Using Shared Vector Representations of Words and Chords in Music for Genre Classification

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Abstract

With so much music readily available for consumption today, it has never been more important to study music perception. In this paper, we represent lyrics and chords in a shared vector space using a phrase-aligned lyrics-and-chords corpus and show that models that use these shared representations can predict musical genre of songs—a perceptual construct of music listening—better than models that do not use these representations. This work adds to our understanding of how lyrics and chords interact with one another in music and has applications in multimodal perception and music information retrieval.

Index Terms: distributed representations, music perception, text classification, automatic genre classification

1. Introduction

Music is a complex, multifaceted, multimodal, perceptual experience that is challenging to analyze. Can a musical structure bestow a new quality to lyrics? How do we perceive music when we hear an instrumental passage and when we hear that same passage with lyrics? How would we categorize a song with lyrics related to pop music, but with chords steeped in the R&B tradition? We use techniques in natural language processing (NLP) to address these questions in this paper.

Many different ways to study music perception, and judgment, exist. Music emotion is one such lens through which to look at human perception of song. Another way to study music perception is through categorization: it is necessary to make a judgment (perception) about a stimulus (music) in order to classify the genre of a song. We use a music genre classification task as a way to investigate how humans perceive musical stimuli. One of the interesting questions is the cross-over and multi-attribute aspects of musical genre that do not necessarily fit clearly into one category. Among other things, this work has implications for how music content is marketed and consumed.

Studying chords and their patterns is useful in automatic genre classification [1, 2]. Additionally, there exist several studies on automatic genre classification using NLP techniques [3]. Other studies combine these NLP techniques with audio information to determine if a multimodal approach is helpful for genre prediction [4, 5]. It remains a topic of interest to determine if symbolic information contained within a lyrical modality and another modality can be complementary for genre classification [6].

Analyzing how a listener perceives music is a research interest in music information retrieval [7], psychology [8], and affective computing [9]. Automatically classifying musical genre can be used for music tagging or providing insights into the mechanisms of human cognition [10]. This is a challenging and interesting task because of the subjective nature of experience.

Learning distributed word representations is a heavily researched topic in NLP [11, 12, 13]. Recently, [14] applied the widely used “word2vec” architecture to chord progressions. Other research has extended this architecture to a bilingual scenario [15, 13]. In this paper, we apply a bilingual approach to two “languages” in music: lyric sequences and chord progressions.

We hypothesize that learning shared representations—that is, embedding words from lyrics and chords in a shared vector space—capture how chord progressions and lyrics affect each other. We create a genre classification task using Billboard listings¹ to show the utility of these shared embeddings in predicting musical genre.

2. Related Work

A number of genre classification tasks exist in the literature [16, 17, 18]. However, these tasks do not use datasets that have lyrical and chordal information aligned together. In previous work, we curated our own dataset with chords and English lyrics side-by-side and used it on a pilot task related to music emotion recognition [19]. In this paper, we collect data from the same online source and use this data for a pilot task related to multi-label music genre classification (see Section 5 for details).

The subjective nature of music perception asks for a more objective, agreed-upon metric for genre classification. For this reason, we use the Billboard charts for musical genre labels. Billboard determines genre by “key fan interactions with music, including album sales and downloads, track downloads, radio airplay and touring as well as streaming and social interactions on Facebook, Twitter, Vevo, Youtube, Spotify and other popular online destinations for music” [20]. Social tags provided by users of online music streaming sites have been shown to be an effective method for classifying music based on their emotional content [21].

Learning word representations from text has been a widely-studied topic in NLP in recent years [11, 12, 14] and [22] have shown the utility of learning chord representations in predicting chord sequences. We adapt an architecture motivated from word2vec for creating bilingual word embeddings, similar to [15].

We then use these embeddings in a multi-label classification task: classifying musical genre. Many techniques have been used for multi-label classification, including k-nearest neighbors (k-NN) classifiers [23], decision trees [24, 25], and neural networks [26]. In this paper, we focus on k-NN classifiers because of their simplicity, fast training times, and shown utility in multi-label classification tasks [27].

