Multiformer: A Head-Configurable Transformer-Based Model for Direct Speech Translation

Gerard Sant, Gerard I. Gállego, Belen Alastruey and Marta R. Costa-Jussà TALP Research Center, Universitat Politècnica de Catalunya, Barcelona

gerard.muniesa@estudiantat.upc.edu

{gerard.ion.gallego, belen.alastruey, marta.ruiz}@upc.edu

Abstract

Transformer-based models have been achieving state-of-the-art results in several fields of Natural Language Processing. However, its direct application to speech tasks is not trivial. The nature of this sequences carries problems such as long sequence lengths and redundancy between adjacent tokens. Therefore, we believe that regular self-attention mechanism might not be well suited for it.

Different approaches have been proposed to overcome these problems, such as the use of efficient attention mechanisms. However, the use of these methods usually comes with a cost, which is a performance reduction caused by information loss. In this study, we present the Multiformer, a Transformer-based model which allows the use of different attention mechanisms on each head. By doing this, the model is able to bias the self-attention towards the extraction of more diverse token interactions, and the information loss is reduced. Finally, we perform an analysis of the head contributions, and we observe that those architectures where all heads relevance is uniformly distributed obtain better results. Our results show that mixing attention patterns along the different heads and layers outperforms our baseline by up to 0.7 BLEU.

1 Introduction

Conventionally, Speech-to-text Translation (ST) task has been addressed through cascade approaches (Ney, 1999), which consists of the concatenation of an Automatic Speech Recognition block (ASR), for the audio transcription, with another Machine Translation block (MT), for the translation of such transcription into the desired language. However, this approach ignores some information present in the audio, since it translates from the audio transcript, and is also vulnerable to error propagation, since an error in the ASR block automatically causes a mistranslation

(Sperber and Paulik, 2020; Bentivogli et al., 2021). Consequently, end-to-end alternatives based on an encoder-decoder structure and attention mechanisms have become increasingly popular in recent years (Anastasopoulos et al., 2016; Duong et al., 2016; Weiss et al., 2017). These are capable of translating the audio without the explicit need for transcription, thus avoiding the problems of the cascade approach and allowing unified optimization of the training parameters.

The advent of the Transformer (Vaswani et al., 2017) revolutionized the MT field, enabling models based on this architecture to achieve the stateof-the-art results. Nowadays, Transformer-based models are used to process all types of data, such as images (Parmar et al., 2018) or speech (Dong et al., 2018; Di Gangi et al., 2019a). However, due to its self-attention mechanism, the vanilla Transformer scales quadratically with the input sequence length, which makes it extremely inefficient when processing long sequences.

In speech tasks, it is common to extract audio features every 10 ms to build the input sequences, which causes them to be considerably longer than text sequences. Moreover, since the representation of a single phoneme requires several tokens (Igras et al., 2013; Ma et al., 2021), the presence of redundancy among the audio tokens is inferred. Therefore, state-of-the-art architectures propose the implementation of down sampling strategies prior to the model collapsing adjacent vectors in a fixed way (Bérard et al., 2018; Di Gangi et al., 2019b; Wang et al., 2020a). Similarly, some studies propose to extract more informative sequences using pretrained compression modules (Salesky et al., 2019; Zhang et al., 2020; Gaido et al., 2021), obtaining considerable translation quality gains. While these achieve good results, we propose another approach, questioning the use of multi-head self-attention (MHSA), originally proposed for text, for the information extraction from speech sequences.

Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Student Research Workshop, pages 277 - 284 July 10-15, 2022 ©2022 Association for Computational Linguistics

The closest work to ours was done by Alastruey et al. (2021), who used Longformer's (Beltagy et al., 2020) local attention pattern as an efficient alternative to self-attention for speech processing. However, they observed that, due to the scarcity of global context in the encoder output, the quality of the translations was slightly hindered. Recently, inspired by Linformer's (Wang et al., 2020b) attention, Papi et al. (2021) proposed ConvAttention as an attention mechanism that, by compressing keys and values, is more efficient and therefore able to directly process long sequences. However, this mechanism is not used as a replacement of the encoder self-attention, but as an extra input processing before a CTC-based compression module (Gaido et al., 2021).

