CodeRAG: Finding Relevant and Necessary Knowledge for Retrieval-Augmented Repository-Level Code Completion

Sheng Zhang[1,†], **Yifan Ding**[1,†], **Shuquan Lian**[1], **Shun Song**[2], **Hui Li**[1,§]
[1]Key Laboratory of Multimedia Trusted Perception and Efficient Computing
Ministry of Education of China, Xiamen University
[2]Ant Group
{sheng, dingyf, shuquanlian}@stu.xmu.edu.cn, songshun.ss@antgroup.com
hui@xmu.edu.cn

Abstract

Repository-level code completion automatically predicts the unfinished code based on the broader information from the repository. Recent strides in Code Large Language Models (code LLMs) have spurred the development of repository-level code completion methods, yielding promising results. Nevertheless, they suffer from issues such as inappropriate query construction, single-path code retrieval, and misalignment between code retriever and code LLM. To address these problems, we introduce CodeRAG, a framework tailored to identify relevant and necessary knowledge for retrieval-augmented repository-level code completion. Its core components include log probability guided query construction, multi-path code retrieval, and preference-aligned BestFit reranking. Extensive experiments on benchmarks ReccEval and CCEval demonstrate that CodeRAG significantly and consistently outperforms state-of-the-art methods. The implementation of CodeRAG is available at https://github.com/KDEGroup/CodeRAG.

1 Introduction

Recent years have witnessed the remarkable success of Large Language Models (LLMs) in various areas (Zhao et al., 2023). As a branch of LLMs, Code Large Language Models (code LLMs), are trained on massive code data, enabling them to comprehend and generate code snippets, thus assisting programmers in coding tasks and boosting development efficiency (Nijkamp et al., 2023; Rozière et al., 2023; Li et al., 2023).

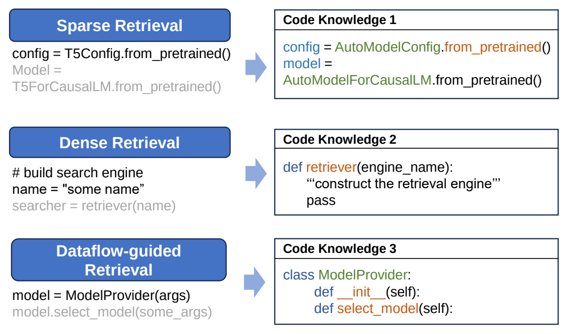
A typical application of code LLMs is code completion, which automatically predicts the unfinished code (Svyatkovskiy et al., 2019). Early code completion methods solely leverage *code context* (i.e., information from the function or source code file that the programmer is working on) (Li et al., 2018; Wang and Li, 2021). However, real-world software source code generally consists of multiple code files with complex interdependencies, which were neglected by early methods. These code files are essential ingredients for programmers to consider when developing unfinished code and they are typically organized as a source code repository. Thus, a practical code completion tool should be *repository-level* and leverage both code context and information retrieved from the entire codebase to provide more accurate and comprehensive code suggestions (Zhang et al., 2023).

Since repository-level code completion can better facilitate collaborative development and software maintenance, there is a surge of work in this direction (Zhang et al., 2023; Liu et al., 2024; Cheng et al., 2024) and most of them consider applying Retrieval-Augmented Generation (RAG), a prevalent solution incorporating external knowledge to help LLMs generate more accurate text (Gao et al., 2023). Based on the idea of RAG, these methods retrieve relevant code knowledge from the entire repository as supplementary to code context when predicting the unfinished code.

Despite the blossom of related approaches, they still suffer from the following shortcomings:

- **P1: Inappropriate Query Construction.** Previous approaches use either the last k lines before the cursor position (Tan et al., 2024) or the last k lines together with the generated code from code LLM (Zhang et al., 2023) as the query for code retrieval and find relevant code knowledge to assist completion, causing information loss and introducing noises. For example, programmers may define key variables and classes, or import packages at the beginning of a file, which are essential for understanding and completing the code accurately. If the last k lines contain irrelevant code, the retrieved code knowledge will

[†]The first two authors contribute equally.
[§]Hui Li is the corresponding authors.



```
config = T5Config.from_pretrained()
Model =
T5ForCausalLM.from_pretrained()
```

```
config = AutoModelConfig.from_pretrained()
model =
AutoModelForCausalLM.from_pretrained()
```

```
# build search engine
name = "some name”
searcher = retriever(name)
```

```
def retriever(engine_name):
    “‘construct the retrieval engine’”
    pass
```

```
model = ModelProvider(args)
model.select_model(some_args)
```

```
class ModelProvider:
        def __init__(self):
        def select_model(self):
```

Figure 1: Examples of different code retrieval paths, where the gray text indicates the code to be generated.

mislead code LLM to generate inaccurate code.

- **P2: Single-path Code Retrieval.** Existing methods either model code as plain text and chuck code to construct the knowledge base for later sparse/dense retrieval (Zhang et al., 2023; Wu et al., 2024), or construct specific data structures (e.g., dataflow graph) representing code for later retrieval (Liu et al., 2024; Cheng et al., 2024). While each method has its unique advantage and may apply to some code completion cases, neither of them can handle all completion cases well. For instance, Fig. 1 depicts three code completion examples and each fits one retrieval method. Sparse retrieval is ideal when the query and code knowledge directly overlap. Dense retrieval is more appropriate when the query and code knowledge are semantically related. In contrast, dataflow-guided retrieval facilitates additional searches based on variable instantiation.
- **P3: Misalignment between Code Retriever and Code LLM.** Similar to other RAG applications (Jin et al., 2024), inconsistencies may exist between retrieved code knowledge and necessary knowledge for code LLM, due to the separate training process and learning objective of code retriever and code LLM. While this issue has recently been studied in various works on RAG for question answering (Zhang et al., 2024; Dong et al., 2024), it is still underexplored for repository-level code completion.

