

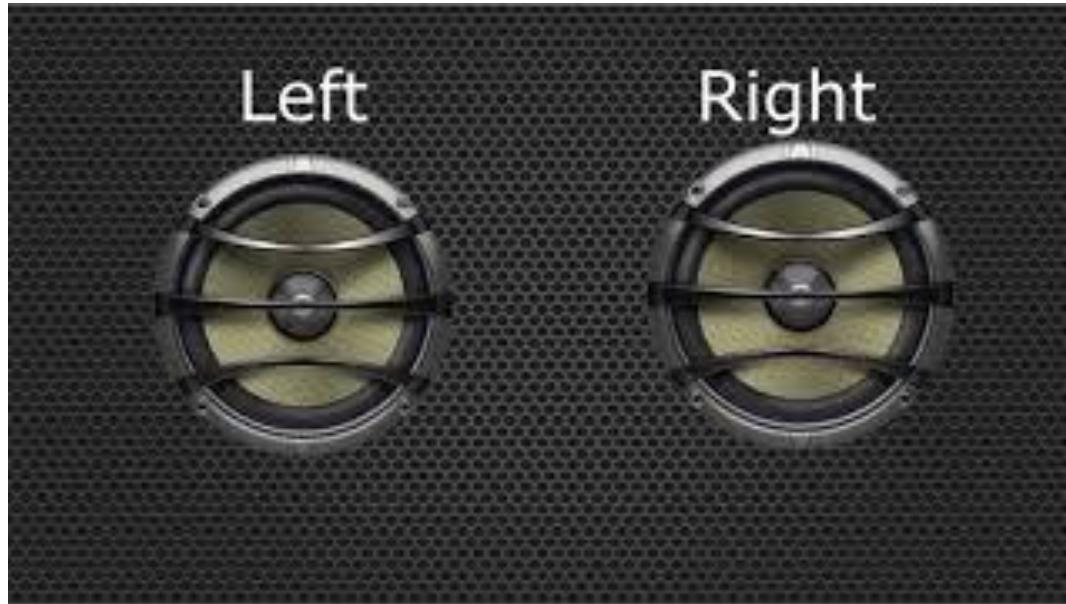
CS 224S / Linguist 285

Spoken Language Processing

Tolúlopé Ògúnṛèmí | Stanford University | Spring 2024

Lecture 12: Speech Recognition Beyond English

Sound check

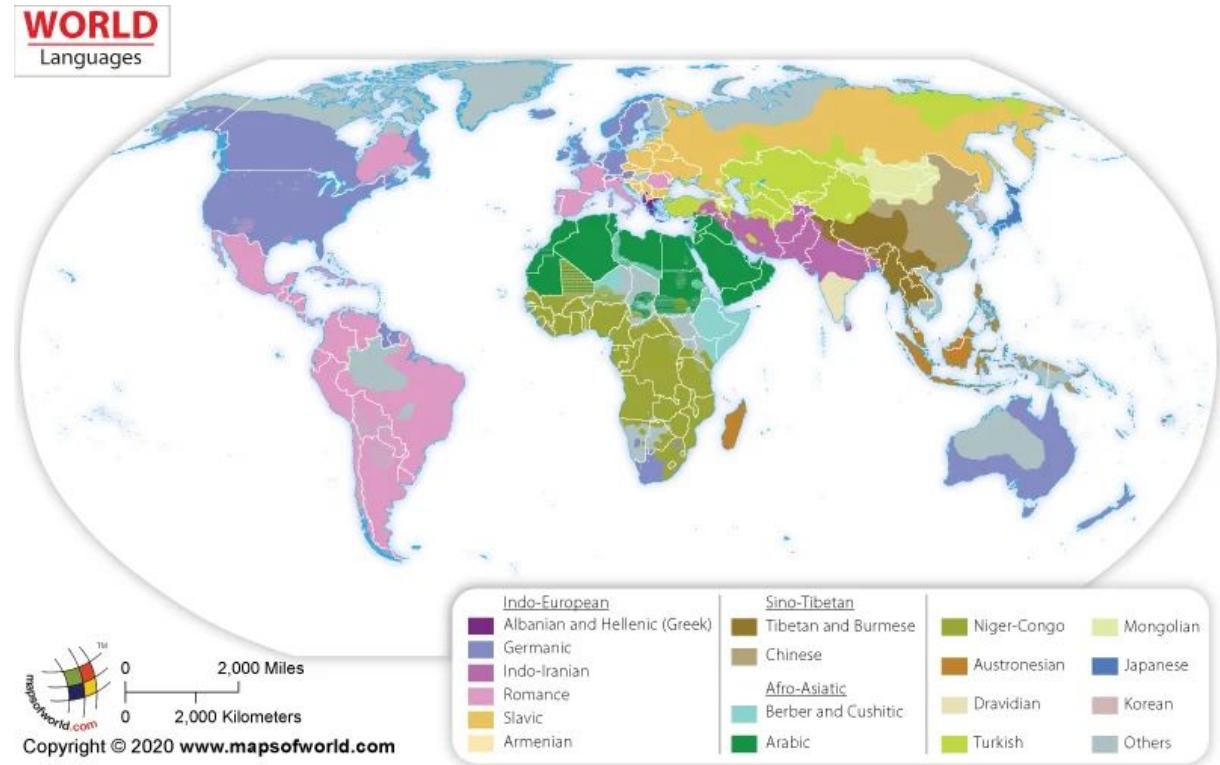


Project Check-Ins

Outline

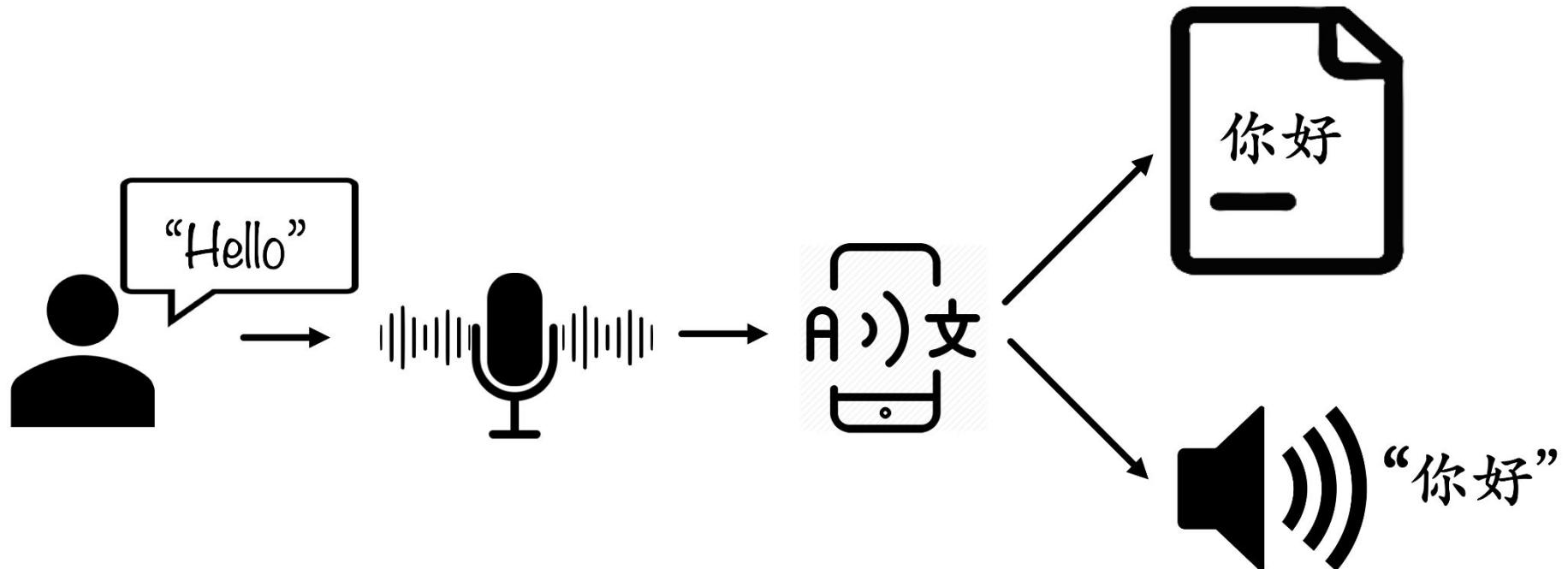
- How languages can differ from English
- Multilingual large pre-trained models
- Datasets and Benchmarks
- Language-specific ASR techniques

There are over 7,000 known languages in the world.



