



Pushing the Limits of Unsupervised Unit Discovery for SSL Speech Representation

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Abstract

The excellent generalization ability of self-supervised learning (SSL) for speech foundation models has garnered significant attention. HuBERT is a successful example that utilizes offline clustering to convert speech features into discrete units for a masked language modeling pretext task. However, simply clustering features as targets by k-means does not fully inspire the model's performance. In this work, we present an unsupervised method to improve SSL targets. Two models are proposed, MonoBERT and PolyBERT, which leverage context-independent and context-dependent phoneme-based units for pre-training. Our models outperform other SSL models significantly on the LibriSpeech benchmark without the need for iterative re-clustering and re-training. Furthermore, our models equipped with context-dependent units even outperform target-improvement models that use labeled data during pre-training. How we progressively improve the unit discovery process is demonstrated through experiments.

Index Terms: Self-supervised learning, representation learning, speech recognition, model generalization, HuBERT

1. Introduction

Self-supervised learning (SSL) has demonstrated remarkable success in representation learning across various fields, including computer vision [1, 2], natural language processing [3, 4], and speech processing [5, 6]. In speech representation learning, SSL methods leverage large amounts of unlabeled audio data in the pre-training stage to construct supervisory signals. HuBERT [6] as a successful example, thanks to the powerful representation capabilities of Transformer [7] architecture and the impressive learning ability of masked language modeling (MLM), exhibits exceptional generalization abilities across various downstream tasks [8, 9, 10, 11]. To generate pseudo units, HuBERT utilizes an offline k -means clustering procedure, which has been shown to be an improvement over previous methods.

Clustering features using k -means alone, however, does not fully utilize the model's performance, and iterative re-clustering and re-training entail substantial computational overhead. To enhance the quality of SSL targets for pre-training, several concurrent works have been proposed. HuBERT-AP [12] proposes generating acoustic pieces as training targets by applying the Byte Pair Encoding (BPE) algorithm to the k -means units, leading to performance improvements. This method still requires the first iteration of pre-training, which fails to reduce computational costs. PBERT [13] suggests using a pre-trained phoneme recognizer to label units for SSL pre-training. CTCBERT [14] proposes incorporating Connectionist Temporal Classification

(CTC) [15] as an auxiliary loss during pre-training based on PBERT, which further enhances the performance on automatic speech recognition (ASR) tasks. However, both methods introduce supervised data during pre-training, which may not be feasible in certain scenarios. Additionally, these methods primarily focus on ASR-related tasks, without exploring whether the model is universal after enhancing the target quality.

The objective of this study is to enhance the representation ability of SSL targets in a fully unsupervised manner during the pre-training stage. We first propose MonoBERT, whose targets are generated from a modified version of wav2Vec-U 2.0 [16]. This simple improvement has resulted in performance enhancement on ASR tasks compared to the original HuBERT. Then, various types of PolyBERT models are investigated, whose targets are context-dependent, and observe continuous performance improvements. Finally, we explore whether our approach results in a universally optimized model. Our model surpasses the baselines on non-ASR tasks related to the content, semantics, and paralinguistics, demonstrating the high generalization ability of our proposed approach.

2. Prerequisite

2.1. Self-Supervised Speech Representation

SSL pre-training followed by supervised fine-tuning has become a prevalent approach for speech representation learning, with demonstrated efficacy in producing universal representations that can be utilized across various speech downstream tasks [8]. This training paradigm typically divides SSL methods into **1)** contrastive learning [17, 18, 19, 5], **2)** predictive learning [6, 20, 21, 22, 23], and **3)** generative learning [24, 25, 26, 27], based on the pretext tasks employed.

Predictive learning is the most used SSL method, which predicts pre-clustered or model-generated targets using input features. Here we introduce HuBERT, a BERT-like predictive learning SSL model that predicts discrete units of masked regions. Given a speech utterance $X = [x_1, x_2, \dots, x_L]$ of length L , HuBERT takes X as the input and outputs a hidden representation $H = [h_1, h_2, \dots, h_T]$, where T is the frame number. MFCC features extracted from waveform or hidden features derived from a pre-trained model are clustered using the k -means algorithm for generating frame-wise discrete units, denoted as $Z = [z_1, z_2, \dots, z_T]$. The model is trained to predict the discrete units Z , where each $z_t \in C$ is a C -class categorical variable. The distribution over the C -class units can be written as:

$$p(c | h_t) = \frac{\exp(\text{sim}(Wh_t, e_c) / \tau)}{\sum_{c'=1}^C \exp(\text{sim}(Wh_t, e_{c'}) / \tau)}, \quad (1)$$

where W is the projection matrix, e_c is the code embedding for unit c , sim is the cosine similarity, and τ is a scaling term. We

