Building a Personalised Song Recommendation System with Spotify Dataset

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ABSTRACT

This project aims to create a personalized music recommendation system using the Spotify dataset, while addressing the demand of scene-based music listening preference and the information cocoons caused by current music recommendation system. The study aims to enhance current similarity-based recommendation strategies by incorporating user preferences and content-based recommendations. A dataset of favoured songs was analysed via Principal Component Analysis and K-Means clustering, resulting in music groups, each labelled by my listening scenario. Each cluster then provided recommendations through Euclidean Distance and cosine similarity. The results showed stylistic consistency within each cluster and largely favourable new song suggestions, effectively broadening my music exposure. This framework offers an innovative approach and exploration to personalized, scenario-based music recommendation systems.

1 INTRODUCTION

Along with the rapid expansion of digital music formats, managing and searching for songs has become significant.[1] Within streaming music services, Spotify 1has more than 75 millions of active users, more than 30 millions of songs plus 20,000 each day, and about 1TB of usage data generate per day.[2] Although recommender systems have been studied extensively, the problem of music recommendation in particular is complicated by the sheer variety of different styles and genres, as well as social and geographic factors that influence listener preferences. [3]

1.1 Personal preference

In my personal listening experience, I have encountered challenges:

(1) The high similarity in recommended songs has narrowed my music spectrum, creating a "recommendation cocoon".

(2) I have a desire to explore novel artists, yet without a proper guide, unsatisfactory songs often disappoint me.

(3) I categorize my music listening into different scenarios, yet there are limited scene-based playlists that cater to my preference.

Thus, I aim to create a recommendation system combining content-based recommendations with listeners' preference, intending to alleviate these issues and broaden the spectrum of the listener's music experience.

1.2 Content-based music recommendation

The content-based approach for music recommendation is built upon analysing the individual attributes or "content" of songs. This approach, derived from principles of information retrieval and filtering[4], recommends songs bearing similarity to those previously enjoyed by the user[5]. Extensive research has been conducted on extracting and comparing acoustic features to find perceptually similar tracks, with attributes such as timbre and rhythm being the most representative. Based on the extracted features, the distance between songs is measured [43]. Three typical similarity measurements are listed below.

(1) K-means clustering with Earth-Mover's Distance: It computes a general distance between Gaussian Mixture Models (GMM) by combining individual distance between gaussian components[7].

(2) Expectation-Maximization with Monte Carlo Sampling: This measurement makes use of vectors sampled directly from the GMMs of the two songs to be compared; the sampling is performed computationally via random number generation[8].

(3) Average Feature Vectors with Euclidean Distance: It calculates low order statistics such as mean and variance over segments[9].

Content-based music recommendation systems resolve some limitations of collaborative filtering methods by using the similarity of acoustic features between songs. However, the effectiveness of this approach in reflecting listeners' preferences remains under-explored.

While these models heavily rely on acoustic features, the selection and optimal use of these features need further investigation. Incorporating additional user information and non-acoustic data could enhance these models[1]. Likewise, defining an appropriate similarity metric to recommend perceptually similar music is challenging, often resulting in suboptimal recommendations. Some researchers have tried to refine these metrics using user preference data, a method that still needs further optimization.

1.3 Scenario-based recommendation

Current music platforms already suggest songs based on listening scenarios like 'songs suitable for work or study', 'playlists for gym sessions', or 'music for a rainy day of introspection'. Combining these scenario-based suggestions with individual music tastes can be an intriguing area to explore. The objective is to enhance listeners' music experience by offering recommendations that align with their personal tastes and specific situations. This venture doesn't claim to revolutionize the field but hopes to provide a fresh angle on music recommendation systems and hopefully inspire further curiosity and research.