We need to process (as many of) the languages of the world (as we can).

Example: Speech Translation



Most of the models we have seen in this class have been trained with only English data.

Languages vary

Languages can have different scripts

Writing system	Scripts	
Alphabet	Roman	napenda utambuzi wa hotuba
	Greek	Λατρεύω την αναγνώριση ομιλίας
	Cyrillic	Би яриа таних дуртай
	Korean	나는 음성 인식을 좋아해요
Semanto-Phonetic	Chinese	我喜欢语音识别
Syllabic Alphabet	Devanāgarī	मलाई बोली पहिचान मन पछ
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Languages can have lexical tone

The pitch of the word changes the meaning of the word

wá



wọ



wà



wò



Languages can have different dialects

English	I don't know what to do
Jordanian Arabic	مش عارف شو اعمل
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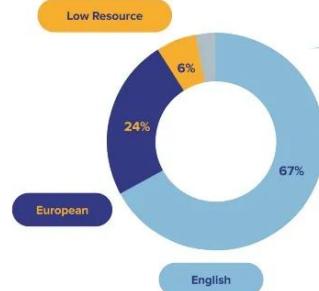
Image from [Bani-Hani et.al., 2017](#)

Languages can have codeswitching

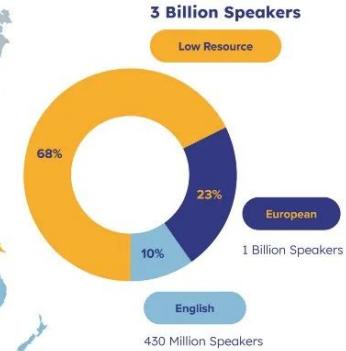


Languages can have can have little data available to train models

NLP Solutions by Language

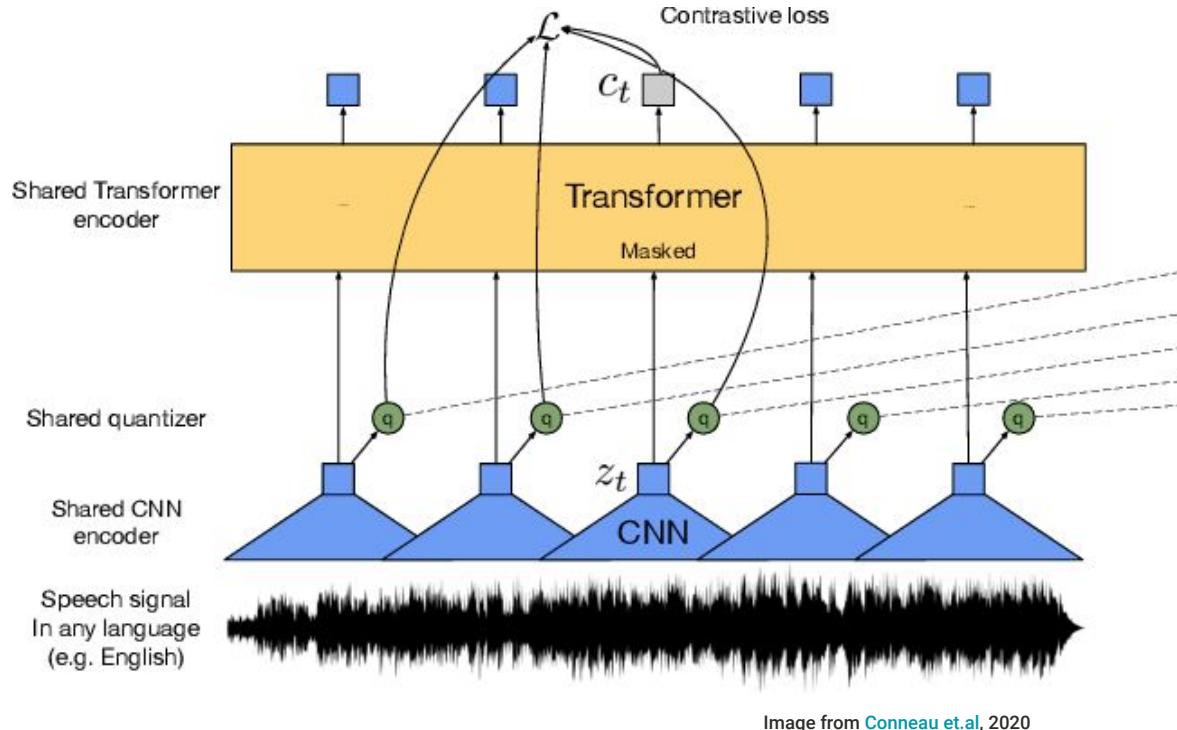


Population Size of Languages



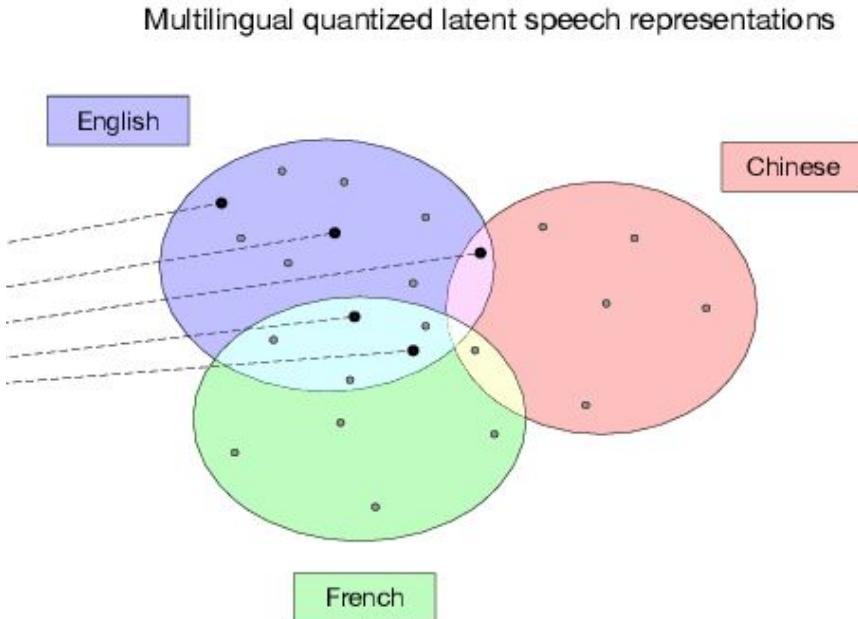
Multilingual large pretrained speech models

