

GrepRAG: An Empirical Study and Optimization of Grep-Like Retrieval for Code Completion

BAOYI WANG*, Zhejiang University, China

XINGLIANG WANG*, Zhejiang University, China

GUOCHANG LI, Zhejiang University, China

CHEN ZHI†, Zhejiang University, China

JUNXIAO HAN, Hangzhou City University, China

XINKUI ZHAO, Zhejiang University, China

NAN WANG, Shenzhou Aerospace Software Technology Co., Ltd., China

SHUIGUANG DENG, Zhejiang University, China

JIANWEI YIN, Zhejiang University, China

Repository-level code completion remains challenging for large language models (LLMs), as it requires reasoning over cross-file dependencies while under limited context windows. To address this challenge, prior work has adopted Retrieval-Augmented Generation (RAG) frameworks based on semantic indexing or structure-aware graph analysis. Although effective, these approaches introduce substantial computational overhead for index construction and maintenance, which hinders their practicality in real-world development. Motivated by common developer workflows that rely on lightweight search utilities (e.g., ripgrep) to locate relevant code, we revisit a fundamental yet underexplored question: how far can simple, index-free lexical retrieval go in supporting repository-level code completion before more complex retrieval mechanisms become necessary? To answer this question, we systematically explore the potential of lightweight, index-free, intent-aware lexical retrieval through extensive empirical analysis. We first introduce Naive GrepRAG, a baseline framework where LLMs autonomously generate ripgrep commands to localize relevant context. Our preliminary experiments show that even this basic implementation achieves performance comparable to sophisticated graph-based baselines. Further analysis reveals that its effectiveness stems from retrieving code fragments that are lexically precise and spatially closer to the completion site. However, we identify key limitations of this approach, including sensitivity to noisy matches caused by high-frequency ambiguous keywords and context fragmentation due to rigid truncation boundaries. To address these issues, we propose GrepRAG, which augments lexical retrieval with a lightweight post-processing pipeline featuring identifier-weighted re-ranking and structure-aware deduplication. Extensive evaluation on CrossCodeEval and RepoEval_Updated demonstrates

*Both authors contributed equally to this research.

†Corresponding author.

Authors' Contact Information: Baoyi Wang, Zhejiang University, Hangzhou, China, wangbaoyi@zju.edu.cn; Xingliang Wang, Zhejiang University, Hangzhou, China, wangxingliang@zju.edu.cn; Guochang Li, Zhejiang University, Hangzhou, China, gcli@zju.edu.cn; Chen Zhi, Zhejiang University, Hangzhou, China, zjuzhichen@zju.edu.cn; Junxiao Han, Hangzhou City University, Hangzhou, China, hanjx@hzcu.edu.cn; Xinkui Zhao, Zhejiang University, Hangzhou, China, zhaoxinkui@zju.edu.cn; Nan Wang, Shenzhou Aerospace Software Technology Co., Ltd., Beijing, China, wangnan02026@163.com; Shiguang Deng, Zhejiang University, Hangzhou, China, dengsg@zju.edu.cn; Jianwei Yin, Zhejiang University, Hangzhou, China, zjuyjw@cs.zju.edu.cn.

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that GrepRAG consistently outperforms state-of-the-art (SOTA) methods. In particular, on CrossCodeEval, GrepRAG achieves 7.04–15.58% relative improvement in code exact match (EM) over the best baseline.

CCS Concepts: • Software and its engineering → Software development techniques.

Additional Key Words and Phrases: Code Completion, Grep, Empirical Study, Large Language Model, Retrieval-Augmented Generation

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1 Introduction

As a core feature of modern Integrated Development Environments (IDEs), code completion plays a pivotal role in enhancing development efficiency [4, 13, 36, 43, 68, 70]. In recent years, automated code completion driven by LLMs has demonstrated remarkable proficiency within single-file or single-function contexts [6, 11, 33, 39, 65, 69]. However, its performance often degrades significantly when applied to repository-level code completion [18, 22, 27, 46, 49]. In large-scale repositories, relevant contextual information is typically fragmented across multiple files and directories due to modular code organization. As a result, crucial dependencies such as class definitions, utility interfaces, and global constants are frequently located outside the local file being edited. Given the limited context window of LLMs, it is infeasible to provide the model with the entire repository. Relying solely on intra-file context therefore misses essential cross-file dependencies [7, 26, 40].

RAG mitigates this contextual deficit by retrieving code snippets most relevant to the current logic at the repository level [17, 34, 61]. Existing RAG methodologies can be primarily categorized into three streams. The first category comprises traditional similarity-based retrieval methods [41, 42, 66], which rank code snippets directly based on cosine similarity [37] or BM25 [38] scores relative to the code completion context. The second category involves structure-aware retrieval [8, 23, 28, 35, 50], which models the repository as a dependency graph via static analysis and leverages graph structural information to locate relevant context. The third category pertains to strategy-optimized retrieval [52]; these methods employ Reinforcement Learning (RL) to train dense retrievers, thereby dynamically optimizing retrieval strategies based on end-to-end completion feedback.

Although existing RAG methods are effective, they often rely on complex preprocessing and index construction, which impose substantial time and computational costs. For example, on the `huggingface_diffusers` repository¹, which contains about 100K lines of Python code, Graph-Coder [28] requires approximately 91 seconds to build the graph index and 7 seconds for retrieval. In contrast, developers typically expect latency below 0.5 seconds, while delays exceeding 2 seconds are considered unacceptable for user experience [48]. Furthermore, software repositories are dynamic, frequent code modifications render static graphs and vector indices stale.

Inspired by human developers, who commonly use simple lexical search tools such as Grep, Ctrl+F, or IDE features like *Go to Definition* and *Go to Implementation* during programming to locate class and method definitions or implementations across files. Such tools are also used to retrieve code fragments with similar naming patterns distributed throughout the repository. This structural or lexically similar information is essential for resolving cross-file dependencies in repository-level code completion. [23] The observation motivates us to reconsider whether the potential of simple lexical retrieval has been fully explored before resorting to complex structural or semantic retrieval mechanisms. In parallel, modern agentic coding systems such as ClaudeCode and Windsurf have

¹<https://github.com/huggingface/diffusers>

preliminarily demonstrated the feasibility of simple lexical matching by integrating Grep tools for multi-turn code question-answering tasks; however, the systematic application and evaluation of such techniques within the specific context of code completion remain unexplored.

To systematically study this problem, we adopt a progressive research that first evaluates the potential of grep-like lexical retrieval for repository-level code completion and then explores methods to improve it. The overall framework is illustrated in Figure 1. First, we introduce Naive GrepRAG, a framework where the LLM autonomously generates `ripgrep` commands for context localization, establishing a performance benchmark for lexical retrieval in repository-level code completion. Our exploratory experiments show that the performance of this naive approach outperforms complex graph-based methods (RQ1).

To further understand why Naive GrepRAG performs effectively, we analyze the retrieval patterns of Naive GrepRAG and identify four main types of keywords, including class names, method names, variable names, and others, which are particularly effective for handling several completion scenarios, such as class declaration completion, method call completion, etc. Compared with baseline failures, Naive GrepRAG succeeds by retrieving code fragments closer to the completion site with more precise lexical queries (RQ2).

However, our analysis in RQ1 reveals that Naive GrepRAG does not cover all cases solved by baseline methods, prompting a investigation of its limitations. Our analysis identifies two main issues: (1) keyword ambiguity, where high-frequency generic terms such as `init` introduce noise; and (2) context redundancy and fragmentation, where overlapping code blocks are truncated without merging. This not only results in redundant information occupying the context window, but also disrupts the integrity of the code flow due to fragmentation (RQ3). Based on these empirical insights, we propose GrepRAG. This enhanced framework introduces a lightweight post-processing pipeline incorporating identifier-weighted re-ranking and structure-aware deduplication. This approach addresses the lack of term weighting in the Jaccard algorithm. It also mitigates the issues of context fragmentation and redundancy caused by Grep-style retrieval. By resolving these problems, GrepRAG significantly improves completion performance while maintaining efficient retrieval.

In summary, the primary contributions of this paper are outlined as follows:

- We evaluate the potential of Naive GrepRAG and demonstrate that even a lightweight, grep-based RAG framework can achieve competitive performance on benchmark datasets.
- We analyze the factors behind Naive GrepRAG’s success, examining its retrieval patterns and contrasting them with failures of RAG-based baselines, providing insights for future retrieval-augmented code completion research.
- We delineate the limitations of Naive GrepRAG and introduce an optimized GrepRAG strategy that incorporates identifier-weighted re-ranking and structure-aware deduplication. This approach tackles keyword ambiguity, context redundancy, and fragmentation, achieving SOTA performance across multiple benchmarks.

2 Motivation

2.1 Quantitative Analysis of Retrieval Latency and Scalability

While existing Vanilla-RAG and GraphRAG [28] approaches demonstrate superior performance in enhancing completion accuracy, their retrieval latency can be substantial in practice. To systematically assess this cost, we measured the retrieval latency of BM25-based Vanilla-RAG and GraphCoder on the repositories of the RepoEval_Updated [28] dataset.

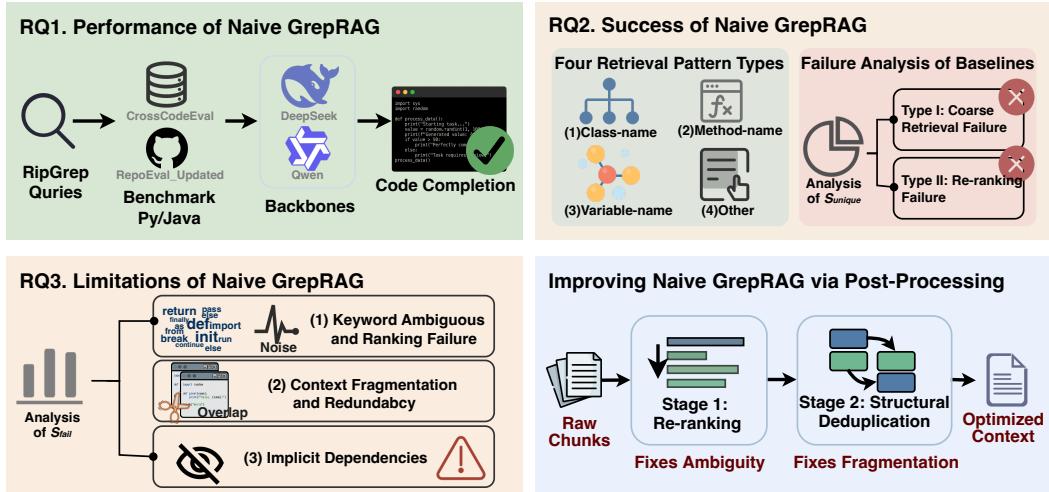


Fig. 1. Overview of the research framework. We first evaluate the effectiveness of Naive GrepRAG (RQ1), analyze the factors contributing to its success (RQ2), identify its limitations (RQ3), and finally propose an optimized GrepRAG equipped with a post-processing pipeline.

Table 1. Average Retrieval Latency (seconds) on RepoEval_Updated Dataset. The time represents the average inference latency of Line and API completion tasks. **Bold** indicates latency exceeding 2 seconds, which is considered unacceptable for real-time completion.

