# Artificial Code-Switching for Cross-Lingual Embedding Alignment

Assignee Research

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**Abstract**

Using task-specific pre-training and leveraging cross-lingual transfer are two of the most popular ways to handle code-switched data. In this paper, we aim to compare the effects of both for the task of sentiment analysis. We work with two Dravidian Code-Switched languages - Tamil-Engish and Malayalam-English and four different BERT based models. We compare the effects of task-specific pre-training and cross-lingual transfer and find that task-specific pre-training results in superior zero-shot and supervised performance when compared to performance achieved by leveraging cross-lingual transfe

## 1 Introduction

This paper examines: Task-Specific Pre-Training and Cross Lingual Transfer for Code-Switched Data. Research question: Does incorporating artificially code-switched data during pre-training improve the alignment of multilingual embedding spaces for cross-lingual semantic textual similarity tasks compared to standard parallel data augmentation?.

## 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 7.5/10.

## 3 Results

14 papers retrieved. 10 claims extracted; 7 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 |
|---|---|---|
| The best performing systems for Tamil-English and Malayalam-English sentiment analysis tasks were built on top of BERT v | ✓ | 0.22 |
| The TweetEval sentiment classifier was trained on a dataset of 60M English Tweets. | ✓ | 0.16 |
| The underlying RoBERTa model in TweetEval was trained on English data and has 160M parameters. | ✓ | 0.19 |
| The Tamil-English dataset contains 10,559 positive, 2,037 negative, and 850 neutral samples. | × | 0.11 |
| The Malayalam-English dataset contains 2,811 positive, 738 negative, and 1,903 neutral samples. | × | 0.09 |
| The Hinglish dataset contains 6,616 positive, 5,892 negative, and 7,492 neutral samples. | × | 0.09 |
| Previous works have shown that mBERT and XLM-RoBERTa based models achieve state of the art performance when dealing with | ✓ | 0.23 |
| The uncased-base XLM-RoBERTa model was trained on 2.5TB of webcrawled data. | ✓ | 0.27 |
| The TweetEval model is a monolingual model trained on an out-of-domain dataset for the task of sentiment analysis of Tam | ✓ | 0.26 |
| The evaluation metrics used are weighted average scores of precision, recall, and F1, calculated based on the number of | ✓ | 0.28 |

## References


- http://arxiv.org/abs/2102.12407v1
- http://arxiv.org/abs/2402.13991v1

- http://arxiv.org/abs/2504.02268v1