Hybrid Graph-Based Content Filtering for Enhanced Music Recommendation

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1 Introduction

The vast amount of music available today presents both an opportunity and a challenge for listeners. With millions of songs spanning different genres, styles, and cultures, discovering new music can be an overwhelming task. In response, platforms like Spotify and Apple Music use personalized recommendation systems that analyze listening history to suggest songs tailored to individual preferences, ensuring users remain engaged with their services. However, personalization comes with a drawback; it creates filter bubbles, environments in which users are repeatedly exposed to familiar and similar content, limiting their opportunity to explore new and diverse music Pariser [2011]. While these bubbles help maintain engagement, they also prevent users from encountering fresh perspectives, artists, and genres that might otherwise enrich their musical experience. This narrowing of recommendations can reduce discovery and, over time, make listening habits more stagnant.

Research suggests that users actually benefit from increased diversity in recommendations. A study on choice overload in recommender systems found that introducing diversity, even at the cost of strict accuracy, can enhance user satisfaction Bollen et al. [2010]. Listeners appreciate variety in their playlists, and providing a balanced mix of familiar and novel songs can make the recommendation experience more enjoyable. Further research has shown that users engage more deeply with music recommendations when smooth transitions guide them toward serendipitous discoveries. In particular, curated transition playlists that blend known preferences with unexpected tracks have been found to promote engagement and satisfaction Taramigkou et al. [2013].

Given the widespread use of recommendation systems and the growing preference for more diverse music suggestions, there is a need for a system that encourages exploration by providing relevant and diverse recommendations.

2 Background and Related Work

Recommender systems are primarily categorized into content-based filtering (CBF) and collaborative filtering (CF). In music recommendations, CBF analyzes audio features like tempo and danceability to suggest songs similar to a user's history Jacob Murel [2023]. While effective for personalization, CBF often confines users to a "genre bubble" with limited exposure to new music Roy and Dutta [2022]. Since similar features are common within genres, CBF lacks genre diversity.

To address this, CF was introduced, leveraging user behavior patterns instead of song features Jacob Murel [2023]. Collaborative filtering recommends items based on the preferences of similar users, promoting novelty when those users have diverse tastes. However, CF encounters the cold-start problem, making it difficult to make personalized recommendations for new users that lack sufficient data. It also often reinforces familiar patterns, especially when popular songs dominate suggestions, making it harder for lesser-known genres to gain visibility Roy and Dutta [2022], Areeb et al. [2023]. Both CBF and CF, therefore, struggle with filter bubbles that limit exposure to diverse content.

For instance, a user primarily listening to hip-hop may only receive hip-hop recommendations, missing related genres like funk or rap Areeb et al. [2023]. User confirmation bias further deepens this cycle Areeb et al. [2023]. Hybrid models, combining CBF, CF, and knowledge graphs, have emerged to enhance diversity. Notably, EARS (Embedding-based Artist Recommender System) utilizes knowledge graph embeddings to capture relationships between artists and genres, improving recommendation diversity Bertram et al. [2023]. While hybrid models improve diversity, they still struggle with nuanced genre relationships. Interestingly, Bertham et al.'s hybrid model showed significantly better diversity performance than a baseline collaborative filtering model when adding domain-specific knowledge as well (2023). This highlights the need for a domain-specific model that can leverage detailed, genre-specific characteristics to enhance recommendations. A domain-specific knowledge graph structures interconnected entities, representing genres as nodes with links based on historical or stylistic influences. Incorporating expert-defined relationships provides meaningful insights beyond basic data patterns Geuens [2024].

Instead of incorporating collaborative filtering in a hybrid model like in EARS, content-based filtering could be considered as a better base model since it reduces popular song repetitions and, therefore, the bubble filter effect. CBF, despite its advantages, faces scalability challenges due to high computational complexity. Filtering approaches are classified as memory-based or model-based Roy and Dutta [2022]. Memory-based methods store user-item interactions but require costly recomputation. Model-based methods, such as clustering, improve scalability by pre-training models for efficient recommendations.

Clustering algorithms iteratively refine cluster assignments and can be optimized by reducing iterations, leveraging random sampling, or distributing computation Tong Hanghang [2023]. Scalable approaches include BIRCH, which reduces input data to subclusters Zhang et al. [1996], and Mini Batch K-Means, which updates centroids using random samples Sculley [2010]. Clustering effectiveness depends on feature quality, as poor input leads to weak recommendations Peng [2023]. Prior research has used an "edge factor" to identify redundancy in clustering models, helping refine diversity in music recommendations Peng [2023].

3 Methods

3.1 Overview

We propose Hybrid Graph-Based Content Filtering (HyG-Con), a music recommendation system that combines content-based filtering (CBF) with a domain-specific knowledge graph to achieve both song relevance and genre diversity. This approach retains the strengths of CBF in tailoring recommendations based on song attributes for similar song selection, as well as leverages the intricate relationships modeled by a knowledge graph to facilitate cross-genre exploration. By integrating these methods, HyG-Con ensures that recommendations are novel but appropriate, effectively reducing filter bubble effects and enhancing the overall discovery experience.

3.2 Data Collection

We utilize two datasets for our analysis: the Spotify Tracks Dataset (Pandya [2023]) and MusicMap (Crauwels [2022]).

The Spotify Tracks Dataset, hosted on Hugging Face, contains 114,000 tracks across 125 genres. Collected via Spotify's Web API and Python, it includes audio features (e.g., danceability, energy, tempo) and metadata (e.g., track name, artist, genre, popularity). We preprocessed the data by removing duplicate tracks, handling null values through imputation or removal, and filtering out tracks with missing key metrics. Genre labels were standardized by trimming spaces, and language-based genres (e.g., "turkish") were excluded to focus on audio-feature-driven genres. Boolean features (e.g., explicit content) were converted to integers (0 or 1), and numeric features (e.g., tempo, loudness) were scaled to a 0–1 range for uniformity. A correlation heatmap (See Appendix Section E) revealed no highly confounding variables requiring removal. See Appendix Section D for more details on data processing.

We build a domain-specific knowledge graph that models genre relationships using historical data from MusicMap (Crauwels [2022]), a resource created by Kwinten Crauwels, a domain expert, in 2023. MusicMap is a comprehensive research project that traces the genealogy of popular music genres, mapping their historical evolution and interconnections. Developed over seven years with insights from over 200 sources, MusicMap systematically examines how genres have influenced each other over time, ultimately shaping the modern-day genres we have today. We limited the connections we incorporated from MusicMap to match the genres we had available in the Spotify Tracks Dataset and some linkages that produced jarring results such as from Pop to Comedy.

3.3 Implementation

3.3.1 Content-Based Filtering

The first component of our system is a content-based filtering (CBF) model, which serves as our baseline approach for music recommendation. This model recommends songs based on the similarity of audio features, ensuring that suggested tracks share key musical characteristics with a given seed song. Each song is represented as a feature vector, incorporating relevant attributes such as danceability, tempo, energy, key, loudness, and mode.