Python Repositories			Java Repositories				
Repository	LOC(K)	VanillaRAG (s)	GraphCoder (s)	Repository	LOC(K)	VanillaRAG (s)	GraphCoder (s)
devchat	3.2	0.036	0.307	chatgpt4j	5.2	0.102	0.249
nemo_aligner	6.8	0.122	0.672	Harmonic-HN	10.5	0.530	0.922
task_weaver	10.9	0.137	0.988	rusty-connector	11.4	0.263	0.622
awslabs_fortuna	16.5	0.237	0.965	NeoGradle	14.4	0.585	1.139
nerfstudio	22.7	0.484	2.056	open-dbt	26.9	0.657	1.198
metagpt	27.1	0.297	2.357	mybatis-flex	64.3	1.688	3.400
opendilab_ACE	59.1	0.877	5.058	rocketmq	120.3	3.040	7.067
diffusers	82.1	3.017	6.900	pixel-dungeon	147.7	5.023	10.836
apple_axlearn	132.3	6.615	9.395	cms-oss	493.5	65.051	28.400
AdaLoRA	577.8	97.265	46.765	FloatingPoint	753.9	53.822	50.463

As shown in Table 1, existing retrieval methods incur substantial latency when applied to large-scale repositories (e.g., AdaLoRA and FloatingPoint, each exceeding 500K lines of code). Specifically, a single retrieval using VanillaRAG or GraphCoder can exceed 40 seconds.

It is important to note that Table 1 reports only the retrieval latency, excluding preprocessing time such as index construction and static graph modeling. This significant temporal overhead prompts a critical reassessment of existing approaches: Is such a computational cost truly unavoidable for acquiring the context necessary for code completion?

Retrieval tools based on lexical retrieval offer an efficient, index-free alternative to the aforementioned latency bottleneck. We conducted preliminary tests using ripgrep, performing retrieval via lexical matching within the RAG framework, thereby avoiding the overhead of index and graph construction. As shown in Table 1 for the diffusers repository, retrieval via ripgrep required only approximately 0.40s, whereas baseline methods consumed between 3s and 7s. This performance disparity becomes even more pronounced in large-scale repositories. For instance, within the

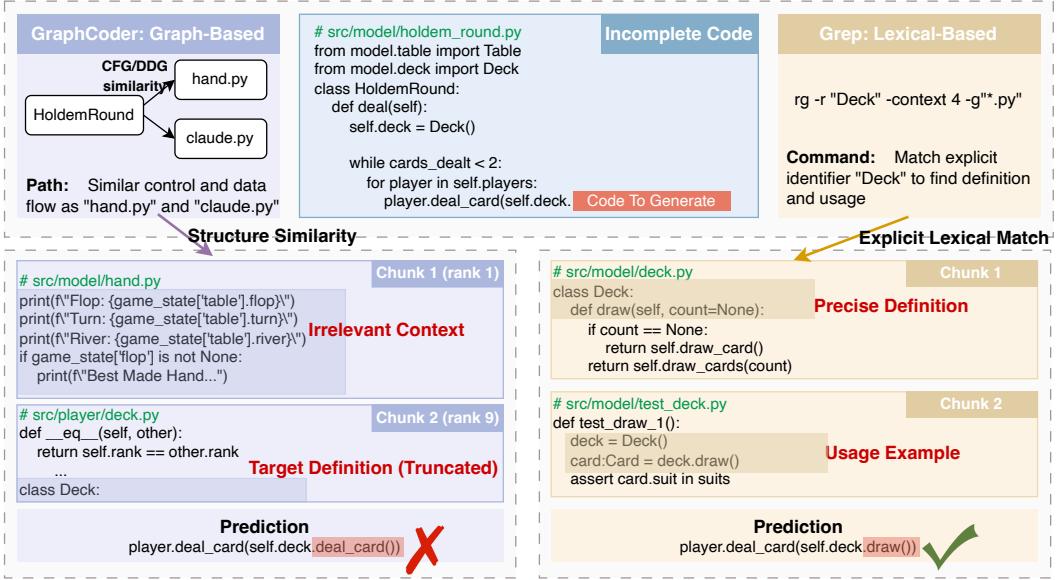


Fig. 2. Comparison of GraphCoder and Grep in a method invocation scenario. **Left:** GraphCoder retrieves irrelevant chunks. **Right:** Grep locates the precise definition and usage examples via lexical retrieval.

FloatingPoint Java repository (containing 754k LOC), the retrieval overhead of existing methods exceeded 50s. In contrast, grep-based retrieval required only 1.45s, representing a reduction to approximately 1/35th of the original time cost. These results suggest that lexical retrieval, when coupled with its zero-indexing requirement, offers a compelling trade-off between efficiency and practicality for large-scale repository-level code completion.

2.2 Qualitative Analysis of Retrieval Effectiveness

While lexical retrieval demonstrates significant efficiency advantages, its ability to capture cross-file dependencies remains uncertain due to the lack of deep semantic reasoning. To investigate this, we conducted a case study using the TexasHoldemAgents repository from the CrossCodeEval [7] dataset. Figure 2 illustrates a representative completion scenario. In the `src/model/holdem_round.py` file, a developer attempts to invoke the `draw()` method of the `self.deck` object within the `deal` function. Since the `Deck` class is defined in a separate file, `src/model/deck.py`, the model must access the precise class definition or method signature to generate an accurate prediction.

We contrast the retrieval behaviors of GraphCoder and ripgrep in this scenario. As shown in Figure 2 (Left), GraphCoder ranks a snippet from `src/player/clause.py` as its most relevant result (rank 1), which contains logging logic and downstream method invocations unrelated to the definition of `Deck`. However, the actual class definition of `Deck` in `src/model/deck.py` is relegated to a much lower rank (rank 9) and retrieved in an incomplete, truncated form. These retrieved results contain noisy and fragmented code blocks that offer little assistance for code completion.

In contrast, lexical retrieval based on explicit identifiers directly located concrete code definitions and usages across the repository. As illustrated in Figure 2 (Right), the Grep command targeted the identifier "Deck" within the completion context, successfully recalling both class definitions and object instantiation code. This combination of definition and usage, facilitated by the lexical retrieval mechanism, provided the model with precise cross-file contextual information, effectively compensating for the absence of semantic reasoning capabilities.

3 Experimental Setup

Based on the aforementioned observations, we design a comprehensive experimental study to systematically evaluate the effectiveness and efficiency of grep-like lexical retrieval for repository-level code completion. This section introduces the experimental setup, including datasets, evaluation metrics, Naive GrepRAG, baseline methods, and implementation details.

3.1 Datasets

We evaluate on two representative code completion benchmarks, CrossCodeEval[7] and RepoEval_Updated[28], with statistics summarized in Table 2.

Table 2. Statistics of the CrossCodeEval and RepoEval_Updated Dataset Subsets

Dataset	Subset	#Repositories	#Files	#Examples	Avg.#Tokens
CrossCodeEval	Python	471	1368	2665	14.45
	Java	239	745	2139	16.76
RepoEval_Updated	Python	10	3258	4000	15.44
	Java	10	8522	4000	17.82

CrossCodeEval.

We use the Python and Java subsets of CrossCodeEval to evaluate the model’s ability to handle scenarios that strictly require cross-file context for accurate code completion. The dataset includes 471 Python and 239 Java repositories, and applies static analysis to exclude samples that can be resolved using only intra-file context. This rigorous filtering ensures that all test cases depend on external context, allowing for a precise assessment of the retrieval module’s effectiveness in locating cross-file information.

RepoEval_Updated.

To evaluate model performance on large-scale repositories, we employ the RepoEval_Updated dataset, derived from RepoEval [66]. This dataset incorporates a task classification mechanism, categorizing tasks into Line-level for general coding and API-level for scenarios necessitating intra-repository API invocations. Comprising a total of 8,000 tasks across Python and Java, the dataset encompasses projects with substantial code volume (with some exceeding 500k LOC), thereby serving as an effective stress test for retrieval latency and scalability.

3.2 Evaluation Metrics

Following CrossCodeEval[7], we assess generation quality across two dimensions: (1) code match, which evaluates overall textual consistency, and (2) identifier match, which focuses on the semantic accuracy of API calls and variables extracted via static analysis. For both dimensions, we employ four metrics: **EM** measures strict equality between the generated sequence and reference. **Edit Similarity (ES)** quantifies similarity based on Levenshtein distance[16] (*Lev*). Additionally, **Recall** and **F1** evaluate content coverage. Notably, for identifier match, identifiers are treated as a set to assess prediction accuracy regardless of order, whereas code match treats code as token sequences. We also report retrieval latency, measured as the average CPU time per query, to evaluate the efficiency of the retrieval process.

3.3 Naive GrepRAG

To investigate the performance of lexical retrieval in repository-level code completion, this study constructs Naive GrepRAG, as illustrated in Figure 3. This framework consists of three phases:

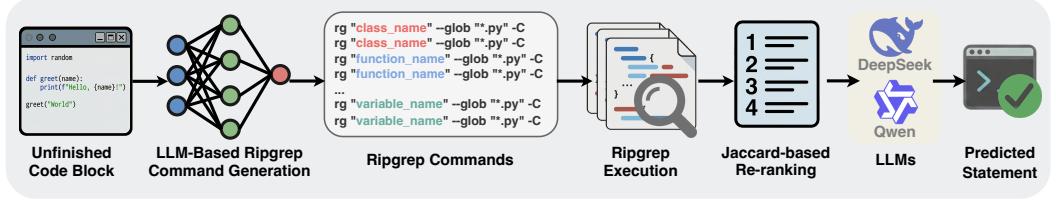


Fig. 3. Overview of the Naive GrepRAG framework.

Grep Query Generation: Given the local context preceding the cursor, C_{local} , the LLM autonomously generates m ripgrep commands, $Q = \{q_1, q_2, \dots, q_m\}$, by analyzing the code’s lexical features, latent dependencies, and the user’s coding intent. In our setting, m is specified as 10 via the prompt, though the actual number of generated commands may vary slightly due to the LLM’s generation behavior. The prompt is provided in the anonymized repository described in Section ??.

Deterministic Execution: The query set, Q , is executed across the repository using the ripgrep retrieval tool, yielding a pool of candidate code snippets through exact string matching.

Context Construction: Inspired by GraphCoder [28], we rank candidate snippets based on their Jaccard similarity [15] with C_{local} . We then select the top- K fragments and concatenate them to form the final prompt context.

3.4 Baselines

We compare GrepRAG against five representative baselines, covering the spectrum from no retrieval to advanced graph-based and learning-based retrieval methods:

- **NoRAG:** The backbone LLM generates code using exclusively intra-file context, without leveraging any external retrieval mechanisms.
- **VanillaRAG:** A standard rag baseline employs the BM25 algorithm to assess the lexical similarity between the code under completion and code blocks within the repository. It retrieves the Top- K most relevant code snippets as context to prompt the LLM for the next statement prediction.
- **GraphCoder [28]:** A structure-aware retrieval methodology. This approach constructs a Code Context Graph (CCG) to capture structural dependencies and adopts a coarse-to-fine retrieval strategy, integrating both lexical and structural information to pinpoint relevant code context.
- **RepoFuse [23]:** A method designed to address the context-latency conundrum. It integrates analogy context (retrieved via code snippet similarity) and rationale context (derived from import dependency analysis), employing a Rank Truncated Generation (RTG) strategy to select the most relevant cross-file contexts within a constrained window.
- **RLCoder [52]:** An annotation-free reinforcement learning retrieval framework. This approach utilizes the weighted perplexity of code generation as the reward signal to train the retriever.

