Teaching a Multilingual Large Language Model to Understand Multilingual Speech via Multi-Instructional Training

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Abstract

Recent advancements in language modeling have led to the emergence of Large Language Models (LLMs) capable of various natural language processing tasks. Despite their success in text-based tasks, applying LLMs to the speech domain remains limited and challenging. This paper presents BLOOMZMMS, a novel model that integrates a multilingual LLM with a multilingual speech encoder, aiming to harness the capabilities of LLMs for speech recognition and beyond. Utilizing a multi-instructional training approach, we demonstrate the transferability of linguistic knowledge from the text to the speech modality. Our experiments, conducted on 1900 hours of transcribed data from 139 languages, establish that a multilingual speech representation can be effectively learned and aligned with a multilingual LLM. While this learned representation initially shows limitations in task generalization, we address this issue by generating synthetic targets in a multi-instructional style. Our zero-shot evaluation results confirm the robustness of our approach across multiple tasks, including speech translation and multilingual spoken language understanding, thereby opening new avenues for applying LLMs in the speech domain.

1 Introduction

Language modeling task involves predicting subsequent text tokens based on a context of preceding ones (Jurafsky and Martin, 2009). Training a language model (LM) requires only raw text samples, as portions of these samples function as their labels, facilitating a self-supervised learning (SSL) approach. The widespread availability of machine-readable text online, coupled with advancements in computational power, has led to the rise of large LMs (LLMs) in recent years. These LLMs not only generate highly fluent natural text but also encode higher-level knowledge within their parameters. This enables them to tackle natural language processing tasks like reading comprehension and machine translation based only on task specific instructions, without needing labeled data (Radford et al., 2019).

SSL has recently made significant strides in the speech domain (Baevski et al., 2020). Most applications of SSL in speech employ an encoder that transforms raw speech signals into high-level representations, serving either as a fixed feature extractor (Yang et al., 2021) or a tunable pretrained model for various downstream tasks (Babu et al., 2021). Incorporating of SSL pretrained encoders into Encoder-Decoder speech recognition models has dramatically reduced the amount of labeled data required for effective training (Chang et al., 2021). However, using SSL pretrained decoders in such models is relatively rare. In certain instances, SSL is part of a joint training process that seeks to learn a shared speech and text representation (Chen et al., 2022). However, this approach often demands a large dataset and considerable computational resources.

Recent work has begun to harness the powerful text generation capabilities of decoder-only LLMs by incorporating them as the decoder component of Encoder-Decoder speech processing models. Wu et al. (2023) adopt the LLaMA-7B LLM for speech translation to English by training a speech encoder from scratch using filter bank acoustic features, 14,000 hours of internal speech data in 14 languages, and outputs of internal translation system as synthetic targets. Outputs of speech encoder are aligned with the text token embedding space using CTC pretraining and downsampled by averaging of consequative frames with the same CTC output label. Ling et al. (2023) adopt the GPT2 XL LLM for fully-formatted English speech recognition by training a speech encoder from scratch using filter bank acoustic features, and 75,000 hours of internal transcribed English speech data. CTC loss is applied to speech encoder outputs as a part of the

Findings of the Association for Computational Linguistics: NAACL 2024, pages 814–834

main training process and speech representations are downsampled by removal of frames classified as CTC blank labels with a predefined threshold. Li et al. (2023) adopt the LLaMA-7B LLM for long-form English speech recognition by incorporating the HuBERT-Large SSL pretrained speech encoder and finetuining it on the LibriSpeech dataset containing 960 hours of transcribed English speech. Outputs of the speech encoder are downsampled by a convolutional module trained as a part of the main training process. Fathullah et al. (2023) adopt the LLaMA-7B LLM for speech recognition in 8 languages by training a speech encoder from scratch using filter bank acoustic features and the Multilingual LibriSpeech dataset containing 50,000 hours of transcribed speech in the same 8 languages. Speech encoder is pretrained with CTC loss and its outputs are downsampled by simple discarding of every n frames. Nachmani et al. (2023) combine an internal pretrained LLM with an internal pretrained speech encoder and finetune it on the automatically transcribed LibriLight dataset containing 60,000 hours of English speech. The training is performed with a combination of the speech transcription and speech continuation tasks. The resulting model is utilized for the spoken language answering task. Most of these studies rely on conventional filter bank features for speech encoding and do not incorporate an SSL pretrained speech encoder, necessitating a large amount of training data. Moreover, scant attention has been given to leveraging the linguistic knowledge stored in LLMs for tasks beyond mere transcription and for languages other than English.

To address these challenges, we propose BLOOMZMMS, a model that fuses a multilingual LLM (BLOOMZ (Muennighoff et al., 2023)) with a multilingual speech encoder (MMS (Pratap et al., 2023)). We argue that multi-instructional training is crucial for transferring linguistic knowledge from the text to speech modality. Our experiments demonstrate that training on 1900 hours of transcribed data from 139 languages yields a multilingual speech representation compatible with a multilingual LLM in the context of Automatic Speech Recognition (ASR) task. Although this representation does not generalize well to other tasks, we show that the issue can be mitigated by generating additional synthetic targets. Our zero-shot evaluations confirm this approach's effectiveness across various tasks, including Spoken Language Translation (SLT) and multilingual spoken Natural Language Inference (NLI). Our training recipes and models are released under the Apache-2.0 license[1].

2 Method

The proposed method is outlined in Figure 1. Our model comprises the pretrained speech encoder, LLM and an intermediate Adaptor module that maps the output of the speech encoder to the latent space of the text token embeddings of the LLM. We train the Adaptor module using pairs of speech recordings and their corresponding text transcriptions, denoted as $\boldsymbol{x}$ and $\boldsymbol{y}^{\text{Transcription}}$ respectively, and keep the parameters of the speech encoder and the LLM frozen. The objective of the Adaptor training is to make its output $\boldsymbol{H}^{\text{Adaptor}}$ obtained from the input speech $\boldsymbol{x}$ as close as possible to the text embedding sequence of the ground truth transcription $\boldsymbol{H}^{\text{Transcription}} = \text{LMEmbedding}(\boldsymbol{y}^{\text{Transcription}})$, where LMEmbedding is the token embedding layer of the LLM.

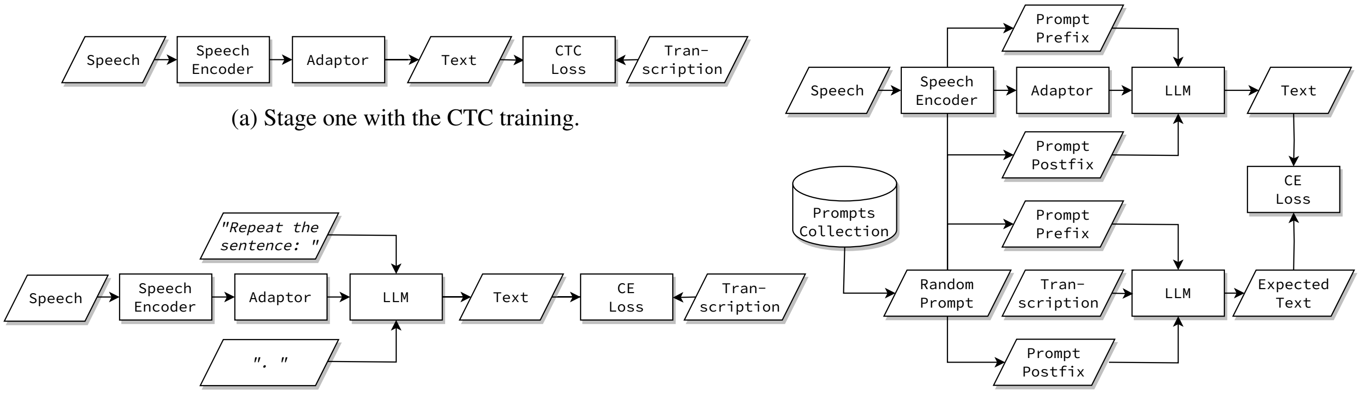
Similarly to previous works on the LLM adaptation to the speech modality (Wu et al., 2023; Fathullah et al., 2023), our training process comprises of the two stages: an alignment of the speech encoder output with the LLM token embedding space, and an integrated optimization of the complete model with the LLM. An attempt to omit either of the two stages in our process leads to the lack of training convergence. We hypothesize that the different training stages help the Adaptor to learn different subtasks like segmentation, ordering and the actual token embedding prediction.

At the first stage of the training, $\boldsymbol{H}^{\text{Adaptor}}$ is projected to the LLM tokens' logits using the frozen output linear layer of the LLM (which is often a transposed token embedding layer), and the Connectionist Temporal Classification (CTC) loss (Graves et al., 2006) is minimized between the LLM token probabilities obtained from the token logits and the transcription:

$$\begin{aligned}
\boldsymbol{H}^{\text{Speech}} &= \text{SpeechEncoder}(\boldsymbol{x}) \\
\boldsymbol{H}^{\text{Adaptor}} &= \text{Adaptor}(\boldsymbol{H}^{\text{Speech}}) \\
p_{\text{CTC}}(\boldsymbol{y}|\boldsymbol{x}) &= \text{Softmax}(\boldsymbol{H}^{\text{Adaptor}}\boldsymbol{W}) \\
\mathcal{L}_{\text{CTC}} &= -\sum_{\boldsymbol{\pi}\in\mathcal{B}^{-1}(\boldsymbol{y}^{\text{Transcription}})} \log p_{\text{CTC}}(\boldsymbol{\pi}|\boldsymbol{x}),
\end{aligned}$$

where the mapping $\mathcal{B}$ removes repeated and blank tokens according to the CTC definition, $\boldsymbol{W} \in$

[1] https://github.com/DigitalPhonetics/bloomzmms



(a) Stage one with the CTC training.

