ONCE-FOR-ALL SEQUENCE COMPRESSION FOR SELF-SUPERVISED SPEECH MODELS

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ABSTRACT
The sequence length along the time axis is often the dominant factor of the computation in speech processing. Works have been proposed to reduce the sequence length for lowering the computational cost in self-supervised speech models. However, different downstream tasks have different tolerance of sequence compressing, so a model that produces a fixed compressing rate may not fit all tasks. In this work, we introduce a once-for-all (OFA) sequence compression framework for self-supervised speech models that supports a continuous range of operating compressing rates. The framework is evaluated on various tasks, showing marginal degradation compared to the fixed compressing rate variants with a smooth performance-efficiency trade-off. We further explore adaptive compressing rate learning, demonstrating the ability to select task-specific preferred frame periods without needing a grid search.

Index Terms— self-supervised learning, sequence compression, once-for-all training

1. INTRODUCTION
Large-scale self-supervised speech models [1, 2, 3] have shown their ability to generate state-of-the-art performance across various downstream tasks [4]. Several compression techniques, such as knowledge distillation and weight pruning [5, 6], have been studied to lower the ever-growing computational barrier of these large-scale models. In addition to parameters, the long input of speech accounts for the computation bottleneck as well. To tackle the issue of long sequences, sub-quadratic attention mechanisms have been actively developed to incorporate with Transformers [7, 8], in order to lower the dependencies of sequence length in memory and runtime. However, these attention mechanisms have various degrees of overhead in practice [9], which pushes another trend of research: reducing the sequence length itself [10, 11, 12, 13].

Subsampling is a commonly used technique to reduce the sequence length and has been widely adopted in automatic speech recognition (ASR) systems [14, 15, 16]. Shortening sequence within self-supervised speech models has been explored in [10, 11] by pairing subsampling with upsampling during the optimization process. Both works demonstrate the effectiveness of computation reduction with subsampling, yet with a limited compressing rate (frame period of 40ms).

Recent works have been proposed to further push the extent of reduction in sequence length for self-supervised speech models [12, 13]. Meng et al. [12] proposed variable-length subsampling with guidance from unsupervised phonetic segments, which push the representation duration (average frame period of 90ms) closer to the duration of phone units. Gao et al. [13] take the data-side approach, truncating audio into shorter segments while retaining the overall duration of audio when pre-training. Despite the two distinct points of view of these approaches [12, 13], both come with similar results showing that shortening the sequence length has different extents of impact on different downstream tasks. Instead of pre-training a fixed compressing rate model, it would be beneficial if the self-supervised model could support multiple operation points during inference, i.e. assigning task-specific compressing rate. The idea of on-demand sequence compression has appeared in the work of Vyas et al. [17], where the pre-trained model can select different configurations when evaluating on downstream tasks. However, the approach has only a few discrete operating points with the sequence compressing rate limited to a factor of 2 and is evaluated on a single ASR task.

As the growing research interest in once-for-all (OFA) models [18, 19], we propose a once-for-all sequence compression framework for self-supervised speech models. To reach a greater compressing rate while having a competitive performance, we build our work on top of Meng et al. [12], a modified version of DistilHuBERT [20] with a variable-length subsampling layer applied. Our proposed framework allows a sweep-through along a broad spectrum of frame periods while having marginal or no degradation compared to the fixed compressing rate variants. Evaluation is performed on nine different downstream tasks that are part of the SUPERB challenge [4, 21], including content, speaker, and semantics-related tasks. In addition, with adaptive compressing rate learning, it is possible to obtain an overall best performance without grid search through the whole spectrum.

2. RELATED WORK
The self-supervised model studied in this paper is DistilHuBERT [20], a distillation framework with a student and a
teacher HuBERT [1] model. Both the student and the teacher models are composed of a CNN feature extractor that converts the input waveform into a sequence of features, followed by a Transformer Encoder. The student model is trained to minimize the distance between the output representation (through prediction heads) and the chosen layers of the teacher model.

In order to compute the frame-wise reconstruction loss, the representation of the student and the teacher model must have the same number of frames along the time axis, the sequence comes with a frame period of 20ms originally. In order to further compress the sequence length, Meng et al. [12] proposed to insert a subsampling layer after the CNN feature extractor of the student model. An identical subsample operation is applied to the hidden representation of the teacher model before computing the loss, to match the sequence length of the representations for distillation.

