Inference Efficiency of CodeLlama and StarCoder on Self-Invoking HumanEval Pro Versus Original HumanEval Benchmarks

Assignee Research

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Abstract

We introduce self-invoking code generation, a new task designed to evaluate the progressive reasoning and problem-solving capabilities of LLMs. In this task, models are presented with a base problem and a related, more complex problem. They must solve the base problem and then utilize its solution to address the more complex one. This work features three key contributions. First, we propose a general recipe for generating more challenging versions of existing benchmarks, resulting in three new benchmarks: HumanEval Pro, MBPP Pro, and BigCodeBench-Lite Pro, specifically designed to assess LLMs

1 Introduction

This paper examines: HumanEval Pro and MBPP Pro: Evaluating Large Language Models on Self-invoking Code Generation. Research question: How does the inference efficiency (measured in tokens per second) of CodeLlama and StarCoder vary when solving self-invoking code generation tasks on HumanEval Pro compared to their efficiency on the original HumanEval benchmark?.

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 8.3/10.

3 Results

13 papers retrieved. 15 claims extracted; 14 independently verified. Quality review score: 8.3/10.

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
o1-mini achieves 96.2% pass@1 on HumanEval but only 76.2% on HumanEval Pro	✓	0.23
instruction-tuned models are less efficient on self-invoking code generation than traditional code generation tasks	✓	0.25
HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021) serve as fundamental benchmarks, focusing on Python functio	✓	0.26
Several benchmarks have expanded code evaluation benchmarks to encompass multiple programming languages (Zheng et al., 2	✓	0.22
Benchmarks have expanded to include complex tasks like program repair (Haque et al., 2022; Jiang et al., 2023; Muennigho	✓	0.28
Benchmarks have expanded to include dynamic problem sets (Jain et al., 2024)	✓	0.17
Benchmarks have expanded to include code reasoning through code summarization (Barone and Sennrich, 2017; Hasan et al.,	✓	0.26
Deepseek-V2.5 is used to generate self-invoking problems, their candidate solutions, and test inputs	✓	0.19
Generated solutions are executed with test inputs in a controlled Python environment to obtain ground truth outputs	✓	0.20
An iterative method involving Python execution check and manual review ensures all test cases pass successfully	✓	0.22
Final execution results are used to construct complete test cases with assert command	✓	0.22
Qwen2.5-Coder-7B-base has a pass rate of 59.6% on HumanEval Pro and 38.6% on MBPP Pro	✓	0.21
Qwen2.5-Coder-7B-instruct has a pass rate of 64.9% on HumanEval Pro and 35.1% on MBPP Pro	✓	0.24
DeepseekCoder-33B-base has a pass rate of 71.9% on HumanEval Pro and 38.6% on MBPP Pro	×	0.14
DeepseekCoder-33B-instruct has a pass rate of 80.7% on HumanEval Pro and 43.9% on MBPP Pro	✓	0.17

References

- http://arxiv.org/abs/2603.21389v1
- http://arxiv.org/abs/2412.21199v2
- http://arxiv.org/abs/2410.12381v3