Abstract

End-to-end speech-to-text translation (ST), which directly translates the source language speech to the target language text, has attracted intensive attention recently. However, the combination of speech recognition and machine translation in a single model poses a heavy burden on the direct cross-modal cross-lingual mapping. To reduce the learning difficulty, we propose SDST, an integral framework with successive decoding for end-to-end speech-to-text translation task. This method is verified in two mainstream datasets. Experiments show that our proposed SDST improves the previous state-of-the-art methods by big margins.

1 Introduction

Speech translation (ST) aims at translating from source language speech into the target language text. Traditionally, it is realized by cascading an automatic speech recognition (ASR) and a machine translation (MT) (Sperber et al., 2017a, 2019b; Zhang et al., 2019; Beck et al., 2019; Cheng et al., 2019). Recently, end-to-end ST has attracted much attention due to its appealing properties, such as lower latency, smaller model size, and less error accumulation (Liu et al., 2019a, 2018; Weiss et al., 2017; Bérard et al., 2018; Duong et al., 2016; Jia et al., 2019).

Although end-to-end systems are very promising, cascaded systems still dominate practical deployment in industry. The possible reasons are: a) Most research work compared cascaded and end-to-end models under identical data situations. However, in practice, the cascaded system can benefit from the accumulating independent speech recognition or machine translation data, while the end-to-end system still suffers from the lack of end-to-end corpora. b) Despite the advantage of reducing error accumulation, the end-to-end system has to integrate multiple complex deep learning tasks into a single model to solve the task, which introduces heavy burden for the cross-modal and cross-lingual mapping. Therefore, it is still an open problem whether end-to-end models or cascaded models are generally stronger.

It is argued that a desirable ST model should take advantages of both end-to-end and cascaded models and acquire the practically acceptable capabilities as follows: a) it should be end-to-end to avoid error accumulation; b) it should be flexible enough to leverage large-scale independent ASR or MT data. At present, few existing end-to-end models can meet all these goals. Most studies resort to pretraining or multitask learning to bridge the benefits of cascaded and end-to-end models (Bansal et al., 2018; Sung et al., 2019; Sperber et al., 2019a). A de-facto framework usually initializes the ST model with the encoder trained from ASR data (i.e. source audio and source text pairs) and then fine-tuned on a speech translation dataset to make the cross-lingual translation. However, it is still challenging for these methods to leverage the bilingual MT data, due to the lack of intermediate text translating stage.

Our idea is motivated by two motivating insights from ASR and MT models. a) An ASR model has intermediate steps to extract acoustic feature and decode phonemes, before emitting transcription; and b) Speech translation can be beneficial by decoding the source speech transcription in addition to the target translation text. We propose a unified speech translation framework with successive decoding for jointly modeling speech recognition and translation consisting of two phases, a source-acoustic modeling phase (SA) and a transcription-translation modeling phase (TT). The SA phase accepts the speech features and generates compressed acoustic representations. For TT phases,
we jointly model both the source and target text in a shared successive decoder, which directly decodes the speech text sequence and the translation sequence at one pass. This architecture is closer to cascaded translation while maintaining the benefits of end-to-end models. The combination of the SA and the first-part output of the TT phase serves as an ASR model; the TT phase along serves as an MT model; while the whole makes an end-to-end speech translation by ignoring the first-part of TT output. Simple and effective, SDST is powerful enough to cover the advantage of ASR, MT, and ST models simultaneously.

The contributions of this paper are as follows: 1) We propose SDST, a unified training framework with successive decoding which bridges the benefits of both cascaded and end-to-end models. 2) As a benefit of explicit multi-phase modeling, SDST facilitates the use of parallel bilingual text corpus, which is difficult for traditional end-to-end ST models. 3) SDST achieves state-of-the-art results on two popular benchmark datasets. We will make the model and code publicly available.

2 Related Works

For speech translation, there are two main research paradigms, the end-to-end model and the cascaded system (Sperber and Paulik, 2020; Jan et al., 2018; nie, 2019).

End-to-end ST Previous works (Bérard et al., 2016; Duong et al., 2016) have given the first proof of the potential for end-to-end speech-to-text translation, which has attracted intensive attentions recently (Vila et al., 2018; Salesky et al., 2018, 2019b; Di Gangi et al., 2019a; Bahar et al., 2019a; Di Gangi et al., 2019b; Inaguma et al., 2020). Many works have proved that pre-training then transferring (Weiss et al., 2017; Bérard et al., 2018; Bansal et al., 2018; Stoian et al., 2020) and multi-task learning (Vydana et al., 2020) can significantly improve the performance of end-to-end models. The two-pass decoding (Sung et al., 2019) and attention-passing (Anastasopoulos and Chang, 2018; Sperber et al., 2019a) techniques are proposed to handle the relatively deeper relationships and alleviate error propagation in end-to-end models. Many data augmentation techniques (Jia et al., 2019; Pino et al., 2019b; Bahar et al., 2019b; Pino et al., 2019a) are proposed to utilize external ASR and MT corpora. Many semi-supervised training (Wang et al., 2019) methods bring great gain to end-to-end models, such as knowledge distillation (Liu et al., 2019a), modality agnostic meta-learning (Indurthi et al., 2019), model adaptation (Di Gangi et al., 2020) and so on. Curriculum learning (Kano et al., 2018; Wang et al., 2020) is proposed to improve performance of ST models. Liu et al. (2019b, 2020) optimize the decoding strategy to achieve low-latency end-to-end speech translation. (Chuang et al., 2020; Salesky and Black, 2020; Salesky et al., 2019a) explore additional features to enhance end-to-end models.

