Quantized Multilingual Pre-Training in USM and Its Impact on Speech-Text Alignment and Downstream Task Transferability

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How does USM's quantized multilingual pre-training affect the alignment of speech and text representations, and what downstream task transferability is observed on language identification or speaker. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Comparison of Self-Supervised Speech Pre-Training Methods on Flemish Dutch. Research question: How does USM's quantized multilingual pre-training affect the alignment of speech and text representations, and what downstream task transferability is observed on language identification or speaker verification compared to non-quantized baselines on benchmarks like VoxCeleb and ML-LID?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

14 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 3.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The APC model uses a Filterbank feature encoder, a GRU aggregator, and aims to reconstruct future frames with an output	×	0.03
The Mockingjay model uses a Filterbank feature encoder, a Bidirectional Transformer aggregator, and aims to reconstruct	×	0.03
The CPC model uses a CNN feature encoder, an LSTM aggregator, and aims to identify future features with an output dimens	×	0.04
The wav2vec model uses a CNN feature encoder, a CNN aggregator, and aims to identify future features with an output dime	×	0.03
The wav2vec 2.0 base model has an output dimension of 768 and contains 95.0M parameters.	×	0.02
The wav2vec 2.0 large model has an output dimension of 1024 and contains 317.3M parameters.	×	0.03
Wav2vec 2.0 combines ideas from wav2vec, vq-wav2vec, and Masked Language Modeling (MLM).	×	0.05
The wav2vec 2.0 encoder computes latent speech representations from the raw waveform using 7 temporal convolution blocks	×	0.03
In wav2vec 2.0, a certain proportion of latent features is masked before being fed to the Transformer aggregator.	×	0.02
In wav2vec 2.0, a quantisation module maps latent feature vectors to discretised versions.	×	0.02
The wav2vec 2.0 training objective is to distinguish the true quantised representation for a masked time step given the	×	0.05
The wav2vec 2.0 base architecture contains 12 Transformer blocks in the aggregator.	×	0.03
The wav2vec 2.0 large architecture contains 24 Transformer blocks in the aggregator.	×	0.02
Contextual features at the output of the wav2vec 2.0 aggregator are duplicated in time to mimic a stride of 10ms instead	×	0.04
Finetuning wav2vec 2.0 on a labelled set involves adding an extra linear layer on top of the context network and applyin	×	0.02

References

- http://arxiv.org/abs/2109.14357v1
- http://arxiv.org/abs/2012.06185v2
- http://arxiv.org/abs/2209.15329v3