MATH250: Graph Algorithms
Final Project Proposal
Graph Algorithms for Feature Extraction in Music Data

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Statement of Topic

The purpose of this project is to explore a novel, graph-based approach to music information retrieval (MIR). Songs are represented using a graph and features are extracted from the graph using various graph algorithms. These features can be used in machine learning applications, such as classification of song by genre or composer.

A weighted digraph $G = (V, E, \omega)$ is generated based on the contents of a single-instrument song S as follows:
$\exists V_{i,j} \in V \iff \exists$ note of pitch i and duration j in S.
$\omega(E_{x,y}) =$ number of times note y is played immediately following note x.
Chords, or any simultaneously played notes, are represented as cliques.
To generalize to multi-instrument songs, a graph can be generated for each instrument's part.

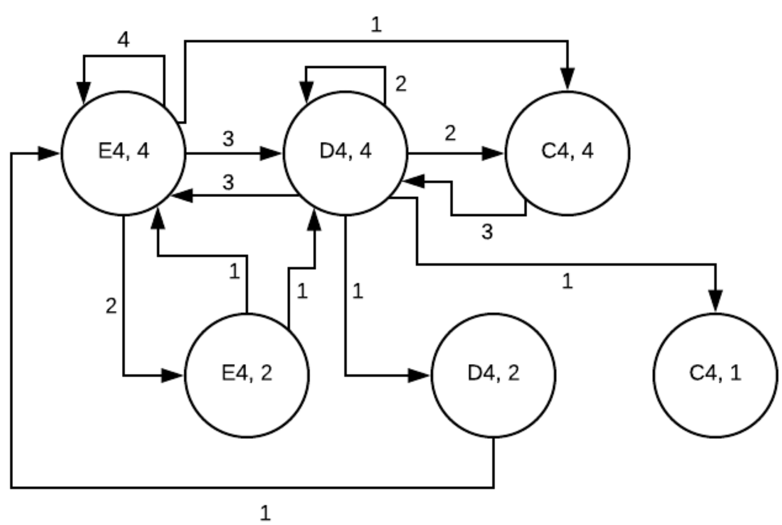

Figure 1: Digraph for 'Mary Had a Little Lamb'

This graph in **Figure 1** condenses and reduces the feature space of a corresponding audio file. Various graph algorithms can be used to extract notable features and further reduce the feature space. In the above graph, Tarjan's algorithm would reveal that there are only two strongly connected components, a feature that could prove useful in distinguishing the genre of the composition.

Goals and Objectives

The main objective of this project is to determine the efficacy of this graph-based MIR process in machine learning tasks. The proposed machine learning task is a common classification problem in MIR: determining the genre or composer of a piece of music. In order to quantify the efficacy, the results will be compared to more traditional feature extraction techniques like Mel Frequency Cepstral Coefficients (MFCC). Furthermore, various classifiers will be used in order to achieve as high an accuracy as possible using the selected features. Basic linear and KNN classifiers will be explored, as their results are relatively easy to understand and potentially insightful. More complicated models such as SVM with kernel, ensemble methods, and possibly neural network/deep models will also be explored.
In order to achieve the aforementioned goal, various types and combinations of features will be explored. Ultimately, an optimal set of features will be selected for the specific classification task. Ideally, this feature set will be able to rival the accuracy of MFCC methods; additionally, the ability for this feature set to generalize to other problems in MIR will be an important measure of efficacy. As such, a final goal is that others will be able to apply the techniques developed in this project to their own work.

Literature Review

Alberto Pinto et al. use a similar approach to modeling music using a graph[1]. Their model seeks to understand the relationship between notes as intervals in order to determine the similarity of melodies. My approach is similar but contains more information (like note duration), and aims to represent an entire song rather than the general structure of a melody. Nonetheless, the approach in the paper is able to peform well at indexing Dutch folk songs.

Amit Tiroshi et al. approach a tangential problem: recommendation using graph-based features[2]. The general approach to their graph analysis draws from classic examples of random walks to build recommendations. It also discusses how graph feature extraction has been used to enhance existing models. Both of these ideas can be useful experiments in the project.

Kenwoo Choi et al. provide an overview of deep learning for music information retrieval. It also discusses MFCCs, how they're used in MIR, and how they can be used in deep networks. The content of this paper will prove useful if this projects delves into deep classification models using graph-features.[3].

Michael Haggblade, Yang Hong, and Kenny Kao explored the problem of music genre classification in CS229 at Stanford University[4]. They provide benchmarks for relevant models, including KNN, SVM, and neural networks. Importantly, they used MFCC for feature extraction. They compared four distinct genres: classical, jazz, metal, and pop and achieve accuracy of 80% overall. The benchmarks provided will provide a useful comparison for the results of my graph-based feature selection.

Timeline

By April 28th: Collect dataset for classification task, translate all data into digraph form.
By April 30th: Run preliminary feature extraction algorithms (Tarjan's, Maximal Matching, MIS, MST, BFS, DFS, etc.). Experiment with classifiers and take notes on preliminary results.
By May 6th: Build on preliminary results, determine optimal set of features/algorithms. Run full model selection process to achieve highest accuracy; copare the results to MFCC methods. Finish initial draft of paper.
By May 8th: Finalize paper and submit on time.

References

[1] Alberto Pinto, Reinier H Van Leuken, M Fatih Demirci, Frans Wiering, and Remco C Veltkamp. Indexing music collections through graph spectra. In *Proc. of the 8th International Conference on Music Information Retrieval (ISMIR'07)*, pages 153–156, 2007.

[2] Amit Tiroshi, Tsvi Kuflik, Shlomo Berkovsky, and Mohamed Ali Kâafar. Graph based recommendations: From data representation to feature extraction and application. *CoRR*, abs/1707.01250, 2017.

[3] Keunwoo Choi, György Fazekas, Kyunghyun Cho, and Mark B. Sandler. A tutorial on deep learning for music information retrieval. *CoRR*, abs/1709.04396, 2017.

[4] Michael Haggblade, Yang Hong, and Kenny Kao. Music genre classification. 2011.