Cascaded ST The most concerned point is how to avoid early decisions, relieve error propagation and better integrate the separately trained ASR and MT modules. To avoid early decisions over transcripts, previous works (Vidal, 1997; Bangalore and Riccardi, 2001; Casacuberta et al., 2004; Pérez et al., 2007) approximate the full integration up to search heuristics with Finite State Transducer (FST) based combination and computation. Woszczyna et al. (1993); Lavie et al. (1996) propose the more simpler \( n \)-best translation approach replacing the sum over all possible transcripts by a sum over only the \( n \)-best transcripts. Lattices and confusion nets (Schultz et al., 2004; Zhang et al., 2005; Bertoldi and Federico, 2005; Matusov et al., 2005, 2008; Sperber et al., 2017a, 2019b; Zhang et al., 2019; Beck et al., 2019) are introduced by follow-up works as more effective and efficient alternatives to solving \( n \)-best lists. To relieve the problem of error propagation and tighter couple cascaded systems: a) robust translation models (Dixon et al., 2011; He et al., 2011; Peitz et al., 2012; Tsvetkov et al., 2014; Ruiz et al., 2015; Sperber et al., 2017b; Cheng et al., 2018, 2019) introduce synthetic ASR errors and ASR related features into the source side of MT corpora. b) Techniques such as domain adaptation (Liu et al., 2003; Fügen, 2008), re-segmention (Matusov et al., 2006), punctuation restoration (Fügen, 2008), disfluency detection (Fitzgerald et al., 2009) and so on, are proposed to provide the translation model with well-formed and domain matched text inputs.

3 Methodology

3.1 Overview

The detailed framework of our method is shown in Figure 1. To be specific, the end-to-end model accepts the original audio feature as input and outputs the target text sequence. We divide our method into two phases, including the source-acoustic mod-
eling phase (SA) and the transcription-translation modeling phase (TT). Firstly, the SA phase accepts the speech features, outputs the acoustic representation, and predicts the acoustic modeling units. In this work, the small-grained unit, phonemes are selected as the acoustic modeling unit. Then, the TT phase accepts the acoustic representation and successively outputs source transcription and target translation text sequences with a shared and successive decoder.

**Problem Formulation** The speech translation corpus usually contains speech-transcription-translation triples. We add phoneme sequences to make up quadruples, denoted as $S = \{(x, u, z, y)\}$ (More details about the data preparation can be seen in Section 4). Specially, $x = (x_1, ..., x_{T_x})$ is a sequence of acoustic features. $u = (u_1, ..., u_{T_u})$, $z = (z_1, ..., z_{T_z})$, and $y = (y_1, ..., y_{T_y})$ represents the corresponding phoneme sequence in source language, transcription in source language and the translation in target language respectively. Meanwhile, $\mathcal{A} = \{(z', y')\}$ represents the external text translation corpus, which can be utilized for pre-training the decoder. Usually, the amount of end-to-end speech translation corpus is much smaller than that of text translation, i.e. $|S| \ll |\mathcal{A}|$.

**3.2 Source-Acoustic Modeling**

The source-acoustic modeling phase takes the input of low-level audio features $x$ and outputs a series of vectors $\hat{h}_{SA}$ corresponding to the phoneme sequence $u$ in the source language. Different from the general sequence-to-sequence models, two modifications are introduced. Firstly, in order to preserve more acoustic information, we introduce the supervision signal of the connectionist temporal classification (CTC) loss function, a scalable, end-to-end approach to monotonic sequence transduction (Graves et al., 2006; Salazar et al., 2019). Secondly, since the length of audio features is much larger than that of source transcription ($T_x \gg T_u$), we introduce a shrinking method which can skip the blank-dominated steps to reduce the encoder length.

**Self-Attention with CTC** General pre-processing includes down-sampling and linear layers. Down-sampling refers to the dimensionality reduction processing of the input audio features in the time and frequency domains. In order to simplify the network, we adopt physical dimensionality reduction, that is, a method of sampling one frame every three frames. The linear layer maps the length of the frequency domain feature of the audio feature to the preset network hidden layer size. After pre-processing, multiple layers of self-attention modules are stacked for feature extraction.

$$\hat{h}_{SA} = \text{Attention}(\text{Linear}(\text{Down-sample}(x)))$$

(1)

Finally, the softmax operator is applied to the result of the affine transformation to obtain the probability of the phoneme sequence. CTC loss is adopted to accelerate the convergence of acoustic modeling.

CTC assumes $T_u \leq T_x$, and defines an intermediate alphabet $\mathcal{Y}' = \mathcal{V} \cup \{\text{blank}\}$. A path $\pi$ is defined as a $T_x$-length sequence of intermediate labels $\pi = (\pi_1, ..., \pi_{T_x}) \in \mathcal{V}^{T_x}$. And a many-to-one mapping is defined from paths to output sequences...
by removing blank symbols and consecutively repeated labels.