Our contribution to ST field is a new Transformer variant, the Multiformer, an architecture based on the S2T Transformer by Wang et al. (2020a). Our architecture enables the use of different attention mechanisms in the same encoder layer, by configuring individually the pattern of each head. With this approach, the Multiformer is able to apply efficient attention mechanisms, while maintaining the ability to learn both local and global content from speech sequences. This diversity among heads in a layer is also meant to stimulate a more varied information extraction and, therefore, reduce the presence of low-relevant heads (Voita et al., 2019; Michel et al., 2019; Bian et al., 2021; Zhang et al., 2021). Furthermore, we explore the use of different head configurations for each encoder layer. This could help to adapt the attention mechanisms to the needs of each layer. To the best of our knowledge, this is the first study that allows this kind of head-wise configuration.

2 Model

In this section, we first introduce a new selfattention module that allows the use of multiple attention mechanisms in parallel (§2.1). Next, we explain the Multiformer (§2.2), which replaces the Transformer encoder MHSA by the new proposed module.

2.1 Multi-head Multi-attention

An increasing number of studies have observed the presence of redundant heads in multi-head selfattention (Michel et al., 2019; Bian et al., 2021; Zhang et al., 2021). Moreover, Voita et al. (2019) even tried to prune them, and observed that the quality of the translations (in MT) was almost not affected. This suggests that the model does not exploit the full potential present in the use of attention heads. In addition, the quadratic time and memory complexity of Self-Attention with respect to the input sequence length makes it impossible to use it directly in Speech tasks. To address this challenge, end-to-end ST models are based on reducing the length of speech sequences, usually by a factor of 4, through compression techniques, so that they can be processed by the Transformer (Di Gangi et al., 2019b; Wang et al., 2020a). However, after this compression, the resulting sequences are still considerably longer and more redundant than their text counterparts. Alastruey et al. (2021) proposed the use of efficient Transformers for ST, but, as observed in different tasks by Tay et al. (2021), they suffer from a drop in performance quality. The main reason for this deterioration is that most efficient Transformers propose strategies that deprive the model of the ability to learn all types of content from the input stream.¹

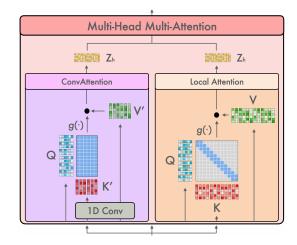


Figure 1: Scheme of the MHMA with the representation of each of the attention mechanisms it incorporates. The function g() denotes the downscaling and computation of the softmax() function.

To solve the aforementioned problems, we propose multi-head multi-attention (MHMA) (Figure 1) which, using heads with different attention mechanisms, is meant to force a more diversified learning, thus (i) hindering the presence of irrelevant heads and (ii) allowing the model to learn both local and global content from the input sequence,

¹In efficient Transformers that approximate the softmax() function (Choromanski et al., 2021) or the attention matrix (Wang et al., 2020b), the quality drop can be attributed to an imperfection in these approximations.

while applying efficient attention mechanisms. The MHMA module is manually set by selecting the type of attention mechanism for each head in each layer within the following ones:

ConvAttention. Efficient attention mechanism proposed by Papi et al. (2021). The ConvAttention compresses the keys and values by means of a convolutional layer, decreasing the size of the attention matrix by a factor of χ , to reduce the original complexity to $O((\frac{n}{\chi})^2)$. By not compressing the queries, they manage to maintain the dimensions of the input sequence at the output.

Local Attention. Attention mechanism with a sliding window pattern (Beltagy et al., 2020). It only computes the product between queries and keys of nearby tokens within the same input sequence, so it is more efficient than the regular Self-Attention. In particular, given a fixed window size w, each token attends to $\frac{w}{2}$ tokens on each side, achieving a linear scaling (O($n \times w$)) of the module complexity. As in Alastruey et al. (2021), this attention pattern is intended to force the learning of local relations, while being more efficient.

