# EFFICIENT SPEECH TRANSLATION WITH DYNAMIC LATENT PERCEIVERS

Ioannis Tsiamas, Gerard I. Gállego, José A. R. Fonollosa Universitat Politècnica de Catalunya, Barcelona Marta R. Costa-jussà Meta AI, Paris

{ioannis.tsiamas,gerard.ion.gallego,jose.fonollosa}@upc.edu

costajussa@meta.com

#### **ABSTRACT**

Transformers have been the dominant architecture for Speech Translation in recent years, achieving significant improvements in translation quality. Since speech signals are longer than their textual counterparts, and due to the quadratic complexity of the Transformer, a down-sampling step is essential for its adoption in Speech Translation. Instead, in this research, we propose to ease the complexity by using a Perceiver encoder to map the speech inputs to a fixed-length latent representation. Furthermore, we introduce a novel way of training Perceivers, with Dynamic Latent Access (DLA), unlocking larger latent spaces without any additional computational overhead. Speech-to-Text Perceivers with DLA can match the performance of a Transformer baseline across three language pairs in MuST-C. Finally, a DLA-trained model is easily adaptable to DLA at inference, and can be flexibly deployed with various computational budgets, without significant drops in translation quality.

Index Terms— Speech Translation, Efficiency, Perceiver

## 1. INTRODUCTION

Speech Translation (ST) has traditionally relied on a *cascade* approach, using two separate systems, an Automatic Speech Recognition (ASR) for transcription and a Machine Translation (MT) for text translation. Recently, the *end-to-end* approach, with a single model, has attracted more interest, having several advantages such as faster inference and no error propagation [1, 2]. The Transformer [3] has been crucial for this change, becoming the standard model in end-to-end ST.

One of the Transformer's key features is the ability to model token-to-token interactions with attention matrices, which imposes a quadratic complexity with respect to the sequence length. Since speech sequences are much longer than text sequences, directly processing speech with a Transformer becomes problematic. Thus, a modification is usually necessary, with down-sampling the speech signal at the input of the encoder [4] or at the input of the attention modules [5]. In this research, we take an alternative approach and propose to map the input speech to a fixed-length latent representation using a Perceiver encoder [6]. This mapping swaps the quadratic

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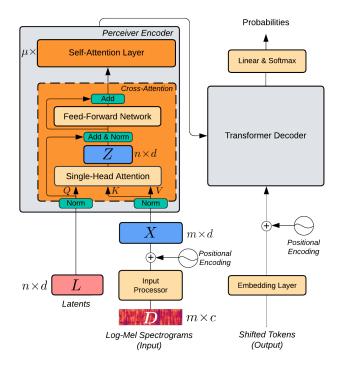


Fig. 1. Speech-to-Text Perceiver

complexity from the sequence length to the number of latents and makes the model only linearly dependent on the sequence length. We show that a Perceiver encoder coupled with a Transformer decoder can obtain competitive results across three language pairs in end-to-end ST. In order to further ease the computational burden of the proposed model, we introduce a novel way of training Perceivers, with Dynamic Latent Access (DLA). Perceivers with DLA have more expressive power, by creating a large latent space, but only using a small part of it at each training step. Consequently, this leads to increased performance without any additional computational overhead. We furthermore demonstrate that DLA can be used for inference, thus gaining large improvements in efficiency with very small drops in translation quality. Finally, we study the complementary nature of DLA at training and inference and show that combined can create a single model that is flexibly used in different scenarios with a varying computational budget. Our code is publicly available.<sup>1</sup>

<sup>1</sup>https://github.com/mt-upc/s2t-perceiver

#### 2. RELEVANT RESEARCH

Many Transformer [3] variants have been proposed for speech tasks. They usually involve changing the encoder, by adding strided convolutional layers to down-sample the input [4, 7]. Further variations include the introduction of convolution inside the attention layers [5, 8]. In this work, we replace the encoder with a Perceiver [6], enabling the model to work on a latent space with an arbitrary number of latents.

