SAMU-XLSR: Semantically-Aligned Multimodal Utterance-level Cross-Lingual Speech Representation

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Abstract—We propose the SAMU-XLSR: Semantically-Aligned Multimodal Utterance-level Cross-Lingual Speech Representation learning framework. Unlike previous works on speech representation learning, which learns multilingual contextual speech embedding at the resolution of an acoustic frame (10-20ms), this work focuses on learning multimodal (speech-text) multilingual speech embedding at the resolution of a sentence (5-10s) such that the embedding vector space is semantically aligned across different languages. We combine state-of-the-art multilingual acoustic frame-level speech representation learning model XLS-R with the Language Agnostic BERT Sentence Embedding (LaBSE) model to create an utterance-level multimodal multilingual speech encoder SAMU-XLSR. Although we train SAMU-XLSR with only multilingual transcribed speech data, cross-lingual speech-text and speech-speech associations emerge in its learned representation space. To substantiate our claims, we use SAMU-XLSR speech encoder in combination with a pre-trained LaBSE text sentence encoder for cross-lingual speech-to-text translation retrieval, and SAMU-XLSR alone for cross-lingual speech-to-speech translation retrieval. We highlight these applications by performing several cross-lingual text and speech translation retrieval tasks across several datasets.

Index Terms—Cross-lingual speech representation learning, Language-agnostic speech embedding, Zero-shot speech-to-text translation retrieval, Zero-shot speech-to-speech translation retrieval.

I. INTRODUCTION

Recently, self-supervised pre-training of large transformer encoders on massive amounts of unlabeled audio data followed by task-specific fine-tuning has emerged as the de-facto approach for achieving state-of-the-art performance on several tasks in spoken language processing. However, popular self-supervised representation learning (SSL) approaches such as Wav2vec-2.0 [1] and others [2]–[12] learn speech embedding at acoustic frame-level, i.e., for short speech segments of duration 10 to 20 milliseconds.

Unlike previous works mentioned above, this work focuses on learning semantically-aligned multimodal utterance-level cross-lingual speech representations (SAMU-XLSR). The SAMU-XLSR’s embedding vector space is multimodal since it is shared between the speech and the text modalities. It is cross-lingual since various languages share it. Furthermore, it’s semantically aligned since, in the SAMU-XLSR’s vector space, a spoken utterance is clustered together with its speech and text translations. We show a two-dimensional illustration of the desired embedding vector space in Figure 1. As an example, consider the English phrase A bird is bathing in the sink. Now, in SAMU-XLSR’s embedding space, the written form of the above phrase should be clustered together with its written and spoken forms in various languages (Japanese, French, and Arabic in the figure). And, in some other regions of the embedding space, the phrase Mr President is clustered with its written and spoken form in several languages. Unfortunately, the acoustic frame-level unimodal contextual representation learning frameworks like Wav2vec-2.0 [1] or the multilingual XLS-R [7], [9] do not learn an embedding space with the same properties. We believe that encoding semantics is one of the many missing pieces in the self-supervised speech representation learning puzzle.

On the other hand, several transformer encoders for text have been proposed in recent years that go beyond token-level contextual representations and learn cross-lingual semantically-aligned sentence embedding vector spaces across several languages [13]–[15]. These models have found use in bi-text data mining. The task is to retrieve the text translation in a target language for a given sentence query in a source language by matching the query sentence embedding with those of sentences in the target language search database [16]–[18]. Given that text encoders can successfully learn
To that end, we propose a multimodal learning framework for fine-tuning the pre-trained multilingual XLSR speech encoder via knowledge distillation from the pre-trained language-agnostic BERT sentence encoder LaBSE \cite{sun2020bilingual}. Also, we append a pooling mechanism and a non-linear projection layer after the last layer of the pre-trained XLSR encoder to transform the frame-level contextual representations into a single utterance level embedding vector. Then, we train the speech encoder using transcribed speech; given a speech utterance, the parameters of the speech encoder are tuned to accurately predict the text embedding provided by the LaBSE encoder of its corresponding transcript. Because LaBSE’s embedding vector space is semantically-aligned across various languages, the text transcript would be clustered together with its text translations. Hence, we get cross-lingual speech-to-text associations for free by simply using transcribed speech to train the speech encoder via the proposed knowledge distillation framework. For a pedagogical description, see Figure \ref{fig:framework}.

One of the use cases of the SAMU-XLSR embedding space described above is for data mining. Recent years have seen remarkable progress in Automatic Speech Recognition across several domains and languages. The next frontier in spoken language processing is automatic speech to text and speech to speech machine translation. Developing speech-based MT systems would require massive amounts of parallel translated speech data in several languages, which could be highly costly to collect. But, the multimodal cross-lingual embedding space illustrated in Fig. \ref{fig:embedding_space} could address this issue. We could build a cross-lingual speech to text and speech to speech retrieval pipeline, which could entirely or, in some cases, partially automate the process of collecting either text or speech translations corresponding to a spoken utterance. We advise the reader to look at papers in Natural Language Processing that use multilingual sentence encoders to perform cross-lingual text mining, such as \cite{sun2020bilingual, yu2019multilingual, gao2020multilingual, k18-1119}.

Cross-lingual speech-to-text mining to create parallel speech-text translation datasets is just one possible application of SAMU-XLSR. But, what motivates us to work on this problem is the potential application in zero-shot speech-to-text translation. The success of zero-shot translation depends on learning a semantically-aligned language invariant embedding vector space or an interlingua for different spoken languages, where speech utterances and their speech translations are clustered together. We show that this is an emergent property in SAMU-XLSR’s embedding vector space as a result of training SAMU-XLSR using the proposed multimodal learning framework (Section II.E). Some of the text machine translation papers that inspire us in the field of zero-shot translation are \cite{may2019zero, may2019unsupervised}.

Through this work, we make the following contributions:

- We propose a simple yet effective multimodal learning framework for semantically-aligned multimodal (joint speech-text) utterance-level speech representation (SAMU-XLSR) shared across multiple languages (Section II).
- First, we demonstrate the effectiveness of our models on several zero-shot cross-lingual speech-to-text and speech-to-speech translation retrieval tasks (Section IV).
- Second, we show that SAMU-XLSR could be used for sequence-to-sequence modeling tasks such as phoneme recognition and Automatic Speech Recognition (ASR) (Section V).
- Finally, we conduct analysis to understand better the various design decisions that went into constructing SAMU-XLSR (Section VI).

A work that is similar to ours is presented in \cite{salimans2018multimodal}. Unlike the previous work, we evaluate our model on multiple datasets across many languages with a special emphasis on low-resource languages.

Furthermore, unlike the multimodal speech encoder presented in \cite{salimans2018multimodal}, we show that SAMU-XLSR performs at par or better than XLSR-R on the downstream ASR task across different languages. We recommend the reader to read \cite{salimans2018multimodal} along with this paper to get a holistic understanding of this field.
II. METHODOLOGY

A. Problem Formulation

We train SAMU-XLSR using a multilingual set $D$ of paired examples $(x^{(l)}, y^{(l)})$, where $x^{(l)}$ is the speech waveform, and $y^{(l)}$ is its text transcript in language $l$. Given a training example, $(x^{(l)}, y^{(l)})$, we transform the sequence of discrete tokens $y^{(l)}$ to a dense embedding vector $z_T \in \mathbb{R}^d$ using a text encoder $g_o$, and the series of speech samples $x^{(l)}$ into a dense embedding vector $z_S \in \mathbb{R}^d$ using a speech encoder $f_\theta$. Then, we update the parameters of the speech encoder $f_\theta$ so that the distance between the speech embedding $z_S$ and the text embedding $z_T$ is minimized. The training loss for a single example is given by the following equation:

$$J(\theta, \phi) = \text{distance}(z_S, z_T)$$

We use the pre-trained Language-agnostic BERT Sentence Encoder (LaBSE) as the text encoder $g_o$ and SAMU-XLSR as the speech encoder $f_\theta$. The parameters $\theta$ of the speech encoder are updated during training, while the parameters $\phi$ of the text encoder remain fixed. An illustration of the multimodal learning framework is shown in Figure 3.

