





On the Nature of Discrete Speech Representations in Multilingual Self-supervised Models

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Language Science and Technology [**LST**]
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Multilingual Self-supervised Speech Models

- **Self-supervision** is an effective paradigm for learning representations of spoken language from raw, **untranscribed audio**
- Self-supervised speech models can be pre-trained on a large sample of languages
 - multilingual models with transferable representations across languages
 - → facilitate transfer learning for **low-resource languages**
- A **shared quantization module** within the model's architecture
 - transforms the continuous acoustic input into a sequence of discrete units

Multilingual XLSR-53 Model

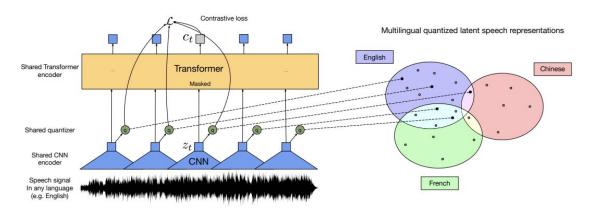


Figure 1: **The XLSR approach.** A shared quantization module over feature encoder representations produces multilingual quantized speech units whose embeddings are then used as targets for a Transformer trained by contrastive learning. The model learns to share discrete tokens across languages, creating bridges across languages. Our approach is inspired by Devlin et al. (2018); Lample & Conneau (2019) and builds on top of wav2vec 2.0 (Baevski et al., 2020c). It requires only raw unlabeled speech audio in multiple languages.

Research Question



Do the discrete units learned by a multilingual speech model represent the same speech sounds across languages?

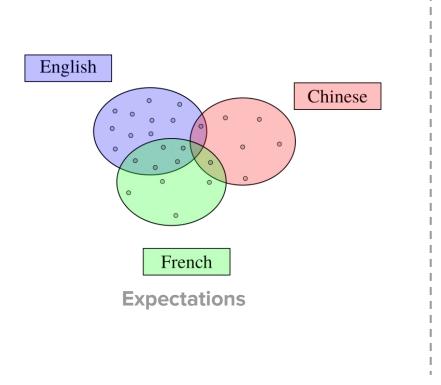
					or	

do they differ based on the specific language being spoken?

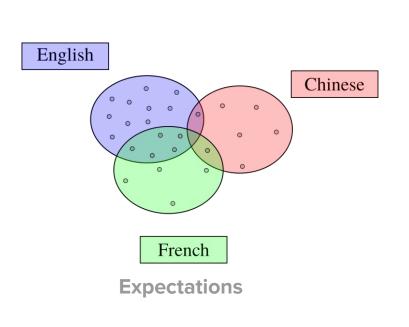
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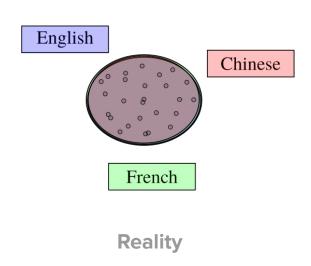
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Discrete Speech Representations



Discrete Speech Representations





(Revised) Research Question

English

Can we predict the language of the speaker from the discrete representation of the utterance?

French

Expectations

French

Reality

(Revised) Research Question

English

Can we predict the language of the speaker from the discrete representation of the utterance?

Spoken Language Identification (SLID) as a probing task

Expectations

Reality

Language Sample

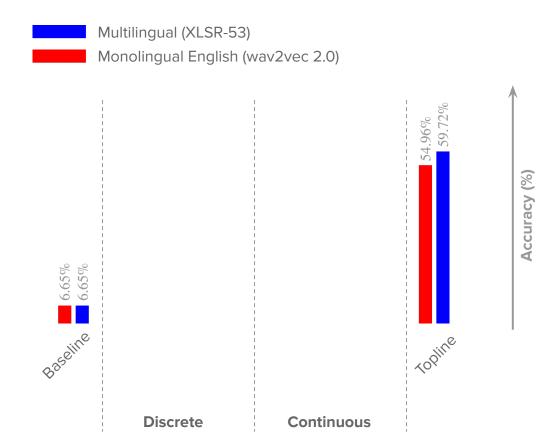
Common Voice speech corpus

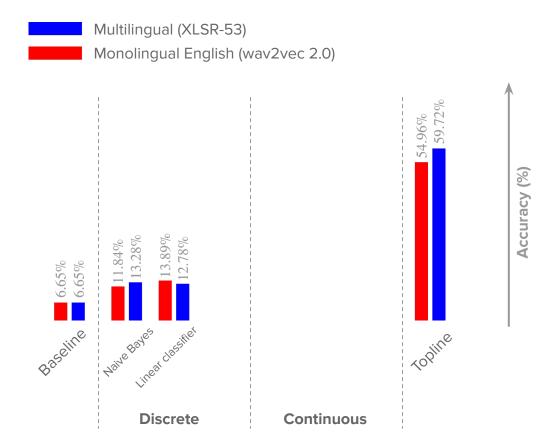
16 Indo-European languages

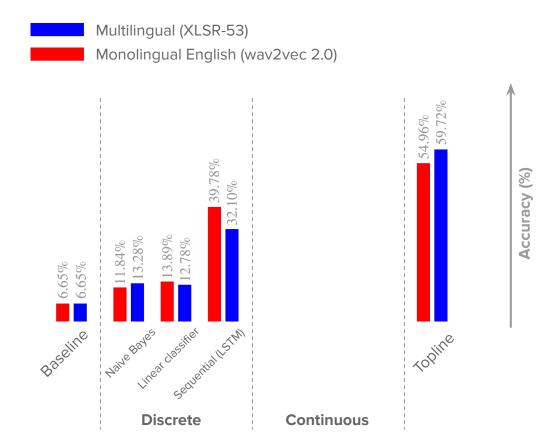
Romance
Catalan
Portuguese
French
Spanish
Italian

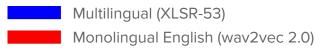
Germanic German Dutch Swedish Frisian Slavic Ukrainian Russian Polish

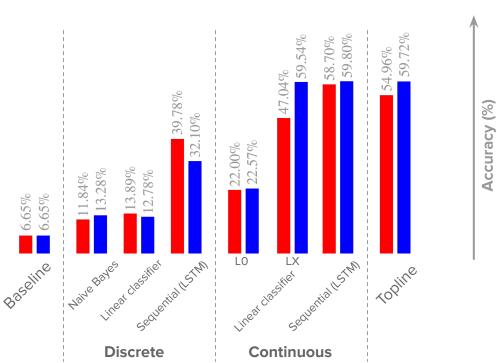
Celtic Welsh Breton Hellenic Greek Indo-Iranian Persian













Latent discrete speech representations correspond to language-universal sub-phonetic events, rather than language-specific, abstract phonemic categories





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