Music Recommendation System using Vector Similarity

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***Abstract*—In the digital age, where millions of songs are readily available, finding personalized music recommendations poses a significant challenge. This study introduces an innovative music recommendation system that leverages segment pitches from the Million Song Dataset (MSD) and lyrical content from the Musixmatch dataset. We use LibROSA to extract segment pitches, process musical features, and compute cosine similarity to suggest similar songs. Additionally, we analyze lyrical content to generate recommendations based on thematic similarity.**

To evaluate our approach, we conducted A/B testing with 24 participants, comparing pitch-based and lyrics-based recommendations. Results show a slight preference for pitch-based recommendations (62% vs. 38% for lyrics-based), indicating that segment pitches may better capture musical similarity. While both features are valuable, segment pitches more closely align with user perceptions of similarity. Future work will focus on integrating additional features such as timbre and expanding the analysis to include personal playlists and recommending similar playlists.

***Index Terms*—Music Recommendation, Segment Pitches, Lyrics, Cosine Similarity, A/B Testing, Million Song Dataset, Musixmatch Dataset**

I. Introduction

With the rapid advancement of technology and the increasing number of smartphone applications, the consumption of entertainment content has changed dramatically. This includes activities like gaming, listening to music, and watching videos. Among these, music listening is one of the most popular forms of entertainment, with an enormous user base. Last year, the UK saw a 10 percent increase in music consumption[1].

We now have access to millions of songs, which can make it difficult for users to find personalized content. Most companies rely on inputs such as listening patterns, user playlists, and the artists users follow to recommend music. While this helps in providing some level of similarity, it often falls short in enabling users to discover new artists and explore unfamiliar music.

Despite advances in music recommendation algorithms, there is still a significant gap in using musical attributes like segment pitches [1] and lyrical content [2] to improve recommendation accuracy. Current systems frequently ignore these features, resulting in recommendations that may not align well with listener's preferences. Segment pitches capture the harmonic and melodic essence of a song, while lyrical content provides insight into its thematic and emotional aspects. By incorporating these elements, we hope to gain a better understanding of musical similarity.

This study proposes an innovative approach to music recommendation based on segment pitches and lyrical content. We believe that using these features will result in more personalized and accurate recommendations than traditional methods. We aim to bridge the gap between user preferences and musical discovery by calculating cosine similarity for song attributes and capturing their similarities.

Our system uses the Million Song Dataset[2] [3] for segment pitches and the Musixmatch Dataset[3] for lyrics. Using these comprehensive datasets, we hope to provide robust, personalized recommendations that capture both the acoustic and thematic sense of music. This dual approach enables us to address all aspects of musical similarity, which could lead to more satisfying user experiences.

To evaluate the effectiveness of our proposed system, we use A/B testing, which compares segment pitch-based and lyrics-based recommendations. This methodology allows us to assess user satisfaction and gain valuable insights into our preferred approach to music recommendation. We hope to address current system limitations while also creating the way for more sophisticated, user-centric music discovery tools.

By improving the accuracy and personalization of music recommendations, we can increase user engagement and help them discover new music and artists that suit their tastes.

II. Related Work

Music recommendation systems have evolved significantly over the years, driven by advances in technology and growing availability of digital music. Various approaches are available to improve the accuracy and personalization of recommendations. This section reviews the development and methodologies in the field, highlighting their strengths and limitations.

Content based filtering recommends items based on the properties of those items and profile of the user preferences. It's like suggesting music based on the genre or artist the user listens to. The system looks at the characteristics of the content you like and tries to find similar items that match those characteristics. However, this method also has

[1]https://www.prsformusic.com/m-magazine/news/uk-recorded-music-market-increased-by-10-in-2023-bpi

[2]http://millionsongdataset.com/

[3]http://millionsongdataset.com/musixmatch/

some limitations, such as over specialization, which tends to recommend items that are very similar to what user has already seen, limiting the exposure to diverse content [4].

Collaborative filtering is one of the earliest and most used technique in the recommendation systems. This method relies on the user behavior, like listening history and rating of the song to generate recommendations based on the preferences of similar users. These systems using this method include two main types of filtering. User based collaborative filtering and item based collaborative filtering [5].

User based CF recommends items by finding the user with similar interests. This method finds out other users with similar interests and preferences and use their data to get recommendations by finding the nearest neighbor [6].

Item-based CF recommends music by calculating the similarity between two items using the score of an item recorded by all users in the system, and then recommending items that are like the target user's previous preferences [7].

Despite its widespread use, CF faces challenges such as the cold-start problem [8], where new users or items with limited data makes it difficult to provide accurate recommendations. Furthermore, CF can suffer from sparsity issues, in which the user-item interaction matrix is nearly empty, resulting in less reliable recommendations [9].

Hybrid music recommendation system is fusion of content based filtering and collaborative filtering techniques, combining both approaches to provide more accurate recommendations. This model combines content analysis and user patterns to provide a comprehensive recommendation experience. By combining these methodologies, the system can offer users a well-rounded selection of music to their preferences, ultimately improving the accuracy and effectiveness of the recommendation process. Despite their effectiveness, hybrid systems can be more complex and computationally intensive to implement, requiring sophisticated integration strategies [10].

Despite these advancements, there is still gaps in using rhythmic musical characteristics and lyrical content into music recommendations. Segment pitches analysis provides information about the harmonic and melodic structure of the songs[4]. According to research, segment pitches can be used in beat tracking, improving recommendation accuracy by capturing more nuanced musical elements [1]. Analysing lyrical content aids in understanding the thematic and emotional aspects of music, which is important tailoring recommendations based on user preferences for specific lyrical themes or moods [2].

