CROSS-MODAL TRANSFER LEARNING FOR MULTILINGUAL SPEECH-TO-TEXT TRANSLATION

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ABSTRACT

We propose an effective approach to utilize pretrained speech and text models to perform speech-to-text translation (ST). Our recipe to achieve cross-modal and cross-lingual transfer learning (XMTL) is simple and generalizable: using an adaptor module to bridge the modules pretrained in different modalities, and an efficient finetuning step which leverages the knowledge from pretrained modules yet making it work on a drastically different downstream task. With this approach, we built a multilingual speech-to-text translation model with pretrained audio encoder (wav2vec) and multilingual text decoder (mBART), which achieves new state-of-the-art on CoVoST 2 ST benchmark [1] for English into 13 languages as well as 6 Romance languages into English with on average +2.8 BLEU and +3.9 BLEU, respectively. On low-resource languages (with less than 10 hours training data), our approach significantly improves the quality of speech-to-text translation with +9.0 BLEU on Portuguese-English and +5.2 BLEU on Dutch-English.

Index Terms— speech-to-text translation, transfer learning

1. INTRODUCTION

One model for all modalities — audio, text, images, video — is a long-term dream of the AI community for its simplicity in deployment, transfer learning, common sense and representation learning across modalities and tasks. Recent advances in pretraining over unlabeled data and then finetuning on labeled data leads to significant performance improvement in text understanding and generation tasks [2] [3] [4] [5]. Lately, such text pretraining and finetuning paradigms have been extended to other modalities: audio [6,7], images [8,9], and video [10]. At the same time, pretraining and finetuning techniques have improved multi-tasking applications significantly, such as multilingual translation, cross-lingual representations, question-answering and so on [11,12,13]. In this paper, we advance the one-model-for-all paradigm further by adapting audio and multilingual text pretraining and finetuning to improve multilingual speech-to-text translation. Our contributions are as follows:

• We propose a simple and effective cross-modal transfer adaptor to bridge the length discrepancy between audio encoder output and text decoder input.

• We propose a recipe for efficient finetuning which is also robust to overfitting and faster to train compared to naive finetuning.

• Using pretrained audio encoder (wav2vec [7]) and multilingual text decoder (mBART), we demonstrate this approach achieves new state-of-the-art on speech-to-text translation for 19 languages in the CoVoST 2 benchmark with very low training cost.

2. METHODS

2.1. Pretrained Modules

Our model leverages pretrained encoder from wav2vec 2.0 [7] for acoustic modeling and pretrained decoder from multilingual BART (mBART) [3] for language modeling.

wav2vec 2.0 is a simple and powerful framework to learn high quality speech representation from unlabelled audio data. It mainly consists of two components: feature encoder and context encoder. The feature encoder, which is built from temporal convolution layers, takes raw audio signal $O$ as input and generates latent speech representation $Z = [z_1, \ldots, z_T]$. They are fed to the transformer based context encoder to generate context representations $C = [c_1, \ldots, c_T]$ with sequence level information. During pre-training, the model is optimized with a contrastive task to distinguish true latent from distractors.

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The input to the context encoder is with span masked. The latent speech representation $Z$ is discretized to $Q = \{q_1, \cdots, q_T\}$ and used as targets for the frames in the masked span.

**mBART** is a sequence-to-sequence generative pretraining scheme. The model incorporates $N$ languages by concatenating data: $D = \{D_1, \ldots, D_N\}$ where each $D_i$ is a collection of monolingual documents in language $i$. mBART is trained as a denoising autoencoder, training to predict the original text $X$ given $g(X)$ where $g$ is a noise function that corrupts text.

We maximize $L_\theta$:

$$L_\theta = \sum_{D_i \in D} \sum_{x \in D_i} \log P(x|g(x); \theta),$$

where $x$ is an instance in language $i$ and the distribution $P$ is defined by the sequence-to-sequence model. This model is pretrained using two types of noise in $g$ — random span masking and order permutation — as described in [3]. We re-use the finetuned mBART50 models from [13] which are pretrained on CommonCrawl monolingual data of 50 languages and then finetuned with bitexs of 49 languages translated from and into English. In the sections below, MBART-ML501N refers to the mBART model finetuned on English to 49 languages, and MBART-ML501N refers to the mBART model finetuned on 49 languages to English. Preliminary experiments showed that using mBART50 without fine-tuning on parallel data was ineffective.

2.2. Connecting Pretrained Modules with Adaptor

We add a lightweight adaptor module in between encoder and decoder to better align the two modules pretrained with different modalities. The adaptor module performs projection and downsampling to alleviate length inconsistency between the audio and text sequences. Specifically, we use a stack of $n$ 1-dimensional convolutional layers with stride 2 to shrink the speech sequence (encoder output) by a factor of $2^n$.

