Unsupervised Cross-lingual Representation Learning for Speech Recognition

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Abstract

This paper presents XLSR which learns cross-lingual speech representations by pretraining a single model from the raw waveform of speech in multiple languages. We build on a concurrently introduced self-supervised model which is trained by solving a contrastive task over masked latent speech representations and jointly learns a quantization of the latents shared across languages. The resulting model is fine-tuned on labeled data and experiments show that cross-lingual pretraining significantly outperforms monolingual pretraining. On the CommonVoice benchmark, XLSR shows a relative phoneme error rate reduction of 72% compared to the best known results. On BABEL, our approach improves word error rate by 16% relative compared to the strongest comparable system. Our approach enables a single multilingual speech recognition model which is competitive to strong individual models. Analysis shows that the latent discrete speech representations are shared across languages with increased sharing for related languages.

1 Introduction

Cross-lingual learning aims to build models which leverage data from other languages to improve performance. This has been a long standing interest in the speech community [9, 37, 21, 20, 11, 45] which includes systems able to transcribe multiple languages [8, 7, 26, 47, 33]. However, the vast majority of work in speech processing has focused on supervised cross-lingual training which requires labeled data in multiple languages. Transcribed speech is often much scarcer than unlabeled speech and requires non-trivial human annotation.

Unsupervised representation learning, or pretraining, does not require labeled data and has received a lot of recent attention in computer vision [24, 10] after much success in natural language processing [44, 15]. For the latter, cross-lingual pretraining has been shown to be very effective, particularly, for low resource languages [36, 14]. In speech processing, most work in this area has focused on monolingual unsupervised representation learning [48, 12, 44, 13, 5, 23, 32, 46, 17, 4].

In this paper, we focus on the cross-lingual setting by learning representations on unlabeled data that generalize across languages. We build on a concurrently introduced pretraining approach [6] which jointly learns contextualized representations of speech as well as a discrete vocabulary of latent speech representations. The latter serves to effectively train the model with a contrastive loss (§ 2). These discrete latent speech representations are shared across languages (Figure 1).
Different to recent work on unsupervised cross-lingual pretraining, we fine-tune the Transformer part of the model instead of freezing all pretrained representations \[43\] or feeding them to a separate downstream model \[34\]. We extend the work of \[43\] by pretraining on multiple languages instead of just English and we experiment on top of a better performing baseline.

We evaluate XLSR on 14 languages of the BABEL benchmark \[19\] which is conversational telephone data and ten languages of CommonVoice \[2\], a corpus of read speech \(\S\ 3\). Multilingual pretraining outperforms monolingual pretraining in most cases, except for resource rich languages and we show that increased model capacity significantly closes the gap. We also demonstrate that XLSR representations can be fine-tuned simultaneously on multiple languages to obtain a multilingual speech recognition system whose performance is competitive to fine-tuning a separate model on each language. On CommonVoice, we report a relative phoneme error rate (PER) reduction of 72% compared to the previous best known results \[43\]. On BABEL we outperform prior supervised multilingual work on a comparable data setup by a relative 38% in terms of character error rate \(\S\ 4\), and by a relative 16% when measuring word error rate \(\S\ 4\).

2 Approach

Unsupervised cross-lingual representation learning has shown great success by pretraining Transformers \[49\] with multilingual masked language models \[15\], \[36\]. In this work, we learn cross-lingual speech representations by extending wav2vec 2.0 \[6\] to the cross-lingual setting. Our approach learns a single set of quantized latent speech representations which are shared across languages. Next, we outline the architecture \(\S\ 2.1\), training \(\S\ 2.2\) and adaptations for cross-lingual training.

