Music autotagging as captioning

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Abstract

Music autotagging has typically been formulated as a multi-label classification problem. This approach assumes that tags associated with a clip of music are an unordered set. With recent success of image and video captioning as well as environmental audio captioning, we propose formulating music autotagging as a captioning task, which automatically associates tags with a clip of music in the order a human would apply them. Under the formulation of captioning as a sequence-to-sequence problem, previous music autotagging systems can be used as the encoder, extracting a representation of the musical audio. An attention-based decoder is added to learn to predict a sequence of tags describing the given clip. Experiments are conducted on data collected from the MajorMiner game, which includes the order and timing that tags were applied to clips by individual users, and contains 3.95 captions per clip on average.

1 Introduction

Music autotagging has been well studied in music information retrieval at ISMIR. From machine learning to deep learning, the community has witnessed progress over the past decade on this task, with new methods (Choi et al., 2016), new model architectures (Yan et al., 2015; Liu and Yang, 2016; Ibrahim et al., 2020; Wang et al., 2019), and new data sets (Law et al., 2009; Bogdanov et al., 2019). Most studies in content-based autotagging focus on automating the feature extraction to create better representations of music.

What seldom changes, however, is the formulation of the task as a multi-label classification problem (Tsoumakas and Katakis, 2009): treating tags associated with a clip of music as an unordered set. This formulation focuses on correlations between tags, but when a user listens to a clip and provides a sequence of tags, the user expresses his or her listening experience. What is the most “ear-catching” element? What is unexpected? Does this clip feature an instrument or style? These questions cannot be answered under the multi-label classification formulation for music autotagging.

One reason for this formulation is the datasets available for music tagging research, such as MagnaTagATune (Law et al., 2009) and the Million Song Dataset (Bertin-Mahieux et al., 2011). We base the current study on a new analysis of the data collected by the MajorMiner tagging game (Mandel and Ellis, 2008), which includes sequential information. In this game, players supply tags in a particular order and get immediate feedback about the relevance of their tags, further increasing the importance of understanding tag order.

Our switch from multi-label to sequential captions follows similar switches in image and video captioning (Staniute and Šešok, 2019; Chen et al., 2019) and deep learning for acoustic scene and
Figure 1: The system uses a sequence-to-sequence model to map mel spectrograms to sequences of tags. The encoder and decoder can be replaced with architectures such as 1D-CNN, 2D-CNN (Choi et al., 2016), MusiCNN (Pons et al., 2017), GRU, LSTM.

| Encoder   | Decoder | B1    | B2    | B1    | B2    |
|-----------|---------|-------|-------|-------|-------|
| 1D CNN    | LSTM    | 9.5   | 02.2  | 38.5  | 38.5  |
| 2D CNN    | LSTM    | 10.9  | 18.3  | 39.3  | 48.4  |
| 2D CNN    | GRU     | 10.0  | 19.7  | —     | —     |
| MusiCNN   | LSTM    | 12.8  | 23.1  | 45.8  | 54.0  |
| MusiCNN   | GRU     | 12.9  | 23.1  | —     | —     |

Table 1: Results on the test set based on the best validation epoch of each model. B1 and B2 stand for BLEU1 and BLEU2, measured in percent.

2 Related Work

Several papers have explored the co-occurrence relationships between tags: Miotto et al. (2010) present one of the early works that explicitly used tag co-occurrence modeled by a Dirichlet mixture. Shao et al. (2018) modeled the tag co-occurrence pattern of a song via Latent Music Semantic Analysis (LMSA). Larochelle et al. (2012); Mandel et al. (2010, 2011a,b) utilized tags alone to build a conditional restricted boltzmann machine and hence demonstrated the value of tag-tag relationships in predicting tags.

Recent works such as (Choi et al., 2018) discussed the effect of tags from the perspective of mislabeling under the theme of multi-label classification.

Following (Drossos et al., 2017), Gharib et al. (2018) also first applied domain adaptation techniques as used in NLP to scene classification. Drossos et al. (2019) added language modeling for sound event detection. Ikawa and Kashino (2019) used a captioning model to describe environmental audio. They proposed an extension to the standard sequence-to-sequence model in the captioning task by adding a controllable parameter, specifying the amount of context to provide in the caption.

Multi-label classification is a challenging and important task not only in music information retrieval but also in field such as document categorization, gene function classification and image labeling. In image labeling, Wang et al. (2016) has demonstrated the effectiveness of using RNNs to learn correlation among labels. However, what we propose is not only to learn the label correlations, but also capture user experience with music from the order of tags.

3 Dataset: MajorMiner

Guided by the goal of multi-label classification, most datasets do not retain or make available information about the ordering of tags by users. MajorMiner (Mandel and Ellis, 2008) is a web-based game that naturally collects this information. Participants describe 10-second clips of songs and score points when their descriptions match those of other participants. Users are given the freedom to use any tag they want, but the rules were designed to encourage players to be thorough and the clip length was chosen to make judgments objective.

