Alternative Measures: A Musicologist Workbench for Popular Music

Beach Clark
Georgia Institute of Technology
Bclark66@gatech.edu

Claire Arthur
Georgia Institute of Technology
Claire.arthur@gatech.edu

ABSTRACT

The objective of this project is to create a digital "workbench" for quantitative analysis of popular music. The workbench is a collection of tools and data that allow for efficient and effective analysis of popular music. This project integrates software from pre-existing analytical tools including music21 but adds methods for collecting data about popular music. The workbench includes tools that allow analysts to compare data from multiple sources. Our working prototype of the workbench contains several novel analytical tools which have the potential to generate new musicological insights through the combination of various datasets. This paper demonstrates some of the currently available tools as well as several sample analyses and features computed from this data that support trend analysis. A future release of the workbench will include a user-friendly UI for non-programmers.

1. INTRODUCTION

One of the challenges to the scholarly analysis of popular music is the difficulty of collecting symbolic data. There are two forms of symbolic musical data: symbolic representations of the music itself (i.e., score-based or MIDI data), and symbolic *metadata*. Metadata can refer to relatively large-scale features *about* a song as a whole (e.g., title, artist, track length, etc.), or may refer to *features* computed from the data such as chord progressions, key estimates, number of sections, etcetera. Since both the raw audio and any published scores for virtually all popular music fall under copyright protection, musicologists wishing to study popular music are largely restricted to the analysis of symbolic metadata. In order to follow trends in the rapidly evolving field of popular music, large volumes of symbolic metadata will have to be curated through automated or semi-automated approaches. Standardized analytical metrics also need to be developed to complement and enhance qualitative analyses. This project focused on three objectives: collecting symbolic musical metadata from multiple sources; integrating newly developed analysis tools with existing tools; and developing a hierarchical model of metrics that can help guide this type of analysis.

1.1 Collecting musical data from multiple sources

Musical analysis is a complex process that involves tasks such as transcribing lyrical, harmonic, rhythmic and melodic information, and doing research into the provenance of the music (i.e. who wrote the lyrics, who wrote the music, who produced the track, etc.). Many computational analysis projects begin with manual collection and analysis of the data, a process that is immensely time consuming. Due to the resources required in curating datasets, many analyses are carried out on relatively small samples (e.g., [19, 25]). However, an additional challenge in *any* analysis is in collecting enough data to be able to make statistically valid inferences about a larger population. Using data that has already been collected can substantially improve the time and resources invested for a given study by allowing analysts to focus on analyzing data instead of collecting it. To use this data effectively, however, multiple sources must be combined, the validity of the data must be tested, and the quality or usefulness of that data further refined. In part, this project investigates the efficacy of using data from midi collections combined with data from commercial sources like Spotify, as well as websites like Ultimate Guitar, to carry out musicological analyses.

The Spotify database contains features and metadata for approximately forty million songs that is continuously updated with new material based on listener tastes. This makes Spotify and similar sites potentially excellent sources for structural data such as song length and number of sections. This project developed a method of collecting and storing data from the Spotify API that makes the data easier to use for musical analysis.

While music listening websites and software (e.g., Spotify, LastFM) are good sources of structural data about music, some musical analysis tasks involve making or using transcriptions of lyrical and harmonic information which are not easily obtained from these sources. Websites like e-Chords [24] and Ultimate Guitar [23], however, contain user-submitted chord transcriptions of popular songs for thousands of songs online. Although the quality of the transcriptions varies, some scholars have found that using these transcriptions in conjunction with other symbolic data can be used to improve the accuracy of automated chord transcription and key detection [15, 17]. This project developed a web scraper for Chordify.net that gathers chord information for selected songs. We tested the validity of this extracted chord information against two known dataset of "expert" chord transcriptions for the same songs [5, 19]. Our results showed that, for certain tasks, such as measuring distributions of chord usage, the differences between the Chordify transcriptions and the experts' transcriptions were not significant.[1] We are currently using Chordify chord transcriptions in an analysis that shows the impact of "harmonic surprise" on listener perceptions.

