EFFICIENT UTILIZATION OF LARGE PRE-TRAINED MODELS FOR LOW RESOURCE ASR

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ABSTRACT

Unsupervised representation learning has recently helped automatic speech recognition (ASR) to tackle tasks with limited labeled data. Following this, hardware limitations and applications give rise to the question how to take advantage of large pre-trained models efficiently and reduce their complexity. In this work, we study a challenging low resource conversational telephony speech corpus from the medical domain in Vietnamese and German. We show the benefits of using unsupervised techniques beyond simple fine-tuning of large pre-trained models, discuss how to adapt them to a practical telephony task including bandwidth transfer and investigate different data conditions for pre-training and fine-tuning. We outperform the project baselines by 22% relative using pre-training techniques. Further gains of 29% can be achieved by refinements of architecture and training and 6% by adding 0.8 h of in-domain adaptation data.

Index Terms— speech recognition, medical ASR, unsupervised pre-training

1. INTRODUCTION

The development of ASR systems has come a long way and established remarkable performance, especially on tasks with sufficient training data. However, varying acoustic and recording conditions and speaking styles as well as a lack of sufficient in-domain training data still pose challenges to the development of accurate models [1]. Unsupervised pre-training has recently allowed to exploit unlabeled audio data which is available at much lower cost, significantly reducing the need for transcribed data. Additionally, the public availability of pre-trained model checkpoints is appealing to reduce training resource consumption both from an economical and environmental point of view.

Nevertheless, these models are often very large, requiring cutting-edge hardware both for training and recognition to satisfy the computational and memory requirements. Moreover, application requirements regarding the real time factor in recognition can be difficult to meet. This gives rise to the question, how to efficiently take advantage of large pre-trained models and how to reduce their complexity in order to meet the demands mentioned above.

Furthermore, despite the feasibility of training ASR systems on very small amounts of labeled data when using pre-trained models, there is certainly room for improvement beyond vanilla fine-tuning of existing models. This paper addresses a challenging real-world low-resource task. Concretely, we use a conversational telephony speech corpus from the medical domain with very small amount of data in Vietnamese and German. This task constitutes a prime example for the application of pre-trained models while still posing several challenges like domain shift regarding the unsupervised models’ training data (conversational speech, acoustic conditions, medical domain), telephony bandwidth and application requirements on limiting the complexity of models and training.

This work shows how to exploit large pre-trained models in a practical scenario with limited resources and has contributions along three main lines. The sampling rate mismatch is addressed beyond simple re-sampling by different proposed modifications of the feature extractor. We reduce model sizes and GPU memory footprint by exploiting intermediate representations and applying freezing schemes. Moreover, we study multi-stage pre-training and fine-tuning to address the data conditions and achieve adaptation for the target task.

2. RELATED WORK

Unsupervised approaches have gained popularity since they have shown a potential of high performance with only little annotated data [2]. Initial work applied this method to an ASR task by running unsupervised pre-training on a large unlabeled dataset, followed by a fine-tuning step with a small annotated dataset [3] [4] [5]. This technique can drastically reduce the amount of labeled data which is necessary to build ASR systems. The successes motivated further research into improving the modeling approach [6] [7] and understanding the individual components [8]. Furthermore, the data used for pre-training and fine-tuning was studied, e.g., in a domain-shift scenario [9] or using multilingual data [10].

Since the unsupervised loss is computed solely based on
the input speech audio without any need for labels, it is particularly appealing in a multilingual scenario. It is straight-forward to apply it for different languages or entirely multilingual data. A number of papers have started investigating this research direction \cite{10,11,12,13}. Before, supervised training with multilingual data could also show improvements for low resource languages by using a separate output layer per language providing speech representations transferable to languages unseen in multilingual training \cite{14}.

Reducing the complexity of large pre-trained models was studied in the literature, e.g. using knowledge distillation \cite{15,16}. Other works suggest that the information learned in intermediate layers is more related to what is helpful for ASR and related tasks \cite{8}, which motivates using these layers as output instead of the whole model allowing to reduce the model size at the same time.

The corpus used in this paper originates from the HYKIST project. The data and work on baselines is presented in \cite{17}, which also elaborates on the challenges of the medical domain. We further extend the work by using unsupervised methods here, especially focusing on the question how to make use of large pre-trained models efficiently.

3. METHODS

We follow the setup described in \cite{17}. It deploys a hybrid neural network (NN)-hidden Markov model (HMM) model based on a Gaussian mixture model (GMM)-HMM alignment of speech and labels. The lexica and 4gram language models (LMs) used for all experiments are described in \cite{17}.

