On Mitigating Code LLM Hallucinations with API Documentation

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Abstract

In this study, we address the issue of API hallucinations in various software engineering contexts. We introduce CloudAPIBench, a new benchmark designed to measure API hallucination occurrences. CloudAPIBench also provides annotations for frequencies of API occurrences in the public domain, allowing us to study API hallucinations at various frequency levels. Our findings reveal that Code LLMs struggle with low frequency APIs: for e.g., GPT-40 achieves only 38.58% valid low frequency API invocations. We demonstrate that Documentation Augmented Generation (DAG) significantly improves performance for low frequency APIs (increase to 47.94% with DAG) but negatively impacts high frequency APIs when using sub-optimal retrievers (a 39.02% absolute drop). To mitigate this, we propose to intelligently trigger DAG where we check against an API index or leverage Code LLMs' confidence scores to retrieve only when needed. We demonstrate that our proposed methods enhance the balance between low and high frequency API performance, resulting in more reliable API invocations (8.20% absolute improvement on CloudAPIBench for GPT-4o).

Introduction 1

Programmers frequently utilize third-party Application Programming Interfaces (APIs) as foundational elements for new software development, particularly in domains like cloud services, web and mobile development, e-commerce, FinTech, and data analytics. These APIs offer essential functionalities, enabling developers to create robust and feature-rich applications efficiently.

Large Language Models for code generation (Code LLMs) are being increasingly used by programmers (Peng et al., 2023; Chen et al., 2021; Dakhel et al., 2023). However, these models can generate incorrect API-related code, known as

API hallucinations (Liu et al., 2024), especially when under-trained on certain under-represented APIs – referred to as *low frequency* APIs (see Figure 1 (left)). This problem is exacerbated by the constant evolution of APIs, including frequent updates and deprecation of existing APIs (McDonnell et al., 2013). Consequently, new, updated, or infrequently used APIs are more prone to hallucinations. To systematically measure the prevalence of such hallucinations, we introduce CloudAPIBench, a benchmark specifically designed to evaluate API hallucinations, focusing on APIs from major cloud service providers like Amazon Web Services (AWS) and Microsoft Azure.

Next, we explore mitigation strategies for API hallucinations. When uncertain about API usage, human developers frequently rely on API documentation. Likewise, we hypothesize that Code LLMs should consult these resources under uncertainty. Hence, to address API hallucinations, we adopt retrieval augmented generation with documentation, i.e., Documentation Augmented Generation (DAG), which has shown early promise (Zhou et al., 2023; Patil et al., 2023).

However, DAG may be unnecessary when APIs are stable or well-covered in the model's training data (i.e., high frequency APIs)—we find that DAG with suboptimal retrievers indeed degrades performance for high frequency APIs, supporting the observation that LLMs are sensitive to irrelevant information (Shi et al., 2023a; Yoran et al., 2023). As such, we also present two simple yet effective strategies that can be easily adapted with DAG to address such pitfalls.

Figure 1 (right) demonstrates how the frequency of an API's occurrence in the public domain affects Code LLMs. We analyze the perplexity of StarCoder2-15B (base model) (Lozhkov et al., 2024) on API tokens across two frequency groups: *low* (\leq 10 occurrences in training data: The Stack v2) and high (≥ 100 occurrences), with detailed fre-

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Figure 1: **Introduction.** (Left) A CloudAPIBench task (yellow) and StarCoder2-15B's response (red) are displayed. The target is a recently released AWS API (Sivasubramanian, 2023), *i.e.*, a *low frequency* API. Due to limited training on such APIs, the Code LLM hallucinates a non-existent API invocation. (**Right**) Given a prompt from CloudAPIBench, we measure the perplexity of the target API tokens using StarCoder2-15B (*lower is better*). The base model handles high frequency APIs well but falters with low frequency ones. While DAG (with imperfect retrievers) improves low frequency API performance, it hurts high frequency API performance due to irrelevant augmentations. This paper's methods and analyses address this limitation of DAG.

quency descriptions in Section 2.2. The base model excels with high frequency APIs but struggles with low frequency ones. While DAG enhances performance for low frequency APIs, it compromises high frequency API performance due to occasional irrelevant augmentations from suboptimal retrievers: these distract the Code LLM's reliance on its internal knowledge, which is sufficient for high frequency APIs. To address DAG's limitations, we explore methods such as inspecting model confidence scores (Jiang et al., 2023; Varshney et al., 2023) and validating model generations against an API index before retrieval. These strategies effectively mitigate DAG's drawbacks, enhancing the reliability of Code LLMs.

We outline our key contributions and the structure of the paper as follows:

- We introduce CloudAPIBench to systematically study real-world API hallucinations; this benchmark evaluates API hallucinations across major cloud SDK APIs, *i.e.*, those by AWS and Azure (Section 2).
- We present a thorough study of DAG to enhance CloudAPIBench performance, identifying the parts of documentation that reduce hallucinations and quantifying the impact of other retrieval components on model efficacy (Section 3).
- We characterize scenarios where DAG may degrade performance and discuss selective retrieval methods to improve Code LLMs' utilization of documentation (**Section 4**).

We believe this is the first work to measure and characterize real-world API hallucinations for vari-

ous Code LLMs and explore strategies to mitigate this issue through documentation.

2 API Hallucinations & CloudAPIBench

We first comment on the impact of API hallucinations in Section 2.1 and introduce CloudAPIBench to measure these in Section 2.2.

2.1 Impact of API Hallucinations

Liu et al. (2024) identify that API hallucinations constitute up to 15% of all hallucinations in stateof-the-art Code LLMs, influencing cloud software engineering where code is API-intensive. These hallucinations can propagate errors, creating a snowball effect (Zhang et al., 2023b). For e.g., a hallucinated API call can lead to hallucinated handling of its response in subsequent code segments, compounding the problem (Ding et al., 2023a). Such incorrect API usage can also introduce security vulnerabilities, like improper data handling, which may lead to attacks or data breaches (Pearce et al., 2021). As adoption of Code LLMs grows, the cognitive burden on developers increases (Barke et al., 2022), as they must trace and rectify both the initial hallucination and all affected code segments. Given this severe impact of API hallucinations, it is critical to explore effective methods for their detection and mitigation, as we study in this work.

2.2 CloudAPIBench

Current benchmarks evaluate various programming skills such as problem solving (Chen et al., 2021; Austin et al., 2021), repository-level coding (Ding et al., 2023b; Liu et al., 2023), and tool



Figure 2: **Composition of CloudAPIBench.** (a) The benchmark comprises diverse APIs from various AWS and Azure services. (b) Word cloud visualizing the services in CloudAPIBench; from AWS **s3** to Azure **computervision**, CloudAPIBench comprises many cloud-based software engineering use-cases.

usage (Patil et al., 2023; Basu et al., 2024). However, a comprehensive benchmark for assessing real-world API hallucinations in software engineering remains absent. To address this, we introduce CloudAPIBench, a benchmark designed to evaluate Code LLMs' abilities to invoke cloud APIs.

Composition. CloudAPIBench is a Python benchmark comprising 622 *synthetic tasks* to prevent data leakage with Code LLMs. Each task requires invoking a specific cloud API from providers like AWS and Azure, reflecting practical software engineering scenarios. Task prompts include imports, variable declarations, and a developer-style comment describing the API's purpose, stopping just before the API invocation. Figure 1 (left) illustrates a sample task and a model response (demonstrating an API hallucination). Figure 2 presents a detailed task distribution, showing that CloudAPIBench captures diverse API invocation scenarios to evaluate Code LLMs comprehensively.

