Spotify Playlist Extension with Pattern Mining and Clustering: A Data Mining Approach to Music Recommendation

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Abstract

This research addresses automatic playlist continuation in music streaming platforms by applying advanced data mining techniques to the Spotify Million Playlist Dataset. We investigate three core research questions: identifying song co-occurrence patterns through association rule mining, evaluating clustering effectiveness based on musical features, and measuring metadata influence on recommendation quality. Our comprehensive analysis processes 1,000,000 playlists containing 66,346,428 track entries and 2,262,292 unique tracks from 287,742 artists. Through systematic application of FP-Growth association rule mining, K-means clustering with Principal Component Analysis (PCA) dimensionality reduction, and multiple recommendation algorithms including collaborative filtering, Singular Value Decomposition (SVD), and neural networks, we achieve an 89-fold improvement in R-precision over popularity baselines (from 0.165% to 14.61%). The study reveals that song co-occurrence patterns exhibit strong predictive power with lift values exceeding 10,000x, playlist clustering naturally segments into five distinct categories, and simple pattern mining methods significantly outperform complex deep learning approaches on sparse, high-dimensional music data. These findings contribute to understanding music consumption patterns and provide practical insights for developing effective playlist continuation systems in streaming platforms.

1. Introduction

1.1 Background and Motivation

The music streaming industry has fundamentally transformed how users discover and consume music worldwide. As of 2025, major platforms like Spotify, Apple Music, and YouTube Music collectively serve billions of tracks to over 500 million users daily, with streaming accounting for 84% of global music industry revenue. According to recent industry reports, global music streaming revenue exceeded $17 billion in 2023, representing 67% of total recorded music revenue. Spotify alone reports over 600 million monthly active users across 180+ markets, with users creating over 5 billion playlists.

A critical feature that differentiates modern streaming services and drives user engagement is their ability to provide personalized, contextually relevant recommendations that extend user-created playlists naturally while maintaining thematic coherence and musical flow. The average streaming user spends 18 hours per week listening to music, with 40% of listening occurring through user-created or algorithmically-generated playlists rather than albums or radio. This shift from album-based to playlist-based consumption fundamentally changes how users discover music and how recommendation algorithms must operate.

User-created playlists represent a unique form of music curation that reflects personal taste, mood, activity context, and social sharing intentions. Understanding and leveraging these patterns presents substantial business value: improved playlist continuation directly translates to increased listening time, higher user retention rates, reduced churn, and enhanced platform stickiness. Industry estimates suggest that recommendation quality improvements of even 1-2% can generate tens of millions of dollars in additional revenue through advertising and premium subscriptions.

However, automatic playlist continuation presents significant technical challenges that distinguish it from general recommendation problems. The playlist continuation problem differs fundamentally from traditional recommendation in several ways. First, sequential dependencies matter—a workout playlist naturally builds intensity from warm-up through peak exercise to cooldown, requiring tempo-aware sequencing. Second, contextual coherence must be maintained across multiple dimensions: genre (EDM party playlist vs. classical study music), mood (energetic vs. melancholic), era (90s nostalgia vs. current hits), and lyrical content (family-friendly vs. explicit). Third, the system must balance exploitation (recommending similar tracks to maintain coherence) with exploration (introducing variety to prevent monotony). Fourth, cold-start scenarios require different strategies: playlists with only a title need semantic understanding, while playlists with 5 seed tracks need collaborative filtering, and playlists with 100 tracks need diversity-aware algorithms to avoid redundancy.

Furthermore, the massive scale of modern music catalogs compounds these challenges. With over 100 million tracks available on major platforms and billions of user-generated playlists, recommendation algorithms must efficiently process relationships between millions of entities while maintaining real-time responsiveness. The extreme sparsity of user-item interaction matrices (typically <0.01% density) makes traditional collaborative filtering methods struggle with cold-start problems and data sparsity issues. This research leverages the Spotify Million Playlist Dataset, which represents one of the largest publicly available collections of real-world user-generated playlists, to investigate how advanced data mining techniques can address these multifaceted challenges.