1.2 Integrating newly developed and existing tools

Once the data curation step is completed, it still has to be analyzed. There are a number of existing tools currently available for symbolic musical analysis, namely music21 and humdrum. Music21 is a Python-based, open source toolkit which provides a needed bridge between the demands of music scholars and of computer researchers [4]. It has an active support community and provides support for a number of analysis tasks such as Roman Numeral Analysis, or metrical analysis. For users who are familiar with music21, taking advantage of existing functionality speeds the analysis process. This project developed a converter to allow symbolic metadata from Spotify to be parsed into music21's native format.

1.3 Post-analysis of extracted features

All of the data sources investigated by this project have been used independently by other researchers (e.g., Dieleman [2], Gauvin [29], Thomas [27]). The present authors recognize that there is value in developing automated methods for feature extraction from this collective data that can be used to systematically analyze large samples, and leverage these methods in the current project.

This metadata may not be appropriate for every analysis task. For example, the pitch vectors from Spotify do not have octave information and result from the integration of multiple voices, making them difficult to use for melodic analysis. For other tasks, such as analysis of form, the same metadata may offer a significant increase in the amount of music to by analyzed than could be covered with other methods. In some cases, however, additional processing of the metadata will be required, and scholars will have to adjust their methodologies to take best advantage of this type of data.

2. RELATED WORK

2.1. Data collection and feature extraction

Similar data collections to those described above have been used in previous work. In 2011, Bertin-Mahieux and Ellis (Columbia University) along with Lamere and Whitman (EchoNest) created the Million Song Dataset (MSD) to address the issue of the lack of data that can be used to analyze popular music [1]. The dataset consisted of a collection of precomputed features extracted from audio along with metatdata from one million popular songs. The project also included code to retrieve audio samples of some of the songs from 7digital. Dieleman, Brakel and Schrauwen used the dataset (in particular Echonest pitch vectors and timbre vectors) to create machine learning models for key detection, artist recognition and genre detection [2]. The MSD has been used by several other scholars (e.g. Gallay [26], Thomas [27]) since its creation, highlighting the value of being able to use pre-collected data from a very large dataset. All features in the MSD were extracted by Echonest. Unfortunately, for popular music scholars, the MSD has not been updated since its creation in 2011. In 2015, Spotify acquired Echonest, creating a continuously updated source for this type of data. To make the metadata more accessible to music scholars, this project created an SQL database to make the Spotify data easier to search and combine with data from other sources.

In 2016, Raffel collected over 178,000 MIDI transcriptions of complete popular songs to support his doctoral research [3]. A somewhat smaller but more rigorous dataset – the McGill Billboard dataset was developed at McGill University [5]. This dataset is a collection of transcriptions of selected songs from the Billboard Hot 100 for the period 1955 – 1991. In total it contains the annotations and audio features corresponding to 890 of the entries from the random sample of *Billboard* chart slots as presented at ISMIR 2011. In 2010, McVicar and De Bie used chord transcriptions from the e-chords website to show that using chord transcriptions from publicly available web resources can improve the accuracy of Hidden Markov models using chroma features from audio [15].

These four projects used collection methods that have important differences. The pitch and timbre vectors were computed from audio using digital signal processing techniques. The MIDI transcriptions were obtained using web scraping software to crawl numerous public MIDI sites. The transcriptions in the McGill Billboard dataset were hand-transcribed by music scholars. The e-chord website is a collection of chord transcriptions that are contributed by users who have varying levels of musical training. Web scraping software was also used to collect the chord transcriptions.

Each_type of data has proven valuable to music scholars. Various types of pitch vectors like the ones in Spotify have been used for music information retrieval tasks such as key detection [2, 7] and chord estimation. MIDI transcriptions have been used for tasks like comparing musical sequences and chord detection [6, 3]. Pitch, timbre, beat and section vectors along with chord transcriptions from web resources have been used to compile historical analyses of trends in popular music [16].

A workbench tool most similar to the present project was developed by Abdallah et. al, called the Digital Music Lab (DML) system, which is a large collection of metadata containing both low-level features and collection-level analyses that is stored in a carefully planned architecture [30]. The DML system contains a rich selection of features similar to those found in the MSD and has a wider selection of genres. The primary differences between the current project and the DML system is that our project is compatible with symbolic music, and allows the user to curate their own dataset from theoretically *any* existing song or work, whereas with the DML the user is limited to songs in the DML system, which is comparatively lacking in popular music data.

