

End-to-End Speech-to-Text Translation: A Survey

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Abstract

Speech-to-text translation pertains to the task of converting speech signals in a language to text in another language. It finds its application in various domains, such as hands-free communication, dictation, video lecture transcription, and translation, to name a few. Automatic Speech Recognition (ASR), as well as Machine Translation(MT) models, play crucial roles in traditional ST translation, enabling the conversion of spoken language in its original form to written text and facilitating seamless cross-lingual communication. ASR recognizes spoken words, while MT translates the transcribed text into the target language. Such disintegrated models suffer from cascaded error propagation and high resource and training costs. As a result, researchers have been exploring end-to-end (E2E) models for ST translation. However, to our knowledge, there is no comprehensive review of existing works on E2E ST. The present survey, therefore, discusses the work in this direction. Our attempt has been to provide a comprehensive review of models employed, metrics, and datasets used for ST tasks, providing challenges and future research direction with new insights. We believe this review will be helpful to researchers working on various applications of ST models.

Keywords: Speech-to-Text Translation, Automatic Speech Recognition, Machine Translation, Modality Bridging

1. Introduction

The Speech-to-Text (ST) translation task aims to convert a speech in one language into text in another language. It finds its applications in various areas such as *automatic subtitling*, *dictations*, *video lecture translations*, *tourism*, *telephone conversations*, to name a few. There are many facets under which the ST problem can be cast. For example, are we performing ST translation online (aka simultaneous translation) or offline? The former is required in live video streaming, while

the latter is helpful for movies where some latency may be allowed. The ST problem is further exacerbated by noisy inputs, low-resource/code-mix languages, and the presence of multiple speakers.

The traditional ST translation methods involve a cascade approach—First, applying automatic speech recognition (ASR) on the given speech and then performing machine translation (MT) on the transcription produced by ASR. Such a cascade model is prone to several issues, such as (a) error in the ASR model can propagate to the MT model, (b) higher cost and training time, and (d) resources required for training. To mitigate such issues, various researchers propose using end-to-end (E2E) models for ST task (Bérard et al., 2016, 2018; Anastasopoulos et al., 2016; Bentivogli et al., 2021; Gangi et al., 2019). E2E models usually employ a single neural network that can be trained end-to-end. Because of simpler training, lower memory footprint, and cost, E2E model development has gained significant momentum in the research community. However, a systematic and comprehensive review of ST works is missing. Concurrently to our work, we find that a review paper (Xu et al., 2023) on ST was published recently. The aforementioned review categorizes existing works mainly based on modeling, data, and application issues. They do not cover the data sets available for the ST tasks nor provide any insights into the cascade vs. E2E model performances. Also, the future open problems provided by them are limited. On the other hand, our work comprehensively reviews the existing models for ST tasks and datasets from a completely different perspective and critically analyzes the existing works; thereafter, we identify several challenges and future research directions. Thus, our work may be deemed complimentary to (Xu et al., 2023).

The following review is structured as follows: In Section 2, we establish the foundation of the ST task through a formal definition, and we subsequently delve into the various metrics and loss functions adopted by different researchers. Moving on to Section 3, we present comprehensive descriptive statistics pertaining to benchmark datasets that have been employed by researchers within this field. Section 4 is dedicated to exploring the different toolkits accessible for addressing E2E ST tasks. In Section 5, we delve into the diverse strategies and approaches employed to tackle the ST problem. Initially, we categorize these approaches based on the frameworks utilized and the characteristics of the data involved. Under the framework categorization in Section 5.1, we provide explanations for both Sequence-to-sequence (seq2seq) frameworks (5.1.1) and Modality-bridging frameworks (5.1.2). Additionally, the seq2seq frameworks are further subcategorized, taking into account scenarios involving ST with MT, ST with ASR, and ST with both MT and ASR. Furthermore, the nature of the data is dissected into

several distinctive settings in Section 5.2, including Low-resource (5.2.1), Code-mixed (5.2.2), Streaming (5.2.3), Unsupervised (5.2.4), and Multilingual (5.2.5). Finally, in Section 6, we explore the prospects for future research and address open problems within the field.

2. Background

This section describes the ST task formally and presents the metrics used to evaluate the performance of the ST model.

2.1. Task Definition

ST task can be defined as translating the given input speech U in one language to translated text V in another language with the transcription text X . The definition, in formal terms, is as follows: Given a dataset $D = \{(\mathbf{u}^i, \mathbf{x}^i, \mathbf{v}^i) | i = 1, 2, \dots, n\}$ of pairs of input speech features $\mathbf{u} = (u_1, u_2, \dots, u_{T_u})$ in a language and output text tokens $\mathbf{v} = (v_1, v_2, \dots, v_{T_v})$ in a different language, the objective of the ST task is to minimize the conditional probability given below:

$$p(\mathbf{v}|\mathbf{u}; \theta) = \prod_{t=1}^{T_v} p(v_t|v_{<t}, \mathbf{u}; \theta) \quad (1)$$

In the above equation, T_u , T_v , and θ are the lengths of input features, the number of output tokens, and the model parameter, respectively. There are n parallel sentences in our corpus, and the model is optimized for negative log-likelihood over these sentences as

$$\ell(\theta|D) = - \sum_{i=1}^n \log P(\mathbf{v}^i|\mathbf{u}^i; \theta) \quad (2)$$

The above optimization is usually solved using an encoder-decoder with an attention approach. Essentially, an encoder maps speech input to a hidden state representation h followed by a decoder which takes the previously generated text tokens $v_{<t}$, encoder hidden state h and attention vector α (Vaswani et al., 2017). Offline ST translation can look at the whole speech before producing output text tokens, whereas online ST can start translation as soon as it sees a few seconds of the speech signal.

2.2. Evaluation Metrics

This section discusses various metrics used to evaluate the E2E ST models. The metrics of E2E ST models are categorized into 2 major performance measures which are **quality** and **latency**. The quality of the E2E ST models is the measure of how close the ST translation is to the target sentence or human-translated sentence. The latency of the E2E ST models is the time taken by the model to translate source speech into the target text.

Quality-based metrics: The quality-based metrics measure how close the translation is to the target sentence, which usually lies in [0, 1]. Most of the existing literature evaluates these scores on *detokenized* output. Standard translation metrics for evaluating ST task performance are presented below:

- **BLEU** Bi-lingual Evaluation Understudy (BLEU) Papineni et al. (2002) is the score of weighted average length of the translated sentence that matched the target sentence. The expression for evaluating BLEU score is given by:

$$BLEU = BP \exp\left(\sum_{n=1}^N w_n \log P_n\right) \quad (3)$$

where the BP , w_n , and P_n are brevity penalty, positive weights that sums to 1, and n-gram precisions of length upto N , respectively.

- **TER** Translation Edit Rate (TER) Snover et al. (2006) is the measure of how much a translated sentence has to be modified in order to match the target sentence. The expression for TER is given by:

$$TER = M/R \quad (4)$$

where M and R are the modifications required in the translated sentence and the average number of reference words, respectively.

- **METEOR** Metric for Evaluation of Translation with Explicit word Ordering (METEOR) Banerjee and Lavie (2005) is the automatic metric that matches the unigrams in the translated text to the referenced text. The expression for METEOR Score is given by:

$$M_Score = F_M * (1 - Penalty_M), \quad (5)$$

where $F_M = \frac{10PR}{R+9P}$, and $Penalty_M = 0.5 * \left(\frac{C}{U}\right)^3$.

The F_M and Penalty_M are the F-Score and the penalty of the METEOR score. P , R , C , and U denote the precision, recall, number of chunks, and number of unigrams matched in the translated text, respectively.

- **BERTScore** The BERTScore Zhang et al. (2019) is an automatic evaluation metric that scores the similarity between the translated text to the referenced text. It takes into account the Recall (R), Precision (P), and Fscore (F), which are expressed as:

$$R = \frac{1}{|v|} \sum_{v_i \in v} \max_{\hat{v}_j \in \hat{v}} v_i^T \hat{v}_j, P = \frac{1}{|\hat{v}|} \sum_{\hat{v}_j \in \hat{v}} \max_{v_i \in v} v_i^T \hat{v}_j, F = 2 \cdot \frac{R \cdot P}{R + P} \quad (6)$$

where v_i and \hat{v}_j are tokens of the sentences in the translated text and the ground truth text.

There are few other evaluation metrics such as TRANSTAC Schlenoff et al. (2009), NIST-Score Doddington (2002) and CHRF Popović (2015) which are less frequently used.

Latency-based metrics: For streaming ST task, researchers report a metric for measuring *latency*, which is defined as the delay incurred in starting to produce the translation. Let \mathbf{u} , \mathbf{v} and $\hat{\mathbf{v}}$ denote the input speech sequence, ground truth text sequence, and system-generated hypothesis sequence, respectively. In the streaming ST task, the model can only produce output with partial input. Suppose $\mathbf{u}_{1:t} = (u_1, \dots, u_t)$, $t < T_u$ has been read when generating v_s , the delay in v_s is defined as (Ma et al., 2020)

$$d_s = \sum_{k=1}^t T_k \quad (7)$$

where T_k is the duration of the speech frame u_k . The latency metrics are evaluated using a method that analyzes a sequence of time delays $[d_1, \dots, d_{T_v}]$.