2.1 Architecture

The model contains a convolutional feature encoder \(f: \mathcal{X} \rightarrow \mathcal{Z}\) to map raw audio \(\mathcal{X}\) to latent speech representations \(z_1, \ldots, z_T\) which are fed to a Transformer network \(g: \mathcal{Z} \rightarrow \mathcal{C}\) to output context representations \(c_1, \ldots, c_T\) \[15\], \[5\], \[4\]. For the purpose of training the model, feature encoder representations are discretized to \(q_1, \ldots, q_T\) with a quantization module \(\mathcal{Z} \rightarrow \mathcal{Q}\) to represent the targets in the self-supervised learning objective (Figure 1 \(\S\ 2.2\).

The feature encoder is composed of seven temporal convolutions with 512 channels and GELU non-linearities \[27\] with strides \((5,2,2,2,2,2,2)\) and kernel sizes \((10,3,3,3,3,2,2)\). Each \(z_t\) represents about 25ms of audio strided by 20ms. The context network architecture follows BERT \[49\], \[15\] and we replace fixed positional embeddings with relative position embeddings implemented as a convolution with kernel size 128 and 16 groups similar to \[39\], \[4\].

Feature encoder outputs \(z\) are discretized to a finite set of representations using product quantization for the purpose of defining targets in the contrastive loss \[51\], \[5\]. Quantized representations are chosen

Figure 1: The XLSR approach. A shared quantization module over feature encoder representations produces multilingual quantized latent speech units whose embeddings are then used as targets for a single Transformer trained with contrastive learning. The model learns to share discrete tokens across languages, creating bridges across languages. Our approach is inspired by \[15\], \[36\] and builds on top of wav2vec 2.0 \[6\]. It requires only raw unsupervised speech audio from multiple languages.
from $G = 2$ codebooks with $V = 320$ entries each and concatenated to obtain $q$. A Gumbel softmax enables choosing discrete codebook entries in a fully differentiable way \cite{jang2016categorical}.

2.2 Training

The model is trained by solving a contrastive task over masked feature encoder outputs. For masking, we sample $p = 0.065$ of all time steps to be starting indices and mask the subsequent $M = 10$ time steps. The objective requires identifying the true quantized latent $\tilde{q}$ for a masked time-step within a set of $K = 100$ distractors $Q_t$ sampled from other masked time-steps: $-\log \frac{\exp(sim(c_t, \tilde{q}))}{\sum_{q_t \sim Q_t} \exp(sim(c_t, q_t))}$ where $c_t$ is the output of the transformer, and $sim(a, b)$ denotes cosine similarity.

This is augmented by a codebook diversity penalty to encourage the model to use all codebook entries \cite{madaan2021data}. We maximize the entropy of the averaged softmax distribution over the codebook entries for each group $\bar{p}_g$ across a batch of utterances: $\frac{1}{G} \sum_{g=1}^{G} -H(\bar{p}_g) = \frac{1}{G} \sum_{g=1}^{G} \sum_{v=1}^{V} \bar{p}_{g,v} \log \bar{p}_{g,v}$.

To stabilize the feature encoder we apply an L2 penalty over the outputs of the feature encoder.

When pretraining on $L$ languages, we form multilingual batches \cite{madaan2021data, bahdanau2016onmt} by sampling speech samples from a multinomial distribution $(p_l)_{l=1,...,L}$ where $p_l \sim \left( \frac{n_l}{N} \right)$, $n_l$ being the number of pretraining hours of language $l$, $N$ the total number of hours, and $\alpha$ the upsampling factor. The parameter $\alpha$ controls the importance given to high-resource versus low-resource languages during pretraining.

3 Experimental setup

3.1 Datasets

**CommonVoice.** The CommonVoice dataset\cite{voice.mozilla.org/en/languages} is a multilingual corpus of read speech comprising more than two thousand hours of speech data in 38 languages \cite{voice.mozilla.org/en/languages}. The amount of data per language ranges from three hours for Swedish ("low-resource") to 353 hours for French and 1350 hours for English ("high-resource"). Following \cite{williams2019multilingual} we consider ten languages: Spanish (es), French (fr), Italian (it), Kyrgyz (ky), Dutch (du), Russian (ru), Swedish (sv), Turkish (tr), Tatar (tt) and Chinese (zh); as well as English (en) for pretraining. We use the November 2019 release for training models, and for fine-tuning we use the evaluation splits from \cite{williams2019multilingual} which include one hour labeled data for training, 20 minutes for validation and one hour for testing. This few-shot evaluation dataset consists of phoneme sequences as output and we report phone error rate (PER) similar to prior work.

