
Unified Segment-to-Segment Framework for Simultaneous Sequence Generation

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Abstract

Simultaneous sequence generation is a pivotal task for real-time scenarios, such as streaming speech recognition, simultaneous machine translation and simultaneous speech translation, where the target sequence is generated while receiving the source sequence. The crux of achieving high-quality generation with low latency lies in identifying the optimal moments for generating, accomplished by learning a mapping between the source and target sequences. However, existing methods often rely on task-specific heuristics for different sequence types, limiting the model’s capacity to adaptively learn the source-target mapping and hindering the exploration of multi-task learning for various simultaneous tasks. In this paper, we propose a unified *segment-to-segment framework (Seg2Seg)* for simultaneous sequence generation, which learns the mapping in an adaptive and unified manner. During the process of simultaneous generation, the model alternates between waiting for a source segment and generating a target segment, making the segment serve as the natural bridge between the source and target. To accomplish this, Seg2Seg introduces a latent segment as the pivot between source to target and explores all potential source-target mappings via the proposed expectation training, thereby learning the optimal moments for generating. Experiments on multiple simultaneous generation tasks demonstrate that Seg2Seg achieves state-of-the-art performance and exhibits better generality across various tasks².

1 Introduction

Recently, there has been a growing interest in simultaneous sequence generation tasks [1, 2, 3, 4, 5, 6, 7, 8, 9] due to the rise of real-time scenarios, such as international conferences, live broadcasts and online subtitles. Unlike conventional sequence generation [10], simultaneous sequence generation receives a streaming source sequence and generates the target sequence simultaneously, in order to provide low-latency feedback [11]. To achieve high-quality generation under such low-latency conditions, simultaneous models must learn to establish a mapping between the target sequence and the source sequence [12] and thereby identify the optimal moments for generating [13].

Directly mapping source and target sequences is non-trivial due to inherent differences between the two sequences, such as modalities or languages, resulting in significant representational and structural gaps. For instance, in streaming automatic speech recognition (Streaming ASR) [8, 9, 14, 15, 16], speech needs to be mapped to text, while simultaneous machine translation (SimulMT) [17, 11, 4, 5, 18, 13] requires the mapping from a source language to a target language (i.e., cross-lingual

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²Code is available at: <https://github.com/ictnlp/Seg2Seg>.

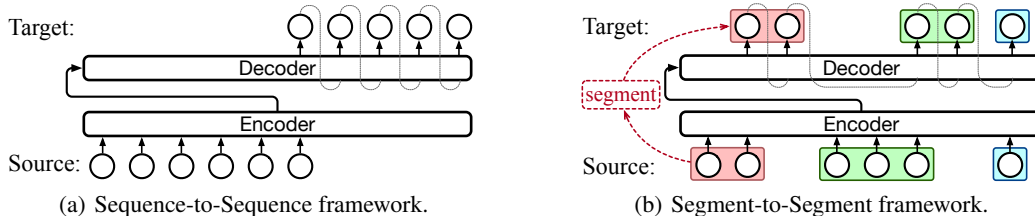


Figure 1: Illustration of the conventional sequence-to-sequence framework for offline generation and the proposed segment-to-segment framework for simultaneous generation.

alignment [19]). Simultaneous speech translation (SimulST) [1, 2, 3, 20, 21] encounters challenges that encompass both cross-modal and cross-lingual aspects. Therefore, developing an approach to bridge source and target is critical to simultaneous sequence generation.

Existing methods for simultaneous generation often rely on task-specific heuristics to bridge the source and target sequences. For example, streaming ASR methods assume a strong correlation between the target token and local speech, employing a fixed-width window to directly predict the corresponding word [22, 9, 14]. SimulMT methods consider that the source and target sequences have similar lengths, employing fixed wait- k policies [4, 23, 18] or attention mechanisms [5, 24, 25] to establish a token-to-token mapping. Such assumptions of similar length limit their ability to handle sequences with significant length differences [12]. SimulST methods divide the speech into multiple segments to overcome length differences [26, 3], and then apply the fixed wait- k policy [20, 27]. These task-specific heuristics not only hinder the adaptive learning of the source-target mapping but also impede the integration of various simultaneous tasks into a unified framework, restricting the potential of utilizing multi-task learning [28, 29, 30] in simultaneous generation tasks.

Under these grounds, we aim to bridge the source and target sequences in an adaptive and unified manner without any task-specific assumptions. In simultaneous generation process, the model necessarily waits for a source segment and outputs a target segment alternately, with each segment comprising one or more tokens. As such, the source sequence and target sequence should correspond in terms of the segment and ideally agree on the segment representation [31], enabling the segment to serve as a natural bridge between source and target. In this paper, we propose a unified *segment-to-segment framework* (*Seg2Seg*) for simultaneous sequence generation, which introduces latent segments as pivots between source and target. As illustrated in Figure 1, given a streaming source sequence, Seg2Seg determines whether the received source tokens can be aggregated into a latent segment. Once aggregated, the latent segment starts emitting the target tokens until the latent segment can no longer emit any further target tokens. Seg2Seg repeats the above steps until finishing generating. To learn when to aggregate and emit, Seg2Seg employs expectation training to explore all possible source-target mappings and find the optimal moments for generating. Experiments on multiple simultaneous generation tasks, including streaming ASR, SimulMT and SimulST, demonstrate that Seg2Seg achieves state-of-the-art performance and exhibits better generality across various simultaneous tasks.

2 Related Work

Streaming ASR Recent streaming ASR methods primarily rely on two approaches: transducer and local attention. Transducer involves a speech encoder and a label predictor, which are aligned via a joiner to determine whether to generate [32, 33, 34]. Local attention approach utilizes monotonic attention to determine whether to generate based on the speech within a local window [6, 7, 35, 22]. Moreover, various methods have been proposed to reduce the latency based on these two approaches by optimizing the alignment process [36, 37, 38, 39, 40].

SimulMT Recent SimulMT methods are mainly based on pre-defined rules or alignment mechanisms. For pre-defined rules, Ma et al. [4] proposed wait- k policy, which waits for k source tokens before alternately waiting/generating one token. Some methods were proposed to improve the flexibility of fixed rules through training [23, 41, 42, 43], simultaneous framework [44, 45], the ensemble of wait- k [46, 18] or post-evaluation [47]. For alignment mechanisms, previous works employ

monotonic attention [5, 24, 31], Gaussian attention [25], binary search [48], non-autoregressive structure [49] or hidden Markov models [13] to learn the alignments between the source and target token-to-token, and make waiting or generating decisions accordingly.

SimulST Recent SimulST methods focus on the segmentation of speech [1, 50, 51, 2]. Ma et al. [26] proposed fixed pre-decision to divide speech into equal-length segments, and applied SimulMT methods such as wait-k [4] and MMA [24]. Some other methods first use CTC results [3, 20], ASR results [52] or integrate-and-firing [27] to detect the number of words in speech, and then apply the wait-k policy. Further, Zhang and Feng [53] proposed ITST, which judges whether the received information is sufficient for translation. Zhang et al. [21] proposed MU-ST, which constructs segmentation labels based on meaning units and uses them to train a segmentation model. Zhang and Feng [54] proposed differentiable segmentation (DiSeg) to directly learn segmentation from the underlying translation model via an unsupervised manner.

Previous methods for simultaneous generation often involve task-specific heuristics, which hinder adaptive learning and limit their applicability to other tasks. The proposed Seg2Seg utilizes the latent segments as pivots to achieve fully adaptive learning of source-target mapping. Furthermore, Seg2Seg serves as a unified framework for various simultaneous generation tasks, making multi-task learning in simultaneous generation feasible.

3 Method

In this paper, we propose a segment-to-segment framework (Seg2Seg) to map the source sequence to the target sequence, using latent segments as the pivots. With the latent segments, Seg2Seg can adaptively learn to map source to target, enabling it to find the optimal moments to generate the target tokens during the simultaneous generation process. Details are introduced in the following sections.

3.1 Mapping with Latent Segments

Seg2Seg leverages the Transformer (encoder-decoder) [55] as the backbone, and further converts the sequence-to-sequence framework to the segment-to-segment framework by introducing latent segments. Formally, we denote the source sequence as $\mathbf{x} = \{x_1, \dots, x_J\}$ with length J , and the target sequence as $\mathbf{y} = \{y_1, \dots, y_I\}$ with length I . In Seg2Seg, the source tokens are first aggregated into several latent segments (source tokens \Rightarrow latent segment), and then the latent segment emits the target tokens (latent segment \Rightarrow target tokens), as shown in Figure 2.

Source tokens \Rightarrow Latent segment For aggregation, Seg2Seg produces a Bernoulli variable a_j for each source token x_j to determine whether the currently received source tokens can be aggregated into a segment. An aggregation probability α_j is predicted as the parameter for the variable a_j , calculated as:

$$\alpha_j = \text{sigmoid}(\text{FFN}(\text{Rep}(x_j))), \quad a_j \sim \text{Bernoulli}(\alpha_j), \quad (1)$$

where $\text{FFN}(\cdot)$ is a feed-forward network, $\text{Rep}(x_j)$ is the representation of x_j , and α_j is aggregation probability at x_j . As shown in Figure 2, if $a_j = 0$, Seg2Seg waits for the next input, otherwise, it aggregates the tokens received after the previous segment into a new segment. Once a latent segment is aggregated, we calculate its representation by summing the representations of all the source tokens it contains. Specifically, the representation of the k^{th} latent segment is denoted as seg_k , calculated as:

$$\text{seg}_k = \mathbf{W}^{\text{src} \rightarrow \text{seg}} \sum_{x_j \in \text{seg}_k} \text{Rep}(x_j), \quad (2)$$

where $\mathbf{W}^{\text{src} \rightarrow \text{seg}}$ is the learnable projection from source to latent segment space.

Latent segment \Rightarrow Target tokens Given latent segment representation, Seg2Seg judges whether seg_k can emit y_i by producing a Bernoulli variable b_{ik} with the emission probability β_{ik} as a

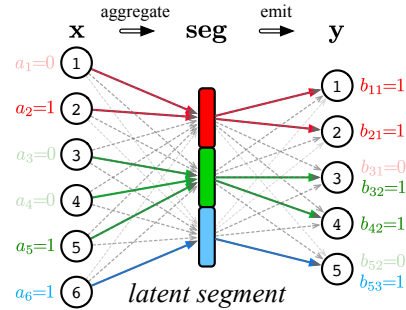


Figure 2: Diagram of source-target mapping with latent segments. The arrows in color and gray represent the mapping in inference and training, respectively.

