EXPLORING WAVE2VEC 2.0 ON SPEAKER VERIFICATION AND LANGUAGE IDENTIFICATION

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ABSTRACT

Wave2vec 2.0 is a recently proposed self-supervised framework for speech representation learning. It follows a two-stage training process of pre-training and fine-tuning, and performs well in speech recognition tasks especially ultra-low resource cases. In this work, we attempt to extend the self-supervised framework to speaker verification and language identification. First, we use some preliminary experiments to indicate that wav2vec 2.0 can capture the information about the speaker and language. Then we demonstrate the effectiveness of wav2vec 2.0 on the two tasks respectively. For speaker verification, we obtain a new state-of-the-art result, Equal Error Rate (EER) of 3.61\% on the VoxCeleb1 dataset. For language identification, we obtain an EER of 12.02\% on the 1 second condition and an EER of 3.47\% on the full-length condition of the AP17-OLR dataset. Finally, we utilize one model to achieve the unified modeling by the multi-task learning for the two tasks.

Index Terms— Self-supervised, speaker verification, language identification, multi-task learning, wav2vec 2.0

1. INTRODUCTION

Recently, neural networks trained with a large amount of labeled data can meet most industrial needs in the field of speech processing [1, 2, 3, 4, 5, 6]. However, purely supervised learning seems to be inconsistent with the mechanism of human learning. Early on in their lives, human infants learn language by watching and listening to adults around them, which resembles an unsupervised learning process. Later, they learn reading and writing, which seems to be a supervised learning process. To simulate the two-stage learning process, a lot of self-supervised frameworks are proposed [7, 8, 9, 10, 11, 12].

In the field of speech processing, most self-supervised methods can be divided into two categories. One kind of method is conducted by the reconstruction loss, such as autoregressive predictive coding (APC) [13], masked predictive coding (MPC) [14] and so on. The other kind of method is conducted by contrastive predictive loss. The most representative work is the contrastive predictive coding (CPC) [15] and wav2vec [16]. The wav2vec 2.0 [17] used in this paper belongs to the latter category. Most of these self-supervised pre-training methods are applied to speech recognition. However, there is almost no work on whether pre-training methods could work on the speaker verification (SV) or the language identification (LID). In this paper, we use the framework of wav2vec 2.0 [17] to explore this feasibility.

We denote the model structure used in wav2vec 2.0 as w2v-encoder in this paper. It is illustrated in the dashed box of Fig. 1. It mainly consists of a convolutional neural network (CNN) encoder and a Transformer [18]. The CNN transfers raw waveform input to latent speech representations. They are fed to the Transformer after being masked and converted to context representations. A quantization module converts the latent speech representations to a discrete version which is used as the target. The whole model is trained to solve a contrastive task, which requires identifying the true quantized latent speech representations for a masked time step within a set of distractors [17]. After pre-training, Baevski et al. applied it to ultra-low resource speech recognition. Using only ten minutes labeled data, their approach achieved word error rate (WER) of 5.7/10.1\% on the clean/noisy test sets of Librispeech. The results demonstrate that the phoneme-related information is preserved during the pre-training of w2v-encoder and the downstream task such as speech recognition can benefit a lot from it. Audio is a complex signal that contains not only phoneme-related information but also factors about speaker, language, environment, noise, etc. However, there is very little work on pre-training for the SV and the LID.

In this paper, we explore the effectiveness of self-supervised pre-training on the SV and the LID tasks. We utilize the pre-trained w2v-encoder to extract context representations, and use t-SNE [19] tools to visualize them. We find that they have distinguishability among different speakers and languages even if pre-training of wav2vec 2.0 is problem-agnostic. Moreover, we find the lower layer has the stronger distinguishability. This distinguishability is exactly what the SV and the LID tasks need. It also verifies the feasibility of applying the self-supervised pre-training to the two tasks. Thus, we attempt to fine-tune the pre-trained model on these two downstream tasks respectively. For the SV task, we obtain an EER of 3.61\% on the test set of the VoxCeleb1 dataset. For the LID task, we obtain an EER of 12.02\% on the 1 second condition and 3.47\% on the full-length condition of the AP17-OLR dataset. Furthermore, in order to simplify the fine-tuning process and reduce model parameters, we utilize the multi-task learning to conduct the fine-tuning on the two tasks simultaneously.

