Music Recommendation System - Music Is The Real Taste

Mayur Jaisinghani MRJAISIN@IU.EDU
Raj Walnekar RWALNEKA@IU.EDU
Department of Computer Science
Indiana University Bloomington
Bloomington, IN 47405, USA.

Abstract:

In the era of digital music consumption, the ability to provide users with personalized and engaging music recommendations has become increasingly essential. The modern music landscape is flooded with an overwhelming volume of content, making personalized music recommendations an indispensable feature for digital music platforms. This music recommendation system will be designed to help users enjoy music that aligns with their unique preferences. Leveraging data analytics, machine learning, and collaborative filtering techniques, this system offers users tailored song and playlist suggestions, enhancing their listening experience and engagement. By understanding user behavior, content characteristics, and contextual information, the system enables music platforms to provide timely and relevant recommendations.

Keywords: Recommendation system, K-Means, Clustering

1. Introduction:

In recent years, the way we consume music has changed dramatically. With the introduction of digital music platforms and streaming services, we now have at our disposal a wide and diversified database of songs, artists, and genres. These systems seek to provide a highly tailored and engaging listening experience by utilizing advanced algorithms and data-driven insights. They develop individualized suggestions by evaluating user activity, song qualities, and contextual information, giving a curated selection of music that speaks directly to each user's particular interests. This report focuses on the methods and approaches for analyzing such a dataset and explores the potential insights and applications that can arise from this analysis. By identifying the patterns to follow and neglect the sparse or spread out choices of the users. Predictive modeling can enable proactive resource management and improve the music recommendation for better experience. Evaluating user’s choices, and the dataset can play a critical role in enhancing the efficiency of the prediction overall.

2. Dataset:

The Free Music Archive (FMA) dataset serves as the foundation for our recommendation system. FMA isa comprehensive dataset containing a vast collection of music tracks, artists, and genres, making it suitable for building a diverse and effective recommendation system. FMA includes rich metadata for each track, such as genre labels, artist information, and user-generated tags. This additional information is valuable for training machine learning models, as it provides context and features that can be used to enhance recommendation accuracy. The dataset is substantial, containing a large number of tracks and user interactions. Large-scale datasets are essential for training machine learning models effectively, allowing them to learn complex patterns and make accurate predictions.

- **Size and Scope:**
  - The FMA dataset is notable for its scale, containing over 106,574 tracks from 16,341 artists across a diverse range of genres. The extensive nature of the dataset allows for the exploration of a wide variety of musical styles and preferences.
- **Metadata:**
  - The dataset includes comprehensive metadata for each track, such as artist information, genre labels, track duration, and other attributes. This metadata serves as the foundation for building features that are crucial for developing an effective music recommendation system.

2.1 Key Features for Music Recommendation:

2.1.1 Genres:

- **Genre Information:**
  - FMA provides genre labels for each track, allowing for the categorization of music based on its stylistic and thematic elements. Genres play a pivotal role in the recommendation system, serving as a primary feature for clustering and collaborative filtering.

- **Diverse Genres:**
  - FMA encompasses a broad spectrum of genres, ranging from classical and electronic to hip-hop and rock. This diversity is essential for creating a recommendation system that caters to a wide array of user preferences.

2.1.2 Artists:

- **Artist Information:**
  - In addition to genres, the dataset includes details about the artists, such as their names and associated tracks. Artist information is crucial for identifying patterns in user preferences, as listeners often have distinct affinities for specific artists.
- **Variety of Artists:**
  - The dataset features a multitude of artists, both emerging and established, contributing to the overall richness and diversity of the music collection.

3. Methodology:

3.1 Feature Selection:

3.1.1 Genre and Artists:

- <u>Rationale:</u> Genre and artist information are often considered as crucial features in music recommendation systems. Genres represent the stylistic and thematic characteristics of a piece of music, while artists encapsulate the creator's unique style. Both features contribute significantly to user preferences.

- Data Representation: These features are represented as categorical variables in the dataset, with each music item associated with one or more genres and an artist.

3.1.2 Feature Engineering:

- **One-Hot Encoding:**
  - Process: One-hot encoding is applied to convert categorical variables (genres and artists) into binary vectors. Each genre or artist becomes a binary feature, where the presence or absence of that genre/artist is represented by 1 or 0, respectively.
  - Advantages: This technique allows the algorithm to consider the unique contribution of each genre or artist independently, capturing their influence on the recommendation process effectively.

