TOWARDS PROPER CONTRASTIVE SELF-SUPERVISED LEARNING STRATEGIES FOR MUSIC AUDIO REPRESENTATION

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ABSTRACT

The common research goal of self-supervised learning is to extract a general representation which an arbitrary downstream task would benefit from. In this work, we investigate music audio representation learned from different contrastive self-supervised learning schemes and empirically evaluate the embedded vectors on various music information retrieval (MIR) tasks where different levels of the music perception are concerned. We analyze the results to discuss the proper direction of contrastive learning strategies for different MIR tasks. We show that these representations convey a comprehensive information about the auditory characteristics of music in general, although each of the self-supervision strategies has its own effectiveness in certain aspect of information.

Index Terms— Self-supervised Learning, Contrastive Learning, Music Audio Representation

1. INTRODUCTION

1.1. Contrastive Self-supervised Learning

Self-supervised learning has great potential in retrieving informative representation from a large amount of unlabeled data. Especially, deep learning architectures for this paradigm have been extensively studied recently in different research fields. Out of the major forms of self-supervision, one that we focus on is the contrastive learning approach that leverages a classification objective for differentiating positive and negative examples. Recent contrastive learning approaches have been especially successful on the general representation learning task in various domains with the emerging innovations on deep learning architectures.

The distributional similarity between samples and the augmentation-invariant data characteristics are the two core elements of contrastive learning scheme in different domains that require careful designs of ‘pretext’ tasks [1]. The distributional similarity inherits the concept of distributed representations for words that have been hugely successful in the natural language processing field. It is achieved by predicting samples that are closely located or more probable to be within a same sequence under certain sequential context. This approach has been widely explored in the language domain [2, 3, 4] and adopted to the audio domain [5, 6] and image domain [7]. On the other hand, various effective data augmentation or transform (e.g. Fourier transform) techniques in different domains have been proposed for extraction of either augmentation-invariant information or the transformation objectives themselves. They have been actively studied for image [8, 9, 10], audio [11, 12, 13], or multimodal [14] self-supervision.

1.2. Self-supervised Learning of Audio Representation

From the two types of self-supervision approaches, an approach leveraging distributional similarity was explored in CPC, APC, Audio ALBERT, and Wav2vec 2.0 for audio representation. [15, 16, 17, 6]. These models are trained to predict the future or masked segments from the input sequence. The learned embeddings are basically targeted to represent underlying coherent characteristic of a certain audio sequence that can discriminate itself from distractors [15], which can be either other sequences or other parts from the same sequence by using a triplet or infoNCE loss function. Vq-wav2vec [18] and Wav2vec 2.0 [6] add quantization steps which force the model to represent an audio segment into a fixed number of discretized labels. This quantization steps along with the diversity loss function [6] encourage the model to focus more on intra-sequence discrimination. These models has been mainly studied towards speech related tasks. COLA [19] is an attempt to train a general purpose audio representation for various sound classification task. It does not take the sequential order into account, however, they chose input and target samples by randomly cropping from the same audio to extract coherent information in a single audio sequence.

On the other hand, the second group of audio self-supervision models are targeted to an objective of extracting augmentation-invariant features [11, 20, 21]. By maximizing agreement between an audio segment and the augmented version of it, these models learn to keep the information that are not affected by the augmentation procedure. They are also
trained with a triplet or infoNCE loss function that leverage distractors to learn inter-sample discriminative features.

The self-supervised embeddings are usually evaluated on a few different downstream tasks from the domain. In the speech domain, they are usually evaluated on two problems; the phoneme recognition and the speaker identification. These two tasks require exactly opposite notions of audio features. The phoneme recognition task would take advantage of speaker-invariant local characteristics of short audio segment, while the speaker identification task would require a phoneme-invariant global feature of a full speech sequence (e.g. timbre). Vq-wav2vec and Wav2vec 2.0 have reached the state-of-the-art level of phoneme recognition scores, while CPC and Audio ALBERT show relatively poor performance. We argue that the performance gap is mainly caused from the quantization step, since the task requires intra-sequence discriminativeness. When it comes to the speaker identification task, however, CPC and Audio ALBERT also achieve the score almost as high as the supervised state-of-the-art. [15, 17, 18, 6]

Self-supervised audio representations are also evaluated on various sound classification tasks. Since these tasks are to classify the entire audio sequence into a single label, intra-sequence discrimination is not as important as in the phoneme recognition task. Most audio data augmentation based approaches are evaluated on these tasks. By carefully designing the augmentation procedures, these models achieved performances comparable to the supervised ones. [11, 20, 21]

1.3. Music Audio Representation

Representational learning aims to extract information that is useful for training wide range of classifiers or other predictors while being less specialized in a single supervised task [15, 22]. In case of music audio, this leads to a question of what level of data characteristic each of different music-related classification tasks would demand.