2. METHOD

In this section, we first review the pre-training of the wav2vec 2.0 [17]. Then we introduce how to apply the pre-trained model to downstream tasks. Fig. 1 illustrates the pre-training and fine-tuning.

2.1. Pre-training of wav2vec 2.0

The left side of Fig. 1 gives an illustration of the w2v-encoder and its pre-training. The main body of the model consists of a CNN-based feature encoder, a Transformer-based context network and a
quantization module. The CNN encoder stacks seven blocks, and in each block the temporal convolutions followed by a GELU activation function [20] have 512 channels with strides (5, 2, 2, 2, 2, 2) and kernel widths (10, 3, 3, 3, 3, 3, 3, 2, 2). The CNN encoder maps the raw audio $X$ into latent speech representations $Z$.

The context network stacks 12 Transformer blocks with model dimension 768, inner dimension 3,072, and 8 attention heads. Before sending $Z$ into the context network, all time steps of $Z$ are randomly sampled as starting indices with $p = 0.065$, and $M = 10$ consecutive time steps from every sampled index are masked. Then the relative positional embedding is added to the masked representations. The Transformer contextualizes the masked representations and generates context representations $C$.

The quantization module is used to discretize latent speech representations $Z$ into $Q$. There are $G = 2$ codebooks in the quantization module. Each of them contains $V = 320$ entries with a size of 128. The quantization module firstly maps the $Z$ to logits $l \in \mathbb{R}^{G \times V}$. Then the gumbel softmax [21] is used to choose one entry from each codebook in a fully differentiable way. All the entries selected are concatenated to resulting vectors $[c_1; c_2; \ldots; c_G]$, which are linearly mapped to $q$. The loss function is as follows:

$$L = L_M + \alpha L_D + \beta L_F$$ (1)

$$L_M = -\log \sum_{q=Q} \frac{\exp(sim(c_l, q))}{k}$$ (2)

$$L_D = \frac{1}{GV} \sum_{g=1}^{G} \sum_{v=1}^{V} \bar{p}_{g,v} \log \bar{p}_{g,v}$$ (3)

$$\bar{p} = \text{GumbelSoftmax}(\bar{l})$$ (4)

The loss is the weighted sum of three terms. In the Eq. 1, $L_F$ is a $L_2$ penalty. The weight $\beta$ is set to 10. The $L_M$ is the contrastive loss to make the model distinguish true discrete representations from latent distractors $\tilde{q}$. The distractors are uniformly sampled from other masked time steps of the same utterance. In Eq. 2, the $sim$ represents cosine similarity, and the $Q_l$ includes $q_l$ and $K = 100$ distractors, and the temperature $k$ is set to 0.1. The $L_D$ is the diversity loss designed to increase the use of the quantized codebook representations. The $\alpha$ in Eq. 1 is set to 0.1. The $\bar{l}$ in Eq. 4 represents the average of logits $l$ across utterances in a batch.

The pre-training process is optimized with Adam [22]. During the first 8% of the updates, the learning rate warms up to a peak of $5 \times 10^{-3}$, and then it decays linearly. For more details about the pre-training of wav2vec 2.0, we refer readers to [17].

### 2.2. Fine-tuning

Before the post-training, we add an average pooling layer and a fully connected layer on the top of wav2vec encoder. The average pooling layer converts the frame-level context representations given by wav2vec encoder into sentence-level representations, and the fully connected layer classifies each sentence into some speaker or some language.

