A Multi-Level Visual Analytics Approach to Artist–Era Alignment in Popular Music

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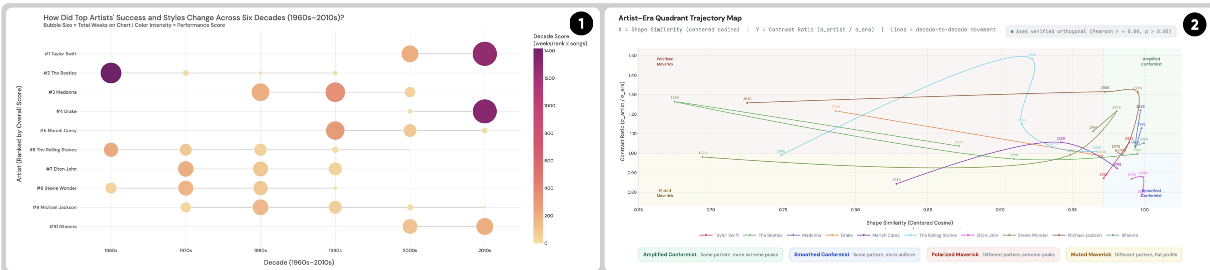

Figure 1: System overview. (1) Artist–Decade Bubble Chart showing performance trajectories across six decades. (2) Quadrant Trajectory Map plotting artist–decade units along shape similarity and contrast ratio. Detail views are shown in Figure 2.

Abstract

Existing computational studies of popular music primarily model aggregate trends or predict chart performance, offering limited support for interpreting artist-level alignment against historical stylistic baselines. We introduce an interactive visual analytics framework that treats each artist–decade as a unit defined relative to an era-specific baseline, characterized along two complementary dimensions: profile shape similarity, capturing directional correspondence with the era's feature pattern, and profile contrast ratio, capturing stylistic intensity relative to the era's dispersion. Together, these dimensions define a quadrant-based trajectory space for reasoning about conformity, divergence, and stylistic amplification or attenuation. Applied to weekly U.S. *Billboard Hot 100* chart entries from the all-time top-10 artists across six decades (1960s–2010s), linked with Spotify audio features, the framework reveals that alignment and intensity can meaningfully diverge across artist trajectories.

Index Terms: Visual Analytics, Longitudinal Analysis, Music Visualization

1 Introduction

Understanding how artists position themselves relative to evolving mainstream norms is central to analyzing longitudinal stylistic change in popular music. The *Billboard Hot 100* provides a historically grounded record for examining such change.

Prior computational studies have largely followed two directions: popularity prediction and aggregate temporal analysis. Prediction-oriented work has examined associations between audio features and chart performance [5, 3], though these models typically treat datasets as temporally homogeneous. Mauch et al. [4] detected discrete stylistic revolutions in U.S. popular music through topic-based audio analysis. In visual analytics, prior systems have supported music exploration through embedding- and timeline-based views [1, 2]. While effective, these approaches operate at aggregate or discrete-cluster levels and frame analysis around proximity-based relationships, leaving the continuous positioning of individual artists relative to era-specific norms underexplored.

Existing approaches do not separate the *direction* of stylistic alignment from its *intensity*. To address this gap, we introduce an interactive visual analytics framework that operationalizes each *artist–decade* relative to an era baseline. Each profile is characterized along two complementary dimensions: *shape similarity*, capturing directional correspondence with the era's feature pattern, and *contrast ratio*, capturing stylistic intensity relative to the era's dispersion. Together, these dimensions define a quadrant-based trajectory space for analyzing stylistic trajectories over time. Applied to weekly U.S. *Billboard Hot 100* chart entries from the all-time top-10 artists across six decades (1960s–2010s), linked with Spotify audio features, the framework enables exploration from era baselines to artist trajectories and song-level deviations, revealing alignment configurations not discernible through aggregate analysis alone.