2.1. Variable-Length Subsampling

Variable-length subsampling outperforms the fixed-length counterpart (average or convolution pooling) under larger compressing rates. We follow [12] to realize variable-length subsampling with Continuous Integrate-and-Fire (CIF) [22]. The CIF module consists of an α module and a CIF function, the α module takes the output sequence from the previous layer and produces a sequence \( \alpha_1, \alpha_2, \ldots, \alpha_T \) of non-negative numbers, then the CIF function will propose a fire event (output a representation) at time \( t \) whenever the accumulated sum up to time \( t \), \( \sum_{i=1}^{t} \alpha_i \), crosses an integer boundary (fire threshold). The value of the output representation at time \( t \) will be the weighted sum of the input representation within the current segmentation where the weight values are the corresponding α weights. The length of output representation depends on the number of firing events. In the case where we have access to phonetic segments, an additional guidance loss can be added to guide the prediction of the CIF module.

3. ONCE-FOR-ALL TRAINING

From the idea of a once-for-all model [18], where a model is trained on multiple subtasks or covers a series of subnetworks, to flexibly support various deployment scenarios, we view different compressing rates as different subtasks. Our model is pre-trained on a range of compressing rates to allow on-demand sequence compression in downstream. The key idea is that we can modify the value of \( \alpha_{1:T} \) predicted by the alpha module before feeding into the CIF function. Below, we discuss how \( \alpha \) is modified at the pre-training time and the inference time to realize once-for-all sequence compressing.

3.1. At Pre-training Time

A scalar \( \lambda \) is introduced, controlling how \( \alpha \) will be modified. At each time step, we randomly sample \( \lambda \in [0, 2) \). Depending on the value of \( \lambda \), modification of \( \alpha \) is done as follows.

**Case 1** For \( \lambda \in [0, 1) \), the modified \( \alpha \) is
\[
\alpha_{i}^{\text{mod}} = \lambda \alpha_{i} + (1 - \lambda) \tag{1}
\]

**Case 2** For \( \lambda \in [1, 2) \), the modified \( \alpha \) is
\[
\alpha_{i}^{\text{mod}} = \frac{(2 - \lambda) \alpha_{i}}{\min\left(\frac{2 - \lambda}{\sum_{i=1}^{T} \alpha_{i}}, 1\right)} \tag{2}
\]

the numerator term linear scales the \( \alpha \) from 1 to 0, and the denominator term ensures that the CIF function locates at least one boundary for an utterance. At \( \lambda = 1 \), both Equation 1 and 2 are reduced to \( \alpha_{1:T}^{\text{mod}} = \alpha_{1:T} \), thus a piecewise linear function \( F \) can combine both equation as \( \alpha_{1:T}^{\text{mod}} = F(\alpha_{1:T}, \lambda; \lambda \in [0, 2]) \), while ensuring the differentiability.
The α modification is essentially up-scaling or down-scaling of the original predicted α weights. Since the original value of $\alpha_{1:T}$ is mapped to 0 to 1 via a Sigmoid function, we would like the modified $\alpha^{\text{mod}}_{1:T}$ to stay in the same range to prevent multiple firing events within a single time step, which will result in duplicated output frames. In the case of up-scaling, naive scaling will result in some time steps having α weights larger than 1, inevitably producing duplicated frames. Thus for up-scaling, the modification is done by interpolating α weights with ones, as in Equation 1. However, Equation 1 cannot be extended to down-scaling, which will result in negative α weights, hence, naive scaling is used when down-scaling, as in Equation 2. As a result, to achieve a larger compressing range, two cases are required.

To summarize, in the case of $\lambda = 0$, the model is equivalent to the vanilla DistilHuBERT, where each timestep fires a representation. In the case of $\lambda = 1$, the model is reduced to a single model in Meng et al. In the case that $\lambda$ is extremely close to 2, i.e. $\lambda \rightarrow 2^-$, the model outputs a single representation per input utterance. The entire once-for-all pre-training framework and the α modification process are illustrated in Figure 1. The guidance loss proposed in Meng et al. is necessary for this framework and is applied to the original $\alpha_{1:T}$.