Multilingual versions of English-only models: wav2vec 2.0 XLSR



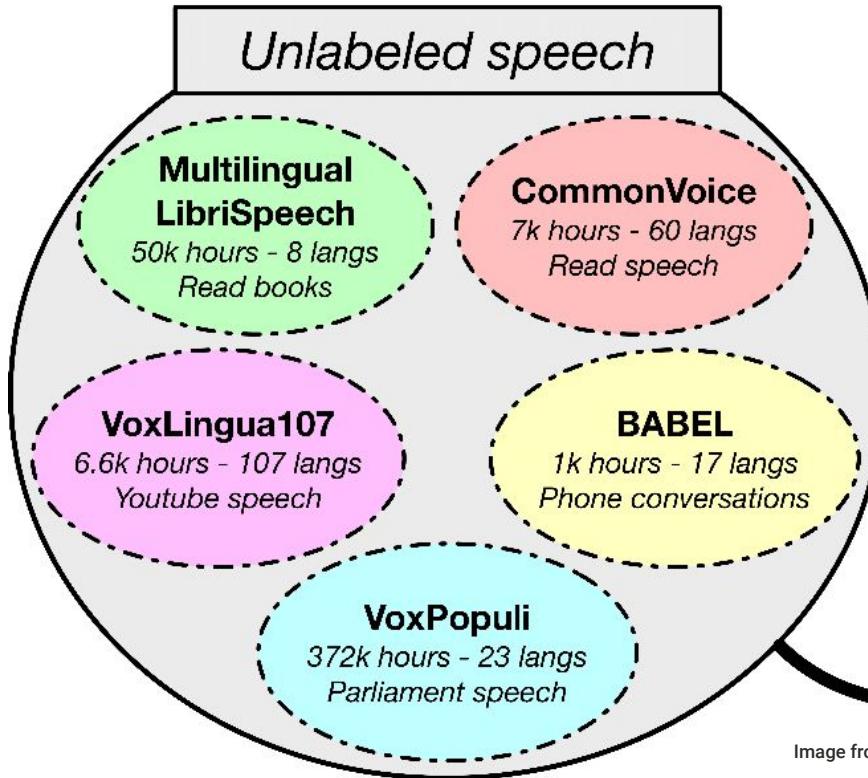
- Trained on Multilingual LibriSpeech, Common Voice and BABEL
- (56,000 hours)
- 53 languages: XLSR-53

Multilingual versions of English-only models: wav2vec 2.0 XLSR



- Latent multilingual speech representations are theorised

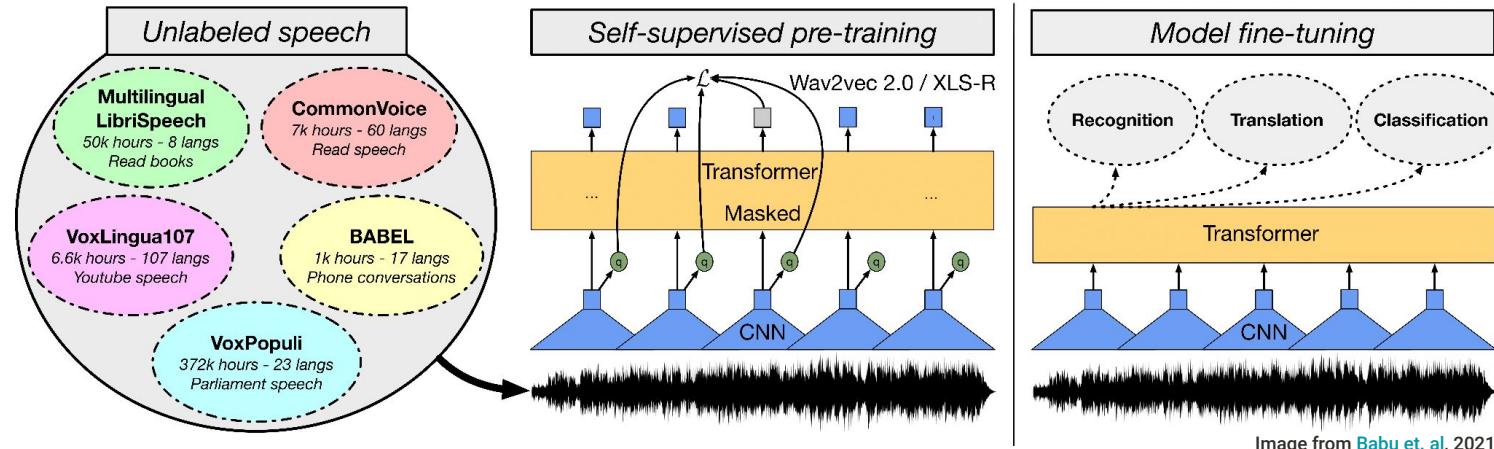
Multilingual versions of English-only models: wav2vec 2.0 XLS-R



- Trained on XLSR datasets and Vox Lingua 107 and Vox Populi, totalling 436,000 hours

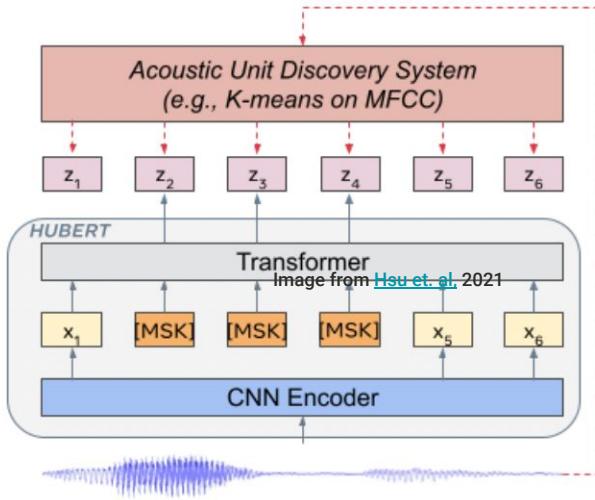
Image from [Babu et. al, 2021](#)

Multilingual versions of English-only models: wav2vec 2.0 XLS-R



- Tested on ASR and AST (Automatic Speech Translation)

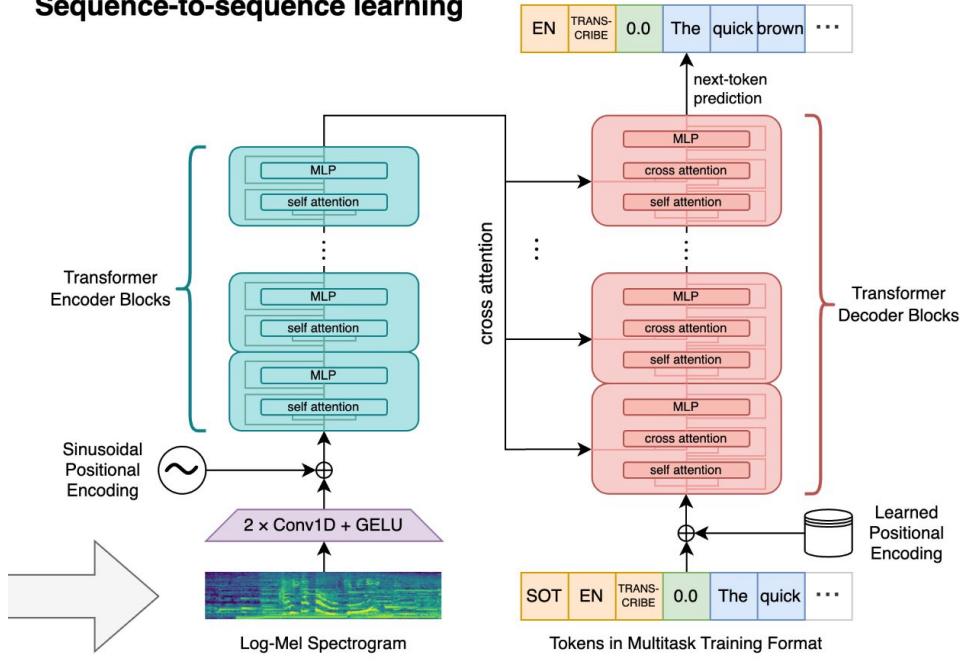
Multilingual versions of English-only models: mHuBERT



- Trained specifically for speech translation in “[Textless Speech-to-Speech Translation on Real Data](#)” (Lee et. al, 2022)
- Trained with the 100,000 hour subset of Vox Populi

Multilingual from the start: Whisper

Sequence-to-sequence learning



- “Multilingual and multitask”
- Trained with 680,000 hours of data
- Training data is not publicly available.