Popular music scholars need easy-to-use methods to collect relevant data about a specific collection. They also need to

[1] This comparison was made by taking the distribution of the counts of all simplified RN hand analyses and comparing against those computed by Chordify.

be able to search the data and visualize it quickly across multiple dimensions without having to develop programming skills to do so. The traditional approach has been to analyze scores, which show the data in a concise and easy to use format. This project proposes additional formats for the data.

3. PROJECT OVERVIEW

This project focuses on three objectives. The first is to identify efficient and effective methods of collecting and curating symbolic data to support musical analysis, including MIDI data collected from multiple sources, hand transcriptions of scores, data from music listening sites like Spotify and chord transcriptions from websites similar to eChord.

The second is to investigate approaches for integrating existing analysis tools with newly developed software.

The third is to demonstrate the concept of combining data from multiple sources by building several datasets to perform representative analyses for musicological tasks.

3.1 Data Collection Methods

As a demonstration of the collection methods in our workbench, we describe the assembly of a subset of musical data for analysis. We chose to examine the weekly list of the "Billboard Hot 100" for the period of 1980 – 1989. A web scraper for the Billboard website was built to retrieve the list and a SQLite3 table was created to enable it to be searched. Data from Spotify for each of the songs was collected using the Spotify API.

Based on the Spotify API documentation, the primary focus of exposing the API is to allow developers to create applications to enhance Spotify premium listeners' experience by recommending songs and playlists from the Spotify collection. Unfortunately for musical analysis, the API search method only supports full text searches. Specifically, filtering parameters are limited to: artist, title, genre, year, market, upc and sirc (https://developer.spotify.com/documentation/web-api/reference/search/search/). Even though the returned data contains large amounts of fine-grained information, it needs further data manipulation to be used in analysis tasks (e.g., section lengths are identified, but need to be grouped and compared according to section *type*—verse, chorus, etc.) To make the data easier to search and filter for the user, we created a new SQLite3 database. Using this database, analysts can now select finer-grained musical features (e.g., section length, number of sections, highest ranking) for specific songs from either source (Spotify or Billboard) in a single location.

An examination of our database schema reveals a number of attributes that can be useful for popular music analysis. For example, our "track_feature" table has metadata elements extracted from Spotify that describe timbral characteristics of a song, such as liveneness, acousticness, speechiness and energy; rhythmic characteristics, such as danceability; and mood characteristics, such as valence (see [28] for definitions of these features). We define additional tables, including: "track_section", "track_bar", "track_beat," and "track_tatum", that contain metadata describing structural and metrical characteristics. The "track_section" table also contains the estimated key and mode (major or minor) of a section. The "billboard_tracks" table has the artist, label, and title of the song, and the weekly ranking (1 – 100) pulled from the Billboard API. Using our new database, it is relatively straightforward to search for specific songs and compute, for example, the average duration, number of sections or standard deviation of the duration of the beats in the song. This allows analysts to answer questions like "is there a trend toward shorter songs in the Billboard Hot 100 during the past 20 years?" or, "Is there a historical trend towards music being more "in the pocket?" (i.e. tightly aligned to a specific pulse without drifting over the course of the song). As a prototype, we also developed an Excel workbook containing the Billboard 1980's song data that allows analysts without programming skills to analyze and visualize the data.[1]

3.2 Integration with Existing Tools

Popular music analysts will continue to need more specialized tools for sophisticated musical tasks such as metrical or Roman Numeral analysis. This project developed a converter to allow symbolic data from Spotify to be parsed into music21. The converter parses pitch, beat onset, duration, tempo, time signature, and bar vectors to create a music21 stream. The resulting stream is a hierarchical representation of the structural features of a song (i.e., section, bars, beats) linked to their timing information derived from the audio. Once the stream has been created, music21 tools can be used to analyze key, quantize or transpose the symbolic data so that it can be compared to other songs. For example, if pitch vectors were retrieved into a music 21stream and segmented by musical event, as was done in [21], our database could be used with music21 to work on various symbolic MIR problems such as chord estimation—something we are, in fact, currently testing.

