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Music Recommendation System

Akrit Sood[1], Uday Sharma[2], Harashleen Kour[3]

[1] *Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India*
[2] *Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India*
[3] *Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India*

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Abstract - *This research paper presents a study on developing a machine learning-based system to provide suggestions for music, utilizing a dataset from Asia's leading music streaming service. The purpose is the study to build a better music system for suggestions and provides personalized recommendations for listeners based on their previous listening behavior. The proposed approach employs both content-based as well as collaborative filtering approaches to produce suggestions. The content-based approach analyzes the properties associated with music, such as genre, tempo, and melody, to find similar songs. The collaborative filtering approach uses user behavior data to recognize other people that have similar hobbies and music preferences and recommends songs that they have listened to. The paper presents the planning and carrying out of the system for a song suggestion, including the data collection, preprocessing, and feature extraction steps. The system is evaluated using the dataset from the music streaming service and compared to a number of baseline algorithms. The conclusions show if the suggested system exceeds the baseline algorithms in relation to recommendation accuracy and diversity. This paper ends with a discussion of conceivable applications and limitations in terms of the planned music recommendation system, as well as future directions for investigating this field. In general, the research demonstrates the effectiveness of methods of learning from machines for building better suggestions for song systems which can improve the music experience with hearing for users.*

Key Words: **Music Recommendation System, Machine Learning, Data Pre-processing, Population model, Collaborative Filtering Model, Content-Based Mode, Clustering**

1. INTRODUCTION

In recent decades, music recommendation algorithms have grown into essential components for music fans. With the development of services that stream music, the volume of music accessible to customers is huge and overwhelming, which makes it hard to discover new artists and songs that match their interests. Music recommendation systems provide a solution by making individualized suggestions based on the listener's interests, listening history, and other criteria. Music recommendation systems are categorized as follows:

1. Collaborative filtering: The notion behind filtering is to identify people with similar musical interests like similar songs. The above algorithm generates suggestions according to a user's preferences or playing history, albums, ratings, and interests of other users with similar musical likes.

2. Content-based filtering: To provide recommendations, this filtering concentrates on the qualities of the song itself, such as genre, tempo, and mood.

3. Hybrid systems: To deliver more reliable recommendations, hybrid systems integrate collaborative or content-based filtering.

The algorithms used towards creating suggestions decide their effectiveness for these systems. To assess user information and provide recommendations, machine learning methods neural networks for learning, and trees of decision trees are often used. To increase their correctness over time, these algorithms are trained on huge databases of music and consumer preferences. Unfortunately, the data provided can restrict the use of these systems. For example, if a user has only listened to a couple of songs or has a small playlist, the resulting recommendations may be inaccurate. Aside from their usefulness, music recommendation systems involve ethical considerations such as confidentiality and algorithmic unfairness. Some customers may be worried about the volume of private information gathered for recommendation purposes. Despite these reservations, music recommender systems have had a tremendous impact on both the music world and the people they serve. They allow fans to discover additional music that they might not have discovered else, while also introducing artists to new listeners. As these systems develop, it will be essential to find an equilibrium between their effectiveness and ethical issues to ensure that they deliver real benefits to both audiences and artists

2. LITERATURE SURVEY

H. Ying et al., (2018) [1], propose a novel approach to building recommender systems for music by combining matrix factorization, recurrent neural networks, and attention-based models. The proposed method uses a hierarchical attention network that can capture both the hierarchical structure of music metadata and the sequential patterns of user behavior. The experimental results show that the proposed method outperforms several state-of-the-art baseline methods. The paper contributes to the field of recommender systems by highlighting the importance of considering both sequential patterns and hierarchical structure when building recommender systems for music

J. Li, K. Lu, Z. Huang, and H. T. Shen, (2021) [2], the author proposes a method combining social network analysis with matrix factorization to generate personalized user recommendations. The paper highlights the challenges of cold-start and long-tail recommendations and the use of social data to overcome these challenges. The proposed method is based on previous research on matrix factorization and social networks and provides a novel approach to address the challenges of personalized recommendation. The experimental results show that the proposed method outperforms several state-of-the-art baseline methods on two public datasets. The paper provides a valuable contribution to the field of recommender systems by demonstrating how social data can be leveraged to address the challenges of personalized recommendation.