- **Average Proportion (AP)** calculates the mean fraction of the source input that is read during the target prediction generating process.

$$AP = \frac{1}{T_y \sum_{k=1}^{T_u} T_k} \sum_{s=1}^{T_v} d_s \quad (8)$$

- **Average Lagging (AL)** measures the distance between the speaker and the

user based on the number of words used in the conversation(Ma et al., 2018).

$$AL = \frac{1}{\tau(T_u)} \sum_{s=1}^{\tau(T_u)} d_s - \hat{d}_s \quad (9)$$

Where $\tau(T_u) = \min\{s \mid d_s = \sum_{k=1}^{T_u} T_k\}$ and \hat{d}_s are the delays of an ideal policy defined as (Ma et al., 2020)

$$\hat{d}_s = (s-1) \sum_{k=1}^{T_u} \frac{T_k}{\hat{T}_v} \quad (10)$$

- **Differentiable Average Lagging (DAL)** One issue with AL is that it is not differentiable because of the min function. To solve this, (Cherry and Foster, 2019) introduces a minimum delay of $1/\gamma$ after each operation and defines DAL as

$$DAL = \frac{1}{T_v} \sum_{s=1}^{T_v} d'_s - \frac{s-1}{\gamma} \quad (11)$$

where

$$d'_s = \begin{cases} d_s, & s = 0 \\ \max(d_s, d'_{s-1} + \gamma), & s > 0 \end{cases} \quad (12)$$

and $\gamma = T_v / \sum_{k=1}^{T_u} T_k$

2.3. Loss Functions

This section discusses the various loss functions used for the E2E ST models. Let $D = (u, x, v)$ be a tuple where u , x , and v are the speech, the transcription text, and the translation text, respectively. The following are the various loss functions that are used to optimize the performance of the E2E ST models:

- **ST Loss** (Ouyang et al., 2022) is defined as the negative log-likelihood of the translation text given the source speech as follows

$$L_{ST} = - \sum_{(u,v) \in D} \log p(v|u) \quad (13)$$

- **MT Loss** (Ouyang et al., 2022) is defined as the negative log-likelihood of

the translation text given the source transcript as follows

$$L_{MT} = - \sum_{(x,v) \in D} \log p(v|x) \quad (14)$$

- **ASR Loss** (Ouyang et al., 2022) is defined as the negative log-likelihood of the transcription text given the source speech as follows

$$L_{MT} = - \sum_{(u,x) \in D} \log p(x|u) \quad (15)$$

- **CTC Loss**(Ren et al., 2020) computes the most likely alignment of output text sequence given input speech sequence by summing over the all possible output sequence paths.

$$L_{CTC} = - \sum_{(u,x) \in D} \sum_{z \in \phi(x)} \log p(z|u) \quad (16)$$

- **Cross-Modal Adaptation Loss** (Liu et al., 2020b) is defined as the sum of all the Mean Squared Errors of the speech and the transcription texts.

$$L_{AD} = \begin{cases} \sum_{(u,x) \in D} MSE(\bar{h}_u, \bar{h}_x); & \text{seq-level} \\ \sum_{(u,x) \in D} MSE(h_u, h_x); & \text{word-level} \end{cases} \quad (17)$$

where h_u and h_x are the speech and word embeddings, and \bar{h}_u and \bar{h}_x are the average speech and word embeddings, respectively. MSE represents the difference between the two embeddings.

- **Cross-Entropy Loss** (Ye et al., 2021) is the negative likelihood of the data combined over all the subtasks such as ASR, MT, ST and also from external-MT.

$$L_\theta = - \sum_{x,v \in D' \cup D_{MT-ext}} \log p(x|v; \theta), \quad (18)$$

where $D' = D_{ASR} \cup D_{MT} \cup D_{ST}$ is the superset of all the parallel subsets data.

- **Distillation Loss** (Liu et al., 2019) The student model not only matches the ground truth, but also the teacher models's output probabilities, which

Datasets	Source Language (Speech)	Target Lan-gage (Text)	Speech (hours)	Speakers	Validation	Gender	Age Group
MuST-C	En	14 lang	0.4K	1.6K	✗	✗	✗
Librispeech	En	Fr	0.2K	1.4K	✓	✓	✓
CoVost	En	11 lang	0.7K	11K	✓	✓	✓
CoVost2	21 lang	En	2.8K	11K	✓	✓	✓
	En	15 lang	0.7K	78K	✓	✓	✓
EuroparlST	4 lang	4 lang	0.25K	✗	✗	✗	✗
VoxPopuli	En	15 lang	1.79K	4.3K	✗	✗	✗
Kosp2e	Ko	En	0.2K	0.2K	✗	✗	✗
GigaST	En	De, Zh	10K	✗	✗	✗	✗
Prabhupadavani	en.bn.bn code- mix	25 lang	0.09K	0.13K	✗	✗	✗
How2	En	Pt	2K	✗	✗	✗	✗

Table 1: Dataset statistics(✓ means that feature is available for the dataset and ✗ means that the feature is unavailable for the dataset)

reduces the variance of the gradients.

$$L_{KD} = - \sum_{(x,v) \in D} \sum_{t=1}^N \sum_{k=1}^{|V|} S(v_t = k | v_{<t}, x) \log T(v_t = k | v_{<t}, x) \quad (19)$$

where S and T denote the output distribution of student and teacher models, respectively.

- **Contrastive Loss** (Ye et al., 2022a) It is computed between the the speech and the transcription text bringing them closer, and pushing the unrelated pairs farther.

$$L_{CON} = - \sum_{(u,x) \in D} \log \frac{\exp(\cos(\bar{h}_u, \bar{h}_x)/\kappa)}{\sum_{\forall x_j \notin h_x} \exp(\cos(\bar{h}_u, \bar{h}_x(x_j))/\kappa)}, \quad (20)$$

where \cos and κ denote the cosine similarity and temperature hyperparameter, respectively.

3. Datasets for ST Tasks

There have been several datasets created for the ST task. Some of them are listed below, and we describe them here briefly. Table 1 provides information on

various dataset statistics, such as hours of speech, the number of speakers, whether the dataset was manually or machine validated, the gender, and the age range to which the speaker belongs. Additionally, the tools required for creating these datasets are (a) *Gentle* (Ochshorn and Hawkins, 2017) for audio-transcription alignment, and (b) *BertAlign*¹ for transcription-translation alignment.

- **How2** (Sanabria et al., 2018) is an ST corpus of English instructional videos having Portuguese translations.
- **Augmented Librispeech** (Kocabiyikoglu et al., 2018) is obtained from the LibriSpeech corpus (Panayotov et al., 2015). It is a speech recognition repository generated using audiobooks of *Gutenberg Project*². This dataset is designed to translate English speech into written French text.
- **MuST-C** (Di Gangi et al., 2019) It is a large *multilingual* ST translation corpus available . It contains translations from English into fourteen additional languages and is compiled from TED Talks. mTEDx (Salesky et al., 2021) is one such multilingual dataset from TED talks.
- **CoVoST and CoVoST 2** (Wang et al., 2020a,c), the datasets are based on *Common Voice* project³. CoVoST is a many-to-one dataset covering 11 languages, while CoVoST 2 offers one-to-many and many-to-one translations for 15 languages.
- **Europarl-ST** (Iranzo-Sánchez et al., 2020) is a collection that contains speech and text data from *European Parliament proceedings* between 2008 and 2012 in four languages. It includes multiple sources and targets for both speech and text.
- **VoxPopuli** (Wang et al., 2021a) dataset is an expansion of Europarl-ST. It includes data from European parliament sessions spanning from 2009 to 2020.
- **Kosp2e** (Cho et al., 2021a) is a Korean (ko) to English(en) ST translation corpus, which contains Korean speech with parallel English texts. The corpus contains data from four different domains: *Zer0th* from news/newspaper,

¹<https://github.com/bfsujason/bertalign>

²<https://www.gutenberg.org/>

³<https://commonvoice.mozilla.org/en>

KSS (Park, 2018) from textbooks, *emphStyleKQC* (Cho et al., 2021b) from AI applications, and *Covid-ED* (Lee et al., 2021) from covid diaries of people which have emotions.

- **GigaST** (Ye et al., 2022b) corpus is a collection of speech translations from English to German and Chinese. It is created using the English ASR GigaSpeech(Chen et al., 2021a), which features 10,000 hours of transcribed speech from various sources such as audioPortugesebooks, podcasts, and YouTube.
- **Prabhupadavani** (Sandhan et al., 2022) is an ST dataset where speech is *multilingual and Code-Mix* with three different languages, English is the primary language, and words and phrases from Sanskrit and Bengali are interjected. The text part has sentences in 25 languages.