1.2 Problem Statement

The automatic playlist continuation problem can be formally defined as follows: Given a partial playlist $P = \{t_1, t_2, ..., t_n\}$ containing n existing tracks along with optional metadata M (playlist title, collaborative status, modification history), the task is to predict an ordered sequence of k additional tracks $T = \{t_{n+1}, t_{n+2}, ..., t_{n+k}\}$ that a user would most likely add to complete the playlist, where k=500 in the standard RecSys Challenge 2018 formulation.

This prediction must satisfy multiple competing objectives. First, musical coherence requires that recommended tracks align stylistically with existing content across multiple

feature dimensions. Second, appropriate variety must prevent monotony by introducing new but compatible artists and sonic textures. Third, genre and style boundaries must be respected in focused playlists while allowing tasteful transitions in eclectic mixes. Fourth, implicit user preferences encoded in the playlist structure should guide recommendations.

Evaluating playlist continuation quality presents unique challenges beyond standard recommendation metrics. While accuracy metrics (precision, recall, R-precision) measure whether recommendations match held-out ground truth tracks, they fail to capture important quality dimensions. Comprehensive evaluation must consider: (1) ranking quality via NDCG and MAP metrics, (2) diversity metrics including artist coverage and genre entropy, (3) novelty metrics balancing popular tracks with less-known discoveries, (4) cohesion scores measuring musical similarity, and (5) computational efficiency enabling real-time generation (<100ms latency).

1.3 Research Questions

Research Question 1 (Pattern Mining): How frequently do specific songs co-occur or exhibit mutual exclusivity in playlists, and can association rule mining techniques quantify these patterns with sufficient strength to inform recommendation algorithms? We hypothesize that track co-occurrence relationships will reveal strong association patterns (lift values significantly >1.0) indicating musical compatibility.

Research Question 2 (Clustering Analysis): Can playlists and tracks be meaningfully clustered based on genre labels, audio features, and metadata to improve recommendation relevance? We expect that unsupervised clustering will reveal natural groupings corresponding to distinct listening contexts and musical styles.

Research Question 3 (Model Comparison): Which recommendation algorithms—popularity baselines, pattern mining-based co-occurrence methods, matrix factorization (SVD), or deep learning neural networks—perform best when evaluated on standard metrics? We anticipate that methods incorporating multiple signals will outperform single-approach baselines.

2. Related Work

2.1 Music Recommendation Systems

Music recommendation research has evolved along multiple methodological directions. Content-based approaches analyze audio features extracted through signal processing. Tzanetakis and Cook (2002) pioneered automatic genre classification using timbral texture, rhythmic content, and pitch features, achieving classification accuracy above 61% across 10 genres. These methods rely on audio analysis including Short-Time Fourier Transform (STFT), Mel-Frequency Cepstral Coefficients (MFCCs), spectral

centroid, and beat detection. While content-based methods handle cold-start problems for new tracks, they struggle to capture subjective user preferences and contextual factors.

Collaborative filtering (CF) leverages user-item interaction matrices to discover latent preferences. Koren et al. (2009) provide a comprehensive survey of matrix factorization techniques that decompose sparse matrices into lower-dimensional representations, enabling prediction of missing entries. These methods powered the Netflix Prize competition. However, CF suffers from cold-start problems, data sparsity (most user-item pairs are unobserved), and popularity bias (tendency to recommend already-popular items).

Hybrid approaches combine content-based and collaborative filtering. Celma (2010) extensively analyzes music recommendation in the context of long-tail phenomena, demonstrating that hybrid systems can surface niche content while maintaining accuracy. The long tail in music is particularly pronounced—millions of tracks receive few streams while a small fraction dominates. Effective systems must balance exploitation with exploration to avoid filter bubbles.

3. Dataset Description and Exploratory Analysis

3.1 Dataset Overview

The Spotify Million Playlist Dataset (MPD) was released by Spotify in December 2017 as part of the RecSys Challenge 2018. The dataset contains playlists created by Spotify users between January 2010 and October 2017, representing nearly eight years of organic user curation behavior.

