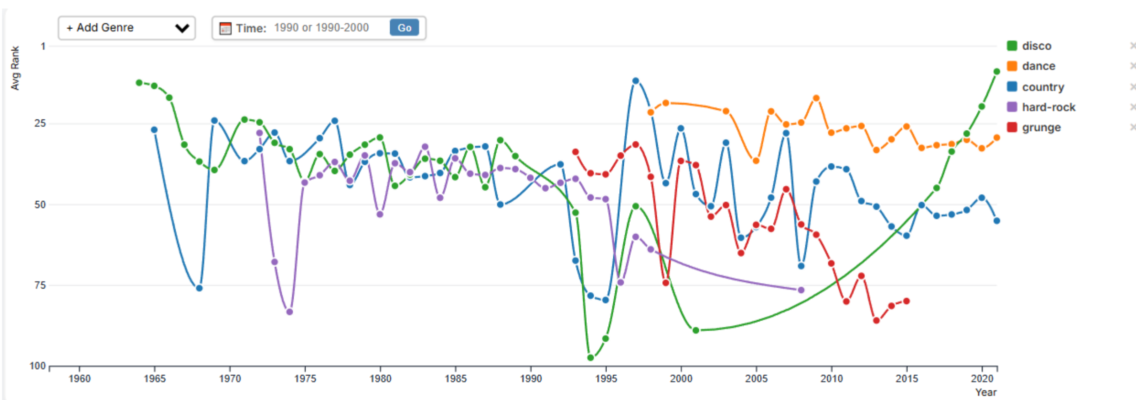


In the paper [1], the authors conclude that there is a strongly correlation between the popularity and specific audio features, particularly high energy and loudness. We can partially confirm this theory.

As we can observe in the above bubble plot, a distinct cluster of popular songs exhibiting high energy and high loudness, is clearly visible on the dashboard. However, we can also observe a significant outlier group, consisting of a high energy and high loudness songs but with low popularity. This suggests that, while songs with high energy and loudness are often associated with a high popularity, they are not the sole determinants.

We can conclude that, while the correlation observed in the paper is clearly visible on the dashboard, other factors play a crucial role in the production of an hit song.

Fourth insight



The paper [**2**] emphasizes that musical popularity is not a static property but a dynamic process driven by shifting public tastes. Our Ranking Plot directly addresses this by abandoning static snapshots in favor of a longitudinal Bump Chart visualization. By plotting the relative rank of genres over time, we capture the volatility and lifecycle of musical trends described in the literature.

This specific visual pattern, the descent of a once-dominant giant and the ascent of new challengers, empirically confirms the paper's conclusion that temporal analysis is critical, as a static aggregate view would fail to capture this evolution.

Conclusion

The final **SpotyVis** dashboard successfully provides an interactive visual analytics platform for exploring the evolution of music through the lens of audio features. We are satisfied with the final result, as it moves beyond simple "top charts" lists and allows users to see the hidden mathematical relationships between songs.

Every component of the visualization serves a specific analytical purpose: the Scatterplot provides the high-level "map" of musical similarity, the Parallel Coordinates plot acts as a precise filter for audio engineering metrics, and the Linked Views (Bubble and Box Plots) provide immediate statistical feedback.

Most importantly, transforming this data into a coordinated interactive web interface produces a far more intuitive and engaging experience for music enthusiasts than browsing static playlists or spreadsheets.

Future Work

During the development of **SpotyVis**, we identified several opportunities to further enhance the tool's capabilities. In particular, it would be interesting to:

- Implement a Search Functionality: adding a search bar that allows users to type a song title or artist and immediately highlight it in the visualization.
- Audio Preview Integration: since the project deals with music, integrating the Spotify Web Playback SDK would allow users to listen to a 30-second preview of a track when clicking a bubble.
- Temporal Animation: implementing a "Time Slider" that automatically scrolls through the decades (from 1960 to 2020) would allow users to watch the t-SNE clusters evolve in real-time.
- Hierarchical Clustering: instead of a fixed $k = 8$ clustering, implementing a hierarchical approach where users can zoom in to split a large cluster (e.g. "Rock") into smaller sub-genres (e.g. "Punk," "Metal," "Classic Rock").
- User-Selectable Presets (Guided Tours): we could add preset buttons that automatically apply the correct brushes to the Parallel Coordinates and highlight the relevant regions in the t-SNE plot.

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Bibliography

[1] Bharati Wukkadada and Somaiya Vidyavihar. Decoding spotify hits: Statistical and predictive analysis of track features driving song popularity. *International Journal of Innovative Science and Research Technology*, 2025.

[2] Leandro Guedes and Carla M.D.S. Freitas. Exploring music rankings with interactive visualization. In *Proceedings of the 13th Encontro Nacional de Inteligência Artificial e Computacional (ENIAC)*. SBC, 2017.

[3] Sarah Clavadetscher, Michael Schlotter, Nadine Christen, Juliane Streitberg, and Michael Burch. Dashboard design: Interactive and visual exploration of spotify songs. In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP)*. SCITEPRESS, 2024.

[4] G. Santucci, G. Blasilli, and S. Lenti. Material of visual analytics course, 2025/2026. Sapienza University of Rome.

Data

Spotify Tracks Dataset
The Hot 100 Songs Dataset
WhoSampled Dataset

Useful Links

https://colorbrewer2.org
https://github.com/d3/d3