2.3. Efficient Finetuning Strategy

For large pretrained models, finetuning all parameters are neither efficient nor stable. We propose a recipe for efficient fine-tuning which is also robust to overfitting yielding 1.3 BLEU improvement in accuracy.

3. EXPERIMENTAL RESULTS

3.1. Experimental Setup

We evaluate our proposed models on CoVoST 2 [14], a multilingual speech-to-text translation corpus with English into 15 languages and 21 languages into English, including low-resource ones (less than 10 hours of speech) such as Portuguese and Dutch.

When using wav2vec 2.0 encoder, we use 16-bit 16kHz monochannel audios as inputs. When using a traditional speech recognition (ASR) encoder, we extract 80-channel log mel-filter bank features (25ms window size and 10ms shift) with utterance-level cepstral mean variance normalization applied. We remove training samples with more than 3,000 frames for GPU memory efficiency. We use the best checkpoint and a beam size of 5 for decoding. We report case-sensitive detokenized BLEU using sacreBLEU [14], except for Japanese and Chinese translations (no word segmentation) where we report character-level BLEU. We implement all our experiments using fairseq S2T [15, 16]. We use label smoothing 0.3, and sweep for the best learning rate in each configuration using validation loss.

We compare to a strong baselines provided by [11], which is Transformer model trained with multilingual corpora from CoVoST with ASR pretraining (ST).

3.2. Bilingual Finetuning

We use XMTL to finetune pretrained wav2vec and mBART-ML501N on bilingual speech translation data on the CoV oST dataset (XMTL-BL). The results for from-English translation can be found in Table 1, where XMTL-BL outperforms the baseline on 9 out of 15 directions, with an average improvement of 0.5 BLEU.

3.3. Multilingual Finetuning

We evaluate our proposed approach on both from English and to English speech translation in CoVoST. Table 1 summarizes the translation quality (BLEU on test set) for all from English directions where the target languages were seen in the pretrained multilingual text decoder. XMTL-Multi achieves the new state-of-the-art for 13 out of 15 language pairs with an average improvement $+2.8$ BLEU over the baseline. The only two languages that didn’t see an improvement are ca and cy, which were not seen in mBART-ML501N pre-training.

Using pretrained English-only audio encoder, we found XMTL-Multi leads to the new state-of-the-art for Romance language family ($+3.9$ BLEU on average) as is shown in Table 2. Especially, for low-resource languages (e.g. it, pt, nl) which has higher WER, XMTL-Multi achieves significant quality improvement with $+2.5$, $+9.0$, $+5.2$ BLEU respectively. However, we found that this approach was ineffective for other languages into English. We hypothesize that this is due to poor transfer from English audio pre-training to non related languages and also due to very little data available for those language pairs. We leave improvements on those language pairs to future work.
| en → | ar | ca | cy | de | et | fa | id | ja |
|------|----|----|----|----|----|----|----|----|
| Baseline | 8.7 | 20.2 | 22.2 | 13.6 | 11.1 | 11.5 | 18.9 | 26.9 |
| + ASR PT | 12.4 | 21.8 | 23.9 | 16.5 | 13.4 | 13.5 | 20.8 | 29.6 |
| + Multi. | 13.0 | 22.3 | 23.7 | 17.3 | 13.9 | 14.5 | 20.3 | 31.9 |
| XMTL-BL | 12.0 | 18.8 | 12.9 | 20.3 | 15.0 | 15.9 | 24.4 | 31.4 |
| XMTL-Multi | 15.3 | 20.3 | 13.2 | 23.2 | 18.6 | 19.6 | 26.5 | 36.9 |

Table 1. Test set BLEU score on (En → XX) multilingual AST with pretrained wav2vec encoder and mBART decoder. ‘XMTL-BL’ refers to using pretrained mBART-ML501N, and finetuning on CoVoST bilingual corpus. The ‘XMTL-multi’ refers to using pretrained mBART-ML501N, and finetuning CoVoST multilingual corpora.

| en → | lv | mn | sl | sv | ta | tr | zh | Avg. ∆ |
|------|----|----|----|----|----|----|----|--------|
| Baseline | 11.5 | 6.6 | 11.5 | 20.1 | 9.9 | 8.9 | 20.6 | - |
| + ASR PT | 13.1 | 9.2 | 16.1 | 22.3 | 11.2 | 10.2 | 25.7 | +2.5 |
| + Multi. | 14.1 | 10.2 | 17.1 | 22.3 | 11.7 | 10.7 | 28.2 | +3.3 |
| XMTL-BL | 14.3 | 6.9 | 17.9 | 26.1 | 12.6 | 10.8 | 21.8 | +3.8 |
| XMTL-Multi | 17.9 | 12.0 | 21.1 | 27.5 | 14.6 | 14.1 | 32.1 | +6.1 |

Table 2. Test set BLEU score on (XX → En) for Romance language family. Pretrained modules are wav2vec encoder and mBART-ML501N decoder. ‘XMTL-Multi’ refers to multilingual finetuning on CoVoST multilingual corpora.

