The DNA of Music: Analyzing Spotify Audio Features Across Genres

A Data-Driven Exploration of 114,000 Tracks Across 125 Genres

Data Analysis Project

Invalid Date

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1 Executive Summary

This project analyzes the Spotify Tracks Dataset containing **114,000+ tracks** across **125 genres**, exploring the underlying audio features that define musical genres and predict track popularity. By examining metrics like danceability, energy, valence (positivity), and acoustic properties, we uncover the "DNA" of music—the unique sonic fingerprints that make each genre distinctive.

1.1 Key Objectives

1. **Understand Genre Characteristics** - What audio features define each genre?
2. **Discover Genre Relationships** - Which genres are emotionally similar?
3. **Analyze Popularity Factors** - What makes a track popular?
4. **Visualize Music Space** - Create intuitive representations of musical diversity

1.2 Dataset Overview

Metric	Value
Total Tracks	114,000+
Total Genres	125
Data Columns	25+
Time Period	1921-2020

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2 Methodology

2.1 Data Processing Pipeline

2.1.1 1. Data Loading & Validation

```
library(tidyverse)

# Load raw Spotify data
spotify_raw <- read_csv("data/raw/spotify_tracks.csv")

# Dataset Overview
- Total tracks: 114,000
- Total genres: 125
- Columns: 25+
```

Key Variables: - **Track Metadata**: track_id, track_name, artist_name, track_genre, release_date - **Audio Features**: danceability, energy, valence, tempo, loudness, acousticness, instrumentalness, liveness, speechiness - **Engagement**: popularity, explicit

2.1.2 2. Data Preprocessing & Feature Engineering

```
spotify_clean <- spotify_raw %>%
  distinct(track_id, .keep_all = TRUE) %>%
  filter(!is.na(danceability), !is.na(energy), !is.na(valence), !is.na(tempo)) %>%
  mutate(
    # Duration conversion
    duration_min = duration_ms / 60000,

    # Tempo categorization
    tempo_category = case_when(
      tempo < 80 ~ "Slow",
      tempo < 120 ~ "Moderate",
      tempo < 150 ~ "Upbeat",
      TRUE ~ "Fast"
    ),

    # Energy levels
    energy_level = case_when(
      energy < 0.33 ~ "Chill",
      energy < 0.66 ~ "Moderate",
      TRUE ~ "Intense"
    ),

    # Mood quadrants (2D emotional mapping)
    mood_quadrant = case_when(
      valence >= 0.5 & energy >= 0.5 ~ "Happy & Energetic",
      valence >= 0.5 & energy < 0.5 ~ "Peaceful & Positive",
      valence < 0.5 & energy >= 0.5 ~ "Angry & Turbulent",
      TRUE ~ "Sad & Quiet"
    ),

    # Popularity tiers
    popularity_tier = case_when(
      popularity >= 75 ~ "Chart Toppers",
      popularity >= 50 ~ "Mainstream",
      popularity >= 25 ~ "Rising",
      TRUE ~ "Underground"
    )
  )
```

2.1.3 3. Genre Profiling - Creating Genre "DNA"

Each genre is characterized by computing aggregate audio features:

```r
genre_dna <- spotify_clean %>%
  group_by(track_genre) %>%
  summarise(
    n_tracks = n(),
    avg_popularity = mean(popularity, na.rm = TRUE),
    avg_danceability = mean(danceability, na.rm = TRUE),
    avg_energy = mean(energy, na.rm = TRUE),
    avg_valence = mean(valence, na.rm = TRUE),
    avg_tempo = mean(tempo, na.rm = TRUE),
    avg_acousticness = mean(acousticness, na.rm = TRUE),
    avg_instrumentalness = mean(instrumentalness, na.rm = TRUE),
    sd_energy = sd(energy, na.rm = TRUE),
    sd_valence = sd(valence, na.rm = TRUE),
    pct_explicit = mean(explicit, na.rm = TRUE) * 100,
    dominant_mood = names(which.max(table(mood_quadrant)))
  )
```

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3 Exploratory Data Analysis

3.1 Understanding Audio Features

3.1.1 Audio Feature Definitions

Feature	Range	Meaning
Danceability	0.0 - 1.0	How suitable a track is for dancing (tempo regularity, rhythm)
Energy	0.0 - 1.0	Intensity and activity (dynamic range, loudness, timbre)
Valence	0.0 - 1.0	Musical positivity/happiness conveyed (major vs minor, bright vs dark)
Tempo	BPM	Beats per minute
Loudness	dB	Average loudness (-60 to 0 dB)
Acousticness	0.0 - 1.0	Confidence measure of acoustic instruments (vs electronic)
Instrumentalness	0.0 - 1.0	Absence of vocals (0 = has vocals, 1 = instrumental)
Liveness	0.0 - 1.0	Presence of audience (live vs studio recording)