¹https://www.billboard.com/charts
Figure 1: Each lyric and chord predicts its lyric and chord context. Here, the B minor chord (Bm) predicts chords around it (dashed lines) and lyrics that are sung during and around the B minor chord (solid and dotted lines). The B minor chord is aligned with the lyric “love” because they are played and sung at the same time, respectively. This is similar to the architecture used by [15].

3. Model

We begin this section by reviewing the standard skip-gram neural network architecture of Mikolov et al. [11]. Given a text corpus, a skip-gram model aims to induce word representations that are useful for predicting the context words surrounding a target word. The autoencoder maximizes the monolingual objective function:

$$MONO_W = \frac{1}{T} \sum_{t=1}^{T} \sum_{-l \leq j \leq l, j \neq 0} \log(p(w_{t+j} | w_t))$$

where $w_1, w_2, ..., w_T$ are words in the training corpus $W$ and $l$ is the size of the window around target word $w_t$, which is also from corpus $W$.

Our proposed model aims to induce representations for two symbolic languages together: lyrics and chords. To this end, we implement a bilingual adaptation of the standard skip-gram, introduced by [15].

Specifically, this approach predicts the neighbors of a given chord $c$ in a chord vocabulary $C$ if it is aligned with a word $w$ in a vocabulary $W$ and vice versa. Effectively, we train a single skip-gram model with a joint vocabulary on parallel corpora in which we enrich the training examples with pairs of words from both chords and lyrics instead of from lyrics or chords alone. As a result, this bilingual method learns embeddings for chords that are dependent on co-occurring lyrics and vice versa.

The training objective function is $MONO_W + MONO_C + CROSS_{WC} + CROSS_C$, where $C$ and $W$ are the corpora for chords and lyrics, respectively. $CROSS_{WC}$ is defined as

$$CROSS_{WC} = \frac{1}{T} \sum_{t=1}^{T} \sum_{-l \leq j \leq l, j \neq 0} \log(p(c_{t+j} | w_t))$$

and $CROSS_C$ is defined as

$$CROSS_C = \frac{1}{T} \sum_{t=1}^{T} \sum_{-l \leq j \leq l, j \neq 0} \log(p(w_{t+j} | c_t))$$

In these cross-lingual objectives $CROSS_{CW}$ and $CROSS_{WC}$, the target index $k$ is found by computing $\lfloor t + L_W/L_C \rfloor$, where $L_W$ and $L_C$ are the sentence lengths of the target language and source language, respectively. Figure 1 shows an example alignment of chords with lyrics.

We use stochastic gradient descent [28] with a learning rate of 0.01 and exponential decay of 0.98 after 10k steps (1 step = 256 word pairs), and negative sampling with 64 samples. A skip-gram window of size five is used for lyrics and a skip-gram window of size one is used for chords. Although there are more lyric tokens than chord tokens, we sample equal number of monolingual and cross-lingual word pairs to make a mini-batch at every step. The resulting embedding space is 200-dimensional.

4. Data

We curated a dataset from UkuTabs arrangements [29]. This website gives users direct access to an archive of over 5,500 popular songs from the 20th and 21st centuries. The wordcloud in Figure 2 shows some of the most prominently featured artists on this website. UkuTabs is sourced by users and systematically verified for quality by moderators. Each song is arranged in individual lines, with each line containing a matching chordal and lyrical passage.

Although other websites—such as ultimate-guitar.com, e-chords.com, and chordie.com—offer more songs, they are not verified for accuracy or do not have a standard format, making them unsuitable for automatically collecting high-quality data.

4.1. Data Collection

We retrieved the text data from every song in UkuTabs that was listed as a chord tablature [29]. For each musical passage that contained chords and lyrics (which we will call a “clip”), we lined up the chords with the lyrics.

We developed a chord caster, which converts all chords in the dataset into one of the four basic chord types: major, minor, dominant 7th, and diminished. This chord caster changed 17,602 of the 428,544 chords in the corpus (4.1%).

If a song’s lyrics were less than 30% English words, the song was not included in the dataset. In addition, if a particular section of a song was repeated, the lyrics and chords were repeated in the dataset. See Figure 3 for an example of a repeated section. Some statistics of the final dataset are given in Table 1.

