Repoformer: Selective Retrieval for Repository-level Code Completion

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Abstract

Recent advances in retrieval-augmented generation (RAG) have initiated a new era in repository-level code completion. However, the invariable use of retrieval in existing frameworks exposes issues in both efficiency and robustness, with a large proportion of the retrieved contexts proving unhelpful or harmful to code language models (code-LMs). To tackle the challenges, we propose a selective RAG framework that abstains from unnecessary retrievals At the core of this framework is Repoformer, a code-LM that both self-determines the necessity of repository-level context based on the context of the current file and learns to be robust to the possibly noisy retrieved contexts. To enhance the model's self-assessment and code completion capabilities, we design a multi-task learning approach that leverages self-supervision from public repositories with a contrastive data labeling paradigm. Extensive evaluations on diverse benchmarks including RepoEval and a new benchmark based on CrossCodeEval reveal that Repoformer not only markedly outperforms existing retrieval-enhanced code LMs, but also reduces the inference latency by as much as 60% without sacrificing the performance. These advancements position our framework as an important step towards more accurate and efficient repository-level code completion.

1. Introduction

Automatic code completion has attracted long-lasting research efforts due to its high practical value in improving programmer productivity (Ye & Fischer, 2002; Hill & Rideout, 2004; Hellendoorn & Devanbu, 2017). One particularly challenging scenario is *repository-level code completion*, where a system is required to complete lines, API invocations, or functions in a file from user repositories. The major difficulty comes from the modular design of software (Parnas, 1972), which introduces local API usages and inter-module dependencies that require the understanding of information beyond the current file. As a result, retrieving and incorporating cross-file repository-level knowledge have been the key research focus (Tu et al., 2014; Hellendoorn & Devanbu, 2017; Svyatkovskiy et al., 2020).

Recently, this trend has been reinforced by a paradigm shift towards *retrieval-augmented generation* (RAG) approaches. RAG systems use an in-repository retriever to gather cross-file contexts such as relevant code, documentation, or APIs. Such knowledge is provided as an extension to the current file's context to enable code language models (code LMs) to generate more accurate code completion. To design effective RAG-based approaches, existing works either improve the retrieval mechanism for prompting black-box code LMs (Lu et al., 2022; Shrivastava et al., 2023b; Zhang et al., 2023) or consider fine-tuning the LM to better leverage a specific type of retrieved context (Ding et al., 2022; Zan et al., 2022).

Despite their promising performance, existing RAG-based approaches have two major weaknesses: *robustness* and *efficiency*. To begin with, when the retrieved knowledge is noisy or uninformative, black-box LMs struggle to maintain their output quality on various tasks such as question answering (Yoran et al., 2023). Repository-level code completion is not an exception: we find that as many as 80% of the retrieved repository contexts fail to improve the code completion accuracy of CodeGen (Nijkamp et al., 2022b) or StarCoder (Li et al., 2023b), and 30% of them actually harm the LMs' performance (Section 4.2). By contrast, existing approaches assume a suboptimal design: *invariably conducting repository-level retrieval for every code completion instance*. Beyond the robustness concerns, this design exposes severe efficiency issues. In large repositories containing millions of lines of code, one retrieval may entail traversing hundreds of thousands of entries, incurring considerable latency cost, not to mention systems that perform frequent or iterative retrieval (Zhang et al., 2023). When the current file is sufficient for the LM to make the target prediction or when the LM cannot further benefit from the retrieved context, the high latency caused by invariable retrieval translate to no improvement in accuracy.

To overcome the two challenges, we argue that *robust RAG training paired with selective retrieval* is the key. In this paper, we introduce a new repository-level code completion framework based on two synergistic ideas:

- **Selective retrieval via self-assessment.** Instead of retrieving invariably, the RAG system *abstains from*

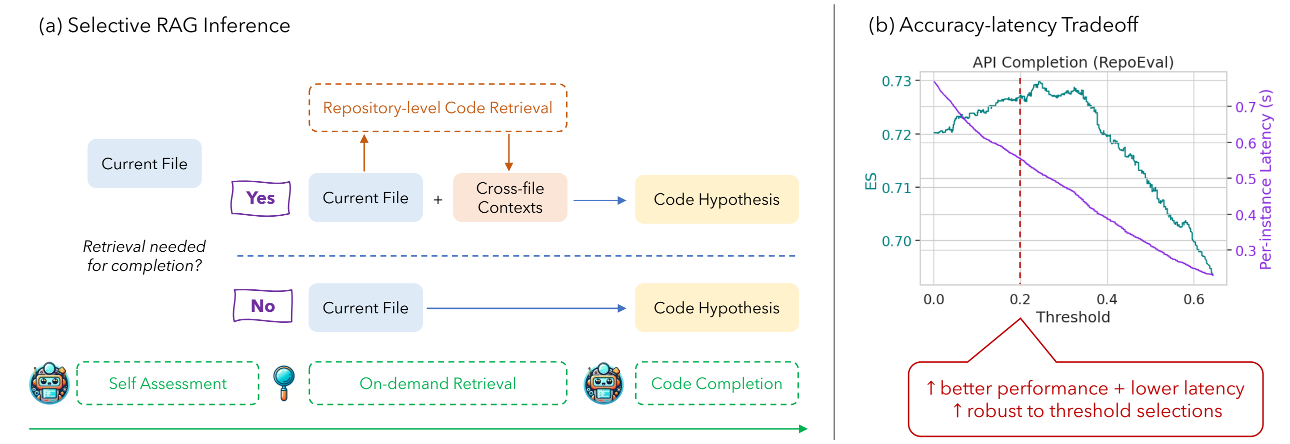

Figure 1. (a) An overview of the proposed selective RAG framework. Given the current file context, REPOFORMER first self-assesses whether retrieval is required and triggers the retriever correspondingly. Then, it makes a hypothesis with the optional retrieved context. (b) Using self-selective retrieval, REPOFORMER achieves better accuracy and better latency than performing retrieval invariably.

unnecessary retrievals. The abstention decision combines critical factors including the task type, the LM's knowledge, and the LM's ability to leverage retrieved contexts. Inspired by Kadavath et al. (2022), we teach the LM to self-assess its knowledge based on the current file and selective trigger the retrieval (Figure 1).

- **Robustly leverage optional and noisy knowledge.** Our model learns to incorporate the information provided by in-repository retrievers, a noisy source of knowledge. In addition, we teach the LM to not overly rely on the retriever by maintaining high output quality when the retriever is not invoked.

We mine self-supervision signals for these two abilities using the public repositories from the Stack (Kocetkov et al., 2022) with a contrastive data labeling paradigm: the LM's predictions with and without the retrieved repository contexts are compared to determine the necessity of retrieval for a randomly sampled blank to fill in (Section 3.3). Finetuning StarCoder on a novel multi-task objective, we obtain REPOFORMER, a code LM capable of *robust code completion with self-triggered retrieval augmentation*.

We conduct comprehensive evaluations of REPOFORMER on a variety of repository-level code completion tasks from RepoEval (Zhang et al., 2023) and a newly created large-scale benchmark based on CrossCodeEval (Ding et al., 2023). Results suggest that with self-triggered selective retrieval, REPOFORMER achieves strong performance, outperforming the same-sized StarCoderBase by more than 3 absolute points for edit similarity across multiple tasks. The 3B REPOFORMER even performs on par with invariable retrieval using the 16B StarCoder. In addition, parallelizing the retrieval decision and RAG execution, our framework enables as much as 60% improvement on the inference latency without harming the accuracy. We also apply REPOFORMER's selective decisions to optimize RAG systems with larger black-box code LMs, improving the performance while reducing the latency of line and API completion to 75%. Finally, we analyze REPOFORMER's threshold robustness, the precision and calibration of its abstention decisions, and its robustness to retrieval. We will release our code, model, and the new evaluation benchmark to facilitate future studies.

2. Related Work

Repository-level Code Completion Accurately completing the code in repositories has been a challenging research problem due to cross-file dependency patterns caused by modular design (Tu et al., 2014). Early works propose application-specific training methods for n-gram LMs (Tu et al., 2014), RNNs (Hellendoorn & Devanbu, 2017; Wang et al., 2021), and Transformers (Svyatkovskiy et al., 2020) to leverage structured knowledge beyond current file's context. With more powerful pre-trained code LMs (Chen et al., 2021; Nijkamp et al., 2022b; Li et al., 2023b), recent studies investigate fine-tuning them to better leverage retrieved knowledge provided in context such as code and documentation snippets (Zan et al., 2022; Ding et al., 2022; Shrivastava et al., 2023a). Other studies show that black-box LMs can already leverage the in-context knowledge, depending how well the knowledge is retrieved and formatted (Lu et al., 2022; Zhou et al., 2023; Shrivastava et al., 2023b; Zhang et al., 2023). This approach saves the effort of constructing the training data and promises better generalization. Orthogonal to these studies, this paper addresses the robustness and efficiency issues caused by of always augmenting LMs with retrieved contexts. We study training code LMs to selectively trigger retrieval based on an assessment of the current file and be robust to the noisy retrieved contexts.