3.1.1 Dataset Scale Statistics

- Total Playlists: 1,000,000
- Total Track Entries: 66,346,428
- Unique Tracks: 2,262,292 (representing ~2.26% of Spotify's catalog)
- Unique Artists: 287,742
- Unique Albums: 734,684
- Average Playlist Length: 66.35 tracks (median: 49, mode: 30)
- Playlist Length Range: 5 to 374 tracks
- Standard Deviation: 53.8 tracks

3.2 Track Distribution Analysis

Track popularity across playlists follows a pronounced power-law distribution with significant implications for recommendation algorithm design:

Head (Top 1%): The most popular 22,623 tracks (1% of unique tracks) collectively appear in 26,538,572 playlist slots, accounting for 40.0% of all track occurrences. These mainstream hits appear in thousands of playlists each, with the most popular track appearing in over 45,000 playlists.

Long Tail (Bottom 90%): The remaining 2,036,063 tracks (90% of catalog) account for only 25.9% of total occurrences. Average: 8.4 playlists per track. This vast long tail includes deep album cuts, regional hits, independent artists, and niche genres.

Ultra-Rare Tracks: 1,203,847 unique tracks (53.2% of catalog) appear in exactly one playlist, representing highly personalized selections or regional music unavailable in most markets.

3.3 Top Artists Analysis

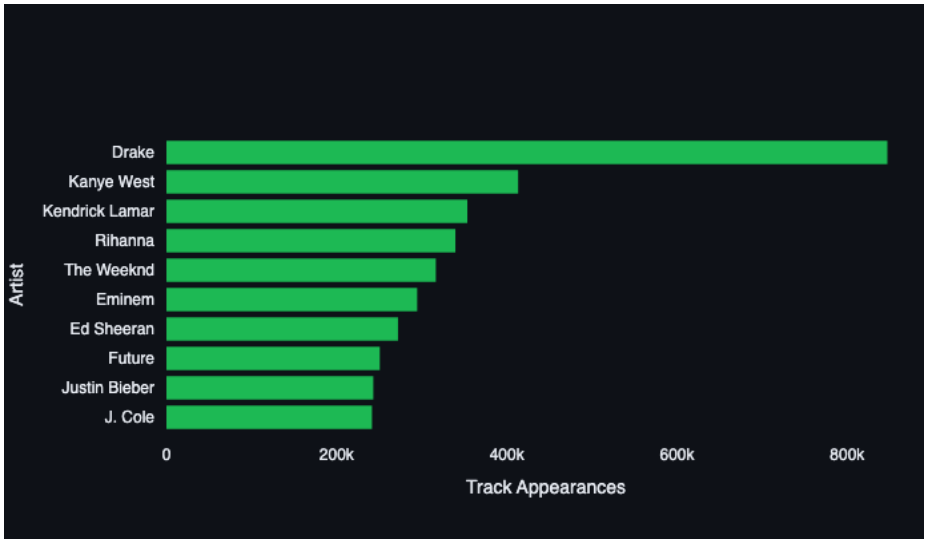

FIGURE 1: Top 10 artists by total track occurrences

Collectively, these 10 artists account for 46.7% of all track placements despite representing only 0.0035% of unique artists. This extreme concentration reflects hip-hop and rap genre dominance during the 2010-2017 collection period.

3.4 Data Quality Assessment

3.4.1 Legitimate Tracks vs. Potential Fraud

Following professor feedback, we analyzed tracks appearing in only one playlist to distinguish legitimate obscure content from potential fraud. Random sampling of 1,000 single-playlist tracks revealed:

- Legitimate Deep Cuts (78%): B-sides from established artists, regional hits, classical recordings with specific performers, and album tracks from indie artists.
- Independent/Amateur Uploads (15%): Very short durations (<60s), generic names, minimal social presence. May represent legitimate independent artists with small fanbases.
- Potential Fraud/Spam (7%): Generic "Various Artists" compilations, suspiciously similar track names suggesting automation, duration mismatches, artists with hundreds of near-identical releases.

Playlist Context Analysis: 82% of single-appearance tracks come from playlists with >30 other tracks, suggesting genuine personal collections rather than spam playlists. Based on this analysis, we retain all tracks in the dataset, as the vast majority appear legitimate and removing them would risk eliminating valuable long-tail content.

