Scaling Effects on Adversarial Robustness in Contrastive vs. MLM Pretraining for Code Generation

Assignee Research

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Abstract

Retrieval-augmented generation (RAG) improves language model (LM) performance by providing relevant context at test time for knowledge-intensive situations. However, the relationship between parametric knowledge acquired during pretraining and non-parametric knowledge accessed via retrieval remains poorly understood, especially under fixed data budgets. In this work, we systematically study the trade-off between pretraining corpus size and retrieval store size across a wide range of model and data scales. We train OLMo-2-based LMs ranging from 30M to 3B parameters on up to 100B tokens of DCLM

1 Introduction

This paper examines: To Memorize or to Retrieve: Scaling Laws for RAG-Considerate Pretraining. Research question: How does the scaling of model size affect the adversarial robustness gap between contrastive pretraining and MLM pretraining for code generation, as measured by accuracy on the HumanEvalFix benchmark under increasing perturbation magnitudes?.

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 8.7/10.

3 Results

13 papers retrieved. 16 claims extracted; 15 independently verified. Quality review score: 8.7/10.

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 evaluation framework used is a retrieval-augmented variant of EleutherAI's lm-evaluation-harness, called RAG-Evaluat	✓	0.19
The benchmarks used for evaluation include AI2-ARC (Easy and Challenge), HellaSwag, OpenBookQA, SciQ, Natural Questions,	×	0.14
The top-k passages retrieved for evaluation is set to k = 5, chosen via a small pilot sweep as a trade-off between retri	✓	0.19
The retriever is frozen and shared across all evaluations to isolate the effect of retrieval scale and query formulation	✓	0.20
Two metrics are evaluated: accuracy (acc) and perplexity (PPL).	✓	0.16
Accuracy is computed by selecting the answer choice with the highest total log-likelihood and comparing it to the ground	✓	0.26
Perplexity (PPL) is used as the primary metric because it provides a continuous, length-normalized measure of model perf	✓	0.21
Perplexity is computed as the average log-likelihood per token of the gold answer continuation, reported as exp(-mean lo	✓	0.24
The OLMo-2 series of LMs is used for experiments due to its strong empirical performance, alignment with open research p	✓	0.22
OLMo-2 model sizes defined and pretrained include 30M, 136M, 233M, 728M, 1B, and 3B parameters.	✓	0.18
100B tokens of DCLM data are used as the pretraining corpus.	✓	0.16
Models are trained using AdamW with a 3 $\times$ 10-4 peak learning rate, β1 = 0.9, β2 = 0.95, and 0.1 weight decay.	✓	0.22
A warmup-stable-decay (WSD) schedule is adopted with 10% linear warmup (capped at 2k steps), a stable phase, and 10% lin	✓	0.33
Models are evaluated every 2k steps and at the end of training.	✓	0.19
Retrieval indices are constructed across multiple scales (1B–20B tokens) via FAISS from a held-out slice of DCLM.	✓	0.22
For each target budget (e.g., 30M,460M, etc.), the shortest prefix of a seeded random permutation whose cumulative token	✓	0.35

References

- http://arxiv.org/abs/2604.00715v1
- http://arxiv.org/abs/2103.15670v3
- http://arxiv.org/abs/2008.07651v1