Adaptive RAG This paper resonates with the recent trend of making the RAG paradigm adaptive. The core question is finding an effective policy for deciding when to retrieve. He et al. (2021) propose to learn the policy of combining the parametric and non-parametric knowledge from history. Li et al. (2023a) and Jiang et al. (2023) suggest that retrieval should be performed only when LMs have a high predictive uncertainty. Mallen et al. (2023) discover that retrieval can be avoided for high frequency facts. Concurrent to this work, two new studies approach adaptive RAG from a learning perspective. SKR (Wang et al., 2023) annotates instances where proprietary LMs fail to answer a question and proposes several methods to predict these instances. Self-RAG (Asai et al., 2023) utilizes GPT-4 (OpenAI, 2023) as a knowledge engine to distill a smaller LM for evaluating whether a question can be benefited from retrieval and whether the retrieved contexts are relevant and properly incorporated. By contrast, this paper highlights the importance of self-knowledge (Kadavath et al., 2022) in forming the selective decision. We introduce a simple yet effective scheme to fine-tune a code LM for faithful self-evaluation without extra modules (SKR), knowledge store (SKR), or labels generated by an oracle LM (Self-RAG). We also note that SKR and Self-RAG mainly experiment in the question answering domain, while this work tackles the challenges specific to repository-level code completion.

3. Approach

In this section, we first briefly formulate the repository-level code completion task and the considered RAG setup, then illustrate the details of the proposed approach.

3.1. Background

Problem Formulation We denote each *repository-level code completion* task as (X_l, X_r, Y, C). Y is the ground truth completion that needs to be generated. In this paper, Y always contains one or more consecutive lines of code. X_l and X_r are the code to the left/right of Y in the same file. We will use left context and right context to refer to them. C is the set of other files in the repository. A code completion system utilizes X_l, X_r, and C to generate a hypothesis $\hat{Y}$.

Retrieval-Augmented Generation We consider RAG-based code completion systems with two components:

- An **in-repository retriever** $\mathcal{R}$ that queries C with information from X_l and X_r and returns relevant cross-file contexts CC. CC consists of k code chunks $cc_1, cc_2, ..., cc_k$, each of which contains consecutive lines of code from a single file.
- A **code LM** $\mathcal{M}$ that leverages X_l, X_r, and CC to output $\hat{Y}$. The inclusion of X_r and CC is optional.

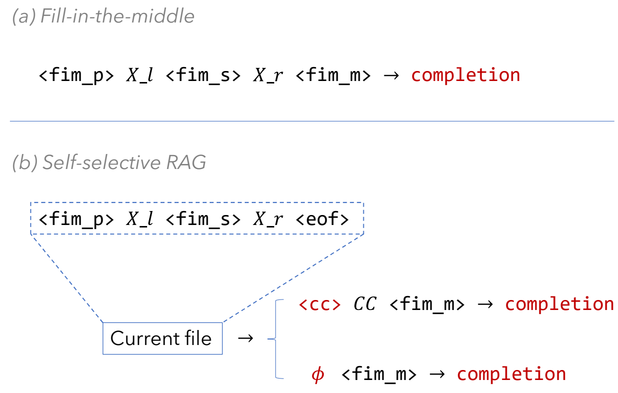

Figure 2. A comparison between the prompting scheme of fill-in-the-middle and self-selective RAG. → denotes the invocation of the LM. LM-generated parts are colored in red. `fim_p`, `fim_s`, and `fim_m` are short for the special tokens for fill-in-the-middle prompting: `fim_prefix`, `fim_suffix`, and `fim_middle`.

The execution of this framework consists four stages: *query formation*, *indexing*, *retrieval*, and *generation*. We detail each of the steps in Section 4.1. It is worth noting that for generation, we use an *infilling* setup, where both X_l and X_r are directly provided in the prompt (Shrivastava et al., 2023b; Pei et al., 2023). We provide further discussions and empirical supports for this design in Appendix B.

3.2. Self-selective RAG for Code Completion

Central to our framework is the idea of *selective RAG*, that the system always explicitly decides whether the LM's generation could benefit from retrieved contexts, and abstains from retrieval when it is deemed unnecessary (Figure 1 (a)).

How to decide when to abstain from retrieval? Two existing heuristics are relevant: (1) performing a *trial retrieval* and only augmenting the high-relevance contexts or (2) performing a *trial generation* and conducting RAG only when the model's uncertainty is high. We find that these two strategies could inform the selective RAG decisions to some extent, but incur a high latency cost and does not generalize well to all generation lengths (Appendix C).

Instead of these heuristics, we introduce a novel *self-selective RAG* mechanism to enable a code LM to self-evaluate (Kadavath et al., 2022) whether its prediction could be improved by additional retrieved contexts. We model self-selective RAG inference as an extension to the fill-in-the-middle generation (Figure 2). After observing X_l and X_r, the LM triggers cross-file retrieval by generating a special token `<cc>` or abstains from retrieval via an empty token ϕ[1]. Then, the LM proceeds the code completion with X_l, X_r, and the optional CC. We mark the end of the

[1]In practice, instead of greedily decoding `<cc>`, we check whether its probability exceeds a certain threshold.

current file with a new token <eof>. This design is necessary to maintain the semantics of <fim_middle> and explicitly trigger the model to self-evaluate.

We highlight the advantages of self-selective RAG:

1. **Comprehensiveness**. The LM is able to make the selective RAG judgment based on the information from both X_l and X_r, its code completion ability, and its ability to leverage the retrieved contexts.
2. **Generality and flexibility**. Both RAG and normal fill-in-the-middle generation are supported, and the LM can seamlessly self-switch between the two modalities. Users can easily modulate the ratio of the two by configuring the retrieval threshold.
3. **Efficiency**. Self-selective RAG completely avoids the retrieval latency cost if retrieval is not triggered. The latency of the selective decision is marginal compared to code generation, and self-evaluation by the code LM does not incur extra memory cost.

3.3. Multi-task Training with Self-supervision

Two abilities are essential to self-selective RAG: accurate self-assessment and robustness to the retrieved context. We introduce a contrastive data labeling scheme to mine the supervision from public repositories, followed by fine-tuning with a novel multi-task objective.

Data construction We randomly sample 18k Python repositories from the Stack (Kocetkov et al., 2022) that have (1) at least three imports per file, (2) at least two local imports per file, and (3) at least five Python files. Then, we follow a three-step procedure to create the fine-tuning data:

1. Sample target lines Y that are either (1) random code chunks of varied lengths or (2) function bodies.
2. Retrieve CC using the current file, with or without Y.
3. Label whether CC can improve a code LM $\mathcal{M}$'s code completion quality (evaluated by ES against Y) by more than a pre-determined threshold T.

The detailed algorithm is presented in Appendix D. We use $\mathcal{M}$ = StarCoderBase-1B and T = 0 to obtain 240k chunk completion and 120k function completion instances, each in the form $(X_l, X_r,\ Y,\ CC,\ label)$. We reserve 500 repositories for validation and use the rest for training.

Verbalization Based on $label$, each instance is verbalized into a sequence for fine-tuning. If $label$ is true, we provide CC after the special token <cc>. Otherwise, we use the template with only X_l and X_r. The two verbalizations correspond to the two branches in Figure 2 (b).

Training Objective We introduce two losses, $\mathcal{L}_{eval}$ for self-assessment and $\mathcal{L}_{gen}$ for code generation.

1. $\mathcal{L}_{eval}$: a cross-encropy loss on predicting <cc> immediately following <eof>.

$$\mathcal{L}_{eval} = -\log p_{\mathcal{M}}(\texttt{<cc>}|X_l, X_r) \tag{1}$$

2. $\mathcal{L}_{gen}$: a cross-encropy loss on the tokens following <fim_middle>. Depending on $label$, $\mathcal{L}_{gen}$ represents either code completion with only in-file information or retrieval-augmented code completion.

$$\mathcal{L}_{gen} = \begin{cases} -\log p_{\mathcal{M}}(Y|X_l, X_r, CC), & \text{if } label \\ -\log p_{\mathcal{M}}(Y|X_l, X_r), & \text{otherwise} \end{cases} \tag{2}$$

The final training objective is $\lambda\mathcal{L}_{eval} + \mathcal{L}_{gen}$, a weighted combination of the two losses. We do not supervise the model on predicting the other tokens in X_l, X_r, CC, or the special tokens for fill-in-the-middle. Teacher forcing is used just as in normal causal language model training.