To efficiently categorize and retrieve similar songs, we employ Mini Batch K-Means Clustering, a model-based approach that efficiently compares feature vectors. We optimize our clustering approach to balance distinctiveness and coverage, ensuring that similar songs are grouped while maintaining diversity across the feature space. To achieve this, we create 500 clusters from our dataset of 104,000 songs, with each cluster containing between 50 and 500 songs. Each cluster is designed to have a minimum of 20 songs, allowing meaningful sampling without needing to traverse multiple clusters. Once the clusters are formed, their centroid feature vectors are used to compare against a seed song's feature vector to identify the most similar cluster. A song is then randomly sampled from that cluster as the recommendation.

In the baseline model, we generate recommendations by sampling 15 songs from the nearest cluster. Alternatively, because this creates cases where a single cluster fails to generate a playlist due to size constraints, we create a stochastic model. In the stochastic model, there is a probability that a random cluster from a set of nearby clusters is selected while sampling 15 songs iteratively from the nearest clusters. Although both of these methods of sampling ensure strong musical relevance, they tend to favor songs from the same genre, limiting diversity.

For example, in Figure 1, given a seed song (e.g., Consideration by Rihanna, R&B genre), we extract its song features and determine the distance between its feature vector and all other centroid feature vectors. Once we find the nearest cluster centroid, we select that cluster and randomly sample a song (e.g., Snooze by SZA, R&B genre). In this example, the recommended song belongs to the same genre as the seed song (R&B). While cross-genre recommendations can occur when songs with similar features cluster together, most songs within a cluster tend to share the same genre due to the natural correlation between musical attributes and genre classification.

3.3.2 Domain-Specific Knowledge Graph

To increase genre diversity, we introduce a domain-specific knowledge graph that leverages historical and semantic relationships between genres to promote seamless genre transitions. In this approach, genres are represented as nodes and edges define the semantic relationships between them. Since each song is labeled with a specific genre, our model can identify its transition genre by traversing the graph. This structure enables the recommendation system to guide users toward new yet related genres, ensuring smooth transitions, such as shifting from R&B to rap.

Our knowledge graph is built using a manually encoded dataset of genres, aligned with Music Map, an expert-curated genre genealogy. This ensures that the genre relationships are structured based on historical evolution and musical similarities. The construction process involved:

1. Grouping 110 genres into their parent genres based on the simplified Music Map model (See Appendix Section A).

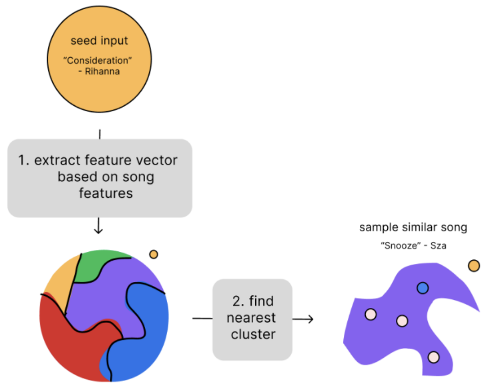

Figure 1: Content-Based Filtering Baseline

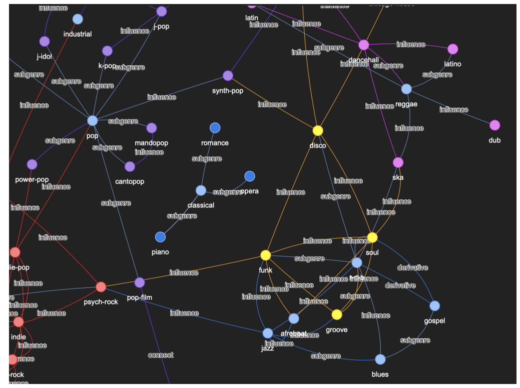

Figure 2: Subset of Knowledge Graph

2. Mapping connections between parent genres to establish broad relationships.
3. Manually identifying key subgenre connections using an interactive genre map that highlights the most significant relationships and descriptions of how genres influence each other.
4. Constructing a complex network of genre transitions by including the most relevant connections between all remaining subgenres.

See Figure 2 for a subset of the constructed knowledge graph. See Appendix Section B for a visualization of the entire knowledge graph.

To determine genre transitions dynamically, we employ graph traversal techniques within our domain-specific knowledge graph. For a given song, we compute the shortest paths from its genre to all others in the graph, identifying potential transitions that maintain musical relevance. Rather than selecting a new genre arbitrarily, we apply a weighted probability to prioritize shorter paths, ensuring that less common paths with fewer connections are not overpowered. Additionally, a distance penalty is introduced, reducing the likelihood of selecting genres that are too far from the original starting genre, which helps preserve coherence in recommendations. See Appendix Section C for the algorithm in depth.

Using this approach, the system randomly selects the next genre based on computed probabilities, allowing for a balance between familiarity and discovery.

3.3.3 Hybrid Model

The Hybrid Model follows the same procedure as the content-based filtering baseline model, but incorporates an additional selection filter influenced by the knowledge graph during the sampling process. The process starts with a seed song (e.g., Consideration by Rihanna), and follows a series of steps to ensure that the final set of recommendations provides both familiarity and variety.

First, the genre of the seed song (e.g., R&B) is identified and mapped into the knowledge graph. The graph then determines a transition genre (e.g., rap), which is stored for the next sampling step (Figure 3). Following the content-based filtering process, the feature vector of the seed song (Consideration by Rihanna) is extracted and compared against cluster centroids. Once the most similar cluster is identified, songs are sampled until a match is found within the transition genre (rap). If no suitable song is found, the system moves to a nearby cluster and repeats the sampling process.

For the next recommendation, the genre transition continues, moving from rap to the next related genre (e.g., hip-hop). The seed song is then compared to all cluster centroids again, and the process repeats (Figure 4). The iterative procedure is conducted 15 times to generate a playlist. This approach ensures that the recommendations are not only relevant to the user's tastes but also diverse, offering a richer and more engaging music discovery experience.

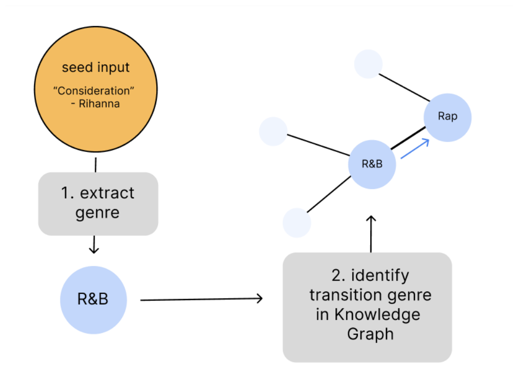

Figure 3: Identifying Transition Genre

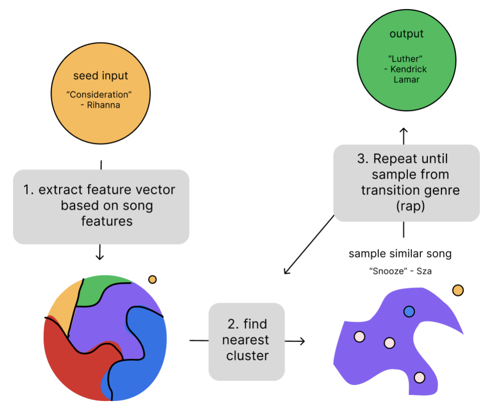

Figure 4: Extracting Genre-Specific Recommendation

4 Experiment

4.1 Quantitative Evaluation

To evaluate the effectiveness of our proposed hybrid recommendation model, HyG-Con, we designed a comparative experiment involving the three different playlist generation strategies:

1. **Content-based filtering baseline**
2. **Stochastic variant**
3. **HyG-Con model**

We used a cleaned and preprocessed dataset of 114,000 Spotify tracks spanning 125 genres, with a few genres removed for being too vague or too diverse. More information about preprocessing is included in Appendix Section D. The manually curated genre genealogy described in our methods was used to construct a knowledge graph that facilitates smooth transitions between genres in a guided manner to avoid erratic genre movements.

