CSC 475 FINAL PROJECT: AUTOMATIC CHORD ESTIMATION USING SCIKIT LEARN

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ABSTRACT

This project aims to investigate and evaluate some of the current strategies for automatic chord estimation. We present a simple HMM-based mode that uses the SciKit Learn framework for detecting chords from audio signals using beat synchronous chroma vectors. SciKit Learn is an open source toolkit in Python for machine learning. We evaluate the effectiveness of Harmonic/Percussive Sound Separation (HPSS) as a preprocessing step by comparing the results of an unaltered data set to the results of a dataset that has undergone HPSS preprocessing, and find that HPSS is a valuable preprocessing step prior to extracting chroma vectors.

1. INTRODUCTION

Chords describe the harmonic content of a piece of music. Automatic estimation of chords has many applications in music information retrieval and music annotation. For example, automatic chord estimation may be used to infer genre and emotional content (minor, sad; major, happy) of a piece, or to identify songs of similar compositional form. It has also been used successfully in detecting coversongs [19].

Automatic chord detection has been a MIREX task since 2008, and has since seen increased improvement, with submissions in 2012 surpassing 72 percent accuracy on unseen data [1]. Hidden Markov Models have been used as a successful modeling strategy in a number of automatic chord estimation models, including [2] [16] [20] and [19]. All of these models use chroma vectors (Pitch Class Profiles) at the feature extraction phase, which represent the pitch content of a song for each sampled window. Each chroma vector is a real valued vector which contains the salience of each of the pitch classes (A, A# . . . G, G#) for a given time window. [1], [16], [19], and [21] have all found that chroma extraction on beats improves results, as chords are most stable between beats.

Another method to improve the resolution of chromagrams is filtering out transient and percussive information that does not contribute to the harmonic content, but may add noise to the extracted chromagram. A simple technique for this is to filter the frequencies where chromas are extracted so that they are restricted to the range with the most pitch content. Another is to suppress harmonic and percussive sounds using harmonic/percussive sound separation (HPSS). It has been noted that applying this preprocessing step can greatly improve chord estimation accuracy [10].

Original Chord Labels	Treated As
Maj, Aug, sus4, sus2	Maj
min, dim	min

Figure 1: Chord Labels

2. OVERVIEW

For this project we used part of the annotated Billboard 100 data set. Our data set included audio files for approximately 650 audio files from the Billboard top 100 chart between the years 1958 and 1991. Each song in the data set includes beat by beat chord annotation [8]. The chords are labeled as either maj, min, aug, dim, sus2, sus4, or N, where N imply no chord is present. A distinction is made between enharmonic labels (for example both G# and Ab occur in the annotations), for a total of 128 chord labels.

For our the scope of our project we reduced this number by combining enharmonic labels and reassigning the chord labels into two classes, major and minor, as seen in Figure 1. Combined with the no chord label, we considered 25 distinct chord labels to train and test our model.

We used two sets of audio data: one unprocessed, and one preprocessed by performing harmonic percussive source separation (HPSS). Each audio file was mixed to mono to reduce processing time. Then, chormagram extraction was performed on the two audio datasets at intervals corresponding to the beat information in the annotated data, and only considered information from octaves 1 through 5 (approximately 60–1000Hz).

After extracting the chromagram for each song in the data set, 63 of the tracks were randomly chosen using the random function in Python and kept as testing data. The rest of the data was used to train our HMM model.

A full overview of our proposed model can be seen in Figure 2.

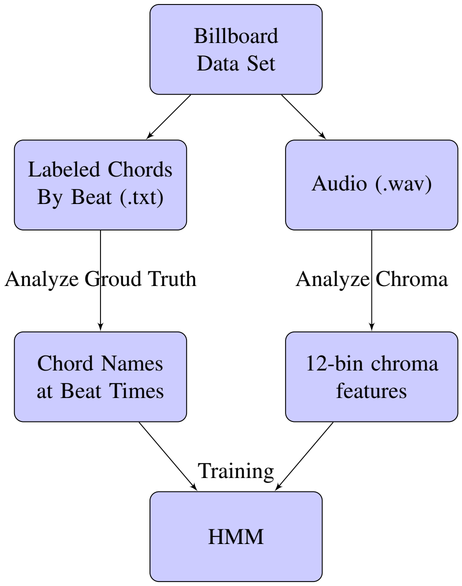


Figure 2: System Overview

3. MODEL

3.1 PreProcessing

In a spectrogram, the harmonic components of a musical signal have a stable pitch and form parallel ridges along the time axis. Transient sounds distribute their frequency content across the entire spectrum and occur during short time frames, which can be seen as spikes in the frequency axis. HPSS produces two signals, one with mostly harmonic content, the other with percussive sounds which is obtained by complementary diffusion on the spectrogram.