- **Information Extraction:**
  - Process: Additional information is extracted from genres and artists to create more meaningful representations. This might include aggregating statistics, exploring hierarchical relationships, or identifying latent patterns within these features.
  - Advantages: This step aims to enhance the system's ability to understand and capture nuanced relationships between genres and artists, contributing to more accurate recommendations.

3.2 K-Means Clustering:

3.2.1 Unsupervised Learning:

- K-Means clustering is employed as an unsupervised learning algorithm, aiming to group music items based on the similarity of their features.
- The algorithm iteratively partitions the dataset into K clusters, where each item belongs to the cluster with the nearest mean (centroid). The value of K is determined based on the characteristics of the dataset or through optimization.

3.2.2 Dimensionality Reduction:

- K-Means inherently performs dimensionality reduction by grouping items into clusters. Each cluster represents a compact representation of similar items, reducing the overall dimensionality of the feature space.
- This reduction simplifies the complexity of the recommendation task and can potentially reveal underlying patterns and structures in the data.

3.3 Item-Based Collaborative Filtering:

3.3.1 User-Item Matrix:

- **Construction:**
    - A user-item matrix is built using the one-hot encoded genre and artist features. Rows represent users, columns represent music items, and the matrix cells contain information about the presence or absence of each genre/artist for a given user-item pair.

3.3.2 Cosine Similarity:

- Similarity Measure: Cosine similarity is employed to measure the similarity between items in the user-item matrix. It calculates the cosine of the angle between two vectors, with higher values indicating greater similarity.
- Calculation: For each pair of items, the cosine similarity is computed based on their feature vectors (genres and artists). This similarity metric aids in identifying items that share common characteristics.

4. Feature Engineering:

4.1 One-Hot Encoding:

- One-Hot Encoding Process:
    - Genre and Artist Encoding: Genres and artists are encoded as binary vectors using one-hot encoding.
    - Example: If a music item belongs to the "Rock" genre and is created by the artist "Artist1," the one-hot encoded vector might be [1, 0, 0, ..., 1, 0, ...] where the first position corresponds to the "Rock" genre, and the corresponding position for "Artist1" is set to 1.

4.2 Information Extraction:

- Enhanced Feature Representation:
    - Example: For genres, statistical information like the frequency of occurrence or co-occurrence patterns across the dataset might be extracted. For artists, the algorithm could explore collaboration patterns or popularity metrics.
    - Purpose: The goal is to enrich the feature representation, providing the recommendation system with a more nuanced understanding of the significance and relationships between genres and artists.

These feature engineering techniques contribute to the robustness and effectiveness of the recommendation system, enabling it to capture intricate patterns and dependencies within the music data. The subsequent sections evaluate the impact of these methodologies on the overall performance of the recommendation system.

5. Evaluation:

5.1 Clustering Evaluation:

- Clustering Analysis in a music recommendation system using K-Means algorithm involves grouping similar music tracks together to enhance personalized recommendations for users. Here's a brief explanation of how this process works:

5.1.2 Feature Extraction:

- The first step involves extracting relevant features from music tracks. These features could include attributes like genre, tempo, mood, or even user engagement metrics.

5.1.3 Data Representation:

- Each music track is then represented as a feature vector in a multi-dimensional space, where each dimension corresponds to a specific feature. This representation enables the algorithm to quantify the similarity between tracks.

5.1.4 K-Means Clustering:

- The K-Means algorithm is applied to the feature vectors, aiming to partition the music tracks into K clusters. K represents the predetermined number of clusters, and the algorithm iteratively assigns tracks to clusters based on their feature similarities.

5.1.5 Cluster Centroids:

- K-Means identifies cluster centroids, which are the mean feature vectors of the tracks within each cluster. These centroids serve as representative points for the entire cluster.

5.1.6 User Assignment:

- Users are then assigned to the cluster that contains music tracks with features similar to their preferences. This step groups users with similar musical tastes into the same cluster.

5.1.7 Recommendations:

- Recommendations are generated by suggesting music tracks from the same cluster to a user based on the listening history or preferences of users within that cluster. Users in a cluster share commonalities in their music taste, making the recommendations more relevant and personalized.