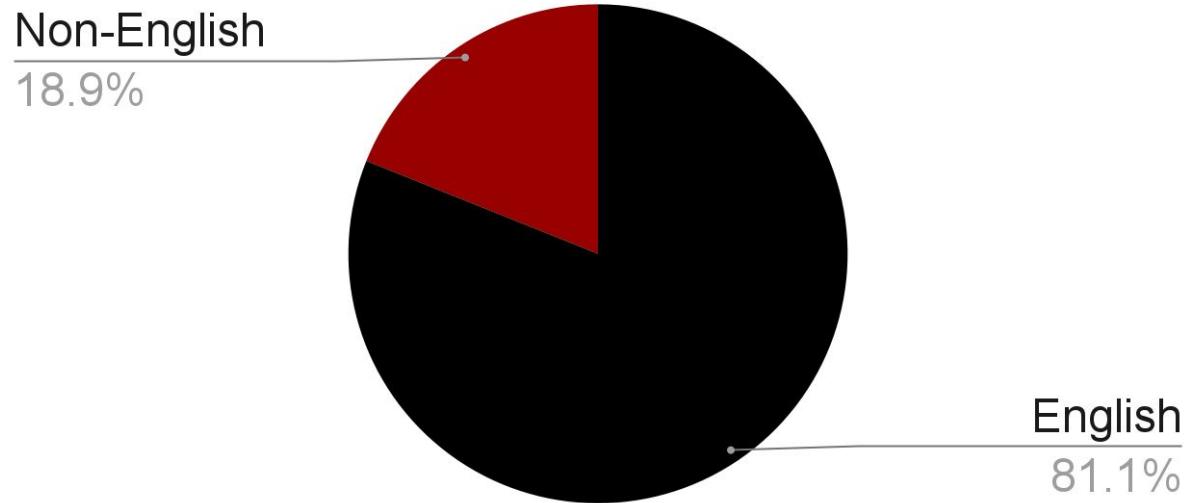
Image from [Radford et. al, 2022](#)

What is the data distribution?

How multilingual are these models?

wav2vec 2.0
XLSR

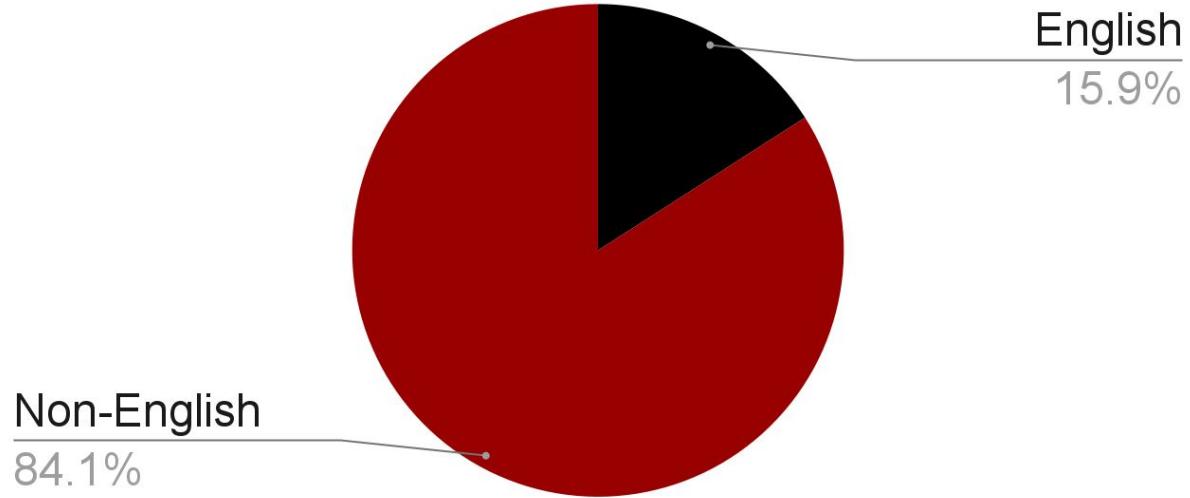
Languages in wav2vec 2.0 XLSR



How multilingual are theses models?

wav2vec 2.0
XLS-R

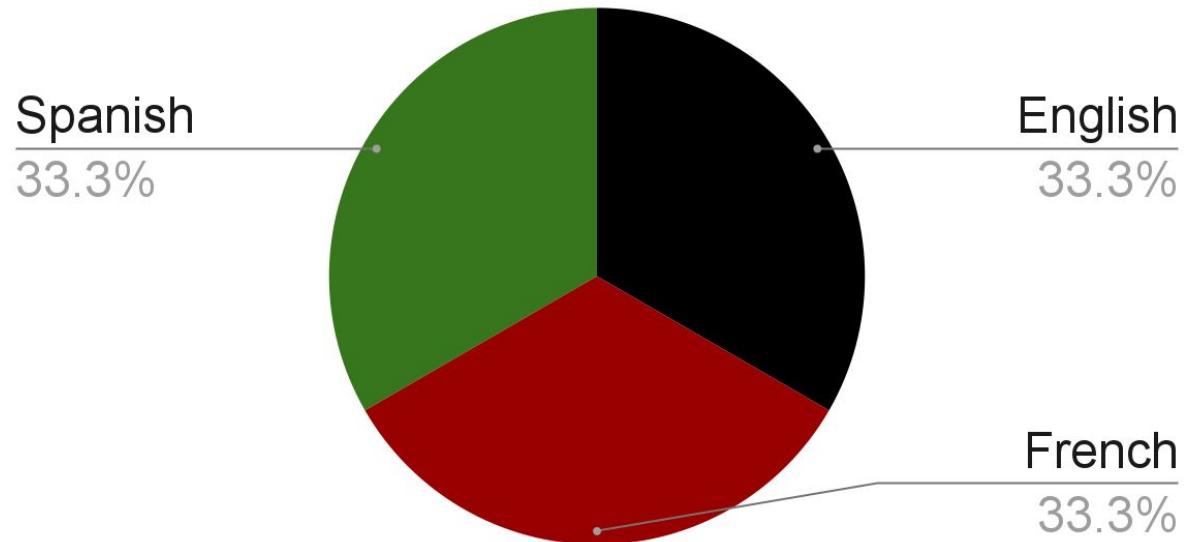
Languages in wav2vec 2.0 XLS-R



How multilingual are these models?

