A FRAMEWORK FOR CONTRASTIVE & GENERATIVE LEARNING OF AUDIO REPRESENTATIONS

Prateek Verma, Julius Smith

Center for Computer Research in Music and Acoustics, Stanford University
prateekv@ccrma.stanford.edu, jos@ccrma.stanford.edu

ABSTRACT
In this paper, we present a framework for contrastive learning for audio representations, in a self supervised framework without access to any ground truth labels. The core idea in self supervised contrastive learning is to map an audio signal and its various augmented versions (representative of salient aspects of audio like pitch, timbre etc.) to a space where they are close together, and are separated from other different signals. In addition we also explore generative models based on state of the art transformer based architectures for learning latent spaces for audio signals, without access to any labels. Here, we map audio signals on a smaller scale to discrete dictionary elements and train transformers to predict the next dictionary element. We only use data as a method of supervision, bypassing the need of labels needed to act as a supervision for training the deep neural networks. We then use a linear classifier head in order to evaluate the performance of our models, for both self supervised contrastive and generative transformer based representations that are learned. Our system achieves considerable performance, compared to a fully supervised method, with access to ground truth labels to train the neural network model. These representations, with availability of large scale audio data show promise in various tasks for audio understanding tasks.

1. INTRODUCTION AND RELATED WORK

The second wave of the development of neural network interest began with the paper by Hinton et al. [1] in 2006, which showed the ability of neural nets to successfully compress images into a meaningful latent representation. There has been a series of recent works with the advent of deep learning and neural networks to represent the signals of interest, viz., image [2, 3], text [4, 5] or audio [6, 7, 8, 9, 10, 11], by a vector representation that is suitable for the task of interest. Broadly, these ideas can be classified into generative [12] or discriminative methods [13]. Within these two there can again be approaches pertaining to supervised and self supervised approaches, which amount to using labels of interest to guide the neural network to learn the representation via the final layers [14][15] or intermediate layers [16] for a particular application. For supervised approaches, the latent spaces are often used to guide one modality into another. As an example, SoundNet [17] used latent spaces of images as a target to guide a deep neural network to learn from waveforms. Due to the availability of large amounts of unlabeled data, such approaches were able to scale and outperform state of the art acoustic understanding works existing at the time. This is mainly because of the size of the dataset used for training [18], and the contents of the latent code encapsulating much richer information than raw labels [19]. The main motivation for the current work, inspired from similar ideas in computer vision [2] and natural language processing [20, 21], is to use the data itself for self-learning or supervision, which we call in this case a self-supervised learning setup. In natural language processing, models such as BERT [21] use masked inputs to predict the entities that were masked, yielding better representation, and solving several downstream tasks. Such ideas have been proposed for audio [22] and video [23] and have shown promising results. Contrastive based loss functions have been proposed in various supervised setups for audio and music understanding [24].

In our first approach, we map augmented versions of the audio signal to the same space while pushing them away from augmented versions of different audio signals. This follows the approach first proposed in [2] and subsequent works. In the generative representation learning method, we draw on advances in representation learning [25] along with the ability of transformer architectures [26] to understand dependencies across time. We propose to learn transformers operating on a learned dictionary of latent space elements using simple clustering algorithms like k-means [27], which is a simple yet powerful variant of vector-quantized variational autoencoders [25]. By learning to predict accurately the next elements of this learned dictionary space, the hypothesis is that we would learn a good representation of the signal, encapsulating what has already happened in the past. Similar ideas
Fig. 1. Various Spectral Data Augmentation Representations a) adding checkboard noise b) time reversal c) flipping d) adding noise e) energy based thresholding f) spectral envelope based representation per spectral slice g) band-stop filtering h) retaining salient spectral peaks. For each of the representations, there can be multiple level of distortions have been proposed in audio problems such as packet loss concealment using deep neural networks [28]. Contributions of the current work are:

i) We propose a framework for training a deep neural network encoder (a convolutional network), using a contrastive loss, purely from data and its augmented variants, for audio understanding. The proposed data augmentation techniques, derived from signal processing, are designed to capture fundamental aspects of audio.

ii) We also propose a dictionary-based generative model based on transformers for learning an audio representation, which can then be used along with a linear head for downstream audio tasks.