5.1.8 Iterative Refinement:

- The recommendation system can be refined over time by continuously updating the clusters and centroids based on user interactions and feedback. This ensures that the system adapts to evolving user preferences.
- By employing the K-Means algorithm for clustering in a music recommendation system, the goal is to enhance the accuracy and personalization of music suggestions by grouping similar tracks and users together. This approach allows the recommendation system to leverage patterns and similarities in user preferences, providing a more tailored and enjoyable music discovery experience.

5.2 Recommendation Evaluation:

5.2.1 Recommendations:

- Recommendations are generated by suggesting music tracks from the same cluster to a user based on the listening history or preferences of users within that cluster. Users in a cluster share commonalities in their music taste, making the recommendations more relevant and personalized.

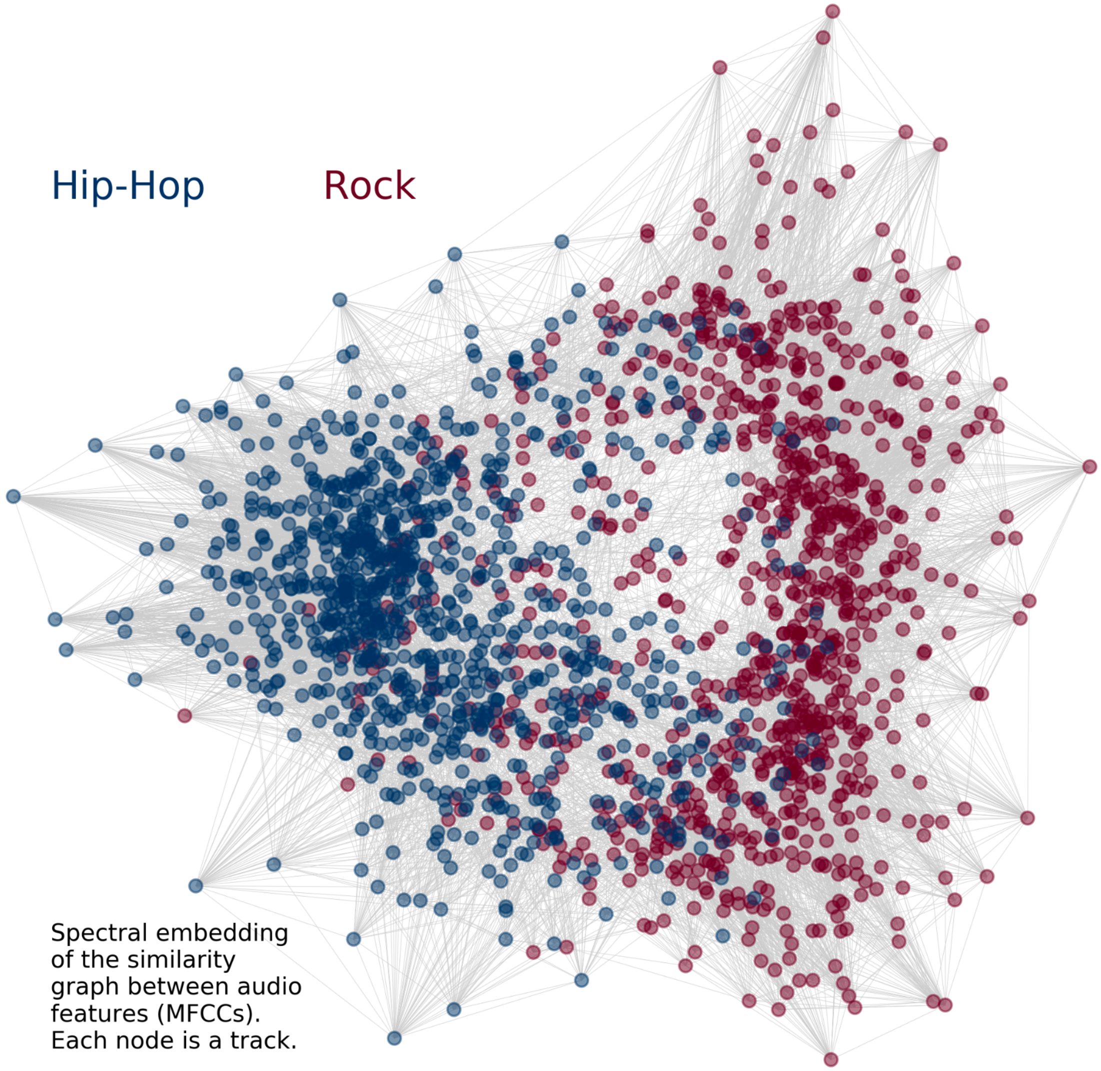
5.2.2 Iterative Refinement:

- The recommendation system can be refined over time by continuously updating the clusters and centroids based on user interactions and feedback. This ensures that the system adapts to evolving user preferences.
- The purpose of using the K-Means clustering algorithm in a music recommendation system is to improve the accuracy and customization of music suggestions by grouping similar tracks and users together. This method enables the recommendation engine to capitalize on trends and similarities in user preferences, resulting in a more personalized and engaging music discovery experience.