2.2 Multiformer

The Multiformer is a Transformer-based architecture inspired by Wang et al. (2020a). The original model consists on a regular Transformer, preceded by two 1D convolutional layers, that help to tackle speech-specific problems such as a longer sequence length or information redundancy in adjacent tokens. The Multiformer proposes to modify the self-attention module on each encoder layer by a MHMA, since we believe that this module could be helpful to deal with speech.

The introduction of MHMA allows the model to learn from different representational and contextual levels. This enables the construction of architectures capable of extracting different kinds of information from the input sequence, while performing more efficient attention mechanisms. In addition, the model is biased towards learning different types of token interactions, hindering the presence of irrelevant heads.

However, the generation of attention diversity at the head level does not address the presence of redundancy between layers noted by Dalvi et al. (2020), who, using linear Center Kernel Alignment (Kornblith et al., 2019), observed that, except for the last two layers, layer redundancy increases throughout the encoder. Moreover, the information

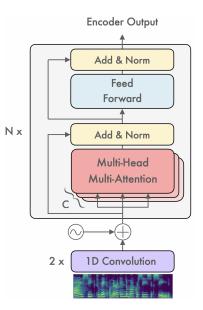


Figure 2: Diagram of the Multiformer encoder. It comprises N layers, each one with C heads that can use different attention mechanisms.

processed by each layer differs, hence using the same MHMA configuration in all encoder layers may not be the optimal.

Therefore, the Multiformer (Figure 2) allows the use of different MHMA configurations, which is meant to create architectures that process the speech sequence in a more progressive manner. This approach emphasizes the learning of different content along the encoder layers, while hampering information redundancy.

3 Heads Contribution Analysis

MHMA allows the use of different attention mechanisms in parallel, therefore we wanted to evaluate the head contribution in each of the encoder layers.

In general, given an input sequence of n tokens $\{\mathbf{x_1}, ..., \mathbf{x_n}\} \in \mathbb{R}^{n \times d}$ and a model with an embeddings dimension d (head dimension d_h), the output of each attention-head $\mathbf{z_i^h} \in \mathbb{R}^{d_h}$ is:

$$\mathbf{z}_{i}^{h} = \sum_{j}^{N} \mathbf{A}_{i,j}^{h} \mathbf{W} \mathbf{v}^{h} \mathbf{x}_{j}$$
(1)

where $\mathbf{A}_{i,j}^{h}$ is the attention weight of token j on token i and $\mathbf{Wv}^{h} \in \mathbb{R}^{d_{h} \times d}$ is the learned projection matrix of the values. The final output representation of the attention module $\mathbf{y}_{i} \in \mathbb{R}^{d}$ is:

$$\mathbf{y}_i = \mathbf{Wo} \operatorname{Concat}\{\mathbf{z}_i^1, ..., \mathbf{z}_i^H\} + \mathbf{b}_o \qquad (2)$$

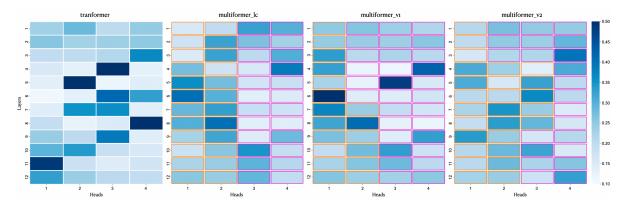


Figure 3: Head relevance for each layer of the proposed models. They have been computed using the median of n contributions (equation 4) from 500 random samples of the en-de training partition. Heads marked in orange use Local Attention while those in purple are using ConvAttention.

with $\mathbf{Wo} \in \mathbb{R}^{d \times H \cdot d_h}$ as the output projection matrix trained jointly with the model, and $\mathbf{b}_o \in \mathbb{R}^d$ referring to the bias. As previously done for interpretability research (Kobayashi et al., 2020), the above expression (equation 2) can be rewritten as follows:

$$\mathbf{y}_i = \sum_h^H \mathbf{W} \mathbf{o}^h \ \mathbf{z}_i^h + \mathbf{b}_o \tag{3}$$

where $\mathbf{Wo}^h \in \mathbb{R}^{d \times d_h}$ is the part of the output projection matrix corresponding to each head. Note that from this last expression, it can be defined $\xi_i^h = \mathbf{Wo}^h \mathbf{z}_i^h \in \mathbb{R}^d$ as the projected output vector of a head.

