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T-Modules: Translation Modules for Zero-Shot Cross-Modal Machine Translation

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Abstract

We present a new approach to perform zero-shot cross-modal transfer between speech and text for translation tasks. Multilingual speech and text are encoded in a joint fixed-size representation space. Then, we compare different approaches to decode these multimodal and multilingual fixed-size representations, enabling zero-shot translation between languages and modalities. All our models are trained without the need of cross-modal labeled translation data. Despite a fixed-size representation, we achieve very competitive results on several text and speech translation tasks. In particular, we outperform the state of the art for zero-shot speech translation on Must-C. We also introduce the first results for zero-shot direct speech-to-speech and text-to-speech translation.

1 Introduction

Most, if not all, current state-of-the-art text and speech translation systems are based on a sequence-to-sequence approach and an attention mechanism to connect the encoder and decoder. Such models require labeled data to be trained end-to-end. For text-to-text (T2T) translation, this labeled data, called bitexts, is available in large amounts for a number of language pairs, in particular since large-scale bitext mining initiatives like ParaCrawl (Bañón et al., 2020) and CCMatrix (Schwenk et al., 2021). Finding training data for speech-to-text (S2T) translation is more challenging, but several data collection efforts exist, like mTEDx (Salesky et al., 2021), CoVoST (Wang et al., 2020a,b), and Must-C (Di Gangi et al., 2019). Finally, speech-to-speech (S2S) translation suffers from scarcity of end-to-end labeled data and current S2S systems are limited to a very small number of language pairs. Very recent works start to consider mining labeled data for S2S, e.g. (Duquenne et al., 2021).

Unsupervised representation learning is very successfully used to initialize the encoder and/or decoder of a sequence-to-sequence model, thereby

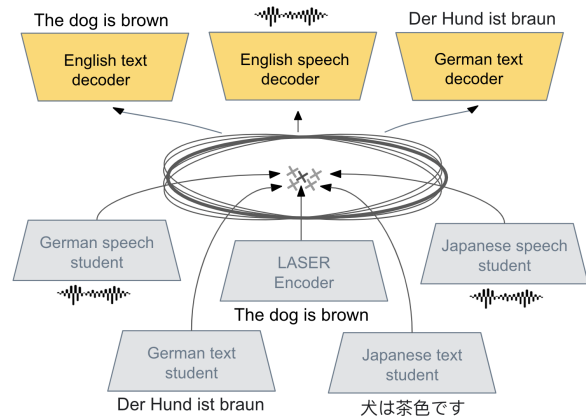


Figure 1: Summary of the model architecture.

lowering the amount of labeled data needed to train or fine-tune the model end-to-end. Approaches include for instance XLM (Conneau and Lample, 2019), XLSR (Conneau et al., 2020), wav2vec (Baevski et al., 2020), data2vec (Baevski et al., 2022) and mSLAM (Bapna et al., 2022).

In this work, we propose a new modular architecture for text and speech translation, which is based on a **common fixed-size multilingual and multimodal internal representation**, and encoders and decoders which are independently trained. We explore several variants of teacher-student training to learn text and speech encoders for multiple languages, which are compatible with the embedding space of the LASER encoder (Artetxe and Schwenk, 2019). In contrast to preceding works on multilingual and multimodal representations, we also train text decoders for multiple languages which are able to generate translations given the joint representation. Finally, we demonstrate that it is possible to train a speech decoder using raw audio only. Figure 1 visualizes the overall approach. We show that these encoders and decoders can be freely combined to achieve very competitive performance in T2T, S2T and (zero-shot) S2S translation.

In summary, our contributions are as follows.

- We apply a teacher-student approach to train multilingual text and speech encoders that are mutually compatible;
- We show that the fixed-size representation can be efficiently decoded into multiple languages;
- We are able to train a speech decoder with raw speech only, which can be paired with our text and speech encoders for multiple languages;
- We achieve very competitive results on several text and speech translation tasks, without any end-to-end labeled data and significantly improve the state of the art for zero-shot speech translation;
- To the best of our knowledge, we are the first to build zero-shot direct S2S translation systems.

2 Related work

Multilingual and multimodal representations

Building multilingual representation for text or speech is key to develop state-of-the-art models based on these modalities. [Conneau and Lample \(2019\)](#) introduce a multilingual pre-training method with good cross-lingual transfer capabilities. [Conneau et al. \(2020\)](#) extend the Wav2vec2 ([Baevski et al., 2020](#)) architecture to the multilingual setting introducing a multilingual pre-trained model for speech. More recently, [Bapna et al. \(2022\)](#) pre-train a multilingual encoder model handling both speech and text in order to benefit from cross-modal transfer between speech and text.