Besides these popular ST datasets, there are some other *smaller* size datasets such as *Fisher*(Cieri et al., 2004), *Call-Home*⁴, *Gordard Corpus*(Godard et al., 2017), *Glosse Audio Corpus*⁵, *BTEC* ⁶, *WSJ*⁷, *IWSLT*⁸, *CHiME-4 Corpus*(Christensen et al., 2010), *Miami Corpus*(Deuchar, 2008), and *MSLT Corpus* (Federmann and Lewis, 2016).

4. Toolkits for ST

In order to facilitate building and training ST models, various researchers have proposed a few toolkits. The toolkits for ST create an environment where the dataset for ST tasks can be pre-processed, and models can be trained, fine-tuned, and evaluated. We provide a short description of these toolkits to make the survey a place for a one-stop-shop for ST modeling.

- **EspNet-ST**⁹ toolkit(Inaguma et al., 2020) is developed as there was no toolkit available for performing the sub-tasks of ST. EspNet-ST provides ASR, LM, E2E-ST, Cascade-ST, MT, and TTS along with examples. It

⁴<https://ca.talkbank.org/access/CallHome/eng.html>

⁵<https://ainu.ninjal.ac.jp/folklore/en/>

⁶http://universal.elra.info/product_info.php?cPath=37_39&products_id=80

⁷<https://catalog.ldc.upenn.edu/LDC93S6A>

⁸<https://iwslt.org/>

⁹<https://github.com/espnet/espnet>

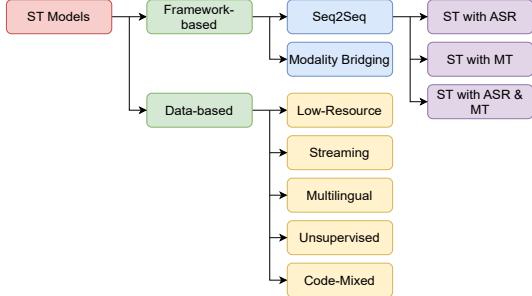


Figure 1: End-to-end ST models taxonomy

also provided pre-trained transformer-based models on various datasets like MUST-C, Libri-trans, Fisher, CALL-HOME, and How2.

- **FairSeq S2T**¹⁰(Wang et al., 2020b) toolkit is an extension to FairSeq(Ott et al., 2019) in which all the functions of EspNet-ST are available. Additionally, it provides the Non-Autoregressive MT, Online ST, and Speech Pretraining. The toolkit also provides state-of-the-art ST models based on RNN, transformers, and conformers. It has an in-built data loader for MuST-C, Librispeech, and CoVoST datasets.
- **NeurST**¹¹ (Zhao et al., 2020) is a lightweight toolkit, as it has no dependency on kaldi[CITE]. It has high computation efficiency using mixed precision and accelerated linear algebra and achieves faster training on large-scale datasets using Horovod and Byteps [CITE].
- **SLT.KIT**¹²(Zenkel et al., 2018) offers ASR, MT and ST models along with some specific features such as CTC and Attention based ASR, ASR with punctuation and a neural MT system.

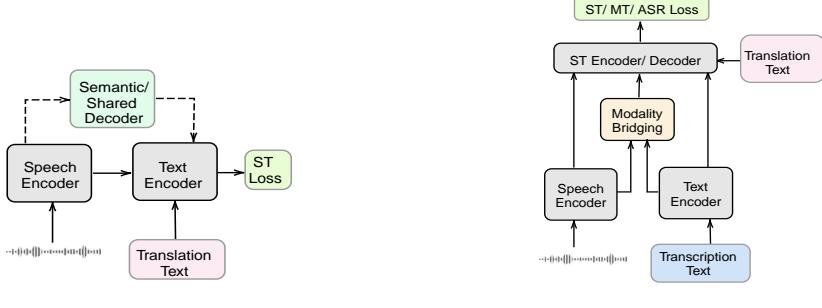
5. End-to-End ST Models

End-to-end models for ST as discussed previously are gaining traction comparably to cascade models. This section presents an overview of E2E models

¹⁰https://github.com/facebookresearch/fairseq/tree/main/examples/speech_to_text

¹¹<https://github.com/bytedance/neurst>

¹²<https://github.com/isl-mt/SLT.KIT>



(a) Framework based on Seq2Seq

(b) Framework based on Modality Bridging

Figure 2: E2E Framework-based ST Models. (a) Seq2Seq model, (b) Seq2Seq with modality bridging component. The dashed arrow denotes optional components.

as shown in Fig. 1. We categorize them under two major E2E themes. The first is based on the framework used, such as ASR/MT as pre-training objectives or modality-bridging technique. The second category is based on the nature of the data. We note that all of these methods rely on encoder-decoder (Seq2Seq) architecture for sequence learning (see Fig.2 (a)), where the encoder receives input from audio and/or text, while the decoder produces the translated text. The categorization presented here is based on which component boosts the ST task performance, as claimed in the papers. As such, the demarcation is not strict, and there may be overlaps in the categories. In addition, our emphasis in the present review of existing works is highlighting the core contribution and limitations as claimed by the authors. That means we look for answers to the question: what is the main technical contribution of authors to solve the ST problem? Thus, wherever possible, we have limited the mathematical description and believe that such details can be found in the related papers. Our attempt is to provide a succinct and clear picture of what works and what does not while addressing the ST problem.

5.1. ST Models based on Frameworks

As mentioned in the previous section, ST models in the literature employ the seq2seq framework alone or in combination with some modality-bridging component.

5.1.1. Seq2Seq Frameworks

A Seq2Seq model generates a sequence of outputs from a sequence of inputs as shown in Fig. 2(a). It has an encoder for speech input, a decoder for text output, and an optional shared/semantic decoder connecting the encoder and the

decoder. The model is usually optimized for the ST loss. The Seq2Seq models have mainly two components that form the core of the models proposed: attention and transformer. This section discusses only the works which do not use external data for training. Models that leverage external data for training such as ASR and/or MT are discussed in the next section.

Attention mechanism is used to concentrate on specific sections of the input data for producing the output (Vaswani et al., 2017). It has been a successful strategy for getting state-of-the-art (SOTA) results in NLP as well as other areas. Below we provide efforts made to handle ST tasks using the attention mechanism within the Seq2Seq framework.

The author in (Bérard et al., 2016) uses a Seq2Seq model that eliminates the need for source transcript in the ST task. They use *convolutional* attention to “remember” and avoid translating the signal twice, which outperforms a hierarchical encoder with better results on *synthetic data*. The same author in (Bérard et al., 2018) uses source transcript and achieves results close to cascade models on LibriSpeech data. In (Duong et al., 2016), the author proposes phone-to-text alignment with a *structural bias* feature in the attention model. The measurement of alignment has been explored in (Anastasopoulos et al., 2016), which used IBM’s translation model as well as *dynamic time warping*¹³. Seq2seq with attention trained using *multitask learning* achieves promising results in (Weiss et al., 2017). These models struggle with *noisy inputs* and *long acoustic signals* (Kim et al., 2017). They use a joint CTC-attention model trained through multitask learning by incorporating *regularizers*. The author uses two decoders where the second decoder seeks *higher level representation (HLR)* from the first decoder besides the encoder via the attention mechanism using a small dataset.

Transformer is the architecture based on multi-headed self-attention (Vaswani et al., 2017) which produces contextualized representation of the input. Because of parallelization and contextual representation, transformers have outperformed RNNs on several NLP tasks. This entails us applying transformers for the ST task as well.

Transformer-based Seq2Seq with *attention* is proposed in (Di Gangi et al., 2019). The architecture has a *quadratic memory complexity*, which involves: (a) CNN to downsample the input, and (b) 2-D attention to address short-range dependencies of spectrograms. In (Alastruey et al., 2022), the weight of some attention

¹³dynamic time warping (DTW) is an algorithm for measuring similarity between two temporal sequences, which may vary in speed.

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Attention (Bérard et al., 2016)	Eliminate Source Transcription	BTEC (Synthetic)	Fr→En	15	46.7
Phone to word Alignment (Duong et al., 2016)	Word-spotting + low resources	CALLHOME	Es→En	38	21.2
FastAlign + DTW (Anastasopoulos et al., 2016)	low resource	CALLHOME	Es→En	38	30.8
Multitask Learning (Weiss et al., 2017)	performance	Fisher	Griko→It	20minutes	53.8
		CALLHOME	Es→En	38	48.7
		Fisher	Es→En	163	17.4
Joint CTC-Attention Model (Kim et al., 2017)	Noisy Signals, long inputs	WSJ1	Es→En	80	(CER-7.36)
		WSJ0	Es→En	15	(CER-14.53)
		Chime-4	Es→En	18	(CER-44.99)
Encoder + Decoder (Bérard et al., 2018)	Cascading	Librispeech	En→Fr	236	22.2
		BTEC (Synthetic)	En→Fr	15	50.7
Quadratic Memory Complexity (Di Gangi et al., 2019)	High training time	IWSLT	En→De	80	8.94
		MuST-C	En→De	408	12.93
Drop weights that attention discards (Alastruey et al., 2022)	Attention for long sequence	MuST-C	En→De	408	22.49
			En→Es	504	27.46
			En→It	465	22.97

Table 2: Performance scores of the models in Seq2Seq framework with the datasets, language pairs, duration of speech, and metric(BLEU).

is avoided for speech tasks, hence decreasing the size of the attention matrix. The transformer encodes the speech features, thereby introducing *local self-attention* with a suitable window size for each layer to reduce the computational complexity.