The conditional probability of a given labelling \( u \in \mathcal{Y}^{T_x} \) can be modeled by marginalizing over all paths corresponding to it:

\[
\log p_{ctc}(u|x) = \log \sum_{\pi \in \mathcal{B}^{-1}(u)} p(\pi | h_{SA})
\]

\[
= \log \sum_{\pi \in \mathcal{B}^{-1}} \sum_{t'} p(\pi_{t'}, t'|h_{SA})
\]

(2)

The distribution over the set \( \mathcal{Y}^{T_x} \) of path \( \pi \) is defined by the probability of a sequence of conditionally-independent outputs, which can be calculated non-autoregressively. And \( p(\pi_{t'}, t'|S) \) is computed by applying the softmax function to logits. Finally, the objective training function during SA phase is defined as:

\[
\mathcal{L}_{SA} = -\log p_{ctc}(u|x)
\]

(3)

**Acoustic Unit Shrinking**  The shrinking layer aims at reducing the potential blank frames, and repeated frames. The details can be seen in the sub-figure of the lower left of Figure 1.

The method is mainly founded on the studies of Chen et al. (2016); Yi et al. (2019). We adopt the implementation by removing the blank frames and averaging the repeated frames. Without the interruption of blank and repeated frames, the language modeling ability would be better in theory. Blank frames can be detected according to the spike characteristics of CTC probability distribution.

\[
h'_{SA} = \text{Shrink}(\hat{h}_{SA}, p_{ctc}(u|x))
\]

(4)

Then, similarly, after shrinking, multiple attention layers are stacked to extract higher-level semantic representations and result in the final output \( h_{SA} \).

\[
h_{SA} = \text{Attention}(h'_{SA})
\]

(5)

**3.3 Transcription-Translation Modeling**

We jointly model the transcription and translation generation in a successive and shared decoder, which takes the acoustic representation \( h_{SA} \) as the input and generates the source text \( z \) and target text \( y \). This TT phase is stacked with \( T \) transformer blocks, consisting of multi-head attention layers and feed-forward networks.

\[
h_{TT} = \text{Transformer}([z, y], h_{SA})
\]

(6)

As shown in Figure 1, the decoder output is the tandem result of the transcription and translation sequences, joined by the task identifier token (“<asr>” for recognition and “<st>” for translation), marked as \([z, y]\). That is to say, the model is able to continuously predict the transcription sequence and the translation sequence. The training objective of the TT phase is the cross entropy between prediction sequence and target sequence.

\[
\mathcal{L}_{TT} = -\log p([z, y]|x)
\]

(7)

Compared with the multi-task learning method, successive decoding can do prediction from easy (transcription) to hard (translation), alleviating the decoding pressure. For example, when predicting the translation sequence, since the corresponding transliteration sequence has been decoded, that is, the intermediate recognition result of the known speech translation, the source of information for decoding the translation sequence can be improved.

**Pre-train the Successive Decoder**  Generally, it is straightforward to use ASR corpus to improve the performance of end-to-end ST, but is non-trivial to utilize MT corpus. Taking advantage of the structure of successive decoding, we propose a method to enhance the performance of end-to-end ST by means of external MT paired data. Inspired by translation language modeling (TLM) in XLM (Lample and Conneau, 2019), we use a masked loss function to pre-train TT phase. Specifically, we use external data in \( A \) to pre-train the parameters of the TT part. Different from the end-to-end training stage, there is no audio feature as input during pre-training, so cross-attention cannot attend to the output of the previous phase. We use an all-zero constant, marked as \( h_{SA}^{\text{blank}} \) to substitute the encoded representations (\( h_{SA} \)) from TT phase to be consistent with fine-tuning. When calculating the objective function, we mask the loss for prediction of the recognition result, and make the decoder predicts the translation sequence when aware of the input of the transcription sequence. The translation loss of the TT phase during pre-training only includes the masked cross entropy:

\[
\mathcal{L}_{TT_{PT}} = -\sum_{i=1}^{T_y} \log p(y_i|z, y_{<i})
\]

(8)
transcription
you must make a dream whirl around the bride
translation
il faudrait faire tourbillonner un songe autour de l' pouse

Table 1: An example of the speech-phoneme-transcription-translation quadruples. Phonemes can be converted from the transcription text.

\[ L = \alpha L_{SA} + (1 - \alpha) L_{TT} \]  

where \( \alpha \) is a tunable parameter to balance the objectives of different phases.

4 Experiments

4.1 Dataset and Preprocessing

We conduct experiments on two popular publicly available datasets, including Augmented LibriSpeech English-French dataset (Kocabiyikoglu et al., 2018) and English-German TED dataset (Jan et al., 2018).

Augmented LibriSpeech Dataset

Augmented LibriSpeech is built by automatically aligning e-books in French with English utterances of LibriSpeech. The dataset includes quadruplets: source audio files in English, transcriptions in English, translations in French from the alignment of e-books, and augmented translation references via Google Translate. Following the previous work (Liu et al., 2019a), we also experiment on the 100 hours clean train set for training, with 2 hours development set and 4 hours test set, corresponding to 47271, 1071, and 2048 utterances respectively.

English-German TED Dataset

English-German TED is the KIT end-to-end speech translation corpus, which is built by automatically aligning English audios with SRT transcripts for English and German from TED. The raw data, including long wave files, English transcriptions, and the corresponding German translations, are segmented with time stamps and made forced alignments using the gentle tool kit\(^1\), according to the officially released version. We utilize the attached timestamps to segment a raw long audio into chunks and remove samples missing the target language translation. It should be noted that some transcriptions are not aligned with the corresponding audio well. Noisy data is harmful to models’ performance, which can be avoided by data filtering, re-alignment and re-segmentation (Liu et al., 2018). In this paper, we directly use the original data as training data to verify our method, with a size of 272 hours and 171121 segmentations. We use dev2010 as validation set, and tst2010, tst2013, tst2014, tst2015 as test set, corresponding to 653, 1337, 793, 957 and 1177 utterances respectively.

