Transformer based unsupervised pre-training for acoustic representation learning

Ruixiong Zhang, Haiwei Wu, Wubo Li, Dongwei Jiang, Wei Zou, Xiangang Li

Didi Chuxing, Beijing, China
{zhangruixiong, wuhaWei, llwubo, jiangdongwei, zouwei, lixiangang}@didiglobal.com

Abstract

Computational audio analysis has become a central issue in associated areas of research and a variety of related applications arisen. However, for many acoustic tasks, the labeled data size may be limited. To handle this problem, We propose an unsupervised pre-training method using Transformer based encoder to learn a general and robust high-level representation for all kinds of acoustic tasks. Experiments have been conducted on three kinds of acoustic tasks: speech translation, speech emotion recognition and sound event detection. All the experiments have shown that pre-training using its own training data can significantly make the model converge faster and improve the performance.

With a larger pre-training data combining MuST-C, Librispeech and ESC-US datasets, for speech translation, the BLEU score can further improve relatively 12.2% on En-De dataset and 8.4% on En-Fr datasets. For sound event detection, the F1 score can further improve absolutely 1.7% on DCASE2018 task5 development set and 2.4% on evaluation set. For speech emotion recognition, the UAR can further improve absolutely 4.3% on IEMOCAP dataset. 

Index Terms: unsupervised pre-training, Transformer, acoustic representation learning

1. Introduction

The goal of acoustic representation learning is to transform the raw or surface feature into high-level features which are more accessible to acoustic tasks[1]. It is critical to make acoustic representations more general and robust to improve the performance of acoustic tasks. However, the labeled data size of the specific acoustic task may be limited so that the learned representations can be less robust and the performance can be vulnerable to unseen data. On the other hand, there exists varieties of acoustic tasks which range from speaker verification[2], speech recognition[3] to event and scene detection[4]. For supervised learning, the learned representation useful for one task may be less suited for another task. It is worthwhile to explore how to utilize all kinds of datasets to learn a general and robust representation for all kinds of acoustic tasks.

Unsupervised pre-training can provide an appealing method to learn more general and robust high-level features that are less specialized towards solving a single supervised task. The training objective of unsupervised pre-training is only related with acoustic feature themselves and not dependent on any other downstream target. Because of this advantage, much more unlabeled data can be utilized so that a larger and more general model can be learned. At the same time, the learned representations can be directly utilized or fine-tuned for specific downstream tasks.

Contrastive Predictive Coding(CPC)[5] has provided a universal unsupervised learning approach to extract useful representations from high-dimensional data. The autoregressive mechanism are used for predicting future information. However, it can only be applied in uni-directional models. Masked Predictive Coding(MPC)[6] has been proposed to pre-train speech data in an unsupervised manner for speech recognition. It uses the bidirectional transformer based architecture and uses Masked-LM[7] like structure to perform predictive coding. The pre-trained representations can be further fine-tuned to improve specific speech recognition tasks. However, the speech or acoustic representation pre-trained from this method has not yet been applied to other kinds of acoustic tasks and also the performance of this unsupervised pre-training method on non-speech audio tasks remains unknown.

In this paper, we get intuition from MPC and utilize a Transformer[8] based unsupervised pre-training method for acoustic representation learning. Transformer based encoder can be pre-trained by a large amount of unlabeled audio from various kinds of datasets. After pre-training, all we should do is to add a decoder layer targeted for downstream tasks and fine-tune the whole model. We have demonstrated that our method can learn a more general and robust acoustic representation which can significantly improve the performance of various kinds of acoustic tasks.