To create useful representations of chords, it is necessary to find a chord’s relation to a song’s tonal center, or key. [30] uses hidden Markov models to estimate musical key for Beatles songs using chord symbols; however, they only use major and minor chords in their study and tested their model on only 110 songs from one artist in one genre. We developed a simple method to estimate the key of every song in our dataset, identifi-
Table 1: Statistics of chords- and lyrics-aligned dataset

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Sample Points</td>
<td>190,165</td>
</tr>
<tr>
<td>Number of Songs</td>
<td>5,304</td>
</tr>
<tr>
<td>Average Chords per Sample</td>
<td>2.2</td>
</tr>
<tr>
<td>Average Words per Sample</td>
<td>8.0</td>
</tr>
<tr>
<td>Number of Artists</td>
<td>1,770</td>
</tr>
</tbody>
</table>

Figure 3: Screenshot from UkuTabs showing a song excerpt. The “x2” indicates that the interlude section is repeated.

Table 2: Number of songs in each Billboard chart in the last 20 years also found in the Ukutabs dataset. The diagonal entries refer to the number of songs that contain a label in a particular genre. The number of “crossover” songs, or songs listed in more than one chart, are entries in the off-diagonals. RnB/HH stands for R&B/Hip-Hop.

<table>
<thead>
<tr>
<th>Genre</th>
<th>Latin</th>
<th>Country</th>
<th>Pop</th>
<th>Rock</th>
<th>RnB/HH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latin</td>
<td>79</td>
<td>7</td>
<td>67</td>
<td>12</td>
<td>21</td>
</tr>
<tr>
<td>Country</td>
<td>7</td>
<td>342</td>
<td>101</td>
<td>64</td>
<td>61</td>
</tr>
<tr>
<td>Pop</td>
<td>67</td>
<td>101</td>
<td>780</td>
<td>198</td>
<td>190</td>
</tr>
<tr>
<td>Rock</td>
<td>12</td>
<td>64</td>
<td>198</td>
<td>620</td>
<td>88</td>
</tr>
<tr>
<td>RnB/HH</td>
<td>21</td>
<td>61</td>
<td>190</td>
<td>88</td>
<td>344</td>
</tr>
</tbody>
</table>

Table 3: A list of models used for multi-label genre classification and their performance in three metrics. The Chords & Lyrics model performs second-best in the harsh Exact Match Ratio (EMR), but has better label accuracy (Accuracy), and label-based, micro-averaged f1-score (f1-score) than baseline models and models that use only chords or only lyrics.

<table>
<thead>
<tr>
<th>Model</th>
<th>EMR</th>
<th>Accuracy</th>
<th>f1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baselines</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most Common Set</td>
<td>23.9%</td>
<td>.350</td>
<td>.413</td>
</tr>
<tr>
<td>Bag of Words</td>
<td>16.8%</td>
<td>.298</td>
<td>.392</td>
</tr>
<tr>
<td><strong>Our models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chords Only</td>
<td>16.5%</td>
<td>.350</td>
<td>.370</td>
</tr>
<tr>
<td>Lyrics Only</td>
<td>18.5%</td>
<td>.362</td>
<td>.402</td>
</tr>
<tr>
<td>Chords &amp; Lyrics</td>
<td>20.4%</td>
<td>.379</td>
<td>.428</td>
</tr>
</tbody>
</table>

5.2. Results

We compared our systems to two baseline models. For our first baseline, we used a classifier that “chooses” the most common labelset. This classifier predicted that every song belonged to only the pop genre. We created a Bag of Words classifier, treating chords and lyrics as one language. While this baseline uses both lyrical and chordal modes, it does not have a notion of chord progressions, lyrical sequences, or chordal and lyrical interaction.

We learned monolingual embeddings for chords and lyrics using the monolingual word2vec architecture to use as two additional models. To create song-level features, we averaged the embeddings. A k-NN classifier was trained on these features, after reducing the dimensionality using principal component analysis [33]. We empirically set the post-PCA dimensionality to be three for all classifiers (this captured >90% of the variability in the data) and used five-fold cross-validation in all experiments.

