ON THE ROLE OF VISUAL CONTEXT IN ENRICHING MUSIC REPRESENTATIONS

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ABSTRACT

Human perception and experience of music is highly context-dependent. Contextual variability contributes to differences in how we interpret and interact with music, challenging the design of robust models for information retrieval. Incorporating multimodal context from diverse sources provides a promising approach toward modeling this variability. Music presented in media such as movies and music videos provide rich multimodal context that modulates underlying human experiences. However, such context modeling is underexplored, as it requires large amounts of multimodal data along with relevant annotations. Self-supervised learning can help address these challenges by automatically extracting rich, high-level correspondences between different modalities, hence alleviating the need for fine-grained annotations at scale. In this study, we propose VCMR – Video-Conditioned Music Representations, a self-supervised learning framework that leverages contextual information from music videos to enhance audio representations and indicates to what extent musical elements are affected or determined by visual context. 1

Index Terms— Self-Supervised Learning, Multimodal Learning, Visual Context, Music Information Retrieval, Music Tagging

1. INTRODUCTION

Music is one of the most popular forms of art and entertainment and is known to encapsulate strong affective characteristics. Music plays a central role in human personal and social experiences (e.g., celebration, grief, nostalgia, or stress). Questions on why music is so intimately connected to human experiences are predominantly related to its ability to induce and regulate our feelings [1, 2]. From a computational point of view however, we are still far from fully understanding the mechanisms that learn music representations from audio and the accompanying music videos. The contextual visual information enhances representations of music audio, as evaluated on the downstream task of music tagging. Experimental results show that the proposed framework can contribute additive robustness to audio representations and indicates to what extent musical elements are affected or determined by visual context. 1

1Code and results available at https://github.com/klean2050/VCMR

Our approach falls in the category of multimodal representation learning algorithms. Representation learning identifies features in data streams that are both efficient and robust in explaining and predicting a number of downstream tasks or labels. These representations are typically learned from a large pre-training dataset in a supervised or unsupervised manner. Thereafter, latent model activations are extracted and used at a specialized downstream task.

2. RELATED WORK

Our approach falls in the category of multimodal representation learning algorithms. Representation learning identifies features in data streams that are both efficient and robust in explaining and predicting a number of downstream tasks or labels. These representations are typically learned from a large pre-training dataset in a supervised or unsupervised manner. Thereafter, latent model activations are extracted and used at a specialized downstream task.

Self-supervised learning is a recently proposed variation of unsupervised representation learning that leverages training objectives derived solely from unlabeled data. Our study is influenced by SimCLR [10] and CLIP frameworks [14]. SimCLR is an efficient SSL model in the vision domain, but has also been effective in speech and audio understanding [15, 16]. By forcing representations of perturbed versions of the input to be close in the embedding space, SimCLR effectively identifies semantically important information in the data. On the other hand, CLIP is trained on a wide variety of images with language supervision, retrieved from the web. In a simi-
ular fashion, both an image encoder and a text encoder are trained to identify matching image-text pairs. CLIP-based learning has already shown robust performance in many audio-related [17], multimodal tasks [11, 18], but its application to music audio is still limited.

SSL applied in Music Information Retrieval, while relatively less explored, holds great potential for music tagging and recommendation systems. CLMR [19] adapts the SimCLR framework to the music audio domain. By applying random 1D transformations like pitch shifting, noise, delay and reverb, the authors manage to learn rich music representations, applicable to music auto-tagging. Regarding multimodal learning between audio and video modalities, most related works focus on cross-modal retrieval for recommendation purposes [20, 21]. However, these studies typically process unconstrained videos that vary in quality and underlying semantics, while rarely considering the impact of visual context on specific musical cues. Modeling music along with language has also gained attention recently [22, 23], due to the advances in language models.

3. THE VCMR FRAMEWORK

Given a dataset of music videos, consisting of raw audio and video data, we design a self-supervised multimodal framework to enrich music audio representations by conditioning them on visual context. The framework consists of a sequence of 3 stages: 1) contrastive pre-training of music audio 2) multimodal contrastive pre-training between audio and aligned video frames 3) supervised fine-tuning of the learned audio representations on music audio tagging.