3.2. At Inference Time

At inference time, one can choose any value of $\lambda \in [0, 2)$. Each distinct value of $\lambda$ is associated with a specific compressing rate. The relation between $\lambda$ and the compressing rate depends on the pre-extracted segments used for guidance loss. Since the variable $\lambda$ is a continuous and differentiable variable that controls the overall sequence length, one can also treat it as a downstream parameter, and adaptively learn the sequence length with downstream tasks. Additional soft constraints on $\lambda$ can be added to control the compressing rate of the model.

4. EXPERIMENTS

Our experiment is based on the DistilHuBERT implementation with the S3PRL toolkit [4]. The pre-training hyperparameters, including the learning rate schedule, batch size, and
distilled layers, are the same as the original implementation. The model is pre-trained on the 960-hour LibriSpeech [23] dataset. We follow [12] for the setting of the α module used in CIF, and generate the segments used for guidance loss from the unsupervised ASR [24] trained on 100-hour LibriSpeech and texts from the LibriSpeech language modeling text.

Our framework is evaluated on a subset of the SUPERB benchmark, including phoneme recognition (PR), automatic speech recognition (ASR), keyword spotting (KS), intent classification (IC), speaker identification (SID), emotion recognition (ER), query by example spoken term detection (QbE), slot filling (SF), and speech translation (ST). Only the last layer is used for downstream evaluation.

4.1. Once-for-All Sequence Compression

Three pre-trained models with different sampling ranges are tested. The models uniform sampled λ from λ ∈ [0, 1], [0, 1.5], and [0, 2] at pre-training time, and with the segment guidance from the unsupervised ASR, they have a compressing range of 20-90ms, 20-160ms, and 20-960ms respectively. The downstream results are shown in Figure 2.

Since our models come with a continuous range of compressing rates, we are able to finely sweep through frame periods up to 960ms. We observe that it is possible to further push the compressing rate for utterance-level tasks, namely KS, IC, SID, and ER, e.g. the KS task retains an accuracy of 92% with a large frame period of nearly 1 second. In addition, the once-for-all model can be evaluated on all the downstream tasks, including tasks that require a smaller frame period, such as ASR and SF, which fails to be performed by a single model with a fixed and larger compressing rate.

In general, the model pre-trained on a smaller compressing range performs slightly better overall. However, the model pre-trained on the largest compressing range still has a comparable performance with the models pre-trained on a fixed compressing rate from previous works while having the versatility of covering a larger spectrum of compressing rates. The efficiency improvement is consistent with the reduction in sequence length, and little overhead is introduced by the CIF module. Specifically, the multiply-accumulate operations (MACs) reduction in the Transformer layers including the CIF module is 68.7% and 90.6% with frame periods around 90ms and 960ms, respectively.

4.2. Adaptive Compressing Rate Learning

As we can select different compressing rates from a continuous range, grid search is a great way to have an overview of the whole landscape. However, instead of grid search through frame periods, it is also possible to obtain a compressing rate that performs close to the overall best result with less effort.

To realize adaptive compressing rate learning, we would like the compressing rate to be learnable while staying in the same range as pre-training. Thus, an additional parameter, serving as the trainable λ, is introduced and mapped to the same sample range as pre-training via a Sigmoid function. Since each task has different characteristics (converge speed etc.), adaptively learning the compressing rate requires some task-specific tuning. The trainable λ is optimized with an SGD optimizer with the momentum set to 0.9 and the learning rate set to 1e-3, 1e-2, and 1e-2 for PR, SF, and IC, respectively. The results are shown in Figure 3. Despite the compressing rate adaptively learned does not generate the overall best result in every case, the outcome is on par with the best result using grid search.

5. CONCLUSION

In this work, we propose a once-for-all sequence compression framework for self-supervised speech models. The proposed once-for-all pre-trained model produces comparable performance with each fixed compressing rate model from previous works under the same frame periods while having the advantage of selecting different compressing rates with the best trade-off during inference considering either the computing resource limitation or task-specific requirements. In addition, with adaptive compressing rate learning, an overall best result for a specific downstream can be obtained without the effort of grid search.
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