(b) Stage two with the transcription task training (T).

(c) Stage two with the multi-instructional training (MI).

Figure 1: Overview of the Adaptor training. At the stage one, the Adaptor parameters are optimized using the CTC loss to directly predict the transcription (a). At the stage two, the Adaptor parameters are optimized using the CE loss applied to the outputs of the LLM while the Adaptor output is enclosed in the prompt's prefix and postfix text and is fed to the LLM input. A prompt can instruct the model to generate a transcription (b) or perform some other task on the speech input (c). In the case of transcription, a ground truth transcription is used as a training target. In the case of other instructions, a training target is obtained by running the LLM inference with the same prompt and ground truth transcription as the input.

$\mathbb{R}^{d\times v}$ is the transposed weight matrix of the token embedding layer, d is the dimensionality of the embedding, and v is the number of tokens in the LLM's vocabulary.

At the second stage, $\boldsymbol{H}^{\text{Adaptor}}$ is concatenated with the token embeddings of the prefix and postfix parts of a text prompt. This joint sequence is then passed through the self-attention layers of the LLM and projected with the transposed token embedding weight matrix W (also serving as the output layer of the LLM) to obtain the LLM prediction. The Cross-Entropy (CE) loss is minimized between the prediction of the LLM for this sequence and the expected LLM output. In case of the speech recognition task, we set the prompt prefix and postfix to `"Repeat the sentence: "` and `". "` respectively:

$$
\begin{aligned}
\boldsymbol{H}^{\text{Prefix}} &= \text{LMEmbedding}(\texttt{"Repeat the sentence: "}) \\
\boldsymbol{H}^{\text{Postfix}} &= \text{LMEmbedding}(\texttt{". "}) \\
\boldsymbol{H}^{\text{LM}} &= \text{LM}((\boldsymbol{H}^{\text{Prefix}}, \boldsymbol{H}^{\text{Adaptor}}, \boldsymbol{H}^{\text{Postfix}})) \\
p_{\text{CE}}(\boldsymbol{y}|\boldsymbol{x}) &= \text{Softmax}(\boldsymbol{H}^{\text{LM}}\boldsymbol{W}) \\
\mathcal{L}_{\text{CE-ASR}} &= -\log p_{\text{CE}}(\boldsymbol{y}^{\text{Transcription}}|\boldsymbol{x}),
\end{aligned}
$$

where LM() denotes the self-attention layers of the LLM. In case of the multi-instructional training, prompts are sampled from a predefined hand crafted collection, while the expected output is set to the output of the LLM for the same prompt using the token embeddings of the ground truth transcription instead of the Adaptor output $\boldsymbol{H}^{\text{Adaptor}}$:

$$
\begin{aligned}
\boldsymbol{H}^{\text{Prefix}} &= \text{LMEmbedding}(\boldsymbol{p}^{i}_{\text{Prefix}}) \\
\boldsymbol{H}^{\text{Postfix}} &= \text{LMEmbedding}(\boldsymbol{p}^{i}_{\text{Postfix}}) \\
\boldsymbol{H}^{\text{LM}} &= \text{LM}((\boldsymbol{H}^{\text{Prefix}}, \boldsymbol{H}^{\text{Adaptor}}, \boldsymbol{H}^{\text{Postfix}})) \\
\boldsymbol{H}^{\text{LM}-\text{Text}} &= \text{LM}((\boldsymbol{H}^{\text{Prefix}}, \boldsymbol{H}^{\text{Transcription}}, \boldsymbol{H}^{\text{Postfix}})) \\
\boldsymbol{y}^{\text{LM}} &= \text{BeamSearch}(\text{Softmax}(\boldsymbol{H}^{\text{LM}-\text{Text}}\boldsymbol{W})) \\
p_{\text{CE}}(\boldsymbol{y}|\boldsymbol{x}) &= \text{Softmax}(\boldsymbol{H}^{\text{LM}}\boldsymbol{W}) \\
\mathcal{L}_{\text{CE-MI}} &= -\log p_{\text{CE}}(\boldsymbol{y}^{\text{LM}}|\boldsymbol{x}),
\end{aligned}
$$

where $\boldsymbol{p}^{i}_{\text{Prefix}}$ and $\boldsymbol{p}^{i}_{\text{Postfix}}$ are the prefix and postfix texts of the i-th prompt in the prompts collection, $i \sim U([1, \ldots, N_{\text{Pr}}])$ is a random number drawn from an uniform distribution over all natural numbers between 1 and N_{Pr}, and N_{Pr} is the number of prompts in the collection.

3 Experiments

3.1 Training and Validation Data

The Adaptor training is performed on the entire training FLEURS dataset (Conneau et al., 2023) and a subset of the Common Voice Corpus 12.0 (Ardila et al., 2020) training dataset with the total amount of 993,660 utterances or 1905 hours of recordings. The Common Voice subset is constructed by selection of up to 25 hours of recordings for each language. Our validation set is the validation set of FLEURS with the total amount of 34,044 utterances or 115 hours of recordings. All transcriptions are taken in an unnormalized format with the true casing and punctuation.

Multi-instructional training labels are synthesized with prompts from the P3 collection (Sanh et al., 2022). The P3 collection is selected because it was employed in the finetuning process of transitioning BLOOM into BLOOMZ. Our objective is to ensure consistent output for both speech and text inputs. To achieve this, we generate text outputs utilizing prompts from the P3 collection, with which the BLOOMZ model is already acquainted. We apply six distinct randomly drawn prompts to a transcription of each original utterance and assign two generated outputs to each of the three speed-perturbed versions of that utterance. The outputs are generated with a greedy search and maximum length of 128 tokens.

3.2 Evaluation Data and Metrics

We evaluate our model on the following established benchmarks: FLEURS (Conneau et al., 2023), MLS (Pratap et al., 2020) and VoxPopuli (Wang et al., 2021a) for the ASR, CoVoST 2 (Wang et al., 2021b) for the SLT, SpeechGLUE (Ashihara et al., 2023) for the spoken General Language Understanding (GLUE) and SpeechXNLI for the multilingual NLI[2]. The results are evaluated using the corresponding metrics: Word Error Rate (WER) and Character Error Rate (CER) for the ASR, BLEU[3] (Papineni et al., 2002) for the SLT, Matthews Correlation Coefficient (MCC) for the CoLA task within SpeechGLUE, and accuracy for the other SpeechGLUE tasks and the SpeechXNLI. Whisper normalization is applied for both reference and hypothesis before evaluating CER/WER in the ASR experiments.

3.3 Experimental Setup

Our model is implemented using ESPnet2 (Watanabe et al., 2021) version 202304 and Hugging Face Transformers (Wolf et al., 2020) version 4.31.0. We use weighted-sum of hidden states (Yang et al., 2021; Chang et al., 2021) of the MMS 1B-ASR-All[4] pretrained model (Pratap et al., 2023) as speech features. We discard all language specific adapters and heads of the MMS 1B-ASR-All model to simplify the implementation while preserving the multilingual properties of our system. The Adaptor module is a VGG/E-Branchformer based encoder (Kim et al., 2023) combined with a convolutional Length Adaptor (Li et al., 2021). The E-Branchformer encoder is configured with 17 layers, each with 2048 hidden units, 8 attention heads, and output dimension of 1024. The Convolutions to Gated MultiLayer Perceptron module has 8192 units and the convolution kernel size is 31. The Length Adaptor module contains a 1-dimensional convolutional layer with stride 2 and reduces the length of input sequence by factor of 2. Self-conditioning on language identity (Chen et al., 2023) is applied during the CTC training. The LLM in our experiments is BLOOMZ 7.1B[5] model (Muennighoff et al., 2023), which itself is BLOOM 7.1B LLM (Scao et al., 2022) finetuned on the xP3 dataset introduced with BLOOMZ. The total number of parameters in our model is 8.6 billions, the number of trainable parameters is 536 millions. We apply 8-bit quantization (Dettmers et al., 2022) to the LLM using the functions from the `bitsandbytes` package version 0.41.1. The training is done with the Adam optimizer (Kingma and Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$, the warmup learning rate scheduler with the maximum learning rate of 10^{-4} and a weight decay of 10^{-6}. 3-way speed perturbation (Ko et al., 2015) data augmentation method is applied to the training data.

The training stage one, **CTC loss training**, is performed on two NVIDIA RTX A6000 GPUs with the global batch size of 7.29 minutes. The number of warmup steps for the learning rate scheduler is set to 25,000. A checkpoint is saved every 23,364 steps and evaluated on the validation dataset. The training is stopped after four consecutive evaluations showing no improvement, it takes 233,640 update steps or 120 hours of training time to reach this condition. A checkpoint with the lowest validation CER from the stage one is used to initialize the model for the stage two.

The training stage two, **CE loss training**, is performed on four NVIDIA RTX A6000 GPUs with the batch size of 37.50 seconds and a gradient accumulation over two batches. The number of warmup steps for the learning rate scheduler is set to 10,000. A checkpoint is saved every 54,381 steps and evaluated on the validation dataset. The training is stopped after four consecutive evaluations showing no improvement. To reach this condition, it takes 652,572 update steps or 132 hours of training on

[2]Following SpeechGLUE, we synthesize a speech version of the XNLI (Conneau et al., 2018) validation subset using the IMS Toucan (Lux et al., 2022) text-to-speech toolkit: https://zenodo.org/records/10900287.