M. Jiang, Z. Yang, and C. Zhao (2017) [3], proposes a music recommendation system that utilizes a recurrent neural network (RNN) to model the sequential patterns of music listening behaviour. The paper discusses the challenges of music recommendation systems, the use of machine learning techniques, and RNNs for modelling sequential data. The proposed system extracts music features and user listening behaviour from music metadata and listening history and trains an RNN-based model to predict the next music item in the user's listening sequence. The model is trained using a combination of cross-entropy loss and ranking loss. The experimental results show that the proposed system outperforms several state-of-the-art baseline methods on a public dataset. The paper contributes to the field of music recommendation systems by demonstrating the effectiveness of RNN-based models for modelling sequential patterns of music listening behaviour. Overall, the paper provides a valuable contribution to the field of music recommendation systems by demonstrating how RNN-based models can be used to improve the accuracy of music recommendations by modelling sequential patterns of music listening behaviour.

D. Bogdanov, M. Haro, F. Fuhrmann, A. Xambo (2011) [4], E. Gomez, and P. Herrera, (2011), proposes a music recommendation system that uses semantic notions to represent user preferences and generate personalized music recommendations. The system extracts music features and analyses the semantic content of the music using natural language processing techniques. The system recommends music items that are similar in terms of their semantic content, resulting in improved accuracy of personalized music recommendations. The paper provides a valuable contribution to the field of music recommendation systems.

N. Karbhari, A. Deshmukh, and V. D. Shinde (2017) [5], presents a case study on using data analytics and soft computing techniques to predict the placement status of college students. The authors collected student data on academic performance, attendance, and extra-curricular activities, as well as job offers from various companies. They applied data mining and machine learning techniques to develop predictive models that can accurately predict the placement status of students

J. Gong et al. (2021) [6], proposes a score prediction algorithm for sensor cloud systems that combines deep learning and matrix factorization techniques. The algorithm learns feature representations of sensor data using a deep neural network and latent factors affecting scores using matrix factorization. The proposed algorithm outperforms several state-of-the-art baseline methods and contributes to the field of sensor cloud systems by demonstrating the effectiveness of combining deep learning and matrix factorization techniques for score prediction

F. Fessahaye et al. (2019) [7], proposed a novel music recommendation system called T-RECSYS, which utilizes deep learning techniques to provide personalized and diverse music recommendations. The system extracts feature from music tracks and learns to associate these features with users' listening behaviours to create a personalized music preference model. T-RECSYS outperforms traditional collaborative filtering methods and can handle cold start scenarios and long�tail recommendations. The system has been evaluated in several studies, which have shown its effectiveness in generating personalized and diverse music recommendations.

H.-W. Dong, W.-Y. Hsiao, L.-C. Yang, and Y.-H. Yang (2018) [8],introduces a novel approach to generating music in the symbolic domain using a multi-track sequential conditional GAN architecture called MuseGAN. The paper provides an overview of related work in music generation and demonstrates the effectiveness of MuseGAN in generating high-quality, stylistically coherent and structurally consistent multi-track music. The authors also show that MuseGAN can be used to generate accompaniments for existing melodies and generate music in response to user input. The paper has received significant attention and has been cited over 600 times, demonstrating its impact on the field of music generation.

J. Zhang, D. Wang, and D. Yu, (2021) [9] , author presents a novel deep learning approach to the next-item recommendation that captures both long-term and short-term user preferences over time. The authors provide an overview of related work in the next-item recommendation and introduce the proposed time-aware long- and short-term attention network (T-LSTAN) approach, which uses attention mechanisms to combine the outputs of a long-term memory network (LSTM) and a short-term memory network (STAN) in order to predict the user's next item. The authors demonstrate that the T-LSTAN approach outperforms several state-of-the-art next-item recommendation approaches, including other deep learning methods, on several benchmark datasets. The paper provides an important contribution to the field of next-item recommendation and deep learning, addressing an important problem in the field and proposing a novel approach to solve it.