2. Related Work

Contrastive Predictive Coding(CPC) provided a universal unsupervised learning approach and the learned representation is able to achieve strong performance on four domains: speech, images, text and reinforcement learning in 3D environments. This model is mainly composed of two parts: a non-linear encoder $g_{enc}$ and an autoregressive model $g_{ar}$. Given an input sequence $(x_1, x_2, ..., x_T)$, $g_{enc}$ encodes observations $x_t$ to a latent embedding space $z_t = g_{enc}(x_t)$ and $g_{ar}$ accepts $z_t$ to produce a context representation $c_t = g_{ar}(z_t)$. Targeting at predicting future observations $x_{t+k}$, a density ratio $f(x_{t+k} | c_t)$ is modelled to maximally preserve the mutual information between $x_{t+k}$ and $c_t$. To optimize $g_{enc}$ and $g_{ar}$, the contrastive loss is minimized:

$$\mathcal{L}_N = -\frac{1}{N} \sum_{x_t \in X} \log \frac{f(x_{t+k} | c_t)}{\sum_{x_{t+k} \in X} f(x_{t+k} | c_t)}$$

where $N$ represents number of samples in $X = x_1, x_2, ..., x_N$, with one positive sample from distribution $p(x_{t+k} | c_t)$ and the rest being negative samples from distribution $p(x_{t+k})$.

Autoregressive Predictive Coding(APC)[9] also proposed an autoregressive model for unsupervised speech representation learning. It used a deep LSTM network and make the model to predict further steps ahead of the current frame during training. APCs have demonstrated a strong capability of extracting useful phone and speaker information.
3. Methodology

To learn a general high-level acoustic representation, we use Transformer based encoder in an unsupervised manner. The architecture of Transformer based encoder is illustrated in Figure 1(a).

For unsupervised pre-training, Figure 1(b) shows our pre-training procedure. 15% of frames of the acoustic feature sequence will be masked by zeros and the object of unsupervised pre-training is similar as that of [6] which is to restore the masked frames given the left and right context features. However, we have two aspects that are different from that of [6]. On one hand, we have different masking mechanism. Generally speaking, the CNN modules of Transformer based encoder provide downsampling mechanism, by which the frames would be N-fold downsampled. Therefore, to reserve the masked information after downsampling operations, we split frames into chunks each of which contains N frames and 15% of all chunks will be selected randomly and all frames of the selected chunks will be masked by zeros. On the other hand, Transformer encoder is followed by a feed-forward layer to output the prediction of which each frame-level prediction predicts corresponding N real frames of the input sequence. With these changes, we also use L1 loss to minimize the gap between the predicted frames and the corresponding real frames.

For fine-tuning, Transformer encoder needs to be pre-trained only once and can be adapted to varieties of acoustic tasks no matter whether the downstream task deal with the speech or non-speech acoustic sequences, and no matter whether the output of the task is a sequence or tag. All we should do is to add a decoder layer after the pre-trained encoder to fine-tune the whole model for specific tasks. The choice of decoder layers is based on the tasks as shown in Figure 1(c).

We can use Transformer decoder for seq-to-seq tasks and specific pooling layers for tagging tasks.

4. Experiments

To prove the effectiveness of our unsupervised pre-training method on various kinds of acoustic tasks, we selected three representative kinds of tasks: speech translation, speech emotion recognition and acoustic event detection.

4.1. Data

For pre-training the model using a larger dataset which can be adapted to various kinds of downstream tasks, we merge MuST-C En-De(408 hours), Librispeech[10](960 hours) and ESC-US[11] (347 hours) datasets into one dataset(almost 1715 hours) and we call it OpenAudio. Among them, ESC is an open dataset for environmental sound classification while ESC-US is a compilation of 250k unlabeled clips. For pre-training, we did not use speed perturbation but for fine-tuning in every downstream task, we used speed perturbation with factor of 0.9 and 1.1 for data augmentation.

We use 40-dimensional Mel filter-banks extracted from the audio signals using window size of 25 ms and step size of 10 ms for pre-training and fine-tuning in all downstream tasks.

4.2. Experimental setups

For Transformer based model, we use the structure discussed before with hidden dimension size of 256, feed-forward size of 2048, attention heads of 4, dropout rate of 0.1 and encoder layers of 12 for all tasks.