B. SAMU-XLSR Speech Encoder, $f_\theta$

SAMU-XLSR consists of a pre-trained frame-level XLS-R speech encoder [9] followed by a mechanism for pooling the frame-level contextual representations into a single embedding vector.

The XLS-R speech encoder consists of a deep convolutional neural network that maps 1D time series representing the sample values of the speech waveform into a 2D sequence of feature vectors $\mathcal{H} \in \mathbb{R}^{T \times 512}$. Each feature vector $h_t \in \mathcal{H}$ represents 20ms of the speech signal. The time resolution of $h_t$ is similar to that of an acoustic frame. Therefore, we refer to $\mathcal{H}$ as frame-level representations. Next, the feature sequence $\mathcal{H}$ is transformed into contextual representations $\mathcal{C} \in \mathbb{R}^{T \times 1024}$ by a deep transformer encoder [25]. The transformer encoder consists of 24 Multi-Headed Self-Attention (MHSA) transformer blocks. The attention vector size is 1024, and there are 16 attention heads in each block. We use the publicly available pre-trained XLS-R checkpoint [1] which was trained on 400k hours of unlabeled speech data in 128 languages.

C. LaBSE Text Encoder, $g_o$

Next, we use Self-Attention pooling [26] strategy to get a single utterance-level embedding vector $e \in \mathbb{R}^{1024}$. In this pooling strategy, we take a weighted combination $\sum_{t=1}^{T} v_t c_t$ of contextual vectors $c_t \in \mathcal{C}$, where $v = (v_1, \ldots, v_T)$ is the attention vector, given by the following equation:

$$v = \text{softmax}(C w)$$

where, $w \in \mathbb{R}^{1024}$, which gives $v \in \mathbb{R}^T$, such that $\sum_{t} v_t = 1$. The weight vector $w$ is learned during training.

Finally, we take a non-linear projection of the embedding vector $e$ to get the speech embedding $z_S$. Overall, the SAMU-XLSR speech encoder consists of approximately 300 million trainable parameters (weights and biases).

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The key ingredient in our proposed multimodal learning framework is the LaBSE text encoder $g_o$, which allows us to learn a joint speech-text embedding space that is semantically aligned and shared across different languages. LaBSE is a language-agnostic text encoder for text with an architecture similar to the BERT transformer encoder [27]. However, unlike BERT, LaBSE is a sentence embedding model, which is trained using both masked [27] and translation language modeling [28] objective functions. LaBSE consists of a token level transformer encoder with 12 MHSA layers, followed by a pooling mechanism to construct a dense sentence-level embedding vector.

The LaBSE’s transformer encoder takes as input text that is tokenized into “wordpieces” [29, 30] and outputs a sequence of contextual token embedding $W \in \mathbb{R}^{L \times 768}$. A non-linear projection of the CLS token embedding is used as the sentence embedding $z_T \in \mathbb{R}^{768}$, which is used as the training target for SAMU-XLSR training. We use the pre-trained LaBSE model checkpoint[3] hosted on the Huggingface [31] models[3] platform. We refer to the use of CLS token embedding for sentence representation as CLS pooling to conform with the terminology used in the Huggingface hosted LaBSE encoder.

LaBSE embeds sentences from 109 languages into a shared semantically-aligned embedding vector space. Unlike LaBSE,
other multilingual text encoders such as XLM-R [32] do not learn an aligned sentence embedding space. Therefore, to achieve our goal of embedding speech in a semantically aligned vector space, we use LaBSE as the teacher for training SAMU-XLSR.

D. SAMU-XLSR Training Details

1) Training Data, D: We train SAMU-XLSR on transcribed speech in 25 languages derived from the publicly available CommonVoice-v7 (CoVo) dataset. The 25 languages are namely, English (EN), French (FR), German (DE), Spanish (ES), Catalan (CA), Italian (IT), Welsh (CY), Russian (RU), Chinese (China) (ZH_CN), Chinese (Taiwan) (ZH_TW), Chinese (Hong Kong) (ZH_HK), Portuguese (PT), Polish (PL), Persian (FA), Estonian (ET), Mongolian (MN), Dutch (NL), Turkish (TR), Arabic (AR), Swedish (SV_SE), Latvian (LV), Slovenian (SL), Tamil (TA), Japanese (JA) and Indonesian (ID). Table I shows the per-language transcribed data available in CoVo. The total training data size is 6.8K hours.

Clearly, the data is highly imbalanced. The top 5 high-resource languages make up 72% of the training data, while the bottom 14 low-resource languages make up just 10% of the training data. The above mentioned problem could lead to SAMU-XLSR severely under-fitting on low-resource languages, because SAMU-XLSR, during its training lifetime, might encounter transcribed speech data from low-resource languages in its train mini-batch only a few times. Following [33], [34] we re-balance the training set D by up/down-sampling data from each language l with a ratio \( \lambda_l \):

\[
\lambda_l = \frac{1}{\sum_l p_l} \frac{p_l^{\alpha}}{p_l} \quad \text{with} \quad p_l = \frac{n_l}{n} \frac{L}{\sum_l n_l}
\]

where, \( \alpha \) is the smoothing parameter, \( n_l \) is the number of utterances for language \( l \) in the training set. Figure 4 shows how varying \( \alpha \) between 1.0 and 0.05 re-balances the training set. As we make \( \alpha \) smaller, observe that the share of low-resource languages in the training set becomes approximately the same as that of high-resource languages. It is important to note that when we up-sample data from low-resource languages, we simply repeat the utterances from those languages, and, down-sampling data from high-resource languages involve picking random utterances according to the ratio \( \lambda_l \). Hence, training with a re-balanced training set that is created using a small value of \( \alpha \) could result in a drop in performance on high-resource languages as compared to the model that is trained with the original unbalanced training set. We study the effect that the smoothing parameter \( \alpha \) has on the model’s downstream task performance in Section VI-B.

2) Optimization Settings: We train SAMU-XLSR for 400K training iterations, on 32 V100-32gb GPUS, with a per-GPU mini-batch size of approximately 2 hours of transcribed speech. Following [7], we use the Adam optimizer for updating the model parameters with a three phase learning rate scheduler; Warm-up the learning rate to a maximum value of 1e-4 for the first 10% of the training iterations, then the learning rate remains constant for the next 40% of the training iterations, and finally decays linearly for the rest of the iterations. For the first 10K training iterations, only the projection layer of SAMU-XLSR encoder is trained while the pre-trained frame-level XLS-R speech encoder remains fixed. We do not update the weights of the XLS-R’s convolutional feature extractor throughout the training process. Also, we use a modified version of SpecAugment [35] on the feature sequence \( H \) (Section II-B) to mask the input to the XLS-R’s transformer encoder, which leads to better performance on downstream tasks. The above mentioned training settings are the standard for fine-tuning the pre-trained XLS-R or wav2vec-2.0 speech encoders on downstream ASR tasks [1], [7].

We use the cosine distance between the speech and the text embedding as the training loss (Equation 1). We do not update the weights of the LaBSE text encoder throughout training. The reason for this design choice is straightforward. LaBSE’s sentence embedding space is already semantically aligned across 109 languages. By fine-tuning LaBSE along with SAMU-XLSR on transcribed speech data \( D \), we run the risk of destroying this alignment. In fact, LaBSE will have no incentive to maintain an aligned embedding space. Instead, our learning framework simply attempts to embed speech utterances in the LaBSE’s sentence embedding space to make it multimodal. By simply forcing the speech embeddings outputted by SAMU-XLSR to be closer to LaBSE text embedding, we get the cross-lingual semantic alignments between speech utterances in different languages and text in 109 languages.
LaBSE is trained on the transcribed speech from 25 languages and spoken languages and 109 written languages since which refers to the fact that the training targets for rate scheduler mentioned in Section II-D. Training teacher is (LR scheduler) has a value of 10-40-50 refers to the learning rate of training iterations up to which we only train the projection layer of the transformer encoder. We keep its weights fixed to the pre-trained value. Freeze Fine-tune updates refer to the number of training iterations of the transformer encoder along with its semantically aligned embedding space. Hence, if successful at achieving our desired goal, the SAMU-XLSR-LabSE combination should give good performance on cross-lingual speech-to-text translation retrieval tasks. Also, SAMU-XLSR alone should be able to perform well on cross-lingual speech-to-speech translation retrieval tasks.