To address these issues, we propose a new framework CodeRAG for finding *relevant* and *necessary* knowledge in retrieval-augmented repository-level code completion. Our contributions are:

- To overcome **P1**, instead of using last k lines, CodeRAG adopts log probability guided probing to construct retrieval query for code retrieval.
- To address **P2**, CodeRAG employs multi-path code retrieval over the constructed code knowledge base to benefit from the unique advantage of each *code-specific* retrieval path.
- To alleviate **P3**, CodeRAG adopts preference-aligned BestFit reranking to efficiently find necessary code knowledge. The retrieved code knowledge is reranked via LLM reranker according to code LLM's preference. To reduce the reranking overhead, we further distill the preference of LLM reranker into a smaller reranker and use it to conduct reranking.
- CodeRAG feeds the reranked code knowledge into code LLM for repository-level code completion. Experiments on benchmarks ReccEval and CCEval show that CodeRAG significantly and consistently exceeds state-of-the-art methods.

2 Our Method CodeRAG

As depicted in Fig. 2, CodeRAG involves five parts: code knowledge base construction (Sec. 2.1), retrieval query construction (Sec. 2.2), multi-path code retrieval (Sec. 2.2.1), preference-aligned BestFit code reranking (Sec. 2.3) and retrieval-augmented repository-level code completion.

2.1 Code Knowledge Base Construction

Constructing code knowledge base involves parsing and processing the code in the repository, transforming code into structured knowledge to enable more efficient retrieval, understanding, and reuse.

To construct the knowledge base for retrieval, general RAG methods typically segment the text corpus based on predefined rules, such as splitting by length or delimiters (Sarthi et al., 2024). However, applying these approaches to code data compromises the structural integrity and leads to the loss of pertinent information. For instance, dividing a class arbitrarily may result in omitting essential class-related details.

To alleviate the above problem, we propose a segmentation strategy tailored to the construction of code knowledge base. Specifically, we consider four elements in constructing the code knowledge base: functions, global variables, class variables, and class functions, as depicted in Fig. 3. For a target code repository, we first extract the Abstract Syntax Tree (AST) of each code file. Then, we extract the four types of elements from ASTs. This way, the code repository can be transformed into a structured knowledge base, including function calls and variable usage, providing data support for repository-level code completion.

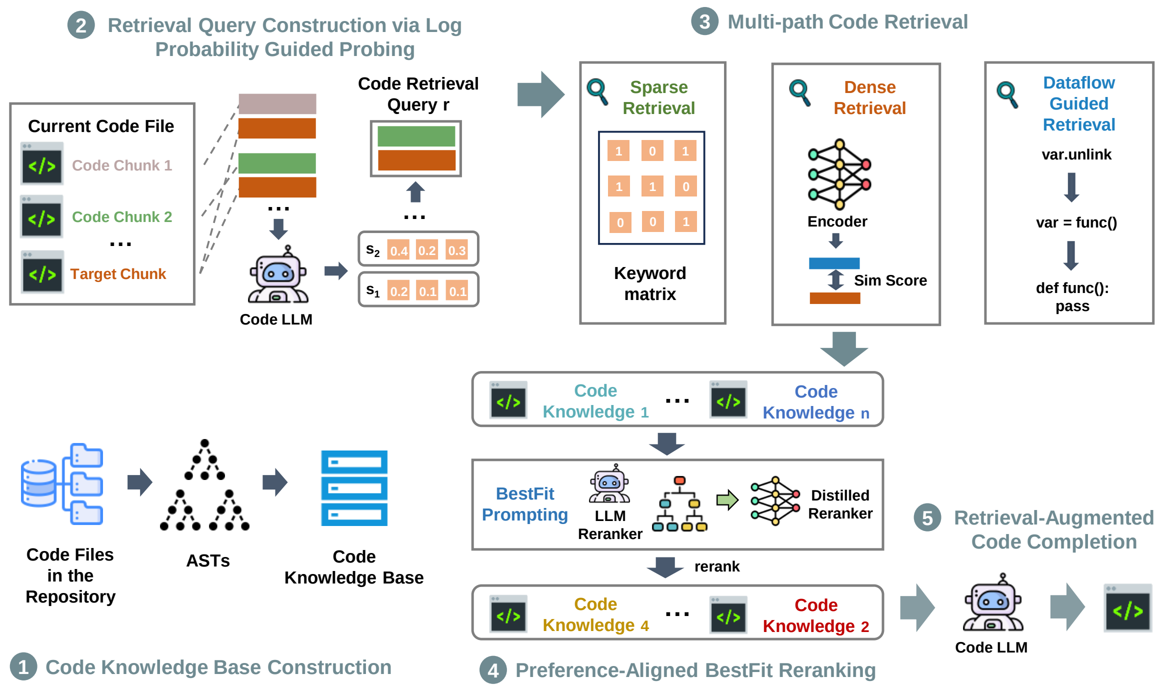
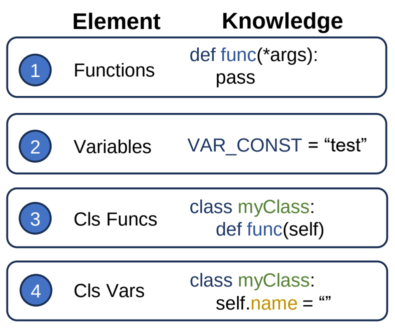


Figure 2: Overview of CodeRAG.