III. Methodology

The methodology for this study consists of four major stages Fig.1 data collection and feature extraction, similarity calculation, recommendation generation, and evaluation via A/B testing. In the first stage, we collect data from the million-song and musixmatch datasets, as well as a specific MP3 file and its lyrics string, and pre-process it to extract features. In the second stage, we calculate cosine similarity using these features to generate similarity matrices. The third step is to generate recommendations based on mp3 file and lyrics, providing users with a list of songs from a million-song dataset. Finally, in the fourth stage, we assess the effectiveness of the recommendation using A/B testing to measure user preference.

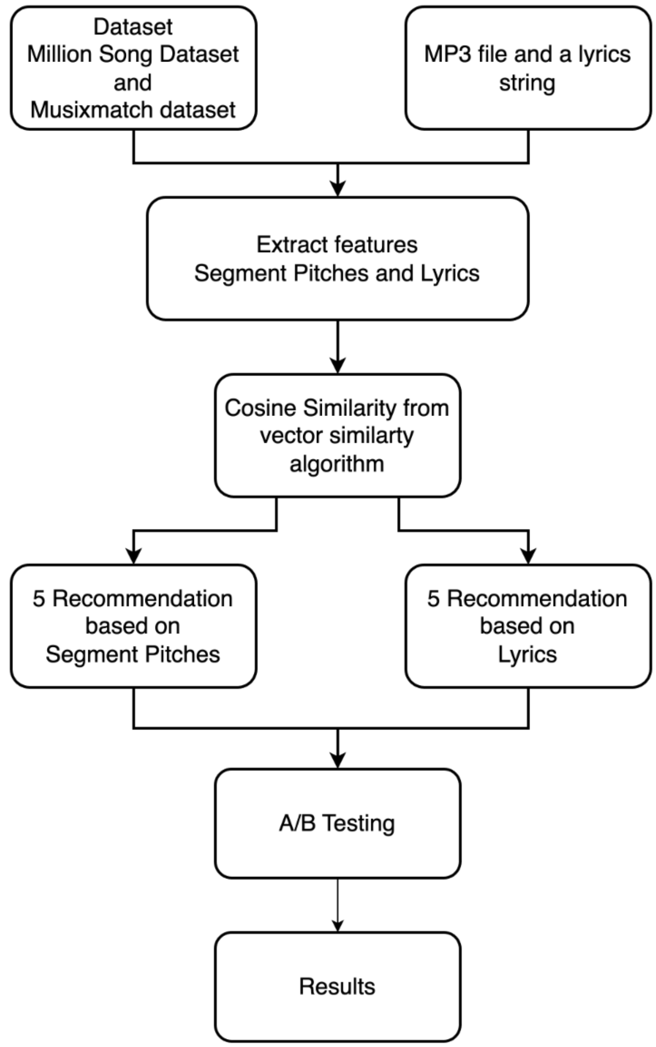

Fig. 1. Flow chart of music recommendation system

A. Data Collection

1) Million Song Dataset: The MSD is a collection of audio features and metadata intended to aid research into music information retrieval and recommendation systems. In this study, we will use a subset of MSD that includes HDF5 files. These files include audio features such as timbre, pitch, and loudness, as well as metadata such as artist and track details.

For our Analysis, the data has been converted and saved in CSV format. This approach is used because it allows for efficient manipulation and examination of the dataset via data analysis.

[4]https://www.sciencedirect.com/science/article/abs/pii/S0885230821000371

This study, we will focus on the segment pitches feature, which provides a 12-dimensional vector representing the pitch content of each segment of music. These vectors captures the relative strength of each pitch class (C, C#, D, D#, E, F, F#, G, G#, A, A#, B). This feature provides insights into harmonic and melodic content, which can be useful for similarity analysis.

This detailed pitch information can aid in understanding the musical pattern and improve the performance of music recommendations. By analyzing these pitch vectors, we aim to uncover relationships between songs and enhance our ability to suggest similar tracks to listeners.

2) Musixmatch Dataset: The MXM dataset contains a collection of song lyrics in bag-of-words format, where each track is described by word counts for a dictionary of the top 5,000 words across the set. For this study, we used songs that are present in both the MSD and MXM datasets. By analyzing the patterns of the words in the lyrics, we aim to capture the thematic and emotional content, enhancing the accuracy of music recommendations. This approach provides users with suggestions that align closely with their lyrical preferences.

3) MP3 Song and Lyrics String: To incorporate real-time data and get recommendations based on them, we used specific MP3 files and their corresponding lyrics strings. These files serve as the test case for our recommendation algorithms.

MP3 files: We used individual MP3 audio files that were not included in the million song dataset. These files represent user input that required recommendations.

Lyrics string: For each MP3 file, we collected the song's complete lyrics as a text string. These lyrics strings are separate from the Musixmatch dataset and represent the entire lyrical content of the songs.

B. Feature Extraction

1) Segment Pitches Extraction from MSD and MP3: For both the Million Song Dataset (MSD) and the provided MP3 file, we extracted segment pitches, which are crucial for capturing the harmonic and melodic essence of the music.

For the MSD, segment pitches were extracted from the HDF5 files. Each song in the MSD is represented by a series of segments, with each segment characterized by a 12-dimensional pitch vector. These vectors indicate the relative strength of each semitone in the chromatic scale for the respective segment, providing a detailed representation of the song's harmonic and melodic content Algorithm.1.

For the provided MP3 file, we used the LibROSA library, a python package for music and audio analysis, to extract features. Librosa provides tools for analysing and transforming audio data, such as chroma features analysis spectral contrast and tempo estimation. In this study, we will focus on extracting chroma features, a 12 dimensional vector representing the pitch class distribution for each segment shown in the Fig.2. This feature extraction involves loading the audio file, segmenting it into smaller parts, and computing the pitch content for each segment Algorithm.2.