2. DATASET AND AUDIO REPRESENTATION

We choose to work with a standard acoustic scene analysis dataset UrbanSound 8K [29]. This dataset contains 8732 labeled sound excerpts (less than 4s) of urban sounds from 10 classes: air conditioner, car horn, children playing, dog bark, drilling, engine idling, gun shot, jackhammer, siren, and street music. We use the folds given along with the meta-data information for all of our experiments. For audio signals not equal to 4s we append them with repeating the signal to make all of the signals 4s in duration to have consistency across the dataset. We choose to represent audio signals as log magnitude mel spectrograms, which have been used in the literature [14]. The audio is downsampled to 16000Hz and converted to its log-magnitude mel-spectral representation with a 10ms hop size, 30ms window, 1024-point FFT, mapped to 128 bins, yielding a 128x400 matrix representation for every audio excerpt present in the dataset, using the librosa library [30]. Without loss of significant resolution, we chose to down-sample from this representation by a factor of 2 to get an interpolated version of the mel-spectrogram at size 64x200. [31] in order to save computation time, without drastically removing the contents of the signal.

3. METHOD

In this section, we explain how we use two distinct approaches to learn audio representations in a self-supervised manner. The two methods, (1) using a framework for contrastive learning and (2) temporal learning based on transformers, are described in the following sections. There are no annotated labels for training purposes—the data itself is used for supervision. Contrastive learning methods, which follow work in vision, combine ideas from traditional signal processing in order to create multiple feature-specific input representations (augmentations) that are then mapped to a common space. In addition to this approach, we also propose the idea of learning a feature representation by predicting what is going to happen next. If a feature vector can encapsulate all the contents of what has happened in the past, then it becomes a sufficient statistic, and can predict the future. In other words, we use future step prediction as a pseudo-task for learning a good representation for the contents of the audio.

3.1. Contrastive Learning

3.1.1. Data-Augmentation

As described in the previous section, the framework proposed by Hinton et al. [2] learns to map the embeddings of different augmentations of the input signal to the same space, and that of different audio signals to different spaces. We have proposed several data augmentation techniques adapted for audio signals. The role of data augmentation in helping to generalize deep neural networks has been widely studied, particularly for audio signals [32, 33]. A point to note is that, as the training set keeps getting larger through augmentation, the size and diversity of the data often become sufficient to achieve
state of the art results \cite{18}, often overcoming model limitations. For this reason, unsupervised approaches of this nature are very promising. Given mel-spectral representation, we do in total 9 augmentation strategies. i) Adding checkboard noise: We randomly turn off alternative time-frequency bins, by a spacing factor of 2,3,4 ii) time reverse and iii) flip upside down mel-spectra iv) do Amplitude scaling in range of +/- 10db v) band-limiting the mel-spectra with random onset and the width of the filter, shared across all the time-bins vi) retaining only spectral peaks vii) retaining t-f bins above certain energy threshold viii) adding random noise ix) extracting the spectral envelop and throwing away spectral peaks.

3.1.2. Algorithm

The algorithm follows the framework proposed by Hinton et. al \cite{2}. We fix our encoders to be a 16-layer VGG neural network architecture (choice to save on computation time), followed by a dense layer which converts the spectral representations to a vector of size 512. Let $X_i$ and $X_j$ be sampled from the same mel-spectral representation $X$, where $i$ and $j$ can be two arbitrary data augmentations sampled from the above mentioned strategies. A fixed convolutional encoder $f_{conv}$, VGG-16 network in this case, transforms the spectral representations to a feature space $e_i$ and $e_j$ respectively. In our case, both are output of a dense layer of size 512 followed after the convolutional layers of the VGG architecture. A 2-layer MLP network, (with 128 neurons each) converts these to a more separable space $z_i$ and $z_j$. For every batch of size $N$, we now create a new batch of size $2\times N$, such that the consecutive elements $(2k, 2k+1)$ are from the same augmented versions of a single mel-spectra. We now compute a distance matrix $s_{i,j}$, of the output vectors of the MLP network, where