3.3 Analysis Examples

In order to validate the efficacy of the approaches to building datasets and using new and existing tools to analyze data, our project developed several comparative analyses. These are described in the following sections.

3.3.1 Large, surface-level features

One reason for building a database of musical data is to ensure that the inferences made from the analyses are statistically valid for some larger population. As mentioned above, previous studies have mentioned the challenges of defining a representative musical population [19]. Here we demonstrate the utility of collecting large amounts of musical data to augment statistical power. We queried the Billboard "Hot 100" for the list of songs on the chart for the period of 1980 through 1989. We then collected feature data from Spotify using our database. For the 10-year period, Figure 1 shows the Billboard Hot 100 had 4,226 total songs of which 3,554 were available on Spotify (79.4%).

As an exploratory exercise, we analyzed several descriptive features extracted from this database for the same set of songs. The following paragraphs describe these sample features. Figure 2 shows a histogram of the distribution of songs produced by various labels for the period 1980 – 1989. The

[1] The workbook used in this analysis is in the github repository at https://github.com/bclark288/alternative-measures

distribution shows that 225 labels produced less than 100 songs each while two labels (Columbia and Atlantic) produced between 240 and 400 songs each. This finding raises additional questions such as whether the same labels continue to dominate in later years and whether there are similarities between the rhythm, pitch, timbre and other musical information for a label. In other words, do labels have a "style"?

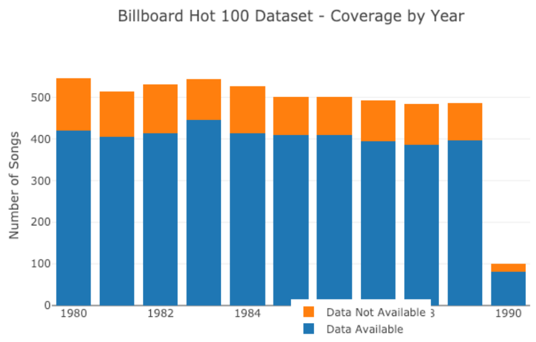

Figure 1. Coverage of songs from the weekly Billboard Hot 100 in the Spotify database for the period 1980 – 1989.

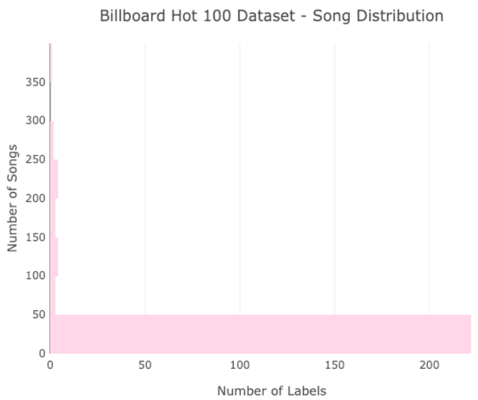

Figure 2. Distribution of Songs Produced by Label.

Figure 3 shows the detail of the number of songs produced by the top 10 labels. Additional questions to be considered are, whether the number of songs on the charts are simply a function of the size of the label, or whether some smaller labels are able to produce better rankings. Answering these questions might give insights into how much of an effect the marketing resources of a label affect the popularity of a recording.

Figure 4 shows the number of songs produced by the top 10 artists for the same period. This figure shows a more even distribution of songs among artists. Additional questions suggested by this analysis are whether artists with popular recordings in a given timeframe (i.e. weeks or months) show similarities in musical features.

Figure 5 shows the average length and number of sections of songs for the period. A section is described in the Spotify developer guide as a portion of a song that shows a significant change in rhythm or timbre [20]. The number of sections according to the Spotify data is higher than would be expected if one equated the word "section" with "verse" or "chorus".