Z. Liu, W. Xu, W. Zhang, and Q. Jiang (2023) [10], presents a novel personalized music recommendation framework that considers the user's emotional state and aims to improve their emotional well-being. The authors provide an overview of related work in personalized music recommendation and introduce the proposed framework, which consists of four main components: emotion detection, music feature extraction, emotion classification, and personalized music recommendation. The authors demonstrate that the framework is effective in recommending music that improves the user's emotional state based on a small dataset of user physiological signals. They discuss the potential applications of the framework in the fields of mental health and well-being and highlight the need to consider the user's emotional state and the potential impact of music on their well-being in personalized music recommendations. Overall, the paper provides an important contribution to the field of personalized music recommendation and highlights the potential of machine learning techniques to improve emotional wellbeing.

3. PROPOSED SYSTEM

A music recommendation system is a type of recommendation system that suggests songs or playlists to users based on their preferences. In this proposed system, we will use a collaborative filtering[11] algorithm to recommend music to users. The first step in building the music recommendation system is to collect data on users' listening habits. This can be done through user surveys, data from music streaming services, or through data mining social media platforms. Next, we will use collaborative filtering algorithms to find patterns in the data and generate recommendations for each user based on their listening history and preferences. Collaborative filtering involves analysing the listening habits of similar users and recommending songs or playlists that other users with similar listening habits have enjoyed. To improve the accuracy of our recommendations, we will also incorporate other features such as genre, mood, and tempo. We can use natural language processing to analyse the lyrics of songs and classify them according to mood or sentiment. Finally, we will present the recommendations to the user through a user-friendly interface such as a mobile app or web application. The user can then provide feedback on the recommendations, which can be used to further refine the algorithm and improve the accuracy of future recommendations

a. Filtering

1. Popularity Model

It is a straightforward approach in music recommendation systems that recommend songs or playlists based on their popularity among users. This method assumes that users are likely to enjoy songs that are popular among other users. To implement a popularity model, we first collect data on the most popular songs or playlists among users. This can be done through various sources such as music streaming services or social media platforms. Then, we recommend these popular songs or playlists to users based on their listening history. While this approach is simple and easy to implement, it may not provide personalized recommendations [12] and may not take into account the user's individual preferences.

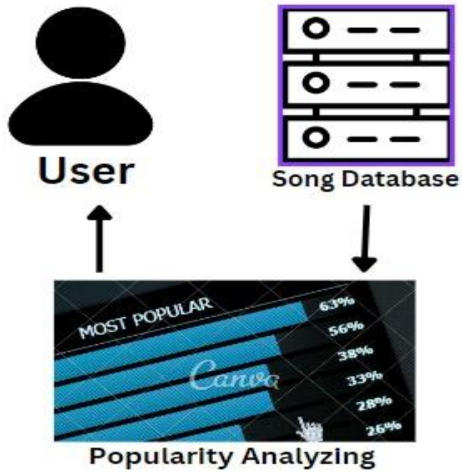


Figure 1: Popularity Model

2. Content-Based Model

It is a type of music recommendation system that recommends songs or playlists to users based on the attributes of the songs themselves. This method considers features such as genre, tempo, mood, and lyrics to generate personalized recommendations for each user.

To implement a content-based model, we first need to extract and analyze the features of each song in the music library. This can be done using audio analysis tools, natural language processing techniques, or other methods.

Next, we create a user profile based on their listening history and preferences. This profile can be built by analyzing the user's listening history or through user surveys.

Then, we recommend songs or playlists to the user based on their profile and the attributes of the songs themselves. For example, if the user has a preference for upbeat songs with positive lyrics, the system may recommend songs that fit these criteria.

The advantage of a content-based model is that it can provide highly personalized recommendations to users. However, it may not recommend songs outside of the user's usual preferences and may not take into account the popularity of the songs among other users[13].