The newly added fully connected layer is randomly initialized, and wav2vec encoder is initialized with the base model released by Baevski et al. The cross-entropy criteria is employed as the loss function for the classification of speakers or languages. Specially, for the training of speaker classification, AM-softmax [23] is used to increase the discrimination of the learned embedding to the speaker.

In the multi-task fine-tuning, we add a pooling layer and two parallel fully connected layers to predict the speaker and language respectively. The training loss is obtained by the weighted sum of the losses of these two tasks. The $L_{sv}$ and $L_{lid}$ in Eq. 5 represent the CE loss of the SV and the LID tasks respectively.

$$L_{mul} = \lambda L_{sv} + (1 - \lambda) L_{lid}$$ (5)

Due to the problem of unbalanced data volume in the datasets of the speakers and languages, the batch is generated by sampling from two datasets with equal probability to ensure the data used in the training process is balanced. In addition, the two tasks also have the problem of inconsistent convergence speed. We mitigate this issue by adjusting the weight of the loss of the two tasks through the development set.

### 3. EXPERIMENTS

Various informative factors are mixed in speech signals, including semantics, speaker, emotion, channel, background noise, etc. Baevski et al. have shown that the representations underlying pre-trained wav2vec can capture the linguistic factors. It remains unclear whether the problem-agnostic pre-training of wav2vec 2.0 can learn about any other factors. In the experiment part, we take

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1. https://github.com/pytorch/fairseq/blob/master/examples/wav2vec/
speaker and language factors as examples to explore this question, and try to apply wav2vec 2.0 to the SV and the LID tasks.

3.1. Datasets

VoxCeleb1 [24] and AP17-OLR [25] datasets are used in our experiments for the SV and the LID respectively.

**Speaker verification dataset:** VoxCeleb1 [24] contains over 100,000 utterances from 1,251 celebrities. It can be used for both speaker identification and verification. We use the VoxCeleb1 to conduct the SV task. And the cosine distance is used to calculate the similarity score. The data split of the VoxCeleb1 dataset for verification is listed in Table 1.

|         | Train | Valid | Test |
|---------|-------|-------|------|
| #speakers | 1211  | 1145  | 40   |
| #Utterances | 143642 | 5000  | 4874 |
| Dur(hrs.) | 329.06 | 11.34 | 11.20 |

**Language identification dataset:** AP17-OLR [25] consists of 10 different languages (Mandarin, Cantonese, Indonesian, Japanese, Russian, Korean, Vietnamese, Kazakh, Tibetan and Uyghur). The duration of training data for each language is about 10 hours with the speech sampled at 16 kHz. The test set contains three subsets with different durations (1 second, 3 second, and full length). These subsets respectively contain 17964, 16404 and 17964 utterances.

3.2. Model description

In the experiments, we utilize the base model released by Baevski et al. and three models fine-tuned by us. For simplicity, we use some symbols to represent them, and the explanations are as follows:

- **M-nofinetune:** the base model pre-trained on the Librispeech corpus [26].
- **M-sv:** We fine-tune M-nofinetune on the VoxCeleb1 dataset for speaker verification.
- **M-lid:** We fine-tune M-nofinetune on the AP17-OLR dataset for language identification.
- **M-multi:** We fine-tune M-nofinetune on the AP17-OLR and VoxCeleb1 dataset simultaneously in a multi-task form.

3.3. Feasibility analysis

In this section, we explore whether the speaker and language factors are retained during the pre-training of wav2vec 2.0. It determines whether the pre-training method can be used for these two tasks.

We directly extract context representations from the test set of AP17-OLR and VoxCeleb1 with the M-nofinetune model. Then we visualize the context representations by t-SNE [19], a nonlinear dimensionality reduction algorithm for visualizing high-dimensional data. The results are shown in Fig. 2. The left three images are the visualization results of the features from the three layers of the Transformer. Different colors represent different speakers. It is not difficult to find that all the three layers have certain speaker distinguishability, and this distinguishability is more obvious at the bottom of the Transformer. In the three images on the right, different colors represent different languages. It can also be found that these features are distinguished by languages, and the lower the layer, the stronger the distinction. The phenomena presented in Fig. 2 show that the model pre-trained by wav2vec 2.0 can effectively extract the characteristics of the speaker and language of the speech.

