Enhancing Low-Resource Code Generation via SALT on MultiPL-E Compared to Parallel Corpus Training

Assignee Research

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Abstract

Large language models have demonstrated the ability to generate both natural language and programming language text. Such models open up the possibility of multi-language code generation: could code generation models generalize knowledge from one language to another? Although contemporary code generation models can generate semantically correct Python code, little is known about their abilities with other languages. We propose MultiPL-E, a system for translating unit test-driven code generation benchmarks to new languages. We create the first massively multilingual code generation benchmark by

1 Introduction

This paper examines: MultiPL-E: A Scalable and Extensible Approach to Benchmarking Neural Code Generation. Research question: Does the SALT approach enhance code generation performance in low-resource programming languages when evaluated on the MultiPL-E benchmark compared to models trained with parallel corpora?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.6/10.

3 Results

13 papers retrieved. 10 claims extracted; 10 independently verified. Quality review score: 8.6/10.

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
HumanEval is a diverse collection of 164 problems, where all problems have tests to check correctness, and most have exa	✓	0.27
The best model evaluated by Fried et al. achieves only a 36% pass rate on Python.	✓	0.29
MBPP is another large, commonly used benchmark of Python problems.	✓	0.22
MultiPL-E supports 19 programming languages, which we categorize into four frequency classes (NICHE, LOW, MEDIUM, or HIG	✓	0.31
Eight of the languages in MultiPL-E had never been used before to measure NL2Code performance.	✓	0.20
MultiPL-E translates unit tests, doctests, Python-specific terminology, and type annotations.	✓	0.19
MultiPL-E provides two parallel benchmarks for code generation in 19 languages encompassing a variety of programming par	✓	0.27
MultiPL-E includes a multi-language parallel evaluation of three models, Codex, InCoder, and CodeGen.	✓	0.18
MultiPL-E explores language frequency effects, the impact of type annotations, and prompt translation sensitivity on cod	✓	0.25
The MultiPL-E system, dataset, and tutorial are available at github.com/nuprl/MultiPL-E.	✓	0.20

References

- `http://arxiv.org/abs/2208.08227v4`

- http://arxiv.org/abs/2412.10008v1
- http://arxiv.org/abs/1603.06785v1