Defining a similarity metric between music audio data encompasses a wide range of perspectives from objective descriptors to human subjective perceptions. As a result, it is considered to be difficult to pinpoint the exact task-relevant information from music audio for an individual music information retrieval (MIR) task [23]. An early work [24] had used mid-level information inferred from audio, user feedback data, and metadata to define multiple different Euclidean metric spaces of music similarity. Another work [25] had proposed the content-based music similarity metric by leveraging a sample of collaborative filter data along with the audio. There also was an in-depth investigation of the characteristics of multiple deep music representations learned from different supervised tasks along with the benefits from multi-task learning approaches [23]. Other recent works [26, 27] employed a triplet network approach on music audio using the similarity metric derived from semantic tag labels.

A recent work [28] leveraged the combination of various contrastive approaches to propose a self-supervised and data efficient learning method for the music auto-tagging task. Their proposed method, CLMR, was evaluated on various auto-tagging datasets to show a comparable performance to supervised models.

While the previous works on the music audio representation were targeted towards a single specific objective, our work focuses on assessing the potential of self-supervised music embeddings as a general representation. Our attempts in this work do not aim at outperforming the state-of-the-art score for each MIR task. Instead, we set up experiments to compare the performance in various MIR tasks between different self-supervision strategies. We investigate to what extent we can benefit from music audio representations learned from some of widely used contrastive learning schemes by analyzing the results on three different MIR tasks (instrument classification, genre classification, and music recommendation) which are considered to represent different aspects of music similarity.

Our experiments are set up using contrastive learning algorithms with variations in input / target instance sampling and model architectures, which are designed to capture different levels the music semantic - global or regional information. Our strategies are categorized in Table 1.

We then use the trained models as feature extractors and evaluate on different MIR tasks, where each task represents a certain abstraction level of information. We compare the self-supervised embeddings with MFCCs which has long been a solid baseline feature in audio classification tasks.

### 2. METHODOLOGIES

#### 2.1. Audio Feature Encoder

For our multiple self-supervision settings, we use the same audio encoding architecture that takes a time-frequency domain representation (mel-spectrogram) as an input.

We build a standard audio 2D CNN architecture with 5 layers of $5 \times 5$ convolutional kernels [29]. Batch normalization and 2D max-pooling are applied to the output of each convolutional layer. The encoder will output a single feature vector for every 3-second sample of mel-spectrogram input. The encoded vectors are then fed into the self-supervision

1[6] conducted an ablation experiment related to this matter.
phase where diverse architectures and objective functions are concerned. Details are provided in our code.\footnote{https://github.com/kunimi00/ContrastiveSSLMusicAudio}

2.2. Contrastive Learning Model Architectures

2.2.1. Siamese Network

We first take a metric learning approach using a siamese network architecture. We experiment with two types of loss functions; an InfoNCE loss and a multi-level InfoNCE loss.

The InfoNCE loss\cite{infoNCE} inherits the concept of noise contrastive estimation \cite{NCE} while computing the mutual information between the encoded representation vectors in order to capture the similarity in the high-level abstraction \cite{InfoNCE}.

Given an anchor audio \(x^n\) with 1 positive segment \(x^p\) and \(N - 1\) negative segments \(\{x^1_n, \ldots, x^{N-1}_n\}\) along with an encoding function \(f\), the InfoNCE loss is computed as follows:

\[
L_{\text{InfoNCE}}(y^n, y^p, \{y^1_n, \ldots, y^{N-1}_n\}) = - \log \frac{\exp(y^n y^p)}{\exp(y^n y^p) + \sum_{j=1}^{N-1} \exp(y^n y^j)},
\]

(1)

where \(y\) denotes the output from the embedding function \(f\) given an input segment \(x\) (\(y = f(x)\)). Although the InfoNCE loss was originally proposed in CPC architecture \cite{CPC} which we will describe in the next section, we adopt it into the siamese network architecture for comparison. \(N - 1\) negative samples \(\{x^n\}\) are randomly sampled from the other tracks in the same minibatch for computational efficiency \cite{CPC}.

Being inspired by previous works \cite{InfoNCE, InfoNCE2}, we also formulate a multi-level convolutional output loss. We add a fully-connected layer on top of outputs from each of 5 convolutional layers of the audio encoder. InfoNCE loss is then computed at each level separately, and later summed up for the final loss term. It can be defined as follows:

\[
L_{\text{InfoNCE-Multi}} = \sum_i^M L_{\text{InfoNCE}}(\hat{y}_i^n, \hat{y}_i^p, \{\hat{y}_{i1n}, \ldots, \hat{y}_{i(N-1)n}\})
\]

(2)

where \(\hat{y}_i\) denotes the output from \(i\)th convolutional layer of the encoder followed by an additional fully-connected layer, and \(M\) denotes the number of layers in the CNN encoder.