4. ANALYSIS

4.1. Ablation on what to finetune, what to freeze

Since the pretrained wav2vec and mBART-ML501N models have a very large number of parameters, finetuning all their parameters on a small speech translation dataset often leads to overfitting [17]. Similar to [18], we conduct a study to find the optimal set of parameters to finetune. All experiments are done using XMTL-BL (793M parameters) finetuned on English-German language pair in CoVoST (290K training examples). The results can be found in Table 3.

We found that the best combination is to finetune layer-norm and self-attention layer in the encoder; and layer-norm, self-attention, and encoder-attention in the decoder. First, finetuning layer norm parameters are crucial so that encoder and decoder parameters are compatible. Second, finetuning the self-attention layers and encoder-decoder attention layers help make the contextualized audio representation of the encoder to work with the text decoder.

To understand how to effectively adapt wav2vec and wave input to text pretrained mBART models, we explore different numbers of convolution layers, stride, kernel sizes, having layer normalization and dropout or not. The configuration and ablation study results can be found in Table 4. We found that 3 layers with stride 2 and layer dropout with one dimensional convolution adaptor provides the best results. For 3 layers with stride 2, we found that appropriate convolution layer dropout ratios play an important role in the performance. The best performance is reached with layer drop ratio 0.3. However, the layer norm hurts the performance. For 4 layers with stride 2, layer dropout hurts the performance. For 3 layers with stride 3, layer dropout also hurts the performance. Our finding is that the adaptor is very sensitive to the exact combination of stride, layer numbers, layer drops and layer norm. It requires hyper-parameter sweeping to locate good adaptor hyper-parameters.
Table 3. Test set BLEU score on (En → XX) multilingual AST with pretrained wav2vec encoder and mBART decoder. ‘XMTL-BL’ refers to using pretrained mBART-ML501N, and finetuning on CoVoST bilingual corpus. The ‘XMTL-multi’ refers to using pretrained mBART-ML501N, and finetuning on CoVoST multilingual corpora.

Table 4. Convolution Adaptor Ablation on en-de with vox wav2vec, finetuning wav2vec self-attention + layer norm, and mBART decoder encoder-attention + layer norm with lr=0.0001

5. RELATED WORK

5.1. Speech Translation

Sequence to sequence based speech translation has shown very good potential over the traditional cascaded system [19, 20, 21], however previous work also indicates its success heavily relies on large amounts of labelled training data, which difficult to acquire. In order to mitigate the data scarcity issue, recent research work focuses on multi-task learning [21, 22, 23, 24, 25, 26], pre-training different components of the model [27, 28], transfer learning [29, 30] and generating synthetic data [31]. These methods aim to use weakly supervised data, i.e. speech-to-transcription or text-to-translation pairs in addition to fully supervised data, i.e. speech-to-translation pairs.

5.2. Self-supervised Pre-Training

This work is partially motivated by the recent success of self-supervised learning for NLP and speech processing applications [5, 2, 32, 33, 34, 35, 3, 13, 36, 37, 38, 7]. Masked language modeling [2] is adopted to sequence to sequence framework [33, 35] and widely used as pre-training methods for multilingual translation task [3, 13]. Contrastive Predictive coding [39] is thriving for speech pre-training and has demonstrated its effectiveness on low resource ASR [36, 7]. Initial results from [40] have shown the effectiveness of the speech self-supervised pre-training [41] for end-to-end ST. In this work, we focus on combining pre-trained components from different modalities (text and speech) and applies them to the ST task. Our work is closely related to [18] which proposed a recipe for adapting pretrained BART or mBART for (text-only) machine translation.

6. CONCLUSION

We propose a simple and effective approach to achieve cross-modal cross-lingual transfer learning that leverages unpaired audio data and multilingual text data. Our approach obtains state-of-the-art results on speech-to-text translation on 19 languages from the CoVoST 2 benchmark. We provide empirical analysis for two key ingredients of the proposed approach, adaptive fine-tuning and encoder-decoder adaptor.
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