WMT14 MT Corpus

We use WMT14\(^2\) English-to-French and English-to-German training data as the external MT parallel corpus (\( \in \mathcal{A} \)) in the expanded experimental setting for broad reproducibility. We pre-processed all of the data of specific language pairs, and filtered sentence pairs whose total length exceeds 500. We shuffled the data and randomly selected a subset of 1 million for the following experiments and analysis.

4.2 Experimental Setup

Our acoustic features are 80-dimensional log-Mel filter banks extracted with a step size of 10ms and window size of 25ms and extended with mean subtraction and variance normalization. The features are stacked with 5 frames to the right. For text data, we lower case all the texts, tokenize and apply normalize punctuations with the Moses scripts\(^3\). For English-Germans source language text data, we remove the punctuation to make the data more consistent with the output of ASR. We apply BPE\(^4\) (Sennrich et al., 2015) to the combination of source and target text to obtain shared subword units. The number of merge operations in BPE is set to \(8k\) for both datasets. In order to simplify, we use the open-source grapheme to phoneme tool\(^5\) to map the transcription to the phoneme sequence (An example in Table 1). The alphabet of labels \(V\) includes the union of sub-word vocabulary and phoneme vocabulary, plus a few special symbols (including

---

\(^1\)https://github.com/lowerquality/gentle
\(^2\)https://www.statmt.org/wmt14/translation-task.html
\(^3\)https://github.com/moses-smt/mosesdecoder
\(^4\)https://github.com/rsennrich/subword-nmt
\(^5\)https://github.com/Kyubyong/g2p
Table 2: Performance for MT, ST tasks on Augmented Librispeech English-French test set. Our proposed SDST achieves the best results in both base and expanded settings.

| Method                                           | Enc Pre-train (speech data) | Dec Pre-train (text data) | BLEU   |
|--------------------------------------------------|-----------------------------|---------------------------|--------|
| **MT system**                                    |                             |                           | 21.51  |
| Transformer MT                                   | -                           | -                         |        |
| **Base setting**                                 |                             |                           |        |
| LSTM ST (Bérard et al., 2018)                    | 12.90                       |                           |        |
| +pre-train+multitask (Bérard et al., 2018)       | ✓                           | ✓                         | 13.40  |
| LSTM ST+pre-train (Inaguma et al., 2020)         | ✓                           | ✓                         | 16.68  |
| Transformer+pre-train (Liu et al., 2019a)        | ✓                           | ✓                         | 14.30  |
| +knowledge distillation (Liu et al., 2019a)      | ✓                           | ✓                         | 17.02  |
| TCEN-LSTM (Wang et al., 2019)                    | ✓                           | ✓                         | 17.05  |
| Transformer+ASR pre-train (Wang et al., 2020)    | ✓                           | ✓                         | 15.97  |
| +curriculum pre-train (Wang et al., 2020)        | ✓                           | ✓                         | 17.66  |
| SDST (ours)                                      |                             |                           | **17.83** |
| **Expanded setting**                             |                             |                           |        |
| LSTM+pre-train+SpecAugment (Bahar et al., 2019b) | ✓(236h)                     | ✓                         | 17.00  |
| Multi-task+pre-train (Inaguma et al., 2019)      | ✓(472h)                     |                           | 16.70  |
| Transformer+ASR pre-train (Wang et al., 2020)    | ✓(960h)                     |                           | 16.90  |
| +curriculum pre-train (Wang et al., 2020)        | ✓(960h)                     |                           | 18.01  |
| SDST (ours)                                      | ✓(100h)                     | ✓(1M)                     | **18.23** |

The maximum decoding length is set to 500 for our models with successive decoding and 250 for other methods on both datasets. $\alpha$ in Equation 9 is set to 0.5 for both datasets (We have searched the value of $\alpha$ using a step of 0.2.). We design different work flows (see Section 5.3) for our method training from scratch and training with pre-training the successive decoder.

5 Results

5.1 Baselines

We compare with systems in different settings:

**Base setting:** ST models are trained with only end-to-end ST corpus.

**Expanded setting:** ST models are trained with end-to-end ST corpus augmented with external ASR and MT corpus.

In the context of expanded setting, Bahar et al. (2019b) apply the SpecAugment (Park et al., 2019) with a total of 236h of speech for ASR pre-training. Inaguma et al. (2019) combine three ST datasets of 472h training data to train a multilingual ST model. Wang et al., 2019 introduce an additional 272h ASR corpus and 41M parallel data from WMT18 to enhance the ST.

**MT system:** Text translation models are trained with manual transcribed transcription-translation pairs, which can be regarded as the upper bound of speech translation tasks.
5.2 Main Results