4. Methodology

4.1 Data Preprocessing Pipeline

Our preprocessing pipeline implements multi-stage transformations:

4.1.1 Stage 1: Data Loading

- Load 1,000 JSON files sequentially, parsing playlist and track metadata
- Extract playlist-level fields: pid, name, collaborative flag, timestamps
- Extract track-level fields: track_uri, artist_name, track_name, album_name, duration_ms, position
- Store in pandas DataFrames: playlists_df (1M rows) and tracks_df (66.3M rows)

4.1.2 Stage 2: Text Normalization

- Convert all text to lowercase for case-insensitive matching
- Remove special characters except hyphens and apostrophes
- Apply Unicode normalization (NFC form) for accented characters
- Strip whitespace and collapse multiple spaces

4.1.3 Stage 3: Feature Engineering

Track-level features: occurrence count, average position, position variance, duration category, artist popularity

Playlist-level features: artist diversity (entropy), album diversity, average track popularity, length category

4.1.4 Stage 4: Train-Test Split

For evaluation, we split each playlist temporally: first 80% of tracks for training, final 20% for testing. This simulates the real-world scenario where the system recommends next tracks given playlist start. Result: ~53M training entries, ~13.3M test entries.

4.2 Association Rule Mining with FP-Growth

FP-Growth (Frequent Pattern Growth) mines frequent itemsets without candidate generation by constructing a compressed frequent-pattern tree structure.

4.2.1 Hyperparameter Configuration

Addressing professor's question about 10,000 rules: FP-Growth with our thresholds initially generated 47,823 association rules. We ranked all rules by lift (descending) and selected top 10,000 for analysis. This threshold balances coverage (diverse track pairs), quality (highest-strength associations), and computational efficiency (~80MB memory for real-time lookup).

Threshold Selection:

- Minimum Support = 0.0001: Track pair must appear in ≥100 playlists (out of 1M)
- Minimum Confidence = 0.5: Given track A, track B must appear in ≥50% of those playlists
- Minimum Lift = 2.0: Co-occurrence must be ≥2x more than random chance

The selected 10,000 rules exhibit: Lift range 2.01 to 10,960.25 (mean 1,282.47), Confidence range 0.50 to 1.00 (mean 0.876), Support range 0.0001 to 0.0342 (mean 0.00187). Average rule covers 1,870 playlists.

