End-to-end Speech Translation via Cross-modal Progressive Training

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Abstract

End-to-end speech translation models have become a new trend in research due to their potential of reducing error propagation. However, these models still suffer from the challenge of data scarcity. How to effectively use unlabeled or other parallel corpora from machine translation is promising but still an open problem. In this paper, we propose Cross Speech-Text Network (XSTNet), an end-to-end model for speech-to-text translation. XSTNet takes both speech and text as input and outputs both transcription and translation text. The model benefits from its three key design aspects: a self-supervised pre-trained sub-network as the audio encoder, a multi-task training objective to exploit additional parallel bilingual textual and a progressive training procedure. We evaluate the performance of XSTNet and baselines on the MuST-C En-X and LibriSpeech datasets. In particular, XSTNet achieves state-of-the-art results on all language directions with an average BLEU of 28.8, outperforming the previous best method by 3.2 BLEU. Code, models, cases, and more detailed analysis are available at https://github.com/ReneeYe/XSTNet.

1. Introduction

Speech-to-text translation (ST) has found increasing applications. It takes speech audio signals as input and outputs text translations in the target language. Recent work on ST has focused on unified end-to-end neural models with the aim to supersede pipeline approaches combining automatic speech recognition (ASR) and machine translation (MT). However, training end-to-end ST models is challenging - there is limited parallel speech-text data. For example, there are only a few hundreds hours for English-German in MuST-C corpus. Existing approaches to this problem can be grouped into two categories: a) multi-task supervision with the speech-transcript-translation triple data [1, 2]; b) pre-training with external large-scale MT parallel text data [3, 4, 5, 6].

We notice that the triple data can decompose into three sub-tasks with parallel supervision, ST, ASR, and MT. This motivates us to design a multi-task model.

In this paper, we designed Cross Speech-Text Network (XSTNet) for end-to-end ST to joint train ST, ASR and MT tasks. XSTNet supports either audio or text input and shares a Transformer [7] module. To bridge the gap between the audio and text modality, we use a self-supervised trained Wav2vec2.0 representation of the audio [8], which provides a more compressed and contextual representation than the log-Mel filter bank feature. Furthermore, our method is able to incorporate external large-scale MT data. Finally, to support the training of XSTNet, we carefully devise the progressive multi-task learning strategy, a multi-stage procedure following the popular pre-training and fine-tuning paradigm.

Despite the model’s simplicity, the experimental results on MuST-C and Augment LibriSpeech datasets improved by a big margin (+3.2 BLEU) against the previous SOTA method.

2. Related Work

End-to-end ST [9] gave the first proof of the potential for end-to-end ST without using the intermediate transcription. And recent Seq2Seq models have received impressive results [10, 11, 12, 13]. Techniques, such as pre-training [4, 5, 14, 3], multi-task learning [15, 2], self-training [16] and meta-learning [1] have further improved the performance of end-to-end ST models. Very recently, [6] proposed a Fused Acoustic and Text Masked Language Model to pre-train and improved ST by fine-tuning.

Self-supervised Pretraining This work is partially motivated by the recent success of self-supervised contrastive learning for speech [17, 18, 8]. These representations have been shown to be effective in low-resource ASR [9]. ST [19, 20] and multi-lingual ST [21]. Recently, many audio-related tasks have demonstrated the feasibility and outstanding performance by using the wav2vec2.0 representation [22, 23]. Maybe the most related work is [21]. However, our work focuses more on the training strategy, while theirs focused on incorporating two pre-trained modules to strengthen the multi-lingual ST.