We pre-trained our model using OpenAudio only once and fine-tuned it on each downstream task. It was trained on 4 GPUs.
with a total batch size of 256 for 50 epochs. We used the Adam optimizer\[12\] with warmup schedule\[8\] according to the formula:

\[
lrate = k \cdot \text{lr}_{\text{model}} \cdot \min(n^{-0.5}, n \cdot \text{warmup} \cdot n^{-1.5})
\]  

(2)

where \(n\) is the step number, \(k = 0.5\) and \(\text{warmup} = 8000\) were chosen for all experiments. For comparison, we also pre-trained our model on each task using its own training data with the same setups as discussed before.

4.3. Speech translation

The aim of speech translation is to translate one language directly from the speech into another language. We used MuST-C English-to-German(En-De) and English-to-French(En-Fr) datasets\[13\] which were commonly used in previous speech translation studies\[14, 15, 16\]. For each target language, MuST-C comprises at least 385 hours of audio recordings from English TED Talks. For fine-tuning, we used a 6-layer Transformer decoder as the decoder layer. To avoid overfitting, we also used label smoothing with the rate of 0.1. Similar to \[16\], we used 8k vocabularies based on byte pair encoding (BPE)\[17\]. It was trained on 4 GPUs with a total batch size of 512 for 50 epochs. We also use the optimizer which is the same as that of pre-training except that \(k = 2.5\) and warmup \(n = 8000\). For evaluating the performance, we restore the checkpoint averaged from best 5 checkpoints during training. We used UAR which is defined as the unweighted average of the class-specific recalls achieved by the system as our metrics.

In our experiments as shown in Table\[1\] we achieve a mean UAR of 64.9\% which is significantly better than the state-of-the-art result on this setup. According to \[21\] and the best of our knowledge, \[22\] and \[23\] presented the best results in the condition that almost match our setups. Specifically, they all use 4 emotion classes and merge happy and excited as one class, except that they used leave-one-speaker-out cross validation and we use leave-one-session-out cross validation. Compared with \[21\] which has provided another unsupervised pre-training method, our Transformer based model with pre-training can achieve better performance.

We can also see that no matter whether the decoder uses an average pooling layer or a multi-head attention layer, the performance gains using pre-training are similar.

4.4. Speech emotion recognition

IEMOCAP database\[19\] is used for our experiments on speech emotion recognition. We used the recordings where majority of annotators agreed on the emotion labels and it contains 4 kinds of emotions: angry, happy, sad and neutral state. Happy and excited emotions were combined as happy in order to balance the number of samples in each emotion class. The dataset contains 5,531 utterances (1,103 angry, 1,636 happy, 1,708 neutral, 1,084 sad) grouped into 5 sessions. We conduct 5-fold cross validation on IEMOCAP, taking samples from 8 speakers as train and development sets and the ones from the remaining 2 speakers as respective testset. We use the macro-averaged F1-score which is calculated for each class separately and averaged over all classes. For fine-tuning, we add an average pooling layer followed by one feed-forward layer. To test the relationship between the performance of unsupervised pre-training and the decoder layer type the model uses, we also conducted experiments on models with a multi-head attention layer\[20\] with 5 heads. It was trained on 4 GPUs with a total batch size of 64 for 25 epochs. We also use the optimizer which is the same as that of pre-training. For evaluating the performance, we restore the checkpoint averaged from best 5 checkpoints during training. We used UAR which is defined as the unweighted average of the class-specific recalls achieved by the system as our metrics.

In our experiments as shown in Table\[2\] we achieve a mean UAR of 64.9\% which is significantly better than the state-of-the-art result on this setup. According to \[21\] and the best of our knowledge, \[22\] and \[23\] presented the best results in the condition that almost match our setups. Specifically, they all use 4 emotion classes and merge happy and excited as one class, except that they used leave-one-speaker-out cross validation and we use leave-one-session-out cross validation. Compared with \[21\] which has provided another unsupervised pre-training method, our Transformer based model with pre-training can achieve better performance.

We can also see that no matter whether the decoder uses an average pooling layer or a multi-head attention layer, the performance gains using pre-training are similar.

