# Music as Data

## Tracing the Evolution of Style and Values with Modern Audio Models

UZH Economics

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# *Chuck Berry (1956) vs. The Beatles (1963)*


**Chuck Berry (1956)**
*Roll Over Beethoven*

Play Audio


**The Beatles (1963)**
*Roll Over Beethoven*

Play Audio

(Audio playback requires a PDF viewer that supports embedded media.)

# Introduction: The Beatles and the Transatlantic Circulation of Sound

- In the early 1960s, The Beatles emerged from Liverpool, absorbing American R&B, Chuck Berry's guitar phrasing, Little Richard's vocal timbre, and Motown's rhythm.
- They translated these Black American musical traditions into a new British pop sound that re-entered the U.S. charts during the "British Invasion"
- Can we measure this diffusion *sonically*: rhythm, tone, and production features — without relying on lyrics or cultural narratives?


**Chuck Berry (1956)**

*Roll Over Beethoven*


**The Beatles (1963)**

*Roll Over Beethoven*

# Research Agenda

**Guiding questions**

1. How do rhythmic, harmonic, and timbral traits evolve over decades?
2. How do they diffuse across regions, scenes, and labels?
3. Which macro shocks (policy, tech, crises) shift sonic traits?
4. What do trait shifts suggest about values?

**Design principles**

- Use audio (not lyrics) to avoid text confounds.
- Prefer interpretable features + learned embeddings.
- Build a panel: track $\times$ year $\times$ place.

# Core Tools + Methods

- **Feature extraction:** *Essentia*, *librosa*: compute interpretable descriptors such as tempo, key, spectral centroid, dynamic range, and rhythmic regularity. Useful for reproducing historical "engineered" traits and cross-validating learned embeddings.
- **Embeddings:** *MERT* or *CLAP/OpenL3* (audio encoders trained on large-scale text–audio corpora). Provide dense, high-level representations of timbre and production style, enabling similarity analysis, clustering, and cultural diffusion tracking.
- **Metadata joins:** *MusicBrainz*, *Discogs*: supply canonical identifiers for track, release, artist, label, and region. Enable linking to year, genre, and country attributes for econometric analysis.

# Two Ways to Use Music as Data

*Two complementary representations: features give interpretability, embeddings give depth.*

**1. Pre-computed / Engineered Features**

- Examples: *tempo, loudness, key, energy, danceability*.
- Extracted via tools like *Essentia, librosa, Echo Nest*.
- Interpretable, standardized, reproducible.

**2. Learned Embeddings**

- Examples: *MERT, CLAP, OpenL3, Wav2Vec2*.
- Derived from deep audio encoders trained on text–audio pairs.
- Capture complex timbral, stylistic, and production features.
- Harder to interpret, but richer and higher-dimensional.

## Engineered Features: The Million Song Dataset (MSD)

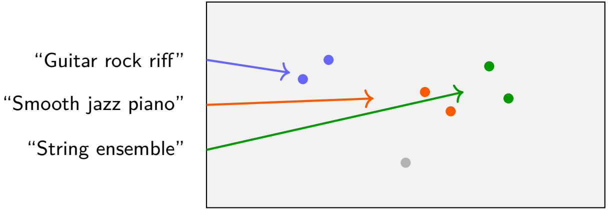
- Large-scale database of $\sim$1 million songs.
- Contains **pre-computed audio features** (not raw audio) generated via Echo Nest algorithms.
- Each row $=$ one track, combining *metadata* and dozens of numerical descriptors.

| **Field** | **Example Value** | **Description** |
|---|---|---|
| track_id | TRMMMYQ128F932D901 | Unique ID for the track |
| artist_name | The Beatles | Artist metadata |
| title | A Hard Day's Night | Song title |
| year | 1964 | Release year |
| tempo | 140.05 | Global tempo (BPM) |
| key | 9 | MIDI key (0=C, 11=B) |
| mode | 1 | 1 $=$ major, 0 $=$ minor |
| loudness | -5.42 | Average loudness (dBFS) |
| energy | 0.812 | Normalized energy (0–1) |
| danceability | 0.645 | From Echo Nest model |

# Learned Embeddings (CLAP / MERT)

- **Goal:** Represent each audio clip as a dense vector capturing musical style.
- **Method:** Deep encoders (e.g., *CLAP*, *MERT*) learn from millions of audio examples — some with text captions, others self-supervised.
- **Result:** Songs that sound alike or share stylistic traits end up close together in embedding space.
- **Applications:**
    - Clustering songs by sound similarity
    - Tracing stylistic drift over time
    - Zero-shot search: “find tracks that sound like R&B jazz”

Shared Embedding Space



# Identification Ideas

- Event study: staggered adoption (e.g., streaming rollout by country).
- Diff-in-diff across regions/labels.
- Validate traits via interpretable features and embeddings.

# Key Papers

- **Serrà et al. (2012), Measuring the Evolution of Contemporary Western Popular Music** Large-scale analysis of pitch, timbre, and loudness (1950–2010) shows reduced timbral variety but increasing loudness and harmonic uniformity.
- **Mauch et al. (2015), The Evolution of Popular Music: USA 1960–2010** Uses audio features and topic modeling to identify stylistic "revolutions" (e.g., 1983, 1991) and long-run trends in harmony and timbre.
- **Interiano et al. (2018), Musical Trends and 50 Years of Data** Analyzes 500,000 songs to show declining happiness and rising relaxation in popular music lyrics and sound.
- **Morrison et al. (2020), Predicting Music Genres from Audio Embeddings** Demonstrates that deep-learned representations (e.g., VGGish, OpenL3) outperform engineered features for genre classification.
- **Tzanetakis & Cook (2002), Musical Genre Classification of Audio Signals** Foundational work introducing timbral, rhythmic, and pitch-based features for automatic genre recognition.
- **Serra & Smith (2020), Computational Approaches to Music Similarity and Style** Reviews how feature extraction and embeddings enable cross-cultural and longitudinal analyses of musical style.

Thank you!