Emotional and Structural Evolution of Modern Music: An Interactive Visual Analytics Map of Spotify Genres (1970-2020)

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GitHub Repository: https://github.com/CassandreLam/Spotify-Visual-Analytics-2025

Abstract— **This paper presents a Visual Analytics system designed to explore the evolution of musical genres and audio features over the last five decades. Leveraging a dataset of over 100,000 Spotify tracks, the system integrates dimensionality reduction (PCA) and unsupervised clustering (K-Means) to project tracks into a semantic musical space. The interface coordinates three main views: a projection map, a temporal evolution stream, and dynamic attribute distributions. The tool allows music analysts to visually correlate low-level audio features, such as valence, energy, and tempo, with high-level genre labels to uncover trends like the "Loudness War" and the acoustic homogenization of Pop music.**

Introduction

The democratization of music streaming has generated massive datasets describing the acoustic properties of songs. However, understanding the structural relationships between genres and their evolution over time remains a challenge due to the high dimensionality of audio data. A simple list of songs cannot reveal how "Rock" in the 1970s differs acoustically from "Rock" in the 2020s. This project aims to answer the following research questions:

- **Structural Analysis**: Can we identify distinct "audio clusters" that transcend traditional marketing genre labels?
- **Temporal Evolution**: How have specific musical traits (e.g., Loudness, Valence) evolved from 1970 to 2020?
- **Genre Profiling**: What is the quantitative acoustic signature of specific sub-genres?

I. Related Work

Standard music streaming interfaces (e.g., Spotify, Apple Music) rely primarily on list-based views and metadata filtering. While effective for retrieval, these interfaces fail to provide a structural overview of the musical space. Previous works in Music Information Retrieval (MIR) have utilized node-link diagrams or self-organizing maps (SOM) to visualize collections. Our approach differs by implementing a projection-based technique (PCA) combined with interaction-triggered analytics (Brushing & Linking), allowing for a fluid exploration of the "audio landscape" rather than just static clustering.

II. Data Abstraction and Preprocessing

The system utilizes the "Spotify Tracks Dataset," comprising multivariate audio features for tracks released between 1970 and 2020.

A. Features Definitions

To ensure meaningful analysis, we selected 9 specific numerical audio features provided by Spotify's API:

- **Valence (0-1):** A measure of musical positiveness. High valence tracks sound happy; low valence tracks sound sad or angry.
- **Energy (0-1):** Represents perceptual intensity and activity.
- **Tempo (BPM):** The speed or pace of the music.
- **Loudness (dB):** The overall loudness, useful for analyzing dynamic range trends.
- **Danceability,Acousticness,Instrumentalness :** Descriptors of rhythm stability and content type.

B. Processing Pipeline

1. Cleaning: We removed entries with missing values or invalid years.
2. Normalization: Since features have different scales (e.g., Loudness in dB vs. Valence in 0-1 range), we applied Z-score standardization to all numerical features. Formally, for each feature x, the transformed value z is calculated as:

$$z = \frac{(x - \mu)}{\sigma}$$

Where μ is the mean and σ is the standard deviation. This ensures that large-magnitude features do not dominate distance calculations.

3. Dimensionality Reduction: We applied Principal Component Analysis (PCA), retaining the first two components ($PC1$, $PC2$) to project the 9D space onto a 2D Scatterplot.
4. Clustering: A K-Means algorithm ($k = 8$) was applied to detect natural groupings (e.g., "Calm/Acoustic", "High Energy") independent of original genre labels.

C. *Visual Interface Design*

The dashboard follows Shneiderman's mantra: *"Overview first, zoom and filter, then details-on-demand."* The layout prevents global scrolling and coordinates three linked views (see Fig. 1).

Fig. 1 : *Dashboard Overview*

a) Main View: The Musical Map

The central component is a Scatterplot visualizing the PCA projection. Each dot represents a track. Position encodes similarity; color encodes either the Original Genre or the computed Audio Cluster. This view supports Semantic Zooming and Brushing to trigger analytics.

b) Temporal View: Evolution Stream

Located at the bottom, this view displays the density of tracks over time (1970-2024). It acts as a **Time Filter**: dragging a window here updates the Main View to show only tracks from a specific decade.

c) Analytics View: Dynamic Profiling

The side panel provides analytics triggered by visual interaction. When a user selects tracks, this panel updates to show:

- **Radar Chart:** Compares the average audio profile (Energy, Valence, etc.) of the selection against the global average.
- **Histograms:** Displays the distribution of **Tempo** and **Loudness** for the selection.