All approaches used MiniBatch K-Means clustering (with hyperparameters `max_iter=10, n_init="auto", reassignment_ratio=0.1`) to group songs based on many audio features like tempo, danceability, and acousticness. Each cluster contained 50–500 songs, with a projected total of 500 clusters.

For the hybrid model, HyG-Con, we began with a seed song and selected subsequent songs by traversing the knowledge graph to identify genre transitions. We then sampled songs from the clusters closest to the new genre, allowing for exploratory but coherent cross-genre recommendations.

We generated 30 playlists of 15 songs each for each of the three methods resulting in 90 playlists total. We started each set of playlists (a set of 3 playlists is one playlist for each of our 3 model types) with the same starting song to ensure comparison was not biased by differing initializations.

4.1.1 Evaluation Metrics

All playlists were evaluated using three key metrics:

- **Intra-List Diversity:** Measures dissimilarity between songs in a playlist.
- **Genre Coverage:** Percentage of genres represented in the playlist.
- **Feature Variance Score:** Captures variation in acoustic features across songs.

These metrics were chosen to emphasize diversity and measure how diverse our recommendations are. This is key to evaluating the effectiveness of our approach as we've framed success.

4.2 Qualitative Evaluation

4.2.1 User Interviews

We conducted two structured interviews to evaluate playlists generated using the HyG-Con method. During each session, an interviewee listened to a 16-song playlist, providing individual song ratings, comments, and overall impressions. We documented their feedback by asking them to rate the overall playlist with a numeric score out of 5 and by capturing explicit comments for each song. Afterward, we organized these observations into detailed tables clearly summarizing song-specific reactions and general playlist feedback, enabling systematic analysis of listener preferences and playlist quality.

4.2.2 User Surveys

We generated 4 sets of playlists from each of the three systems and compiled them into playlists. This resulted in 12 playlists total and 3 per rater. Each team member listened to the playlist and rated it based on enjoyability, relevance, diversity, and the proportion of songs they would skip. We then computed average ratings to assess the effectiveness of each recommendation strategy.

5 Results

5.1 Quantitative Performance on Metrics

As seen in Table 1, the HyG-Con strategy achieves the highest intra-list diversity (29.912), significantly outperforming the Baseline (2.899) and Stochastic (3.067) strategies. However, HyG-Con also results in the highest feature variance (56.386), which is undesirable. Additionally, HyG-Con provides slightly better genre coverage (0.062) compared to Baseline (0.052) and Stochastic (0.055), but its genre coverage varies more widely. The Stochastic strategy slightly outperforms the Baseline across all metrics, indicating modest improvements over the initial approach. We visualize these results in Figure 5.

Table 1: Evaluation Metrics for Recommendation Strategies

Strategy	**Metric**	**Average**	**Range (Min - Max)**
Baseline	Intra-list Diversity	2.899	(2.263 - 3.716)
	Feature Variance	0.350	(0.206 - 0.564)
	Genre Coverage	0.052	(0.030 - 0.071)
Stochastic	Intra-list Diversity	3.067	(2.269 - 3.627)
	Feature Variance	0.393	(0.213 - 0.546)
	Genre Coverage	0.055	(0.040 - 0.071)
Genre-guided	Intra-list Diversity	29.912	(11.906 - 43.239)
	Feature Variance	56.386	(7.897 - 120.900)
	Genre Coverage	0.062	(0.020 - 0.101)

5.2 User Interviews

Interview 1: (See Appendix Section F.1.1 for Playlist and Notes)

The participant gives the HyG-Con-generated playlist an overall rating of 1.5 out of 5. The interviewee indicates the playlist starts on a strong note with the opening track, "Who's The Boss" by DJ Sneak, setting high expectations. However, they note the playlist quickly deteriorates due to inconsistent genre choices and abrupt shifts. Specifically, the participant mentions dissatisfaction with ambient movie scores, unrelated instrumental songs, and tracks that do not align with the intended genre. The interviewee explicitly calls some selections "boring," "weird instrumental," or simply inappropriate

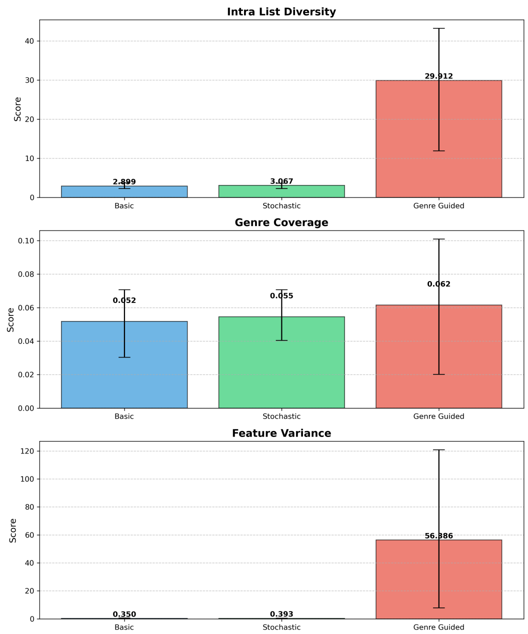

Figure 5: Evaluation Results Visualization

for the intended listening experience, clearly preferring greater consistency and smoother transitions between songs.

Interview 2: (See Appendix Section F.1.2 for Playlist and Notes)

The participant assigns the playlist an overall rating of 2 out of 5. The interviewee appreciates the initial synth-pop and retro tracks, highlighting songs like "Slap & Tickle" by Squeeze and "Left and Right" by Charlie Puth and Jung Kook positively. However, the participant criticizes abrupt transitions between synth-pop, reggaeton, and international tracks, describing the shifts as "too abrupt" and jarring. Although the participant values experiencing various genres, they emphasize the importance of intentional, smoother transitions to improve overall playlist cohesion and listener enjoyment.

5.3 User Surveys

From the survey results, we find that the HyG-Con model performed only slightly better than our baselines. In enjoyment it achieved the highest average score. In terms of relevance, the HyG-Con model had a much higher average score. For diversity, both the Baseline and Stochastic models achieved perfect scores of 5.00, while the HyG-Con model scored slightly lower at 4.50. However, for the proportion of songs skipped, the HyG-Con model had the lowest average skip rate.