3.4. Implementation details

We fine-tune StarCoderBase-1B and StarCoderBase-3B on the created dataset. We use $\lambda = 1.0$, learning rate 2e-5, batch size 512, 50 warmup steps, and a linear learning rate decay. The models are trained for 2 epochs, which takes 6 hours for the 1B model and 9 hours for the 3B model with 8 Nvidia A100 GPUs (40G memory). Our implementation is based on Jain et al. (2023)[2]. We call our models REPOFORMER-1B/3B as they are designed to actively leverage the repository context.

Hyperparameter optimization We conduct a grid search with StarCoderBase-1B on the following search space: learning rate {1e-5, 2e-5, 5e-5}, λ {0.2, 1.0, 2.0, 5.0}, training epochs {1, 2, 5}, and warmup steps {50, 100}. The best hyperparameters are selected based on the code completion ES on the validation dataset.

4. Experiment

In this section, we first investigate whether retrieval augmentation is helpful for RAG with black-box code LMs. Then we show that our framework allows the model to both avoid unnecessary retrievals and be more robust to the retrieved contexts, resulting in much better accuracy and latency.

[2] https://github.com/amazon-science/ContraCLM

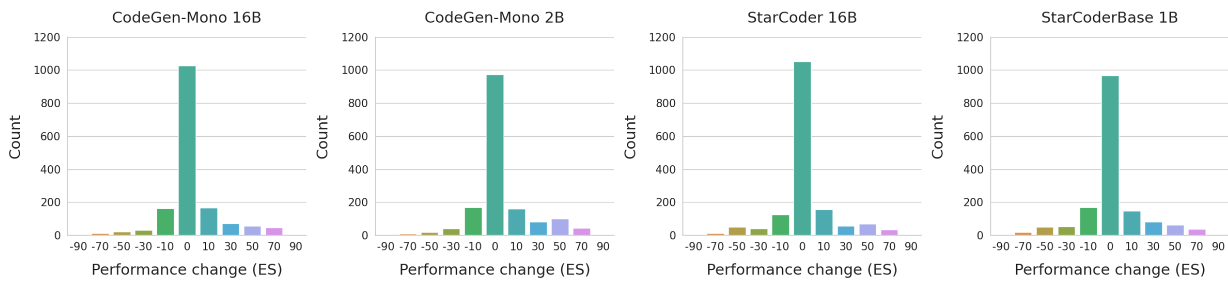

Figure 3. The performance gain on RepoEval API completion exhibited by four models from retrieved cross-file context. Each bucket contains values ranging from label-10 to label+10 except for the central bucket, which corresponds to exactly 0. The retrieved context only improves the performance in around 20% of instances. The trend is consistent across all the evaluated LMs.

Model	Size	Performance (UT)		UT Change		
		$X_l + X_r$	$X_l + X_r + CC$	↓	=	↑
CodeGen-Mono	16B	23.74	24.18	23	407	25
CodeGen-Mono	2B	30.55	32.51	18	400	37
StarCoder	16B	34.73	42.86	16	386	53
StarCoderBase	1B	22.20	25.71	16	407	32

Table 1. The performance change on RepoEval function completion exhibited by four models from retrieved cross-file context. For the majority of the instances, the retrieved context does not improve the performance. "↑", "=", "↓" denotes performance increase, no performance change, and performance drop.

4.1. Experimental Setup

Datasets We use RepoEval (Zhang et al., 2023), which consists of line completion, API completion, and function completion tasks created from 32 recent Python repositories. To improve the repository coverage, we additionally leverage 1500 raw Python repositories from CrossCodeEval (Ding et al., 2023) to create chunk completion and function completion instances. We call this dataset CCEval. More details regarding CCEval are presented in Appendix D.

Metrics We evaluate $\hat{Y}$ with both reference-based and execution-based evaluation. For reference-based evaluation, exact match (EM) and edit similarity (ES) are reported. Following Zhang et al. (2023), ES is defined as

$$ES(\hat{Y}, Y) = \frac{1 - Lev(\hat{Y}, Y)}{\max(|\hat{Y}|, |Y|)}, \tag{3}$$

where Lev is the Levenshtein distance (Levenshtein et al., 1966). For execution-based evaluation, we report the unit test pass rate (UT). $\hat{Y}$ is said to pass the unit tests if replacing Y with $\hat{Y}$ does not cause any unit test to fail.

Models **CodeGen-Mono** (Nijkamp et al., 2022a) is pretrained sequentially on natural language, multilingual code, and a Python corpus. **StarCoder** and **StarCoderBase** (Li et al., 2023b) are trained with fill-in-the-middle ability on a large corpus of multilingual code, GitHub issues, Git commits, and Jupyter notebooks. StarCoder is obtained by training StarCoderBase with an additional Python corpus. In this paper, we experiment with the 2B and 16B versions of CodeGen-Mono, the 1B, 3B, and 7B versions of StarCoderBase, as well as the 16B StarCoder.

Detailed RAG Setup Below, we describe the four steps we follow for executing RAG. We further detail the hyperparameters for retrieval, generation, and post-processing in Appendix A.

1. **Query Formation.** A query is constructed based on X_l. We always use a fixed number of lines at the end of X_l (i.e., immediately preceding Y) as the query.

2. **Indexing.** All files in C are divided into code chunks of the same size as the query. We present details regarding window sizes and stride sizes in Appendix A.

3. **Retrieval.** A similarity function f is used to compare the query with every chunk and identify k most similar code chunks. We use Jaccard similarity (Jaccard, 1912) for f for the main results. Fragment alignment (Lu et al., 2022) is then applied: for each of the k most similar code chunks, the chunk immediately following is included in CC instead of the original chunk.

4. **Generation.** CC is concatenated with the in-file context as a prompt for $\mathcal{M}$. We verbalize CC as comments to the program (see prompts in Appendix A).

4.2. Is retrieval always helpful?

As a proof of concept, we first show that on all tasks from RepoEval (line, API, and function completion), the retrieved context is usually not beneficial at the *instance-level*.

In Figure 3 and Table 1, we evaluate RAG with four black-box code LMs on API completion and function completion from RepoEval. For each model, we compute the instance-level performance change from current file code completion (X_l and X_r) to retrieval-augmented code completion

Model	Size	Selection Policy	RepoEval						CCEval		
			Line		API		Function		Chunk		Function
			EM	ES	EM	ES	UT	ES	EM	ES	ES
No Retrieval											
StarCoderBase	1B	-	43.44	67.77	37.81	66.54	22.20	47.65	31.08	60.09	47.49
StarCoderBase	3B	-	49.00	72.12	40.44	69.02	24.84	51.22	36.14	64.65	49.88
StarCoderBase	7B	-	51.88	74.03	43.31	70.79	25.49	52.28	38.88	66.61	52.45
StarCoder	16B	-	55.25	76.07	44.50	71.00	34.73	53.60	42.58	69.40	54.20
Invariable Retrieval											
StarCoderBase	1B	-	51.19	72.30	43.94	69.17	25.71	55.64	37.22	63.73	50.50
StarCoderBase	3B	-	56.69	76.68	47.00	72.62	29.67	57.68	42.26	67.74	53.39
StarCoderBase	7B	-	59.44	78.15	**49.56**	73.65	31.43	58.51	44.44	69.53	55.41
StarCoder	16B	-	61.25	79.24	51.12	74.50	42.86	60.96	47.90	71.90	58.06
Selective Retrieval											
Repoformer	1B	self selection	51.90	74.50	43.50	71.00	24.00	53.10	38.52	68.08	52.09
Repoformer	1B	<cc> prob	54.40	76.00	46.10	72.70	28.79	57.30	41.92	69.97	53.71
Repoformer	3B	self selection	56.30	77.60	46.10	73.60	28.57	54.70	42.06	70.70	54.47
Repoformer	3B	<cc> prob	**59.63**	**79.02**	49.31	**74.96**	**32.96**	**60.56**	**46.66**	**72.23**	**56.24**

Table 2. Experiment results on RepoEval and CCEval. The best performance is underlined. The best performance among models under 10B is boldfaced. Compared to StarCoderBase of the same size, Repoformer exhibits a strong performance, with Repoformer-3B outperforming other invariable retrieval models under 10B in most of the tasks. More importantly, Repoformer consumes lower retrieval budget via selective retrieval. Among the two selective policies, <cc> prob enables the best selective RAG performance.