$$s_{i,j} = z_i^Tz_j/\|z_i\|\|z_j\|.$$  The loss function which is minimized is negative cross entropy loss which is defined below, with $\tau$ being the temperature parameter,

$$l(i,j) = -\log \frac{e^{s_{i,j}/\tau}}{\sum_{k\neq i} e^{s_{i,k}/\tau}}$$

and the total which we minimize is,

$$\mathcal{L} = \frac{1}{2N} \sum_{k=1}^N [l(2k-1, 2k) + l(2k, 2k-1)]$$

Intuitively, we in a way, take softmax over rows of the distance matrix, and try to make similar augmented versions of the same spectra closer. We tweak with various hyper-parameters with respect to this setup, choosing $\tau$ from [0.1, 0.5, 1] and batch size [64, 128, 256].

3.2. Generative learning using Transformers

In this approach, we combine the strengths of two unsupervised learning approaches, viz., k-means clustering and transformer-based dependency learning. The goal here is to learn a representation of an audio signal using self supervision without access to labels, during training of a neural network.

3.2.1. Latent space learning

We deploy a two-step approach for this setup. We convert audio snippets into discrete latent spaces. For the audio input consisting of log-magnitude, mel-scale spectrogram input (64 spectral bins and 200 frame times), we convert the audio signal into patches of width 4 frames, which is a design choice. The goal is to learn, and convert the input mel spectrogram according to a discrete latent code based dictionary. VQ-VAE \cite{25} is a variant of vector quantization, the simplest one from the family, being k-means clustering. There has been previous work on converting audio into latent-space based meaningful representation \cite{15}. We take spectrogram patches of 4 spectral frames across frequency, and train auto-encoders taking input as 64x4 (defined henceforth patch of audio spectra), with three-layer fully connected encoder and decoders with 1024 neurons in each layer, and the size of the bottleneck layer set to 16. For all of the dataset, we convert the mel-spectrogram representation into a discrete latent code based dictionary. We deploy a two-step approach for this setup. We convert audio snippets into discrete latent spaces. For the audio input consisting of log-magnitude, mel-scale spectrogram input (64 spectral bins and 200 frame times), we convert the audio signal into patches of width 4 frames, which is a design choice. The goal is to learn, and convert the input mel spectrogram according to a discrete latent code based dictionary. VQ-VAE \cite{25} is a variant of vector quantization, the simplest one from the family, being k-means clustering. There has been previous work on converting audio into latent-space based meaningful representation \cite{15}. We take spectrogram patches of 4 spectral frames across frequency, and train auto-encoders taking input as 64x4 (defined henceforth patch of audio spectra), with three-layer fully connected encoder and decoders with 1024 neurons in each layer, and the size of the bottleneck layer set to 16. For all of the dataset, we convert the mel-spectrogram representation into a discrete latent code based dictionary. VQ-VAE \cite{25} is a variant of vector quantization, the simplest one from the family, being k-means clustering. There has been previous work on converting audio into latent-space based meaningful representation \cite{15}. We take spectrogram patches of 4 spectral frames across frequency, and train auto-encoders taking input as 64x4 (defined henceforth patch of audio spectra), with three-layer fully connected encoder and decoders with 1024 neurons in each layer, and the size of the bottleneck layer set to 16. For all of the dataset, we convert the mel-spectrogram representation into a discrete latent code based dictionary. VQ-VAE \cite{25} is a variant of vector quantization, the simplest one from the family, being k-means clustering. There has been previous work on converting audio into latent-space based meaningful representation \cite{15}. We take spectrogram patches of 4 spectral frames across frequency, and train auto-encoders taking input as 64x4 (defined henceforth patch of audio spectra), with three-layer fully connected encoder and decoders with 1024 neurons in each layer, and the size of the bottleneck layer set to 16. For all of the dataset, we convert the mel-spectrogram representation into a discrete latent code based dictionary.
3.2.2. Transformers on discrete latent spaces