3.1. Input Audio & Video features

We use raw audio data at 16 kHz. For the video modality, we use the pre-trained CLIP [14] model to generate robust video features for multimodal learning. We first downsample each video to 5 frames per second, use CLIP to produce a 512-dimensional feature vector for each frame, and then average these vectors every second. Thus, each second of video is represented by a single 512-dimensional feature vector. It has been shown [20] that the CLIP model produces robust representations for videos since it is trained on a larger corpus of image–text pairs than models trained on ImageNet.

3.2. Music Pre-Training

For the first step of our algorithm we perform self-supervised pre-training on the single modality of music audio waveforms. Our model takes an input music waveform, extracts two random subsegments of 6.15 seconds and produces two augmented views by applying a series of transformations in a randomized manner (e.g., pitch shifting, gaussian noise, reverb and frequency filtering). The resulting 2 views of the input are passed through a SampleCNN [24] that has been efficient in encoding music signals [25, 4]. The input resolution is determined by the architecture of SampleCNN, since its layer configuration is built so as to transform an input waveform to a single feature over 512 filter channels. This limits our design choices to specific combinations of encoder blocks and kernel sizes. A resolution of 6.15 seconds is achieved by only altering the kernel size of SampleCNN’s first convolutional layer. We chose the specific resolution to account for more available video context during training, while we also present an ablation study on the specific parameter.

The encoder outputs two 512-D embeddings, one for each view. To facilitate the contrastive learning approach, the two views are first projected to an embedding space of lower dimension and then contrasted within the training batch, where positive pairs are formed between the two views of the same input and all the remaining combinations of views are considered negative pairs. The resulting objective is the NT-Xent loss, adopted from the SimCLR study:

\[
\ell_{i,j} = -\log \frac{\exp (\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp (\text{sim}(z_i, z_k)/\tau)}
\]  

(1)

Here, \( N \) is the batch size and \((z_i, z_j)\) the considered pair of views. We utilize the cosine similarity \( \text{sim}(\cdot) \) as the pairwise distance metric between the embeddings and we empirically tune the temperature parameter \( \tau \). After training, we discard the latent projector that we used to compute the NT-Xent loss.

3.3. Multimodal Pre-Training

For the second step of our algorithm we perform multimodal contrastive pre-training between the audio and the video modality. Specifically, we follow a similar approach to the first step, except that we now form multimodal pairs and the encoders differ. For the music modality we retrieve the previously trained SampleCNN backbone, whereas for the video modality we use a simple 2-layer LSTM architecture on the pre-trained embeddings. We follow this approach since we are primarily interested in conditioning the audio embeddings with the respective visual context, instead of learning a bidirectional common representation. At this stage we do not apply any augmentation to the music modality other than the random input cropping. For the video modality we likewise select the segment that corresponds to the extracted audio interval.

Similar to the previous step, we get a 512-D output embedding for the music modality and a 512-D embedding for the video modality through a single fully-connected layer. We then project the embeddings to a lower dimensional space and apply an NT-Xent objective within the training batch. Positive pairs are now considered only

Fig. 1. Overview of the proposed VCMR framework. 1) Contrastive pre-training of music audio 2) Multimodal contrastive pre-training between audio and aligned video frames 3) Supervised fine-tuning on music auto-tagging.
the music-video pairs of the same video. After training we discard both projectors and video LSTM network to solely store the music audio backbone for the fine-tuning tasks.

3.4. Fine-Tuning Framework

The evaluation of the learned representations is commonly done through a series of downstream tasks, in which the backbone model is kept frozen and its output representations are tested after applying a single or multi-layer perceptron (MLP). Here we use the pre-trained music encoder as a backbone and apply a 2-layer MLP to transform the 512-D embeddings to the label space of our tasks.

4. EXPERIMENTAL SETUP

4.1. Music Video Dataset

To pre-train our model (first and second step) we need a large-scale dataset of music videos that provides both music and video modalities. However, due to inherent limitations in collecting music-related data, such as copyright issues, carefully curated datasets of this kind are scarce and of limited scale, e.g., Harmonix [26]. In this study, we obtain official music videos directly from YouTube. YouTube-music-video-5M is a list of such clips, provided as YouTube identifiers. We obtain official music videos directly from YouTube. YouTube-music-video-5M is a list of such clips, provided as YouTube identifiers and released in 2018 by K. Choi. Among the listed 5,119,955 videos we extract 20150 (about 700 hours) for our pre-training task, also providing their respective YouTube IDs.