(X_l, X_r, and CC). Detailed prompts are discussed in Appendix A. The results reveal an intriguing *80-20 rule*: retrieval improves LMs' performance on only 20% instances. For most of the instances (60% for API completion and 85% for function completion), providing the retrieved contexts to the code LMs neither improves nor harms their performance. Further, in many instances, retrieval augmentation harms performance. The observed trends are consistent for both API and function completion and for both small-sized LMs ($\leq 2B$) and moderate-to-large LMs ($16B$). Together, these findings highlight the room for improvement for the robustness and efficiency of repository-level code completion. The generality of this observation is further confirmed by an analysis of Repoformer's training data (Appendix D).

4.3. Repoformer achieves strong selective RAG performance for code completion

Next, we present the main evaluation of Repoformer on RepoEval and CCEval, including three settings:

1. **No Retrieval**. We benchmark the StarCoder family with only X_l and X_r in the prompt.
2. **Invariable Retrieval**. We benchmark StarCoder with CC always provided in addition to X_l and X_r.
3. **Selective Retrieval**. We benchmark Repoformer by providing X_l and X_r in the prompt, optionally augmented with CC according to two selective policies:
   - **Self-selection**. If <cfc> is the most likely token following <eof>, retrieval is performed.
   - **<cc> prob**. If probability of <cc> following <eof> is greater than a threshold T, retrieval is performed on this instance[3].

Table 2 suggests that compared to no retrieval and invariable retrieval using StarCoderBase of the same size, Repoformer's selective retrieval strategy exhibits strong performance improvements. Via the <cc> prob strategy, Repoformer-3B is able to outperform StarCoderBase-7B on all the tasks and metrics except EM for API completion, even outperforming the 5x larger StarCoder model in terms of ES for API and Chunk completion. The threshold-controlled <cc> prob strategy outperforms the self-selection strategy on all the tasks. In the next section, we show that the two strategies represent different trade-off between accuracy and inference latency.

4.4. Repoformer improves inference efficiency

In this section, we illustrate the benefits of Repoformer for saving the inference latency during online serving.

Latency Model We assume that the repository is pre-split into code chunks. Given a code completion instance, the system issues three processes at the same time:

- P1: make a retrieval decision using Repoformer.
- P2: using $\mathcal{M}$, generate $\hat{Y}$ without CC.

[3]We find that $T = 0.15$ for function completion and $T = 0.2$ for the other tasks generally works well. In this paper, we always follow these two thresholds unless otherwise stated.

	Selective Strategy	API Completion		Line Completion	
		ES	Speedup	ES	Speedup
1B	invariable retrieval	72.02	0%	75.91	0%
	self selection	71.04	69% ↑	74.50	61% ↑
	<cc> prob	72.72	28% ↑	76.00	27% ↑
3B	invariable retrieval	74.66	0%	78.68	0%
	self selection	73.60	46% ↑	77.60	43% ↑
	<cc> prob	74.96	17% ↑	79.02	16% ↑

Table 3. The accuracy-latency tradeoff of REPOFORMER with two self-selective RAG paradigms. Compare to the invariable retrieval baseline, the <cc> prob strategy consistency demonstrates gains in both accuracy and latency. The self selection strategy shows much larger latency gains with a small performance degradation.

- P3: retrieve CC and generate $\hat{Y}$ with CC using $\mathcal{M}$.

Depending on the result of P1, the system waits for either P2 or P3 and ignores the other process. If REPOFORMER is used as $\mathcal{M}$, P1 can be merged with P2 by forcing the model to generate a hypothesis without CC after collecting the retrieval decision.

We consider three latency terms: (1) T_s, time required for the selective decision, (2) T_r, the retrieval latency, and (3) T_g, the generation latency. Therefore, the latency for P1, P2, and P3 are T_s, T_g, and $T_r + T_g$. When $\mathcal{M}$ is REPOFORMER or a model larger than REPOFORMER, it is safe to assume $T_s < T_g < T_r + T_g$. Therefore, the latency for the entire system is either T_g or $T_r + T_g$ depending on P1.

Table 3 presents the accuracy-latency trade-off with $\mathcal{M}$ = REPOFORMER. We measure all the results using a single Nvidia A100 GPU (80G) with the vllm library (Kwon et al., 2023). Line and API Completion are presented to cover generation of short and moderate lengths[4]. We observe that both selective strategies can improve the latency significantly, with a different trade-off: using a fixed threshold for <cc> prob results in improvements for both accuracy and latency compared to invariable retrieval, while using self selection results in a much larger latency gain with a small performance degradation.

Can REPOFORMER still improve the inference latency with *a larger model as* $\mathcal{M}$? We use <cc> prob with REPOFORMER-1B as the selective policy and use the 7x larger STARCODERBASE-7B and the 16x larger STARCODER as $\mathcal{M}$. As shown in Table 4, the selective predictions from REPOFORMER successfully improves both the performance of RAG these black-box models while reducing the latency by approximately 25%, suggesting the transferability of the selective decisions. We report the results on all tasks and all thresholds in Appendix E.1.

[4]We skip the function completion results as RepoEval uses very small repositories for function completion for easier unit testing.

	Selective Strategy	API Completion		Line Completion	
		ES	Speedup	ES	Speedup
7B	invariable retrieval	73.65	0%	78.15	0%
	REPOFORMER-1B	74.10	24% ↑	78.31	25% ↑
16B	invariable retrieval	74.50	0%	79.24	0%
	REPOFORMER-1B	74.84	24% ↑	79.48	24% ↑

Table 4. The accuracy-latency tradeoff of STARCODER with REPOFORMER-1B as the policy model for selective RAG. Compare to the invariable retrieval baseline, the selective RAG strategy consistency improves both accuracy and inference latency.

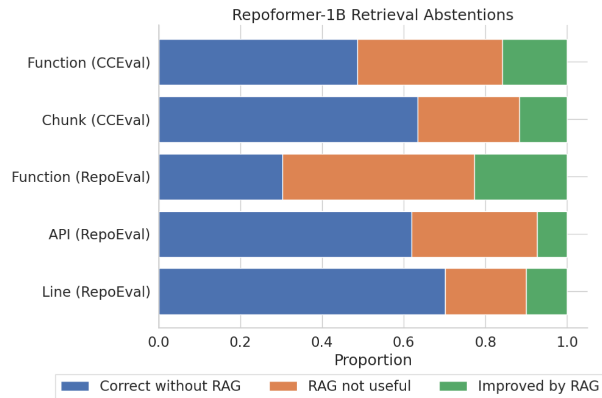

Figure 4. An analysis of the instances where REPOFORMER-1B abstains from retrieval. We divide the instances into (1) the model answering correctly without retrieval (blue), the model making a mistake that cannot be improved by retrieval (yellow), and the model achieving better performance when retrieval is performed (green). The precision of abstention is at or over 0.8 on all tasks.

5. Analysis

In this section, we present further analyses and ablation studies on REPOFORMER-1B.

Is REPOFORMER sensitive to threshold settings? In Figure 1 (b), we present the code completion accuracy and latency of REPOFORMER as a function of the threshold for the <cc> prob strategy. As the threshold increases, the model's overall code completion performance first increases due to avoiding possibly misleading retrieved contexts. At threshold 0.4, the model still maintains the same level of performance compared to full retrieval augmentation, with latency reduced by 50%. This result demonstrates that REPOFORMER is able to accommodate various settings of the threshold and provide good accuracy-latency trade-off. We provide the visualization for other tasks in Appendix E.1.

Does REPOFORMER make precise and calibrated selective retrieval decisions? In Figure 4, we evaluate the precision of REPOFORMER's decisions by inspecting the instances where it abstains from retrieval via the <cc> prob strategy. We find that the model's abstention is accu-

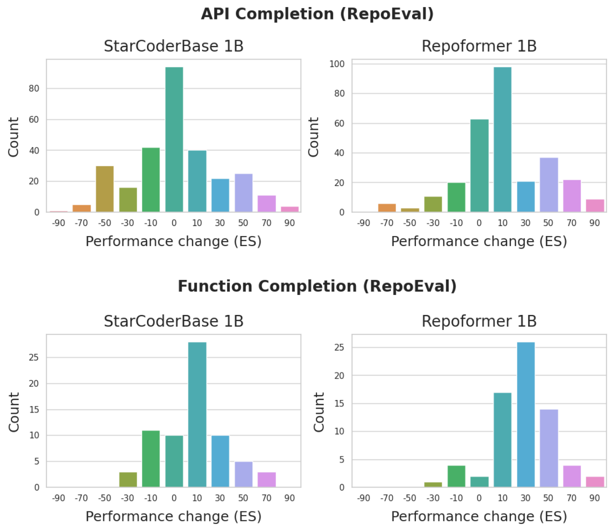

Figure 5. The performance change on RepoEval from retrieved cross-file context. Compared to StarCoder, REPOFORMER is better at leveraging CC for the self-selected instances.