Enjoyability Ratings

User	Baseline	Stochastic	HyG-Con
1	3	4	5
2	3	3	4
3	3	3	4
4	3	3	4
Average	3.00	3.25	4.25

Diversity Ratings

User	Baseline	Stochastic	HyG-Con
1	5	5	4
2	5	5	5
3	5	5	4
4	5	5	5
Average	5.00	5.00	4.50

Relevance Ratings

User	Baseline	Stochastic	HyG-Con
1	2	3	5
2	2	2	4
3	2	2	3
4	2	3	3
Average	2.00	2.50	3.75

Proportion of Songs Skipped

User	Baseline	Stochastic	HyG-Con
1	31.25%	18.75%	6.25%
2	31.25%	31.25%	12.5%
3	31.25%	37.5%	18.75%
4	37.5%	31.25%	18.75%
Average	32.81%	29.69%	14.06%

6 Discussion

Our evaluation of the different methods seems to reinforce prior findings. Both the content filtering baseline model and the stochastic baseline model consistently recommended tracks with high acoustic similarity, while the diversity was limited. This is what we expected because it reflects a limited exploratory range, reinforcing the ”genre bubble” problem by recommending songs that are often too similar and confined to the same or adjacent genres.

We also find smoothness in our genre transitions for our hybrid model. Paths generated from this method often started in a given genre (e.g., punk rock) and smoothly moved into related ones (e.g., post-punk, indie rock, garage rock). While genre transitions were semantically meaningful, the model did not account for audio similarity, sometimes producing songs with jarring tempo or mood shifts, which highlights the value of integrating feature similarity for a more balanced and engaging user experience.

Compared to both the baseline and stochastic variants, HyG-Con provided playlists that were both exploratory and musically coherent. We also compared the similarity and diversity between outputs of the CBF model and the hybrid model using both feature-based metrics and human evaluation. The hybrid approach promoted cross-genre discovery without sacrificing listener engagement.

Although our user surveys suggested that the HyG-Con model was an improvement over the Baseline and Stochastic model, supporting what we saw quantitatively, the user interviews were disheartening. The subjects we interviewed were dissatisfied overall with the performance of the recommendation, and it paled in comparison to commercial music recommendation. While we can’t compare our locally trained model to a commercial one, this feedback suggests that our approach doesn’t live up to the expectations that state of the art proprietary models have set for consumers.

Along these lines we find a tradeoff between diversity and variance in playlists generated by HyG-Con when compared to baseline models. When diversity increases, feature variance also increases which increases the likelihood that users will find the differences between songs jarring. We note that there is a balance to strike between diversity and variance that might be best chosen by the listener themselves.

7 Future Work

Future work could incorporate an additional metric to evaluate user satisfaction more comprehensively. While the current metrics provide valuable insights, adding a direct satisfaction metric will allow us to better capture how users feel about the overall playlist experience beyond enjoyability, relevance, and diversity. This addition will help us ensure techniques align more closely with listeners’ preferences.

Future work could also explore the effects of playlist length on the evaluated metrics. By analyzing how varying the number of songs in a playlist impacts enjoyability, relevance, diversity, and the proportion of songs skipped, we can determine its impact on technique evaluation. This could also provide intuition into how playlist size influences user interaction with music recommendation systems in general.

Lastly, the hybrid approach could be extended to make use of a more complex clustering method. Specifically, a system could operate where the knowledge graph traverses different sets of clusters, with each set containing only songs from a specific genre, and uses the hybrid approach to determine the transition genre from the current song. This could help prevent the model from sampling from too dissimilar of clusters if there are none of the desired genre in the nearest few clusters of the baseline clustering.

8 Conclusion

HyG-Con breaks the filter bubble and provides a richer, more engaging music discovery experience by seamlessly transitioning users across genres. Unlike traditional recommendation systems that confine users within familiar genres, we use a knowledge graph to transition between genres and prevent the injection of collaborative bubbles. By generating transition playlists that guide users from one genre to another through meaningful connections, we balance personalization with diversity and ensure that recommendations are relevant and refreshing.

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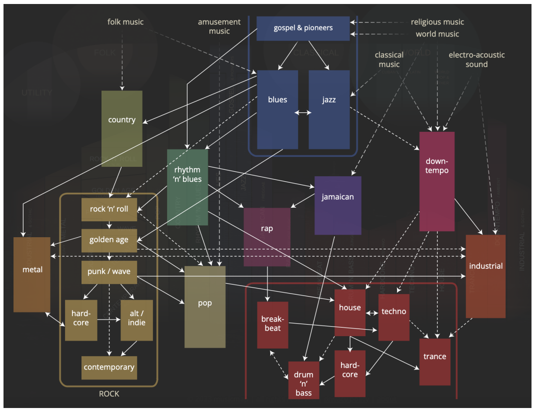
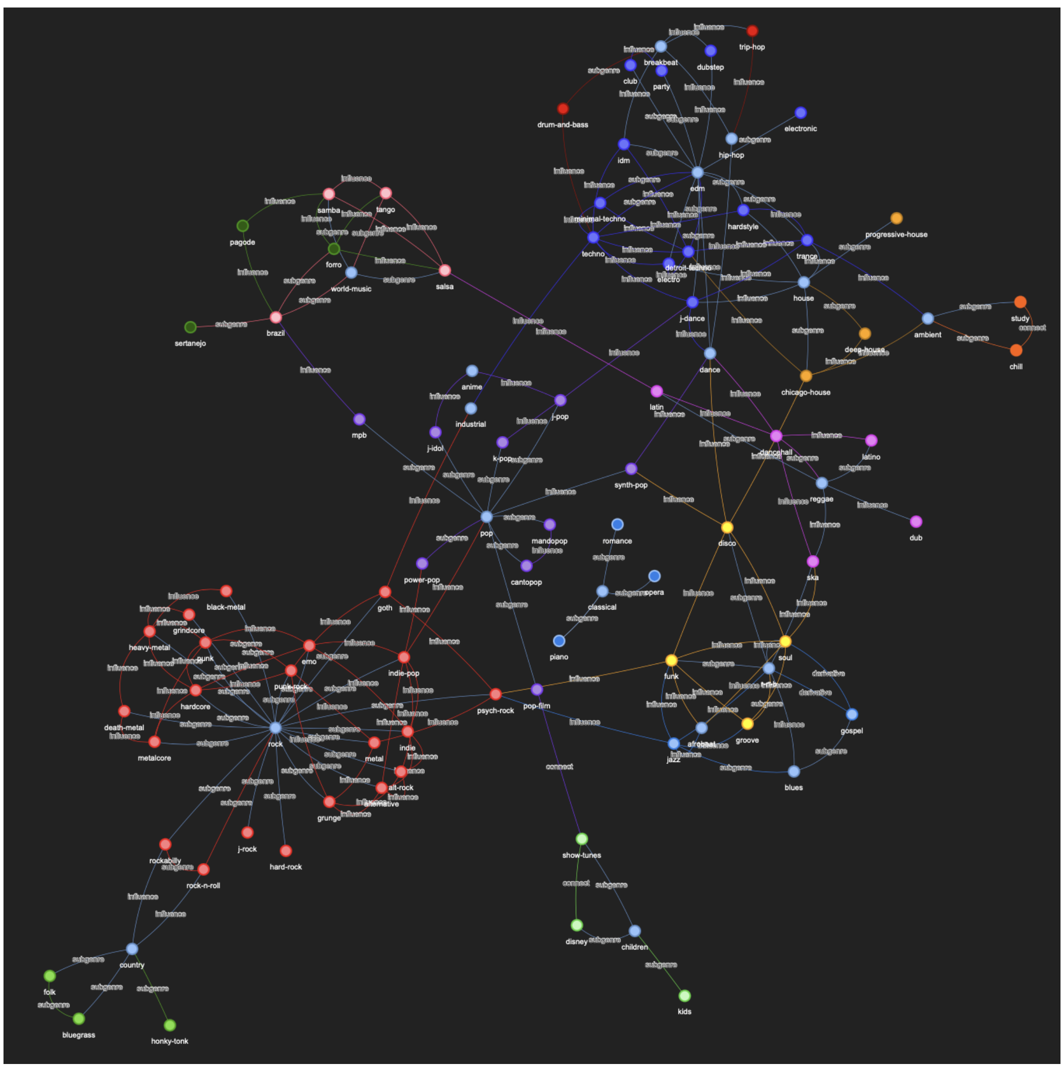
A Parent Genre Associations from MusicMap