In table 2, we present performance scores (BLUE/CER) of various ST models based on the Seq2Seq framework. We note that many of these results are not directly comparable since they use different amounts of speech data for testing.

Findings: Our study of Seq2Seq-based frameworks for ST task reveals that (a) structural bias can be obtained by stacked/pyramidal RNN and alignment smoothing, (b) regularizers such as transitivity and invertibility improves Character Error Rate, (c) HLR helps in transcription as well as translation, and (d) changing the self-attention of the encoder with a logarithmic distance penalty enhances translation.

ST with ASR: In this section, we delve into the research that leverages ASR data to pre-train a Seq2Seq model, subsequently fine-tuning the model for the ST translation task.

Curriculum pre-training (Wang et al., 2020d) refers to the use of ASR data for pre-training an Seq2Seq model, which is transformer-based, allowing it to learn transcription. The author argues that if the model is further pre-trained on learning semantic concepts (via *frame-based masked language modeling*) and word align-

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Curriculum Pre-training + Decoder Pre-training (Wang et al., 2020d)	Heavy burden on Encoder	Librispeech	En→Fr	236	18.01
		IWSLT	En→De	271	18.15
Listen Understand Translate (Dong et al., 2021a)	lack of parallel corpus	Librispeech	En→Fr	100	17.75
		IWSLT	En→De	272	16.35
		TED	En→Zh	524	20.84
NAFM + Parameterized Distance Penalty (Zhang et al., 2022)	lack of transcripts	MuST-C	En→Xx	452	25.2
		CoVoST-2	Xx→En	427	11.7
			En→Xx	427	17.3
		Librispeech Kosp2e	En→Fr	100	18.9
			Ko→En	190	5.8

Table 3: Performance scores of the ST models with ASR showing the datasets, language pairs, duration of speech, and metric(BLEU).

ment (via *frame-based bilingual lexical translation*), it boosts the ST task performance. Specifically, existing E2E models either pre-train the encoder or use multi-task learning for ST tasks. As such, the encoder cannot isolate the learning of three tasks: transcription, semantic concept, and alignment, which are segregated by *dividing the labor*, and experiments prove the theoretical claims. Listen, Understand, and Translate (LUT) from (Dong et al., 2021a) uses the seq2seq model with *external ASR data*. Their primary contribution is to introduce a *semantic encoder network*, whose task is to use the encoder’s output from transcription to minimize the mean-squared loss between the semantic representations and the BERT embeddings of the target text. Such a strategy implicitly builds and trains an NMT model for translation. (Zhang et al., 2022) uses *neural acoustic feature modeling* (NAFM) to obtain the speech features from the audio instead of using *Fbank*, which leads to information loss.

The BLUE scores are given in Table 3 to provide readers with the quantitative scores of ST models employing ASR data.

ST using MT: This section discusses approaches that use either MT data for pre-training or directly using pre-trained MT in the ST decoder. These techniques rely on the idea of generating *pseudotext* and then translating them using MT. In (Bansal et al., 2017), the author uses the *Unsupervised Term Discovery* (UTD) approach to group repeated words into pseudo-text, which is subsequently used for training an MT model for bag-of-words using the parallel pseudo-text and target translations. The main advantage of such a system is that it can translate some content words under low-resource settings. The overall results are not very promising on the Spanish-English Call-Home dataset. Another limitation of this work is that the approach is *not* an E2E in a true sense as it involves two models—

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Unsupervised Term Discovery (Bansal et al., 2017)	low resource (no ASR & no MT)	CALLHOME	Es→En	11	(Recall-54.4)
Pre-trained ASR & MT (Jia et al., 2019)	lack of parallel corpus	Librispeech	En→Es	-	26.7
Knowledge Distillation (Liu et al., 2019)	one model for SR & TT	Librispeech	En→Fr	100	22.91
		MuST-C	En→Zh	542	19.55
KD with word-level/ seq.-level/ seq-interpolation (Gaido et al., 2020)	seq2seq for ASR & MT	Librispeech	En→Fr	100	16.8

Table 4: Performance scores of the ST models with MT showing the datasets, language pairs, duration of speech, and metric(BLEU).

a UTD and then an MT model. A weakly supervised learning method for ST (Jia et al., 2019) that outperforms multi-task learning takes advantage of the MT and TTS synthesis models, which are pre-trained. In their study, (Liu et al., 2019) a transformer-based “teacher” model for the MT task and a “student” model for the ST task are trained via *knowledge distillation* (KD). They, however, rely on *source language* text and do not improve upon the pipeline system. Following along, (Gaido et al., 2020) explores *word*, *sentence* and *sequence-interpolation* based KD approaches for transferring knowledge from pre-trained MT to ST model. Empirical results of ST models trained using MT auxiliary data are presented in Table 4.

Findings: (a) *UTD suffers from low recall and precision, and (b) transferring knowledge via KD from pre-trained MT to ST causes gender bias, omission of sentences, and generic verbal-tense choice.*

ST using both MT and ASR: This section elucidates the work that employs both MT and ASR data for ST tasks.

In (Bahar et al., 2019), the author presents a comparison of various E2E ST architectures such as direct, multitask many-to-one, one-to-many, tied-cascade, and tied-triangle and shows faster convergence when the CTC loss is combined with other losses. They show that pre-trained models with ASR and MT losses achieve promising results. Contrary to claims of (Anastasopoulos and Chiang, 2018), *tied-triangle* architecture is no better than a direct model when fine-tuned properly. Since the ST task is similar to the MT task from the output perspective, works such as XSTNet (Ye et al., 2021) utilize *external* MT data to pre-train the encoder-decoder network extensively, then fine-tune it using parallel corpus data of MT, ST, ASR, and external MT data for optimizing the model using what they call *progressive training*. They achieve impressive performance on MuST-C and augmented Librispeech data. They also demonstrate improved per-

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Tied multi-task learning with regularizers (Anastasopoulos and Chiang, 2018)	low resource on speech transcription & translation	CALLHOME	Es→En	20	28.8
		Glossed Audio Corpus ¹⁴	Ainu→En	2.5	20.3
		Godard Corpus ¹⁵	Mboshi→Fr	4.4	24.7
CTC loss (Bahar et al., 2019)	unknown segmentation of input sequence	IWSLT	En→De	390	24.43
Cross Speech-Net Network (XST-Net) (Ye et al., 2021)	Error Propagation	Librispeech	En→Fr	200	15.74
		MuST-C	En→De	408	27.8
			En→Es	504	30.8
			En→Fr	492	38.0
			En→It	465	26.4
			En→Nl	442	31.2
			En→Pt	385	32.4
			En→Ro	432	25.7
			En→Ru	489	18.5
		Librispeech	En→Fr	200	21.5
Speech & Text Joint Pre-training (Tang et al., 2022)	subtask interference	MuST-C	En→Es	504	33.1
			En→Fr	492	39.7

Table 5: Performance of the ST models with both ASR & MT showing the datasets, language pairs, duration of speech, and metric(BLEU).

formance on auxiliary tasks of MT and ASR. STPT model (Tang et al., 2022) proposes four sub-tasks for multitask pre-training: text-to-text (T2T), which is self-supervised; speech-to-phoneme which is supervised; acoustic learning, which is self-supervised, and ST which is supervised. Only T2T and ST tasks would subsequently be used for fine-tuning. Despite pre-training on “unlabeled” speech data, they obtained superior results on MuST-C data for the ST task. Table 5 shows BLUE scores of models utilizing both ASR and MT data.

Findings: (a) *Progressive training needs a huge data and training time in order to achieve superior results,* (b) *multitask pre-training can be used to leverage unlabeled speech data.*

Other: In (Sperber et al., 2019), the author analyzes that the cascade ST models, which use ASR and MT models, require less data than the direct ST models. But the drawback of the cascade two-stage ST models is to *propagate errors* from ASR to MT models and thus to ST model. Therefore, the author introduces an *Attention-Passing Model* (APM), which only passes high-attention vectors from the audio encoder to the translation text for decoding.