For unsupervised training, a two-stage training setup is applied. First, the wav2vec 2.0 framework is used to pre-train an NN on unlabeled (monolingual or multilingual) data using the contrastive loss and diversity loss as described in \cite{5}. Subsequently, a fine-tuning is conducted on target language data by initializing the NN used in the acoustic model (AM) of the hybrid model with a checkpoint from pre-training, adding a softmax output layer and training with the frame-wise cross-entropy (fCE) loss using the alignment mentioned above as e.g. in \cite{18}. In addition to pre-training own models on our custom data, we also investigate exploiting a publicly available model, i.e., XLSR-53 \cite{10}. This was pre-trained on 56 kli of speech data from 53 different languages for 800k steps (19 epochs) and we use the checkpoint that was not fine-tuned to any language. Furthermore, we experiment with using the XLSR-53 model as an initialization for wav2vec 2.0 pre-training on our custom data followed by regular fine-tuning.

The 24 Transformer blocks used in the Large architecture impose high demands on the graphics processing unit (GPU) memory. Trading GPU memory against a decreased batch size leads to significantly longer training times. Prior work has shown that representations from intermediate layers of pre-trained models contain information that is useful for ASR, even more than the output of the final layers \cite{8}. Motivated by this observation, we propose to reduce the model size by cutting off the wav2vec 2.0 Large encoder after the $N^{th}$ Transformer block and refer to the model as $Large_{1:N}$. This can be done for pre-training already or for fine-tuning only.

4. EXPERIMENTS

In this section, we describe our experimental setups. We use RETURNN \cite{19} for supervised training and Fairseq \cite{20} for unsupervised wav2vec 2.0 training. Decoding is performed with RASR \cite{21}. We convert the Fairseq models to RETURNN models with an automatic conversion toolkit. We plan to publish training and decoding configurations online.

4.1. Data

Within the HYKIST project, a corpus of telephone conversations between patients, doctors and interpreters was recorded \cite{17}. We denote it as $D_{ih}$ here. It is split into adapt, dev and test sets where the adaptation set contains 0.8 h and 4.7 h for Vietnamese and German, respectively. Additionally, we use an annotated in-house dataset of 8 kHz sampled conversational telephone speech in each language (219 h/177 h) for fine-tuning and the combination of the audio data together with more Arabic data (768 h), which is the third considered language in the project. We denote it as $D_{ah}$ and represent the respective language by superscript V, G, A or VGA for the joint multilingual data. Data statistics are presented in \cite{17}.

4.2. Investigation of Data Conditions in Pre-Training

We investigate different data conditions for pre-training and present the results in Table \cite{1}. All these models are fine-tuned using $Large_{1:A}$ and are trained until full convergence on the in-house data of the respective language. The number of epochs for pre-training is selected based on best downstream word error rate (WER) on Vietnamese. As a baseline, we show results when fine-tuning from scratch (random initialization) in the first row.

Note that the wav2vec 2.0 model was adapted to operate on 8 kHz sampled data by halving the stride of the feature extractor’s last convolutional layer. Section \cite{3,4} studies this in more detail. Furthermore, preliminary experiments showed that it is generally helpful to keep more encoder blocks in $Large_{1:N}$. However, we found 8 blocks to be a good trade-off between having a sufficiently large batch size and a model size that still fits into memory.

**Single stage pre-training:** For both languages, pre-training on the monolingual in-house data shows relative word error rate reductions (WERRs) of mostly 2-4%, even though no additional data is included for pre-training here. Next, we look at models pre-trained on multilingual data. Combining the Arabic, German and Vietnamese in-house data to do a custom multilingual pre-training clearly outperforms...
the monolingual baselines relative in WER by about 14% for Vietnamese and 11% for German. Simply using the XLSR-53 checkpoint directly for fine-tuning also shows gains in a straightforward way. Moreover, it is worth noting that other ways to deal with the different bandwidth show additional gains as discussed in Section 4.3.