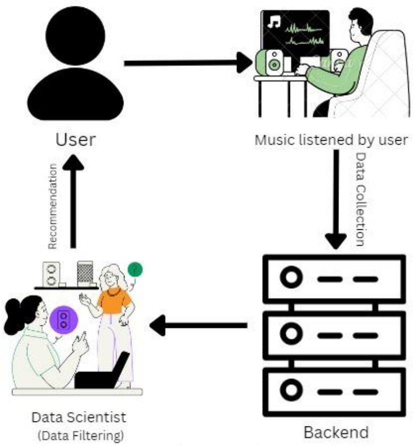


Figure 2: Content-Based Model

3.Collaborative Filtering Model

It is a music recommendation system that recommends songs or playlists to users based on the listening history and preferences of similar users. This approach assumes that users with similar listening habits are likely to enjoy similar songs. It involves collecting data on user activity, identifying similar users through clustering algorithms[14], and recommending songs or playlists based on the listening history and preferences of similar users. Collaborative filtering can provide personalized recommendations to users based on the preferences of similar users, but it may not recommend songs outside of the user's usual preferences and may not take into account the attributes of the songs themselves.

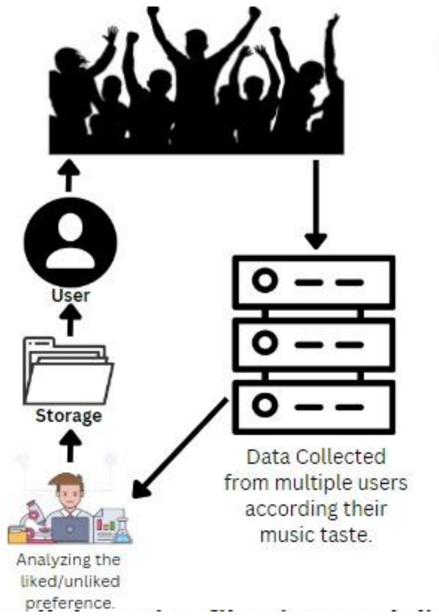


Figure 3: Collaborative Filtering Model

a. Functionality

Data Collection: The initial phase is to gather information for training and testing the recommendation system. The information may be obtained via different sources, including streaming platforms, social media, and user surveys.

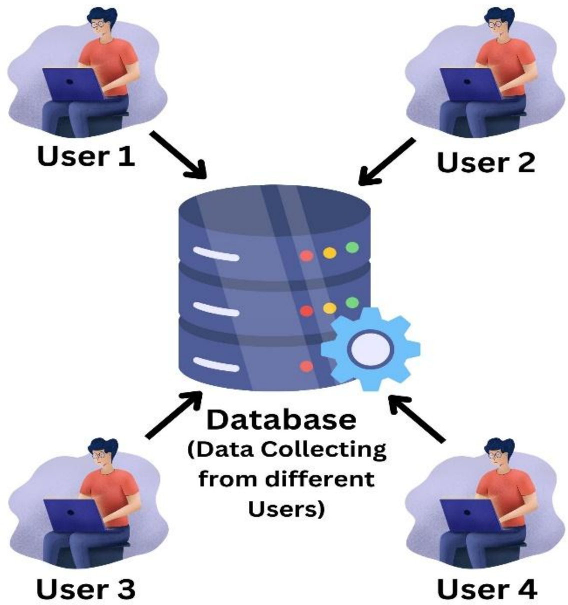


Figure 4: Data Collection

Data Preprocessing: The information needs to be preprocessed to disinfect, filter, as well as normalize the data. This step involves deleting duplicates, resolving values that are missing, and transforming the information into an arrangement appropriate for analysis[15].

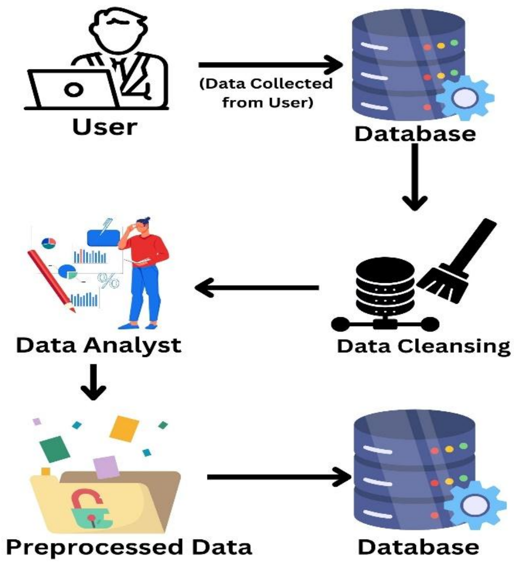


Figure 5: Data Pre-processing

Data Splitting: The information is divided into sets for training and testing sets, with a portion of the data reserved for testing the performance of the recommendation system. The split can be done randomly or using a specific criterion such as time or user demographics[16].