[3]Using the SacreBLEU tool (Post, 2018).

[4]https://huggingface.co/facebook/mms-1b-all

[5]https://huggingface.co/bigscience/bloomz-7b1

the transcription targets, 2,664,669 update steps or 686 hours on the multi-instructional targets, and 2,501,526 update steps or 644 hours on the combined set of targets. A checkpoint with the highest validation token prediction accuracy from the second step is used for the zero-shot evaluations.

We decode with the beam search of size 5 and set the maximum output sequence to 192 tokens to obtain the model predictions for the ASR and SLT evaluations. The GLUE and NLI evaluations restrict the output to the possible answer options corresponding to a task and limits the beam size and maximum output sequence respectively. For example, for a yes/no question the possible outputs are `yes` or `no`, the beam size is 2 and the maximum output sequence is 1. All evaluations are executed on one NVIDIA RTX A6000 GPU.

4 Results

4.1 Multitasking

Task	Dataset	Metrics	Training targets		
			T	MI	TMI
ASR	FLEURS	CER↓	**12.0**	88.5	12.4
SLT	CoVoST 2 X→En	BLEU↑	3.0	14.1	**15.6**
GLUE	SpeechGLUE	Acc./MCC ↑	41.7	54.4	**55.9**
NLI	SpeechXNLI	Acc. ↑	35.8	**41.6**	41.4

Table 1: Comparative performance metrics across various speech processing tasks using different training targets: transcription (T), synthetic multi-instructional (MI) and their combination (TMI).

Table 1 presents evaluation results of our model across various speech processing tasks, including multilingual ASR, SLT, spoken GLUE, and multilingual NLI. These evaluations test three versions of the model, which are trained using different training targets: transcription only (T), Multi-Instruction (MI), and a combination of both (TMI). When the model is trained solely on the transcription task, it achieves good performance for the ASR task itself, with a CER of 12.0. However, this specialized training does not generalize well to more sophisticated tasks like SLT, GLUE, or NLI, as evidenced by the notably lower performance metrics. On the other hand, training the model on MI synthetic targets shows significant improvement in performing other tasks such as SLT, GLUE, and NLI. The BLEU score for SLT, for example, increases to 14.1 and the average accuracy/MCC score for GLUE rises to 54.4. Despite these gains,

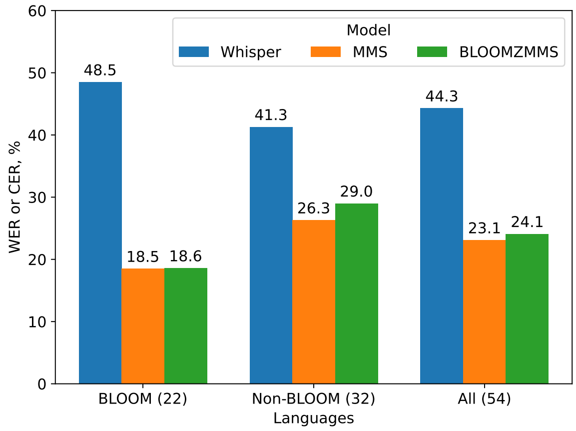


Figure 2: Comparative evaluation of speech recognition performance between the BLOOMZMMS TMI model and previous works, multi-domain MMS (1B) (Pratap et al., 2023) and Whisper large-v2 (Radford et al., 2023), on the FLEURS-54 evaluation dataset. All numbers are WER except for Thai, Lao, Burmese, and Khmer languages.

the MI-only training leads to a significant drop in performance for the ASR task, registering a CER of 88.5. Combining both transcription and MI targets enables the model to perform well across all tested tasks. In addition to maintaining strong performance in ASR (CER of 12.4), this training configuration also leads to improvements in two out of the three non-ASR tasks. These results underscore the benefits of integrating ASR and MI targets.

4.2 Speech Recognition

Dataset	Languages	Training targets		
		T	MI	TMI
FLEURS (CER)	BLOOM (34)	12.9	70.0	**12.8**
	Non-BLOOM (68)	**11.6**	86.4	12.2
	All (102)	**12.0**	80.9	12.4
MLS	BLOOM (4)	27.0	25.0	**20.6**
	Non-BLOOM (4)	**11.5**	72.4	12.2
	All (8)	19.3	48.7	**16.4**
VoxPopuli	BLOOM (3)	21.3	22.0	**17.3**
	Non-BLOOM (11)	22.2	104.6	**22.0**
	All (14)	22.0	86.9	**21.0**

Table 2: Comparative evaluation of speech recognition performance depending on the training targets. Results are stratified by language exposure during BLOOM training and evaluated using WER, except for the FLEURS dataset that uses CER for compatibility with previous works.

Table 2 presents a comparative analysis of ASR performance for the BLOOMZMMS model with the T, MI and TMI training targets. Results are further divided based on whether the languages were seen during the training of the BLOOM model or not. For languages that were part of the BLOOM model training, the TMI model generally performs better than the T model. The opposite is true for the non-BLOOM languages. This is expected as training on the MI targets puts stronger stress on the distillation of the LLM knowledge and its encoding to the Adaptor parameters. This effect is more pronounced on the MLS and VoxPopuli datasets, which represent recording conditions and linguistic content slightly different from our training data. Nevertheless, both T and TMI BLOOMZMMS models perform comparably on the in-domain FLEURS dataset independently from the language, suggesting that the Adaptor can effectively leverage the outputs of the MMS speech encoder in order to compensate for the lack of language familiarity by the LLM.

Following the MMS paper, we separate a subset of FLEURS testing dataset for the 54 languages that are supported by the Whisper model, and compare the results of the BLOOMZMMS TMI model to the results of the multi-domain MMS (1B) and Whisper large-v2 models. The MMS model is essentially the same speech encoder as used by BLOOMZMMS, but with a number of language-specific components, namely adapter parameters, output vocabulary, and n-gram model utilized during decoding. Despite removal of the language-specific components and addition of the other speech processing tasks, such as SLT, BLOOMZMMS manages to keep the ASR performance on a comparable level to the original MMS model. While also being a multitask model, BLOOMZMMS outperforms the other strong multitask alternative, Whisper large-v2, by a large margin on this massively multilingual low-resource ASR benchmark, albeit potentially due to being trained on in-domain data, in contrast to Whisper.

4.3 Speech Translation

Table 3 presents the zero-shot evaluation results for SLT using the CoVoST 2 dataset. The BLOOMZ LM exhibits a nascent ability to translate languages that it has not been trained on, and when this knowledge is transferred to the speech modality, there's only a minor loss in accuracy. Interestingly, the performance gap between the BLOOMZMMS model and gold transcriptions is more pronounced for the BLOOM languages. This indicates that the quality of knowledge transfer from text to speech depends on the initial linguistic knowledge in the text-based LLM. Consequently, weaknesses present in the LLM tend to amplify when transferred to the speech modality, suggesting that the proposed method might benefit from some form of regularization to mitigate this effect.

Dataset	Languages	Training targets			*Gold*
		T	MI	TMI	
X→En	BLOOM (8)	7.0	25.9	**26.8**	*35.5*
	Non-BLOOM (13)	0.6	8.4	**8.7**	*11.3*
	All (21)	3.0	15.1	**15.6**	*20.5*
En→X	BLOOM (5)	1.1	10.9	**11.0**	*17.5*
	Non-BLOOM (10)	0.3	0.9	**1.0**	*1.7*
	All (15)	0.5	4.2	**4.3**	*7.0*

Table 3: Comparative evaluation of zero-shot speech translation performance depending on the training targets using the CoVoST 2 dataset. Results are stratified by language exposure during BLOOM training and evaluated using BLEU metrics[6]. Results on text inputs (*Gold*) are given for comparison.

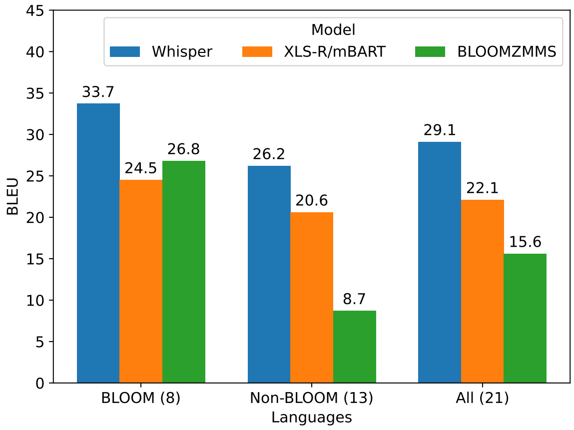


Figure 3: Comparative evaluation of speech translation performance between the BLOOMZMMS TMI model and previous works, XLS-R/mBART (Babu et al., 2021) and Whisper large-v2 (Radford et al., 2023), on the CoVoST 2 X→En evaluation set.