2 METHODOLOGY

In this project, a dataset of over 170,000 songs from Spotify serves as the primary data source. A subset of this dataset, referred to as 'my_song', is created containing songs I personally prefer. Principal Component Analysis (PCA) is applied to both 'my_song' and 'all_song' datasets. Following this, K-means clustering is performed on the 14 acoustic features from 'my_song' to create distinct clusters of similar songs. Each of these clusters is labelled according to the listening scenario it best represents based on my personal experience and preferences. This clustering model is then expanded to the 'all_song' dataset, effectively categorizing all songs into the defined listening scenarios. Within each cluster, two different recommendation systems are developed, one utilizing Euclidean Distance and the other using Cosine Similarity, to provide personalized, scenario-based music recommendations.

2.1 Dimensionality Reduction

Given the high-dimensional nature of the dataset, Principal Component Analysis (PCA) was employed to condense the data into fewer dimensions while preserving as much information as possible. This approach identifies the point where the explained variance graph sharply bends or 'elbows', indicating the most valuable components.

In this case, the graph exhibited a significant change in slope at the second component, leading to the decision of setting the number of principal components to two for further analysis. After reducing the data to two dimensions through PCA, I employed the 'elbow point method' to determine the optimal number of clusters for the KMeans algorithm, which came out to be four. Subsequently, I extrapolated the KMeans clustering results to the entire song dataset.

2.2 Clustering

After reducing the data to two dimensions through PCA, I employed the 'elbow point method' to determine the optimal number of clusters for the KMeans algorithm, which came out to be four. Subsequently, I then expanded the KMeans clustering results to the entire song dataset.

Even though the songs used for clustering were all familiar to me, interpreting the essence of each cluster based solely on the clustering outcomes was challenging. Hence, I selected four features that I believe best represent my specific music preferences to characterize each cluster. These features were 'valence', 'danceability', 'energy', and 'loudness.

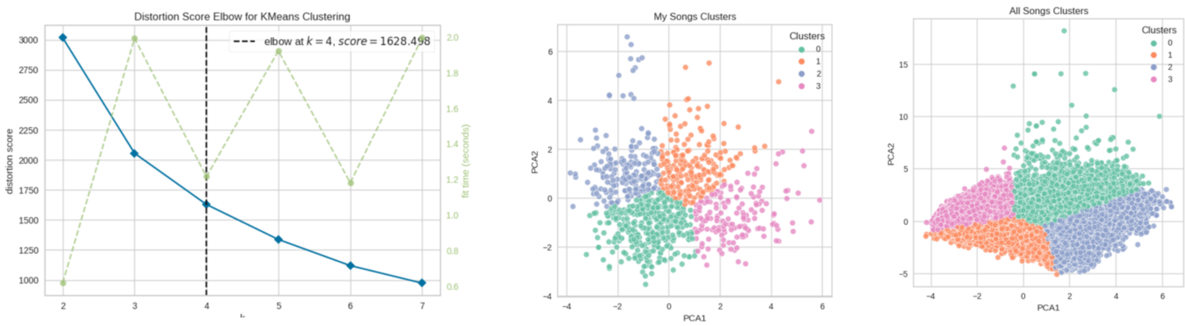

Figure1: From left to right, Distortion Score Elbow for KMeans Clustering, My Songs Clusters; All Songs Clusters.

The analysis resulted in four distinct clusters:

(1) Cluster 0 – 'Dynamic Rhythms'

The music in this cluster is vibrant and high-energy, invigorating and engaging the listener. This makes it an ideal choice for situations where you need a boost of energy or to set an upbeat mood, such as during a workout, a run, or at a party.

(2) Cluster 1 – 'Calm and Quiet'

The songs in this category are slow-paced, with lower volume, offering a sense of peace. They are suitable for moments that call for relaxation or concentration, like during meditation, reading, or before going to sleep.

(3) Cluster 2 – ‘Energetic Joy’

This cluster is characterized by its high-energy, joyous melodies that uplift the listener's spirits. These songs would be perfect for happy gatherings, celebratory occasions, or while doing household chores to keep the mood light and cheerful.