HPSS was completed using Python code provided by [25]. The audio is first transformed into the frequency domain. For each frequency the current FFT window is replaced with the median of the l frequency bins surround it [12]. In our implementation, a kernel size of 23 gave the best results given the broad range of audio styles present in the Billboard dataset. When l was larger than 40, the attack of harmonic components became too slow, which is valuable information during chroma extraction.

$$Y(n) = median\,\{X(n-k:n+k), l = (l-2)/2\}$$

The percussive suppressed spectrogram is used to create a soft mask based on Wiener filtering, which is then applied to the original spectrogram. Afterwards the ISFT is used to obtain the harmonic audio. Our system only makes use of the harmonics; however, the separated percussive audio could be a useful pre-processing step for beat extraction in future work.

[20] discusses a model very similar to our goals. Using the Beatles annotated data set, a 74.24 percent chord recognition rate was achieved without HPSS, and a 78.48 percent chord recognition rate was achieved with it. Our results also show similar gains after using the preprocessed audio.

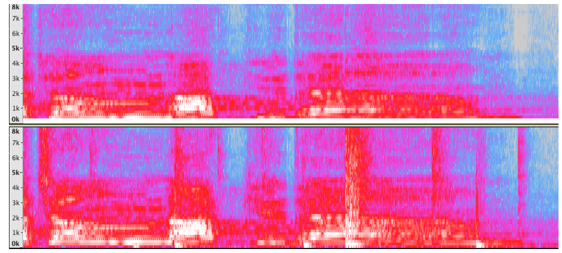


Figure 3: Top: Harmonic result of HPSS, Bottom: Original Signal

3.2 Chromagram Computation

To compute the 12-dimensional chroma vectors (or Pitch Class Profiles), we used the Chroma method available in Marsyas, and restricted the frequencies between Octave 1 and 5 (approximately 60–1000Hz).

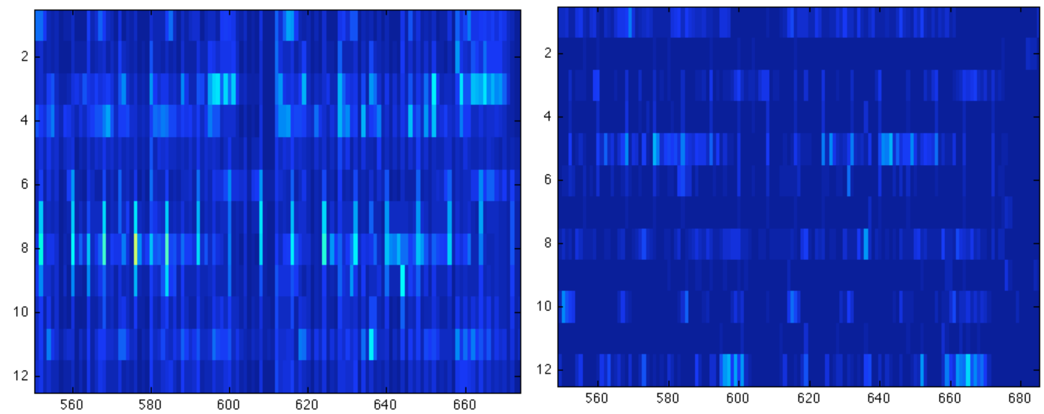
Because most chord transitions occur on beats, extracting chorma information for windows corresponding to each beat has shown to be beneficial to creating an more accurate automatic chord estimation model. For example, in [21], extracting chroma vectors on beats improved the results by 6 percent. This method exploits the stability of chords between beats, and reduces the overall computational cost by reducing the total number of windows [1]. Because the Billboard data is annotation at beat times, this approach naturally lines up with our ground truth data.

Two sets of chromagrams were calculated for our dataset, one set with HPSS applied to the audio, and one set without. A comparison of the resulting chromagrams for part of the song ‘Help Is On The Way’ by the Little River Band can be seen in figures 4a and 4b respectively. In these figures, the y-axis corresponds to the chord labels $C(1)$, $C\#(2)$, $D(3)$, etc. It's clear to see that after the HPSS processing, the chromas become much cleaner.

3.3 Hidden Markov Models

Hidden Markov Models (HMMs) are a probabalistic model for time-series data. Because chord sequences are continuous, Hidden Markov Models have become a common method for for automatic chord estimation and adapts well to the continuous nature of chord sequences. In this model, a given chord depends only on the previous chord predicted while all the other chords are hidden. For each song in our data set, the set of chorma vectors are the observations, while the chord labels are our states.

To create our model, we used the SciKit Learn framework; however, because the framework is designed for unsupervised learning, we needed to calculate the prior probability, covariance and mean of the chromas (which are represented as a 12-dimensional Gaussian distribution) to construct our initial transition matrix. This transition matrix represents the probability of one chord transitioning



(a) Extracted Chroma Vector

(b) Extracted Chroma Vector after HPSS

to another, independent of the previous chords. This was based off of Dan Ellis' Matlab code available through Labrosa. Due to the large size of our dataset, using Matlab was infeasible for processing time, so this was rewritten into Python to be fed into SciKit's GaussianHMM model.

