

# Linguistic Diversity Impact on Multilingual Self-Supervised Speech Models

Assignee Research

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## Abstract

Self-supervised learning (SSL) has transformed speech processing, yet its reliance on massive pre-training datasets remains a bottleneck. While robustness is often attributed to scale and diversity, the role of the data distribution is less understood. We systematically examine how curated subsets of pre-training data influence Automatic Speech Recognition (ASR) performance. Surprisingly, optimizing for acoustic, speaker, or linguistic diversity yields no clear improvements over random sampling. Instead, we find that prioritizing the longest utterances achieves superior ASR results while using

## 1 Introduction

This paper examines: A Study of Data Selection Strategies for Pre-training Self-Supervised Speech Models. Research question: How does the linguistic diversity of pre-training data influence the multilingual capabilities of self-supervised speech models, as evaluated by WER on the MLS and Babel benchmarks?.

## 2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.5/10.

## 3 Results

9 papers retrieved. 21 claims extracted; 19 independently verified. Quality review score: 7.5/10.

## 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 |
|-------------------------------------------------------------------------------------------------------------------------------|----------|------------|
| Diversity-based sampling methods did not yield significant improvements over the baseline.                                    | ✓        | 0.19       |
| The speaker-based method on the large split achieved a word error rate of 17.97 on the test set.                              | ✓        | 0.29       |
| The random baseline achieved a word error rate of 18.54 on the test set.                                                      | ✓        | 0.19       |
| The all baseline achieved a word error rate of 18.08 on the test set.                                                         | ✓        | 0.18       |
| Utterance length-based methods consistently outperformed both baselines.                                                      | ✓        | 0.19       |
| On the medium split, selecting the longest utterances reduced the word error rate to 19.02 on the test set.                   | ✓        | 0.27       |
| Combining speaker diversity with utterance length further improved performance to 18.97 on the test set.                      | ✓        | 0.23       |
| On the large split, length-based sampling methods reached 17.77 and 17.42 word error rates, respectively.                     | ✓        | 0.27       |
| Length-based sampling substantially reduced pre-training time by about 24% compared to the all baseline.                      | ✓        | 0.20       |
| The best performing models were pre-trained on subsets consisting of longer utterances.                                       | ✓        | 0.19       |
| The combined method (speaker diversity with utterance length) performed best overall.                                         | ✓        | 0.17       |
| The gains over length-only sampling were relatively small.                                                                    | ✓        | 0.16       |
| Training times for the medium split were similar across all methods.                                                          | ✓        | 0.18       |
| Length-based sampling methods trained about 24% faster on the large split compared to the all baseline.                       | ✓        | 0.21       |
| The dynamic batching strategy with longer utterances lowers per-step computational cost.                                      | ✓        | 0.21       |
| Prior experiments in the Loquacious dataset used models of similar size but with a conformer encoder-decoder architecture     | ✓        | 0.25       |
| The 100M parameter supervised model provides a useful reference for comparison.                                               | ✓        | 0.16       |
| Enforcing diversity in the pre-training data yields no significant improvement in downstream ASR performance.                 | ✓        | 0.21       |
| Selecting the longest utterances for pre-training achieves superior ASR performance while requiring only half of the original | ✓        | 0.24       |
| Length-based sampling reduces pre-training time by 24% on a large-scale corpus.                                               | ×        | 0.14       |
| Code used in the experiments is made public for                                                                               | ×        | 0.12       |

## References

- <http://arxiv.org/abs/2601.20896v2>
- <http://arxiv.org/abs/2509.05359v1>
- <http://arxiv.org/abs/2604.22203v1>