Inspired by Kobayashi et al. (2020), for each layer, we define the contribution of each head to the attention output y_i as the Euclidean norm of the projected output vector of heads:

$$c_{i,h} = ||\xi_i^h||_2 \tag{4}$$

4 Experiments

In this section we first explain the training details (\$4.1) in order to ensure reproducibility of experiments.² Then we briefly describe Multiformer architectures and the procedure we followed (\$4.2).

4.1 Experimental Settings

The Multiformer architectures have been trained on 3 different language directions of the MuST-C dataset (Cattoni et al., 2021). This corpus consists of audio, transcriptions, and translations of TED talks in English. MuST-C provides 8 language directions ranging in size from 385 (Portuguese) to 504 (Spanish) hours of transcribed and translated speech.

To ensure a faithful comparison with the baseline model, the small architecture of the S2T Transformer in Fairseq (Wang et al., 2020a), all our models consist of 12 encoder layers, 6 decoder layers and 4 heads in each attention layer. The embedding dimension of the model is 256. Moreover, following the baseline architecture, we have kept the convolutional layers with downsampling prior to the model.

For the ConvAttention, we use a kernel size of 5 and a stride of 2, reducing the length of keys and values to the half. Regarding the Local Attention, as in Alastruey et al. (2021) we have chosen a window size of 64 tokens. These hyperparameters have been employed in all Multiformer architectures. For a detailed description of training parameters, see appendix A.

4.2 Experiments Description

First, we trained two architectures based on a single attention mechanism (Local or ConvAttention), in order to obtain a comparison between models with and without diversity.

After this, we trained the first Multiformer architecture, the *multiformer_lc*. It has a configuration of the MHMA with 2 heads of ConvAttention and 2 heads of Local Attention for all encoder layers. Then, we analyzed the contribution of each head following the methodology described in §3. This allowed us to better understand the needs of each layer, and to propose architectures based on this. From Figure 3, it can be seen that in the first 3 layers, the *multiformer_lc* assigns low rele-

²Code available: https://github.com/mt-upc/ fairseq/tree/multiformer

Model	en-de			en-fr			en-es			$Avg(\Delta\%)$
	BLEU	$\Delta BLEU$	$\Delta\%$	BLEU	Δ BLEU	$\Delta\%$	BLEU	$\Delta BLEU$	$\Delta\%$	$ $ Avg($\Delta 70$)
baseline	22.65	-	-	32.97	-	-	26.99	-	-	-
local_attention	22.69	+0.04	+0.17	33.00	+0.03	+0.09	27.10	+0.11	+0.41	+0.22
conv_attention	22.45	-0.20	-0.88	33.07	+0.10	+0.30	26.96	-0.04	-0.15	-0.73
multiformer_lc	22.80	+0.15	+0.66	33.25	+0.28	+0.85	27.56	+0.57	+2.11	+1.21
multiformer_v1	23.16	+0.51	+2.25	33.10	+0.13	+0.39	27.68	+0.69	+2.56	+1.73
multiformer_v2	22.98	+0.33	+1.46	33.26	+0.29	+0.88	27.44	+0.45	+1.67	+1.34

Table 1: BLEU results in 3 different language directions of the MuST-C dataset, English \rightarrow German (en-de), English \rightarrow French (en-fr) and English \rightarrow Spanish (en-es). Relative improvements are calculated with respect to the baseline (Wang et al., 2020a).

vance to the representations extracted by one of the Local Attention heads, which could indicate the prioritization of the global context in the first layers. In the middle layers, a change in this trend is observed, with Local Attention heads acquiring more importance. As for the last layers, we see an equal relevance distribution between heads of both mechanisms.

These observations have motivated the training of the $multiformer_v1$, which tries to correct the abandonment of Local Attention heads observed in the initial layers. It consists of substituting a Local Attention head for a ConvAttention head in the first six layers of the encoder.