An important obstacle to good joint speech/text representations is the length mismatch between audio and text. On the other hand, several works have studied how to encode sentences in a fixed-size representation ([Feng et al., 2020](#); [Artetxe and Schwenk, 2019](#); [Reimers and Gurevych, 2019](#)). In the multilingual setting, these works highlight that paraphrases and translations are close in the sentence embedding space, enabling large-scale bitext mining. Recently, [Duquenne et al. \(2021\)](#) extended the existing LASER model ([Artetxe and Schwenk, 2019](#)) built for multilingual text to the speech modality for several spoken languages. They show that this joint speech/text fixed-size representation can be efficiently used for large-scale mining of speech against text and even speech against speech.

Zero-shot transfer in Machine Translation In Machine Translation, cross-lingual transfer to improve low-resource language directions has been widely studied. One way to encourage cross-lingual transfer is building a massively multilingual translation system as ([Fan et al., 2021](#)). Some other works such as ([Zhang et al., 2022](#)) make an efficient use of MT data involving a pivot language thanks to weight freezing strategies to force representations to be close to the pivot language representations. One extreme scenario of cross-lingual transfer learning is called zero-shot transfer, where you learn to translate one language and directly apply the decoding process to an unseen language. Several methods have been tried to improve zero-shot transfer. [Arivazhagan et al. \(2019\)](#); [Pham et al. \(2019\)](#) add language similarity regularization on pooled representations of encoders outputs as an auxiliary loss to a MT objective in order to improve zero-shot transfer. [Liao et al. \(2021\)](#); [Vázquez et al. \(2018\)](#); [Lu et al. \(2018\)](#) introduce shared weights between language-specific encoders and decoders, commonly called an interlingua that captures language-independent semantic information. Finally, [Escolano et al. \(2020a, 2021a, 2020b\)](#) focus on incremental learning of language-specific encoders-decoders using cross-entropy loss, alternately freezing parts of the model to ensure a shared representation between languages.

Zero-shot transfer in Speech Translation Recent research focuses on direct speech translation where an encoder-decoder model directly translates speech into text ([Bérard et al., 2016](#); [Bansal et al., 2017](#); [Weiss et al., 2017](#)). Direct speech translation models are closing the gap with their cascaded counterparts ([Li et al., 2020](#); [Babu et al., 2021](#); [Bapna et al., 2022](#)). Several works add MT data in S2T translation training, using an auxiliary loss to bridge the modality gap, like adversarial ([Alinejad and Sarkar, 2020](#)), or distance ([Dong et al., 2021](#); [Liu et al., 2020](#)) regularization. ([Xu et al., 2021](#)) and ([Li et al., 2020](#)) use adaptor modules to address the length mismatch between audio and text representations. Several works studied how to efficiently perform zero-shot cross-modal transfer from text to speech in the frame of direct speech translation. Following ([Escolano et al., 2020a, 2021a, 2020b](#)) presented above for text, [Escolano et al.](#) learn a speech encoder compatible with decoders trained on text only, freezing the text decoder during training and using cross-entropy on the output of the de-

coder. This is the most similar work like ours, however they did not use any joint fixed-representation and their zero-shot results using only speech transcriptions lagged behind supervised setting by a large margin. Other works such as (Dinh et al., 2022; Dinh, 2021) studied zero-shot speech translation employing a cross-modal similarity regularization as an auxiliary loss. However, they obtained low zero-shot results possibly due to the mismatch in the encoder output lengths between speech and text.

Direct speech-to-speech translation Finally, there is a surge of research interest in direct speech-to-speech translation (Jia et al., 2019, 2021; Lee et al., 2022a). An encoder-decoder model directly translates speech in a language into speech in another language without the need to generate text as an intermediate step. Speech-to-speech translation research suffers from data scarcity of aligned speech with speech in different languages and often uses synthetic speech to overcome this issue.

Recently, Lee et al. (2022b) introduce the first direct speech-to-speech model based on real speech data as target. They propose a speech normalization technique in order to normalize the target speech with respect to speaker and prosody. Lee et al. (2022a,b) extract HuBERT units of target speech as targets for a unit decoder during training. At test time, a vocoder is used to transform output units into speech. To the best of our knowledge, no work has tried to develop a direct speech-to-speech translation system in a zero-shot setting.

3 Exploring training strategies

The purpose of this work is to build a common fixed-size representation for multilingual speech and multilingual text that can be decoded in text and speech in different languages. We want to build language-specific encoders and decoders compatible with this fixed-size representation. Plugging one encoder with one decoder from different modalities and/or different languages enables performing zero-shot cross-modal translation.