2.2.2. Contrastive Predictive Coding (CPC)

The core idea of CPC \cite{CPC} is to learn high-level features that are coherent along the whole sequence. To do so, they defined a loss term using InfoNCE, where the mutual information between the latent feature extracted from the present input sequence and the one from a future segment is maximized. It can also be interpreted as a metric learning architecture with adity use of sequential information of the input data over time. CPC loss is formulated as follows:

\[
L_{\text{CPC}} = - \sum_k \log p(c_t | f(x_{t+k}), \{f(x_1^n), \ldots, f(x_{N-1}_n)\})
\]

\[
= \sum_k L_{\text{InfoNCE}}(c_t, y_{t+k}, \{y_1^n, \ldots, y_{N-1}^{n}\})
\]

(3)

where \(c_t\) is the output from the last timestep \(t\) of a sequential module (1-layered GRU), given a sequence of encoded vectors from the CNN module using \(t\) consecutive audio segments. \(x_{t+k}\) is a positive sample that is \(k\) segments away from the \(t\)-th segment within the same track. Again, we sample \(N\)-1 negative samples \(\{x^n\}\) from other tracks in the same minibatch. We denote our CPC model as MelCPC since we take the mel-spectrogram input unlike the original one.

2.3. Target Instance Strategies

2.3.1. Audio augmentation

For audio augmentation, we use pitch shifting, time stretching, reverberation, noise addition, and polarity inversion\cite{Augmentation}. We randomly choose from \(-2, -1, 1, 2\) semitones for pitch shifting, and stretch time with a speed factor randomly chosen from a range between 0.8 to 1.2. We apply reverberation and noise addition with a probability of 50%, individually.

2.3.2. Sampling strategies

For the sampling strategy of the positive instances, we take two different options. One is taking an adjacent segment of the anchor segment and the other is taking a random segment from the same track. For the former, we left a 0.5 second gap between the neighboring segments to avoid ‘shortcuts’ where the network simply learns to capture edge continuity \cite{EdgeContinuity}. For the latter one, we sample uniformly random segments from the rest of the track. As a music audio clip generally has very dynamic changes over sequence in auditory characteristics, an adjacent sample is more probable to be more similar to the input than a random sample from the entire sequence. We take one positive sample and use \(N - 1\) other samples from the same training batch as negatives, as forementioned \cite{Training}.

3. DATASET

For the training of self-supervised models, we choose the subset of 0.2M tracks from MSD \cite{MSD} which has been used as a benchmark split for training music auto-tagging models in previous works \cite{AutoTagging, MSD}. It is also the same subset used to train the supervised auto-tagging models that we compare with (Section 4.1).

As for the audio input, we downsample each recording to 16 kHz and compute mel-spectrogram with 512-point Hanning window, 512-point FFT and 256-point hop. We standardize the input across all training data for each experiment. A segment of 188 frames (3s) is fed into the encoder for
the siamese networks, and 752 frames (12s) for the MelCPC model.

4. EXPERIMENTS

To first verify that our proposed model’s performance is comparable to the state-of-the-art level, we evaluate it on the same benchmark test set of MSD where the previous state-of-the-art works on music auto-tagging have been evaluated on.

We then evaluate the self-supervised embeddings on three different downstream MIR tasks. We suppose that each of these tasks indicates measuring a different level of music audio similarity. The genre classification task would require high-level understanding of comprehensive audio information, whereas the instrument classification task would benefit from low-level details that represent the timbral information. The music recommendation task deals with the most subjective and abstractive aspects of music audio among the three.

Following a standard procedure for evaluating the representational power of a pre-trained embeddings [10], all experiments are conducted in a transfer learning setting where model weights are fixed after being trained to function as a feature encoder. After encoding each segment of the input audio into an embedding, we summarize it into a concatenated vector of mean and standard deviation for each dimension. For the MelCPC model, we feed the entire sequence of segments to the trained model at once, and use the outputs from all timesteps of GRU module to obtain the summarized vector. We evaluated the summarized vectors using a support vector machine with a linear kernel and a linear logistic regression classifier [35]. For downstream tasks, we also use MFCCs as input for the baseline experiment.

4.1. Comparison with State-of-the-art

Although our main objective is not about outperforming existing methodologies in a specific task, we still aim to verify that our models have comparable representational power to the state-of-the-arts in an arbitrary task. We compare one of our model, MelCPC, with two state-of-the-art fully-supervised models [36, 37] and a recent self-supervised model [28] on the music auto-tagging task. All models are trained and evaluated with the same benchmark split of MSD (201,680 training / 11,774 validation / 28,435 test samples) annotated with 50 tags. For self-supervised models, an additional linear logistic regression classifier is trained using the output from the pre-trained self-supervised model.