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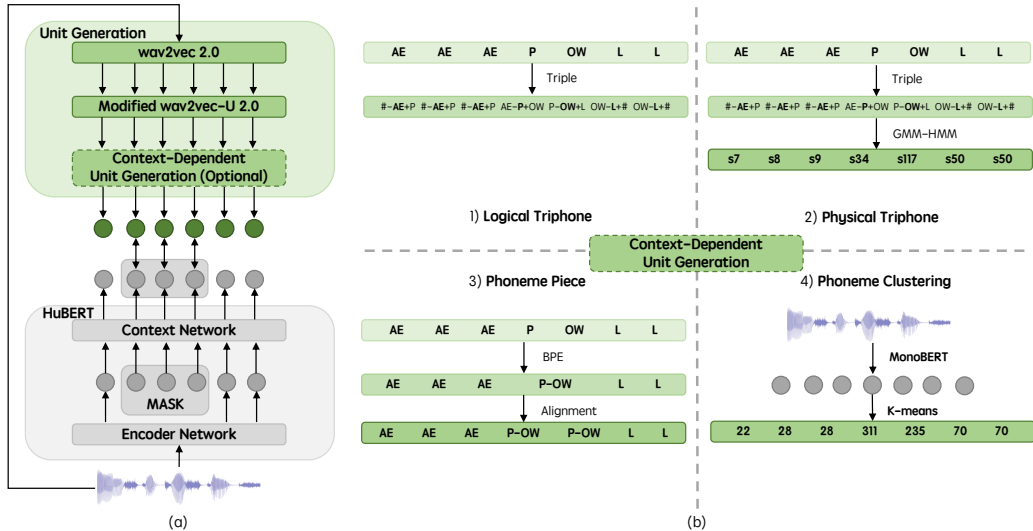


Figure 1: (a) illustrates the model structures of MonoBERT and PolyBERT (w/o and w/ Context-Dependent Unit Generation). (b) shows different ways to generate context-dependent units for PolyBERT. All phoneme-based units are obtained with unsupervised methods.

compute HuBERT loss on the masked M frames, denoted as:

$$L = - \sum_{t \in M} \log p(z_t | h_t) \quad (2)$$

2.2. Unsupervised Speech Recognition

Liu et al. [28] demonstrate the first successful unsupervised phoneme recognition through a Generative Adversarial Network (GAN) [29], which is a proof-of-concept experiment. wav2vec-U [16] is the first model to achieve unsupervised speech recognition on a range of speech recognition benchmarks. wav2vec-U 2.0 [30] is an optimization of wav2vec-U, reducing the complex and heavy preprocessing steps. The core idea of wav2vec-U 2.0 is to train a generator \mathcal{G} and a discriminator \mathcal{C} using adversarial training, which can be written as:

$$\min_{\mathcal{G}} \max_{\mathcal{C}} \mathbb{E}_{Y_u} [\log \mathcal{C}(Y_u)] + \mathbb{E}_X [\log(1 - \mathcal{C}(\mathcal{G}(X)))] - \lambda \mathcal{L}_{gp} + \gamma \mathcal{L}_{sp} + \eta \mathcal{L}_{pd} + \delta \mathcal{L}_{ss}, \quad (3)$$

where X is the sequence of the speech features from a pre-trained wav2vec 2.0, and $\mathcal{G}(X)$ is the transcription output. The generator \mathcal{G} is trained to generate phoneme sequences as realistically as possible. Y_u is the unpaired phoneme sequence with randomly inserted silence. The discriminator \mathcal{C} is trained to assign higher scores to real phoneme sequences Y_u and lower scores to generated phoneme sequences $\mathcal{G}(X)$. The generator and the discriminator are both parameterized with convolutional neural networks. \mathcal{L}_{gp} refers to gradient penalty [31], \mathcal{L}_{sp} refers to segment smoothness penalty, \mathcal{L}_{pd} refers to phoneme diversity loss, and \mathcal{L}_{ss} refers to auxiliary self-supervised objective. λ , γ , η and δ are the weights corresponding to the above four losses. In the inference stage, only the generator is used to obtain the phoneme-transcription sequences corresponding to speech.