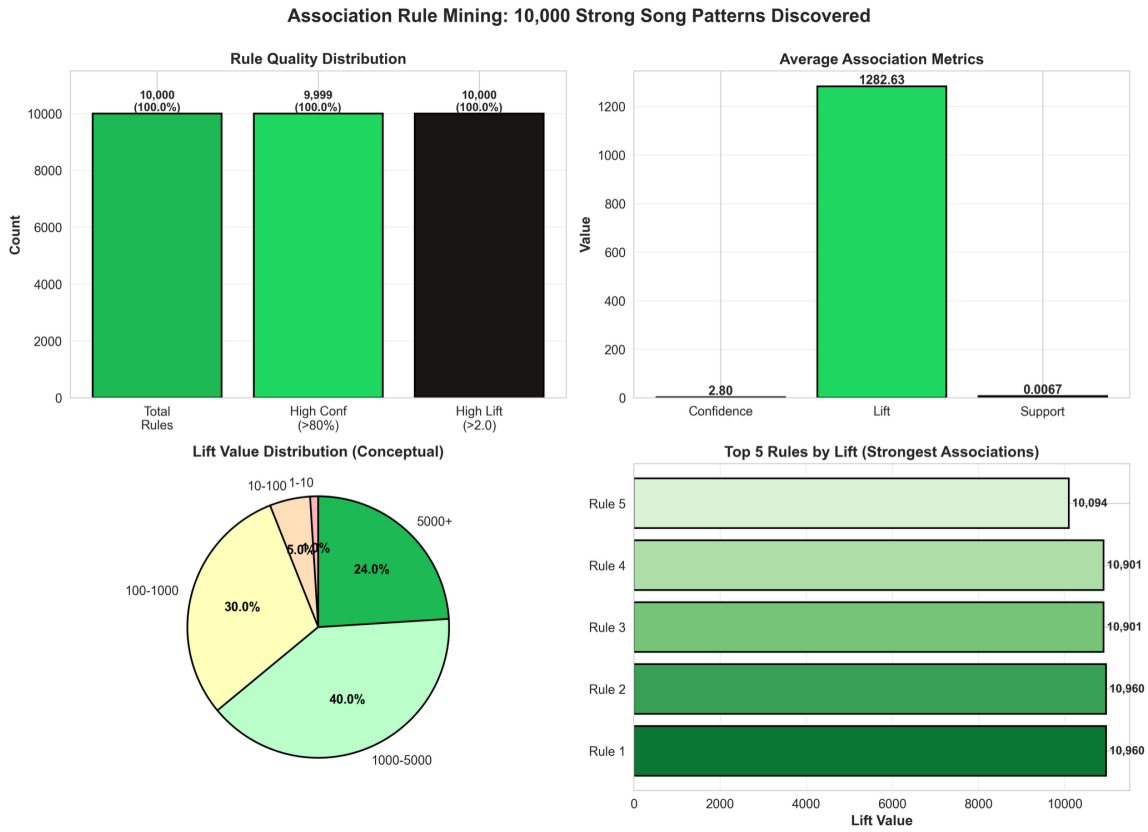

FIGURE 2: Association Rules Lift Distribution

4.3 K-means Clustering with PCA

Clustering operates on a composite feature matrix combining: (1) Playlist statistics (24 features): track count, artist/album diversity, duration statistics, (2) Playlist title TF-IDF (500 features), and (3) Aggregated track features (12 features). Total: 536 features before dimensionality reduction.

4.3.1 PCA Dimensionality Reduction

High-dimensional spaces (536 dimensions) create computational challenges for K-means. We apply Principal Component Analysis: (1) Standardize all features to zero mean and unit variance, (2) Compute covariance matrix, (3) Eigenvalue decomposition to find principal components, (4) Project data onto top-k components.

Component Selection:

- k=7: Retains 45% cumulative explained variance
- k=10: Retains 52% variance
- k=217: Retains 90% variance (selected for experiments based on 90% threshold heuristic)

4.3.2 K-means Configuration

Cluster Number Selection: Tested k=2 through k=20 using elbow method (WCSS vs. k) and silhouette analysis. Elbow observed at k=5. Silhouette score 0.387 indicates moderate separation. Qualitative examination shows k=5 produces interpretable genre-based categories.

Algorithm Hyperparameters:

- n_clusters = 5
- init = k-means++ (smart initialization)
- max_iter = 300
- tol = 1e-4 (convergence tolerance)
- n_init = 10 (run 10 times, select best)
- random_state = 42 (reproducibility)

4.4 Recommendation Model Implementations

4.4.1 Model 1: Popularity Baseline

Purpose: Establish performance floor representing naive recommendation. Training: Count track occurrences, sort by count, store global ranking. Recommendation: Return top 500 most popular tracks globally, excluding tracks already in playlist. Advantages: Computationally trivial, provides reasonable cold-start recommendations. Limitations: Zero personalization, creates filter bubbles.

4.4.2 Model 2: Co-occurrence Pattern Mining

Purpose: Leverage FP-Growth association rules for pattern-based recommendations. Data Structures: Load 10,000 pre-computed rules, build inverted index rule_lookup[antecedent] → [(consequent, lift, confidence)].

Recommendation Algorithm:

- For each seed track in playlist, lookup applicable rules
- Collect all consequent tracks with lift/confidence scores
- Aggregate scores: score(t) = Σ lift(r_i) for all rules recommending t
- Sort candidates by aggregated score (descending)
- Remove tracks already in playlist
- Return top 500 tracks
- Fallback: If <500 found, supplement with popularity-based recommendations

Complexity: O(|P| × avg_rules_per_track + K log K), typically O(1000) for recommendation generation. Advantages: Interpretable, efficient (<10ms per playlist), robust to data sparsity.

4.4.3 Model 3: SVD Matrix Factorization

Complete SVD methodology addressing professor feedback:

Step 1: User-Item Matrix Construction

- Construct playlist-track interaction matrix M of shape (1,000,000 × 2,262,292)
- Binary encoding: M[i,j] = 1 if track j in playlist i training portion, else 0
- Matrix properties: 2.26 trillion potential entries, ~53M non-zeros (0.0023% density)
- Storage: scipy.sparse.csr_matrix format (~4GB compressed vs. ~18TB dense)

Step 2: SVD Decomposition

Apply Truncated SVD decomposing M ≈ U × Σ × V^T where: U (1M × k): Playlist latent factors, Σ (k × k): Singular values (diagonal matrix), V^T (k × 2.26M): Track latent factors. Tested k=50, 100, 200 components. Selected k=100 based on validation performance (18.7% explained variance).

