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Recommendation system for song data using K-Means and K-Medoids Clustering algorithm

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Abstract— The ability to anticipate user preferences is crucial to recommendation systems. A personalised recommendation must take into account the listener's existing musical preferences as well as any changes to the "kind" of songs. This paper proposes a personalised next-song recommendation system. It utilizes Web API for Spotify to record the song features. K-means and K-medoids clustering algorithms are employed to identify similar songs using attributes. It is identified to which cluster the input music belongs. Content-based clustering is the term used for this. By computing the similarity measure, the songs that are "near" to the input song are identified next. Based on popularity metrics for this list of songs, the set of songs that should be played in order are identified.

Keywords—Recommendation, K-means Clustering, K-Medoids Clustering

I. Introduction

A person needs music at various points in their lives. A person's life is filled with joy and happiness as a result. Music contains the essence of life and provides us with immense tranquilly. The amount of songs that are available is greater than what one person can listen to in a lifetime. Sometimes it is difficult for someone to select from millions of songs, and there is a good probability that they will pass up music that would have been appropriate for the situation.

Today, all study and effort are focused on predicting, using a user's whole song history, the types of songs the user would enjoy. Here, recommendations are being made for music without taking mood into account. It's possible for a user to enjoy both upbeat party songs and calming soundtrack, but in order to propose a song in any of these categories, it's also important to understand the user's present mood. If a person is in the mood to listen to a party song, he wouldn't want the app to suggest a slow song that is statistically appropriate based on his past listening choices but just inappropriate for the moment.

Therefore, we can find a solution to this issue by posing the following question: Given the song the user is now listening to, which song would the user prefer to hear next? We are attempting to provide an answer to this query with this project. A recommender system, in the widest sense, is one that anticipates the ratings a user would give a certain item. The user will then be presented with a rating of these recommendations.

By utilizing clustering techniques, we are looking for similarities between the song being played by the listener

and the list of songs present in our dataset. After creating a playlist of songs that are similar to the one being listened to,

the project uses a system of user recommendations based on popularity to suggest the next song.

II.RELATED WORKS

Sheela Kathavate of BMS Institute of Technology and Management Bangalore, India in February 2021 used algorithms such as the Collaborative Filtering Model, Popularity Model, and Content Based Model. The author achieved 96% accuracy on the algorithm for music recommendations. The author endeavour to add additional artists and languages in the future, which will improve the recommendation and give users even better playlists. Future uses might involve developing an emotional detection system that would make music recommendations based on our facial expressions [1].

B.Srikanth and V.Nagalakshmi of GITAM (Deemed to be University) in April 2020 proposed a model using SVD Algorithm which is a machine learning algorithm used in the songs recommender system. The Nearest Neighborhood Model and SVD (Singular Value Decomposition) algorithms were employed in this study. Techniques including the Collaborative Based Model, the Popularity Based Model, and the Content Based Model were employed. This analysis is still in its early stages. There were several restrictions, such as prejudice based on popularity and human efforts[2].

Ninad Marathe, Parth Sanghavi, Varsha Verma, and Dr. Prashant Nitnaware of PCE in Navi Mumbai, India in November 2021 recommended feature selection, angular distance, euclidean distance, and cosine similarity in their survey. Techniques for content-based and collaborative filtering. The model, which is displayed on the frontend, ultimately predicts the seven songs that are the most similar. There were several restrictions that their approach couldn't fully address. over-specialization and serendipity as a problem, did not employ a content-based algorithm, did not make the music recommendation system a real-time system, and did not attempt to recommend music using clustering techniques. The main focus of future research will be on user-centric music recommendation systems. Future music producers should be able to guide users in making rational musical choices.[3]

Shefali Garg and Fangyan SUN from Indian Institute of Technology, Kanpur in April 2014 used SVD, KNN, and popularity-based models in tests on content-based models using collaborative filtering algorithms based on latent factors and metadata. For the memory-based collaborative filtering approach, the authors obtained the best results. Latent factor models based on SVD produce superior outcomes to popularity-based model. The authors contend that if authors had more memory and processing power, we could have used the entire collection of available metadata and training data, and the content-based model would have performed better. Even the popularity model outperforms the K-NN model in terms of performance.[4]

Muhammad Arief Budiman and Gst. Ayu Vida Mastrika Giri of Udayana University in Bali, Indonesia in May 2019 proposed a model using Cosine Similarity, K-Nearest Neighbor, and collaborative filtering. A system that may suggest songs based on musicians who are related to one another is created as a result of this research.[5]

III.MATERIALS AND METHODS

A. DATASET

The most popular audio streaming service, Spotify, provides a database with a huge variety of songs and an API that is accessible to developers via their web API.