Initially, more than 100k tracks were selected at random and downloaded from the first 2 lists of YouTube-music-video-5M. After manually inspecting a subset of the videos, we realized that a significant number of them (about 20%) were not official music videos but either lyric videos, audio releases of still images or even song covers of amateur musicians. We thus proceeded to clean the dataset and remove all such files. A discriminative characteristic of these, compared to official music videos, is that they typically include very sparse scene changes. Thus, we extracted scene information with the PySceneDetect tool2 and automatically discarded all videos that were shown to include scenes lasting more than 30 seconds.

4.2. Evaluation Protocol

We consider music tagging as the downstream task to evaluate our approach and observe to what extent visual context enriches musical information. Following the literature, we use average area under the receiver operating characteristic curve (ROC-AUC) and average precision (PR-AUC) to measure model performance. PR-AUC is considered because ROC-AUC can be over-optimistic for imbalanced cases [27]. We evaluate on the test set of the utilized datasets, averaged over three training sessions with different random seeds. We divide each test track into segments of the selected length with 50% overlap and average their predictions. We list the datasets below:

MagnaTagATune (MTAT) dataset [28] consists of 25,000 music clips from 6,622 unique tracks. These are provided in pieces of about 30 seconds each, of which we segment fragments for training, using the pre-configured training splits. We test our model in predicting the top 50 semantic tags in this dataset. These are provided by human listeners and describe both analytical elements like instrumentation, and affective like mood or theme.

MTG-Jamendo (MTG-M) [29] is an open-source dataset for music auto-tagging. It contains over 55,000 full audio tracks with 195 tags categories (87 genre tags, 40 instrument tags, and 57 mood tags). It is built using music available at Jamendo under Creative Commons licenses and tags provided by content uploaders. For our study we use a subset of the dataset that has been used in the Emotion and Theme Recognition in Music Task within the MediaEval challenge [30]. This autotagging-moodtheme subset includes 18,486 audio tracks with mood and theme annotations. In total, there are 57 tags, distributed in a multi-label fashion.

4.3. Implementation Details

The sampleCNN encoder takes as input waveforms of 6.15 seconds, randomly chunked from the 15-second audio input, at a sample rate of 16 kHz. It consists of 9 consecutive 1-D convolution blocks with 3-sample kernels. Each convolution layer is followed by batch normalization, ReLU activation and max pooling layers, while the output flattened embedding size is 512 samples. The model yields a lightweight scheme of 2.6M parameters. For details regarding the augmentation transforms applied to the audio waveforms, the reader is encouraged to consult CLMR [19].

We used a batch size of 128 samples to pre-train and fine-tune our models (64 during music pre-training due to memory constraints). We pre-trained for 50 epochs, determined empirically from the validation loss history. We then fine-tuned for up to 50 epochs on each downstream task. In all experiments we used Adam optimizer. During multimodal pre-training we kept the first 4 encoder blocks frozen, while, during fine-tuning, the whole encoder was frozen. We used a global learning rate of 0.001, with a weight decay of 1e-6. The temperature parameter was empirically determined as $\tau = 0.1$. Our primary models were trained on 4 × NVIDIA GeForce RTX 2080 GPUs for a total of 17 hours end-to-end.

5. EXPERIMENTAL RESULTS

5.1. Music Tagging Benchmark

The main aim of this study is to evaluate the quantitative and qualitative effects of conditioning audio representation learning of music to visual media context. In Table 4.3 we present the performance scores on the music tagging downstream task for the two datasets. The proposed model (VCMR) significantly out-performs its audio-only counterpart in all cases. For MagnaTagATune, VCMR scores 11.7% higher in ROC-AUC and 12.7% higher in the more challenging PR-AUC score. For MTG-Jamendo, VCMR is similarly 12.9% out-performs its audio-only counterpart in all cases.