Algorithm 1 Extract song features from MSD dataset

Require: dataset_path (path to directory containing .h5 files)
Ensure: CSV file containing extracted features and metadata

Initialize empty list data
for each file in dataset_path and its subdirectories **do**
    if file extension is .h5 **then**
        Load song features from file
        Load metadata (artist name, song title, album name) from file
        Extract song ID from file name
        Append to data:
            {song_id, segments_pitches (as JSON string),
            artist_name, song_title, album_name}
        Print error message
    end if
end for
Convert data to pandas DataFrame
Save DataFrame to CSV file 'song_features.csv'
Print success message

Algorithm 2 Extract segment pitches features from MP3 file

Require: *file_path* (path to the audio file)
Ensure: Dictionary containing normalized chroma features

function EXTRACT_FEATURES(file_path)
    Load the audio file from *file_path* with the original sample rate
    Compute chroma features using Short-Time Fourier Transform (STFT)
    Average the chroma features across the time axis
    Normalize the chroma features:
        $chroma\_normalized = \frac{chroma - \text{mean}(chroma)}{\text{std}(chroma)}$
    return {*'segments_pitches'*: *chroma_normalized*}
end function

2) Lyrics Extraction from MXM dataset: For the MXM dataset, we process the lyrics data which is already in a bag-of-words format. Each track is described by word count for a dictionary of the top 5000 words across the set Algorithm 3.

For the lyrical string, we used the Natural Language toolkit(NLTK), a library for natural language processing in python, to pre-process the text. This includes tokenization, removing words, and converting the text into a format for similarity calculation. By analysing the lyrical content of the

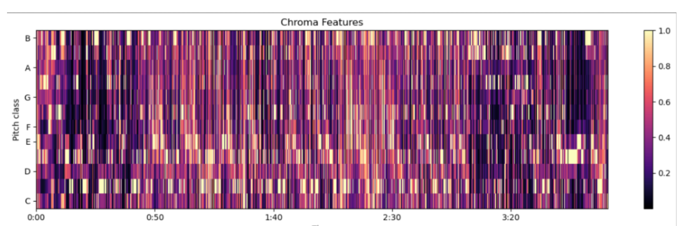

Fig. 2. Segment pitches for MP3 file

Algorithm 3 Merge and process MXM(lyrics) dataset

Require: song_features.csv, lyrics.csv, words.csv
Ensure: Combined and processed dataset
Load song_features.csv into DataFrame df1
Load lyrics.csv into DataFrame df2
Load words.csv into DataFrame df3
Merge df1 and df2 on song_id and track_id
Merge result with df3 on word column
Save merged DataFrame to 'combined_data.csv'
Load 'combined_data.csv' into data_comb
Remove 'mxm_tid' column from data_comb
Remove 'is_test' column from data_comb
return data_comb

song, we can capture the thematic and emotional aspects of the music, which are crucial for providing personalized recommendations Algorithm.3.

IV. Similarity Calculation

After pre-processing the data, the next step is to calculate song similarity scores for segment pitches and lyrical content. To measure these similarities, we will use cosine similarity [11] function, which is effective for measuring distances between two vectors in a multidimensional space [12].

A. Cosine Similarity

Cosine similarity is used to measure the similarity between two vectors. This metric is chosen because it effectively captures the angular difference between vectors, making it ideal for high-dimensional data such as pitch and word count vectors. The formula for cosine similarity is as follows:

$$\text{Cosine Similarity} = \frac{A \cdot B}{\|A\|\|B\|} \tag{1}$$

In this formula(1), A and B represents the vector been compared, and $||A||$ and $||B||$ are their magnitudes. The cosine similarity ranges from -1 to 1, where 1 indicates identical orientation, 0 indicates orthogonality, and -1 indicates opposite orientation[5].

The Dot product of two vectors, A and B, is calculate using the formula (2), here A_i and B_i are the corresponding components of vectors A and B

$$\text{Dot Product} = A \cdot B = \sum_{i=1}^{n} A_i \times B_i \tag{2}$$

The magnitude of the vector A and B, denoted as $||A||$, is calculated using the formula (3) where A_i represents the $i-$th component of the vector a.

$$\text{Magnitude of A} = \|\mathbf{A}\| = \sqrt{\sum_{i=1}^{n} A_i^2} \tag{3}$$

[5]https://en.wikipedia.org/wiki/Cosine$_{similarity}$

1) Pitch Similarity Calculation:

For calculating the pitch similarity, we used the segment pitches extracted from both MSD and MP3 file. This implementation closely follows the Algorithm.4.

Algorithm 4 Song recommendation based on segment pitches

Require: *new_song_features*, *df* (DataFrame of song features), *top_n* (number of recommendations)
Ensure: List of top *n* recommended songs
function COMPUTE_SIMILARITY(features1, features2)
    Calculate cosine similarity between *features1* and *features2*
    return similarity
end function
function RECOMMEND_SONGS(new_song_features, df, top_n)
    Initialize empty list *similarities*
    for each row in *df* **do**
        Extract song features
        Compute similarity with *new_song_features*
        Append song ID, similarity, artist name, title, and album to *similarities*
    end for
    Sort *similarities* by similarity score in descending order
    return top *n* results
end function
Main Execution:
Call *recommend_songs* with *new_song_features* and *df*
Print recommended songs

In this algorithm, the cosine function from scipy.spatial.distance is used to calculate the cosine distance between the two pitch vectors. we subtract this value from 1 to convert the distance to a similarity measure.