The user stores and gives metadata about the artist, album, and tracks from the data catalogue. The goal of the cluster analysis used in this study was to automatically classify trendy music using Spotify's list of musical characteristics. In order to train our models, the dataset is created using the information obtained from the Spotify API. The dataset contains 10444 songs and 20 different features as described in fig.1 and fig.2

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	liveness	valence	tempo	duration_ms
0	0.782787	0.320	0.867161	0.060331	0.840361	0.00000	0.082863	0.585540	0.377600	0.133347
1	0.813525	0.793	0.911314	0.093039	0.012550	0.00000	0.095968	0.689409	0.514180	0.128744
2	0.721311	0.225	0.748152	0.109834	0.905622	0.65700	0.106855	0.247454	0.497855	0.174910
3	0.636270	0.601	0.893328	0.163536	0.052410	0.00000	0.463710	0.465377	0.484285	0.114141
4	0.721311	0.758	0.927478	0.044420	0.233936	0.00144	0.093145	0.543788	0.497843	0.152235

Fig.1. Non-Categorical Data

	artist	key	mode	time_signature	label
0	Maroon 5	11	1	4	toplists
1	Dua Lipa	11	0	4	toplists
2	Billie Eilish	6	0	4	toplists
3	Arizona Zervas	6	0	5	toplists
4	Post Malone	0	1	4	toplists

Fig.2.Categorical Data

DATASET FEATURES:

- Track name: Name of the Track to identify which song it is.
- Artist name: Name of the Artist/Singer
- Duration: The length of the track in milliseconds.
- Preview: Link to the song's 30-second previews
- Key: The tonal core of a song is represented by the key.
- Popularity: The popularity of the track. The range of the value will be 0 to 100, with 100 being the most popular. This defines how popular a particular song is[3].
- Danceability: A song's danceability is determined by a number of musical factors, including tempo, rhythm stability, beat intensity, and overall regularity. The least danceable value is 0.0, and the most danceable value is 1.0.
- Energy: Energy, which ranges from 0.0 to 1.0, is a perceptual unit of intensity and activity. In general, energetic music has a quick, loud, and noisy feeling. Rock and metal, for instance, will be highly energetic.
- Instrumentals: determines whether a track is vocal-free. The likelihood that a track is vocal-free increases as the instrumental ness value approaches 1.0.
- Loudness: Decibels(dB) represent how loud a track is overall. The main acoustic characteristic that psychologically relates to physical power is loudness.

B. K-Means Clustering

- K-means clustering can be a useful technique for song recommendation. The basic idea behind k-means clustering is to group similar items together based on certain features or characteristics. In the context of song recommendation, the features could be things like the genre, tempo, instrumentation, and even the song's mood.[6]
- To use k-means clustering for song recommendation, prior to using any features or characteristics as inputs for the clustering process, it must first identify them. Then, data on a large number of songs would need to be gathered, including details on these qualities.
- After gathering the data, by using k-means clustering to put the songs in groups based on how similar they are. For instance, it might put all the songs in one cluster that have the same speed and instrumentation and all the songs in another cluster that have a different tempo and instrumentation.[6]
- Overall, k-means clustering can be a powerful tool for song recommendation, as it allows you to group songs together based on their similarity, and use these groups to make recommendations. However, it is important to remember that clustering algorithms are only as good as the data that you feed into them, so it is crucial to collect high-quality data on the songs that you want to recommend.