**BABEL.** This dataset\cite{catalog.ldc.upenn.edu/byyear} is a multilingual corpus of conversational telephone speech from the IARPA program, which includes Asian and African languages \cite{khudanpur2014babel}. We adopt the same data setup as \cite{khudanpur2014babel} and pretrain on ten languages: Bengali (bn), Cantonese (zh), Georgian (ka), Haitian (ht), Karmanji (ku), Pashto (ps), Tamil (ta), Turkish (tr), Tokpisin (tp), Vietnamese (vi). We evaluate cross-lingual transfer on four other languages, i.e., models are not pretrained on these languages: Assamese (as), Tagalog (tl), Swahili (sw), Lao (lo). We train a multilingual model in ten languages and monolingual models in 14 languages. We use the same speech audio for pretraining and fine-tuning, and no unlabeled speech provided by BABEL. We use the dev folder of the BABEL dataset as our test set as ‘eval’ has not been open-sourced, and use 10% of the training set as dev data. We report character error rate (CER). All audio is resampled to 16kHz. For comparison with \cite{williams2019multilingual} only, we train 4-gram n-gram language models on CommonCrawl data \cite{https://catalog.ldc.upenn.edu/byyear} for Assamese (140MiB of text data), Swahili (2GiB), Tamil (4.8GiB) and Lao (763MiB); for this experiment only we report word error rate (WER).

3.2 Training details

**Pretraining** Models are implemented in fairseq \cite{ott2019fairseq}. We evaluate two architectures with the same feature encoder (\S 2.1) but different Transformer settings: Base with 12 blocks, model dimension 768, inner dimension (FFN) 3072 and 8 attention heads; and Large with 24 blocks, model dimension 1024, inner dimension 4096 and 16 attention heads; both use dropout 0.1. For Base, we crop 250k samples, or 15.6sec of audio, and pack up to 1.4m samples on each GPU. For Large, we crop 320k samples, or 15.6sec of audio, and pack up to 1.4m samples on each GPU.
samples and put up to 1.2m samples on a GPU. Batches are sampled using a factor \( \alpha \in \{0.5, 1\} \). We use 16 GPUs for small datasets (typically monolingual) and 64 GPUs for large datasets (typically multilingual), and use Adam\(^3\) where the learning rate is warmed up for the first 10% of updates to a peak of 1e-5 (Base) or 1e-3 (Large), and then linearly decayed over a total of 250k updates.

**Fine-tuning.** To fine-tune the model we add a classifier representing the output vocabulary of the respective downstream task on top of the model and train on the labeled data with a Connectionist Temporal Classification (CTC) loss\(^2\). Weights of the feature encoder are not updated at fine-tuning time. We determine the best learning rates setting in \([2e-5, 6e-5]\) based on dev set error rate. The learning rate schedule has three phases: warm up for the first 10% of updates, keep constant for 40% and then linearly decay for the remainder. For CommonVoice we fine-tune for 20k updates and on BABEL for 50k updates on 2 GPUs for the Base model and 4 GPUs for the Large model.

### 3.3 Pretrained models

We use the Base architecture unless otherwise stated. For CommonVoice, we pretrain an English model on 1350h, and ten monolingual models on each pretraining set. For comparison with the English model, we train Base and Large multilingual models on 1350h of data: 793h of speech audio from the 10 evaluation languages plus 557h of English audio. We upsample low-resource languages with \( \alpha = 0.5 \) and train a model with \( \alpha = 1 \) for comparison (unbalanced). For multilingual fine-tuning, we either separate or share phoneme vocabularies across languages.