Model	Selective Policy	Chunk Completion T	%RAG	ES	Function Completion T	%RAG	ES
SC	-	-	0%	60.09	-	0%	47.49
	-	-	100%	63.73	-	100%	50.50
RF	-	-	0%	66.22	-	0%	49.77
	<cc> prob	0.20	75%	69.97	0.15	76%	53.71
	-	-	100%	69.95	-	100%	53.56
A1	-	-	0%	66.14	-	0%	49.25
	<cc> prob	0.99	100%	70.21	0.99	100%	53.93
	-	-	100%	70.21	-	100%	53.93
A2	-	-	0%	66.49	-	0%	49.02
	-	-	100%	70.45	-	100%	53.90
A3	-	-	0%	66.49	-	0%	49.01
	-	-	100%	69.60	-	100%	53.58
A4	-	-	0%	64.96	-	0%	25.44
	<cc> prob	0.10	86%	69.35	0.10	83%	26.50
	-	-	100%	69.19	-	100%	26.35

Table 5. Ablation study results. We report the performance on two tasks from the CCEval dataset. **SC** = StarCoderBase-1B. **RF** = REPOFORMER-1B. **T** = threshold for the retrieval policy. We find T = 0.10 works better for A4 and thus applied it for all the A4 results. **%RAG** = ratio of instances where RAG is performed.

rate for over 80% instances across all the tasks. We also evaluate the calibration of the selective decisions (full results in Appendix E.2). REPOFORMER-1B generally makes near-calibrated predictions for Line and API Completion while the calibration is non-optimal for function completion with UT employed as the metric. We hypothesize that this could be caused by using ES to create the training signal and encourage future work to devise methods for labeling the quality of function completion more effectively.

Is REPOFORMER more robust to CC? In Figure 5, we show the performance change caused by CC on the instances where REPOFORMER-1B requests for retrieval. Compared to STARCODERBASE-1B, REPOFORMER exhibits more frequent and greater performance gains upon observing CC. The instances with performance drop is also significantly reduced, indicating an increased robustness.

Ablation Study We perform ablation studies of REPOFORMER-1B on several alternative design choices:

- (**A1**) Combining $\mathcal{L}_{eval}$ and $\mathcal{L}_{gen}$ as a single cross-entropy loss. In general, this down-weights $\mathcal{L}_{eval}$.
- (**A2**) Removing the self-evaluation loss $\mathcal{L}_{eval}$.
- (**A3**) Further removing all the CC from A2. This amounts to only training the model on infilling.
- (**A4**) Placing `<cc>` and CC after `<fim_middle>` and marking its end with a new token `<cc_end>`. This item mainly studies whether training the model to recognize CC as part of the infilling is more beneficial.

We fine-tune StarCoderBase-1B with the same setup as REPOFORMER and present the results on CCEval in Table 5. Since A1 and A4 are trained on self-evaluation loss, we also test them on self-selective RAG. From Table 5, we observe that although A1 has slightly better RAG performance, it fails to make meaningful selective predictions: the conditional probability of <cc> is nearly 1 for all the instances. For A2, the results suggests that learning the self-evaluation ability only slightly affects its best-achievable RAG performance. For A3, it has the same performance for in-file completion as A2, but not as good as RAG performance, indicating the necessity of fine-tuning with CC. Finally, we observe that A4 achieves reasonable performance for chunk completion but performs much worse for function completion. We hypothesize that placing CC within the infilling section breaks the fill-in-the-middle semantics that StarCoder was pre-trained on.

6. Conclusion

In this paper, we propose a new RAG-based repository-level code completion framework. Our framework addresses the robustness and efficiency issues of existing RAG-based approaches through two important techniques: (1) selective retrieval via self assessment and (2) robust training to leverage noisy retrieved knowledge. Our framework is powered by REPOFORMER, a code LM that intelligently self-triggers retrieval and robustly incorporates the retrieved knowledge. Extensive evaluations demonstrate our approach's superiority in enhancing the accuracy while significantly reducing the latency, showcasing its potential in practical coding environments. This work opens up new avenues for RAG-based repository-level code completion and motivates for the development of more intelligent retrieval-augmented LMs.

Discussion We now discuss several limitations and future directions of this work.

- **Further speeding up large LMs.** We have shown the effectiveness of REPOFORMER for making selective predictions that transfer to large models. Future work could consider further exploiting its utility for large models in more complex settings such as speculative decoding (Chen et al., 2023; Leviathan et al., 2023). As REPOFORMER is optimized for RAG, using it as the draft model could result in fewer rejections compared to the other similar-sized small LMs.
- **More languages and tasks.** Although we mainly experiment on Python, selective RAG is a generic paradigm and could be extended to a multilingual setting. More granularity beyond line, API, or functions could also be considered, such as those defined with language-specific constructs.
- **Improving long-form completion.** For function completion, we explored a simple one-time retrieval strategy. However, the knowledge required could vary at different positions in the generation and thus the LM could be benefited by retrieval in the middle of generation. Considering multiple retrievals and adapting REPOFORMER to better perform long-formed generation is thus an important research topic.
- **Personalized retrieval policy.** This paper applies a uniform selective policy across repositories. However, certain repositories could be inherently more RAG-friendly by exhibiting a higher level of duplication (Zhang et al., 2023). Adapting the selective RAG paradigm towards accurate personalized policies could be an important research direction.

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A. Detailed RAG Setup

In this section, we describe the details of retrieval and generation adopted in this paper.

Retrieval We set the query size for line, API, and chunk completion and set 50 for function completion. The indexing granularity is changed to always align with the task types. For indexing, we use half of the query size as the stride size. Despite the duplication caused by the overlap between adjacent chunks, we argue that this design improves retrieval accuracy with tolerable cost, as the number of files is limited in a repository compared to large open-domain code corpora. We always find $k = 10$ top-similarity results and follow the segment alignment strategy to return the code chunks immediately following the top-similarity chunks. Unless otherwise specified, Jaccard similarity (Jaccard, 1912) is used as the similarity function f. We explored other choices mentioned in **??** but find them failing to outperform Jaccard similarity.

Generation Recent literature demonstrates the effectiveness of directly providing the retrieved information as part of the context of LMs (Ram et al., 2023; Shi et al., 2023). Following these studies, we directly concatenate the in-file context with CC to provide it to the model (Figure 1). To prompt CodeGen-Mono, we use the following input ordering:

```
[Right Context] [Cross-file Context] [Left Context]
```

To prompt StarCoder, we use the following fill-in-the-middle-prompt:

```
<fim_prefix> [Left Context] <fim_suffix> [Right Context] [Cross-file Context] <fim_middle>
```

For the cross-file contexts, we add a # symbol to present them as comments and add the following line before each cc_i:

```
# the below code fragment can be found in: [file path]
```

After concatenating the verbalized cc_i together, we add another line to the start of the CC:

```
# Here are some relevant code fragments from other files of the repo:
```

For the in-file completion baselines such as in Section 4.2 and Appendix B, our prompts are exactly the previous prompts with the `[Cross-file Context]` part removed.

For all the experiments, we follow previous work and use greedy search (Zhang et al., 2023; Ding et al., 2023). We left-truncate the left context to 1024 tokens, right-truncate the right context to 512 tokens, and right-truncate the cross-file context to 512 tokens. The max generation length is set to 50 tokens for line, API, and chunk completion instances, and 256 for function completion instances. We perform different post-processing operations for different tasks. For line, API, and chunk completion, we truncate the prediction to having the same number of lines as in Y. For function completion, we first add a placeholder `pass` statement to X_l and use tree-sitter[5] to determine the index of the function in the file. Then, we concatenate the X_l and $\hat{Y}$, parse the string again with tree-sitter, and extract the function body as the final $\hat{Y}$ if the string can be parsed. Otherwise, we directly return the raw $\hat{Y}$ without post-processing.

B. Why infilling?

As part of the in-file context, X_r contains rich information about how the future execution relies on the code in the hole. Right contexts are also shown useful for closely relevant tasks such as function call argument completion (Pei et al., 2023). However, previous literature such as Zhang et al. (2023) suggests splitting X_r and retrieving code chunks from it. With the availability of code LMs trained on fill-in-the-middle such as StarCoder, we argue that directly providing X_r in the prompt is more preferable.