The Perceivers [6, 9] is a family of attention-based encoders that do not depend on inductive biases and can thus be applied to different modalities with very few modifications. One of their key features is that they project the input to a fixed-length latent representation, alleviating the quadratic scaling problem of the Transformer [3]. The latents are learned parameters and their number is a hyperparameter, which remains fixed throughout training and inference. The Perceiver obtains competitive results on language understanding, image classification, and multimodal audio-video tasks. In this research, we take advantage of the scaling properties of the Perceiver to tackle Speech Translation, a sequence-to-sequence task that is characterized by long source sequences.

The PerceiverAR [10] is an autoregressive decoder that uses the previous context as a latent initialization, and can thus allow for varying compute at inference time. On the contrary, our proposed method, DLA, selects latents *dynamically* for each example and can be utilized at both training and inference time. Our method is also similar to techniques like LayerDrop [11], which helps in training deeper models without raising the computational costs. Instead of a deeper model, DLA allows training a Perceiver on large latent spaces that can be fully or partially used at inference time.

### 3. PROPOSED METHODOLOGY

### 3.1. Speech-to-Text Perceiver

The Speech-to-Text Perceiver (Fig. 1) employs a Perceiver encoder [9] coupled with a Transformer decoder [3]. The Perceiver encoder consists of an initial cross-attention layer, followed by several self-attention layers. The input to the Perceiver encoder is log-Mel spectrograms  $D \in \mathbb{R}^{m \times c}$ , where m is the number of frames in the input and c is the number of frequency bins. The input is first processed with a 2-layer non-strided convolutional network, followed by an addition of sinusoidal positional embeddings [3], to obtain  $X \in \mathbb{R}^{m \times d}$ , where d is the dimensionality of the model. A set of n ddimensional latent vectors  $L \in \mathbb{R}^{n \times d}$  is also passed to the encoder. The latent vectors are parameters, that are randomly initialized and learned during training. The cross-attention layer uses a single-headed attention module [3] to map the latent vectors L and the processed input X to a latent representation  $Z \in \mathbb{R}^{n \times d}$ , which is then passed through a feedforward network. Layer normalization [12] is applied to both

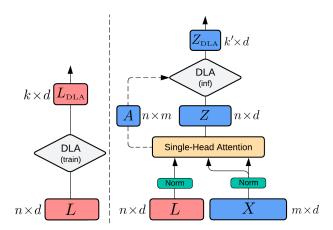


Fig. 2. Dynamic Latent Access. (a) Training (b) Inference

the inputs L, X of the attention, and to its output Z. Inputs to the attention and feed-forward modules are added residually to their outputs. The output of the cross-attention layer is then processed by  $\mu$  self-attention layers [3] and passed to the Transformer decoder, which produces the output token probabilities.

### 3.2. Dynamic Latent Access

Since the input is mapped to a latent space of size n, the complexity with respect to the input length m is only linear, i.e.  $\mathcal{O}(nm)$ , unlike the quadratic one of a Transformer encoder,  $\mathcal{O}(m^2)$ . This is a significant advantage, especially in the domain of ST, which is characterized by long input sequences that can even reach lengths of  $m = 3,000^2$ . The size of the latent space n is a hyperparameter, and in general higher values will provide more expressive power to the encoder. But due to the self-attention layers in the Perceiver encoder, there is now a quadratic complexity with respect to n. More specifically,  $\mathcal{O}(nm + \mu n^2)$  for the whole encoder, where  $\mu$  is the number of self-attention layers. Additionally, the choice of n provides flexibility only once, before the training, and then the model is bound to it. To signify the benefits of the Perceiver encoder, we propose a novel way of utilizing the latent space, with Dynamic Latent Access (DLA). The proposed method can be used both at training (DLA<sub>train</sub>) and inference (DLA<sub>inf</sub>). At training time, DLA samples for each example randomly a set of k latent vectors,  $L_{\text{DLA}} \in \mathbb{R}^{k \times d}$ , where  $k \leq n$  (Fig. 2a). Thus, DLA<sub>train</sub> can provide access to large latent space with size n, providing more capacity to the encoder, while being computationally bound only to k. DLA can also be used at inference and avoid the computationally expensive generation with n latent vectors, in favor of k' < n.  $DLA_{inf}$  is applied to the latent representation Z, and selects a set of k' vectors  $Z_{\text{DLA}} \in \mathbb{R}^{k' \times d}$ , by maximizing the diversity within the set (Fig. 2b). To achieve this, we found that it