(4) Cluster 3 – ‘Chill and Mellow’

The music in this cluster has a relaxed and comfortable rhythm with moderate energy. It provides a chilled and mellow vibe that fits well with leisure time, rest, or a leisurely afternoon.

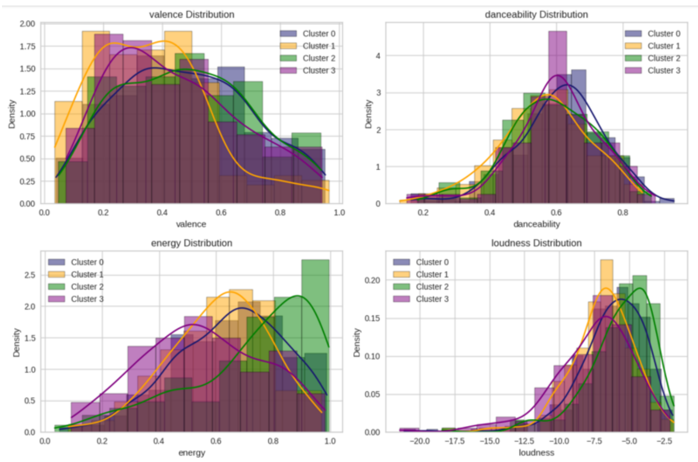

Figure2: The 4 special features of distribution of the 4 clusters.

2.3 Recommendation System

With the clusters in place, a personalised music recommendation system was built within each cluster. For the first two clusters, the Euclidean distance was used to calculate the similarity between songs. This was achieved by using the centre of the clusters as reference points, from which the distances to all other songs in the clusters were calculated. For the remaining two clusters, cosine similarity was used instead. The choice of the similarity metric was influenced by the size of the cluster and the overall data structure.

(1) Cluster 0- ‘Dynamic Rhythms’

In the first cluster, the reference point for this calculation is the centre of cluster 0 which includes all the songs. To ensure the recommendations not only align with my existing preferences but also introduce me to new music, a 'radius' of influence is established based on distance. This radius is divided into three groups. From the closest group (group 1), five songs are recommended. From the next group (group 2), three songs are suggested, and from the farthest group (group 3), two songs are recommended. Selection of songs within each group is performed randomly. The system recommends five songs from the closest group (group 1), three from the next (group 2), and two from the farthest (group 3). Song selection within each group is random.

(2) Cluster 1 – ‘Calm and Quiet’

The distance is calculated using the centre of my personal cluster 1. Interestingly, most songs are clustered around the centre of 'my cluster 1'. I've adjusted the recommendation count to favour closer songs, setting it to [7, 2, 1].

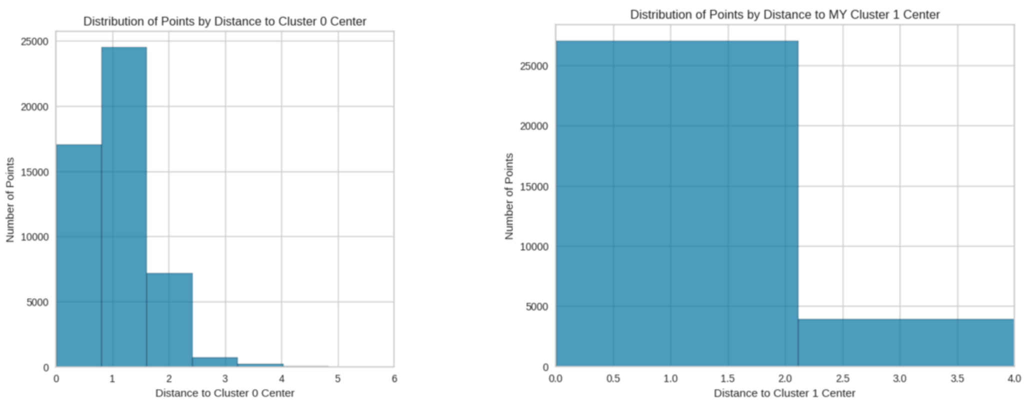

Figure3: Distribution of Points by Distance to Cluster 0 Center, Distribution of Points by Distance to MY Cluster 1 Center. (From left to right)

(3) Cluster 2 – ‘'Energetic Joy’

To better manage and manipulate the data related to cluster 2, I merged the dataframe of my songs with the dataframe of cluster 2. This was done based on the indexes, keeping only the 'name' and 'artists' columns of my songs. After merging, unnecessary columns were dropped, and the remaining columns were renamed appropriately for clarity.