mHuBERT

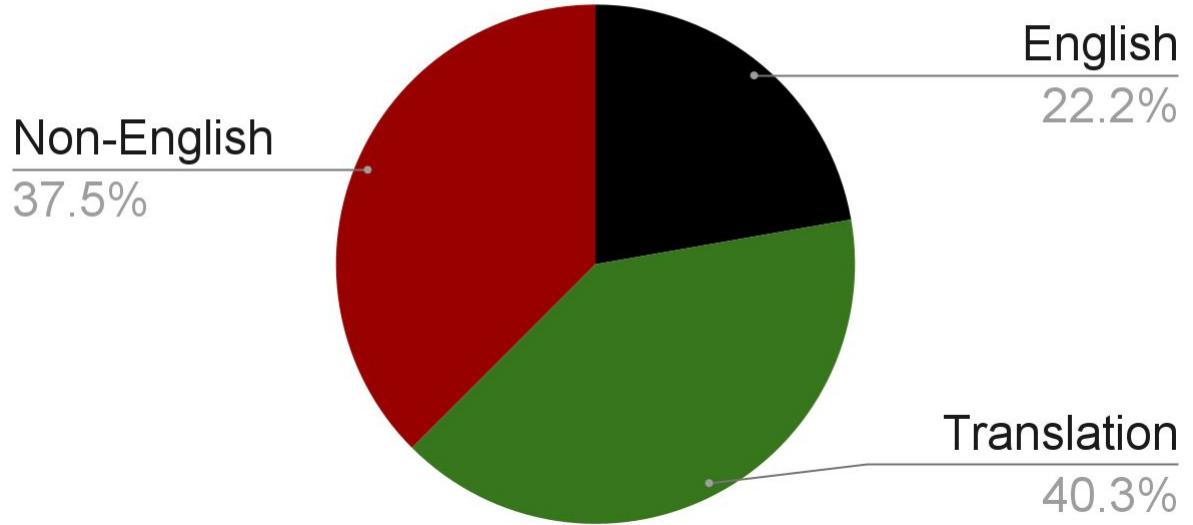
Languages in mHuBERT



How multilingual are these models?

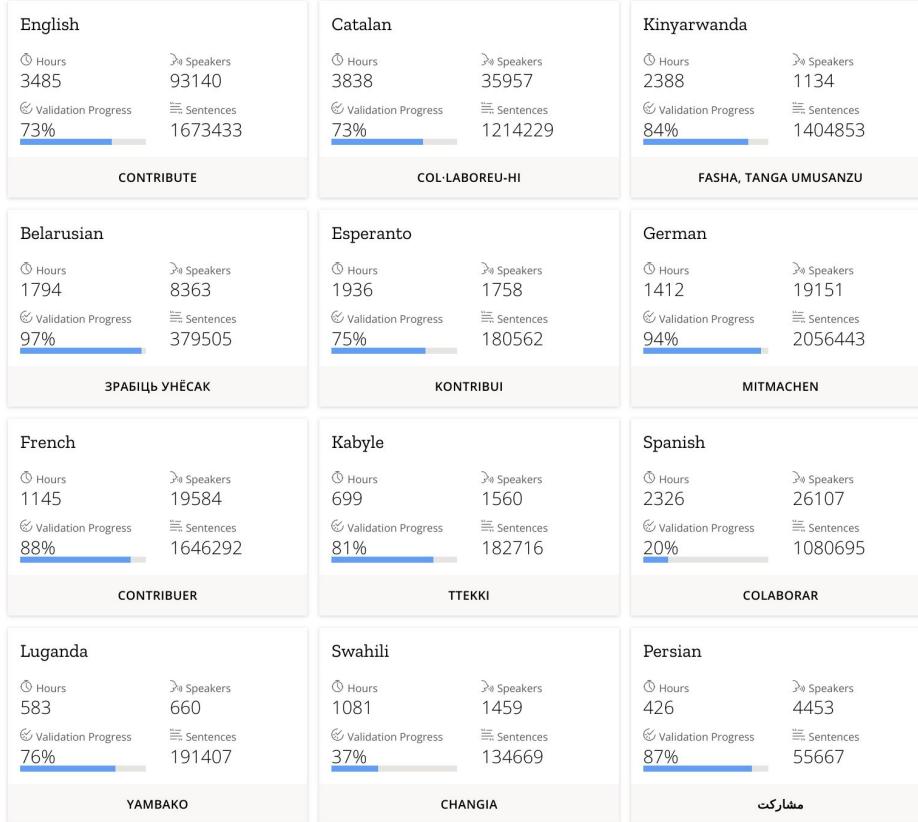
Whisper

Languages in Whisper



Open Source Multilingual Datasets: CommonVoice and Yodas

Common Voice



- Multilingual living dataset
- 30,000 recorded hours covering 124 languages
- Anyone can set up a Common Voice page for their language
- Anyone can record utterances for the dataset
- Dataset is noisier than LibriSpeech due to less controlled recording environments