API Frequency Annotations. CloudAPIBench also contains the *API frequency* for APIs, *i.e.*, how often they occur in The Stack v2 (Lozhkov et al., 2024). As The Stack v2 is one of the largest open code pre-training datasets, we assume that our API frequencies approximates the distribution of APIs in public sources. Hence, this can be used to explore the relationship between hallucination rates and API frequencies for various Code LLMs.

To enhance interpretability, we classify API frequencies into three categories: Low (0 - 10 occurrences), *Medium* (11 - 100), and *High* (\geq 101). Since this treats APIs within the same class as identical, we minimize confounding factors (such as invocation complexity) by selecting diverse APIs within each class. This approach parallels the categorization of concepts based on popularity or pretraining frequencies (Razeghi et al., 2022; Mallen



Figure 3: **Valid API Invocation.** Using the API documentation, we create an API stub to capture correct usage. A candidate invocation is valid if it successfully binds to the stub. Here, delete_message requires *at least* one required argument for successful binding.

et al., 2022). To our knowledge, this is the first granular analysis of a Code LLM's pre-training corpus. Detailed API frequency distributions in CloudAPIBench are provided in Appendix A.1.

Construction. We construct CloudAPIBench with the goal of scaling coverage to multiple APIs from various providers. First, we source API specifications from official documentation to index their correct usage. Next, we determine each API's frequency in The Stack v2 by counting function definitions and calls with the same names as the APIs in relevant files. We select APIs for CloudAPIBench while ensuring diversity of invocation complexity and frequency. Using Claude 3 Sonnet (Anthropic, 2024), we convert API descriptions into developerstyle comments, and create prompts with necessary imports, declarations, and a descriptive comment before the API call. We provide elaborate details of this process in Appendix A.2, and present more samples from CloudAPIBench in Appendix A.4.

Evaluation Metric. We introduce the **valid API invocation** metric, which verifies if an API is invoked according to its syntax. We obtain this syntax by tracking the API's arguments and whether they are required. The metric is computed as follows: we create a dummy function mirroring the API's signature (*i.e.*, API stub (Zhu et al., 2023)). A candidate invocation is tested against this stub, and only successful bindings indicate validity. This evaluation method bypasses the intricacies of static analysis (Patil et al., 2023) and is more robust than string matching (Ding et al., 2023b), ensuring reliable and scalable evaluations. Figure 3 illustrates this process. See Appendix A.3 for more details.

Model	HumanEval	CloudAPIBench				
wiodei	pass@1	High Frequency	Medium Frequency	Low Frequency		
StarCoder2-3B	31.44	84.39	37.33	11.61		
StarCoder2-7B	34.09	86.34	47.33	9.36		
StarCoder2-15B	44.15	88.78	57.33	24.72		
Google CodeGemma-2B	27.28	79.51	26.67	4.49		
Google CodeGemma-7B	40.13	87.80	52.67	12.36		
IBM Granite-Code-3B		83.41	44.67	17.23		
IBM Granite-Code-8B		85.85	62.67	28.09		
IBM Granite-Code-20B		87.80	69.33	32.21		
DeepSeekCoder-1.3B	32.13	79.02	22.67	5.24		
DeepSeekCoder-6.7B	45.83	88.78	52.00	13.48		
DeepSeekCoder-33B	52.45	90.24	70.00	34.83		
GPT-40	90.20	93.66	78.67	38.58		

Table 1: **Results on CloudAPIBench.** We present Valid API Invocation (%) results on CloudAPIBench for various Code LLMs, categorized by API frequency in The Stack v2. For comparison, we also include HumanEval (Chen et al., 2021) results from BigCode (2024) and OpenAI (2024). While Code LLMs excel on high-frequency APIs, their performance drops severely on low-frequency APIs, despite strong results on general programming tasks like HumanEval.

2.3 Evaluation & Results

Models. We evaluate the following recent Code LLMs (and sizes) on CloudAPIBench: StarCoder2-{3B, 7B, 15B} (Lozhkov et al., 2024), DeepSeekCoder-{1.3B, 6.7B, 33B} (Guo et al., 2024), Google CodeGemma-{2B, 7B} (Team et al., 2024), IBM Granite-Code-{3B, 8B, 20B} (Mishra et al., 2024b) and GPT-4o (gpt-4o-2024-05-13) (OpenAI, 2024).

Inference. We use greedy decoding, generating one sequence per task up to 256 tokens, and postprocess until the first function call; this is evaluated for validity as detailed in Section 2.2. This strategy is used throughout this work consistently. For instruction-tuned models, we specify a system prompt indicating the model to generate only the API invocation (see Appendix A.3).

Results. Table 1 presents the performance of all models on CloudAPIBench and HumanEval (for a reference of generic performance). Key observations include:

– *API Hallucinations*. All Code LLMs exhibit API hallucinations to a certain degree. These primarily occur due to (1) usage of non-existing APIs, (2) incorrect usage of the target API or, (3) usage of incorrect existing APIs. We illustrate these failure cases in Appendix A.5.

- API Frequency Trends. A strong correlation exists between API frequency and valid API invocations: high frequency APIs yield fewer hallucinations, while low frequency APIs result in more. While this is expected, this trend verifies the applicability of our API frequency annotations.

- *Low Frequency APIs*. Despite strong performance on high frequency APIs and generic benchmarks, all models exhibit high hallucination rates for low frequency APIs. This disparity highlights the value of CloudAPIBench in pinpointing scenarios where Code LLMs are prone to hallucinate. We dive deeper into various low frequency API failure cases for all models in Appendix A.6.

Given the poor performance on low frequency APIs, we now explore the use of documentation to enhance performance on CloudAPIBench.

3 Documentation Augmented Generation (DAG)

In this section, we see how DAG enhances performance on CloudAPIBench. We first outline the key components of DAG: augmentation design, retrieval index and retriever, in Section 3.1. Subsequently, we discuss how different design choices affect downstream performance in Section 3.2.

3.1 Setup

Overview. Following Zhang et al. (2023a); Jiang et al. (2023), we implement an iterative pipeline for DAG. Starting with a prompt, the Code LLM generates a hypothetical API invocation. This invocation forms a query to retrieve documentation for similar APIs. The retrieved documentation is processed



Figure 4: **DAG Overview.** Starting with a CloudAPIBench task, we sample an API invocation from the Code LLM. This is used to retrieve documentation for the matching APIs. We then augment the prompt with the documentation and re-trigger the model.

and appended to the original prompt, after which inference is re-triggered. This process is illustrated in Figure 4.

Query Formulation & Retrieval Index. Given a CloudAPIBench task, the Code LLM generates a candidate API invocation, which we process as the query. This query focuses solely on API-relevant keywords, excluding any distractor prompt content (Jiang et al., 2023; Zhang et al., 2023a; Eghbali and Pradel, 2024). Our retrieval index includes all collected AWS and Azure APIs, identified using *keys* prepared similarly as the queries.

Retriever. We develop a retriever with configurable precision to study the effect of retrieval accuracy on CloudAPIBench. For an x% precision@k setting, we return k documents via BM25, ensuring that the target API's documentation is included x% of the time. This approach allows us to examine the impact of varying retrieval precision (x). We chose BM25 for its simplicity (Patil et al., 2023; Cheng et al., 2023), though our results are likely robust to different retrievers.