	Element	Knowledge
1	Functions	def func(*args): pass
2	Variables	VAR_CONST = "test"

3	Cls Funcs	class myClass:
		def func(self)

4	Cls Vars	class myClass:
		self.name = ""

Figure 3: Examples of Code Knowledge Base Items.

2.2 Retrieval Query Construction via Log Probability Guided Probing

In standard RAG, a retrieval query conveys the user intent from the user query or consists of a specific text chunk from a document. Using the retrieval query, the RAG framework can retrieve relevant knowledge from the knowledge base to assist text generation. In existing repository-level code completion methods, the concept of retrieval query shifts to represent an incomplete code segment (Zhang et al., 2023), which could be an unfinished function, a partially defined variable, or a method call within a class (i.e., code context).

To overcome the limitation of using the last k lines as the code retrieval query (i.e., **P1** illustrated in Sec. 1), we propose to construct the code retrieval query based on the log probability gain. Alg. 1 depicts the overall procedure for code retrieval query construction. The core idea is to use

```
Algorithm 1: Construct Retrieval Query
  Input: $C$ (code file to be completed), $f$ (chunk
         length), $m$ (number of generation step), $g$
         (number of selected chunks)
  Output: $r$ (code retrieval query)
  Function QueryConstruction($C, f, m, g$):
      Divide $C$ into fine-grained chunks and each chunk
        having $f$ lines.
      for each chunk $c_i$ do
          if $c_i$ is the target chunk then
              Pass.
          Concatenate $c_i$ to the target chunk.
          Feed the concatenation into code LLM to
            generate $m$ new tokens.
          Record the highest log probability for all tokens
            in the vocabulary at each generation step.
          Sum $m$ probability scores as the confidence
            score $s_i$.
      Select the top-$g$ chunks with the highest
        confidence scores $s$.
      Concatenate the $g$ chunks with the target chunk as
        the retrieval query $r$.
      return $r$.
```

log probability to find the fine-grained code chunks that are most important to constructing code retrieval query. In repository-level code completion, we can view log probability as the confidence of code LLMs, given the code retrieval query. In other words, log probability can reveal the relevance of the code chunks in the retrieval query.

As shown in Alg. 1, we first chunk the code file that the programmer is working on into fine-grained pieces and each of them contains f lines. Then, we concatenate each fine-grained chunk to the chunk containing unfinished code (the target chunk) as the probe and feed it to code LLM to generate m tokens. For simplicity, we choose the token with the maximum log probability at each step and use CodeT5p-220m[1] as code LLM for this step. The sum of the log probabilities for all generated token is recorded as the relevance score for the fine-grained chunk corresponding to the probe. Finally, the top-g fine-grained chunks with the highest relevance scores are concatenated together with the target chunk as the retrieval query.

2.2.1 Multi-path Code Retrieval

As an essential part of RAG, code retriever finds relevant code knowledge from code knowledge base according to the code retrieval query. Early code retrieval methods rely on traditional information retrieval methods like TF-IDF and BM25 (sparse retrieval), and recent code retrieval approaches commonly adopt embedding based methods (Dense Retrieval) (Sun et al., 2024). Most recently, Cheng et al. (2024) find that dataflow can also be used to guide code retrieval (dataflow-guided retrieval). These methods consider code retrieval from a single perspective and retrieve word-matching knowledge, semantically relevant knowledge, or knowledge having data dependency relations with the target chunk. Each of them has its unique advantages and can well provide retrieved code knowledge for some code completion cases. Hence, we argue that conducting a multi-path code retrieval can better offer code knowledge for later code completion. Our designed multi-path code retrieval step involves the following three code retrieval paths:

Sparse Retrieval. Sparse retrieval relies on keyword matching between the retrieval query and code knowledge in the code knowledge base, which identifies exact or closely related keywords within the codebase, to obtain relevant invocation details, API calls, and code snippets that share similar structures or functionality. Sparse retrieval is efficient and particularly effective when searching syntactically similar code or commonly used functions, as it can quickly pinpoint segments that contain specific terms or identifiers. We use TF-IDF (Jones, 2004) for sparse retrieval.

Dense Retrieval. Dense retrieval leverages an encoding model to encode the retrieval query and code knowledge in the code knowledge base into representations. The query is encoded at the chunk level, whereas the items in the knowledge base are either at the function level (functions) or the line level (variables). Code knowledge that has high similarity with the retrieval query w.r.t. their representations is retrieved. We use cosine similarity as the similarity measure and adopt the pre-trained encoder in CodeT5p-220m as the encoding model.

Dataflow-Guided Retrieval. It finds relevant information w.r.t. the target chunk in the current code file according to data dependency relations. Following Cheng et al. (2024), we first formulate the unfinished code file into a dataflow graph. Once the graph is built, we can retrieve the dependency starting from the last unfinished line in the dataflow graph as the retrieved code knowledge.