4.5. Sound event detection

We used DCASE2018 task5 dataset\[24\] for sound event detection. It contains a continuous recording of one person living in a vacation home over a period of one week. The continuous recordings were split into audio segments of 10s and each segment represents one activity. The dataset presents 10 kinds of activities like cooking, eating and so on. The DCASE2018 task5 has provided development and evaluation datasets for
4.6. Effect on convergence

The experiments have also shown that pre-training can not only improve the performance but make the model converge faster.

Figure 2: Convergence curve with and without pre-training on three datasets: (a) DCASE2018 task5 dataset on which the F1 score at each epoch was tracked. (b) MuST-C En-De dataset on which the translated accuracy at each epoch was tracked. (c) IEMOCAP on which the UAR at each epoch was tracked.

Table 3: Results of sound event detection (Note: Method and Data represent pre-training method and pre-training data respectively, DCASE represents DCASE2018 task5 dataset)

| Method          | Data     | Dev. | Eval. |
|-----------------|----------|------|-------|
| Inoue et al. [25] | -        | 90.0 | 88.4  |
| Liu et al. [26]  | -        | 89.8 | 87.5  |
| Liao et al. [27] | -        | 89.8 | 86.7  |
| Transformer     | Ours     | DCASE| 90.4  | 86.6  |
| + Attention pooling | Ours | OpenAudio | 91.0 | 87.5  |
| + Attention pooling | Ours | OpenAudio | 91.2 | 87.8  |

5. Conclusion

In this work, we explored Transformer based encoder with Masked-LM like pre-training for acoustic representation learning. We conducted experiments on three kinds of tasks: speech translation, speech emotion recognition, sound event detection. We pre-train the model with a large dataset combining Librispeech, MuST-C and ESC-US datasets and fine-tune it on each task. Results have shown that for speech translation, the BLEU score can improve relatively 12.2% and 8.4% on MuST-C En-De and En-Fr datasets respectively compared with that of Transformer without pre-training and performed better than that of Transformer pre-trained by ASR. For sound event detection, the F1 score can improve absolutely 1.7% and 2.4% on DCASE2018 task5 development set and evaluation set compared with that of our base Transformer. For speech emotion recognition, the UAR can improve absolutely 4.3% on IEMOCAP dataset compared with that of our base Transformer.

On the other hand, compared with the En-De dataset, both the DCASE2018 task5 and IEMOCAP dataset are relatively smaller. Meanwhile severe instability (obvious decrease of metrics at some epochs) has also been shown from the convergence curve of Base in Figure 2(a) and 2(c). Accordingly, because our pre-training method utilized much more datasets, the model using pre-training has presented much more stability than that of Base. Our pre-training method can significantly stabilize the convergence process on relatively small datasets.
6. References

[1] G. Tzanetakis and P. Cook, “Marsyas: A framework for audio analysis,” Organised sound, vol. 4, no. 3, pp. 169–175, 2000.

[2] D. A. Reynolds, T. F. Quatieri, and R. B. Dunn, “Speaker verification using adapted gaussian mixture models,” Digital signal processing, vol. 10, no. 1-3, pp. 19–41, 2000.

[3] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian, P. Schwarz et al., “The kaldi speech recognition toolkit,” in IEEE 2011 workshop on automatic speech recognition and understanding, no. CONF. IEEE Signal Processing Society, 2011.

[4] B. W. Schuller, S. Steidl, A. Batliner, P. B. Marschik, H. Baumstei- ter, F. Dong, S. Hantke, F. B. Pokorny, E.-M. Rathner, K. D. Bartl-Pokorny et al., “The interspeech 2018 computational paralinguistics challenge: Atypical & self-assessed affect, crying & heart beats,” in Interspeech, 2018, pp. 122–126.

[5] A. v. d. Oord, Y. Li, and O. Vinyals, “Representation learning with contrastive predictive coding,” arXiv preprint arXiv:1807.03748, 2018.

[6] D. Jiang, X. Lei, W. Li, N. Luo, Y. Hu, W. Zou, and X. Li, “Improving transformer-based speech recognition using unsupervised pre-training,” arXiv preprint:1910.09932, 2019.

[7] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pretraining of deep bidirectional transformers for language understanding,” arXiv preprint:10.4805, 2018.