Table 4.3. Downstream music tagging performance on the MagnaTagATune (MTAT) and MTG-Jamendo (MTG-) datasets, compared to CLMR [19] and fully supervised models. * For a fair comparison, we report the transfer results of CLMR pre-trained on Million Song Dataset [34]. † We include fully supervised models as reference.

| Model          | Dataset  | ROC-AUC | PR-AUC |
|----------------|----------|---------|--------|
| Audio-Only (ours) | MTAT     | 77.4%   | 22.6%  |
| VCMR (ours)    | MTAT     | 89.1%   | 35.3%  |
| * CLMR [19]    | MTAT     | 87.8%   | 33.1%  |
| † SampleCNN [31] | MTAT    | 90.6%   | 44.2%  |
| † HarmonicCNN [32] | MTAT | 91.3%   | 46.1%  |
| Audio-Only (ours) | MTG-M   | 57.8%   | 5.3%   |
| VCMR (ours)    | MTG-M    | 70.7%   | 10.1%  |
| † MediaEval 2020 [33] | MTG-M | 76.6%   | 15.0%  |

2https://github.com/keunwoocohi/YouTube-music-video-5M
3https://github.com/Breakthrough/PySceneDetect
4https://jamendo.com
and 4.8% better, respectively, underscoring the additional information related to mood and affect. Our implementation is also better than CLMR, reported in a transfer learning setting, similar to our experimental setup. VCMR still underperforms popular supervised baselines, also listed in Table 4.3, however this comparison is essentially bound to the scale of our pre-training dataset.

5.2. Tag-wise Performance

The derived results suggest that visual conditioning enhances music representations in media in multiple ways. However, we are also interested in determining which music elements are mainly affected and to what extent. To this end, we further look into tag-wise performance differences between VCMR and the audio-only baseline. For MTG-Jamendo, the utilized subset is already specialized in affective elements, hence we focus on MagnaTagATune, whose labels we group into 4 semantic classes: Genre, Mood, Instruments and Vocals. In Figure 2 we compare the average PR-AUC of the two models in each of these groups. We deduce that VCMR is consistently better in all categories, and provides the largest improvements for the instrument and vocals categories. Intuitively, visual depictions of the instruments played during a song, or who is singing, assists the network in disentangling these tags. Similar trends occur when evaluating the framework based on ROC-AUC scores.

5.3. Input Resolution

Our base network implementation uses audio and video data at samples of 6.15 seconds. This resolution is determined by the architecture choices of the SampleCNN encoder and was chosen to account for larger context in the learning process, especially with respect to video conditioning. We evaluate this premise by running an ablation study over alternative input resolutions that are permitted by the SampleCNN structure. Specifically, we consider input lengths of 3.07, 3.69 and 4.96 seconds, apart from our base implementation. We note that [19] used 3.69 seconds input length, whereas [33] used 5 seconds, but within a different architecture.

We plot the results for both datasets in Figure 4. VCMR appears robust across time-scales, with the increased resolution resulting in a slightly increasing trend. On the other hand, the audio-only model shows a reverse trend, where smaller input sizes account favorably for its performance. The discrepancy of the optimal input length between the two models indicates that audio learning focuses on learning small-scale features, whereas video conditioning can disseminate information and context from multiple scales. Still, in all time scales, VCMR out-performs the audio-only baseline.

5.4. Data Efficiency

An essential component of an efficient learning representation is the robustness it shows when fine-tuned with limited data sources (data scarcity). For the task of music tagging, we simulate data scarcity by constraining the available labeled training samples for both datasets. The results, plotted in Figure 3, show a slight increasing trend, as expected in all cases. VCMR indeed shows smaller incremental improvements as data size increases, almost matching full training performance with 10% of the training data. This fact indicates its additive robustness compared to the audio-only model.

6. CONCLUSION

In this study we proposed VCMR, a multimodal framework for music representations that we train on music audio, conditioned on accompanying visual context, obtained from official video releases. VCMR enhances music audio representations without embedding any explicit visual features, as evaluated on music tagging. It particularly showed improved robustness both in terms of the utilized training data and the input resolution, compared to the audio-only baseline. In the future, we will incorporate additional objectives, like cross-modal retrieval, to evaluate video conditioning, whereas a direction of interest would be the investigation of which explicit visual features contribute to the model’s improved performance.
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