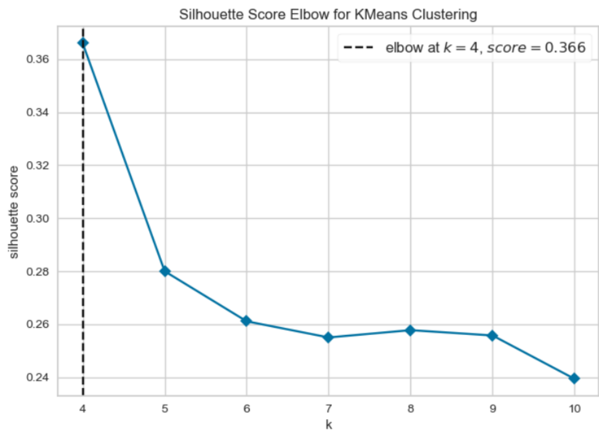
C. K-Medoids Clustering

- Data points known as "medoids" serve as the cluster's focal point in the unsupervised clustering process known as K-Medoids. A medoid is a location in the cluster whose total distance to all of the items in the cluster, also known as dissimilarity, is at a minimum.[7]

- The distance can be measured using any suitable distance function, including the Manhattan distance and the Euclidean distance. As a result, the K - medoids algorithm chooses K medoids from our data sample to partition the data into K clusters.[7]
- This method is applied and it is observed that because the first k medoids are picked at random, different results can be obtained from different runs on the same dataset.

D. MODEL BUILDING

- Data collection: Collect data on songs, including audio features such as tempo, key, and genre, as well as information on the artist and album. This data can be obtained from online music databases such as Spotify or Last.fm.
- User feedback: Allow users to provide feedback on recommended songs, such as by rating them on a scale of 1 to 5 stars or by indicating whether they liked or disliked the song. This feedback can be used to improve the accuracy of future recommendations.
- Machine learning algorithm: Use a machine learning algorithm such as collaborative or content-based filtering to generate recommendations based on the user's listening history, preferences, and feedback. Collaborative filtering uses the listening habits of other users with similar tastes to recommend songs, while content-based filtering uses the audio features of the songs themselves to make recommendations.[8]
- Recommendation engine: Create a recommendation engine incorporating the machine learning algorithm to generate personalized song recommendations for each user based on their listening history, preferences, and feedback.[8]
- Continuous learning: Continuously update the machine learning algorithm and recommendation engine based on user feedback and new data to ensure that the recommendations remain relevant and accurate over time.
- Find the relationships between the dataset's noncategorical columns first. Finding a correlation between non-categorical data will help with this. A few characteristics, such as energy and loudness, valence and danceability, and danceability and loudness, have strong correlations. This demonstrates the need to minimize the data's dimensionality. To test if cluster formation is feasible, the data can be normalized using min-max scaling.
- Apply K-means and K-medoids both to see which one would have better accuracy and can be applied to get required output.
- Accuracy of K-means is 83% and that of K-medoids was not fixed as it obtains different results for different runs on the same dataset because it is done randomly.
- To categorise unlabelled data, the K means clustering technique is used, which tries to find groups with data based on the number of groups taken into consideration. The objective is to identify a collection of clusters that had a considerable number of details but did not divide the data into underwhelmingly small clusters or confusingly big clusters.
- A Silhouette analysis is performed to determine the separation distance between the created clusters. The Mean Silhouette Coefficient vs. K Line Chart is then drawn. The value of k can be found from the graph that will work best for k-means clustering procedure that is being used in this project as shown in results.1 and results.4.



Results.1 Silhouette Chart using k-Means

$$pD = \frac{Popularity}{(DistanceOfSongFromCurrentSongs)^2}$$

Where:

pD: popularityDistance

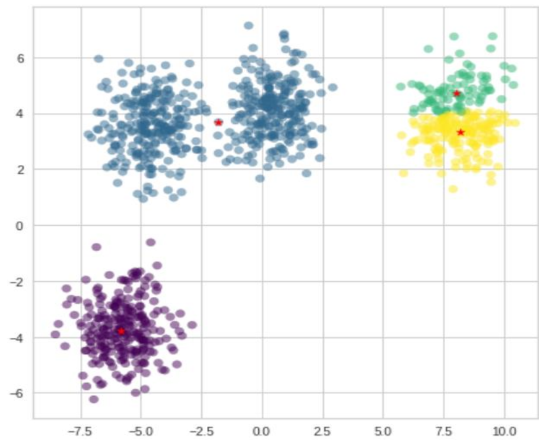
Popularity: Value provided in the dataset for each song