For sparse and dense retrieval, we use the constructed retrieval query to retrieve j results from each path. If data dependency exists in the dataflow graph, we retrieve dependency-related code via dataflow-guided retrieval. After receiving all retrieved results from three paths, we add them to a retrieval list containing n (i.e., $2j + 1$) results.

2.3 Find Necessary Code Knowledge through Preference-Aligned BestFit Reranking

The retrieved code knowledge is used to augment the code completion prompt, directly affecting the quality of code completion. Solely using the multi-path code retriever may not provide an appropriate order of relevant knowledge. The reason is the misalignment between the code retriever and code LLM, which is caused by their separate training objectives (Zhang et al., 2024). Therefore, we further deploy a reranking module that reranks retrieved code knowledge according to code LLM's preference and only keep top-u code knowledge ($u < n$).

2.3.1 BestFit Code Reranking

To address the misalignment, a natural way is to train the reranker using feedback signals from code LLM. However, in repository-level code completion, it is very difficult to acquire feedback from code LLM that can perfectly show the quality of the generated code. One possible solution is applying unit tests on the generated code from code LLM (Ma et al., 2025). While conducting unit tests is possible for function-level code completion, it is costly in the repository-level setting where the complete project must be executed in order to see the impact of inserting generated code. Besides, unlike function-level code completion where inputs

[1] https://huggingface.co/Salesforce/codet5p-220m

Which of the retrieved code snippets is most helpful for completing the following code snippet?

The code snippet to be completed:
{query}

The retrieved code snippet(s):
{code snippets}

Please provide only the label of the most helpful retrieved code snippet, enclosed in square brackets, within the answer tags. For example, if the code snippet C is the most helpful, the answer should be: <answer>[C]</answer>

Figure 4: Prompt for LLM-based BESTFIT reranking.

and outputs to unit test are easy to design, crafting inputs and labeling outputs to unit tests in the repository-level setting is much harder (e.g., more execution parameters or outputs are not variables).

Considering the above difficulty, an alternative is to apply an LLM as a zero-shot reranker (Sun et al., 2023). And the LLM is instructed to directly produce the reranking list of the retrieval code knowledge pieces according to their relevance to the query. Although recent studies (Sun et al., 2023; Pradeep et al., 2023) have shown the strong ability of LLMs on zero-shot document reranking, we empirically find that this listwise prompting solution does not work well on reranking code knowledge: (1) LLMs with a few billion parameters that can be deployed locally more easily do not strictly adhere to listwise prompting, while calling APIs of online LLMs that have much larger model sizes and can understand and strictly follow listwise prompting incurs high overhead. (2) Listwise prompting itself is computationally intensive since the reranking list is generated token by token. LLM reranker must do one inference for each next token prediction during reranking list generation.

To overcome this issue, we propose BESTFIT code reranking that prompts the LLM reranker to pick the most relevant code knowledge from the retrieval list to the query. The prompt is listed in Fig. 4. This way, the inference cost is significantly reduced as we only need a single forward pass of the LLM reranker. Fig. 5 depicts the difference between listwise and BESTFIT code reranking. Moreover, we find that an LLM with a few billion parameters can strictly follow BESTFIT prompting. Hence, we directly use Qwen3-8B as LLM reranker[2], avoiding additional instructing tuning of LLM reranker or calling online LLM APIs.

[2]https://huggingface.co/Qwen/Qwen3-8B

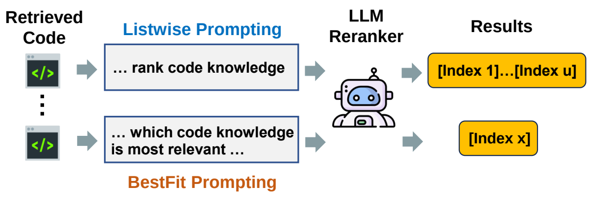


Figure 5: A comparison between listwise code reranking and BESTFIT code reranking.

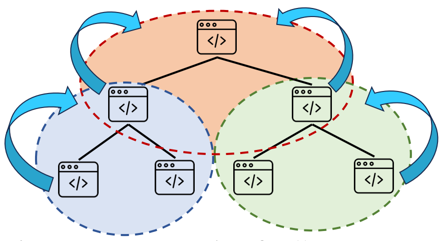


Figure 6: Heap sort operation finally moves top-u code knowledge pieces to the top. Each circle denotes a window of 3 code knowledge pieces.

To avoid exceeding LLM's input length, we implement a sliding window strategy that divides the retrieval list into several equal-sized windows, and the adjacent two windows share one code knowledge. Fig. 6 provides an example with a window size of 3. Each time, we feed one window to LLM reranker and ask it to pick only the most helpful code knowledge. Inspired by prior work (Qin et al., 2024; Zhuang et al., 2024) that uses sorting algorithms to speed up LLM-based pairwise reranking, we apply heap sort to accelerate BESTFIT code reranking. Windows are organized as a heap tree and each time we use LLM reranker as the comparator to find the most relevant code in a window. Heap sort can quickly find the top-u most relevant code knowledge in the reranking list. We choose heap sort instead of other sorting methods due to its simplicity and the complexity $\mathcal{O}(NlogN)$.

