

Music Genre Classification

Ajay Prasad¹, Sriram Sundaraj²

Department Of Computer Science and Engineering,
National Institute of Technology
Trichy, India 620015.
ajayrfhp1710@gmail.com

Department Of Computer Science and Engineering,
National Institute of Technology
Trichy, India 620015.
ssundarraj@gmail.com

Abstract: *The purpose of this research is to build a machine learning model to predict the genre of a song. This paper analyzes a song as a wave and determines the factors involved and predicts the genre. Application of the model is primarily to automatize the process of genre identification which shall aid in building of music recommendation systems.*

Keywords: Machine Learning, Music Genre, Prediction, Support Vector Machines, Classification, Supervised Learning, Intelligence, Automation.

1. Introduction

Automatic music genre classification is an application of artificial intelligence, more specifically machine learning, that builds a system that predicts the genre of a song. It is fairly simple for a human being to identify the genre of a song. One thinks about how fast the beat of the song is, the mood the song, the video of the song, etc. All these help create a mental picture of the song and thus the genres associated with it are determined. Automatic genre classification can be useful to solve some very interesting problems such as making song recommendations, finding similar songs, finding people who will like that particular song. Intelligence and automation are the core ideas that drove us to making this system.

2. Related Work

Several models have been made to solve this problem like Music Genre Classification with the Million Song Dataset [1], which uses audio features and lyrical features. The Model builds a bag of words for the lyrical features. For the audio features, they used the MFCC (Mel-frequency cepstral coefficients)[2]. Their work was unique in how they used lyrical features.

Another paper along the same lines is Automatic Musical Genre Classification Of Audio Signals [3]. A vector of size 9 (mean-Centroid, mean-Rolloff, mean-Flux, mean-Zero-Crossings, std-Centroid, std-Rolloff, std-Flux, std-Zero-Crossings, Low-Energy) was used as their Musical-Surface Features vector. Rhythm features were determined and their model was built using both the vectors.

3. Feature Extraction

Our work differs from existing literature in the way we treat song as a wave and as a song as well, meaning some features were based on wave properties, and other features

were based on song level characteristics. The feature vector is of length 19.

3.1 Calculation of MFCC

MFCC is a representation of the power spectrum of sound. A high-level description of MFCC Calculation is explained below.

The signal is framed into short frames. For each frame, the periodogram estimate of the power spectrum is calculated. The Mel filter-bank to the power spectra is applied, the energy is summed in each filter. The logarithm of all filter-bank energies is taken. The Discrete Cosine Transform (DCT) of the log filter-bank energies is taken. Discrete Cosine Transform (DCT) coefficients 2-13 are saved and the rest are discarded. MFCC was calculated using the open source sci-kit audiolabs library. Feature vector contribution is 13.

3.2 Calculation of Scale

An approximation was used to calculate the scale of the song. The five most frequently occurring frequencies in the song were taken in groups of five. This led to the length of the frequency vector being five.

3.3 Calculation of Tempo

Another song level indicator we used was the tempo of the song. Scaperot's tool, an open source library was used to find the beats per minute of the song. One feature is contributed to feature vector.

4. Dataset Description

Finger-Printing of the songs was done using the eyeD3 library. Artist, album name and title of the song were obtained. Pygn, an open source tool, a wrapper over rhythm API was used to obtain the genre of the song. Using a local collection of

637 songs, we extracted features and with the genre obtained from Pyn our dataset was prepared. The target genres were Urban, Classical, Electronica, Jazz, Pop, Soundtrack, Alternative And Punk, Rock, Other.

Soundtrack, Other, Jazz, Classical and traditional were ignored due to low number of samples. Genre converted from string to integers through a map to suit models construction and prediction. Samples with missing genres were ignored.

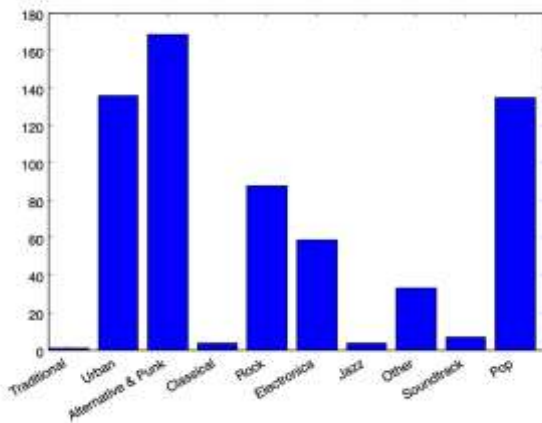


Figure 1: Dataset distribution

4. Models

For building the models, we used the SCI-KIT [9] library. The models we used are the standard classification algorithms Logistic Regression, Support Vector Machine and K-Nearest Neighbours.

5. Results

From the dataset, 150 songs were randomly picked and reserved for testing the accuracy of the model. The genre of the test songs are known. Predictions were made for this test data model wise and genre wise and results have been prepared. Results are on a percentage scale.

Table 1: GENRE TO MODEL ACCURACY MATRIX

Margin	Electronica	Urban	Alternative and Punk	Pop	Rock
Logistic Regression	0	56.52	49.1	28.57	50
Knearest Neighbours	33	42.85	59.45	30	0
Support Vector Machines	25	56.25	57.14	29.16	25

References

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Author Profiles

Ajay Prasadh Viswanathan pursuing B.Tech in Computer Science In National Institute of Technology, Trichy (2012-2016 Batch). Did software engineering internship in Flipkart in the summer of 2015. Worked on demand forecasting to forecast sales for stocking and pricing.

Sriram Sundarraj pursuing B.Tech in Computer Science In National Institute of Technology, Trichy (2012-2016 Batch). Did software engineering internship in Flipkart in the summer of 2015. Worked on the analytics platform for supply chain management, will start working for VISA Inc from July 2016.