Findings: *APM requires less data than cascade ST models.*

5.1.2. Seq2Seq with Modality Bridging

A method for learning a combined representation of text and speech is called *modality bridging* (see fig.2 (b)). Both speech and text in an ST task represent

the same semantic meaning. Hence, a good ST model should learn a representation such that embeddings of both modalities for similar speech-text pairs lie close to each other. It is believed that low performance on ST tasks is due to models not learning aligned representations of speech and text. Therefore, different authors have devised different ways to fill the gap, which fall into five major approaches: (a) adapters, (b) contrastive learning, (c) Knowledge-distillation, (d) optimal transport, and (e) mix-up strategy. Below we discuss the works utilizing these approaches and show the pros and cons.

Adapters are small modules integrated with pre-trained networks for specific tasks (Houlsby et al., 2019). They have performed at par with fine-tuning-based approaches while requiring only a fraction of trainable parameters. For example, in (Zhao et al., 2022; Gállego et al., 2021), the modality gap is filled using *adapter layers*, which is a *multi-headed self-attention* with pooling operation. The author uses Wave2Vec 2.0 (Baevski et al., 2020) for speech-feature extraction, wherein self-attention layers in the transformer are equipped with pooling operation for dimensionality reduction to match text representation.

Contrastive learning approximates the “semantic” distance in the input space using a simple distance in the target space after mapping input patterns onto the target space (Chopra et al., 2005). It tries to bring positive instances closer while pushing negative ones apart. It has been used excessively in both supervised and unsupervised settings for learning representations. Below, we provide details of works leveraging contrastive learning loss for modality bridging.

The author in (Zhang et al., 2023) performs the *explicit knowledge transfer* through contrastive learning. They learn *frame* and *sentence-level speech* feature representation and use *whitening* (Su et al., 2021) to alleviate the MT representation degeneration. In (Liu et al., 2019), they decouple the encoder representation into three parts: acoustic encoder, shrinking (done via CTC) of acoustic encoder output, and semantic encoder for modality-gap bridging. Using a contrastive learning architecture, Chimera (Han et al., 2021) trains a *semantic memory module* which is shared for overcoming the modality distance. XSTNet (Ye et al., 2021) augmented with contrastive loss (Ye et al., 2022a) investigates three different methods: *span masked representation*, *word-repetition* and *cut-off*. It is also found that contrastive loss is better than CTC and L2 loss. The same author in (Ouyang et al., 2022) proposes *word-aligned contrastive learning* (WACO) by forming average speech and word embedding of the same word as positive pair while of different words as negative pairs. CSTNet is a *self-supervised* learning framework based on contrastive learning (using a mix of triplet losses)(Khurana et al., 2020). On top of the CTC loss, the boundary-based speech length shrinking

mechanism is applied in (Zeng et al., 2022). The authors claim that if *boundary-based shrinking* is applied with other modality-bridging techniques, such as contrastive loss, it can further improve the model performance. The approach presented achieves lower inference speed and memory footprint.

Knowledge-distillation (Hinton et al., 2015) is a mechanism to *distill* information from a trained and large “teacher” model to a smaller and efficient “student” model. It has been used with L_2 loss in (Huzaifah and Kukanov, 2023) to address the modality gap issue.

Optimal transport (Peyré et al., 2019) is a mechanism for comparing two *probability distributions*. In the ST task, speech and text representations may be deemed as two probability distributions. Recently, (Le et al., 2023) used optimal transport (OT) and CTC together in order to close the modality gap during the pre-training phase. They show significant gains in BLUE score when the ST model is fine-tuned without any external data compared to multitask learning.

Mix-up strategy Speech-Text Manifold Mixup (STEMM) (Fang et al., 2022) strategy uses speech embedding and mixes embeddings of speech and text into encoder-decoder of a translation model for bridging the modality gap under the *self-supervised learning* framework.

Table 6 presents the performance scores of ST models based on modality-bridging techniques. We can observe that mixup strategy achieves the highest BLUE score on En-De pair. Whereas boundary-based speech length shrinking mechanism matches the score when combined with other modality-bridging techniques.

Findings: (a) adapters can shrink the speech length as well as the modality distance between the text and speech representations while requiring a small number of trainable parameters, (b) Contrastive loss is better than CTC and L_2 loss for modality-bridging, (c) boundary-based speech length shrinking combined with contrastive loss can improve the ST task performance.

5.2. ST Models based on the Nature of Available Data

In the previous section, we provided an overview of the ST models based on the frameworks used. The present section provides readers with another perspective on E2E ST models. In particular, it discusses the E2E ST models categorized based on the nature of the data, such as data is low-resource, streaming, multilingual, etc. Given the specific challenges they pose, we believe such a categorization might be interesting to researchers.

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Knowledge Distillation (Liu et al., 2019)	performance of text translation	LibriSpeech	En→Fr	100	17.02
		MuST-C	En→Zh	542	19.55
M-Adapter + W2V2 + mBart (Baevski et al., 2020)	training gap between Pre-training & Fine-tuning the modality	MuST-C	En→De	408	25.9
			En→Ro	432	24.62
			En→Fr	492	37.34
Chimera (Han et al., 2021)	projecting audio & text to a common semantic representation	MuST-C	En→De	408	27.1
			En→Fr	492	35.6
			En→Ru	489	17.4
			En→Es	504	30.6
			En→It	465	25.0
			En→Ro	432	24.0
			En→Pt	385	30.2
			En→Nl	442	29.2
		LibriSpeech	En→Fr	492	19.4
ConST (XSTNet + Contrastive Loss) (Ye et al., 2021)	closes modality gap	MuST-C	En→De	408	28.3
			En→Es	504	32.0
			En→Fr	492	38.3
			En→It	465	27.2
			En→Nl	442	31.7
			En→Pt	385	33.1
			En→Ro	432	25.6
			En→Ru	489	18.9
W2V2 + mBart + Adapter (Gállego et al., 2021; Zhao et al., 2022)	slow convergence speed	MuST-C	En→De	408	28.22
		IWSLT	En→De	390	21.43
WACO (Ouyang et al., 2022)	limited parallel data (1-hour)	MuST-C	En→De	1	17.5
		IWSLT	Mt→En	1	13.3
AdaTrans (Zeng et al., 2022)	closing gap between length of speech & text	MuST-C	En→De	408	28.7
			En→Fr	492	38.7
			En→Ru	489	19.0
STEMM (Fang et al., 2022)	Speech representation	MuST-C	En→De	408	28.7
			En→Fr	492	37.4
			En→Ru	489	17.8
			En→Es	504	31.0
			En→It	465	25.8
			En→Ro	432	24.5
			En→Pt	385	31.7
			En→Nl	442	30.5
CTC loss + Optimal Transport (Siamese-PT) (Le et al., 2023)	without change in architecture	MuST-C	En→De	408	27.9
			En→Es	504	31.8
			En→Fr	492	39.2
			En→It	465	27.7
			En→Nl	442	31.7
			En→Pt	385	34.2
			En→Ro	432	27.0
			En→Ru	489	18.5
		CoVoST-2	En→Xx	-	21.5
			Xx→En	-	25.5
Fine & Coarse Granularity Contrastive Learning (Zhang et al., 2023)	limited knowledge transfer ability	MuST-C	En→De	408	25.9
			En→Fr	492	38.3
			En→Ru	489	19.7
			En→Es	504	31.9
			En→It	465	27.3
			En→Ro	432	26.8
			En→Pt	385	32.7
			En→Nl	442	31.6

Table 6: Performance of the ST models using modality bridging. The datasets, language pairs, duration of speech, and metric(BLEU) are shown.

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Encoder-Decoder + Attention (Bansal et al., 2018)	Low- resource	Fisher	Es→En	20	20.2
Unsupervised subtasks + W2V2 + mBart (Wang et al., 2022a)	Pseudo-labels & low downstream performance	Godard Corpus CoVoST	Mboshi→Fr Fr→En	4 264	7.1 40.1
			Es→En	113	43.8
			Ru→En	16	48.6
			Et→En	3	19.0
			Lv→En	2	25.0
			En→Es	-	38.5
			En→Ru	-	22.2
			En→Fr	-	22.1

Table 7: performance of ST models on low resource languages with the datasets, language pairs, duration of speech, and metric(BLEU).

5.2.1. ST in Low-Resource settings

A low-resource language (LRL) is one where speech and/or text data is available in smaller quantity— usually not enough to pre-train Seq2Seq models. As such, LRLs present challenges of their own such as overfitting and poor generalization. This section will discuss works where ST models are developed especially for low-resource languages. The proposed models under this category have generic architecture as shown in Fig.3a which is similar to Seq2Seq ST models. We find the approaches mainly use pre-training the encoder on high-resource ASR data and subsequent fine-tuning on ST data. For example, (Bansal et al., 2018) empirically demonstrates 100% performance improvement on ST tasks. They find that if the ASR language differs from the source and target languages, then *pre-training* on ASR data enhances ST task performance. Though the BLUE score is improved, the absolute BLUE score is only 7.1. In (Wang et al., 2022a), the unsupervised ST is implemented for low-resource settings using pseudo-labels from unsupervised cascade models. Table 7 presents scores of LRL ST models.

