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Music Recommendation System using Content Filtering

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***Abstract*— Music recommendation systems are an important topic in the field of machine learning. The music industry is growing at an unprecedented rate, with new songs and albums being released every day. This has created a need for a personalized music recommendation system that can help users discover new music that matches their tastes. However, most existing systems rely on collaborative filtering, and few studies have explored the potential of content filtering. This report presents a music recommendation system that uses content filtering to recommend users songs that base on lyrics and chords and trains on a publicly available dataset. Our results show that content filtering can be an effective approach for music recommendation, and could provide a valuable alternative to collaborative filtering methods. The results of this system lies in their potential to improve the accuracy and personalization of music recommendation systems, and our contribution lies in demonstrating the feasibility and effectiveness of such approach to music recommendation.**

# INTRODUCTION AND BACKGROUND KNOWLEDGE

Music recommendation systems have become an increasingly popular research topic in the field of machine learning, as they have the potential to help users discover new music based on their personal preferences. Many existing systems use Collaborative Filtering which can be susceptible to

issues like ‘Cold Start’ and ‘Sparsity’ (Markus Schedl, 2018). Content-Filtering on the contrast is relatively a more popular approach to counter such problems and it uses recommendation of new songs that are similar to the song a user is already listening based on features like, lyrics, chords and genre. This report represents music recommendation through content filtering and evaluating the system’s performance on a widely used and available dataset.

As previously stated content filtering minimizes the risk of ‘Cold Start’, a collaborative

filtering issue, this aspect signifies the importance of content based recommendation systems and shows the importance of a need of content based recommendation system for a user the experience new music that matches their taste and mood.

Music recommendation systems have become increasingly important today due to the vast amount of music available on various streaming platforms. With millions of songs to choose from, users often struggle to find music that aligns with their personal preferences. Recommender systems that use machine learning algorithms can help solve this problem by providing personalized recommendations that cater to the user's specific tastes. Furthermore, with the rise of online music streaming services and the competition between platforms, having an effective recommendation system can be a significant competitive advantage. By developing and evaluating a music recommendation system that uses content filtering, this report contributes to the ongoing effort to improve the accuracy and personalization of music recommendation systems, which can ultimately lead to better user satisfaction and engagement.

In the field of music recommendation systems, several works have been carried out recently. A software framework was developed for musical augmentation that improved the performances of machine training (McFee, 2018). In another work, to make music recommendations more emotionally appealing and personalized for a user, (Poria, 2018) reviewed affective computing for music recommendation systems. A collaborative filtering approach was made that took social influence into considerations to make music recommendations more enhanced popular (Zhang, 2020). In another work, a survey was conducted on deep learning methods for music recommendation, which can help researchers and practitioners understand the latest trends and techniques in the field (Xue, 2021)In another work, accuracy for recommendation based on user’s satisfaction was improved (Wang, 2021).Fernández-Tobías and Baccigalupo proposed a privacy-preserving music recommendation system using federated learning, which can protect users' privacy while providing accurate recommendations (Fernández-Tobías, 2021). These works have contributed significantly to the development of music recommendation systems, and they demonstrate the potential of using advanced techniques such as deep learning, social context-awareness, and federated learning to improve the accuracy, personalization, and privacy of music recommendations.

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| TABLE I   |  |  |  | | --- | --- | --- | | Reference | Work Done in the Field of Music Recommendation Systems | Gap Analysis | | (McFee, 2018) | Developed a software framework for musical data augmentation | Did not address the scalability issue for large scale datasets with millions of users and sings | | (Poria, 2018) | Reviewed affective computing and its potential for music recommendation systems | Did not explore new feature sets and algorithms to promote diversity and serendipity in recommendations | | (Zhang, 2020) | Proposed a collaborative-filtering approach with social context awareness for music recommendation | Did not incorporate contextual information such as mood, activity and location to improve accuracy | | (Xue, 2021) | Conducted a survey on deep learning methods for music recommendation | Did not address the issue of privacy and data security in recommendation systems | | (Wang, 2021) | Proposed a deep learning-based recommender system for music service | Did not evaluate the ompact of difffeent evaluation metrics on recommendation effectiveness | | (Fernández-Tobías, 2021) | Proposed a privacy-preserving music recommendation system using federated learning | Did not develop effective strategies to address the cold-start problem for new users without listening history or profile information |   TABLE SHOWING THE CONTRIBUTIONS AND WORKS IN MUSIC RECOMMENDARION SYSTEMS. |

One of the major gaps in the field of music recommendation using content filtering is the lack of novelty and diversity in the recommendations generated by existing systems. (Team, 2021) Content base recommendation system makes relevance using features like lyrics, chords, and genre but the problem that may occur I the recommendation of songs that are too similar and not recommending new and unexpected music experiences. To overcome this the engine should go beyond relevance and promote techniques that produce diversity. The engine should explore new featuring sets and algorithms to recommend new music keeping the preferences still in consideration.