D. *Case Studies and Insights*

Using the tool, we derived the following insights:

Insight 1: The "Loudness War"

Comparing the sonic profiles of the 1970s against the 2010s via the Temporal View reveals a drastic structural shift in the Loudness Histogram (Fig. 3). Tracks from the 1970s exhibit a broad, natural distribution centered around -12 dB, reflecting the analog era's focus on dynamic range and fidelity. Conversely, the 2010s profile shows an aggressive, narrow peak near -5 dB, visually confirming the industry-wide phenomenon known as the "Loudness War."

This trend indicates that modern digital production systematically employs heavy dynamic range compression and brick-wall limiting. The goal has shifted from preserving musical nuance to maximizing perceived volume on mobile devices and streaming platforms, pushing audio signals dangerously close to the digital ceiling of 0 dB. This sacrifice of dynamics for sheer volume highlights how technological constraints and consumption habits have reshaped the acoustic engineering of popular music.

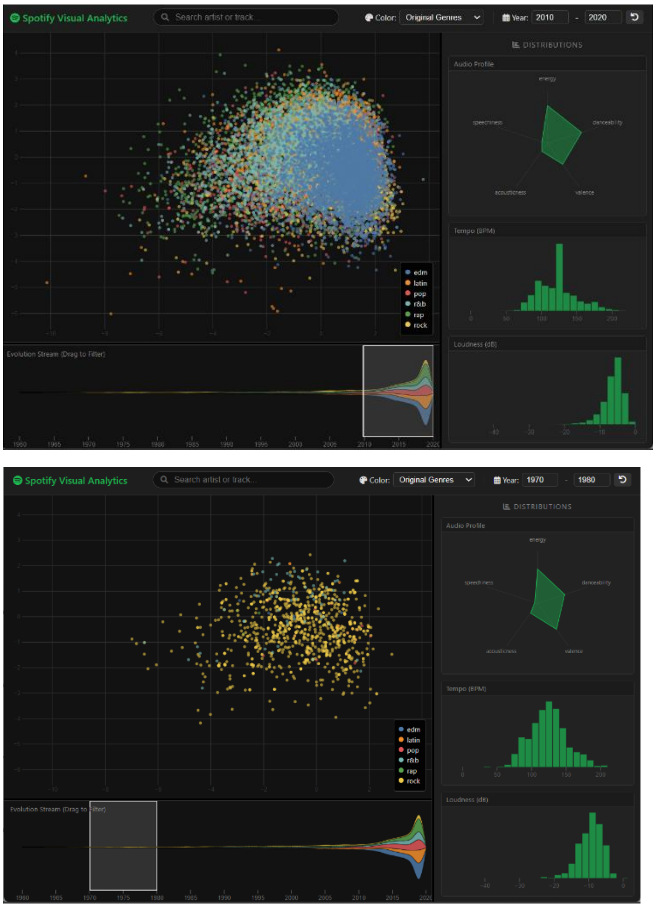

Fig. 3 : *Observation from the 2010s (on the top) Vs. 1970s (on the bottom).*

Insight 2: The "Sad Banger" Paradox (Historical Valence Drop)

Utilizing the Timeline to contrast eras uncovers a striking emotional paradox in modern music. In the 1980s, the Radar Chart displays a strong correlation between high Valence (positivity) and high Energy, typified by upbeat, optimistic Pop anthems. However, in the post-2015 era, a divergence occurs: while Energy and Danceability remain maximized, the Valence metric drops significantly.

This validates the contemporary "Sad Banger" trend, where mainstream tracks are engineered with high-tempo rhythms for clubs (high danceability) but composed in minor keys with melancholic lyrics (low valence). Furthermore, the spatial Map View reveals that the 'Rock' genre occupies the widest distribution area, confirming its historical acoustic diversity. In stark contrast, modern digital genres (Pop, EDM) form dense, tightly clustered clouds, suggesting a standardization of production techniques and a reduction in sonic variety within the digital age.

