CROSS-TASK PRE-TRAINING FOR ACOUSTIC SCENE CLASSIFICATION

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ABSTRACT

Acoustic scene classification (ASC) and acoustic event detection (AED) are different but related tasks. Acoustic scenes can be shaped by occurred acoustic events which can provide useful information in training ASC tasks. However, most of the datasets are provided without either the acoustic event or scene labels. Therefore, we explored cross-task pre-training mechanism to utilize acoustic event information extracted from the pre-trained model to optimize the ASC task. We present three cross-task pre-training architectures and evaluated them in feature-based and fine-tuning strategies on two datasets respectively: TAU Urban Acoustic Scenes 2019 dataset and TUT Acoustic Scenes 2017 dataset. Results have shown that cross-task pre-training mechanism can significantly improve the performance of ASC tasks and the performance of our best model improved relatively 9.5% in the TAU Urban Acoustic Scenes 2019 dataset, and also improved 10% in the TUT Acoustic Scenes 2017 dataset compared with the official baseline.

Index Terms — cross-task, pre-training, acoustic scene classification, multi-head attention, acoustic event detection

Table 1. Recording examples with its acoustic events and its corresponding recorded scene

| Acoustic Events                          | Acoustic scene   |
|-----------------------------------------|------------------|
| traffic noise, roadway noise, crowd noise| Street with traffic |
| report, aeroengine noise, crowd noise    | Airport           |
| music, conversation, television sound    | Home             |

However, most of the datasets are provided without either the acoustic event or scene labels. Unsupervised pre-training has been proven to help deep learning [11, 12, 13]. In the area of computational audio analysis, the embeddings extracted from the pre-trained VGGish model have been proven to outperform raw features on the AED task [14]. In this paper, we introduce pre-training mechanism in cross-task learning. The models we presented use the acoustic event representations from the pre-trained module to improve the performance of ASC tasks. At the same time, there are two strategies [12] to use pre-trained representations to downstream tasks: feature-based and fine-tuning. We analyzed the performance of these two strategies in cross-task learning respectively. To our knowledge, it is the first time to utilize acoustic event information in a pre-trained manner to improve the performance of the ASC model. On the other hand, our proposed models are all an extension of the original model, therefore it can be transferred to any other fundamental architectures with little change.

As a single label classification task, the ASC task shares similarities with all other tasks based on time-based media and the key issue of this kind of tasks is how to map temporal frames to one target label [9]. At the same time, researchers are concerned with high acoustic variability caused by variable recording locations and situations [8]. Therefore, attention-based pooling mechanism is promising and has attracted more and more attention [15, 16, 17] because of its trainable pooling weights and frame dependent nature. There-
fore, in this paper, we use the attention-based pooling function in our fundamental architecture. At the same time, we propose a new cross-task model based on the architecture of transformer\cite{13} before the attention-based pooling layer. We believe that it can feed more advanced features to the attention-based pooling layer.

2. METHODOLOGY

To explore the effectiveness of acoustic event information from pre-trained models to ASC tasks, we present three cross-task models: VGGish Embedding Based Model(VEM) which directly replace the raw feature with pre-trained embeddings, Joint Representation based Model(JRM) which treats the raw feature and the pre-trained embeddings as two modals and Cross-task Multi-head Attention Model(CMAM) which utilize multi-head attention mechanism to combine information from different sources. All of them are build on the same fundamental architecture for comparison. And all of them use the VGGish model as the pre-trained model which is trained using a larger acoustic event dataset called the Audio Set\cite{19}. In this section, we describe our fundamental architecture, three proposed cross-task models respectively.

2.1. Fundamental Architecture

The core modules of the ASC network are the encoder to extract high level features and the pooling layer to map temporal representations to one representation\cite{14,20}. These two modules in our fundamental architecture are described below.

Because of the previous successful application of CNN-based layers to audio classification tasks\cite{21}, our fundamental architecture uses CNN-based layers before the pooling layer as our encoder to extract high level features. Its structure is shown in Figure 1.

![Fig. 1. Structure of CNN-based encoder](image1.png)

The attention-based pooling function with multiple heads outperforms the pooling with a single head and has achieved superior performance in the area of speaker recognition\cite{22}. We use it as our pooling function. Its structure is shown in Figure 2.