Finally, the *multiformer_v2* is built more strictly from the analysis. It incorporates 3 different MHMA configurations. In the first 3 layers, it uses 1 head of Local Attention and 3 heads of ConvAttention. The next 5 layers (from the 4th to the 8th) use 3 Local Attention heads and 1 ConvAttention head, to finish the remaining 4 layers with 2 heads of each type.

In general, it is clear that, whereas the baseline uses few heads in most layers, Multiformer architectures³ force the model to have a more uniformly distributed contribution between heads.

5 Results

First, it can be observed from Table 1, that the efficient architecture based only on Local Attention (*local_attention*) already obtains the same results as the baseline, suggesting the presence of unnecessary computations in self-attention. Unlike previous works (Alastruey et al., 2021), this architecture maintains the convolutional layers, so the amount of global content within the attention mechanism is higher using the same window size. On the other hand, while the architecture based exclusively on ConvAttention (*conv_attention*), man-

ages to achieve baseline results in English \rightarrow French (en-fr) and English \rightarrow Spanish (en-es), its score in English \rightarrow German (en-de) drops 0.2 BLEU, suggesting the need for a higher resolution extraction of representations for that language pair.

Secondly, analyzing the heads contribution of the baseline architecture, we can observe that the heads contribution tends to accumulate in few heads. This means we obtain similar conclusions than Voita et al. (2019), but for the ST setting. Furthermore, our work goes one step further, showing that those architectures where the heads contribution is uniformly distributed, obtain a higher performance. This finding confirms that, in ST, some heads on a regular Transformer tend to learn irrelevant information. This shows that MHSA might not be as capable as expected of extracting different kinds of patterns, unless it is biased on purpose towards doing so.

In particular, all Multiformer variants improve the results obtained by the baseline and the *local_attention* and *conv_attention* architectures. However, these improvements are not equal in all languages pairs, and go from 0.15 to 0.57 BLEU for *multiformer_lc*, from 0.13 to 0.69 BLEU for *multiformer_v1* and from 0.29 to 0.45 BLEU for *multiformer_v2*, becoming the latter the architecture with the most robust gains.

6 Conclusions

In this paper, we present the Multiformer, the first Transformer-based model that allows to combine different attention mechanisms in the MHSA module. This helps the model extracting different types of token interactions from each head, hence preventing the appearance of irrelevant heads. By applying this diversity of attention patterns with efficient mechanisms, the model is able to maintain both local and global context across encoder layers while being more efficient. Experiments on 3

³More details in Table 2 in the Appendices.

language pairs show that all Multiformer architectures outperform the results achieved by the S2T Transformer in the ST task, with an improvement up to 0.69 BLEU for the English-Spanish direction in the *multiformer_v1*.

7 Acknowledgements

This work was partially funded by the ADAVOICE project, PID2019-107579RB-I00 / AEI / 10.13039/501100011033, and the UPC INIREC scholarship n°3522. We would like to thank Javier Ferrando for his advice on the heads contribution analysis.

References

- Belen Alastruey, Gerard I. Gállego, and Marta R. Costajussà. 2021. Efficient transformer for direct speech translation.
- Antonios Anastasopoulos, David Chiang, and Long Duong. 2016. An unsupervised probability model for speech-to-translation alignment of low-resource languages. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1255–1263, Austin, Texas. Association for Computational Linguistics.
- Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. Longformer: The long-document transformer.
- Luisa Bentivogli, Mauro Cettolo, Marco Gaido, Alina Karakanta, Alberto Martinelli, Matteo Negri, and Marco Turchi. 2021. Cascade versus direct speech translation: Do the differences still make a difference? In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2873–2887, Online. Association for Computational Linguistics.
- Yuchen Bian, Jiaji Huang, Xingyu Cai, Jiahong Yuan, and Kenneth Church. 2021. On attention redundancy: A comprehensive study. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 930–945, Online. Association for Computational Linguistics.
- Alexandre Bérard, Laurent Besacier, Ali Can Kocabiyikoglu, and Olivier Pietquin. 2018. End-to-end automatic speech translation of audiobooks. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 6224–6228.
- Roldano Cattoni, Mattia Antonino Di Gangi, Luisa Bentivogli, Matteo Negri, and Marco Turchi. 2021. Mustc: A multilingual corpus for end-to-end speech translation. *Computer Speech & Language*, 66:101155.