To this end, we first study how to efficiently decode fixed-size sentence representation for text. Second, we study how to improve similarity for sentence embeddings between languages. After an ablation study on the Japanese-English text translation direction, we extend the best training strategy to several other languages and a new modality, speech.

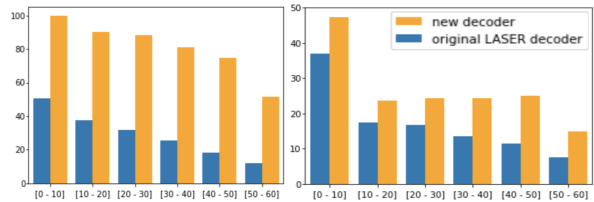


Figure 2: BLEU vs. sentence length on FLORES-devtest. English auto-encoding (left), German-to-English translation (right).

3.1 Better decoding of sentence embeddings

Motivations Multilingual sentence embeddings have been widely studied in the research community to perform bitext mining. For instance, LASER (Artetxe and Schwenk, 2019) is a multilingual sentence embedding space, where sentences are close in the embedding space if they are paraphrases or translations. LASER has been successfully used for large-scale bitext mining like in the CCMatrix project (Schwenk et al., 2021). LASER has been trained with a decoding objective, whereas other works like LaBSE (Feng et al., 2020) have been trained with a contrastive objective.

First, we studied how multilingual sentence embeddings can be efficiently decoded. We focused on LASER as it originally has a decoder, and we studied how we can improve the decoding of sentence embeddings. As an initial experiment, we evaluated auto-encoding of English sentences from FLORES (Goyal et al., 2022) in Figure 2 left, with the original LASER encoder and decoder, bucketing sentences by length, and reporting BLEU scores. The LASER encoder handles several languages: decoding these multilingual embeddings enables to translate the input sentence into English with the original LASER decoder. We report the BLEU scores for the different sentence lengths in Figure 2 right for the German-English translation direction from FLORES. We notice that BLEU scores are low for both auto-encoding and translation tasks and decrease with the sentence length. The fixed-size representation seems to be a bottleneck for decoding tasks, especially for long sentences. However, the original LASER decoder is really shallow (one LSTM decoder layer), an interesting question is: can we improve decoding by training a new deeper decoder?

Training new decoders We chose to train a new decoder to decode LASER sentence embeddings, with a transformer architecture and 12 layers. To

train this new decoder, we use an auto-encoding objective, feeding raw English sentences to the model: we use original LASER encoder, whose weights are not updated during training, and plug a new transformer decoder to decode the fixed-size sentence representation output by the LASER encoder (the decoder attends on the sentence embedding output by the encoder). We used 15B English sentences from CCnet (Wenzek et al., 2019) to train the decoder. We compare the new decoder with original LASER decoder on the auto-encoding task and the German-English translation task of FLORES in Figure 2.

Results First, we notice an important boost on the auto-encoding task with the new decoder, with high BLEU scores even for sentences with more than 50 words. Second, training a new decoder with an auto-encoding objective improves the decoding of sentence embeddings from another language, German. The new decoder can be directly applied to German sentence embeddings because German embeddings are supposed to be close to their English translations encoded with LASER.

3.2 Making languages closer

Motivations To get an idea of the closeness of translations in the LASER space, we inspected the L2 squared distances of sentence embeddings in different languages to their English translations sentence embeddings. A detailed analysis can be found in the appendix. We noticed that high resource languages are closer in the LASER space to English, compared to low resource languages.

We studied how our newly trained decoder is performing on a more distant language in LASER space, Japanese. We report the results of the ja-en translation task using the original decoder and the new decoder in Table 1. We notice that both decoders performs poorly on the ja-en translation tasks, and that the original LASER decoder leads to better results. An hypothesis is that the new decoder has over-fitted English embeddings leading to bad generalization on distant Japanese embeddings.

Teacher-student training of text encoders To overcome this issue, we suggest to follow a method introduced by Reimers and Gurevych (2020), where new encoders are trained to fit an existing sentence embedding space. Here, we are trying to make the Japanese translations closer to English embeddings in our 1024 dimensional space.

	ja-en
Original encoder + original decoder	6.9
Original encoder + new decoder	5.5
Student - BOS pooling + new decoder	19.5
Student - max pooling + new decoder	22.5
Student - max pooling + original decoder	12.2
Student - max pooling & CE + new decoder	22.6

Table 1: BLEU scores for ja-en on FLORES devtest

The original LASER encoder is fixed during training to encode English translation, behaving as the teacher, while we train a new Japanese encoder as a student to fit English sentence embeddings. We use bitexts from CCMatrix for the ja-en pair to train the Japanese text student. Following (Reimers and Gurevych, 2020), we minimize the MSE loss (equivalent to L2 squared distance) between the generated Japanese sentence embedding and the target English sentence embedding.