Table 3 shows the results for the emotion classification task. The Chords Only model and Lyrics Only model refer to a k-NN model that uses embeddings learnt only using chord progressions and lyric sequences, respectively. The Chords & Lyrics model uses word embeddings learnt jointly using lyrics word sequences and chord progressions, as described in Section 3.

The Exact Matching Ratio (EMR) metric is the number of test examples that have labelsets that exactly match the predicted labelsets, divided by the number of test examples:

$$EMR = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}(Y_i = Z_i)$$

(4)

where $\mathbb{I}(\cdot)$ is the indicator function, $Y_i$ is the true labelset, and
\( Z_i \) is the predicted label.

The Label Accuracy metric rewards correctly predicted labels and penalizes incorrectly predicted labels. Concretely:

\[
H = \frac{1}{N} \sum_{i=1}^{N} \frac{|Y_i \cap Z_i|}{|Y_i \cup Z_i|}
\]

(5)

Label-based, micro-averaged f1-score involves aggregating the contributions of all classes to determine precision and recall measures and computing the f1-score from these aggregated measures [34]. The stringent EMR metric favored the Most Common Set classifier. However, in another common metric for multi-label classification (label accuracy), the Lyrics only model outperformed the baseline models, and the chords-and-lyrics embeddings model outperformed all other models in both label accuracy and f1-score. That the embeddings-based models performed well according to the label accuracy metric suggests that these models are predicting correct labels for songs even if the predicted labelset does not perfectly match the actual labelset. The Chords & Lyrics model's outperforming other models in label accuracy and f1-score shows the utility of using a multimodal approach to study music perception.

6. Discussion

The current dataset is limited by the coverage of UkuTabs data, which has a bias towards music that is playable by ukelele musicians, but the method we present can be performed on any dataset that contains accurate lyrics and chords in parallel. While our representations are useful for genre classification, we want to evaluate the performance of our models with respect to models that use auditory features. Fusing audio information (such as rhythm and harmony) with our symbolic representations of these songs may result in a model that can better classify musical genre, providing a deeper understanding of how we perceive music. If audio features do not contribute to a model, it suggests that music perception may be better modeled using symbolic representations of songs4. State-of-the-art models for music genre classification, such as RAkel models, may also demonstrate better performance than the k-NN classifiers used in this study [27].

The chord caster we developed is untested and may be inaccurate for as much as 4.1% of the chords in the UkuTabs corpus. Using chord detection algorithms (like those mentioned in [35]) and state-of-the-art speech-to-text algorithms, our system could be used on any song for which the user contains the audio.

While our objective function for creating embeddings placed equal emphasis on all terms, different weight coefficients may be used to emphasize the mono-lingual lyrical or chordal terms or the cross-lingual components of the objective function. Choosing to do this would change the resultant features used in the genre classification task presented. To avoid using embeddings that were overly influenced by any of the four terms in the objective function, we opted to set the weight coefficients for each term to 1. Further study is necessary to determine if emphasizing certain terms in the objective function results in shared representations that are better-suited for musical genre prediction.

Discarding songs that contained 30% or less words in English did not have a great effect on the performance of the classification models. In fact, only one song listed in the Billboard Latin charts and the UkuTabs dataset contained Spanish lyrics (“Feliz Navidad” by José Feliciano). Our key estimator performed well on the 50 songs that were tested. However, more investigation is necessary to determine if this simple estimator generalizes well. If it does, this estimation method may be a valuable, computationally-inexpensive way to estimate musical key.

7. Conclusions

We obtained a dataset that contains 190,165 musical segments from 5,304 pop songs, with lyrics and corresponding chords. Using this data, we developed a shared vector representation of the lyrics and chords together. We tested our representation on a genre classification task by using a k-NN classifier on the average of the embeddings to predict genre labels given by the Billboard charts. We developed three models to predict genre: a model using only chord embeddings, a model using only lyric embeddings, and a model using joint chord-and-lyric embeddings. The model that uses joint embeddings significantly outperformed the baseline models and monolingual embedding models in three multi-label classification metrics, demonstrating the utility of taking a multimodal approach to music perception. We can apply this work to many areas, including multimodal human perception, automatic genre classification, and music information retrieval.

8. Acknowledgements

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9. References