**XLSR-53 as pre-training initialization:** Alternatively, we can exploit XLSR-53$_{1.8}$ by using it as an initialization for custom pre-training. This helps both in the monolingual case with WERRs of 10-13% as well as the multilingual case. In the latter, the gains are much smaller, only on Vietnamese dev the benefit is similar. This indicates that the diverse and multilingual data used in XLSR-53 helps more for our pre-training on monolingual and thus less diverse data. Additionally, we pre-train a Large model initialized with XLSR-53 and subsequently reduce it to the smaller size for fine-tuning. This usually outperforms pre-training with the smaller Large$_{1.8}$ by small margins of up to 2% at the expense of higher resource consumption in pre-training, except for degradations on Vietnamese with DN/AG. We also observe that the gains on the in-house test set are usually smaller, indicating that pre-training especially helps to obtain systems that are more robust to domain changes.

We can thus conclude that pre-training helps to improve over fine-tuning from scratch in all experiments and multilingual data for pre-training is better than (more limited) monolingual data. Initializing the pre-training with XLSR-53 helps, especially in the monolingual case. Additionally, we show that continuing the pre-training of XLSR-53 on custom data is a simple way to improve the results further. Finally, the trends are similar for Vietnamese and German and the following experiments will therefore be done on Vietnamese only.

### 4.3. Sampling Rate Mismatch

One obvious challenge for the data at hand is the telephone speech, which does not match the 16 kHz sampling rate used for the original model [5]. The feature extractor can be adapted in order to operate on 8 kHz sampled data while still outputting representations with the same frame shift of 20 ms by halving the stride of a convolutional layer from the feature extractor. If the stride is even, the adjustment is straightforward. However, for the stride of 5 in the first layer, we alternate between moving the kernel by 2 and 3 frames, effectively halving the stride. This can be implemented by nearest neighbor up-sampling followed by a convolution with stride 5 and dilation 2, losing the advantage of lower complexity for cases without up-sampling though. We also halve the kernel size by summing pairs of adjacent weights here.

Another trivial solution to counter this is re-sampling all data to 16 kHz as done e.g. in [9]. We use both up-sampling as part of the model in TensorFlow as well as creating an up-sampled copy of the data using FFmpeg for experiments where no 8 kHz sampled data was seen in pre-training.

The results are shown in Table 2. When directly fine-tuning XLSR-53$_{1.8}$, up-sampling works better than adjusting the feature extractor, likely because no 8 kHz sampled data was seen in pre-training. When modifying strides, it is best to do it in the first layer keeping the same receptive field for all layers. When pre-training on 8 kHz sampled data from scratch, the results are very close for all modified layers. However, it is better to modify the last layer when doing continued pre-training with XLSR-53$_{1.8}$. Results with intermediate layers are between first and last layers and not shown here.

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| Architecture | Init | Data (in-house) | Epochs | Fine-tuning | Viet. WER [%] | Ger. WER [%] |
|--------------|------|----------------|--------|-------------|--------------|--------------|
| Large$_{1.8}$ | random | none | none | 33 | HYKIST dev 32.1, test 36.6 | HYKIST dev 21.3, test 14.3 |
| XLSR-53$_{1.8}$ | target language only | 100 | 31.4 | HYKIST dev 33.4, test 12.6 | HYKIST dev 20.8, test 14.1 |
| XLSR-53$_{1.8}$ | all (multilingual) | 300 | 26.8 | HYKIST dev 28.7, test 12.2 | HYKIST dev 20.7, test 18.2 |
| Large | XLSR-53 | none | none | 25 | HYKIST dev 29.4, test 11.4 | HYKIST dev 20.7, test 17.9 |
| Large | XLSR-53 | target language only | 100 | HYKIST dev 29.4, test 11.4 | HYKIST dev 20.7, test 17.9 |
| Large | XLSR-53 | all (multilingual) | 30 | HYKIST dev 27.4, test 11.3 | HYKIST dev 20.6, test 17.8 |
| Large | XLSR-53 | all (multilingual) | 175 | HYKIST dev 27.8, test 11.5 | HYKIST dev 20.1, test 17.8 |

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| Data up-sampling to 16kHz | NN layer | Pre-training init/data | WER [%] |
|---------------------------|----------|------------------------|--------|
| TensorFlow | none | XLSR-53$_{1.8}$/none | HYKIST dev 25.6, test 29.4 | HYKIST dev 11.2 |
| FFmpeg | first | XLSR-53$_{1.8}$/none | HYKIST dev 24.7, test 28.8 |
| | last | XLSR-53$_{1.8}$/none | HYKIST dev 25.4, test 29.4 |
| | first | scratch/all in-house | HYKIST dev 27.6, test 31.9 |
| | last | XLSR-53$_{1.8}$/all in-house | HYKIST dev 26.9, test 28.5 |
| | first | XLSR-53$_{1.8}$/all in-house | HYKIST dev 26.8, test 28.7 |
| | last | XLSR-53$_{1.8}$/all in-house | HYKIST dev 26.9, test 27.2 |

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Table 1: WERs [%] for both Vietnamese and German. Pre-trainings have been done with random initialization or using the public XLSR-53 checkpoint as initialization. Pre-training "none" with random initialization means fine-tuning from scratch. All fine-tunings use the Large$_{1.8}$ architecture and are trained until full convergence on the in-house data of the respective language.