The Japanese encoder is not trained from scratch, but we fine-tune XLM-R large. To extract the sentence embedding, we tested two methods: The classical output of the encoder corresponding to the beginning-of-sentence (BOS) token, a method widely used for text classification ; or max-pooling of the encoder outputs, less common but LASER has been trained with such pooling method.

Finally, we tested another objective that is supposed to better match with our decoding task: we encode the Japanese sentence with the encoder being trained, decode the pooled sentence embedding with our new decoder which weights are not updated during training, and we compute the cross entropy loss of the output of the new decoder with the English target sentence. The training was unstable when using XLM-R weights as initialization. Therefore, instead of fine-tuning XLM-R, we fine-tune the encoder obtained from our previous method (trained with MSE loss), which leads to a stable training. We report all the results in Table 1. For text-to-text translation results, we use spBLEU of M2M-100 with the public checkpoint and script to evaluate on FLORES.

Results In Table 1, we first notice that learning a new Japanese student significantly improve the results for the ja-en translation task. The best pooling method seems to be max-pooling, maybe because LASER has been trained with max-pooling. The second step of fine-tuning with cross entropy loss does not improve the results for our ja-en translation task, despite of the significant decrease of

cross entropy valid loss during this second step fine-tuning. This validates the use a simple MSE loss which seems sufficient for future decoding purposes and is a lot cheaper in term of computation compared to cross entropy loss. We conclude that learning a new Japanese student with max-pooling and MSE loss leads to the best results. Using this new Japanese encoder, our new decoder significantly outperforms the original LASER encoder.

These experiments show that LASER sentence embeddings can be better decoded by training a new decoder on a large amount of raw text data. This new decoder can be used to decode sentence embeddings from other languages handled by LASER. However, translations are still more or less distant in the space, making them explicitly closer with a MSE loss objective significantly improves the results on a translation task. Therefore, we decide to extend this idea to other languages and a new modality, speech, to see if it can help performing cross-modal translation tasks.

4 Overall architecture

Text student encoders We now want to train several text students for different languages, in order to plug, at test time, these encoders to different decoders to perform translation tasks. We decide to use LASER **English** embeddings as our teacher. This English space has proven to have good semantic properties: paraphrases are close in the embedding space, and makes it a good teacher for English translations. Moreover, most of MT data involve English translations that we will use to learn our text students. We focus on 7 languages, namely, German, French, Spanish, Catalan, Japanese, Turkish, and Mongolian. We use CCMatrix bi-texts to learn our text students, and bi-texts mined with LASER3 (Heffernan et al., 2022) for Mongolian.

Text decoders We saw above that we can train a new English decoder with raw English data, using a fixed encoder and an auto-encoding objective. However, such an approach can lead to over-fitting to English sentence embeddings and bad generalization on other languages. We made languages closer together in our 1024 dimensional space thanks to our new student encoders but translations are not perfectly mapped to a real English sentence embedding in this continuous space. Therefore, we explore different methods to make the decoders robust locally in the sentence embedding space in order to generalize better on unseen languages.

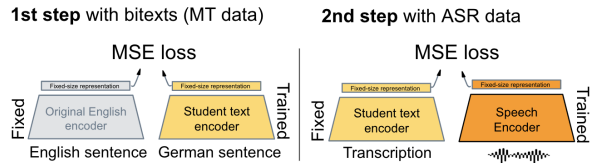


Figure 3: Incremental learning of a speech student.

First, we can improve our decoder training with an auto-encoding objective by adding synthetic noise in the sentence embedding space. We add noise to a sentence embedding by multiplying it by $1 + \epsilon$, with $\epsilon \sim \mathcal{N}(0, \alpha)$. In our experiments, we took $\alpha = 0.25$, which leads to an empirical average L2 squared distance of approx. 0.05. between the noisy embedding and the original embedding.

Second, we tested another approach to make our decoder robust to translations in the sentence embedding space: we added bi-texts from the de-en direction to the training of the English decoder.

Finally, we trained decoders for five non-English languages to see how it behaves for other languages. All text decoders are 12-layers transformer decoders.