2) Lyrics Similarity Calculation:

Similarly, we process the bag of words representations form the musixmatch dataset and the input lyrics string. The algorithm is as follows Algorithm.5

Algorithm 5 Recommend songs based on lyrics similarity

Require: *input_lyrics*, *track_word_matrix*, *top_n*
Ensure: List of top *n* recommended songs
Vectorize *input_lyrics* using *CountVectorizer*
Compute cosine similarity between *input_lyrics* and *track_word_matrix*
Sort similarity scores in descending order
Select top *n* songs with highest similarity
Print recommendations

This algorithm first creates a track-word matrix from the merged dataset. It then uses countVectorizer to convert the input lyrics to a word count vector. Cosine similarity is calculated between this input vector and each row of the track word matrix using sklearn's cosine similarity function.

```
Song ID: TRBHCVQ12903CF8E90, Similarity: 0.8737, Artist: Joe Lynn Turner, Title: Two Lights [Bonus Track], Album: Second Hand Life: The Delux
e Edition
Song ID: TRAOHAH128F425CD57, Similarity: 0.8675, Artist: Mars Ill, Title: Saturday Night Special, Album: Pro*Pain
Song ID: TRAZRXP12903CBD6A9, Similarity: 0.8599, Artist: Vonray, Title: Part Of Me (LP Version), Album: Vonray
Song ID: TRARWYL128F423B96A, Similarity: 0.8482, Artist: Singing Melody, Title: Lived My Life, Album: Expression
Song ID: TRAECSU128F426A84A, Similarity: 0.8458, Artist: Headhunter, Title: Signs Of Insanity, Album: A Bizarre Gardening Accident
```

