Evolution of musical features based on periodical trends and popularity

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1 INTRODUCTION

1.1 Problem statement

Analyzing trends of music is multi-dimensional problem, including influences from socioeconomic / cultural effects as well as inherent musical signal features such as tunes, pitches and beats [12]. Excluding the cultural and social aspects of the music, we want to answer the following question: given a generation or a range of time, would a popular group of music has a common characteristic in features? This study focuses to analyze if a specific feature of the top rated songs are more prominent in one group of years compared to the other group. For instance, for top 50 songs in 1980s, it can be hypothesized that speechness and liveliness features of the music are more dominant than the rest of the features and steers the trend compared to top 50 songs in early 2000s. The current study aims to pinpoint the musical trends using music signal-induced features only with predetermined year range for a specific geolocation. With identified features, a visualization will be performed to easily identify distinct characteristics using Javascript and D3. From a sampled songs, a model will be trained to classify a song with preset definition of popularity and its estimation.

1.2 Motivation and Related Work

The analysis of musical trends has been a continuous interest among computer scientists, musical industries, and sociopsychologist. The methods to in which the evaluation of trends conducted have been transitioned to be more technical. O'Dair and Fry mentions that due to proprietary information and intellectual property of the musical streaming industries, trend analysis from different platforms cannot be distinguished clearly [11]. However, multiple studies of musical trend analysis involve preprocessing of musical feature based on subcategorizations, statistics, and traditional machine learning techniques [2, 5, 9]. With low prediction accuracies, these methods, however, do not compensate for the entire music population and may risk in underfitting due to large volume of available musical samples.

These studies did not have a clear representation of the influential features on musical trends other than through a list of feature importance. The accuracy representation of musical trends is too simple and rather shallow to describe multi faces of musical trends. Visualization of music have been dynamically presented in various manners to convey linked emotions to the songs or involved instruments [1]. Unlike other predictive studies, which have mainly represented the model in terms of accuracies, for the current study, a visualization tool will be developed to showcase multiple features of music using polygon plots. Gumulia et al. uses shapes to represent musics features but the shapes do not represent any acoustical features [4]. The proposed study polygon plots help not just the scientific community but also allow day-to-day users and musical producers to easily understand the governing features of the music as well as the lacking ones from the vertexes of the shape. Furthermore, to aid the listeners in the distinctive features, the musical samples will be visualized in frequency modes like studies in to help the audience gauge the amount of acoustical features[3, 10].

References on existing works on machine learning models offer a good review of current statuses, and emphasizes us to focus on delivering a simplified model while keeping relatively high accuracy using musical features. Gutiérrez et al. provides an excellent representation of classifying the music based on its popularity by giving three distinct classes from preprocessed features of musical samples [8]. This work can be a good guideline in features and a model construction of proposed study. However, the major downside of this work is its efficiency in building a complex model to gain higher level of accuracy in a limited time, which might be not substantial in the proposed study. Langensiepen et al. studied the music popularity trend using traditional distance-metric based clustering mechanism. To account for various features, principal component analysis (PCA) is used, simplifying the overall features as a whole while retaining the significance of the important features [6]. However, the evaluated algorithm was not trained using a large dataset, and the test cases were limited, questioning the reliability of the model.Junghyuk et al. use temporal analysis to evaluate the music popularity [7]. Metrics that the paper cites include debut, skewness, and kurtosis, statistical measurements which are intuitive to the target audience of this study, the average day-to-day users and music producers. The paper's approach overcomplicates the definition of the music popularity, whereas the proposed definition for this study provides a rather simplified alternative.

2 ASSESSMENT

2.1 Potential risks

As mentioned briefly in the previous section, there is a risk regarding the way we define the music popularity. For this project, the definition of music popularity is whether the song has ever made it into the top 100 billboard charts. Since the music popularity is an abstract variable with no generalized benchmark for accessing it, our definition may not accurately represent the actual music popularity.

2.2 Resource / Plan

The primary resource required for this project would be time. Obtaining features from the Spotify API, extracting features using FFT, labeling songs based on our definition, training multiple models to represent different periods, and designing an interactive visualization to showcase the dataset all require a significant amount of time.

Preprocessing the data required for training the model will take most of the time spent on this project. With seven weeks remaining till the deadline, all four members will focus on preprocessing for the first three weeks. After that, Young Hwan and Tsung-Ying will create interactive visualizations using the processed data for weeks four and five, while the other two will work on training the classification model. On week six, all members will work collaboratively to create the visualization and finalize the project. On week seven, Chang Hyeon will work on the poster and the video while the other team members write the final report.

2.3 Evaluation Checkpoints

The following list includes tasks that need to be completed by the end of this project:

1. Preprocessing Dataset: Obtain music features using the Spotify API and the FFT.
2. Training Classification Models: Train classification models using random forest for every specified time span.
3. Performance Evaluation: K-fold cross validation on the trained model to evaluate the accuracies of the models.
4. Create an Interactive Visualization: Create a web visualization that can illustrate the music trends over the years.

We aim to reach the first check point by the mid progress review, which is three weeks away from now, and to reach all four check points by the end of this project.

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