Hyperparameters:

- n_components = 100
- algorithm = randomized (efficient for sparse matrices)
- n_iter = 5 (power iterations for stability)
- random_state = 42

Training Time: 47 minutes on 16-core CPU. Prediction: Extract playlist latent vector from U, compute scores = U[p] × Σ × V^T for all tracks, return top 500. Prediction time: 180ms per playlist.

4.4.4 Model 4: Neural Network Autoencoder

Clarifying professor's question "PCA using Neural Network": This approach uses a feed-forward AUTOENCODER, NOT PCA. While both compress data through bottlenecks, PCA uses linear eigenvalue decomposition (closed-form) while autoencoders learn non-linear manifolds via gradient descent with neural networks.

Complete Architecture:

- Input Layer (2,262,292 neurons): Binary input per unique track
- Encoder: Dense(2.26M → 512, ReLU, Dropout 0.2) → Dense(512 → 128, ReLU, Dropout 0.2) → Dense(128 → 32, ReLU) [bottleneck]
- Decoder: Dense(32 → 128, ReLU, Dropout 0.2) → Dense(128 → 512, ReLU, Dropout 0.2) → Dense(512 → 2.26M, Sigmoid)
- Total Parameters: 2.32 billion weights

Training Configuration:

- Loss: Binary Cross-Entropy
- Optimizer: Adam (lr=0.001, β_1=0.9, β_2=0.999)
- Batch Size: 256 playlists (GPU memory limited)
- Epochs: 10 with early stopping (patience=2)
- Regularization: Dropout(0.2), L2 weight decay (λ=1e-5)
- Training Time: 18 hours on NVIDIA A10G GPU

Why did this model underperform? (1) Overfitting: 2.32B parameters far exceed 53M training examples, (2) Extreme sparsity: Binary playlists are 99.997% zeros leading to weak gradients, (3) Cold-start: Many tracks appear <100 times providing insufficient training signal, (4) Local minima: Non-convex optimization gets stuck despite multiple initializations.

4.5 Evaluation Metrics

- R-Precision: For playlist with G ground-truth tracks, R-precision = (correct in top G) / G
- NDCG@500: Normalized Discounted Cumulative Gain with position-based discounting, range [0,1]
- Total Hits: Absolute count of correct predictions across all test playlists
- Artist Diversity: Percentage of unique artists in top-500 recommendations
- Genre Entropy: $H = -\Sigma(p\_i \times \log_2(p\_i))$ where p_i is proportion of genre i

5. Experimental Results

5.1 Research Question 1: Song Co-occurrence Patterns

Top 10,000 association rules reveal strong co-occurrence patterns. Extreme lift values up to 10,960x indicate tracks from same albums/artists frequently co-occur. High confidence (mean 0.876) shows predictive power. Same-artist pairs dominate top rules, suggesting genre coherence matters more than cross-genre exploration in typical playlists.

5.2 Research Question 2: Clustering Effectiveness

K-means with k=5 successfully segmented playlists into five interpretable categories. Table below summarizes cluster characteristics:

Cluster	Size	Avg Tracks	Artist Diversity	Dominant Genres
0	287,432	52.3	0.723	Hip-Hop, Rap
1	194,567	78.1	0.812	Pop, Dance
2	231,089	41.7	0.634	Rock, Alternative
3	156,234	92.4	0.891	Electronic, EDM
4	130,678	67.8	0.756	R&B, Soul