3.5 Implementation Details

We evaluate all methods using DeepSeek-V3.2-EXP and Qwen3-Coder-Plus with the sampling temperature set to 0 for reproducibility. For RAG-based approaches, we standardize the retrieval budget to the Top- $K = 10$ code snippets and limit the total context length to 4,096 tokens to ensure a fair comparison. For our method, the number of ripgrep queries is set to $m = 10$ via the prompt. Methods that require GPU acceleration are executed on a single NVIDIA A6000 GPU, while retrieval latency is measured on the same CPU environment.

4 Evaluating the Potential of Naive GrepRAG

In this chapter, we conduct a systematic empirical study to explore the potential of Naive GrepRAG in repository-level scenarios. We first evaluate its end-to-end completion performance against sophisticated baselines (RQ1), then dissect the mechanisms behind its success (RQ2), and finally diagnose its limitations to inform directions for optimization (RQ3).

4.1 RQ1: Evaluating the Performance of Naive GrepRAG

4.1.1 Motivation. The primary objective of this research question is to quantitatively validate the feasibility of the Naive GrepRAG framework and to investigate whether simply using LLM-generated grep commands to retrieve code context can effectively improve end-to-end code completion performance. We conduct this preliminary validation on the CrossCodeEval[7] benchmark.

4.1.2 Analysis of End-to-End Performance. Table 3 summarizes the performance comparison between Naive GrepRAG and five baselines across the Python and Java subsets. To validate the generalizability of our approach and mitigate potential bias from specific model capabilities, we employ DeepSeek-V3.2-EXP and Qwen3-Coder-Plus as backbone models. Based on the experimental results, we derive the following key findings:

Experimental results show that Naive GrepRAG consistently outperforms comparative baselines across all evaluated metrics. In the Python subset under the DeepSeek-V3.2-EXP setting, our method achieves an EM rate of 38.61%, substantially exceeding the traditional Vanilla RAG (24.99%) and RLCoder (36.59%). Similarly, in the Java subset, Naive GrepRAG establishes a new benchmark with an EM of 41.70%. Furthermore, it attains the highest scores on both identifier EM and F1 metrics, indicating that precise character-level matching via `ripgrep` provides superior accuracy over vector-based retrieval in locating definitions of identifiers, such as functions and variables.

The retrieval time column highlights the practical efficiency of `ripgrep`. Our method achieves an average retrieval latency of less than 0.02s, outperforming approaches such as GraphCoder and RepoFuse, and substantially reducing the computational cost of the retrieval process.

Table 3. Performance comparison between Naive GrepRAG and baselines on CrossCodeEval

Lang	Method	Retrieval Time(s)	DeepSeek-V3.2-EXP								Qwen3-Coder-Plus							
			Code				Identifier				Code				Identifier			
			EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1
Python	No RAG	—	15.57	66.58	82.38	81.73	22.74	66.80	57.03	55.78	17.45	67.77	81.46	81.99	25.55	67.84	57.21	56.86
	Vanilla RAG	0.1482	24.99	71.10	85.03	84.15	33.47	71.62	64.42	62.76	27.24	72.58	84.81	84.60	36.40	73.29	64.87	64.12
	GraphCoder	0.2582	19.44	68.83	83.46	82.94	27.54	69.26	60.31	59.05	21.76	69.81	83.21	83.14	30.17	70.06	60.78	60.17
	RepoFuse	1.6400	27.50	72.27	85.74	84.77	36.25	73.11	66.58	64.93	29.87	73.75	85.52	85.29	39.25	74.78	67.01	66.17
	RLCoder	—	36.59	76.92	88.90	87.27	47.32	78.01	74.23	72.16	40.04	79.30	88.67	88.32	51.14	80.64	75.64	74.74
	Naive GrepRAG	0.0186	38.61	77.54	89.08	87.50	48.33	78.67	74.59	72.33	40.79	79.82	88.96	88.52	51.52	80.97	75.96	74.85
Java	No RAG	—	22.49	71.96	85.89	85.85	30.95	72.13	65.13	64.11	21.79	70.87	83.79	84.30	30.39	70.82	62.74	62.55
	Vanilla RAG	0.1015	29.64	74.96	87.50	87.44	39.46	75.51	69.65	68.67	28.99	73.64	85.51	85.94	37.54	73.77	67.28	66.91
	GraphCoder	0.1110	25.20	73.09	86.19	86.26	34.27	73.26	66.77	65.95	24.12	71.44	84.31	84.75	32.40	71.48	63.83	63.72
	RepoFuse	0.0938	38.62	78.36	89.23	89.12	50.35	79.34	75.54	74.65	39.97	77.62	87.43	87.91	50.44	78.36	73.72	73.57
	RLCoder	—	39.46	78.84	89.60	89.22	51.24	79.87	76.55	75.24	41.19	78.13	87.70	88.20	51.38	78.89	74.58	74.35
	Naive GrepRAG	0.0173	41.70	78.93	89.93	89.33	52.17	79.95	76.62	75.67	41.42	78.31	87.92	88.67	51.90	79.02	74.69	74.77

* Retrieval time for RLCoder is not reported due to its reliance on GPU-based inference.

4.1.3 Analysis of Solved Instance Overlap. We utilize a Venn diagram (Figure 4) to visually compare the solution sets of Naive GrepRAG, VanillaRAG, GraphCoder [28], RepoFuse [23], and RLCoder [52] under EM (EM=100%), using DeepSeek-V3.2-EXP as the underlying LLM. In the Python dataset, GrepRAG uniquely resolved **161** instances where baselines failed, a figure significantly higher than the number of instances unique to RepoFuse (24). The Java dataset exhibits a similar trend,

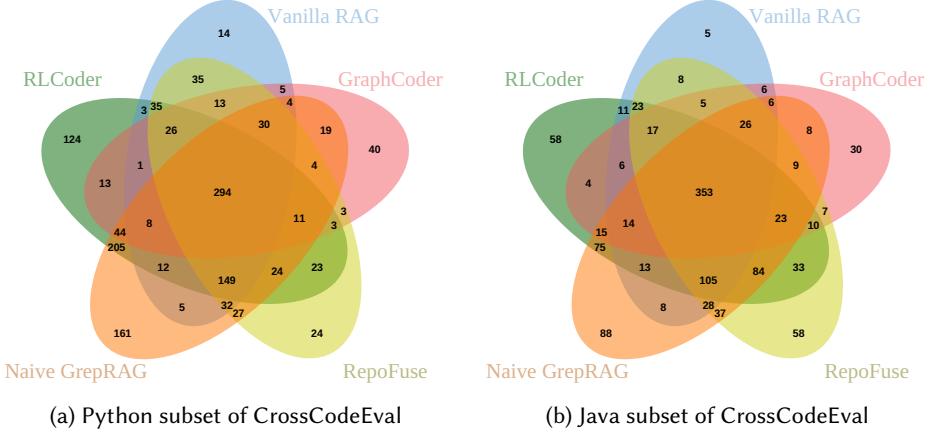


Fig. 4. Comparison of distinct solved cases across systems in the CrossCodeEval dataset.

confirming that explicit literal retrieval effectively captures precise keyword matches often overlooked by semantic models. Furthermore, we observe that instances successfully solved by all models simultaneously account for only 20%–30% of the total (Python: 294/1391, Java: 353/1173), indicating a substantial divergence in solution spaces. Notably, GrepRAG contributed the largest unique solution set (accounting for 11.6% in Python). This phenomenon not only validates the complementarity between different retrieval strategies but also suggests that a subset of code completion tasks inherently relies on explicit lexical pattern matching.

4.2 RQ2: Analyzing the Success of Naive GrepRAG

4.2.1 Motivation. While RQ1 has shown the effectiveness of Naive GrepRAG, the reasons behind its success remain unclear. We analyze its internal retrieval patterns and examine why it succeeds where other RAG-based baselines fail.

4.2.2 Analysis of Retrieval Patterns. To characterize retrieval patterns, we analyze $N = 45,615$ ripgrep commands (25,366 Python, 20,249 Java). Using a 95% confidence level and a 5% margin of error, we perform stratified random sampling by programming language, yielding a sample of 381 commands (212 Python, 169 Java).

Our analysis reveals that Naive GrepRAG retrieval behaviors can be understood at two levels: basic retrieval patterns and advanced retrieval strategies.

Basic Retrieval Patterns At the individual command level, the keywords are primarily categorized into four types, each keyword type corresponds to a specific information retrieval target and plays a role in different code completion scenarios.

- **Class-name Retrieval (35.96%)** When a ripgrep command uses a class name, its main goal is to reveal the object’s type and member structure, which is crucial in the following two completion scenarios: (1) Method call completion (`obj .`): The LLM uses the object’s class name to retrieve its definition, directly accessing its attributes and methods to guide member completion. (2) Class declaration completion (`class C extends P`): When a class inherits from a parent, the LLM uses the parent class name to retrieve its definition, obtaining attributes and methods as structural references for completing the subclass.
- **Method-name Retrieval (41.47%)** ripgrep commands that use method names as keywords are primarily used to locate the definition and usage of the target method within the codebase, providing direct references for completing calls or implementations.

(1) Arguments completion (`obj.method(...)`): The LLM uses the method identifier to retrieve its signature across the repository, obtaining parameters and return type, and also retrieves call examples elsewhere in the project to guide argument filling and usage patterns. (2) Method body completion (`def method(...):`): When a method is only provided with a function signature but lacks a concrete implementation, the LLM retrieves same-name or fuzzy-matched methods to reference their internal logic, assisting in implementing the target method.

- **Variable-name Retrieval (18.37%)** This retrieves variable definitions and assignments to understand types, initial values, and usage. Global variables such as `CONFIG_PATH` are traced to their definitions for configuration or state information, while frequent local variables appearing near the code region being completed are retrieved to provide usage references for completion.
- **Others (4.20%)** A small portion uses strings or non-standard identifiers to locate similar code fragments, which the model references to aid target code completion.

Advanced Retrieval Strategies Beyond keyword matching, Naive GrepRAG exhibits sophisticated behaviors by enhancing single-query recall and orchestrating multiple queries for a holistic view.

- **Fuzzy Matching via Wildcards.** Notably, 23.5% of the sampled commands utilize wildcard patterns. Rather than strict identity matching, these queries aim to retrieve code snippets with similar naming patterns (e.g., `class.*ConfigModel` matching implementations like `DataConfigModel`). This allows the model to reference these semantically related definitions as prototypes, facilitating completion by mimicking their structure even when the exact identifier in the target context is unknown or lacks a direct counterpart.
- **Multi-Query Retrieval.** A key characteristic of Naive GrepRAG is its ability to generate a query set rather than relying on isolated commands. For example, when performing argument completion (`obj.method(...)`), class-name queries retrieve the receiver's class definition, exposing available method signatures and implementations. Method-name queries help locate the target method and its callsites, revealing method parameters and return types. Variable-name queries surface other usages of the same variable, offering additional clues about expected arguments and return values. By aggregating these results, Naive GrepRAG leverages multiple, partially overlapping lexical views to facilitate code completion, significantly improving retrieval robustness and reducing reliance on any single query.