B Visualization of Full Knowledge Graph



C Weighting Algorithm for Knowledge Graph Paths

For Starting Genre $s \in$ All Possible Genres G

For Potential Endpoint Genre $e \in G$

For each path p from s to $e \in P_{s,e}$

Assign p a score of $\frac{1}{|P_{s,e}|}$

Multiply the score by a distance penalty of $\frac{1}{\text{path length}(p)^{\text{penalty hyperparameter + 1}}}$

Note: Default penalty hyperparameter is 3

Take the sum of scores for p as total score for e

Normalize total scores across e to create probability distribution

Sample from the probability distribution for s to select a final Endpoint Genre

D Data Preprocessing

We perform several preprocessing steps on the dataset to ensure quality, consistency, and compatibility with clustering algorithms.

D.1 Basic Cleaning

We begin by addressing common inconsistencies within the dataset:

- We remove leading and trailing spaces from textual fields and drop duplicate records.
- We drop rows where genres are based on language rather than audio features, as they would introduce noise unrelated to musical characteristics.
- We remove additional genres identified through the knowledge graph as having inconsistent connections, further improving the dataset's reliability for clustering.

D.2 Scaling Numeric Features

Next, we scale numeric audio features to standardize their range and distribution, ensuring each feature contributes equally to the clustering results.

D.3 Encoding Genre Labels

To prepare categorical genre data for clustering, we consider two encoding approaches:

- **One-hot encoding**: This approach retains categorical information without imposing ordinality. However, it would introduce significant sparsity and create over 100 additional columns, complicating clustering.
- **Label encoding**: This method resolves sparsity issues by assigning each genre a numeric label, greatly simplifying clustering computations. Although label encoding introduces potential ordinal relationships between genres (which do not inherently exist), we decide this compromise is necessary for practical clustering purposes.

After careful consideration, we proceed with label encoding to maintain manageable dimensionality and facilitate effective clustering.

D.4 Included Features

After preprocessing, we include the following features in our analysis:

```
['track_id', 'artists', 'album_name', 'track_name', 'popularity',
'duration_ms', 'explicit', 'danceability', 'energy', 'key', 'loudness',
'mode', 'speechiness', 'acousticness', 'instrumentalness', 'liveness',
'valence', 'tempo', 'time_signature', 'track_genre', 'encoded_genre']
```

D.5 Inclusion of Time Signature

We specifically choose to include time signature as a feature. This decision is based on the understanding that rhythmic structure significantly influences musical feel and genre classification. Tracks with distinct time signatures (e.g., 3/4, 4/4, or 7/4) exhibit unique rhythmic patterns valuable for clustering tracks according to genre or rhythmic feel.

E Correlation Heatmap

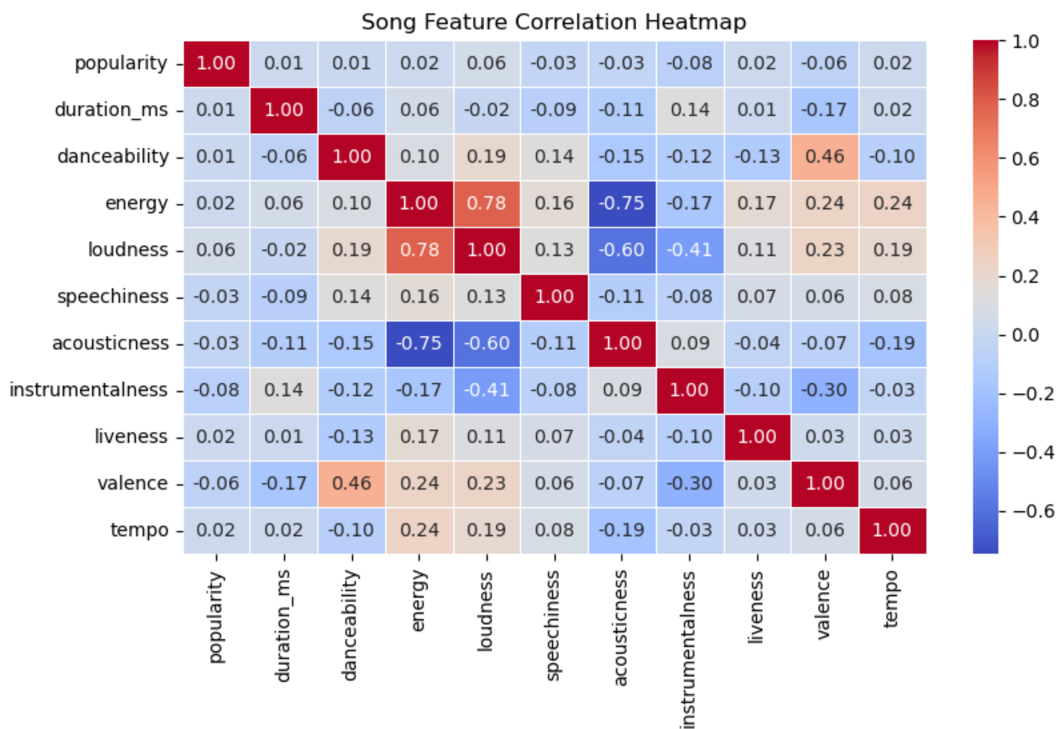


Figure 6: Correlation Heatmap

Takeaways:

- Songs that are louder have more energy
- Songs that are happier (valence) are more danceable
- Songs that are more acoustic have less energy and are less loud
- Songs that are more instrumental are also less loud

F User Reviews

Modern streaming services such as Spotify and Apple Music invest billions of dollars into developing their recommendation systems, employing large teams of engineers, data scientists, and musicologists to fine-tune user experiences. As a result, users today are accustomed to highly personalized and seamless music recommendations that feel almost flawless.

