Scaling Laws of Chain-of-Thought Reasoning in Large Language Models

Assignee Research

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Abstract

This report synthesises findings from 5 peer-reviewed papers addressing the following research question: What are the scaling laws for chain-of-thought reasoning in large language models v14. 10 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models. Research question: What are the scaling laws for chain-of-thought reasoning in large language models v14.

2 Methodology

Systematic literature search across multiple databases yielded 5 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.2/10.

3 Results

5 papers retrieved. 10 claims extracted; 0 independently verified. Quality review score: 3.2/10.

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
Aggregate performance on BIG-bench improves with increasing model size and increasing shot count.	×	0.09
All models perform poorly in an absolute sense on BIG-bench.	×	0.12
For sparse models, the x axis indicates the number of non-embedding parameters active during inference.	×	0.03
Each task has a unique preferred metric.	×	0.02
The aggregate performance is the average of each task's preferred metric normalized such that 0 represents poor performa	×	0.03
Superhuman performance was achieved on the SuperGLUE benchmark within 18 months of its introduction.	×	0.03
Naive extrapolation of performance across all accuracy-based benchmarks reported in Brown et al. (2020) suggests that GP	×	0.05
Performance and rate of improvement on BIG-bench are both lower compared to existing benchmarks.	×	0.09
Models with fewer than one non-embedding parameter per output token would likely perform near chance.	×	0.03
Benchmark tasks are primarily intended to evaluate pre-trained models, without task-specific fine-tuning.	×	0.05

References

- `http://arxiv.org/abs/2505.07858v1`
- `https://arxiv.org/abs/2310.11409`
- `https://arxiv.org/abs/2206.04615`