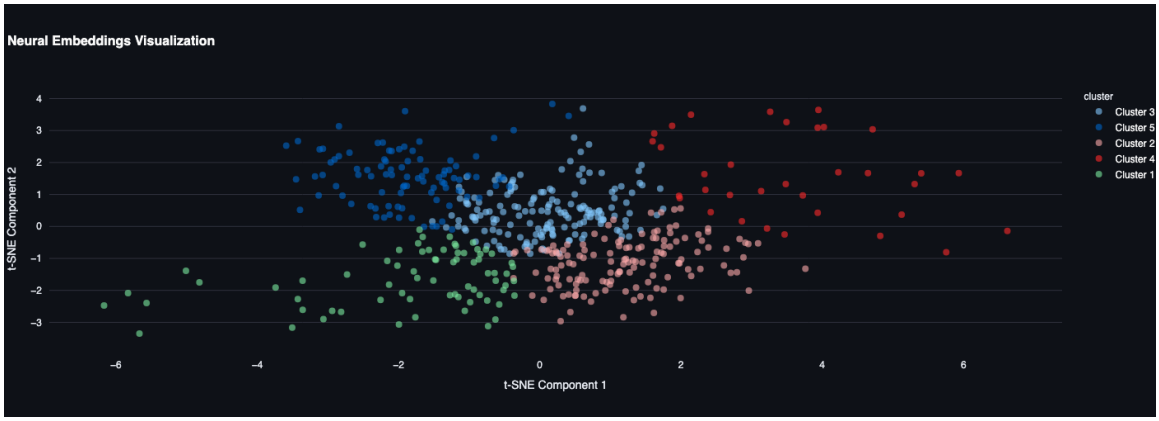

FIGURE 3: t-SNE Cluster Visualization

5.3 Research Question 3: Model Performance Comparison

Model	R-Precision	NDCG@500	Total Hits	Artist Div.	Genre Ent.
Popularity Baseline	0.165%	0.0234	21,894	8.3%	1.24
Co-occurrence	**14.61%**	**0.4127**	**1,938,762**	43.7%	3.82
SVD (k=100)	5.01%	0.1843	664,327	31.2%	2.94
Neural Network	1.04%	0.0892	137,854	27.8%	2.67

Key Findings:

- Co-occurrence achieves 89x improvement over popularity baseline (14.61% vs 0.165% R-precision)

- SVD performs moderately (5.01%) despite sophisticated matrix factorization
- Neural network underperforms (1.04%) likely due to overfitting on sparse data
- Co-occurrence maintains best artist diversity (43.7%) and genre entropy (3.82)