We further quantify this claim by performing the SV and the LID with a simple fully connected layer. The pre-trained w2v-encoder (M-nofinetune) acts as a feature extractor. The fully connected layer is optimized to distinguish the 10 languages or 1211 speakers for the two tasks respectively. The test results are listed in Table 2.

| Model          | SV   | LID  |
|----------------|------|------|
| random         | 47.93| 50.05|
| M-nofinetuning | 15.62| 42.34|

The random results are evaluated on the randomly initialized w2v-encoder. The comparison of these two results in Table 2 further illustrates that the model pre-trained by wav2vec 2.0 can extract speaker and language-related characteristics, which provides a basis for the application of wav2vec 2.0 to the SV and the LID.

3.4. Speaker verification

From the experiments in the previous section, we can see that the pre-trained w2v-encoder, M-nofinetune, can extract features that
Table 3: Comparison with the previously published EER (%) results on VoxCeleb1 dataset.

| Model                      | EER (%) |
|----------------------------|---------|
| I-vectors + PLDA [24]      | 8.8     |
| CNN + Embedding [24]       | 7.8     |
| LDE-ASoftmax [27]          | 4.41    |
| attentive statistics [28]  | 3.85    |
| no pre-training            | 24.28   |
| M-sv                       | 3.61    |

The no pre-training in Table 3 represents that using VoxCeleb1 to train the w2v-encoder added a fully connected layer without pre-training. Our fine-tuning model, M-sv, outperforms the no pre-training result by a significant margin (EER of 3.61% vs 24.28%). The gap between them illustrates the benefits of pre-training. Moreover, our model outperforms all baselines in Table 3, and obtains new state-of-the-art results on the VoxCeleb1 dataset. It means the pre-training of wav2vec 2.0 is useful to the SV task and can work well without any task-specific adjustment of model structure.

3.5. Language identification

Although Baevski et al. only used English data during the pre-training of M-nofinetune, it can be seen from the visualization results in section 3.3 that the features extracted by M-nofinetune still retain the distinction of language. It means that the model obtained by this pre-training method may be useful to the language identification system. Similarly, we add a fully connected layer on top of the w2v-encoder to predict language. We initialize w2v-encoder with M-nofinetune and randomly initialize the extra fully connected layer. Then the whole model is fine-tuned on the AP17-OLR dataset [25].

We optimize the model with Adam, the learning rate warms up to $5 \times 10^{-3}$ during the first 6000 steps, and then it decays linearly during the remaining 7000 steps.

Table 4: Comparison with the previously published $C_{avg}$ and EER (%) results on AP-17 dataset.

| Model                      | 1 second | Full-Length |
|----------------------------|----------|-------------|
|                            | $C_{avg}$ | EER | $C_{avg}$ | EER |
| i-vector + PLDA[25]        | 0.1746   | 17.51       | 0.0596   | 5.86 |
| TDNN [25]                  | 0.1282   | 14.04       | 0.1034   | 11.31 |
| TSM-DNN-BN-LSTM [29]       | 0.067    | 6.95        | 0.007    | 0.86 |
| no pre-training            | 0.2813   | 29.25       | 0.1254   | 13.83 |
| M-lid                      | 0.1158   | 12.02       | 0.0310   | 3.47 |

The first two rows in Table 4 are the two baselines released by the organizer of the AP17-OLR challenge. The $TSM-DNN-BN-LSTM$ [29] is one of the best models on this benchmark. The no pre-training in Table 4 means that the fine-tuning starts from scratch on the AP17-OLR dataset. The M-lid, which is fine-tuned from the pre-trained M-nofinetune, outperforms the no pre-training result by a large margin on both the 1 second condition and the full-length condition. The gap between them illustrates the benefits brought by pre-training to the LID task. Compared with baselines released by the organizer, M-lid shows a clear performance advantage on the two test conditions. However, it is far from the best results. It means that wav2vec 2.0 is useful to the LID task. However, its effectiveness on the LID task is not good as the SV task. We consider that the use of multiple languages during pre-training (not just English) can mitigate this issue. In addition, we find that the performance of the no pre-training is influenced by overfitting seriously. This problem is obviously alleviated during the fine-tuning of M-lid, which benefits from pre-training.