For BABEL, we train a monolingual model on each of the 14 languages, as well as a Base and Large multilingual model on a total of 650 hours of speech audio in ten languages. Since the amount of data in each language is more balanced than for CommonVoice, we use \( \alpha = 1 \). The same speech audio is used for pretraining and fine-tuning and we use separate character sets for multilingual fine-tuning.

### 4 Results

In our experiments, we first show that our approach is very effective for learning generic cross-lingual representations in an unsupervised way. Pretraining a single model on multiple languages significantly outperforms the previous state of the art on CommonVoice, as well as our own monolingual models. Second, we demonstrate the positive impact of cross-lingual transfer on low-resource languages and provide a better understanding of the trade-off between high-resource and low-resource languages. Third, by fine-tuning a multilingual model on many languages at once, we show that we can obtain a single model for all languages with strong performance. Finally, we analyse the impact of language similarity on cross-lingual transfer, and show that, to some extent, our multilingual pretrained model implicitly learns to cluster related languages.

#### 4.1 Effectiveness of unsupervised cross-lingual representation learning

In what follows, we compare XLSR to several baselines and show that unsupervised cross-lingual representation learning is very effective. We provide a comprehensive analysis of the impact of different pretraining methods on automatic speech recognition in Table 1, 2 and 3.

**4.1.1 Multilingual outperforms monolingual pretraining and prior art**

We first compare monolingual (XLSR-Monolingual) to multilingual (XLSR-10) pretrained models (Base) fine-tuned individually on each language (ft=1). On CommonVoice, XLSR-10 obtains 13.6 PER on average (Avg), a relative PER reduction of 49% compared to XLSR-Monolingual (Table 1). On BABEL, XLSR-10 improves over XLSR-Monolingual by 18% relative CER (Table 2) and by more over supervised training (Training from scratch)\(^\text{4}\). Pretraining on multiple languages results in cross-lingual transfer and better speech representations.

Compared to prior work, XLSR-10 Large reduces PER by 72% relative to m-CPC\(^\text{43}\) on CommonVoice (Table 1). On BABEL, comparison to prior work is challenging because most work evaluates on the eval set\(^\text{45,43,42}\), only available to IARPA BABEL participants who tune on the public dev set which non-participants use as test set. This makes comparison difficult. Since we adopted the same

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\(^3\)We did not tune this setting extensively and will tune it further in the next version of the paper.
| Model                          | D | #pt | #ft | es | fr | it | ky | nl | ru | sv | tr | tt | zh | Avg |
|-------------------------------|---|-----|-----|----|----|----|----|----|----|----|----|----|----|-----|
| Number of pretraining hours per language | 168h | 353h | 90h | 17h | 29h | 55h | 3h | 11h | 17h | 50h | 793h |
| Number of fine-tuning hours per language | 1h | 1h | 1h | 1h | 1h | 1h | 1h | 1h | 1h | 1h | 10h |

**Baselines from previous work**

| Model | D | #pt | #ft | es | fr | it | ky | nl | ru | sv | tr | tt | zh | Avg |
|-------|---|-----|-----|----|----|----|----|----|----|----|----|----|----|----|
| m-CPC † [43] | LS | 10h | 1h | 38.7 | 49.3 | 42.1 | 40.7 | 44.4 | 45.2 | 48.8 | 49.7 | 44.0 | 55.5 | 45.8 |
| m-CPC † [43] | LS | 360h | 10h | 38.0 | 47.1 | 40.5 | 41.2 | 42.5 | 43.7 | 47.5 | 47.3 | 42.0 | 55.0 | 44.5 |
| Fer et al. † [18] | BBL | all | 10h | 36.6 | 48.3 | 39.0 | 38.7 | 47.9 | 45.2 | 52.6 | 43.4 | 42.5 | 45.4 | 44.9 |

