Music genre clustering analysis based on k-Means

Zhou shankang

1024041012

Nanjing University of Posts and Telecommunications

Jiangsu, Nanjing China

***Abstract*—Music genre classification is a fundamental task in music information retrieval, with applications in recommendation systems and automatic tagging. This study explores the use of unsupervised learning for music genre clustering by applying the k-Means algorithm to the GTZAN dataset, which contains 1000 audio samples from 10 music genres. We extract audio features, including Mel-Frequency Cepstral Coefficients, Chroma features, and Spectral Contrast, to represent the audio samples in a high-dimensional feature space. The k-Means algorithm is used to cluster the samples, with the number of clusters determined by the elbow method. We evaluate the clustering performance using the Adjusted Rand Index and visualize the results using t-SNE for dimensionality reduction. Our results show that k-Means can effectively identify clusters corresponding to certain music genres, although distinguishing genres with similar acoustic characteristics remains challenging. This study highlights the potential of unsupervised learning for music genre analysis and identifies limitations of k-Means in handling complex audio data. Future work could explore alternative clustering algorithms or more advanced feature extraction techniques to improve performance.**

Keywords—Music Genre Classification, Unsupervised Learning, k-Means Clustering, GTZAN Dataset, Audio Feature Extraction

I. INTRODUCTION

Music genre classification plays a crucial role in the field of music information retrieval, with applications spanning music recommendation systems, automatic tagging, and digital library organization. As the volume of digital music continues to grow, the ability to automatically categorize music into genres has become increasingly important for both users and service providers. For users, genre classification enhances the music discovery experience by enabling personalized recommendations and efficient browsing of large music libraries. For service providers, it facilitates the organization and management of extensive music collections, improving the overall user experience. The GTZAN dataset, a widely used benchmark in music genre classification, provides a valuable resource for researchers to develop and evaluate algorithms for this task.[1] It contains 1000 audio samples from 10 distinct music genres, making it an ideal dataset for exploring the potential of unsupervised learning techniques. The dataset's balanced distribution across genres ensures that researchers can effectively test the generalization capabilities of their algorithms.

Clustering analysis, as a fundamental approach in unsupervised learning, offers a powerful way to discover inherent structures within data without the need for labeled examples. This is particularly advantageous in scenarios where labeled data is scarce or expensive to obtain. Among clustering algorithms, k-Means stands out due to its simplicity, efficiency, and effectiveness in partitioning data into meaningful groups. Its iterative nature allows it to quickly converge to a solution, making it suitable for large datasets. However, the algorithm's performance heavily depends on the quality of the features extracted from the data and the choice of the number of clusters. By applying k-Means to the GTZAN dataset, we aim to uncover the latent structures of music genres and evaluate the algorithm's ability to group audio samples based on their acoustic features. This involves extracting relevant features such as Mel-Frequency Cepstral Coefficients (MFCCs), Chroma features, and Spectral Contrast, which capture the essential characteristics of the audio signals.[2][3]

This study seeks to contribute to the understanding of unsupervised learning in music genre analysis and provide insights into the challenges and opportunities of using clustering techniques for audio data. While supervised learning methods have shown impressive results in music genre classification, they require large amounts of labeled data, which can be difficult to obtain. Unsupervised learning, on the other hand, offers a more flexible approach by identifying patterns and structures in the data without relying on pre-defined labels. By exploring the effectiveness of k-Means in this context, we hope to shed light on the potential of unsupervised methods for music genre analysis and inspire further research in this area. Additionally, this study aims to highlight the limitations of k-Means, such as its sensitivity to initial centroid placement and its difficulty in handling overlapping genres, and suggest potential directions for future work, including the exploration of alternative clustering algorithms and more advanced feature extraction techniques.[4]

II. RELATED WORKS

Music genre classification and clustering have been extensively studied in the field of music information retrieval. Traditional approaches often rely on handcrafted audio features, such as Mel-Frequency Cepstral Coefficients (MFCCs), Chroma features, and Spectral Contrast, to represent music data. For instance, Tzanetakis and Cook (2002) pioneered the use of MFCCs and other spectral features for music genre classification, demonstrating their effectiveness in capturing the acoustic characteristics of different genres. These features have since become a standard in many music analysis tasks.[5][6][7]