Given this standard, experimental or academic recommender systems, especially those not backed by massive datasets or infrastructure may be judged more harshly. Listeners subconsciously compare them to commercial-grade algorithms, making even reasonable recommendations feel lacking. The feedback below reflects this contrast, highlighting where our hybrid system succeeded and where it fell short according to user expectations.

F.1 Interview Playlist Reviews and Feedback

F.1.1 Review 1

#	Song Name	Artist(s)	Score	Comment
1	Who's The Boss	DJ Sneak	4	—
2	Elevator (Going Up) - Album Mix	Louie Vega; Monique Bingham	2	—
3	So Sick	Jubël	1	Sounds like target music
4	Live Without Existing - CD Version	A-Lusion; Scope DJ; Second Identity	1	Shirtless British dude music
5	Time Moves On - Doctor Dru Remix	Brigado Crew; Ubbah; Doctor Dru	3	Groovy
6	Maroon Bells Variation	Kelpe	1	Doesn't match genre
7	Summertime Is Here	Theo Parrish	2	Very long. Interesting though
8	Cleo's Theme	Theo Parrish	1	Same as last
9	Aja	Jay Daniel	1	Not techno, weird instrumental
10	You Drive Me Crazy - Supernova Remix	Paul Johnson; Zoe Thorn; Supernova	2	Interesting
11	Appointments	Julien Baker	1	Boring
12	It's Only (feat. Zyra) - ODESZA VIP Remix	ODESZA; Zyra	3	—
13	Part of a Major Thing	Matt Large	—	—
14	Wrong Floor	Cliff Martinez	1	I don't want to listen to movie scores
15	Acid Rush - Extended Vokal mixX	Mike Dunn	2	—
16	When the Going Gets Tough, The Tough Get Going	Billy Ocean	2	—

Table 2: Review 1 Playlist Feedback with Scores and Comments

Overall Playlist Rating: 1.5 / 5

Overall, this playlist wasn't good. The first song set a high expectation, but it immediately went downhill after that. The playlist had about 3 house/EDM tracks with weird instrumentals and ambient movie scores in between them. More consistency would be preferred.

F.1.2 Review 2

Overall Playlist Rating: 2 / 5

It started off good but it switched between synth and reggae and then transitioned to international pop. I appreciate the experience of being exposed to different genres but the shift was too abrupt.

#	Song Name	Artist(s)	Score	Comment
1	Slap & Tickle	Squeeze	4	Good for synth-pop, appreciate the retro vibe
2	Dámelo To	Selena Gomez;Myke Towers	1	basic and vibe didn't flow
3	Pobre Diabla	Don Omar	3	Good flow from number 2 but different from original
4	Return to Air	Bonobo	2	very different from 2 and 3 but went back to synth
5	Hipnotízame	Wisin; Yandel	2	back to reggaeton vibe
6	Protection	Massive Attack;Tracey Thorn	4	a vibe and in the same era of retro but another genre
7	RUMBATÓN	Daddy Yankee	1	back to raggaeton
8	Christmas Without You	Ava Max	1	horrible doesn't match at all
9	Here Comes the Rain Again - Remastered Version	Eurythmics;Annie Lennox;Dave Stewart	4	back to retro and synth vibe
10	Left and Right	Charlie Puth;Jung Kook	5	synth pop and good vibe
11	Voices Carry - Single Mix	'Til Tuesday	4	synth pop from the 80s
12	Ambarsariya	Sona Mohapatra	1	different cultural style
13	O Tempo se Transforma em Memória	Ana Carolina	2	matched with international era of previous but not like original
14	So High	Sidhu Moose Wala	1	what??? Still international music
15	Shojo S	SCANDAL	1	still international
16	Channa Ve	Akhil Sachdeva;Mansheel Gujral	1	—

Table 3: Review 2 Playlist Feedback with Scores and Comments

F.2 Survey Reviews and Feedback

Survey Question: Please rate this playlist on enjoyability, relevance, and diversity from 1-5. Also include the number of songs you would skip.

F.2.1 User 1

User Survey 1.1 Baseline Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 2/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 5/16 (31.25%)

User Survey 1.2 Stochastic Playlist Ratings:

- **Enjoyability:** 4/5
- **Relevance:** 3/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 3/16 (18.75%)

User Survey 1.3 HyG-Con Playlist Ratings:

- **Enjoyability:** 5/5
- **Relevance:** 5/5
- **Diversity:** 4/5
- **Proportion of Songs Skipped:** 1/16 (6.25%)

Table 4: User Survey 1.1 Baseline Playlist

#	Artist(s)	Track Name	Genre
1	Reznyck	Maseratiphoïde	club
2	Eartheater	How To Fight	club
3	Darius Rucker	Wagon Wheel	country
4	Brett Eldredge	Bring You Back	country
5	Gabby Barrett	Footprints on the Moon	country
6	Selena Gomez	Back To You - From 13 Reasons Why – Season 2 Soundtrack	dance
7	Wolfgang Amadeus Mozart; Arthur Grumiaux; Walter Klien	Sonata for Piano and Violin in F, K.377: 2a. Tema con variazioni: Tema	classical
8	Riley Green	Hell Of A Way To Go - Live	country
9	Franz Liszt; Nelson Freire	Années de pèlerinage: 1e année: Suisse, S.160: 2. Au lac de Wallenstadt	classical
10	Doja Cat	Boss Bitch	dance
11	Shamanes Crew	Hasta La Mañana	dancehall
12	fenekot	Habits (Stay High)	chill
13	Avicii	The Nights	dance
14	Hotcaller; Nexy	Damn	club
15	Lady Gaga	Born This Way	dance
16	Don Williams	Some Broken Hearts Never Mend	country

Table 5: User Survey 1.2 Stochastic Playlist

#	Artist(s)	Track Name	Genre
1	Reznyck	Maseratiphoïde	club
2	Vince Gill; Jenny Gill	Let There Be Peace On Earth	country
3	ODESZA; Bettye LaVette	The Last Goodbye (feat. Bettye LaVette)	chill
4	Wolfgang Amadeus Mozart; Heinz Holliger; Hermann Baumann; Michel Gasciarrino; Henk Guldemond; Orlando Quartet	Divertimento No. 11 in D, K.251 "Nannerl-Septett": 4c. Menuetto (Tema con variazioni): Var. II	classical
5	Sean Paul; Tory Lanez	Tek Weh Yuh Heart	dancehall
6	untrusted; creamy; 11:11 Music Group	sweater weather / i wanna be your girlfriend	chill
7	Alesso; Marshmello; James Bay	Chasing Stars	dance
8	Charlie Puth	Light Switch	dance
9	Kraff Gad; 9Mill	N.P.T	dancehall
10	Morgan Evans	Country Outta My Girl	country
11	Spice	TAPE MEASURE	dancehall
12	Canned Heat	Goin' Up The Country	country
13	Blackhaine	Stained Materials - Edit	club
14	Yxng Bane	Needed Time	dancehall
15	Kacey Musgraves	Feliz Navidad	country
16	Midland	East Bound And Down	country