**Our monolingual models**

| Model | D | #pt | #ft | es | fr | it | ky | nl | ru | sv | tr | tt | zh | Avg |
|-------|---|-----|-----|----|----|----|----|----|----|----|----|----|----|----|
| XLSR-English | CV | en | 1 | 1 | 13.7 | 20.0 | 19.1 | 13.2 | 19.4 | 18.6 | 21.1 | 15.5 | 11.5 | 27.1 |
| XLSR-Monolingual | CV | mo | 1 | 1 | 6.8 | 10.4 | 10.9 | 29.6 | 37.4 | 11.6 | 63.6 | 44.0 | 21.4 | 31.4 |

**Our multilingual models**

| Model | D | #pt | #ft | es | fr | it | ky | nl | ru | sv | tr | tt | zh | Avg |
|-------|---|-----|-----|----|----|----|----|----|----|----|----|----|----|----|
| XLSR-10 (unbalanced) | CV | all | 10 | 9.7 | 13.6 | 15.2 | 11.1 | 18.1 | 13.7 | 21.4 | 14.2 | 9.7 | 25.8 | 15.3 |
| XLSR-10 | CV | 10h | 10 | 9.4 | 14.2 | 14.1 | 8.4 | 16.1 | 11.0 | 20.7 | 11.2 | 7.6 | 24.0 | 13.6 |
| XLSR-10 (separate vocab) | CV | 10 | 10 | 10.0 | 13.8 | 14.0 | 8.8 | 16.5 | 11.6 | 21.4 | 12.0 | 8.7 | 24.5 | 14.1 |
| XLSR-10 (shared vocab) | CV | all | 10 | 9.4 | 13.4 | 13.8 | 8.6 | 16.3 | 11.2 | 21.0 | 11.7 | 8.3 | 24.5 | 13.8 |

**Our multilingual models (Large)**

| Model | D | #pt | #ft | es | fr | it | ky | nl | ru | sv | tr | tt | zh | Avg |
|-------|---|-----|-----|----|----|----|----|----|----|----|----|----|----|----|
| XLSR-10 | CV | all | 10 | 7.9 | 12.6 | 11.7 | 7.0 | 14.0 | 9.3 | 20.6 | 9.7 | 7.2 | 22.8 | 12.3 |
| XLSR-10 (separate vocab) | CV | 10 | 10 | 8.1 | 12.1 | 11.9 | 7.1 | 13.9 | 9.8 | 21.0 | 10.4 | 7.6 | 22.3 | 12.4 |
| XLSR-10 (shared vocab) | CV | 10 | 10 | 7.7 | 12.2 | 11.6 | 7.0 | 13.8 | 9.3 | 20.8 | 10.1 | 7.3 | 22.3 | 12.2 |

Table 1: **CommonVoice results using phoneme error rate (PER).** We pretrain models on either one language (pt = 1) or 10 languages (pt = 10); and fine-tune on each language (ft = 1) or all languages (ft = 10). D indicates the pretraining data, LS for English LibriSpeech (100h or 360h), BBL for BABEL (1070h), CV for English CommonVoice (1350h), CV mo for monolingual (see number of pretraining hours per language) and CV all for multilingual (1350h). Languages can be high-resource (es, fr, it) or low-resource (e.g. ky, sv, tr, tt). Baseline results † are taken from [43].

4.1.2 Multilingual pretraining outperforms English-only training

To isolate the impact of multilingual training versus simply training on more data, we pretrain an English-only CommonVoice model (XLSR-English) on the same amount of data as the multilingual model (1350h) and compare the two. Table 1 shows that on average, XLSR-English significantly improves over the monolingual models (average PER of 26.7 vs. 17.9 PER) but multilingual pretraining performs even better at 13.6 PER, a 24% relative PER reduction over XLSR-English. This shows that adding more training data is not the only reason for the improved accuracy: the similarity between the languages used in pretraining and fine-tuning also plays an important role.