Transformers [26] have revolutionized the field of natural language processing in achieving state of art results in language understanding, and synthesis and many more. The ability of these models to understand context much better than RNNs, dilated convolutions has been the reason we choose to work with them. A more detailed description is mentioned in [26], and is beyond the scope of the current work. Briefly, they use multiple attention heads in order to understand salient features, and use feed-forward nets to transform the features it is attending to a more appropriate latent space depending on the problem of interest. For our problem, we draw inspiration from the work for sentiment neuron [20] and other generative models like BERT [22][21]. If we can predict what is going to happen next given the previous context, then we can encapsulate the contents of the audio signal. This vector can then be used for classification of downstream task of interest using a linear head.

The exploration space is vast (number of attention heads, Transformer layers, size of the dictionary etc), and with the availability of limited computing resources, we come up with the following experimental setup. We predict the next time step from the previous input representation. We take context as half of the input signal i.e. 25 discrete points in our codebook corresponding to the mel-spectral patches, with the number of clusters (vocab) being 256. The model consists of 128 dimensional feed forward neural network, with 3 layers as an encoder in each Transformer module, with 8 attention heads and the size of our embedding fixed as 32. A Dense layer converts the output embedding to a smaller 16-dimensional representation. For regularization, for 20% of the training steps, we corrupt the inputs by a random factor deciding how many inputs to corrupt for a particular training step. In order to predict the next code, we predict a 256 dimensional output (corresponding to one hot vector of next code), from the flattened output of last layer of Transformer followed by a softmax layer, to minimize the cross entropy loss between the desired one hot label, and the logits predicted by the network. The training was carried out for 50 epochs using a learning rate of 1e-4, and then decaying it by a factor of 10, every 20 epochs using Adam optimizer [34] using V100 GPUs in TensorFlow framework [35] in the Google Cloud environment.

| Method                                      | Accuracy |
|---------------------------------------------|----------|
| VGG Supervised without Aug                  | 71.3 %   |
| Contrastive Loss (VGG encoder)              | 55.6 %   |
| Transformer (Predicting next code)          | 60.1 %   |

Fig. 3. Results of our experiments These are the results obtained after a preliminary parameter search for optimal batch size and temperature $\tau$, for contrastive loss based approach, and number of attention heads, dimensions of feed forward network, latent code etc, for Transformers

We believe this is indeed a promising direction, and with much larger exploration of hyper-parameters we can narrow this gap in future (optimal choice of latent code size, $\tau$ etc. Our work shows viability of contrastive and generative based approaches for audio understanding. Since we do not train our models on annotated data, the model performance can show considerable gains with pre-training on large amounts of dataset e.g [14], as performance often improves with more training data. [18]. In this study, we compared two methods with almost the same amount of training data in a controlled experimental setting. Further, these results also show the power of generative models, in achieving strong results, with a fraction of parameters that are used in contrastive based approaches. The idea of combining clustering based dictionary learning approach with that of Transformer is a powerful concept that has many applications ahead.

5. CONCLUSION AND FUTURE WORK

We have proposed a method based on two distinct approaches: i) contrastive learning based on data augmentation, and ii) transformer-based next-element prediction for audio representation learning. We show how our method achieves considerable performance purely by training the deep neural networks on the data, and using a linear head, (as opposed to multilayer nonlinear heads with labels) to classify the learned representations for various applications. The strengths of contrastive and transformer-based representation learning methods suggest various applications in problems where large scale labeling is not feasible. We can envision various modifications of the existing algorithm such as different loss functions, using state of the art encoders, and combining these ideas with clustering and multitask learning for achieving even better performance, purely in a self supervised setup. These self-supervised learned embeddings can further be combined with other neural architectures for various applications in vision, speech, and natural language processing.
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