| Method               | Enc Pre-train (speech data) | Dec Pre-train (text data) | tst2010 | tst2013 | tst2014 | tst2015 | Avg |
|----------------------|-----------------------------|---------------------------|---------|---------|---------|---------|-----|
| **MT system**        |                             |                           |         |         |         |         |     |
| Transformer MT       | -                           | -                         | 25.72   | 27.87   | 22.23   | 23.58   | 24.85 |
| **Base setting**     |                             |                           |         |         |         |         |     |
| ESPnet (Inaguma et al., 2020) |                   | 13.77                     | 12.50   | 11.50   | 12.68   | 12.61   |     |
| +enc pre-train       | ✓                           |                           | 14.46   | 13.12   | 11.62   | 11.30   | 12.63 |
| +enc dec pre-train   | ✓                           | ✓                         | 14.98   | 13.54   | 12.33   | 11.67   | 13.13 |
| Transformer+ASR pre-train (Wang et al., 2020) | ✓                            |                           | 15.35   | -       | -       | -       |     |
| +curriculum pre-train (Wang et al., 2020) | ✓                            |                           | 16.27   | -       | -       | -       |     |
| SDST (ours)          |                             |                           | 19.54   | 16.30   | 14.53   | 14.62   | 16.70 |
| **Expanded setting** |                             |                           |         |         |         |         |     |
| Multi-task (Inaguma et al., 2019) | ✓                          | ✓                         | 14.60   | -       | -       | -       |     |
| TCEN-LSTM (Wang et al., 2019) | ✓                          | ✓                         | 17.61   | 17.67   | 15.73   | 14.94   | 16.49 |
| SDST (ours)          | ✓                          |                           | 18.15   | -       | -       | -       |     |

Table 3: Performance (BLEU) for MT, ST tasks on English-German TED test sets. *: re-implemented by Wang et al. (2020). Our proposed SDST consistently achieves the best performance across all test sets.

Results on English-German TED For En-De experiments, we compared the performance with existing end-to-end methods in Table 3. Unlike that of Librispeech English-French, this dataset is noisy, and the transcriptions do not align well with the corresponding audios. As a result, there is a wide gap between the performance of the end-to-end ST and the upper bound of the ST. We suppose it would be more beneficial to carry out data filtering. Overall, our method had a +3 points advantage in BLEU as compared to competitors. This trend is consistent with that in the Librispeech dataset.

Comparison with Cascaded Systems In Table 4, we compare the performance of our E2E models with the cascaded systems. It shows that E2E models are comparable on En→Fr task both for base setting and expanded setting, proving our method’s capacity to combine the separate ASR and MT tasks in a model. However, there still exists some gap for E2E models with the cascaded system on En→De task for the expanded setting. We resort...
to the reason: Librispeech (audiobook scene) with a single speaker, slower speaking speed and standard pronunciation, is a relatively easy domain for speech translation. While TED (lecture scene) is a difficult domain for speech translation, due to spoken disfluency, various speaking speed, substandard pronunciation, multiple speakers and so on. And more capacity is needed to model a hard task then easy one for neural networks with the rich data resources.

5.3 Work Flows for Different Settings

We design different work flows for our method training from scratch (marked as work flow #1) and training with pre-training the successive decoder (marked as work flow #2). For work flow #1, ST model is totally supervised training from scratch with \((x, u, y) \in S\), as Equation 9. For work flow #2, training is done as the following three steps: 

a) pre-training the successive decoder with \((z', y') \in A\) with cross-entropy, as Section 3.3. b) freezing the decoder and pre-training the acoustic modeling with \((x, u) \in S\) with CTC loss, as Section 3.2. c) fine-tuning the ST model with \((x, u, z, y) \in S\), as Equation 9 (the same as work flow #1). Work flow #2 is determined after many attempts to better avoid the catastrophic forgetting of pre-trained knowledge. Figure 2 shows the convergence curve on the English-French validation set of the two work flows. It proves that work flow #2 with pre-training the successive decoder can get a better initialization and converge better benefiting from our flexible model structure.

5.4 Ablation Study

We use an ablation study to evaluate the importance of different modules in our methods. The results in Table 5 show that all the methods adapted are positive for the model performance, and the benefits of different parts can be superimposed. Models with successive decoding are able to predict both the recognition and translation, for which we also report WER and PER to evaluate the performance of different modeling phase. It has been proved that SD can bring a gain of 1 BLEU compared with the base model and pre-training decoder can bring improvements to all three metrics.

|       | BLEU↑ | WER↓ | PER↓ |
|-------|-------|------|------|
| SDST  | 18.23 | 14.60| 10.30|
| w/o PT Dec | 17.51 | 15.30| 11.90|
| w/o SD | 16.57 | -    | -    |
| w/o Shrink | 16.40 | -    | -    |
| w/o SA loss * | 15.48 | -    | -    |
| w/o SA loss | 11.24 | -    | -    |

Table 5: Benefits of each component in SDST on En-Fr test set. “PT Dec” stands for pre-training the successive decoder. “SD” represents using the successive decoder. “*” means using ASR pre-training as initialization.

| Speech #1 | Transcript | Target       | Base ST                  | SDST                  |
|-----------|------------|--------------|--------------------------|-----------------------|
| Speech #2 | Transcript | Target       | Base ST                  | SDST                  |
| Speech #3 | Transcript | Target       | Base ST                  | SDST                  |

Table 6: Examples of speech translation generated by SDST and the baseline ST model. Words in red highlight the difference. Words underlined, as generated by SDST, contributes to the improved translation results.

5.5 Case Study on English-French

The case study is displayed in Table 6. The analysis shows that SDST has obvious structural advantages in solving missed translation, mistranslation, and fault tolerance. For instance: #1, the base model missed the translation of “yes” in the audio, whereas our method produced a completely correct translation. After listening to the original audio, it is suspected that the missing translation is due to
an unusual pause between “doctor” and “yes”. #2, the base model mistranslated the “aboard” in the audio into “vers l avant” (“forward” in English), yet our method could correctly translate it into “a bord” based on the correct transcription prediction. The reason for the mistranslation may be that the audio clips are pronounced similarly, thus confusing the translation model. #3, the base model translated erroneously most of the content, and our model also predicted “today” in the audio as “to day”. However, in the end, our method was able to predict the translation result completely and correctly.