4.1.3 Learned representations transfer well to unseen languages

To better assess the cross-lingual transfer of the learned representations, we evaluate the XLSR-10 BABEL model on four languages not seen during pretraining. We fine-tune this model on each language, and compare it to monolingual models pretrained specifically on these languages. Table 1 shows that a multilingual model not pretrained on any data from the four languages, still outperforms XLSR-Monolingual, reducing average CER from 29 to 22.8 which compares to results from previous work of 36.8 CER [11]. This further suggests that the learned representations capture generic features of the speech signal which transfer to many languages.

4.2 Understanding cross-lingual transfer learning

In this section, we examine several properties of unsupervised cross-lingual representation learning for speech recognition. We show that it is particularly effective on low-resource languages, then describe the transfer-interference trade-off which benefits low resource languages but hurts high resource languages. Finally, we show that adding capacity is important for multilingual pretraining.
### 4.2.1 Cross-lingual transfer learning improves low-resource language understanding

Unsupervised cross-lingual representation learning and cross-lingual transfer are particularly effective on low-resource languages. On CommonVoice, the separation between high-resource and low-resource languages is more salient than for BABEL. We distinguish between low-resource and high-resource based on the amount of available unlabeled speech data. For example, French and Spanish have 353h and 168h and are thus high-resource, while Swedish and Turkish have 3h and 11h and are low-resource. Monolingual models perform poorly on low-resource languages but this is where cross-lingual transfer is most effective: XLSR-10 reduces PER over XLSR-Monolingual by a relative 67% on Swedish, 72% on Turkish, 72% on Kyrgyz, and 64% on Tatar.

On BABEL, the amount of monolingual data ranges between 30 hours for Swahili and 130 hours for Cantonese, with a mean of 65h per language. The results (Table 2 and 3) show that the multilingual model outperforms the monolingual model on all languages, but the biggest gains are obtained on the four lowest-resource languages: Georgian (ka), Kurmanji (ku), Tokpisin (tp) and Swahili (sw).

### 4.2.2 The transfer-interference trade-off: high-resource vs. low-resource

The results per language on CommonVoice (Table 1) show what is known as the transfer-interference trade-off [3]; for low-resource languages (e.g. ky, nl, sv, tr, tt), multilingual models outperform monolingual models because of positive transfer, however multilingual models perform worse on high-resource languages (es, fr, it), due to interference. Data from multiple languages enables better speech representations that transfer to low-resource languages but the model also needs to share its capacity across languages which degrades performance on high-resource languages.

For a given model capacity, the language sampling parameter $\alpha$ (see § 2) controls this trade-off. Table 1 shows that training according to the true language distribution, XLSR-10 (unbalanced) using $\alpha = 1$, performs less well than XLSR-10, where more capacity is allocated to low-resource languages via $\alpha = 0.5$. The sole exception being French, the language with the most data. On average the unbalanced model obtains 15.3 PER while the balanced model obtains 13.6.

### 4.2.3 Increasing capacity for a multilingual pretrained model

The interference problem can be alleviated by adding more capacity to the multilingual model [3,14]: the gap between multilingual models and monolingual models for high-resource languages can be reduced by increasing model capacity. In this work, we only study the impact of adding more capacity to the multilingual model, by training an XLSR-10 Large model. On CommonVoice, the Large model reduces PER by relative 9.6% compared to Base, reducing average PER from 13.6 to 12.3. There are no gains on very low-resource languages like Swedish but significant gains on Spanish, French and...
Italian. On BABEL, average CER is reduced by a relative 6.8%. This shows that the multilingual model benefits from more capacity overall, and in particular for high-resource languages.