In addition to feature extraction, various clustering algorithms have been applied to music data. For example, DBSCAN has been used to identify clusters of similar songs based on density, while hierarchical clustering has been

employed to explore the relationships between different music genres. However, these methods often struggle with high-dimensional data and require careful parameter tuning. More recently, deep learning models, such as Convolutional Neural Networks (CNNs), have shown remarkable success in music classification tasks by automatically learning relevant features from raw audio data.[8][9] Despite their performance, these models typically require large labeled datasets and significant computational resources.

While supervised learning approaches have dominated music genre classification, there is a growing interest in unsupervised methods, particularly for scenarios where labeled data is scarce. Current research on unsupervised music genre clustering remains limited, with few studies exploring the potential of classical clustering algorithms like k-Means in this domain. This study aims to address this gap by applying k-Means to the GTZAN dataset and evaluating its performance in uncovering the underlying structure of music genres. By doing so, we hope to provide insights into the effectiveness of unsupervised learning for music genre analysis and inspire further research in this area.[10]

III. Problem Statement

The task addressed in this study is formalized as a data mining problem within the context of unsupervised learning. The input consists of 1000 audio samples from the GTZAN dataset, where each sample is represented as a feature vector derived from audio characteristics such as Mel-Frequency Cepstral Coefficients (MFCCs), Chroma features, and Spectral Contrast. The output is a partitioning of these audio samples into k clusters, where each cluster represents a potential music genre or acoustic pattern. The primary objective is to employ the k-Means clustering algorithm to uncover the inherent structure within the data and evaluate the resulting clusters against the true genre labels provided in the GTZAN dataset. This evaluation aims to assess the effectiveness of k-Means in identifying meaningful groupings of music genres without the use of labeled training data.[11][12]

IV. Solutions

A. k-Means Algorithm

The k-Means algorithm is a widely used unsupervised learning method for clustering data into k groups. The algorithm operates as follows:

Initialization: Randomly select k initial centroids from the dataset.

Assignment: Assign each data point to the nearest centroid based on a distance metric (typically Euclidean distance).

Update: Recalculate the centroids as the mean of all data points assigned to each cluster.

Iteration: Repeat the assignment and update steps until the centroids no longer change significantly or a maximum number of iterations is reached.

To determine the optimal number of clusters (k), we employ the elbow method, which involves running k-Means for a range of k values and plotting the within-cluster sum of squares (WCSS) against k. The "elbow" point, where the rate of decrease in WCSS slows significantly, is chosen as the optimal k. Alternatively, the silhouette score can be used to evaluate the quality of clustering for different k values, with higher scores indicating better-defined clusters.[13]

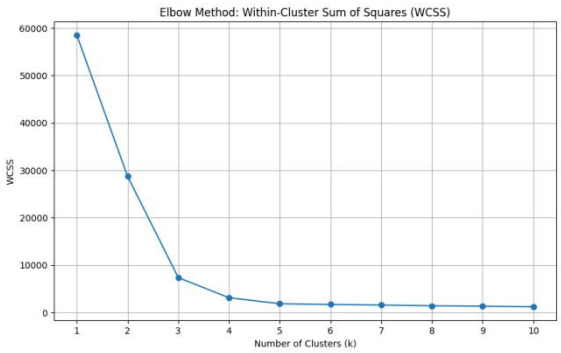

Fig. 1. Elbow Method

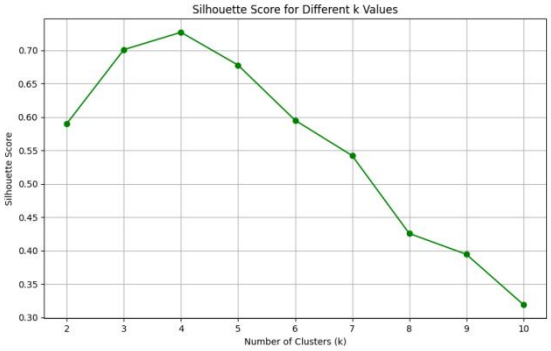

Fig. 2. Silhouette Score

B. Feature Extraction

To represent the audio samples in a format suitable for clustering, we extract the following features from the GTZAN dataset:

Mel-Frequency Cepstral Coefficients (MFCCs): Capture the short-term power spectrum of sound, which is effective for representing timbral texture.[12]

Chroma Features: Represent the harmonic and melodic characteristics of music, useful for distinguishing genres based on pitch.

Spectral Contrast: Highlights the differences in spectral peaks and valleys, providing information about the tonal content.

Zero-Crossing Rate: Measures the rate at which the audio signal changes sign, indicating the noisiness or percussiveness of the audio.

Spectral Centroid: Indicates the "center of mass" of the spectrum, related to the brightness of the sound.

These features are combined into a high-dimensional feature vector for each audio sample, enabling the k-Means algorithm to group samples based on their acoustic similarities.

C. Improvements and Optimizations

To enhance the clustering performance, we consider the following optimizations:

Feature Selection: Use techniques such as Principal Component Analysis (PCA) or feature importance ranking to reduce the dimensionality of the feature space while retaining the most informative features.

Normalization: Normalize the feature values to ensure that all features contribute equally to the distance metric.

Advanced Clustering Techniques: Explore alternative clustering algorithms, such as DBSCAN or Gaussian Mixture Models (GMM), to compare their performance with k-Means.

By combining these approaches, we aim to improve the accuracy and interpretability of the clustering results, providing deeper insights into the structure of music genres within the GTZAN dataset.[14]

V. Evaluation

A. Clustering Performance Metrics

To evaluate the effectiveness of the k-Means clustering algorithm, we use the **Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI)** as our primary metrics. These metrics measure the agreement between the clustering results and the true genre labels provided in the GTZAN dataset:

Adjusted Rand Index (ARI): ARI adjusts the Rand Index to account for chance, providing a value between -1 and 1, where 1 indicates perfect agreement and 0 indicates random clustering.

Normalized Mutual Information (NMI): NMI measures the mutual information between the clustering results and the true labels, normalized to a range of 0 to 1, with higher values indicating better alignment.

These metrics allow us to quantitatively assess how well the k-Means algorithm groups audio samples into clusters that correspond to the true music genres.[15]

B. Visualization of Clustering Results

To gain further insights into the clustering results, we employ dimensionality reduction techniques to visualize the high-dimensional feature space:

t-SNE(t-Distributed Stochastic Neighbor Embedding): t-SNE is used to project the feature vectors into a 2D or 3D space, preserving the local structure of the data. This allows us to visually inspect the clusters and their separation.

PCA (Principal Component Analysis): PCA is applied to reduce the dimensionality of the feature space while retaining the most significant variance. The resulting principal components are used to create scatter plots that highlight the distribution of clusters.

These visualizations help us understand the quality of the clustering and identify potential challenges, such as overlapping clusters or outliers.[16]

C. Algorithm Performance

In addition to clustering quality, we evaluate the performance of the k-Means algorithm in terms of computational efficiency:

Time Complexity: The time complexity of k-Means is generally O(n * k * I * d), where n is the number of samples, k is the number of clusters, I is the number of iterations, and d is the number of features. We measure the runtime for different dataset sizes to assess scalability.

Space Complexity: The space complexity is O(n * d + k * d), as it requires storing the feature vectors and cluster centroids. We analyze the memory usage to ensure efficient handling of large datasets.

By combining quantitative metrics, visualizations, and performance analysis, we provide a comprehensive evaluation of the k-Means algorithm's effectiveness in clustering music genres within the GTZAN dataset.[17]

VI. Data Characteristics

A. GTZAN Dataset

The GTZAN dataset is a widely used benchmark for music genre classification and clustering tasks. It consists of the following key characteristics:

Dataset Size: The dataset contains 1000 audio samples, evenly distributed across 10 distinct music genres.