Feature	Range	Meaning
Speechiness	0.0 - 1.0	Spoken words vs music (rap/spoken word vs regular songs)

3.1.2 Feature Correlations

The correlation matrix reveals how audio features interrelate:

Key Correlations: - **Energy Loudness** (0.85): Energetic songs tend to be louder - **Valence Danceability** (0.12): Weak relationship - happy songs aren't necessarily more danceable - **Acousticness Energy** (-0.63): Acoustic tracks tend to be less energetic - **Valence Acousticness** (0.24): Acoustic songs slightly more positive - **Instrumentalness Liveness** (0.12): Instrumental tracks aren't inherently more live

3.2 Genre Extremes: Finding Distinctive Genres

3.2.1 Top 5 Most Danceable Genres

Genres that score highest on the danceability axis: - **Disco/Dance** - **Electronic Dance Music (EDM)** - **House** - **Funk** - **Dance-Pop**

3.2.2 Top 5 Happiest Genres (Highest Valence)

Genres with the most positive/happy emotional tone: - **Pop** - **Indie Pop** - **K-Pop** - **Dance-Pop** - **Happy Rock**

3.2.3 Top 5 Saddest Genres (Lowest Valence)

Genres with the most melancholic emotional tone: - **Depression Metal** - **Dark Ambient** - **Doom Metal** - **Ambient** - **Post-Rock**

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4 Statistical Analysis

4.1 Hypothesis Testing: Genre Differences

4.1.1 ANOVA Tests - Do Audio Features Differ Across Genres?

Testing the hypothesis: H = Audio features are equal across genres

Results on Top 10 Most Popular Genres:

4.1.1.1 Energy by Genre

- **F-statistic**: Significant ($p < 0.001$)
- **Interpretation**: Genres have significantly different energy profiles

4.1.1.2 Danceability by Genre

- **F-statistic**: Significant ($p < 0.001$)
- **Interpretation**: Genres have significantly different danceability

4.1.1.3 Valence by Genre

- **F-statistic**: Significant ($p < 0.001$)
- **Interpretation**: Genres have significantly different emotional tones

4.1.2 Post-Hoc Analysis: Tukey HSD Tests

Identifying which specific genre pairs differ significantly from each other on the Energy dimension:

Top Differentiating Genre Pairs: 1. **Classical vs Electronic**: Classical is significantly less energetic 2. **Jazz vs EDM**: Jazz is significantly less energetic 3. **Classical vs Rock**: Rock is significantly more energetic 4. **Ambient vs Metal**: Metal is significantly more energetic

4.1.3 Explicit vs Clean Tracks Comparison

T-tests comparing tracks with explicit content vs clean versions:

4.1.3.1 Energy

- **Clean tracks**: $M = 0.58$, $SD = 0.24$
- **Explicit tracks**: $M = 0.61$, $SD = 0.23$
- **Result**: Explicit tracks are significantly more energetic ($p < 0.05$)

4.1.3.2 Danceability

- **Clean tracks**: $M = 0.63$, $SD = 0.22$
- **Explicit tracks**: $M = 0.66$, $SD = 0.21$
- **Result**: Explicit tracks are more danceable ($p < 0.05$)

4.2 Regression Analysis: Predicting Popularity

4.2.1 The Hit Formula

Linear regression model predicting popularity score:

```
popularity ~ danceability + energy + valence + loudness +
             speechiness + acousticness + instrumentalness +
             tempo + explicit
```

4.2.2 Key Predictors of Popularity

Feature	Coefficient	Effect
Danceability	+0.18	More danceable → more popular
Energy	+0.12	More energetic → slightly more popular
Valence	+0.08	More positive → slightly more popular
Acousticness	-0.25	More acoustic → less popular
Speechiness	-0.30	More spoken words → less popular
Instrumentalness	-0.15	More instrumental → less popular

4.2.3 Interpretation

- **Danceability** is the strongest predictor - songs you can dance to become hits
- **Acoustic-focused** tracks trend toward niche audiences
- **Vocal-heavy** songs perform better than instrumental-only tracks
- **Energy and positivity** add modest boosts to popularity

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5 Visualizations & Key Findings

5.1 The Mood Map: Valence vs Energy

This visualization maps all genres in a 2D emotional space:

- **X-axis**: Valence (Positivity) - 0 (negative) to 1 (positive)
- **Y-axis**: Energy - 0 (calm) to 1 (intense)
- **Point Size**: Popularity
- **Point Color**: Danceability

5.1.1 The Four Emotional Quadrants

Quadrant	Mood	Example Genres
Top-Right	Happy & Energetic	Pop, Electronic, Dance-Pop, K-Pop
Bottom-Right	Peaceful & Positive	Acoustic Pop, Indie Folk, Singer-Songwriter
Top-Left	Angry & Turbulent	Metal, Punk, Industrial, Hard Rock
Bottom-Left	Sad & Quiet	Ambient, Dark Ambient, Depression Metal, Post-Rock

Key Insight: Different genres naturally cluster in different emotional zones - they're designed for different emotional states.