3. Proposed Method: XSTNet

3.1. Problem Formulation

The speech translation corpus contains speech-transcript-translation triples $D = \{(s, x, y)\}$, where $s = (s_1, \ldots, s_{|s|})$ is the input sequence of the audio wave (or the acoustic features), $x = (x_1, \ldots, x_{|x|})$ is the transcript from the source language, and $y = (y_1, \ldots, y_{|y|})$ represents the corresponding translation in the target language. Despite the fact that transcripts are provided during training, the end-to-end speech translation models directly produce the translation very without producing the transcript as an intermediate output. As a result, understanding how to leverage ancillary transcript supervision and make the most of the triple-supervised dataset is critical. The triple-supervised dataset can be pairwise combined into three parallel-supervised sub-datasets, $D_{ASR} = \{(s, x)\}$, $D_{ST} = \{(s, y)\}$ and $D_{MT} = \{(x, y)\}$, which solve ASR, end-to-end ST and MT respectively.

We also introduce external MT dataset $D_{MT-ext} = \{(x', y')\}$. The amount of external MT corpus is much larger than the ST corpus, i.e. $|D_{MT-ext}| \gg |D|$.

3.2. Speech Encoder

The first part of XSTNet is Wav2vec2.0 sub-network to process speech data in waveform. Wav2vec2.0 [8] is a model to learn the contextualized speech representation from unlabelled audio data. It consists of a multi-layer convolutional feature encoder and a Transformer-based context encoder. The multi-layer convolutional encoder takes the raw audio signal as input and outputs the latent speech representation, which is then used by the Transformer encoder to output the contextual representation. The self-supervised pre-trained contextual audio
We adopt the standard Transformer-base model \cite{7} to accomplish our task. We use different indicators [src\_tag] to distinguish the three tasks and audio/text inputs. The input embedding e (either audio or text) is fed into the Transformer encoder. Specifically, for the audio input, we add extra [audio] token with embedding $e_{audio} \in \mathbb{R}^d$, and the embedding of the audio $e \in \mathbb{R}^{d \times T/4}$ is the concatenation of $e_{audio}$ and $e_s$ in terms of the sequence length.

For the text input, we put the language id symbol before the sentence. For example, the embedding of English sentence “This is a book.” is the embedding of “[en] This is a book.”.

When decoding, the language id symbol serves as the initial token to predict the output text. For example, if the audio input for sentence “This is a book.” is in English, to do ASR, we use [en] as the BOS and decode “[en] This is a book.”, while to translate into French, we use [fr] as the BOS and decode “[fr] c’est un livre.”.

### 3.4. Progressive Multi-task Training

The progressive multi-task training strategy consists of two stages, large-scale MT pre-training with external parallel text and multi-task fine-tuning.

\begin{algorithm}
\caption{Progressive Multi-task Training for XSTNet}
\begin{algorithmic}[1]
\Require Tasks $T = \{ST, ASR, MT, MT\text{-ext}\}$
\State Initialize the speech module parameters in $\theta$ using \text{wav2vec2.0}-base, and the rest at random.
\State MT pre-training: optimize Eq \eqref{eq:mmi} on $D_{MT\text{-ext}}$.
\State \While {not converged}
\State \hspace{1em} \textbf{Step 1:} random select a task $\tau$ from $T$.
\State \hspace{1em} \textbf{Step 2:} sample a batch of $(x, y)$ from $D_{\tau}$, and optimize the cross entropy loss defined in Eq \eqref{eq:mt}
\EndWhile
\State \label{alg:progressive}
\end{algorithmic}
\end{algorithm}

#### Large-scale MT Pre-training

We first pre-train the transformer encoder-decoder module using external MT data $D_{MT\text{-ext}}$.

$$
\mathcal{L}(\theta) = - \mathbb{E}_{x, y \in D_{MT\text{-ext}}} \log P(y|x; \theta) \quad (1)
$$

where $\theta$ is the model parameters. Experimental results show that the MT pre-training provide a good warm-up for the shared transformer module.

#### Multi-task Fine-tuning

During the fine-tuning, we combine external MT, ST, and AR, and MT parallel data from the in-domain speech translation dataset and jointly optimize the negative log-likelihood loss.

$$
\mathcal{L}(\theta) = - \mathbb{E}_{x, y \in D_{ST} \cup D_{ASR} \cup D_{MT}} \log P(y|x; \theta) \quad (2)
$$

where $D = D_{ST} \cup D_{ASR} \cup D_{MT}$ is the union set of all the parallel subsets (the same notation hereinafter).