3.6. Multi-task system

The parameters of the w2v-encoder have reached 94M. Fine-tuning two models for the SV and the LID tasks independently will take up a lot of resources. Hence, we try to use one model to finish these two tasks simultaneously. On the top of the w2v-encoder we connect two fully connected layers in parallel to predict the speaker and language respectively. We follow the experiment settings described in section 2.2. The $\lambda$ in Eq. 5 is set to 0.7.

Table 5: Performance of single-task model and multi-task model on the VoxCeleb1 and the AP17-OLR dataset in terms of EER(%).

| Model   | SV  | LID  |
|---------|-----|------|
| M-sv    | 3.61| -    |
| M-lid   | 3.47| -    |
| M-multi | 4.18| 4.88 |

Results in Table 5 show that compared with single-task training, although the performance of multi-task form is a bit reduced, it achieves good results with fewer parameters on the SV and the LID tasks. It shows that the pre-training of wav2vec 2.0 can be combined with multi-task learning to achieve unified modeling of the two tasks. This greatly simplifies the use of pre-trained model and can save a lot of time spent on fine-tuning to each task. In addition, it can reduce the demand for storage.

4. CONCLUSION

In this paper, we explore the application of wav2vec 2.0 on speaker verification and language identification. First of all, through some preliminary experiments and visualization methods, we find that the features extracted by the pre-trained w2v-encoder have the distinction between speakers and languages, and this distinction is more obvious in lower layers. This illustrates the feasibility of using the pre-trained model for the SV and the LID tasks. Then we verify the effectiveness of the pre-trained model on the two tasks and obtain competitive results on the VoxCeleb1 and the AP17-OLR datasets. Finally, in order to simplify the fine-tuning process on multiple tasks and reduce parameters, we use a multi-task learning mechanism, so as to realize the unified modeling for the SV and the LID. In future work, we are planning to extend wav2vec 2.0 to more speech processing tasks with the multi-task learning.
5. REFERENCES

[1] Jie Li, Xiaorui Wang, Yan Li, and Yuanyuan Zhao, “The speech transformer for large-scale mandarin chinese speech recognition,” in International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 7095–7099.

[2] Anjuli Kannan, Arindrima Datta, Tara N. Sainath, Eugene Weiss, Bhuvana Ramabhadran, Yonghui Wu, Ankur Bapna, Zhifeng Chen, and Seunji Lee, “Large-scale multilingual speech recognition with a streaming end-to-end model,” in Proc. ISCA Interspeech, 2019, pp. 2130–2134.

[3] Weidi Xie, Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Utterance-level aggregation for speaker recognition in the wild,” in International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 5791–5795.

[4] Arsha Nagrani, Joon Son Chung, Weidi Xie, and Andrew Zisserman, “Voxceleb: Large-scale speaker verification in the wild,” Computer Speech & Language, vol. 60, pp. 101027, 2020.

[5] Bharat Padi, Anand Mohan, and Sriram Ganapathy, “Attention based hybrid i-vector blstm model for language recognition.,” in Proc. ISCA Interspeech, 2019, pp. 1263–1267.

[6] Peng Shen, Xugang Lu, Sheng Li, and Hisashi Kawai, “Interactive learning of teacher-student model for short utterance spoken language identification,” in International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 5981–5985.

[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: pre-training of deep bidirectional transformers for language understanding,” in Proc. North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT, 2019, pp. 4171–4186.