Findings: *Low-resource ST can be tackled via either pre-train on ASR data, and then fine-tuning on ST data or using pseudo-labels.*

5.2.2. Code-Mix ST

Code-Mix language refers to speech where one *primary* language is used, but words or phrases from *other (embedded)* languages are also included. We find that there exist only a few works on code-mix ST. In (Weller et al., 2022), the code-mix dataset is created with the existing publicly available corpora Fisher

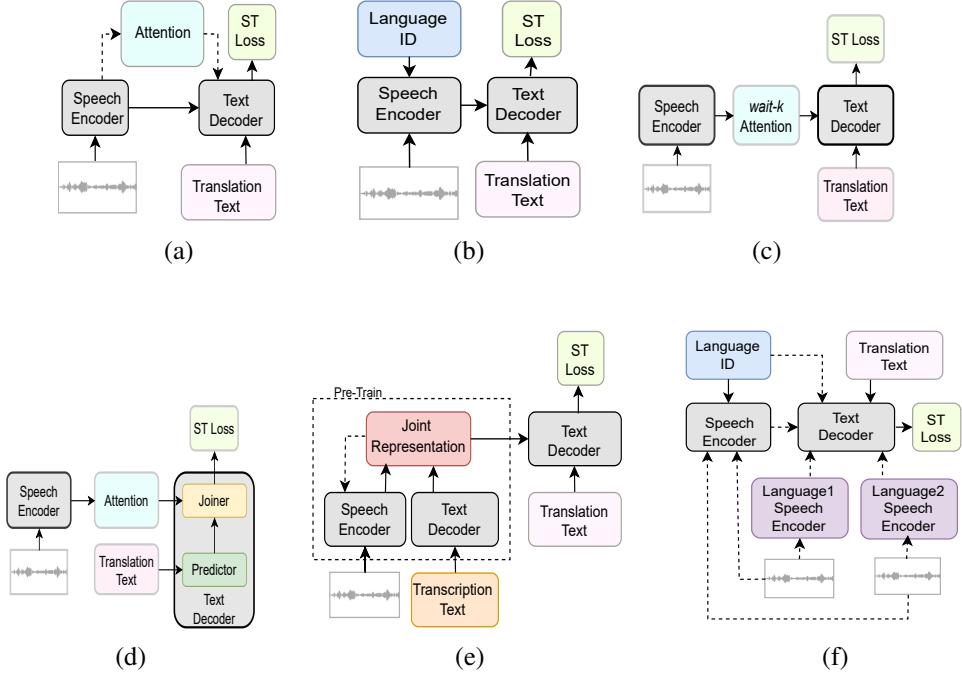


Figure 3: E2E ST Models based on the nature of the data. (a) Low-resource ST, (b) Code-Mix ST, (c) Wait-K based Streaming ST, (d) RNN-T based Streaming ST, (e) Unsupervised ST, and (f) Multilingual ST. The dashed arrow denotes optional components.

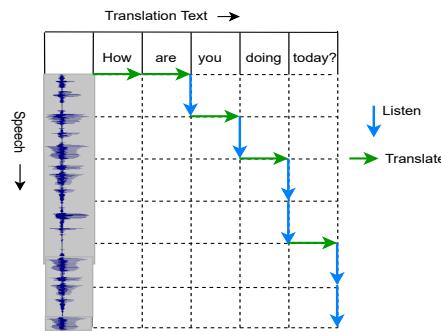


Figure 4: Wait-k strategy for streaming ST setting. In this, the decoder waits for k input speech segments before starting to output. Thereafter, it produces one token for every source segment. The figure showcases the scenario with $k = 2$.

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Joint Transcription & Translation + LID (Weller et al., 2022)	Mixed Language Speech	Fisher	Es/En→En	15	26.2
		Miami	Es/En→Ca	13	18.3

Table 8: Performance of ST code-mix Models: Datasets, Language Pairs, Speech Duration, and BLEU Metric.

(Cieri et al., 2004) and Miami¹⁶. As shown in Fig. 3b, Code-mix ST models feed language ID in addition to speech input to the encoder of the Seq2Seq model (Weller et al., 2022). The Wav2Vec 2.0, an acoustic encoder, and mBART, a multilingual decoder, are used for both languages with an attention layer applied for the *embedded* language. The results are shown in Table 8.

Findings: Standard ST models achieve good results on code-mix data with low-resource setting and no fine-tuning, especially when encoders and decoders are pre-trained, and multilingual models are used.

5.2.3. ST in Streaming Setting

ST in the streaming setting is the task of simultaneous translation (SST) (Goldman-Eisler, 1972; Fügen et al., 2007; Grissom II et al., 2014), that is, the translation of the input as soon as it arrives without waiting for the entire input. It finds application in online speech translation and video dubbing, *inter alia*. Traditionally, the streaming ST problem has been solved by feeding the segmented output of a streaming ASR model to a streaming MT model (Iranzo-Sánchez et al., 2020; Oda et al., 2014). However, due to the cascade nature of the model, it is prone to high latency and error propagation.

The generic architecture of the streaming ST model is shown in Fig. 3c and 3d. The streaming or simultaneous ST problem has been approached in broadly the following ways: Wait-K, Segmentation, Integrate-and-Fire (IF), and transducers/unidirectional transformers. These techniques are combined with Seq2Seq frameworks to devise streaming ST models.

Wait-K policy (Ma et al., 2018) learns the parameters θ of the model by optimizing the negative log-likelihood $-\sum_{(\mathbf{u}, \mathbf{v}) \in D} \log p(\mathbf{v}|\mathbf{u}; k; \theta)$, where k is the number of segments to look before starting translation (see Fig. 4). The probability $p(\cdot)$ is calculated as

¹⁶<https://github.com/apple/ml-code-switched-speech-translation>

$$p(\mathbf{v}|\mathbf{u}; k; \theta) = \prod_{t=1}^{T_v} p(v_t | v_{<t}, u_{t+k}; \theta) \quad (21)$$

Wait-K policy guarantees that the model can look at $t + k - 1$ speech segments while predicting token y_t (Ren et al., 2020). However, one limitation of the Wait-K policy is that it fails to do a beam search while decoding except for long-tail (Ma et al., 2018). To solve this problem, (Zeng et al., 2021) proposes a Wait-K stride-N policy. It essentially is a Wait-K policy with the addition of N READ and WRITE operations until the end of the sentence after reading the first K-segments. In order to determine the K-segments, (Chen et al., 2021b) leverages streaming ASR to guide the direct simultaneous ST decoding via beam search.

As discussed above, determining when to write is crucial for efficient SST. Contrary to Wait-K policy, **Segmentation** can be performed on the embedded speech using either an incremental BEAM search (Yan et al., 2023) or using attention mechanism (Papi et al., 2022). Essentially, these works adapt offline ST to SST showing spectacular performance on benchmark datasets. Note that the models proposed in (Yan et al., 2023; Papi et al., 2022) train models in a cascade manner while the inference is E2E.

The aforementioned works require that encoded speech be segmented so that the decoder can apply the Wait-K policy. The goal of segmentation is to identify the word, sub-word, or phone boundary which are usually not even (due to silences, longer syllables, etc.). That means the number of acoustic units varies with time in each segments. *Monotonic-segmented Streaming ST* (MoSST) (Dong et al., 2021b) is based on learning when to translate, which has a *monotonic segmentation module* located between the acoustic encoder and the transformer. It has an **Integrate-and-Fire** (IF) neuron (Abbott, 1999), which fires above a threshold when the context is developed. If the context is not developed, the neuron receives signals and keeps accumulating the acoustic vectors. IF strategy has shown impressive performance in simultaneous ASR (Dong and Xu, 2019) and ST (Chang and yi Lee, 2022). It can be used for monotonic segmentation of the speech input along with adaptive decision strategy (Dong et al., 2021b).

RNN-T are transducers that can output text sequences given the input speech sequence in an online/streaming fashion (Graves, 2012). For example, *Cross-Attention Augmented Transducer* (CAAT) optimizes translation and policy models in tandem (Liu et al., 2021). They eliminate the RNN-T's strict monotonic restriction for reordering in the translation. The use of transformers to reduce the multi-step memory footprint causes a significant delay for CAAT. The use of

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
SimulSpeech + Attention-level KD + Data-level KD (Ren et al., 2020)	online streaming setting	MuST-C	En→Es	496	22.49
MosST (Dong et al., 2021b)	finding boundaries for acoustic units	MuST-C	En→De	408	24.9
			En→Fr	492	35.3
CAAT (Liu et al., 2021)	policy & model for re-ordering in translation	MuST-C	En→De	408	22.3
Transformer Transducer(TT) (Xue et al., 2022)	High Inference latency & error propagation	MSLT Corpus	En→De	50K	30.7
LAMASSU (Wang et al., 2022b)	Joint ASR & ST Model	(closed dataset)	En→Zh	50K	35.6
			En→De	10K	23.6
			En→Zh	10K	25.5
			De→En	10K	23.3

Table 9: Performance of the ST models for Streaming (Simultaneous Translation) data: Datasets, language pairs, duration of speech, and Metric(BLEU).

regularization terms and substantial hyperparameter adjustment are some limitations of CAAT. An extension of it in (Xue et al., 2022) leverages *Transformer Transducer* (TT) networks with attention pooling for streaming E2E ST tasks. *Attention* divides the input audio into chunks of specific sizes. At any time, processing any input frame x_t can only see frames within its own chunk and a fixed number of left chunks. By sharing the encoder, they also propose a variant to handle E2E ST tasks in **multilingual** settings. The adaptive READ and WRITE policy choices between encoder output and ground truth contributed to its success. The same authors (Wang et al., 2022b) propose to combine the benefits of *language-specific* and *language-agnostic* encoders within the TT framework. A shared encoder takes LIDs as gating values and computes weights for each language through the source LID scheduling scheme. The empirical results demonstrate superior performance and lesser trainable parameters compared to bilingual ST. The results of SST models are shown in Table 9.