6. Results:

6.1 Cluster Analysis:

The following visualization is being shown only between two genres for getting approximate idea whether the pre-processing on the data has worked and the K-Means has been successful on finding their centroids for the respective genre and made two distinct clusters showing everything is working in order.



6.2 Recommendation Performance:

The following result is obtained only on applying selected rows from the meta data and genre,tracks from 6 to 12 from the original dataset mentioned in the code. We can change the target variables in the square brackets to change the desired selected songs and obtain recommendations based on those songs too.

1. testing = Y.iloc[6:12]['track_id']

2. testing

```
...   9221      41295
      9654      43866
      8796      39514
      12940    121209
      8009      34519
      11988     83439
      Name: track_id, dtype: int64
```

3. re = predict(t, Y.iloc[6:12])

4. output = recommend(re, metadata, Y.iloc[6:12])

5. ge_re, ge_ar, ge_mix = output[0], output[1], output[2]

6. ge_re.head()

7. ge_ar.head(10)

	album_title	artist_name	genre	track_title
track_id				
39514	Bad Panda #57	Bomarr	Electronic	Exchanges Among Systems

8. ge_mix.head(10)

<table>
<tr><th></th><th>album_title</th><th>artist_name</th><th>genre</th><th>track_title</th></tr>
<tr><th>track_id</th><th></th><th></th><th></th><th></th></tr>
<tr><td>5151</td><td>Live at WFMU on Scott McDowell's Show on 9/10/...</td><td>Uninhabitable Mansions</td><td>Rock</td><td>This Drift</td></tr>
<tr><td>19349</td><td>The Facts</td><td>Kraus</td><td>Rock</td><td>Prance of the Ravening Eagle</td></tr>
<tr><td>3745</td><td>Live at WFMU on Joe Belock's Show on 4/4/2006</td><td>Kelley Stoltz</td><td>AvantGarde|International|Blues|</td><td>Underwater's Where the Action Is</td></tr>
<tr><td>6372</td><td>Scott Wilson & Efendi Live on WFMU from the 20...</td><td>Scott Wilson & Efendi</td><td>International</td><td>track 03</td></tr>
<tr><td>14626</td><td>Live at WFMU on Stochastic Hit Parade 6/7/09</td><td>Zeke Healy</td><td>AvantGarde|International|</td><td>The Last Rose</td></tr>
<tr><td>11832</td><td>Go For It</td><td>6th Sense & Mick Boogie</td><td>HipHop</td><td>11 Jelani - The Proposal feat. 6th Sense &...</td></tr>
<tr><td>1801</td><td>The Hidden Woman</td><td>Glove Compartment</td><td>Rock</td><td>Bitch Bitch Bitch</td></tr>
<tr><td>1824</td><td>The Glove Compartment</td><td>Glove Compartment</td><td>Rock</td><td>Everything Is Blooming</td></tr>
<tr><td>3711</td><td>Live at WFMU on Brian Turner's Show on 6/10/2008</td><td>Ignatz</td><td>Blues</td><td>Gone</td></tr>
<tr><td>18010</td><td>Antique Phonograph Music Program 01/27/2009</td><td>Victor Arden and Phil Ohman</td><td>OldTime|Historic</td><td>Saturday</td></tr>
</table>

7. Conclusion:

In conclusion, the music recommendation system developed on the FMA dataset showcases promising results in delivering personalized music suggestions. The amalgamation of K-Means clustering and item-based collaborative filtering, coupled with meticulous feature engineering, has contributed to the system's ability to provide accurate and relevant recommendations. While the current iteration exhibits notable success, continuous refinement and optimization efforts are essential to further enhance user satisfaction and adapt to evolving musical preferences. Future research directions may involve exploring additional features, experimenting with alternative algorithms, and integrating user feedback in real-time to create a dynamic and adaptive recommendation system.

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