2.3.2 Distilled Reranker

Even though BESTFIT code reranking only requires the LLM reranker to have a few billion parameters, directly employing the LLM reranker may still incur a high computational cost. Hence, we distill the preference of the LLM reranker into a much smaller reranker model.

To train the distilled reranker, we first use a data augmentation strategy (Alg. 2) to construct distillation training data. We use unfinished code in the training data to formulate code retrieval queries and conduct multi-path code retrieval to produce initial retrieval lists. Then, we conduct data augmentation by generating multiple variations of each initial retrieval list $\mathcal{L}$, where each variation contains differ-

Algorithm 2: Construct Distillation Data

```
Input: $r$ (code retrieval query), $\mathcal{L}$
       (initial retrieval list for $r$), $\mathcal{N}$ (sample
       numbers)
Output: $\mathcal{S}$ (distillation training sample for $r$)
Function DataConstruction($r$, $\mathcal{L}$):
    for $i$ in $\mathcal{N}$ do
        for $j = 1$ to 3 do
            Randomly pick $i$ code knowledge from $\mathcal{L}$ as
              the retrieved code snippet(s) {code
              snippets} in Fig. 4.
            $\mathcal{C} \leftarrow [\,]$
            for $z = 1$ to 5 do
                Use BestFit reranking prompt in Fig. 4
                  to guide LLM reranker to select [C]
                  from {code snippets}.
                Add [C] to $\mathcal{C}$.
            if One code knowledge [C] occurs at least
              four times in $\mathcal{C}$ then
                Add {$r$, {code snippets}, [$C$]} to $\mathcal{S}$.
    return $\mathcal{S}$.
```

ing amounts of code knowledge. After that, we use LLM reranker with BestFit prompting to select the most helpful code knowledge from each generated variation, repeating this process five times to assess selection consistency. When LLM reranker demonstrates high confidence in its selections (i.e., when consistent choices appear in at least four out of five trials), the generated list, together with the corresponding code retrieval query and consensus selection, is treated as a distillation training sample $\mathcal{S}$. This way, $\mathcal{S}$ reflects LLM reranker's most reliable decision patterns. We use all curated distillation samples to fine-tune Qwen3-0.6B[3], the backbone of the distilled reranker, using LoRA (Hu et al., 2022) and token-level cross-entropy loss.

Finally, the trained distilled reranker is used in CodeRAG to actually rerank the retrieved code knowledge and CodeRAG retains top-u code knowledge in the reranking list ($u < n$).

2.4 Putting All Together

During completion, for an unfinished code file, CodeRAG firstly constructs the corresponding code retrieval query r. Then CodeRAG uses r to conduct multi-path code retrieval over the code knowledge base and retrieves top-n relevant code knowledge. After that, CodeRAG leverages the BestFit reranker to rank the n relevant code knowledge and retains the top-u necessary code knowledge pieces. Finally, the code context of the unfinished code file is concatenated with the u pieces of code knowledge, and the result is fed into code LLM to generate the completion.

3 Experiment

3.1 Evaluation Settings

Metrics. We use prevalent metrics (Liu et al., 2024; Zhang et al., 2023) for evaluation:

- **Code Match.** Exact Match (EM) and Edit Similarity (ES)[4] are employed to assess code alignment. EM is 1 when the generated code is identical to the ground-truth answer, and 0 otherwise. ES provides a more nuanced evaluation, calculated as ES $= 1 - \text{Lev}(x, y)/max(\|x\|, \|y\|)$, where Lev$(\cdot)$ denotes the Levenshtein distance.
- **Identifier Match**. We utilize EM and F1 scores to evaluate the alignment of identifiers in the generated code and the ground-truth answer.

Baselines. We use several representative repository-level code completion baselines: Zero-Shot, CCFinder (Ding et al., 2024), RG-1 (Zhang et al., 2023), RepoCoder (Zhang et al., 2023), DraCo (Cheng et al., 2024), RepoFuse (Liang et al., 2024), and Repoformer-3B (Wu et al., 2024).

Code LLMs. We use four representative code LLMs with different parameter numbers as code generators: CodeGen-350M[5] (Nijkamp et al., 2023), SantaCoder-1.1B[6] (Allal et al., 2023), StarCoder2-3B[7] (Lozhkov et al., 2024), and Qwen2.5-Coder-7B[8] (Hui et al., 2024).

Datasets. We use benchmarks ReccEval (Cheng et al., 2024) and CCEval (Ding et al., 2023).

Environment and Hyper-Parameters. We use a machine with two Intel(R) Xeon(R) Silver 4314 CPU @ 2.40GHz and one NVIDIA A800 GPU for experiments. The maximum number of generation tokens is set to 48. The temperature during generation is set to 0. The maximum input length of all code LLMs is set to 2,048 by default. We use the Text Generation Inference[9] framework to accelerate LLM inference. By default, we use LLM reranker in CodeRAG. We set f and g to 3 and 1

[3]https://huggingface.co/Qwen/Qwen3-0.6B

[4]Note that the paper of DraCo adopts a different way to measure ES (see https://github.com/nju-websoft/DraCo?tab=readme-ov-file#evaluation). We follow the definition of ES used in the paper of RepoCoder.

