Attention as a Perspective for Learning Tempo-invariant Audio Queries

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Abstract

Current models for audio–sheet music retrieval via multimodal embedding space learning use convolutional neural networks with a fixed-size window for the input audio. Depending on the tempo of a query performance, this window captures more or less musical content, while notehead density in the score is largely tempo-independent. In this work we address this disparity with a soft attention mechanism, which allows the model to encode only those parts of an audio excerpt that are most relevant with respect to efficient query codes. Empirical results on classical piano music indicate that attention is beneficial for retrieval performance, and exhibits intuitively appealing behavior.

1. Introduction

Cross-modal embedding models have demonstrated the ability to retrieve sheet music using an audio query, and vice versa, based on just the raw audio and visual signal (Dorfer et al., 2017). A limitation of the system was that the field of view into both modalities had a fixed size. This is most pronounced for audio: a human listener can easily recognize the same piece of music played in very different tempi, but when the audio is segmented into spectrogram excerpts with a fixed number of time steps, these contain disparate amounts of musical content, relative to what the model has seen during training. The tempo can also change within a single query, especially in live retrieval settings.

We propose applying an attention mechanism (Olah & Carter, 2016; Chan et al., 2016; Bahdanau et al., 2014; Mnih et al., 2014; Xu et al., 2015; Vaswani et al., 2017; Southall et al., 2017) over the audio input, to distinguish parts of the audio that are in fact useful for finding the corresponding sheet music snippets. The system can then adapt to tempo changes: both to lower and to higher densities of musical events. Our experiments show that attention is indeed a promising way to obtain tempo-invariant embeddings for cross-modal retrieval.

2. Audio–Sheet Music Embedding Space Learning with Attention

We approach the cross-modal audio-sheet music retrieval problem by learning a low-dimensional multimodal embedding space (32 dimensions) for both snippets of sheet music and excerpts of music audio. We desire for each modality a projection into a shared space where semantically similar items of the two modalities are projected close together, and dissimilar items far apart. Once the input modalities are embedded in such a space, cross-modal retrieval is performed using simple distance measures and nearest-neighbor search.

We train the embedding space using convolutional neural networks; Figure 1 sketches the network architecture. The baseline model (without attention) consists of two convolutional pathways: one is responsible for embedding the sheet music, and the other for embedding the audio excerpt. The key part of the network is the canonically correlated embedding layer (Dorfer et al., 2018b), which forces the two pathways to learn representations that can then be projected into a shared space (and finds these projections); the desired properties of this multimodal embedding space are enforced by training with pairwise ranking loss (Kiros et al., 2014).
Figure 2. Audio queries (all 168 frames) and corresponding attention vectors of model BL + AT + LC. Note, that when the music gets slower (see right most example) and covers less onsets, the attention mechanisms starts to consider a larger temporal context.

This is the basic structure of the model recently described and evaluated in (Dorfer et al., 2017). This attention-less model serves as a baseline in our experiments.

As already mentioned, this model trains and operates on fixed-size input windows from both modalities. At runtime, the input audio (or sheet music) query therefore has to be broken down into excerpts of the given size. When processing audio played in different tempi, the fixed-size excerpts contain significantly less (or more) musical content – esp. onsets – than excerpts that the model has been trained on. One may of course combat this with data augmentation, but a more general solution is to simply let the model read as much information from the input excerpt as it needs.

We explore using a soft attention mechanism for this purpose. First, we substantially increase the audio field of view (number of spectrogram frames), up to a factor of four. Next, we add to the model the attention pathway \( h \), which is implemented as a softmax layer that outputs a weight \( a_t \) for each input spectrogram frame in \( A \). Before feeding the spectrogram to the audio embedding network \( g \), we multiply each frame with its attention weight. This enables the model to cancel out irrelevant parts of the query.

### 3. Experimental Evaluation and Discussion

In our retrieval experiments, we use a dataset of classical piano music, MSMD (Dorfer et al., 2018a). It contains 479 pieces of 53 composers, including Bach, Mozart, Beethoven and Chopin, totalling 1,129 pages of sheet music and 15+ hours of audio, with fine-grained cross-modal alignment between note onsets and noteheads. The scores and audio are both synthesized based on LilyPond, but results in (Dorfer et al., 2018a) suggest that the embedding models trained on this data do generalize to real scores and performances. Our experiments are carried out on aligned snippets of sheet music and spectrogram excerpts, as indicated in Figure 1. Given an audio excerpt as a search query, we aim to retrieve (only) the corresponding snippet of sheet music of the respective piece.

As an experimental baseline, we use a model similar to the one presented in (Dorfer et al., 2017), which does not use attention (denoted as BL). The second model we consider follows exactly the same architecture, but is additionally equipped with the soft attention mechanism described above (BL + AT). The temporal context for both models is 84 frames (≈ 4 seconds), twice as much compared to (Dorfer et al., 2018a). The third model is the same as BL + AT but is given a larger temporal context (168 frames) for the audio spectrogram (BL + AT + LC). This should reveal if and how the model will learn to focus on the relevant parts in the audio, depending on the musical content it is presented with. The sheet music snippet has the same dimensions (80 × 100 pixels) for all models, implying that the audio network has to adapt to this fixed condition. As evaluation measures we compute the Recall@k (R@k), the Mean Reciprocal Rank (MRR), as well as the Median Rank (MR, low is better).

Table 1 summarizes our results. The attention mechanism (BL + AT) improves the retrieval performance over the baseline consistently across all retrieval metrics. With increased temporal context of the attention model (BL + AT + LC) we achieve another substantial jump in performance.

To investigate whether the attention mechanism behaves according to our intuition, we plot audio queries along with their attention weights in Figure 2. Depending on the spectrogram content, the model indeed attends to whatever it believes is a representative counterpart of the target sheet music snippet. Since the fixed-size sheet snippets contain roughly similar amounts of notes, as the density of noteheads is independent on the tempo of the piece, attention is sharply peaked when the density of notes in the audio is high, and conversely it is distributed more evenly when there are fewer notes in the audio excerpt.

Given the improved retrieval performance and the intuitive behavior of the model, we think this is a promising line of research for reducing the sensitivity of cross-modal music retrieval models to the audio input window size. By extension, this is a step towards tempo-invariant representations, at least in the context of retrieval.

| Model       | R@1  | R@5  | R@25 | MRR  | MR  |
|-------------|------|------|------|------|-----|
| BL          | 41.4 | 63.8 | 77.2 | 51.8 | 2   |
| BL + AT     | 47.6 | 68.2 | 79.4 | 57.1 | 2   |
| BL + AT + LC| 55.5 | 77.1 | 85.8 | 65.1 | 1   |

Table 1. Comparison of retrieval results (10,000 candidates).
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