4.2.3 Failure Analysis of RAG-based Baselines. The above retrieval patterns primarily rely on lexical matching of explicit identifiers. While conceptually simple, they can successfully solve a subset of test cases that other RAG-based baselines fail to solve. We analyze the set S_{unique} , which consists of 249 test cases (161 Python, 88 Java) that are correctly completed by Naive GrepRAG ($EM = 100\%$), in order to investigate why these baselines fail on these cases.

Despite differences in their implementation, these baselines share a two-stage workflow: initial lexical retrieval (BM25/Jaccard), followed by re-ranking mechanism. Specifically, GraphCoder and RLCoder first perform coarse retrieval using Jaccard or BM25, then refine with structural or semantic similarity; RepoFuse merges BM25 Top- k results with structurally retrieved code blocks before final re-ranking. Based on this workflow, we categorize the failures of baselines on S_{unique} into two mutually exclusive types.

- **Type I: Coarse Retrieval Failure.** In this type, baselines fail to include the critical context in the initial lexical retrieval stage, indicating that the failure occurs at the front end of the retrieval pipeline, before any baseline-specific re-ranking takes place.
- **Type II: Re-ranking Failure.** In this type, baselines retrieve core code blocks in coarse retrieval, but re-ranking fails to prioritize them.

Table 4. Breakdown of failure modes on S_{unique} .

Method	Python (%)		Java (%)	
	Recall Failure	Re-ranking Failure	Recall Failure	Re-ranking Failure
GraphCoder	73.3	26.7	76.1	23.9
RLCoder	68.9	31.1	70.5	29.5
RepoFuse	64.6	35.4	65.9	34.1

Given that the context retrieved by RAG methods typically comprises multiple discrete code blocks, we quantify the coverage of critical context by baselines’ retrieval results using a threshold-based set overlap metric. Here, the set of code fragments retrieved by Naive GrepRAG for each sample serves as the golden context, denoted C_{gold} . For each baseline, we define the coverage of C_{gold} by its retrieved set $C_{retrieved}$ as the line-level intersection ratio:

$$I(C_{retrieved}, C_{gold}) = \frac{|Lines(C_{retrieved}) \cap Lines(C_{gold})|}{|Lines(C_{gold})|} \quad (1)$$

We set the determination threshold at $\tau = 0.8$, meaning a retrieval result effectively recalls the core information if it covers more than 80% of the code lines in the golden context. This threshold accommodates minor boundary discrepancies introduced by different chunking granularities while ensuring that the essential informational content is preserved. A sensitivity analysis over various thresholds confirmed consistent trends, for simplicity, we only report results for $\tau = 0.8$.

As shown in Table 4, most baseline failures on S_{unique} are due to coarse retrieval. This failure is mainly caused by the limitations of global lexical similarity metrics, such as BM25 and Jaccard, which emphasize overall token overlap rather than identifiers closely related to the completion site. This indicates that current RAG methods relying on BM25 or Jaccard for coarse retrieval can be problematic for code completion. In contrast, Naive GrepRAG retrieves explicit identifiers at the completion site, allowing precise recall of locally and structurally relevant code. For example, in member-access completion (obj.), it reliably retrieves the class definition of obj. Under BM25- or Jaccard-based coarse retrieval, such class definitions often exhibit weak global lexical overlap with the surrounding context and are therefore filtered out before any re-ranking can take place. For RepoFuse, although it incorporates structural dependencies, its coarse retrieval stage still lacks explicit matching of local variable or method identifiers, leading to similar recall failures.

We next analyze re-ranking failures, which primarily stem from the baselines’ inability to prioritize precise identifier matches. Specifically, GraphCoder emphasizes structural similarity (e.g., similar loop patterns), which can be irrelevant to the actual completion target. RLCoder uses a fine-tuned retriever to encode semantic similarity. While it captures conceptually related code, it often fails to rank exact method or variable names highly and its results are less interpretable. RepoFuse combines BM25-based lexical retrieval with call-chain-based dependency signals. However, its re-ranking stage still lacks the precision of Naive GrepRAG in emphasizing local identifiers, resulting in weak attention to identifiers with identical names.

Overall, Naive GrepRAG succeeds because it retrieves code fragments more closely related to the completion site and uses more precise query keywords, whereas baselines fail due to inaccurate initial retrieval and re-ranking failures.

4.3 RQ3: Limitations of Naive GrepRAG

4.3.1 Motivation. In the Venn analysis of RQ1, we observe that the solution space of Naive GrepRAG does not fully cover that of the baselines, which means there exist scenarios where a baseline

succeeds while Naive GrepRAG fails. This research question aims to investigate the limitations of Naive GrepRAG and provide insights for subsequent improvements.

4.3.2 Methodology. We construct a failure dataset, denoted as S_{fail} , comprising test cases where Naive GrepRAG fails to generate a correct prediction (EM=0%) whereas at least one of the other RAG-based baselines succeeded. We conduct a quantitative census of all samples meeting these criteria (362 Python and 281 Java cases).

We focus on the actual retrieval pipeline of Naive GrepRAG. Following the classification approach in RQ2, we categorize failures into recall failure and re-ranking failure. Recall failure occurs when the Naive GrepRAG fails to retrieve the golden context by the ripgrep command set, whereas re-ranking failure occurs when the golden context is successfully retrieved but not assigned a sufficiently high rank.

4.3.3 Analysis Results. Based on the aforementioned classification criteria, we analyze 643 failure samples. The data reveals that re-ranking failure is the dominant factor, accounting for approximately 71.5% of Python cases and 75.1% of Java cases, while recall failure constitutes the remaining 28.5% and 24.9%, respectively. We perform open coding on these samples to identify typical failure scenarios. To ensure coding rigor, the first two authors independently annotated the samples, achieving a Cohen's kappa of 0.82, indicating substantial agreement. Through this process, we categorize failures into three representative classes: two reflecting distinct patterns of re-ranking failure, and one corresponding to the fundamental limitation of recall failure.

Keyword Ambiguity and Re-ranking Failure: When queries involve high-frequency generic identifiers such as `init`, `config`, or `run`, ripgrep retrieves a large number of irrelevant documents containing identical keywords but lacking semantic relevance. In the presence of such noise, current Naive GrepRAG relies on Jaccard similarity to compute the token overlap rate between retrieved chunks and the query. This approach cannot effectively distinguish frequent stop words from task-specific identifiers. Consequently, noise chunks containing numerous frequent terms accrue artificially high Jaccard scores, displacing the code blocks that actually contain the relevant context from the Top-K candidates.

Context Fragmentation and Redundancy: Even when the correct context successfully enters the Top-K, its structural organization often exhibits issues. As illustrated in Figure 5, two independent ripgrep queries targeting distinct keywords ("load_config" and "process_data") respectively matched adjacent regions within the same file. The independent retrieval mechanism of grep primarily induces information redundancy, resulting in the duplicate retention of the overlapping code region (L5–8) in the final input, wastefully consuming the finite token budget. Furthermore, this mechanism precipitates semantic discontinuity, where the snippet containing the variable `data_path`'s usage site (Chunk 2) obtains a higher relevance score than its definition site (Chunk 1). This results in a sequence where usage precedes definition in the context ultimately fed to the LLM. Such physical fragmentation and chronological disorder disrupt the logical flow of the code, exacerbating the difficulty for the LLM to comprehend the context.

Implicit Dependencies: It represents a fundamental limitation of lexical retrieval. The failures mainly arise when the current context lacks explicit structural relationships, such as inheritance, making it difficult for the Naive GrepRAG to locate the critical context using ripgrep commands.

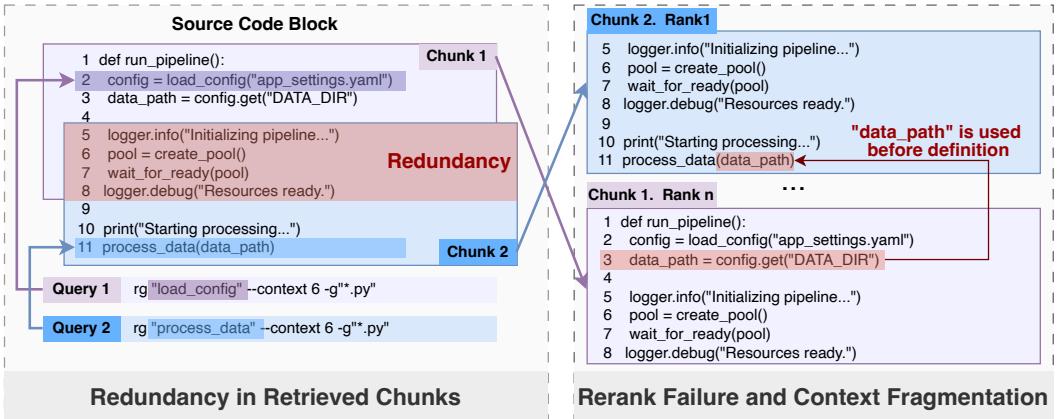


Fig. 5. Redundancy and Context Fragmentation. Two independent grep queries hit adjacent regions within the same file.

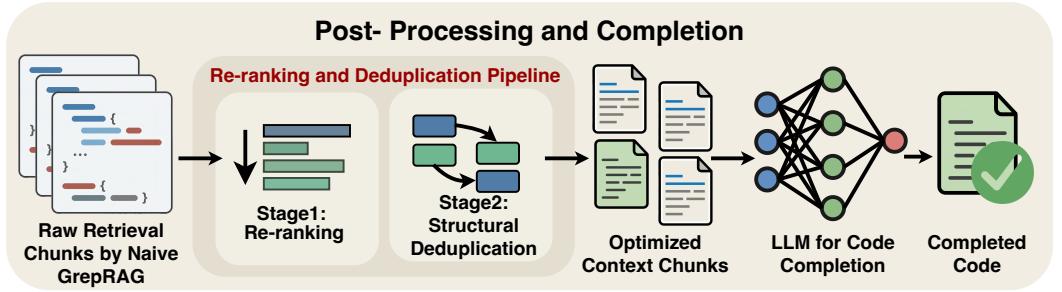


Fig. 6. Post-processing pipeline built upon the Naive GrepRAG framework.

5 Improving Naive GrepRAG via Post-Processing

5.1 Overview

RQ3 reveals that although Naive GrepRAG exhibits an exceptionally high recall rate, the primitive Jaccard re-ranking mechanism is inadequate for addressing keyword ambiguity, resulting in distractor documents with identical keywords but low semantic relevance. Furthermore, the absence of a deduplication mechanism leads to context redundancy and fragmentation. Consequently, this section investigates whether an efficient post-processing module can be introduced to resolve ranking bottlenecks and redundancy issues.

5.2 Approach

As shown in Figure 6, our approach builds upon the Naive GrepRAG pipeline by retaining the original ripgrep-based retrieval process and introducing two cascaded post-processing steps applied to the retrieved chunks.