Fig. 3. Songs recommended by the segment pitch system.

```
Song ID: TRARBBK128F427ED68, Similarity: 0.5062, Artist: Koffi Olomide, Title: Elle Et Moi, Album: Tcha Tcho
Song ID: TRAWYNV128F92F5E7E, Similarity: 0.4910, Artist: Guns N' Roses, Title: Catcher In The Rye, Album: Chinese Democracy
Song ID: TRADGWP128F42618E4, Similarity: 0.4343, Artist: Madilu System, Title: Vincent, Album: La Bonne Humeur
Song ID: TRAEROB12903CE3E7D, Similarity: 0.5342, Artist: Pepper, Title: Stormtrooper (Live), Album: Kona Gold
Song ID: TRAWSJK128F42767F2, Similarity: 0.5578, Artist: Ini Kamoze, Title: Here Comes The Hotstepper, Album: 100 R&B Classics – The Anthems
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Fig. 4. Songs recommended by the lyrics system.

V. Recommendation Generation

After calculating cosine similarity, we will generate the recommendations by selecting the top n songs with the highest similarity scores. For segment pitch recommendations, we selected the songs with the highest cosine similarity to the input songs pitch vector. Similarly for lyrics based recommendations, we choose songs with the highest cosine similarity to the input songs lyrics vector.

We then compare these two recommendations to analyze the effectiveness. By providing users with both set of recommendations, we aim to assess which approach results in higher user satisfaction and engagement.

VI. Results and Evaluation via A/B Testing

1) Results: For the song "Right Now" by Akon, two recommendation systems were employed: pitch-based and lyrics-based. Each system produced a list of recommended songs with their respective similarity scores. The original song was used in two forms: as an MP3 file for pitch analysis and as a lyrics string for lyrics analysis.

The pitch based similarity identified the following songs as similar to "Right Now" by Akon, with their corresponding similarity scores Fig.3.

The Lyrics based similarity recommended the following list of songs similar to "Right Now" by Akon, along with their similarity scores Fig.4.

2) AB Testing: To evaluate the effectiveness of our recommendation system, we conducted A/B testing [13] to compare both the segment pitches based and lyrics based systems. Its important to note this evaluation was conducted with a limited sample size of 24 participants, which should be considered with interpreting the results in Fig.5.

In our approach, we selected two songs along with their lyrics and generated recommendations for both the systems. Users are presented with a form that displayed the recommendations without indicating which system they came from. They were asked to select the recommendation they felt was most similar to each original mp3 song.

Gender	Age	What kind of Genres do you like?	When you listen to new music, do you prefer it because of the lyrics or the rhythm?	Which recommendation do you prefer?	Which one do you prefer?
Male	20-25	Electronic Music	Both	Recommendation 1-1	Recommendation 2-1
Male	20-25	Electronic Music	Rhythm	Recommendation 1-1	Recommendation 2-2
Female	35-40	Rhythm	Rhythm	Recommendation 1-1	Recommendation 2-2
Male	20-25	Rhythm	Both	Recommendation 1-2	Recommendation 2-2
Male	25-30	Electronic Music	Lyrics	Recommendation 1-1	Recommendation 2-1

Fig. 5. Dataset generated through user evaluation.

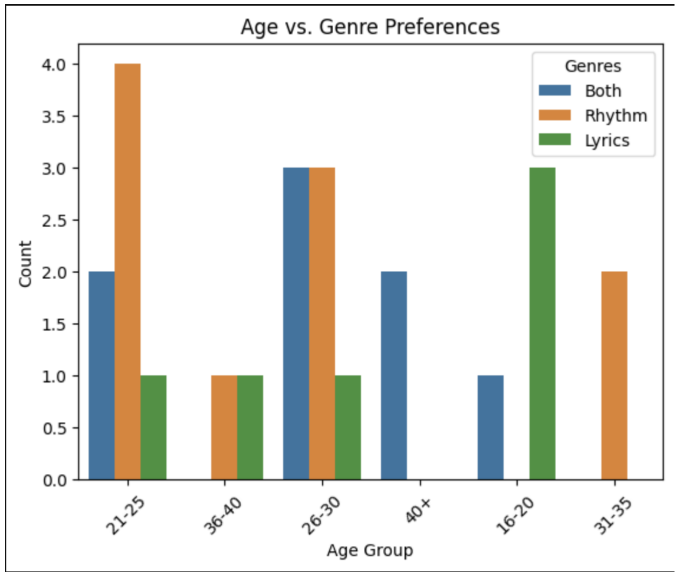

Fig. 6. Age vs Genre preferences

For Song 1, Recommendation 1-1 was based on segment pitches, while Recommendation 1-2 was based on lyrics. Similarly, for Song 2, Recommendation 2-1 was based on segment pitches, and Recommendation 2-2 was based on lyrics. We also collected additional data to obtain more insightful and accurate representations of the users' preferences.

We observed variations in the music genres preferences across different age groups. The 21-25 and 26-30 age group showed the most diverse tastes, encompassing genres such as Rhythm, Electronic music, Rock, Heavy Metal etc. Other age groups displayed more focused preferences Fig.6.

When looking for new music, 41.7% of respondents preferred rhythm, 33.3% valued both lyrics and rhythm equally. and 25% preferred lyrics. While this suggests a slight preference for rhythm Fig.7.

For song 1, the lyrics based recommendation (1-2) was slightly preferred over the segment pitches-based recommendation (1-1), with 13 preferences compared to 11 Fig.8. However, for song 2, the segment pitches-based recommendation (2-1) was significantly preferred over the lyrics-based recommendation (2-2), with 17 preferences compared to 7 Fig.9.

A more detailed analysis of the recommendations for Song 1 reveals interesting patterns when considering users' general music preferences. We observed that among users who typically prefer rhythm when discovering new music, in this case 6 selected recommendation 1-1, which was based on segment pitches. Similarly, 4 users who generally prefer lyrics chose recommendation 1-2, which was based on lyrical content. This alignment between users' general music preferences and their choices in the A/B test suggests that our recommendation system is effectively catering to different listener preferences.

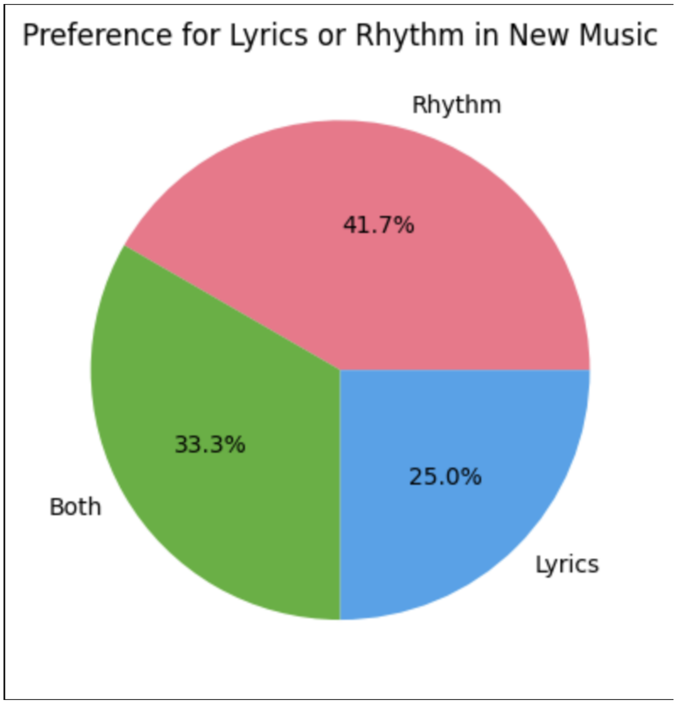

Fig. 7. Users prefer to discover new recommendations based on.

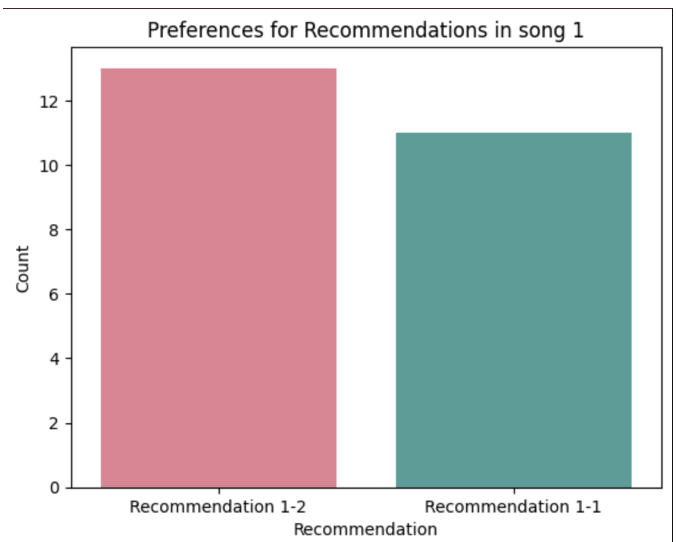