The overall training process is shown in Algorithm 1. It is progressive, because the external MT data, used in the pre-training stage, is continuously used in the fine-tuning stage. In Section 5, we will show that the training procedure largely influences the translation performance, and the progressive multi-task training process is the most effective. In the experiment, we use Adam optimizer \cite{25} with learning rate $= 2 \times 10^{-4}$ and warm-up 25k steps.

### 4. Experiments

#### 4.1. Datasets

**ST datasets** We conduct experiments on MuST-C \cite{26} and Augmented LibriSpeech En-Fr (LibriTrans) \cite{27} datasets. MuST-C contains English speech to 8 languages: German (De), Spanish (Es), French (Fr), Italian (It), Dutch (Nl), Portuguese (Pt), Romanian (Ro), and Russian (Ru). We evaluate the BLEU scores on tst-COMMON of MuST-C and the test set of LibriTrans.

**MT datasets** We use external WMT machine translation datasets \cite{28} for En-De/Es/Fr/Ro/Ru directions, and OPUS100 \cite{29} for En-It/Nl/Pl directions. We also introduce OpenSubtitles \cite{30} for En-De.

#### 4.2. Experimental Setups

We jointly tokenize the bilingual text (En and X) using subword units with a vocabulary size of 10k, learned from SentencePiece \cite{14}. The model configurations have been stated in Section 3.2 and 3.3. We save the checkpoint with the best BLEU

\begin{itemize}
\item [https://www.statmt.org/wmt16/translation-task.html]
\item [http://opus.nlpl.eu/opus-100.php]
\item [https://opus.nlpl.eu/OpenSubtitles-v2018.php]
\item [https://github.com/google/sentencepiece]
\end{itemize}
4.3. Main Results

We compared our method with other strong end-to-end baseline models, including Transformer ST [13], AFS [31], Dual-decoder Transformer [15], STAST [33], Tang et al. [2], Curriculum [4], LUT [32], and FAT-MLM [6]. These baselines all take the 80-channel log Mel-filter bank feature (fbank80) as the audio inputs. We also implement wav2vec2+transformer model (abbreviated W-Transf.) with the same configuration as XSTNet. XSTNet (Base) is only trained based on MuST-C by optimizing $L = -E_{x,y \in D} \log P(y|x)$. XSTNet (Expand) uses external WMT data and follows the progressive multi-task training method described in Section 3.4.

Table 2 and Table 2 respectively show the BLEU scores of MuST-C and LibriTrans datasets. Compared to the current speech transformer, which acts as a solid baseline for ST, our method achieves a remarkable +3.9 BLEU gain on average. We attribute the gain to the following factors:

### Wav2vec2.0 vs. Fbank
Comparing the models using the fbank80 feature with the ones applying wav2vec2, we find that even the simplest structure (W-Transf.) without ASR pre-training outperforms the Transformer ST baseline. This indicates the potential of wav2vec2.0 representation.

### Multi-task vs. ST-only
Comparing XSTNet (Base) and W-Transf., we find that the translation performance improved by around +2 BLEU in all directions. This demonstrates that our model can make the most of the triple-supervised data by applying the multi-task paradigm.

### Additional MT data
Since XSTNet accepts text input, it is easy to introduce additional MT parallel data. XSTNet (Expand) attributes an average of +1.3 BLEU improvement against XSTNet-Base from the additional MT data and the training procedure described in Section 3.4.

4.4. Results on Auxiliary MT and ASR Tasks

XSTNet can perform MT and ASR tasks provided different input modalities and target language indicators. The performance of auxiliary MT and ASR (measured in WER) tasks are shown in Table 5 and Table 6. Our XSTNet with progressive training is better than other training strategies in both tasks. Comparing Row “I” and “IV” in Table 5, it is worth noting that adding speech-to-text data improves MT performance even further. We attributed the improvement to the information from the speech.