Common Voice

Marathi Common Voice

Kinyarwanda Common Voice

Attempting to open source datasets: Yodas

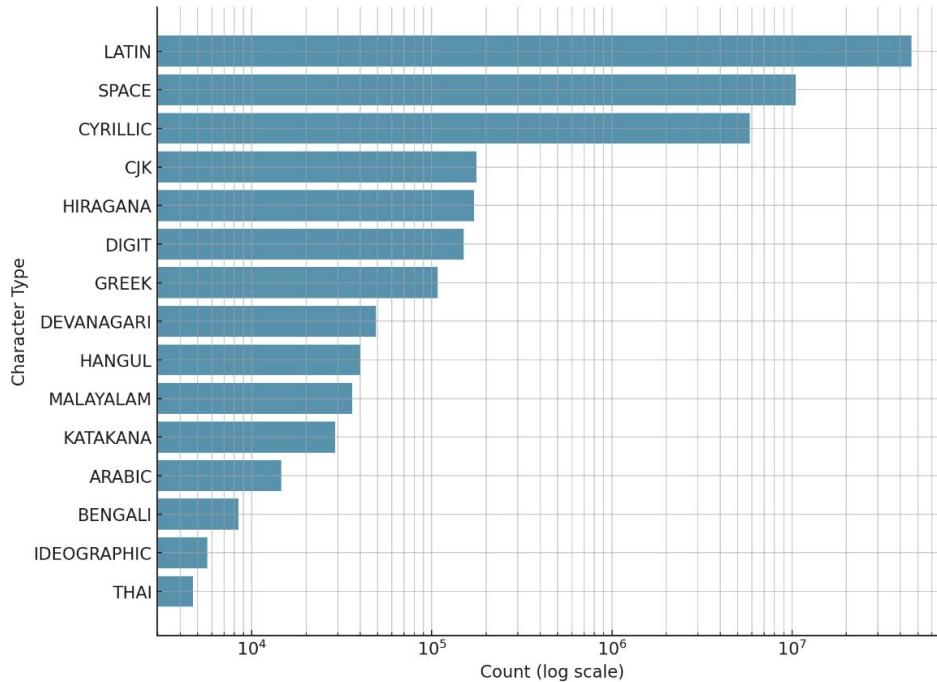


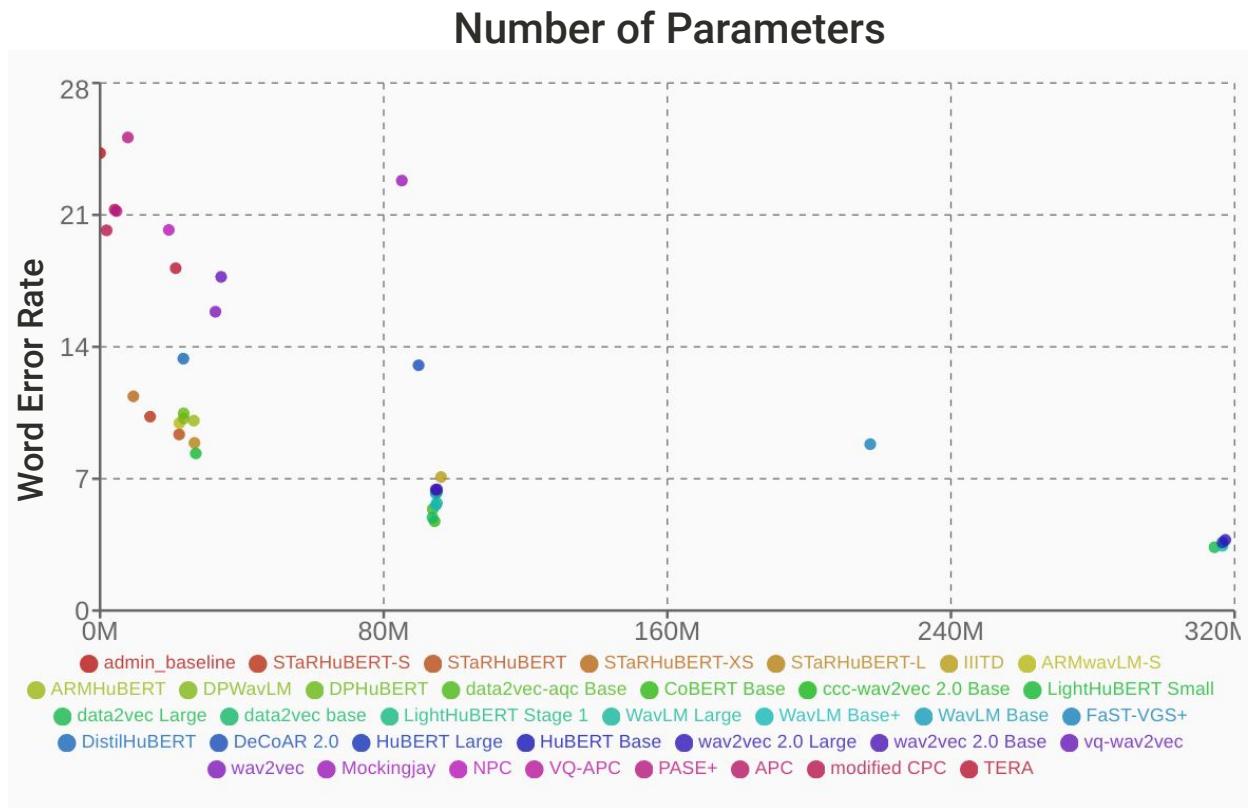
Image from [WAVLab post](#)

- [Youtube-Oriented Dataset for Audio and Speech](#)
- Result of a 6-month crawl of YouTube followed by alignment of transcript to audio.
- 500,000 hours of data across 140 languages.
- 420,000 hours of transcribed data

Benchmarking large models multilingually: ML-SUPERB

SUPERB

Speech processing Universal
PERformance Benchmark



ML-SUPERB

Multilingual Speech
processing Universal
PERformance Benchmark

Automatic speech
recognition and language
identification for 143
languages

Method	Mono-ASR ↓	Multi-ASR (Normal) ↓	Multi-ASR (Few-shot) ↓	LID ↑
HuBERT Base	35.3	31.4	42.7	86.1
HuBERT Large	32.2	37.7	43.5	64.1
Mandarin HuBER...	45.6	43.2	46.6	85.3
Mandarin HuBER...	33.7	39.6	45.1	57.3
Robust wav2vec 2...	35.7	31.1	42.2	72.1

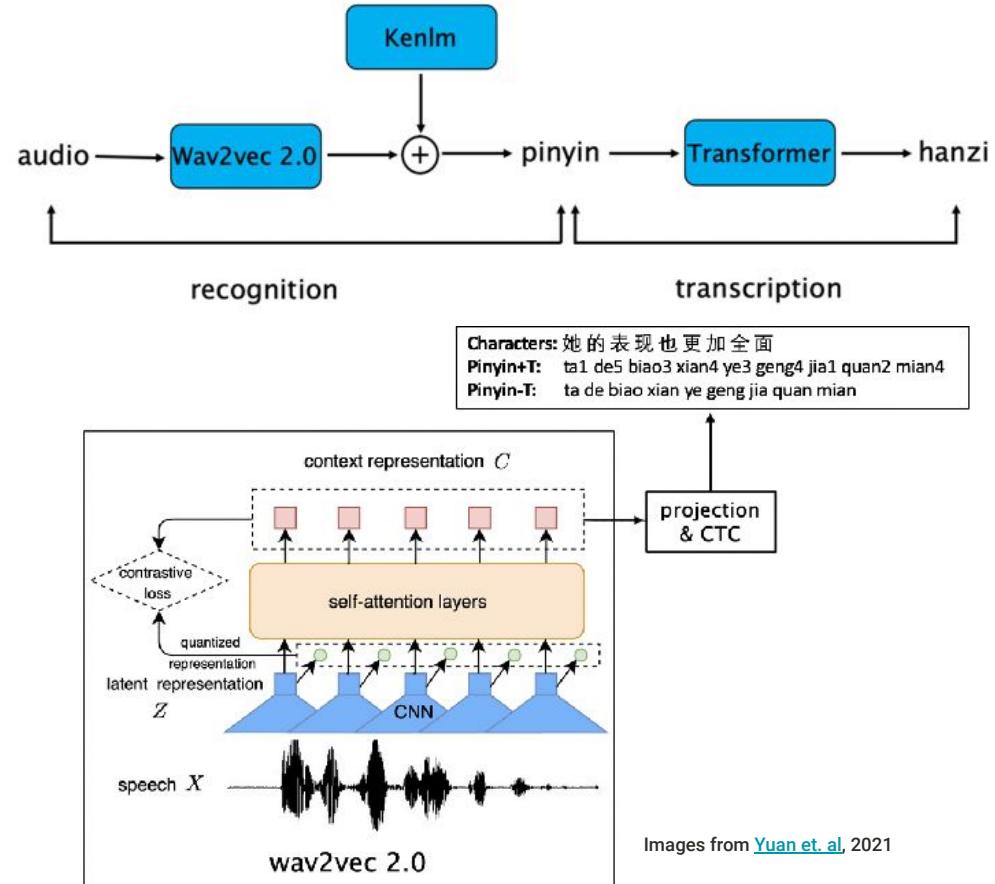
Language-specific techniques

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	Tamil	நான் பேச்சு அங்கீகாரத்தை விரும்புகிறேன்
Abjad	Arabic	أنا أحب التعرف على الكلام
	Hebrew	אני אוהב זיהוי דיבור

Using different representations

Incorporating Pinyin for Mandarin Chinese - intermediary phonetic representation



Images from [Yuan et. al, 2021](#)

Languages can have lexical tone

The pitch of the word changes the meaning of the word

wá



wọ



wà



wò



Tonal languages: can we find tones in the representations?

Shen et. al find that models behave similarly to native and non-native human participants in tone and consonant perception studies, but they do not follow the same developmental trajectory.