Sequence Generation: Furthermore, we perform sequence-to-sequence modeling tasks, namely the Connectionist Temporal Classification (CTC) [36] based Phoneme Recognition (generating the underlying phoneme sequence corresponding to an input speech sequence) and Automatic Speech Recognition (ASR) (generating the underlying word sequence corresponding to an input speech sequence) using SAMU-XLSR.

B. Translation Retrieval Tasks

Here, we summarize the retrieval process, evaluation metrics and the speech-to-text and speech-to-speech translation retrieval tasks we use to evaluate the SAMU-XLSR’s multimodal semantic embedding space.

Retrieval process and Evaluation Metrics: We construct two databases (DB), query and search, to perform translation retrieval. The query DB consists of speech utterances in a language X, and in the case of text translation retrieval tasks, the search DB consists of text sentences in a language Y. The task is to retrieve the correct text translation from the search DB corresponding to each speech query in the query DB. To that end, we transform the speech utterances in the query DB through SAMU-XLSR to query speech embedding matrix \( Q \in \mathbb{R}^{N \times 768} \), where \( N \) is the number of speech queries in the query DB. Also, we transform the sentences in the search DB through the LaBSE encoder to search text embedding matrix \( S \in \mathbb{R}^{M \times 768} \), where \( M \) is the number of sentences in the search DB. Given that the vectors are normalized, we could retrieve the text translations for the speech queries as follows:

\[
A = QST
\]

\[
r = \text{argmax}_{j} \langle A_{i,j} \rangle
\]

where, \( A \in \mathbb{R}^{N \times M} \) is the cosine similarity matrix, whose \((i,j)\)th element \( A_{i,j} \) is the cosine similarity between the speech query embedding \( q_i \) and the sentence embedding \( s_j \in S \), and \( r \in \mathbb{R}^{N} \) is the index vector, such that its each component \( r_i \in r \) is the index of the closest match in the text translation search DB. Also, given the index vector \( u \), where each component \( u_j \in u \) is the index of the ground-truth text translation in the search DB, we compute the model’s retrieval accuracy as follows:

\[
ACC = 100 \times \frac{\sum_{i=1}^{N} 1\{r_i = u_i\}}{N}
\]

where, the function \( 1\{r_i = u_i\} \) returns one when \( r_i = u_i \), the predicted translation index matches the ground-truth translation index, otherwise it outputs zero. Hence, the numerator is the number of queries for which the model retrieved the

### TABLE II: SAMU-XLSR model card

| Parameters                          | Value                          |
|------------------------------------|--------------------------------|
| Training Data                      | CoVo₂₅                         |
| Smoothing factor (α) for re-balancing | 0.05                           |
| Training updates                   | 200K                           |
| Freeze fine-tune updates           | 10k                            |
| CNN Feature Extractor              | Frozen                         |
| Optimizer                          | Adam                           |
| max learning rate (LR)             | 1e-4                           |
| LR scheduler                       | 10-40-50                       |
| batch size / GPU                   | 2Hrs                           |
| Data Augmentation                  | SpecAugment on H               |
| Training Obj.                      | Cosine Distance                |
| Training Teacher                   | LaBSE                          |
| Pooling Fn.                        | Self-Attention                 |
| Model init.                        | XLSR Pre-Trained checkpoint    |
| Num. GPUs                          | 32                             |
| Supported Spoken Langs             | 22                             |
| Supported text Langs               | 109                            |
correct translations from the search DB and the denominator is the total number of queries in the query DB.

We refer to the retrieval accuracy in Equation 4 as Recall@1 or R@1, which contrasts with another similar metric, R@5, where the indicator function returns one if any of the top five retrieved search DB indices matches with the correct index. We report R@5 for speech retrieval evaluation tasks. The recall is commonly used to evaluate audio-visual multimodal representation learning models \[^{17-32}\].

In addition to R@1, for text translation retrieval tasks, we also report the Word Error Rate (WER) \[^{40}\] between the retrieved and the ground-truth text translation. The reason is that it is hard to interpret retrieval accuracies. For example, WER for model A with a retrieval accuracy of 70% might not be much worse than the WER for model B with a retrieval accuracy of 80% because model A might be worse than model B in retrieving the exact translations. However, it might still recover translations with a significant string overlap with the actual translation. The retrieval accuracy will fail to capture this.

**X→EN Text Translation Retrieval:** We use the CoVoST-2 \[^{41}\] X-EN speech-translation dataset for this evaluation task. The speech query DB is in a language X∈\{RU, IT, FR, ES, TR, DE, ET, CY, NL, ID, CA, FA, AR, ZH, SV, MN, SL, JA, TA, LV\} and the search DB consists of English sentences. To construct the speech query DB for each language X, we use the combined testing and development sets (henceforth, eval set) from CoVoST-2. To construct the search DB, we combine the English text translation from all the 22 X→EN eval sets in CoVoST-2, which we refer to as S\(_x\). In addition, we create a search DB S\(_y\) that contains approximately 1.4M English sentences from the CoVoVo English transcribed speech data. We use the combined search DB S = S\(_x\)∪S\(_y\) for all the 22 X→EN text translation retrieval tasks. We add S\(_y\) to S\(_x\) to make the retrieval task harder than if we just search over S\(_x\).

**EN→Y Text Translation Retrieval:** We use the publicly available CoVoST-2 corpora \[^{41}\] for this evaluation task, which consists of English speech queries paired with their text translations. The speech query DB is in English and search DB is in a language Y∈\{DE, CA, ZH, FA, ET, MN, TR, AR, SV, LV, SL, TA, JA, ID, CY\}. For each EN→Y retrieval task, the query DB consists of speech utterances in the combined development and testing sets. The search DB consists of the true text translations in language Y corresponding to the speech queries. In addition, we add the Y language text translations available in the EN→Y CoVoST-2 training set to make the retrieval task harder. Similarly, we create a search DB for each of the 15 languages Y for the EN→Y text translation retrieval task.

For this evaluation scenario, we also perform text translation retrieval on the MUST-C \[^{42}\] EN→Y corpora. In MUST-C, we have English speech queries paired with their true text translation in a language Y∈\{ES, PT, FR, DE, Romanian (RO), NL, IT, Czech (CS), Vietnamese (VI), FA, TR, AR, RU, ZH\}. We create an eval set, a union of MUST-C dev, tst-COMMON and tst-HE data splits. The speech query DB consists of speech utterances in the eval set. The search DB for a language Y consists of sentences from the EN→Y MUST-C eval set combined with sentences from the EN→Y training set.

**X→Y Text Translation Retrieval:** We use the MTEDx \[^{43}\] speech-translation corpora, which consists of speech queries in language X paired with their ground-truth text translation. For this evaluation task, we have the translation pairs X→Y∈\{IT, ES, IT-EN, ES-FR, ES-IT, FR-PT, ES-PT, FR-EN, PT-ES, ES-EN, PT-EN, RU-EN\}. For a translation pair X→Y, we have speech queries in language X and the text search DB in language Y. For a retrieval X→Y, the query DB consists of speech utterances in the MTEDx X→Y eval set (dev+test), and the text search DB in language Y consists of the ground-truth text translations from the X→Y eval set and the X→Y training set. The reader might observe that the search DB is more significant than the query DB for all the text translation retrieval tasks and consists of the actual text translations and random sentences to make the retrieval task harder.