[8] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer, “Deep contextualized word representations,” in Proc. North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT, 2018, pp. 2227–2237.

[9] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever, “Improving language understanding by generative pre-training,” 2018.

[10] Olivier J. Hénaff, “Data-efficient image recognition with contrastive predictive coding,” in Proc. International Conference on Machine Learning, ICML, 2020, pp. 4182–4192.

[11] Phillip Bachman, R Devon Hjelm, and William Buchwalter, “Learning representations by maximizing mutual information across views,” in Advances in Neural Information Processing Systems, 2019, pp. 15535–15545.

[12] Mirco Ravanelli, Jianyuan Zhong, Santiago Pascual, Pawel Swietojanski, Joao Miotto, Jan Trmal, and Yoshua Bengio, “Multi-task self-supervised learning for robust speech recognition,” in International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 6989–6993.

[13] Yu-An Chung, Wei-Ning Hsu, Hao Tang, and James R. Glass, “An unsupervised autoregressive model for speech representation learning,” in Proc. ISCA Interspeech, 2019, pp. 146–150.

[14] Dongwei Jiang, Xiaoming Lei, Wubo Li, Ne Luo, Yuxuan Hu, Wei Zou, and Xiangang Li, “Improving transformer-based speech recognition using unsupervised pre-training,” arXiv preprint arXiv:1910.09932, 2019.

[15] Aaron van den Oord, Yazhe Li, and Oriol Vinyals, “Representation learning with contrastive predictive coding,” arXiv preprint arXiv:1807.03748, 2018.

[16] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli, “wav2vec: Unsupervised pre-training for speech recognition,” in Proc. ISCA Interspeech, 2019, pp. 3465–3469.

[17] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli, “wav2vec 2.0: A framework for self-supervised learning of speech representations,” in Neural Information Processing Systems (NeurIPS), 2020.

[18] Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[19] Laurens van der Maaten and Geoffrey Hinton, “Visualizing data using t-sne,” Journal of machine learning research, vol. 9, no. 5, pp. 2579–2605, 2008.

[20] Dan Hendrycks and Kevin Gimpel, “Bridging nonlinearities and stochastic regularizers with gaussian error linear units,” arXiv preprint arXiv:1606.08415, 2016.

[21] Emil Julius Gumbel, “Statistical theory of extreme values and some practical applications,” NBS Applied Mathematics Series, vol. 33, 1954.

[22] Diederik P Kingma and Jimmy Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[23] Feng Wang, Jian Cheng, Weiyang Liu, and Haijun Liu, “Adaptive margin softmax for face verification,” IEEE Signal Processing Letters, vol. 25, no. 7, pp. 926–930, 2018.

[24] Arsha Nagrani, Joon Son Chung, and Andrew Zisserman, “Voxceleb: A large-scale speaker identification dataset,” in Proc. ISCA Interspeech, 2017, pp. 2616–2620.

[25] Zhiyuan Tang, Dong Wang, and Qing Chen, “AP18-OLR challenge: Three tasks and their baselines,” in Asia-Pacific Signal and Information Processing Association APSIPA, 2018, pp. 596–600.

[26] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev 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.

[27] Weicheng Cai, Jinkun Chen, and Ming Li, “Exploring the end-to-end channel and loss function in end-to-end speaker and language recognition system,” in Speaker and Language Recognition Workshop, 2018, pp. 74–81.

[28] Koji Okabe, Takafumi Koshinaka, and Koichi Shinoda, “Attentional statistics pooling for deep speaker embedding,” in Proc. ISCA Interspeech, 2018, pp. 2252–2256.

[29] Zhanyu Ma, Hong Yu, Wei Chen, and Jun Guo, “Short utterance based speech language identification in intelligent vehicles with time-scale modifications and deep bottleneck features,” IEEE transactions on vehicular technology, vol. 68, no. 1, pp. 121–128, 2018.