Figure 3 shows the comparison of the BLOOMZMMS TMI model with the previous works, XLS-R/mBART and Whisper large-v2, for the X→En translation direction. XLS-R/mBART is a strong baseline, which is finetuned on complete CoVoST 2 training data. Whisper large-v2 has not seen any CoVoST 2 data during training, but has been supervised by a large amount of other speech translation data. BLOOMZMMS TMI has not been

[6] sacreBLEU signature: nrefs:1 | case:mixed | eff:no | tok:13a | smooth:exp | version:2.3.1.

exposed to any gold labeled speech translation samples during training. Remarkably, the zero-shot BLOOMZMMS model outperforms the supervised task-specific XLS-R/mBART model for the languages previously seen during BLOOM training. This impressive result is primarily due to the strong performance of the BLOOMZ LLM, which is successfully transferred to the speech modality via the multi-instructional training. However, there is a notable gap with the multitask Whisper large-v2 model, primarily attributed to the poor performance on unseen languages of the LLM we utilize.

Dataset	Languages	Training targets			*Gold*
		T	MI	TMI	
X→En	BLOOM (33)	1.2	30.6	**30.8**	*44.4*
	Non-BLOOM (67)	0.5	**8.6**	8.3	*12.5*
	All (100)	0.7	**15.9**	15.7	*23.1*
En→X	BLOOM (33)	18.1	24.7	**24.8**	*30.0*
	Non-BLOOM (67)	1.1	**1.2**	**1.2**	*1.9*
	All (100)	6.7	8.9	**9.0**	*11.2*

Table 4: Comparative evaluation of zero-shot speech translation performance depending on the training targets using the FLEURS dataset. Results are stratified by language exposure during BLOOM training and evaluated using BLEU metrics. Results on text inputs (*Gold*) are given for comparison.

In order to expand language coverage, we evaluate our model for the SLT performance on the FLEURS dataset as well, and present the results in Table 4. As suggested by Radford et al. (2023), we use target language transcriptions for the sentences with the same ID as reference translations. Our evaluation does not include Afrikaans, because the version of the dataset we use[7] does not include any sentence IDs shared between Afrikaans and English. The multilingual properties of the BLOOMZ model, which serves as a decoder of our model, enable us to report the SLT results with non-English target languages as well, for the first time on the FLEURS dataset to the best of our knowledge. The results confirm the good transferability of translation capabilities from text to speech modality with the MI and TMI training targets for a wider range of languages seen in the BLOOM training data. The fair translation performance from unseen languages to English, as observed in the CoVoST 2 dataset, can also be seen across a wider range of languages in the FLEURS dataset.

[7] https://huggingface.co/datasets/google/fleurs

Task	Training targets			*Gold*
	T	MI	TMI	
CoLA	-0.4	4.0	**10.3**	*14.3*
SST-2	50.3	**77.8**	76.9	*94.0*
MRPC	32.8	57.4	**64.0**	*86.3*
QQP	64.3	**77.3**	76.4	*91.2*
MNLI-m	41.0	52.3	**52.9**	*62.4*
MNLI-mm	40.8	54.2	**54.8**	*62.6*
QNLI	50.1	**61.0**	59.9	*64.3*
RTE	50.9	**59.2**	57.0	*70.0*
WNLI	45.1	46.5	**50.7**	*56.3*
Avg. w/o WNLI	41.7	54.4	**55.9**	*66.8*

Table 5: Zero-shot evaluation of spoken GLUE tasks using the SpeechGLUE dataset. All results are accuracy scores, except for CoLA that uses MCC. The STS-B task is excluded because the LLM failed to provide interpretable results.

Languages	Training targets			*Gold*
	T	MI	TMI	
BLOOM (9)	36.3	**42.8**	**42.8**	*54.2*
Non-BLOOM (6)	35.1	**39.7**	39.4	*43.9*
All (15)	35.8	**41.6**	41.4	*50.1*

Table 6: Zero-shot evaluation of multilingual spoken NLI using the SpeechXNLI dataset. All results are accuracy scores.

4.4 Spoken Language Understanding

Tables 5 and 6 provide the results of zero-shot evaluation of BLOOMZMMS models on spoken GLUE tasks in English using the SpeechGLUE dataset and on spoken NLI tasks in multiple languages using the SpeechXNLI dataset. It is worth noting that the combined TMI training targets result in better performance on the English GLUE tasks, but have a mixed impact on the NLI tasks based on the languages trained in BLOOM and those that were not. For the BLOOM languages, the TMI model equals the MI-only model in accuracy, whereas it performs worse on the non-BLOOM languages. Together with the SLT results, this observation again hints at the effect of the LLM's weaknesses amplification during the transfer from the text to speech modality.

4.5 Visual Analysis

Following the example of (Fathullah et al., 2023), we display the cosine similarity between the text and speech embeddings for the three variants of BLOOMZMMS for a French and a Finnish utterance from the FLEURS evaluation dataset (Figure 4). Consistent with the objective metrics from our

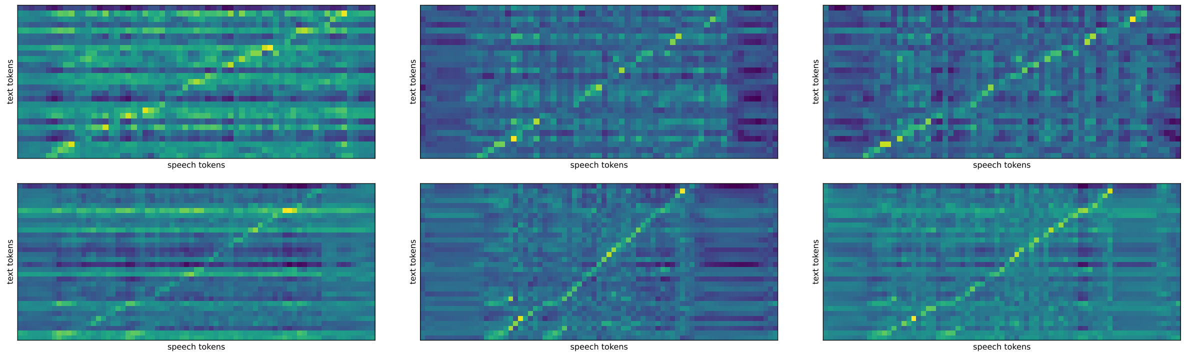


Figure 4: Cosine similarity between the text and speech embeddings for two FLEURS evaluation utterances. Rows correspond to French and Finnish languages (seen and unseen by BLOOM). Columns represent the T, MI and TMI models.

experiments, the model trained on the transcription targets shows the noisiest alignments for the both languages, while the MI training targets offer better alignment for a language unseen by BLOOM and the combined training targets work better for a language seen by BLOOM.

5 Conclusion

In this paper we present BLOOMZMMS, a multilingual multitask speech processing model that combines a multilingual LLM and a pretrained multilingual speech encoder. Our investigation into two training strategies revealed their combined efficacy in a broad spectrum of spoken language processing tasks, a conclusion bolstered by zero-shot evaluations on multiple benchmarks.

Limitations

Our setup is based on pretrained models and, given that our experiments solely rely on ASR data for supervision and the pretrained models remain frozen, the performance in tasks beyond ASR is limited by the capabilities of the utilized pretrained models. For example, the SLT results cannot be better than the translation results of the BLOOMZ model on text input.

While we demonstrate the benefits of multi-instructional training in terms of task generalization in transferring LLM abilities from text to speech modality, our evaluation is limited to a fixed collection of instructions. It does not investigate the impact of varying combinations of instructions more broadly and whether the performance on a certain task depends on its presence in the multi-instructional training data. Furthermore, we do not compare synthetic label generation with the use of ground truth labels, a comparison that holds particular significance for the SLT task. A substantial amount of ground truth labeled data is available for the SLT task. Utilizing this data could likely enhance the model's performance for this task, and potentially others as well. Finally, the slight performance degradation observed in the in-domain ASR dataset with TMI training could potentially be mitigated by more effectively balancing between transcription and multi-instructional data.

Our study is based on a small set of speech processing tasks, and does not consider such tasks as spoken question answering, spoken document summarization and other generative tasks. In addition to that, our evaluation is restricted to the properties of the used evaluation data. For the ASR and SLT tasks, it is read speech recorded on a close distance microphone. For the speech understanding tasks, we rely on a single speaker speech synthesis. It should not be assumed that the proposed model would work equally well or poorly for unseen tasks or new recording conditions, such as far field noisy conversational speech with possibly overlapping speakers. Assuming the model's performance without empirical testing in various scenarios could lead to risks, particularly depending on its application. This risk should be mitigated through preliminary testing specific to each use case. Additionally, it is advisable to cross-check the model's outputs with independent information sources.