Both features are relatively stable on average for the entire period, but questions to be answered might be whether the length and type of sections vary when chart rank is considered. Another question might be whether the tempo of a group of songs varies from one section to another, and if so, how much. One unexpected result of this analysis was that

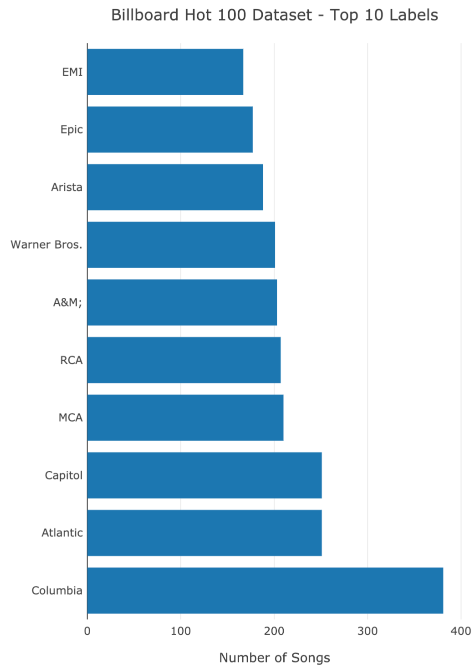

Figure 3. Detail of Songs Produced by the Top 10 Labels 1980 – 1989.

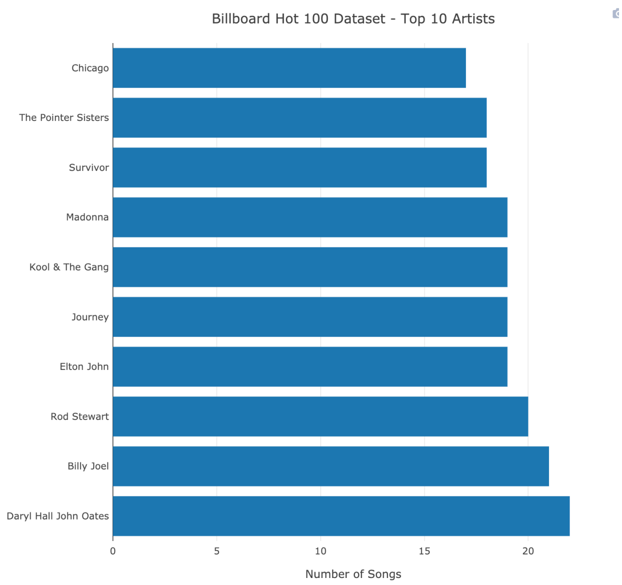

Figure 4. Songs Produced by the Top 10 Artists 1980 – 1989.

on average, the songs in this time period were nearly 4 minutes long.

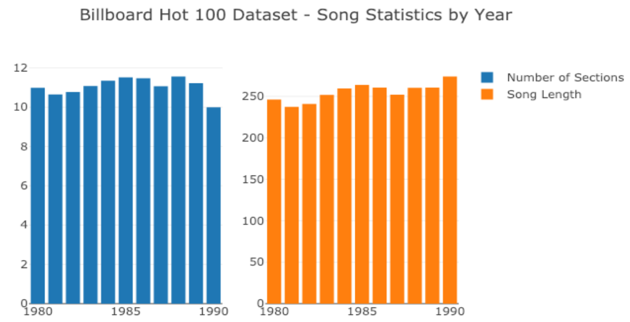

Figure 5. Average Number of Sections and Average Song Length.

Figure 6 shows a scatter plot of the number of sections vs. section tempo for each of the songs for the period. The number of sections seems to cluster at between 7 and 20 and the tempo clusters between 50 and 200. The project compared section lengths of selected songs from this data with descriptions made by a human annotator [22]. The section boundaries did not match exactly. However, they were similar enough to warrant further investigation into how song structure computed from audio features differs with that of human annotators. Another interesting question raised by this data is how often the tempo of sections changes within a given song.