Speech student encoders Duquenne et al. (2021) showed that it is possible to learn speech students compatible with the LASER text space. The training of speech students is similar to the one presented above for text. They fine-tune XLSR, a multilingual pretrained model for speech and minimized the cosine loss between the output of the speech encoder and the target LASER sentence embedding. We adapt this approach using a bigger XLSR model (Babu et al., 2021) with more than two billion parameters and extracting the fixed-size representation for speech with max-pooling to follow what we have done for text students. We minimize the MSE loss between the output of the speech encoder and the transcription/translation encoded by one of our text encoders. Unlike (Duquenne et al., 2021), we did not use the original LASER encoder to encode text transcripts but our newly trained text students which are supposed to be close to the LASER English embeddings. As in (Duquenne et al., 2021), we can use either transcriptions or written translations as teachers for our speech student. We used CoVoST 2, a speech translation dataset, as our training data. Figure 3 summarizes the process to train a speech student with transcriptions only: First, we train a text student for the language we want to cover, we will

	de	fr	es	ca	ja	tr	mn
<i>This work - zero-shot except for de-en</i>							
en-en decoder	40.7	41.9	30.4	36.7	22.5	32.8	13.0
en-en+noise decoder	39.5	40.6	29.4	35.8	23.7	33.2	16.4
en-en+de-en decoder	44.2	44.9	32.6	40.7	26.5	37.3	19.4
<i>Previous works - supervised</i>							
M2M-100 (12B - 48 layers) (Fan et al., 2021)	44.7	45.5	31.1	42.5	26.1	36.9	20.9
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	48.0	49.9	35.2	46.2	32.7	44.2	23.9

Table 2: BLEU on FLORES devtest for text-to-text xx-en translation using different English decoders.

use this encoder to encode transcriptions. Then, we train a speech student to fit text embeddings output by our text student.

Speech decoders In this last part, we introduce a speech decoder in our framework, which can be learnt with raw speech data. We focus on English speech decoding but it could be extended to other languages. To learn to decode English speech, we follow the work done by Lee et al. (2022b), who learn to decode HuBERT units. At test time, the generated units are transformed into speech using a vocoder.

One method is to follow the same approach presented for raw text data to learn an English decoder. The English speech encoder previously trained to fit LASER text space on CoVoST 2 training set is used to encode raw speech, and its weights are not updated during training. We trained a unit decoder to decode sentence embeddings output by the speech encoder. The unit targets correspond to the one of the input speech as we are trying to auto-encode speech. We follow the recipe of Lee et al. (2022b) to prepare target units as we are dealing with real speech data: we extract HuBERT units from input speech, normalize the units with the speech normalizer used in Lee et al. (2022b). This preparation of target data is done unsupervisedly and any raw speech data can be processed with this method. We summarize the speech decoder training in Figure 4. Another method is to leverage English speech recognition data where English text transcripts are encoded through LASER

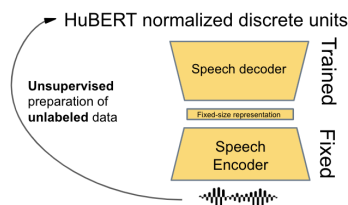


Figure 4: Speech decoder training.

encoder which weights are fixed during training and a decoder predicts the sequence of units of the corresponding speech.

Once the English speech decoder is trained, we can plug any text or speech encoder to perform direct text-to-speech or speech-to-speech translation in a zero-shot way.

5 Results and discussion

Text-to-text translation As presented in section 4, we test different strategies to train an English decoder. When training a decoder with raw text data, we use 15 billion English sentences extracted from CCnet (Wenzek et al., 2019). When training with additional bi-text data, we use bi-texts from CCMatrix (Schwenk et al., 2021), and the English part of the bi-texts for the auxiliary auto-encoding loss in order to have a good balance between bi-texts and raw data. We present the results for text-to-text translation for xx-en directions in Table 2 for the different decoder training methods on FLORES devtest. *en-en decoder* corresponds to the decoder trained with an auto-encoding objective, *en-en+noise decoder* corresponds to the decoder trained with an auto-encoding objective and additional noise in the sentence embedding space, and *en-en+de-en decoder* corresponds to the decoder trained with a combination of de-en bitexts and english raw data. We compare our zero-shot text-to-text translation results with two supervised baselines: M2M-100 (Fan et al., 2021), a massively multilingual trained on many-to-many training data from different sources, with 24 encoder layers and 24 decoder layers; and Deepnet (Wang et al., 2022) a recent work trained on 1932 language directions from different sources with 100 encoder layers and 100 decoder layers. We put these results as a supervised reference but we recall that in our framework, we perform zero-shot text-to-text translation for most of the language pairs. Please note the cross-lingual transfer we obtain thanks to our training

	de	fr	es	ca	tr	ja	mn
Speech training hours in CoVoST 2	184h	264h	113h	136h	4h	2h	3h
This work - zero-shot							
en-en decoder	27.3	32.2	34.0	24.7	7.4	3.3	0.1
en-en+noise decoder	29.2	33.3	35.3	27.3	10.1	5.2	0.3
en-en+de-en decoder	33.0	35.7	37.1	30.2	11.2	6.1	1.0
Previous work - zero-shot							
mSLAM (Bapna et al., 2022) cross-modal zero-shot	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Previous works - supervised							
XLSR (2B) (Babu et al., 2021)	33.6	37.6	39.2	33.8	16.7	3.5	1.6
mSLAM (2B) (Bapna et al., 2022)	35.9	39.0	41.0	35.4	24.2	3.3	0.8