To illustrate, we investigate the effect of directly providing X_r in the prompt for CodeGen-Mono 16B and StarCoder on current-file code completion and retrieval-augmented code completion. Figure 6 presents the performance on RepoEval with different types of contexts provided in the prompt. Whether cross-file contexts are present or not, providing right contexts can greatly improve the code completion performance. The gain is consistent for both API and function completion. Compared to CodeGen, StarCoder can better leverage the right context to generate more accurate code. Overall, we observe that leveraging the entire right context to perform infilling represents a much stronger baseline. Therefore, in this paper we have exclusively focused on the infilling setting with StarCoder.

[5] https://tree-sitter.github.io/tree-sitter/

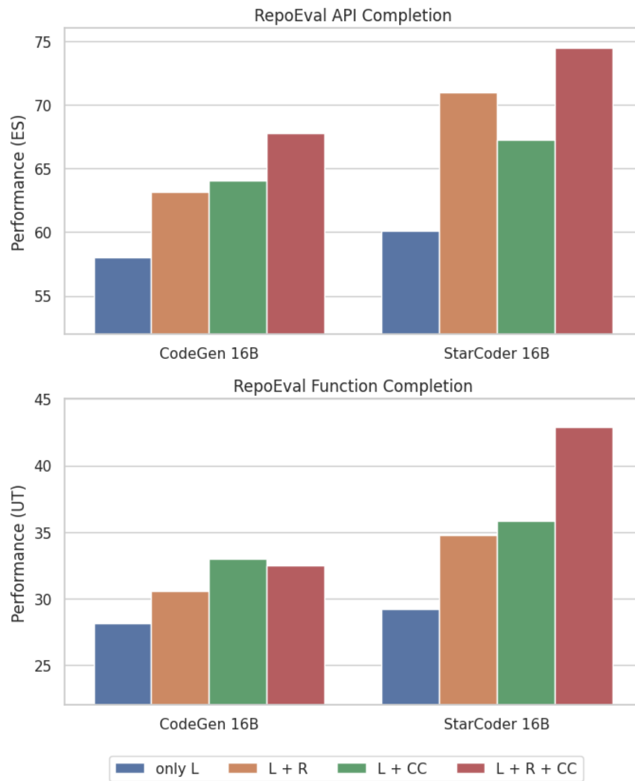

Figure 6. A comparison between four prompting strategies for RepoEval by combining left context (L), right context (R), and cross-file contexts (CC). Leveraging right contexts to build infilling-style prompt generally improves the performance regardless whether CC is present or not. StarCoder exhibits larger gains from right contexts, potentially due to its fill-in-the-middle pre-training.

C. Trial Retrieval and Trial Generation

In this section, we present a detailed evaluation of two selective RAG strategies: trial retrieval and trial generation.

C.1. Trial Retrieval

To gauge the relevance of retrieved context, using the similarity scores from the retrievers is a natural option. In this section, we investigate *trial retrieval* as a baseline for informing the decisions for selective RAG. We apply three off-the-shelf retrievers on RepoEval. For each retriever, we score each of the instances with the similarity between the top-1 retrieved code chunk and the query. The score is compared to a threshold decide whether the prompt should feature CC or not. If score is higher than the threshold, we use top-10 code chunks retrieved by the same retriever as the cross-file context. We consider the following three retrievers:

- **jaccard**: the Jaccard index (Jaccard, 1912).
- **weighted_ngram**: the weighted n-gram matching term introduced in the CodeBLEU metric (Ren et al., 2020).
- **unixcoder**: the cosine similarity of UniXcoder embedding (Guo et al., 2022).

Figure 7 presents the selective RAG performance of StarCoder under different budgets.We observe that the retrievers' similarity scores serve as a promising signal for deciding whether the retrieved information can improve the RAG performance. For most retrievers and tasks, the performance of full retrieval could be reached with at most 60% retrieval budget. This trend also aligns with the remark in Zhang et al. (2023) on the correlation between in-repository duplication and the gain from CC. However, it is worth noting that this strategy brings no latency gain as it still implements invariable retrieval. In addition, the knowledge of whether the LM could be benefited by the retrieved context is not leveraged.

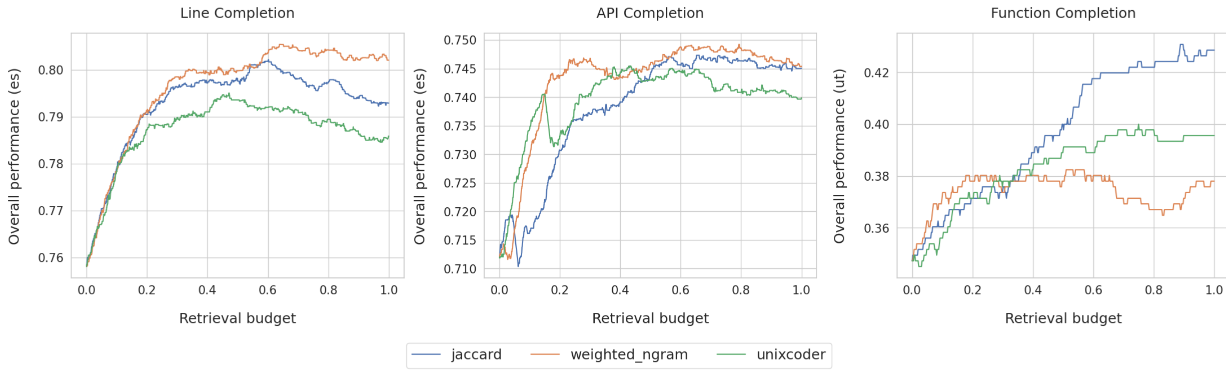

Figure 7. A comparison of the effectiveness of different similarity functions for selective RAG with StarCoder 16B. We plot the retrieval budget in the x-axis, which is the percentage of instances to perform retrieval. We report score on the entire testing dataset for each budget. Specifically, the retriever's similarity score is used select a subset to perform retrieval, and for the other instances in-file completion is performed without retrieval. In most of the cases, 40% retrieval can be saved without sacrificing the code completion performance.

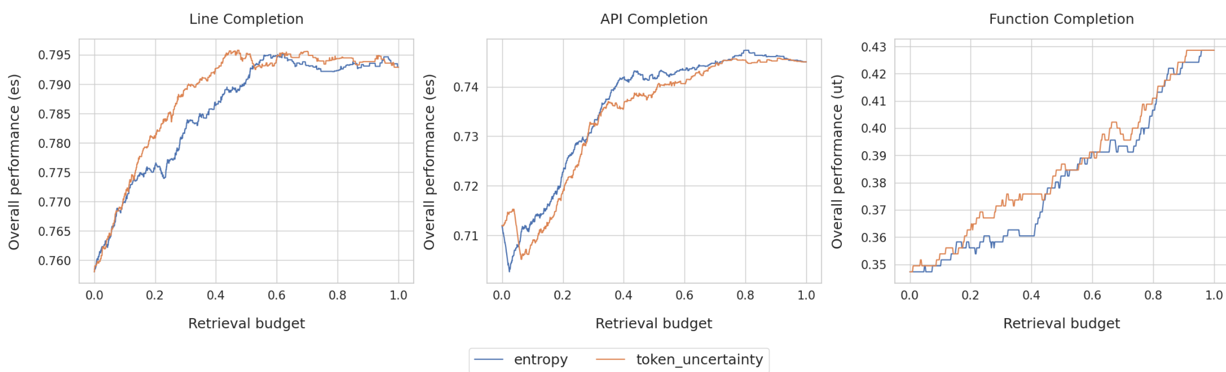

Figure 8. A comparison of the effectiveness of two uncertainty metrics for selective RAG with StarCoder 16B. We plot the retrieval budget in the x-axis and report score on the entire testing dataset for each budget. We observe that the uncertainty-based metrics fail for long sequence generation such as function completion. Token uncertainty outperforms entropy for line completion while entropy is slightly better for API completion. Overall, we find that uncertainty-based selective RAG is not as effective as retriever-based (Figure 7).

C.2. Trial Generation

Next, we evaluate two uncertainty-based selective RAG strategies that have been explored by previous works.

- **entropy**: the sequence-level entropy as used in (Li et al., 2023a). We estimate the entropy by performing vanilla sampling for 20 times.
- **token uncertainty**: the probability of the most unlikely token in the sequence decoded with greedy search, as used in Jiang et al. (2023). This metric can be seen as the lower bound of the per-token maximum probability.

Figure 8 presents the selective RAG performance of StarCoder under different budgets, similar to the previous evaluation setting. We find that the selective RAG performance of uncertainty-based metrics is inconsistent across sequence lengths. As the length of $\hat{Y}$ increases (from line to API, and form API to function), the effectiveness of uncertainty-based metrics drops significantly. In addition, the selective performance cannot outperform the methods based on trial retrieval.

