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1 Music Genre Classification via MFCC Analysis

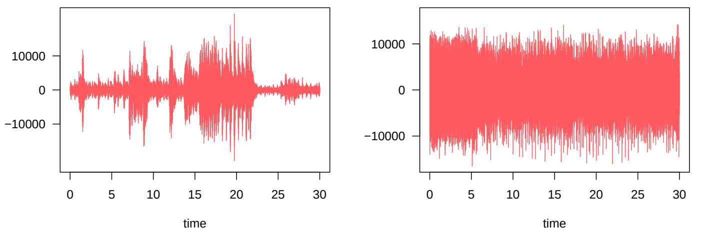

Figure 1: Audio Waveforms of the files `jazz.00000.wav` (left) and `metal.00001.wav` (right).

The goal of this project is to try music genre classification, utilizing audio feature extraction techniques together with clustering and classification data mining techniques. For this purpose, the GTZAN Genre Collection dataset [6] will be used. The dataset consists of 1000 audio tracks, each 30 seconds long. It contains 10 genres, each represented by 100 tracks. The tracks are all 22050 Hz monophonic 16-bit audio files in `.au` format. It's important to note, that this is a legacy dataset, collected from various sources, including personal CDs, radio and microphone recordings, with inconsistent quality [5]. Nevertheless, it's sufficient for our use case. Visualizations of audio signals from the dataset are displayed in Figure 1.

2 MFCC Audio Feature Extraction

Mel-frequency cepstrum coefficients (MFCCs) are a representation of the audio signal in the form of a unique spectrum. It's known for taking a complex audio signal and translating it into a simplified version that captures the essential components to the human ear. Applications of MFCCs include speech recognition [1] and music genre classification [3]. Various literature suggests that the first 12 coefficients are sufficient for speech recognition, while it's recommended to use $20 - 40$ coefficients for musical audio signals. The precise number of coefficients can be determined by means of experimentation, and in context of this project, the first 30 coefficients were used. The `tuneR` package [4] was utilized for extracting the MFCCs. Visualization of MFCCs is displayed in Figure 2.

3 K-Means Clustering

While clustering all 10 genres by MFCC features produces adequate results at first sight, only two genres were picked for simplification purposes. Results are displayed in Table 1. Additionally, silhouette coefficient plot of the Pop and Metal genres clustering results is displayed in Figure 3.

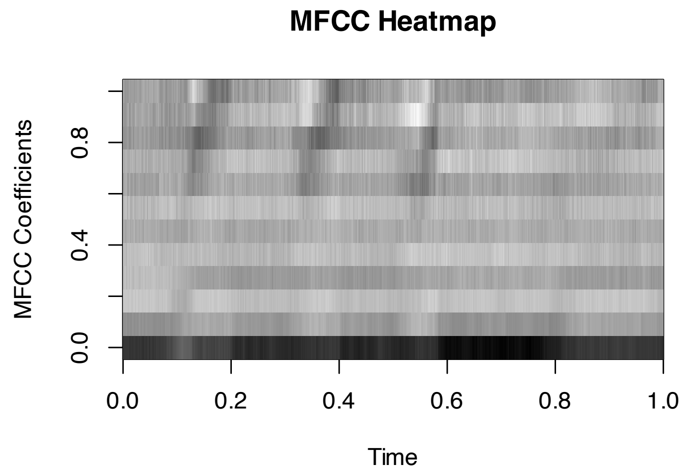

Figure 2: MFCC heatmap of the file `classical.00015.wav`.

Genre Pair	Cluster Sizes	Variance Ratio (%)
Pop vs Metal	106, 94	46.8
Jazz vs Rock	84, 116	34.3
Reggae vs Classical	95, 104	26.1
Country vs Disco	104, 96	40.9

Table 1: K-Means Clustering Results for Different Genre Pairs.

4 Classification using Support Vector Machines (SVM)

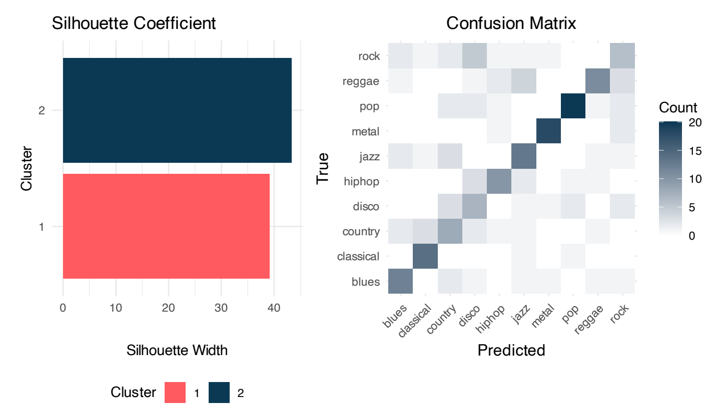

Figure 3: Pop vs Metal silhouette plot (left), Confusion matrix for all genres (right).

For the classification task SVM classifier was utilized with the *radial* kernel, yielding a 0.604 accuracy. This reflects the best result, achieved by trying different amounts of MFCC coefficients. The model can be potentially improved by adding features like the spectral centroid and zero crossing rate, that capture nuances related to dynamics and tonality of the given audio sample. The `seewave` package [2] can be utilized for extraction of additional features.

References

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