<sup>&</sup>lt;sup>2</sup>Log-Mel filterbanks for a speech segment of 30 seconds.

works best to utilize the attention weights  $A \in \mathbb{R}^{n \times m}$ . For each example, we apply L2-normalization, compute the cosine similarity matrix  $S \in \mathbb{R}^{n \times n}$ , and iteratively choose latents up to k'. For step  $1 \le l \le k'$ , we select  $Z_i$ , such that  $i = \operatorname{argmin}_{\operatorname{row}}(\max_{\operatorname{col}}|S^{(l-1)}|)$ . Where  $S^{(l-1)} \in \mathbb{R}^{n \times (l-1)}$  is the similarity of all n latents with the l-1 selected ones, and  $S^{(0)} = S$ . Diagonal and selected indices in  $S^{(l-1)}$  are masked.

### 4. EXPERIMENTAL SETUP

**Data.** For our experiments we are using MuST-C [13], which is based on TED talks, and more specifically the pairs of English to German (En-De, 408 hours) from version 2.0, and the pairs of English to Spanish (En-Es, 504 hours), and English to Russian (En-Ru, 489 hours) from version 1.0.

**Speech-to-Text Perceivers.** The Speech-to-Text Perceiver (S2T-Perceiver) models have 1 cross-attention layer and 12 self-attention layers in the encoder and 6 decoder layers, with dimensionality d = 256. Apart from the Perceiver crossattention, which is single-headed, 4 heads are used in the rest of the attention modules. The feed-forward layers have a hidden dimension of 2048 and GELU activations [14]. Both the encoder and decoder are using pre-LN [15]. The latent array has the same dimensionality as the model (256) and is initialized with a truncated normal distribution with 0 mean and 0.05 standard deviation. A 2-layer non-strided convolutional network with 1024 inner channels, output dimensionality of 256, GLU activations [16] and kernel sizes of 5 process the 80-dimensional log-Mel spectrograms. Dropout of 0.15 is applied to all self-attention layers in the encoder and all layers in the decoder. Contrary to what is done usually in the Transformer [3], we found it crucial to the training stability of the model to *not* scale by  $\sqrt{d}$  the processed input.

**Baseline.** The Speech-to-Text Transformer (S2T-Transformer) has a similar architecture<sup>3</sup>. To achieve the same number of parameters with the S2T-Perceiver (32.5m), we use 13 encoder layers. We also use GELU activations. The 2-layer convolutional network has strides of 2 instead of 1, thus down-sampling the input by a rate of 4.

**Training.** For training all the models we are using AdamW [18] with a base learning rate of 0.002, a warm-up of 5,000 steps, and an inverse square root scheduler. We use gradient accumulation to scale the effective batch size to 512 examples. We use SpecAugment [19] for data augmentation and label smoothing of 0.1. The target vocabularies are learned with SentencePiece [20] and have a size of 8,000. We stop training when performance does not improve for 15 consecutive epochs. The encoders are initialized from the same model configuration, pre-trained on the ASR part of the data. Models are implemented and trained with FAIRSEO [17].

**Evaluation.** We average the 10 best checkpoints in the development set and generate with a beam search of 5. Evalua-

tion is done by measuring BLEU [21] using sacreBLEU [22]. Each experiment is repeated with 3 different seeds, and we report the average BLEU.