Identifier-Weighted Re-ranking. To address the keyword ambiguity issue analyzed previously, we require an algorithm that effectively penalizes frequent generic identifiers while rewarding low-frequency, task-specific identifiers. BM25 introduces an IDF factor that suppresses the contribution of frequent terms and relatively amplifies the weight of rare identifiers. Consequently, replacing the re-ranking strategy with BM25 yields a more principled and discriminative ranking. For each chunk C_i retrieved by Grep, we regard it as a document and the code under completion as the query

to calculate a relevance score. This step outputs a candidate list L_{ranked} , sorted in descending order of relevance. This does not contradict our findings in RQ2. This highlights that BM25 is effective for assigning differential weights in a completion-aware candidate set, but may be unsuitable as a coarse, global retriever in code completion.

Structure-Aware De-duplication and Fusion. To mitigate token wastage and semantic discontinuity, we devise a fusion strategy based on line number intervals. This mechanism parses the physical line number range of each chunk to precisely identify physically overlapping or adjacent code snippets. Subsequently, we execute a concatenation operation to merge fragmented snippets into complete, contiguous semantic blocks, thereby reconstructing the logical flow of the code while eliminating redundancy. To balance computational overhead with performance, we process only the Top-N% (set to 50% in our experiments) of candidate blocks from L_{ranked} .

Finally, we select the Top-K blocks from the de-duplicated list to serve as input to the LLM, while strictly limiting the total context length to 4,096 tokens.

5.3 Main Results

Table 5 presents the primary performance metrics of GrepRAG across two datasets. The results indicate that GrepRAG achieves substantial improvements across all evaluation dimensions on the CrossCodeEval [7] dataset. Furthermore, these gains maintain high consistency across different backbone models. For Python completion tasks using DeepSeek-V3.2-EXP as the backbone, GrepRAG improves the code EM from 38.61% (Naive version) to 42.29%, and increases the identifier F1 from 72.33 to 75.15. These results significantly outperform baseline models such as RepoFuse, establishing a new SOTA. Notably, this performance enhancement is not confined to specific backbone models; when employing Qwen3-Coder-Plus for completion, GrepRAG similarly propels the code EM on Python tasks to 44.62%, significantly surpassing both the baselines and Naive GrepRAG. Overall, across different tasks and backbone models on CrossCodeEval, GrepRAG improves code EM by 7.04%–15.58% and identifier EM by 5.02%–11.50% relative to the best-performing baselines. This confirms that our framework does not rely on the parameter preferences of specific models, but rather provides a generalized context augmentation capability.

The RepoEval_Updated [28] dataset consists of repositories with a significantly larger code volume. In this scenario, GrepRAG demonstrates exceptional noise robustness. Particularly in API-level tasks, the model performance improves significantly compared to the Naive version. On the Python subset, code EM increases by 13.8% (35.75 → 40.70), and on the Java subset by 13.4% (40.27 → 45.67). This trend is similarly observed on the Qwen3-Coder-Plus model.

5.4 Ablation Study: Dissecting the Improvement

To quantify the contribution of each component, we conduct an ablation study on the CrossCodeEval dataset (Table 6). We compare four variants, and the results demonstrate that structure-aware deduplication contributes more substantially to performance gains:

GrepRAG (Naive): The baseline configuration. Due to the absence of deduplication and weighted re-ranking, its performance is constrained by redundancy and noise.

GrepRAG w/o Dedup: Replaces the re-ranking strategy from Jaccard to BM25 exclusively (without deduplication). The results indicate relatively marginal performance gains; the EM on Python DeepSeek-V3.2-EXP increased only from 38.61% to 39.12%, a rise of 0.51%. This suggests that while BM25 optimizes ranking weights, solely refining the ranking algorithm struggles to break the bottleneck of insufficient information density when the context window is occupied by a substantial volume of repetitive code fragments.

Table 5. Performance comparison on CrossCodeEval and RepoEval_Updated

Dataset	Task	Lang	Method	DeepSeek-V3.2-EXP								Qwen3-Coder-Plus								
				Retrieval				Code				Identifier				Code				
				Time(s)	EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1
CrossCodeEval	Line Level	Python	No RAG	—	15.57	66.58	82.38	81.73	22.74	66.80	57.03	55.78	17.45	67.77	81.46	81.99	25.55	67.84	57.21	56.86
			Vanilla RAG	0.1482	24.99	71.10	85.03	84.15	33.47	71.62	64.42	62.76	27.24	72.58	84.81	84.60	36.40	73.29	64.87	64.12
			GraphCoder	0.2582	19.44	68.83	83.46	82.94	27.54	69.26	60.31	59.05	21.76	69.81	83.21	83.14	30.17	70.06	60.78	60.17
			RepoFuse	1.6400	27.50	72.27	85.74	84.77	36.25	73.11	66.58	64.92	29.87	73.75	85.52	85.29	39.25	74.78	67.01	66.17
			RLCoder	—	36.59	76.92	88.90	87.27	47.32	78.01	74.23	72.16	40.04	79.30	88.67	88.32	51.14	80.64	75.64	74.74
			Naive GrepRAG	0.0186	38.61	77.54	89.08	87.50	48.33	78.67	74.59	72.33	40.79	79.82	88.96	88.52	51.52	80.97	75.96	74.85
			GrepRAG	0.0197	42.29	79.66	89.53	88.50	52.76	80.76	76.84	75.15	44.62	81.32	89.58	89.45	55.87	82.62	77.90	77.29
			No RAG	—	22.49	71.96	85.89	85.85	30.95	72.13	65.13	64.11	21.79	70.87	83.79	84.30	30.39	70.82	62.74	62.55
RepoEval_Updated	Java	Python	Vanilla RAG	0.1015	29.64	74.96	87.50	87.44	39.46	75.51	69.65	68.67	28.99	73.64	85.51	85.94	37.54	73.77	67.28	66.91
			GraphCoder	0.1110	25.20	73.09	86.19	86.26	34.27	73.24	66.77	65.95	24.12	71.44	84.31	84.75	32.40	71.48	63.83	63.72
			RepoFuse	0.0938	38.62	78.36	89.23	89.12	50.35	79.34	75.54	74.65	39.97	77.62	87.43	87.91	50.44	78.36	73.72	73.57
			RLCoder	—	39.46	78.84	89.60	89.22	51.24	79.87	76.55	75.24	41.19	78.13	87.70	88.20	51.38	78.89	74.58	74.35
			Naive GrepRAG	0.0173	41.70	78.93	89.93	89.33	52.17	79.95	76.62	75.67	41.42	78.31	87.92	88.67	51.90	79.02	74.69	74.77
			GrepRAG	0.0181	43.15	80.07	89.78	89.53	53.81	80.88	77.41	76.57	44.09	79.95	88.98	89.29	54.09	80.69	76.83	76.57
			No RAG	—	34.25	64.29	82.79	80.36	40.80	66.16	59.09	56.15	51.20	74.02	85.58	85.14	56.50	75.22	67.78	66.64
			Vanilla RAG	10.04	36.90	65.20	83.33	80.71	43.25	66.85	60.26	57.56	52.40	75.12	86.81	85.95	57.80	76.14	69.49	68.12
CrossCodeEval	Line Level	Java	GraphCoder	7.63	43.70	67.95	83.30	81.42	49.50	69.94	63.28	61.05	56.70	77.41	87.92	87.32	62.10	78.68	71.98	70.81
			RepoFuse	23.03	36.85	65.71	84.43	81.41	43.65	67.61	60.96	57.95	51.30	74.00	86.36	85.39	56.80	75.31	68.79	67.51
			RLCoder	—	42.60	68.82	84.95	82.48	48.85	70.61	64.96	61.89	57.70	77.91	88.24	87.63	62.70	78.76	72.02	70.88
			Naive GrepRAG	0.51	41.45	68.14	85.33	82.88	47.85	69.72	63.09	60.36	57.65	77.43	87.84	87.69	62.10	77.69	71.26	69.83
			GrepRAG	0.62	44.90	69.92	86.49	83.74	50.98	71.78	65.67	62.56	59.05	78.27	88.49	87.74	64.10	79.58	72.54	71.60
			No RAG	—	34.25	64.29	82.79	80.36	40.80	66.16	59.09	56.15	45.55	75.87	86.16	86.31	55.00	77.06	70.48	69.93
			Vanilla RAG	15.04	35.00	67.22	82.88	81.73	44.20	69.21	63.07	60.81	48.40	77.03	87.14	87.16	57.50	77.91	71.80	71.17
			GraphCoder	10.49	39.30	69.59	83.35	82.67	48.05	71.17	64.58	62.89	51.40	78.63	87.72	87.97	60.05	79.66	72.94	72.50
RepoEval_Updated	Java	Python	RepoFuse	1.96	33.95	66.87	83.08	81.54	45.49	68.02	62.57	60.10	47.80	77.03	86.62	86.92	57.40	77.88	71.59	71.12
			RLCoder	—	40.10	70.67	85.16	83.88	49.05	72.34	67.05	64.69	53.00	79.05	88.15	88.26	61.50	80.00	74.03	73.48
			Naive GrepRAG	0.26	40.50	70.66	85.01	83.88	49.95	72.94	66.66	64.57	53.67	79.01	88.03	88.28	62.05	80.74	73.97	73.20
			GrepRAG	0.28	43.65	72.14	85.92	84.55	52.40	73.90	68.83	66.41	54.55	79.29	88.18	88.92	63.35	80.61	74.50	73.85
			No RAG	—	34.40	65.80	83.13	83.22	38.10	67.22	61.96	61.28	48.35	72.95	84.53	85.99	51.10	73.54	69.14	69.87
			Vanilla RAG	11.78	32.65	63.79	79.12	78.83	36.42	63.24	56.37	55.61	41.37	70.52	81.74	82.68	46.32	69.82	63.50	68.68
			GraphCoder	7.54	40.60	67.33	82.63	83.04	44.60	68.55	64.26	63.78	52.65	75.98	86.30	87.89	55.55	76.51	72.63	73.61
			RepoFuse	50.99	35.40	66.36	83.70	83.52	40.20	67.75	63.83	62.23	49.45	73.65	85.14	86.53	52.45	74.22	69.84	70.60
CrossCodeEval	API Level	Java	RLCoder	—	39.85	67.64	83.45	83.60	44.09	69.12	65.39	64.05	52.65	75.40	85.78	87.43	55.45	78.12	71.46	72.44
			Naive GrepRAG	0.39	35.75	65.36	82.86	82.79	40.05	66.70	61.84	60.84	50.97	75.49	85.12	86.27	53.23	74.45	70.02	70.87
			GrepRAG	0.49	40.70	68.86	84.61	84.50	45.15	70.07	65.98	64.91	53.35	76.18	86.94	88.36	56.40	77.07	73.18	73.83
			No RAG	—	35.22	70.11	83.93	83.81	41.77	69.40	63.64	62.83	43.17	73.81	84.35	84.95	47.27	73.09	67.33	67.37
			Vanilla RAG	36.28	31.82	63.42	79.12	78.83	36.42	63.24	56.37	55.61	41.37	70.52	81.74	82.68	46.32	69.82	63.50	63.59
			GraphCoder	29.64	42.87	70.34	82.58	82.79	47.82	70.23	64.27	63.85	53.73	73.97	87.65	88.05	58.93	78.81	74.02	74.03
			RepoFuse	11.13	37.43	65.48	80.33	79.93	42.56	67.33	59.43	58.88	42.42	72.89	84.28	84.81	46.67	72.11	65.97	66.13
			RLCoder	—	41.62	70.18	83.18	82.81	46.42	69.92	64.74	64.02	52.83	78.34	86.98	87.48	57.53	77.47	72.85	72.87
RepoEval_Updated	Java	Python	Naive GrepRAG	1.06	40.27	69.70	82.90	82.50	45.47	69.69	63.64	62.99	51.65	77.32	85.34	87.16	56.18	77.04	71.48	71.06
			GrepRAG	1.16	45.67	73.35	85.60	85.19	51.08	73.28	68.00	67.16	54.93	79.58	87.96	88.63	59.37	79.05	74.21	74.20

GrepRAG w/o BM25: This variant retains the original Jaccard ranking while adding the deduplication module. It achieves a substantial performance improvement, reaching an EM of 41.93% on Python DeepSeek-V3.2-EXP—an increase of 3.32% over Naive GrepRAG. This gain is considerably larger than that obtained by merely replacing the ranking algorithm.