D. Data Creation Algorithm for REPOFORMER and CCEval

We present the full self-supervised data creation algorithm in Algorithm 1 (for chunk completion data) and Algorithm 2 (for function completion data). $R_{filtered}$ stands for the remaining repositories after applying the filtering criteria in Section 3.3. In the next section, we present further analyses on the training data distribution.

Algorithm 1 Repoformer Data Creation (Chunk Completion)

Input: Filtered set of repositories $R_{filtered}$, language model $\mathcal{M}$, label threshold T
Output: chunk completion training dataset $\mathcal{D}$
$\mathcal{D} \leftarrow \emptyset$
for each $r \in R_{filtered}$ **do**
  $\mathcal{D}_r \leftarrow \emptyset$
  $\mathcal{C}_{raw} \leftarrow$ Break r into non-overlapping chunks of 10 lines each
  $\mathcal{C}_r \leftarrow$ Cluster $\mathcal{C}_{raw}$ with KMeans using TF-IDF features, with the constraint $|\mathcal{C}_r| = 0.2|\mathcal{C}_{raw}|$
  for each $c \in \mathcal{C}_r$ **do**
    $k \sim$ Poisson($\lambda = 3$)
    $s \leftarrow$ Randomly sample a chunk from c
    $Y \leftarrow$ Cut a sub-chunk from s that spans k consecutive lines
    $X_l, X_r \leftarrow$ Recover the in-file left context and right context corresponding to Y
    if $rand(0, 1) > 0.5$ **then**
      $\mathcal{Q} \leftarrow$ Concatenate(last $5k$ lines of X_l, Y, first $5k$ lines of X_r)
    else
      $\mathcal{Q} \leftarrow$ Concatenate(last $5k$ lines of X_l, first $5k$ lines of X_r)
    end if
    $CC \leftarrow$ Retrieve top-3 cross-file contexts from r using $\mathcal{Q}$ via jaccard similarity, each of length $10k$
    $\hat{Y}_{base} \leftarrow \mathcal{M}(X_l, X_r)$
    $\hat{Y}_{RAG} \leftarrow \mathcal{M}(X_l, X_r, CC)$
    $label \leftarrow ES(\hat{Y}_{RAG}, Y) - ES(\hat{Y}_{base}, Y) > T$ // boolean value
    Append $(X_l, X_r,\ Y,\ CC,\ label)$ to $\mathcal{D}_r$
  end for
  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_r$
end for

Algorithm 2 Repoformer Data Creation (Function Completion)

Input: Filtered set of repositories $R_{filtered}$, language model $\mathcal{M}$, label threshold T
Output: function completion training dataset $\mathcal{D}$
$\mathcal{D} \leftarrow \emptyset$
for each $r \in R_{filtered}$ **do**
  $\mathcal{D}_r \leftarrow \emptyset$
  $\mathcal{C}_{raw} \leftarrow$ Gather all the functions between 3 and 30 lines
  $\mathcal{C}_r \leftarrow$ Cluster $\mathcal{C}_{raw}$ with KMeans using TF-IDF features, with the constraint $|\mathcal{C}_r| = 0.2|\mathcal{C}_{raw}|$
  for each $c \in \mathcal{C}_r$ **do**
    $s \leftarrow$ Randomly sample a function from c
    $Y \leftarrow$ Cut only the body part of the function
    $X_l, X_r \leftarrow$ Recover the in-file left context and right context corresponding to Y
    if $rand(0, 1) > 0.5$ **then**
      $\mathcal{Q} \leftarrow$ Concatenate(last 20 lines of X_l, Y, first 20 lines of X_r)
    else
      $\mathcal{Q} \leftarrow$ Concatenate(last 20 lines of X_l, first 20 lines of X_r)
    end if
    $CC \leftarrow$ Retrieve top-3 cross-file contexts from r using $\mathcal{Q}$ via jaccard similarity, each of length $10k$
    $\hat{Y}_{base} \leftarrow \mathcal{M}(X_l, X_r)$
    $\hat{Y}_{RAG} \leftarrow \mathcal{M}(X_l, X_r, CC)$
    $label \leftarrow ES(\hat{Y}_{RAG}, Y) - ES(\hat{Y}_{base}, Y) > T$ // boolean value
    Append $(X_l, X_r,\ Y,\ CC,\ label)$ to $\mathcal{D}_r$
  end for
  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_r$
end for

Training Data Analysis For the 240k chunk completion and 120k function completion instances, we plot the performance change after providing CC in Figure 9. In total, 30.18% chunk completion instances and 35.16% function completion instances are labeled with positive. The average length of Y is 3.53 lines for chunk completion and 11.77 lines for function completion.

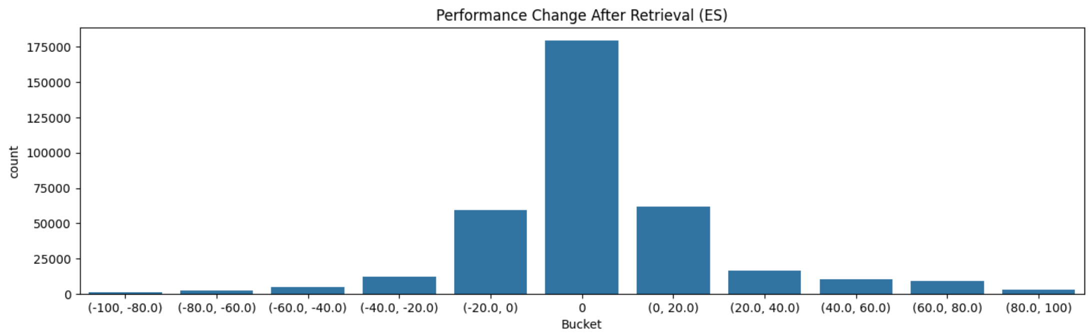

Figure 9. The performance gain on REPOFORMER training data exhibited by StarCoderBase-1B from retrieved cross-file context. The sign of the performance change is used to generate the label for REPOFORMER training. Each (start, end) bucket contains values ranging from start to end except for the central bucket, which corresponds to exactly 0.

CCEval Benchmarking Dataset Creation One drawback of RepoEval is its limited repository coverage. To verify the performance on diverse repositories, we collect and curate a new evaluation dataset for repository-level code completion.

- **Repository collection.** We first solicited 1744 raw Python repositories from the authors of CrossCodeEval (Ding et al., 2023). These repositories were created between 2023-03-05 to 2023-06-15 and collected on 2023-09-01. They have been ensured to not overlap with the Stack (Kocetkov et al., 2022).
- **Target line sampling.** We avoided using the CrossCodeEval benchmark as the original benchmark explicit removed the instances where StarCoderBase-1B can correctly answer without the retrieved context. To simulate a more natural distribution of code completion, we sample new blanks from the raw repositories. Specifically, we run Algorithm 1 and Algorithm 2 to gather chunk completion and function completion instances.
- **Data analysis** In Table 6, we present the basic statistics of RepoEval and CCEval.

	RepoEval			**CCEval**	
	Line	**API**	**Function**	**Chunk**	**Function**
# repositories	16	16	16	944	1460
# instances	1600	1600	455	5000	5000
$\|X_l\|_{line}$	30.7	30.8	31.1	24.7	31.7
$\|X_l\|_{token}$	796.3	890.7	761.1	661.9	672.1
$\|X_r\|_{line}$	15.1	13.9	16.2	12.9	14.4
$\|X_r\|_{token}$	449.9	430.4	412.4	404.2	371.3
$\|Y\|_{line}$	1.0	2.1	7.8	1.47	9.5
$\|Y\|_{token}$	12.0	25.4	97.8	19.2	111.2

Table 6. Descriptive statistics of RepoEval and CCEval. For $|Y|$, $|X_l|$, and $|X_r|$, we report both the number of lines as well as the number of tokens (using the StarCoder tokenizer) in the groundtruth, left context, and the right context.

E. Extended Analyses

E.1. Full Latency-Accuracy Visualizations

In this section, we present the latency-accuracy trade-off plots for REPOFORMER-1B, REPOFORMER-3B, STARCODERBASE-7B, and STARCODER on the three tasks from RepoEval. We use self-selective RAG for the REPOFORMER models and for STARCODER, we use REPOFORMER-1B to make the selective RAG decisions. The results are presented in Figure 11 to Figure 14. Overall, we observe that no matter for self-selective RAG or making selective predictions for a larger model, REPOFORMER is able to improve the accuracy and latency at the same time. The improvement is more apparent in the line and API completion tasks. For function completion, as discussed in the main text, RepoEval uses very small repositories to enable easy unit testing. As a result, the retrieval overhead is low in general and thus does not significantly affect the latency of the entire RAG system.

