Reciprocal vs. Batch Normalization Efficiency in Code Generation Models

Assignee Research

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Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: What is the efficiency trade-off between using reciprocal normalization versus standard batch normalization in code generation models when evaluated on inference latency and throughput for tasks. Current search techniques are limited to standard RAG query-document applications. In this paper, we propose a novel technique to expand the code and index for predicting the required APIs, directly enabling high-quality, end-to-end code generation for auto-completion and. 13 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: DeepCodeSeek: Real-Time API Retrieval for Context-Aware Code Generation. Research question: What is the efficiency trade-off between using reciprocal normalization versus standard batch normalization in code generation models when evaluated on inference latency and throughput for tasks requiring library-specific API calls?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

10 papers retrieved. 13 claims extracted; 0 independently verified. Quality review score: 3.8/10.

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 model successfully retrieves the correct ArrayUtil API as the top result.	×	0.03
The abstraction to natural language causes the correct API to be ranked second.	×	0.09
This method also retrieves the correct ArrayUtil API as the top result, demonstrating the effectiveness of using code-ba	×	0.06
The embedding model is instructed to find relevant APIs based on JSDoc for a given code snippet.	×	0.04
The reranker model uses a prefix, suffix, and an instruction to judge whether a document meets the query requirements.	×	0.04
The LLM Judge for Dataset Intent uses a system and user prompt pair to judge the intent of a dataset.	×	0.04
The approach is a multi-stage retrieval pipeline designed to provide highly relevant Script Includes for code completion	×	0.08
The pipeline begins with setting a baseline and incorporates several techniques to progressively refine the search space	×	0.03
The core components of the method include a Knowledge Graph for Search Space Reduction, Enriched Indexing, and LLM-Power	×	0.03
The Knowledge Graph (KG) constructed from platform metadata is used to prune the search space.	×	0.02
The structured index groups all methods belonging to a single Script Include under their parent namespace.	×	0.02
The index is enriched with SI code metadata and their corresponding structured JSDoc, including API usage examples.	×	0.06
The LLM at runtime generates more descriptive and effective queries by analyzing the partial code.	×	0.03

References

- http://arxiv.org/abs/2509.25716v1
- http://arxiv.org/abs/2112.10474v1
- http://arxiv.org/abs/2505.21514v1