6 Conclusion
We propose SDST, a novel and unified training framework for jointly end-to-end speech recognition and speech translation. We use the successive decoding strategy to realize the sequential prediction of the transcription and translation sequences, which is more in line with human cognitive principles. Additionally, CTC auxiliary loss, shrinking operation and pre-training the decoder strategies are adopted to enhance our method benefiting from the flexible structure.

References
2019. The IWSLT 2019 Evaluation Campaign. Zenodo.
Antonios Anastasopoulos and David Chiang. 2018. Tied multitask learning for neural speech translation. arXiv preprint arXiv:1802.06655.
Parnia Bahar, Tobias Bieschke, and Hermann Ney. 2019a. A comparative study on end-to-end speech to text translation. arXiv preprint arXiv:1911.08870.
Parnia Bahar, Albert Zeyer, Ralf Schlüter, and Hermann Ney. 2019b. On using specaugment for end-to-end speech translation. arXiv preprint arXiv:1911.08876.
Srinivas Bangalore and Giuseppe Riccardi. 2001. A finite-state approach to machine translation. In IEEE Workshop on Automatic Speech Recognition and Understanding, 2001. ASRU’01., pages 381–388. IEEE.
Sameer Bansal, Herman Kamper, Karen Livescu, Adam Lopez, and Sharon Goldwater. 2018. Pre-training on high-resource speech recognition improves low-resource speech-to-text translation. arXiv preprint arXiv:1809.01431.
Daniel Beck, Trevor Cohn, and Gholamreza Haffari. 2019. Neural speech translation using lattice transformations and graph networks. In Proceedings of the Thirteenth Workshop on Graph-Based Methods for Natural Language Processing (TextGraphs-13), pages 26–31.
Alexandre Bédard, Laurent Besacier, Ali Can Kobayikoglu, and Olivier Pietquin. 2018. End-to-end automatic speech translation of audiobooks. In ICASSP, pages 6224–6228. IEEE.
Alexandre Bédard, Olivier Pietquin, Christophe Servan, and Laurent Besacier. 2016. Listen and translate: A proof of concept for end-to-end speech-to-text translation. arXiv preprint arXiv:1612.01744.
Nicola Bertoldi and Marcello Federico. 2005. A new decoder for spoken language translation based on confusion networks. In IEEE Workshop on Automatic Speech Recognition and Understanding, 2005., pages 86–91. IEEE.
Francisco Casacuberta, Hermann Ney, Franz Josef Och, Enrique Vidal, Juan Miguel Vilar, Sergio Barrachina, Ismael Garcia-Varea, David Llorens, César Martine, Sirko Molau, et al. 2004. Some approaches to statistical and finite-state speech-to-speech translation. Computer Speech & Language, 18(1):25–47.
Zhehuai Chen, Yimeng Zhuang, Yanmin Qian, and Kai Yu. 2016. Phone synchronous speech recognition with ctc lattices. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 25(1):90–101.
Qiao Cheng, Meiyuan Fang, Yaqian Han, Jin Huang, and Yitao Duan. 2019. Breaking the data barrier: Towards robust speech translation via adversarial stability training. arXiv preprint arXiv:1909.11430.
Yong Cheng, Zhaopeng Tu, Fandong Meng, Junjie Zhai, and Yang Liu. 2018. Towards robust neural machine translation. arXiv preprint arXiv:1805.06130.
Shun-Po Chuang, Tzu-Wei Sung, Alexander H Liu, and Hung-yi Lee. 2020. Worse wer, but better bleu? leveraging word embedding as intermediate in multitask end-to-end speech translation. arXiv preprint arXiv:2005.10679.
Mattia A Di Gangi, Matteo Negri, and Marco Turchi. 2019a. Adapting transformer to end-to-end spoken language translation. In INTERSPEECH 2019, pages 1133–1137. International Speech Communication Association (ISCA).
Mattia A Di Gangi, Viet-Nhat Nguyen, Matteo Negri, and Marco Turchi. 2020. Instance-based model adaptation for direct speech translation. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7914–7918. IEEE.
Mattia Antonino Di Gangi, Matteo Negri, Roldano Cattoni, Dessi Roberto, and Marco Turchi. 2019b. Enhancing transformer for end-to-end speech-to-text translation. In Machine Translation Summit XVII,
Paul R Dixon, Andrew Finch, Chiori Hori, and Hideki Kashioka. 2011. Investigation on the effects of asr tuning on speech translation performance. In International Workshop on Spoken Language Translation (IWSLT) 2011.

Long Duong, Antonios Anastasopoulos, David Chiang, Steven Bird, and Trevor Cohn. 2016. An attentional model for speech translation without transcription. In NAACL, pages 949–959.

Erin Fitzgerald, Keith B Hall, and Frederick Jelinek. 2009. Reconstructing false start errors in spontaneous speech text.

Christian Fügen. 2008. A system for simultaneous translation of lectures and speeches. Ph.D. thesis, Verlag nicht ermittelbar.

Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. 2006. Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In ICML, pages 369–376. ACM.

Xiaodong He, Li Deng, and Alex Acero. 2011. Why word error rate is not a good metric for speech recognizer training for the speech translation task? In 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5632–5635. IEEE.