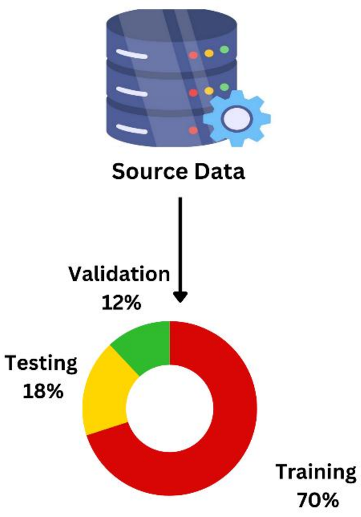


Figure 6: Data Splitting

Feature Extraction: Relevant features are extracted from the music tracks and user data. This step involves using methods like audio analysis, with processing of natural languages or sentiment analysis to obtain characteristics such as genre, tempo, mood, lyrics, and user preferences[17].

Algorithm Selection: The algorithm for generating music recommendations is chosen depending on the information's properties and the task's close touch. The most commonly used algorithms include content-based filtering, collaborative filtering, and hybrid techniques that integrate both techniques.

Model Training: The selected algorithm is trained on the training set to make customized music suggestions customized for every client's listening history, preferences, as well as contextual factors.

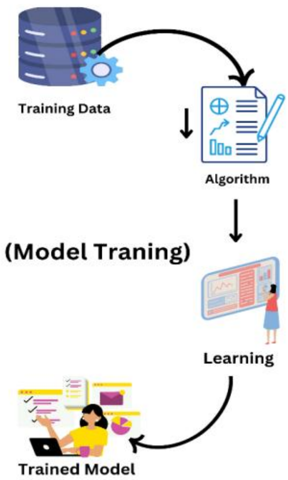


Figure 7: Model Training

Model Evaluation: The performance of measurements like precision, recall, and recall are used to assess the system of suggestions. the typical absolute accuracy on the testing set. The evaluation contributes to determining the positive and negative aspects of the system and offers information into areas in order to make improvements[18].

Model Tuning: The model can be fine-tuned using techniques such as hyperparameter tuning, feature engineering, and data augmentation to improve its performance.

b. Implementation

Data Collection: Collect user data from Asia's leading music streaming service.

Data Preprocessing: Cleaning and preparing the information to guarantee its quality as well as consistency.

Exploratory Data Analysis: Conduct exploratory data analysis to understand user behavior and preferences.

Feature Engineering: Use data analysis techniques to create relevant features for the recommendation system.

Model Selection: Select appropriate machine learning algorithms for building the recommendation system.

Model Training: It is the process of teaching a machine learning algorithm to recognize patterns in data.

Model Evaluation: It is the process of assessing a model's performance on new data.

Hyperparameter Tuning: Optimize the model hyperparameters to enhance efficiency.

Deployment: Deploy the framework of suggestions in the music streaming service platform.

Monitoring and Maintenance: Monitor the recommendation system's performance and make necessary adjustments to maintain its effectiveness.