#### 5. RESULTS

We experiment with S2T-Perceivers, with and without the use of DLA<sub>train</sub>, and compare them with S2T-Transformer baselines. Models without DLA<sub>train</sub> use k = n, while models with DLA<sub>train</sub> use larger n, and we set k to n/4. In the upper part of Table 1, we can observe that the S2T-Perceiver obtains competitive results compared to the baseline, with increasing performance for larger number of latents n. More specifically, with k = n = 512, across the three language pairs, the S2T-Perceiver has an average BLEU score of 22.21, which is 0.37 points behind the baseline. In the lower part of Table 1, we observe further gains in all configurations with the inclusion of  $DLA_{train}$ , without increasing the number of latents kused during training. With DLA<sub>train</sub>, the S2T-Perceiver with k=512 can on average match the performance of the baseline, and surpass it for En-Ru, with a BLEU score of 15.60. The S2T-Perceiver with k=256 is also competitive with the inclusion of DLA<sub>train</sub>, and reaches a higher BLEU than the S2T-Perceiver with k = n = 512, while being more efficient since it uses half the number of latents during training.

	En-De	En-Es	En-Ru	Average
S2T-Transformer	24.37	27.95	15.41	22.58
<b>S2T-Perceiver</b> $(k = n)$				
k = n = 128	22.44	25.37	14.06	20.62
k = n = 256	23.59	26.78	14.99	21.79
k=n=512	23.96	27.31	15.34	22.21
+ DLA <sub>train</sub> $(k < n)$				
k = 128 $n = 512$	22.71	26.35	14.56	21.21
k = 256 $n = 1024$	24.03	27.67	15.27	22.32
k = 512 $n = 2048$	<u>24.23</u>	<u>27.84</u>	<u>15.60</u>	<u>22.56</u>

**Table 1.** BLEU( $\uparrow$ ) scores on tst-COMMON. n is the total number of latents. k is the number of latents for DLA<sub>train</sub>. Bold is best overall. Underlined is best S2T-Perceiver.

Following, we apply  $DLA_{inf}$  with number of latents k', and show its impact on the translation quality and efficiency (Table 2). We use floating-point operations (FLOPs) as a measure of efficiency, where less is better. For an S2T-Perceiver with different k' we estimate the total FLOPs required at inference time for the tst-COMMON subset<sup>4</sup> and present them relatively to the ones required by the S2T-Transformer. We use the best configuration of the S2T-Perceiver, trained with k=512 and n=2048 (last row of Table 1). We observe that although a full inference with k'=2048 is very inefficient compared to the S2T-Transformer, we can scale down k' substantially without significant losses in translation quality. Specifically, scaling k' down to n/8=256, drops the

<sup>&</sup>lt;sup>3</sup>We train the s2t\_transformer\_s architecture from FAIRSEQ [17].

<sup>&</sup>lt;sup>4</sup>We do not consider batching and beam search.

average BLEU only by 0.1 absolute points, while it requires  $0.85\times$  the FLOPs of the S2T-Transformer. We only start observing measurable drops in relative BLEU when scaling k' down to n/16=128, where BLEU is at  $0.95\times$ , but with the FLOPs required further reduced to  $0.59\times$ .

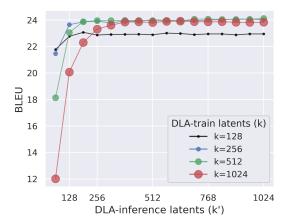
		EL ODG (1)			
	En-De	En-Es	En-Ru	Avg (Relative)	FLOPS (\$)
S2T-Transformer	24.37	27.95	15.41	22.58 (1.00×)	1.00×
S2T-Perceiver					
k' = 2048	24.23	27.84	15.60	$22.56 (1.00 \times)$	$5.50 \times$
k' = 1024	24.19	27.95	15.64	<b>22.59</b> (1.00×)	$2.59 \times$
k' = 512	24.15	27.83	15.67	$22.55 (1.00 \times)$	$1.39 \times$
k' = 256	24.01	27.74	15.67	22.47 (1.00×)	$0.85 \times$
k' = 192	23.79	27.48	15.49	$22.25 (0.99 \times)$	$0.72 \times$
k' = 128	23.15	26.56	14.94	$21.55 (0.95 \times)$	$0.59 \times$
k' = 64	18.53	21.50	11.95	17.33 (0.77×)	$0.47 \times$