Distance Of Song From Current Song: Euclideon distance of the song from the current song

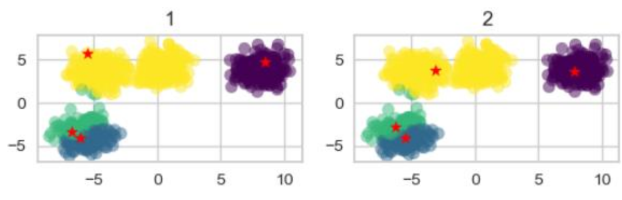
V. EXPERIMENTAL RESULT

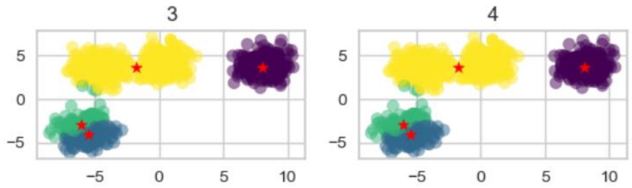
One common approach to recommending songs to users is collaborative filtering, which involves recommending songs based on the listening behavior of other users who have similar tastes to the user in question. Experimental studies have shown that collaborative filtering can be effective in recommending songs to users, particularly in the context of large-scale music streaming services such as Spotify.

Another approach is content-based filtering, which involves recommending songs based on the characteristics of the songs themselves, such as their genre, tempo, and lyrics. Experimental studies have shown that content-based filtering can also be effective in recommending songs, particularly for users who have niche or specific music tastes.



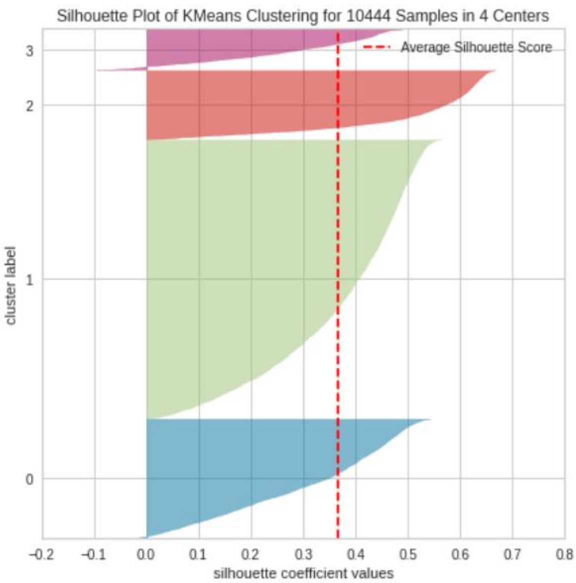
Results.2. Final Plot of K-Mediods





Results.3. Plot of K-Medoids Process

But K-medoids method obtains different results for different runs on the same dataset because the first k medoids are chosen randomly.When K-means clustering technique is applied, an accuracy of about 83% is seen



Results.4. K-Means Silhouette plot

In comparison to that of K-medoids which doesn't have a fix accuracy, a fix and perfect accuracy of 83% is best as shown in Results.2 and Results.3.The effectiveness of song recommendation algorithms can depend on a variety of factors, including the quality of the data used to train the algorithms, the specific algorithms used, and the user preferences being considered.

II. CONCLUSION

This was suggested for a next-song recommendation that we utilize in Spotify's web API. The issue is which music would the user prefer to hear after the one they are now listening to? To produce a playlist of songs that are related to the present issue, we, therefore, establish a dataset using clustering techniques. The technique that is required is popularity-based.

The goal of the cluster analysis used in this work is to automatically classify trendy music using Spotify's list of musical characteristics. In this paper K-means and K-medoids clustering techniques are applied. The accuracy of K-means algorithm is 83% which is better than that of K-medoids and so this is used to build the model.

While collaborative filtering uses information from the browsing habits of other users to suggest a track, content-based filtering concentrates on making suggestions based on the acoustic characteristics of the music.[8]

The traditional music genres are challenged by this method, which also offers fresh insight into how music might be automatically categorized into several popular categories based on musical characteristics and possibly provide improved recommendations.

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