| Model                      | #pt | #ft | it | es | de | en | ru | ka | zh |
|----------------------------|-----|-----|----|----|----|----|----|----|----|
| XLSR-Monolingual           | 1   | 1   | 47.6 | 16.8 | 24.3 | 25.4 | 27 | 27.2 | 28.1 | 30.6 |

Table 5: **Impact of language similarity on cross-lingual transfer.** We simulate a low-resource language scenario by using only 5 hours of Italian CommonVoice data and add 50 hours from another language for pretraining. We fine-tune on 1 hour of Italian supervised data.
4.4 On the role of language similarity on cross-lingual transfer

Next, we study the impact of language similarity on cross-lingual transfer and then analyze the multilingual token embedding space where we find that languages are clustered.

4.4.1 Low-resource languages benefit more from similar higher-resource languages

We consider Italian as the low-resource language for which we assume only 5h of unlabeled data is available. We pretrain models on the 5h as well as 50h of unlabeled data from several other languages: Italian, Spanish, German, English, Russian, Kabyle and Chinese. Finally, we fine-tune each model on 1h of Italian labeled data. Table 5 shows that adding more unlabeled data helps overall, but adding data from related languages gives the largest improvement, e.g., Spanish. Distant languages, e.g., Kabyle or Chinese are less effective. In order to improve performance on a low-resource language, it is best to add unlabeled data from a closely-related language.

4.4.2 Analyzing the shared discrete speech representations

To analyze the shared quantized latent speech representations, or discrete tokens, we train two models: one on 12 languages of CommonVoice and another on 17 languages of BABEL. For each model, we run the quantizer of our model on train and dev speech samples from each language, and compute a frequency vector of the discrete tokens. The resulting frequencies are normalized for each language to obtain vectors of size $V \times G$, the number of discrete latent speech representations. The vectors represent the empirical probability distribution over the shared discrete latents. Next, we construct an affinity matrix between languages by computing the Jensen-Shannon symmetric similarity between vectors. Finally, we cluster languages using K-Means and then perform a PCA with two dimensions.

Figure 2a, 2b and 2c show the visualizations, where colors correspond to the clusters obtained by K-Means. Note, that we perform K-Means before PCA to avoid loss of information, and that PCA may make some points appear closer than they are in original vectors. We see that the model shares more discrete tokens for similar languages, e.g., it groups Basque, Catalan, Spanish and Italian, or English, German and French, or Arabic and Kabyle (see Figure 2a), and Mandarin (zh-CN and zh-TW), although this information is lost in the PCA visualization. Figure 2b shows that the model may also isolate a language, such as Chinese-HongKong (Cantonese), which is not close to any other language because it shares fewer discrete tokens with other languages.

For BABEL (Figure 2c), we also find language groupings such as Bengali/Assamese which belong to the same family, or Zulu and Swahili which both have long vowels. However one could argue that Pashto and Kurmanji should be closer to each other since they are both Iranian languages. The purpose of this analysis is not to recover full language families but to better understand how our model allocates the latent representations across languages. Interestingly, Italian is closer to Spanish, the most effective language in the previous experiment (Table 5). Future work may investigate whether encouraging shared tokens between similar languages could further help cross-lingual transfer.

Figure 2: Visualization of language similarities learned by the model

(a) CV-12 model. (b) CV-12 model + zh-HK. (c) BABEL-17 model.
5 Conclusion

In this work, we investigated unsupervised cross-lingual speech representations learned from the raw waveform. We show that pretraining on data in multiple languages improves both over monolingual pretraining as well as prior work, with the largest improvements on low-resource languages. Fine-tuning the model on multiple languages at once enables a single multilingual speech recognition model competitive to individually fine-tuned models. Analysis of the discrete latent speech representations reveals that the model shares capacity across languages and particularly so with related languages.

Broader Impact

There are around 7,000 languages in the world and many more dialects. Collecting large amounts of labeled data is out of reach for all but a handful of languages. Our approach can help to build better speech recognition systems for low resource languages and thus make this technology more equally accessible.

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