Fig. 8. Evaluators preference for song 1

To visualize this data, we created a heatmaps Fig.10 that illustrates the relationship between users' music preferences (Rhythm, Lyrics, or Both) and their choices between the two recommendation systems for Song 1.

A similar analysis was conducted for Song 2, revealing even more pronounced preferences. Among users who typically prefer rhythm when discovering new music, 8 selected recommendation 2-1, which was based on segment pitches. In contrast, only 2 users who generally prefer lyrics chose recommendation 2-2, which was based on lyrical content.

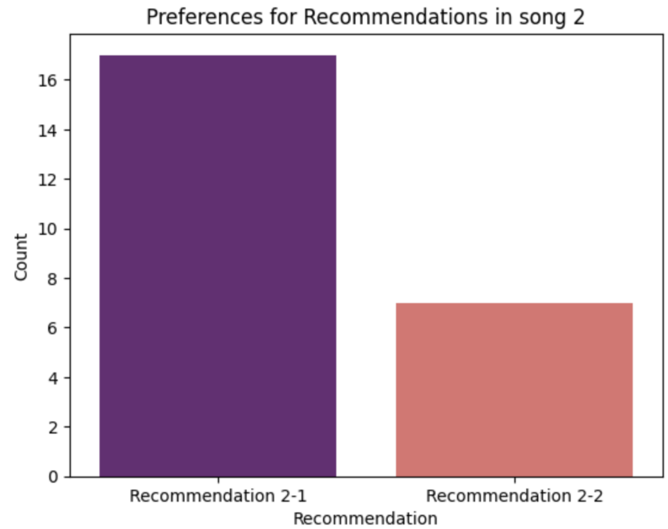

Fig. 9. Evaluators preference for song 2

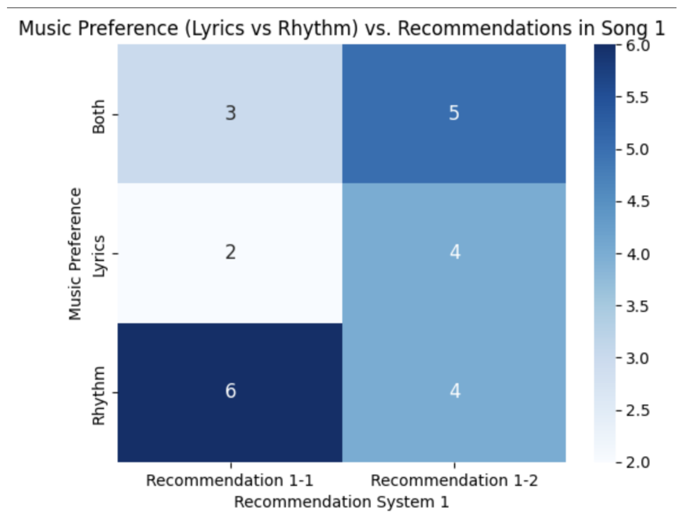

Fig. 10. Heatmap of Music Preference vs. Recommendations for Song 1

This stark difference suggests that for Song 2, the segment pitch-based recommendation was particularly effective, even for some users who typically prefer lyrics. To visualize this data, we created heatmap for Song 2 Fig.11 that illustrate the relationship between user's music preferences and their choices between the two recommendation systems.

These heatmaps provide a clear visual representation of how users' general music preferences correlate with their choices in our A/B test. The darker cells indicate a higher number of users in each category. For Song 1, we see a relatively balanced distribution, with rhythm-preferring users slightly favoring the pitch-based recommendation. For Song 2, there's a strong preference for the pitch-based recommendation across all user groups.

The contrast between Song 1 and Song 2 results is particularly interesting. While Song 1 showed a more balanced prefer-

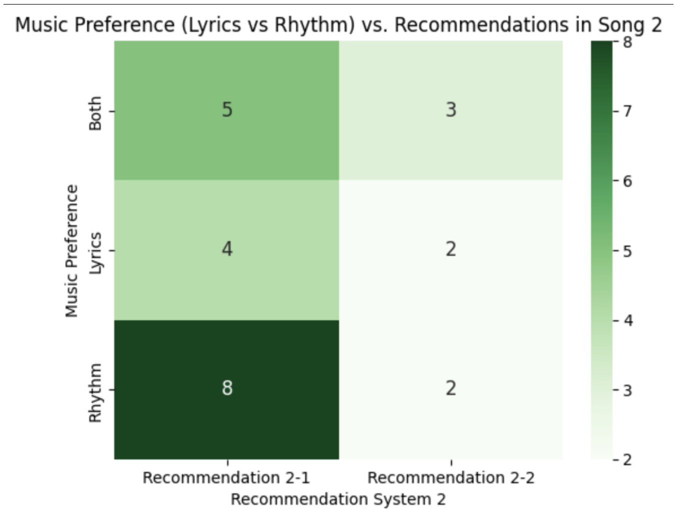

Fig. 11. Heatmap of Music Preference vs. Recommendations for Song 1

ence between pitch-based and lyrics-based recommendations, Song 2 demonstrated a strong bias towards the pitch-based recommendation. This suggests that the effectiveness of each recommendation method may vary depending on the specific characteristics of the song in question.

These findings further support the effectiveness of our dual-approach recommendation system, as it appears to successfully match users with recommendations that align with their stated preferences for either rhythm or lyrics, while also adapting to the unique characteristics of each song. This analysis provides valuable insights into the performance of our recommendation algorithms and their ability to cater to diverse user preferences and song attributes.

These results, while based on limited samples, provide interesting insights. The effectiveness of segment pitches vs lyrics based recommendations appears to vary depending on the song. For one song, lyrics based recommendations were slightly preferred, while other, segment pitches were strongly preferred. The preference for rhythm when finding new music (41.7%) is consistent with the strong preference for segment pitch-based recommendations.

Overall, when combining the evaluations for both songs, 62% of users preferred recommendations based on segment pitches, while 38% preferred those based on lyrics

VII. Conclusion and Feature Scope

This study represents a significant step toward the development of more user-centric music recommendation systems by leveraging both segment pitches and lyrical content. By applying cosine similarity to analyze these two distinct aspects of musical composition, our system offers a more nuanced understanding of songs. Segment pitches provide insights into the melodic and harmonic structure, while lyrical analysis reveals thematic and semantic similarities.

The implementation of A/B testing in our methodology allows for a rigorous evaluation of system performance, measuring user satisfaction with the recommendations. This approach ensures that the system can be continuously refined to better meet user preferences and expectations.

Our future work will focus on enhancing the system's penalization capabilities. We aim to develop a feature that analyzes a user's personal playlist to generate a unique vector matrix. This matrix will then be used to recommend various playlists, increasing the diversity and number of song recommendations. This advancement aims to provide users with a broader selection of music that matches their specific preferences, potentially introducing them to a wider range of artists and genres.

In conclusion, this study underscores the potential of integrating segment pitches and lyrical content into music recommendation systems. By doing so, we aim to offer more accurate and personalized music recommendations, enhancing the overall listening experience and encouraging the discovery of new music. This approach also addresses the issue of cold start in collaborative filtering method by requiring no prior data and assisting users in discovering new artists. Positive user feedback from our evaluation phase demonstrates the effectiveness of segment pitch-based recommendations, validates our approach, and serves as a solid foundation for future improvements and expansions.

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Appendix:

Song 1:

Recommendation produced by segment pitching system based on Akon's song "Right Now."