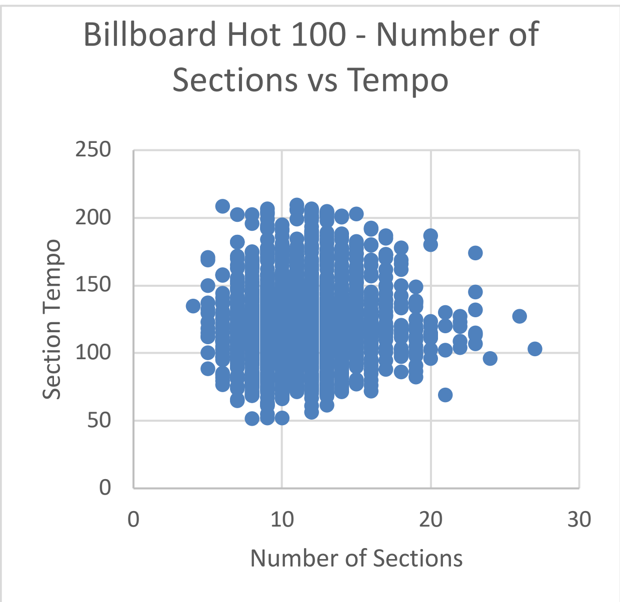

Figure 6. Section Tempo vs Number of Sections for Billboard Hot 100 songs from 1980 – 1989.

Figure 7 shows a portion of an Excel Pivot Table that shows the modality, tempo and section boundaries for a selection of songs by Bruce Springsteen. High level structural analytics such as the examples above can be used to identify songs that have unusual structural characteristics for a deeper analysis.

Figure 8 shows a portion of a detailed breakdown of the metric structure of "Just Got Paid" by ZZ Top. The graph shows the relationship between pitch events, bars, beats (the numerator of the time signature) and tatums (defined as the lowest regular pulse train that a listener intuitively infers from the timing of perceived musical events) [20]. Figure 9 shows a breakdown of the length of each bar in seconds for "Just Got Paid". This visualization not only shows the variability in tempo, but that there is a detectable pattern. As mentioned above, this type of detailed analysis can be helpful in troubleshooting large scale analysis systems. It can also be useful to help conceptualize which low-level audio features contribute to a given style.

Average of tempo	Column Labels	
Row Labels	0	1
Bruce Springsteen	131.4411095	125.4315651
Born In The USA		108.8407
0		120.841
26.23255		120.885
57.9783		120.902
145.30752		120.937
177.05396		120.931
184.99255		120.878
208.80727		120.917
241.07735		121.152
255.94716		120.964
281.52897		0
Brilliant Disguise		126.4764545
Cover Me	120.9813333	120.6081667
Dancing In The Dark	147.618	147.603
Fade Away	105.119	105.3159
Fire	134.7676667	135.137
Glory Days	114.788	118.4452222
Hungry Heart	109.87825	110.1416667
I'm Goin' Down	132.94	132.43625
I'm On Fire	139.4036667	139.506
My Hometown		118.036
One Step Up	150.089	150.293625
Tunnel Of Love		117.073
War	120.07	120.059125
Madonna	116.4961409	122.7400299

Figure 7. Excel Pivot table of Modality and Tempo of Selected Song Sections. Numbers in the left column under the heading "Born in the USA" are start times of each section. The two columns on the right are the tempo of the section. If the tempo is under the heading "0", the section is minor. "1" is major.

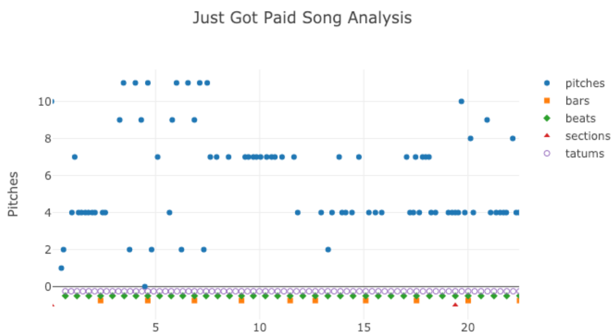

Figure 8. Detailed Song Analysis of one section of "Just Got Paid".

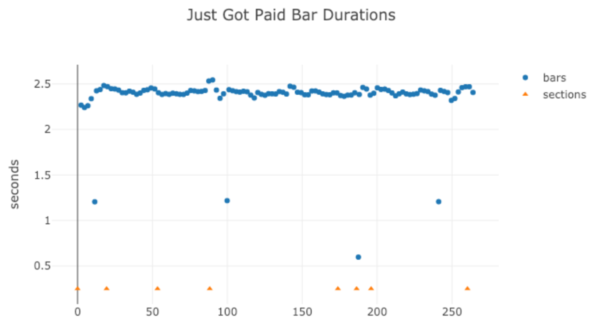

Figure 9. Graph of bar durations from "Just Got Paid".