Hirofumi Inaguma, Kevin Duh, Tatsuya Kawahara, and Shinji Watanabe. 2019. Multilingual end-to-end speech translation. arXiv preprint arXiv:1910.00254.

Hirofumi Inaguma, Shun Kiyono, Kevin Duh, Shigeki Karita, Nelson Enrique Yalta Soplin, Tomoki Hayashi, and Shinji Watanabe. 2020. Espnet-st: All-in-one speech translation toolkit. arXiv preprint arXiv:2004.10234.

Sathish Indurthi, Houjeung Han, Nikhil Kumar Lakumarapu, Beomseok Lee, Insoo Chung, Sangha Kim, and Chanwoo Kim. 2019. Data efficient direct speech-to-text translation with modality agnostic meta-learning. arXiv preprint arXiv:1911.04283.

Niehues Jan, Roldano Cattoni, Stüker Sebastian, Mauro Cettolo, Marco Turchi, and Marcello Federico. 2018. The iwslt 2018 evaluation campaign. In International Workshop on Spoken Language Translation, pages 2–6.

Ye Jia, Melvin Johnson, Wolfgang Macherey, Ron J Weiss, Yuan Cao, Chung-Cheng Chiu, Naveen Ari, Stella Laurengo, and Yonghui Wu. 2019. Leveraging weakly supervised data to improve end-to-end speech-to-text translation. In ICASSP, pages 7180–7184. IEEE.

Takatomo Kano, Sakriani Sakti, and Satoshi Nakamura. 2018. Structured-based curriculum learning for end-to-end english-japanese speech translation. arXiv preprint arXiv:1802.06003.

Ali Can Kocabiyikoglu, Laurent Besacier, and Olivier Kraif. 2018. Augmenting librispeech with french translations: A multimodal corpus for direct speech translation evaluation. arXiv preprint arXiv:1802.03142.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. arXiv preprint arXiv:1901.07291.

Alon Lavie, Donna Gates, Marsal Gavaldà, Laura Mayfield, Alex Waibel, and Lori Levin. 1996. Multilingual translation of spontaneously spoken language in a limited domain. In Proceedings of the 16th conference on Computational linguistics-Volume 1, pages 442–447. Association for Computational Linguistics.

Dan Liu, Junhua Liu, Wu Guo, Shifu Xiong, Zhiqiang Ma, Rui Song, Chongliang Wu, and Quan Liu. 2018. The ustc-nel speech translation system at iwslt 2018. arXiv preprint arXiv:1812.02455.

Danni Liu, Gerasimos Spanakis, and Jan Niehues. 2020. Low-latency sequence-to-sequence speech recognition and translation by partial hypothesis selection. arXiv preprint arXiv:2005.11185.

Fu-Hua Liu, Liang Gu, Yuqing Gao, and Michael Picheny. 2003. Use of statistical n-gram models in natural language generation for machine translation. In 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03)., volume 1, pages I–I. IEEE.

Yuchen Liu, Hao Xiong, Zhongjun He, Jiajun Zhang, Hua Wu, Haifeng Wang, and Chengqing Zong. 2019a. End-to-end speech translation with knowledge distillation. arXiv preprint arXiv:1904.08075.

Yuchen Liu, Jiajun Zhang, Hao Xiong, Long Zhou, Zhongjun He, Hua Wu, Haifeng Wang, and Chengqing Zong. 2019b. Synchronous speech recognition and speech-to-text translation with interactive decoding. arXiv preprint arXiv:1912.07240.

Evgeny Matusov, Björn Hoffmeister, and Hermann Ney. 2008. Spoken language translation systems************ asr word lattice translation with exhaustive reordering is possible. In Ninth Annual Conference of the International Speech Communication Association.

Evgeny Matusov, Arne Mauser, and Hermann Ney. 2006. Automatic sentence segmentation and punctuation prediction for spoken language translation. In International Workshop on Spoken Language Translation (IWSLT) 2006.
Evgeny Matusov, Hermann Ney, and Ralph Schluter. 2005. Phrase-based translation of speech recognizer word lattices using loglinear model combination. In *IEEE Workshop on Automatic Speech Recognition and Understanding*, 2005, pages 110–115. IEEE.

Daniel S Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D Cubuk, and Quoc V Le. 2019. SpecAugment: A simple data augmentation method for automatic speech recognition. *arXiv preprint arXiv:1904.08779*.

Stephan Peitz, Simon Wiesler, Markus Nußbaum-Thom, and Hermann Ney. 2012. Spoken language translation using automatically transcribed text in training. In *International Workshop on Spoken Language Translation (IWSLT) 2012*.

Alicia Pérez, Víctor Gujarrubia, Raquel Justo, M Inés Torres, and Francisco Casacuberta. 2007. A comparison of linguistically and statistically enhanced models for speech-to-speech machine translation. In *International Workshop on Spoken Language Translation (IWSLT) 2007*.

Juan Pino, Liezl Puzon, Jiatao Gu, Xutai Ma, Arya D McCarthy, and Deepak Gopinath. 2019a. Harnessing indirect training data for end-to-end automatic speech translation: Tricks of the trade. In *Proceedings of the 16th International Workshop on Spoken Language Translation (IWSLT)*.

Juan Pino, Liezl Puzon, Jiatao Gu, Xutai Ma, Arya D McCarthy, and Deepak Gopinath. 2019b. Leverage out-of-task data for end-to-end automatic speech translation. *arXiv preprint arXiv:1909.06515*.