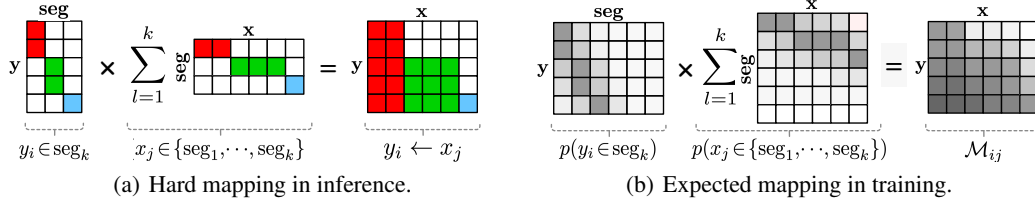


Figure 3: Illustration of source-target mapping in inference and training. (a) The color indicates which latent segment the token belongs to, and the final matrix indicates whether the model receives x_j when generating y_i (i.e., the cross-attention, where the white space is masked out because those source tokens are not received yet.). (b) The shade indicates the probability that the token belongs to different latent segments, and the final matrix indicates the probability that y_i can pay attention to x_j .

parameter. Specifically, b_{ik} is calculated as a dot-product form:

$$\beta_{ik} = \text{sigmoid} \left(\frac{\mathbf{W}^{\text{tgt} \rightarrow \text{seg}} \text{Rep}(y_{i-1}) \cdot \text{seg}_k^\top}{\sqrt{d}} \right), \quad b_{ik} \sim \text{Bernoulli}(\beta_{ik}), \quad (3)$$

where $\mathbf{W}^{\text{tgt} \rightarrow \text{seg}}$ is the learnable projection from target to latent segment space, and d is the input dimension. During emission, if $b_{ik} = 1$, Seg2Seg generates y_i based on the current received source tokens, otherwise it stops emitting and waits for the next input. Take Figure 2 as an example, y_3 will not be emitted from seg_1 as $b_{31} = 0$. After aggregating seg_2 , y_3 is emitted from seg_2 as $b_{32} = 1$.

Overall, Seg2Seg alternates between waiting for enough source tokens to aggregate a latent segment (i.e., wait until $a_j = 1$), and outputting the target tokens until the current latent segment can no longer emit any further tokens (i.e., output until $b_{ik} = 0$). Take the mapping in Figure 2 for instance, Seg2Seg waits for 2 source tokens and generates 2 target tokens, then waits for 3 and generates 2 tokens, then waits for 1 and generates 1 token. Figure 3(a) gives the corresponding mapping in matrix form, where the final matrix indicates whether the model receives x_j when generating y_i .

3.2 Training

During training, Seg2Seg tends to learn the aggregation and emission in an adaptive manner. However, a significant challenge arises from the use of Bernoulli variables a_j and b_{ik} for aggregation and emission, which prevents the back-propagation [56, 57] to the aggregation probability α_j and emission probability β_{ik} . To address this issue, we propose expectation training that employs α_j and β_{ik} instead of Bernoulli variables to calculate the expected mapping, which can be jointly trained with the underlying Transformer model. As illustrated in Figure 3, in expectation training, the source tokens and target tokens are no longer forced to be associated with a single latent segment, but rather can belong to multiple latent segments by probability.

For the aggregation process from source tokens to latent segment, we introduce $p(x_j \in \text{seg}_k)$ to represent the probability that x_j belongs to the latent segment seg_k . Since the aggregation process is monotonic with the streaming source sequence, i.e., which segment x_j belongs to is only related to x_{j-1} , $p(x_j \in \text{seg}_k)$ can be calculated via dynamic programming:

$$p(x_j \in \text{seg}_k) = p(x_{j-1} \in \text{seg}_{k-1}) \times \alpha_{j-1} + p(x_{j-1} \in \text{seg}_k) \times (1 - \alpha_{j-1}). \quad (4)$$

We consider all possible latent segments in the expectation training, so k ranges from 1 to J (i.e., aggregate at most J segments with one token in each segment), even if the source tokens may belong to the later latent segment with a small probability, as shown in Figure 3(b). With $p(x_j \in \text{seg}_k)$, we calculate the expected representation of latent segment by weighting all source tokens:

$$\text{seg}_k = \mathbf{W}^{\text{src} \rightarrow \text{seg}} \sum_{j=1}^J p(x_j \in \text{seg}_k) \times \text{Rep}(x_j). \quad (5)$$

For the emission process from latent segment to target tokens, we introduce $p(y_i \in \text{seg}_k)$ to represent the probability that y_i can be emitted from latent segment seg_k . Since the emission process is mono-

tonic with the simultaneous generation, $p(y_i \in \text{seg}_k)$ can be calculated via dynamic programming:

$$p(y_i \in \text{seg}_k) = \beta_{i,k} \sum_{l=1}^k \left(p(y_{i-1} \in \text{seg}_l) \prod_{m=l}^{k-1} (1 - \beta_{i,m}) \right). \quad (6)$$

We give a detailed introduction to the dynamic programming algorithm in Appendix A.

Learning Mapping To adaptively learn α and β , we jointly train $p(x_j \in \text{seg}_k)$ and $p(y_i \in \text{seg}_k)$ with Transformer via the cross-entropy loss \mathcal{L}_{ce} . During inference, each target token in Seg2Seg no longer focuses on all source tokens, but can only pay attention to the source token within the same latent segment or the previous segments (i.e., the current received tokens), as shown in Figure 3(a). So in training, we calculate the probability that y_i can pay attention to x_j , denoted as \mathcal{M}_{ij} :

$$\mathcal{M}_{ij} = \sum_k p(y_i \in \text{seg}_k) \times p(x_j \in \{\text{seg}_1, \dots, \text{seg}_k\}) = \sum_k p(y_i \in \text{seg}_k) \times \sum_{l=1}^k p(x_j \in \text{seg}_l). \quad (7)$$

Then, we multiply the mapping \mathcal{M}_{ij} with the original cross-attention [53, 58] and normalize it to get the final attention distribution, which is used to calculate the expected target representation. By jointly training mapping and generation via the cross-entropy loss \mathcal{L}_{ce} , Seg2Seg will assign higher \mathcal{M}_{ij} between those related source and target tokens, thereby learning a reasonable mapping.

Learning Latency Besides learning mapping for high-quality generation, we also introduce a latency loss $\mathcal{L}_{latency}$ to encourage low latency. We utilize two commonly used latency metrics, consecutive wait (CW) [17] and average lagging (AL) [4], to calculate the expected latency of Seg2Seg, where CW measures the number of latent segments (i.e., streaming degree [25]), and AL measures the lagging of target token (i.e., lagging degree). Therefore, $\mathcal{L}_{latency}$ is calculated as:

$$\begin{aligned} \mathcal{L}_{latency} &= \mathcal{C}_{CW}(\alpha) + \mathcal{C}_{AL}(\mathcal{M}), \\ \text{where } \mathcal{C}_{CW}(\alpha) &= \left\| \sum_{j=1}^{|\mathbf{x}|} \alpha_j - \lambda |\mathbf{y}| \right\|_2 + \left\| \sum \text{MaxPool} \left(\alpha_i, \left\lfloor \frac{|\mathbf{x}|}{\lambda |\mathbf{y}|} \right\rfloor \right) - \lambda |\mathbf{y}| \right\|_2, \\ \mathcal{C}_{AL}(\mathcal{M}) &= \frac{1}{|\mathbf{y}|} \sum_{i=1}^{|\mathbf{y}|} \sum_{j=1}^{|\mathbf{x}|} \mathcal{M}_{ij}. \end{aligned} \quad (8)$$

For the number of latent segments $\mathcal{C}_{CW}(\alpha)$, following Zhang and Feng [54], we constrain Seg2Seg via the expected segment number $\sum_{j=1}^{|\mathbf{y}|} \alpha_j$ and the uniformity of aggregation, where $\text{MaxPool}(\cdot)$ is the max polling operation with kernel size of $\left\lfloor \frac{|\mathbf{x}|}{\lambda |\mathbf{y}|} \right\rfloor$. For the expected lagging $\mathcal{C}_{AL}(\mathcal{M})$, we constrain the expected lagging $\sum_{j=1}^{|\mathbf{y}|} \mathcal{M}_{ij}$ of target token y_i . λ is a hyperparameter that controls the overall latency of Seg2Seg. A larger λ encourages Seg2Seg to aggregate more latent segments, thereby achieving low latency. When $\lambda \rightarrow 0$, the number of latent segments decreases and latency becomes higher, finally degenerating into a sequence-to-sequence framework when $\lambda = 0$.

Overall, the total training objective of Seg2Seg is the trade-off between \mathcal{L}_{ce} for generation quality and $\mathcal{L}_{latency}$ for generation latency, calculated as:

$$\mathcal{L} = \mathcal{L}_{ce} + \mathcal{L}_{latency}. \quad (9)$$

3.3 Inference

In inference, we set $a_j = 1$ when $\alpha_j \geq 0.5$ and $b_{ik} = 1$ when $\beta_{ik} \geq 0.5$ without sampling [24, 13]. Algorithm 1 illustrates the specific inference process of Seg2Seg. Given a streaming source sequence, Seg2Seg continuously repeats the process of aggregating source tokens into a latent segment (lines 2-6) when $a_j = 1$ and then emitting target tokens from the latent segment (lines 8-12) while $b_{ik} = 1$, until the generation process is completed.

Owing to generating the target sequence in units of segment, it is natural for Seg2Seg to use beam search inside each target segment. Therefore, in the following experiments, we set the size of the beam search for each segment to 5.

Algorithm 1 Inference of Segment-to-Segment Framework

Input: Source sequence \mathbf{x} .
Output: Target sequence $\hat{\mathbf{y}}$.
Initialization: Received source sequence $\hat{\mathbf{x}} = []$; Target sequence $\hat{\mathbf{y}} = [(\text{bos})]$; Index $j=0, i=1, k=1$.

```
1: while  $\hat{y}_{i-1} \neq \langle \text{eos} \rangle$  do
2:
3:   while  $a_j == 0$  and  $\hat{\mathbf{x}} \neq \mathbf{x}$  do ▷ WAIT
4:     Wait for the next source token  $x_{j+1}$ ;
5:      $\hat{\mathbf{x}} \leftarrow \hat{\mathbf{x}} + x_{j+1}$ ;
6:      $j \leftarrow j + 1$ ;
7:   end
8:
9:   Calculate representation of latent segment  $\text{seg}_k$  according to Eq.(2);
10:
11:  while  $(b_{ik} == 1$  or  $\hat{\mathbf{x}} == \mathbf{x})$  and  $\hat{y}_{i-1} \neq \langle \text{eos} \rangle$  do ▷ Generate
12:    Generate the target token  $\hat{y}_i$  based on  $\hat{\mathbf{x}}$ ;
13:     $\hat{\mathbf{y}} \leftarrow \hat{\mathbf{y}} + \hat{y}_i$ ;
14:     $i \leftarrow i + 1$ ;
15:  end
16:
17:   $k \leftarrow k + 1$ ;
18: end
19: return  $\hat{\mathbf{y}}$ ;
```

4 Experiments

4.1 Datasets

We conduct experiments on the most common benchmarks of three representative simultaneous generation tasks, including streaming ASR, SimulMT and SimulST.