E.2. Calibration of REPOFORMER's Selective Retrieval Prediction

We evaluate the calibration of REPOFORMER-1B's selective decisions. Figure 10 plots the probability of <cc> against the probability of the model's performance could be improved by the CC, measured by comparing the prediction with and without CC. When ES is used as the evaluation metric, REPOFORMER-1B generally makes near-calibrated predictions for Line and API Completion. However, when it comes to longer-formed function completion, especially when UT is employed as the metric, REPOFORMER-1B's predictions are not calibrated. One possible reason is the use of ES as the training signal. We encourage future work to devise methods for effectively labeling the correctness of function completion. In addition, future work should consider training REPOFORMER to perform multiple self-assessments for long-form generations.

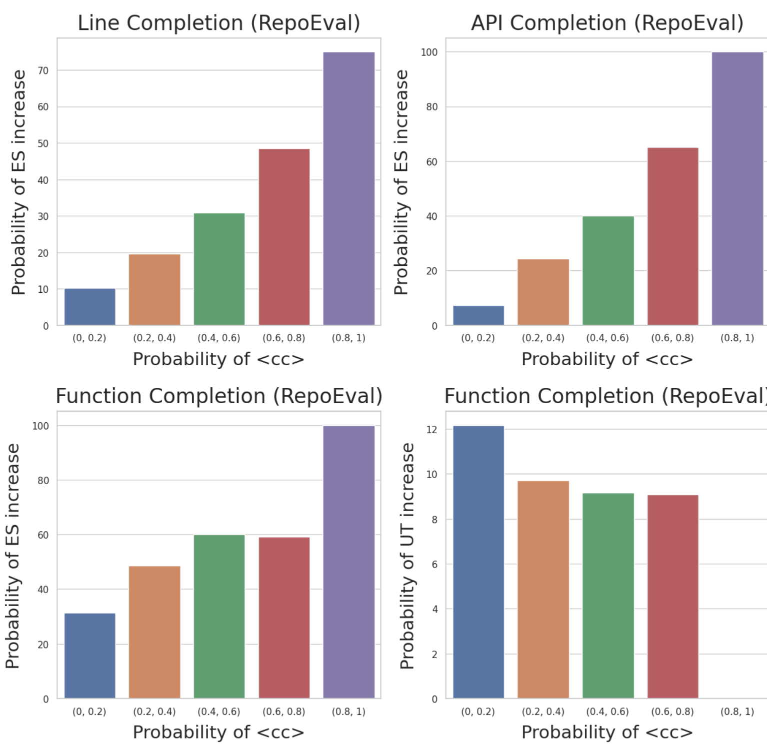

Figure 10. The calibration of selective retrieval predictions. REPOFORMER makes generally calibrated predictions when ES is used as the metric and the generation is of moderate lengths. The prediction is not calibrated for function completion when the metric is UT.

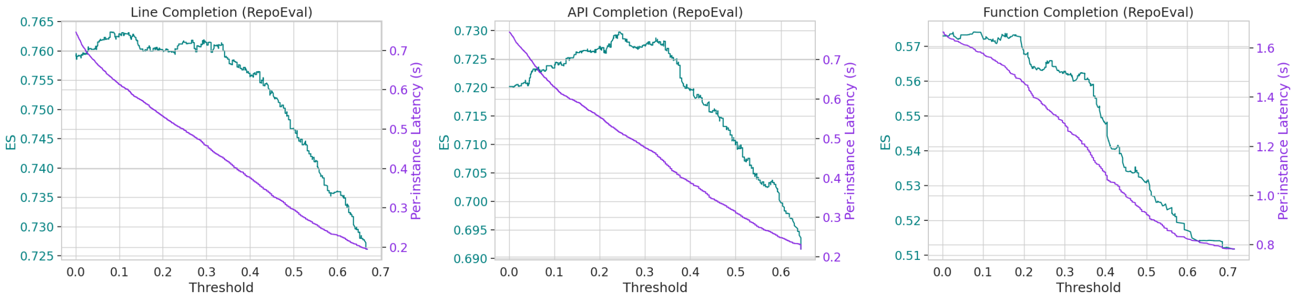

Figure 11. Latency-accuracy trade-off of self-selective RAG for REPOFORMER-1B.

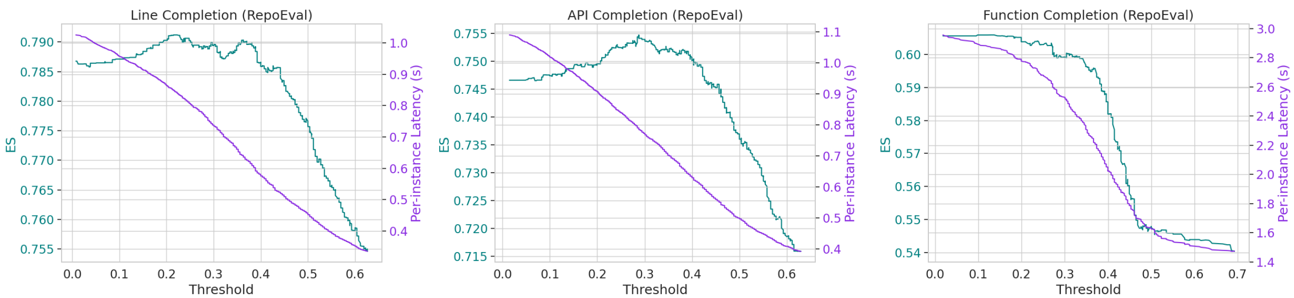

Figure 12. Latency-accuracy trade-off of self-selective RAG for REPOFORMER-3B.

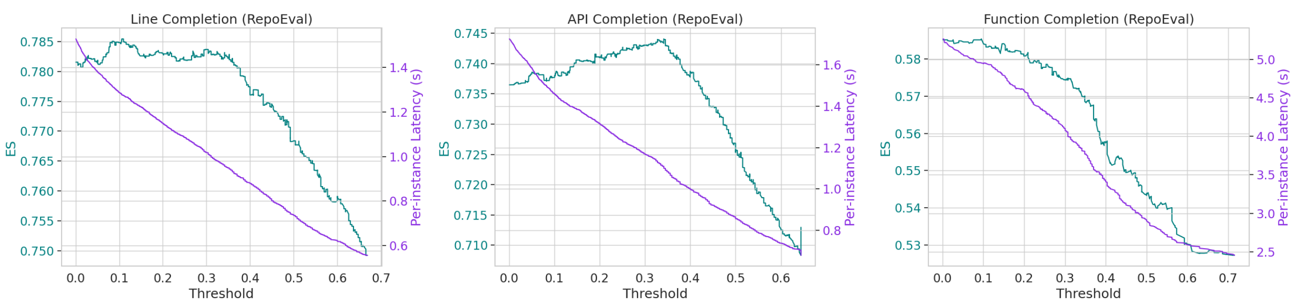

Figure 13. Latency-accuracy trade-off of selective RAG for STARCODERBASE-7B. REPOFORMER-1B is used for the selective decisions.

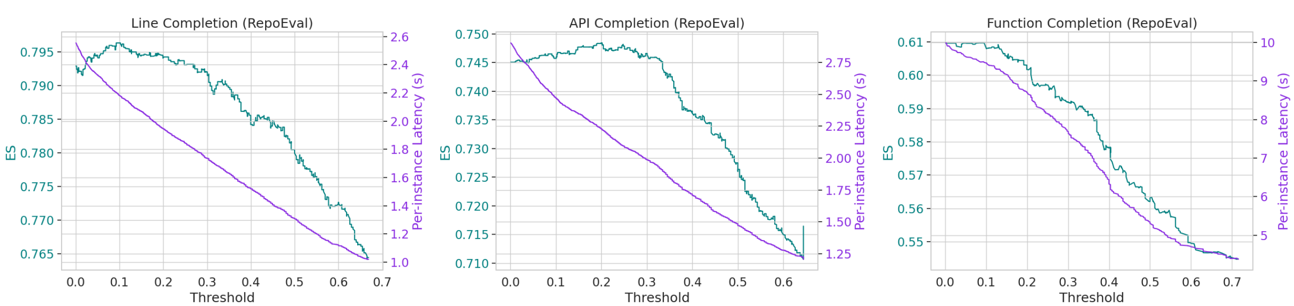

Figure 14. Latency-accuracy trade-off of selective RAG for STARCODER. REPOFORMER-1B is used for the selective decisions.