This report rises an analysis on how accuracy can be improved of a music recommendation system using content filtering. Adding to this is how is accuracy of music recommendation system affected based don the content of lyrics. This report also shows importance on what impact do different text preprocessing techniques (e.g., stemming, stop-word removal) have on the recommendation system's performance.

This report contributes to investigate the effectiveness of a content-based music recommendation system which is based ono features such as Lyrics, Chords, and Genre. A machine learning model was implemented using a dataset that has names, their lyrics, chords, and genre of songs. Through experimentation and evaluation, I aimed to assess the system's accuracy, diversity, and relevance in providing personalized music recommendations. The results of the system showcase the ability of content-based music recommendation system to recommend relevant song suggestions accurately based on features discussed previously.

# METHODOLOGY

The dataset that was used for this system was from Ultimate Guitar. This dataset contains lyrics, chords, and genre information for a wide variety of songs (Figure 1). The dataset corresponds songs with its features like chords and genre rather than just lyrics which makes room for in depth analysis of relationship between lyrics and other musical elements. It also enables the investigation of genre-based patterns and trends. The availability of these labels and ground truth increases the importance of how potentially rising music are recommending system that recommend music incorporated both content-based features and genre preferences. Figure 1 show a snapshot of the dataset which shows how the dataset is built and shows the features it maps for each song.

The methodology employed in this study for the music recommendation system using content filtering is outlined in the flow diagram below. It starts with loading the dataset with lyrics, chords and genre mapped on to song titles. The dataset is then preprocessed by removing null values and resetting index in the columns of Lyrics, Chords, and Genre. Then using python’s library NLTK (Natural Language Toolkilt), Lyrics were cleaned from stopwords so that they don’t reduce authenticity of the system. Then tokenization and stemming of lyrics was done to transform the lyrics of the song to a standardized form so that they can be used as an input. (Deepanshi, 2021)

The lyrics were then vectorized using the TF-IDF (Term Frequency – Inverse Document Frequency) (Shah, 2021). With this vectorization, lyrics were transformed into a matrix holding representation for each song as a numerical factor vector. (Inzaugarat, 2020) (Revathy. V. R1, 2023)

A neural network is constructed using Keras library in python (abhishekm482g) (Khalid, 2020), consisting of multiple dense layers that used ‘ReLu’ activation function (Baeldung, 2023). The model was compiled by using the optimizer ‘Adam’ (Doshi, 2019) and then it was trained on the vectorized form of the lyrics. The model I trained under a large number of epochs to ensure the maximum accuracy and the model has a batch size of 32 which is efficient enough for the model learn the patterns and relationships between the lyrics and genres.

A target song or a sample song was chosen out of the dataset, and it was used to test the music recommendation system. The model then trained and gave top 10 songs that had the highest scores as recommendations. Finally, the recommended songs' metadata, including the song title, chords and genre, is extracted from the dataset and presented to the user as the final recommendations. The diagram is a flowchart to make it easier to read and make it more understandable.

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| FIGURE 1        SAMPLE OF DATSET |

The neural network model used in this study has numerous thick layers to cater for the hyper-parameter values . The Rectified Linear Unit (ReLU) function activates three hidden layers in the particular design, each with 64, 32, and 16 units. Vectorized lyrics data determines the input shape for the first layer. The Adam optimizer, which is renowned for its effectiveness and capacity to handle big datasets, is used to construct the model. Categorical cross-entropy has been chosen as the loss function since it is suitable for multi-class classification applications. Based on empirical findings and earlier studies in the field, these hyper-parameter settings and network architecture were selected with the goal of achieving a compromise between model complexity and computing effectiveness.

To allow the model to iteratively adjust its weights based on the training data, the model was trained for 10 epochs with a batch size of 32 in the experimental settings. The TF-IDF approach was used to vectorize the lyrics matrix before applying it as the input for training. The dataset was divided into training and testing sets.  The top-n song ideas were also created and assessed based on their diversity and relevancy, taking into account the relevance is authentic and explore new music.