[5]https://huggingface.co/Salesforce/codegen-350M-mono

[6]https://huggingface.co/bigcode/santacoder

[7]https://huggingface.co/bigcode/starcoder2-3b

[8]https://huggingface.co/Qwen/Qwen2.5-Coder-7B

[9]https://huggingface.co/docs/text-generation-inference/index

Table 1: Performance on ReccEval (Use 100% data for evaluation). Bold and underlined values indicate the best and the second-best results, respectively.

Methods	CodeGen-350M				SantaCoder-1.1B				StarCoder2-3B				Qwen2.5-Coder-7B			
	Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match	
	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1
Zero-Shot	4.04	38.36	9.74	26.06	6.27	42.22	12.89	30.08	7.86	45.04	14.44	33.34	11.48	47.72	18.37	36.43
CCFinder	16.50	47.71	23.34	40.12	19.08	50.99	26.67	43.31	28.12	58.93	36.44	53.42	28.43	58.95	36.76	53.09
RG-1	20.04	50.30	26.53	41.35	24.07	54.72	31.26	46.29	29.35	59.43	36.76	52.27	33.01	61.55	40.15	54.68
RepoCoder	23.96	53.27	31.01	45.87	26.78	56.59	34.31	49.07	34.27	63.09	42.30	57.39	34.99	62.71	42.38	56.20
DraCo	21.85	51.44	29.44	45.92	30.27	59.38	38.97	55.50	36.57	64.31	45.61	61.42	39.99	66.26	48.55	63.41
RepoFuse	21.20	51.18	27.81	43.84	28.73	57.89	36.50	51.74	33.88	61.96	41.43	56.52	38.24	65.11	45.88	60.11
CodeRAG$_{\text{llmr}}$	**26.81**	**55.54**	**34.02**	**50.13**	**36.17**	**63.00**	**44.17**	**59.64**	**42.69**	**68.07**	**51.34**	**65.73**	**47.48**	**70.82**	**55.47**	**68.68**

Table 2: Performance on CCEval (Use 100% data for evaluation). Bold and underlined values indicate the best and the second-best results, respectively.

Methods	CodeGen-350M				SantaCoder-1.1B				StarCoder2-3B				Qwen2.5-Coder-7B			
	Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match	
	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1
Zero-Shot	2.70	43.02	8.26	37.85	4.35	46.52	10.58	41.88	6.53	48.56	12.91	44.52	11.11	52.19	18.09	48.35
CCFinder	10.58	48.65	17.19	45.96	14.63	53.44	23.08	51.90	21.08	58.11	29.42	57.46	24.80	59.52	33.47	62.61
RG-1	8.78	49.54	16.47	46.33	12.83	53.78	21.99	51.76	17.78	57.74	27.35	56.55	22.51	61.84	32.91	60.68
RepoCoder	10.58	51.07	19.06	48.93	15.12	55.66	24.62	53.78	21.24	60.90	31.56	60.00	25.89	63.65	36.21	63.09
DraCo	12.83	50.71	20.33	48.91	19.70	57.17	29.04	56.82	26.68	62.11	36.29	62.75	30.69	65.46	40.64	66.26
RepoFuse	11.22	50.78	19.29	48.77	17.64	56.52	27.02	55.65	23.34	61.28	33.43	61.16	27.73	64.76	38.39	64.82
CodeRAG$_{\text{llmr}}$	**14.11**	**52.44**	**22.28**	**51.56**	**22.89**	**59.92**	**32.42**	**60.24**	**30.66**	**65.46**	**41.13**	**66.62**	**35.20**	**68.93**	**45.97**	**70.47**

Table 3: Performance of RepoFormer-3B (Use 100% data for evaluation). "l": only use left context. "lr": use both left and right contexts.

Dataset	RepoFormer-3B			
	Code Match		Identifier Match	
	EM	ES	EM	F1
ReccEval$_l$	12.88	48.21	19.81	36.93
CCEval$_l$	8.18	50.19	15.53	46.25
CCEval$_{lr}$	25.29	63.45	33.77	61.48

in Alg. 1, respectively. We set j to 15 in multi-path code retrieval and u to 10 in reranking. We use $\mathcal{N} = \{2, 3, 4, 5, 6, 7\}$ in Alg. 2.

3.2 Evaluation Results

3.2.1 Overall Performance

We first report the results when using all data for evaluation in Tab. 1 and Tab. 2. In this case, LLM reranker (i.e., CodeRAG$_{\text{llmr}}$) is used instead of distilled reranker (i.e., CodeRAG$_{\text{disr}}$) since distilled reranker requires training data. The results of splitting data for training and evaluating the distilled reranker are analyzed in Sec. 3.2.3. The results of RepoFormer-3B are provided separately in Tab. 3 since it does not rely on extra code LLM to generate code. From the results, we can observe:

- Zero-Shot shows the worst performance across all settings, indicating that solely relying on code LLMs cannot provide satisfying completion.
- CCFinder and RG-1 using general RAG techniques significantly outperforms Zero-Shot but they are surpassed by more sophisticated approaches. The results indicate that general RAG indeed enhances completion but the improvements are limited since general RAG is not tailored to repository-level code completion.
- RepoCoder consistently outperforms CCFinder and RG-1, demonstrating that iterative retrieval (Shao et al., 2023) exceeds naive RAG in repository-level code completion.
- DraCo and RepoFuse show competitive performance and they show much better results than other baselines when larger code LLMs are used, showing that larger code LLMs may better understand data dependence features, which are explored by DraCo and RepoFuse.
- RepoFormer-3B using only left context (ReccEval$_l$ and CCEval$_l$) lags behind other methods except Zero-Shot. The reason is that it is optimized to consider both left and right contexts while all other methods are designed to only consider left context. Unlike ReccEval where the right context for each completion case is unknown, CCEval has both left and right contexts. We can see that RepoFormer-3B which takes both left and right parts as input (CCEval$_{lr}$) surpasses CCEval$_l$, but it is still worse than CodeRAG using StarCoder2-3B which has the same model size as RepoFormer-3B.
- CodeRAG achieves the best performance across all settings, showing its effectiveness. Besides,

the performance gains over baselines consistently exist as the size of code LLM varies, showing the robustness of CodeRAG.