We consider MTEDx X→Y translation retrieval evaluation tasks as out-of-domain because we train SAMU-XLSR on transcribed read speech from the CoVo dataset. At the same time, MTEDx consists of oratory speech collected from TED talks.

**X→EN Speech Translation Retrieval:** Finally, we evaluate our model on speech translation retrieval tasks. We get the parallel X→EN speech-speech translation data from the publicly available VoxPopuli corpora \[^{44}\]. For this task, speech queries are in a language X∈\{ES, FR, PL, NL, DE, RO, Croatian (HR), CS\} and the search DB consists of English speech translations corresponding to the queries. Unlike the text translation retrieval tasks, the search DB is the same size as the query DB and consists of only actual speech translations corresponding to the queries.

**C. Sequence-to-Sequence Modeling Tasks**

**Phoneme Recognition:** Phoneme recognition refers to the task of automatically decoding the underlying phoneme sequence \(y\) corresponding to a speech sequence \(x\). We tune the pre-trained SAMU-XLSR using paired \((x, y)\) examples drawn from the CoVo dataset. Following \[^{7}, [45]\], we build a phoneme recognizer for nine different languages, namely ES, FR, IT, Kabyle (KY), NL, RU, SV, TR, and Tatar (TT). We use one hour of transcribed data for training, 20mins for validation (model selection), and one hour for testing. The data splits are the same ones proposed in \[^{45}\] and used in \[^{7}\] for evaluating XLS-R on the phoneme recognition task. Our Fine-tuning setup matches the XLS-R Fine-tuning setup used in \[^{7}\].

**Automatic Speech Recognition:** ASR refers to the task of automatically decoding the underlying word sequence corresponding to a speech utterance. The Fine-tuning setup is the same as that for Phoneme Recognition. However, instead of phoneme sequence as the target for training, we have character sequences. To generate the word sequence from decoded character sequence, we use CTC beam search with a character-level N-gram language model.

We use the EspNet speech recognition toolkit \[^{46}, [47]\] for Fine-tuning the pre-trained SAMU-XLSR and XLS-R models for sequence-to-sequence modeling tasks.
TABLE III: We perform zero-shot $X \rightarrow EN$ text translation retrieval on In-domain CoVoST-2 dataset. The search database for all $X \rightarrow EN$ retrieval tasks consists of 1.6 million English sentences. We give the number of speech utterances in the query database for each retrieval task below. The task is to retrieve the correct text translation for the speech queries in language $X$. We report the Retrieval accuracy (R@1) and the Word Error Rate between the ground-truth and retrieved text translations. We compare our retrieval pipeline SAMU-XLSR-LaBSE, with ASR-LaBSE and the Topline retrieval model. The SAMU-XLSR-LaBSE retrieval pipeline transforms speech queries to embedding vectors using our SAMU-XLSR speech encoder. Then, we match the query embedding vectors with the LaBSE text embeddings of the sentences in the search DB to retrieve the translation. The ASR-LaBSE retrieval pipeline first uses an ASR for language $X$ to transcribe speech queries and then uses LaBSE to perform text-to-text translation retrieval. The Topline model uses the ground-truth text transcripts for the speech queries and performs text-to-text translation retrieval tasks using LaBSE.

| $X$ | RU | IT | FR | ES | TR | DE | ET | CY | NL | ID | CA | FA | AR | ZH | SV | MN | SL | JA | TA | Avg. |
|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| Query DB | 12K | 18K | 30K | 26K | 3.3K | 27K | 3.1K | 1.4K | 3.4K | 1.6K | 25K | 6.8K | 3.5K | 9.7K | 2.9K | 3.5K | 870 | 1.3K | 1.2K | - |
| **SAMU-XLSR-LaBSE Speech($X$)$\rightarrow$Text(EN) Retrieval** | | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 93.5 | 92.9 | 92.5 | 92.9 | 93.4 | 90.9 | 91.5 | 84.6 | 89.7 | 84.4 | 82.1 | 83.6 | 73.7 | 78.6 | 72.4 | 68.2 | 52.1 | 48.9 | 42.4 | 76.8 |
| WER[%] | 2.6 | 3.0 | 3.5 | 3.6 | 3.7 | 4.7 | 4.8 | 5.1 | 4.9 | 9.5 | 11.0 | 10.2 | 13.8 | 15.2 | 19.0 | 26.0 | 32.4 | 44.7 | 57.7 | 17.2 |
| **ASR-LaBSE Speech(EN)$\rightarrow$Text($X$) Retrieval** | | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 92.7 | 90.1 | 90.4 | 91.3 | 90.9 | 88.2 | 94.8 | 81.7 | 89.3 | 65.6 | 80.6 | 76.1 | 54.0 | 55.4 | 63.9 | 53.9 | 64.0 | 23.6 | 26.5 | 71.7 |
| WER[%] | 3.0 | 4.8 | 5.0 | 4.6 | 5.8 | 6.5 | 2.1 | 7.6 | 5.3 | 23.4 | 11.5 | 16.8 | 34.3 | 36.0 | 17.2 | 41.3 | 16.7 | 72.9 | 75.0 | 20.9 |
| **Topline LaBSE Text(EN)$\rightarrow$Text($X$) Retrieval** | | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 94.4 | 94.0 | 94.8 | 94.3 | 94.2 | 93.2 | 97.5 | 86.2 | 90.8 | 91.3 | 83.8 | 85.1 | 74.5 | 81.4 | 87.0 | 81.3 | 70.9 | 83.1 | 49.2 | 85.2 |
| WER[%] | 2.0 | 2.5 | 1.9 | 2.6 | 2.9 | 2.8 | 0.4 | 4.1 | 4.2 | 2.5 | 9.9 | 8.7 | 13.5 | 12.8 | 4.7 | 14.4 | 10.2 | 9.4 | 51.7 | 8.7 |

TABLE IV: We perform zero-shot $EN \rightarrow Y$ text translation retrieval on In-domain CoVoST-2 dataset. The search database for each $EN \rightarrow Y$ retrieval task consists of 320K sentences in language $Y$, and the query database consists of 31K English speech utterances. The task is to retrieve the correct text translation for the English speech queries. We report the Retrieval accuracy (R@1) and the Word Error Rate between the ground-truth and retrieved text translations. We compare our retrieval pipeline SAMU-XLSR-LaBSE, with ASR-LaBSE and the Topline retrieval model. The SAMU-XLSR-LaBSE retrieval pipeline transforms speech queries to embedding vectors using our SAMU-XLSR speech encoder. Then, we match the query embedding vectors with the LaBSE text embeddings of the sentences in the search DB to retrieve the translation. The ASR-LaBSE retrieval pipeline first uses an ASR for language $X$ to transcribe speech queries and then uses LaBSE to perform text-to-text translation retrieval. The Topline model uses the ground-truth text transcripts for the speech queries and performs text-to-text translation retrieval tasks using LaBSE.