GrepRAG (Full): The complete configuration. This combination achieves the optimal performance (42.29%), demonstrating that once the deduplication mechanism secures information breadth, the precise ranking of BM25 further optimizes information precision. The two exhibit a favorable orthogonal complementarity.

5.5 Generalization of Ripgrep Command Generation

To verify that the performance gains achieved by our framework stem from genuine model agnosticism rather than parameter biases of specific models, we evaluated the generalization capability of the ripgrep command generation module on the CrossCodeEval dataset. As shown in Table 7, we deployed DeepSeek-V3.2-EXP and Qwen3-Coder-Plus as instruction generators. Results show that the choice of instruction generator has little effect on downstream code completion performance.

Table 6. Ablation Study: Impact of Re-ranking and De-duplication on CrossCodeEval.

Lang	Method (Component)	Retrieval Time(s)	DeepSeek-V3.2-EXP								Qwen3-Coder-Plus							
			Code				Identifier				Code				Identifier			
			EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1
Python	GrepRAG (Naive)	0.0186	38.61	77.54	89.08	87.50	48.33	78.67	74.59	72.33	40.79	79.82	88.96	88.52	51.52	80.97	75.96	74.85
	GrepRAG w/o Dedup	0.0189	39.12	77.96	89.42	87.85	49.21	79.32	75.47	73.02	41.35	79.94	89.13	89.03	52.12	81.20	76.24	75.39
	GrepRAG w/o BM25	0.0192	41.93	79.05	89.49	88.04	51.83	80.12	76.19	74.93	43.29	80.71	89.42	89.23	54.38	82.13	77.21	76.84
	GrepRAG (Full)	0.0197	42.29	79.66	89.53	88.50	52.76	80.76	76.84	75.15	44.62	81.32	89.58	89.45	55.87	82.62	77.90	77.29
Java	GrepRAG (Naive)	0.0173	41.70	78.93	89.93	89.33	52.17	79.95	76.62	75.67	41.42	78.31	87.92	88.67	51.90	79.02	74.69	74.77
	GrepRAG w/o Dedup	0.0175	41.91	79.35	89.97	89.42	52.88	80.02	76.75	75.81	41.92	78.60	88.16	88.84	52.63	79.80	74.91	75.03
	GrepRAG w/o BM25	0.0179	42.87	79.92	89.69	89.77	53.34	80.62	77.10	76.31	43.89	79.03	88.57	89.03	53.76	80.42	76.19	76.03
	GrepRAG (Full)	0.0181	43.15	80.07	89.78	89.83	53.81	80.88	77.41	76.57	44.09	79.95	88.98	89.29	54.09	80.69	76.83	76.57

Table 7. Generalization Study of Ripgrep Command Generation across Different Instruction Generators and Code Completion Backbones on CrossCodeEval.

Lang	Method	DeepSeek-V3.2-EXP								Qwen3-Coder-Plus							
		Code				Identifier				Code				Identifier			
		EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1	EM	ES	Recall	F1
Python	GrepRAG w/ DeepSeek	42.29	79.66	89.53	88.50	52.76	80.76	76.84	75.15	44.62	81.32	89.58	89.45	55.87	82.62	77.90	77.29
	GrepRAG w/ Qwen	41.03	79.03	89.15	88.38	52.20	80.20	75.89	74.69	44.21	80.96	89.05	89.07	54.91	82.07	76.70	76.45
Java	GrepRAG w/ DeepSeek	43.15	80.07	89.78	89.83	53.81	80.88	77.41	76.57	44.09	79.95	88.98	89.29	54.09	80.69	76.83	76.57
	GrepRAG w/ Qwen	42.57	79.30	89.67	89.38	53.09	80.39	77.25	75.93	43.65	79.14	88.31	89.05	53.76	79.64	75.47	75.24

This suggests that the ability to autonomously generate code retrieval instructions is not unique to a specific model but a general capability of modern LLMs. This ensures the stability of our framework across diverse LLM architectures.

5.6 Hyperparameter Sensitivity Analysis

On the large-scale RepoEval_Updated dataset, we investigated a critical hyperparameter N within the post-processing stage. This parameter denotes the percentage of candidate fragments (Top-N%) selected from the BM25 ranked list prior to the execution of the deduplication operation. We comprehensively evaluated the trends of four core metrics (code match EM/ES, identifier match EM/F1) as the value of N varies from 10% to 90%, as illustrated in Figure 7.

The experimental results exhibit a highly consistent inverted U-shaped pattern, indicating that the selection of N is pivotal for constructing high-quality context.

When $N < 50\%$, performance drops markedly. Due to severe redundancy in large repositories, the head of the BM25 list is often dominated by semantically identical blocks from different locations. Consequently, after performing deduplication, the effective Top list may collapse to only 1–2 blocks, leaving the LLM context window underutilized.

At $N = 50\%$, the model consistently achieves peak performance on both Python and Java across all metrics. This indicates that $N = 50\%$ provides a robust balance between candidate coverage and information density. We therefore adopt $N = 50\%$ as the default setting in GrepRAG.

When $N > 50\%$, performance plateaus or slightly degrades, as low-relevance blocks from the tail of the BM25 ranking contribute little to Top-K selection and may introduce additional noise.

6 Discussion

Mitigating LLM Overhead for Retrieval Command Generation Although the physical retrieval cost of ripgrep is minimal (on the order of milliseconds), generating retrieval commands with a general-purpose LLM still incurs additional inference latency due to the **model scale** and **output**

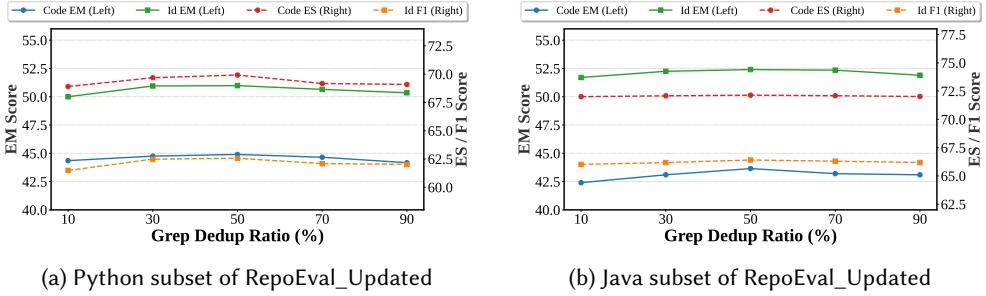


Fig. 7. Sensitivity analysis of the de-duplication candidate pool size (N) on RepoEval_Updated. The trends indicate that $N \approx 50\%$ achieves the optimal balance between context diversity and noise reduction.

token length. To address this issue, we optimize the process from two complementary perspectives: **output constraints** and **knowledge distillation**.

Regarding output length, we observe that grep commands exhibit highly templated characteristics, such as fixed parameters and rigid formats. Accordingly, when fine-tuning Qwen3-0.6B, the model is tasked only with predicting the core retrieval keywords, while the remaining command structure is directly instantiated from a static template. This design substantially reduces the number of generated tokens and thus lowers inference latency. For distillation, since the quality of the teacher model directly determines the performance upper bound of supervised fine-tuning [67], we employ `claude-opus-4-5-20251101`, a model with strong code generation capabilities, as the teacher to construct high-quality training data.

As shown in Table 8, on the line-level Python and Java tasks of the RepoEval_Updated dataset, the fine-tuned 0.6B model surpasses substantially larger general-purpose models in completion quality, achieving a dual optimization of performance and computational cost.

The RAG pipeline time reported in the table includes the end-to-end cost of indexing and retrieval for baseline methods, while for GrepRAG it refers to the combined time of `ripgrep` command generation and retrieval execution. The GrepRAG (DeepSeek-V3.2-EXP) variant is excluded from this comparison due to additional network latency introduced by API-based `ripgrep` command invocation. We observe that GrepRAG (0.6B Distilled) exhibits substantially lower RAG pipeline time than graph-based baseline methods. Moreover, the time required for `ripgrep` command generation has constant time complexity ($O(1)$), as it depends only on the local context of the current editing window and is independent of repository size. In contrast, graph-based approaches typically incur $O(N)$ or higher time overhead as the repository scale grows. Consequently, our method offers superior scalability and deployment practicality for large-scale, frequently evolving industrial code repositories where index maintenance is often a bottleneck.

Potential Data Contamination. A primary potential threat lies in the possibility that the pre-training corpora of LLMs may encompass portions of the evaluation benchmarks (Cross-CodeEval/RepoEval_Updated), thereby introducing memorization bias into the assessment results. Although we cannot entirely rule out data overlap, the core conclusions of this study are premised on relative performance gains, rather than absolute scores. All baseline methods and our proposed approach utilize identical backbone models. The significant improvements observed in GrepRAG relative to baselines provide compelling evidence that the performance gains stem from more precise context retrieval, rather than knowledge leakage within the model parameters.

Table 8. Efficacy Analysis of Knowledge Distillation. Evaluation on the RepoEval_Updated dataset for line-level Python and Java code completion using DeepSeek-V3.2-EXP as the backbone model.