Streaming ASR We apply LibriSpeech³ benchmark [59], which consists of 960 hours English audio. We use `dev-clean` (5.4 hours) and `dev-other` (5.3 hours) as validation sets, and `test-clean` (5.4 hours) and `test-other` (5.1 hours) as test sets, where `test-other` set contains more noisy audio. For speech, we use the raw 16-bit 16kHz mono-channel audio wave. For text, we use SentencePiece [60] to generate a unigram vocabulary of size 10000.

SimulMT We apply WMT15⁴ German→English (De→En) benchmark, including 4.5M sentence pairs for training. We use `newstest2013` as validation set (3000 pairs), and `newstest2015` as test set (2169 pairs). 32K BPE [61] is applied and vocabulary is shared across languages.

SimulST We apply MuST-C⁵ English→German (En→De) (408 hours, 234K pairs) and English → Spanish (En→Es) (504 hours, 270K pairs) benchmarks [62]. We use `dev` as validation set (1423 pairs for En→De, 1316 pairs for En→Es) and `test-COMMON` as test set (2641 pairs for En→De, 2502 pairs for En→Es), respectively. The pre-processing is the same as streaming ASR tasks.

4.2 Systems Settings

We conducted experiments on several strong baselines for all three tasks, described as follows.

Offline [55] model waits for the complete source sequence before generating the target sequence. Offline model is decoded with beam 5.

Streaming Automatic Speech Recognition (Streaming ASR)

T-T [34] uses Transformer Transducer to determine waiting/generating via alignments from the joiner between the speech encoder and text predictor. Some methods, including ConstAlign [36], FastEmit [37] and SelfAlign [38] are proposed to further reduce the latency of the Transducer.

³<https://www.openslr.org/12>

⁴<https://www.statmt.org/wmt15/>

⁵<https://ict.fbk.eu/must-c>

MoChA [22] applies monotonic chunkwise attention to generate the target token based on the speech within a local window. Various training methods, such as DeCoT [39], MinLT [39] and CTC [40], are proposed to further constrain the latency of MoChA.

Simultaneous Machine Translation (SimulMT)

Wait-k [4] first waits for k source tokens, and then alternately generates and waits for one token.

Multipath Wait-k [23] trains a wait-k model via randomly sampling different k between batches.

MoE Wait-k [18] applies mixture-of-experts (MoE) to learn multiple wait-k policies during training.

Adaptive Wait-k [46] trains a set of wait-k models (e.g., from wait-1 to wait-13), and heuristically composites these models based on their outputs during inference.

MMA [24] applies monotonic multi-head attention and predicts a variable to indicate waiting or generating, which are trained through monotonic attention [35].

GMA [25] introduces Gaussian multi-head attention and uses a Gaussian prior to learn the alignments via attention. With alignments, GMA decides when to start translating based on the aligned positions.

GSiMT [63] generates waiting/generating decisions, and considers all possible decisions in training.

HMT [63] proposes Hidden Markov Transformer, which uses a HMM to correspond translating moments with the target tokens, thereby learning the optimal translating moments for generating.

Simultaneous Speech Translation (SimulST)

Wait-k, MMA [26] for SimulMT can be applied to SimulST by making a fixed pre-decision to split the speech into $280ms$ durations, where each duration corresponds to one word.

Wait-k-Stride-n [20] generates n tokens every $n \times 280ms$ to address the issue of length differences between speech and text. We set $n=2$ following their best result.

SimulSpeech [3] divides the speech based on a CTC word detector, and then applies wait-k policy.

SH [52] uses the shortest hypothesis in ASR results as word number, and then applies wait-k policy.

RealTrans [20] detects the word number in the streaming speech via counting the blank in CTC results, and then applies the wait-k-stride-n policy.

MMA-CMDR [64] incorporates cross-modal decision regularization to MMA, which leverages the transcription of speech to improve the decision of MMA.

MoSST [27] uses the integrate-and-firing method [65] to segment the speech based on the cumulative acoustic information, and then applies the wait-k policy.

ITST [53] quantifies the transported information from source to target, and subsequently determines whether to generate output based on the accumulated received information.

MU-ST [21] trains an external segmentation model based on the constructed data to detect the meaning unit, and uses it to decide whether to generate.

DiSeg [54] jointly learns the speech segmentation with the underlying translation model via the proposed differentiable segmentation in an unsupervised manner.

All implementations are adapted from Fairseq Library [66]. In Seg2Seg, we use the standard Transformer-Base (6 encoder and 6 decoder layers) [55] for SimulMT. For streaming ASR and SimulST, we replace the word embedding layer in Transformer-Base with a pre-trained Wav2Vec2.0⁶ [67] to extract the acoustic embedding, and the rest remains the same as SimulMT.

Evaluation We use SimulEval⁷ [68] to evaluate the quality and latency of simultaneous generation. For streaming ASR, following Inaguma and Kawahara [40], we use word error rate (WER) for the quality and the mean alignment delay for the latency, which considers the average difference between generating moments and ground-truth alignments. For SimulMT, following Ma et al. [4] and Zhang and Feng [13], we use BLEU [69] for the generation quality and average lagging (AL) [4] for latency, which measures the average offsets that outputs lag behind inputs (using token as the unit of AL). For SimulST, following Ma et al. [26], we use sacreBLEU [70] for the generation quality and average lagging (AL) for latency (using millisecond ms as the unit of AL). Refer to Appendix C for the detailed calculation of the latency metrics.

⁶dl.fbaipublicfiles.com/fairseq/wav2vec/wav2vec_small.pt

⁷<https://github.com/facebookresearch/SimulEval>

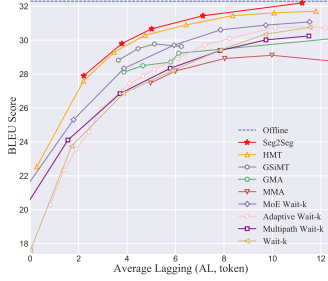
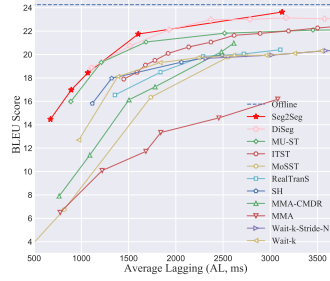
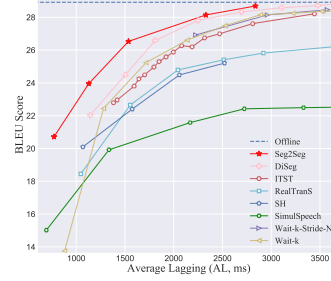


Figure 4: SimulMT results of quality v.s. latency (AL, tokens) on WMT15 De→En.



(a) En→De



(b) En→Es

Figure 5: SimulST results of quality v.s. latency (AL, *ms*) on MuST-C En→De and En→Es.

4.3 Main Results

Results on Streaming ASR Table 1 reports the results on streaming ASR, where Seg2Seg exhibits a better trade-off between generation quality and latency. Compared with T-T using the transducer to align speech and text token-to-token [34], or MoChA generating text based on local speech [22], Seg2Seg adaptively learns source-target mapping through latent segments, thereby performing better.

Results on SimulMT Consistent with the previous methods [4, 24, 13], we adjust the value of λ (refer to Eq.(8)) to show the performance of Seg2Seg under varying latency. Figure 4 shows that Seg2Seg outperforms previous SimulMT methods at all latency. Compared to methods based on pre-defined rules, such as wait-k and MoE wait-k, Seg2Seg is more flexible in making generating/waiting decisions, achieving significant advantages. Other methods, such as MMA, GMA and HMT, align the target and source token-to-token. However, since the alignment between the two languages may not be one-to-one [4], some local reordering and multi-word structures can affect the performance [12]. By mapping source to target at the segment level, Seg2Seg is more in line with the simultaneous generation process and mitigates these issues, ultimately achieving state-of-the-art performance.

Results on SimulST For the most challenging SimulST in Figure 5, Seg2Seg achieves state-of-the-art performance, especially at low latency. Most of the previous SimulST methods either segment the speech into fixed lengths [26, 64] or detect the number of words in the speech [3, 52, 20, 27] and then apply a wait-k policy, where both non-derivable word detection and wait-k policy hinder the adaptive learning of the model. Owing to the proposed expectation training, Seg2Seg is completely differentiable and able to jointly learn the mapping from the source to the latent segment and from the latent segment to the target, thereby finding the optimal moments for generating.

4.4 Superiority of Unified Framework on Multi-task Learning

In the sequence-to-sequence framework, multi-task learning composed of ASR, MT and ST is shown to improve the performance on difficult tasks (e.g. speech translation) by sharing knowledge among different tasks [71, 72, 73]. However, in previous simultaneous generation methods, different tasks often involve different architectures and heuristics, leaving no room for multi-task learning. Owing to not involving any task-related heuristics, the proposed unified segment-to-segment framework provides a possibility to apply multi-task learning in simultaneous generation. In Seg2Seg, multi-task learning can include streaming ASR, SimulMT and SimulST, and these three tasks share all parameters, except that SimulMT has a text embedding and streaming ASR/SimulST have a shared speech embedding.

Table 1: Streaming ASR results.

Systems	WER(\downarrow)		Latency(\downarrow)
	clean	other	
Offline	3.51	8.49	-
T-T	3.40	9.50	610
+ConstAlign	4.00	11.10	328
+FastEmit	4.00	10.40	195
+SelfAlign	4.00	10.70	145
MoChA	4.80	14.20	320
+CTC	4.00	11.20	240
+DeCoT	3.90	11.60	240
+MinLT	4.50	11.70	320
Seg2Seg	3.55	8.73	324

Figure 6 demonstrates the improvements brought by multi-task learning on the most challenging SimulST task. By employing multi-task learning in a unified framework, Seg2Seg can achieve further improvements. Specifically, jointly training with streaming ASR yields more discernible improvements, which is mainly because the monotonic properties between speech and text inherent in streaming ASR assist SimulST in learning the source-target mapping [52, 27, 64, 54]. Therefore, the unified Seg2Seg facilitates the sharing of knowledge among various simultaneous tasks through multi-task learning and is helpful for the difficult tasks, such as SimulST.