Table 3: BLEU on CoVoST 2 test set for zero-shot speech-to-text translation (xx \rightarrow en).

method: the English decoder has never seen Spanish embeddings before but is able to achieve competitive results compared to supervised baselines.

In Table 2, we see that adding synthetic noise to the sentence embeddings helps translating low resource languages unseen by the decoder. However, it slightly decreases the performance on high resource languages. Moreover, natural noise from de-en translations leads to even better results for both high and low resource languages, getting closer to the state-of-the-art MT results which have been obtained with end-to-end training.

Finally, we trained decoders for German, French, Spanish, Turkish and Mongolian in order to be able to translate from any of our languages to any other. A detailed analysis of the translation tasks with these new decoders can be found in the appendix. Similar to what we noticed with our English decoder, we obtain excellent zero-shot cross-lingual transfer: the German decoder has never seen Japanese embeddings before and Japanese has never been aligned to German. However, the ja-de results are competitive compared to state-of-the-art translation models trained in an end-to-end way with much more data.

Speech-to-text translation Then, we tried to plug the decoders trained on text data to our speech encoders in order to perform zero-shot speech-to-text translation. We trained independent speech student encoders for German, French, Turkish, Japanese and Mongolian spoken languages on the CoVoST 2 training set. For Catalan and Spanish, we trained a single speech student encoder for both languages as they have high language similarity. We report direct speech translation results in Table 3 for speech encoders trained with transcriptions as teachers. We have put several baselines for direct speech translation: two supervised baselines

Teacher mode:	Transcript.		Translation		Both	
	de	ja	de	ja	de	ja
en-en	27.3	3.3	27.9	3.5	28.1	3.1
en-en+noise	29.2	5.2	28.8	4.4	30.2	5.2
en-en+de-en	33.0	6.1	30.6	4.6	33.6	5.4

Table 4: BLEU on CoVoST 2 test set for different teachers and decoders for zero-shot speech-to-text translation.

based on finetuning XLSR (Babu et al., 2021) or mSLAM (Bapna et al., 2022) with speech translation data. We also put the results on zero-shot cross-modal transfer from text to speech with the mSLAM pre-trained multimodal encoder, which is not working in this zero-shot setting.

In our framework, the de-en speech translation direction benefits from cross-modal transfer while all other directions benefit from both cross-modal and cross-lingual transfer as the decoder has been trained on text and has only seen English and German embeddings. In this zero-shot cross-modal setting, we notice that the results are really competitive compared to supervised baselines trained end-to-end. Moreover, the supervised baselines use speech translation data, whereas our approach does not need speech translation data but only transcriptions. Except for Turkish, which has a really different morphological structure compared to English, speech translation results are close to their supervised counterpart trained with XLSR. An interest-

	State of the art	Our models
en \rightarrow de	6.77	23.78
en \rightarrow fr	10.85	32.71
en \rightarrow es	6.75	27.43

Table 5: BLEU on Must-C test set for zero-shot speech translation, compared to the state of the art for zero-shot approaches by (Escolano et al., 2021b).

	es-en	fr-en
Zero-shot text-to-speech		
trained on raw speech from CoVoST	10.0	9.5
trained on raw speech from MLS + Common Voice	22.8	20.9
trained on <i>en</i> ASR data from MLS + Common Voice	24.4	23.5
Zero-shot speech-to-speech		
trained on raw speech from CoVoST	9.9	9.1
trained on raw speech from MLS + Common Voice	21.3	19.8
trained on <i>en</i> ASR data from MLS + Common Voice	22.4	21.1

(a) This work: *zero-shot* results

	es-en	fr-en
Supervised speech-to-speech translation		
trained on VP	9.2	9.6
trained on VP + mined data	15.1	15.9
Supervised speech-to-speech via text pivot		
trained on VP+EuroparlST+CoVoST	26.9	27.3

(b) Results from previous *supervised* models trained by Lee et al. (2022b) on real (non synthetic) data. The speech-to-speech via text pivot baseline relies on speech-to-text by Wang et al. (2021).