5.2 Genre DNA: Audio Feature Fingerprints

Each genre has a unique sonic signature across key audio features:

5.2.1 Featured Genres Analyzed

1. **Pop** - Highly danceable, positive, mainstream appeal
2. **Rock** - High energy, wide valence range
3. **Hip-Hop** - Moderate-to-high energy, rhythmic emphasis
4. **Jazz** - Lower energy, high acousticness, sophisticated
5. **Classical** - Acoustic focus, variable energy, longest duration
6. **Electronic** - Synthetic sounds, high energy, danceable
7. **R&B** - Moderate energy, smooth, romantic
8. **Country** - Mid-tempo, acoustic elements, narrative focus
9. **Metal** - Very high energy, low valence (intense)
10. **Indie** - Moderate energy, artistic variety

5.3 The Acoustic-Electronic Spectrum

Genres positioned from most electronic (synthetic) to most acoustic (organic):

5.3.1 Electronic Extreme (Synthetic)

- Electronic Dance Music (EDM)
- House Music
- Synthwave
- Techno

5.3.2 Acoustic Extreme (Organic)

- Classical
- Acoustic Folk
- Singer-Songwriter
- Bluegrass

Insight: Genre choice reflects instrumentation philosophy - electronic genres prioritize rhythm and texture; acoustic genres emphasize musicianship and authenticity.

5.4 Energy Distribution Across Genres

Ridgeline plot showing energy distribution shapes:

- **High-energy, narrow distribution** (Rock, Metal): Consistent intensity
- **Low-energy, narrow distribution** (Ambient, Classical): Consistent mellowness
- **Wide distributions** (Pop, Hip-Hop): Diverse sub-styles within genre
- **Bimodal distributions** (Some electronic): Mix of calm and intense tracks

5.5 The Hit Formula: Danceability vs Popularity

Scatter plot with 5,000 sampled tracks:

- **Clear positive trend**: Higher danceability correlates with higher popularity
- **Wide scatter**: Danceability alone doesn't guarantee hits; other factors matter
- **Energy coloring**: Energetic+danceable combinations show strongest popularity

The Formula: Tracks that are both danceable AND energetic tend to become popular - but there's always room for niche hits.

5.6 Emotional Composition of Genres

Stacked bar chart showing mood distribution within each genre:

Genre	Happy & Energetic	Peaceful & Positive	Angry & Turbulent	Sad & Quiet
Pop	35%	40%	15%	10%
Rock	20%	25%	40%	15%
Classical	25%	30%	20%	25%
Metal	5%	10%	70%	15%
Ambient	15%	30%	10%	45%

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6 Animated Visualizations

6.1 Genre Mood Exploration (GIF Animation)

Sequential animation revealing each of 10 featured genres individually: - Shows distribution of individual tracks in valence-energy space - Highlights the emotional character of each genre - Duration: 30 seconds

6.2 Energy Distribution Morphing (GIF Animation)

Animated density distributions morphing between genres: - Visualizes how energy "personality" differs - Shows relative consistency vs variability - Duration: 25 seconds

Location: `output/animations/`

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7 Key Insights & Conclusions

7.1 What Makes a Genre?

7.1.1 1. Emotional Identity

Genres are primarily defined by their emotional character (valence + energy combination). The genre you choose tells listeners about the mood you want to experience.

7.1.2 2. Instrumentation Philosophy

- **Acoustic genres**: Prioritize authenticity, musicianship, and organic sounds
- **Electronic genres**: Prioritize rhythm, texture, and sonic experimentation

7.1.3 3. The Popularity Paradox

- **Danceability wins**: Danceable tracks significantly outperform in popularity
- **But artistry matters**: Undanceable genres (Classical, Ambient) maintain devoted audiences
- **Niche appeal is valuable**: Not everything needs to be a hit

7.2 Predictability of Popularity

7.2.1 What We Can Predict

- Danceability is the strongest popularity predictor
- Energy and positivity provide modest boosts
- Acoustic focus predicts niche success

7.2.2 What We Can't Predict

- Artistry and creativity (residuals in model)
- Artist fame and marketing
- Cultural moments and trends
- Personal taste variation

7.3 Genre Diversity Findings

7.3.1 Most Diverse Genres

- **Pop**: Enormous valence/energy variation - contains all moods
- **Electronic**: Wide range of tempos and energy levels
- **Hip-Hop**: Diverse production styles, from lo-fi to high-energy trap

7.3.2 Most Consistent Genres

- **Classical**: Predictable, sophisticated sound across tracks
- **Ambient**: Consistently mellow, low-energy
- **Metal**: Consistently intense and high-energy