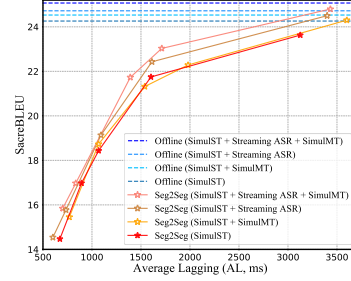


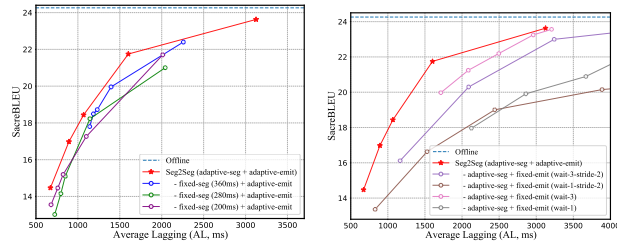
Figure 6: SimulST results on MuST-C En→De with multi-task learning.

5 Analysis

We conducted extensive analyses to investigate the specific improvements of Seg2Seg. Unless otherwise specified, all the results are reported on SimulST with MuST-C En→De test set, which is more difficult simultaneous generation task. Refer to Appendix B for more extended analyses.

5.1 Improvements of Adaptive Learning

Seg2Seg learns the mappings from source to segment and from segment to target in an adaptive manner, without any task-specific assumptions. To verify the effect of adaptive learning, we respectively replace the source-to-segment and segment-to-target mappings with heuristic rules, such as fixed-length segment (i.e., fixed-seg) [26] and wait-k/wait-k-stride-n policy (i.e., fixed-emit) [4, 20], and show the SimulST En→De results in Figure 7.



(a) w/o adaptive aggregation. (b) w/o adaptive emission.

Figure 7: Improvements brought by adaptive learning.

The results show that adaptive learning significantly outperforms heuristic rules. Compared with dividing the source into fixed lengths of 200/280/360ms, Seg2Seg can adaptively determine whether the received source token can be aggregated into a latent segment, bringing about 1 BLEU improvement. Compared with the rule-based wait-k policy, Seg2Seg judges whether to emit the target token based on the latent segment, thus finding more reasonable generating moments [5].

5.2 Quality of Aggregation and Emission

Seg2Seg learns aggregation and emission adaptively, so we further explore the quality of aggregation and emission, respectively. We apply streaming ASR and SimulMT tasks for evaluation. The detailed calculation of the metrics for aggregation and emission quality are shown in Appendix B.1.

Aggregation Quality To verify whether Seg2Seg can aggregate the source tokens into a latent segment at the appropriate moments in streaming ASR, following Zhang and Feng [54], we conduct experiments on the Buckeye dataset⁸ [78], which is a speech segmentation benchmark with the annotated word boundaries. Table 2 shows the segmentation quality of Seg2Seg with some segmentation baselines, and the metrics include precision (P), recall (R) and R-value (comprehensive score) [79]. Seg2Seg achieves better segmentation precision and higher

Table 2: Segmentation accuracy of Seg2Seg.

Systems	P(↑)	R(↑)	R-value(↑)
ES K-Means [74]	30.7	18.0	39.7
BES GMM [75]	31.7	13.8	37.9
VQ-CPC [76]	18.2	54.1	-86.5
VQ-VAE [76]	16.4	56.8	-126.5
DSegKNN [77]	30.9	32.0	40.7
Fixed(280ms)	28.1	16.3	38.4
Seg2Seg	41.1	18.1	41.2

⁸<https://buckeyecorpus.osu.edu>

comprehensive score R-value, showing that Seg2Seg can perform aggregation and segment the speech at reasonable moments (i.e., token boundaries instead of breaking the continuous speech of a word [27]).

Emission Quality To verify whether the model emits at reasonable moments, we follow Zhang and Feng [31] to evaluate the emission quality in SimulMT based on alignments. We apply RWTH⁹ De→En alignment dataset, and calculated the proportion of the model emitting the target token after receiving its aligned source token, used as the emission accuracy. Figure 8 shows that Seg2Seg can receive more aligned source tokens before emitting under the same latency, meaning that Seg2Seg finds more favorable moments for generating and achieves high-quality generation.

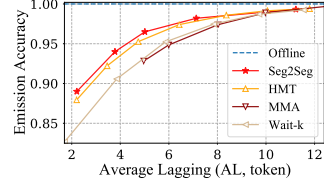


Figure 8: Emission accuracy of Seg2Seg in SimulMT.

5.3 Effect of Latent Segments

To investigate whether the latent segments can act as a bridge between the source and target, we calculate the representations of the source tokens ($\sum_{x_j \in \text{seg}_k} x_j$), target tokens ($\sum_{y_i \in \text{seg}_k} y_i$), and latent segment seg_k within each segment during SimulST on En→De. We then apply the T-SNE dimensionality reduction algorithm to project these representations into a 2D space. By doing so, we obtain a bivariate kernel density estimation of the representation distribution of source segment, target segment and latent segments, depicted in Figure 9. The visualization clearly demonstrates that the latent segment locates between the source and target sequences in the representation space, effectively serving as a bridge connecting the source and target.

Furthermore, we calculate the cosine similarity between the representations of the source, target and latent segments, as shown in Table 3. It is evident that the similarity between the source and target representations is low, posing a challenge for the model to directly map the source to the target. Conversely, the similarity between the latent segment and the source, as well as the latent segment and the target, is significantly higher. Hence, by introducing the latent segment as a pivot, the model can more easily learn the mapping from the source to the latent segment, and subsequently from the latent segment to the target, thereby finding the optimal moments for generating and achieving better performance.

Table 3: Representational similarity with the latent segment.

	Similarity
source \Leftrightarrow target	0.53 %
source \Leftrightarrow segment	20.01 %
segment \Leftrightarrow target	14.66 %

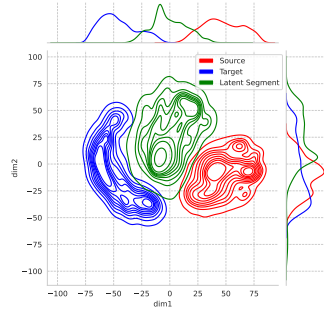


Figure 9: Bivariate kernel density estimation visualization on the representations of source, target and latent segment.

6 Conclusion

In this paper, we propose a unified segment-to-segment framework for simultaneous sequence generation, which bridges the source and target sequences using latent segments as pivots. Unified Seg2Seg enables the handling of multiple simultaneous generation tasks and facilitates multi-task learning. Experiments and analyses show the superiority of Seg2Seg on performance and generalization.

Limitations

The proposed Seg2Seg employs the encoder-decoder architecture as its backbone, and exhibits better generality across multiple simultaneous generation tasks. In addition to its primary application on generation tasks, the encoder (aggregation process) or decoder (emission process) of Seg2Seg can also be separately used for some real-time tasks based on encoder-only or decoder-only architecture, such as streaming tagging and online parsing. We leave this for further exploration in future work.

⁹<https://www-i6.informatik.rwth-aachen.de/goldAlignment/>

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References

- [1] Christian Fügen, Alex Waibel, and Muntsin Kolss. Simultaneous translation of lectures and speeches. *Machine Translation*, 21(4):209–252, 2007. ISSN 09226567, 15730573. URL <https://link.springer.com/article/10.1007/s10590-008-9047-0>.
- [2] Yusuke Oda, Graham Neubig, Sakriani Sakti, Tomoki Toda, and Satoshi Nakamura. Optimizing segmentation strategies for simultaneous speech translation. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 551–556, Baltimore, Maryland, June 2014. Association for Computational Linguistics. doi: 10.3115/v1/P14-2090. URL <https://aclanthology.org/P14-2090>.
- [3] Yi Ren, Jinglin Liu, Xu Tan, Chen Zhang, Tao Qin, Zhou Zhao, and Tie-Yan Liu. Simul-Speech: End-to-end simultaneous speech to text translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3787–3796, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.350. URL <https://aclanthology.org/2020.acl-main.350>.
- [4] Mingbo Ma, Liang Huang, Hao Xiong, Renjie Zheng, Kaibo Liu, Baigong Zheng, Chuanqiang Zhang, Zhongjun He, Hairong Liu, Xing Li, Hua Wu, and Haifeng Wang. STACL: Simultaneous translation with implicit anticipation and controllable latency using prefix-to-prefix framework. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3025–3036, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1289. URL <https://www.aclweb.org/anthology/P19-1289>.
- [5] Naveen Arivazhagan, Colin Cherry, Wolfgang Macherey, Chung-Cheng Chiu, Semih Yavuz, Ruoming Pang, Wei Li, and Colin Raffel. Monotonic infinite lookback attention for simultaneous machine translation. In Anna Korhonen, David Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1313–1323, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1126. URL <https://aclanthology.org/P19-1126>.
- [6] William Chan and Ian Lane. On Online Attention-Based Speech Recognition and Joint Mandarin Character-Pinyin Training. In *Proc. Interspeech 2016*, pages 3404–3408, 2016. doi: 10.21437/Interspeech.2016-334. URL https://www.isca-speech.org/archive/interspeech_2016/chan16c_interspeech.html.
- [7] Junfeng Hou, Shiliang Zhang, and Li-Rong Dai. Gaussian prediction based attention for online end-to-end speech recognition. In *Proc. Interspeech 2017*, pages 3692–3696, 2017. doi: 10.21437/Interspeech.2017-751. URL <http://dx.doi.org/10.21437/Interspeech.2017-751>.
- [8] Bo Li, Anmol Gulati, Jiahui Yu, Tara N. Sainath, Chung-Cheng Chiu, Arun Narayanan, Shuo-Yiin Chang, Ruoming Pang, Yanzhang He, James Qin, Wei Han, Qiao Liang, Yu Zhang, Trevor Strohman, and Yonghui Wu. A better and faster end-to-end model for streaming asr. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5634–5638, 2021. doi: 10.1109/ICASSP39728.2021.9413899. URL <https://ieeexplore.ieee.org/iel7/9413349/9413350/09413899.pdf>.
- [9] Bo Li, Shuo-yiin Chang, Tara N. Sainath, Ruoming Pang, Yanzhang He, Trevor Strohman, and Yonghui Wu. Towards fast and accurate streaming end-to-end asr. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6069–6073, 2020. doi: 10.1109/ICASSP40776.2020.9054715.
- [10] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K.Q. Weinberger, editors, *Advances in Neural Information Processing Systems*, volume 27. Curran Associates, Inc., 2014. URL https://proceedings.neurips.cc/paper_files/paper/2014/file/a14ac55a4f27472c5d894ec1c3c743d2-Paper.pdf.