![Fig. 2. Structure of attention-based pooling function with multiple heads](image2.png)

2.2. VGGish Embedding based Model

In most unsupervised pre-training cases, the raw features are replaced with the pre-trained features\cite{11}. We explored the performance of this strategy in the cross-task case. As shown in Figure 3, the main difference between the fundamental architecture and the VGGish embedding based model is the input to the CNN-based encoder. The intuition of the model has parallels with that of other unsupervised pre-training models. The pre-trained VGGish embedding contains not only the scene-related information extracted from the raw feature but also the event-related information from the pre-trained model.

![Fig. 3. Structure of VEM](image3.png)

2.3. Joint Representation based Model

The VGGish embedding based model has its limits. Because of the limitation of the size of the VGGish embedding, useful information have to be discarded without enough extracting or encoding processes. Inspired by\cite{23}, we can treat the raw feature and the pre-trained VGGish embedding as two modals. This is followed by the intuition that the
pre-trained VGGish embedding contains information about acoustic events part of which can never be learned from raw features. To maximize the information usage from the cross-task modal, the join representation based model is presented. As shown in Figure 4, the raw feature and the pre-trained VGGish embedding are firstly fed into two separate modules. These two modules have similar structures but different weights. After the process and extraction of these two modules, two high level features from different sources are concatenated. The concatenated feature is then fed into the fully-connected layer to predict the probabilities of target labels.

**2.4. Cross-task Multi-head Attention Model**

As mentioned above, the attention-based pooling function plays a significant role in ASC tasks. Our intuition is to feed more advanced features to the attention-based pooling layer. On the other hand, transformer-based models have achieved great performance in many kinds of acoustic fields\[24,25\]. Therefore, the cross-task multi-head attention model is presented. Unlike the hard concatenation of two features extracted from the raw and the pre-trained embedding in JRM, the contribution of the VGGish embedding is more dynamic. As shown in Figure 5, we firstly add the positional encoding using sine and cosine functions mentioned in \[18\] to the pre-trained embedding to inject positional information. And then the embedding is fed into the multi-head self attention layer and computed as follow equations:

\[
Q = HW^Q \tag{1}
\]

\[
K = HW^K \tag{2}
\]

\[
V = HW^V \tag{3}
\]

where $H$ is the embedding and $W^Q$, $W^K$, and $W^V$ are parameter matrices. Then the output $Q$, $K$, $V$ are split into $N$ heads on the channel dimension. The output of the multi-head self attention layer is computed as follow equations:

\[
O_i = \text{softmax}(\frac{Q_iK^T}{\sqrt{d}})V_i \tag{4}
\]

\[
O_a = \text{Concat}(O_i W^O) \tag{5}
\]

\[
O = \text{LayerNorm}(\text{Dropout}(O_a) + H) \tag{6}
\]

where $Q_i, K_i, V_i$ are the $i$-th head of $Q, K, V$ and the $\text{Concat}$ function concatenates output of all heads. $d$ is the dimension of queries. The $W^O$ is the parameter matrix. The size of the final output $O$ is the same as the input $H$. And then $O$ is used to attend features extracted from the raw feature. The attention function here is similar to the multi-head self attention layer mentioned before except that the query matrix and the key matrix here are computed using different inputs.

**3. EXPERIMENTS**

**3.1. Dataset**

We train and evaluate the model using the TUT Acoustic Scenes 2017 development dataset [5] and the TAU Urban Acoustic Scenes 2019 development dataset [6] respectively. As mentioned in [5], the TUT Acoustic Scenes 2017 development dataset contains 15 acoustic scene labels and audio segments with a length of 10 seconds. The experiments in TUT Acoustic Scenes 2017 dataset were conducted using a four-fold cross-validation setup. The TAU Urban Acoustic Scenes 2019 development dataset contains 10 acoustic scene labels and the length of audio is also 10 seconds.

**3.2. Model setups**

The Fundamental Architecture (FA) based model, VEM, JRM, CMAM were trained and evaluated using the feature-based and fine-tuning strategy respectively. To figure out
whether the larger architecture or the pre-trained information leads to the performance change from the FA based model to the proposed model, we also trained and evaluated each model from scratch. Also the official baseline of each dataset is listed. Concrete model setups are shown in Table 2.