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A Evaluation Scores

A.1 Speech Recognition

Language	WER, %			CER, %		
	T	MI	TMI	T	MI	TMI
Afrikaans	24.55	73.55	25.11	11.48	49.00	11.60
Amharic	33.27	252.00	35.29	13.00	239.76	13.94
Arabic	28.21	72.32	26.87	12.50	55.77	11.46
Armenian	23.49	221.59	25.98	8.35	171.45	9.13
Assamese	20.67	111.94	22.43	16.12	97.06	17.59
Asturian	22.00	62.90	24.30	8.24	31.56	10.45
Azerbaijani	26.11	153.81	27.31	7.05	116.91	7.66
Belarusian	16.80	163.77	17.52	7.04	114.60	7.00
Bengali	5.36	58.87	6.02	4.12	54.77	4.82
Bosnian	15.62	68.29	15.97	5.57	44.96	5.73
Bulgarian	16.17	119.36	16.00	5.74	99.81	5.79
Burmese	46.24	92.22	47.42	39.87	76.31	40.82
Cantonese Chinese	42.94	142.09	37.88	19.18	92.69	17.77
Catalan	5.27	17.66	6.38	3.39	11.70	4.29
Cebuano	14.94	73.46	15.23	6.34	53.49	6.22
Croatian	22.09	81.07	21.93	11.64	53.73	11.66
Czech	14.08	85.25	14.46	5.19	55.41	5.22
Danish	25.80	85.27	25.48	10.53	53.11	9.78
Dutch	12.94	78.68	13.77	5.20	51.60	5.66
English	6.11	12.01	5.85	4.29	8.29	4.24
Estonian	15.03	87.18	16.26	4.13	53.03	7.21
Filipino	13.05	63.70	13.64	5.13	45.66	5.25
Finnish	16.65	90.32	17.75	4.58	54.73	5.00
French	5.20	13.61	5.04	3.29	9.25	3.36
Fula	51.09	106.50	50.40	20.47	77.03	18.87
Galician	15.30	62.75	15.18	6.88	29.57	6.08
Ganda	41.03	127.78	41.32	10.67	85.24	10.78
Georgian	30.98	260.91	31.80	10.44	160.02	10.76
German	11.66	81.32	11.45	4.93	52.19	4.76
Greek	20.99	145.51	22.68	8.55	123.39	9.50
Gujarati	14.01	94.25	11.62	10.55	88.46	8.97
Hausa	25.50	92.04	25.54	9.14	65.99	8.87
Hebrew	53.53	196.05	53.93	24.07	152.62	25.17
Hindi	10.74	42.76	9.11	8.46	39.51	7.17
Hungarian	21.07	106.88	21.51	6.82	66.61	6.96
Icelandic	35.32	115.87	36.01	10.52	67.09	11.18
Igbo	41.68	134.93	42.42	22.65	112.95	23.82
Indonesian	5.84	30.87	5.37	3.84	22.66	3.77
Irish	58.24	122.34	60.19	28.42	82.76	29.45
Italian	7.16	56.15	7.25	3.77	34.05	3.78
Japanese	94.35	321.61	101.43	23.82	155.45	28.23
Javanese	19.71	132.97	21.40	7.25	99.08	8.57
Kabuverdianu	20.70	79.69	19.64	8.01	52.42	7.16
Kamba	45.84	147.72	47.05	17.85	107.02	20.67
Kannada	24.16	100.43	15.65	18.69	96.71	12.84
Kazakh	17.26	155.52	17.55	5.78	117.24	5.84
Khmer	50.99	107.49	59.89	29.21	97.01	35.90

Language	WER, %			CER, %		
	T	MI	TMI	T	MI	TMI
Korean	42.39	164.91	48.85	16.70	183.41	20.96
Kyrgyz	18.16	164.98	18.33	5.25	124.54	5.08
Lao	69.97	120.78	74.54	50.98	105.17	54.48
Latvian	15.73	93.54	16.50	4.94	55.89	5.27
Lingala	14.15	116.21	15.66	6.88	91.66	8.86
Lithuanian	20.96	102.37	21.59	6.64	63.12	6.63
Luo	26.80	81.87	26.44	6.77	56.46	7.27
Luxembourgish	34.45	140.89	36.66	11.87	90.38	13.19
Macedonian	11.29	124.75	11.04	4.17	101.96	4.07
Malay	16.48	77.65	17.55	8.86	57.36	8.94
Malayalam	17.47	95.27	14.61	14.11	89.51	11.89
Maltese	16.37	104.21	16.38	6.33	75.53	5.77
Mandarin Chinese	36.12	103.75	32.73	15.63	58.45	14.24
Maori	22.50	94.78	22.79	9.90	69.21	9.65
Marathi	11.13	83.43	9.66	8.76	72.61	7.55
Mongolian	33.30	159.58	34.57	10.37	135.18	11.24
Nepali	13.32	77.91	9.77	10.28	68.06	7.48
Northern-Sotho	27.13	99.29	27.03	14.08	74.31	13.88
Norwegian	19.26	67.88	20.11	6.95	42.36	7.05
Nyanja	35.21	116.14	34.56	13.08	82.44	12.56
Occitan	31.98	89.00	33.23	13.11	53.19	13.24
Oriya	26.79	113.60	24.98	19.84	100.74	18.93
Oromo	64.94	105.36	68.18	17.51	59.86	18.12
Pashto	48.14	190.56	52.98	21.68	138.96	24.79
Persian	18.07	128.77	18.63	6.92	94.73	6.99
Polish	13.82	104.07	15.22	5.56	71.10	5.90
Portuguese	4.45	17.50	4.71	3.09	12.42	3.31
Punjabi	21.03	111.35	20.46	15.41	97.24	15.56
Romanian	14.51	88.13	15.67	6.08	54.48	6.40
Russian	19.32	123.15	19.16	6.52	96.07	6.10
Serbian	57.70	131.08	55.88	47.03	109.11	45.26
Shona	22.28	141.53	24.29	7.35	91.81	9.15
Sindhi	28.99	181.61	31.50	12.44	145.41	14.03
Slovak	12.17	85.16	12.52	4.87	53.21	4.99
Slovenian	18.38	86.15	18.37	6.91	59.06	6.61
Somali	45.93	122.01	45.82	16.41	76.23	17.14
Sorani-Kurdish	39.09	139.68	40.47	11.56	107.75	12.02
Spanish	3.65	10.52	3.66	2.53	7.74	2.62
Swahili	10.81	85.55	12.31	5.84	65.39	7.02
Swedish	21.50	78.59	21.92	7.44	49.06	7.52
Tajik	17.81	166.92	18.54	6.87	125.87	7.16
Tamil	14.14	77.87	9.80	11.92	73.81	7.78
Telugu	22.68	99.79	19.13	17.32	94.83	15.12
Thai	36.60	161.15	38.97	15.76	100.18	17.44
Turkish	18.39	129.47	19.59	5.30	97.46	5.82
Ukrainian	17.86	134.65	18.04	5.12	105.12	4.86
Umbundu	46.97	155.61	47.71	16.44	104.41	17.33
Urdu	96.48	129.51	86.06	49.48	86.81	44.44
Uzbek	26.77	99.35	26.61	8.58	65.17	8.34
Vietnamese	25.37	65.35	23.84	20.20	55.97	19.19
Welsh	28.34	75.28	29.78	10.49	44.37	10.80
Wolof	35.70	104.97	37.68	14.97	78.91	17.38
Xhosa	34.67	162.98	38.63	10.90	99.80	14.64

Language	WER, %			CER, %		
	T	MI	TMI	T	MI	TMI
Yoruba	55.10	129.76	65.13	29.54	109.40	39.49
Zulu	31.56	148.55	33.56	10.46	93.27	13.11
Median	21.75	104.14	21.93	9.00	76.27	9.05
Average	26.70	110.47	27.20	12.03	80.94	12.41

Table 9: Speech recognition results on the FLEURS evaluation dataset, broken down by language and training targets.

Language	WER, %			CER, %		
	T	MI	TMI	T	MI	TMI
Dutch	13.03	71.04	14.10	4.15	51.80	4.99
English	36.14	23.79	26.08	26.51	17.76	18.77
French	21.92	23.41	17.28	15.71	17.61	12.35
German	10.62	76.19	11.29	4.28	52.03	4.64
Italian	13.34	48.41	14.18	3.72	29.77	4.26
Polish	8.89	93.88	9.25	2.41	63.78	2.29
Portuguese	33.68	28.03	25.53	23.07	20.32	17.10
Spanish	16.47	24.67	13.57	10.64	19.15	9.10
Median	14.91	38.22	14.14	7.46	25.04	7.04
Average	19.26	48.68	16.41	11.31	34.03	9.18

Table 12: Speech recognition results on the Multilingual LibriSpeech evaluation dataset, broken down by language and training targets.

Language	WER, %			CER, %		
	T	MI	TMI	T	MI	TMI
Croatian	25.24	92.13	23.74	10.55	65.04	10.94
Czech	14.25	108.21	16.18	7.70	70.56	9.40
Dutch	24.72	98.76	21.62	16.34	70.28	13.77
English	21.00	18.31	16.14	15.53	13.79	11.62
Estonian	17.73	133.44	17.73	7.75	89.95	6.71
Finnish	21.25	115.89	20.80	10.35	71.74	9.22
French	23.12	25.54	18.91	16.60	19.93	13.79
German	25.78	101.91	24.96	17.28	68.95	16.74
Hungarian	18.86	119.21	19.02	8.70	77.14	8.27
Italian	26.17	78.50	28.29	19.64	55.93	20.43
Latvian	25.61	145.96	31.86	13.73	102.17	22.62
Polish	17.66	123.45	17.00	11.32	86.39	11.34
Romanian	18.61	99.78	20.88	8.59	62.19	9.72
Slovak	17.79	110.26	18.21	9.80	69.64	9.51
Slovenian	33.59	102.96	31.15	25.08	80.19	24.66
Spanish	19.79	22.07	16.76	14.43	16.40	11.82
Median	21.12	102.43	19.91	12.52	69.96	11.48
Average	21.95	93.52	21.45	13.34	63.77	13.16

Table 15: Speech recognition results on the VoxPopuli evaluation dataset, broken down by language and training targets.