- [11] Jiatao Gu, Graham Neubig, Kyunghyun Cho, and Victor O.K. Li. Learning to translate in real-time with neural machine translation. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 1053–1062, Valencia, Spain, April 2017. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/E17-1099>.
- [12] Shaolei Zhang, Shoutao Guo, and Yang Feng. Wait-info policy: Balancing source and target at information level for simultaneous machine translation. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 2249–2263, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-emnlp.166. URL <https://aclanthology.org/2022.findings-emnlp.166>.
- [13] Shaolei Zhang and Yang Feng. Hidden markov transformer for simultaneous machine translation. In *The Eleventh International Conference on Learning Representations*, 2023. URL <https://openreview.net/forum?id=9y0HFvaAYD6>.
- [14] Hirofumi Inaguma, Masato Mimura, and Tatsuya Kawahara. Enhancing Monotonic Multihead Attention for Streaming ASR. In *Proc. Interspeech 2020*, pages 2137–2141, 2020. doi: 10.21437/Interspeech.2020-1780. URL <http://dx.doi.org/10.21437/Interspeech.2020-1780>.
- [15] Niko Moritz, Takaaki Hori, and Jonathan Le. Streaming automatic speech recognition with the transformer model. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6074–6078, 2020. doi: 10.1109/ICASSP40776.2020.9054476. URL <https://ieeexplore.ieee.org/document/9054476>.
- [16] Jiahui Yu, Wei Han, Anmol Gulati, Chung-Cheng Chiu, Bo Li, Tara N Sainath, Yonghui Wu, and Ruoming Pang. Dual-mode {asr}: Unify and improve streaming {asr} with full-context modeling. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=Pz_dcqfcKW8.
- [17] Kyunghyun Cho and Masha Esipova. Can neural machine translation do simultaneous translation? *CoRR*, abs/1606.02012, 2016. URL <http://arxiv.org/abs/1606.02012>.
- [18] Shaolei Zhang and Yang Feng. Universal simultaneous machine translation with mixture-of-experts wait-k policy. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7306–7317, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.581. URL <https://aclanthology.org/2021.emnlp-main.581>.
- [19] Shaolei Zhang, Qingkai Fang, Zhuocheng Zhang, Zhengrui Ma, Yan Zhou, Langlin Huang, Mengyu Bu, Shangdong Gui, Yunji Chen, Xilin Chen, and Yang Feng. Bayling: Bridging cross-lingual alignment and instruction following through interactive translation for large language models, 2023. URL <https://arxiv.org/abs/2306.10968>.
- [20] Xingshan Zeng, Liangyou Li, and Qun Liu. RealTranS: End-to-end simultaneous speech translation with convolutional weighted-shrinking transformer. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 2461–2474, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.218. URL <https://aclanthology.org/2021.findings-acl.218>.
- [21] Ruiqing Zhang, Zhongjun He, Hua Wu, and Haifeng Wang. Learning adaptive segmentation policy for end-to-end simultaneous translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7862–7874, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.542. URL <https://aclanthology.org/2022.acl-long.542>.
- [22] Chung-Cheng Chiu* and Colin Raffel*. Monotonic chunkwise attention. In *International Conference on Learning Representations*, 2018. URL <https://openreview.net/forum?id=Hko85p1CW>.

- [23] Maha Elbayad, Laurent Besacier, and Jakob Verbeek. Efficient Wait-k Models for Simultaneous Machine Translation, 2020. URL <http://dx.doi.org/10.21437/Interspeech.2020-1241>.
- [24] Xutai Ma, Juan Miguel Pino, James Cross, Liezl Puzon, and Jiatao Gu. Monotonic multihead attention. In *International Conference on Learning Representations*, 2020. URL <https://openreview.net/forum?id=Hyg96gBKPS>.
- [25] Shaolei Zhang and Yang Feng. Gaussian multi-head attention for simultaneous machine translation. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 3019–3030, Dublin, Ireland, May 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.findings-acl.238>.
- [26] Xutai Ma, Juan Pino, and Philipp Koehn. SimulMT to SimulST: Adapting simultaneous text translation to end-to-end simultaneous speech translation. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing*, pages 582–587, Suzhou, China, December 2020. Association for Computational Linguistics. URL <https://aclanthology.org/2020.aacl-main.58>.
- [27] Qian Dong, Yaoming Zhu, Mingxuan Wang, and Lei Li. Learning when to translate for streaming speech. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 680–694, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.50. URL <https://aclanthology.org/2022.acl-long.50>.
- [28] Sebastian Ruder. An Overview of Multi-Task Learning in Deep Neural Networks. *arXiv e-prints*, art. arXiv:1706.05098, June 2017. doi: 10.48550/arXiv.1706.05098.
- [29] Yu Zhang and Qiang Yang. An overview of multi-task learning. *National Science Review*, 5(1): 30–43, 09 2017. ISSN 2095-5138. doi: 10.1093/nsr/nwx105. URL <https://doi.org/10.1093/nsr/nwx105>.
- [30] Antonios Anastasopoulos and David Chiang. Tied multitask learning for neural speech translation. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 82–91, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1008. URL <https://aclanthology.org/N18-1008>.
- [31] Shaolei Zhang and Yang Feng. Modeling dual read/write paths for simultaneous machine translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2461–2477, Dublin, Ireland, May 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.acl-long.176>.
- [32] Alex Graves. Sequence transduction with recurrent neural networks. *arXiv preprint arXiv:1211.3711*, 2012. URL <https://arxiv.org/abs/1211.3711>.
- [33] Navdeep Jaitly, David Sussillo, Quoc V. Le, Oriol Vinyals, Ilya Sutskever, and Samy Bengio. A neural transducer, 2016. URL <https://arxiv.org/abs/1511.04868>.
- [34] Ching-Feng Yeh, Jay Mahadeokar, Kaustubh Kalgaonkar, Yongqiang Wang, Duc Le, Mahaveer Jain, Kjell Schubert, Christian Fuegen, and Michael L Seltzer. Transformer-transducer: End-to-end speech recognition with self-attention. *arXiv preprint arXiv:1910.12977*, 2019. URL <https://arxiv.org/abs/1910.12977>.
- [35] Colin Raffel, Minh-Thang Luong, Peter J. Liu, Ron J. Weiss, and Douglas Eck. Online and linear-time attention by enforcing monotonic alignments. In Doina Precup and Yee Whye Teh, editors, *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 2837–2846. PMLR, 06–11 Aug 2017. URL <https://proceedings.mlr.press/v70/raffel17a.html>.

- [36] Tara N. Sainath, Ruoming Pang, David Rybach, Basi García, and Trevor Strohman. Emitting Word Timings with End-to-End Models. In *Proc. Interspeech 2020*, pages 3615–3619, 2020. doi: 10.21437/Interspeech.2020-1059. URL <http://dx.doi.org/10.21437/Interspeech.2020-1059>.
- [37] Jiahui Yu, Chung-Cheng Chiu, Bo Li, Shuo-yiin Chang, Tara N Sainath, Yanzhang He, Arun Narayanan, Wei Han, Anmol Gulati, Yonghui Wu, et al. Fastemit: Low-latency streaming asr with sequence-level emission regularization. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6004–6008. IEEE, 2021. URL <https://ieeexplore.ieee.org/abstract/document/9413803/>.
- [38] Jaeyoung Kim, Han Lu, Anshuman Tripathi, Qian Zhang, and Hasim Sak. Reducing Streaming ASR Model Delay with Self Alignment. In *Proc. Interspeech 2021*, pages 3440–3444, 2021. doi: 10.21437/Interspeech.2021-322. URL https://www.isca-speech.org/archive/pdfs/interspeech_2021/kim21j_interspeech.pdf.
- [39] Hirofumi Inaguma, Yashesh Gaur, Liang Lu, Jinyu Li, and Yifan Gong. Minimum latency training strategies for streaming sequence-to-sequence asr. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6064–6068, 2020. doi: 10.1109/ICASSP40776.2020.9054098. URL <https://ieeexplore.ieee.org/abstract/document/9054098/>.
- [40] Hirofumi Inaguma and Tatsuya Kawahara. Alignment knowledge distillation for online streaming attention-based speech recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 31:1371–1385, 2023. doi: 10.1109/TASLP.2021.3133217. URL <https://ieeexplore.ieee.org/abstract/document/9640576/>.
- [41] Shaolei Zhang, Yang Feng, and Liangyou Li. Future-guided incremental transformer for simultaneous translation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(16):14428–14436, May 2021. URL <https://ojs.aaai.org/index.php/AAAI/article/view/17696>.
- [42] Shaolei Zhang and Yang Feng. ICT’s system for AutoSimTrans 2021: Robust char-level simultaneous translation. In *Proceedings of the Second Workshop on Automatic Simultaneous Translation*, pages 1–11, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.autosimtrans-1.1. URL <https://aclanthology.org/2021.autosimtrans-1.1>.
- [43] Shoutao Guo, Shaolei Zhang, and Yang Feng. Simultaneous machine translation with tailored reference. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. Association for Computational Linguistics, December 2023. URL <https://arxiv.org/abs/2310.13588>.
- [44] Shaolei Zhang and Yang Feng. Reducing position bias in simultaneous machine translation with length-aware framework. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6775–6788, Dublin, Ireland, May 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.acl-long.467>.
- [45] Shoutao Guo, Shaolei Zhang, and Yang Feng. Glancing future for simultaneous machine translation, 2023. URL <https://arxiv.org/abs/2309.06179>.
- [46] Baigong Zheng, Kaibo Liu, Renjie Zheng, Mingbo Ma, Hairong Liu, and Liang Huang. Simultaneous translation policies: From fixed to adaptive. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2847–2853, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.254. URL <https://www.aclweb.org/anthology/2020.acl-main.254>.
- [47] Shoutao Guo, Shaolei Zhang, and Yang Feng. Turning fixed to adaptive: Integrating post-evaluation into simultaneous machine translation. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 2264–2278, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-emnlp.167. URL <https://aclanthology.org/2022.findings-emnlp.167>.