- Krzysztof Marcin Choromanski, Valerii Likhosherstov, David Dohan, Xingyou Song, Andreea Gane, Tamas Sarlos, Peter Hawkins, Jared Quincy Davis, Afroz Mohiuddin, Lukasz Kaiser, David Benjamin Belanger, Lucy J Colwell, and Adrian Weller. 2021. Rethinking attention with performers. In International Conference on Learning Representations.
- Fahim Dalvi, Hassan Sajjad, Nadir Durrani, and Yonatan Belinkov. 2020. Analyzing redundancy in pretrained transformer models. In *Proceedings of the* 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4908–4926, Online. Association for Computational Linguistics.
- Mattia A Di Gangi, Matteo Negri, and Marco Turchi. 2019a. Adapting transformer to end-to-end spoken language translation. In *INTERSPEECH 2019*. International Speech Communication Association.
- Mattia Antonino Di Gangi, Matteo Negri, Roldano Cattoni, Roberto Dessi, and Marco Turchi. 2019b. Enhancing transformer for end-to-end speech-to-text translation. In *Proceedings of Machine Translation Summit XVII: Research Track*, pages 21–31, Dublin, Ireland. European Association for Machine Translation.
- Linhao Dong, Shuang Xu, and Bo Xu. 2018. Speechtransformer: A no-recurrence sequence-to-sequence model for speech recognition. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5884–5888.
- Long Duong, Antonios Anastasopoulos, David Chiang, Steven Bird, and Trevor Cohn. 2016. An attentional model for speech translation without transcription. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 949–959, San Diego, California. Association for Computational Linguistics.
- Marco Gaido, Mauro Cettolo, Matteo Negri, and Marco Turchi. 2021. CTC-based compression for direct speech translation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 690–696, Online. Association for Computational Linguistics.
- Magdalena Igras, Bartosz Ziółko, and Mariusz Ziółko. 2013. Length of phonemes in a context of their positions in polish sentences. In 2013 International Conference on Signal Processing and Multimedia Applications (SIGMAP), pages 59–64.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations*.
- Goro Kobayashi, Tatsuki Kuribayashi, Sho Yokoi, and Kentaro Inui. 2020. Attention is not only a weight: Analyzing transformers with vector norms. In Proceedings of the 2020 Conference on Empirical

Methods in Natural Language Processing (EMNLP), pages 7057–7075, Online. Association for Computational Linguistics.

- Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. 2019. Similarity of neural network representations revisited. In *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 3519–3529. PMLR.
- Guodong Ma, Pengfei Hu, Jian Kang, Shen Huang, and Hao Huang. 2021. Leveraging Phone Mask Training for Phonetic-Reduction-Robust E2E Uyghur Speech Recognition. In *Proc. Interspeech 2021*.
- Paul Michel, Omer Levy, and Graham Neubig. 2019. Are sixteen heads really better than one? *Advances in neural information processing systems*, 32.
- H. Ney. 1999. Speech translation: coupling of recognition and translation. In 1999 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings. ICASSP99.
- Sara Papi, Marco Gaido, Matteo Negri, and Marco Turchi. 2021. Speechformer: Reducing information loss in direct speech translation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1698–1706, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. 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. Association for Computational Linguistics.
- Niki Parmar, Ashish Vaswani, Jakob Uszkoreit, Lukasz Kaiser, Noam Shazeer, Alexander Ku, and Dustin Tran. 2018. Image transformer. In *Proceedings of the 35th International Conference on Machine Learning*, Proceedings of Machine Learning Research. PMLR.
- Elizabeth Salesky, Matthias Sperber, and Alan W Black. 2019. Exploring phoneme-level speech representations for end-to-end speech translation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1835–1841, Florence, Italy. Association for Computational Linguistics.
- Matthias Sperber and Matthias Paulik. 2020. Speech translation and the end-to-end promise: Taking stock of where we are. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7409–7421, Online. Association for Computational Linguistics.
- Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision.