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Fig. 4 : *Observation of High Valence in 1980s.*

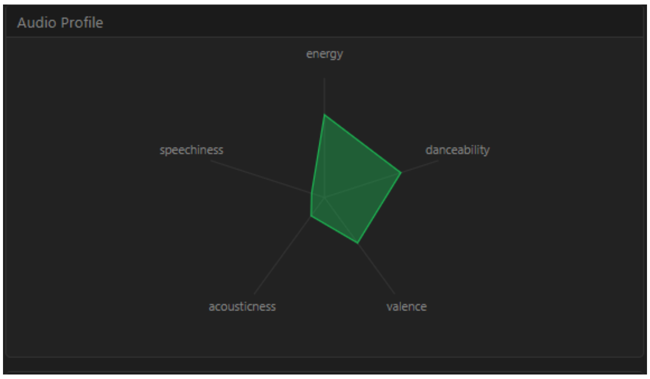

Fig. 5: *Observation of 'Sad' Valence in 1980s.*

Insight 3: The "Great Acceleration" (1990s vs 2010s)

Analyzing the Tempo Histogram across decades reveals a major rhythmic transformation driven by genre cycles. The 1990s display a distinct "Downtempo" profile, with the distribution shifting leftwards towards a median of ~106 BPM. This era was defined by the dominance of "Golden Age" Hip-Hop, R&B, and Trip-Hop, genres that relied on slower, swing-heavy breakbeats and sampled loops.

In sharp contrast, the 2010s mark a period of rapid acceleration, with the median tempo jumping to ~123 BPM and a massive concentration appearing precisely around 128 BPM. This specific value is the industry standard for Electronic Dance Music (EDM) and House music. This shift visualizes the global "EDM boom" of the early 2010s (e.g., Avicii, David Guetta), which imposed a rigid, quantized tempo structure on Pop music, effectively marking the decade as one of the fastest and most rhythmically uniform in modern music history.

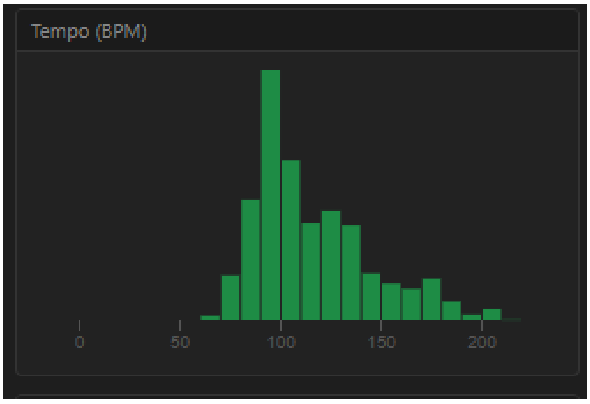

Fig. 6: *1990s: Downtempo Era (~106 BPM).*

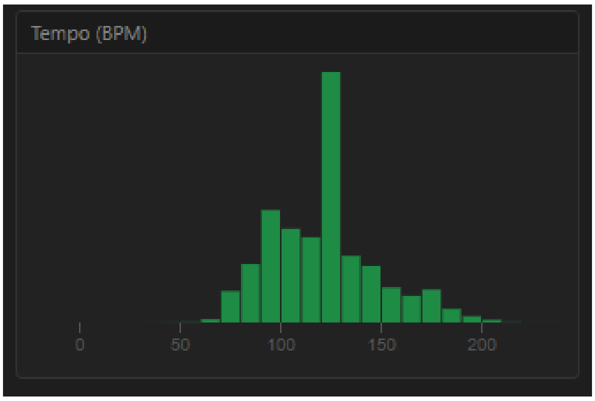

Fig.7 : *2010s: EDM Acceleration (~123 BPM).*

E. Conclusion

The "Spotify Visual Analytics" system successfully combines dimensionality reduction with interactive exploration. By coordinating a projection map with temporal filters and attribute profilers, it allows users to deconstruct the complex history of modern music. The inclusion of feature definitions in the analysis loop proves that music perception can be quantified and visually explored.

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