2 Interactive Visualization

Analytic Tasks. Informed by a formative interview with an expert, the system supports three analytic tasks from overview to detail:

- **T1:** Trace artist trajectories across decades.
- **T2:** Examine song-level performance and audio profiles.
- **T3:** Quantify and compare artist–era stylistic alignment.

Preprocessing. We integrate weekly U.S. *Billboard Hot 100* chart data (1960s–2010s) with *Spotify* audio features for the all-time top-10 artists. Rank 1–10 refers to positions on Billboard's weekly consumption-based chart, with eligibility governed by Billboard. Artists are ranked by the following score: $\left(\sum_{\text{songs}} \frac{\text{weeks}_i}{\text{avg\_rank}_i}\right) \times \log\big(1 + |\text{Songs}|\big)$, where $\frac{\text{weeks}_i}{\text{avg\_rank}_i}$ represents each song's contribution and $|\text{Songs}|$ denotes the artist's distinct song count. We use five interpretable Spotify audio features: valence (musical positivity), energy (perceived intensity and activity), danceability (suitability for dancing), acousticness (likelihood of an acoustic recording), and liveness (likelihood of a live performance).

2.1 Visual Encoding

The system comprises four coordinated views (Figures 1–2), illustrated using Michael Jackson's 1990s profile as a running example.

❶ Artist–Decade Bubble Chart. The main view supports (T1) by visualizing artist performance trajectories across six decades. Each bubble represents an artist–decade pair, with x-position encoding decade, y-position encoding artist rank, size encoding total chart appearances, and color intensity encoding the decade-specific

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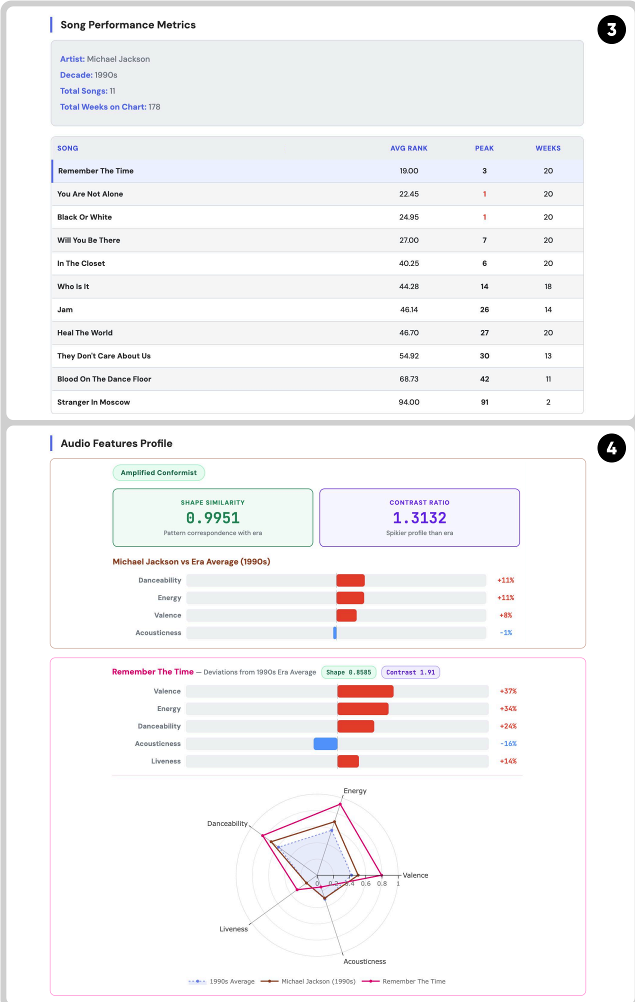

Figure 2: Michael Jackson (1990s) and “Remember The Time” selected. (3) Song Performance Table listing charting metrics. (4) Audio Features Profile displaying quadrant classification, per-feature deviations from the era average, and a song-level radar overlay.

performance score, $\sum_{\text{songs}} \frac{\text{weeks}_i}{\text{avg\_rank}_i} \times |\text{Songs}|_d$, where $|\text{Songs}|_d$ is the distinct song count within that decade. Connecting lines trace each artist's career path, allowing users to identify sustained activity or era-specific prominence. In the running example, Michael Jackson's 1990s bubble reflects 178 chart appearances across 11 distinct songs, a contraction from his peak 1980s activity (266 appearances) that the connecting line makes immediately apparent.