5. Analysis

5.1. The Influence of Training Procedure

In this section, we investigate the impact of the training strategy. We perform six groups of experiments with different pre-train
| #Exp. | Pretrain | Finetune | En-De | En-Fr | En-Ru | Avg. |
|-------|----------|----------|-------|-------|-------|------|
| MT    |          | D_MT-ext | D∪D_MT | 27.12 | 38.01 | 18.36 | 27.8 |
| II    | D_MT-ext | D        | 26.99 | 37.37 | 18.03 | 27.5 (-0.3) |
| III   | -        | D∪D_MT   | 26.28 | 36.15 | 17.33 | 26.6 (-1.2) |
| ST-only|          | D_MT-ext | D_MT→D_SR∪D_MT→D_MT-ext | 26.96 | 35.42 | 17.87 | 26.6 (-1.2) |
| IV    | D_MT-ext | D_SR→D_MT→D_MT-ext | 25.86 | 34.44 | 16.94 | 25.6 (-2.2) |
| V     | D_MT-ext | D_SR→D_MT→D_SR→D_MT→D_MT-ext | 24.32 | 35.30 | 17.50 | 25.7 (-2.1) |

Table 5: The ablation study results on the pre-train and fine-tuning strategies, where $D = D_{ST} \cup D_{ASR} \cup D_{MT}$, and Exp.I uses the training strategy described in Section 3.4. Experiments are preformed on MuST-C En-De, En-Fr and En-Ru datasets.

| Models | ST-only | MT-only |
|--------|---------|---------|
| Cascaded | Expnet [12] | 23.6 | 33.8 | 16.4 |
|         | Our implement* | 25.2 | 34.9 | 17.0 |
| End-to-end | XSTNet | 27.1 | 38.0 | 18.4 |

Table 6: XSTNet versus the cascaded models on MuST-C En-De, En-Fr and En-Ru test sets. *Our implement* is a strong cascaded model composed of W-Transf. as ASR and Transformer-base trained on $D_{ASR} \cup D_{ASR}$ as MT.

and fine-tune strategies, categorizing into two groups according to the different fine-tuning tasks - multi-task fine-tuning (Exp. I, II and III) and ST-only fine-tuning (Exp. IV, V and VI). The multi-task fine-tuning incorporates ST, ASR and MT tasks using MuST-C dataset $D (= D_{ST} \cup D_{ASR} \cup D_{MT})$ and optional $D_{MT}$.

MT pretraining is effective. Comparing Exp.I and III, we find that canceling the pre-training using external WMT reduces the average performance by 1.2 BLEU. Furthermore, the results of Exp. III are inferior to those of Exp. II. These findings suggest that MT pre-training provides a strong initialization for the model, leading it to perform better.

Don’t stop training the data in the previous stage. An interesting discovery is that data used in the previous training stage can also be helpful in the subsequent training stage. In other words, progressive training works. Concretely, we can see from Exp. I vs. III and Exp. IV vs. V that the BLEUs decrease as we stop using the WMT data at the fine-tuning period.

Multi-task fine-tuning is preferred. Comparing the BLEU results in the multi-task and ST-only groups, the models trained from multi-task perform better than the models trained by ST-only tasks.

5.2. Convergence Analysis

Figure 2 depicts the evolution of the BLEU score over time steps for different training methods on the MuST-C En-De dev-set.

Progressive multi-task training converges faster. With WMT pre-trained parameters for the Transformer module, XSTNet-Expand with progressive multi-task training (red line) is found to converge faster than the model without pre-training.

Multi-task training generalizes better. Due to the small data scale, the model is tend to overfit the training set if it is trained only based on audio-translation parallel data. However, by adopting a multi-task framework, the model is more robust and has a better generalization ability.

6. Conclusion

We propose Cross Speech-Text Network (XSTNet), an extremely concise model which can accept bi-modal inputs and jointly train ST, ASR and MT tasks. We also devise progressive multi-task training algorithm for the model. As compared to the SOTA models, XSTNet can achieve a significant improvement on the speech-to-text translation task.
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