A.2 Speech Translation

Language	BLEU			chrF		
	T	MI	TMI	T	MI	TMI
Arabic	0.93	9.33	8.69	3.88	34.00	33.56
Catalan	2.27	20.63	20.97	21.42	46.17	46.35
Estonian	0.47	0.25	0.31	15.78	13.78	14.37
German	1.23	4.85	4.85	18.04	26.86	26.67
Indonesian	1.93	21.66	22.53	17.26	49.34	49.67
Japanese	0.02	0.00	0.03	0.93	4.52	3.60
Latvian	0.00	0.08	0.14	0.00	9.60	11.11
Mandarin Chinese	0.14	0.00	0.31	4.90	16.43	17.92
Mongolian	0.00	0.05	0.08	0.00	0.77	0.80
Persian	0.12	0.00	0.04	1.08	8.72	8.20
Slovenian	0.00	0.15	0.19	1.67	10.55	11.63
Swedish	0.00	2.85	3.22	1.00	19.54	20.62
Tamil	0.00	2.68	2.66	2.51	31.71	31.33
Turkish	0.00	0.23	0.23	1.60	10.26	11.76
Welsh	0.90	0.34	0.44	15.33	11.86	12.54
Median	0.12	0.25	0.31	2.51	13.78	14.37
Average	0.53	4.21	4.31	7.03	19.61	20.01

Table 18: Speech translation results on the CoVoST-2 English $\rightarrow$ X evaluation dataset, broken down by target language and training targets.

	Language	BLEU			chrF		
		T	MI	TMI	T	MI	TMI
High	French	4.29	30.11	31.13	29.08	54.46	55.45
	German	1.99	18.92	19.27	21.70	41.70	41.84
	Spanish	4.66	33.64	34.78	28.68	58.59	59.39
	Catalan	2.17	27.66	28.12	23.41	52.06	52.43
Mid	Persian	0.06	1.46	1.34	0.38	15.65	15.76
	Italian	1.92	26.91	27.30	26.27	52.28	52.35
	Russian	0.92	24.55	23.22	3.82	49.13	47.80
	Portugese	15.68	41.74	42.58	32.76	62.82	63.33
	Mandarin Chinese	0.00	10.21	10.87	0.03	30.12	30.74
Low	Turkish	0.00	1.25	1.30	11.23	14.36	14.65
	Arabic	21.16	29.11	29.67	34.86	50.41	50.69
	Estonian	0.12	0.41	0.52	16.56	15.20	16.31
	Mongolian	0.00	0.17	0.00	0.68	13.12	13.10
	Dutch	1.03	15.35	15.29	20.37	34.78	34.40
	Swedish	0.56	8.75	10.32	13.36	24.29	25.09
	Latvian	0.00	0.83	0.79	9.30	11.77	11.08
	Slovenian	0.00	2.91	3.47	11.14	14.70	14.94
	Tamil	0.00	2.38	2.63	0.43	17.14	17.15
	Japanese	0.00	7.65	9.45	0.37	22.40	25.70
	Indonesian	8.31	32.53	34.36	20.85	49.26	51.67
	Welsh	0.57	0.49	0.87	13.46	12.41	13.66
	Median	0.57	10.21	10.87	13.46	30.12	30.74
	Average	3.02	15.10	15.58	15.18	33.17	33.69

Table 21: Speech translation results on the CoVoST-2 X $\rightarrow$ English evaluation dataset, broken down by source language and training targets.

Language	BLEU			chrF		
	T	MI	TMI	T	MI	TMI
Amharic	0.25	0.00	0.00	0.64	0.47	0.52
Arabic	6.27	13.09	13.72	27.62	42.08	42.79
Armenian	0.26	0.00	0.00	0.48	0.45	0.43
Assamese	9.46	16.45	16.73	14.95	44.10	41.78
Asturian	2.07	9.81	10.16	25.38	44.77	44.63
Azerbaijani	0.46	0.00	0.19	14.31	12.64	13.88
Belarusian	0.29	0.00	0.21	0.70	1.20	1.12
Bengali	37.46	48.13	51.21	45.43	69.01	71.23
Bosnian	1.13	0.67	0.65	19.49	17.84	18.37
Bulgarian	0.54	0.33	0.33	0.79	1.54	1.49
Burmese	0.00	0.00	0.00	0.55	0.48	0.49
Cantonese Chinese	0.43	4.45	5.22	14.51	38.15	38.02
Catalan	35.35	49.12	50.26	53.42	70.47	71.09
Cebuano	2.61	1.63	2.07	19.66	16.63	18.27
Croatian	1.01	0.41	0.47	19.30	15.23	16.57
Czech	1.26	0.60	0.67	18.27	14.39	14.96
Danish	2.03	1.58	1.82	24.57	21.05	23.28
Dutch	1.85	1.59	1.54	23.85	22.04	22.49
Estonian	1.00	0.70	0.61	19.36	17.82	18.23
Filipino	2.62	1.45	1.56	18.29	16.97	17.39
Finnish	0.51	0.16	0.27	17.34	13.67	15.35
French	48.16	47.03	46.79	64.13	68.64	68.29
Fula	1.66	0.82	1.10	19.18	16.60	17.85
Galician	3.67	7.35	7.70	28.64	42.04	41.92
Ganda	2.22	1.29	1.39	17.06	15.40	16.04
Georgian	0.45	0.17	0.19	0.81	0.68	0.75
German	1.78	5.21	4.74	21.93	29.53	29.10
Greek	0.61	0.35	0.42	1.02	6.36	4.97
Gujarati	37.03	44.08	46.30	42.58	63.97	65.91
Hausa	1.55	0.80	0.77	16.56	14.06	14.79
Hebrew	0.57	0.23	0.36	1.09	1.41	1.26
Hindi	44.51	41.86	42.28	49.76	62.36	62.57
Hungarian	0.79	0.40	0.44	16.58	14.26	15.08
Icelandic	0.67	0.39	0.46	16.05	14.39	15.17
Igbo	2.06	2.66	2.88	17.11	18.26	18.39
Indonesian	39.06	50.40	50.81	54.08	71.86	71.92
Irish	1.65	1.06	1.12	17.19	15.00	15.54
Italian	2.07	8.61	8.02	25.28	36.03	35.54
Japanese	0.00	0.00	0.00	0.98	4.60	3.71
Javanese	2.05	2.87	2.74	20.80	28.13	28.13
Kabuverdianu	1.60	1.15	1.15	21.76	21.05	20.78
Kamba	2.47	1.24	1.34	18.30	12.48	14.10
Kannada	13.18	34.07	33.41	21.44	58.91	58.71
Kazakh	0.31	0.00	0.19	0.79	0.73	0.77
Khmer	0.78	0.49	0.56	2.59	2.22	2.29
Korean	0.51	0.17	0.33	2.61	1.75	2.39
Kyrgyz	0.21	0.00	0.00	0.78	0.70	0.72
Lao	1.37	0.93	1.03	3.65	3.04	3.21
Latvian	0.51	0.29	0.30	16.61	14.39	15.32
Lingala	1.93	4.20	3.70	17.99	23.79	22.38

Language	BLEU			chrF		
	T	MI	TMI	T	MI	TMI
Lithuanian	0.73	0.46	0.50	17.79	14.21	14.94
Luo	1.85	1.16	1.04	19.11	17.04	17.75
Luxembourgish	1.37	0.76	0.85	22.00	21.29	21.39
Macedonian	0.44	0.29	0.28	0.79	0.69	0.84
Malay	2.78	8.70	8.39	21.47	33.24	32.56
Malayalam	17.57	37.10	35.49	28.47	63.61	62.40
Maltese	1.68	1.23	1.15	20.40	18.72	19.21
Mandarin Chinese	2.82	3.27	5.90	38.25	32.76	36.63
Maori	1.85	1.31	1.52	17.99	17.35	17.56
Marathi	32.62	35.88	34.27	40.74	59.79	59.00
Mongolian	0.36	0.24	0.00	0.63	0.55	0.56
Nepali	19.35	40.99	42.16	26.63	64.08	63.41
Northern-Sotho	2.55	3.66	3.11	18.83	19.75	18.79
Norwegian	1.37	1.46	1.54	23.22	22.77	23.29
Nyanja	2.85	2.07	2.02	19.25	20.81	20.07
Occitan	1.67	3.73	3.51	25.67	34.52	33.53
Oriya	0.47	0.13	0.28	0.57	0.43	0.51
Oromo	0.00	0.00	0.00	14.18	13.03	13.84
Pashto	0.00	0.00	0.00	1.14	1.49	1.54
Persian	0.00	0.00	0.27	2.65	11.47	11.90
Polish	0.90	0.47	0.57	17.06	14.28	15.81
Portuguese	54.85	50.25	51.00	69.09	70.93	71.39
Punjabi	20.37	42.40	42.00	22.38	59.49	59.60
Romanian	1.40	1.30	1.40	23.50	21.84	22.65
Russian	0.51	0.97	0.99	0.72	6.75	8.30
Serbian	0.41	0.25	0.24	0.77	0.61	0.67
Shona	2.01	1.22	1.40	18.18	17.39	17.94
Sindhi	0.40	0.24	0.19	0.71	1.62	2.87
Slovak	1.08	0.54	0.75	18.24	14.86	15.72
Slovenian	1.05	0.44	0.50	18.90	14.85	16.05
Somali	1.82	1.17	1.34	15.50	14.17	14.73
Sorani-Kurdish	0.20	0.00	0.00	0.42	0.37	0.40
Spanish	30.80	29.44	28.79	51.37	56.27	55.64
Swahili	14.55	25.42	24.09	31.47	53.62	51.67
Swedish	1.65	1.68	1.67	24.06	22.28	23.66
Tajik	0.24	0.19	0.24	0.82	0.73	0.76
Tamil	26.38	52.30	49.51	34.49	73.57	72.05
Telugu	22.59	43.72	42.08	30.87	65.49	65.33
Thai	0.25	0.17	0.20	1.22	1.04	1.08
Turkish	0.78	0.47	0.54	17.27	15.20	16.30
Ukrainian	0.40	0.19	0.20	0.68	0.75	0.94
Umbundu	0.92	0.37	0.51	15.53	10.79	12.96
Urdu	26.11	35.76	37.54	31.93	55.39	55.79
Uzbek	0.33	0.25	0.32	16.21	15.02	16.05
Vietnamese	36.77	46.80	48.49	45.92	61.95	63.22
Welsh	1.50	0.94	1.14	18.45	16.36	17.32
Wolof	1.25	1.08	1.15	18.73	17.96	18.39
Xhosa	1.62	1.13	1.12	18.85	17.90	18.39
Yoruba	1.83	3.62	3.52	14.02	18.54	18.18
Zulu	1.13	0.98	0.77	17.29	17.21	17.22
Median	1.53	1.11	1.13	18.25	17.00	17.66
Average	6.67	8.95	9.03	18.71	23.69	24.01

Table 24: Speech translation results on the FLEURS English $\rightarrow$ X evaluation dataset, broken down by target language and training targets.