❷ Quadrant Trajectory Map. Each artist–decade pair is plotted in a 2D space defined by two complementary metrics. The x-axis encodes *shape similarity*—centered cosine similarity between the artist's mean audio feature vector and the era centroid—capturing directional correspondence. The y-axis encodes *contrast ratio* ($\sigma_{\text{artist}}/\sigma_{\text{era}}$), capturing whether the artist's profile is more extreme or uniform than the era norm. A Pearson correlation test over all 33 artist–decade pairs showed no significant linear association between the two axes ($r = -0.19$, $p = .30$), suggesting that they capture distinct dimensions. The space is partitioned by a median-based boundary on shape similarity and a theoretically grounded boundary on contrast ratio ($\sigma_{\text{artist}}/\sigma_{\text{era}} = 1.0$), defining four quadrants: *Amplified Conformist* (high shape, high contrast), *Smoothed Conformist* (high shape, low contrast), *Polarized Maverick* (low shape, high contrast), and *Muted Maverick* (low shape, low contrast). Lines connect each artist's consecutive decade positions, enabling trajectory tracing (T1, T3). In the running example, Michael Jackson's 1990s position (shape = 0.995, contrast = 1.313) places him in the *Amplified Conformist* quadrant, indicating strong directional alignment with the era baseline and amplified stylistic intensity—shifted upward from his 1980s position (shape = 0.984, contrast = 0.995), which sat near the quadrant boundary.

❸ Song Table and ❹ Audio Profiles. Clicking a bubble in the main view reveals two coordinated panels. The left panel displays a ranked table with average rank, peak rank, and weeks on chart, supporting (T2). In the running example, the table lists *Remember The Time* (avg. rank 19.0, peak 3, 20 weeks) and *You Are Not Alone* (avg. rank 22.5, peak 1, 20 weeks) among the top entries. The right panel presents three components. First, an *Alignment Badge* supporting (T3) displays shape similarity and contrast ratio and classifies the artist–decade pair into one of the four quadrants defined above. Second, an *Artist–Era Deviation* chart—a diverging bar chart supporting (T3)—displays how the artist's audio features in the selected decade deviate from the era average across five dimensions (valence, energy, danceability, acousticness, liveness). In the running example, the deviation chart reveals that despite near-perfect directional alignment, Michael Jackson's 1990s profile exhibits pronounced positive deviations in energy (+0.11) and danceability (+0.11)—the amplification pattern suggested by the quadrant position but not decomposed into individual features. Selecting a song row updates the right panel with a *Song Signature*: a diverging bar chart showing per-song deviations from the era average, and a radar chart overlaying decade, artist, and song-level profiles for direct comparison, supporting (T2) and (T3).

3 Expert Case Study and Discussion

We conducted an open-ended, think-aloud session with a domain expert in commercial music production and chart dynamics (5+ years of experience). The participant noted that the quadrant-based framing surfaces distinctions that are difficult to capture using conventional chart metrics or genre labels alone, pointing to Madonna (1980s–2000s) as consistently occupying the *Amplified Conformist* quadrant and Elton John as remaining within the *Smoothed Conformist* quadrant.

Limitations and Future Work. This study relies on a single-participant exploratory session and a dataset limited to ten artists, constraining the generalizability of the findings. However, the core metrics—centered cosine similarity and contrast ratio—are independent of corpus size, feature set, or temporal granularity and can be applied to larger artist pools, alternative audio descriptors, or sub-decade intervals. Future work may evaluate scalability through multi-participant studies, expanded datasets, cross-artist analysis, and trajectory pattern mining to identify common career pathways.

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