3.2.2 Ablation Study

To assess the contribution of each part in CodeRAG, we compare CodeRAG with its variations on ReccEval in Tab. 4. Subscripts "df", "s", "d" and "lr" indicate using dataflow-guided retrieval, sparse retrieval, dense retrieval and LLM reranker, respectively. Hence, CodeRAG$_{\mathrm{df+s+d+lr}}$ is identical to CodeRAG$_{\mathrm{llmr}}$ in Tab. 1.

From the results, we can observe that incorporating more retrieval paths brings improvements to code completion in most cases. Besides, using reranking module can significantly boost performance. These findings highlight the effectiveness of each component of CodeRAG in improving repository-level code completion.

3.2.3 Comparisons between LLM Reranker and Distilled Reranker

We further compare the results of using LLM reranker (CodeRAG$_{\mathrm{llmr}}$) and using distilled reranker (CodeRAG$_{\mathrm{disr}}$) on ReccEval in Tab. 5. As CodeRAG$_{\mathrm{disr}}$ requires training, we randomly sample 70% data for training and the remaining 30% data is used for testing. The results in Tab. 5 are reported over the test data. From the results, we can observe that using the distilled reranker affects the performance compared to using LLM reranker, but the performance is still competitive.

3.2.4 Computational Cost

Tab. 6 provides the average cost for a query on ReccEval, excluding the cost of code LLM. We can see that DraCo is the fastest since it only uses a single-way, dataflow-guided retrieval, and no similarity search is needed. Other methods are slower than DraCo as they all require similarity search. CodeRAG incurs higher cost than baselines since it uses more ways of retrieval, applies log probability guided probing and a distilled reranker from BestFit code reranking. However, the cost of CodeRAG is close to RepoCoder and RepoFuse even though we do not use advanced acceleration methods. Considering the significant improvements of CodeRAG over baselines, we believe the subtle increase of overhead is acceptable.

Tab. 7 reports the average cost for each step of CodeRAG on ReccEval. We can see that the largest cost comes from query construction. Note that, for multi-path code retrieval, the cost is decided by the slowest path (i.e., dataflow-guided retrieval).

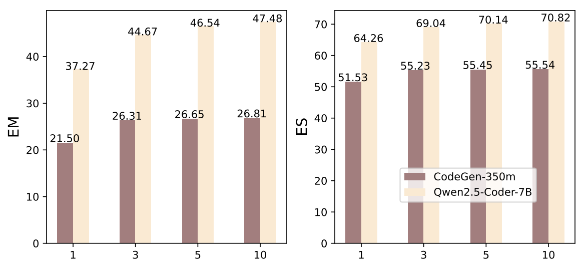


Figure 7: Impacts of numbers of retained reranked code knowledge on ReccEval (Use 100% data for evaluation).

Since the main goal of this work is not accelerating code completion and we do not apply advanced acceleration techniques, we believe the cost of CodeRAG can be further reduced and it will not hinder the practical use of CodeRAG. We suggest some possible directions, including constructing retrieval query in batches and parallelization, accelerating log probability guided probing through applying an inference speedup framework (e.g., vLLM[10]) on the prober LLM, using fast sparse and dense retrieval libraries (e.g., Faiss[11]) and distilling LLM reranker into a smaller distilled reranker.

3.2.5 Impacts of Numbers of Retained Reranked Code Knowledge Pieces

The reranking step in CodeRAG only retains top-u pieces of relevant code knowledge. In Fig. 7, we report the different results w.r.t. EM and ES (code match) when setting u to 1, 3, 5 and 10. From the results, we can observe that:

- Regardless of the used code LLM, using a larger u can enhance the quality of code completion.
- The improvements are noticeable when u is increased from a small value (e.g., increase from 1 to 3), but the enhancement becomes marginal when u further grows (e.g., increase from 5 to 10). The diminishing improvement suggests that larger u may potentially introduce less relevant and necessary code knowledge that does not significantly contribute to code completion.

4 Related Work

Recently, there is a surge of works on repository-level code completion. RepoFusion (Shrivastava et al., 2023) models the entire repository structure for context-aware completion. RepoCoder (Zhang et al., 2023) employs an iterative code retrieval

[10]https://github.com/vllm-project/vllm
[11]https://github.com/facebookresearch/faiss

Table 4: Comparisons among different variations of CodeRAG on ReccEval (Use 100% data for evaluation). Bold and underlined values indicate the best and the second-best results, respectively.