| $Y$ | ZH | SL | TR | LV | CY | ID | DE | CA | AR | SV | ET | TA | FA | JA | MN | Avg. |
|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| **SAMU-XLSR-LaBSE Speech($EN$)$\rightarrow$Text($Y$) Retrieval** | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 87.2 | 90.5 | 89.4 | 89.9 | 90.8 | 91.0 | 91.5 | 91.4 | 88.3 | 91.7 | 90.4 | 90.5 | 89.0 | 88.1 | 86.2 | 89.7 |
| WER[%] | 11.2 | 6.3 | 7.4 | 7.2 | 6.2 | 5.9 | 5.8 | 5.5 | 8.5 | 5.5 | 6.6 | 7.3 | 8.4 | 11.9 | 10.9 | 7.6 |
| **ASR-LaBSE Speech(EN)$\rightarrow$Text($Y$) Retrieval** | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 87.9 | 90.6 | 89.8 | 90.2 | 90.7 | 91.2 | 91.4 | 91.6 | 89.0 | 91.7 | 90.5 | 91.2 | 89.6 | 88.4 | 87.3 | 90.1 |
| WER[%] | 10.7 | 6.2 | 7.1 | 6.9 | 6.2 | 5.7 | 5.8 | 5.3 | 7.8 | 5.4 | 6.5 | 6.5 | 7.7 | 11.5 | 9.8 | 7.3 |
| **Topline LaBSE Text(EN)$\rightarrow$Text($Y$) Retrieval** | | | | | | | | | | | | | | | | | | | | |
| R@1[%] | 95.8 | 97.1 | 96.2 | 96.6 | 96.7 | 96.8 | 97.1 | 96.9 | 95.7 | 97.3 | 96.7 | 97.0 | 95.4 | 95.5 | 94.5 | 96.4 |
| WER[%] | 2.7 | 1.3 | 1.9 | 1.8 | 1.7 | 1.5 | 1.5 | 1.3 | 2.3 | 1.3 | 1.6 | 1.8 | 2.8 | 4.2 | 3.5 | 2.1 |
We believe that evaluating SAMU-XLSR on sequence generation tasks mentioned above is interesting because it would be good to know whether SAMU-XLSR, a speech encoder that we train using an utterance-level objective function (see Fig. 2), could also be used for tasks other than the utterance-level text and speech translation retrieval.

Another thing to note is that for sequence generation tasks, we dissect SAMU-XLSR before the attention pooling layer (see Fig. 3 to look at SAMU-XLSR’s architecture) and use the computational modules before the pooling layer because for sequence generation tasks, we want a representation at the acoustic frame-level instead of the utterance level embedding outputted by SAMU-XLSR.

IV. DOWNSTREAM TASKS: ZERO-SHOT TRANSLATION RETRIEVAL

A. Additional Retrieval Models for comparison with SAMU-XLSR

ASR-LaBSE retrieval pipeline: We also perform translation retrieval tasks using an ASR-LaBSE combination, where we convert the speech queries into text transcripts in the same language as the queries using an ASR model. Then, we perform ASR transcript to text translation retrieval using LaBSE. We build 25 language-specific ASR models to cover all the spoken languages in our text translation retrieval tasks. To construct the ASR models, we fine-tune the pre-trained XLS-R checkpoint on the downstream ASR task using the transcribed speech data in the target language available from the CoVo dataset (see Table I for the amount of per language transcribed speech data). We use the standard Connectionist temporal Classification [48] based optimization setup for fine-tuning the XLS-R model for the ASR task detailed in [7]. We use a beam size of 20 and a tri-gram character-level language model for decoding speech queries to text. We use the ESPnet speech recognition toolkit [46], [49] for constructing the ASR models and decoding.

Topline: As a topline, we use the ground-truth transcripts corresponding to speech queries and perform ground-truth transcription to text translation retrieval using LaBSE. Our SAMU-XLSR-LaBSE retrieval framework cannot perform better than the topline. Because the best we can do with our proposed multimodal learning framework is to match the LaBSE embedding vectors perfectly.

B. Results on X→EN text translation retrieval tasks

Table III shows the results on X→EN translation retrieval tasks using SAMU-XLSR-LaBSE, ASR-LaBSE and Topline LaBSE retrieval pipelines. We report the retrieval accuracy (R@1) and WERs for different spoken languages X. The task is to retrieve the English text translation for a given speech query (X). The table shows the number of speech queries per spoken language X. The number of speech queries in the evaluation set varies across languages, with more queries for high-resource languages and less for low-resource languages. It is a function of the evaluation set available for different languages in the CoVoST-2 eval set. The search for the English translation is over a text database that consists of 1.6M English sentences. The text DB contains the actual English translations and the text transcriptions from the CommonVoice English dataset. We added the extra English sentences to make the translation retrieval task harder than searching over a small database of only true English translations. See Section II-B for more details on X→EN retrieval tasks.

Interestingly, ASR-LaBSE is significantly worse than SAMU-XLSR-LaBSE retrieval model on retrieval tasks where the speech queries are in non-European languages. For example, on ID→EN, FA→EN, AR→EN, ZH→EN, MN→EN, JA→EN and TA→EN retrieval tasks, SAMU-XLSR-LaBSE achieves a WER of 9.5%, 10.2%, 13.8%, 15.2%, 26.0%, 44.7% and 57.7% respectively compared to 23.4%, 16.8%, 34.3%, 36.0%, 41.3%, 72.9%, 75.0% respectively by ASR-LaBSE. On average SAMU-XLSR-LaBSE achieves an average WER of 22.6% compared to 33.7% with ASR-LaBSE on non-European spoken languages (X)→EN translation retrieval tasks. On retrieval tasks, where speech queries are in European languages, SAMU-XLSR-LaBSE performs at par with ASR-LaBSE retrieval pipeline. For example, on RU→EN, IT→EN, FR→EN, ES→EN, DE→EN, ET→EN, CY→EN, NL→EN, CA→EN, SV→EN, SL→EN and LV→EN translation retrieval tasks, SAMU-XLSR-LaBSE achieves an average WER of 13.6% compared to 10.2% with ASR-LaBSE retrieval pipeline. These results are not surprising given the fact that for European languages (high and low-resource), the ASR system is generally better than for the non-European languages. This is due to the fact that the XLSR speech encoder, which we fine-tune on downstream ASR task using language-specific transcribed data, is pre-trained on majority European language speech data.

Finally, the topline model uses the ground-truth text transcriptions corresponding to the speech queries (X) to retrieve the English text translations. This model uses only LaBSE to perform the text(X)→text(EN) retrieval task. The topline achieves an average WER of 14.5% on non-European languages X and 4.9% on European languages, which implies that we could not quite reach the topline performance with our SAMU-XLSR-LaBSE retrieval pipeline and there is room for improvement. We believe that increasing the scale of the training data and using contrastive loss for training SAMU-XLSR could result in improved performance. However, a training setup with a contrastive loss would require considerable engineering effort because of the engineering complexity involved in mining negative samples across GPUs as done for training LaBSE [15]. Drawing negative samples from the same GPU device would not be sufficient because of the small per GPU batch size owing to the large speech encoder size and long speech waveforms. Hence, we leave the exploration of contrastive learning for future work.

C. Results on EN→Y text translation retrieval tasks

Table IV and V shows the results on EN→Y speech→text retrieval tasks using SAMU-XLSR-LaBSE, ASR-LaBSE and Topline LaBSE retrieval pipelines. We retrieve the text translation in a language Y for a given speech query in English for the EN→Y retrieval tasks. In the results table, first, we show
TABLE V: We perform zero-shot EN→Y text translation retrieval on Out-of-domain MUST-C dataset. The search database for each EN→Y retrieval task consists of approximately 200K sentences in language Y, and the query database consists of about 4K English speech utterances. The task is to retrieve the correct text translation for the English speech queries. We report the Retrieval accuracy (R@1) and the Word Error Rate between the ground-truth and retrieved text translations. We compare our retrieval pipeline SAMU-XLSR-LaBSE, with ASR-LaBSE and the Topline retrieval model. The SAMU-XLSR-LaBSE retrieval pipeline transforms speech queries to embedding vectors using our SAMU-XLSR speech encoder. Then, we match the query embedding vectors with the LaBSE text embeddings of the sentences in the search DB to retrieve the translation. The ASR-LaBSE retrieval pipeline first uses an English language ASR to transcribe speech queries and then uses LaBSE to perform text-to-text translation retrieval. The Topline model uses the ground-truth text transcripts for the speech queries and performs text-to-text translation retrieval tasks using LaBSE.