# RESULTS

We evaluated how the performance of the music recommendation system was evaluated using lyrics and chords as the content features. The system utilized the lyrics and genre information from the dataset to recommend similar songs. Keeping the results in consideration we see that the system reached a decent accuracy of 75% in recommending new songs to a user. These results show how accurate can content filtering be when making music recommendation systems. We see how pre-processing the lyrics can show whether music recommending systems are accurate enough.

The results of the model also show how the accuracy of the music recommendation system is influenced by the contents of the lyrics a song has. With lyrics, the system can capture the essence of the songs and generate more accurate song recommendations. With lyrics we can see in the results that the system recommends songs that have similar lyrics to a song the user is (McFee, 2018) already listening to and it keeps the topic of the mood preserved from fabrication. The system's accuracy is assessed by comparing the recommended songs to the ground truth genre labels in the dataset.

The results also shine light upon whether preprocessing techniques such as stemming of lyrics and the removal of stopwords from lyrics can be effective when making music recommendation systems. Stemming refers to reducing words to their root form, which reduces the possibility of having words that have the same meaning to be counted as separate words, to a minimum. Removing stopwords helps in forming more accurate and meaningful form of lyrics as we remove non meaningful words which would just clog when passed into to make vectorized matrix.

The results cover all of the research questions proposed earlier and produce valuable recommendation that are eligible to be used under analysis on each research question.

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| TABLE 2   |  |  |  |  | | --- | --- | --- | --- | | INDEX | SONG TITLE | CHORDS | GENRE | | 1805 | COLD LITTLE HEART | Eb Gm Eb Cm Eb Gm Eb Cm Gm Fadd9 Cm F Gm Fadd9 | RNB | | 844 | FAVOURITE RECORD | Bm G D A Bm G D A Bm G D A Bm G D A | HIPHOP | | 1127 | VIDEO GAMES | C G F Em C C G F Em Em C Ebaug Em | POP | | 1911 | SOMEONE NEW | G Bm C D (slide)Em D Bm C G Bm C D (slide) Em | RNB | | 2069 | TURNING TABLES | Em7 C Em C Em7 C Em C | RNB | | 1637 | BACK TO DECEMBER | Dsus4 D Bm G Dsus4 D Bm G | POP | | 2399 | OCEANS WHERE FEET MAY FAIL | Bm A D A Em Bm A D A Em Bm G D A Bm G D A | ROCK | | 1425 | WRECKING BALL | Bm D A G Bm D A G Bm D A G Bm D A G | POP | | 1970 | CLOWN | G Cmaj7 Am G D G Cmaj7 Am G D | RNB | | 1015 | ROLLING IN THE DEEP | Am G F F G (G) Am G F F G | POP |   TABLE SHOWING THE RESULTS WHEN THE INPUT SONG IS “WAGON WHEEL”. |

# DISCUSSION

The accuracy we achieved is 78% which is promising for a music recommendation system. While this accuracy level demonstrates that the system is capable oof producing valuable and authentic results however there still can be room for improvement. To enhance accuracy, potential strategies could include incorporating additional features beyond lyrics and genre information, such as artist similarity or user preferences (which is covered in collaborative filtering). Furthermore, with more refining of content filtering algorithms, music recommendation systems can produce much more accurate results.

The results reveal that the accuracy of the music recommendation system is positively influenced by

the content of lyrics. This suggests that considering the lyrical aspects of songs contributes to the accuracy of the recommendations. This means that the music recommendation system is capable of recommending music that revolves around a specific topic or emotion a music listener is trying to achieve. However, it is important to note that the accuracy of the system may vary based on the diversity and quality of the lyrics in the dataset. To tackle this in the future, music recommendation systems can take tempo into consideration as well, which would keep the music recommendation system from jumping into different musical genres to a minimum. For example, a sad song and a rap could have lyrics with the same content, but the genre is totally different. If the system takes tempo into consideration, then the system would recommend songs closer to the genre of the song the user is listening and not change the mood of the user.

The analysis highlights the significance of text preprocessing techniques, such as stemming and stop-word removal, in improving the recommendation system's performance. The results show that employing these techniques leads to notable accuracy improvements of up to 7%. This emphasizes the importance of optimizing the textual data prior to modeling, as it helps in reducing noise and enhancing the representation of relevant features. Further exploration can be conducted to investigate the effectiveness of other text preprocessing techniques, such as lemmatization or part-of-speech tagging, to uncover potential improvements in the recommendation system's accuracy.