Findings: (a) *RNN-T* are able to reduce memory footprint at the expense of translation delay, (b) adaptive read-write policy improves ST task performance.

5.2.4. Unsupervised ST

There is an abundance of unlabeled speech and text data. Since manual annotation and creating a parallel corpus is costly, the natural instinct is to exploit unlabeled data for training ST models. This section reviews works where researchers make use of the *unlabeled* speech data to advance the ST task performance.

In (Wang et al., 2021b), the author leverages large-scale *self*- and *semi-supervised* learning. They pre-train a *Wave2Vec 2.0* as an encoder on Libri-light data (Kahn et al., 2019), and the decoder is randomly initialized. The entire model is opti-

Models/Techniques	Problem Solved	Dataset	Language Pair	Speech (hours)	Metric (BLEU)
Teacher-Student Model (W2V2 + self-training + dec. w/o LM) (Kahn et al., 2019)	Unlabelled Speech & Data	CoVoST-2	En→De	430	27.2
			En→Ca	430	35.6
			En→Ar	430	20.8
			En→Tr	430	18.9

Table 10: Performance of ST models trained in an unsupervised setting: Datasets, Language Pairs, Speech Duration, and BLEU Score Analysis.

mized on CoVoST 2 ST data, and the encoder is *frozen*. Thereby, *self-training* is executed to generate pseudo-labels for Libri-light data. The Wav2Vec 2.0 is a “*student*” model which is fine-tuned with ground truth CoVoST 2 data and pseudo labels. Finally, a language model (LM) is trained on *CommonCrawl* data and combined with the ST model to generate text via *beam-search* decoding. Following along, for training E2E model, (Wang et al., 2021b) produces pseudo-labels by cascading ASR, text *de-normalization*, and MT in an *Unsupervised* manner. In (Li et al., 2020), Wave2Vec 2.0 and mBART are optimized for domain adaption using *in-domain* data. According to experimental results, the proposed method is effective for E2E models without pre-training. However, between supervised and unsupervised pre-trained models performance gap is encountered, which may be investigated in future works. The results of applying unsupervised ST models are presented in Table 10.

Findings: (a) *Pre-trained acoustic and language models combined with pseudo-labels using self-training perform well for unsupervised ST translation,* (b) *domain adaptation is another approach for unsupervised ST.*

5.2.5. Multilingual ST

The multilingual ST model aims to translate from/to multiple speech input/output languages. It can be one of many-to-one, one-to-many, or many-to-many. The ST models solve multilinguality issues using mainly three approaches: (a) language ID, (b) dual-decoder, and (c) pre-trained models.

Language ID (LID) is the *identification label* that allows one to identify the target language and explicitly translate the speech simultaneously. The existing works handle *multilinguality* using LID either with encoder or decoder. In (Inaguma et al., 2019), the model uses LID in the decoder for one-to-many and many-to-many translation. They demonstrate impressive performance in translation from high-resource to low-resource languages without using any transcript data from LRL. However, using the LID embedding in the decoder (Gangi et al.,

2019) is shown to underperform than using it in the encoder. The author shows that LID can be either *concatenated* or *merged* with the inputs and, when pre-trained with ASR data, can result in superior performance than the one-to-one system. The model, however, performs poorly when trained on many *unrelated* target languages. One-to-many and many-to-one multilingual ST systems of (Wang et al., 2020c,a) provide a good set of baselines for research purposes.

Dual-decoder model is the transformer with two decoders, one for each ASR and ST, and the *dual-attention* mechanism. In (Le et al., 2020), a dual-decoder model is proposed to optimize it for ASR and ST tasks jointly. The author hypothesizes that a dual-attention mechanism can benefit each task by transferring knowledge instantly or in *wait-k* policy mechanism. Their model generalizes earlier models proposed for one-to-many and bilingual ST models.

Pre-trained Multilingual Models use a pre-trained encoder and decoder for acoustic modeling and language modeling, respectively. In (Li et al., 2020; Tran et al., 2020), the author shows that efficiently fine-tuning *mBART*, which is a pre-trained multilingual decoder (Liu et al., 2020a) can achieve SOTA results on CoVoST data on *zero-shot* cross-lingual and multilingual translation tasks. Along similar lines, (Le et al., 2021) shows that inserting *adapters* in between layers of the encoder-decoder framework and tuning them can improve the ST task performance over bilingual ST models. The comparative performance statistics of multilingual ST models are presented in Table 11.

Findings: (a) *Language ID token works well with the encoder,* (b) *Mixed data training with language ID can transfer learning from HRL to LRL,* (c) *LID training with ASR data on unrelated languages does not work well,* (d) *adapters can help boost multilingual pre-trained models translation performance.*

5.3. Discussion

The works presented so far show that E2E ST models have been improved tremendously. ST models' improved performance is likely due to leveraging pre-trained ASR/MT models or the respective corpus to train ST encoders/decoders. Weakly labeled/pseudo labels are another way to create more data for training ST models. Contrastive learning, mix-up strategy, adapters, and optimal transport are a few ways to bridge the modality gap.

Applying unsupervised ASR and MT with the Wav2Vec 2.0 encoder and mBART decoder in a low-resource setting yields good results for ST models. When considering online data streaming, using the IF neuron for context building and translation improves results compared to using CAAT, which had latency issues due to

Table 11: Comparison of multilingual ST models performance Using Datasets, Language Pairs, Speech Length, and the BLEU Metric.

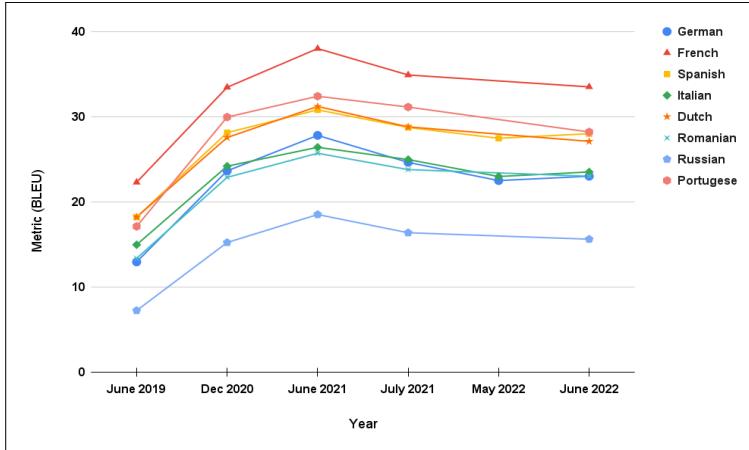


Figure 5: Performance of ST models on MuST-C data over a period of three years.

reordering for translation tasks introduced by RNN-T. mBART handles multilingual settings well by using a dual attention mechanism that facilitates knowledge transfer. Additionally, inserting adapters between the encoder and decoder layers improves performance. In the unsupervised ST setting, the SOTA results were achieved by training Wav2Vec 2.0 on data within the same domain as the speech. We see that *k-wait policy* is used in the streaming settings with segmentation and Multilingual settings with a dual-attention mechanism. In both cases, it yields good results. Also, *adapters* are used in modality bridging and multilingual settings with pre-trained models, which improves the performance. Standard ST models perform satisfactorily on Code-Mix data requiring no fine-tuning. However, there has been limited study on Code-Mix data.

5.4. Overall Performance Trend of E2E ST approaches in Common Benchmarks

In this section, we analyze the performance evolution of ST models based on the MuST-C dataset, as depicted in Figure 5. We selected the MuST-C dataset due to its widespread adoption by researchers since its introduction in 2019. Figure 5 reveals a consistent enhancement in the performance of ST models over time. A noteworthy breakthrough is observed in June 2021, attributed to the work of Ye et al. (2021). This particular model achieved superior results by incorporating various key factors, including the utilization of Wav2Vec 2.0 for feature representation in place of fBank, the integration of a pre-trained MT decoder trained on extensive parallel MT data, and the application of multi-task fine-tuning across ASR, MT, and ST data.