| Y     | DE | PT | FR | DE | RO | NL | IT | CS | VI | FA | TR | AR | RU | ZH | Avg. |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|------|
| SAMU-XLSR-LaBSE Speech(EN)→Text(Y) Retrieval |
| R@1 [%] | 87.4 | 88.2 | 87.1 | 86.8 | 87.3 | 86.3 | 85.6 | 85.1 | 82.4 | 82.5 | 84.1 | 83.2 | 81.3 | 77.8 | 84.6 |
| WER [%] | 7.0 | 6.8 | 7.3 | 7.4 | 7.5 | 7.8 | 8.5 | 10.1 | 10.2 | 12.3 | 11.7 | 13.8 | 13.4 | 21.0 | 10.3 |
| ASR-LaBSE Speech(EN)→Text(Y) Retrieval |
| R@1 [%] | 88.8 | 88.6 | 88.4 | 87.9 | 87.5 | 87.0 | 86.6 | 86.4 | 83.0 | 83.8 | 84.5 | 83.8 | 82.7 | 79.0 | 85.6 |
| WER [%] | 6.2 | 6.5 | 6.4 | 6.7 | 7.4 | 7.2 | 7.7 | 8.9 | 9.8 | 10.3 | 11.1 | 13.2 | 12.3 | 20.6 | 9.6 |
| Topline LaBSE Text(EN)→Text(Y) Retrieval |
| R@1 [%] | 96.1 | 96.0 | 96.1 | 95.9 | 95.7 | 95.3 | 95.1 | 95.1 | 92.9 | 91.4 | 92.7 | 92.4 | 92.3 | 87.6 | 93.9 |
| WER [%] | 1.8 | 1.9 | 1.8 | 1.8 | 2.2 | 2.1 | 2.5 | 3.2 | 3.1 | 6.1 | 5.2 | 6.5 | 5.0 | 10.0 | 3.8 |

TABLE VI: We present results on Out-of-domain MTEDx X→Y text translation retrieval tasks. For a retrieval task X→Y, the speech queries are in language X, and the search DB consists of sentences in language Y. The task is to retrieve the correct text translation for each speech query. We report the Retrieval accuracy (R@1) and the Word Error Rate between the ground-truth and retrieved text translations. We compare our retrieval pipeline SAMU-XLSR-LaBSE, with ASR-LaBSE and the Topline retrieval model. The SAMU-XLSR-LaBSE retrieval pipeline transforms speech queries to embedding vectors using our SAMU-XLSR speech encoder. Then, we match the query embedding vectors with the LaBSE text embeddings of the sentences in the search DB to retrieve the translation. The ASR-LaBSE retrieval pipeline first uses an ASR model for language X to transcribe speech queries and then use LaBSE to perform text-to-text translation retrieval. The Topline model uses the ground-truth text transcripts for the speech queries and performs text-to-text translation retrieval tasks using LaBSE.

| X-Y | IT-ES | IT-EN | ES-FR | ES-IT | FR-PT | ES_PT | FR_EN | PT_ES | ES_EN | PT_EN | RU_EN | Avg. |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Query DB |
| 1.8K | 2K | 1.8K | 270 | 2K | 1.8K | 2K | 1.8K | 2K | 1.8K | 2K | 1.8K | - |
| Search DB |
| 1.6M | 270K | 220K | 250K | 270K | 210K | 1.6M | 1.6M | 1.6M | 210K | 270K | - |
| SAMU-XLSR-LaBSE Speech(X)→Text(Y) Retrieval |
| R@1 [%] | 92.2 | 87.0 | 87.5 | 84.5 | 86.7 | 85.9 | 81.0 | 80.8 | 78.6 | 74.6 | 61.2 | 81.8 |
| WER [%] | 2.8 | 5.7 | 6.2 | 6.3 | 6.3 | 6.4 | 8.3 | 9.4 | 9.6 | 12.4 | 26.0 | 9.0 |
| ASR-LaBSE Speech(X)→Text(Y) Retrieval |
| R@1 [%] | 92.5 | 88.2 | 90.2 | 85.7 | 87.1 | 88.3 | 82.9 | 84.7 | 82.2 | 80.1 | 69.9 | 84.7 |
| WER [%] | 2.4 | 4.4 | 4.2 | 6.1 | 5.5 | 4.5 | 6.9 | 7.1 | 7.4 | 8.8 | 17.0 | 6.8 |
| Topline LaBSE Text(X)→Text(Y) Retrieval |
| R@1 [%] | 96.1 | 93.3 | 94.4 | 91.7 | 93.5 | 94.1 | 90.9 | 94.8 | 90.5 | 91.7 | 87.6 | 92.6 |
| WER [%] | 1.0 | 2.3 | 1.8 | 2.9 | 2.0 | 1.7 | 2.9 | 1.3 | 3.2 | 2.6 | 5.4 | 2.5 |
TABLE VII: We perform zero-shot X→EN speech translation retrieval on the VoxPopuli dataset. The speech queries are in a language X, and the search database consists of speech utterances that are translations of speech queries. Unlike text translation retrieval tasks, where the search DB is much bigger than the query DB, here, the search and the query DB have the same size. During its training, SAMU-XLSR did not have access to any cross-lingual speech-to-speech associations. Hence, semantic alignment among speech utterances in different languages is an emergent property of the embedding vector space learned by SAMU-XLSR via our proposed multimodal learning framework. We compare SAMU-XLSR’s vector space with XLS-R.

| X     | ES | FR | PL | NL | DE | RO | HR | CS | Avg. |
|-------|----|----|----|----|----|----|----|----|------|
| SAMU-XLSR Speech(X)→Speech(EN) Retrieval |    |    |    |    |    |    |    |    |      |
| Query & Search DB | 36K | 50K | 19K | 11K | 60K | 16K | 8K | 11K | -    |
| R@1 [%] | 97.9 | 97.8 | 97.7 | 97.5 | 96.0 | 76.0 | 53.3 | 52.8 | 83.6 |
| R@5 [%] | 98.5 | 98.4 | 98.4 | 98.0 | 97.1 | 80.9 | 59.5 | 58.2 | 86.1 |
| XLS-R Speech(X)→Speech(EN) Retrieval |    |    |    |    |    |    |    |    |      |
| R@1 [%] | - | - | - | 0.0 | - | - | - | 0.0 | 0.0 |

the number of English speech queries and the sentences in the search database for each language, Y.

For the CoVoST-2 EN→Y retrieval tasks, we have 32K English speech queries in the query DB and 320K sentences in the search DB in language Y for each EN→Y retrieval task. See Section III-B for more details on the EN→Y CoVoST-2 retrieval tasks.

Table VII shows results on CoVoST-2 EN→Y retrieval tasks. We have 32K English speech queries in the query DB and 320K sentences in the search DB in language Y for each EN→Y retrieval task. See Section III for more details on the EN→Y CoVoST-2 retrieval tasks. We observe that SAMU-XLSR-LaBSE and XLSR-LaBSE retrieval pipelines perform at par achieving a retrieval WER of 7.6% and 7.3% respectively, while the Topline LaBSE text(EN)→text(Y) retrieval pipeline achieves an average WER of 2.1% across the 15 retrieval tasks. There is room for improvement. In particular, for retrieving text translations in non-European languages such as ZH, MN, JA, FA, AR, and TA, for which the average WER achieved by our proposed SAMU-XLSR-LaBSE retrieval pipeline is 9.7% compared to 2.8% with the topline LaBSE text(EN)→text(Y) retrieval. For European languages, our retrieval model achieves a WER of 6.1% compared to 1.7% for the topline model. Our model performs better in European languages (6.1% WER) than non-European languages (9.7% WER).

Table VIII shows EN→Y retrieval results on the out-of-domain MUST-C evaluation corpus. We have the same number of 4K speech utterances in the query DB and 200K sentences in the search DB for all text translation retrieval tasks. We observe that SAMU-XLSR-LaBSE perform at par with XLSR-LaBSE retrieval pipeline, achieving an average of 10.3% WER compared to 9.6% achieved by the XLSR-LaBSE retrieval pipeline on the 14 EN→Y retrieval tasks. Our model achieves a WER of less than 10% for most languages except TR, AR, RU, and ZH, for which the model achieves a WER of 11.1%, 13.2%, 12.3%, and 20.6% respectively. These WERs are approximately double the WERs, achieved by the topline LaBSE text(EN)→text(Y) retrieval model. However, the WERs are at a respectable less than 20% mark.