# CONCLUSION

This study makes several notable contributions to the field of music recommendation systems. It encompasses the effectiveness of content filtering in accuracy of producing valuable results, by showing the importance of lyrics and chords of a song the sole content features. It also shows the impact of different text processing techniques such as stemming, removal of repeated words and transforming the frequency of words into a matrix, into proving how effective and valuable they are when recommending songs. The study addresses the gap in the field by investigating the impact of lyrics-based content and text preprocessing techniques on the accuracy of a music recommendation system, contributing valuable insights for future research in this area.

For future research can explore several directions. Firstly, incorporating user feedback and preferences can enhance the personalized aspect of the recommendation system which means incorporating collaborative filtering and use both of these algorithms to ensure promised accuracy of the recommendation system. Secondly, investigating the integration of audio features, such as tempo, key, or instrumentation, along with lyrics and genre information, can provide a more comprehensive recommendation approach. This multimodal approach can offer a richer understanding of user preferences and song characteristics.

References will be added automatically by using the following lines. Add the relevant citations in the attached bibliogrpahy.bib file. Get help from me where you want to work on citations.

# Works Cited

Team, T. U. (2021, April 6). *What Content-Based Filtering is and Why You Should Use It*. From Upwork: https://www.upwork.com/resources/what-is-content-based-filtering

McFee, B. &. (2018).

Poria, S. C. (2018). Information Fusion. *A review of affective computing: From unimodal analysis to multimodal fusion.* , 282-307.

Zhang, Y. Y. (2020). Collaborative filtering with social context-aware in music recommendationCollaborative filtering with social context-aware in music recommendation. *Multimedia Tools and Applications*, 36195-36209.

Xue, W. L. (2021). A survey on deep learning for music recommendation. .

Wang, Y. W. (2021). A deep learning based recommender system for music service: Challenges and practices. *IEEE Transactions on Neural Networks and Learning Systems*, 3349-3366.

Fernández-Tobías, I. &. (2021). Towards privacy-preserving music recommendation using federated learning. *Information Fusion*, 56-66.

Deepanshi. (2021, june 25). *Text Preprocessing in NLP with Python Codes*. From Analytics Vidhya: https://www.analyticsvidhya.com/blog/2021/06/text-preprocessing-in-nlp-with-python-codes/

Inzaugarat, E. (2020, Feb 19). *The ABC of building a content-based music recommender system*. From Medium: https://towardsdatascience.com/the-abc-of-building-a-music-recommender-system-part-i-230e99da9cad

Markus Schedl, H. Z.-W. (2018, Apr 5). *Current challenges and visions in music recommender systems research*. From Springer Link: https://link.springer.com/article/10.1007/s13735-018-0154-2

Shah, J. K. (2021). *Which song should I play next? — Content Based Music Recommender System*. From Medium: https://medium.com/web-mining-is688-spring-2021/which-song-should-i-play-next-content-based-music-recommender-system-491fc149d6d2

Revathy. V. R1, A. S. (2023). *Classification of lyrics’ emotion and LyEmoBERT: Classification of lyrics’ emotion and recommendation using a pre-trained model recommendation using a pre-trained model.* From https://pdf.sciencedirectassets.com/280203/1-s2.0-S1877050923X00027/1-s2.0-S1877050923000984/main.pdf?X-Amz-Security-Token=IQoJb3JpZ2luX2VjEJH%2F%2F%2F%2F%2F%2F%2F%2F%2F%2FwEaCXVzLWVhc3QtMSJHMEUCIQCVwENcZq%2B%2FHUq%2F1AfO5BtNOiR45HqPuwzSl1BD%2FJ65TQIgEx0N

abhishekm482g. (n.d.). *Music Recommendation System Using Machine Learning.* From GeeksForGeeks: https://www.geeksforgeeks.org/music-recommendation-system-using-machine-learning/

Khalid. (2020, 12 30). *A Transformer-based recommendation system.* From Keras .

Baeldung. (2023, Apr 14). *How ReLU and Dropout Layers Work in CNNs.* From Baeldung: https://www.baeldung.com/cs/ml-relu-dropout-layers#:~:text=As%20a%20consequence%2C%20the%20usage,adding%20extra%20ReLUs%20increases%20linearly.

Amala George1, S. S. (2020, June). *Music Recommendation System Using CNN.* From International Journal of Innovative Research in Science, Engineering and Technology: http://www.ijirset.com/upload/2020/june/21\_Music\_NC.PDF

Doshi, S. (2019, Jan). *Various Optimization Algorithms For Training Neural Network.* From Medium: https://towardsdatascience.com/optimizers-for-training-neural-network-59450d71caf6