Augmentation Design. We prepend the retrieved documentation to the original prompt as a Python docstring after postprocessing. We test various augmentation strategies, each capturing different levels of API information and token count efficiencies: (1) API Name Only, (2) API Description, (3) API Specification, (4) API Description + Specification, and (5) Full Documentation. Figure 5 shows "API Specification" while additional details and examples are in Appendix B.1.

3.2 Experiments & Results

In this section, we perform ablations on various DAG components to analyze their impact on API hallucinations.

Experimental Setup. We present results from abla-



Figure 5: **API Specification Augmentation.** Augmented prompt for the Oracle retriever with one retrieval. The "API Specification" (blue) contains the API name and a list of its required & optional arguments, providing an efficient summary of the documentation.

tions on StarCoder2-3B. When testing a component (e.g., retriever precision), other components (e.g., number of retrievals) are held constant to isolate the effect. We also report the average valid API invocations across all tasks in CloudAPIBench for a concise performance measure, wherever indicated. Augmentation Design. Our objective is to determine the most useful and efficient information to retain from an API's documentation for augmentation. So, we use an Oracle retriever to fetch only one documentation; this guarantees that the relevant information is present somewhere in the documentation. Results are presented in Figure 6, showing valid API invocation rates and the number of tokens introduced per augmentation across all APIs. "API Name Only" and "API Description" do not significantly reduce hallucination rates, as they lack detailed API syntax. However, adding "API Specification" dramatically improves model performance $(41.80\% \rightarrow 86.82\%$ on average), indicating that detailed API specifications are crucial. While "Full Documentation" optimizes performance, it is highly token-inefficient (685.24 tokens per augmentation). "API Description + Specification" strikes an optimal balance between token efficiency and performance, so, we adopt this design for all subsequent experiments.

Precision of Retriever. Results are displayed in Figure 7a. Here, we retrieve one document and vary the retriever's precision. As anticipated, the API hallucination rate decreases as retriever precision increases. Low frequency APIs show improvement

			–	[1024, 2047]						•		。 。 》
Augmentation Design	Avg. Tokens	Valid API Inv. (%)	en Co	[512, 1023]· [256, 511]·							0	ب _ه ک
Base Model		41.80	Token	[128, 255]			•		-	•	0	. ⁹ Dcation
API Name Only	36.07	52.73	tion	[64, 127]			-•-	-•		•		.4 U
API Description	78.80	53.22	inta	[32, 63]				-0				API
API Specification	52.57	86.82	Augmentation	[16, 31] :		Ť					0	.2 P
API Desc. + API Spec.	94.55	<u>87.14</u>	Aug	[0, 0]								S
Full Documentation	685.24	88.75		I	Base Model	API Name	API Desc.	API	API Desc. +Spec.	Full Doc.	J – 0	.0
			-		Houer		menta			Doc.		

Figure 6: Augmentation Design Results. (Left) Displays average tokens introduced per augmentation using the StarCoder2-3B tokenizer and average performance on CloudAPIBench for each augmentation design. (Right) Visualizes performance for *low frequency* APIs: the y-axis shows binned sequence lengths (exponential scale; capped at 2048), bubble color indicates performance, and bubble size indicates fraction of samples per bin. The improvements from API Specification are dramatic, though "Full Documentation" introduces too many tokens.



Figure 7: **Precision and No. of Retrievals.** (a) While most low precision retrievers hurt performance on high frequency APIs, they may benefit low frequency APIs. (b) 1 retrieval hurts performance on high frequency APIs, but this is somewhat recovered as number of retrievals increases.

over the base model even with low precision retrievers, while high frequency APIs require precision > 80% to match the base model's performance. Thus, at most precision levels, DAG induces higher hallucination rates for high frequency APIs compared to the base model (e.g., $84.39\% \rightarrow 67.32\%$ valid API invocations at 50% precision), underscoring Code LLMs' sensitivity to irrelevant augmentations (Shi et al., 2023a).

Number of Retrievals. Here we maintain the retriever precision at 50%. Figure 7b illustrates our findings. For low-frequency APIs, one or more retrievals consistently enhance performance. Conversely, high-frequency APIs show a sharp decline with one retrieval, partially recovered with two or more. This indicates that irrelevant augmentations can lead to unexpected behavior in Code LLMs, *especially* when a single augmentation conflicts with the model's internal knowledge.

Discussion. Our experiments above show that

DAG *significantly* reduces hallucinations for low frequency APIs. However, high frequency APIs may suffer performance drops with DAG due to irrelevant retrievals. This issue can potentially be resolved by allowing the Code LLM to use its internal knowledge for high frequency APIs, bypassing DAG; this forms the core of the next section.

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4 Improving DAG: When to Retrieve?

Given that suboptimal retrievers can increase hallucination rates with DAG, we investigate strategies to address this issue. By triggering DAG *selectively* – primarily when the Code LLM lacks knowledge of the target API – we can mitigate the negative impact of suboptimal retrievals, and allow the model to invoke APIs correctly using its internal knowledge. We discuss two strategies towards this here.

4.1 Index Lookup

Method. This simple technique verifies if the API name invoked during the first iteration generation exists in the API index. If not, the Code LLM is trying to call a non-existing API, and DAG provides the necessary references. Thus, DAG is not triggered for existing APIs; since this is likely to happen for high-frequency APIs, we expect fewer imprecise DAG triggers with this method.

Experimental Setup. As before, we perform ablations with StarCoder2-3B. We use a 50% precision retriever to retrieve one documentation.

Results. Table 2 presents the results. The index lookup method significantly reduces the regressions introduced by DAG for high-frequency APIs, even showing slight improvements over the base model. However, this gain comes at the expense of

Method	High Freq.	Low Freq.	Avg.
Base Model	84.39	11.61	41.80
DAG	67.32	46.07	54.50
DAG + Index Lookup	85.37	35.96	54.98

Table 2: **Index Lookup.** Triggering DAG only for nonexistent APIs reduces unnecessary retrievals for highfrequency APIs, enhancing performance. However, this also induces slight regressions for low-frequency APIs. [*Avg.* indicates performance across all frequencies.]

reduced retrievals for low-frequency APIs: sometimes, the model invokes an existing incorrect API or incorrectly invokes the target API, leading to more hallucinations compared to DAG. Overall, this method shows promise for enhancing DAG.

4.2 API Invocation Confidence

Background: LLM Calibration. Prior work has highlighted that LLM probabilities are wellcalibrated, allowing for uncertainty estimation for various tasks (Kadavath et al., 2022; Si et al., 2023; Jiang et al., 2023; Li et al., 2023). As such, leveraging a Code LLM's probabilities to predict potential hallucinations, we could selectively trigger DAG for those scenarios.

To quantify a Code LLM's uncertainty during API invocation, we define **API invocation con-fidence** as the *minimum* probability among all predicted API name (sub-)tokens (see Figure 8). This minimum captures minor uncertainties in API prediction better than other aggregators like the mean (Varshney et al., 2023; Jiang et al., 2023). The focus remains on the API name, not the entire invocation, as Code LLMs may show low confidence in tokens in the face of multiple alternatives (*e.g.*, constants in API arguments, *etc.*; this represents aleatoric uncertainty (Yadkori et al., 2024)).