Table 6: User Survey 1.3 HyG-Con Playlist

#	Artist(s)	Track Name	Genre
1	Reznyck	Maseratiphoïde	club
2	DJ Ötzi; Xtreme Sound	Wenn Gott so will - Xtreme Sound Remix	party
3	NIVIRO	The Ghost	edm
4	Haezer	Dumb	club
5	ILLENIUM; Teddy Swims	All That Really Matters	edm
6	Querox; Phaxe	Tripical Moon	trance
7	Noisecontrollers; Bass Modulators	Electric Solar	hardstyle
8	Hyperflow	Namah Shiva	trance
9	Omar S	Ganymede	detroit-techno
10	Tiësto; Hardwell; Matthew Koma	Written In Reverse	trance
11	Matoma; Brando	The Bender	house
12	Technoboy; Shayla	Oh My God - Technoboy Dib Dub	hardstyle
13	David Guetta; Bebe Rexha; REAPER	I'm Good (Blue) - REAPER Extended Remix	edm
14	Robert Hood	A System Of Mirrors	detroit-techno
15	Major Lazer; Nyla; Fuse ODG	Light It Up - Remix	edm
16	TOKYO ROSE; ZABO; Aloma Steele	Last Goodbye	club

F.3 User 2

Table 7: User Survey 2.1 Baseline Playlist

#	Artist(s)	Track Name	Genre
1	Gusttavo Lima	Ponto G	sertanejo
2	Henrique & Juliano	Seu Perfil - Ao Vivo	sertanejo
3	Akatu	O Amor Não Tem Culpa / Eu Nunca Amei Assim - Ao Vivo	samba
4	Reinaldo	Retrato cantado de um amor	samba
5	João Bosco & Vinicius	Eu Vou Morrer De Amor	sertanejo
6	Nico; uChill	These Days - Slowed + Reverb	singer-songwriter
7	Víctor Manuelle	En Nombre de los Dos	salsa
8	Okieriete Onaodowan; Daveed Diggs; Lin-Manuel Miranda; Leslie Odom Jr.; Anthony Ramos	The Story of Tonight - Reprise	show-tunes
9	Clayton & Romário	Talismã / 24 Horas De Amor - Ao Vivo	sertanejo
10	Osho Jain; Sanchi	Kaun Apna	singer-songwriter
11	Mindi Dickstein; Jason Howland; 'Little Women' Original Broadway Cast	An Operatic Tragedy	show-tunes
12	Jorge & Mateus	Goiânia Me Espera - Ao Vivo Em Goiânia / 2007	sertanejo
13	Jubiläumscast Wien 2012	So wie man denkt	show-tunes
14	Zeca Pagodinho	Uma Prova De Amor - Ao Vivo	samba
15	Carin Filipcic	I´m An American Woman	show-tunes
16	Akatu	Deixa Tudo Como Tá / Melhor Eu Ir	samba

User Survey 2.1 Baseline Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 2/5

- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 5/16 (31.25%)

Table 8: User Survey 2.2 Stochastic Playlist

#	Artist(s)	Track Name	Genre
1	Gusttavo Lima	Ponto G	sertanejo
2	Krystina Alabado	Yellow SUV	show-tunes
3	Eric Carmen	Hungry Eyes - From "Dirty Dancing" Soundtrack	singer-songwriter
4	Tito Nieves	Le Gusta Que La Vean	salsa
5	Katinguelê; Transcontinental FM 104,7	Impossível Te Esquecer (Acústico da Trans)	samba
6	Chess In Concert	1956 - Budapest Is Rising	show-tunes
7	Jax	Victoria's Secret	singer-songwriter
8	Carolee Carmello; Matthew Morrison; Aidan Gemme; Christopher Paul Richards; Sawyer Nunes; Alex Dreier	Finale - Original Broadway Cast Recording	show-tunes
9	Atitude 67	Dia X - Ao Vivo	sertanejo
10	Santanu Sahu; SITAL SAHU; Prakash Kumbhar; Jogesh Jojo	Lal Lal Lipstick	samba
11	Zeca Pagodinho	Uma Prova De Amor - Ao Vivo	samba
12	Raghav Chaitanya	Lamhe	singer-songwriter
13	Matheus & Kauan	Quarta Cadeira - Acústico	sertanejo
14	Vou pro Sereno; Xande De Pilares	Tá Escrito (feat. Xande de Pilares) - Ao Vivo	samba
15	James Taylor	Santa Claus Is Coming To Town	singer-songwriter
16	Jan Ammann	Gott, warum?	show-tunes

User Survey 2.2 Stochastic Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 2/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 5/16 (31.25%)

User Survey 2.3 HyG-Con Playlist Ratings:

- **Enjoyability:** 4/5
- **Relevance:** 4/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 2/16 (12.5%)

F.4 User 3

Baseline Playlist

User Survey 3.1 Baseline Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 2/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 5/16 (31.25%)

User Survey 3.2 Stochastic Playlist Ratings:

Table 9: User Survey 2.3 HyG-Con Playlist

#	Artist(s)	Track Name	Genre
1	Gusttavo Lima	Ponto G	sertanejo
2	Lobão	Me Chama (Deluxe Version)	brazil
3	Tierry; Wesley Safadão	Diabinha - Ao Vivo	sertanejo
4	Zarastruta; Jean Tassy; Patricio Sid; Don	Nômade VII	brazil
5	Paulo Ricardo	Tudo Por Nada	mpb
6	Adriana Arydes	Halellujah - Ao Vivo	brazil
7	Henrique & Diego	Oh Delícia - Ao Vivo	sertanejo
8	Gabriela Rocha	Leão - Ao Vivo	brazil
9	Matogrosso & Mathias	Boate Azul - Ao Vivo	sertanejo
10	Raimundos; Érica Martins	A mais pedida	brazil
11	Lauana Prado	É Nisso Que Dá / Sem Me Controlar / Mala Pronta - Ao Vivo	sertanejo
12	Racionais MC's; DJ Cia	Preto Zica	brazil
13	Nosso Sentimento	Sonho de Amor - Ao Vivo	pagode
14	Detonautas Roque Clube	Quando o sol se for	brazil
15	Dj Chris No Beat; Rafael Frare	Dona - Ao Vivo	sertanejo
16	Nívea Soares; Isaias Saad	Só Existe Um Lugar - Ao Vivo	brazil

Table 10: User Survey 3.1 Baseline Playlist

#	Artist(s)	Track Name	Genre
1	Höhner	Wenn et Hätz dich röf	party
2	Ferrugem	Será que é amor / Agora viu que me perdeu e chora / Trilha do amor - Ao Vivo	pagode
3	Laura Sullivan	The Name of Life - Felt Piano Version (From "Spirited Away")	piano
4	Mr. Dan; Analaga; Péricles	Copacabana (Bum Bum Pro Alto)	pagode
5	Paveier	Hau op die Trumm	party
6	Anstandslos & Durchgeknallt; JONA; Jerome	Wenn die Welt untergeht - Jerome Remix	party
7	Yiruma	May Be	piano
8	Markus Becker; Oliver DeVille	Micky Maus - Wir geh'n noch nicht nach Haus - Villa-Mix	party
9	Michelle	Scheißkerl	party
10	Mickie Krause	Biste braun, kriegste Fraun - Version 2015	party
11	Toque De Prima	Cabô, Meu Pai	pagode
12	Vou pro Sereno	Nada pra Fazer / Nascente da Paz - Ao Vivo	pagode
13	Kate Bush	Wuthering Heights	piano
14	Grupo Revelação	Zé Meningite	pagode
15	Luciano Pavarotti	Nessun Dorma	opera
16	Fäaschtbänkler	Konfetti	party