Language Pair	Model/Technique	Dataset	Speech (hours)	Setting	Metric (BLEU)
En→De	Transformer Transducer (Xue et al., 2022)	MSLT Corpus	50K	Online Streaming	30.7
En→Zh					35.6
En→Fr	Speech & Text Joint Pre-Training (Tang et al., 2022)	MuST-C	492	ST with ASR & MT	39.7
En→Es	Unsupervised subtasks + W2V2 + mBart (Wang et al., 2022a)	CoVoST-2	-	Low-Resource	38.5
En→Ru			-		22.2
Ru→En			16		48.6
En→It	CTC loss + Optimal Transport (Siamese-Pt) (Le et al., 2023)	MuST-C	465	Modality bridging	27.7
En→Pt			385		34.2
En→Ro			432		27.0
En→Ni	ConST & Siamese-Pt (Ye et al., 2021)	MuST-C	442	Modality Bridging	31.7
Es→En	Multitask learning (Kim et al., 2017)	CALLHOME	38	Sequence to Sequence	48.7
Fr→En	Attention (Bérard et al., 2016)	BTEC	15	Sequence to Sequence	46.7
Ko→En	NAFM (Zhang et al., 2022)	Kosp2e	190	ST with ASR	5.8
De→En	LAMASSU (Wang et al., 2022b)	(closed dataset)	10K	Online streaming	23.3
Ca→En	LNA + Zero-Shot Learning (Li et al., 2020)	CoVoST-2	136	Multilingual	31.8
Pt→En			10		24.1
Ni→En			7		25.7
Zh→En			10		9.1

Table 12: SOTA performance in High-Resource Language Pairs: Dataset, Models, Speech Duration, Settings, and BLEU Score Analysis (- means the data is not mentioned explicitly in the paper)

5.5. SOTA Performance on High and Low-Resource Languages

In Table 12 and 13, we have compiled the SOTA performance of the ST models on high and low-resource language pairs, respectively, available at the time of writing which is Sep 2023. The tables show which models following which techniques are able to obtain the SOTA performance. Such a table gives a bird-eye view as well as where the performance of ST models stands today. We can observe from Table 12 that there are a few HRLs such as Ko and Zh where the performance of ST models is poor. Similarly, the results in Table 13 showcase really small BLUE scores for languages such as Mn, Si, Ta, Id, Ja, and Sv. Therefore, there is an immediate need to improve the performance of ST models for these languages.

6. Future Directions for Research

This section highlights challenges that need the attention of researchers working on ST problems.

Language Pair	Model/Technique	Dataset	Speech (hours)	Setting	Metric (BLEU)
Griko→It	FastAlign + DTW (Anastasopoulos et al., 2016)	Fisher	20minutes	Sequence to Sequence framework	(Fscore:53.8)
Ainu→En	Tied Multitask Learning with regularizers (Anastasopoulos and Chiang, 2018)	Glossed Corpus	Audio 2.5	ST with ASR & MT	20.3
Mboshi→Fr		Godard Corpus	4.4		24.7
Mt→En	WACO (Ouyang et al., 2022)	IWSLT	1	Modality Bridging	13.3
Et→En	Unsupervised + W2V2 + mBart (Wang et al., 2022a)	CoVoST-2	3	Low-Resource	19.0
Lv→En			2		25.0
En→Ar	Teacher-Student (W2V2 + self-training + dec w/o LM) (Kahn et al., 2019)	CoVoST-2	430	Unsupervised	20.8
En→Ca					35.6
En→Tr					18.9
Sl→En	LNA + Zero Shot Learning (Li et al., 2020)	CoVoST-2	2	Multi-Lingual	5.6
Sv→En			2		5.9
Fa→En			49		11.0
Tr→En			4		11.2
Mn→En			3		1.2
Ar→En			2		6.4
Cy→En			2		9.0
Ta→En			2		0.9
Ja→En			1		2.1
Id→En			1		3.7
En→Cy			430		30.6
En→Ét			430		22.2
En→Fa			430		21.5
En→Id			430		29.9
En→Ja			430		39.3
En→Lv			430		21.5
En→Mn			430		14.8
En→Sl			430		25.1
En→Sv			430		30.4
En→Ta			430		17.8

Table 13: SOTA performance in Low-Resource Language Pairs: Dataset, Models, Speech Duration, Settings, and BLEU Score Analysis

6.1. Cascade vs End-to-End Models

As argued and presented through comprehensive experiments by (Bentivogli et al., 2021), the performance gaps between cascade and E2E ST models are bridged. However, as shown by (Agrawal et al., 2023) in a recent IWSLT 2023 subtitling generation task, the performance of cascade models is far superior to E2E models for offline ST tasks evaluated on all metrics. Furthermore, as far as our understanding, no thorough assessment has been done for low-resource languages that use E2E and cascade models. It may be interesting to compare E2E and cascade ST models on various ST datasets.

6.2. ST on Code-Mix data

We find that there is only one study on the ST model that uses code-mix data as an input. A code-mix data has problems, such as different lexicons, syntax, and scarcity of labeled data. Therefore, it will be interesting to (a) create Code-Mix ST datasets incorporating more languages, (b) see how the existing ST models perform on code-mix ST data?, and (c) Can pre-training in many languages assist in tackling the code-mixing issue.

6.3. Domain-Invariant Models

ST models developed for one domain do not scale well to other domains, as shown in the recent IWSLT 2023. Here domain in-variance setting is the ST model which is trained in some language combination (say Eng-De) and needs to be adapted to other language combinations (e.g., Eng-Hi). Transfer learning/continual learning can be explored to develop generic models.

6.4. Discrepancy between Automatic and Human Evaluation

There may be discrepancies and disagreements among various metrics used to report ST task results. They do not match the mean option score (MOS) provided by human evaluators (Agrawal et al., 2023). For example, if a system evaluates the BLUE score between a ground truth sentence “*Police shot the culprit with a gun*” and hypothesis sentence “*Police use a gun to shot the culprit*”, it is 0! However, both sentences above might be deemed appropriate translations of an utterance *semantically* by an ST system. Such an argument is supported by dubbing artists who often change the voice of the sentence to simplify it or make it more pleasing.¹⁷

¹⁷In the movie “Pirates of the Caribbean”, Jack Sparrow asks Bloom how long he can go for the girl. The original answer from Bloom is “I can die for her!”. Whereas Hindi dubbing is “Till the

Therefore, we call for the attention of researchers to develop and use metrics that match human evaluations semantically. An approach could be to subject the ground truth and hypothesis sentences under *semantic textual similarity* tasks and score them accordingly.

6.5. Handling Ambient Noise

In our literature survey, we find that little has been done to deal with ambient noises. Ambient noise, background music, cross-talk, and non-verbal sounds may create difficulty in ST model learning. The model must distinguish between a meaningful utterance and ambient noise— a non-trivial task.

6.6. Handling Multiple Speakers

It is common in the real world where the audio/video has multiple speakers, each of which may have its own accent (cf., An Asian and American talking to each other in English), dialect, pitch, and accent. Performing *speech separation* may be useful before feeding it to the ST model for improved performance.

6.7. Handling Speaker Diarization

Speaker diarization refers to demarcating the timing of speakers in a multiple-speaker speech. So far, the datasets for ST do not have speaker boundary marks. Creating speaker-diarized ST data in a multilingual setting will be interesting to test the ST models’ robustness.

6.8. Multilingual and Simultaneous ST

Multilingual ST has gained momentum recently due to its importance in the real world. For example, a single speech must be broadcast to multilingual communities (e.g., a conference is attended by a diverse group of people). It can be one-to-many, many-to-one, and many-to-many languages ST. Our literature survey shows that only a few works exist to target one-to-many and many-to-one, whereas many-to-many is few (Inaguma et al., 2019). Besides, there is an opportunity to explore simultaneous multilingual ST, which is the most practical setting.

dying breadth”

6.9. Low-resource ST Datasets and Models

Most existing works have focused on building ST models and datasets for high-resource languages. As we know, the success of ST models relies on the parallel speech-text corpus; building ST datasets for low-resource languages requires immediate attention. Further, a few works, such as (Bansal et al., 2018), have reported ST task results on the Mboshi-French pair; however, the BLUE score is poor. Therefore, building models that transfer learning from language pairs with high to low resources is warranted.

7. Conclusion

This survey paper delves into the most recent advancements in E2E ST translation works. Our discussion includes models, evaluation metrics, and datasets used to train ST models. We review various frameworks for ST models and highlight previous research in this field. The categorization of ST models is based on the kind of data they handle and the models employed. Additionally, we discuss potential future directions for improving speech-to-text translation. Our findings suggest that the gap between cascade and E2E system performance in both online and offline settings is narrowing. However, for some language pairs, the gap is still wide and therefore, additional work is warranted. Our goal in the present ST survey is to offer valuable insight into this topic and drive advancements in ST research. We believe that such reviews will be interesting to researchers.

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