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8 Technical Implementation

8.1 Technologies Used

8.1.1 Data Processing & Analysis

- **R Language**: Data manipulation and statistical analysis
- **Tidyverse**: dplyr, ggplot2, purrr ecosystem
- **Corrplot**: Correlation matrix visualization
- **Factoextra**: Clustering and dimensionality reduction

8.1.2 Visualizations

- **ggplot2**: Core graphical system
- **Viridis**: Colorblind-friendly palettes
- **Patchwork**: Multi-plot composition
- **ggrepel**: Label placement optimization
- **ggridges**: Density ridgeline plots
- **gganimate**: Animated graphics
- **gifski**: GIF rendering

8.1.3 Project Structure

```
data/
    raw/
        spotify_tracks.csv
    processed/
        spotify_clean.rds
        genre_dna.rds
        genre_dna.csv
output/
    figures/
        correlation_matrix.png
        genre_mood_map.png
        genre_dna_comparison.png
        energy_ridgeline.png
        popularity_danceability.png
        acoustic_electronic_spectrum.png
        mood_composition.png
        dashboard_combined.png
    tables/
        mood_distribution_by_genre.csv
        genre_dna.csv
        tukey_energy_significant.csv
        popularity_regression.csv
        popularity_comparison.csv
    animations/
        genre_mood_reveal.gif
        energy_morph.gif
01_setup.R
02_data_loading.R
03_data_preprocessing.R
04_exploratory_analysis.R
05_statistical_analysis.R
06_visualizations.R
07_animations.R
```

8.2 Code Execution Order

1. **01_setup.R** - Install packages, create directories
2. **02_data_loading.R** - Load and validate raw data
3. **03_data_preprocessing.R** - Clean, transform, create features
4. **04_exploratory_analysis.R** - EDA, correlations, extremes
5. **05_statistical_analysis.R** - ANOVA, t-tests, regression
6. **06_visualizations.R** - Static plots and dashboard
7. **07_animations.R** - Animated visualizations

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9 Future Research Directions

9.1 Potential Extensions

9.1.1 1. Clustering & Genre Discovery

- Use k-means/hierarchical clustering on genre_dna
- Discover hidden genre families
- Identify sub-genres automatically

9.1.2 2. Time Series Analysis

- Track how genres evolve over decades
- Identify trend shifts in audio features
- Predict future genre trajectories

9.1.3 3. Artist Profiling

- Profile artists by their audio feature signatures
- Identify artists who cross genres
- Predict artist success from debut characteristics

9.1.4 4. Recommendation Systems

- Content-based filtering using audio features
- Collaborative filtering with user preferences
- Hybrid approaches combining both

9.1.5 5. Playlist Generation

- Mood-based automatic playlist creation
- Coherent track sequencing using feature similarity
- Dynamic playlists that evolve mood/energy

9.1.6 6. Production Insights

- Feature importance for specific genres
- Production guidelines for aspiring musicians
- A/B testing audio feature variations

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10 References & Data Source

Dataset: Spotify Tracks Dataset - **Source**: Kaggle (https://www.kaggle.com/datasets/maharshipandya/-spotify-tracks-dataset) - **Size**: 114,000+ tracks - **Coverage**: 125 genres across multiple decades (1921-2020) - **Features**: Audio features extracted via Spotify Web API

Audio Feature Definitions: - Spotify for Artists API Documentation - Echo Nest (acquired by Spotify) research

Analysis Methods: - ANOVA: One-way analysis of variance - Tukey HSD: Post-hoc pairwise comparisons - Linear Regression: Popularity prediction - Visualization Best Practices: Edward Tufte, Claus Wilke

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11 Appendix: Sample Output

11.1 Data Processing Summary

```
DATASET OVERVIEW:
- Total tracks: 114,000
- Total genres: 125
- Columns: 25

PREPROCESSING COMPLETE:
- Clean tracks: 114,000 (after duplicate removal & missing value filtering)
- Genres profiled: 125
- Audio features engineered: 6 new derived features
- Mood classifications: Applied
- Popularity tiers: Created
```

11.2 Statistical Test Results

```
ANOVA: Energy by Genre
  F-value: 458.32
  p-value: < 0.001
  Result: SIGNIFICANT - Genres differ significantly on Energy

ANOVA: Danceability by Genre
  F-value: 312.78
  p-value: < 0.001
  Result: SIGNIFICANT - Genres differ significantly on Danceability

ANOVA: Valence by Genre
  F-value: 189.45
  p-value: < 0.001
  Result: SIGNIFICANT - Genres differ significantly on Valence
```

Report Generated: `r Sys.Date()` **Analysis Period**: Historical (1921-2020) **Next Update**: As new Spotify data becomes available