- [48] Shoutao Guo, Shaolei Zhang, and Yang Feng. Learning optimal policy for simultaneous machine translation via binary search. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2318–2333, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.130. URL <https://aclanthology.org/2023.acl-long.130>.
- [49] Zhengrui Ma, Shaolei Zhang, Shoutao Guo, Chenze Shao, Min Zhang, and Yang Feng. Non-autoregressive streaming transformer for simultaneous translation, 2023. URL <https://arxiv.org/abs/2310.14883>.
- [50] Mahsa Yarmohammadi, Vivek Kumar Rangarajan Sridhar, Srinivas Bangalore, and Baskaran Sankaran. Incremental segmentation and decoding strategies for simultaneous translation. In *Proceedings of the Sixth International Joint Conference on Natural Language Processing*, pages 1032–1036, Nagoya, Japan, October 2013. Asian Federation of Natural Language Processing. URL <https://aclanthology.org/I13-1141>.
- [51] Vivek Kumar Rangarajan Sridhar, John Chen, Srinivas Bangalore, Andrej Ljolje, and Rathinavelu Chengalvarayan. Segmentation strategies for streaming speech translation. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 230–238, Atlanta, Georgia, June 2013. Association for Computational Linguistics. URL <https://aclanthology.org/N13-1023>.
- [52] Junkun Chen, Mingbo Ma, Renjie Zheng, and Liang Huang. Direct simultaneous speech-to-text translation assisted by synchronized streaming ASR. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4618–4624, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.406. URL <https://aclanthology.org/2021.findings-acl.406>.
- [53] Shaolei Zhang and Yang Feng. Information-transport-based policy for simultaneous translation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 992–1013, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.65. URL <https://aclanthology.org/2022.emnlp-main.65>.
- [54] Shaolei Zhang and Yang Feng. End-to-end simultaneous speech translation with differentiable segmentation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 7659–7680, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-acl.485. URL <https://aclanthology.org/2023.findings-acl.485>.
- [55] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 5998–6008. Curran Associates, Inc., 2017. URL <http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf>.
- [56] Ruslan Salakhutdinov and Geoffrey Hinton. Semantic hashing. *International Journal of Approximate Reasoning*, 50(7):969–978, 2009. ISSN 0888-613X. doi: <https://doi.org/10.1016/j.ijar.2008.11.006>. URL <https://www.sciencedirect.com/science/article/pii/S0888613X08001813>. Special Section on Graphical Models and Information Retrieval.
- [57] Jakob Foerster, Ioannis Alexandros Assael, Nando de Freitas, and Shimon Whiteson. Learning to communicate with deep multi-agent reinforcement learning. In D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc., 2016. URL <https://proceedings.neurips.cc/paper/2016/file/c7635bfd99248a2cdef8249ef7bfbef4-Paper.pdf>.
- [58] Shaolei Zhang and Yang Feng. Modeling concentrated cross-attention for neural machine translation with Gaussian mixture model. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 1401–1411, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.121. URL <https://aclanthology.org/2021.findings-emnlp.121>.

- [59] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. Librispeech: An asr corpus based on public domain audio books. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5206–5210, 2015. doi: 10.1109/ICASSP.2015.7178964.
- [60] Taku Kudo and John Richardson. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71, Brussels, Belgium, November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-2012. URL <https://aclanthology.org/D18-2012>.
- [61] Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany, August 2016. Association for Computational Linguistics. doi: 10.18653/v1/P16-1162. URL <https://www.aclweb.org/anthology/P16-1162>.
- [62] Mattia A. Di Gangi, Roldano Cattoni, Luisa Bentivogli, Matteo Negri, and Marco Turchi. MuST-C: a Multilingual Speech Translation Corpus. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2012–2017, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1202. URL <https://aclanthology.org/N19-1202>.
- [63] Yishu Miao, Phil Blunsom, and Lucia Specia. A generative framework for simultaneous machine translation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6697–6706, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. URL <https://aclanthology.org/2021.emnlp-main.536>.
- [64] Mohd Abbas Zaidi, Beomseok Lee, Sangha Kim, and Chanwoo Kim. Cross-Modal Decision Regularization for Simultaneous Speech Translation. In *Proc. Interspeech 2022*, pages 116–120, 2022. doi: 10.21437/Interspeech.2022-10617. URL https://www.isca-speech.org/archive/interspeech_2022/zaidi22_interspeech.html.
- [65] Linhao Dong and Bo Xu. Cif: Continuous integrate-and-fire for end-to-end speech recognition. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6079–6083, 2020. doi: 10.1109/ICASSP40776.2020.9054250. URL <https://ieeexplore.ieee.org/iel7/9040208/9052899/09054250.pdf>.
- [66] Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 48–53, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-4009. URL <https://www.aclweb.org/anthology/N19-4009>.
- [67] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 12449–12460. Curran Associates, Inc., 2020. URL <https://proceedings.neurips.cc/paper/2020/file/92d1e1eb1cd6f9fba3227870bb6d7f07-Paper.pdf>.
- [68] Xutai Ma, Mohammad Javad Dousti, Changhan Wang, Jiatao Gu, and Juan Pino. SIMULEVAL: An evaluation toolkit for simultaneous translation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 144–150, Online, October 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-demos.19. URL <https://aclanthology.org/2020.emnlp-demos.19>.
- [69] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association*

- for *Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073135. URL <https://www.aclweb.org/anthology/P02-1040>.
- [70] Matt Post. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6319. URL <https://www.aclweb.org/anthology/W18-6319>.
- [71] Qingkai Fang, Rong Ye, Lei Li, Yang Feng, and Mingxuan Wang. STEMM: Self-learning with speech-text manifold mixup for speech translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7050–7062, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.486. URL <https://aclanthology.org/2022.acl-long.486>.
- [72] Qingkai Fang and Yang Feng. Understanding and bridging the modality gap for speech translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15864–15881, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.884. URL <https://aclanthology.org/2023.acl-long.884>.
- [73] Yan Zhou, Qingkai Fang, and Yang Feng. CMOT: Cross-modal mixup via optimal transport for speech translation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7873–7887, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.436. URL <https://aclanthology.org/2023.acl-long.436>.
- [74] Herman Kamper, Karen Livescu, and Sharon Goldwater. An embedded segmental k-means model for unsupervised segmentation and clustering of speech. In *2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 719–726, 2017. doi: 10.1109/ASRU.2017.8269008. URL https://www.kamperh.com/papers/kamper+livescu+goldwater_asru2017.pdf.
- [75] Herman Kamper, Aren Jansen, and Sharon Goldwater. A segmental framework for fully-unsupervised large-vocabulary speech recognition. *Computer Speech & Language*, 46:154–174, 2017. ISSN 0885-2308. doi: <https://doi.org/10.1016/j.csl.2017.04.008>. URL <https://www.sciencedirect.com/science/article/pii/S0885230816301905>.
- [76] Herman Kamper and Benjamin van Niekerk. Towards unsupervised phone and word segmentation using self-supervised vector-quantized neural networks. *arXiv e-prints*, art. arXiv:2012.07551, December 2020. URL <https://ui.adsabs.harvard.edu/abs/2020arXiv201207551K>.
- [77] Tzeviya Sylvia Fuchs, Yedid Hoshen, and Joseph Keshet. Unsupervised word segmentation using k nearest neighbors. *arXiv preprint arXiv:2204.13094*, 2022. URL <https://arxiv.org/abs/2204.13094>.
- [78] Mark A. Pitt, Keith Johnson, Elizabeth Hume, Scott Kiesling, and William Raymond. The buckeye corpus of conversational speech: labeling conventions and a test of transcriber reliability. *Speech Communication*, 45(1):89–95, 2005. ISSN 0167-6393. doi: <https://doi.org/10.1016/j.specom.2004.09.001>. URL <https://www.sciencedirect.com/science/article/pii/S0167639304000974>.
- [79] Okko Räsänen, Unto Laine, and Toomas Altsaar. An improved speech segmentation quality measure: the r-value. In *10th Interspeech Conference, Brighton, UK, September 6-10, 2009*, 2009. URL <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=91ff68c684116aeaa4de8b407fa79bbf1e05dc3c>.
- [80] Kris Demuyne and Tom Laureys. A comparison of different approaches to automatic speech segmentation. In Petr Sojka, Ivan Kopeček, and Karel Pala, editors, *Text, Speech and Dialogue*, pages 277–284, Berlin, Heidelberg, 2002. Springer Berlin Heidelberg. ISBN 978-3-540-46154-8. URL https://link.springer.com/chapter/10.1007/3-540-46154-X_38.

A Dynamic Programming of Mapping

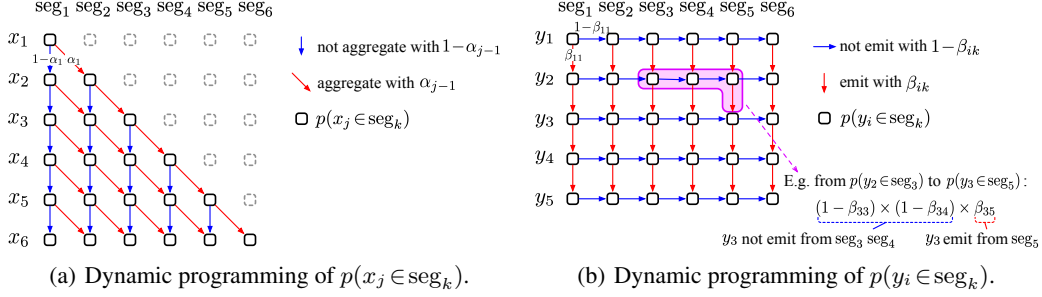


Figure 10: Schematic diagram of the dynamic programming of mapping in expectation training.

In Sec.3.2, we propose expectation training for Seg2Seg to learn when to aggregate and emit through $p(x_j \in \text{seg}_k)$ and $p(y_i \in \text{seg}_k)$. Given the monotonic property of simultaneous sequence generation tasks, we can calculate $p(x_j \in \text{seg}_k)$ and $p(y_i \in \text{seg}_k)$ using a dynamic programming algorithm. In the following sections, we will provide a detailed explanation of the dynamic programming approach.

A.1 Source Tokens to Latent Segment

Given the streaming source sequence, Seg2Seg predicts aggregation probability α_j for x_j to represent the probability of aggregating the received source tokens into a latent segment at x_j . Given aggregation probability α_j , we calculate $p(x_i \in \text{seg}_k)$ via dynamic programming.

The whole aggregation process is monotonic with inputs, which means that the $(k+1)^{\text{th}}$ latent segment can only be aggregated once the k^{th} segment has already been aggregated. Additionally, each latent segment must be aggregated by at least one source token, otherwise a latent segment without representation would be meaningless. As a result, whether x_j belongs to latent segment seg_k depends on which segment that x_{j-1} is located in, consisting of 3 situations:

- If $x_{j-1} \in \text{seg}_{k-1}$: As illustrated by the red line in Figure 10(a), x_j belongs to latent segment seg_k when Seg2Seg aggregate at x_{j-1} with probability α_{j-1} ;
- If $x_{j-1} \in \text{seg}_k$: As illustrated by the blue line in Figure 10(a), x_j belongs to latent segment seg_k (i.e., the same latent segment with x_{j-1}) when Seg2Seg does not aggregate at x_{j-1} with probability $1 - \alpha_{j-1}$;
- Otherwise: x_j can not belong to seg_k anyway, i.e., with probability 0.