### Table 2. Model setups

|                        | FA Extension in VEM | Extension in JRM | Extension in CMAM |
|------------------------|---------------------|------------------|------------------|
| Acoustic Feature(log-mel energies of 64 dimensions, extracted from 25ms segments with 10ms overlap, size: T=64×2) | VGGish Module(output size:N=10×96×64) | | |
| CNN layers: 4          |                     |                  |                  |
| Kernel size: 3×3       |                     |                  |                  |
| Strides: 1×1           |                     |                  |                  |
| Channels: 64, 128, 256, 512 |                  |                  |                  |
| Maxpooling size: 2×2   | Multi-head attention: Attention heads: 8 query dim: 2048 Total parameters: ~33M |
| Total parameters: ~1.47M | Output size: (T×4×512) | FC layers: 1 | Optimizer: Adam |

We use classification accuracy as our metrics. It is calculated as average of the class-wise accuracy which is calculated as the number of correctly classified segments among the total segment number of this class.

### 3.3. Experimental Results And Discussion

Results are shown in Table 3. For VEM, we can see that VEM performed the worst. It is reasonable because other than unsupervised pre-training in which the model is trained using fundamental information like the co-occurrence of words in sentences in NLP tasks, cross-task pre-training leads to inevitable mix of unrelated noise with the useful information. And unlike JRM with a relative deep CNN-based encoder to advance process the pre-trained embedding, CMAM with attention mechanism to dynamically adjust the contribution of the pre-trained embedding, VEM has no such structure to support a cross-task learning.

For JRM, We can see in both datasets, the performance with the model trained from scratch is better than that of the FA based model. This indicated that the larger architecture itself can help improve the performance. However, in the feature-based strategy, unstable performance was presented in different datasets. This is mainly due to the hard concatenation of the high level features extracted from the raw feature and the pre-trained embedding. The contribution of the pre-trained embedding can not be adjusted properly as with in VEM.

For CMAM, CMAM with the feature-based strategy performed the best in both datasets. On one hand, the feature-based strategy performed better than the strategy from scratch. It indicated that CMAM has effectively utilized cross-task pre-trained information. On the other hand, the performance is much better than that of JRM although the number of parameters in CMAM and JRM are similar. It indicated that the architecture of CMAM has more advantage to utilize cross-task pre-trained information.

However, all fine-tuning strategies failed to learn a better model and the performance is similar with that of strategies trained from scratch. We considered that this is mainly because we use the same learning rate in the whole model. In this situation, there is no proper global learning rate to converge the model in a suitable location and at the same time guarantee that the pre-trained information can not be washed away.

### Table 3. Experimental results

|                        | TUT Acoustic Scenes 2017(%) | TAU Urban Acoustic Scenes 2019(%) |
|------------------------|-----------------------------|----------------------------------|
| Baseline[5, 26]        | 78.4                        | 62.5                             |
| **Fundamental Architecture** | 81.7                        | 66.5                             |
| VEM                    | From scratch                | -                                |
|                       | Featured-based              | 72.1                             | 57.3                             |
|                       | Fine-tuning                 | -                                | -                                |
| JRM                    | From scratch                | 83.0                             | 67.2                             |
|                       | Featured-based              | 83.7                             | 63.4                             |
|                       | Fine-tuning                 | 83.2                             | 66.8                             |
| CMAM                   | From scratch                | 83.2                             | 65.1                             |
|                       | Featured-based              | 85.8                             | 68.8                             |
|                       | Fine-tuning                 | 83.1                             | 65.3                             |

### 4. CONCLUSION

In this paper, we explored cross-task pre-training for acoustic scene classification. We presented three architectures with the cross-task pre-trained module including VEM, JRM and CMAM. At the same time, we explored feature-based and fine-tuning strategies. Experimental results indicated that JRM and CMAM both can utilize the cross-task information extracted from the pre-trained module. And CMAM with the feature-based strategy has more advantages in cross-task learning. As Adding the pre-trained module does not change the fundamental architecture, the pre-trained module part can be transferred to any other ASC models. It is promising to use CMAM to further improve the state-of-the-art performance of all acoustic scene related tasks.
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