Evidence from various Code LLMs, shown in Figure 9a, confirms their calibration for API invocation on CloudAPIBench. A strong positive correlation is observed between API invocation confidence and correct API usage, indicating that confidence levels can preemptively identify likely hallucinations (*i.e.*, they capture epistemic uncertainty (Yadkori et al., 2024)).

Method. We measure the API invocation confidence of the first iteration of generation, and if this is below a certain *fixed threshold*, indicating the model's lack of knowledge about the target API, we trigger DAG to assist the model.

Experimental Setup. Towards finding an optimal

<pre>from azure.servicefabric import ServiceFabricClientAPIs</pre>							
# Restart instances or replicas in a given partition							
response =	<mark>client.re</mark> s	start_pa	rtition(
applica	tion_name=	="fabric	:/MyAppli	cation",			
Target API: start_partition_restart							
	fuiget in i	. scarc_p		cocur c			
Pred. Token	Pred. Token restart partition (\n\t						
		-					
Probability	0.41	0.83	0.21	0.48	0.41		
y							
(min.)							
API Invocation Confidence: 0.21							

Figure 8: **API Invocation Confidence.** We estimate the model's uncertainty by taking the minimum probability of the predicted API name tokens (orange in table).

configuration, we vary the threshold of API invocation confidence below which to trigger DAG, and measure the API hallucination rate for StarCoder2-3B. As before, we use a 50% precision retriever with one retrieved document.

Results. Figure 9b shows the relation between the confidence threshold and valid API invocations. As we raise the threshold, DAG is triggered more often, leading to a consistent reduction in hallucinations for low frequency APIs. Conversely, high frequency APIs remain largely unaffected until a certain point, beyond which irrelevant augmentations start causing hallucinations. The optimal threshold balances improved performance for low frequency APIs without significant regressions for high frequency APIs; for StarCoder2-3B, this optimal range is approximately 0.7 - 0.8.



Figure 9: **API Invocation Confidence Results.** (a) API invocation confidence scores are well-calibrated on CloudAPIBench for a range of Code LLMs. (b) By triggering DAG when the API invocation confidence is below a certain threshold, we can control regressions on high frequency APIs while maintaining good performance on low frequency APIs.

4.3 DAG++ & Discussion

Having seen the benefits of the above approaches, we now discuss how DAG can be effectively improved by combining these, *i.e.*, DAG++. In this

Model	Method	Retrieval Triggered (%)			Valid API Invocations (%)			
Widdel	wieniou	High Freq.	Med. Freq.	Low Freq.	High Freq.	Med. Freq.	Low Freq.	Avg.
	Base Model	0.00	0.00	0.00	87.80	52.67	12.36	46.95
Google CodeGemma-7B	DAG	100.00	100.00	100.00	$61.95_{(-25.85)}$	$56.00_{(+3.33)}$	$46.44_{(+34.08)}$	$53.86_{(+6.91)}$
	DAG++	20.98	44.67	74.16	88.29(+0.49)	$65.33_{(+12.67)}$	$43.07_{(+30.71)}$	$63.34_{(+16.40)}$
	Base Model	0.00	0.00	0.00	88.78	57.33	24.72	53.70
StarCoder2-15B	DAG	100.00	100.00	100.00	$69.76_{(-19.02)}$	$58.67_{(+1.33)}$	$49.44_{(+24.72)}$	$58.36_{(+4.66)}$
	DAG++	20.98	43.33	70.41	88.78(+0.00)	$58.67_{(+1.33)}$	$46.44_{(+21.72)}$	$63.34_{(+9.65)}$
	Base Model	0.00	0.00	0.00	87.80	69.33	32.21	59.49
IBM Granite-Code-20B	DAG	100.00	100.00	100.00	$70.24_{(-17.56)}$	$63.33_{(-6.00)}$	$44.19_{(+11.99)}$	$57.40_{(-2.09)}$
	DAG++	15.12	29.33	66.29	$89.76_{(+1.95)}$	$71.33_{(+2.00)}$	$45.69_{(+13.48)}$	$66.40_{(+6.91)}$
	Base Model	0.00	0.00	0.00	90.24	70.00	34.83	61.58
DeepSeekCoder-33B	DAG	100.00	100.00	100.00	$69.27_{(-20.98)}$	$64.00_{(-6.00)}$	$51.31_{(+16.48)}$	$60.29_{(-1.29)}$
	DAG++	20.49	30.67	59.55	$86.83_{(-3.41)}$	$71.33_{(+1.33)}$	$55.43_{(+20.60)}$	$69.61_{(+8.04)}$
GPT-40	Base Model	0.00	0.00	0.00	93.66	78.67	38.58	66.40
	DAG	100.00	100.00	100.00	$54.63_{(-39.02)}$	$53.33_{(-25.33)}$	$47.94_{(+9.36)}$	$51.45_{(-14.95)}$
	DAG++	3.41	9.33	50.56	$94.15_{(+0.49)}$	82.00(+3.33)	$55.43_{(+16.85)}$	$74.60_{(+8.20)}$

Table 3: **DAG++ Results.** We present the performance on CloudAPIBench and the (%) of retrieval triggers for high/low frequency APIs, with absolute improvements over the base model shown in subscript. It is noteworthy that DAG++ significantly reduces the frequency of retrievals for high frequency APIs while appropriately decides to retrieve for low frequency APIs; by smartly triggering retrieval, DAG++ attains top performance on CloudAPIBench for all models.

method, we trigger DAG *iff* the API in the first iteration of generation does not exist in the index *OR* is being invoked with an API invocation confidence below a fixed threshold. We anticipate that this would help combine the benefits of both the discussed approaches.

Experimental Setup. We use a 50% precision retriever with one retrieval, consistent with previous experiments. Further, we fix the confidence threshold to be 0.8. Finally, to investigate the generalizability of our findings, we evaluate the largest models of all model families from Table 1.

Results. The results are shown in Table 3. For each model, show how often retrieval is triggered and the resulting performance on CloudAPIBench. We make the following key observations:

- *Trigger of Retrievals.* We first examine how often retrieval is triggered with each method. The base model never triggers retrieval, DAG always does, and DAG++ selectively retrieves documentation. DAG++ exhibits a *strong negative correlation* between retrieval trigger frequency and API frequency: it triggers retrieval more often for low frequency APIs and less for high frequency APIs, aligning with the principle of retrieval *only when necessary*. For *e.g.*, with GPT-40, DAG++ retrieves only 3.41% of the time for high frequency APIs indicating minimal need for documentation; conversely, retrieval is triggered 50.56% of the time for low frequency APIs, supplementing the model's

limited knowledge with relevant documentation.

-DAG v/s DAG++. Table 3 also shows the performances (and absolute improvements over the base model in subscript) of various models on CloudAPIBench. As noted in Section 3, while DAG significantly boosts low frequency API performance, it degrades high frequency API performance. For instance, GPT-40 experiences a 39.02% drop in performance for high frequency APIs with DAG, highlighting the the model's sensitivity to irrelevant augmentations. DAG++ successfully mitigates this issue for high frequency APIs while maintaining or improving gains on low frequency APIs. Overall, DAG++ outperforms DAG indicating that selective retrieval of API documentation, that respects API frequency, aids performance on CloudAPIBench.

- *Generalizability*. All model families demonstrate similar enhancement trends with DAG++, despite architectural and training differences. This underscores the generalizability of the importance of selectively retrieving API documentation when Code LLMs lack API specific knowledge. Additionally, scaling trends with model sizes (Kaplan et al., 2020; Wang et al., 2023a) are evident: average performance monotonically improves with model size in Table 3. Finally, DAG++ reveals that larger models require fewer retrievals for optimal performance, suggesting that they are more efficient at memorizing API syntax, even for low frequency APIs.