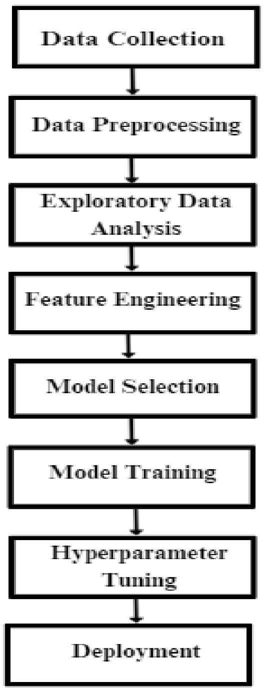
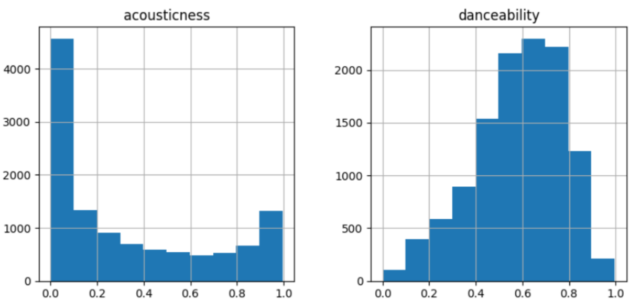
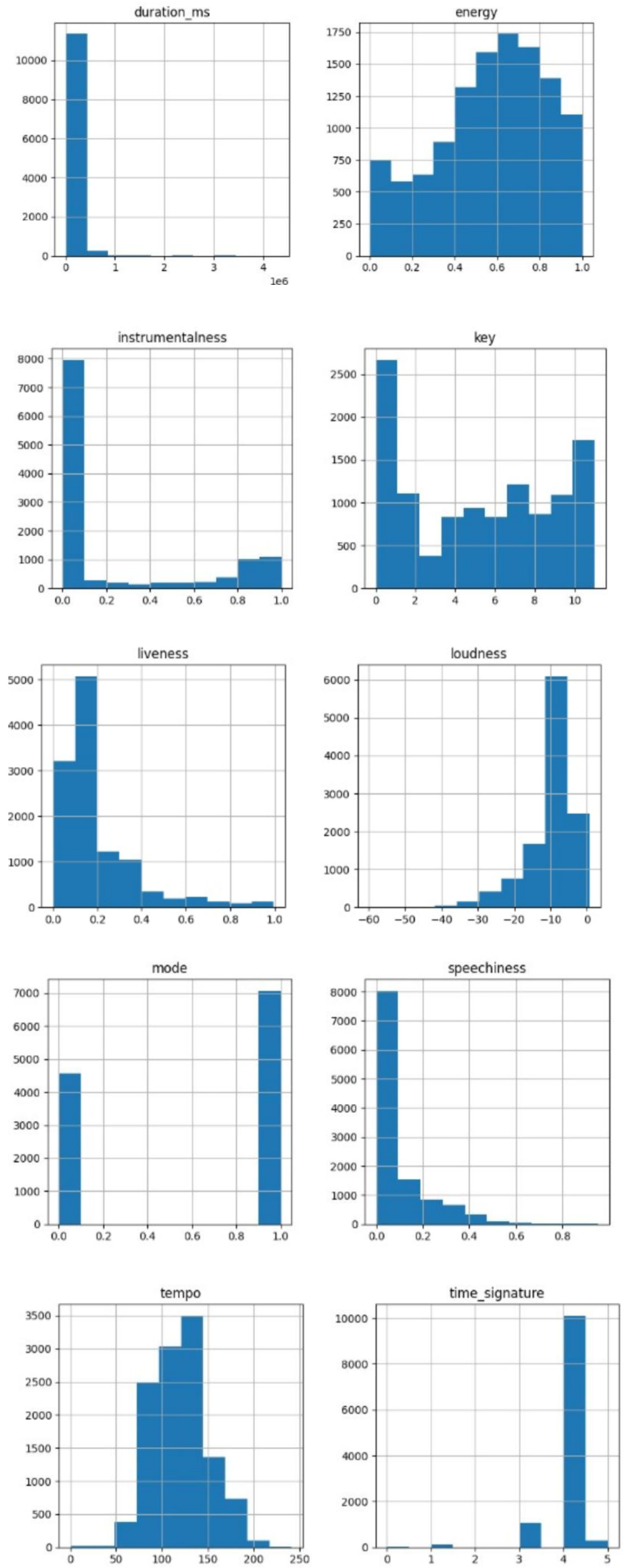


Figure 8: Flow Chart

In [Figure 8], The flowchart represents the step-by-step process for developing a music recommendation system. It outlines the key stages involved in building an effective recommendation system for a music streaming service. The caption, "Music Recommendation System Development Process," succinctly describes the main purpose and focus of the flowchart.