Table 11: User Survey 3.2 Stochastic Playlist

#	Artist(s)	Track Name	Genre
1	Höhner	Wenn et Hätz dich röf	party
2	George Winston	Peppermint Patty	new-age
3	Alfredo Kraus; Symphony Orchestra of Madrid; Kurt Sanderling	Carmen, Act II: "La fleur que tu m'avais jetée" (Don Jose)	opera
4	Ina Colada	Wer nicht springt der muss bezahlen	party
5	Turma do Pagode; Netinho De Paula	Beijo Geladinho / Cohab City (feat. Netinho De Paula) - Ao Vivo	pagode
6	Jorge Aragão	Na rua, na chuva, na fazenda (Casinha de sapê) - Ao vivo	pagode
7	Matthias Reim	Ich geb uns nicht auf	party
8	Yao Chen	Purity	piano
9	Buddy	Tausendmal berührt	party
10	Sabbotage	Hömma Samma Womma Nomma (Bier trinken gehen)	party
11	Michael Wendler	180 Grad - 2006	party
12	Il Volo	Notte Stellata (The Swan) - Live From The Detroit Opera House	opera
13	Bernward Koch	The Enchanted Path	new-age
14	Jim Brickman	Morning Has Broken	new-age
15	Giuseppe Verdi; Riccardo Muti; Montserrat Caballé; New Philharmonia Orchestra	Verdi: Aida, Act 1: "Ritorna vincitor!" (Aida)	opera
16	Elton John; Britney Spears	Hold Me Closer	piano

- **Enjoyability:** 3/5
- **Relevance:** 2/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 6/16 (37.5%)

Table 12: User Survey 3.3 HyG-Con Playlist

#	Artist(s)	Track Name	Genre
1	Höhner	Wenn et Hätz dich röf	party
2	SWARM	The End of All Things	club
3	DJ Düse	Voll wie Düse / Das was bleibt / Für immer und ewig - Hitmix	party
4	Donbor	D411	club
5	Peter Wackel	Ladioo - Arena-Hitmix	party
6	SIERRA; Z6b3r	Hide - Z6B3R Remix	club
7	Buddy; Pazoo	Wir haben Grund zum Feiern!	party
8	SWARM; I-Exist	In My Dreams	club
9	Norman Langen	Bis zum letzten Atemzug	party
10	Linn da Quebrada	Tomara	club
11	Topic; Robin Schulz; Nico Santos; Paul van Dyk	In Your Arms (For An Angel)	edm
12	Susumu Yokota	King Dragonfly	idm
13	Agoria; Blasé	3 Letters	techno
14	ONYVAA	006 B2	detroit-techno
15	The Chainsmokers	The One	edm
16	The Chainsmokers; Winona Oak	Hope	electro

User Survey 3.3 HyG-Con Playlist Ratings:

- **Enjoyability:** 4/5
- **Relevance:** 3/5
- **Diversity:** 4/5
- **Proportion of Songs Skipped:** 3/16 (18.75%)

F.5 User 4

Table 13: User Survey 4.1 Baseline Playlist

#	Artist(s)	Track Name	Genre
1	Boney M.	Rivers of Babylon	disco
2	Seth Troxler	Junkyard Tool - Original Mix	detroit-techno
3	Mr. Vegas	Heads High	dancehall
4	Derrick May	Some More Spaced Out	detroit-techno
5	Rick James	Super Freak	disco
6	Extazy	Noc taka czarna	disco
7	The Black Dahlia Murder	Stygiophobic	death-metal
8	HUGEL; Westend; Cumbiafrica	Aguila ft. Cumbiafrica	deep-house
9	Transmetal	Muerto en la Cruz	death-metal
10	Surgeon	Floorshow - 1.2	detroit-techno
11	Alfred Heinrichs; Haexxa	Illusion feat. Haexxa	deep-house
12	Rose Royce	Car Wash - Long Version	disco
13	Goretrade	Rejecting the Lies	death-metal
14	Batu Onat	Prisoners of Love	deep-house
15	Theo Parrish	Fallen Funk	detroit-techno
16	Omar S; Diviniti	Here with Me	detroit-techno

User Survey 4.1 Baseline Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 2/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 6/16 (37.5%)

Table 14: User Survey 4.2 Stochastic Playlist

#	Artist(s)	Track Name	Genre
1	Boney M.	Rivers of Babylon	disco
2	James Hype; HARLEE	Afraid (feat. HARLEE)	deep-house
3	Robert Hood	Teflon	detroit-techno
4	Miss May I	Crawl	death-metal
5	Ilkay Sencan	Clap	deep-house
6	Christopher Martin	Paper Loving	dancehall
7	Omah Lay	bend you	dancehall
8	ONYVAA	Lucid	detroit-techno
9	The Avener; Phoebe Killdeer	Fade Out Lines - The Avener Rework	deep-house
10	Opeth	The Devil's Orchard	death-metal
11	James Hype; Pia Mia; PS1	Good Luck (feat. Pia Mia) - PS1 Remix	deep-house
12	Navos; Galantis; YOU	What It Feels Like	deep-house
13	Entombed	Left Hand Path	death-metal
14	Transmetal	Enviado del Infierno	death-metal
15	Slayer	War Ensemble	death-metal
16	Drexciya	Bang-Bang	detroit-techno

User Survey 4.2 Stochastic Playlist Ratings:

- **Enjoyability:** 3/5
- **Relevance:** 3/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 5/16 (31.25%)

Table 15: User Survey 4.3 - HyG-Con Playlist

#	Artist(s)	Track Name	Genre
1	Boney M.	Rivers of Babylon	disco
2	Pet Shop Boys	It's a Sin	synth-pop
3	Almklausi; Specktakel	Mama Laudaaa - Apres Ski Edition	disco
4	The Supremes	Little Bright Star - Stereo	soul
5	UM44K	Não dá mais - Acústico	r-n-b
6	Adele	Oh My God	soul
7	Hugh Masekela	Been Such A Long Time Gone	afrobeat
8	Snoop Dogg; Wiz Khalifa; Bruno Mars	Young, Wild	Free
funk			
9	Olivia Dean	The Hardest Part	soul
10	Sabotage; Sombra; Bastardo	Cocaína	r-n-b
11	Mc Don Juan; Luíza & Maurílio	Saudade do Ex	funk
12	Lulu Santos	Adivinha o quê	r-n-b
13	Adele	Don't You Remember	soul
14	Ricardo Lemvo	Africa Havana Paris	afrobeat
15	Anitta; Missy Elliott	Lobby	funk
16	Stevie Wonder	Saturn	soul

User Survey 4.3 HyG-Con Playlist Ratings:

- **Enjoyability:** 4/5
- **Relevance:** 3/5
- **Diversity:** 5/5
- **Proportion of Songs Skipped:** 3/16 (18.75%)