3. Method

The overall architecture of our models is shown in Figure 1 (a), which consists of a unit generation module (Section 3.1) and a BERT-based backbone network (Section 3.2). The core idea of our method is to improve the model’s representation ability by replacing the SSL targets in the pre-training stage. Based on this, we proposed two types of models:

MonoBERT. MonoBERT uses the frame-wise monophonic pseudo units generated by the modified wav2vec-U 2.0. Instead of conducting the clustering and training loop iteration by iteration as HuBERT, MonoBERT trains the model from scratch for one iteration, without requiring a secondary loop.

PolyBERT. PolyBERT uses context-dependent phoneme-based pseudo units generated by the unit generation module. The same as MonoBERT, PolyBERT only needs to be trained for one iteration. As shown in Figure 1 (b), we explore four ways to generate context-dependent units. Details and results are described in Section 4.3.

3.1. Pseudo Units Generation

Unlike obtaining the units using the k -means clustering algorithm in the original HuBERT paper, we use phoneme-based pseudo units for conducting the following SSL procedure. The generation of frame-wise phoneme-based pseudo units is benefited from a modified wav2vec-U 2.0. Generally, phoneme sequences generated by the original wav2vec-U 2.0 are not aligned with the speech, which cannot be used as SSL targets. Translation invariance is a natural feature of the convolutional neural network which could help. After training a convolutional neural network (the generator \mathcal{G}), its stride can be adjusted without a constraint. When the stride is set to 1 and deduplication is disabled, monophonic pseudo units are obtained at the frame level, which can be directly utilized for MonoBERT training.

3.2. Backbone Network

To construct the backbone network, we adopt the widely used BERT-based model architecture as mainstream SSL models [5, 6], which contains an encoder network and a context network. The encoder network is a 7-layer 1-D convolutional neural network with kernel sizes of (5, 2, 2, 2, 2, 2) and strides of (10, 3, 3, 3, 3, 2, 2). It takes the raw audio input \mathcal{X} at a sample rate of 16,000 Hz and downsamples it to a frequency of 50 Hz. The output representations have a dimension of 512. After that, a linear projection is applied to transform the dimension of representations from 512 to 768, followed by a mask matrix to corrupt the representations for conducting the MLM task. The context network is a 12-layer standard Transformer. Each Transformer block is set to 768 model-dimension, 3072 inner-dimension, and has 8 attention heads. This results in a total of

95M parameters of the model. The context network takes the masked version of the 768-dimension representations as input. The final output \mathcal{H} of the backbone is used for computing the HuBERT loss with the prepared offline targets \mathcal{Z} . The model is optimized to predict discrete units on masked regions.

4. Experiments

4.1. Dataset

In this paper, we conduct our experiments on the mainstream LibriSpeech [32] 960h-100h benchmark. For unsupervised pre-training, we use the full set of the LibriSpeech corpus with 960-hour (including `train-clean-100`, `train-clean-360`, `train-other-500`) unlabeled data. For supervised fine-tuning, the 100-hour (`train-clean-100`) split from the LibriSpeech corpus is considered. We conduct the evaluation on `dev-clean/other` and `test-clean/other` from the LibriSpeech corpus, each of which contains 10-hour speech data with human-labeled transcriptions.

4.2. Implementation Details

To enhance the representation ability of SSL targets during the pre-training phase, our methods maximize the inheritance of the hyperparameters from the HuBERT model without conducting extensive hyperparameter search. This demonstrates the effectiveness of our methods and ensures a fair comparison.

Pre-Training. The pre-training is conducted on NVIDIA GeForce RTX 3090 GPUs from scratch, and we simulate 32 GPUs by using 8 GPUs and setting the update frequency to 4. The max token number within a batch is set to 1400000 on each GPU. For the mask strategy, each time-step has a probability of $p = 8\%$ to be selected as the starting index and the subsequent $l = 10$ time-steps are masked. For the optimizing strategy, we use Adam [33] with a peak learning rate of 0.0005 and a weight decay of 0.01. All models are trained for 400k steps, with 8% proportion of warm-up and 92% proportion of linear decay.

Fine-Tuning. The fine-tuning is conducted on 8 GPUs with a max token number of 3200000. CTC loss is adopted to keep consistent with the baseline models. All models are tuned for 80k steps, with [10%, 40%, 50%] proportion of warm-up, hold-on, and linearly decay. For the optimizing strategy, we use Adam with a peak learning rate of 0.00003. During the fine-tuning stage, CNN parameters are fixed permanently and Transformer parameters are fixed for the first 10k steps. We conduct validation and model selection on the `dev-other` subset.