Language	BLEU			chrF		
	T	MI	TMI	T	MI	TMI
Amharic	0.00	0.10	0.13	0.23	9.70	10.59
Arabic	0.00	40.03	38.68	0.44	60.02	60.08
Armenian	0.00	0.22	0.16	0.30	12.22	12.14
Assamese	0.14	32.00	34.53	0.36	53.57	54.93
Asturian	1.29	36.49	35.08	24.29	60.08	58.55
Azerbaijani	0.23	1.71	2.15	14.78	18.81	18.49
Belarusian	0.00	3.06	2.75	0.62	22.39	22.69
Bengali	0.34	36.65	37.60	0.42	59.06	59.43
Bosnian	0.67	8.08	7.14	18.97	29.14	27.16
Bulgarian	0.36	17.15	15.83	1.19	42.10	39.51
Burmese	0.00	0.32	0.13	0.14	8.90	2.68
Cantonese Chinese	0.00	20.51	24.36	1.35	40.93	46.39
Catalan	3.60	49.63	49.47	27.98	71.20	71.10
Cebuano	1.61	3.88	3.85	20.21	22.63	22.79
Croatian	0.62	8.68	8.59	17.30	29.55	28.44
Czech	0.61	9.00	10.04	17.38	30.42	29.01
Danish	1.14	15.90	15.41	23.89	40.56	39.21
Dutch	1.45	18.48	17.04	24.92	45.34	42.89
Estonian	0.31	2.10	1.72	18.91	19.14	19.46
Filipino	1.29	3.40	4.01	19.66	22.15	22.58
Finnish	0.32	2.49	2.62	18.16	18.66	19.17
French	7.94	45.35	44.67	32.60	67.77	67.68
Fula	0.72	1.05	1.48	16.62	13.47	14.55
Galician	1.22	41.94	40.65	25.49	65.93	65.26
Ganda	1.18	18.44	17.60	16.68	36.82	36.11
Georgian	0.07	0.20	0.21	0.43	13.49	13.23
German	1.20	36.00	33.68	23.82	59.34	57.43
Greek	0.17	6.37	6.21	0.99	26.82	27.17
Gujarati	0.22	36.33	36.29	0.67	58.34	58.08
Hausa	0.43	1.05	1.26	15.21	12.84	15.20
Hebrew	0.13	1.29	1.37	1.72	16.41	17.12
Hindi	0.63	39.83	41.96	0.83	61.32	62.88
Hungarian	0.37	1.99	2.34	17.05	18.48	19.19
Icelandic	0.00	2.08	2.40	15.36	15.55	16.57
Igbo	1.11	15.93	16.52	15.25	34.57	35.07
Indonesian	1.82	45.64	45.57	21.43	66.67	66.50
Irish	0.31	0.57	0.74	16.96	14.26	15.72
Italian	0.78	31.57	31.09	25.77	59.67	58.60
Japanese	0.00	14.12	15.19	0.26	34.84	36.55
Javanese	0.61	8.37	8.62	19.03	29.17	29.15
Kabuverdianu	0.91	21.50	18.24	20.98	43.23	38.59
Kamba	1.34	4.32	3.55	16.28	19.15	18.70
Kannada	0.32	32.33	32.37	0.71	53.96	54.26
Kazakh	0.00	1.51	1.46	0.59	18.03	17.72
Khmer	0.01	1.02	0.62	0.96	13.27	13.12
Korean	0.00	3.88	3.16	0.46	21.65	20.84
Kyrgyz	0.13	1.10	1.03	0.55	16.63	16.69
Lao	0.10	1.26	0.66	1.36	11.41	6.71
Latvian	0.00	2.08	2.28	16.62	19.47	19.11
Lingala	0.94	21.06	20.01	16.97	41.34	39.68

Language	BLEU			chrF		
	T	MI	TMI	T	MI	TMI
Lithuanian	0.26	2.88	2.76	17.68	21.19	20.15
Luo	0.88	1.62	1.72	18.16	15.90	17.31
Luxembourgish	0.73	4.93	6.32	22.68	27.13	28.97
Macedonian	0.18	16.05	15.28	0.85	39.64	38.03
Malay	1.17	39.34	36.23	20.05	61.61	59.43
Malayalam	0.17	33.81	33.97	0.53	55.61	55.82
Maltese	0.86	3.79	4.31	21.14	22.09	24.00
Mandarin Chinese	0.00	25.39	28.15	1.67	47.25	50.67
Maori	1.16	1.02	1.47	17.30	12.23	15.04
Marathi	0.36	34.57	34.83	0.59	56.50	56.79
Mongolian	0.07	1.14	1.09	0.37	15.69	15.58
Nepali	0.53	38.47	39.51	0.84	59.55	60.40
Northern-Sotho	1.89	21.53	19.67	19.21	40.28	37.66
Norwegian	0.89	16.80	15.61	22.98	39.70	38.24
Nyanja	1.74	20.25	18.51	19.15	39.93	37.72
Occitan	0.74	37.59	36.38	25.82	61.36	59.98
Oriya	0.40	34.31	34.39	0.55	56.03	56.29
Oromo	0.00	0.00	0.00	14.63	11.12	15.17
Pashto	0.00	1.43	1.24	0.39	12.65	14.64
Persian	0.00	8.29	9.31	0.36	29.72	31.61
Polish	0.36	8.77	8.67	17.62	32.04	31.12
Portuguese	4.19	51.43	50.88	27.19	72.55	71.97
Punjabi	0.20	35.54	35.94	0.47	56.70	57.49
Romanian	0.90	23.08	19.88	24.80	48.30	44.61
Russian	0.65	26.62	24.75	2.26	51.51	49.17
Serbian	0.31	13.38	11.59	9.99	35.41	33.44
Shona	1.24	18.03	15.79	18.82	38.37	35.68
Sindhi	0.23	1.51	1.76	0.66	14.88	16.77
Slovak	0.45	6.69	6.71	17.76	27.78	26.39
Slovenian	0.31	3.39	3.31	17.98	22.74	22.55
Somali	0.43	0.80	0.89	15.08	12.28	14.65
Sorani-Kurdish	0.00	0.80	0.83	0.26	11.47	11.27
Spanish	1.30	38.84	38.14	25.48	63.95	63.67
Swahili	1.26	39.96	40.52	16.04	60.48	60.71
Swedish	0.86	18.38	18.09	23.47	41.82	40.74
Tajik	0.00	1.15	1.05	0.47	16.00	15.90
Tamil	1.43	31.29	32.42	1.52	52.13	54.22
Telugu	1.00	29.02	32.01	1.58	51.14	53.91
Thai	0.00	1.12	0.93	0.96	16.46	16.51
Turkish	0.34	3.84	3.94	17.18	21.28	21.73
Ukrainian	0.13	15.77	15.46	1.03	40.79	38.48
Umbundu	0.21	2.18	1.46	14.67	13.28	13.82
Urdu	1.68	32.62	31.91	2.20	53.99	53.91
Uzbek	0.11	0.75	0.79	17.11	14.21	17.17
Vietnamese	0.74	20.35	24.98	11.63	42.00	45.84
Welsh	0.95	1.41	1.60	17.99	16.89	18.12
Wolof	1.10	10.34	8.68	16.40	28.06	26.26
Xhosa	0.72	21.52	19.08	18.71	41.34	38.80
Yoruba	1.03	13.93	16.23	11.84	32.25	34.95
Zulu	0.50	23.34	20.13	17.82	42.55	40.54
Median	0.43	11.86	10.81	15.70	32.15	32.52
Average	0.71	15.87	15.72	11.87	34.78	34.69

Table 27: Speech translation results on FLEURS X $\rightarrow$ English evaluation dataset, broken down by source language and training targets.