Table 6: BLEU on CoVoST 2 test set for text-to-speech and speech-to-speech translation

ing direction is ja-en, as we have a large amount of ja-en MT data but a really small amount of speech transcription data. For this task, we nearly doubled the BLEU score compared to supervised baselines without the need of ST data.

We tested the different possible teachers for speech encoder training, namely transcription teacher (already presented), translation teacher, and both transcription and translation teachers. When using translation teacher, we use English text as the written translations from CoVoST 2. We focus on two language directions, de-en (high resource) and ja-en (low resource). Results are shown in Table 4. We notice that a translation teacher is better if using the en-en decoder, which was expected as the decoder was trained on English embeddings. However, when using a decoder trained on noisy embeddings or with additional bi-texts, results are better for speech encoders trained with transcription teacher rather than translation teacher. It may come from the fact that there exists a one-to-one mapping between transcriptions and audios, but not for audio and written translation (there can be several possible translations). For our high resource direction de-en, the best results are achieved when using both transcriptions and translations as teacher, reaching same performance level as with the end-to-end speech translation training of XLSR.

Finally, we trained an English speech student with transcriptions on the Must-C training set and compare our approach with the zero-shot approach by Escolano et al. (2021b). We report the results in Table 5. We notice significant improvements in the BLEU score compared to the previous SOTA for zero-shot speech translation on the Must-C dataset.

Translation of text/speech into speech As presented in the section 4, we trained English speech decoders with raw English speech only or English speech transcriptions. We present three training set-

tings: one decoder trained on raw English speech data from CoVoST (~ 400 h), another trained on raw English speech data from both Common Voice ($\sim 2,000$ h) and Multilingual Librispeech (MLS) ($\sim 40,000$ h), and finally another trained on English speech transcription data from both Common Voice and Multilingual Librispeech. At test time, we can now plug these English speech decoders to any text or speech encoder. We focused on es-en and fr-en language directions that have previously been covered for direct speech-to-speech translation (see Table 6). We also present text-to-speech translation results, plugging text encoders to our speech decoders.

Following Lee et al. (2022a,b) the evaluation is done by transcribing the output speech with an open-sourced ASR system for English and evaluating the BLEU score of the transcribed speech with target text from CoVoST. We compare these results to a supervised baseline (Lee et al., 2022b) trained on real speech-to-speech translation data from Voxpopuli (Wang et al., 2021) and mined data from (Duquenne et al., 2021). We also provide a strong supervised baseline composed of a Speech-to-text translation model from (Wang et al., 2021) that is trained on a significant amount of speech translation data from Voxpopuli, EuroparlST and CoVoST, followed by a text-to-unit model.

In Table 6, we notice that our speech decoders achieve strong results for this zero-shot setting, even with a limited amount of raw speech data. Incorporating much more raw speech data in the training, significantly improves the results. Using textual representation as input helps in speech decoder training, leading to best results. To the best of our knowledge, these are the first results for zero-shot direct speech-to-speech translation.

This last experiment again highlights the compatibility between representations for different languages and modalities. Our approach enables to

efficiently leverage raw speech data for T2S and S2S tasks.

6 Conclusion

In this work, we studied how to build a common fixed-size representation for text and speech in different languages, to perform zero-shot cross-modal translation. By imposing a fixed-size representation and aligning explicitly languages and modalities, we have overcome the sentence length mismatch between audio and text, and obtained multilingual and multimodal representations compatible with decoders trained on other languages and/or modalities in a zero-shot setting. We were able to build text and speech encoders for multiple languages compatible with text decoders for multiple languages as well as an English speech decoder. Our zero-shot cross-modal translation results for direct speech-to-text, text-to-speech and speech-to-speech translation define a new zero-shot state-of-the-art baseline. To the best of our knowledge, this is the first work tackling zero-shot direct text-to-speech and speech-to-speech translation.

Finally, we highlighted the modularity of our architecture; all type of data can be used to train decoders (unlabeled text or speech data ; T2T, S2T, S2S translation data; speech transcription data). Using more types of training data may further enhance the robustness of the decoder to other languages or other modalities.

Limitations

We highlighted the modularity of our architecture, learning separately encoders and decoders. While it can be seen as a strength, as one does not need to retrain the whole system to add a new language to the framework, it can also be seen as a limitation as the number of modules increases linearly with the number of languages. Moreover, training multiple separate modules requires more time and computation than one multilingual model. Multilingual training of encoders or decoders is left for future work.