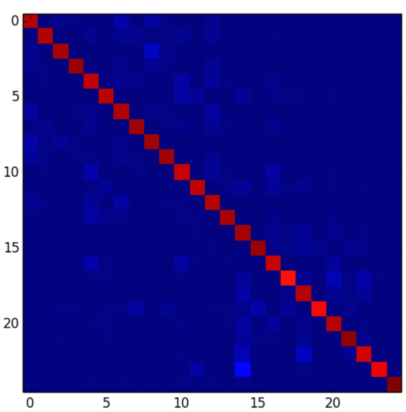


Figure 5: Transition Matrix

SciKit uses the Expectation Maximization (EM) algorithm to train the model and the Viterbi algorithm to predict the most likely chord progression given a sequence of chroma vectors. The number of iterations for the EM algorithm is specified by the user. For comparison, we also trained our unprocessed and our processed data using 2, 10, and 100 iterations of the unsupervised EM algorithm. We also ran a random subset of 100 songs from each data set though 500 iterations.

To test our model, we used two training and testing sets. First, the model was trained and tested with all of the data. Secondly, 63 random songs were removed from the data set and reserved for testing while the rest were used to training.

3.4 Evaluation

Figure 6 shows the results of our system for the processed and non processed audio. Although we fed initial values into the SciKit framework, using this framework for supervised learning was not in any way optimal. Despite creating the initial values to train the data with supervised learning, we were unable to optimize the Viterbi algorithm to find the optimal path through the states. Because it uses recognition, and not a forced alignment technique, the algorithm assumes any chord may follow another, even if those state transitions never appeared in the training data. [24] discusses the impact of this optimization on an EM-Trained HMM chord model. Without the forced alignment, results using chromagrams were as low as 10 percent on a small set of Beatles song data. When forced alignment was used, and the algorithm only assumed progressions in the test data were valid, results on the same test set increased by over 16 percent.

	64 Test Set Avg	64 Test Max
Non-Processed	1.0%	20.7%
HPSS	1.5%	19.9%
Non-Processed — 2 Iter	3.2%	44.7%
HPSS — 2 Iter	3.7%	60.5%
Non-Processed — 10 Iter	3.5%	38.9%
HPSS — 10 Iter	4.1%	36.5%
Non-Processed — 100 Iter	4.2%	17.1%
HPSS — 100 Iter	5.1%	18.0%
100 Songs — 500 Iter	5.5%	20.1%
HPSS 100 Songs — 500 Iter	6.2%	25.8%

Figure 6: Results Table

We also found that the testing results ofter predicted the wrong starting chord. An example of this is a song in they key of Ab major, but the first predicted chord is Bb major. It is likely that the model with keep predicting chords relative to Bb major, and therefore will miss-classify all of the chords for that particular song.

Despite having low results, our model does still show in increased accuracy when HPSS is used on the audio data.

It also shows increased accuracy as the number of iterations in training the EM algorithm increases, which is to be expected. The motivation to evaluation only 100 songs at 500 iterations was processing time, but it is likely that with the entire test set, similar results would be achieved.

The final column in figure 6 shows the accuracy for the highest scoring song for each run. It's interesting to note that while the model fails on most songs, on some it can achieve accuracy up to 60 percent.

4. CONCLUSION AND FUTURE WORK

We have introduced a simple beat-synchronous automatic chord estimation model and evaluated the effectiveness of HPSS as a preprocessing step. Despite having low results, it is still clear that preprocessing the audio with HPSS improves the output of the system. Unfortunately, SciKit Learn's HMM model is not efficient for supervised systems, even when the initial data is given to it. This is because the Viterbi algorithm is not able to be optimized. We also discovered as we worked on this project, that SciKit lean will be removing their HMM implementation from their framework; however, this code will still be available through the HMMLean GitHub. There is also currently an extension of this framework, called seqlearn, that is in development to extend the framework to supervised learning. Future iterations of this project could be improved by using seqlearn if it's development continues. Otherwise, continuing to write Dan Ellis' Matlab implementation into Python could be a good starting point for creating a more effective model.

The estimation model could also be improved by taking into account more information about the music context. For example, information about key could be used to choose a reasonable starting chord, or limit the choices of chords for the current song. Limiting the chord choices has potential for problems if the song relies on out of key chords, or has a key change at any point. Information about the time signature of a song could be used to decide when chord changes occur. A simple way to add this in would be to penalize chords from changing on weak beats. In both cases this extra information could be encoded in a Markov Logic Network as suggested in [5].

The chroma vectors we extracted could also be improved beyond HPSS. For example, [1] suggests that tuning using Harte's tuning algorithm is a staple of most modern algorithms. Some older papers such as [21] mention microtuning of the human voice as well as percussive sounds as sources of classification error.

Each song in the Billboard dataset also includes key information. It is possible to use the HMM model to simultaneously estimate the chords and the key of an input audio file [1], so a future implementation may use this data to predict key information as well as chords.

5. ROLES

- Sondra — Chroma Extraction, Background Research, Paper
- Lee — Chroma Extraction, Supervised Learning Code, Paper
- Robert — HPSS processing, Data Management, Paper

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