Lang	Method	RAG Pipeline Time(s)	Code Match				Identifier Match			
			EM	ES	Recall	F1	EM	ES	Recall	F1
Python	Vanilla RAG	12.14	36.90	65.20	83.33	80.71	43.25	66.85	60.26	57.56
	GraphCoder	>60	43.70	67.95	83.30	81.42	49.50	69.94	63.28	61.05
	RepoFuse	>60	36.85	65.71	84.43	81.41	43.65	67.61	60.96	57.95
	RLCoder	—	42.60	68.82	84.95	82.48	48.85	70.61	64.96	61.89
	GrepRAG (Qwen3-0.6B)	2.05	36.31	64.65	83.01	80.46	42.46	66.35	60.01	57.19
	GrepRAG (DeepSeek-V3.2-EXP)	—	44.90	69.92	86.49	83.74	50.98	71.78	65.67	62.56
	GrepRAG (0.6B Distilled)	1.93	44.95	69.98	86.67	83.93	51.40	71.92	65.78	62.90
Java	Vanilla RAG	16.84	35.00	67.22	82.88	81.73	44.20	69.21	63.07	60.81
	GraphCoder	>60	39.30	69.59	83.35	82.67	48.05	71.17	64.58	62.89
	RepoFuse	>60	33.95	66.87	83.08	81.54	42.95	68.02	62.57	60.10
	RLCoder	—	40.10	70.67	85.16	83.88	49.05	72.34	67.05	64.69
	GrepRAG (Qwen3-0.6B)	1.89	34.46	66.49	82.83	81.36	43.57	68.38	62.48	59.41
	GrepRAG (DeepSeek-V3.2-EXP)	—	43.65	72.14	85.92	84.55	52.40	73.90	68.83	66.41
	GrepRAG (0.6B Distilled)	1.69	44.95	73.23	86.39	85.14	53.35	75.15	69.75	67.35

* The RAG Pipeline Time for GraphCoder and RepoFuse is marked as >60 to indicate that the latency exceeds 1 minute.

7 Related Work

7.1 Large Language Models for Code

The rapid evolution of LLMs has profoundly reshaped AI research, advancing natural language and multi-modal understanding [5, 51, 62, 63] while significantly boosting automated code completion and other software engineering tasks [31, 47, 53–55, 57, 58, 65]. Contingent upon the accessibility of model weights, existing technical paradigms are primarily categorized into two distinct classes: proprietary closed-source and open-source. Within this landscape, proprietary models[1, 45], such as the GPT-5.2 series, Gemini3, and Claude Opus 4.5, are generally regarded as performance benchmarks for evaluating code generation capabilities. Simultaneously, the open-source community offers a plethora of robust alternatives, encompassing both general-purpose foundation models such as DeepSeek-V3[10, 24, 25] and Qwen 3[2, 14, 59, 60], as well as domain-specific models explicitly optimized for programming languages, including Code Llama[39] and StarCoder[20, 29].

7.2 Repository-level Code Completion

While the aforementioned models excel in handling intra-file logic [29], they struggle in repository-level scenarios. Due to the highly modular nature of code logic, critical class definitions, function interfaces, and global constants are typically dispersed across disparate files. Consequently, models constrained by limited context windows fail to capture global semantics [26, 32, 40]. To address this challenge, RAG techniques have been introduced, aiming to retrieve relevant cross-file context from the global codebase to augment the generation process [8, 41, 42, 44, 56]. Existing technical paradigms have evolved primarily along three distinct directions.

Early research predominantly adopted similarity-based retrieval paradigms, utilizing semantic or lexical matching to locate reference information [12, 21, 30]. For instance, AceCoder [19] and APICoder [64] retrieve similar code snippets and API documentation, respectively, whereas RepoCoder [66] dynamically expands query semantics through an iterative Generate-then-Retrieve loop. Although these methods extend the context window, their reliance on BM25 or vector similarity makes it difficult to capture the intrinsic logical dependencies of code. In response, structure-aware methods incorporate static analysis techniques, attempting to explicitly model the topological relationships of code [3, 9]. Works such as GraphCoder [28], RepoHyper [35], and Cocomic [8] construct code context graphs or repository-wide dependency graphs to acquire

structured information; RepoFuse [23] further integrates noise filtering mechanisms upon this foundation. However, complex graph construction and traversal processes inevitably introduce high computational latency. Recent research has shifted towards strategy optimization and alignment, striving to bridge the objective gap between retrieval and generation tasks. RLCoder [52] employs reinforcement learning for end-to-end fine-tuning of the retriever, utilizing generation probability as the optimization objective. Similarly, AlignCoder enhances query semantics by generating candidate completions and trains a dedicated retriever using feedback signals, thereby enabling the retrieval strategy to dynamically adapt to the inference requirements of downstream models.

8 Conclusion

This paper demonstrates the effectiveness of lightweight lexical retrieval for code completion. Our experiments show that Naive GrepRAG can achieve competitive performance by capturing explicit lexical dependencies, but suffers under noisy and fragmented contexts. To overcome these limitations, we propose GrepRAG, combining identifier-weighted re-ranking with structural deduplication. Experiments on CrossCodeEval and RepoEval_Updated demonstrate consistent improvements over strong baselines, establishing a new SOTA. Future work will investigate adaptive routing to better support implicit dependency scenarios.

References

- [1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774* (2023).
- [2] Imtiaz Ahmed, Sadman Islam, Partha Protim Datta, Imran Kabir, Naseef Ur Rahman Chowdhury, and Ahshanul Haque. 2025. Qwen 2.5: A comprehensive review of the leading resource-efficient llm with potentioal to surpass all competitors. *Authorea Preprints* (2025).
- [3] Miltiadis Allamanis, Marc Brockschmidt, and Mahmoud Khademi. 2017. Learning to represent programs with graphs. *arXiv preprint arXiv:1711.00740* (2017).
- [4] Sven Amann, Sebastian Proksch, Sarah Nadi, and Mira Mezini. 2016. A study of visual studio usage in practice. In *2016 ieee 23rd international conference on software analysis, evolution, and reengineering (saner)*, Vol. 1. IEEE, 124–134.
- [5] Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. 2025. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923* (2025).
- [6] Mark Chen. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374* (2021).
- [7] Yangruibo Ding, Zijian Wang, Wasi Ahmad, Hantian Ding, Ming Tan, Nihal Jain, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, et al. 2023. Crosscodeeval: A diverse and multilingual benchmark for cross-file code completion. *Advances in Neural Information Processing Systems* 36 (2023), 46701–46723.
- [8] Yangruibo Ding, Zijian Wang, Wasi Uddin Ahmad, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, and Bing Xiang. 2022. Cocomic: Code completion by jointly modeling in-file and cross-file context. *arXiv preprint arXiv:2212.10007* (2022).
- [9] Daya Guo, Shuo Ren, Shuai Lu, Zhangyin Feng, Duyu Tang, Shujie Liu, Long Zhou, Nan Duan, Alexey Svyatkovskiy, Shengyu Fu, et al. 2020. Graphcodebert: Pre-training code representations with data flow. *arXiv preprint arXiv:2009.08366* (2020).
- [10] Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Yu Wu, YK Li, et al. 2024. DeepSeek-Coder: When the Large Language Model Meets Programming—The Rise of Code Intelligence. *arXiv preprint arXiv:2401.14196* (2024).
- [11] Junxiao Han, Shuguang Deng, David Lo, Chen Zhi, Jianwei Yin, and Xin Xia. 2021. An empirical study of the landscape of open source projects in Baidu, Alibaba, and Tencent. In *2021 IEEE/ACM 43rd International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE, 298–307.
- [12] Tatsunori B Hashimoto, Kelvin Guu, Yonatan Oren, and Percy S Liang. 2018. A retrieve-and-edit framework for predicting structured outputs. *Advances in Neural Information Processing Systems* 31 (2018).
- [13] Abram Hindle, Earl T Barr, Mark Gabel, Zhendong Su, and Premkumar Devanbu. 2016. On the naturalness of software. *Commun. ACM* 59, 5 (2016), 122–131.
- [14] Binyuan Hui, Jian Yang, Zeyu Cui, Jiaxi Yang, Dayiheng Liu, Lei Zhang, Tianyu Liu, Jiajun Zhang, Bowen Yu, Keming Lu, et al. 2024. Qwen2. 5-coder technical report. *arXiv preprint arXiv:2409.12186* (2024).

- [15] Paul Jaccard. 1901. Distribution de la flore alpine dans le bassin des Dranses et dans quelques régions voisines. *Bull Soc Vaudoise Sci Nat* 37 (1901), 241–272.
- [16] Vladimir I. Levenshtein. 1965. Binary codes capable of correcting deletions, insertions, and reversals. *Soviet physics. Doklady* 10 (1965), 707–710. <https://api.semanticscholar.org/CorpusID:60827152>
- [17] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-augmented generation for knowledge-intensive NLP tasks (*NIPS '20*). Curran Associates Inc., Red Hook, NY, USA, Article 793, 16 pages.
- [18] Guochang Li, Yuchen Liu, Zhen Qin, Yunkun Wang, Jianping Zhong, Chen Zhi, Binhu Li, Fei Huang, Yongbin Li, and Shuguang Deng. 2025. Empowering RepoQA-Agent based on Reinforcement Learning Driven by Monte-carlo Tree Search. *arXiv preprint arXiv:2510.26287* (2025).
- [19] Jia Li, Yunfei Zhao, Yongmin Li, Ge Li, and Zhi Jin. 2023. Acecoder: Utilizing existing code to enhance code generation. *arXiv preprint arXiv:2303.17780* (2023).
- [20] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. 2023. Starcoder: may the source be with you! *arXiv preprint arXiv:2305.06161* (2023).
- [21] Xiaonan Li, Yeyun Gong, Yelong Shen, Xipeng Qiu, Hang Zhang, Bolun Yao, Weizhen Qi, Daxin Jiang, Weizhu Chen, and Nan Duan. 2022. CodeRetriever: Large-scale contrastive pre-training for code search. *arXiv preprint arXiv:2201.10866* (2022).
- [22] Zeju Li, Changran Xu, Zhengyuan Shi, Zedong Peng, Yi Liu, Yunhao Zhou, Lingfeng Zhou, Chengyu Ma, Jianyuan Zhong, Xi Wang, et al. 2025. Deepcircuitx: A comprehensive repository-level dataset for rtl code understanding, generation, and ppa analysis. *arXiv preprint arXiv:2502.18297* (2025).
- [23] Ming Liang, Xiaoheng Xie, Gehao Zhang, Xunjin Zheng, Peng Di, Hongwei Chen, Chengpeng Wang, Gang Fan, et al. 2024. Repofuse: Repository-level code completion with fused dual context. *arXiv preprint arXiv:2402.14323* (2024).
- [24] Aixin Liu, Bei Feng, Bin Wang, Bingxuan Wang, Bo Liu, Chenggang Zhao, Chengqi Deng, Chong Ruan, Damai Dai, Daya Guo, et al. 2024. Deepseek-v2: A strong, economical, and efficient mixture-of-experts language model. *arXiv preprint arXiv:2405.04434* (2024).
- [25] Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, et al. 2024. Deepseek-v3 technical report. *arXiv preprint arXiv:2412.19437* (2024).
- [26] Nelson F Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. 2023. Lost in the middle: How language models use long contexts. *arXiv preprint arXiv:2307.03172* (2023).
- [27] Tianyang Liu, Canwen Xu, and Julian McAuley. 2023. Repobench: Benchmarking repository-level code auto-completion systems. *arXiv preprint arXiv:2306.03091* (2023).
- [28] Wei Liu, Ailun Yu, Daoguang Zan, Bo Shen, Wei Zhang, Haiyan Zhao, Zhi Jin, and Qianxiang Wang. 2024. Graphcoder: Enhancing repository-level code completion via code context graph-based retrieval and language model. *arXiv preprint arXiv:2406.07003* (2024).
- [29] Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtiar, Jiawei Liu, Yuxiang Wei, et al. 2024. Starcoder 2 and the stack v2: The next generation. *arXiv preprint arXiv:2402.19173* (2024).
- [30] Shuai Lu, Nan Duan, Hojae Han, Daya Guo, Seung-won Hwang, and Alexey Svyatkovskiy. 2022. Reacc: A retrieval-augmented code completion framework. *arXiv preprint arXiv:2203.07722* (2022).
- [31] Mohamed Nejjar, Luca Zacharias, Fabian Stiehle, and Ingo Weber. 2025. Llms for science: Usage for code generation and data analysis. *Journal of Software: Evolution and Process* 37, 1 (2025), e2723.
- [32] Ansong Ni, Pengcheng Yin, Yilun Zhao, Martin Riddell, Troy Feng, Rui Shen, Stephen Yin, Ye Liu, Semih Yavuz, Caiming Xiong, Shafiq Joty, Yingbo Zhou, Dragomir Radev, Arman Cohan, and Arman Cohan. 2024. L2CEval: Evaluating Language-to-Code Generation Capabilities of Large Language Models. *Transactions of the Association for Computational Linguistics* 12 (2024), 1311–1329. doi:10.1162/tacl_a_00705
- [33] Zhenyu Pan, Xuefeng Song, Yunkun Wang, Rongyu Cao, Binhu Li, Yongbin Li, and Han Liu. 2025. Do Code LLMs Understand Design Patterns?. In *2025 IEEE/ACM International Workshop on Large Language Models for Code (LLM4Code)*. IEEE, 209–212.
- [34] Md Rizwan Parvez, Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. 2021. Retrieval augmented code generation and summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2021*. 2719–2734.
- [35] Huy Nhat Phan, Hoang Nhat Phan, Tien N Nguyen, and Nghi DQ Bui. 2024. Repohyper: Better context retrieval is all you need for repository-level code completion. *CoRR* (2024).
- [36] Veselin Raychev, Martin Vechev, and Eran Yahav. 2014. Code completion with statistical language models. In *Proceedings of the 35th ACM SIGPLAN conference on programming language design and implementation*. 419–428.