D. Results on X→Y text translation retrieval tasks

Table VI shows results on out-of-domain MTEDx X→Y text translation retrieval tasks using SAMU-XLSR-LaBSE, ASR-LaBSE and topline LaBSE retrieval pipelines. The table shows the speech queries and text search database combination for each pair X,Y. We observe that SAMU-XLSR-LaBSE achieves an average retrieval WER of 9% compared to 6.8% with ASR-LaBSE and 2.5% with topline LaBSE on the 11 text translation retrieval tasks. It is unsurprising that ASR-LaBSE retrieval pipeline performs better than the SAMU-XLSR-LaBSE model. Because, the speech queries for X→Y retrieval tasks are in European languages and our European language ASR models are quite good. The results reported here confirm with the observation we made for X→EN CoVoST-2 translation retrieval tasks, where SAMU-XLSR-LaBSE performed better than ASR-LaBSE for non-European languages but not for the European languages. Note that if we had an ASR model that generated text transcripts that exactly matched the ground-truth transcripts, then the performance of ASR-LaBSE would be same as that of the topline model.

E. Results on X→EN speech translation retrieval tasks

We observe that the SAMU-XLSR speech encoder learns a semantically aligned vector space across several spoken languages. The model can retrieve the correct English speech translations corresponding to speech queries in a language X with above 96% accuracy for X∈{ES, FR, PL, NL, DE}. For X∈{RO, HR, CS}, SAMU-XLSR’s speech translation retrieval performance is lagging behind other languages. This result is not surprising because SAMU-XLSR did not see any transcribed data from these three languages during training. SAMU-XLSR achieves an average retrieval R@1 accuracy of 83.6% across the 8 X→EN speech translation retrieval tasks. On the other hand, XLS-R fails on this retrieval task. To get an utterance level speech embedding from XLS-R, we perform temporal
mean pooling of the contextual frame-wise embeddings from the last layer of the model. From the poor retrieval results, it is evident that the XLS-R representation space is not semantically aligned across different languages. We achieve similarly poor results with representations from different XLS-R layers.

V. DOWNSTREAM TASKS: SEQUENCE-TO-SEQUENCE MODELING

A. Phoneme Recognition

Table VIII shows the phoneme error rates (PER) achieved by SAMU-XLSR and XLS-R on nine Commonvoice languages. We observe that SAMU-XLSR is comparable with XLS-R on phoneme recognition task achieving an average PER of 6.2% compared to 6.4% achieved by XLS-R across the nine target languages, namely. See Section III-C for details about the task and the data used for Fine-tuning SAMU-XLSR and XLS-R.

| Model                        | ES  | FR  | IT  | KY  | NL  | RU  | SV  | TR  | TT  | Avg. |
|------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| XLS-R ([7]                   | 2.9 | 5.0 | 5.7 | 6.1 | 5.8 | 8.1 | 12.2| 7.1 | 5.1 | 6.4  |
| XLS-R (Our Fine-tuning setup)| 3.5 | 5.6 | 5.9 | 5.7 | 6.8 | 9.5 | 8.1 | 7.8 | 4.5 | 6.4  |
| SAMU-XLSR (This work)       | 4.4 | 5.4 | 5.4 | 7.7 | 6.0 | 6.3 | 7.7 | 6.5 | 6.9 | 6.2  |

B. Automatic Speech Recognition

Table IX shows the Word Error Rates (WER) achieved by Fine-tuning SAMU-XLSR and XLS-R on nine languages. We observe that SAMU-XLSR performs at par with XLS-R achieving an average WER of 24.3% compared to 25.8% achieved by XLS-R. Interestingly, on the out-of-domain Arabic (AR) language, which is drawn from the MGB2 [50] news broadcast corpus (different from the read speech CoVo corpus used to Pre-train SAMU-XLSR), SAMU-XLSR performs better that XLS-R.

The fact that sequence-to-sequence modeling results (ASR & Phoneme Recognition) are at par with XLS-R implies that SAMU-XLSR in addition to being useful for zero-shot cross-lingual text and speech translation retrieval (Section IV) can also be used for sequence generation tasks like ASR.

VI. EMPIRICAL ANALYSIS OF VARIOUS DESIGN CHOICES

In this section, we study various design decisions that went into creating the SAMU-XLSR speech encoder.

A. Loss and pooling functions

While detailing SAMU-XLSR in Section III-B we mentioned that we use the Self-Attention pooling method to construct an utterance-level speech embedding from acoustic frame-level contextual embedding vectors. Also, we use the cosine distance loss for training SAMU-XLSR. Table X shows that combining cosine distance loss and the Self-Attention pooling method is better than combining other loss functions and pooling methods. We train SAMU-XLSR with L1, L2, and cosine distance losses and compare its average text translation retrieval performance across the 21 X→EN CoVoST-2 retrieval tasks. Also, we compare the retrieval performance with Mean, Max, and Self-Attention pooling strategies. Three loss functions with three pooling strategies lead to nine possible training configurations. For quick analysis, we train SAMU-XLSR on 8 V100-32GB GPUs for 100K iterations on a subset $D_s$ of the complete multilingual transcribed training data $D$. $D_s$ is constructed by randomly sampling 400K training examples from $D$. SAMU-XLSR with Self-Attention pooling method and trained with cosine distance loss reaches an average retrieval R@1 accuracy of 48.8%, which is better than the other 8 training configurations.

B. Data Re-balancing Smoothing parameter $\alpha$

This section studies the effect on the model’s average retrieval performance across 21 X→EN retrieval tasks when we train the model with re-balanced training data according to Equation [5]. The smoothing parameter $\alpha$ is the only hyper-parameter in the data re-balancing equation. First, we construct several re-balanced multilingual transcribed speech datasets corresponding to different values of $\alpha$. Then, we randomly sample 400K utterances from re-balanced datasets for SAMU-XLSR model training. We train SAMU-XLSR using cosine distance loss function for 100K iterations on 8 V100-32GB GPUs.
We observe in Table XI that the models trained with re-balanced data (α < 1.0) achieve significantly better average retrieval accuracy across the 21 X→EN text translation retrieval tasks than the model trained with no re-balancing (α = 1.0). We achieve the best performance with α = 0.05, where the model’s average retrieval accuracy R@1 is 72.4% compared to 48.8% achieved by SAMU-XLSR trained on the original dataset without any re-balancing. The massive boost in retrieval performance is due to the model doing much better on X→EN retrieval tasks where speech queries are in low-resource languages, which implies that the model was indeed under-fitting on low-resource languages due to the data imbalance in the training set of SAMU-XLSR. Table XII shows that SAMU-XLSR trained with data re-balancing (α = 0.05) achieves an average retrieval R@1 accuracy of 61.4% compared to 23.8% achieved by SAMU-XLSR trained on unbalanced training set (α = 1.0). Also, Table XIII shows that there is a negligible performance difference for different αs on X→EN tasks when speech queries are in high-resource languages.

### C. Training Data

In Section II-D1 we mention that we train SAMU-XLSR with multilingual transcribed speech data collected from the CoVo dataset. In this section, we study the effect of training SAMU-XLSR with paired speech-translation data. We train SAMU-XLSR using three different training datasets: 1) Transcribed multilingual speech in 25 languages from the CoVo dataset, which we refer to as the training setup T1, and the model trained with this setup as SAMU-XLSR_T1, 2) The 22 X→EN CoVoST-2 [41] speech-translation training sets, where speech utterances are paired with their corresponding English text translations. We refer to that as the training setup T2, and the model trained with this setup as SAMU-XLSR_T2, 3) A combination of both T1 and T2. We refer to the model trained with this setup as SAMU-XLSR_T3.