**Table 2.** BLEU scores and relative FLOPs on tst-COMMON. DLA<sub>inf</sub> with k' latents. S2T-Perceiver (k = 512, n = 2048)

Next, we investigate the degree of compatibility between DLA<sub>train</sub> and DLA<sub>inf</sub>. In Fig. 3 we compare four different S2T-Perceivers, which have access to the same number of latents n = 1024 but use different DLA<sub>train</sub> k latents (128, 256, 512 and 1024). The configuration with n = k = 1024 essentially does not use DLA<sub>train</sub>. For each model, we apply DLA<sub>inf</sub> with different values of k' and report the BLEU scores on the En-De tst-COMMON. We observe that the S2T-Perceiver without DLA<sub>train</sub> (red line) is not easily adaptable to a small number of inference latents k', experiencing large drops in translation quality. On the other side, models with DLA<sub>train</sub> are much more compatible to DLA<sub>inf</sub>, retaining most of their original BLEU scores for small values of k'. The range below k'=256 is particularly important, having the configurations that are more efficient than the S2T-Transformer (Table 2). We also notice that smaller values of k allow for better adaptability to DLA<sub>inf</sub>, where the model with k = 256 only witnesses a drop in BLEU for an extremely small number of inference latents k' = 64. These findings indicate that DLA<sub>train</sub> does not only increases performance with full inference, but also largely enables  $DLA_{inf}$  for small values of k'. Finally, training with k = 128 also facilitates high adaptability but overall performance is sub-optimal, showing that no further gains are possible by setting k to values below n/4.

In the ablations of Table 3 we find that not using a convolution network to process the log-Mel spectrograms for the S2T-Perceiver, drops the average BLEU score by 1.36 points. Contrary to [6], we design a modality-specific architecture for a task suffering from data scarcity [1, 2], and thus we observe that introducing inductive biases through convolution is beneficial. Furthermore, we notice that down-sampling with a rate of 4, as done in the S2T-Transformer, reduces performance by 0.34 BLEU. This suggests that the cross-attention can extract richer representations by accessing the whole sequence.

Finally, we study the latent selection process of DLA<sub>inf</sub>



**Fig. 3.** BLEU( $\uparrow$ ) scores of S2T-Perceivers (n=1024) on En-De tst-COMMON as a function of latents at inference k'.

Input Proc.	DS rate	En-De	En-Es	En-Ru	Average
1	$\times 1$	24.23	27.84	15.60	22.56
✓	$\times 4$	23.99	27.45	15.23	22.22
X	$\times 1$	22.71	26.41	14.47	21.20

**Table 3**. Ablations on Input Processor and down-sampling of the S2T-Perceiver (k = 512, n = 2048) on tst-COMMON.

(k'=128) for the S2T-Perceiver with n=1024 in En-De tst-COMMON. In Fig. 4 we observe that the model without DLA<sub>train</sub> (k=1024) has a tendency to under-use most of the available latents (left side), compared to the model that uses DLA<sub>train</sub> (k=256). This might explain the performance difference between the two models (Fig. 3, k'=128), but also leaves room for improving DLA, since we ideally want a pool of available latents that are selected uniformly at inference.

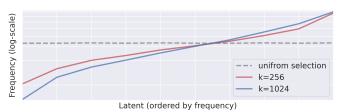


Fig. 4. Latent selection frequency with DLA<sub>inf</sub>.

### 6. CONCLUSIONS

We presented a new paradigm for Speech Translation which relies on projecting the speech signal to an arbitrary-length latent space with a Perceiver. Furthermore, we introduced a method that allows the Perceiver to dynamically use part of a large latent space, boosting performance without additional costs. This also creates a single model that can flexibly operate on different computational budgets at inference time, with little loss in performance. Future research will take advantage of the proposed method's efficiency to model the much longer sequences required for context-aware Speech Translation.

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