Decoding. In the decoding stage, we use the Viterbi algorithm or an additional 4-gram language model. The beam size is set to 1500 during the beam search. We conduct testing on `dev-clean/other` and `test-clean/other` subsets.

4.3. Unit Exploration

To create MonoBERT, we initially utilize frame-wise context-independent pseudo monophones as SSL targets, as explained in Section 3.1. The vocabulary size in our experiments is 40, with 39 monophones and a single silence token. As shown in Table 2, the MonoBERT yields 10.9/8.5% relative WER reductions on `dev-clean/other` subsets and 12.7/11.4% relative WER reductions on `test-clean/other` subsets compared to HuBERT. Higher-quality target representations are constructed by fusing contextual information. As shown in Figure 1 (b), we explore four ways to conduct the context-dependent unit generation, which make the PolyBERTs:

Logical Triphone. We generate the logical triphone format

of the central monophone from the preceding one and the following one. However, this will make the vocabulary size upper bounded by 40^3 , which is too large. We select the 500 most frequently occurring logical triphones in the entire corpus as new tokens, and other logical triphones are still represented by the central monophones, which brings the vocabulary to size 540. We call this model PolyBERT-LT. PolyBERT-LT has a similar performance to MonoBERT.

Physical Triphone. We build a decision tree to handle the state binding of the sparse logical triphones. We use Kaldi[34] to train a GMM-HMM model and set the leaves number of the tree to 500, which leads to a number of 448 states until convergence. We use the binded states as the SSL targets and call these units “physical triphones”. We call this model PolyBERT-PT. PolyBERT-PT significantly surpasses HuBERT and MonoBERT, proving the effectiveness of the method.

Phoneme Piece. We leverage sentencepiece[35] on the deduplicated pseudo monophones to automatically merge the highly frequent ones into new tokens. We call these units “phoneme pieces”. We use open-source code ¹ to implement the sentencepiece algorithm and set the vocabulary size to 500. Since SSL training needs alignment, we reassign the merged tokens with their corresponding phoneme pieces. We call this model PolyBERT-PP. PolyBERT-PP also has a significant improvement compared with HuBERT and MonoBERT.

Phoneme Clustering. HuBERT adopts iterative re-clustering and re-training to boost the representation ability, which could be helpful to our exploration of target quality. Following the unsupervised unit discovery procedure in HuBERT, we use MonoBERT to extract speech features and cluster them with the k -means algorithm. We set the number of cluster centers to 500 and take the IDs of the cluster centers as the SSL targets. We call this model PolyBERT-PC. However, this leads to a performance drop, indicating that phoneme-based units are not suitable for iterative re-clustering.

Model	WER%(↓)			
	dev-clean	dev-other	test-clean	test-other
HuBERT	5.5	13.0	6.3	13.2
MonoBERT	4.9	11.9	5.5	11.7
PolyBERT-LT	5.1	12.0	5.3	11.7
PolyBERT-PT	4.5	11.0	4.9	11.1
PolyBERT-PP	4.8	11.4	4.9	11.3
PolyBERT-PC	5.3	13.9	5.6	14.3

Table 2: Exploration towards different context-dependent units. We compare the performance on four subsets (`dev-clean/other` & `test-clean/other`) pre-trained on LibriSpeech `train-960` and fine-tuned on `train-clean-100` without a language model.

4.4. ASR Task Results

Table 1 shows the results of MonoBERT and PolyBERT on the LibriSpeech 960h-100h benchmark compared to other state-of-the-art models. The models are pre-trained on LibriSpeech `train-960`, and fine-tuned on LibriSpeech `train-clean-100` subset. We compare the Word Error Rate (WER) of different models on `dev-clean/other` and `test/other` with and without the language model, respectively. To sum up, MonoBERT achieves 12.7/11.4% relative WER reduction on `test-clean/other` subsets over HuBERT without a language model, and 5.9/6.2% relative WER reduction on `test-clean/other` with a 4-gram language model.