By combining these situations, $p(x_i \in \text{seg}_k)$ is calculated as:

$$p(x_j \in \text{seg}_k) = p(x_{j-1} \in \text{seg}_{k-1}) \times \alpha_{j-1} + p(x_{j-1} \in \text{seg}_k) \times (1 - \alpha_{j-1}), \quad (10)$$

where the initialization is

$$p(x_1 \in \text{seg}_k) = \begin{cases} 1 & \text{if } k = 1 \\ 0 & \text{if } k \neq 1 \end{cases}, \quad (11)$$

because the first source token inevitably belongs to the first segment. With the above dynamic programming algorithm, we can calculate $p(x_j \in \text{seg}_k)$, for $j = 1, \dots, J$ and $k = 1, \dots, J$.

A.2 Latent Segment to Target Tokens

After getting the latent segments, Seg2Seg predicts the emission probability β_{ik} , which indicates the probability of emitting the target token y_i from the latent segment seg_k . With the emission probability β_{ik} , we compute $p(y_i \in \text{seg}_k)$ using dynamic programming as well. Note that there is one difference between the aggregation process and the emission process when employing dynamic programming. In the aggregation process, each latent segment must be aggregated by at least one

source token. However, in the emission process, the latent segment has the option to not generate any target token, as not all source tokens have corresponding target tokens.

Whether y_i belongs to latent segment seg_k depends on which segment that y_{i-1} is emitted from, consisting of 3 situations:

- If $y_{i-1} \in \text{seg}_k$: y_i is emitted from latent segment seg_k with probability β_{ik} ;
- If $y_{i-1} \in \text{seg}_l$ for $l = 1, \dots, k-1$: y_i is emitted from latent segment seg_k when y_i is not emitted from seg_l to seg_{k-1} , and then emitted from seg_k . Taking Figure 10(b) as an example, if $y_2 \in \text{seg}_3$, the premise of $y_3 \in \text{seg}_5$ is that y_3 is not emitted from seg_3 and seg_4 , and is emitted from seg_5 . Formally, the probability is calculated as:

$$\beta_{ik} \times \prod_{m=l}^{k-1} (1 - \beta_{i,m}), \quad (12)$$

where $\prod_{m=l}^{k-1} (1 - \beta_{i,m})$ is the probability that y_i is not emitted from seg_l to seg_{k-1} ;

- If $y_{i-1} \in \text{seg}_l$ for $l = k+1, \dots$: y_i can not be emitted from seg_k anyway, as the emission process is monotonic, i.e., with probability 0.

By combining these situations, $p(y_i \in \text{seg}_k)$ is calculated as:

$$p(y_i \in \text{seg}_k) = \beta_{i,k} \sum_{l=1}^k \left(p(y_{i-1} \in \text{seg}_l) \prod_{m=l}^{k-1} (1 - \beta_{i,m}) \right), \quad (13)$$

where the initialization is

$$p(y_1 \in \text{seg}_k) = \beta_{1,k} \prod_{m=1}^{k-1} (1 - \beta_{1,m}). \quad (14)$$

With the above dynamic programming algorithm, we can calculate $p(y_i \in \text{seg}_k)$, for $i = 1, \dots, I$ and $k = 1, \dots, J$.

B Extended Analyses

B.1 Detailed Calculation of Aggregation and Emission Quality

In Sec.5.2, we evaluate the aggregation and emission quality of Seg2Seg. Here, we give detailed calculations of aggregation and emission quality.

Aggregation Quality We verify whether Seg2Seg can aggregate (segment) the source speech sequence at the appropriate moments on the speech segmentation task [80]. For our evaluation, we utilize the Buckeye dataset, where the ground-truth segmentation is based on word units. Evaluation metrics consist of precision (P), recall (R), and the comprehensive score R-value. Note that since the ground-truth segmentation in Buckeye is in units of words, and the aggregation of Seg2Seg is in units of segments, which makes the segment number of Seg2Seg may be less than the ground-truth segment number, so precision can better reflect whether the aggregation moments of Seg2Seg is reasonable. R-value [79] is a more robust comprehensive metric for speech segmentation task, calculated as:

$$\text{R-value} = 1 - \frac{|r_1| + |r_2|}{2}, \quad (15)$$

$$\text{where } r_1 = \sqrt{(1-R)^2 + \left(\frac{R}{P} - 1\right)^2}, \quad r_2 = \frac{-\left(\frac{R}{P} - 1\right) + R - 1}{\sqrt{2}}. \quad (16)$$

A larger R-value indicates better segmentation quality, where R-value = 100% if and only if $P = 100\%$ and $R = 100\%$.

Emission Quality We verify whether Seg2Seg can emit the target token at appropriate moments in SimulMT. In simultaneous machine translation, it is crucial for the model to emit the corresponding target token after receiving its aligned source token [5], so the alignments can be used as the basis for

judging whether the emitting moments are reasonable. Following Zhang and Feng [31], Guo et al. [47], Zhang and Feng [13], we calculate the proportion of the ground-truth aligned source tokens received before emitting as the emission quality. We apply RWTH¹⁰ De→En alignment dataset and denote the ground-truth aligned source position of y_i as a_i , while use t_i to record the emitting moments of y_i . Then, the emission quality is calculated as:

$$\text{Score} = \frac{1}{|y|} \sum_{i=1}^{|y|} \mathbb{1}_{a_i \leq t_i}, \quad \text{where } \mathbb{1}_{a_i \leq t_i} = \begin{cases} 1, & a_i \leq t_i \\ 0, & a_i > t_i \end{cases}. \quad (17)$$

B.2 Visualization of Mapping

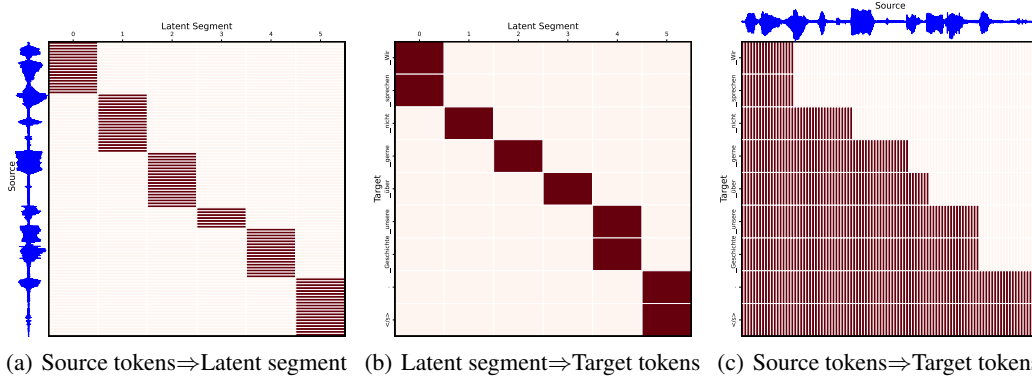


Figure 11: Visualization of the mapping with the latent segment during inference on En→De SimulST (Case #2258). The red rectangles in (a) and (b) indicate the correspondence between token and latent segment. (c) indicates the received source tokens when generating each target token. The English meaning of target sequence: Wir (_we) sprechen (_speak) nicht (_not) gerne (_gladly) über (_about) unsere (_our) Geschichte (_story).

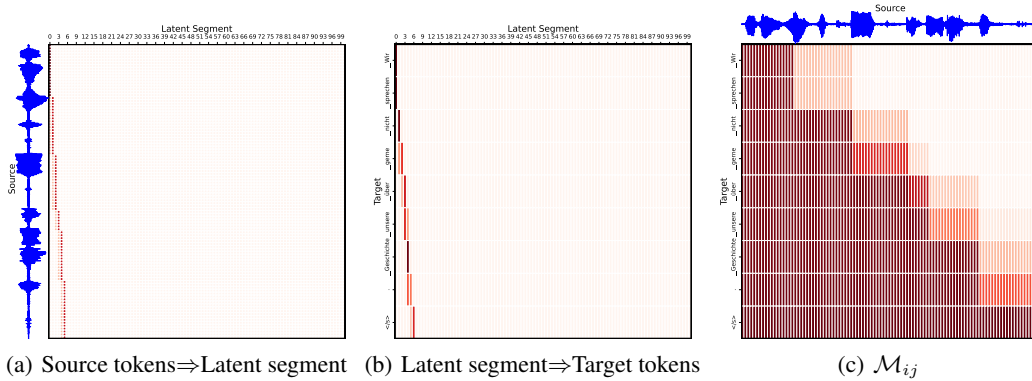


Figure 12: Visualization of the mapping with the latent segment during training on En→De SimulST (Case #2258). The shade of red rectangles in (a) and (b) indicate the probability that the token belongs to different latent segments. (c) indicates the probability that y_i can pay attention to x_j . Note that Seg2Seg considers all possible latent segments during training, so there are more latent segments in (a) and (b) than inference.

We visualize the proposed source-target mapping with the latent segment as the pivot in Figure 11 and 12, where the case is from the most challenging SimulST task.

Inference Figure 11 shows the mapping during inference. Seg2Seg effectively aggregates a lengthy speech sequence (approximately 101 tokens) into 6 latent segments, and then these 6 latent segments

¹⁰<https://www-i6.informatik.rwth-aachen.de/goldAlignment/>

emit 8 target tokens. As depicted in Figure 11(a), Seg2Seg exhibits high-quality aggregation by selectively splitting and aggregating the speech at appropriate boundaries, thereby preserving the integrity of the acoustic information [27]. During emission, Seg2Seg exhibits the ability to generate multi-word structures, such as ‘*unsere Geschichte*’ (meaning ‘*our history*’ in English), within the same latent segment. Overall, Seg2Seg achieves good source-to-target mapping through adaptive aggregation and emission.

Expectation Training Figure 12 shows the mapping during training. In expectation training, Seg2Seg considers all possible latent segments, with the number of segments ranging from 1 to J , shown in Figure 12(a) and 12(b). By incorporating the constraint of the latency loss on the number of segments, Seg2Seg can effectively learn to aggregate an appropriate number of latent segments. Furthermore, Figure 12(c) demonstrates the probability that each target token can pay attention to the source token (referred to as \mathcal{M}_{ij} in Eq.(7)). This expectation aligns well with the inference process depicted in Figure 11(c), thereby highlighting the effectiveness of expectation training.