5 Related Work

Program Synthesis & API Invocations. Code LLMs are actively being used for automatic program synthesis (Rozière et al., 2023; Guo et al., 2024). Relevant to our study is API invocation generation (Qin et al., 2023; Patil et al., 2023), often done on tool-usage benchmarks that do not account for the distribution of APIs in the public domain. We develop CloudAPIBench, a benchmark targeting cloud-based software engineering scenarios, that includes API frequency annotations, allowing for nuanced failure analyses and targeted improvements through DAG. Works such as Zhou et al. (2023); Patil et al. (2023); Eghbali and Pradel (2024); Zan et al. (2023) also use documentation to improve API generation, but their evaluations do not capture the granularities discussed here.

LLM Hallucinations. LLMs may generate factually incorrect statements about concepts, diminishing their utility (Mishra et al., 2024a; Kang et al., 2023; Lee et al., 2023). As such, several works have emerged to deal with this issue. Some works focus on hallucination detection by exploiting the well-calibrated nature of LLMs (Kadavath et al., 2022; Si et al., 2023; Li et al., 2023) and using model confidence scores (Jiang et al., 2023; Varshney et al., 2023). Closest to our work, Liu et al. (2024), give a taxonomy of hallucinations for code generation. While they focus on identifying hallucinations with Code LLMs, we focus on mitigating API hallucinations using documentation.

Retrieval Augmented Generation (RAG). RAG supplements language models by retrieving from external data-stores (Asai et al., 2023a). Some studies use fixed algorithms for retrieval (Wang et al., 2023b; Shi et al., 2023b; Patil et al., 2023), while others adopt adaptive retrieval through special tokens (Asai et al., 2023b) or model confidence scores (Jiang et al., 2023). In this work, we establish how to use selective retrieval effectively to mitigate API hallucinations with documentation.

6 Conclusion & Future Work

In this work, we thoroughly investigate API hallucinations and demonstrate mitigation strategies for various Code LLMs. We introduce CloudAPIBench, a benchmark to measure API hallucinations for diverse AWS and Azure APIs, including API frequencies to categorize low, medium, and high frequency APIs. We adapt RAG with documentation (DAG) to inform Code LLMs about the correct syntax during inference. We discuss which parts of documentation are important and how various retrieval components affect hallucinations. While DAG significantly enhances lowfrequency API performance, it can degrade highfrequency API performance with irrelevant retrievals. We tackle this issue by *selectively* triggering retrievals through index lookup and API invocation confidence thresholding, and combine these methods in DAG++ leading to top performance on CloudAPIBench across Code LLMs. Future research could extend CloudAPIBench for longcontext evaluations, explore DAG beyond iterative generation, and improve DAG by enhancing Code LLMs' robustness to irrelevant augmentations.

7 Limitations

Scope of CloudAPIBench. CloudAPIBench is a Python only benchmark containing short synthetic prompts to evaluate API hallucinations. While these represent various software-engineering scenarios, these might not represent all real-world cloud API invocations across different programming languages and contexts.

Construction of CloudAPIBench. We create CloudAPIBench using a multi-step process as discussed in Section 2.2 and Appendix A.2. Some of these steps are based on carefully crafted heuristics such as a customized logic to estimate API frequencies. Given that our findings are consistent with literature and also match our expectations, the impact of the approximations employed, if any, should be limited.

Iterative generations for DAG. In this work, we have adopted an iterative approach to DAG where we generate, retrieve and re-generate. Due to the overhead introduced by this iterative process, it may not be suitable for scenarios where latency is crucial.

8 Ethics Statement

Use of Generative AI. Code generation models are subject to ethical risks as these models can generate harmful content or content similar to their pre-training data. For real world applications, the generated content should ideally be reviewed by human developers and should be executed in sandbox environments. For the scope of experiments in this work, these risks are relatively low.

Compute. Use of deep learning models is computationally expensive and raises environmental

concerns. We have not trained any models as part of this work, so, the computational footprint is relatively low. All experiments for this paper were done using 4 NVIDIA A100 machines.

References

- Anthropic. 2024. Introducing the next generation of claude. https://www.anthropic.com/news/ claude-3-family [Accessed: (March 4, 2024)].
- Akari Asai, Sewon Min, Zexuan Zhong, and Danqi Chen. 2023a. Retrieval-based language models and applications. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics* (Volume 6: Tutorial Abstracts), pages 41–46, Toronto, Canada. Association for Computational Linguistics.
- Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. 2023b. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *Preprint*, arXiv:2310.11511.
- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. 2021. Program synthesis with large language models. *Preprint*, arXiv:2108.07732.
- Shraddha Barke, Michael B. James, and Nadia Polikarpova. 2022. Grounded copilot: How programmers interact with code-generating models. *Preprint*, arXiv:2206.15000.
- Kinjal Basu, Ibrahim Abdelaziz, Subhajit Chaudhury, Soham Dan, Maxwell Crouse, Asim Munawar, Sadhana Kumaravel, Vinod Muthusamy, Pavan Kapanipathi, and Luis A. Lastras. 2024. Api-blend: A comprehensive corpora for training and benchmarking api llms. *Preprint*, arXiv:2402.15491.
- BigCode. 2024. Big code models leaderboard - a hugging face space by bigcode. https://huggingface.co/spaces/bigcode/ bigcode-models-leaderboard [Accessed: (June 12, 2024)].
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder,

Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code. *Preprint*, arXiv:2107.03374.

- Xin Cheng, Di Luo, Xiuying Chen, Lemao Liu, Dongyan Zhao, and Rui Yan. 2023. Lift yourself up: Retrieval-augmented text generation with self memory. *Preprint*, arXiv:2305.02437.
- Arghavan Moradi Dakhel, Vahid Majdinasab, Amin Nikanjam, Foutse Khomh, Michel C. Desmarais, Zhen Ming, and Jiang. 2023. Github copilot ai pair programmer: Asset or liability? *Preprint*, arXiv:2206.15331.
- Hantian Ding, Varun Kumar, Yuchen Tian, Zijian Wang, Rob Kwiatkowski, Xiaopeng Li, Murali Krishna Ramanathan, Baishakhi Ray, Parminder Bhatia, and Sudipta Sengupta. 2023a. A static evaluation of code completion by large language models. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 5: Industry Track), pages 347–360, Toronto, Canada. Association for Computational Linguistics.
- Yangruibo Ding, Zijian Wang, Wasi Uddin Ahmad, Hantian Ding, Ming Tan, Nihal Jain, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, and Bing Xiang. 2023b. Crosscodeeval: A diverse and multilingual benchmark for cross-file code completion. *Preprint*, arXiv:2310.11248.
- Aryaz Eghbali and Michael Pradel. 2024. Dehallucinator: Iterative grounding for llm-based code completion. *Preprint*, arXiv:2401.01701.
- Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y. Wu, Y. K. Li, Fuli Luo, Yingfei Xiong, and Wenfeng Liang. 2024. Deepseek-coder: When the large language model meets programming – the rise of code intelligence. *Preprint*, arXiv:2401.14196.
- Zhengbao Jiang, Frank F. Xu, Luyu Gao, Zhiqing Sun, Qian Liu, Jane Dwivedi-Yu, Yiming Yang, Jamie Callan, and Graham Neubig. 2023. Active retrieval augmented generation. *Preprint*, arXiv:2305.06983.
- Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, Scott Johnston, Sheer El-Showk, Andy Jones, Nelson Elhage, Tristan Hume, Anna Chen, Yuntao Bai, Sam Bowman, Stanislav Fort, Deep Ganguli, Danny Hernandez, Josh Jacobson, Jackson Kernion, Shauna Kravec, Liane Lovitt, Kamal Ndousse, Catherine Olsson, Sam Ringer, Dario Amodei, Tom Brown, Jack Clark, Nicholas Joseph, Ben Mann, Sam McCandlish, Chris Olah, and Jared Kaplan. 2022. Language models (mostly) know what they know. *Preprint*, arXiv:2207.05221.
- Haoqiang Kang, Juntong Ni, and Huaxiu Yao. 2023. Ever: Mitigating hallucination in large language models through real-time verification and rectification. *Preprint*, arXiv:2311.09114.

- Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling laws for neural language models. *Preprint*, arXiv:2001.08361.
- Hyunji Lee, Sejune Joo, Chaeeun Kim, Joel Jang, Doyoung Kim, Kyoung-Woon On, and Minjoon Seo. 2023. How well do large language models truly ground? *Preprint*, arXiv:2311.09069.
- Junyi Li, Tianyi Tang, Wayne Xin Zhao, Jingyuan Wang, Jian-Yun Nie, and Ji-Rong Wen. 2023. The web can be your oyster for improving large language models. *Preprint*, arXiv:2305.10998.
- Fang Liu, Yang Liu, Lin Shi, Houkun Huang, Ruifeng Wang, Zhen Yang, and Li Zhang. 2024. Exploring and evaluating hallucinations in llm-powered code generation. *arXiv preprint arXiv:2404.00971*.
- Tianyang Liu, Canwen Xu, and Julian McAuley. 2023. Repobench: Benchmarking repositorylevel code auto-completion systems. *Preprint*, arXiv:2306.03091.
- Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtar, Jiawei Liu, Yuxiang Wei, Tianyang Liu, Max Tian, Denis Kocetkov, Arthur Zucker, Younes Belkada, Zijian Wang, Qian Liu, Dmitry Abulkhanov, Indraneil Paul, Zhuang Li, Wen-Ding Li, Megan Risdal, Jia Li, Jian Zhu, Terry Yue Zhuo, Evgenii Zheltonozhskii, Nii Osae Osae Dade, Wenhao Yu, Lucas Krauß, Naman Jain, Yixuan Su, Xuanli He, Manan Dey, Edoardo Abati, Yekun Chai, Niklas Muennighoff, Xiangru Tang, Muhtasham Oblokulov, Christopher Akiki, Marc Marone, Chenghao Mou, Mayank Mishra, Alex Gu, Binyuan Hui, Tri Dao, Armel Zebaze, Olivier Dehaene, Nicolas Patry, Canwen Xu, Julian McAuley, Han Hu, Torsten Scholak, Sebastien Paquet, Jennifer Robinson, Carolyn Jane Anderson, Nicolas Chapados, Mostofa Patwary, Nima Tajbakhsh, Yacine Jernite, Carlos Muñoz Ferrandis, Lingming Zhang, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. 2024. Starcoder 2 and the stack v2: The next generation. Preprint, arXiv:2402.19173.
- Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. 2022. When not to trust language models: Investigating effectiveness of parametric and non-parametric memories. *Preprint*, arXiv:2212.10511.
- Tyler McDonnell, Baishakhi Ray, and Miryung Kim. 2013. An empirical study of api stability and adoption in the android ecosystem. In 2013 IEEE International Conference on Software Maintenance, pages 70–79. IEEE.
- Abhika Mishra, Akari Asai, Vidhisha Balachandran, Yizhong Wang, Graham Neubig, Yulia Tsvetkov, and Hannaneh Hajishirzi. 2024a. Fine-grained hallucination detection and editing for language models. *Preprint*, arXiv:2401.06855.

- Mayank Mishra, Matt Stallone, Gaoyuan Zhang, Yikang Shen, Aditya Prasad, Adriana Meza Soria, Michele Merler, Parameswaran Selvam, Saptha Surendran, Shivdeep Singh, Manish Sethi, Xuan-Hong Dang, Pengyuan Li, Kun-Lung Wu, Syed Zawad, Andrew Coleman, Matthew White, Mark Lewis, Raju Pavuluri, Yan Koyfman, Boris Lublinsky, Maximilien de Bayser, Ibrahim Abdelaziz, Kinjal Basu, Mayank Agarwal, Yi Zhou, Chris Johnson, Aanchal Goyal, Hima Patel, Yousaf Shah, Petros Zerfos, Heiko Ludwig, Asim Munawar, Maxwell Crouse, Pavan Kapanipathi, Shweta Salaria, Bob Calio, Sophia Wen, Seetharami Seelam, Brian Belgodere, Carlos Fonseca, Amith Singhee, Nirmit Desai, David D. Cox, Ruchir Puri, and Rameswar Panda. 2024b. Granite code models: A family of open foundation models for code intelligence. *Preprint*, arXiv:2405.04324.
- OpenAI. 2024. Hello gpt-4o. https://openai. com/index/hello-gpt-4o/ [Accessed: (June 19, 2024)].
- Shishir G. Patil, Tianjun Zhang, Xin Wang, and Joseph E. Gonzalez. 2023. Gorilla: Large language model connected with massive apis. *Preprint*, arXiv:2305.15334.
- Hammond Pearce, Baleegh Ahmad, Benjamin Tan, Brendan Dolan-Gavitt, and Ramesh Karri. 2021. Asleep at the keyboard? assessing the security of github copilot's code contributions. *Preprint*, arXiv:2108.09293.
- Sida Peng, Eirini Kalliamvakou, Peter Cihon, and Mert Demirer. 2023. The impact of ai on developer productivity: Evidence from github copilot. *Preprint*, arXiv:2302.06590.
- Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Lauren Hong, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. 2023. Toolllm: Facilitating large language models to master 16000+ real-world apis. *Preprint*, arXiv:2307.16789.
- Yasaman Razeghi, Robert L. Logan IV, Matt Gardner, and Sameer Singh. 2022. Impact of pretraining term frequencies on few-shot reasoning. *Preprint*, arXiv:2202.07206.
- Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Romain Sauvestre, Tal Remez, Jérémy Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. 2023. Code Ilama: Open foundation models for code. *Preprint*, arXiv:2308.12950.
- Freda Shi, Xinyun Chen, Kanishka Misra, Nathan Scales, David Dohan, Ed Chi, Nathanael Schärli, and Denny Zhou. 2023a. Large language models can

be easily distracted by irrelevant context. *Preprint*, arXiv:2302.00093.

- Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen tau Yih. 2023b. Replug: Retrievalaugmented black-box language models. *Preprint*, arXiv:2301.12652.
- Chenglei Si, Zhe Gan, Zhengyuan Yang, Shuohang Wang, Jianfeng Wang, Jordan Boyd-Graber, and Lijuan Wang. 2023. Prompting gpt-3 to be reliable. *Preprint*, arXiv:2210.09150.
- Swami Sivasubramanian. 2023. Announcing new tools for building with generative ai on aws. [Accessed: (June 15, 2024)].
- CodeGemma Team, Ale Jakse Hartman, Andrea Hu, Christopher A. Choquette-Choo, Heri Zhao, Jane Fine, Jeffrey Hui, Jingyue Shen, Joe Kelley, Joshua Howland, Kshitij Bansal, Luke Vilnis, Mateo Wirth, Nam Nguyen, Paul Michel, Peter Choy, Pratik Joshi, Ravin Kumar, Sarmad Hashmi, Shubham Agrawal, Siqi Zuo, Tris Warkentin, and Zhitao et al. Gong. 2024. Codegemma: Open code models based on gemma.
- Neeraj Varshney, Wenlin Yao, Hongming Zhang, Jianshu Chen, and Dong Yu. 2023. A stitch in time saves nine: Detecting and mitigating hallucinations of llms by validating low-confidence generation. *Preprint*, arXiv:2307.03987.
- Boxin Wang, Wei Ping, Peng Xu, Lawrence McAfee, Zihan Liu, Mohammad Shoeybi, Yi Dong, Oleksii Kuchaiev, Bo Li, Chaowei Xiao, Anima Anandkumar, and Bryan Catanzaro. 2023a. Shall we pretrain autoregressive language models with retrieval? a comprehensive study. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 7763–7786, Singapore. Association for Computational Linguistics.
- Yile Wang, Peng Li, Maosong Sun, and Yang Liu. 2023b. Self-knowledge guided retrieval augmentation for large language models. *Preprint*, arXiv:2310.05002.
- Yasin Abbasi Yadkori, Ilja Kuzborskij, András György, and Csaba Szepesvári. 2024. To believe or not to believe your llm. *Preprint*, arXiv:2406.02543.
- Ori Yoran, Tomer Wolfson, Ori Ram, and Jonathan Berant. 2023. Making retrieval-augmented language models robust to irrelevant context. *Preprint*, arXiv:2310.01558.
- YouType. 2024. mypy_boto3_builder. https://github.com/youtype/mypy_boto3_builder/.
- Daoguang Zan, Bei Chen, Yongshun Gong, Junzhi Cao, Fengji Zhang, Bingchao Wu, Bei Guan, Yilong Yin, and Yongji Wang. 2023. Private-libraryoriented code generation with large language models. *Preprint*, arXiv:2307.15370.

- Fengji Zhang, Bei Chen, Yue Zhang, Jacky Keung, Jin Liu, Daoguang Zan, Yi Mao, Jian-Guang Lou, and Weizhu Chen. 2023a. Repocoder: Repository-level code completion through iterative retrieval and generation. *Preprint*, arXiv:2303.12570.
- Muru Zhang, Ofir Press, William Merrill, Alisa Liu, and Noah A. Smith. 2023b. How language model hallucinations can snowball. *Preprint*, arXiv:2305.13534.
- Shuyan Zhou, Uri Alon, Frank F. Xu, Zhiruo Wang, Zhengbao Jiang, and Graham Neubig. 2023. Docprompting: Generating code by retrieving the docs. *Preprint*, arXiv:2207.05987.
- Hengcheng Zhu, Lili Wei, Valerio Terragni, Yepang Liu, Shing-Chi Cheung, Jiarong Wu, Qin Sheng, Bing Zhang, and Lihong Song. 2023. Stubcoder: Automated generation and repair of stub code for mock objects. ACM Transactions on Software Engineering and Methodology, 33(1):1–31.

Supplementary Material: Appendices



Figure 10: **CloudAPIBench API Frequency Distribution.** y-axis shows number of tasks in CloudAPIBench satisfying the respective criterion.

A CloudAPIBench

A.1 Composition

We give more details about the composition of CloudAPIBench here. CloudAPIBench comprises several AWS and Azure APIs, each annotated with an API frequency proportional to the API's representation in public sources. Figure 10 shows the API frequency distribution across three bins: low, medium and high, for both AWS and Azure.

A.2 Construction

We follow a multi-step procedure to obtain synthetic evaluation tasks in Python for AWS and Azure APIs to include in CloudAPIBench. A summary of the process is shown in Figure 11. We describe each step in detail here.



Figure 11: Summary of steps to construct CloudAPIBench.

- 1. **Download The Stack v2.** We download The Stack v2 from its official repository on HuggingFace and SoftwareHeritage (Lozhkov et al., 2024).
- 2. Locate Documentation & Syntax. We use boto3 1.34.108 for AWS and the Python package azure-sdk-for-python for Azure. For AWS, we use the mypy_boto3_builder tool (YouType, 2024) to create API stubs for all AWS APIs; this helps us obtain the list of APIs. We obtain the official documentation for each of these by scraping the boto3 webpage for the respective APIs. For Azure, the complete docstring in the source code for an API's definition is its documentation.
- 3. Extract source specific code. We identify source specific code samples in The Stack v2 so that we restrict the count of API frequencies to only these. For AWS, source specific files are those that import one of {boto3, botocore} or contain one of {aws, boto, amazon} in the filepath. Similarly, Azure specific samples are those that import azure or contain azure in the filepath.
- 4. Extract API specification. For Azure, the complete documentation is available as a doc-string in the respective function definitions for that API. Using tree-sitter, we parse the code files to obtain the list of APIs, their correct usages and complete docstrings for Azure, for as many APIs as possible. For AWS, we parse API stubs obtained using mypy_boto3_builder to curate the API specifications. This also serves as the index of APIs that we use in our experiments.
- 5. Measure API frequencies. Given the list of APIs for a source, we count the number of times functions with the name as an API are invoked or defined within the source specific code samples identified above. We use several heuristics to avoid edge cases and maintain reliability. Nevertheless, some noise may creep in and we acknowledge that this process is far from perfect. However, the findings based off of these API frequencies align with our expectations, indicating their reliability.

- 6. Sample APIs for evaluation. While sampling APIs for evaluation, we take care to ensure diversity with respect to API frequencies (uniform sampling from each frequency class as far as possible) and invocation complexity (within each frequency class, there should be uniform distribution of the number of required arguments required by APIs). This ensures that CloudAPIBench is diverse and represents diverse software-engineering scenarios, from low to high frequency, and from APIs that are easy to invoke to those that require careful recall of API syntax. Further each API may appear in CloudAPIBench up to 3 times with different prompts.
- 7. **Translate API descriptions.** Each sample in CloudAPIBench contains a comment that expresses the intent to invoke the API. We obtain this comment by instructing Claude 3 Sonnet (Anthropic, 2024) to translate the documentation description of the API into 3 concise developer style comments. We use few-shot prompting to do this, and upon manual inspection of dozens of responses, find that Claude is able to do this task reliably. As such, we use Claude's responses as comments describing the intent to invoke the APIs, fixing any issues that were noticed manually.
- 8. **Construct synthetic prompts.** As the final step, for the selected APIs, we create synthetic prompts by creating an incomplete code sample: these start with relevant imports, contain necessary variable declarations, include the comment expressing the intent to invoke an API, and end just before the API invocation. Manual inspection revealed that in a few cases, multiple APIs may be suitable targets for a task, and in such cases we manually enumerate all the possible targets to the best of our knowledge.

A.3 Evaluation

Metric Calculation. When more than one target API is identified, as described in Appendix A.2, we consider the candidate to be valid as long as it satisfies the syntax of any one of the target APIs.

Inference. While base models can be directly evaluated on CloudAPIBench, instruction-tuned models need to be instructed to generate an API invocation. We use a system prompt to achieve this; this is shown in Listing 1.