Table 2: WERs [%] on Vietnamese for up-sampling as well as adjustments to 8 kHz sampling rate at different feature extractor layers.
Table 3: WERs [%] on Vietnamese after continued pre-training with Large on \( D_{ih}^{N} \). Fine-tuning is done on \( D_{ih}^{H} \) using different cut-outs with partial freezing, optimizing only the last eight Transformer blocks.

| Fine-tuning cut-out | WER [%] | \( D_{ih}^{N} \) | \( D_{ih}^{H} \) |
|---------------------|---------|----------------|----------------|
|                     | HYKIST  | dev            | test           |
| 8                   | 28.5    | 27.6           | 11.7           |
| 11                  | 21.8    | 25.2           | 10.4           |
| 13                  | 20.0    | 23.1           | 10.1           |
| 15                  | 18.6    | 20.2           | 10.1           |
| 18                  | 18.6    | 19.4           | 9.6            |
| 21                  | 19.3    | 20.5           | 9.8            |
| 24                  | 21.4    | 22.3           | 10.7           |

4.4. Freezing Schedule and Partial Freezing

During fine-tuning in \([5]\), initially only the output layer is updated while the feature extractor is not trained at all. The experiments so far always updated all weights based on the intuition that modifying the strides requires further training also in the feature extractor. Further experimentation not presented in detail here showed, that this helps for direct fine-tuning of \( XLSR-53_{1-8} \), however, keeping the freezing schedule is better when using checkpoints pre-trained on 8 kHz sampled data.

The choice of using encoder blocks 1-8 above was motivated by memory limitations in fine-tuning. Alternatively, we propose partial freezing where we use more blocks but only train the last 8 and freeze the rest of the model including the feature extractor. The results are depicted in Table 4. The first row with 8 blocks is the baseline where all blocks are trainable. We can observe that using more blocks indeed helps to improve the performance at the expense of a larger model but with little increase in training time and memory consumption during fine-tuning. Notably, the best results are obtained with 18 blocks, not with the full model.

4.5. Exploitation of Labeled Target Domain Data

So far, only out-of-domain data was used for training. As described in Section 4.1, a small dataset for adaptation to the target medical domain \( D_{ih}^{N} \) exists. In Table 5, we investigate how to exploit this data best. First, we observe that it is possible to train a model with only labeled HYKIST data achieving WERs well below 40% after continued pre-training on \( D_{ih}^{N} \) which is not the case when directly fine-tuning \( XLSR-53_{1-8} \). Regarding the fine-tuning schedule, it is best to fine-tune on \( D_{ih}^{H} \) first and then adapt on \( D_{ih}^{N} \). Using \( XLSR-53_{1-8} \) as initialization in custom pre-training helps for all fine-tuning data conditions. In contrast, an additional pre-training stage on \( D_{ih}^{H} \) does not change the results significantly.

Finally, we combine the above insights by using the continued pre-training with the Large model adapted in the last stride, add the freezing schedule for fine-tuning and pick the best cut-out from Table 3. Moreover, we study whether only updating the last \( M \) blocks during supervised HYKIST adaptation can be beneficial and present the results in Table 4. While this was more beneficial for smaller models in preliminary experiments, it only yields marginal gains on test for \( XLSR-53_{1-8} \).

5. CONCLUSION

In this work, we investigate how to use large pre-trained models efficiently for ASR on a challenging low resource task. The sampling rate mismatch is addressed by modifications of the feature extractor. We reduce the model size effectively by using intermediate representations of the pre-trained model in fine-tuning. The proposed freezing scheme allows rel. WERRs of at least 18% without requiring more GPU memory in training. Moreover, we experiment with different data conditions showing that the multi-stage approach outperforms the vanilla application of \( XLSR-53 \) by a 5% rel. WERR and additional adaption on 0.8 of in-domain data is still beneficial for pre-trained models. The final model outperforms the supervised baseline without adaptation \([7]\) by 48% rel. in WER.

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