In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2818–2826.

- Yi Tay, Mostafa Dehghani, Samira Abnar, Yikang Shen, Dara Bahri, Philip Pham, Jinfeng Rao, Liu Yang, Sebastian Ruder, and Donald Metzler. 2021. Long range arena : A benchmark for efficient transformers. In *International Conference on Learning Representations*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.
- Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. 2019. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5797–5808, Florence, Italy. Association for Computational Linguistics.
- Changhan Wang, Yun Tang, Xutai Ma, Anne Wu, Dmytro Okhonko, and Juan Pino. 2020a. Fairseq S2T: Fast speech-to-text modeling with fairseq. 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: System Demonstrations, pages 33–39, Suzhou, China. Association for Computational Linguistics.
- Sinong Wang, Belinda Z. Li, Madian Khabsa, Han Fang, and Hao Ma. 2020b. Linformer: Self-attention with linear complexity.
- Ron J Weiss, Jan Chorowski, Navdeep Jaitly, Yonghui Wu, and Zhifeng Chen. 2017. Sequence-to-sequence models can directly translate foreign speech. *Proc. Interspeech 2017*, pages 2625–2629.
- Biao Zhang, Ivan Titov, Barry Haddow, and Rico Sennrich. 2020. Adaptive feature selection for end-toend speech translation. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2533–2544, Online. Association for Computational Linguistics.
- Tianfu Zhang, Heyan Huang, Chong Feng, and Longbing Cao. 2021. Enlivening redundant heads in multihead self-attention for machine translation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3238– 3248, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Name		MHMA Configurations				
conv_attention	$12 \times (4 \times Conv(5,2))$	-	-			
local_attention	$12 \times (4 \times Local (64))$	-	-			
multiformer_lc	$12 \times \begin{pmatrix} 2 \times \ Local \ (64) \\ 2 \times \ Conv \ (5,2) \end{pmatrix}$	-	-			
multiformer_v1	$6 \times \left(\begin{smallmatrix} 1 \times & Local (64) \\ 3 \times & Conv (5,2) \end{smallmatrix}\right)$	$6 \times \begin{pmatrix} 2 \times Local (64) \\ 2 \times Conv (5, 2) \end{pmatrix}$	-			
multiformer_v2	$3 \times \left(\begin{smallmatrix} 1 \times & Local \ (64) \\ 3 \times & Conv \ (5,2) \end{smallmatrix}\right)$	$5 \times \begin{pmatrix} 3 \times \ Local \ (64) \\ 1 \times \ Conv \ (5,2) \end{pmatrix}$	$4 \times \begin{pmatrix} 2 \times \ Local (64) \\ 2 \times \ Conv (5,2) \end{pmatrix}$			

Table 2: Multiformer architectures. The notation for each configuration is as follows: $N_{layers} \times (N_{heads} \times Attention(hyperparameters)).$

A Detailed Experimental Settings

The training has been performed using the label smoothed cross entropy loss (Szegedy et al., 2016) and the Adam optimizer (Kingma and Ba, 2015). The learning rate has been set to $2 \cdot 10^{-3}$ with an inverse square-root scheduler and 10,000 warm-up updates. We have set a maximum number of 32,000 tokens for the construction of the mini-batches and an update frequency of 5. The training has been hosted on 2 NVIDIA GeForce RTX 2080 Ti GPUs until the completion of 50,000 updates. For a better performance in ST, models have been pretrained in ASR (Bérard et al., 2018).⁴ For this pretraining, all the parameters have been set as in ST, with the exception of the learning rate, which has been set to $1 \cdot 10^{-3}$.

For the S2T evaluation of the architectures, we averaged the 7 checkpoints around the best one and then computed the BLEU score (Papineni et al., 2002).

To visualize the layer-level relevance of each head (Figure 3), we computed the median of the contributions (\$3) of each head for all the tokens in 500 random samples. Since we want to observe which head is the most relevant during training, the en-de training partition was used.

⁴For the use of the ASR pretrained encoder in ST training, the best checkpoint has been used, being this the one that obtains the lowest loss.