B.3 Case Study

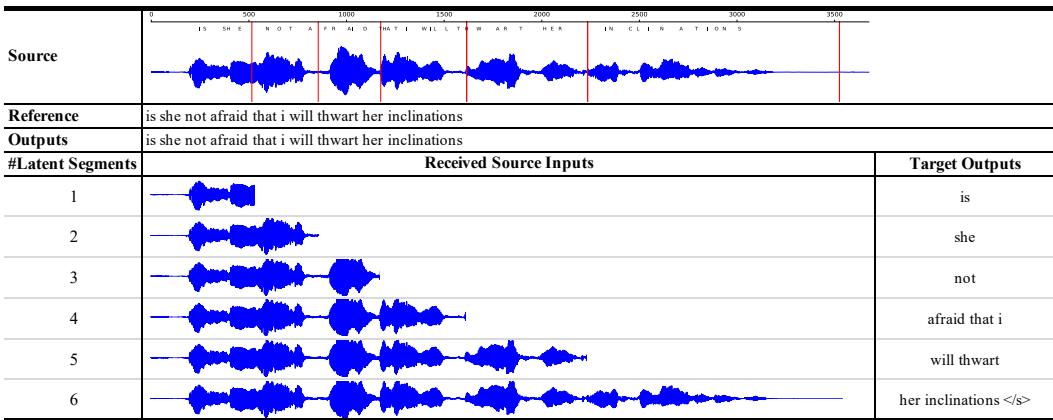


Figure 13: Case study (#4992-23283-0015 in LibriSpeech) of Seg2Seg on streaming ASR task. To demonstrate the simultaneous generation process, we correspond target outputs and received source inputs to show the moments of generating each target token.

#Latent Segments	Received Source Inputs	Target Outputs
1	ein	a
2	ein Lot@@ to@@	Lot@@ to
3	ein Lot@@ to@@ spieler	player
4	ein Lot@@ to@@ spieler aus Har@@	from
5	ein Lot@@ to@@ spieler aus Har@@ vey	Har@@ vey
6	ein Lot@@ to@@ spieler aus Har@@ vey ist	is
7	ein Lot@@ to@@ spieler aus Har@@ vey ist diesen Monat dra@@ n	this mon@@ th . </s>

Figure 14: Case study (#1366 in WMT15 De→En) of Seg2Seg on SimulMT task. To demonstrate the simultaneous generation process, we correspond target outputs and received source inputs to show the moments of generating each target token.

Figure 13, 14 and 15 visualize the simultaneous generation process of Seg2Seg on the cases from streaming ASR, SimulMT and SimulST. In Streaming ASR and SimulST, for a clear illustration, we use an external offline speech-text alignment tool¹¹ to align the transcription with the speech sequence, and the aligned transcription is displayed above the speech waveform.

¹¹https://pytorch.org/audio/main/tutorials/forced_alignment_tutorial.html

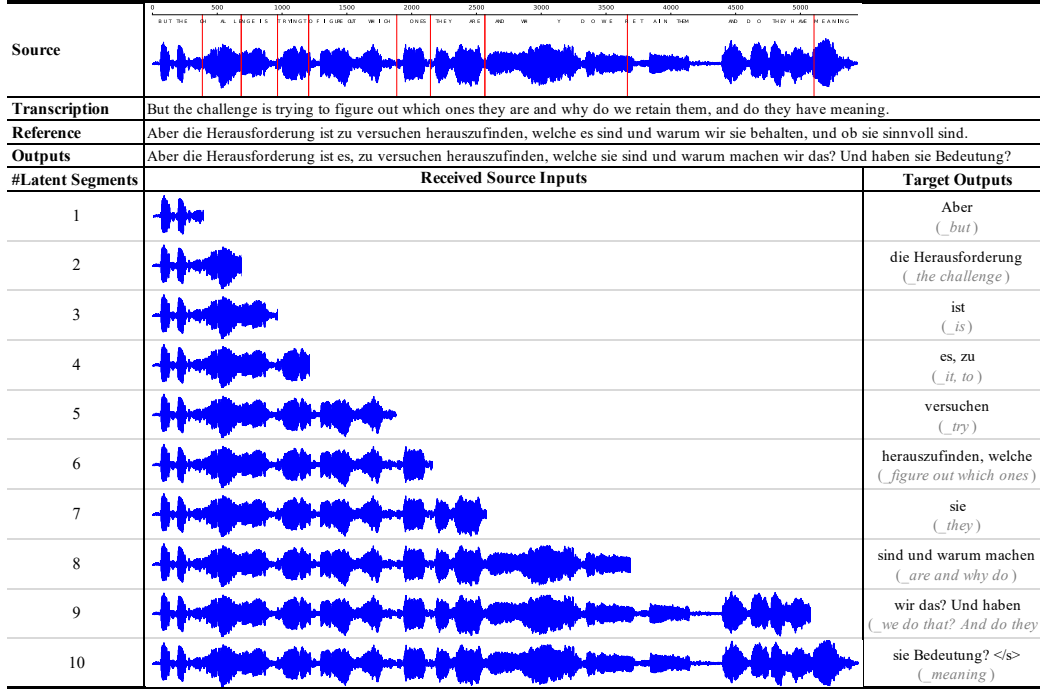


Figure 15: Case study (#1166_119 in MuST-C En→De) of Seg2Seg on SimulST task. To demonstrate the simultaneous generation process, we correspond target outputs and received source inputs to show the moments of generating each target token.

Case of Streaming ASR As shown in Figure 13, the target sequence and source sequence in streaming ASR often exhibit a predominantly monotonic relationship, and Seg2Seg can handle this monotonic mapping well. Seg2Seg can segment and aggregate source sequences at speech boundaries, and then emit the corresponding target sequences accurately.

Case of SimulMT Figure 14 shows a case on SimulMT. Seg2Seg can generate the target token after receiving the corresponding source tokens, e.g., generating ‘Lot@@ to’ after receiving ‘Lot@@ to’, generating ‘player’ after receiving ‘spieler’ and generating ‘Har@@ vey’ after receiving ‘Har@@ vey’, which effectively ensures the generation quality of SimulMT. Besides, for some related target tokens, especially the subwords after the bpe operation, Seg2Seg can emit them together from the same latent segment, thereby achieving lower latency.

Case of SimulST Figure 15 shows a case on SimulST, which is more challenging as the source and target sequences involve different modalities and languages. Despite these evident differences, Seg2Seg demonstrates its capability to find the reasonable generating moments, such as generating ‘herauszufinden’ after receiving ‘figure out’ in the speech, and generating ‘Bedeutung’ after receiving ‘meaning’ in the speech. This is mainly attributed to expectation training, which explores all possible mappings in training, allowing Seg2Seg to learn to aggregate and emit at reasonable moments. As seen, Seg2Seg aggregates the related speech frame into the same latent segment and will not break the acoustic integrity of the speech. For emission, Seg2Seg can accurately determine whether a latent segment can emit the target token, where almost all emitted target outputs are correspond to the source speech contained in the latent segment.

C Latency Metrics

For the latency evaluation of simultaneous generation task, we use mean alignment delay for streaming ASR and average lagging for SimulMT and SimulST.

Mean Alignment Delay [40] is defined as the average word time difference between the ground-truth alignments (speech and transcription) and generating moments:

$$D_{\text{mean}} = \frac{1}{|\mathbf{y}|} \sum_{i=1}^{|\mathbf{y}|} (\hat{t}_i - t_i), \quad (18)$$

where t_i is the ground-truth alignment of y_i , and \hat{t}_i is the generating moment of y_i .

Average Lagging (AL) [4] evaluates the average number of tokens (for SimulMT) or speech duration (for SimulST) that target outputs lag behind the source inputs. We use t_i to denote the generating moments of y_i , and AL is calculated as:

$$\text{AL} = \frac{1}{\tau} \sum_{i=1}^{\tau} t_i - \frac{i-1}{|\mathbf{y}|/|\mathbf{x}|}, \quad \text{where } \tau = \underset{i}{\text{argmin}} (t_i = |\mathbf{x}|). \quad (19)$$

In addition to average lagging, we also use some other latency metrics for SimulMT and SimulST, described as follow.

Consecutive Wait (CW) [11] evaluates the average number of source tokens waited between two target tokens, i.e., the number of segments:

$$\text{CW} = \frac{|\mathbf{x}|}{\sum_{i=1}^{|\mathbf{y}|} \mathbb{1}_{t_i - t_{i-1} > 0}}, \quad (20)$$

where $\mathbb{1}_{t_i - t_{i-1} > 0}$ counts the number of $t_i - t_{i-1} > 0$, i.e., the number of segments. It is worth mentioning that the latency loss $\mathcal{L}_{\text{latency}}$ in training employs the denominator part of the CW metric, as the numerator is a constant.

Average Proportion (AP) [17] evaluates the proportion between the number of received source tokens and the total number of source tokens, calculated as:

$$\text{AP} = \frac{1}{|\mathbf{x}|/|\mathbf{y}|} \sum_{i=1}^{|\mathbf{y}|} t_i. \quad (21)$$

Differentiable Average Lagging (DAL) [5] is a differentiable version of average lagging, calculated as:

$$\text{DAL} = \frac{1}{|\mathbf{y}|} \sum_{i=1}^{|\mathbf{y}|} t'_i - \frac{i-1}{|\mathbf{x}|/|\mathbf{y}|}, \quad \text{where } t'_i = \begin{cases} t_i & i = 1 \\ \max\left(t_i, t'_{i-1} + \frac{|\mathbf{x}|}{|\mathbf{y}|}\right) & i > 1 \end{cases}. \quad (22)$$

D Numerical Results

Table 4, 5 and 6 report the numerical results of Seg2Seg on SimulMT and SimulST, where λ a hyperparameter that controls the overall latency of Seg2Seg (refer to Eq.(8)).

Table 4: Numerical results of Seg2Seg on De→En SimulMT.

SimulMT on WMT15 De→En					
λ	CW	AP	AL	DAL	BLEU
0.4	1.78	0.60	2.21	4.52	27.90
0.3	2.30	0.63	3.78	5.83	29.28
0.2	2.63	0.71	5.01	7.06	30.67
0.1	5.07	0.81	7.13	13.89	31.44
0.05	7.20	0.85	11.23	15.32	32.20

Table 5: Numerical results of Seg2Seg on En→De SimulST.

SimulST on MuST-C En→De					
λ	CW	AP	AL	DAL	BLEU
0.4	588.99	0.68	672.58	1444.73	14.47
0.3	653.43	0.71	893.27	1533.80	16.98
0.2	831.69	0.73	1068.11	1736.00	18.44
0.1	1563.63	0.79	1602.01	2477.97	21.75
0.05	2532.03	0.92	3125.51	4121.58	23.63

Table 6: Numerical results of Seg2Seg on En→Es SimulST.

SimulST on MuST-C En→Es					
λ	CW	AP	AL	DAL	BLEU
0.4	682.84	0.71	772.23	1645.60	20.72
0.3	874.32	0.74	1129.03	1891.32	23.96
0.2	1676.52	0.80	1536.29	2724.39	26.53
0.1	1963.08	0.82	2329.22	3022.22	28.14
0.05	2326.10	0.89	2838.15	4074.75	28.69