Using Music Information Retrieval Feature Selection to Generate Music Suggestions

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1 Abstract

Music-streaming services like Spotify and Soundcloud have revolutionized the music industry and have become increasingly competitive with their music suggestion generators. These generators utilize machine learning to suggest songs to add to specific playlists and to generate entire playlists of songs based on a users music listening history. We plan to create our own music suggestion models for individual songs and playlist curation utilizing K-nearest neighbors and Naive Bayes clustering algorithms. The growing field of Music Information Retrieval (MIR) focuses on extracting meaningful features from the raw music files. We plan on experimenting with various features and finding the ideal combination for single song and playlist suggestions. We will use our personal music collections (4,000 songs) for the data, partitioning the data into training, development, and testing categories. Our overall evaluation of success will be subjective but we will provide the tool to WJHU, the Hopkins student radio station, for their evaluation.

2 Methods

Machine Learning Algorithms:

- K-Nearest Neighbors for suggesting songs similar to other songs (Using the title of the song as the label). This is useful for suggestions because it finds the data points that have the most similar features which should indicate similar songs.
- Naive Bayes clustering for creating playlists. A cluster represents a set of songs such that the features of the songs inside will be similar enough so that they would go well together in a playlist.

Feature Extraction:

- Zero Crossing Rate
  measures noisiness
- Root Mean Square
  measures loudness

- Spectral Centroid
  measures how dark or light a song is
- Spectral Rolloff
  measures how much energy is in lower frequencies
- Spectral Flux
- Spectral Variability
  measures how flat the spectrum is and if some frequency regions are much more prominent than others
- Strongest Partial
  primitive form of pitch tracking
- Mel-Frequency Cepstral Coefficients (MFCC)
  measures timbre
- Rhythm Histogram (RH)
  histogram of Rhythm Pattern (RP), modulation magnitude per modulation frequency
- Statistical Spectrum Descriptor (SSD)
  description of each of the 24 critical bands of the Sonogram by 7 statistical measures
- Can use change in RH and SSD over time as additional features

3 Resources

Python Libraries: Numpy and scikits.talkbox
Feature extraction:
Rhythm Pattern Extractor (http://www.ifs.tuwien.ac.at/mir/downloads.html, MATLAB and Java),
MARSYAS (http://marsyas.sness.net/ http://sourceforge.net/projects/marsyas, C++),
jMIR (http://jmir.sourceforge.net/, Java),
mirtoolbox (http://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/mirtoolbox, MATLAB),
BeatRoot (http://www.elec.qmul.ac.uk/people/simond/beatroot/index.html, Java),
CLAM (http://clam-project.org/, C++),
M2K (http://www.music-ir.org/evaluation/m2k/, Java),
IPython Music Feature Extractor (http://www.ifs.tuwien.ac.at/ schindler/lectures/, Python),

4 Milestones

4.1 Must achieve

A model that produces song recommendations based on a single song provided by the user

4.2 Expected to achieve

A model that produces song recommendations based on multiple songs provided by the user (playlist recommendation)

4.3 Would like to achieve

A model that produces playlists based on a single song provided by the user

5 Final Writeup

1. Introduction: General introduction about project and why we chose to do music analysis
2. Background: Background about machine learning in music recommendation, techniques in music information retrieval (MIR)
3. Explanation of machine learning algorithms used: K-Nearest Neighbors and Naive Bayes clustering as well as explanation of data preparation (train/dev/held out data), feature extraction, hyper-parameter tuning
4. Detailed description of work done and how progress was made over time
5. Description of results including examples of song suggestions
6. Evaluation of overall success, comparison to proposal, things to improve and future improvements

6 Bibliography

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