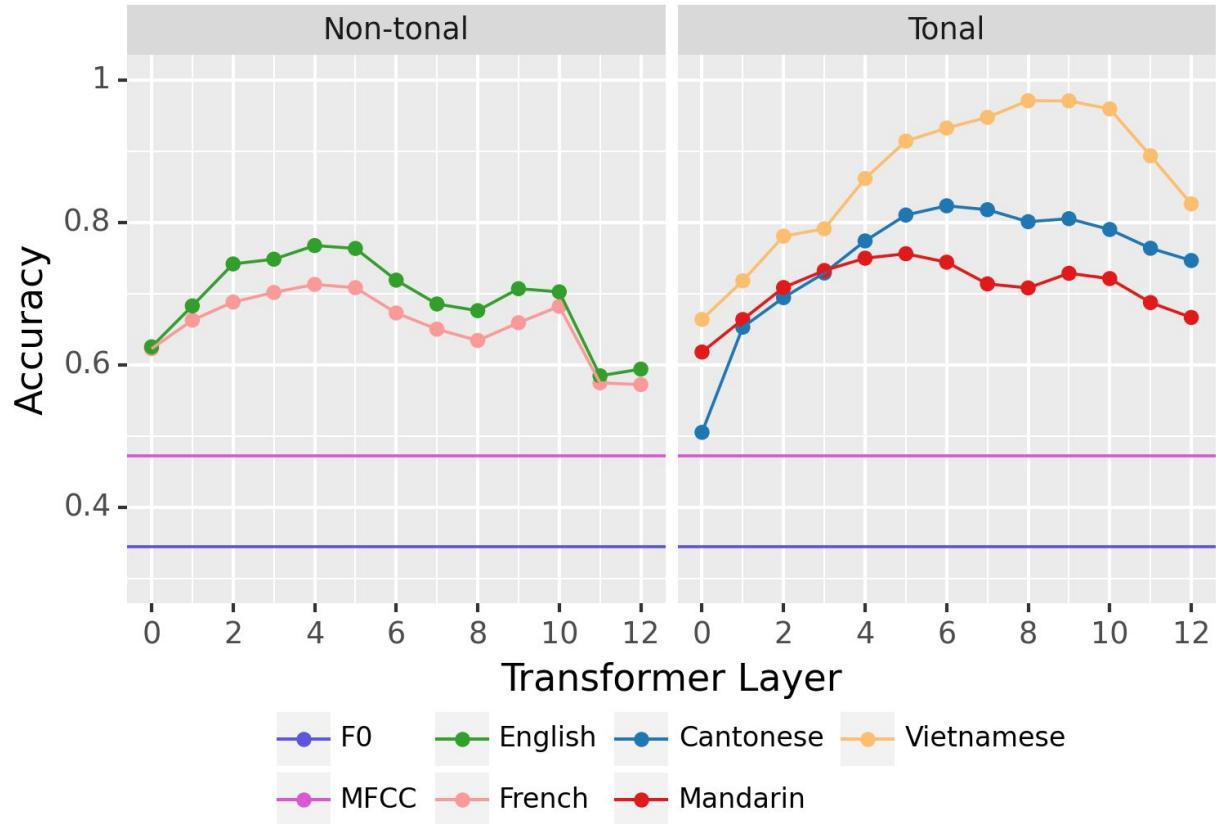


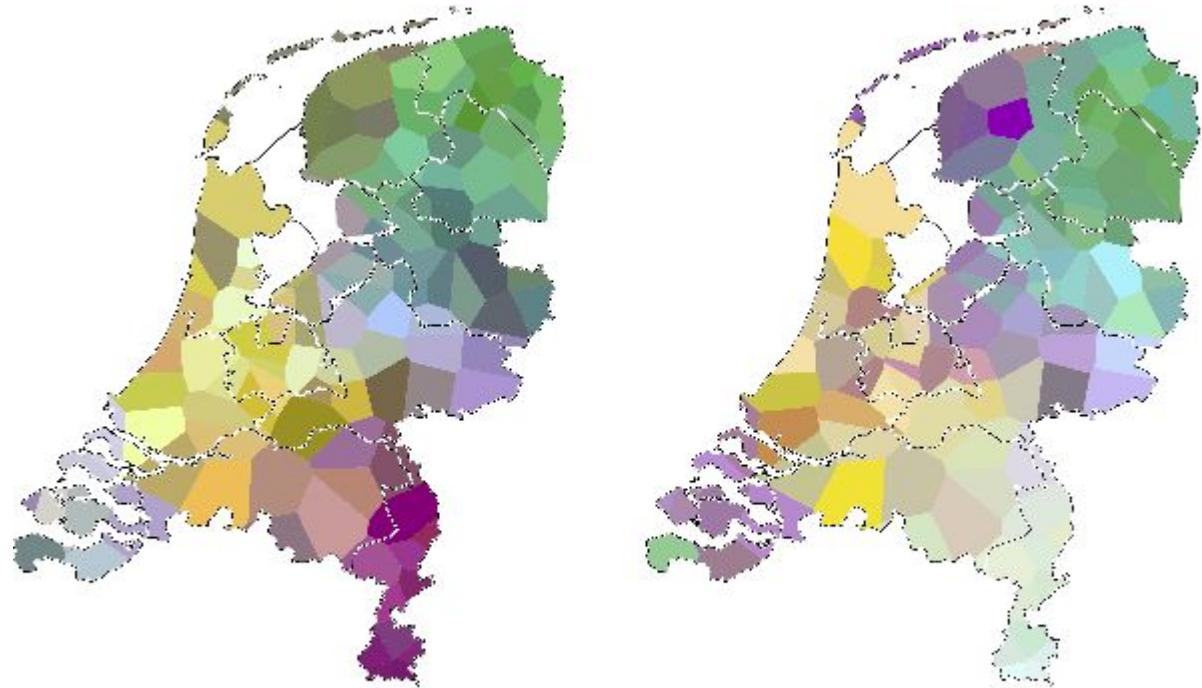
Image from [Shen et. al., 2024](#)

Languages can have different dialects

English	I don't know what to do
Jordanian Arabic	مش عارف شو اعمل
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Image from [Bani-Hani et.al., 2017](#)

Next week!



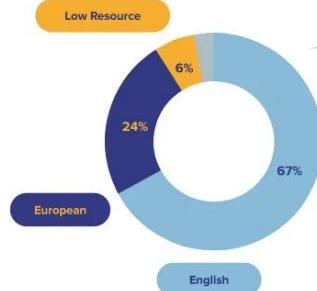
(a) XLSR-n1 layer 15

(b) LD

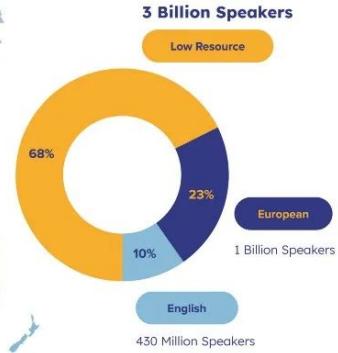
Image from [Bartelds & Wieling, 2022](#)

Languages can have can have little data available to train models

NLP Solutions by Language



Population Size of Languages



Making datasets

ÌròyìnSpeech: A
multi-purpose Yorùbá
Speech Corpus



Making monolingual versions of large pretrained speech models

HUBERT-TR: REVIVING TURKISH AUTOMATIC SPEECH RECOGNITION WITH
SELF-SUPERVISED SPEECH REPRESENTATION LEARNING

Ali Safaya *, *Engin Erzin*

KUIS AI Center
Computer Engineering Department
Koç University

**Using Radio Archives for Low-Resource Speech Recognition:
Towards an Intelligent Virtual Assistant for Illiterate Users**

Moussa Doumbouya,¹ Lisa Einstein,^{1,2} Chris Piech²

¹ GNCode

² Stanford University

moussa@gncode.org, lisae@stanford.edu, piech@cs.stanford.edu

**Different scripts
leverage CTC - no
need for huge
language model**



Languages can have codeswitching



What is code-switching?

The mixing of words, phrases and sentences from two distinct grammatical (sub) systems across sentence boundaries within the same speech event.

(Bokomba, 1988)

I'll tell you exactly when I have to leave, at ten o'clock. **Y**
son las nueve y cuarto.

**Off-the-shelf multilingual models don't work
well in this scenario.**

[Ògúnrèmí et. al, 2023](#)

How can we improve the performance of large multilingual models on code-switched data?