```
Song ID: TRBHCVQ12903CF8E90, Similarity: 0.8737, Artist: Joe Lynn Turner, Title: Two Lights [Bonus Track], Album: Second Hand Life: The Delux
e Edition
Song ID: TRAOHAH128F425CD57, Similarity: 0.8675, Artist: Mars Ill, Title: Saturday Night Special, Album: Pro*Pain
Song ID: TRAZRXP12903CBD6A9, Similarity: 0.8599, Artist: Vonray, Title: Part Of Me (LP Version), Album: Vonray
Song ID: TRARWYL128F423B96A, Similarity: 0.8482, Artist: Singing Melody, Title: Lived My Life, Album: Expression
Song ID: TRAECSU128F426A84A, Similarity: 0.8458, Artist: Headhunter, Title: Signs Of Insanity, Album: A Bizarre Gardening Accident
```

Lyrics system-produced recommendation based on the lyrics to Akon's song "Right Now."

```
Song ID: TRARBBK128F427ED68, Similarity: 0.5062, Artist: Koffi Olomide, Title: Elle Et Moi, Album: Tcha Tcho
Song ID: TRAWYNV128F92F5E7E, Similarity: 0.4910, Artist: Guns N' Roses, Title: Catcher In The Rye, Album: Chinese Democracy
Song ID: TRADGWP128F42618E4, Similarity: 0.4343, Artist: Madilu System, Title: Vincent, Album: La Bonne Humeur
Song ID: TRAEROB12903CE3E7D, Similarity: 0.5342, Artist: Pepper, Title: Stormtrooper (Live), Album: Kona Gold
Song ID: TRAWSJK128F42767F2, Similarity: 0.5578, Artist: Ini Kamoze, Title: Here Comes The Hotstepper, Album: 100 R&B Classics - The Anthems
```

Song 2:

Recommendation produced by segment pitching system based on Linkin park's song "Numb"

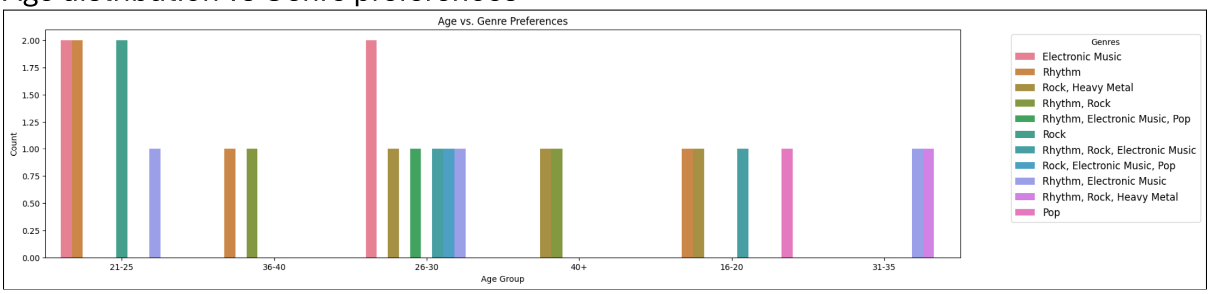
```
Song ID: TRBFQOC128F9313B77, Similarity: 0.9161, Artist: Yolandita Monge, Title: Cierra Los Ojos Y Juntos Recordemos - Original, Album: Yolan
dita Monge Selected Hits Vol. 1
Song ID: TRAYKZI128F932B9E8, Similarity: 0.9085, Artist: Evergreen Terrace, Title: We're Always Losing Blood, Album: Almost Home
Song ID: TRAXWFZ128F9349D17, Similarity: 0.9017, Artist: Greis, Title: Le Choix, Album: 2
Song ID: TRAWIXK12903CE8E34, Similarity: 0.9009, Artist: Rick Ross, Title: Single Again (Remix), Album: Legendary
Song ID: TRAVPHB128F92DA4F5, Similarity: 0.8965, Artist: Hatiras, Title: Lost In Space, Album: Arrival
```

Lyrics system-produced recommendation based on the lyrics to Linkin park's song "Numb"

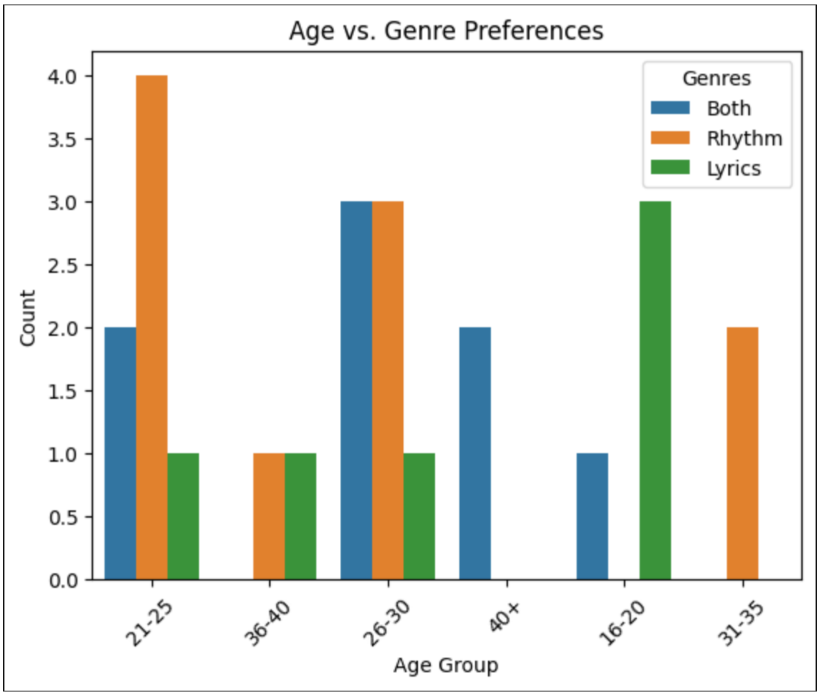
```
Song ID: TRAFTCT128F425A900, Similarity: 0.6483, Artist: Rick Astley, Title: Close To You, Album: Portrait
Song ID: TRAQSWI128F9343039, Similarity: 0.6751, Artist: Shawn Colvin, Title: Cry Like An Angel, Album: Steady On
Song ID: TRACBWP128C7196948, Similarity: 0.6446, Artist: 3 Doors Down, Title: It's Not Me, Album: Here Without You
Song ID: TRAEUIW12903D018F0, Similarity: 0.6403, Artist: Jack Johnson, Title: You And Your Heart, Album: You And Your Heart
Song ID: TRAEWLF128F42B1F89, Similarity: 0.6459, Artist: Information Society, Title: More to This, Album: Synthesizer
```

Analysis of data:

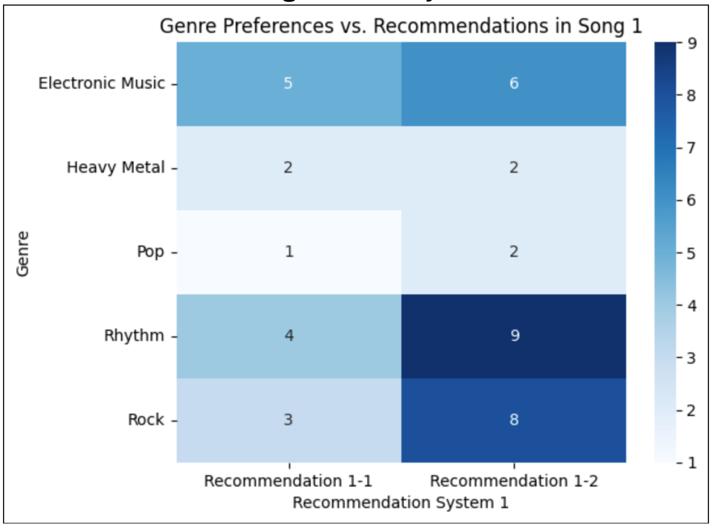
Age distribution vs Genre preferences



Age Vs Genre users prefer when selecting new music