Figure 10 shows a heatmap with pitch class transitions from the song "Ghostbusters". The pitch data from Spotify has proven to be more difficult to use in large scale analysis. However, as mentioned above, researchers have used chroma vectors similar to the Spotify chroma vectors with additional preprocessing to predict harmony. As an experiment, this project converted the pitch information from Spotify for "Little Sister" to midi format using music21 and then played the resulting stream in GarageBand. Based on listening to the output, it is unlikely that this data can be used for melodic analysis without significant filtering.

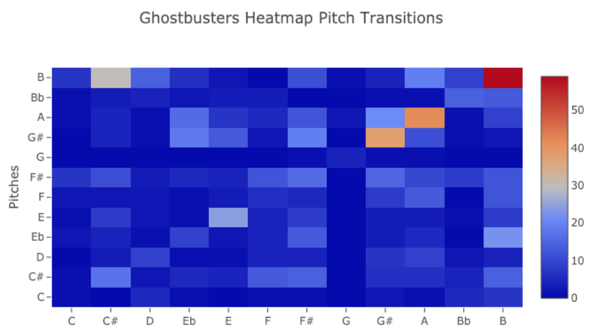

Figure 10. Pitch Transitions heatmap from "Ghostbusters".

3.3.2 Chord detection

Learning chord progressions is an important skill in analyzing popular music. As a result, websites like Ultimate Guitar and eChords have become popular resources for informal music education. However, given the level of effort and experience required to transcribe the harmonic content of popular songs, there has been considerable motivation to develop automated chord transcription algorithms [18]. These algorithms typically are applied to raw audio data. However, since we are largely trying to evaluate the utility of the symbolic data (e.g., pitch vectors) output from Spotify, we investigated four approaches to using existing tools and data to perform chord estimation. Code for the models is in a github repository at https://github.com/bclark288/alternative-measures.

Music21 has key finding algorithms based on the Krumhansl-Schmuckler algorithm. Research by Delgado and Napoles suggests that this key finding algorithm can be adapted to the task of chord recognition [6]. As a prototype, we developed a tool to parse Spotify song data (as described in section 3.2 above), analyze the harmonic content, and compare the results of the analysis to ground truth harmonic analysis data (McGill Billboard project). The overall accuracy for the prototype was 11.6%.[1] Although the overall accuracy of this approach was low, the errors showed a tendency to be relatively close to the ground truth harmonically.

Research suggests that using pattern matching in combination with Hidden Markov models (HMM) can yield good results in chord estimation. In collaboration with Nestor Napoles, this project modified a pattern-matching/HMM model to accept pitch vectors from Spotify in place of the chroma vectors computed from NNLS. Results for this model were also disappointing (significantly less than 50%, using the same accuracy measure as identified above). Possible reasons for the weak results were related to the difficulty of computing segments from the pitch class vectors and aligning them with the timing of the ground truth data.

In an effort to improve the accuracy of chord detection using pitch and timbre vectors, a convolutional recurrent neural network was developed. We tested this using a dataset of chroma and timbre vectors for 890 popular songs from the McGill Billboard dataset.

Accuracy using this model was considerably better (over 50% training accuracy using the measure described above), although still not at standard performance accuracy for this type of algorithm. The poor results suggest at least two factors are inhibiting the usefulness of precomputed pitch vectors for harmonic analysis: the challenge of aligning segments with ground truth labels, and a need for additional filtering or preprocessing of the pitch vectors.

In sum, since we do not have access to the audio, nor to the algorithms that produced the pitch vector data, using this aggregated data for harmonic analysis remains a complex computational problem. However, we are continuing to evaluate other possible solutions, as the success of a model such as this one would be of high value.