Methods	CodeGen-350M				SantaCoder-1.1B				StarCoder2-3B				Qwen2.5-Coder-7B			
	Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match	
	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1
CodeRAG$_{s}$	22.07	51.31	29.03	44.80	23.95	56.37	31.36	47.71	33.83	62.03	41.95	57.18	39.89	59.46	36.76	61.24
CodeRAG$_{d}$	20.49	50.36	27.33	43.41	23.04	55.58	30.52	46.90	32.81	61.53	41.18	56.55	39.66	58.47	36.05	60.90
CodeRAG$_{d+s}$	22.88	51.95	29.42	45.51	24.90	57.23	32.38	48.58	35.27	63.23	43.80	58.96	41.95	59.59	37.95	62.14
CodeRAG$_{df}$	21.28	50.94	28.82	45.20	25.68	57.38	33.98	50.99	35.13	63.25	43.91	60.15	41.86	59.06	37.61	62.79
CodeRAG$_{df+s}$	24.21	53.01	31.93	47.94	27.18	59.52	35.47	52.10	39.85	66.35	48.72	64.01	44.21	62.36	52.80	66.62
CodeRAG$_{df+s+d}$	23.89	52.86	31.56	47.80	27.70	59.96	36.10	52.72	40.52	66.87	49.65	64.83	44.61	68.81	53.75	66.57
CodeRAG$_{df+s+d+lr}$	**26.81**	**55.54**	**34.02**	**50.13**	**36.17**	**63.00**	**44.17**	**59.64**	**42.69**	**68.07**	**51.34**	**65.73**	**47.48**	**70.82**	**55.47**	**68.68**

Table 5: Performance on ReccEval (Use 30% data for evaluation). Bold and underlined values indicate the best and the second-best results, respectively.

Methods	CodeGen-350M				SantaCoder-1.1B				StarCoder2-3B				Qwen2.5-Coder-7B			
	Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match		Code Match		Identifier Match	
	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1	EM	ES	EM	F1
Zero-Shot	4.46	38.09	9.33	26.24	6.87	42.52	13.22	30.28	8.30	44.81	13.99	33.17	12.20	47.55	18.20	36.36
CCFinder	17.68	48.31	23.73	40.82	19.58	50.93	26.76	43.24	28.24	59.22	36.13	53.50	29.52	59.04	37.11	53.36
RG-1	17.63	48.94	24.07	39.54	24.04	54.80	31.06	46.44	29.63	58.96	35.73	51.81	33.52	61.59	39.67	54.93
RepoCoder	20.35	50.84	27.21	42.78	26.86	56.79	34.24	49.22	35.21	63.14	41.82	57.26	34.65	62.19	41.16	55.52
DraCo	22.71	51.83	29.98	46.40	30.19	59.70	39.21	55.66	36.60	64.78	45.41	61.76	39.98	66.23	48.18	62.82
RepoFuse	21.58	51.54	28.81	44.70	29.98	58.60	37.62	52.71	34.03	62.24	41.62	56.94	39.11	65.54	46.03	60.13
CodeRAG$_{llmr}$	**27.73**	**55.73**	**34.75**	**49.97**	**35.83**	**63.32**	**44.08**	**59.79**	**43.31**	**68.54**	**51.10**	**65.78**	**47.57**	**70.82**	**54.84**	**68.38**
CodeRAG$_{disr}$	23.58	53.31	30.55	47.20	32.65	61.37	41.16	57.06	39.88	66.21	47.62	62.89	44.34	68.42	52.18	64.47

Table 6: Average cost (second) for a query on ReccEval, excluding the cost for code generation of code LLM.

RepoCoder	DraCo	RepoFuse	CodeRAG
0.21	0.04	0.15	0.23

Table 7: Average cost (second) for each step of CodeRAG on ReccEval.

QueryQuery	Multi-path Retrieval			Distilled
Construction	Sparse	Dense	Dataflow	Reranker
0.14	0.002	0.015	0.03	0.06

and generation mechanism. CoCoMIC (Ding et al., 2024) enhances accuracy by combining cross-file and intra-file contexts. RepoFormer (Wu et al., 2024) fine-tunes models to dynamically decide context retrieval needs. GraphCoder (Liu et al., 2024) models control-flow dependency, data dependency, and control dependency to construct code knowledge graphs for code completion. ProCC (Tan et al., 2024) integrates prompt engineering with contextual bandits for multi-perspective code completion.

DraCo (Cheng et al., 2024) and RepoFuse (Liang et al., 2024) are closely related to CodeRAG. DraCo retrieves dataflow-guided information to augment code completion prompt. RepoFuse (Liang et al., 2024) fuses analogy context and rationale context, and uses a code LM like UniXcoder (Guo et al., 2022) to choose the most similar chunks to the target chunk to construct code completion prompt. Despite their accuracy, they do not fully address problems discussed in Sec. 1.

5 Conclusion

We present a novel framework CodeRAG for repository-level code completion CodeRAG. Its core parts include the log probability guided query construction, a multi-path code retrieval mechanism, and preference-aligned reranking. Experiments demonstrate that CodeRAG significantly and consistently outperforms state-of-the-art methods on benchmarks. In the future, we plan to explore joint training of code retriever and code LLM to further alleviate their misalignment.

Limitations

We address the misalignment between code retriever and code LLM from the perspective of designing rerankers and modifying retrieval results while code LLM is not updated accordingly. This idea may not fully alleviate the misalignment, and future work may involve designing new strategies, such as joint training or more efficient interfacing mechanisms for both code retrieval and code LLM.

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