a. Observation





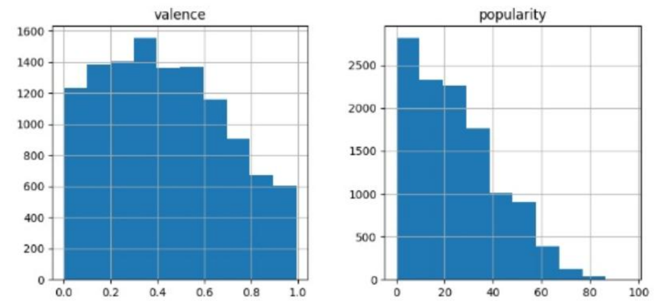


Figure 9: Analyzing Data Characteristics

In [Figure 9], It provide valuable insights into the data's characteristics, including its distribution, central tendency, presence of outliers, and data range and spread. By analyzing these aspects, you can make informed decisions, gain a deeper understanding of the dataset, and guide further data preprocessing, feature engineering, or model selection[19].

In [Figure 12], Based on a dataset of popular tracks on Spotify, this graph clusters songs into 15 (based on the elbow method) distinct groups based on their instrumental and energy with the centroid of each cluster highlighted[20].

5. Result

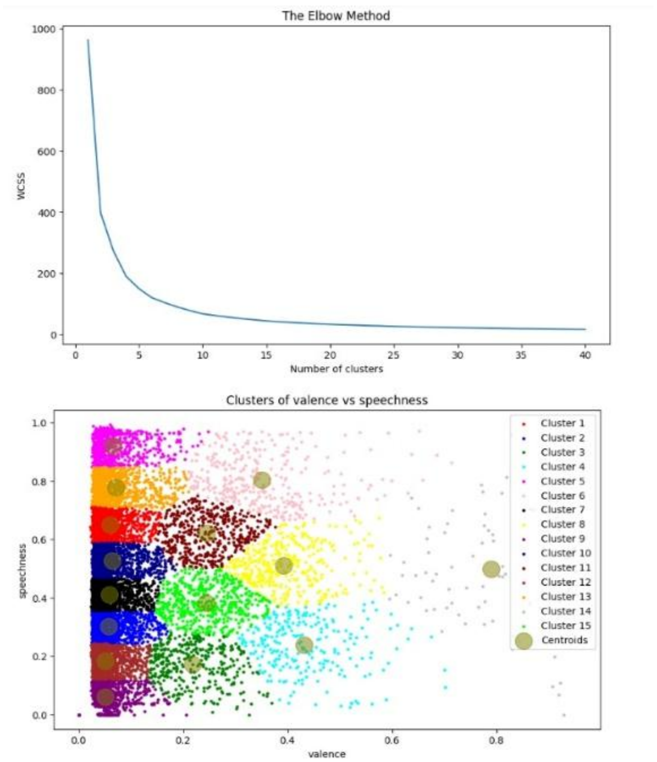


Figure 10: Clusters of valence VS speechness

In [Figure 10], Based on a dataset of popular tracks on Spotify, this graph clusters songs into 15 (based on the elbow method) distinct groups based on their valence and speechness with the centroid of each cluster highlighted.

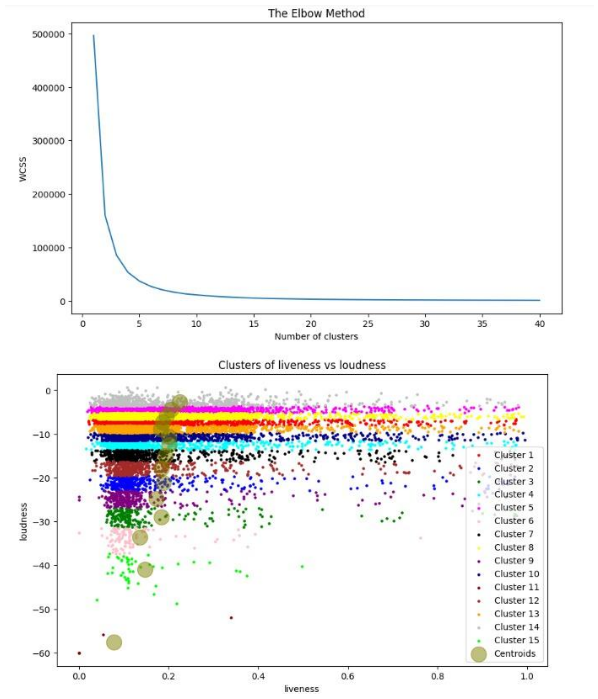


Figure 11 : Clusters of Liveness VS Loudness

In [Figure 11], Based on a dataset of popular tracks on Spotify, this graph clusters songs into 15 (based on the elbow method) distinct groups based on their liveness and loudness with the centroid of each cluster highlighted.