4. CONCLUSIONS

4.1 Spotify database and data collection

This project demonstrated the utility of using symbolic data computed from audio and extracted from the Spotify database for certain musical analysis tasks such as comparing songs on the basis of length, number of sections and modality of sections. Our goal is to implement a method that relies on data extracted from a large, continuously updated data source (i.e., Spotify) in combination with other sources so that researchers may be able to examine musical questions via a larger and more appropriate sample of data. By creating new tools to extract novel features, samples can be easily analyzed to see how they compare (e.g. how do popular songs from 1980 – 1989 compare to songs from the past year).

[1] Accuracy was determined by dividing the total number of correct chord labels produced by the model by the total number of labels in the ground truth dataset).

While we demonstrated the utility of the workbench for relatively large-scale or surface features, the disappointing results of our attempts at chord recognition shows that the data may not be suited for every task.

Although this project focused on developing tools to collect data from Spotify, work by other researchers also demonstrated the efficacy of collecting data from sources like eChords and the sites that house midi transcriptions of popular songs. These sites also give access to lyrical content—a musical feature that is grossly understudied [23].
Additionally, sites like Spotify and Soundcloud give invaluable insights into audience perception. Review sites (e.g., genius.com) can provide valuable information relating to important musical features as well as audience perception information. Thus, we feel that the ideal dataset for analysis of popular music will contain data from multiple sources.

4.2 Integration with existing tools

Our sample analyses demonstrated the value of analyzing data from different sources using a toolkit with ready-to-use routines by developing a converter for music21 that parses Spotify data into a music21 stream. Computational analysis toolkits such as music21 have useful components that perform melodic, rhythmic and harmonic analysis. By integrating our workbench with these existing tools, we take advantage of their existing functionality.

At present, we are currently developing a web scraping tool to collect chord information from Ultimate Guitar.com and Chordify.net. Given that other researchers have used chord transcriptions from websites like e-chords.com [15], future work will need to include integrating the prototype with existing tools such as music21, etc. As popular music scholars develop more quantitative analyses of popular music, extensions to the existing tools as well as novel tools and features will need to be developed. A priority for future improvements to our workbench is to include friendly user interfaces to allow some of the tasks to be performed by people without any software development or programming skills.

4.3 Comparative analysis

Finally, our project demonstrated the value of performing comparative musical analysis by combining data across multiple sources (e.g., finding Billboard hits within the Spotify dataset). We evaluated the usability of the data itself as well as developed new features for comparison. Given the complexity of some types of analysis (e.g., harmonic analysis), more difficult tasks will require substantial manual intervention. However, we aim to include several automated tools like the ones shown here to handle routine tasks, which will ultimately improve both the quality and timeliness of an analyst's work.

5. FUTURE WORK

While this project focused on proof-of-concept prototypes to demonstrate the value of updating/creating musicology tools to make them easier to use in the study of popular music, additional work is needed in the following areas:

5.1 User Interface

The prototypes developed in this project are still mostly dependent on the users having python programming skills. The excel workbook (e.g., see Figure 12) developed to perform some of the example comparative analyses is an example of the type of tool that can be used to improve an analyst's workflow. Since there are many existing popular tools for data visualization, (e.g. Sharepoint/PowerBI, Tableau, Plotly), future work will include such tools as well as developing an online version of the workbench featuring user-friendly interfaces for non-programmers.

5.2 Chord detection

The three initial prototypes for chord detection from Spotify pitch class profiles show that more work is needed. However, given the importance of harmony in popular music, development of this feature will be valuable. Other research in this area that suggests that pitch class vectors similar to those output from Spotify (i.e. EchoNest pitch class profiles) can be used for key or chord detection [2], and, that chord detection may be improved with some additional processing [7]. One key challenge that will have to be addressed in future work is the alignment of the time segments in the Spotify data with the segments in the ground truth dataset [13].

5.3 Development of new metadata

In this paper, our analyses made use of computed metadata such as average song length, average section length, and section modality to aid the analysis of popular music and to discover features that define musical style. Future work will create frameworks for more complex schema that, for example, could deal with the analysis at the intersection of multiple features (e.g., form and harmonic content). This will dramatically facilitate the cross-comparison of multiple features such as chord progressions, rhythmic patterns and timbre to identify elements of style.

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