¹<https://github.com/google/sentencepiece>

Model	Pre-training Data		Language Model	WER%(↓)			
	Unsupervised	Supervised		dev-clean	dev-other	test-clean	test-other
<i>Self-Supervised Methods</i>							
HuBERT [6]	960h	-	None	5.5	13.0	6.3	13.2
			4-gram	2.7	7.8	3.4	8.1
WavLM [20]	960h	-	None	-	-	5.7	12.0
			4-gram	-	-	3.4	7.7
<i>Our Methods</i>							
MonoBERT	960h	-	None	4.9	11.9	5.5	11.7
			4-gram	2.7	7.3	3.2	7.6
PolyBERT	960h	-	None	4.5	11.0	4.9	11.1
			4-gram	2.5	7.0	3.1	7.3
<i>Semi-Supervised Methods</i>							
PBERT [13]	960h	100h	None	4.6	11.7	4.8	11.8
			4-gram	2.6	7.3	3.2	7.7
CTCBERT [14]	960h	100h	None	4.6	11.3	4.8	11.3
			4-gram	2.5	7.1	3.1	7.4

Table 1: WER on LibriSpeech corpus. We compare the performance on four subsets (dev-clean/other & test-clean/other) with (4-gram) and without (None) language model. The PolyBERT here refers to PolyBERT-PT. The performance of all models comes from their papers except for HuBERT without a language model, for which we fine-tune their public released model.

While PolyBERT achieves 22.2/15.9% relative WER reduction on test-clean/other subsets over HuBERT without a language model, and 8.8/9.9% relative WER reduction on test-clean/other with a 4-gram language model.

Our approach is also compared with other concurrent methods that intend to enhance the quality of SSL targets. Despite not using any supervised data during the pre-training phase, PolyBERT surpasses their models, indicating that our techniques produce SSL targets of high quality that are beneficial for the ASR downstream task.

4.5. Non-ASR Task Results

SSL pre-training has been widely proven to be effective on different downstream tasks. So it is meaningful to explore whether our context-dependent phoneme-based representations maintain the advantage of SSL pre-training on non-ASR tasks. SUPERB [8] is a leaderboard to test the performance of the pre-trained models. It provides a series of tasks to investigate four aspects of speech including speaker, content, semantics, and paralinguistics. We pick one task from each of the four aspects and evaluate our method:

Speaker Identification (SID, Speaker). SID categorizes each utterance into its corresponding speaker identity using a multi-class classification approach. The VoxCeleb1 dataset [36] is adopted for evaluation. The speakers in the predefined set remain consistent across both training and testing.

Keyword Spotting (KS, Content). KS identifies preregistered keywords by categorizing utterances into a predefined set of words. The Speech Commands dataset v1.0 [37] is utilized to perform this task. This dataset contains ten classes of keywords, a class for silence, and an additional unknown class to account for false positives.

Intent Classification (IC, Semantics). IC categorizes utterances into predefined classes to determine the speaker’s intent. The Fluent Speech Commands dataset [38] is employed for this task. Each utterance is associated with three intent labels: action, object, and location in this dataset.

Emotion Recognition (ER, Paralinguistics). ER predicts the emotional state of each utterance by assigning it to an emotion class. The IEMOCAP dataset [39] is utilized. The unbalanced emotion classes are excluded and the final four classes are (neutral, happy, sad, and angry).

Table 3 shows the results of different pre-trained models on the four non-ASR tasks. PolyBERT slightly drops on the SID task. A possible explanation is that the phone-based units are independent of the speaker information compared to units generated from a k -means model. It is amazing that PolyBERT surpasses baselines on KS, IC, and ER tasks, which shows that context-dependent phoneme-based representations have the ability to improve non-ASR tasks including content, semantics, and paralinguistics, demonstrating our methods obtain universal speech representations.

Model	Acc%(↑)			
	SID	KS	IC	ER
FBANK	8.5E-4	8.63	9.10	35.39
wav2vec [18]	56.56	95.59	84.92	59.79
wav2vec 2.0 [5]	75.18	96.23	92.35	63.43
HuBERT [6]	81.42	96.30	98.34	64.92
PolyBERT	77.52	96.66	98.60	65.59

Table 3: Evaluate speech representation ability on various downstream tasks. All four tasks use accuracy (Acc%) as the evaluation metric.

5. Conclusion

This paper studies the acquisition of universal speech representations by unsupervised exploration of phone-based SSL units. Two models are proposed: MonoBERT and PolyBERT. MonoBERT utilizes context-independent phoneme-based units from a modified version of wav2Vec-U 2.0, while PolyBERT employs context-dependent phoneme-based units for SSL pre-training. The performance of our models is evaluated on both ASR and non-ASR tasks. The results indicate our models perform remarkably better than the baselines in ASR tasks, and even outperform other models that enhance target quality by adding labeled data during pre-training. Moreover, other than ASR, our model surpasses the baseline in content-related, semantics-related, and paralinguistics-related tasks. These demonstrate that our models produce universal speech representations.

6. Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 62206171 and No.62106140), the International Cooperation Project of PCL, and Alibaba Group through Alibaba Innovative Research Program.

7. References

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