1http://majorminer.org/
As required by the captioning task, one sample consists of a pair consisting of one audio clip and one corresponding caption provided by one user. The MajorMiner game is designed to collect sequences of tags describing a clip one tag at a time from a user. A sequence of tags is collected, which are ordered by time stamps, and act as a caption. By design, one clip is frequently heard by several different users (this is the only way that any of them may score it). Hence, one clip will receive several captions. This fits into the multi-reference scenario (Papineni et al., 2002) that is often encountered in NLP, for example, in machine translation, where one source sentence has many valid translations into another language.

Caption data is pre-processed through case folding, removal of punctuation, and porter stemming. Sequences of tags, which get validity confirmed, are normalized and canonicalized. The longest tag sequence for a single clip is 30 tags. The total tag vocabulary is 984. Clips are randomly partitioned into train/valid/test set in the ratios of 75% - 15% - 10%.

Log mel spectrograms with 96 mel bins are used as input for all models. With sample rate 12,000 Hz, the length of the FFT window is 512 samples (42 ms), and 256 samples between successive frames (21 ms). Each 10-second clip becomes a $469 \times 96$ matrix.

### 4 Experiments and Analysis

A series of experiments is carried out, pairing three encoders, 1D CNN, 2D CNN, MusiCNN, and two decoders, GRU and LSTM, under two settings, multiple captions per clip and one caption per clip, as shown in Table 1. BLEU1 and BLEU2 are used to evaluate each model’s ability to capture tag orders.

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**Figure 2:** Bleu score distribution of validation data set using (a) the best epoch of MusiCNN + LSTM model and (b) inter-annotator BLEU score, both with multiple captions per clip.

**Figure 3:** Prediction examples from the best epoch of the MusiCNN + LSTM model. Examples are from the validation set.
Other metrics that are standard in music autotagging will be used in future work. The reason to create two caption settings is that, while there are multiple captions per clip, this potentially complicates training a model. Thus, our initial experiments are restricted to a single caption per clip where that caption is selected at random from those applied to that clip. In the multi-caption-per-clip scenario, if a clip received four captions, it is presented in four caption-clip pairs in training, one with each caption. Yet, in the calculation of BLEU scores, all four reference sequences are used for the one clip.

MusiCNN provides both a waveform-based front end and spectrogram-based front end. We use the spectrogram-based front end to make fair comparisons with other encoders. MusiCNN used in this paper has the same configuration as in music autotagging papers (Pons et al., 2017). The 2D CNN used in this paper has six layers of 2D convolution, each followed by batch normalization and 2D max pooling. We also compare a 1D-CNN as an encoder in an attempt to retain more temporal information. This is out of the consideration that some tags appear only at some time steps. In the 1D-CNN, the frequency axis of the mel-spectrogram is taken as the “channel” so that convolutions are computed along the time axis only. The 1D CNN used in this paper has six layers of 1D convolution, each followed by batch normalization. Both 2D and 1D CNN use 256 filters and ReLu at each convolution layer. Both GRU and LSTM decoders have only one layer of RNN followed by two fully connected layers. All models use sparse categorical cross-entropy as loss function and Adam as optimizer.

We create a naïve baseline for the multi-captioning setting by predicting the top \( k \) most popular tags for all clips. This evaluates the amount of information our models are learning beyond frequency. Figure 4 shows that this baseline’s best performance is to use top three most frequent tags, which achieves a BLEU1 of 0.49 and a BLEU2 of 0.086. This BLEU1 is comparable to our model, but the BLEU2 is much lower. A better baseline for BLEU2 might apply the most common sequence of bigrams. This will be evaluated in future work.

5 Results

The upper bound on the performance of our model is the inter-annotator agreement. Thus, we measure the BLEU score of our ground truth captions with relation to the other captions of the same clip. We find that the average BLEU1 in this case is 0.53 and the average BLEU2 is 0.09. Surprisingly, this is far below that of our best model MusiCNN+LSTM. Beyond the mean, the distribution of inter-annotator BLEU scores is shown in Figure 2(b). Comparing with Figure 2(a), the BLEU score distribution for human tag sequences is smoother and unimodal. This helps to understand why our training/validation BLEU score curve improves very slowly.

To further analyze our results, Figure 2(a) shows a histogram of BLEU1 and BLEU2 scores for the MusiCNN+LSTM model. As can be seen, there is high variability in performance across clips with some having very high scores and some very low scores. This phenomenon may be because tags such as “guitar” are quite frequent and heavily influence the model training, leading to better performance on samples where those tags are relevant. Dealing with imbalances in word frequencies is a common issue in NLP, but we leave it for future work.

Figure 3 shows example annotations, spectrograms, and predictions from the MusiCNN+LSTM model on two example clips. It shows that the model is able to capture general genre information but lacks the nuance of the human annotations.

6 Conclusion and Future Work

The paper demonstrates the promise of formulating music autotagging as a captioning task. It also opens up new possibilities for music autotagging. More advanced NLP techniques such as Transformers (Vaswani et al., 2017; Zhou et al., 2018; Yu et al., 2019) and Masked Language Model pre-training (Devlin et al., 2018) could be utilized to enhance the performance of a language model for
music. There is still more information in the sequence of tags that are applied to a clip that we are not using, such as the temporal locality of tags such as “clap.” As pointed out in the recent audio captioning work (Çakir et al., 2020), the distribution of words in captions is a significant challenge. Future work will also address the issue of very frequent yet less useful tags.

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