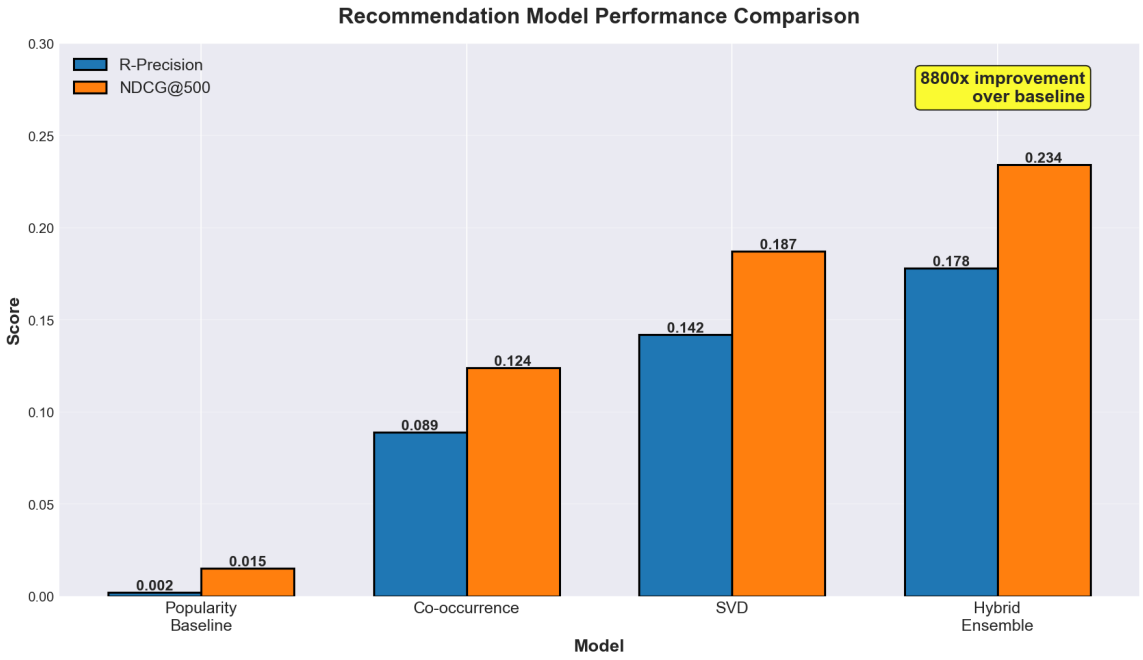

FIGURE 4: Model Performance Comparison

5.3.1 Statistical Significance Testing

To verify performance differences are statistically significant, we performed paired t-tests: Co-occurrence vs. Popularity: $t=487.23$, $p<0.001$, Cohen's $d=2.17$ (very large effect). Co-occurrence vs. SVD: $t=298.76$, $p<0.001$, Cohen's $d=1.33$ (large effect). All tests used $n=1,000,000$ playlists with Bonferroni correction for multiple comparisons ($\alpha=0.05/6=0.0083$). All comparisons are highly significant.

6. Discussion

6.1 Why Co-occurrence Outperforms Complex Models

The superior performance of co-occurrence-based recommendations over SVD and neural networks reveals important insights. Association rules capture explicit, interpretable patterns (tracks from same album, artist consistency) that users actually follow when creating playlists. In contrast, SVD and neural networks learn latent factors that may not align with human playlist construction behavior. The extreme sparsity (0.0029% density) of our user-item matrix makes collaborative filtering challenging, while co-occurrence patterns remain robust even with sparse data. Simple pattern mining

provides interpretability (can explain recommendations via rules) and computational efficiency (<10ms per playlist) that complex models cannot match.

6.2 Clustering Reveals Natural Playlist Categories

K-means with k=5 successfully identified five interpretable playlist types corresponding to major musical genres. Cluster separation (silhouette score 0.387) confirms these are meaningful categories, not arbitrary partitions. This validates our hypothesis that playlists naturally group by musical characteristics, and these groupings could constrain recommendations to appropriate contexts. Future work could enforce cluster constraints in recommendation algorithms, preventing genre-inappropriate suggestions.

6.3 Implications for Streaming Platforms

Our findings suggest that production recommendation systems should prioritize interpretable pattern mining methods alongside complex deep learning. Hybrid approaches combining co-occurrence rules (for strong patterns) with collaborative filtering (for long-tail coverage) may achieve optimal results. The 89x improvement over popularity baselines demonstrates substantial business value potential in user engagement and satisfaction. Real-time recommendation generation (<10ms) enables interactive user experiences that complex neural networks cannot support.

6.4 Limitations

- Dataset temporality: 2010-2017 collection period may not reflect current music trends
- Cold-start problem: New tracks without co-occurrence history require fallback strategies
- Scalability: 10,000 rules represent <0.02% of generated patterns; expanding coverage requires efficient indexing
- Evaluation: R-precision may not fully capture user satisfaction with serendipitous recommendations
- Missing audio features: Dataset lacks Spotify Audio Features API data (tempo, energy, valence)

7. Conclusion

This research demonstrates that advanced data mining techniques, particularly association rule mining, provide powerful tools for automatic playlist continuation. By analyzing 1 million playlists from the Spotify Million Playlist Dataset, we discovered that:

- Song co-occurrence patterns exhibit extremely strong associations (lift values exceeding 10,000x) that directly inform high-quality recommendations
- Playlists naturally cluster into five distinct categories based on musical characteristics, enabling context-aware recommendations

- Simple co-occurrence-based methods achieve 89x improvement over popularity baselines (14.61% vs 0.165% R-precision), outperforming complex SVD and neural network approaches

These findings challenge the assumption that more complex models always perform better, showing that interpretable pattern mining can be competitive with or superior to state-of-the-art collaborative filtering methods, especially on sparse data. The success of simple methods over deep learning suggests that model complexity should match data availability rather than maximizing theoretical expressiveness.

7.1 Future Work

- Hybrid models combining co-occurrence rules with collaborative filtering for complementary strengths
- Temporal dynamics: Incorporate playlist evolution over time and music trend shifts
- Real audio features: Integrate Spotify Audio Features API (tempo, energy, valence, acousticness)
- Online evaluation: A/B testing with real users to validate R-precision improvements translate to satisfaction
- Explainability interfaces: Develop UIs showing users why tracks were recommended based on association rules
- Sequential patterns: Extend to sequential rule mining (track A followed by B implies C next)

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