[8] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[9] Y.-A. Chung, W.-N. Hsu, H. Tang, and J. Glass, “An unsupervised autoregressive model for speech representation learning,” arXiv preprint arXiv:1904.03240, 2019.

[10] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: an asr corpus based on public domain audio books,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 5206–5210.

[11] K. J. Piszczak, “Esc: Dataset for environmental sound classification,” in Proceedings of the 23rd ACM international conference on Multimedia, 2015, pp. 1015–1018.

[12] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[13] M. A. Di Gangi, R. Cattoni, L. Bentiveglio, M. Negri, and M. Turchi, “Must-c: a multilingual speech translation corpus,” in 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2019, pp. 2012–2017.

[14] S. Indurthi, H. Han, N. K. Lakumarapa, B. Lee, I. Chung, S. Kim, and C. Kim, “End-end speech-to-text translation with modality agnostic meta-learning,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7904–7908.

[15] M. A. D. Gangi, M. Negri, and M. Turchi, “Adapting transformer to end-to-end spoken language translation,” in Interspeech 2019, 2019.

[16] H. Inaguma, S. Kiyono, K. Duh, S. Karita, N. E. Y. Soplin, T. Hayashi, and S. Watanabe, “Esponet-st: All-in-one speech translation toolkit,” arXiv preprint arXiv:2004.10234, 2020.

[17] R. Schmich, B. Haddow, and A. Birch, “Neural machine translation of rare words with subword units,” in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Berlin, Germany: Association for Computational Linguistics, Aug. 2016, pp. 1715–1725. [Online]. Available: https://www.aclweb.org/anthology/P16-1162

[18] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “Bleu: a method for automatic evaluation of machine translation,” in Proceedings of the 40th annual meeting on association for computational linguistics. Association for Computational Linguistics, 2002, pp. 311–318.

[19] C. Busso, M. Bulut, C.-C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J. N. Chang, S. Lee, and S. S. Narayanan, “Iemocap: Interactive emotional dyadic action capture database,” Language resources and evaluation, vol. 42, no. 4, p. 335, 2008.

[20] Y. Zhu, T. Ko, D. Snyder, B. Mak, and D. Povey, “Self-attentive speaker embeddings for text-independent speaker verification,” in Interspeech, 2018, pp. 3573–3577.

[21] M. Neumann and T. Vu, “Improving speech emotion recognition with unsupervised representation learning on unlabeled speech,” in International Conference on Acoustics, Speech, and Signal Processing, 2019, 2019.

[22] V. Rozgic, S. Ananthakrishnan, S. Saleem, R. Kumar, and R. Prasad, “Ensemble of svm trees for multimodal emotion recognition,” in Signal Information Processing Association Summit And Conference, 2012.

[23] R. Xia and Y. Liu, “Leveraging valence and activation information via multi-task learning for categorical emotion recognition,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 5301–5305.

[24] G. Dekkers, L. Vauvreinien, B. Thoen, M. W. Adhana, H. Brouckxon, T. van Waterschoot, B. Vanrumste, M. Verhelst, and P. Karsmakers, “The SINS database for detection of daily activities in a home environment using an acoustic sensor network,” in Proceedings of the Detection and Classification of Acoustic Scenes and Events 2017 Workshop (DCASE2017), November 2017, pp. 32–36.

[25] T. Inoue, P. Vinayavekhi, S. Wang, D. Wood, N. Greco, and R. Tachibana, “Domestic activities classification based on CNN using shuffling and mixing data augmentation,” DCASE2018 Challenge, Tech. Rep., September 2018.

[26] H. Liu, F. Wang, X. Liu, and D. Guo, “An ensemble system for domestic activity recognition,” DCASE2018 Challenge, Tech. Rep., September 2018.

[27] H.-W. Liao, J.-Y. Huang, S.-S. Lan, T.-H. Lee, Y.-W. Liu, and M.-S. Bai, “DCASE 2018 task 5 challenge technical report: Sound event classification by a deep neural network with attention and minimum variance distortionless response enhancement,” DCASE2018 Challenge, Tech. Rep., September 2018.