Nicholas Ruiz, Qin Gao, William Lewis, and Marcello Federico. 2015. Adapting machine translation models toward misrecognized speech with text-to-speech pronunciation rules and acoustic confusability. In *Sixteenth Annual Conference of the International Speech Communication Association*.

Julian Salazar, Katrin Kirchhoff, and Zhiheng Huang. 2019. Self-attention networks for connectionist temporal classification in speech recognition. In *ICASSP*, pages 7115–7119. IEEE.

Elizabeth Salesky and Alan W Black. 2020. Phone features improve speech translation. *arXiv preprint arXiv:2005.13681*.

Elizabeth Salesky, Susanne Burger, Jan Niehues, and Alex Waibel. 2018. Towards fluent translations from disfluent speech. In *2018 IEEE Spoken Language Technology Workshop (SLT)*, pages 921–926. IEEE.

Elizabeth Salesky, Matthias Sperber, and Alan W Black. 2019a. Exploring phoneme-level speech representations for end-to-end speech translation. *arXiv preprint arXiv:1906.01199*.

Elizabeth Salesky, Matthias Sperber, and Alex Waibel. 2019b. Fluent translations from disfluent speech in end-to-end speech translation. *arXiv preprint arXiv:1906.00556*.

Tanja Schultz, Szu-Chen Jou, Stephan Vogel, and Shirin Saleem. 2004. Using word lattice information for a tighter coupling in speech translation systems. In *Eighth International Conference on Spoken Language Processing*.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2015. Neural machine translation of rare words with subword units. *arXiv preprint arXiv:1508.07909*.

Matthias Sperber, Graham Neubig, Jan Niehues, and Alex Waibel. 2017a. Neural lattice-to-sequence models for uncertain inputs. *arXiv preprint arXiv:1704.00559*.

Matthias Sperber, Graham Neubig, Jan Niehues, and Alex Waibel. 2019a. Attention-passing models for robust and data-efficient end-to-end speech translation. *TACL*, 7:313–325.

Matthias Sperber, Graham Neubig, Ngoc-Quan Pham, and Alex Waibel. 2019b. Self-attentional models for lattice inputs. *arXiv preprint arXiv:1906.01617*.

Matthias Sperber, Jan Niehues, and Alex Waibel. 2017b. Toward robust neural machine translation for noisy input sequences. In *International Workshop on Spoken Language Translation (IWSLT)*.

Matthias Sperber and Matthias Paulik. 2020. Speech translation and the end-to-end promise: Taking stock of where we are. *arXiv preprint arXiv:2004.06358*.

Mihaela C Stoian, Sameer Bansal, and Sharon Goldwater. 2020. Analyzing asr pretraining for low-resource speech-to-text translation. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7909–7913. IEEE.

Tzu-Wei Sung, Jun-You Liu, Hung-yi Lee, and Lishan Lee. 2019. Towards end-to-end speech-to-text translation with two-pass decoding. In *ICASSP*, pages 7175–7179. IEEE.

Yulia Tsvetkov, Florian Metze, and Chris Dyer. 2014. Augmenting translation models with simulated acoustic confusions for improved spoken language translation. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics*, pages 616–625.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *NIPS*, pages 5998–6008.

Enrique Vidal. 1997. Finite-state speech-to-speech translation. In *1997 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 1, pages 111–114. IEEE.

Laura Cross Vila, Carlos Escolano, José AR Fonollosa, and Marta R Costa-jussà. 2018. End-to-end speech translation with the transformer. In *IberSPEECH*, pages 60–63.
Hari Krishna Vydana, Martin Karafi’at, Katerina Zmolikova, Luk’as Burget, and Honza Cernocky. 2020. Jointly trained transformers models for spoken language translation. *arXiv preprint arXiv:2004.12111*.

Chengyi Wang, Yu Wu, Shujie Liu, Zhenglu Yang, and Ming Zhou. 2019. Bridging the gap between pre-training and fine-tuning for end-to-end speech translation. *arXiv preprint arXiv:1909.07575*.

Chengyi Wang, Yu Wu, Shujie Liu, Ming Zhou, and Zhenglu Yang. 2020. Curriculum pre-training for end-to-end speech translation. *arXiv preprint arXiv:2004.10093*.

Ron J Weiss, Jan Chorowski, Navdeep Jaitly, Yonghui Wu, and Zhifeng Chen. 2017. Sequence-to-sequence models can directly translate foreign speech. *arXiv preprint arXiv:1703.08581*.

Monika Woszczyna, Noah Coccaro, Andreas Eisele, Alon Lavie, A McNair, Thomas Polzin, Ivica Rogina, Carolyn Penstein Rosé, Tilo Sloboda, Masaru Tomita, et al. 1993. Recent advances in janus: a speech translation system. In *Proceedings of the workshop on Human Language Technology*, pages 211–216. Association for Computational Linguistics.

Cheng Yi, Feng Wang, and Bo Xu. 2019. Ectc-docd: An end-to-end structure with ctc encoder and ocd decoder for speech recognition. *Proc. Interspeech 2019*, pages 4420–4424.

Pei Zhang, Boxing Chen, Niyu Ge, and Kai Fan. 2019. Lattice transformer for speech translation. *arXiv preprint arXiv:1906.05551*.

Ruiqiang Zhang, Genichiro Kikui, Hirofumi Yamamoto, and Wai-Kit Lo. 2005. A decoding algorithm for word lattice translation in speech translation. In *International Workshop on Spoken Language Translation (IWSLT) 2005*.