A.4 CloudAPIBench Samples

We show more samples from CloudAPIBench for illustration purposes here. Azure samples are shown in Figure 12 and AWS samples are shown in Figure 13. Each sample also shows the target API and the frequency classification of the API.

A.5 Hallucination Categorization & Illustration

We classify API hallucinations into three broad categories:

- 1. Usage of incorrect existing API. This occurs when the Code LLM attempts to invoke an API that exists but does not fulfill the task (see Figure 14a).
- 2. **Invalid usage of target API**. This occurs when the Code LLM attempts to invoke the correct API but does so incorrectly due to an invalid configuration of arguments; here the model may either pass arguments that the API does not accept or not pass a correct combination of required and optional arguments (see Figure 14b).
- 3. Usage of non-existing API. This occurs when the Code LLM attempts to invoke an API that does not exist (see Figure 14c).

A.6 Analyzing Low Frequency API Failures

We look closer into the various modes of failure for low frequency APIs in Table 4. We present this analysis for the largest model in each model family.

As shown, most failures arise when the models try to invoke a non-existing API or use the target API incorrectly. This goes to show the lack of knowledge about low frequency APIs, and the propensity to hallucinate under these scenarios in Code LLMs.

Model	Valid (%) Invalid (%)		Invalid API Invocations Breakdown				
Iviouei	valiu (70)	Ilivaliu (%)	Usage of incorrect existing	Invalid usage of target	Usage of non-existing		
Google CodeGemma-7B	12.36	87.64	10.68	35.47	53.85		
StarCoder2-15B	24.72	75.28	10.95	33.33	55.72		
IBM Granite-Code-20B	32.21	67.79	17.13	23.76	59.12		
DeepSeekCoder-33B	34.83	65.17	15.52	31.03	53.45		
GPT-40	38.58	61.42	13.41	33.54	53.05		

Table 4: **Results on CloudAPIBench for low frequency APIs.** We first show the fraction of valid and invalid API invocations for low frequency APIs for various models. The invalid API invocations are categorized into various types of failures. Notably, > 50% failures occur due to the models attempting to invoke non-existing APIs.

```
You are code completion model. You generate code starting from the end of the prompt
given to you. You will give your output surrounded by backticks.
Notably, the prompt requires you to complete an API invocation. Complete the API
invocation and stop there. Do not write any code other than the single API
invocation.
As an example you will be given a code input. And you should return your output as:
You are code complete the API
You are code input. And you should return your output as:
You are code complete the API
You are code input. And you should return your output as:
```

Listing 1: System prompt to evaluate instruction-tuned models such as GPT-40 on CloudAPIBench.

```
from azure.communication.callautomation import CallConnectionClient
from consts import client_args, client_kwargs
# initialize callautomation client
client = CallConnectionClient(*client_args, **client_kwargs)
```

```
# Send DTMF tones to the current call
response = client.
```

Target API: send_dtmf_tones ; Frequency: Low

```
from azure.storage.blob import ContainerClient
from consts import client_args, client_kwargs
# initialize blob client
client = ContainerClient(*client_args, **client_kwargs)
# Mark blobs or snapshots for deletion
response = client.
Target API: delete_blobs ; Frequency: Medium
```

Figure 12: Azure samples from CloudAPIBench.

```
import boto3
# initialize networkmanager client
client = boto3.client("networkmanager")
# Get details of network resources for a global network
response = client.
```

Target API: get_network_resources ; Frequency: Low

```
import boto3
# initialize iam client
client = boto3.client("iam")
# Add a user to an IAM group
response = client.
Target API: add_user_to_group ; Frequency: High
```



B Documentation Augmented Generation (DAG)

B.1 Augmentation Designs

We define and illustrate various augmentation designs in this section.

- API Name Only. We include only the name of the retrieved APIs as augmentation. This can test if the Code LLM can invoke the correct API just by referencing its name during inference.
- API Description. We include the name and a short description of the API. For Azure the short description is the first sentence from the API's docstring, whereas for AWS the short description is the first 5 sentences from the API's documentation on the boto3 webpage. We choose 5 here as we found, in several cases, the first 2 - 3 sentences to be irrelevant to the API's description.
- API Specification. This is a concise summary of the syntax of the API. It includes the name of the API and the list of required and optional arguments without specifying any descriptions of the arguments.

- API Description + API Specification. This includes the description as defined above along with the specification as discussed above.
- Full Docstring. This uses the entire collected documentation as augmentation. Since this can be arbitrarily large, especially for AWS documentation, we right-truncate the documentation up to 5000 characters before augmenting. This assumes that the necessary information to invoke the API is within the first 5000 characters.

We illustrate these strategies in Figure 15. We skip "API Description + API Specification" in the figure as it is a combination of "API Description" and "API Specification".

Target API: get_deployed_application_health ; Frequency: Low

(a) The model is attempting to invoke an API that exists (get_application_health) but does not match the task description for the target API (get_deployed_application_health).

```
import boto3
# initialize autoscaling client
client = boto3.client("autoscaling")
# Finish lifecycle action with specified result
response = client.complete_lifecycle_action(
    LifecycleHookName="my-lifecycle-hook",
    AutoScalingGroupName="my-auto-scaling-group",
    LifecycleActionResult="CONTINUE",
    LifecycleHookToken="my-lifecycle-hook-token",
)
```

Target API: complete_lifecycle_action ; Frequency: High

(b) For this high frequency API, the model passes an argument that the API does not accept (red). Notably, all other arguments passed here are valid.

```
from azure.servicefabric import ServiceFabricClientAPIs
from consts import client_args, client_kwargs
# initialize servicefabric client
client = ServiceFabricClientAPIs(*client_args, **client_kwargs)
# Get latest upgrade details for compose deployment
response = client.get_latest_upgrade_details(
    resource_group_name="resource-group-name",
    cluster_name="cluster-name",
    deployment_name="compose-deployment-name",
    )
Target API: get_compose_deployment_upgrade_progress ; Frequency: Low
```

(c) The model is attempting to invoke a non-existent API here.

Figure 14: **API Hallucination Scenarios.** We show three different ways in which Code LLMs hallucinate for tasks on CloudAPIBench. Here the model responses are from Google CodeGemma-7B.

Use the following API information as reference: API name: list_identity_pool_usage Service/Client name: cognito-sync ====================================	""" Use the following API information as reference: API name: list_identity_pool_usage Service/Client name: cognito-sync Description: Gets a list of identity pools registered with Cognito. ListIdentityPoolUsage can only be called	""" Use the following API information a reference: API name: list_identity_pool_usage Service/Client name: cognito-sync Gets a list of identity pools registered with Cognito. ListIdentityPoolUsage can only be called with developer credentials. You cannot make this API call with			
<pre>""" Use the following API information as reference: API name: list_identity_pool_usage Service/Client name: cognito-sync Optional arguments: NextToken MaxResults ====================================</pre>	<pre>with developer credentials. You cannot make this API call with the temporary user credentials provided by Cognito Identity. ====================================</pre>	<pre>the temporary user credentials provided by Cognito Identity. See also: AWS API Documentation Request Syntax response = client.list_identity_pool_usage(NextToken='string', MaxResults=123) ================================</pre>			
API Specification		Full Documentation			

Figure 15: **API augmentation designs**. Illustrated for the AWS API: list_identity_pool_usage. "Full Documentation" is truncated to fit in the figure.