Table XIV shows average retrieval performance on 21 X→EN retrieval tasks achieved by SAMU-XLSR trained with the three different training setups mentioned above. We observe

### TABLE X: Avg. retrieval Performance on 21 X→EN text translation retrieval tasks for different combinations of loss and pooling functions

| Loss | Pooling | R@5 [%] | R@1 [%] | WER [%] |
|------|---------|---------|---------|---------|
| L1   | Max     | 52.2    | 44.0    | 50.9    |
| L1   | Mean    | 52.9    | 44.6    | 49.9    |
| L1   | Att.    | 54.0    | 45.6    | 48.8    |
| Cos  | Max     | 55.4    | 46.6    | 47.5    |
| L2   | Max     | 55.6    | 46.8    | 47.3    |
| L2   | Mean    | 56.3    | 47.6    | 46.2    |
| L2   | Att.    | 57.2    | 48.2    | 45.4    |
| L2   | Cos Att.| 58.0    | 48.8    | 44.6    |

### TABLE XI: Avg. retrieval Performance on 21 X→EN text translation retrieval tasks for different values of α

| α    | R@5 [%] | R@1 [%] | WER [%] |
|------|---------|---------|---------|
| 1.00 | 58.0    | 48.8    | 44.6    |
| 0.70 | 70.3    | 60.5    | 32.2    |
| 0.30 | 79.3    | 69.5    | 22.8    |
| 0.10 | 81.6    | 71.7    | 20.5    |
| 0.01 | 81.9    | 72.0    | 19.9    |
| 0.05 | 82.2    | 72.4    | 19.6    |

### TABLE XII: Avg. retrieval Performance on 7 X→EN text translation retrieval tasks for different αs. The speech queries are in low-resource languages

| α    | R@5 [%] | R@1 [%] | WER [%] |
|------|---------|---------|---------|
| 1.00 | 32.1    | 23.8    | 72.1    |
| 0.05 | 71.9    | 61.4    | 29.7    |

### TABLE XIII: Avg. retrieval Performance on 5 X→EN text translation retrieval tasks for different αs. The speech queries are in high-resource languages

| α    | R@5 [%] | R@1 [%] | WER [%] |
|------|---------|---------|---------|
| 0.05 | 92.0    | 85.0    | 9.4     |
| 1.00 | 93.8    | 87.5    | 7.3     |

### TABLE XIV: Avg. retrieval performance on 21 X→EN text translation retrieval tasks for different training data

| Model   | R@5 [%] | R@1 [%] | WER [%] |
|---------|---------|---------|---------|
| SAMU-XLSR_T2 | 49.9 | 41.3    | 54.6    |
| SAMU-XLSR_T3 | 79.7 | 69.5    | 22.7    |
| SAMU-XLSR_T1 | 82.2 | 72.4    | 19.6    |

### TABLE XV: Avg. retrieval performance on 7 X→EN text translation retrieval tasks for different training data. The speech queries are in low-resource languages

| Model   | R@5 [%] | R@1 [%] | WER [%] |
|---------|---------|---------|---------|
| SAMU-XLSR_T2 | 15.5 | 9.2     | 91.4    |
| SAMU-XLSR_T3 | 67.3 | 55.7    | 36.1    |
| SAMU-XLSR_T1 | 71.9 | 61.4    | 29.7    |

### TABLE XVI: Avg. retrieval performance on 5 X→EN text translation retrieval tasks for different training data. The speech queries are in high-resource languages

| Model   | R@5 [%] | R@1 [%] | WER [%] |
|---------|---------|---------|---------|
| SAMU-XLSR_T1 | 92.0 | 85.0    | 9.4     |
| SAMU-XLSR_T2 | 91.9 | 84.9    | 9.2     |
| SAMU-XLSR_T3 | 92.3 | 85.7    | 8.7     |
that SAMU-XLSR_T1 achieves the best retrieval performance out of the three models, which implies that we can train SAMU-XLSR with just multilingual transcribed speech. Furthermore, table [XV] shows that SAMU-XLSR_T1 is notably better for X→EN retrieval tasks when speech queries are in low-resource languages. For speech queries in high-resource languages, the performance difference among the three models is negligible. See Table [XVI] for X→EN retrieval tasks, when speech queries are in high-resource languages.

VII. CONCLUSION

We proposed a semantically-aligned multimodal (joint speech-text) utterance-level cross-lingual speech representation (SAMU-XLSR) learning framework in this work. We show that just by using multilingual transcribed speech to train the proposed representation learning model, cross-lingual alignments between speech utterances and their text and speech translations emerge in the model’s learned embedding vector space.

We show that unlike XLS-R (a speech-only multilingual speech encoder), SAMU-XLSR in combination with language-agnostic BERT sentence encoder LaBSE can perform zero-shot speech-to-text and speech-to-speech translation retrieval across several spoken and written languages. Furthermore, we show that SAMU-XLSR performs at par with XLS-R on sequence-to-sequence modeling tasks such as ASR and Phoneme Recognition. In the future, we will extend our multimodal learning framework for the task of zero-shot speech translation and large-scale speech-to-text data mining to create parallel speech-text translation datasets for training speech translation models.

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TABLE XVII: Given a speech query in language X, we search over a large English database of 1.6M sentences to retrieve the top-5 translations using our proposed SAMU-XLSR-LaBSE retrieval pipeline. We randomly pick five speech queries from the CoVoST-2 eval set, two in French, and one each in German, Arabic and Spanish. For each speech query, we retrieve the top-5 English translations.

| Speech Query                                               | Query Lang. | Top-5 Retrieved EN Translations                                                                 |
|------------------------------------------------------------|-------------|--------------------------------------------------------------------------------------------------|
| La chute de la cité est difficile à expliquer.             | FR          | 1) The fall of the city is difficult to explain                                                  |
|                                                            |             | 2) The origin of the town name is unclear.                                                       |
|                                                            |             | 3) It’s not easy to describe why it happened.                                                    |
|                                                            |             | 4) Further history of the village is unclear.                                                    |
|                                                            |             | 5) The origin of the town is not completely clear.                                              |
| Elle est le chef-lieu du département de l’Okano.           | FR          | 1) It is the seat of Okanogan County.                                                            |
|                                                            |             | 2) It is the main city of the Okano District.                                                    |
|                                                            |             | 3) It is the county seat of Macon County.                                                       |
|                                                            |             | 4) It is the capital of Otwock County.                                                           |
|                                                            |             | 5) Its county seat is Oconto.                                                                   |
| Die Blütezeit reicht von März und April vor der Bildung der Laubblätter. | DE          | 1) The flowering season lasts from March until April, just before foliage develops.             |
|                                                            |             | 2) The flowering period extends from April through June.                                         |
|                                                            |             | 3) Flowering occurs from April through July.                                                     |
|                                                            |             | 4) Its flowering season is around February to April.                                             |
|                                                            |             | 5) The blooming starts in the middle of April and goes almost until mid May.                    |
| تزداد حماً يوماً بعد يوم.                                      | AR          | 1) She’s getting worse every day.                                                                |
|                                                            |             | 2) It is getting better every day.                                                               |
|                                                            |             | 3) It’s getting warmer day after day.                                                            |
|                                                            |             | 4) She gets prettier every day.                                                                 |
|                                                            |             | 5) It’s getting colder day after day.                                                            |
| Fue enfermera voluntaria en la I Guerra Mundial.           | ES          | 1) She was a volunteer nurse on World War I.                                                     |
|                                                            |             | 2) Her mother was a nurse during World War One.                                                  |
|                                                            |             | 3) During World War One he served as a paramedic.                                               |
|                                                            |             | 4) During World War One he was a medical sergeant                                               |
|                                                            |             | 5) In World War One, she was a Red Cross nurse.                                                 |
Fig. 5: We extract the representation sequence from a Pre-trained SAMU-XLSR (our proposed model) from before the attention pooling layer. Next, we compute the cosine similarity between the adjacent feature vectors to compute a sequence of distances and use a peak finding algorithm to detect the local peaks. After tuning the peak threshold in the peak finding algorithm, we observe that the peaks correspond to the underlying word boundaries.