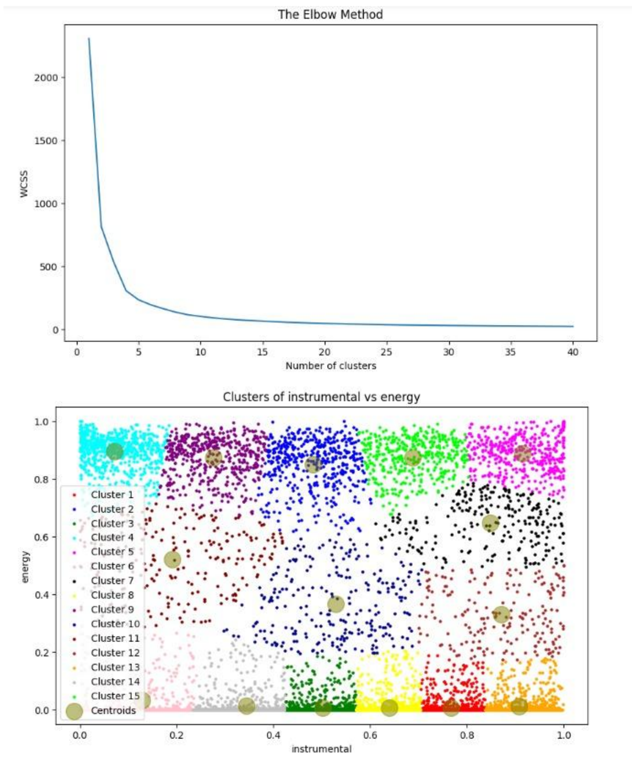


Figure 12: Energy VS Instrumental

In [Figure 12], Based on a dataset of popular tracks on Spotify, this graph clusters songs into 15 (based on the elbow method) distinct groups based on their instrumental and energy with the centroid of each cluster highlighted[20].

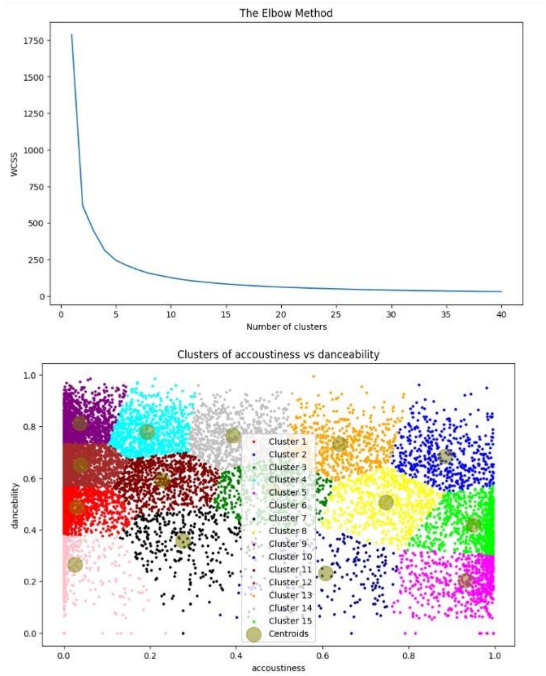


Figure 13: Dancebility VS accoustiness

In [Figure 13], Based on a dataset of popular tracks on Spotify, this graph clusters songs into 15(based on the elbow method) distinct groups based on their danceability and accoustiness with the centroid of each cluster highlighted.

6. CONCLUSIONS

Music recommendation systems have come a long way in the last two decades, with many ML algorithms and approaches being proposed and implemented. Techniques that utilize collaborative filtering, content-based, and extensive learning approaches having everything has been shown to become efficient in making music recommendations. However, there is still room for improvement, and researchers are actively exploring new data sources and feedback mechanisms to create even more accurate and personalized music recommendation systems.

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