Evaluators selected genres they like vs the recommendation they selected for song 1.



Google form for user evaluation:

Music Recommendation system.

Thank you for agreeing to participate in our music recommendation system evaluation! This study focuses on a music recommendation system built on two platforms. One makes recommendations based on lyrics, while the other bases them on segment pitches. This service evaluation is being carried out for an internal academic project at Queen Mary University in London.

By participating in this survey, you agree to:

- Answer questions related to the evaluation of the music recommendation system.
- Understand that your data will be used for internal academic research purposes only.

Privacy Statement

All data collected through this form, including any comments or information you provide, will be used solely for the purpose of this academic project and will not be shared outside of Queen Mary University of London. No information will be published in any way that could identify you.

Contact

If you have any questions regarding this evaluation or the privacy statement, please contact at: s.rambha@se23.qmul.ac.uk.

vivekrambha@gmail.com Switch account

Not shared

* Indicates required question

Gender *

- Male
- Female
- Prefer not to say

Age *

- 14 and below
- 15-20
- 21-25
- 26-30
- 31-35
- 36-40
- 40+

What kind of Genres do you like? *

- Rhythm
- Rock
- Electronic Music
- Heavy Metal
- Pop
- Other:

When you listen to new music, do you prefer it because of the lyrics or the rhythm? *

- Lyrics
- Rhythm
- Both

The following suggestions were generated using this song.

Please choose the recommendation that you believe best suits the song mentioned above

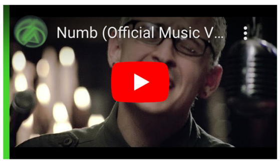
Recommendation 1-1

Recommendation 1-2

Which recommendation do you prefer? *

- ○ Recommendation 1-1
- ○ Recommendation 1-2

The following suggestions were generated using this song.



Please choose the recommendation that you believe best suits the song mentioned above

Recommendation 2-1

Recommendation 2-2

Which one do you prefer? *

- ○ Recommendation 2-1
- ○ Recommendation 2-2

Submit

Clear form

ds

Vector from MSD dataset.

$a = [-0.2225, 1.4665, -0.9294, 2.0402, -0.7911, -0.6268,$
$0.1259, -1.1369, -0.1788, -1.1077, 0.3183, 1.0423]$

Vector from mp3 song.

$b = [-0.4136, 1.2081, -0.3040, 1.9280, 0.5874, -1.1016,$
$-0.2902, -1.4989, -0.3499, -1.2000, 0.5188, 0.9160.]$

Calculate Dot product of two vectors.

$$a.b = \sum_{i=1}^{n} a_i \times b_i$$

$$= (-0.2225 \times -0.4136) + (1.4665 \times 1.2081) + (-0.9294 \times -0.3040) + \cdots$$

$$= 10.4850.$$

Calculate the magnitude.

$$\|a\| = \sqrt{\sum_{i=1}^{n} a_i^2}$$

$$\|a\| = \sqrt{(-0.2225)^2 + (1.4665)^2 + \cdots}$$

$$= 3.4640.$$

$$\|b\| = \sqrt{(-0.4136)^2 + (1.2081)^2 + \cdots}$$

$$= 3.4640$$

Calculate Cosine Similarity.

$$\text{Cosine Similarity} = \frac{a.b}{||a|| \times ||b||}$$

$$= \frac{10.4850}{3.4640 \times 3.4640}$$

$$= 0.874.$$