4.2. Genre Classification

We set up a genre classification experiment using FMA small dataset [38] which contains 8,000 tracks annotated with 8 different genres. We use the provided official splits.

| Supervision | Model                | AUC-ROC |
|-------------|----------------------|---------|
| supervised  | Transformer [37]     | 0.897   |
| supervised  | musicnn [36]         | 0.880   |
| self-supervised | CLMR [28]    | 0.857   |
| self-supervised | MelCPC (ours) | 0.856   |

Table 2. Auto-tagging results on MSD benchmark subset.

4.3. Instrument Classification

For the instrument classification task, we use the training subset from IRMAS dataset following the setting from [23]. There are 6,705 multi-instrumental audio clips (3s long) annotated with a predominant instrument class. As our audio encoder will output a single feature vector for 3-second long inputs, we do not need a summarizing step. We train a support vector machine and a linear logistic regression classifier [35] using MFCC and the pre-trained embeddings for evaluation.

4.4. Music Recommendation

AOTM 2011 dataset [39] is used for the music recommendation task. Tracks overlapping with the training set of our self-supervised models are excluded, along with playlists that contain too few or many tracks and ambiguous categories. 21,088 tracks in 7,245 playlists are remained from the original set.

We adopt the evaluation protocol used in [40]. Given 3 query items (tracks) from each playlist, a recommender algorithm is asked to return the remaining ground-truth items. We run ItemKNN-CBF [41, 42] using cosine distance function to predict the rankings of the ground-truth items. To avoid heavy computation on all item-item pairs, we follow the evaluation scheme from [43] by pairing each ground-truth item with 100 random negative items. Hit ratio@10 (HR@10) and mean percentile rank (MPR) are measured from the ranked lists. HR@10 computes the fraction of times that the ground-truth items are among the top 10 returned items, and MPR is a position-aware metric that assigns larger weights to higher positions (i.e., 1/i for the i-th position in the ranked list).

5. RESULTS AND DISCUSSION

5.1. Comparison with State-of-the-art

From Table 2, we can verify that our model has comparable representational power even with the state-of-the-art level models [36, 37] that are trained with the same audio set in a fully-supervised manner. It also shows a similar performance with a recently proposed self-supervised music embedding model that employs the combination of various contrastive learning techniques on audio [28].

5.2. Genre Classification Results

Table 3 shows experimental results for the genre classification problem. As the genre classification task relies on high level
understanding of music audio, MelCPC employing sequential information to better summarize higher level data abstraction over time performs better than siamese networks that only take singular segments to be compared. It is also interesting to see that the multi-layer output model performs worse than a single-layer output model for adjacent sampling-based and augmentation-based models, indicating that the lower level features are not helping when it comes to a problem of high level music understanding in those cases.

However, when sampling targets randomly from the entire track, multi-layer output model outperforms. We suspect that this is because, in case of leveraging more similar audio segments as input and target (adjacent sampling and augmentation), features extracted from low level convolutional layers can be redundant, while more informative features can be extracted when less similar input and target segments are sampled from the entire track. We find similar trend in music recommendation task also.

### 5.3. Instrument Classification Results

The instrument classification results are also shown in Table 3. In this task, multi-layer output models outperform single output ones in all cases. When employing single-layer output, data-augmentation approach shows the highest score among all siamese networks. However, using a multi-layer output model for sampling approaches increased the performance in a greater deal, resulting the best performing model to be the one with adjacent target sampling approach. This indicates that, for the data augmentation approach, adding multi-layer outputs is not as helpful as in in-track sampling approaches because audio augmentation already concerns low-level information to some degree. MelCPC performed better than all single output siamese networks, but still poorer than multi-level output ones.

### 5.4. Music Recommendation Results

As shown in Table 3, recommendation task results show very similar trend to the genre classification results. The MelCPC model shows the best performance, and we suspect that this is because the recommendation task deals with rather imperative and subjective level of information. It is not easy to define what level of auditory perception is concerned with regard to music recommendation, but we can induce from the results that higher level information is more related.

#### 5.5. Target Instance Strategies

Regarding the target instance strategies overall, sampling an positive segment from the same audio track gives a better cue for the genre classification and the recommendation task than for the instrument classification task. When sampling, choosing an adjacent segment was more effective than randomly picking from the entire sequence for all cases.

### 6. CONCLUSION AND FUTURE WORK

In this work, we explore diverse directions of self-supervision strategies for different MIR tasks. We verify that, since MIR tasks cover wide range of auditory characteristics and are generally a more subjective matter compared to other audio domains, it is important to carefully choose right strategies of self-supervision for a certain desired task.

For future works, MIR tasks that require intra-sequence discriminative representation, such as music transcription or chord recognition, can further be considered. As complex as MIR tasks are compared to speech or general sound classification problems, novel self-supervision architectures or pretext tasks [1] specially targeted to music audio analysis might contribute to some breakthroughs.

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