B Training Dataset

Language	Utterances			Hours		
	FLEURS	CV	Total	FLEURS	CV	Total
Abkhaz	-	16,412	16,412	-	25.00	25.00
Afrikaans	1,025	-	1,025	3.58	-	3.58
Amharic	3,155	-	3,155	11.04	-	11.04
Arabic	2,098	21,948	24,046	6.02	25.00	31.02
Armenian	3,048	617	3,665	10.33	1.07	11.40
Assamese	2,776	831	3,607	10.35	1.34	11.69
Asturian	2,507	118	2,625	7.51	0.14	7.65
Azerbaijani	2,660	39	2,699	9.28	0.05	9.32
Basaa	-	763	763	-	0.93	0.93
Bashkir	-	20,836	20,836	-	25.00	25.00
Basque	-	10,904	10,904	-	15.92	15.92
Belarusian	2,410	18,347	20,757	9.31	25.00	34.31
Bengali	2,992	15,598	18,590	10.61	25.00	35.61
Bosnian	3,086	-	3,086	9.96	-	9.96
Breton	-	2,644	2,644	-	2.12	2.12
Bulgarian	2,966	3,212	6,178	9.45	4.65	14.10
Burmese	3,041	-	3,041	12.00	-	12.00
Cantonese Chinese	1,908	2,959	4,867	6.98	3.38	10.36
Catalan	2,294	16,188	18,482	7.39	25.00	32.39
Cebuano	3,242	-	3,242	12.00	-	12.00
Chuvash	-	1,538	1,538	-	2.06	2.06
Croatian	3,449	-	3,449	11.68	-	11.68
Czech	2,806	14,815	17,621	8.41	19.57	27.97
Danish	2,461	2,734	5,195	7.48	3.29	10.77
Dhivehi	-	2,682	2,682	-	3.81	3.81
Dutch	2,915	20,257	23,172	7.65	25.00	32.65
English	2,594	15,835	18,429	7.43	25.00	32.43
Erzya	-	1,241	1,241	-	1.97	1.97
Esperanto	-	14,503	14,503	-	25.00	25.00
Estonian	2,495	3,137	5,632	7.26	5.82	13.07
Filipino	1,868	-	1,868	7.57	-	7.57
Finnish	2,699	2,121	4,820	8.77	2.73	11.50
French	3,190	17,412	20,602	10.31	25.00	35.31
Frisian	-	3,799	3,799	-	5.21	5.21
Fula	3,136	-	3,136	12.89	-	12.89
Galician	2,172	5,021	7,193	6.67	6.36	13.03
Ganda	2,302	-	2,302	10.95	-	10.95
Georgian	1,478	3,944	5,422	4.96	6.27	11.22
German	2,984	15,766	18,750	8.99	25.00	33.99
Greek	3,210	1,919	5,129	10.01	2.08	12.09
Guarani	-	1,393	1,393	-	1.53	1.53
Gujarati	3,141	-	3,141	8.95	-	8.95
Hakha Chin	-	817	817	-	0.65	0.65
Hausa	3,171	1,930	5,101	12.77	2.28	15.05
Hebrew	3,235	-	3,235	9.42	-	9.42
Hill Mari	-	7,173	7,173	-	8.40	8.40
Hindi	2,114	4,437	6,551	6.61	5.23	11.84
Hungarian	3,091	7,744	10,835	9.27	10.86	20.13

Language	Utterances			Hours		
	FLEURS	CV	Total	FLEURS	CV	Total
Icelandic	924	-	924	2.83	-	2.83
Igbo	2,632	8	2,640	11.72	0.01	11.73
Indonesian	2,568	5,040	7,608	9.01	7.78	16.79
Interlingua	-	5,030	5,030	-	5.22	5.22
Irish	2,800	537	3,337	11.71	0.58	12.29
Italian	3,026	17,032	20,058	8.98	25.00	33.98
Japanese	2,291	7,211	9,502	7.42	9.94	17.36
Javanese	3,042	-	3,042	11.12	-	11.12
Kabuverdianu	2,694	-	2,694	10.33	-	10.33
Kabyle	-	26,356	26,356	-	25.00	25.00
Kamba	3,268	-	3,268	14.06	-	14.06
Kannada	2,270	-	2,270	8.16	-	8.16
Kazakh	3,186	453	3,639	11.68	0.63	12.31
Khmer	1,661	-	1,661	6.98	-	6.98
Kinyarwanda	-	17,733	17,733	-	25.00	25.00
Korean	2,304	94	2,398	7.92	0.16	8.08
Kurmanji Kurdish	-	4,426	4,426	-	4.88	4.88
Kyrgyz	2,816	1,787	4,603	9.31	2.32	11.63
Lao	1,793	-	1,793	7.20	-	7.20
Latvian	2,105	2,734	4,839	6.49	2.38	8.87
Lingala	2,991	-	2,991	14.60	-	14.60
Lithuanian	2,929	5,196	8,125	9.68	7.12	16.80
Luganda	-	15,037	15,037	-	25.00	25.00
Luo	2,294	-	2,294	9.14	-	9.14
Luxembourgish	2,486	-	2,486	8.33	-	8.33
Macedonian	2,333	115	2,448	6.77	0.16	6.93
Malay	2,658	-	2,658	9.48	-	9.48
Malayalam	3,031	459	3,490	9.95	0.54	10.50
Maltese	2,891	1,944	4,835	9.89	2.42	12.30
Mandarin Chinese	3,239	6,655	9,894	9.68	6.00	15.68
Maori	2,940	-	2,940	15.10	-	15.10
Marathi	3,250	2,238	5,488	11.78	3.71	15.49
Meadow Mari	-	19,365	19,365	-	25.00	25.00
Moksha	-	173	173	-	0.26	0.26
Mongolian	2,971	2,149	5,120	10.50	3.07	13.57
Nepali	3,322	167	3,489	11.18	0.18	11.36
Northern-Sotho	1,570	-	1,570	8.69	-	8.69
Norwegian	3,156	314	3,470	10.82	0.38	11.20
Nyanja	2,649	-	2,649	10.40	-	10.40
Occitan	3,295	41	3,336	13.45	0.06	13.52
Odia	-	482	482	-	0.68	0.68
Oriya	1,079	-	1,079	3.42	-	3.42
Oromo	1,688	-	1,688	6.51	-	6.51
Pashto	2,494	-	2,494	8.72	-	8.72
Persian	3,077	23,479	26,556	11.86	25.00	36.86
Polish	2,839	16,916	19,755	9.17	24.80	33.97
Portuguese	2,782	19,282	22,064	10.09	21.94	32.04
Punjabi	1,917	695	2,612	6.32	1.02	7.34
Quechua Chanka	-	1	1	-	0.00	0.00
Romanian	2,887	5,113	8,000	10.10	5.65	15.75
Romansh Sursilvan	-	1,552	1,552	-	2.43	2.43
Romansh Vallader	-	671	671	-	1.18	1.18
Russian	2,559	17,444	20,003	8.03	25.00	33.04

Language	Utterances			Hours		
	FLEURS	CV	Total	FLEURS	CV	Total
Sakha	-	1,594	1,594	-	2.63	2.63
Santali (Ol Chiki)	-	279	279	-	0.37	0.37
Saraiki	-	1,256	1,256	-	1.22	1.22
Sardinian	-	458	458	-	0.53	0.53
Serbian	2,919	1,380	4,299	10.44	1.05	11.49
Shona	2,442	-	2,442	9.78	-	9.78
Sindhi	3,420	-	3,420	12.11	-	12.11
Slovak	1,955	2,967	4,922	5.86	3.11	8.97
Slovenian	2,504	1,461	3,965	7.69	1.43	9.13
Somali	3,051	-	3,051	12.31	-	12.31
Sorani-Kurdish	3,028	7,010	10,038	10.34	8.03	18.37
Sorbian, Upper	-	808	808	-	1.48	1.48
Spanish	2,795	17,155	19,950	8.80	25.00	33.80
Swahili	2,993	16,481	19,474	12.71	25.00	37.71
Swedish	2,372	7,421	9,793	8.25	8.20	16.44
Taiwanese (Minnan)	-	1,646	1,646	-	1.20	1.20
Tajik	2,289	-	2,289	8.53	-	8.53
Tamil	2,351	13,775	16,126	8.53	25.00	33.53
Tatar	-	9,565	9,565	-	10.11	10.11
Telugu	2,296	-	2,296	7.87	-	7.87
Thai	2,596	21,797	24,393	8.44	25.00	33.44
Tigre	-	10	10	-	0.01	0.01
Tigrinya	-	10	10	-	0.02	0.02
Toki Pona	-	2,450	2,450	-	2.34	2.34
Turkish	2,521	26,036	28,557	8.27	25.00	33.27
Twi	-	12	12	-	0.01	0.01
Ukrainian	2,805	15,749	18,554	9.00	18.64	27.64
Umbundu	1,149	-	1,149	6.44	-	6.44
Urdu	2,101	4,130	6,231	6.96	4.98	11.94
Uyghur	-	4,421	4,421	-	7.43	7.43
Uzbek	2,939	22,042	24,981	10.05	25.00	35.05
Vietnamese	2,988	2,475	5,463	9.03	3.12	12.15
Votic	-	96	96	-	0.11	0.11
Welsh	3,354	7,769	11,123	11.56	11.06	22.62
Wolof	2,263	-	2,263	8.58	-	8.58
Xhosa	3,430	-	3,430	13.01	-	13.01
Yoruba	2,293	39	2,332	9.60	0.07	9.67
Zulu	2,720	-	2,720	13.54	-	13.54
Median	2,748	2,963	3,470	9.27	3.76	11.36
Total	268,000	725,660	993,660	950.09	954.98	1905.07

Table 30: Training data breakdown by language and source dataset (CV stands for Common Voice).