(4) Cluster 3 – ‘Chill and Mellow’

One observation I had from the recommendations for clusters 0, 1, and 2 was the prevalence of ‘ancient’ songs in the suggestions. While this had led to some delightful discoveries, as a member of Generation Z, I tend to prefer more recent music. I decided to limit the time frame for the song selection in cluster 3 to between the years 1990 and 2020. This decision not only caters to my taste for contemporary music but also has a practical aspect as it can reduce computational time by narrowing down the potential candidate songs for recommendation.

3 RESULTS

Based on my personal listening experience throughout the course of this project, the tailored music recommendation system was able to generate largely satisfying results. Here are some key observations:

Diverse Song Selection - The system successfully broadened my musical horizons by introducing new songs that I hadn't encountered before. It offered a fresh and diverse selection of songs that not only aligned with my tastes, but also expanded my music repertoire.

Accurate Scenario Match - Each of the four clusters created in the recommendation system accurately represented distinct listening scenarios. Songs recommended from the

'Dynamic Rhythms', 'Calm and Quiet', 'Energetic Joy', and 'Chill and Mellow' clusters respectively mirrored the mood and vibe of their designated scenarios.

Personalization - There were, however, instances where the recommended songs did not align completely with my preferences. This suggests that there is room for further refining the recommendation algorithm. The use of more complex similarity metrics, inclusion of more musical features, or incorporation of user feedback could potentially improve the quality of recommendation.

In conclusion, this project has effectively demonstrated the potential of a scenario-based music recommendation system. By integrating the user's musical preference with specific listening scenarios, the system provides a more personalized and contextually suitable selection of songs. It paves the way for future research and improvements in the field of music recommendation systems.

4 DISCUSSIONS

The creation of a personalized music recommendation system using the Spotify dataset led to the successful formation of distinct clusters representing different facets of my own musical preferences. Despite this, the project highlighted potential areas for enhancement.

(1) Calculation Method

The Euclidean distance and cosine similarity measures used for recommendations could be replaced with more nuanced methods or potentially deep learning approaches for better accuracy. The use of PCA for dimensionality reduction, though computationally efficient, may have caused some data loss, suggesting the need to explore other dimensionality reduction techniques.

(2) Inclusion of Other Factors

Incorporating a temporal aspect into the recommendation system could cater to my evolving tastes. Other unexplored factors such as social, cultural, popularity or even biological influences could potentially enhance the system's ability to provide a more holistic view of a user's music preferences.

(3) Model Validation and Testing

The project lacked robust model validation or testing procedures, which is a vital aspect of future research to ensure the generalizability and robustness of the recommendation system.

5 CONCLUSIONS

This project effectively developed a personalised music recommendation system using the Spotify dataset. Utilising Principal Component Analysis for dimensionality reduction and clustering for personalised categorization, distinct music clusters were successfully created. The clusters namely 'Dynamic Rhythms', 'Calm and Quiet', 'Energetic Joy', and 'Chill and Mellow', facilitated a meaningful way of recommending music that aligns with the user's unique taste.

The project showed promise in providing tailored music recommendations, demonstrating the potential of data-driven techniques in enhancing user experiences. However, certain limitations surfaced, including potential information loss due to PCA, basic similarity measures, and a lack of inclusion of broader influencing factors. These limitations offer avenues for future research to refine and improve the system.

Overall, this project provided valuable insights into personalised music recommendation systems, laying a solid foundation for further enhancement and development in this field.

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