- [37] Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084* (2019).
- [38] Stephen Robertson, Hugo Zaragoza, et al. 2009. The probabilistic relevance framework: BM25 and beyond. *Foundations and Trends® in Information Retrieval* 3, 4 (2009), 333–389.
- [39] Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Romain Sauvestre, Tal Remez, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950* (2023).
- [40] Freda Shi, Xinyun Chen, Kanishka Misra, Nathan Scales, David Dohan, Ed H Chi, Nathanael Schärli, and Denny Zhou. 2023. Large language models can be easily distracted by irrelevant context. In *International Conference on Machine Learning*. PMLR, 31210–31227.
- [41] Disha Shrivastava, Denis Kocetkov, Harm de Vries, Dzmitry Bahdanau, and Torsten Scholak. 2023. Repofusion: Training code models to understand your repository. *arXiv preprint arXiv:2306.10998* (2023).
- [42] Disha Shrivastava, Hugo Larochelle, and Daniel Tarlow. 2023. Repository-level prompt generation for large language models of code. In *International Conference on Machine Learning*. PMLR, 31693–31715.
- [43] Zhensu Sun, Xiaoning Du, Fu Song, Shangwen Wang, Mingze Ni, Li Li, and David Lo. 2025. Don’t complete it! Preventing unhelpful code completion for productive and sustainable neural code completion systems. *ACM Transactions on Software Engineering and Methodology* 34, 1 (2025), 1–22.
- [44] Hanzhuo Tan, Qi Luo, Ling Jiang, Zizheng Zhan, Jing Li, Haotian Zhang, and Yuqun Zhang. 2024. Prompt-based code completion via multi-retrieval augmented generation. *ACM Transactions on Software Engineering and Methodology* (2024).
- [45] Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican, et al. 2023. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805* (2023).
- [46] Helena Vasconcelos, Gagan Bansal, Adam Journey, Q Vera Liao, and Jennifer Wortman Vaughan. 2025. Generation probabilities are not enough: Uncertainty highlighting in ai code completions. *ACM Transactions on Computer-Human Interaction* 32, 1 (2025), 1–30.
- [47] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).
- [48] Chaozheng Wang, Junhao Hu, Cuiyun Gao, Yu Jin, Tao Xie, Hailiang Huang, Zhenyu Lei, and Yuetang Deng. 2023. How practitioners expect code completion?. In *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 1294–1306.
- [49] Chong Wang, Jian Zhang, Yebo Feng, Tianlin Li, Weisong Sun, Yang Liu, and Xin Peng. 2025. Teaching code llms to use autocompletion tools in repository-level code generation. *ACM Transactions on Software Engineering and Methodology* 34, 7 (2025), 1–27.
- [50] Xingliang Wang, Baoyi Wang, Chen Zhi, Junxiao Han, Xinkui Zhao, Jianwei Yin, and Shuiguang Deng. 2025. GRACE: Graph-Guided Repository-Aware Code Completion through Hierarchical Code Fusion. *arXiv preprint arXiv:2509.05980* (2025).
- [51] Yibo Wang, Lei Wang, Yue Deng, Keming Wu, Yao Xiao, Huanjin Yao, Liwei Kang, Hai Ye, Yongcheng Jing, and Lidong Bing. 2026. DeepResearchEval: An Automated Framework for Deep Research Task Construction and Agentic Evaluation. *arXiv preprint arXiv:2601.09688* (2026).
- [52] Yanlin Wang, Yanli Wang, Daya Guo, Jiachi Chen, Ruikai Zhang, Yuchi Ma, and Zibin Zheng. 2024. Rlcoder: Reinforcement learning for repository-level code completion. *arXiv preprint arXiv:2407.19487* (2024).
- [53] Yunkun Wang, Yue Zhang, Guochang Li, Chen Zhi, Binhua Li, Fei Huang, Yongbin Li, and Shuiguang Deng. 2025. InspectCoder: Dynamic Analysis-Enabled Self Repair through interactive LLM-Debugger Collaboration. *arXiv preprint arXiv:2510.18327* (2025).
- [54] Yunkun Wang, Yue Zhang, Zhen Qin, Chen Zhi, Binhua Li, Fei Huang, Yongbin Li, and Shuiguang Deng. 2025. ExploraCoder: Advancing code generation for multiple unseen APIs via planning and chained exploration. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 18124–18145.
- [55] Zixuan Wu, Chen Zhi, Junxiao Han, Shuiguang Deng, and Jianwei Yin. 2025. LLMApHub: A Large Collection of LLM-based Applications for the Research Community. In *Proceedings of the 33rd ACM International Conference on the Foundations of Software Engineering*, 1254–1255.
- [56] Shitao Xiao, Zheng Liu, Peitian Zhang, Niklas Muennighoff, Defu Lian, and Jian-Yun Nie. 2024. C-pack: Packed resources for general chinese embeddings. In *Proceedings of the 47th international ACM SIGIR conference on research and development in information retrieval*, 641–649.
- [57] Haoran Xu, Chen Zhi, Junxiao Han, Xinkui Zhao, Jianwei Yin, and Shuiguang Deng. 2025. Revisiting Vulnerability Patch Localization: An Empirical Study and LLM-Based Solution. *arXiv preprint arXiv:2509.15777* (2025).

- [58] Haoran Xu, Chen Zhi, Tianyu Xiang, Zixuan Wu, Gaorong Zhang, Xinkui Zhao, Jianwei Yin, and Shuiguang Deng. 2025. Prioritizing Large-Scale Natural Language Test Cases at OPPO. In *2025 IEEE/ACM 47th International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE, 458–468.
- [59] An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengan Huang, Chenxu Lv, et al. 2025. Qwen3 technical report. *arXiv preprint arXiv:2505.09388* (2025).
- [60] Jian Yang, Wei Zhang, Yibo Miao, Shanghaioran Quan, Zhenhe Wu, Qiyao Peng, Liqun Yang, Tianyu Liu, Zeyu Cui, Binyuan Hui, et al. 2025. Qwen2. 5-xCoder: Multi-Agent Collaboration for Multilingual Code Instruction Tuning. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 13121–13131.
- [61] Zezhou Yang, Sirong Chen, Cuiyun Gao, Zhenhao Li, Xing Hu, Kui Liu, and Xin Xia. 2025. An empirical study of retrieval-augmented code generation: Challenges and opportunities. *ACM Transactions on Software Engineering and Methodology* (2025).
- [62] Zuhao Yang, Sudong Wang, Kaichen Zhang, Keming Wu, Sicong Leng, Yifan Zhang, Bo Li, Chengwei Qin, Shijian Lu, Xinxuan Li, et al. 2025. Longvt: Incentivizing" thinking with long videos" via native tool calling. *arXiv preprint arXiv:2511.20785* (2025).
- [63] Yang Yao, Yixu Wang, Yuxuan Zhang, Yi Lu, Tianle Gu, Lingyu Li, Dingyi Zhao, Keming Wu, Haozhe Wang, Ping Nie, et al. 2025. A Rigorous Benchmark with Multidimensional Evaluation for Deep Research Agents: From Answers to Reports. *arXiv preprint arXiv:2510.02190* (2025).
- [64] Daoguang Zan, Bei Chen, Zeqi Lin, Bei Guan, Yongji Wang, and Jian-Guang Lou. 2022. When language model meets private library. *arXiv preprint arXiv:2210.17236* (2022).
- [65] Daoguang Zan, Bei Chen, Fengji Zhang, Dianjie Lu, Bingchao Wu, Bei Guan, Yongji Wang, and Jian-Guang Lou. 2022. Large language models meet NL2Code: A survey. *arXiv preprint arXiv:2212.09420* (2022).
- [66] Fengji Zhang, Bei Chen, Yue Zhang, Jacky Keung, Jin Liu, Daoguang Zan, Yi Mao, Jian-Guang Lou, and Weizhu Chen. 2023. Repocoder: Repository-level code completion through iterative retrieval and generation. *arXiv preprint arXiv:2303.12570* (2023).
- [67] Kaichen Zhang, Keming Wu, Zuhao Yang, Bo Li, Kairui Hu, Bin Wang, Ziwei Liu, Xingxuan Li, and Lidong Bing. 2025. OpenMMReasoner: Pushing the Frontiers for Multimodal Reasoning with an Open and General Recipe. *arXiv preprint arXiv:2511.16334* (2025).
- [68] Xinkui Zhao, Rongkai Liu, Yifan Zhang, Chen Zhi, Lufei Zhang, Guanjie Cheng, Yueshen Xu, Shuiguang Deng, and Jianwei Yin. 2025. Completion by Comprehension: Guiding Code Generation with Multi-Granularity Understanding. *arXiv preprint arXiv:2512.04538* (2025).
- [69] Chen Zhi, Liye Cheng, Meilin Liu, Xinkui Zhao, Yueshen Xu, and Shuiguang Deng. 2024. LLM-powered Zero-shot Online Log Parsing. In *2024 IEEE International Conference on Web Services (ICWS)*. IEEE, 877–887.
- [70] Albert Ziegler, Eirini Kalliamvakou, X Alice Li, Andrew Rice, Devon Rifkin, Shawn Simister, Ganesh Sittampalam, and Edward Aftandilian. 2022. Productivity assessment of neural code completion. In *Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming*. 21–29.