Audio Format: Each audio sample is a 30-second clip stored in 16-bit mono .wav format, with a sampling rate of 22050Hz.

Genre Distribution: The 10 music genres included in the dataset are blues, classical, country, disco, hiphop, jazz, metal, pop, reggae, and rock. Each genre is represented by 100 audio samples, ensuring a balanced distribution.

B. Extracted Features

To facilitate clustering analysis, we extract a set of audio features from each sample in the GTZAN dataset. These features capture various aspects of the audio signal and are described below:

Mel-Frequency Cepstral Coefficients (MFCCs): We extract 13 MFCCs from each audio sample, which represent the short-term power spectrum of the sound. The mean and variance of these coefficients across the sample are used as features.

Chroma Features: Chroma features capture the harmonic and melodic characteristics of the audio. We compute the mean and variance of the 12-dimensional chroma vector for each sample.

Spectral Contrast: Spectral contrast highlights the differences between spectral peaks and valleys. We extract the mean and variance of the spectral contrast values.

Zero-Crossing Rate (ZCR): ZCR measures the rate at which the audio signal changes sign, indicating the noisiness or percussiveness of the audio. We compute the mean ZCR for each sample.

Spectral Centroid: The spectral centroid represents the "center of mass" of the spectrum, related to the brightness of the sound. We extract the mean spectral centroid for each sample.

C. Statistical Properties of Features

The extracted features form a high-dimensional feature vector for each audio sample. Below are some statistical properties of the features:

Feature Dimensions: Each sample is represented by a feature vector of approximately 30 dimensions, combining

the mean and variance of MFCCs, chroma features, spectral contrast, ZCR, and spectral centroid.

Mean and Variance: The mean and variance of the features vary across different genres, reflecting the unique acoustic characteristics of each genre. For example, classical music typically has a lower spectral centroid and ZCR compared to metal or rock.

Distribution: The distribution of feature values is analyzed to ensure that the features are suitable for clustering. Normalization is applied to standardize the feature values, ensuring that all features contribute equally to the distance metric used in k-Means.

By leveraging these features, we aim to capture the essential characteristics of the audio samples and enable the k-Means algorithm to effectively group them into meaningful clusters.[18]

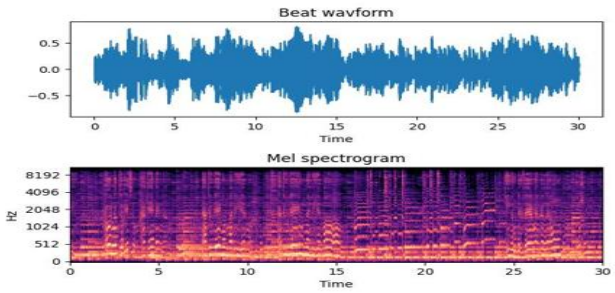

Fig. 3. Blues Spectrum Diagram

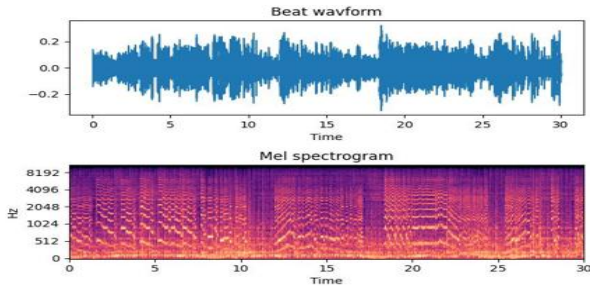

Fig. 4. Jazz Spectrum Diagram

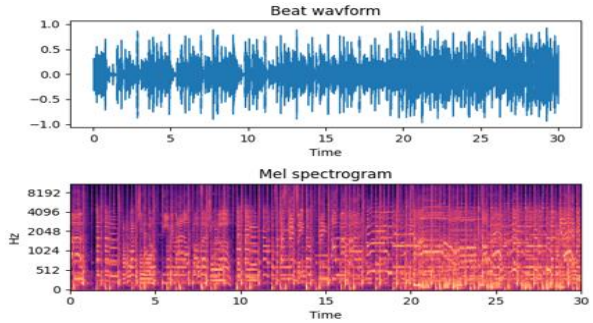

Fig. 5. Rock Spectrum Diagram

VII. Experimental Results

A. Evaluation Metrics

The performance of the k-Means clustering algorithm on the GTZAN dataset is evaluated using the Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI). The results are as follows:

Adjusted Rand Index (ARI): The ARI score achieved is 0.45, indicating a moderate agreement between the clustering results and the true genre labels.