[Ògúnràmí et. al.](#), 2023

Data: South African Soap Opera Clips



Four South-African
languages
code-switched
with English

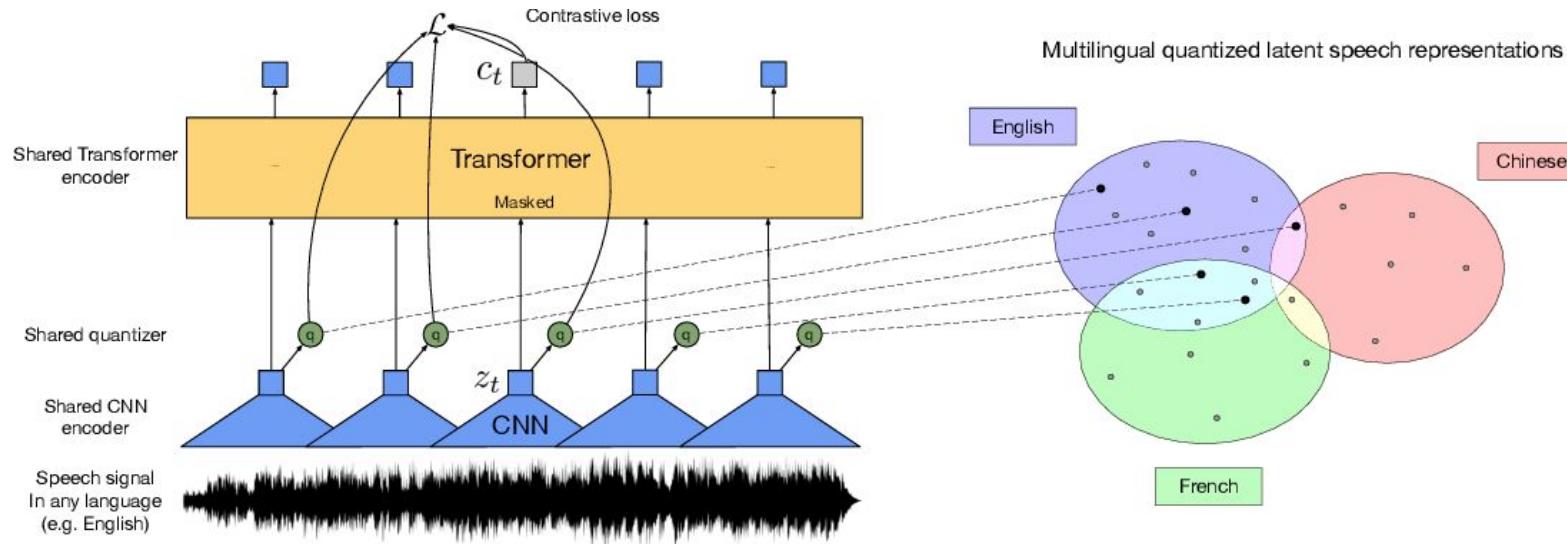
3 - 6 hours per
language

[Ògúnrèmí et. al.](#), 2023

Data: South African Soap Opera Clips

Lang par	Train	Dev	Test	Total
Eng-Zul	4.81h	0.13h	0.51h	5.45h
Eng-Xho	2.68h	0.23h	0.23h	3.14h
Eng-Tsn	2.33h	0.23h	0.30h	2.86h
Eng-Sot	2.36h	0.21h	0.26h	2.83h

Model: wav2vec 2.0 XLSR



[Ógúnrèmí et. al, 2023](#)

Does incorporating language information help?

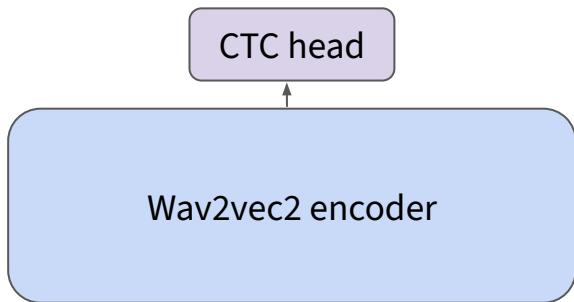
what if etholwa amaphoyisa kuqala

<eng> what if </eng> <zul> etholwa amaphoyisa kuqala TAGS
</zul>

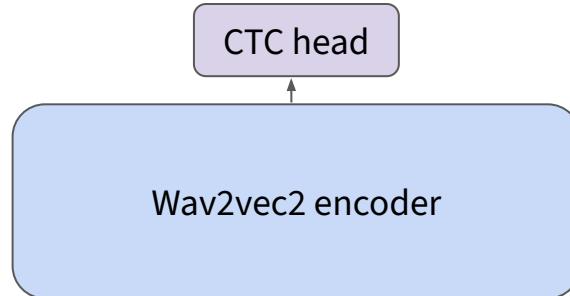
WHAT IF etholwa amaphoyisa kuqala CASING

We fine-tune (with a CTC head) first on the language pair along with additional data, then on the language pair itself

Step 1



Step 2



language +
pair

A: monolingual data
B: the rest of the soap opera
corpus

language
pair

We find that finetuning with utterances in the same domain (soap opera data) but different, neighbouring languages improve performance over finetuning a single language pair.

[Ògúnrèmí et. al](#), 2023

Language is varied

wá

wà

napenda utambuzi wa hotuba

λατρεύω την αναγνώριση ομιλίας

나는 음성 인식을 좋아해요

ମଲାଙ୍କ ବୋଲି ପହିଚାନ ମନ ପଢ଼

ఘంఘంగార్వ జాମాఫుడ

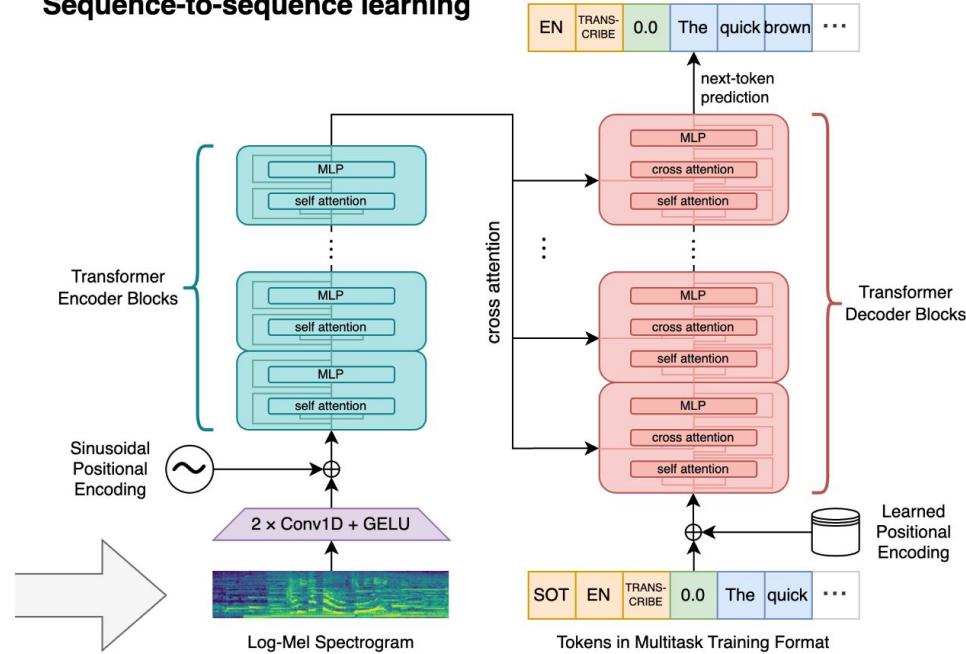
ନ୍ରାଣ୍ ପେଚ୍‌ସ୍ ଆନ୍‌କୀକାରତ୍ତେତ
ବିଗ୍ରମ୍‌ପୁକିରେଣ୍

أنا أحب التعرف على الكلام



**Surprisingly, all
you need to do
is chuck a
bunch of data
into a model.**

Sequence-to-sequence learning



Thank You