In machine translation, sequence-to-sequence models with fixed-size sentence representation were replaced by sequence-to-sequence models with attention that showed important performance boost for long sentences. Our work shows that competitive performance can still be achieved with fixed-size sentence representations and enables efficient compatibility between languages and modal-

ities. However, very long sequences, beyond usual sentence length, are expected to perform less well.

We showed that it is possible to learn an English speech decoder with raw speech data, it would be interesting to extend this to other languages as target speech, and see how our method performs for a low resource spoken language.

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A Appendix

A.1 Distances in LASER text space

We report the L2 squared distances of sentence embeddings in different languages to their English translations sentence embeddings in LASER space.

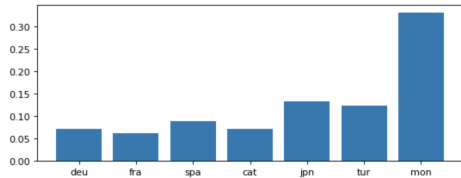


Figure 5: L2 squared distances to English embeddings in LASER space for translations from FLORES devtest

A.2 Other text decoders

With the conclusion that bi-text data can help the decoder be robust to other unseen languages, we trained decoders for German, French, Spanish, Turkish and Mongolian. We use en-xx bitexts, in addition to raw xx data to train the decoders. For all decoder trainings, we use bi-texts from CCMatrix (Schwenk et al., 2021), for the auto-encoding loss we use one side of the bi-texts corresponding to the language that we are trying to decode, except for Mongolian where we take all the raw Mongolian text data from CCnet. (Wenzek et al., 2019). We present the results in Table 7.

A.3 Training details

We use Fairseq to train our models. Text student encoders are trained on 32 Tesla V100 GPUs with a learning rate set to 10^{-4} , maximum number of tokens by GPU is 1400, and update frequency is set to 4. Speech student encoders are trained on 48 Tesla V100 GPUs for a few days, with same learning rate as text students, maximum number of sentences is set to 32 by GPU. Text decoders are trained with the same configuration as mBART. Speech decoders are trained on 48 Tesla V100 GPUs with a learning rate set to $3 \cdot 10^{-4}$, maximum number of sentences is set to 32 by GPU and update frequency is set to 4.

	en	de	fr	es	ca	ja	tr	mn
Translation into German								
<i>This work - zero-shot expect for en-de</i>								
de-de+en-de decoder	39.1	—	32.6	24.6	29.2	20.9	27.9	12.8
<i>Previous works - supervised</i>								
M2M-100 (12B - 48 layers) (Fan et al., 2021)	42.1	—	34.5	27.1	30.9	21.4	28.4	15.9
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	46.0	—	36.2	29.2	32.5	24.7	31.9	21.7
Translation into Spanish								
<i>This work - zero-shot expect for en-es</i>								
es-es+en-es decoder	29.1	25.9	26.8	—	26.3	18.6	22.8	12.2
<i>Previous works - supervised</i>								
M2M-100 (12B - 48 layers) (Fan et al., 2021)	30.3	27.2	28.2	—	26.6	19.4	24.0	14.9
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	32.2	28.3	28.8	—	26.9	21.5	25.9	18.8
Translation into French								
<i>This work - zero-shot expect for en-fr</i>								
fr-fr+en-fr decoder	49.1	38.3	—	31.2	37.6	25.3	33.4	16.6
<i>Previous works - supervised</i>								
M2M-100 (12B - 48 layers) (Fan et al., 2021)	51.4	42	—	32.8	39.7	26.6	35.1	20.8
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	54.7	43.4	—	35.2	41.6	29.9	38.2	26.6
Translation into Turkish								
<i>This work - zero-shot expect for en-tr</i>								
tr-tr+en-tr decoder	31.2	27.1	26.4	21.5	24.2	19.1	—	13.7
<i>Previous works - supervised</i>								
M2M-100 (12B - 48 layers) (Fan et al., 2021)	32.8	26.9	26.6	22.3	24.3	18.6	—	16.1
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	39.5	32.0	31.6	26.2	28.2	23.2	—	21.0
Translation into Mongolian								
<i>This work - zero-shot expect for en-mn</i>								
mn-mn+en-mn decoder	15.7	15.8	15.2	13.6	15.2	13.5	15.4	—
<i>Previous works - supervised</i>								
M2M-100 (12B - 48 layers) (Fan et al., 2021)	12.0	10.7	10.9	9.2	10.8	9.3	11.0	—
Deepnet (3.2B - 200 layers) (Wang et al., 2022)	18.3	16.8	16.2	15.0	15.8	13.7	15.9	—

Table 7: BLEU on FLORES devtest for text-to-text translation for de, es, fr, tr and mn decoders