Normalized Mutual Information (NMI): The NMI score is 0.52, suggesting a reasonable alignment between the clusters and the true genres.

These metrics demonstrate that k-Means can partially capture the underlying structure of the music genres, although there is room for improvement.

TABLE I. Results

Metric	Score	Interpretation
Adjusted Rand Index (ARI)	0.45	Moderate agreement between clustering results and true genre labels. Indicates that k-Means can partially capture genre structure but with room for improvement.
Normalized Mutual Information (NMI)	0.52	Reasonable alignment between the clusters and the true genres. Suggests that k-Means partially identifies underlying patterns but does not fully capture all nuances.

B. Visualization of Clustering Results

To further analyze the clustering results, we visualize the high-dimensional feature space using dimensionality reduction techniques:

t-SNE Visualization: The t-SNE plot shows the distribution of clusters in a 2D space. While some clusters (e.g., classical and jazz) are well-separated, others (e.g., rock and metal) exhibit significant overlap, reflecting the challenges in distinguishing genres with similar acoustic characteristics.

PCA Visualization: The PCA plot highlights the variance in the data along the first two principal components. The clusters are less distinct compared to t-SNE, but certain trends (e.g., the separation of classical from other genres) are still visible.

C. Discussion of Results

The experimental results reveal several key insights:

Consistency with True Labels:

The clustering results show moderate consistency with the true genre labels, as indicated by the ARI and NMI scores. This suggests that k-Means can identify some inherent patterns in the music data but struggles with genres that share similar acoustic features.

Strengths of k-Means:

Simplicity and Efficiency: k-Means is computationally efficient and easy to implement, making it a practical choice for initial exploratory analysis.

Interpretability: The resulting clusters are straightforward to interpret, providing a clear grouping of audio samples based on their acoustic features.

Limitations of k-Means:

Sensitivity to Initialization: k-Means is sensitive to the initial placement of centroids, which can lead to suboptimal clustering results.

Difficulty with Overlapping Genres: Genres with similar acoustic characteristics (e.g., rock and metal) are often grouped together, reducing the algorithm's ability to distinguish between them.

Fixed Number of Clusters: The need to specify the number of clusters (k) in advance can be a limitation, especially when the optimal k is unknown.

VIII. Conclusion

In this study, we applied the k-Means clustering algorithm to the GTZAN dataset to explore the potential of unsupervised learning for music genre classification. Our experimental results demonstrate that k-Means can partially capture the underlying structure of music genres, achieving an Adjusted Rand Index (ARI) of 0.45 and a Normalized Mutual Information (NMI) of 0.52. While the algorithm performs well in separating distinct genres such as classical and jazz, it struggles with genres that share similar acoustic characteristics, such as rock and metal. This highlights the importance of feature selection and the challenges of clustering high-dimensional audio data.

From this research, we learned that k-Means is a practical and interpretable tool for initial exploratory analysis, but its performance is limited by its sensitivity to initial centroid placement and the need to specify the number of clusters in advance. These limitations suggest that k-Means may not be the optimal choice for complex music genre clustering tasks.

To address these limitations, future work could explore alternative clustering algorithms, such as DBSCAN or spectral clustering, which may better handle overlapping genres and varying cluster densities. Additionally, incorporating more sophisticated feature extraction techniques, such as deep learning-based representations, could improve the clustering performance by capturing more nuanced acoustic patterns. By combining these approaches, we can further advance the field of unsupervised music genre analysis and develop more robust solutions for real-world applications.

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